

Enhanced Kidney Stone Identification Using Ultrasonographic Images in Image Processing

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Abstract: Stones, cysts, urinary tract obstruction, birth defects, and malignant cells are just some of the problems that may manifest in the kidneys. Kidney stone disease occurs when a stone is formed in the kidney or elsewhere in the urinary system. There may be no ill effects from passing the little stone. Pain in the lower back or abdomen may be experienced if a stone develops to a size greater than 5 millimetres and blocks the ureter. Thus, a method of detecting kidney stones is required to prevent future medical complications. The primary goal of this work is to use different image processing algorithms to identify the kidney stone in a digital ultrasound picture of the kidney. Yet, owing to poor contrast and the presence of speckle noise, the ultrasound-generated picture is unfit for further processing. Although improving the ultrasound picture quality by denoising methods was also a focus of the research, this was also investigated. More so, the improved ultrasound picture is utilised to pinpoint the precise location of the stone. The primary objective of this work was to provide a simple and efficient method for locating kidney stone. As this can be done on any computer, any healthy person may potentially check for a kidney stone using ultrasound and begin the process of dissolving it right away. Depending on the size and position of the lesion, these methods greatly aid the doctor in proceeding with further treatment.

Keywords: kidney stones, computed tomography, image processing, Ultrasonographic Images

1. Introduction

People often ignore the warning signs of renal illness until it has already done significant harm. In addition, the prevalence and incidence of kidney disease continues to rise day by day. Thus, early identification and prevention are necessary to protect patients from developing renal problems. Ultrasound, magnetic resonance imaging (MRI), computed tomography (CT) scan, etc. are only a few examples of the many diagnostic tools accessible in contemporary medicine. Regarding the diagnosis of a certain illness, each of these methods has advantages and disadvantages. Medical professionals choose ultrasonic imaging because it is safe (no radiation) and affordable (less expensive). In addition, it may be used to diagnose structural problems including cysts and stones, as well as to estimate kidney size and location. A kidney that isn't

working properly poses serious risks to human health, therefore we can't overlook the issue. In order to properly remove anomalies such as a kidney stone, cyst, or tumour by surgery, early detection and localization of the illness is essential. With procedures involving the kidneys, pinpointing the exact site of the problem is crucial. Diagnosing renal illness with ultrasonic imaging is a difficult endeavour because of poor contrast and speckle noise. In order to overcome this obstacle, an automated method for analysing ultrasound images is necessary. Kidney stones form when small crystals build in the kidney's innermost structures. Depending on the size of the stone, it might become stuck in the ureters or pass through [1]. The most common causes of kidney stones include changes in diet, extreme obesity, certain medications, and severe dehydration. It is possible to aid in preventing additional kidney stones if they can be predicted and treated early challenges posed by injury to the urinary system or kidneys. Delaying therapy might lead to irreversible renal failure or possibly be the cause of cancer [2].

Experts in the medical area, study the anatomy and physiology of living things in great detail so that they may identify and cure abnormalities with greater efficiency. Medical diagnosis may be made more quickly and correctly because of advances in medical image processing [3, 4]. The advancement of computer-aided automation has allowed for the use of artificial intelligence approaches, such as various machine learning (ML) and deep learning (DL) algorithms in image

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processing, to achieve better results in the field of medical image processing [4].

The purpose of the current proposal is to provide a new optimised TL model for efficient kidney stone categorization. Using the GTO technique, the hyperparameters of the learning model are fine-tuned. Medical professionals may use a number of imaging modalities, including X-rays, CT scans, and MRIs, to provide a clearer picture of a patient's condition (MRI). Computed tomography scans (CT) are often used and readily accessible. Several kidney problems may be identified and monitored using these procedures. Stone disease, kidney cysts, hydronephrosis (urinary tract obstruction), congenital malformations, and urinary tract infections are all examples of such abnormalities [5]. In addition, the identification of such anatomical characteristics is crucial for the effective management and surgical treatment of such disorders. Because to their poor contrast and speckle, kidney stones make ultrasound imaging a difficult and subjective process for diagnosis noise. In order to address this issue, various imaging techniques are employed. When it comes to identifying stone disease, a non-contrast-enhanced CT scan is considered the preferred method according to Petrik et al. (2016).

CT scan functionality stone density, stone structure, and skin-to-stone distance are only some of the information provided by MRI that sets it apart from other imaging modalities and makes it invaluable for patient counselling and treatment decision-making. Noise introduced into X-ray or CT pictures acquired under less-than-ideal settings may compromise their ability to identify pathologies, abnormalities, or malignant cells [6]. Many different filters for image processing have been suggested for eliminating noise. The effectiveness of these methods varies with the various sources of noise in the picture.

The process of estimating original, clean pictures from corrupted or noisy ones is known as image restoration. Image corruption comes in various forms, including motion blur, camera noise, and a lack of focus. With diagnostic imaging, doctors may learn more about a patient's internal organs and choose the best course of treatment. This may be accomplished by the use of both external and internal sources of energy, as well as the study of CT scans of the kidneys. CT scans are the gold standard for imaging the kidney because of how simple, quick, and affordable they are [7]. The existence and location of microcalcifications in the kidney provide crucial information for imaging the organ; this anatomical data may be collected with high-resolution technologies employing CT scans. Although the capacity to automate and analyze rehabilitative images is a useful way to help doctors, there is yet no all-encompassing imaging

technique for all CT scan uses and purposes [8][9]. In order to safeguard and enhance the most crucial clinical data without providing superfluous curios, computer projects and processing approaches that collect the data and information gathered from medical imaging scanners must be diligently built. Intelligently designed computer processing algorithms, applications, and software may further improve diagnostic information from medical pictures; hence, we presented a Matlab-based application to clarify borders for stones in kidneys.

Why doctors even bother treating kidney stones, is an intriguing subject. To begin, this is a painful sickness for which painkillers are just a temporary solution and the permanent solution is stone removal. Additionally, painkillers do not reduce discomfort. Findings from seminal observational studies in past showed that large kidney stones (staghorn stones) were associated with up to a 30% 10-year death risk in individuals in the 1970s who were treated conservatively (without surgical removal). Additionally, one-fourth of these people had urinary tract infections that were so severe that they significantly hampered kidney function. This article's goal was to use effective segmentation algorithms to give medical practitioners trustworthy information about the presence of kidney stones on CT images [10].

For this reason, automated detection must use image filtering as one of its primary operations in order to provide an efficient stone detection system. The stone will then be automatically identified using segmentation and morphological analysis, mitigating the possibility of a wrong identification owing to variances in the competence of the judge. Several nephrolith identification specialists have reported various methods for pinpointing kidney stone in MRI images. In the academic community, the need for robust segmentation has been repeatedly emphasised. There is an idea that says accurate stone identification is impossible without a method of segmentation that is both powerful and efficient [11].

After CT image enhancement and cleaning, the target region may be retrieved. Stones in the kidneys are deposits made of several inorganic compounds, most often calcium and acid. At the beginning, most individuals with kidney stones don't experience any pain, but the problem worsens with time. Having a precise and reliable method for locating concretion is crucial for a successful surgical procedure. Sometimes a nephrolith may show up on a CT scan but will go unnoticed by a person.

Thus, we favoured automated approaches based on artificial intelligence and digital image processing for identifying kidney stones in CT images (ANN) Renal calculus, or kidney stone development, is the medical term for the creation of crystals in the urine as a result of

substance concentration or other variables. No one is immune to kidney stones, and most cases go undetected until the patient has significant abdominal pain or notices a change in the colour of their urine. Additionally, individuals with kidney stones often exhibit nonspecific symptoms, such as fever, pain, and nausea.

Kidney stones need to be diagnosed as soon as possible so that the right medical care may be administered. Constantly passing stones may cause the kidneys to atrophy and decrease in size. It also plays a role in determining whether or not a person will develop chronic kidney disease or end up with chronic renal failure. Nevertheless, since it often has no symptoms, it is commonly found in people who are being evaluated for other conditions, such as cardiovascular disease (CVD), diabetes, or issues with the urogenital system.

2. Literature Review

According to [1], recent years have seen a rise in the use of image processing methods across a range of medical specialities, namely for improving diagnostic and treatment-initiating images. The existence of kidney stones is identified and reported using an image processing-based detection approach. A kidney stone may be fatal if not diagnosed appropriately, and some individuals who have early signs of stone formation in their kidneys do not recognise them as an infection, leading to progressive damage to the organ. Imaging modalities including computed tomography (CT), x-rays, and ultrasound may help in the diagnosis of kidney disorders. The authors used MATLAB to analyse the genitourinary system and locate the kidney stone. Low-pre-processing methods utilised during the enhancement phase are deemed to be essential for both accurate picture analysis and improved image quality.

When it comes to training neural networks, Back Propagation Network is the algorithm of choice. For the purpose of implementing an automated kidney stone categorization, it is used for processing the picture and data [2]. Human inspection is the standard method for classifying kidney stones and detecting them in medical resonance pictures. Due of its inefficiency in dealing with vast amounts of data, this approach is inaccurate. Sometimes, magnetic resonance (MR) images will include imperfections that can't be remedied due to human mistake. As a result, serious errors arise when attempting to classify characteristics or illnesses in images. Nevertheless, extracting the area of interest using a back propagation network technique has showed considerable promise via the use of AI-based technologies like neural networks and feature extraction. This study used a Back Propagation Network to detect kidney stones. There are two steps to the decision making process: 1.Extraction of Features Identifying categories in pictures (2). Principal

component analysis is used for feature extraction, and a Back Propagation Neural Network (BPN) is used for picture classification (BPN). The Fuzzy C-Mean (FCM) clustering technique is introduced as a means of segmentation in this paper. Training time and accuracy estimates were used to evaluate the BPN classifier's performance. In comparison to other neural network-based approaches, Back Propagation Network provides more accurate categorization.

Under the rib cage, the kidneys form a pair of fist-shaped organs [3]. Maintaining healthy kidney function is crucial for overall well-being. Malnutrition weakened bones, and nerve damage are just some of the side effects of kidney disease, which occurs when the kidneys are unable to function normally. It is possible that the kidneys may cease working altogether if the condition progresses unchecked. Stones, cancer, congenital abnormalities, urinary tract obstruction, etc., may also lead to kidney problems. Nephrolithiasis, which refers to the presence of kidney stones, is a very painful condition. Predicting the precise location of kidney cancers is crucial for surgical procedures. The CT scan images have low contrast and noise, which makes manual kidney abnormality detection difficult. So, it is very desirable to have an accurate and intelligent system automatically predict the stone, as this would be quite helpful when administering therapy. The primary goal of this work is to create software capable of automatically identifying stones in CT scans. Stone may be efficiently classified using a learning model called a Support Vector Machine (SVM). The kidneys with stones and the healthy kidneys are separated into two distinct regions of the vector space. The picture may be improved using tools like histogram equalisation and Emboss, which use directionally calculated colour differences, before the stone is classified. Existing methods may distort the actual data, which in turn makes the system less reliable. After analysing 156 CT samples that included both a kidney with a stone or tumour and a healthy kidney, the system was able to achieve an accuracy of 98.71 percent.

Renal calculi, more often referred to as kidney stones, are crystalline masses that are formed in the urinary tract [4]. It is crucial for surgical procedures to diagnose the exact location of urinary calculus. The presence of speckle noise in ultrasound pictures makes it challenging to manually identify urinary calculus, necessitating the use of automated tools for kidney stone diagnosis. Changes in kidney shape and location, as well as limb oedema, may be diagnosed using ultrasound imaging; additional imaging methods can detect kidney abnormalities such as stones, cysts, urinary tract obstruction, congenital defects, and malignant cells. Appropriate image processing methods may help with this problem. In a study by Rajput

et al. [4], an image-processing approach to detect kidney stones automatically and without manual inspection was suggested. This research also included a review of the literature and a comparison of several algorithms for detecting urinary calculi in human bodies.

In [5], the author offered a method that used deep learning models to automatically identify kidney stones using the CT images that were designed specifically for use with deep learning algorithms. In a comparison of the effectiveness of several deep learning models, VGG series was shown to be the most effective. Using the VGG16 architecture, we were able to achieve a 99% detection rate for kidney stones. Furthermore, the stratified K-fold cross validation technique was used to assess the model's efficacy. Furthermore, Grad-CAM, short for Gradient-weighted Class Activation Mapping, was used to pinpoint the kidney stone's location. Briefly, they used a VGG model server to categorise a CT image, a Grad-Cam to locate the region of interest, and a human verifier to ensure accuracy.

3. Data and Methodology

MATLAB is a high-performance programming language system used by researchers for analysis of data, development of algorithm generating various models through iterations helping to automate the work. The MATLAB software package includes extra toolboxes. For typical applications including artificial neural networks, symbolic calculations, computational imaging, system control design, and statistics, these toolboxes were developed. It provides a user-friendly environment in which problems and answers may be written in standard mathematical notation. The method was realized in MATLAB.

Given that the Matlab Image Processing Toolbox is a collection of tools that expands the capabilities of the Matlab numerical computing environment. The toolkit is adaptable to a variety of image-processing tasks, including enhancement and analysis. Applications of linear filtering and filter design, as well as region-of-interest operations. MATLAB image processing toolbox provided all the equations and functions utilised in this analysis.

Edge based segmentation

Image dilation is the next process. In this case, the binary gradient mask highlights the image's high-contrast lines. The shape of the thing being studied is not completely captured by these lines. Distinct voids in the lines bordering the original picture may be seen when compared to this one. By stretching the Sobel picture using the `strel` function's linear structural components, these lines of emptiness are filled in. The vertical structuring element is used to expand the binary gradient

mask, and then the horizontal structuring element is used to further expand the mask. The picture is enlarged via the `imdilate` tool. The next step is to seal any openings inside the structure. The expanded gradient mask does a good job of revealing the cell's contours, but it leaves significant gaps inside the cell itself. We use the `imfill` operation to fill up these spaces. Then the border objects with connections must go. While the target cell was effectively segmented, other objects were also discovered. The `imclearborder` command may be used to get rid of any items in an image that are attached to the border. In order to get rid of diagonal connections, we set the connectivity in the `imclearborder` function to 4. The next stage is to refine the object's surface.

Lastly, we use a diamond structuring element to erode the picture twice to smooth out the segmented object and return it to its original appearance. Via the use of the `strel` function, we produce the diamond skeleton. Other methods of showing the segmented item include outlining the cell that was segmented. The function `bwperim` is responsible for producing the outline.

A subfield of machine learning, "deep learning" consists of what amounts to a 3-layered neural network. Although, they can "learn" from massive amounts of data, but their capacities are still inferior to those of the human brain. A single layer neural network may still produce approximative predictions, however more hidden layers may help modify and improve the accuracy.

Prior research has indicated that the process known as "CT" involves rapidly shifting a narrow x-ray radiation beam around the frame while it is focused on a patient. Each computer's processing is then used to encourage the creation of cross-divided facial features or "slices" of the body.. Tomographic pictures, which show a cross-section of a structure, are more informative than traditional X-rays. A 3D model of the anatomy of patient's body is built by digitally "shapely" piecing together each individual slice so that anomalies and normal structures may be precisely labelled and sectioned.

With a CT scanner, the radioactive source is powered by a motor and spins inside the hole of a doughnut-shaped base, rather than the radioactive tube used in traditional radiography. The patient has a CT scan while lying on a revolving bed that slowly moves around a stage, while a television set rotates around them, generating small X-ray photons through the screen. By positioning a number of mathematical radiation detectors at right angles to the radioactive source, CT scanners create a kind of correction film. The X-rays are detected and sent to a computer after they have passed through the person. By arranging image slices individually or symmetrically to create a single piece, a 3D accurate duplicate of the patient

can be created, displaying the patient's frame, procedures, tissues, as well as some problems the doctor is reluctant to point out.

When it comes to diagnosing kidney injuries and diseases, CT scans of the kidneys may be more accurate than traditional X-rays of the kidneys, ureters, and bladder

(known as KUB X-rays). CT scans can detect abnormalities like tumors or lesions, obstructive diseases such as kidney stones, congenital abnormalities, polycystic uropathy, and fluid buildup around the kidneys with great precision. This is possible by performing a CT scan on one or both kidneys, which can also detect the location of abscesses.

Block Diagram

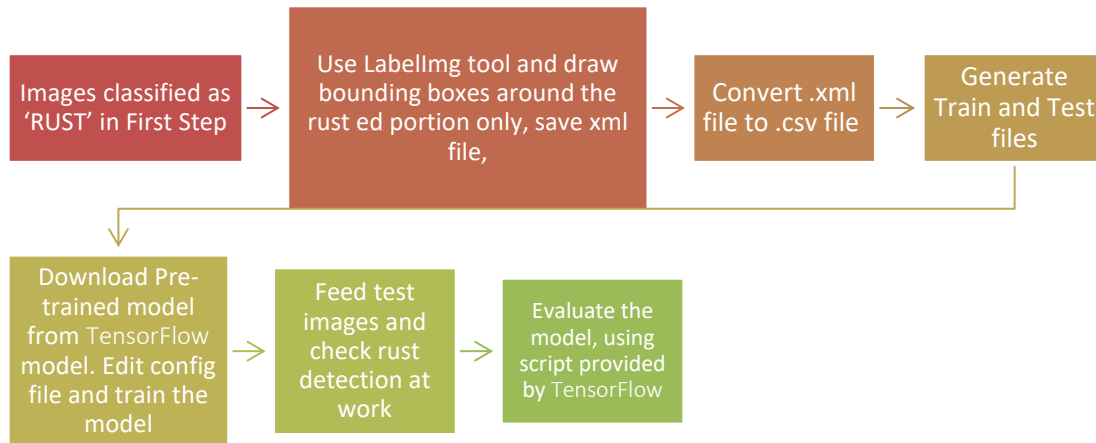


Fig 1. Block Diagram of Kidney Stone Detection System

Kidney stones, , are formed due to the minerals in urine. These stones are caused by a combination of environmental and hereditary causes. Excess body fat, a poor diet, certain drugs, and chronic dehydration all have a role. Kidney stones may affect people of any race, religion, or nationality. Diagnosis and detection of this kidney stone may need a combination of blood testing, urine tests, and imaging studies. Scan techniques vary between CT scans, ultrasonic scans, and Doppler scans. Automatization is now used in the medical field. Computerized diagnosis has given birth to a number of problems that were not previously understood, such as the

need for accurate and dependable findings and the use of appropriate algorithms. Diagnostics in medicine are notoriously tricky and very subjective. When it comes to making medical diagnoses, a neural network, a kind of soft computing, has been demonstrated to be better than other methods because of its ability to learn and then do partial detection. Feature extraction and watershed are two neural network methods that we use in this research on the issue of kidney stone identification. Training data is performed in two different ways at first. The data gleaned from kidney stone patients' blood results may be useful to hospitals and laboratories.

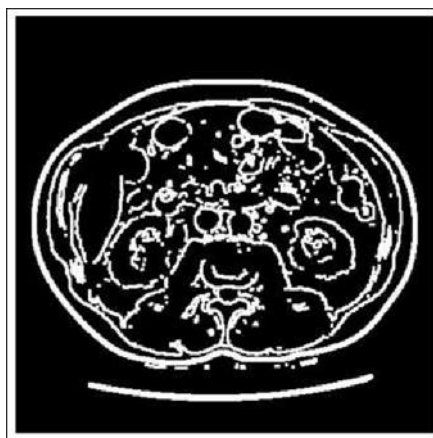


Fig 2: Dilated Gradient Image

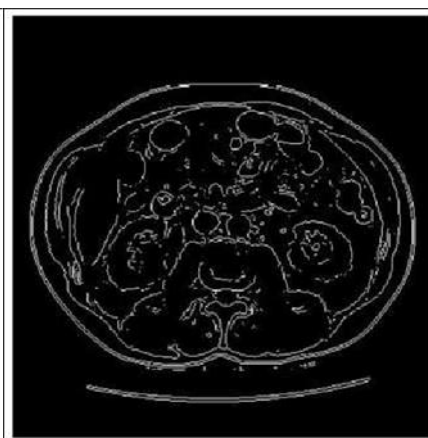


Fig 3: Binary Gradient Image

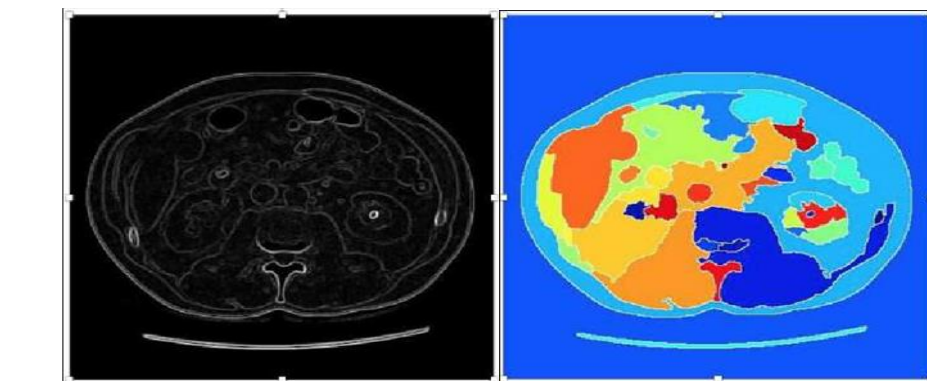


Fig 4 Magnitude Image

Fig 5: Colored Watershed Matrix Image

4. Discussion:

Timely and accurate identification of kidney stones is crucial for appropriate management and treatment planning. Image processing techniques coupled with machine learning algorithms have shown promise in enhancing kidney stone identification, addressing the limitations of conventional ultrasonography.

One of the key image-processing approaches used in kidney stone identification is edge detection. Edge detection algorithms, such as Canny, Sobel, or Laplacian of Gaussian (LoG), can highlight the boundaries and edges of kidney stones, improving their visibility in ultrasonographic images [12]. This technique enhances the contrast between the kidney stone and surrounding tissues, aiding clinicians in accurate stone localization and sizing.

Another example of image processing in kidney stone identification is texture analysis. Texture analysis techniques, such as Gray Level Co-occurrence Matrix (GLCM) or Local Binary Patterns (LBP), extract textural features from ultrasonographic images [13, 14]. These features can differentiate between kidney stones and normal renal parenchyma, enabling more reliable and automated stone detection.

Machine learning algorithms have also been applied to improve kidney stone identification using ultrasonographic images. Supervised learning methods, like Support Vector Machines (SVM) or Random Forests, have been trained on labeled datasets of ultrasonographic images to classify kidney stones accurately [15]. Such algorithms can distinguish between different types of stones, such as calcium oxalate, uric acid, or struvite stones, based on their characteristic features, aiding in personalized treatment plans.

Convolutional neural networks (CNNs), in particular, have shown exceptional effectiveness in determining the presence of kidney stones from ultrasonographic pictures [16, 17]. CNNs can automatically learn hierarchical features from data and have the potential to outperform

traditional machine-learning methods. One study that used a deep learning CNN model to identify kidney stones with an amazing accuracy of over 95% was published in the *Journal of Medical Systems* (June 2021), demonstrating the important role that deep learning plays in kidney stone diagnosis.

Despite the promising results, there are challenges in applying image processing and machine learning to kidney stone identification. One major challenge is the presence of artifacts and speckle noise in ultrasonographic images, which can affect the accuracy of stone detection algorithms. Furthermore, the availability of annotated datasets for training machine learning models remains limited, hindering the development of more robust and generalized algorithms.

5. Conclusion

In this study, we compared many segmentation methods for finding kidney stones. Edge-based segmentation, watershed-based segmentation, and threshold segmentation are the segmentation methods being studied. Also, we recommend watershed techniques for kidney stone detection based on our studies. Researchers may try to apply different segmentation techniques to the problem of kidney stone identification in the future, or they may strive to improve the effectiveness and quality of a good analytic algorithm. Another fascinating undertaking is to expand the area of analysis, which will enable the use of different segmentation methods for the detection and tracking of various kidney ailments. Consisting of kidney stones, kidney cysts, hydronephrosis (urinary tract obstruction), congenital malformations, and malignancies of the urinary system, these conditions are abnormalities..

References

- [1] Janarthanan, S., Ashok, A. Guruprasad, S. S., Mounesa, P. Madhan Mohan, M. and Baluprithviraj, K. N., "Investigation of Kidney Stone Detection using Image Processing," *2022 International Conference on Edge Computing and Applications*

- (ICECAA), Tamilnadu, India, 2022, pp. 946-951, doi: 10.1109/ICECAA55415.2022.9936089.
- [2] M. Akshaya, R. Nithushaa, N. S. M. Raja and S. Padmapriya, "Kidney Stone Detection Using Neural Networks," *2020 International Conference on System, Computation, Automation and Networking (ICSCAN)*, Pondicherry, India, 2020, pp. 1-4, doi: 10.1109/ICSCAN49426.2020.9262335..
- [3] Soni and A. Rai, "Kidney Stone Recognition and Extraction using Directional Emboss & SVM from Computed Tomography Images," *2020 Third International Conference on Multimedia Processing, Communication & Information Technology (MPCIT)*, Shivamogga, India, 2020, pp. 57-62, doi: 10.1109/MPCIT51588.2020.9350388.
- [4] S. Rajput, A. Singh and R. Gupta, "Automated Kidney Stone Detection Using Image Processing Techniques," *2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, Noida, India, 2021, pp. 1-5, doi: 10.1109/ICRITO51393.2021.9596175..
- [5] M. B, N. Mohan, S. K. S and S. K. P, "Automated Detection of Kidney Stone Using Deep Learning Models," *2022 2nd International Conference on Intelligent Technologies (CONIT)*, Hubli, India, 2022, pp. 1-5, doi: 10.1109/CONIT55038.2022.9847894.
- [6] J. Jendeberg, P. Thunberg, and M. Lidén, "Differentiation of distal ureteral stones and pelvic phleboliths using a convolutional neural network," *Urolithiasis*, Feb. 2020, doi: <https://doi.org/10.1007/s00240-020-01180-z>.
- [7] R. Anand, V. Sowmya, Vijaykrishnamenon, E. A. Gopalakrishnan, And K. P. Soman, "Modified Vgg Deep Learning Architecture For Covid-19 Classification Using Bio-Medical Images," *IOP Conference Series: Materials Science and Engineering*, vol. 1084, no. 1, p. 012001, Mar. 2021, doi: <https://doi.org/10.1088/1757-899x/1084/1/012001>.
- [8] Aksakalli, S. Kaçdioğlu, and Y. S. Hanay, "Kidney X-ray Images Classification using Machine Learning and Deep Learning Methods," *Balkan Journal of Electrical and Computer Engineering*, pp. 144–151, Apr. 2021, doi: <https://doi.org/10.17694/bajece.878116>.
- [9] Verma, M. Nath, P. Tripathi, and K. K. Saini, "Analysis and identification of kidney stone using Kth nearest neighbour (KNN) and support vector machine (SVM) classification techniques," *Pattern Recognition and Image Analysis*, vol. 27, no. 3, pp. 574–580, Jul. 2017, doi: <https://doi.org/10.1134/s1054661817030294>.
- [10] M. Alwan And S. Sadek, "Investigation of Kidney Stone Using a Microstrip Patch Antenna Scanning System," *Journal of Diagnostics*, vol. 3, no. 1, pp. 1–10, 2016, doi: <https://doi.org/10.18488/journal.98/2016.3.1/98.1.1.10..>
- [11] R. Islam, F. Mahbub, S. Abdul Kadir Al-Nahiu, S. Banerjee Akash, R. Rashidul Hasan and A. Rahman, "Design of an On-Body Rectangular Microstrip Patch Antenna for the Diagnosis of Breast Cancer Using S-Band", *Proceedings of Sixth International Congress on Information and Communication Technology*, pp. 1033-1044, 2022
- [12] Stoecker, W. V., Zhang, Z., Moss, R. H., Umbaugh, S. E., & Ercal, F. (1997). Boundary detection techniques in medical image processing. *General Anatomy*, 4, 1.
- [13] Hafizah, W. M., Supriyanto, E., & Yunus, J. (2012, May). Feature extraction of kidney ultrasound images based on intensity histogram and Gray level co-occurrence matrix. In *2012 Sixth Asia Modelling Symposium* (pp. 115-120). IEEE.
- [14] HusseinAli, A., Hasan, E. H., & Naemah, M. R. Kidney Texture Classification Using Local Binary Pattern and Geometrical Features.
- [15] Qadri, S. (2021). Role of Machine Vision for Identification of Kidney Stones Using Multi Features Analysis. *Lahore Garrison University Research Journal of Computer Science and Information Technology*, 5(3), 1-14.
- [16] Alkurdy, N. H., Aljobouri, H. K., & Wadi, Z. K. (2023). Ultrasound renal stone diagnosis based on convolutional neural network and vgg16 features. *Int J Electr Comput Eng*, 13(3), 3440-3448.
- [17] Vishmitha, D., Yoshika, K., Sivalakshmi, P., Chowdary, V., Shanthi, K. G., & Yamini, M. (2022, September). Kidney Stone Detection Using Deep Learning and Transfer Learning. In *2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA)* (pp. 987-992). IEEE.
- [18] Ravanappan, P. ., Ilanchezhian, P. ., Chandrasekaran, N. ., Prabu, S. ., & Saranya, N. N. . (2023). Secure Blockchain Transactions for Electronic Health Records based on an Improved Attribute-Based Signature Scheme (IASS). *International Journal on Recent and Innovation*

Trends in Computing and Communication, 11(4s), 77–83. <https://doi.org/10.17762/ijritcc.v11i4s.6309>

[19] Prof. Virendra Umale. (2020). Design and Analysis of Low Power Dual Edge Triggered Mechanism Flip-Flop Employing Power Gating Methodology. International Journal of New Practices in

Management and Engineering, 6(01), 26 - 31. <https://doi.org/10.17762/ijnpme.v6i01.53>

[20] Sharma, R., Dhabliya, D. A review of automatic irrigation system through IoT (2019) International Journal of Control and Automation, 12 (6 Special Issue), pp. 24-2