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# Urinary Tract Infections (UTIs): Laboratory diagnosis - The role of artificial intelligence and smart diagnosis

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**Abstract---Background:** Urinary tract infections (UTIs) are prevalent outpatient conditions affecting up to 50% of individuals, with diagnostic errors common in clinical settings. The traditional reliance on clinical criteria alone yields a diagnostic error rate of about 33%, necessitating improved diagnostic methods. **Aim:** This mini-review evaluates the role of artificial intelligence (AI) and smart diagnostic tools in enhancing UTI diagnosis, particularly within vulnerable populations. **Methods:** A comprehensive literature review was conducted, assessing 782 articles, of which 14 met the inclusion criteria for AI applications in UTI diagnosis. These studies were categorized based on their focus: uncomplicated UTIs, complicated UTIs, and specific demographic groups. **Results:** The review revealed that 12 studies employed machine learning techniques while 2 utilized deep learning. The most frequently used models included artificial neural networks (ANNs) and extreme gradient boosting (XGBoost). Key variables influencing predictive models encompassed demographic data, anamnesis, and comorbidities. Notably, models for diagnosing uncomplicated UTIs achieved accuracy rates of up to 98.3%, while approaches for complicated UTIs demonstrated area under the curve (AUC) values ranging from 0.71 to 0.904. AI models were particularly effective in stratifying high-risk subgroups, including pregnant women and children, with models achieving AUCs of 0.82 and 0.83 for specific populations. **Conclusion:** AI-driven diagnostic systems significantly enhance the accuracy and efficiency of UTI diagnosis, reducing the reliance on traditional culture methods and mitigating the risk of unnecessary antibiotic use. The integration of these models into clinical practice could optimize patient care, particularly for susceptible populations.

**Keywords---**urinary tract infections, artificial intelligence, machine learning, diagnosis, vulnerable populations, healthcare efficiency.

## Introduction

Urinary tract infections (UTIs) represent the most widespread outpatient conditions, impacting approximately 50% of individuals at some point in their lives [1]. The prevalence of UTIs escalates with advancing age, with nearly 10% of postmenopausal women reporting a UTI in the preceding year [2]. Additionally, UTIs are a common diagnosis in emergency departments (EDs) and are associated with significant diagnostic inaccuracies [3]. Relying solely on clinical criteria, the diagnostic error rate for UTIs is roughly 33% [4]. Various classification systems for UTIs have been proposed; however, the fundamental definition revolves around the detection of bacteria in the urinary tract, coupled with associated symptoms. UTIs are categorized into uncomplicated and complicated types, with the latter posing the risk of severe outcomes such as urosepsis if not properly managed [5]. The diagnostic algorithm for patients with suspected UTIs comprises several phases, with each successive phase facilitating more informed diagnostic evaluations to achieve an accurate diagnosis. Liquid-based laboratories, including urine analysis through microscopy and culture, serve as the standard for the initial diagnosis of UTIs, aiding in the identification of urinary system pathologies and guiding the need for instrumental evaluation [6, 7]. It is now recognized that changes in urine associated with UTIs may also occur in non-infectious urinary tract conditions, resulting in reduced accuracy of urine microscopy [8]. Furthermore, urine culture presents multiple limitations, being time-intensive and prone to contamination, which can lead to erroneous antibiotic prescriptions, excessive use of antibiotics, resistance development, and delayed treatment [9]. The integration of AI within the medical field has progressed significantly, particularly in the realm of intelligent decision-making for clinical practices [10]. Current findings indicate that AI-based models can notably enhance physicians' efficiency when assessing UTI patients [11]. Nevertheless, many recent reviews have concentrated on the application of AI using limited datasets, focusing only on select AI algorithms or providing narrative summaries without comprehensively analyzing all relevant studies. Therefore, this mini-review aims to evaluate the current landscape of AI-based systems as support tools in UTI diagnosis.

## Collected Data

Out of the 782 articles reviewed, only 14 studies on AI models relevant to UTIs met the inclusion criteria (Fig. 1). These studies can be categorized based on the contexts for which the AI models were developed: (1) diagnosis of uncomplicated UTIs and symptom checkers, (2) diagnosis of complicated UTIs, and (3) diagnosis of UTIs within specific demographic groups. Among these studies, 12 utilized machine learning techniques while two employed deep learning approaches. The predominant machine learning model identified was the artificial neural network (ANN), featured in six studies, followed by extreme gradient boosting (XGBoost) in three, support vector machine (SVM) in one, CatBoost in one, and ensemble learning model (ELM) in one. Demographic parameters were incorporated as predictive inputs in 10 out of 14 (71.4%) studies, primarily focusing on age ( $n=9$ ) and gender ( $n=9$ ), with race and weight mentioned in one study each, particularly involving pediatric patients. Anamnesis was considered in 7 out of 14 (50%) studies, which included previous UTI history ( $n=4$ ), prior antibiotic

treatment failures (n = 1), previous urine culture results (n = 1), and invasive urethral procedures (n = 1). Comorbidities were addressed in 3 out of 14 (21.4%) studies, focusing on diabetes (n = 2), pneumonia (n = 2), stroke classification (n = 1), and mixed cerebrovascular disease (n = 1), with the latter two specifically related to AI decision support for stroke patients. UTI-associated symptoms were incorporated in 7 out of 14 (50%) studies, including dysuria (n = 4), fever (n = 3), suprapubic pain (n = 3), frequency and urgency (n = 1), pollakiuria (n = 1), and urinary incontinence (n = 1). Urinalysis was utilized as a prognostic input in 7 out of 14 (50%) studies; two of these relied solely on dipstick tests. When urine microscopy was employed, red blood cells (RBCs), white blood cells (WBCs), bacterial presence, nitrites, epithelial cells, and glucose were analyzed in 2, 3, 2, 1, 1, and 1 studies, respectively. One study included urine cloudiness as a feature. Imaging data were incorporated in 3 out of 14 (21.4%), where one study examined the cystoscopic appearance of the lower urinary tract and two studies focused on ultrasound imaging for assessing hydronephrosis and vesicoureteral reflux grades. Additional variables not previously categorized included length of stay (LOS) (n = 3), duration of urethral catheterization (n = 2), immunological urine markers (n = 1), ward (n = 1), serum creatinine and albumin (n = 1 each), glucocorticosteroid use (n = 1), and duration of immobility (n = 1). Performance metrics, validation types, and the aforementioned data are discussed and presented in the review.

### **AI-Based Diagnosis for Uncomplicated UTIs and Symptom Checkers**

Research focusing on AI models for diagnosing uncomplicated UTIs and symptom checking. The study conducted by Ozkan et al. [12••] aimed to evaluate the accuracy of various AI models in predicting cystitis and non-specific urethritis based on similar urinary symptoms. Anamnesis, urinalysis, and ultrasound data from 59 participants were utilized as a training and validation dataset. Four distinct AI techniques were employed: decision trees (DT), random forests (RF), support vector machines (SVM), and artificial neural networks (ANN). Comparisons revealed that the ANN model demonstrated the highest accuracy for UTI detection, achieving a rate of 98.3%. This model necessitated only the variables of pollakiuria, erythrocyturia, and suprapubic pain to reach a diagnosis with an accuracy comparable to clinical assessments (Fig. 2). The structure of the ANN model indicated that UTIs could be classified without the need for costly laboratory tests, ultrasounds, or invasive procedures, resulting in lower diagnostic costs and expedited decision-making.

The impetus behind Gadalla et al.'s [13] study was the prevalent practice of administering empirical antibiotics to women exhibiting uncomplicated UTI symptoms, which can contribute to antibiotic misuse and the emergence of antimicrobial resistance. The authors explored 17 clinical and 42 immunological predictors for bacterial culture using a random forest or SVM model, enhanced by recursive feature elimination (RFE). Urine cloudiness emerged as the most effective clinical predictor for diagnosing UTIs. Notably, integrating the selected immunological biomarkers with clinical features (including cloudiness) did not enhance predictive capabilities. Dhanda et al. [14] introduced the NoMicro model, which excludes urine microscopy and instead relies on dipstick test results. They developed NoMicro models based on several machine learning classifiers,

including XGBoost, RF, and ANN, to evaluate their performance. The primary outcome focused on pathogenic urine cultures yielding  $\geq 100,000$  colony-forming units. Predictor variables encompassed age, gender, dipstick urinalysis results (nitrites, leukocytes, clarity, glucose, protein, blood), dysuria, abdominal pain, and history of UTIs. Results indicated that the AUC for the NoMicro model reached 0.85 in external validation, showing no statistically significant difference compared to the version that included urine microscopy results. Arches et al. [15] developed an application for analyzing urine test strips via smartphones, achieving an overall accuracy rate of 96.03% and a reliability rate of  $\geq 0.9$  among 65 participants, which is considered excellent.

### **AI-Based Diagnosis for Complicated UTIs**

Research focused on AI models for diagnosing complicated UTIs is collected and analyzed. Møller et al. [16] aimed to develop two predictive models using data from both the index admission and historical patient information to assess the risk of developing a UTI at hospital entry and after 48 hours (hospital-acquired UTI, HA-UTI). The methodology involved five machine learning models, utilizing features such as demographic data, laboratory results, medical history, and clinical information. Unstructured data, including narrative text from electronic medical records, was processed into a structured format using natural language processing. The area under the curve (AUC) for the entry model ranged from 0.82 to 0.84, while the AUC for predicting HA-UTI varied from 0.71 to 0.77. Taylor et al. [17] conducted a single-center, multi-site, retrospective cohort analysis involving adults in the emergency department, utilizing urine culture results, clinical symptoms, and blood tests. Six machine learning algorithms—random forests (RF), XGBoost, SVM, adaptive boosting, elastic net, and ANN—were employed to develop UTI prediction models based on both comprehensive (211 variables) and reduced (10 variables) datasets. XGBoost emerged as the best-performing method with an AUC of 0.904, demonstrating greater sensitivity compared to documented UTI diagnoses. Practical implementation of the algorithm indicated that approximately 1 in 4 patients could be reclassified from false positive to true negative, and 1 in 11 from false negative to true positive. Mancini et al. [18] developed a machine learning model to predict the likelihood of multidrug-resistant (MDR) UTI in hospitalized patients, introducing a user-friendly cloud platform named Data Science as a Service (DSaaS) for healthcare operators without specialized programming skills. Using a dataset of 1486 hospitalized patients, variables such as sex, age, ward, and time period were analyzed. CatBoost demonstrated the highest predictive performance across all metrics.

Cai et al. [19] described two ANN-based models aimed at predicting the failure of fluoroquinolone-based therapy (model 1) and fosfomycin-based therapy (model 2) among patients with recurrent UTIs. The input data predominantly included previous urine culture profiles and antibiotic therapy types. After training, the ANN achieved a sensitivity of 87.8% and specificity of 97.3% in predicting the efficacy of empirical therapy. Interestingly, prior use of a specific antibiotic class was not a significant risk factor for developing resistance to that class, except for fluoroquinolones; the most critical predictor of resistance was the use of other antibiotic classes. Chen et al. [20] compared logistic regression (LR) and ANN

models to define UTI risk following cystoscopy, with the aim of reducing antibiotic overuse. The input data included previous UTI history and cystoscopic findings such as benign prostatic hyperplasia (BPH), diverticulum, trabeculation, blood clots, cystocele, stones, and tumors. The ANN model exhibited high accuracy (85%), sensitivity (80%), and specificity (88%). Lastly, Hong et al. [21] developed a prediction model for assessing urosepsis risk in patients with upper urinary tract calculi, utilizing an ANN model. The predictive inputs comprised various clinical and laboratory features along with hydronephrosis severity. The AUC in the validation set reached 0.95, indicating that the model could effectively provide urosepsis risk assessments for patients with upper urinary tract calculi.

### **AI-Based Diagnosis in Susceptible Subgroups for UTIs**

Papers detailing AI-based models for diagnosing uncomplicated UTIs in susceptible subgroups are summarized and analyzed. Pregnant women and children represent key populations at higher risk for UTIs, necessitating tailored diagnostic and treatment protocols. Physiological changes during pregnancy, including immunologic and urinary tract alterations, increase susceptibility to UTIs. Progesterone-induced relaxation of smooth muscles and compression from the growing uterus lead to dilation of the ureters and renal calyces, while vesicoureteral reflux may also occur, exacerbating the risk of infections [22]. In children, UTIs rank among the most common bacterial infections, with equal prevalence in males and females during the first year of life, transitioning to a higher prevalence in females thereafter [23]. This heightened risk underscores the importance of developing AI-driven decision support models. Bertsimas et al. [24] created a machine learning model aimed at better stratifying pediatric patients with vesicoureteral reflux complicated by UTIs. Input variables included the grade of vesicoureteral reflux, serum creatinine levels, race/gender, fever, dysuria, and weight, achieving an area under the curve (AUC) of 0.82. This model enhances the identification of patients who will benefit most from continuous antibiotic prophylaxis, allowing for a personalized treatment approach while minimizing unnecessary antibiotic use.

Burton et al. [25] introduced methods to enhance the efficiency of urine culture results for pregnant women and children by streamlining the number of samples to be cultured. They evaluated two classification approaches: a heuristic method combining urine white blood cell (WBC) and bacterial counts, and typical machine learning models such as random forests, neural networks, and XGBoost, using independent features like demographics and prior urine culture results. The optimal solution involved training three separate XGBoost algorithms for pregnant patients, children, and other categories. This approach yielded a 41% reduction in workload while maintaining a sensitivity of 95% for each patient group, demonstrating the potential of supervised machine learning to enhance service efficiency in public healthcare settings. Immobile stroke patients constitute another vulnerable subgroup, with UTI prevalence estimated at 19%. Infections can exacerbate the physical impairments caused by strokes, creating a detrimental cycle [26]. Zhu et al. [27] developed a prognostic model to assess UTI risk among immobile stroke patients, evaluating six machine learning models alongside an ensemble model. The ensemble model demonstrated the best performance metrics, achieving an AUC of up to 0.82 in both internal and

external validation sets. Xu et al. [28] developed a prediction model for identifying UTI risk in immobile stroke patients, employing a Siamese network architecture, which consists of two or more identical subnetworks. This model utilized commonly used clinical criteria to identify at-risk patients and was validated with a nationwide dataset of 3,982 Chinese patients. The Siamese network achieved an AUC of 0.83, outperforming other machine learning models in predicting UTIs among immobile stroke patients.

## Conclusion

The integration of artificial intelligence (AI) into the diagnostic processes for urinary tract infections (UTIs) represents a significant advancement in improving patient outcomes and healthcare efficiency. Traditional diagnostic methods, primarily reliant on urine cultures and clinical evaluations, have been associated with high rates of misdiagnosis and delayed treatment. This review highlights how AI models can effectively bridge these gaps, offering accurate, rapid, and cost-effective diagnostic alternatives. AI-based systems have demonstrated impressive accuracy rates, particularly in diagnosing uncomplicated UTIs, with models achieving accuracies as high as 98.3%. The ability of these systems to incorporate diverse data inputs—such as demographic information, clinical symptoms, and laboratory results—enables a more comprehensive assessment of patient risk factors. This multifaceted approach not only enhances diagnostic precision but also facilitates early intervention, crucial for preventing complications associated with complicated UTIs. Moreover, the review underscores the potential of AI in addressing the specific needs of vulnerable populations, such as pregnant women and children, who are at a heightened risk for UTIs. Tailored AI models have been developed to predict UTI risks in these groups, optimizing diagnostic protocols and treatment strategies to reduce unnecessary antibiotic prescriptions. By personalizing care, these systems can mitigate the threat of antimicrobial resistance, a growing concern in the management of UTIs. Despite these advancements, there are challenges to the widespread implementation of AI in clinical settings. Issues related to data quality, integration with existing health information systems, and clinician acceptance must be addressed to fully realize the benefits of AI in UTI diagnostics. Future research should focus on larger, multicentric studies to validate these models and explore their integration into routine clinical practice. In conclusion, AI presents a transformative opportunity for the diagnosis and management of UTIs, promising to enhance diagnostic accuracy, improve patient care, and ultimately contribute to more effective healthcare delivery. Continued investment in AI research and development will be essential in harnessing its full potential in this critical area of medicine.

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## التهابات المسالك البولية (UTIs): التشخيص المختبري - دور الذكاء الاصطناعي والتشخيص الذكي

### الملخص:

**الخلفية:** تُعد التهابات المسالك البولية (UTIs) حالات شائعة بين المرضى الخارجيين تؤثر على ما يصل إلى 50% من الأفراد، وتكون الأخطاء التشخيصية شائعة في البيئات السريرية. الاعتماد التقليدي على المعايير السريرية وحدها يؤدي إلى معدل خطأ تشخيصي يبلغ حوالي 33%، مما يستدعي تحسين طرق التشخيص.

**الهدف:** يهدف هذا المراجعة الصغيرة إلى تقييم دور الذكاء الاصطناعي (AI) وأدوات التشخيص الذكي في تعزيز تشخيص التهاب المسالك البولية، خصوصاً بين الفئات الضعيفة.

**الطرق:** تم إجراء مراجعة شاملة للأدبيات، حيث تم تقييم 782 مقالاً، منها 14 مقالاً استوفى معايير الإدراج لتطبيقات الذكاء الاصطناعي في تشخيص التهابات المسالك البولية. تم تصنيف هذه الدراسات بناءً على تركيزها: التهابات المسالك البولية غير المعقدة، و التهابات المسالك البولية المعقدة، والمجموعات السكانية المحددة.

**النتائج:** كشفت المراجعة أن 12 دراسة استخدمت تقنيات تعلم الآلة بينما استخدمت 2 التعلم العميق. كانت النماذج الأكثر استخداماً تشمل الشبكات العصبية الاصطناعية (ANN) وتعزيز التدرج الأقصى (XGBoost). تضمنت المتغيرات الرئيسية التي تؤثر على النماذج التنبؤية البيانات الديموغرافية، التاريخ الطبي، والأمراض المصاحبة. ومن الملحوظ أن النماذج المستخدمة لتشخيص التهابات المسالك البولية غير المعقدة حققت دقة تصل إلى 98.3%، في حين أظهرت الأساليب المستخدمة لتشخيص التهابات المسالك البولية المعقدة قيم منطقة تحت المنحنى (AUC) تتراوح بين 0.71 إلى 0.904. كانت نماذج الذكاء الاصطناعي فعالة بشكل خاص في تصنيف الفئات عالية المخاطر، بما في ذلك النساء الحوامل والأطفال، حيث حققت النماذج قيم AUC تصل إلى 0.82 و 0.83 لمجموعات سكانية محددة.

**الخاتمة:** تعزز أنظمة التشخيص المعتمدة على الذكاء الاصطناعي بشكل كبير من دقة وكفاءة تشخيص التهابات المسالك البولية، مما يقلل الاعتماد على الطرق التقليدية للزراعة ويخفف من خطر استخدام المضادات الحيوية غير الضرورية. يمكن أن يؤدي دمج هذه النماذج في الممارسة السريرية إلى تحسين رعاية المرضى، لا سيما بالنسبة للفئات المعرضة للخطر.

**الكلمات المفتاحية:** التهابات المسالك البولية، الذكاء الاصطناعي، تعلم الآلة، التشخيص، الفئات الضعيفة، كفاءة الرعاية الصحية.