Author Manuscript
Author Manuscript
Author Manuscript

Published in final edited form as:
Nat Rev Nephrol. 2020 February ; 16(2): 71–72. doi:10.1038/s41581-019-0243-3.

Artificial intelligence approaches to improve kidney care

Parisa Rashidi[1], **Azra Bihorac**[2]

[1]iHeal Lab, Department of Medicine, Department of Biomedical Engineering, University of Florida, Gainesville, FL, USA

[2]Precision and Intelligent Systems in Medicine, Department of Medicine, University of Florida, Gainesville, FL, USA

Abstract

Artificial intelligence is increasingly being used to improve diagnosis and prognostication for acute and chronic kidney diseases. Studies published in 2019 relied on a variety of available data sources towards this objective, including electronic health records, intraoperative physiological signals, kidney ultrasound imaging, and digitized biopsy specimens.

The ‘Advancing American Kidney Health’ Initiative by the Department of Health and Human Services introduced prevention and treatment of kidney disease as a top healthcare priority in United States.[1] Kidney disease affects one in seven adult Americans, ranks among the top ten leading causes of death, accounts for 23% of all Medicare spending yet half of all kidney patients are not aware of their disease. This bold call for innovation in reducing the risk of kidney failure and improving access to and quality of person-centered treatment options, including kidney transplantation, emphases the need for new technologies in diagnosis, prevention, treatment and awareness of acute and chronic kidney diseases. In recent years, the artificial intelligence (AI) field has significantly changed the way digital data is analyzed and used. Far removed from the depiction of “general AI” in science fiction, current AI is designed to perform only a narrow task, for example face recognition or speech recognition, and in those tasks often can far outperform humans.[2] In medicine, when a narrow application of AI is shown to outperform humans, such as in processing of digital images, the potential for low cost automation, speed and precision provides a foundation for improved medical care.[3]

Acute kidney injury (AKI), one of the most common medical conditions affecting up to 25% of all hospital admissions[4], has prohibitively bad outcomes, high cost and low awareness among patients and providers. Besides improving the automation of AKI diagnosis within the electronic health record, the development of accurate and autonomous prediction models for AKI has the potential to augment clinical care.[4] Existing clinical practice relies on healthcare providers to diagnose AKI using change in serum creatinine, as a surrogate for kidney filtration function, and to use their clinical judgment to identify and treat patients at risk for AKI. In an effort to automate, standardize and improve accuracy of early prediction, Tomasev et al.[5] developed a deep recurrent neural network model predicting AKI risk using

* abihorac@ufl.edu.

clinical data of 700,000 patients, mainly men, from the Veterans Health Administration. The model was able to predict risk for 55.8% of inpatient AKI episodes, and 90.2% of AKI cases requiring dialysis, with a lead time of 48 hours and a 2:1 false alert ratio. The model has excellent performance, but interpretability and actionability of the model remain an issue since the top three predictors of future AKI episode are preadmission and most recent serum creatinine and serum calcium. With improvement in generalizability (the current model is trained on an almost exclusively male cohort) and with prospective validation of reproducibility of reported performance, this model may be a valuable tool for clinical decision-making.

Adhkari et al[6] analyzed intraoperative physiologic time-series data for 2,911 surgical patients to predict the risk of postoperative AKI using dynamic integration of preoperative and intraoperative data. They demonstrated that adjustment of the previously validated preoperative *MySurgeryRisk AKI* model[7] with routine intraoperative clinical and physiological data improves the performance and accuracy of the model. By integrating intraoperative features, the updated model correctly reclassified 40% of the high-risk patients that initially were considered as low-risk. This approach shows the importance of incorporating intraoperative data in surgical AKI risk models and confirms the importance of the dynamic adjustment of the risk models with the continuous data streams generated during episode of care.

The application of AI for analyses of medical images has huge potential in nephrology. Kuo et al.[8] developed a convolutional deep learning model for automated estimation of glomerular filtration rate (eGFR) and CKD status using kidney ultrasound images annotated for kidney length and labeled with eGFR measurements derived from patients' corresponding serum creatinine values. Although the correlation coefficient between model based GFR estimation and creatinine-based GFR estimations was 0.74, the lack of a gold-standard for GFR annotation was a major drawback. Using a model-estimated eGFR <60 ml/min/1.73 m^2 to determine CKD status, they demonstrated an accuracy of 85.6% that was higher compared to paired assessments of four experienced nephrologists (60.3%–80.1%). While the specificity was high (92.1%), sensitivity was only moderate (60.7%). This approach provides a promising proof of concept of how machine learning can be used for cost-effective expansion of clinical utility of kidney ultrasound images. Hermsen et al.[9] expanded the use of machine learning for automated analyses of digital histopathologic images of kidney. They trained a convolutional neural network for multiclass segmentation using 40 annotated whole-slide images of stained kidney transplant biopsies. The multiclass segmentation performance for ten tissue classes was tested in four independent data sets, including both biopsy and nephrectomy samples containing both cortex and medulla. The best segmented class was "glomeruli", followed by "tubuli combined" and "interstitium." The network detected 92.7% of all glomeruli in nephrectomy samples, with 10.4% false positives. In whole transplant biopsies, the mean intraclass correlation coefficient for glomerular counting performed by pathologists versus the network was 0.94.

These recent approaches provide more precise, effective, and often more convenient methods for assessing kidney health in different settings. Nonetheless, despite recent progress, AI in nephrology still faces many challenges. Currently AI models are optimized to use one type of data e.g. imaging, physiological signals, or clinical data. We expect that future AI models will integrate heterogonous data to improve robustness and accuracy. It is essential to incorporate a representative cohort of patients into these models, to achieve model fairness and address any source of bias based on gender, ethnicity, or other factors. It is equally important to develop models that improve access to person-centered treatment options and provide improved recommendation for kidney transplant. We expect that AI models will rely on disruptive innovations in smart and connected health as well, especially sensors that can accurately capture granular data in outpatient and inpatient settings.[10] Untimely, AI models need to be objectively evaluated in prospective and multi-center validation studies, paving the way for translational studies and FDA approval of AI algorithms in nephrology.

References

1. United States Department of Health and Human Services. Advancing American Kidney Health. (2019). <https://aspe.hhs.gov/system/files/pdf/262046/AdvancingAmericanKidneyHealth.pdf>.
2. Vinyals O et al. Grandmaster level in StarCraft II using multi-agent reinforcement learning. Nature, doi:10.1038/s41586-019-1724-z (2019).
3. American Medical Association. Augmented intelligence in health care. (2019). <https://www.ama-assn.org/system/files/2019-08/ai-2018-board-policy-summary.pdf>.
4. Al-Jaghbeer M, Dealmeida D, Bilderback A, Ambrosino R & Kellum JA Clinical Decision Support for In-Hospital AKI. J Am Soc Nephrol 29, 654–660, doi:10.1681/ASN.2017070765 (2018). [PubMed: 29097621]
5. Tomašev N et al. A clinically applicable approach to continuous prediction of future acute kidney injury. Nature 572, 116 (2019). [PubMed: 31367026]
6. Adhikari L et al. Improved predictive models for acute kidney injury with IDEA: Intraoperative Data Embedded Analytics. PloS one 14, e0214904 (2019). [PubMed: 30947282]
7. Bihorac A et al. MySurgeryRisk: Development and Validation of a Machine-learning Risk Algorithm for Major Complications and Death After Surgery. Ann Surg 269, 652–662, doi:10.1097/SLA.0000000000002706 (2019). [PubMed: 29489489]
8. Kuo C-C et al. Automation of the kidney function prediction and classification through ultrasound-based kidney imaging using deep learning. npj Digital Medicine 2, 29 (2019). [PubMed: 31304376]
9. Hermsen M et al. Deep Learning-Based Histopathologic Assessment of Kidney Tissue. J Am Soc Nephrol 30, 1968–1979, doi:10.1681/ASN.2019020144 (2019). [PubMed: 31488607]
10. Davoudi A et al. Intelligent ICU for Autonomous Patient Monitoring Using Pervasive Sensing and Deep Learning. Scientific reports 9 (2019).

Key Advances

- **Continuous forecasting of the risk for kidney disease using data from electronic health records**: predicting future inpatient episodes of acute kidney injury with lead times of up to 48 hours.
- **Dynamic prediction of risk for postoperative acute kidney injury using intraoperative physiologic signals**: improving prediction of post-operative acute kidney injury by utilizing intraoperative physiological signals.
- **Noninvasive diagnosis and monitoring of chronic kidney disease**: determining the estimated glomerular filtration rate and stage of chronic kidney disease using ultrasound kidney imaging.
- **Histopathologic segmentation:** automated analysis of transplant biopsies and nephrectomy samples.

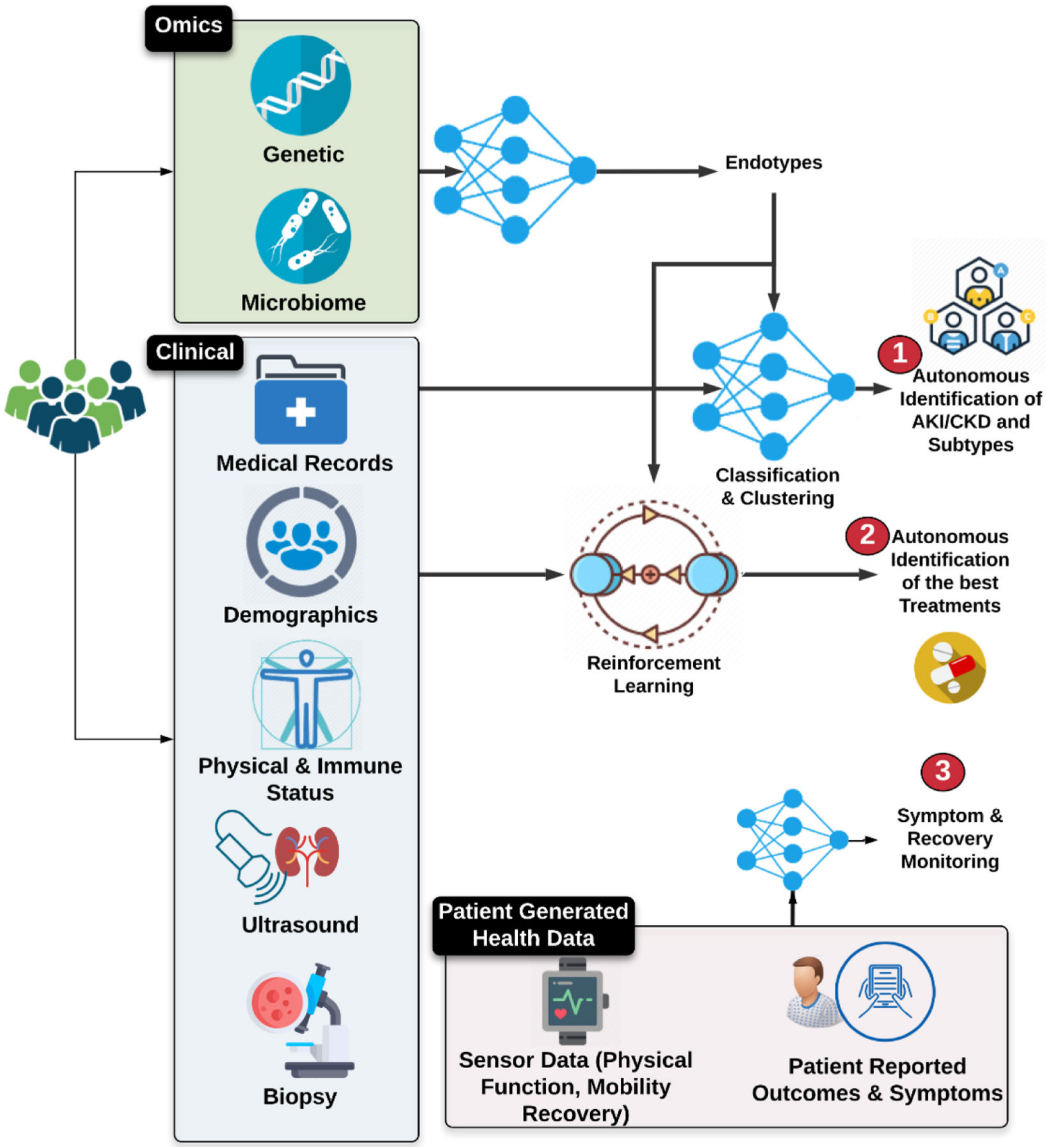

Figure 1.

Proposed conceptual framework for use of AI in future nephrology research.