



Temporal shift and predictive performance of machine learning for heart transplant outcomes

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Background

Outcome prediction following heart transplant is critical to explaining risks and benefits to patients and decision-making when considering potential organ offers. Given the large number of potential variables to be considered, this task may be most efficiently performed using machine learning (ML). We trained and tested ML and statistical algorithms to predict outcomes following cardiac transplant using the United Network of Organ Sharing (UNOS) database.

Methods

We included 59,590 adult and 8,349 pediatric patients enrolled in the UNOS database between January 1994 and December 2016 who underwent cardiac transplantation. We evaluated 3 classification and 3 survival methods. Algorithms were evaluated using shuffled 10-fold cross-validation (CV) and rolling CV. Predictive performance for 1 year and 90 days all-cause mortality was characterized using the area under the receiver-operating characteristic curve (AUC) with 95% confidence interval.

Results

In total, 8,394 (12.4%) patients died within 1 year of transplant. For predicting 1-year survival, using the shuffled 10-fold CV, Random Forest achieved the highest AUC (0.893; 0.889-0.897) followed by XGBoost and logistic regression. In the rolling CV, prediction performance was more modest and comparable among the models with XGBoost and Logistic regression achieving the highest AUC 0.657 (0.647-0.667) and 0.641 (0.631-0.651), respectively. There was a trend toward higher prediction performance in pediatric patients.

Conclusions

Our study suggests that ML and statistical models can be used to predict mortality post-transplant, but based on the results from rolling CV, the overall prediction performance will be limited by temporal shifts inpatient and donor selection.

Section snippets

Patient population

We included adult and pediatric patients enrolled in the UNOS database between January 1994 and December 2016 who underwent cardiac transplantation ($n = 73,678$). We excluded patients undergoing combined heart and lung transplant ($n = 842$), patients with

less than 365 days follow-up for death ($n = 3,301$), and patients with fewer than 80 variables available ($n=1,596$ see SupplementalFigure 1) since missing variables may influence the accuracy of ML predictions. In total, 67,939 patients were...

Patient population

In total, 67,939 patients were included with median age 54 (IQR 39-61) and 49,351 (72.6%) male. In the overall population, there were 59,590 adult and 8,349 pediatric patients. During the first year, 8,394 (12.4%) patients died including 7,435 (12.4%) adult patients and 959 (11.5%) pediatric patients. As expected, there were significant differences between pediatric and adult populations as shown in Table 1. Population characteristics in patients who survived 1 year compared to patients who...

Discussion

In this study, we applied popular ML and statistical methods to predict death within thefirst-yearpost-cardiac transplant. In the shuffled 10-fold CV, we demonstrated substantial improvements in predictive performance with tree-based models. However, there was less of a difference when predictive performance was assessed using the rolling CV procedure, which likely provides a better estimate of prospective model performance. The results of our study suggest that ML and statistical models...

Conclusions

Our study suggests that ML and statistical models could be used to improve prediction of mortality in the first-year post-transplant. However, the prospective prediction performance of risk prediction models will be impacted by temporal shifts in patient and donor selection. Future studies are needed to investigate methods to account for temporal shift, clarify different aspects of clinical implementation, and evaluate the net clinical impact of integrating risk predictions on post-transplant...

Author contributions

Robert Miller contributed to study design, data analysis, manuscript preparation, and manuscript revisions. František Sabovčík contributed to study design, data analysis, manuscript preparation, and manuscript revisions. Nicholas Cauwenberghs contributed to data analysis and manuscript revisions Celine Vens contributed to study design and manuscript revisions. Kiran Khush contributed to study design and manuscript revisions. Paul Heidenreich contributed to study design and manuscript revisions. ...

Disclosure statement

The authors have no relevant conflicts of interest to disclose...

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References (46)

DC Chambers *et al.*
[The international thoracic organ transplant registry of the international society for heart and lung transplantation: 37th adult lung transplantation report; 2020; focus on deceased donor characteristics](#)
J Heart Lung Transplant (2020)

M Colvin *et al.*

OPTN/SRTR 2018 annual data report: heart

Am J Transplant (2020)

RM Reed *et al.*

Cardiac size and sex-matching in heart transplantation: size matters in matters of sex and the heart

JACC Heart Fail (2014)

EP Kransdorf *et al.*

Predicted heart mass is the optimal metric for size match in heart transplantation

J Heart Lung Transplant (2019)

RJH Miller *et al.*

Outcomes in patients undergoing cardiac retransplantation: a propensity matched cohort analysis of the UNOS Registry

J Heart Lung Transplant (2019)

KK Khush *et al.*

Great variability in donor heart acceptance practices across the United States

Am J Transplant (2020)

DL Joyce *et al.*

Predicting 1-year cardiac transplantation survival using a donor-recipient risk-assessment tool

J Thorac Cardiovasc Surg (2018)

BD Ershoff *et al.*

Training and validation of deep neural networks for the prediction of 90-day post-liver transplant mortality using unos registry data

Transplant Proc (2020)

S Senanayake *et al.*

Machine learning in predicting graft failure following kidney transplantation: a systematic review of published predictive models

Int J Med Informatics (2019)

DH Wolpert

Stacked generalization

Neural Netw (1992)

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2023, Cardiology Clinics

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