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Predicting prognosis in patients with stroke treated with intravenous alteplase through blood pressure changes: A machine learning-based approach

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Abstract

The use of machine learning (ML) in predicting disease prognosis has increased, and researchers have adopted different methods for variable selection to optimize early screening for AIS to determine its prognosis as soon as possible. We aimed to improve the understanding of the predictors of poor functional outcome at three months after discharge in AIS patients treated with intravenous thrombolysis and to construct a highly effective prognostic model to improve prediction accuracy. And four ML methods (random forest, support vector machine, naive Bayesian, and logistic regression) were used to screen and recombine the features for construction of an ML prognostic model. A total of 352 patients that had experienced AIS and had been treated with intravenous thrombolysis were recruited. The variables included in the model were NIHSS on admission, age, white blood cell count, percentage of neutrophils and triglyceride after thrombolysis, tirofiban, early neurological deterioration, early neurological improvement, and BP at each time point or period. The model's area under the curve for predicting 30-day modified Rankin scale was 0.790 with random forest, 0.542 with support vector machine, 0.411 with naive Bayesian, and 0.661 with logistic regression. The random forest model was shown to accurately evaluate the prognosis of AIS patients treated with intravenous thrombolysis, and therefore they may be helpful for accurate and personalized secondary prevention. The model offers improved prediction accuracy that may reduce rates of misdiagnosis and missed diagnosis in patients with AIS.

KEYWORDS
intravenous thrombolysis, ischemic stroke, machine learning, nursing, prognosis

1 | INTRODUCTION

Acute ischemic stroke (AIS) is the most important subtype of stroke and the leading cause of death and disability among adults in China, accounting for 72.9% of all stroke cases.[1,2] One of the most effective drugs for AIS treatment is recombinant tissue plasminogen activator, administered by intravenous infusions for the onset of early (within 3–4.5 h).[3–5] Several studies have shown that 11.8%–33.1% of patients with AIS had early neurological deterioration, 2%–2.4% had symptomatic intracranial hemorrhage, and 31.1–47.6% still lived

dependently after three months.[6–9] The risk of high blood pressure is one of the most important and simple indicators affecting prognosis. Meanwhile, the clinical significance of monitoring and managing blood pressure during intravenous thrombolytic therapy for the prevention of adverse prognosis in patients with AIS remains an area of active investigation.

With the development of artificial intelligence technology and the integration of medical big data, machine learning (ML) algorithms are now widely used in the field of medicine, and have gradually become an important tool to assist clinical decision-making and predict clinical prognosis.[10–12] ML uses algorithms to parse and learn from data to make predictions or decisions about real-world events. In establishing a forecast model, ML can overcome the limitation of traditional algorithms being unable to fully explain the mutual influence between variables function and lack of accuracy. Furthermore, ML affords better generalization performance for models through increased variables and sample size, which can effectively apply to different patients. ML has previously been applied to research on disease prognosis and achieved good results.[13]

However, at present, there are no different forms of supervised and unsupervised learning algorithms that are being used to identify and predict blood pressure and other measures of prognosis risk with AIS patients undergoing intravenous thrombolysis. Therefore, the main objective of this research was to develop a decision-support tool for improving the management of extremely high blood pressure during the first 24 h after AIS by using ML techniques. Constructing a highly effective prognostic model including blood pressure may improve the accuracy of prognostic prediction in AIS patients undergoing intravenous thrombolysis.

WHAT IS ALREADY KNOWN ABOUT THE TOPIC?

- Stroke guidelines indicate that monitoring BP within 24 h from the beginning of intravenous thrombolytic therapy in patients with AIS is essential due to the high incidence of complications.
- Several studies have shown that high blood pressure levels are associated with the prognosis of patients with AIS, such as changes in neurological function, hemorrhaging-related complications, and modified Rankin scale scores.

WHAT THIS PAPER ADDS

- The time points of blood pressure focus on the admission, immediate completion of thrombolysis, 0—2 h, 2—8 h, 8—24 h starting with thrombolysis, and the most commonly used parameters are average value, maximum value, minimum value, range, and successive coefficient of variation were one of the independent influencing factors.
- Models including blood pressure indicators can be trained to predict poor prognosis using ML, especially the random forest.

2 | METHODS

2.1 | Study design and participants

Patients with AIS who had participated in a prospective cohort study between November 2019 and September 2020 and received alteplase were recruited for this study at a comprehensive stroke center (Xuanwu Hospital, Capital Medical University, Beijing, China). The inclusion criteria were as follows: (1) being ≥18 years of age; (2) having been treated for intravenous thrombolysis using the thrombolytic medication alteplase within 3—4.5 h after symptom onset; (3) having received 10% of a total dose of alteplase (Boehringer Ingelheim Pharma GmbH, Ingelheim, Germany) calculated as 0.9 mg/kg (maximum 90 mg) and administered as an intravenous bolus with the remaining 90% given as an infusion over the course of 1 h; (4) having been followed up for 3 months. The exclusion criteria were as follows: (1) having received subsequent endovascular treatment combined with intravenous thrombolysis; (2) having no definitive evidence of focal hyperintensities in clinically relevant areas on initial or follow-up diffusion-weighted imaging; (3) having absent prognostic data; (4) missing 90% of the information from the data collection form; (4) having had one or more adverse post-discharge outcomes caused by a non-stroke event such as a fall or a fracture.

2.2 | Ethics statement

The protocol for this study was approved by the Ethical Committee of Xuanwu Hospital and conformed to the principles outlined in the Declaration of Helsinki. Written informed consent was obtained from all patients. Prior to enrollment, all patients were informed of the study procedures.

2.3 | Data collection

Medical records were retrospectively reviewed by nurses who were blinded to patient outcomes. The following clinical factors were recorded: age; sex; body mass index; medical history such as hypertension, diabetes, hyperlipidemia, coronary heart disease, previous cerebral infarction or transient ischemic attack, or atrial fibrillation; administration of antiplatelet aggregation medication and modified Rankin Scale score before admission; smoking or drinking; multiple intravenous thrombolysis treatments; onset to treatment time; door-to-needle time; Trial of Org 10172 in Acute Stroke Treatment (TOAST) classification; laboratory values before and after thrombolysis (26 parameters from routine blood, biochemical, and coagulation tests); administration of intravenous antihypertensive drugs or tirofiban; placement of gastric and urinary tubes; peripheral or intracranial hemorrhage; early neurological function improvement or deterioration. About blood pressure, we have seen that the time points focus on the admission, immediate completion of thrombolysis, 0—2 h, 2—8 h, 8—24 h starting with thrombolysis, and the most commonly used parameters are average value, maximum value, minimum value, range

(maximum–minimum), and successive coefficient of variation (see Tables 1, 2, and 3).

The primary functional outcome was the modified Rankin Scale score at 90 days after stroke onset which included physical function, activity, and engagement. This scale is an effective index for evaluating neurological deficits, has been widely used to evaluate post-stroke disability, and can reflect the changes in functional status sensitively. Therefore, it is an effective tool for distinguishing the changes of mild to moderate disability in patients, especially those with mild stroke. Centralized telephone follow-up was carried out by centralized visitors with unified training. The main follow-up methods were outpatient clinic and telephone. A score of 0–2 points was considered a good prognosis and 3–6 points was defined as a poor prognosis.[14]

2.4 | Data pre-processing

The data pre-processing process was performed using Python and includes: ①Records containing outliers, which were identified by boxplot, were excluded. ②The median imputation method was used to impute missing values in derivation cohorts. ③The categorical variables were converted into numerical values with dummy encoding, and the continuous features were standardized by removing the mean and scaling to unit variance. ④Variables with a missing ratio of >90% in each column were deleted; variables with a single category proportion >90% in each column were deleted. Finally, A total of 119 datasets were obtained (see Tables 1, 2, and 3).

2.5 | Feature selection

ML uses the Boruta screening method to extract features from the database.[15] The process is as follows: ① Randomly scramble the values of each feature of the feature matrix, and splice them with the original features to form a new feature matrix. ② Using the new feature matrix as input, training the model that can output the feature importance. ③ Calculating the z values of the new features and the original features; ④ find out the maximum z value in the new features and record it as Z max. ⑤ The original features with Z value greater than Z max are marked as important. Original features smaller than Z max are marked as unimportant. The original features smaller than Z max are permanently removed from the feature set. ⑥ Delete all the disturbed features; ⑦ Repeat the above process until all features are marked as important or unimportant.

2.6 | Model training and evaluation

The data was divided into 60% in the training set and 40% in the test set using the train_test_split package from the Python Scikit–Learn library. The training set data was used for model training, and the test set data was used for model evaluation and selection. The four ML algorithms included naive bayes, support vector machine, random forest, and logistic regression.[16–18] Figure 1 shows the processing and modeling pipeline.

In this study, for model derivation, we adopted 10-fold cross-validation, which is a standard way of optimizing the model with inner test data and has been used in a previous study. Sensitivity, specificity, accuracy, and the area under curve (AUC) were used to evaluate the prediction effect of the recognition model based on the training and test sets.

2.7 | Statistical analysis

Continuous data was reported as means ± standard deviation and analyzed using an independent samples *t*-test with normal distribution. Otherwise, comparison between two groups was performed using the Mann–Whitney U test. Categorical data were presented as frequency and percentages and analyzed using the chi-square test. All tests were two sided and $p < .05$ was considered statistically significant. The strengths of the performance were determined by estimating the odds ratios (OR) and their 95% confidence interval (CI). All statistical analyses were performed using SPSS version 22.0 (IBM Corp., Armonk, NY, US).

3 | RESULTS

A total number of 391 AIS patients were included in this study, with 352 (90.03%) followed up after three months. Among them, 13 patients with missing data, 1 was discharged from the hospital with a primary diagnosis other than ischemic stroke, and 25 were lost to follow-up. The train set and test set included 211 (60%) and 141 (40%) patient-level observations, respectively. In Tables 1–3, the patients were compared based on diverse characteristics such as demographic characteristics, medical history, stroke severity, and others. The average age of patients was 62.48 ± 11.81 years (range 25–97 years) and a total of 256 (72.7%) patients were men.

3.1 | BP indicators related with poor prognosis

Feature selection was performed using the Boruta package which reduced the number of features from 119 to 17. Within 24 h from the beginning to the end of thrombolysis, blood pressure at each time point has an important correlation with the poor prognosis of stroke patients, including blood pressure on admission, Immediate diastolic blood pressure after thrombolysis, mean and max diastolic blood pressure 2 h after thrombolysis, mean and max systolic blood pressure 2–8 h after thrombolysis, max systolic blood pressure 8–24 h after thrombolysis, mean blood pressure and max diastolic blood pressure during 24 h after thrombolysis. In addition, NIHSS on admission, age, white blood cell count, percentage of neutrophils and

TABLE 1 Descriptive statistics of continuous variables.

Variables	Good prognosis $n = 241$	Poor prognosis $n = 111$	p value
Baseline NIHSS score	4.67 ± 2.83	8.20 ± 5.43	<.001
Age (year)	60.96 ± 11.16	65.79 ± 12.53	<.001
Body mass index (kg/m^2)	25.16 ± 3.75	25.17 ± 3.94	.901
Onset to treatment time (min)	154.89 ± 65.99	160.54 ± 57.36	.419
Door-to-needle time (min)	29.73 ± 15.14	30.12 ± 12.90	.276
SBP on admission (mmHg)	151.00 ± 25.91	159.09 ± 26.25	.005
DBP on admission (mmHg)	84.34 ± 15.23	91.36 ± 14.45	<.001
Immediate SBP after thrombolysis (mmHg)	145.79 ± 21.02	150.47 ± 18.91	.027
Immediate DBP after thrombolysis (mmHg)	81.26 ± 11.44	87.32 ± 13.43	<.001
Before thrombolysis			
White blood cell count (*10^9/L)	7.75 ± 2.52	7.45 ± 2.18	.318
Percentage of neutrophils (%)	66.01 ± 12.28	68.05 ± 11.31	.115
Red blood cell count (*10^{12}/L)	4.70 ± 0.55	4.66 ± 0.62	.581
Hemoglobin (g/L)	144.79 ± 15.23	143.45 ± 18.01	.575
Hematocrit (%)	42.94 ± 4.43	42.69 ± 4.85	.736
Platelet count (*10^9/L)	223.76 ± 56.82	213.95 ± 64.02	.055
Alanine transaminase (IU/L)	23.37 ± 14.19	23.54 ± 16.22	.844
Aspartate transaminase (IU/L)	27.91 ± 11.16	28.51 ± 11.52	.529
Creatinine (μmol/L)	67.05 ± 15.86	68.66 ± 35.24	.569
Urea nitrogen (mmol/L)	5.89 ± 1.73	6.22 ± 2.15	.275
Glucose (mmol/L)	8.61 ± 4.14	9.89 ± 7.35	.321
Uric acid (μmol/L)	330.75 ± 79.48	330.20 ± 91.85	.997
Triglyceride (mmol/L)	2.29 ± 1.93	1.92 ± 1.47	.079
Cholesterol (mmol/L)	4.75 ± 1.18	4.63 ± 1.18	.557
Low-density lipoprotein (mmol/L)	2.88 ± 1.19	2.78 ± 0.99	.872
Prothrombin time activity (%)	102.71 ± 13.10	99.97 ± 13.65	.072
Prothrombin time (INR)	1.00 ± 0.09	1.01 ± 0.09	.094
Prothrombin time(s)	12.98 ± 0.79	13.14 ± 0.94	.088
Thrombin time(s)	15.86 ± 1.46	15.96 ± 1.61	.922
Activated partial thrombin time(s)	34.60 ± 4.91	34.27 ± 3.94	.429
Fibrinogen (g/L)	3.48 ± 0.83	3.57 ± 1.06	.374
After thrombolysis			
White blood cell count (*10^9/L)	7.60 ± 2.29	8.35 ± 2.51	.004
Percentage of neutrophils (%)	68.01 ± 12.13	73.21 ± 11.32	<.001
Red blood cell count (*10^{12}/L)	4.38 ± 0.49	4.42 ± 0.55	.416
Hemoglobin (g/L)	136.27 ± 14.26	137.06 ± 16.79	.479
Hematocrit (%)	40.37 ± 3.93	40.54 ± 4.39	.460
Platelet count (*10^9/L)	214.85 ± 53.91	210.72 ± 60.33	.422
Alanine transaminase (IU/L)	19.58 ± 13.13	20.78 ± 16.61	.672
Aspartate transaminase (IU/L)	23.10 ± 10.44	24.87 ± 10.55	.036
Creatinine (μmol/L)	61.74 ± 14.58	63.34 ± 30.56	.533
Urea nitrogen (mmol/L)	4.92 ± 1.40	5.38 ± 2.15	.178
Glucose (mmol/L)	6.58 ± 2.88	7.40 ± 3.20	.003
Uric acid (μmol/L)	324.83 ± 82.20	310.23 ± 96.05	.105

(Continues)

TABLE 1 (Continued)

Variables	Good prognosis $n = 241$	Poor prognosis $n = 111$	p value
Triglyceride (mmol/L)	1.73 ± 1.59	1.37 ± 1.27	.001
Cholesterol (mmol/L)	4.18 ± 1.67	4.11 ± 1.06	.880
Low-density lipoprotein (mmol/L)	2.49 ± 0.88	2.45 ± 0.89	.758
Prothrombin time activity (%)	92.72 ± 15.50	91.04 ± 15.42	.268
Prothrombin time (INR)	1.09 ± 0.28	1.08 ± 0.13	.479
Prothrombin time(s)	13.91 ± 3.39	13.84 ± 1.34	.381
Thrombin time(s)	18.65 ± 6.12	18.66 ± 5.09	.496
Activated partial thrombin time(s)	37.79 ± 6.08	36.49 ± 5.07	.021
Fibrinogen (g/L)	2.49 ± 0.66	2.63 ± 0.88	.050
D-dimers (mg/mL)	2.57 ± 4.26	4.10 ± 10.05	.017
Glycosylated hemoglobin (%)	6.53 ± 1.70	6.92 ± 2.10	.173
Homocysteine (μmol/L)	16.68 ± 10.46	18.30 ± 14.45	.798
High sensitivity C-reactive protein (g/L)	4.53 ± 7.08	6.22 ± 9.58	.021
Erythrocyte sedimentation rate (%)	5.71 ± 6.34	7.60 ± 11.79	.315
Hospitalization days(d)	6.23 ± 1.88	7.39 ± 2.81	<.001

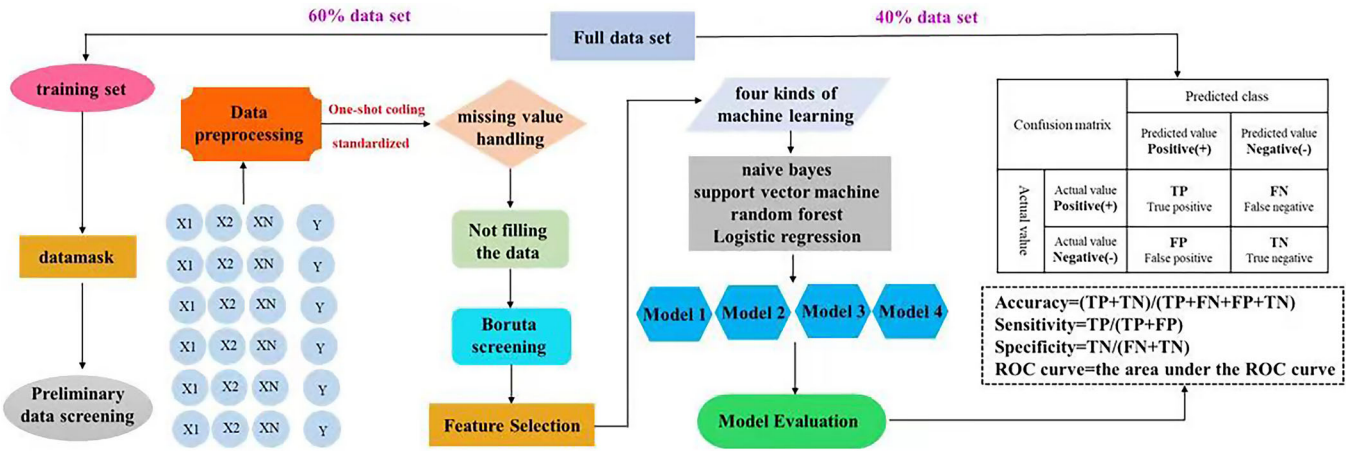

FIGURE 1 Flowchart of risk prediction model for AIS patients with poor prognosis based on machine learning.

triglyceride after thrombolysis, tirofiban, early neurological deterioration and improvement were obtained.

3.2 | Models can be trained to predict poor prognosis using ML

The performance metrics, AUC, sensitivity, specificity, and accuracy, for all the three models with training set and test set are displayed. As shown in Table 4 and Figure 2, the random forest performed significantly AUC better than others (0.790 vs. 0.542, 0.411 and 0.661). The sensitivity, and accuracy of random forest also was higher comparing other ML models, 0.761, 0.522, respectively.

4 | DISCUSSION

Timely identification of the influencing factors of short-term prognosis and improvement of various preventable risk factors through targeted treatment or secondary prevention can effectively improve the prognosis of patients after AIS. Thus, this study developed a successful risk prediction model for short-term poor prognosis in AIS patients undergoing intravenous thrombolysis based on three ML algorithms. And the result also stress the importance of blood pressure monitor and management to prognosis.

In previous studies, the following prediction models were developed based on logistic regression analysis. (1) The MOST (multimodal outcome score for stroke thrombolysis) model for predicting good

TABLE 2 Descriptive statistics of categorical variables.

Variables	Good prognosis $n = 241$	Poor prognosis $n = 111$	p value
Sex (man)	175 (72.6%)	66 (27.4%)	.944
Hypertension	152 (63.1%)	70 (63.1%)	.999
Diabetes	81 (33.6%)	48 (43.2%)	.081
Hyperlipidemia	192 (79.7%)	85 (76.6%)	.510
Coronary heart disease	48 (19.9%)	27 (24.3%)	.348
Atrial fibrillation	20 (8.3%)	14 (12.6%)	.203
stroke	51 (21.1%)	32 (28.8%)	.115
Transient ischemic attack	7 (2.9%)	4 (3.6%)	.726
Aspirin or clopidogrel on admission	11 (15.9%)	3 (9.7%)	.601
Smoking	115 (47.7%)	44 (39.6%)	.322
Drinking	97 (40.2%)	37 (33.3%)	.324
Multiple thrombolysis	7 (2.9%)	3 (2.7%)	.916
modified Rankin Scale score before thrombolysis			<.001
0 score	1 (0.4%)	0 (0)	
1 scores	34 (14.1%)	5 (4.5%)	
2 scores	75 (31.1%)	12 (10.8%)	
3 scores	69 (28.6%)	24 (21.6%)	
4 scores	59 (24.5%)	62 (55.9%)	
5 scores	3 (1.2%)	8 (7.2%)	
tirofiban	23 (9.5%)	34 (30.6%)	<.001
TOAST classification			<.001
Large-artery atherosclerosis	158 (65.6%)	91 (82.0%)	
Cardioembolism	12 (5.0%)	8 (7.2%)	
Small-artery occlusion	62 (25.7%)	8 (7.2%)	
Stroke of other determined cause	1 (0.4%)	3 (2.7%)	
Stroke of undetermined cause	8 (3.3%)	1 (0.9%)	
Intravenous antihypertensive medication	31 (12.9%)	23 (20.7%)	.057
Gastric catheter	1 (0.4%)	10 (0.9%)	<.001
Urinary catheter	3 (1.2%)	10 (9.0%)	.001
Intracranial hemorrhage	4 (1.7%)	9 (8.1%)	.003
Peripheral bleeding	88 (36.5%)	44 (39.6%)	.574
Early neurological deterioration	13 (5.4%)	54 (48.6%)	<.001
Early neurological improvement	114 (47.3%)	16 (14.4%)	<.001

outcomes included five predictive variables (NIHSS score, Alberta Stroke Program Early CT score, proximal vascular occlusion, systolic blood pressure, and early recanalization).[19] The sensitivity and specificity were 77% and 82.1%, respectively. (2) The Stroke-TPI (Thrombolytic Predictive Instrument) model for predicting good prognosis included seven predictive variables (sex, age, systolic blood pressure, diabetes, NIHSS score, previous stroke, and onset to treatment time).[20] The AUC was 0.775. (3) The ASTRAL (acute stroke registry and analysis of Lausanne) model for predicting poor prognosis included six variables (age, NIHSS score, onset to treatment time, visual field, blood glucose, and level of consciousness).[21] The AUC was 0.790. (4) The iScore model, DRAGON model, and others.[22–24] A prediction model suitable for clinical application not only requires a good prediction effect, but also low cost of data collection, low difficulty of development, and convenience of use. A good prediction model also needs to have clinical universality and generalization. Most of the variables contained in the above prediction models are relatively complex, making them difficult to obtain and apply quickly and conveniently in clinical practice. Additionally, the larger the amount of data, the more representative data are included, and the better the prediction effect the model will have.

In this study, a total of 119 variables were included, and 17 were selected for prediction. These included 8 indicators of NIHSS on

TABLE 3 Descriptive statistics of blood pressure variables.

Variables	Good prognosis $n = 241$	Poor prognosis $n = 111$	p value
BP at 24 h after thrombolysis			
Mean SBP	139.07 ± 16.25	145.30 ± 16.97	.001
SBP maximum	167.63 ± 22.11	174.84 ± 21.26	.007
SBP minimum	113.74 ± 14.60	117.84 ± 15.56	.022
SBP range	53.89 ± 16.12	57.00 ± 16.65	.084
SBP successive variation	3.91 ± 1.09	4.22 ± 1.28	.057
Mean DBP	76.95 ± 8.75	80.68 ± 9.61	<.001
DBP maximum	96.45 ± 11.41	100.98 ± 14.09	.002
DBP minimum	59.28 ± 9.32	61.27 ± 10.57	.007
DBP range	37.17 ± 10.76	39.71 ± 13.89	.062
DBP successive variation	2.95 ± 0.83	3.11 ± 1.00	.170
2 h BP after thrombolysis			
Mean SBP	147.51 ± 19.42	147.59 ± 15.32	.938
SBP maximum	165.74 ± 26.62	164.58 ± 17.80	.941
SBP minimum	129.83 ± 19.02	130.23 ± 17.21	.994
SBP range	35.91 ± 20.39	34.35 ± 16.68	.997
SBP successive variation	12.71 ± 6.13	12.08 ± 6.18	.777
Mean DBP	80.86 ± 10.48	83.66 ± 9.46	.232
DBP maximum	91.94 ± 12.13	98.29 ± 15.26	.044
DBP minimum	70.22 ± 11.00	71.16 ± 10.18	.512
DBP range	21.72 ± 11.20	27.13 ± 15.24	.061
DBP successive variation	8.36 ± 4.87	9.54 ± 4.26	.139
2-8 h BP after thrombolysis			
Mean SBP	136.57 ± 18.21	141.27 ± 17.84	.206
SBP maximum	152.75 ± 19.28	156.13 ± 19.11	.314
SBP minimum	121.74 ± 18.12	126.16 ± 16.89	.209
SBP range	31.01 ± 12.01	29.97 ± 12.63	.604
SBP successive variation	10.90 ± 4.31	11.47 ± 4.80	.633
Mean DBP	75.89 ± 9.54	75.00 ± 8.15	.723
DBP maximum	88.20 ± 10.76	87.84 ± 10.77	.777
DBP minimum	64.16 ± 10.44	62.71 ± 8.97	.504
DBP range	24.04 ± 10.09	25.13 ± 9.61	.323
DBP successive variation	9.04 ± 3.87	9.22 ± 4.18	.715
8-16 h BP after thrombolysis			
Mean SBP	103.65 ± 13.24	104.78 ± 14.48	.633
SBP maximum	156.13 ± 20.41	158.58 ± 21.01	.543
SBP minimum	119.13 ± 16.41	119.55 ± 17.33	.958
SBP range	37.00 ± 11.42	39.03 ± 14.83	.760
SBP successive variation	11.74 ± 4.02	12.98 ± 5.36	.423
Mean DBP	56.13 ± 7.05	56.61 ± 7.47	.794
DBP maximum	89.57 ± 11.66	87.03 ± 8.97	.323
DBP minimum	62.13 ± 9.44	61.03 ± 8.24	.502
DBP range	27.43 ± 9.21	26.00 ± 7.58	.765
DBP successive variation	9.10 ± 3.25	8.96 ± 2.50	.961

TABLE 4 Comparison of four ML prediction performance.

	Support vector machine		Random forest		Naive bayes		Logistic regression	
variables	Training set	Test set	Training set	Test set	Training set	Test set	Training set	Test set
Sensitivity	0.524 (0.460,0.529)	0.490 (0.424,0.597)	0.761 (0.727,0.768)	0.464 (0.458,0.615)	0.596 (0.570,0.621)	0.643 (0.504,0.644)	0.476 (0.447,0.491)	0.477 (0.396,0.537)
Specificity	0.483 (0.482,0.552)	0.545 (0.401,0.607)	0.522 (0.492,0.544)	0.500 (0.303,0.511)	0.522 (0.466,0.523)	0.393 (0.388,0.575)	0.633 (0.595,0.640)	0.485 (0.467,0.681)
Accuracy	0.805 (0.800,0.823)	0.857 (0.728,0.857)	0.801 (0.705,0.914)	0.800 (0.705,0.914)	0.796 (0.788,0.819)	0.886 (0.672,0.930)	0.818 (0.813,0.844)	0.857 (0.673,0.908)
AUC	0.542 (0.494,0.545)	0.439 (0.310,0.671)	0.790 (0.750,0.794)	0.570 (0.532,0.801)	0.411 (0.368,0.425)	0.223 (0.206,0.547)	0.661 (0.623,0.665)	0.492 (0.401,0.758)

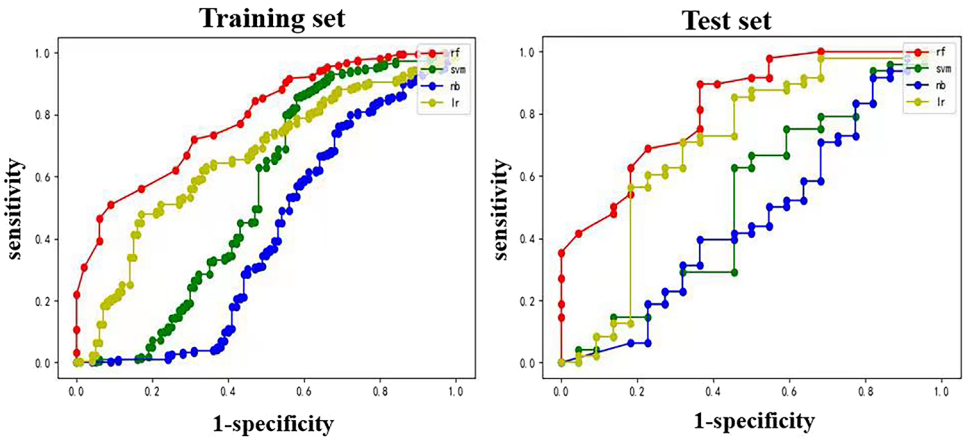

FIGURE 2 Comparison of ROC curve between three ML model.

admission, age, white blood cell count, percentage of neutrophils and triglyceride after thrombolysis, tirofiban, early neurological deterioration and improvement, besides blood pressure. A more severe neurological deficit, clinical manifestations of gradual progression, and stepwise aggravation after onset may indicate a larger size of cerebral infarction or severe destruction of the blood-brain barrier and may further increase the risk of hemorrhage transformation.[25–26] Soni et al found that age is an important influencing factor of bleeding and poor prognosis after thrombolysis, and age interacts with other risk factors, which has greater overall poor prognosis risk than individual variables alone.[27] Several Studies have shown that lowering triglyceride levels can reduce the recurrence risk of patients who have recently suffered from stroke.[28,29] As convenient markers of systemic inflammation, peripheral white blood cell count and neutrophil percentage are considered to destroy the stability of atherosclerotic plaques. At the same time, a large number of platelet-activating factors and oxygen free radicals are released, which aggravate hypoperfusion and cause ischemic injury, affect the establishment of collateral circulation, affect microcirculation, and finally induce poor prognosis after thrombolysis.[30,31]

Some studies have shown that the blood pressure at a certain point in 24 h or the average value in a certain time period is related to the prognosis of patients with thrombolysis. Yong and colleagues showed that blood pressure, especially 8–24 h after thrombolysis, is negatively correlated with prognosis.[32] Ahmed and colleagues indicated that blood pressure at baseline, 2 h and 24 h after thrombolysis was "U" correlated with prognosis.[33]

In a previous study, Alaka and colleagues showed that ML and logistic regression had a certain accuracy in predicting functional prognosis (AUC 0.66–0.71).[34] Additionally, Monteiro and colleagues found that ML could improve the AUC of predicting modified Rankin Scale at 3 months to 0.808.[35] However, no predictive model for poor prognosis in patients with intravenous thrombolytic therapy has yet been retrieved. The results of the present study show that the prediction model based on logistic regression analysis can assist medical staff in achieving an improved accuracy rate, thereby reducing rates of misdiagnosis and missed diagnosis in the process of screening patients with a high risk of poor prognosis. From the perspective of classifying the prediction accuracy of the prediction model, the poor prognosis prediction model constructed by ML algorithm based on random forest and support vector machine was successful with high prediction accuracy and good performance.

5 | CONCLUSIONS

In this study, a prediction model based on different ML algorithms was developed for the risk prediction of poor prognosis patients with AIS

undergoing intravenous thrombolysis. The advantages of this study are as follows. First, there are few prediction models for poor prognosis in AIS patients undergoing intravenous thrombolysis. This research method can be used in subsequent studies. Second, the indicators included in our study are easy to obtain in clinical practice and have a good correlation with poor prognosis, so as to achieve a good prediction effect and facilitate the practical application of medical staff. Third, our study randomly divided the population into two parts and conducted internal verification of the established model to ensure the reliability of its results. Finally, our study verified the importance of blood pressure at different time points and time periods from the start of intravenous thrombolysis to 24 h for prognosis. This study also has certain limitations: the included sample size is small, the model has not been verified externally, and it still needs to be verified in a large sample and multi-center external population to ensure accuracy and reliability.

AUTHOR CONTRIBUTIONS

Conceptualization: Kaiting Fan, Wenya Cao, Hong Chang. Data curation:Kaiting Fan, Fei Tian, Hong Chang. Investigation:Kaiting Fan, Hong Chang. Methodology:Kaiting Fan, Wenya Cao. Project administration:Kaiting Fan, Hong Chang, Fei Tian. Supervision: Kaiting Fan, Hong Chang. Visualization:Kaiting Fan. Writing—original draft: Kaiting Fan. Writing—review & editing: Kaiting Fan, Wenya Cao, Hong Chang.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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