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A Machine-Learning Model Based on Clinical Features for the Prediction of Severe Dysphagia After Ischemic Stroke

Feng Ye[1,*], Liang-Ling Cheng[1,*], Wei-Min Li[2], Ying Guo[3], Xiao-Fang Fan[2]

[1]Wuxi School of Medicine, Jiangnan University, Wuxi, People's Republic of China; [2]Department of Ultrasonography, Affiliated Hospital of Jiangnan University, Wuxi, People's Republic of China; [3]Department of Neurology, Affiliated Hospital of Jiangnan University, Wuxi, People's Republic of China

*These authors contributed equally to this work

Correspondence: Xiao-Fang Fan, Department of Ultrasonography, Affiliated Hospital of Jiangnan University, Wuxi, People's Republic of China, Email fanxiaolll@126.com

Background: This study aimed to construct machine-learning models for prediction of severe dysphagia after ischemic stroke based on clinical features and identify significant clinical predictors.

Methods: Patients hospitalized with dysphagia after ischemic stroke in Affiliated Hospital of Jiangnan University were retrospectively analyzed and randomly divided into training and validation sets at a ratio of 7:3. Additional patients from Huai'an Hospital were selected as test set. 19 relevant clinical characteristics were collected. According to the water swallowing test (WST), patients were divided into severe dysphagia group and non-severe dysphagia group. K-nearest neighbor (KNN), decision tree (DT), random forest (RF), support vector machine (SVM), light gradient boosting machine (LGBM), and extreme gradient boosting (XGBoost) were applied to predict severe dysphagia. Receiver operating characteristic (ROC) curves were plotted, the area under the ROC (AUC) was calculated to assess predictive power, and DeLong's test was used to compare the AUCs among six models. Finally, an optimal model was obtained, and significant clinical predictors of severe dysphagia after stroke were screened.

Results: A total of 724 patients were enrolled, 422 in training set, 182 in validation set and 120 in test set, respectively, with no statistically differences in baseline information ($P>0.05$). In the training set, the AUCs of KNN, DT, RF, SVM and XGBoost were higher than that of LGBM ($P<0.05$). In the validation and test sets, the AUCs of XGBoost were also higher. The performance metrics of XGBoost were better in terms of accuracy, precision, recall, and F1-score. Therefore, XGBoost was the best model, with good clinical practicality. Furthermore, the top five features based on XGBoost were NIHSS score, BI, BMI, age and time since stroke onset.

Conclusion: Among all clinical feature-based machine-learning models for the prediction of severe dysphagia after ischemic stroke, XGBoost had the best predictive value.

Keywords: ischemic stroke, dysphagia, machine learning, predictive model

Introduction

Stroke is the leading cause of death globally, with ischemic stroke being the most common type, accounting for approximately 80% of all strokes.[1,2] Dysphagia remains one of the most frequent complications of stroke, with an incidence of 37–78%,[3,4] of which severe dysphagia will not only cause malnutrition due to poor nutritional uptake but may also result in dehydration, aspiration pneumonia, asphyxia, and other serious consequences, thereby leading to poor prognosis and even death.[5] Therefore, the early prediction, prevention, and treatment of severe dysphagia after stroke are of great clinical importance.

Current research on dysphagia after stroke mainly focuses on evaluation tools, risk factors, prevention, and treatment; however, no effective and unified prediction model has been developed. As a branch of artificial intelligence (AI), machine learning can process a large amount of multidimensional data, which goes beyond traditional statistical methods

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to some extent.[6] There is no doubt that machine learning is increasingly used in the medical field in terms of diagnosis, treatment and prognosis of diseases, and has notable predictive advantages.[7–9]

Based on clinical features, this study aimed to construct machine-learning models for the prediction of dysphagia grade after ischemic stroke, identify significant clinical predictors of severe dysphagia, and shed light on the clinical optimization of dysphagia management.

Materials and Methods

Study Population

All procedures involving human participants were performed in accordance with the Declaration of Helsinki (2013). The ethics committee of Affiliated Hospital of Jiangnan University approved this retrospective study (LS2024245). The requirement for individual consent for this retrospective study was waived. We retrospectively recruited 724 hospitalized patients with dysphagia after ischemic stroke from December 2021 to November 2024 in the Department of Neurology of the Affiliated Hospital of Jiangnan University and Huai'an Hospital. The inclusion criteria were as follows: (1) confirmed ischemic stroke on MRI, with typical clinical symptoms; (2) medically stable, with no digestive function; (3) suspicious or abnormal results of the first swallowing function assessment within 72 h after stroke; (4) normal swallowing function before onset. Patients were excluded if they (1) had disorders of consciousness or cognitive function; (2) had difficulties in hearing, understanding, or communication; (3) had severe organ dysfunction in the heart, brain, or kidney; (4) had dysphagia probably caused by other diseases.

Assessment of Swallowing Function

The WST was used to assess swallowing function within 72 h of admission. All patients were seated comfortably and asked to drink 30 mL of water. Drinking time and signs of choking were recorded: Grade I: no choking on drinking trial without interruption; Grade II: no choking on drinking trial with interruption; Grade III: choking on drinking trial without interruption; Grade IV: choking on drinking trial with interruption; Grade V: unable to finish drinking trial and several choking episodes. Patients in Grades II–III and IV–V were further divided into the non-severe dysphagia and severe dysphagia groups, respectively.

Baseline Information

19 clinical characteristics were collected through literature reading,[3,10–14] including age, time since stroke onset, sex (male=0, female=1), hypertension (no=0, yes=1), hyperlipidemia (no=0, yes=1), diabetes (no=0, yes=1), muscle strength (higher than level 3=0, lower than level 3=1), smoking history (no=0, yes=1), drinking history (no=0, yes=1), National Institute of Health Stroke Scale (NIHSS) score, Barthel index (BI), cough (no=0, yes=1), dysarthria (no=0, yes=1), body mass index (BMI), location of the stroke (cortical stroke=1, subcortical stroke=2, cerebellar stroke=3, brainstem stroke=4, mixed/multifocal stroke=5), motor dysfunction (no=0, yes=1), cognitive dysfunction (no=0, yes=1), history of atrial fibrillation (no=0, yes=1) and history of cerebral infarction (no=0, yes=1).

Model Construction and Evaluation

Eligible patients in the Affiliated Hospital of Jiangnan University were randomly divided into training and validation sets at a ratio of 7:3. Patients from Huai'an Hospital were used to test models. According to the results of some literatures about machine learning,[15–19] K-nearest neighbor (KNN), decision tree (DT), random forest (RF), support vector machine (SVM), light gradient boosting machine (LGBM), and extreme gradient boosting (XGBoost) were applied to predict severe dysphagia. Receiver operating characteristic (ROC) curves were plotted against the original propensity score, the area under the ROC (AUC) was calculated to assess predictive power, and DeLong's test was used to compare the AUCs among the six models. Finally, an optimal model was obtained, and significant clinical predictors of severe dysphagia after stroke were screened.

Statistical Analysis

Normally distributed continuous variables were expressed as mean ± standard deviation, non-normally distributed variables were expressed as median and interquartile range (IQR), the differences between two groups were assessed using independent *t*-test or Mann–Whitney *U*-test. Categorical variables were presented as counts (%), the differences between two groups were assessed using the chi-square test or Fisher's exact test. Missing data was deleted including the data row. ROC curves were plotted against the original propensity score, AUCs were calculated to assess predictive power and DeLong's test was used to compare the performance of the 6 models. Confounding factors were controlled by specifying the inclusion conditions of study subjects, assigning study subjects to different groups according to the principle of randomization to eliminate the influence of confounding factors. All statistical analyses were performed using SPSS, Version 26.0, and R software, Version 4.2.1. The threshold for significance was set at $P<0.05$.

Results

Baseline Information Characteristics in Training Set, Validation Set and Test Set

724 patients were enrolled in this study (308 patients with severe dysphagia and 416 without severe dysphagia). 604 patients from Department of Neurology in Affiliated Hospital of Jiangnan University were divided into training set and validation set according to 7:3 for simple cross-validation, with 422 (189 with severe dysphagia and 233 without severe dysphagia) in the training set and 182 (74 with severe dysphagia and 108 without severe dysphagia) in the validation set. 120 patients (45 with severe dysphagia and 75 without severe dysphagia) from Department of Neurology in Huai'an Hospital were collected in the test set. No significant differences were found in the baseline characteristics ($P>0.05$). Details are presented in Table 1.

Table 1 Baseline Characteristics in Different Sets (N=724)

Indicators	All (N=724)	Training Set (n=422)	Validation Set (n=182)	Test Set (n=120)
Group				
Non-severe group, n(%)	416(57.5)	233(55.2)	108 (62.6)	75 (62.5)
Severe group, n(%)	308(42.5)	189(44.8)	74 (37.4)	45(37.5)
Age	72.89±8.71	73.29±9.29	72.82±7.89	71.49±7.87
NHISS score	3(1,5)	3.92±3.43	3(2,6)	3(1,6)
BI	65(40,90)	60(35,85)	60(31.3,85)	70(25,90)
BMI	23.71±3.04	23.79±2.98	23.31±3.01	24.08±3.27
Time interval	7 (4,15)	7 (4,16)	7 (3,15)	7 (4,16)
Gender				
Male, n(%)	429 (59.3)	251 (59.5)	111 (61)	67 (55.8)
Female, n(%)	295 (40.7)	171 (40.5)	71 (39)	53 (44.2)
Muscle force				
>3, n(%)	417 (57.6)	240 (56.9)	108 (59.3)	69 (57.5)
≤3, n(%)	307 (42.4)	182 (43.1)	74 (40.7)	51 (42.5)
Hypertension				
No, n(%)	199 (27.5)	124 (29.4)	46 (25.3)	29 (24.2)

(*Continued*)

Table 1 (Continued).

Indicators	All (N=724)	Training Set (n=422)	Validation Set (n=182)	Test Set (n=120)
Yes n(%)	525 (72.5)	298 (70.6)	136 (74.7)	91 (75.8)
Hyperlipidemia				
No, n(%)	606 (83.7)	358 (84.8)	153 (84.1)	95 (79.2)
Yes, n(%)	118 (16.3)	64 (15.2)	29 (15.9)	25 (20.8)
Diabetes				
No, n(%)	440 (60.8)	256 (60.7)	104 (57.1)	80 (66.7)
Yes, n(%)	284 (39.2)	166 (39.3)	78 (42.9)	40 (33.3)
Smoke				
No, n(%)	549 (75.8)	321 (76.1)	126 (69.2)	102 (85)
Yes, n(%)	175 (24.2)	101 (23.9)	56 (30.8)	18 (15)
Drink				
No, n(%)	603 (83.3)	349 (82.7)	146 (80.2)	108 (90)
Yes, n(%)	121 (16.7)	73 (17.3)	36 (19.8)	12 (10)
Cough				
No, n(%)	553 (76.4)	319 (75.6)	140 (76.9)	94 (78.3)
Yes, n(%)	171 (23.6)	103 (24.4)	42 (23.1)	26 (21.7)
Dysarthria				
No, n(%)	367 (50.7)	223 (52.8)	89 (48.9)	55 (45.8)
Yes, n(%)	357 (49.3)	199 (47.2)	93 (51.1)	65 (54.2)
History of infarction				
No, n(%)	456 (63)	264 (62.6)	109 (59.9)	83 (69.2)
Yes, n(%)	268 (37)	158 (37.4)	73 (40.1)	37 (30.8)
Dyskinesia				
No, n(%)	446 (61.6)	263 (62.3)	119 (65.4)	64 (53.3)
Yes, n(%)	278 (38.4)	159 (37.7)	63 (34.6)	56 (46.7)
Cognitive dysfunction				
No, n(%)	622 (85.9)	352 (83.4)	163 (89.6)	107 (89.2)
Yes, n(%)	102 (14.1)	70 (16.6)	19 (10.4)	13 (10.8)
History of atrial fibrillation				
No, n(%)	631 (87.2)	361 (85.6)	162 (89)	108 (90)
Yes, n(%)	93 (12.8)	61 (14.4)	20 (11)	12 (10)
Location of stroke				
Cortical stroke	127 (17.5)	71 (16.8)	34 (18.7)	22 (18.3)

(*Continued*)

Table 1 (Continued).

Indicators	All (N=724)	Training Set (n=422)	Validation Set (n=182)	Test Set (n=120)
Subcortical stroke	151 (20.8)	87 (20.6)	36 (19.8)	28 (23.3)
Cerebellar stroke	120 (16.6)	69 (16.4)	30 (16.5)	21 (17.5)
Brainstem stroke	112 (15.5)	74 (17.5)	18 (9.9)	20 (16.7)
Mixed/multifocal stroke	214 (29.6)	121 (28.7)	64 (35.1)	29 (24.2)

Construction and Predictive Power of the 6 Models

Predictive Power of the 6 Models can been seen in Figure1. In the training set, ROC analysis revealed that the AUCs of KNN (1.000; 95% CI: 0.999–1.000), DT (0.890; 95% CI: 0.858–0.922), RF (1.000, 95% CI: 1.000–1.000), SVM (0.895, 95% CI: 0.865–0.925) and XGBoost (0.991; 95% CI: 0.985–0.997) were all significantly higher than those of LGBM (0.841, 95% CI: 0.804–0.878), with $P<0.05$ (Figure 1A).

In the validation set, the AUC of XGBoost (0.916, 95% CI: 0.849–0.983) was significantly higher than that of SVM (0.905, 95% CI: 0.834–0.975), KNN (0.787, 95% CI: 0.690–0.885), DT (0.796, 95% CI: 0.706–0.887), RF (0.891, 95% CI: 0.821–0.961) and LGBM (0.500, 95% CI: 0.500–0.500), with $P<0.05$ (Figure 1B).

In the test set, the AUC of XGBoost (0.959, 95% CI: 0.926–0.992) was also highest among six machine models, with SVM (0.935, 95% CI: 0.893–0.977), KNN (0.671, 95% CI: 0.589–0.752), DT (0.706, 95% CI: 0.632–0.780), RF (0.850, 95% CI: 0.780–0.919) and LGBM (0.500, 95% CI: 0.500–0.500), with $P<0.05$ (Figure 1C).

Performance Metrics of the 6 Models

Among the six machine-learning models, RF and KNN demonstrated the best performance in terms of accuracy, precision, recall, and F1-score in training set but achieved lower scores in the validation and test sets. LGBM demonstrated poor performance metrics in the training, validation and test sets. As shown in Table 2, XGBoost was better in all sets in terms of accuracy, precision, recall, and F1-score; therefore, XGBoost was the optimal model, with good clinical practicality.

Importance of Predictors Using XGBoost and RF Model

The RF and KNN models had the highest AUCs in the training set, but the KNN do not rank the importance of features because of its working principle, therefore, we used XGBoost and RF models to analyse the importance of the predictors

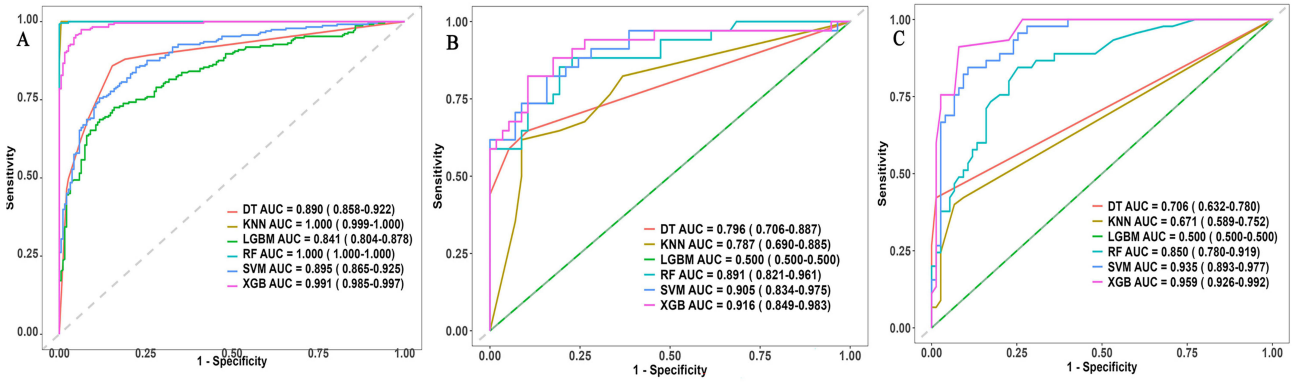

Figure 1 AUCs of six machine-learning models in the different sets. (**A**) AUCs in the training set. (**B**) AUCs in the validation set. (**C**) AUCs in the test set.

Table 2 Performance Metrics of Six Machine Learning Models in Predicting swallowing Disorders after Ischemic Stroke

Model	Data Set	Precision	Recall	Accuracy	F1-Score
RF	Training set	1.000	1.000	1.000	1.000
	Validation set	0.781	0.735	0.824	0.758
	Test set	1.000	0.156	0.683	0.269
XGBoost	Training set	0.868	0.843	0.905	0.855
	Validation set	0.781	0.735	0.846	0.758
	Test set	0.941	0.356	0.750	0.516
DT	Training set	0.757	0.841	0.872	0.797
	Validation set	0.588	0.870	0.813	0.702
	Test set	0.267	1.000	0.725	0.421
SVM	Training set	0.051	0.086	0.166	0.064
	Validation set	0.115	0.176	0.187	0.140
	Test set	0.198	0.400	0.167	0.265
KNN	Training set	1.000	1.000	1.000	1.000
	Validation set	0.667	0.647	0.747	0.657
	Test set	0.667	0.089	0.641	0.157
LGBM	Training set	0.332	1.000	0.332	0.498
	Validation set	0.374	1.000	0.374	0.544
	Test set	0.375	1.000	0.375	0.545

Abbreviations: RF, random forest; XGBoost, extreme gradient boosting; DT, decision tree; SVM, support, vector machine; KNN, K-nearest neighbor; LGBM, light gradient boosting machine.

(Figure 2). In the RF model, the top five indicators of importance were NIHSS score, BI, age, BMI and location of ischemic stroke (Figure 2A). In the XGBoost model, the top five indicators of importance were NIHSS score, BI, BMI, age and time since stroke onset (Figure 2B).

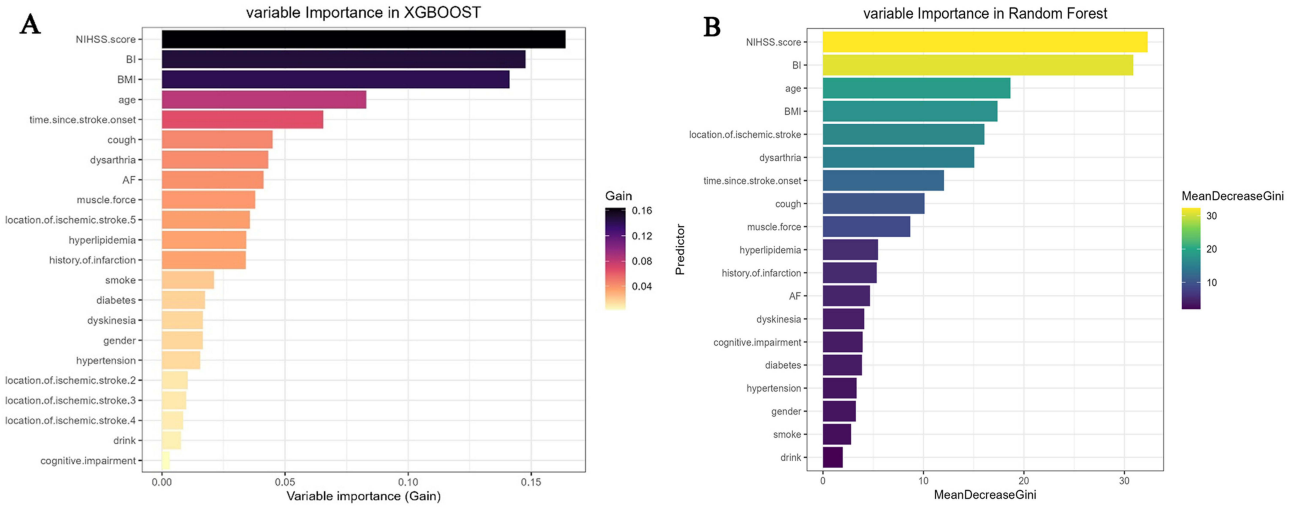

Figure 2 The importance of clinical features in machine-learning models. (**A**) Variable importance in XGBoost model. (**B**) Variable importance in RF model.

Discussion

Dysphagia remains a common complication of ischemic stroke and can lead to serious clinical consequences. Therefore, being able to make an early prediction of dysphagia grade after stroke is crucial. As a branch of AI, machine learning mainly includes logistic regression, SVM, neural network, Bayesian network, DT, and RF, and has been applied in the neural field.[19] By processing a large amount of resources to fuse computer science and statistics with medical research, machine learning can effectively identify specific features highly correlated with the results, thereby eliminating subjective differences of observers. By retrospectively analyzing 724 patients with dysphagia after ischemic stroke and applying six machine-learning models (KNN, DT, RF, SVM, LGBM, and XGBoost), XGBoost was identified as the optimal model, with good clinical practicality.

Six machine-learning models were selected to predict severe dysphagia after ischemic stroke: KNN, DT, RF, SVM, LGBM, and XGBoost. ROC analysis revealed that the AUCs of KNN, DT, RF, SVM, and XGBoost were significantly higher than that of LGBM in the training set, indicating that the five models had relatively good predictive power. However, in the validation and test sets, the AUCs of XGBoost were significantly higher than those of the other five models. Subsequent analysis of the performance metrics revealed that XGBoost was better in terms of accuracy, precision, recall, and F1-score; therefore, XGBoost was the optimal model, with good clinical practicality. As an optimized distributed gradient enhancement library, XGBoost is designed to implement efficient, flexible, and portable machine-learning algorithms whose core worth lies in the use of gradient-boosting algorithms to minimize loss functions; in each iteration, XGBoost learns a new model to fit the residuals of previous models, thereby gradually reducing prediction errors.[20,21]

In addition, the top five indicators based on XGBoost were NIHSS score, BI, BMI, age and time since stroke onset. Studies have shown that the NIHSS offers the advantages of reliability, validity, and sensitivity and is positively correlated with degree of neurological impairment. In addition, several items in the NIHSS are related to swallowing function,[22–24] so the observation and evaluation of swallowing function should be strengthened in patients with higher NIHSS scores. In summary, the NIHSS score was considered an independent risk factor for the occurrence of dysphagia after stroke. Our study obtained similar results in that age was one of the risk factors for severe dysphagia in patients with ischemic stroke. The Barthel index is used to measure performance in basic/physical activities of daily living, with a lower score indicating a higher possibility of dysphagia after stroke in patients with changes in motor function. Consistent with previous studies, our results identified that BI is a risk factor for severe dysphagia.[25] Total or partial impairment of swallowing can lead to reduced food intake, progressive weight loss, and nutrient deficiencies, leading to malnutrition, which is an independent correlation factor for poor prognosis in stroke patients.[26] Dysphagia is closely related to malnutrition, and dysphagia significantly affects the nutritional status of patients, and dysphagia can aggravate dysphagia through neuromuscular dysfunction, which forms a vicious cycle through mutual causation. It is recommended that all stroke patients undergo routine nutritional examination to improve their rehabilitation potential and prevent malnutrition during rehabilitation.[27] It has been demonstrated that the physiological function of swallowing changes with age. Specifically, the reduction in muscle mass and connective tissue elasticity in older people leads to loss of strength and range of motion, and these age-related changes can negatively affect the effective flow of substances being swallowed through the upper aerodigestive tract. Hence, the higher the age, the higher the risk of dysphagia.[28–30] Our study found that, time since stroke onset played an significant role in dysphagia occurence after stroke. This has been shown in other studies as well,[31,32] the patient's brain damage will be more severe over time, which increases the risk of swallowing disorders to some extent. Therefore, patients not only should be teached about typical and less common stroke symptoms and signs but also be provided the fastest means of transportation to a stroke unit and the best chances to get treatment early.

This study had some limitations. First, the retrospective design may have led to a selection bias. Second, the information we included is finite, and using a cohort including more clinical and pathological characteristics to train a model would help further improve the performance of ML model. Third, the sample size was relatively small, and thus a prospective study with a larger sample size is needed to verify our results.

Conclusion

In conclusion, machine learning models can predict severe dysphagia after ischemic stroke preciously, and XGBoost has a better predictive value. To make it easier for others to use this model, we could develop a Web APP based on the XGBoost model in the future. For wider adoption in practice, more sample sizes are necessary. We need to collect more relevant indicators of patients and enter their information into the model. Then, the model outputted a probability of disphagia after ischemic stroke, thus providing a diagnostic basis for the clinical assessment of severe dysphagia after ischemic stroke.

Ethical Statement

The authors are accountable for all aspects of this work, and ensure that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. All procedures involving human participants were performed in accordance with the Declaration of Helsinki (2013). The Ethics Committee of Affiliated Hospital of Jiangnan University approved this retrospective study and waived the requirement for informed consent. Patient information, such as name, age, sex, occupation, address, ID card, related diseases, and treatment plan, was provided by the Affiliated Hospital of Jiangnan University during the treatment period for the illness. Owing to the privacy of patients, the Affiliated Hospital of Jiangnan University maintained the confidentiality of the above information.

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Disclosure

The authors declare that they have no conflicts of interest.

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