# YOLOv8 Kidney Guard: Smart Imaging for Stone Detection Using Deep Learning

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***Abstract*— A common urological condition that can lead to severe pain and complications is kidney stones. Kidney stones must be identified and diagnosed as soon as possible in order to provide appropriate care. This study uses the YOLO (You Only Look Once) object detection framework to propose a novel kidney stone detection method. Yolo is a well-known object detection technology that works well in medical imaging because of its accurate and real-time capabilities. We make use of a dataset of medical photos that show kidney stones in both positive and negative cases. Using this dataset, the YOLO model is trained to identify the traits and features of kidney stones. The trained model performance is then measured using Mean Average Precision (mAP), a commonly used metric in object detection tasks, on a different test dataset. Significant progress in artificial intelligence has been made with the help of the deep learning algorithms which suggests the programmed recognition of kidney stones (whether or not they contain stones) using captured medical images. Kidney stone diagnosis can be recommended automatically with this method.In addition to identifying kidney stones, this model also displays the stone's location in the output image. The outcomes show how effective the suggested YOLO-based kidney stone detection method is. The model locates and classifies kidney stones in medical images with accuracy, as evidenced by its high mAP value of 0.92. Because YOLO is real-time, it is a useful tool for quick screening and diagnosis, allowing patients with kidney stones to receive treatment on time.**

***Keywords*— *YOLOv8 , Kidney Stone, Roboflow annotate***

## I. Introduction

The formation of solid, microscopic crystals inside the kidney is known as a kidney stone. Depends upon the size of the stone, it may stick or come out of the ureters. Kidney stones are primarily caused by certain medical treatments, excessive obesity, diet, and dehydration. Early kidney stone detection can help prevent kidney infections and other urinary tract complications. Treatment delays may result in irreversible kidney failure or even serve as a trigger for cancer.Experts in the medical field become familiar with the internal organs and tissues of living things in order to identify and treat abnormalities more quickly. In the end, medical image processing techniques aid physicians in making accurate and timely diagnosis. The advancement of computer-aided automation has led to the superior medical image processing effects of applying artificial intelligence techniques, such as various machine learning (ML) and deep learning (DL) algorithms in image processing, to a particular level.

One of the most frequent complaints is kidney pain, though the frequency of complaints in emergency and medical settings varies. According to prevalence studies (Shang et al., 2021; M. K. Shahina and H. S. Mahesh., 2019) [1,2], this rate is steadily rising to 20%. In the United States (US), kidney stones affect roughly 9% of individuals between the ages of 20 and 74 (A. Altintaş et al., 2010) [3]. There is a critical likelihood that someone with kidney stones will visit the emergency room. In the US, this number is reported to reach 1,000,000 annually, and between 1997 and 2019, it doubled (I. Shakhnoza et al., 2023) [4]. Simultaneously, the disease's incidence increased from 1988 to 1994 compared to 1976 to 1980. Between 2007 and 2016, there was a noticeable increase in this rate (Vaishy. N.et.al, 2023)[5]. These days, the medical industry is the primary target for Artificial Intelligence (AI). Using Deep Learning algorithm and machine learning algorithms in conjunction with medical images, numerous studies have been conducted across multiple fields. These methods have proven effective in a variety of domains, including lesion detection (Yan et al., 2018), disease classification (P. T. Akkasaligar et al., 2017), and medical image segmentation (Megana. G et al., 2022). Medical goods and services require a high level of dependability. The first step towards fully trusting these products is understanding the reasoning behind artificial intelligence's decision-making.It offers explainable AI (xAI) at a high learning performance level and explains the reasoning behind the choice. This allows for a more thorough discussion of the decision's justification and its correctness. AI-based research has been conducted recently in a variety of fields, including the medical field and Agri field (S.S.P et al., 2023 and P.K et al). Developing tools that let radiologists help with illness detection is the primary goal of AI-assisted diagnosis.

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Segmentation and localization (S.S. Pandi. et al., 2023), parkision segmentation and localization (S. Anantha Sivaprakasam et al., 2022), kidney stone segmentation and localization (Baygin et al., 2019), and computerized tomography image classification systems based on condition are a few examples of these systems. Since kidney stone and cyst detection is the initial step in treatment, selecting an accurate imaging method is crucial. The most accurate diagnosis can be made using non-contrast abdominal computed tomography (CT), but the patient must endure radiation exposure.Conversely, ultrasonography is less sensitive than CT, but it has the benefit of not requiring radiation during use. Kidney stones are evaluated using the expensive and challenging 3D imaging method used in the MR imaging technique (Weston et al., 2019). In order to help radiologists identify kidney stones and cysts, computer-aided diagnosis, or CAD, was created. An essential first step is accurately identifying the placement of the kidney stone and cyst.

Effective determination of stones is crucial for providing quantitative information and ensuring that no abnormalities are overlooked. Automated systems capable of detecting and pinpointing these stones offer significant benefits to radiologists by highlighting their locations, thereby improving diagnostic accuracy and efficiency in medical imaging. In this study, a model powered by xAI was created to use CT images to identify hard-to-distinguish small stones and cysts that were induced by doctors. The key objective of this study is to support long-term disease analysis procedures in order to reduce error rates and save time in physician-made decisions.

## II. Literature Survey

Understanding current research, scholarly papers, and pertinent articles about concurrent data access, locking mechanisms, and methods to guarantee data consistency in a shared database environment were the main goals of the project's literature review.

[6] Kidney stones are a hard deposit of salt and minerals that build up in the kidneys; frequently, these deposits include calcium and uric acid. Most kidney stone sufferers are initially unaware of their condition, and their organs gradually become worse. Finding the detailed localization of a kidney stone is crucial for surgical procedures for physicians. Most ultrasound images contain speckle noise, which is impossible for humans to eliminate. The problems with kidney stones in the human body and image processing techniques for their detection are the focus of this paper. methods such as morphological analysis, segmentation, and preprocessing. The efficiency of the techniques is determined by analyzing and evaluating the results based on the output parameters.

[7] The most popular algorithm for neural network training is Back Propagation Network. It is utilized in the image and data processing to apply an automated classification system for kidney stones. Human examination is the traditional method for classifying medical resonance kidney images and detecting kidney stones. Because handling large amounts of data is impractical, this method is not accurate. Operator errors can introduce inherent noise into Magnetic Resonance (MR) images [3]. This results in diseases and classification features in image processing that are sincerely inaccurate. However, the use of artificial intelligence-based techniques in conjunction with neural networks and feature extraction has demonstrated significant promise in this field for the extraction of the region of interest through the use of back propagation network algorithms [8]. The Back Propagation Network was used in this study to achieve the kidney stone detection goal. Making decisions happens in two steps: 1. Extraction of features 2. Classification of images. Principal component analysis is used to extract features, and back propagation networks (BPN) [9] are used to classify images. The segmentation method utilizing the Fuzzy C-Mean (FCM) clustering algorithm is presented in this work. Training execution and classification accuracy were used to estimate the BPN classifier's performance. Compared to other neural network-based classification techniques, more accurate classifications are provided by Back Propagation Network.

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Kidney stones are crushed on the target during a procedure called extracorporeal shock wave lithotripsy (ESWL). Even when the kidney stone is not the focal point, the patient's body receives sound waves. The sound waves can harm the kidney's soft tissue if the stone is not in the focal point. A feedback mechanism that uses the images[10,11] from the ESWL device to determine the location of kidney stones can prevent this damage. An automated system to identify kidney stones from X-ray images is developed in this study.

Renal calculi, another name for kidney stones, are solid masses composed of crystals. For surgical procedures, it is essential to identify the precise location of urinary calculi. It is necessary to use automated techniques for the detection of kidney stones in ultrasound images because it is challenging to manually detect the urinary calculus due to speckle noise in the images. One imaging modality that can be used to diagnose kidney abnormalities is ultrasound imaging. These abnormalities can include limb swelling and alterations in shape and position. Other kidney abnormalities include kidney formation, cysts, blockages in the urine, congenital defects, and cancerous cells. With the right image processing methods, this problem can be solved. The method for automatically identifying kidney stones without the need for human intervention is proposed in this paper. In addition, a review of the literature and a comparative analysis of the various algorithms for urine calculus detection in human bodies that are currently available are presented in this report.

Kidney stone formation is the term for urine crystallization brought on by chemical concentrations or a genetic predisposition. Globally, the incidence of kidney diseases is on the rise, and most affected individuals are asymptomatic because the illness gradually damages the kidney before presenting symptoms. Kidney stones can also occur in newborns, though they are usually not noticed until they cause excruciating stomach pain or have an unusual color to their urine. The earlier kidney stones are detected, the easier it is to take action. The kidney stone location techniques covered in this article employ a variety of image processing stages. Filters are used as the first step in photo preparation. As the image is smoothed through this process, noise is also eliminated. After that, the guided active contour technique is used to segment the pre-processed images. The next step involves applying convolutional neural network technology to diagnose disease [12,13] based on renal imaging data. CT is the preferred imaging method because it has less noise than other imaging modalities like X-ray and ultrasound.

The suggested work uses the Level set segmentation method to identify kidney stones. Regions of interest are first segmented and input images preprocessed. One effective technique for effectively resolving the segmentation problem is level set segmentation. CT scans are diagnostic instruments with a variety of applications. Basically, CT machines use X-rays to slice through the body, saving the images as computer files. The CT images are preprocessed in order to crop the input image. The input image is segmented using the level set segmentation technique following the preprocessing step. In order to find the size and location of the stone, the segmented images are finally examined. This paper presents a dynamic study on current machine learning (ML) applications in the detection of kidney stones. Of all the challenges facing the physiological system, kidney stone disease has one of the highest rates of morbidity worldwide. The current study has several problems, including poor image quality, size analysis over time, and kidney stone similarity. To facilitate detection and choose the best performance, a thorough examination of multiple machine learning algorithms has been done. More research on cutting-edge diagnostics, early detection, and creative approaches is still needed in the quest for a successful kidney stone treatment plan. The designer of a real-time system has support from a wide range of scientific articles that have been gathered and reviewed. Maybe in order to detect a kidney stone, it is necessary to use a preferred method that offers accuracy.

## III. Methodology

The MRI images are more complex, these provide high resolution picture of bones and soft tissues which is more complex to segment and analysis, which is in turn reducing the mis-prediction. The main objective is to determine Kidney stone at any size under any circumstance using a minimum number of MRI images at the highest accuracy.The data is gathered , which contains various MRI images of kidney. These MRI images are annotated using Roboflow Annotate to label objects in the images with boxes. Bounding boxes are the most widely used kind of annotation in computer vision, and this technique is referred to by that name. Rectangular boxes called bounding boxes are used to indicate where the target object is located. The x and y axis coordinates in the rectangle's upper-left and lower-right corners, respectively, whixh is used to determine them.For every object in the picture, there is one bounding-box (BBox) annotation in each text file. The annotations fall between 0 and 1 and are normalized to the size of the image.

The bounding box are represented in the format :

< object-class-ID> <X center> <Y center> <Box width> < height>

Image_x_c=(bx_x_lft + bx_x_wid/2)/image_wid

Image_y_c = (bx_y_tp +bx_hei/2)/image_hei

Image_width = bx_width/im_width

Image_height = box_hei/image_hei

After annotation, these images are preprocessed to make the model well functioned for all types of MRI Images.Data augmentation is a method that uses pre-existing data to create modified copies of a dataset, thereby artificially expanding the training set. In this study we have generated a dataset by rotating the MRI images to 15°, shearing the images to add variability to perspective to help the model be more resilient to different quality of images.Grayscale conversion and resizing the images for a smaller file size and faster training. Model training consists of two important phases: testing phase or a validation phase and training phase . During the training phase the model extracts the random batch of images from the training dataset, passes these images through the model and receives the resulting bounding box of all detected objects and their classes. Pass the outcome to the loss function, which compares the output that was received with the accurate results that were obtained from the annotation files for these pictures. The amount of error is computed by the loss function. The optimizer receives the loss function result and modifies the model weights according to the degree of error in the right direction. The next cycle's errors are decreased as a result.Stochastic Gradient Descent optimizer is used to modifies the weight of the model.

There are three primary parts in YOLOv8 architecture, backbone, neck and head. Acting as the backbone, the central core is built with the New CSP-Darknet53 structure, which is an improved variant of the Darknet architecture that was used in previous iterations. Representation learning and feature extraction are based on this fundamental component. The neck is an important intermediary that connects the head and the backbone, allowing information to flow and integrate more easily. YOLOv8 improves feature fusion and contextual understanding by implementing the SPPF and New CSP-PAN structures within the neck. Last but not least, the head uses the YOLOv3 Head design to produce the final output. This part processes the combined features to generate accurate and highly efficient precise object detections.Together, these interconnected components synergistically contribute to the effectiveness and robustness of YOLOv8 in object detection tasks. Figure.1 shows the proposed model work flow architecture.

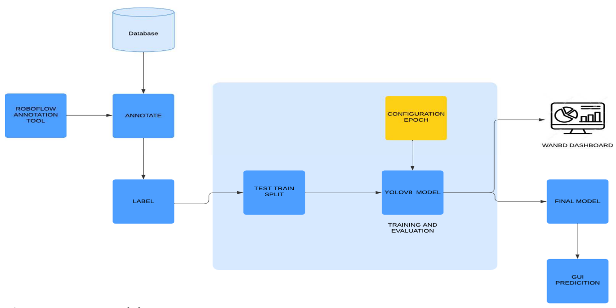


Fig 1. System Architecture

## IV. Results & Discussions

We have developed a user-friendly web interface shown in figure.2 and figure.3 that facilitates seamless interaction in our kidney stone detection project, which uses the YOLO (You Only Look Once) object detection

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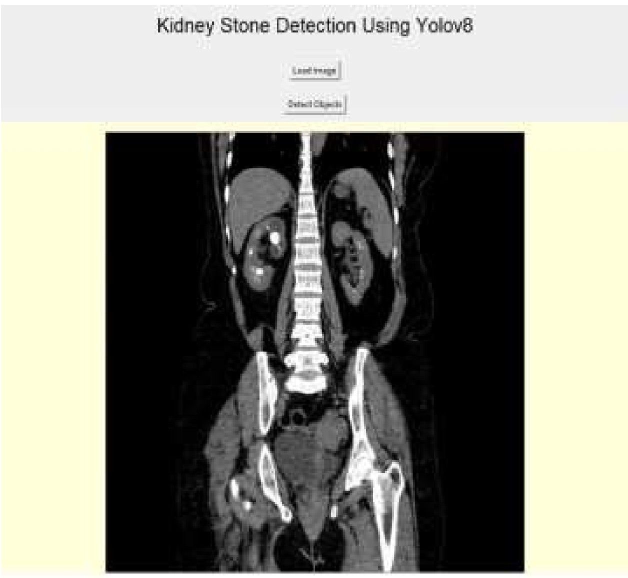
framework. This interface enables medical professionals to upload medical images for kidney stone detection. With a mean Average Precision (mAP) value of 0.92, the model demonstrates its remarkable accuracy in kidney stone identification and classification within medical images. We carefully weed out low-confidence detections using YOLO's confidence scores, which improves the accuracy of our model's predictions. Two classes are under examination in this evaluation: "B" for kidney stones and "M" for non-stone areas. Both classes show impressive metrics such as recall, precision, and map at an IoU threshold of 0.5 as well as map over a wider range of IoU thresholds (50-95). An essential step in our model development is the annotation process, which marks regions of interest in each image—like kidney stones—by hand to guarantee accurate training data. This project essentially demonstrates the effective use of YOLO for kidney stone detection, providing a dependable means of early diagnosis and enabling prompt medical interventions, thus enhancing patient outcomes in the field of urological care. Figure 2 and Figure.3 shows the result of the MRI Images uploaded in the website. Figure.4. shows the result of the proposed model loss during training and testing period. Figure.5 shows the model AUC Score. Figure.6. shows the proposed model accuracy compared with training and testing period.




(a)

Figure.2. MRI Image Uploaded in the Website


(b)

Figure.3. MRI Result Image


Figure.4. Proposed Model Loss Calculation

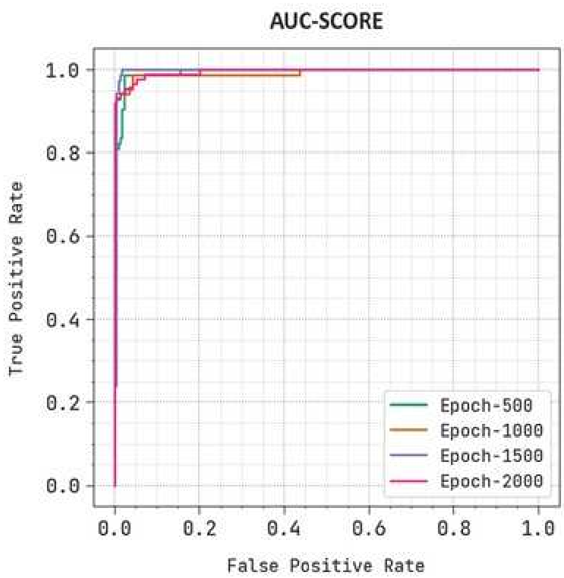



Figure.5. Proposed model auc score calculation

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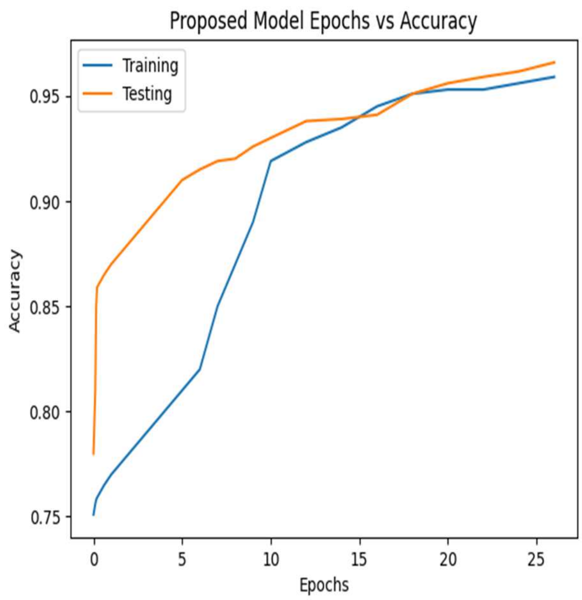


Figure.6. Proposed Model Accuracy Calculation

## V. Conclusion

In conclusion, this study introduces a novel and efficient approach for the early detection of kidney stones using the YOLO (You Only Look Once) object detection framework. Kidney stones are a prevalent urological condition that can lead to severe pain and complications, emphasizing the importance of timely intervention and treatment. By leveraging a dataset of medical images encompassing positive and negative instances of kidney stones, the YOLO model was trained to learn the distinctive features and characteristics associated with these conditions. The evaluation of the trained model on a separate test dataset, using the Mean Average Precision (mAP) metric, revealed a high level of accuracy in terms of object detection. The application of deep learning methods, specifically utilizing coronal computed tomography (CT) images, further advances the field of artificial intelligence in automating the detection and diagnosis of kidney stones. This innovative approach not only demonstrates the efficacy of the YOLO-based kidney stone detection system but also highlights its real-time capabilities, making it a practical and efficient tool for rapid screening and diagnosis. The high mAP value obtained in the evaluation process underscores the model's accuracy in locating and classifying kidney stones within medical images. This level of precision is crucial in providing healthcare professionals with reliable information, enabling timely medical interventions for patients affected by kidney stones. Further scopes for enhancing the kidney stone detection project include integrating additional imaging modalities for multi-modal fusion, optimizing the model for real-time deployment, implementing automated reporting systems, developing algorithms for longitudinal analysis of kidney stone progression, conducting clinical integration and validation studies, integrating the system into telemedicine platforms for remote consultations, creating patient education materials, and establishing mechanisms for continuous improvement and updates. By addressing these areas, the project can evolve into a comprehensive tool for improving kidney stone diagnosis, treatment, and patient care outcomes.

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