A Machine Learning-Based Approach to Predicting Acute Kidney Injury and Associated Medication Regimen Use in Critically Ill Adults

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Introduction

AKI is common in the ICU affecting 25-65% of adults and is associated with poorer outcomes including doubling the risk of death during hospitalization.[1] Critically ill patients are at the highest risk for experiencing adverse drug events. It has been estimated that on average patients receive greater than 30 medications during their ICU stay.[2] The MRCI scoring tool evaluates the characteristics of the prescribed regimen and a higher score has resulted in an increase in medication errors and unfavorable clinical outcomes.[3]

Purpose

Our primary aim of this retrospective cohort study was to evaluate the performance of several machine learning models to predict AKI in the ICU using MRCI scores.

Methodology

322 adult critically ill electronic health records were analyzed from February 1 to August 30, 2020. Patients excluded were long-term care patients, history of renal replacement or kidney transplantation. AKI status was determined using both SCr-and UO-based methods based upon The 2012 Kidney Disease Improving Global Outcomes (KDIGO) classification system. (Figure 1).

Figure 1: 2012 Kidney Disease Improving Global Outcomes (KDIGO) classification system.

Stage	SCr	UO
1	1.5-1.9 times baseline OR ≥ 0.3 mg/dL increase	<0.5mL/kg/hr for 6-12 hours
2	2.0-2.9 times baseline	<0.5mL/kg/hr ≥12hrs
3	3.0 times baseline OR Increase SCr to >4 mg/dL	<0.3mL/kg/hr for ≥24 hrs OR Anuria for ≥12 hrs

Descriptive statistics were conducted using an independent t-test, chi-square test, or fisher's exact test for continuous and categorical variables, respectively. Predictors of interest included MRCI scores at time of hospitalization, evaluation of 14 medication classes, and patient demographics. Machine learning algorithms used were logistic classifier, random forest, and XGBoost. Predictors of interest were ranked by variable importance to aid in the prediction of AKI.

Results

Table 1 describes baseline characteristics related to AKI vs No-AKI. Patients with AKI had significantly greater MRCI scores within 24 hours of admission and higher acute respiratory failure with hypoxia and hypokalemia. Patients who experienced AKI more commonly received endocrine agents (39.2%), pulmonary agents (23.5%), and vasopressors (20.3%) on first day of ICU admission.

Table 1: Baseline Characteristics

Measure	AKI (n =153)	No-AKI (n= 166)	*p*-value
Demographics			
Age (years) (IQR)	65.0 (52.0-76.0)	64.0 (50.2-72.8)	0.46
BMI (kg/m^2) (IQR)	28.1 (23.8-33.9)	26.5 (22.9-31.3)	0.04
Male/Female (%)	84 (54.9)/69 (45.1)	91 (54.8)/75 (45.2)	> 0.9
Health Insurance (%)			0.05
Commercial	79 (51.6)	104 (62.7)	
Public	74 (48.4)	62 (37.4)	
Race (%)			0.09
White	91 (59.5)	115 (69.3)	
Non-White	62 (40.5)	51 (30.7)	
MRCI score outpatient	35.0 (16.5-60.0)	23.75 (9.25-49.6)	0.007
MRCI score within 24 hours	69.0 (46.0-97.0)	54.5 (33.6-80.1)	< 0.001
Diagnosis (%)			
Hyperlipidemia	71 (46.4)	71 (42.8)	0.6
Acute respiratory failure with hypoxia	73 (47.7)	51 (30.7)	0.002
Hypertension	44 (28.8)	63 (38.0)	0.11
Acidosis	55 (36.0)	48 (28.9)	0.19
Hypokalemia	59 (38.6)	44 (26.5)	0.03
Medication by Class (%)			
Analgesic/Sedatives	79 (51.6)	83 (50.0)	0.858
Cardiovascular	53 (34.6)	57 (34.3)	> 0.9
Diuretics	11 (7.2)	14 (8.4)	0.84
Endocrine	60 (39.2)	59 (35.5)	0.57
Gastrointestinal	70 (45.8)	75 (45.2)	> 0.9
Genitourinary	8 (5.2)	9 (5.4)	> 0.9
Hematologic/Anticoagulants	67 (43.8)	75 (45.2)	0.82
Intravenous Fluid/ Electrolytes	90 (58.8)	108 (65.1)	0.30
Neuromuscular Blockers	1 (0.7)	2 (1.2)	> 0.9
Psychiatric	35 (22.9)	38 (22.9)	> 0.9
Pulmonary	36 (23.5)	32 (19.3)	0.41
Vasopressor Agents	31 (20.3)	22 (13.3)	0.13
Vitamin Supplements	26 (17.0)	21 (12.7)	0.3

Table 2 describes the performance of the three machine learning models.

ML Models	Overall Accuracy	Sensitivity	Specificity	PPV	NPV
LRG	0.63 [0.50-0.74]	0.57 [0.39-0.73]	0.69 [0.51-0.83]	0.66 [0.47-0.81]	0.60 [0.43-0.75]
RF	0.60 [0.47-0.71]	0.54 [0.37-0.70]	0.67 [0.48-0.82]	0.66 [0.47-0.81]	0.55 [0.38-0.71]
XGB	0.74 [0.62-0.83]	0.68 [0.50-0.82]	0.8 [0.63-0.92]	0.78 [0.60-0.91]	0.7 [0.53-0.83]

Figure 2 Performance (mean[CI]) of the machine learning algorithms to predict AKI.

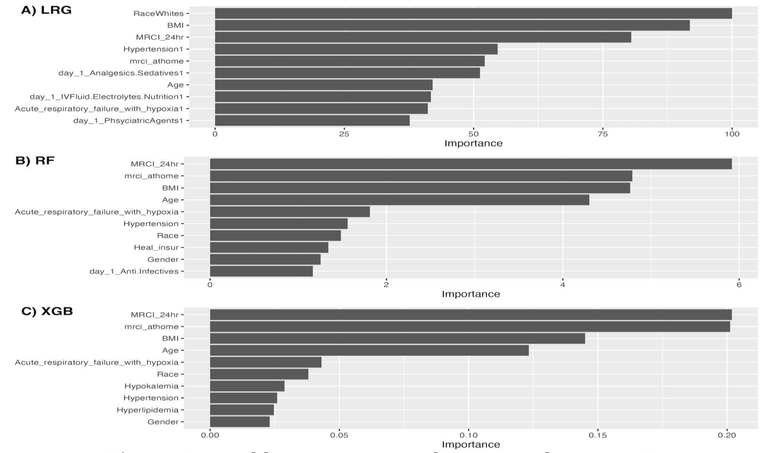

Figure 3 Variable importance ranking in predicting AKI.

The XGBoost model had the highest prediction accuracy of AKI (74%) and had an average sensitivity of (68%). Top variables of importance in predicting AKI were MRCI scores at 24 hours and outpatient medication use, BMI, age, and acute respiratory failure with hypoxia.

Conclusion

Our study accurately predicted AKI in the ICU setting 74% of the time suggesting that incorporation of an MRCI score into the clinical decision-making process may aid clinicians in the early identification of at-risk patients to proactively implement preventative care strategies.

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