Engineering Research Express

PAPER

# Detection of kidney stone using digital image processing: a holistic approach

IOP Publishing Eng. Res. Express 4 (2022) 035040 https://doi.org/10.1088/2631-8695/ac8b65

Engineering Research Express

RECEIVED
27 May 2022

REVISED
17 August 2022

ACCEPTED FOR PUBLICATION
19 August 2022

PUBLISHED
2 September 2022

PAPER

# Detection of kidney stone using digital image processing: a holistic approach

**Angshuman Khan**[1,*], **Rupayan Das**[2,*] and **M C Parameshwara**[3]

[1] Department of Electronics and Communication Engineering, University of Engineering and Management, Jaipur, Rajasthan-303807, India
[2] Department of Computer Science and Engineering, University of Engineering and Management, Jaipur, Rajasthan-303807, India
[3] Department of Electronics and Communication, Vemana Institute of Technology, Koramangala, VTU, Bengaluru-560034, Karnataka, India
[*] Author to whom any correspondence should be address.

**E-mail:** angshumankhan2910@gmail.com, rupayan11@gmail.com and pmcvit@gmail.com

**Keywords:** speckle suppression, ultrasound image, median filters, thresholding, image processing

## Abstract

This study presents an ultrasound speckle suppression method to detect the stones in the human kidney. An initial image is first improved using image enhancement techniques, which are used to change the image's intensities. Next, median filters smooth the picture and eliminate noise. Pre-processed images are segmented using a thresholding technique. The median filter extracts impulsive noise from salt-and-pepper noise. The suggested approach locates stones using location coordinates. Hospital and clinical ultrasound images were used to evaluate the proposed scheme and algorithm. The suggested scheme has been assessed by different performance measuring parameters. Physicians are likely to benefit from the research in terms of clinical diagnosis and educational training. Based on 50 test cases, the proposed plan was correct 96.82% of the time and sensitive 92.16% of the time. Furthermore, the peak signal to noise ratio is 1.82, and the average signal to noise ratio is 1.58, demonstrating the efficacy of the proposed approach.

## 1. Introduction

The kidney is a vital organ in the human body. Kidney stones have been a widespread problem in recent years. Kidney stones are solid pieces of material that form as a result of minerals in the urine. They are caused by a combination of genetic and environmental factors. It can also be caused by being overweight, eating certain foods, using certain medications, and not drinking enough water. Kidney stones affect people of all races, cultures, and locations. Blood tests, urine tests, and scans are all utilized to diagnose this kidney stone. If the stone is not identified early on, the situation might get serious, and surgery may be required to remove the stone. Image processing is a very effective way to properly detect the stone. Imaging is the most important component in the medical field. A clinician can examine the internal organs using medical imaging. CT scans, Ultrasound scans, and Doppler scans all have different scanning methods [1]. Nowadays, the automated technique is being employed in the medical industry to analyse diseases. Many frequent issues may arise due to the diagnosis by automation, such as the use of inaccurate results, inadequate algorithms, etc. Generally, the process of medical diagnosis is very complex and hazy. Additionally, several mathematical approaches were previously utilized to identify kidney stones using ultrasound images [2]. Among all the approaches for detecting kidney stones, image processing has the most advantages since it analyses the stone with great precision. Ultrasound imaging is one of the current non-invasive, low-cost, and commonly utilized imaging modalities for assessing renal disorders [3, 4]. The contribution of this work is summarized as follows.

1. Efficient speckle reduction approach is presented in this work.
2. The proposed scheme uses simple median filter instead of Gabor filter to make the image smooth and noise free.

3. Thresholding technique is used to perform image segmentation that makes the segmentation process strong.
4. Appropriate coordinate system is used to detect the stone correctly.
5. The proposed methodology is tested on practical ultrasound images collected from hospital.

The following is how the rest of the paper is organized: The existing works are covered in section 2. The problem statement and the proposed methodology was explained in section 3 and section 4, respectively. Results and analysis in presented in section 5. Finally, section 6 concludes the work.

## 2. Existing works

Several image-based screening technologies are now available for kidney stones, which are summarized in this section. A person's life might be placed at risk if an incorrect diagnosis is made of kidney stones in the body. Many imaging-based screening approaches are available to detect kidney stones today, and the following section summarizes these. The rotating sono-test was developed by Sun *et al* in 1994 to capture sonographic images of multiple edges [4]. Their strategy entails limiting specific vitality capacities because physically estimating kidney capacity is time-consuming and complicated. In article [5], the authors described a robust, efficient, multi-scale and non-linear thresholding scheme in which an original picture is split into two pieces using an adaptive filter. After being translated into a multi-scale defined wavelet domain, the coefficients of wavelet are then treated using a soft thresholding technique. While pursuing resolvable details, this approach substantially decreases speckle noise. According to the findings in [6, 7] , the main compositions of kidney stones are calcium oxalate (80%), calcium phosphate (70%), carbapatite (10%), uric acid (19%), and cystine (1%). In addition to that, the authors have pointed out various clinical elements such as stone passage, urological therapy of stones, and how stone-forming people's renal function is affected. Tsao, Chang, and Lin in [8] analysed the exact position of palpable urinary calculus and demonstrated its problems which are crucial for extracorporeal shock wave lithotripsy. Because it constantly uses stun waves to detect kidney stones. But the miss-hit of shock waves may harm the tissue badly. Their investigation revealed that the spot clamour exists in all ultrasonic images that should be removed.

In 2012, Sadeghi *et al* looked at the radiographic method, which employs an X-beam to hunt for stones more quickly and precisely. It demonstrates that most urethral stones are dull and cloudy. The barrier is that exact and precise recognition is limited in this manner [9]. In 2013, Rahman and Uddin created and implemented a system for segmenting the human kidney from ultrasound pictures, which can be used during surgical procedures such as punctures. After restoring an input picture, use the Gabor filter to minimize speckle noise and smooth the output image. Histogram equalization is used to improve the image quality [10]. By lowering specific vitality levels that confirm the presence of urinary calculus in a specific area, Viswanath and Gunasundari improved accuracy in 2014. To complete the procedure, the artificial neural network idea was effectively applied [11]. According to the article [12], authors have proposed a novel method for detecting the kidney stones. According to this report, ultrasound is far superior to computed tomography. In 2015, Viswanath and Gunasundari again an improved kidney stone detection procedure. To reduce speckle noise, the ultrasound picture is pre-processed and recovered. The reconstructed image is smoothed using a Gabor filter before being improved with histogram equalization. The stone area is detected using double-level set segmentation [13]. The three-dimensional kidney model created by Mallala *et al* was created using a c-arm tomographic imaging approach. Their findings demonstrated that c-arm tomography images of the kidney might yield matrices for the diagnosis of kidney stones. Unfortunately, evaluated tomography images of the kidney increase susceptibility to more radioactivity compare to traditional x-ray imaging, particularly in patients seeking frequent monitoring and youngsters with fewer bones [14]. In order to detect the kidney stones, the work [15] has applied a level set-based segmentation approach. In this approach, the input image is pre-processed and the region of interest is partitioned. In [16], the authors explored kidney stones in the human body and shown the way to identify them using image processing techniques. The technique uses pre-processing segmentation and morphological analysis. In [17], the authors have presented an image processing technique for detecting kidney stones without the use of humans. The segmentation and morphological studies have been done for the technique. The authors in [18] proposed a novel technique using Gabor transform to detect the edges in the computerized tomography (CT) and magnetic resonance image (MRI) images. The technique is very useful to detect the kidney stones as well. In [19], the authors introduced an automated kidney detection technique using 3-dimensional ultrasound image. This technique mainly determines the shape of the kidney. The scheme can also be used to detect the kidney stone. The work [20] mainly pointed out several image processing based methodology to detect stones in Gall Bladder. The work [21] proposed an improved scheme to detect stone in kidney from the ultrasound images. The scheme has used an improved image segmentation method in order to increase the accuracy. In order to predict and

**Table 1.** Comparative analysis of proposed and existing kidney stone detection schemes.

| Scheme | Speckle noise reduced? | Strength of image Segmentation | Image type | Signal to noise ratio | Detection accuracy? |
|---|---|---|---|---|---|
| [16] | No | Partially strong | Ultrasound image | Low | Low |
| [17] | No | Strong | Ultrasound image | Low | Low |
| [21] | No | Partially strong | Ultrasound image | Low | Low |
| [23] | Partially | Partially strong | Ultrasound image | Average | Low |
| Proposed scheme | Yes | Strong | Ultrasound image | High | High |

estimate the quality of the image, the authors of [22] suggested a methodology of extracting some local features of image. The work can show the future direction for detecting the kidney stones more accurately. In [23], authors examined an advanced scheme to detect the proper location of the stone. The work is divided in to several sub-phases such as pre-processing, segmentation, detection, and classification. The authors of [24] have proposed an efficient image classification method called ExDark19. The scheme has used transfer to detect kidney stones from CT images. The iterative neighbourhood component analysis (INCA) is incorporated to choose the most informative & significant feature vectors and then selected vectors are classified using k nearest neighbour (kNN) classifier with a ten-fold cross-validation technique to detect the stones. In order to reduce the inaccuracy in detecting stone, the authors of [25] have proposed back propagation network (BPN). The BPN can reduce the noise and detect classify the kidney stone properly. The work [26] has used bilateral filter, Adaptive Histogram Equalization, and watershed algorithm for the purpose of removing the noise, enhancing the image contrast, and image segmentation respectively to detect the kidney stone efficiently.

But, despite of having several research works on kidney stone detection, some of the recent works such as [23–26] are still suffering from the following limitations.

1. Many of them does not focus on reducing the unwanted signal from the ultrasound pictures as well as the quality of the image. Therefore, clinicians may have difficulty identifying small kidney stones and their location.
2. The segmentation process is not so strong towards detecting the stone.
3. The co-ordinates system is not able to detect & locate the stone accurately.
4. The schemes are not lightweight in terms of execution time and memory.

To address & mitigate the above research gaps we have proposed an efficient speckle suppression approach for ultrasound images to detect and locate kidney stone. On the contrary, the main motivation for this work is the shortcomings of the works mentioned earlier. In this work the kidney stone is discovered with its right placement from an ultrasound image. According to the literature review, the methodology and analysis involve manual data calculations that are time demanding. The proposed solution is reliable and reduces data processing time while maintaining accuracy. The comparative analysis of proposed and existing kidney stone detection schemes is presented in table 1.

## 3. Problem statement

Kidney-stones can be a life-threatening situation. Therefore, timely diagnosis is very essential. To ensure the efficacy of surgical operations, it is necessary to precisely diagnose kidney stones. Speckle noise and poor contrast in ultrasound pictures of the kidney make it difficult to detect stones. As a result, doctors may find it tough and confusing to recognize tiny kidney stones and their nature. To solve this problem, an image processing-based detection technique is proposed to determine the exact location of the stones.

## 4. Proposed methodology

The proposed method for detecting kidney stones is divided into several phases such as: image collection, feature extraction, image enhancement, image adjustment, segmentation, and morphological analysis. The detailed description of all phases is presented below.


**Figure 1.** Sample collected image-1.

### 4.1. Image collection

From multiple online datasets [27, 28] and radiologists, clinical ultrasound images are obtained. During August 2021, clinical emergency ultrasound photographs were collected from the Radiology department of St. Lukes Roosevelt Hospital, NY, United States, which are available online. Let us consider that the total collected image dataset is $d$. The dataset for quality images, $q = i(n)$, $n = 1, 2,...,N$. The quality is determined using a perception-based image quality evaluator score [24] with score $< = 40$. One image shown in figure 1 is chosen from the collection and put through the stone detecting process.

### 4.2. Feature extraction

In this work we use unsupervised learning technique called Principle Component Analysis (PCA) as feature extraction technique. The feature extraction technique is mainly executed with 5 phases such as: collecting data set, partitioning the data set, structuring the data set, calculating eigen values & eigen vectors, and finally the evaluating the new features by removing the duplicated and unwanted features. The detailed steps of PCA-based feature extraction is shown in figure 2.

### 4.3. Image enhancement

The goal of image enhancement is to slow down the deterioration of the ultrasound image that occurs during scanning acquisition. Noise, blurring, and camera misfocus can all cause degradation. The level set function is employed in this system to ensure proper orientation. It is under the image preprocessing step. The Merriman and Sethian methods are popular for image enhancement, especially for smoothening the curves and removing shrinks. The average intensity in the small neighbourhood is $\phi(m, n)$, and the median is $\vartheta(m, n)$, then the evolution between $\max(p,\ 0)$ and $\min(p,\ 0)$ is expressed using equation (1). The enhanced image corresponding to input image-1 is shown in figure 3.

$$w(m) = \begin{cases} \max(p,\ 0), & \text{if } \phi(m,\ n) < \vartheta(m,\ n), \\ \min(p,\ 0), & \text{otherwise} \end{cases} \tag{1}$$

### 4.4. Image adjustment

The CT images must be adjusted in the desired location, and the gray image region must be binarized. The system in MATLAB initially reads the grayscale image and sets the images matrix. A comparison is made using a threshold value of 20, with any pixel greater than 20 being classified as binary 1 and any pixel less than 20 as binary 0. As a result, the grayscale has been binarized. Figure 4 shows the adjusted image corresponding to input image-1.

### 4.5. Photo segmentation

It splits a digital photo into a set of pixels referred to as superpixels. This stage utilizes a clustering technique [18], which divides the input image into many groups depending on their intrinsic range from each other. It is being used to pinpoint the relevant features or the exact location in which the majority of the study must take place. Here, 250 pixels are kept as a threshold value to get the region of interest and wash out the extraneous parts. It is also called thresholding [19]. The segmented image corresponding to image-1 is shown in figure 5.

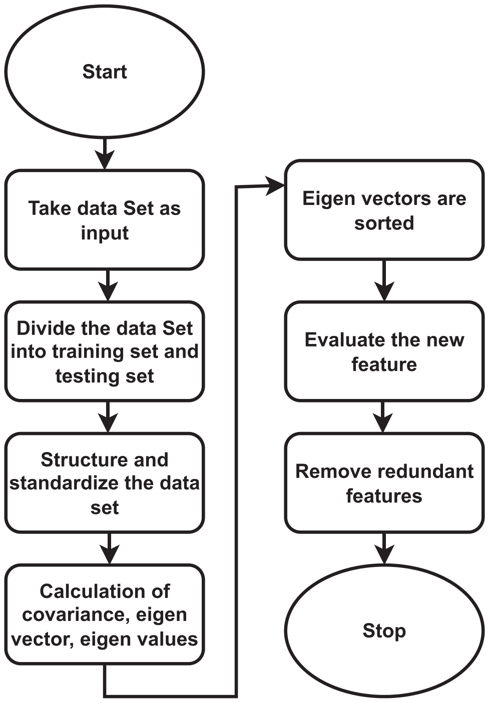


**Figure 2.** Steps of PCA-based feature extraction.


**Figure 3.** Enhanced image-1.

### 4.6. Morphological analysis

Morphological analysis transforms an objects shape [20] from one form to another. Morphological techniques are used to smooth the region of interest. Morphological procedures are used to process images based on their forms when organizing elements. It removes unnecessary information (pixels) from the outer part of the region of interest during processing. A closed parameter-based planar curve or surface is considered as $T(n, t)$: $[0, 1]mU^{+} \rightarrow U^{k}$. If $k = 3$ then it is the surface, and $k = 2$, then it is the planar curve. Here, $t$ is the time created by the starting curves movement $T_0(n)$ in the inward direction $R$. If $H$ is a force function, then the curve evolution equation is expressed as equation (2) and (3).

$$T(n,\ t = 0) = T_0(n) \tag{2}$$

$$T_t = H\bar{R} \tag{3}$$

In this experiment, a rectangular polygon is considered as a region of interest. The matrix representations of the coordinates of the vertices of a rectangle $ABCD$ are: vertex $A = [x_1, y_1]$, vertex $B = [x_1 + 200, y_1]$, vertex $C = [x_1 + 200, y_1 + 40]$, and vertex $D = [x_1, y_1 + 40]$, where, $x_1 = r/2, y_1 = c/3$, (r = row and c = column).

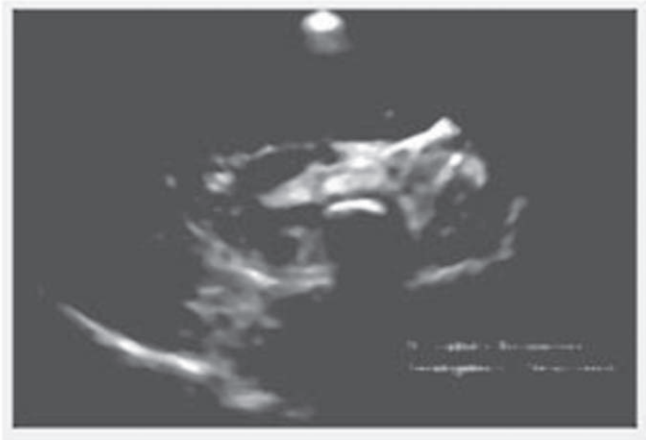

**Figure 4.** Adjusted image-1.

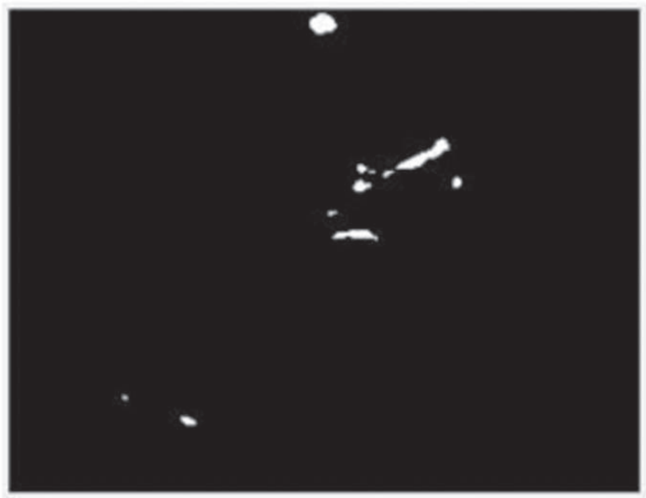

**Figure 5.** Segmented image-1.

The final output shows the shape and location of the stone inside the kidney. The number of detected stones is one, and the location is [164, 107]. After implementing the proposed technique, there were some discrepancies in the exact position of the kidney stone, which could be addressed by adjusting the intensity of each ultrasound imaging of the kidney stone. Using the provided methods, stone detection accuracy was 96.82%. Physicians can employ the proposed technology as an approved therapy approach to remove kidney stones in a timely manner. The final output with possible one detected stone for image-1 is shown in figure 6.

For second sample image-2 shown in figure 7 was analysed using the same method, and two potential stones were found after the final output, as shown in figure 8. Because there are two stones found, the locations are [431, 329] and [465, 338].

### 4.7. Description of proposed scheme

The procedure of the proposed scheme is presented through algorithm 1. The proposed image processing model first takes a fresh RGB image as an input which is collected from clinical laboratory. Thereafter, we convert the image from RGB to Gray and keep pixel values greater than 20 (threshold value) in order to binarized the gray scale image. From the literature review, we observed that the process of binarization provides better result for the pixels greater than 20. Now if there exist holes at the background then we need to fill those holes as a part of morphological operation. Then removes all connected components that have fewer than 1000 pixels. In this experiment, a rectangular polygon is considered as a region of interest. This region of interest is further pre-processed and presented in RGB matrix form by using matrix representation, manipulation and intensity mapping of the multiple copies of image (denoted as F in algorithm 1). After that, the pre-processed RGB image

**Figure 6.** Final output with possible one detected stone for image-1.

**Figure 7.** Collected sample image-2.

**Figure 8.** Final output with possible two detected stones at image-2.

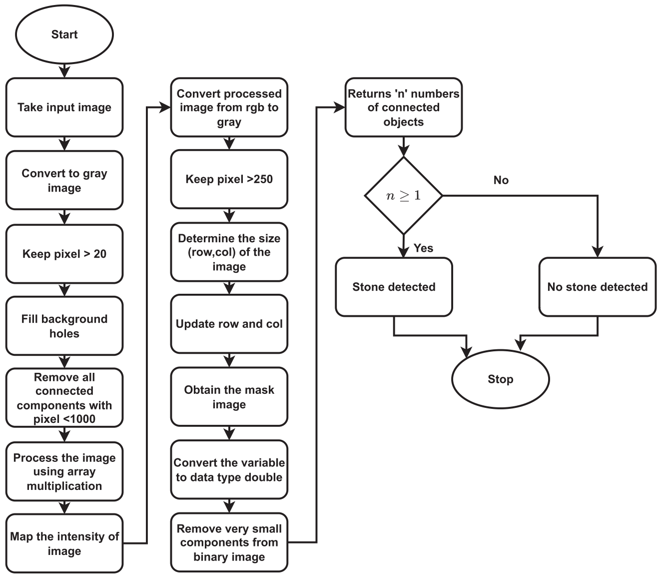


**Figure 9.** Flow chart of proposed scheme.

is converted into gray scale image. In order to reduce the noise, we perform median filtering process in the pre-processing step of the image. We generally try to keep the pixel more than 250 so that noise is reduced. After pre-processing the image, we determine the size of the image. The calculated size of the image is further used to rescale the image in order to enhance the quality. Next, we determine the mask as binary image using interactive polygon technique. Then we remove all the connected components of the binary image that have fewer than 4 pixels. After that, the label of the binary image is determined and number of connected components are determined. If the number of connected components of the produced binary image is greater than or equals to 1 then we can conclude that the kidney stone is detected. Otherwise, for any other conditions, we cannot confirm the detection of kidney stone. The flowchart of our proposed algorithm is shown in figure 9.

**Algorithm 1.** Stone detecting procedure

Input: An input image X
Output: Print either 'Stone is detected' or "No stone is detected"
$A \leftarrow imread(X)$ ▷ read input image X and store the information to variable A
$Z \leftarrow rgb2gray(A)$ ▷ converts RGB image to gray scale image and store it to Z
$C \leftarrow (Z > 20)$ ▷ keep the pixel value which are greater than 20 (threshold value) to binarized the image]
$D \leftarrow imfill(C, 'holes')$ ▷ fill the background holes and save the image to D
$F \leftarrow bwareaopen(D, 1000)$ ▷ removes all connected components that have fewer than 1000 pixels
$Preprocessed\ \ Image \leftarrow uint8(double(a).*\ repmat(F, [113]))$ ▷ matrix representation and manipulation of the copies of F
$Preprocessed\ \ Image \leftarrow (imadjust(Preprocessed\ \ Image, [0.30.7], []) + 50)$ ▷ intensity mapping
$U \leftarrow rgb2gray(Preprocessed\ \ Image)$ ▷ converts RGB image to gray scale image and store it to U
$M \leftarrow medfilt2(U, [55])$ ▷ performs median filtering
$P \leftarrow (M > 250)$ ▷ keep the pixel value which are greater than 250
$[rc] \leftarrow size(P)$ ▷ returns the array (P) length
$x1 \leftarrow r/2$ ▷ initialization of x coordinates
$y1 \leftarrow c/3$ ▷ initialization of x coordinates
$row \leftarrow [x1\ x1 + 200\ x1 + 200\ x1]$ ▷ updation of row of the matrix of binary image $col \leftarrow [y1\ y1\ y1 + 40\ y1 + 40]$ ▷ updation of row of the matrix of binary image
$BW \leftarrow roipoly(P, row, col)$ ▷ returns mask as binary image BW using interactive polygon technique
$k1 \leftarrow (P.*\ double(BW))$ ▷ convert the data type of binary image into double precision
$N \leftarrow bwareaopen(k1, 4)$ ▷ removes all connected components that have fewer than 4 pixels
$[ya\ \ number] \leftarrow bwlabel(N)$ ▷ finding the label of binary image
**if** $N \geqslant 1$ **then**
print ('Stone is Detected')
**else** ▷ displaying the result
print ('No Stone is Detected')
**end if**

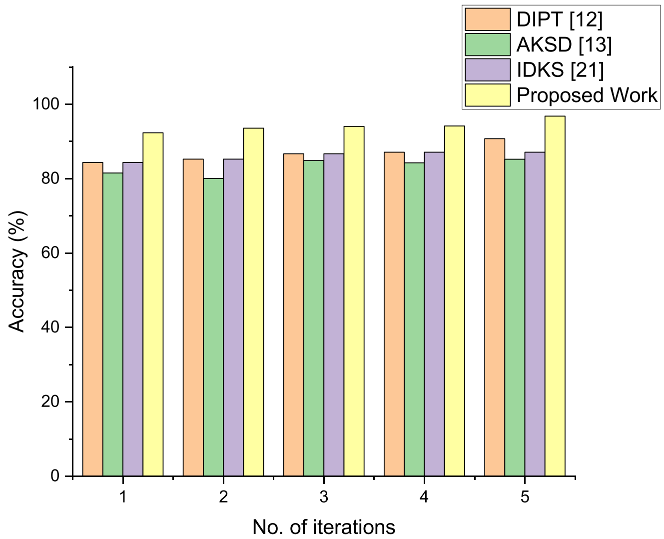


**Figure 10.** Comparison of accuracy of proposed and base line algorithms.

**Table 2.** Performance analysis of existing kidney stone detection schemes with respect to 50 test cases.

| Scheme | Peak signal to noise ratio | Signal to noise ratio | Accuracy (%) | Sensitivity (%) |
|---|---|---|---|---|
| DIPT [16] | 0.92 | 0.88 | 90.75 | 88 |
| AKSD [17] | 1.20 | 1.02 | 85.22 | 85 |
| IDKS [21] | 1.10 | 0.98 | 87.11 | 90.11 |
| Proposed scheme | 1.82 | 1.58 | 96.82 | 92.16 |

### 4.8. Time complexity and Scalability of proposed scheme

In this sub-section we determine the time complexity of the proposed algorithm. At first, we take an image with size $n^*m$. Next to store the image we need $n^*m$ matrix. So to store and represent an image $O(n^2)$ time is required. Thereafter the time complexity for PCA-based feature extraction phase is $O(f^{3*}d^3)$ where $f$, & $d$ indicates number data points and number of features respectively. For rest of the steps like image enhancement, adjustment, segmentation, and morphological analysis again $O(n^2)$ time is required. So in total we need $O(n^2) + O(f^{3*}d^3)$ time to execute the proposed algorithm. Along with the time complexity we also observed the performance of the proposed scheme by varying the number of samples (test cases). We have increased the number of samples from 50 (base-line figure) to 100 and observed that even if the number of samples are more, our scheme still can perform well in linear fashion. Hence, the proposed scheme is scalable.

## 5. Results and analysis

To carry out the proposed analysis, the framework first examines images of ultrasound scans of patients with stones in MATLAB 2017b platform. After that, we create the organizing component before moving on to the rest of the procedure. The final outcomes of the suggested scheme are shown in figure 6 and figure 8, which are produced using the methodology mentioned earlier. In addition, the comparative analysis of the proposed work and three base line schemes such as DIPT [16], AKSD [17], and IDKS [21] are shown in figure 10. It has been observed that our scheme performs better compare to other existing schemes after 5th iteration. We considered following parameters in order to compare our work.

1. Signal to noise ratio: It determines the noise suppression in multiplicative coherent pictures, which is mostly used in coherence imaging.
2. Accuracy: It indicates the True Positive & True Negative Rate.
3. Sensitivity: is also referred as True Positive Rate.

4. Peak signal to noise ratio: It is the ratio of the maximum achievable value (power) to the power of distortion noise. After rebuilding, it identifies the losses and lossy compression.

The performance our proposed scheme is compared with base-line schemes with respect to above-mentioned parameters and presented in table 2.

## 6. Conclusion

Pre-processing, fragmentation, and the feature extraction on the input image are the basic and key functions of our proposed scheme for spotting the presence of kidney stones. The feature extraction approach was used to measure the precise coordinates of the stone and the overall appearance of the stones created from the picture. Doctors could intelligently diagnose kidney stones following the surgery by using a composite of all three methods. The accuracy of the proposed method is 96.82%, which is acceptable compared to base line algorithms but we can extend the work by proposing artificial neural network-based methodology to achieve more accuracy. Moreover, we can propose Internet of Things (IoT) based stone detection module which can contribute to several emerging research works like IoT-based healthcare, tele-medicine technology, etc.

## Data availability statement

No new data were created or analysed in this study.

## ORCID iDs

Angshuman Khan https://orcid.org/0000-0002-1298-628X
Rupayan Das https://orcid.org/0000-0002-3713-2459
M C Parameshwara https://orcid.org/0000-0002-8401-8114

## References

[1] Raja R A and Ranjani J J 2013 Segment based detection and quantification of kidney stones and its symmetric analysis using texture properties based on logical operators with ultra sound scanning *International Journal of Computer Applications* **1** 8–15
[2] Manikandan S and Rajamani V 2008 A mathematical approach for feature selection & image retrieval of ultra sound kidney image databases *European Journal of Scientific Research* **24** 163–71
[3] Hafizah W M and Supriyanto E 2012 Automatic generation of region of interest for kidney ultrasound images using texture analysis *International Journal of Biology and Biomedical Engineering* **3** 26–34
[4] Sun Y N, Lee J S, Chang J C and Yao W J 1994 Three-dimensional reconstruction of kidney from ultrasonic images *In: IEEE Workshop on Biomedical Image Analysis* 43–9
[5] Hao X, Gao S and Gao X 1999 A novel multiscale nonlinear thresholding method for ultrasonic speckle suppressing *IEEE Trans. Med. Imaging* **18** 787–94
[6] Coe F L and Evan A 2005 Worcester E. Kidney stone disease *J. Clin. Invest.* **115** 2598–608
[7] Singh V R and Singh S 1998 Ultrasonic parameters of renal calculi *In: IEEE XX Annual International Conference on Engineering in Medicine and Biology Society* **2** 862–5
[8] Tsao J, Chang L H and Lin C H 2005 Ultrasonic renal-stone detection and identification for extracorporeal lithotripsy *In: IEEE Engineering in Medicine and Biology 27th Annual Conference* 6254–7
[9] Sadeghi M, Shafiee M, Memarzadeh-zavareh F and Shafieirad H A 2012 New method for the diagnosis of urinary tract stone in radiographs with image processing *II International Conference on Computer Science and Network Technology* 2242–4
[10] Rahman T and Uddin M S 2013 Speckle noise reduction and segmentation of kidney regions from ultrasound image *In: International Conference on Informatics, Electronics and Vision (ICIEV)* 1–5
[11] Viswanath K and Gunasundari R 2014 Design and analysis performance of kidney stone detection from ultrasound image by level set segmentation and ANN classification *In: International Conference on Advances in Computing, Communications and Informatics (ICACCI)* 407–14
[12] Cunitz B *et al* 2014 Improved detection of kidney stones using an optimized Doppler imaging sequence *In: IEEE International Ultrasonics Symposium* 452–5
[13] Viswanath K and Gunasundari R 2015 Analysis and implementation of kidney stone detection by reaction diffusion level set segmentation using xilinx system generator on fpga, VLSI design (https://doi.org/10.1155/2015/581961)
[14] Malalla N A, Sun P, Chen Y, Lipkin M E, Preminger G M and Qin J 2016 C-arm technique with distance driven for nephrolithiasis and kidney stones detection: Preliminary study *IEEE-EMBS International Conference on Biomedical and Health Informatics* **BHI** 164–7
[15] Akkasaligar P T, Biradar S and Kumbar V 2017 Kidney stone detection in computed tomography images *International Conference on Smart Technologies For Smart Nation (SmartTechCon)* 353–6
[16] Suresh M B and Abhishek M R 2021 Kidney stone detection using digital image processing techniques *Third International Conference on Inventive Research in Computing Applications (ICIRCA)* 556–61
[17] Rajput S, Singh A and Gupta R 2021 Automated kidney stone detection using image processing techniques *In: International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)* 1–5

[18] Sungheetha D A 2020 GTIKF-gabor-transform incorporated K-means and fuzzy C means clustering for edge detection in CT and MRI *Journal of Soft Computing Paradigm* **2** 111–9

[19] Marsousi M, Plataniotis K N and Stergiopoulos S 2014 Shape-based kidney detection and segmentation three-dimensional abdominal ultrasound images *In: IEEE 36th Annual International Conference of Engineering in Medicine and Biology Society* 2890–4

[20] Garg S, Walia A, Singh A and Mishra A 2017 A study on shape detection: an unexplored parameter in the gall stones identification *In: International Conference on Smart Systems, Innovation and Computing* 445–54

[21] Goel R and Jain A 2020 Improved detection of kidney stone in ultrasound images using segmentation techniques *Advances in Data and Information Sciences* (Berlin: Springer) pp 623–41

[22] Venkatanath N, Praneeth D, Bh M C, Channappayya S S and Medasani S S 2015 Blind image quality evaluation using perception-based features *In: 21st National Conference on Communications (NCC)* 1–6

[23] Valencia F A C, Munoj J J A M and Montano F M J 2022 Stone detection in kidney with image processing technique: CT images *Journal of Positive School Psychology* **6** 7643–53

[24] Baygin M, Yaman O, Barua P D, Dogan S, Tuncer T and Acharya U R 2022 Exemplar darknet19 feature generation technique for automated kidney stone detection with coronal CT images *Artif. Intell. Med.* **127** 102274

[25] Karthik P and Vikas A L 2021 Kidney stone detection using image processing and neural networks *Annals of the Romanian Society for Cell Biology* **25** 13112–9

[26] Borges T, Rai A, Raj D, Ather D and Gupta K 2022 Kidney stone detection using ultrasound images 310–7

[27] Geertsma T 2021 *Ultrasound Images & Clips* https://www.ultrasoundcases.info/fornix-rupture-745, Accessed (online): August

[28] Antony J 2021 Ultrasound images of diseases of the kidneys https://www.ultrasound-images.com, Accessed (online): August