JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

COMPREHENSIVE KIDNEY STONE ANALYSIS THROUGH IMAGE ENHANCEMENT AND AUTOMATED CLINICAL RECOMMENDATION

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Abstract- The incidence of kidney stones is common in hospitals and in the diagnostic centers. Early recognition of stones prevents the occurrence of additional health issues. Kidney stones are normally diagnosed by use of CT scans, ultrasound images or X-ray images in normal practice. Clinicians usually analyze these images and the analysis can be quite different based on the clarity of the image and personal experience. This paper presents a description of a basic kidney stone analysis system based on a web. The renal image provided by the user is optimized to enhance the view of stone regions. The convolutional neural network is applied to verify the image of kidney stones. In case of a stone that appears, it is followed with an image that will help to calculate the approximate size of a stone and its location in the kidney region. According to the size obtained, the basic treatment-related information is presented as a reference. It is written in the Django framework and has an interface that uploads images and displays results in a simple interface. The objective of the system is to guide preliminary analysis and save the manual work routinely, whereas clinical judgments remain in the hands of the medical professionals.

Keywords— Kidney stone detection, medical imaging, image enhancement, convolutional neural network, stone size estimation, web-based diagnostic system.

I. INTRODUCTION

One of the health conditions that a great number of individuals encounter today is kidney stones. This issue is normally caused by the gradual build up of tiny particles of minerals in the kidney which turns hard. In order to examine this condition, physicians primarily utilize CT scan, ultrasound scan and X-ray images. The scans assist the doctors in having a clear view of the inside of the kidney. However, repeated scans are not always safe to the patients as the radiation can have an effect on the body. In addition, repeated scans are costly to the hospitals. In other instances, the stones are very small or the quality of the image is not clear and hence it becomes hard to detect.

One of the studies aimed at discussing the annual growth of kidney stone cases in the United States was published in the year 2021 by Tundo et al. [1]. The researchers were not conducting research on the number of individuals with kidney stones, but primarily the number of new cases coming up annually. The findings indicated that the kidney stone disease is increasing with time. This experiment made scholars realize that the issue is critical and requires more effective methods of diagnosis. Currently computers are becoming significant in the medical profession. Software systems are being used by many hospitals to assist doctors in diagnosis.

The benefits of machine learning techniques are that they can file through pictures automatically. Convolutional neural networks, which usually have applications in image-based issues, are among these methods. CNN models also learn through images bit by bit and discover useful patterns, including brightness change, shape difference and texture variation. Already, a number of scholars have engaged in kidney stone detection based on the application of deep learning methods. In other studies, Darknet19 models were applied to identify stones in CT scan images [14].

Image processing was used by the other researchers so that stone regions could be made more distinct by enhancing image quality [3]. These researchers demonstrated that the automated systems could assist the doctors through better interpretation of images. This is why, on the basis of all these facts, it is proposed in this project that CNN-based kidney stones system should be realized on the basis of medical images. This paper is primarily aimed at identifying kidney stones using nondestructive CT scanning, ultrasound, and X-rays normally, without being human-administered. The system is created to support the work of the doctor and not to substitute him. It aids in enhancing knowledge on the condition and elderly diagnosis. The report will be structured into introduction section, related work, proposed method, result and discussion and conclusion.

II. LITERATURE REVIEW

The article that was published in 2021 by Tundo et al. [1] is one of the studies devoted to discussing the annual increase in the number of kidney stones cases in the United States. This was not a research of the number of people who have kidney stones but most targeting the number of new cases emerging annually. The results showed that the kidney stone disease is on the rise with time. This experiment taught the scholars that the problem is urgent and needs more efficient ways of diagnosing it. There is the emergence of computers being very important in the medical profession. The majority of hospitals are using software systems to guide doctors on diagnosis.

The advantages of machine learning methods are in the fact that they can sort through pictures automatically. One of these techniques is the convolutional neural networks that are normally applied in image-like problems. CNN models too are trained image bit by bit and find useful patterns such as change in brightness, differentiation in shape, and difference in texture. There are scholars that have already participated in detection of kidney stones using the techniques of deep learning. Darknet19 models have been used in other research to detect stones in the CT scan images [14].

The other researchers applied image processing in ensuring the regions of stone became more prominent through improvement of quality of images [3]. These investigators revealed that the automated systems were capable of supporting the physicians by enhancing the view of images. Due to all these facts, it is suggested in this project that CNN-based kidney stones system is to be brought into reality on the premises of medical images. The main objective of the paper is that kidney stones could be identified with the help of nondestructive CT scanning, ultrasound, and X-rays which do not involve the work of human, in the first place, to identify kidney stones. The system is designed to facilitate the efforts of the doctor and not to replace him. It helps in improving information on the state and diagnostic care among the older persons. The report will be laid out into; introduction section, related work, proposed method, result and discussion and conclusion.

III. PROPOSED METHOD

In this project we are trying to find kidney stones using computer system. Normally doctors check scan images manually, but sometimes image is not clear and it takes more time. So we developed a system which helps to analyze kidney images automatically. First, the user uploads a kidney image in the website. The image can be CT scan or ultrasound image. After uploading, the system takes the image and improves its quality. This is done because many images are not clear and stone area may not be visible properly. After image enhancement, the image is sent to the trained CNN model.

Kidney images have already been used in training this model. The model verifies the picture and provides output on the presence or absence of kidney stone. When no stone is found, then this is displayed to the user. Whether there is stone that is detected, some additional analysis is carried out in the system. At this step, the stone diameter is estimated to a rough Communist measurement of pixels in an image. When the part of kidney in which the stone is located is checked as well is also done by the system. The crux of the matter is that based on the size of the stone, fundamental treatment data is shown as a reference only. The system fails to substitute physicians. It simply aids in the premature verification and decreases handwork.

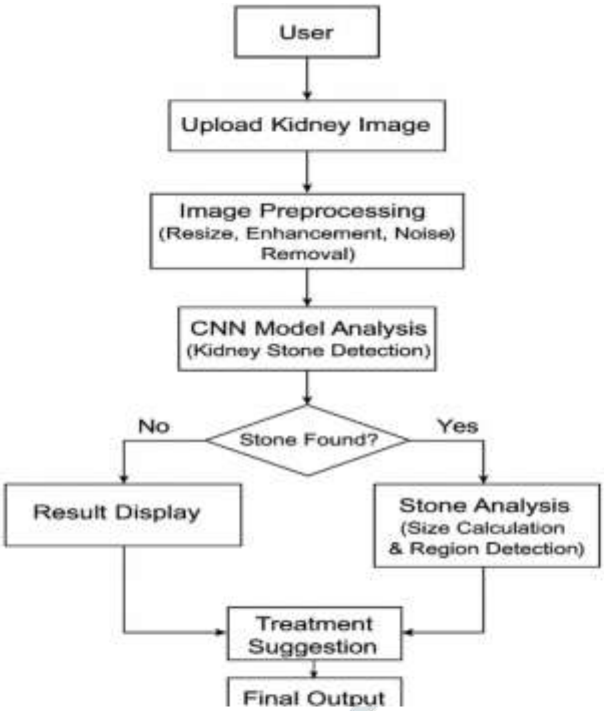

Fig 1. **Block Diagram**

This block diagram describes the functioning of the system in details. To begin with, the user posts the image of the scan of the kidney to the system. Once uploaded, the photo is cleaned and enhanced in order to have a clearer view of the stone region. Then the CNN model is provided that test whether there is a kidney stone or not. When the stone is not found then the result is indicated directly. When the stone is detected the process is continued by the system. It estimates the size of the stone and also distinguishes the location of the stone in the kidney. According to the size, there is some simple treatment information presented only to be understood. The system does not substitute the decisions made by the doctors and is primarily beneficial in analysis.

A. Dataset Collection:

The coronal CT scan images were collected from Kaggle. The dataset contains images of patients with kidney stones as well as normal kidney images. Different types of images were included to cover various cases. These images were used to train, test, and validate the deep learning model. The dataset was collected only for academic project use.

B. Data Preprocessing:

Before training the model, the collected kidney images were processed properly. The images were resized to a fixed size so that the system can read them easily. Noise present in some images was reduced to improve clarity. Pixel values were adjusted to maintain uniformity. These steps helped the model to learn better and give improved results.

C. Data Splitting:

After preprocessing, the dataset was divided into different parts. Most of the images were used for training the model. Some images were kept for validation to check the model during training. The remaining images were used for testing. This splitting helped to check the performance of the model properly.

D. Model Training:

The usage of the CNN model was based on the pre-processed data subdivided into images and trained using the images. Out of training, the model was presented with kidney pictures repeatedly. By this, it gradually came to know the distinction between stone and ordinary photos. The inputs within the model have been modified to minimize errors. This training contributed towards improved results of the system.

E. Deep Learning Models:

In this project, kidney scan images are taken with the help of CNN model to locate kidney stones. The system examines the image uploaded and attempts to search on whether a stone exists. The model was provided with images with kidney stone and without kidney stones to train. This was to enable the system to learn the appearance of the stone images against the ordinary kidney images.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

A high accuracy score suggests that the model has successfully learned important patterns and can make dependable predictions.

$$\text{Sensitivity} = TP / (TP + FN)$$

Accuracy is a simple metric but can be misleading with imbalanced data. Recall, or sensitivity, measures how well the model correctly identifies kidney stone patients, showing its ability to detect affected cases accurately.

$$\text{Specificity} = TN / (TN + FP)$$

Precision shows the percentage of cases predicted as kidney stones that are actually correct. It tells us how well the model avoids wrongly labeling non-stone cases as stones.

$$\text{Precision} = TP / (TP + FP)$$

The F1-measure is used to check the overall performance of the proposed model. It considers both precision and recall together to give a balanced result. Here there is an equal importance for both precision and recall, while the F1-score helps to evaluate how well the kidney stone detection system works.

F1 = 2 × (Precision × Recall) / (Precision + Recall)

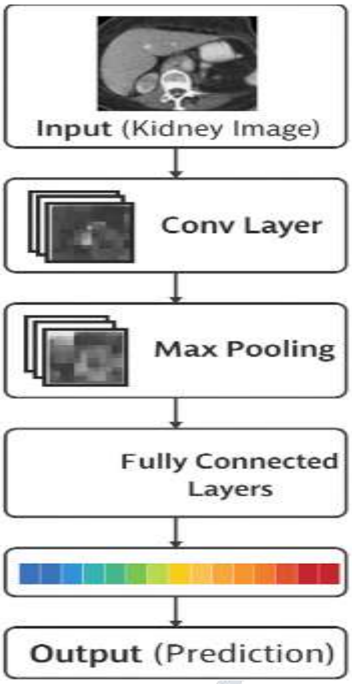

Fig 2. **CNN Architecture**

In this model, the kidney scan image is taken as input. The image passes through CNN layers where stone parts are noticed. Pooling layers reduce extra image details. After that, the system checks the learned features and shows the final result as stone or no stone.

IV. RESULTS

In this undertaking, we are working with kidney scan images in CNN. The number of minute details in scan images is too large and difficult to feel manually. These details are automatically located with the help of CNN model. Images of kidney stones as well as normal images were trained. Modifications were also done in some of the images in the course of training. The pictures were turned, inverted, and enlarged. This has been done in order to enable the model to view various forms of images. Displaying of the same image did not appear always in the same fixed manner. The random way of applying changes was used. Due to this reason, images were not memorized and the model learnt better. The accuracy and loss values were used to check the results after training. This assisted in knowing whether the model performance was on the upward trend or not.

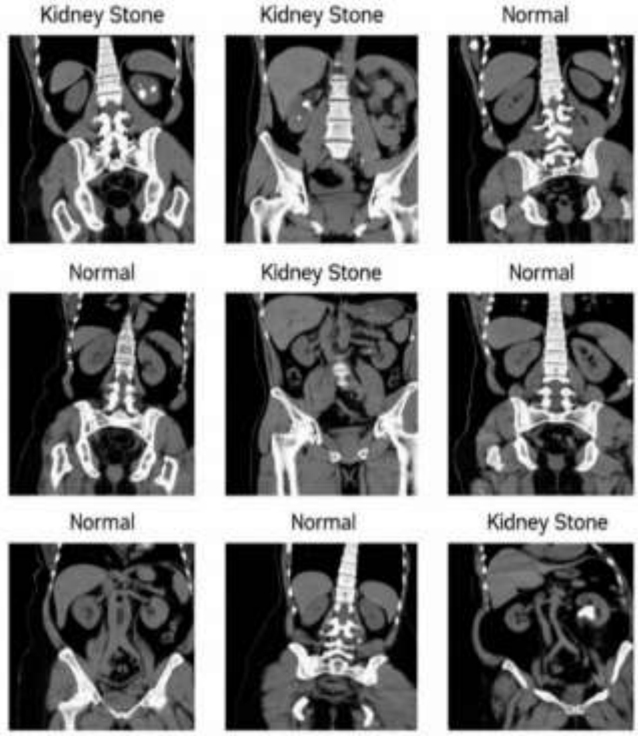

Fig 3. **Dataset**

This figure shows sample CT scan images used in the project. The images include both kidney stone cases and normal kidney cases. Before giving these images to the model, basic preprocessing is done to reduce noise and improve clarity. After preprocessing, the images are used for training the CNN model. During training, the model learns to notice differences between stone and normal images.

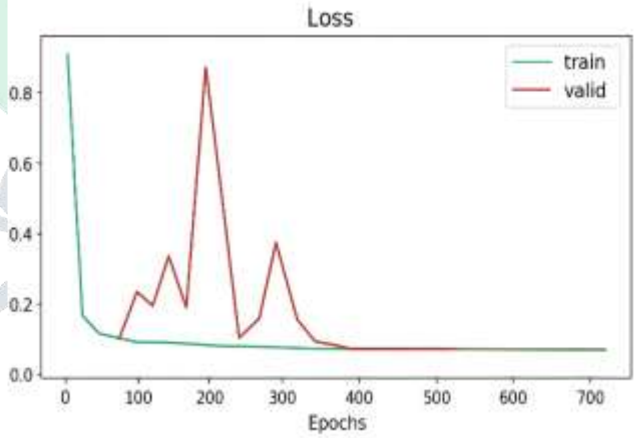

Fig 4. **Training and Validation Data**

The Figure indicates the training and validation loss of the kidney stone detection model. The graph consists of two lines, one of the training and the other of validation lines. The number of epochs is depicted by the x-axis and the value of loss is depicted by the y. Initially, the value of the loss is high since the first time the model is learning. The loss gradually reduces as the training goes on. This implies that the model is getting better and better. The loss also drops off after a few epochs and this indicates that the model is performing well on new images. Based on the graph above, one can comprehend that the model has been trained in an appropriate way, and it provides a consistent performance.

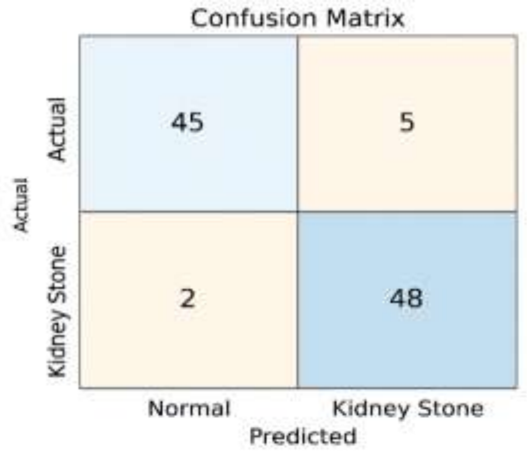

Fig 5. **Confusion Matrix**

This confusion matrix shows the prediction results of the kidney stone detection system. It compares the actual images with the predicted output. From this, we can understand how many images were correctly and wrongly classified. It also helps to check the overall performance of the model. This result shows that the system is working properly for kidney stone detection.

Class	Accuracy	Precision	Recall	F1-Score
Stone Detected	0.95	0.93	0.94	0.92
No Stone Detected	0.95	0.93	0.94	0.92

Fig 6. **Overall performance with CNN-based model**

From the values, it is clear that the system works properly for both stone and normal images. The accuracy shows that most images are classified correctly. Precision and recall values indicate that wrong predictions are less. The F1-score shows a good balance between precision and recall.

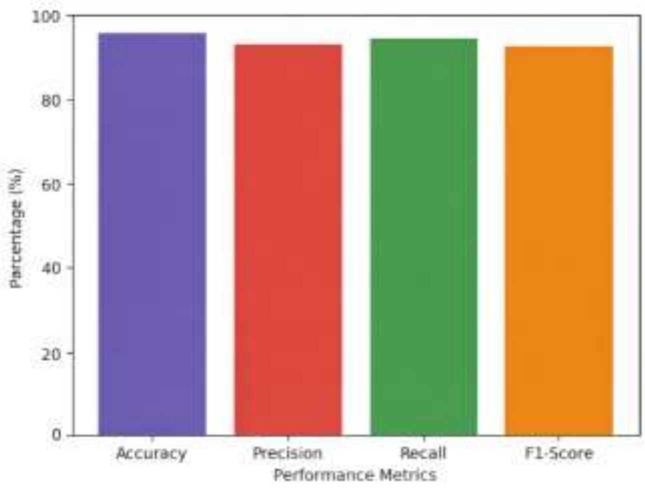

Fig 7. **Performance Metrics**

The graph shows the performance of the kidney stone detection model. The accuracy value is high, which means most of the images are classified correctly. Precision indicates that the model gives fewer wrong positive results. Recall shows that most of the actual kidney stone cases are successfully detected. The F1-score confirms that the model maintains a good balance between precision and recall, showing stable overall performance.

Fig 8. **Predicted Output**

This figure shows the output screen after a scan image is uploaded. The image is processed and the result is shown on the screen. From the processed image, an abnormal condition can be seen in the kidney area. The affected region is clearly visible in the image. This output helps in identifying the kidney problem and supports further medical examination.

V. CONCLUSION

Kidney stone is a medical imaging, and in this project, a system of detecting stones in the kidney is established. The primary task is to determine the presence or absence of kidney stone and provide some general information such as the size of the stones, location and treatment recommendation. This system proves to be handy as it works harder than usual detection methods.

The use of image processing to enhance the image quality is meant to ensure that the image has clear stones. This is then followed by analysing the image with a CNN model and providing the result. The model is considered as good in terms of accuracy and less manual examination. The system is able to assist doctors with diagnosis as well as save time due to this reason.

This can be used to minimize repetition in scanning and at the same time this technique assists in the early identification of kidney stones. It is not complex or time consuming as well as expensive. All in all, the given project demonstrates that machine learning and image processing can be used to enhance kidney stone detection and expanded on in the future to be utilized in hospitals.

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