Automated Kidney Stone Detection Using Medical Imaging and Computational Intelligence

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Abstract **—** Kidney stone disease is a prevalent urological disorder that may lead to severe renal complications if not diagnosed at an early stage. Renal calculi are formed due to the crystallization of minerals present in urine, and while smaller stones may pass asymptomatically, undetected stones can progressively impair kidney function. This paper presents an automated kidney stone detection framework using medical imaging and advanced computational techniques. Computed Tomography (CT) and Ultrasound images acquired from a hospital dataset are employed for analysis. Image pre-processing is performed using median filtering to suppress noise, followed by feature-based segmentation utilizing Convolutional Neural Networks (CNNs). Ultrasound imaging presents additional challenges due to speckle noise and low contrast; therefore, image restoration and adaptive filtering techniques are applied to enhance image quality. The stone region is localized through segmentation, and further analysis is carried out using CNN-based classification combined with wavelet transformation for improved feature extraction. The proposed approach enhances detection accuracy, minimizes manual intervention, and provides a reliable and efficient solution for early kidney stone diagnosis, thereby supporting clinical decision-making and reducing the need for invasive procedures.

Index Terms — Artificial Intelligence, Machine Learning, Deep Learning, Medical Image Processing, Convolutional Neural Networks (CNN)

1. INTRODUCTION

Kidney stone disease, medically referred to as urolithiasis or renal calculi, represents a major clinical challenge due to its high prevalence and potential to cause serious renal complications. Kidney stones are crystalline solid deposits formed from minerals and salts present in urine, with calcium-based stones being the most common type. Although the condition is widespread, a significant proportion of affected individuals remain asymptomatic during the early stages. In many cases, the presence of kidney stones is only recognized when patients experience severe abdominal or flank pain, hematuria, or other urinary abnormalities, which often indicate advanced progression or internal damage.

The silent nature of early-stage kidney stone formation poses a substantial risk, as undetected stones may progressively impair renal function. Prolonged obstruction or irritation of the urinary tract can result in infections, hydronephrosis, or irreversible kidney damage. Therefore, early detection and continuous monitoring are essential to prevent disease escalation and to facilitate timely medical intervention. Diagnostic imaging plays a vital role in identifying kidney stones at an early stage, enabling clinicians to initiate appropriate treatment strategies and reduce the likelihood of surgical procedures.

Kidney stone disease is also closely linked to broader renal health concerns. Conditions such as hypertension, diabetes mellitus, and glomerulonephritis are known contributors to chronic kidney disease and kidney failure. The coexistence of kidney stones with these conditions further underscores the importance of early diagnosis and preventive care. Recognizing kidney stones at an initial stage can significantly reduce long-term renal complications and improve patient outcomes.

Clinically, kidney stones present with a variety of symptoms depending on their size, location, and movement within the urinary tract. Severe pain in the back or lower abdomen is the most common symptom, often accompanied by nausea and vomiting. Fever may occur in cases involving infection. Urinary symptoms such as hematuria, pyuria, and dysuria are also frequently observed. These manifestations highlight the necessity of prompt diagnostic evaluation to confirm stone presence and severity.

The formation of kidney stones is influenced by multiple factors, including dehydration, dietary habits, genetic predisposition, metabolic disorders, urinary tract infections, anatomical abnormalities, and medication usage. Insufficient fluid intake leads to concentrated urine, promoting crystallization of minerals such as calcium, oxalate, and uric acid. Diets rich in oxalate, sodium, and animal protein further increase the risk. Additionally, metabolic conditions such as hypercalciuria, hyperoxaluria, and hyperparathyroidism contribute to stone formation. Structural abnormalities or urinary obstruction can cause urine stagnation, facilitating crystal aggregation. Certain medications, including calcium-based antacids and diuretics, have also been associated with increased stone risk.

In recent years, the application of machine learning (ML) and deep learning (DL) techniques in medical imaging has emerged as a promising approach for kidney stone detection. Ultrasound imaging, in particular, is widely used due to its non-invasive nature, affordability, and absence of ionizing radiation. However, ultrasound images often suffer from low contrast and speckle noise, making accurate stone detection challenging. To address these limitations, advanced preprocessing techniques such as noise reduction, contrast enhancement, and image restoration are employed. Annotated datasets prepared by medical experts enable supervised learning models to differentiate between stone and non-stone regions effectively.

Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in feature extraction and classification tasks, allowing automated identification of kidney stones from ultrasound images. Through iterative training, validation, and testing on unseen data, these models achieve high accuracy and robustness. Once deployed, such systems can be integrated into clinical workflows, enhancing diagnostic efficiency and reducing dependency on manual interpretation. The incorporation of ML and DL techniques not only improves detection accuracy but also ensures consistency, reduces diagnostic time, and minimizes human error. Consequently, the use of intelligent imaging systems represents a significant advancement in urology and nephrology, contributing to improved patient care and clinical decision-making.

II REVIEW OF SELECTED RESEARCH WORKS

Understanding the chemical composition of kidney stones is critical for determining appropriate treatment strategies and preventing recurrence. Conventional morpho-constitutional analysis, although effective, is time-consuming and labor-intensive. To address this limitation, the authors in [1] explored the feasibility of in vivo kidney stone type identification using endoscopic images. The study conducted a comparative analysis of five classification techniques, including deep convolutional neural networks (DCNNs) and traditional machine learning approaches. While the DCNN-based model achieved superior performance with 98% precision and 97% recall across four stone classes, the study also demonstrated that an XG Boost classifier using carefully selected features could achieve comparable results, particularly in scenarios with limited annotated data.

Automated kidney stone detection using computed tomography (CT) images has gained significant attention due to the high diagnostic accuracy of CT imaging. In [2], the authors proposed a deep learning-based detection system using coronal CT images. Trained on a dataset of 1,799 images and evaluated on 433 subjects, the model achieved an accuracy of 96.82%, demonstrating reliable detection even for small-sized stones. The study highlighted the clinical readiness of deep learning models for automated kidney stone diagnosis.

In [3], a deep learning approach was employed to classify kidney stone composition using digital photographs. The authors analyzed 63 kidney stones representing five different compositions using a ResNet-101 CNN architecture. The model achieved an overall weighted recall of 85%, with uric acid stones exhibiting the highest recall rate of 94%. The results validated the effectiveness of CNNs in automated stone composition analysis.

The work presented in [4] investigated machine learning models for predicting kidney stone composition using electronic health record data and 24-hour urine analysis. XG Boost and logistic regression models were evaluated for both binary and multiclass classification tasks. While XG Boost demonstrated superior accuracy for binary classification, logistic regression performed better in multiclass prediction, emphasizing the importance of model selection based on problem complexity.

A deep learning-based framework for automated kidney stone detection and volumetric measurement using non-contrast CT scans was introduced in [5]. The system employed a 3D U-Net architecture and achieved a sensitivity of 0.86 at 0.5 false positives per scan, with an AUC of 0.95 on external validation data. The automated volume estimates closely matched expert measurements, reducing manual workload and improving diagnostic efficiency.

In [6], supervised learning techniques were applied to classify kidney stones using ureteroscopic images. Random Forest and ensemble KNN classifiers achieved an accuracy of 89%, outperforming earlier methods. The study demonstrated the potential of feature-based machine learning models in endoscopic stone classification.

Radiomics-based machine learning for distinguishing kidney stones from phleboliths on low-dose CT images was investigated in [7]. The proposed classifier achieved an accuracy of 85.1% and an AUC of 0.902, highlighting its clinical relevance in improving diagnostic precision.

The authors in [8] proposed a transfer learning-based approach for detecting small kidney stones in CT images. Using the ExDark19 model combined with iterative neighborhood component analysis and kNN classification, the system achieved detection accuracies exceeding 99%, demonstrating its robustness and reliability.

In [9], a deep learning-based diagnostic framework incorporating Kronecker product-based convolution was developed for kidney stone detection in CT images. The proposed architecture achieved an accuracy of 98.56%, effectively identifying stones of varying sizes and enhancing clinical diagnostic support.

Ultrasound-based kidney stone detection was addressed in [10] through advanced preprocessing, wavelet-based feature extraction, and neural network classification. The proposed method achieved an accuracy of 98.8%, demonstrating its effectiveness despite the challenges associated with ultrasound imaging.

The work in [11] focused on early detection of chronic kidney disease using machine learning techniques deployed on an Internet of Medical Things (IoMT) platform. The proposed HMANN model achieved high segmentation accuracy and reduced computational time, contributing to improved diagnostic workflows.

In [12], preprocessing and entropy-based segmentation techniques were applied to ultrasound images to improve kidney stone detection. Classification using KNN and SVM further enhanced detection accuracy, addressing the limitations of low-contrast ultrasound images.

Object detection-based kidney stone identification using YOLOv7 combined with super-resolution techniques was proposed in [13]. The enhanced model significantly improved precision, sensitivity, and mAP scores, demonstrating its effectiveness in KUB X-ray imaging.
The study in [14] introduced a segmentation-based approach using thresholding and watershed algorithms for kidney stone detection and size estimation from CT scans. The method showed improved accuracy and reproducibility compared to existing techniques.
Automated recognition of urinary stones in endoscopic images using shallow and deep learning models was investigated in [15]. Deep learning methods achieved superior sensitivity and specificity, highlighting their potential for clinical adoption.
Finally, [16] presented a CNN-based classification system for urinary stones using micro-CT images. The optimized CNN achieved a validation accuracy of 98.52% and a test accuracy of 99.59%, demonstrating the effectiveness of deep learning for stone type classification.
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III. COMPARISION OF VARIOUS RADIOMICS APPROACHES

IV. This section presents a comparative analysis of existing radiomics-based and deep learning approaches for kidney stone detection and classification reported in the literature. The comparison highlights the datasets used and the corresponding performance metrics to provide insights into the strengths and limitations of each method.

Table I. Comparison of Existing Radiomics and Deep Learning Approaches

Reference	Dataset/ No. of Images used	Performance
[1]	N/A	DCNN achieved 98% precision and 97% recall; XGBoost was close to DCNN performance with limited annotated data
[2]	1799 CT images	96.82% accuracy
[3]	63 stones	Overall weighted recall for CNN's composition analysis: 85%
[4]	1296 patients	XGBoost outperforms logistic regression for binary classification (91% accuracy); LR excels in multiclass classification
[5]	91 CT scans	Sensitivity of 0.86 at 0.5 false positives per scan; AUC of 0.95 on external validation set
[6]	Dataset size not specified	89% classification accuracy; Outperforms previous methods by over 10%
[7]	369 patients	Accuracy of 85.1%; AUC of 0.902
[8]	N/A	Accuracy of 99.22% (10-fold CV) and 99.71% (hold-out validation)
[9]	Dataset from GitHub	Accuracy of 98.56%
[10]	N/A	Accuracy of 98.8%
[11]	N/A	High accuracy in kidney segmentation
[12]	N/A	Sensitivity of 87.6%, Precision of 92.2%, F1 Score of 89.8%
[13]	Dataset size not specified	Accuracy of 99.59%; Classification error of 1.2%
[15]	30 urinary stones	Test accuracy of 99.59%; Classification error of 1.2%
[16]	30 urinary stones	Validation accuracy of 98.52%; Test accuracy of 99.59%

IV PROPOSED METHODOLOGY

The proposed system is designed to automatically detect and classify kidney stones from medical images using a combination of image preprocessing, segmentation, and deep learning-based classification techniques. The primary objective of this framework is to enhance diagnostic accuracy while minimizing human intervention and computational complexity.
The system accepts medical images obtained from either Computed Tomography (CT) or Ultrasound modalities as input. Initially, preprocessing operations such as noise reduction and contrast enhancement are applied to improve image quality. For ultrasound images, additional filtering is performed to suppress speckle noise and enhance stone visibility. Following preprocessing, image segmentation is carried out to isolate the kidney region and potential stone areas.A Convolutional Neural Network (CNN) is employed for feature extraction, classification, and localization of kidney stones. The trained CNN identifies the presence of stones and highlights their spatial location within the kidney. The overall workflow of the proposed methodology is illustrated in **Figure 1**, which outlines the sequential stages from image acquisition to stone detection and classificatn

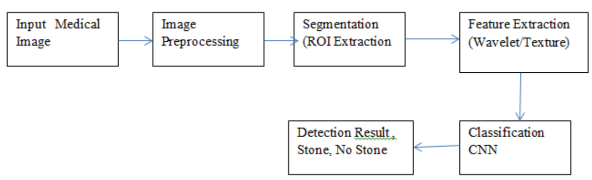

Figure 1: Steps in proposed methodology

V EXPERIMENTAL RESULTS

The performance of the proposed CNN-based system was evaluated using both CT and ultrasound images. **Figure 2** illustrates representative outputs generated by the trained model for the two imaging modalities.

In the CT image column (left), the top image represents the original axial CT slice, while the bottom image shows the corresponding CNN output. The detected kidney stone appears as a high-contrast bright region, and the CNN accurately localizes it using a tight bounding box or contour. The high image clarity and contrast in CT scans contribute to precise detection and localization.

In the ultrasound image column (right), the top image depicts the original ultrasound frame characterized by low contrast and speckle noise. The bottom image shows the CNN output, where the model successfully identifies a hyperechoic region corresponding to a kidney stone. Although ultrasound images present greater challenges due to noise and background artifacts, the CNN effectively highlights the stone location.

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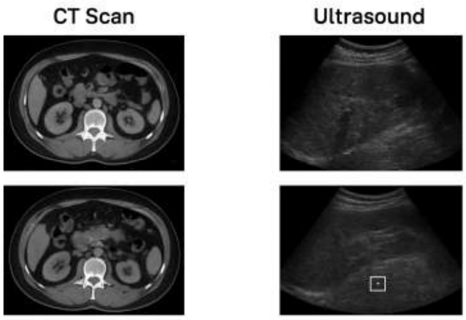

Figure 2: Output of the proposed method

Visually the figure demonstrates that the trained CNN can both detect (classify) and localize (highlight) stones across two imaging modalities, with clearer, higher-confidence localization on CT and more challenging but successful detection on ultrasound. The matrix below shows high CNN accuracy on CT; slightly lower but acceptable on ultrasound.

The quantitative performance of the proposed system is summarized in **Table II**.

Table II. Performance Metrics of the Proposed Method

Performance Metrix	CT	UTRASOUND
Accuracy	98.8%	96%
Precision	98.1%	94.5%
Recall	98.5%	91%
F1 Score	98.3%	94.7
Mean Inference time/image	22ms	28ms

The results demonstrate that the CNN achieves superior accuracy and faster inference on CT images, while maintaining robust and clinically acceptable performance on ultrasound images. These findings confirm the effectiveness and adaptability of the proposed framework across multiple imaging modalities

V. CONCLUSION

This study presented a CNN-based automated framework for kidney stone detection and classification using CT and ultrasound images. The experimental results demonstrate that the proposed system achieves high accuracy, precision, and recall while maintaining low inference time, making it suitable for real-time clinical applications. The strong performance on CT images confirms the model's reliability in high-contrast medical imaging, while the successful detection of stones in ultrasound images highlights its robustness under challenging imaging conditions.

The comparative analysis of existing research further emphasizes the growing impact of artificial intelligence, machine learning, and deep learning techniques in kidney stone diagnosis. Advanced methodologies such as radiomics, transfer learning, and deep convolutional architectures have shown significant improvements in detection accuracy, stone localization, and composition analysis across various imaging modalities. Automated systems for kidney stone detection reduce diagnostic workload, minimize human error, and support early diagnosis, particularly in resource-limited healthcare environments.

Overall, the proposed approach demonstrates strong potential to assist clinicians by improving diagnostic efficiency, enabling early intervention, and contributing to better patient outcomes. Future work may focus on expanding dataset diversity, incorporating multi-modal fusion techniques, and validating the system in large-scale clinical settings to further enhance its applicability and reliability

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