재활치료과학 제 11 권 제 4 호
Therapeutic Science for Rehabilitation
Vol. 11. No. 4. 2022.
https://doi.org/10.22683/tsnr.2022.11.4.023

Predicting Functional Outcomes of Patients With Stroke Using Machine Learning: A Systematic Review

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Abstract

Objective : To summarize clinical and demographic variables and machine learning uses for predicting functional outcomes of patients with stroke.

Methods : We searched PubMed, CINAHL and Web of Science to identify published articles from 2010 to 2021. The search terms were "machine learning OR data mining AND stroke AND function OR prediction OR/AND rehabilitation". Articles exclusively using brain imaging techniques, deep learning method and articles without available full text were excluded in this study.

Results : Nine articles were selected for this study. Support vector machines (19.05%) and random forests (19.05%) were two most frequently used machine learning models. Five articles (55.56%) demonstrated that the impact of patient initial and/or discharge assessment scores such as modified ranking scale (mRS) or functional independence measure (FIM) on stroke patients' functional outcomes was higher than their clinical characteristics.

Conclusions : This study showed that patient initial and/or discharge assessment scores such as mRS or FIM could influence their functional outcomes more than their clinical characteristics. Evaluating and reviewing initial and or discharge functional outcomes of patients with stroke might be required to develop the optimal therapeutic interventions to enhance functional outcomes of patients with stroke.

Keywords : Machine learning, Occupational therapy, Physical therapy, Recovery of function, Rehabilitation research, Stroke

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|| 접수일: 2022.06.24 || 심사일: 2022.06.28
|| 게재승인일: 2022.08.11

Ⅰ. Introduction

Strokes are the most common cause of decreased motor and cognitive function (Ward, 2017). Decreased motor functions are affected by motor performance skills and client factors due to a spasticity, limited range of motion, and lack of muscle power (Korpershoek et al., 2011). Stroke causes damage to the cerebral structures responsible for cognitive functions, so cognitive functions such as attention, memory, and problem-solving function are impaired (Al-Qazzaz et al., 2014; Caro et al., 2018). These problems impede the patients from returning to their regular routines, such as activities of daily living, work, social participation, sleep, and leisure (Mercier et al., 2001).

Health professionals—such as doctors, nurses, physical therapists, and occupational therapists—are involved in helping stroke patients lead independent lives again (Clarke & Forster, 2015). This process includes stroke patient admission to the hospital and return to the community post discharge. After acute care is complete, stroke patients who have dysfunction focus on rehabilitation (Young & Forster, 2007). Accurate evaluation and evidence-based interventions are required to maximize the effectiveness of rehabilitation (Dworzynski et al., 2015). The accurate assessment requires participant evaluation through a reliable, valid assessment tool (Dworzynski et al., 2015). Also, to provide evidence-based interventions, it is necessary to establish an appropriate intervention plan for the participants, based on assessment and clinical research (Platz, 2019).

Predicting a stroke patient's function can provides assistance in their rehabilitation, such as goal setting and intervention planning (Iwamoto et al., 2020). Several studies predicting function in stroke patients have suggested that these advantages are the purpose of the study. Based on predicted function, health care professionals such as occupational therapists, physical therapists, and speech therapists set short-term and long-term goals for stroke patients and plan interventions to achieve them (Heo et al., 2019). This may increase the motivation of stroke patients and improve their understanding of the intervention process (Siegert & Taylor, 2004). It can also be used to educate patients' families and caregivers based on predicted functions. This training includes suggestions for home modifications and aids to use when returning home after discharge (Cheong et al., 2020).

Previously, data-based studies have been conducted to analyze factors that are positively related to functional recovery in stroke participants using correlation and regression analysis (Elloker et al., 2019; Maso et al., 2019). However, the use of machine learning (ML), a methodology that effectively analyzes this and effectively understands patterns of vast amounts of data, has been prominent due to the recent increase in the amount and quality of data. ML is an area of computer engineering wherein a computer learns data and derives results based on it; it is the core technology of the 4th industrial revolution (Jordan & Mitchell, 2015). More complicated ML (i.e. decision tree (DT), random forest (RF), support vector machine (SVM) and classification and regression tree (CART)) can compensate for correlation and regression analysis's shortcomings. ML can explain and predict complex social phenomena based on data (Stylianou et al., 2015; Ij, 2018). Regression analysis can analyze the change of the dependent variable according to the change of the main independent variable, but it fits the data to a mathematical regression formula, and in the case of a nonlinear ML model, the average out occurs (Stylianou et al., 2015; Woo et al., 2019). In addition, traditional statistical approaches such as correlation and regression analysis should meet statistical assumptions in order to be applied (Ij, 2018). However, since non-parametric ML method has the advantage of exploring patterns in given data and analyzing trends even if statistical assumptions are not met. Also, ML can extract important characteristics among various characteristics of objects and build a model that can predict and classify dependent variables set by researchers.

Recently, studies have been conducted to predict the function of stroke patients by applying various ML-based algorithms such as regression analysis, decision trees, and ensemble models (Harari et al., 2020; Lin et al., 2018; Sirsat et al., 2020). It is used to predict and explain dependent variables such as functions at the time of discharge of stroke participants by extracting important features among various variables such as demographic, social psychological, physical, and cognitive functions. These studies can provide health professionals with additional information necessary for the treatment and rehabilitation of stroke participants. Therefore, our study aimed to systematically review studies that applied ML methods to predict the function of stroke participants. Through this study, we derive and summarize used ML algorithms, evaluation methods, variables, and selected feature importance for predicting patient functions used in the study.

Ⅱ. Methods

1. Search strategy

We employed PubMed, CINAHL and Web of Science (WoS) to review literature. We used the keywords “machine learning OR data mining AND stroke AND function OR prediction OR/AND rehabilitation” on three database. The search keywords and database were decided by two researcher.

2. Eligibility criteria

The inclusion and exclusion criteria were determined by two researchers. The inclusion criteria were as follows: first, participants should suffer from a stroke or cerebrovascular accident. Second, articles should predict the physical or cognitive function of subjects using ML algorithms (i.e., DT, SVM, and CART). We follow to the reference their definition in ML selection for this study (Sirsat et al., 2020). Third, the articles should be published between 2010 and February 2021. The exclusion criteria were as follows: first, articles using only brain imaging techniques. Second, articles use only the deep learning method. Third, review, thesis, or dissertation article. Four, articles without available full texts. Fifth, articles not written the Korean or English.

3. Study selection

Two researchers were independently involved and performed in this process, and disagreements were resolved through discussions. All searched articles

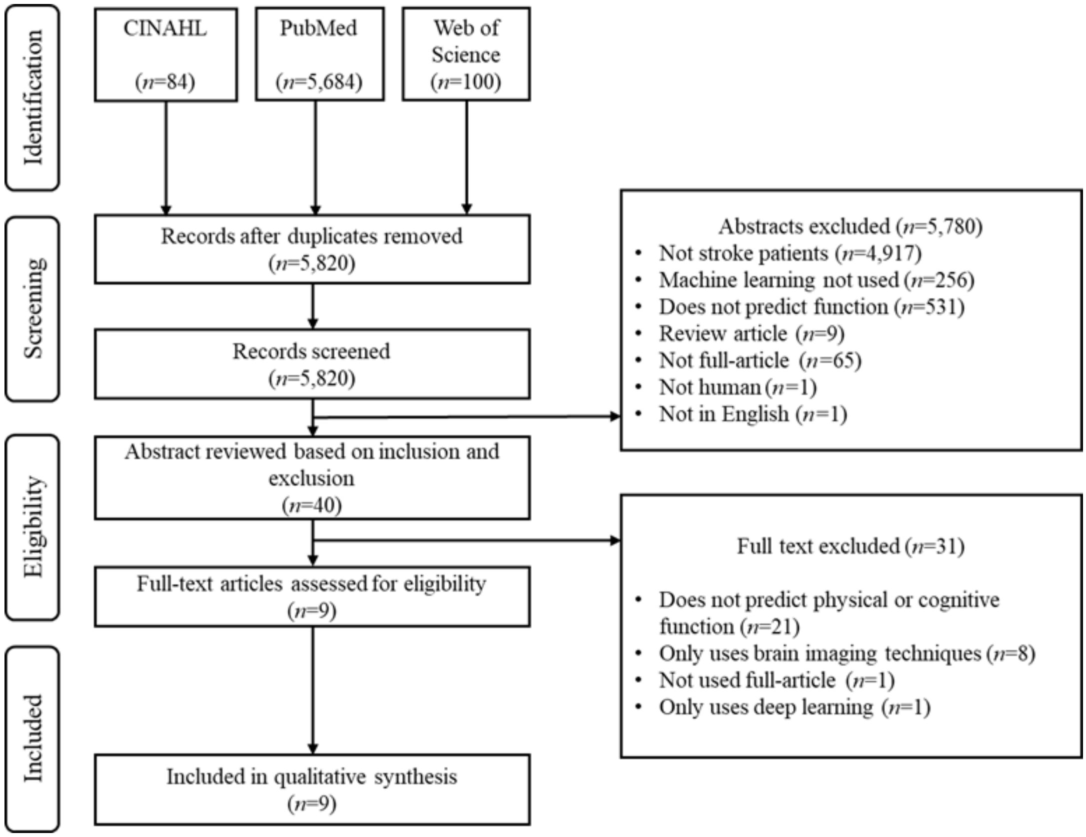

Figure 1. Search Process

were registered during the screening process. Subsequently, duplicate articles were removed. Then, the abstracts were reviewed, and the papers were screened based on the inclusion and exclusion criteria (Figure 1).

4. Data extraction

We summarized the selected articles with the characteristics of a study (authors, research field of authors, objective), participant information (sample size, type of stroke), ML characteristics (used ML algorithm, method of evaluation and value of performance such as the area under the receiver operating characteristic curve (AUC) or accuracy); independent and dependent variables; and selected feature importance for prediction outcomes. The feature importance is a function of machine learning that extracts the most important variable among used all variables when predicting dependent variables. The feature importance indicates the magnitude of variables on outcome prediction, so this study extracted and presented the top 5 important features among each article.

5. Reporting quality assessment

We did not assess the quality of the studies and risk of bias because our research aimed to describe the algorithms, methods of evaluation, and used variables. Instead, we followed the reporting quality assessment through the adjusted transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) as reported Wang et al. (2020). The adjusted TRIPOD checklist was developed for regression modeling. In the study by Wang et al. (2020), an adjusted term specifically for ML: 10a was presented as a specific type of model and 15a was presented as the full prediction model.

Ⅲ. Results

The results of the search process are shown in Figure 1. Numerous articles were found by searching for articles using key terms. First, we searched for articles in PubMed, CINAHL and WoS using the search terms. We found articles (PubMed=5,684, CINAHL=84, WoS=100). Next, we removed duplicate articles (*n*=48) and excluded the criteria (*n*=5,780). The two researchers read the full-text article (*n*=40) and excluded the articles that did not meet the inclusion criteria (*n*=31) (Figure 1). Finally, we selected and analyzed nine studies.

1. Independent and dependent variables

The independent and dependent variables used are presented in Table 1. The independent variables were divided into two groups. One of them was demographic and clinical characteristics (e.g., age, history of previous disease, body mass index, medication, stroke subtype, and laboratory findings). And the other are initial or discharge assessment tool score (e.g., modified ranking scale (mRS score), grip strength, functional independence measure (FIM) score). The dependent variables were divided into two groups; the prediction of participant mortality (Scrutinio et al., 2020), that of long-term outcomes or discharge assessment score (e.g., 90-day functional impairment risk, 90-day stroke outcome, toileting independence), function of daily routine of participants at discharge (e.g., self-care activities, Barthel index score and mRS score).

2. Important features for prediction function

Each article reported the selected features' importance among independent variables for the prediction function presented in Table 1. Among the selected articles, the seven articles were reported feature importance. The Lin et al. (2018) study found that motor activity log (MAL), mRS, instrumental activities of daily living (IADL) function, concise Chinese aphasia test (CCAT), Barthel index (BI) score was selected important feature for predicting BI score at discharge in stroke patient. The Lin et al. (2020) study reported that the selected feature to predict the 90-day outcome was initial 30-day mRS and discharge BI score. For toileting independence in discharge of stroke patient, the mRS, age, FIM score, independence degree, whether rehabilitation doctor was certified was selected as importance feature (Imura et al., 2021). The Iwamoto et al. (2020) study presented that the important feature to predict the mRS score at discharge was transfer to bed, chair, wheelchair score of FIM, transfer to the toilet score of FIM, and a bathing score of FIM. In the study by Scrutinio et al. (2020), he selected feature importance to predict three-years mortality in stroke patients was the demographic and clinical characteristics such as age, length of follow-up,

Table 1. Characteristics of Articles

Study	Participants	ML algorithm used	Type of predict function	Information used	Method of evaluation	Selected top 5 features for prediction function	
Lin et al. (2018)	356	LR, SVM, RF, SVM with linear Kernel, Linear regression	BI status at discharge	mRS, BI, FOIS, MNA, QoL, IADL, BBT, gait speed, 6WMT, FMA, MMSE, MAL, and CCAT	AUC, RMSE, MAE	MAL, mRS, IADL, CCAT, BI	
Alaka et al. (2020)	614	RF, SVM, C5.0, ABM, CART, LR, LASSO	mRS after 90-day	Participant characteristics	Sensitivity, specificity, AUC, MCC	Age, NHISS, SBP, glucose, DBP	
Heo et al. (2019)	2,604	DNN, RF, LR	mRS score	Participant demographics, initial NIHSS scores, stroke subtypes, history of previous diseases and medication, laboratory findings, and mRS score	AUC	-	
Harari et al. (2020)	50	LASSO	Discharge assessment score of FIM, TMWT, 6MWT, and BBS	Demographic information, stroke characteristics, scores of FIM, TMWT, 6MWT, and BS from the admission assessment	R2, R2adj, MAE, MAEn	For FIM	FIM, BBS, BMI, TMWT, 6MWT
						For TMWT	TMWT, 6MWT, BMI, age, BBS
						For 6MWT	TMWT, 6MWT, age, BBS
						For BBS	BBS, 6MWT, FIM, TMWT, age
Scrutinio et al. (2020)	1,207	RF, GB, ADA-B	Three-years mortality	Age, marital status, history of previous diseases, time from stroke onset to rehabilitation admission, and FIM scores	Sensitivity, specificity, accuracy, precision, NPV, AUC	Age, length of follow-up, CMG group, time between stroke onset and rehabilitation admission, overall FIM	

ABM=Adaptive Boost Machine; ADA-B=ADA-Boost; ADL=Activities of Daily Living; ANN=Artificial Neural Network; ASTRAL=Acute Stroke Registry and Analysis of Lausanne; AUC=the Area Under the receiver operating characteristic Curve; BBT=Box and Block Test; BBS=Berg Balance Score; BI=Barthel Index; CAD=Coronary Artery Disease; CHAID=Chi-squared Automatic Interaction Detection; CART=Classification and Regression Tree; CCAT=Concise Chinese Aphasia Test; C5.0=C5.0 decision tree; DBP=Diastolic Blood Pressure; DNN=Deep Neural Network; FIM=Functional Independence Measure; FMA=Fugl-Meyer Assessment scale; FOIS=Functional Oral Intake Scale; GB=Gradient Boosting; IADL=Instrumental Activities of Daily Living; LASSO=Least Absolute Shrinkage and Selection Operation; LR=Logistic Regression; MAE=Mean Absolute Error; MAEn=range of observed values; MAL=Motor Activity Log; mRS=modified Rankin Scale; MCC=Mathew's Correlation Coefficient; MMSE=Mini-Mental State Examination; MNA=Mini Nutrition Assessment; NIHSS=National Institutes of Health Stroke Scale; NPV=Negative Predictive Value; QoL=European Quality of Life five dimensions questionnaire; RF=Random Forest; R2=percentage of variance explained; R2adj=adjusted ted R2; SBP=Systolic Blood Pressure; sEMG=surface Electromyography; SVM=Support Vector Machine; TMWT=Ten-Meter Walk Test; PPV=Positive Predictive Value; 6WMT=Six-Min Walk Test

Table 1. Characteristics of Articles (Continued)

Study	Participants	ML algorithm used	Type of predict function	Information used	Method of evaluation	Selected top 5 features for prediction function	
Suzuki et al. (2020)	177	Non-linear SVM	Self-care activities (FIM)	Grip strength	Accuracy	-	
Lin et al. (2020)	35,798	SVM, RF, ANN	mRS score after 90-day	Clinical feature set (203 features), whole feature set (206 features), and selected features (mRS, BI, NIHSS)	Precision, sensitivity, F1-score, AUC	For ischemic stroke	For hemorrhagic stroke
						30-day mRS score, toilet use, mobility, dressing, grooming	30-day mRS score, toilet use, mobility, feeding, bathing, discharge mRS
Imura et al. (2021)	1,046	CHAID	Toileting score of FIM	Demographic and clinical characteristics, ADL before onset, mRS, FIM and rehabilitative factor	AUC	mRS, Age, FIM score, independence degree, rehabilitation doctor	
Iwamoto et al. (2020)	994	CART	mRS score at discharge	Demographic and clinical characteristics, brunnstrom stage, FIM and mRS at admission	AUC	FIM transfer to bed, chair and wheelchair score, FIM bathing score, FIM transfer toilet score	

ABM=Adaptive Boost Machine; ADA-B=ADA-Boost; ADL=Activities of Daily Living; ANN=Artificial Neural Network; ASTRAL=Acute Stroke Registry and Analysis of Lausanne; AUC=the Area Under the receiver operating characteristic Curve; BBT=Box and Block Test; BBS=Berg Balance Score; BI=Barthel Index; CAD=Coronary Artery Disease; CHAID=Chi-squared Automatic Interaction Detection; CART=Classification and Regression Tree; CCAT=Concise Chinese Aphasia Test; C5.0=C5.0 decision tree; DBP=Diastolic Blood Pressure; DNN=Deep Neural Network; FIM=Functional Independence Measure; FMA=Fugl-Meyer Assessment scale; FOIS=Functional Oral Intake Scale; GB=Gradient Boosting; IADL=Instrumental Activities of Daily Living; LASSO=Least Absolute Shrinkage and Selection Operation; LR=Logistic Regression; MAE=Mean Absolute Error; MAEn=range of observed values; MAL=Motor Activity Log; mRS=modified Rankin Scale; MCC=Mathew's Correlation Coefficient; MMSE=Mini-Mental State Examination; MNA=Mini Nutrition Assessment; NIHSS=National Institutes of Health Stroke Scale; NPV=Negative Predictive Value; QoL=European Quality of Life five dimensions questionnaire; RF=Random Forest; R2=percentage of variance explained; R2adj=adjusted ted R2; SBP=Systolic Blood Pressure; sEMG=surface Electromyography; SVM=Support Vector Machine; TMWT=Ten-Meter Walk Test; PPV=Positive Predictive Value; 6WMT=Six-Min Walk Test

CMG group, time between stroke onset and rehabilitation admission, overall FIM. On the hand, Alaka et al. (2020) study showed demographic and clinical characteristics such as age, systolic blood pressure (SBP), glucose, diastolic blood pressure (DBP) was selected for predicting the 90-day mRS in stroke patient.

3. Machine learning algorithm

Table 2 presents the ML algorithm used. Twelve-one supervised ML algorithms were used. Among them, SVM (19.05%) and random forests (19.05%) were used most frequently. Followed by, logistic regression (9.52%), LASSO regression (9.52%) and CART were used for function prediction in stroke participants. The following algorithms were used once (4.76%): artificial neural networks (ANN), DT, deep neural network (DNN), Adaboost, linear regression, gradient boosting and chi-squared automatic interaction detection (CHAID) (Table 2).

Table 2. Machine Learning Algorithms Used for Classification/Prediction

ML algorithms	Frequency (%)
Support vector machine	4 (19.05)
Artificial neural networks	1 (4.76)
Classification and regression tree	2 (9.52)
Decision tree	1 (4.76)
Random forest	4 (19.05)
Deep neural network	1 (4.76)
Logistic regression	2 (9.52)
Lasso regression	2 (9.52)
AdaBoost	1 (4.76)
Linear regression	1 (4.76)
Gradient boosting	1 (4.76)
Chi-squared automatic interaction detection	1 (4.76)
Total	21 (100)

ML=Machine Learning

4. Evaluation methods of machine learning algorithm used

Thirteen evaluation methods were used for the performance test of the ML used. Table 1 presents the method used. Seven articles used the area under the receiver operating characteristic curve (AUC) (28%), that is most frequently used for evaluating prediction model. Followed by the sensitivity was used each three articles (12%).

5. Prediction performance of ML algorithms

Table 3 presents the result of performance in each ML algorithm. This result was prepared based on AUC, and the mean absolute error (MAE) and accuracy of the two articles that did not use AUC were described. Among the seven articles using AUC, two articles used a single machine learning algorithm, and the other articles used various machine learning algorithms to compare performance based on AUC. Lin et al. (2018), Lin et al. (2020), and Alaka et al. (2020)'s study have presented the result of research that the performance of SVM was better than other ML algorithms. Heo et al. (2019)'s study presented deep neural network (DNN) as a better performance ML algorithm among RF, logistic regression (LR), and DNN, and Scrutinio et al. (2020)'study presented RF and gradient boosting (GB) as algorithms with good

Table 3. The Result of Performance in Each Machine Learning Algorithms

Study	ML algorithm	Predictive performance	
Lin et al. (2018)	LR	0.76 (0.73-0.78)	
	RF	0.77 (0.71-0.82)	
	SVM	0.78 (0.75-0.81)	
Alaka et al. (2020)	RF	0.70 (0.66-0.75)	
	SVM	0.71 (0.65-0.75)	
	C5.0	0.66 (0.63-0.72)	
	ABM	0.67 (0.65-0.73)	
	CART	0.69 (0.64-0.73)	
	LR	0.69 (0.65-0.73)	
	LASSO	0.67 (0.60-0.73)	
Heo et al. (2019)	DNN	0.89 (0.87-0.90)	
	RF	0.86 (0.84-0.88)	
	LR	0.85 (0.83-0.87)	
Harari et al. (2020)	LASSO[*]	For FIM	7.6
		For TMWT	0.26
		For 6MWT	73.2
		For BBS	6.4
Scrutinio et al. (2020)	RF	0.93 (0.90-0.95)	
	GB	0.93 (0.90-0.95)	
	ADA-B	0.91 (0.88-0.94)	
Suzuki et al. (2020)	SVM[**]	For eating	0.71±0.04
		For grooming	0.77±0.03
		For dressing the upper body	0.75±0.03
		For dressing the lower body	0.72±0.05
		For bathing	0.68±0.03
Lin et al. (2020)	ANN	For ischemic stroke	0.97
		For hemorrhagic stroke	0.96
	RF	For ischemic stroke	0.96
		For hemorrhagic stroke	0.97
	SVM	For ischemic stroke	0.97
		For hemorrhagic stroke	0.97
Imura et al. (2021)	CHAID	0.80 (0.77-0.83)	
Iwamoto et al. (2020)	CART	0.83 (0.80-0.86)	

[*]The value is mean absolute error (MAE); [**]The value is accuracy; ABM= Adaptive Boost Machine; ADA-B= ADA-Boost; ANN= Artificial Neural Network; AUC= the Area Under the receiver operating characteristic Curve; BBT= Box and Block Test; CHAID= Chi-squared Automatic Interaction Detection; CART= Classification and Regression Tree; C5.0= C5.0 decision tree; DNN= Deep Neural Network; FIM= Functional Independence Measure; GB= Gradient Boosting; LASSO= Least Absolute Shrinkage and Selection Operation; LR= Logistic Regression; RF= Random Forest; SVM= Support Vector Machine; TMWT= Ten-Meter Walk Test; 6WMT= Six-Min Walk Test

prediction performance than other ML algorithms.

6. Quality assessment

Thirty-one checklists were assessed for each study. The clear definition of outcome (6a), blind assessment of the outcome (6b), blind assessment of the predictors (7b), method of missing data (9), description of predictors handled (10a), provides details on risk group (11), unadjusted association between predictor and outcome (14b), and presentation of the full prediction model were unreported in almost all studies. However, other checklists have been reported in most articles (Figure 2).

7. Affiliation and department of authors

Table 4 presents the affiliation and department of the first author of each article. Among the nine

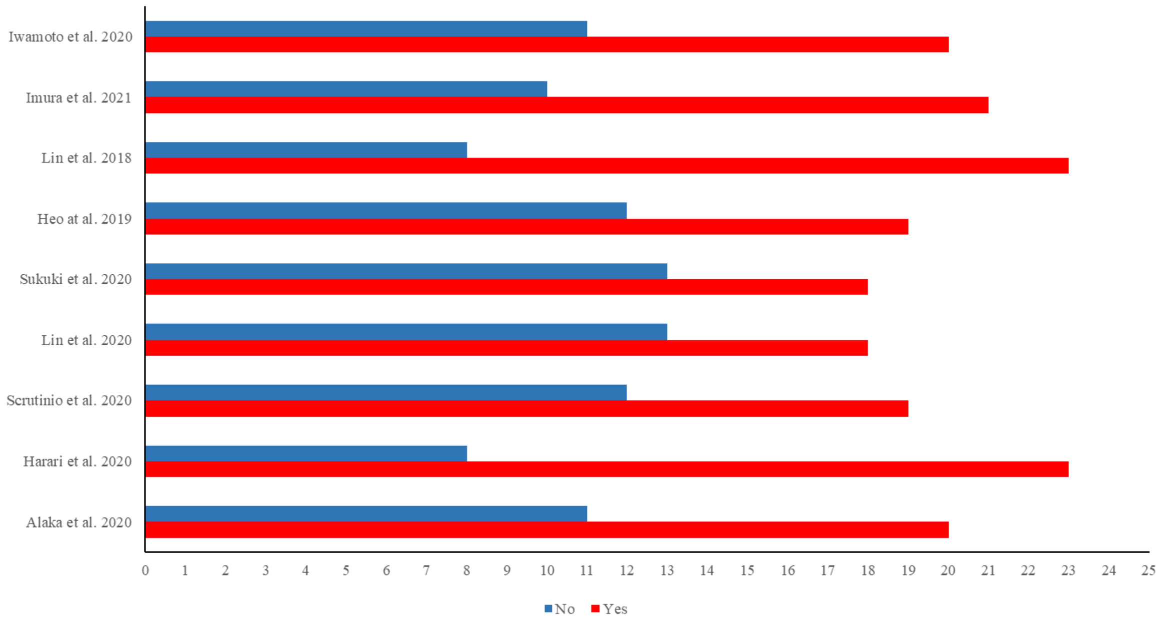

Figure 2. Number of Criteria Reported in Each Article

Table 4. The Information of the First Author in Each Article

Study		Information of first author
Lin et al. (2018)	Affiliation	University
	Department	Physical medicine & rehabilitation, Information management
Alaka et al. (2020)	Affiliation	University
	Department	Community health sciences
Heo et al. (2019)	Affiliation	University
	Department	Neurology
Harari et al. (2020)	Affiliation	University
	Department	Physical medicine & rehabilitation

Table 4. The Information of the First Author in Each Article (Continued)

Study		Information of first author
Scrutinio et al. (2020)	Affiliation	Research institute
	Department	Cardioangiology rehabilitation
Suzuki et al. (2020)	Affiliation	University
	Department	Health sciences
Lin et al. (2020)	Affiliation	National institutes
	Department	Information technology, Bioinformatics
Imura et al. (2021)	Affiliation	University
	Department	Rehabilitation
Iwamoto et al. (2020)	Affiliation	Hospital
	Department	Rehabilitation

studies, Lin et al., (2018), Harari et al., (2020), and Heo et al., (2019) had at least one first author. The first author of Lin et al., (2018) was three people, one majoring in Physical Medicine & Rehabilitation, and the other two majors in information management. The first author of Heo et al. (2019) study was two people, with the same affiliation and department. Also, the first author of Harari et al. (2020) study was two people, with the same affiliation and department. Most of the first authors belonged to the university, other than the national institute and hospitals.

Ⅳ. Discussion

We systematically reviewed the studies applying ML methods to predict functionality recovery in stroke patients. Through this study, we attempted to summarize the information obtained by applying ML and to suggest its utilization. Nine articles were selected for analysis. The results of this study were obtained by summarizing the independent and dependent variables used to predict the functional recovery in stroke patients, importance of the variables, types of ML algorithms, methods of ML algorithm evaluation, predictive performance and research field of authors.

Through this study, we derive the result that one of the most frequently used ML algorithms to predict the function of stroke patients is random forest. Random forest is based on a decision tree model and has an advantage in explanatory power over other ML algorithms (Byeon, 2020; Schonlau & Zou, 2020). The random forest shapes a rule-based tree to produce results that can explain a group of predictors. In addition, when establishing a predictive model, it shows important features to distinguish predictors by extracting the most important features among variables. A study by Imura et al. (2021) shows that ML studies can provide beneficial information for clinicians (Imura et al., 2021). Through the decision tree presented in Imura el al. (2021)'s study, important variables and criteria can be understood to predict toilet independence in stroke patients. Through the development of a model of the random forest algorithm, occupational and physical therapy clinicians can understand the demographic characteristics of the group of predictors, the state of psychosocial factors, and the functional state. In addition, it is possible to recognize which variables have a large impact to predict functional recovery in stroke patients and apply them to rehabilitation intervention plans.

In this study, we extracted the variables that are the most important when predicting the prognosis of stroke patients in seven out of nine selected articles. Five of seven articles reported that the assessment score was more important than the clinical characteristics of stroke patients. When the rehabilitation process begins, occupational or physical therapists first evaluate stroke patients' function(American Occupational Therapy Association, 2020). These initial assessment scores can help therapists understand the patients and can also provide assistance in predicting prognosis, as in the results of this study. This represents the importance of the initial assessment and further extends the utilization of the assessment scores.

Another major purpose of ML is to create models with high predictive performance. In ML, the algorithm with the better predictive performance among various algorithms is selected as the final model through the data partition or the cross-validation method (Singh et al., 2016). Among the studies using one or more ML algorithms selected in this study, the models with the highest predictive performance were SVM and RF. Lin et al. (2018) and Alaka et al. (2020)'s studies presented a better predictive performance of RF and SVM than LR. Also, Heo et al. (2019)'s study showed good predictive performance of RF than LR, a traditional statistical method. The goal of an SVM is to find the best hyperplane to classify data patterns and to achieve the goal by choosing from a set of hyperplanes that maximize the distance between the hyperplanes and the closest data (Meyer & Wien, 2001; Jakkula, 2006). SVM is one of the algorithms with good predictive power in ML. except for ensemble models, and has the advantage of being able to apply whether the dependent variable is continuous or categorical (Jakkula, 2006; Son et al., 2010). RF is an ensemble model based on a DT, and as described above, it is an algorithm with good predictive performance. The reason that RF is an algorithm with excellent predictive power is that it extracts data through bootstrap sampling and creates and combines a variable number of decision trees (Byeon, 2020; Schonlau & Zou, 2020). These results will serve as a basis for using SVM and RF to predict the prognosis or functional outcome of patients with stroke or other diseases using ML.

Rehabilitation professionals identify a problem encountered by a participant and provide evidence-based intervention to enhance their remaining function (Clarke & Forster, 2015). They evaluated the participant function in the first session of occupational or physical therapy and established intervention goals and plans (American Occupational Therapy Association, 2020). By using ML to predict stroke patient function, based on their assessment scores, occupational or physical therapists can plan interventions by considering the predicted functionality. Further, if the participant function improves with progress, ML will be able to predict the function again and modify the goal accordingly. Previous studies have predicted functional outcomes and quality of life after intervention through ML based on demographic, clinical, and neurophysiological data before intervention in stroke patients, and reported high predictive performance (Tozlu et al., 2020; Liao et al., 2022). These findings imply that appropriate interventions can be planned by targeting the functional outcomes after intervention predicted by information from pre-intervention stroke patients. Setting goals is an important process in rehabilitation programs for stroke patients (Lin et al., 2020). Target arbitration based on goal setting not only increases the rehabilitation effectiveness of the participants but also accelerates improvements to the participant functionality (Fishman et al., 2021; Siegert & Taylor, 2004). If this process is repeated, it can provide optimal rehabilitation for patients suffering from stroke patient.

1. Limitations of the study

The studies that reported intervention effects via ML articles were excluded. The purpose of the study was to systematically analyze the study that predicted functional recovery based on the demographic characteristics and assessment scores of stroke patients. Since the types and application methods of intervention vary, the process of systematic analysis and the method of presenting results were in a different direction from the purpose of this study, so this should be discussed through future research.

V. Conclusion

We analyzed research that predicted the function of stroke patients using ML. Consequently, we selected nine articles for analysis. Based on them, we summarized the important variables for predicting outcomes in stroke patients, use of ML algorithms, and methods for evaluating validity. Our findings examined the manner in which predicting the function of stroke patients using ML can be applied in occupational and physical therapy. Furthermore, this study encourages ML-based research to further expand the occupational and physical therapy domain.

Acknowledgment

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2021S1A3A2A 02096338). In addition, this research was supported in part by grant# K12 HD055929 from the National Institutes of Health (NIH). Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the NIH.

References

Al-Qazzaz, N. K., Ali, S. H., Ahmad, S. A., Islam, S., & Mohamad, K. (2014). Cognitive impairment and memory dysfunction after a stroke diagnosis: A post-stroke memory assessment. *Neuropsychiatric Dsease and Treatment, 10*, 1677-1691. http://doi.org/10.2147/NDT.S67184

Alaka, S. A., Menon, B. K., Brobbey, A., Williamson, T., Goyal, M., Demchuk, A. M., Hill, M. D., & Sajobi, T. T. (2020). Functional outcome prediction in ischemic stroke: A comparison of machine learning algorithms and regression models. *Frontiers in Neurology, 11.*

https://doi.org/10.3389/fneur.2020.00889
American Occupational Therapy Association. (2020). Occupational therapy practice framework: Domain and process. *American Journal of Occupational Therapy, 74*(S2), 1-85. https://doi.org/10.5014/ajot.2020.74S2001
Byeon, H. (2020). Is the Random Forest algorithm suitable for predicting Parkinson's disease with mild cognitive impairment out of Parkinson's disease with normal cognition? *International Journal of Environmental Research and Public Health, 17*(7), 2594-2608. https://doi.org/10.3390/ijerph17072594
Caro, C. C., Costa, J. D., & da Cruz, D. M. C. (2018). Burden and quality of life of family caregivers of stroke patients. *Occupational Therapy in Health Care, 32*(2), 154-171. https://doi.org/10.1080/07380577.2018.1449046
Cheong, M. J., Jeon, B., & Noh, S. E. (2020). A protocol for systematic review and meta-analysis on psychosocial factors related to rehabilitation motivation of stroke patients. *Medicine, 99*(52), e23727-e23727. http://doi.org/10.1097/MD.0000000000023727
Clarke, D. J., & Forster, A. (2015). Improving post-stroke recovery: The role of the multidisciplinary health care team. *Journal of Multidisciplinary Healthcare, 8*, 433-442. http://doi.org/10.2147/JMDH.S68764
Dworzynski, K., Ritchie, G., & Playford, E. D. (2015). Stroke rehabilitation: Long-term rehabilitation after stroke. *Clinical Medicine, 15*(5), 461-464. http://doi.org/10.7861/clinmedicine.15-5-461
Elloker, T., Rhoda, A., Arowoiya, A., & Lawal, I. U. (2019). Factors predicting community participation in patients living with stroke, in the Western Cape, South Africa. *Disability and Rehabilitation, 41*(22), 2640-2647. https://doi.org/10.1080/09638288.2018.1473509
Fishman, K. N., Ashbaugh, A. R., & Swartz, R. H. (2021). Goal setting improves cognitive performance in a randomized trial of chronic stroke survivors. *Stroke, 52*(2), 458-470. https://doi.org/10.1161/STROKEAHA.120.032131
Harari, Y., O'Brien, M. K., Lieber, R. L., & Jayaraman, A. (2020). Inpatient stroke rehabilitation: Prediction of clinical outcomes using a machine-learning approach. *Journal of NeuroEngineering and Rehabilitation, 17*(1), 1-10. https://doi.org/10.1186/s12984-020-00704-3
Heo, J., Yoon, J. G., Park, H., Kim, Y. D., Nam, H. S., & Heo, J. H. (2019). Machine learning-based model for prediction of outcomes in acute stroke. *Stroke, 50*(5), 1263-1265. https://doi.org/10.1161/STROKEAHA.118.024293
Ij, H. (2018). Statistics versus machine learning. *Nature Methods, 15*(4), 233-234. https://doi.org/10.1038/nmeth.4642
Iwamoto, Y., Imura, T., Tanaka, R., Imada, N., Inagawa, T., Araki, H., & Araki, O. (2020). Development and validation of machine learning-based prediction for dependence in the activities of daily living after stroke inpatient rehabilitation: A decision-tree analysis. *Journal of Stroke and Cerebrovascular Diseases, 29*(12), 1-6. https://doi.org/10.1016/j.jstrokecerebrovasdis.2020.105332
Imura, T., Inoue, Y., Tanaka, R., Matsuba, J., & Umayahara, Y. (2021). Clinical features for identifying the possibility of toileting independence after convalescent inpatient rehabilitation in severe stroke patients: A decision tree analysis based on a nationwide Japan rehabilitation database. *Journal of Stroke and Cerebrovascular Diseases, 30*(2), 1-8. https://doi.org/10.1016/j.jstrokecerebrovasdis.2020.105483
Jakkula, V. (2006). *Tutorial on support vector machine (svm).* School of EECS, Washington State University. https://course.ccs.neu.edu/cs5100f11/resources/jakkula.pdf
Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255-260. http://doi.org/10.1126/science.aaa8415
Korpershoek, C., van der Bijl, J., & Hafsteinsdóttir, T. B. (2011). Self-efficacy and its influence on recovery of patients with stroke: A systematic review. *Journal of Advanced Nursing, 67*(9), 1876-1894. https://doi.org/10.1111/j.1365-2648.2011.05659.x
Liao, W. W., Hsieh, Y. W., Lee, T. H., Chen, C. L., & Wu, C. Y. (2022). Machine learning predicts clinically significant health related quality of life improvement after sensorimotor rehabilitation interventions in chronic stroke. *Scientific Reports, 12*(1), 1-10. https://doi.org/10.1038/s41598-022-14986-1

Lin, W., Chen, C., Tseng, Y. J., Tsai, Y. T., Chang, C. Y., Wang, H. Y., & Chen, C. K. (2018). Predicting post-stroke activities of daily living through a machine learning-based approach on initiating rehabilitation. *International Journal of Medical Informatics, 111*, 159-164. https://doi.org/10.1016/j.ijmedinf.2018.01.002

Lin, C., Hsu, K., Johnson, K. R., Fann, Y. C., Tsai, C., Sun, Y., Lien, L., Chang, W., Chen, P., Lin, C., & Hsu, C. Y. (2020). Evaluation of machine learning methods to stroke outcome prediction using a nationwide disease registry. *Computer Methods and Programs in Biomedicine, 190*, 1-14. https://doi.org/10.1016/j.cmpb.2020.105381

Maso, I., Pinto, E. B., Monteiro, M., Makhoul, M., Mendel, T., Jesus, P. A., & Oliveira-Filho, J. (2019). A simple hospital mobility scale for acute ischemic stroke patients predicts long-term functional outcome. *Neurorehabilitation and Neural Repair, 33*(8), 614-622. https://doi.org/10.1177/1545968319856894

Mercier, L., Audet, T., Hébert, R., Rochette, A., & Dubois, M. F. (2001). Impact of motor, cognitive, and perceptual disorders on ability to perform activities of daily living after stroke. *Stroke, 32*(11), 2602-2608. https://doi.org/10.1161/hs1101.098154

Meyer, D., & Wien, F. T. (2001). Support vector machines. *R News, 1*(3), 23-26.

Platz, T. (2019). Evidence-based guidelines and clinical pathways in stroke rehabilitation-an international perspective. *Frontiers in Neurology, 10,* 1-7. https://doi.org/10.3389/fneur.2019.00200

Schonlau, M., & Zou, R. Y. (2020). The random forest algorithm for statistical learning. *Stata Journal, 20*(1), 3-29. https://doi.org/10.1177/1536867X20909688

Scrutinio, D., Ricciardi, C., Donisi, L., Losavio, E., Battista, P., Guida, P., Cesarelli, M., Pagano, G., & D'Addio, G. (2020). Machine learning to predict mortality after rehabilitation among patients with severe stroke. *Scientific Reports, 10*(1), 1-10. https://doi.org/10.1038/s41598-020-77243-3

Siegert, R. J., & Taylor, W. J. (2004). Theoretical aspects of goal-setting and motivation in rehabilitation. *Disability and Rehabilitation, 26*(1), 1-8. https://doi.org/10.1080/09638280410001644932

Singh, A., Thakur, N., & Sharma, A. (2016). A review of supervised machine learning algorithms. *In 2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom), 2016,* 1310-1315.

Sirsat, M. S., Fermé, E., & Câmara, J. (2020). Machine learning for brain stroke: A review. *Journal of Stroke and Cerebrovascular Diseases, 29*(10), 1-17. https://doi.org/10.1016/j.jstrokecerebrovasdis.2020.105162

Son, Y. J., Kim, H. G., Kim, E. H., Choi, S., & Lee, S. K. (2010). Application of support vector machine for prediction of medication adherence in heart failure patients. *Healthcare Informatics Research, 16*(4), 253-259. https://doi.org/10.4258/hir.2010.16.4.253

Stylianou, N., Akbarov, A., Kontopantelis, E., Buchan, I., & Dunn, K. W. (2015). Mortality risk prediction in burn injury: Comparison of logistic regression with machine learning approaches. *Burns, 41*(5), 925-934. https://doi.org/10.1016/j.burns.2015.03.016

Suzuki, M., Sugimura, S., Suzuki, T., Sasaki, S., Abe, N., Tokito, T., & Hamaguchi, T. (2020). Machine-learning prediction of self-care activity by grip strengths of both hands in poststroke hemiplegia. *Medicine, 99*(11). http://doi.org/10.1097/MD.0000000000019512

Tozlu, C., Edwards, D., Boes, A., Labar, D., Tsagaris, K. Z., Silverstein, J., Lane, H. P., Subuncu, M. R., Liu, C., & Kuceyeski, A. (2020). Machine learning methods predict individual upper-limb motor impairment following therapy in chronic stroke. *Neurorehabilitation and Neural Repair, 34*(5), 428-439. https://doi.org/10.1177/1545968320909796

Wang, W., Kiik, M., Peek, N., Curcin, V., Marshall, I. J., Rudd, A. G., Wang, Y., Douiri, A., Wolfe, C. D., & Bray, B. (2020). A systematic review of machine learning models for predicting outcomes of stroke with structured data. *PLoS One, 15*(6), 1-16. https://doi.org/10.1371/journal.pone.0234722

Ward, N. S. (2017). Restoring brain function after stroke—bridging the gap between animals and humans. *Nature Reviews Neurology, 13*(4), 244-255. https://doi.org/10.1038/nrneurol.2017.34

Woo, Y. C., Lee, S. Y., Choi, W., Ahn, C. W., & Baek, O. K. (2019). Trend of utilization of machine learning technology for digital healthcare data analysis. *Electronics and Telecommunications Trends, 34*(1), 98-110. https://doi.org/10.22648/ETRI.2019.J.340109

Young, J., & Forster, A. (2007). Rehabilitation after stroke. *British Medical Journal, 334*, 86-90. https://doi.org/10.1136/bmj.39059.456794.68

국문초록

머신러닝을 활용한 뇌졸중 환자의 기능적 결과 예측: 체계적 고찰

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목적 : 본 연구는 뇌졸중 환자의 기능적 결과를 예측하기 위한 인구통계학적 및 임상학적 특징과 머신러닝의 사용을 체계적으로 분석하고 요약하기 위해 수행되었다.

연구방법 : PubMed, CINAHL과 Web of Science를 사용하여 2010년부터 2021년 사이에 게재된 연구를 검색하였다. 주요 검색어는 “machine learning OR data mining AND stroke AND function OR prediction OR/AND rehabilitation”을 사용하였다. 뇌 이미지 처리 기법만을 분석한 연구, 딥러닝만 적용한 연구와 전체 본문을 열람할 수 없는 연구는 제외되었다.

결과 : 검색한 결과, 총 9편의 국내외 논문을 선정했다. 선정된 논문에서 가장 많이 사용된 머신러닝 알고리즘은 서포트 벡터 머신(support vector machine, 19.05%)과 랜덤포레스트(random forest, 19.05%)였다. 9개 중 7개의 연구에서 뇌졸중 환자의 기능을 예측하기 위해 중요하다고 추출된 변수를 결과로 제시했다. 그 결과, 5개(55.56%)의 연구에서 뇌졸중 환자의 기능을 예측하기 위해 환자의 임상적 특성이 아닌 modified ranking scale (mRS) 및 functional independence measure (FIM)과 같은 초기 또는 퇴원 평가 점수가 중요하다고 도출되었다.

결론 : 이 연구는 mRS 및 FIM과 같은 뇌졸중 환자의 초기 또는 퇴원 평가 점수가 임상적 특성보다 기능적 결과에 더 많은 영향을 미칠 수 있음을 나타냈다. 따라서, 뇌졸중 환자의 기능적 결과를 향상시키기 위한 최적의 중재를 개발하고 적용하기 위해서는 뇌졸중 환자의 초기 및 퇴원 시 기능적 결과를 평가하고 검토하는 것이 필요하다.

주제어 : 기능회복, 뇌졸중, 머신러닝, 물리치료, 작업치료, 재활연구