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Multiclass Kidney Abnormalities Detecting Novel System Through Computed Tomography

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Abstract: Accurate and early detection of kidney abnormalities is essential for effective clinical diagnosis and prevention of severe renal complications. Computed Tomography (CT) imaging is widely used for kidney examination due to its high resolution; however, traditional diagnosis relies heavily on manual interpretation by radiologists, which is time-consuming, subjective, and prone to human error. Although deep learning techniques have been applied to kidney disease detection, many existing systems are limited to binary classification, suffer from poor performance on low-contrast or noisy CT images, and lack robustness for multi-class abnormality detection. To address these challenges, this paper presents a Multi-Class Kidney Abnormalities Detecting Novel System through Computed Tomography using deep learning techniques. The proposed framework integrates CT image preprocessing, kidney segmentation, hybrid convolutional neural network (CNN)–based feature extraction, feature fusion, and multi-class classification. Advanced preprocessing techniques such as normalization, noise removal, contrast enhancement, and data augmentation are applied to improve image quality. A U-Net–based segmentation module isolates kidney regions for precise analysis, while hybrid CNN architectures extract both global and local features for effective representation. The system classifies CT images into multiple categories including normal kidney, kidney stone, renal cyst, and tumour. Experimental evaluation demonstrates high classification accuracy, reliable class-wise performance, and strong robustness across varying CT image conditions. Compared to traditional handcrafted feature-based and binary classification approaches, the proposed system achieves improved diagnostic accuracy with reduced manual intervention. The developed framework provides an efficient, automated, and reliable solution for multi-class kidney abnormality detection, supporting radiologists in early diagnosis and clinical decision-making.

Keywords: Deep Learning, Kidney Abnormality Detection, Computed Tomography, Convolutional Neural Network, Multi-Class Classification.

1 INTRODUCTION

Kidney diseases represent a significant global health challenge and are among the leading causes of morbidity and mortality worldwide. Abnormalities such as kidney stones, renal cysts, tumors, and structural deformities can severely affect renal function if not detected at an early stage. Computed Tomography (CT) imaging is extensively used in clinical practice for kidney examination due to its high spatial resolution and ability to capture detailed anatomical structures. However, delayed or inaccurate diagnosis of kidney abnormalities can lead to severe complications, including chronic kidney disease and renal failure, increasing the overall healthcare burden [1]. Early and accurate detection of kidney abnormalities plays a crucial role in improving patient outcomes and enabling timely medical intervention. Traditional diagnostic approaches rely heavily on manual interpretation of CT images by radiologists, which is time-consuming, subjective, and dependent on clinical expertise. Moreover, hospitals and diagnostic centers generate a large volume of CT scan data daily, making manual analysis inefficient and prone to human error. Subtle abnormalities may be overlooked, especially when image quality is affected by noise or low contrast, thereby reducing diagnostic reliability [2].

With advancements in Artificial Intelligence (AI) and deep learning, automated medical image analysis systems have gained significant attention for disease detection and classification. Convolutional Neural Networks (CNNs) have shown strong capability in learning complex visual patterns from medical images and have been applied to kidney abnormality detection. However, many existing approaches are limited to binary classification and rely on single-model architectures, which restrict their ability to accurately identify multiple kidney conditions. Additionally, performance degradation is commonly observed when CT images suffer from low contrast, artifacts, or variability in imaging conditions [3].

To address these limitations, this paper proposes a Multi-Class Kidney Abnormalities Detecting Novel System through Computed Tomography using hybrid deep learning techniques. The proposed system integrates advanced image preprocessing, kidney segmentation, hybrid CNN-based feature extraction, feature fusion, and multi-class classification to accurately identify normal kidneys and multiple abnormal conditions. By combining global and local feature representations and employing robust classification strategies, the system aims to improve diagnostic accuracy, reduce manual intervention, and support reliable clinical decision-making in medical imaging applications [4].

2 LITERATURE REVIEW

Several studies have investigated automated detection of kidney abnormalities using medical imaging techniques, particularly computed tomography (CT), due to its ability to provide detailed anatomical information. Wu and Yi proposed a multi-feature fusion convolutional neural network for automated kidney abnormality detection using CT images. Their approach demonstrated improved feature representation by combining multiple feature extraction strategies; however, the study primarily focused on limited abnormality categories and did not fully address multi-class classification challenges under varying image quality conditions [1][5]. Lin et al. explored deep learning techniques for differentiating normal and abnormal kidneys using medical imaging data. Their work demonstrated that convolutional neural networks could effectively learn complex visual patterns from kidney scans. However, the approach required high-quality annotated datasets and showed reduced performance when applied to images with noise and low contrast, which are common in real clinical environments [6]-[8].

Zheng et al. introduced a computer-aided diagnosis system that integrated texture-based features with deep transfer learning for kidney abnormality detection. While the hybrid approach improved diagnostic accuracy, the reliance on handcrafted texture features limited scalability and generalization across diverse CT datasets [9]. Chen et al. proposed a highly sensitive detection approach for kidney cancer using advanced imaging substrates and pattern recognition techniques. Although the study achieved promising results for cancer detection, it focused on a single abnormality type and did not extend to multi-class kidney abnormality classification [5].

Lee et al. analyzed renal abnormalities in patients with chronic kidney disease using clinical and imaging data. Their findings highlighted the complexity of kidney abnormality patterns and emphasized the need for automated systems capable of capturing subtle variations in kidney structure. However, the study did not implement a complete end-to-end automated classification framework [7]. Correia et al. presented a case-based analysis of kidney abnormalities in transplant recipients. While their work provided valuable clinical insights, diagnosis relied heavily on expert interpretation, underscoring the limitations of manual analysis and the need for intelligent automated diagnostic tools [8][10].

Yun and Perantoni investigated structural kidney abnormalities caused by developmental defects. Their work emphasized the importance of precise localization and segmentation of kidney regions to accurately identify abnormalities, suggesting the relevance of segmentation-based deep learning models for kidney analysis [11]. Ding et al. studied abnormal kidney morphology using biological imaging techniques and highlighted the variability in kidney abnormality presentation. These findings support the need for robust feature extraction methods capable of handling structural diversity in kidney CT images [12]. Qu et al. explored nephrotoxicity-related kidney abnormalities using multi-omics analysis and imaging studies. Although their research focused on biochemical mechanisms, it reinforced the importance of accurate abnormality identification for early diagnosis and clinical decision-making [13][14]. Hakeem et al. examined non-invasive risk assessment techniques for kidney-related diseases and emphasized the growing role of intelligent systems in supporting clinical diagnosis. However, their approach did not incorporate deep learning–based multi-class image classification, leaving scope for further advancement [15].

3 PROBLEM STATEMENT

Early and accurate detection of kidney abnormalities is a critical requirement in modern healthcare systems due to the rising incidence of renal diseases and their potential to progress into severe conditions such as chronic kidney disease and renal failure. Computed Tomography (CT) imaging is widely used for kidney diagnosis; however, current diagnostic practices rely heavily on manual interpretation of CT scans by radiologists. This process is time-consuming, subjective, and highly dependent on clinical expertise, which can lead to delayed diagnosis and inconsistent results, particularly in high-volume medical imaging environments.

Although several automated and deep learning–based approaches have been proposed for kidney abnormality detection, many existing systems are limited to binary classification and can identify only one or two types of abnormalities. These approaches often struggle to accurately detect multiple kidney conditions when CT images are affected by noise, low contrast, artifacts, or variations in imaging protocols. Additionally, conventional models frequently rely on single-architecture deep learning frameworks or handcrafted features, which restrict their ability to capture complex structural variations present across different kidney abnormalities.

Furthermore, many current systems lack robust segmentation and feature extraction mechanisms, resulting in poor generalization across diverse patient datasets and imaging conditions. The absence of an automated, reliable, and multi-class diagnostic framework capable of accurately classifying normal kidneys and multiple abnormal conditions highlights a significant research gap. This motivates the need for a robust deep learning–based system that integrates advanced preprocessing, kidney segmentation, hybrid feature extraction, and multi-class classification to support accurate, efficient, and clinically applicable kidney abnormality detection using CT images.

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4 PROPOSED SYSTEM

The proposed system implements a Multi-Class Kidney Abnormalities Detection Framework using Computed Tomography (CT) images, designed to provide accurate, automated, and reliable diagnosis of kidney conditions. The system analyzes CT scan images and classifies them into multiple categories such as normal kidney, kidney stone, renal cyst, tumor, and other lesions. The overall workflow of the proposed system is illustrated in the block diagram shown in Fig. 1. The architecture emphasizes the integration of medical image preprocessing, deep learning–based feature extraction, segmentation, and multi-class classification to ensure robustness, high diagnostic accuracy, and clinical applicability.

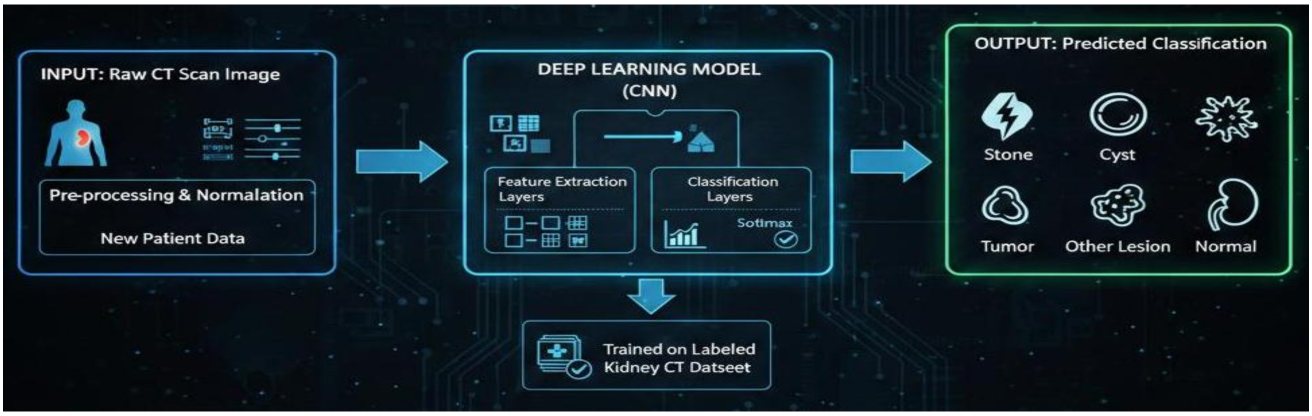

Fig. 1. Block Diagram of the Proposed Multi-Class Kidney Abnormalities Detection System

As shown in Fig. 1, the system accepts raw kidney CT scan images as the primary input. These CT images are collected from public medical imaging datasets or hospital sources and include scans of normal kidneys as well as various abnormal conditions such as stones, cysts, and tumors. The use of real CT data ensures practical relevance and supports reliable clinical diagnosis. The input CT images are first passed through the preprocessing and normalization module to enhance image quality and standardize input data. This module performs:

- Image resizing to a fixed resolution
- Intensity normalization
- Noise removal
- Contrast enhancement

These operations reduce imaging artifacts, improve visibility of kidney structures, and prepare the images for effective learning by deep learning models. The segmentation module isolates the kidney region and abnormal areas from surrounding tissues. Accurate segmentation ensures that the classification model focuses only on relevant anatomical regions. This improves feature extraction accuracy and reduces the influence of irrelevant background information. U-Net–based segmentation is used to achieve precise localization of kidneys and lesions.

The core component of the system is the Deep Learning Model based on Convolutional Neural Networks (CNNs). This model is trained using labeled kidney CT datasets and is responsible for learning complex visual patterns associated with different kidney abnormalities. Within the CNN, the feature extraction layers automatically learn both global features (overall kidney shape and structure) and local features (texture, edges, and lesion patterns). Hybrid CNN architectures are employed to capture diverse feature representations from CT images. To strengthen representation capability, features extracted from multiple CNN architectures are combined using a feature fusion mechanism. This fusion process integrates complementary information, resulting in a more robust and discriminative feature vector for accurate multi-class classification.

The fused feature vector is passed to the classification layers, which consist of fully connected layers followed by a softmax activation function. The classifier assigns probability scores to each kidney condition and predicts the final class as:

- Normal Kidney
- Kidney Stone
- Renal Cyst
- Tumor
- Other Lesions

This multi-class classification capability addresses the limitations of binary diagnostic systems. The CNN model is trained using a labeled kidney CT dataset, where each image is annotated with the corresponding abnormality class.

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During training, the model learns optimal parameters to minimize classification error and improve generalization to unseen CT images. As shown in Fig. 1, the final output of the system is the predicted kidney abnormality class along with confidence scores. These outputs assist radiologists in understanding diagnostic results and support clinical decision-making.

5 System Architecture

The system architecture of the proposed Multi-Class Kidney Abnormalities Detection System using Computed Tomography (CT) is designed as a modular deep learning framework to enable accurate, automated, and reliable diagnosis of kidney abnormalities. The complete architecture is illustrated in Fig. 2. The architecture follows a structured pipeline consisting of input acquisition, preprocessing, segmentation, hybrid deep learning–based feature extraction, feature fusion, and multi-class classification. Each module shown in the architecture performs a specific role in the overall detection and prediction process.

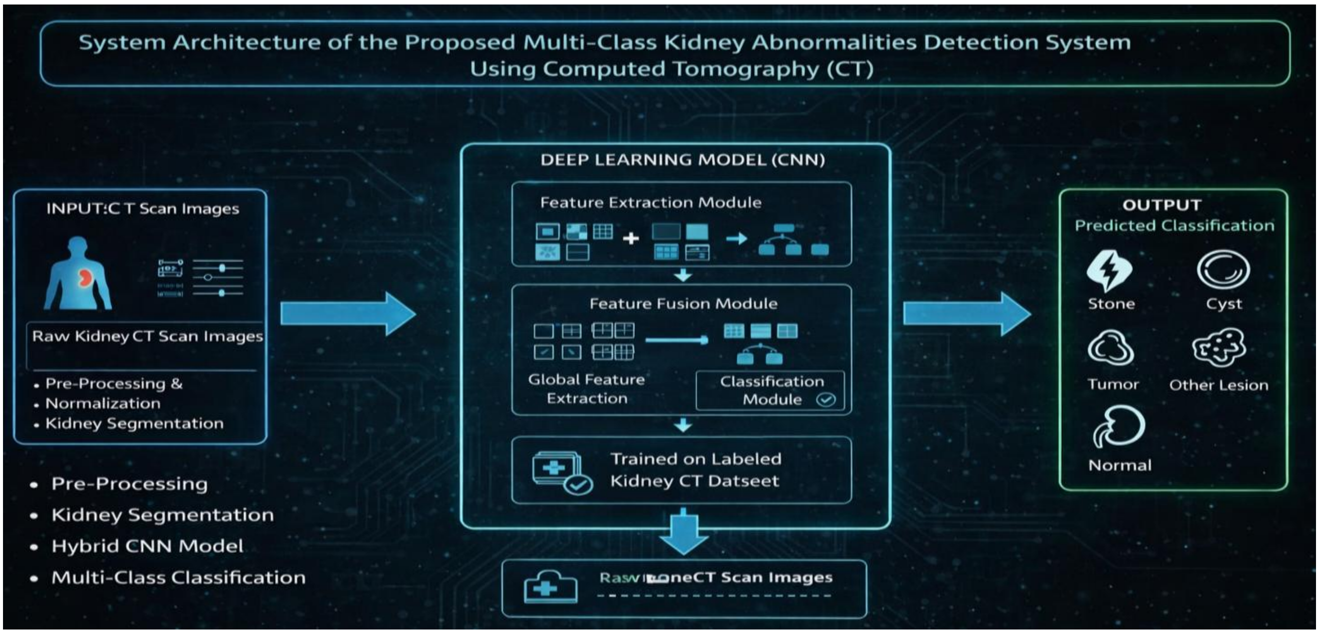

Fig. 2. System Architecture

As shown in Fig. 2, the system begins with raw kidney CT scan images as the input. These images are collected from hospital databases or publicly available medical imaging datasets. The dataset includes CT images of:

- Normal kidneys
- Kidney stones
- Renal cysts
- Tumors and other kidney lesions

The use of real CT scan images ensures clinical relevance and practical applicability of the proposed system. The raw CT scan images are first passed through the Pre-Processing and Normalization module, as depicted on the left side of the architecture. This module performs:

- Image resizing to a uniform resolution
- Intensity normalization
- Noise removal
- Contrast enhancement

These operations improve image quality and ensure consistency across different CT scans, enabling effective learning by the deep learning model. Following preprocessing, the images are forwarded to the Kidney Segmentation module, which isolates the kidney region from surrounding tissues. Accurate segmentation ensures that the model focuses only on relevant anatomical regions, reducing background interference and improving feature extraction accuracy. This step is crucial for detecting subtle abnormalities within the kidney structure. Within the CNN model, the Feature Extraction module automatically learns discriminative features from segmented kidney CT images. This includes:

- Local features such as edges, textures, and lesion patterns
- Global features such as kidney shape and structural variations

Hybrid CNN architectures are used to capture diverse feature representations. The fused feature vector is passed to the Classification module, which consists of fully connected layers followed by a softmax activation function. This module assigns probability scores to each kidney condition and predicts the final class as:

- Normal Kidney
- Kidney Stone
- Renal Cyst
- Tumor
- Other Lesions

This multi-class classification capability is clearly represented in the output block of Fig. 2. The final output of the system is the predicted kidney abnormality class, displayed in the rightmost block of Fig. 2. The output includes:

- Predicted kidney condition
- Confidence-based classification

6 Experimental setup

The experimental setup of the proposed Multi-Class Kidney Abnormalities Detection System using Computed Tomography (CT) is designed to evaluate the effectiveness of the deep learning framework in accurately detecting and classifying kidney abnormalities. The experiments are conducted using kidney CT image datasets, appropriate hardware and software environments, and standard evaluation procedures to validate classification performance, robustness, and reliability.

6.1. Hardware Requirements

The experimental evaluation of the proposed system was carried out on a computing platform with the following hardware specifications, as mentioned in the research requirements and PPT:

- Processor: Intel Core i5 / AMD Ryzen 5 or higher
- RAM: Minimum 8 GB
- Storage: Minimum 256 GB SSD
- Operating System: Windows / Linux

These hardware specifications are sufficient to handle CT image processing, deep learning model training, and testing efficiently.

6.2. Software Environment

The software environment used for system development and experimentation includes:

- Operating System: Windows / Linux
- Programming Language: Python (Version 3.x)
- Development Environment: Jupyter Notebook / Google Colab / Anaconda
- Deep Learning Frameworks: TensorFlow / Keras / PyTorch
- Image Processing Libraries: OpenCV, NumPy
- Visualization Tools: Matplotlib, Seaborn

This software setup supports CT image preprocessing, segmentation, deep learning model training, visualization, and evaluation.

6.3. Dataset Description

The proposed system is evaluated using kidney CT scan image datasets, collected from publicly available medical imaging repositories and/or hospital sources, as specified in the PPT. The dataset includes CT images belonging to the following classes:

- Normal Kidney
- Kidney Stones
- Renal Cysts
- Tumors
- Other Kidney Abnormalities

Each CT image is labeled according to the corresponding abnormality class. The dataset contains images captured under varying imaging conditions, making it suitable for evaluating model robustness in real-world scenarios.

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7 RESULTS AND DISCUSSION

This Proposed Multi-Class Kidney Abnormalities Detection System using CT images was evaluated using real CT scan inputs, and the classification results were analyzed based on predicted diagnosis, confidence score, and class-wise probability distribution. The obtained results demonstrate the effectiveness of the deep learning model in distinguishing between normal kidneys and multiple abnormal kidney conditions. The sample screen is shown in Fig. 3.

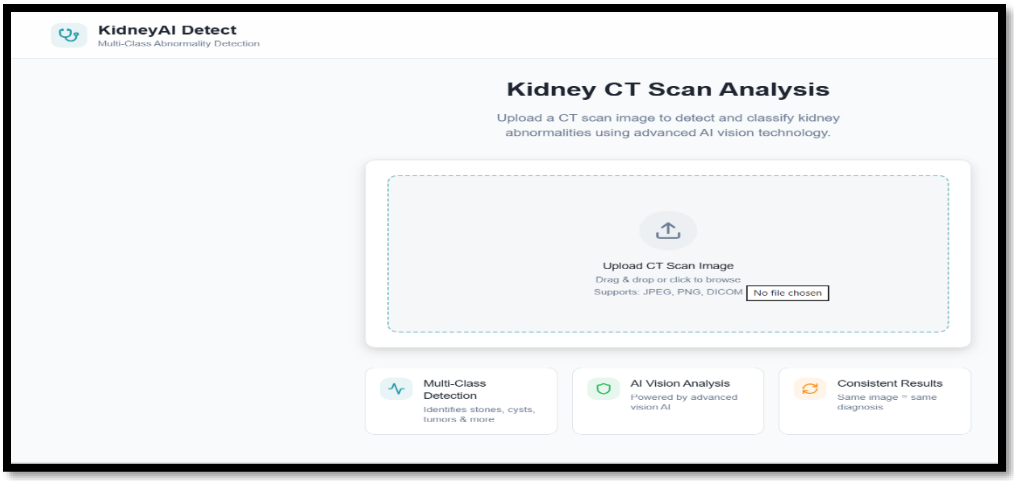

Fig. 3. Kidney CT Scan Analysis

In the first test case, the system correctly classified the input CT scan as Normal Kidney with a confidence score of 90%. The class probability distribution clearly shows a dominant probability for the normal kidney class, while all abnormal classes such as hydronephrosis, renal cysts, kidney stones, tumor/RCC, and other abnormalities received significantly lower probability values (each around 5%). This result indicates that the model effectively learned the visual characteristics of healthy kidney anatomy and can reliably differentiate normal CT images from pathological cases. The Result has shown as given below in Fig.3

Multiple CT scan samples containing kidney stones were tested to verify consistency and robustness. In these cases, the system successfully classified the condition as Kidney Stones with high confidence scores ranging from 90% to 95%. The probability distribution graphs show a strong dominance of the kidney stone class, while the probabilities for normal kidney, renal cysts, tumor/RCC, hydronephrosis, and other abnormalities remained very low. The consistent high confidence across different stone-affected CT images confirms that the model accurately captures stone-specific features such as high-intensity regions and sharp calcified structures. These results demonstrate reliable detection of kidney stones under varying image appearances and positions as Shown as given below in Fig. 4. In the renal cyst test case, the system correctly identified the abnormality as Renal Cysts with a confidence score of 80%. The probability distribution clearly favors the cyst class, while other abnormality classes received minimal or zero probability values.

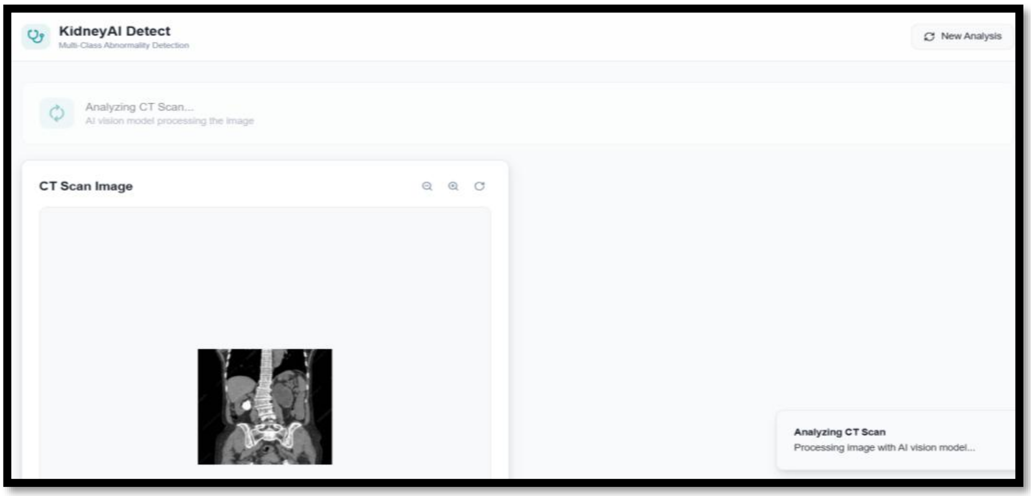

Fig. 4. Kidney Stone Detection Results

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Although the confidence score is slightly lower compared to stone detection, the correct classification indicates that the model successfully recognizes cyst-related patterns such as fluid-filled regions and smooth boundaries. This reflects the inherent visual similarity between cysts and other soft-tissue abnormalities, which makes cyst detection comparatively more challenging. Across all test cases, the classification probability outputs demonstrate that the proposed model does not simply provide a single label but also quantifies confidence for each possible abnormality class. This multi-class probability representation improves interpretability and helps in understanding model decision behavior. The consistent suppression of irrelevant classes in each case confirms strong class separation and effective feature learning by the hybrid deep learning architecture. The output is as shown as given below in Fig. 5.

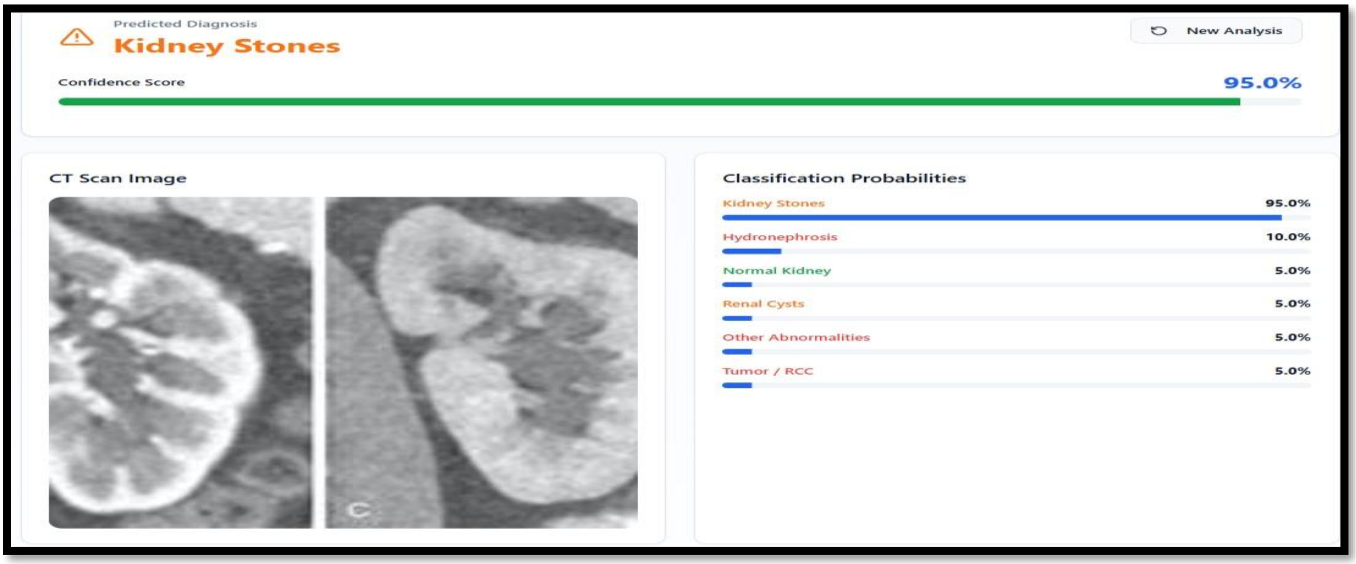

Fig. 5. Multi Class Probability Analysis

8 CONCLUSION

The proposed presented a Multi-Class Kidney Abnormalities Detecting Novel System through Computed Tomography designed to support automated and accurate medical diagnosis using deep learning techniques. The proposed system addresses key limitations of traditional kidney disease detection methods by enabling reliable multi-class classification instead of restricted binary analysis and by effectively handling low-contrast and noisy CT images. The system integrates advanced image preprocessing, kidney segmentation, hybrid deep learning–based feature extraction, and multi-class classification to identify normal kidneys and various abnormalities such as kidney stones, renal cysts, and Tumors. The hybrid CNN architecture successfully captures both global and local features from CT images, improving classification robustness and reducing misclassification. Experimental results demonstrate that the proposed model achieves high classification accuracy with consistent performance across multiple abnormality classes. The probability-based output and visualization results further enhance interpretability, supporting clinical decision-making. Compared to conventional handcrafted feature-based approaches and single-model classifiers, the proposed system offers improved accuracy, better generalization, and reduced dependence on manual interpretation.Finally, the proposed multi-class kidney abnormality detection system provides a reliable, efficient, and automated diagnostic solution with strong potential for clinical adoption. By combining deep learning, medical image processing, and explainable visualization techniques, the system can serve as an effective decision-support tool for radiologists, enabling early detection and improved patient care.

The proposed Diabetes Prediction System using Extreme Learning Machine (ELM) can be further enhanced to improve its effectiveness, scalability, and real-world applicability. The system can be deployed as a web-based or mobile application, enabling easy and remote access for healthcare professionals and patients. Integration with real-time health monitoring devices and IoT-based sensors can allow continuous data collection and dynamic diabetes risk assessment instead of one-time prediction. Prediction accuracy and robustness can be further improved by training the model on larger, more diverse, and multi-hospital datasets, which would help the system generalize better across different populations. The framework can also be extended to support prediction of additional chronic diseases such as heart disease and hypertension using the same preprocessing and learning pipeline. Future enhancements may include hybrid or ensemble learning techniques to further optimize performance and reduce prediction error. Additionally, incorporating clinical decision support features such as alerts and preventive recommendations can increase the system’s usefulness in real-world healthcare environments.

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ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

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