Merging Machine Learning and Patient Preference: A Contemporary, Comprehensive, Patient-Centered Tool for Risk Prediction Prior to Percutaneous Coronary Intervention

FRANKEL CARDIOVASCULAR CENTER
MICHIGAN MEDICINE

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Background

- Personalized and accurate risk prediction of post-procedural adverse events and outcomes after percutaneous coronary intervention (PCI) is critical to weighing treatment options and shared decision-making.
- Both patients and clinicians tend to overestimate the benefit and underestimate the risk of harm associated with procedures like coronary angiography and PCI.

Objective

- We hypothesized that with machine learning algorithms and patient feedback, we would be able to create accurate models to predict a comprehensive list of post-PCI complications and present the results to patients and providers in a clear and easily understandable manner.
- With accurate personalized risk prediction of post-PCI complications, it could allow for (1) enhanced medical decision-making and informed consent process; (2) tailored treatment decisions to maximize safety and patient outcomes; and (3) comparative benchmarking assist with health system quality improvement.

Methods

- A semiquantitative survey was given to 66 individuals to define preferred list of post-PCI outcomes and the optimal display of risk model outputs.
- Retrospective Cohort study
- 71,963 PCI procedures from the BMC2 registry from 48 hospitals in Michigan from 4/1/2018 to 9/30/2020
- Random forest and XGBoost risk prediction models using 23 pre-procedural clinical and laboratory variables.
- Models created in training cohort (75%) and performance evaluated in separate testing cohort (25%) using area under the receiver-operating characteristic curve (AUC)
- Outcomes include in-hospital mortality, acute kidney injury (AKI), new initiation of dialysis, transfusion, and major bleeding.

Results

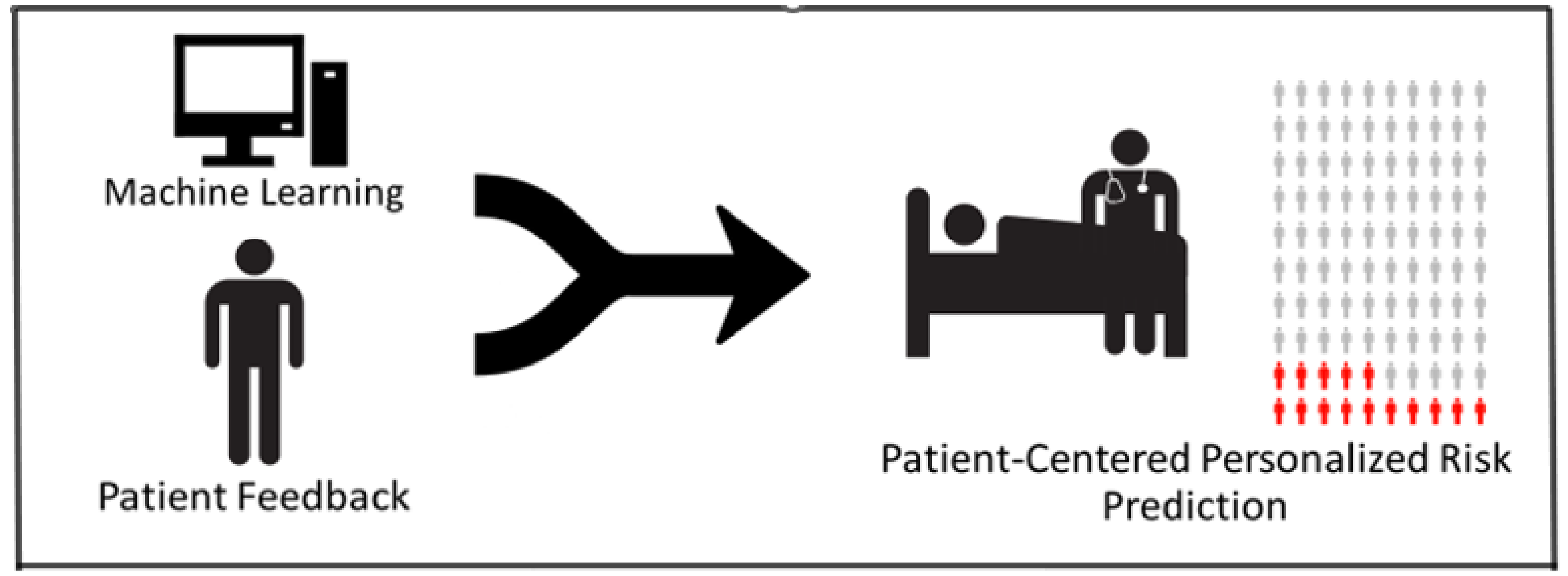

Figure 1: The combination of patient feedback and a machine learning algorithm allowed for the creation of a patient-centered personalized risk-prediction tool.

Table 1: Patient Characteristics

Demographics	Overall (n=71,963)	Clinical Data	Overall (n=71,963)
Age, Mean (SD)	66.6 (11.7)	Creatinine, mg/dL	1.2 (1.1)
Sex, Female, n (%)	34,374 (31.9)	Hemoglobin, g/dL	13.4 (2.1)
Race, n (%)		Total Cholesterol, mg/dL	164.7 (49.0)
White	89,830 (83.3)	HDL, mg/dL	42.7 (13.7)
Black	9,689 (9.0)	LVEF, mean % (SD)	50.8 (13.5)
Comorbidities, n (%)		Prior Diagnostic Cath, n (%)	62,842 (58.3)
Diabetes	45,071 (41.8)	Clinical Status, n (%)	
Prior PCI	48,470 (45.0)	Elective	43,374 (40.3)
Cerebrovascular Disease	17,657 (16.4)	Urgent	45,435 (42.2)
Prior CABG	17,054 (15.8)	Emergent	18,658 (17.3)
PAD	10,010 (13.9)	Salvage	292 (0.3)
Lung Disease	21,073 (19.6)	Cardiovascular Instability, n (%)	24,200 (22.5)
Current/Former Tobacco Use	68,266 (64.9)	Ventricular Support, n (%)	6,016 (5.6)
Heart Failure		Cardiac Arrest, n (%)	2,599 (2.4)
NYHA I-II	12,918 (18.0)	Positive Stress testing result, n (%)	27,203 (25.3)
NYHA III-IV	8,391 (10.7)	PCI Indication, n (%)	
Frailty (CSHA)		Stable Angina	10,336 (9.6)
Not Frail	68,495 (63.8)	Unstable Angina	6,295 (5.8)
Intermediately Frail	28,802 (26.8)	NSTE-ACS	43,786 (40.7)
Severely Frail	10,066 (9.3)	STEMI	17,368 (16.1)

Table 1: Patient characteristics

Outcome	Overall Events n (%)	XGBoost Model Performance AUC (95%CI)
Mortality	1,264 (1.76)	0.950 (0.939-0.962)
AKI	1,712 (2.64)	0.889 (0.874-0.904)
Dialysis	295 (0.41)	0.949 (0.928-0.969)
Major Bleeding	631 (0.89)	0.892 (0.861-0.922)
Transfusion	1,746 (2.43)	0.918 (0.905-0.931)

Table 2: Event frequency and model performance by AUC for each outcome.

Trial Our Risk-Prediction Tool

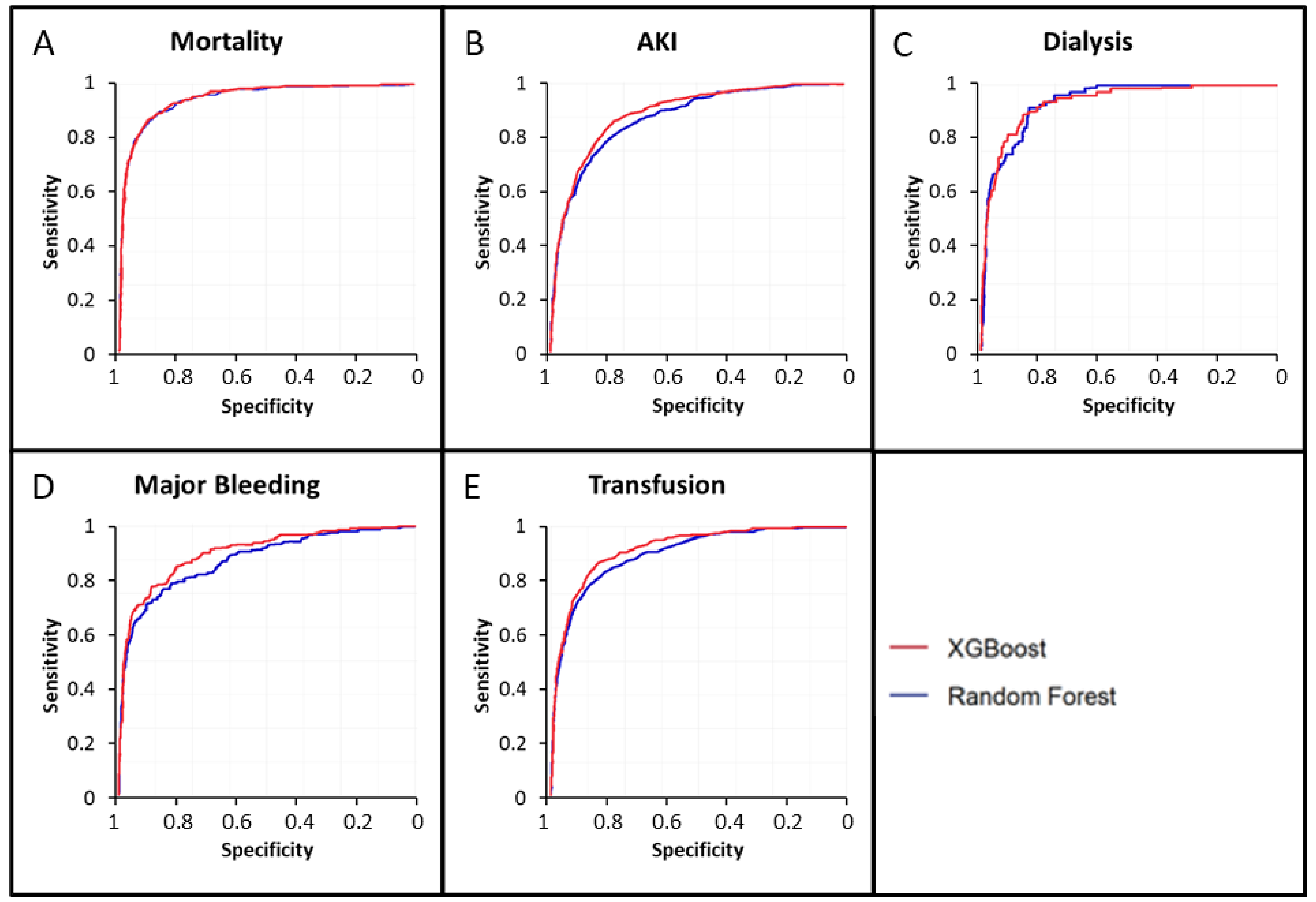

Figure 1: AUC curve for XGBoost and Random Forest model performance for in-hospital mortality (A), AKI (B), dialysis (C), major bleeding (D), and transfusion (E).

Conclusion

- Using common pre-procedural risk factors, we designed an XGBoost machine learning model that accurately predicts individualized post-PCI outcomes.
- Utilizing patient feedback, we created a patient-centered tool to clearly display risks to patients and providers (see QR code).

Limitations

- Inclusion of data from all non-federal hospitals in the state of Michigan makes it generalizable to the broader PCI patient population.
- Lack of confirmatory analysis of an independent dataset

References

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