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Review

Machine Learning Techniques for the Prediction of Functional Outcomes in the Rehabilitation of Post-Stroke Patients: A Scoping Review

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Abstract: Stroke is one of the main causes of long-term disabilities, increasing the cost of national healthcare systems due to the elevated costs of rigorous treatment that is required, as well as personal cost because of the decreased ability of the patient to work. Traditional rehabilitation strategies rely heavily on individual clinical data and the caregiver's experience to evaluate the patient and not in data extracted from population data. The use of machine learning (ML) algorithms can offer evaluation tools that will lead to new personalized interventions. The aim of this scoping review is to introduce the reader to key directions of ML techniques for the prediction of functional outcomes in stroke rehabilitation and identify future scientific research directions. The search of the relevant literature was performed using PubMed and Semantic Scholar online databases. Full-text articles were included if they focused on ML in predicting the functional outcome of stroke rehabilitation. A total of 26 out of the 265 articles met our inclusion criteria. The selected studies included ML approaches and were directly related to the inclusion criteria. ML can play a key role in supporting decision making during pre- and post-treatment interventions for post-stroke survivors, by utilizing multidisciplinary data sources.

Keywords: post-stroke; artificial intelligence; prognosis; outcome assessment; rehabilitation

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1. Introduction

Stroke, as a result of either a sudden brain blood supply interruption or local brain blood vessel eruption [1], may cause paralysis (plegia) or weakness (paresis), with detrimental consequences on daily activities, such as dressing, eating, and walking, as well as problems with memory, cognition, speaking, emotion control, numbness, and pain [2–4]. An aging population and the interaction of risk factors enhance the risk of stroke, leading to an increased number of people with long-term disabilities [3,5]. Forms of stroke rehabilitation include a mixture of pharmacologic and nonpharmacologic interventions that target physiological and functional deficits; however, traditional one-size-fits-all approaches often leave a considerable portion of patients without effective treatment. The design of effective interventions has proven a challenging task due to the high variability of patients' level of impairment and symptoms [6–8]. Hence, the development of personalized assessment/prognostic tools that could lead to better risk stratification and prediction of functional outcomes, based on past and current data, is necessary. Innovative, evidence-based strategies that can utilize longitudinal, multisource population data could aid individual rehabilitation by shaping personalized interventions, both at admission and throughout the patient's path of care.

To this end, classical statistical approaches such as linear regression have been employed to model post-stroke rehabilitation and predict functional outcomes, using a binary (good or poor) classification or specific score outcomes. These models, which are typically based on standard scales and relevant clinical data, fail to incorporate meaningful factors that are detrimental to patient-specific recovery pathways, such as the level of family or community support and the cultural level. On the contrary, advanced artificial intelligence (AI)-based correlation models, such as machine learning algorithms, can analyze large, inhomogeneous datasets, map nonlinearities between multiple input and output variables, and extract patterns among various clinical outcomes.

ML is the study of how machines (i.e., learning algorithms) can learn patterns or complex relationships from daily data and produce trained mathematical models linking target variables of interest with a huge number of covariates. Furthermore, deep learning (DL) is defined as a subfield of ML concerned with learning algorithms inspired by the function and structure of the brain [7]. DL provides an alternative architecture system by overcoming the burden of feature engineering. Hence, ML has the ability to cope with high-dimensionality data and complex cases [9,10], going beyond the traditional statistical approaches and overcoming significant limitations in the prediction of the functional outcome in the rehabilitation of post-stroke survivors, offering valuable tools in the field of stroke rehabilitation [3].

Currently, various ML techniques have been employed to model individual disease pathways, and their contribution plays a key role in the scientific community. For example, in the case of knee osteoarthritis, several ML-based patient-specific prediction models have been developed (e.g., ML models for diagnosis, post-treatment assessment, and segmentation in knee osteoarthritis) [11]. Moreover, ML demonstrated excellent performances in predicting the outcome for several neurosurgical conditions [12,13]. In addition, Bivard et al. demonstrated the importance of AI and imaging in stroke management [14]. Furthermore, they presented the need for AI tools for the quick assessment of meaningful imaging data and to support clinical decisions.

In this context, the current scoping review was carried out to (i) investigate ML methods employed to predict functional outcome in stroke rehabilitation, (ii) identify current trends in this field, and (iii) identify the existing literature gap for future scientific approaches. Compared to the already available literature on the field of post-stroke rehabilitation [15], this paper focuses specifically on the various ML models being used to predict functional outcomes in stroke rehabilitation, as well as their specific characteristics and underlying principles. By providing an in-depth examination of these models, the paper aims to shed light on the current state of the field and identify trends and areas for future research. Overall, the primary aim of the paper is to provide a comprehensive overview of the ML approaches being used in this area of study.

2. Materials and Methods

This scoping review employed the 22-item Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) [16].

2.1. Literature Searches

The structured literature search was conducted using the online databases PubMed and Semantic Scholar. Furthermore, a manual search was performed in order to add records identified through other sources.

For the online databases, the search terms were as follows: "machine learning" OR "deep learning" OR "artificial Intelligence" OR "neural networks" OR "support vector machine" OR "random forest" AND "stroke" OR "brain ischemia" OR "cerebral ischemi*" OR "post stroke" OR "poststroke" AND "rehabilitation" OR "physical therapy" OR "physiotherapy" OR "rehab*" AND "prediction" OR "predict*" OR "prognosis".

2.2. Eligibility Criteria

2.2.1. Inclusion Criteria

In this survey, only peer-reviewed journal articles were considered by authors. Furthermore, the time period for the literature review was determined to be from 2010 until 26 October 2022. This work only included studies for post-stroke patients that made use of AI tools for the prediction of the functional outcome in rehabilitation.

2.2.2. Exclusion Criteria

Due to recent advances in big data analytics, today's proliferation of data, and the extended use of AI tools in the rehabilitation of post-stroke patients, articles published before 2010 were excluded from the review. Conference proceedings, non-English papers, and studies with non-survivors of stroke, nonhuman subjects, and nonhuman protocols were excluded. In addition, review papers and unavailable full-text articles were excluded.

2.3. Data Extraction

Data extraction was performed by two reviewers (C.K. and G.G.) who screened the titles, abstracts, and full texts of the selected studies. First, all studies were imported into Mendeley in order to remove duplicates. Title and abstract screening was performed to identify articles that generally met the inclusion criteria. Any disagreements on studies with unclear relevance were resolved by discussion between C.K. and G.G. At the end, studies were included if they met a list of specific requirements. Specifically, these were the application domain, data sources, outcome assessment, number of subjects employed, ML models (learning algorithms), validation, and findings.

3. Results

A total of 265 articles were recorded from the online search after the deletion of duplicated articles. Subsequently, after screening the titles and abstracts, 39 articles were identified. Finally, 26 articles met the inclusion criteria and were, thus, considered acceptable for qualitative synthesis. Figure 1 depicts the workflow diagram of the screening methodology based on PRISMA-ScR guidelines.

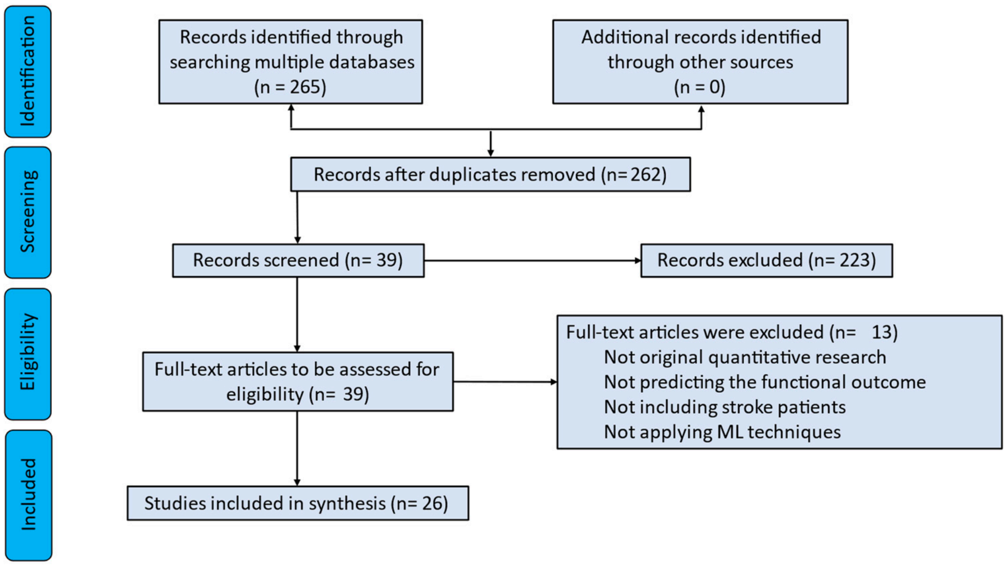

Figure 1. Workflow diagram of screening methodology.

All the identified studies used ML techniques in order to predict functional outcomes in the rehabilitation of post-stroke patients. Studies that (i) applied traditional statistical approaches, (ii) did not include stroke patients (or stroke survivors), or (iii) did not perform original quantitative research were excluded.

The studies, which were recorded in this scoping review, were divided into two categories with respect to the application domain: (i) motor function (17 studies), and (ii) upper extremities (nine studies). Only one of 26 studies had the primary task of predicting functional outcomes for both domains of application. This study was presented within the motor function category.

3.1. Terminology and Definitions

3.1.1. Functional Outcomes

- Modified Rankin scale (mRS) is a measure for the degree of disability in post-stroke patients, and it is used to identify the level of functional independence [17];
- Barthel index (BI)/modified Barthel index (MBI) measures somebody's ability to function independently [18,19];
- Functional independence measure (FIM) is an indicator of patient disability which is based on the International Classification of Impairment, Disabilities, and Handicaps for use in the medical system in the United States (McDowell and Newell, 1996) [20];
- Functional ambulation categories (FAC) test evaluates the ambulation ability. Specifically, FAC is a functional walking test [21];
- Fugl–Meyer assessment (FMA) scale assesses the sensorimotor impairment in post-stroke hemiparesis patients [22];
- Modified Brunnstrom classification (MBC) score is used to categorize the function of the affected hand [23];
- Wolf motor function test (WMFT) quantifies the motor ability for the upper extremities (UE) through functional and timed tasks [24];
- Fugl–Meyer assessment, upper extremity (FMA-UE) consists of items that reflect the motor function, and it is useful for an accurate evaluation of UE paresis and to rehabilitation practice [25];
- Ten-meter walk test (TMWT) measures the walking ability in post-stroke patients [26];
- Six-minute walk test (SMWT) assesses the aerobic capacity and walking endurance [27];
- Berg balance scale (BBS) evaluates fall risk and balance outcomes [28];
- Motor activity log (MAL) measures the functional upper limb performance in real life [29];
- National Institutes of Health stroke scale (NIHSS) rates stroke severity [30];
- Stroke impact scale (SIS) assesses physical functioning [31].

3.1.2. Prediction Horizon

The predictions of functional outcomes up to 3 months were considered as the short-term prediction horizon. The prognosis for 3–6 months was defined as the long-term prediction horizon ($\geq$3 months).

3.1.3. Stages of Stroke Recovery

- The acute phase corresponds to the first 7 days, the early subacute phase extends from 7 days to 3 months, the late subacute phase extends from 3 to 6 months, and the chronic phase extends to $\geq$6 months

3.1.4. ML Terminology

- Classification is the task that predicts the class (or label) of given input data. A common classification problem is the prediction of functional independence status based on mRS, which is a binary problem (class 1: mRS < 2 and class 2: mRS $\geq$ 2) [32]. Regression predicts a continuous outcome (target variable) on the basis of values of multiple predictor variables. For example, a regression task is the prediction of the Barthel index score at discharge from a rehabilitation unit [33].

3.1.5. Abbreviations of the Employed ML Models

- Support vector machines: SVMs,

- Decision trees: DTs,
- Logistic regression: LR,
- Regularized logistic regression: RLR,
- Extreme gradient boosting: XGB,
- Cox regression: COX,
- Naïve Bayes classifier: NBC,
- Random forest: RF,
- k-nearest neighbors: KNN,
- Linear discriminant analysis: LDA,
- Support vector regression: SVR,
- Epsilon regression: ER,
- Multiple linear regression: MLR,
- Chi-square automatic interaction detector: CHAID,
- Gradient boosting decision tree: GBDT,
- Convolutional neural network: CNN,
- Artificial neural network: ANN,
- Elastic net: EN,
- Enhanced probabilistic neural network: EPNN
- Neural dynamic classification: NDC

3.1.6. Performance Metrics

- Accuracy measures how often the classifier correctly predicts the label of an observation. Sensitivity provides how many of the actual positive cases are predicted correctly (true positive) from the ML model. Specificity gives the number of actual negative cases that are predicted correctly (true negative). Area under the receiver operating characteristic curve (AUC) is an effective metric to summarize the overall predictive accuracy.
- R^2 or coefficient of determination is the proportion of the variation in the dependent (target) variable that is predictable from the multiple predictor variables. Mean absolute error (MAE) is the average of all absolute errors in a set of predictions. Root-mean-square error (RMSE) or root-mean-square deviation (RMSD) is the standard deviation of the prediction errors (residuals).

3.2. Motor Function

Studies in the motor function category (Table 1) were divided into two groups as shown in Figure 2.

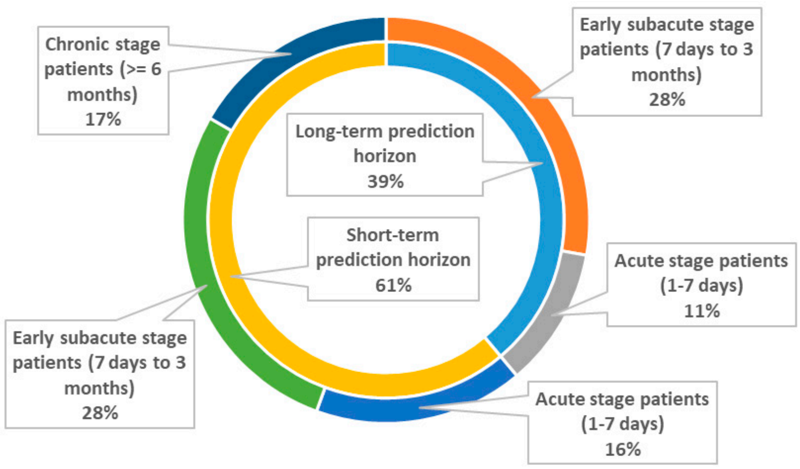

Figure 2. Employed studies in motor function category according to prediction horizon.

3.2.1. Long Term Prediction Horizon (≥3 Months)

Overall, seven out of 17 studies in this category were aimed at predicting functional outcomes 3 months or greater after the acute phase or the admission of post-stroke patients in a rehabilitation unit.

Classification studies: To predict the modified Rankin scale (mRS) at 3 months, Park et al. employed five ML models trained on a variety of features such as demographic factors, laboratory findings, stroke-related factors, and comorbidities at the acute phase [32]. The best performance was achieved from the regularized logistic regression model (AUC = 86%). Lin et al. worked on the prediction of mRS employing a hybrid artificial neural network (ANN) and three ML models (ANN, support vector machine (SVM), and RF) on preadmission and inpatient data (AUC: 94%) [34]. The prediction performance was further improved (AUC = 97%) by adding data from the first follow-up visit at 30 days. In the task of predicting the Barthel index (BI) at discharge, Chang et al. trained eight well-known classifiers on 77 predictors from early subacute recovery stage patients [35]. The best AUC score (AUC = 88.7%) for the prediction of the BI status was achieved by a random forest (RF) classifier. On the same task, Lin et al. employed RF, SVM, and logistic regression (LR) models on a dataset including various motor function scores and clinical data [36]. They recorded an AUC of 79% using either RF or LR algorithms. In contrast with the aforementioned studies, Kim et al. utilized three well-known ML models, namely, LR, RF, and deep neural networks (DNNs), for the prediction of motor outcomes at 6 months after stroke using clinical data from early subacute recovery stage patients [23]. For the lower limbs, they used a functional ambulation category (FAC) score as an outcome, and they achieved the best performance with DNN (AUC = 82.2%). The outcome for the upper limbs was defined as a modified Brunnstrom classification (MBC) score, and the best prediction performance was also achieved by the DNN model (AUC = 90.6%).

Regression studies: Jiang et al. worked on the prediction of the functional outcome (FO) in ischemic stroke at 3 months [37]. In order to improve the prediction of FO, they proposed a new index for multiple chronic conditions (MCCs). They employed functional outcomes and clinical data in combination with a multiple linear regression model, and they recorded an R^2 of 0.32. Furthermore, synergistic interactions and novel predictors, such as the pre-stroke mRS score, congestive heart failure (CHF), and other neurologic disorders, were identified. In addition, Katsuki et al. worked on the prediction of the functional independence measure (FIM) score after the acute care hospital, utilizing a deep learning framework [38]. They achieved the best score (R^2 = 0.972) using data from the acute care ward admission and Kaifukuki (convalescent) Rehabilitation Ward (KRW) admission. They employed outcome measures for up to 150 days. Lastly, Lin et al. predicted the BI score at discharge (3 months) using various motor function scores and clinical data from the early subacute recovery stage as inputs [36]. A MAE of 9.86 was achieved by the SVM regressor.

3.2.2. Short-Term Prediction Horizon (<3 Months)

Classification studies: Thakkar et al. worked on the prediction of motor function improvement 3–4 weeks after contemporary task-oriented interventions in chronic stroke patients [39]. They utilized KNN and ANN classifiers to predict the FMA scale. Employing features such as age, side of lesion, gender, baseline functional status, motor function time since stroke, and quality of life 6 months or higher after stroke, they demonstrated that the best AUC score of 89% was achieved by the KNN model. Furthermore, Liao et al. worked on the same task [40]. They developed machine learning models in order to predict health-related quality of life improvement (HRQOL) after sensorimotor rehabilitation interventions at 3–4 weeks. They employed 132 chronic post-stroke patients, and they achieved the best accuracy (85%) using an RF classifier. Sohn et al. worked on rehabilitation prognosis in ischemic stroke patients by employing brainstem auditory evoked potential (BAEP) and ML models [41]. They employed features such as the basal K-MBI score, age, and three interpeak latencies (IPLs) from the early subacute phase. An AUC of 90% was finally achieved for the prediction of the Korean version of the modified Barthel index (K-MBI) with an ANN model. In another work, Chen et al. using demographics, medical history, and outcome assessments, proposed models for the prediction of 30 day readmission for stroke [42]. They employed six well-known classifiers, and the best 93% accuracy was achieved by an artificial neural network (ANN) in an external dataset.

In contrast with the other studies, Lai et al. worked on the prediction of mRS and NIHSS at discharge (28 $\pm$ 3 days) using a pretrained VGG-16 convolutional neural network (CNN) [43]. They employed 44 post-stroke patients at the acute phase, and they presented 92.7% and 93.2% accuracy for the prediction of NHSS and mRS, respectively. Campagnini et al. proposed predictive models for functional prognosis based on MBI [44]. The best accuracy (76.2%) was achieved by an RF classifier, and they used Shapley additive explanations (SHAP) in order to highlight the contribution of each predictor in the model output. In the most recent study, Lin et al. used pretrained deep learning models to predict Fugl–Meyer assessment of the lower extremity 2 weeks after robotic-assisted stretching training in only 15 chronic stroke patients [45]. They applied the leave-one-out cross-validation strategy, and they achieved 91.845% accuracy. Furthermore, they worked on the interpretation of the model output by applying the SHAP model.

Regression studies: Harari et al. used baseline clinical data (acute phase) in combination with a Lasso regression ML model [46]. They developed predictive ML models for four different functional outcomes (FIM, TMWT, SMWT, and BBS) at discharge in early-stage strokes (acute inpatient rehabilitation phase) and demonstrated an MAE of 13–15% for predictions on new patients. Moreover, Sale et al. worked on cognitive and motor improvement for early-stage stroke patients at discharge based on BI and FIM scores [33]. They employed an SVM regressor and presented that the RMSE ranged from 4.28 for discharge cognitive FIM to 22.6 for discharge BI. In another work, Rajashekar et al. proposed nested regression models with the aim of predicting the 30 day NIHSS score [47]. They used imaging data and measurable clinical data, which were obtained up to 6 h after stroke. In this study, they developed a SVM regression model based on nonmodifiable and modifiable risk factors and two nested SVM regression models that aggregate image-based and clinical features that differ at the feature selection (FS) method. The first employed the relief FS technique, and the second employed the lesion-symptom mapping technique. The best performance scores were achieved by the Mrelief model (MAE = 3.55, RMSE = 4.34, and R^2 = 0.43).

Table 1. Findings and characteristics of included ML studies for motor function category.

Authors	Year	Application Domain	Intervention	Input Data	Outcome Assessment	Employed Subjects	Learning Type	Learning Algorithms	Validation	Results
Lin et al. [45]	2022	Prediction of a treatment's outcome using a deep learning (DL) prognosis model	Robotic-assisted stretching training	Biomechanical measurement, clinical measurement, and EEG measurement	FMA of lower extremity at 2 weeks	15 post-stroke (6 months)	Classification	Pretrained DL models and SHAP	Leave-one-out cross-validation (LOOCV)	91.84% accuracy
Campagnini et al. [44]	2022	Development of predictive models for the functional prognosis of stroke patients	At least three hours of rehabilitation per day	Demographics and clinical, cognitive and functional evaluations	MBI at 40 days	278 post-stroke at admission in intensive rehabilitation treatment	Classification	EN RLR, SVM, RF, KNN, and SHAP	Fivefold cross-validation loop was deployed for hyperparameter optimization, while an external 10-fold loop was adopted for test set identification	RF obtained the best overall results on the accuracy (76.2%), balanced accuracy (74.3%), sensitivity (0.80), and specificity (0.68)
Lai et al. [43]	2022	Prediction of functional outcomes of stroke	Hospitalization	MRI	mRS and NIHSS at admission and discharge (28 ± 3 days)	44 stroke patients (acute phase)	Classification	Pretrained VGG-16 CNN	Training (90%)/testing (10%)	NHSS: mixed men and women, the diagnostic accuracy was 92.7%, the sensitivity was 88.9%, and the specificity was 96.4%. MRS: mixed men and women, the diagnostic accuracy was 93.2%, the sensitivity was 90.0%, and the specificity was 97.0%.
Chen et al. [42]	2022	Prediction of 30 day readmission for stroke patients	Post-acute care	Demographics, medical history, and outcome assessments	30 day readmission	1476 patients within the first 30 days of stoke onset	Classification	ANN, KNN, RF, SVM, NBC, and COX models	Training data set (70%) and a test dataset (30%); 167 patients were used for external validation	ANN 93% in external dataset
Liao et al. [40]	2022	Prediction of clinically significant HRQOL improvements of chronic stroke patients	Sensorimotor rehabilitation interventions	Demographics and baseline cognitive, motor, sensory, functional, and HRQOL attributes	SIS at 3 to 4 weeks	132 people with chronic stroke	Classification	RF, KNN, ANN, SVM, and LR	Training data set (70%) and a test dataset (30%); 10-f cv in training	The accuracy of the RF model was 85%, precision was 0.88, recall was 0.85, the F1 score was 0.85, and the AUC-ROC was 0.86

Table 1. *Cont.*

Authors	Year	Application Domain	Intervention	Input Data	Outcome Assessment	Employed Subjects	Learning Type	Learning Algorithms	Validation	Results
Park et al. [32]	2021	Prediction of functional outcome at 3 months	Hospitalization	Clinical data of personal and stroke-related factors (<7 days)	mRS	1066 patients with acute ischemic stroke (mean age 65.8 ± 11.3 years favorable outcome group and 74.4 ± 11.4 years unfavorable outcome group)	Classification	RLR, SVM, RF, KNN, and XGB	Training data set (70%) and a test dataset (30%); 10-f cv in training	RLR achieved 86% AUC
Chang. et al. [35]	2021	Prediction of post-stroke functional outcomes at 3 months	Post-Acute Care-Cerebrovascular Disease (PAC-CVD) program	Demographic parameters, functional assessments, comorbidities, and complications (77 predictors, within 1 month post-stroke)	BI at discharge	577 post-stroke patients (mean age 64.6 ± 12.6 years)	Classification	DTs, NBC, KNN, LDA, AdaBoost, SVM, LR, and RF	Fivefold cv	ML models AUC scores ranged from 0.83 to 0.887. RF achieved the best AUC score.
Katsuki et al. [38]	2021	Prediction models for total FIM scores at the discharge of KRW (up to 150 days)	Rehabilitation up to 150 days at Kaifukuki (convalescent) Rehabilitation Ward (KRW) system	Clinical data and CT at acute care ward and functional assessments at KRW (2–4 weeks after acute care ward)	FIM score at discharge	122 stroke patients (mean age 71 years)	Regression	Prediction One (Sony Network Communications Inc., Tokyo, Japan)	Training (50%, inside 5-fold cv)/validation (50%).	R^2 up to 0.972
Rajashekar et al. [47]	2021	Prediction of the 30 day NIH stroke scale (NIHSS) at 30 days after stroke symptom onset	Hospitalization	Imaging features from MRI or CT scan (acquired between 18 h and 5 days from symptom onset) and measurable clinical data (obtained after stroke and up to 6 h post)	NIHSS	221 acute ischemic stroke patients (mean age: 69 years) from ESCAPE and iKNOW trials	Regression	ER mode was implemented using in a radial kernel SVR framework. Three proposed models: an SVR, an SVR with Relief, and a SVR with lesion/symptom mapping technique	Training (80%)/ testing (20%)	M_{relief} achieved MAE = 3.55, RMSE = 4.34, and R^2 = 0.43

Table 1. *Cont.*

Authors	Year	Application Domain	Intervention	Input Data	Outcome Assessment	Employed Subjects	Learning Type	Learning Algorithms	Validation	Results
Kim et al. [23]	2021	Prediction of motor function outcome in stroke patients at 6 months	Rehabilitation center	Clinical data (14 input variables, from early stage at 7–30 days after stroke onset)	MBC for upper limbs and FAC for lower limbs	1056 consecutive stroke patients (mean age 59.92 ± 13.94 years)	Classification	DNN, LR, and RF	Training (70%)/validation set (21%)/testing set (9%)	Upper-limb function: DNN model achieved AUC = 0.906 Lower-limb function: DNN, LR, and RF models achieved AUC scores 0.822, 0.768, and 0.802, respectively
Sohn et al. [41]	2021	Prediction of rehabilitation prognosis in stroke patients using Brainstem Auditory Evoked Potential (BAEP) at 8 to 114 days	Brainstem auditory evoked potential A proper rehabilitation program was applied during hospitalization	Basal K-MBI score, age, and three IPLs (2 weeks of admission on average)	Korean version of the modified Barthel index (K-MBI)	181 subjects with ischemic stroke (mean age 68.15 ± 11.68 years)	Classification and regression	ANN and SVM	Training (70%, inside 5-fold cv)/testing (30%)	ANN exploiting the BAEP IPLs together with the basal K-MBI score and age achieved 92% sensitivity, 90% specificity, and 90% AUC
Jiang et al. [37]	2021	A new index for multiple chronic conditions (MCCs) was proposed for prediction of post-stroke functional outcome (FO) at 90 days	Hospitalization	Pre-stroke functional, cognitive, and psychosocial impairments was ascertained from the baseline interview (after 24 h)	MCCs	1035 patients with ischemic stroke (mean age 68 ± 12.1 years)	Regression	MLR	Training (90%, inside 5-fold cv)/validation (10%)	MCC by MLR: R^2 = 0.32
Thakkar et al. [39]	2020	Prediction of motor function improvements in chronic stroke patients after 3–4 weeks of rehabilitation	Contemporary task-oriented intervention	Age, side of lesion, gender, baseline functional status, motor function, time since stroke, and quality of life (more than 6 months post stroke)	FMA	239 chronic stroke patients (mean age 54.72 ± 11.12 years)	Classification	KNN and ANN	Training (80%, inside 10-fold cv)/testing (20%)	KNN model accuracy = 85.42% and AUC = 0.89

Table 1. *Cont.*

Authors	Year	Application Domain	Intervention	Input Data	Outcome Assessment	Employed Subjects	Learning Type	Learning Algorithms	Validation	Results
Harari et al. [46]	2020	Development of predictive models for four standardized clinical outcome measures at discharge (acute phase)	Acute inpatient rehabilitation	Demographics, stroke characteristics, and scores of clinical tests at first week of admission	FIM, TMWT, SMWT, and BBS	50 stroke survivors (mean age 57.5 ± 14.15 years)	Regression	Lasso regression	LOOCV	R^2 = 70–77% and MAEn = 13–15% for predicting the outcomes of new patients
Lin et al. [34]	2020	Prediction of functional mRS outcome at 90 days after stroke	Hospitalization	Clinical data (impatient elements and data from 30 days follow-up visit)	mRS	5328 females and 24,965 males (mean onset age 69.71 ± 12.62 years and 65.40 ± 12.64 years)	Classification	SVM, RF, ANN, and hybrid ANN	10-time repeated hold-out (30%) with 10-fold cv in training	Baseline and follow-up data achieved improved AUC scores to 0.97
Sale et al. [33]	2018	Prediction of functional outcomes at discharge in ischemic stroke patients in early stage after rehabilitation treatment	Daily 3 h physiotherapy session	Functional and clinical data (24 h from the admission at the rehabilitation unit)	BI and FIM	55 sub-acute stroke patients (15 ± 10 days from stroke onset)	Regression	SVM	20 repetitions-training (70%, inside 5-fold cv)/testing (30%)	RMSE ranged from 4.28 for discharge (T1) cognitive FIM to 22.6 for discharge (T1) BI.
Lin et al. [36]	2018	Predicting the BI statuses of the patients at discharge after PAC-CVD program at 3 months	PAC-CVD program	MRS, BI, FOIS, MNA, QoL, IADL, BBT, gait speed, 6MWT, FuglUE, FuglSEN, MMSE, MAL, CCAT, age, and length of stay in the acute stroke ward prior to admission to the PAC-CVD ward (stroke onset time within 1 month)	BI status at discharge	313 post-stroke patients (mean age for patients with high BI at discharge 58.25 ± 13.44, with medium BI 63.20 ± 11.34, and low BI 69.77 ± 11.89)	Classification and regression	LR, SVM, and RF (classification task) SVM with linear kernel and linear regression (regression task)	Fivefold cv	AUC score for LR and RF algorithms was 0.79 and for SVM algorithm was 0.77 SVM and linear regression models achieved mean absolute errors of 9.86 and 9.95, respectively

3.3. Upper Extremities

Studies involved in the upper extremities category also showed variability with respect to the functional outcome prediction horizon (Table 2). Specifically, the short-term prediction horizon group included (i) one study with a prediction horizon of 4 weeks, (ii) one study with a prediction horizon of 6 weeks, (iii) two studies with a 3 week prediction horizon, and (iv) two studies with a 2 week prediction horizon. Only one study with a 9 month prediction horizon and two studies with a 3 month prediction horizon were included in the long-term prediction horizon group (Figure 3).

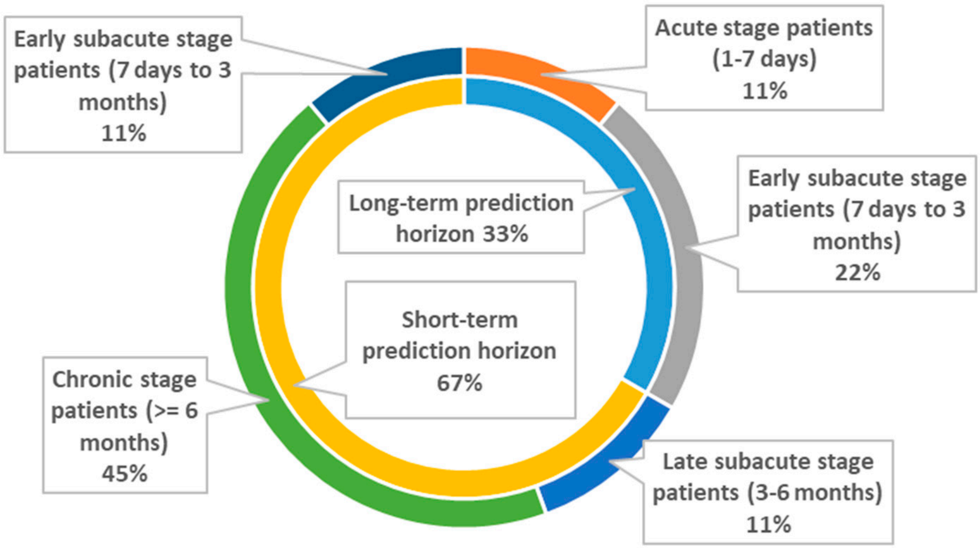

Figure 3. Employed studies in upper extremities category according to prediction horizon.

3.3.1. Long-Term Prediction Horizon (≥3 Months)

Both studies in this category focused on the prediction of the FMA-UE score as the main outcome at 3 months. Liu et al. employed bagging and gradient boosting decision tree (GBDT) classifiers with the aim of predicting individual motor outcomes after stroke [48]. On the basis of baseline whole-brain volumes and motor data from the acute phase, the Bagging classifier achieved the best AUC score at 89.74%. In the latter study, Koch et al. predicted the natural recovery (differences between FMA-UE) using SVM classifiers [49]. This study employed three different MRI (3T) datasets 2–4 weeks after stroke onset, namely, SEOUL, GENEVA, and PARIS. The SEOUL dataset was used for the training and internal validation of the trained models. The GENEVA and PARIS datasets were used for external validation and generalization, respectively. In external validation, employing the GENEVA dataset, an accuracy of 60% was achieved. In another study, Razak et al. worked on the long-term prediction of mRS at 9 months. They applied three ML models and achieved the best AUC score of 97.7% by using LR [50].

3.3.2. Short-Term Prediction Horizon (<3 Months)

Classification studies: Three out of five studies in this subcategory applied interventions based on constraint-induced movement therapy (CI therapy) to predict functional outcomes at 2 up to 3 weeks for chronic stroke patients. Rafiei et al. proposed an enhanced probabilistic neural network (EPNN) model for the prediction of the improvement of the more affected arm in use for daily activities [51]. Employing features such as demographics and baseline clinical characteristics (e.g., MAL, WMFT, SWMT, and MCA) they achieved accuracy nearly at 100% for the motor activity log (MAL). In another study, George et al. worked on the prediction of the response to upper extremity rehabilitation based on the Wolf motor function test (WMFT) [52]. They concluded that gross motor ability plays a key role, and they demonstrated 94.7% accuracy by employing data from somatosensory and motor in combination with an EPNN model. Using the same outcome (WMFT), George et al. worked on the prediction of motor recovery for upper-limb motor ability by using three ML models (EPNN, PNN, and KNN) and data such as tactile sensation, proprioceptive function, motor performance, and the stroke-affected side [53]. They demonstrated almost perfect predictive performance in this task (100% accuracy) from the EPNN model. In contrast with the aforementioned studies, Iwamoto et al. applied single-joint hybrid assistive limb (HAL-SJ) rehabilitation in order to identify stroke patients with improvement of upper-limb motor function based on the difference of the FMA-UE at 30 days [54]. They used the chi-square automatic interaction detector (CHAID) model, and they achieved 81.7% classification accuracy.

Regression studies: Lin et al. proposed a CNN-based approach for the prognosis of the recovery rate at 2 weeks after the brain–computer interaction (BCI) rehabilitation for patients in the late subacute stage of recovery [55]. This rate was derived from the FMU score after the 2 weeks of BCI training minus the baseline score, and then divided by the baseline FMU score minus the maximum score. Employing a CNN model on electroencephalographic (EEG) functional connectivity and EEG power spectrum baseline data, they presented an excellent R^2 of 0.98. In another study, Tozlu et al. employed several ML models for the prediction of the post-intervention FMA-UE score at 6 weeks for chronic stroke patients [56]. In this task, the elastic net (EN) trained on demographic, clinical, neurophysiological, and imaging data (3T MRI) presented significantly better scores than the remaining ML models (R^2 = 0.91).

Table 2. Findings and characteristics of included ML studies for upper extremities category.

Authors	Year	Application Domain	Intervention	Input Data	Outcome Assessment	Employed Subjects	Learning Type	Learning Algorithms	Validation	Results
Iwamoto et al. [54]	2022	Identification of stroke patients who will obtain clinically important improvement at 30 days	Single-joint hybrid assistive limb (HAL-SJ) rehabilitation	Sex, age, days from stroke onset to the initiation of HAL-SJ rehabilitation, cognitive functions, and upper-limb motor functions	Difference of the FMA-UE at 30 days	71 patients with subacute stroke	Classification	DT analysis CHAID model	-	Acc = 81.7% and AUC = 0.89
Razak et al. [50]	2022	Prediction of ipsilateral hand (ILH) impairment at 9 months	Hospitalization	Demographic variables, behavioral, clinical, and neuropsychological data, medical history, thrombolysis treatment, stroke delay, and NIHSS discharge	mRS at 9 months	209 subacute patients	Classification	LR, LR-bootstrapping, and cv with LASSO and RF	Training (70%)/testing (30%) for the LR	LR achieved AUC = 0.98
Liu et al. [48]	2022	Prediction of motor improvement outcome at 3 months	Routine rehabilitation therapies	Baseline whole-brain volumes and motor data (FMA-UE scores) 1 week after symptom onset (<7 days)	Differences between FMA-UE from Week 1 to Week 12 (84 ± 4 days)	56 patients with subcortical infarction (mean age 53.5 years at proportional group and 53 years at poor group)	Classification	Bagging and GBDT	Fivefold cv	Bagging classifier achieved 87.71% accuracy, 93.77% sensitivity, and 89.74% AUC
Lin et al. [55]	2021	Prediction of the outcome of BCI training for upper limbs at 2 weeks	Brain-computer interaction (BCI) training	EEG functional connectivity and EEG power spectrum (first-ever stroke within 6 months)	Recovery rate (FMA-UE score after the 2 weeks of BCI training minus the baseline score and then divided by the baseline FMA-UE score minus maximum score)	11 stroke patients (aged 20–80 years)	Regression	CNN	LOOCV	R^2 = 0.98 and RMSE = 0.89
Koch et al. [49]	2021	Prediction of structural connectome and motor recovery for upper limbs in natural recovery at 3 months	Natural recovery	SEOUL dataset (3T MRI), GENEVA dataset (3T MRI), and PARIS dataset (3T MRI) were recorded at 2–4 weeks after stroke	Proportional recovery (the change in FMU over time was related to the maximal amount of potential recovery)	92 after stroke patients (SEOUL: mean age 58 ± 12.6 years, GENEVA mean age 58 ± 12.2 years, and PARIS mean age 55 ± 16.7 years)	Classification	SVM (classification task)	SEOUL dataset in 5-fold cv as internal validation/GENEVA dataset as external validation	At GENEVA dataset (external validation) an accuracy = 60% and precision = 53% were achieved
Tozlu et al. [56]	2020	Prediction of the individual upper-limb motor impairment in chronic stroke at 6 weeks	18 therapeutic sessions over a 6-week period	Demographic, clinical, neurophysiological, and imaging variables (3T MRI) with first-time hemorrhagic or ischemic stroke within 3 to 12 months	FMU	102 stroke patients (aged 54–66 years)	Regression	EN, SVM, ANN, classification and regression trees, and RF	10-fold cv	R^2_{EN} = 0.91, R^2_{RF} = 0.88, R^2_{ANN} = 0.83, R^2_{SVM} = 0.79, R^2_{CART} = 0.70

Table 2. *Cont.*

Authors	Year	Application Domain	Intervention	Input Data	Outcome Assessment	Employed Subjects	Learning Type	Learning Algorithms	Validation	Results
Rafiei et al. [51]	2019	Prediction of the improved use of the more affected arm at 3 weeks	Constraint-induced movement therapy	Demographics and baseline clinical characteristics (MAL, WMFT, SWMT, and MCA) (admission date: >6 months of stroke onset)	MAL	47 people with chronic (>6 months) mild to moderate upper-extremity hemiparesis	Classification	EPNN and NDC algorithm	Leave-one-out approach	Accuracy ≈ 100%
George et al. [52]	2017	Prediction of the response at 2 weeks of upper-extremity rehabilitation	Virtual-reality gaming (constraint-induced movement therapy was incorporated)	Data from motor and somatosensory (at admission >6 months after stroke)	WMFT	19 patients with chronic stroke (>6 months) with mild to moderate upper-extremity hemiparesis (aged 14.1–69.6 years)	Classification	EPNN	Leave-one-out approach	Accuracy for the gaming (94.7%) and combined datasets (94.5%)
George et al. [53]	2017	Prediction of the extent of motor recovery for upper-limb motor ability at 3 weeks	Constraint-induced movement therapy	BKT, SWTM, 15 timed items of the WMFT, and stroke-affected side (at admission >6 months after stroke)	WMFT	35 post-stroke patients (mean age 60 years)	Classification	EPNN, KNN, and PNN	Leave-one-out approach	EPPN yielded 100% accuracy

4. Discussion

In this scoping review, 26 original articles were identified that presented the current usage of ML techniques in the challenge of predicting both short- and long-term functional outcomes prior to rehabilitation interventions in post-stroke survivors. Figure 4 depicts the increasing trend of published ML related studies in the field. This work reinforces the need for (i) new AI tools that could predict long-term recovery rates from the first hours of hospital admission after stroke, and (ii) furthering our understanding of the mechanism behind the rehabilitation progress toward the formulation of personalized rehabilitation strategies for stroke patients. ML techniques could play a prime role in these directions by extracting valuable knowledge from various types of clinical data (e.g., images, musculoskeletal biomarkers, and kinematics data) and finding new strategies that could utilize data from every possible data source.

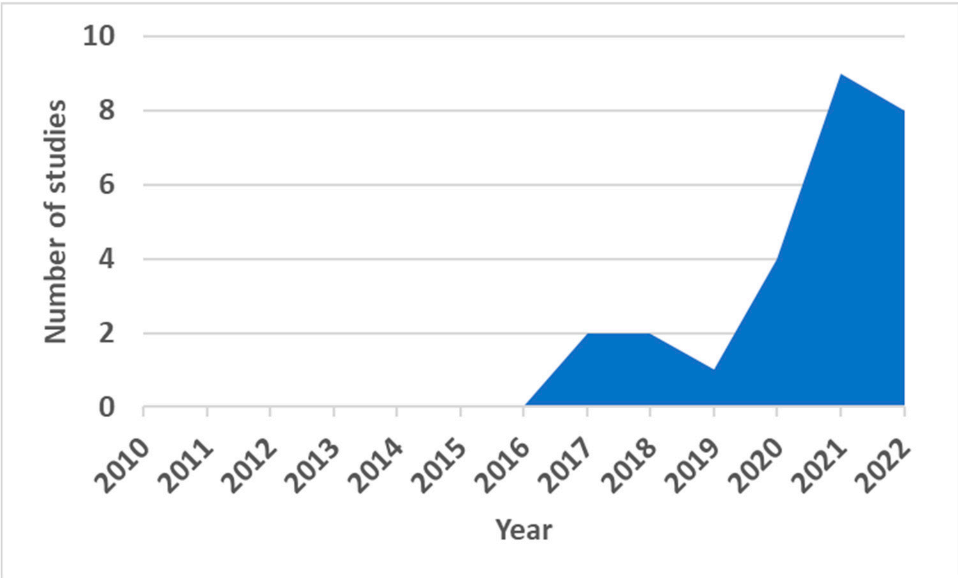

Figure 4. ML employment in the prediction of functional outcomes in rehabilitation in post-stroke survivors.

In earlier years, the lack of computational power, the limited ability to collect data from different sources, the reduced capacity to store big data, and the nature of the disease (e.g., limited number of study participants) could be characterized as blocking factors for the development of related studies. All of the above contributed to the reduced number of studies before 2019, as observed by the literature review.

In the motor function category, the authors observed that the interval for predicting functional outcomes varied from 8 days to 6 months. The majority of the studies focused on predicting functional outcomes within the first 3 months (10 out of 17 studies) from the beginning of the respective intervention. All these studies employed early-stage post-stroke survivors. They also noted that the baseline recordings at admission range from 18 h up to 1 month after stroke onset.

In the upper extremities category, the long-term prediction of functional outcome also varies. Specifically, two studies at 2 weeks, two studies at 3 weeks, one study at 4 weeks, one study at 6 weeks, two studies at 3 months, one study at 6 months, and one study at 9 months were recorded. In this category, the baseline recordings were quite different. These studies included measurements for patients who developed a stroke within 6 months before admission, studies with patients older than 6 months, and three studies with measurements from early-stage patients at 7–30 days after stroke onset.

Overall, nine regression and 20 classification approaches were recorded. Regarding the type of the ML models that were reported in this scoping review, SVMs and applications of NN models proved to be the most frequently used models in both survey categories. The choice of SVMs could be attributed to the fact that this classifier is computationally efficient in high-dimensional spaces and generalizes well in practice. Image-based features (e.g., MRI and CT) were included in only six of the 26 studies. These studies first applied feature engineering techniques and then various ML models, with SVMs being the most frequently used. EEG data as the main input were also employed only in one study that used CNNs to predict the outcome of BCI training during the first session. Several approaches were recorded as validation strategies. The two most common strategies were k-fold cross-validation and hold out (10–30%) with k-fold cross-validation on the training set. Furthermore, it is worth noting that two of the 26 studies used unknown datasets for external validation.

Various functional outcome assessment scores were used. The most frequent scores were FMA, FMU, BI, FIM, and mRS. Overall, only five of the recorded studies relied on data from the acute stage of patients' recovery (1–7 days) to develop ML prediction models. In addition, 15 of the recorded studies were based on data from early subacute stage patients (7 days to 3 months) for both categories. Furthermore, in the upper extremities category, the majority of the studies employed chronic stroke survivors.

It is worth noting that a small number of the studies included in our review (two out of 26) employed explainability techniques, such as the SHAP model or graphical models, to interpret the results of their machine learning models. Additionally, two of the studies made use of transfer learning, a technique commonly used in deep learning to address the challenge of limited data availability and provide effective solutions for medical prediction tasks. In these studies, pretrained models such as the VGG-16 CNN were utilized, and deep learning was employed for both classification and regression tasks. Although some of the studies included relatively small sample sizes ($n \leq 50$), the deep learning models performed satisfactorily in these cases. However, it is important to note that further validation of these models using external datasets is necessary to fully establish their validity and generalizability. Future work should focus on developing new advanced AI tools such as graphical models, explainability models, transfer learning, and Siamese CNN to enhance our understanding of the mechanism behind the decision-making process of the proposed predictive models. Additionally, combining data (at patient admission with less than 72 h from stroke onset) from a variety of data sources (e.g., imaging from MRI and CT, musculoskeletal biomarkers using OpenSim, and electroencephalogram) with the aforementioned AI tools could provide robust decision support tools capable of formulating or implementing appropriate personalized rehabilitation protocols for each patient.

The exclusion of the gray literature and the fact that only two online databases were used may have led to the identification of a relatively small number of included studies, and this could be considered a limitation of this scoping review.

5. Conclusions

This scoping review focused specifically on the identification of best-performing ML models being used to predict functional outcomes in stroke rehabilitation. AI tools could play key role in the management of the post-stroke patients. Specifically, state-of-the-art ML models have already been used for the prediction of the functional outcomes in the rehabilitation of post-stroke patients. This scoping review led to the conclusion that AI tools could predict long-term recovery rates from the first hours of hospital admission after stroke. To achieve this goal, big data and the use of pretrained deep learning models are required. In conclusion, the authors are convinced that understanding the mechanism behind the recovery of post-stroke survivors, on the basis of the extraction of knowledge from reliable, multisource data using advanced ML tools, could augment our ability to reliably assess the recovery progress before any clinical intervention. Hence, ML in this field could have a prime role in shaping new personalized rehabilitation strategies with a direct impact on the quality of life of stroke survivors and the healthcare system.

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