MACHINE LEARNING MODELS IMPROVE POST-TRANSPLANT SURVIVAL PREDICTIONS

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INTRODUCTION

At present, no outcome model in the field of transplantation surgery can incorporate all available patient- and donor-specific parameters at the time of transplantation to guide organ allocation decisions. Artificial Intelligence (AI) models can synthesize a greater number of input parameters by identifying non-linear trends in data.

Hypothesis: Machine learning models will be more accurate than regression techniques in predicting mortality after liver transplantations.

METHODS

- We created **four machine learning predictive models:**
  - Random Forest (RF) model
  - AdaBoost (AB) ensemble-based model
  - Naïve Bayes (NB) model
  - Logistic Regression (LR) model
- We selected all **109,742** adult patients from the UNOS database who underwent one recorded orthotopic liver transplantation.
- All transplantation parameters which would be known to a clinician at the time of transplant discharge were included, totaling **323 features**.
- We performed **10-fold cross validation.**
  - This involved random sampling, dividing our data into training (75%) and test (25%) sets 10 times.
  - Each iteration we trained our five models on the training data and tested the predictive power of these models on their test sets.
- We **measured the average 10-fold cross validated model performance** with classification accuracy (CA), and area under the receiver operator curve (AUC) metrics.
- Right censoring of data was accounted for by exclusion, for each survival target we predicted.

RESULTS

Figure 1. Receiver Operator Curves of Machine Learning Models for Predicting 1-Month Post-Liver Transplant Survival

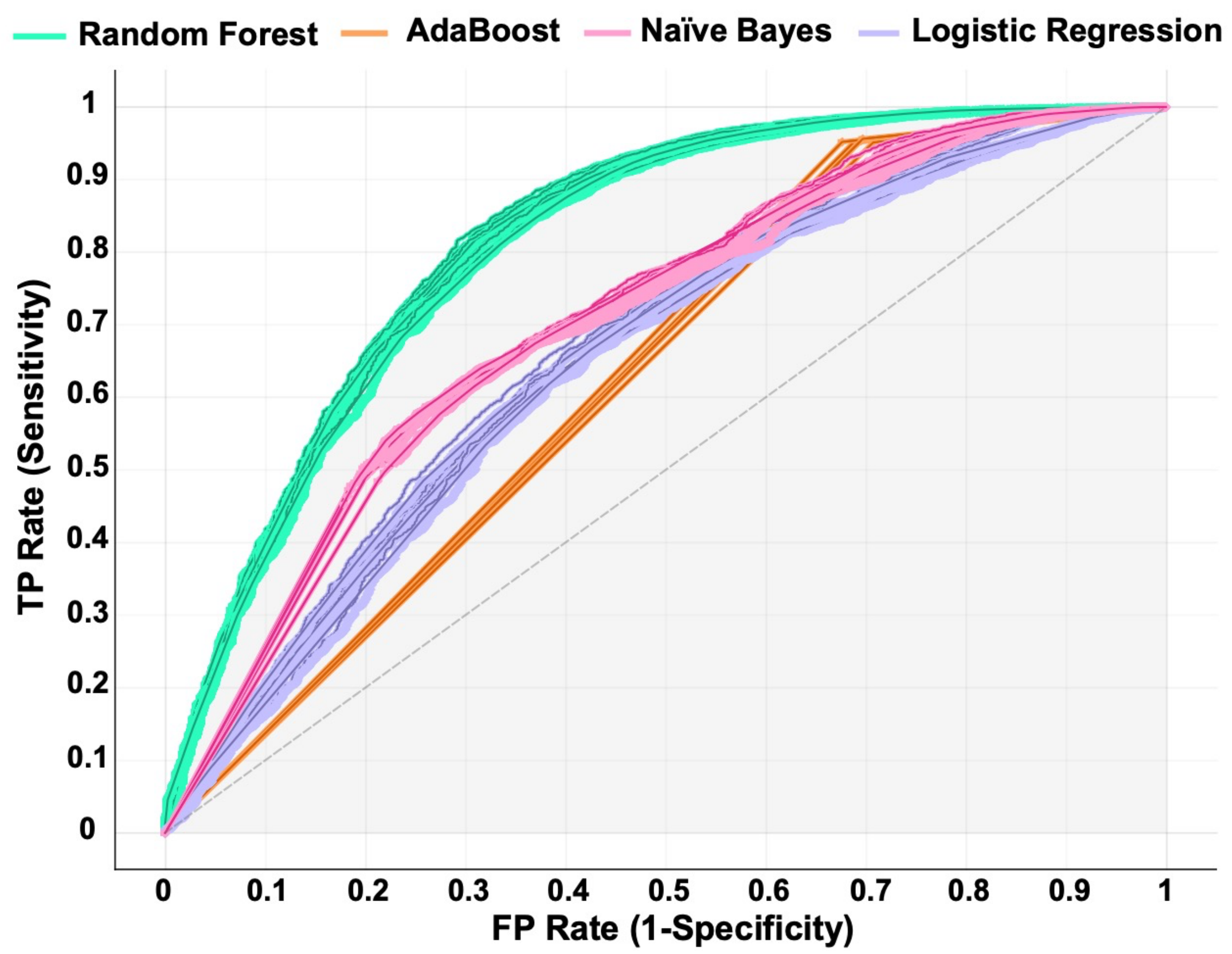

Figure 2. Receiver Operator Curves of Machine Learning Models for Predicting 5-Year Post-Liver Transplant Survival

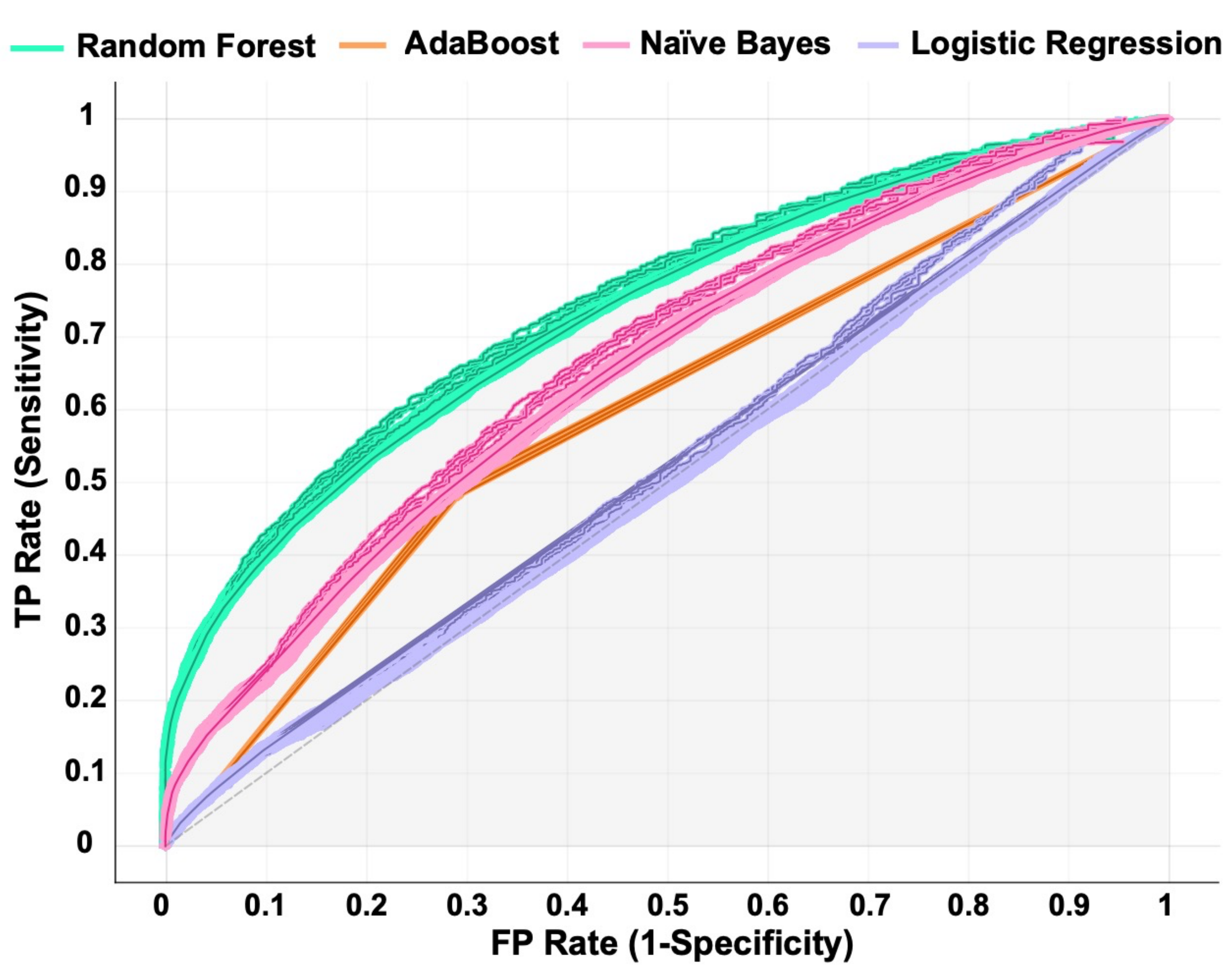

Table 1. Prediction of 1-Month Post-Transplant Survival Status

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.8097	0.9436	0.9172	0.9385	0.9436
Naive Bayes	0.6992	0.7228	0.7959	0.9142	0.7228
Logistic Regression	0.6512	0.9428	0.9151	0.8889	0.9428
AdaBoost	0.6299	0.9157	0.9174	0.9191	0.9157

Table 2. Prediction of 3-Month Post-Transplant Survival Status

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.7918	0.9155	0.8816	0.9096	0.9155
Naive Bayes	0.6949	0.7161	0.7734	0.8709	0.7161
Logistic Regression	0.6501	0.9100	0.8676	0.8541	0.9100
AdaBoost	0.6364	0.8771	0.8786	0.8801	0.8771

Table 3. Prediction of 1-Year Post-Transplant Survival Status

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.7465	0.8570	0.8076	0.8555	0.8570
Naive Bayes	0.6551	0.6799	0.7168	0.7806	0.6799
Logistic Regression	0.6076	0.8425	0.7736	0.7897	0.8425
AdaBoost	0.6036	0.7840	0.7862	0.7885	0.7840

Table 4. Prediction of 3-Year Post-Transplant Survival Status

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.7263	0.7732	0.7153	0.7876	0.7732
Naive Bayes	0.6376	0.6383	0.6535	0.6802	0.6383
Logistic Regression	0.5412	0.7333	0.6247	0.6921	0.7333
AdaBoost	0.5957	0.6813	0.6821	0.6829	0.6813

Table 5. Prediction of 5-Year Post-Transplant Survival Status

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.7326	0.7177	0.6716	0.7429	0.7177
Naive Bayes	0.6505	0.6000	0.6079	0.6356	0.6000
Logistic Regression	0.5060	0.6403	0.5045	0.6311	0.6403
AdaBoost	0.5992	0.6293	0.6297	0.6301	0.6293

[1]Classification accuracy
[2]F1=[2* (precision * recall)/ (precision + recall)]

CONCLUSIONS

- Accurate modeling of survival after transplantation surgery is essential
  - Can influence clinical decision-making
  - Sets appropriate expectations for patients and clinicians
- **Predicting survival *post*-liver transplantation is difficult**
  - Procedure itself induces large changes in disease pathology and clinical picture
- Currently, most post transplant survival predictive models are generalized linear models
  - **SOFT score (2008)**
    - 13 recipient factors, 4 donor factors and 2 operative factors, the SOFT score predicts **3-month** post-operative mortality with an AUC (c-statistic) of **0.70**
  - **Pedi-SOFT score (2015)**
    - Predicts survival with a c-statistic of **0.74**
    - One of the best current predictive survival indexes
- **Random Forest machine learning method produced accurate** and precise models for post-transplantation survival predictions
  - **3 – month** survival prediction AUC:
    - **Random Forest, 0.80**
  - **5 – year** survival prediction AUC:
    - **Random Forest, 0.73**
  - Likely due to finding **non-linear associations in these data**
- We should consider incorporating **machine learning** methods into **construction of transplant outcome models**
- Investigation into using machine learning methods to **assist clinicians in allocation decisions is warranted**

Nothing to disclose