Brain Neurorehabil. 2022 Nov;15(3):e26
https://doi.org/10.12786/bn.2022.15.e26
pISSN 1976-8753·eISSN 2383-9910

Brain & NeuroRehabilitation

Special Review

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Use of Machine Learning in Stroke Rehabilitation: A Narrative Review

OPEN ACCESS

Yoo Jin Choo, Min Cheol Chang

Received: Jul 1, 2022
Revised: Sep 9, 2022
Accepted: Oct 7, 2022
Published online: Oct 31, 2022

Correspondence to
Min Cheol Chang
Department of Physical Medicine and Rehabilitation, College of Medicine, Yeungnam University, 170 Hyeonchung-ro, Nam-gu, Daegu 42415, Korea.
Email: wheel633@gmail.com

HIGHLIGHTS

- A narrative review was conducted of machine learning applications and research in the field of stroke rehabilitation.
- Commonly used machine learning models in medical research include random forest, logistic regression, and deep neural networks.
- Machine learning can be used for various purposes, such as predicting function, recovery, and rehabilitation of stroke patients.

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Yoo Jin Choo, **Min Cheol Chang**

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Min Cheol Chang
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Email: wheel633@gmail.com

ORCID iDs
Yoo Jin Choo
https://orcid.org/0000-0002-3820-2279
Min Cheol Chang
https://orcid.org/0000-0002-7629-7213

Funding
This work was supported by a grant from the Chunma Medical Research Foundation, Korea, 2022.

Conflict of Interest
The authors have no potential conflicts of interest to disclose.

ABSTRACT

A narrative review was conducted of machine learning applications and research in the field of stroke rehabilitation. The machine learning models commonly used in medical research include random forest, logistic regression, and deep neural networks. Convolutional neural networks (CNNs), a type of deep neural network, are typically used for image analysis. Machine learning has been used in stroke rehabilitation to predict recovery of motor function using a large amount of clinical data as input. Recent studies on predicting motor function have trained CNN models using magnetic resonance images as input data together with clinical data to increase the accuracy of motor function prediction models. Additionally, a model interpreting videofluoroscopic swallowing studies was developed and investigated. In the future, we anticipate that machine learning will be actively used to treat stroke patients, such as predicting the occurrence of depression and the recovery of language, cognitive, and sensory function, as well as prescribing appropriate rehabilitation treatments.

Keywords: Machine Learning; Artificial Intelligence; Stroke; Rehabilitation; Deep Learning

INTRODUCTION

Machine learning, an artificial intelligence (AI) technique, enables computer systems to learn patterns and rules from information and data provided without explicit programming [1]. Machine learning can be largely divided into unsupervised, supervised, reinforcement, and deep learning. Unsupervised learning involves predicting the results of new data by grouping data without ground-truth labels based on similar features [2]; it is somewhat more difficult than supervised learning because patterns and shapes are determined from unlabeled data [2,3]. Supervised learning involves using data with ground-truth labels for learning. Generally, classification or regression is conducted in the learning process by simultaneously providing input and output values [4]. Reinforcement learning involves a defined agent recognizing the current state and selecting a behavior or order of behaviors that maximize rewards among selectable behaviors in a certain environment [2,5]. Unlike supervised learning, reinforcement learning does not necessarily use a training set that consists of input and output pairs or explicitly correct and incorrect behaviors [5]. Deep learning is a set of machine learning algorithms that attempt high-level abstractions by combining several nonlinear transformations [6]. Deep learning, which uses a large amount of data to train and create a model capable of processing new data [7], has been applied in various fields, including computer vision, voice recognition, natural language processing, and voice/signal processing, producing advanced outcomes [6]. The widely recognized advantages of machine learning include its ability to identify interactions between several variables and detect useful information in time-series, clinical, and imaging data [8]. Applying conventional machine learning may be more appropriate depending on the data size and type, but deep learning may be more useful when analyzing big data and detecting useful information in image data [8]. Large amounts of information and image data are generated regarding the clinical condition of stroke patients [9]. Accordingly, we believe that machine learning can be used to process clinical and image data and be advantageous in stroke rehabilitation. Numerous studies have investigated applications of machine learning in stroke research. Most studies have focused on predicting the prognosis after a stroke using clinical data or on predicting functional recovery and screening lesions using magnetic resonance (MR) images or videofluoroscopic swallowing study (VFSS) data [10-13].

In this study, we describe machine learning and its use in the field of stroke rehabilitation based on previous studies.

REPRESENTATIVE MACHINE LEARNING MODELS

The algorithm models commonly used for machine learning are random forest, boosting, support vector machine, logistic regression, and deep neural networks. The random forest method is a type of supervised learning that prevents overfitting by creating multiple decision trees and averaging the results from each decision tree (**Fig. 1A**) [14]. Thus, a random forest can be considered an ensemble model that performs predictions by collecting classification results from several decision trees constructed during training [15]. A decision tree is trained by identifying optimal features and an optimal critical point that can effectively classify the features of the input data [14]. However, the random forest method randomly selects multiple decision trees and identifies a model composed of a set of decision trees with optimal features among several sets of decision trees [16]. The random forest method has the advantage of determining each input data point, but the disadvantage of being difficult to visualize [16,17]. Furthermore, the most important limitation of the random forest approach is that generalizing a dataset is difficult owing to the high probability of the accuracy or area under the receiver operating characteristic curve being different for each patient cohort [18].

In recent years, frequently-used ensemble approaches, such as eXtreme Gradient Boosting, the Light Gradient Boosting Machine, and CatBoost have been considered to outperform the random forest method. Boosting is an ensemble technique used to create a powerful prediction model by combining several weak decision trees [19]. Gradient boosting is a representative algorithm implemented using the boosting technique, and eXtreme Gradient Boosting is a library implemented for parallel learning using gradient boosting. eXtreme Gradient Boosting demonstrates excellent predictive performance in regression and classification domains and has faster learning and classification speeds than gradient boosting models. Furthermore, it is a robust method because it is equipped with an overfitting control function, but it tends to react sensitively to learning data because it uses tree-based learning; in addition, tuning is difficult owing to complicated hyperparameters [20]. The Light Gradient Boosting Machine method uses leaf-wise tree segmentation and continuously segments leaf nodes with maximum data loss without considering the balance

https://doi.org/10.12786/bn.2022.15.e26

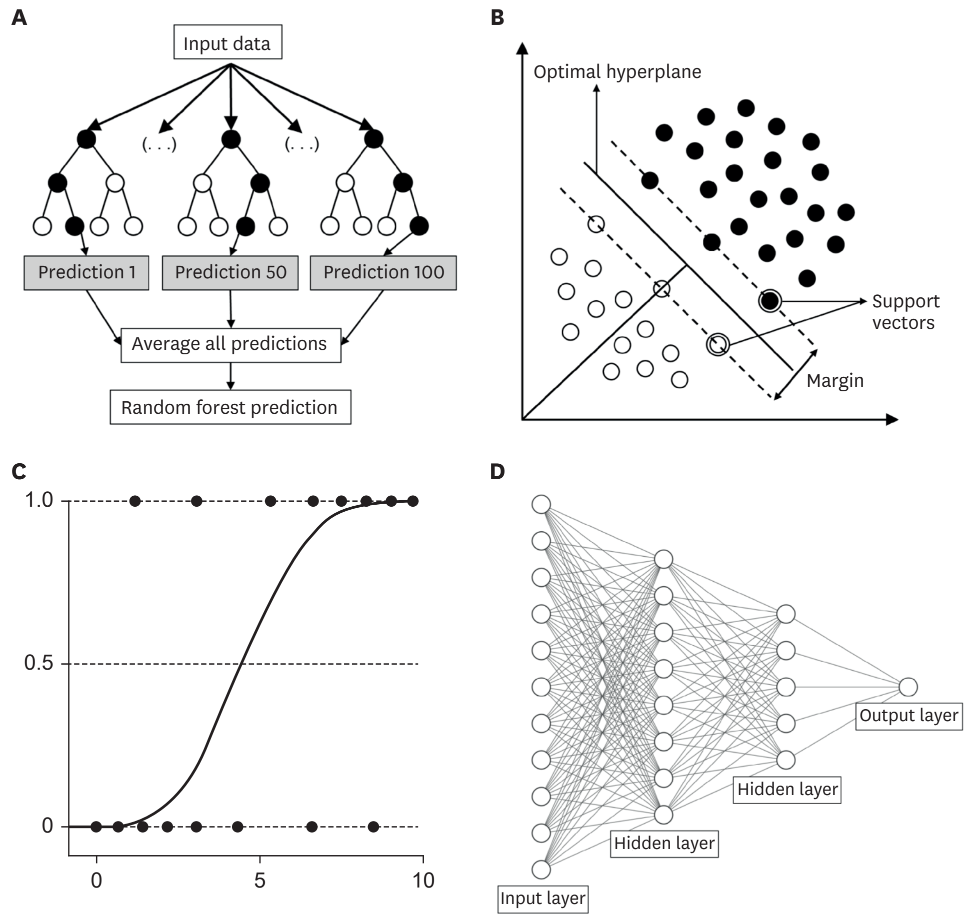

Fig. 1. Basic structure of each type of machine learning: (A) random forest, (B) support vector machine, (C) logistic regression, and (D) deep neural network.

of the tree; this method can minimize prediction error loss compared with a level-wise tree segmentation method. The Light Gradient Boosting Machine method uses less memory and has a short training time, automatic transformation, and optimal segmentation of categorical features; however, caution is required when using a small dataset because of the high probability of overfitting [21]. CatBoost has the advantage of solving the overfitting problem of gradient boosting and improving the learning speed of the algorithm over eXtreme Gradient Boosting and Light Gradient Boosting Machine. CatBoost is optimized for creating a prediction model for a categorical variable, in which input data can be used without an encoding process. However, missing data are not processed, and it is inappropriate to apply CatBoost to datasets with large amounts of missing data [22].

A support vector machine is a supervised learning model that divides a group of data by drawing a reference line or plane for data classification (**Fig. 1B**) [23]. A support vector machine determines the side of the boundary to which new data instances belong based on the divided datasets [24]. The reference line or plane is drawn as far away from each data point as possible [24]. Support vector machines have the advantage of providing a visual representation of data classification results [25]. Although support vector machines are powerful classifiers, they have several drawbacks. Various kernel and model parameter combinations must be tested to determine an optimal model in which the learning speed

https://doi.org/10.12786/bn.2022.15.e26

decreases as the number of features or examples increases in the input dataset [26]. Furthermore, the inner workings of support vector machines may be difficult to understand because the model is based on complicated mathematical systems, and interpreting the results is challenging [26].

Logistic regression is an algorithm that applies the linear regression method for classification and is included in supervised learning models (**Fig. 1C**) [27]. This technique models the linear relationships between at least one independent variable and one dependent variable. The dependent variable is determined by calculating and applying weights for each independent variable [28]. To develop a linear regression model, the regression coefficients and errors allow the generated linear relationship to adequately fit the provided data [28]. A logistic regression model provides both classification and probability and has the advantage of better understanding the contribution of each variable to the final fit [29]. However, the performance tends to degrade when a decision boundary is nonlinear, and interpreting the weights is difficult because each weight is multiplied instead of added [30].

As a machine learning method, a deep neural network model is trained in an artificial neural network structure based on the neural network structure of the human brain (**Fig. 1D**) [31]. An artificial neural network consists of several hidden layers between the input and output layers [32]. When the input data are fed to the deep neural network, the input value is multiplied by weights at the nodes constituting each layer, and the output data are produced through an activation function [32]. Parameters such as the loss function, learning rate, optimizer, batch size, and the number of epochs and iterations are varied by researchers to generate a deep neural network, with an optimal model selected by evaluating and comparing the accuracy of each model generated [33,34]. The multiple layers of complex networks appear to effectively represent the complex nature of the input and output variables [32]. This characteristic of deep neural networks allows the analysis of image data in addition to clinical data [32,33]. A convolutional neural network (CNN), which uses multiple channels of two-dimensional data as input and repeatedly transforms them using convolution and pooling operations, is a representative deep neural network (**Fig. 2**) [32,34]. These processes enable the extraction of useful features from input data. Consequently, CNNs have been used to identify image patterns and process image data [32]. Transformers are another type of model frequently used in the computer vision field. A transformer is a neural network that learns context and meaning by tracking relationships within sequential data [35]. Transformers are powerful neural network models that can detect subtle changes in the meaning of data elements apart from each other as their relationships change by applying evolving mathematical techniques that are referred to as attention or self-attention [35]. Transformers can learn from voice, image, and text data and have been used in various types of technologies, including

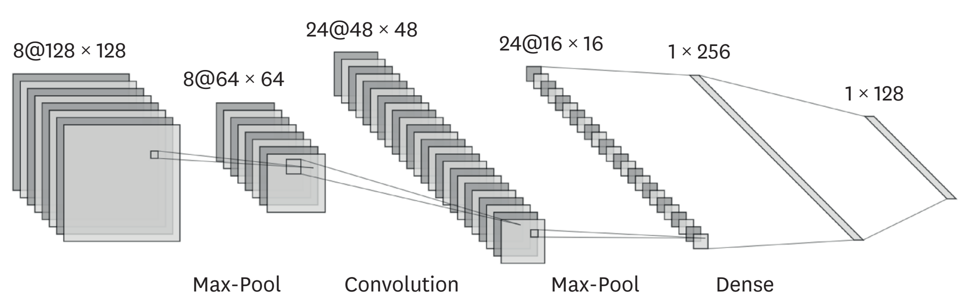

Fig. 2. Basic structure of a convolutional neural network.

https://doi.org/10.12786/bn.2022.15.e26

translation, real-time conversion of voice to text, information extraction, and automatic question answering [36]. The fundamental drawback of transformers is that controlling attention is difficult. For example, a translator can only process character strings of a fixed length, while excessively long sentences must be segmented into segments or chunks of a certain number [37]. Nonetheless, the computation used in transformers is suitable for parallel processing, enabling a fast execution speed. Moreover, transformers are the most widely used neural network model in recent years owing to outstanding performance compared with CNNs and recurrent neural networks [35].

MACHINE LEARNING ALGORITHMS TRAINED ON CLINICAL DATA

Analyzing numerous input data to produce significant results using conventional statistical analysis methods is challenging. However, when the number of input data is large, machine learning, particularly deep learning, can be useful for identifying associations between data and producing meaningful outcomes.

The process of developing a machine learning algorithm using a large amount of clinical data as input is as follows. First, clinical data used for machine learning are collected. The clinical data are divided into input and target data, arranged and stored as CSV files [38]. For machine learning algorithms, programming languages such as Python, R, and Python-based deep learning frameworks such as PyTorch, TensorFlow, and Keras are typically used [39]. The data, divided into input and target data, are loaded onto the platform and converted into the NumPy array format for analysis using machine learning [39]. Subsequently, the data are stacked in a column and standardized. The data are then divided into training and test datasets, and the machine learning model is trained [39]. The accuracy of the model is tested, and the results are primarily presented in terms of accuracy, the receiver operating characteristic curve, and the area under the curve (AUC) [39]. In recent research, the precision-recall curve and Matthews correlation coefficient have been considered as ways to evaluate the performance of AI algorithms that use an imbalanced dataset, such as clinical data [40,41]. The precision-recall curve expresses precision and recall by changing the threshold, which is a parameter, and the accuracy of a model's prediction can be identified using a graph [42]. The Matthews correlation coefficient is typically used for addressing a binary classification problem as it evaluates the performance of AI algorithms by considering the balance ratio of four confusion matrix categories (true positive, true negative, false positive, and false negative) [41]. In the field of stroke rehabilitation, patients' clinical data have been used as input variables to develop machine learning algorithms to predict their functional outcomes. In 2017, Gupta et al. [10] collected more than 200 types of clinical data from 575 patients with intracerebral hemorrhage (ICH); these data included demographic data, state at admission, laboratory results, therapeutic tools, neurological findings, complications, medical history, and state at discharge. Gupta et al. [10] then classified the functional outcomes at 3 and 12 months after ICH onset as "good" or "poor" based on the National Institutes of Health Stroke Scale score, modified Rankin Scale score, Acute Physiology and Chronic Health Stroke Scale score, and Glasgow Coma Scale. They used a random forest model and obtained AUCs between 0.87 and 0.89. In 2018, Lin et al. [11] recruited 313 stroke patients and collected their clinical data during the early stage following stroke onset. Their data included the Barthel index, Berg balance scale, Fugl–Meyer assessment, 6-minute walk test, Mini-Mental State Examination, aphasia test, and dysphagia scale, which were used as input variables. The functional status at discharge was used as the output variable and was classified into three categories according to the Barthel index: ≥ 91, slight dependence; 61–90, moderate dependence; ≤ 60, extreme dependence. Random forest, logistic regression, and support vector machine models were used to develop the machine learning algorithm models, and the AUCs of the models were 0.792, 0.762, and 0.774, respectively. In 2019, Heo et al. [43] recruited 2,604 patients and collected data based on 38 variables, including age, sex, time from onset at admission, blood pressure, previous medical history, National Institutes of Health Stroke Scale score, and laboratory findings, to develop machine learning models for predicting motor outcomes 3 months post-stroke. They classified motor outcomes as "favorable" and "poor" following the measured modified Rankin Scale at 3 months post-stroke: ≤ 2: favorable, > 2: poor. The AUCs of the logistic regression, random forest, and deep neural networks were 0.849, 0.857, and 0.888, respectively.

However, it is difficult to apply models for the prognosis of patients with stroke that use a large amount of clinical data as input in the clinical domain because each hospital has different clinical data and tools for evaluating patient conditions. If any input and output variables used in model development are omitted, the developed model cannot be applied. Therefore, Kim et al. [44] recruited 833 stroke patients in 2022 and developed a model for predicting upper and lower extremity function using only essential patient data as input: age, sex, type of stroke (ischemic or hemorrhagic), modified Brunnstrom classification, functional ambulatory category, and Medical Research Council score at an early stage (8–30 days following stroke onset). The model produced AUCs of 0.736–0.836. Random forest, logistic regression, and deep neural network methods were used for model development, and the performance of the deep neural network was the highest.

Furthermore, based on data from 474 stroke patients in 2021, Choo et al. [45] constructed a model for predicting the necessity of applying an ankle-foot orthosis in early-stage patients 6 months following stroke onset. The prediction performances of the random forest, logistic regression, and deep neural network models were 0.855, 0.845, and 0.887, respectively.

MACHINE LEARNING ALGORITHMS TRAINED ON IMAGE DATA

Several attempts have recently been made to construct models for predicting the prognosis of stroke patients by learning from brain MR images. In 2021, Kim et al. [13] recruited 221 corona radiata infarct patients and developed a CNN model to predict the independent gait of patients 6 months following the onset of the infarct by extracting three T2-axial consecutive brain MR images at the levels of the lateral ventricle body from each patient as input data; the AUC of the model was 0.751. In 2021, Liang et al. [46] developed an algorithm that predicted post-stroke somatosensory function using the MR images and tactile discrimination test results of 40 patients with chronic stroke. Linear regression and a support vector machine model were used to develop the prediction model; two engineered feature pools (i.e., low- and high-order functional connectivity, or low-order functional connectivity only) and four prediction models were built and evaluated. Consequently, a regression model that used both low- and high-order functional connectivity predicted the results based on the correlation coefficient ($r = 0.54$, $p = 0.0002$). In 2022, Kim et al. [47] used clinical data, including age, sex, modified Brunnstrom classification, functional ambulation score, and Medical Research Council score at an early stage (8–30 days following stroke onset), and MR image data (three images from each patient) of the same 221 corona radiata infarct patients as input to develop the prediction model. This study demonstrated that an integrated algorithm trained using clinical data of patients and brain MR images could improve the accuracy of the prediction of long-term upper extremity function and ambulatory outcomes. In 2022, Meng et al. [48] developed a model that predicted hemorrhagic transformation using multiple parameter MR images of 71 patients with acute ischemic stroke. Multiple-parameter MR images were divided into normal regions of interest (ROIs) and abnormal ROIs to build a radiomics model using the random forest method. The radiomics model with an all-ROI feature obtained an AUC of 0.871, whereas the model with only an abnormal ROI feature obtained an AUC of 0.831. The AUC was further improved to 0.911 when the radiomics feature and clinical data were combined. This model may significantly help doctors diagnose the hemorrhage transformation of patients with acute ischemic stroke. In 2022, Mutke et al. [49] collected MR images and clinical data of 210 patients with acute ischemic stroke and large vessel occlusion for whom mechanical thrombectomy was performed. The data were used to predict favorable and poor outcomes after mechanical thrombectomy. The AUCs for two prediction scenarios were examined using seven machine learning algorithms: ElasticNet, generalized linear model, Lasso algorithm, multilayer perceptron, naive Bayes, support vector machine classifier, and tree boosting. Tree boosting provided the highest accuracy in the prediction models for favorable and poor outcomes, with the AUCs of both prediction models being 0.73. In 2022, Shin et al. [50] developed a CNN model for functional prediction using the brain MR images of 1,233 patients during early-stage stroke onset (20.8 images on average); the entire image was configured in three dimensions at the entire-brain level as the input data. The prediction performance in terms of the AUC of the upper extremity function was 0.768, and that of the lower extremity function was 0.828.

Dysphagia is a common complication in stroke patients [51], causing pneumonia and potentially resulting in death; thus, accurately evaluating the incidence of dysphagia is critical [51]. The standard diagnostic tool for dysphagia is the VFSS [12]. In 2022, Kim et al. [12] used the VFSS image data of 190 dysphagia patients, including 190 stroke patients, to construct an AI model using a CNN that distinguished “normal,” “penetration,” and “aspiration.” The developed model exhibited a high accuracy, with AUCs of 0.942, 0.878, and 1.000, respectively.

Numerous algorithms are being developed for using medical image data, such as MR images and computed tomography, to help diagnose and make treatment decisions. However, it must not be overlooked that using a high-quality dataset is a prerequisite for obtaining excellent learning and analysis results when using image data. According to professional organizations such as the Radiological Society of North America and the American Association of Physicists in Medicine, the systematic curation of high-quality image datasets affects AI development speed [52]. Therefore, caution should be taken not to use low-quality image data, including low-resolution, excessively small, and noisy images, for analysis and evaluation [53].

CONCLUSION

We reviewed machine learning research and its applications in the field of stroke rehabilitation. To date, machine learning models have been developed to predict the prognosis of motor function in stroke patients using clinical data and MR images as input data. Moreover, a machine learning model was developed to interpret the VFSS test. The

 https://doi.org/10.12786/bn.2022.15.e26

results of previous studies imply that machine learning can be useful in clinical settings; such studies are important foundations for developing more valuable and accurate AI algorithms. However, most research on machine learning has focused on the internal validation of retrospective data, with insufficient research that performed external validation. Therefore, future studies should perform external validation to ensure that a similar level of performance can be demonstrated even when using data from diverse regions or countries to reduce generalization errors. AI is expected to be applied in predicting depression and language, cognitive, and sensory function recovery in stroke patients. However, for further improving the clinical usefulness of AI in the stroke rehabilitation field, simply predicting a favorable or poor outcome for patients after they suffer from stroke may be insufficient. Practical AI algorithms can be developed for healthcare professionals and patients, such as prescribing appropriate treatment for each patient in real time according to individual characteristics during clinical practice or predicting and providing rehabilitation treatment periods and costs. We expect AI to be increasingly applied in the future for various purposes in the stroke rehabilitation field. A basic knowledge of machine learning is essential for understanding research results and conducting research using machine learning. We hope that clinicians in the stroke rehabilitation field find this review useful for studying and understanding machine learning.

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