Clinical Interventions in Aging

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ORIGINAL RESEARCH

Machine Learning Based Prediction of Postoperative Acute Kidney Injury Risk in Coronary Artery Bypass Grafting Patients

Yang Zhang[1,*], Dabei Cai[2,*], Ye Deng[2,*], Zhu Wang[1], Zhihan Zhang[1], Hu Zhang[1], Qingjie Wang[2], Shoujie Feng[1], Ling Sun[3], Jun Wei[1]

[1]Department of Cardiovascular Surgery, The Affiliated Hospital of Xuzhou Medical University, Xuzhou, 221000, People's Republic of China; [2]Department of Cardiology, The Third Affiliated Hospital of Nanjing Medical University, Changzhou, Jiangsu, 213000, People's Republic of China; [3]Department of Cardiology, The Affiliated Wuxi People's Hospital of Nanjing Medical University, Wuxi People's Hospital, Wuxi Medical Center, Nanjing Medical University, Wuxi, 214023, People's Republic of China

*These authors contributed equally to this work

Correspondence: Ling Sun, Department of Cardiology, The Affiliated Wuxi People's Hospital of Nanjing Medical University, Wuxi People's Hospital, Wuxi Medical Center, Nanjing Medical University, Wuxi, 214023, People's Republic of China, Email sunling85125@hotmail.com; Jun Wei, Department of Cardiovascular Surgery, The Affiliated Hospital of Xuzhou Medical University, Xuzhou, 221000, People's Republic of China, Email weijunseu@outlook.com

Background: Coronary artery bypass grafting (CABG) is key for severe coronary artery disease, but postoperative acute kidney injury (AKI) may increase mortality and prolong hospital stays. Reliable models for early prediction of post-CABG AKI remain lacking.

Methods: Data of 520 CABG patients (September 2021–December 2024) from the Affiliated Hospital of Xuzhou Medical University were collected, and the patients were divided into a training group (70%, for model building) and a validation group (30%). Key variables were screened through Least Absolute Shrinkage and Selection Operator (LASSO) regression, followed by the construction of six machine learning models: Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Logistic Regression (LR), Light Gradient Boosting Machine (LightGBM), Softmax Regression, and Support Vector Machine (SVM). The SHapley Additive exPlanations (SHAP) was used to quantify feature importance.

Results: The incidence of post-CABG AKI was 25.96%, and the median age of patients in the AKI group was significantly higher than that in the non-AKI group (66.09 ± 8.15 vs 64.32 ± 7.76, p = 0.025). In the training group, the XGBoost model using the top 5 important variables outperformed other models (Area Under the Curve [AUC] = 0.89, 95% Confidence Interval [CI]: 0.86–0.91), followed by the LightGBM model using the top 5 important variables and the RF model using the top 5 important variables (both had an AUC of 0.88; 95% CI: 0.85–0.90 and 0.85–0.91, respectively). In the validation group, the LR model using the top 15 important variables and the Softmax Regression model using the top 15 important variables maintained the highest stability (both had an AUC of 0.86, 95% CI: 0.79–0.92). SHAP analysis confirmed that estimated glomerular filtration rate (eGFR), intraoperative epinephrine use and calcium levels were the top three predictive factors.

Conclusion: The machine learning models constructed in this study can effectively predict post-CABG AKI, facilitating early identification of high-risk patients.

Keywords: coronary artery bypass grafting, acute kidney injury, machine learning, prediction model, area under the receiver operating characteristic curve

Introduction

Cardiovascular diseases, especially coronary artery disease (CAD), are the leading cause of death worldwide.[1] Coronary artery bypass grafting (CABG) is the main means of treatment for severe coronary heart disease (CHD) and is the preferred treatment for revascularization in patients with severe multivessel disease and complex coronary artery

Received: 11 June 2025
Accepted: 6 November 2025
Published: 15 November 2025

disease.[2,3] However, a variety of complications can occur after CABG, with acute kidney injury (AKI) being particularly common, occurring in 15–30%.[4–6] AKI not only affects the prognosis of patients but also increases the economic burden, which is mainly manifested by increased serum creatinine and decreased urine output,[7] and is closely related to increased mortality, prolonged hospital stay and increased medical costs.[8,9] Although serum creatinine (SCr) levels are often used as a diagnostic marker and grading basis for AKI, early studies have found a lag.[10] Given the rapid progression of AKI and the high mortality rate, early identification and intervention of such patients are essential to reduce morbidity and reduce the healthcare burden.[11–14] Unfortunately, there is a lack of effective clinical prediction models for early detection of AKI. Failure to identify and treat patients at high risk of AKI after CABG may lead to the progression of chronic renal failure or even end-stage renal disease, further increasing the risk of death. The high morbidity and mortality of AKI after cardiac surgery underscores its urgency as an important issue. However, the pathogenesis of AKI after CABG is complex and not fully understood.[15] Therefore, clarifying the risk factors of AKI after CABG and exploring effective prediction models have become key issues to be solved urgently.

Machine learning, an important branch of artificial intelligence, is a scientific technology that learns patterns from complex data through algorithms to predict behavioral outcomes and trends.[16] It possesses powerful capabilities in feature extraction, matching, and information integration, enabling it to learn completely driven by data without pre-assuming the relationship between input variables and output results, thus forming an efficient approach distinct from traditional rule-based programming. This characteristic has made it widely applied in medical fields such as outcome prediction, diagnosis, medical image analysis, and treatment.[17,18] However, Machine learning-based predictive models for post-CABG AKI remain scarce. This study addresses this gap by integrating preoperative baseline data (eg, renal function, diabetes history) and intraoperative time-series physiological metrics (eg, urine output, hemodynamics) to develop a robust Machine learning model for cardiac surgery-associated acute kidney injury (CSAAKI), offering a novel paradigm for early postoperative AKI warning (early warning).

Materials and Methods

Patients' Enrollment

The preoperative and intraoperative data of 520 patients who underwent CABG in the Department of Cardiac and Vascular Surgery of the Affiliated Hospital of Xuzhou Medical University from September 1, 2021 to December 31, 2024 were collected. The inclusion criteria were: 1. Coronary artery bypass surgery in our hospital; 2. Age ≥ 18 years; The exclusion criteria are: 1. Repeat CABG surgery; 2. No perioperative medical records. The study was conducted in accordance with the Declaration of Helsinki (revised in 2013). This study was approved by the Medical Ethics Committee of the Affiliated Hospital of Xuzhou Medical University (No. XYFY2025-KL154-01) and written informed consent was obtained from all participants.

Data Collection

Demographic characteristics: age, gender, body mass index, underlying diseases (hypertension, diabetes, neurological lesions, etc.), smoking history, cardiac function grade (New York Heart Association grade (NYHA grade)), Canadian Cardiovascular Society grade (CCS grade), blood type, etc. Preoperative medication: nitrates, statins, β blockers, diuretics, antibiotics, etc. Preoperative auxiliary examinations: electrocardiogram, cardiac color ultrasound (ejection fraction, etc.) Preoperative laboratory parameters: chloride, sodium, potassium, urea nitrogen, creatinine clearance, serum creatinine, direct bilirubin, total bilirubin, albumin, total protein, Alanine Aminotransferase (ALT), Aspartate Aminotransferase (AST), platelets, hematocrit, lymphocyte count, white blood cell count, neutrophil count, red blood cell count, hemoglobin, procalcitonin (PCT), Creatine kinase isoenzyme (CK-MB), troponin T (TnT), B-type natriuretic peptide (BNP), glycosylated hemoglobin (HbA1c). Preoperative coagulation function: activated partial thromboplastin time (APTT), prothrombin time (PT), international normalized ratio (INR). Intraoperative parameters: surgery-related: duration of surgery, extracorporeal bypass management (including temperature regulation); Intraoperative management: intraoperative medication, blood loss, intraoperative urine output; Number of intraoperative grafts. Immediate post-operative indicator: postoperative creatinine value.

Model Construction and Evaluation

Six machine learning models were constructed based on the features selected by the training cohort. The models used are: random forest (RF) model, extreme gradient boosting (XGBoost) model, Logistic regression (LR) model, Light Gradient Boosting Machine (LightGBM) model, Softmax Regression model and Support Vector Machine (SVM) model. Due to the small amount of data in this study, it is avoided.

RF is a model that can be used for both regression and classification.[19] It is one of the most popular integration methods and falls under the specific category of bagging methods. This approach can be described as a technique of using a group of weak learners together to create a stronger aggregate learner. XGBoost is an optimized distributed gradient boosting library designed to be efficient, flexible, and portable. It implements machine learning algorithms under the gradient boosting framework.[19] Traditional LR models are also used for model building.[19] The LightGBM model is an efficient gradient boosting framework, which is designed for large-scale data and high-dimensional features, and is commonly used for machine learning tasks such as classification and regression.[20] Softmax regression has become a core method for multi-class classification tasks by leveraging probabilistic outputs and cross-entropy optimization.[21] SVM aims to find a hyperplane in the feature space that optimally separates data into distinct classes. For non-linear datasets, the "kernel trick" enables SVMs to map the input data into a higher-dimensional space, where a linear separation becomes feasible.[22] Grid Search Cross-Validation is a method of systematically traversing parameter combinations and combining cross-validation to evaluate model performance to find the optimal hyperparameters. In view of the limited scale of the dataset in this study, in order to effectively improve the generalization ability of the model and reduce the risk of overfitting, we deeply embed the grid search cross-validation method into the above machine learning algorithm framework. By systematically traversing the hyperparameter combination space and using cross-validation to evaluate the performance of each combination for multiple rounds, a more robust model evaluation system is constructed while fully mining the data feature information, so as to obtain the optimal model configuration with high fitting degree and strong stability.

Study Endpoint

The endpoint of the study was AKI during hospitalization, and the change in renal function at admission and serum creatinine level after admission was comprehensively evaluated according to the glomerular filtration rate, and the estimated Glomerular Filtration Rate (eGFR) was estimated according to the Modification of Diet in Renal Disease (MDRD) study equation at the time of admission calculated according to the first serum creatinine level and age, and the calculation formula was as follows:[23]

$$eGFR\ [mL/(min*1.73m2)] = 186*\ (SCr)^{-1.154}*\ (age)^{-0.23}$$

The definition of AKI is based on serum creatinine (SCr) criteria for the overall outcome of kidney disease improvement (KDIGO).[24,25] Due to difficulties in urine output statistics in clinical work. Therefore, the diagnostic criteria for this article are: SCr elevation ≥0.3 mg/dL or SCr ≥26.5 mmol/L within 48 hours; 2.7 days of known or presumed SCr elevation ≥1.5 times baseline. where the baseline SCr value is defined as the last SCr value detected closest to the day of surgery within one week prior to undergoing extracorporeal cardiac surgery.

Statistical Analysis

The collected data was standardized, normalized, outliers were eliminated, and the KNN algorithm (n = 5) was used to fill in the gaps. Encode and transform different types of data to make them suitable for machine learning algorithm input requirements. The study cohort consisted of 520 patients, including a heterogeneous sample of AKI and non-AKI patients, with AKI patients accounting for only 25.96% of the entire cohort and non-AKI patients accounting for 74.04% of the entire cohort. However, the proportion of these two types is quite different, which may lead to the low prediction accuracy of the prediction model, so to solve the problem of classification imbalance, we use the Synthetic Minority Oversampling Technique (SMOTE).[26,27] The SMOTE method is an effective tool to solve the problem of uneven data distribution, which preprocesses the data in the training queue before constructing the model.

In the research related to heart bypass surgery conducted at our hospital, there are two main types of surgery, namely stop-skip bypass and non-stop skip bypass. Stop-skip surgery requires the help of cardiopulmonary bypass equipment to temporarily stop the heart beating during the operation, creating a relatively static and bloodless clear vision for the surgical operation, which is conducive to the fine vascular anastomosis operation. However, during this process, cardiopulmonary bypass may trigger a systemic inflammatory response that affects hemodynamic stability, which in turn has a potential adverse effect on renal perfusion.

Non-stop bypass surgery avoids the use of cardiopulmonary bypass and completes the vascular bypass in the state of continuous beating of the heart. This procedure minimizes the risk of complications associated with cardiopulmonary bypass, but requires high skill and experience from the surgeon, who needs to accurately complete the vascular anastomosis with limited operating space and heart beating interference.

In terms of anesthesia, our hospital uses mask oxygen induction anesthesia for heart bypass surgery. Before the surgery begins, the patient is inhaled with a high concentration of oxygen through a mask to maximize the body's oxygen reserves. Subsequently, the appropriate dose of anesthetic drug is slowly administered to gradually bring the patient into anesthesia. This induction anesthesia method can ensure that the patient can receive the operation smoothly in a painless and unconscious state, while maintaining the stability of important physiological functions such as breathing and circulation. Good anesthesia effect is essential for maintaining intraoperative hemodynamic stability, which is directly related to the blood perfusion of the kidneys, and is closely related to the occurrence and development of acute kidney injury after cardiac bypass surgery. The subsequent construction of the machine learning model for acute kidney injury after cardiac bypass surgery will fully consider the potential impact of these two surgical methods and the unified anesthesia method, and dig deep into the data characteristics and rules to improve the accuracy and reliability of the model prediction.

Importance rankings for all variables were obtained by the SHapley Additive exPlanation (SHAP) method. SHAP can interpret the output of any machine learning model. Taking its name from SHapley additive interpretation and inspired by cooperative game theory, SHAP constructs an additive explanation model in which all features are considered contributors. SHAP provides a solid theoretical foundation for achieving local and global interpretability. The advantage of the SHAP value is that it not only gives us a SHAP value to assess the importance of the feature but it also shows us the positive or negative impact of the impact.[27,28]

SPSS 26.0 was used for data analysis in this study; Use Python (version 3.9.11, Python Software Foundation, Chicago, USA). Normally distributed measurement data are expressed as mean (standard deviation). Frequency and percentage were used for categorical variables, chi-square test or Fisher's exact test was used for differences between groups, median and interquartile range (IQR) was used for continuous variables, and differences between groups were determined using the Mann–Whitney *U*-test.

Results

Baseline Characteristics

After applying the inclusion and exclusion criteria, 520 patients with heart bypass were extracted from the database, and entered the final analysis. The incidence of AKI after heart bypass surgery was 25.96%, there was no difference in the proportion of men and women in the AKI group and non-acute kidney injury (Non-AKI) group (p = 0.90), and the median age of the AKI group was (66.09 ± 8.15) There was a statistically significant difference in median age between the non-AKI group and the non-AKI group (64.32 ± 7.76) (p = 0.025). Other baseline characteristics of the patient are shown in Table 1.

Feature Selection for Models

In the feature screening phase, we employed the Least Absolute Shrinkage and Selection Operator (LASSO) binary logistic regression model—an approach that not only filters out non-significant features but also mitigates overfitting. To determine the optimal model parameters, we conducted 10-fold cross-validation, which ultimately enabled the selection of 31 key variables (Figure 1). The 31 variables including: Age, Alcohol, Hypertension, Pulmonary Hypertension, Atrial

Table 1 Baseline Characteristics

	AKI (n = 135)	Non-AKI (n = 385)	P-value
Demographic:			
Age	66.09 ± 8.15	64.32 ± 7.76	0.025
Alcohol	44 (32.59%)	156 (40.52%)	0.104
Comorbidities:			
Hypertension	91 (67.41%)	238 (61.82%)	0.247
Pulmonary Hypertension	22 (16.30%)	18 (4.68%)	< 0.001
Atrial Fibrillation	8 (5.9%)	0 (0%)	< 0.001
Laboratory results:			
GGT	40.79 ± 47.45	32.26 ± 33.88	0.025
Albumin	40.38 ± 4.56	42.32 ± 3.73	< 0.001
Albumin/Globulin Ratio	1.57 ± 0.30	1.67 ± 0.32	0.003
eGFR	98.89 ± 23.14	108.59 ± 17.11	< 0.001
Sodium	140.11 ± 3.06	140.47 ± 2.56	0.179
HbA1c	7.05 ± 1.74	6.60 ± 1.21	0.001
MCHC	326.43 ± 10.28	328.75 ± 10.57	0.028
Percentage of Eosinophils	2.38 ± 3.35	2.07 ± 1.62	0.301
Calcium	2.23 ± 0.12	2.26 ± 0.11	0.003
Preoperative Medication:			
Hypoglycemic Drug	44 (32.59%)	75 (19.48%)	0.002
Insulin	22 (16.30%)	28 (7.27%)	0.002
Beta-Blocker	111 (82.22%)	311 (80.78%)	0.712
Intraoperative variables:			
Combined Surgery	18 (13.33%)	9 (2.34%)	< 0.001
DOS	343.27 ± 87.72	323.56 ± 65.91	0.007
IOUO	1299.52 ± 726.13	1558.3 ± 809.59	0.001
DOA	397.96 ± 91.77	369.31 ± 120.22	0.012
Epinephrine	29 (21.48%)	17 (4.42%)	< 0.001
Cell Saver	224.59 ± 235.10	169.10 ± 208.14	0.016
Isoprenaline	6 (4.44%)	1 (0.26%)	< 0.001
Dopamine	13 (9.63%)	12 (3.12%)	0.002
Potassium Chloride	60 (44.44%)	204 (52.99%)	0.088
Atropine	4 (2.96%)	3 (0.78%)	0.058
Palonosetron	45 (33.33%)	96 (24.94%)	0.059

(*Continued*)

https://doi.org/10.2147/CIA.S543303

Table 1 (Continued).

	AKI (n = 135)	Non-AKI (n = 385)	P-value
Mannitol	1 (0.74%)	0 (0%)	0.091
Amiodarone	3 (2.22%)	11 (2.86%)	0.695
DMT	0.74 ± 0.89	0.52 ± 0.65	0.009

Notes: Data are presented as median (interquartile range) or number (%).
Abbreviations: GGT, Gamma-glutamyl transferase; eGFR, estimated Glomerular Filtration Rate; MCHC, Mean Corpuscular Hemoglobin Concentration; DOS, Duration of Surgery; IOUO, Intraoperative Urine Output; DOA, Duration of Anesthesia; DMT, Duration of Minimum Temperature.

Fibrillation, Gamma-glutamyl Transferase (GGT), Albumin, Albumin/Globulin Ratio, eGFR, Sodium, Glycated Hemoglobin A1c (HbA1c), Mean Corpus Mean Corpuscular Hemoglobin Concentration (MCHC), Percentage of Eosinophils, Calcium, Hypoglycemic Drug, Insulin, Beta-Blocker, Combined Surgery, Duration of Surgery (DOS), Intraoperative Urine Output (IOUO), Duration of Anesthesia (DOA), Epinephrine, Cell Saver, Isoprenaline, Dopamine, Potassium Chloride, Atropine, Palonosetron, Mannitol, Amiodarone, and Duration of Minimum Temperature (DMT). Subsequently, based on these 31 key variables (ranked in descending order of importance, with the full list provided for enhanced model interpretability and practical application), we developed a series of machine learning models. These models were constructed using variable subsets of different sizes, specifically incorporating the top 5, 10, 15, 20, 25, and all 31 key variables, to evaluate the impact of variable quantity on model performance.

Machine Learning Models in the Training Cohort

We developed six machine learning algorithms: LR, Softmax Regression, RF, LightGBM, XGBoost, and SVM. Based on the importance ranking of the 31 key variables screened by LASSO regression, we sequentially adopted the top 5, top 10, top 15, top 20, top 25 variables, and all 31 variables. By gradually increasing the number of included variables, we divided the variables of different quantities into 6 groups and input them into the 6 machine learning algorithms, respectively, to construct different machine learning models. The amount of data in this paper is small, and the generalization ability and accuracy of the model are often difficult to guarantee. In order to improve the calculation accuracy of the model, you can add grid search cross-validation to the selected algorithm. This approach, which combines the advantages of grid search and cross-validation, can effectively optimize the hyperparameters of the model, thereby improving the performance of the model under limited data. The machine learning models using the first 5 important features in the training cohort were as follows: the AUC of the LR model was 0.79 (95% CI: 0.75, 0.83), and the AUC of the Softmax model was 0.79 (95% CI: 0.75, 0.83), the AUC of the RF model was 0.88 (95% CI: 0.85, 0.91), and the AUC of the LightGBM model was 0.88 (95% CI: 0.85, 0.90). The AUC of XGBoost model was 0.89 (95% CI: 0.86, 0.91), and that of SVM model was 0.82 (95% CI: 0.78, 0.85). All machine learning models performed the best in the training cohort with XGBoost, while the LR model and Softmax model performed the worst. We gradually increase the number of included variables to develop different machine learning models. The ROC curve shows the ROC curve for each model in the training cohort (Figure 2). The performance of all models is shown in the training cohort as the number of variables increases.

Machine Learning Models in the Validation Cohort

Validation was carried out in a validation cohort of 156 cases, and in all developed machine learning models, the AUC performance of each dataset was synthesized, and the model performance was closely related to the characteristics of the dataset. LR and Softmax performed best on most datasets due to their stable and high AUC values, and the AUC of the LR model for the first five variables (LR-5) was 0.79 (95% CI: 0.70–0.87). The LR model for the first 10 variables (LR-10) had an AUC of 0.81, (95% CI: 0.74–0.88); For the LR model of the first 15 variables (LR-15), the AUC was 0.86, (95% CI: 0.79–0.92); The LR model for the first 20 variables (LR-20) had an AUC of 0.84, (95% CI: 0.77–0.90); The LR

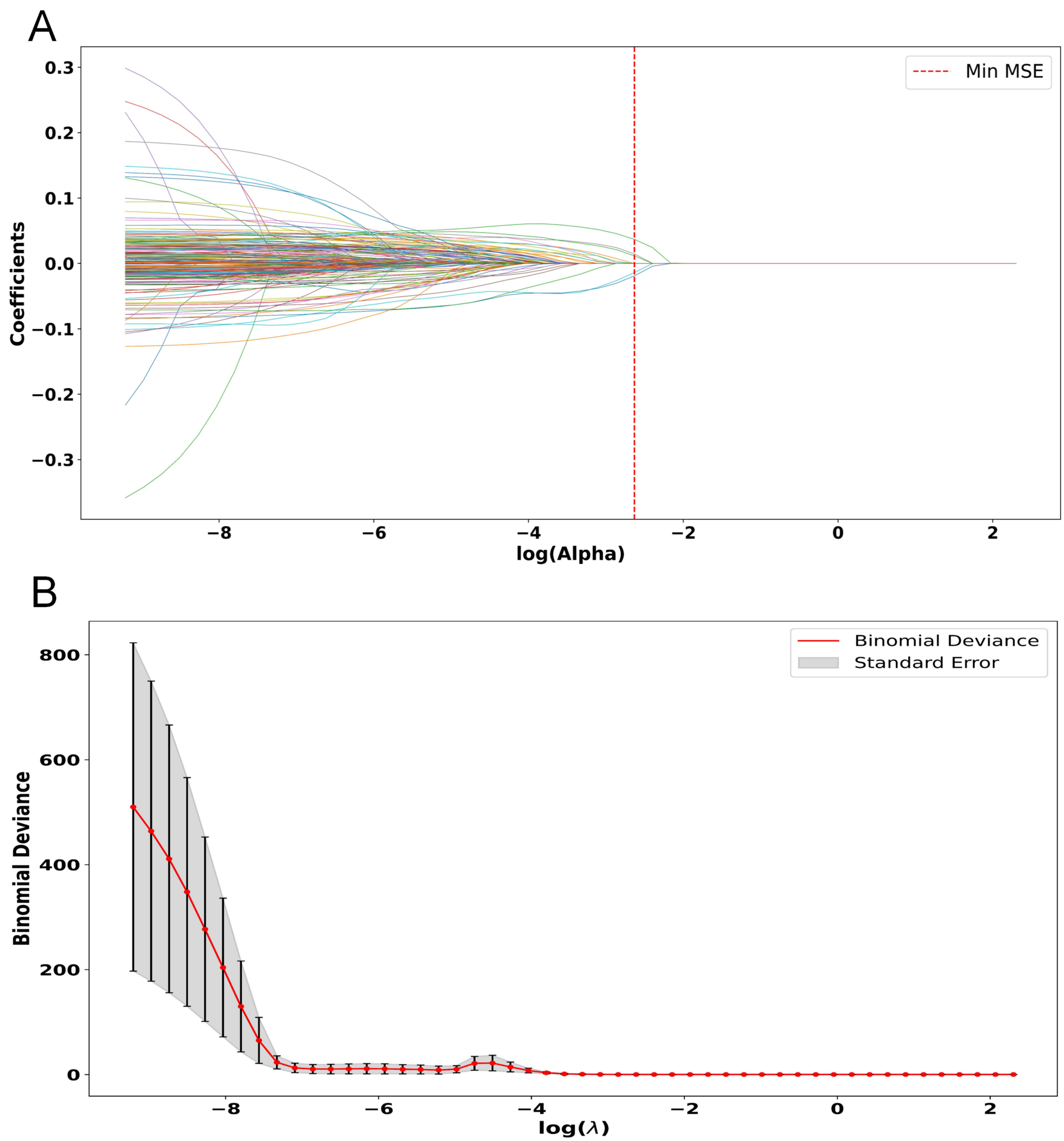

Figure 1 The result of LASSO regression. (**A**) LASSO coefficient curves for 194 risk factors. (**B**) LASSO coefficient path plot. Selected 31 risk factors with the help of LASSO regression analysis.

model for the first 25 variables (LR-25) had an AUC of 0.82, (95% CI: 0.74–0.89); The LR model for the first 31 variables (LR-31) had an AUC of 0.82, (95% CI: 0.74–0.88). The Softmax model for the first five variables (Softmax-5) had an AUC of 0.79 (95% CI: 0.70–0.87); The Softmax model for the first 10 variables (Softmax-10) had an AUC of 0.81 (95% CI: 0.74–0.88); The Softmax model for the first 15 variables (Softmax-15) had an AUC of 0.86, (95% CI: 0.79–0.92); The Softmax model for the first 20 variables (Softmax-20) had an AUC of 0.84 (95% CI: 0.77–0.90); The Softmax model for the first 25 variables (Softmax-25) had an AUC of 0.82 (95% CI: 0.74–0.88); The Softmax model for the first 31 variables (Softmax-31) had an AUC of 0.82 (95% CI: 0.74–0.88). The SVM was the worst-performing

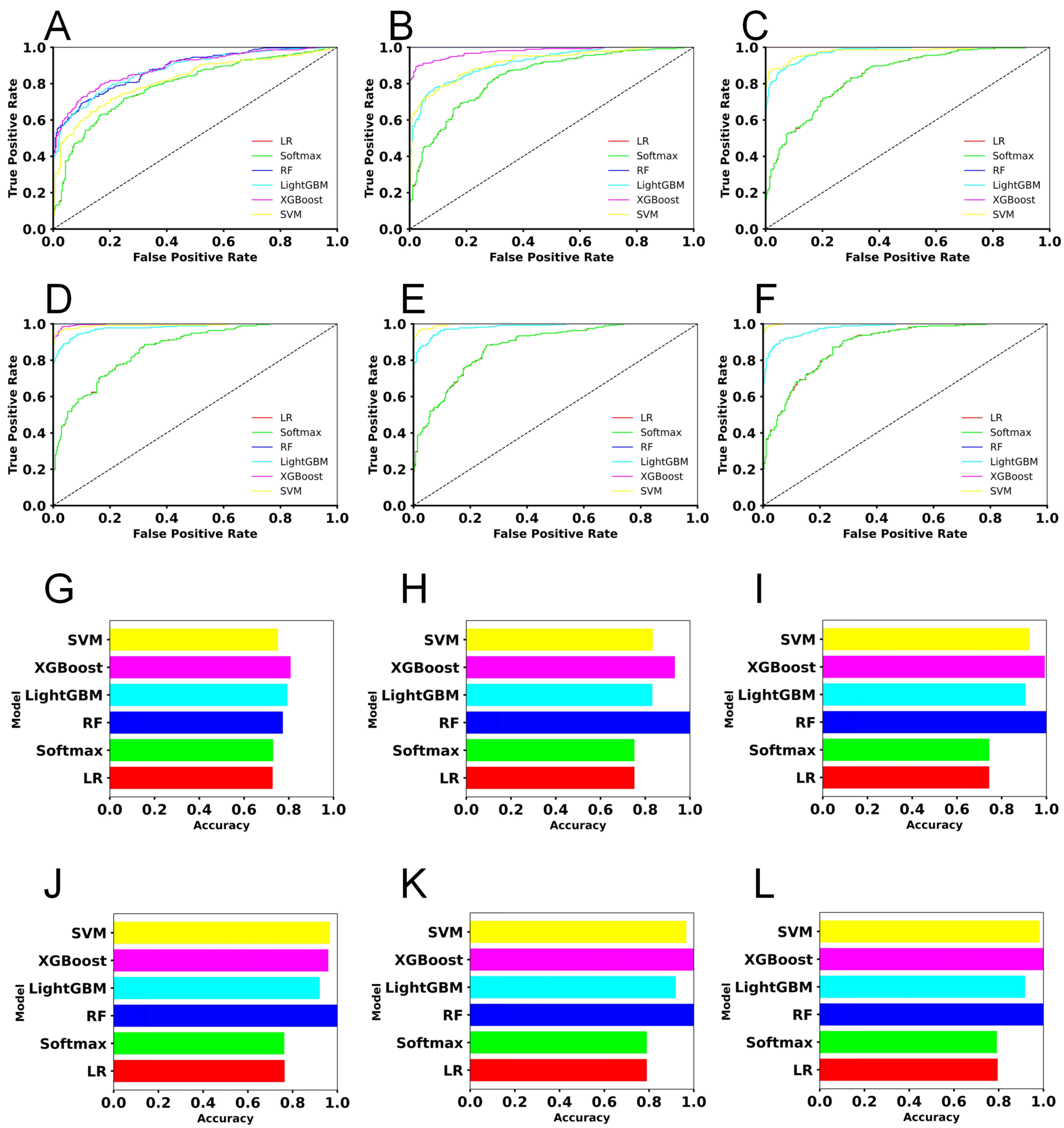

Figure 2 The ROC curves for machine learning models and the performances of all models in test cohort. The X-axis in 2G-2L represents the AUC values of each model. Top 5 variables (**A** and **G**); top 10 variables (**B** and **H**); top 15 variables (**C** and **I**); top 20 variables (**D** and **J**); top 25 variables (**E** and **K**); top 31 variables (**F** and **L**).

algorithm due to its low and gradually decreasing AUC value, and the SVM model for the first five variables (SVM-5) with AUC of 0.79, (95% CI: 0.67–0.86), SVM model for the first 10 variables (SVM-10), AUC 0.77, (95% CI: 0.69–0.85), SVM model for the first 15 variables (SVM-15), AUC 0.69, (95% CI: 0.59–0.78), SVM model for the first 20 variables (SVM-20), AUC of 0.69, (95% CI: 0.58–0.78), AUC of 0.69 (95% CI: 0.0.59–0.79) for SVM model for the first 25 variables (SVM-25), AUC 0.65 (95% CI: 0.55–0.75) for SVM model for the first 31 variables (SVM-31). Random forest stood out in the first 25 and 31 variables of the dataset, with AUC of 0.80 (95% CI: 0.72–0.87) and 0.81 (95% CI: 0.72–0.88), showing good adaptability to complex feature interactions; LightGBM and XGBoost have potential, but their performance fluctuates greatly. ROC curves for each model are shown (Figure 3). The performance of all models is shown in the validation queue. At the same time, as the number of variables increases, a dynamic plot of the area under the ROC curve for all machine learning models in the cohort is validated (Figure 4) and the dynamic plot of the area under the ROC curve of all machine learning models in the training cohort (Figure 4).

Feature Importance

To enhance the interpretability of the model's results, we employed the SHAP algorithm. It explains the model's output, identifies features with significant predictive impacts, and visually shows features' positive/negative impacts. Further, we

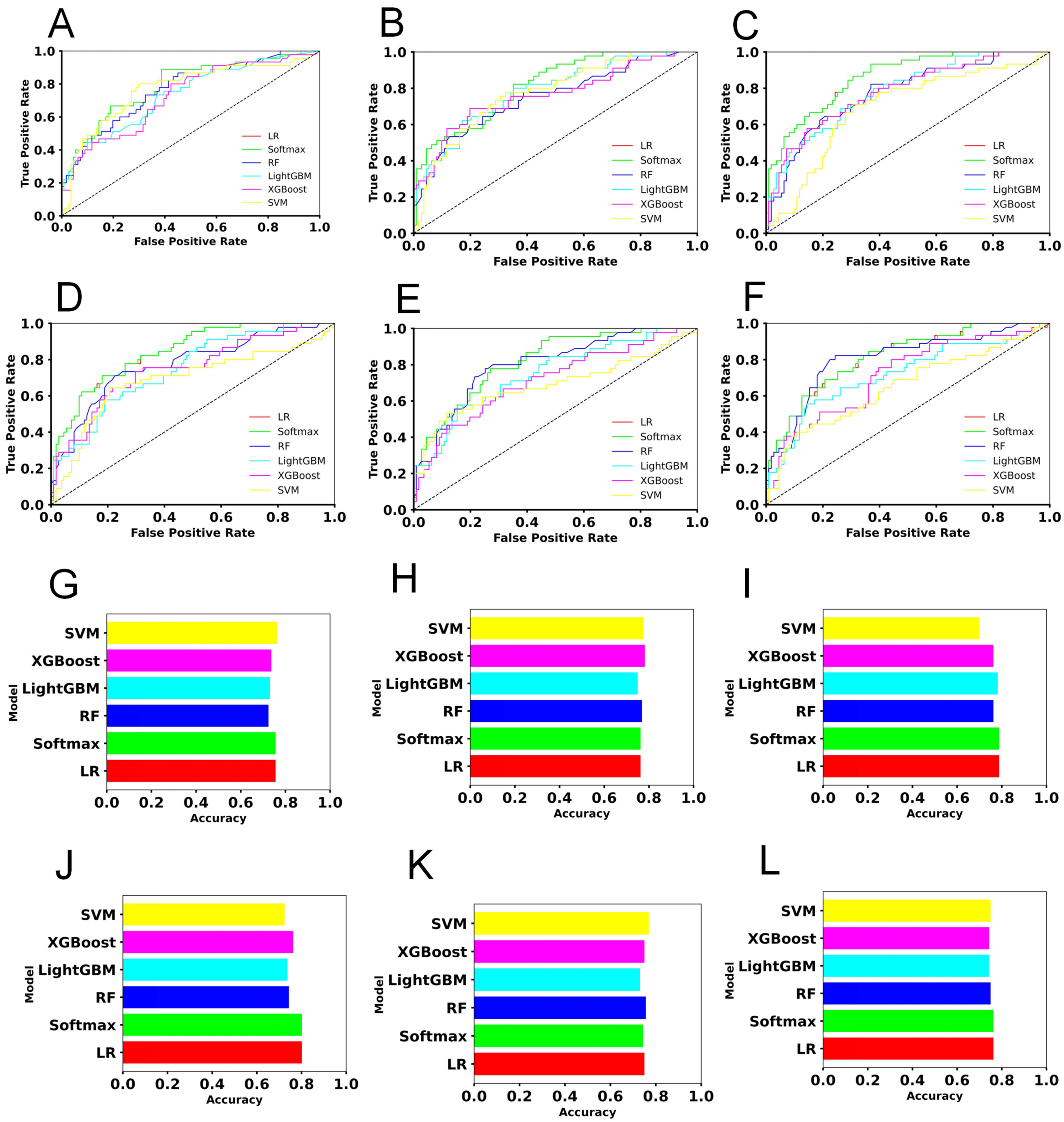

Figure 3 The ROC curves for machine learning models and the performances of all models in validation cohort. The X-axis in 3G-3L represents the AUC values of each model. Top 5 variables (**A** and **G**); top 10 variables (**B** and **H**); top 15 variables (**C** and **I**); top 20 variables (**D** and **J**); top 25 variables (**E** and **K**); top 31 variables (**F** and **L**).

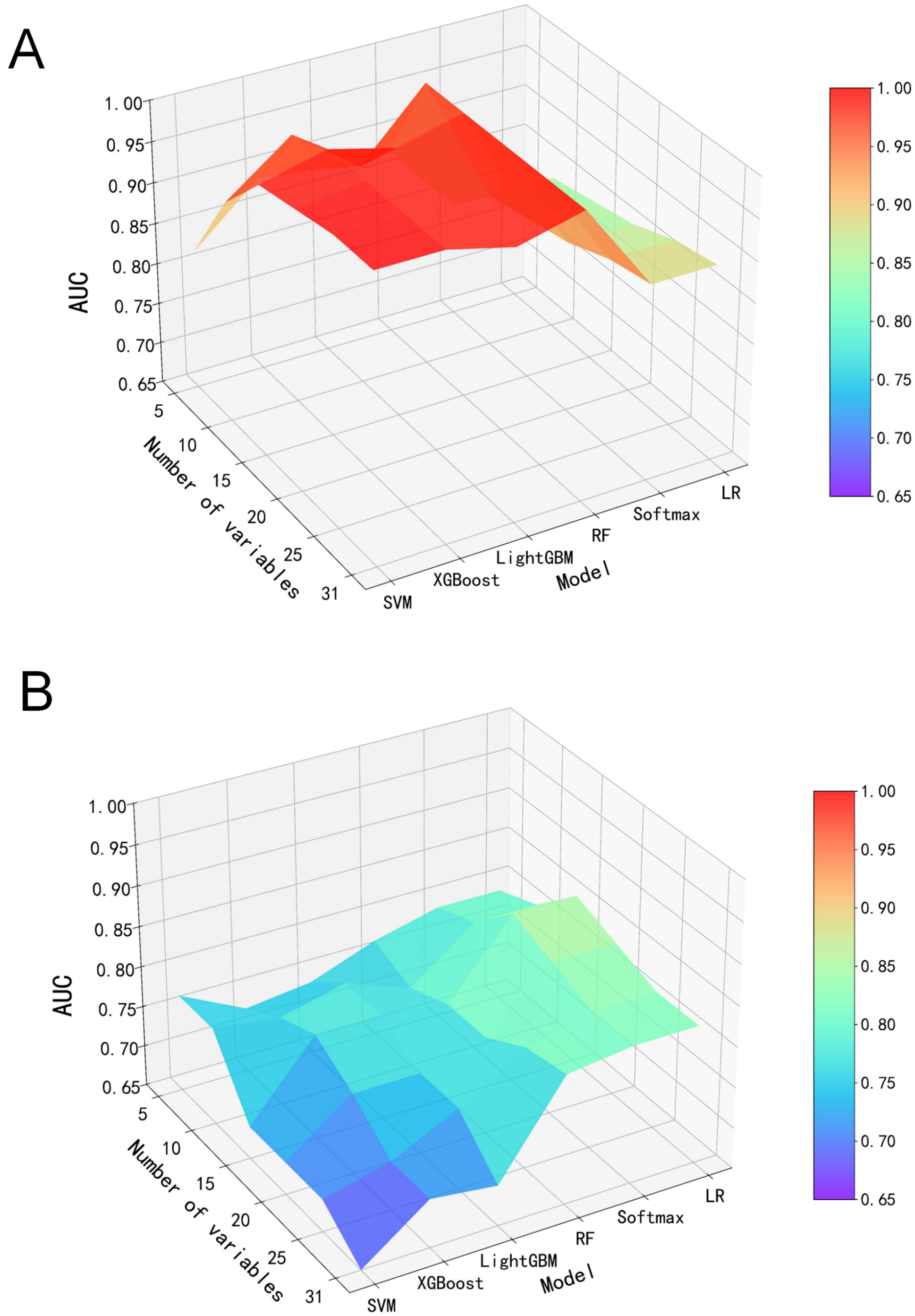

Figure 4 Dynamic plot of the area under the ROC curve for all machine learning models; training cohort (**A**); validation cohort (**B**). The x-axis represents the number of variables included in the model, the y-axis represents different kinds of models, and the z-axis represents the AUC values of each model.

utilize the SHAP algorithm to plot variable correlation graphs (as shown in Figure 5).[29] These charts include single-sample feature influence plots, feature distribution heat maps in the context of sample clustering, feature importance histograms, and feature density scatter plots. The SHAP value is used to measure the importance of a feature, and its algorithm relies on the XGBoost classification algorithm and provides an intrinsic measure of importance for each feature.[29]

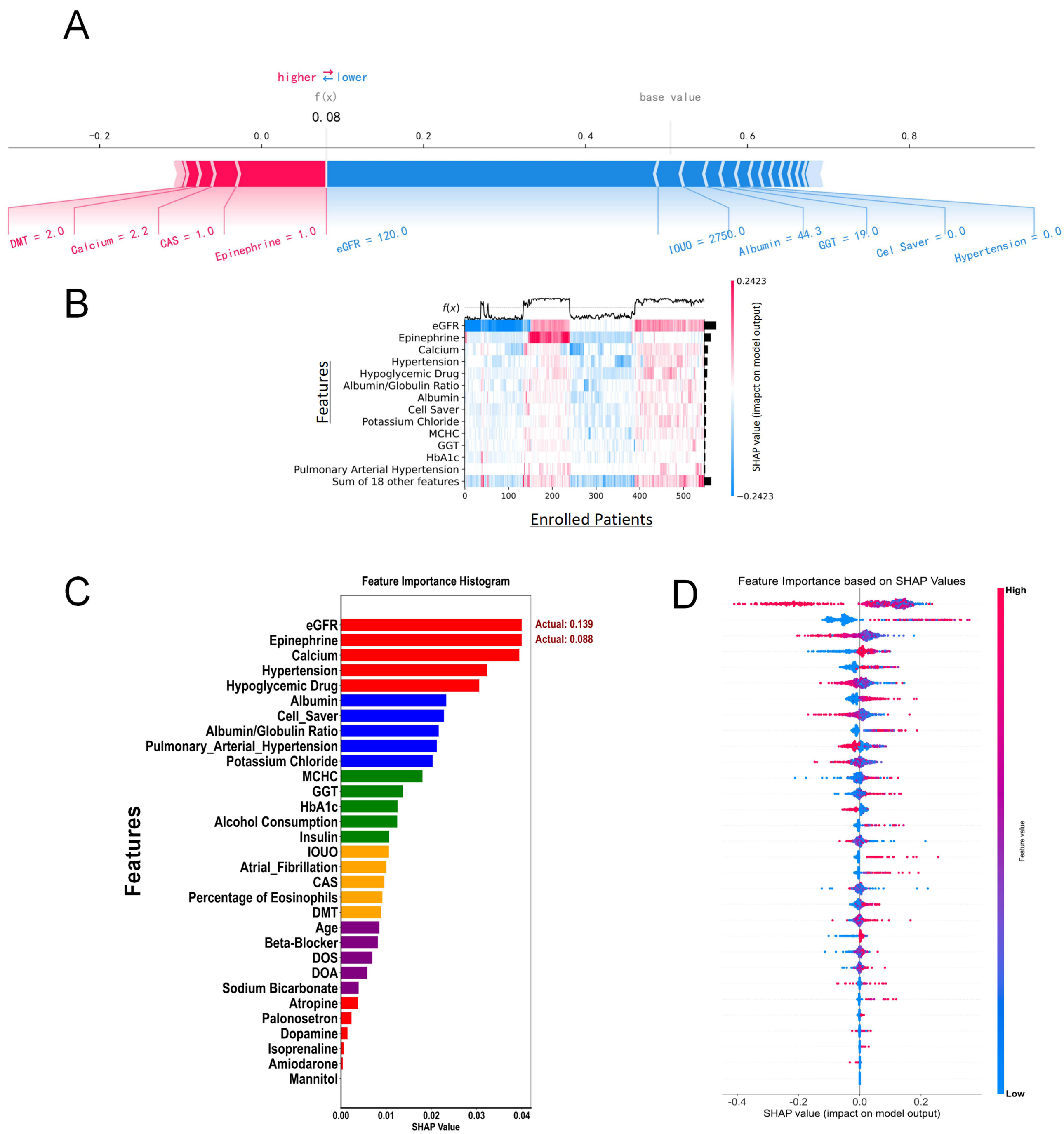

Figure 5 Single-sample feature impact map (**A**) heat map of feature distribution under sample clustering (**B**) histogram of feature importance (**C**) scatter plot of feature density (**D**).

Discussion

In this study, a prediction model for AKI after CABG was successfully developed based on machine learning algorithms. Through comprehensive analysis of preoperative and intraoperative data from 520 patients, LASSO regression was used for feature selection, combined with SHAP algorithm to interpret model output, and finally a variety of machine learning models including LR, Softmax, RF, LightGBM, XGBoost and SVM were constructed and validated. These models have demonstrated good feasibility and utility in predicting AKI after CABG.

AKI is a syndrome of sudden loss of renal excretion, usually accompanied by oliguria, that lasts from hours to days.[30] The pathogenesis is complex, involving multiple factors such as ischemia-reperfusion injury, surgical trauma, inflammation, and oxidation.[31,32] CHD is one of the manifestations of coronary systemic atherosclerosis, many patients with CHD also have renovascular disease, and hemodynamic instability and hypoperfusion syndrome reduce renal perfusion, increasing the risk of prerenal AKI, which may progress to nephrogenic AKI if left untreated.[33] Despite advances in renal replacement therapy, AKI is associated with poor outcomes and significantly affects surgical mortality, intensive care unit resources, and length of hospital stay.[34] Currently, there is a lack of widely accepted prediction models for AKI after cardiac surgery in China.

Traditional risk scoring models (such as Cardiac postoperative Argi score,[35] Cleveland Clinic score,[36] Mehta score,[37] simplified renal index score,[38] etc). It has been tried in clinical practice to predict the risk of AKI after cardiac surgery, but these models do not perform well in terms of discriminant power and correction effect, and lack sufficient convincing and broad applicability. Therefore, it is urgent to develop a risk prediction model for postoperative cardiac AKI that is suitable for clinical practice and has efficient predictive performance.

With the continuous progress of medical informatics, machine learning, as an important branch of artificial intelligence, has gradually become a promising tool in the field of clinical predictive models.[39,40] Although prediction models based on traditional statistics have been widely reported, machine learning models specifically for AKI after CABG have yet to be developed. Traditional statistical methods usually first establish the key relationships between variables and specific outcomes, and then link these variables by generating equations or functions, which makes prediction models based on traditional statistics highly interpretable. In contrast, machine learning methods assume that there is some meaningful relationship between the independent and dependent variables, and directly look for the path that best connects the two variables. Due to the natural advantage of machine learning algorithms in capturing nonlinear relationships, some cardiac surgeons are advocating the use of new machine learning-based models to predict AKI associated with cardiac surgery as an alternative to traditional clinical scoring tools.[41] However, the algorithms produced by machine learning methods often have varying degrees of opacity and are often referred to as "black boxes", which makes the model difficult to interpret and hinders the widespread application of machine learning in clinical practice to a certain extent.

In this study, six machine learning algorithms that excel in structured data classification tasks are selected, including XGBoost, LR, LightGBM, RF, Softmax, and SVM. As an ensemble learning technology, XGBoost is known for its high accuracy and fast processing capabilities, especially in high-dimensional data and missing values. The LR model facilitates the understanding of the model decision-making process due to its excellent interpretability. As an efficient linear model, LightGBM performs strongly in binary classification scenarios, and its storage efficiency is better than XGBoost, making it more advantageous in processing large datasets. RF is also an important approach in the field of ensemble learning, which is highly adaptable to high-dimensional data and missing values. Softmax is a generalized linear regression model for multi-categorical problems, which can convert the predictions of multiple categories into a form of probability distribution, which is well interpretable and logical for easy understanding and analysis. As a supervised learning algorithm, SVM has strong classification ability by finding the optimal hyperplane to separate data, especially when processing high-dimensional data, and can also effectively process nonlinear data through kernel techniques. These algorithms have been extensively validated in many practical applications, and although there are other algorithms to choose from, these six algorithms are ideal for building predictive models in this study due to their excellent performance and reliability.

In this study, we first applied the LASSO regression model to simplify 194 sets of clinical data. Subsequently, we determined the optimal parameters of the model through 10-fold cross-validation, and based on this, further screened out 31 key features with non-zero coefficients. This feature selection process not only helps machine learning models effectively eliminate invalid variables but also accurately captures the correlation between features and clinical outcomes, thereby significantly improving the predictive performance of the model. Moreover, the value of this method is not limited to model optimization, it also provides a new perspective for research on disease mechanisms, assisting clinicians in gaining a deeper understanding of the dynamic changes in patients' conditions. LASSO regression is a penalty term-based variable selection method that reduces model complexity and improves prediction accuracy by compressing the coefficients of non-significant variables to filter features.[35] It performs both variable selection and complexity regularization when fitting generalized linear models, and is suitable for modeling and prediction of continuous, binary or multivariate discrete variables.[39] In addition, LASSO regression can effectively avoid overfitting by adjusting parameters to control model complexity.[40]

Although LASSO regression can screen for characteristic variables, it cannot directly calculate the effect of characteristic variables on predicting clinical outcomes.[39] The SHAP algorithm, on the other hand, explains its contribution to the model prediction by calculating the SHapley value of each eigenvariable, thereby revealing how the eigenvariable affects the prediction outcome.[41] In this study, the SHAP algorithm was used to analyze the key factors influencing the prediction of CAS-AKI by the prediction model, and it was found that eGFR, intraoperative epinephrine application, calcium ion, history of hypertension, and preoperative glucose-lowering drug use were the top five important variables. Several studies have confirmed that preoperative eGFR is an independent risk factor for AKI after CABG surgery.[6,42,43] Charat et al listed eGFR as an important risk factor for predicting AKI after cardiac surgery in their Machine learning model.[44] In this study, the eGFR value of the AKI group was 98.89 ± 23.14, while the eGFR of the non-AKI group was 108.59 ± 17.11, which was significantly different ($p < 0.001$). This highlights the importance of close preoperative monitoring of eGFR for the prevention of postoperative AKI in patients undergoing cardiopulmonary bypass cardiac surgery.[45–47] In addition, the SHAP algorithm also showed that the longer the duration of anesthesia, the more common postoperative AKI became. This may be because prolonged duration of general anesthesia can lead to poor blood supply to the kidneys, which increases the risk of impaired kidney function. Zhang et al also found that the risk of postoperative AKI increased significantly with prolonged anesthesia and decreased intraoperative urine output during liver transplantation.[48] This suggests that prolonged anesthesia and increased anesthetic medication may prolong renal artery constriction, which in turn exacerbates renal injury leading to AKI. However, the specific effect of anesthesia timing and intraoperative urine output on other procedure-related AKI requires further study.

One of the great strengths of this study is that the use of SHAP values unravels the "black box" of machine learning models. Although traditional risk scoring models have identified risk factors such as preoperative HGB, preoperative renal function, age, duration of surgery, left ventricular ejection fraction, body mass index, and hypertension,[36–38,49–52] insufficient attention has been paid to important intraoperative factors such as intraoperative urine output, intravenous fluid volume, blood product transfusion, and dynamic changes in hemodynamic features. Notably, pulmonary hypertension (PAH) is listed as a risk factor, PAH is an important risk factor for AKI after transcatheter aortic valve implantation,[53] and is strongly associated with right heart function,[54] and right heart failure has been reported to be associated with severe AKI after cardiac surgery,[55] with PAH being one of the top five risk factors, providing a new perspective for clinical decision-making. And in our study, in addition to some traditional risk factors (such as diabetes, etc.), we also screened a number of intraoperative related risk factors (such as intraoperative urine output, intraoperative epinephrine application, intraoperative mechanical blood transfusion, etc). Hemodynamic changes, blood product transfusion, intraoperative fluid replacement, and intraoperative urine output all reflect acute responses to renal hypoperfusion and corresponding management measures. These factors, combined with the patient's preoperative health condition susceptibility to acute stress and the large intraoperative dynamic physiological response, determine the patient's overall response to surgery. Based on these findings, software can be developed in the future that can identify high-risk patients and thus optimize treatment strategies after cardiac surgery.

The model constructed in this study focuses on the early risk assessment of postoperative AKI in patients undergoing CABG. It can quantitatively predict the risk of AKI in patients based on key preoperative and intraoperative variables before typical clinical manifestations of renal dysfunction appear. The early risk warning capability of the model can provide a reference for the clinical formulation of individualized prevention strategies. It should also be noted that this model still has certain limitations: limited by the scope of variable selection and the model's prediction logic, the current model can only assess the risk of AKI occurrence and cannot further distinguish the specific etiological types of AKI (eg, renal hypoperfusion caused by prerenal factors, renal parenchymal injury induced by intrinsic renal factors, etc). In clinical practice, there are significant differences in treatment protocols for AKI of different etiologies (for example, prerenal AKI requires prioritized improvement of circulatory perfusion, while intrinsic renal AKI may require adjustment of nephrotoxic drug use or targeted intervention for renal parenchymal injury). The lack of this etiology-distinguishing

https://doi.org/10.2147/CIA.S543303

capability may to a certain extent affect the application value of the model in guiding clinical precise treatment. Future studies may consider incorporating more specific variables related to AKI etiology (such as biomarkers like kidney injury molecule-1 and neutrophil gelatinase-associated lipocalin) and optimizing the model structure by combining multi-modal data (eg, imaging examinations, pathological indicators) to improve the model's ability to identify AKI etiologies and further expand its clinical application scenarios.

In the field of risk stratification for patients undergoing coronary artery surgery, several risk models have been developed for identifying high-risk individuals and guiding individualized treatment in patients after CABG, with the PRECISE-HBR score being a typical example.[56] Originally created to address the need for bleeding risk assessment after percutaneous coronary intervention (PCI), this score quantifies the risk of major bleeding events in PCI patients within 1 year using 7 easily accessible clinical indicators, providing a reference for formulating postoperative antiplatelet therapy regimens and monitoring bleeding.[57] Its advantages lie in being developed based on multicenter real-world data and clinical trials (with a derivation cohort of nearly 30,000 patients) and validated in multiple external cohorts, resulting in a large sample size, broad population coverage, higher generalizability and reliability. Additionally, its simplified set of variables eliminates the need for complex testing, making it convenient for clinical use. By contrast, the model constructed in this study for predicting AKI after CABG adopts machine learning algorithms combined with LASSO variable selection. Compared with the linear regression relied on by traditional scoring systems, it can more accurately capture non-linear relationships and interactions between variables, leading to superior predictive performance (eg, in terms of AUC value). However, the current model is based on single-center retrospective data, with limited sample size and population diversity, which may affect its external validity. In the future, we should draw on the development experience of the PRECISE-HBR score to expand the sample size, incorporate multicenter prospective data, supplement AKI-related specific indicators, and improve the model's interpretability. This will allow us to balance predictive accuracy with clinical convenience, ultimately achieving precise assessment of AKI after CABG and facilitating individualized treatment in the future.

The current study has several limitations. Firstly, the sample size is relatively small. This may weaken the statistical power of results and limit the model's generalizability to broader CABG populations. As a retrospective study, it also carries potential selection bias (eg, excluding patients with incomplete records or lost to follow-up, leading to a sample that may not fully represent the overall cohort). Secondly, the machine learning model has weak interpretability and a typical "black box" characteristic: while it can provide accurate risk predictions, its internal logic (eg, how variables interact to affect outcomes or the weight of key factors) remains unclear, which may reduce clinicians' trust in its recommendations and hinder exploration of AKI-related mechanisms. Thirdly, this model is currently unable to distinguish between different etiologies of AKI. Future studies will optimize the model by incorporating etiology-specific variables and multimodal data to enhance its ability to identify AKI etiologies.

Conclusion

The machine learning models constructed in this study can effectively predict post-CABG AKI, facilitating early identification of high-risk patients, which may further support clinicians in formulating personalized perioperative management strategies to reduce the risk of AKI.

Funding

This study was supported by Key Project of Jiangsu Provincial Health Commission (K2024014), Construction Project of High-Level Hospital of Jiangsu Province (GSPJS202404, GSPJS202518), Changzhou High Level Medical Talents Training Project (2022CZBJ054), Postgraduate Practice Innovation Program of Jiangsu Province (SJCX24_0748), Young Talents Program of Wuxi Medical Center to Nanjing Medical University (WMCQ202403), General Projects of Wuxi Medical Center to Nanjing Medical University (WMCG202408), Clinical Research Project of Wuxi Medical Center to Nanjing Medical University (WMCC202505) and Changzhou Talent Program (CQ20240067).

Disclosure

The authors report no conflicts of interest in this work.

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