# Development of a Machine Learning Model for Early Prediction of Perioperative Acute Kidney Injury in Patients with Acute Type A Aortic Dissection

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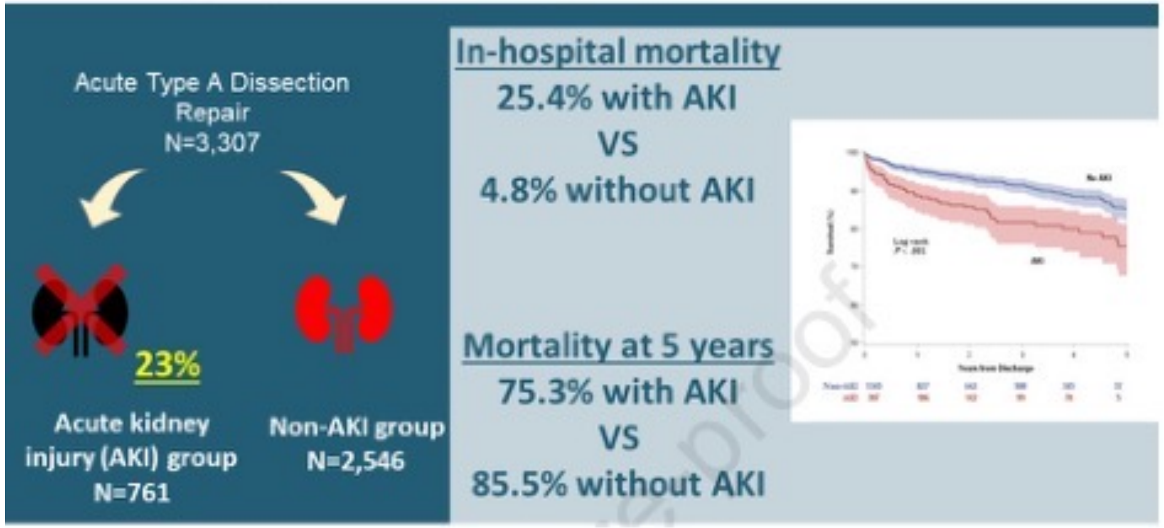
# ATAAD&AKI

IRAD Aortic Dissection




Other single center study post-operative AKI:

**40-55%**

Other cardiac surgery: **CABG：10-20%**

**AVR：17-23%**

**AKI represents a frequent postoperative complication in ATAAD patients, associated with both early and long-term postoperative prognoses.**

Arnaoutakis GJ, *The Annals of Thoracic Surgery*, 2022
Crit Care. 2014; Acta Anaesthesiol Scand. 2016
Interact Cardiovasc Thorac Surg. 2016；J Am Coll Cardiol. 2015

# Research on the Correlates of AKI Following ATAAD Surgery

| | OR (95% CI) | P |
|---|---|---|
| Age ( per 10 years) | 1.30 (1.15-1.48) | <0.001 |
| Male | 1.39 (1.03-1.88) | 0.03 |
| BMI>30kg/m2 | 2.16 (1.51-3.09) | <0.001 |
| History of hypertension | 1.37 (1.04-1.82) | 0.03 |
| eGFR< 60 ml/min/1.73$^2$ | 0.93 (0.68-1.27) | 0.66 |
| Cardiac arrest | 1.80 (0.91-3.63) | 0.09 |
| Preoperative renal malperfusion | 4.39 (2.23-9.07) | <0.001 |
| Other preoperative malperfusion syndrome[a] | 2.10 (1.55-2.86) | <0.001 |

| | | |
|---|---|---|
| Hypertension | 1.61 (1.09-2.36) | .02 |
| Chronic kidney disease | 4.08 (2.61-6.39) | < .001 |
| Diabetes mellitus | 1.58 (1.05-2.39) | .03 |
| Presenting signs | | |
| CVA | 1.34 (0.67-2.67) | .4 |
| Spinal cord ischemia | 3.94 (1.44-10.8) | .008 |
| Lower extremity ischemia | 2.41 (1.63-3.57) | < .001 |
| Distal extent of dissection | | |
| Aortic arch | 0.78 (0.51-1.2) | .26 |
| Abdominal aorta | 1.39 (1.0-1.93) | .049 |
| CPB time | 1.01 (1.01-1.01) | < .001 |

**Risk factors for AKI following ATAAD surgery are intricate and diverse.**

Helgason D, *The Annals of Thoracic Surgery,2020*

Arnaoutakis GJ, *The Annals of Thoracic Surgery*, 2022

# Etiology of Post-operative AKI

- Patients Basic Conditions ( Symptoms、Underlying Disease)
- Involvement of renal arteries (renal perfusion)
- Operation Factors ( CPB time、Aortic-clamp time )

Aortic Dissection Involving Renal Arteries

**Early identification of risk factors and timely intervention can reduce the incidence.**

# Patient Inclusion

**Inclusion Criteria**

Patients with acute Type A aortic dissection who underwent surgery at Fuwai Hospital from January 2014 to December 2019.

**Exclusion Criteria**

**Outcome**

Post-operative AKI

1. Patients who did not undergo surgical intervention.
2. Intraoperative mortality.
3. Lack of preoperative or postoperative serum creatinine values.
4. Preoperative use of Continuous Renal Replacement Therapy (CRRT).

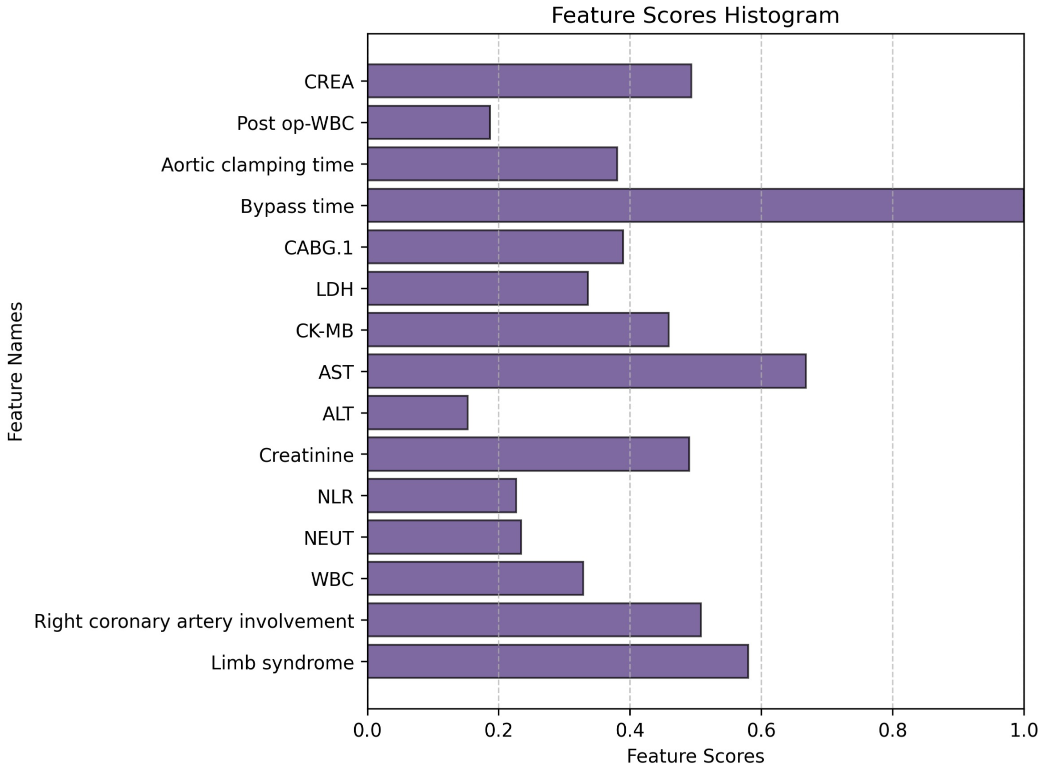
# Baseline Information

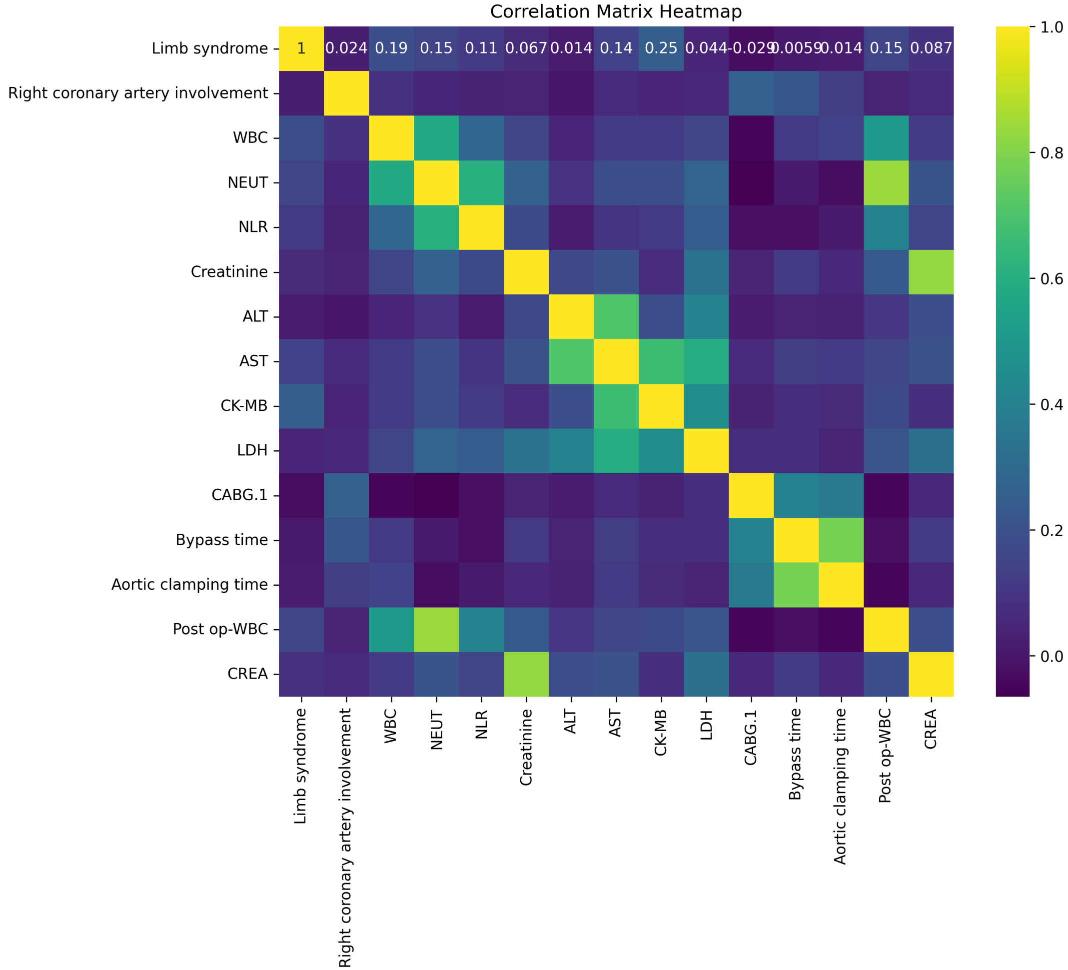
| Characteristic | ML Learning Model | | p-value | Outcome | | p-value |
|---|---|---|---|---|---|---|
| | Training Set N = 512 | Test Set N = 128 | | Non-AKI N=566 | AKI N=74 | |
| Age | 47 ± 10 | 47 ± 11 | 0.859 | 46 ± 10 | 49 ± 11 | 0.055 |
| BMI | 26.1 (24.0, 28.4) | 26.3 (24.0, 28.4) | 0.845 | 26.1 (23.9, 28.4) | 26.7 (24.5, 29.3) | 0.264 |
| Male | 401(78.32%) | 104(81.25%) | 0.467 | 452(79.86%) | 53(71.62%) | 0.102 |
| Hypertension | 437(85.35%) | 100 (78.13%) | 0.047 | 475 (83.92%) | 62 (83.78%) | 0.976 |
| Diabetes | 17 (3.32%) | 3 (2.34%) | 0.778 | 18 (3.18%) | 2 (2.70%) | >0.999 |
| Marfan Syndrome | 41 (8.01%) | 17 (13.28%) | 0.063 | 54 (9.54%) | 4 (5.41%) | 0.244 |
| Smoking History | 223 (43.55%) | 70 (54.69%) | 0.024 | 268 (47.35%) | 25 (33.78%) | 0.028 |
| CAD | 1 (0.20%) | 1 (0.78%) | 0.360 | 1 (0.18%) | 1 (1.35%) | 0.218 |
| Family History of AA or Aortic Dissection | 8 (1.56%) | 1 (0.78%) | 0.696 | 9 (1.59%) | 0 (0.00%) | 0.608 |
| Previous Cardiac Surgery | 16 (3.13%) | 5 (3.91%) | 0.588 | 19 (3.36%) | 2 (2.70%) | >0.999 |
| Debakey-I | 488 (95.31%) | 115 (89.84%) | 0.018 | 532 (93.99%) | 71 (95.95%) | 0.790 |
| Time to Surgery | 53 (33, 96) | 66 (36, 144) | 0.034 | 57 (34, 102) | 46 (31, 82) | 0.027 |

| Characteristic | ML Learning Model | | p-value | Outcome | | p-value |
|---|---|---|---|---|---|---|
| | Training Set N = 512 | Test Set, N = 128 | | Non-AKI N=566 | AKI N=74 | |
| WBC | 11.8 (9.6, 14.6) | 11.2 (8.8, 14.4) | 0.092 | 11.5 (9.4, 14.2) | 13.3 (10.5, 17.8) | 0.002 |
| RBC | 4.40 ± 0.55 | 4.35 ± 0.55 | 0.387 | 4.39 ± 0.54 | 4.37 ± 0.64 | 0.859 |
| NEUT | 1.18 (0.89, 1.57) | 1.19 (0.82, 1.66) | 0.901 | 9.4 (7.4, 12.0) | 11.0 (8.5, 14.9) | 0.002 |
| LYMPH | 1.18 (0.89, 1.57) | 1.19 (0.82, 1.66) | 0.901 | 1.20 (0.89, 1.58) | 1.08 (0.84, 1.60) | 0.140 |
| NLR | 8.2 (5.3, 12.6) | 8.4 (5.2, 11.4) | 0.443 | 8.1 (5.1, 12.3) | 9.4 (7.0, 14.0) | 0.008 |
| CRP | 16 (5, 71) | 26 (8, 86) | 0.151 | 18 (6, 75) | 15 (4, 105) | 0.864 |
| ALT | 20 (13, 33) | 20 (13, 29) | 0.578 | 20 (13, 32) | 22 (14, 42) | 0.045 |
| AST | 21 (15, 31) | 21 (16, 28) | 0.909 | 20 (15, 29) | 28 (19, 50) | <0.001 |
| CKMB | 10 (7, 16) | 11 (7, 15) | 0.854 | 10 (7, 15) | 14 (8, 25) | 0.005 |
| LDH | 193 (161, 240) | 194 (159, 231) | 0.488 | 188 (158, 232) | 224 (185, 312) | <0.001 |
| D-dimer | 6.8 (3.1, 17.4) | 6.4 (2.9, 15.0) | 0.492 | 6.2 (2.9, 16.2) | 12.7 (4.0, 20.0) | 0.004 |
| PLT | 173 (139, 214) | 179 (142, 221) | 0.468 | 173 (143, 210) | 153 (129, 193) | 0.012 |

Result

# Features Selection and Correlations



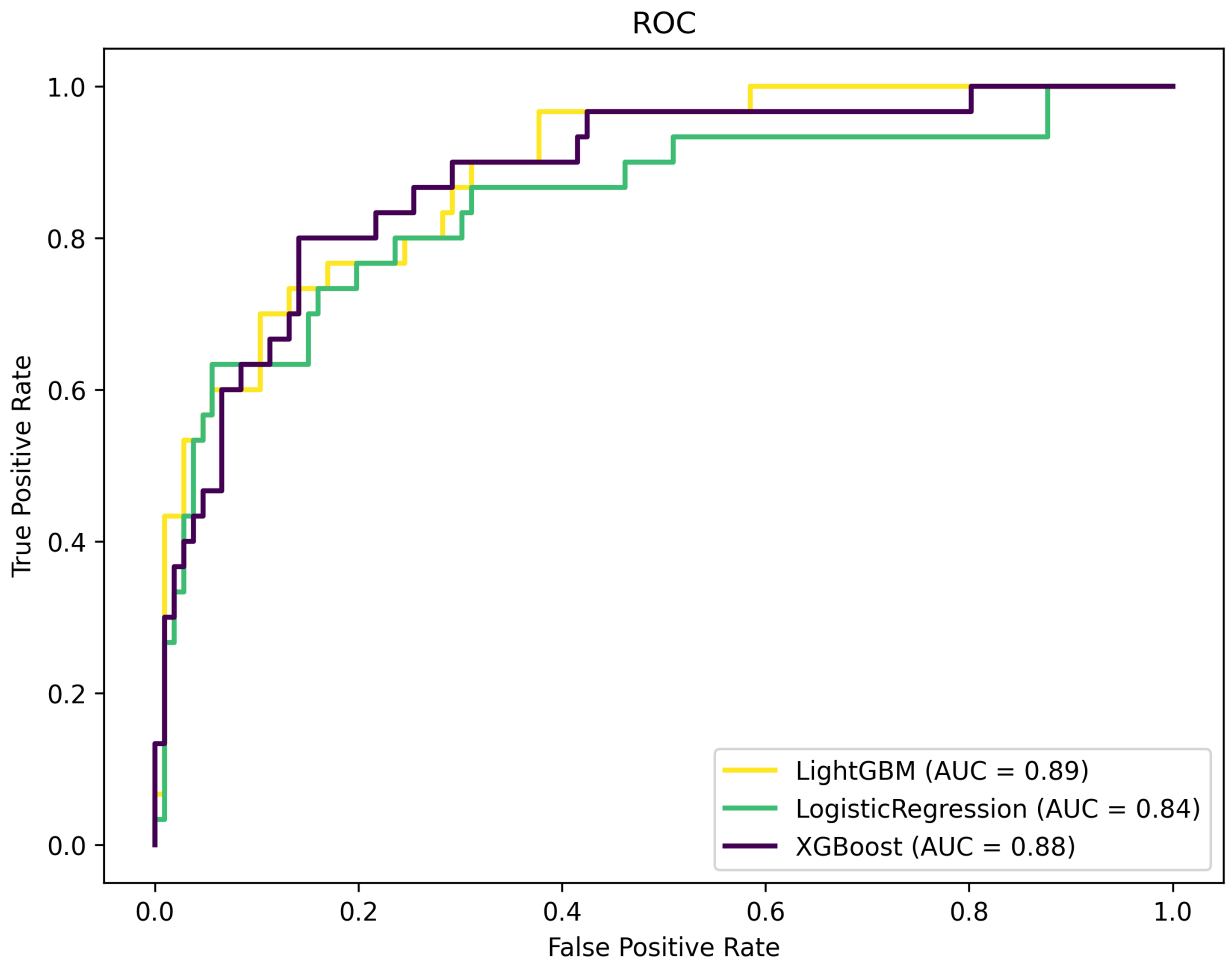




**Extract Features Could be Recognized As Independent Risk Factors**

Result

# Model Evaluation

## ROC Curve



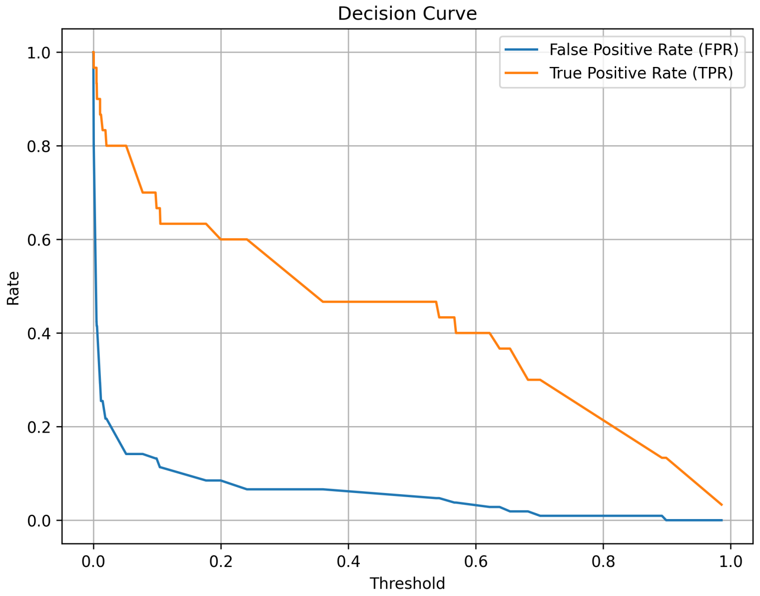

| | AUC | ACC |
|---|---|---|
| LightGBM | **0.8874213836477987** | **0.8676470588235294** |
| LogisticRegression | 0.8433962264150944 | 0.8014705882352942 |
| XGBoost | 0.879245283018868 | 0.8455882352941176 |

**LightGBM>XGBoost>LR**

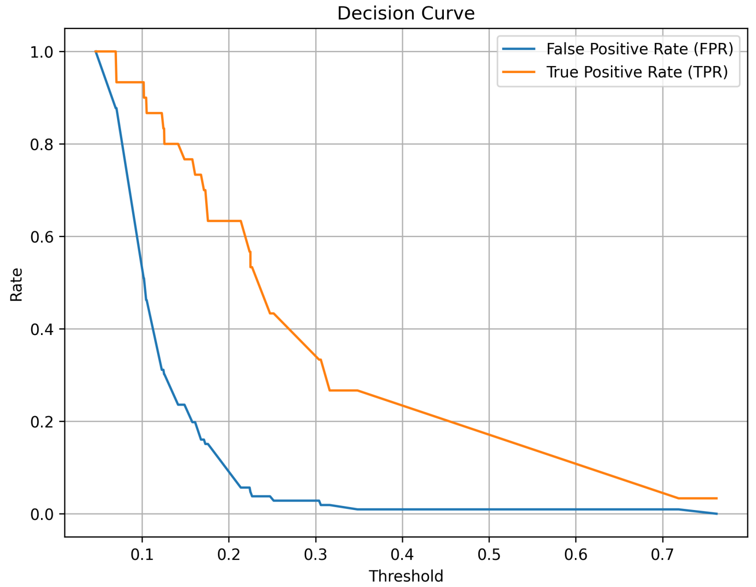
Result

# Model Evaluation

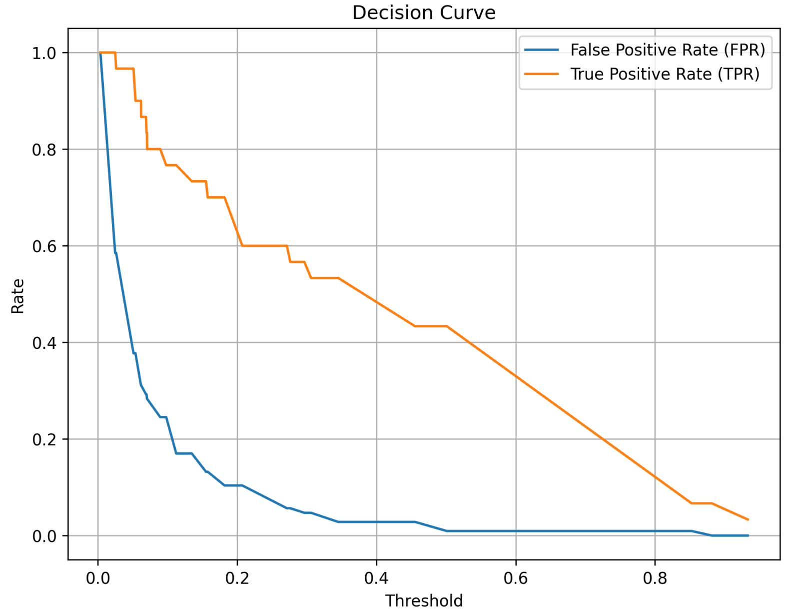
## Decision Curve




XGBoost



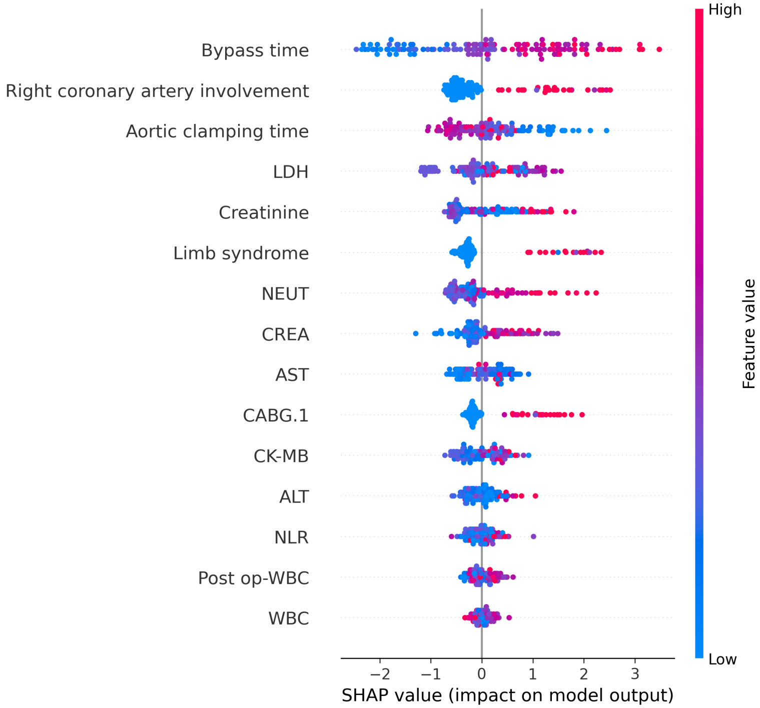

LR



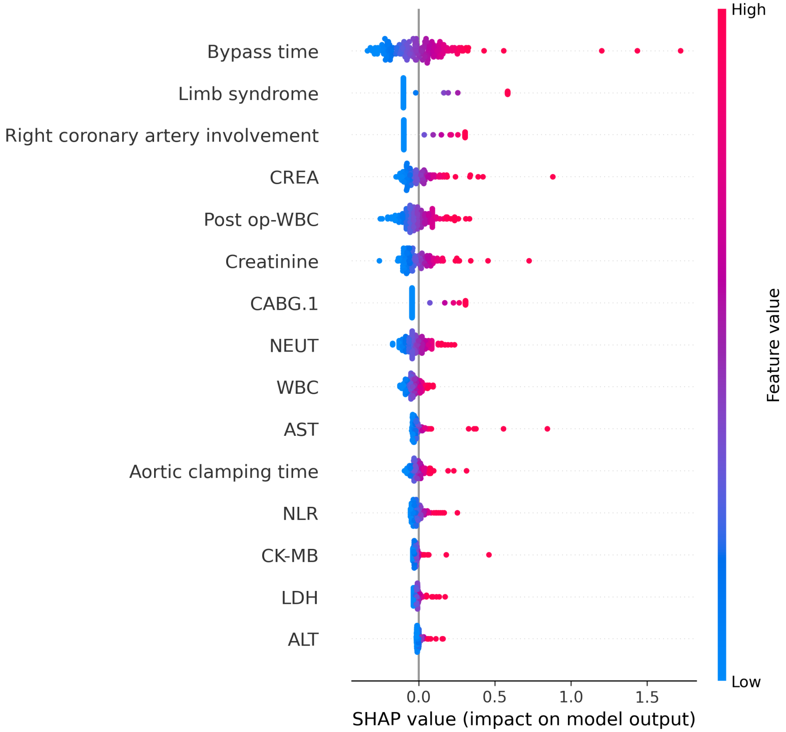

LightGBM

# Model Explanation

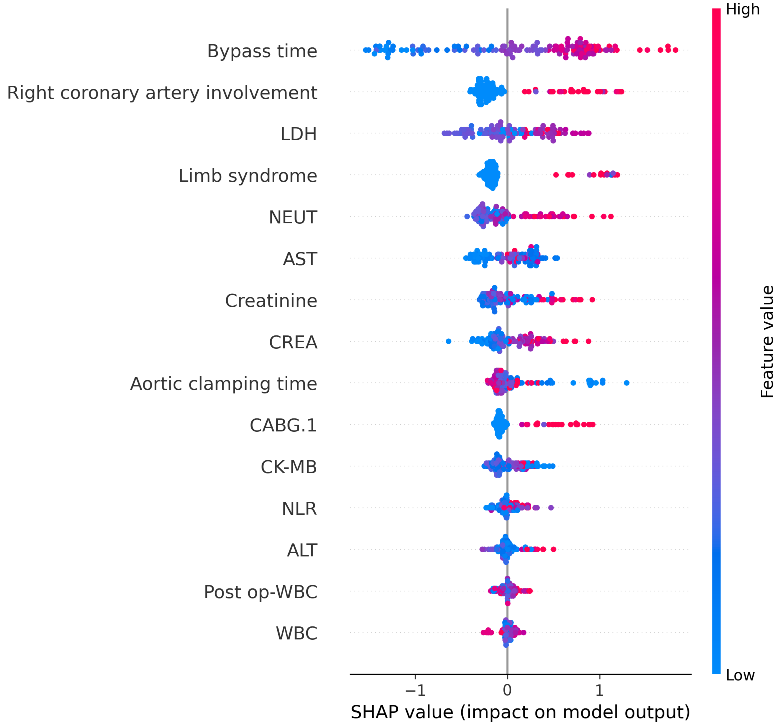
## SHAP




XGBoost




LR




LightGBM

# Conclusion

**Perioperative highly correlated indicators can serve as independent risk factors for postoperative Acute Kidney Injury (AKI) in Acute Type A Aortic Dissection (ATAAD).**

**Machine Learning (ML) models demonstrate superior predictive efficacy compared to traditional methods.**

# Development of a Machine Learning Model for Early Prediction of Perioperative Acute Kidney Injury in Patients with Acute Type A Aortic Dissection

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## Objective

To develop an advanced predictive model for acute kidney injury (AKI) in patients diagnosed with acute type A aortic dissection (ATAAD) by novel machine learning (ML) algorithms to timely intervention and improving prognosis.

## Method

From January 2014 to December 2019, a total of 640 patients diagnosed with ATAAD was enrolled in. The study leveraged the Scikit-learn toolkit and employed one-way analysis of variance (ANOVA) to identify and select pertinent risk factors that exhibited significant associations with the occurrence of AKI. A Synthetic Minority Over-sampling Technique was subsequently employed to address data imbalances. For the construction of the predictive model, a set of ML algorithms, comprising Logistic Regression (LR), XGBoost, and LightGBM, was utilized. The performance of these models was assessed in terms of the area under the curve (AUC) and accuracy (ACC). The Shapley Additive Explanations (SHAP) interpreter was implemented to provide insights into the key risk factors contributing to AKI.

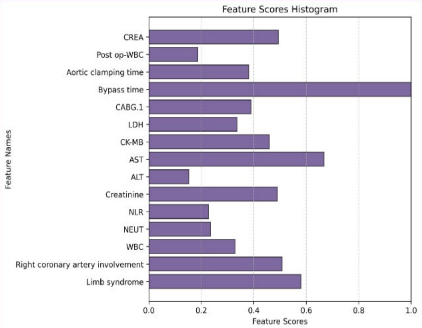


Fig.1 Top 15 features associated with ATAAD postoperative AKI

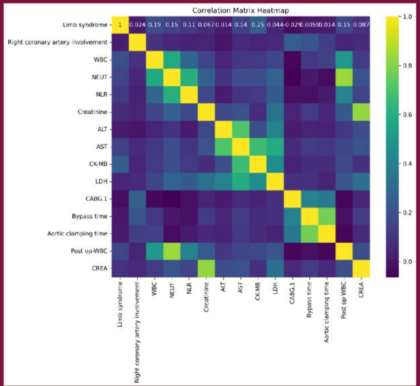


Fig.2 Heatmap of Correlation between features

## Results

Among the ATAAD patients considered in the study, 74 individuals (11.56%) developed AKI during the post-operative phase of hospitalization. Fifteen highly relevant and statistically significant variables were identified for inclusion in the predictive model. These variables encompassed factors such as the duration of cardiopulmonary bypass (CPB), pre-operative AST levels, the presence of limb syndrome, involvement of the right coronary artery, pre-operative and post-operative creatinine levels, creatine kinase-MB (CK-MB) levels, aortic clamping duration, combined CABG surgery, pre-operative and post-operative WBC counts, lactate dehydrogenase (LDH) levels, the neutrophil-lymphocyte ratio, ALT levels, and neutrophil counts. The predictive models, including LR, XGBoost, and LightGBM, exhibited AUC values of 0.843, 0.879, and 0.887, along with ACC values of 0.801, 0.845, and 0.867, respectively. Notably, the LightGBM model emerged as the most promising model with the highest predictive performance, demonstrating its clinical applicability.

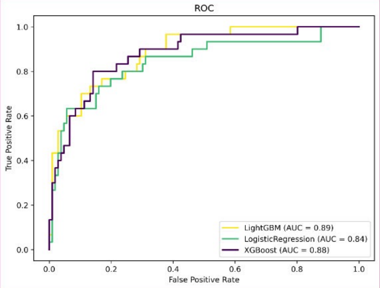


Fig.4 ROC curve of three predictive model

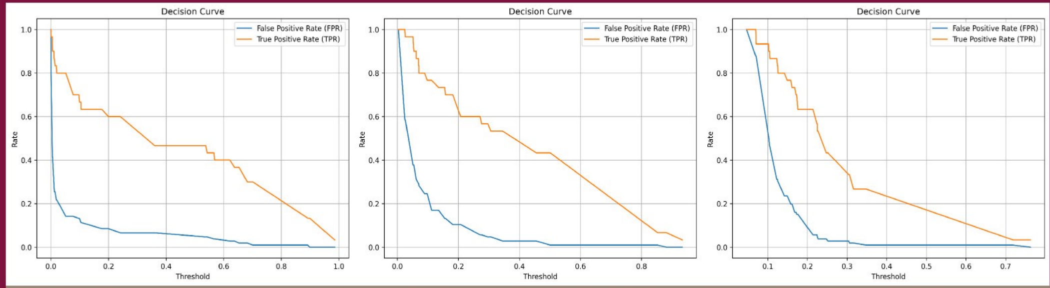


Fig.5 Decision curve of three predictive model (From left to right: XGBoost, LightGBM and Logistic Regression)

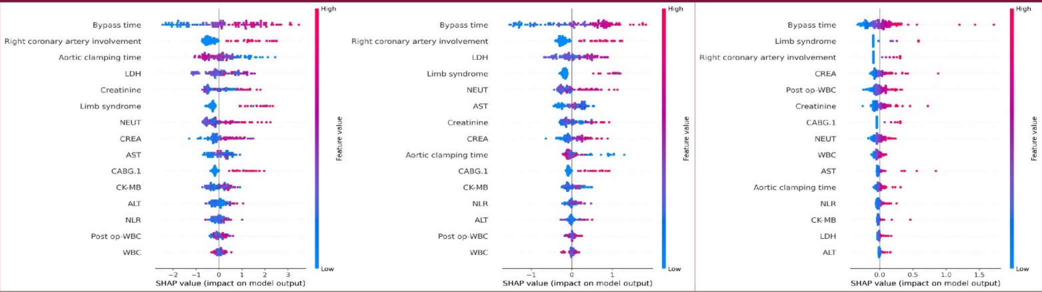


Fig.5 SHAP value of three predictive model (From left to right: XGBoost, LightGBM and Logistic Regression)

## Conclusion

Machine learning models have demonstrated substantial predictive capabilities for identifying postoperative AKI in patients with ATAAD. This study has highlighted a set of variables that can be considered as independent risk factors,offering opportunities for early intervention and improved patient outcomes.