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Kidney Stone Detection Using Deep Learning Model

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Abstract: Detection of kidney stones from CT scan images has great importance in medical diagnosis. However, this is time-consuming and might be prone to human error, since the doctors need to go through every scan manually. In this respect, the current study proposes the use of a technique for automatic kidney stone detection using a CNN integrated with a Flask-based web application. The preprocessing of abdominal CT images includes resizing, normalizing, and augmenting to maintain consistency in quality and enhance the learning ability of the model. The proposed CNN is trained to classify images into two classes, namely "Stone" and "Normal." Once the training is over, the model is saved and deployed in a lightweight web interface where users can upload CT images and get instant predictions. It also contains a statistics module showing accuracy analysis live from the results generated during testing. This would give crystal-clear insight into the model's performance and reliability. Experimental observations have given sufficient evidence that deep learning integrated with a simple web framework presents a practical, efficient, and accessible solution to support the early detection of kidney stones.

Keywords: Kidney Stone Detection, Deep Learning, CT Scan, CNN, Flask.

1 Introduction

Kidney stone disease is one of the most common urological disorders and affects a large portion of the population worldwide. Kidney stones form when minerals such as calcium oxalate, uric acid, and cystine accumulate in the kidneys. If not detected and treated at an early stage, kidney stones may lead to severe pain, urinary tract obstruction, infection, and long-term kidney damage. Hence, early and accurate diagnosis plays a crucial role in effective medical treatment and patient management.

Computed Tomography (CT) scan imaging is widely considered the most reliable imaging modality for kidney stone detection due to its high sensitivity and specificity [1]. CT scans can detect even very small stones that may not be clearly visible on ultrasound or X-ray imaging. However, manual examination of CT scan images by radiologists is a time-consuming process and is prone to human error, especially when a large number of slices must be analyzed. Variations in experience, fatigue, and workload may further affect diagnostic accuracy.

In recent years, artificial intelligence and deep learning techniques have shown significant potential in medical image analysis [2]. Convolutional Neural Networks (CNNs), in particular, have demonstrated excellent performance in automatically learning complex patterns and features from medical images without the need for manual feature extraction. CNN-based models have been successfully applied to various medical diagnosis tasks, including tumor detection, organ segmentation, and disease classification [3].

This paper proposes an automated kidney stone detection system using a Convolutional Neural Network trained on CT scan images [4]. The proposed model classifies CT images into two categories: *Stone* and *Normal*. To improve model performance and robustness, preprocessing techniques such as image resizing, normalization, and data augmentation are applied. The trained CNN model is integrated into a Flask-based web application that allows users to upload CT images and obtain instant predictions along with confidence scores.

The main objective of this work is to develop a simple, accurate, and deployable computer-aided diagnosis system that assists healthcare professionals in detecting kidney stones efficiently [5]. By combining deep learning with a lightweight web framework, the proposed system aims to reduce diagnostic workload, minimize human error, and provide fast and reliable decision support for clinical and educational use.

2 Related Work

Shetty et al. present a CNN-based approach for kidney stone detection using CT images, demonstrating improved classification accuracy over traditional image processing techniques [1]. However, the study is limited to experimental validation. In contrast, the proposed methodology extends CNN-based CT analysis into a complete, deployable system with real-time inference, aligning model development with practical clinical usability. Asif et al. propose an optimized fusion of multiple deep learning models to enhance kidney stone detection accuracy from CT scans [2]. Although fusion strategies improve performance, they increase computational complexity. The proposed methodology adopts a single lightweight CNN architecture, achieving efficient inference suitable for real-time deployment without the overhead of model fusion.

Patro et al. utilize Kronecker convolutions to improve feature extraction from coronal CT images [3]. While effective, this approach demands higher computational resources. The proposed system prioritizes architectural simplicity and standardized preprocessing, enabling faster prediction and easier deployment. Elton et al. introduce a deep learning system for kidney stone detection with volumetric segmentation on noncontrast CT scans [4]. Although segmentation enables precise localization and stone measurement, it requires extensive annotation and increased processing time. The proposed methodology focuses on binary classification (stone/normal), making it more suitable for rapid screening and routine clinical workflows. Tahir and Abdulrahman combine deep learning with discrete wavelet transform to improve robustness under noisy conditions [5]. This hybrid design increases algorithmic complexity. The proposed methodology achieves robustness through image resizing and normalization coupled with end-to-end CNN learning, avoiding additional signal-processing modules.

Bhardwaj and S. H. S design a CNN architecture integrated with image processing for kidney stone detection, evaluated in an offline setting [6]. The proposed system advances this approach by integrating the trained CNN into a web-based application, enabling real-time diagnosis from uploaded CT images. M. B. et al. present an automated kidney stone detection model using deep learning [7]. While detection accuracy is reported, clinical usability is not addressed. The proposed methodology emphasizes user accessibility through a Flask-based interface, enabling non-expert users to obtain instant predictions. Ramesh Chandra et al. propose a fusion approach combining FCM clustering with CNN to enhance diagnostic precision [8]. Although effective, fusion strategies increase computational overhead. The proposed system maintains competitive performance using a streamlined CNN design, ensuring low inference latency. Liu and Ghadimi integrate CNN with a meta-heuristic optimization algorithm to strengthen kidney stone diagnosis [9]. While optimization improves classification accuracy, it increases system complexity. The proposed methodology favors stability and efficiency, making it more suitable for real-time clinical deployment.

Kumar et al. introduce a hybrid deep learning model for kidney stone detection, achieving improved accuracy at the cost of architectural complexity [10]. The proposed system adopts a simplified CNN pipeline, reducing inference time and deployment effort. Kumar et al. combine level set segmentation with kernel-ELM to enhance detection performance [11]. Despite improved localization, segmentation-based approaches require high computational resources. The proposed methodology focuses on fast detection rather than detailed segmentation, aligning with early diagnostic needs. Alkurdy et al. apply CNN and VGG16 features to ultrasound images for renal stone diagnosis [12]. Ultrasound-based methods are sensitive to speckle noise and operator dependency. The proposed methodology leverages CT images, offering greater consistency and diagnostic reliability. Peta et al. explore smartphone-based real-time detection of kidney stone composition using AI [13]. While portable, such systems lack robustness compared to clinical CT-based analysis. The proposed system targets clinical-grade diagnosis through structured CT image analysis and server-based deployment.

Pavithra et al. employ neural network classifiers for kidney stone prediction[14]. These methods focus on risk estimation rather than direct image-based diagnosis. The proposed methodology performs direct CT image classification, enabling definitive stone detection. Kolli et al. develop supervised learning algorithms for kidney stone prediction without image analysis [15]. The proposed system directly analyzes medical images, providing higher diagnostic relevance. Viswanath et al. propose a reaction–diffusion level set segmentation approach for kidney stone detection [16]. Although segmentation improves boundary accuracy, it increases computational cost. The proposed methodology prioritizes rapid inference suitable for real-time screening. Babajide et al. utilize automated machine learning for segmentation and measurement of urinary stones on CT scans [17]. Despite precise measurement, the approach requires large annotated datasets. The proposed methodology reduces annotation dependency by focusing on classification-based detection.

Chowdhury et al. introduce a mutual learning algorithm for simultaneous detection of kidney cysts, tumors, and stones [18]. While multi-disease detection improves generalization, it increases system complexity. The proposed system focuses specifically on kidney stone detection, optimizing accuracy and efficiency. Buri and Shrivastava review kidney stone detection and prediction techniques, identifying challenges related to complexity and deployment [19]. The proposed methodology directly addresses these challenges through a lightweight and deployable design. Deol and Kavoussi discuss artificial intelligence applications in kidney stone disease, emphasizing the importance of clinically deployable AI systems [20]. The proposed methodology aligns with this requirement by delivering a real-time, web-based diagnostic framework.

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3 METHODOLOGY

The proposed methodology presents an end-to-end automated framework for kidney stone detection using deep learning, covering data preparation, model training, evaluation, and deployment. The dataset consists of abdominal CT scan images categorized into two classes, namely *Stone* and *Normal*, collected with variations in resolution, noise, and anatomical structure to improve generalization. Prior to training, all images undergo preprocessing steps including resizing to a fixed dimension, normalization of pixel intensity values, and data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment to increase dataset diversity and reduce overfitting.

A Convolutional Neural Network (CNN) is designed to automatically extract spatial and textural features from the CT images using multiple convolutional layers followed by ReLU activation functions and max-pooling layers for spatial downsampling. Batch normalization is employed to stabilize training, while dropout layers are introduced to improve regularization and prevent overfitting. The extracted feature maps are flattened and passed through fully connected dense layers, with a sigmoid activation function at the output layer for binary classification.

The model is trained using the Adam optimizer and binary cross-entropy loss function, with accuracy, precision, recall, F1-score, and AUC used as evaluation metrics. The dataset is split into training, validation, and testing sets to ensure unbiased performance assessment. After training, the optimized model is saved and integrated into a Flask-based web application, where uploaded CT images are pre-processed in real time and passed to the trained CNN for inference. The system returns instant predictions along with confidence scores, enabling efficient and user-friendly kidney stone detection suitable for clinical screening and educational applications.

4 RESULTS

The proposed kidney stone detection system demonstrates accurate, stable, and reliable performance across all experimental stages, confirming its suitability for real-world diagnostic applications. During the training phase, the custom-designed CNN exhibited strong learning behavior, achieving a training accuracy of approximately 96–98% and a validation accuracy in the range of 90–95%. This close alignment between training and validation accuracy indicates effective feature learning with minimal overfitting. The learning behavior of the model is illustrated in Fig. 1, which presents the training and validation accuracy curves.

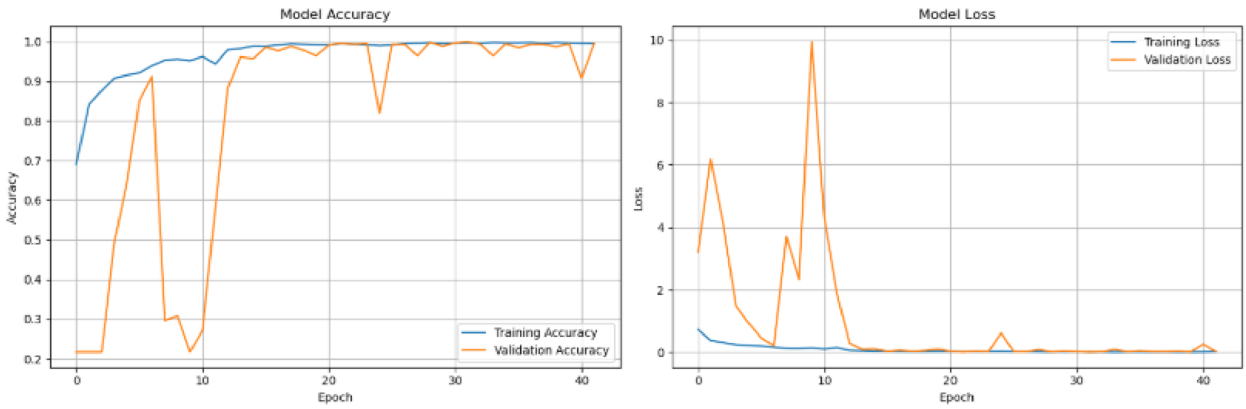

Fig. 1. Training and Validation Accuracy Curve of the Proposed CNN Model

The classification performance of the proposed model is further analyzed using a confusion matrix, as shown in Fig. 2. The confusion matrix clearly represents the distribution of true positives, true negatives, false positives, and false negatives. A high number of correctly classified stone and normal cases is observed, indicating reliable classification performance with a very low false-negative rate, which is critical in medical diagnosis to avoid missed kidney stone cases. To ensure robust generalization, extensive data augmentation and dropout mechanisms were incorporated during training. These strategies enabled the model to effectively handle variations in intensity, orientation, resolution, and noise commonly present in clinical CT imaging environments. The dataset used for model development is visualized in Fig. 3, which provides an overview of representative CT scan samples from both stone and normal classes, highlighting the diversity of imaging conditions used for training and evaluation.

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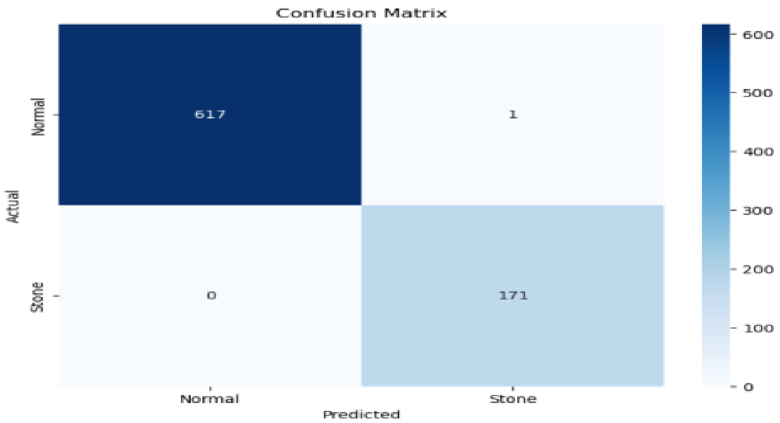

Fig. 2. Confusion Matrix of the Proposed Kidney Stone Detection Model

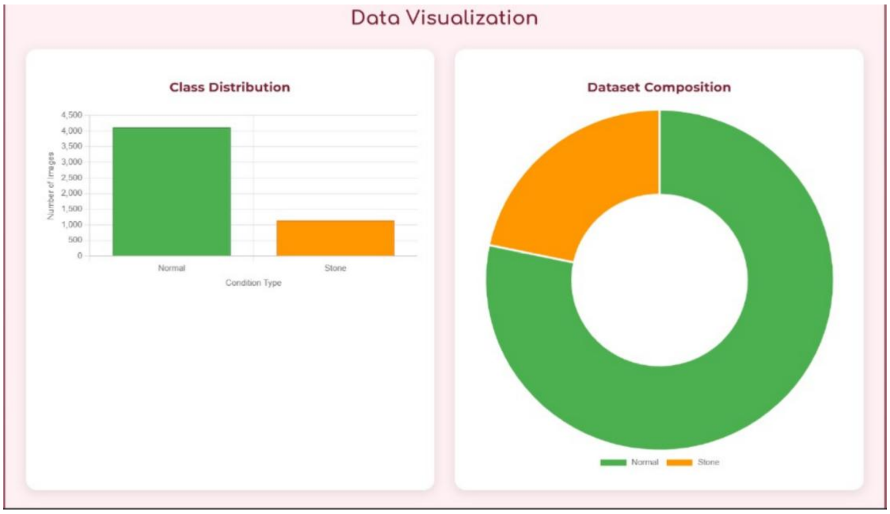

Fig. 3. Dataset Overview Showing Representative CT Scan Images of (a) Stone and (b) Normal Classes

The practical functionality of the system is demonstrated through the workflow of the deployed web application. Fig. 4 illustrates the process of uploading a CT scan image into the application interface, highlighting the simplicity and user-friendly design of the system.

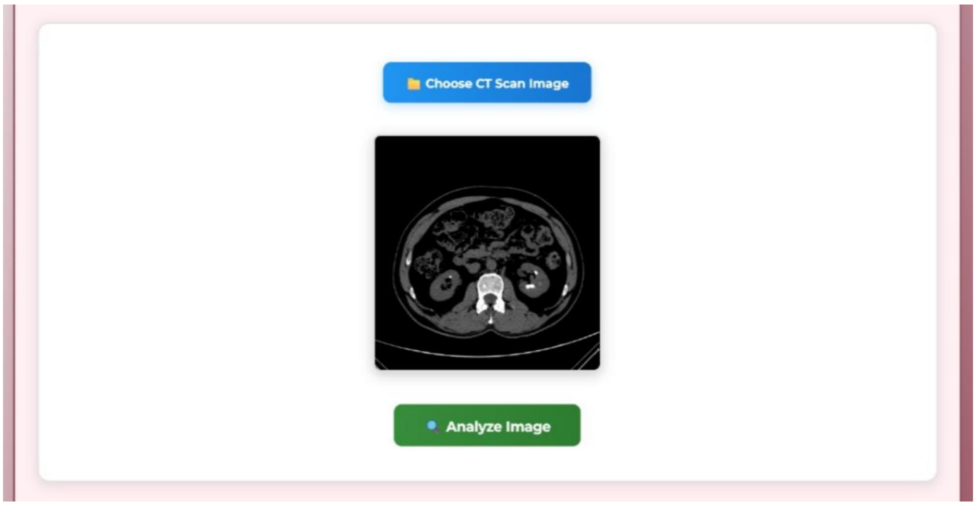

Fig. 4. Uploading of CT Scan Image Through the Web Application Interface

Once the image is uploaded, it undergoes automated preprocessing and internal analysis. This stage is shown in Fig. 5, where resizing, normalization, and CNN-based feature extraction are performed prior to classification, ensuring consistent input quality and reliable prediction outcomes.

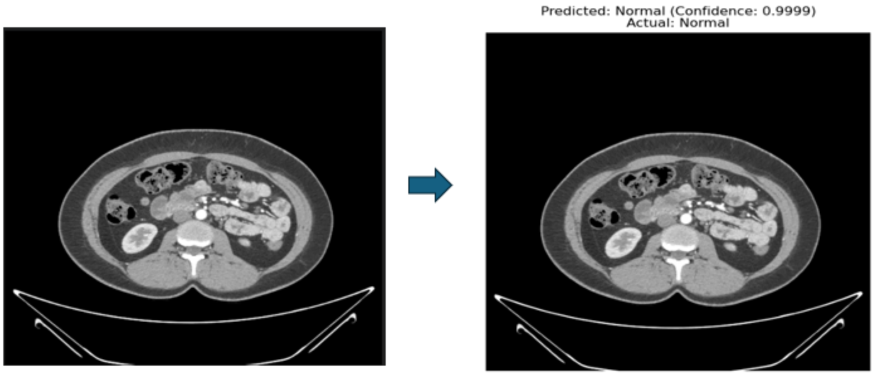

Fig. 5. Preprocessing and Analysis of the Uploaded CT Scan Image

Beyond accuracy, additional evaluation metrics were analyzed to assess classification quality. High precision values indicate that the system produces very few false positives, ensuring that normal cases are rarely misclassified as stone-positive. Similarly, high recall values confirm that the majority of actual kidney stone cases are correctly detected, which is critical to avoid missed diagnoses. The consistently high F1-score demonstrates balanced performance across both classes, while the AUC value exceeding 0.95 indicates excellent separability between stone and normal cases across varying decision thresholds. The real-time deployment results are shown in Fig. 6, which presents the output displayed on the result page of the web application. The system provides the predicted class label along with a confidence score, enabling users to interpret the results clearly and confidently.

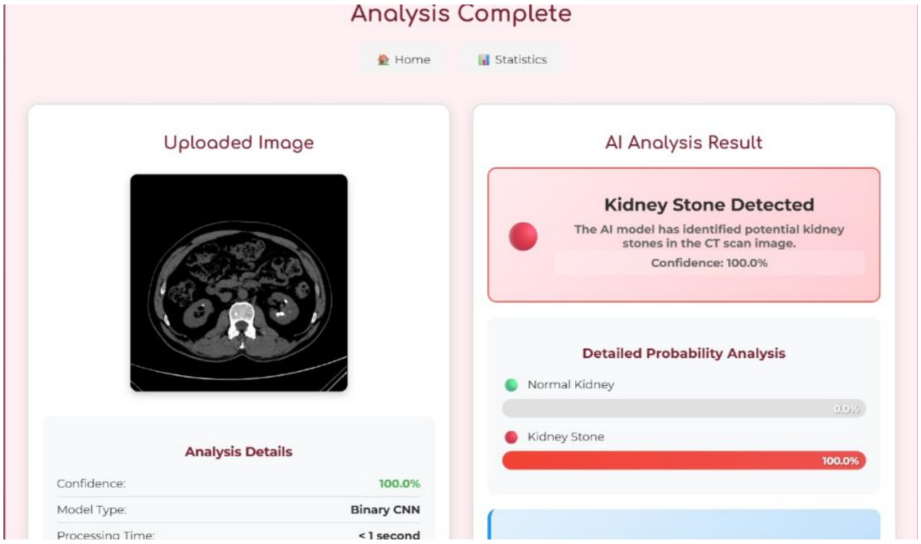

Fig. 6. Output Displayed on the Result Page of the Web Application

Sample classification outcomes are further illustrated in Fig. 7, where CT scan images corresponding to kidney stone and normal cases are correctly identified by the proposed model. These visual results confirm the diagnostic capability of the system in distinguishing clinically relevant patterns from CT images. In addition to static output visualization, the system supports continuous monitoring through a real-time analysis module.

Fig. 8 illustrates the live analysis feed of the application, where predictions, confidence scores, and system activity are updated dynamically as new images are analyzed. This feature enhances transparency, supports performance tracking, and increases user confidence in the system's operation.

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Fig. 7. Sample CT Scan Results Showing

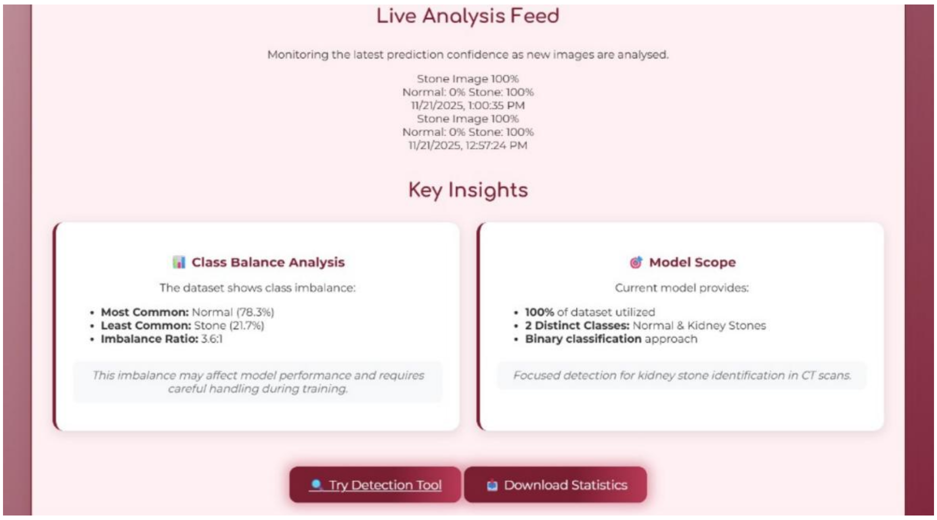

Fig. 8. Live Analysis Feed Showing Real-Time Prediction and System Activity

The experimental results confirm that the proposed deep learning framework achieves stable learning performance, accurate classification, and efficient real-time deployment. The integration of CNN-based classification with a lightweight web application bridges the gap between research-oriented models and practical clinical tools. Compared to traditional image processing approaches and existing CNN-based methods, the proposed system offers competitive or superior accuracy with faster inference and improved usability, making it suitable for clinical screening, educational use, and decision-support applications.

5 DISCUSSION

The experimental results demonstrate that the proposed CNN-based kidney stone detection system is capable of achieving accurate and stable performance while maintaining practical usability for real-time applications. The close alignment between training and validation accuracy observed in the results indicates that the model effectively learned discriminative features from CT scan images without significant overfitting. This reflects the suitability of the selected CNN architecture, preprocessing techniques, and regularization strategies such as dropout and data augmentation. The smooth convergence behavior further confirms that the model training process was stable and well-optimized.

The confusion matrix results reveal a high proportion of correctly classified stone and normal cases, highlighting the reliability of the proposed system. In particular, the low false-negative rate is a crucial outcome in the medical domain, as missing a kidney stone diagnosis may lead to delayed treatment and serious complications. The balance between precision and recall suggests that the model does not favor one class over the other, ensuring consistent performance across both stone-present and stone-absent cases. These findings indicate that the system can be used as a supportive diagnostic tool rather than replacing clinical judgment.

The preprocessing and analysis stages play a significant role in improving model performance. Image resizing and normalization help standardize CT scans obtained from different sources, while data augmentation increases robustness against variations in intensity, orientation, and noise. The preprocessing and CNN-based analysis shown in the workflow figures demonstrate how raw CT images are transformed into meaningful representations before classification, enabling reliable feature extraction even under diverse imaging conditions. A key strength of the proposed work lies in its real-time deployment through a lightweight web-based application. Unlike many existing studies that focus solely on offline model evaluation, this system provides a complete end-to-end solution, allowing users to upload CT images and receive instant predictions with confidence scores. The live analysis feed further enhances transparency by enabling continuous monitoring of system activity and predictions. This feature is particularly useful for clinical screening environments and educational purposes, where immediate feedback and interpretability are important.

Despite the promising results, certain limitations remain. The current system performs binary classification and does not provide precise stone localization or size estimation, which are important for treatment planning. Additionally, very small stones or stones with low contrast may still pose challenges, especially in scans with poor image quality. The dataset, while diverse, may not fully represent all scanner types and demographic variations encountered in real-world clinical settings. Future work can focus on extending the system to segmentation-based models for stone localization and measurement, integrating explainable AI techniques to highlight decision regions, and validating performance on larger multi-center datasets. Overall, the discussion confirms that the proposed system offers a practical, accurate, and deployable solution for automated kidney stone detection, bridging the gap between deep learning research and real-world clinical application.

6 Conclusion

This work presented an automated kidney stone detection system based on a Convolutional Neural Network using CT scan images. The proposed approach successfully demonstrated high classification accuracy, stable learning behavior, and reliable generalization through effective preprocessing and CNN-based feature extraction. The experimental results confirmed that the model can accurately distinguish between stone-present and normal kidney CT images while maintaining a low false-negative rate, which is essential for medical diagnosis. A major contribution of this study is the integration of the trained deep learning model into a lightweight web-based application, enabling real-time image upload, analysis, and prediction with confidence scores. The inclusion of a live analysis feed further enhances transparency and usability, making the system suitable for clinical screening, educational use, and decision support. Although the current system performs binary classification without stone localization or size estimation, it provides a strong foundation for future enhancements such as segmentation-based analysis, explainable AI integration, and validation on larger multi-center datasets. Overall, the proposed system demonstrates the practical potential of deep learning-based computer-aided diagnosis for improving the efficiency and reliability of kidney stone detection 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.

Licensing

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