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Artificial intelligence to predict AKI: is it a breakthrough?

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Abstract

A new study of deep learning based on electronic health records promises to forecast acute kidney injury up to 48 hours before it can be diagnosed clinically. However, employing data science to predict acute kidney injury might be more challenging than it seems.

Acute kidney injury (AKI) complicates 10–25% of hospital admissions¹, making it one of the most common conditions in modern medicine. This high incidence, coupled with hospital mortality of over 20%² and estimated health-care costs in excess of US\$100 billion worldwide, makes AKI a conspicuous target for disruptive technology. One opportunity lies in the early identification of patients at risk, and this is where the DeepMind project has focused its artificial intelligence, as recently reported in *Nature*³. In this study, Tomašev and colleagues describe a deep learning model for continuous risk prediction of future AKI using electronic health records (EHRs). Their model was developed on EHRs from over 700,000 patients and could predict 55.8% of all inpatient episodes of AKI with lead times of up to 48 hours and a 2:1 false alert ratio. Other emerging applications of deep learning algorithms for continuous risk prediction and monitoring using EHR data (for example, in sepsis) have demonstrated similar promise⁴. Such technology applied to AKI would constitute ‘kidney telemetry’ and could revolutionize the care of hospitalized patients, moving us from reactive to proactive management. However, is the DeepMind technology really that disruptive?

To answer this question, we first need to consider what AKI is, how it occurs and when. AKI is not a disease per se, but rather a loose collection of syndromes⁵, including kidney-specific diseases such as interstitial nephritis, those that are part of systemic conditions such as sepsis and heart failure, or those that arise from treatments such as surgery or cancer chemotherapy. The timing of AKI and its clinical manifestations are not random — they relate to both the type and the severity of injury. For example, a nephrotoxic drug such as cisplatin might not cause damage until a cumulative toxicity threshold has been reached, and this may take several doses. Furthermore, an emerging injury might not manifest clinically for several hours. In such a scenario, the prolonged lead time creates an opportunity to identify subtle cues of a developing injury. Conversely, in cases of sepsis-associated AKI, most patients already have AKI when they seek medical attention⁶. Similarly, surgery-associated AKI

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usually manifests in the first 12–24 hours⁷, and in such cases there is very little, if any, data to mine. Therefore, in many cases, deep learning algorithms might default to warning about what has already occurred rather than making predictions about the future. Nonetheless, this ability might still be of considerable value.

Although some smaller studies failed to show that AKI alert systems improved patient outcomes⁸, recent reports have demonstrated improvements in hospital duration^{1,2} and mortality¹. In fact, the analytics in DeepMind³ and in other successful alert systems^{1,2} might provide crucial information about premorbid kidney function that could be used to diagnose AKI. However, a considerable limitation in all of these systems is that they rely on serum creatinine. Although considerable information might be derived from the serum creatinine trend, creatinine is still an imperfect marker of AKI. Assessment of AKI based on serum creatinine alone failed to identify AKI in 37.8% of adult patients or 67.2% of paediatric patients with low urine output^{9,10}. In the future, AKI diagnoses might be exclusively based on biomarkers of kidney damage, but, currently, AKI is a clinical diagnosis based not only on serum creatinine and urine output but also on the clinical context — this complexity is difficult to programme.

The performance of the DeepMind algorithm is impressive and corresponds to a sensitivity of 55.8% and a specificity of 82.7%, based on the reported 2:1 false alert ratio and 13.4% prevalence³. This performance is certainly in the range required for regulatory approval. By comparison, Nephrocheck (Astute Medical, San Diego, CA), which is the only FDA-approved AKI diagnostic test, has a sensitivity of 62% and specificity of 82% at a cut-off value of 0.9 for stage 2–3 AKI. The decision of DeepMind scientists to focus on all stages of AKI³ is arguable, since stage 1 events are less clearly associated with clinical outcomes and might be harder to validate using clinical adjudication. Independent validation might also prove difficult given the large number of failures in the history of risk prediction models for AKI in general. The reasons for these failures are unclear but probably relate to the considerable heterogeneity among centres in the use of potentially nephrotoxic drugs, such as radiocontrast, and other approaches to treatment, including fluid management.

These limitations notwithstanding, the DeepMind technology could prove valuable for at least some patients, and the concept of a kidney telemetry system is certainly attractive. Is the technology truly disruptive, at its current stage? Perhaps not, but if it can be tied to biological markers of disease and implemented into clinical decision-making (Fig. 1), it could be.

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Competing interests

J.A.K. received honoraria for consulting and grant support from Astute Medical, Biomerieux and Bioparto. A.B. and University of Florida have patents pending on the real-time use of clinical data for risk prediction of sepsis-associated and surgery-associated AKI using machine learning models.

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Fig. 1 |. Implementation of deep learning algorithms to identify patients at high risk of AKI. Deep learning algorithms developed to support clinical decisions in real time should be based on integrated patient information, including electronic health records (EHRs) with detailed medical history (including ongoing problems and procedures), physiological parameters (such as vital signs and laboratory results) and medication details. Acute kidney injury (AKI) risk scores derived from such an algorithm would stratify patients and inform clinical decisions, including the use of additional diagnostics to enable personalized treatment.