IJMA

INTERNATIONAL JOURNAL OF MEDICAL ARTS

VOLUME 6, ISSUE 12, December 2024

P- ISSN: 2636-4174
E- ISSN: 2682-3780

Available online at Journal Website
https://ijma.journals.ekb.eg/
Main Subject [Internal Medicine]

Review Article

Artificial Intelligence in Kidney Diseases: The Reality and Prospects

Ahmed Salama Al-Adl*

Department of Internal Medicine, Damietta Faculty of Medicine, Al-Azhar University, Damietta, Egypt.

Article information
Received: 26-09-2024
Accepted: 13-11-2024
DOI: 10.21608/ijma.2024.324175.2044.

*Corresponding author
Email: salama76@gmail.com; salama139@azhar.edu.eg

Citation: Al-Adl AS. Artificial Intelligence in Kidney Diseases: The Reality and Prospects. IJMA 2024 Dec; 6 [12]: 5142-5152. doi: 10.21608/ijma.2024.324175.2044.

Abstract

Background: Artificial intelligence [AI] is defined as the science and engineering of building intelligent machines that have the capacity to learn and emulate human intellect. Many of us may believe that AI is somewhat sophisticated that we do not want to get associated with since we are doctors, know our specialization, and do not need any artificial assistance. But fortunately, or unfortunately, this is not a selection. We live wrapped in AI.

Summary and Conclusion: Artificial intelligence is rapidly being employed in nephrology, among other medical fields. AI's function in kidney disease involves warning the presence of CKD, performing diagnostic imaging, determining pathology, and directing treatment. We've come a long way, from empirical medicine to evidence-based medicine and now artificial intelligence. Although artificial intelligence is still in its early phases, it has the potential to grow in the future. AI has various challenges, including data quality, privacy, and regulatory concerns, a lack of standardization among centers, and a lack of verification.

Keywords: Artificial intelligence; Chronic Kidney Disease; Artificial Neural Network; Machine learning.

INTRODUCTION

The frequent etiology of kidney disease, which is brought on by diabetes, hypertension, obesity, and aging, makes it a serious public health concern. These disorders are also becoming more common. According to the Global Burden of Diseases, Injuries, and Risk Factors Study 2015, 750 million persons worldwide suffer from kidney disease [1]. The burden of kidney disease on society is enormous. According to a 2017 survey, the annual cost was roughly $1,205 for patients with stage 3 chronic kidney disease [CKD3], $1963 for those with CKD4, $8,035 for those with CKD5, and $34,554 for those requiring hemodialysis [2]. It is therefore critical to identify kidney illness early and take steps to prevent it from progressing to end-stage renal disease.

A growing number of research studies are assessing the potential uses of artificial intelligence [AI] in the context of kidney diseases, making it a potentially useful tool in healthcare. To appreciate the changing environment of AI research in renal illness, a bibliometric study is needed [3].

Artificial intelligence [AI] is defined as the science and engineering of building intelligent machines that have the capacity to learn and emulate human intellect. Many of us may believe that AI is something sophisticated that we do not want to contract with since we are doctors, know our specialization, and do not want any artificial support. But fortunately, or unfortunately, this is not a choice. We live wrapped in AI: Amazon, Google, Alexa, Tesla, Roomba, Siri, Deep L, facial recognition on our mobile telephone, etc., as well as, more newly, Open AI with its Chat bot "Chat GPT" [Generative pretrained transformer], and its customized image designer, Copilot, DALL-E2. Chat GPT is a large language model [LLM] based on the GPT [4]. With the development of robots in 1956, artificial intelligence [AI] was formally launched. Since then, it has significantly advanced and is now a standard tool in many industries, including banking[5], agriculture [6], and medicine [7]. Additionally, it significantly lowers the time that people spend engaging in extremely risky activities [8].

Following the explosion of numeric data obtainability, and the capacity of AI algorithms to integrate and learn from enormous datasets, AI has been widely employed in clinical policymaking, biomedical research, and medical education [9]. The US Food and Drug Administration [FDA] and other regulatory authorities have authorized clinicians to utilize AI-based technologies in a variety of medical sectors [10]. AI applications also expand into the physical realm, with robotic prostheses, physical task support systems, and mobile manipulators aiding in the delivery of telehealth. Numerous endoscopy manufacturers have launched their AI devices on the marketplace with regulatory agreement in Europe and Asia[11]. Nephrology appears to have all of the attributes to lend itself to AI research and developments, particularly the kidney transplantation [KT] area [12]. The field of AI in renal diseases is dynamic and fast-evolving and provides vital information for spotting emerging patterns, technological advancements, and multidisciplinary partnerships that contribute to the advancement of knowledge in this important subject [3].

Definition of Artificial Intelligence [AI]

Artificial Intelligence [AI], simply refers to the capacity of machines to simulate human cognitive functions, like learning, problem-solving, and decision-making, and propelled by algorithms and machine learning techniques that facilitate data analysis, identify patterns, and make predictions. Artificial Intelligence [AI], is considered as the science and engineering of making intelligent machines able to mimic human intelligence [12].

Forms of Artificial Intelligence [AI] [Figure 1]

Machine learning

Machine learning [ML] is a branch of artificial intelligence focused on developing computer programs capable of accessing data and learning from it without explicit programming for a particular task. This sets ML apart from traditional statistics [13].

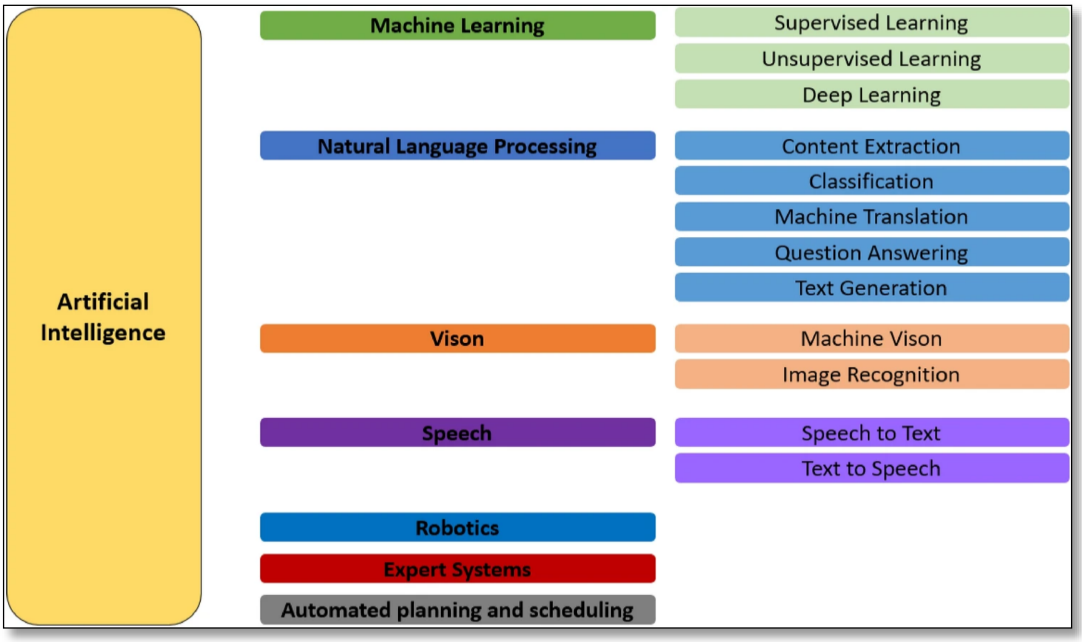

Figure [1]: Types of Artificial Intelligence [AI] [12].

ML employs algorithms to examine, understand, and learn from a specific dataset, and based on the insights gained, make optimal decisions. As in the case of predicting 10-year kidney graft survival, we input a database containing various variables such as recipient age, gender, history of rejection, infections, etc., and each kidney transplant instance is categorized as either having survived or failed by 10 years. The algorithm then utilizes this data to identify the function that correlates the input variables with the output values[12] . Afterward, the trained algorithm produces a model that can forecast the output for new input values that were not part of the training data. The predictors or features are the input to any ML algorithm, while the output from the algorithm is known as the target or label. In deep learning, a machine can be given raw data and can automatically identify the desired representations or features for detection or classification [12] . Let's consider a scenario where a model needs to determine whether an image contains a malignant tumor. The algorithm is organized into multiple layers in deep learning to form an artificial neural network [ANN]. ANNs are designed to imitate the structure of the human brain. An ANN consists of a single input layer, the possibility of hidden layers, and a single output layer. These layers are composed of rows of "neurons." The configuration includes the quantity of neurons in each layer and the quantity of layers [12].

Natural Language Processing [NLP]

Natural Language Processing [NLP] is a discipline of AI concerned with the interface between computers and human language. Definitely, NLP attempts to enable computers to comprehend and produce natural language, which allows computers to understand both spoken speech and written material. as well as to perform various tasks such as text generation, text classification, machine translation, and information extraction [Figure 2] [3].

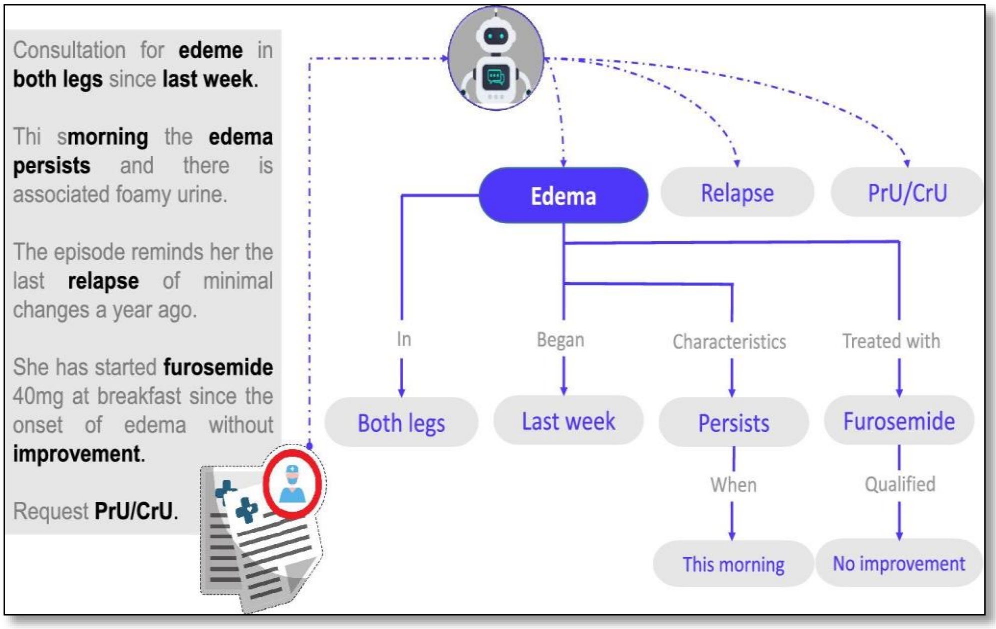

Figure [2]: Use of NLP to extract data from medical records. NLP, a branch of AI, can convert the human language used in medical records, which may include typing errors, into a computer-understandable language in the form of algorithms [3].

Robotics

Robotics uses artificial intelligence to create and construct robots or devices that can execute tasks independently or semi-autonomously. In general, robotics incorporates various AI technology components, such as natural language processing, machine learning, and perception. AI-based robots are already in use in a variety of areas, including healthcare, retail, and manufacturing, and may be used to assist with product development **[13].**

Box [1]. Definitions of the Core Concepts Used in Medical Artificial Intelligence [MAI] **[13]**

Algorithm: a set of rules that precisely defines a sequence of operations.
Artificial intelligence [AI]: a set of algorithms that enable computations making it possible to perceive, reason, and act.
Augmented intelligence: an alternative conceptualization of artificial intelligence that focuses on enhancing human intelligence rather than replacing it.
Machine learning [ML]: a branch of artificial intelligence in which algorithms have the ability to learn and improve from experience, without being explicitly programmed for a specific task.
Supervised learning: a set of machine learning algorithms that have the ability to learn from labeled data and make predictions.
Unsupervised learning: a set of machine learning algorithms that have the ability to infer the structure of unlabeled data.
Support vector machine [SVM]: a supervised machine learning algorithm that can classify data and detect outliers by constructing adapted hyperplanes, in which data belonging to different categories are linearly separated. SVM is fast but often not as accurate as other approaches such as deep learning.
Random forest algorithm [RF]: a supervised machine learning algorithm that builds multiple decision trees to obtain a more precise prediction or classification: the output of the algorithm corresponds to the output of the majority of the trees. RF is a fast algorithm that performs well even if data are incomplete; however, RF interpretability is questionable.
Perceptron: historically, the first model of artificial neurons used in neural networks. Perceptrons are characterized by a finite number of weighted binary inputs and 1 binary output. If the weighted sum of the inputs exceeds an arbitrary threshold value called a bias, the neuron is activated and its output is 1; otherwise, the output of the neuron is 0.
Sigmoid neuron: an improved model of artificial neurons based on perceptrons. Sigmoid neurons are characterized by input values between 0 and 1; their output, which also lies between 0 and 1, is the value of the activation function of the neuron, usually the sigmoid function. Contrary to perceptrons, sigmoid neurons in a neural network can take advantage of learning algorithms for the network to automatically learn from data sets.
Artificial neural network [ANN]: a supervised or unsupervised machine learning algorithm based on a set of artificial neurons organized in layers, which can approximate complex functions involved in classification or prediction processes.
Deep learning: a supervised or unsupervised machine learning algorithm based on neural networks, often specialized in image recognition, which has multiple layers of nonlinear processing units for feature extraction and transformation.
Big data: refers to data sets that are too large or too complex for standard data processing techniques. Such data sets are encountered in large clinical trials or genomic studies [for example, DNA methylation or RNA sequencing results]; these data sets can potentially be analyzed by artificial intelligence algorithms.

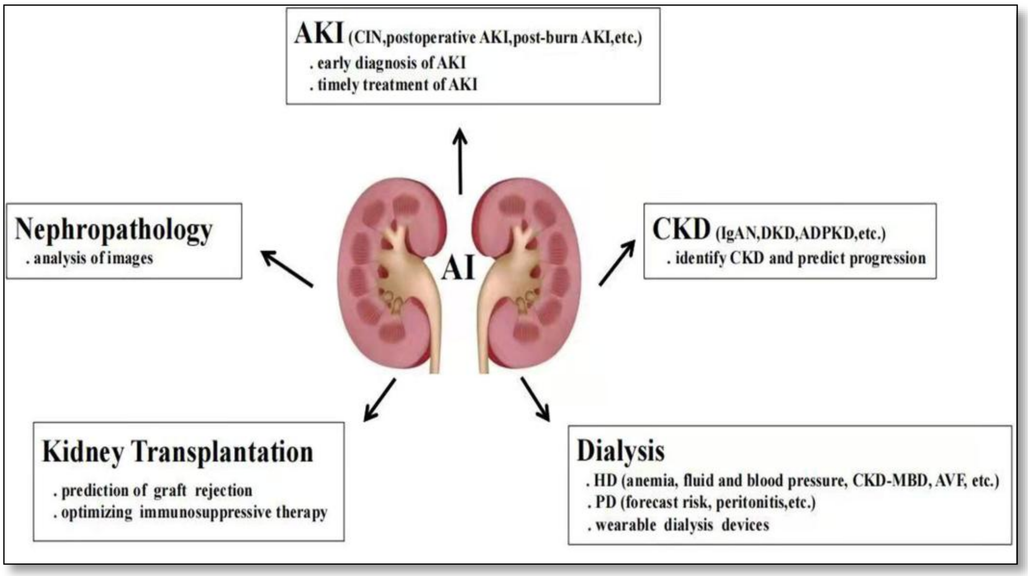

Figure [3]: Clinical applications of AI in kidney diseases. CKD-MBD: Chronic kidney disease-mineral and bone disorder; AVF: arteriovenous fistula [14]

Application of AI for Kidney Diseases

In order to help with early diagnosis and prompt treatment, artificial intelligence [AI] is frequently utilized in the clinical diagnosis and treatment of renal illnesses, particularly acute kidney injury [AKI] patients. AI can predict risk and optimize therapy for patients with chronic kidney disease [CKD], hemodialysis [HD], peritoneal dialysis [PD], and kidney transplant patients. AI is also capable of analyzing renal biopsy pictures for pathological diagnosis. [figure 3] [14].

1- Diagnosis:

Clinicians can make more informed decisions with AI, resulting in better patient outcomes. However, it is critical to guarantee that the use of AI in diagnosis is done in an ethical and transparent manner, with adequate safeguards in place to preserve patient privacy and autonomy. Overall, the use of AI in diagnosis has huge potential to enhance medical practice, and physicians must embrace this technology and integrate it into their regular practices [4]. The diagnosis of chronic kidney diseases is now being impacted by the application of artificial intelligence. A random forest algorithm has been created to allow for the early detection of chronic kidney disease [CKD][15]. Through the use of ML methods, scientists have identified metabolic signatures linked to pediatric CKD by establishing connections between sphingomyelin-ceramide and plasmalogen dysmetabolism with focal segmental glomerulosclerosis [16].

Using image recognition, researchers have effectively replicated the ability of nephropathologists to extract diagnostic, prognostic, and therapeutic data from native or transplanted kidney biopsies [17].

Computer Aided Diagnosis [CAD] involves using medical images and computer image processing to evaluate the characteristics of the area of interest, which can help doctors quickly and accurately identify and analyze lesions [18]. The kidney's most common genetic condition is autosomal dominant polycystic kidney disease [ADPKD], which involves the gradual development of renal cysts leading to increasing kidney size and declining renal function. Total kidney volume [TKV], a crucial biomarker for assessing ADPKD progression, is conventionally measured using stereology and manual segmentation in Computed Tomography [CT] and Magnetic Resonance Imaging. The accuracy of this method depends on user-input parameters. Therefore, it is essential to develop rapid and precise TKV measurement techniques, with computer-aided design [CAD] being a promising option.

In 2017, **Sharma *et al.*** [20] utilized a deep learning-based automated segmentation technique to calculate TKV from CT scans of 244 ADPKD patients. This innovative approach enables quicker and more consistent diagnosis and TKV measurement, aligning with manual segmentation by clinical professionals. Similarly, **Kline *et al.* in 2017** [21] employed an automated method to segment the kidney and estimate TKV using 2,400 MR images. Their approach mimicked a multi-observer strategy to create a reliable and accurate method for kidney segmentation and TKV computation. However, CAD technology can only provide an initial diagnosis. If certain attributes are not covered in the training dataset, they need to be evaluated by a clinician before being incorporated into the training model to ensure continuous learning and improved diagnostic capability. In **2019**, **van Gastel and colleagues** [22] successfully created an entirely automated method for segmenting total kidney volume [TKV] using a deep learning network. They applied this method to 540 abdominal magnetic resonance images of ADPKD patients, specifically [T2-weighted HASTE coronal sequences]. The TKV measurements obtained through the automated technique show a significant correlation with TKV measurements obtained through manual tracing.

Pathological diagnosis

Kidney interstitial fibrosis is an indicator of the presence and severity of chronic kidney disease. The traditional method of visually assessing the quantity is crucial for diagnosing kidney conditions. The Banff schema is utilized to categorize grades of renal allograft rejection. Visual scoring is susceptible to variability among pathologists and may lack reliability or reproducibility. Utilizing computer-aided diagnosis [CAD] can reduce pathologists' workload and offers the advantage of precision and rigor. **Tey *et al.*** [23] developed an automated system to quantify interstitial fibrosis in 40 images and tested it on 70 patients with kidney disease to determine the error rate. The study revealed an average error rate of 9%. The system was deemed to be an effective quantification tool serving as a diagnostic aid.

In 2019, **Kannan and colleagues** [24] developed a deep learning system to accurately detect and segment glomeruli in digital images of human kidney biopsies. They used a convolutional neural network [CNN] multilabel classifier for segmentation, which successfully identified worldwide sclerosis glomeruli in the test data. This demonstrates the potential of deep learning in recognizing complex histologic features in digitized human kidney biopsies. Artificial intelligence can be utilized across all stages of tissue analysis and in integrating and analyzing data from various fields to make data-driven decisions about an individual patient's diagnosis, prognosis, and treatment. AI is a promising approach expected to enhance the histological assessment of both native and transplanted kidneys. The evolution of this new technology is eagerly anticipated, and nephropathologists should embrace and implement these new technologies in the global fight against kidney disease.

The use of AI assists in categorizing the activity and chronicity of lupus nephritis and decreases variability between different observers. This categorization is based on various parameters including GN class, SLE GN activity index, Endocapillary hypercellularity, Leukocyte infiltration, Subendothelial hyaline deposits, Fibrinoid necrosis/karyorrhexis, SLE GN chronicity index, Cellular crescents, Glomerulosclerosis, Fibrous crescents, Interstitial fibrosis, and Tubular atrophy [17].

Prediction of outcomes and Alerting systems

Before the widespread adoption of machine learning in healthcare, doctors often relied on prediction scores or scales to help determine the best course of action for patients. These prediction scores typically encompass traditional risk factors as well as additional variables such as histology or imaging tests. Machine learning techniques have been employed in the development of these scores.

Table [1] includes the IgAN-tool [25] and the Prediction system for the risk of allograft loss in patients receiving kidney transplants [iBox risk prediction score] [26]**.** Scores have also been developed to predict the risk of acute kidney injury [AKI] in different patient populations, such as the postop-MAKE score [27], which estimates the risk of AKI in patients with normal renal function undergoing cardiac surgery, and AKI risk scores in patients with heart failure [28]**.**

Table [1]: Tools and scores by AI for Prediction of outcomes and Alerting systems in kidney diseases [4]**.**

Field	Study	Scenario	Purpose	Algorithm	Performance	Limitations
Glomerular disease	IgAN-tool [Asia] [25]	Multicenter, retrospective Prediction: patients with IgAN from multiple centers in China [*n* = 2047]	ESKD prediction for IgAN patients Model based on 10 clinical, laboratory, and histological variables	XGBoost algorithm	High discriminatory power: C-statistic of 0.84 [95% CI 0.80–0.88] for the validation cohort	The study only performed on Asian patients
Kidney transplant	IBox [26]	Prediction: kidney transplant recipients [*n* = 7557] from 10 medical centers across Europe and USA	Prediction of allograft failure Eight functional, histological, and immunological prognostic factors combined into a risk score	Cox regression with boot-strapping for validation	C index 0.18 [95% CI 0.79–0.83] Validation cohorts: Europe: C index 0.81 [95% CI 0.78–0.84] US: C index 0.80 [95% CI 0.76–0.84]	Emerging predictors post-transplant missing. Adherence is not taken into account. Validation in daily clinical practice remains to be analyzed
AKI	Postop-MAKE [27]	Prediction: patients with normal renal function undergoing cardiac surgery with cardiopulmonary bypass	Prediction model based on nine preoperative variables [clinical, laboratory, imaging] that predict the risk of developing AKI after surgery	Nanogram. Logistic regression was performed with variables selected using LASSO	High discriminatory power: AUC of 0.740 [95% CI 0.726–0.753] in the validation group	Single-center retrospective study; treatment protocols for these patients could vary from center to center

AI Alerting Systems for Acute Kidney Injury

In 2015, Streams software was developed by Google with the capability to potentially forecast AKI and notify healthcare providers about the requirement for early intervention [29]**.** Subsequently, the application of AI in AKI started to attract increasing interest from researchers. In 2019, **Tomaše and colleagues** [30] developed a model that accurately predicted 55.8% of inpatient episodes of AKI and 90.2% of AKI requiring dialysis in a study involving 703,782 adult patients. In **2018, Lee and co-authors** [31] conducted a retrospective review of 2,010 patients who underwent cardiac surgery. They trained AKI prediction models using six machine learning techniques: decision tree, random forest [RF], extreme gradient boosting, support vector machine [SVM], neural network classifier, and deep learning. The study revealed that the machine learning technique of extreme gradient boosting outperformed traditional logistic regression analysis and previous risk scores in predicting both all stages of AKI and stage 2 or 3 AKI following cardiac surgery, potentially aiding in the evaluation of the condition. **Yin and colleagues** [32] conducted a retrospective study on 8,800 patients who received contrast administration. Their aim was to develop a model using the machine learning method of RF to predict Contrast-induced nephropathy [CIN], which is the third leading cause of all hospital-acquired renal failure. The model showed a high level of predictability for CIN development and could potentially indicate preventive measures for CIN. In a study by **Mohamadlou *et al.*** [33]**,** boosted ensemble decision trees were utilized to construct an AKI prediction model based on historical data from more than 300,000 hospitalized patients. The algorithm demonstrated strong predictive abilities in identifying patients at risk of developing AKI. Specifically, the prediction accuracy was higher for patients with patterns resembling AKI. These methods empower physicians to potentially intervene before kidney injury manifests. Another research discovered that machine learning models [multivariate logistic regression, RF, and artificial neural networks [ANN]] were able to forecast the onset of AKI following admission to the ICU in a group of 23,950 patients with a respectable AUC [average AUC 0.783] [34].

AI Alerting System for Chronic Kidney Disease:

Reports have indicated that AI applications have been used to detect the presence of CKD. In Australia, a trial initiative utilized e-technologies to identify CKD [Electronic Diagnosis and Management Assistance to Primary Care in Chronic Kidney Disease; EMAP-CKD]. The program involved the development of software equipped with algorithms that were trained to recognize patients at risk and to request appropriate screening tests for CKD [35].

The cost and mortality of patients can be predicted by AI. In 2019, **Lin *et al*.** [36] suggested that using AI modeling could offer reliable data on one-year outcomes post-dialysis in elderly and super-aged groups. They found that individuals with cancer, alcohol-related disease, stroke, chronic obstructive pulmonary disease [COPD], previous hip fracture, osteoporosis, dementia, and previous respiratory failure incurred higher medical costs and had elevated mortality rates.

In a study by **Kanda *et al.*** [37] in 2019, factors associated with progressive CKD were identified from a healthy population during a health checkpoint using a Bayesian network and artificial intelligence. The factors considered included hypertension, time-series changes in the prognostic category of CKD, proteinuria, and eGFR.

2- Guiding treatment

Decisions making are made based on guidelines that are developed after extensive research. As a result, these recommendations are population-based, and they must be modified based on each unique situation. Personalized and precise treatment plans are essential. Analyzing the connection between treatment plans and effectiveness in a large patient population using AI can help in developing models based on effectiveness and risk factors. This can assist in selecting treatment plans and enhancing clinical effectiveness. Research on renal disease is scarce, especially in hemodialysis patients.

Anemia treatment

Anemia is one of the most prevalent comorbidities seen in hemodialysis patients. As renal function declines, the prevalence and severity of anemia steadily increase [38]**.** Anemia in CKD results mainly from insufficient production of erythropoietin [EPO] [39]. Erythropoietin-stimulating agents [ESAs] are commonly used by clinicians to increase EPO and elevate hemoglobin [Hb] levels. However, the confirmed toxicity of ESAs is concerning, as they can elevate the risk of cardiovascular events, tumor progression, and mortality [40]. It has been noted that these toxicities are associated with dosage [41]. Identifying an appropriate therapy tailored to each patient's specific condition is crucial. Computer-driven approaches have made significant advancements in providing erythropoietic dosage information for patients with chronic kidney disease. At first, the keys used were just digital versions of the traditional paper-based anemia management protocols. The real personalization came about through the use of advanced modeling methods like artificial neural networks, physiological models, and feedback control systems [42].

In 2014 **Barbieri** recommended appropriate ESAs dosages using Machine Learning [Multilayer Perceptron, MLP] and a linear model developed for predicting ESAs therapeutic response. The MLP prediction model has an accuracy of higher than 90%. The MLP model beats earlier techniques for Hb prediction [43]. To assess the model's impact, the researchers conducted a 24-month retrospective analysis in 2016 with 752 more hemodialysis patients. According to the model predictions, median ESA consumption reduced while on-target Hb readings increased. Furthermore, Hb fluctuation has significantly decreased. The approach might assist to improve anemic outcomes of patients on hemodialysis by limiting ESAs dose, with the potential to lower treatment costs[44]. The model might aid in increasing the percentage of Hb in the range while reducing the intake of ESAs with lower Hb variations. Meanwhile, transfusion, hospitalization, and cardiovascular events have all decreased. Finally, the model was a useful tool for doctors seeking to lower the risks and costs associated with ESA treatment. However, the sample size was small, and the follow-up period was inadequate to determine the model's influence on cardiovascular morbidity and death. At that time, the model was only utilized for hemodialysis patients; more studies should be conducted to confirm the efficacy of anemia therapy in pre-dialysis and peritoneal dialysis patients. Furthermore, these techniques are data-intensive and often work well in areas where sufficient data is available to predict the ESA reaction, but are unable to extrapolate beyond these ranges [42].

Role of AI in Blood pressure control and fluid volume management in Hemodialysis

Patients undergoing hemodialysis require careful monitoring of blood pressure [BP] and fluid volume, as these are crucial measurements. The prevalence of hypertension in ESRD patients varies from 40 to 90% based on the BP criteria used, the selected population, and the measurement period [45]. Managing blood pressure often involves reducing extracellular fluid volume overload, which in turn increases the risk of intradialytic hypotension. Both intradialytic hypotension and persistent hypertension are associated with poor prognosis. EuCliD® is an international electronic health record repository that enables point-of-care data capture for routine clinical practice information[46]. **Barbieri *et al.*** [46] created a multiple-endpoint model based on 766,000 recordings in 2019 that predicted session-specific Kt/V, fluid volume clearance, heart rate, and blood pressure by utilizing this abundance of data. The model's precision and accuracy are promising. In addition to the already constrained single-endpoint treatment options, the model could aid in the optimal decision-making process in multidimensional settings.

3- Wearable Dialysis Devices

Dialysis is the main treatment for ESRD, and it has a significant impact on patients' lives. Some patients may struggle with the hemodynamic instability of intermittent dialysis, but there is optimism about the development of wearable artificial kidneys. Wearable dialysis systems have the capability to analyze equipment alarms, dialysis parameters, and patient-related data in real-time, offering immediate feedback [47]. The combination of artificial intelligence and regenerative medicine technologies led to the development of wearable dialysis devices. These devices are capable of conducting continuous dialysis, effectively eliminating toxins, and do not impact hemodynamics [see Figure 4]. A study involving 15 ESRD patients assessed the devices and found that dialysis was successful without any adverse reactions. The devices have been granted breakthrough device status by the American Food and Drug Administration.

However, due to the small sample size, further research involving larger patient populations is necessary to improve the model in the future [47]. Another motivating wearable artificial kidney is a 5-kg miniaturized device with a sorbent-based hemodialysis system that is worn on the waist like a toolkit belt. It is currently in development at the University of Washington, USA. A clinical trial involving 10 patients who received therapy with the wearable artificial kidney for 24 hours was halted after the 7th subject, due to device-related technical issues. These issues included an excessive presence of carbon dioxide bubbles in the dialysate circuit, tubing kinks, and variable pump function causing fluctuations in blood and dialysate flow rates [48].

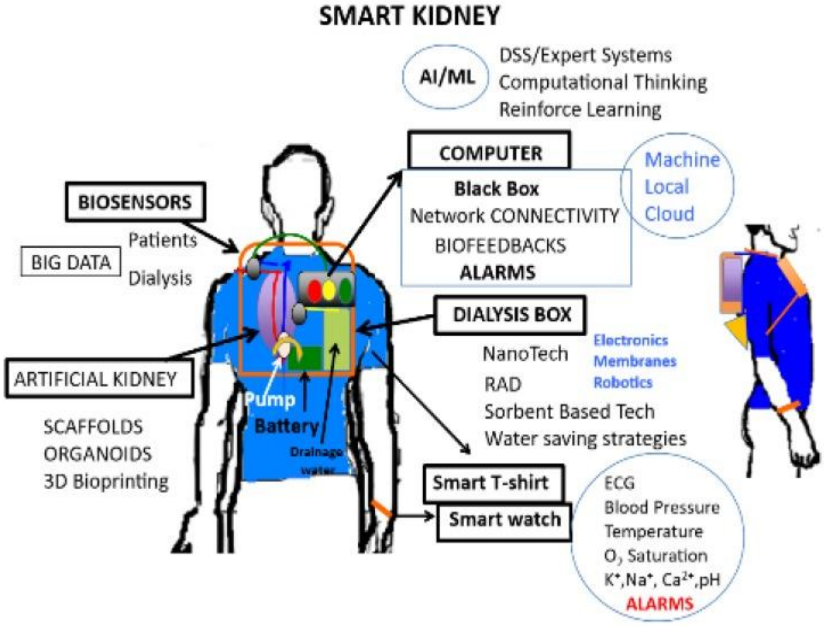

Figure [4]: Artificial intelligence includes the science and engineering for developing smart wearable artificial kidneys [47]

4- Implantable Renal Assist Device [iRAD]

The implanted Renal Assist Device [iRAD] is an incredible innovation, designed to replicate the structure and function of kidneys using micromachining techniques. This bionic device features a silicon nanopore membrane and a bioreactor of live kidney cells to concentrate ultrafiltrate into urine. It is enclosed in a body-friendly box and connected to a patient's circulatory system and bladder. Although it has shown success in animal models [49], further development is needed to adapt it for clinical use [50]. Additionally, experts have discovered MXene Sorbents for the Elimination of Urea from Dialysate, offering potential for designing a miniaturized dialysate regeneration system for a wearable artificial kidney [51].

5- AI Assistance of Needle Insertion in Hemodialysis Patients

In the field of health care, robotics are gradually being integrated, particularly in surgical procedures. One example is the da Vinci® Surgical System, which incorporates a high-definition 3D computer vision system [assisted by machine learning] and small wristed instruments capable of more complex bending and rotation than the human hand. Additionally, a robotic system for autonomous image-guided needle insertion has been developed for tasks such as blood draws and intravenous insertions. This system combines robotics, AI, computer vision, and image technology [Figure 5] [52]. The important thing to note is that a dialysis machine does not function as an AI-powered robot. It lacks the ability to adapt to its surroundings in ways that haven't been explicitly taught by humans. However, it's not difficult to envision future dialysis robots that can perform complex sequences of actions automatically or in a semi-autonomous manner. Additionally, there are reports of achieving accurate needle insertion [within 3 mm error] in common target sites, including the kidneys, by using a CT-guided robotic system [53]. The suggested method of robot registration and operation based on optical tracking enables precise three-dimensional needle manipulation during ultrasound-guided percutaneous renal access [PRA] procedures, resulting in improved precision and reduced time [54].

5- Kidney transplantation

Another common treatment for ESRD is kidney transplantation. But because of the limited availability of kidneys and strict technical requirements, only a small number of individuals can receive the benefits of kidney transplantation. The optimization of transplantation parameters and adjustment of recipient, donor, and transplant procedural variables are crucial for predicting the result of kidney transplantation. In a retrospective analysis by **Lofaro *et al.*,** 80 renal transplant patients with 5-year follow-up were studied. Classification trees were used to create two predictive models, revealing six highly influential variables for patient outcomes. These models achieved AUC values of 0.847 and 0.824 respectively. Another study included 4754 systemic lupus erythematosus patients who received kidney transplants. Three machine learning algorithms were employed to establish predictive models. The AUC of the ANN model [0.73], based on six variables, outperformed the logistic regression based on six variables selected by Weka [0.73] and classification trees [0.70]. The findings indicated superior predictive performance of the ANN model compared to other models [55]. In 2019, **Abdeltawab and colleagues** [56] developed a computer-aided diagnosis [CAD] system using deep learning. This system integrates imaging markers and clinical biomarkers to detect acute renal transplant rejection at an early stage. The overall accuracy of the system is 92.9%, with a sensitivity of 93.3% and specificity of 92.3% in distinguishing rejected kidney transplants from non-rejected ones.

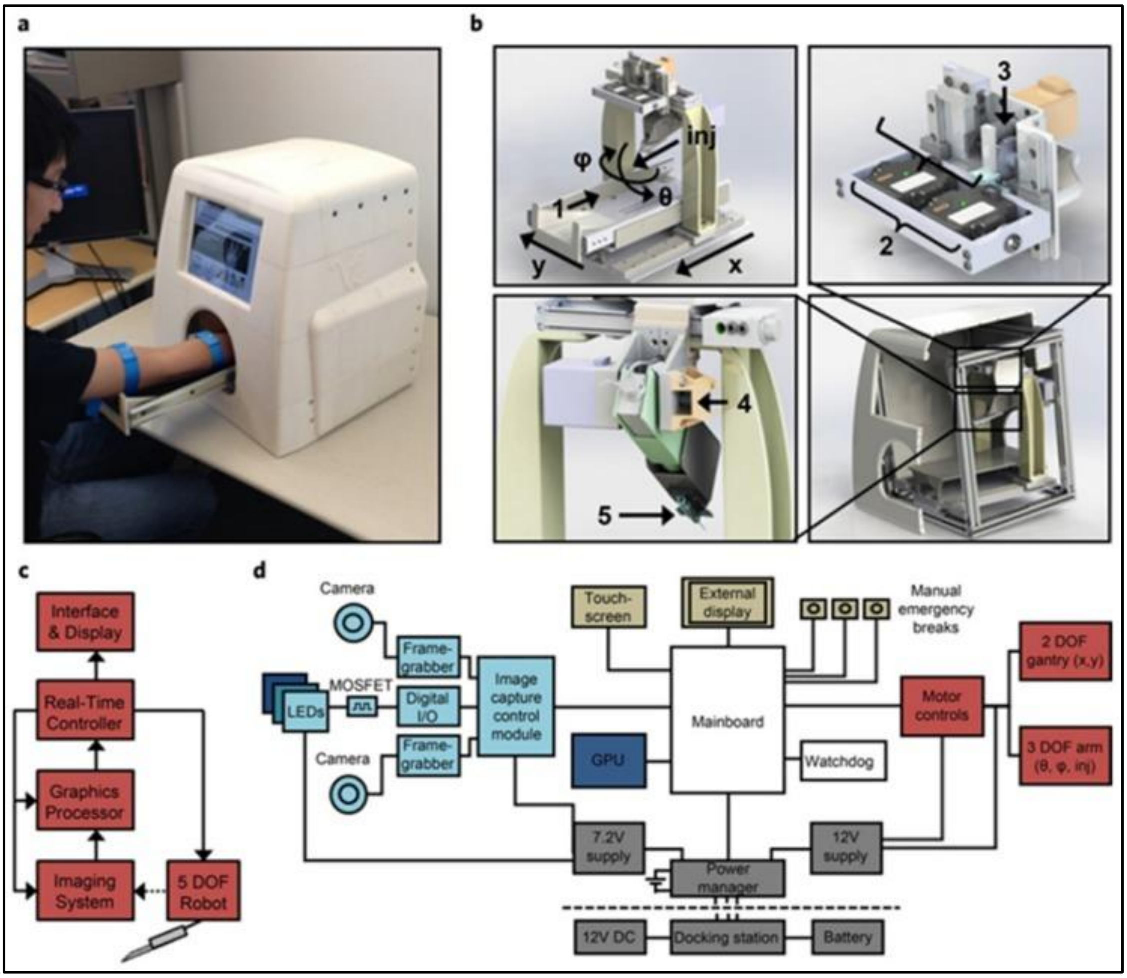

Figure [5]: System plan and building for automated cannula insertion. [a] Functional prototype. [b] Major functional components. [c] Device data flow. [d] The hardware architecture is assembled by function [52].

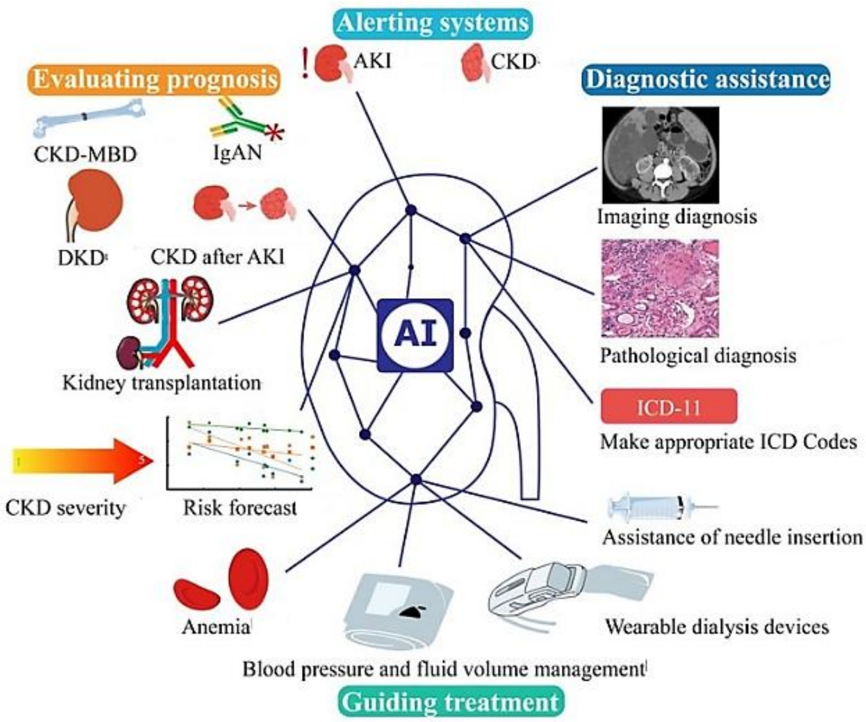

Figure [6]: showing the conclusion of AI applications in kidney disease in alerting systems, diagnostic support, guiding treatment, and assessing prognosis. AKI, acute kidney disease. CKD, chronic kidney disease. CKD-MBD, Chronic Kidney Disease - Mineral and Bone Disorder. IgAN, IgA nephropathy [57]

Challenges of AI

Careful consideration of the risks and challenges linked to AI technology is crucial, and implementing measures to minimize these risks is essential. The following are some of the challenges:

Data access and quality: Obtaining data sets for machine learning requires using a trustworthy source of pertinent data that is clean, easily accessible, well-organized, and secure. In nephrology, a common issue is the limited availability of data due to the rarity of many diseases and the lower prevalence of kidney disorders compared to other medical conditions [4].

Data privacy and security: When utilizing AI in nephrology, it's important to prioritize data protection. Patient information is sensitive and must be safeguarded in compliance with applicable laws like the General Data Protection Regulation [GDPR] in the European Union [EU]. Before analysis or storage in a different location from where it was gathered, patient data should be anonymized or pseudonymized. It's crucial to ensure the secure handling of patient data and to inform patients about the usage of their data. Any AI tool or project should incorporate a secure data management environment for handling sensitive data [4].

Bias: The potential for bias in AI algorithms poses an additional concern. If biased data is used to train an AI program, it could perpetuate or worsen existing biases in the healthcare system. For instance, if an AI system is trained on data primarily from white patients with focal glomerulosclerosis, it might struggle to accurately identify or classify the condition in patients from other racial or ethnic backgrounds. To mitigate the risk of bias, AI algorithms need to be trained using diverse and inclusive data sets[4] .

Trustworthiness: People tend to trust things that are easy to understand, and doctors are a good example of this. The main challenge with implementing AI in medicine is the uncertainty surrounding how learning models and inputs can predict outcomes and guide medical interventions. It is essential to have explainable AI to ensure transparency in AI decisions and the processes leading to those decisions, in order to avoid the opaque nature of many AI solutions.

Various techniques can be used to address this issue. For example, methods such as feature importance rank the variables used by an AI model based on their impact on prediction results, providing insight into how each input influences the decision-making process. However, even with such techniques, OpenAI has acknowledged a lack of complete understanding of how ChatGPT operates and the absence of tools to explore the decision-making processes of newer models. This lack of understanding has led governments to implement measures to regulate and restrict the uncontrolled expansion of AI. One approach to enhancing trust in the field of nephrology is to educate the nephrological community about AI [4] .

Computing power: The main technologies behind artificial intelligence are machine learning and deep learning, but their effective operation requires an increasing number of cores and GPUs, which are not always readily available. The primary challenge for the industry is to meet the computational capacity needed to process the extensive amounts of data essential for developing AI systems.

Naturally, there is a significant environmental impact associated with the increased processing power. This poses a major barrier for many AI research projects and has raised concerns within the AI community. Consequently, there have been calls for greater transparency, optimization of training cycles, and a heightened focus on "green AI," which aims to generate innovative results without increasing, and preferably reducing, computational costs [58].

AI integration: Healthcare providers who are not experienced in using EHRs are still prevalent. It's a fact that there is limited interoperability, and incorporating AI into EHRs is often impractical in many healthcare settings, despite efforts by the EU to standardize them and the USA already having some shared patient information in place[4] .

AI Specialists: A data scientist or data engineer, possessing specialized skills and knowledge, is required for integrating, deploying, and implementing AI. The scarcity and high cost of these specialists pose a significant challenge to implementing AI in healthcare or research settings, as they often prefer joining well-compensated large organizations over working in public settings, such as most hospitals or research centers in Europe [4].

Legal issues: AI algorithms pose a potential risk of errors, despite their ability to rapidly and accurately process large amounts of data. It is essential to implement mechanisms for identifying and correcting these errors to ensure the safety and effectiveness of the technology. While AI technologies will currently support nephrologists in decision-making, they will not replace experienced professionals. If AI algorithms violate any laws or regulations, the company may face legal repercussions [4].

Summary and Conclusion

Artificial intelligence is rapidly being employed in nephrology, among other medical fields. AI's function in kidney disease involves warning the presence of CKD, performing diagnostic imaging, determining pathology, and directing treatment. Medicine showed significant progress, moving from traditional medicine to evidence-based medicine, and now to AI. While AI is still in its early stages, it holds promise for further development. AI faces several hurdles, such as data accuracy, privacy and regulatory issues, lack of uniformity across facilities, and absence of validation. The potential benefits of AI implementation are significant, but it's crucial to recognize and address the associated risks and challenges. AI will soon become a common tool for nephrologists, so it's important for the nephrology community to be well-informed about this technology. To effectively implement AI, it's essential to have a grasp of the fundamental concepts of AI and how models are developed.

Although AI won't take the place of nephrologists, those who can effectively integrate it into their practice will likely enhance their abilities as doctors for their patients. It's important to acknowledge that the traditional responsibilities of healthcare professionals will have to change to accommodate the use of AI in clinical practice, and continuous education and training will be necessary to ensure ethical and successful use of AI.

Conflict of Interest and Financial Disclosure: None

REFERENCES

1. Global Burden of Disease Study 2015; DALYs and HALE Collaborators. Global, regional, and national disability-adjusted life-years [DALYs] for 315 diseases and injuries and healthy life expectancy [HALE], 1990-2015: a systematic analysis for the Global Burden of Disease Study 2015. Lancet [London, England]. 2016; 388: 1603-58. doi: 10.1016/S0140-6736[16]31460-X.

2. Kim SH, Jo MW, Go DS, Ryu DR, Park J. Economic burden of chronic kidney disease in Korea using national sample cohort. J Nephrol. 2017; 30: 787-93. doi: 10.1007/s40620-017-0380-3.

3. Wu CC, Islam MM, Poly TN, Weng YC. Artificial Intelligence in Kidney Disease: A Comprehensive Study and Directions for Future Research. Diagnostics [Basel]. 2024 Feb 12;14[4]:397. doi: 10.3390/ diagnostics14040397.

4. Fayos De Arizón L, Viera ER, Pilco M, Perera A, De Maeztu G, et al. Artificial intelligence: a new field of knowledge for nephrologists? Clin Kidney J. 2023;16[12]:2314-2326. doi: 10.1093/ckj/sfad182.

5. Doumpos M, Zopounidis C, Platanakis E, Zhang W. Operational research and artificial intelligence methods in banking. Euro J Operational Res 2023; 306 [1]: 1-16. doi: 10.1016/j.ejor.2022. 04.027

6. Biswas A, Kumari A, Gaikwad DS, Pandey DK. Revolutionizing Biological Science: The Synergy of Genomics in Health, Bioinformatics, Agriculture, and Artificial Intelligence. OMICS. 2023 Dec;27[12]: 550-569. doi: 10.1089/omi.2023.0197.

7. Gómez-González E, Gomez E, Márquez-Rivas J, Guerrero-Claro M, Fernández-Lizaranzu I, Relimpio-López MI et al. Artificial intelligence in medicine and healthcare: a review and classification of current and near-future applications and their ethical and social Impact. arXiv Prepr arXiv200109778; 2020: 1-20. doi: 10.48550/arXiv.2001.09778

8. Caselli M, Fracasso A, Traverso S. Robots and risk of COVID-19 workplace contagion: Evidence from Italy. Technol Forecast Soc Change. 2021;173:121097. doi: 10.1016/j.techfore.2021.121097.

9. Benjamens S, Dhunnoo P, Meskó B. The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database. Npj Digit Med 2020; 3[1]:118. doi: 10. 1038/ s41746- 020- 00324-0.

10. Smith JA, Abhari RE, Hussain Z, Heneghan C, Collins GS, Carr AJ. Industry ties and evidence in public comments on the FDA framework for modifications to artificial intelligence/machine learning-based medical devices: a cross sectional study. BMJ Open. 2020 Oct 14;10[10]:e039969. doi: 10.1136/bmjopen-2020-039969.

11. Mori Y, Neumann H, Misawa M, Kudo SE, Bretthauer M. Artificial intelligence in colonoscopy - Now on the market. What's next? J Gastroenterol Hepatol. 2021 Jan;36[1]:7-11. doi: 10.1111/jgh.15339.

12. Badrouchi S, Bacha MM, Hedri H, Ben Abdallah T, Abderrahim E. Toward generalizing the use of artificial intelligence in nephrology and kidney transplantation. J Nephrol. 2023 May;36[4]:1087-1100. doi: 10.1007/s40620-022-01529-0.

13. Niel O, Bastard P. Artificial Intelligence in Nephrology: Core Concepts, Clinical Applications, and Perspectives. Am J Kidney Dis. 2019 Dec; 74 [6]:803-810. doi: 10.1053/j.ajkd.2019.05.020.

14. Yao L, Zhang H, Zhang M, Chen X, Zhang J, Huang J, Zhang L. Application of artificial intelligence in renal disease. Clinical eHealth 2021; 4: 54–61 doi: 10.1016/j.ceh.2021.11.003.

15. Senan EM, Al-Adhaileh MH, Alsaade FW, Aldhyani THH, Alqarni AA, Alsharif N, et al. Diagnosis of Chronic Kidney Disease Using Effective Classification Algorithms and Recursive Feature Elimination Techniques. J Healthc Eng. 2021 Jun 9; 2021:1004767. doi: 10.1155/2021/1004767.

16. Lee AM, Hu J, Xu Y, Abraham AG, Xiao R, Coresh J, et al.; CKD Biomarkers Consortium. Using Machine Learning to Identify Metabolomic Signatures of Pediatric Chronic Kidney Disease Etiology. J Am Soc Nephrol. 2022 Feb;33[2]:375-386. doi: 10.1681/ASN.2021040538.

17. Becker JU, Mayerich D, Padmanabhan M, Barratt J, Ernst A, Boor P, et al. Artificial intelligence and machine learning in nephropathology. Kidney Int. 2020 Jul;98[1]:65-75. doi: 10.1016/j.kint.2020.02.027.

18. Venuthurupalli SK, Hoy WE, Healy HG, Cameron A, Fassett RG. CKD Screening and Surveillance in Australia: Past, Present, and Future. Kidney Int Rep. 2017;3[1]:36-46. doi: 10.1016/j.ekir.2017.09.012.

19. Grantham JJ. The etiology, pathogenesis, and treatment of autosomal dominant polycystic kidney disease: recent advances. Am J Kidney Dis. 1996;28[6]:788-803. doi: 10.1016/s0272-6386[96]90378-9.

20. Sharma K, Rupprecht C, Caroli A, Aparicio MC, Remuzzi A, Baust M, Navab N. Automatic Segmentation of Kidneys using Deep Learning for Total Kidney Volume Quantification in Autosomal Dominant Polycystic Kidney Disease. Sci Rep. 2017 May 17;7[1]:2049. doi: 10.1038/s41598-017-01779-0.

21. Kline TL, Korfiatis P, Edwards ME, Blais JD, Czerwiec FS, Harris PC, et al. Performance of an Artificial Multi-observer Deep Neural Network for Fully Automated Segmentation of Polycystic Kidneys. J Digit Imaging. 2017 Aug;30[4]:442-448. doi: 10.1007/s10278-017-9978-1.

22. van Gastel MDA, Edwards ME, Torres VE, Erickson BJ, Gansevoort RT, Kline TL. Automatic Measurement of Kidney and Liver Volumes from MR Images of Patients Affected by Autosomal Dominant Polycystic Kidney Disease. J Am Soc Nephrol. 2019 Aug;30 [8]: 1514-1522. doi: 10.1681/ASN.2018090902.

23. Tey WK, Kuang YC, Ooi MP, Khoo JJ. Automated quantification of renal interstitial fibrosis for computer-aided diagnosis: A comprehensive tissue structure segmentation method. Comput Methods Programs Biomed. 2018 Mar;155:109-120. doi: 10.1016/j.cmpb.2017.12.004.

24. Kannan S, Morgan LA, Liang B, Cheung MG, Lin CQ, Mun D, et al. Segmentation of Glomeruli Within Trichrome Images Using Deep Learning. Kidney Int Rep. 2019 Apr 15;4[7]:955-962. doi: 10.1016/ j.ekir.2019.04.008.

25. Schena FP, Magistroni R, Narducci F, Abbrescia DI, Anelli VW, Di Noia T. Artificial intelligence in glomerular diseases. Pediatr Nephrol. 2022 Nov;37[11]:2533-2545. doi: 10.1007/s00467-021-05419-8.

26. Loupy A, Aubert O, Orandi BJ, Naesens M, Bouatou Y, Raynaud M, et al. Prediction system for risk of allograft loss in patients receiving kidney transplants: international derivation and validation study. BMJ. 2019 Sep 17;366:l4923. doi: 10.1136/bmj.l4923.

27. Hu P, Mo Z, Chen Y, Wu Y, Song L, Zhang L, et al. Derivation and validation of a model to predict acute kidney injury following cardiac surgery in patients with normal renal function. Ren Fail. 2021 Dec;43[1]:1205-1213. doi: 10.1080/0886022X.2021.1960563.

28. Zhou LZ, Yang XB, Guan Y, Xu X, Tan MT, Hou FF, Chen PY. Development and Validation of a Risk Score for Prediction of Acute Kidney Injury in Patients With Acute Decompensated Heart Failure: A Prospective Cohort Study in China. J Am Heart Assoc. 2016 Nov 16; 5[11]: e004035. doi: 10.1161/JAHA.116.004035.

29. Powles J, Hodson H. Google DeepMind and healthcare in an age of algorithms. Health Technol [Berl]. 2017;7[4]:351-367. doi: 10.1007/s12553-017-0179-1.

30. Tomašev N, Glorot X, Rae JW, Zielinski M, Askham H, Saraiva A, et al. A clinically applicable approach to continuous prediction of future acute kidney injury. Nature. 2019 Aug;572[7767]:116-119. doi: 10.1038/s41586-019-1390-1.

31. Lee HC, Yoon HK, Nam K, Cho YJ, Kim TK, Kim WH, Bahk JH. Derivation and Validation of Machine Learning Approaches to Predict Acute Kidney Injury after Cardiac Surgery. J Clin Med. 2018 Oct 3;7[10]:322. doi: 10.3390/jcm7100322.

32. Yin WJ, Yi YH, Guan XF, Zhou LY, Wang JL, Li DY, Zuo XC. Preprocedural Prediction Model for Contrast-Induced Nephropathy Patients. J Am Heart Assoc. 2017 Feb 3;6[2]:e004498. doi: 10.1161/JAHA.116.004498.

33. Mohamadlou H, Lynn-Palevsky A, Barton C, Chettipally U, Shieh L, Calvert J, Saber NR, Das R. Prediction of Acute Kidney Injury With a Machine Learning Algorithm Using Electronic Health Record Data. Can J Kidney Health Dis. 2018 Jun 8;5:2054358118776326. doi: 10.1177/2054358118776326.

34. Zimmerman LP, Reyfman PA, Smith ADR, Zeng Z, Kho A, Sanchez-Pinto LN, Luo Y. Early prediction of acute kidney injury following ICU admission using a multivariate panel of physiological measurements. BMC Med Inform Decis Mak. 2019 Jan 31;19 [Suppl 1]: 16. doi: 10.1186/s12911-019-0733-z.

35. Shah H. The DeepMind debacle demands dialogue on data. Nature. 2017 Jul 19;547[7663]:259. doi: 10.1038/547259a.

36. Lin SY, Hsieh MH, Lin CL, Hsieh MJ, Hsu WH, Lin CC, Hsu CY, Kao CH. Artificial Intelligence Prediction Model for the Cost and Mortality of Renal Replacement Therapy in Aged and Super-Aged Populations in Taiwan. J Clin Med. 2019 Jul 9;8[7]:995. doi: 10.3390/jcm8070995.

37. Kanda E, Kanno Y, Katsukawa F. Identifying progressive CKD from healthy population using Bayesian network and artificial intelligence: A worksite-based cohort study. Sci Rep. 2019 Mar 25;9[1]:5082. doi: 10.1038/s41598-019-41663-7.

38. Stauffer ME, Fan T. Prevalence of anemia in chronic kidney disease in the United States. PLoS One. 2014 Jan 2;9[1]:e84943. doi: 10.1371/journal.pone.0084943.

39. Artunc F, Risler T. Serum erythropoietin concentrations and responses to anaemia in patients with or without chronic kidney disease. Nephrol Dial Transplant. 2007 Oct;22[10]:2900-8. doi: 10.1093/ndt/gfm316.

40. Coyne DW. Anemia in chronic kidney disease treating the numbers, not the patients. JAMA Intern Med. 2014 May;174[5]:708-9. doi: 10.1001/jamainternmed.2013.13305.

41. Phrommintikul A, Haas SJ, Elsik M, Krum H. Mortality and target haemoglobin concentrations in anaemic patients with chronic kidney disease treated with erythropoietin: a meta-analysis. Lancet. 2007 Feb 3;369[9559]:381-8. doi: 10.1016/S0140-6736[07]60194-9.

42. Brier ME, Gaweda AE, Aronoff GR. Personalized Anemia Management and Precision Medicine in ESA and Iron Pharmacology in End-Stage Kidney Disease. Semin Nephrol. 2018 Jul;38[4]:410-417. doi: 10.1016/j.semnephrol.2018.05.010.

43. Barbieri C, Mari F, Stopper A, Gatti E, Escandell-Montero P, Martínez-Martínez JM, Martín-Guerrero JD. A new machine learning approach for predicting the response to anemia treatment in a large cohort of End Stage Renal Disease patients undergoing dialysis. Comput Biol Med. 2015 Jun;61:56-61. doi: 10.1016/j.compbiomed.2015.03.019.

44. Barbieri C, Molina M, Ponce P, Tothova M, Cattinelli I, Ion Titapiccolo J, et al. An international observational study suggests that artificial intelligence for clinical decision support optimizes anemia management in hemodialysis patients. Kidney Int. 2016 Aug; 90[2]: 422-429. doi: 10.1016/j.kint.2016.03.036.

45. Agarwal R, Nissenson AR, Batlle D, Coyne DW, Trout JR, Warnock DG. Prevalence, treatment, and control of hypertension in chronic hemodialysis patients in the United States. Am J Med. 2003 Sep;115 [4]:291-7. doi: 10.1016/s0002-9343[03]00366-8.

46. Barbieri C, Cattinelli I, Neri L, Mari F, Ramos R, Brancaccio D, Canaud B, Stuard S. Development of an Artificial Intelligence Model to Guide the Management of Blood Pressure, Fluid Volume, and Dialysis Dose in End-Stage Kidney Disease Patients: Proof of Concept and First Clinical Assessment. Kidney Dis [Basel]. 2019 Feb; 5[1]: 28-33. doi: 10.1159/000493479.

47. Hueso M, Navarro E, Sandoval D, Cruzado JM. Progress in the Development and Challenges for the Use of Artificial Kidneys and Wearable Dialysis Devices. Kidney Dis [Basel]. 2019 Feb;5[1]:3-10. doi: 10.1159/000492932.

47. Gura V, Rivara MB, Bieber S, Munshi R, Smith NC, Linke L, et al. A wearable artificial kidney for patients with end-stage renal disease. JCI Insight. 2016 Jun 2;1[8]:e86397. doi: 10.1172/jci.insight.86397.

49. Kim S, Fissell WH, Humes DH, Roy S. Current strategies and challenges in engineering a bioartificial kidney. Front Biosci [Elite Ed]. 2015 Jan 1;7[2]:215-28. doi: 10.2741/E729.

50. Kensinger C, Karp S, Kant R, Chui BW, Goldman K, Yeager T, et al. First Implantation of Silicon Nanopore Membrane Hemofilters. ASAIO J. 2016 Jul-Aug;62[4]:491-5. doi: 10.1097/MAT.0000000000000367.

51. Meng F, Seredych M, Chen C, Gura V, Mikhalovsky S, Sandeman S, et al. MXene Sorbents for Removal of Urea from Dialysate: A Step toward the Wearable Artificial Kidney. ACS Nano. 2018 Oct 23;12[10]:10518-10528. doi: 10.1021/acsnano.8b06494.

52. Chen A, Nikitczuk K, Nikitczuk J, Maguire T, Yarmush M. Portable robot for autonomous venipuncture using 3D near infrared image guidance. Technology [Singap World Sci]. 2013 Sep;1[1]:72-87. doi: 10.1142/S2339547813500064.

53. Ben-David E, Shochat M, Roth I, Nissenbaum I, Sosna J, Goldberg SN. Evaluation of a CT-Guided Robotic System for Precise Percutaneous Needle Insertion. J Vasc Interv Radiol. 2018 Oct;29[10]:1440-1446. doi: 10.1016/j.jvir.2018.01.002.

54. Zhang D, Li Z, Chen K, Xiong J, Zhang X, Wang L. An optical tracker based robot registration and servoing method for ultrasound guided percutaneous renal access. Biomed Eng Online. 2013 May 24;12:47. doi: 10.1186/1475-925X-12-47.

55. Lofaro D, Maestripieri S, Greco R, Papalia T, Mancuso D, Conforti D, Bonofiglio R. Prediction of chronic allograft nephropathy using classification trees. Transplant Proc. 2010 May;42[4]:1130-3. doi: 10.1016/j.transproceed.2010.03.062.

56. Abdeltawab H, Shehata M, Shalaby A, Khalifa F, Mahmoud A, El-Ghar MA, et al. A Novel CNN-Based CAD System for Early Assessment of Transplanted Kidney Dysfunction. Sci Rep. 2019 Apr 11;9[1]: 5948. doi: 10.1038/s41598-019-42431-3.

57. Yuan Q, Zhang H, Deng T, Tang S, Yuan X, Tang W, et al. Role of Artificial Intelligence in Kidney Disease. Int J Med Sci. 2020 Apr 6;17[7]:970-984. doi: 10.7150/ijms.42078.

58. Dhar P. The carbon impact of artificial intelligence. Nat Mach Intell 2020; 2 :423–5. doi: 10.1038/S42256- 020- 0219- 9

IJMA

INTERNATIONAL JOURNAL OF MEDICAL ARTS

VOLUME 6, ISSUE 12, December 2024

P- ISSN: 2636-4174
E- ISSN: 2682-3780