Commentary: Welcome to the Machine…

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Central Message: Acute Kidney Injury following Cardiac Surgery could potentially be dynamically predicted using newer machine learning models.

Central Picture Legend: Kamal R. Khabbaz, MD (L) and Adnan A. Khan, MD (R)

The perioperative period following cardiac surgery requires diligent monitoring for the prevention of post-operative complications in vital organs. Non-pulsatile flow to the kidneys precipitates an ischemic state often resulting in unavoidable consequences, with acute kidney injury (AKI) occurring in 5-30% of patients.\(^1,2\) Treating AKI after it occurs is usually supportive and palliative, and the key to prevention is early detection and prediction.

The ability to accurately and dynamically predict common post-operative outcomes, such as AKI, would be an incredibly vital tool at any clinician’s disposal. Many risk prediction tools currently exist, and several novel urinary biomarkers have been studied for diagnosis of AKI; but none currently offer a feasible real-time ability to assess a patient’s current risk following cardiac surgery.\(^3-5\) Previous iterations of machine learning and acute kidney injury prediction have yielded significant and promising results.\(^6-9\)

In this edition of the Journal, Ryan and colleagues\(^10\) report their experience utilizing a machine learning model using data from a MIMIC-IV database, including intensive care unit (ICU) data. By training and testing a model on a cohort of 4,267 patients, they accurately hourly predicted
AKI with an area of receiver under the operating characteristics curve (ROC-AUC) of 0.82; they were even more accurate with prediction of stage 2 or greater (ROC-AUC of 0.95). While utilizing hemodynamic variables at intervals as short as 13 minutes, as in their case of input/output, the model provides less latency to the identification to potential high-risk patients.

Certain limitations must be addressed in the current model. This model only had 4,267 patients for both training and testing, a relatively small sample size for an advanced algorithm, particularly one with a diverse cohort such as patients undergoing cardiac surgery. Potential ways to improve the strength of the model would be to incorporate the expanding list of urinary biomarkers (tissue inhibitor of metalloproteinases-2 and insulin like growth factor-binding protein 7) which are currently used clinically to predict AKI. Intraoperative variables such as: cross-clamp time, prolonged aortic cross clamp on cardiopulmonary bypass (CBP), and medication administration during CBP are integral to the determining the state of perfusion of the kidney during cardiac surgery and are known to be associated with worse outcomes. The total incidence of AKI in their dataset is not congruent with nationally published data as their overall incidence, irrespective of stage, was 62%; the severity of renal disease in their patient cohort could be affecting results.

Ryan and colleagues offer a tantalizing look into the future of personalized medicine. Their model could potentially serve to augment a clinician’s ability to discern which patients would benefit from intensive perioperative monitoring and would assist in a timely hemodynamic intervention prior to subclinical renal damage. The next iteration of this model with a larger dataset and incorporation of aforementioned variables would be crucial to determine its viability.
and prospective adoption into Electronic Health Record (EHR) systems. Welcome to the world of machine learning.

References


