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석사학위논문

Predicting Intracerebral Hemorrhage After Intravenous Thrombolysis in Acute Ischemic Stroke Using Machine Learning

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2024년 8월

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이 논문을 석사학위 논문으로 제출함

2024년 8월

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1. Introduction

Intravenous thrombolysis (IVT) is a widely used and effective treatment for patients with acute ischemic stroke (AIS) (1-3). However, previous studies have shown an increased possibility of intracerebral hemorrhage (ICH) in patients who received IVT (1,2,4). Severe ICH can be life-threatening, and accurately predicting the likelihood of ICH post IVT could facilitate tailored treatment strategies and improve patient care. For instance, if the risk of recurrent ischemic stroke is high and the risk of bleeding is low, additional antiplatelet therapy may be initiated earlier (5). Conversely, if the risk of ICH is high, the blood pressure may be lowered (6). Numerous scoring systems have been developed to evaluate the risk of ICH in patients with AIS following IVT. However, their practical utility is limited by the relatively low accuracy (7-11). This limitation may be due to the complexity of factors influencing ICH after IVT, with existing models often relying on a limited subset of variables (4,10). Attempts to improve prediction accuracy using machine learning (ML) have shown promising results (10,12). Therefore, ML presents a variable alternative to enhance prediction accuracy. This study aimed to predict the risk of ICH within 24 h after IVT in patients with AIS using ML.

2. Materials and Methods

2.1. Study population

This retrospective study enrolled patients with AIS who received IVT at the emergency center of Keimyung University Dongsan Hospital between September 2019 and May 2023. Within 24 h of IVT treatment, all patients underwent brain computed tomography (CT) or magnetic resonance imaging (MRI) to assess ICH risk, with evaluations performed by two neurologists. Initially, ICH was classified into four subgroups (hemorrhagic infarction type 1, hemorrhagic infarction type 2, parenchymal hematoma type 1, and parenchymal hematoma type 2) according to European-Australasian Acute Stroke Study (ECASS II) classification system (13). However, due to the small sample size and relatively low incidence of ICH following IVT, four groups were consolidated into a single ICH group. Exclusion criteria included patients who underwent additional endovascular therapy post-IVT, those who received IVT beyond 4 h and 30 min from symptom onset, individuals who received only a bolus dose of tissue plasminogen activator (t-PA), patients ultimately diagnosed with transient ischemic attack (TIA) or ocular ischemic syndrome (OIS), those lacking initial CT or MRI within 24 h post-IVT, and those lacking lipid profile data. The study was approved by the institutional review board of Keimyung University Dongsan Hospital (No. 2024-05-040).

2.2. Data collection

A total of 36 variables were collected. Demographic factors (age, sex, height, weight, and smoking history), past medical history (including hypertension, diabetes, dyslipidemia, atrial fibrillation, previous coronary artery disease, and previous stroke), past medication history (including anticoagulants, antiplatelets, antihypertensives, and statins), baseline laboratory test results, the dose of t-PA administered (0.6 mg/kg or 0.9 mg/kg), admission blood pressure (both systolic and diastolic), baseline National Institute of Health Stroke Scale (NIHSS) score, and onset-to-treatment time (OTT) were recorded. The collateral status of the brain was evaluated using the Tan score via brain computed tomography angiography (CTA), and the initial Alberta Stroke Program Early Computed Tomography (ASPECT) score was also included in the comprehensive database (10,12,14). Both the Tan score and ASPECT scores were calculated by two neurologists. Patients with Tan scores of 1 or 2, and those with a Tan score of 3, were classified in to two groups: those with collateral circulation defects and those without. For patients with cerebral infarction mainly affecting the posterior circulation territory, posterior ASPECT scores were calculated in lieu of the standard ASPECT score (15).

2.3. Machine learning process

Thirty-six variables were used as independent variables, whereas the dependent variable in this study was the occurrence of ICH following IVT. Feature selection was conducted to enhance prediction accuracy using the heuristic, filter, and wrapper methods. In the heuristic method, three studies were referenced for variable

selection, and two neurologists ultimately determined initial systolic blood pressure (SBP), NIHSS score, platelet count, OTT, initial ASPECT score, use of antiplatelet medication, and the presence of collateral defect on initial CTA as relevant variables (4,14,15). The filter method, which relies on the internal data structure of features, selected features based on their p-values. For the wrapper method, the recursive feature elimination (RFE) method was used for variable selection. This method begins with all features and progressively eliminates the least important ones based on their ranking determined by the underlying ML algorithm. This process continues until the desired number of features is achieved, thus optimizing the model's performance by focusing on the most informative features (16). Logistic regression (LR), random forest (RF), support vector machine (SVM), and extreme gradient boosting (XGBoost) models from scikit-learn were selected as the ML algorithms. All cases were randomly divided into a 70% training set and 30% testing set, ensuring an equal proportion of ICH cases in each set. To address the small sample size, a 5-fold cross-validation method was employed. The performance of the four ML models was compared on the testing sets using the area under the receiver operating characteristic curve (AUC), with AUC values rounded to the second decimal place. Additionally, the performance of ML models was further evaluated using a calibration curve.

2.4. Statistical analysis

The analysis was performed using Python version 3.10 (Python Software Foundation, USA). Initially, all continuous variables were

assessed for normality of distribution. Variables following a normal distribution are presented as the mean \pm standard deviation, whereas those not following a normal distribution are expressed as the median \pm interquartile range. Categorical variables are presented as percentages. Two-sample t-tests or Mann-Whitney U tests were employed to compare continuous data between groups, depending on the normality of distribution. For categorical data, comparisons were made using the χ^2 test or Fisher's exact test. Each variable was examined for significant differences between the groups with and without ICH, with a significance level of $p < 0.05$ considered statistically significant. Variance inflation factors (VIF) and correlation matrix were used to assess multicollinearity between variables.

3. Results

Out of the total 137 patients who underwent thrombolysis, 109 were included in this retrospective study. Among the excluded patients, 6 patients received IVT beyond 4.5 h from symptom onset, 2 patients received only a bolus dose of t-PA, 16 patients were diagnosed as TIA or OIS, and 4 patients lacked initial brain CTA, brain MRI within 24 h post-IVT, or lipid profile test results (Figure 1).

Among the included 109 patients, 15 patients (13.8%) were found to have ICH. The baseline characteristics are shown in Table 1. Patients who developed ICH after IVT had a lower initial ASPECT score ($p < 0.01$) and platelet counts ($p < 0.05$) and higher rates of collateral defects on initial brain CTA ($p < 0.05$), higher NIHSS score ($p < 0.01$), and higher initial diastolic blood pressure (DBP) ($p < 0.05$). It was confirmed that variables with considerable differences between the two groups did not significantly affect each other, as assessed through the variance inflation factors and correlation matrix (Table 2, Figure 2).

Initially, all 36 features were applied to four ML models, resulting in AUC values of 0.66 (95% confidence interval [CI], 0.51-0.81) for the LR model, 0.57 (95% CI, 0.41-0.73) for the RF model, 0.51 (95% CI, 0.35-0.68) for the SVM model, and 0.62 (95% CI, 0.43-0.81) for the XGBoost model (Figure 3). However, given the challenge of practical application with a large number of variables and the relatively modest accuracy, feature selection methods were employed, including heuristic, filter, and wrapper methods. These feature selection methods were initially applied to the RF model to determine which method yielded the best results.

The AUC using the heuristic method was 0.72 (95% CI, 0.56-0.89). In the filter method, features were selected based on their p-values, with 3, 5, 7 and 10 features chosen in the ascending order of significance. The selected features were ASPECT score, presence of collateral defect, NIHSS score, platelet count, initial DBP, triglyceride (TG), serum estimated glomerular filtration rate (eGFR), previous history of statin medication, blood urea nitrogen, and high-density lipoprotein (HDL) in order. The AUC values were 0.57 (95% CI, 0.37-0.77) for three features, 0.76 (95% CI, 0.63-0.89) for five features, 0.75 (95% CI 0.63-0.96) for seven features, and 0.81 (95% CI, 0.71-0.91) for ten features. In the wrapper method, eight features (initial DBP, NIHSS score, platelet count, eGFR, international normalization ratio, TG, HDL, and ASPECT score) were finally selected, resulting in an AUC result of 0.63 (95% CI, 0.61-0.65).

When comparing the three methods for feature selection, the filter method demonstrated the best performance. Features selected through the filter method were subsequently applied to LR, SVM, and XGBoost models using the same approach. The results are presented in Figure 4 and Table 3. The LR model, incorporating five features (ASPECT score, presence of collateral defect, NIHSS score, platelet count, and initial DBP), exhibited the best performance, with an AUC of 0.88 (95% CI, 0.83-0.94).

Further, the performance of ML models using five features was evaluated using a calibration curve (Figure 5). The LR model demonstrated the best performance, exhibiting reasonably good calibration for predicted values above approximately 0.5. However, approximately 66% of the predicted values were between the range of

0.1 to 0.5, and in this range, the predicted values tended to be lower than the actual values.

Table 1A. Baseline Characteristics of Patients Enrolled

	Overall (n=109)	No ICH (n=94)	Any ICH (n=15)	P-value
General characteristics				
Age, mean (SD)	68.6 (11.5)	69.1 (11.3)	65.6 (12.3)	0.317
Male, n (%)	73 (67.0)	64 (68.1)	9 (60.0)	0.563
Height, mean (SD)	163.2 (9.3)	163.3 (9.5)	163.1 (7.9)	0.936
Weight, median [IQR]	62.0 [58.0,70.0]	63.0 [58.0,70.0]	60.0 [58.0,64.0]	0.309
Smoking history, n (%)	50 (45.9)	44 (46.8)	6 (40.0)	0.832
Medical history, n (%)				
Hypertension	76 (69.7)	65 (69.1)	11 (73.3)	1.000
Diabetes mellitus	40 (36.7)	35 (37.2)	5 (33.3)	0.998
Dyslipidemia	67 (61.5)	57 (60.6)	10 (66.7)	0.873
Atrial fibrillation	20 (18.3)	17 (18.1)	3 (20.0)	1.000
Coronary artery disease	23 (21.1)	18 (19.1)	5 (33.3)	0.303
Previous stroke	22 (20.2)	18 (19.1)	4 (26.7)	0.498
Medication history, n (%)				
Antiplatelets	33 (30.3)	30 (31.9)	3 (20.0)	0.546
Anticoagulants	6 (5.5)	5 (5.3)	1 (6.7)	1.000
Antihypertensives	30 (27.5)	26 (27.7)	4 (26.7)	1.000
Statins	11 (10.1)	8 (8.5)	3 (20.0)	0.176
Baseline laboratory test				
WBC, median [IQR]	7.3 [6.0,9.1]	7.2 [6.0,9.1]	7.3 [6.1,9.4]	0.699
Platelet, mean (SD)	233.8 (68.4)	241.2 (65.6)	187.0 (69.1)	0.011
Hemoglobin, median [IQR]	14.1 [12.3,14.7]	14.1 [12.3,14.8]	14.0 [12.2,14.5]	0.812
BUN, median [IQR]	17.0 [13.0,20.0]	16.0 [13.0,20.0]	18.0 [15.0,20.5]	0.182
Creatinine, median [IQR]	0.9 [0.7,1.0]	0.8 [0.7,1.0]	0.9 [0.8,1.0]	0.426
eGFR, median [IQR]	81.2 [67.4,97.2]	83.2 [69.2,98.8]	70.2 [64.8,89.4]	0.167
PT INR, median [IQR]	1.0 [0.9,1.0]	1.0 [0.9,1.0]	1.0 [0.9,1.0]	0.975
PT sec, median [IQR]	11.2 [10.8,11.7]	11.2 [10.8,11.7]	11.0 [10.7,11.9]	0.685
C-reactive protein, median [IQR]	0.1 [0.1,0.3]	0.1 [0.1,0.3]	0.2 [0.1,0.2]	0.775

Table 1B. Baseline Characteristics of Patients Enrolled (continued)

	Overall (n=109)	No ICH (n=94)	Any ICH (n=15)	P-value
Baseline laboratory test				
Total cholesterol, median [IQR]	170.0 [134.0,201.0]	169.5 [135.0,201.0]	177.0 [117.5,202.0]	0.947
Triglyceride, median [IQR]	117.0 [75.0,173.0]	123.0 [82.5,175.5]	82.0 [58.5,126.0]	0.068
HDL, median [IQR]	45.0 [38.0,54.0]	45.0 [38.0,52.8]	53.0 [36.0,66.0]	0.215
LDL, median [IQR]	109.0 [78.0,131.0]	108.5 [78.2,130.8]	114.0 [58.0,126.5]	0.695
Blood glucose, median [IQR]	123.0 [109.0,147.0]	122.0 [106.5,146.8]	124.0 [117.0,148.0]	0.423
tPA dose, n (%)				1.000
0.9mg/kg	93 (85.3)	80 (85.1)	13 (86.7)	
0.6mg/kg	16 (14.7)	14 (14.9)	2 (13.3)	
Tan score (%)				0.003
Tan 3	86 (78.9)	79 (84.0)	7 (46.7)	
Tan 2 or Tan 1	23 (21.1)	15 (16.0)	8 (53.3)	
Clinical and imaging features				
Initial SBP, median [IQR]	150.0 [138.0,170.0]	150.0 [133.2,169.8]	150.0 [140.0,175.0]	0.456
Initial DBP, median [IQR]	90.0 [80.0,100.0]	90.0 [80.0,100.0]	100.0 [90.0,110.0]	0.014
NIHSS, median [IQR]	6.0 [4.0,10.0]	5.0 [3.0,9.0]	11.0 [6.5,13.5]	0.005
OTT, median [IQR]	110.0 [87.0,175.0]	112.0 [88.5,177.2]	110.0 [82.0,162.5]	0.816
Initial ASPECT score, median [IQR]	10.0 [10.0,10.0]	10.0 [10.0,10.0]	9.0 [8.5,10.0]	0.002

ASPECT: Alberta Stroke Program Early Computed Tomography; BUN: blood urea nitrogen; DBP: diastolic blood pressure; eGFR: estimated glomerular filtration rate; HDL: high-density lipoprotein; ICH: intracerebral hemorrhage; INR: international normalized ratio; IQR: interquartile range; LDL: low-density lipoprotein, NIHSS: National Institutes of Health Stroke Scale; OTT: onset-to-treatment time; PT: prothrombin time; SBP: systolic blood pressure; SD: standard deviation; tPA: tissue plasminogen activator; WBC: white blood cell.

Table 2. Variance Inflation Factor between Different Variables

Features	VIF	Features	VIF
Age	82.94806804	LDL	120.5832653
Height	497.8565508	Blood glucose	13.81718899
Weight	84.53175372	OTT	9.930787041
Initial SBP	90.04988019	Initial ASPECT score	184.3804461
Initial DBP	55.13009022	Sex	7.498242062
NIHSS	6.61521778	Coronary artery disease	2.905662775
Hemoglobin	124.7836308	Smoking history	3.194394931
WBC	18.23270104	Hypertension	5.458637878
Platelet	22.92176091	Diabetes mellitus	2.816784905
BUN	18.87950825	Dyslipidemia	4.077100799
Creatinine	7.022926152	Atrial fibrillation	2.072823455
eGFR	25.48206392	Previous stroke	2.733034165
PT INR	236.5650409	Anticoagulants	2.204319842
PT sec	197.5418311	Antihypertensives	2.764212687
C-reactive protein	2.080243885	Statins	1.977648932
Total cholesterol	259.0316857	Antiplatelets	2.960934928
Triglyceride	11.38152299	tPA dose	2.136595837
HDL	34.90608383	Tan score	8.936351393

ASPECT: Alberta Stroke Program Early Computed Tomography; BUN: blood urea nitrogen; DBP: diastolic blood pressure; eGFR: estimated glomerular filtration rate; HDL: high-density lipoprotein; INR: international normalized ratio; LDL: low-density lipoprotein; NIHSS: National Institutes of Health Stroke Scale; OTT: onset-to-treatment time; PT: prothrombin time; SBP: systolic blood pressure; tPA: tissue plasminogen activator; VIF: variance inflation factor; WBC: white blood cell.

Table 3. Result of Applying the Selected Variables Using the Filter Method to Four Different Machine Learning Models

Number of features	Logistic regression	Random forest	XGBoost	SVM
3 features	0.75 (95% CI, 0.63, 0.86)	0.57 (95% CI, 0.37, 0.77)	0.49 (95% CI, 0.36, 0.62)	0.46 (95% CI, 0.20, 0.72)
5 features	0.88 (95% CI, 0.83, 0.94)	0.76 (95% CI, 0.63, 0.89)	0.64 (95% CI, 0.53, 0.74)	0.81 (95% CI, 0.73, 0.88)
7 features	0.80 (95% CI, 0.62, 0.98)	0.75 (95% CI, 0.63, 0.86)	0.64 (95% CI, 0.46, 0.81)	0.72 (95% CI, 0.59, 0.84)
10 features	0.77 (95% CI, 0.58, 0.95)	0.81(95% CI, 0.71, 0.91)	0.65 (95% CI, 0.49, 0.81)	0.66 (95% CI, 0.58, 0.74)

CI: confidence interval; SVM: support vector machine; XGBoost: extreme gradient boosting.

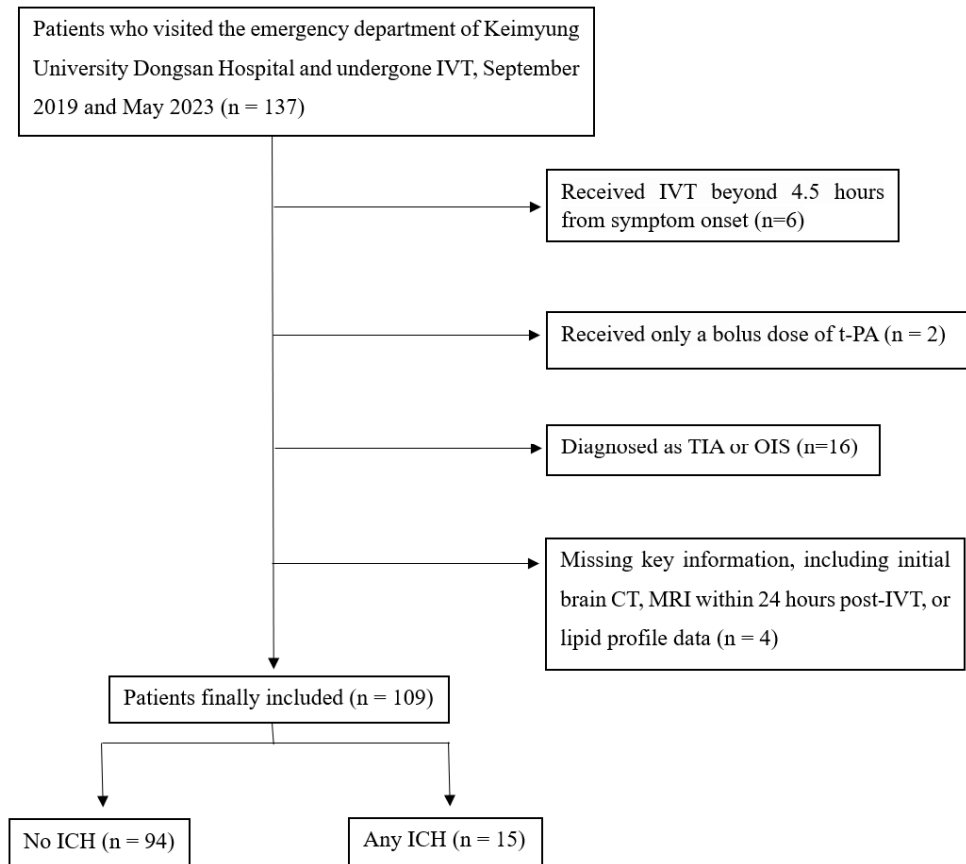


Figure 1. Flowchart of the data included in machine learning process.

CT: computed tomography; ICH: intracerebral hemorrhage;
 IVT: intravenous thrombolysis; MRI: magnetic resonance
 imaging; OIS: ocular ischemic syndrome; TIA: transient
 ischemic attack.

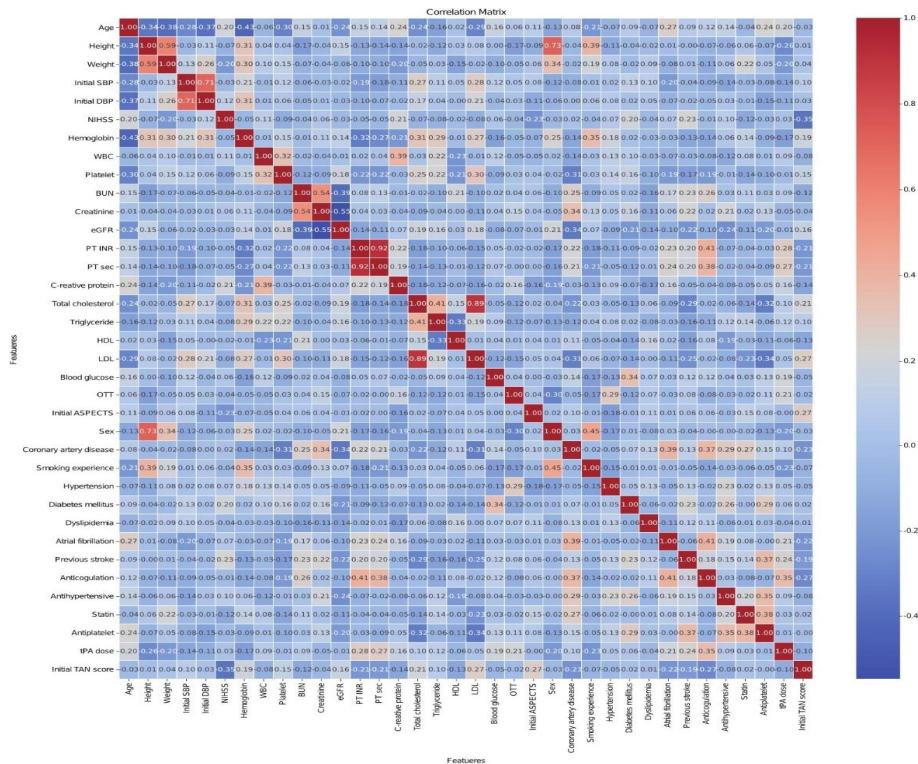


Figure 2. Correlation matrix of variables. There was no significant correlation between variables that had differences between the two groups. ASPECTS: Alberta Stroke Program Early Computed Tomography Score; BUN: blood urea nitrogen; DBP: diastolic blood pressure; eGFR: estimated glomerular filtration rate; HDL: high-density lipoprotein; INR: international normalized ratio; LDL: low-density lipoprotein; NIHSS: National Institutes of Health Stroke Scale; OTT: onset-to-treatment time; PT: prothrombin time; SBP: systolic blood pressure; tPA: tissue plasminogen activator; VIF: variance inflation factor; WBC: white blood cell.

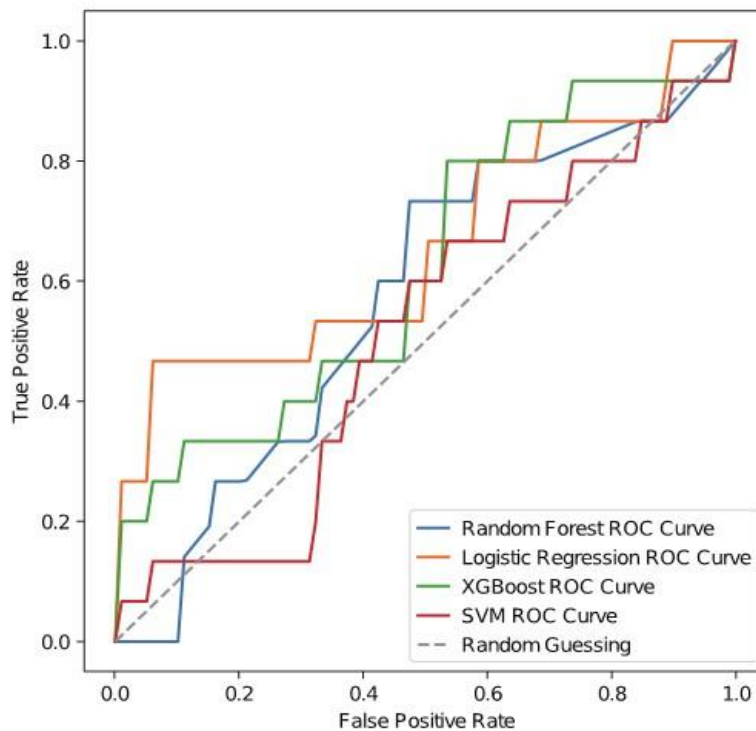


Figure 3. Result of area under the receiver operating characteristics curves without feature selection on four machine learning models. ROC: receiver operating characteristics; SVM: support vector machine; XGBoost: extreme gradient boosting.

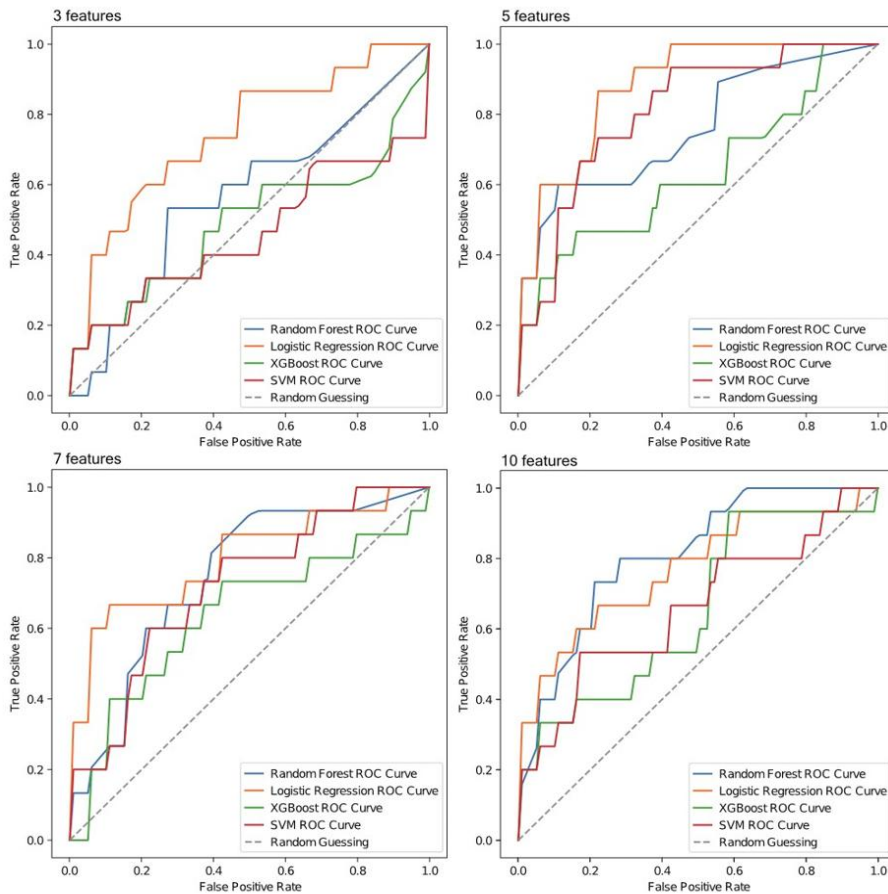


Figure 4. Result of area under the receiver operating characteristics curves with feature selection based on the filter method on four machine learning models. ROC: receiver operating characteristics; SVM: support vector machine; XGBoost: extreme gradient boosting.

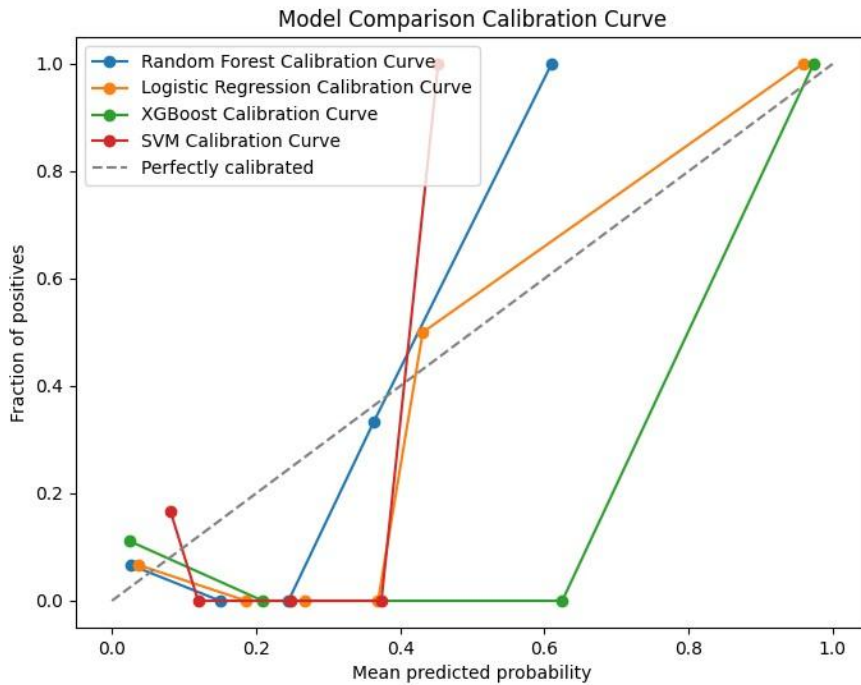


Figure 5. Calibration curves of machine learning models using five features. SVM: support vector machine; XGBoost: extreme gradient boosting.

4. Discussion

This study employed four different ML algorithms to predict ICH following IVT in patients with AIS. Unlike previous studies that focused on predicting hemorrhagic transformation or symptomatic ICH using ML, the present study included vital radiological findings, such as the ASPECT score and collateral defects on CTA (10,11). Both the ASPECT score and presence of collateral defects are pivotal factors that increase the risk of ICH after IVT (4,14,15). This study demonstrated a higher AUC compared to previous studies, suggesting that the incorporation of radiological information may have improved the model's performance (10,11).

The findings of this study have several potential applications in the clinical field. For instance, current guidelines recommend delaying the initiation of antiplatelet therapy until 24 h after IVT due to the uncertainty regarding the risk associated with antithrombotic therapy within the first 24 h post IVT (3,17). Accurately predicting the likelihood of ICH after IVT could facilitate the earlier administration of additional medication (5). Moreover, the five important variables identified in this study can be evaluated prior to the administration of t-PA. Therefore, given its high accuracy, even in external validation with larger datasets, ML algorithms may aid in decision-making regarding t-PA administration for patients with AIS. For instance, if the risk of ICH is deemed too high, antiplatelet therapy may be preferred over

IVT (3).

In this study, the LR model demonstrated the best performance, using the 'ASPECT score', 'presence of collateral defect', 'NIHSS score', 'platelet count', and 'initial DBP' as the five most important features. With the exception of DBP, these variables have been identified in previous studies as significant factors influencing the occurrence of ICH following IVT (4,10,18,19). While blood pressure is known to play a crucial role in post-thrombolytic ICH, previous studies have indicated that SBP rather than DBP has a significant impact (6,19). The specific reason for the notable influence of DBP in this study remains unclear. However, given the relatively small number of patients included compared to other studies, the potential for errors due to the small sample size cannot be excluded (10,18,19).

Four different classification ML models were employed in this study. Both RF and XGBoost can be categorized as types of decision trees. However, unlike RF, XGBoost represents a variation of the gradient boosting algorithm, wherein multiple decision trees are sequentially trained to rectify errors (20). This distinction led us to include both approaches. Based on the findings of other studies, it was anticipated that the performance of other ML models would surpass that of LR (10,21). Furthermore, it was presumed that the feature selection method using the RFE method would also demonstrate superior performance. Nevertheless, LR using the filter method exhibited the best performance, potentially attributable to the

limited size of the dataset. With a larger patient cohort, different results may arise.

This study has several limitations. First, being a single-center based retrospective study, it necessitates external validation with larger datasets sourced from multiple centers. Although 5-fold cross-validation was used to mitigate the impact of the small sample size, certain constraints persisted. For instance, patients were initially categorized into three groups based on the Tan score. However, due to the limited number of patients with collateral defects, those with Tan 1 and Tan 2 scores were merged. Furthermore, the dependent variables were categorized into only two groups, likely due to the small sample size. Second, the clinical applicability of the study is restricted as it categorizes outcomes into only two groups: with or without ICH. Furthermore, the exclusion of patients undergoing mechanical thrombectomy limits its application in clinical settings. Third, the calibration curve reveals that over 80% of predicted values fall below 0.5, with the majority lying below the perfectly calibrated line. This suggests a potential issue of under-forecasting, likely stemming from the small sample size and low proportion of hemorrhagic stroke patients in the research dataset. When compared to other studies, the incidence rate of ICH does not exhibit significant differences, emphasizing the necessity for validation with a larger patient dataset (2,4,10). Last, in this study, the ASPECT and Tan scores were manually assessed by two neurologists. Scores can vary depending on the rater's expertise,

particularly the ASPECT score. Recent technological advancements, such as automated ASPECT score software, have emerged, and utilizing scores evaluated by such programs as independent variables may enhance the performance of future models (22).

5. Summary

This study highlights the potential of using ML techniques to improve ICH prediction in patients with AIS following IVT. Among the four models investigated, the LR model using five clinical variables (ASPECT score, presence of collateral defect, NIHSS score, platelet count, and initial DBP) demonstrated the best performance. However, this model exhibited suboptimal calibration on the curve. Therefore, further validation with a larger patient population is needed.

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Predicting Intracerebral Hemorrhage After Intravenous Thrombolysis in Acute Ischemic Stroke Using Machine Learning

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(Abstract)

Intravenous thrombolysis (IVT) is an effective treatment for acute ischemic stroke. However, it poses the risk of intracerebral hemorrhage (ICH). This study aimed to predict the occurrence of ICH after IVT using four machine learning (ML) models (logistic regression, random forest, support vector machine, and extreme gradient boosting models). A total of 109 patients were enrolled, with 15 developing ICH. The analysis included 36 variables. Patients who developed ICH exhibited lower Alberta Stroke Program Early Computed Tomography (ASPECT) scores and platelet counts and had higher National Institutes of Health Stroke Scale (NIHSS) scores, and diastolic blood pressure (DBP). Furthermore, the incidence of

collateral defects was higher in the ICH group. Three feature selection methods (heuristic, filter and wrapper) were tested with a random forest model to enhance ML model performance, with the filter method yielding the best results. Features selected based on their p-values were applied to ML models in sets of 3, 5, 7, and 10. The logistic regression model using five features (ASPECT score, presence of collateral defect, NIHSS score, platelet count, and DBP) demonstrated the best performance. Given the study's small sample size and calibration curve analysis results, further investigation with a larger patient cohort is warranted.

급성 허혈성 뇌졸중에서 기계학습을 이용한 정맥내 혈전용해술 후 뇌출혈 발생 예측

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(초록)

정맥내 혈전용해술은 급성 허혈성 뇌졸중에서 효과적인 치료법이다. 그러나 정맥내 혈전용해술 시행 이후에는 뇌출혈 발생의 위험이 있다. 이 연구의 목적은 네 가지 기계학습 모델 (로지스틱 회귀, 랜덤 포레스트, 서포트 벡터 머신 그리고 XGBoost 모델)을 사용하여 정맥 내 혈전용해술 이후 뇌출혈의 발생을 예측하는 것이다. 총 109명의 환자가 등록되었으며, 이 중 15명의 환자에서 뇌출혈이 확인되었다. 분석에는 총 36가지의 변수가 포함되었다. 뇌출혈 발생 환자들은 ASPECT 점수와 혈소판 수치가 낮았고 뇌 컴퓨터 단층촬영 혈관조영술에서 혈류 결핍이 확인되었다. 또한 NIHSS 점수 및 확장기혈압이 뇌출혈 발생 환자들에서 높았다. 기계 학습 모델의 성능을 향상시키기 위해 세 가지 특성 선택 방법 (heuristic, filter, wrapper)이 랜덤 포레스트 모델에 적용되었으며, filter 방법이 가장 좋은 성능을 보였다. P-값에 기반하여 3개, 5개, 7개, 10개의 특성이

선택되었고, 이를 4가지 기계학습모델에 적용하였다. 최종적으로 ASPECT 점수, 혈류 공급의 장애, NIHSS 점수, 혈소판 수 및 확장기혈압을 활용한 로지스틱 회귀 모델이 평균 AUC 0.88로 가장 우수한 성능을 보였다. 그러나 표본의 크기가 작으며, 보정 곡선 분석 결과를 고려하였을 때, 보다 큰 환자 집단을 대상으로 한 추가 연구가 필요하겠다.