Real-Time Binary Classification of Kidney Stones in Medical Imaging Using YOLO

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Abstract

Kidney stones are a prevalent urological condition affecting millions worldwide, leading to significant discomfort and healthcare costs. Timely and accurate diagnosis is crucial for effective treatment and management. This paper presents a novel approach using the YOLO (You Only Look Once) deep learning model for the real-time binary classification of kidney stones in medical imaging. Our method aims to assist urologists by providing rapid, reliable diagnostic support, thereby improving patient outcomes and optimizing clinical workflows. We detail the methodology, including data collection, preprocessing, model training, and evaluation. Experimental results demonstrate the efficacy of our approach, highlighting its potential for integration into clinical practice.

CCS CONCEPTS • Health Informatics • Computer Vision • Machine Learning

Additional Keywords and Phrases: Kidney Stone Detection, YOLO Algorithm, Medical Imaging, Deep Learning, Real-Time Diagnosis, Urology

1. Introduction

Kidney stone disease, or nephrolithiasis, affects approximately 12% of the global population, with a recurrence rate of up to 50% within five years [1]. The rising incidence and recurrent nature of this condition necessitate efficient diagnostic tools to aid urologists. Traditional diagnostic methods, such as CT scans and ultrasounds, are effective but time-consuming and reliant on expert interpretation. This research introduces a real-time binary classification system for kidney stones using the YOLO algorithm, aiming to streamline diagnosis, reduce errors, and improve patient care. By implementing an automated detection system, we can potentially reduce diagnostic time and enhance the accuracy of identifying kidney stones, ultimately leading to better patient outcomes and more efficient use of medical resources [2].

2. Review of Related Literature

Extensive research has explored various machine learning techniques for medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated significant success in image classification tasks, including medical imaging [3]. For instance, a study by Litjens et al. [4] reviewed deep learning applications in radiology, highlighting the potential of CNNs in improving diagnostic accuracy. YOLO, a state-of-the-art object detection model, has shown promise in real-time applications due to its speed and precision [5]. Redmon et al. [6] introduced YOLO and demonstrated its superiority in real-time object detection tasks compared to traditional methods.

Recent studies have specifically addressed kidney stone detection. Park et al. [7] utilized deep learning to identify kidney stones in ultrasound images, achieving high accuracy. Similarly, a study by To assist urologists in making swift and accurate diagnoses, improve patient care, and reduce healthcare costs by enhancing diagnostic accuracy and efficiency.

Liu et al. [8] applied CNNs to CT images for kidney stone classification, with promising results. Despite these advancements, there is a lack of solutions offering real-time processing capabilities essential for clinical environments. For instance, traditional methods such as the Hounsfield unit analysis in CT scans, while accurate, are not feasible for real-time analysis due to computational complexity and the need for manual interpretation [9]. Advanced methods such as three-dimensional segmentation and feature extraction techniques have also been explored, yet they often require extensive preprocessing and are computationally expensive, limiting their real-time application potential [10].

Furthermore, the YOLO model's ability to perform classification and localization tasks in a single pass makes it an ideal candidate for real-time medical applications. Studies have shown that YOLO can be effectively adapted for various medical imaging tasks, including tumor detection and organ segmentation [11]. Its architecture, which balances speed and accuracy, allows for rapid analysis without compromising diagnostic quality [12].

Data augmentation and preprocessing play critical roles in enhancing the performance of deep learning models. Techniques such as rotation, flipping, and contrast adjustment can significantly improve model robustness and generalization [13]. Additionally, the integration of transfer learning has been shown to enhance the performance of CNNs by leveraging pre-trained models on large datasets, thereby reducing the need for extensive medical image datasets, which are often difficult to obtain [14].

Our approach builds on these foundations, leveraging YOLO for the binary classification of kidney stones in medical images. By focusing on real-time performance, we aim to bridge the gap between high diagnostic accuracy and the practical needs of clinical settings. The integration of advanced preprocessing techniques and transfer learning further enhances the model's performance, ensuring robust and reliable kidney stone detection in diverse clinical scenarios [15].

3. Methodology

3.1 Data Collection

Data was sourced from a public medical image repository containing labeled CT scans of patients diagnosed with kidney stones. The dataset comprised 1,376 images, divided into training (70%), validation (15%), and test (15%) sets. The dataset was annotated by experienced radiologists to ensure accuracy and consistency in labeling [16].

3.2 Data Preprocessing

Preprocessing steps included image resizing, normalization, and augmentation. Images were resized to 416x416 pixels to match YOLO's input requirements. Normalization involved scaling pixel values to the range [0, 1]. Augmentation techniques, such as rotation, flipping, and contrast adjustment, were applied to enhance model robustness [17]. Additionally, noise reduction techniques were implemented to minimize the impact of artifacts and improve image quality [18].

1. **Normalization:** Adjusting pixel values to a standard range.
2. **Augmentation:** Applying random transformations to create additional training samples.
3. **Enhancement:** Improving image quality through contrast adjustment and noise reduction.

3.3 Model Training

We implemented YOLOv8 for its balance between speed and accuracy. The model was trained using a binary cross-entropy loss function and the Adam optimizer, with an initial learning rate of 0.001. Training involved 100 epochs with early stopping based on validation loss to prevent overfitting. Transfer learning was utilized by initializing the model with weights pre-trained on the ImageNet dataset, which helped in achieving faster convergence and better performance [19].

1. **Data Loading:** Efficiently loading and batching data for training.
2. **Model Initialization:** Setting up the YOLOv8 architecture with pre-trained weights.
3. **Fine-Tuning:** Adjusting the model parameters using the kidney stone dataset.
4. **Optimization:** Using Adam optimizer to reduce the loss function.

3.4 Evaluation

Model performance was assessed using accuracy, precision, recall, and F1-score. The test set results showed an accuracy of 95%, precision of 94%, recall of 96%, and an F1-score of 95%, indicating the model's high reliability for real-time kidney stone classification. Additionally, the model's performance was compared with other state-of-the-art methods, demonstrating superior speed and comparable accuracy [20].

1. **Performance Metrics:** Calculating precision, recall, F1-score, and mAP.
2. **Confusion Matrix:** Analyzing true positives, false positives, true negatives, and false negatives.
3. **ROC Curve:** Plotting the Receiver Operating Characteristic curve to assess the model's performance.

3.5 Deployment

For real-time application, the trained model was integrated into a web-based interface, allowing urologists to upload CT images and receive immediate binary classification results. This system will be tested in a clinical setting, demonstrating its practical utility in assisting with rapid diagnosis. The deployment process involved:

1. **Model Integration:** Embedding the trained model into a web application.
2. **User Interface:** Developing a user-friendly interface for image upload and result display.
3. **Clinical Testing:** Validating the system's performance in a real-world clinical environment.

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