Predicting Postoperative Outcomes Using Real-Time Blood Pressure Waveform Assessment During Non-Cardiac Surgery

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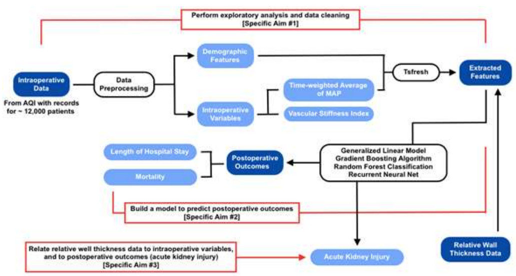
Introduction

Intraoperative blood pressure is a correlated with various postoperative outcomes such as acute kidney injury and mortality. Previous studies have shown:

1) assessments of intraoperative blood pressure curves to determine time under a certain mean arterial pressure (MAP) and metrics of blood pressure variability are associated with 30-day postoperative mortality after noncardiac surgery, and 2) the slope of systolic and diastolic blood pressure curves correlate to physiologic vascular stiffness.

Using this information as building blocks we have built a model to provide guidance on blood pressure maintenance during surgery.

Objectives



Materials and Methods

After applying exclusion criteria, we obtained a final cohort size of 3032 elevated risk non cardiac surgery patients care for at Johns Hopkins Hospital. Only 3% of patients experienced in-hospital mortality, thus, we used SMOTEENN to rebalance training data to have 47% alive and 53% deceased.

Time-weighted average (TWA) of the mean arterial pressure (MAP): 1) calculated MAP as the average arterial pressure throughout one cardiac cycle 2) calculated TWA as the area above and below several threshold values.

Ambulatory arterial stiffness index: calculated as 1 minus the regression slope of diastolic over systolic blood pressure.

Results

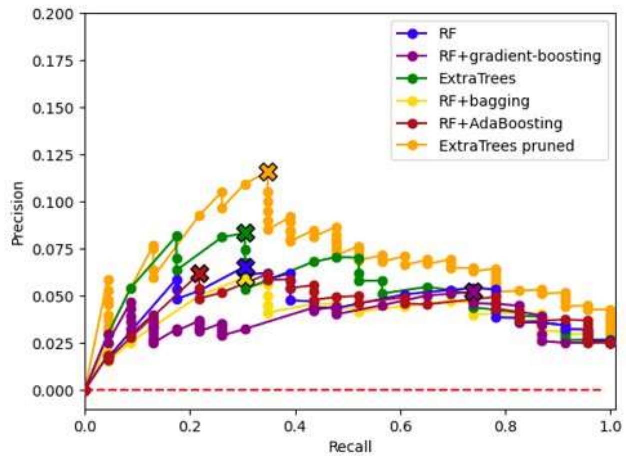


Figure 1—Precision Recall Curves for Models
The threshold and maximized precision for each model are denoted by X's

We created several models in attempts to find one that would predict in-hospital mortality the best. In addition we utilized methods to tune our model's hyperparameters and pruned our feature space based on feature importance and cross validation methods. The precision recall curves for each of our models are shown in Figure 1. We had varying degrees of precision and recall across our models as shown in Table 1

Model	AUC	Precision Majority	Recall Majority	Precision Minority	Recall Minority	Average F1-score
Basic Random Forest Classifier	0.61	0.98	0.90	0.04	0.17	0.51
Random Forest Classifier with SMOTEENN	0.71	0.98	0.92	0.08	0.26	0.54
Random Forest Classifier AdaBoost	0.70	0.98	0.90	0.06	0.22	0.52
Random Forest Classifier Boosting (Extra Trees)	0.72	0.98	0.91	0.08	0.30	0.53
Random Forest Classifier Pruning (Extra Trees)	0.80	0.98	0.90	0.08	0.35	0.54

Table 1—Model Comparison
Comparing AUC, Precision, Recall, and F-1 Scores across all models created. Green font representing places where the model improved and red represents places were the subsequent model regressed.

Top 10 Before Pruning	Importance	Top 10 After Pruning	Importance
Gender F	0.03	Van Walravens Score	0.12
Gender M	0.03	HCUP readmission score	0.09
Van Walraven score	0.02	ASA Physical Status IV	0.06
HCUP readmission score	0.02	Last Location of Max in waveform	0.06
ASA Physical Status II	0.02	First Location of Max in waveform	0.06
ASA Physical Status IV	0.02	Last Location of Min in waveform	0.06
Age	0.01	First Location of Min in waveform	0.06
Duplicate Max in waveform	0.01	Gender F	0.05
Last Location of Max in waveform	0.01	Gender M	0.05
First Location of Max in waveform	0.01	Age	0.05

Table 2 — Top 10 Features Before and After Pruning
Features in red are features that fell out of the top 10 after pruning while features in green are features that moved up in importance post-pruning.

Model(paper)	Sample Size	Type of Features	Outcome	AUC	Top Features
Postoperative risk-stratification model[1]	2905 patients who received coronary artery bypass (465 AE, 2430 no AE)	Combined	Adverse events	0.79	IABP or inotropes
		Preoperative		0.75	IBdRBCU CHF with NYHA IV
		Intraoperative		0.74	IBdFFPU Creatinine level
Prediction model using intraoperative hemodynamic monitoring data[2]	101 patients with orthotopic liver transplantation	Preoperative	180-day mortality	0.53	Platelets
		Combined		0.82	Serum Creatinine Area SVI < 40ml/m2
		Preoperative	Acute Kidney Injury	0.72	Area SpO2 < 90% Serum direct bilirubin
		Combined		0.82	MAD CVP
Our Model	3032 patients who received noncardiac surgery (2935 Alive, 97 Deceased)	Combined	In-Hospital Mortality	0.80	Van Walravens Score HCUP readmission score ASA Physical Status IV Last Location of Max in waveform

Table 3 – Comparison to Other Similar Models in Literature
These other models either had smaller number of patients, had the type of surgery, had follow up dataset and used different hemodynamic dataset.

Conclusion

This is not the first study that tries to incorporate intraoperative data in predicting the surgery outcome. Intraoperative data has been used in both the cardiac and noncardiac surgeries to improve the risk-stratification model and the inclusion of intraoperative data generally improved the AUC. In a risk-stratification model built with 2900 patients who received cardiac surgery, the AUC improved from 0.75 to 0.79. The AUC also improved from 0.72 to 0.82 in an acute kidney injury prediction model made with 100 patients who received noncardiac surgery. Our Model had a similar AUC with 0.80 while utilizing variables that are more easily obtained. Unfortunately our derived measures for blood pressure and variability and vascular stiffness were not found as important features in our model.

[1] Durant TJ, Jean RA, Huang C, et al. Evaluation of a Risk Stratification Model Using Preoperative and Intraoperative Data for Major Morbidity or Mortality After Cardiac Surgical Treatment. JAMA Network Open. 2020;3(12). doi:10.1001/jamanetworkopen.2020.28361
[2] Prasad V, Guerrisi M, Dauri M, et al. Prediction of postoperative outcomes using intraoperative hemodynamic monitoring data. Scientific Reports. 2017;7(1). doi:10.1038/s41598-017-16233-