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Original Article

A prognostic model for interventional thrombectomy in patients with acute ischemic stroke based on a BP neural network, random forest model and decision tree model

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Abstract: Objective: To investigate the predictive effect of a Back propagation (BP) neural network model, a random forest (RF) model and a decision tree model on the prognosis of interventional thrombolectomy for acute ischemic stroke (AIS) patients. Methods: A total of 255 patients with AIS admitted to the Department of Neurology, Beiliu People's Hospital of Guangxi from March 2018 to February 2022 were retrospectively included, all of whom received interventional thromposectomy. Patients' prognosis was determined by the modified Rankin Scale (mRs) at 3 months after surgery, including the good prognosis group (mRs≤2 points) and the poor prognosis group (mRs 3-6 points). Clinical data of the two groups were collected to explore and screen the factors affecting poor clinical prognosis. Based on the selected influencing factors, the BP neural network, RF model, and decision tree models were established respectively, and their predictive performances were verified. Results: All the three models predicted the same verification set data. The prediction accuracy, sensitivity and specificity of the BP neural network model were 0.961, 0.983 and 0.875, respectively. The prediction accuracy, sensitivity and specificity of the RF model were 0.948, 0.952 and 0.933, respectively. The prediction accuracy, sensitivity and specificity of the decision tree model were 0.882, 0.953 and 0.667, respectively. Conclusion: The three prediction models have shown good diagnostic efficacy and stability in the preliminary study of the prognosis of AIS mediated thrombectomy, which has important guiding significance for clinical prognosis assessment and selection of appropriate surgical population. The prediction model can be selected according to the actual situation of patients to provide more efficient guidance for clinicians.

Keywords: Acute ischemic stroke, interventional thrombectomy, BP neural network, random forest, decision tree, prognostic model

Introduction

Stroke is the primary cause of disability and death among Chinese residents, among which ischemic stroke accounts for the highest proportion, reaching more than 80% [1]. Acute ischemic stroke (AIS) is caused by multiple causes of ischemic cerebral hypoperfusion and acute cerebral artery occlusion. In the early stage of AIS, ischemic localized nerve injury, hypoxic apoptosis or necrosis of brain tissue may occur, eventually leading to disability and death [2, 3]. The treatment of AIS and the improvement of the prognosis outcome should be aimed at restoring effective reperfusion of occlusive cerebral vessels as soon as possible and rescuing the ischemic penumbra area. The current clinical treatments for AIS mainly include brain tissue protection, anti-platelet aggregation, and intravenous thrombolytic therapy, among which intravenous thrombolytic therapy is more commonly used. However, studies have found that the time window of intravenous thrombolytic therapy is relatively short, and most AIS patients have missed the best treatment opportunity at the time of treatment [4]. In recent years, further clinical studies have found that interventional therapy can quickly restore blood perfusion in the infarct area and reduce nerve damage [5]. However, it is still difficult for some patients with AIS to obtain an ideal prognosis after interventional therapy. At present, there are few studies related to the early prediction of prognosis of patients with AIS after interventional thrombectomy.

Early warning of AIS and corresponding intervention measures based on patients' clinical data have been confirmed in some studies to effectively improve the prognosis of patients with AIS and reduce related deaths. With the increasing maturity of data mining technology, disease risk prediction models based on clinical data and artificial intelligence continue to emerge and have been well promoted in the medical field, which is related to the high guiding value of data mining technology for disease diagnosis, risk assessment and prognosis judgment. For example, the neural network model that mimics simulation of a large number of neuron nodes in the human brain to form a model, the decision tree model that quickly mines effective information from massive data and presents simple and readable rules in the form of tree graph, and Random forests (RF) models with high classification accuracy and fault tolerance can be improved through decision tree integration [6, 7]. In this study, complete clinical information of patients was collected through the electronic medical record system. Based on the clinical data and machine learning algorithm, the prognosis prediction model of AIS interventional thrombectomy was established, and its predictive performances was evaluated.

Materials and methods

Basic information

Patients with AIS who received interventional thrombolysis in the Department of Neurology of Beiliu People's Hospital from March 2018 to February 2022 (255 cases) were retrospectively included. Inclusion criteria: ① Clinical findings, imaging findings, biochemical indicators and serological examinations were consistent with the diagnostic criteria for AIS [8]; ② Patients diagnosed for the first time and meeting the criteria for interventional thrombectomy; ③ All patients received interventional therapy in Beiliu People's Hospital and were followed up for 3-6 months. Exclusion criteria: ① Intracranial hemorrhage, subarachnoid hemorrhage or known bleeding tendency; ② Patients with brain tumor, cerebral hernia, blood disease or severe organ failure; ③ Patients in the acute stage of infectious disease; ④ Patients who have recently undergone surgery, minimally invasive surgery or other invasive treatments; ⑤ Patients who cannot cooperate with reexamination and follow-up after interventional treatment. The study was approved by the Beiliu People's Hospital Ethics Committee.

Sample size calculation: The incidence of poor prognosis after interventional thrombectomy is about 20%, according to data from reference studies. Assuming that the incidence of poor prognosis in this study is 40%, it is expected that 10 variables of multivariate regression model will be included in this study eventually. Sample size was calculated according to the mean number of variable events (EPV), EPV= 10, sample size = number of included variables *EPV/incidence =10*10/40%=250 cases.

Methods

Data collection: Relevant data of the included sample set were collected, including gender, age, BMI, NIHSS, pulmonary infection, hypertension, coronary heart disease, history of diabetes, atrial fibrillation, smoking and drinking history, vascular occlusion, time from onset to admission, time from onset to vascular opening, intravenous thrombolysis, number of thrombectomies, whether tirofiban was used, time of operation, postoperative systolic blood pressure level, systolic blood pressure at 24 hours after surgery, degree of recirculation 36 h after surgery, preoperative white blood cell count, neutrophil count, lymphocyte count, hemoglobin, hematocrit, platelet count, International Normalized ratio, fibrinogen, albumin, total bilirubin, aspartate aminotransferase, alanine aminotransferase, cystatin, creatinine, urea, uric acid, C-reactive protein (CRP), blood glucose, total cholesterol (TC), triglycerides, high density lipoprotein (HDL-L), low density lipoprotein (LDL-L), blood sodium, blood calcium, blood potassium, serum homocysteine (Hcy).

Evaluation and grouping: The modified Rankin Scale (mRS) was used to evaluate the prognosis of patients 3 months after the intervention, in which ≤2 points was used for the good prognosis group and 3-6 points was used for the poor prognosis group.

Statistical methods

SPSS 25.0 and R 4.1.2 were used to analyze the data of this study. Continuous variables (conforming to Gaussian distribution) were described as mean ± standard deviation ($\overline{x}\pm s$), and t-test was used for comparison. The classification variables were described as n (%), and χ^2 test was used for comparison. Single factor analysis was used to screen the relevant influencing factors of the sample set, and these factors were respectively incorporated into the BP neural network model, RF model and decision tree model. In all three models, patients were divided into a training set and a test set in a 7:3 ratio according to machine learning Settings. All three models were trained with training sets, and the model effects were validated and evaluated with test sets. The accuracy, sensitivity, specificity, recall rate, and accuracy of the three models were calculated to evaluate and compare the diagnostic effects of the different models. The test level of statistical analysis was $\alpha=0.05$.

Construction of prediction model

BP neural network model: Backward propagation (BP) algorithm was used for modeling. Ten variables were selected as input variables and prognosis (1= bad, 2= good) as output variables, hidden layer set as automatic calculation, BP neural network model was constructed. The importance value of each input variable was sorted, and the most significant influencing factors on the output variable was taken as the reference basis for standardization and the importance values were obtained. The standardized importance value represents the influence degree of each factor on the output variable.

RF model: R4.1.2 software, "random forest" program package (including parameters mtry and ntree) was used to construct the RF classification recognition model. The value of parameter 'mtry' was the value obtained by taking the square root of the number of variables in the data set. The number of input variables of the random forest model in this study was 10, so the parameter mtry was set to 3. Ntree was the number of decision trees included in the random forest (default: 500); According to the relationship between the error rate and the number of the model, the appropriate number of decision trees was adjusted to establish the model. We also ranked the importance of the variables by indicating "Mean Decrease Accuracy" and "Mean Decrease Gini" after variable replacement.

Decision tree model: The "rpart" program package was used to select whether END occurred after thrombolysis as the "dependent variable" and 10 selected variables as the "independent variable". Cross-validation was used for pruning, the minimum sample size of parent node and child parent node was set, and the decision tree model was generated.

Results

Clinical data

Among the 256 patients, 205 cases (80.08%) with mRs≤2 were in the good prognosis group, while 51 cases (19.92%) with mRs 3-6 were in the poor prognosis group. Age, NIHSS, coronary heart disease, time from onset to admission, time from onset to vascular opening, number of thrombi removal, degree of recanalization 36 h after surgery, CRP, TC and Hcy in the poor prognosis group were compared with those in the good prognosis group, were statistically significant (all $P < 0.05$). There was no statistical significance in other indexes between the two groups ($P > 0.05$), are shown in **Table 1**.

Establishment of BP neural network, RF and decision tree model for prognosis of AIS interventional thrombectomy

Ten factors with $P > 0.05$ (age, NIHSS, coronary heart disease, time from onset to hospital admission, time from onset to vascular opening, the number of recanalization's, the degree of recanalization, CRP, total cholesterol and Hcy) were respectively included in the BP neural network, RF and decision tree models.

BP neural network: The 10 factors with significant differences in univariate analysis were used as input variables, and the prognostic outcome (bad or good) was taken as output variables. The BP neural network model was constructed with the test set data (**Figure 1**). There

Table 1. Comparison of clinical data between the two groups

project	poor prognosis group (*n*=51)	good prognosis group (*n*=205)	t/χ^2	*P*
Gender (Male/female)	31/20	131/74	0.171	0.679
Age (years)	75.63±7.14	71.70±8.97	0.908	0.004
BMI (Kg/m^2)	22.61±2.15	22.38±2.50	0.598	0.553
NIHSS (points)	18.98±4.73	17.70±3.59	2.127	0.034
Infection of the lungs [n (%)]	12 (23.53)	51 (24.88)	0.040	0.841
Hypertension [n (%)]	13 (25.49)	42 (20.49)	0.606	0.436
Diabetes [n (%)]	12 (23.53)	33 (16.10)	1.557	0.212
Coronary heart disease [n (%)]	18 (35.29)	34 (16.59)	8.831	0.003
Atrial fibrillation [n (%)]	8 (15.69)	28 (13.66)	0.139	0.709
Smoking [n (%)]	9 (17.65)	44 (21.45)	0.362	0.547
Drinking [n (%)]	12 (23.53)	40 (19.51)	0.407	0.523
Occlusive blood vessel [n (%)]			0.766	0.382
Forward circulation	43 (84.31)	182 (88.78)		
After circulation	8 (15.69)	23 (11.22)		
Time from onset to admission (h)	6.04±2.01	4.83±1.42	4.940	< 0.001
Time from onset to vascular opening (h)	6.93±2.03	5.14±1.58	6.772	< 0.001
Intravenous thrombolysis [n (%)]			0.002	0.962
Yes	36 (70.59)	114 (55.61)		
No	15 (29.41)	61 (29.76)		
Number of thrombectomy (times)			5.431	0.020
≥3	40 (78.43)	125 (60.97)		
< 3	11 (21.57)	80 (39.02)		
Whether tirofiban was used [n (%)]			2.875	0.090
Yes	26 (50.98)	131 (63.90)		
No	25 (49.02)	74 (36.10)		
Time of operation (h)	1.81±0.59	1.78±0.59	0.417	0.530
Postoperative systolic blood pressure (mm Hg)	111.84±16.22	110.32±15.31	0.630	0.530
Systolic blood pressure at 24 hours after surgery (mm Hg)	110.88±17.73	111.66±15.54	-0.310	0.757
Degree of recanalization 36 h after operation [n (%)]			11.642	0.003
Complete repain	18 (35.29)	125 (60.98)		
Partial retransmission	28 (54.90)	63 (30.73)		
No reconnection	5 (9.80)	17 (8.29)		
Preoperative white blood cell count (×10^9/L)	9.60±2.53	9.45±2.97	0.342	0.746
Neutrophil count (×10^9/L)	7.96±2.33	8.47±4.48	-1.326	0.186
Lymphocyte count (×10^9/L)	1.94±0.55	1.92±0.52	0.510	0.834
Hemoglobin (g/L)	126.41±13.81	125.49±13.17	0.441	0.660
Hematocrit (%)	0.44±0.01	0.45±0.01	-0.592	0.555
Platelet count (×10^9/L)	195.35±43.89	192.74±44.12	0.378	0.706
International Normalized ratio (%)	0.89±0.13	0.90±0.11	-0.537	0.591
Fibrinogen (g/L)	3.23±0.84	3.17±0.87	0.394	0.694
Albumin (g/L)	42.28±3.73	42.19±3.89	0.162	0.872
Total bilirubin (μmol/L)	11.74±3.83	12.31±3.74	-0.968	0.334
Aspartic acid aminotransferase (U/L)	18.67±3.93	18.43±4.27	0.359	0.720
Alanine aminotransferase (U/L)	19.21±5.36	18.58±5.20	0.776	0.438
Cystatin (mg/L)	0.81±0.17	0.75±0.24	1.629	0.104
Creatinine (μmol/L)	79.04±13.17	81.20±12.56	-1.083	0.280

Uric acid (μmol/l)	401.34±54.33	395.32±50.62	-0.477	0.633
CRP (mg/L)	10.23±1.62	6.72±1.48	14.928	< 0.001
Blood glucose (mmol/L)	5.89±0.82	5.93±0.84	-0.369	0.713
TC (mmol/L)	4.41±1.13	4.03±1.04	2.301	0.022
Triglyceride (mmol/L)	2.43±0.88	2.45±0.83	-0.104	0.917
HDL-L (mmol/L)	1.70±0.56	1.75±0.56	-0.541	0.589
LDL-L (mmol/L)	3.78±0.93	3.80±0.99	-0.086	0.932
Blood sodium (mmol/L)	138.59±7.94	137.92±8.38	0.516	0.606
Blood potassium (mmol/L)	4.17±1.07	4.19±1.12	0.063	0.920
Blood calcium (mmol/L)	1.90±0.45	1.89±0.48	0.140	0.889
Hcy (μmol/L)	25.90±3.94	21.73±3.19	7.941	< 0.001

Note: Body mass index (BMI); National Institute of Health stroke scale (NIHSS); C-reactive protein (CRP); Total Cholesterol (TC).

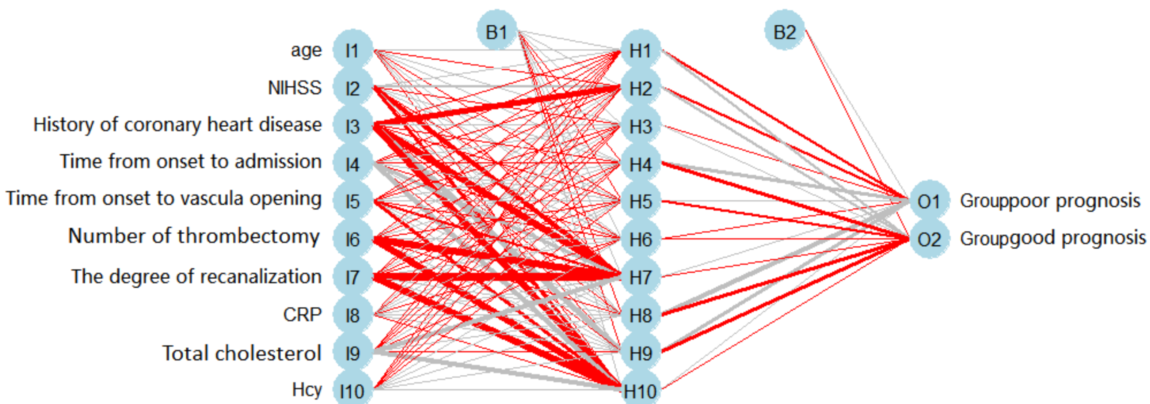

Figure 1. BP neural network model. NIHSS: National Institute of Health stroke scale; CRP: C-reactive protein; I: Input layer; B: Hidden layer; O: Output layer.

were 10 nodes in the input layer of the neural model, which are H1, H2, H3, H4, H5, H6, H7, H8, H9 and H10. According to the influence degree of input factors on the network, the following sequence map was made, as shown in **Figure 2**. The influence degree from high to low is as follows: history of coronary heart disease, CRP, total cholesterol, time from onset to admission, Hcy, age, time from onset to vascular opening, the degree of recanalization, number of thrombectomy, and NIHSS.

RF model: In R software, "Randomforest" package was used to construct RF classification recognition model. The mtry parameter defaults to the second root of the input variable in the data set. In this study, the input variables number of the model was 10, then mtry was set to 3. The parameter ntree refers to the number of decision trees contained in the random forest, which determines the number of votes and the accuracy of the random forest vote. The ntree parameter was set to 1500 based on the value of mtry to 3, and the R program was run to observe the change in the model error rate (**Figure 3**). As can be seen from the figure, when ntree =950, the variation range of model error rate began to decrease and becomes stable. Therefore, we use parameters mtry =3 and ntree =950 to establish the optimal model. Random forest models can also rank the importance of independent variables by "Mean Decrease Accuracy" and "Mean Decrease Gini". Based on the value "Mean Decrease Accuracy", we can know that the important factors affecting the prognosis of patients with AIS interventional thromposectomy are: CRP, Hcy, time from onset to vascular opening, time from onset to admission, total cholesterol, NIHSS, number of thrombectomy, the degree of recanalization, age, History of coronary heart disease, as shown in **Figure 4**.

Decision tree: In the process of model construction, the decision tree algorithm splits and prunes the generated tree, and the CRP and

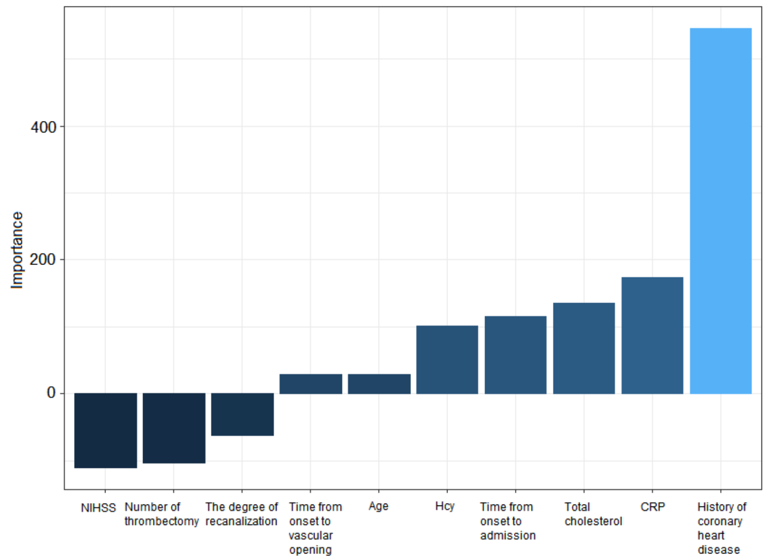

Figure 2. Sequential map of influencing factors of poor prognosis after interventional thrombectomy in AIS. NIHSS: National Institute of Health stroke scale; CRP: C-reactive protein.

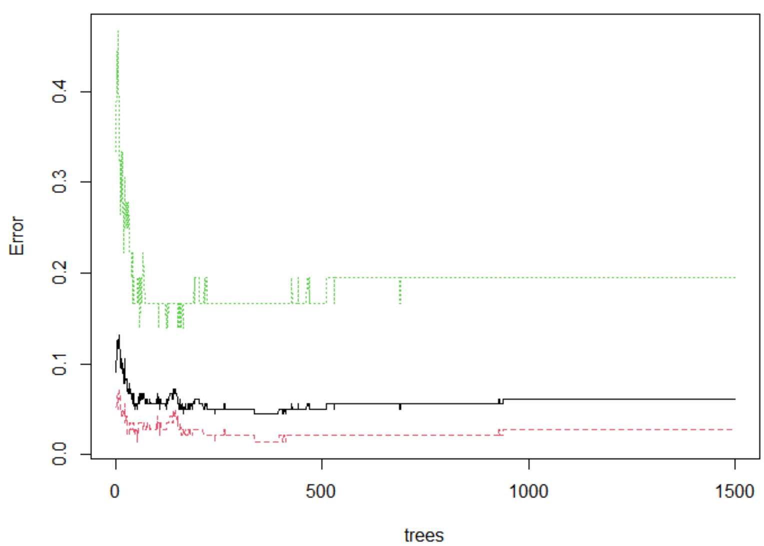

Figure 3. Relationship between model error rate and RF tree order. Green lines: poor prognosis group; Black lines: Out of Bag (OOB); Red line: good prognosis group.

total cholesterol were respectively entered into the prediction model. CRP, as the root node, is the most important decision variable, followed by total cholesterol, as shown in **Figure 5**. We can judge a patient's prognosis based on their CRP and total cholesterol levels. The incidence of poor prognosis of AIS patients with CRP ≥8.1 was 26%; and the incidence of poor prognosis in AIS patients with total cholesterol ≥3.9 was 15%.

Comparison of the prediction effect of the three models

In order to more intuitively compare the model effects of BP neural network, RF and decision tree, this part adopts the hierarchical sampling method to randomly extract the training data set and validation data set according to the ratio of 3:1 to construct the three models. The same training set was applied to train the three models, and the same validation data set was applied to each model to evaluate and compare the model effects. As shown in **Table 2**. The prediction accuracy, sensitivity and specificity, recall rate, accuracy, F1-score and AUC of BP neural network model were 0.961, 0.983, 0.875, 0.983, 0.967, 0.976 and 0.979 respectively. The prediction accuracy, sensitivity and specificity, recall rate, accuracy, F1-score and AUC of RF model were 0.948, 0.952, 0.933, 0.952, 0.983, 0.967 and 0.986, respectively. The prediction accuracy, sensitivity and specificity, recall rate, accuracy, F1-score and AUC of decision tree model were 0.882, 0.953, 0.667, 0.953, 0.897, 0.924 and 0.938, respectively. It can be seen that the prediction effects of the three models were similar.

Discussion

The key to improve the prognostic function of AIS patients and reduce the death of patients is to open blocked blood vessels as soon as possible and restore blood perfusion as soon as possible. At present, intravenous thrombolysis is the main treatment in clinic. However, the recanalization success rate of major artery occlusion is low, and the time requirements is high, which leads to limited clinical efficacy. The fatality rate can still be at 20% and the disabil-

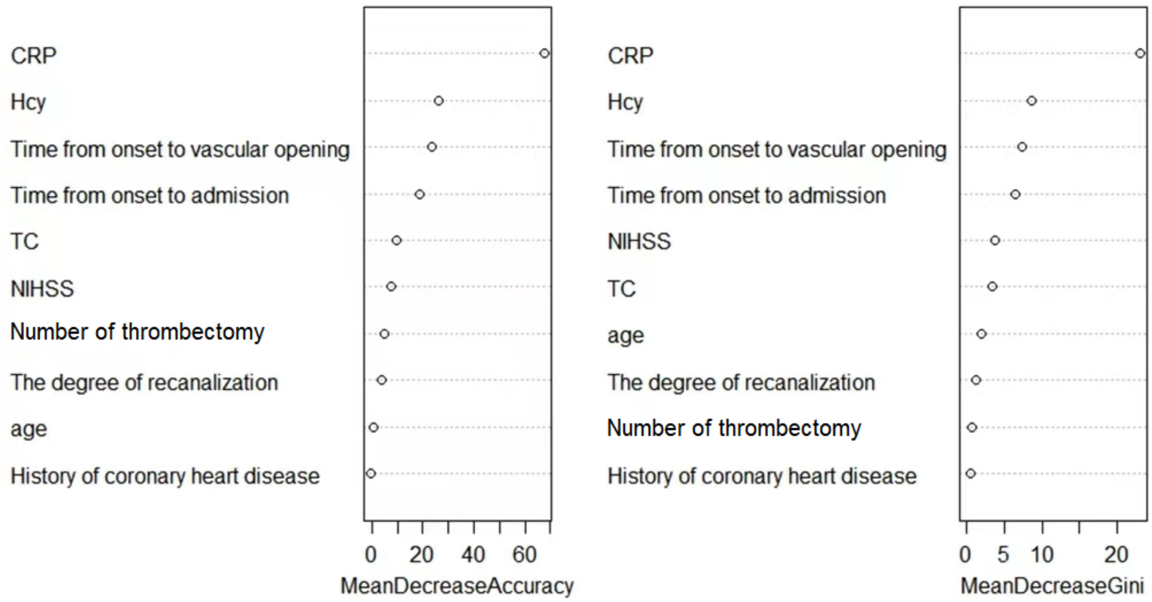

Figure 4. Importance ranking of characteristic variables. NIHSS: National Institute of Health stroke scale; CRP: C-reactive protein; TC: Total Cholesterol.

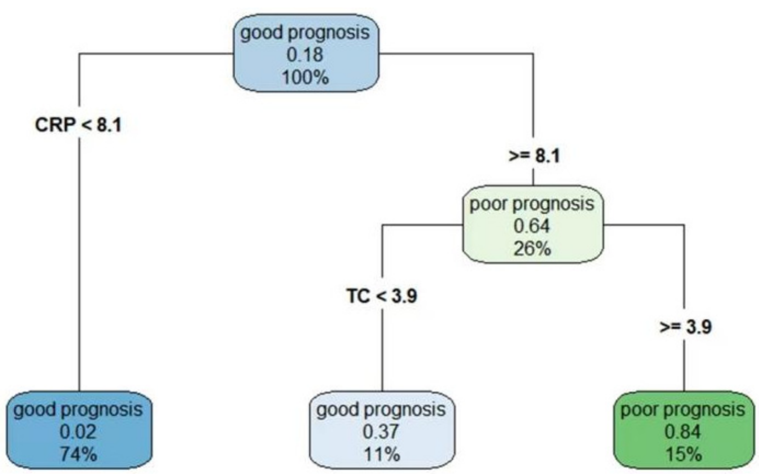

Figure 5. Decision tree model for prognosis of interventional thrombolectomy in AIS. CRP: C-reactive protein; TC: Total Cholesterol.

ity rate at more than 60% after 3 months of intravenous thrombolytic therapy [9, 10]. With the continuous improvement and the improvement of interventional thrombectomy technique, the clinical therapeutic effect of AIS patients in our country has been greatly improved. It can directly and quickly open the blocked blood vessels in AIS patients and restore blood perfusion. Besides, it has relatively wide requirements for the time window, and has advantages of small trauma, small dosages of intraoperative thrombolysis drugs, fewer adverse reactions, easy recovery after surgery and higher prognosis level [11]. However, although interventional therapy has been widely recognized in the treatment of AIS patients, its prognosis is still not ideal. Therefore, in interventional thrombectomy, the evaluation of the prognosis is extremely important, and the evaluation of the prognosis of patients has important guiding significance for the selection of the appropriate surgical population. At present, there have been many studies on prognosis prediction of stroke patients after interventional thrombectomy, such as age, NIHSS score, complicated coronary heart disease, etc., which provide important parameters for the evaluation of prognosis of AIS patients after interventional thrombectomy [12, 13].

However, current studies on prognostic factors of patients with AIS after interventional thrombectomy remain controversial. With the rapid increase in the amount of clinical medical research data, the data is becoming more com-

Table 2. Comparison of the prediction effects of the three models

model	BP neural network	RF	decision making tree
Accuracy	0.961	0.948	0.882
Sensitivity	0.983	0.952	0.953
Specificity	0.875	0.933	0.667
recall rate	0.983	0.952	0.953
Accuracy	0.967	0.983	0.897
F1-score	0.976	0.967	0.924
AUC	0.979	0.986	0.938

plex and diversified, and it has become difficult for the current medical research and development to dig out more meaningful information from the massive amount of data. The evaluation tools, evaluation models and management models used by traditional methods are mostly constructed based on clinical experience and still lack statistical support. The evaluation process is also susceptible to the influence of the assessor's own knowledge level, and there are problems such as strong subjectivity and insufficient accuracy of the evaluation results, which obviously cannot meet the current research needs. For massive and complex medical data, the machine learning algorithm is an important method in the field of artificial intelligence. Its predictive performance has been proven in the evaluation and prevention of diseases, auxiliary diagnosis, resource allocation and patient management, etc. For example, BP neural network algorithm is a prediction model that can handle nonlinear relations, and the RF model has high robustness. Large data sets can be processed efficiently [14-16]. In this study, the clinical data of 255 patients with AIS were retrospectively collected, and the BP neural network model, RF model, and decision tree model were established respectively to predict the prognosis of interventional thrombolectomy of AIS. The optimal parameters were selected as far as possible to establish the models, so as to better improve the predictive effect. Through comparative analysis, it was found that the overall prediction performance of the three models is high, up to more than 80.00%, except for the low specificity of the decision tree, which is 66.70%. It can be seen that the predicted effect of the three models is similar. The reason may be related to the excellent performance of the BP neural network, the RF algorithm and the decision tree, which are very handy in dealing with fitting problems.

In this study, 10 variables associated with the prognosis of interventional thrombus removal for AIS were screened out through single-factor analysis, which were age, NIHSS, coronary heart disease, time from onset to admission, time from onset to vascular opening, number of thrombus removal, degree of recanalization, CRP, total cholesterol and Hcy. These influencing factors were consistent with current clinical studies. It also provides some valuable information for clinical practice. For example, a high preoperative NIHSS score indicates that the patient has a more serious neurological impairment before surgery, and it also indicates that the patient's prognosis function rehabilitation is more difficult. The causative basis of coronary heart disease is similar to that of AIS. Although interventional therapy is minimally invasive, its operation may invade patients' blood vessels, and mechanical dilation within a certain limit may cause vascular endothelial dysfunction, thus aggravating cardiovascular adverse events induced by coronary heart disease and leading to poor prognosis [17]. The prolonged time from onset to admission of some AIS patients leads to increased edema in the cerebral infarction area, excessive apoptosis, and increased adverse effects on nerve function. After interventional treatment, patients have severe neurological impairment coupled with older age. As a major morbidity group, most of them cannot tolerate surgical treatment, which is not conducive to the recovery of nerve cells, leading to poor prognosis [18]. A number of large randomized controlled trials (RCTS) in foreign countries have set the upper age limit of endovascular therapy as ≤80 years old or 85 years old and achieved positive results [19, 20]. In clinical practice, patients older than 80 years old will also be carefully considered to perform mechanical thrombectomy.

In the process of interventional thrombectomy, the condition of the patient's impacted blood vessels and the location of the infarct are all related to the operation time. If the patient's condition is complicated, the operation time may be relatively prolonged, thus delaying the opening time of the blocked blood vessels and the time of restoring blood perfusion, leading to poor prognosis. The influence of multiple thrombectomies on prognosis may be related to delayed recalculation time, cerebrovascular injury, destruction of the blood-brain barrier and other factors, so surgeon need to control the number of thrombectomies, and try not to exceed 3 in the actual operation [21, 22]. In a retrospective study of 354 patients with mechanical thrombectomy in the Solitaire Stent Acute Stroke Registry (NASA), 256 (72.3%) had successful vascular reperfusion and 116 (49.6%) had poor prognosis. Revealing that three OR more thrombectomy operations was a significant independent predictor of poor prognosis within 90 days (OR=2.62, 95% CI 1.03~6.69, P=0.023) with good predictive power in the prediction model (C-index =0.80). If complete recanalization can be achieved 36 h after surgery, it indicates that the blood flow recovery of the patient's infarction area is better, which can provide an ideal basis for the prognosis of functional rehabilitation and cell repair; otherwise, it can lead to a decline in the prognosis level. The injuries of nerve cells, vascular endothelial cells and brain cells, such as ischemia and hypoxia in AIS patients, can cause an inflammatory stress response in the body and aggravate the condition of patients. The serum CRP level of AIS patients before surgery is higher when the inflammatory response is severe, and the trauma of interventional operation can further aggravate the inflammatory response, increasing the risk of reinfarction after treatment with poor prognosis [23, 24]. Total cholesterol and Hcy were independent risk factors for atherosclerosis, and the mechanism of abnormal increase in their expression levels was complex, but their overexpression can promote the occurrence, progression and poor prognosis of AIS and cardiovascular diseases. In this study, based on the single factor analysis of the selected influencing factors and the establishment of a prediction model, which provides a practical new idea for clinicians [25, 26].

This study has some shortcomings, first of all, this study was a single-center study with limited sample sources, which may lead to certain selective bias and some limitations on the predictive performance of the model. The follow-up study will use a larger and more comprehensive sample size for further verification and research.

In this study, clinical data of interventional thrombectomy for AIS patients were used to obtain 10 prognostic factors affecting interventional thrombectomy for AIS patients by univariate analysis. Based on these factors, machine learning algorithms were used to establish a BP neural network, RF and decision tree models respectively, in order to evaluate the predictive performance of the models and provide more efficient guidance for clinicians.

Conclusion

In summary, the three prediction models all showed good diagnostic efficacy and stability in the preliminary study on the prognosis of AIS mediated thrombectomy, which has important guiding significance for clinical prognosis assessment and selection of appropriate surgical population. The prediction model can be selected according to the actual situation of patients to provide more efficient guidance for clinicians.

Disclosure of conflict of interest

None.

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