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Development and External Validation of a Machine Learning–Based Clinical Prediction Model for Postoperative Ischemic Stroke in Patients Undergoing Coronary Artery Bypass Grafting: Validation Using the eICU Collaborative Research Database

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Abstract

Background

Postoperative ischemic stroke is a serious complication following coronary artery bypass grafting (CABG) and is associated with substantial adverse clinical consequences. Existing risk scores have limited discriminatory ability for predicting postoperative ischemic stroke, whereas previously developed machine learning models have predominantly been derived from single-center cohorts and often lack adequate independent external validation. This study aimed to develop and externally validate a machine learning model for predicting ischemic stroke after CABG.

Methods

This retrospective study included 938 patients who underwent CABG at Beijing Anzhen Hospital, Capital Medical University, between 2019 and 2021 as the model development cohort. An independent cohort of 1,177 patients derived from the eICU Collaborative Research Database was used for external validation.Feature selection was first performed using the Boruta algorithm, followed by univariable ROC analysis of the Boruta-confirmed variables; the seven variables with the highest discriminatory performance were retained as the final feature set. Five machine learning models were subsequently developed. Model performance was comprehensively evaluated using receiver operating characteristic (ROC) curves, precision-recall (PR) curves, calibration curves, and decision curve analysis (DCA). SHapley Additive exPlanations (SHAP) analysis was further performed to interpret the predictions of the best-performing model and quantify the relative contribution of individual predictors. Results: Among the five machine learning algorithms evaluated, the random forest (RF) model demonstrated the best overall predictive performance. The RF model achieved a mean AUC of 0.934 in 10-fold cross-validation and an AUC of 0.764 (95% CI, 0.703–0.826) in the external eICU validation cohort. SHAP analysis identified red blood cell distribution width–coefficient of variation (RDW-CV), arterial oxygen content (CaO_2), systemic immune-inflammation index (SII), hematocrit (HCT), body surface area (BSA), estimated glomerular filtration rate (eGFR), and a history of ischemic stroke as the most influential predictors of postoperative ischemic stroke. Conclusions: The RF model developed in this study demonstrated good discriminatory performance for predicting ischemic stroke after CABG and maintained moderate predictive performance in an independent external eICU cohort. This model may serve as an early risk-stratification tool to facilitate the identification of patients at high risk of postoperative ischemic stroke and support individualized perioperative monitoring and preventive strategies.

Introduction

Coronary artery bypass grafting is an important revascularization strategy for patients with complex coronary artery disease. Despite advances in surgical techniques, perioperative management, and postoperative care, stroke remains one of the most serious complications after CABG. A nationwide

SWEDEHEART study involving 36,898 patients reported a perioperative stroke incidence of 1.2%, with stroke associated with more than a twofold increase in overall mortality and a particularly high risk of death within 30 days after surgery[1]. Similarly, among 20,582 patients undergoing isolated CABG, the 30-day mortality rate was 20.4% in patients with postoperative stroke compared with 1.8% in those without stroke[2]. These findings highlight the substantial prognostic impact of postoperative stroke despite its relatively low incidence.

Stroke after CABG is multifactorial and may result from cerebral embolization related to aortic manipulation, cerebral hypoperfusion, pre-existing cerebrovascular disease, and perioperative arrhythmias[3]. Early and delayed postoperative strokes may also differ in their underlying mechanisms, risk factors, and prognosis[4]. Previous studies have identified advanced age, prior stroke, peripheral vascular disease, renal dysfunction, perioperative myocardial infarction, and re-exploration for bleeding as potential risk factors[1, 2]. However, the complex interactions among demographic characteristics, comorbidities, laboratory parameters, and perioperative factors make individualized risk prediction challenging.

Traditional risk scores and regression-based models have been explored for postoperative stroke prediction. For example, the CHA_2DS_2-VASc score has shown potential predictive value for ischemic stroke after CABG, but the supporting study included only 383 patients and eight stroke events, limiting the robustness and generalizability of its findings[5]. Machine learning methods may offer advantages by capturing nonlinear relationships and complex interactions among clinical variables. Previous studies have applied machine learning to predict mortality, major complications, readmission, and healthcare utilization after CABG[6]. More recently, a machine learning model for postoperative stroke wa-s developed in a single-center cohort of 1,200 CABG patients[7]. However, both the training and testing datasets were derived from the same institution, and independent external validation was lacking.

Therefore, external validation in an independent population is essential before such models can be generalized to broader clinical settings. The eICU Collaborative Research Database (eICU-CRD) is a large multicenter critical care database containing more than 200,000 ICU admissions from hospitals across the United States[8]. In this study, we aimed to develop a machine learning-based model for predicting postoperative ischemic stroke after CABG and externally validate its performance using the eICU-CRD. The model may facilitate early risk stratification and identification of high-risk patients, thereby supporting intensified neurological monitoring and targeted preventive strategies.

Materials and Methods

2.1 Data Sources and Study Population

This retrospective cohort study included patients with coronary artery disease who underwent CABG at the Department of Cardiac Surgery, Beijing Anzhen Hospital, Capital Medical University, between 2019

and 2021. After applying the predefined eligibility criteria, 938 eligible patients were included in the development cohort. The primary outcome was postoperative ischemic stroke. The exclusion criteria were as follows: (1) concomitant cardiac or major vascular procedures, such as valvular or aortic surgery; (2) concomitant malignancy or other severe diseases associated with limited life expectancy; and (3) incomplete medical records or missing key clinical data. Postoperative ischemic stroke was defined according to the criteria recommended by the American Heart Association/American Stroke Association (AHA/ASA)[9].

The Beijing Anzhen Hospital cohort was used for model development and internal cross-validation. In addition, 1,177 eligible patients undergoing CABG were identified from the eICU Collaborative Research Database (eICU-CRD, version 2.0) and used as an independent external validation cohort to evaluate model generalizability.The study was approved by the Ethics Committee of Beijing Anzhen Hospital, Capital Medical University (Approval No. PJKT2024-211), and was conducted in accordance with the Declaration of Helsinki.The eICU-CRD is a large multicenter critical care database containing 200,859 ICU encounters from 139,367 unique patients admitted to 335 ICUs across 208 hospitals in the United States between 2014 and 2015[8]. It contains high-granularity clinical information, including demographics, vital signs, laboratory measurements, diagnoses, medications, clinical interventions, and severity-of-illness measures. All patient data were de-identified in accordance with the Health Insurance Portability and Accountability Act (HIPAA) Safe Harbor provisions.

2.2 Feature Extraction

Candidate predictors included demographic characteristics, vital signs, medical history, hematological and inflammatory markers, biochemical parameters, coagulation indices, and arterial blood gas variables. Demographic and vital-sign variables included age, sex, body mass index (BMI),, body surface area (BSA), systolic blood pressure, and heart rate. Medical history included previous ischemic stroke, hypertension, diabetes mellitus, hyperlipidemia, and prior myocardial infarction. Hematological and inflammatory markers included white blood cell count (WBC), hematocrit (HCT), red cell distribution width-coefficient of variation (RDW-CV), neutrophil-to-lymphocyte ratio (NLR), and systemic immune-inflammation index (SII). Biochemical parameters included creatinine, estimated glomerular filtration rate (eGFR), glucose, B-type natriuretic peptide (BNP), and high-sensitivity cardiac troponin I (hs-cTnI). Coagulation indices included prothrombin time (PT), activated partial thromboplastin time (APTT), and international normalized ratio (INR). Arterial blood gas variables included pH, PaO_2, $PaCO_2$, arterial oxygen content (CaO_2), and lactate. For laboratory and arterial blood gas variables with multiple measurements, the first available value after admission was used for analysis.

2.3 Calculation of Composite Indices

Four derived composite indices were additionally calculated to characterize systemic inflammation, metabolic status, and oxygen-carrying capacity. The neutrophil-to-lymphocyte ratio (NLR) was calculated as NLR = neutrophil count / lymphocyte count, while the systemic immune-inflammation index (SII) was calculated as SII = platelet count × neutrophil count / lymphocyte count; both indices integrate

information from circulating inflammatory and immune cells. The lactate-to-glucose ratio (LGR), reflecting the relationship between lactate accumulation and glucose metabolism, was calculated as LGR = lactate / glucose. Arterial oxygen content (CaO_2), which represents the oxygen-carrying capacity of arterial blood, was calculated as $CaO_2 = (1.34 \times Hb \times SaO_2) + (0.003 \times PaO_2)$, where Hb represents hemoglobin concentration, SaO_2 represents arterial oxygen saturation expressed as a fraction, and PaO_2 represents the arterial partial pressure of oxygen.

2.4 Model Development, Validation, and Interpretation

The overall modeling workflow is presented in Fig. 1, and the univariable AUC values of the candidate predictors are shown in Fig. 2. Feature selection was first performed in the development cohort using the Boruta algorithm, a random forest-based feature selection method that compares the importance of original variables with that of randomly generated shadow features. Variables whose importance consistently exceeded the maximum importance o f the shadow features across multiple iterations were considered relevant and retained for subsequent analysis, whereas unimportant variables were excluded. The results of Boruta feature selection are presented in Fig. 4.

Subsequently, univariable ROC analyses were performed for the variables retained by Boruta, and the corresponding AUC values were calculated. The seven Boruta-confirmed variables with the highest discriminatory performance were retained as the final predictors for model development. Five machine learning algorithms were developed using the selected predictors: logistic regression (LR), random forest (RF), extreme gradient boosting (XGBoost), k-nearest neighbors (KNN), and decision tree (DT). Model performance was evaluated using 10-fold cross-validation in the development cohort. Discrimination was primarily assessed using the area under the receiver operating characteristic curve (AUC), together with sensitivity, specificity, accuracy, and F1 score. Precision-recall (PR) curves were used to further evaluate the ability of the models to identify outcome events, whereas calibration curves were used to assess agreement between predicted and observed risks. Decision curve analysis (DCA) was performed to evaluate the clinical net benefit across a range of threshold probabilities. The best-performing model was selected based on its overall predictive performance. After model development, all model parameters were fixed, and the final model was applied to the independent eICU external validation cohort to assess its external predictive performance and generalizability.

Finally, SHapley Additive exPlanations (SHAP) analysis was performed to interpret the best-performing model. SHAP values, derived from cooperative game theory, quantify the contribution of each predictor to model predictions. Global feature importance was assessed using the mean absolute SHAP value, while SHAP distribution plots were used to illustrate the direction and magnitude of the contribution of individual predictors to model output.

2.5 Statistical Analysis

The proportion of missing data was initially assessed for each variable. Variables with more than 30% missing values were excluded from further analyses. For variables with 10%–30% missing data, missing values were imputed using a random forest-based imputation method, whereas variables with less than

10% missing data were imputed using the mean value. All statistical analyses were performed using R software (version 4.4.2).Continuous variables were assessed for distributional characteristics. Normally distributed continuous variables are presented as the mean ± standard deviation (SD), and between-group comparisons were performed using the independent-samples t test. Non-normally distributed continuous variables are presented as the median and interquartile range (IQR), and comparisons between groups were performed using the Mann–Whitney U test. Categorical variables are expressed as counts and percentages [n (%)], and between-group comparisons were conducted using Pearson's χ^2 test or Fisher's exact test, as appropriate. All statistical tests were two-sided, and a P value < 0.05 was considered statistically significant.

Result

3.1:Baseline characteristics:

A total of 938 patients were included in the development cohort, including 170 (18.12%) patients who developed postoperative ischemic stroke and 768 (81.88%) who did not. The mean age of the overall cohort was 62.12 ± 8.83 years, and 710 (75.69%) patients were male. Detailed baseline demographic, clinical, and laboratory characteristics are presented in Table 1. Compared with patients without postoperative ischemic stroke, those who developed ischemic stroke were older, were more frequently female, and had higher systolic blood pressure and a greater prevalence of previous ischemic stroke, hypertension, and diabetes (all P < 0.05). Regarding laboratory parameters, patients with postoperative ischemic stroke had significantly higher SII and glucose levels, whereas HCT, eGFR, and CaO_2 were significantly lower. Significant between-group differences were also observed in RDW-CV, CK-MB, BNP, several coagulation-related parameters, fibrinogen, and LGR (all P < 0.05).

3.2 Feature Selection Using the Boruta Algorithm

To identify candidate predictors with potential prognostic value, feature selection was performed using the Boruta algorithm. Boruta evaluates the importance of each original feature by comparing it with that of randomly generated shadow features. In the Boruta plot, the x-axis represents the candidate variables, whereas the y-axis represents the Z-scores obtained during repeated iterations. The boxplots illustrate the distribution of Z-scores for each variable. Features highlighted in green were classified as confirmed important features, those in yellow as tentative features, and those in red as rejected features. Variables confirmed as important by the Boruta algorithm were initially retained as candidate predictors. Subsequently, AUC was calculated for each candidate variable to assess its individual discriminatory ability for postoperative ischemic stroke. Considering predictive performance and model parsimony, the seven variables with the highest AUC values were ultimately selected for model development: SII, HCT, RDW-CV, history of ischemic stroke, CaO_2, eGFR, and BSA (Fig. 2).

3.3 Performance Comparison of Five Machine Learning Algorithms

Five machine learning algorithms were compared for the prediction of postoperative ischemic stroke in patients undergoing CABG. Model performance was comprehensively evaluated using ROC curves, DCA, cross-validation, and PR curves to assess discrimination, robustness, and potential clinical utility (Fig. 3A–D). In addition, an independent cohort derived from the eICU database was used for external validation to evaluate the generalizability of the developed models. In the comparative model evaluation, the RF model demonstrated the highest AUC (0.950), followed by XGBoost (0.941), logistic regression (0.930), KNN (0.923), and decision tree (0.889). DCA further demonstrated that the RF model yielded a relatively greater net benefit across a broad range of threshold probabilities, particularly within the intermediate threshold range, suggesting its potential clinical utility for predicting postoperative ischemic stroke (Fig. 3B). Detailed performance metrics for each model, including sensitivity, specificity, AUC, accuracy, F1-score, and Cohen's kappa coefficient, are presented in Table 2. Overall, the RF model showed the best performance, with an F1-score of 0.746 and a kappa coefficient of 0.699. Pairwise comparisons of model AUCs using the DeLong test demonstrated significant differences between XGBoost and decision tree (P = 0.012) and between random forest and decision tree (P = 0.016), whereas the remaining pairwise comparisons did not reach statistical significance (Table 3). Considering its numerically highest AUC, favorable F1-score and kappa coefficient, DCA performance, and overall balance of discrimination and classification performance, the RF model was selected as the optimal model. Internal validation using 10-fold cross-validation further demonstrated stable discrimination of the RF model, with a mean cross-validated AUC of 0.934 (Fig. 4). In the independent eICU external validation cohort, the RF model retained moderate discriminative ability, achieving an AUC of 0.764 (95% CI, 0.703–0.826) (Fig. 5A). A confusion matrix was also generated for the external validation cohort to illustrate the model's classification performance in distinguishing patients with and without postoperative ischemic stroke (Fig. 5B).

3.4 Model Interpretability Analysis

To further elucidate the prediction mechanism of the random forest model and quantify the contribution of individual predictors to postoperative ischemic stroke risk, SHAP analysis was performed for the optimal RF model. Figure 6A presents the SHAP summary plot for the seven predictors included in the final model. The x-axis represents the SHAP value, which reflects both the direction and magnitude of the contribution of each feature to the model output. Positive SHAP values indicate that a feature contributes to a higher predicted probability of postoperative ischemic stroke, whereas negative SHAP values indicate a contribution toward a lower predicted probability. Each point represents the SHAP value of an individual patient for a given feature, and the color of the point reflects the corresponding feature value, with higher and lower feature values represented by different colors. Features were ranked according to their mean absolute SHAP values, reflecting their overall contributions to model prediction. Figure 6B further illustrates the global feature importance of the RF model based on the mean absolute SHAP values. Among the seven predictors incorporated into the final model—SII, HCT, RDW-CV, history of ischemic stroke, CaO_2, eGFR, and BSA—the magnitude of contribution to the prediction of postoperative ischemic stroke varied across features. In addition, SHAP dependence plots were generated to explore the potential nonlinear relationships between key predictors and the model output and to characterize

how changes in individual feature values influenced the predicted risk of postoperative ischemic stroke. Finally, patient-level SHAP explanations were provided to illustrate how individual predictors jointly contributed to the model-generated risk estimates for representative patients (Fig. 6C and D), thereby improving the transparency and clinical interpretability of the RF model.

Discussion

In the present study, we developed and compared five machine learning models for predicting postoperative ischemic stroke in patients undergoing CABG. Based on a comprehensive evaluation of model discrimination, classification performance, and potential clinical utility—including AUC, DCA, sensitivity, specificity, accuracy, and F1-score—the RF model demonstrated the best overall performance and was therefore selected as the optimal model. Pairwise DeLong tests showed significant AUC differences between XGBoost and decision tree and between RF and decision tree, whereas the remaining pairwise comparisons were not statistically significant. The RF model achieved the highest AUC of 0.950 in the comparative model evaluation, and the mean AUC obtained from 10-fold cross-validation was 0.934. Feature selection using the Boruta algorithm followed by assessment of individual discriminatory performance identified seven predictors for inclusion in the final model: SII, CaO_2, HCT, BSA, RDW-CV, eGFR, and history of ischemic stroke. Importantly, the model was further evaluated in an independent cohort derived from the eICU database, in which it retained moderate discriminatory performance, with an AUC of 0.764 (95% CI, 0.703–0.826). This external validation provided an additional assessment of model transportability across different patient populations and healthcare settings.

Machine learning approaches have increasingly been applied to risk prediction for stroke after coronary revascularization and CABG. Lin et al. included 5,757 patients with coronary artery disease undergoing coronary revascularization from the MIMIC-IV database and compared several machine learning algorithms. Their CatBoost model achieved an AUC of 0.760 in the testing set; however, both the training and testing samples were derived from the same MIMIC-IV cohort through random data splitting, and no independent external validation was performed[10]. Chen et al. subsequently developed machine learning models for postoperative stroke among 1,200 patients undergoing CABG, with the RF model demonstrating the highest AUC of approximately 0.901. Nevertheless, this was a single-center study in which the training and testing cohorts were derived from the same institution, and the authors acknowledged that the absence of external validation could limit model generalizability[7]. Si et al. further developed machine learning models for stroke prediction after coronary revascularization using MIMIC-IV data. Their CatBoost model achieved an AUC of approximately 0.851 in the validation set. Although separate training, validation, and testing subsets were established, all were generated from the same source population and therefore represented internal rather than independent external validation[11]. More recently, Pei et al. developed a machine learning-enhanced model for predicting ischemic stroke after CABG, in which the gradient boosting machine achieved an AUC of 0.874 for in-hospital ischemic stroke. However, the absence of external validation was likewise acknowledged as an important

limitation[12]. Collectively, these studies demonstrate the potential of machine learning for postoperative stroke risk prediction but also highlight the persistent uncertainty regarding model transportability across institutions and populations. In contrast, the present study combined internal cross-validation with independent external validation using the eICU database. This cross-database validation provides a more stringent assessment of model robustness and transportability and therefore represents an important step toward future multicenter and prospective evaluation.

Previous risk prediction studies for stroke following CABG have predominantly focused on demographic characteristics, pre-existing cerebrovascular and systemic vascular disease, diabetes, impaired renal function, cardiac dysfunction, and perioperative factors. An early CABG-specific stroke prediction model developed by Charlesworth et al. incorporated age, sex, diabetes, vascular disease, renal failure or elevated creatinine, reduced left ventricular ejection fraction, and urgent or emergency surgery as major predictors[13]. More recent studies have expanded the spectrum of candidate predictors to include a history of ischemic stroke, carotid artery stenosis, renal function, and hematologic and coagulation-related parameters. For example, a recent study of patients undergoing off-pump CABG identified previous ischemic stroke and RDW-CV, among other variables, as important predictors of postoperative acute ischemic stroke[14]. Hematologic parameters, including HCT, have also been considered in machine learning models for stroke following coronary revascularization. Consistent with these findings, our model incorporated a history of stroke, eGFR, RDW-CV, and HCT, thereby capturing complementary information regarding baseline cerebrovascular vulnerability, renal function, and hematologic status.

Of particular interest, the present study also incorporated SII and CaO_2, two parameters that have been relatively underexplored in previous CABG-specific stroke prediction models. These variables may complement conventional predictors by representing two distinct pathophysiological domains: systemic inflammation and thrombotic propensity on the one hand, and arterial oxygen-carrying capacity on the other. SII integrates neutrophil, platelet, and lymphocyte counts and may provide a composite representation of systemic inflammatory activity, immune status, and thrombotic tendency. Dey et al. reported that elevated preoperative SII was associated with adverse short-term outcomes after elective off-pump CABG, supporting the potential prognostic relevance of systemic inflammatory burden in patients undergoing coronary surgery[15]. Moreover, Zhang et al., in a cohort of 40,670 older patients undergoing non-cardiac surgery, demonstrated that an elevated preoperative SII was independently associated with an increased risk of perioperative ischemic stroke; patients with an SII ≥ 583 had a significantly greater risk of perioperative ischemic stroke[16]. Although direct evidence specifically linking SII to postoperative stroke after CABG remains limited, these observations support the biological plausibility of an inflammation–thrombosis pathway contributing to perioperative cerebral ischemic events. Our findings therefore suggest that SII may provide potentially useful information for risk stratification in patients undergoing CABG, although its incremental predictive value requires further dedicated evaluation.

CaO_2, in contrast, reflects the oxygen-carrying capacity of arterial blood and is a key determinant of systemic oxygen delivery. During CABG, particularly in procedures involving CPB, hemodilution, anemia, impaired oxygenation, and fluctuations in systemic perfusion may compromise effective cerebral oxygen delivery and increase susceptibility to ischemic brain injury. Karkouti et al. demonstrated that lower nadir HCT during CPB was associated with an increased risk of perioperative stroke in patients undergoing cardiac surgery, providing clinical evidence linking reduced blood oxygen-carrying capacity with cerebral ischemic risk[17]. Furthermore, a recent scoping review evaluating oxygen delivery during CPB found that reduced intraoperative oxygen delivery was frequently observed among patients who subsequently developed neurological complications, including cerebrovascular events, although the available evidence remains heterogeneous and no universally accepted critical oxygen-delivery threshold has been established[18]. Compared with isolated measurements such as hemoglobin, HCT, PaO_2, or SaO_2, CaO_2 integrates hemoglobin-dependent oxygen-carrying capacity with arterial oxygenation and may therefore provide a more physiologically integrated measure of oxygen availability. Nevertheless, because previous evidence has largely focused on intraoperative HCT or systemic oxygen delivery rather than preoperative CaO_2 itself, the present finding should be considered hypothesis-generating and warrants validation in dedicated prospective studies.

Taken together, SII and CaO_2 may provide complementary information regarding two important mechanisms implicated in perioperative cerebral injury: inflammation–thrombosis and impaired oxygen delivery. Their inclusion alongside conventional clinical predictors may enable a more multidimensional characterization of postoperative stroke risk. However, because the present study did not formally quantify the incremental predictive value of SII and CaO_2 beyond conventional predictors using nested model comparisons, changes in AUC, net reclassification improvement, or integrated discrimination improvement, it cannot yet be concluded that these variables independently improve model performance. Future studies should specifically evaluate their incremental prognostic contribution.

Several limitations of this study should be acknowledged. First, the development cohort was derived from a retrospective, single-center real-world database. Consequently, selection bias, information bias, and residual or unmeasured confounding cannot be excluded. Second, although independent external validation was performed using the eICU database, the development cohort originated from a single institution and the external evaluation relied on only one additional database. Differences in patient characteristics, clinical practices, variable definitions, and data acquisition between the development and external validation cohorts may also have influenced model performance. Therefore, the stability and transportability of the model across broader geographic regions, healthcare systems, and surgical centers require further evaluation in large multicenter prospective cohorts.

Conclusion

In this study, we developed and compared multiple machine learning models for predicting postoperative ischemic stroke in patients undergoing CABG and externally validated the optimal RF model using an

independent eICU cohort. A history of ischemic stroke, eGFR, RDW-CV, HCT, SII, CaO_2, and BSA were retained as predictors in the final model. Notably, SII and CaO_2 may provide complementary information regarding systemic inflammation–thrombosis and arterial oxygen-carrying capacity, respectively, thereby extending conventional clinical risk characterization from distinct pathophysiological perspectives. The externally validated model may serve as an adjunctive tool for perioperative risk stratification and facilitate earlier identification of patients at increased risk of postoperative ischemic stroke. Nevertheless, further multicenter prospective validation and clinical impact assessment are required before its routine implementation in clinical practice.

Declarations

Conflicts of interest:

The author reported no potential conflict.

Human Ethics and Consent to Participate declarations

This retrospective study was approved by the Ethics Committee of Beijing Anzhen Hospital (Approval No. 2025269x) with a waiver of the requirement for informed consent from the study participants. All analyses were conducted on anonymized/de-identified data, strictly protecting participant privacy

Clinical trial number

not applicable.

statement of authorship

This author takes responsibility for all aspects of the reliability and freedom from bias of the data presented and their discussed interpretation

Consent to Participate

declaration: This retrospective study did not require informed consent from participants.

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Author Contribution

:Siji Chen: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. Shuanglei Zhao: Writing – original draft, Methodology, Data curation. Yang Zhao,Hongxu Song: Investigation, Data curation. Jiazhen Mei,Shuanglei Zhao: Investigation, Data curation. Mingxiu Wen, Jiazhen Meii,Qi Wen: Methodology, Data curation. Ming Gong: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Data curation

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Tables

Tables 1 to 3 are available in the Supplementary Files section.

Figures

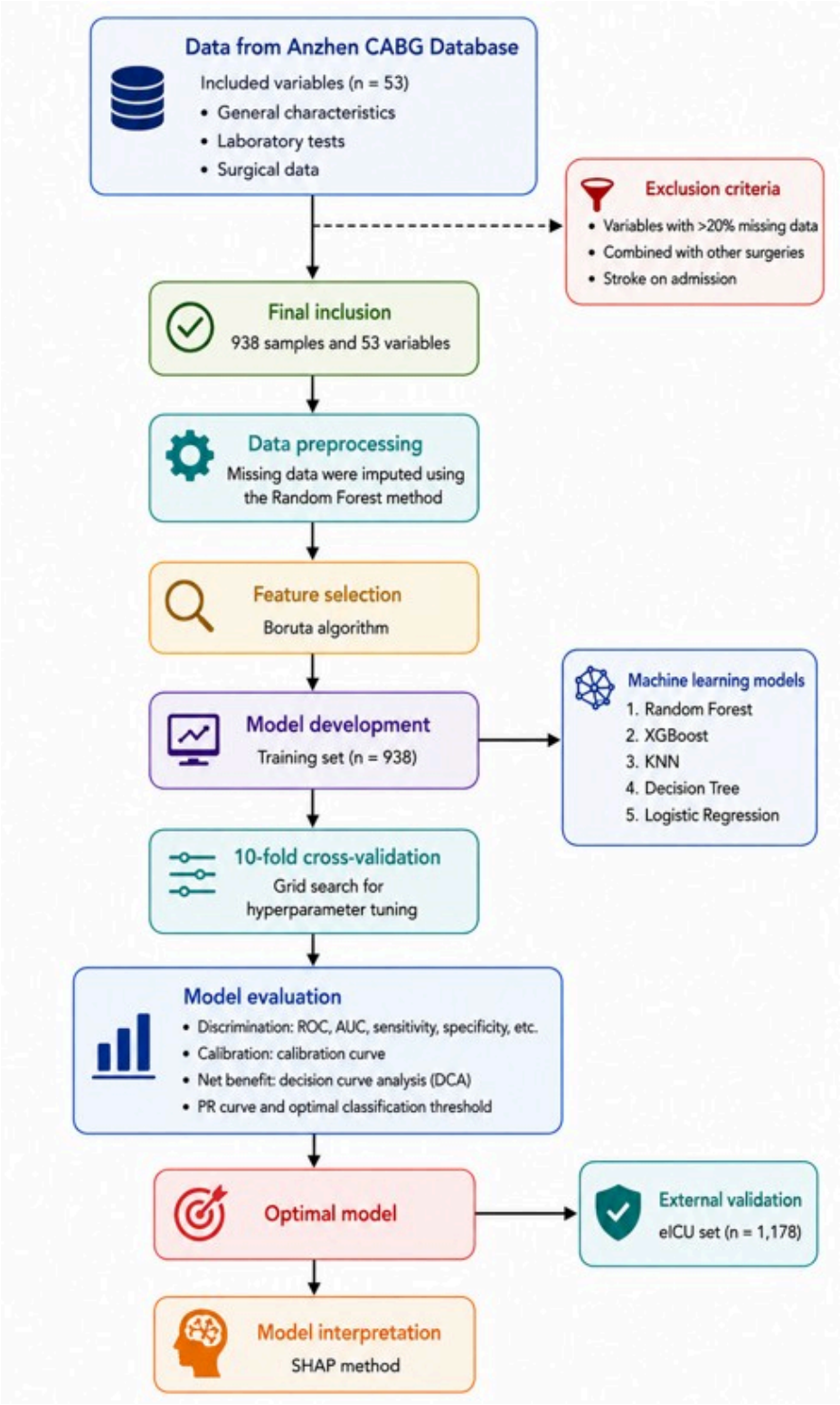


Figure 1

Flowchart of model construction

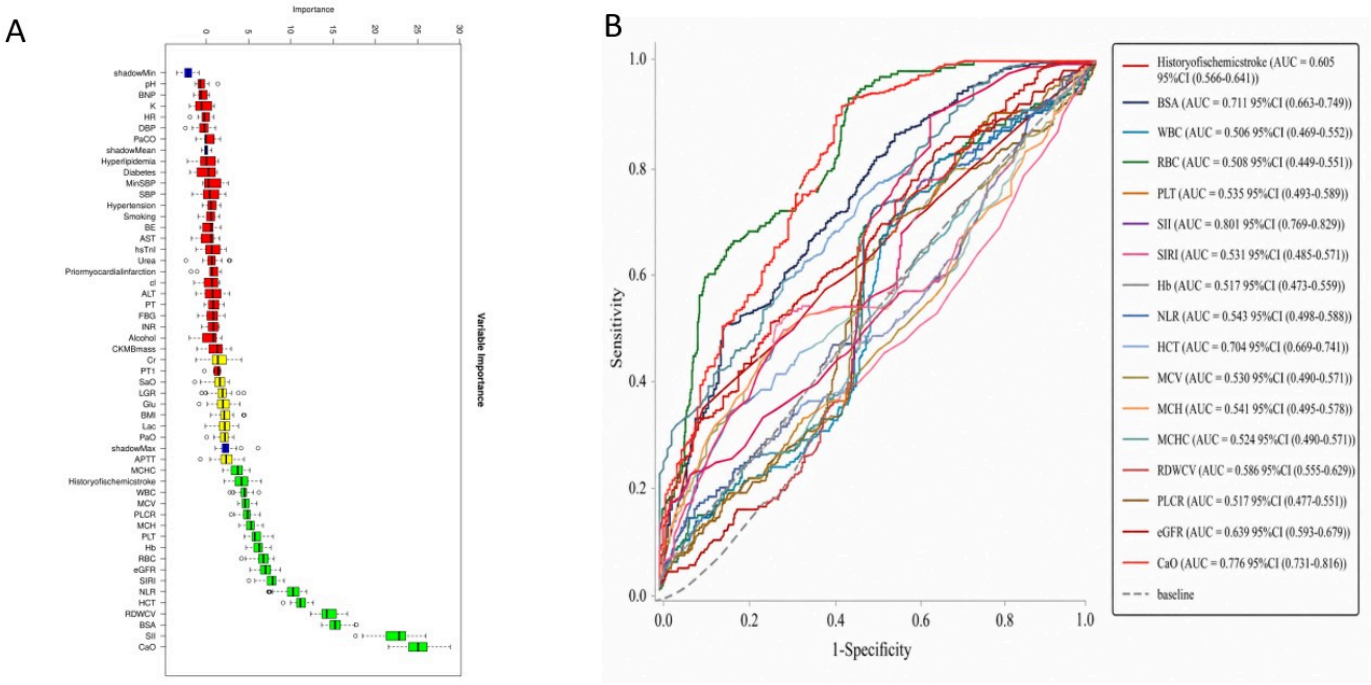


Figure 2

Feature selection using the Boruta algorithm and evaluation of the discriminatory performance of the selected variables.(**A**) Variable importance assessed using the Boruta algorithm. Green boxes represent confirmed important variables retained for subsequent analysis, red boxes indicate rejected variables, yellow boxes indicate tentative variables, and blue boxes represent shadow attributes used as reference features. (**B**) Receiver operating characteristic (ROC) curves of the variables confirmed by the Boruta algorithm for discriminating the study outcome. The area under the ROC curve (AUC) and corresponding 95% confidence interval (CI) for each variable are presented in the legend. The grey dashed diagonal line represents the reference line of no discrimination (AUC = 0.50).

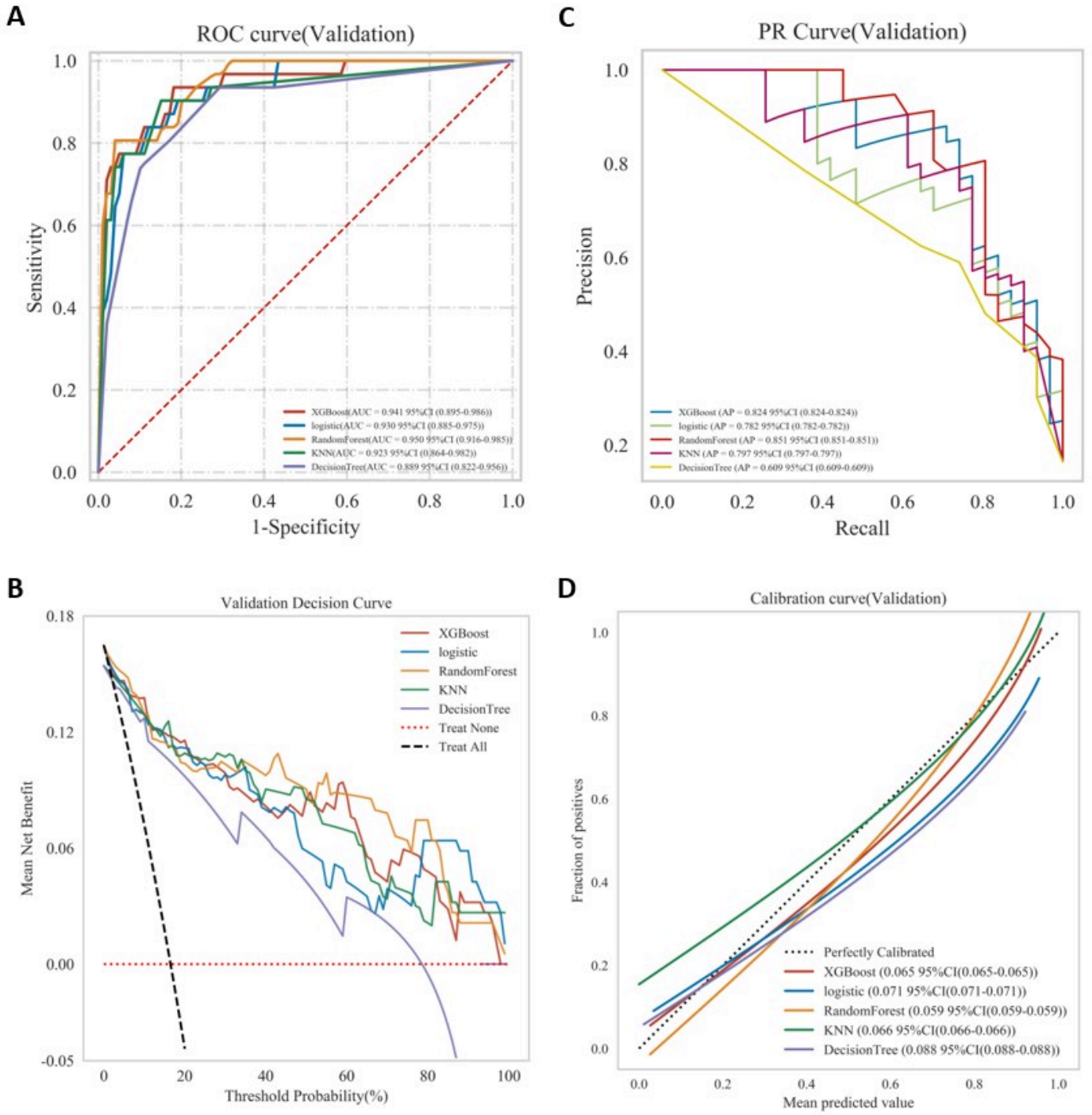


Figure 3

(A) Receiver Operating Characteristic (ROC) curves for the validation cohorts. The curves illustrate the discriminatory ability of different predictive models, with the area under the ROC curve (AUC) values displayed for seven models. **(B)** Decision Curve Analysis (DCA) for the validation cohorts. The curves show the net benefit of each model across various threshold probabilities, comparing them with the "Treat All" and "Treat None" strategies, indicating their potential clinical utility.**(C)** The Precision-Recall (PR) curve demonstrates the model's performance in classifying the positive class, particularly under

class imbalance(**D**)Calibration Curves for the validation cohorts. The curves verify the degree of conformity between the apparent line and the ideal line.

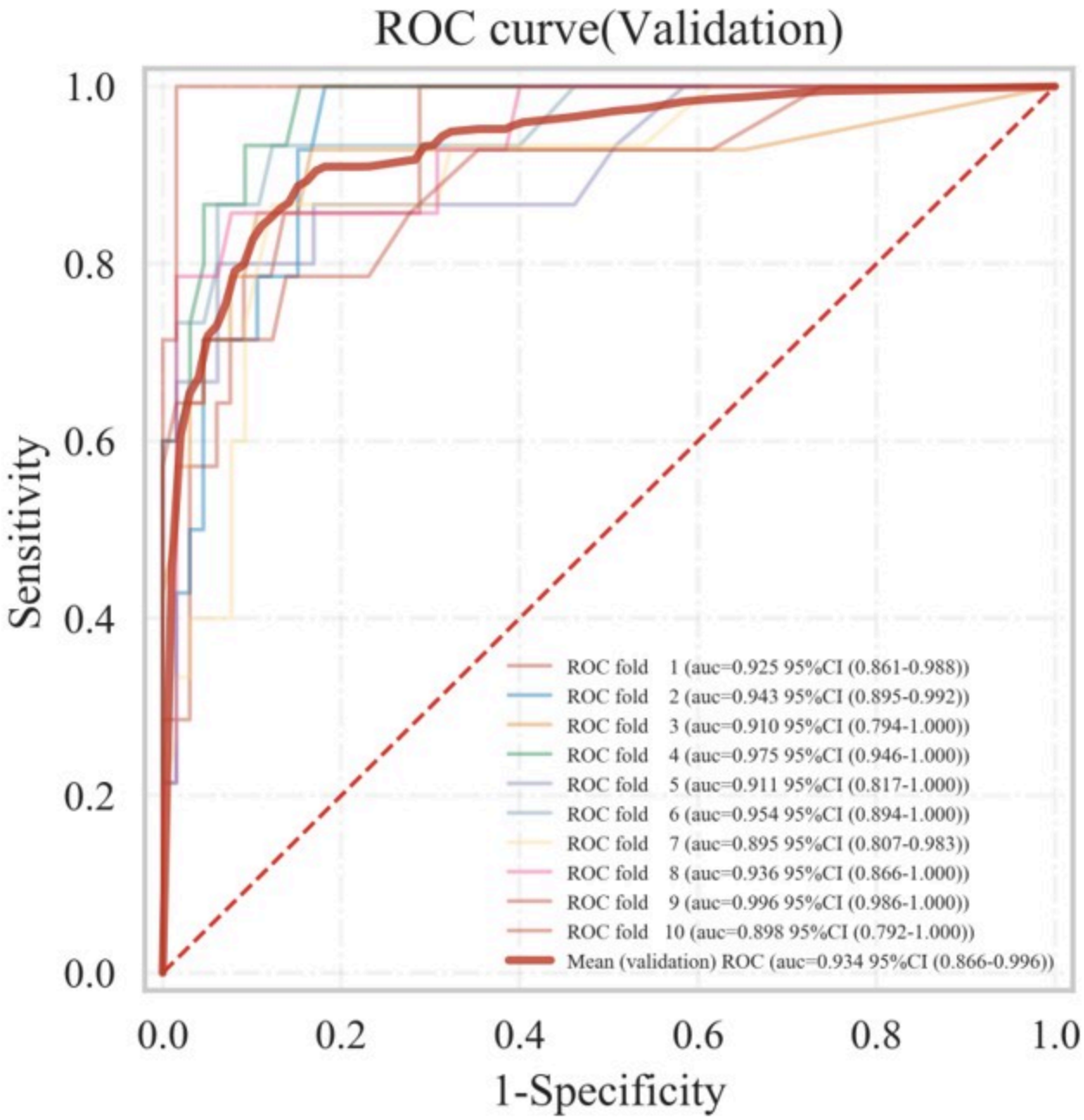


Figure 4

Average ROC from 10-fold cross-validation (internal)

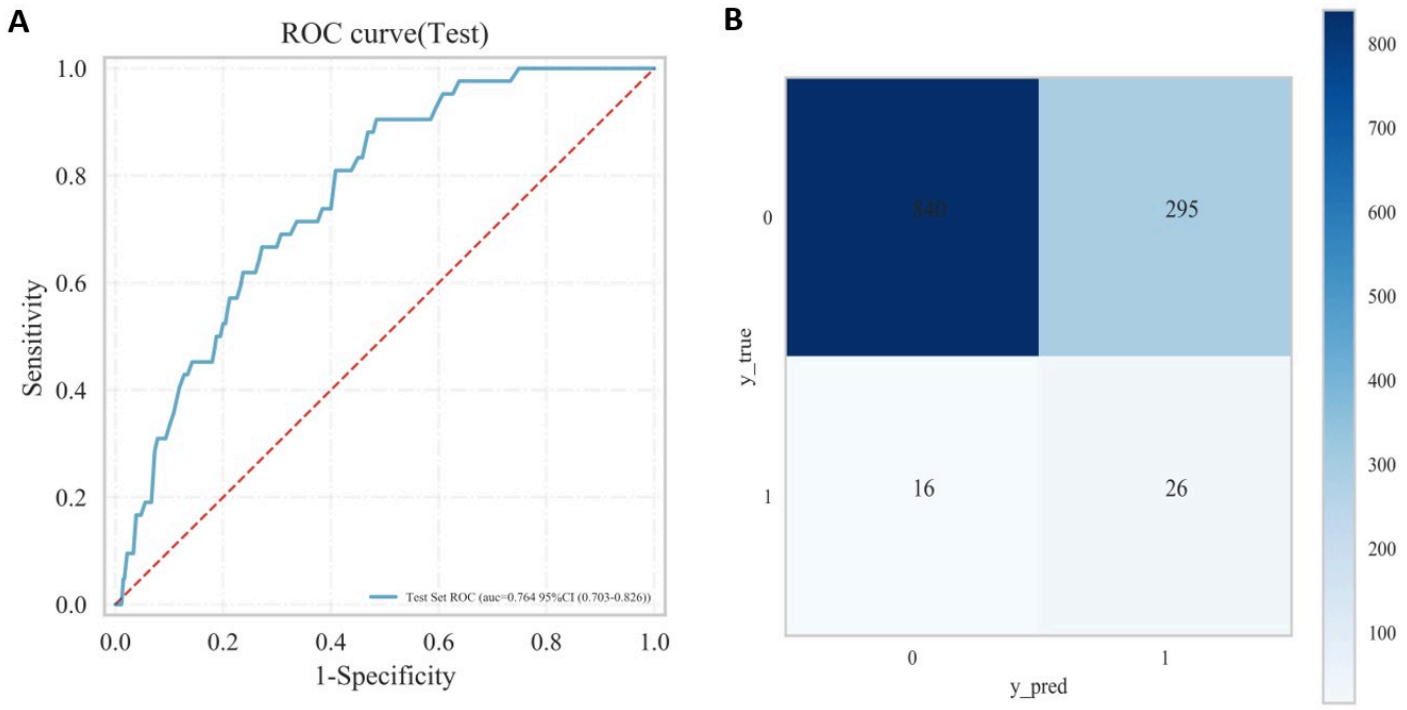


Figure 5

Performance of the prediction model in the eICU external validation cohort. (**A**) Receiver operating characteristic (ROC) curve of the model in the eICU external validation cohort. (**B**) Corresponding confusion matrix showing the model's classification performance.

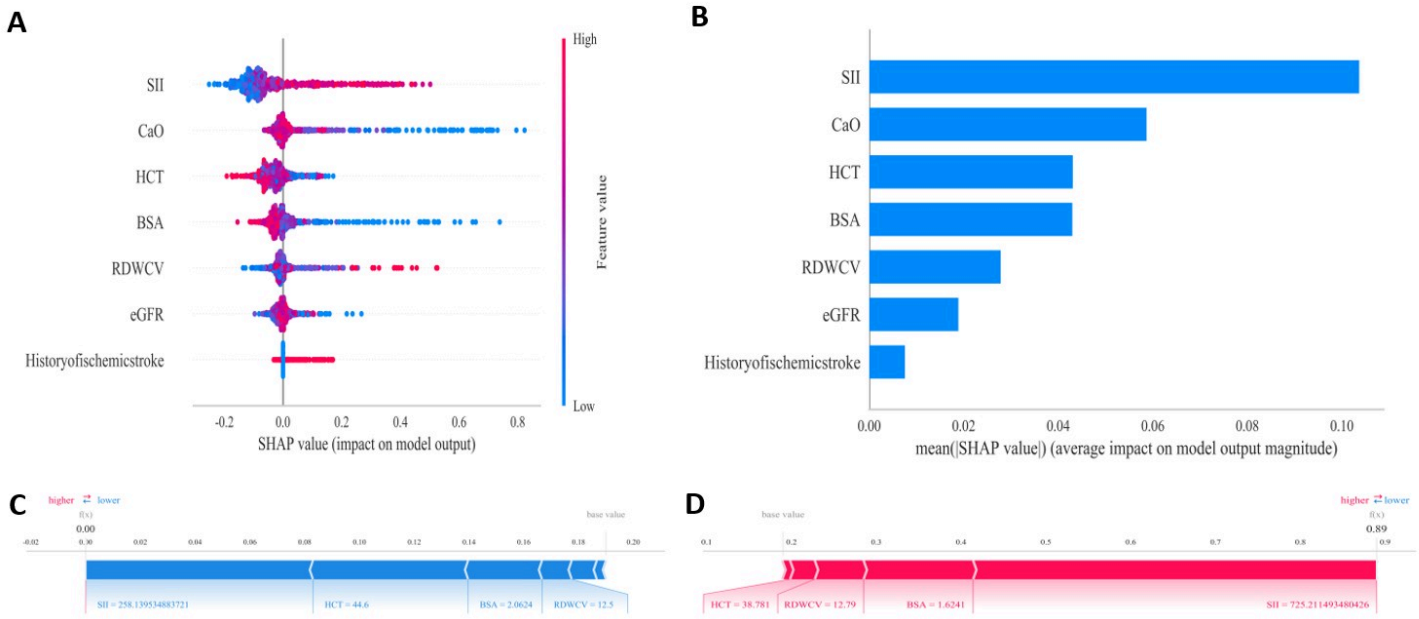


Figure 6

SHAP (Shapley Additive explanations) analysis of the model. (A) SHAP summary plot visualizing the distribution of SHAP values for each feature. Each dot represents an individual data point, with the x-axis showing the SHAP value (feature's impact on the model output) and the color representing the feature value (red for higher values blue for lower values).(B) Bar plot showing the mean SHAP values for the top features ranked by their contribution to stroke prediction in TAAD patients. (C&D):two examples of SHAP predictions for the purpose of demonstration.

Supplementary Files

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

- Tables.docx