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Machine Learning for Risk Prediction of Recurrent AKI in Adult Patients After Hospital Discharge

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Abstract. Recurrent AKI has been found common among hospitalized patients after discharge, and early prediction may allow timely intervention and optimized post-discharge treatment [1]. There are significant gaps in the literature regarding the risk prediction on the post-AKI population, and most current works only included a limited number of pre-selected variables [2]. In this study, we built and compared machine learning models using both knowledge-based and data-driven features in predicting the risk of recurrent AKI within 1-year of discharge. Our results showed that the additional use of data-driven features statistically improved the model performances, with best AUC=0.766 by using logistic regression.

Keywords. Recurrent AKI, risk prediction

1. Introduction

Acute kidney injury (AKI) is characterized as rapid loss of kidney function [3]. The United States Renal Data System (USRDS) reported significant increasing trends in hospitalizations for AKI over the past decade, affecting 62.1 per 1,000 person-years in 2020 [4]. In addition to the increasing prevalence, researchers also found that AKI patients may be at a high risk of readmission and another AKI onset, contributing to substantial costs and burden on public health services and resources [1].

Among hospitalized patients with AKI, recurrent AKI (r-AKI) has been found to be common after discharge with nearly a third of elderly AKI patients being readmitted with AKI within 12 months [1]. Despite a large body of research in the risk panel of AKI during admission, there are significant gaps in the literature regarding the risk prediction of r-AKI. Most existing studies used variables pre-selected based on domain knowledge, which may not be able to provide a comprehensive view of the risks [2]. Electronic health records (EHR) are emerging as rich sources of information for increased insights but also as challenging data sources with high dimensionality for building prediction models.

In the present study, longitudinal EHR data was used, including knowledge-driven features from the literature and data-driven features collected from administrative codes, to build risk models of recurrent AKI during 1-year post-discharge period with comparative performance of various machine learning approaches.

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2. Methods

A retrospective study was conducted using a research clinical data repository of patients administered through the University of Minnesota seen at M Health Fairview, a health system in greater Minnesota and western Wisconsin, USA, (IRB approval STUDY00005536) from October 2015 to October 2020.

AKI is defined by the KDIGO serum creatinine (SCr) diagnostic criterion or procedure record of dialysis and renal transplant therapy during hospitalization [3]. ICD codes for AKI were not used given the poor performance and potential time lag in identifying AKI [5]. Comorbid conditions of diabetes, hypertension, heart failure and chronic kidney disease were identified by related ICD codes [5,6]. In this study, r-AKI is defined as a patient who had AKI recovered at hospital discharge (final SCr returned to ≤50% above baseline SCr) and had another AKI onset occurred inpatient or outpatient within 1 year post discharge [7]. A look-back period of 1 year from the date of hospital admission was used to determine baseline renal function. Missing SCr baseline were imputed using back-calculation of MDRD formula [8].

Patients with the following characteristics were included: (1) adults admitted for any reasons, with AKI during stay and final SCr at discharge returned to 'recovery' level, and (2) had SCr measured inpatient or outpatient within 1-year post discharge.

Patient features were constructed from EHR records prior to the discharge date and categorized as knowledge-based or data-driven feature sets described as below:

Knowledge-based features (n=22) were derived from commonly used and known risk predictors of AKI, including inter-correlated conditions with AKI, the last measured lab tests and vitals, length of stay, AKI stage and use of emergency/ICU [1-3,6,7]. Missing values were imputed with age/gender-adjusted average measure from the literature [9,10]. All categorical variables were processed by one-hot encoding and numerical features (including AKI stage) were rescaled between -1 and 1.

Data-driven features (n=20,529) included all administrative codes reported during the admission with the following three types: (1) diagnosis, DX, (2) procedure, PROC, and (3) drug, RX. Given the massive volume and text format of administrative codes, an analogy method of natural language processing was applied. Top 100 bag-of-words represented features with TF-IDF weights were concatenated with knowledge-based features for predictive modeling. Features with correlation coefficients >0.85 were removed. A total of 316 features were used for risk modeling.

Machine learning algorithms, including Logistic regression (LR) and random forest (RF), were applied to build risk models using (1) only knowledge-based features and (2) combination of knowledge-based and data-driven features. Grid search was used for hyperparameter tuning, and models were trained with class weights assigned and 3x repeated 10-fold cross validation. Performance and feature importance for each model were compared, using R v4.1.2 (caret 6.0-93; tuneRanger 0.5).

3. Results

A total of 8 machine learning models were constructed to predict the occurrence of r-AKI with 1-year post discharge. Detailed experimental results are presented as below.

The full study cohort consisted of 15,102 hospitalizations, among which, 7,389 were 1st time admission with AKI. The full cohort and subgroups shared similar patient characteristics. Mean age was 60 years old and ~54% were male. Around 61% had emergency or ICU service and average length of stay was 10 days.

Table 1. Stage of AKI during hospitalization of post discharge.

		Full Cohort (n = 15102)		**1st Time Admission (n = 7389)**	
Max AKI stage during stay, n(%)	1	15777	(55.29%)	2814	(38.08%)
	2	2191	(7.68%)	807	(10.92%)
	3	10585	(37.10%)	3768	(50.99%)
Max AKI stage within 1 year, n(%)	0	7343	(25.74%)	2083	(28.19%)
	1	7355	(25.78%)	1207	(16.34%)
	2	1537	(5.39%)	485	(6.56%)
	3	12318	(43.17%)	3614	(48.91%)

31 unique features were obtained from the top 10 important features across all models. SCr at discharge was presented as the most important feature in predicting r-AKI in most models. A total of 9 features were top ranked by at least half of the models, which are, SCr, PROC_80197(Therapeutic Drug Assays), AKI_IP_Scale (AKI stage rescaled), WBC (white blood cell), RX_199058 (mycophenolate mofetil), CKD (chronic kidney disease), Lymph (lymphocytes), BUN (bun urea nitrogen) and Age.

When only using knowledge-based features with full cohort, both RF and LR (Figure 1.a,c) algorithms had SCr, WBC, AKI_IP_Scale, BUN and Age as the top 10 important features. The RF model also found blood pressure, AST(aspartate aminotransferase) and LOS (length of stay) important in predicting r-AKI, whereas the LR model found CKD, diabetes (DM), IP_ER_ICU (emergency/ICU service) and sex to be more important. ICD_D63.1 (Anemia in CKD) and ICD_Z94.83 (Pancreas transplant status) were important in RF and LR models, respectively. Meanwhile, when using all features, most of the important features were data-driven in the LR model (Figure 1.b,d).

Similar rankings were observed in the experiments on the subgroup of 1st time admission with AKI (Figure 1.e-h) with minor shuffles. Except for 'AKI_IP_Scale', it was represented as the 3rd important feature in models (Figure 1.a-c) using the full cohort; however, in the subgroup cohort, it was not top ranked by RF (Figure 1.e-f).

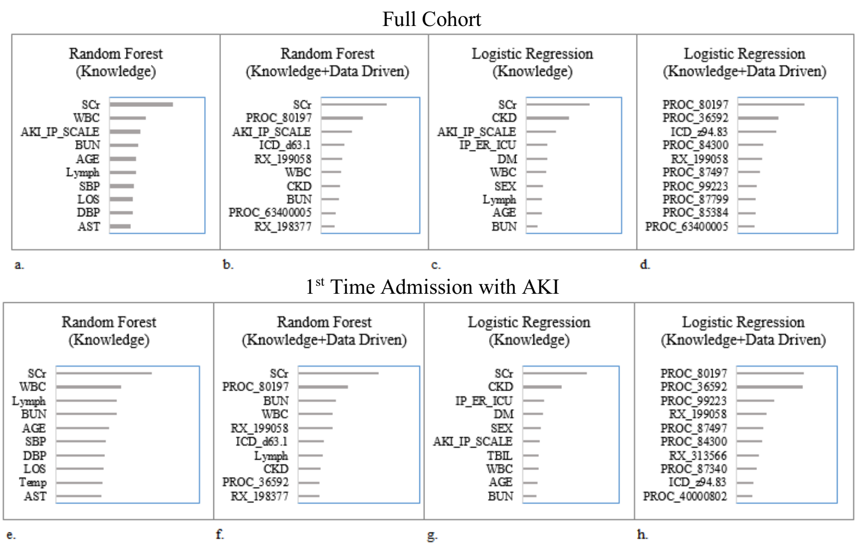

Figure 1. Top 10 important features in predictive models using different feature sets and cohorts.

Performance measures were obtained using test dataset, and AUC were compared by applying bootstrap method. Using all features, all models showed improved performance across most measures (all pairwise p-values <0.001) than models using knowledge-based features alone, except for the sensitivities of full cohort – LR models. In general, we observed good accuracy, specificity and precision for most models, but the sensitivity was highly inconsistent, ranging from 0.439 to 0.821.

For the subgroup cohort, no statistical differences in AUC were found between two algorithms. However, in the full cohort, we found that LR outperformed RF models with statistically significant higher AUC. A trade-off between sensitivity and specificity was observed when implementing two algorithms in both cohorts. The best performed model used all features with LR in the full cohort, with AUC=0.766.

Table 2. Performance of predict models. Abbreviations: RF, random forest; LR, logistic regression; K, knowledge-based features; D, data-driven features; 0.95 CI : 0.95 confidence intervals from 10000 bootstrap.

Cohort	Model	Feature	Accuracy	Precision	Sensitivity	Specificity	AUC (0.95 CI)
Full	RF	K	0.809	0.884	0.439	0.886	0.662 (0.640-0.684)
		K+D	0.829	0.899	0.519	0.894	0.706 (0.684-0.729)
	LR	K	0.688	0.947	0.821	0.661	0.741 (0.722-0.759)
		K+D	0.724	0.952	0.701	0.831	0.766 (0.747-0.784)
1st time admission	RF	K	0.712	0.803	0.504	0.795	0.649 (0.622-0.676)
		K+D	0.758	0.833	0.578	0.829	0.703 (0.677-0.729)
	LR	K	0.632	0.851	0.736	0.591	0.664 (0.637-0.689)
		K+D	0.681	0.880	0.777	0.644	0.710 (0.685-0.735)

4. Discussion

In this study, we developed risk models to predict the occurrence of r-AKI within 1-year post discharge. Our study cohort consisted of an older population. We observed that 17%-27% of them had diagnosis or procedure codes for renal transplant during the same AKI admission and >70% had r-AKI, indicating an underestimated burden of r-AKI and potential gaps in post-discharge care for this population. The application of machine learning methods using EHR data allows researchers to predict the risk of r-AKI and to further facilitate decision making on hospital discharge and follow-up treatment plans.

We observed that knowledge-based features were useful in predicting r-AKI with high precision but moderate AUC. By adding data-driven features, model performance has been statistically improved in general. Our best performing model (AUC=0.766) was achieved by using LR with all features in the full cohort, and LR consistently had similar or better performance than RF. Interestingly, the top 10 features were very different in logistic models after adding data-driven features, which may suggest some risk factors that require more attention. For example, ICD_Z94.83 (Pancreas transplant status) was top ranked in our best performing model, and pancreatitis could contribute to AKI [11]. However, some top ranked features were less interpretable, such as PROC_87799 (infectious antigen detection).

Our study has several limitations. Firstly, the research findings were derived from a retrospective study without follow-up data, and there is a lack of a formal definition of r-AKI or by inpatients versus outpatients. The requirement of SCr measured during 1-year post-discharge might introduce bias to a sicker population. Secondly, our filter method for feature selection might remove potentially important features and limit the performance of random forest. Given the hierarchy structure of administrative coding, the tree-lasso method might be considered as a potential solution.

5. Conclusions

We conducted a retrospective study on predictive modeling of the risk of r-AKI within 1-year post discharge among adult patients with AKI. To the best of knowledge, the study is the first to predict the risk of r-AKI using knowledge-based and data-driven data from EHR. Results showed the combination of both feature sets using logistic regression led to the best performance. Findings of top important features in predicting r-AKI may suggest opportunities for early intervention and optimized post-discharge treatment plans.

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