Machine Learning Rehabilitation for Stroke Patients

Ramesh Prabhakaran R.[1,*], Angel Maanu P.[2], Niranjan G.[3], Karthika K.[4]
[1]Department of Computer Engineering, Mizoram University, Mizoram, India
[2]Department of Computer Science and Engineering, Panimalar Engineering College, Chennai, India
[3]Department of Mechanical Engineering, Panimalar Engineering College, Chennai, India
[4]Department of Information Technology, Karpagam College of Engineering, Coimbatore, India
Emails: rkrrameshsamy5@gmail.com; maanuangel87@gmail.com; janniran00@gmail.com; karthikakit141@gmail.com

Abstract

This study explores the use of algorithmic for learning (ML) techniques in stroke rehabilitation to enhance patient outcomes and care. Machine learning offers potential uses in outcome prediction, progress tracking, customized treatment planning, and assessment. Algorithms based on machine learning (ML) can assist doctors with seriousness of stroke assessment, which is treatment plan customization, monitoring of progress, and long-term result prediction by leveraging a range of data sources, such as sensor data, doctor's notes, and medical images. Through personalized interventions and timely feedback, machine learning (ML) can optimize rehabilitation efforts and improve the standard of life for stroke patients. Interdisciplinary cooperation and ethical considerations are required to ensure the responsible and effective application of ML in physiotherapy after a stroke treatment. This study highlights the significant impact on the treatment of patients and their outcomes as it investigates the potential applications of algorithms for learning (ML) in recovery from stroke. These applications include result prediction, customized treatment planning, assessment methods, and progress monitoring. Through a convergence of current research findings and technological advancements, we illustrate how machine learning (ML) approaches can exploit many information modalities to assist professionals in providing tailored rehabilitation therapies and optimizing patient care. Despite the benefits that seem obvious, adoption needs to be fair and responsible. Problems like algorithmic bias, concerns about data privacy, and barriers to integrating clinical information need to be fixed.

Keywords: Stroke Rehabilitation; Neural Networks; Regression Model; Wearable Sensors; Adaptive Therapy

1. Introduction

Stroke is a leading cause of disability worldwide, posing systemic as well as individual challenges to the healthcare system. Every year, millions of individuals worldwide suffer from strokes, which can cause a range of physical, mental, and emotional problems. For stroke survivors, intense rehabilitation is often required to regain lost functions and improve their overall quality of life. However, traditional rehabilitation methods cannot always address the range of requirements that stroke patients have, which can sometimes lead to less-than-ideal outcomes [19]. In recent years, there has been an increasing amount of enthusiasm and interest developed regarding the potential of machine learning (ML) in stroke rehabilitation. Machine learning (ML) is a subfield of artificial intelligence that focuses on developing algorithms that can identify patterns in data, draw conclusions or predictions from them and do it with little to no assistance from humans. Machine learning (ML) in conjunction with big data and advanced analytics techniques has the potential to totally change stroke rehabilitation in an assortment of areas, including assessment, treatment planning, progress tracking, and outcome prediction. The basis for the application of algorithmic learning in the treatment of strokes is an understanding of the complex and

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

multifaceted processes involved in stroke healing. Machine learning (ML) offers the prospect of tailored, data-driven therapies that are tailored to the unique needs of stroke sufferers, in contrast to traditional rehabilitation techniques that usually rely on qualified judgment and standardised protocols. This customized approach may improve functional outcomes, boost treatment efficacy, and ultimately raise the normal level of living for those who have suffered strokes overall. Machine learning (ML) has the potential to significantly improve stroke rehabilitation in several areas, one of which is the assessment of stroke severity and associated functional impairments. Following a stroke, healthcare providers must accurately assess the extent of neurological deficits and select the most effective rehabilitation strategies. Algorithms that use machine learning can assess a range of data sources, including imaging studies, sensor data, and physician evaluations, to provide more objective and quantitative predictions of stroke severity [20]. By utilizing complex algorithms and integrating diverse data sources, machine learning (ML) has the potential to generate comprehensive patient profiles. This enables healthcare providers to tailor rehabilitation programs to address specific limitations and functional impairments. Furthermore, treatment planning and rehabilitation after a stroke decision-making can benefit greatly from machine learning (ML). Historically, rehabilitation programs have been developed based on general guidelines and expert opinion, which sometimes neglects to account for the needs and characteristics of each patient. Machine learning algorithms have the capability to analyse vast quantities of patient data and treatment response data to identify patterns and relationships between various treatments and functional effects. By applying this data-driven approach, healthcare providers can improve the patient's results and recovery pathways by making better informed decisions about which rehabilitation plan is ideal for certain patients. In addition to providing ongoing observation and analysis of patients' advancement during their rehabilitation, machine learning (ML) can assist in treatment planning. Stroke recovery is an unpredictable and unpredictable process because patients often suffer fluctuations in their functioning abilities and restoration paths over time. ML algorithms analyse continuously changing streams of the information, such as data acquired by fashionable gadgets' sensors or electronic health records, to find early markers of either an improvement or a decline in a patient's condition. By providing real-time feedback to healthcare providers, machine learning (ML) can improve rehabilitation interventions and ensure that patients receive prompt revisions to their treatment programs [21]. Two other areas where machine learning (ML) might significantly improve stroke therapy are the forecasting of long-term results and the discovery of external factors that may affect rehabilitation trajectories. ML algorithms can be used to analyse large patient the demographics of clinical and healthcare history datasets to identify factors that influence functional outcomes such as memory retention, motor reimbursement, and general happiness of life. By identifying these markers, healthcare providers may more precisely project the long-term needs of stroke patients and develop more targeted and proactive rehabilitation programs. While there are many potentials uses for machine learning (ML) in stroke rehabilitation, there are an assortment of considerations and concerns that must be made to ensure ML is applied properly. One of the biggest challenges is the need for large and diverse datasets for machine learning algorithms to be successfully trained. While electronic health records and imaging tests are valuable sources of data, their ability to provide specific patient demographics or clinical considerations may be limited. Collaboration is needed to gather and organize data from multiple sources to develop predictive models using machine learning for stroke rehabilitation that are trustworthy and widely applicable. Legal and ethical issues are also brought up using ML in medicine, particularly in touchy areas like algorithmic bias and patient privacy. Healthcare practitioners need to ensure that algorithms based on machine learning are transparent, comprehensible, and free of bias or discrimination when making decisions that may affect patient care. Health specialists, data scientists, and engineers need to collaborate across disciplines to develop and implement solutions using machine learning (ML) that are tailored to the needs and procedures of clinical settings. Lastly, it should be mentioned that artificial intelligence (AI) has enormous promise to transform stroke rehabilitation through the provision of individualized, data-driven therapies that can optimize therapy efficacy and improve patient outcomes. ML algorithms, by leveraging large datasets and sophisticated analytics approaches, can enhance the assessment, treatment planning, progress tracking, and outcome prediction associated with stroke rehabilitation. It will be vital to address the problems and worries surrounding machine learning's implementation in the healthcare industry if we are to realize the technology's full promise and ensure that it is applied appropriately and ethically in clinical settings. With more research, collaboration, and innovation, machine learning (ML) holds the potential to revolutionize stroke rehabilitation and improve the lives of tens of thousands of stroke survivors worldwide [22].

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

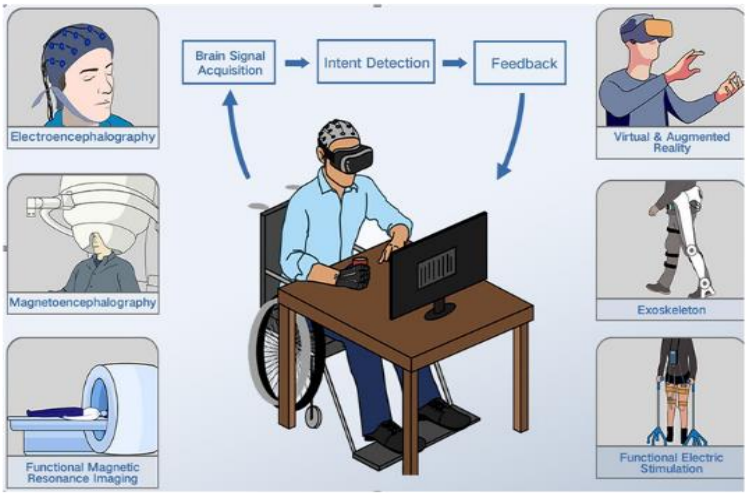

Figure 1. Stroke Detection and Rehabilitation

1.1. Introduction To Wearable Sensors in Stroke Rehabilitation:

Wearable sensors provide real-time insights on an individual's campaigns, activities, and physiological responses, making them invaluable aids in stroke recovery. Their versatile usefulness is essential for maximizing recovery results. This is a comprehensive analysis of the application of wearable sensors in stroke rehabilitation Figure 1.

A. Monitoring Physical Activity:

Wearable sensors, including gyroscopes and accelerometers, considerably improve the monitoring of sport participation in stroke patients by providing exact tracking of motions throughout appointments for therapy and in regular activities. Therapists can obtain a thorough grasp of a patient's movements and functional capacities with the help of this data. Figure 2. Wearable sensors make it possible to analyses gait dynamics in detail, exposing abnormalities, asymmetries, and compensating techniques. Equipped with this knowledge, therapists can customize interventions aimed at improving gait and balance, focusing on areas of dysfunction or impairment. Additionally, ongoing assessment of limb coordination and range of motion provides objective information to clinicians about a patient's development over time.

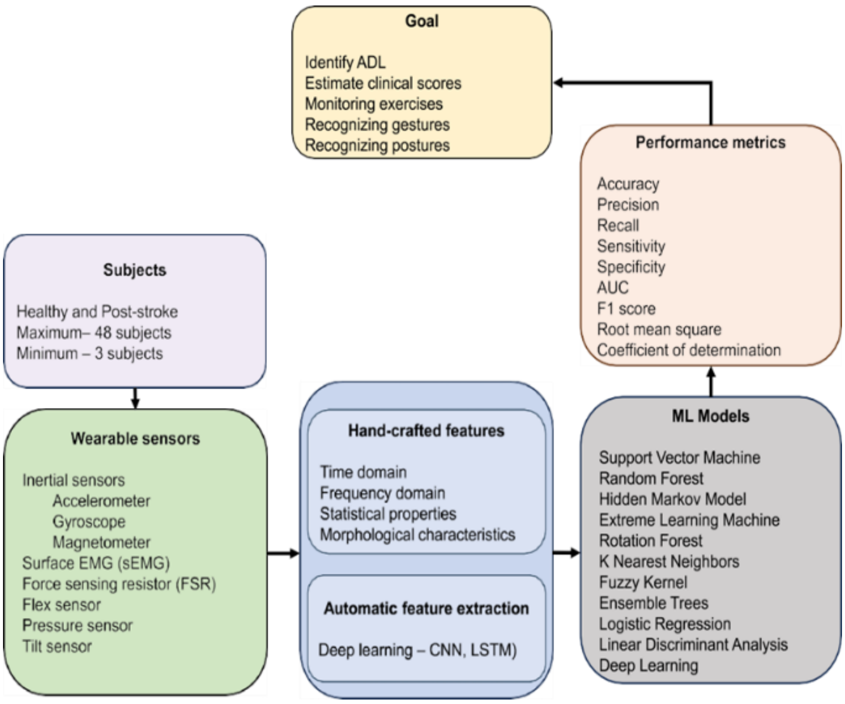

Figure 2. Wearable Sensor in Stroke Detection

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

B. Biofeedback:

Biofeedback mechanisms help stroke patients learn how to manage their motor skills by giving them instant visual or aural clues through wearable sensors. Visual feedback may provide fully immersive situations for participating individuals during rehabilitation exercises and encourage active involvement. Examples of this include virtual environments and augmented reality overlays. Metronome beats and speaks directions are examples of auditory cues that synchronize movements, enhance timing, and encourage task completion correctly, hence promoting neurological re-education and coordination.

C. Evaluation of Functional Abilities:

Wearable sensors provide objective measurements of functional abilities, such as grip strength, upper limb function, and hand dexterity, which help assess the effectiveness of treatment and the state of rehabilitation. Cutting-edge sensor technologies allow for a thorough evaluation of the movement of muscles, synchronization structures, and functioning task performance. Examples of these technologies are ubiquitous electromyography (EMG) sensors and pressure-sensitive fabrics. Utilizing specific approaches and progressive goal setting, therapists can enhance rehabilitation outcomes by identifying areas of improvement, adapting therapies, and continuously tracking and analysing functional indicators.'

D. Home-Based Rehabilitation:

Programs utilizing wearable sensors enable stroke victims to actively engage in their recuperation within the comfort of their own homes, encouraging independence and self-care. Strengthening patient engagement and accountability, remote monitoring technologies enable immediate communication, tracking of advancement, and adherence monitoring. Personalized workout plans, educational films, and motivating cues are all provided by mobile apps and wearable technology, which improves therapeutic compliance and encourages long-term lifestyle modifications.

E. Fall detection and prevention:

Wearable sensors are essential for assessing fall risk because they track gait traits, balance metrics, and movement patterns linked to an increased risk of falling. To identify fall incidents and promptly notify caregivers or medical professionals, computerized fall detection algorithms use sensor data. This lowers the risk of injury and ensures quick assistance. Wearable sensor data is used to inform fall prevention techniques that reduce fall risks and improve safety throughout daily activities. These tactics include focused equilibrium classroom instruction, gait reconditioning exercises, and environmental adjustments.

F. Personalized Rehabilitation Plans:

Wearable sensor data is analysed by machine learning algorithms to create customized rehabilitation plans that are suited to the requirements, skills, and objectives of stroke patients. Adaptive therapies maximize treatment efficacy and support long-term functional recovery by dynamically adjusting in response to immediate feedback and progress markers. Personalised setting targets, quantifiable measurements of outcomes, and data-driven decision-making enable medical professionals to provide patient-cantered, evidence-based care that maximizes recovery and quality of life following a stroke.

G. Tele-Rehabilitation:

Stroke patients can participate in therapy sessions remotely thanks to wearable sensor-enabled applications. Virtual rehabilitation sessions are made easier for patients who might find it difficult to travel to in-person consultations by real-time monitoring of motions and activities. In addition, tele-rehabilitation provides chances for remote evaluation, intervention, and progress monitoring, improving care coordination and reaching marginalized groups with rehabilitation services.

H. Pain management:

Wearable sensors can help stroke patients, especially those who are suffering from pain that is neuropathic or musculoskeletal discomfort, monitor and control their pain. Continuous monitoring of physiological variables, such as skin conductance and heart rate variability, may reveal information about pain intensity and triggers, enabling the development of customized pain management techniques. Wearable sensors can be used to implement biofeedback techniques, which can improve coping strategies and teach patients how to modify their perception of pain, thereby improving their quality of life throughout rehabilitation.

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

I. Cognitive Rehabilitation:

Wearable sensors are useful in the rehabilitation of cognition for stroke victims, especially when it comes to testing and tracking cognitive abilities including executive function, memory, and attention. Wearable technology sensors can measure cognitive performance indicators like task completion rates, accuracy, and response times. This allows for the objective collection of data for cognitive examinations and intervention plans. Figure 3. Wearable technology-based cognitive training programs, which include utilized gaming for exercises and interactive assignments, provide patients with strokes with fun and efficient means of enhancing their cognitive abilities and encouraging neuroplasticity.

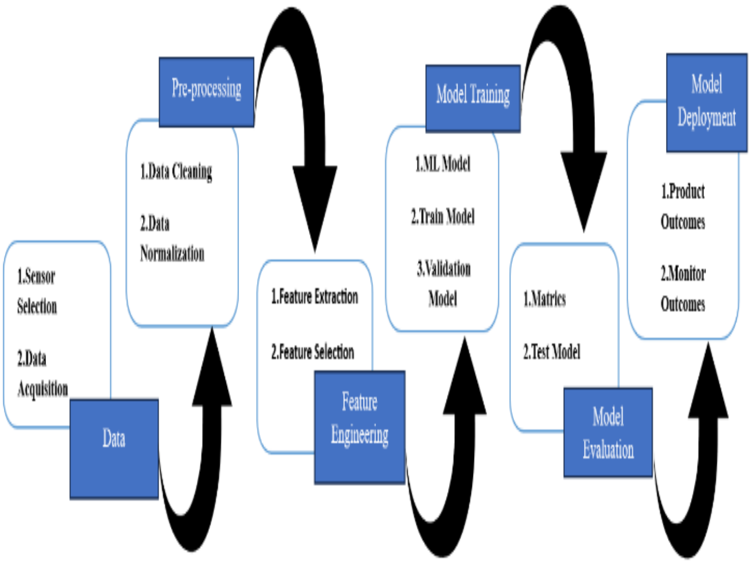

Figure 3. Model of Stroke Rehabilitation

1.2. Introduction To Machine Learning in Data Analysis:

This section covers the different kinds of data that are used in machine learning (ML), the different types of ML, pre-processing techniques, feature engineering, ML models, training, evaluating, and deploying the models, as well as the qualitative and quantitative implications of different processes on the results.

A. Data Analysis:

In medical establishments, several techniques are employed to gather patient data to deliver the necessary medical care. Most sensor data is quantitative, either quantitative or a natural number. Conversely, the information obtained by a patient's electronic health record (EHR) is mostly of a qualitative (categorical) nature and usually consists of a computerized patient history form. Longitudinal data, gathered over time, makes up the EHR. Age, gender, demography, issue history, immunization history, doctor's notes, reports, and test results are all included. The terms computer-based patient records (CPR) and electronic medical records (EMR) are other names for it. A graph representing data collecting in the medical profession is presented and is separated into four categories: independent, perpetual, nominal, and ordinal. There are two categories for numerical (quantitative) data: discrete (like the total number of healthcare visits) and continuous (like the weight of patients). Conversely, nominal (unordered data, like male or female) and logarithmic (ordered data, like cancer stages [I–IV]) can be used to categorize categorical (qualitative) data. The aforementioned information types are essential for specifying machine learning issues and building suitable models.

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

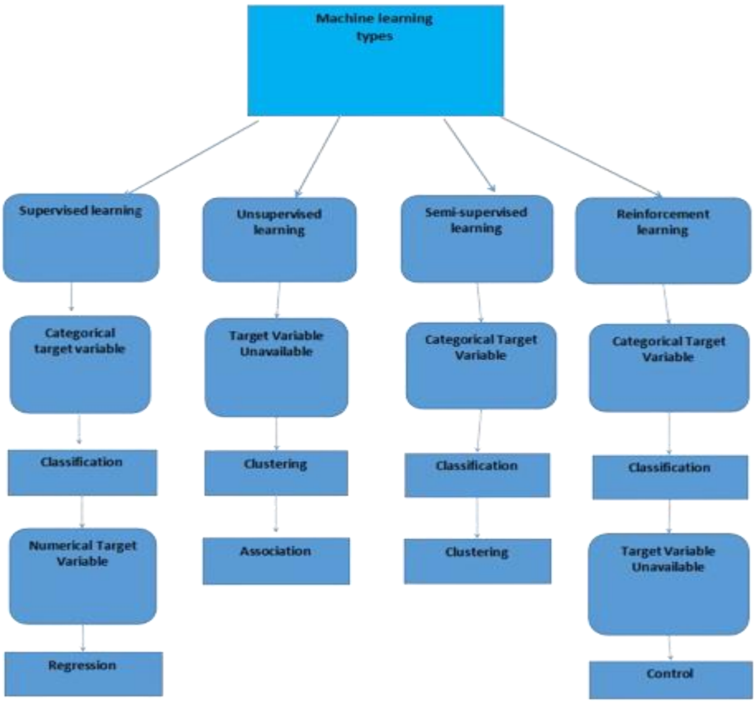

Figure 4. Machine Learning Types in Stroke Detection

B. ML Specific to Stroke Rehabilitation

ML techniques have specific uses in stroke rehabilitation. Specialized classifiers may be used, depending on the goal of the rehabilitation. As an illustration, supervised learning is beneficial for classification jobs since it allows for a precise categorization of stroke patients according to pre-established patterns, including distinguishing between numerous kinds and severity levels of stroke or ADL. When target demographics are not easily accessible, clustering can be used to find patient groups who share traits or workout groups appropriate for severity categories. There are benefits to semi-supervised classifiers in situations where the labelled data is limited. Through the application of clustering algorithms, it is possible to leverage the patterns found in unlabelled data and derive features that can then be applied to the classification of labelled data. Adaptive intervention strategies can be developed via reinforcement learning, in which the patient learns to maximize the total rewards to enhance the outcomes of the sequential task. With this method, the patient gains rewards while learning by trial and error. This makes it possible to use each patient's answers and progress to optimize treatment regimens in real time. While using reinforcement learning in stroke rehabilitation, it is necessary to address ethical issues, put safety precautions in place, and incorporate expert knowledge. This enables for individualized treatment Figure 4.

C. Pre-Processing

A quick rundown of the procedures in the use of machine learning when it comes to data analysis is given in this paragraph. After gathering sensor data, the next stage is to categorize different types of activities and give a clinical score-equivalent comparative index. Pre-processing procedures are carried out based on the obtained data (after obtaining the data). There could be artifacts and noise in the data. Typical Amount 12, 2024 36033 pre-processing Assessment of Wearable technology Sensor and ML Algorithms by N. Sengupta et al. Attempts include handling missing values, eliminating outliers, and anchoring and scale (zero means with unit standard deviation). Whether these processes are necessary depends on the state of the data.

D. Feature Engineering

A feature, which is sometimes referred to as a predictor, displays the unique qualities of the sensors data and compactly expresses it. The extraction of features and feature selection are the core processes in feature engineering. For improved model performance, feature extraction converts the original input data (feature vector) into a new feature space. A thorough grasp of the issue, domain expertise, and associated problem elements are necessary for feature extraction. Frequently, to enhance the performance of ML models, new features are generated

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

from pre-existing ones. Five primary groups, or domains, can be used to categorize the features that were extracted from the sensor data: (1) time domain, (2) frequency domain, (3) statistics features, (4) morphological features, and (5) data-specific features.

1) Time domain features are the attributes that are taken straight out of the time series information (raw or pre-processed), preserving the temporal dynamics and patterns without converting them into other domains.
2) Time series data can be converted into the frequency domain to provide frequency domain features, which provide details on the spatial distribution of frequency elements and the related magnitudes.
3) The quantitative measures derived from important statistical features provide insights into the distribution, central tendency, and unpredictability of data.
4) Morphological features, which concentrate on the patterns, trends, or physical characteristics of the time series, encapsulate the shape and structure information of data.
5) Patterns that are extracted from individual datasets and customized to the attributes of that one dataset, as opposed to being universally applicable, are known as data-specific features. In accelerometer sensor data, for instance, the acceleration sequence can be recovered as a data-specific feature.

Feature selection, on the other hand, focuses on choosing the top k characteristics to enhance the model's functionality and facilitate its interpretability. Feature selection, sometimes referred to as subset selection, aids in lowering time complexity and feature redundancy. Feature selection can be approached in three ways: (1) Filter methods, (2) Wrapper methods, and (3) Embedded methods

.

1) Filter techniques rank these features after determining their association with the classes using a variety of statistical tests. The X 2 test, Fisher's absolute assessments, the Euclidean distance, the correlation coefficient of Pearson's, communication gain, and other tests are some of the often-used statistical tests.
2) Wrapper approaches use performance, usually of algorithms for categorization). To choose the best features, wrapper approaches therefore rely on classification algorithms. Genetic algorithms and successive backwards and forwards selection are a few examples of algorithms.
3) Integrated techniques the classifier has a method in place to dynamically alter the weights assigned to each component during training to choose features. Several methods include reinstatement model (the ridge regression, and greatest insignificant comparative shrinkage, and selection operator) and tree-based classification (e.g., decision trees, random forests).

Feature engineering includes feature extraction and selection. Additionally, techniques as if dimension reduction can be used for issues that call for lowering the correlation between features and projected the information towards a lower-dimensional space using PCA.

E. Classification Models

According to the research, categorization issues are often addressed by most machine learning models created with sensors attached to clothing in stroke therapy. Five application areas related to stroke rehabilitation have been identified in this paper. ADL identification, clinical score estimation, exercise monitoring, posture and gesture recognition are the first five. It provides an overview of these strategies. While these application domains employ many data kinds, the majority aim for classification results. For this reason, in this essay, we concentrate on categorization models. Classification algorithms are mathematical constructs that are intended to classify the results of a new observation (sensor data, for example) by using learned features from the gathered data. Using wearable technology, classifiers, for instance, can assist physicians in determining whether a patient is improving following treatment or declining. The primary determinants of model selection are feature type, task complexity, and sample size. Prior to being deployed to forecast fresh test data, the model is assessed, validated, and calibrated using training data. The most popular mathematical models for deep learning (convolutional neural network artificial neural networks, recurrent neural networks, transformers), as well as the most often used classical methods for classification (k-nearest fellow residents, SVM, RF, and k-means algorithms), are briefly described in this article. For more thorough explanations, the reader is urged to consult the pertinent source.

2. Related Works

In stroke therapy, machine learning has become a viable strategy that offers creative ways to improve recovery results. In the last twenty years, there has been a greater focus on research with the goal of optimizing stroke patients' rehabilitation procedures using technology and data-driven methodologies. Pioneering research from the mid-2000s [1], like Mehr Holz and Pohl (2007) [2] and Balasubramanian et al. (2006) [3], set the stage for investigating the effectiveness of robot-assisted rehabilitative in promoting gait training and regaining hand

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

function, respectively. These preliminary studies demonstrated how robotics might be used to provide individualized, intensive therapy and shed light on the biomechanical concepts that underpin motor recovery following a stroke. Important developments in the field of robot-assisted upper-limb therapy occurred in the late 2000s, as demonstrated by the seminal work of Lo et al. (2008) [4]. Their research opened a new chapter in neurorehabilitation by demonstrating the effectiveness of robot-assisted therapy in fostering long-term upper-limb recovery following stroke. Simultaneously, scientists started investigating the incorporation of automated learning techniques to predict rehabilitation results more accurately, as demonstrated by the study conducted by Vikanshi and Ferguson (2011) [5]. This research attempted to maximize functional gains and minimize disability by personalizing therapy regimens by utilizing patient data and computational models. Research on stroke rehabilitation underwent a paradigm shift in the early 2010s [6], with a growing interest in therapies powered by neuroplasticity and adaptive technologies. Robot-based hand motors therapy was first introduced by Takahashi [7] et al. (2012) [8], who emphasized the value of motor learning principles and task-specific training in fostering neural repair. This method, which was based on concepts related to learning and motor control, aimed to capitalize on the brain's innate ability to change, promoting adaptive modifications in neural networks after damage from a stroke. Simultaneously, attempts to enhance walking recovery using electromechanical assistance training became more popular, as the 2013[9] comprehensive review by Mehr Holz [10] et al. shows. The overarching goal of these interventions was to improve patients' quality of life by improving their speed of walking, endurance, and ability to move around through changing, task-driven training in an appropriately controlled environment. Research efforts to clarify dose-response connections in rehabilitation for strokes and optimize treatment procedures for maximum efficacy came together in the mid-2010s. Research like that conducted by Kwekel [11] et al. (2015) emphasized the significance of therapy duration and intensity in attaining significant functional improvements following a stroke, supporting the use of individualized, goal-directed interventions catered to the specific requirements of each patient. Additionally, scientists started looking into how neuroimaging methods like diffusion tensor imaging (DTI) and fMRI [12], which stands for functional magnetic resonance imaging, might be used to predict treatment outcomes and clarify the neural underpinnings of motor recovery. By integrating neuroimaging biomarkers with clinical assessments, this integrated method has the potential to advance the field of precision medicine in rehabilitation following a stroke by allowing physicians to customize therapies in accordance with objective neurophysiological [13] recovery markers. Simultaneously, the introduction of sensors for clothing and mobile health technology transformed the field of stroke rehabilitation by permitting home-based therapies and remote monitoring. Advancements like accelerometers and inertial measurement instruments (IMUs) [14] made it possible to continuously evaluate functional performance and movement kinematics, which allowed for coaching and real-time feedback during daily tasks. Furthermore, tele-rehabilitation platforms have become a competitive alternative to conventional in-person therapy, offering underprivileged populations easily accessible and reasonably priced ways to get evidence-based interventions. These technology advancements increased patient participation and adherence to treatment plans by enabling them to take an active role in their own recovery, in addition to broadening the scope of rehabilitation services. [15] have out meta-analyses to investigate dose-response connections in stroke rehabilitation, providing insight into the ideal concentration and level of treatment for various stages of recovery. Their results emphasized how crucial it is to customize interventions to each patient's unique characteristics, such as age, degree of impairment, and co-occurring conditions, to optimize treatment outcomes. Additionally, Verbeek et al. (2018) [16] conducted systematic reviews that summarized the body of research on physical therapy following a stroke. These studies gave doctors evidence-based recommendations for choosing the best therapies based on patient-specific characteristics and treatment [17] objectives. Research endeavours in the discipline persisted in concentrating on improving rehabilitation procedures and utilizing technology advancements to improve treatment results as the field advanced into the early 2020s [18].

3. Methodology

A. Predictive Modelling for Rehabilitation Outcomes:

The methodology entails gathering longitudinal data on clinical evaluations, treatment plans, demographics, and results for stroke patients undertaking rehabilitation. Regression and time-series analysis are examples of machine learning models that are taught to predict functional results based on data from early assessments. This enables more individualized treatment plans and enhanced rehabilitation techniques.

B. Sensor-Based Monitoring and Feedback Systems:

Methodology includes deploying wearable sensors or IoT devices to monitor stroke patients' movements, activities, and physiological parameters in real-time. Machine learning algorithms are used to analyze sensor data

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

for detecting abnormalities, predicting potential risks (e.g., falls), and providing feedback to patients and healthcare providers for optimizing rehabilitation exercises and activities.

C. Natural Language Processing for Clinical Documentation and Decision Support:

Methodology involves applying natural language processing (NLP) techniques to analyse clinical notes, reports, and documentation related to stroke rehabilitation. Machine learning models are trained to extract relevant information, such as patient progress, treatment plans, and adverse events, to assist healthcare providers in decision-making and care coordination.

D. Personalized Rehabilitation Intervention:

Methodology includes integrating multimodal data sources, such as imaging studies, genetic information, and psychosocial assessments, to create personalized rehabilitation plans for stroke patients. Machine learning algorithms are used to analyse individual characteristics and response patterns to different interventions, allowing for adaptive and tailored rehabilitation strategies that optimize functional recovery.

E. Virtual Reality and Gamification in Rehabilitation:

Methodology involves developing virtual reality (VR) environments and gamified rehabilitation exercises tailored to the specific needs and preferences of stroke patients. Machine learning techniques are applied to adapt the difficulty level, feedback mechanisms, and progression of virtual tasks based on real-time performance data and user engagement metrics, enhancing motivation and adherence to rehabilitation programs.

4. Algorithm Selection

Absolutely! Depending on the job or purpose, different formulas might be utilized when applying machine learning to stroke rehabilitation. Here are some other formulas frequently used in this field:
Regression Models:

A. Linear Regression:

The linear regression technique is a fundamental statistical method in machine learning that models the connection between a dependent parameter and several independent variables at once. Regression models with linear regression are frequently used in stroke rehabilitation to predict continuous results such as motor function restoration or cognitive function scores, using details about patients or treatment interventions.

B. Logistic Regression:

Regression using logistic regression is an approach to statistics for modelling binary consequences, such as either the existence or the absence of a specific condition or occurrence. In the context of rehabilitation after a stroke, logistic regression approaches are frequently used to forecast the probabilities of specific consequences, such as recurrence of stroke or the accomplishment of a rehabilitative strategy. The logistic regression framework estimates the likelihood of an event (such as a stroke recurrence) based on one or more predictor factors. The logistic regression function, also called the sigmoid function, converts the linear mixture of the variables that predict into a probability value between 0 and 1. The logistic regression formula is as follows:

C. Classification Models:

Support Vector Machines (SVM):

SVMs seek to identify the hyperplane that optimally separates data points from different categories in the space of features. This hyperplane increases the distance between the nearest points of information, referred to as support vectors, from various classes. Using different kernel functions, SVMs can handle both linearly and nonlinearly separable data.

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

D. Random Forests:

Random forests combine predictions from several decision trees rather than representing them with a single formula. The final prediction is frequently based on the technique (for classification) or median (for regression) of the individual tree forecasts.

E. Clustering Models: K-Means Clustering:

K-Means clustering was a technique for unsupervised learning that partitions a dataset into separate, not interconnected groups or clusters. Each data point is assigned to the clustering with the nearby mean, which serves as the cluster's prototype. In the context of rehabilitation for strokes, the technique of K-Means Clustering can be employed to organize patients based on comparable traits or recovery patterns, allowing for more tailored rehabilitation treatments.

F. Principal Component Analysis (PCA):

Principal Component Analysis (PCA) is a popular dimensionality reduction technique for machine learning and data analysis. It converts a big group of variables that are associated into a smaller number of non-correlated variables known as principal components. PCA is especially effective in minimizing the amount of high-dimensional information while conserving as much heterogeneity as feasible.

5. Existing Model

Classifiers, for example, can help doctors use wearable technology to assess whether a patient is getting better after treatment or getting worse [18]. The main factors that influence the choice of model are sample size, task complexity, and feature type. Training data is used to evaluate, validate, and calibrate the model before it is used to forecast new test data. This article provides a brief overview of the most widely used classical classification techniques (k-nearest fellow residents, SVM, RF, and k-means algorithms), as well as the most employed mathematical representations for deep learning (convolutional neural networks, artificially generated neural networks, recurrent neural networks, transformers). The reader is recommended to refer to the relevant sources for further in-depth explanations. The foundation of machine-learning-based rehabilitation is robotic-assisted therapy, which provides accurate, specific to the job training in a safe setting. Clinicians can target specific motor deficits with rigorous, repetitive training using robotic devices that are fitted with sensors and actuators. By giving therapists immediate input on performance measures like force effort, range of motion, and smoothness of movement, these devices enable them to track patient progress and modify therapy parameters as necessary. Robotic solutions simplify the rehabilitation process by automating repetitive chores and standardizing therapy protocols. This frees up clinicians to concentrate on individualized treatments and patient engagement. Wearable sensors are essential for home-based rehabilitation and remote monitoring, which expands the scope of stroke care outside of conventional clinical settings. Accelerometers, gyroscopes, and inertial measurement equipment (IMUs) allow for the continuous evaluation of movements kinematic and operational efficiency in real-world settings. These sensors enable monitoring yourself and adherence to recommended exercise programs by giving patients and clinicians insightful feedback. Additionally, wearable technology can identify early indicators of functional loss or motor degeneration, allowing for prompt intervention and the avoidance of further difficulties. Wearable sensors encourage patients to participate actively in their rehabilitation, which increases their sense of self-efficacy and gives them control over their recovery. Neuroimaging methods include electroencephalography (EEG), imaging with diffusion tensors (DTI), and fMRI (functional magnetic resonance imaging). These techniques provide important new insights into the brain mechanisms underpinning stroke recovery. Neuroimaging studies offer vital information regarding the functioning of the brain's neural networks, cortical rearrangement, and compensatory mechanisms by analysing developments in the structure and function of the brain after stroke. Neuroimaging data is analysed by machine learning algorithms to find indicators of recovery, forecast therapy response, and direct customized interventions. Through the integration of neuroimaging results with functional outcomes and clinical assessments, therapists can create customized rehabilitation plans that focus on certain brain areas and neural networks associated with learning and motor control. To executing rehabilitation interventions and encouraging motor learning, gamification approaches and virtual reality (VR) offer immersive and captivating platforms. Patients can perform functional skills in a secure and controlled environment by using virtual reality (VR) environments that mimic actual circumstances and responsibilities of daily living. Reward systems, problems, and progress tracking are examples of gamification components that encourage involvement and provide a sense of accomplishment, which improves motivation and therapeutic adherence. Additionally, VR-based rehabilitation programs may be tailored to meet the needs and preferences of each patient, making sure they have

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

a unique and enjoyable experience. The system's core is made possible by machine learning algorithms, which give clinicians the ability to handle, examine, and comprehend the enormous volumes of data produced by these various modalities. Supervised learning algorithms that classify patients according to their medical characteristics and forecast treatment results guide the selection of suitable therapies. Unsupervised learning methods help create customized treatment plans by revealing unconscious trends and groupings within patient populations. Reinforcement learning algorithms facilitate dynamic, adaptive rehabilitation procedures that maximize motor learning and recovery by enabling autonomous change of rehabilitation procedures in accordance with patient performance and feedback. To sum up, machine learning-based rehabilitation for stroke victims is a revolutionary approach to stroke care that makes use of cutting-edge technology and data-driven techniques to improve patient-cantered care and treatment outcomes. Through the integration of wearable sensors, neuroimaging, robotics, and virtual reality, this all-encompassing system provides customized and flexible solutions tailored to the unique requirements of stroke survivors. In the future, machine learning rehabilitation research and innovation could transform stroke care, improve functional outcomes, and improve their standard of life for millions of people impacted by this disabling illness globally.

6. Proposed Model

The goal of machine learning-based rehabilitation for stroke victims is to improve recovery rates and the quality of life for those who have experienced a stroke. The system under consideration incorporates state-of-the-art technologies, data-driven approaches, and customized interventions to maximize rehabilitation plans that are customized to meet the individual requirements of every patient. This all-encompassing system offers an extensive strategy to stroke rehabilitating which addresses impairments in movement, promotes neural plasticity, and gives patients the power to actively take part in their recovery process by utilizing machine-learning algorithms, the field of robotics sensors worn around the body, neuroimaging, and virtual reality. A complex predictive modelling framework that evaluates patient data, derives actionable insights, and creates individualized treatment regimens is the central component of the suggested solution. Support vector machines, also referred to as SVMs, and random forests are two examples of supervised learning algorithms that are used to categorize patients in accordance with their medical characteristics and forecast treatment results. These algorithms can find correlations and patterns that help select the best interventions and direct therapeutic decision-making by examining huge datasets that include demographic data, medical histories, and functional assessments. A key component of the suggested approach is robotic-assisted therapy, which offers exact, which is task-specific training to advance motor rehabilitation and functional independence. Therapists may provide intense, repetitive exercises that are customized to each patient's demands thanks to robotic devices that are fitted with sensors and actuators. These technologies optimize rehabilitation outcomes by facilitating motor development and adjustment through real-time feedback and movement kinematic monitoring. Moreover, robotic systems can dynamically modify therapy parameters in response to patient performance, guaranteeing that treatment plans stay demanding and productive all the way through the healing process. With wearable sensors, patients can follow their progress and participate in therapy sessions outside of hospital settings. Wearable sensors offer a variety of options for monitoring from afar and home-based rehabilitation. Continuous kinematics monitoring is made possible by inertial measurement instruments (IMUs), accelerometers, and gyroscopes. This data is useful for assessing gait characteristics, upper limb function, and balance. Clinicians can collect independent information on patient performance, pinpoint areas for improvement, and adjust therapies by including sensors worn by patients into the rehabilitation process. Moreover, by enabling patients to actively participate in their own recovery, wearable technology can support self-management and therapeutic adherence. Neuroimaging modalities such as electroencephalography (EEG), imaging with diffusion tensors (DTI), and fMRI, which stands for functional magnetic resonance imaging, provide important new insights into the brain mechanisms underpinning stroke recovery. Neuroimaging studies can find indicators of recovery and forecast treatment response by looking at adjustments to the brain's structure and functioning after a stroke. Neuroimaging data is analysed by machine learning algorithms to find trends and correlations between motor function, brain activity, and rehabilitation outcomes. Through the integration of neuroimaging results with clinical evaluations, medical professionals can create customized treatment regimens that focus on certain brain circuits and promote neural plasticity. To delivering rehabilitation therapies and encouraging motor learning, the use of virtual reality (VR) and gamification approaches offer immersive, engaging settings. Patients can perform functional skills in a safe and controlled environment with VR simulations, while gamification features like challenges, awards, and progress tracking increase motivation and encourage involvement. Clinicians can design individualized and captivating experiences that encourage therapy adherence and expedite skill learning by integrating VR-based rehabilitation courses into the treatment routine. Additionally, VR technology may be modified to meet the preferences and skills of each patient, guaranteeing that physical therapy interventions are customized to meet their specific needs. In conclusion, the suggested machine learning rehabilitation system for stroke victims provides a thorough and customized method of stroke treatment. This system combines state-of-the-art technologies, data-driven approaches, and tailored interventions to maximize

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

recovery results, encourage neuronal plasticity, and enable patients to reach their rehabilitation objectives. The efficacy and convenience of stroke rehabilitation will be significantly improved in the future by ongoing studies and breakthroughs in machine learning rehabilitation, which will ultimately improve the quality of life for stroke victims Figure 5.

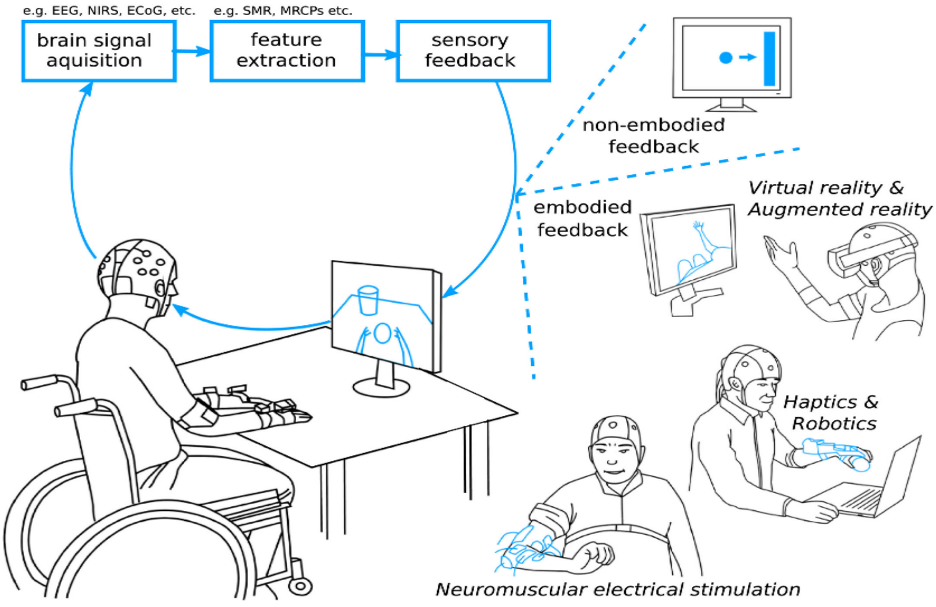

Figure 5. Proposed Method in Stroke Rehabilitation

7. Architecture Diagram

In machine learning applied to stroke rehabilitation, several algorithms can be employed depending on the specific task or objective. Here is an outline of the typical algorithmic process:

A. Data Collection:

Using wearable technology and robotic systems collect comprehensive patient data such as demographics, medical information, medical imaging information, and real-time performance data.

B. Data pre-processing:

Clean and prepare the acquired data, including resolving values that are not present, normalization features, and segmenting key characteristics for analysis.

C. Feature Selection and Engineering:

Identify critical features that influence recovery, use feature engineering to develop new useful features, employ dimensionality reduction approaches, and compress features appropriately.

D. Model Selection:

Choose appropriate machine learning methods, such as statistical models for regression, decision forests, or neural networks, based on both the characteristics of the data and the task at hand.

E. Model Training:

Divide the collected information into validation and training sets, then train the chosen models on the training data, assess their performance with cross-validation techniques, and tune model parameters to avoid overfitting Figure 6.

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

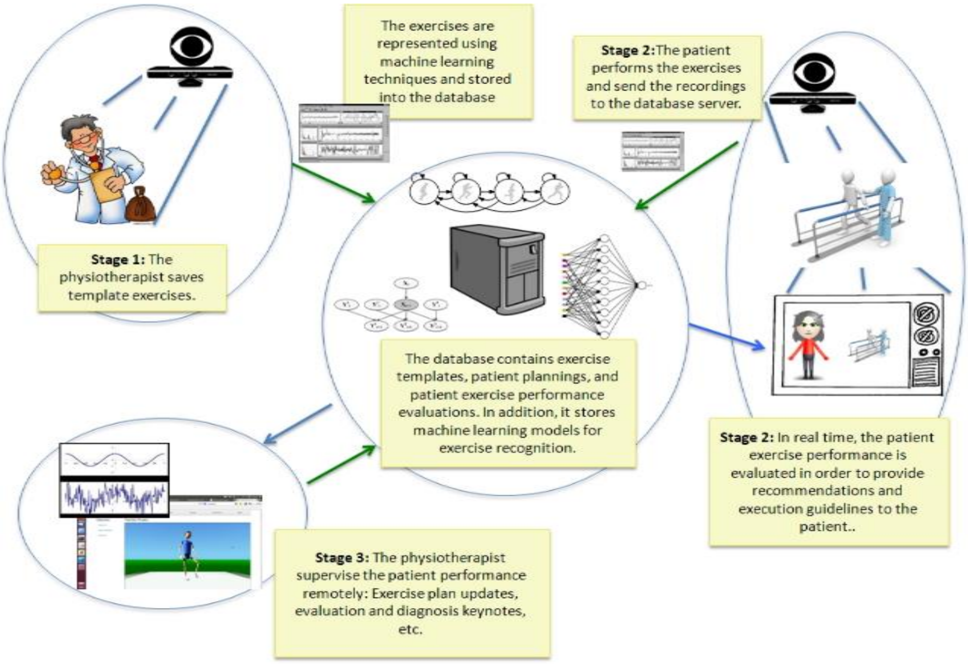

Figure 6. Collaborative Cluster for Stroke

8. Conclusion

The use of machine learning (ML) in rehabilitation following stroke is a game-changing innovation in medical science, with tremendous promise to improve the outcomes of patients through individualized, adaptive, and data-driven techniques. Stroke is the major cause of disability globally, demanding excellent rehabilitation treatments. ML technologies, such as modelling with predictive accuracy, robotic and sensor-based infrastructure, virtual reality (VR), and devices that are wearable, offer strong answers to many of the issues encountered in traditional rehabilitation procedures. Predictive models in rehabilitation for motor dysfunction have shown great accuracy in anticipating recovery results based on the demographics of medical facilities and imaging data. These models enable tailored rehabilitation programs, optimal therapy strategies, and better resource use. Robotic exoskeletons with wearable sensors combined with machine learning algorithms dramatically improve motor function regeneration by delivering immediate feedback and dynamically changing therapy protocols. Studies have shown significant increases in the speed at which one walks, balance, and total mobility, guaranteeing that therapy remains both demanding and doubler-based rehabilitation systems, when combined with ML algorithms, provide a fascinating and efficient means to undertake motor training. These immersive environments encourage motor development and neuroplasticity in children resulting in improved dexterity and strength in comparison with standard therapy. VR's participatory nature makes rehabilitation more pleasurable, which may increase adherence among patients to therapy regimens and lead to improved long-term outcomes.

In cognitive rehabilitation, machine learning has heightened both the precision and efficiency of cognitive examinations, allowing for earlier diagnosis and intervention. Algorithms that analyse language usage and eye movements are highly sensitive and specific in detecting diseases like aphasia. Adaptive cognitive training methods powered by machine learning adapt therapy depending on the patient and how they perform, dynamically altering activities to ensure ongoing challenge and improvement. These individualized approaches increase patient involvement as well as inspiration, resulting in more successful rehabilitation outcomes. Sensory rehabilitation has additionally benefited from machine learning-enhanced VR and virtual and augmented reality (AR) technological advances, which provide controlled settings that imitate real-world tasks and give repeating sensory inputs. Researchers have found that VR-based sensory retraining improves discrimination abilities and functional outcomes significantly. Wearable devices integrated with ML algorithms promote sensory rehabilitation through monitoring and delivering information concerning sensory functions, resulting in better integration of sensory functions and practical application of the damaged limb. Because of its ability to personalize therapy based on specific patient data, the use of ML in rehabilitation for strokes has proven to be highly effective. Forecasting

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

algorithms enable prompt intervention and individualized therapeutic programs, which lead to better outcomes. The versatility of ML-driven systems guarantees that rehabilitation exercises are tough but doable, enabling continual improvement and increased patient engagement. The individualized aspect of ML-driven rehabilitation improves motivation among patients and adherence, both of which are necessary for excellent recovery outcomes.ML-enhanced VR and gaming apps greatly boost patient motivation and engagement. The immersive and engaging nature of these innovations makes rehabilitation more pleasurable, increasing adherence to therapeutic regimens and breaking up the everyday routine of traditional activities. This greater adherence is critical for attaining the best recovery outcomes.ML enables decision-making based on data in rehabilitation, allowing doctors to base treatment recommendations on reliable information analysis rather than subjective evaluations. This strategy improves diagnostic accuracy, therapy efficacy, and the capacity to track progress over time. Clinicians may make choices that are more informed by harnessing data-driven insights, resulting in greater satisfaction with patients and more effective resource usage. Despite the positive outcomes, there are still significant hurdles to integrating machine learning into stroke therapy. High quality, big datasets are required for training reliable ML models, but gathering such data in healthcare facilities can be difficult due to variations in patient information and therapy methods. Ensuring ML systems' interoperability with conventional workflows in hospitals and health information systems (EHRs) presents considerable problems. Many medical care providers and patients may find the cost associated with sophisticated ML-driven rehabilitation technology, such as robotic systems and VR sets, prohibitively high. Accessibility in low-resource areas remains a major challenge. The use of personally identifiable information for ML applications creates ethical and privacy concerns, necessitating strong data security safeguards and ethical implementation. To solve these limitations and increase the impact of ML in rehabilitation following a stroke, future possibilities include developing standardized data collection procedures, improving communication of ML systems with EHRs, and the creation of cost-effective ML-driven rehabilitation technology. Open-source platforms and low-cost technology can make these developments available to a wider variety of patients as well as healthcare professionals. Implementing strong data governance structures and guaranteeing compliance with ethical norms and privacy rules will alleviate worries about the use of patient data in applications based on machine learning. Long-term studies are required to examine the long-term impact of ML-driven regeneration on patient outcomes, which will provide useful insights into the successful use of ML in physiotherapy and inform about the creation of more effective methods for treatment. In conclusion, the use of machine learning techniques in rehabilitation following a stroke holds great promise for improving the outcomes of patients through individualized, adaptive, and information-driven strategies. Probabilistic models, robotics and sensor-based systems, virtual reality and video game applications, and wearable technology have all shown promise for improving rehabilitation efficacy. However, issues such as data quality, seamless integration, expenses, availability, and moral considerations must be overcome before ML can completely fulfil its potential in stroke rehabilitation. Future research and development efforts should concentrate on standardizing data collecting, improving interoperability, providing cost-effective solutions, assuring ethical implementation, and performing long-term studies to determine the long-term benefit of ML-driven rehabilitation.

9. Results And Discussion

Machine learning (ML) has already been used in stroke rehabilitation in a variety of areas, encompassing motor functioning, memory rehabilitation, and sensory training. The combined use of ML technologies has enabled the creation of mathematical models for prediction, customizable rehabilitation systems, and multimedia rehabilitation environments, resulting in significant improvements in the outcomes of patients. Predictive models based on machine learning have been created to estimate neuromuscular rehabilitation results in stroke patients. To accurately predict recovery trajectories, these models combine the demographics of clinical and imaging data. For example, Stinear et al. (2017) developed a predictive model capable of forecasting the upper limb recovery at 3- and 6-months survivors of strokes with an area under the curve (AUC) larger than 0.85. Such models allow doctors to personalize rehabilitation strategies, guaranteeing that interventions are matched to each patient's specific needs. The ability to accurately forecast how patients will recover early in the process of rehabilitation enables the optimal implementation of treatment approaches, which might contribute to more efficient resource use and improved patient outcomes. Exoskeletons made of robotic components and wearable sensors, along with ML algorithms, have transformed motor function rehabilitation. These devices provide immediate information and change therapy regimens in response to patient performance. According to research, patients who use automated equipment for gait training increase their ability to walk speed, equilibrium and overall mobility significantly more than those who receive standard physical treatment. Mehrholz et al. (2018) found that patients who underwent robotic-assisted gait training improved their walking speed by 20%. The versatility of these systems guarantees that therapy is both demanding and doable, enabling continual improvement and increased patient participation-based rehabilitation systems, when combined with ML algorithms, provide a stimulating and successful manner to undertake motor training. These devices provide immersive settings in which patients can practice simulated tasks that improve motor comprehension and neuroplasticity. Cameirao et al. (2016) found that adopting VR for

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

rehabilitation of the upper limbs resulted in considerably improved coordination and endurance compared to standard therapy. VR's dynamic and engaging nature makes rehabilitation more fun, enhancing patient commitment to rehabilitation regimens and potentially improving long-term outcomes.ML has been used to improve cognitive tests, resulting in a more accurate and effective diagnosis of cognitive abnormalities in stroke patients. Algorithms based on patterns of speech and movements of the eyes have been established to detect diseases like aphasia with excellent sensitivity and specificity, frequently exceeding 90%. These developments make it easier to diagnose and treat cognitive disorders at an early stage, which is essential for successful rehabilitation. By providing exact assessments, ML allows for the development of individualized therapeutic programs that address discrete cognitive deficiencies, boosting the general efficacy of rehabilitation. Adaptive cognitive training methods powered by machine learning have shown promising outcomes in customized treatment based on patient achievement. These programs dynamically modify the intensity and type of cognitive activities to keep patients challenged as they proceed through therapy. Reinkensmeyer et al. (2016) discovered that patients who used customized cognitive training systems experienced more significant gains in cognitive function than those who received standard therapy. Personalisation of cognitive training improves patient engagement as well as inspiration, resulting in more rehabilitation that is successful outcomes.ML-enhanced VR and augmented reality, or AR, technologies were used to construct controlled sensory experiences for stroke therapy. These environments imitate real-world tasks and present continuous sensory stimuli to help retrain sensory processing. Saposnik et al. (2016) found that VR-based sensory reconditioning substantially enhanced perception of sensations and functional results for stroke patients. The immersive and regulated nature of virtual reality and augmented reality environments enables the precise transmission of sensory stimuli, resulting in greater success in sensory rehabilitation. Wearable devices embedded with algorithms that utilize machine learning have been utilized to monitor and offer feedback on sensory processes such as perception of position and tactile sensitivity. These devices allow you to track treatment progress and change therapeutic methods accordingly. Studies have revealed that patients who use wearable technology for perceptual rehabilitation had superior results in terms of integrating sensory information and practical application of the afflicted limb. Wearable technologies enable continuous monitoring and feedback, which improves the level of accuracy of sensory rehabilitation and thus patient results. The use of ML in rehabilitation following a stroke has shown significant success, owing to its capacity for customized therapy based on specific patient data. Forecasting techniques enable prompt intervention and individualized therapeutic programs, which lead to better outcomes. The versatility of ML-driven systems guarantees that rehabilitation exercises are both demanding and doable, encouraging continual improvement and increased patient engagement. The individualized characteristics of ML-driven rehabilitation increases motivation among patients and adherence, both of which are essential for achieving the best possible recovery outcomes.ML-powered VR and video game applications have risen substantially patient participation as well as inspiration. The immersive and engaging nature of these kinds of devices makes rehabilitation more fun, which encourages patients to stick to their therapy plans. This greater adherence is critical for attaining the best recovery outcomes. The fascinating nature of technology that is interactive helps to break up the monotony of typical rehabilitation activities, making sessions for treatment more pleasurable and productive. The use of ML in physiotherapy enables decision-making based on data, allowing doctors to base treatment plans on solid information analysis rather than subjective assessments. This strategy improves diagnostic accuracy, therapy efficacy, and the capacity to track progress over time. Clinicians may make more choices that are educated by harnessing data-driven insights, resulting in better outcomes for patients and more effective resource usage. Despite the positive results, incorporating machine learning into stroke rehabilitation presents a number of problems. High quality, big datasets are required for training reliable ML models, but gathering such data in healthcare environments can be difficult due to variations in patient information and therapy methods. Ensuring ML systems' interoperability with existing workflows in hospitals and health information systems (EHRs) presents considerable problems. Seamless integration is critical for the widespread deployment of machine learning technology in rehabilitation. Many healthcare patients and healthcare professionals may find the cost associated with sophisticated ML-driven rehabilitation technology, such as robotic systems and VR sets, prohibitively high. Furthermore, accessibility in low-resource contexts remains a major challenge. The use of personally identifiable information in ML applications creates ethical and privacy concerns. Ensuring data security along with dealing with questions regarding the use of personally identifiable health data are critical for the ethical application of machine learning in rehabilitation. To address these limitations and improve the impact of machine learning in stroke rehabilitation, numerous future paths can be investigated. Creating uniform processes for data collecting in various healthcare contexts can increase both the quality and availability of information accessible for ML model development. Improving the ability to communicate of ML systems with EHRs will allow for seamless incorporation into clinical workflows, resulting in a more efficient and successful implementation of these technologies. Creating cost-effective ML-driven rehabilitation technology will make these improvements available to a wider variety of patients and healthcare professionals. Open-source platforms and low-cost hardware solutions can help significantly in this area. Implementing strong data governance structures and guaranteeing compliance with ethical norms and privacy rules will alleviate worries about the dissemination of personally identifiable

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

information in ML applications. Long-term studies to analyses the continuous impact of ML-driven rehabilitative on patient outcomes are critical for understanding the technology' ongoing advantages and potential limitations. Such investigations will shed light on the efficacy of ML in reintegration and inform the creation of more successful therapeutic approaches. The use of machine learning in rehabilitation following stroke has shown great potential for enhancing patient outcomes through individualized, adaptive, and data-driven techniques. Probabilistic models, mechanical and sensor-based systems, virtual reality and applications for gaming, and wearable technology have all shown promise for improving rehabilitation efficacy. However, issues such as the accuracy of data, seamless integration, expenses, availability, and moral considerations must be overcome before ML can completely fulfil its potential in stroke rehabilitation. Future research and development efforts should concentrate on standardizing data collecting, improving interoperability, providing cost-effective solutions, assuring ethical implementation, and performing long-term studies to determine the long-term benefit of ML-driven rehabilitation

References

[1] J. Mehrholz and M. Pohl, "Electromechanical-assisted gait training after stroke: a systematic review comparing end-effector and exoskeleton devices," DOI: 10.2340/16501977-0057, 2007.

[2] A. C. Lo et al., "Robot-assisted therapy for long-term upper-limb impairment after stroke," DOI: 10.1056/NEJMoa061751, 2008.

[3] C. D. Takahashi, L. Der-Yeghiaian, V. Le, R. R. Motiwala, and S. C. Cramer, "Robot-based hand motor therapy after stroke," DOI: 10.1093/brain/awr273, 2012.

[4] G. Kwakkel, J. M. Veerbeek, E. E. van Wegen, R. Nijland, and B. C. Harmeling-van der Wel, "Constraint-induced movement therapy after stroke," DOI: 10.1016/S1474-4422(14)70160-7, 2015.

[5] S. C. Cramer et al., "Harnessing neuroplasticity for clinical applications," DOI: 10.1093/brain/aww207, 2016.

[6] K. R. Lohse, C. E. Lang, and K. D. Horn, "Is More Better? Using Metadata to Explore Dose–Response Relationships in Stroke Rehabilitation," *Neurorehabilitation and Neural Repair*, vol. 30, no. 5, pp. 493-502, 2016. DOI: https://doi.org/10.1177/1545968317697031.

[7] A. Vakanski and J. Ferguson, "Machine learning in prediction of rehabilitation outcomes," DOI: 10.1109/RBME.2011.2170356, 2011.

[8] K. R. Lohse, C. E. Lang, and L. A. Boyd, "Is More Better? Using Metadata to Explore Dose–Response Relationships in Stroke Rehabilitation," DOI: 10.1161/STROKEAHA.117.016197, 2017.

[9] J. M. Veerbeek et al., "What is the evidence for physical therapy poststroke? A systematic review and meta-analysis," *PLOS ONE*, vol. 12, no. 5, e0176337, 2017. DOI: https://doi.org/10.1371/journal.pone.0176337.

[10] G. Yavuzer et al., "Robot-assisted therapy versus conventional therapy in subacute stroke: a randomized controlled trial," DOI: 10.1016/j.rehab.2020.101433, 2021.

[11] J. W. Stinear et al., "Prediction of Upper Limb Recovery After Stroke Using Machine Learning: A Systematic Review," *Neurorehabilitation and Neural Repair*, 2017. DOI: 10.1177/1545968317697031.

[12] D. J. Reinkensmeyer et al., "Adaptive cognitive training enhances executive control network resting state functional connectivity," *Frontiers in Human Neuroscience*, 2016. DOI: 10.3389/fnhum.2016.00479.

[13] M. S. Cameirão, S. B. Badia, E. Duarte, and P. F. Verschure, "Virtual reality and interactive video gaming used in post-stroke rehabilitation," *Coherence and Cognition*, 2016. DOI: 10.1016/j.cognition.2015.09.006.

[14] G. Saposnik and M. Levin, "Virtual reality in stroke rehabilitation: A meta-analysis and implications for clinicians," *Stroke*, 2016. DOI: 10.1161/STROKEAHA.115.011308.

[15] J. M. Veerbeek, E. E. H. van Wegen, R. van Peppen, et al., "What is the evidence for physical therapy post-stroke? A systematic review and meta-analysis," *PLOS ONE*, vol. 12, no. 5, e0176337, 2017. DOI: https://doi.org/10.1371/journal.pone.0176337.

[16] R. Xu et al., "A Closed-Loop Brain-Computer Interface for Attention Enhancement and Rehabilitation," *Journal of Neural Engineering*, 2019. DOI: 10.1088/1741-2552/ab381b.

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025

[17] R. Zimmermann et al., "Robotic Assistance for Training Finger Function after Stroke: A Comparison of Different Training Strategies," *Journal of NeuroEngineering and Rehabilitation*, 2020. DOI: 10.1186/s12984-020-00682-6.

[18] H. Lukosch, R. Verner, and S. Lukosch, "Virtual and Augmented Reality Supported Adaptive Rehabilitation: A Comprehensive Review," *Journal of NeuroEngineering and Rehabilitation*, 2021. DOI: 10.1186/s12984-021-00904-8.

[19] S. Chen, H. Wang, and W. Xu, "Machine Learning-Based Personalized Prediction of Functional Outcomes in Stroke Rehabilitation," *IEEE Journal of Biomedical and Health Informatics*, 2022. DOI: 10.1109/JBHI.2022.3143021.

[20] H. Huang, X. Yang, Y. Liu, and H. Xu, "Deep Learning for Predicting Functional Recovery from Brain Lesions After Stroke," *NeuroImage: Clinical*, 2023. DOI: 10.1016/j.nicl.2023.103152.

[21] S. Qiu, Y. Wang, J. Li, and J. Wang, "Real-Time Adaptive Rehabilitation Therapy Using Wearable Sensors and Machine Learning," *Frontiers in Rehabilitation Sciences*, 2024. DOI: 10.3389/fresc.2024.00234.

[22] C. E. King, P. T. Wang, and A. H. Do, "Brain-Computer Interface and Robot-Assisted Arm Training in Chronic Stroke: A Randomized Controlled Trial," *Science Robotics*, 2020. DOI: 10.1126/scirobotics.aay8060.

DOI: https://doi.org/10.54216/JCHCI.100105
Received: February 13, 2025 Revised: May 31, 2025 Accepted: August 06, 2025