Perioperative Risk Assessment to Predict Hemodynamic Instability in Cardiac Surgery Patients

Ime Essien, Zihan Yu, Rishika Vadlamudi, Sile Wang, Xinyue Gu, Judy Zhou
PIs: Joseph Walpole, Jochen Steppan, Joseph Greenstein, Casey Taylor
Biomedical Engineering
Johns Hopkins University
JOHNS HOPKINS WHITING SCHOOL of ENGINEERING

Abstract

Cardiac surgeries often involve risks of hemodynamic instability, which can lead to extended ICU stays and increased healthcare costs. Current models primarily use pre- and post-operative data, neglecting intraoperative dynamics that are crucial for real-time patient management.

This project employs a structured approach to predict postoperative outcomes in cardiac surgery patients, integrating **feature extraction** from **intraoperative data** and **predictive modeling** using machine learning. The methodology includes exploratory analysis and advanced feature engineering. A risk classification model categorizes patients by ICU stay risk, and feature validation using **Shapley analysis** assesses the impact of novel engineered indicators, creating a comprehensive framework to improve perioperative care.

Intraoperative medication dosages and the novel indicator, stiffness, were identified as key predictors for the classification target of ICU length of stay by feature validation. The successful results of Random Forest and KNN classifier models demonstrate that intraoperative data enhances risk assessment for cardiac surgery patients.

Introduction

This project aims to enhance the prediction of hemodynamic instability in patients undergoing cardiac surgeries with cardiopulmonary bypass, a significant challenge despite advances in medical technology. By incorporating comprehensive real cardiac surgery patient data from clinical PIs—including demographic data, intraoperative time series, ICU length of stay, and post-surgery complications—our framework focuses on dynamic changes during surgery that current models often overlook, such as real-time pulmonary arterial pressure signals and medication dosages.

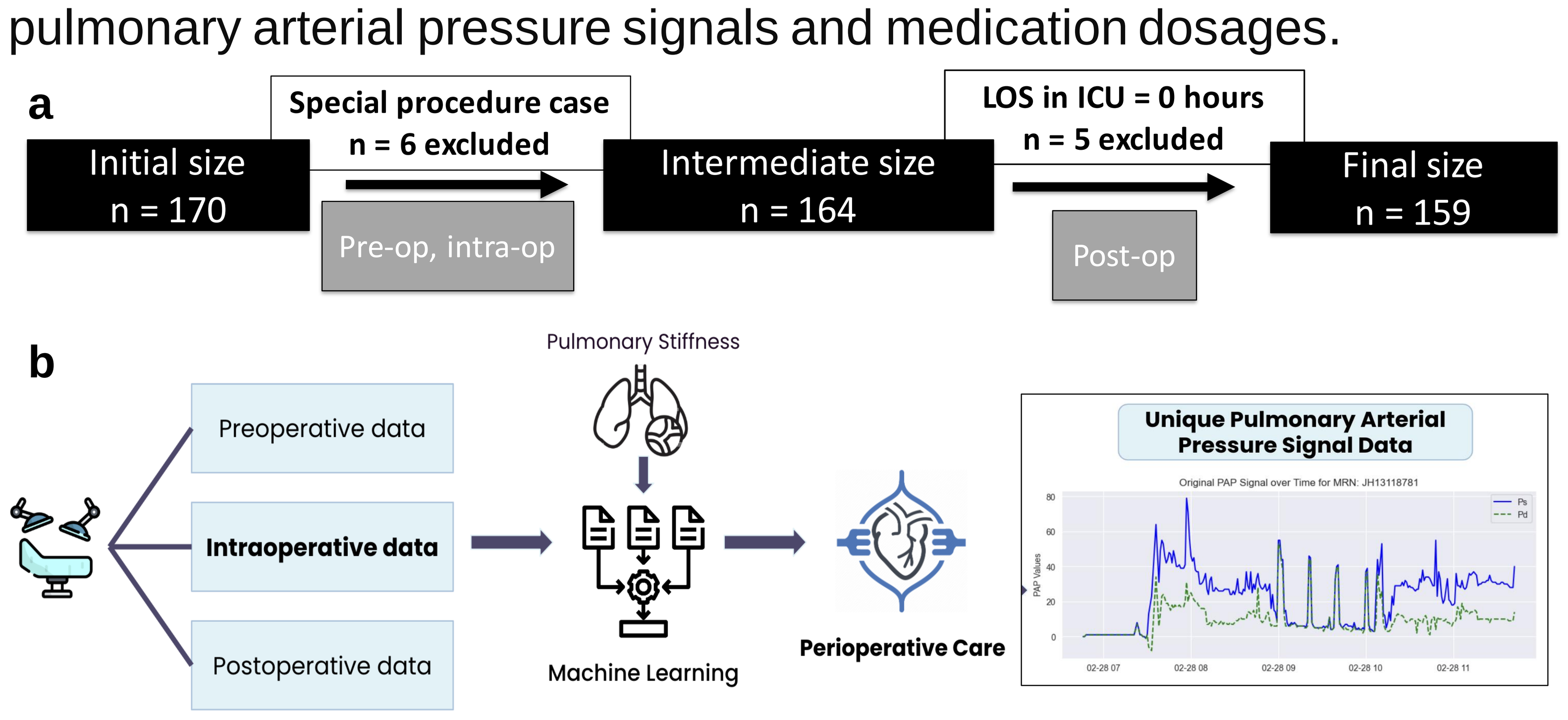


Fig 1: a. The inclusion/exclusion criteria for the patient dataset. b. The framework of the predictive analysis, integrating novel indicator stiffness from intraoperative data.

Utilizing advanced machine learning techniques, we analyze intraoperative data, extracting time-series features like stiffness indices from pressure signals and integrating demographic and surgical variables. This approach provides a more accurate and real-time assessment of patient risk, leveraging predictive analytics and feature importance analysis to forecast critical outcomes and potentially transform perioperative care for cardiac surgery patients.

Classification Model Results

Task: Classification of patients' ICU length of stay as >56h.

Classifiers: KNN, SVM, Naïve Bayes, Logistic Regression, Random Forest, Voting Classifier (Ensemble model)

KNN Results: 87% classification accuracy, 88% F1 score (CI 1).
Random Forest Results: 85% classification accuracy, 86% F1 score (CI 1).

Voting Classifier Results: 123 correct classifications out of 147; 79% classification accuracy, 76% F1 score (CI 1)

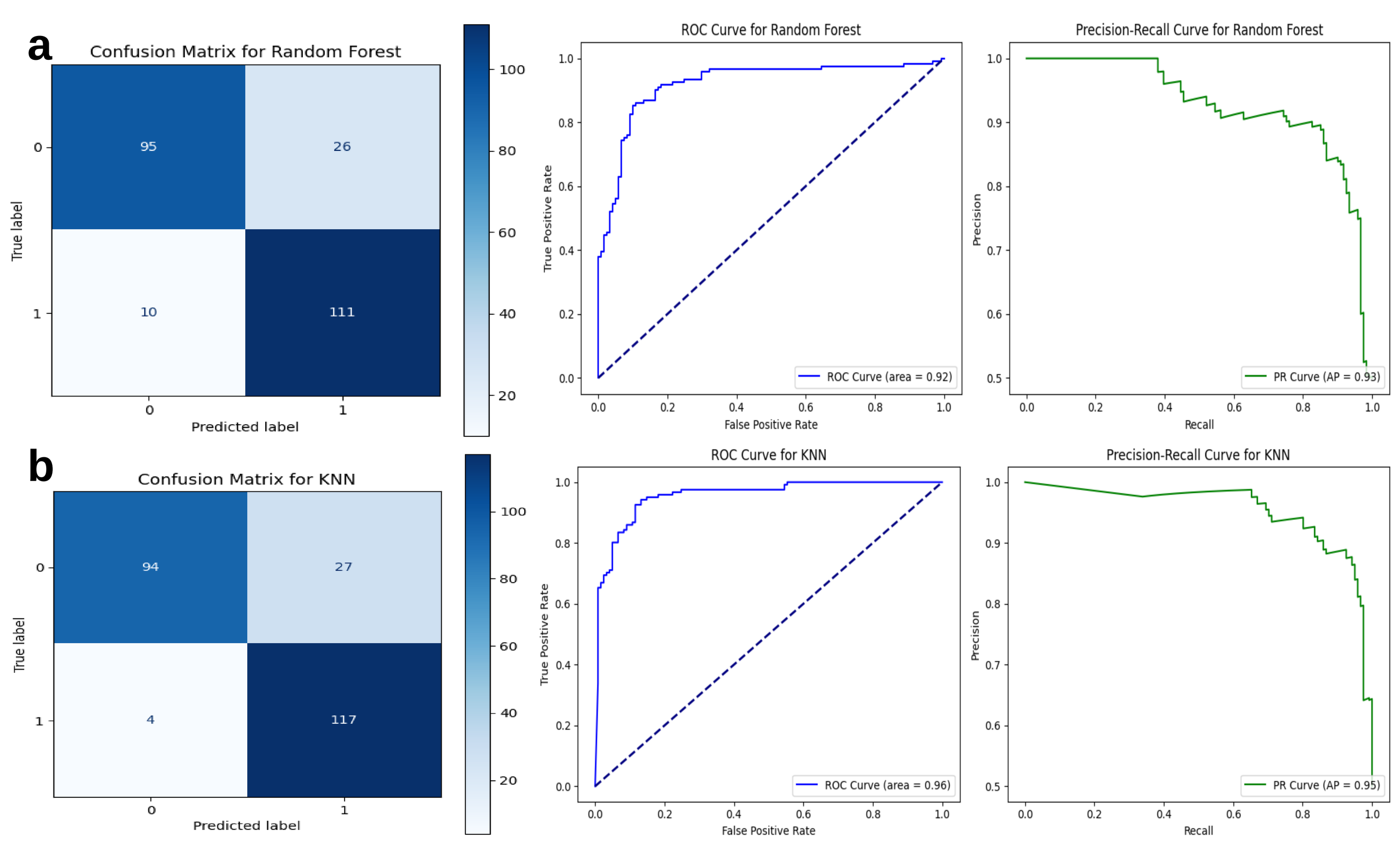


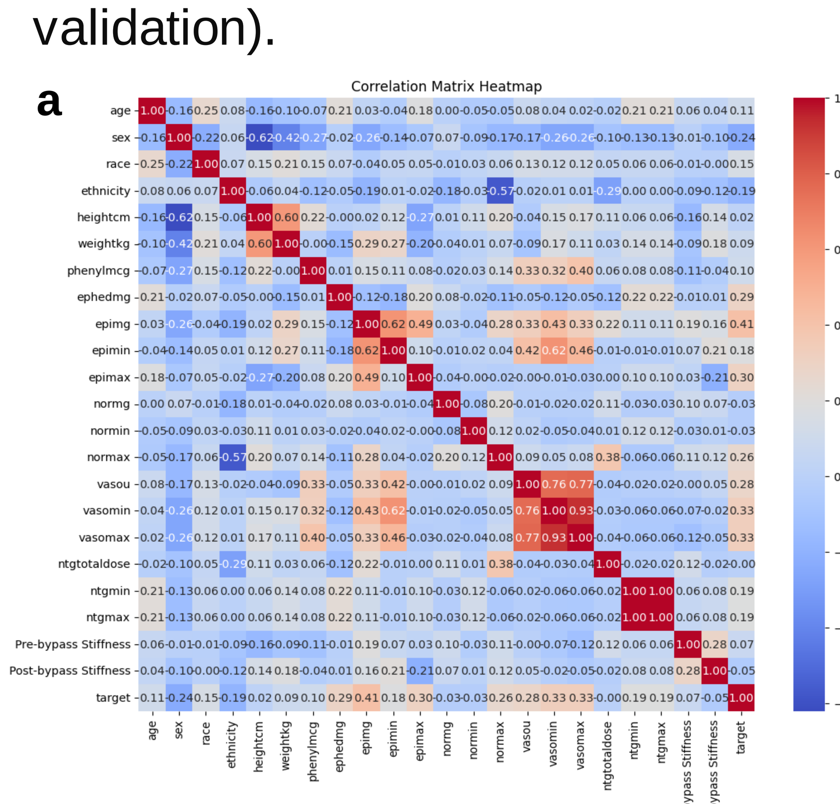
Fig. 2: a. Random Forest Results: 114 correct classifications out of 147, b. KNN Results: 118 correct classification out of 147

Feature Validation and Importance

Feature Validation Strategies:

Shapley Value calculations, Permutation Importance, and Sequential Feature Selection. Score calculated as mean rank of each feature.

Pre- and post-bypass stiffness independently provide novel insights (correlation analysis), ranking in the top 10 important features alongside intraoperative medications (feature validation).



b

Feature	Score
Pre-bypass Stiffness	4.67
epimg	5.00
sex	5.67
ntgmax	8.67
ntgtotaldose	8.67
Post-bypass Stiffness	9.00
ntgmin	9.00

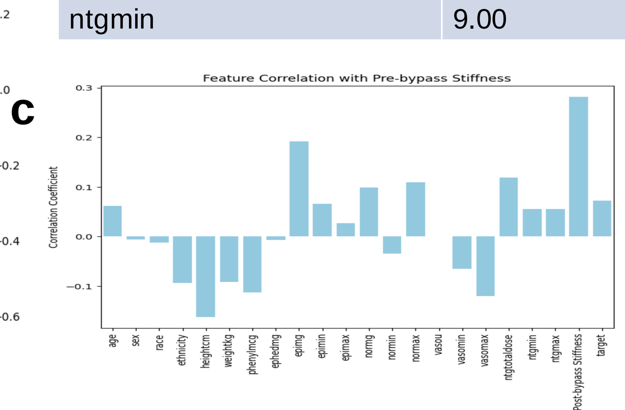


Fig. 3 a. Feature importance correlation matrix from Classification task. b. Summarized table showing most important features ranked by feature validation strategies. c. Feature correlation with Stiffness indicator

Methods

Exploratory Data Analysis:
Extensive exploratory data analysis to uncover underlying patterns and anomalies. Data cleaning to ensure data integrity for advanced analysis. Time series data was standardized and normalized.

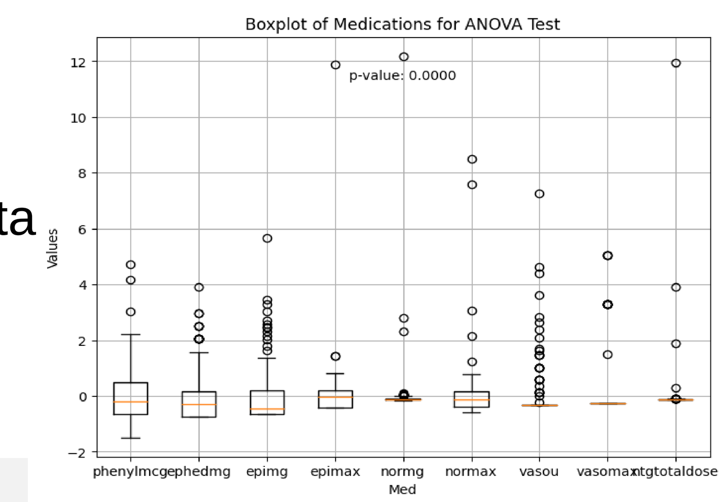


Fig. 4 ANOVA statistical test validated intraoperative data significance.

Data Processing and Feature Engineering:

A novel method was developed to extract stiffness indices from time-series pulmonary arterial pressure data.

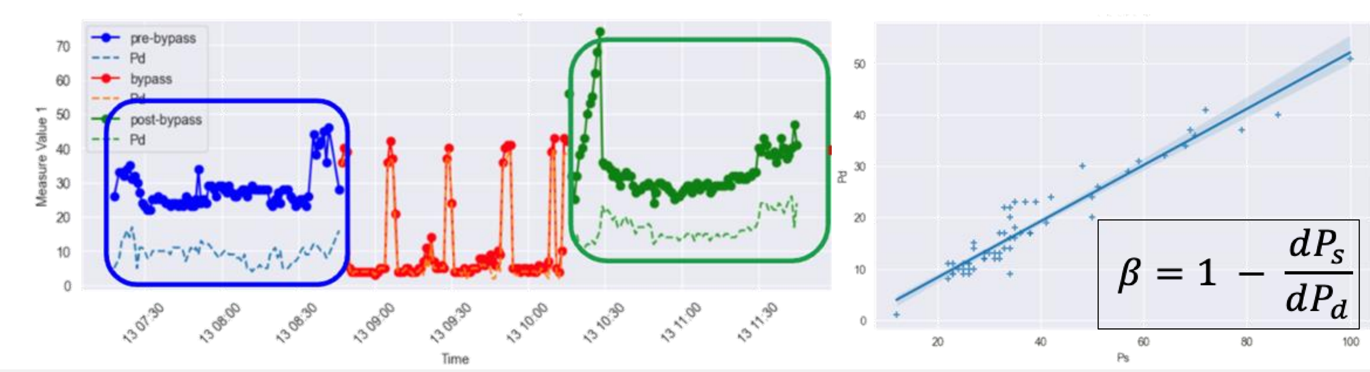


Fig. 5 Pre- and post-pulmonary stiffness calculation process. Identify bypass periods, plot systolic and diastolic pressure and derive slope to calculate index.

Predictive Modeling:
Machine learning models were implemented and optimized through extensive hyperparameter tuning and cross-validation for the classification and regression tasks. Feature validation strategies and correlation matrices were employed to determine feature importance.

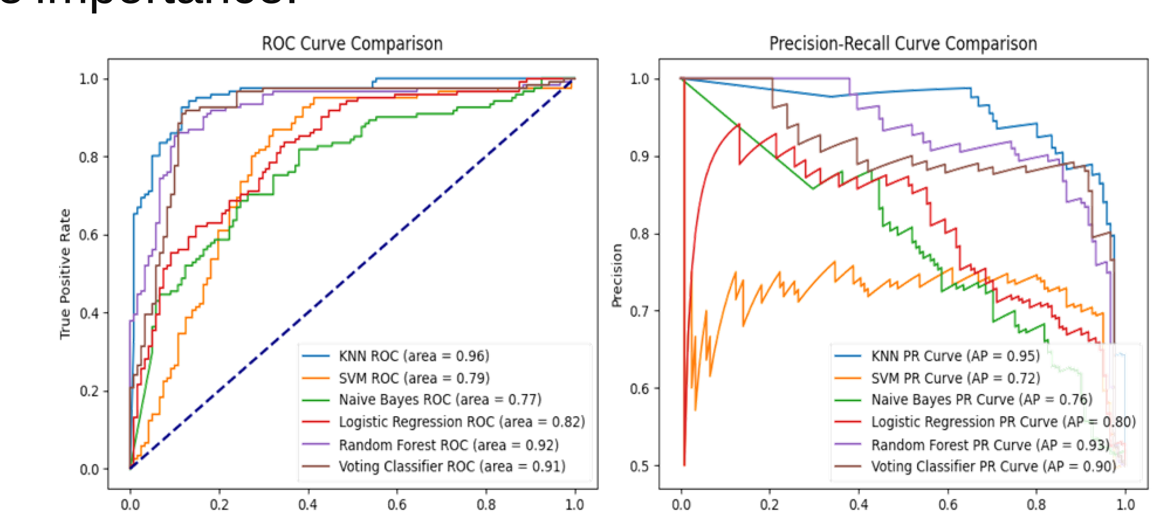


Fig. 6 Comparative ROC and PR curves for classifiers in predictive modeling task.

Conclusion

In conclusion, our project effectively addresses risk assessment in cardiac surgery by utilizing a pioneering combination of preoperative echocardiograms, vital sign monitoring, and detailed patient comorbidity data. We developed a predictive model that incorporates pulmonary vascular stiffness as a novel risk factor and anticipates intraoperative events requiring immediate intervention.

This approach has been validated by identifying intraoperative medication dosages and pulmonary stiffness as key predictors for ICU length of stay. The successful implementation of machine learning classifiers underscores the enhanced risk assessment provided by using intraoperative data. The results from this project could lead to new protocols for risk assessment in cardiac surgeries, thereby improving patient outcomes and care standards.