International Journal of Basic & Clinical Pharmacology
Chiluveru S et al. Int J Basic Clin Pharmacol. 2026 Mar;15(2):400-409
http://www.ijbcp.com
pISSN 2319-2003 | eISSN 2279-0780

DOI: https://dx.doi.org/10.18203/2319-2003.ijbcp20260446

Review Article

Artificial intelligence approaches in early detection and clinical management of acute and chronic kidney diseases

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Received: 27 December 2025
Revised: 08 February 2026
Accepted: 09 February 2026

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ABSTRACT

Acute kidney injury (AKI) and chronic kidney disease (CKD) are major global health burdens that are often detected late due to the limitations of conventional biomarkers such as serum creatinine and estimated glomerular filtration rate. Artificial intelligence (AI) has emerged as a powerful tool capable of analyzing complex, high-dimensional clinical data to improve risk stratification, early detection, prognosis and personalized management of kidney diseases. This review evaluates the current applications of AI in the diagnosis, prediction and clinical management of AKI and CKD and compares its performance with traditional diagnostic approaches. A comprehensive literature search was conducted up to October 2025 using Google Scholar, PubMed, Web of Science and Scopus. Studies focusing on AI-based predictive modeling, imaging analysis, biomarker discovery and clinical decision support in nephrology were included. Of 150 screened articles, 51 met the inclusion criteria.AI-based models demonstrated superior accuracy for early AKI detection compared with serum creatinine alone (AUC>0.85 vs. 0.65) and improved prediction of CKD progression, cardiovascular outcomes, and dialysis initiation. Additionally, AI-assisted imaging enhanced renal pathology detection, while decision-support systems optimized drug dosing and dialysis parameters. Despite these advances, challenges such as algorithmic bias, interpretability, data heterogeneity, and ethical concerns remain. Overall, AI holds substantial potential to transform nephrology through earlier diagnosis, improved prognostication, and individualized treatment, though robust regulatory frameworks and large prospective studies are essential before widespread clinical implementation.

Keywords: Artificial intelligence, Machine learning, Acute kidney injury, Chronic kidney disease, Early detection, Nephrology, Predictive modelling

INTRODUCTION

Kidney disease is a major global public health concern, driven by diabetes, hypertension, obesity, and aging. The global burden of diseases study 2015 estimates that nearly 750 million people worldwide are affected, imposing a substantial healthcare burden. AKI is characterized by a rapid decline in renal function, manifested by reduced glomerular filtration rate, elevated serum creatinine and urea levels, and disturbances in fluid, electrolyte, and acid-base balance. AKI affects 10-15% of hospitalized patients and upto 50% of those in intensive care units, with approximately 10% requiring renal replacement therapy (RRT), mortality rates reaching 23-50% in severe cases.[1]

CKD is a progressive and irreversible condition affecting approximately 13.4% of the population. Its asymptomatic progression often delays diagnosis until advanced stages. Both AKI and CKD significantly increase the risk of end-stage renal disease, cardiovascular complications, and premature mortality, highlighting the importance of early detection and effective management.[2] Traditional biomarkers such as albuminuria, estimated glomerular filtration rate, and serum creatinine lack sensitivity for early disease detection, as creatinine rises only after significant nephron loss.[3] Consequently, advanced predictive approaches are needed. AI, ML, and related technologies enable analysis of large, complex clinical datasets to identify high-risk patients. Recent advances in ML and deep learning have improved early diagnosis, risk stratification, and individualized management of AKI and CKD, offering potential improvements in patient outcomes.[4,5] Thus, article provides a comprehensive overview of AI applications in renal pathology and the potential for transforming nephrology by allowing early detection, individualized management, and data-driven treatment pathways for both AKI and CKD. Integration of these models into clinical practice, supported by rigorous validation and ethical frameworks, could significantly enhance renal outcomes and healthcare efficiency.

AI IN EARLY DETECTION OF KIDNEY DISEASES

Early detection of kidney injury is essential for effective treatment. Conventional biomarkers, such as serum creatinine and BUN, rise only after significant damage, limiting early diagnosis. AI shows promise for early AKI and CKD detection through machine learning (ML), deep learning, and natural language processing (NLP), analyzing complex data to identify patterns and risk factors missed by traditional methods.[6] These models continuously learn, enabling individualized risk prediction, reducing diagnostic delays, and supporting evidence-based clinical decisions.[7]

AI IN AKI DETECTION

Predictive models from electronic health records (EHR)

Research on AKI pathophysiology has identified early biomarkers such as neutrophil gelatinase-associated lipoprotein (NGAL), γ-glutamyl transpeptidase (GGT), kidney injury molecule-1 (KIM-1), microRNA (miRNA), and excess reactive oxygen species (RONS). These biomarkers rise in blood or urine before clinical renal dysfunction, making them more sensitive for early AKI detection than serum creatinine and urine output. Advanced biosensors, including optical, electrochemical, and surface plasmon resonance (SPR) platforms, enable highly sensitive and selective detection using nanotechnology and DNA-based techniques.[8]

ML

ML focuses on algorithms that can learn by mimicking human learning behavior and has the potential to increase the precision of disease detection. Theoretically, ML can correctly identify early AKI by unlocking the potential of "ground truth" data, where the correlation between data and outcomes is known, assuming that there are adequate biological and patient datasets available.[9]

Methods of ML to predict AKI

Methods of ML to predict AKI shown in Table 1 below.

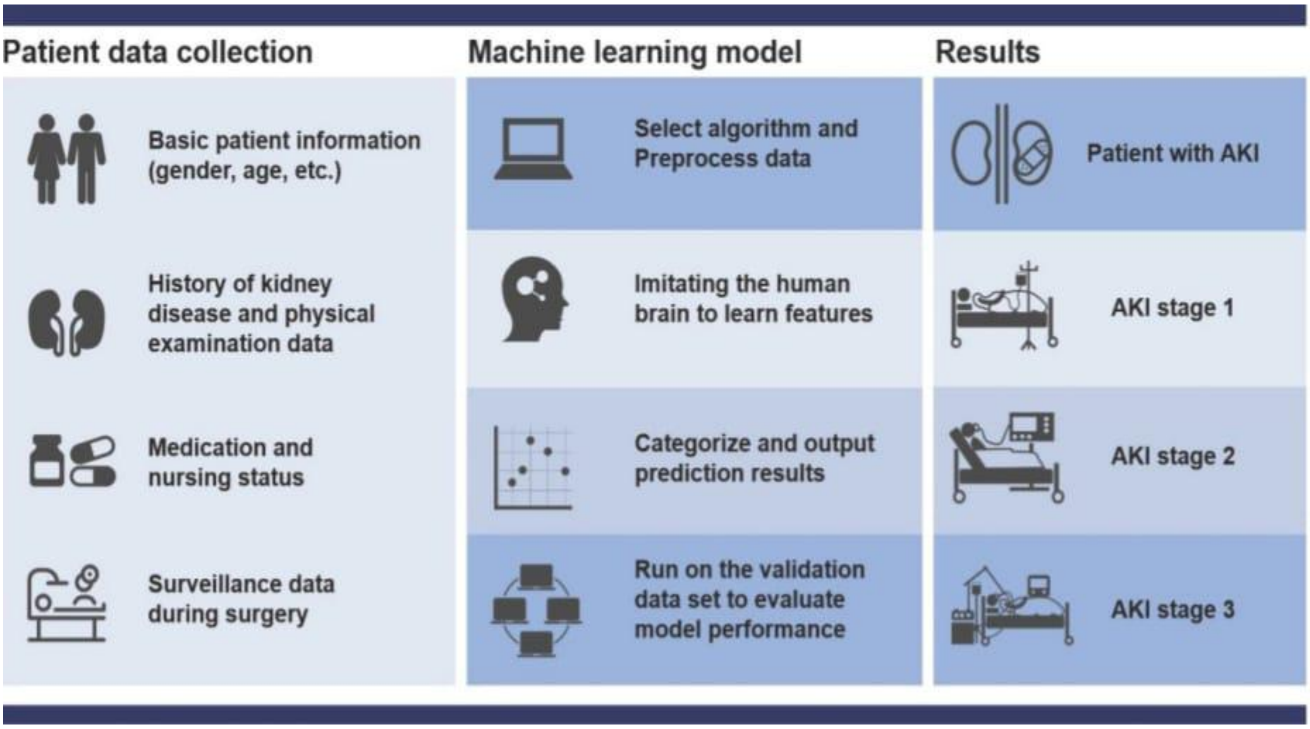

Figure 1: Flow chart of ML to predict AKI.

*First collect basic data, then organise the data and select the most suitable algorithm for modeling, and then continue to test and verify the model until the output is reasonable. The prediction results include the probability of patients with various grades of AKI (stage 1-3).

Table 1: Methods of ML to predict AKI.

Categories	Modelling methods	Dataset source	Limitations	Optimal AUC
Preoperative AKI risk prediction	RF	The university of Florida health integrated data repository	Single center study, no clear definition of features	0.88
	LR	The hospital database, EHR, chart review and catheterization reports in the Erasmus medical center	Single center study, urine output was not considered when defining AKI	0.79
AKI prediction during surgery	SVM, LR, RF, GBDT, DNN	The preoperative assessment record, anesthesia record and EHR	Single center study, ignoring some key features	0.85
	LR, decision tree, SVM, RF, GBDT	Electronic medical records and records on intraoperative variables at far eastern memorial hospital	Single center research, manual input of features, data imbalance	0.84
	DNN	Perioperative data warehouse	Single center reaseach, loss of creatinine value caused lots of cases to be lost	0.792
Postoperative AKI real time prediction	RNN	EHR at a tertiary care center for cardiovascular diseases	The observation period for patients varies in length	0.90
ICU AKI prediction	RF	The multidisciplinary epidemiology and translational research in intensive care data mart	Unbalanced data sources, AKI was not manually reviewed, incomple AKI definition	0.88
	RF	The EPaNIC multicenter randomized clinical trial database	NGAL is only measurd in the verification queue	0.84
	Integrated classification learning	The PICU and CTICU of three independent tertiary care pediatric intensive care centers	Urine volume standards were not considered when defining AKI, patients with uremia were not excluded.	0.89
AKI prediction in all hospital wards	RNN	The U.S. department of veterans affairs clinical database	Representative cases are uneven	0.92
	GBDT	The clinical research data warehouse at the university of Chicago	Urine volume standards were not considered in the definition of AKI, baseline SCR was inaccurate	0.90
	LR	The Yale New Haven Health System	The drug dose is not considered I the drug variables	0.81
Interpretable AKI prediction model	TCN	Her of all residents of four Danish Municipalities	The definition of need improvement	0.88
Cross site transportability model for AKI prediction	GBDT	HER data from a source healthcare system	Baseline SCR is inaccurate, miss the key variables of HR, BOS and Braden scale score	0.92

AKI-bidirectional encoder representations from transformers model

Bidirectional encoder representations from transformers (BERT) is a contextual word representation model based on a multi-layer bidirectional transformer encoder using self-attention. Unlike unidirectional models, BERT is pre-trained using a masked language model (MLM) to learn deep bidirectional representations. AKI-related clinical notes used to train AKI-BERT were obtained from the MIMIC-III dataset, with AKI defined according to

KDIGO guidelines. For AKI prediction, BERT undergoes task-specific fine-tuning by initializing pre-trained parameters, adding task-specific layers, and updating all model parameters to minimize prediction loss.[10]

AI IN CKD DETECTION

ML models are widely used to predict CKD progression by analyzing patient records and biomarkers. Advanced ML techniques, such as support vector machines (SVMs) and artificial neural networks (ANN), effectively model complex non-linear interactions within clinical data. Comparative studies have evaluated classifiers including random forest, SVM, XGBoost, and k-Nearest Neighbours to enhance predictive accuracy and enable timely intervention.[11]

DL approaches further improve early detection and prognosis by identifying subtle pathogenic changes in high-dimensional data. Integration of DL models into clinical workflows enhances sensitivity and specificity, supporting automated clinician-assistive systems for CKD management. Proposed DL frameworks include convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and ensemble models.[12]

ARTIFICIAL NEURAL NETWORK

The ANN, also known as the neural network (NN), is a computational model that is based on the structure and functionality of biological NNs. NNs are a bioinspired data processing system that allows computers to learn in ways that are analogous to the human brain. A NN is made up of a linked group of artificial neurons that analyze data using a connectionist approach to computation. In most circumstances, an ANN is an adaptive system that changes its structure in response to external (input) or internal information that passes through the network during the learning phase. It is the most prominent and widely adopted model among all AI application paradigms.[13]

SUPPORT VECTOR MACHINE

The SVM creates a separation hyperplane, which divides the labelled data into classes and assesses whether a new data value falls above or below the boundary. There may be multiple hyperplanes and the one with the greatest difference between data points is picked. Figure 2 depicts the maximum hyperplanes and margins of the support vector machine. The equation for the hyperplane that separates 2 classes is as follows: $D(x)=w0+w1a1+w2a2$

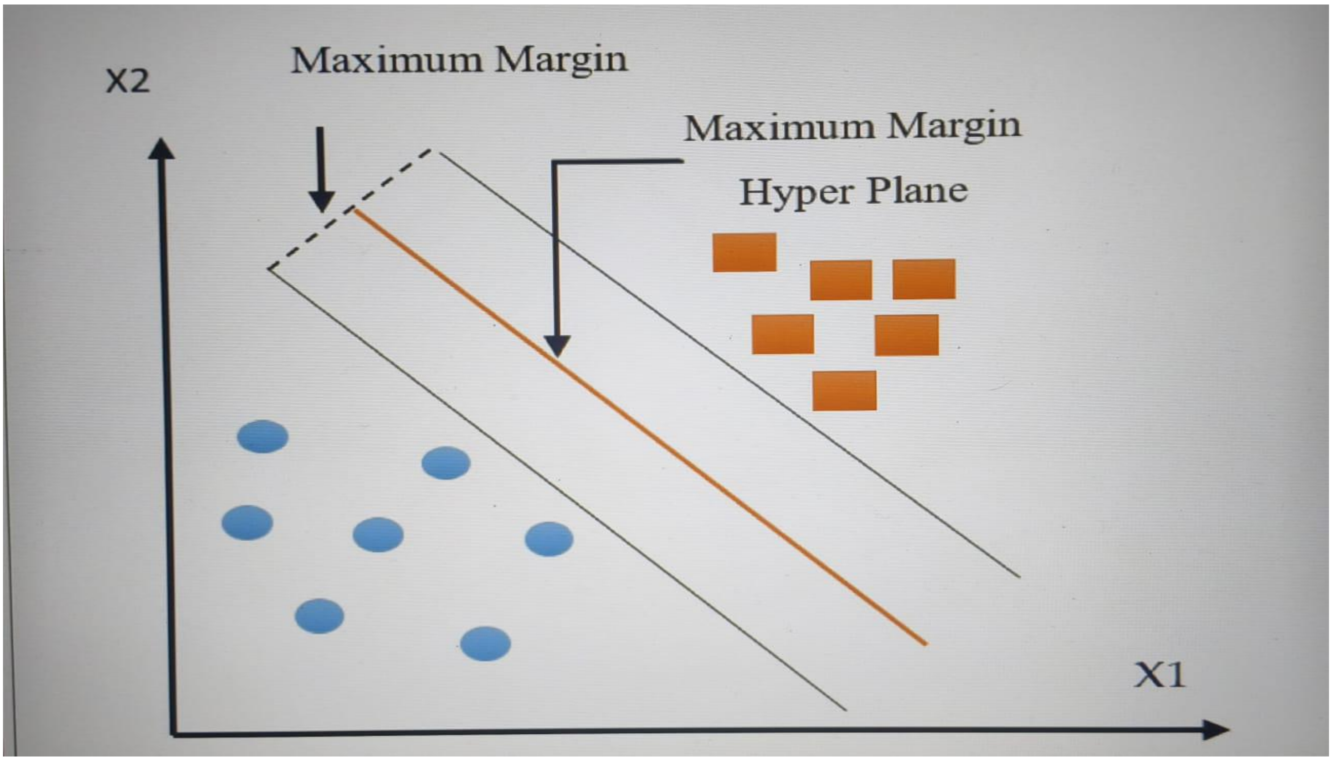

Figure 2: Support vector machine.

The equation for the maximum-margin hyperplane is $x=b+\sum i\propto iyia(i) \times a$

Here, i is the support vector, and yi is the training instance's a(i) class value. The learning algorithm determines the numerical values b and αi.[14]

Internet of medical things platform

The internet of medical things (IoMT), also known as healthcare IoT, comprises interconnected medical devices and applications that transmit data to cloud platforms such as AWS. IoMT systems enable continuous monitoring of clinical parameters, including ICU and ECG data, and support early detection and management of renal and other diseases. Figure 3 illustrates the application of deep learning for CKD detection within an IoMT framework.[15]

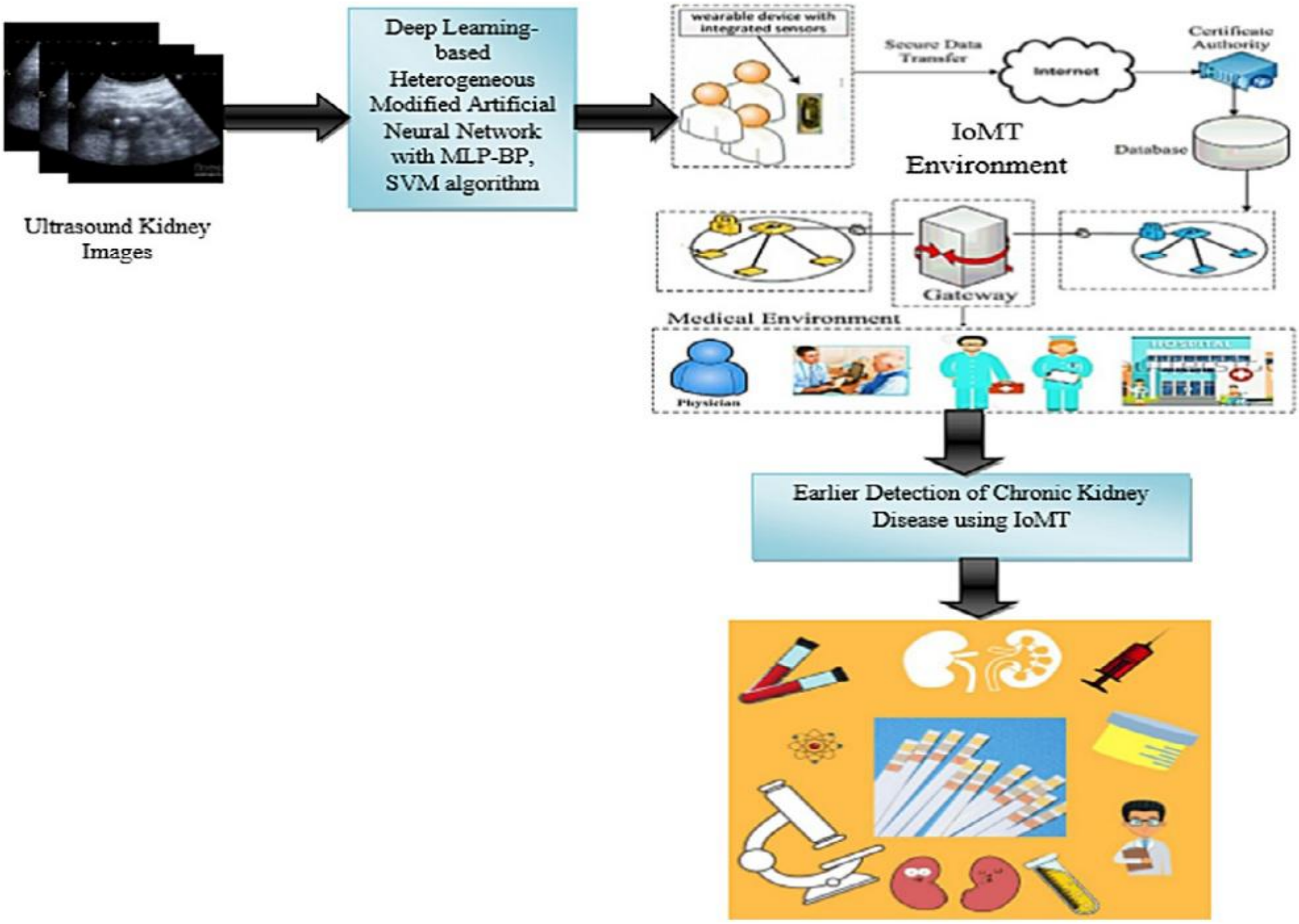

Figure 3: Chronic kidney detection using deep learning on IoMT platform.

AI IN DIAGNOSIS OF KIDNEY DISEASES

Accurate diagnosis of kidney diseases is challenging due to overlapping clinical features, delayed biomarker responses, and etiological heterogeneity. AI enhances diagnostic accuracy and speed in AKI and CKD by integrating clinical, laboratory, imaging, and pathological data.[16]

Differentiation of AKI and CKD

Conventional markers such as serum creatinine and blood urea nitrogen often fail to distinguish AKI from CKD in early stages. AI models trained on large datasets analyze dynamic changes in creatinine, urine output, and patient history to improve differentiation. Predictive models, including logistic regression, gradient boosting, and eXtreme Gradient Boosting, have demonstrated strong performance in intensive care settings using datasets such as MIMIC-III and eICU. However, challenges remain regarding data availability and generalizability across diverse populations. AI models have also been developed to predict AKI-related adverse outcomes and postoperative AKI.[17]

AI enables real-time AKI risk prediction, supporting personalized medication and fluid management, and facilitates kidney transplant monitoring through immunological and genetic data analysis to optimize immunosuppressive therapy.[18] In CKD, ML models analyze laboratory results, demographics, and medical history to detect early disease and predict progression to ESRD. These systems identify subtle functional changes and complex risk patterns, enabling early intervention and personalized management strategies, including medication optimization, dietary planning, and fluid management in dialysis patients.[19]

Laboratory data and biomarkers

For classification tasks, AI models such as decision trees, random forests, and SVMs are used to distinguish among renal diseases. DL models, including RNNs and CNNs, particularly LSTM networks, are effective for sequential data analysis and image-based diagnosis. Bayesian networks support probabilistic outcome prediction, while rule-based expert systems apply domain knowledge for clinical decision-making. Ensemble techniques, such as bagging and boosting, further enhance predictive performance.[20]

NLP methods extract clinically relevant information from EHR, and generative adversarial networks (GANs) generate synthetic medical images for data augmentation. These approaches support renal mass classification, disease subtype identification, progression prediction, and diagnostic assistance. Model selection depends on data type, diagnostic objectives, and available resources, with ensemble strategies often yielding improved diagnostic accuracy.[21]

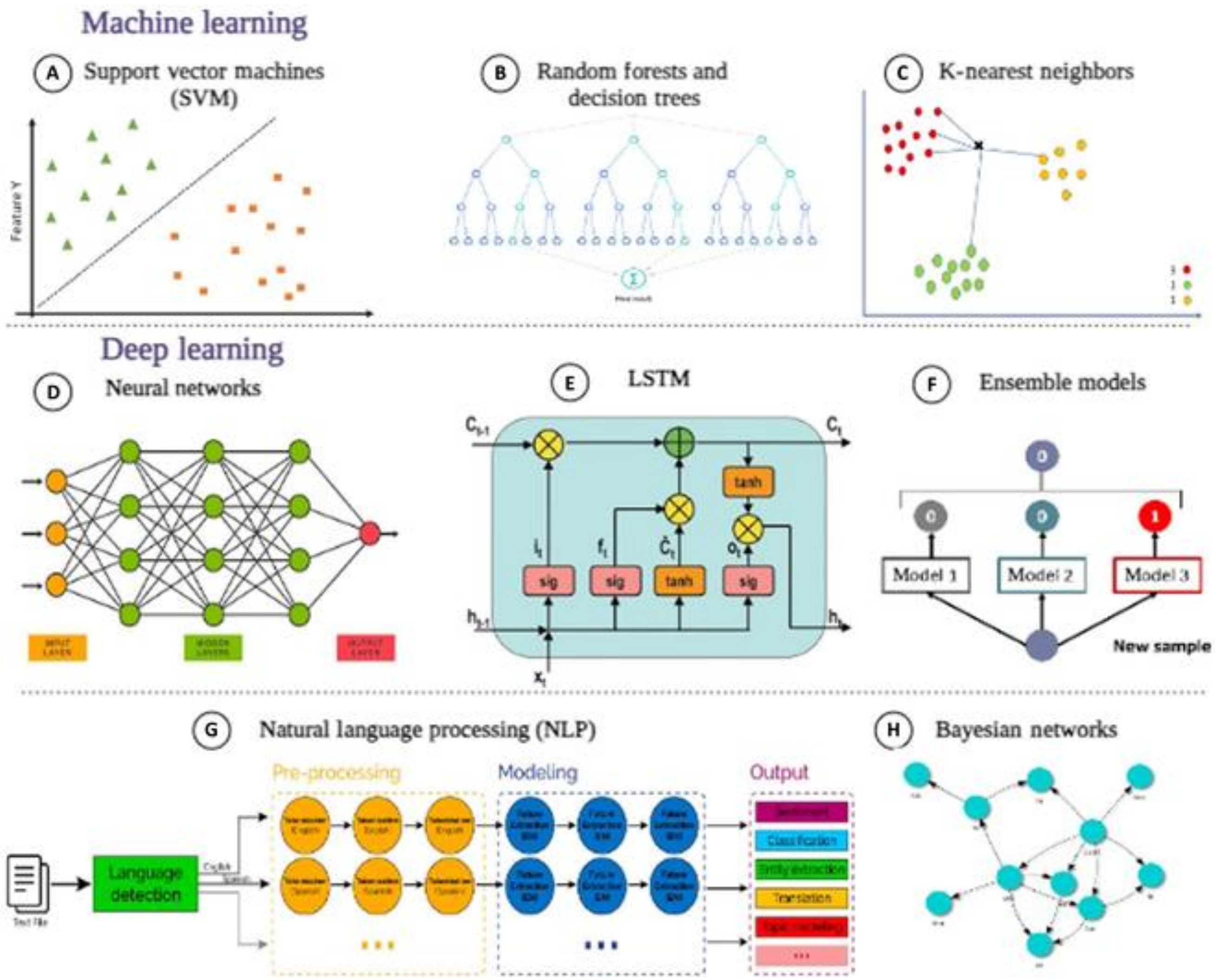

Figure 4: Types of ML and DL models for the diagnosis of kidney diseases.

BIOSENSOR INNOVATIONS

Electrochemical, plasmonic, nanoparticle-based and molecular probe biosensors have developed as attractive platforms for point-of-care (POC) devices, taking advantage of enhanced surface chemistry. These technologies play an important role in finding and measuring developing AKI and CKD biomarkers, allowing for prompt therapies to reduce renal impairment.[22]

Image-based diagnosis

In order to identify structural alterations such cortical thinning, hydronephrosis and cystic lesions, AI-assisted image recognition has been used on renal ultrasonography, CT and MRI scans. Measurements of kidney volume and cortical thickness, which are essential for determining the course of CKD, can be made by automated segmentation models.AI and radiomics can be used to derive imaging biomarkers that could be used to predict renal disease before visual interpretation.[23]

Clinical relevance

AI-based diagnostic tools provide faster, more accurate, and more thorough evaluations than traditional methods. By incorporating it into daily practice, nephrologists may be able to improve patient outcomes, decrease misclassification, and make prompt judgments.[24]

AI IN GUIDING THE TREATMENT OF ACUTE KIDNEY DISEASE

AI may assess treatment protocols and patient outcomes, create models based on efficacy and risk variables, guide treatment protocol selection, and enhance therapeutic efficacy. The application of AI to aid in therapeutic decision-making is growing in the context of AKI, a condition whose management is complicated and urgent due to abrupt changes in renal function.[25]

AI for treatment decision support in AKI

AI is used in healthcare to detect AKI and alert physicians via e-alerts. While e-alerts change clinical practice, they alone have not improved outcomes. Integrating e-alerts with care bundles forms a clinical decision support system, widely applied in sepsis, mechanical ventilation, and central venous catheter management, improving compliance and reducing complications such as catheter-related bloodstream infections and ventilator-associated pneumonia.[26] AKI care bundles may include volume assessment, drug toxicity evaluation, and kidney function monitoring. AI-based clinical decision support systems go beyond static recommendations by analyzing trends in serum creatinine, urine output, hemodynamics, inflammatory markers, and comorbidities to provide personalized treatment. These systems guide interventions such as fluid resuscitation, diuretics, vasopressors, or early nephrology referral, improving outcomes in sepsis, shock, and surgical AKI.[27]

AI in drug dosing adjustment during AKI

AKI presents a major challenge in clinical pharmacotherapy, as rapid and unpredictable declines in renal function significantly alter drug pharmacokinetics. Conventional dose adjustment methods rely on serum creatinine–based equations and estimated glomerular filtration rate (eGFR), which are often unreliable during dynamic renal changes, increasing the risk of underdosing or toxicity, particularly for drugs with narrow therapeutic indices.[28] AI offers a patient-specific, real-time alternative to traditional guideline-based dosing.[29] AI-based dosing models predict renal function trajectories by integrating multiple clinical variables, including longitudinal creatinine trends, urine output, hemodynamic parameters, age, body weight, comorbidities, and laboratory biomarkers, rather than depending on static eGFR values. ML and deep learning approaches can detect early renal deterioration and predict future drug clearance, enabling proactive dose adjustment before clinically evident toxicity occurs.[30]

Integration of AI algorithms with therapeutic drug monitoring (TDM), Bayesian pharmacokinetic models, and adaptive dosing platforms such as DoseMeRx and InsightRx allows personalized titration of medications including vancomycin, aminoglycosides, and anticoagulants. These systems have demonstrated improved target attainment, reduced nephrotoxicity, and better clinical outcomes, particularly in critical care settings.[31] AI can also be embedded within EHR to generate alerts for AKI onset or renally adjusted medications, reducing prescribing errors and inter-clinician variability while improving workflow efficiency.[32] Despite its promise, challenges remain related to external validation, clinical integration, and medicolegal considerations. Advances in AKI biomarkers and real-time renal monitoring are expected to support more autonomous, closed-loop AI-guided dosing systems.[33]

AI-assisted timing and modality for RRT

In AKI patients, AI improves decision-making for RRT initiation and modality. By integrating clinical factors, laboratory biomarkers, hemodynamics, and real-time trends, AI predicts dialysis needs earlier and more accurately than traditional criteria, reducing unnecessary or delayed RRT.[34] Key challenges include validation across diverse settings, seamless EHR and device integration, and ethical considerations. Addressing these limitations could allow AI-guided RRT to provide patient-specific, real-time, outcome-optimized renal support in critical care.[35]

AI-assisted fluid and hemodynamic management

AI is increasingly applied to fluid and hemodynamic management in critically ill patients with or at risk of AKI. Traditional measures-central venous pressure, urine output, mean arterial pressure, and lab markers-are delayed or indirect, often leading to under-resuscitation, renal hypoperfusion, or fluid overload.[36] AI models continuously analyze high-frequency data, including arterial waveforms, ventilator parameters, and microcirculation, enabling real-time prediction of fluid responsiveness and shock progression. This supports personalized guidance for fluid, vasopressor, or inotrope administration, shifting care from reactive to predictive.[37]

ML algorithms also optimize fluid removal in RRT by predicting intradialytic hypotension and adjusting ultrafiltration rates.[38] This precision approach is particularly valuable in postoperative AKI, septic shock, and cardiorenal syndrome. Despite adoption barriers such as validation and device integration, AI-assisted hemodynamic management may evolve into closed-loop, algorithm-guided therapy.[39]

AI in guiding the treatment of CKD

AI is increasingly applied to CKD management, shifting care from population-level, guideline-based approaches to personalized, data-driven therapy. Traditional markers-serum creatinine, eGFR, albuminuria, and comorbidities-do not fully capture disease progression or treatment response.[40] AI models trained on longitudinal clinical, laboratory, lifestyle, and genomic data enable proactive prediction of CKD progression, complications, and treatment response, supporting precision prescribing of therapies such as dietary interventions, SGLT2 inhibitors, mineralocorticoid receptor antagonists, and renin-angiotensin blockers.[41] AI also optimizes medication dosing and reduces adverse events by integrating with EHRs to suggest renal-adjusted doses, flag nephrotoxic drugs, and predict hyperkalemia, anemia, or mineral-bone disorders for early intervention.[42] Remote patient monitoring with AI enhances home-based CKD management and adherence.[43]

In advanced CKD, AI guides timing for dialysis initiation, vascular access, and transplant referral, and supports shared decision-making based on patient-specific risk-benefit profiles.[44] These approaches enable predictive, individualized care, improving outcomes and quality of life while addressing clinical, ethical, and regulatory challenges.

Limitations

AI has shown promise in nephrology, but a number of obstacles prevent its broad use in clinical settings. The full integration of AI into the treatment of AKI and CKD requires addressing these restrictions, which come from the technological, clinical, ethical, and regulatory realms.[45]

Data quality and availability

Large, high-quality datasets are necessary for training AI models. However, missing, inconsistent or insufficient data is frequently found in EHR. The generalizability of AI algorithms is diminished by variations in imaging protocols, laboratory techniques, and clinical documentation amongst hospitals. Robust model development is hampered by the scarcity of annotated nephrology datasets, particularly in low- and middle-income nations.[46]

Generalizability and bias

AI models that have been trained on particular populations could not function effectively in other geographic or demographic groups. Predictions that are unfair can be caused by bias in training data, such as the overrepresentation of particular age or racial groups. Additional obstacles to worldwide adoption include the variations in healthcare delivery systems among nations.[47]

Interpretability and transparency

Deep learning models in particular are examples of AI systems that operate as "black boxes," making predictions without offering precise justifications. In important decision-making, a lack of interpretability limits acceptability and undermines physician trust. Although they are being investigated, explainable AI (XAI) techniques are still in the early phases of development.[48]

Legal and ethical issues

Concerns about patient data privacy and confidentiality are significant, especially when utilizing cloud-based AI platforms and large-scale EHRs. Accountability concerns are still unresolved, if a recommendation made by an AI system causes harm to a patient, who is responsible the software developer or the clinician? Over-reliance on AI and the possibility of replacing human judgment in delicate clinical decisions are ethical conundrums.[49]

Clinical validation and implementation

Numerous AI models exhibit impressive results in past research, but they need prospective clinical trials to validate their practicality.AI integration into current healthcare systems necessitates a large investment in workflow reform, infrastructure and clinician training. There are currently no standardized standards for clearance and oversight of AI in medicine, and regulatory frameworks are constantly developing.[50]

Cost and resource constraints

Significant financial and technological resources are needed for the development, validation, and upkeep of AI systems. Implementing AI solutions in environments with low resources may be difficult because of a lack of infrastructure and qualified staff.[51]

CONCLUSION

AI is transforming nephrology by enhancing early detection, diagnosis, prognosis, and management of AKI and CKD. Traditional markers like serum creatinine, eGFR, and albuminuria are limited by delayed detection and low sensitivity, whereas AI can analyze multidimensional datasets-including EHR, imaging, biomarkers, and wearable sensor data-to provide earlier and more accurate predictions. AI applications support detection, risk stratification, personalized therapy, dialysis optimization, and transplant outcome prediction, complementing clinical expertise rather than replacing it.

Challenges remain, including data quality, algorithmic bias, interpretability, ethical concerns, prospective validation, and cost-effective implementation within regulatory frameworks. With interdisciplinary collaboration, open model development, and thorough clinical validation, AI can bridge the gap between data-driven insights and clinical practice, enabling earlier interventions, individualized treatments, and improved patient outcomes. By integrating AI into routine nephrology care, there is potential to significantly reduce the global burden of kidney disease and enhance patient quality of life.

Funding: No funding sources
Conflict of interest: None declared
Ethical approval: Not required

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Cite this article as: Chiluveru S, Hassan R, Kayala HS, Eereli R. Artificial intelligence approaches in early detection and clinical management of acute and chronic kidney diseases. Int J Basic Clin Pharmacol 2026;15:400-9.