

Artificial Intelligence Across the Kidney Disease Continuum: A Systematic Review of Applications from Acute Kidney Injury to Precision Nephrology

Running title: AI across the kidney disease continuum: a systematic review

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ABSTRACT

Background: Artificial intelligence (AI), including machine learning and deep learning (DL), is increasingly applied in nephrology, but evidence remains fragmented across clinical domains. **Objectives:** To systematically identify, appraise and synthesise original studies evaluating AI applications across the kidney disease continuum. **Methods:** We searched PubMed/MEDLINE, Scopus, Web of Science and Google Scholar for studies published from January 2015 to December 2024. Original studies developing, validating or implementing AI models in kidney disease were eligible. Two reviewers independently screened records and extracted data. Risk of bias was assessed with PROBAST, and certainty of evidence with GRADE principles. Owing to heterogeneity, findings were synthesised narratively by clinical domain following SWiM guidance. **Results:** Of 3,200 records, 142 studies met the inclusion criteria: acute kidney injury (AKI; n = 24), chronic kidney disease (CKD; n = 51), renal histopathology (n = 7), renal imaging (n = 5), dialysis (n = 25), transplantation (n = 3), diabetic kidney disease (n = 3), urolithiasis (n = 6), renal cell carcinoma (n = 6) and other renal conditions (n = 12). Reported discrimination was generally high (most AUCs 0.78–0.96). DL achieved more than 90% accuracy in imaging and histopathology tasks. Most studies were retrospective and single-centre, few were externally validated, calibration was seldom reported, and 20 CKD studies reused one 400-record public dataset. Few evaluated prospective deployment. **Conclusions:** AI models show promising discrimination throughout nephrology, but the certainty of evidence is low to moderate. External validation, calibration reporting, adherence to TRIPOD+AI and prospective impact trials are needed before routine clinical adoption. **Registration:** Not prospectively registered.

Keywords: artificial intelligence; machine learning; deep learning; acute kidney injury; chronic kidney disease; dialysis; kidney transplantation; systematic review

INTRODUCTION

Kidney disease is a major and growing global health burden. Acute kidney injury (AKI) affects approximately one in five hospitalised adults and more than half of patients in intensive care units, and is independently associated with mortality, prolonged hospitalisation and subsequent chronic kidney disease (CKD) [1,2]. CKD affects an estimated 9–10% of the world's population, is now among the leading causes of death worldwide, and imposes a disproportionate burden on low- and middle-income countries [3,4]. Across this continuum, from AKI through CKD to

kidney failure requiring dialysis or transplantation, care is limited by late diagnosis. Serum creatinine and urine output, the cornerstones of the KDIGO definitions, are delayed and insensitive markers of injury, and conventional risk equations capture only a fraction of the heterogeneity in disease progression [5]. Artificial intelligence (AI), encompassing machine learning (ML) and deep learning (DL), can model nonlinear interactions within high-dimensional data such as electronic health records (EHRs), physiological time series, medical images and digitised histopathology [6,7]. Nephrology is particularly suited

to these methods because routine care generates dense, longitudinal laboratory data, imaging and biopsy material [8]. Over the past decade, AI applications have expanded from early prediction of AKI in hospitalised patients to automated biopsy interpretation, intradialytic risk prediction, graft survival modelling and opportunistic detection of kidney disease from retinal photographs and electrocardiograms.

Several narrative reviews have described this field, but most focus on a single domain, do not apply a systematic search and do not formally appraise risk of bias. Methodological surveys in other specialties have shown that ML prediction models are frequently at high risk of bias and often offer no performance advantage over well-specified logistic regression [9,10]. A systematic, cross-domain synthesis that weighs reported performance against study quality is therefore needed to inform clinicians, researchers and health systems.

Objectives

The primary objective of this review was to systematically identify, appraise and synthesise original studies evaluating AI across the kidney disease continuum, comprising AKI, CKD, diabetic kidney disease (DKD), renal imaging, renal histopathology, dialysis, kidney transplantation, urolithiasis, renal cell carcinoma (RCC) and other renal conditions. The secondary objectives were to (i) summarise reported diagnostic and predictive performance and, where available, comparisons with conventional models; (ii) characterise the data sources and modalities used; (iii) identify the clinical settings in which AI shows the greatest promise; (iv) evaluate validation strategies, risk of bias and generalisability; and (v) identify translational, ethical and methodological gaps to guide future research.

Methods

Protocol and Reporting

This systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [11]. Literature searches are reported in line with PRISMA-S [12], and the narrative synthesis follows the Synthesis Without Meta-analysis (SWiM) guideline [13]. The completed PRISMA 2020 checklist is provided as Supplementary File 1.

Eligibility criteria

Eligibility was defined using the PICOS framework.

- **Population:** adults or children with, or at risk of, a kidney condition, including AKI, CKD, DKD, kidney failure on dialysis, kidney transplant recipients, urolithiasis, renal neoplasms and other nephrological disorders.
- **Intervention/exposure:** an AI method, including supervised or unsupervised ML

(e.g., random forest, gradient boosting, support vector machines, Bayesian networks), artificial neural networks and DL (convolutional, recurrent, long short-term memory and transformer architectures), radiomics or computational pathology.

- **Comparator:** conventional statistical models, clinical scores, clinician assessment or reference-standard diagnosis, where reported (a comparator was not mandatory).
- **Outcomes:** at least one quantitative performance measure (e.g., area under the receiver operating characteristic curve [AUC], C-index, accuracy, sensitivity, specificity, F1-score, Dice coefficient) or a clinical or process outcome.
- **Study design:** original studies of AI model development, validation or implementation (retrospective or prospective cohort, case-control or cross-sectional designs, including multicentre database analyses and full-length peer-reviewed conference papers).

We excluded reviews, editorials, commentaries and abstracts without full data; animal and in vitro studies; studies applying only conventional regression without an AI component; studies in which the kidney was not the target organ or outcome; studies without extractable performance metrics; and duplicate reports of the same cohort (the most complete report was retained). Only English-language reports published between 1 January 2015 and 31 December 2024 were eligible.

Information Sources and Search Strategy

PubMed/MEDLINE, Scopus and Web of Science were searched from 1 January 2015 to 31 December 2024; Google Scholar was used as a supplementary source to improve recall of grey and conference literature [14]. Reference lists of included studies were hand-searched. The search combined controlled vocabulary (MeSH) and free-text terms for AI and kidney disease. The PubMed strategy was:

("Artificial Intelligence"[Mesh] OR "Machine Learning"[Mesh] OR "Deep Learning"[Mesh] OR "machine learning" OR "deep learning" OR "neural network*" OR "radiomics") AND ("Kidney Diseases"[Mesh] OR "kidney disease*" OR "renal disease*" OR "acute kidney injury" OR "chronic kidney disease" OR "dialysis" OR "kidney transplant*" OR "renal cell carcinoma" OR "kidney calculi" OR "nephrology") AND ("prediction" OR "diagnosis" OR "prognosis" OR "imaging" OR "histopathology")

The strategy was adapted for each database; full strategies for all sources are given in Supplementary File 2.

Study Selection

Records were imported into a reference manager and de-duplicated. Two reviewers independently screened

titles and abstracts and then assessed full texts against the eligibility criteria. Disagreements were resolved by discussion, with adjudication by a third reviewer when required. Before final synthesis, all included reports were re-appraised against the eligibility criteria; reports excluded at this stage are listed with reasons in Supplementary Table S1.

Data Extraction

A standardised extraction form was developed and pilot-tested. Two reviewers independently extracted study characteristics (first author, year, country, design, setting), population and data source (EHR, registry, imaging, histopathology, physiological signals), sample size, AI method, clinical task (detection, diagnosis, prediction, prognosis, phenotyping, treatment optimisation), comparator, performance metrics, and validation strategy (internal, temporal, external or prospective). Discrepancies were resolved by consensus.

Risk of Bias and Certainty of Evidence

Prediction model studies were assessed with the Prediction model Risk Of Bias ASsessment Tool (PROBAST) across four domains: participants,

predictors, outcome and analysis [15,16]. Studies that were not prediction-model studies (e.g., implementation reports) were appraised using structured criteria for observational research [17]. Each study was rated as low, high or unclear risk of bias overall. The certainty of evidence for each clinical domain was judged using principles adapted from GRADE, considering risk of bias, inconsistency, indirectness, imprecision and publication bias [18].

Synthesis Methods

Meta-analysis was not appropriate because of substantial heterogeneity in populations, outcome definitions, model architectures, validation strategies and performance metrics. Studies were therefore grouped by clinical domain (AKI, CKD, histopathology, imaging, dialysis, transplantation, DKD, urolithiasis, RCC and other conditions) and synthesised narratively according to SWiM and established guidance on narrative synthesis [13,19]. Within each domain, studies were compared by data modality, AI method, clinical task, reported performance and validation strategy. Performance is presented as reported by the original authors; ranges are given rather than pooled estimates.

Supplementary Table S1. Reports excluded at final eligibility re-appraisal, with reasons

Study	Full citation	Reason for exclusion
Bell S et al. (2020)	Bell S, James MT, Farmer CKT, et al. Development and external validation of an acute kidney injury risk score for use in the general population. <i>Clin Kidney J.</i> 2020;13:402-412.	Conventional logistic regression risk score; no AI/ML component
Mathis MR et al. (2020)	Mathis MR, Naik BI, Freundlich RE, et al. Preoperative risk and the association between hypotension and postoperative acute kidney injury. <i>Anesthesiology.</i> 2020;132:461-475.	Association study using conventional statistics; no AI/ML component
Naser MN et al. (2021)	Naser MN, Al-Ghatam R, Darwish AH, et al. Risk factors, predictions, and progression of acute kidney injury in hospitalized COVID-19 patients: an observational retrospective cohort study. <i>PLoS One.</i> 2021;16:e0257253.	Observational risk-factor study; no AI/ML component
Ram S, Gupta S (2019)	Ram S, Gupta S. Machine learning-based diseases diagnosis system considering dataset features. In: <i>Emerging Trends Expert Appl Security.</i> Singapore: Springer; 2019.	Generic disease-diagnosis system; no kidney-specific extractable performance data
Akatsuka A et al. (2022)	Akatsuka A, Horai Y, Akatsuka A. Automated Recognition of Glomerular Lesions in the Kidneys of Mice by Using Deep Learning. <i>J Pathol Inform.</i> 2022;13:100129.	Animal (murine) study
Yasodhara A et al. (2021)	Yasodhara A, Dong V, Azhie A, Goldenberg A, Bhat M. Identifying modifiable predictors of long-term survival in liver transplant recipients with diabetes mellitus using machine learning. <i>Liver Transpl.</i> 2021;27(4):536-547.	Liver transplant population; kidney not target organ
Loupy A et al. (2019)	Loupy A, Aubert O, Orandi BJ, Duong van Huyen JP, Brault C, Zhang H, et al. Prediction system for risk of allograft loss in patients receiving kidney transplants: International derivation and validation study. <i>BMJ.</i> 2019;366:l4923.	Cox regression prognostic system (iBox); no AI/ML component (cited in Discussion as a conventional benchmark)

Leung RK et al. (2013)	Leung RK, Wang Y, Ma RC, Luk AO, Lam V, Ng M, et al. Using a multi-staged strategy based on machine learning and mathematical modeling to predict genotype-phenotype risk patterns in diabetic kidney disease: a prospective case-control cohort analysis. BMC Nephrol. 2013;14:162.	Published outside the 2015–2024 search window
Kordzadeh A et al. (2021)	Kordzadeh A, Hanif MA, Ramirez MJ, Railton N, Prionidis I, Browne T. Prediction, pattern recognition and modelling of complications post-endovascular infra renal aneurysm repair by artificial intelligence. Vascular. 2021;29:171-82.	Complications after endovascular aortic aneurysm repair; kidney not target organ
Dagliati A et al. (2018)	Dagliati A, Marini S, Sacchi L, Cogni G, Teliti M, Tibollo V, et al. Machine learning methods to predict diabetes complications. J Diabetes Sci Technol. 2018;12:295-302.	Duplicate entry of an included study
Galloway CD et al. (2019)	Galloway CD, Valys AV, Shreibati JB, Treiman DL, Petterson FL, Gundotra VP, et al. Development and validation of a deep-learning model to screen for hyperkalemia from the electrocardiogram. JAMA Cardiol. 2019;4:428-36.	Duplicate entry of an included study

Reports excluded at the initial full-text stage (remaining exclusions in Figure 1) should be itemised by reason by the review team. Supplementary Table S2 (study-level PROBAST judgements) is provided as a separate file.

RESULTS

Study Selection and Characteristics

The search identified 3,200 records, of which 2,450 remained after removal of duplicates. After title and abstract screening, 310 full-text reports were assessed and 142 studies were included (Figure 1). Studies addressed AKI (n = 24), CKD (n = 51), renal histopathology (n = 7), renal imaging (n = 5), dialysis (n = 25), kidney transplantation (n = 3), DKD (n = 3), urolithiasis (n = 6), RCC (n = 6) and other renal conditions (n = 12). Table 1 summarises the evidence by domain, and study-level characteristics are presented in Tables 2–11.

Figure 1. PRISMA 2020 flow diagram of study identification, screening and inclusion. AKI, acute kidney injury; CKD, chronic kidney disease; DKD, diabetic kidney disease; RCC, renal cell carcinoma.

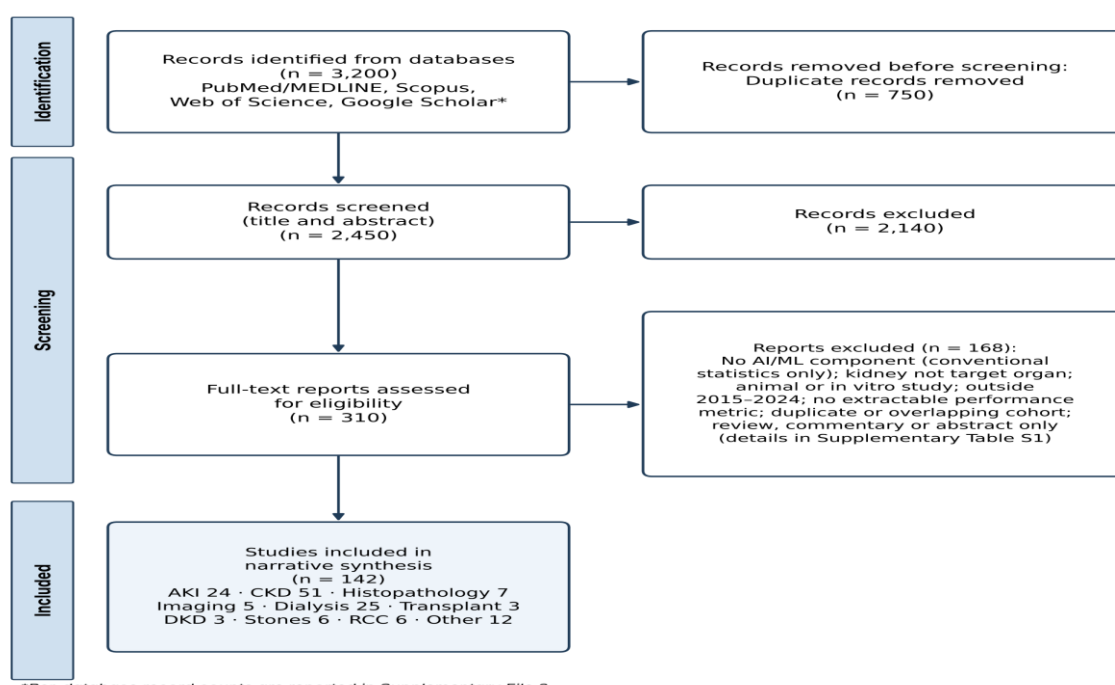


Table 1. Summary of included evidence by clinical domain (n = 142)

Domain (Table)	Studies, n	Principal data sources	Dominant AI methods	Reported performance (range)	Main limitations
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Domain (Table)	Studies, n	Principal data sources	Dominant AI methods	Reported performance (range)	Main limitations
Acute kidney injury (Table 2)	24	EHR, ICU time series, perioperative data	GBM/XGBoost, RF, RNN/LSTM, CNN	AUC $\approx$ 0.78–0.97	Few external validations; transportability loss across sites
Chronic kidney disease (Table 3)	51	Public UCI dataset (n = 400; 20 studies), EHR, registries, retina, biopsy	RF, XGBoost, ANN/DNN, CNN	Accuracy often >90% (UCI); AUC $\approx$ 0.73–0.91 for progression	Small reused dataset; optimism; calibration rarely reported
Renal histopathology (Table 4)	7	Whole-slide images, IF and EM images	CNN (ResNet, BiT, attention CNN)	Accuracy $\approx$ 90–96%; AUC up to 0.99	Staining/scanner variability; limited multicentre data
Renal imaging (Table 5)	5	CT, ultrasound, MRI	CNN, U-Net	Accuracy 92.9–100%; AUC 0.96	Single public CT dataset in two studies
Dialysis (Table 6)	25	Session-level HD data, registries, AVF sounds/images	GBM, RF, XGBoost, DL, ANN	AUC 0.68–0.99; accuracy 82–99%	Mostly retrospective; few outcome studies
Kidney transplantation (Table 7)	3	National registries, multicentre cohorts	DeepSurv, DeepHit, RF, DISPO	C-index 0.66; AUC 0.86	No clear gain over Cox-based tools
Diabetic kidney disease (Table 8)	3	Hospital EHR, NHANES	XGBoost, RF, rule extraction	AUC 0.75–0.95; accuracy 78–89%	Single-centre; heterogeneous DKD definitions
Urolithiasis (Table 9)	6	Non-contrast CT, digital stone images	CNN (ResNet, U-Net, StoneNet)	Accuracy >95% (two studies)	Small datasets; limited external testing
Renal cell carcinoma (Table 10)	6	CT, whole-slide images, genomics	CNN, vision transformer, multimodal DL	Dice 0.87; C-index 0.78	Retrospective; variable endpoints
Other renal conditions (Table 11)	12	ECG, biopsy WSI, ultrasound, CT	CNN, ANN, RF	AUC 0.82–0.93	Heterogeneous tasks; few validations

Abbreviations: AI, artificial intelligence; ANN, artificial neural network; AUC, area under the receiver operating characteristic curve; AVF, arteriovenous fistula; CNN, convolutional neural network; CT, computed tomography; DL, deep learning; DNN, deep neural network; ECG, electrocardiogram; EHR, electronic health record; GBM, gradient boosting machine; HD, haemodialysis; ICU, intensive care unit; LR, logistic regression; LSTM, long short-term memory; ML, machine learning; MRI, magnetic resonance imaging; PD, peritoneal dialysis; RF, random forest; RNN, recurrent neural network; SVM, support vector machine; WSI, whole-slide image; XGBoost, extreme gradient boosting.

Most studies were retrospective model-development studies using EHR, registry, imaging or public benchmark datasets; prospective evaluations were rare. Ensemble tree-based methods (random forest, gradient boosting, XGBoost) predominated for tabular clinical data, whereas convolutional neural networks dominated imaging and histopathology tasks. Reported discrimination was generally high, with most AUCs between 0.78 and 0.96.

Risk of Bias in Included Studies

The analysis domain of PROBAST was the main source of concern. Twenty CKD studies (and one further study using an augmented version) developed

and tested models on the same publicly available 400-record UCI CKD dataset, typically with random train–test splits and no external validation [45–49,53,60,64–66,68–72,74,76,79,85,86,90]. This combination of small sample size, repeated use of a single curated dataset and reliance on accuracy rather than calibrated risk is associated with optimism and high risk of bias. Similarly, two imaging studies reporting accuracy of 99–100% used the same public CT dataset [102,104]. Calibration was seldom reported, the handling of missing data and hyperparameter tuning were often incompletely described, and few studies reported adherence to TRIPOD or TRIPOD+AI. External or cross-site validation was explicitly reported in a

minority of studies [33,40,83,93,94,96,98,133,150], and prospective evaluation or deployment in fewer still

[106,119,123,129,131]. Study-level PROBAST judgements are presented in Supplementary Table S2.

Artificial intelligence in acute kidney injury

Twenty-four studies evaluated AI for AKI (Table 2).

Table 2. Artificial intelligence applications in acute kidney injury (n = 24)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
20	Lee HC et al. (2018)	2,010 cardiac surgery patients	Decision Tree, Random Forest, XGBoost	Predict postoperative AKI	AUC 0.78
21	Adhikari L et al. (2019)	2,911 surgical patients (University of Florida)	IDEA ML Model	Early postoperative AKI prediction	AUC 0.86
22	Tomašev N et al. (2019)	703,782 patients	Recurrent Neural Network	Continuous AKI prediction	Predicted 55.8% AKI; 90.2% dialysis-requiring AKI
23	Yin WJ et al. (2017)	8,800 patients	Random Forest	Contrast-induced nephropathy prediction	Good discrimination
24	Zimmerman LP et al. (2019)	23,950 ICU patients (MIMIC-III)	Logistic Regression, RF, ANN	Predict AKI within 72 h	AUC $\approx$ 0.78
25	Xu Z et al. (2020)	37,486 EHR patients	Memory-Network Deep Learning	AKI subphenotyping	Novel phenotype identification
26	Rashidi HH et al. (2020)	Burn/trauma cohort	DNN, RF, SVM	Early AKI recognition	AUC 0.92
27	Morid MA et al. (2020)	22,542 ICU patients	Temporal Pattern ML	Predict AKI adverse events	Accurate temporal prediction
28	Lei L et al. (2020)	1,173 liver resection patients	Machine-learning algorithms	Postoperative AKI prediction	Significant predictive accuracy
29	Kate RJ et al. (2020)	44,691 hospitalized patients	ML prediction model	Inpatient AKI prediction	Improved early detection
30	Zhang Z et al. (2019)	2,456 critical care patients	ML models	Volume responsiveness in AKI	Clinically useful prediction
31	Xu Z et al. (2019)	58,976 ICU patients	Machine Learning	Mortality prediction in AKI	Effective stratification
32	Alfieri F et al. (2021)	35,573 ICU patients (eICU + MIMIC)	CNN + Logistic Regression	Severe AKI prediction via urine output	AUC 0.89

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
33	Alfieri F et al. (2022)	10,596 ICU patients (external validation)	Deep Learning	External validation of AKI model	AUC 0.91
34	Bredt LC et al. (2022)	145 liver transplant patients	ANN + Logistic Regression	Post-transplant AKI prediction	AUC 0.81
35	He ZL et al. (2021)	493 transplant patients	RF, SVM, Decision Tree	Predict AKI after DCD transplant	AUC 0.85
36	Hu C et al. (2022)	22,360 ICU patients (MIMIC-IV)	XGBoost, Random Forest	Prognosis in established AKI	High predictive performance reported
37	Lei VJ et al. (2019)	42,615 major noncardiac surgery patients	GBM, RF, penalised LR	Postoperative AKI (pre- + intraoperative data)	AUC $\approx$ 0.82
38	Liu WT et al. (2022)	Hospitalised patients with heart failure	ML model	AKI in heart failure	Good discrimination reported
39	Lu JY et al. (2022)	COVID-19 inpatients, two centres	LSTM	AKI onset in COVID-19	AUC $\approx$ 0.96
40	Song X et al. (2020)	EHR data, six US health systems	GBM with explainability	Cross-site transportability of AKI model	Performance fell across sites
41	Yue S et al. (2022)	ICU patients with sepsis (MIMIC-III)	XGBoost and other ML	Sepsis-associated AKI	Good discrimination (XGBoost best)
42	Zhang Y et al. (2021)	Adult deceased-donor liver transplant recipients	Explainable supervised ML	AKI after liver transplantation	Good discrimination reported
43	Wazir S et al. (2022)	Neonates in NICUs (STARZ study, India)	ML-derived risk score	Neonatal AKI risk stratification	AUC $\approx$ 0.97

Ref. numbers correspond to the reference list. Performance metrics are as reported by the original study authors. Abbreviations: AI, artificial intelligence; ANN, artificial neural network; AUC, area under the receiver operating characteristic curve; AVF, arteriovenous fistula; CNN, convolutional neural network; CT, computed tomography; DL, deep learning; DNN, deep neural network; ECG, electrocardiogram; EHR, electronic health record; GBM, gradient boosting machine; HD, haemodialysis; ICU, intensive care unit; LR, logistic regression; LSTM, long short-term memory; ML, machine learning; MRI, magnetic resonance imaging; PD, peritoneal dialysis; RF, random forest; RNN, recurrent neural network; SVM, support vector machine; WSI, whole-slide image; XGBoost, extreme gradient boosting.

Perioperative prediction. Ensemble models using preoperative and intraoperative variables predicted postoperative AKI after cardiac surgery, major noncardiac surgery and hepatic resection, with AUCs of 0.78–0.86, generally outperforming conventional risk scores [20,21,28,37].

Continuous prediction in hospitalised patients. A recurrent neural network trained on EHR data from 703,782 patients predicted 55.8% of all inpatient AKI episodes and 90.2% of AKI requiring dialysis up to 48 hours before onset [22]. Continual inpatient prediction models have shown similar feasibility [29]. However, a cross-site evaluation across six health systems demonstrated a measurable loss of performance when models were transported between institutions, highlighting the importance of local validation [40].

Critical care and time-series modelling. In intensive care, models built on high-frequency physiological data and temporal patterns achieved good

discrimination, including an AUC of approximately 0.78 for prediction within 72 hours of ICU admission [24,27]. A DL model based on urine output changes predicted severe AKI with an AUC of 0.89 and retained an AUC of 0.91 in external validation [32,33].

Context-specific models. AI models were tailored to contrast exposure, burn and trauma, liver transplantation, heart failure, sepsis and COVID-19, with reported AUCs of approximately 0.81–0.96 [23,26,34,35,38,39,41,42].

Prognosis and phenotyping. Models predicted mortality, adverse outcomes and fluid responsiveness in patients with established AKI [30,31,36]. Memory-network models using structured and unstructured EHR data identified clinically distinct AKI subphenotypes, supporting a move towards precision nephrology [25]. In neonates, an ML-derived risk score (STARZ) achieved an AUC of approximately 0.97 [43].

Artificial intelligence in chronic kidney disease

Fifty-one studies evaluated AI in CKD (Table 3).

Table 3. Artificial intelligence applications in chronic kidney disease (n = 51)

Ref.	Study (year)	Design / data source	Sample	AI technique	Clinical aim / outcome
44	Akter et al. (2023)	Retrospective database study (NHIS S Korea)	~1 million records	CKD.Net hybrid deep learning model	Prediction of CKD stages and monitoring eGFR/creatinine
45	Akter et al. (2021)	Public dataset (UCI repository)	400 records	ANN, LSTM, Bi-LSTM, GRU, MLP	Early CKD detection and risk identification
46	Almansour et al. (2019)	Clinical dataset	400 records	ANN vs SVM	Early CKD diagnosis
47	Arulanthu & Perumal (2020)	IoT-cloud decision system	400 records	Logistic Regression	Remote CKD prediction
48	Arumugham et al. (2023)	Public dataset	400 records	Explainable DNN	Early-stage CKD detection
49	Bandera et al. (2023)	Analytical modeling	400 records	GBM, AdaBoost, RF + DEMATEL	Feature-driven CKD progression prediction
50	Bellocchio et al. (2021)	Multicenter European cohort	>30,000 patients	PROGRES-CKD algorithm	Prediction of ESKD risk

Ref.	Study (year)	Design / data source	Sample	AI technique	Clinical aim / outcome
51	Bermudez-Lopez et al. (2019)	NEFR ONA cohort	395 patients	RF + NMR profiling	Atherosclerotic risk stratification
52	Chen et al. (2020)	Imaging-based study	100 imaging cases	Adaptive Hybrid CNN	Imaging-driven CKD diagnosis
53	Elhoseny et al. (2019)	Public dataset	400 records	Dynamic ACO classifier	CKD classification
54	Hamedan et al. (2020)	Clinical dataset	216 patients	Fuzzy expert system	Clinical decision support
55	Inaguma et al. (2020)	Hospital registry	9,911 patients	RF + Logistic Regression	Prediction of rapid eGFR decline
56	Islam & Ripon (2019)	Multicenter dataset	2,800 cases	Boosting + Ant-Miner	Rule-based CKD prediction
57	Kanda et al. (2019)	Population cohort	7,465 individuals	Bayesian Network + SVM	Identification of CKD risk
58	Kanda et al. (2022)	National claims database	>100,000 patients	XGBoost, DNN	Predict renal outcomes in hyperkalemia
59	Kandasamy et al. (2023)	MIMIC-IV database	40,000 patients	GMM + RBFNN	Disease progression modeling
60	Lakshmana prabu et al. (2019)	IoT clinical DSS	400 records	PSO-optimized DNN	CKD severity prediction
61	Lee et al. (2022)	Hospital big-data cohort	11,661 patients	RF, XGBoost, LGBM	ESRD prediction post-sepsis
62	Lokuarachchi et al. (2020)	CKDu cohort	609 patients	ANN, CNN, RF	CKDu risk prediction
63	Marechal et al. (2022)	Histopathology analysis	241 samples	Dual CNN architecture	Automated histologic prognostication
64	Moreno-Sánchez (2023)	Explorable AI study	400 records	RF, XGBoost	Early CKD diagnosis
65	Nunez et al. (2022)	Hybrid datasets	400+ cases	SVM, kNN, NB	Low-cost ML diagnostic model
66	Ogunleye & Wang (2020)	Public dataset	400 records	XGBoost comparison	CKD diagnosis optimization

Ref.	Study (year)	Design / data source	Sample	AI technique	Clinical aim / outcome
67	Pareek et al. (2023)	Experimental study	NA	CNN	Early CKD stage detection
68	Patel et al. (2022)	Comparative ML study	400 records	RF, SVM, XGBoost	Prognostic classification
69	Pati et al. (2023)	Ensemble learning	400 records	ANN + Bagging/Voting	CKD prediction enhancement
70	Poonia et al. (2022)	Feature-selection ML	400 records	Logistic Regression + ML	Diagnostic classification
71	Priya & Saranya (2023)	Optimization-based ML	400 records	ANN + HGSAPSO	CKD prediction
72	Rabby et al. (2019)	Comparative ML analysis	400 records	Multiple classifiers	Algorithm comparison
73	Rady & Anwar (2019)	Data-mining study	361 patients	PNN, SVM	CKD stage classification
74	Rajeshwari & Yogish (2022)	Clinical ML	400 records	RF, NB, DT	CKD prediction
75	Rashid et al. (2022)	Augmented AI model	189+ datasets	PSO-ANN hybrid	Feature-driven CKD prediction
76	Revathi et al. (2023)	Imbalanced dataset study	400 records	ANN, SVM	Performance analysis
77	Song et al. (2020)	Longitudinal cohort	14,039 diabetics	Gradient Boosting	CKD risk prediction
78	Tran et al. (2023)	Clinical cohort	534 patients	RF, DL models	Mortality prediction
79	Wang (2020)	ML modeling	400 cases	Logistic Regression, DNN	CKD diagnosis
80	Xiao et al. (2019)	Translational study	551 patients	ElasticNet, RF, XGBoost	CKD progression modeling
81	Dagliati et al. (2018)	Diabetes cohort	1,000 patients	LR, NB, RF	Prediction of diabetic nephropathy
82	Chauhan et al. (2020)	Biomarker–EHR integration	871 + 498 patients	Random Forest	KidneyIntelX prognostic validation

Ref.	Study (year)	Design / data source	Sample	AI technique	Clinical aim / outcome
83	Chan et al. (2021)	Multicenter validation	1,146 patients	Random Forest	DKD progression prediction
84	Lin et al. (2019)	National registry	48,153 patients	ANN, RF	Mortality and dialysis outcomes
85	Alikhan et al. (2023)	Big-data AI	400 records	SACNN + optimization	CKD classification
86	Al-Momani et al. (2022)	ML comparison	400 records	ANN, SVM	CKD detection
87	Bhaskar & Manikandan (2019)	Biosensor-AI	1,000 samples	CNN + SVM	Salivary urea CKD detection
88	Granal et al. (2022)	Nutritional ML study	375 patients	Bayesian NN	Potassium intake estimation
89	Jayapandian et al. (2021)	Digital pathology	459 WSIs	U-Net deep learning	Histologic segmentation
90	Khamparia et al. (2020)	Deep autoencoder	400 records	Stacked Autoencoder	CKD classification
91	Kumar et al. (2023)	Imaging-AI study	5,617 patients	Hybrid fuzzy-DL	Image-based CKD recognition
92	Pilia et al. (2019)	Simulation study	71 ECGs	Bayesian NN	Electrolyte prediction
93	Sabanayagam et al. (2020)	Population imaging	>20,000 images	CondenseNet DL	Retinal-based CKD detection
94	Zhang et al. (2021)	Multicenter imaging	115,344 images	ResNet DL	Fundus-based CKD prediction

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Detection and diagnosis. Supervised ML and DL classifiers frequently reported accuracies above 90% for CKD detection [44–46,48,53,66,69,90]. As noted above, most of these estimates derive from the same small public dataset and should be regarded as proof of concept. Population-scale models using routine laboratory data, including a hybrid DL model trained on approximately one million national health-

screening records, provide stronger evidence for scalable screening [44].

Progression and outcome prediction. Models predicting rapid eGFR decline, kidney failure, cardiovascular events and mortality achieved moderate-to-high discrimination (AUCs approximately 0.73–0.91) [50,55,57,58,61,78,80,84]. Models incorporating longitudinal data outperformed models

using baseline variables alone, consistent with the dynamic nature of CKD progression [77]. In diabetes, ML models integrating plasma biomarkers with EHR data (KidneyIntelX) improved prediction of progressive DKD compared with standard clinical models [81–83].

Imaging, histopathology and extrarenal signals. DL models segmented kidney cortex structures on whole-slide images and quantified prognostic histological features [63,89], and image-based DL models detected CKD from renal imaging [52,91]. DL applied to retinal

photographs detected CKD with good discrimination in community and external cohorts [93,94]. Electrocardiographic estimation of potassium and calcium [92] and salivary urea biosensing [87] point to non-invasive monitoring strategies.

Clinical decision support. Explainable AI, Bayesian networks and fuzzy expert systems enabled transparent risk stratification and identification of modifiable risk factors [48,54,57,64,88], and IoT- and cloud-based platforms demonstrated technical feasibility for remote monitoring [47,52,60].

Table 4. Artificial intelligence applications in renal histopathology (n = 7)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
95	Hao et al. (2020)	1,199 WSIs of 1,281 membranous nephropathy (MN) and healthy patients from Chinese centers	MN-Net model, ResNet model	Diagnosis of MN through detection and classification of glomeruli in renal pathological images	Precision: 95.34%, F1-Score: 97.62%, Accuracy: 95.69%
96	Lu et al. (2022)	22,081 glomerular WSIs from 157 kidney cancer patients + 2,340 external validation images	BiT-S model, BiT-M model	Detection and classification of Global GlomeruloSclerosis (GGS) using WSIs	F1-Score (BiT-M): 77.80% (internal), AUC-ROC 0.99 (external)
97	Yamaguchi et al. (2021)	10,102 glomerular images from 293 WSIs across Japanese institutions	ResNet model (ImageNet pre-trained)	Detection of renal pathologies by classification of glomerular images	AUC-ROC 0.98 (capillary collapse), 0.91 (fibrous crescent)
98	Kers et al. (2022)	5,844 digital WSIs of kidney allograft biopsies from 1,948 patients	Convolutional Neural Network (CNN)	Automated analysis of transplant kidney biopsy pathology	Demonstrated robust performance for histologic assessment
99	Alsadi et al. (2022)	Electron microscopy images of native renal biopsies	Deep learning (CNN)	Detection of electron-dense immune deposits	Feasibility of automated detection shown

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
100	Pesce et al. (2022)	Renal biopsy glomerular images	IBM Watson + shallow neural networks	Identification of glomerulosclerosis	Accurate sclerotic vs non-sclerotic classification
101	Zhang L et al. (2022)	Direct immunofluorescence images of renal biopsies	Multiple-attention CNN	Classification of immunofluorescence patterns	High classification accuracy reported

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Seven studies applied DL to renal biopsy images (Table 4).

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97	Yamaguchi et al. (2021)	10,102 glomerular images from 293 WSIs across Japanese institutions	ResNet model (ImageNet pre-trained)	Detection of renal pathologies by classification of glomerular images	AUC-ROC 0.98 (capillary collapse), 0.91 (fibrous crescent)

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100	Pesce et al. (2022)	Renal biopsy glomerular images	IBM Watson + shallow neural networks	Identification of glomerulosclerosis	Accurate sclerotic vs non-sclerotic classification
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Convolutional neural networks classified glomeruli in membranous nephropathy with 95.7% accuracy [95] and detected global glomerulosclerosis with an external AUC of 0.99 [96]. A ResNet-based model identified glomerular lesions such as capillary collapse and fibrous crescents with AUCs of 0.91–0.98 [97]. Other applications included multicentre classification of kidney transplant pathology [98], detection of electron-dense immune deposits [99], identification of glomerulosclerosis [100] and classification of immunofluorescence patterns [101]. Variability in staining, scanners and annotation protocols remains a barrier to generalisation.

Artificial intelligence in renal imaging

Five studies addressed renal imaging (Table 5).

Table 5. Artificial intelligence applications in renal imaging (n = 5)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
102	Altalbe et al. (2023)	12,446 CT images from multiple hospitals	Convolutional Neural Network (CNN)	Diagnosis and classification of renal cysts, tumors, stones, and normal kidneys using CT imaging	Accuracy: 99.2%; F1-score: 98.7%

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
103	Les et al. (2020)	1,692 CT images of kidney lesions from 138 patients (Military Institute of Medicine, Warsaw, Poland)	U-Net + Expectation–Maximization Thresholding (EMT) + Salp Swarm Algorithm (SSA)	Detection of kidney boundaries on CT images for lesion identification	F1-score: 89.3%
104	Subramanian et al. (2023)	12,446 CT images of renal stones from multiple hospitals (Bangladesh)	CNN model; Optimized CNN model	Classification and detection of renal cysts, tumors, and stones	Accuracy (Optimized CNN): ~100%
105	Tsai et al. (2022)	1,599 pediatric ultrasound images (Taichung Veterans General Hospital, Taiwan)	ResNet (ImageNet pre-trained)	Detection of pediatric renal anomalies using ultrasound imaging	Accuracy: 92.9%; AUC-ROC 0.96
106	Potretzke et al. (2023)	MRI images of patients with Autosomal Dominant Polycystic Kidney Disease (ADPKD)	Deep learning (CNN) segmentation	Evaluation of MR-derived total kidney volume	High agreement with manual segmentation; low interobserver variability

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CNNs classified cysts, tumours and stones on CT with accuracies of 99–100% [102,104], although both studies used the same public dataset. Kidney boundary detection on CT achieved an F1-score of 89.3% [103], and a transfer-learning model detected paediatric renal anomalies on ultrasound with an AUC of 0.96 [105]. An AI algorithm for MRI-derived total kidney volume in autosomal dominant polycystic kidney disease was implemented in routine clinical practice, with agreement comparable to manual segmentation [106].

Artificial intelligence in dialysis

Twenty-five studies evaluated AI in dialysis (Table 6).

Table 6. Artificial intelligence applications in dialysis (n = 25)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
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Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
107	Balamuthusamy et al. (2023)	200 HD patients with AVF/AVG (USA EHRs)	XGBoost, Random Forest, Non-linear regression	Predict AV access re-intervention	Accuracy: 86%
108	Song et al. (2023)	153 AVF sounds (40 patients, Taiwan)	ResNet + ANN	Home detection of AVF stenosis	Accuracy & F1-score: >90%
109	Garbelli et al. (2022)	46,292 AVF flow measurements (5,940 patients, Europe)	BINCM, CORN, REGM	Predict AVF flow levels	MAE: 0.27
110	Ota et al. (2020)	3,994 AVF sounds (20 patients, Japan)	CNN + LSTM + GRU	Diagnose AVF stenosis	Accuracy: 82%; AUC 0.75–0.92
111	Hong et al. (2023)	314,534 HD sessions (3,906 patients, China)	Random Forest, GBM, Logistic Regression	Predict intradialytic hypotension (IDH)	AUC 0.81
112	Li et al. (2022)	1,239 HD sessions + ICU datasets	bCOWOA-KELM	Predict IDH via blood indices	Accuracy: 92.41%
113	Kim et al. (2022)	63,640 dialysis sessions	Logistic Regression, Deep Learning, RF, XGBoost	Predict IDH	AUROC: 0.864–0.905
114	Mohammed et al. (2023)	1,000 HD patients	RDLCDC-IDH	Diagnose/classify IDH	Accuracy: 97.7%
115	Othman et al. (2022)	6,000 HD sessions (Egypt)	MLP, kNN, SVM, DT, GBM, RF	Early prediction of HD complications	Accuracy (RF): 98%
116	Shih et al. (2020)	80 physiological parameters (30 patients)	CNN + Transfer Learning (VGG-16)	Early warning of dialysis discomfort	Accuracy: 99%
117	Lee et al. (2021)	261,647 HD sessions (9,292 patients)	Deep Learning	Predict IDH	AUC: 0.94
118	Zhang et al. (2021)	1,341 AV access images (USA clinics)	Transfer Learning + CNN	Classify AV access aneurysms	AUC 0.96

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
119	Barbieri et al. (2019)	766,000 dialysis sessions (EuCliD database)	Artificial Neural Network (ANN)	Predict fluid removal & dialysis parameters	MAE: 0.13–9.3
120	Ohara et al. (2021)	298 HD sessions (Japan)	AISACS model	Anemia management	Accuracy: up to 87%
121	Kanda et al. (2020)	79,860 HD patients (Japan registry)	Clustering + SVM/LR/DL	Screen high-risk HD patients	Accuracy: 94.8%
122	Siga et al. (2020)	4,915 HD patients (France cohort)	Optimized Bayesian Network, Logistic Regression	Predict mortality	AUC 0.78
123	Tang et al. (2023)	433 HD patients (Taiwan)	LGBM, CatBoost, RF, XGBoost	Survival prediction post-COVID vaccination	F1-score (LGBM): 95%
124	Monaghan et al. (2021)	40,490 HD patients (USA)	XGBoost	Detect undiagnosed COVID-19	AUC 0.68
125	Kong et al. (2021)	23,992 PD patients (China)	SVM, RF, kNN, Logistic Regression	Predict prolonged hospital stay	AUC 0.76
126	Wu et al. (2020)	22,859 PD patients	CART, RF, GBM	Predict prolonged hospital stay	AUC (RF) 0.76
127	Liao et al. (2023)	242 MHD patients (China)	Multiple ML classifiers	Identify sarcopenia	AUC 0.78–0.87
128	Zhang et al. (2017)	83 PD patients	SVM, ANN, RF	Detect pathogen-specific immune fingerprints	AUC: 0.993
129	Chaudhuri et al. (2021)	182 HD patients	XGBoost	ML-directed interventions to reduce hospitalization	Improved outcomes reported
130	Brito et al. (2022)	2,489 exams (Portugal HIS)	IBk, kStar, REPTree, RF	Classify serum creatinine in PD	Accuracy (RF): 95.86%
131	Cheng et al. (2023)	440 ESKD patients (Taiwan)	AI Chatbot for PD care	Support PD self-management	Patient satisfaction: 90%

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Vascular access. ML and DL models predicted arteriovenous access re-intervention (accuracy 86%) [107], detected fistula stenosis from bruit recordings (accuracy 82% to more than 90%) [108,110], predicted access flow [109] and classified access aneurysms from clinical photographs (AUC 0.96) [118].

Intradialytic complications. Models predicted intradialytic hypotension with AUCs of 0.81–0.94 (accuracy up to 97.7%), the strongest being a DL model trained on 261,647 sessions [111–114,117]. Other models provided early warning of haemodialysis complications [115,116].

Treatment optimisation. An artificial neural network trained on approximately 766,000 sessions guided fluid removal, blood pressure and dialysis dose [119], and an AI-supported anaemia control system supported erythropoiesis-stimulating agent dosing (prediction accuracy up to 87%) [120].

Risk stratification and outcomes. Models identified high-risk patients (accuracy 94.8% in a 79,860-patient registry) [121], predicted mortality and survival [122,123], detected undiagnosed SARS-CoV-2 infection [124], classified serum creatinine values in peritoneal dialysis [130], predicted prolonged hospitalisation and sarcopenia [125–127], and identified pathogen-specific immune fingerprints in peritoneal dialysis-associated peritonitis (AUC 0.99) [128]. Notably, ML-directed interventions were associated with reduced hospitalisation rates [129], and an AI chatbot supporting peritoneal dialysis self-management achieved 90% patient satisfaction [131].

Artificial intelligence in kidney transplantation

Three studies modelled transplant outcomes (Table 7).

Table 7. Artificial intelligence applications in kidney transplantation (n = 3)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
132	Paquette et al. (2022)	180,141 kidney transplant recipients (Scientific Registry of Transplant Recipients, USA)	DeepSurv, DeepHit, Random Forest, Recurrent Neural Network	Prediction of graft survival probability after deceased donor kidney transplantation	C-index (DeepHit) 0.66
133	Raynaud et al. (2021)	13,608 transplant recipients from 18 academic centers (Europe, USA, South America)	DISPO model	Dynamic prediction of renal survival among kidney transplant recipients	AUC-ROC 0.86
134	Bae et al. (2019)	120,818 deceased-donor transplant recipients and 376,272 waitlisted candidates (2005–2016)	Random Forest, Weibull regression models	Predict survival after deceased-donor transplantation based on donor–recipient combination	5-year survival: 78.9% (KDPI 20), 70.7% (KDPI 80)

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Deep survival models (DeepSurv, DeepHit) applied to 180,141 recipients achieved a C-index of 0.66 for graft survival [132]. The international DISPO model, developed in 13,608 recipients from 18 centres, dynamically predicted kidney allograft survival with an AUC of 0.86 [133], and random-forest models estimated survival according to donor–recipient combination to inform the use of marginal kidneys [134]. DL applied to transplant biopsies further identified histological features predictive of graft loss [98,159].

Artificial intelligence in diabetic kidney disease

Three studies focused on DKD (Table 8).

Table 8. Artificial intelligence applications in diabetic kidney disease (n = 3)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
135	Ou et al. (2023)	53,477 diabetic patients (Taipei Veterans General Hospital, Taiwan)	Logistic Regression, Extra Trees, Random Forest, GBDT, XGBoost, LightGBM	Prediction of ESRD in newly diagnosed diabetic patients	AUC-ROC (XGBoost) 0.95
136	Xu et al. (2020)	1,117 EHRs of T2DM patients (Beijing Pinggu Hospital, China)	k-Nearest Neighbor, Logistic Regression, Random Forest, Decision Tree	Early detection of DKD	Accuracy (RF): 89.15%; F1-score: 94%
137	Hayashi (2019)	1,466 diabetic and pre-diabetic individuals (NHANES database, USA)	Re-RX rule extraction algorithm	Detection of early DKD based on albuminuria	Accuracy: 77.56%; AUC-ROC 0.75

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XGBoost predicted kidney failure in 53,477 patients with newly diagnosed type 2 diabetes (AUC 0.95) [135], random forest detected early DKD with 89.2% accuracy [136], and rule-extraction methods detected low-level albuminuria (AUC 0.75) [137]. Biomarker-enhanced models described under CKD complement these findings [82,83].

Artificial intelligence in urolithiasis

Six studies addressed kidney stones (Table 9).

Table 9. Artificial intelligence applications in urolithiasis (n = 6)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
138	Black et al. (2020)	127 digital renal images of 63 kidney stones	ResNet model	Prediction of kidney stone composition	Demonstrated accurate compositional classification

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
139	Shabaniyan et al. (2019)	254 PCNL and CKD patients	QDA, kNN, MLP, SVM (with Sequential Feature Selection + Fisher Discriminant Analysis)	Prediction of post-PCNL outcomes	Effective predictive modeling reported
140	Asif et al. (2023)	1,799 CT images of 433 patients	StoneNet deep learning model	Detection of kidney stones optimized for mobile-device deployment	High diagnostic performance demonstrated
141	Li et al. (2022)	260 renal CT scans	3D U-Net, Res U-Net, SegNet, DeepLab-v3, UNETR	Automated detection and segmentation of kidney stones	Accurate segmentation-based detection
142	Parakh et al. (2019)	535 renal polycystic CT images	GrayNet-SB, ImageNet-SB, Random-SB	Detection of stones within urinary tract	Reliable identification performance
143	Yildirim et al. (2021)	1,799 non-contrast CT (NCCT) images of 433 patients	ResNet model	Detection of kidney stones using NCCT imaging	Accuracy 96.82%

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DL detected stones on non-contrast CT with accuracies above 95% [140,143], and segmentation and detection networks performed reliably across datasets [141,142]. AI also predicted stone composition from digital stone images [138] and outcomes after percutaneous nephrolithotomy [139].

Artificial intelligence in renal cell carcinoma

Six studies addressed RCC (Table 10).

Table 10. Artificial intelligence applications in renal cell carcinoma (n = 6)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
144	Chen et al. (2023)	126,345 CT images	VB-MrFo-Net + Random Forest + SVM	Tumor segmentation, grade stratification, and prognosis prediction in ccRCC	Dice 0.87; grading AUC 0.75–0.78; prognostic HR 2.5–3.8 across four cohorts

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
145	Nasir et al. (2022)	3,300 kidney cancer images	Transfer Learning (AlexNet) with SGDM/ADAM/RMSProp optimizers	Early diagnosis of renal cancer integrated with IoT and blockchain security	Improved diagnostic efficiency reported
146	Schulz et al. (2021)	230 clear-cell RCC patients	MMDLM (Multimodal Deep Learning Model)	Prognosis prediction in ccRCC	C-index 0.78; 5-year survival AUC 0.92 (cross-validation)
147	Wessels et al. (2023)	709 renal whole-slide images (WSIs)	DINO-ViT self-supervised vision transformer	Prediction of disease-specific survival in ccRCC	Strong prognostic discrimination demonstrated
148	Gondim et al. (2023)	252 renal neoplasm WSIs	AI-based image classifier (Google AutoML Vision)	Multi-class histopathologic classification of kidney tumors	Accurate automated classification achieved
149	Jhumka et al. (2023)	9,527 CT images	ResNet + Explainable AI	Detection and classification of kidney cancers and stones	High interpretability with robust detection performance

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A CT-based framework segmented clear-cell RCC (Dice 0.87), stratified nuclear grade (AUC 0.75–0.78) and predicted prognosis across four cohorts [144]. A multimodal DL model combining histopathology, CT and genomic data predicted survival (C-index 0.78) [146], and a self-supervised vision transformer predicted disease-specific survival from whole-slide images [147]. Other studies addressed multi-class classification of renal neoplasms, transfer-learning diagnosis and explainable detection of renal masses [145,148,149].

Artificial intelligence in other renal conditions

Twelve studies addressed other conditions (Table 11).

Table 11. Artificial intelligence applications in other renal conditions (n = 12)

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
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Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
150	Galloway CD et al. (2019)	1,638,546 ECGs (Mayo Clinic, USA; multisite validation)	Convolutional Neural Network (CNN)	Hyperkalemia detection using ECG	AUC-ROC 0.88
151	Konieczny A et al. (2021)	80 biopsy-proven IgA nephropathy patients (Poland)	RF, MLP, DT, NB, AdaBoost, SVM, kNN	Prediction of renal function deterioration in IgAN	Accuracy (RF): 80.25%
152	Schena FP et al. (2021)	1,115 IgAN patients (VALIGA cohort, Europe)	ANN (classification + regression)	Prediction of ESKD and time-to-onset	AUC-ROC 0.82 (5-year); 0.89 (10-year)
153	Kuo CC et al. (2019)	4,505 kidney ultrasound images (1,299 patients, Taiwan)	ResNet, XGBoost	Prediction of renal function decline (eGFR-based)	Accuracy: 85.6%; AUC-ROC 0.90
154	Tang ZY et al. (2022)	1,727 biopsy ultrasound images (251 patients, Taiwan)	Mask R-CNN + Dual-Path CNN	Detection and grading of IFTA	Dice: 94.9%; F1-score: 81.9%
155	Lee J et al. (2022)	107,471 histopathology images (161 biopsies, USA)	Transfer Learning + Bag-of-Words + Clustering + RF	Prediction of kidney function and 1-year eGFR change	AUC-ROC 0.93 (current); 0.80 (1-year)
156	Ginley B et al. (2021)	205 whole-slide images (Portugal, USA, South Korea)	DeepLab-v3 + ResNet	Detection of IFTA, tubular atrophy, glomerulosclerosis	MCC: 67–89%
157	Nan Y et al. (2022)	400 WSIs (IgAN + controls)	SegNet + UAAN + FISS loss	Fine-grained glomerular lesion detection	Accuracy: 95.17%
158	Onthoni DD et al. (2020)	110 contrast-enhanced CT images (97 ADPKD patients)	SSD Inception-v2	Polycystic kidney detection	mAP: 94%
159	Yi Z et al. (2022)	789 transplant biopsies (616 patients, USA & Australia)	U-Net + Mask R-CNN	Detection of IFTA and leukocyte infiltration	Recall: 77–85%

Ref.	Study (year)	Data source / sample	AI technique	Clinical aim	Key performance
160	Liu Y et al. (2023)	88 post-transplant patients (China)	SVM, LR, RF, kNN, LGBM, XGBoost	Prediction of severe <i>Pneumocystis pneumonia</i>	AUC-ROC (RF) 0.92
161	Lassau N et al. (2019)	4,170 multimodal radiologic images (France)	Machine Learning models	Detection and characterization of renal tissue lesions	Accuracy: $\approx$ 84%

Ref. numbers correspond to the reference list. Performance metrics are as reported by the original study authors. Abbreviations: AI, artificial intelligence; ANN, artificial neural network; AUC, area under the receiver operating characteristic curve; AVF, arteriovenous fistula; CNN, convolutional neural network; CT, computed tomography; DL, deep learning; DNN, deep neural network; ECG, electrocardiogram; EHR, electronic health record; GBM, gradient boosting machine; HD, haemodialysis; ICU, intensive care unit; LR, logistic regression; LSTM, long short-term memory; ML, machine learning; MRI, magnetic resonance imaging; PD, peritoneal dialysis; RF, random forest; RNN, recurrent neural network; SVM, support vector machine; WSI, whole-slide image; XGBoost, extreme gradient boosting.

A DL model detected hyperkalaemia from the electrocardiogram with an AUC of approximately 0.88 [150]. ML and ANN-based tools predicted kidney function decline and kidney failure in IgA nephropathy (AUC 0.82 at 5 years and 0.89 at 10 years) [151,152]. DL on kidney ultrasound predicted eGFR-based kidney function (AUC 0.90) and graded interstitial fibrosis and tubular atrophy [153,154]. Computational pathology quantified interstitial fibrosis, tubular atrophy and glomerular lesions [155–157,159], and further applications included polycystic kidney localisation on CT, prediction of *Pneumocystis pneumonia* after transplantation and multimodal radiology challenges [158,160,161].

Certainty of evidence

Using GRADE principles, the certainty of evidence was judged moderate for AKI prediction and for DL-based imaging and histopathology classification, and low for CKD detection, dialysis, transplantation, DKD, urolithiasis and RCC. The main reasons for downgrading were risk of bias (retrospective designs, small or reused datasets, absent calibration), indirectness (few studies measuring clinical outcomes) and possible publication bias.

DISCUSSION

Summary of main findings

This systematic review of 142 studies shows that AI has been applied across the entire kidney disease continuum and consistently reports high discriminative performance, particularly for AKI prediction, image-based diagnosis and digital pathology. The evidence base is, however, predominantly retrospective and pre-implementation. External validation, calibration and prospective evaluation of clinical impact remain the exception rather than the rule, and the certainty of evidence is low to moderate.

Interpretation in the context of existing evidence

AKI is the most mature domain. Large EHR-based models can anticipate AKI hours to days before creatinine-based diagnosis [22], and urine-output models have survived external validation [33]. Yet early prediction has not translated into better outcomes: in a multicentre randomised trial, electronic AKI alerts did not reduce progression, dialysis or death [162]. Prediction alone is insufficient; it must be linked to effective actions such as nephrotoxin stewardship, haemodynamic optimisation or biomarker-guided care bundles. The marked loss of performance when AKI models are transported across sites [40], echoing the poor external performance of a widely deployed proprietary sepsis model [163], shows that institution-specific validation and monitoring are prerequisites for deployment.

In CKD, the apparent near-perfect diagnostic accuracy should be interpreted cautiously. More than one-third of CKD studies used the same 400-record benchmark dataset, which is small, curated and unrepresentative of real-world screening populations. CKD is diagnosed from eGFR and albuminuria, so classifying it from routine laboratory values adds little clinical value; the more meaningful targets are prediction of progression and opportunistic detection from non-renal data. Here, the evidence is more encouraging: biomarker-enhanced risk scores [82,83], temporally aware models [77] and retinal DL models validated in external cohorts [93,94] address unmet needs, particularly for screening in resource-limited settings.

Image- and pathology-based applications are closest to clinical use. DL achieved expert-level performance in glomerular classification and lesion quantification [95–97,156], and an MRI kidney-volume algorithm has been integrated into routine practice [106]. These tools may reduce inter-observer variability and workload, but they depend on consistent staining, scanning and

annotation, and multicentre validation remains limited [98].

In dialysis, AI is moving from prediction to management, including fluid and anaemia management, ML-directed interventions associated with fewer hospitalisations, and patient-facing chatbots [119,120,129,131]. Session-level prediction of intradialytic hypotension is a high-value target because the data are dense and actionable [117]. In transplantation, ML has not yet clearly outperformed well-specified conventional models: the Cox-based iBox system achieved a C-index of about 0.81 for allograft loss [164], higher than that of deep survival models trained on registry data [132]. This is consistent with evidence from other fields that ML offers no systematic performance advantage over logistic regression for tabular clinical prediction [10].

Methodological considerations and translational barriers

Several recurring weaknesses limit the credibility of reported performance. First, discrimination was emphasised at the expense of calibration, although poorly calibrated models can mislead clinical decisions [165]. Second, the analysis domain of PROBAST was frequently compromised by small samples, random-split validation and data leakage, consistent with systematic evaluations of ML prediction research [9]. Third, interpretability was inconsistently addressed. Explainability methods such as SHAP can make tree-based models more transparent and support clinician trust [166], but they do not substitute for external validation. Finally, models trained on non-representative data may encode and amplify health inequities, as shown for a widely used population-health algorithm [167]. Studies from low- and middle-income countries were mostly small, single-centre or benchmark-dataset analyses, and prospectively validated models for South Asian populations, where CKD of unknown aetiology and community-acquired AKI are common, are lacking.

Strengths and limitations

This review has several strengths: a broad, cross-domain scope, a multi-database search, duplicate screening and extraction, formal risk-of-bias assessment with PROBAST, GRADE-based certainty assessment, and transparent re-appraisal of eligibility. It also has limitations. First, heterogeneity in outcomes, definitions and metrics precluded meta-analysis, so performance ranges cannot be interpreted as pooled estimates. Second, we included only English-language publications, and using Google Scholar as a supplementary source may have introduced records of variable quality. Third, the search ended in December 2024, so recent developments, including large language models and foundation models in nephrology, are not captured. Fourth, publication bias is likely because studies

reporting favourable performance are more often published. Finally, reported metrics were extracted as presented by study authors and could not be independently verified.

Implications for practice and research

For clinicians, current AI tools should be regarded as decision support requiring local validation, not as autonomous diagnostic systems. For researchers, priorities include: (i) development on large, diverse, multicentre datasets with external and temporal validation; (ii) reporting of calibration, decision-curve analysis and fairness metrics in accordance with TRIPOD+AI [168]; (iii) staged clinical evaluation following DECIDE-AI, followed by randomised trials reported according to SPIRIT-AI and CONSORT-AI [169–171]; (iv) multimodal models integrating clinical, imaging, histological and molecular data to support mechanism-based precision nephrology; and (v) implementation research addressing workflow integration, cost-effectiveness, governance and equitable performance in under-represented populations.

CONCLUSIONS

AI shows consistently promising discrimination across the kidney disease continuum, from early AKI prediction and CKD risk stratification to automated image and biopsy interpretation, dialysis management and transplant outcome prediction. However, the evidence remains largely retrospective, inconsistently validated and at high risk of bias, and its impact on patient outcomes is largely untested. Rigorous external validation, transparent reporting and prospective impact trials are needed to move AI from promising algorithms to safe, equitable and effective tools for nephrology practice.

Declarations

Ethics approval and consent to participate: Not applicable. This systematic review analysed data from previously published studies and did not involve human participants or identifiable data.

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REFERENCES

1. Susantitaphong P, Cruz DN, Cerda J, Abulfaraj M, Alqahtani F, Koulouridis I, et al. World incidence of AKI: a meta-analysis. *Clin J Am Soc Nephrol*. 2013;8(9):1482-93.
2. Hoste EA, Bagshaw SM, Bellomo R, Cely CM, Colman R, Cruz DN, et al. Epidemiology of acute kidney injury in critically ill patients: the multinational AKI-EPI study. *Intensive Care Med*. 2015;41(8):1411-23.
3. GBD Chronic Kidney Disease Collaboration. Global, regional, and national burden of chronic kidney disease, 1990-2017: a systematic analysis for the Global Burden of Disease Study 2017. *Lancet*. 2020;395(10225):709-33.
4. Kovesdy CP. Epidemiology of chronic kidney disease: an update 2022. *Kidney Int Suppl* (2011). 2022;12(1):7-11.
5. Kidney Disease: Improving Global Outcomes (KDIGO) Acute Kidney Injury Work Group. KDIGO clinical practice guideline for acute kidney injury. *Kidney Int Suppl*. 2012;2(1):1-138.
6. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. *N Engl J Med*. 2019;380(14):1347-58.
7. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med*. 2019;25(1):44-56.
8. Niel O, Bastard P. Artificial intelligence in nephrology: core concepts, clinical applications, and perspectives. *Am J Kidney Dis*. 2019;74(6):803-10.
9. Andaur Navarro CL, Damen JAA, Takada T, Nijman SWJ, Dhiman P, Ma J, et al. Risk of bias in studies on prediction models developed using supervised machine learning techniques: systematic review. *BMJ*. 2021;375:n2281.
10. Christodoulou E, Ma J, Collins GS, Steyerberg EW, Verbakel JY, Van Calster B. A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models. *J Clin Epidemiol*. 2019;110:12-22.
11. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*. 2021;372:n71.
12. Rethlefsen ML, Kirtley S, Waffenschmidt S, Ayala AP, Moher D, Page MJ, et al. PRISMA-S: an extension to the PRISMA statement for reporting literature searches in systematic reviews. *Syst Rev*. 2021;10(1):39.
13. Campbell M, McKenzie JE, Sowden A, Katikireddi SV, Brennan SE, Ellis S, et al. Synthesis without meta-analysis (SWiM) in systematic reviews: reporting guideline. *BMJ*. 2020;368:l6890.
14. Bramer WM, Rethlefsen ML, Kleijnen J, Franco OH. Optimal database combinations for literature searches in systematic reviews. *Syst Rev*. 2017;6:245.
15. Wolff RF, Moons KGM, Riley RD, Whiting PF, Westwood M, Collins GS, et al. PROBAST: a tool to assess the risk of bias and applicability of prediction model studies. *Ann Intern Med*. 2019;170(1):51-8.
16. Moons KGM, Wolff RF, Riley RD, Whiting PF, Westwood M, Collins GS, et al. PROBAST: a tool to assess risk of bias and applicability of prediction model studies: explanation and elaboration. *Ann Intern Med*. 2019;170(1):W1-33.
17. Sanderson S, Tatt ID, Higgins JPT. Tools for assessing quality and susceptibility to bias in observational studies. *Int J Epidemiol*. 2007;36(3):666-676.
18. Guyatt GH, Oxman AD, Vist GE, Kunz R, Falck-Ytter Y, Alonso-Coello P, et al. GRADE: an emerging consensus on rating quality of evidence and strength of recommendations. *BMJ*. 2008;336(7650):924-6.
19. Popay J, Roberts H, Sowden A, Petticrew M, Arai L, Rodgers M, et al. Guidance on the conduct of narrative synthesis in systematic reviews: a product from the ESRC Methods Programme. Lancaster: Lancaster University; 2006.
20. Lee HC, Yoon HK, Nam K, et al. Derivation and validation of machine learning approaches to predict acute kidney injury after cardiac surgery. *J Clin Med*. 2018;7(10):322.
21. Adhikari L, Ozrazgat-Baslanti T, Ruppert M, et al. Improved predictive models for acute kidney injury with IDEA: intraoperative data embedded analytics. *PLoS One*. 2019;14:e0214904.
22. 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;572(7767):116-9.
23. Yin WJ, Yi YH, Guan XF, et al. Preprocedural prediction model for contrast-induced nephropathy patients. *J Am Heart Assoc*. 2017;6:e004498.
24. Zimmerman LP, Reyfman PA, Smith ADR, et al. Early prediction of acute kidney injury following ICU admission using a multivariate panel of physiological measurements. *BMC Med Inform Decis Mak*. 2019;19:16.
25. Xu Z, Chou J, Zhang XS, et al. Identifying subphenotypes of acute kidney injury using structured and unstructured electronic health record data with memory networks. *J Biomed Inform*. 2020;102:103361.

26. Rashidi HH, Sen S, Palmieri TL, et al. Early recognition of burn- and trauma-related acute kidney injury: a pilot comparison of machine learning techniques. *Sci Rep.* 2020;10:205.
27. Morid MA, Sheng ORL, Del Fiore G, et al. Temporal pattern detection to predict adverse events in critical care: case study with acute kidney injury. *JMIR Med Inform.* 2020;8:e14272.
28. Lei L, Wang Y, Xue Q, et al. A comparative study of machine learning algorithms for predicting acute kidney injury after liver cancer resection. *PeerJ.* 2020;8:e8583.
29. Kate RJ, Pearce N, Mazumdar D, Nilakantan V. A continual prediction model for inpatient acute kidney injury. *Comput Biol Med.* 2020;116:103580.
30. Zhang Z, Ho KM, Hong Y. Machine learning for the prediction of volume responsiveness in patients with oliguric acute kidney injury in critical care. *Crit Care.* 2019;23:112.
31. Xu Z, Luo Y, Adekanlatu P, et al. Stratified mortality prediction of patients with acute kidney injury in critical care. *Stud Health Technol Inform.* 2019;264:462-466.
32. Alfieri F, Ancona A, Tripepi G, et al. A deep-learning model to continuously predict severe acute kidney injury based on urine output changes in critically ill patients. *J Nephrol.* 2021;34:1875-1886.
33. Alfieri F, Ancona A, Tripepi G, et al. External validation of a deep-learning model to predict severe acute kidney injury based on urine output changes in critically ill patients. *J Nephrol.* 2022;35:2047-2056.
34. Bredt LC, Peres LAB, Risso M, Barros LCA. Risk factors and prediction of acute kidney injury after liver transplantation: logistic regression and artificial neural network approaches. *World J Hepatol.* 2022;14:570-582.
35. He ZL, Zhou JB, Liu ZK, et al. Application of machine learning models for predicting acute kidney injury following donation after cardiac death liver transplantation. *Hepatobiliary Pancreat Dis Int.* 2021;20:222-231.
36. Hu C, Tan Q, Zhang Q, et al. Application of interpretable machine learning for early prediction of prognosis in acute kidney injury. *Comput Struct Biotechnol J.* 2022;20:2861-2870.
37. Lei VJ, Luong T, Shan E, et al. Risk stratification for postoperative acute kidney injury in major noncardiac surgery using preoperative and intraoperative data. *JAMA Netw Open.* 2019;2:e1916921.
38. Liu WT, Liu XQ, Jiang TT, et al. Using a machine learning model to predict the development of acute kidney injury in patients with heart failure. *Front Cardiovasc Med.* 2022;9:911987.
39. Lu JY, Zhu J, Zhu J, Duong TQ. Long short-term memory machine learning of longitudinal clinical data accurately predicts acute kidney injury onset in COVID-19: a two-center study. *Int J Infect Dis.* 2022;122:802-810.
40. Song X, Yu ASL, Kellum JA, et al. Cross-site transportability of an explainable artificial intelligence model for acute kidney injury prediction. *Nat Commun.* 2020;11:5668.
41. Yue S, Li S, Huang X, et al. Machine learning for the prediction of acute kidney injury in patients with sepsis. *J Transl Med.* 2022;20:215.
42. Zhang Y, Yang D, Liu Z, et al. An explainable supervised machine learning predictor of acute kidney injury after adult deceased donor liver transplantation. *J Transl Med.* 2021;19:321.
43. Wazir S, Sethi SK, Agarwal G, et al. Neonatal acute kidney injury risk stratification score (STARZ study). *Pediatr Res.* 2022;91:1141-1148.
44. Akter S, Ahmed M, Al Imran A, Habib A, Ul Haque R, Rahman S, et al. CKD.Net: A novel deep learning hybrid model for effective, real-time automated screening tool towards prediction of multi stages of CKD along with eGFR and creatinine. *Expert Syst Appl.* 2023;223:119851.
45. Akter S, Habib A, Islam A, Hossen S, Fahim WA, Sarkar PR, et al. Comprehensive performance assessment of deep learning models in early prediction and risk identification of chronic kidney disease. *IEEE Access.* 2021;9:165184-165206.
46. Almansour NA, Syed HF, Khayat NR, Altheeb RK, Juri RE, Alhiyafi J, et al. Neural network and support vector machine for the prediction of chronic kidney disease: A comparative study. *Comput Biol Med.* 2019;109:101-111.
47. Arulanthu P, Perumal E. An intelligent IoT with cloud centric medical decision support system for chronic kidney disease prediction. *Int J Imaging Syst Technol.* 2020;30:815-827.
48. Arumugham V, Sankaralingam BP, Jayachandran UM, Krishna KVSSRA, Sundarraj S, Mohammed M. An explainable deep learning model for prediction of early-stage chronic kidney disease. *Comput Intell.* 2023;39:1022-1038.
49. Bandera NH, Arizaga JMM, Reyes ER. Assessment and prediction of chronic kidney using an improved neutrosophic artificial intelligence model. *Int J Neutrosophic Sci.* 2023;21:174-183.
50. Bellocchio F, Lonati C, Ion Titapiccolo J, Nadal J, Meiselbach H, Schmid M, et al. Validation of a novel predictive algorithm for kidney failure in patients suffering from chronic kidney disease: The prognostic reasoning system for chronic kidney disease (PROGRES-CKD). *Int J Environ Res Public Health.* 2021;18:12649.
51. Bermudez-Lopez M, Forne C, Amigo N, Bozic M, Arroyo D, Bretones T, et al. An in-depth analysis shows a hidden atherogenic lipoprotein profile in non-diabetic chronic kidney disease

patients. *Expert Opin Ther Targets*. 2019;23:619-630.

52. Chen G, Ding C, Li Y, Hu X, Li X, Ren L, et al. Prediction of chronic kidney disease using adaptive hybridized deep convolutional neural network on the Internet of Medical Things platform. *IEEE Access*. 2020;8:100497-100508.

53. Elhoseny M, Shankar K, Uthayakumar J. Intelligent diagnostic prediction and classification system for chronic kidney disease. *Sci Rep*. 2019;9:9583.

54. Hamedan F, Orooji A, Sanadgol H, Sheikhtaheri A. Clinical decision support system to predict chronic kidney disease: A fuzzy expert system approach. *Int J Med Inform*. 2020;138:104134.

55. Inaguma D, Kitagawa A, Yanagiya R, Koseki A, Iwamori T, Kudo M, et al. Increasing tendency of urine protein is a risk factor for rapid eGFR decline in patients with CKD: a machine learning-based prediction model by using a big database. *PLoS One*. 2020;15(9):e0239262.

56. Arif-Ul-Islam, Ripon SH. Rule induction and prediction of chronic kidney disease using boosting classifiers, Ant-Miner and J48 decision tree. In: *Proceedings of the 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*; Cox's Bazar, Bangladesh. 2019. p. 1-6.

57. 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;9:5082.

58. Kanda E, Okami S, Kohsaka S, Okada M, Ma X, Kimura T, et al. Machine learning models predicting cardiovascular and renal outcomes and mortality in patients with hyperkalemia. *Nutrients*. 2022;14:4614.

59. Kandasamy N, Chaussalet T, Basukoski A. A conceptual framework to predict disease progressions in patients with chronic kidney disease, using machine learning and process mining. *Stud Health Technol Inform*. 2023;305:190-193.

60. Lakshmanaprabu SK, Mohanty SN, Sheeba RS, Krishnamoorthy S, Uthayakumar J, Shankar K. Online clinical decision support system using optimal deep neural networks. *Appl Soft Comput*. 2019;81:105487.

61. Lee KH, Chu YC, Tsai MT, Tseng WC, Lin YP, Ou SM, et al. Artificial intelligence for risk prediction of end-stage renal disease in sepsis survivors with chronic kidney disease. *Biomedicines*. 2022;10:546.

62. Lokuarachchi DN, Tharindu Manoj JV, Weerasooriya MNH, Waseem MNM, Aslam F, Kumarasinghe N, et al. Prediction of CKDu using

KDQOL score, ankle swelling and risk factor analysis using neural networks. In: *Proceedings of the 2020 2nd International Conference on Advancements in Computing (ICAC)*; Malabe, Sri Lanka. 2020. p. 91-96.

63. Marechal E, Jaugey A, Tarris G, Paindavoin M, Seibel J, Martin L, et al. Automatic evaluation of histological prognostic factors using two consecutive convolutional neural networks on kidney samples. *Clin J Am Soc Nephrol*. 2022;17:260-270.

64. Moreno-Sánchez PA. Data-driven early diagnosis of chronic kidney disease: Development and evaluation of an explainable AI model. *IEEE Access*. 2023;11:38359-38369.

65. Nunez I, Navarro N, Saldana Barrios J. First experiences in developing a low-cost machine learning prototype model using an open access dataset of chronic kidney diseases: A case study. In: *Proceedings of UCAmI*; Córdoba, Spain. 2022. p. 181-188.

66. Ogunleye A, Wang Q-G. XGBoost model for chronic kidney disease diagnosis. *IEEE/ACM Trans Comput Biol Bioinform*. 2020;17:2131-2140.

67. Pareek NK, Soni D, Degadwala S. Early stage chronic kidney disease prediction using convolution neural network. In: *Proceedings of ICAAAIC*; Salem, India. 2023. p. 16-20.

68. Patel S, Patel R, Ganatra N, Khant S, Patel A. Experimental study and performance analysis of supervised machine learning algorithms for prognosis of chronic kidney disease. In: *Proceedings of ICEEICT*; Trichy, India. 2022. p. 1-6.

69. Pati A, Parhi M, Pattanayak BK. Ensemble deep learning approach for chronic kidney disease prediction. *AIP Conf Proc*. 2023;2819:030002.

70. Poonia RC, Gupta MK, Abunadi I, Albraikan AA, Al-Wesabi FN, Hamza MA, et al. Intelligent diagnostic prediction and classification models for detection of kidney disease. *Healthcare (Basel)*. 2022;10:371.

71. Priya S, Saranya N. Intelligent approach for accurate prediction of chronic diseases. *CSSE*. 2023;46:2571-2587.

72. Rabby AKMSA, Mamata R, Laboni MA, Ohidujjaman, Abujar S. Machine learning applied to kidney disease prediction: Comparison study. In: *Proceedings of ICCCNT*; Kanpur, India. 2019. p. 1-7.

73. Rady E-HA, Anwar AS. Prediction of kidney disease stages using data mining algorithms. *Inform Med Unlocked*. 2019;15:100178.

74. Rajeshwari, Yogish HK. Prediction of chronic kidney disease using machine learning technique. In: *Proceedings of CCIP*; Bengaluru, India. 2022. p. 1-6.

75. Rashid J, Batool S, Kim J, Wasif Nisar M, Hussain A, Juneja S, et al. Augmented artificial intelligence approach for chronic diseases prediction. *Front Public Health*. 2022;10:860396.
76. Revathi M, Raghuraman G, Visumathi J. Performance analysis of machine learning algorithms in prediction of chronic kidney disease on an imbalanced dataset. In: *Inventive Computation and Information Technologies*. Singapore: Springer; 2023. p. 149-168.
77. Song X, Waitman LR, Yu ASL, Robbins DC, Hu Y, Liu M. Longitudinal risk prediction of chronic kidney disease in diabetic patients using a temporal-enhanced gradient boosting machine. *JMIR Med Inform*. 2020;8:e15510.
78. Tran NTD, Balezeaux M, Granal M, Fouque D, Ducher M, Fauvel JP. Prediction of all-cause mortality for chronic kidney disease patients using four models of machine learning. *Nephrol Dial Transplant*. 2023;38:1691-1699.
79. Wang B. Kidney disease diagnosis based on machine learning. In: *Proceedings of CDS; Stanford, CA, USA*. 2020. p. 307-310.
80. Xiao J, Ding R, Xu X, Guan H, Feng X, Sun T, et al. Comparison and development of machine learning tools in prediction of chronic kidney disease progression. *J Transl Med*. 2019;17:119.
81. Dagliati A, Marini S, Sacchi L, Cogni G, Teliti M, Tibollo V, et al. Machine learning methods to predict diabetes complications. *J Diabetes Sci Technol*. 2018;12:295-302.
82. Chauhan K, Nadkarni GN, Fleming F, et al. Initial validation of KidneyIntelX integrating biomarkers and EHR data to predict kidney outcomes. *Kidney360*. 2020;1:731-739.
83. Chan L, Nadkarni GN, Fleming F, et al. Machine learning risk score using biomarker and electronic patient data to predict progression of diabetic kidney disease. *Diabetologia*. 2021;64:1504-1515.
84. Lin SY, Hsieh MH, Lin CL, et al. 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;8(7):995.
85. Alikhan JS, Alageswaran R, Amali SMJ. Self-attention CNN optimized for CKD diagnosis in big data system. *Biomed Signal Process Control*. 2023;85:105011.
86. Al-Momani R, Al-Mustafa G, Zeidan R, Alquran H, Mustafa WA, Alkhayyat A. CKD detection using machine learning technique. In: *Proceedings of IICETA; 2022*. p. 153-158.
87. Bhaskar N, Manikandan S. Deep-learning-based system for automated sensing of chronic kidney disease. *IEEE Sens Lett*. 2019;3:7001904.
88. Granal M, Slimani L, Florens N, Sens F, Pelletier C, Pszczolinski R, et al. Prediction tool to estimate potassium diet in CKD patients: The UniverSel study. *Nutrients*. 2022;14:2419.
89. Jayapandian CP, Chen Y, Janowczyk AR, Palmer MB, Cassol CA, Sekulic M, et al. Deep learning-based segmentation of histologic kidney cortex structures. *Kidney Int*. 2021;99:86-101.
90. Khamparia A, Saini G, Pandey B, Tiwari S, Gupta D, Khanna A. CKD classification with multimedia data learning using deep stacked autoencoder network. *Multimed Tools Appl*. 2020;79:35425-35440.
91. Kumar K, Pradeepa M, Mahdal M, Verma S, RajaRao MVLN, Ramesh JVN. Deep learning approach for kidney disease recognition and prediction through image processing. *Appl Sci*. 2023;13:3621.
92. Pilia N, Mesa MH, Dossel O, Loewe A. ECG-based estimation of potassium and calcium concentrations: Proof of concept. In: *IEEE EMBC; 2019*. p. 2610-2613.
93. Sabanayagam C, Xu D, Ting DSW, Nusinovici S, Banu R, Hamzah H, et al. Deep learning algorithm to detect chronic kidney disease from retinal photographs in community-based populations. *Lancet Digit Health*. 2020;2:e295-e302.
94. Zhang K, Liu X, Xu J, et al. Deep-learning models for the detection and incidence prediction of chronic kidney disease and type 2 diabetes from retinal fundus images. *Nat Biomed Eng*. 2021;5:533-45.
95. Hao F, Li M, Liu X, Li X, Yue J, Han W. Classification of glomeruli with membranous nephropathy on renal digital pathological images with deep learning. In: *Proceedings of the 2020 Conference on Artificial Intelligence and Healthcare; 2020 Oct 23-25; Taiyuan, China*. New York: Association for Computing Machinery; 2020. p. 239-43.
96. Lu Y, Yang H, Asad Z, Zhu Z, Yao T, Xu J, et al. Holistic Fine-Grained Global Glomerulosclerosis Characterization: From Detection to Unbalanced Classification. *J Med Imaging*. 2022;9:014005.
97. Yamaguchi R, Kawazoe Y, Shimamoto K, Shinohara E, Tsukamoto T, Shintani-Domoto Y, et al. Glomerular classification using convolutional neural networks based on defined annotation criteria and concordance evaluation among clinicians. *Kidney Int Rep*. 2021;6(3):716-26.
98. Kers J, Bülow RD, Klinkhammer BM, Breimer GE, Fontana F, Abiola AA, et al. Deep Learning-Based Classification of Kidney Transplant Pathology: A Retrospective, Multicentre, Proof-of-Concept Study. *Lancet Digit Health*. 2022;4:e18-e26.

99. Alsadi A, Majeed N, Saeed D, Dharmamer Y, Singh M, Patel T. A deep-learning approach at automated detection of electron-dense immune deposits in medical renal biopsies. *J Nephropathol.* 2022;11:e17123.
100. Pesce F, Albanese F, Mallardi D, Rossini M, Pasculli G, Suavo-Bulzis P, et al. Identification of Glomerulosclerosis Using IBM Watson and Shallow Neural Networks. *J Nephrol.* 2022;35:1235-1242.
101. Zhang L, Li M, Wu Y, Hao F, Wang C, Han W, et al. Classification of Renal Biopsy Direct Immunofluorescence Image Using Multiple Attention Convolutional Neural Network. *Comput Methods Programs Biomed.* 2022;214:106532.
102. Altalbe A, Javed A. Applying Customized Convolutional Neural Network to Kidney Image Volumes for Kidney Disease Detection. *CSSE.* 2023;47:2119-34.
103. Les T, Markiewicz T, Dziekiewicz M, Lorent M. Kidney Boundary Detection Algorithm Based on Extended Maxima Transformations for Computed Tomography Diagnosis. *Appl Sci.* 2020;10:7512.
104. Subramanian RR, Abilakshmi A, Kalyani T, Sunayana P, Monalisa G, Chaithanya CV. Design and Evaluation of a Deep Learning Aided Approach for Kidney Stone Detection in CT Scan Images. In: *Proceedings of the 2023 International Conference on Applied Intelligence and Sustainable Computing (ICAISC)*, Dharwad, India, 16-17 June 2023. p. 1-6.
105. Tsai MC, Lu HHS, Chang YC, Huang YC, Fu LS. Automatic Screening of Pediatric Renal Ultrasound Abnormalities: Deep Learning and Transfer Learning Approach. *JMIR Med Inform.* 2022;10:e40878.
106. Potretzke TA, Korfiatis P, Blezek DJ, et al. Clinical implementation of an artificial intelligence algorithm for magnetic resonance-derived measurement of total kidney volume. *Mayo Clin Proc.* 2023;98(5):689-700.
107. Balamuthusamy S, Dhanabalsamy N, Thankavel B, Bala M, Pfaffle A. Utility of machine learning (ML) analytics on real time risk stratification and re-intervention risk prediction on AV access outcomes and cost. *J Vasc Access.* 2024;25(4):1224-8.
108. Song WT, Chen CC, Yu ZW, Huang HC. An effective AI model for automatically detecting arteriovenous fistula stenosis. *Sci Rep.* 2023;13:17659.
109. Garbelli M, Neri L, Bellocchio F. Arteriovenous fistula flow level prediction through ordinal classifier methods. *CEUR Workshop Proc.* 2022;3307:12-9.
110. Ota K, Nishiura Y, Ishihara S, Adachi H, Yamamoto T, Hamano T. Evaluation of hemodialysis arteriovenous bruit by deep learning. *Sensors (Basel).* 2020;20:4852.
111. Hong D, Chang H, He X, Zhan Y, Tong R, Wu X, et al. Construction of an early alert system for intradialytic hypotension before initiating hemodialysis based on machine learning. *Kidney Dis (Basel).* 2023;9:433-42.
112. Li Y, Zhao D, Liu G, Liu Y, Bano Y, Ibrohimov A, et al. Intradialytic hypotension prediction using covariance matrix-driven whale optimizer with orthogonal structure-assisted extreme learning machine. *Front Neuroinform.* 2022;16:956423.
113. Kim HW, Heo SJ, Kim M, et al. Deep learning model for predicting intradialytic hypotension without privacy infringement: a retrospective two-center study. *Front Med (Lausanne).* 2022;9:878858.
114. Mohammed IH, Obaid MK, Hadi MR, Alzubaidi LH, Mohammed A, Hassan AR. Artificial intelligence based robust clinical data classification for intradialytic hypotension diagnosis. In: *Proc 2023 6th Int Conf Eng Technol Appl (IICETA)*. Al-Najaf, Iraq; 2023. p. 78-84.
115. Othman M, Elbasha AM, Naga YS, Moussa ND. Early prediction of hemodialysis complications employing ensemble techniques. *Biomed Eng Online.* 2022;21:74.
116. Shih C, Lai Y, Chen C, Chu WCC. An early warning system for hemodialysis complications utilizing transfer learning from HD IoT dataset. In: *Proc 2020 IEEE 44th Annu Comput Softw Appl Conf (COMPSAC)*. Madrid, Spain; 2020. p. 759-67.
117. Lee H, Yun D, Yoo J, et al. Deep learning model for real-time prediction of intradialytic hypotension. *Clin J Am Soc Nephrol.* 2021;16:396-406.
118. Zhang H, Preddie D, Krackov W, Sor M, Waguespack P, Kuang Z, et al. Deep learning to classify arteriovenous access aneurysms in hemodialysis patients. *Clin Kidney J.* 2022;15(4):829-30.
119. Barbieri C, Cattinelli I, Neri L, Mari F, Ramos R, Brancaccio D, et al. 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;5:28-33.
120. Ohara T, Ikeda H, Sugitani Y, Suito H, Huynh VQH, Kinomura M, et al. Artificial intelligence supported anemia control system (AISACS) to prevent anemia in maintenance hemodialysis patients. *Int J Med Sci.* 2021;18:1831-9.
121. Kanda E, Epureanu BI, Adachi T, Tsuruta Y, Kikuchi K, Kashihara N, et al. Application of

- explainable ensemble artificial intelligence model to categorization of hemodialysis-patient and treatment using nationwide real-world data in Japan. *PLoS One*. 2020;15:e0233491.
122. Siga MM, Ducher M, Florens N, Roth H, Mahloul N, Fouque D, et al. Prediction of all-cause mortality in haemodialysis patients using a Bayesian network. *Nephrol Dial Transplant*. 2020;35:1420-5.
 123. Tang SY, Chen TH, Kuo KL, Huang JN, Kuo CT, Chu YC. Using artificial intelligence algorithms to predict the overall survival of hemodialysis patients during the COVID-19 pandemic: a prospective cohort study. *J Chin Med Assoc*. 2023;86:1020-7.
 124. Monaghan CK, Larkin JW, Chaudhuri S, Han H, Jiao Y, Bermudez KM, et al. Machine learning for prediction of patients on hemodialysis with an undetected SARS-CoV-2 infection. *Kidney360*. 2021;2:456-68.
 125. Kong G, Wu J, Chu H, Yang C, Lin Y, Lin K, et al. Predicting prolonged length of hospital stay for peritoneal dialysis-treated patients using stacked generalization: model development and validation study. *JMIR Med Inform*. 2021;9:e17886.
 126. Wu J, Kong G, Lin Y, Chu H, Yang C, Shi Y, et al. Development of a scoring tool for predicting prolonged length of hospital stay in peritoneal dialysis patients through data mining. *Ann Transl Med*. 2020;8:1437.
 127. Liao H, Yang Y, Zeng Y, Qiu Y, Chen Y, Zhu L, et al. Use machine learning to help identify possible sarcopenia cases in maintenance hemodialysis patients. *BMC Nephrol*. 2023;24:34.
 128. Zhang J, Friberg IM, Kift-Morgan A, et al. Machine-learning algorithms define pathogen-specific local immune fingerprints in peritoneal dialysis patients with bacterial infections. *Kidney Int*. 2017;92:179-91.
 129. Chaudhuri S, Han H, Usvyat L, et al. Machine learning directed interventions associate with decreased hospitalization rates in hemodialysis patients. *Int J Med Inform*. 2021;153:104541.
 130. Brito C, Esteves M, Peixoto H, Abelha A, Machado J. A data mining approach to classify serum creatinine values in patients undergoing continuous ambulatory peritoneal dialysis. *Wirel Netw*. 2022;28:1269-77.
 131. Cheng CI, Lin WJ, Liu HT, Chen YT, Chiang CK, Hung KY. Implementation of artificial intelligence chatbot in peritoneal dialysis nursing care: experience from a Taiwan medical center. *Nephrology (Carlton)*. 2023;28:655-62.
 132. Paquette FX, Ghassemi A, Bukhtiyarova O, Cisse M, Gagnon N, Della Vecchia A, et al. Machine learning support for decision-making in kidney transplantation: Step-by-step development of a technological solution. *JMIR Med Inform*. 2022;10:e34554.
 133. Raynaud M, Aubert O, Divard G, Reese PP, Kamar N, Yoo D, et al. Dynamic prediction of renal survival among deeply phenotyped kidney transplant recipients using artificial intelligence: An observational, international, multicohort study. *Lancet Digit Health*. 2021;3:e795-e805.
 134. Bae S, Massie AB, Thomas AG, Segev DL, Desai NM, Garonzik-Wang JM, et al. Who can tolerate a marginal kidney? Predicting survival after deceased donor kidney transplant by donor-recipient combination. *Am J Transplant*. 2019;19(2):425-433.
 135. Ou SM, Tsai MT, Lee KH, Tseng WC, Yang CY, Chen TH, et al. Prediction of the risk of developing end-stage renal diseases in newly diagnosed type 2 diabetes mellitus using artificial intelligence algorithms. *BioData Min*. 2023;16:8.
 136. Xu H, Kong Y, Tan S. Predictive modeling of diabetic kidney disease using random forest algorithm along with feature selection. In: *Proc 1st Int Symp Artif Intell Med Sci*; 2020 Sep 11-13; Beijing, China. New York: ACM; 2020. p. 23-27.
 137. Hayashi Y. Detection of lower albuminuria levels and early development of diabetic kidney disease using an artificial intelligence-based rule extraction approach. *Diagnostics (Basel)*. 2019;9:133.
 138. Black KM, Law H, Aldoukhi A, Deng J, Ghani KR. Deep learning computer vision algorithm for detecting kidney stone composition. *BJU Int*. 2020;125:920-924.
 139. Shabaniyan T, Parsaei H, Aminsharifi A, Movahedi MM, Jahromi AT, Pouyesh S, et al. An artificial intelligence based clinical decision support system for large kidney stone treatment. *Australas Phys Eng Sci Med*. 2019;42:771-779.
 140. Asif S, Zhao M, Chen X, Zhu Y. StoneNet: An efficient lightweight model based on depthwise separable convolutions for kidney stone detection from CT images. *Interdiscip Sci Comput Life Sci*. 2023;15:633-652.
 141. Li D, Xiao C, Liu Y, Chen Z, Hassan H, Su L, et al. Deep segmentation networks for segmenting kidneys and detecting kidney stones in unenhanced abdominal CT images. *Diagnostics (Basel)*. 2022;12:1788.
 142. Parakh A, Lee H, Lee JH, Eisner BH, Sahani DV, Do S. Urinary stone detection on CT images using deep convolutional neural networks: evaluation of model performance and generalization. *Radiol Artif Intell*. 2019;1:e180066.
 143. Yildirim K, Bozdog PG, Talo M, Yildirim O, Karabatak M, Acharya UR. Deep learning model for automated kidney stone detection using coronal CT images. *Comput Biol Med*. 2021;135:104569.

144. Chen S, Song D, Chen L, Guo T, Jiang B, Liu A, et al. Artificial intelligence-based non-invasive tumor segmentation, grade stratification and prognosis prediction for clear-cell renal-cell carcinoma. *Precis Clin Med.* 2023;6:pbad019.
145. Nasir MU, Zubair M, Ghazal TM, Khan MF, Ahmad M, Rahman AU, et al. Kidney cancer prediction empowered with blockchain security using transfer learning. *Sensors (Basel).* 2022;22:7483.
146. Schulz S, Woerl A-C, Jungmann F, Glasner C, Stenzel P, Strobl S, et al. Multimodal deep learning for prognosis prediction in renal cancer. *Front Oncol.* 2021;11:788740.
147. Wessels F, Schmitt M, Krieghoff-Henning E, Nientiedt M, Waldbillig F, Neuberger M, et al. A self-supervised vision transformer to predict survival from histopathology in renal cell carcinoma. *World J Urol.* 2023;41:2233-2241.
148. Gondim DD, Al-Obaidy KI, Idrees MT, Eble JN, Cheng L. Artificial intelligence-based multi-class histopathologic classification of kidney neoplasms. *J Pathol Inform.* 2023;14:100299.
149. Jhumka K, Khan MHM, Mungloo-Dilmohamud Z, Fedally SA. Classification of kidney abnormalities using deep learning with explainable AI. In: *Proc 2023 Sixth Int Conf Women Data Sci Prince Sultan Univ (WiDS PSU); 2023 Mar 14-15; Riyadh, Saudi Arabia.* p. 133-137.
150. Galloway CD, Valys AV, Shreibati JB, Treiman DL, Petterson FL, Gundotra VP, et al. Development and validation of a deep-learning model to screen for hyperkalemia from the electrocardiogram. *JAMA Cardiol.* 2019;4:428-36.
151. Konieczny A, Stojanowski J, Krajewska M, Kuształ M. Machine learning in prediction of IgA nephropathy outcome: a comparative approach. *J Pers Med.* 2021;11:312.
152. Schena FP, Anelli VW, Trotta J, Di Noia T, Manno C, Tripepi G, et al. Development and testing of an artificial intelligence tool for predicting end-stage kidney disease in patients with immunoglobulin A nephropathy. *Kidney Int.* 2021;99:1179-88.
153. Kuo CC, Chang CM, Liu KT, Lin WK, Chiang HY, Chung CW, et al. Automation of the kidney function prediction and classification through ultrasound-based kidney imaging using deep learning. *npj Digit Med.* 2019;2:29.
154. Tang ZY, Lin YC, Shen CC. Dual-path convolutional neural network for chronic kidney disease classification in ultrasound echography. In: *Proc IEEE Int Ultrasonics Symp.* 2022. p. 1-4.
155. Lee J, Warner E, Shaikhouni S, Bitzer M, Kretzler M, Gipson D, et al. Unsupervised machine learning for identifying important visual features through bag-of-words using histopathology data from chronic kidney disease. *Sci Rep.* 2022;12:4832.
156. Ginley B, Jen KY, Han SS, Rodrigues L, Jain S, Fogo AB, et al. Automated computational detection of interstitial fibrosis, tubular atrophy, and glomerulosclerosis. *J Am Soc Nephrol.* 2021;32:837-50.
157. Nan Y, Li F, Tang P, Zhang G, Zeng C, Xie G, et al. Automatic fine-grained glomerular lesion recognition in kidney pathology. *Pattern Recognit.* 2022;127:108648.
158. Onthoni DD, Sheng TW, Sahoo PK, Wang LJ, Gupta P. Deep learning assisted localization of polycystic kidney on contrast-enhanced CT images. *Diagnostics (Basel).* 2020;10:1113.
159. Yi Z, Salem F, Menon MC, Keung K, Xi C, Hultin S, et al. Deep learning identified pathological abnormalities predictive of graft loss in kidney transplant biopsies. *Kidney Int.* 2022;101:288-98.
160. Liu Y, Qiu T, Hu H, Kong C, Zhang Y, Wang T, et al. Machine learning models for prediction of severe *Pneumocystis carinii* pneumonia after kidney transplantation: a single-center retrospective study. *Diagnostics (Basel).* 2023;13:2735.
161. Lassau N, Estienne T, de Vomecourt P, Azoulay M, Cagnol J, Garcia G, et al. Five simultaneous artificial intelligence data challenges on ultrasound, CT, and MRI. *Diagn Interv Imaging.* 2019;100:199-209.
162. Wilson FP, Martin M, Yamamoto Y, Partridge C, Moreira E, Arora T, et al. Electronic health record alerts for acute kidney injury: multicenter, randomized clinical trial. *BMJ.* 2021;372:m4786.
163. Wong A, Otles E, Donnelly JP, Krumm A, McCullough J, DeTroyer-Cooley O, et al. External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients. *JAMA Intern Med.* 2021;181(8):1065-70.
164. Loupy A, Aubert O, Orandi BJ, Duong van Huyen JP, Brault C, Zhang H, et al. Prediction system for risk of allograft loss in patients receiving kidney transplants: International derivation and validation study. *BMJ.* 2019;366:l4923.
165. Van Calster B, McLernon DJ, van Smeden M, Wynants L, Steyerberg EW; Topic Group 'Evaluating diagnostic tests and prediction models' of the STRATOS initiative. Calibration: the Achilles heel of predictive analytics. *BMC Med.* 2019;17(1):230.
166. Lundberg SM, Nair B, Vavilala MS, Horibe M, Eisses MJ, Adams T, et al. Explainable machine-learning predictions for the prevention of hypoxaemia during surgery. *Nat Biomed Eng.* 2018;2(10):749-60.

167. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. *Science*. 2019;366(6464):447-53.
168. Collins GS, Moons KGM, Dhiman P, Riley RD, Beam AL, Van Calster B, et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. *BMJ*. 2024;385:e078378.
169. Vasey B, Nagendran M, Campbell B, Clifton DA, Collins GS, Denaxas S, et al. Reporting guideline for the early-stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *Nat Med*. 2022;28(5):924-33.
170. Cruz Rivera S, Liu X, Chan AW, Denniston AK, Calvert MJ; SPIRIT-AI and CONSORT-AI Working Group. Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension. *Nat Med*. 2020;26(9):1351-63.
171. Liu X, Cruz Rivera S, Moher D, Calvert MJ, Denniston AK; SPIRIT-AI and CONSORT-AI Working Group. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension. *Nat Med*. 2020;26(9):1364-74.