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THE ROLE OF ARTIFICIAL INTELLIGENCE IN MODERN UROLOGY: A SYSTEMATIC OVERVIEW

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ABSTRACT

Introduction and Purpose: Artificial intelligence (AI) is a revolutionary tool assisting diagnostics treatment, and prognosis of treatment outcomes in various medical fields, including urology. The purpose of this review is to outline contemporary uses of AI techniques in clinical urology and evaluate their effect on the quality of patient care, considering limitations and future research directions.
State of Knowledge: AI uses in urology consist of, inter alia, evaluation of radiological and histopathological images (for example, in prostate cancer diagnosis), treatment prediction outcomes (e.g., bladder cancer), individualization of treatment, improvement in surgical planning decisions and assistance in perioperative care. Machine learning algorithms are applied to recognize pathological changes with high accuracy, often like the assessments of experts. Natural language processing (NLP) algorithms are utilized in the analysis of medical documentation and streamlining information flow. Despite quick development, complete integration of AI into daily clinical practice faces barriers related to data quality, model interpretability, and legal and ethical aspects.
Summary: Artificial intelligence has excellent potential for enhancing diagnostic and therapeutic accuracy in urology. Nonetheless, additional clinical research, standardization and validation with multi-center datasets are required. The appropriate implementation of AI in urological practice can lead to personalized, more efficient patient management.

KEYWORDS
Urology, Artificial Intelligence, Machine Learning, Prostatic Neoplasms, Diagnostic Imaging, Clinical Decision-Making

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Introduction

The technological progress in medicine in recent decades has led to an exponential growth in accessible medical data and the creation of sophisticated methods of analysis.[1] In this situation, artificial intelligence, encompassing machine learning (ML) and deep learning (DL), has emerged as a fundamental tool assisting diagnostic, therapeutic, and prognostic procedures in a wide range of clinical specialties.[2] Urology, being a dynamically evolving medical discipline, has particularly gained from the implementation of contemporary IT technologies in clinical practice.[3,4]

AI uses in urology cover a wide spectrum—from analysis of medical imaging (MRI, CT, ultrasound) in the diagnostics of prostate cancer, via decision support during surgery, to automated processing of clinical and laboratory data in order to determine the risk of disease recurrence or effectiveness of treatment.[5] AI is applied in numerous areas of urology, including oncological urology, gynecological urology, and pediatric urology, making diagnostic and therapeutic procedures more efficient relative to conventional methods.[6,7]

Objectives of the Work

The objective of this work is to provide an overview of the state of the art in the utilization of AI tools in clinical urology. The most important accomplishments, the prospective advantages, limitations, and challenges of introducing AI in this area will be presented. Special consideration will be given to applications in urogenital cancer diagnosis, treatment planning, and processing of big patient data.

Materials and Methods

For the composition of this article, databases including PubMed, Google Scholar, and ResearchGate were queried with the following terms: Urology; Artificial Intelligence; Machine Learning; Prostatic Neoplasms; Diagnostic Imaging; Clinical Decision-Making in relation to AI.

Current State of Knowledge

The application of AI in urology is increasingly widespread in both clinical practice and scientific research. Thanks to processing large datasets and analyzing medical images, AI supports diagnostics, treatment outcome prediction, therapeutic decision-making, and patient monitoring.[3-7] Below is an overview of the current knowledge according to selected conditions.

Prostate Gland Cancer (Prostate)

Diagnostics

Prostate cancer is the most common malignant tumor in men in developed countries. Due to tumor heterogeneity and challenges in differentiating clinically significant cases from benign changes, AI has found broad application in diagnostics. Deep learning models analyze multiparametric MRI (mpMRI) images, enabling automatic detection of suspicious lesions with accuracy comparable to experienced radiologists.[8-12] Additionally, AI supports the evaluation of histopathological specimens (digital pathology), automating classification according to the Gleason scale. Deep learning-based models, such as convolutional neural networks, analyze entire histopathological images (whole-slide images) and can assign the appropriate Gleason category with accuracy comparable to or exceeding that of urological pathologists. One system, Deep Learning System (DLS), achieved 71.7% concordance with expert opinions (95% CI 67.9–75.3%), significantly higher than general pathologists (58.0%).[13] Another system based on the 'Carcino-Net' approach showed significant improvement in classifying prostate biopsy samples, offering precise segmentation and Gleason pattern assessment.[14] Studies from 2020 confirmed that automated systems achieve diagnostic effectiveness comparable to experts, with a kappa above 0.90.[15] Moreover, using AI tools to support pathologists significantly improved agreement—median kappa increased from 0.799 to 0.872 ($p = 0.019$), illustrating the synergy between humans and machines.[16] For tumors classified in the PI-RADS scale category 3, which indicates uncertainty in confirming or excluding disease, machine learning models based on data such as age, prostate-specific antigen (PSA), prostate volume, PSA density, and previous biopsies facilitate decisions about whether to perform a prostate biopsy or continue clinical observation without it.[17,18]

Treatment

AI algorithms considering patient age, PSA level, biopsy results, MRI data, and other clinical factors assist in decision-making between active surveillance, radical treatment, and focal therapy.[19] In robotic surgery, AI-supported systems enable precise planning and real-time tracking of surgical tools, improving safety and efficiency in procedures such as robot-assisted radical prostatectomy.[20] An additional application of AI could be the assessment of the risk of postoperative complications, such as incontinence, allowing for patient qualification into appropriate risk groups and significantly individualizing rehabilitation processes.[21]

Bladder Cancer

Bladder cancer has a high rate of recurrence, up to 50–70% for non-invasive bladder cancer. Thus, patients need frequent and expensive follow-up investigations, most commonly cystoscopy.[22] Contemporary AI systems assist with cystoscopy image analysis—algorithms based on neural networks evaluate texture, color, and architecture of mucosal lesions, allowing automatic lesion suspect detection. For instance, Mask R-CNN model with ResNeXt-101-32×8d-FPN backbone was evaluated on 10,991 infrared and white light images with sensitivity of 95%, specificity of 93.7%, and diagnostic accuracy of 94.1%—comparable or better than physicians' results.[23] AI also assists with the analysis of urine cytology and novel molecular assays such as cfDNA tests. Multi-omics cfDNA analysis from urine (mutation load, mutational burden, and copy number profiling) by random forest machine learning had a sensitivity of 87% for residual disease (MRD) detection, demonstrating great potential for early detection and monitoring of bladder cancer.[24]

Predictive models assessing recurrence and progression risk of bladder cancer, initially based on classical clinical scales like EORTC and CUETO, are now being improved with machine learning methods. Deep learning approaches demonstrate higher risk stratification accuracy than traditional tables.[25] Classifiers such as support vector machines (SVM) and random forests predict non-muscle invasive bladder cancer (NMIBC) recurrences within two years with over 90% accuracy.[26] In immunotherapy, particular attention is paid to genetic signatures based on fibroblast gene expression combined with CD8+ lymphocyte presence. These models better predict responses to BCG and PD-1/PD-L1 inhibitors, potentially improving patient outcomes.[27] Further studies, including the UROMOL2016 cohort, confirmed that multi-gene signatures may indicate benefits from BCG and alternative protein therapies.[28] Immunological and proteomic analyses enable identification of patients most likely to benefit from immune checkpoint inhibitors in advanced bladder cancer.[29] Such approaches represent a clear step toward personalized urology: therapy selection based on individual molecular-immunological profiles can increase treatment efficacy, reduce unnecessary side effects, and improve clinical outcomes.

Kidney Cancer

Kidney nodules are usually found incidentally on routine imaging, including ultrasound, CT, or MRI. The significant clinical challenge is the reliable differentiation of benign changes, for example, angiomyolipoma (AML), from malignant tumors, such as clear cell renal cell carcinoma (ccRCC) and less frequent subtypes like medullary renal carcinoma.[30-32] In recent years, there has been a great role for machine learning and deep learning models in the diagnostics of renal tumor imaging. Radiomic analysis—quantitative feature extraction such as texture, shape, vascular patterns, and signal intensity distribution—allows better differentiation of tumor types, significantly aiding clinical decision-making.[33,34] These models not only differentiate between benign and malignant lesions but also permit exact identification of renal cell carcinoma subtypes, which are highly relevant for treatment planning and prognosis prediction.[35] Such diagnostic aids enhance accuracy and substantially decrease unnecessary biopsies and inappropriate surgical procedures, as well as reduce diagnosis time and increase radiologists' efficiency.

In therapy, AI models are increasingly affecting therapeutic choices, particularly between partial and radical nephrectomy. Algorithms interpret imaging information, taking into account parameters such as tumor location, size, shape, and relationship with important anatomical structures like renal vessels and the collecting system, in order to forecast whether partial nephrectomy will be safe and efficacious or whether radical nephrectomy is required, and in this way preserve renal function and quality of life.[36-38]

Urinary System Stones

Urinary stones are prevalent and recurrent, impacting a considerable percentage of the population, with incidence on the increase globally as a result of lifestyle, diet, and aging societies.[42] One of the main clinical challenges is the effective and swift diagnosis of stones, particularly in urgent conditions such as renal colic. AI, most notably deep neural networks (CNN), has a growing significant part in the analysis of CT and ultrasound images. Major successes comprise:

- Stone detection: A CNN model trained on non-contrast CT data had 86% sensitivity with 0.5 false positives per scan (AUC = 0.95) and very good volume measurement agreement (r2 = 0.95). A further cascade CNN method on CT images had AUC = 0.954, sensitivity 94%, and specificity 96%.[44]
- Size and location measurement: CT-based algorithms (e.g., U-Net + CNN classifier) identify stones with millimeter precision, while volumetric segmentation achieves 0.95 precision and sensitivity.[44]

Application in USG

AI is also being utilized in the diagnosis of kidney stones from ultrasound, which—although less sensitive than CT—is safe, cheap, and universally available. Deep learning algorithms, particularly convolutional neural networks (CNN), have the potential to automatically detect stones on ultrasound based on echogenicity, acoustic shadowing, and position.[45-47] This enhances diagnostic sensitivity, decreases diagnosis time, and minimizes subjective interpretation error, particularly among less experienced diagnosticians. These programs can also measure stone size and quantity, aiding in subsequent therapeutic planning.

Moreover, multimodal imaging data-trained classification models facilitate segmentation and classification by stone size, location, and structure. These algorithms aid treatment planning, including ESWL versus ureteroscopy, by expediting diagnosis, reducing interpretative discrepancies, decreasing unwarranted intervention, and streamlining diagnostic timelines in the setting of acute colic.[48,49] Not only does automating the process expedite diagnosis, but it also eliminates human errors in image interpretation, particularly relevant in emergency room and screening diagnostics. Moreover, AI has the capability to follow recurrent stone formers by comparing sequential imaging studies and detecting interval changes over time, informing interventional treatment or conservative management changes.

AI algorithm application in CT and USG image analysis improves the accuracy of detection of small stones and assists in clinical classification, resulting in more individualized and efficient therapy. Stone composition (e.g., calcium oxalate, uric acid) is also predicted using machine learning, facilitating therapy planning and prevention.[50]

Predictive AI models aid in decision-making on the optimal stone treatment, such as ESWL, ureteroscopy (URSL), or percutaneous nephrolithotomy (PCNL). ML algorithms and radiomics evaluate clinical information (stone size, location, morphometric characteristics, procedural history) and imaging parameters (e.g., Hounsfield units density) to predict the probability of successful stone clearance and the risk of failure or complications. This enables:

- ESWL efficacy prediction: a radiomics model had an AUC of 0.91 for the first ESWL sessions and 0.76 for further sessions, which would guide method selection.[51]
- Pre dicting stone-free rates following PCNL: radiomics and clinical information models achieve an AUC of 0.85 with approximately 78% accuracy, facilitating patient qualification for the procedure.[52]
- Evaluating risks of complication and treatment success: neural network analyses provide 81–98% sensitivity and accuracy in the prediction of stone-free status, transfusion requirement, or further procedures.[53]

These systems render diagnostics quicker, more accurate, minimize ineffective interventions, and decrease complication risks, particularly in acute colic attacks.

By automating image analysis, diagnosis speed increases, human errors decrease, and personalized treatment approaches become feasible. AI can also predict stone composition, supporting tailored therapy and prevention strategies.[50]

Lower Urinary Tract Symptoms (LUTS)

LUTS, or lower urinary tract symptoms, present numerous diagnostic difficulties since early complaints are subjective in nature. These symptoms most commonly arise due to benign prostatic hyperplasia, overactive bladder, or incontinence. Diagnostics are based on subjective evaluations and urodynamic investigations. AI algorithms interpret micturition diary data, uroflowmetry reports, and urine sensor recordings (e.g., wearable sensors), making it possible to detect disease-specific patterns.[54-57] Moreover, natural language processing (NLP) is employed to retrieve information from medical records.[58]

AI is also becoming more involved in diagnostics as well as in individualizing treatment for LUTS. In pharmacotherapy or behavioral therapy, algorithms based on clinical information (age, sex, type of symptoms, severity, comorbidities, prior responses) can foresee the probability of efficacy of certain medications (e.g., alpha-blockers, anticholinergics, antimuscarinics, beta-3 agonists) and the risk of side effects.[59] This optimizes drug choice by physicians and minimizes trial-and-error intervals.

In more severe cases, e.g., bladder overactivity (OAB) or incontinence, AI predicts the response to neuromodulation treatments (e.g., sacral nerve stimulation) or surgery (e.g., TVT/TOT sling placement, reconstructive operations).[60] Clinical, biomechanical (e.g., urodynamics), and behavioral data-driven predictive models can identify patients with the highest potential to respond to invasive treatments.[61]

Additionally, AI systems are increasingly used for continuous monitoring of LUTS patients via mobile apps and wearable sensors, enabling remote control of treatment effects and dynamic therapy adjustments. Algorithms analyze micturition patterns, reported symptoms, and medication interactions in real-time.[62,63]

Challenges and Limitations of AI Implementation in Urology

In spite of its enormous potential and encouraging research outcomes, widespread implementation of AI in clinical routine is hampered by important limitations and challenges. Knowledge of these barriers is essential for successful and safe implementation of AI solutions in urological practice.

Data Quality and Availability

The quality of training data significantly determines the performance of AI models. Medical data are frequently incomplete, heterogeneous, inconsistent, or have documentation errors. Models developed from small, homogeneous populations might not generalize well to other groups of patients (population bias). Furthermore, data acquired from various centers might differ in format, diagnostic equipment, and protocols, making it challenging to develop universal solutions. In addition, the way data are split into training, validation, and test sets plays a critical role in ensuring robust model evaluation. Improper splitting can lead to data leakage or overfitting, while a well-designed validation process helps assess generalizability and detect potential biases early in development. [64]

Insufficient Standardization and Clinical Validation

Most of AI models, while faring well in retrospective or experimental testing, have not been proven in real-world clinical practice. Prospective, multicenter studies with diverse populations are lacking. Standardization of assessment methods for AI safety and effectiveness is required prior to the incorporation of these tools into decision support systems.[64]

Legal and Ethical Aspects

AI implementation entails major legal issues such as liability for decisions made wrongly, data protection, and patient privacy. Processing big datasets, such as images and genetic data, will have to meet GDPR and national regulations. There are also ethical considerations such as patient autonomy, possible dehumanization of care, and the status of the physician as a decision-maker when faced with 'intelligent' systems.[65,66]

Acceptance by Medical Professionals

AI implementation needs not just technological infrastructure but also a shift in the mindset of medical personnel. Resistance may arise due to lack of understanding and faith in algorithms, concerns about reducing the role of the physician, and problems with interpreting AI findings. Hence, educating medical professionals in the fundamentals of data analysis and AI system use is critical.[67,68]

Technical Infrastructure and Costs

Creating, implementing, and sustaining AI systems entail expenses that are daunting, particularly for smaller centers. Proper IT infrastructure—servers, data archiving, security—is also necessary, which can take years of investment and commitment on the part of public or private institutions.[69,70]

Overview of Current Knowledge

The use of AI in urology is evolving at a fast pace, particularly in oncology, and is dramatically enhancing diagnostic precision and the efficiency and individualization of therapy. Machine learning (ML) and deep learning (DL) algorithms are utilized in the analysis of radiological images like MRI, CT, and ultrasound, facilitating automatic detection of pathological alterations with precision matching or surpassing human experts. In prostate cancer diagnosis, for instance, AI assists in mpMRI analysis, histopathological grading based on Gleason, and therapeutic decision-making for active surveillance, radical therapy, or focal treatment.

AI also contributes to personalized therapy using clinical, genetic, and imaging data to develop predictive models. These models are used to predict recurrence risk, response to treatment (i.e., immunotherapy or BCG therapy), and complications after surgery. This enables more accurate, individualized patient management in accordance with the tenets of personalized medicine.

Despite its promise, AI use in urology has important limitations. Most solutions rely on analysis of retrospective data and have yet to be sufficiently validated in prospective trials with heterogeneous groups of patients. Standardized assessment methodologies and straightforward recommendations for the implementation of AI in hospital IT systems are lacking.

Legal and ethical considerations, such as data privacy, liability, and algorithm transparency (explainable AI), are other challenges. Physician trust is important—only if they accept and comprehend AI recommendations can there be effective clinical adoption.

Finally, AI can transform urology by enhancing diagnostics, treatment, and monitoring of patients. Nevertheless, to achieve this, additional research, development of regulations, education of users, and support of infrastructure are needed.

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