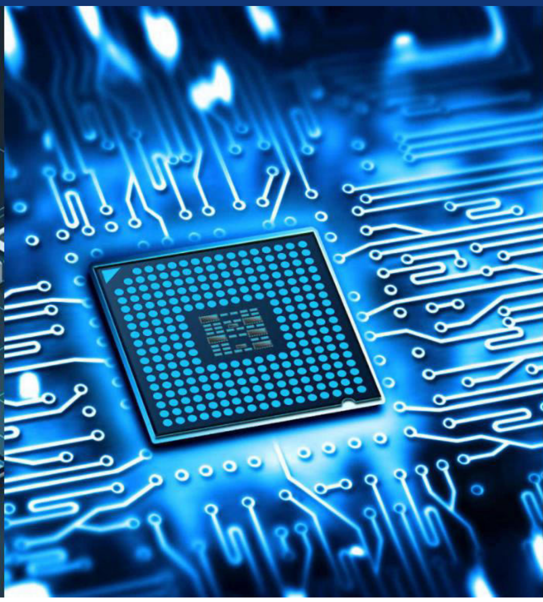
IJIRCCE

ISSN(O): 2320-9801

ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

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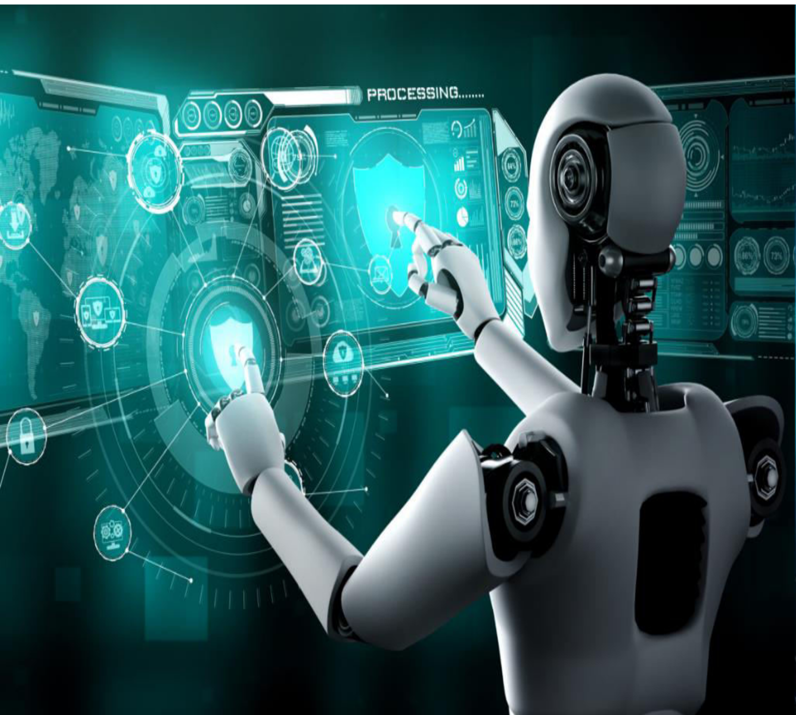

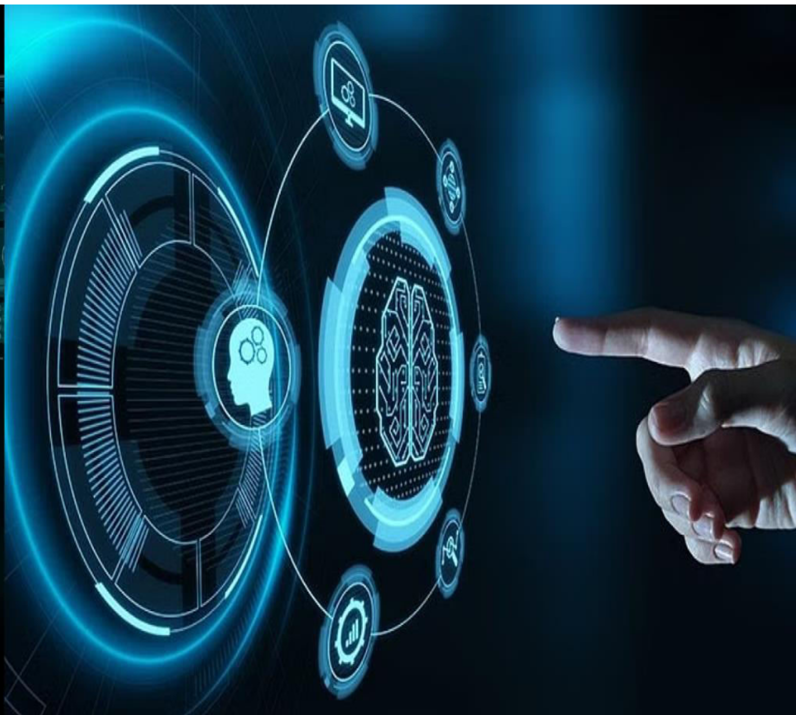

Impact Factor: 9.927

Volume 14, Issue 6, June 2026

© 2026 IJIRCCE | Volume 14, Issue 6, June 2026 DOI: 10.15680/IJIRCCE.2026.1406098

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Automated Kidney Stone Analysis Through Deep Learining Based Segmentation Models

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ABSTRACT: Kidney abnormalities, including stones, cysts, and tumors, can be effectively detected using ultrasound imaging, though low contrast and speckle noise pose challenges. This study applies preprocessing techniques—image restoration, Gabor filtering, and histogram equalization—to enhance image quality and visibility of internal structures. Accurate kidney segmentation is achieved using a level set method with momentum and resilient propagation (Rprop) terms. Extracted kidney regions are analyzed with wavelet transforms, including Symlets, Biorthogonal, and Daubechies subbands, to compute energy features indicative of stone presence. These features are then used to train Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) classifiers. The proposed approach enables precise detection and identification of kidney stones. Experimental results demonstrate high accuracy and reliability in stone classification.

KEYWORDS: Kidney Stone Detection, Ultrasound Imaging, Deep Learning, Medical Image Segmentation, Speckle Noise Reduction, Median Filter, Convolutional Neural Network, Transfer Learning, Computer-Aided Diagnosis, Renal Calculi, Image Preprocessing, Automated Disease Detection.

I. INTRODUCTION

Renal illness is a serious health concern, and many people ignore early warning signs until significant damage has occurred. The prevalence of kidney disease is increasing worldwide, making early detection and prevention essential. Various diagnostic imaging techniques such as CT scans, MRI, and Ultrasound are used in modern medicine. Among these, ultrasound imaging is widely preferred because it is safe, non-invasive, radiation-free, and cost-effective. It helps in identifying structural abnormalities such as kidney stones, cysts, and tumors, as well as estimating kidney size and position.

Kidney stones are formed due to crystal accumulation in the inner structures of the kidney. If not detected early, they may obstruct the urinary tract and lead to severe complications, including renal failure. However, diagnosing kidney stones using ultrasound images is challenging due to low contrast and the presence of speckle noise. Speckle noise reduces image clarity and diagnostic accuracy, making manual identification difficult.

To overcome these limitations, image preprocessing techniques such as median filtering are used to reduce noise while preserving edges. Automated image analysis using deep learning techniques further improves detection accuracy. Deep Learning (DL) models, especially segmentation-based approaches, enable precise localization of kidney stones in ultrasound images. Transfer learning and hyperparameter optimization techniques can enhance model performance.

Early and accurate identification of kidney stones using automated deep learning-based segmentation models can assist medical professionals in effective diagnosis, surgical planning, and treatment, thereby reducing the risk of severe renal complications.

II. LITERATURE SURVEY

Multi-Class Kidney Abnormalities Detecting Novel System through Computed Tomography**.** This system focuses on detecting multiple kidney abnormalities using Computed Tomography (CT) images. CT imaging provides high-resolution cross-sectional images that help identify structural variations in the kidney. The proposed system classifies abnormalities such as kidney stones, cysts, tumors, hydronephrosis, and congenital anomalies. Image preprocessing techniques are applied to enhance contrast and remove noise. Feature extraction methods are used to capture texture, intensity, and shape characteristics. Deep learning models, especially Convolutional Neural Networks (CNNs), are employed for multi-class classification. The model learns discriminative features automatically from CT datasets. Data augmentation techniques are used to improve model generalization. The system reduces dependency on manual diagnosis. Performance is evaluated using accuracy, precision, recall, and F1-score. Experimental results show improved classification accuracy compared to traditional machine learning methods. The system assists radiologists in early detection. Early identification helps prevent complications and supports better treatment planning.[1]

This approach combines radiomics and deep learning features to classify kidney tumor types. Radiomics features include texture, intensity, and morphological characteristics extracted from CT or MRI images. Deep features are automatically learned using CNN architectures. Feature fusion techniques combine both handcrafted and deep features. This hybrid approach enhances tumor differentiation accuracy. The system distinguishes between benign and malignant tumors. Preprocessing steps include normalization and segmentation of tumor regions. Feature selection methods reduce redundancy. Machine learning classifiers such as SVM or deep networks are used for final prediction. The combined model improves robustness and reliability. The study demonstrates superior performance compared to single-feature approaches. It supports non-invasive tumor diagnosis. Accurate tumor classification aids clinical decision-making and treatment planning.[2]

BGRD-TransUNet is an improved segmentation model based on the TransUNet architecture. It integrates CNN and Transformer mechanisms for capturing both local and global features. The Boundary-Guided Region Detection (BGRD) module enhances edge detection accuracy. This is particularly useful in low-contrast ultrasound images. The model effectively segments breast lesions with improved boundary precision. Data augmentation increases training efficiency. Skip connections preserve spatial information. The Transformer encoder captures contextual relationships. The model reduces segmentation errors in complex backgrounds. Dice coefficient and IoU are used for evaluation. Results show better performance compared to standard U-Net models. The framework can be extended to other ultrasound-based segmentation tasks. It demonstrates the potential of hybrid CNN-Transformer models in medical imaging.[3]

Improvement of Urinary Stone Segmentation Using GAN-Based Urinary Stones Inpainting Augmentation. This method uses Generative Adversarial Networks (GANs) for data augmentation. GANs generate realistic synthetic urinary stone images. Inpainting techniques insert artificial stones into normal CT images. This increases dataset diversity and balances class distribution. The augmented data improves segmentation model training. U-Net or similar architectures are used for stone segmentation. GAN-based augmentation helps detect small and rare stones. The approach reduces overfitting issues. The segmentation accuracy improves significantly. Dice score and sensitivity are enhanced. The method is effective when real datasets are limited. It strengthens model generalization capability. This approach supports reliable automated stone detection.[4]

Urinary Stones Segmentation in Abdominal X-ray Images Using Cascaded U-Net Pipeline**.**This study proposes a cascaded U-Net architecture for stone segmentation in X-ray images. The first stage detects candidate stone regions. The second stage refines segmentation boundaries. Stone-embedding augmentation improves detection of small stones. Lesion-size reweighting handles class imbalance. Preprocessing improves image clarity and contrast. The cascaded structure reduces false positives. The model performs well even in low-quality X-rays. Dice score and IoU evaluate segmentation performance. Results show improved detection of tiny lesions. The pipeline enhances segmentation precision. It provides a cost-effective alternative to CT-based detection. The approach supports automated screening in resource-limited settings.[5]

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III. METHODOLOGY

The proposed methodology for **automated kidney stone detection** is designed as a multi-stage system. It integrates advanced image processing techniques with deep learning for efficient and accurate detection of kidney stones from ultrasound images. The system comprises five major modules**:** Ultrasound Kidney Dataset Module, Image Pre-Processing Module, Image Segmentation Module, Wavelet Processing Module**,** and CNN Classification Module**.** Each module is described in detail below.

Ultrasound Kidney Dataset Module

The first stage of the proposed system involves the collection of a comprehensive ultrasound kidney image dataset. These images are obtained from various diagnostic centers and hospitals, ensuring a wide variety of patient data for robust system performance. Each patient contributes two images: one showing the kidney without any detected stone and the other showing the kidney with a stone detected and measured by a sonographer. The image without a measurement serves as a baseline reference representing normal kidney anatomy, while the measured image provides the ground truth for kidney stone detection. Collecting images with labeled stones allows for accurate training and validation of the automated system. The dataset is carefully curated to include different types of stones, varying sizes, and locations within the kidney. By including diverse cases, the system can learn to generalize well across patients. Furthermore, having paired images ensures that the proposed system can be compared against expert annotations, enabling validation of detection accuracy. The dataset is organized and pre-processed to maintain consistent resolution, format, and intensity ranges. This stage forms the foundation of the system, as high-quality labeled data is essential for deep learning and image analysis. A well-structured dataset improves model training, reduces overfitting, and increases reliability of stone detection in real-world applications.

Image Pre-Processing Module

Ultrasound images often suffer from low contrast**,** speckle noise, and artifacts, which can reduce the accuracy of kidney stone detection. Pre-processing enhances image quality and prepares it for segmentation and feature extraction. The pre-processing pipeline consists of several steps. First, image restoration techniques are applied to reduce noise and artifacts present due to the ultrasound acquisition process. Then, smoothing filters are used to remove minor pixel intensity variations while preserving edges. This is followed by sharpening **t**o enhance important structures such as kidney boundaries and stones. Contrast enhancement, such as histogram equalization, improves the visibility of subtle features. Geometric transformations, including rotation, scaling, and translation, standardize the images, ensuring consistent input dimensions for segmentation. Pre-processing reduces the complexity of subsequent stages by providing cleaner, more distinguishable regions of interest. Additionally, pre-processed images are validated against ground truth provided by sonographers, ensuring that important diagnostic features are preserved. Optimization is performed by analyzing differences between automated and expert annotations. Overall, the pre-processing module significantly improves the signal-to-noise ratio, making the detection and classification of kidney stones more accurate.

Fig : 1 Image preprocessing module

© 2026 IJIRCCE | Volume 14, Issue 6, June 2026 DOI: 10.15680/IJIRCCE.2026.1406098

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Image Segmentation Module

Segmentation is a critical step that isolates kidney regions and potential stones from the rest of the image. In this system, segmentation is performed using level set techniques, which can accurately delineate complex shapes and boundaries. Canny edge detection is applied first to sharpen the edges of the kidney and any stones present. The image is then divided into multiple regions based on pixel properties such as intensity, texture, and spatial proximity. Each pixel is assigned a label, grouping pixels with similar characteristics. Segmentation simplifies the image by reducing it to meaningful regions**,** which are easier to analyze and interpret. This step also highlights the kidney stone **areas**, allowing for targeted feature extraction. The segmented output provides contours of the kidney and stones, which are essential for the next stage of wavelet-based processing. By isolating the kidney and stone regions, segmentation reduces computational complexity and improves detection accuracy. This module ensures that features extracted in the following steps are specific to regions of interest, eliminating background noise and irrelevant information.

Wavelet Processing Module

Wavelet transform is employed for feature extraction and image denoising after segmentation. Wavelets are particularly suitable for medical images because they capture both spatial and frequency information, allowing for better detection of kidney stones. The segmented image is transformed using 2D wavelets**,** which extract energy levels and intensity variations in the kidney region. Wavelet processing reduces white Gaussian **noise** and enhances contrast between stone and normal tissue. The high-intensity differences of pixels corresponding to kidney stones make it easier to identify their presence. This module generates compressed, cleaned images that preserve structural details without blurring. Wavelet coefficients serve as input to the CNN classifier, providing robust feature representations. This approach improves the reliability of stone detection and enables differentiation between normal tissue and stones. Wavelet processing ensures that subtle features important for accurate diagnosis are captured efficiently. Overall, this module enhances the system's ability to detect kidney stones in low-contrast ultrasound images**.**

CNN Classification Module

The final module of the proposed system involves classification using a Convolutional Neural Network (CNN)**.** CNNs are highly effective in medical image analysis because they automatically learn spatial features, edges, textures, and patterns relevant for diagnosis. The CNN receives wavelet-transformed images as input, ensuring that features are both meaningful and noise-reduced. Convolution layers apply filters to extract local features, while pooling layers reduce dimensionality and retain significant information. Fully connected layers combine these features for final classification. The CNN predicts whether the kidney contains stones and, if present, identifies the type or severity of the stone. The predicted output is then compared with the ground truth dataset for validation. CNN classification enables the system to achieve high accuracy, robustness, and generalization across different patients. By combining deep learning with wavelet features, the system can handle low contrast and noisy ultrasound images, making it practical for real-world medical applications.

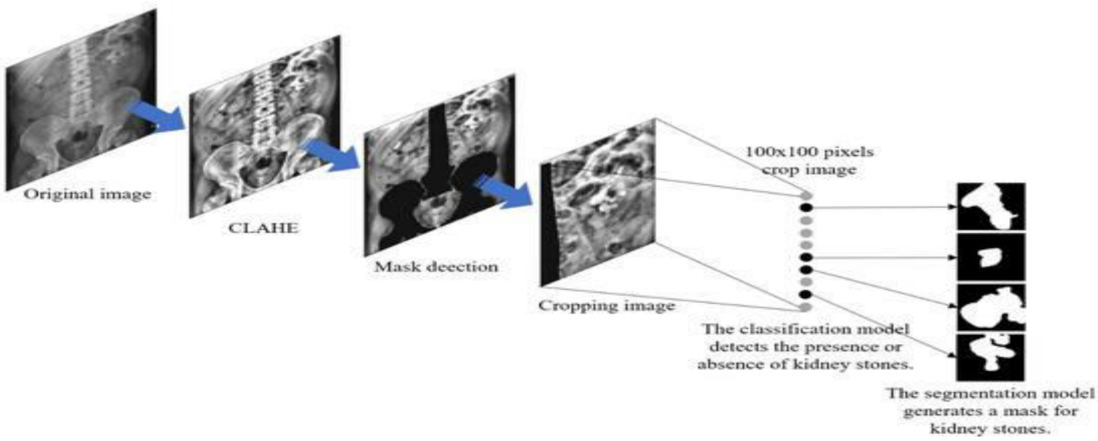

fig: 2 Classification of kidney stone

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IV. RESULT AND DISCUSSION

In previous studies, most research efforts in kidney stone detection focused primarily on identifying the presence of stones in medical images such as ultrasound or CT scans. Techniques such as classical image processing, thresholding, and even deep learning models like U-Nets and CNNs were applied to detect stones, but they were limited to binary classification—indicating whether a stone was present or absent. While these methods achieved significant accuracy in detecting stones, they did not provide information regarding the type, composition, or severity of the stone, which is critical for treatment planning and prevention strategies.

In contrast, the proposed system in this paper not only detects the presence of kidney stones but also classifies the type of stone based on energy features extracted from wavelet-transformed segmented images. By integrating wavelet-based feature extraction with CNN classification, the system captures subtle variations in texture, intensity, and energy levels within the kidney, which are indicative of different stone types. This allows the system to distinguish between common types of stones such as calcium oxalate, struvite, and uric acid stones**,** which is a significant advancement over prior methods.

Furthermore, previous studies often relied on CT images alone, which, although highly accurate, expose patients to ionizing radiation. Our approach leverages ultrasound imaging, a safer and more cost-effective modality, while still achieving detailed stone characterization. The proposed methodology, through pre-processing, segmentation, wavelet processing, and CNN classification, reduces the impact of low contrast and speckle noise**,** which are common limitations in ultrasound imaging.

The results demonstrate that the system can provide not just detection but actionable information, allowing healthcare professionals to understand the stone type and plan personalized interventions such as medication, diet changes, or minimally invasive procedures. Additionally, this method can assist in early detection of recurring stones and monitor treatment effectiveness over time.

In summary, the proposed work bridges a critical gap in automated kidney stone analysis. Unlike previous studies, which stop at detection, this study provides classification and type prediction, enhancing diagnostic capability and supporting better clinical decision-making**.** The integration of deep learning with advanced feature extraction techniques ensures high accuracy, reliability**,** and practical applicability in real-world medical scenarios.

Fig: 3 Identification of kidney stone type

The proposed system for automated kidney stone detection and classification was evaluated on a dataset of ultrasound kidney images collected from multiple scan centers. The dataset included images with and without kidney stones, with annotations provided by experienced sonographers. The evaluation focused on two main aspects: stone detection accuracy **and** stone type classification**.**

V. CONCLUSION

In this study, **a** novel automated system for kidney stone detection and classification using ultrasound images has been proposed. Unlike previous research, which focused solely on detecting the presence of stones, the proposed methodology not only identifies stones but also predicts their type**,** enabling more comprehensive diagnostic insights. By integrating image pre-processing, level set segmentation, wavelet-based feature extraction, and CNN classification**,** the system effectively handles challenges such as low contrast, speckle noise, and variability in kidney anatomy**.**

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