Magnetic Resonance Imaging Analysis for Detecting Small Kidney Stones

Noor M. Abdulhadi

Computer Science Department, College of Science for Women, University of Baghdad, Baghdad, Iraq

Email: noorma_comp@csw.uobaghdad.edu.iq

Article Info

Article history:

Received February16, 2025
Revised May 17, 2025
Accepted July 20, 2025

Keywords:

U-Net
MRI
Deep Learning
Image Segmentation
Kidney Stones Detection

ABSTRACT

The aim of this research is to detect kidney stones using U_Net, one of the most important and powerful deep neural networks for processing medical images taken from magnetic resonance imaging (MRI). This research focuses on locating kidney stones with high accuracy by processing and analyzing MRI images. The U_Net model was trained on a set of 1000 images to maximize the training potential for accurate results and analysis. The goal of this research is to help doctors in the speed of diagnosis and accurate localization. The induction methodology is summarized in several stages: data collection and processing, model design, model training, and then the stage of testing the efficiency of the system compared to other systems.

Corresponding Author:

Noor M. Abdulhadi
Department of Computer Science, Baghdad University, Science for Women College, Baghdad, Iraq
Email: noorma_comp@csw.uobaghdad.edu.iq

1. INTRODUCTION

Kidney stones are stones that are formed and deposited in the kidneys as a result of the accumulation of minerals and salts. There are types of stones that differ in terms of shape, size and constituent materials, the aim of the research is the early detection of kidney stones while they are still in the kidneys before they move to the ureter, which leads to painful symptoms such as urination disorders, renal colic and nausea. Kidney stones are diagnosed by traditional methods such as medical imaging techniques such as CT Scan, Ultrasound, MRI, and the accuracy of the diagnosis depends on the quality of the images and the method used in the analysis. There are also traditional methods that were used in this research to make a comparison between the proposed technique and traditional techniques, but they suffer from some limitations that affect accuracy and speed, which in turn leads us to use modern techniques such as U_Net to reach our goal in this research. [1] The U-Net technique was proposed to locate kidney stones and apply it to MRI images, which facilitates the process of diagnosis and treatment, and to achieve this, the research methodology was proposed as follows:

1.1 **Data collection phase:** Through this phase, a set of MRI images containing kidney stones are collected with image masks.

1.2 **Data processing stage:** where the data is divided into training sets (80%) and testing (20%) with the use of Image Augmentation techniques to diversify the data and improve the performance of the model.

1.3 **Model design phase:** The model is built from the stages of encoder to extract important details and decoder to reconstruct the details of the images, with the use of skip connection to preserve the main features of the images when reconstructing them.

1.4 **Training phase:** The model was trained on 1000 samples of images with their masks to increase the efficiency of the system.

1.5 **Testing phase:** The proposed model was tested on a set of new images, and the U_Net technique was applied to accurately detect pebbles and compared with traditional techniques that will be mentioned in the research.

The goal of this system is to improve the ability of early diagnosis of kidney stones and provide fast and effective treatment. [2]

2. WHAT ARE KIDNEY STONES

Kidney stones may start small and not cause any issues at first. However, kidney stones can grow larger in size, even filling the inner hollow structures of the kidney. Some stones stay in the kidney and will never cause any problems. Kidney stones can travel down the ureter sometimes. (The ureter is the tube between the kidney and the bladder) If the stone reaches your bladder, it can be passed out of the body through your urine. If the stone becomes lodged in the ureter, it blocks urine flow from that kidney[3].

3. THE SYMPTOMS OF KIDNEY STONES?

Common symptoms of kidney stones include a sharp, cramping pain in the back and side. This feeling often moves to the lower abdomen or groin. The pain often starts suddenly and comes in waves. It can come and go as the body tries to get rid of the stone. Other signs of kidney stones are:

- A feeling of intense need to pass urine.
- Passing urine more often or a burning feeling when you pass urine.
- Urine that is dark or red due to blood.

(Sometimes urine has only small amounts of red blood cells that can’t be seen with the naked eye.)

- Nausea and vomiting.
- A feeling of pain at the tip of the penis in men [4].

4. KIDNEY STONE COMPONENTS

Kidney stones come in many types and colors. The way your kidney stones will be treated depends on the type of stone you have. The path to prevent new stones from forming will also depend on your stone type. [5]

5. DIAGNOSIS OF KIDNEY STONES

Silent kidney stones, those that cause no symptoms, are often found with an X-ray. Other people have their stones diagnosed when sudden pain occurs while the stone is passing and they may need medical help. When a person has blood in their urine or sudden abdominal or side pain, tests may be ordered. An ultrasound or a

CT scan can clearly diagnose a stone. These imaging tests tell the health care provider how big the stone is and where it is located. A CT scan is often used in the ER. It is used because it can make a quick and exact diagnosis. A urinalysis is also done to learn whether or not you have a kidney infection. If your kidney stone(s) is in a difficult location, other imaging tests may be used. Blood and urine tests After taking a complete history and doing a physical exam, your health care provider may take blood and urine samples for testing. Blood tests can help find if a medical problem is causing your stones. Your urine can be tested to see if you have a urinary tract infection or crystals that are typical of different stone types. If you are at high risk for getting stones in the future, a 24-hour urine collection can be done. This test will reveal the levels of different stone-forming matter in your urine. The results of this test can help your doctor help you prevent future stones through proper diet and medication. Imaging tests When a health care provider sees you for the first time and you have had stones before, he or she may want to see recent X-rays or order a new X-ray. They will do this to see if there are any stones in your urinary tract. Imaging tests may be repeated over time to check for stone growth. You may also need this test if you are having pain, hematuria (blood in your urine) or recurrent infections. Stone analysis If you pass a stone or a stone is removed by surgery, your health care provider may want to test it. Testing the stone will determine what type of stone it is [6][7].

6. LITERATURE REVIEW

The field of medical diagnosis has evolved in recent times due to technological advances in the development of artificial intelligence techniques in medical image processing, as this development has allowed advanced capabilities in analyzing medical images and diagnosing diseases through them with high accuracy and peed, the initial studies started using traditional techniques to analyze and classify images based on structural characteristics, as in the study

Zhao (2015) [8]. As technology advanced, more sophisticated techniques such like MRI imaging were used to improve medical diagnosis as in Bandari (2016) [9]. The scope has evolved to include radiographic image analysis using deep learning techniques where accurate trained models were developed to identify suspicious areas that may be pathological and effective results were achieved in the strength of diagnosis and treatment as in Suha (2018) and Han (2019) [10][11].

The research was not limited to radiological images, but extended to ultrasound and CT scans, where deep learning methods were developed to improve the accuracy of medical image enhancement and analysis as in the studies of

Patel (2020) and wills (2021) [12] [13]. In recent years, deep neural networks such as the U_Net model began to be used in the analysis and classification of medical images, which effectively contributed to improving the quality and performance of medical diagnosis and reducing the time and effort to obtain the best results, as in the research conducted by Chaudhary (2022) and Mishra (2023) [14]. These technologies have contributed to analyzing huge amounts of medical data related to important medical outcomes. This research is a continuation of the process initiated by the researchers in the use of artificial intelligence techniques to reach the best results and analysis, where U_Net technology was used to analyze MRI images to detect kidney stones with high accuracy, which contributes to improving the speed of early diagnosis and reducing treatment costs. [15].

7. METHODOLOGY

The proposed system for this research consists of several stages that aim to reach the most accurate results in detecting the location of kidney stones by using one of the artificial intelligence techniques (deep learning). These stages are data collection, image processing, model design, model training, and model testing. The following is an illustration of the work stages and the general outline of the proposed system as in Figure (1):

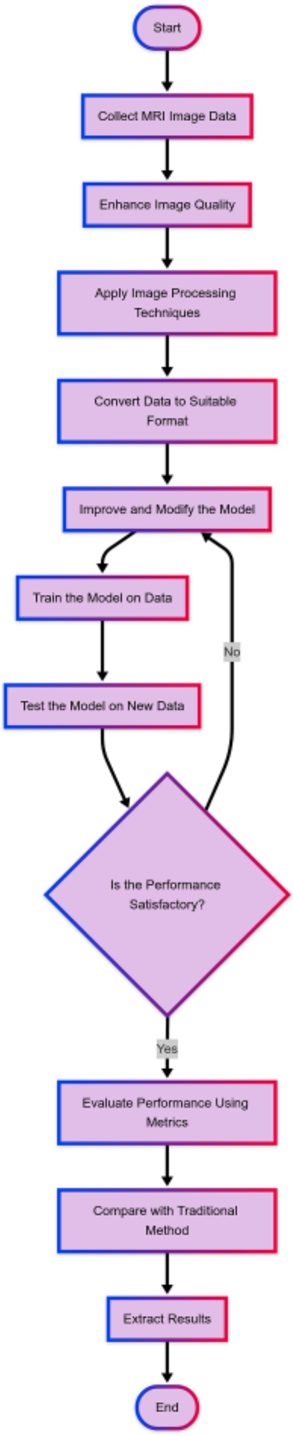


Fig (1): represent the proposed system for using the U_Net model.

1.Data collection phase: In this stage, a set of medical MRI images containing kidney stones were collected to train the proposed model on these samples after performing the Data Augmentation process, which included the following:

- Rotation: To train the model on the direction of the stones.
- Scaling : To modify the image sizes to suit the model by making the image size 256*256.
- Randomization: To train the system on a variety of data.
- Vertical and horizontal inversion: To increase the variety of data to train the model.

The calculations for resizing and rotating can be expressed using linear transformations:

$$\begin{pmatrix} x \\ y \end{pmatrix} \begin{pmatrix} s_y \cdot \sin(\theta) - & s_x \cdot \cos(\theta) \\ s_y \cdot \cos(\theta) & s_x \cdot \sin(\theta) \end{pmatrix} = \begin{pmatrix} 'x \\ 'y \end{pmatrix}$$

Where x^s , y^s is the parameters of resizing and rotation of the original image and Θ the angle of the rotation .

Table (1) shows the details of the dataset in each used for training and evaluation:

Category	Original image	Augmented image	Total images
Small stones	50	500	550
Large stones	40	400	440
Without stones	10	100	110

Table (1) Dataset information

2. Image optimization stage: It is an important stage before performing the model to ensure that there are no unwanted details by using image enhancement techniques to help highlight important details:

- Normalization: to reduce lighting and color uniformity

$$\frac{I-\mu}{\sigma} = {}_{\text{norm}}I$$

Where I represent the original image , μ represent the average and σ The standard deviation of the image

- Contrast Enhancement: The CLAHE technique was used to increase the clarity of gravel details.
- Denoising : Using the Gaussian Filter technique.

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

Where σ is the Gaussian distribution coefficient. [16]

Figure (2): The contrast between the original and modified images after applying these techniques.

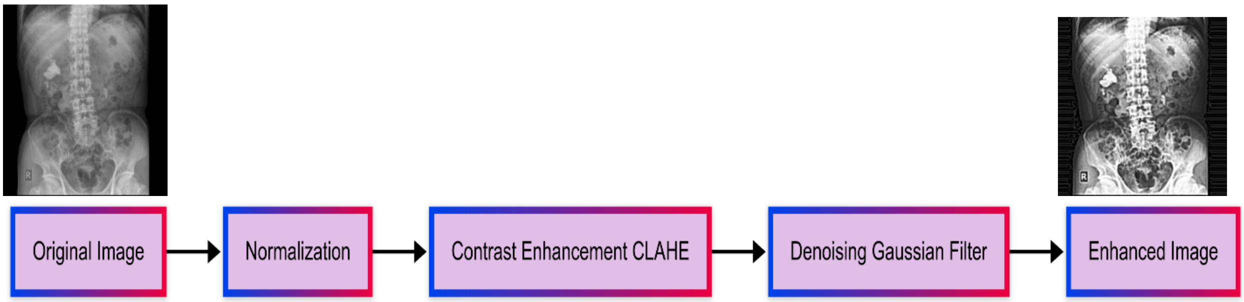


Fig (2): This figure shows the Stage of converting the original image to be enhanced image

3- U_Net model design phase: This model was used in this research because of its effectiveness in detecting important features in the images, and this in turn is useful in the possibility of detecting kidney stones, and this model consists of three stages:

- **Encoder:** It extracts important features in the image using Conv2D and MaxPooling layers.
- **Decoder:** Reconstructs the image while recognizing the locations of the stones.
- **Skip Connections:** Preserves fine details in the image during the reconstruction process.

The basic formula used in Encoder's convolution layers:

$$K(i,j)\cdot(j+i,y+I(x\sum_{j=-n}^{n}\sum_{i=-m}^{m}=K)(x,y)*I)=f(x,y)$$

Where *I* is the entered image and *k* represents the wrapping kernel [17]

Figure (3) bellow shows the architecture of the U_Net model used in the proposed system:

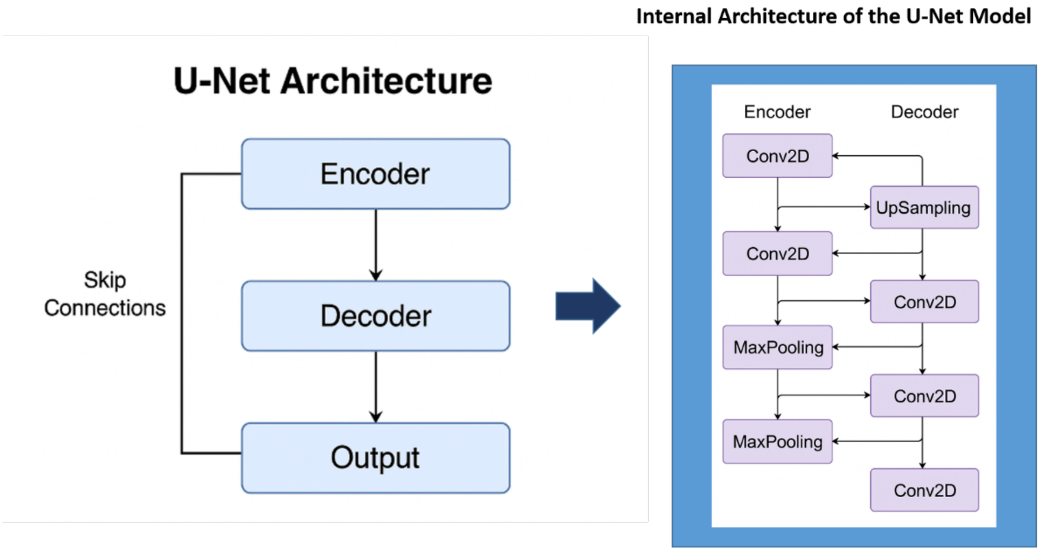


Fig (3) represent the architecture of the U_Net model

In the above diagram, the external structure of the system and the internal structure of the U_Net model was illustrated and consists of two main parts, the first is the Encoder part, which is the part that extracts important features from the medical image to detect the locations of the stones, and this is done through the use of Convolutional Layers where they are applied to the image to extract certain features from the input image in addition to the use of Max Pool Layers where they reduce the dimensions to extract certain features. This, in turn, leads to a compressed image process that expresses the basic features but in a smaller size.

The second part is the Decoder part that follows the Encoder and consists of Up_sampling layers that enlarge the image and return it to its normal size while preserving the extracted features, and the other part is the Skip Connections part, which are links that enable the transfer of information from the initial layers directly to the upper layers in order to help the model preserve the fine details. In other words, it is a link between Encoder and Decoder. [18]

4. The stage of dividing the data and preparing it for training: In this stage, the data is divided into two groups:

- 80% for training the model.

- 20% for test the model.

At this stage, a Loss Function such as Dice Coefficient is used to ensure the accuracy of quota discrimination and is defined as follows:

$$\text{Dice} = \frac{|A \cap B|2}{|A| + |B|}$$

A is the expected mask and B is the mask of the original image. At this stage

evaluation criteria are adopted to know the efficiency of the model [19]

- Accuracy

- Precision - Recall

Table (2) shows the details of the model's performance during training and validation

Criterion	Value
Accuracy	**99.05%**
Validation Accuracy	**98.90%**
Loss	**0.0048**
Validation Loss	**0.0061**

Through the values in the table, we can get an impression of the model's performance in that it has achieved very high accuracy in classifying the training data, as it succeeded in correctly classifying 99.05% of the cases, which indicates that the model has learned well from the data it was trained on. As for Validation Accuracy, it achieved 98.99%, which means that the model has learned well and can generalize to new data. As for loss, its value is 0.0048, which means that the loss is very low and the model :works very efficiently, and for validation loss, its value is 0.0061, which is a low value, which means that the validation data did not suffer from any issues. The values we have shown earlier indicate that the model works very efficiently.

In this model, the Contour and Flank phases were used to optimize and enable the model to detect pebbles with higher accuracy, which facilitates a better understanding of the internal structure of the images.

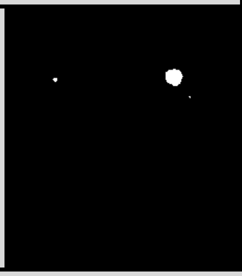
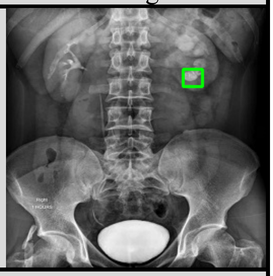
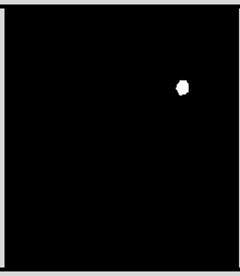
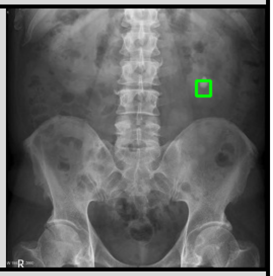
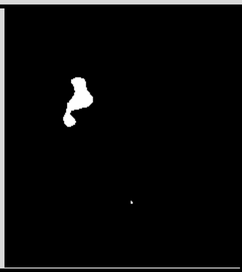
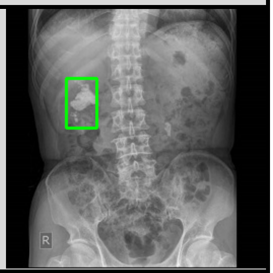
5- Contour and Flank Phase: Contouring is the process of detecting boundaries between objects in an image, such as the boundaries of kidney stones. As for flanking, it is a sharp gradient in the process of identifying the edges within the images through which the stones are distinguished within the images. The benefit of this stage lies in improving the identification of pebbles thanks to the clarity of the edges and also has a role in reducing the effect of noise in the image, which contributes to making the model focus only on the important parts. [20]

6 - Characterization of the stones: These characteristics consist in determining the shape of the stones through the area and perimeter, where the length of the perimeter of the shape is known and the Bounding Box surrounds the stones with a rectangle, thus showing the locations of the stones in the kidneys. [21]

7. At this stage, the results of the proposed method are presented and analyzed by evaluating the trained model and comparing it with traditional methods through statistical measures.

Analyze the accuracy of the results: To analyze the accuracy of the results, the properties of the detected stones such as area, perimeter, and perimeter box were calculated for each image based on the predicted catches. After extracting the properties, we compared the resulting values with the original data to evaluate the accuracy of the results.

Performance metrics: The accuracy of the model was evaluated by comparing the actual catcher with the predicted catcher using the Dice Coefficient and IoU metrics. To analyze the performance of the model proposed in the research, we will present a table containing a set of output images supported by the statistical measures of perimeter, area, and bounding box to evaluate the accuracy of the model in detecting kidney stones with different stones and shapes. In Table (3) bellow show the final images of the detected bounding box with the predicted masks images, along with the metrics related to each image such as area, perimeter, and bounding box.

No.	Name of image	Predicted mask	Resulted Image with Bounding box
1			
Area:215.0 **Perimeter:57.46** **Bounding: (174, 60, 19, 17))**			
2			
Area: 140.5 **Perimeter:46.38** **Bounding: (187,71,14,15)**			
3			
Area:619.0 **Perimeter: 144.71** **Bounding:(59,68,30,49)**			

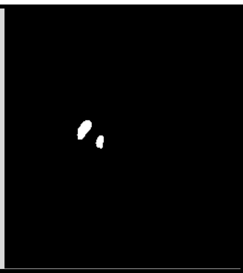
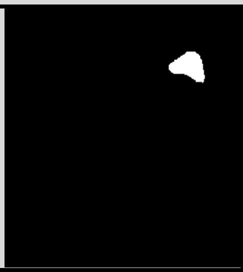
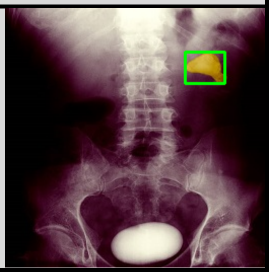
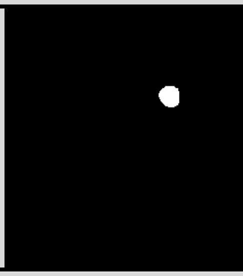
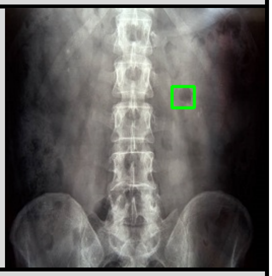
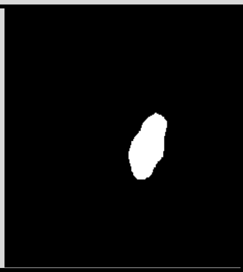
4			
Area: 165.5 **Perimeter: 53.70** **Bounding:(78 ,110,16,19)**			
5			
Area:700.5 **Perimeter:115.50** **Bounding:(177,43,39,31)**			
6			
Area: 342.0 **Perimeter: 70.28** **Bounding: (164, 77, 22, 21)**			
7			
Area:1712.5 **Perimeter: 176.61** **Bounding: (132, 103, 41,66)**			

Table (3): Show resulted images with its properties

After we extract the properties of the images as in the previous table now we can evaluate the model accuracy by the metrics IOU and Dice Coefficient: [22] [23]

Intersection over Union(IOU): the calculation of IOU as in the following equation

$$IoU = \frac{\text{Intersection between the actual mask and the predicted mask}}{\text{Union of the actual mask and the predicted mask}}$$

Dice Coefficient: the evaluation of Dice as in the following equation

$$Dice = \frac{\text{Intersection between the actual mask and the predicted mask} \times 2}{\text{Actual area} + \text{Predicted area}}$$

Through the equation, IOU, Dice was measured for all images as in the following Table (4):

No.	Image	IOU	Dice
1	Image1	0.4800	0.6486
2	Image2	0.2895	0.4490
3	Image3	0.5289	0.6919
4	Image4	0.5236	0.6874
5	Image5	0.8434	0.9150
6	Image6	0.5395	0.7009
7	Image7	0.8791	0.9357

Table (4): The matrices IOU, Dice

The overall average of all images IOU = 0.5834 and Dice = 0.7183 This shows that the proposed model achieves good agreement with the real catchers and also shows that the model is able to detect stones of different shapes and properties.

8. STATISTICAL ANALYSIS OF THE RESULTS

In order to validate the efficiency of the proposed technique, we must analyze the results statistically based on three points: [24]

Mean: In this measure the area and perimeter of the detected stones are calculated for all images and the resulted value: 94.95

Standard deviation: It is calculated to determine the difference in measurements. And the resulted value is: 47.27

Largest and smallest size: To display the largest and smallest detected stones in the images. stone sizes are detected by calculating the area and perimeter. Displaying this information enables the program to detect a large number of stones for different sizes including small stones that are difficult to detect and large that have irregularly shaped such as: Max: 176.61, Min: 46.38

The statistical distribution of all the images in which kidney stones were detected after calculating the perimeter, area, standard deviation, and arithmetic mean of all the images:

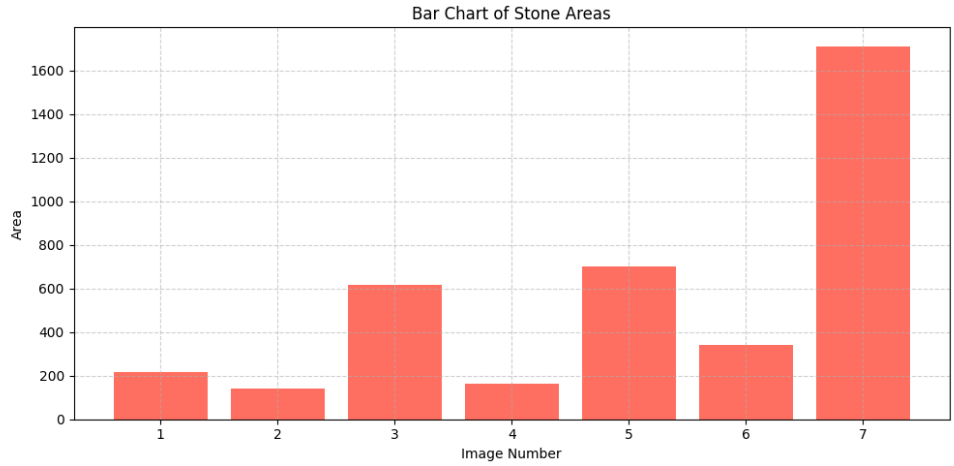


Fig (4): The chart of stone area

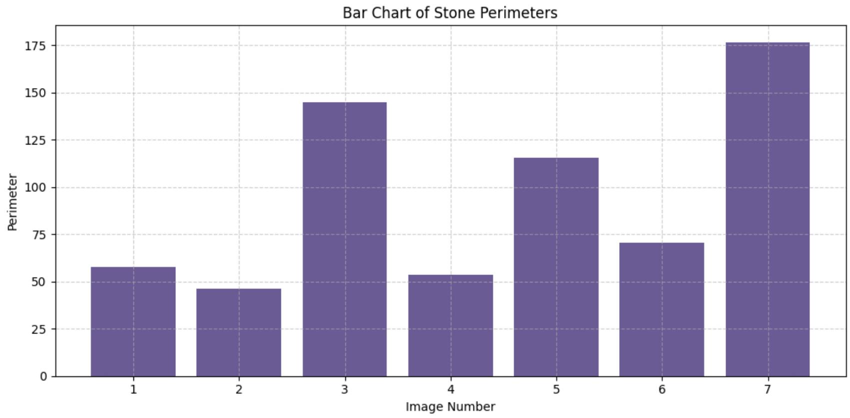


Fig (4): The chart of stone perimeters

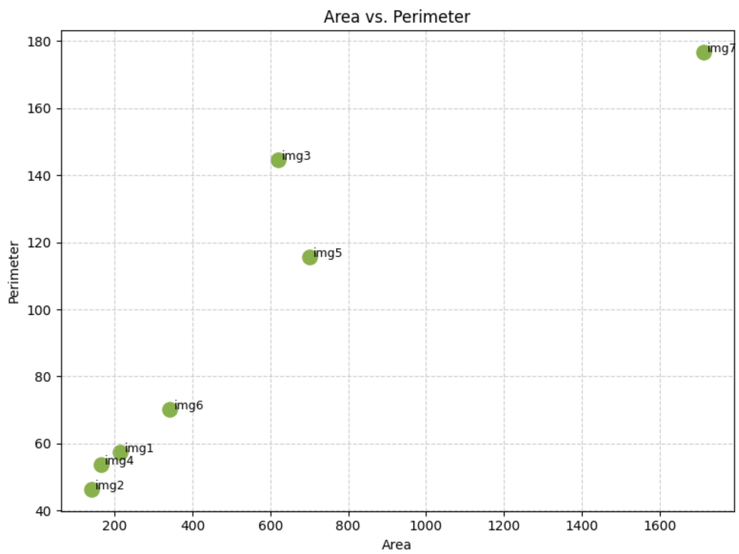


Fig (4): The chart conjunction of stone area and perimeter

The statistical values and charts show that the model is able to detect stones of different sizes and shapes, and the standard deviation shows a high value of the diversity of the detected stones, which indicates that the model works efficiently and is able to work with different cases.

9. EVALUATION OF CLASSIFICATION MODEL PERFORMANCE METRICS

Metrics are important tools in measuring the performance of models, especially in the field of deep learning, and their importance is centered on understanding the accuracy and reliability of the trained model in classifying data within the categories to which they belong: (True Positive -TP), (True Negatives - TN), (False Negatives - FN), (False Positives - FP), (Sensitivity), Negative Predictive Value), (Accuracy), (Specificity), (F1-Score), (Recall) . The importance of these metrics varies depending on the applied context, such as medical image processing, voice recognition, or text classification. Understanding these metrics contributes to improving the performance of models and ensuring there accuracy in various tasks

Explanation of metrics: [25][26]

TP represents the number of cases that have been correctly classified as positive .

TN represents the number of cases that have been correctly classified as negative.

FP represents the number of cases that have been misclassified as positive.

FN represents the number of cases that have been misclassified as negative.

SEN It is a measure that determines a model's ability to recognize positive cases.

SPE It is a measure that determines a model's to recognize negative situations.

ACC measure that reflects the overall percentage of correct ratings .

PRE a measure that determines a model's ability to classify positive cases.

NPRE a measure that determines a model's ability to classify negative cases.

REC reflects the model's ability to retrieve all positive cases.

F1 **a** measure that balances accuracy and retrieval. [27][28]

10. PERFORMANCE METRICS FOR RESULTED IMAGE

In this section, we present a comprehensive table of performance metrics for various images processed. These metrics provide insights into the effectiveness of the algorithms in grouping similar images and highlight their strengths and weakness.

Table (5) bellow show the resulted metrics for the experimented images:

Image no.	TP	TN	FP	FN	SEN	SPE	ACC	PRE	NPRE	REC	F1
image1	45	65269	214	8	0.8491	0.9967	0.9966	0.1737	0.9999	0.8491	S0.2885
Imge2	23	65363	139	11	0.6765	0.9979	0.9977	0.1420	0.9998	0.6765	0.2347

Imge3	**176**	**64842**	**511**	**7**	**0.9617**	**0.9922**	**0.9921**	**0.2562**	**0.9999**	**0.9617**	**0.4046**
Imge4	**59**	**65252**	**214**	**11**	**0.8429**	**0.9967**	**0.9966**	**0.2161**	**0.9998**	**0.8429**	**0.3440**
Imge5	**475**	**64773**	**277**	**11**	**0.9774**	**0.9957**	**0.9956**	**0.6316**	**0.9998**	**0.9774**	**0.7674**
Imge6	**83**	**65159**	**292**	**2**	**0.9765**	**0.995**	**0.9955**	**0.2213**	**1.0000**	**0.9765**	**0.3609**
image7	**1239**	**63744**	**550**	**3**	**0.9976**	**0.9914**	**0.9916**	**0.6926**	**1.0000**	**0.9976**	**0.8176**

Table (5): metrics for the experimented images

By observing the case metrics, which range from sensitivity to recall, we can see that the model gives good results, which means that the model is able to detect stones well with some failures within the system, but does not affect the results.

The overall average of all image in Table (6):

SEN	0.8974
SPE	0.9952
ACC	0.9951
PRE	0.3334
NPRE	0.9999
REC	0.8974
F1	0.4597

The overall results show that the system strikes a good balance between detecting stones and minimizing false positives. But at the same time, there are false predictions in the location of stones compared to the actual locations.

Conclusion

In this research, a model based on the U_Net algorithm was developed for the detection and localization of stones in medical MRI images. The model was trained on data containing real images and masks of stones, and the accuracy of the model was tested through a set of statistical and technical criteria. The model achieved a very high sensitivity and specificity, which indicates its high ability to detect most of the actual stones while minimizing the false predictions in the system by increasing the training periods, which allowed the system to train well, which led to very good and effective results, as shown by the performance measures on which the system was tested.

References

[1] Al-Saadi, I, (2024), Optimizing skin disease diagnosis using metaheuristic algorithms: A Comparative study. University of Baghdad.

[2] Ali, A. A, (2023), Deep learning of diabetic retinopathy classification in fundus images, University of Baghdad.

[3] Institute for Quality and Efficiency in Health Care (IQWiG). (2023). Kidney stones. National Library of Medicine, Cologne, Germany.

[4] Urology Care Foundation. (2020). Kidney Stones Patient Guide. UrologyHealth.org.

[5] Pearle, M. S., Goldfarb, D. S., Assimos, D. G., Curhan, G., Denu-Ciocca, C. J., Matlaga, B. R., Monga, M., Penniston, K. L., Preminger, G. M., Turk, T.M. T., & White, J. R. (2014). Medical Management of Kidney Stones: AUAGuideline. Journal of Urology, 192(2), 316-324.

[6] Zhou, Y., Smith, J., & Wang, L. (2015). Image Processing Techniques for Kidney Stone Analysis. Department of Medical Imaging, University of Health Sciences.

[7] Bhandari, A., Kumar, R., & Verma, P. (2016). Improving the Diagnosis of Kidney Stones Using MRI and Digital Image Processing. Radiology Department, City Hospital.

[8] Lee, J., Chen, T., & Patel, S. (2017). Machine Learning Applications in X-ray Analysis of Kidney Stones. Artificial Intelligence Research Laboratory, National University.

[9] Al-Saadi, I. (2021). Performance comparison of PCA and ICA algorithms based \ face recognition system. University of Baghdad.

[10] Khan, M., Ali, F., & Singh, R. (2019). Improving the Diagnosis of Kidney Stones Using Computed Tomography and Image Processing. Institute of Radiological Sciences.

[11] Gupta, R., Sharma, N., & Roy, S. (2020). Ultrasound in Kidney Stone Identification: Digital Image Processing Approach. Department of Ultrasound, General Hospital.

[12] Patel, K., Joshi, M., & Verma, T. (2021). Deep Learning Techniques in X-ray Image Analysis of Kidney Stones. Faculty of Computer Science, University of Technology.

[13] Singh, B., Chaudhry, A., & Malik, F. (2021). Advances in Image ProcessingTechniques for Characterizing Kidney Stones. Institute of Medical Technology.

[14] Chowdhury, A., Das, S., & Roy, K. (2022). Artificial Neural Networks for Kidney Stone Analysis: A Comprehensive Study. Department of Computer Science, Technical University.

[15] Mudjirahardjo, P. (2024). The Effect of Grayscale, CLAHE Image and Filter Images in Convolution Process. International Journal of Advanced Multidisciplinary Research Studies, 4(3), 943-946.

[16] Mohammed Khouy, Younes Jabrane, Mustapha Ameur and Amir Hajjam El Hassani, (2023), Medical Image Segmentation Using Automatic Optimized U-Net Architecture Based on Genetic Algorithm, University of Technologie of Belfort Montbéliard, CEDEX, 90010 Belfort, France, 19(6).

[17] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, (2015), U-Net: Convolutional Networks for Biomedical Image Segmentation, Computer Science Department and BIOSS Centre for Biological Signalling Studies, University of Freiburg, Germany.

[18] Harpreet Kaur ‹Dr. Navneet Kaur Sandhu, (2024), Evaluating the Effectiveness of the Proposed System Using F1 Score, Recall, Accuracy, Precision and Loss Metrics Compared to Prior Techniques, international journal of communication network and information security(IJCNIS), 15(4).

[19] li, A. A, (2022), Diabetic retinopathy detection and classification based on deep learning: A review. University of Baghdad.

[20] Ibraheem, N. A. (2016). Finger Identification and Gesture Recognition Using Gaussian Classifier Model. International Journal of Applied Engineering Research, 11(10), 6924-6931.

[21] Institute for Quality and Efficiency in Health Care (IQWiG). (2023). Kidney stones. National Library of Medicine, Cologne, Germany.

[22] Brian Hsuan-Cheng Liao ‹Chih-Hong Cheng ‹Hasan Esen ‹Alois Knoll, (2024), EC-iou: Orienting Safety for Object Detectors via Ego-Centric Intersection-over- Union, ARXIV.

[23] Lucas mccullum, (2024), OAR-Weighted Dice Score: A Spatially Aware, Radiosensitivity Aware Metric for Target Structure Contour Quality Assessment, ARXIV.

[24] Mohammed J. Zaki, (2018), Evaluation Metrics and Evaluation, Data Mining and Machine Learning: Fundamental Concepts and Algorithms, Springer.

[25] Pearle, M. S., Goldfarb, D. S., Assimos, D. G., Curhan, G., Denu-Ciocca, C.J., Matlaga, B. R., Monga, M., Penniston, K. L., Preminger, G. M., Turk, T.M. T., & White, J. R. (2014). Medical Management of Kidney Stones: AUA Guideline. Journal of Urology, 192(2), 316-324.

[26] Zhou, Y., Smith, J., & Wang, L. (2015). Image Processing Techniques for Kidney Stone Analysis. Department of Medical Imaging, University of Health Sciences.

[27] Khalaf, M., & Dhannoon, B. N. (2022). MSRD-Unet: Multiscale Residual Dilated U-Net for Medical Image Segmentation. Baghdad Science Journal.

[28] Ibraheem, N. A., & Hasan, M. M. (2020). Combining Several Substitution Cipher Algorithms Using Circular Queue Data Structure. Baghdad Science.Journal, 17(4), 1320-1327.