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COMPARATIVE ANALYSIS OF YOLOv8 AND YOLOv11 FOR REAL TIME KIDNEY STONE DETECTION USING CT IMAGES

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Abstract: This project is a web-based system that uses the cutting-edge AI models YOLOv8 and YOLOv11 to help detect kidney stones in real-time. A user-friendly web interface allows users to upload medical images, such as CT scans. The image is analyzed by the system, which then uses bounding boxes to highlight any kidney stones that are found. The results are displayed clearly with labels and confidence scores. Tailwind CSS is used to style the interface for a responsive and contemporary appearance. The system also makes useful recommendations in three areas medical, food, and exercise based on the detection. Both patients and healthcare professionals are intended to benefit from these suggestions. All things considered, this platform integrates AI and healthcare in an easy-to-use manner for clinical and educational applications.

***Index Terms* - YOLOv8, YOLOv11, Tailwind CSS, Kidney stone, Bounding Box.**

I. INTRODUCTION

Millions of people worldwide suffer from kidney stones, one of the most common urinary tract conditions. Urinary tract infections, chronic kidney damage, and excruciating pain can all be avoided with early detection and the right care. Conventional detection techniques frequently require medical professionals to manually analyze CT or ultrasound images, which can be laborious and prone to human error. In order to tackle this issue, our project presents a real-time kidney stone detection system that utilizes deep learning and computer vision technologies.The YOLO (You Only Look Once) object detection models, namely YOLOv8 and YOLOv11, are used in this system because they are renowned for their accuracy and speed in locating and identifying objects in photos. The web application lets users upload medical images, uses the chosen YOLO model to process them, and then provides a visual output with bounding boxes that highlights kidney stones that have been found. The interface provides a clear and educational user experience by displaying the uploaded and processed images side by side with detection confidence levels. Furthermore, based on the detection, the application offers customized solutions divided into three categories: food, exercise, and medical advice. The platform's use of Tailwind CSS guarantees a cutting-edge, responsive design. With easily accessible AI-based diagnostics, this system seeks to assist medical professionals and increase patient awareness.

II.LITERATURE SURVEY

1. "Hybrid Deep Learning Framework for Classification of Kidney CT: A Review " by Dhruv Gupta et al. (2025):

Medical image classification is an important field of study that makes use of cutting-edge computational methods to enhance disease diagnosis and treatment planning. This field has been revolutionized by deep learning models, particularly Convolutional Neural Networks (CNNs), which offer accurate and automated analysis of complicated medical images. In order to categorize kidney CT images into four groups—normal, stone, cyst, and tumor—this study presents a hybrid deep learning model that combines a pre-trained ResNet101 with a custom CNN. The suggested model achieves 100% testing accuracy and 99.73% training accuracy by utilizing feature fusion to improve classification accuracy.The hybrid CNN model performs better than the standalone ResNet101 using a dataset of 12,446 CT images and sophisticated feature mapping techniques.

2. "A Reliable Kidney Stone Detection Method Using Inductive Transfer-Based Ensemble Deep Neural Networks: A Review " by S.N. Murthy el al. (2025):

This study suggests a dependable technique for kidney stone detection that makes use of ensemble deep neural networks based on inductive transfer. By integrating YOLO detection algorithms with a variety of classification models, such as DarkNet19, InceptionV3, and ResNet101,The method improves the accuracy of diagnosis. Classification is further improved by combining the Xception model with feature extraction methods, which also provide an intuitive interface for real-time testing**.**

3. "A Hybrid Model for Kidney Stone Detection Using Deep Learning: A Review" by Praveen Kumar el al. (2024):

Kidney stones are becoming more commonplace worldwide, so early and precise detection is crucial for successful treatment. This study combines two potent deep learning models to present a novel approach for kidney stone detection: Residual networks (ResNet) and convolutional neural networks (CNN). Combining these two models enhances the system's capacity to identify kidney stones of various shapes and sizes and allows it to extract significant features from medical images, including CT and ultrasound scans. In order to help the model learn and adjust to various real-world scenarios, it was trained on a range of photos featuring kidney stones that were clearly marked. This hybrid CNN/ResNet model outperformed using High levels of accuracy, sensitivity, and specificity in stone detection can be achieved with CNN or ResNet alone. Additionally, it was discovered to function effectively even in cases where there was noise or variations in the image quality. According to this study, physicians may find the hybrid model to be a helpful tool in diagnosing kidney stones more quickly and accurately, which could result in patients receiving treatment more quickly and experiencing better health outcomes.

4."Optimized YOLOv5 Architecture for Superior Kidney Stone Detection in CT Scans: A Review" by Christian Daul et al. (2024)

An enhanced YOLOv5 architecture designed specifically for kidney stone detection in CT scans is presented in this work. The model improves the detection of tiny stones, as small as 2 mm, which are frequently missed in conventional methods by integrating attention mechanisms and SE blocks.evaluations. When compared to other cutting-edge models, the suggested model performs better in terms of precision, recall, mAP, and inference time.

5. "5. Deep Learning Algorithm (YOLOv7) for Automated Renal Mass Detection on Contrast-Enhanced MRI: A 2D and 2.5D Evaluation of Results: A Review " by Maria Merino et al. (2024):

This study dives into how the YOLOv7 deep learning algorithm can be used for the automated detection of renal masses in contrast-enhanced MRI scans. It looks at both 2D and 2.5D analyses, showcasing how effective the model is at accurately spotting renal masses, which can really help with clinical decision-making.

III.EXISTING SYSTEM

The current methods for detecting kidney stones mainly depend on traditional diagnostic techniques like ultrasound, CT scans, and X-rays, which are interpreted by radiologists. Some more advanced systems use basic computer-aided detection (CAD) tools to help spot stones in medical images. While these methods can be effective, they often take a lot of time and are prone to human error. Certain research systems employ conventional machine learning algorithms such as SVM or KNN, which rely heavily on features that are manually crafted. Occasionally, older deep learning models are utilized, but they typically lack real-time inference and end-to-end automation. These systems often struggle with adaptability, particularly when it comes to small or overlapping stones, and they can be inefficient when handling large datasets. Additionally, most systems don't offer immediate visual feedback, user interaction, or treatment recommendations, which limits their usefulness in clinical environments and remote diagnosis situations. Traditional CAD and ML methods usually require a lot of preprocessing and specialized knowledge to pull out relevant features. Their inflexibility makes it tough to adjust to differences in image quality, patient anatomy, or various imaging devices. Plus, limited integration with web platforms or mobile apps further hinders accessibility in areas that need it most. In many cases, these systems aren't optimized for speed, resulting in delays in both diagnosis and treatment planning.

Disadvantages

• High dependancy and on expert radiologists for interpretation

There's a significant reliance on expert radiologists to accurately interpret medical images, and their specialized knowledge is essential for making the right diagnosis. However, this dependence can cause delays, particularly when there aren't enough experts available. Additionally, differences in experience can impact the consistency of the results. By automating or assisting with interpretation through AI, we can help lessen this reliance.

• Time consuming and mot suitable for real time analysis

Interpreting medical images can be quite a lengthy and tedious task, as it demands a thorough examination by experienced radiologists. This often hinders the ability to give immediate feedback or assist in real-time decision-making during crucial moments. Such delays can affect timely treatment and ultimately influence patient outcomes. There's a pressing need for quicker and more automated solutions to tackle these challenges.

• Limited accuracy in detecting small or overlaping stones

Detecting small or overlapping stones in medical images can be a real challenge, even for seasoned radiologists. These stones often camouflage themselves among nearby tissues or hide behind other structures, making them easy to overlook. This can really impact the accuracy of diagnoses and might result in delays or incorrect treatments. Traditional imaging methods sometimes just don't have the resolution or clarity needed to catch these details. Consequently, patients may find themselves needing multiple scans or extra tests to confirm whether stones are present. Enhancing detection techniques is crucial for achieving quicker and more reliable diagnoses.

• Lack of integration with interactive user interface

Many medical imaging systems struggle with seamless integration into user-friendly interfaces, making them a bit of a hassle for healthcare professionals. When the interface isn't intuitive, tasks like navigating images, adjusting views, or pinpointing areas of concern can become tedious and time-consuming. This can hinder doctors from swiftly analyzing and sharing their findings. A more interactive interface could streamline workflows, enhance accuracy, and ultimately save precious time. Plus, it would allow for a more straightforward way to merge patient data with imaging results all in one spot. By improving this integration, we can pave the way for quicker and more effective clinical decisions.

IV. PROPOSED SYSTEM

The proposed system rolls out a cutting-edge, AI-driven web application designed for real-time kidney stone detection, leveraging sophisticated deep learning techniques. It combines the power of the YOLOv8 and YOLOv11 object detection models to scrutinize uploaded kidney X-ray or CT images, clearly marking stones with bounding boxes. Users have the flexibility to choose their preferred model and will receive both the original and annotated images, complete with confidence scores for the detected stones. The system boasts an intuitive and responsive user interface crafted with Tailwind CSS, ensuring a polished look and a smooth user experience. Plus, it provides tailored remedy suggestions—covering Medical, Food, and Exercise categories—based on the detection results. Accessible through any web browser, this application is perfect for healthcare professionals and patients alike, eliminating the need for specialized hardware or software installations. Ultimately, this system enhances diagnostic support, minimizes human error, and effectively connects automated detection with actionable insights for timely medical intervention.

Advantages

• Real time and automated kidney stone detection

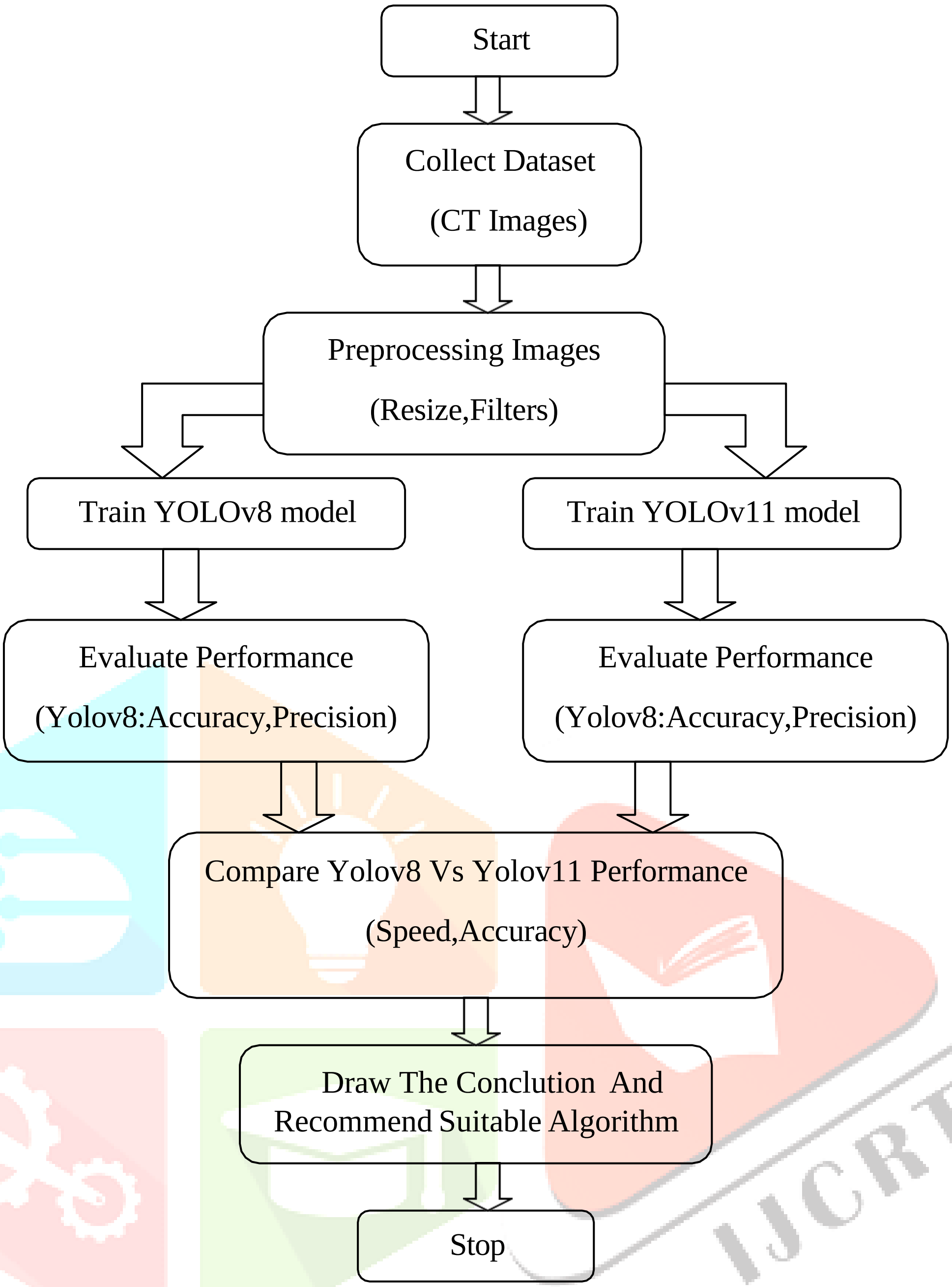
Real-time and automated kidney stone detection allows stones to be identified instantly as the medical images are captured, without waiting for manual review by a radiologist. This speeds up diagnosis, especially in urgent cases, and helps doctors make faster treatment decisions. Automated systems can consistently detect stones, reducing the risk of human error or oversight. They are also capable of spotting stones of various sizes and positions more efficiently. This approach improves both accuracy and patient care by streamlining the diagnostic process.

•Duel model support for flexible accuracy and performance

Dual model support allows a system to switch between two modes — one focused on high accuracy and the other on faster performance. This flexibility helps balance the need for precise results during detailed analysis and quick responses in time-sensitive situations. Users can choose the mode that best fits their current clinical need, whether it's speed or accuracy. This approach makes the system more efficient and adaptable to different scenarios. Overall, it enhances both the reliability and usability of medical image analysis tools.

•User friendly web interface with instant visual feedback

A user-friendly web interface with instant visual feedback makes it easier for doctors and medical staff to interact with imaging systems. It allows them to view, zoom, and analyze medical images quickly and clearly, without complicated steps. Instant feedback helps highlight important findings right away, reducing the chances of missing critical details. This smooth interaction saves time and improves confidence in diagnosis. A well-designed interface also makes training easier for new users and supports faster decision-making in clinical settings.



V.METHODOLOGY

This study compares YOLOv8 and YOLOv11 models for real-time kidney stone detection using CT images. Both models are trained on the same labeled dataset and tested to measure their accuracy, precision, recall, mAP, and detection speed. YOLOv8's reliable performance is compared with YOLOv11's newer features to check for improvements in accuracy and efficiency. Testing is done under the same conditions to ensure a fair comparison. This helps decide which model is more suitable for real-world medical use.

Collect Data set:

Collecting a high-quality, diverse dataset of CT and MRI kidney images is crucial for accurate kidney stone detection. These imaging techniques provide detailed anatomical information, making them ideal for detecting stones of various sizes and locations. Data can be gathered through partnerships with hospitals, publicly available medical repositories, or synthetic data augmentation if privacy concerns arise. The dataset should cover different stone types, patient demographics, and include detailed metadata and annotations from radiologists. Proper dataset quality and size ensure better model performance and generalization, particularly when handling complex or noisy images. Ethical considerations, such as anonymizing personal information, are essential.

Preprocess images:

Preprocessing raw medical images is crucial for preparing CT/MRI scans for deep learning models like YOLO. This involves resizing images to a consistent size, normalizing pixel values, and applying noise reduction techniques to improve image quality. Data augmentation methods, such as rotation and zooming, help increase dataset diversity and reduce overfitting. Annotating kidney stones with bounding boxes in YOLO format is also essential. Additional steps like contrast enhancement and splitting the dataset into training, validation, and test sets ensure effective model training and evaluation. Overall, preprocessing ensures the model gets clean, uniform inputs for accurate detection

Train Yolov8 model:

In this step, the YOLOv8 model is trained using the preprocessed and labeled kidney stone dataset. The model learns to detect stones by predicting bounding boxes and confidence scores, adjusting its weights through backpropagation and optimizers like Adam or SGD. Key hyperparameters like learning rate, batch size, and epochs are tuned for the best results. Validation data is used during training to avoid overfitting and ensure the model generalizes well. YOLOv8's advanced architecture helps in accurately detecting stones, even in complex or small regions. Once trained, the model's final weights are saved for testing and real-world evaluation.

Test Yolo v11 model:

In this phase, the YOLOv11 model is tested on CT or MRI kidney images to check its ability to detect stones on unseen data. The model predicts bounding boxes and confidence scores, which are compared to ground-truth labels to measure accuracy, precision, recall, and speed. YOLOv11 likely includes advanced features for better detection of small or unclear stones. This step focuses only on evaluating performance — no further training is done. The results help assess how well YOLOv11 handles real-time detection and whether it performs better than YOLOv8 in clinical scenarios.

Evaluate Yolov8 Model:

Once the YOLOv8 model has been trained, it's crucial to evaluate its performance using a variety of key metrics to see how well it can detect kidney stones. Accuracy is all about how often the model gets its predictions right—essentially, how frequently it correctly identifies stones. But when it comes to object detection, accuracy alone doesn't cut it. That's where precision comes in; it tells us how many of the predicted stones are actually correct, giving us insight into how well the model avoids false positives. Then there's recall, which measures how many of the actual stones the model successfully detected, helping us understand the false negative rate. A high recall is vital because it means fewer stones are missed, which is critical for clinical diagnosis. FPS, or Frames Per Second, gauges the model's speed—essentially, how many images it can process in real time, which is important for integrating it into diagnostic tools or mobile health apps. These metrics are usually calculated on a validation or test set of CT/MRI scans. To get a clearer picture of performance, confusion matrices, Precision-Recall curves, and F1-scores can also be generated. The model is tested under various image conditions, like different contrast levels or stone sizes, to evaluate its robustness. Evaluations might also include analyzing visual outputs, where the predicted bounding boxes are overlaid on the original images to visually assess detection quality. By combining these quantitative and qualitative insights, we can refine the model and make comparisons. In the end, this process helps confirm whether YOLOv8 is accurate, fast, and reliable enough for clinical use, especially when it comes to identifying both common and rare presentations of kidney stones.

Evaluate Yolov11 Model:

This step focuses on evaluating the YOLOv11 model using the same metrics as YOLOv8, such as accuracy, precision, recall, and FPS, to check its performance on kidney stone detection. YOLOv11 may have advanced features like improved layers or transformer modules for better results. The model is tested on both normal and challenging cases to assess its robustness. Hardware efficiency, like GPU usage and model size, is also considered for real-time deployment. Visual checks help confirm the quality of its predictions. This evaluation shows whether YOLOv11 outperforms YOLOv8 for medical use.

Compare Yolov8 vs Yolov11:

This step compares YOLOv8 and YOLOv11 to see which model is better for kidney stone detection. Key metrics like accuracy, precision, recall, FPS, and mAP are used for fair evaluation on the same dataset. Both models' predictions are analyzed through graphs and visual outputs for clear comparison. Factors like inference speed, model size, and hardware compatibility are also considered for real-time use. The analysis highlights each model's strengths, such as YOLOv11's advanced detection in tricky cases or YOLOv8's efficiency. In the end, this helps decide which model fits best for clinical applications.

VI.CONCLUSION

This project showcases the incredible potential of blending deep learning with web technologies to enhance healthcare diagnostics, particularly in the realm of kidney stone detection and personalized treatment suggestions. By utilizing cutting-edge YOLO object detection models, like YOLOv8 and YOLOv11, the system can analyze CT or MRI images uploaded by users, accurately identifying kidney stones with impressive speed and precision. These models facilitate real-time analysis, allowing users not only to spot kidney stones but also to gauge the severity of their condition through visual overlays and confidence scores, giving them vital insights into their health.

The user-friendly web interface, crafted with Flask for the backend and Tailwind CSS for a sleek, responsive frontend, ensures smooth interactions—users can effortlessly upload their images, choose their preferred detection model, and instantly see the results. Plus, the integration of the Ultralytics YOLO framework guarantees seamless model deployment and execution, delivering reliable performance even for intricate image processing tasks.

A standout feature of this project is the remedies module, which provides personalized medical advice, dietary recommendations, and exercise plans based on the severity of the detected kidney stones. This not only aids in treating existing stones but also promotes preventive strategies to minimize recurrence, encouraging users to embrace a healthier lifestyle. In this way, the system evolves from a mere diagnostic tool into a comprehensive health companion. The true power of this platform lies in its accessibility and its ability to democratize healthcare, making expert-level diagnostic tools available to a broader audience without requiring specialized medical training. By merging cutting-edge artificial intelligence with practical web deployment, the system illustrates how deep learning can be effectively applied in real-world medical scenarios.

The design is not only scalable but also modular, making it super easy to expand into other areas of healthcare imaging. This includes things like spotting tumors, cysts, or other organ issues, which really widens the system's potential impact. Plus, with automation and instant feedback, the platform lightens the load for healthcare professionals, allowing for quicker triage and better patient prioritization. On the technical side, the thoughtful integration of Flask for routing and API management, Tailwind CSS for styling, and the Ultralytics YOLO package for inference shows a well-rounded approach to creating applications that are not just efficient but also easy to maintain and scale.

Additionally, incorporating features like graphical comparisons of detection models, performance stats, and visual explanations really boosts transparency, helping users grasp the detection process more easily. This builds trust and encourages users to take proactive steps in managing their kidney health. By tapping into modern DevOps practices, we can also look into cloud-based deployment to make the system accessible worldwide, maximizing its usefulness. In summary, this project is a well-rounded solution that not only effectively detects kidney stones using cutting-edge deep learning techniques but also aids users in managing their condition through engaging web interactions and tailored recommendations. It connects the dots between complex AI algorithms and real-world healthcare applications, giving us a sneak peek into the future of accessible, efficient, and smart medical diagnostics that can save time, alleviate suffering, and enhance lives.

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