Prediction of unplanned readmission after open reduction internal fixation of closed ankle fractures: an ensemble approach and risk calculator

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INTRODUCTION:

Ankle fractures are the most common fractures of the foot and ankle. While outcomes after ORIF are typically favorable, unplanned readmission is a source of considerable cost and morbidity. Accurate prediction of readmission would thus be useful for patients and healthcare systems. Machine learning models for prediction of unplanned readmission after ankle ORIF remain scarce. We aim to develop an ensemble machine learning algorithm for prediction of unplanned 30-day readmission after closed ankle ORIF. Additionally, we aim to identify the patient features most important for model performance. Finally, we aim to develop a web-based risk calculator to predict risk of unplanned readmission.

METHODS:

This is a retrospective cohort study of adult patients who underwent ORIF for closed ankle fracture at any non-federal California hospital between 2015-2017. The primary outcome was readmission within 30 days. We developed an ensemble machine learning model predicting complication risk using AutoPrognosis, an automated machine learning framework that configures the optimally performing ensemble of machine learning-based prognostic models. We compared this model with logistic regression and four standard machine learning models (XGBoost, gradient boosting, AdaBoost, random forest). Discrimination was assessed using area under the receiver operating characteristic curve (AUROC) and area under the precision-recall curve (AUPRC). Calibration was assessed with calibration slope, calibration intercept, and Brier scores. We also ranked importance of each included feature for model performance utilizing a partial dependence function.

RESULTS:

A total of 3,776 patients met inclusion criteria for this study, with 306 cases (8.1%) of 30-day readmission after index ORIF. The ensemble algorithm demonstrated the highest discrimination of the tested models (AUROC 0.694). This model was well-calibrated with a calibration slope of 1.039, calibration intercept of -0.041, and Brier score of 0.070. The null model Brier score was 0.074. The features most important for the ensemble model included: prior pleural effusion or pneumothorax, pneumonia, metastatic cancer, coronary atherosclerosis, psychiatric comorbidity, chronic kidney disease, and morbid obesity (Table 1). We built a web-based risk calculator utilizing the ensemble model: https://risk-calculator-ankle-orif.herokuapp.com/. A screenshot of the calculator for a sample patient is provided in Figure 1.

DISCUSSION AND CONCLUSION:

We report a well-calibrated ensemble model for prediction of unplanned 30-day readmission after closed ankle ORIF. To our knowledge, this represents the first machine learning model that predicts unplanned readmission after closed ankle ORIF with superior risk prediction compared to logistic regression. To facilitate ease of use of this tool, we additionally developed a web-based risk calculator that may allow providers to accurately risk-stratify patients and decrease likelihood of readmission. Potentially modifiable risk factors such as psychiatric comorbidity can be optimized prior to fixation to reduce the risk of adverse outcomes. While no model can replace a physician's judgment, we aim to provide accurate information regarding the risk of unplanned readmission that a physician and patient can consult to improve pre-operative shared decision-making and patient counseling.

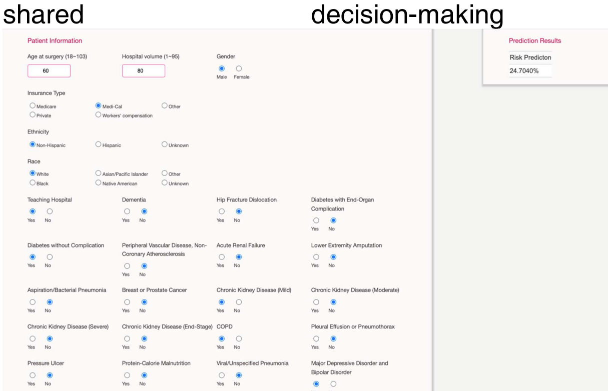

Table 1. Relative feature importance for unplanned readmission after ORIF of closed ankle fractures

Feature	Rank in ensemble model	Change to risk prediction
Binary features		
Prior pleural effusion or pneumothorax	1	0.0534
Prior viral or unspecified pneumonia	2	0.0502
Metastatic cancer	3	0.0455
Coronary atherosclerosis	4	0.0432
Prior brief psychotic disorder	5	0.0427
Mild chronic kidney disease	6	0.0352
History of medical complications	7	0.0313
Pressure ulcer	8	0.0257
Schizophrenia	9	0.0241
Morbid obesity	10	0.0239
Continuous features		
Number of comorbidities	1	0.0203
Age	2	0.0035
Hospital volume	3	-0.0017