Review Article

The role of AI in Detection and Diagnosis of Kidney stone

Tamil Eniyan AKM[1], Premkumar Gopalsamy[1], Senthil M[2]

From, [1]Pharmacy Practice, J.K.K.Nattraja College of Pharmacy, Kumarapalayam-638183, Namakkal District, Tamil Nadu, India, [2]Associate professor, Pharmacy Practice, J.K.K.Nattraja College of Pharmacy, Kumarapalayam – 638183, Namakkal District, Tamil Nadu, India.

ABSTRACT

Background: Kidney stone disease (nephrolithiasis) is a prevalent and recurrent condition, affecting approximately 12–15% of the Indian population. Conventional diagnostic modalities such as computed tomography (CT), ultrasound (US), and X-ray imaging are widely used but have notable limitations, including radiation exposure, operator dependency, variability in interpretation, and reduced sensitivity for small or radiolucent stones. **Objective:** To evaluate the role of artificial intelligence in the detection and diagnosis of kidney stones across various imaging modalities and clinical applications. **Methods:** This narrative review evaluates recent studies on AI applications in nephrolithiasis, focusing on machine learning (ML) and deep learning (DL) techniques applied to imaging modalities (CT, US, X-ray), clinical prediction models, and advanced analytical methods such as spectroscopy and microscopy. **Results:** AI-based models significantly enhance diagnostic performance by enabling automated detection, segmentation, and characterization of kidney stones, achieving accuracies exceeding 90% in several studies. AI improves imaging interpretation across CT, US, and X-ray while reducing observer variability and enabling low-dose imaging protocols. Additionally, AI demonstrates strong predictive capabilities for clinical outcomes, including spontaneous stone passage, extracorporeal shock wave lithotripsy (ESWL) success, and endourological procedure outcomes, often outperforming traditional statistical models. AI also enables accurate identification of stone composition through imaging data and advanced analytical techniques, supporting personalized treatment strategies. **Conclusion:** Artificial intelligence represents a transformative advancement in kidney stone management by improving diagnostic accuracy, reducing variability, and facilitating personalized care. However, further large-scale validation and integration into clinical workflows are required to ensure widespread adoption and optimal patient outcomes.

Key words: Kidney stones; Nephrolithiasis; Artificial intelligence; Machine learning; Deep learning; Medical imaging; Diagnosis; Prediction

Kidney stone disease (nephrolithiasis) is a common condition characterized by the formation of hard mineral deposits within the kidneys. If left untreated, it can lead to serious complications, including obstruction, infection, and renal damage [1]. The prevalence of kidney stone disease in India is estimated to be approximately 12–15%, affecting nearly 5–7 million individuals annually [2]. Certain regions, often referred to as the “stone belt” of India—including Uttarakhand, Maharashtra, Gujarat, and Rajasthan—show higher incidence rates due to factors such as climate conditions, dietary habits, water quality, and genetic predisposition [3]. The majority of kidney stones are composed of calcium oxalate and calcium phosphate [4].

Despite advances in medical imaging, the detection and diagnosis of kidney stones remain challenging. Commonly used imaging modalities, including computed tomography (CT), ultrasound (US), and X-ray, have several limitations, such as reduced sensitivity for small or radiolucent stones, operator dependency, and variability in interpretation [5,6]. Additionally, determining the chemical composition of kidney stones often requires labor-intensive laboratory techniques, such as Fourier transform infrared spectroscopy (FTIR), which are time-consuming and prone to human error [7]. Artificial intelligence (AI) has emerged as a promising solution to address these challenges. AI techniques, particularly machine learning (ML) and deep learning (DL), have demonstrated high accuracy in analyzing medical images and identifying kidney stones with improved precision. These technologies also enable automated assessment of stone characteristics and prediction of clinical outcomes based on patient data. This review aims to evaluate the role of artificial

Access this article online

Received – 16th April 2026
Initial Review – 22nd April 2026
Accepted – 23rd April 2026

Quick Response code

DOI: 10.32677/ejms.v11i2.8223

Correspondence to: Dr. Senthil M, Department of Pharmacy Practice, J.K.K.Nattraja College of Pharmacy, Kumarapalayam – 638183, Namakkal District, Tamil Nadu, India.

Email: senpharm@gmail.com

intelligence in enhancing the detection, diagnosis, and management of kidney stones.

CURRENT DIAGNOSTIC METHODS AND LIMITATION

Computed Tomography (CT)

Computed Tomography (CT) has emerged as the gold-standard imaging technique in the detection of kidney stones [8]. Notably, this scan has high sensitivity and specificity rates in the detection of kidney stones. While it is effective and has many advantages for detecting kidney stones, this modality also has certain drawbacks [9,10].

Advantages of CT in Kidney Stone Diagnosis

Non-contrast CT scans are very sensitive in diagnosing kidney stones since they identify them with a sensitivity rate of around 95%–98% and specificity exceeding 98% [11-13]. They are beneficial as they enable clinicians to make an instant assessment of stone-related problems since they provide a fast-diagnostic result in emergency cases [14]. Moreover, this scanning is helpful because it allows for the assessment of the whole anatomy of the urinary system, which makes it very useful when surgery becomes necessary [15,16]. Finally, CT scans are beneficial since they can diagnose other diseases with similar symptoms, such as appendicitis or diverticulitis [17].

Ultrasound (US)

It has been demonstrated that ultrasound (US) plays a crucial role in nephrolithiasis diagnosis and management [22]. Despite its various benefits, there are several disadvantages to using ultrasound in diagnosing and managing kidney stones.

Advantages of Ultrasound in Kidney Stone Management

Ultrasound (US) can prove to be quite beneficial in comparison with other methods of imaging, e.g., computed tomography (CT). One of its main advantages is being free from radiation, which allows using it repeatedly without harm to the patient's health. In addition to being free from radiation, it is also more economical, thus saving costs associated with treatment [23]. Finally, the wide spread of ultrasound makes it more accessible for patients due to its presence in many clinics [24].

X-rays for Kidney Stones

X-ray imaging, including the kidney-ureter-bladder (KUB) X-ray examination, has long been used to diagnose kidney stones [29]. Although this possesses have several benefits, low sensitivity and specificity must be considered while employing it clinically.

Advantages of X-rays in Kidney Stone Diagnosis

The use of X-ray imaging allows achieving several important benefits in the evaluation of nephrolithiasis patients. It is a non-invasive procedure; no contrast agents or injections are required. Moreover, the examination is performed quickly, allowing to diagnose stones rapidly and make decisions concerning further actions. Finally, X-rays are relatively cheap compared to other imaging procedures, such as CT or MRI. KUB X-rays also allow to monitor known kidney stones and evaluate their size, quantity, and growth dynamics [30].

Limitations

Computed Tomography (CT): Even though CT scanning has many benefits when used for diagnosing kidney stones, it still has certain disadvantages that should be mentioned. First, it exposes patients to ionizing radiation that may cause cancer in the future if that procedure was done repetitively [18]. Second, it is very expensive when compared to other imaging modalities like ultrasound or conventional radiography [19]. Third, it leads to overdiagnosis, i.e., the detection of clinically insignificant stones and subsequent treatment [20]. Fourth, although rare, there is a possibility of failing to identify extremely small (<3 mm) stones due to their size or location [21].

Ultrasound: There are numerous disadvantages associated with the use of US in the management of nephrolithiasis [25]. First, ultrasound tends to overestimate the stone size in comparison with CT, which is 1.9 mm on average. Moreover, there are significant differences between the sizes of stones detected by CT and US; they tend to be bigger in the latter case [26]. The sensitivity of US for detecting ureteric and renal stones is 45% and 94% and 88%, respectively, resulting in the high rate of false-negative results, especially concerning small and difficult-to-localize stones [27]. In addition, the accuracy of US depends not only on patient-specific factors, but also the observer, who conducts a study, and technical problems, like acoustic shadows in the case of mid/distal ureteral stones [28].

X-rays: However, KUB X-rays have several disadvantages associated with their usage in nephrolithiasis diagnosis. First of all, their sensitivity varies between 45% and 85%, with smaller stones (< 5 mm) usually missed due to their radiolucency. Secondly, stone detection is significantly affected by their chemical composition, with calcium stones of various types easily detectable because of high radiodensity, while struvite stones, cystine stones, and especially uric acid stones (due to their radiolucency) remain unobserved on X-rays [31].

Thirdly, anatomical resolution of X-ray imaging is much lower compared to CT, meaning that it is hard to determine the structures of the urinary system or possible complications, such as hydronephrosis [30]. Furthermore, observer error is another disadvantage of X-rays, meaning that results might differ depending on the radiologist's level of experience [31].

APPLICATIONS OF AI IN KIDNEY STONE DETECTION

Kidney Stones Detection with CT scan

Artificial intelligence significantly improves the interpretation of CT images for kidney stone diagnosis by enabling detailed analysis of stone characteristics. Computed tomography remains the gold standard for kidney stone detection due to its high sensitivity and specificity [32]. AI enhances CT imaging through automated detection and segmentation of kidney stones. Deep learning algorithms can process large volumes of imaging data to identify even small stones and provide detailed characterization [33]. These models are trained to recognize features indicative of stones regardless of their composition or location within the urinary system [34].

In addition, AI models estimate the size and density of kidney stones from CT images. Stone size is an important factor in determining appropriate management strategies, while density, measured in Hounsfield units, provides insight into stone composition such as calcium oxalate or uric acid. Density measurements also help predict the success of extracorporeal shock wave lithotripsy (ESWL) [35]. AI further assists in differentiating kidney stones from other calcifications, including phleboliths and vascular deposits, by analyzing complex imaging patterns [36]. It also enables low-dose CT imaging by preserving image quality while reducing radiation exposure through advanced reconstruction techniques [37].

Kidney Stone Detection in X-ray Imaging

Artificial intelligence enhances the diagnostic capability of X-ray imaging, a widely available and cost-effective method for kidney stone detection. However, conventional X-ray imaging is limited by low sensitivity, overlapping anatomical structures, and variability in interpretation [38]. AI improves X-ray image analysis by enhancing contrast and resolution, enabling clearer differentiation between kidney stones and surrounding tissues. This is particularly useful for detecting small or faint stones [39]. Machine learning models analyze features such as stone shape, size, density, and location to identify subtle patterns that may not be easily visible, thereby improving detection accuracy [40].

In addition, AI-based noise reduction techniques maintain image quality in low-dose imaging, supporting safer diagnostic practices and allowing repeated examinations without significant radiation risk [41]. It further helps classify and distinguish stones with the help of AI. It may separate kidney stone from any calcification such as phlebolith or vascular deposit on the basis of any unique radiological signs. This lowers down false positivity and makes diagnosis highly accurate.

Ultrasound Diagnosis of Kidney Stones

Artificial intelligence enhances ultrasound imaging, making it a more reliable tool for kidney stone diagnosis. Ultrasound is widely used due to its non-invasive nature and absence of radiation exposure, although its effectiveness is limited by operator dependency and variability in image quality [42]. AI reduces operator dependency by enabling consistent and automated detection of kidney stones. Machine learning algorithms trained on large datasets can identify stones accurately regardless of the operator's experience or equipment used [43].

Automated detection systems identify hyperechoic structures associated with kidney stones and distinguish them from similar artifacts such as calcifications or gas using advanced pattern recognition techniques [23]. AI also improves image processing by optimizing contrast and resolution, facilitating better visualization of kidney stones in challenging conditions such as obesity or anatomical variations [24]. Furthermore, AI supports real-time monitoring and tracking of stone movement, which may assist in assessing the risk of obstruction and guiding clinical decision-making [43]. It also enhances the detection of small or early-stage stones, enabling timely intervention (Table 1).

Table 1: Studies on AI in Kidney Stone Diagnosis

Study	Imaging Modality	AI Technique	Key Findings
Selvarani S, Rajendran P [44]	Ultrasound	Meta-Heuristic Support Vector Machine (SVM)	Achieved 98.8% accuracy in detecting renal calculi from ultrasound images after noise reduction using an Adaptive Mean Median Filter.
Jendeberg J, Thunberg P, Lidén M [45]	CT	Convolutional Neural Network (CNN)	The CNN differentiated distal ureteral stones from pelvic phleboliths with a sensitivity of 94%, specificity of 90%, and accuracy of 92%.
Aksakallı I, Kaçdıoğlu S, Hanay Y S [46]	X-ray	Machine Learning & Deep Learning	Decision Tree Classifier achieved the highest F1 score rate of 85.3% for classifying kidney stone status in X-ray images.
Kobayashi M et al. [47]	X-ray	Convolutional Neural Network (CNN)	Developed a CAD model with an F score of 0.752; sensitivity was 87.2% and PPV was 66.2% for detecting urinary tract stones on plain X-rays.
Parakh A et al. [48]	CT	Cascading Convolutional Neural Networks (CNN)	Achieved an AUC of 0.92-0.95 for stone detection on unenhanced CT scans; accuracy reached up to 95% with enhanced generalization across different scanners.

AI IN OUTCOME PREDICTION FOR MANAGEMENT

Outcome Prediction of Conservative Management

Many symptomatic ureteral stones require urological treatment. The assessment of spontaneous stone passage (SSP) represents an essential problem related to outcome prediction. An accurate outcome prediction is very important in terms of optimal patient management and the avoidance of superfluous procedures. In their study, Cummings et al. [49] developed ANN with feed-forward back propagation for the prediction of SSP.

This model was characterized by an efficiency rate of 76% in predicting the necessity of the intervention; in addition, symptoms' duration was determined to be the most significant predictor. Dal Moro et al. [50] developed a hybrid model integrating logistic regression, ANN, and support vector machines (SVM), achieving a sensitivity of 84.5% and specificity of 86.9%. Stone size, duration of symptoms, and stone location were identified as key predictors. Park et al. [51] reported superior predictive performance of machine learning models compared to logistic regression. The machine learning model demonstrated higher accuracy (AUC = 0.881) than logistic regression (AUC = 0.817) for stones measuring 5–10 mm. These studies underscore AI's ability to integrate clinical variables for SSP prediction, improving diagnostic confidence and patient care.

Prediction of Extracorporeal Shockwave Lithotripsy (ESWL) Outcomes

ESWL is considered a choice non-invasive therapy for urinary stones, but the outcome of such therapy is hard to predict due to variable predictors involved. AI techniques have been proven to provide great potential for enhancing prediction accuracy. Poulakis et al. [52] have applied an ANN algorithm to predict lower pole stone clearance and have obtained 92% accuracy. The study revealed that urinary transport factors and anatomy-related factors served as predictors.

According to Moorthy and Krishnan [53], ANN algorithm for predicting fragmentation of stones with the use of CT images was proved to be accurate with the rate of 90%. Yang et al. [54] used decision tree models to predict post-extracorporeal shock wave lithotripsy (ESWL) stone-free rates (SFR), reporting an accuracy of 87.9%. Median stone density and volume were identified as the main predictors. AI-based models are excellent at exploiting imaging data and patient-specific variables to minimize variability and optimize the planning for ESWL.

Predictive Potential for Outcomes in Endourological Procedures

In cases of PCNL, AI is contributing significantly in predicting certain parameters, which include SFR, complications, and blood transfusions following the procedure. Aminsharifi et al. [55] used artificial neural networks (ANNs) to predict outcomes following percutaneous nephrolithotomy (PCNL), achieving an accuracy of over 80%. Stone size and morphology were identified as important predictive variables. Zhao et al. [56] demonstrated the superiority of artificial intelligence models, particularly support vector machines (SVM), in predicting stone-free rates (SFR) after PCNL compared to conventional methods, with an AUC of 0.879. Chen et al. (2021) employed DNN in predicting sepsis following PCNL and reported greater prediction efficiency compared to LASSO models with an AUC of 0.874 [57]. Integration of AI in predicting endourological outcomes will ensure personalized treatment planning and mitigate the risks associated with invasive procedures.

AI for the Elucidation of Stone Disease Chemistry and Composition

Predicting stone disease (urological stone disease), particularly primary or recurrent stone disease, is necessary for preventing stone diseases from occurring or minimizing the adverse effects that stone disease could bring to the kidneys. Artificial intelligence has been used as a means of uncovering the complicated interaction of various clinical and biochemical variables that lead to an increased tendency to develop stones.

Association of stone disease risk with blood, urine chemistry, and other clinical factors

There is a growing trend toward the application of AI techniques to identify key biochemical and clinical factors associated with stone disease. For example, studies based on ANNs proved that there is high risk prediction value for CaOx saturation level and urinary urea concentration in predicting stones' development among men. This result held true both for the patients who did and those who did not have the history of stone disease [58, 59]. The ensemble learning technique that considered 42 parameters related to clinical and biochemical aspects made possible 97.1% accurate predictions about the risk of stone disease occurrence [60]. Moreover, some studies employing ML algorithms highlighted risk factors for big kidney stones (>20 mm). These factors were high blood pressure, old age, low level of CaOx supersaturation, and high protein content in stone compositions [61].

In addition, AI tools proved their capacity to accurately predict the deviation in 24-hour urine analytes that are necessary for stone disease. Such clinical factors as BMI, age, and gender could serve as predictors of this condition as well [62]. When it came to recurrent cases of stone disease, ANNs proved to predict recurrence with almost 90% accuracy by measuring urinary natrium, phosphorus, and CaOx levels [63]. Besides, ANN models incorporating genetic information classified patients with predisposition to stone disease with accuracy up to 89% [64]. One more study that worked with microscope images suggested that identification based on the use of convolution neural networks resulted in 74% higher success in identifying CaOx crystals in the urine sediment than a traditional method for predicting the formation of CaOx stones [65]. The efficacy of myoinositol hexakisphosphate analogues as a means of preventing CaOx nephropathies or stones was demonstrated by another study analyzing the crystallography of CaOx under the effect of crystallization inhibitors using electron microscopy images and machine learning techniques [66].

Detection of Stone Composition by Using CT Imaging

AI along with CT imaging helps in stone composition detection effectively. CT imaging gives radiographic images that allow AI algorithms to classify stones with a higher degree of accuracy. In one study, algorithms based on multiparametric techniques, which are fed with CT imaging details, have given 100% accuracy to classify UA stone from non-UA stones with 75% accuracy among non-UA stones [67].

Another study showed an improvement in classification among non-UA stones with accuracy increased up to 88% using rapid voltage switching dual energy CT imaging [68]. A SVM model fed with details from CT texture analysis has given an AUC value of 0.965 and 94.4% sensitivity with 93.7% specificity in detecting UA stones [69]. Neural network algorithms that have been developed based on spectral CT imaging have shown excellent results, such as per-voxel 91.1% accurate and 87.1% - 90.4% accurate for independent validation, even for compound stones [70]. Moreover, AI has further shown that classification of calcium oxalate monohydrate (COM) stones is possible using spectral CT imaging by achieving an AUC value of 0.933 up to 88.3% accuracy [71].

Classification of Stone Type through Endoscopy Images

Another way to classify stone composition is through intraoperative imaging and AI assistance. AI algorithms based on CNN can give accuracies up to 98% in detecting stone compositions when fed with macroscopic images [72, 73]. Such AI algorithms outperform traditional methods in identifying stone classes such as whewellite, uric acid, struvite, and cysteine [34]. Recently, through endoscopic images during ureteroscopy operations, CNN model algorithms have also been created, which show stone compositions with a precision rate of 97% [74]. Meta-learning techniques improve the efficiency of CNN-based models, especially when there are differences between image characteristics [75]. Large-scale data analysis has given AUC values over 0.97 for CNN models in cases where there are more than one composition of stones [76].

Composition of Stone Detection by Other Innovative Techniques

Advanced approaches and AI integration have helped increase the efficiency of stone composition detection. The microtomography images classified using the CNN model have yielded an accuracy of up to 98.52% for differentiating among calcium stones, uric acid stones, and stones with mixed components [77]. In another study, the artificial intelligence algorithm, based on the dielectric properties dataset, has proven highly effective (accuracy rate – 98.17%) [78]. The Raman Spectroscopy technology, which analyzes the spectra of stones, has achieved 96.3% sensitivity in detecting stones of the major chemical classes via the ML approach [79]. There is also an innovative approach involving smartphone microcopy and utilizing the CNN model to achieve 88% accuracy for distinguishing among CaOx, UA, cysteine, and struvite stones [80].

CONCLUSION

In conclusion, the application of Artificial Intelligence (AI) in the process of detecting and diagnosing kidney stones is an innovative improvement in medical technology. Given the prevalence of kidney stones, especially in areas like India, there has been a pressing need for improvement in both efficiency and diagnostic accuracy. While there are many benefits in current imaging technologies like computed tomography (CT), ultrasound, and X-ray, their sensitivity to smaller kidney stones is relatively low. As such, Artificial Intelligence (AI) presents a revolutionary method of improving the abilities of these diagnostic technologies. There can be potential use of advanced algorithms to analyze images provided by such diagnostic machines with machine learning algorithms leading to enhanced detection of the stones and richer descriptions without requiring interpretation.

This minimizes the chances of error in the diagnosis process and ensures that each person can get personalized treatment depending on his/her condition. One of the advantages of actual predictive ability on patient outcomes in real-time stone movement includes provision of highly proactive management modality. Furthermore, early intervention from AI technologies and performing less unnecessary medical procedure improves health outcomes while reducing costs of health management. Future developments in AI technologies will make the diagnosis of kidney stones easier and more efficient than ever before.

With further research into the efficacy of the technologies, there can be widespread acceptance of such algorithms in diagnostic processes for patients suffering from various conditions, including nephrolithiasis. This innovation in medicine serves as a light at the end of the tunnel for many people suffering from kidney stones.

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Funding: Nil; Conflicts of Interest: None Stated.

How to cite this article: Tamil Eniyan AKM, Premkumar G, Senthil M. The role of AI in Detection and Diagnosis of Kidney stone. Eastern J Med Sci. 2026; 11(2):23-30 .