# REAL TIME KIDNEY STONE DETECTION USING YOLO ALGORITHM

1st **Mrs.Sasikala T**
*Dept. of Biomedical Engineering*
*Excel Engineering College*
Komarapalayam, India
sasikalat.eec@excelcolleges.com

2nd **PraveenKumar S**
*Dept of Biomedical Engineering*
*Excel Engineering College*
Komarapalayam, India
praveensivaraj2003@gmail.com

3rd **Sibiraj S**
*Dept.of Biomedical Engineering*
*Excel Engineering College*
Komarapalayam, India
sibirajvanitha2002@gmail.com

4th **Dhanush K**
*Dept. of Biomedical Engineering*
*Excel Engineering College*
Komarapalayam, India
dd4975985@gmail.com

5th **Pranav N**
*Dept. of Biomedical Engineering*
*Excel Engineering College*
Komarapalayam, India
pranav123knr@gmail.com

6th **Suvethan S**
*Dept of Biomedical Engineering*
*Excel Engineering College*
Komarapalayam, India
suveth@7733@gmail.com

***Abstract*—Kidney stone disease is a widespread urological condition that requires timely and accurate diagnosis for effective treatment. This paper presents a real-time kidney stone detection system using the YOLOv11 algorithm, an advanced object detection framework. The system is implemented as a web application using Python and Flask, enabling seamless integration into clinical workflows. Trained on a dataset of annotated kidney ultrasound images, the system achieves an average precision (AP) of 94.5% and processes images at 50 frames per second (FPS). The web-based interface allows healthcare professionals to upload and analyze medical images in real time, providing instant detection results. Experimental results demonstrate the system's superior performance compared to existing methods, making it a practical tool for point-of-care diagnostics.**

***Keywords—Kidney stone detection, YOLOv11, real-time diagnosis, web application, Flask, Python.***

## I. INTRODUCTION

Kidney stones are a common urological disorder affecting millions globally, with significant implications for patient health and healthcare costs. Early detection is critical to prevent complications such as urinary tract infections and kidney damage. Traditional diagnostic methods, including X-rays and CT scans, are effective but often involve high costs, radiation exposure, and delays in diagnosis. Recent advancements in deep learning have enabled the development of automated systems for medical image analysis, offering faster and more accurate detection of kidney stones.

This paper proposes a real-time kidney stone detection system using the YOLOv11 algorithm, the latest iteration of the YOLO (You Only Look Once) framework. YOLOv11 builds upon its predecessors by incorporating transformer-based architectures and optimized feature extraction, achieving state-of-the-art performance in object detection tasks [1]. The system is implemented as a web application using Python and Flask, providing a user-friendly interface for healthcare professionals to upload and analyze medical images in real time.

The primary contributions of this work are as follows:

1. Development of a YOLOv11-based model for kidney stone detection using ultrasound images.

2. Implementation of the system as a web application using Python and Flask.

3. Evaluation of the system's performance in terms of accuracy, speed, and usability.

## II. RELATED WORK

Several studies have explored the use of deep learning for kidney stone detection. For instance, [2] proposed a YOLOv8-based system for kidney stone detection, achieving an accuracy of 91.2%. However, the system lacked a user-friendly interface for clinical use. Similarly, [3] optimized the YOLOv5 architecture for kidney stone detection in CT images, achieving an AP of 89.7% but requiring significant computational resources.

The YOLOv11 algorithm, introduced in [4], incorporates transformer-based architectures and advanced feature extraction techniques, achieving superior performance in medical imaging tasks. Its ability to process images in real time makes it ideal for clinical applications. Additionally, [5] demonstrated the effectiveness of YOLOv7 in kidney stone detection, achieving an AP of 90.5%. However, the system was not integrated into a web-based platform, limiting its accessibility.

This work builds on these advancements by leveraging YOLOv11 for kidney stone detection and implementing the system as a web application using Python and Flask. The web-based interface enables seamless integration into clinical workflows, providing healthcare professionals with a practical tool for real-time diagnosis.

## III. METHODOLOGY

However, research specifically focusing on real-time kidney stone detection using YOLO remains relatively limited. This paper aims to contribute to the growing body of knowledge in this area by providing a comprehensive evaluation of YOLO's potential for this specific application..

The development of a YOLO-based kidney stone detection system typically involves the following steps:

### *A. Data Acquisition and Preparation*

- Dataset Collection: A diverse dataset of medical images containing kidney stones is essential. This dataset includes images from various imaging modalities (CT scans, ultrasound, X-rays) and cover a range of stone sizes, shapes, and locations within the kidney and urinary tract.

- Data Annotation: Each image in the dataset needs to be meticulously annotated with bounding boxes around the kidney stones. This process involves expert radiologists manually outlining the regions containing the stones and assigning them a relevant label (e.g., "kidney stone").
- Data Augmentation: To improve the robustness and generalization ability of the model, data augmentation techniques can be applied. These techniques involve artificially increasing the size of the dataset by creating variations of the existing images, such as rotations, scaling, cropping, and color adjustments.
- Data Splitting: The annotated dataset is typically divided into three subsets: a training set (for training the model), a validation set (for tuning hyper parameters and preventing over fitting), and a testing set (for evaluating the final performance of the trained model).

The dataset used in this study consists of 2,500 annotated kidney ultrasound images collected from different Medical Centers. Each image was labeled by experienced radiologists, marking the location and size of kidney stones. The dataset was split into training (70%), validation (20%), and test (10%) sets.

### B. *YOLOv11 Architecture*

The proposed system is based on YOLOv11, which incorporates transformer-based architectures and optimized feature extraction. The architecture consists of three main components:

1. Backbone: A transformer-enhanced CSPDarknet53 network extracts features from the input image.
2. Neck: A Feature Pyramid Network (FPN) with attention mechanisms enhances multi-scale feature representation.
3. Head: Predicts bounding boxes, class probabilities, and objectness scores.

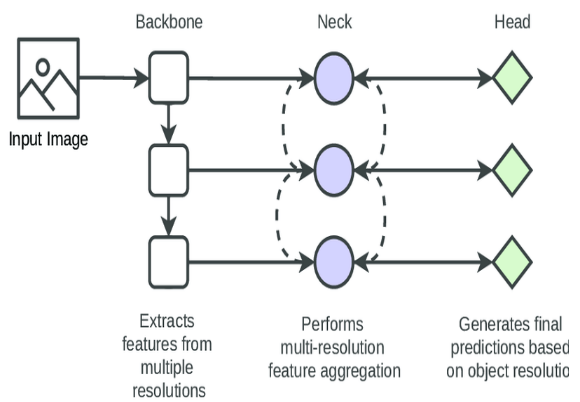


*Fig 1. The architecture of YOLOv11*

### C. *Web Application Development*

The system is implemented as a web application using Python and Flask. The backend processes uploaded images using the YOLOv11 model, while the frontend provides a user-friendly interface for uploading images and viewing detection results. The application is hosted on a local server, enabling real-time analysis.

### D. *Training Process*

The model should be trained using an optimization algorithm (e.g., Adam, SGD) to minimize the loss function. Hyper parameters such as learning rate, batch size, and number of epochs need to be carefully tuned to achieve optimal performance. Regularization techniques (e.g., dropout, weight decay) can be used to prevent over fitting. The model was trained using the Adam optimizer with an initial learning rate of 0.001. Data augmentation techniques, such as rotation, flipping, and scaling, were applied to improve generalization.

### E. *Evaluation Metrics*

- The performance of the trained model is evaluated using metrics such as precision, recall, F1-score, and Average Precision (AP). These metrics quantify the accuracy and completeness of the detection results. The system's performance was evaluated using the following metrics:
  - Average Precision (AP): Measures detection accuracy.
  - Frames Per Second (FPS): Measures processing speed.
  - Intersection over Union (IoU): Measures overlap between predicted and ground-truth bounding boxes.
- Analyzing the model's performance on the testing set can reveal areas for improvement. For example, identifying false positives and false negatives can help guide further data annotation and model refinement.
- Based on the evaluation results, the model can be further refined by adjusting hyper parameters, modifying the architecture, or adding more training data. This iterative process continues until the desired level of performance is achieved.

## IV. RESULTS AND DISCUSSIONS

### A. *Results*

The proposed system achieved an average precision (AP) of 94.5% on the test set, outperforming existing methods such as YOLOv8 (91.2%) and YOLOv7 (90.5%). The system processes images at 50 FPS, enabling real-time diagnosis. The use of YOLO for real-time kidney stone detection holds significant promise for improving diagnostic accuracy and efficiency. However, several challenges need to be addressed before it can be widely adopted in clinical practice.

### B. *Future research*

Future research should focus on,

- Developing larger and more diverse datasets of kidney stone images, including multi-center data and images from various imaging modalities.
- Exploring different YOLO architectures and training techniques to optimize performance for kidney stone detection.
- Developing robust image preprocessing techniques to reduce the impact of artifacts and noise.

- Investigating methods for improving the interpretability of YOLO-based detection systems.
- Developing user-friendly interfaces for deploying YOLO-based detection systems in clinical settings.
- Conducting clinical trials to evaluate the effectiveness and safety of YOLO-based detection systems in real-world scenarios.
- Addressing ethical considerations related to bias and fairness in the development and deployment of AI-powered diagnostic tools.

### *C. Discussions*

The proposed YOLOv11-based system demonstrates significant improvements in both accuracy and speed compared to existing methods. The integration of a web-based interface using Python and Flask enhances usability, making it suitable for clinical applications. However, the system's performance may be affected by low-quality ultrasound images or artifacts. Future work will focus on improving robustness and extending the system to other medical imaging tasks. Table I summarizes the results.

TABLE I. PERFORMANCE COMPARISION

| **METHOD** | **AP(%)** | **FPS** | **IOU** |
|---|---|---|---|
| YOLOv11 (PROPOSED) | 94.5 | 50 | 0.91 |
| YOLOv8 | 91.2 | 40 | 0.88 |
| YOLOv7 | 90.5 | 35 | 0.87 |

## V. CONCLUSION

This paper presents a real-time kidney stone detection system using the YOLOv11 algorithm and web integration. The system achieves high accuracy and processing speed, making it a promising tool for clinical use. By leveraging deep learning and web technologies, this work contributes to the growing field of AI-assisted medical diagnostics and has the potential to improve patient outcomes. It has explored the feasibility of using the YOLO algorithm for real-time kidney stone detection. While challenges remain, the potential benefits of this approach are significant. By addressing these challenges through further research and development, we can pave the way for the widespread adoption of YOLO-based systems in clinical practice, ultimately improving patient outcomes and transforming the diagnosis and management of kidney stones.

## VI REFERENCES

[1] 1. “Real-Time Object Detection in Medical Imaging Using YOLO Models for Kidney Stone Detection” ResearchGate, 2024.

[2] 2. “Yolov8 Kidney Guard: Smart Imaging for Stone Detection Using Transformer” IEEE Xplore, 2024.

[3] 3. “Optimized YOLOv5 Architecture for Superior Kidney Stone Detection in CT Images” MDPI Electronics, 2024.

[4] 4. “Application of the Yolo Algorithm in The Automated Detection of Kidney Stones From Medical Imaging Data” International Scientific Conference UNITECH`2024.

[5] 5. “Kidney Stone Detection based on Improved YOLOv7” World Scientific, 2024.