Development of a Novel Prognostic Model to Predict 6-Month Swallowing Recovery After Ischemic Stroke

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Background and Purpose—The aim of this study was to explore clinical and radiological prognostic factors for long-term swallowing recovery in patients with poststroke dysphagia and to develop and validate a prognostic model using a machine learning algorithm.

Methods—Consecutive patients (N=137) with acute ischemic stroke referred for swallowing examinations were retrospectively reviewed. Dysphagia was monitored in the 6 months poststroke period and then analyzed using the Kaplan-Meier method and Cox regression model for clinical and radiological factors. Bayesian network models were developed using potential prognostic factors to classify patients into those with good (no need for tube feeding or diet modification for 6 months) and poor (tube feeding or diet modification for 6 months) recovery of swallowing function.

Results—Twenty-four (17.5%) patients showed persistent dysphagia for the first 6 months with a mean duration of 65.6 days. The time duration of poststroke dysphagia significantly differed by tube feeding status, clinical dysphagia scale, sex, severe white matter hyperintensities, and bilateral lesions at the corona radiata, basal ganglia, or internal capsule (CR/BG/IC). Among these factors, tube feeding status (P<0.001), bilateral lesions at CR/BG/IC (P=0.001), and clinical dysphagia scale (P=0.042) were significant prognostic factors in a multivariate analysis using Cox regression models. The tree-augmented network classifier, based on 10 factors (sex, lesions at CR, BG/IC, and insula, laterality, anterolateral territory of the brain stem, bilateral lesions at CR/BG/IC, severe white matter hyperintensities, clinical dysphagia scale, and tube feeding status), performed better than other benchmarking classifiers developed in this study.

Conclusions—Initial dysphagia severity and bilateral lesions at CR/BG/IC are revealed to be significant prognostic factors for 6-month swallowing recovery. The prediction of 6-month swallowing recovery was feasible based on clinical and radiological factors using the Bayesian network model. We emphasize the importance of bilateral subcortical lesions as prognostic factors that can be utilized to develop prediction models for long-term swallowing recovery. **(*Stroke*. 2020;51:440-448. DOI: 10.1161/STROKEAHA.119.027439.)**

Key Words: deglutition ■ machine learning ■ prognosis ■ stroke ■ survival analysis

Dysphagia is one of the most common complications after ischemic stroke. Despite the relatively benign clinical course, 13% to 18% of patients with poststroke dysphagia can still have persistent dysphagia up to 6 months from the stroke onset.[1,2] It is crucial to detect high-risk patients who are predicted to exhibit prolonged dysphagia to provide sufficient nutritional support and to prevent aspiration pneumonia. Delayed decision on the proper feeding route or unnecessary restraint of oral intake can interfere with the outcome of swallowing function after stroke.[3] Poststroke dysphagia can also lead to increased institutionalization rate after discharge and poor functional capacity in the long term.[4]

Prediction of long-term swallowing recovery is important in management of poststroke care. It enables clinicians to select appropriate evaluation plans, establish therapeutic strategies, and support counseling for patients and their families by individualizing a specific recovery trajectory.[5,6] Knowledge of factors for functional swallowing recovery is essential in developing a prognostic model for poststroke dysphagia with high accuracy. For poststroke dysphagia, numerous clinical and radiological factors have been revealed to be associated with short-term (<1 month) swallowing recovery: older age,[7,8] the African race,[7] National Institutes of Health Stroke Scale (NIHSS),[7–11] initial risk of aspiration,[8,11] initial impairment of oral intake,[8] intubation,[11] dysarthria,[11] severe white

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matter hyperintensities (WMH),[12] bilateral involvement,[9,11] cortical lesions,[7] and lesions of frontal area,[10] insula,[8,10,13–15] corona radiata,[14] and internal capsule.[13] However, relatively few studies have investigated the prognostic factors for long-term (3–6 months) swallowing recovery: older age, sex, dysarthria, dysphonia, decreased gag reflex, initial dysphagia severity, such as aspiration signs or symptoms, and bilateral involvement.[1,16,17] Particularly, there has been a lack of studies on anatomic locations or types of brain lesions for long-term swallowing recovery compared with those for short-term swallowing recovery in poststroke dysphagia.

Therefore, the aim of this study was to investigate clinical and radiological prognostic factors predicting long-term swallowing recovery in the retrospective cohorts and to develop and validate a machine learning–based prognostic model for long-term swallowing outcomes using clinical and radiological factors in poststroke dysphagia. In this study, we used Bayesian networks as a machine learning algorithm that allows to create probabilistic graphical models based on Bäyes theorem.[18] Bayesian networks have been gaining great interest in the development of decision-support systems for personalized patient care, with several advantages including good interpretability, concept of conditional independence, easy feature selection, and computation efficiency.[18,19]

Methods

Study Population

The data that support the findings of this study are available from the corresponding author upon reasonable request. The study population included all consecutive patients with acute ischemic stroke between January 1, 2014 and June 31, 2018, who were referred to videofluoroscopic swallowing study (VFSS) due to swallowing difficulty. In the evaluation process, swallowing function of patients was routinely assessed by a standardized screening test or clinical examinations by physicians and referred to VFSS if poststroke dysphagia was suspected. All the medical records of the patients were retrospectively reviewed. Exclusion criteria were as follows: concomitant neurological diseases that can result in swallowing dysfunction, age <19 years, tracheostomy, unconsciousness, premorbid dysphagia, and no records of brain magnetic resonance imaging. Data from patients with poor swallowing recovery who were monitored for <4 months of follow-up were also excluded for the development process of the classification model. This study was approved by the institutional review board, and informed consent was exempted from the retrospective review. The procedures were performed in accordance with all relevant guidelines and regulations.

Data Collection

Demographic, neurological, and swallowing characteristics were obtained from the patients including age (≥65 years), sex, stroke severity in terms of NIHSS at admission, stroke location, vascular territory of brain stem,[20,21] stroke laterality, multifocal lesions, bilateral lesions at the corona radiata, basal ganglia, or internal capsule (CR/BG/IC; Figure 1), severity of WMH, clinical dysphagia scale (CDS),[22] and recommended tube feeding (TF) at initial VFSS. Stroke severity was categorized as mild (0–6), moderate (7–16), or severe (17–40) stroke, according to the NIHSS.[23] The vascular territory of brain stem could be overlapped in patients if the infarcted areas were large enough to involve several vascular territories simultaneously. Bilateral lesions at CR/BG/IC and severity of WMH were independently evaluated by 2 physiatrists. Bilateral lesions at CR/BG/IC included both acute and chronic lesions that were evaluated using diffusion-weighted and fluid-attenuated inversion recovery images. To differentiate cerebrospinal fluid-like foci from old lesions, cases that fulfilled ≥3 criteria were considered to be Virchow-Robin spaces and were therefore excluded. These criteria were as follows (1) ≤2 mm; (2) smooth round, oval, or linear shape; (3) without surrounding hyperintensity on fluid-attenuated inversion recovery images; and (4) symmetrical foci in bilateral hemispheres.[24,25] WMH in the periventricular and deep white matter were evaluated using fluid-attenuated inversion recovery images of the initial magnetic resonance imaging based on the Fazekas rating scale.[26] Severe WMH were defined as the sum of the Fazekas rating scale ≥5 for paraventricular and deep white matter.[27] CDS was assessed during the initial VFSS. It was dichotomized into mild (<20) and moderate-to-severe (≥20) dysphagia. Initial VFSS refers to the first VFSS performed after stroke occurrence. Physiatrists conducted CDS and VFSS to assess swallowing function and establish feeding strategies including tube placement and diet modification. The feeding status was followed-up in patients with persistent dysphagia at the outpatient clinic or in the subsequent VFSSs. The interval of VFSS and outpatient clinic was every <4 weeks during the initial phase and gradually prolonged to 1 to 3 months considering the progress of swallowing recovery. The outcome of this study was the swallowing functional level at 6 months after stroke onset. When swallowing function did not necessitate tube placement or diet modification for nutrition, it was considered as good prognosis, whereas when either of them was needed, it was considered as poor prognosis.

Statistical Analyses

The demographic, neurological, and swallowing characteristics were compared between patients with good and poor prognosis using independent-samples t test for continuous variables and χ^2 test or Fisher exact test for categorical variables. In the survival analysis, the event of interest was defined as the first successful return to prestroke diet. The time to the first return to prestroke diet was analyzed using the Kaplan-Meier method, and covariates, including the demographic, neurological, and swallowing characteristics, were analyzed using a stratified log-rank test. To identify potential prognostic factors, Cox proportional-hazards models were used for each covariate. Factors with $P<0.2$ were used as covariates in the multivariate analysis of Cox proportional-hazards models, and the forward variable selection method was applied to control for multicollinearity. The statistical analyses for survival analysis were conducted using SPSS software (version 19; SPSS Inc, Chicago, IL), and the significance level was set at $P<0.05$.

Development and Validation of the Prognostic Model

For the development of the prognostic model for 6-month swallowing recovery, Bayesian network models were used to classify stroke patients into those with good (<6 months) and poor (≥≥6 months) swallowing prognosis. The process of learning a Bayesian network from data consisted of structural learning to identify the graphical structure of the network and parameter learning to estimate the association between conditional probability distributions and the network's digraph.[18] The aim of this process was to explore optimal Bayesian network structures for a parameter set that best represents a given dataset with labeled instances.[28] For the structural and parameter learning in this study, tree-augmented network models with a greedy hill-climbing algorithm and semi-naïve network models were constructed using the 5-fold cross-validated estimates of predictive accuracy as a score.[29] Two types of feature selection were conducted: selection of feature variables with $P<0.2$ in the Cox proportional-hazards analyses of the survival model for the tree-augmented network models and feature variables with $P<0.5$ using a forward sequential feature selection and joining algorithm for the semi-naïve network models. Additionally, a support vector machine was used to benchmark the performance of the developed Bayesian network models after hyperparameter optimization.

During the training and validation processes, the whole dataset was divided into training and test set in the ratio of 75:25. The

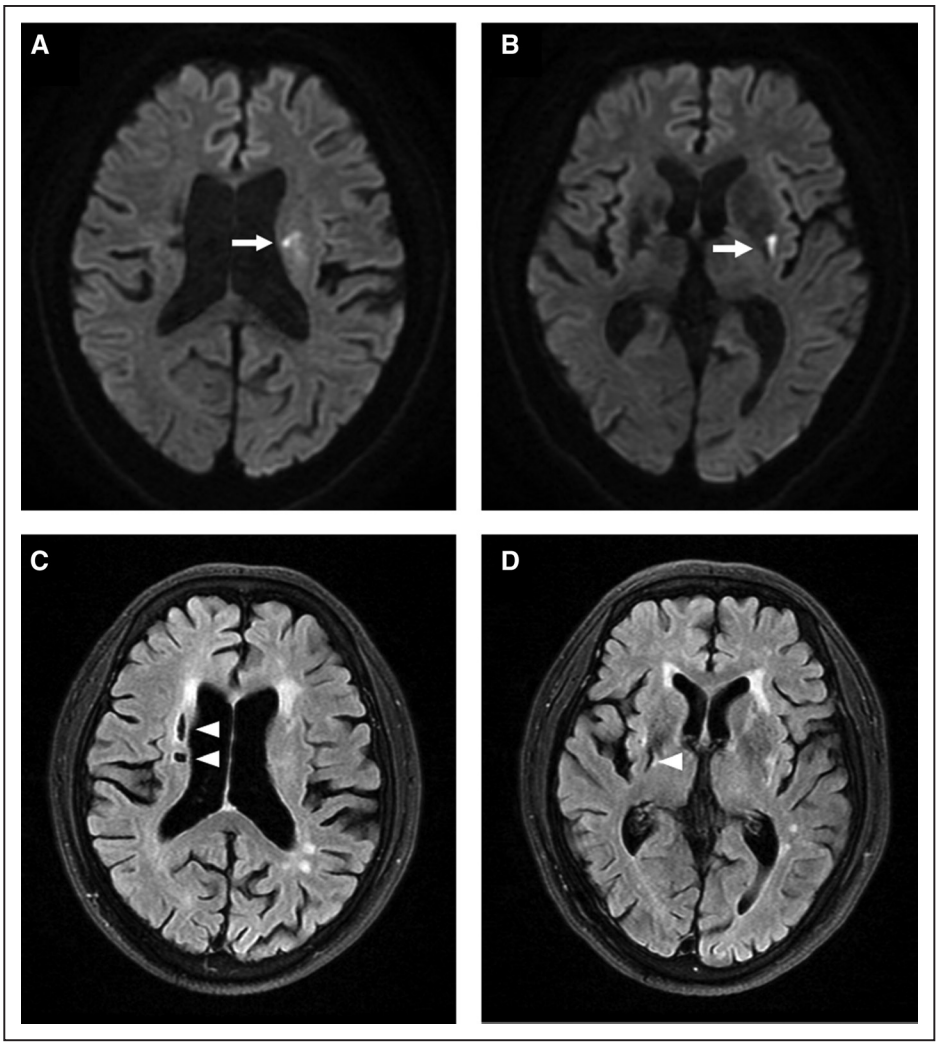

Figure 1. Diffusion-weighted and fluid-attenuated inversion recovery images from a representative case with bilateral lesions at the corona radiata, basal ganglia or internal capsule. These images correspond to a 75-year-old male who was diagnosed with acute infarction (arrow) at the corona radiata (**A**) and basal ganglia/internal capsule (**B**) of the left hemisphere, and old lesions (arrowhead) at the corona radiata (**C**) and basal ganglia/internal capsule (**D**) of the right hemisphere. This patient showed persistent severe oropharyngeal dysphagia even 6 mo after stroke.

training set was randomly partitioned into 5 subsets of almost equal size for 5-fold cross-validation. One partition was selected as the validation set, and the rest of the partitions were used to train the predictive models. To reduce the error cost by mitigating the class imbalance between the patients with good and poor prognosis in the dataset, the adaptive synthetic sampling algorithm was implemented for the minority class as an oversampling algorithm.[30] It is a systematic method of oversampling that adaptively creates different amounts of synthetic data, which need to be generated for minority class to compensate for the skewed distributions according to their density distributions.[30,31] For the learning and validation process, 5-fold cross-validation was used during the process of oversampling by generating synthetic samples for only training partitions, to avoid overfitting and over-optimistic estimates.[32] This can prevent contamination of the synthetic samples generated from the training partitions into the test set. Finally, the model performance was evaluated on the test set using 3 metrics: an area under the receiver operating characteristic (ROC) curve, an F1 score, and the Matthews correlation coefficient, which were regarded as good options for the metrics used to assess the predictive performance of the models constructed from the imbalanced dataset.[33–35] The whole process of analyses was performed using R version 3.4.2 (The R Foundation, Vienna, Austria) with the bnclassify, caret, and kernlab packages for the development and validation of prognostic models based on Bayesian networks and support vector machine and the imbalance package for the oversampling of minority class.

Results

Clinical Information

A total of 187 patients with poststroke dysphagia referred to VFSS were identified in this study, and 137 patients met the inclusion criteria. The information on demographic, neurological, and swallowing characteristics is shown in Table 1. The mean age of the study group was 68.7 (±14.0) years, and 69 (50.4%) patients were males. The mean duration from stroke onset to initial VFSS was 16.8 (±8.3) days. Significant differences were observed between the patients with good (n=113, 82.5%) and poor (n=24, 17.5%) prognosis for variables including age ≥65 years (P=0.023), male sex (P=0.008), anterolateral territory of brain stem (P=0.021), bilateral lesions at CR/BG/IC (P<0.001), severe WMH (P=0.011), CDS ≥20 (P=0.001), and recommended TF at initial VFSS (P<0.001).

Table 1. Clinical Characteristics

	Total (N=137)	Good Prognosis (n=113)	Poor Prognosis (n=24)	Odds Ratio (95% CI)	*P* Value
Age ≥65 y	100 (73.0)	78 (69.0)	22 (91.7)	4.94 (1.10–22.2)	0.023*
Sex					
Male	69 (50.4)	51 (45.1)	18 (75.0)	3.65 (1.35–9.87)	0.008*
Female	68 (49.6)	62 (54.9)	6 (25.0)	1.00	
NIHSS at admission†					
Mild (0–6)	48 (36.1)	35 (32.1)	13 (54.2)	2.04 (0.59–7.07)	0.116
Moderate (7–16)	59 (44.4)	52 (47.7)	7 (29.2)	0.74 (0.20–2.79)	
Severe (17–40)	26 (19.5)	22 (20.2)	4 (16.7)	1.00	
Vascular territory of brain stem					
Anteromedial territory	14 (10.2)	11 (9.7)	3 (12.5)	1.33 (0.34–5.16)	0.712
Anterolateral territory	12 (8.8)	7 (6.2)	5 (20.8)	3.99 (1.15–13.9)	0.021*
Lateral territory	13 (9.5)	10 (8.8)	3 (12.5)	1.47 (0.37–5.81)	0.700
Posterior territory	1 (0.7)	1 (0.9)	0 (0.0)	…	1.000
Lesion laterality					
Right	56 (40.9)	50 (44.2)	6 (25.0)	0.72 (0.13–4.02)	0.152
Left	67 (48.9)	51 (45.1)	16 (66.7)	1.88 (0.38–9.31)	
Bilateral	14 (10.2)	12 (10.6)	2 (8.3)	1.00	
Lesion location					
Frontal lobe	64 (46.7)	56 (49.6)	8 (33.3)	0.51 (0.20–1.28)	0.148
Parietal lobe	49 (35.8)	42 (37.2)	7 (29.2)	0.70 (0.27–1.82)	0.458
Temporal lobe	38 (27.7)	31 (27.4)	7 (29.2)	1.09 (0.41–2.88)	0.863
Occipital lobe	14 (10.2)	13 (11.5)	1 (4.2)	0.33 (0.04–2.69)	0.281
CR	53 (38.7)	41 (36.3)	12 (50.0)	1.76 (0.72–4.27)	0.210
BG/IC	54 (39.4)	42 (37.2)	12 (50.0)	1.69 (0.70–4.10)	0.243
Insula	33 (24.1)	25 (22.1)	8 (33.3)	1.76 (0.68–4.59)	0.243
Thalamus	9 (6.6)	7 (6.2)	2 (8.3)	1.38 (0.27–7.08)	0.657
Midbrain	2 (1.5)	2 (1.8)	0 (0.0)	…	1.000
Pons	15 (10.9)	12 (10.6)	3 (12.5)	1.20 (0.31–4.64)	0.727
Medulla oblongata	15 (10.9)	11 (9.7)	4 (16.7)	1.86 (0.54–6.41)	0.300
Cerebellum	12 (8.8)	10 (8.8)	2 (8.3)	0.94 (0.19–4.58)	1.000
Multifocal lesions	18 (13.1)	16 (14.2)	2 (8.3)	0.55 (0.12–2.57)	0.739
Bilateral lesions at CR/BG/IC	30 (21.9)	17 (15.0)	13 (54.2)	6.67 (2.57–17.33)	<0.001*
Severe white matter hyperintensities	22 (16.1)	14 (12.4)	8 (33.3)	3.54 (1.28–9.77)	0.011*
Clinical dysphagia scale ≥20	49 (35.8)	33 (29.2)	16 (66.7)	4.85 (1.89–12.42)	0.001*
Recommended TF at initial VFSS	27 (19.7)	10 (8.8)	17 (70.8)	25.01 (8.38–74.68)	<0.001*

BG indicates basal ganglia; CR, corona radiata; IC, internal capsule; NIHSS, National Institutes of Health Stroke Scale; TF, tube feeding; and VFSS, videofluoroscopic swallowing study.

*$P<0.05$.

†Four patients were not included in the analysis for NIHSS at admission due to missing data.

No significant difference for each lesion location was observed between patients with good and poor prognosis. During the 6-month follow-up period, the swallowing functional status was identified based on VFSS records in 96 (70.1%) patients and medical records in the other patients until their swallowing function recovered to prestroke status. The number of patients who were lost to follow-up was 7 (5.1%), and the mean duration of the follow-up for these patients was 152.0±21.3 days.

Survival Analyses

The Kaplan-Meier estimates indicated that the mean duration of swallowing recovery was 65.6 days (95% CI, 54.8–76.5), as

shown in Figure 2A. According to the subgroup analysis, the mean duration of the patients with good prognosis was 41.0 days (95% CI, 33.5–48.5). In the log-rank test, the duration of swallowing recovery was significantly different depending on the covariates including recommended TF at initial VFSS (P<0.001), CDS ≥20 (P=0.001), male sex (P=0.010), bilateral lesions at CR/BG/IC (P<0.001), and severe WMH (P=0.010), which are shown in Figure 2B through 2D and Figure 3. The results of univariate and multivariate Cox proportional-hazards models for the risk of poor swallowing recovery are shown in Table 2.

Bayesian Network Models

Table 3 showed the results of the performance evaluation for the prediction models. In the prediction of 6-month swallowing recovery, the classifier based on tree-augmented network models with a greedy hill-climbing algorithm outperformed the other classifiers based on the semi-naïve network models model and support vector machine, with an area under the ROC curve of 0.802, an F1 score of 0.906, and an Matthews correlation coefficient of 0.575. The graphical representations of the prediction models using tree-augmented network models and semi-naïve network models were shown in the online-only Data Supplement, respectively.

Discussion

This study aimed to identify the clinical and radiological prognostic factors for long-term swallowing function in patients with poststroke dysphagia and develop prognostic models to predict its long-term swallowing recovery. The results of the survival analysis indicated that the 6-month swallowing recovery after stroke differed significantly depending on clinical (recommended TF at initial VFSS, CDS, and male sex) and radiological factors (bilateral lesions at CR/BG/IC and severe WMH). Particularly, bilateral lesions at CR/BG/IC were newly reported as a significant prognostic factor of poststroke dysphagia in this study. The tree augmented Bayesian network model was proposed to predict 6-month swallowing recovery, which showed feasible results in achieving an area under the

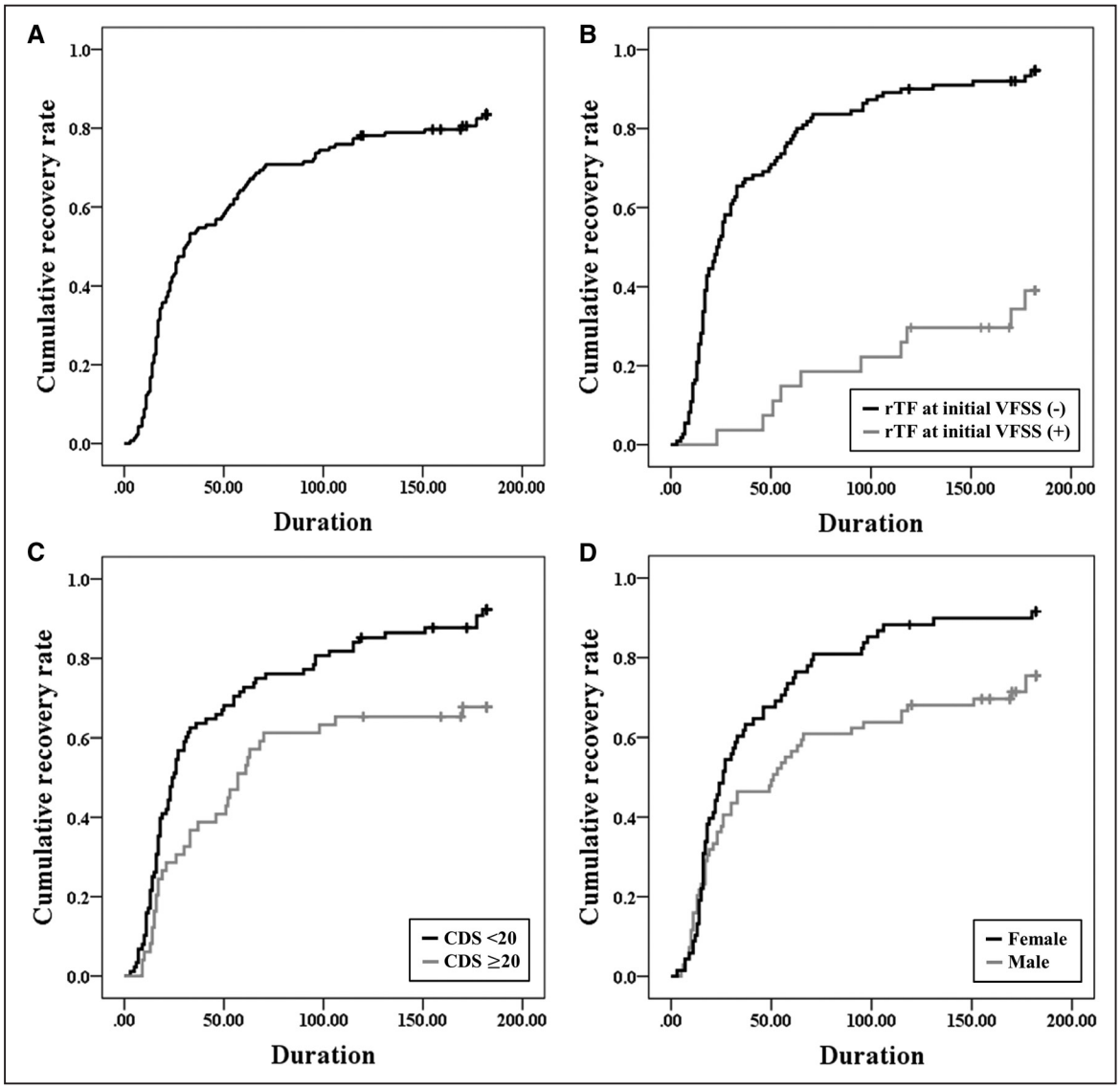

Figure 2. Kaplan-Meier plots for swallowing recovery in patients with poststroke dysphagia. Kaplan-Meier estimates are shown for overall swallowing recovery (**A**) and swallowing recovery depending on clinical factors: recommended tube feeding (rTF) at initial videofluoroscopic swallowing study (VFSS; **B**), clinical dysphagia scale (CDS; **C**), and sex (**D**).

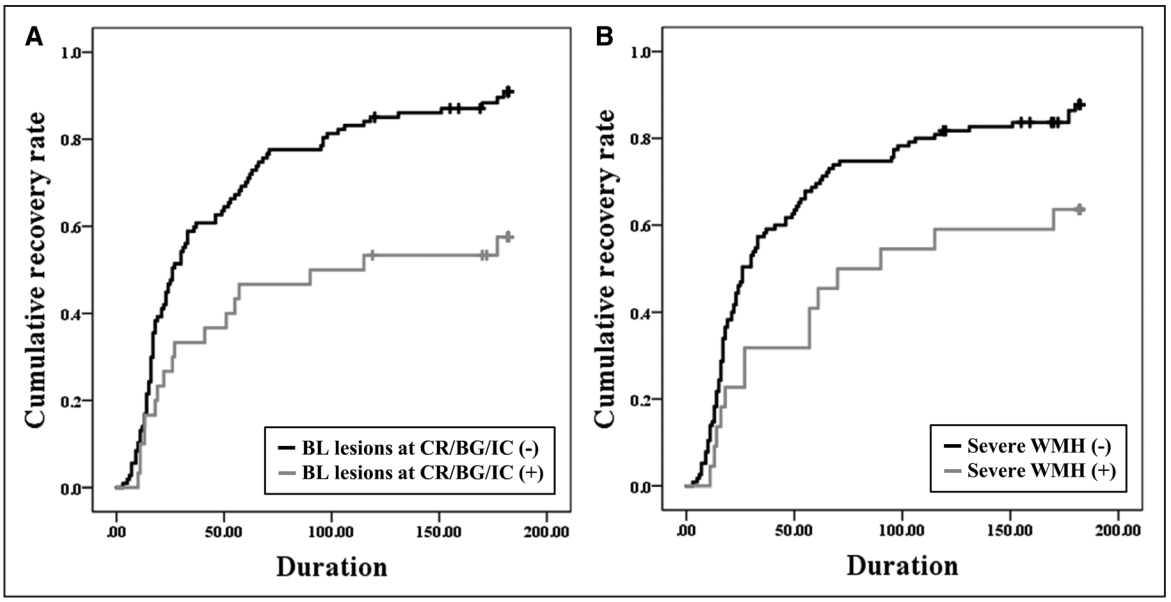

Figure 3. Kaplan-Meier plots for swallowing recovery in patients with poststroke dysphagia. Kaplan-Meier estimates are shown for swallowing recovery depending on radiological factors: bilateral (BL) lesions at corona radiata (CR), basal ganglia (BG), or internal capsule (IC; **A**) and severe white matter hyperintensities (WMH; **B**).

ROC curve of 0.802 utilizing 10 clinical and radiological factors based on the survival analysis.

Prognostic models for poststroke dysphagia have been developed to predict the feeding status that requires tube placement in previous studies. Dubin et al[7] developed prognostic models to predict feeding via gastrostomy tube based on the logistic regression using variables known by 24 hours from admission, including age ≥80 years, NIHSS score 8 to 14 (and >14), the African race, and infarct location involving the cortex. More robust prognostic models were established on the prospective cohorts by Galovic et al[8] to predict the recovery of oral intake and return to prestroke diet on day 7 and 30. Five factors, including age ≥70 years, NIHSS at admission, lesion of the frontal operculum, initial risk of aspiration, and initial score of functional oral intake scale, were selected to develop the prognostic score system with external multicenter validation. In the present study, the Bayesian network-based prognostic models were developed utilizing clinical and radiological factors to predict 6-month swallowing recovery. The proposed model incorporates 10 factors that include sex, lesions at CR, BG/IC, and insula, lesion laterality, anterolateral territory of brain stem, bilateral lesions at CR/

Table 2. Univariate and Multivariate Cox Proportional-Hazards Models for the Risk of Poor Recovery of Swallowing Function

	Univariate Analysis		Multivariate Analysis	
Variables	Hazard Ratio (95% CI)	*P* Value	Hazard Ratio (95% CI)	*P* Value
Male sex	1.62 (1.12–2.37)	0.011*		
CR	1.46 (0.99–2.14)	0.056		
BG/IC	1.36 (0.93–1.99)	0.118		
Insula	1.47 (0.94–2.30)	0.088		
Lesion laterality	0.77 (0.56–1.05)	0.094		
Right	1.00	…		
Left	1.18 (0.63–2.21)	0.617		
Bilateral	0.70 (0.37–1.31)	0.257		
Anterolateral territory of brain stem	1.72 (0.80–3.71)	0.167		
Bilateral lesions at CR/BG/IC	2.46 (1.46–4.14)	0.001*	2.38 (1.41-4.03)	0.001*
Severe WMH	2.09 (1.21–3.61)	0.008*		
Clinical dysphagia scale ≥20	1.94 (1.29–2.93)	0.001*	1.53 (1.02-2.31)	0.042*
Recommended TF at initial VFSS	6.64 (3.42–2.87)	<0.001*	5.93 (3.04-11.57)	<0.001*

BG indicates basal ganglia; CR, corona radiata; IC, internal capsule; TF, tube feeding; VFSS, videofluoroscopic swallowing study; and WMH, white matter hyperintensities.

*$P<0.05$.

Table 3. Results of Performance Evaluation for the Prediction Models

	Tree-Augmented Network Model	Semi-naïve Network Model	Support Vector Machine
AUC	0.802	0.755	0.780
F1 score	0.906	0.885	0.809
Matthews correlation coefficient	0.575	0.510	0.461

AUC indicates area under the receiver operating characteristic curve.

BG/IC, severe WMH, CDS, and recommended TF at initial VFSS. Because the majority of spontaneous recovery occurs within the first 6 months after stroke, 6-month swallowing recovery can be the primary end point of persistent dysphagia in patients with ischemic stroke and used as the clinical outcome in this study.[36,37] The prediction of short- and long-term swallowing recovery can be complemented by the prognostic models from previous and current studies and may contribute to optimize dysphagia evaluation, management, and education for individuals with ischemic stroke.

Initial dysphagia severity was the most significant prognostic factor for long-term recovery of swallowing function in the present study. This finding is not surprising given that initial dysphagia severity can reflect the degree of initial neurological injury specific to swallowing function. Initial dysphagia severity has been regarded as the most significant prognostic factors for both short- and long-term recovery in previous studies.[1,8,11,16,17,38] On the contrary, initial stroke severity measured by NIHSS did not show any significant association with long-term recovery of swallowing function. Considering that NIHSS is one of the most important prognostic factors for functional recovery after stroke, prognosis of long-term swallowing recovery needs to be considered separately.[23]

Interestingly, this study revealed that the bilateral lesions at CR/BG/IC could be a novel prognostic factor significantly associated with poor swallowing recovery. Because swallowing is physiologically regulated by the brain in a bilateral, asymmetrical manner, it induces high variability of the functional representation of swallowing impairment in patients with unilateral stroke.[39] Bilateral stroke can lead to the deterioration of swallowing recovery because it may diminish compensatory reorganization from the undamaged side of the brain.[40] The current study presents the need to assess old lesions of CR/BG/IC at the contralesional side, even if those did not cause any neurological symptom or sequelae following the previous stroke. Functional representation masked by compensation of the unaffected brain might be deteriorated with subsequent insults at contralateral hemisphere. In previous case studies, a combination of new and old bilateral lesions resulting in severe dysphagia has been reported as Foix-Chavany-Marie syndrome.[41–44] Bilateral operculum or CR have been suggested as primary lesion locations, although the syndrome can be represented in various forms of stroke.[42] A plausible hypothesis on the cause of severe pharyngeal paralysis is that it occurs due to a bilateral disruption of corticobulbar tracts to the ambiguous and the hypoglossal nuclei, involving cranial nerves 9, 10, and 12.[41,43] Additionally, bilateral lacunar infarcts at BG or subcortical white matter can cause vascular Parkinsonism, which may be associated with poststroke dysphagia and poor recovery of swallowing function.[45,46] Neuroimaging research studies based on tractography or metabolic activity are warranted to investigate the relationship between injury severity of bilateral corticobulbar tracts or basal ganglia and functional changes during swallowing recovery.

A Bayesian network model to predict long-term swallowing recovery after ischemic stroke was developed by selecting the feature variables based on the survival analyses, which resulted in the achievement of the prediction performance with an ROC curve of 0.802. The adaptive synthetic sampling algorithm was one of the class rebalancing techniques that led to an improvement in prediction performance by alleviating class imbalance between patients with good and poor prognosis. The area under the ROC curve, the F1 score, and the Matthews correlation coefficient showed good discrimination. In addition to the prediction performance, good interpretability of the Bayesian network model is a great strength for decision making in medicine, where errors can have a dire consequence.[47] In this study, the tree augmented Bayesian network model intuitively showed connections between feature variables, including initial dysphagia severity measured with recommended TF at initial VFSS or CDS and radiological factors, such as bilateral lesions at CR/BG/IC and severe WMH. It may implicate that the impact of these radiological factors on long-term swallowing recovery is necessarily interpreted along with initial dysphagia severity. This can be a good approach to predict swallowing recovery after stroke because bilateral lesions at CR/BG/IC or severe WMH alone cannot exhibit the severity of brain injury related with swallowing function.

The present study has several limitations. First, the class was imbalanced, and the sample size was small, particularly for the patients with poor prognosis. To overcome these issues, adaptive synthetic sampling was used to synthesize data in poor prognosis and rebalance proportion of the class, which could improve the classification performance. Cross-validation was conducted during oversampling to avoid overfitting and over-optimistic estimates. The developed model was evaluated using the only test set that was not contaminated with the training set. Second, the data collection was conducted retrospectively. However, the missing data was nearly none for all variables, except for the NIHSS score of 4 patients. To consider the development of classification model, patients without information on swallowing function for a period longer than 4 months after the stroke were excluded. Third, the retrospective cohorts of the present study may not include ischemic stroke patients with very mild or very severe dysphagia who were not required or unable to undergo VFSS. Those can represent patients with poststroke dysphagia who are needed to be evaluated for swallowing function in general clinical practice. Fourth, external validation was not performed in this study. Future study is needed to include model validation for datasets from other independent institutions.

Conclusions

The results of the present study showed that initial dysphagia severity and bilateral lesions at CR/BG/IC were the significant prognostic factors associated with 6-month swallowing recovery in poststroke dysphagia. Prediction of 6-month

swallowing recovery was feasible using the proposed Bayesian network model based on 10 important clinical and radiological factors. This study emphasizes that bilateral subcortical lesions are important prognostic factors that can be utilized to develop prognostic models for long-term swallowing recovery. Future studies are warranted to include larger patient cohorts with external validation for developing prognostic models of poststroke dysphagia to be applicable in clinical practice.

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Disclosures

The authors are planning to apply for a patent associated with this work.

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