Japanese Journal of Comprehensive Rehabilitation Science (2020)

Original Article

Relationship between the number of samples and the accuracy of the prediction model for dressing independence using artificial neural networks in stroke patients

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ABSTRACT
Fujita T, Ohashi T, Yamane K, Yamamoto Y, Sone T, Ohira Y, Otsuki K, Iokawa K. Relationship between the number of samples and the accuracy of the prediction model for dressing independence using artificial neural networks in stroke patients. Jpn J Compr Rehabil Sci 2020; 11: 28−34.
Objective: To determine the lower limit of the number of samples that is useful for creating a prediction model on dressing independence in stroke patients by using artificial neural networks.
Methods: Five datasets consisting of 120, 100, 80, 60, and 40 were created from 121 stroke patients by repeated random sampling. The models for predicting independent dressing one month after admission were created by an artificial neural network and logistic regression in each dataset from the variables upon admission to the convalescent rehabilitation ward. The accuracy of both models was compared.
Results: The accuracy of the artificial neural network model was significantly higher than that of the logistic regression model in the 120, 100, and 80 patient datasets, and there were no differences in the accuracy of both models in the 60 and 40 patient datasets.
Conclusion: Our results suggested that the lower limit of the number of samples for creating a useful prediction model of dressing independence by using artificial neural networks is approximately 80.

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Accepted: January 7, 2020.
Conflicts of interest: There are no conflicts of interest to declare.

Key words: stroke, prediction, activities of daily living

Introduction

Stroke is one of the leading causes of long-term disability [1]. In rehabilitation, the prognosis of the activities of daily living (ADLs) should be predicted to set goals, plan interventions, prepare the necessary human and physical environments, and promote family support. Various reports have investigated different ADL prognostic methods; however, the generalization of results is often limited [2, 3]. The creation of an ADL prediction model in each facility has been shown to improve the accuracy of the prediction [4].

However, the number of usable data is small when creating a prediction model at each single facility. Fujita et al. [5] examined a method that creates a highly accurate ADL prediction model even for small samples at each single facility and reported that artificial neural networks are useful. They also reported that when a prediction model for dressing independence was created using 83 samples, the accuracy of the artificial neural network model was higher than that of logistic regression and decision trees. However, the lower limit of the number of samples needed to maintain sufficient accuracy of the artificial neural network has not been clarified. Thus, we examined the relationship between the accuracy of the prediction model based on artificial neural networks and the number of learning samples to determine the lower limit of the number of samples needed to create a useful prediction model for dressing independence using artificial neural networks.

doi.org/10.11336/jjcrs.11.28

Methods

This was a retrospective observational study that collected and analyzed information from the medical records of patients. A total of 121 stroke patients who were admitted and discharged from the convalescent rehabilitation ward of a hospital were recruited into this study. The inclusion criteria were follows: (1) diagnosis of initial cerebral hemorrhage or cerebral infarction, (2) unilateral supratentorial lesion, (3) inability to dress independently upon admission (≤5 points for the FIM® instrument [version 3] [6, 7], dressing the upper body, lower body, or both), and (4) no missing analysis data described later. This study was reviewed and approved by the ethical review boards of Kita-Fukushima Medical Center and Tohoku Fukushi University (no. 72, RS180601).

Models that predict whether patients can independently dress themselves at one month after admission were studied. Dressing independence was assessed on the basis of the score in the FIM® instrument in dressing the upper body and lower body items at one month after admission. The FIM® instrument dressing items consist of the upper and lower bodies; however, the lower scores of both were adopted in this study: ≥6 points indicates independence and ≤5 points indicates dependence. The following were collected as dependent variables: age [8], dressing performance prior to practice [9], trunk function [8, 10], visuospatial perception [8], and balance [11, 12] upon admission, which have been reportedly associated with dressing performance. The FIM® instrument score for dressing item was used as an index of dressing performance upon admission, the Stroke Impairment Assessment Set (SIAS) [13] was used as trunk function and visuospatial recognition indices, and the Berg balance scale (BBS) [14] as a balance index. In addition to these variables, the upper limb function on the affected and unaffected sides, cognitive function, and poststroke duration, which have been reportedly associated with ADL prognosis, were also added in this study. The Simple Test for Evaluating Hand Function (STEF) [15] was used as an index of upper limb function, whereas the revised Hasegawa Dementia Scale (HDS-R) [16] was used as an index of cognitive function.

Five datasets of 120, 100, 80, 60, and 40 were created from 121 stroke patients by repeated random sampling to investigate the relationship between the accuracy and number of samples of the prediction model for dressing independence created by artificial neural networks. Thereafter, the accuracy of the prediction model created using each dataset was compared. The accuracy of the model created using the artificial neural network was examined by comparing it with the model created by logistic regression, which is a widely used technique. The procedure used for creating a model by using artificial neural networks and logistic regression was as follows: first, patients were classified into two categories, namely, the dressing independent group (FIM® instrument dressing item of ≥6 points at one month after admission) and the dressing dependent group (FIM® instrument dressing item of ≤5 points). Each variable upon admission was compared between the groups to select the variables to be included in the prediction model in each of the five data sets with different numbers of samples. Student's *t*-test, the chi-square test, and the Mann-Whitney *U* test were used for comparison. Second, the logistic regression with stepwise forward selection method (likelihood ratio) was performed using the variable upon admission, which was significant by comparison between groups, as an independent variable and the dressing independence or dependence at one month postadmission as a dependent variable. The artificial neural network model was a hierarchical multilayer perceptron with one intermediate layer in this study, whereas the independent variable was selected using the logistic regression to create the logistic regression and artificial neural network models with the same independent variable. To prevent overfitting, the ratio between learning and testing samples (used to track errors during training) in the artificial neural network was set to 9:1. Furthermore, when variables consisting of ≥5 grade scale (i.e., items except SIAS trunk and visuospatial perception) were used as independent variables in the artificial neural network, they were included in the model after being converted into a four-grade scale based on the quartile by considering the number of small samples. In models created with multilayer perceptron, the initial values for weighting from the input to the intermediate layer are randomly determined, and the prediction accuracy is dependent on these values. Thus, the initial values were reset 10 times, and the model with the highest prediction accuracy was used.

The accuracy of models created using the artificial neural network and logistic regression was compared by stratified 10-fold cross-validation. The dataset was randomly split 10-fold, and the model was created using 9 parts of the dataset. The model accuracy was verified using the remaining data, and this process was repeated 10 times. In this procedure, logistic regression with the forced entry method was used to retain the independent variables used in the model. In the 10-fold cross-validation, the classification accuracy, sensitivity, specificity, positive predictive value, and negative predictive value in the artificial neural network and logistic regression models were calculated and compared using the Wilcoxon rank sum test. The level of significance was set at 5% for all tests, and all analyses were performed using SPSS Statistics version 25 (IBM Corp., Armonk, NY, USA).

Results

Table 1 shows the attributes, cognitive and physical functions, and dressing performance of the patients in each dataset. As regards the results of the comparison

Table 1. Attributes, physical and cognitive functions, and dressing performance of the study patients in each dataset.

Variables	Dataset 1 (*n* = 120)	Dataset 2 (*n* = 100)	Dataset 3 (*n* = 80)	Dataset 4 (*n* = 60)	Dataset 5 (*n* = 40)
Age, years, mean (SD)	75.2 (12.4)	75.4 (12.6)	75.6 (13.0)	74.8 (13.0)	74.8 (14.3)
Gender, men, *n* (%)	62 (51.7)	57 (57.0)	43 (53.8)	32 (53.3)	22 (55.0)
Affected side, right, *n* (%)	56 (46.7)	51 (51.0)	37 (46.3)	25 (41.7)	20 (50.0)
Post-stroke time at admission, days, mean (SD)	30.2 (11.7)	29.3 (11.2)	29.4 (11.1)	31.4 (12.0)	28.4 (11.9)
SIAS verticality at admission, points, median (IQR)	3 (2−3)	3 (2−3)	3 (2−3)	3 (2−3)	3 (1−3)
SIAS abdominal muscle strength at admission, points, median (IQR)	2 (1−2)	2 (1−2)	2 (0.5−2)	2 (1−2)	2 (1−2)
SIAS visuospatial perception at admission, points, median (IQR)	3 (3−3)	3 (3−3)	3 (3−3)	3 (3−3)	3 (3−3)
Berg balance scale at admission, points, mean (SD)	20.5 (16.8)	21.3 (16.6)	20.3 (17.1)	20.5 (16.6)	21.6 (16.3)
STEF affected side at admission, points, mean (SD)	75.1 (21.0)	76.3 (20.6)	75.2 (22.2)	75.7 (20.6)	73.1 (25.4)
STEF unaffected side at admission, points, mean (SD)	25.8 (32.8)	27.5 (33.5)	24.5 (32.9)	27.3 (32.8)	31.7 (33.9)
HDS-R at admission, points, mean (SD)	19.7 (7.9)	19.5 (7.9)	19.5 (7.9)	20.9 (7.2)	19.6 (7.6)
Dressing performance at admission					
FIM® upper body dressing, points, median (IQR)	3.0 (1.0−4.0)	3.0 (1.0−4.5)	3.0 (1.0−4.0)	3.0 (1.0−4.0)	3.0 (1.0−4.5)
FIM® lower body dressing, points, median (IQR)	2.0 (1.0−4.0)	2.0 (1.0−4.0)	2.0 (1.0−4.0)	2.0 (1.0−4.0)	2.0 (1.0−5.0)
The lower score on FIM® for dressing the upper and lower body, points, median (IQR)	2.0 (1.0−4.0)	2.0 (1.0−4.0)	2.0 (1.0−4.0)	2.0 (1.0−4.0)	2.0 (1.0−4.0)
Dressing performance at 1-month after admission					
FIM® upper body dressing, points, median (IQR)	5.0 (2.0−6.0)	5.0 (2.5−6.0)	5.0 (2.0−6.0)	4.5 (2.5−6.0)	5.0 (2.0−6.0)
FIM® lower body dressing, points, median (IQR)	4.0 (2.0−6.0)	5.0 (2.0−6.0)	4.0 (2.0−6.0)	4.5 (2.5−6.0)	4.5 (2.0−6.0)
The lower score on FIM® for dressing the upper and lower body, points, median (IQR)	4.0 (2.0−6.0)	5.0 (2.0−6.0)	4.0 (2.0−6.0)	4.0 (2.0−6.0)	4.0 (2.0−6.0)
Independence of upper body dressing, *n* (%)	39 (32.5)	34 (34.0)	26 (32.5)	20 (33.3)	14 (35.0)
Independence of lower body dressing, *n* (%)	37 (30.8)	32 (32.0)	24 (30.0)	19 (31.7)	12 (30.0)
Independence of both upper and lower body dressing, *n* (%)	37 (30.8)	32 (32.0)	24 (30.0)	19 (31.7)	12 (30.0)

Abbreviations: SIAS, stroke impairment assessment set; HDS-R, revised Hasegawa's dementia scale; STEF, simple test for evaluating hand function.

of the variables between the dressing independence or dependence groups upon admission and at one month after admission, the differences in all variables on all datasets were significant, except for age and STEF on the affected side of the 100 patient dataset (Table 2).

The results of the logistic regression with significant variables on the comparison between groups as independent variables, BBS, and STEF on the unaffected side and SIAS verticality were selected as independent variables of the model in the dataset of 120 patients. BBS and STEF on the unaffected side and time poststroke were selected in the dataset containing 100 patients, and BBS and HDS-R were selected in the dataset of 80 patients. Age, BBS, and

Table 2. Variables with significant differences when comparing dressing independent and dependent groups at 1 month after admission.

	Variables at admission
n=120	Age, Poststroke time at admission, FIM® dressing, SIAS verticality, SIAS abdominal muscle strength, SIAS visuospatial perception, Berg balance scale, STEF affected side, STEF unaffected side, HDS-R
n=100	Post-stroke time at admission, FIM® dressing, SIAS verticality, SIAS abdominal muscle strength, SIAS visuospatial perception, Berg balance scale, STEF unaffected side, HDS-R
n=80	Age, Poststroke time at admission, FIM® dressing, SIAS verticality, SIAS abdominal muscle strength, SIAS visuospatial perception, Berg balance scale, STEF affected side, STEF unaffected side, HDS-R
n=60	Age, Poststroke time at admission, FIM® dressing, SIAS verticality, SIAS abdominal muscle strength, SIAS visuospatial perception, Berg balance scale, STEF affected side, STEF unaffected side, HDS-R
n=40	Age, Poststroke time at admission, FIM® dressing, SIAS verticality, SIAS abdominal muscle strength, SIAS visuospatial perception, Berg balance scale, STEF affected side, STEF unaffected side, HDS-R

Abbreviations: SIAS, stroke impairment assessment set; HDS-R, revised Hasegawa's dementia scale; STEF, simple test for evaluating hand function.

Table 3. Comparison of the performance of artificial neural network and logistic regression models.

		Accuracy (%)	PPV (%)	NPV (%)	Sensitivity (%)	Specificity (%)
n=120	ANN[a]	88.3 *	83.2	91.7 *	81.7 *	91.4
	LR[a]	80.0	72.7	85.4	65.8	86.7
n=100	ANN[b]	84.0	82.2 *	86.9	68.3	91.0
	LR[b]	75.0	65.8	80.5	56.7	83.6
n=80	ANN[c]	85.0 *	86.7	85.9	63.3	94.3
	LR[c]	73.8	69.7	82.8	56.7	82.7
n=60	ANN[d]	83.3	80.0	89.0	75.0	88.5
	LR[d]	80.0	73.3	87.5	70.0	86.0
n=40	ANN[e]	90.0	83.3	100.0	100.0	86.7
	LR[e]	82.5	85.4	88.3	70.0	90.0

*$p < 0.05$.
Abbreviations: ANN, artificial neural network; LR, logistic regression; PPV, positive-predictive value; NPV, negative-predictive value.
[a]Models created by SIAS verticality, Berg balance scale, and STEF on unaffected side.
[b]Models created by time poststroke, Berg balance scale, and STEF on unaffected side.
[c]Models created by Berg balance scale and revised Hasegawa's dementia scale.
[d]Models created by age, Berg balance scale, and STEF on unaffected side.
[e]Models created by Berg balance scale, and STEF on unaffected side.

STEF on the unaffected side were selected in the dataset of 60 patients, and BBS and STEF on the unaffected side were selected in the dataset of 40 patients.

When comparing the accuracy of the created artificial neural network and the logistic regression model in the datasets of 120, 100, and 80 patients, the artificial neural network model exceeded the logistic regression model in terms of classification accuracy, sensitivity, specificity, positive predictive value, and negative predictive value. The differences in classification accuracy, sensitivity, and negative predictive value were significant in the dataset of 120 patients, the differences in positive predictive value were significant in the dataset of 100 patients, and the differences in classification accuracy were significant in the dataset of 80 patients (Table 3). However, the difference between the accuracy of the artificial neural network and the logistic regression model was not significant in the datasets containing 40 and 60 patients.

Discussion

In medical practice, many studies have created various prediction models by using artificial neural networks and have compared their accuracy with logistic regression models. Although some reports demonstrated no difference in prediction performance between artificial neural networks and logistic regression models [17−22], many others concluded that artificial neural networks are superior [23−31]. In recent years, a systematic review and meta-analysis on the outcomes of trauma patients [32] also reported that artificial neural network models have better performance than logistic regression. Furthermore, the authors reported that even in a small sample of 83 patients, artificial neural networks successfully created models with higher prediction accuracy than logistic regression in terms of predicting the dressing independence of stroke patients [5]. By contrast, no studies have verified the difference in accuracy between artificial neural networks and logistic regression by changing the number of samples, and only a few reports used a small number of samples (i.e., 100). Therefore, the lower limit on the number of samples needed to create a useful prediction model by using artificial neural networks is unknown.

Our results suggested that the lower limit on the number of samples to create a useful prediction model for dressing independence when using artificial neural networks is approximately 80 and that the advantage may be lost if the number of samples is <60. In a sample of approximately 80 patients, the artificial neural network successfully created a model with higher accuracy than logistic regression; this is consistent with the result of a previous study [5]. In the dataset of 100 patients, the difference in the classification accuracy between the artificial neural network and logistic regression was not significant compared with that in the datasets of 120 and 80 patients; however, the artificial neural network exceeded the logistic regression in all positive predictive values, negative predictive values, sensitivities, and specificities. Sensitivity and specificity or the positive and negative predictive values are in a tradeoff relationship; therefore, if only one of them is high, it does not mean that the prediction accuracy is superior. However, in the dataset of 100 patients, all sensitivities, specificities, positive predictive values, and negative predictive values of artificial neural networks were higher than those of the logistic regression, in addition to the significant differences observed in the positive predictive value. Therefore, we believe that the prediction accuracy of the artificial neural network model was also higher than that of the logistic regression even in the dataset of 100 patients. The artificial neural network exceeded all of the classification accuracy, positive predictive value, negative predictive value, sensitivity, and specificity in the dataset of 60 patients; however, the values of both were very similar and there was no significant difference. We found no difference in accuracy between the two models in the dataset of 60 patients.

In this study, the dressing performance of the upper and lower bodies was comprehensively addressed because we believe that the ability of stroke patients to perform a series of dressing activities without monitoring or assistance should be carefully monitored. However, the results of the FIM® instrument of the upper and lower body items showed that the lower body scored slightly lower than the upper body. This means that whether a series of dressing activities can be performed independently depends largely on whether the lower body can be independently dressed. Therefore, the results of this study may strongly reflect the performance of lower body dressing.

The findings of this study will be useful in the creation of a unique model that predicts the dressing independence at a single facility in a rehabilitation center. In other words, when creating a prediction model for dressing independence at a single facility with >80 samples, an artificial neural network should be used to improve the prediction accuracy. If the number of samples is ≤60, logistic regression can be expected to create a model with the same accuracy as an artificial neural network. Future studies should verify whether the results differ when performing separate analyses between the upper and lower bodies. Although this study focused on dressing independence, whether the same result can be obtained with another ADL should be confirmed. Furthermore, whether the same results can be obtained with data from other facilities should also be confirmed to examine the influence of changing the independent variables of the model.

Acknowledgments

This work was supported by a grant from the Japanese Society for the Promotion of Science Grants-in-Aid for Scientific Research (grant no. 18K17728). The use of the FIM® instrument to collect data for this research study was authorized and conducted in accordance with the term of a special purpose license granted to the licensee by Uniform Data System for Medical Rehabilitation (UDSMR). The licensee has not been trained by UDSMR in the use of the FIM® instrument, and the patient data collected during the course of this research study has not been submitted to or processed by UDSMR. No implication is intended that such data has been or will be subjected to the standard data processing procedures of UDSMR or that it is otherwise comparable with the data processed by UDSMR. FIM® is a trademark of UDSMR, a division of UB Foundation Activities, Inc.

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