Kidney Stone Detection using Ultrasound Images

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ABSTRACT
Kidney stones are small, hard pieces of solid material in the urinary tract that can cause severe pain in the abdomen if there is a delay in the treatment. They can occur due to an excess of certain wastes and less fluid intake in the bloodstream. Here, we have made a program to assist while detecting the presence of the stone. For the detection, we have a dataset of 69 cropped ultrasound images. After the collection, we have denoised and enhanced the images using various techniques. To reduce the noise and highlight the crucial details, we have tested the effectiveness of a combination of filters such as Gaussian Blur with Laplacian filter, Median blur with Laplacian Filter, Gabor Filter, and Bilateral Filter. We concluded that the Bilateral filter is the most effective. After this, we proceeded to the next phase, Adaptive Histogram Equalization, which helps in enhancing the contrast. To showcase the separation of the stone from its shadow, we used the watershed algorithm in segmentation. In the end, we have added markers to differentiate the regions of interest.

Keywords—Kidney Stones, Ultrasound Images, Bilateral Filter, Gabor Filter, Gaussian Blur, Median Blur, Laplacian Filter, CLAHE, Watershed Segmentation

I. INTRODUCTION

Kidneys are bean-shaped organs, a part of the urinary tract, and located below the rib cage [1]. They help in filtering the blood, thereby removing wastes and extra water. Which is excreted in the form of urine. Other functions of the organ include:

- They help in the production of red blood cells.
- They produce hormones that help control blood pressure.
- They create vitamin D that keeps our bones strong and healthy.
- They balance the fluids in the body.
- Control calcium metabolism.

As seen above, kidneys are an integral part of the urinary system, and their failure can cause hazardous risks to the human body. Therefore, it is crucial to detect any abnormality that may exist. Kidneys have various abnormalities such as cancerous cells, congenital anomalies, formation of stones, blockage of urine, and cysts [2]. Among these, kidney stone disease is a disease when a solid material appears in the urinary tract. If the piece is small, then it might pass without any symptoms. If the stone grows more than 5 millimetres, it can cause blockage in the ureter thus resulting in severe pain in the abdomen or lower back. In India, about 12% of the population is diagnosed with Kidney Stones [3]. Hence, it is necessary to have an approach to detect the stone in the kidney to avoid further health issues.

Currently, Computed Tomography (CT) scans are the primary technology used to detect Kidney Stones. CT Scans are no longer more efficient than Ultrasounds according to a study conducted at 15 medical centres published in [4]. Apart from this, while capturing CT scans, patients are exposed to radiation [5]. Excessive amounts of radiation are carcinogenic in nature, so the first step in detecting a kidney stone must be the use of an ultrasound. They are a cost-friendly, radiation-less alternative to CT scans. Figure 1 shows the shows presence of kidney stone in a kidney using an ultrasound image.

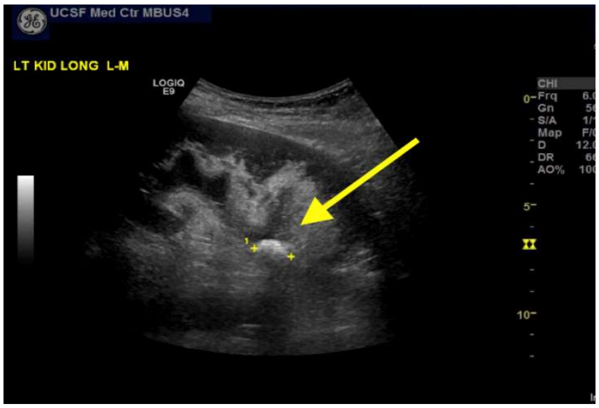

Fig. 1. Ultrasound of kidney stone [6]

Ultrasounds contain speckle noise [7] and need image pre-processing to increase the contrast and to reduce the noise, making it easier to detect the stone. In this research paper, we have focused on identifying kidney stones by applying various filters. The filters used here include a combination of Gaussian blur and Laplacian filter, Median blur and Laplacian filter, Bilateral Filter, and Gabor filter. After deciding the filter best suited for the problem, we have used image segmentation techniques and increased contrast using Adaptive Histogram Equalization. Apart from this, we have also tested how the various filters affect the ultrasound images.

This research paper proceeds as follows: In section two, we have defined the problem statement, section three focuses on the literature review, in section four, we have discussed the methodology we have opted for, in the fifth section, we have discussed the experiment's results. In the final section, we have mentioned the conclusion and the future work.

II. Problem Statement

Kidney failure can lead to anaemia [8], high blood pressure, diabetes, weaken your bones and even cause nerve damage or blood and heart diseases [9]. If treatment is not done on time, it can make the ureter narrow or block it completely. It might lead to urine build-up or raises the risks of infections. Thereby, adding excess strain on the kidney. Thus, the detection of kidney stones at the earliest is of extreme importance. Ultrasound contains speckle-noise so, they need image pre-processing to increase the contrast and reduce noise, making it easier to detect the stone. To provide a solution for the issue at hand, we have developed a program to spot the stone. Some filters are applied to reduce noise and enhance image quality. We have also attempted to increase contrast in the images by adaptive histogram equalization. To intensify the shadow of the stone, we have used watershed segmentation. In the end, we have amplified the regions of interest by marking the pipeline. There is a need for a better technique to act as a supporting tool for beginners and expert doctors to detect stones with better accuracy in ultrasound images. There was little to no dataset available related to our project, so we have created a new dataset of 69 ultrasounds to implement the project.First, confirm that you have the correct template for your paper size. This template has been tailored for output on the A4 paper size. If you are using US letter-sized paper, please close this file and download the Microsoft Word, Letter file.

III. Literature Review

Viswanath et al. [10] proposed to overcome the challenges faced while detecting kidney stones using ultrasound images by applying image processing techniques. Their first step included removing speckle noise using an image restoration process, they then proceeded to smoothen the resultant image with Gabor Filter and enhance it using Histogram Equalization. Moreover, they applied level set segmentation twice to detect the region where the stone is present. This extracted region is then given to Daubechies, Symlets and Biorthogonal lifting scheme wavelet sub-bands to extract energy levels, which help in providing evidence of the presence of the stone. Pathak et al. [11] have proposed a dynamic algorithm based on cellular automata and nonlocal means for suppression of the speckle noise in US images. This method is flexible as cellular modelling can model low-level noise. Loganayagi et al. [12] stated that the bilateral filter is the best filter to reduce the speckle noise in ultrasound images. Apart from this, their study also tested out Non-Local Mean filter, median filter, and SRAD (Speckle Reducing Anisotropic Diffusion) filter to reduce speckle noise and enhance ultrasound images. Mean Absolute Error was used for overall performance and Structural Similarity Index Measure for testing bilateral filter on the ultrasounds. Ebrahimi et al. [13] developed KUB-CT (Kidney Urine Belly computed tomography) an imaging modality that helps in improving kidney stone diagnosis and screening. They used geometry principles and various image processing techniques to define the segmentation and boundary of the kidney area, to help improve the process of detecting a kidney stone. Their model marked the stones and gave an output providing the location and size of the stone based on pixel count. Brisbane et al. [14] did a comprehensive study on the different methods that can be used to detect kidney stones. They concluded that even though ultrasonography is the best process, it is relatively noisier and poor in quality. Pathak et al. [15] developed a semi-automatic application to help a medical professional detect the region where the stone is present in an ultrasound image. The practitioner needs to select a region which is then analysed to help in the detection process. On this selected region, feature extraction is applied. Features like Entropy, Contrast, Correlation and Angular second moment have been used. They used a KNN classifier to train their dataset. Thein et al. [16] developed an independent pre-processing algorithm to assist the kidney stone detection process in CT scans. They applied three thresholding algorithms based on size, location and intensity on unwanted regions to remove them. Kumar et al. [17] tested the effectiveness of five optimization algorithms, namely, k-median clustering, guaranteed convergence particle swarm optimization (GCPSO), particle swarm optimization, k-means clustering, and inertia-weighted particle swarm optimization to detect tumour in lungs. Out of the five algorithms it was found that GCPSO had the highest accuracy of 95.89%. Selvarani et al. [18] investigated an approach to detect renal calculi in raw ultrasound images by using a Meta-Heuristic Support Vector Machine classifier. They applied an adaptive mean median filter to remove speckle noises and then performed segmentation to employ conventional Grey-level co-occurrence matrix and K-Means features for extraction and classification with the help of the Meta-Heuristic Support Vector Machine Classifier. Mishr et al. [19] proposed an algorithm that uses Back-Propagation Network to reduce speckle noise and then extract features using grey-level co-occurrence matrix, thus presenting a segmentation based, Fuzzy C-Mean clustering algorithm to detect kidney stones in CT scans. Vineela et al. [20] proposed pre-processing, segmentation and finally a morphological analysis on the resulting image, that helps in detecting the exact shape and location of the stone.

The table given below summarizes the research paper reviewed to help in the implementation of this project.

TABLE I. SUMMARY OF RESEARCH PAPERS REVIEWED

Author(s)	Year	Remarks
Viswanath et al. [10]	2015	The model is trained by MLP (multilayer perceptron) and backpropagation (BP) ANN classification giving an accuracy of 98.8%. This work is implemented on Vertex-2 Pro FPGA using Xilinx System Generator.
Pathak, et al. [11]	2015	This paper discusses algorithms based on nonlocal means and cellular automata in order to suppress speckle noise. The algorithm is used to de-noise X-ray images, SAR images, and MRI images.
Loganayagi, et al. [12]	2015	Applied four different filters, claimed that the bilateral filter is the best to reduce the speckle noise in ultrasound images. They have used RMSE for image quality analysis, SNR to compare noise with useful signal strength, PSNR for maximum amplitude of signal, MAE for overall performance and SSIM for testing bilateral filter on the ultrasounds.
Ebrahimi et al. [13]	2015	They have developed a semi-automated KUB CT image analysis prototype in order to provide technical support while detecting Kidney Stones. This program is useful for screening and diagnosis of the stone, but is only a tool and can use the opinion of an expert.
Brisbane, et al. [14]	2016	The proposed methodology has been done by pre-processing the ultrasound image followed by segmentation and finally Wavelet's processing on the result. The energy levels of the image are extracted and provide evidence about the presence of stone. The model is trained by multilayer perceptron and backpropagation ANN classification. This work is implemented on Vertex-2 Pro FPGA using Xilinx System Generator.
Pathak, et al. [15]	2016	Identification is based on analysis of the features of the region. Their system consists of feature extraction and classification. Feature extraction is carried out on the data and testing image dataset. KNN classifiers played a major role in identifying the stone.
Thein, et al. [16]	2018	This research paper had developed three algorithms to assist the segmentation process in CT images. Algorithms were based on intensity, location and size and remove undesirable regions.
Kumar, et al. [17]	2019	Performance of five optimization algorithms, k-median clustering, k-means clustering, guaranteed convergence particle swarm optimization, particle swarm optimization, and inertia-weighted, to extract the tumour from the lung, the image has been implemented and analysed.

Selvarani, et al.[18]	2019	Applied SVM to improve the accuracy while detecting stones. They have created an impact as the FAR rate is low while improving FRR. This model also is readily showcased to the physicians to get the clinical feedback so as to tune the classifier to the finest quality.
Mishr, et al. [19]	2020	Their proposed method includes pre-processing with the use of GLCM feature extraction, dataset education, Back Propagation Neural Network, and watershed set of rules and segmentation of kidney stones using the Fuzzy C-Means method.
T. Vineela, et al. [20]	2020	In this study, pre-processing of image is followed by its segmentation and finally performing morphological analysis on the resulting image. The resulting image helped in detecting the exact location of stone and further the edge detection method was used to identify the shape and structure of the stones formed.

IV. METHODOLOGY

A. Architecture Diagram

This section of the paper shows the basic architectural design of our model. Figure 2 displays a brief insight of the basic structure of the model. First stage includes providing an input image, then applying various image enhancement techniques. The third step is histogram equalization, followed by image segmentation, and marking. The final step includes providing the output.

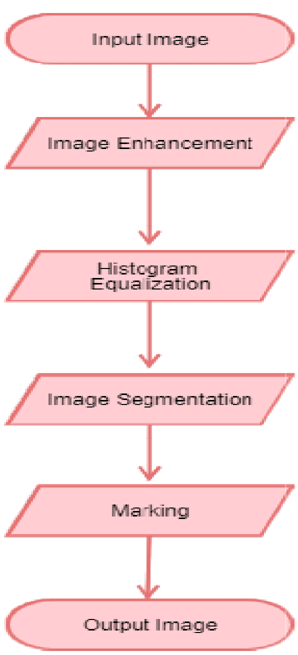

Fig. 2. Architecture Diagram

B. Algorithms and Pseudo Code

The data will be collected from various sources. After collecting the data, we will proceed towards our work.

1. **Image Enhancement** – The image enhancement has been done by various approaches for this we have taken the combination of different filters:

- **Gaussian Blur + Laplacian Filter:** Gaussian Blur has been applied to reduce sensitivity of the Laplacian filter. Gaussian blur helps blur the image in order to reduce details and noise [21]. In 2-D, gaussian has the form:

$$G(a,b) = \frac{1}{2\pi\sigma^2} e^{-\frac{a^2+b^2}{2\sigma^2}}$$

Where, $\sigma = 1$ is the standard deviation of the distribution and the mean is (0,0)

Gaussian blur has four parameters where, src represents the source of the image, dst is the destination and ksize represents the size of the kernel. Sigmax is a double type variable that represents the standard deviation in x direction in the gaussian kernel.

Laplacian filter is a linear filter that helps in highlighting the change in intensity [22]. Therefore, it plays a major role in edge detecting programs. This filter is often applied after smoothening so as to reduce the sensitivity to noise. Usually here, the input and output type are grey level images.

In Laplacian filter, a window with a value works with the value of neighbourhood pixels. These values are called filter coefficients. The result produced by this filter is the sum of the product of corresponding image values and the filter coefficients. This produces an image that has strong edges.

The Laplacian L(a,b) of an image with intensity I(a,b) is given by:

$$L(a,b) = \frac{\partial^2 I}{\partial a^2} + \frac{\partial^2 I}{\partial b^2}$$

The 2-D Laplacian of Gaussian (LoG) function with standard deviation σ has the form:

$$log(a,b) = \frac{1}{\pi\sigma^4}\left[1 - \frac{a^2+b^2}{2\sigma^2}\right] e^{-\frac{a^2+b^2}{2\sigma^2}}$$

- **Median Blur + Laplacian Filter:**we have also applied median blur as it has been proved to be more effective for low-level noises like salt-and-pepper noise, speckle noise, etc. Median blur replaces each pixel value by the median of its neighbours [23]. Due to this, we can eliminate pixels which don't contribute to the surroundings. It is a non-linear operation. It is highly used while reducing salt and pepper noise.

- **Bilateral Filter:** A bilateral filter preserves edges while reducing noise and smoothening the image [24]. Bilateral filter ensures that while blurring images only pixels that have similar values to the central pixels are considered. This helps in maintaining the intensity change and preserving the edges.

It begins with linear gaussian smoothening:

$$g(a) = (f * G^8)(a) = \int_R f(b)G^8(a-b)\,db$$

Here, the weight for $f(b) = G(a-b)$and depends on distance $||a-b||$. This filter also adds a weighting term which depends on tonal distance $f(b) - f(a)$. The final result is:

$$g(a) = \frac{\int_R f(b)G^8(a-b)G^t\big(f(a)-f(b)\big)db}{\int_R G^8(a-b)G^t\big(f(a)-f(b)\big)db}$$

The bilateral filter has three arguments, "d" which represents the diameter of the neighbouring pixels, "sigmaColor" this represents the value of σ in the color space and "sigmaColor" it represents the value of σ in coordinate space.

- **Gabor Filter:**In the application of the Gabor filter, the image is refined with optimal resolution in both frequency and spatial domains [25]. When input image is processed using this filter the patterns are easily highlighted. It is a linear filter that helps in texture analysis, feature extraction or edge detection. They are special type of band pass filters; they have a specific band of frequencies that are allowed. The rest are rejected.

The equation for Gabor filter is as follows:

$$g(a,b;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda}+\psi\right)\right)$$

2. **Adaptive Histogram Equalization** –It is a technique that adjusts the intensity of the given image to enhance the contrast [26]. Here intensity values of the pixels are assigned in the input image in a way such that the output image contains a uniform distribution of intensities. Adaptive Histogram Equalization helps in improving contrast and obtaining a uniform histogram. This process leads to an increase in contrast of the shadow of the stone and the stone itself. Thus, making the stone more visible.

One major drawback while using histogram equalization is that while increasing the contrast it simultaneously increases the noise present in the image. To control this, we use CLAHE (contrast limited adaptive histogram equalization). This results in higher quality images.

In adaptive histogram equalization, there are two parameters, clipLimit, this sets the threshold for contrast limiting, and tileGridSize, it sets the number of tiles in columns and rows.

3. **Image Segmentation** – here, we partition the image into distinct regions such that these regions contain pixels that have similar attributes [27]. The regions are useful for image interpretation or analysis, if they strongly relate to features or objects of interest. Meaningful segmentation is the gateway from low-level image processing transforming a colour or greyscale image to one or more images to high-level image description in terms of scenes, objects, and features. For performing this, we need to partition our stone from the rest of the image. The type of Image Segmentation used here will be Watersheds. Here we divide the image into peaks (high intensity) and valleys (low). We fill the valleys (points of minima or background) with water of different colours (labels) [28]. As the water rises, depending on the gradients (peaks) nearby, water from distinct valleys of different colours will start to merge. To avert this, we need to build barriers in the area where the water is mixing. Also, we resume the process of filling water until all the gradients are underwater. The barriers that are created are the result of image segmentation. Now, the shadow gets separated from the stone to give a clear image of the stone.

Marking – It assists us in labelling or identifying a region or spot in the processing pipeline [29]. When we add a marker in the pipeline it allows us to refer the image that is being processed at that point of time. Moreover, it specifies the location of the region in the pipeline for other modules present.

V. Result and Discussion Literature Review

A total of 4 filters have been tested to enrich the quality of an ultrasound image, namely:

1. **Gabor Filter:** This is a linear filter generally used for texture analysis. It facilitates in analysing any specific frequency content in the images around the region of analysis. Given below is Figure 3(a) which shows input image, that is ultrasound image before application of Gabor Filter. Figure 3(b) shows output image, or image after application of Gabor Filter.

ORIGINAL **FINAL**

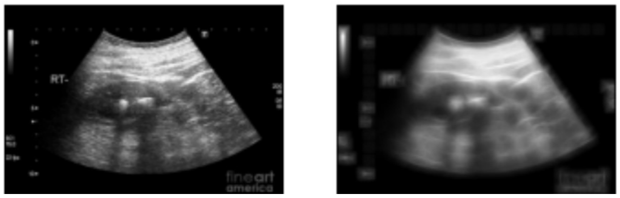

Fig. 3 (a) Original Image **(b)** Image after Gabor Filter

2. **Bilateral Filter:** It helps in preserving images while smoothening images. It further reduces noise and highlights the details as it replaces only pixels that have similar values to the central pixels are considered. This helps in maintaining the intensity change and preserving the edges. Given below are figures 4 (a) and (b), they show ultrasound image before and after application of bilateral filter respectively.

ORIGINAL **FINAL**

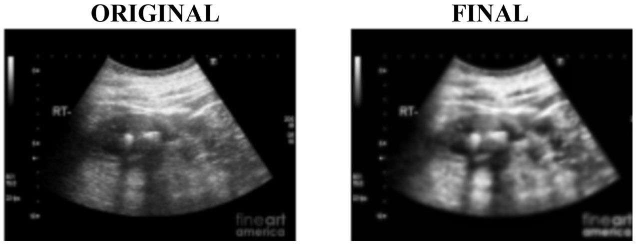

Fig. 4 (a) Original Image **(b)** Image after Bilateral Filter

3. **Median blur + Laplacian Filter:** The median filter is a non-linear filter that is usually eases the process of removing noise from an ultrasound image while retaining the edges. So, this method is effective against particulate noises like salt and pepper noise. Given below are figures 5 (a) and (b), they show ultrasound image before and after application of the combination of Median Blur and Laplacian filter.

ORIGINAL **FINAL**

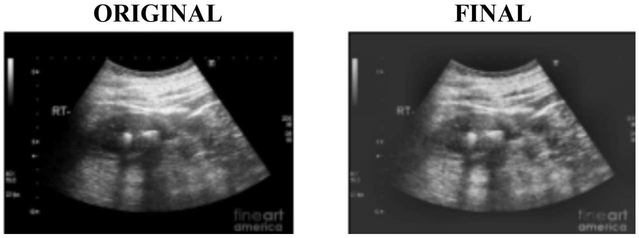

Fig. 5 (a) Original Image **(b)** Image after Filter

4. **Gaussian blur + Laplacian Filter:** This method helps in reducing image noise and the details present. But details are crucial in detecting the stone so we eliminated it. Given below is Figure 6(a) which shows input image, that is ultrasound image before application of any filter. Figure 6(b) shows output image, or image after application of the combination of Gaussian Blur and Laplacian Filter.

ORIGINAL **FINAL**

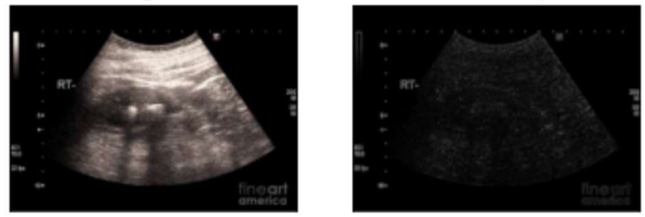

Fig. 6 (a) Original Image **(b)** Image after Filter

Out of the 4, we have noticed that Bilateral Filter was effective on most of the ultrasounds though not all. Median blur + Laplacian Filter and Gaussian blur + Laplacian Filter worked perfectly with fewer images. After the application of filters, we enhanced the contrast of the image, to do so our first pick was histogram equalization but due to increase in noise we shifted to adaptive histogram equalization. The next step in our project included the application of watershed segmentation to separate the shadow from the stone. This helps in detecting the stone. Our final step was marking. Here we added a marker to specify the location in the pipeline being processed at a given point of time. Given below are figures 7 (a) and (b), they show ultrasound image before and after application of our model respectively**.**

ORIGINAL **FINAL**

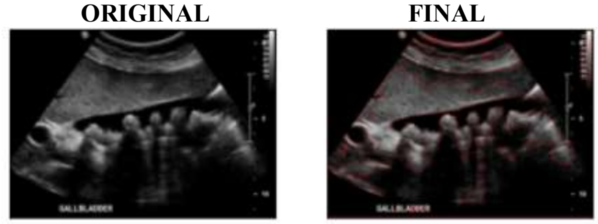

Fig. 7 (a) Original Image **(b)** Image after Filter

VI. CONCLUSION AND FUTURE SCOPE

The initial phase of our paper including creating a dataset of images, and analysing the performance of four different types of filters; Bilateral filter, Median blur with Laplacian filter, Gabor filter, and a combination of Gaussian and Laplacian filter. After analysing the images, we concluded that the bilateral filter provides the best results. The next stage included the application of CLAHE to increase the contrast and make the shadow easier to detect. In the end, the restored image underwent watershed image segmentation and marking. The output showed a distinct location of the stone.

In the future, we can focus on significantly improving the performance of bilateral filter, this can be achieved by replacing the filter kernels or hybridization. We can also design and develop the real-time implementation of the proposed methodology by interfacing it with the right equipment. This project can be implemented on a larger dataset to test the effectiveness of the various filters and techniques to get higher quality images. This project can also be reused with ease as it is flexible in most of the modules. The system can be further extended as per user and administrative requirements to encompass other aspects of kidney stone detection for hospital or personal use. There is still scope to make the project more user friendly.

REFERENCES

[1] Stevens, L. M. (2009). Kidney failure. JAMA, 301(6), 686. https://doi.org/10.1001/jama.301.6.686

[2] O'Brien, J., Buckley, O., Doody, O., Ward, E., Persaud, T., & Torreggiani, W. (2008). Imaging of Horseshoe Kidneys and their complications. Journal of Medical Imaging and Radiation Oncology, 52(3), 216–226. https://doi.org/10.1111/j.1440-1673.2008.01950.x

[3] M. Guha, H. Banerjee, P. Mitra, and M. Das, "The demographic diversity of food intake and prevalence of kidney stone diseases in the Indian continent," Foods, vol. 8, no. 1. MDPI Multidisciplinary Digital Publishing Institute, 2019. doi: 10.3390/foods8010037.

[4] R. Smith-Bindman et al., "Ultrasonography versus Computed Tomography for Suspected Nephrolithiasis," New England Journal of Medicine, vol. 371, no. 12, pp. 1100–1110, Sep. 2014, doi: 10.1056/nejmoa1404446.

[5] Mathews, J. D., Forsythe, A. V., Brady, Z., Butler, M. W., Goergen, S. K., Byrnes, G. B., Giles, G. G., Wallace, A. B., Anderson, P. R., Guiver, T. A., McGale, P., Cain, T. M., Dowty, J. G., Bickerstaffe, A. C., & Darby, S. C. (2013). Cancer risk in 680 000 people exposed to computed tomography scans in childhood or adolescence: Data linkage study of 11 million Australians. BMJ, 346(may21 1). https://doi.org/10.1136/bmj.f2360

[6] https://chilab.ucsf.edu/ultrasound-guided-pcnl-innovation-comes-patient-safety-and-treatment-efficacy-not-radiation-exposure

[7] Al-karawi, D., Ibrahim, D., Al Assam, H., Du, H., & Jassim, S. A. (2021). A model-based adaptive method for speckle noise reduction in ultrasound images of ovarian tumours: A new approach. Multimodal Image Exploitation and Learning 2021. https://doi.org/10.1117/12.2587671

[8] Deicher, R., & Hörl, W. H. (2003). Anaemia as a risk factor for the progression of chronic kidney disease. Current Opinion in Nephrology and Hypertension, 12(2), 139–143. https://doi.org/10.1097/00041552-200303000-00003

[9] Ninomiya, T. (2018). Chronic kidney disease as a risk factor for cardiovascular disease. Encyclopedia of Cardiovascular Research and Medicine, 600–608. https://doi.org/10.1016/b978-0-12-809657-4.99612-1

[10] K. Viswanath, R. Gunasundari, and S. A. Hussain, "Analysis of kidney stone detection by reaction diffusion level set segmentation and Xilinx System generator," ACM International Conference Proceeding Series, vol. 06-07-Marc, 2015, doi: 10.1145/2743065.2743101

[11] M. Pathak, "A Technique to Suppress Speckle in Ultrasound Images using Nonlocal Mean and Cellular Automata," Indian Journal of Science and Technology, vol. 8, no. 1, pp. 1–6, 2015, doi: 10.17485/ijst/2016/v9i13/86291.

[12] T. Loganayagi and K. R. Kashwan, "A robust edge preserving bilateral filter for ultrasound kidney image," Indian Journal of Science and Technology, vol. 8, no. 23, 2015, doi: 10.17485/ijst/2015/v8i23/73052.

[13] S. Ebrahimi and V. Y. Mariano, "Image Quality Improvement in Kidney Stone Detection on Computed Tomography Images," Journal of Image and Graphics, vol. 3, no. 1, pp. 40–46, 2015, doi: 10.18178/joig.3.1.40-46.

[14] W. Brisbane, M. R. Bailey, and M. D. Sorensen, "An overview of kidney stone imaging techniques," Nature Reviews Urology, vol. 13, no. 11. Nature Publishing Group, pp. 654–662, Nov. 01, 2016. doi: 10.1038/nrurol.2016.154.

[15] M. Pathak, H. Sadawarti, and S. Singh, "Features extraction and classification for detection of kidney stone region in ultrasound images," International Journal of Multidisciplinary Research and Development, vol. 3, no. 5, pp. 81–83, 2016, [Online]. Available: www.allsubjectjournal.com

[16] N. Thein, H. A. Nugroho, T. B. Adji, and K. Hamamoto, "An image preprocessing method for kidney stone segmentation in CT scan images," 2018 International Conference on Computer Engineering, Network and Intelligent Multimedia, CENIM 2018 - Proceeding, pp. 147–150, 2018, doi: 10.1109/CENIM.2018.8710933.

[17] K. Senthil Kumar, K. Venkatalakshmi, and K. Karthikeyan, "Lung Cancer Detection Using Image Segmentation by means of Various Evolutionary Algorithms," Computational and Mathematical Methods in Medicine, vol. 2019, 2019, doi: 10.1155/2019/4909846.

[18] 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, Sep. 2019, doi: 10.1007/s10916-019-1407-1.

[19] R. Mishr, A. Bhattacharjee, M. Gayathri, and C. Malathy, "Kidney stone detection with ct images using neural network," International Journal of Psychosocial Rehabilitation, no. May, 2020, doi: 10.37200/IJPR/V24I8/PR280269.

[20] T. Vineela, R. V. G. L. Akhila, T. Anusha, Y. Nandini, and S. Bindu, "Kidney Stone Analysis Using Digital Image Processing," no. 3, pp. 3–6, 2020.

[21] E. S. Gedraite and M. Hadad, "Investigation on the effect of a Gaussian Blur in image filtering and segmentation," Proceedings ELMAR-2011, 2011, pp. 393-396.

[22] P. Padungweang, C. Lursinsap and K. Sunat, "Univariate Filter Technique for Unsupervised Feature Selection Using a New Laplacian Score Based Local Nearest Neighbors," 2009 Asia-Pacific Conference on Information Processing, 2009, pp. 196-200, doi: 10.1109/APCIP.2009.185.

[23] U. Techavipoo et al., "Implementation of Asymmetric Kernel Median Filtering for Real-Time Ultrasound Imaging," 2018 11th Biomedical Engineering International Conference (BMEiCON), 2018, pp. 1-5, doi: 10.1109/BMEiCON.2018.8609959.

[24] Sylvain Paris; Pierre Kornprobst; Jack Tumblin; Frédo Durand, (2009) Bilateral Filtering: Theory and Applications.

[25] C. Low, A. B. Teoh and C. Ng, "Multi-Fold Gabor, PCA, and ICA Filter Convolution Descriptor for Face Recognition," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 29, no. 1, pp. 115-129, Jan. 2019, doi: 10.1109/TCSVT.2017.2761829.

[26] S. Muniyappan, A. Allirani and S. Saraswathi, "A novel approach for image enhancement by using contrast limited adaptive histogram equalization method," 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), 2013, pp. 1-6, doi: 10.1109/ICCCNT.2013.6726470.

[27] P. Yin, R. Yuan, Y. Cheng and Q. Wu, "Deep Guidance Network for Biomedical Image Segmentation," in IEEE Access, vol. 8, pp. 116106-116116, 2020, doi: 10.1109/ACCESS.2020.3002835.

[28] Fabijanska, "Normalized cuts and watersheds for image segmentation," IET Conference on Image Processing (IPR 2012), 2012, pp. 1-6, doi: 10.1049/cp.2012.0440.

[29] D. W. Kim and M. L. Comer, "Channel detection in microscope images of materials using marked point process modeling," 2015 IEEE International Conference on Image Processing (ICIP), 2015, pp. 3054-3058, doi: 10.1109/ICIP.2015.7351364.