Date of publication DEC-31, 2022, date of current version DEC-06, 2022.
www.computingonline.net / computing@computingonline.net

*Print ISSN 1727-6209*
*Online ISSN 2312-5381*
*DOI 10.47839/ijc.21.4.2780*

# Entropy Based Segmentation Model for Kidney Stone and Cyst on Ultrasound Image

**MINO GEORGE, ANITA HADADI BHIMASENA**
Department of Computer Science, CHRIST (Deemed to be University), Bengaluru, India.
(e-mail: minogeorge@res.christuniversity.in, anita.hb@christuniversity.in)

Corresponding author: Mino George (e-mail: minogeorge@res.christuniversity.in).

**ABSTRACT** Segmentation of abnormal masses in kidney images is a tough task. One of the main challenges is the presence of speckle noise, which will restrain the valuable information for the medical practitioners. Hence, the detection and segmentation of the affected regions vary in accuracies. The proposed model includes pre-processing and segmentation of the diseased region. The pre-processing consists of Gaussian filtering and Contrast Limited Adaptive Histogram Equalization (CLHE) to improve the clarity of the images. Further, segmentation has been done based on the entropy of the image and gamma correction has been done to improve the overall brightness of the images. An optimal global threshold value is selected to extract the region of interest and measures the area. The model is analyzed with statistical parameters like Jaccard index and Dice coefficient and compared with the ground truth images. To check the accuracy of the segmentation, relative error is calculated. This framework can be used by radiologists in diagnosing kidney patients.

**KEYWORDS** Pre-processing; Segmentation; Image filters; Kidney diseases; Entropy; Gamma correction; Kidney ultrasound; Thresholding; Kidney stone; Kidney Cyst.

## I. INTRODUCTION

ULTRASOUND imaging is considering as the initial diagnostic tool in detecting all types of kidney diseases. Kidney diseases occurs when the kidneys become damaged and unable to perform their functions. A kidney ultrasound is used to assess the size, location, and shape of the kidneys. It can detect cysts, calculi (stone), abscesses, obstructions, fluid collection, and infections within or around the kidneys. This mode of imaging can be repeated many times because of it is harmless and economic nature. However, certain difficulties are present in precise kidney diseases diagnosis. The major issue is presence of speckle noise, and this makes the poor-quality images. Sometimes the edges of the images are blurred and this may mislead the radiologist. Kidney stone and cyst are those kinds of diseases which requires accurate diagnosis.

An efficient automated stone and cyst segmentation method is not much addressed. The heterogenous structure and the similar pixel intensity regions for a non- stone and cyst region makes segmentation difficult and time consuming. Segmenting the ROI accurately in the kidney image is difficult because the stones and cysts does not have fixed size, shape or location. These problems are adequately handled in the proposed model. Moreover, doctors are detecting and measuring the size and location of these regions by manually. Hence, it is very much important to have an advanced framework, which can improve the quality and segment the diseased region automatically.

The propose model focus at accurate detection and measuring of stones and cysts. The paper is organized in different sections as follows. Section II, presents the related work and the proposed framework is shown in Section III. Section IV, explains the results and analysis. The last, section V includes conclusion.

## II. RELATED WORK

Denoising of US images is a challenging task. Denoising plays a vital role in accurate diseases diagnosis. A comparative study on various filter such as median, Gaussian Weiner and Gabor filters has been done in [1, 2]. A review on of different wavelet functions which is widely used for filtering is discussed in [3]. The author states that Daubechies and Symlet provide almost same results and to de-noise very noisy images (PSNR < 15 dB) a first filter order is preferred. whereas as the noise level increases the wavelet functions with higher filter order (3rd–4th order) are more effective. A novel Bayesian Multiscale method for speckle removal is presented in [4]. An automatic region of interest generation for kidney ultrasound images is proposed in [5]. In this, the median filter, Wiener filter and Gaussian low-pass filter were implemented to reduce the speckle. The Gaussian low-pass filter, threshold value of 0.7 gave highest ROI which scored 100% of accuracy. Hence, the proposed model uses gaussian filter to eliminate the speckle noises.

Segmenting the exact region of cysts and stone without any human intervention requires highly efficient models. Active Shape Model (ASM) is a widely accepted technique in image segmentation. The model has proved to be more efficient and reliable. Global Shape Priors help to solve the shape variability and in mixing the models for the segmentation [6]. Segmentation of kidney organ in 2D and 3D images were carried out by using active shape models [6, 7]. The combination of region information and global shape prior in the active contour method improves the speed of the segmentation. However, the boundaries that appear are unclear [8, 9]. Tamilselvi and Thangaraj developed a Computer Aided Design (CAD) system for stone detection and early prediction using seed region growing segmentation method and it yielded 99.8% of accuracy [10]. A multi-kernel k-means clustering algorithm is applied to segment the cysts and tumor regions in the kidney US images. The proposed model discusses about the hybridization of linear and quadratic kernel and it achieves good segmentation accuracy [11]. However, the kidney region is selected manually. Several studies have demonstrated that the kidney disease detection could be improved without manual kidney segmentation. There were many researches focusing on kidney stone and tumor with better accuracies [12]. But an automatic cyst and stone detection model is not yet designed. There were many deep learning-based approaches are developed for segmentation and classification, which performs excellently [13]. However, there is an inconsistency in the outcome and they have opted a manual kidney segmentation technique. Hence, the proposed model segments the kidney diseases automatically and achieves better accuracy.

A Dynamic Graph Cuts Method is applied to segment the kidneys in US images [14]. Renal calculi and cysts are extracted using region-based contour method in [15]. Segmentation using networks is explained [16]. In this paper, pixel classification networks to segment the kidneys automatically. A technique called recursive minimum cross entropy is used to perform efficient segmentation in [17]. The proposed method makes use of local statistics of the image.

Active contour method is a widely used model to extract the kidney region [18]. Texture and shape play an important role in kidney segmentation [19]. Classification of Kidney images using texture properties based on Logical operators is proposed [20]. The paper deals with the idea of different regions of an image are identified based on texture properties. Considering only renal stones, many methods are proposed, region growing algorithm is used to extract the kidney stones parameters are extracted from the segmented region [21]. To segment only the kidney stone, k-means is used and extracted in [22].

Recent developments in the renal imaging field are discussed in [23]. Various methods and advancements in the ultrasound imaging modality is explained. Also, a comprehensive review on automated localization and segmentation techniques are carried out in [24]. Majority of the researches in the literature review are carried out with manually segmented kidney region. Besides that, many methods lack accuracy but still, some are showing good performance. An automatic kidney disease system is proposed in this paper [25]. In this paper, we have proposed an automatic segmentation model for both cysts and stones which is not much addressed. Currently, the radiologists are diagnosing the stones and cysts manually and this is time consuming. There are chances to develop discrepancies in opinions among doctors in disease diagnosis. The decisions may vary from one doctor to another depends on the experience. Thus, proposed model will assist the doctors in decision making.

## III. METHODOLOGY

The proposed model detects and segments the kidney cysts and stones in the US images. This model consists of various steps such as pre-processing, segmentation and results analysis**.** Each step includes different methods. The ground truth image and the experimentally obtained image is compared to assess the accuracy of segmentation. Therefore, Jaccard dice and dice coefficient of the output image is calculated. The proposed framework is shown in Fig. 1.

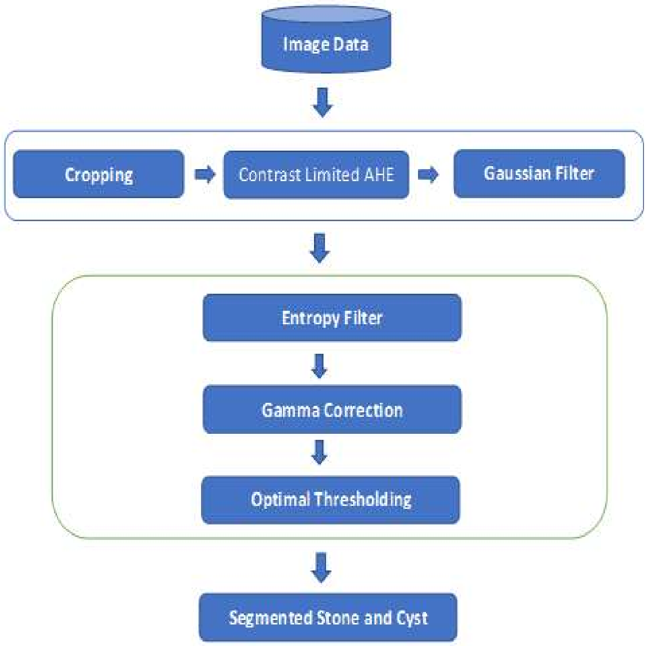


Figure 1. Flow diagram of proposed model

### A. IMAGE DATA SET

The dataset consists of US images of kidney cysts and stones collected from the hospital. The images are acquired from Nemio XG, Thoshiba, General Electricals and Samsung ultrasound machines with linear transducers having a frequency of 3.5 to 5 MHz. The images are collected with the help of a radiologist and each lesion in the dataset was outlined manually. The images include multiple stones and cysts. Before collecting and saving removed all the patient details from the images. The disease details such as stones and cysts size and location are collected from the radiologist. All the two categories of image have different dimensions such as cyst images are of 576X720 and stone images are of 614X820 pixel size. These images are cropped into 200x400 size manually. Thus, all the textual markings are removed. Sample images of kidney stone and cyst are shown in Fig. 2.

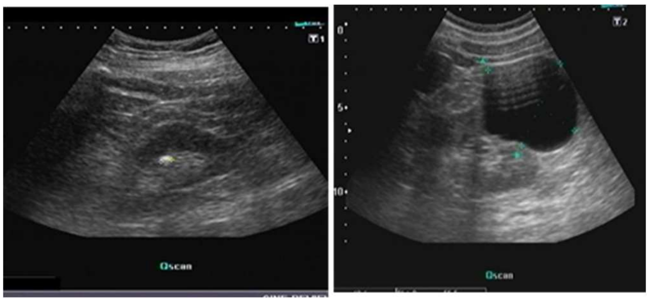

Figure 2. Sample images of kidney cyst and stone

### B. PRE-PROCESSING

The US images are degraded with the presence of speckle noise. Due to this noise, the resolution and contrast are affected and this affect the disease diagnosis. So, speckle removal is an important step in pre-processing. Gaussian filter is one of the most widely used image filter, which helps to filter the noises. It removes the high frequency components from the images as it is a non-uniform low pass filter. It is used to blur and remove the noise from the images. The Gaussian smoothing works by using the 2-D distribution as a point-spread function, and this is achieved by convolution. The σ is the standard deviation and it plays a vital role in the behaviour of Gaussian function. The distribution is assumed to have a mean of zero. The larger values of σ, wider peak, means greater blurring. Kernel size must increase with increasing σ to maintain the Gaussian nature of the filter. At the edge of the kernels, coefficients must be close to 0. Further, the denoised images are enhanced by Contrast Limited Adaptive Histogram Equalization technique (CLAHE), which helps to adjust the contrast and enhancing the edges of the image. This method limits the increased amplification of contrast. It is used to restore the image by removing the noise without significantly blurring the structures in the image. It operates on small regions, called tiles, instead of entire image. The image with gamma value 3 returns more accurate output image. The enhanced image is shown in Fig. 3.

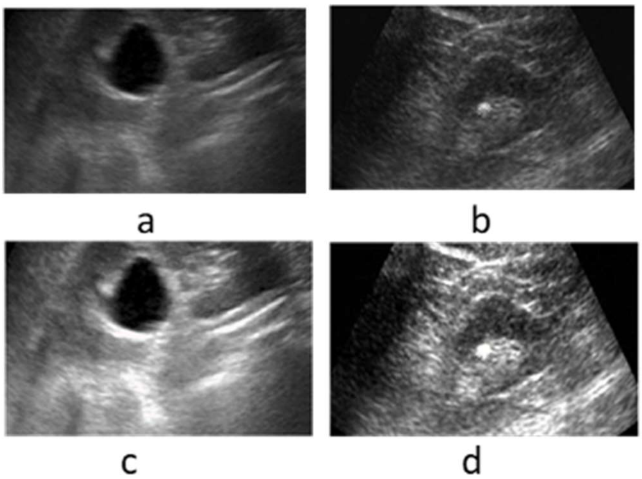


Figure 3. a and b are the original images of kidney cyst and stone. c and d are the enhanced images

### C. SEGMENTATION

Segmentation finds a group of pixels which carries similar features and attributes. Clustering of these pixels can be based on the similar, dissimilar pixels and discrete pixel values. In ultrasound images, the number of similar intensity pixels are numerous. Thus, texture features are more suitable for segmentation. Entropy evaluates the intensity difference between the pixels in the image [26]. When the variance of intensity is high, the contrast is also high. If the difference between the maximum and minimum gray intensities are small, the image has low entropy and low contrast. An entropy-based segmentation can provide good information about the distribution of gray levels p(x) or the intensity of multiple colour components present in an image. The concept of Shannon entropy is used to describe an image, where it defines the minimum descriptive complexity of a random variable.

In image analysis, if all the pixels having same intensities, the image will generate a minimal entropy value. However, if each pixel of an image represents a specific intensity, then the image will produce maximum entropy. Different textures maintain different gray level intensities to the pixels. Hence, pixel intensities are related to texture, entropy can be applied for texture-based segmentation. The ROI is clearly visible in entropy filtered image, however, to measure the size of the region needs more processing. At this point, gamma correction is applied to enhance the dark and light intensity of the image and improves the brightness [27]. It performs nonlinear methods to every pixel. A stable gamma value is required and it should not be too maximum and minimum. The images are saturated by a gamma value of 3.

An optimal threshold value is applied to separate the ROI from image regions. Global thresholding finds the threshold value based on the histogram of the complete pixel intensity distribution of the image. An optimal threshold value T is selected to extract the cyst and stone regions. The optimal threshold value T is calculated as the gray level that has a minimum value between two overlapping distributions. The algorithm is as follows:

Step 1: An initial value T is selected.

Step 2: The histogram shows two groups of mean values s1 and s2. In that s1 >T and s2<T values are calculated.

Step 3: New threshold is calculated by the following formula T = ½ (s1+s2).

Step 4: Step 2 is repeated until the threshold is stabilized.

The selection of T is an important step, which affects the quality of the segmented ROI. After thresholding, the stones and cysts images are converted to binary format. The area is calculated and it nothing but the number of pixels covered the regions and converted to mm$^2$, using the formula (1).

$$Area = \sqrt{p}X0.264, \tag{1}$$

where, $p$ is the total number of pixels in the segmented stone and cyst region. The square root of p is multiplied with 0.264, because 1 mm is equal to 0.264 pixels [11]. Fig. 4 and Fig. 5 shows the area of a cyst and stone in pixels. The area of the segmented region is compared with the ground truth images to check the accuracy of the proposed model. Also, the output is checked with an expert radiologist. The relative error is measured and results are shown in Table 1.

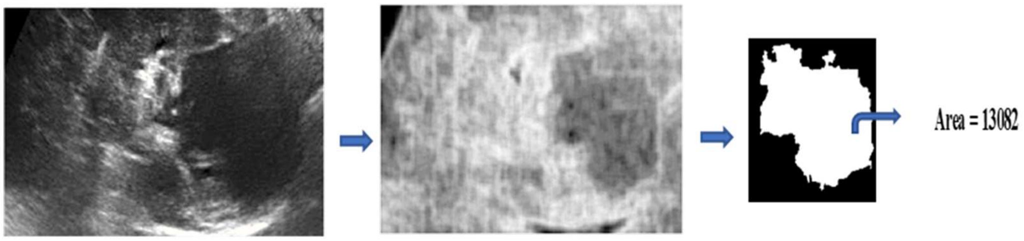


Figure 4. Area calculation of kidney cyst

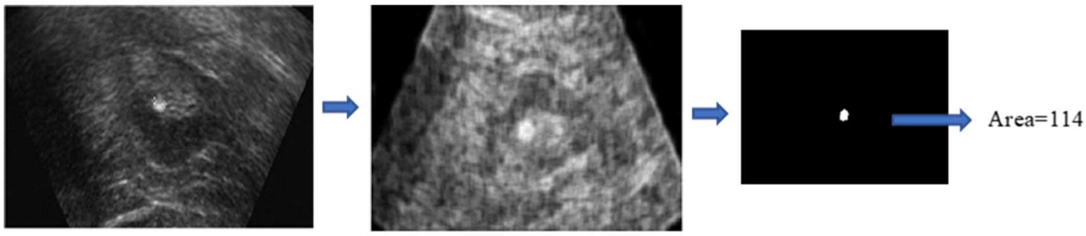


Figure 5. Area calculation of kidney stone

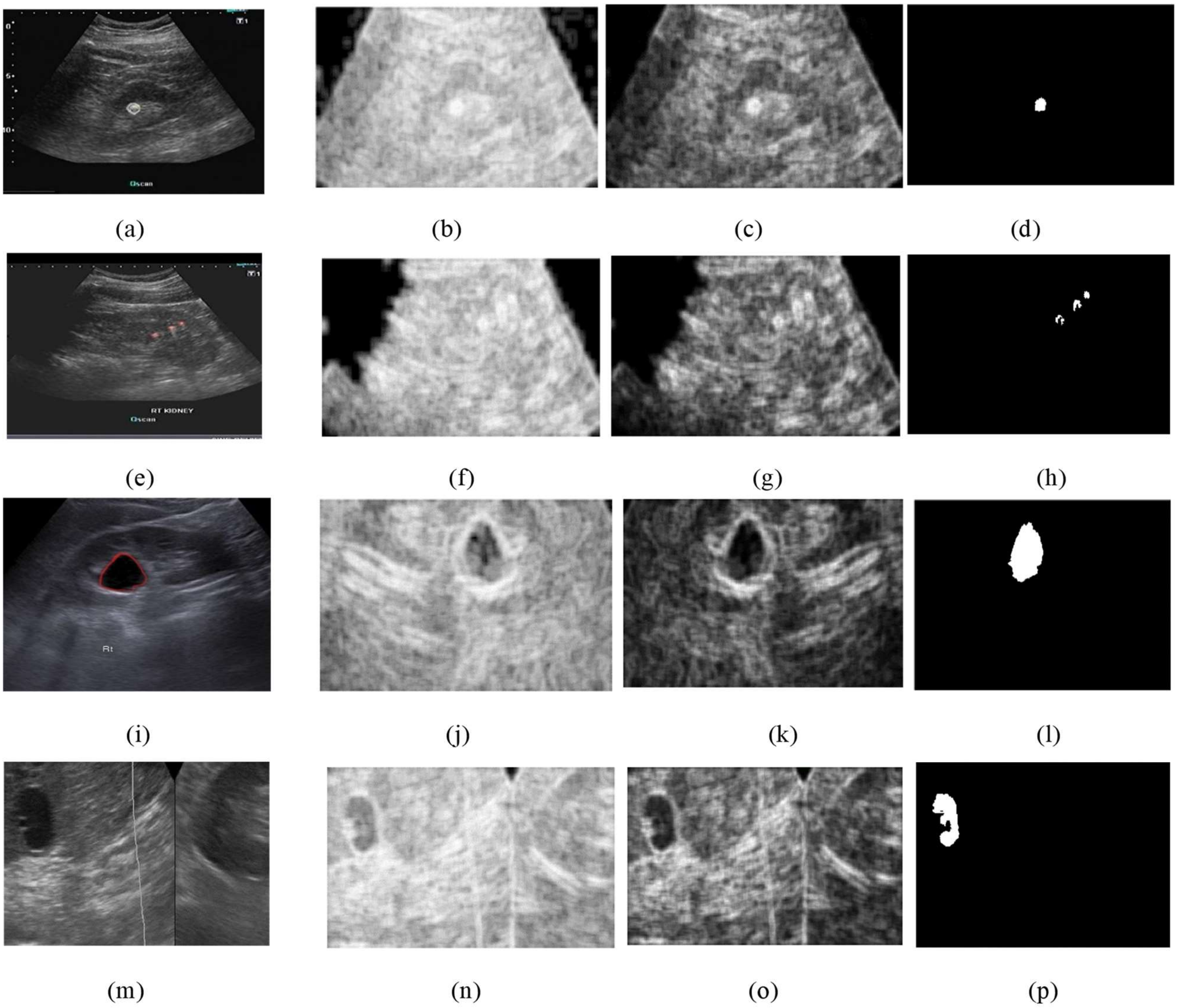


Figure 6. Segmentation of stones and cysts. (a) and (e) are the ground truth stone images. (b) and (f)are the entropy filtered images. (c) and (g) are the gamma corrected images. (d) and (h) are the segmented stone images. (i) and (m) are the ground truth images. (j) and (n) are the entropy filtered cyst images. (k) and (o) are the gamma value corrected one and (l) and (p) are the segmented cyst regions.

### *D. PERFORMANCE ANALYSIS*

Segmentation process is evaluated using certain statistical parameters like dice similarity coefficient and Jaccard coefficient [28]. These parameters cross checked the accuracy of proposed segmentation model and ground truth images. Both the metrics are calculated by the following formulas (4)(5). The resultant value of both parameters lies in between 0 and 1. The resultant value 1, refers an exact match of the images and 0 means mismatch of the images.

$$\text{Dice Similarity }(\text{P1},\text{P2}) = \frac{2|P1 \cap P2|}{|P1| + |P2|}, \quad (2)$$

$$\text{Jaccard Coefficient }(\text{P1},\text{P2}) = \frac{\text{P1} \cap \text{P2}}{\text{P1} \cup \text{P2}}, \quad (3)$$

$$\text{Relative error} = \frac{\text{Measured Value} - \text{Real Value}}{\text{Real Value}}. \quad (4)$$

## IV. RESULT AND ANALYSIS

The implementation of the proposed model is on Intel core i5, having 8 GB RAM and the software is MATLAB R2020a. The collected input images are kidney ultrasound images of different dimensions are converted to 200X400 size. The image analysis is started with noise removal, which is carried out by Gaussian filtering. The cyst and stone image are treated similarly, both are de-speckled with Gaussian kernel. Further, image contrast is enhanced by CLAHE technique. The US images after pre-processing is displayed in Fig. 2. In the segmentation stage, the histogram equalization technique helped increasing brightness. The entropy filtered image is shown in Fig. 2.

The area of the segmented ROI is calculated by taking the number of pixels covering the ROI region. The resultant value is converted to mm using the equation (3). The Table 1 displays the comparison of proposed model result and experts result of stone. The relative error is calculated by comparing the sizes of stones segmented manually and by proposed model using equation (6). Table 2, shows the comparative analysis of cysts sizes obtained by experimentally and manually. The relative error rate is high in certain cases.

**Table 1. Evaluation of experimentally obtained and manually obtained stone results**

| Sample Stone Images | Stone Size (mm2) | | Error Rate (%) |
|---|---|---|---|
| | Obtained by proposed model | Obtained Manually | |
| S 1 | 3.742 | 3.512 | 6.55 |
| S 2 | 2.112 | 2.192 | 3.65 |

**Table 2. Evaluation of experimentally obtained and manually obtained cyst results**

| Sample Cyst Images | Cyst Size (mm2) | | Error Rate (%) |
|---|---|---|---|
| | Obtained by proposed model | Obtained Manually | |
| C1 | 13.427 | 15.174 | 11.53 |
| C 2 | 10.697 | 11.225 | 4.72 |

The values are expressed in percentage and it ranges from 0.36 to 6.55% to 11.53%. The proposed model detects and measures the kidney stones more efficiently. However, the performance of proposed model is not much significant in kidney cysts size measurement. There is a notable difference between manually segmented cyst size and experimentally segmented cysts.

Table 3. shows the performance analysis results. The proposed model for kidney stone and cyst detection and measurement performs good with high jaccard index and dice coefficient with less relative error. However, the proposed model requires more efficiency in measuring kidney cyst. The statistical performance metrics like jaccard and dice coefficients are ranges from .53 to .66 to .79 to .81. The proposed automatic segmentation model shows significant results in stone detection and its size measurements. Thus, the model can reduce the burden of the radiologist in diagnosing the renal calculi disease patients.

Compared with the segmentation models that are built upon level-set techniques show ex'ent results [10], but it requires manual segmentation operations. To detect the cyst and stone, there are many other manual and semi-automatic kidney segmentation approaches were proposed [29]. The designed model processes the input images and detects the stone and cyst regions automatically. Automatic segmentation of stone and cyst with high accuracy rates are the main accomplishments of this model. The proposed model is mainly designed for kidney stones and cysts detection. In this area of research, a fully automatic kidney stone and cyst segmentation process is not addressed. The proposed model achieves a high accuracy in automatic segmentation and classification.

**Table 3. Statistical parameters for the proposed model**

| Sample Images | Jaccard Index | Dice Coefficient |
|---|---|---|
| S 1 | 0.825 | 0.839 |
| S 2 | 0.862 | 0.775 |
| C 1 | 0.804 | 0.816 |
| C 2 | 0.799 | 0.889 |

## V. CONCLUSION

The heterogeneous structure makes the analysis of kidney images difficult. The presence of additive noise is another issue for the poor image quality. Hence, it is very difficult to diagnose the diseases for the radiologists. In this paper, a segmentation model has been proposed to segment the stone and cyst. Instead of manual segmentation, the designed model is focused on automatic detection of stone and cyst. Besides that, the proposed model is a hybrid model and achieves good accuracy results. The model shows less error rate with renal stone and cyst segmentation. Further, planning to fine tune the model to obtain cyst and tumor regions and also to work with greater number of images.

## REFERENCES

[1] T. Joel and R. Sivakumar, "Despeckling of ultrasound medical images: Survey," *J. Image Graphics*, vol. 1, no. 3, pp. 161–166, 2013. https://doi.org/10.12720/joig.1.3.161-165.

[2] W. M. Hafizah, and E. Supriyanto, "Comparative evaluation of ultrasound kidney image enhancement techniques," *International*

*Journal of Computer Applications*, vol. 21, no. 7, pp. 15-19, 2011. https://doi.org/10.5120/2524-3432.

[3] F. Adamo, G. Andria, F. Attivissimo, A. M. L. Lanzolla, and M. Spadavecchia, "A comparative study on mother wavelet selection in ultrasound image denoising," *Measurement*, vol. 46, no. 8, pp. 2447-2456, 2013. https://doi.org/10.1016/j.measurement.2013.04.064.

[4] A. Achim, A. Bezerianos, and P. Tsakalides, "Novel Bayesian multiscale method for speckle removal in medical ultrasound images," *IEEE Transactions on Medical Imaging*, vol. 20, no. 8, pp. 772-783, 2001. https://doi.org/10.1109/42.938245.

[5] T. Rahman, and M. S. Uddin, "Speckle noise reduction and segmentation of kidney regions from ultrasound image," *Proceedings of the 2013 IEEE International Conference on Informatics, Electronics and Vision (ICIEV)*, 2013, pp. 1-5. https://doi.org/10.1109/ICIEV.2013.6572601.

[6] C. S. Mendoza, X. Kang, N. Safdar, E. Myers, C. A. Peters, and M. G. Linguraru, "Kidney segmentation in ultrasound via genetic initialization and active shape models with rotation correction," *Proceedings of the 2013 IEEE 10th International Symposium on Biomedical Imaging*, 2013, pp. 69-72. https://doi.org/10.1109/ISBI.2013.6556414.

[7] J. J. Cerrolaza, N. Safdar, E. Biggs, J. Jago, C. A. Peters, and M. G. Linguraru. "Renal segmentation from 3D ultrasound via fuzzy appearance models and patient-specific alpha shapes," *IEEE Transactions on Medical Imaging*, vol. 35, no. 11, pp. 2393-2402, 2016. https://doi.org/10.1109/TMI.2016.2572641.

[8] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan, A. Mittal, "Pneumonia detection using CNN based feature extraction," *Proceedings of the 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, 2019, pp. 1-7. https://doi.org/10.1109/ICECCT.2019.8869364.

[9] S. Sudharson, P. Kokil, "Computer-aided diagnosis system for the classification of multi-class kidney abnormalities in the noisy ultrasound images," *Computer Methods and Programs in Biomedicine*, vol. 205, 106071, 2021. https://doi.org/10.1016/j.cmpb.2021.106071.

[10] P. R. Tamilselvi, and P. Thangaraj, "Segmentation of calculi from ultrasound kidney images by region indictor with contour segmentation method," Global Journal of Computer Science and Technology, vol. 11, no. 22, pp. 43-51, 2012.

[11] A. Nithya, A. Appathurai, N. Venkatadri, D. R. Ramji, C. A. Palagan, "Kidney disease detection and segmentation using artificial neural network and multi-kernel k-means clustering for ultrasound images," *Measurement*, vol. 1, no. 149, 106952, 2020. https://doi.org/10.1016/j.measurement.2019.106952.

[12] D. Selvathi, and S. Bama, "Phase based distance regularized level set for the segmentation of ultrasound kidney images," *Pattern Recognition Letters*, vol. 86, pp. 9-17, 2017. https://doi.org/10.1016/j.patrec.2016.12.002.

[13] T. Mangayarkarasi, and D. Najumnissa Jamal, "PNN-based analysis system to classify renal pathologies in kidney ultrasound images," *Proceedings of the 2017 2nd IEEE International Conference on Computing and Communications Technologies (ICCCT)*, 2017, pp. 123-126. https://doi.org/10.1109/ICCCT2.2017.7972258.

[14] Q. Zheng, S. Warner, G. Tasian, and Y. Fan, "A dynamic graph cuts method with integrated multiple feature maps for segmenting kidneys in 2D ultrasound images," *Academic Radiology*, vol. 25, no. 9, pp. 1136-1145, 2018. https://doi.org/10.1016/j.acra.2018.01.004.

[15] P.R. Tamilselvi, and P. Thangaraj, "Computer aided diagnosis system for stone detection and early detection of kidney stones," *Journal of Computer Science*, vol. 7, no. 2, pp. 250, 2011. https://doi.org/10.3844/jcssp.2011.250.254.

[16] S. Yin, Q. Peng, H. Li, Z. Zhang, X. You, K. Fischer, S. L. Furth, G. E. Tasian, and Y. Fan, "Automatic kidney segmentation in ultrasound images using subsequent boundary distance regression and pixelwise classification networks," *Medical Image Analysis*, vol. 60, pp. 101602, 2020. https://doi.org/10.1016/j.media.2019.101602.

[17] A. K. Bedi, and R. K. Sunkaria, "Statistical recursive minimum cross entropy for ultrasound image segmentation," *Multimedia Tools and Applications*, Springer, pp. 1-21, 2022. https://doi.org/10.1007/s11042-022-12050-8.

[18] S. Sudharson, P. Kokil, "An ensemble of deep neural networks for kidney ultrasound image classification," *Computer Methods and Programs in Biomedicine*, vol. 197, 105709, 2020. https://doi.org/10.1016/j.cmpb.2020.105709.

[19] J. Xie, Y. Jiang, and H.-T. Tsui, "Segmentation of kidney from ultrasound images based on texture and shape priors," *IEEE Transactions on Medical Imaging*, vol. 24, no. 1, pp. 45-57, 2005. https://doi.org/10.1109/TMI.2004.837792.

[20] E. Kohilavani, E. Thangaselvi, and O. Revathy, "Analysis and classification of ultrasound kidney images using texture properties based on logical operators," *International Journal of Engineering and Technology*, vol. 2, no. 5, pp. 750-755, 2012.

[21] R. Goel, and A. Jain, "Improved detection of kidney stone in ultrasound images using segmentation techniques," *Advances in Data and Information Sciences*, vol. 94, pp. 623-641, Springer, Singapore, 2020. https://doi.org/10.1007/978-981-15-0694-9_58.

[22] S. Selvarani, and P. Rajendran, "Detection of renal calculi in ultrasound image using meta-heuristic support vector machine," *Journal of Medical Systems*, vol.43, no. 9, pp. 1-9, 2019. https://doi.org/10.1007/s10916-019-1407-1.

[23] J.-M. Correas, D. Anglicheau, D. Joly, J.-L. Gennisson, M. Tanter, and O. Hélénon, "Ultrasound-based imaging methods of the kidney – recent developments," *Kidney International*, vol. 90, no. 6, pp. 1199-1210, 2016. https://doi.org/10.1016/j.kint.2016.06.042.

[24] K. M. Meiburger, U. Rajendra Acharya, and F. Molinari, "Automated localization and segmentation techniques for B-mode ultrasound images: A review," *Computers in Biology and Medicine*, vol. 92, pp. 210-235, 2018. https://doi.org/10.1016/j.compbiomed.2017.11.018.

[25] R. Vasanthselvakumar, M. Balasubramanian, and S. Palanivel, "Pattern analysis of kidney diseases for detection and classification using ultrasound b-mode images," *International Journal of Pure Applied Math*, vol. 117, no. 15, pp. 635-653, 2017.

[26] A. L. Barbieri, G. F. De Arruda, F. A. Rodrigues, O. M. Bruno, and L. da Fontoura Costa, "An entropy-based approach to automatic image segmentation of satellite images," *Physica A: Statistical Mechanics and its Applications*, vol. 390, no. 3, pp. 512-518, 2011. https://doi.org/10.1016/j.physa.2010.10.015.

[27] S. Kollem, K. Rama Linga Reddy, D. Srinivasa Rao, "Modified transform-based gamma correction for MRI tumor image denoising and segmentation by optimized Histon-based elephant herding algorithm," *International Journal of Imaging Systems and Technology*, vol. 30, no. 4, pp. 1271-1293, 2020. https://doi.org/10.1002/ima.22429.

[28] R. Shi, K. Ngi Ngan, and S. Li, "Jaccard index compensation for object segmentation evaluation," *Proceedings of the 2014 IEEE International Conference on Image Processing (ICIP)*, 2014, pp. 4457-4461. https://doi.org/10.1109/ICIP.2014.7025904.

[29] S. Sudharson, and P. Kokil, "Computer-aided diagnosis system for the classification of multi-class kidney abnormalities in the noisy ultrasound images," *Computer Methods and Programs in Biomedicine*, vol. 205, p.106071, 2021. https://doi.org/10.1016/j.cmpb.2021.106071.

***MINO GEORGE** received her MPhil in Computer Science from CHRIST (deemed to be university), Bengaluru, India, in 2018. Currently she is doing PhD in image processing from CHRIST University. Her research interest includes applications in machine learning for analysis of medical image processing.*

***ANITA HADADI BHIMASENA** is presently working as an Associate Professor in Department of Computer Science, CHRIST (Deemed to be University), Bengaluru, India. She has more than 15 years of experience of teaching. She received her PhD degree in 2014 at Gulbarga University, Karnataka, India. Her main research interests are Digital Image Processing, Deep Learning, Sound Processing, Machine Learning, Medical Image Processing and Signal Processing. Currently she is guiding MPhil and PhD students*