ESICM EUROPEAN SOCIETY OF INTENSIVE CARE MEDICINE
The Intensive Connection
LIVES 2021

A Computational Model to Predict Hospital Readmission

S. Glaister[1] H. Kim[1], R. Stevens[2]
1 Department of Biomedical Engineering, Johns Hopkins University, Baltimore, United States of America
2 Anesthesiology and Critical Care Medicine, Johns Hopkins Hospital, Baltimore, United States of America

LCICM

INTRODUCTION

ICU readmission is associated with adverse clinical outcomes and increased healthcare resource utilization. There is an unmet need for more accurate and reliable prediction methods to determine risk of ICU readmission.

OBJECTIVES

The aim of this study was:
(a) to predict the risk of ICU readmission by training a machine learning (ML) model with clinical and physiological data extracted from a large ICU database, and
(b) to identify specific feature patterns that are associated with high readmission risk.

METHODS

We analyzed patient data from the eICU Collaborative Research Database, which contains high resolution data on >200,000 admissions in >200 hospitals across the United States. We identified cases as ICU stays of patients who were readmitted 1-72 hours after their discharge. The control group consisted in ICU stays of patients who were discharged alive and not readmitted. Predictive features were extracted from the 24h period preceding ICU discharge and included comprehensive SOFA scores, physiologic time series data (heart rate, systolic blood pressure, diastolic blood pressure), as well as patient demographics. The features from the case and control groups were used to train Generalized Linear Models (GLM), random forest and XGBoost models. The optimal weighting was tested and found for each model to account for the large class imbalance (25-fold more controls than cases). Model performance was determined by area under the receiver operating characteristic curve (AUC) analysis.

RESULTS

We identified 4,654 patients who were readmitted and 115,535 patients who were not. Hospital mortality of readmitted patients was nearly twofold higher (12.2% vs 6.3%). The XGBoost model had the highest discrimination with an AUC of 0.68 (0.71, 0.66), sensitivity of .64 (.82, .46) and specificity of .62 (.64,.59), while the random forest and GLM models had AUCs of 0.66 (.67, .65) and 0.66 (.69, .62) respectively. The feature rankings for the random forest model based on node impurity were as follows (node impurities in parenthesis): age (100), average respiratory rate (79.80), difference from the average non-readmitted ICU patient's discharge hour (74.48), urine output (66.63), ICU length of stay (63.30), delta of heart sign change (55.55), BMI (53.50), systolic blood pressure (51.39), minimum heart rate (50.08), IBW devine (49.60), average minimum heart rate (49.55), admission height (48.59), minimum mean heart rate (58.3), systolic blood pressure (48.13), mean blood pressure (46.40), heart rate (45.00), GCS (43.98), minimum max heart rate (43.90).

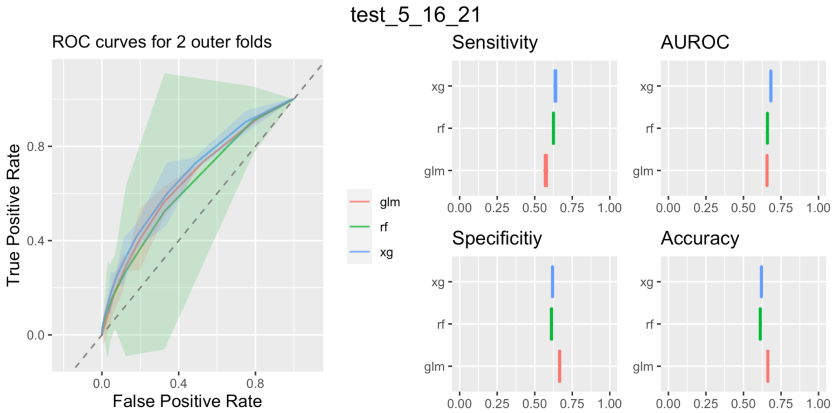

Figure 1. ROC curves and performance metric plots for the three different models trained on the population.

CONCLUSIONS

ML algorithms trained with data available in the 24 hours preceding ICU discharge are able to predict the probability of ICU readmission. Ongoing investigation into model iterations with an expanded feature space and sub-grouped by disease category, hospital size, or specific hospital are expected to enhance model performance and clinical impact.

ACKNOWLEDGEMENTS

A huge thank you to the other members of my lab, (the Laboratory of Computation Intensive Care Medicine at Hopkins), whose collaboration was key to this project

REFERENCES

1. Kramer A, Kiggins T, and Zimmerman J. intensive care unit readmissions in U.S. hospitals: Patient characteristics, risk factors, and outcomes. Critical Care Medicine 40(1):3–10, January 2012. DOI: 10.1097/CCM.0b013e31822d751e
2. Min X, Yu b, and Wang F. Predictive Modeling of the Hospital Readmission Risk from Patients' Claims Data Using Machine learning: A Case Study on COPD. Scientific Reports (2019) 9:2362 https://doi.org/10.1038/s41598-019-39071-y
3. The eICU Collaborative Research Database, a freely available multi-center database for critical care research. Pollard TJ, Johnson AEW, Raffa JD, Celi LA, Mark RG and Badawi O. Scientific Data (2018). DOI: http://dx.doi.org/10.1038/sdata.2018.178.

MODEL TYPE:	GLM	RF	XGBOOST
AUC (95% CI)	.66 (.69, .62)	.66 (.67, .65)	.68 (.71, .66)
Sensitivty (95% CI)	.57 (.79, .36)	.62 (.72, .53)	.64 (.82, .46)
Specificity (95% CI)	.67 (.76, .57)	.61 (.74, .48)	.62 (.64, .59)