iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IX Month of publication: September 2025

DOI: https://doi.org/10.22214/ijraset.2025.74105

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

Kidney Stone Detection Using Advanced Deep Neural Networks

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Abstract: Chronic kidney disease (CKD) is a widespread medical issue that results from diminished kidney function and, in severe cases, leads to kidney failure. One of the contributing factors to impaired kidney performance is the development of kidney stones. Since this condition often shows no noticeable symptoms during its early stages, timely and accurate diagnosis is crucial to preventing serious complications. In this research, we propose a highly effective and reliable method for detecting kidney stones by leveraging ensemble deep learning models enhanced through inductive transfer learning. The methodology incorporates data from two main sources: the Kidney Data and the CT Kidney Stone datasets. For classification purposes, a variety of deep learning architectures were utilized, including DarkNet19, InceptionV3, ResNet101, DenseNet169, MobileNetV2, VGG16, GoogleNet, AlexNet, ShuffleNet, SqueezeNet, and a custom-designed DNN model (FindWell). These models were further supported by feature extraction and selection processes using the ReliefF algorithm. Classification accuracy was validated through K-Nearest Neighbors (KNN) and K-Fold cross-validation techniques. For the detection task, different models from the YOLO (You Only Look Once) family—namely YOLO v5x6, v5s6, v8n, and v9n—were deployed to identify kidney stones in imaging data. In addition, the Xception architecture was applied for a comprehensive analysis of the dataset. This integrated approach of combining multiple cutting-edge algorithms enhances both the precision and speed of kidney stone identification, which can significantly aid in the early diagnosis and treatment of patients suffering from chronic kidney-related disorders.
Keywords: Deep learning, Computed tomography, Kidney stone, Transfer learning, Ensemble network, Xception, Classification and Detection.

I. INTRODUCTION

Kidney-related illnesses impact individuals across all age groups and genders. Identifying these conditions early is essential to preventing severe complications. For instance, if left untreated, chronic kidney disease (CKD) can become life-threatening. Similarly, kidney stones, though seemingly minor in the early stages, can lead to more serious kidney issues if not detected promptly. Catching small kidney stones early plays a significant role in stopping the progression toward chronic kidney conditions.

There has been a steady global rise in kidney disease cases, particularly in developing countries where there is a notable shortage of nephrologists. This shortage often leaves many patients without access to timely and effective medical attention. Regular monitoring and screening—especially through imaging technologies—are vital for managing kidney health. However, these diagnostic procedures are often time-consuming and can place a heavy workload on healthcare providers, increasing the risk of oversight or misdiagnosis.

In response to these challenges, automated systems have been introduced to assist in the early identification of kidney disorders. These computer-based tools aim to reduce the burden on medical professionals, minimize human error, and provide faster and more objective diagnostic results. Such solutions not only improve accuracy but also offer consistent and dependable support in medical decision-making. As a result, these technologies contribute to more efficient and reliable healthcare outcomes in kidney disease management.

II. LITERATURE SURVEY

Serrat et al. [1] developed the MyStone system, which offers an automated approach for classifying kidney stones using sophisticated algorithms applied to medical images. Their system demonstrated high efficacy in accurately categorizing stones based on specific features extracted from the imaging data. The integration of advanced techniques in their model underscores the potential of automated solutions in simplifying complex diagnostic tasks.

Martínez et al. [2] proposed an automated classification method for kidney stone images captured during ureteroscopy, employing ensemble learning techniques. By leveraging multiple models in a combined framework, their approach significantly improved classification accuracy. The use of ensemble learning effectively mitigates individual model weaknesses, enhancing the overall performance of the classification system.

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Verma et al. [3] explored the application of K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) for kidney stone identification. Their analysis demonstrated the potential of traditional ML models in accurately distinguishing between various types of stones. The study emphasized the importance of selecting appropriate classification techniques tailored to specific imaging datasets, as these models rely on distinct feature extraction methods for high accuracy.

De Perrot et al. [4] investigated the differentiation between kidney stones and phleboliths in low-dose CT scans using radiomics and ML. Their approach employed advanced feature extraction and analysis techniques to ensure precise differentiation, which is critical in reducing diagnostic errors. The study highlights the growing relevance of radiomics, which involves the extraction of quantitative data from medical images, as a powerful tool in medical diagnosis.

Manoj et al. [5] presented a study on the automated detection of kidney stones using DL models. Their research focused on optimizing DL architectures for the specific task of kidney stone detection, achieving notable improvements in detection rates. The study underscores the importance of tailoring DL models to the unique characteristics of kidney imaging datasets to enhance diagnostic reliability.

III.METHODOLOGY OF PROPOSED SYSTEM

The proposed system introduces an efficient and robust approach for kidney stone detection using inductive transfer-based ensemble deep neural networks, leveraging advanced classification and detection algorithms alongside feature selection techniques. For classification, a diverse set of deep learning models, including DarkNet19 [17], InceptionV3, ResNet101, DenseNet169 [16], MobileNetV2 [15], VGG16, GoogleNet [14], AlexNet [14], ShuffleNet, SqueezeNet, and Xception, are employed. Feature extraction and selection are optimized using ReliefF [19], coupled with KNN utilizing K-Fold validation to enhance predictive accuracy. For detection, state-of-the-art models such as YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n are incorporated, ensuring precise identification of kidney stones. The system is designed to analyze data from two datasets—Kidney Data and CT Kidney Stone Data [18] —focusing on the integration of feature selection techniques with deep learning models to improve accuracy and efficiency. This ensemble framework aims to provide a reliable and scalable solution for early kidney stone detection, addressing the asymptomatic nature of the condition and reducing potential health risks.

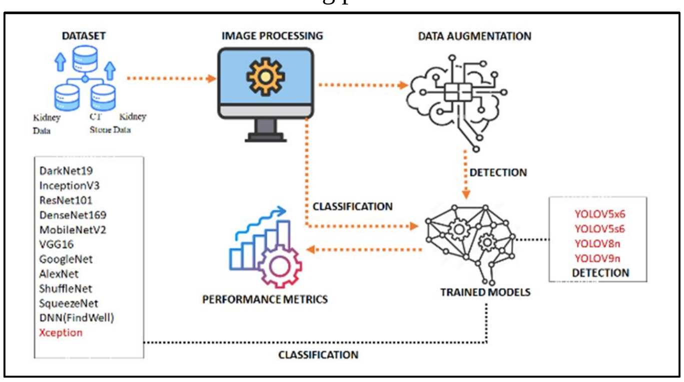

Fig.1 Proposed Architecture

The system architecture (fig. 1) utilizes a dataset of Kidney data and CT Kidney Stone data , which is pre-processed and augmented to enhance the training data. This data is then fed into various deep learning models for classification and detection tasks. The performance of these models is evaluated using performance metrics. The trained models can be used for further applications in medical imaging.

A. Dataset Collection

The dataset collection includes two key datasets: the Kidney Data and CT Kidney Stone Data. The Kidney Data encompasses various kidney conditions, while the CT Kidney Stone Data contains labeled CT scans categorized into Normal, Tumor, Stone, and Cyst classes. This dataset, available on Kaggle, is designed for use in medical image classification and diagnostic applications, with the goal of improving kidney disease detection using machine learning and image processing techniques. The dataset provides a diverse set of images for training models.

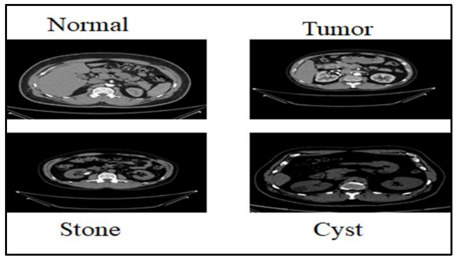

Fig.2 Dataset Images

B. Pre-Processing

In the pre-processing step, we focus on preparing the dataset for modeling. This includes image processing and data augmentation to ensure high-quality input for the prediction model.

1) *Image Processing*
- For Classification: Images are processed using techniques such as rescaling, shear transformation, zooming, horizontal flipping, and reshaping via an Image Data Generator. Features are then extracted using CNN and HOG methods, including steps like resizing, color conversion, and appending labels for further analysis.
- For Detection: Images are converted into blob objects, classes are defined, bounding boxes are set, and arrays are transformed into NumPy arrays. The process also includes adding annotations, converting BGR images to RGB, creating masks, resizing images, loading pre-trained models, reading network layers, and extracting output layers for detection.

2) *Data Augmentation:* For data augmentation in detection, random image transformations are applied to introduce variability into the dataset. This includes rotating the images to simulate different angles and perspectives, and performing other transformations to adjust aspects like scale and position. These augmentations help to build a more diverse training set, improving model generalization and robustness for object detection tasks.

C. Algorithms

1) *For Classification*
- DarkNet19: A lightweight convolutional neural network often applied in detection systems, valued for its ability to process data quickly while still producing reliable classification accuracy.
- InceptionV3: A deep CNN that makes use of inception modules, where multiple filter sizes are combined in the same block, helping the model capture fine and coarse details efficiently with reduced computation.
- ResNet101: A residual network with 101 layers, designed with skip (shortcut) connections that prevent vanishing gradient problems and make it easier to train very deep models.
- DenseNet169: A dense connectivity model in which every layer passes information to all subsequent layers, improving gradient flow, encouraging feature reuse, and enhancing classification performance.
- MobileNetV2: An efficient architecture built for mobile and embedded platforms, offering real-time predictions with a smaller model size and lower computational cost.
- VGG16: A classic CNN with 16 layers, structured with a series of stacked convolutional blocks followed by fully connected layers, widely recognized for its simplicity and effectiveness.
- GoogleNet: A deep model that employs inception modules, combining different convolution kernel sizes within the same layer to capture diverse feature representations while maintaining efficiency.
- AlexNet: One of the earliest influential CNNs, known for using ReLU activation, dropout regularization, and data augmentation to significantly improve classification results on large datasets.
- ShuffleNet: A lightweight architecture that applies channel shuffle operations to increase speed and efficiency, making it suitable for mobile applications.
- SqueezeNet: A compact CNN that achieves accuracy comparable to AlexNet while using far fewer parameters, making it practical for deployment in resource-limited settings.
- DNN (FindWell): A task-specific deep neural network adapted for specialized domains such as medical imaging, employing advanced layers to handle complex image classification effectively.
- Xception: A modern CNN that extends the inception design by replacing standard convolutions with depthwise separable convolutions, resulting in better efficiency and higher accuracy.

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2) *For Detection*

- YOLOV5x6: A high-capacity version of the YOLO series, designed to deliver accurate object detection while maintaining real-time processing speeds.
- YOLOV5s6: A smaller and faster version of YOLOv5, optimized for use in edge and mobile environments where resources are limited.
- YOLOV8n: An updated YOLO model providing a balance between detection accuracy and speed, suitable for different application settings.
- YOLOV9n: The most recent YOLO release, offering enhanced precision and optimized real-time performance, even in complex detection scenarios.

IV. RESULTS AND DISCUSSION

Accuracy:

$$Accuracy = \frac{\text{TP + TN}}{\text{TP + FP + TN + FN}} (1)$$

Precision:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (2)$$

Recall:

$$Recall = \frac{\text{TP}}{\text{TP + FN}} (3)$$

F1-Score:

$$F1\,Score = 2 * \frac{Recall \times Precision}{Recall + Precision} * 100 (1)$$

mAP:

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k (5)$$

Table(1) presents the evaluation of performance metrics, namely accuracy, precision, recall, and F1-score, for each of the algorithms. Among the compared models, Xception achieves the highest values across all metrics, demonstrating superior performance. The table further provides a side-by-side comparison of how the remaining algorithms perform with respect to these measures.

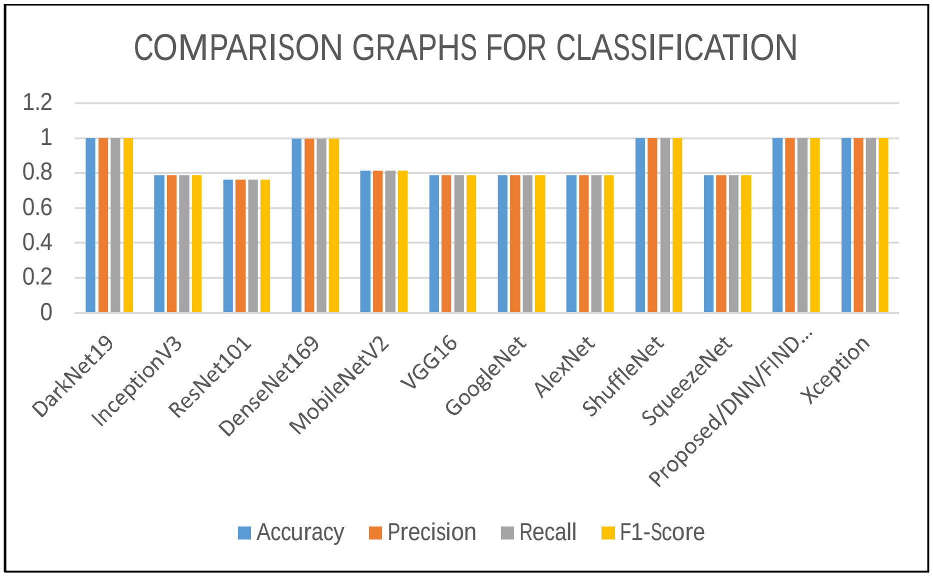
Table(2) evaluate the performance metrics—precision, recall, mAP—for each algorithm. Across all metrics, the YOLOV5s6 consistently outperforms all other algorithms. The tables also offer a comparative analysis of the metrics for the other algorithms.

Model	Accuracy	Precision	Recall	F1-Score
DarkNet19	1.000	1.000	1.000	1.000
InceptionV3	0.787	0.787	0.787	0.787
ResNet101	0.762	0.762	0.762	0.762
DenseNet169	0.995	0.995	0.995	0.995
MobileNetV2	0.814	0.814	0.814	0.814
VGG16	0.787	0.787	0.787	0.787
GoogleNet	0.787	0.787	0.787	0.787
AlexNet	0.787	0.787	0.787	0.787
ShuffleNet	0.999	0.999	0.999	0.999
SqueezeNet	0.787	0.787	0.787	0.787
Proposed/DNN/FINDWELL	1.000	1.000	1.000	1.000
Xception	1.000	1.000	1.000	1.000

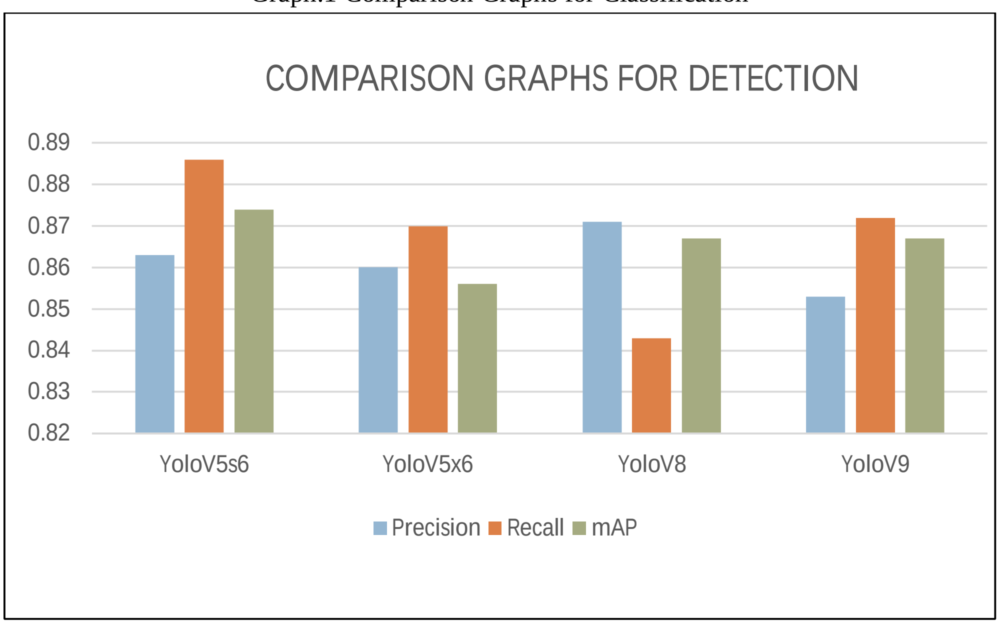
Table.1 Performance Evaluation Metrics for Classification

Model	Precision	Recall	mAP
YoloV5s6	0.863	0.886	0.874
YoloV5x6	0.860	0.870	0.856
YoloV8	0.871	0.843	0.867
YoloV9	0.853	0.872	0.867

Table.2 Performance Evaluation Metrics for Detection



Graph.1 Comparison Graphs for Classification



Graph.2 Comparison Graphs for Detection

Graph (1) uses different colors to represent the metrics: accuracy in light blue, precision in orange, recall in grey, and F1-score in light yellow. Compared to the other models, Xception consistently records the highest values across all four measures, highlighting its superior performance. The graphical representation clearly demonstrates these outcomes.

Graph (2) depicts precision in ice blue, recall in orange, and mAP in olive green. In this case, YOLOv5s6 outperforms the other detection models, achieving the best results across the reported metrics. The visual plots provide a clear illustration of these findings.

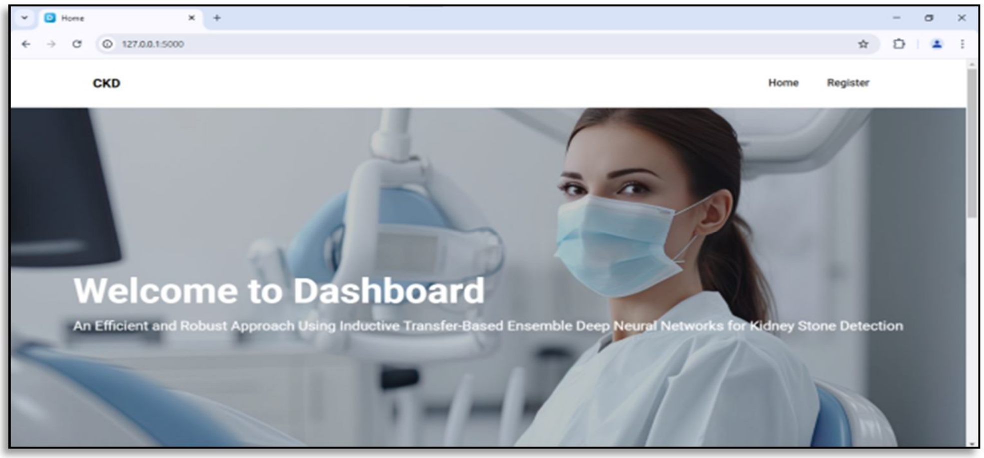


Fig.3 Dashboard

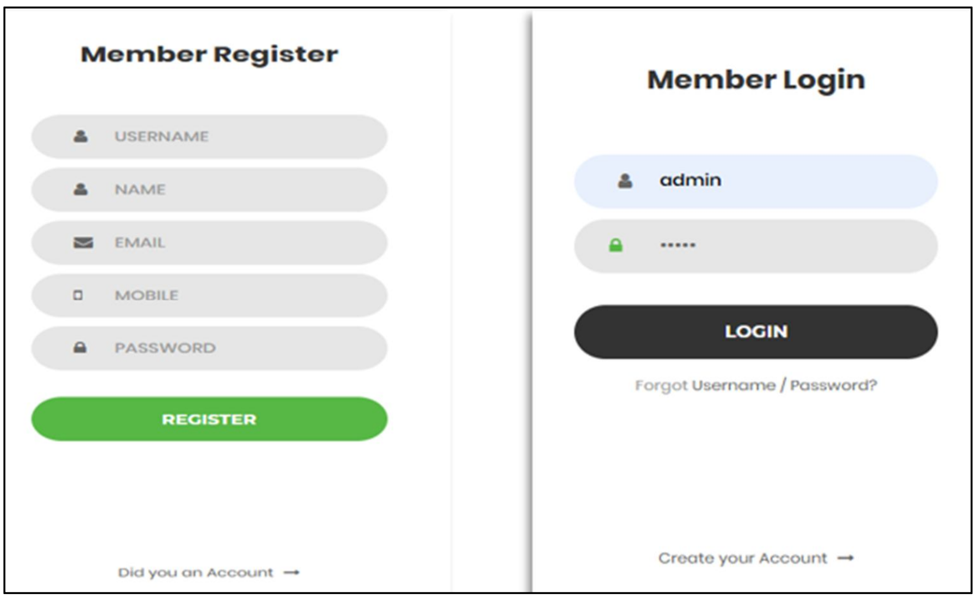


Fig.4 Register and Login Page

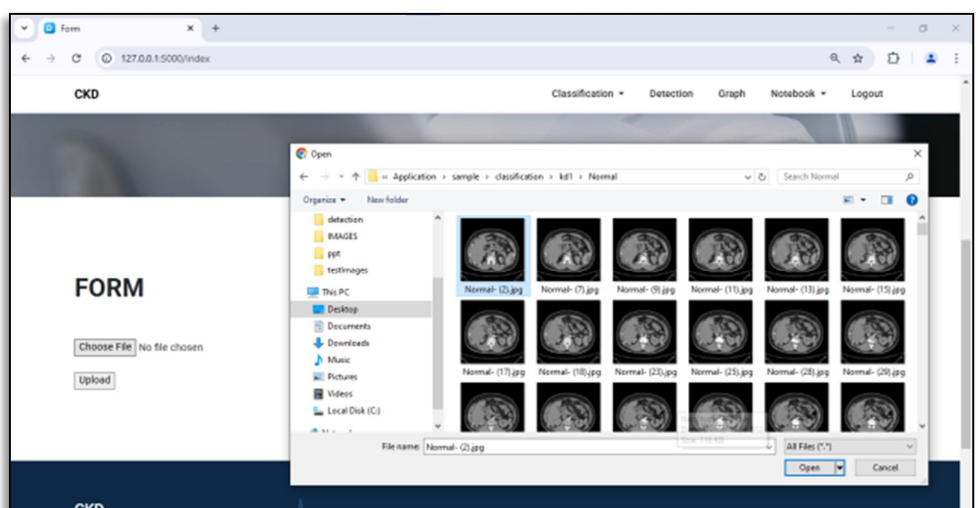


Fig.5 Test Case 1

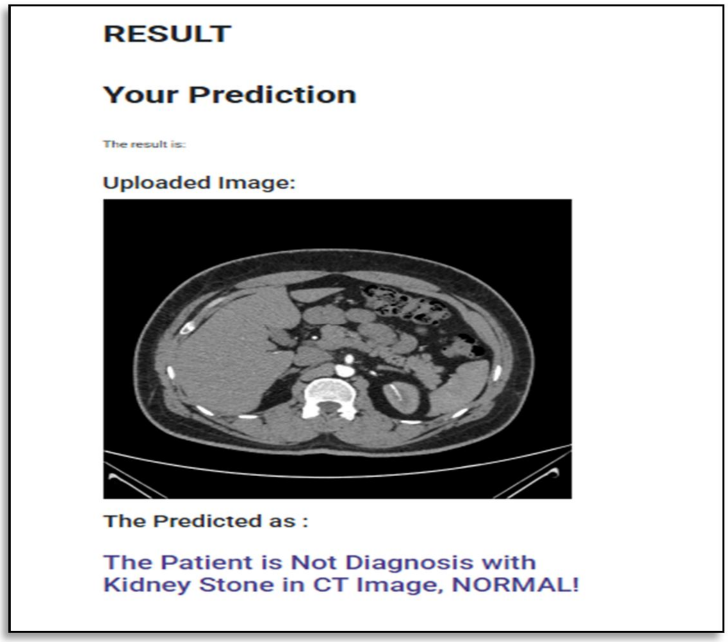


Fig.6 Results of Test case 1

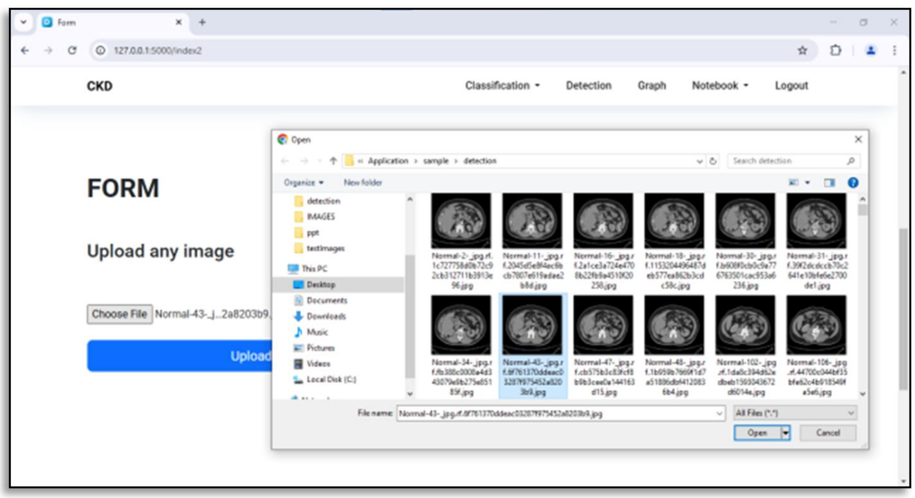


Fig.8 Test case 2

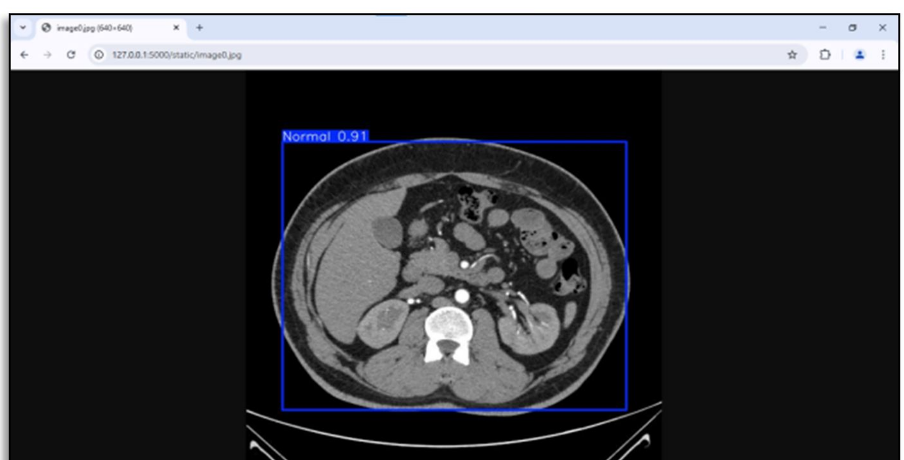


Fig.9 Results of Test case 2

V. FUTURE SCOPE

Looking ahead, this work can be extended in several ways. Future studies could investigate the use of transformer-based models and generative adversarial networks (GANs) to enhance feature extraction and create high-quality synthetic images for training. The adoption of hybrid models and more sophisticated ensemble techniques could further improve system accuracy and robustness. Additionally, incorporating attention mechanisms and exploring unsupervised or semi-supervised learning approaches may optimize classification and detection processes. Expanding the system to diverse and larger datasets will also strengthen generalization, ensuring more reliable performance in real-world clinical settings. With these advancements, the project holds the potential to significantly contribute to more efficient and accurate kidney stone diagnosis in medical practice.

VI. CONCLUSION

This project successfully demonstrates the effectiveness of advanced deep learning methods for detecting and classifying kidney stones. By applying models such as DarkNet19, ResNet101, DenseNet169, and Xception, the system was able to achieve strong performance in analyzing CT scan images. These deep learning architectures are capable of extracting significant features from medical images, which allows accurate identification of different types and sizes of kidney stones. The integration of YOLOv5 and YOLOv8 further strengthened the system by enabling real-time detection and precise localization of abnormalities. Techniques such as data augmentation, feature extraction, and ensemble learning played a key role in improving both accuracy and reliability. Altogether, the proposed system provides a holistic approach to tackling the challenge of kidney stone diagnosis. This project emphasizes the role of advanced technologies in supporting healthcare professionals and improving patient care.

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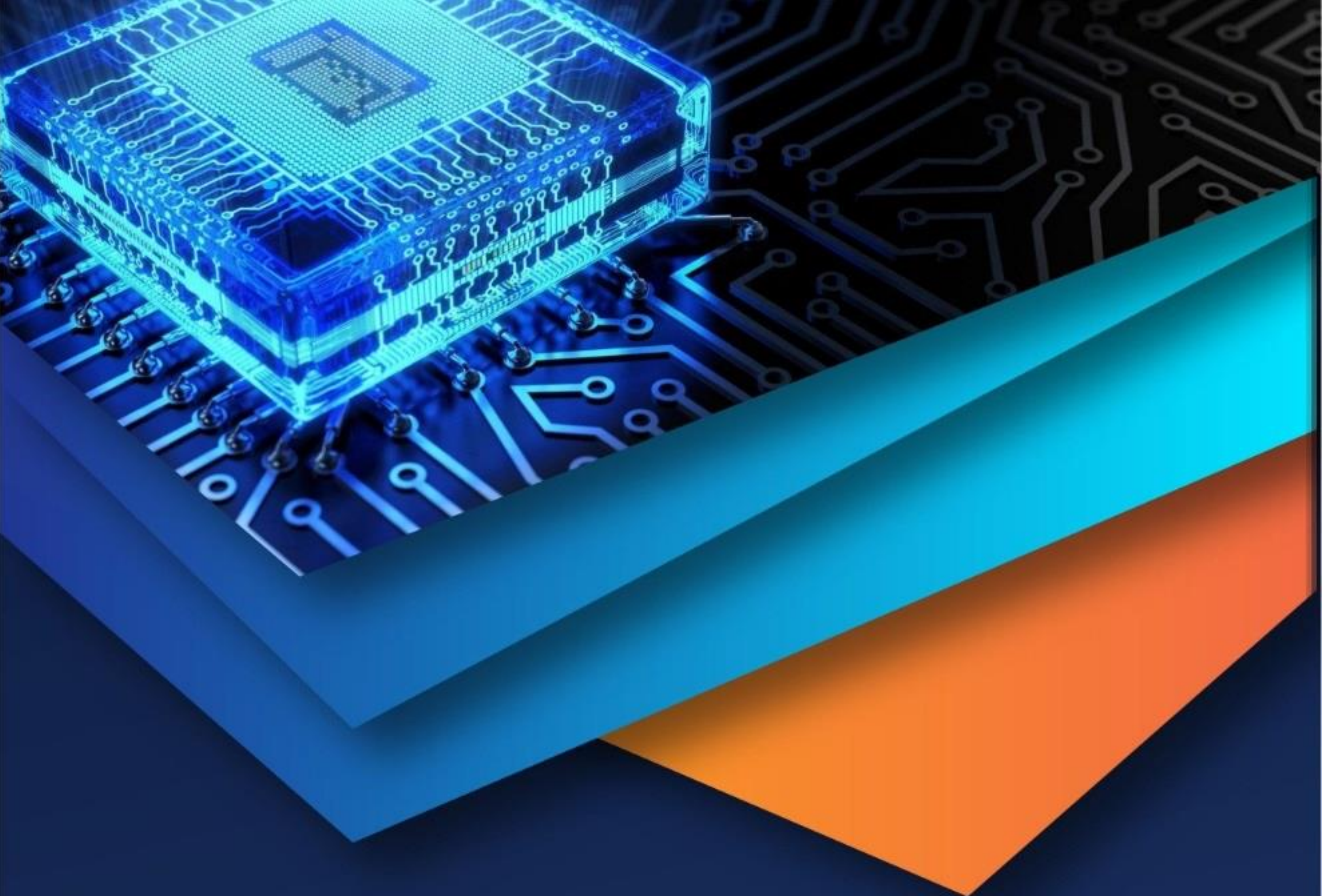

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