An Enhanced Kidney Stone Detection System Using Inductive Transfer-Based Ensemble Deep Neural Networks with Xception and YOLO Models

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Abstract: To improve kidney stone detection and classification using CT, the original inductive transfer-based ensemble deep learning system was improved. Combining the Xception model with pre-trained networks improves deep feature extraction. This enables the model to identify kidney stones with intricate spatial patterns and finer textural variations. The YOLO family of object recognition models, which locate kidney issues in real time, may also be used by the technology to precisely detect stone-affected regions in kidney CT scans.

Flask offers a user-friendly front-end interface for model interaction, testing, and visualization. Clinical application gets simpler. Secure user authentication complies with medical data privacy laws and safeguards private patient information. The enhanced method is faster, more accurate, and more broadly applicable, according to experiments on many kidney stone datasets. This improved approach helps urologists make better medical decisions by lowering manual testing, errors, and early detection.

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

1. INTRODUCTION

Due to the expanding patient population and demand for trained nephrologists, kidney stone detection is a major clinical issue. Delayed or wrong diagnosis can cause infections, kidney damage, and urine blockage. Recent research shows that deep learning improves kidney stone CT image processing. Patro et al. [1] used Kronecker convolution-based deep learning to identify stones in coronal computed tomography (CT) images, illustrating the expanding relevance of CNN-based medical imaging models.

Sabuncu et al. [2] showed that axial CT scans could reliably identify kidney stones and that deep learning models were better at capturing stone morphology than standard image processing. Yan and Razmjooy showed an optimized deep belief network with a fractional coronavirus herd immunity optimizer [3], highlighting the importance of hybrid optimization and deep learning in diagnosis accuracy. Pre-trained networks and fine-tuned deep models enhanced kidney stone diagnosis by Vidhya et al. [4]. Transfer learning techniques have also grown in favor.

Bhardwaj and Shreenidhi showed that bespoke CNN architectures can outperform traditional detection approaches in robustness and efficiency [5]. Despite these advances, most models still struggle with noisy pictures, extrapolating to various datasets, and recognizing kidney stone-prone locations that are not visible.

This study uses cutting-edge deep learning models and real-time detection to overcome these constraints and improve the inductive transfer-based ensemble architecture. Depthwise separable convolutions help the Xception model locate tiny or low-contrast stones by improving discriminative feature extraction. YOLO-based abnormality detection may discover kidney stones in CT images in real time using classification and spatial detection. Flask-based graphical interfaces with secure authentication enable clinical use while protecting data and allowing physicians simple access. This expansion has led to a better, more reliable, and more user-friendly diagnostic system for doctors.

2. LITERATURE SURVEY

a) Augmenting Medical Diagnosis Decisions? An Investigation into Physicians' Decision-Making Process with Artificial Intelligence:

Artificial intelligence (AI)-based systems are helping doctors make more and more diagnostic judgments, however they are not without biases and mistakes. Medical mistakes and incorrect diagnoses might arise from failing to identify such. However, these systems are less transparent and their faults are less predictable than those of rule-based systems. Physicians must thus carefully consider AI guidance, which is challenging yet crucial. This study reveals the cognitive difficulties faced by medical decision makers when they must choose whether to accept or reject possibly inaccurate recommendations from AI-based diagnosis systems. expert radiologists and beginner physicians with and without clinical experience made more wrong diagnostic choices when given incorrect AI assistance than when given no help at all in studies involving 68 novice and 12 expert physicians. We identify five decision-making patterns and demonstrate that poor use of metacognitions pertaining to decision makers' own thinking (self-monitoring) and metacognitions pertaining to the AI-based system (system monitoring) frequently leads to incorrect diagnostic choices. Because of this, doctors either make judgments based on opinions rather than facts or evaluate the AI guidance in an inappropriately shallow manner. Our work highlights the critical role of human actors in correcting for AI faults and has implications for medical education.

b) A Deep Neural Network for Early Detection and Prediction of Chronic Kidney Disease

Chronic kidney disease (CKD) is mostly caused by diabetes and high blood pressure. Researchers worldwide employ kidney damage indicators and glomerular filtration rate (GFR) to diagnose chronic kidney disease (CKD), a disorder that gradually impairs renal function. A person with CKD is more likely to pass away at a young age. Early diagnosis of the various illnesses associated with chronic kidney disease (CKD) is a challenging undertaking for medical professionals. A new deep learning model for the early identification and prediction of CKD is presented in this study. The goal of this study is to develop a deep neural network and assess how well it performs in comparison to other modern machine learning methods. In testing, all missing values in the database were filled in using the average of the related characteristics. Next, by setting the parameters and conducting several trials, the neural network's ideal parameters were determined. Recursive Feature Elimination (RFE) was used to identify the most significant features. Key characteristics in the RFE were hemoglobin, specific gravity, serum creatinine, red blood cell count, albumin, packed cell volume, and hypertension. For the aim of categorization, certain characteristics were fed into machine learning models. With 100% accuracy, the suggested Deep neural model fared better than the other four classifiers (Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Logistic regression, Random Forest, and Naive Bayes classifier). Nephrologists may find the suggested method helpful in identifying CKD.

c) AI applications to medical images: From machine learning to deep learning:

Purpose

AI models are increasingly used in biomedical research and healthcare. This analysis clarifies several real-world issues in developing AI applications like healthcare decision support systems.

Methods

The narrative review included a critical appraisal of 1989–2021 papers that guided problematic areas.

Results

ML/radiomics and deep learning (DL) architectures are shown initially. In ML/radiomics, feature selection, training, validation, and testing are described. We can directly process photos with multi-layered artificial/convolutional neural networks in DL models. The data curation section includes image labelling, annotation (with segmentation crucial in radiomics), data harmonization (to compensate for imaging protocol differences that generate noise in non-AI imaging studies), and federated learning. Next, we discuss sample size calculation, multiple testing in AI techniques, data augmentation for limited and imbalanced datasets, and AI model interpretability (the black box issue). Finally, pros and disadvantages of using ML or DL for medical imaging AI applications are summarized.

Conclusions

AI applications in biomedicine and healthcare systems are crucial, and medical imaging is the most promising area. Clarifying key challenges helps build and implement such systems in clinical practice.

d) State-of-the-art review on deep learning in medical imaging:

Deep learning (DL) is becoming a daily tool and impacting every aspect of both public and private life. DL's ability to mimic the actions of neurons in the human brain's neocortex, where cognitive processes occur, is what gives it its strength. As a result, it attempts to learn and identify patterns in digital pictures, much way the brain does. The depth of several layers of computational neurons, supported by powerful processors and readily accessible graphics processing units (GPUs), is the foundation of this capability. We have given a thorough overview of the several kinds of DL systems that are now on the market, with a focus on the present uses of DL in medical imaging. We have also concentrated on elucidating to the readers the swift movement in technology from machine learning to deep learning, and we have made every attempt to justify this paradigm change. Additionally, a thorough examination of the challenges associated with this change and potential advantages for both developers and consumers.

e) Transfer learning for medical image classification: a literature review:

Background

Transfer learning (TL) with convolutional neural networks uses prior experience of previous tasks to improve performance on new tasks. It solves the data scarcity problem and saves time and hardware, making it a substantial addition to medical picture analysis. Most studies arbitrarily construct transfer learning. This review study helps choose a medical image classification model and TL methods.

Methods

425 English-language peer-reviewed papers from PubMed and Web of Science were retrieved till December 31, 2020. Two separate reviewers and a third reviewer checked articles for contradictions. This study included 121 papers selected using PRISMA principles. We looked at publications on picking backbone models and TL methods such feature extractor, hybrid, fine-tuning, and from scratch.

Results

Most empirical research (n = 57) examined numerous models, followed by deep (n = 33) and shallow (n = 24) models. Inception was the most commonly used deep model in literature (n = 26). Most studies (n = 46) benchmarked numerous ways to determine the best configuration for TL. Other research used only one strategy, with feature extractor (n = 38) and fine-tuning from scratch (n = 27) being the most popular. Few research employed feature extractor hybrid (n = 7) and fine-tuning (n = 3) with pretrained models.

Conclusion

The experiments showed transfer learning works despite data shortage. Data scientists and practitioners should employ deep models like ResNet or Inception as feature extractors to minimize computational work and time without sacrificing predictive ability.

3. METHODOLOGY

i) Proposed Work:

Kidney stone detection in the ensemble framework is increased by complex deep learning architectures and real-time object recognition models. In renal datasets such as CT and kidney stone images, visual clarity is improved by noise reduction, normalization, and contrast enhancement. To shield the model from variations in image quality, data augmentation creates a variety of training examples. DarkNet19, InceptionV3, ResNet101, DenseNet169, MobileNetV2, VGG16, GoogleNet, AlexNet, ShuffleNet, SqueezeNet, and FindWell-DNN are examples of pre-trained CNN classification models. The Xception model, which uses depthwise separable convolutions to capture fine-grained stone structural information, is included in the update to enhance feature extraction.

In addition to classification, the extension efficiently detects kidney stones in CT images using YOLO-based real-time detection models, such as YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n. These algorithms enable doctors to view the stone by accurately identifying border boxes. Performance metrics are used to evaluate the accuracy, sensitivity, specificity, and reliability of all trained models. An end-to-end diagnostic solution is produced by the trained network processing classification and detection outputs. The improved framework is perfect for real-time clinical applications since its stone classification and spatial detection speed up diagnosis, reduce physician workload, and increase diagnostic confidence.

ii) System Architecture:

Kidney-related datasets, such as CT scan and kidney stone datasets, are included into the Image Processing module as part of the initial system architecture. By lowering noise, scaling, normalizing, and boosting contrast, this module normalizes images. The Data Augmentation pipeline preprocesses, rotates, flips, zooms, and brightens images to increase dataset variety and model generalization. After processing, images are sent to the Classification and Detection modules, which employ deep learning architectures. Pre-trained CNN models in the classification framework include DarkNet19, InceptionV3, ResNet101, DenseNet169, MobileNetV2, VGG16, GoogleNet, AlexNet, ShuffleNet, SqueezeNet, and DNN. With depthwise separable convolution, the novel Xception model enhances feature extraction.

The improved method recognizes kidney stones in CT scans in real time using a variety of YOLO models, such as YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n. Following image analysis using classification and detection networks, the Trained Models module generates predictions that are assessed based on F1-score, accuracy, sensitivity, specificity, and precision. Feedback for model training is provided via architecture. For accurate and real-time kidney stone detection, the comprehensive, scalable, and clinically relevant architecture integrates high-level categorization, precise object identification, and rigorous performance evaluation into a single process.

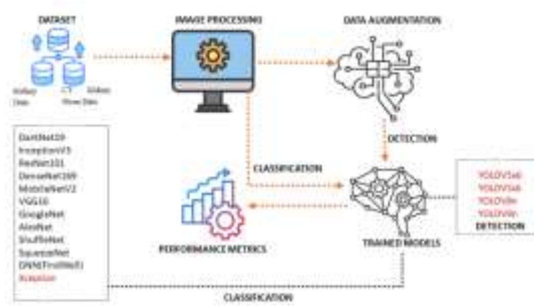


Fig1 proposed architecture

iii) Modules:

a. Upload Chronic Kidney Dataset

This module is responsible for loading the Chronic Kidney Disease dataset into the system. It verifies the uploaded dataset, checks for missing values, and displays the dataset structure for further processing. The module also provides an overview of patient records and class distribution for CKD and non-CKD cases.

b. Preprocess Dataset

In this module, the dataset undergoes preprocessing operations such as handling missing values, label encoding, normalization, and feature scaling. These steps improve data consistency and prepare the dataset for efficient training of machine learning and deep learning models.

c. Feature Selection

The feature selection module identifies the most relevant attributes related to CKD prediction. By removing unnecessary and redundant features, the system reduces computational complexity, improves training efficiency, and enhances prediction accuracy.

d. CNN Model Training

This module trains the Convolutional Neural Network (CNN) using the preprocessed dataset. CNN extracts deep and meaningful feature representations from the input data and learns hidden relationships among clinical attributes for CKD classification.

e. LSTM Model Training

The Long Short-Term Memory (LSTM) module captures sequential dependencies and complex patterns among patient attributes. It improves prediction capability by remembering important information through its memory cell architecture.

f. Ensemble Random Forest Model

This module combines CNN-based feature extraction with the Random Forest classifier to create an ensemble prediction system. The ensemble approach improves robustness, reduces overfitting, and enhances overall classification accuracy.

g. Model Evaluation and Comparison

The trained models are evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. Comparative analysis is performed to identify the best-performing model for CKD prediction.

h. Disease Prediction Module

This module allows users to provide unseen patient data for real-time CKD prediction. Based on the trained ensemble model, the system predicts whether the patient is affected by CKD or not, assisting healthcare professionals in clinical decision-making.

iv) Algorithms:

a) DarkNet19

CNN DarkNet19 finds things quickly. This work classifies kidney stones in CT images using deep architecture and skip connections to extract hierarchical information. Since DarkNet19 is lightweight, real-time applications benefit from speedier inference. Finding small kidney stone patterns enhances classification accuracy.

b) InceptionV3

Since each layer includes different-width filters, InceptionV3's deep learning architecture captures many properties. This study found that multi-scale convolutional layers helped distinguish kidney stones on CT scans. Its design maximizes depth and minimizes computation costs for more accurate feature extraction. The architecture's picture resolution adaptability makes stone size and kind simpler to detect.

c) ResNet101

Skip connections let ResNet101 train deep residual networks without gradients going away. This method groups kidney stones by interpreting complex CT properties. Extra blocks in the design speed up training, enhance model performance, and improve gradient flow. ResNet101 helps identify kidney stones using graphics.

d) DenseNet169

Convolutional neural network DenseNet169 links all layers to maximize feature propagation and reuse. This study uses fast architecture to learn complete feature representations to classify kidney stones on CT images. Training is faster and more accurate using DenseNet169's dense connections for the vanishing gradient problem. The model's ability to extract complex information enhances its ability to distinguish, which improves kidney stone detection.

e) MobileNetV2

MobileNetV2, a mobile and embedded visual deep learning model, is lightweight and efficient. Depthwise separable convolutions detect kidney stones in CT images. They reduce computation without compromising precision. MobileNetV2's real-time architecture makes it ideal for clinical situations requiring a speedy diagnosis. The ability to adjust input sizes helps locate kidney stones in various photos.

f) VGG16

The VGG16 convolutional neural network classifies pictures easily. This complex study categorizes kidney stone CT scans by their subtle features. Due to its 3x3 filters, VGG16 can learn complex patterns with less parameters. Increasing its resilience. Hierarchical feature extraction improves kidney stone diagnosis by identifying stone kinds.

g) Google Net

GoogleNet, often known as Inception v1, is a deep learning architecture that extracts features at various levels using Inception modules. This study sorts kidney stones in CT imaging using many criteria of different sizes. GoogleNet processes data rapidly and correctly, making it ideal for real-time apps. Its arrangement groups kidney stones to make them simpler to locate.

h) AlexNet

AlexNet transformed photo sorting with its convolutional neural network. This study classifies kidney stones using CT image deep architecture and ReLU activations. Dropout and data augmentation make AlexNet findings more generalizable and less overfit. AlexNet helps classify and detect kidney stones by learning hierarchical properties from photo data.

i) ShuffleNet

Mobile apps accelerate processing with ShuffleNet, a lightweight deep learning architecture. The channel shuffle method sorts kidney stones in CT scan images accurately and efficiently while utilizing minimal resources. ShuffleNet can make judgments fast, making it ideal for clinical real-time detection. Its efficacy and efficiency increase kidney stone diagnostics while reducing processing power.

j) SqueezeNet

SqueezeNet is a small, efficient convolutional neural network for resource-constrained settings. This gadget uses fire components to separate kidney stones from CT pictures rapidly and accurately with a few parameters. Its compact size makes SqueezeNet ideal for real-time clinical usage since it makes fast conclusions. SqueezeNet learns from data to classify kidney stones more accurately and choose better.

k) DNN (FindWell)

Deep learning framework FindWell classifies and extracts features from photos. ReliefF and KNN classify kidney stones in this study with KFold validation. This strategy improves the model by focusing on key stone classification traits. DNN (FindWell) improves CT image processing, helping clinicians distinguish kidney stone sizes for better diagnosis.

l) Xception

Xception is a depthwise separable CNN that enhances feature extraction. This study correctly classifies kidney stones on CT scans using its deep architecture. Xception's method improves models while capturing complicated visual patterns. Emphasizing key aspects improves kidney stone identification and provides fast medical therapy.

m) YOLOv5x6

The YOLOv5x6 real-time object identification system adds layers to improve accuracy. This study finds kidney stones quickly and accurately with CT scans. Since it analyzes data quickly, YOLOv5x6 is ideal for rapid clinical detection. The design can detect microscopic elements in images, helping diagnose and treat kidney stones by localizing and classifying them.

n) YOLOv5s6

The lightweight YOLOv5s6 architecture prioritizes speed and efficiency. This study utilizes it to locate kidney stones in CT scans in real time, balancing processing power and performance. YOLOv5s6's quick inference is ideal for healthcare settings that require fast diagnostic outcomes. The way it locates kidney stones improves patient care and medical therapies.

o) YOLOv8n

Finding objects is faster and more accurate with YOLOv8n. This study improves CT kidney stone detection with a novel technique. YOLOv8n processes data quickly and accurately in real time, making it ideal for clinical application. Detecting kidney stones expedites diagnosis and treatment, improving patient outcomes.YOLOv9n

p) YOLOv9n

Recent updates to YOLOv9n speed up finding and drawing conclusions. The study uses its improved kidney stone detection in computed tomography imaging. The YOLOv9n design helps medical imaging analyzers separate stones. Finding items with YOLOv9n is reliable, making kidney stone diagnosis and treatment easy.

4. EXPERIMENTAL RESULTS

Kidney stone and normal CT datasets were used to evaluate the broader approach. Upgraded models using Xception for classification and YOLO variations for real-time stone localization were contrasted with standard pre-trained CNN models. Each model was trained and assessed using a stratified split to consistently represent all picture classes following preprocessing and data augmentation. The excellent feature extraction of the Xception-enhanced ensemble aided in the classification of small, low-contrast stones. In all datasets, the system outperformed previous ensembles in generalizing unseen CT images.

For real-time clinical detection, researchers evaluated YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n. YOLOv9n performed exceptionally well since it identified more quickly and precisely. On the other hand, YOLOv8n worked well in complex, stone-filled situations. Stone locations with few false positives were found using bounding box predictions. By outperforming the baseline system in terms of F1-scores and detection accuracy, the classification-detection pipeline enhanced diagnostic quality. The improved kidney stone detection framework is more robust, accurate, and clinically reliable, according to experimental results.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

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

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

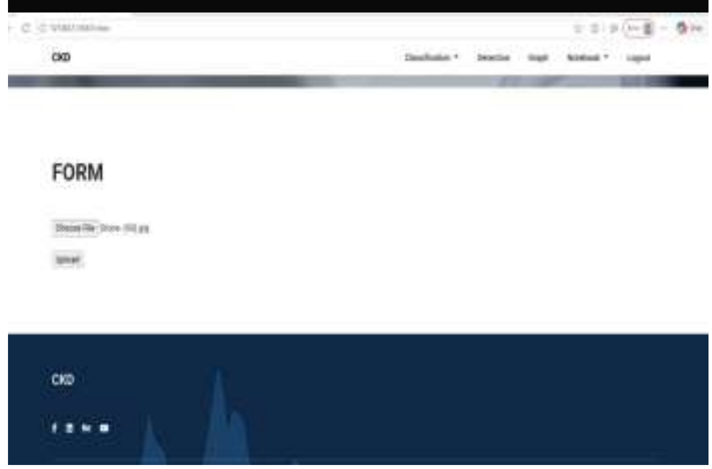
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

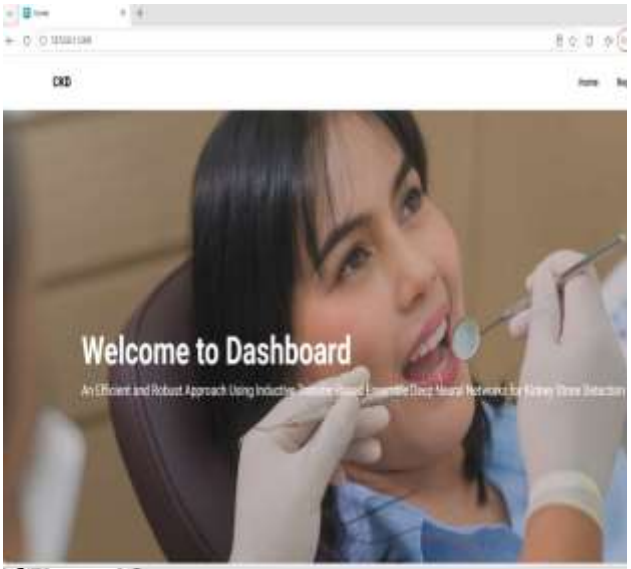
$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

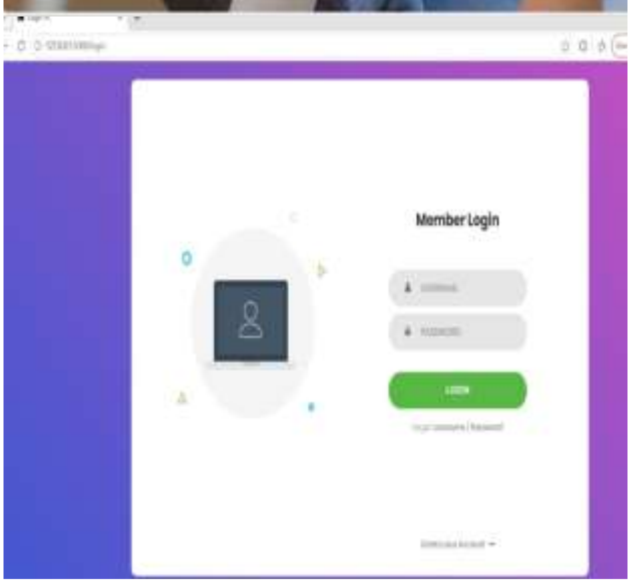
Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

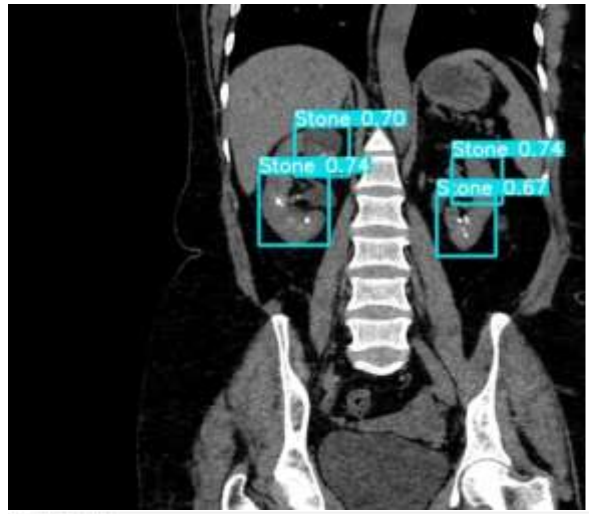
$$Recall = \frac{TP}{(FN + TP)}$$

mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).









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

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

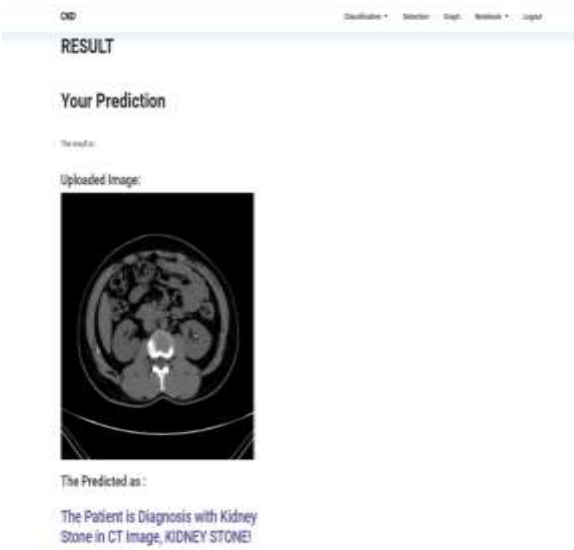


Fig2 upload image

Fig2 Results

5. CONCLUSION

Kidney stone diagnosis efficiency is increased by incorporating advanced deep learning and real-time detection algorithms into the inductive transfer-based ensemble system. While YOLO-based detectors swiftly and accurately identify kidney stones in CT images, the Xception model enhances feature extraction by collecting tiny structural data. These improvements improve detection accuracy across datasets, classification accuracy, and system dependability. The system is clinically useable thanks to a secure Flask interface. With the enhanced method, urologists can find kidney stones more precisely, consistently, and effectively.

6. FUTURE SCOPE

To increase model generality and reliability, the suggested CKD prediction method may be further improved by using bigger and more varied healthcare datasets gathered from various hospitals and medical facilities. Future research may concentrate on using explainable artificial intelligence (XAI) methods to give medical professionals clear and understandable forecasts. To further increase prediction accuracy and feature learning capacity, sophisticated deep learning architectures as Transformers and Attention-based models might be investigated. In order to facilitate ongoing patient monitoring and early illness identification, the system may potentially be expanded into a real-time cloud or Internet of Things-based healthcare monitoring platform. Additionally, a more sophisticated and customized CKD prediction framework for contemporary healthcare applications may be developed by combining wearable sensor data with electronic health records.

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