Building a Prediction Model for Postoperative Acute Kidney Injury using Machine Learning: The CMC-AKIX Model

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BACKGROUND

- Acute kidney injury (AKI) is a common complication that affects up to 5-7.5% of total admitted patients and 20% of patients in the intensive care unit (ICU). AKI is associated with increased morbidity and in-hospital mortality.
- Among AKI of admitted patients, postoperative AKI affects up to 40%.
- There are many factors associated with postoperative AKI.
- Several risk scoring tools for postoperative AKI have been described.
- However, their limitations are heterogeneity of the study population, inclusion of a small number of centers, and lack of external validation.

AIMS

The aim of this study was to build a risk prediction model for postoperative AKI using machine learning methods from a multicenter cohort.

METHODS AND MATERIALS

Design : Retrospective cohort study using data extracted from CMC-CDW (the Catholic Medical Center-Clinical Data Warehouse).

Patients : Adult patients who underwent general anesthesia surgery from 1st March 2009 to 31st December 2019 at 7 hospitals of the Catholic University of Korea.

Definition of Postoperative AKI

AKI within 30 days after surgery using the KDIGO criteria:

- Increase of serum creatinine at least 1.5 times the baseline value **or**
- Initiation of renal replacement therapy within 30 days of the postoperative period

Primary Outcomes : AKI within 30 days after surgery

Data Collection : Data was extracted from the Catholic Medical Center-Clinical Data Warehouse (CMC-CDW)

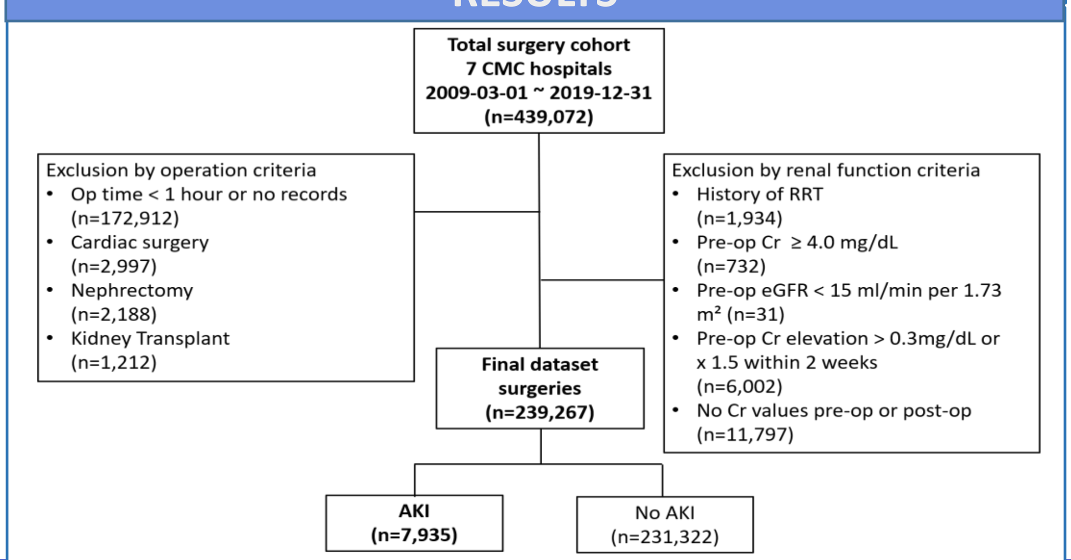
Models

Model 1 (40 variables)	**Basic**: Age, Sex, Systolic blood pressure, Diastolic blood pressure, Body mass index, **Underlying**: Chronic kidney disease, Diabetes mellitus, Hypertension, Cerebrovascular disease, Coronary artery disease, Chronic obstructive pulmonary disease, Liver cirrhosis, **Operation**: Emergency operation, Operation duration, **Medication**: ACEi or ARB usage, NSAIDs usage, **Laboratory**: eGFR, Blood levels of creatinine, Total protein, Albumin, AST, ALT, Urea nitrogen, Sodium, Potassium, Chloride, Calcium, Creatine phosphokinase, Lactic dehydrogenase, C-reactive protein, Glucose, Hemoglobin, Hematocrit, and White blood cell count, Urine specific gravity and Urine protein
Model 2 (11 variables)	**Basic**: Age, Sex, **Underlying**: Diabetes mellitus, **Operation**: Emergency operation, Operation duration, **Medication**: ACEi or ARB usage, **Laboratory**: Blood levels of albumin, Hemoglobin, and Sodium, eGFR and Urine protein
Model 3 (14 variables)	**Basic**: Age, Sex, Systolic blood pressure, Diastolic blood pressure, **Operation**: Operation duration, **Laboratory**: eGFR, Blood levels of creatinine, Albumin, Sodium, Potassium, Chloride, Glucose, and Lactic dehydrogenase and Urine protein

Statistics

- Machine learning analysis was performed using Python version 3.8.5.
- Models applied were Light gradient boosting machine (LGBM), logistic regression, decision tree, random forest, Light gradient boosting machine (LGBM), Naïve Bayes and deep neural networks (DNN).
- Model performance was measured by area under the curve (AUC) of the receiver-operating characteristic (ROC), accuracy, precision, specificity, recall and F1 score.

RESULTS



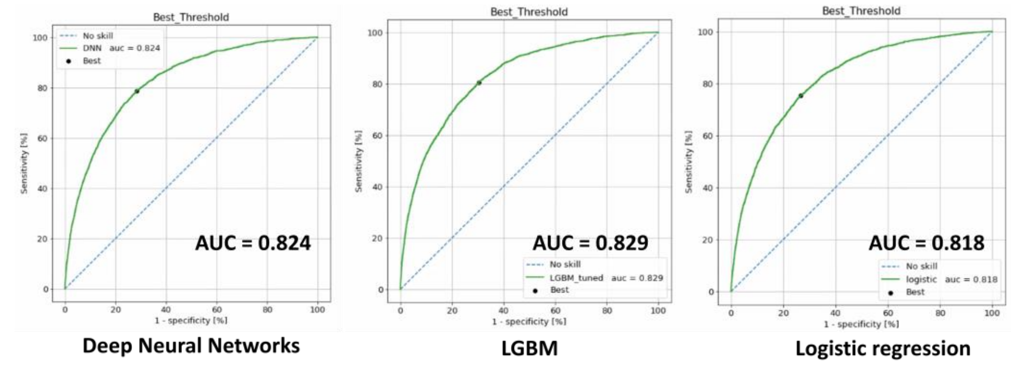
RESULTS

- The 6 different statistical analysis methods were run on various combinations of 40 independent preoperative predictors that we had selected.
- **Model 1** included all 40 preoperative variables and surgical characteristics; **DNN (AUC = 0.821) and light GBM (AUC = 0.823)** demonstrated the best prediction performance.
- **Model 2** included 11 variables from the SPARK (Simple Postoperative AKI Risk) classification; **DNN** showed the highest performance **(AUC = 0.806)**.
- **Model 3** included variables that were found significant on multivariable analysis; **DNN** also showed the highest performance **(AUC = 0.807)**.

Table 1. Performance metrics of postoperative AKI prediction models.

Analysis	Model	AUC	Accuracy	Precision	Specificity	F1 score
DNN	**1**	**0.821**	0.955	0.375	0.998	0.041
	2	**0.806**	0.966	0.407	0.999	0.021
	3	**0.807**	0.955	0.380	0.999	0.032
Logistic Regression	1	0.811	0.955	0.363	0.998	0.054
	2	0.784	0.966	0.333	1.000	0.007
	3	0.802	0.955	0.310	0.998	0.043
Decision Tree	1	0.672	0.956	0	1.000	0
	2	0.666	0.967	0	1.000	0
	3	0.672	0.956	0	1.000	0
Random Forest	1	0.803	0.956	0.571	1.000	0.007
	2	0.767	0.967	0.440	1.000	0.010
	3	0.778	0.956	0.455	1.000	0.009
Light GBM	**1**	**0.823**	0.955	0.360	0.998	0.053
	2	0.803	0.966	0.356	1.000	0.014
	3	0.801	0.955	0.328	0.998	0.037
Naïve Bayes	1	0.780	0.861	0.145	0.881	0.218
	2	0.766	0.884	0.112	0.902	0.171
	3	0.782	0.895	0.162	0.921	0.218

Figure 1. ROC curve for prediction of post-op AKI based on Model 1



CONCLUSIONS

- We propose a machine learning-based postoperative AKI prediction tool, the **CMC-AKIX .**
- We used all 40 variables including individual patients' preoperative characteristics, surgical information and laboratory data.
- This model is a user-friendly online program, and one can use it even all variables are not included.
- This tool may guide preoperative counseling and decision making and perioperative care.

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