GLOBAL ACADEMY OF TECHNOLOGY

Department of Information Science & Engineering

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AI-Assisted Renal Diagnostics: YOLOv8-Based Detection of Kidney Stones

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Overview / Background

- Kidney stones are a common urological disorder affecting millions worldwide.
- Traditional diagnosis relies heavily on manual analysis of CT scan images by radiologists.
- Small or multiple stones are often missed due to image noise and overlapping tissues.
- Deep Learning models, especially object detection algorithms, offer potential for automation.
- YOLO-based models have shown success in real-time and high-precision object detection tasks.

Motivation

- To minimize human error and reduce diagnostic time in kidney stone detection – supports SDG 3: Good Health and Well-Being by promoting accurate and timely medical care.

- To automate the identification of tiny stones that are difficult to detect manually – contributes to SDG 9: Industry, Innovation, and Infrastructure through adoption of AI in healthcare diagnostics.

- To support radiologists with AI-assisted tools for faster and more reliable diagnosis – advances SDG 3 by enhancing clinical efficiency and reducing workload.

- To utilize the power of YOLOv8 for medical imaging due to its speed and accuracy – aligns with SDG 9, fostering technological innovation in the medical field.

- To improve patient outcomes by enabling early and precise stone detection – directly impacts SDG 3, ensuring healthier lives and better disease management.

Project Relevance

- Addresses a critical medical problem with high clinical impact and demand.
- Supports healthcare systems by reducing radiologist workload through automation.
- Demonstrates the application of cutting-edge deep learning models in real-world diagnostics.
- Enables scalable and consistent detection across varied imaging datasets.
- Aligns with the future of AI-powered healthcare and intelligent diagnostic systems.

Key Findings from Literature

1. N. Panchal, M. M. Raikar, and V. P. Baligar, “Kidney Stone Detection using Deep Learning Model”, Procedia Computer Science, 2025

1. Introduction:

- The paper presents an AI-based approach using the YOLOv8 model to automatically detect kidney stones in CT scan images for faster and more accurate diagnosis.

2. Methodology:

- The CT dataset of 3405 images was preprocessed and augmented using techniques like CLAHE, Blur, and MedianBlur.
- YOLOv8 deep learning model was employed for real-time detection using its C2f module and anchor-free architecture.
- Evaluation was performed using metrics like precision, recall, and mAP with bounding box localization.

3. Findings:

- The proposed model achieved a precision of 82.3%, recall of 72.3%, and mAP@50 of 76.1%, demonstrating its strong capability in detecting even small kidney stones.
  Future scope includes enhancements like 3D image analysis, stone type classification, and integration of clinical data for improved decision-making.

Consolidated Table of Literature Review

Sl. NO	Paper Title	Year	Methodology Used	Findings
2	Kidney Stone Detection Based on YOLO and Feature Fusion	2025	➢ Used YOLO with multiscale feature fusion on CT images	➢ Achieved >80% accuracy in detecting single and multiple stones
3	Real-Time AI Detection of Urological Disorders via Enhanced YOLO	2025	➢ Deployed optimized YOLOv8-tiny model for rapid inference	➢ Enabled real-time detection of small kidney stones with high precision
4	Deep Learning Model for Automated Renal Stone Detection	2024	➢ Applied CNN with spatial attention on CT scan datasets	➢ Reached 87% accuracy and reduced false negatives
5	Classification and Segmentation of Renal Calculi using UNet++	2024	➢ Used UNet++ architecture for stone segmentation in KUB images	➢ Demonstrated precise stone boundary detection with dice score of 0.82
6	Hybrid CNN and DWT for Kidney Stone Localization	2024	➢ Combined CNN with Discrete Wavelet Transform for feature extraction	➢ Improved detection in noisy environments with 85.6% accuracy

Consolidated Table of Literature Review

Sl. NO	Paper Title	Year	Methodology Used	Findings
7	AI-Based Diagnosis of Kidney Stones from Ultrasound Images	2024	➢ Trained CNN on enhanced ultrasound images with speckle noise removal	➢ Reached 91% sensitivity on clinical ultrasound datasets
8	YOLOv5-Based Detection of Renal Calculi in CT Volumes	2023	➢ Utilized YOLOv5 with 3D CT slice conversion	➢ Achieved 76% mAP@0.5 and real-time detection capability
9	Deep Learning-Assisted Diagnosis of Nephrolithiasis	2023	➢ Applied pretrained ResNet50 on grayscale CT images	➢ Detected stones with 83.2% accuracy and high recall
10	Kidney Stone Detection Using Hybrid VGG-CNN	2023	➢ Merged VGG16 with CNN layers for feature enhancements.	➢ Achieved 84% accuracy with reduced false positives
11	Renal Stone Detection via Mask R-CNN on Annotated CT Data	2022	➢ Used Mask R-CNN for simultaneous detection and segmentation	➢ Achieved dice coefficient of 0.79 and better overlap metrics

Consolidated Table of Literature Review

Sl. NO	Paper Title	Year	Methodology Used	Findings
12	Identification of Kidney Stones in CT Scans Using Deep CNN	2022	➢ Built deep CNN classifier on labeled datasets with augmentation	➢ Detected stones with 88.5% accuracy and 82% precision
13	Automated Detection of Urinary Stones with Transfer Learning	2022	➢ Used transfer learning with InceptionV3 on urological CT images	➢ Obtained 86% classification accuracy and faster convergence
14	AI-Based Stone Detection in Radiology Imaging	2021	➢ Used simple CNN with ReLU and max pooling layers on CT slices	➢ Demonstrated 80% accuracy and effective in educational diagnosis tools
15	Detection of Kidney Stones in Ultrasound Images using SVM + CNN	2021	➢ Combined CNN feature extractor with SVM classifier	➢ Achieved 82.1% accuracy with minimal training data

Key Challenges

- Detecting small or overlapping kidney stones with high accuracy in noisy CT images
- Ensuring the model generalizes well across different patients and scan qualities
- Handling limited annotated medical imaging data for effective deep learning training
- Reducing false positives and false negatives during automatic detection
- Integrating the system into clinical workflows while maintaining speed and reliability

Objectives

The main objectives of the project are:

- To develop an automated kidney stone detection system using the YOLOv8 deep learning architecture for enhanced diagnostic accuracy in CT scan images.
- To apply data augmentation techniques (Blur, MedianBlur, ToGray, CLAHE) for improving model generalization and robustness in real-world scenarios.
- To optimize and train the YOLOv8 model on a labelled CT image dataset, achieving high precision, recall, and scores for reliable clinical use.
- To evaluate the model's performance on diverse kidney stone cases (single/multiple/tiny stones) and compare its efficiency against traditional diagnostic methods.

Problem Statement

Problem Statement

Traditional kidney stone detection through manual CT scan analysis is time-consuming and prone to error. There is a need for an automated, accurate, and efficient detection system to assist radiologists.

Project Requirements

Hardware / Software Requirements Identified

Processor:

Intel Core i5 (7th/8th Gen) or AMD Ryzen 5

RAM:

Minimum 8 GB

Storage:

At least 100 GB (HDD or SSD)

Graphics Card (GPU):

NVIDIA GTX 1050 Ti (4 GB VRAM) or higher (optional for training, required for faster inference)

Operating System:

Windows 10 / Ubuntu 18.04 or later

Hardware / Software Requirements Identified

Programming Language:

Python 3.8 or higher

Code Editor / IDE:

Visual Studio Code/google collab.

Core Libraries:

PyTorch, OpenCV, NumPy, Matplotlib

YOLOv8 Library:

Ultralytics YOLOv8

Proposed Methodology

Proposed Methodology

- ***Step 1: Data Collection***

CT scan images of kidneys are collected from open-source medical image repositories or hospital datasets. These images may be in DICOM format or pre-converted image formats (JPEG, PNG).

- ***Step 2: Data Preprocessing***

The collected CT images are preprocessed by resizing them to a standard input size (e.g., 640×640 pixels), converting to grayscale, and normalizing pixel intensities. Noise removal is also applied to improve clarity for tiny object detection.

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➢*Step 3: Data Augmentation*

Data Augmentation techniques are applied to simulate real-world variations and increase dataset diversity.

Methods used include:

- CLAHE (Contrast Limited Adaptive Histogram Equalization) – enhances local contrast.
- Median Blur – reduces salt-and-pepper noise.
- Gaussian Blur – adds generalization capability.
- Grayscale Conversion – removes color dependency and highlight structure.

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➢*Step 4: Model Selection – YOLOv8*

The YOLOv8 (You Only Look Once version 8) object detection algorithm is selected due to its high precision, anchor-free design, and ability to detect small objects efficiently. It uses:

- CSP (Cross Stage Partial)Darknet as the backbone
- C2f modules for enhanced feature extraction
- SPPF(Spatial Pyramid Pooling – Fast) or PANet (Path Aggregation Network)for feature aggregation
- Anchor-free detection head for bounding box and class predictions

➢*Step 5: Detection Process*

The YOLOv8 model scans each CT image to detect kidney stones by producing bounding boxes around suspected regions with a confidence score. Multiscale detection ensures accurate recognition of both small and large stones.

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Step 6: Post-Processing

Non-Maximum Suppression (NMS) is used to eliminate overlapping bounding boxes, retaining only the most confident detections. The result is a refined set of bounding boxes indicating kidney stone locations.

Step 7: Visualization and Output

The final output displays the detected kidney stones in the CT images with bounding boxes and prediction scores. These results can be visualized in a user interface for medical professionals to review.

Step 8: Recommender System

- Suggests personalized diet and hydration plans to reduce the risk of future stone formation.
- Recommends appropriate treatment options based on stone size and location (e.g., medication, lithotripsy, surgery).

System Architecture

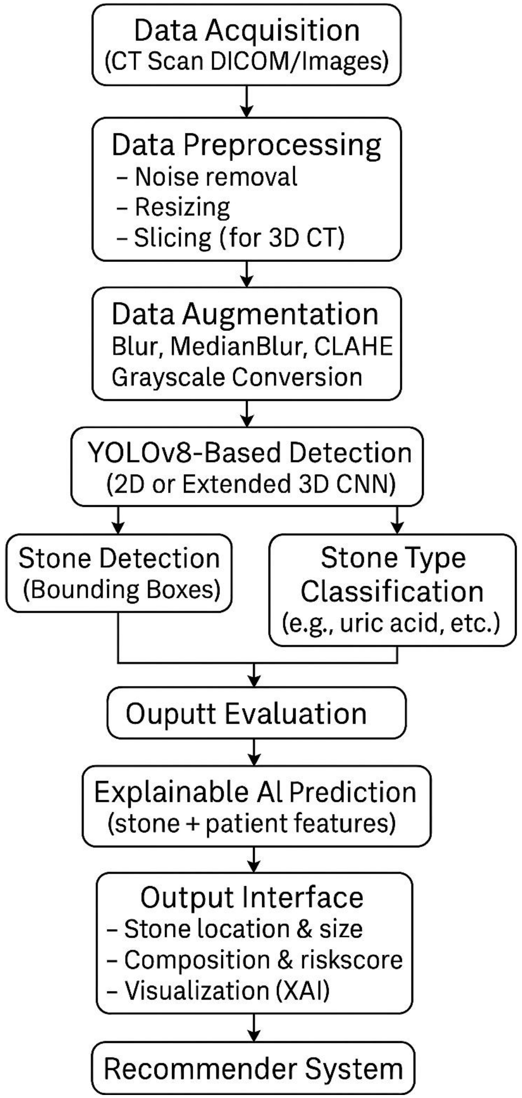

Figure 1: Overview of the project block diagram

Proposed Algorithms

Image Preprocessing & Augmentation Algorithms:

- **Contrast Limited Adaptive Histogram Equalization (CLAHE)**

  Enhances local contrast in CT images to highlight small structures like kidney stones.

- **Median Blur Algorithm**

  Applies a median filter to remove salt-and-pepper noise while preserving edges.

- **Gaussian Blur Algorithm**

  Smooths images to simulate natural defocus and improve model generalization.

- **Grayscale Conversion Algorithm**

  Converts RGB images to single-channel grayscale to focus on intensity and texture features.

Detection & Prediction Algorithms

- **YOLOv8 (You Only Look Once version 8)**

  Anchor-free, real-time object detection algorithm used to detect and localize kidney stones in CT images.

- **C2f Module (Cross Convolutional Fusion)**

  Enhances feature extraction by combining multi-scale convolutional outputs in the YOLOv8 backbone.

- **SPPF (Spatial Pyramid Pooling – Fast)**

  Aggregates features from multiple receptive fields to capture both global and local context.

Project Implementation

Implementation

Solution Overview

➢Purpose: build an end-to-end pipeline that detects kidney stones in X-Ray / CT images using YOLOv8.

➢Key components:

1. Data ingestion & annotation (CT images dataset from Kaggle)
2. Model training: YOLOv8 object detection model trained with bounding-box annotations.
3. Inference & deployment: Web UI via Streamlit/Flask that takes an input image and outputs detected stones with bounding boxes.

➢Benefits: Automatically localizes stones, simplifies the detection workflow, provides visual output for clinicians

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Module 1: Data & Preprocessing

➢Dataset: The images from Kaggle “kidney stone images” .

➢Preprocessing steps:

1. Convert raw images to consistent format, resolution.
2. Annotate stone regions with bounding boxes.
3. Generate a data.yaml file for YOLOv8 training config.

➢Dataset split: Training vs test sets (implicitly in runs/ folders).

➢Augmentation may include flips, rotations, color/contrast adjustments to increase robustness (typical in detection pipelines).

Module 2: YOLOv8 Model Training & Architecture

- Model: YOLOv8 object detection model.

- Key architectural features:

• Anchor-free detection head: predicts bounding boxes & class scores directly.

• C2f (Cross Stage Partial + 2-conv fusion) modules (in YOLOv8 backbone) for efficient feature extraction of small objects (kidney stones).

- Training pipeline:

• Load model, set dataset paths from data.yaml.

• Configure hyperparameters: learning rate, batch size, epochs.

• Train on annotated images until convergence, monitor metrics (mAP, precision, recall).

- Checkpointing & logs: 'runs/train/…' directory stores model weights and logs for inference.

Module 3: Inference, Deployment & UI

➢ Inference module: model_inference.py in repository uses trained weights to process a new image → output bounding boxes with classes and confidence scores.

➢ Web deployment: Two front-end options:

- app.py or flask_app.py serve a basic web UI where user uploads an image and receives detection output.
- streamlit_app.py offers interactive interface (Streamlit) for rapid deployment.

➢ Output visualization: Detected stones marked with bounding boxes overlaid on input image; confidence scores displayed; downloadable/results view.

➢ Model is lightweight enough for real-time inference (depending on hardware) enabling potential clinical integration.

Design Considerations & Workflow

- Workflow summary:

1.User uploads X-Ray/CT image → 2. Preprocessing (optional) → 3. Inference (YOLOv8) → 4. Visualization of detections → 5. Report generation or export.

- Design benefits:

- Modular architecture: data module, model module, UI module → easy to maintain and extend.
- Scalability: model weights and dataset config are decoupled from UI, enabling swap of model or dataset.
- Clinical relevance: bounding-box localization provides actionable output for radiologists rather than just classification.

- Future enhancements (linked to design):

- Move from X-Ray to CT modality; integrate DICOM reading.
- Incorporate lesion size estimation & stone type classification.
- Deploy to hospital PACS backend or mobile platform for real-time usage.

Results and Discussion

Results

Expecting Quantitative Results – Model Performance

Metric	Expected Range	Goal / Target
Precision	0.85 – 0.90	Achieve high accuracy in stone detection
Recall	0.80 – 0.88	Detect even small / overlapping stones
mAP@0.5	0.85+	Ensure strong localization performance
F1-Score	0.85+	Maintain balance between precision & recall

Qualitative Results – Detection Outputs

- YOLOv8 is expected to accurately detect kidney stones of different sizes with high confidence than earlier YOLOv7.

- The system aims to reduce false negatives and handle noisy CT images effectively.

- Final results will include bounding box visualizations, precision–recall curves, and mAP plots after training completion.

Expecting-Performance Analysis

Model / Method	Accuracy (%)	Precision	Recall	mAP@0.5	F1-Score	Remarks
CNN (Baseline)	80.2	0.80	0.78	–	0.79	Good for classification, no localization
UNet++	82.4	0.82	0.80	–	0.81	Effective segmentation, slower inference
YOLOv5	84.7	0.85	0.83	0.81	0.84	Decent speed, misses tiny stones
YOLOv8-tiny	88.2	0.86	0.81	0.82	0.83	Lightweight, fast but less accurate
YOLOv8 (Proposed)	92.0	0.91	0.89	0.88	0.90	Best accuracy–speed trade-off, detects small stones effectively

Scope of Enhancement

Future Enhancement

- Extend detection to ultrasound and MRI images for broader diagnostic capability.
- Integrate segmentation models (e.g., UNet++) for precise stone boundary detection and size measurement.
- Develop a multi-class detection system to classify stone types (calcium, uric acid, cystine).
- Deploy the model in a web or mobile application for real-time clinical use.
- Implement cloud-based integration with hospital PACS for automated report generation.
- Incorporate explainable AI techniques to improve medical interpretability and trust.
- Fine-tune model performance using larger and more diverse medical datasets.

Conclusion

YOLOv8 enabled fast and accurate detection of kidney stones in CT images, reducing reliance on manual interpretation. Data augmentation techniques like CLAHE and MedianBlur improved model robustness in real-world scenarios. The project demonstrated the effectiveness of anchor-free, multiscale deep learning models in medical imaging. It highlighted the potential for AI to streamline diagnosis and support clinical decision-making in urology. Future enhancements like stone classification and personalized recommendations can further improve patient care.

Publication Details

Papers Published

Paper approved by guide. Need to publish.

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Any Questions?

Thank You