Renal Recovery Prediction of Acute Kidney Injury Requiring Dialysis in Critically Ill Adults by Artificial Intelligence Approach

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Abstract

Renal recovery after dialysis-requiring acute kidney injury (AKI-D) is a vital patient-centered and clinical outcome in critical care. However, a good model for AKI-D recovery is lacking. Therefore, we developed and validated clinical applicable machine learning models for predicting AKI-D recovery with predictors collected within 3 days after dialysis initiation.

Introduction

Non-recovery of renal function after AKI-D is associated with longer ICU length of stay, higher mortality and economic burden. The final goal for managing patients with AKI-D is to achieve recovery. When it comes to critical ill patients, timely and early prediction those at the highest probability for future renal recovery is paramount. Thus, developed a precise prediction model soon after dialysis initiation might facilitate decision making and improve patient care in the context of AKI-D in ICUs.

Methods and Materials

In this retrospective cohort study in an academic medical center in Taiwan between January 2015 and December 2020, 1,389 patients experiencing AKI-D during ICU stays were enrolled (Figure 1). The cohort was partitioned into training (2015-2019) and temporal testing (throughout 2020) subsets. We developed and validated several models (eXtreme Gradient Boosting [XGBoost], random forest, logistic regression, and neural network) for predicting kidney recovery from dialysis (patients survived for more than 30 days after discontinuing dialysis before hospital discharge). The dataset included 79 routinely collected candidate variables known on or prior to the first 3 days of dialysis (Figure 2). In addition, we computed the predictor importance to the models.

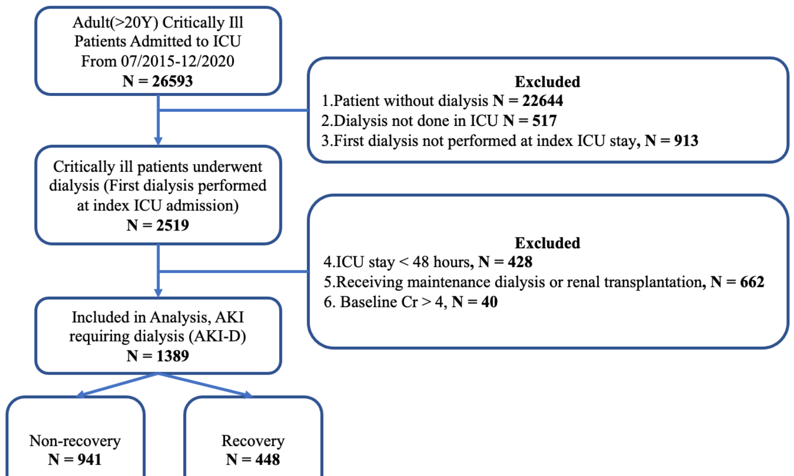

Figure 1. Flowchart of patient selection and outcome categorization

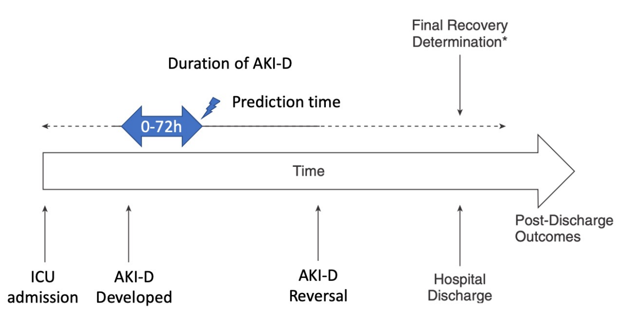

Figure 2. Conceptual model

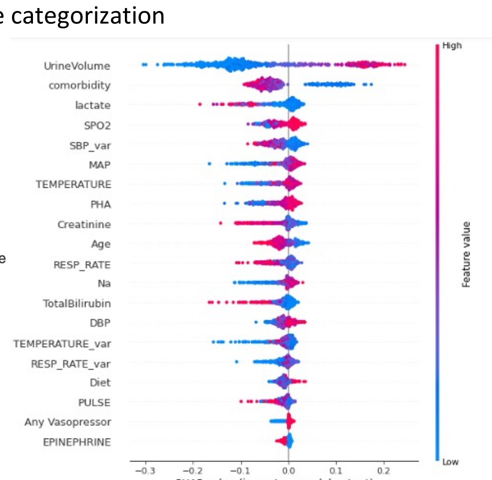

Figure 3. Top 20 SHAP value to illustrate the renal recovery prediction model at feature level.

Results

We identified 1,138 eligible patients in the training cohort and 251 patients in the temporal testing dataset. Renal recovery at discharge was developed in 32.9% (n = 374/1138) and 29.5% (n = 74/251) of patients in the training and testing cohorts, respectively. Among the different algorithms, the random forest had the highest area under the receiver operating characteristic (AUROC) curve on the training and validation dataset (sensitivity: 0.43, specificity: 0.92, AUROC: 0.82, precision: 0.80, and accuracy: 0.78) (Table 1).

Features of urine volume, comorbidity, lactate value, and saturation of peripheral oxygen (SpO2) were vital drivers of the model's prediction (Figure 3). Performance of the models on the training and testing cohorts were indistinguishable. The calibration plot of the model showed excellent consistency between the prediction probability and the actual probability.

In sensitivity analyses, we applied Least Absolute Shrinkage and Selection Operator (LASSO) regression selection to construct 24-variable prediction models. The results of the model evaluation for the random forest model were unchanged (AUROC of 0.80, 0.80–0.81). Besides, we shortened the prediction window, the predictor obtained AUROCs of 0.78 and 0.81 for AKI-D recovery on critically ill patients at 24- and 48-hour windows, respectively.

Table 1. Performance of the four models in the development and the temporal testiing cohort

	Classifier	Sens	Spec	Brier-Score	Accuracy	Percision_1	Percision_0	F score (2:1)	AUROC
Validation (2015-2019)	Xgboost	0.638±0.09	0.791±0.05	0.251±0.04	0.749±0.04	0.550±0.11	0.848±0.02	0.615±0.09	0.809±0.04
	RF	0.426±0.13	0.920±0.03	0.219±0.02	0.781±0.02	0.678±0.12	0.803±0.03	0.457±0.13	0.821±0.05
	LR	0.677±0.06	0.759±0.06	0.264±0.05	0.736±0.05	0.531±0.11	0.855±0.02	0.639±0.07	0.804±0.04
	NN	0.630±0.15	0.768±0.08	0.268±0.04	0.732±0.04	0.526±0.09	0.846±0.04	0.600±0.12	0.785±0.05
Testing (2020)	Xgboost	0.722	0.791	0.226	0.774	0.539	0.894	0.676	0.859
	RF	0.504	0.949	0.163	0.837	0.770	0.850	0.541	0.857
	LR	0.752	0.781	0.226	0.774	0.538	0.903	0.697	0.848
	NN	0.594	0.901	0.177	0.823	0.669	0.868	0.608	0.858

Discussion

Non-recovery of renal function after AKI requiring dialysis is associated with increased morbidity and mortality and high health care cost. Existing prediction tools for renal function recovery after AKI-D lack the ability to identify patients at high probability for renal recovery in the early stage. To address this gap, we constructed a prediction model using four machine learning models on this single center critical care database comprising 26,593 ICU admissions. The models developed in the study achieved good discrimination for predicting renal recovery. Moreover, the models possessed good discrimination despite a shorter prediction time window or the use of less variables chosen by LASSO, suggesting the potential clinical utility.

Conclusions

We successfully applied early prediction models of renal recovery in ICU patients with AKI-D using data routinely obtained within three days after dialysis initiation. These findings may assist critical care physicians in prognostic stratification and resources allocation soon after patients survive the acute stage. External validation of this machine learning approach is required in future studies.

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