Applications of Artificial Intelligence in Urological Practises: Systematic Review and Future Directions

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DOI: https://doi.org/10.63001/tbs.2026.v21.i02.S.I(2).pp1146-1167

KEYWORDS

Artificial Intelligence,
Urology,
Machine Learning,
Deep Learning.

Received on:
28-04-2026

Accepted on:
16-05-2026

Published on:
26-05-2026

Abstract

Urological diseases such as prostate cancer, bladder cancer, kidney cancer, benign prostatic hyperplasia (BPH), and kidney stones represent a significant global health burden. Over the past decade, data-driven approaches, particularly Artificial Intelligence (AI), have emerged as transformative tools in urology for clinical practice, diagnosis, preoperative planning, and patient management. In this systematic review, we examined published research on the applications of AI in urology and compared findings across diagnostic, prognostic, and interventional domains. Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) have enabled predictive modelling for prostate, bladder, and kidney cancer, facilitating early detection, risk stratification, and outcome prediction. AI-driven image analysis has enhanced the interpretation of ultrasound, CT, and MRI data, while robotic-assisted systems have improved surgical precision, reduced operating times, and provided intraoperative guidance. Beyond the operating room, personalized medicine and long-term patient monitoring have been supported by AI-based decision support systems, Chatbot, and wearable technologies. Despite these advancements, challenges remain in terms of data heterogeneity, algorithm transparency, clinical integration, and ethical considerations, particularly regarding privacy and bias. Our review highlights both the strengths and limitations of current AI applications in urology and underscores the future trajectory of AI-driven precision medicine to optimize outcomes and transform patient care.

1. Introduction

Urological diseases, including Benign Prostatic Hyperplasia (BPH), Bladder Cancer, Prostate Cancer, Renal Cell Carcinoma (RCC), Pediatric Urology, Renal Transplants, and Urolithiasis, represent a major health burden worldwide, affecting millions of patients of all age groups. BPH alone affects more than 200 million men worldwide, resulting in Lower Urinary Tract Symptoms (LUTS) that can have a substantial negative effect on quality of life and productivity.

Throughout the past ten years, AI has evolved into a game changer in urology with regards to diagnosis, prognosis or treatment planning and surgical decision-making. In early investigations (2018 to 2025), AI was tested in the interpretation of imaging, histopathological analysis and prediction of surgical outcomes. Computer-aided identification of imaging-based features in BPH histology and DL for urinary stone detection [1] Studies from 2018 to 2025 develop deeper into mechanisms: radiomics-based survival prediction in bladder prostate cancers (Takeda et al. 2024; Wang et al. 2025) explainable AI for prostate MRI. DL applied to pediatric ultrasound and hydronephrosis segmentation [4] and AI-determined risk stratification in renal transplantation [5]. In research related to bladder carcinoma, AI has been demonstrated to provide more accurate or at least similar predictions of mortality compared with classical statistical models and achieved over 80% accuracy [6, 7]. The number of publications dramatically increased in the past 7 years (2018–2025) regarding this topic. Computing power, datasets and imagery have been some of the biggest factors behind that, but most of the AI systems are still early in development and will need to be validated before they can become a part of clinical practices. AI technologies such as Machine Learning (ML), Deep Learning (DL), Radiomics, and Natural Language Processing (NLP) are showing the potential to address these challenges. With enhanced diagnostic accuracy up to 96.3% in histological diagnosis of BPH, advanced treatment response assessment at an early stage, and better patient stratification or CTA staging [8, 9].

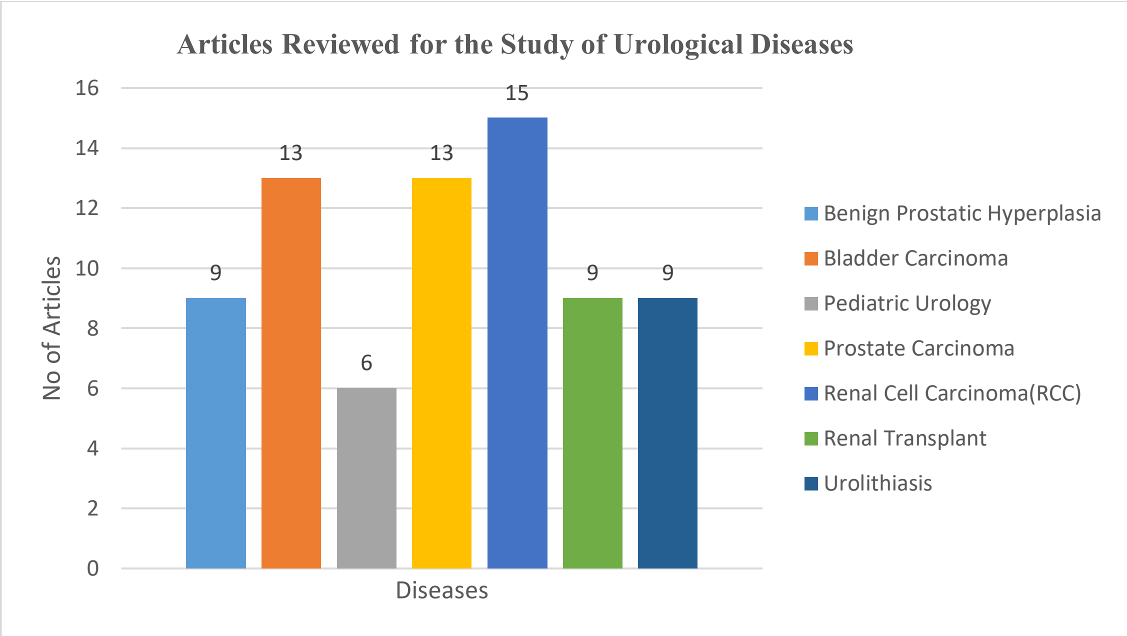
The purpose of this systematic review (2018-2025) is to provide a comprehensive overview of the potential use of AI in urological diseases such as BPH, Bladder Cancer, Prostate Cancer, RCC, Pediatric Urinary Stone Disease and underdevelopment, along with a comparison analysis of their diagnostic and prognostic accuracy when compared with traditional techniques. Review is despite many studies in the past few years; this field still suffers from existing heterogeneity of AI models and small sample size; the absence of multicenter testing implies a lack of generalizability and failure to translate an interesting finding into practice. Based on the current evidence, this review aims to describe opportunities of AI, adoption trends in AI and future prospects of AI in shaping precision urological study.

2. AI in Urology

Artificial Intelligence (AI) has found broad applications in urological studies, where imaging, pathology, and clinical data play a vital role in diagnosis and treatment. In Prostate Cancer, Convolutional Neural Networks (CNNs), U-Nets, and radiomics-based models are widely used for MRI interpretation, biopsy guidance and Gleason score prediction that achieving accuracies often above 90% [10, 11]. In Kidney Cancer, CT and MRI-based DL models such as CNNs and U-Nets have demonstrated accuracies up to 99% for classification, segmentation, and survival prediction [12, 13]. For Bladder Cancer, AI applications range from urine cytology analysis to radio genomic prediction models, with accuracies consistently around 90-95% [14, 15]. In stone disease, Support Vector Machines (SVMs), CNNs, and ensemble models like CatBoost have been used for CT stone detection, Percutaneous Nephrolithotomy (PCNL) and Retrograde Intrarenal Surgery (RIRS) outcome prediction, and complication risk analysis, with some models reaching up to 99% accuracy [1, 16]. Furthermore, in renal transplantation, ML models including ANNs, SVMs, XGBoost, and gradient boosting have been applied for donor-recipient matching, graft survival, and readmission prediction that achieving accuracies between 85-99% [17, 18]. Collectively, these advances demonstrate AI's transformative role in urology by improving diagnostic precision, enabling risk stratification, and supporting personalised treatment decisions.

The graphical representation (Mentioned in Graph No. 1) summarises a total of 74 AI-related urology studies distributed across seven major disease categories. The highest number of studies were conducted in Renal Cell Carcinoma (15 articles), reflecting the growing role of AI in tumour classification, segmentation, and survival prediction. Bladder carcinoma (13 articles) and Prostate carcinoma (13 articles) also show substantial research activity, emphasising AI's importance in cancer detection and staging. Moderate attention has been given to Benign Prostatic Hyperplasia (9 studies) and Urolithiasis (9 studies), focusing on diagnosis and surgical outcomes. Renal transplant (9 studies) represents a significant area, particularly in graft survival and donor-recipient matching. Pediatric urology (6 studies) remains underrepresented, signifying opportunities for future AI research. Overall, AI applications in urological-related diseases lead the research scenarios.

Graph No.1 Clinical and Research Consequences in Urological Studies



3. Urological Diseases Studies

3.1 Benign Prostatic Hyperplasia (BPH)

Benign Prostatic Hyperplasia (BPH) is one of the most common urinary tract disorders affecting men's health in a global and crucial problem of both clinical and research measures. The problem of patient outcomes has substantially improved, and a few accurate surgical decisions have been reported under the study of AI. Deep Learning (DL) strategy for prostate image analysis efficiently improved diagnostic efficacy to make BPH identification more successful. However, radiomics and machine learning progression have provided non-invasive and differential diagnoses. Figure 1 shows the advancing benign prostatic hyperplasia diagnosis and treatment flow.

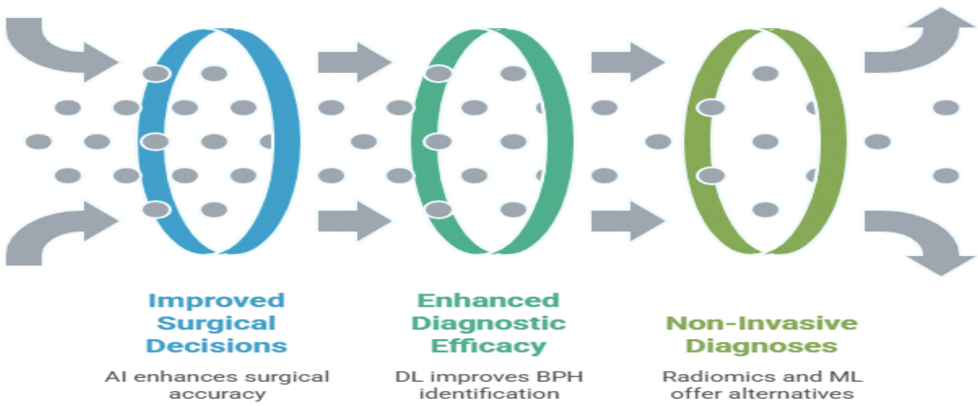


Figure:1 Advancing BPH Diagnosis and Treatment

Table No. 1: Comparative Performance of AI Models in Benign Prostatic Hyperplasia

Author (Year)	Objective	AI Models Used	Accuracy
Nazri et al. (2018) [19]	Automated detection and classification of BPH using imaging	VGG16 CNN	95%
Shah et al. 2022 [20]	Review of AI in BPH diagnosis and management	Fuzzy logic, Computer vision	90%, 96.3%
Chen et al. 2023 [21]	MRI radiomics for subtype prediction	SVM	87%
Zhang et al. 2023 [22]	Differentiating BPH vs PCa using DCE-MRI	Bi-directional CLSTM	92%
Wang et al. 2024 [23]	Biomarker identification for BPH	WGCNA + Random Forest	88%
Syafie and Rismayanti 2025 [24]	Automated diagnosis from prostate images	DenseNet121 (Transfer Learning)	94.1%
Lama et al. 2025 [25]	Differentiating BPH from PCa, outcome prediction	ML + DL on MRI, ultrasound, biomarkers	>90%
Wang et al. 2025b [11]	Predicting treatment response with WSI + MRI radiomics	ANN-MLP, RF, KNN	90%
Guo et al. 2025 [9]	Multimodal LLMs for cystoscopy interpretation	ChatGPT-4V, Claude 3.5	89%

Recent BPH studies clearly indicate a shift from monomodal deep learning models to multimodal and hybrid AI models. In mentioned Table No:1 prior work Nazri et al. (2018) demonstrated that imaging analysis with CNN, in particular VGG16, can be used for automated BPH detection with a high diagnostic accuracy 95%, proving that deep learning derivations are applicable in prostate imaging[19]. Further reviews and studies of methodology expanded on the AI paradigm Shah et al. (2022)[20] described high results for fuzzy logic and computer vision methods 90-96.3% in BPH diagnosis and treatment. Specialized modalities were further explored using radiomics and progressive modelling Chen et al. (2023)[21] applied MRI radiomics SVM to identify BPH subtypes 87%, and Zhang et al. (2023) [22] utilized bi-directional CLSTM on DCE-MRI to distinguish BPH from prostate cancer with an accuracy of 92%. Together, these studies represent a move towards more complex architectures that potentially can identify spatial progressive and textural biomarkers appropriate to prostate disease.

In comparative performance mentioned Table, No: 1 Recent development (2024-2025) reveals a promising direction in biomarker discovery, transfer learning, and multimodal fusion to enhance the reliability of diagnostics and clinical applicability. Wang et al. (2024) [23] applied WGCNA and Random Forest to screen out key molecular biomarkers related to BPH 88% accuracy which highlighted significance of omics-driven AI. Transfer learning also enhanced the development of imaging-based diagnosis [24] with DenseNet121 94.1%. Multimodal approaches combining MRI, ultrasound, histopathology, and biomarkers consistently attained >90% accuracy, effectively differentiating diseases and predicting outcomes [11, 25]. And while slightly lower performance 89% accuracy, the appearance of multimodal large language models for cystoscopy interpretation [26] signifies a paradigm shift towards explainable, clinician-interactive AI. Together these results indicate that CNN and radiomics models are still promising for BPH detection but BPH management in the future might invention in multimodal, explainable AI considering imaging, biomarkers and clinical context to guide precision urology [25, 27, 28].

3.2 Bladder Cancer (BC)

Bladder Cancer is among the most prevalent and recurrent malignancies worldwide, posing major challenges in diagnosis and treatment Jansen et al. 2020 [29]. Conventional modalities such as cystoscopy, histopathology, and imaging are limited by inter-observer variability and restricted predictive accuracy Bhambhvani et al. 2021 [30]. In recent years, AI technologies including DL, radiomics, and various ML approaches have been increasingly applied to improve diagnostic precision and prognostic evaluation. State-of-the-art AI-based studies have demonstrated significant advantages over traditional methods, offering enhanced accuracy and reproducibility in BC management Arita et al. 2025 [8]. Figure 2 shows management of bladder cancer treatment.

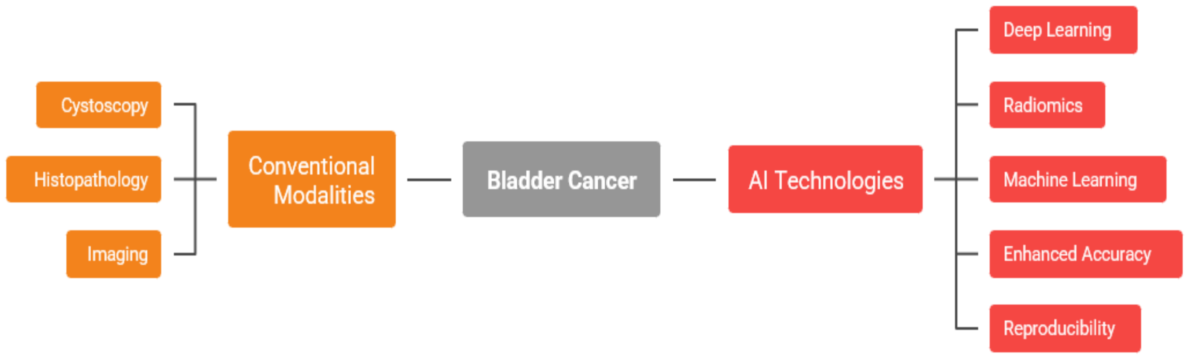


Figure 2: AI in bladder cancer management.

Table No. 2: Comparative performance of AI models in bladder cancer

Author (Year)	Objective	AI Models Used	Accuracy
Jansen et al. 2020 [29]	Tumor segmentation in NMIBC	U-Net + VGG16	74%
Bhambhvani et al. 2021 [30]	Prognosis prediction (OS, DSS) using SEER dataset (161,227 patients)	ANN	81%, 80%
Ślusarczyk et al. 2023 [6]	Prognostic modeling of T1 NMIBC (32,060 cases)	ANN vs Logistic Regression	79%, 73%
He et al. 2024 [31]	Prediction of muscle-invasive BC	Radiomics, Deep Learning	89%, 91%, 92%
Demir et al. 2024 [14]	Classification of blood & urine droplet patterns	ResNet-18 CNN (ImageNet pretrained)	97%, 95%
Liu et al. 2024 [15]	Urine cytology diagnosis with AIxURO	DL segmentation	93.9%
Alqahtani et al. 2024 [32]	Grading and performance classification	MLP, Logistic Regression	94%, 88%
Zhao et al. 2024 [33]	Prognostic prediction using RNA-seq data	ANN	~80%
Arita et al. 2025 [8]	mpMRI with delta-radiomics and SVM	Radiomics, SVM	97%, 96%
Dai et al. 2025 [7]	Post-cystectomy survival prediction	6 ML models	87%
Xiao et al. 2025 [34]	Lymphovascular invasion prediction	ResNet50 CNN	82%
Zhao et al. 2025 [35]	Multi-modality BC diagnosis	GHL-Net + Ensemble ML	95%, 92%
Kostakopoulos et al. 2025 [36]	Cytology & histology-based BC diagnosis	U-Net + ResNet50	91-90%

Progress in non-muscle-invasive muscle-invasive BC research Mentioned in Table No:2 in particular illustrates how AI is increasingly being applied to imaging, pathology, cytology, and large-scale clinical data. Early segmentation-based approaches e.g. Jansen et al. (2020) [29] combined U-Net and VGG16 for NMIBC tumor segmentation with reasonable accuracy 74%, indicating also the difficulties of early lesion segmentation. Population-level prognostic modeling utilizing registry data demonstrated improved performance Bhambhvani et al. (2021) [30] applied ANN on the SEER dataset consisting of more than 161,000 patients to estimate overall and disease-specific survival with an accuracy of 80-81%, and Ślusarczyk et al. (2023) [6] found that ANN surpassed logistic regression accuracy of 79% vs. 73% in predicting T1 NMIBC. Recent works have attempted to combine radiomics and deep learning techniques with He et al. (2024) [31] attaining a high accuracy 89-92% of predicting muscle-invasive and Demir et al. (2024) [14] reaching great classification performances 95-97% accuracy with a pretrained ResNet-18 on blood and urine droplet patterns. The results demonstrate the advantage of deep CNNs and feature enhancement in complex BC phenotyping.

In Table No:2 comparative performance 2024-2025 published studies analyses suggest an orientation toward multimodal system AI and outcome prediction models. Urine cytology AI-based tools like AIxURO reached 93.9% accuracy in the real-life diagnostic examination [37] and grading and performance prediction models based on MLP and logistic regression reached accuracy of 94% [32]. RNA-seq based genomic prognostication using ANN attained moderate accuracy ~80% [33] in line with the promise and complexity of omics prediction. High-implementation of AI.

performance radiomics was followed by Arita et al. (2025) [38], who demonstrated that delta-radiomics analysis with SVM on mpMRI showed an accuracy of 96-97% and ensemble or gradient-boosted models yielded favorable survival prediction after cystectomy accuracy 87[7]. Lymphvascular invasion was predicted by CNN-based models 82% accuracy [39] and multimodal diagnostic systems comprising imaging, cytology and histology attained 90-95% accuracy [35, 40]. Taken together these results in the literature suggest that DL and ensemble methods especially when cross-modally integrated, provide the best, most clinically translatable performances for the diagnosis, grading and prognosis of bladder cancer, highlighting the increasing importance to render these models explainable and prospectively validated[29, 35, 41].

3.3 Pediatric Urology (PU)

Pediatric urology is a vital subspecialty where AI is only beginning to be applied for diagnosis, surgical planning, and prediction of long-term outcomes in children. Distinct adults, children face unique anatomical and developmental challenges, such as vesicoureteral reflux, hydronephrosis, and congenital urinary abnormalities, which require timely recognition and treatment. Globally, pediatric urology faces critical issues including a shortage of trained pediatric urologists and radiologists, limited access to advanced imaging in low-resource settings, and variability in diagnostic standards across regions. Figure 3 shows the pediatric urology challenges, improved pediatric urology and

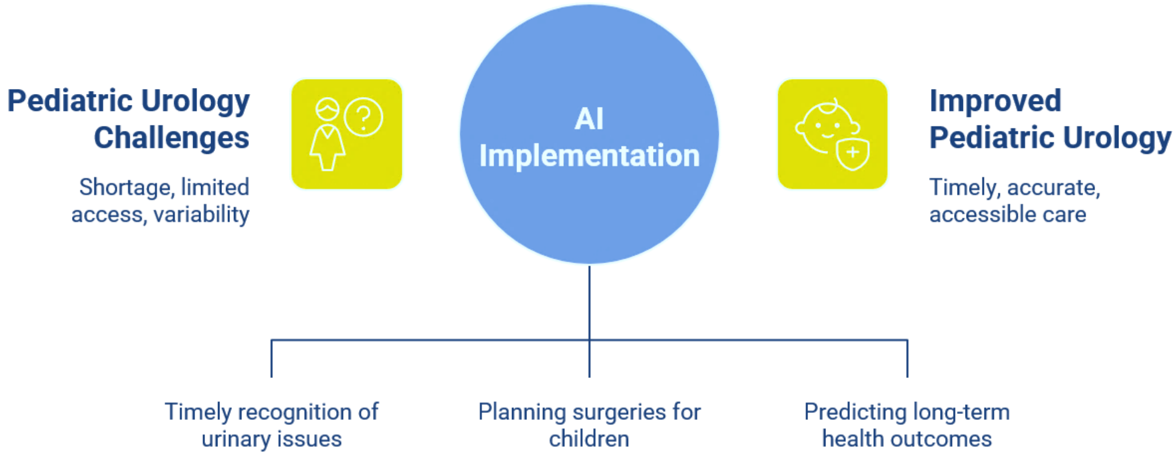


Figure 3: AI enhances pediatric urology

Table No. 3: Comparative performance of AI models in pediatric urology

Author (Year)	Objective	AI Models Used	Accuracy
Khondker et al. 2022 [42]	Diagnosis of hydronephrosis, Posterior Urethral Valves (PUV) and VUR	SVM, CNN, ANN, CNN hybrids	96%, 98% (PUV, ANN), 97% (VUR, CNN hybrids)
Tsai et al. 2022 [43]	Pediatric renal ultrasound for hydronephrosis detection	ResNet-50	94.1%
Song et al. 2022 [4]	Hydronephrosis quantification	DeepLabV3+, Ensemble models	DSC >91%
Chowdhury et al. 2024 [44]	Prediction of bladder overactivity and VUR	CNN + Random Forest	92%
Aboud et al. 2025 [45]	Classification of hypospadias	CNN + Logistic Regression	90-93%
Nedbal et al. 2025 [16]	Prediction of sepsis and intraoperative complications in URS	CatBoost, Random Forest	99%, 97.7%

In mentioned Table No:3 indicate an increasing success of AI in paediatric and functional urology which incorporated under bladder dysfunctions and ureteric drainage obstruction or complication-related disorders. "Early multi-model approaches" section 3.1 Khondker et al. (2022) [46] considered SVM, CNN, ANN and hybrid CNN frameworks for the detection of hydronephrosis, Posterior Urethral Valves (PUV) and Vesicoureteral Reflux (VUR). Tsai et al. (2022) [43] also utilized a deep residual network ResNet-50 on a data set of pediatric renal ultrasound for differentiating VUR to reconstructors and represent the relevance of transfer severely learning for ultrasound-based hydronephrosis screening. song et al. (2022) proposed an approach towards quantitative analysis of using DeepLabV3+ and collective segmentation models with a Dice similarity coefficient of >91% repeating AI's potential to offer reproducible and objective severity grading as opposed to simple binary classification.

A Table No:3 the recent studies (2024-2025) demonstrate a distinct movement toward predictive modeling and perioperative risk assessment with the potential utility of AI now growing from diagnosis to clinical decision-making. Chowdhury et. al (2024) [44] achieved an accuracy of 92% combining CNN features with Random Forest classifiers to classify bladder overactivity and VUR validating the superiority of hybrid deep classical ML approaches. Central Nervous System (CNS) anomaly classification was also improved with AI incorporation Aboud et al. (2025) [45] specified 90-93% accuracy with CNNs combined with logistic regression for hypospadias gradation. In particular Nedbal et al. (2025) [47] attained outstanding predictive performance (99% for sepsis, 97.7% for intraoperative complications) employing CatBoost and RF on pit points which highlights the significance of ensemble learning based on structured perioperative data. Taken together these results indicate that although CNN-based models currently dominate imaging-based tasks ensemble and hybrid AI models appear to be playing an increasingly important role in risk prediction and outcome forecasting which further suggests that AI can serve as a catalytic tool in the ulation of pediatric and functional urology care [16, 46, 48].

3.4 Prostate Cancer (PC)

Prostate Cancer is the other frequently occurring cancer in men and it´s difficult to correctly diagnose and treat with today's tools as Prostate-Specific Antigen (PSA) tests, MRI scans and biopsies can give unclear or mixed results [49]. AI is currently applied to enhance these aspects, since the decision accuracy of MRI images, biopsy images, or blood/molecular data analysis is stronger based on directly to improve overall detection sensitivity and specificity by analyzing MRI and biopsy imaging, as well as blood data or molecular with a higher level of reliability than once thought possible. [50, 51]. Several of the new AI models have delivered impressive results, outperforming even doctors in detection of aggressive cancers and helping to minimize human errors [2, 52]. Furthermore, the use of AI also increases reliability and facilitates the synergistic integration of all different aspects for a more personalized treatment [53, 54] Explaining these recent studies is essential to get a sense of how good AI is, what are the benefits it provides and what problems such as small datasets or not external testing yet must be reported to use AI on daily clinical care [55, 56]. Figure 4 shows improving diagnosis and treatment for prostate cancer with AI.

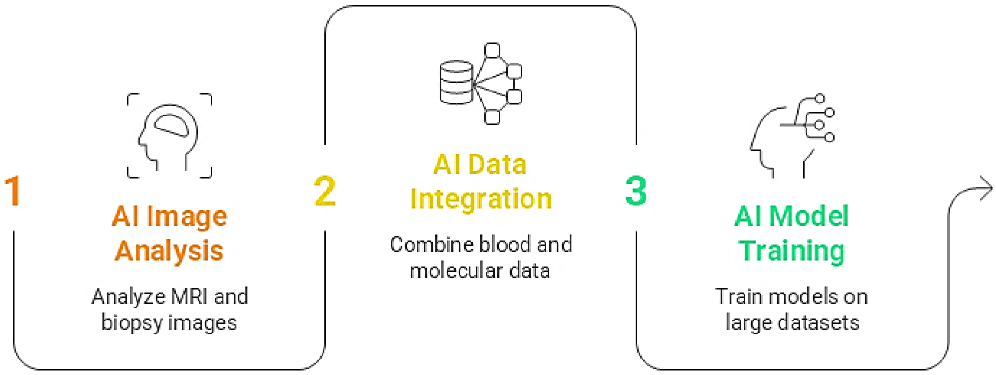


Figure 4: Improving prostate cancer diagnosis with AI

Table No. 4: Comparative performance of AI models in Prostate Cancer

Author (Year)	Objective	AI Models Used	Accuracy
Gunashekar et al.(2022) [10]	Tumor segmentation on mpMRI using histology	U-Net CNN	62%
Sunoqrot et al. (2022) [56]	Review of AI in prostate MRI (segmentation, csPCa detection)	CNNs, nnU-Net	Up to 95%
Gabriele et al. (2023) [49]	Serum-based prostate cancer prediction	Random Forest (RF)	93%
Li et al. (2024) [55]	TRUS biopsy image classification	Feature Pyramid Network (FPN)	93%
Talaat et al. (2024) [54]	mpMRI interpretation	Improved ResNet50	96.1%

Takeda et al. (2024) [2]	PSA, ultrasound, MRI integration for PCa detection	CNN + SVM	88%
Yang et al. (2025) [50]	Prostate cancer detection with efficient learning	Green U-shaped Learning (GUSL)	>90%
Urso et al. (2025) [53]	PSMA PET staging	Radiomics + ML	91%
Wang et al. (2025) [52]	Predict Gleason ≥7	2.5D DL + Radiomics	92%
Zhong et al. (2025) [51]	RNA signature validation	Nine-gene RNA signature	91%
Arafa et al. (2025) [57]	Prostate cancer detection	ML (Extra Trees, RF)	96%
Taguelmimt et al. (2025) [58]	MRI + clinical data integration	Hybrid ML/DL	>82%
Badiezadeh et al [59]	PCa detection	Mamba H-vmunet	92%

In Mentioned Table No:4 exactness the fact that AI provides a powerful tool to improve PCa detection, segmentation and risk stratification 9-79 the recent literature indicates an evolution in the methodology with increasing performance as models consider multimodal data and more advanced architectures. Early segmentation studies based on histology-guided mpMRI, e.g., Gunashekar et al. (2022) [10], achieved rather meagre results with U-Net 62% accuracy, highlighting the underlying difficulties in accurately describing tumour boundaries. In contrast general overview and benchmarking studies such as Sunoqrot et al. (2022) [56] demonstrated that state-of-the-art CNN-based models as well as NNU-Net based models can reach up to 95% accuracy in segmentation and clinically significant PCa detection. In addition to imaging structured data-based models had good predictive performance and Gabriele et al. (2023) [49] reported a 93% accuracy with RF on serum biomarkers as well as Li et al. (2024) [55] and Talaat et al. (2024) [54] who presented an accuracy of 93% and 96.1% respectively using advanced CNNs FPN and enhanced ResNet50 for TRUS biopsy and mpMRI reading. These results in accord highlight the need for architectural designs to be closely followed with task-specific feature extraction in order to represent high-fidelity PCa.

The Table No:4 2024-2025 studies' interpretations demonstrate a definitive outcome toward multimodal integration optimized learning methods, and molecular profiling for improved clinical utility. Multimodal methods such as PSA with ultrasound and MRI Takeda et al., 2024 [2] reached good results 88% accuracy by the way and learning strategies i.e. Green U-Shaped Learning (GUSL) achieved on PCa detection accuracy of over 90% Yang et al., 2025 [60]. The radiomics-based methods for staging and grading also improved predicting power with accuracies of PSMA PET staging and Gleason ≥7 prediction of 91-92% reported by Urso et al. (2025) [61] and Wang et al. (2025c) [52], respectively. Molecular AI such as RNA-signature validation Zhong et al. (2025) [51] attained 91% accuracy substantiating the increasing significance of genomics. Integrative ML/DL strategies that combine imaging with clinical variables including ensemble and hybrid models similarly report impressive accuracy in 82-96% accuracy (Arafa et al., 2025 [57]; Taguelmimt et al. (2025) [58] and novel architectures like Mamba H-vmunet further yield superior detection performance that achieved 92% accuracy Badiezadeh et al [59]. In summary the findings suggest that multimodal hybrid and explainable AI system designs appear to have the most potential for clinical Prostate Cancer diagnosis and risk stratification among the other investigated systems [50, 54, 56].

3.5 Renal Cell Cancer (RCC)

RCC is the most common form of kidney cancer approximately 85-90% cases of renal neoplasm globally. It is a serious health problem the incidence of which is increasing and with poor survival in advanced stages. Early detection is critical because localized RCC can frequently be cured surgically and the 5-yr survival rate of metastatic disease is substantially lower. Current diagnostic media such as CT, MRI and histopathology while effective. This global burden signifies the increasing importance of AI based tools to make accurate diagnosis and patient management decisions in RCC [62, 63]. In figure 5 shows AI in renal cell cancer pathway.

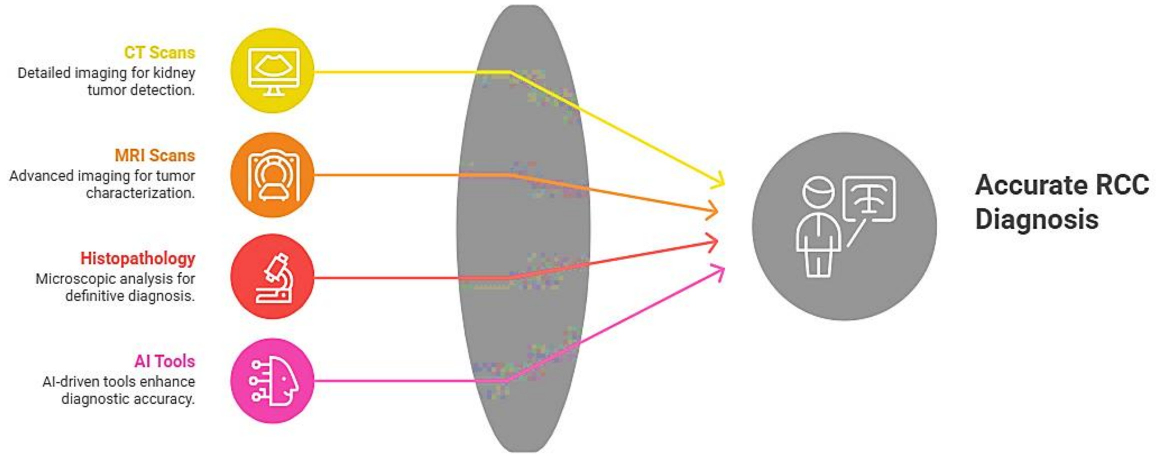


Figure 5: AI in renal cell cancer pathway.

Table No. 5: Comparative performance of AI models in Renal Cell Cancer

Author (Year)	Objective	AI Models Used	Accuracy
Baghdadi et al. 2020 [12]	RCC classification from CT	Deep Learning (DL)	95%
Nikpanah et al. 2021 [64]	Differentiate ccRCC from oncocytoma (MRI)	Deep Learning (DL)	90%
Qiliang Peng1 2021 [65]	Survival prediction using molecular features	Molecular feature integration	73–86%
Giulietti et al. 2021 [62]	Survival prediction using molecular features	Molecular feature integration	73–86%
Kowalewski et al. 2022 [66]	RCC detection from imaging	CNN	Up to 98%
Toda et al. 2022 [67]	CT-based multi-center RCC detection	U-Net	93%
Zhao et al. 2023 [13]	Kidney segmentation & classification (CT)	CNN	99%, 90.6%
Lin et al. 2023 [68]	Intraoperative imaging analysis	CNN	97%
Distante et al. 2023 [69]	Histopathology-based RCC diagnosis	AI on histopathology	Up to 99%
Knudsen et al. 2024 [70]	Survival prediction using genomic data	Genomics-based AI	93%
Song and Park 2024 [71]	Treatment decision support	Gradient Boosting	95%
Du et al. 2025 [72]	MRI fusion for RCC classification	Fusion CNN	86%
Dai et al. 2025 [73]	Survival prediction across datasets	AI survival prediction models	70–80%
Najem et al. 2025 [63]	Metastasis prediction	Radiogenomic AI	93%
Gouravani et al. 2025 [74]	Meta-analysis of AI in RCC	CNN, U-Net, Collaborative ML	>90% (up to 99%)

Current progress mentioned Table:5 in Renal Cell Cancer (RCC) highlights the growing contribution of AI within the domains of imaging histopathology, genomics and clinical decision support. Early imaging-based classification research studies for example Baghdadi et al. (2020) [12] and Nikpanah et al. (2021)

[64] demonstrated that deep learning architectures could predict RCC subtypes accurately on CT and MRI with 90-95% accuracy. Molecularly driven survival prediction studies by Qiliang Peng (2021) [65] and Giulietti et al. (2021)[62] showed slightly less favourable results 73-86% underlining the complexity and heterogeneity of RCC biology. Following work in imaging-related practice demonstrated significant performance enhancements. Kowalewski et al. (2022)[66] announced a maximum of 98% accuracy in RCC classification based on CNNs and strong generalizability 93% accuracy with multi-center CT data in the study of Toda et al. (2022) [67] by U-Net. Highly optimized CNNs based frameworks pushed the results even further Zhao et al. (2023) [13] reached accuracy 99% and 90.6% for kidney segmentation and RCC classification respectively while Lin et al. (2023) [68] introduced a 97% accuracy for intraoperative imaging analysis. Histopathology-based AI approached near-expert performance with Distante et al. (2023) [69] reporting accuracies up to 99% confirming the robustness of deep learning in microscopic tissue characterization.

In mentioned Table:5 from recent research (2024-2025) now suggest integrated predictive, clinically meaningful AI tools. Genomics-based survival prediction improved significantly with Knudsen et al. (2024) [70] reported an accuracy of 93% suggesting that more refined molecular feature selection and larger data sets allow for improved prognostic reliability. Decentralized learning-enabled treatment decision support based on gradient boosting also showed superior performance 95% accuracy. Song & Park, (2024) [71] testify to AI's potential in Going beyond diagnosis. Multimodal fusion methods based on MRI features demonstrated modest but encouraging performance that achieved 86% accuracy, Du et al., (2025)[72], whereas cross-dataset survival analysis exposed the persistent issue of over-generalization 70-80% accuracy, Dai et al. (2025)[73]. Radio genomic schemes for metastasis prediction attained a good accuracy 93%, Najem et al. (2025) [63] and thus demonstrate that imaging phenotypes can be effectively associated with molecular data. An exhaustive meta-study by Gouravani et al. (2025)[74] validated that CNNs, U-Net as well as collaborative ML models typically achieve >90% accuracy with the highest performance nearing 99% accuracy thus the finding that multimodal. AI methods are also the most robust and clinically translatable approach for detection, prognostication and treatment prediction of RCC is further reinforced [12, 69, 74].

3.6 Renal Transplant

AI in renal transplantation is important as it provides solutions to key problems such as diagnosis, prognosis and patient management. New studies demonstrate the ability of AI to predict rejection, long-term graft survival and hospital readmission and other donor recipient risk factors. [75] trained an AI model for precise detection of kidney transplant rejection and [76] created dynamic prediction models for renal survival based on international multicohort data. Similarly, [5] enlist Explainable AI (XAI) models for 30-day readmissions prediction while [77] used AI to predict long-term outcomes. In figure 6 shows AI enhances renal transplantation through advanced solutions.

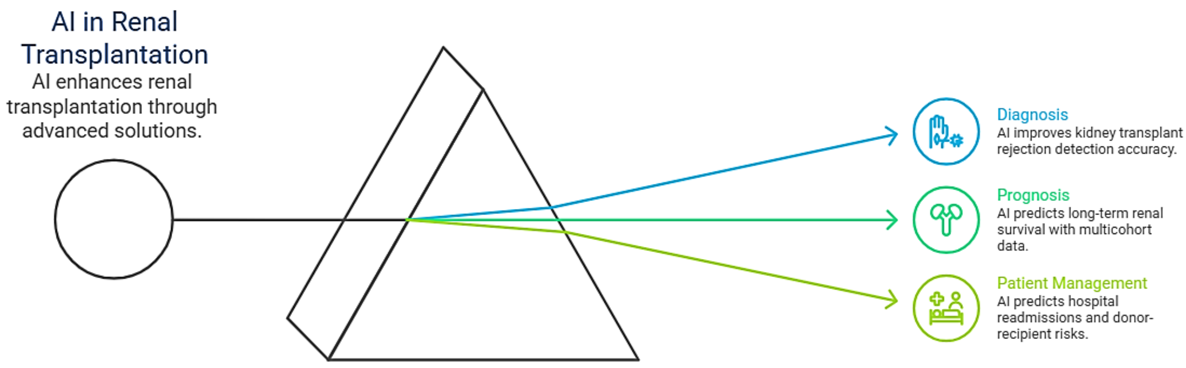


Figure 6: AI role in renal transplantation

Table No. 6: Comparative performance of AI Models in Renal Transplant

Author (Year)	Objective	AI Models Used	Accuracy
Burlacu et al. 2020 [17]	Predictive modeling in transplantation	ANN, SVM	92%
Thongprayoon et al. 2020 [78]	Big data applications for graft survival & allocation	ML (Big Data models)	85-90%
Raynaud et al. 2021 [76]	Longitudinal follow-up survival prediction	Bayesian joint model	86%
Thongprayoon et al. 2023 [79]	Risk stratification in diabetic donor kidney transplants	Consensus clustering	92%
Badrouchi et al. 2023 [77]	Compare 35 algorithms for graft survival prediction	XGBoost + RF feature selection	90%
Kotsifa and Mavroeidis 2024 [80]	Review of AI in transplantation applications	Multiple AI models	80-95%
Fayzullin et al. 2024 [75]	Renal biopsy pathology analysis	CNN	92-95%
He et al. 2025 [18]	Three-decade summary of AI in transplantation	Gradient Boosting, survival modeling	Up to 99%
Alnazari et al. 2025 [5]	30-day readmission prediction	Interpretable Gradient Boosting	80%

In Table No:6 initial studies by Burlacu et al. (2020) [17] and Thongprayoon et al. (2020) [78] demonstrated that prognostic models based on ANN, SVM and other high-dimensional ML methods are able to predict transplant outcomes and graft survival with accuracies up to 85-92%, confirming the potential of AI-based decision assistance. Then, Raynaud et al. (2021) [76] developed Bayesian joint models to jointly model longitudinal clinical data for improving survival predictiveness. Since 2023, there has been a growing trend towards ensemble and clustering-based techniques e.g., Thongprayoon et al. (2023)[79] utilized consensus clustering for better risk stratification in diabetic donor transplants, meanwhile, Badrouchi et al. (2023) [77] showed that XGBoost with Random Forest (RF) as feature selection outperformed 35 other algorithms, with an accuracy of approximately 90%. Systematic reviews also supported that different AI algorithms can attain high predictive performance 80-95% on transplantation-related tasks [80].

Table No:6 the advancement of performance could be attributed to the improvement of data fusion, model optimization and more attention to clinic related index. Currently, deep learning methods CNN-based renal biopsy, etc. obtain the accuracy of 92-95%, comparable to that of expert pathologists and minimizing inter-observer variability[75]. Large-scale surveys and meta-analyses demonstrate that current ensemble and survival-based approaches could obtain near-perfect accuracy e.g., up to 99% in a retrospective scenario [81]which further underline their applicability towards precision medicine. Yet, recent trends towards explainable and interpretable AI such as interpretable gradient boosting within the context of 30-day readmission prediction [5] highlight the importance of a trade-off between predictive performance and explainability for clinical trust and adoption. The literature points to ensemble and explainable AI models as the best candidates to enable safe, accurate and clinically applicable kidney transplantation decision-support systems.

3.7 Urolithiasis

The use of AI in urolithiasis is growing to assist in the diagnosis, prediction of treatment, and evaluation of surgical outcomes. Deep learning-based detection system, such as CNNs on CT images have been shown to demonstrate high accuracy for stone detection [1] and ML based predictors are also more effective in postoperative outcome prediction of procedures like Percutaneous Nephrolithotomy (PCNL) and Retrograde Intrarenal Surgery (RIRS) compared with conventional scoring systems [82, 83]. AI is also useful in determining ureteroscopy complications [84]. Furthermore, several other studies are shedding light on AI's increasing contribution to ESWL, with ML and CT-based techniques showing improved accuracy in the prediction of treatment success than that provided by clinical assessment [85–87]. New models such as Urinary Stones Classification net (USCnet) appear to hold the potential for preoperative stratification of stone type and risk of infection [88]. In figure 7 shows role of AI in urolithiasis management to improve the diagnosis and treatment.

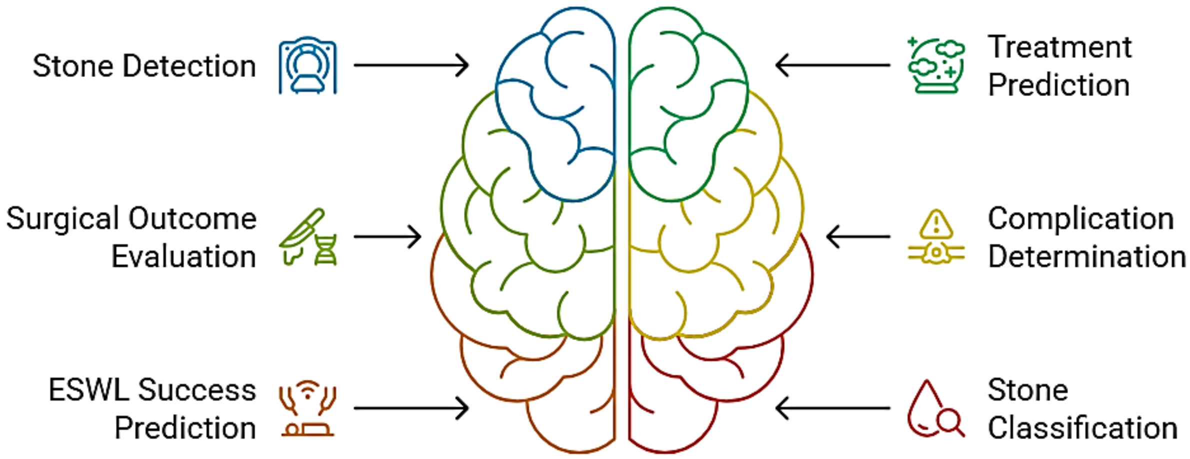


Figure 7: AI's Role in Urolithiasis Management

Table No. 7: Comparative performance of AI Models in Urolithiasis

Author (Year)	Objective	AI Models Used	Accuracy
Parakh et al. 2019 [1]	CT stone detection	Cascading CNN with GrayNet	95%
Aminsharifi et al. 2020 [82]	Predict PCNL outcomes	SVM	92%
Wu et al. 2023 [89]	Infection stone detection	AdaBoost	87.7%
Nakamae et al. 2024 [85]	Stone classification	SVM	74%
Song et al. 2024 [86]	Genetic-based stone prediction (SNV)	CNN (ResNet50)	92.4%
Lee et al. 2025 [83]	Predict stone-free status after RIRS	Cox regression (univariate + multivariable)	77.1%
Talyshinskii et al. 2025 [87]	Systematic analysis of AI in urolithiasis	Multiple AI models	>80%
Nedbal et al. 2025 [84]	Predict fURSL complications (6,669 cases)	CatBoost	99.2%
Pan et al. 2025 [88]	CT + clinical data integration (USCnet framework)	USCnet framework	87%

Recent studies on urolithiasis/kidney stone disease reveal an advancing role of artificial intelligence from imaging-based detection models to outcome prediction and complication risk stratification. In mentioned Table No: 7 previous work Parakh et al. (2019)[1] demonstrated the potential of deep learning for stone detection on CT, cascaded CNN using GrayNet reached 95% accuracy, whereas

Aminsharifi et al. (2020)[82] proved that classical machine learning (SVM) can be utilized to accurately forecast percutaneous nephrolithotomy (PCNL) outcomes 92% accuracy. Later research varied targets as well as data typology Wu et al. (2023)[89] engaged adaptive boosting for infection stone detection with 87.7% accuracy in contrast, Nakamae et al. (2024)[85] obtained poorer results 74% accuracy by applying SVM for the stone classification, revealing the difficulty in multiclass stone composition analysis. New more complex data modalities also appeared, including genetic-based prediction, where Song et al. (2024)[86] used a ResNet50 CNN model on Single Nucleotide Variant (SNV) data with an accuracy of 92.4% underscoring the expanding importance of molecular AI in imaging.

The studies in 2025 describes a decisive movement to integrated clinical decision support and prediction of perioperative risk. Traditional statistical survival modeling continued to be applicable in Table No: 7 Lee et al. (2025)[83] reported modest accuracy 77.1% for stone-free prediction after retrograde intrarenal surgery employing Cox regression, highlighting the usefulness of interpretability but also performance limitations in this regard. Ensemble learning approaches on large-scale were usually more predictive, especially Nedbal et al. (2025)[84], which brought the best result with 99.2% accuracy by Cat-Boost for predicting the flexible Ureteroscopic Lithotripsy (fURSL) complications with 6,669 cases, showing the superior performance of gradient-boosting methods on structured clinical data. Multimodal integration became more popular as well; Pan et al. (2025)[88] integrated CT imaging and clinical features with the USCnet model 87% accuracy, indicative of an inclination for holistic modeling of patients. The systematic review by Talyshinskii et al. (2025) confirmed that the majority of modern AI models in urolithiasis exhibit >80% accuracy, further validating the statement that ensemble and multimodal AI approaches are most likely to provide robust, clinically scalable solutions for detecting stones, predicting outcomes and managing complications [1, 82, 84].

Table No. 8: Comparative table of AI applications in Urology

Disease	Reviewed Articles	AI Models Used	Key Applications	Performance (Accuracy)
BPH	9	CNN, SVM, RF, CLSTM, GPT-4, DenseNet, ANN-MLP	Diagnosis, subtype prediction, cystoscopy analysis, drug response prediction	95%,
Bladder Cancer	13	U-Net, VGG16, ANN, SVM, CNN, GBM, XGBoost	Tumor grading, prognosis, survival prediction, LVI/metastasis detection	87-96%
Pediatric Urology	6	CNN, RF, ANN, SVM, CatBoost, ResNet-50	Hydronephrosis detection, VUR/PUV diagnosis, hypospadias detection, surgical planning	92-99%
Prostate Cancer	13	U-Net, ResNet, CNN, RF, Extra Trees, Multimodal DL	Tumor detection, biopsy/MRI assistance, staging, aggressiveness prediction	96%,
RCC (Renal Cell Carcinoma)	15	CNN, U-Net, ResNet, GBM, Radiogenomics DL	Tumor detection, subtype classification, prognosis, survival modelling	95%,
Renal Transplant	9	ANN, SVM, RF, XGBoost, CNN, Bayesian Models	Rejection prediction, graft survival, readmission risk	79-95%
Urolithiasis	9	CNN, SVM, RF, CatBoost, USCnet	Stone detection, type classification, surgical outcome prediction, ESWL success prediction	95-99%

CNN: Convolutional Neural Network, SVM: Support Vector Machine, RF: Random Forest, CLSTM: Convolutional Long Short-Term Memo, GPT-4: Generative Pre-trained Transformer-4, DenseNet: Densely Connected Convolutional Network, ANN-MLP: Artificial Neural Network – Multi-Layer Perceptron, U-Net: CNN-based segmentation model, VGG16: Visual Geometry Group-16, GBM: Gradient Boosting Machine, XGBoost: Extreme Gradient Boosting, CatBoost: Categorical Boosting, ResNet-50: Residual Neural Network-50, Multimodal DL: Multimodal Deep Learning, Radiogenomics DL: Radiogenomics-based Deep Learning, USCnet: Urolithiasis Stone Classification Network. ANN: Artificial Neural Network.

In this review highlights the applications of various AI models in the most common urological diseases. (Mentioned in Table No. 8) BPH articles working models such as CNN, SVM, RF, and GPT-4 for diagnosing, predicting subtypes, analyzing cystoscopy and drug response with approximately 95% of accuracy. In Bladder Cancer researchers used U-Net, VGG16, ANN and boosting models to tumor grading prognosis and metastasis detection with 87-96% of accuracy. A Pediatric Urology studies most commonly applied CNNs, RF and ResNet-50 to detect hydronephrosis, diagnose VUR/PUV and support surgical planning with an accuracy of 92-99%. For Prostate Cancer articles with models such as U-Net, ResNet and multimodal DL were dedicated to tumor detection MRI/biopsy assistance, staging and aggressiveness prediction with an average accuracy of 96%. Renal Cell Carcinoma (RCC) utilizing CNN, U-Net, ResNet and radio genomics for tumor detection, classification and survival modeling also reported an accuracy approaching 95%. In renal transplant used ANN, SVM, RF and Bayesian models to predict rejection and graft survival as well as risk for readmission advising 79-95% accuracy. Urolithiasis research applied CNN, RF, SVM, CatBoost and USCnet with accuracy of 95-99% for detecting stones, classifying types and predicting surgical outcomes. AI models demonstrate high performance consistently in diverse urologic applications.

4. Future Considerations

Future consideration of AI in urology should focus on moving beyond small single-center retrospective studies toward large multicenter trials with standardized datasets to ensure generalizability. Integration of radiomics, genomics, and multimodal DL can improve precision in diagnosis, prognosis, and treatment planning across BPH, Bladder Cancer, Pediatric Urology, Prostate Cancer, RCC, Renal Transplantation and Urolithiasis [1, 2, 19, 29, 45, 72, 75].

Future models should also address explainability and interpretability to build trust among clinicians, while incorporating AI-assisted decision support tools into routine workflows. Ethical considerations including data privacy, fairness, and patient consent must be ensured before clinical translation becomes routine practice.

5. Conclusion

Urology has progressed rapidly with AI now assisting doctors in better diagnosing, predicting outcomes and treatment planning for conditions such as BPH, Bladder Cancer, Prostate Cancer, RCC, Pediatric Urology issues, Renal Transplants and Urolithiasis. The findings from several studies demonstrate high accuracy of diagnostics and very often to exceeds 90-95% in some cases even it is higher than that tools like cystoscopy, symptom scores and statistical models [6–8]. These findings underscore the effective applicability of AI to moderate human-related mistakes and enable customized, evidence-based medicine. However, even with these successes, current AI research are still challenged with significant limitations like small datasets, single-center studies, absence of external validation and heterogeneity of employed algorithms. Many models are well-performing in experiments but they fail to get robust results between different population and hospitals due to different demographical distributions [18, 44, 76]. Standardization multicenter validation and seamless integration into clinical workflow for the general population of urology patients will be major hurdles for safe implementation of AI in urology.

In future, doctors and AI will partner to detect diseases early select the most effective treatments and track patients over time. Future directions are anticipated toward large-scale collaborative datasets, explainable AI models and ethical guidelines for trust and transparency [2, 5, 52]. Solving these challenges will enable AI to transition from research to routine clinical practice driving the future of precision urology and impacting outcome for millions of patients globally.

6. Limitations

Many studies use small or single-center datasets which reduces the generalizability of results. Lack of external validation and standardized data pipelines makes it hard to compare models across studies. Some AI systems work like "black boxes," offering predictions without clear explanations which limits clinical trust. Data privacy and ethical issues also remain concerns especially when sharing sensitive medical records. Most studies are retrospective and very few have been tested in real-world multi-center clinical trials. These factors slow down the safe adoption of AI in everyday urological practice.

References:

1. Parakh A, Lee H, Lee JH, et al (2019) Urinary stone detection on ct images using deep convolutional neural networks: Evaluation of model performance and generalization. Radiol Artif Intell 1:. https://doi.org/10.1148/ryai.2019180066
2. Takeda H, Akatsuka J, Kiriyama T, et al (2024) Clinically Significant Prostate Cancer Prediction Using Multimodal Deep Learning with Prostate-Specific Antigen Restriction. Current Oncology 31:7180–7189. https://doi.org/10.3390/curroncol31110530
3. Wang B, Gong Z, Su P, et al (2025) Multi-machine learning model based on radiomics features to predict prognosis of muscle-invasive bladder cancer. BMC Cancer 25:. https://doi.org/10.1186/s12885-025-14279-6
4. Song SH, Han JH, Kim KS, et al (2022) Deep-learning segmentation of ultrasound images for automated calculation of the hydronephrosis area to renal parenchyma ratio. Investig Clin Urol 63:455–463. https://doi.org/10.4111/icu.20220085
5. Alnazari N, Alanazi OI, Alosaimi MO, et al (2025) Development of explainable artificial intelligence based machine learning model for predicting 30-day hospital readmission after renal transplantation. BMC Nephrol 26:. https://doi.org/10.1186/s12882-025-04128-w
6. Ślusarczyk A, Zapała P, Olszewska-Ślusarczyk Z, Radziszewski P (2023) The prediction of cancer-specific mortality in T1 non-muscle-invasive bladder cancer: comparison of logistic regression and artificial neural network: a SEER population-based study. Int Urol Nephrol 55:2205–2213. https://doi.org/10.1007/s11255-023-03655-5
7. Dai L, Ye K, Yao G, et al (2025) Using machine learning for predicting cancer-specific mortality in bladder cancer patients undergoing radical cystectomy: a SEER-based study. BMC Cancer 25:. https://doi.org/10.1186/s12885-025-13942-2
8. Arita Y, Kwee TC, Akin O, et al (2025) Multiparametric MRI and artificial intelligence in predicting and monitoring treatment response in bladder cancer. Insights Imaging 16
9. Guo L, Zuo Y, Yisha Z, et al (2025) Diagnostic performance of advanced large language models in cystoscopy: evidence from a retrospective study and clinical cases. BMC Urol 25:. https://doi.org/10.1186/s12894-025-01740-8

10. Gunashekar DD, Bielak L, Hägele L, et al (2022) Explainable AI for CNN-based prostate tumor segmentation in multi-parametric MRI correlated to whole mount histopathology. Radiation Oncology 17:. https://doi.org/10.1186/s13014-022-02035-0

11. Wang J, Tang W, Zhu J, et al (2025) Predicting the pathological subdiagnosis of benign prostatic hyperplasia with MRI radiomics: A noninvasive approach. VIEW 6:. https://doi.org/10.1002/VIW.20240092

12. Baghdadi A, Aldhaam NA, Elsayed AS, et al (2020) Automated differentiation of benign renal oncocytoma and chromophobe renal cell carcinoma on computed tomography using deep learning. BJU Int 125:553–560. https://doi.org/10.1111/bju.14985

13. Zhao T, Sun Z, Guo Y, et al (2023) Automatic renal mass segmentation and classification on CT images based on 3D U-Net and ResNet algorithms. Front Oncol 13:. https://doi.org/10.3389/fonc.2023.1169922

14. Demir R, Koc S, Ozturk DG, et al (2024) Artificial intelligence assisted patient blood and urine droplet pattern analysis for non-invasive and accurate diagnosis of bladder cancer. Sci Rep 14:. https://doi.org/10.1038/s41598-024-52728-7

15. Liu TJ, Yang WC, Huang SM, et al (2024) Evaluating artificial intelligence–enhanced digital urine cytology for bladder cancer diagnosis. Cancer Cytopathol 132:686–695. https://doi.org/10.1002/cncy.22884

16. Nedbal C, Gauhar V, Adithya S, et al (2025) A novel predictive method for URS and laser lithotripsy using machine learning and explainable AI: results from the FLEXOR international database. World J Urol 43:. https://doi.org/10.1007/s00345-025-05551-2

17. Burlacu A, Iftene A, Jugrin D, et al (2020) Using Artificial Intelligence Resources in Dialysis and Kidney Transplant Patients: A Literature Review. Biomed Res. Int. 2020

18. He YJ, Liu PL, Wei T, et al (2025) Artificial intelligence in kidney transplantation: a 30-year bibliometric analysis of research trends, innovations, and future directions. Ren. Fail. 47

19. Nazri A, Mazlan N, Muharam F (2018) Research article Penyek: Automated brown planthopper detection from imperfect sticky pad images using deep convolutional neural network. PLoS One 13:. https://doi.org/10.1371/journal.pone.0208501

20. Shah M, Naik N, Hameed BZ, et al (2022) Current Applications of Artificial Intelligence in Benign Prostatic Hyperplasia. Turk. J. Urol. 48:262–267

21. Chen Y, Xu H, Xu H, et al (2023) Exploration of diagnostic biomarkers, microenvironment characteristics, and ursolic acid's therapeutic effect for benign prostate hyperplasia. Int J Biol Sci 19:4242–4258. https://doi.org/10.7150/ijbs.85739

22. Zhang Y, Li W, Zhang Z, et al (2023) Differential diagnosis of prostate cancer and benign prostatic hyperplasia based on DCE-MRI using bi-directional CLSTM deep learning and radiomics. Med Biol Eng Comput 61:757–771. https://doi.org/10.1007/s11517-022-02759-x

23. Wang YX, Wang J, Liu J, Zhu HX (2024) Immune-related diagnostic markers for benign prostatic hyperplasia and their potential as drug targets. Front Immunol 15:. https://doi.org/10.3389/fimmu.2024.1516362

24. Syafie L, Rismayanti N (2025) Automated Diagnosis of Benign

Prostatic Hyperplasia Using Deep Learning on RGB Prostate Images. International Journal of Artificial Intelligence in Medical Issues 3:41–50. https://doi.org/10.56705/ijaimi.v3i1.251

25. Lama J, Winograd J, Codelia-Anjum A, et al (2025) AI for BPH Surgical Decision-Making: Cost Effectiveness and Outcomes. Curr. Urol. Rep. 26

26. Guo L, Zuo Y, Yisha Z, et al (2025) Diagnostic performance of advanced large language models in cystoscopy: evidence from a retrospective study and clinical cases. BMC Urol 25:. https://doi.org/10.1186/s12894-025-01740-8

27. Nazri A, Mazlan N, Muharam F (2018) Research article Penyek: Automated brown planthopper detection from imperfect sticky pad images using deep convolutional neural network. PLoS One 13:. https://doi.org/10.1371/journal.pone.0208501

28. Shah M, Naik N, Hameed BZ, et al (2022) Current Applications of Artificial Intelligence in Benign Prostatic Hyperplasia. Turk. J. Urol. 48

29. Jansen I, Lucas M, Bosschieter J, et al (2020) Automated Detection and Grading of Non–Muscle-Invasive Urothelial Cell Carcinoma of the Bladder. American Journal of Pathology 190:1483–1490. https://doi.org/10.1016/j.ajpath.2020.03.013

30. Bhambhvani HP, Zamora A, Shkolyar E, et al (2021) Development of robust artificial neural networks for prediction of 5-year survival in bladder cancer. Urologic Oncology: Seminars and Original Investigations 39:193.e7-193.e12. https://doi.org/10.1016/j.urolonc.2020.05.009

31. He C, Xu H, Yuan E, et al (2024) The accuracy and quality of image-based artificial intelligence for muscle-invasive bladder cancer prediction. Insights Imaging 15

32. Alqahtani A, Bhattacharjee S, Almopti A, et al (2024) Radiomics-based machine learning approach for the prediction of grade and stage in upper urinary tract urothelial carcinoma: a step towards virtual biopsy. Int J Surg 110:3258–3268. https://doi.org/10.1097/JS9.0000000000001483

33. Zhao F, Zhang K, Ma L, Huang Y (2024) Identification of epithelial-related artificial neural network prognostic models for the prediction of bladder cancer prognosis through comprehensive analysis of single-cell and bulk RNA sequencing. Heliyon 10:. https://doi.org/10.1016/j.heliyon.2024.e34632

34. Xiao B, Lv Y, Peng C, et al (2025) Deep learning feature-based model for predicting lymphovascular invasion in urothelial carcinoma of bladder using CT images. Insights Imaging 16:. https://doi.org/10.1186/s13244-025-01988-6

35. Zhao H, Miao C, Zhu Y, et al (2025) An end-to-end interpretable machine-learning-based framework for early-stage diagnosis of gallbladder cancer using multi-modality medical data. BMC Cancer 25:. https://doi.org/10.1186/s12885-025-14462-9

36. Kostakopoulos N, Argyropoulos V, Bellos T, et al (2025) Artificial Intelligence and Novel Technologies for the Diagnosis of Upper Tract Urothelial Carcinoma. Medicina (Lithuania) 61

37. Liu TJ, Yang WC, Huang SM, et al (2024) Evaluating artificial intelligence–enhanced digital urine cytology for bladder cancer diagnosis. Cancer Cytopathol 132:686–695. https://doi.org/10.1002/cncy.22884

38. Arita Y, Kwee TC, Akin O, et al (2025) Multiparametric MRI and

artificial intelligence in predicting and monitoring treatment response in bladder cancer. Insights Imaging 16

39. Xiao B, Lv Y, Peng C, et al (2025) Deep learning feature-based model for predicting lymphovascular invasion in urothelial carcinoma of bladder using CT images. Insights Imaging 16:. https://doi.org/10.1186/s13244-025-01988-6

40. Kostakopoulos N, Argyropoulos V, Bellos T, et al (2025) Artificial Intelligence and Novel Technologies for the Diagnosis of Upper Tract Urothelial Carcinoma. Medicina (Lithuania) 61

41. He C, Xu H, Yuan E, et al (2024) The accuracy and quality of image-based artificial intelligence for muscle-invasive bladder cancer prediction. Insights Imaging 15

42. Khondker A, Kwong JCC, Malik S, et al (2022) The state of artificial intelligence in pediatric urology. Frontiers in Urology 2

43. Tsai MC, Lu HHS, Chang YC, et al (2022) Automatic Screening of Pediatric Renal Ultrasound Abnormalities: Deep Learning and Transfer Learning Approach. JMIR Med Inform 10:. https://doi.org/10.2196/40878

44. Chowdhury AT, Salam A, Naznine M, et al (2024) Artificial Intelligence Tools in Pediatric Urology: A Comprehensive Review of Recent Advances. Diagnostics 14

45. Aboud M, M Kadhim S, Radif M (2025) Bridging AI and Pediatric Urology: The Role of the Comprehensive Hypospadias Classification and Surgical Complexity Score (CHC-SCS) Integration into a Low-Resources Pediatric Surgery Setting. American Journal of Clinical Medicine Research 13:32–39. https://doi.org/10.12691/ajcmr-13-2-3

46. Khondker A, Kwong JCC, Malik S, et al (2022) The state of artificial intelligence in pediatric urology. Frontiers in Urology 2

47. Nedbal C, Gauhar V, Herrmann T, et al (2025) Simulation-based training in minimally invasive surgical therapies (MIST): current evidence and future directions for artificial intelligence integration—a systematic review by EAU endourology. World J. Urol. 43

48. Song SH, Han JH, Kim KS, et al (2022) Deep-learning segmentation of ultrasound images for automated calculation of the hydronephrosis area to renal parenchyma ratio. Investig Clin Urol 63:455–463. https://doi.org/10.4111/icu.20220085

49. Gabriele C, Aracri F, Prestagiacomo LE, et al (2023) Development of a predictive model to distinguish prostate cancer from benign prostatic hyperplasia by integrating serum glycoproteomics and clinical variables. Clin Proteomics 20:. https://doi.org/10.1186/s12014-023-09439-4

50. Yang J, Magoulianitis V, Alexander CAC, et al (2025) GUSL: A Novel and Efficient Machine Learning Model for Prostate Segmentation on MRI

51. Zhong X, Yang Y, He H, et al (2025) Integrating multi-cohort machine learning and clinical sample validation to explore peripheral blood mRNA diagnostic biomarkers for prostate cancer. Cancer Cell International 25:. https://doi.org/10.1186/s12935-025-03788-w

52. Wang Y, Xin Y, Zhang B, et al (2025) Assessment of prostate cancer aggressiveness through the combined analysis of prostate MRI and 2.5D deep learning models. Front Oncol 15:. https://doi.org/10.3389/fonc.2025.1539537

53. Urso L, Badrane I, Manco L, et al (2025) The Role of Radiomics and

Artificial Intelligence Applied to Staging PSMA PET in Assessing Prostate Cancer Aggressiveness. J. Clin. Med. 14

54. Talaat FM, El-Sappagh S, Alnowaiser K, Hassan E (2024) Improved prostate cancer diagnosis using a modified ResNet50-based deep learning architecture. BMC Med Inform Decis Mak 24:. https://doi.org/10.1186/s12911-024-02419-0

55. Li S, Ye X, Tian H, et al (2024) An artificial intelligence model based on transrectal ultrasound images of biopsy needle tract tissues to differentiate prostate cancer. Postgrad Med J 100:228–236. https://doi.org/10.1093/postmj/qgad127

56. Sunoqrot MRS, Saha A, Hosseinzadeh M, et al (2022) Artificial intelligence for prostate MRI: open datasets, available applications, and grand challenges. Eur Radiol Exp 6:. https://doi.org/10.1186/s41747-022-00288-8

57. Arafa MA, Farhat KH, Aly SF, et al (2025) Prediction of prostate biopsy outcomes at different cut-offs of prostate-specific antigen using machine learning: a multicenter study. J Egypt Natl Canc Inst 37:. https://doi.org/10.1186/s43046-025-00265-3

58. Taguelmimt K, Andrade-Miranda G, Harb H, et al (2025) Towards more reliable prostate cancer detection: Incorporating clinical data and uncertainty in MRI deep learning. Comput Biol Med 194:. https://doi.org/10.1016/j.compbiomed.2025.110440

59. Badiezadeh A, Malekmohammadi A, Mirhassani M, et al Segmentation Strategies in Deep Learning for Prostate Cancer Diagnosis: A Comparative Study of Mamba, SAM, and YOLO

60. Yang J, Magoulianitis V, Alexander CAC, et al (2025) GUSL: A Novel and Efficient Machine Learning Model for Prostate Segmentation on MRI

61. Urso L, Badrane I, Manco L, et al (2025) The Role of Radiomics and Artificial Intelligence Applied to Staging PSMA PET in Assessing Prostate Cancer Aggressiveness. J. Clin. Med. 14

62. Giulietti M, Cecati M, Sabanovic B, et al (2021) diagnostics The Role of Artificial Intelligence in the Diagnosis and Prognosis of Renal Cell Tumors. https://doi.org/10.3390/diagnostics

63. Najem EJ, Shaikh MJS, Shinagare AB, Krajewski KM (2025) Navigating advanced renal cell carcinoma in the era of artificial intelligence. Cancer Imaging 25

64. Nikpanah M, Xu Z, Jin D, et al (2021) A deep-learning based artificial intelligence (AI) approach for differentiation of clear cell renal cell carcinoma from oncocytoma on multi-phasic MRI. Clin Imaging 77:291–298. https://doi.org/10.1016/j.clinimag.2021.06.016

65. Qiliang Peng1 2,*, Yi Shen3,*, Kai Fu4,*, Zheng Dai4, Lu Jin4, Dongrong Yang4, Jin Zhu4 (2021) Artificial intelligence prediction model for overall survival of clear cell renal cell carcinoma based on a 21-gene molecular prognostic score system. Aging 13:7361–7381. https://doi.org/10.18632/aging.202594

66. Kowalewski KF, Egen L, Fischetti CE, et al (2022) Artificial intelligence for renal cancer: From imaging to histology and beyond. Asian J. Urol. 9:243–252

67. Toda N, Hashimoto M, Arita Y, et al (2022) Deep Learning Algorithm for Fully Automated Detection of Small (≤4 cm) Renal Cell Carcinoma in Contrast-Enhanced Computed Tomography Using a Multicenter Database. Invest Radiol 57:327–333.

https://doi.org/10.1097/RLI.0000000000000842

68. Lin Z, Yang W, Zhang W, et al (2023) Recognizing pathology of renal tumor from macroscopic cross-section image by deep learning. Biomed Eng Online 22:. https://doi.org/10.1186/s12938-023-01064-4

69. Distante A, Marandino L, Bertolo R, et al (2023) Artificial Intelligence in Renal Cell Carcinoma Histopathology: Current Applications and Future Perspectives. Diagnostics 13

70. Knudsen JE, Rich JM, Ma R (2024) Artificial Intelligence in Pathomics and Genomics of Renal Cell Carcinoma. Urologic Clinics of North America 51:47–62

71. Song WH, Park M (2024) RCC-Supporter: supporting renal cell carcinoma treatment decision-making using machine learning. BMC Med Inform Decis Mak 24:. https://doi.org/10.1186/s12911-024-02660-7

72. Du G, Chen L, Wen B, et al (2025) Deep learning-based prediction of tumor aggressiveness in RCC using multiparametric MRI: a pilot study. Int Urol Nephrol 57:1365–1379. https://doi.org/10.1007/s11255-024-04300-5

73. Dai H, Zhao K, Zhao Y, et al (2025) Machine learning model in multi-omics perspective demystifies the prognostic significance of crotonylation heterogeneity in clear cell renal cell carcinoma. BMC Urol 25:229. https://doi.org/10.1186/s12894-025-01914-4

74. Gouravani M, Shahrabi Farahani M, Salehi MA, et al (2025) Diagnostic performance of artificial intelligence in detection of renal cell carcinoma: a systematic review and meta-analysis. BMC Cancer 25

75. Fayzullin A, Ivanova E, Grinin V, et al (2024) Towards accurate and efficient diagnoses in nephropathology: An AI-based approach for assessing kidney transplant rejection. Comput Struct Biotechnol J 24:571–582. https://doi.org/10.1016/j.csbj.2024.08.011

76. Raynaud M, Aubert O, Divard G, et al (2021) Dynamic prediction of renal survival among deeply phenotyped kidney transplant recipients using artificial intelligence: an observational, international, multicohort study. Lancet Digit Health 3:e795–e805. https://doi.org/10.1016/S2589-7500(21)00209-0

77. Badrouchi S, Bacha MM, Ahmed A, et al (2023) Predicting long-term outcomes of kidney transplantation in the era of artificial intelligence. Sci Rep 13:. https://doi.org/10.1038/s41598-023-48645-w

78. Thongprayoon C, Kaewput W, Kovvuru K, et al (2020) Promises of big data and artificial intelligence in nephrology and transplantation. J. Clin. Med. 9

79. Thongprayoon C, Miao J, Jadlowiec CC, et al (2023) Differences between Kidney Transplant Recipients from Deceased Donors with Diabetes Mellitus as Identified by Machine Learning Consensus Clustering. J Pers Med 13:. https://doi.org/10.3390/jpm13071094

80. Kotsifa E, Mavroeidis VK (2024) Present and Future Applications of Artificial Intelligence in Kidney Transplantation. J. Clin. Med. 13

81. He YJ, Liu PL, Wei T, et al (2025) Artificial intelligence in kidney transplantation: a 30-year bibliometric analysis of research trends, innovations, and future directions. Ren. Fail. 47

82. Aminsharifi A, Irani D, Tayebi S, et al (2020) Predicting the Postoperative Outcome of Percutaneous Nephrolithotomy with Machine Learning System: Software

Validation and Comparative Analysis with Guy's Stone Score and the CROES Nomogram. J Endourol 34:692–699. https://doi.org/10.1089/end.2019.0475

83. Lee HY, Tung YH, Elises JC, et al (2025) Machine learning-based prediction of stone-free rate after retrograde intrarenal surgery for lower pole renal stones. World J Urol 43:. https://doi.org/10.1007/s00345-025-05762-7

84. Nedbal C, Gauhar V, Adithya S, et al (2025) Predictors and associations of complications in ureteroscopy for stone disease using AI: outcomes from the FLEXOR registry. Urolithiasis 53:. https://doi.org/10.1007/s00240-025-01763-8

85. Nakamae Y, Deguchi R, Nemoto M, et al (2024) AI prediction of extracorporeal shock wave lithotripsy outcomes for ureteral stones by machine learning-based analysis with a variety of stone and patient characteristics. Urolithiasis 52:. https://doi.org/10.1007/s00240-023-01506-7

86. Song R, Liu B, Xu H (2024) CT-based deep learning model for predicting the success of extracorporeal shock wave lithotripsy in treating ureteral stones larger than 1 cm. Urolithiasis 52:. https://doi.org/10.1007/s00240-024-01656-2

87. Talyshinskii A, Juliebø-Jones P, Tzelves L, et al (2025) Current state of AI for shockwave lithotripsy: a systematic review from YAU and EAU endourology. World J. Urol. 43

88. Pan J, Chen H, Huang C, et al (2025) Development and evaluation of USCnet: an AI-based model for preoperative prediction of infectious and non-infectious urolithiasis. World J Urol 43:. https://doi.org/10.1007/s00345-025-05492-w

89. Wu Y, Mo Q, Xie Y, et al (2023) A retrospective study using machine learning to develop predictive model to identify urinary infection stones in vivo. Urolithiasis 51:. https://doi.org/10.1007/s00240-023-01457-z