Shaping Tomorrow's Nephrology: Insight-Driven Kidney Care
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Machine Learning Prediction of Drug-Induced Acute Kidney Injury Across Inpatient and Outpatient Settings Using Real-World Electronic Health Records

Sang Hun Eum[1], Sung Goo Yoo[2], Wona Choi[2], Seok Joon Shin[1], Hoon Suk Park[3], Byung Ha Chung[3], In Young Choi[2], Hye Eun Yoon[3]
[1]Department of Internal Medicine-Nephrology, Incheon St. Mary's hospital, The Catholic University of Korea, Korea, Republic of
[2]Department of Department of Medical Informatics, College of Medicine, The Catholic University of Korea, Korea, Republic of
[3]Department of Internal Medicine-Nephrology, The Catholic University of Korea Seoul St. Mary's Hospital , Korea, Republic of
[4]Department of Transplantation Research Center, College of Medicine, The Catholic University of Korea, Korea, Republic of

Objectives : Drug-induced acute kidney injury (DI-AKI) is a common and potentially preventable cause of acute kidney injury (AKI). Existing predictive models frequently focus on specific inpatient populations, leaving a gap in predicting DI-AKI across generalized inpatient and outpatient settings where polypharmacy is prevalent. We aimed to develop and validate prediction models using real-world electronic health record (EHR) data to preemptively stratify DI-AKI risk associated with nephrotoxic medications across both settings.
Methods : We conducted a retrospective cohort study using the multicenter EHR database (2 academic hospitals in South Korea, 2006–2022). The cohort included adults receiving nephrotoxic medications including antibiotics, nonsteroidal anti-inflammatory drugs, diuretics, renin-angiotensin system inhibitors, and sodium glucose cotransporter-2 inhibitors. We evaluated four machine learning algorithms (Histogram-based Gradient Boosting [HGB], XGBoost, Random Forest, and Logistic Regression) for risk prediction. Furthermore, a generalized linear mixed-effects logistic regression was utilized to identify independent clinical predictors while accounting for within-patient clustering.
Results : The analytic cohort comprised 82,284 patients and 325,602 medication administration events, with an overall AKI incidence of 14.1%. Gradient-boosting models yielded the highest discriminative performance, with HGB achieving an area under the receiver operating characteristic curve of 0.827 and an area under the precision-recall curve of 0.477. Mixed-effects analysis identified medication exposure duration and baseline kidney function as primary independent predictors of DI-AKI. Applications of predefined alert threshold in the test set achieved 90.1% sensitivity. A three-tier traffic-light risk stratification system successfully categorized 49.3% of all AKI events in the high-risk (Red) tier (46.6% observed incidence), compared to a 2.9% incidence in the low-risk (Green) tier.
Conclusions : This EHR-based DI-AKI prediction model can provide clinically actionable risk stratification in both inpatient and outpatient settings. By identifying modifiable risk factors and translating probabilistic risk into an interpretable traffic-light framework, this approach can facilitate targeted monitoring and optimize nephrotoxic medication stewardship.

Fig2.png

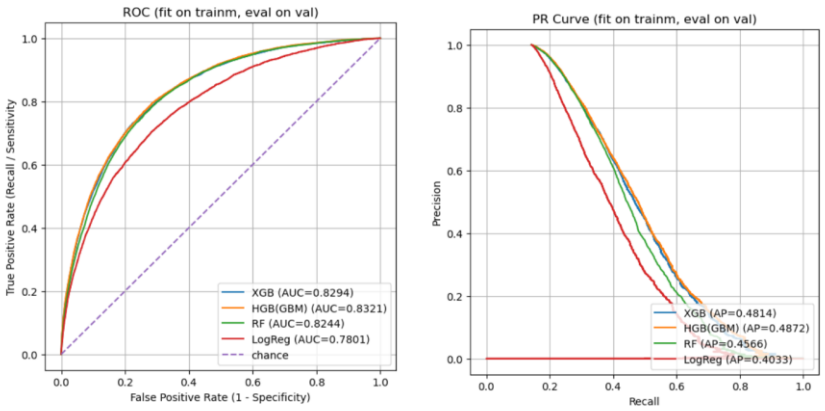
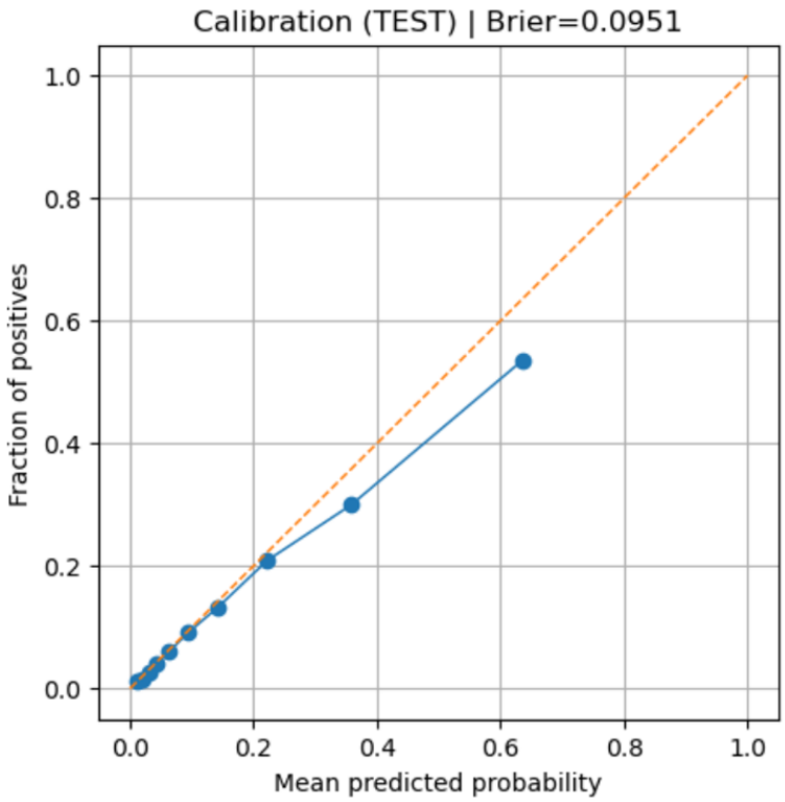

ROC (fit on trainm, eval on val)
True Positive Rate (Recall / Sensitivity)
False Positive Rate (1 - Specificity)
XGB (AUC=0.8294)
HGB(GBM) (AUC=0.8321)
RF (AUC=0.8244)
LogReg (AUC=0.7801)
chance
PR Curve (fit on trainm, eval on val)
Precision
Recall
XGB (AP=0.4814)
HGB(GBM) (AP=0.4872)
RF (AP=0.4566)
LogReg (AP=0.4033)

Fig2.png


Calibration (TEST) | Brier=0.0951
Fraction of positives
Mean predicted probability