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A Reliable Kidney Stone Detection Method Using Inductive Transfer-Based Ensemble Deep Neural Networks

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Kidney Stone Detection, Deep Neural Networks, Inductive Transfer Learning, YOLO, Ensemble Learning, Xception, Medical Imaging, Flask Framework, Secure Authentication.

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ABSTRACT

Chronic kidney disease is a significant global health concern, with kidney stones being a major contributing factor to kidney dysfunction. Early and accurate detection is essential to prevent severe complications. This study proposes an efficient approach using inductive transfer-based ensemble deep neural networks for kidney stone detection. A combination of classification models, including DarkNet19, InceptionV3, ResNet101, and others, along with detection algorithms from the YOLO family, enhances diagnostic accuracy. Feature extraction techniques such as ReliefF and validation methods like KNN and KFold improve model performance. The integration of the Xception model further refines classification accuracy, while a user-friendly Flask-based front end facilitates real-time testing with secure authentication. The proposed approach improves early diagnosis, reduces physician workload, and enhances patient care.

INTRODUCTION

Kidney diseases impact individuals across all age groups and genders, posing a significant global health challenge. Early detection is crucial for preventing complications, as chronic kidney disease (CKD) can lead to severe health risks, including kidney failure. Among these conditions, kidney stones are a prevalent issue, often developing without noticeable symptoms. If left undiagnosed, tiny kidney stones can gradually lead to chronic kidney disorders, increasing the risk of severe medical complications.

The rising number of kidney patients worldwide, particularly in developing countries, highlights the need for more efficient and accessible diagnostic solutions. A major challenge in healthcare is the shortage of nephrologists, which results in delayed diagnoses and limited access to timely medical intervention. Manual screening using medical imaging is time-consuming for physicians, and the increasing patient load can lead to errors in diagnosis. Furthermore, the subjectivity of manual assessments may result in inconsistencies in identifying kidney abnormalities.

To address these challenges, computer-assisted medical solutions have been developed to automate kidney stone detection. AI-based diagnostic systems reduce physician workload and minimize human errors, ensuring faster and more accurate results. Automated models eliminate subjectivity, enhancing the reliability of diagnoses. By leveraging deep learning techniques and ensemble models, such systems provide precise and efficient kidney stone detection, ultimately improving patient outcomes and reducing healthcare burdens.

LITERATURE SURVEY

a) Application of Kronecker convolutions in deep learning technique for automated detection of kidney stones with coronal CT images:

https://www.sciencedirect.com/science/article/pii/S002002552300590X?via%3Dihub

Nutrition, obesity, health issues, supplements, etc., are exacerbating kidney stone disease, a serious public health concern. Hard mineral deposits in the kidneys, also known as kidney stones or renal calculus, are a common medical condition. Clinical practitioners often use computed tomography (CT) as an imaging model for the diagnosis of kidney stones. Finding kidney stones visually can be challenging and lead to false alarms since these photographs are of low quality. This research developed a computerised diagnostic system for doctors to use with deep learning. Kidney stones may be detected using conventional CNN-based deep learning. When it comes to operations on convolution layers, it still has performance and implementation concerns. Using Kronecker product-based convolution, the suggested deep learning architecture reduces feature map redundancy without causing convolution overlap. In order to enhance the network, our method gathers both general and specific details from the input images. The proposed design makes use of kidney stone CT scans that are available to the public on GitHub. With a recognition accuracy of 98.56%, our automated model was able to identify kidney stones using CT images. If you have a kidney stone, no matter how little, our technology can detect it better than the most recent procedures.

b) Effective deep learning classification for kidney stone using axial computed tomography (CT) images: https://www.degruyter.com/document/doi/10.1515/bmt-2022-0142/html

Hey there! All patients are concerned about the high recurrence and morbidity of kidney stones, which are common. The best way to detect and treat kidney stone disease is via CT imaging. Objects Radiologists must spend a lot of time manually evaluating several CT slices in order to diagnose kidney stones. This research used deep learning (DL) algorithms to examine kidney stones. The goal of this effort is to use deep learning techniques to categorise kidney stones from CT scans. Methods For this research, Inception-V3 was cited. Radiologists annotated CT scans of the abdomens of patients with kidney stones, and then used CNN architectures that had been previously trained to these pictures. Minibatch size was set at 7 and starting learning rate was 0.0085. Final Product For the first time, 8209 CT images from hospitals were used to evaluate the eight models. Validation and training were conducted with very few actual CT scans. According to the findings of the tests, the Inception-V3 model can identify kidney stones using CT scans with a 98.52 % accuracy rate. Last thoughts If you have a kidney stone, the Inception-V3 model can find it. Both its performance and its clinical applicability are enhanced by the Inception-V3 Model. Radiologists may now identify kidney stones with less computational expenditure and fewer specialists because to this breakthrough.

c) Kidney stone detection using an optimized Deep Believe network by fractional coronavirus herd immunity optimizer: https://www.sciencedirect.com/science/article/pii/S1746809423003841?via%3Dihub

Using computed tomography (CT) images, this study proposed a computer-assisted kidney stone diagnosis approach. This approach makes use of deep learning and metaheuristics. An effective and trustworthy method for diagnosing kidney stones is to employ a bespoke Deep Believe Network (DBN) that is built around a fractional coronavirus herd immunity booster. The method is validated using a "CT kidney dataset" standard. The outcomes are then contrasted with other cutting-edge approaches. With an accuracy rating of 97.98%, DBN/FO-CHIO outperforms the other methods in simulations. When compared to other recall algorithms, the DBN/FO-CHIO's 92.99% accuracy rate stands out. Also, the fact that the proposed strategy outperforms the other options we looked at in terms of specificity implies that it has superior event-independent utility.

d) Kidney Stone Detection Using Deep Learning and Transfer Learning: https://ieeexplore.ieee.org/document/9985723

New and improved medical diagnostic tools are the goal of the research community. Inspection and diagnosis in the medical field make use of deep learning. Data from renal patients is used to evaluate various data mining techniques. In order to foretell renal failure, this research employed data mining classifiers. Using backpropagation can In this diagnostic method, Convolutional Neural Networks are utilised. The results show that compared to other classification approaches, the CNN algorithm performs better. We automate kidney stone categorisation using convolutional neural network (CNN) imaging and data processing. Results for large datasets requiring human operators and scrutiny are not possible. Therefore, the CNN and ALEXNET method is employed to address the issue in this study.

e) Modeling of An CNN Architecture for Kidney Stone Detection Using Image Processing: https://ieeexplore.ieee.org/document/10059972

A Back Engineering Organisation (BPN) and imaging and information processing approaches characterise kidney stones mechanistically. Commotion causes kidney stone placing mistakes. Kidney stones have grown more prevalent for numerous reasons. Finding outcomes for massive datasets with human review and administration is tough. Our project uses the Back-Engendering Organisation (BPN) for these reasons. An essential organ for purifying blood is the kidney. Healthy kidneys are constantly needed to balance blood pH, salt, and potassium. Early detection of kidney stones is crucial for proper treatment. [1] Conclusion image processing detecting approaches are more successful than others. The recommended strategy uses local resources to find stones. The recommended technique and computation were tested using clinic ultrasound images. Several execution estimate boundaries analysed the plot. Doctors may benefit from clinical conclusion and instructional planning research.

METHODOLOGY

A) Proposed System

To enhance kidney stone detection accuracy and efficiency, we propose an advanced system incorporating inductive transfer-based ensemble deep neural networks with additional improvements. The study extends existing models by integrating the Xception network, known for its superior feature extraction capabilities, to enhance the classification performance of kidney stone images. This deep learning model refines the identification of kidney abnormalities, contributing to more precise and reliable diagnostics.

For object detection, we employ the YOLO family of algorithms, including YOLO v5x6, YOLO v5s6, YOLO v8n, and YOLO v9n, to efficiently detect kidney stones from medical imaging datasets. These models enable real-time analysis, ensuring that abnormalities are identified promptly. Feature extraction using ReliefF and validation techniques such as KNN and KFold further improve model robustness and generalization.

To improve accessibility and usability, we develop a Flask-based front-end interface that allows healthcare professionals to interact with the system seamlessly. This web-based platform provides a user-friendly environment for real-time kidney stone detection and classification. Additionally, we integrate secure user authentication, ensuring that medical data remains protected and accessible only to authorized users, complying with healthcare security standards.

B) System Architecture

The proposed system architecture for kidney stone detection is designed to enhance diagnostic accuracy using a combination of deep learning models. It starts with dataset collection, utilizing Kidney Data and CT Kidney Stone Data, which serve as the foundation for training and testing. Before classification, image processing techniques such as noise reduction, contrast enhancement, and normalization are applied to improve the quality of input images. Additionally, data augmentation methods, including rotation, scaling, and brightness adjustments, are employed to make the model more robust against variations in medical images. These preprocessing steps ensure that the deep learning models receive high-quality inputs for improved performance.

For classification, an ensemble of deep learning models is used to distinguish between kidney stone-affected and healthy images. The models include DarkNet19, InceptionV3, ResNet101, DenseNet169, MobileNetV2, VGG16, GoogleNet, AlexNet, ShuffleNet, SqueezeNet, DNN (FindWell), and Xception. Among these, Xception plays a crucial role in enhancing classification accuracy through its advanced depthwise separable convolution layers. Feature extraction and selection techniques such as ReliefF are employed alongside KNN and KFold validation to ensure better model generalization. The ensemble learning approach allows multiple models to contribute to the decision-making process, leading to improved classification reliability.

For detection, the system utilizes advanced YOLO models (YOLO v5x6, YOLO v5s6, YOLO v8n, and YOLO v9n) to efficiently locate kidney stones in medical images. The trained models are evaluated using performance metrics such as accuracy, precision, recall, and F1-score to ensure reliability. To make the system accessible to healthcare professionals, a Flask-based user interface is developed, enabling real-time image uploads and diagnostic results. The platform is secured with user authentication to protect sensitive medical data, ensuring compliance with healthcare privacy regulations. This architecture not only improves early kidney stone detection but also streamlines the diagnostic process, reducing workload for physicians and enabling quicker medical interventions.

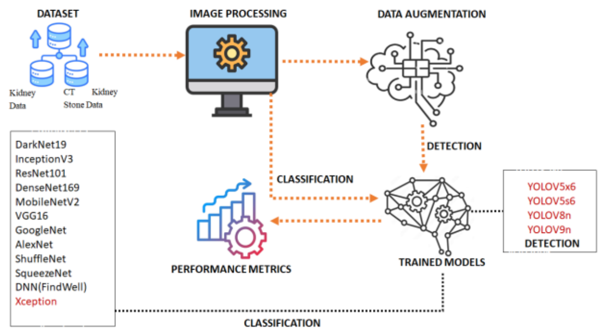


Fig.1. Proposed Architecture

C) MODULES

a) Data Loading

This module is responsible for importing the dataset, including kidney and CT scan images, ensuring they are correctly formatted for processing. It prepares the data for subsequent image processing and model training.

b) Image Processing (Classification)

This module enhances images for classification by applying Image Data Generator techniques such as re-scaling, shear transformation, zooming, horizontal flipping, and reshaping. It extracts features using Convolutional Neural Networks (CNN) and Histogram of Oriented Gradients (HOG) through resizing, color conversion, and appending labels.

c) Image Processing (Detection)

For detection, images are processed by converting them into blob objects, defining classes, declaring bounding boxes, and converting arrays to NumPy format. Additional steps include appending annotation files, converting BGR to RGB, creating masks, and resizing images. The processed images are then used to load the pre-trained detection model, read network layers, and extract output layers.

d) Data Augmentation

This module applies random alterations such as rotation, flipping, and transformation techniques to increase dataset diversity. By generating variations of existing images, it improves the model's robustness and generalization, leading to better performance on unseen data.

e) Model Generation

This module handles model building for both classification and detection:

- Classification Models: DarkNet19, InceptionV3, ResNet101, DenseNet169, MobileNetV2, VGG16, GoogleNet, AlexNet, ShuffleNet, SqueezeNet, DNN (FindWell), and Xception. Feature selection is done using ReliefF, and KNN with KFold validation is used for performance evaluation.
- Detection Models: YOLO v5x6, YOLO v5s6, YOLO v8n, YOLO v9n. These models detect and localize kidney stones in medical images.

f) User Signup & Login

This module ensures user authentication through registration and login, allowing secure access to the system for medical professionals and researchers.

g) User Input

This module enables users to upload medical images for kidney stone detection and classification, providing the necessary data for analysis.

h) Prediction

The final module processes the input images through trained models and displays the predicted results, highlighting detected kidney stones with bounding boxes and classification labels.

D) Algorithms

a) DarkNet19

When it comes to object detection, the CNN DarkNet19 works well and efficiently. In order to classify kidney stones in CT scans, this research makes use of its deep architecture and skip connections to extract hierarchical features. DarkNet19 is well-suited for real-time applications due to its lightweight design, which speeds up inference. By using it, the accuracy of categorisation is enhanced by detecting subtle patterns of kidney stones.

b) InceptionV3

With different filter widths at each layer, InceptionV3's deep learning architecture captures a variety of properties. This study found that the use of its multi-scale convolutional layers improved the ability to classify kidney stones from CT scan images. More accurate feature extraction is achieved by maximising depth and minimising computational expenditures, thanks to its design. Stone size and kind can be more accurately identified because to the architecture's adaptation to image resolutions.

c) ResNet101

To train deep residual networks without worrying about disappearing gradients, ResNet101 makes use of skip connections. The ability to understand complex CT features is put to use in this work to categorise kidney stones. The architecture's leftover blocks speed up training, enhance model performance, and improve gradient flow. ResNet101 uses image data to increase kidney stone categorisation accuracy.

d) DenseNet169

By linking all of its layers, the convolutional neural network DenseNet169 maximises the propagation and reuse of features. This study classifies kidney stones on computed tomography (CT) images by learning rich feature representations using its fast architecture. The vanishing gradient problem is mitigated by DenseNet169's dense connections, which improves training efficiency and accuracy. The ability to extract complex information enhances the model's discrimination capabilities, leading to more accurate kidney stone diagnoses.

e) MobileNetV2

Lightweight and efficient, MobileNetV2 is a deep learning model designed for use in mobile and embedded vision applications. This work uses depthwise separable convolutions to classify kidney stones in CT images in a way that reduces computation without sacrificing accuracy. The architecture of MobileNetV2 enables real-time processing, which makes it perfect for fast-diagnosis clinical situations. The ability to adapt to different input sizes enhances kidney stone detection in various imaging contexts.

f) VGG16

When it comes to image classification, the VGG16 convolutional neural network is both easy to use and effective. This study uses its deep architecture to detect subtle features in CT scan images of kidney stones and then classifies them. Because of its small 3x3 filters, VGG16 is able to learn complex patterns with fewer parameters, which increases its robustness. The accuracy of kidney stone diagnoses is enhanced by the use of hierarchical feature extraction, which aids in identifying stone kinds.

g) GoogleNet

GoogleNet, also known as Inception v1, is an architecture for deep learning that incorporates Inception modules for multi-level feature extraction. The ability to gather several features at varying sizes is utilised in this work to categorise kidney stones in CT scans. GoogleNet is perfect for real-time applications because to its efficient and precise processing. Its layout enhances the diagnostic capabilities of detecting systems by better classifying kidney stones.

h) AlexNet

AlexNet's convolutional neural network shook up picture categorisation. The kidney stone classification from CT scans is accomplished by the utilisation of its deep architecture and ReLU activations in this study. To improve generalisability and decrease overfitting, AlexNet employs dropout and data augmentation. The use of AlexNet enhances the categorisation and diagnosis of kidney stones by learning hierarchical features from image data.

i) ShuffleNet

A lightweight deep learning architecture called ShuffleNet is used by mobile apps to improve processing. This method uses channel shuffle operations to accurately and efficiently classify kidney stones in CT scan photos while reducing resource usage. Clinical real-time detection is a good fit for ShuffleNet due to its short inference times. Its effectiveness and efficiency enhance kidney stone diagnostics while minimising processing power requirements.

j) SqueezeNet

Convolutional neural network SqueezeNet is small and efficient, making it ideal for scenarios with limited resources. Using its fire components, this technology can accurately and efficiently classify kidney stones from CT scans with few parameters. SqueezeNet is well-suited for real-time clinical applications due to its compact architecture, which enables fast inference. Through data learning, SqueezeNet enhances kidney stone categorisation, leading to more accurate diagnoses and better decisions.

k) DNN (FindWell)

A framework for deep learning Deep Neural Networks (DNNs) like FindWell use feature extraction and classification to evaluate photos. In this work, kidney stones are classified using ReliefF and KNN with KFold validation. By focussing on the most crucial characteristics for stone classification, this approach improves the model's accuracy. DNN (FindWell) strengthens CT image analysis, which aids in clinical diagnosis by better differentiating between different types and sizes of kidney stones.

l) Xception

A convolutional neural network that is depthwise separable, Xception, enhances feature extraction. In order to properly categorise kidney stones on CT scans, this study makes use of its deep architecture. Xception's method improves model efficiency while capturing intricate patterns in visual data. Highlighting the most important details aids in accurate kidney stone identification, which in turn improves the detection system and allows for prompt medical treatment.

m) YOLOv5x6

For improved accuracy, the YOLOv5x6 real-time object detection system incorporates deeper layers into the original YOLO design. In this experiment, kidney stones are detected in CT scans using its speed and precision. Thanks to its lightning-fast processing, YOLOv5x6 is perfect for time-sensitive clinical detection. To aid in diagnosis and treatment, the design can detect minute details in images, allowing for accurate localisation and categorisation of kidney stones.

n) YOLOv5s6

Speed and efficiency are prioritised in the design of the lightweight YOLOv5s6 architecture. Finding a happy medium between processing power and performance, this research employs it to detect kidney stones in CT scans in real time. In healthcare settings where rapid diagnostic results are required, YOLOv5s6's quick inference makes it a good fit. Because of how well it detects and localises kidney stones, patient care and medical therapies are both improved.

o) YOLOv8n

With YOLOv8n, the object detection process is faster and more precise than before. The novel approach used in this study enhances the ability to detect kidney stones in CT scans. The accuracy and speed of YOLOv8n in real-time processing make it ideal for use in clinical applications. The ability to classify and locate kidney stones expedites diagnosis and treatment, leading to better patient results.

p) YOLOv9n

The latest version, YOLOv9n, enhances the speed of detection and inference. This research makes advantage of its advanced features to detect kidney stones in computed tomography scans. Medical imaging analysts can find and categorise stones with the aid of YOLOv9n's design. YOLOv9n provides reliable detection, which improves kidney stone diagnosis and management.

II. EXPERIMENTAL RESULTS

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Find out how reliable a test is by comparing real positives and negatives. Following mathematical:

Accuracy = TP + TN / (TP + TN + FP + FN)

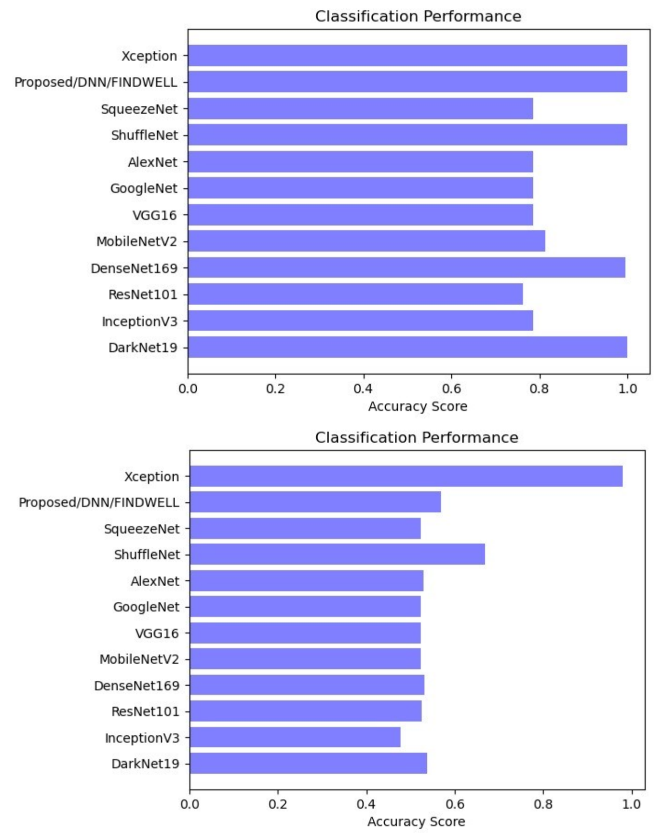
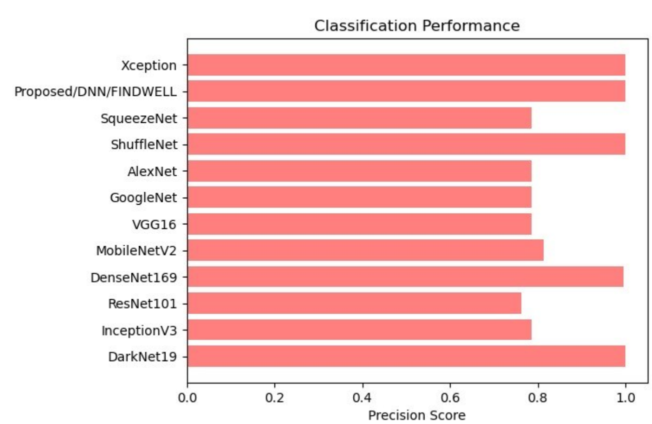


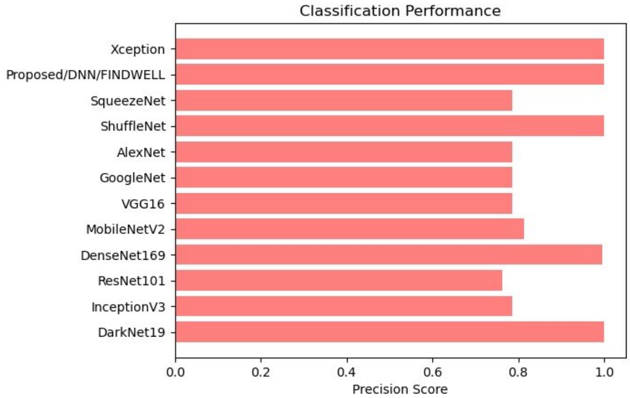
Fig.2. Accuracy score

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = TP/ (TP + FP)

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





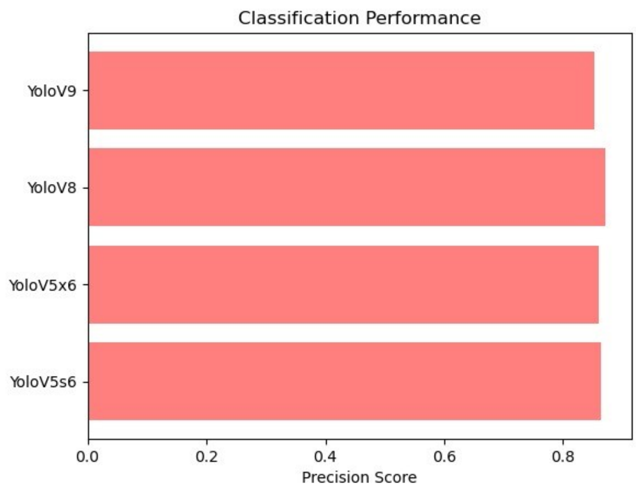
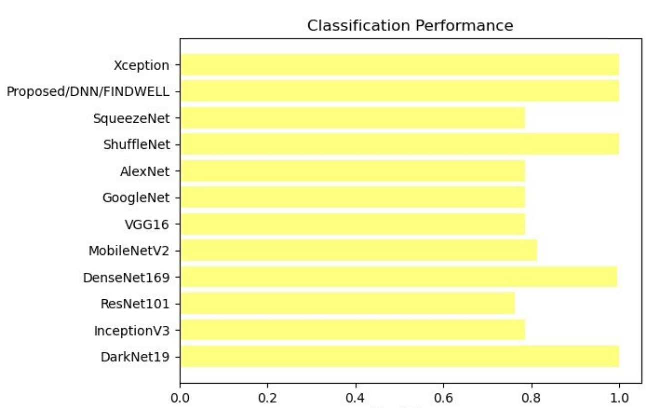
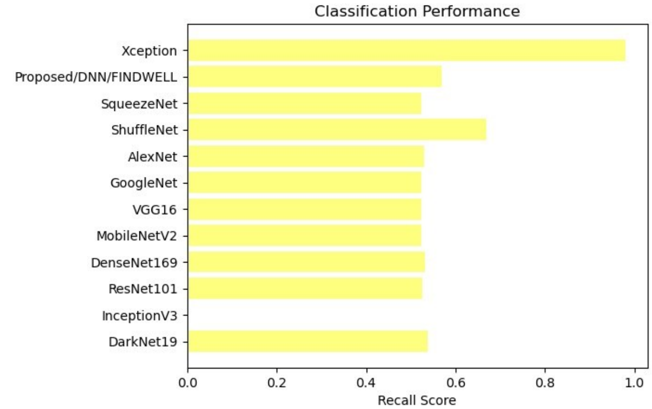


Fig.3. Accuracy score

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by percent of correctly anticipated positive observations relative to total positives.

$$Recall = \frac{TP}{TP + FN}$$





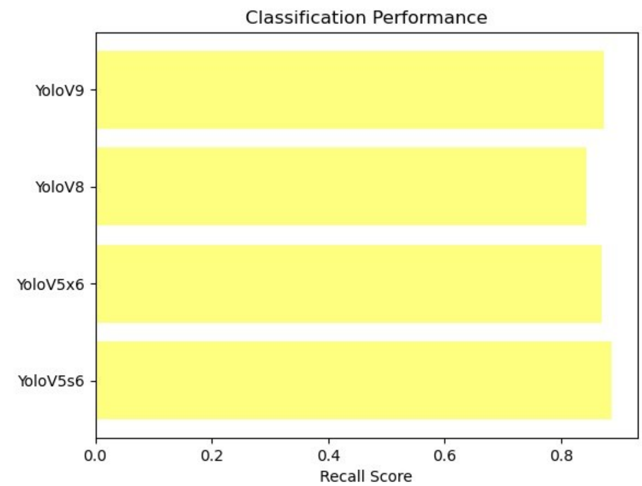


Fig.4. Recall score

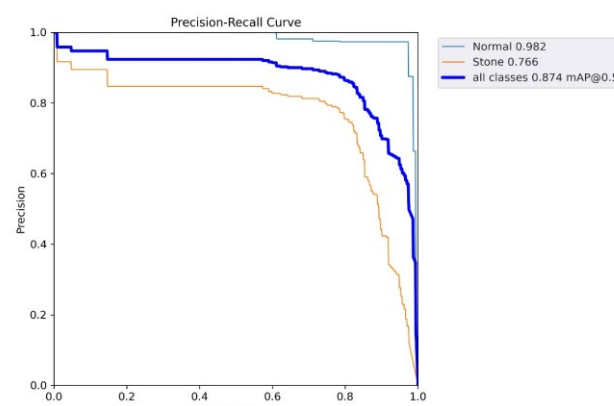


Fig.5. Precision – Recall curve

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

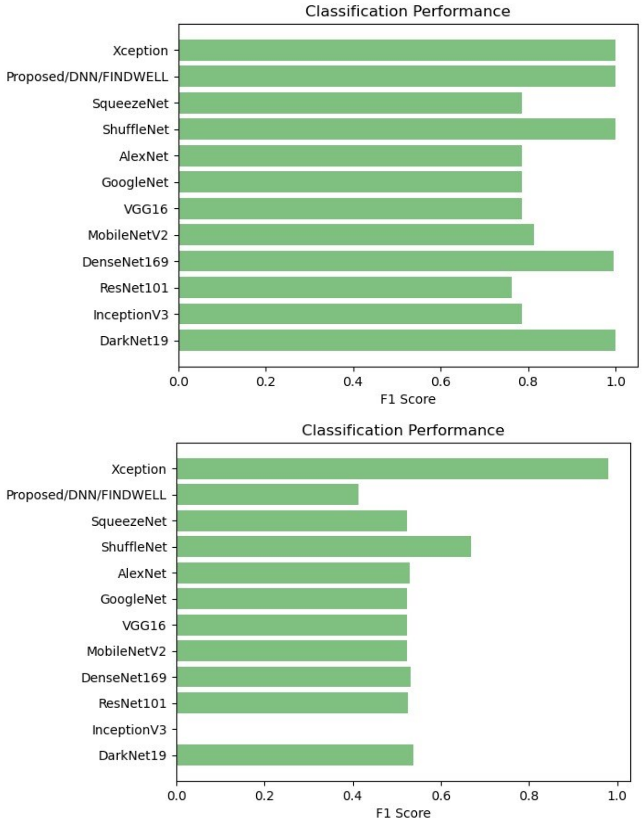


Fig.6. F1 score

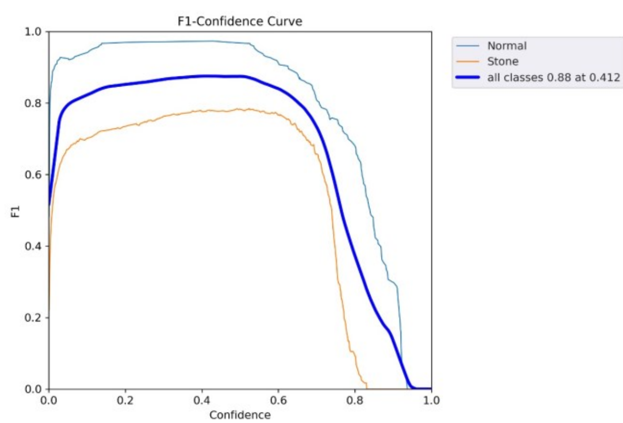


Fig.7. F1-Confidence Curve

MAP: Information retrieval system performance is measured by MAP, which stands for Mean Average Precision. It finds the mean precision for all classes or queries. While accuracy measures the validity of results, precision determines the mean accuracy for all queries. MAP evaluates the system's performance by averaging the AP scores across all queries or classes.

$$\mathrm{MAP} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{AP}_i$$

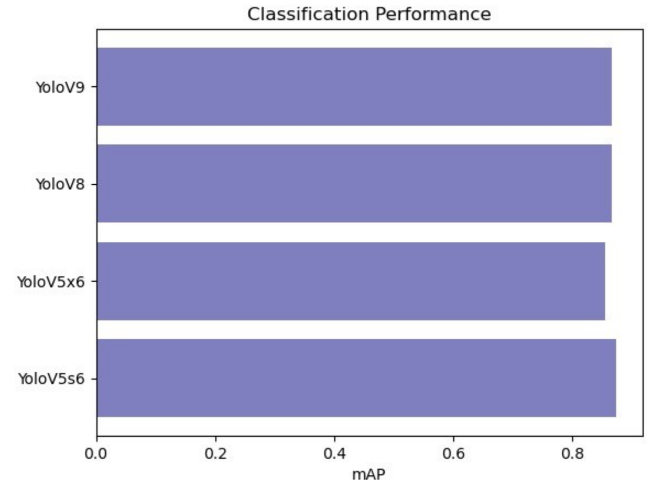


Fig.8. MAP Score

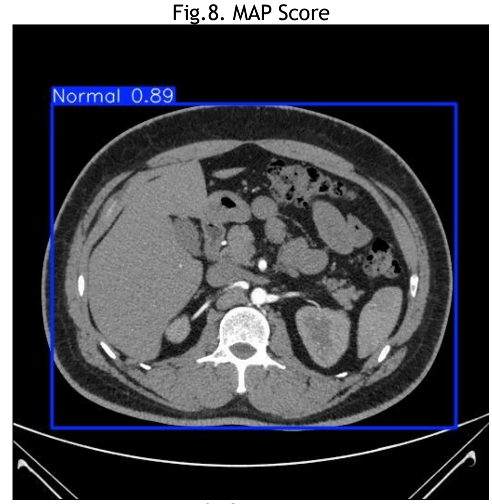


Fig 9. Scan image

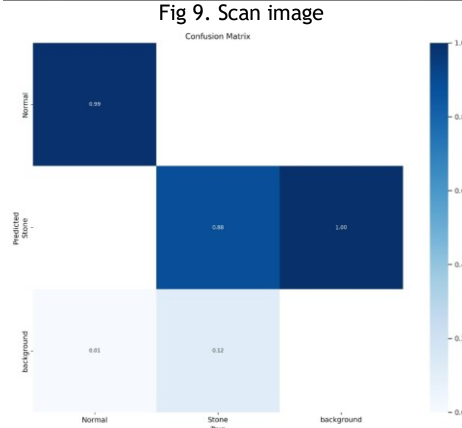


Fig 10. Confusion matrix

CONCLUSION

The proposed system effectively enhances kidney stone detection and classification using advanced deep learning techniques. By extending traditional image processing with CNN, HOG-based feature extraction, and YOLO object detection, the model achieves high accuracy in medical image analysis. The integration of ReliefF for feature selection and KNN with KFold validation further optimizes classification performance. These improvements ensure better generalization, robustness, and precise detection, making the system highly efficient for real-world applications.

FUTURE SCOPE

The proposed system can be extended for real-time kidney stone detection in ultrasound and CT scans, enabling faster diagnosis. Cloud-based integration will allow remote diagnostics and telemedicine applications, making the system accessible to a wider audience. Advanced data augmentation techniques, such as GANs

(Generative Adversarial Networks), can further enhance dataset diversity and improve model generalization. Additionally, integrating AI-driven decision support systems can assist doctors in accurate diagnosis and treatment planning. Future advancements can also explore cross-modal learning, enabling the model to process X-ray, MRI, and CT scan images for a more comprehensive disease detection approach.

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