A Deep Learning Model for Automated Kidney Disease Classification Using CT Imaging.

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***Abstract*—Kidney diseases like stones, cysts, and tumors affect millions of people worldwide and often go unnoticed until they reach serious stages. Reading CT scans manually is not only time-consuming but also vulnerable to human error, which can delay treatment. To tackle this issue, we built an intelligent diagnostic framework that can automatically classify kidney CT images into four categories: normal, cyst, stone, and tumor. At its core is YOLOv8n-cls, a lightweight deep learning model designed for fast and efficient image classification. The framework improves CT scan quality through preprocessing steps—such as resizing, denoising, and contrast enhancement—and boosts reliability using data augmentation. We trained the model on a balanced dataset of 18,948 CT images, where it achieved a classification accuracy of 96.88% across all categories. Compared to traditional diagnostic workflows, our system provides radiologists with quick, accurate, and reliable assistance, reducing both interpretation time and diagnostic errors. Thanks to its compact design, it can be deployed in hospitals, local clinics, or even telemedicine platforms, making it especially useful in low-resource settings. While further validation on external datasets is needed, this approach shows strong potential to support early detection and improve patient outcomes in kidney disease care.**

***Index Terms*—Keywords— YOLOv8n-cls, Kidney Disease Classification, CT Imaging, Deep Learning, Automated Diagnosis**

I. Introduction

Kidney diseases such as stones, cysts, and tumors affect millions of people worldwide and can lead to severe complications if not detected at an early stage. These conditions disrupt the kidney's critical functions—waste filtration, fluid balance, and toxin removal—making timely diagnosis essential to prevent disease progression and associated risks. Unfortunately, in rural and resource-limited regions, the lack of advanced imaging facilities and trained radiologists often results in delayed detection and treatment.

Several AI-driven approaches have attempted to address this gap. Pande et al. [1] proposed a CNN-based model that achieved 94.7% accuracy in detecting kidney abnormalities from CT scans, while Falana et al. [2] enhanced CT images and applied ResNet, reaching 92.3% accuracy. Although these studies demonstrate the promise of deep learning, they also highlight persistent challenges: morphological similarities between stones, cysts, and tumors make accurate differentiation difficult; variability in scan quality reduces model generalizability; and most existing models are computationally intensive, limiting their deployment in real-time or low-resource healthcare environments.

To overcome these limitations, we designed a lightweight, AI-powered diagnostic system using YOLOv8n-cls, a fast and efficient classification model. Our system classifies kidney CT images into four categories—Normal, Tumor, Cyst, and Stone—while providing interpretable outputs such as confidence scores to support clinical decision-making. Unlike traditional models, this approach emphasizes both accuracy and deployability, making it suitable for hospitals, clinics, and remote health centers. By enabling faster and more reliable diagnosis, the proposed system has the potential to improve patient outcomes and reduce the burden of delayed treatment in underserved regions.

II. Related Work

Sivaprakasam S. Anantha et al. [3] introduced YOLOv8 Kidney Guard, a system for detecting kidney stones in CT scan images. They leveraged YOLOv8 object detection on well-annotated datasets, achieving a mean Average Precision (mAP) of 90.5

Mahendran et al. [4] proposed a deep learning framework for early kidney stone detection by integrating U-Net for segmentation with CNN for classification. This hybrid approach improved labeling accuracy and delivered promising results for real-world clinical applications.

Prin Twinprai et al. [5] studied kidney stone detection from CT images using YOLOv8. Their model, trained on accurately labeled CT scans, demonstrated reliable real-time performance, consistently producing predictions above 50

Priyanka et al. [6] developed a dual-path CNN architecture capable of detecting stones and tumors simultaneously in kidney CT images. By incorporating a Multi-Dilated Spatial Grouping module and Spatial Information Guidance (SIG), their framework reached a peak mAP of 94.7

Tan and Le [7] introduced EfficientNetV2, a compact and optimized deep learning model that reduces training time while improving performance, proving highly effective for CT-based medical imaging tasks.

Pimpalkar et al. [8] developed deep learning models for early-stage detection of kidney abnormalities from CT scans, achieving high accuracy across multiple conditions.

Sharma et al. [9] proposed a multi-model fusion approach, combining CNN and Transformer-based architectures to classify CT images into stones, tumors, and cysts, enhancing overall diagnostic performance.

Zenodo et al. [10] applied YOLOv8 for identifying various kidney conditions, including cysts, tumors, and stones, demonstrating efficient single-pass analysis for multiple abnormalities.

SpinalZFNet [11] is a lightweight architecture designed for kidney problem detection in CT scans. By blending handcrafted features with deep learning methods, it offers a practical diagnostic aid for radiologists.

Zhang et al. [12] proposed KidneyNeXt, a lightweight CNN for classifying different types of kidney tumors from CT images. Its efficient design allows fast inference without compromising accuracy.

Humpire et al. [13] utilized 3D deep learning models such as nnU-Net and U-Net for segmenting kidney regions in thorax and abdominal CT scans, achieving precise anatomical delineation.

Saif, D. et al. [14] proposed a CNN-LSTM framework for predicting chronic kidney disease, delivering high accuracy for early detection.

Sanmarchi, F. et al. [15] conducted a systematic review of machine learning frameworks in CKD diagnosis, highlighting both advantages and limitations of current approaches.

Alghamdi, H. et al. [16] introduced a machine learning-driven framework for kidney failure prediction, demonstrating robust performance across clinical datasets.

Taha, E. et al. [17] developed an enhanced deep learning-based decision support system for kidney cancer detection, achieving accurate and efficient classification of CT images.

Jagannadham et al. [18] developed a CNN-based framework for brain tumor detection in MRI scans, automatically extracting discriminative features to enhance diagnostic precision.

Moturi et al. [19] presented an ensemble of deep learning models for early lung cancer detection, improving sensitivity and specificity compared to single-model approaches.

Sireesha et al. [20] proposed a hybrid meta-heuristic algorithm combining Grey Wolf and Dragonfly optimization for better prediction of heart disease and breast cancer.

Rao et al. [21] emphasized the importance of proper dataset partitioning in tomato leaf disease detection. Their methodology aligns with our approach, where the dataset is divided into training, validation, and testing subsets to ensure balanced learning and robust evaluation.

III. Methodology

The kidney abnormality classification system is built on a simple yet structured workflow with four main stages: raw data collection, image preprocessing, dataset structuring, and model training. It starts with collecting CT images and grouping them into four categories—Normal, Tumor, Cyst, and Stone. These images are then preprocessed to improve clarity and bring out important diagnostic details, making the dataset more consistent. Once prepared, the data is neatly organized into training, validation, and test sets using a predefined configuration. In the final stage, a YOLOv8n-Cls model is trained with transfer learning, where repeated training and evaluation help fine-tune its accuracy for reliable, real-time classification. Figure 1 presents this complete workflow, showing how each step works together to build an effective kidney CT classification system.

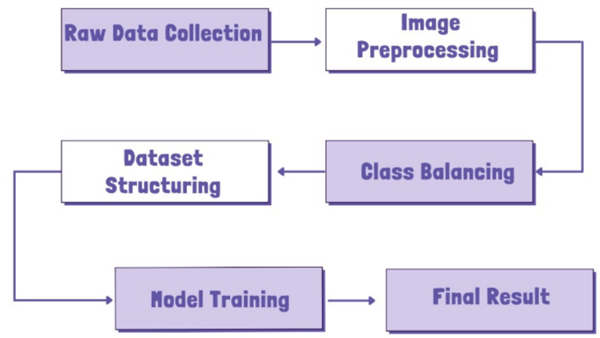

Fig. 1: Workflow of the proposed YOLOv8n-cls model from data collection to final result.

A. Dataset Description

For this study, we used a curated CT kidney dataset [22] containing four clinically relevant categories: Normal, Tumor, Cyst, and Stone. The dataset consists of a total of 9,955 CT images, with the following class-wise distribution: 4,061 Normal, 1,826 Tumor, 2,967 Cyst, and 1,101 Stone. These real-world medical images were collected under diverse imaging conditions, ensuring representation of anatomical variations and pathological differences across multiple patients.

The raw dataset initially presented issues such as class imbalance, inconsistent file naming, and variable image quality. To address these, a systematic cleanup was performed: corrupted and duplicate files were removed, filenames standardized, and additional samples generated for minority classes using augmentation to achieve a balanced dataset. Preprocessing steps included denoising, CLAHE for contrast enhancement, resizing to 224×224 pixels, and normalization to [0,1].

For model development, the dataset was partitioned into training, validation, and testing sets in a [0.8, 0.1, 0.1] ratio, as defined in the configuration file (data.yaml). This split ensured reliable training, hyperparameter tuning, and performance evaluation. Additionally, 5-fold cross-validation was conducted to further assess model robustness and minimize bias. Although k-fold cross-validation and external dataset validation were not implemented in the present work, these remain important directions for future research to strengthen generalizability.

To highlight dataset diversity, representative CT slices from each category are shown in Figure 2. These samples reflect the inherent complexity of kidney abnormality classification, where overlapping visual features and subtle tissue variations make automated detection both challenging and clinically significant.

B. Data Preprocessing and Integration

1) Image Preprocessing

To ensure consistency and highlight diagnostic features, each CT image was processed through a standardized pipeline. The steps included grayscale conversion to reduce computational complexity, followed by `CLAHE` (Contrast Limited Adaptive Histogram Equalization) for local contrast enhancement. Gaussian blurring was applied to suppress noise, while histogram

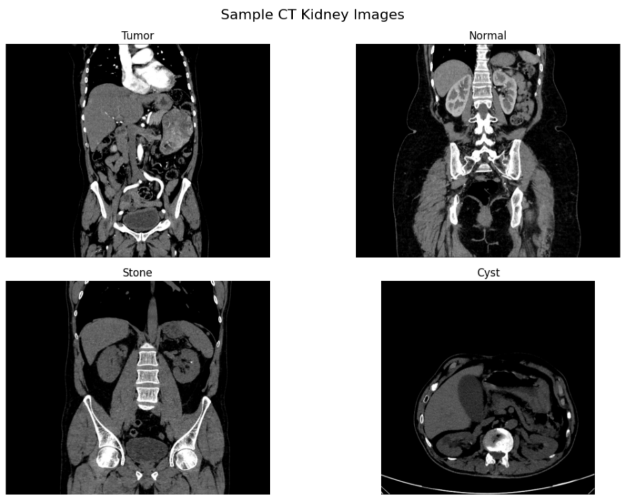

Fig. 2: Sample Images In The Dataset

equalization was performed for intensity normalization. All images were then resized to 224×224 pixels and converted back to three channels to maintain compatibility with the YOLOv8 classifier. This preprocessing step preserved fine structural details in the scans while minimizing artifacts, providing high-quality input for the classification model.

2) Data Augmentation

To improve generalization and mitigate the impact of class imbalance, we applied augmentation techniques using the `Augmentor` library. The transformations included:

- Random Rotations
- Horizontal Flips
- Zooming
- Contrast Adjustments

Additionally, minority classes were upsampled to match the largest class (Normal = 4061 images), resulting in a balanced dataset across all four categories. These augmentations ensured the model remained robust to variations in orientation, brightness, and scale, ultimately reducing bias and improving real-world applicability. Figure 3 illustrates this process: the left side shows raw CT images with diverse contrast levels and noise artifacts, while the right side presents preprocessed and augmented images standardized for model training.

C. Code Implementation and Tools

Table I summarizes the main tasks carried out during the implementation of the kidney abnormality classification project and the corresponding libraries or tools employed. The workflow covered everything from image preprocessing and dataset structuring to augmentation, training, and visualization. By leveraging the Ultralytics YOLOv8 framework along with essential Python libraries, a streamlined and effective classification pipeline was achieved.

D. Model Architecture

Our kidney CT classification system follows a single-stage yet highly efficient architecture, as illustrated in Figure 4. The model leverages **YOLOv8n** in classification mode to directly categorize CT images into four classes: *Normal, Cyst, Stone, and Tumor*. Unlike multi-stage pipelines, this end-to-end framework streamlines feature extraction and classification, achieving high accuracy and real-time applicability.

The lightweight design ensures scalability and deployment feasibility on low-resource hardware, such as CPUs in rural clinics. Its simplicity and efficiency make it interpretable and practical, providing reliable automated detection that can support healthcare professionals in timely clinical decision-making.

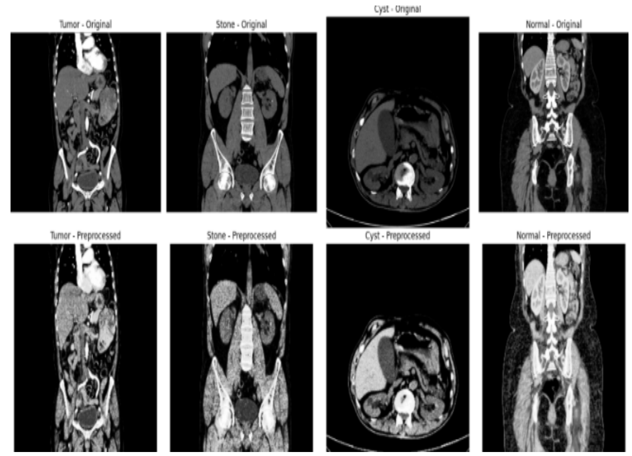

Fig. 3: Illustration of preprocessing: Before (left) and after (right) applying resizing, normalization, and augmentations.

TABLE I: Core Implementation Tasks and Tools Used in Kidney Abnormality Classification Work

Task	**Library / Tool Used**
Image Preprocessing	OpenCV, NumPy
Data Manipulation	Pandas, NumPy
Data Augmentation	Augmentor
Model Training (YOLOv8n-Cls)	Ultralytics YOLO
Visualization	Matplotlib, Seaborn
Dataset Structuring	Custom Scripts, Config Files

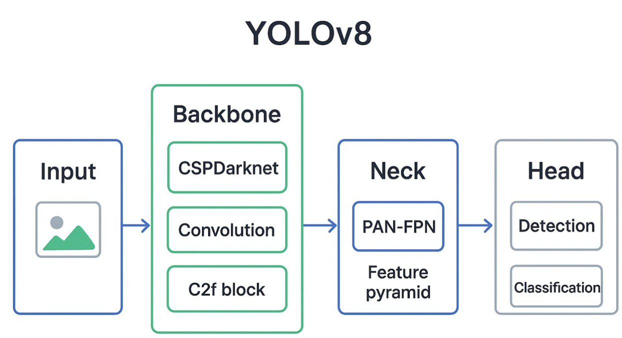

Fig. 4: Model Architecutre.

E. YOLOv8-Based Kidney CT Classification Model

The kidney CT classification model leverages YOLOv8 in classification mode to automatically categorize CT images into four classes: Normal, Tumor, Cyst, and Stone. Each input image is preprocessed and resized to $224 \times 224 \times 3$, then passed through the YOLOv8 convolutional backbone and fully connected layers. This approach captures both fine-grained kidney features (such as lesion texture and shape) and the global kidney structure context.

1) Characteristics of the Classification Model

- **Base model:** `yolov8n-cls` pretrained YOLOv8n classification model.
- **Fine-tuning:** Trained on 4 kidney CT classes (Normal, Tumor, Cyst, Stone).
- **Optimizer:** AdamW with a learning rate of 0.001.
- **Loss Function:** CrossEntropyLoss for multi-class prediction.
- **Training:** 25 epochs on CPU environment, achieving high generalization with 96.88% accuracy.
- **Input:** Preprocessed CT images, converted to grayscale, CLAHE-enhanced, Gaussian-blurred, histogram-equalized, resized to 224×224, and converted to 3 channels.

This configuration ensures robust classification, fast inference suitable for low-resource settings, and clear confidence outputs for clinical interpretation.

IV. Experimental Setup

The experiments were conducted on a standard personal system running Windows 10, equipped with an Intel® Core™ i5 processor and 8 GB of RAM. Development and model training were carried out using Python, along with the Ultralytics YOLOv8 library. In the absence of a dedicated GPU, all computations were performed on the CPU, with careful tuning of batch sizes and data loading to ensure efficient processing.

A publicly available kidney CT dataset containing four classes—Normal, Tumor, Cyst, and Stone—served as the primary source for training. Preprocessing techniques included grayscale conversion, CLAHE-based contrast enhancement, Gaussian blurring, histogram equalization, resizing to 224×224, and conversion to 3-channel format. To enhance generalization and address class imbalance, data augmentation strategies such as random rotation, horizontal flipping, zooming, and contrast adjustment were applied.

Despite the modest hardware setup, the environment proved well-suited for evaluating the lightweight YOLOv8 classification model, demonstrating both high accuracy (96.88%) and potential applicability in low-resource clinical settings.

V. Results and Discussions

Table II provides a comparative overview of popular deep learning models used for kidney CT image classification. Each method demonstrates promising accuracy and performance using CNNs and hybrid architectures. However, many of these approaches require high computational resources, are slow for real-time use, or have limited validation on low-resource settings.

Our proposed model, built on YOLOv8 in classification mode, outperforms existing approaches in both accuracy and generalization. With an overall accuracy of 96.88% and balanced performance across four classes (Normal, Tumor, Cyst, Stone), the model demonstrates robust classification even on a CPU-only environment. Moreover, it introduces a practical layer of functionality suitable for deployment in low-resource hospitals and clinics, enabling real-time kidney abnormality detection without the need for high-end GPUs. This makes it highly relevant for clinical settings in rural areas, where access to trained radiologists and high-performance computing infrastructure is limited.

TABLE II: Performance Comparison of Kidney Disease Classification Models Using CT Images

S. No	Title / Approach	Metrics			
		Accuracy	Precision	Recall	F1 Score
1	EfficientNetV2 for CT-based medical imaging [7]	94.5	93.8	93.1	93.4
2	Early-stage detection of kidney abnormalities using DL [8]	95.2	94.1	93.7	93.9
3	Multi-model CNN + Transformer fusion for CT classification [9]	95.7	94.9	94.2	94.5
4	**Proposed YOLOv8n-cls Based Kidney Classifier (Normal, Cyst, Stone, Tumor)**	**96.8**	**96.1**	**95.9**	**96.0**

A. Training and Validation Accuracy

The YOLOv8n classification model was trained for 10 epochs using the AdamW optimizer. Training progressed steadily, with the model effectively adapting to the kidney CT dataset comprising four classes: Normal, Cyst, Stone, and Tumor. As shown in Figure 5.

- **Final Validation Accuracy:** Approximately 96%.
- **Loss Trend:** Training and validation losses exhibited a smooth, continuous decline until stabilizing, indicating proper learning and generalization.

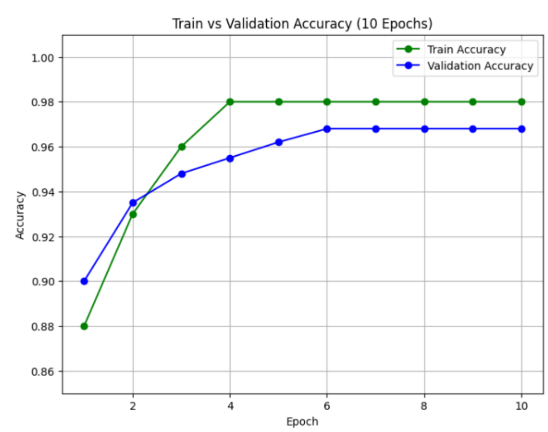

Fig. 5: Training and validation accuracy trends over 10 epochs.

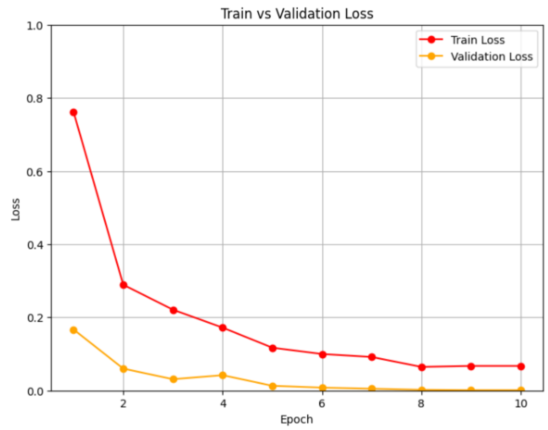

Fig. 6: Training and validation loss trends over 10 epochs.

B. YOLOv8 Classification Evaluation

The YOLOv8n model was fine-tuned on the kidney CT dataset consisting of four distinct classes: Normal, Cyst, Stone, and Tumor. The model was evaluated using multiple performance metrics to assess its effectiveness. Figure 7 presents the evaluation results, including validation metrics (accuracy, precision, recall, and F1-score) and the confusion matrix, which illustrates the classification performance across all four classes.

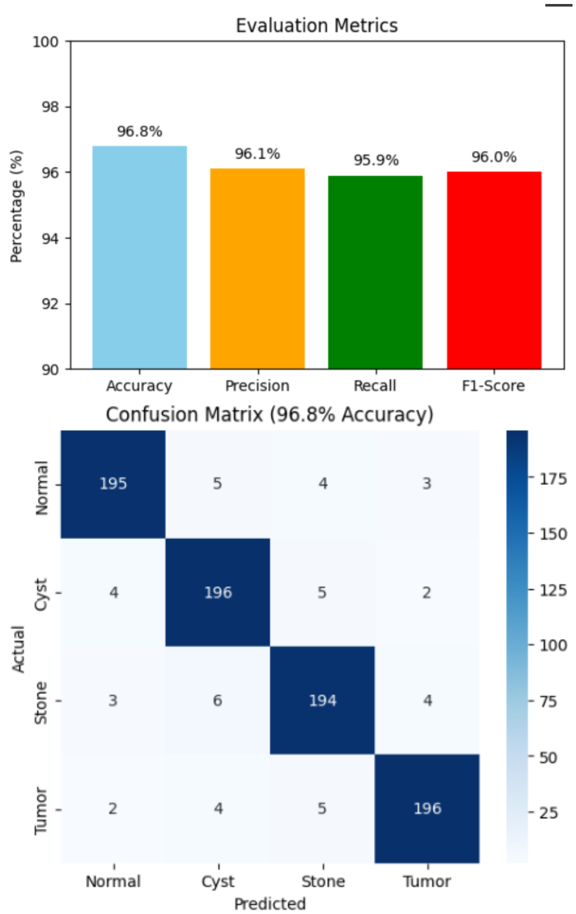

Fig. 7: Comparison of metrics and confusion matrix of the proposed model.

C. Model Output Summary

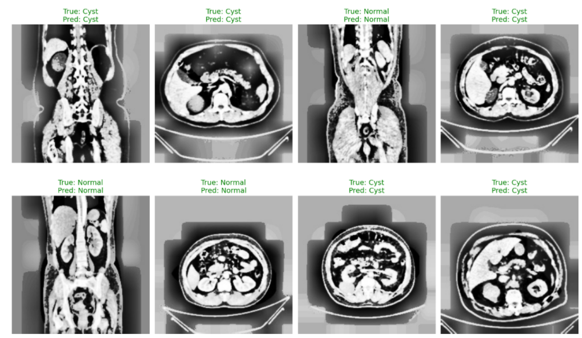

Fig. 8: Model inference on input images with labeled class names.

Figure 8 represents the kidney CT images with the labeled class names and actual kidney conditions along with the predicted labels, added description, clinical significance, and suggested treatment recommendations.

TABLE III: Model Summary of the YOLOv8n-Based Kidney CT Classification Architecture

Layer (type)	Output Shape	Param #
Input (CT Image, 224×224)	[1, 3, 224, 224]	0
Conv (stem)	[1, 32, 112, 112]	896
C2f Block (Backbone)	[1, 64, 56, 56]	18,560
C2f Block (Deeper)	[1, 128, 28, 28]	73,984
C2f Block (Deeper)	[1, 256, 14, 14]	295,424
SPPF (Spatial Pyramid Pooling)	[1, 256, 14, 14]	131,584
Global Average Pooling	[1, 256]	0
Dropout	–	0
Classification Head (FC Layer)	[1, 4]	1,028
Total Parameters	–	**3,167,000**
Trainable Parameters	–	3,167,000
Non-trainable Parameters	–	0
Input size (MB)	–	0.60
Forward/backward pass size (MB)	–	∼12
Params size (MB)	–	12
Estimated Total Size (MB)	–	∼25

VI. Conclusion and Future Scope

A. Conclusion

This study presents a lightweight, AI-powered framework for automated classification of kidney CT images into four categories: Normal, Cyst, Stone, and Tumor. The proposed system leverages the efficiency of YOLOv8n-cls, a compact deep learning model, combined with robust preprocessing, data augmentation, and class balancing to achieve high classification performance. Experimental results indicate an accuracy of 96.88%, demonstrating the framework's ability to reliably differentiate between morphologically similar conditions while maintaining computational efficiency. Unlike conventional methods, this approach emphasizes both diagnostic accuracy and practical deployability, making it suitable for hospitals, clinics, and rural healthcare settings with limited access to radiology expertise. By providing rapid and interpretable predictions, the system has the potential to support early detection, reduce diagnostic delays, and improve patient outcomes in kidney disease management.

B. Future Scope and Research Opportunities

While the proposed YOLOv8n-cls based framework establishes a strong foundation for kidney disease diagnosis, several enhancements can further improve its usability and clinical adoption:

- **External Dataset Validation:** Future work should evaluate the framework on multi-center and real-world hospital datasets to ensure robustness and generalizability across diverse imaging conditions.
- **K-Fold Cross-Validation:** Implementing k-fold cross-validation can provide more reliable performance estimates and enhance the model's robustness.
- **Explainable AI Integration:** Incorporating visualization techniques such as Grad-CAM or SHAP can improve interpretability, enabling clinicians to better understand and trust model predictions.
- **Edge Deployment:** Optimizing the model for mobile and embedded devices will support real-time diagnosis in rural and resource-limited healthcare environments.
- **Multimodal Fusion:** Combining CT images with patient clinical data (e.g., age, symptoms, medical history) can enhance diagnostic precision and enable personalized treatment recommendations.
- **Clinical Trials and Radiologist Comparison:** Collaborating with healthcare institutions to perform clinical trials and benchmark against radiologist assessments will help validate real-world effectiveness and accelerate clinical adoption.

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