Development and Validation of a Prognostic Nomogram for Cerebral Infarction Patients in Intensive Care Units: a Retrospective Cohort Study

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Research Article

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Abstract

OBJECTIVES: Our study aimed to establish a utility risk prediction model for the prognosis of patients with cerebral infarction.

BACKGROUND: Despite large number of studies focus on the prognosis risk factors of patients with cerebral infarction, there were still lack of utility and visual risk prediction model for predicting the in-hospital mortality of patients with cerebral infarction.

METHODS: The study is a retrospective cohort study. The lasso regression model was used for data dimension reduction and feature selection. Model of hospital mortality of cerebral infarction patients was developed by multivariable logistic regression analysis. Calibration and discrimination were used to assess the performance of the nomogram. Decision curve analysis (DCA) was used to evaluate the clinical utility of the model.

RESULTS: Overall, 1,564 patients (1315 survivals and 249 deaths) with cerebral infarction included in our research from MIMIC-IV database. The incident of in-hospital mortality is 15.9%. Lasso regression model verified that age, white blood cell count, anion gap (AG), SOFA score were significantly correlated with hospital mortality. The risk prediction model demonstrated a good discrimination with an AUC of ROC 0.789 (95% CI 0.752–0.826) in training set and 0.829 (95% CI 0.791–0.867) in test set. The calibration plot of risk prediction model showed predicted probabilities against observed death rates indicated excellent concordance. DCA showed that this model has good clinical benefits.

Conclusion: We developed a nomogram that predicts hospital mortality in patients with cerebral infarction according to the real world's data. The nomogram exhibited excellent discrimination and calibration capacity, favoring its clinical utility.

Introduction

According to the data released by the World Health Organization, in the past decade from 2000 to 2012, stroke had become the 2rd leading cause of death in the world [1–2], which was second to heart disease, with high incidence, morbidity, recurrence, disability and mortality rate [1,3].

Cerebral infarction (CI, also known as ischemic stroke) is a common cerebrovascular disease [4–5]. Cerebral infarction refers to the cause of cerebral blood circulation disorder, which leads to cerebral vascular blockage or severe stenosis, reduces cerebral blood perfusion, and then leads to the death of brain tissue in the cerebral vascular supply area due to ischemia and hypoxia [6]. Clinically, it is described as sudden local or diffuse neurological deficit. New local cerebral infarction lesions are showed on head computed tomography (CT) or magnetic resonance imaging (MRI)[7]. The great majority of critically ill CI patients are in the intensive care unit (ICU)[8]. While, not all of them benefit from the care of ICU. It is urgently needed to develop a risk stratification for those CI patients to make efficient decisions. Nomograms are great prognostic tools to predict clinical events by integrating potential clinical events

with patients' performance status. Nomograms have been widely used for tumor prognosis, to predict the long-term survival and recurrence[9].

A nomogram was applied to predict mortality rate in ischemic stroke patients recently [10]. We hypothesized a nomogram for the risk stratification of critically ill patients with CI in the ICU. This study was committed to identify prognostic factors for mortality of critically ill patients with CI and based on a multivariable logistic regression model. The performance and clinical benefits of the nomogram were assessed in a validation cohort. Totally, the nomogram could be greatly applied for high-risk patients and clinical decision.

Methods

Data Source

The primary data of our study was derived from MIMIC-IV database (version 1.0). MIMIC-IV database is an extensive database, and contained all medical record numbers corresponding to patients admitted to an intensive care unit (ICU) or the emergency department between 2008-2019 in the Beth Israel Deaconess Medical Center (BIDMC)[11]. The version 1.0 is the lasted version of MIMIC-IV database. One of our authors (C.J, certification ID: 8979131) gained permission to documented the database after online training at the National Institutes of Health (NIH). Our research was conducted entirely on publicly available and anonymized data. Therefore, individual patient consents were not required. All methods were carried out in accordance with relevant guidelines to protect the privacy of patients.

Population selection

We included the data of adult patients (aged >18 years old) diagnosed with cerebral infarction at hospital admission from the MIMIC-IV database by the International Classification of Diseases version 9 diagnosis codes and version 10 diagnosis codes. The exclusion criteria were: (I) Incomplete or unobtainable documented or other vital medical data records; (II) During pregnancy and the postpartum period; (III) Missing the data of blood biochemical and blood gas analysis; (IV) Missing survival outcome data.

Clinical and laboratory data

Patients’ baseline characteristics (age, height, weight) and comorbidity (diabetes, hypertension, chronic lung disease, myocardial infarction, heart failure, et al) were collected. The first document of vital signs data and laboratory tests data of cardiac arrest patients admitted to the hospital were extracted. Vital signs data included systolic blood pressure (SBP), diastolic blood pressure (DBP), mean blood pressure (MBP), body temperature (T), heart rate (HR), respiratory rate (RR), pulse oximetry derived oxygen saturation (SPO_2). Laboratory tests data included creatinine, blood urea nitrogen (BUN), anion gap, PH, lactate, chloride, glucose, hemoglobin, hematocrit, white blood cell count, platelet count, serum potassium, serum sodium, calcium, and prothrombin time (PT). The sequential organ failure assessment

(SOFA) score[12] were also calculated for each patient. The endpoint of our study was in-hospital mortality which was defined as survival status at hospital discharge.

Statistical Analysis

Multiple imputation was performed to process the missing variable data (less than 20% of total variable data), and the severe variable data missing (more than 20% of total variable data) was abandoned to form a new dataset[13]. The new dataset was randomly divided into two parts on a 7/3 scale, one parts (70%) as the training set and another parts (30%) as the test set. Training set was used for model development (derivation cohort) and test set was used for model validation (validation cohort). Continuous variables that do not conform to normal distribution were documented as medians with upper and lower quartiles, otherwise, documented as the mean ± standard deviation (SD). Group comparisons were performed using the t-test or Wilcoxon rank-sum test for continuous variables, and the chi-square test or Fisher's exact test for categorical variables. First, lasso regression was used to conduct preliminary screening of the predictors based on the whole study database, and screened out the predictors with large regression coefficients. Second, multivariate regression analysis was used to analyze the above screened predictors and identify independent risk factors in training dataset. Thirdly, multivariate regression analysis analyzed the above independent risk factors again and established the risk prediction model in training dataset. The scores for predictors were calculated based on coefficients of logistic regression variables in the model. The visualization of model was demonstrated by nomogram. The discrimination of risk prediction model for in-hospital mortality of cardiac arrest patients was assessed by receiver operating characteristic (ROC) curve analysis. The area under the curve (AUC) of the ROC curve more than 0.7 was regarded as good discrimination. The degree of fitting of the prediction model was assessed by calibration curve analysis which tested by Hosmer-Lemeshow test. The decision curve analysis (DCA) was conducted to evaluate the clinical utility of the nomogram through quantifying net benefits against a range of threshold probabilities. The validation of model capabilities were used by test set. These results were expressed as odds ratio (OR) with 95% confidence intervals (CIs). All tests were 2-tailed tests, and $p \leq 0.05$ was considered statistically significant. Statistical analyses were performed using R version 3.6.3 (R Foundation for Statistical Computing, Vienna, Austria).

Results

The characteristics of study patients

Totally, 1,564 eligible patients (734 males and 830 females) with an average age of 77.99±0.39 years old were included in our study finally, more details about the data extraction process and missing data as shown in Supplementary Table S1 and Table S2. In the present study, 249 patients (116 males and 133 females) died during hospitalization, with the incidence of in-hospital mortality was 15.9%. Death group in hospital tend to older with malignant cancer, and have higher level of anion gap, BUN, Glucose and WBC count (As showed in Table1). After the whole sample was randomly divided into a training set and a

test set with the proportion of 7: 3, there were no significant differences in observed clinical variables between the training set and the validation set (As showed in Table2).

Table 1
The characteristic of included subjects

Characteristic	Total (n=1564)	Survival (n=1315)	death (n=249)	P value
Age (years old)	77.99±0.39	70.65±0.43	79.02±0.73	<0.001
Man	734 (46.93%)	618 (47.00%)	116 (46.59%)	0.992
Weight	78.49±0.52	79.18±0.57	74.81±1.19	0.001
SBP	136.62±0.46	136.81±0.50	135.62±1.25	0.375
DBP	71.78±0.31	72.48±0.34	68.11±0.75	<0.001
MBP (mmHg)	89.04±0.31	89.59±0.34	86.10±0.76	<0.001
Heart rate (beats/minute)	79.72±0.37	78.88±0.39	84.17±0.10	<0.001
Respiratory rate (beats/minute)	19.26±0.08	19.05±0.08	20.35±0.25	<0.001
Temperature (°C)	36.91±0.01	36.89±0.01	37.02±0.04	<0.001
SPO2 (%)	96.97±0.05	96.92±0.05	97.93±0.24	0.208
Comorbidities, n (%)				
Diabetes	540 (34.53%)	445 (33.84%)	95 (38.15%)	0.402
myocardial infarction	181 (11.57%)	146 (11.10%)	35 (14.06%)	0.284
congestive heart failure	383 (24.49%)	302 (22.97%)	81 (32.53%)	0.018
Chronic pulmonary disease	264 (16.88%)	227 (17.26%)	37 (14.86%)	0.486
dementia	87 (5.56%)	68 (5.17%)	19 (7.63%)	0.191
Renal disease	270 (17.26%)	219 (16.65%)	51 (20.48%)	0.259
Malignant cancer	109 (6.97%)	77 (5.86%)	32 (12.85%)	<0.001
Severe liver disease	7 (0.45%)	4 (0.3%)	3 (1.20%)	0.087
Laboratory parameters				
anion gap (mEq/L)	14.88±0.07	14.64±0.08	16.08±0.22	<0.001
BUN (mg/dL)	20.99±0.35	19.89±0.33	26.82±1.25	<0.001
Bicarbonate (mmol/L)	23.63±0.08	23.82±0.09	22.67±0.22	<0.001
Creatinine (mg/dL)	1.14±0.03	1.12±0.03	1.26±0.06	0.0382

SBP: systolic blood pressure; DBP: diastolic blood pressure; MBP: mean blood pressure; SPO2: pulse oximetry derived oxygen saturation; BUN: blood urea nitrogen; PT: prothrombin time; WBC: white blood cell; SOFA: sequential organ failure assessment; ICU: intensive care unit; HOS: hospital; LOS: length of stay.

Characteristic	Total (n=1564)	Survival (n=1315)	death (n=249)	P value
Chloride (mmol/L)	104.09±0.12	103.97±0.12	104.70±0.36	0.055
Glucose (mg/dL)	136.82±1.31	133.34±1.37	155.21±3.70	<0.001
calcium	8.78±0.02	8.81±0.02	8.65±0.05	0.001
Hematocrit (%)	37.20±0.14	37.36±0.15	36.30±0.38	0.009
Hemoglobin (g/dL)	12.29±0.05	12.36±0.08	11.94±0.14	0.005
Platelet (10^9/L)	235.07±2.33	235.90±2.56	230.79±5.57	0.397
Potassium (mmol/L)	4.11±0.01	4.10±0.01	4.17±0.04	0.070
PT (s)	13.67±0.10	13.54±0.11	14.37±0.26	0.003
Sodium (mmol/L)	139.75±0.10	139.68±0.10	140.14±0.32	0.168
WBC (10^9/L)	10.52±0.11	10.13±0.11	12.62±0.35	<0.001
SOFA Scoring	3.54±0.06	3.19±0.06	5.39±0.18	<0.001
ICU LOS (days)	4.03±0.19	3.94±0.13	4.55±0.35	<0.001
HOS LOS (days)	10.25±0.50	10.79±0.31	7.40±0.61	<0.001

SBP: systolic blood pressure; DBP: diastolic blood pressure; MBP: mean blood pressure; SPO2: pulse oximetry derived oxygen saturation; BUN: blood urea nitrogen; PT: prothrombin time; WBC: white blood cell; SOFA: sequential organ failure assessment; ICU: intensive care unit; HOS: hospital; LOS: length of stay.

Table 2
The characteristic of training dataset and test dataset subjects

Characteristic	Total (n=1564)	Training set (n=1094)	Test set (n=470)	P value
Age (years old)	71.99±0.39	72.00±0.47	71.96±0.73	0.966
Man	734 (46.93%)	518 (47.35%)	216 (45.96%)	0.798
Weight	78.49±0.52	78.47±0.63	78.54±0.91	0.949
SBP	136.62±0.46	136.26±0.55	137.48±0.87	0.234
DBP	71.78±0.31	71.70±0.37	71.98±0.57	0.689
MBP (mmHg)	89.04±0.31	88.88±0.37	74.80±0.42	0.444
Heart rate (beats/minute)	79.72±0.37	79.58±0.44	89.40±0.57	0.542
Respiratory rate (beats/minute)	19.26±0.08	19.22±0.10	19.35±0.15	0.474
Temperature (°C)	36.91±0.01	36.91±0.01	36.93±0.02	0.441
SPO2 (%)	96.97±0.05	96.99±0.06	96.94±0.10	0.684
Comorbidities, n (%)				
Diabetes	540 (34.53%)	381 (34.83%)	159 (33.83%)	0.833
myocardial infarction	181 (11.57%)	124 (11.33%)	57 (12.13%)	0.753
congestive heart failure	383 (24.49%)	268 (24.50%)	115 (24.47%)	1.00
Chronic pulmonary disease	264 (16.88%)	181 (16.54%)	83 (17.66%)	0.703
dementia	87 (5.56%)	62 (5.67%)	25 (5.32%)	0.888
Renal disease	270 (17.26%)	196 (17.92%)	74 (15.75%)	0.420
Malignant cancer	109 (6.97%)	68 (6.22%)	41 (8.7%)	0.121
Severe liver disease	7 (0.45%)	5 (0.46%)	2 (0.43%)	1.00
Laboratory parameters				
anion gap	14.88±0.07	14.93±0.09	14.72±0.14	0.201
BUN (mg/dL)	20.99±0.35	21.18±0.42	20.57±0.62	0.417
Bicarbonate (mmol/L)	23.63±0.08	23.58±0.10	23.78±0.15	0.266

SBP: systolic blood pressure; DBP: diastolic blood pressure; MBP: mean blood pressure; SPO2: pulse oximetry derived oxygen saturation; BUN: blood urea nitrogen; PT: prothrombin time; WBC: white blood cell; SOFA: sequential organ failure assessment; ICU: intensive care unit; HOS: hospital; LOS: length of stay.

Characteristic	Total (n=1564)	Training set (n=1094)	Test set (n=470)	P value
Creatinine (mg/dL)	1.14±0.03	1.11±0.03	1.20±0.07	0.198
Chloride (mmol/L)	104.09±0.12	104.08±0.14	104.11±0.21	0.895
Glucose (mg/dL)	136.82±1.31	136.92±1.55	136.59±2.43	0.908
calcium	8.78±0.02	8.80±0.02	8.76±0.03	0.267
Hematocrit (%)	37.20±0.14	37.21±0.17	37.16±0.28	0.860
Hemoglobin (g/dL)	12.29±0.05	12.28±0.06	12.31±0.10	0.816
Platelet (10^9/L)	235.07±2.33	238.64±2.92	229.23±3.98	0.058
Potassium (mmol/L)	4.11±0.01	4.10±0.02	4.13±0.02	0.380
PT (s)	13.67±0.10	13.65±0.12	13.72±0.18	0.753
Sodium (mmol/L)	139.75±0.10	139.77±0.12	139.72±0.17	0.826
WBC (10^9/L)	10.52±0.11	10.62±0.13	10.31±0.20	0.200
SOFA Scoring	3.54±0.06	3.56±0.08	3.50±0.12	0.670
ICU LOS (days)	4.03±0.19	4.01±0.25	4.07±0.37	0.566
HOS LOS (days)	10.25±0.50	10.23±0.73	10.31±0.98	0.465
In-hospital death	249 (15.92%)	174 (15.90%)	75 (15.96%)	1.00

SBP: systolic blood pressure; DBP: diastolic blood pressure; MBP: mean blood pressure; SPO2: pulse oximetry derived oxygen saturation; BUN: blood urea nitrogen; PT: prothrombin time; WBC: white blood cell; SOFA: sequential organ failure assessment; ICU: intensive care unit; HOS: hospital; LOS: length of stay.

Independent risk factors for cardiac arrest

Lasso regression shrinks coefficients for less important variables to zero, which was useful for preliminary selection of predictors. Lasso regression model demonstrated that there were 4 predictors with large regression coefficient (age, anion gap, WBC count, SOFA score), as showed in figure 1 (a) and figure 1 (b). Multivariable regression analysis determined age (OR: 1.004; 95% CI: 1.003-1.005; P<0.001), anion gap (OR: 1.014; 95% CI: 1.010-1.018; P<0.001), WBC count (OR: 1.010; 95% CI: 1.004-1.016; P<0.001) and SOFA score (OR: 1.035; 95% CI: 1.028-1.042; P<0.001) as the independent predicting factors for in-hospital mortality of patients with cerebral infarction (As showed in Table 3).

Table 3
Univariable and multivariable analysis of risk factors

variable	Unltivariable analysis		Multivariable analysis	
	OR (95% CI)	P value	OR (95% CI)	P value
Age	1.005 (1.004-1.006)	<0.001	1.004 (1.003-1.005)	<0.001
WBC	1.019 (1.014-1.023)	<0.001	1.014 (1.010-1.018)	<0.001
Aniongap	1.022 (1.016-1.029)	<0.001	1.010 (1.004-1.016)	<0.001
SOFA	1.046 (1.039-1.053)	<0.001	1.035 (1.028-1.042)	<0.001
WBC: white blood cell; SOFA: sequential organ failure assessment.				

Prediction model for predicting the risk of in-hospital mortality by nomogram

The prediction model included age, anion gap, WBC count, SOFA score which were determined as independent predicting factors to predict the risk of in-hospital mortality for patients with cerebral infarction. For example, a 80-years-old patient with clinical data of admission as followed: WBC: $15 * 10^9$, aniongap: 20 mEq/L, SOFA score: 8 points. His risk factor score was 70 points, 30 points, 22.5 points and 37.2 points, respectively. Then his total score was about 160 points, and the risk of in-hospital mortality was 52%. (As showed in Figure 2).

Performance evaluation and validation of prediction model

ROC curve analysis for the training set showed that our risk prediction model has a good discrimination (AUC of ROC: 0.789; 95% CI 0.752–0.826, as showed in Figure 3(a)). We validated the prediction model in the test set, and the result showed that the present prediction model also has a good discrimination in test set (AUC of ROC: 0.829; 0.791–0.867, as showed in Figure 3(b)). Furthermore, we performed calibration curve analysis on the prediction model. The calibration curve plot showed that predicted probabilities against observed death rates indicated excellent concordance (as showed in Figure 3(c)). In the test set, the calibration curve plot also showed excellent concordance between the predicted probabilities and the observed mortality (as showed in Figure 3(d)). In addition, we performed decision curve analysis to evaluate the clinical utility of the prediction model. DCA curve revealed that this prediction model has a good utility clinical practice (as showed in Figure 3(e) and Figure 3(f)).

Discussion

Our study collected clinical information of 1,564 patients with CI in ICU (1315 survivals and 249 deaths) with cerebral infarction from MIMIC-IV database. This nomogram did great performance for both the primary and validation cohort as assessed by the lasso curves analysis, the calibration curves analysis, the decision curve analysis, the nomogram table and ROC curves. So, our nomogram could be greatly

applied to clinical practice. Nomograms predict one's probability of a clinical event using individual information and variables, they have become a usual prognostic model in oncology[14]. This study provided an easy-to-use prognostic nomogram for the first time with 4 clinical factors, which is collected on the first-day admission for critically ill patients with CI, the nomogram could meliorate one's risk stratification and prevent death of critically ill patients with CI in time.

Cerebral infarction is a major disease that endangers modern people's health. Patients with cerebral infarction are likely to have sequelae if the treatment is not appropriate, with high incidence and mortality, which result in economic and health loads to our country and people. Substantial critically ill patients with CI are admitted to ICU[8]. While not all CI patients benefit from ICU care. In order to do risk stratification to make more efficient decisions for CI patients, we used the nomograms through integrating individual risk factors with performance status to forecast the clinical events. We hypothesized that a nomogram on account of a multivariable Cox regression model in a primary cohort, can also be applicable to CI patients' risk stratification in ICU.

Age is one of the most essential risk factors in cerebrovascular diseases [15–16], such as cerebral infarction[17], transient ischemic attack (TIA)[18], Intracerebral hemorrhage (ICH)[19], and intracranial aneurysm[20]. Our study also found age was an independent predict factors for the prognosis of cerebral infarction patients in intensive care units. Generally, serum aniongap (AG) rising resulted in over accumulation of organic acid or excessive loss of anions[21]. The excessive generation of lactate and pyruvate in serum result to common reason for AG cumulation [22–23]. Serum AG count could be applied as a prognostic indicator to have evaluation for patients with CI in a short-term, higher AG on the first-day-admission was related to increased risk of all-cause mortality, a few patients who were in ICU had higher AG count[24]. WBC count is an important risk factor and is related with delayed cerebral ischemia[25]. High WBC count is also referred to mortality and pneumonia after acute ischemic stroke, which might be induced by stress and inflammatory response, it is reported that higher WBC is associated with mortality after acute stroke[26]. SOFA score is a sequential organ failure assessment score system, and applies to data collected in 24 hours of intensive care units' admission. The SOFA score evaluation contents include respiratory, cardiovascular (BP, vasoactive drug use), renal, hepatic, neurological and haematological (platelet number) systems[27–28]. Totally, in our study those 4 factors are reliable prognostic factors for mortality of critically ill CI patients in the ICU, and these 4 factors also could contribute to clinical work.

Besides, we assessed the nomogram with properties and clinical benefits to prove its accuracy and utility. The nomogram was applied to clinical practice easily and identified high-risk patients and guided decision-making. Timely prognostic assessment is essential because of CI's treatment time window is narrow. It's especially essential to discriminate high-risk patients as early as possible to carry on further active intervention measures for a better prognosis. Currently, bio-markers catch much attention. Higher AG counting was related to increased incidence of all-cause mortality, which guided to monitor cerebral infarction and the formulation of secondary prevention strategies[24].

While there are still some several problems to be solved. First, some previously reported risk factors (transient ischemic attack, atrial fibrillation, smoking and alcohol use, blood lipid, blood glucose, blood homocysteine) of CI[27,29–30], were not proven to be related to the death in hospital in our study. So, the prognostic value of these factors for CI should be reconfirmed in future studies. National Institute of Health stroke scale (NIHSS) score and Modified Rankin Scale (MRS) score were not be contained in present study due to the complexity of their score and difficult to obtain in MIMIC-IV database. Thus, future studies can compare our nomogram with the two scoring models. Last, the nomogram model still needed extra more samples to confirm application and reliability, more external cohort would further solid the reliability and significance of the nomogram model.

Conclusion

Our developed nomogram with excellent discrimination and calibration capacity, benefitting its utility, could predict hospital mortality in patients with CI according to the real world's data.

Abbreviations

CI: cerebral infarction; ICD: International Classification of Diseases; AUC: area under the curve; ROC: receiver operating characteristic; CI: confidence intervals; SBP: systolic blood pressure; DBP: diastolic blood pressure; MBP: mean blood pressure; SPO2: pulse oximetry derived oxygen saturation; BUN: blood urea nitrogen; PT: prothrombin time; WBC: white blood cell; SOFA: sequential organ failure assessment; ICU: intensive care unit; HOS: hospital; LOS: length of stay.

Declarations

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Competing interests: All other authors have no conflict of interest.

Authors' contributions: CJ conceived and designed research; CJ collected data and conducted research; CJ, YM and LQ analyzed and interpreted data; YM and CJ wrote the initial paper; XGP and ZR revised the paper; CJ approved the final version to be submitted. CJ had primary responsibility for final content. All authors read and approved the final manuscript.

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Figures

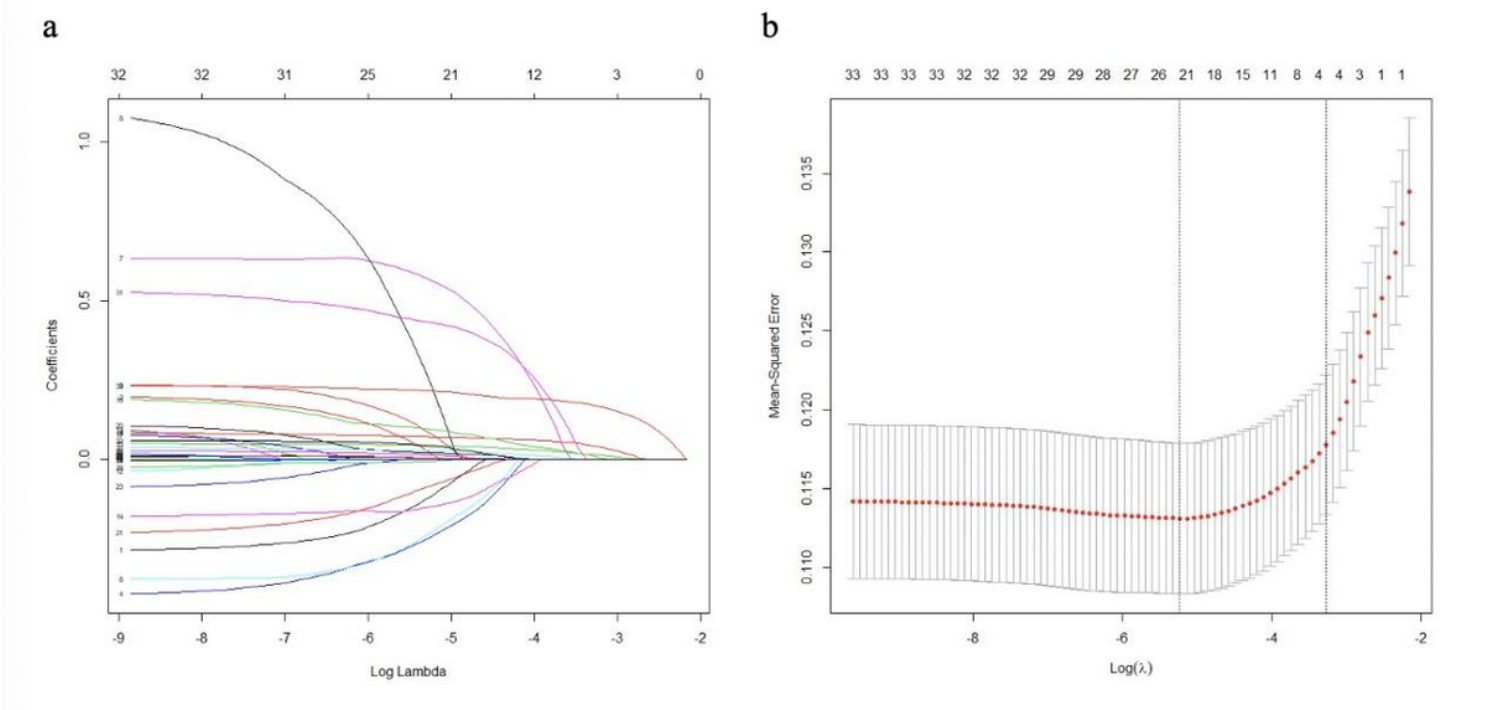

Figure 1

Texture feature selection using the least absolute shrinkage and selection operator (LASSO) binary logistic regression model. (a) Each curve in the fifigure represents the change trajectory of each independent variable coeffificient. The ordinate is the value of the coeffificient, the lower abscissa is log(λ), and the upper abscissa is the number of non-zero coeffificients in the model at this time. (b) 10-fold cross-cross validation fifitting and then select the model, and at the same time have a more accurate estimate of the performance of the model. For each λ value, around the mean value of the target parameter shown by the red dot, we can get a confifidence interval for the target parameter. The two dashed lines indicate two special λ values:c (cvfifit$lambda.min, cvfifit$lambda.1se). The mean squared error was plotted vs. log(λ).

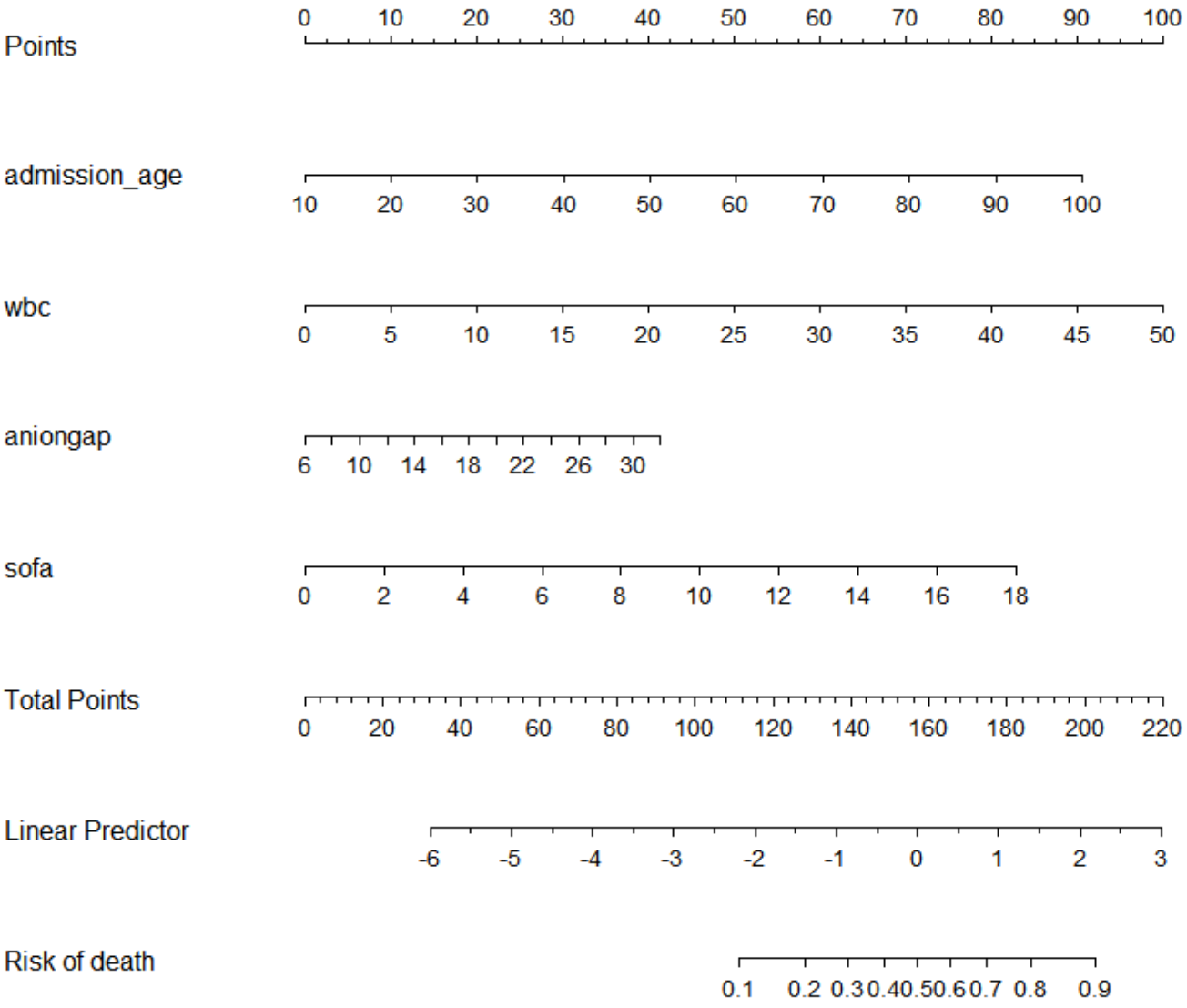

Figure 2

The nomogram for predict the risk of in-hospital mortality in cerebral infarction patients in intensive care units. The top row of the 'Points' represented a scale for each risk factors, points of each predictor were acquired by drawing a straight line upward from the corresponding value to the "Points" line. Then sum the points received from each predictor and located the number on the "Total Points" axis. To conclude the patient's sort of probability for in-hospital mortality, draw a straight line down to the corresponding "Risk of death" axis.

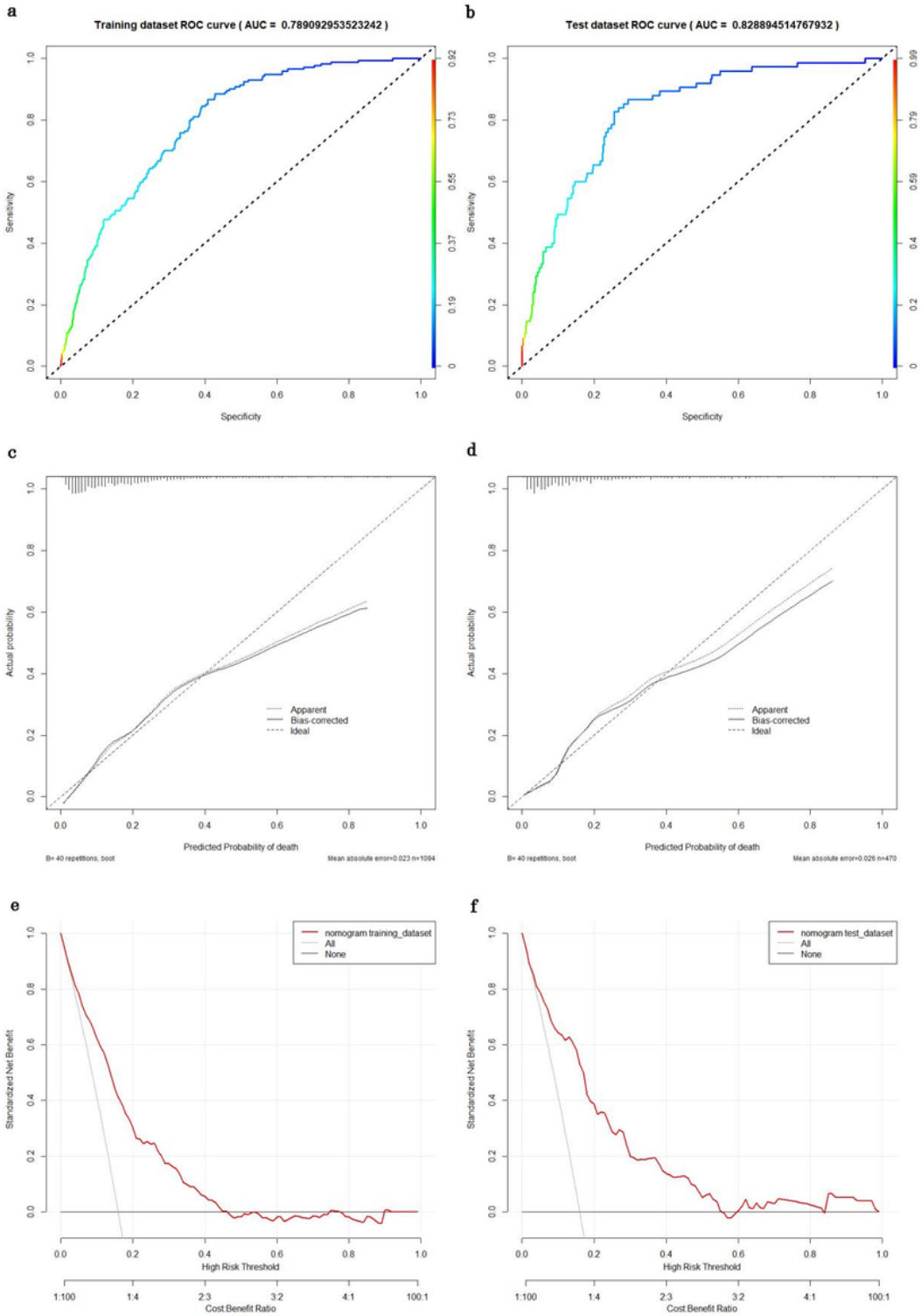

Figure 3

3(a): Receiver operating characteristic (ROC) curve of the nomogram in training set. The area under the curve (AUC) of ROC was 0.789 (95% CI: 0.752–0.826). 3(b): Receiver operating characteristic (ROC) curve of the nomogram in test set. The area under the curve (AUC) of ROC was 0.829 (95% CI 0.791–0.867). 3(c): Calibration curve of the nomogram in training set. The x-axis represents the predicted probability of in-hospital mortality of post-cardiac arrest patients. The y-axis represents the actual in-hospital mortality

of post-cardiac arrest patients. The diagonal dotted line represents a perfect prediction by an ideal model. The solid line represents the performance of the nomogram, of which a closer fit to the diagonal dotted line represents a better prediction. The figure showed that the prediction model have a good predictive ability. 3(d): Calibration curve of the nomogram in test set. The x-axis represents the predicted probability of in-hospital mortality of post-cardiac arrest patients. The y-axis represents the actual in-hospital mortality of post-cardiac arrest patients. The diagonal dotted line represents a perfect prediction by an ideal model. The solid line represents the performance of the nomogram, of which a closer fit to the diagonal dotted line represents a better prediction. The figure showed that the prediction model have a good predictive ability. 3(e): Decision curve analysis of the nomogram for post-cardiac arrest patients (training set) The DCA curve of the nomogram for post-cardiac arrest patients. Solid line: The patient does not apply the nomogram, and the net income is zero; Gray line: All patients used the nomogram. The further the red solid line was from the dotted line, the greater the clinical application value. 3(f): The validation for the DCA curve of the nomogram for post-cardiac arrest patients (test set). Solid line: The patient does not apply the nomogram, and the net income is zero; Gray line: All patients used the nomogram. The further the red solid line was from the dotted line, the greater the clinical application value.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- TableS1andTableS2.docx