Review Article

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The evolution of artificial intelligence (AI) in nephrology: advantages and disadvantages

Abstract

Artificial intelligence (AI) has emerged as a new tool to help save lives, treat diseases, and conduct research. The first artificial intelligence research in the field of nephrology came from Egypt, Africa, and it was directed to predict and adjust the quality of hemodialysis sessions for patients even before they started the session, which saved time and money. Similarly, the application of AI in the field of transplantation comparing the accuracy of AI with multivariate statistics in the prediction of graft survival was done in Egypt. With advances in digital networking and the global spread of the internet, applications of AI have been expanded and now involve the field of research. AI can now start a research project, write a review article, and even plan a research design. In this paper, we discuss how AI can be used in various fields of nephrology, emphasizing the benefits over the drawbacks.

Keywords: machine language, glomerulonephritis, transplantation, renal replacement therapy, computer sciences

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Abbreviations: AI, artificial intelligence; CKD, chronic kidney diseases; EMPA, electronic diagnosis and management assistance to primary care; ANN, artificial neural networks; SVM, support vector machines; PCSK9, proprotein convertase subtilisin-kexin type; TKV, total kidney volume; ADPKD, autosomal dominant polycystic kidney disease; CNN, convolutional neural network; EPO, erythropoietin; MPC, model predictive control; MPL, multiple perception layer; IRAD, implantable renal assist device; AUC, area under concentration over time curve

Introduction

Kidney disease is a major public health problem caused mainly by hypertension, diabetes, obesity, and aging. Around 750 million people worldwide are affected by kidney disease according to the Global Burden of Diseases, Injuries, and Risk Factors Study.[1] Kidney disease is also associated with a huge burden on the patient and the health system.[2] Therefore, early identification of kidney disease and prevention of its progression is highly important. Artificial intelligence (AI) now plays an essential role in our daily activities, academics, and the field of medicine. AI according to McCarthy who is the father of the field is defined as the science and engineering of intelligent machines that behave in a way that could be considered intelligent if it was human being.[1] In the previous decades, the rapid growth in computer power, the development of new techniques, and the introduction of large database systems greatly influenced the ability of AI to address a wide range of problems.[2] Despite few studies addressing AI in kidney diseases, its potential in the management of kidney diseases is well known. Instead of replacing clinicians, AI will enhance clinicians, ability in their day-to-day clinical practice.

Hemodialysis

As early as 2001, an artificial intelligence model was trained on information extracted from direct analysis of dialysate blood urea nitrogen every 30 minutes during the hemodialysis session which was able to outline intradialytic profiling according to individual clinical needs.[3] Data mining and patient intelligent clustering technologies were able to predict urea kinetics during hemodialysis sessions and required time to achieve adequate sessions which minimized cost and maximized adequacy.[4] Du A et al.,[5] used a machine learning fuzzy system to assess adequacy of hemodialysis.[5]

Role of AI in chronic kidney disease (CKD)

A pilot program utilizing e-technologies to identify CKD was done in Australia (Electronic Diagnosis and Management Assistance to Primary Care in Chronic Kidney Disease; EMPA-CKD). This was based on algorithms trained to detect at risk patients and to conduct appropriate screening tests for CKD.[6] Almansour et al.,[7] predicted the early stages of CKD by comparing Artificial Neural Networks (ANN) and Support Vector Machines (SVM) in 400 patients. ANN was superior to SVM with success of 99.5% and 97.75% respectively.[7] Bermudez-Lopez utilized Random Forest (RF) to show that the Proprotein Convertase Subtilisin-Kexin type (PCSK9) is an important factor distinguishing diabetic CKD from non-diabetic CKD.[8] Kazemi et al.,[9] identified early stone disease in a group of 936 patients using the final ensemble-based model with an accuracy of 91.1% .[9] Kanishk et al used an automated segmentation method of deep learning for total kidney volume (TKV) computed on CT dataset of 224 autosomal dominant polycystic kidney disease (ADPKD) patients. This resulted in rapid and reproducible diagnosis of ADPKD.[10] TKV assessed by the automated approach correlated well with the manual approach but was associated with high precision and low bias.[11] Wei et al created an automated quantification system for measuring interstitial fibrosis in 40 images and utilized 70 patients to prove the error rate which was 9% Figure 1.[12]

Erythropoietin (EPO)

Gaweda et al.,[13] showed that the Model Predictive Control (MPC) based on the Artificial Neural Network (ANN) model of EPO may result in better anemia management.[13] Barbieri et al.,[14] utilized the Multiple Perception Layer (MPL) and linear model have been successfully used to predict ESA response and identify dosages with an accuracy of more than 90 %.[14] This model improves hemoglobin concentration and decreases erythropoiesis stimulating agent requirement. Another artificial intelligence model developed by Barbieri et al.,[15] to Guide the management of blood pressure, fluid volume, and dialysis dose in end-stage kidney disease Patients.[15]

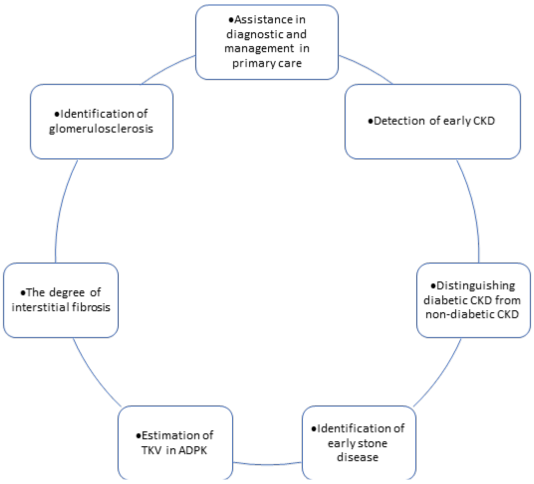

Figure 1 Describes different role of artificial intelligence in chronic kidney disease (CKD).

Wearable kidney

The combination of AI and regenerative medicine technology was used to make wearable dialysis devices.[16] These devices perform continuous dialysis and clear toxins reliably with minimal effect on hemodynamics of the patients. The devices were tested on 15 patients safely and are now approved by the FDA. Further studies are required to involve more patients to get the maximum experience from this model in the future.[17] Implantable Renal Assist Device (IRAD) is the use of micro-machining techniques to fabricate a biohybrid system capable of mimicking renal morphology and function. The device was used successfully in animal models, but not yet upgraded to clinical setup.[18]

Prediction of risk of calciphylaxis

Mariano et al developed a data analysis system by Random Forest algorithm to quantify the degree of association between calcium, phosphate, and parathyroid home in 1,758 hemodialysis patients.[19] Kleiman et al.,[20] utilized a similar Random Forest algorithm to make a model predicting risk for development of calciphylaxis in CKD.[20]

Prediction of risk of developing chronic kidney disease (CKD)

Machine learning has been used to predict type 2 diabetes complications from 1000 patients. Factors such as gender, age, time from diagnosis, body mass index, glycated hemoglobin, hypertension, and smoking contributed more than others. Further studies are required to improve the model performance.[21]

Transplantation

In 2008, Akl et al.,[22] developed a well-validated and reasonably precise Cox regression-based nomogram for predicting 5-year kidney graft survival.[22] Later, the same team challenged the results of the nomogram with an AI model. The results of the AI model were more accurate and sensitive than the Cox regression-based nomogram in predicting 5-year kidney graft survival.[23] Naqvi et al.,[24] reported that using machine learning methods, the created model predicted graft survival with area under curve scores of 82%, 69%, and 81% within one year, five years, and seventeen years, respectively. This model significantly performed better when compared with the existing conventional models. Yoo et al.,[25] reported that machine learning methods using donor's variables, recipient's variables, and immunological factors in combination with survival statistics had better performance in the prediction of graft survival than the conventional model that was Cox-regression based. Another study investigated the efficacy and characteristics of various data mining methods in predicting living donor graft survival. When compared to other Classifiers, Decision Tree and Rule Based Classifiers had higher accuracy and interpretability.[26]

AI has also been reported to be useful in predicting the risk of delayed graft function in transplant patients.[27] Tang et al.,[28] developed eight different models using various machine learning methods for the prediction of the stable dose of tacrolimus in kidney transplant patients and compared their performances with the traditional multiple linear regression model. The model developed by the regression tree performed better than other models including the multiple linear regression model.

Immunosuppression

Niel et al.,[29] developed a model that was able to calculate the area under concentration over time curve (AUC) for tacrolimus using an artificial neural network. Although AUC provides better clinical correlates;[30] it requires multiple timed blood sampling which makes it expensive and cumbersome, especially in pediatric and geriatric patients. The model developed by Brunet et al.,[30] had the advantage of having better performance than other models; being fast, cheaper, and simpler to perform.

Graft rejection

Kazi et al.,[31] developed an algorithm that was based on Bayesian belief network which included other histological features in addition to the conventional tubulitis and intimal arteritis used in the Banff classification. The developed model improved the accuracy of diagnosis of acute transplant rejection even when the expertise of an experienced histopathologist was not available. Furness et al.,[32] also developed a model that was useful in making the diagnosis of acute cellular graft rejection using a neural network. The model was created from 12 different histological features from 146 renal biopsies. The diagnostic performance of this model was found to be better than the use of the conventional methods. In fact, it was observed that a pathology trainee was able to make a more accurate diagnosis than the experienced pathologist with this model. Applications of AI in Transplantation are summarized in Figure 2.

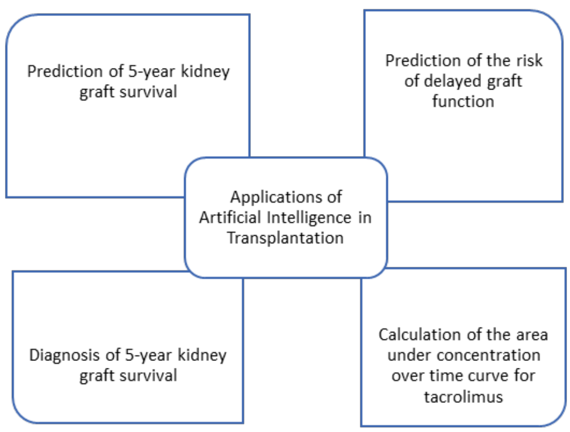

Figure 2 Applications of artificial intelligence in transplantation.

Prediction of survival in Cancer bladder

In 2009, we conducted a study to compare the performance of artificial intelligence with other prognostic models including nomograms and Cox multivariate statistical analysis. In this study artificial neural networks outperformed the risk group stratification model and nomogram construction in predicting patient 5-year survival probability, and in terms of sensitivity and specificity.[33]

Writing nephrology research

Recently, ChatGPT emerged as a powerful AI tool for researchers, so we predicted that it would be interesting to interview artificial intelligence (ChatGPT) and ask the following question: "What is the probable role of AI in conducting research? And ChatGPT had the following paragraphs summarizing the answer which are completely written by ChatGPT including the references. "According to recent research, artificial intelligence (AI) has the potential to transform research writing by improving efficiency and providing continuous feedback to authors.[34] AI-based tools for research writing can facilitate common research tasks such as literature review, data visualization, as well as provide feedback to authors in improving their writing and proofreading.[35] AI-powered digital writing assistants have been found to be effective in improving the writing skills of students in higher education. Researchers predict that AI will outperform humans in many activities related to writing, such as writing high-school essays, by 2026. However, the use of AI in research writing also raises ethical concerns, such as the potential for AI-generated content to introduce false or plagiarized content into published literature.[36] It is important to understand the advantages and limitations of AI in research writing and to consider the ethical implications of its use".[37] Until writing this review, AI cannot start research from scratch or build an accurate hypothesis rather it can improved the writing, comparison, and track outcome of a research.

Conclusion

AI is now becoming part of many medical disciplines including nephrology. The role of AI in nephrology and transplantation includes alerting the presence of CKD, diagnostic imaging, pathological diagnosis, and guiding treatments. We have come a long way from empirical medicine to evidence-based medicine and now AI. Although AI is still in its infancy, it has the potential for improvement in the future. There are some challenges facing AI which include data quality, privacy and legal issues, lack of standardization between centers, and lack of verification.

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Conflicts of interest

The authors declares that there is no conflict of interest.

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