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Chao-Jung Huang, Brian Wu, Xiaodong Li, Yongxia Han, Yaqi Zhang, Shiying Hao, Xuefeng B. Ling, "Predicting 1-year mortality of acute kidney injury: a risk model using electronic health records," Proc. SPIE 11792, International Forum on Medical Imaging in Asia 2021, 117920C (20 April 2021); doi: 10.1117/12.2590704

SPIE.

Event: International Forum on Medical Imaging in Asia 2021, 2021, Taipei, Taiwan

Predicting 1-Year Mortality of Acute Kidney Injury: A Risk Model Using Electronic Health Records

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ABSTRACT

Acute kidney injury (AKI) is associated with increased morbidity and mortality in intensive care units (ICU). The sudden episode of kidney failure may lead to end-stage renal disease (ESRD) or deaths, and has been related to significantly increasing costs of ICU admissions and treatments. Early prediction of AKI inpatient mortality will help decision-making, and benefit resource allocation in ICU. Therefore, it is crucial to develop an early warning system for AKI prediction. We aimed to create a more comprehensive predictive model for 1-year AKI mortality. A cohort of 2,247 patients with AKI was assembled, of which the in-hospital mortality was 36.67%. Longitudinal data of each patient were collected from the Medical Information Mart for Intensive Care III (MIMIC-III) dataset. An interpretable XGBoost risk model was developed and validated by 10-fold cross validation. Model predictors included 11 routinely collected AKI-related laboratory measurements, 8 complications of AKI, and demographic data. An artificial neural network (ANN) model was also developed in parallel for comparison. The XGBoost model demonstrated an area under the receiver-operating characteristic curve (AUC) of 0.83, which was superior to ANN (AUC = 0.79). Our model was able to predict mortality of AKI in ICU with high accuracy. Our model can predict 1-year AKI mortality. Furthermore, it had great potential for identifying at-risk patients in ICU. These findings indicated that our approach might offer opportunities for better resource utilization and better administration of AKI.

Keywords: Acute kidney injury, intensive care unit (ICU), end-stage renal disease (ESRD), early warning system, medical information mart for intensive care III (MIMIC-III), artificial neural network (ANN)

1. INTRODUCTION

Prevention, detection, and management of acute kidney injury is a challenge for all intensive care clinicians, because of high incidence and mortality. AKI has imposed a major resource burden on the global healthcare system with an estimated 13.3 million cases annually and 1.4 million of AKI related deaths occur low- and middle-income countries [1]. Acute kidney injury inpatient mortality prediction models can help clinicians to make better treatment decisions and allocate resources to patients based on their available resources and demand.

Although age is an important factor in determining the disease progression of AKI [2], several papers still show that excessive exposure to nephrotoxins, need for ventilation and other medical conditions contribute significantly to the progression of AKI [3][4][5][6]. Diagnosis of AKI is based on mainly two factors, serum creatinine and urine output. AKI is diagnosed when serum creatinine level is greater than 26.5 μmol/L or when urine output decreases to

International Forum on Medical Imaging in Asia 2021, edited by Ruey-Feng Chang, Proc. of SPIE
Vol. 11792, 117920C · © 2021 SPIE · CCC code: 0277-786X/21/$21 · doi: 10.1117/12.2590704

0.5ml/kg/hr for 6 to 12 hours [7]. While these two factors assess the severity, our modeling focuses on AKI mortality. A paper from Hospital Universitário Walter Cantídio identified four main characteristics of critically ill patients with AKI, including age, hypotension, sepsis, and kidney failure [8]. Results show that severity of AKI is positively correlated to age and hypotension, in which patients have 2% higher mortality rate when mean arterial blood pressure is less than 80 mmHg and 15% higher when patients are 65 years old or older [8]. Sepsis and kidney

failure are the main complications of AKI that indicate critically ill patients with unacceptable mortality [8].

To help hospitals and clinicians make better treatment decisions and allocate resources based on patients' needs, a highly comprehensive mortality predictive model would play a huge role in giving hospitals an idea of what might happen to AKI patients in the near future. In the following, we cite some related works about AKI prediction. Lin et al. [9] used the random forest model to predict AKI in the ICU. The article also pointed out an ongoing debate between random forest models and logistic regression models such as SVN and ANN. Cheng et al. [10] achieved AUC of 0.76 achieved with random forest which can predict AKI events 1-day prior. However, the study is based on younger cohorts (18 to 64 years old), while older cohorts tend to have higher AKI risk. In our study, we choose a cohort with an average age of 63.9 to prevent this uncertainty. Huang et al. [11] compared 9 models created by the XGBoost method with the NCDR CathPCI registry. The same article also found that these models outperformed models created by stepwise selection or lasso regularization with logistic regression.

Our proposed model aims to predict AKI mortality within one year. We decided to use XGBoost [12] as our main algorithm, we also use artificial neural networks (ANN) as our second model to compare accuracy and performance. We also use 8 complications of AKI as input features, allowing the model to process a variety of information for better performance. Our study focuses on AKI mortality rather than the creatinine level which is more difficult to interpret without understanding specific scientific relevance.

2. METHODOLOGY

It is difficult to predict whether a patient with AKI will die with solely demographic features as shown by a previously studied AKI prediction model, which indicates that among comorbidity, medication, and demographic features, the last contributes least to risk prediction results [13]. We included a variety of lab tests and related AKI complications, along with patient demographics to our predictive model. The database that we will be using is MIMIC-III, which is an openly available dataset developed by the MIT Lab for Computational Physiology, comprises deidentified health data associated with ~60,000 intensive care unit admissions. Among the forty-six thousand patients in the dataset, around four thousand have AKI and around a thousand have died of AKI, with an average age of 63.9.

Total feature comprises Selected features comprise 11 laboratory tests and 8 AKI-related comorbidities, as well as basic demographics data including age and gender. Table 1 shows all 21 features categorized into demographics, laboratory tests, and comorbidities. The laboratory tests include creatinine level, urine output, prothrombin time, hematocrit and hemoglobin level, white blood cells count, blood urea nitrogen, serum bicarbonate, serum sodium, platelet count, and blood pressure [12]. The related AKI comorbidities include cancer, hypotension, anemia, septic shock, hemorrhage, acidosis, kidney failure, and hypertension.

Firstly, this is a retrospective study incorporating the MIMIC III database, which contains 46,520 de-identified patients. For a specific patient, each admission to the hospital might have slight variation in terms of lab tests, but for simplicity, we consider each admission as a distinct patient. Since we are predicting mortality within 1 year, we first calculate the time it takes for a patient to die since admission, if the time is less than a year, we consider the patient has died, otherwise the patient is considered to have survived. As for missing data, we replace those with the average of all AKI patients for that laboratory result.

In Table 2, patients' population is divided based on gender and age, with the majority being men (56%) and older than 70 years old (40%). It is also worth noting that there are only 2 AKI patients older than 90 years old. In the MIMIC-III database, patients who were 89 years old or older were treated differently due to their age, which would lead to bias. However, to eliminate possible bias, we still excluded patients who were 89 years old or older. Table 2 also shows that the majority of death triggered by AKI happens without hospital care.

Table 1. All Features in Categories

Lab Features	Demographics and AKI-related Comorbidities
Creatinine	Age
Urine output	Gender
PT (Prothrombin time)	Cancer
Hemotocrit	Kidney failure
Hemoglobin	Hypotension
White blood cells	Septic shock
Blood urea Nitrogen	Anemia
Serum bicarbonate	Hemorrhage
Serum sodium	Acidosis
Platelet count	Hypertension
Blood pressure	

Table 2. AKI patient population and demographic characteristics related data.

Demographic Overview	Characteristic	Total Patients (n = 2247)
Gender	Female	934 (42%)
	Male	1313 (58%)
Age	18-30	57 (3%)
	30-40	92 (4%)
	40-50	237 (11%)
	50-60	380 (17%)
	60-69	493 (22%)
	70-89	896 (40%)
	90+	2(<0.1%)
Death During Hospitalized Stay	Yes	831(37%)
	No	1416(63%)

3. RESULTS

For our XGBoost model, we used a ten-fold cross-validation. Table 3 shows the performance of different models based on different folds, from 1-fold to 10-fold. All in all, there is no significant difference between the results which confirms that our model trained by the XGBoost algorithm, along with the input features, is relatively stable as it shows no significant fluctuations in both ACC and AUROC while changing the number of folds for cross validation. After

averaging the 10 models ranging from 1 to 10-fold, XGBoost model achieves an accuracy of 0.81 and AUROC of 0.82, outperforming those of ANN (0.70, 0.79).

Table 3. Performance of different models

Model		ACC	AUROC
Individual XGBoost Model	1	0.807	0.818
	2	0.812	0.822
	3	0.815	0.828
	4	0.807	0.825
	5	0.811	0.819
	6	0.809	0.827
	7	0.801	0.822
	8	0.814	0.823
	9	0.811	0.828
	10	0.803	0.824
	Average	0.809	0.824

As seen from figure 1, among all features, platelet count, blood urea nitrogen, and prothrombin time show most dominance in predicting AKI mortality for patients in the MIMIC-III database. In addition, among all features, gender seems to be the less effective in contributing to the prediction power of our model. Also, it's worthy to note that the feature ranking results for XGBoost model is consistent with those of the ANN model.

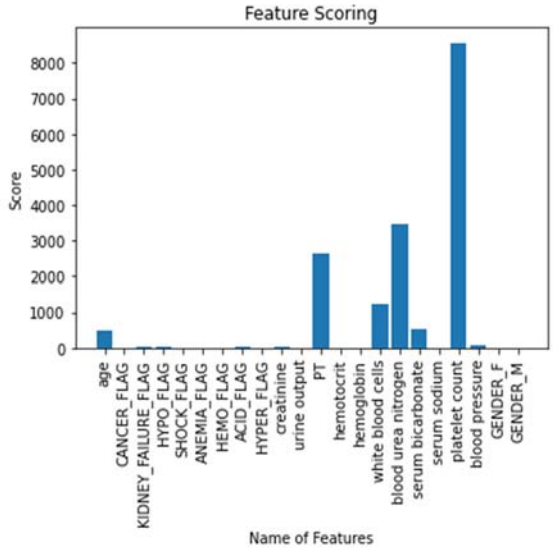

Figure 1. Feature Ranking Scores

Since XGBoost is suitable for relatively small number of variables, it fits our model which has relatively few input features as we have only 11 AKI-related laboratory measurements and 8 complications of AKI, along with demographics data, whereas ANNs are best on data with large number of variables. As for our ANN model, we specifically created a multilayer perceptron (MLP) in which we built a fully connected neural network with five fully connected layers and an output layer which gives us results on whether the AKI patients survived or not. In the end, our XGBoost model outperforms the ANN model in all metrics except for NPV. Our XGBoost model with a 10-fold cross validation split achieved a score of 0.829 (AUC) and Figure 2 show that.is slightly better than ANN (0.79).

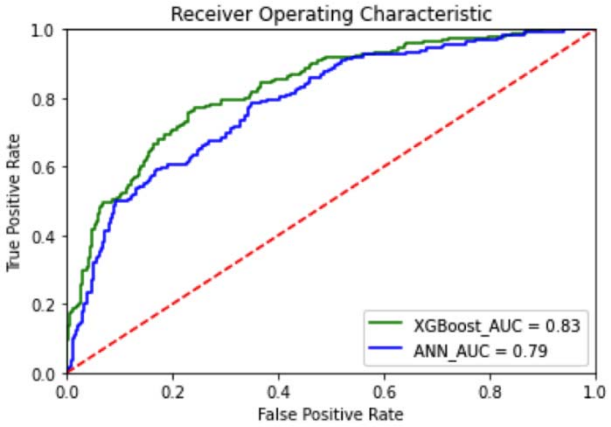

Figure 2. ROC Curves for XGBoost and ANN algorithms

We split our datasets into 80% training and 20% testing to predict sensitivity and specificity. Then we compare accuracy, positive predictive value (PPV), negative predictive value (NPV), sensitivity and specificity between ANN and XGBoost in Table 4. The ANN model shows that sensitivity (0.73) is significantly favored over PPV (0.38), which further explains that the model is willing to accept false alarms as it predicts deceased AKI patients. However, for XGBoost, PPV (0.69) and sensitivity (0.81) are significantly higher than those of the ANN, which indicates that the XGBoost model predicts deceased AKI patients much better than the ANN, with lower number of false alarms. The results further confirm that the XGBoost based model is more precise and accurate than the ANN model, which again indicates the capability of XGBoost on data with small number of variables.

Table 4. Results for ANN and XGboost models

Models	Accuracy	PPV	NPV	Sensitivity	Specificity
ANN	0.70	0.38	0.91	0.73	0.70
XGBoost (10 –fold)	0.81	0.69	0.83	0.81	0.94

4. CONCLUSION

Acute kidney injury inpatient mortality prediction model can help clinicians make better treatment decisions and allocate resources to patients according to availability and demand. Our study applies XGBoost and ANN algorithms to build our AKI mortality model to predict 1-year mortality. The results show that the XGBoost model performs significantly better than the ANN model in most metrics, including accuracy, AUC, PPV, sensitivity, and specificity.

Our study is limited to model development and missing data handling. To improve, we may begin with hyperparameters tuning for the ANN model, to result in a less performance gap with the XGBoost model. Then, rather than replacing the missing laboratory data with the average of all AKI patients, we could have replaced the missing

data with the average of the specific patient's admissions to the hospital. Furthermore, more AKI-related comorbidities could be added in for various input features to train better mortality prediction in our model owing to the majority of our features are laboratory measurement results. Finally, we could have tried utilizing other algorithms such as linear regression to see whether different algorithms matter.

ACKNOWLEDGMENTS

The authors thank the All Vista Healthcare Center, Ministry of Science and Technology, Taiwan for the support.

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