Predicting Hyperkalemia in the ICU and Evaluation of Generalizability and Interpretability

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Introduction

Hyperkalemia is a rare but potentially life-threatening condition that may lead to fatal cardiac arrhythmias. Identifying patients at high risk for hyperkalemia may allow providers to adjust clinical management. Previous literature investigating hyperkalemia in hospitalized patients mostly focused on evaluating the association of clinical features with the development of hyperkalemia, and the only predictive models that we are aware of are based on medication administration and electrocardiograms [1–4]. Our goal is to present a methodology to build predictive models to identify patients at high risk of developing hyperkalemia using observations from the first day of ICU admission. While most patients with hyperkalemia in the ICU also have AKI, it is important to capture those with normal kidney function because their hyperkalemia is easier to miss.

Methods and Materials

Definitions

We defined hyperkalemia as K≥6 mEq/L, and filtered out erroneous lab values by including these constraints: (i) potassium ≥6 mEq/L with no other potassium tests within 6 hours, (ii) two potassium results in 6 hours with both results ≥6 mEq/L, (iii) one potassium level ≥6 mEq/L with calcium gluconate administration.

Scenarios

We have two clinical scenarios as follows: (i) Case 1: AKI within 7 days of admission to the ICU, followed by hyperkalemia within the next 7 days, (ii) Case 2: Hyperkalemia within 14 days of admission to the ICU, with or without AKI. For both clinical cases, the training set was composed of patients who developed hyperkalemia between admission day 1 to 14. To investigate increasing lead times, subgroups of patients who developed hyperkalemia between day n to 14 were selected as a test set ($n : 2 \ldots 4$) (Figure 1).

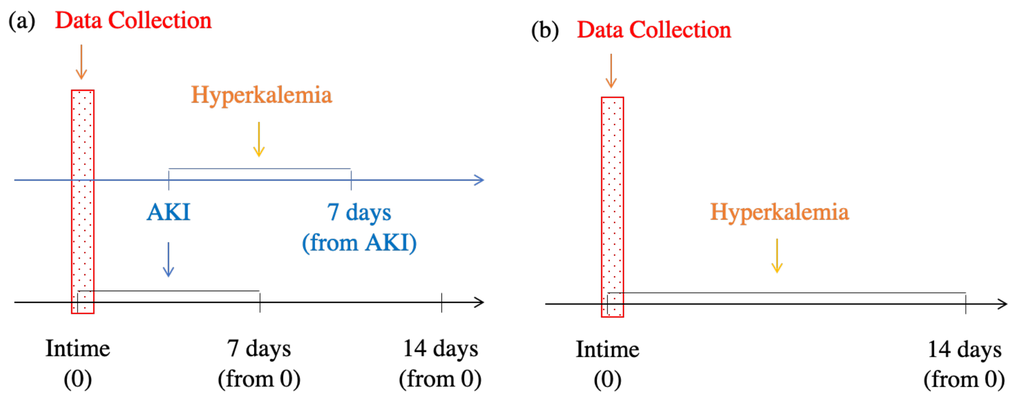

Figure1: Data timeframe for predicting hyperkalemia. (a) Case1 (b) Case2

Cohort Selection

We included the first ICU admission for all patients between the ages of 18 and 90. After exclusion criteria adjustment, the number of patients in this study was 43,798 (hyperkalemia:1,048) for Case 1 and 83,565 (hyperkalemia:1,821) for Case 2 with variables. We collected demographics data, laboratory variables, AKI stage (severity), fluid balance, IV fluid use and medications use within 24h of admission that were closest to admission time.

Model

LR (Logistic Regression), RF (Random Forest), and XGBoost were trained with balancing the class frequency, and tested over different lead times across the scenarios with providing the importance of features in this project is interpreted with local model-agnostic SHAP (SHapley Additive exPlanation) values.

Results

We ran our models with and without the AKI stage as a feature, and found that all of our models were in close agreement. The performance and feature importance analysis is shown in Table 1 and Figure 2. The performances of RF and XGBoost in Case 2 are consistently higher than the performance of models in Case 1. In addition, the performance decreased in both cases when hyperkalemia occurred later in the hospitalization.

Testdate	Model	AKI Cohort (Case 1)	General Cohort (Case 2)
1st∼14th	LR	0.79 (0.77−0.81)	0.81 (0.80−0.82)
	RF	0.81 (0.80−0.82)	0.85 (0.84−0.85)
	XGB	0.81 (0.79−0.82)	0.85 (0.85−0.86)
2nd∼14th	LR	0.75 (0.74−0.76)	0.72 (0.71−0.74)
	RF	0.78 (0.77−0.79)	0.80 (0.79−0.81)
	XGB	0.78 (0.76−0.79)	0.80 (0.78−0.81)
3rd∼14th	LR	0.70 (0.69−0.72)	0.71 (0.70−0.72)
	RF	0.73 (0.72−0.74)	0.80 (0.79−0.81)
	XGB	0.73 (0.72−0.74)	0.80 (0.78−0.81)
4th∼14th	LR	0.70 (0.69−0.71)	0.72 (0.71−0.73)
	RF	0.74 (0.71−0.76)	0.80 (0.78−0.82)
	XGB	0.73 (0.70−0.75)	0.80 (0.78−0.82)

Table1: Model performance (AUC).

Top features in RF and XGBoost models in both clinical cases include high phosphate, high admission potassium, high fluid balance, and vasopressor use. In addition, AKI stage was also an important feature in Case 2.

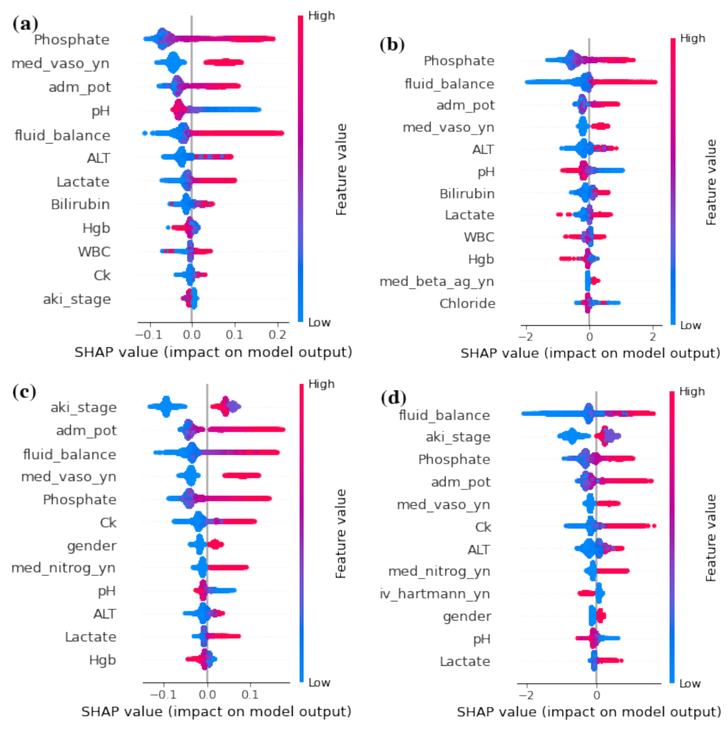

Figure2: Top 10 SHAP values
(a) RF(Case1) (b) XGBoost(Case1) (c) RF(Case2) (d) XGBoost(Case2).

Conclusion

In both clinical scenarios, the decrease in performance over time is likely due to the relatively longer duration of forward prediction using only admission parameters. Among the top features, vasopressor use and positive fluid balance. These two features are associated with hemodynamic instability and increased morbidity and mortality. The AKI stage is not important in Case 1 (where all patients have AKI), but is important in Case 2 (which includes patients with and without AKI). This could mean that AKI, regardless of stage, increases the risk of hyperkalemia. There are many potential reasons for this, including the small cohort size and the definition of AKI severity [5]. As emphasized in a recent commentary, a deeper understanding of the patterns discovered in clinical datasets to infer causation is necessary prior to adoption rather than simply evaluating algorithms on multiple datasets [6]. We developed models to predict hyperkalemia in critically ill patients, with a focus on applicability to various clinical scenarios and interpretability.

Citation

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