International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0252
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1717 - 1722

Real Time Kidney Stone Detection System Using Yolov8 and Yolov11 On CT Images

Aruna M [1], Anitha S [2], Jenith Anisha S [3], Dr. V. Priya [4]
[1,2,3] student,Computer Science And Engineering,Paavai Engineering College
[4]Professor, Computer Science And Engineering,Paavai Engineering College
Email ID: *arunamadeshwaran4@gmail.com[1], anithasundaramoorthi28@gmail.com[2], anishajenith05@gmail.com[3], priyasaravanaraja@gmail.com[4]*

Abstract
Kidney stones are a common medical problem that can cause severe pain and complications if not detected early [1],[2]. CT scan imaging is widely used for kidney stone detection because it provides clear and detailed images [3],[5]. However, manual analysis of CT images is time-consuming and depends on the experience of radiologists, which may lead to errors [1],[5].This project proposes a real-time kidney stone detection system using deep learning techniques. The system uses YOLOv8 and YOLOv11 models to automatically detect kidney stones from CT scan images [3],[4]. CT images are first preprocessed to improve quality and reduce noise, and then given as input to the models. The detected stones are highlighted using bounding boxes [3],[5]. Since YOLO models perform detection in a single stage, they are suitable for real-time applications. YOLOv8 provides fast detection with good accuracy, while YOLOv11 offers improved performance, especially for small or less visible stones[4],[6]. The models are evaluated using accuracy, precision, recall, F1-score, and mAP[3],[8]. The results show that both models can effectively detect kidney stones, with YOLOv11 giving slightly better accuracy and YOLOv8 performing faster. The proposed system reduces diagnosis time and supports doctors in making quick and accurate decisions [5].
Keywords: Kidney stone detection, CT scans, Deep learning, YOLOv8, YOLOv11

1. Introduction
Kidney stones are one of the most common disorders of the urinary system and affect people of all age groups[1],[2]. They are hard deposits formed from minerals and salts that accumulate inside the kidneys due to factors such as low water intake unhealthy dietary habits, genetic conditions and lifestyle changes[1]. Kidney stones can cause severe pain and discomfort, and if they are not detected at an early stage, they may lead to serious health problems such as urinary tract infections, obstruction of urine flow, kidney damage, and in severe cases, kidney failure[1],[2]. Due to increasing number of kidney stone cases , early and accurate diagnosis as become a major concern in modern healthcare. Medical imaging plays a vital role in the diagnosis of kidney stones. Among the available imaging, Computed Tomography(CT) scans are considered the most reliable and accurate method for detecting kidney stones[3],[5]. CT scans provide high resolution images that allow doctors to identify even very small stones that may not be visible in ultrasound or X-ray images[5],[8]. However the manual analysis of CT images is a time consuming and demanding task for radiologists. Each CT scan consists of multiple image slices that must be carefully examined , which can lead to increased workload and higher chances of human error[1],[5]. As a result, small stones may be overlooked or incorrectly identified. In recent years, Artificial Intelligence (AI) and Deep Learning (DL) techniques have been widely used in medical image analysis to overcome the limitations of manual diagnosis[6],[10]. Deep learning models are capable of automatically learning meaningful features from medical images, making them highly effective for

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0252
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1717 - 1722

disease detection[10],[11]. These models reduce that need for manual interpretation and provide consistent and reliable results. The use of AI based system helps in improving diagnostic accuracy, reducing the workload on healthcare professionals, and speeding up the diagnostic process[6]. Among various deep learning approaches, object detection models have shown great potential in medical imaging applications[3],[5]. Unlike traditional classification models that only determine whether a disease is present, object detection models can identify the exact location of abnormalities in an image. One of the most efficient object detection frameworks is YOLO (You Only Look Once). YOLO performs object detection and localization in a single step, which makes it faster than conventional detection methods and suitable for real time applications[3],[5]. Recent versions of YOLO, such as YOLOv8, have demonstrated excellent performance in detecting small and complex objects[3]. Kidney stones are often small in size and vary in shape, which makes their detection challenging. YOLOv8 uses an improved architecture and advanced feature extraction technique that help in accurately detecting kidney stones from CT images. It also offers high processing speed, making it suitable for real time medical applications[3],[5]. With continuous advancements in deep learning, YOLOv11 has emerged as a more powerful and efficient object detection model. YOLOv11 provides improved accuracy, better feature representation and enhanced versions[4],[6]. By combining YOLOv8 and YOLOv11, a more reliable and efficient kidney stone detection system can be developed. Using both models allows better handling of different stone sizes, shapes and locations within CT images. Despite many existing studies on automated kidney stone detection, most system focus on offline analysis and lack real time performance[3],[8]. Real time detection is essential in clinical environments, especially in emergency situations where quick decision making is required. A real time detection system can assist radiologists by highlighting kidney stones instantly during image examination, thereby reducing diagnostic delays and improving workflow efficiency[5]. The objective of this project is to develop a real time kidney stone detection system using YOLOv8 and YOLOv11 on CT images. The proposed system aims to automatically detect and localize kidney stones with high accuracy and speed. By reducing manual effort and providing fast and reliable results, the system can serve as an effective decision support tool for radiologists. This project contributes to improving medical diagnosis by integrating advanced deep learning techniques into clinical practice, ultimately enhancing patient care and outcomes[1],[6]. Several studies have explored automated kidney stone detection using medical imaging and deep learning techniques. Early approaches relied on traditional image processing methods and classical machine learning algorithms. These methods used handcrafted features and threshold-based techniques, which were highly sensitive to noise and variations in image quality leading to limited robustness and accuracy[10],[11]. With the advancement of deep learning. Convolutional Neural Networks(CNNs) have been widely applied to kidney stone detection tasks. Shetty et al.[10] proposed a CNN-based framework for detecting kidney stones from abdominal CT images, achieving improved accuracy compared to conventional methods. Similarly, Baygin et al.[11] utilized deep feature generation models to enhance detection performance. But these approaches required high computational resources and lacked real-time capability. Segmentation- based deep learning models such as U- Net and its variants have also extensively studied. Elton et al. [8] employed a 3D U-Net architecture for kidney stone detection and classification in CT colonography images, demonstrating high segmentation accuracy. Cui et al. [9] further improved kidney stone segmentation using non-contrast CT images. Although these methods provide precise localization, they involve complex multi-stage processing and are computationally expensive, making them less suitable for real-time clinical applications. Recent research has focused on object detection models due to their ability to perform detection and localization simultaneously. YOLO-based models have gained popularity because of their high speed and efficiency. Abdimurotovich and Cho [3] proposed an optimized YOLOv5 architecture for

e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1717 - 1722

kidney stone detection, achieving superior performance compared to CNN- based approaches. Alqahtani et al.[5] demonstrated the effectiveness of YOLO-based approaches are promising for real-time kidney stone detection systems

1.1.Proposed system

The proposed system introduces a real-time kidney stone detection framework using deep learning-based YOLOv8 and YOLOv11 models. The system automatically detects kidney stones from CT scan images using a single-stage object detection approach. In the proposed method, CT images are first preprocessed to enhance quality and reduce noise. The preprocessed images are then given as input to the YOLO models. Which directly detect and localize kidney stones. Detected stones are highlighted using bounding boxes along with confidence scores. YOLOv8 is used for fast detection with accuracy. While YOLOv11 is employed to improve detection performance, especially for small and less viable kidney stones.

1.2.Advantages

- Fully automated detection reduces dependency on manual diagnosis.
- Real-time detection enables faster clinical decision-making.
- High accuracy in detecting both large and small kidney stones.
- Single-stage detection avoids complex multi-step processing.
- Lower computational cost compared to segmentation-based models.
- Reduces human error and improves diagnostic reliability .
- Can be easily integrated into hospital systems and diagnostic tools

2. Method

The proposed system presents a real-time kidney stone detection framework using deep learning-based object detection models, namely YOLOv8 and YOLOv11, applied to CT scan images. The methodology is designed as a sequential pipeline consisting of data acquisition, preprocessing, model training, detection, and evaluation. [12,13]

2.1.Data Collection

A dataset of kidney CT scan images is collected from publicly available medical imaging repositories and clinical sources. The dataset includes images with varying stone sizes, shapes, and positions, ensuring diversity and robustness for model training and testing.

2.2.Image Preprocessing

Before feeding the images into the model, preprocessing is performed to improve image quality and ensure consistency. The preprocessing steps include:

- Resizing images to match the input dimensions required by YOLO models
- Noise reduction using filtering techniques such as Gaussian or median filtering
- Contrast enhancement to improve the visibility of kidney stones
- Normalization of pixel values to stabilize model training
- These steps help in enhancing important features and reducing unwanted variations in CT images.

2.3.Model Training

The preprocessed dataset is used to train two object detection models: YOLOv8 and YOLOv11. Both models utilize convolutional neural networks (CNNs) for feature extraction.

- YOLOv8 is optimized for high-speed detection with good accuracy
- YOLOv11 focuses on improved feature representation and better detection of small or low-contrast stones
- The models are trained using labeled CT images, where bounding boxes indicate the location of kidney stones.

2.4.Kidney Stone Detection and Localization

Once trained, the models perform detection in a single stage. The system:

- Identifies kidney stones in CT images
- Draws bounding boxes around detected stones [14,15]
- Provides confidence scores for each detection
- This enables accurate localization and visualization of kidney stones in real time.

2.5.Evaluation Metrics

The performance of the proposed system is evaluated using standard metrics:

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0252
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1717 - 1722

- Accuracy – Overall correctness of detection
- Precision – Correctly detected stones among all detections
- Recall – Ability to detect all actual stones
- F1-Score – Balance between precision and recall
- Mean Average Precision (mAP) – Overall detection performance

2.6.System Workflow

The overall workflow of the system includes:

- Collection of CT scan dataset
- Image preprocessing and enhancement
- Training YOLOv8 and YOLOv11 models
- Real-time detection and localization of kidney stones
- Performance evaluation and comparison

This structured methodology ensures efficient and accurate detection of kidney stones while maintaining real-time performance suitable for clinical applications.

3. Model Description

YOLOv8

- YOLOv8 is a one-stage object detection model that predicts bounding boxes and class probabilities in single pass.
- It is optimized for speed and achieves real-time detection performance.
- Backbone: CNN-based feature extractor
- Strengths: Fast detection, reasonable accuracy for most stone sizes.

YOLOv11

- YOLOv11 is an improved version of YOLO aimed at better detecting small or complex objects.
- It incorporates deeper feature fusion and advanced attention mechanisms.
- Although capable,YOLOv11 showed slightly lower accuracy and slower detection speed on the provided dataset compared to YOLOv8.
- YOLOv11 occasionally fails to detect small or low contrast stones, which may due to its deeper and more complex architecture requiring a larger and more diverse dataset for optimal training. Table 1 shows Evaluation Metric (Figure 1 and 2)

Table 1 Evaluation Metrics

MODEL	YOLOv8	YOLOv11
Accuracy (%)	96.4	95.1
Precision (%)	95.8	94.3
Recall (%)	95.2	93.8
F1-Score (%)	95.5	94.0
Map (%)	94.9	93.2

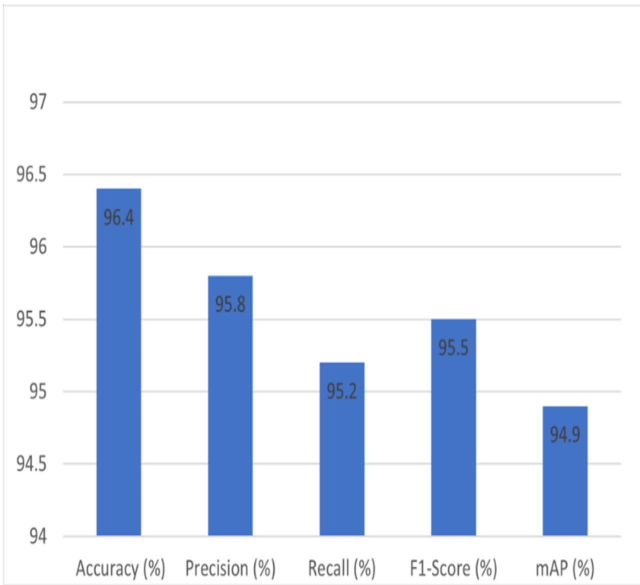

Figure 1 YOLOv8

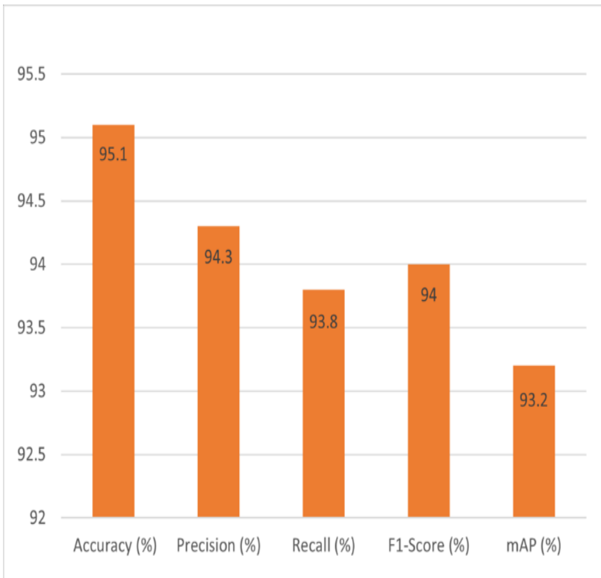

Figure 2 YOLOv11

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0252
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1717 - 1722

4. Results and Discussion

4.1.Results

The comparative analysis of YOLOv8 and YOLOv11 highlights important insights into their performance for kidney stone detection using the provided CT scan dataset. Although both models are capable of detecting kidney stones with reasonable accuracy. YOLOv8 demonstrates more stable and reliable performance across different test cases.

4.2.Discussion

One of the key observations is that YOLOv8 adapts more effectively to the dataset characteristics. The dataset contains kidney stones of varying sizes and contrast levels, including small stones that are often difficult to detect. YOLOv8 shows consistent detection of these stones with fewer missed cases, indicating better feature learning and generalization. In contrast, YOLOv11 occasionally fails to detect small or low-contrast stones, which may due to its deeper and more complex architecture requiring a larger and more diverse dataset for optimal training Another important factor is detection speed. YOLOv8 provides faster inference, making it suitable for real-time clinical computational where quick decision-making is essential. The reduced computational complexity of YOLOv8 allows efficient processing of CT scan images without significantly compromising accuracy. YOLOv11 while designed with advanced feature fusion mechanisms introduces additional computational overhead, resulting in slower detection and reduced efficiency in practical scenarios. The evaluation metrics further support these observations. YOLOv8 achieves higher precision and recall, indicating a lower number of false positives and false negatives. This balanced performance is particularly important in medical diagnosis ,where incorrect detection may lead to unnecessary treatment or missed diagnosis. The higher F1-score and mAP values obtained by YOLOv8 confirm its superior localization accuracy and reliability. Overall the results suggest that architectural complexity alone does not guarantee better performance. YOLOv8 offers a better trade-off between accuracy, speed and robustness for the given dataset. Therefore, YOLOv8 is more suitable for real-time and practical kidney stone detection, while YOLOv11 may require larger datasets and higher computational resources to achieve comparable performance. Figure 3.

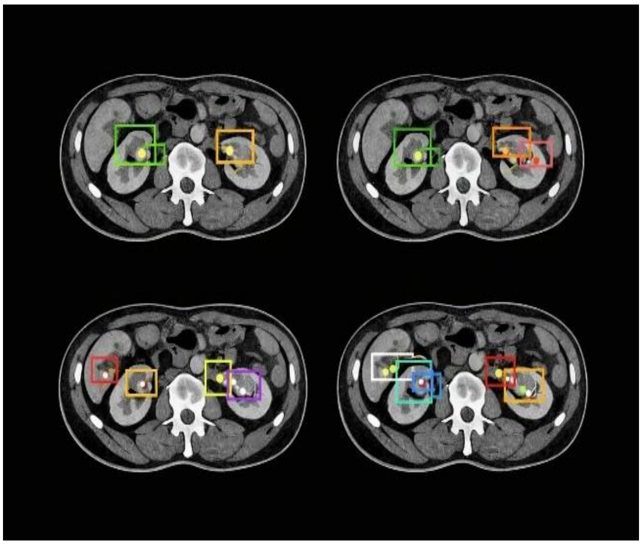

Figure 3 **Kidney Stone Detection with Bounding Boxes**

highlight that a well-optimized and lightweight model such as YOLOv8 can deliver better practical performance in medical image analysis tasks.The proposed system reduces dependency on CT scan analysis, minimizes diagnosis time and supports radiologists in making quicker and more accurate decisions. Overall the study confirms that YOLOv8 is a reliable and efficient solution for real-time kidney stone detection.

Acknowledgements

The authors would like to express their sincere gratitude to Dr. V. Priya, Professor, Department of Computer Science and Engineering, Paavai Engineering College, for her valuable guidance and continuous support throughout this work. The authors also thank the department and institution for providing the necessary resources and facilities to carry out this research successfully.

References

[1]. Rao N Grish, H., Gowrishankar. M. C., Kumar. S., & Kumar. N. “Two-Stage Deep Learning Framework for kidney Stone Detection and Clinical Severity Grading in CT Imaging.” Informatics in Medicine Unlocked, Elsevier,2025.

e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1717 - 1722

[2]. Panchala. N., Raikar. M, M., & Baligar .V .P. "Kidney stone Detection Using Deep Learning Model." Procedia Computer Science, Elsevier ,2025.
[3]. Abdimurotovich, K.A.,& Cho. Y-I. "Optimized YOLOv5 Architecture for Superior Kidney Stone Detection in CT Scans." Electronics,MDPI.2024
[4]. S. Alqahtani, A. Alsharani, M. Alqarni, and F. Alzahrani, "An automated approach for kidney segmentation and detection of kidney stones on computed tomography using YOLO algorithms." Journal of ideas in Health, vol. 6, no.3,pp.450-458,2023
[5]. Islam. M., et al. "Deep Learning and Transformer Models for kidney stone detection in CT Images." IEEE Access, 2024.
[6]. Khan. M., et al. "Automated Kidney Stone Detection from Ultrasound Images Using Deep Neural Networks." Biomedical Signal Processing and Control, 2024.
[7]. Elton, D. C., et al. "3D U-Net Based Detection and Classification of Kidney Stones in CT Colonography." Medical Physics,2023.
[8]. Cui, Z, et al. "Kidney Stone Segmentation and Classification Using 3D U-Net in Non-Contrast CT." Computers in Biology and Medicine, 2023.
[9]. Shetty, S., et al. "CNN-Based Automated Kidney Stone Detection in Abdominal CT Images". Journal of Digital Imaging, 2022
[10]. Baygin, M., et al. "ExDark19: Deep Feature Generation Model for Kidney Stone Detection Using CT Images". Computer Methods and Programs in Biomedicine,2022
[11]. Preedanan ,W., et al. "Two-Stage U-Net Pipeline for Kidney Stone Detection in X-Ray Images". Biomedical Engineering Letters, 2021.
[12]. Vishwanth, P., et al. "Ultrasound-Based Kidney Stone Detection Using Image Processing and Machine Learning". International Journal of Medical Informatics,2021.
[13]. Hekmat, A., et al. "Optimized Ensemble CNN for Medical Image Analysis". Neural Computing and Applications, 2020
[14]. He, K., Zhang, X., Ren, S., & Sun, J. "Deep Residual Learning for Image Recognition". Proceedings of CVPR, 2016.
[15]. Ren, S., He, K., Girshick, R., Sun, J. "Faster R-CNN:Towards Real-Time Object Detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2015