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Automated Detection of Kidney Stones and Their Characteristics in Kidney Ultrasound Images: Size, Area, and Location

Gurjeet Kaur[1], Dr. Sukhwinder Singh[2]

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Abstract: Ultrasound imaging is a widely adopted modality for kidney stone detection owing to its non-invasive nature and cost-effectiveness. However, challenges such as speckle noise and low contrast hinder the accuracy of diagnoses. This research addresses these challenges by focusing on enhancing ultrasound image quality, specifically targeting the precise localization and measurement of kidney stones. The proposed system employs Median filtering and contrast enhancement techniques to mitigate speckle noise and improve image quality, presenting a thorough comparative analysis with alternative filters. Additionally, the study explores the utilization of the Laplacian function for stone localization and size measurement. Moreover, this research introduces a Computer-Aided System for Kidney Stone Detection in Ultrasound Images, leveraging a Convolutional Neural Network (CNN). The balanced dataset, consisting of 9416 images categorized as 'Normal' and 'Stone,' facilitates robust training and testing of the CNN. Trained with Stochastic Gradient Descent (SGD), the CNN exhibits excellent performance with a training accuracy of 99.10% and a test accuracy of 99.11%.

Keywords: *Ultrasound Images, Speckle Noise, Stone Localization, Stone Size Measurement, Laplacian Function, CNN*

1. Introduction

Globally, kidney stones, also referred to as renal calculi, present a significant health challenge. The prevalence of kidney stones has been steadily rising, underscoring the need for advanced diagnostic tools to facilitate early detection and appropriate intervention. This paper addresses the imperative for an automated system to improve the quality of ultrasound kidney images, aiming to detect and categorize kidney stone sizes through the utilization of ultrasound images. Ultrasound imaging stands out for being non-invasive, radiation-free, cost-effective, and providing real-time insights into a person's internal structure, aiding doctors in identifying potential health risks or abnormalities. Despite its effectiveness in large medical applications due to absorption and speed, ultrasound imaging is often hindered by signal dependence, limiting the resolution of comparisons, and posing challenges in human interpretation and diagnosis. Consequently, speckle noise reduction becomes a crucial focus in medical ultrasound image processing.

In [1], a research author explores a patch-based low-level technique to mitigate noise in ultrasound images. Various methods, including Median filters, Gaber filters, Weiner filters, and Gaussian filters [2] [3], are employed to eliminate speckle noise, emphasizing the necessity to despeckle ultrasound images for improved quality and better differentiation of adjacent tissue boundaries. The linear elastic theory, proposed in [4], calculates the depth of shock wave scattering by determining fluid pressure, providing a treatment approach for various types of kidneys stones through external fluid immersion. Factors such as poor illumination, aperture size, shutter size, and others impact the range and grey level of each pixel, influencing image flaws. Contrast enhancement [5] [6] is proposed as a solution in such situations, aiming to improve contrast. 19 filters discussed to enhance the quality of kidney ultrasound images in a comprehensive study [14].

This concise overview explores recent developments in ultrasound imaging concerning the detection and sizing of kidney stones. The focus is on stone-specific algorithms (S-mode) and the evaluation of posterior acoustic shadow. Research by P.C May illustrates the effectiveness of S-mode in enhancing stone contrast and resolution, leading to precise visualization and sizing of renal stones. The identification of a posterior acoustic shadow emerges as a crucial indicator, aiding in differentiating stones larger than 5 mm. Comparative analyses with CT scans consistently demonstrate high accuracy rates, with S-mode surpassing conventional clinical ultrasound systems in stone visualization. Potential clinical implications include predicting spontaneous passage for stones lacking a shadow and guiding treatment decisions based on improved accuracy in stone characterization. These advancements hold promise for influencing clinical practices in kidney stone management [10]. A one more study address kidney stone size overestimation in ultrasound imaging, utilizing various modalities. Findings reveal that measuring the width of the acoustic shadow offers a more accurate assessment of true stone size, with

[11]Research Scholar, Punjabi University, Patiala, India
[2]Head, Department of computer science, Guru Hargobind Sahib Khalsa Girls college, Karhali Sahib, Patiala, India
** Corresponding Author Email: gurjeetkaurmangat@gmail.com*

harmonic imaging showing the highest precision. The incorporation of shadow measurements in ultrasound imaging holds the potential to enhance kidney stone sizing accuracy, as evidenced by 78% accuracy within 1 mm, comparable to clinical computerized tomography resolution [11].

The review notes ultrasound's cost-effectiveness and accessibility for nephrolithiasis but acknowledges limitations in sensitivity and accuracy, particularly in stone size measurement compared to computed tomography (CT). Despite advancements, CT is deemed superior. While the European Association of Urology recommends ultrasound as the initial investigation, the review concludes it may be suitable in specific situations but does not qualify as the ideal imaging technique for comprehensive nephrolithiasis assessment [12]. A retrospective study evaluates the sensitivity and specificity of ultrasonography (US) in detecting renal calculi and assesses its accuracy in determining stone size, examining the implications for counseling decisions. Findings reveal that US has limitations, with a sensitivity of 54% and a tendency to overestimate stone sizes in the 0–10 mm range. The study suggests that when using US alone, one in five patients may be inappropriately counseled. Combining plain abdominal film and US improves sensitivity to 78%, but some patients (37%) may still receive inappropriate counseling for observation. The conclusion underscores the need for caution in relying solely on US for clinical decision-making, emphasizing the potential necessity for additional imaging modalities to ensure accurate assessments and appropriate counseling [13]. Furthermore, very limited research work has been found on the measurement of kidney stone size, albeit with a limited sample size [6-9].

In a comparative study, author [15] assessed three neural network algorithms—Radial Basis Function, Learning Vector Quantization, and Multilayer Perception with Back Propagation—for recognizing kidney stone disease. Their experiment, conducted on a dataset of 1000 instances, revealed that the Multilayer Perception with Back Propagation algorithm outperformed others, achieving an accuracy of 92%. Additionally, a study [16] introduced a three-dimensional ultrasound system for automated kidney detection and segmentation, achieving a detection rate of 92.86% with a probabilistic kidney shape model. [17] proposed a method for kidney stone segmentation in ultrasound images, attaining 95% accuracy for non-stone images and 90% for stone images. Soumya and Narayanan [18] presented a computer-aided system for kidney disease detection with a manual region-of-interest selection, achieving a classification accuracy of 92%. Ranjitha [19] developed a system for kidney stone detection based on feature extraction and Principal Component Analysis, achieving 87.5% accuracy and 100% precision on a dataset of 26 ultrasound images. Additionally, Vaish and Bharath [20] designed an Android application for abnormality detection in B-mode ultrasound images, utilizing the Viola Jones algorithm and SVM classifier to achieve a detection accuracy of 90.91%.

A comprehensive review of existing literature outlines current methodologies in kidney stone detection, emphasizing the limitations and challenges faced by conventional approaches. The integration of advanced image processing techniques and machine learning algorithms is explored as a promising avenue for improving accuracy and efficiency.

The paper is organized into five sections: Noise Reduction and Image Quality Enhancement (Section II), Detection of Kidney Stone Size (Section III), Proposed Model (Section IV) and the conclusion of the research paper (Section V).

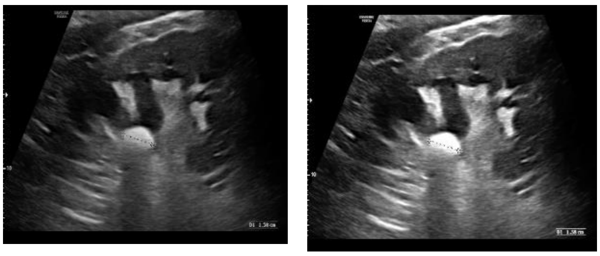
follow.

2. Noise Reduction and Image Enhancement

Low contrast and speckle noise pose challenges in ultrasound images. To address these issues in kidney ultrasound images, including speckle noise, acoustic noise, Gaussian noise, and other irregularities, preprocessing becomes imperative. This phase encompasses noise suppression, image restoration, contrast enhancement, smoothing, and sharpening, aiming to enhance the overall quality of ultrasound images. The methods employed include noise suppression, preservation of vital information, clarification of item boundaries, improvement of the region of interest's contrast, and reduction of background speckle. In the proposed model, various filters such as Bilateral, Gaussian, Median, and Blur filters are considered for speckle noise removal and image quality enhancement. The effectiveness of these filters is evaluated using metrics such as SSIM (Structural Similarity Index), PSNR (Peak Signal-to-Noise Ratio), and MSE (Mean Squared Error). The results of this evaluation, presented in Table-1, aid in selecting the optimal filter for noise suppression and overall image quality improvement.

Structural Similarity Index (SSIM): - The Structural Similarity Index (SSIM) serves as a metric for evaluating the similarity between two images. It considers luminance, contrast, and structure, proving particularly valuable in evaluating image quality degradation resulting from processes like compression, filtering, or transmission errors. SSIM values span from -1 to 1, with 1 denoting perfect similarity. Higher SSIM values are indicative of superior image quality. **Peak Signal-to-Noise Ratio (PSNR):** PSNR stands as a widely-used metric for quantifying the quality of a compressed or reconstructed image. It achieves this by measuring the ratio of the maximum possible power of a signal to the power of corrupting noise that impacts the fidelity of its representation. A higher PSNR corresponds to enhanced image quality, and it is often expressed in decibels (dB). **Mean Squared Error (MSE):** MSE serves as a measure of the average squared differences between corresponding pixels in the original and processed images. In the realm of image processing, MSE is employed to evaluate the quality of an image by calculating the average of squared errors between the original and compressed or reconstructed images. A lower MSE signifies superior image quality. Following the analysis, the outcome suggests the application of a Median filter to improve image quality and reduce speckle noise. The Median filter, being a non-linear digital filtering method, plays a role in noise reduction, particularly speckle noise. In this process, each pixel's value is substituted with the median value of its neighbouring pixels. Utilizing a Median filter contributes to refining image quality by smoothing noise and maintaining edge details.

Contrast Enhancement: Contrast enhancement involves a method to improve the clarity of ultrasound images, facilitating superior object edge detection as shown in figure: -1. The utilization of encv2.convertScaleAbs plays a pivotal role in this process, allowing the adjustment of the image's value range to heighten contrast and attain uniform intensity. This function achieves its goal by scaling and shifting pixel values based on specified alpha and beta parameters. The underlying objective is to augment the contrast of an input image, with the enhancement formula being expressed as new_pixel = alpha * original_pixel + beta. The alpha parameter serves as a contrast control, determining the extent of pixel value scaling, where a higher alpha corresponds to increased contrast (default set at 2.5). Meanwhile, the beta parameter functions as a brightness control, being added to each pixel value post-scaling with alpha (default set at 0).



Grayscale image　　Contrast enhanced image

Fig 1 Enhanced Image

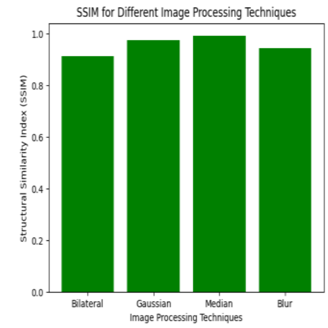
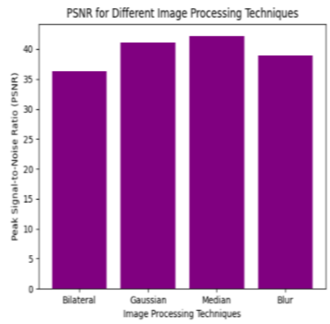
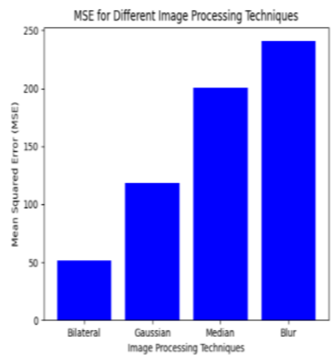
Filters/metrics	SSIM/PSNR/MSE	Comparison graphs
 Original Image	SSIM: 1.0 PSNR: 100 MSE: 0.0	
 Bilateral Filter	SSIM: 0.912580495 PSNR: 36.27934848 MSE: 51.56430081	
 Guassian Filter	SSIM: 0.974065011 PSNR: 41.06174115 MSE: 118.66057285	
 Median Filter	SSIM: 0.991307134 PSNR: 42.12787737 MSE: 200.4794760	
 Blur Filter	SSIM: 0.943623654 PSNR: 38.94561944 MSE: 240.62825311	

Fig 2: Enhanced Image Results

3. Detection of Kidney Stone Size

Detecting stone size from kidney ultrasound images involves utilizing image processing and computer vision techniques. Here is a general outline of the steps of proposed model to locate stone and calculate stone size as shown in Figure 3.

1.Image Acquisition: A dataset of kidney ultrasound images collected from various scan centres and hospitals. Each set of images includes two samples from the same patient: one with the detection of a kidney stone by a doctor or sonographer, and the other without the detection of a kidney stone problem. In dataset of kidney ultrasound images where, for each patient, two ultrasound images have been collected: **Image without Measurement of Kidney Stone:** This image serves as a reference or baseline, where the sonographer did not measure or detect any kidney stone. It represents the patient's kidney status when no stone is observed or measured during the ultrasound examination. **Image with Measurement by**

Sonographer: This image includes the measurement of a kidney stone by the sonographer. It indicates the presence of a kidney stone as identified and measured during the ultrasound examination. This dataset is valuable for tasks related to medical image analysis, particularly for developing and evaluating algorithms for kidney stone detection and comparing the proposed system result with actual result calculated by doctors.

2.Preprocessing: Remove noise and artifacts from the images and enhance contrast to make the stone boundaries more distinguishable. A median filter is applied to enhance image quality and reduce speckle noise. The selection of this filter is made after a comprehensive comparison using metrics such as PSNR, SSIM, and MIS. Additionally, the process involves grayscale conversion, contrast enhancement, and resizing the image to dimensions of 512x512. Collectively, these steps contribute to creating an optimized and refined input for subsequent analyses.

3.Image Segmentation: Segment the kidney region from the ultrasound image is done manually.

4.Feature Extraction: Extract relevant features from the segmented regions, such as area, perimeter, shape, and intensity characteristics.

5.Stone Size Estimation: Utilize the extracted features to estimate the size of the stones. Depending on the specific characteristics of the stones in ultrasound images, automatically detect stone perimeter in pixels and fix a specific value to calculate the result in form of centimetre(cm) and millimetre(mm).

6.Validation and Optimization: Comparing the outcome of proposed technique with the results obtained by sonographers or doctors is a crucial step in validating and optimizing any medical image processing or analysis method. **Validation:** Establish a ground truth by using the results provided by sonographers or doctors as the reference standard. This means that the measurements or findings by the healthcare professionals are considered the gold standard for validation. **Optimization:** By understanding features or aspects of the images contribute most to the differences between proposed method results and those of sonographers. This analysis can guide further optimization efforts.

Stone localization and size measurement Algorithm: The stone detection process involves a comprehensive image processing pipeline aimed at identifying and analysing stones within images. Beginning with Laplacian sharpening in Step 1, the pipeline enhances image details and edges. Subsequently, the background is removed using the rembg library in Step 2, resulting in a refined image. Step 3 employs contour detection and drawing to locate and outline stone areas. The final step, Step 4, analyses contours, providing valuable information about the stones, including their number and size. The integrated approach yields a robust stone detection system, with each step contributing to the accurate identification and characterization of stones within the images. All the steps for stone localization and size measurement, are discussed following with kidney ultrasound image namely “input image”:

Input Image

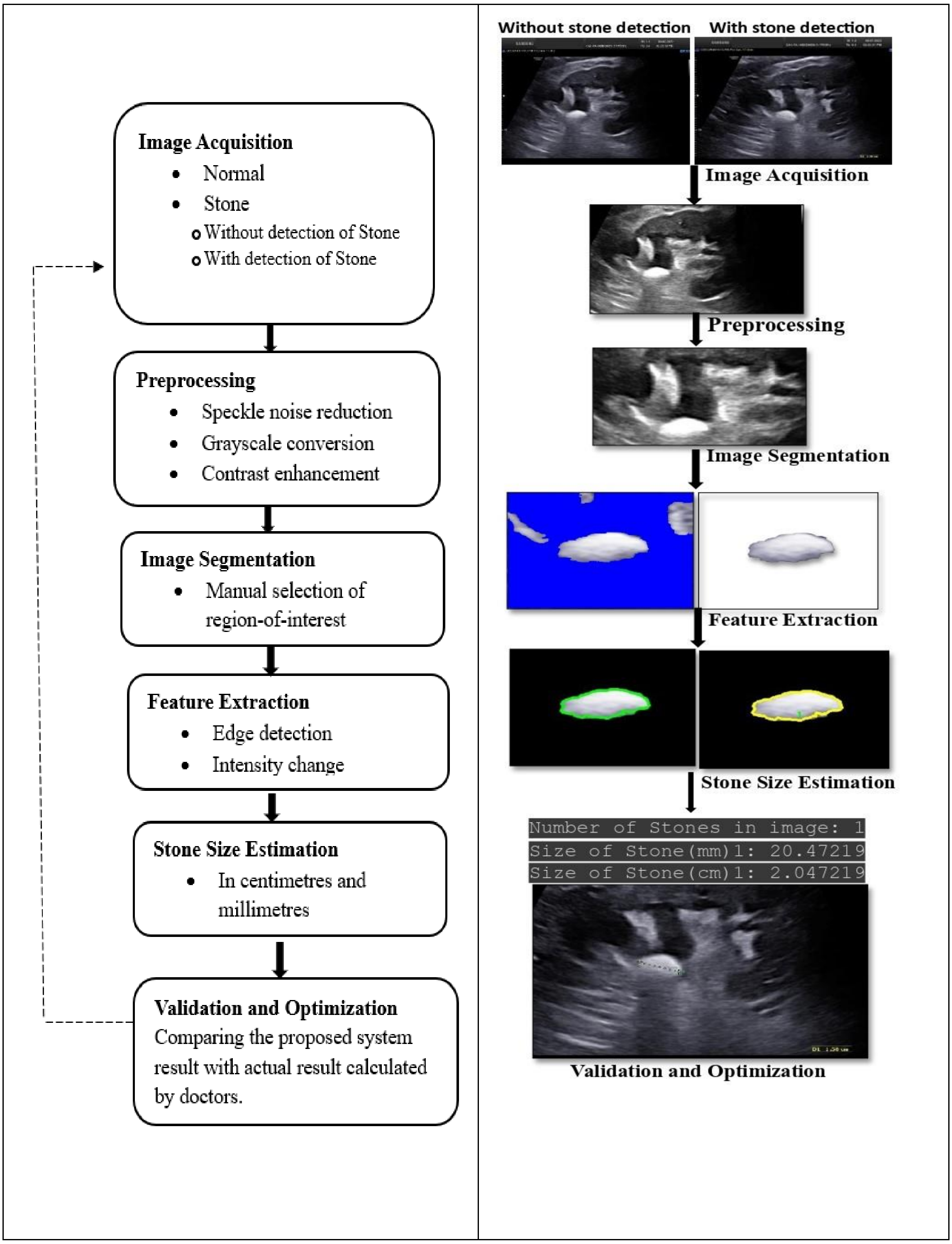


Fig 3 Methodology

Step1: Laplacian Operator: The cv2.Laplacian function is used to apply the Laplacian operator to the input image. The Laplacian operator is a second-order derivative filter that highlights regions of rapid intensity change in an image. It is commonly used for edge detection and image sharpening. The Laplacian-filtered image is then subtracted from the original image with a scaling factor (par) and get resultant image as image-1 as shown following. This process enhances the edges and details in the image.

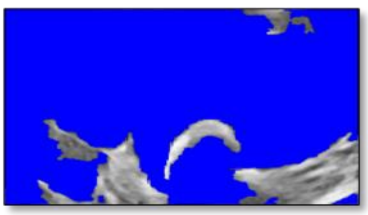


Image-1

Step2: In this step, rembg library is used which is a Python library that provides a straightforward way to remove the background from images. The primary purpose of rembg is to perform accurate and efficient background removal, often used in applications where isolating the main subject from the background is essential. The remove function from the rembg library to remove the background is applied on image-1 and save the output image with the removed background as shown following (image-2).

Image-2

Step3: Contour Detection and Contour Drawing is applied on image-2 to locate and outline the stone area as shown in image-3.

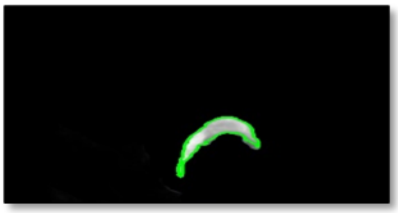
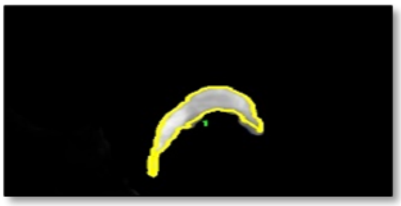


Image-3

Step-4: here analysing contours which are indicating to stones in an image, and provides information about the area, perimeter, and centroid of each contour. The result is then saved as an image with drawn contours and labelled with contour numbers as shown in "output image."



Output image

The outcome of our proposed method, measuring at 2.8 cm, is strikingly close to the doctors' measurement of 2.10 cm, as illustrated in Table-3. This alignment underscores the effectiveness and accuracy of method, showcasing its reliability in producing results that closely mirror those obtained through professional medical measurements.

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Proposed method

```
Number of Stones in image:1
Size of Stone(mm)1: 28.85251290930642
Size of Stone(cm)1: 2.885251290930642
```

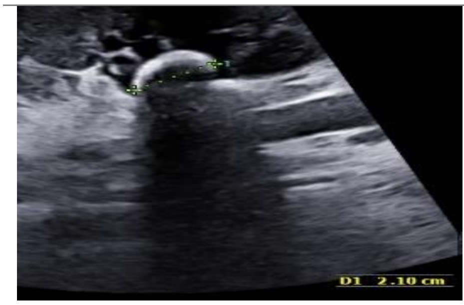
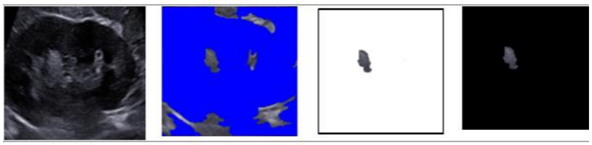


Fig 4 Accuracy

In Figure-5, the results of an additional experiment are depicted, featuring a normal image with no stones. The image elegantly demonstrates the robustness of method, revealing no detected objects and, consequently, no labels applied. This underscores the specificity of approach, affirming its ability to accurately discern and abstain from false positives in the absence of stones, thus enhancing its reliability in varied imaging scenarios.



Input Image	Image:1	Image:2	Image:3

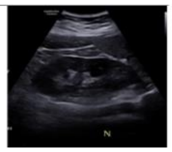
Proposed method	Doctors' measurement
Number of Stones in image: 0	

Fig 5 Results

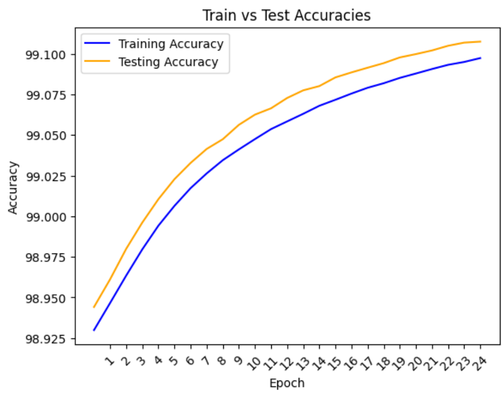
4. Proposed Method

This section outlines the comprehensive methodology employed in developing the proposed Computer-Aided System for Kidney Stone Detection. The research introduces an innovative image classification model built on a Convolutional Neural Network (CNN) architecture, emphasizing key contributions that enhance its effectiveness in spatial relationship tasks, particularly in image-centric applications. A crucial innovation lies in the optimization of parallel processing through the Data Parallel module, enhancing the model's scalability for large datasets and computationally demanding tasks. The model's adaptability, dynamically assessing GPU availability for seamless transitions across diverse computing environments, further underscores its practicality. The incorporation of the Cross-Entropy Loss function and Stochastic Gradient Descent (SGD) optimizer contributes to the model's stability and convergence, aligning with established practices in image classification. Additionally, the inclusion of a ResNet-based architecture enhances the model's performance, leveraging residual connections for improved training and convergence. The well-structured training loop, covering both training and evaluation phases with a focus on critical metrics like accuracy and loss, ensures a comprehensive approach to model assessment. The dataset description highlights the foundation of the model, comprising 9416 images categorized into 'Normal' and 'Stone,' with a balanced distribution for training (7533 images) and testing (1883 images). The preprocessing stage employs a median filter, grayscale conversion, contrast enhancement, and image resizing to optimize input quality for subsequent analyses. The CNN architecture, configured for kidney stone image classification, consists of three convolutional layers with max-pooling layers, culminating in two fully connected layers. Exceptionally high accuracies of 99.10% in training and 99.11% in testing validate the model's robustness through rigorous evaluation on 7533 training images and 1883 testing images as shown in Figure 6. Overall, this methodology lays a solid foundation for the proposed Computer-Aided System's efficacy in kidney stone detection, combining innovative design choices with thorough evaluation processes. In Evaluation Matrices, a total of 600 images featuring stones and 400 normal images were meticulously chosen from the dataset for detailed analysis. The resulting confusion matrix, derived from the model evaluation, is presented below:

ACTUAL\PREDICTED	STONE	NORMAL
STONE	595	5
NORMAL	4	396

Confusion matrix

The model's effectiveness was assessed using this metrics to offer a comprehensive evaluation: Accuracy: 99.1% Precision: 99.17%, and F1 Score: 99.25%. Collectively, these metrics affirm the model's proficiency in accurately distinguishing between stone and normal images, showcasing high precision and overall accuracy.



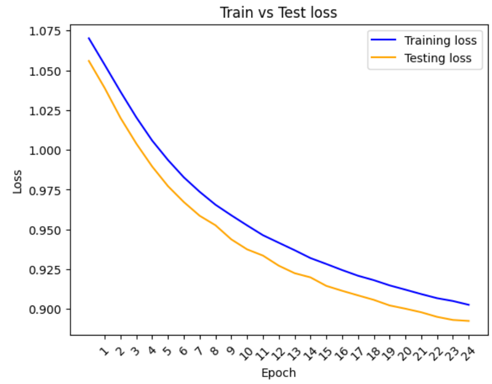


Fig 6 Train vs Test Loss

5. Conclusion

AThis research paper presents a novel approach for enhancing kidney ultrasound image quality and automating the detection and classification of kidney stone sizes. By effectively addressing speckle noise through median filtering and contrast enhancement, the study significantly improves image clarity. Additionally, the study explores the utilization of the Laplacian function for stone localization and size measurement. The developed Computer-Aided System, based on a Convolutional Neural Network, demonstrates exceptional accuracy in stone detection, with training and test accuracies surpassing 99%. The proposed methodology, incorporating advanced image processing techniques, holds promise for enhancing healthcare outcomes in kidney stone management, presenting a valuable contribution to the field.

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