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Abstract— **Kidney stones are a widespread health problem that can cause severe pain and require urgent medical attention. Accurately identifying and distinguishing kidney stones from other structures in medical images can be challenging due to their varying size, shape, and location. To assist healthcare professionals in making a diagnosis, computer-aided diagnosis systems can be useful, but precise segmentation of the region of interest is crucial. Although CT imaging is a commonly used diagnostic tool for kidney stones, it can be difficult to differentiate stones from other structures, leading to false positives. This study proposes a method to minimize false positives and extract essential structural information for the accurate diagnosis of kidney stones using image processing techniques for kidney organ segmentation with a mean Intersection over Union (IoU) of 76.79%. Additionally, the study aims to leverage machine learning algorithm, Linear Regression, to classify CT scans with multiple stones and improved the accuracy and reliability of disease diagnosis by 93.93%.**

Keywords*— *Computed Tomography(CT) scans, Image processing, K-means clustering, Kidney Stone, Region of Interest(ROI) extraction, Segmentation.

I. Introduction

Kidneys are the important organs located on each side of the spine below the ribcage, responsible for filtering waste and fluids from the blood, regulating blood pressure, and producing hormones for red blood cell production and bone health. Certain substances such as calcium oxalate, uric acid, struvite, and cystine found in urine can combine and form kidney stones, which can lead to intense pain as they travel through the urinary system. Treatment options vary depending on the size of the stone, with smaller ones often passing naturally with medication and fluids, and larger ones requiring surgery to break up the stone and remove it. Kidney stones Fig.1.[1], can be classified by their location and chemical makeup and can form in various areas of the kidney or ureter, causing significant discomfort and pain in the lower back and groin. Nephrolithiasis, also known as kidney stone disease or urolithiasis, has been recognized as one of the oldest diseases in medical history [2]. Statistics suggest that kidney stone formation affects approximately 1-15% of individuals at some point in their lives, with the prevalence and incidence of the disease increasing globally[2]. Hence, early detection is critical to prevent kidney function decline or kidney dilation, which can worsen chronic kidney disease or chronic renal failure in patients who are unaware of their condition. Asymptomatic kidney stones are frequently detected during medical examinations for other conditions, such as cardiovascular disease or diabetes. Medical tools such as ultrasound imaging, computed tomography (CT), and X-rays with intravenous pyelogram (IVP) can assist in diagnosing kidney stones. Among these, CT scans are particularly popular due to their efficiency and accuracy in detecting kidney stones and pathology in both symptomatic and asymptomatic patients.

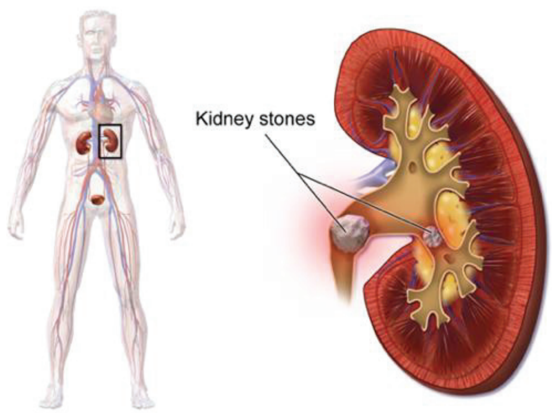

Fig. 1. Human Kidney [1]

Medical image processing has played a crucial role in computer-aided diagnosis in recent years, assisting radiologists in evaluating medical imagery and identifying abnormal findings. However, segmenting kidney stones in CT scans remains a challenge due to complex abdominal structures, heterogeneous tissue nature, unclear boundaries, similarities with adjacent organs, noise, and partial volume effect. The focus of this study was to develop an algorithm for preprocessing medical images to accurately segment kidney stones in CT scans, without depending on user input. The study employed two main techniques to achieve its goals. Firstly, it localized the kidney region in the medical images, and secondly, it developed a method to segment kidney stones from the extracted kidney region. The pixel accuracy of the segmentation was evaluated using the Jaccard index as a measure. In addition, the study extracted features using linear regression analysis to classify whether a CT scan contained one or multiple kidney stones. The paper has been structured in the following manner: Section II presents related studies, Section III discusses the proposed methodology, and Section IV presents the results obtained from the proposed method. Lastly, section V discusses the future scope and section VI concludes the work.

II. Related studies

A novel model[3] for kidney stone detection has been developed using image enhancement and feature extraction techniques. The Adaptive Super Pixel Method is used to increase the information in enhanced images, and the Simple method is preferred for the label fusion procedure in multi-atlas-based segmentation. Active contour segmentation is used to split the pixels of the image and extract features such as entropy, standard deviation, maximum pixel values, and mean values, which aid in stone detection and examination. The Radial Basis Function Network (RBFN), a high-level machine learning method, is used for accurate classification in identifying patients with kidney stones. RBFN is more intuitive than other methods and uses prototypes from the training set to classify new inputs based on their Euclidean distance. The proposed method is advantageous in its ability to operate on large quantities of data, detect anomalies and patterns automatically, and simplify the analysis of complex medical images for easier kidney stone detection.

This study[4] developed an algorithm that can accurately segment kidney stone diagnosis in CT images. It first removed soft organ using intensity-based thresholding with two threshold values. Then bony skeleton, which is the largest unwanted structure, was removed by finding the largest object in the image. Last, bed mat and noise were eliminated using location-based thresholding in the X, Y, and Z directions. The proposed algorithm is not robust but was able to successfully remove the bed mat and reduce noise, resulting in an accurate segmentation of kidney stones in CT images.

The study[5] detailed various techniques used for detecting kidney stones using ultrasound imaging, which aimed to enhance image quality, reduce noise, and improve diagnostic accuracy. Techniques such as filtering, noise de-speckling, and adaptive equalization were employed to improve image quality, contrast, and sharpness. Image segmentation and filtering were utilized to cluster pixels and minimize noise while preserving edges. Feature extraction was used for efficient processing of large amounts of data. Pixel intensity measured the grey intensity displayed in a specific image area. Masking defined a small picture fragment and applied it to a larger image, while the median filter reduced impulsive noise. The polygon region of interest was defined by a polygon that specified its shape and position and used for filtering or other operations.

A novel approach[6] was developed for automatic recognition of kidney stones in early stages, which was accurate, economical, and convenient. The approach involved inspecting CT scans to determine if the kidneys were healthy or affected by stones. The system used an embossing differential filter and support vector machine (SVM) for processing kidney CT scan images and improving contrast through the HE technique. The altered image was processed through the embossing operation for better visibility of low disproportion. Embossing used a horizontal and vertical kernel for edge detection operations. SVM was advantageous for classifying two different classes of data in two shells and constructing a hyperplane that could be valuable for regression. The developed system was proficient in recognizing kidney stones effectively. Segmentation was used to analyze the region of concern, which was necessary for identifying the influenced region affected by the stone. Segmentation categorized veins, blood vessels effectively, and was executed through a thresholding operation by replacing low-intensity pixels with non-active pixels and high-intensity pixels with active pixels using a threshold value.

The study[7] conducted a comprehensive analysis of the detection and analysis of kidney stones using various image processing techniques. Preprocessing methods were employed to improve image quality, followed by adaptive equalization to enhance image contrast. Morphological operations were then performed to detect the region of interest, and segmentation techniques were used to divide the image into smaller segments. Feature extraction was used to reduce the complexity of the system, and boundary outlining was carried out to depict regions of interest clearly. Detection was achieved through a combination of edge and contour detection methods, with Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), and Structure Similarity Index (SSIM) used as quality measurements between the original and filtered images.

The study[8] discusses two main challenges in computer-assisted medical diagnosis for recognizing kidneys in CT scans. The first challenge is to enhance the image visualization, which is critical to prevent kidneys from being invisible due to incorrect brightness correction parameters. The second challenge is to accurately identify the kidneys, which can be limited to specific sub-areas in the lower part of the image. To address this, starting points were selected based on the overlap of binary masks created from kidney contours marked manually on tomographic images. To precisely define the kidney boundaries, the Canny edge detection process was applied, and a binary image containing all detected edges was obtained. The largest areas were selected by removing small and inconsistent areas, and coefficients such as geometrically circularity coefficient and geometrically consistence coefficient were calculated for each disjoint area containing the recognized edge. Finally, a pixel brightness coefficient was also considered in the selection process to identify the object with the highest value as the kidney boundary.

III. METHODOLOGY

The proposed approach first aims to locate the kidneys and then segment kidney stones. The methodology involves several steps, including pre-processing, extracting kidney region, segmentation through thresholding, and classification using machine learning algorithm. Fig. 2. shows the block diagram of the proposed methodology.

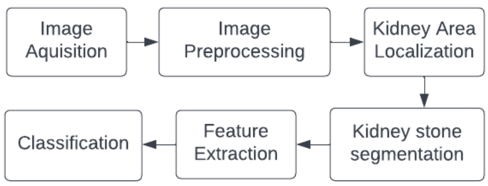

Fig. 2. Block Diagram

A. *Image Acquisition:*

The proposed method was evaluated on a dataset of 107 CT images as shown in Fig.3[9], which was obtained from various hospitals in Dhaka, Bangladesh via PACS. The patients in the dataset had already been diagnosed with kidney tumors, cysts, normal conditions, or kidney stones. The dataset included both axial and coronal cuts from contrast and non-contrast studies, following a whole abdomen and urogram protocol.

B. *Image Preprocessing*

The purpose of image preprocessing is to eliminate extraneous and irrelevant data from images and improve their features for further processing. Fig.4. shows the block diagram for steps involved in image preprocessing. In the context of kidney stone detection, preprocessing is mainly concerned with removing noise and unnecessary regions from abdominal CT images.

Kidney stone

Fig. 3. Stone influenced kidney CT scan[9]

The purpose of image preprocessing is to eliminate extraneous and irrelevant data from images and improve their features for further processing. Fig.4. shows the block diagram for steps involved in image preprocessing. In the context of kidney stone detection, preprocessing is mainly concerned with removing noise and unnecessary regions from abdominal CT images. A median which removes salt and pepper noise while Gaussian filter which effectively smooths images by reducing noise while preserving the edges and details of the image is commonly used to improve the quality of images. On the other hand, unsharp masking is a sharpening technique that enhances the details and edges of an image.

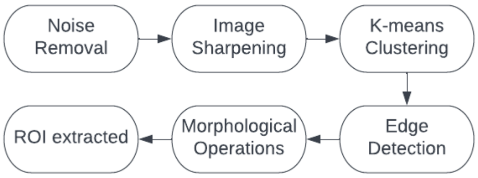

Fig. 4. Steps involved in Image Preprocessing

Edge detection in images can be facilitated by using the K-means clustering technique. Prior to applying K-means, it is common to detect unnecessary edges in the image. However, by utilizing K-means clustering, these extraneous edges can be removed, and the remaining edges can be more accurately identified and emphasized. In an image, an edge represents the boundary between two areas with distinct properties in terms of their darkness or lightness. Algorithms designed for detecting edges, such as the Canny edge detector Fig.5.(a), are used to locate and extract these boundaries in an image[10]. These algorithms typically involve calculating the derivatives of the pixel values in the image and identifying areas with high intensity changes, which are then used to determine the location of edges.

Dilation and erosion are essential morphological operations that are used to improve the clarity of images by processing a small grid of numbers known as structuring elements or kernels. Dilation is used to transform the pixels of the border into pixels of the interior, making it useful for modifying the pixels surrounding the object of interest. Erosion, on the other hand, is used to shrink the object and remove insignificant areas of the image outside the object. In medical image analysis, such as analyzing CT scans to extract the region of interest (ROI), such as the kidneys, these operations can be used to remove soft organs and bone parts from the image. CT scans typically contain specific sub-regions where the kidneys are situated, located in the lower portion of the image on both the left and right sides[11]. The study uses contour detection to identify the ROI and removes contours whose area is less than 300. Next, the study applies thresholding based on the area to further refine the ROI, and finally, applies erosion to increase the area around the kidney in an approximate shape, resulting in a more accurate and precise ROI Fig.5.(b),(c).

Fig. 5. (a) Result of Canny edge detector

Fig.5.(b) Region of Interest(ROI)

Fig.5.(c) Kidney Location Mask

Fig.6. shows the final output of the preprocessing step.

Fig. 6. .Final Processed Image

Fig.7. depicts the block diagram for further processing of segmentation and feature extraction for classification.

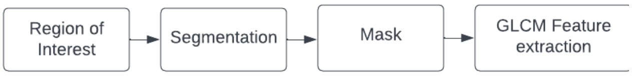

Fig. 7. Steps involved in segmentation.

C. Segmentation

Segmentation: Image segmentation is the process of dividing an image into multiple regions or segments, each with similar visual properties such as color, texture, or intensity. Various algorithms can be used for image segmentation, and one commonly used technique for distinguishing object from background is thresholding. In thresholding, a threshold value is selected based on the intensity of the pixels, and each pixel value of the image (pixel intensity) is compared to this specified threshold. Thus, dividing pixel intensities into two groups, one where pixel intensities are less than threshold and other where these are greater than threshold. In our case, the image was first preprocessed to enhance its quality, and then thresholding technique was applied to segment the image[12]. Specifically, a threshold value of 200 was selected, and any pixel intensity below this value was set to zero. This resulted in a binary image where the pixels in the segmented regions had intensity values of either 0 or 255 as shown in Fig.8. In this binary representation, the value of 0 indicated the presence of the background, while 255 represented the white region, which corresponded to the stones in our case. By using thresholding, it becomes easier to extract the desired features from the image and perform subsequent image processing operations.

Fig. 8. Kidney stone segmented mask

D. Feature Extraction

Feature extraction is a crucial step that involves identifying and extracting the relevant information from an image to focus on the important details[2]. In the proposed method, Grey Level Cooccurrence Matrix(GLCM) features such as contrast, dissimilarity, homogeneity, energy, correlation, and ASM were extracted. These features represent various statistical properties of the co-occurrence matrix, providing insights into the structure of the segmented region[13]. The mask variable serves as the input to calculate the GLCM matrix and prepares GLCM features for a single distance (d=1) and four angles (angles=[0, np.pi/4, np.pi/2, 3*np.pi/4]) for co-occurrence calculations. These GLCM features can help to describe the qualities of an image segment, which can be valuable in detecting and examining stones or other objects. Some additional features such as area, mean, and standard deviation were also extracted. After extracting these features, it is possible to identify key characteristics of the segmented region that can be used for further analysis or comparison with other regions.

E. Classification

Artificial Neural Networks (ANNs) are powerful tools for recognizing complex patterns by utilizing interconnected computational neurons that adjust weight values during the mapping process[14]. In the case of detecting kidney stones, a two-phase approach is adopted - a training phase to adjust the weights of the ANN using a training dataset, and an evaluation phase to assess the network's predictive ability using a separate test dataset. ANNs employ artificial neurons that receive inputs, compute a 'net' input by using weights and input signals, apply a linear threshold filter using a bias, and transmit the output to another neuron. The study utilized a Linear Regression model to identify different occurrences of kidney stones in CT scan images. The feature extraction process was performed initially, followed by the classification stage, where the extracted features were utilized to predict whether an image contained a single stone or multiple stones. The method achieved an accuracy of 93.93%, making it highly suitable for the early and precise detection of kidney stone images.

IV. Results

The IoU(Intersection over Union) metric, or Jaccard index, is a numerical way to gauge the level of overlap between two sets, often visualized as masks. It provides a measure of how much the sets have in common, by calculating the ratio of their shared elements to the total number of elements in both sets. This metric is commonly used in tasks involving image segmentation to assess the similarity between a predicted mask and the actual mask. The formula for Jaccard index is:

$$J(A, B) = |A \cap B| / |A \cup B|$$

where A and B are two sets, $|A|$ denotes the number of elements in set A, and $\cap$ and $\cup$ represent the intersection and union operations, respectively. In image segmentation, A and B are typically the ground truth (i.e., the manually annotated or labeled image) and the predicted mask (i.e., the output of the segmentation algorithm), respectively. The Jaccard index measures the proportion of pixels that are correctly classified as either belonging to the object of interest (i.e., true positives) or not (i.e., true negatives) relative to the total number of pixels in both A and B. The proposed method achieved a mean Intersection over Union (IoU) of 76.79%

and produced segmentation results overlayed on the original image as shown in Fig.9.

The system was trained on 107 CT scan images of kidneys, of which 66 contained multiple stones and 41 contained only one stone. The system correctly detected stones in 31 of these images, resulting in an accuracy of 93.93%. There were no false positives, but only 2 false negatives, as shown in Table 1. The precision value of the proposed model was 1.0, the recall was 0.9, and the F1 score was 0.95. Furthermore, the ROC (Receiver Operating Characteristic) curve which is a graphical illustration of the effectiveness of a binary classification model displays the relationship between the true positive rate (TPR) and false positive rate (FPR) at various thresholds

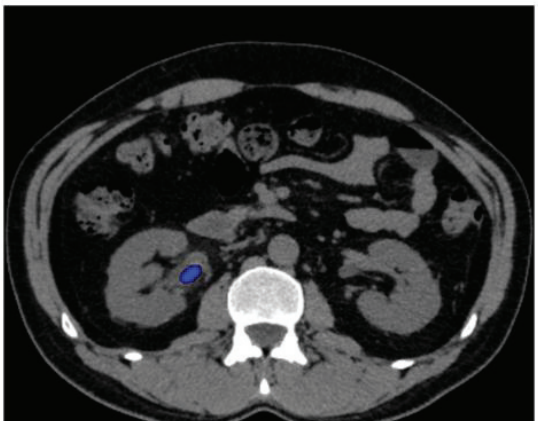

Fig. 9. Masked image with original Kidney CT scan.

TPR is the proportion of actual positives correctly identified by the model, while FPR is the proportion of actual negatives incorrectly identified as positive by the model[15]. In Fig.10. presents the ROC curve for the proposed model.

TABLE I. RESULT ANALYSIS

Total Testing Cases	33
True Positive(TP)	13
True Negative(TN)	18
False Positive(FP)	0
False Negative(FN)	2

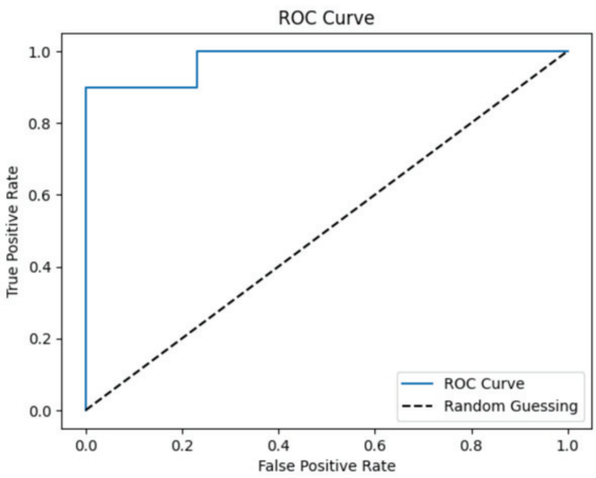

Fig. 10. Proposed model ROC.

V. DISCUSSION

The proposed kidney stone segmentation technique would be highly advantageous in precisely detecting kidney stones and could potentially be extended to other datasets in the future. The current limitation of this system is the restricted number of available CT images, but utilizing a larger dataset would significantly improve the accuracy. Furthermore, as a future direction, alternative segmentation methods could be explored and compared with popular deep learning techniques to enhance the results. Additionally, the extraction of the region of interest could also be improved.

VI. CONCLUSION

This study proposes an effective approach to accurately detect kidney stones from CT scan images in a short processing time. The initial step involved obtaining a region of interest through noise removal techniques and morphological operations. Binary segmentation was then applied to the kidney images to segment stones from the background and achieved 76.79% of meanIoU. To achieve better classification, Linear Regression was employed resulting in a high accuracy of 93.93% on a system trained with 107 CT scan samples containing both multi-stone kidneys and kidneys with only one stone, using the parameters of TP, TN, FP, and FN. Automated identification is becoming increasingly popular in the medical field, as it can save both human health and financial resources. To further enhance accuracy and detect multiple stones in the kidney, additional techniques and filters may be utilized in the future.

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