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KIDNEY DISEASE PREDICTION USING CONVOLUTIONAL NEURAL NETWORK ALGORITHM

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ABSTRACT

Renal calculus, more commonly known as kidney disease formation, is characterized by the formation of crystals in the urine caused by substance concentration or genetic susceptibility. The precise segmentation of kidneys and kidney tumors can help medical specialists to diagnose diseases and improve treatment planning, which is highly required in clinical practice. Manual segmentation of the kidneys is extremely time-consuming and prone to variability between different specialists due to their heterogeneity. Because of this hard work, computational techniques, such as deep convolutional neural networks, have become popular in kidney segmentation tasks to assist in the early diagnosis of kidney tumors. All persons are susceptible to kidney stones, even infants, and yet, the majority of kidney stone cases remain undetected except in cases where extreme abdominal pain is exhibited or abnormal urine color is observed. In addition, people with kidney stones exhibit common signs such as fever, pain and nausea that are easily associated to other conditions. Kidney stone detection is important particularly in its early stages to facilitate intervention or to receive proper medical treatment. The presence or the recurring presence of kidney stone decreases kidney functions and dilation of the kidney. This paper presents a technique for detection of kidney stones through different steps of image processing. The first step is the image pre-processing using filters in which image gets smoothed as well as the noise is removed from the image. Next, the image segmentation is performed on the preprocessed image using guided active contour method. Then using Convolutional neural network algorithm to identify the diseases in kidney images. The imaging modality used is CT because it has low noise compared to other modalities such as x-ray and ultrasound.

KEY WORDS: Kidney Stone, Features extraction, Deep learning, Medical images, Convolutional neural network

1. INTRODUCTION

The kidney is a vital organ in the human body. Kidney stones have been a widespread problem in recent years [11]. Kidney stones are solid pieces of material that form as a result of minerals in the urine. They are caused by a combination of genetic and environmental factors. It can also be caused by being overweight, eating certain foods, using certain medications, and not drinking enough water [12]. Kidney stones affect people of all races, cultures, and locations. Blood tests, urine tests, and scans are all utilized to diagnose this kidney stone. If the stone is not identified early on, the situation might get serious, and surgery may be required to remove the stone. Image processing is a very effective way to properly detect the stone [13]. Imaging is the most important component in the medical field. A clinician can examine the internal organs using medical imaging. CT scans, Ultrasound scans, and Doppler scans all have different scanning methods. Nowadays, the automated technique is being employed in the medical industry to analyse diseases [14]. Many frequent issues may arise due to the diagnosis by automation, such as the use of inaccurate results, inadequate algorithms, etc. Generally, the process of medical diagnosis is very complex and hazy. Additionally, several mathematical approaches were previously utilized to identify kidney stones using ultrasound images. Among all the approaches for detecting kidney stones, image processing has the most advantages since it analyses the stone with great precision. Ultrasound imaging is one of the current non-invasive, low-cost, and commonly utilized imaging modalities for assessing renal disorders. Kidney stone disease is one of the major life-threatening ailments persisting worldwide [15]. The stone diseases remain unnoticed in the initial stage, which in turn damages the kidney as they develop. A majority of people are affected by kidney failure due to diabetes mellitus, hypertension, glomerulonephritis, and so forth. Since kidney malfunctioning can be menacing, diagnosis of the problem in the initial stages is advisable. Ultrasound (US) image is one of the currently available methods with non-invasive low cost and widely used imaging techniques for analysing kidney diseases [16]. Fig 1 shows the stones in kidney

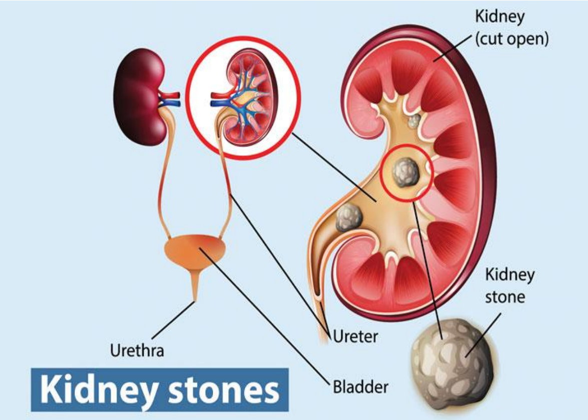

Fig 1: Kidney stones

2. RELATED WORKS

Abubaker Abdelrahman, et.al,…[1] discusses ways of segmenting kidneys and kidney tumors using deep learning and building blocks, as well as state-of-the-art approaches and implementation tools. The existing techniques serve two purposes: segmenting tumors correctly and compensating for the lack of training data. Based on adequate training data, DL is capable of adequately segmenting kidney tumors. With proper pre-processing, weight initialization, sophisticated training schemes, segmentation with unambiguous borders, and obtaining additional information for pixel classification, ensemble approaches and U-Net-based models have significant potential for improving the state-of-the-art. The absence of a large-scale medical training dataset is a primary reason for the poor performance of many segmentation algorithms. As a starting point for future development, overall, kidney and renal tumor segmentation challenges have been met with great success. It received a large number of submissions and continues to be a significant and hard benchmark for 3D segmentation. However, extending the use of these systems outside the sampled population for the test set would be desirable since it was obtained from individuals who shared the same geographic region and healthcare system and a multi-institutional cohort with a prospectively generated test set. Additional imaging modalities, such as magnetic resonance imaging (MRI) or contrast-enhanced ultrasound (CEUS), may be employed to increase the diagnostic algorithm's accuracy when CT alone is used

Gianmarco Santini, et.al,…[2] presented an automatic method for semantic segmentation of kidneys and kidney cancerous tissue from contrastographic CT acquisitions. Precise characterization of the kidney and kidney tumor characteristics is of outmost importance in the context of kidney cancer treatment, especially for nephron sparing surgery which requires a precise localization of the tissues to be removed. The need for accurate and automatic delineation tools is at the origin of the KiTS19 challenge. It aims at accelerating the research and development in this field to aid prognosis and treatment planning by providing a characterized dataset of 300 CT scans to be segmented. To address the challenge, we proposed an automatic, multi-stage, 2.5D deep learning-based segmentation approach based on Residual UNet framework. An ensambling operation is added at the end to combine prediction results from previous stages reducing the variance between single models. Our neural network segmentation algorithm reaches a mean Dice score of 0.96 and 0.74 for kidney and kidney tumors, respectively on 90 unseen test cases. The results obtained are promising and could be improved by incorporating prior knowledge about the benign cysts that regularly lower the tumor segmentation results.

Junyoung Park, et.al,…[3] showed that the deep learning approach is highly accurate in renal parenchyma segmentation in CT images acquired in kidney SPECT/CT studies and is useful for automated measurement of GFR. The CNN outcomes yielded remarkably high Dice coefficient (0.89) with manual segmentation, leading to the strong correlations in %ID and GFR between the manual and automatic methods. Automatically drawing VOIs only on renal parenchyma but excluding cysts and tumours is a challenging task because their CT intensities are very similar in non-contrast-enhanced CT images obtained in SPECT/CT studies. Although the proposed method performed the segmentation correctly in most cases as shown in Supplementary Figure S4, there were several cases in which the segmentation was not accurate. Supplementary Figure S5 is such a case in which a renal mass (yellow arrows) was incorrectly included although renal pelvis was well excluded (red arrows). Because this patient (male, 164 cm, 58kg) was relatively smaller than others,

insufficient data for training deep CNN to properly handle such unusual cases would be the cause of inaccurate segmentation. In spite of such inaccuracy, the GFR error in this patient was only 2.48% because the radioactivity in the tumour was very low. Because we trained the CNN to draw VOIs on the renal parenchyma of both kidneys, there was error in the patient with only a single kidney. In Supplementary Figure S6, the CNN drew a long narrow VOI on the liver parenchyma (yellow arrow) of a patient who does not have a right kidney.

Fuat Türk, et.al,…[4] proposed a new hybrid V-Net model using the superior features of existing V-Net models. We ran four models, including the hybrid V-Net model, on this dataset and performed kidney and tumor segmentation separately. The results showed that the hybrid V-Net model yielded more successful results for kidney and renal tumor segmentation than other V-Net models, with rates of 0.977 and 0.865 DSC, respectively. This study showed that V-Net models successfully perform organ and tumor segmentation via computerized images and that more successful models can be developed from existing V-Net models by considering the encoding and decoding stages separately. More suitable models could be designed for multiple organ segmentation using medical images. This study could also be used as a guide for future hybrid models as the success of the implementation of the hybrid V-Net model for the first time was positively contributed to by the ResNet++ architecture. The ResNet++ architecture was applied only to the output layer, making it possible to capture small details in the segmentation. This situation is extremely important for model design because each parameter can only be successful when added to the appropriate blocks of the model. The results presented here suggest that more research regarding the hyperparameters of this model is pertinent.

Kiran Choudhari, et.al,…[5] implemented U-Net semantic segmentation model was used for Kidney and tumor segmentation. The proposed method was applied on a data set provided by KiTS challenge 2019. Other deep learning model like E-Net was also tried in this phase however due to unsatisfactory results it was not included. The data set consisted of Nifty images of 300 patients CT images, where each CT varied based on the number of slices ranging from 52 to 611 slices per CT of a patient. Medical Image Segmentation is a challenging field in the area of Computer Vision. In this paper U-Net deep learning model was used for semantic segmentation. The reason for shortlisting U-Net was its suitability on small data set and also it was originally designed for Biomedical Image segmentation process. Visual representations of the predicted results have shown promising results using U-Net. Experimental results were computed on two different cases. Case No 1, includes testing the method on images for which labelled information was available and considering only those slices where the presence of kidney was detected. Case No 2, involves testing the method on those images who's labelled information was not available and applying the method on all the CT slices with respect to a patient. Experimental results was based on a metric called IOU (Intersection over Union) score which is one of the most commonly used metric in semantic segmentation

Andriy Myronenko, et.al,…[6] proposed an end-to-end 3D framework for reliable and automated segmentation of kidneys and kidney tumors. Our network consists of a an encoder-decoder architecture equipped with a boundary stream that processes the edge information separately and is supervised by edge-aware losses. We have validated the effectiveness of our approach by training and testing our model on 2019 MICCAI KiTS Kidney Tumor Segmentation Challenge dataset. Our method has achieved dice scores of 0.9742 and 0.8103 for kidney and tumor repetitively and an overall composite dice score of 0.8923 and ranks 9th overall in terms of composite dice among 100 participants of this challenge. In this work, we propose an end-to-end boundary aware fully Convolutional Neural Networks (CNNs) for reliable kidney and kidney tumor semantic segmentation from arterial phase abdominal 3D CT scans. We propose a segmentation network consisting of an encoder-decoder architecture that specifically accounts for organ and tumor edge information by devising a dedicated boundary branch supervised by edge-aware loss terms.

Luana Batista da Cruza, et.al,..[7] presented a fully automatic method for kidneys segmentation with tumors in CT. For this, two CNN models were used and a post-processing technique. Besides, image processing techniques, such as normalization and histogram specification, were applied. The first CNN model, based on AlexNet, was used for CT slice classification to reduce the scope of the problem. The second model was the U-Net, used for precise kidneys segmentation. Finally, the result of the proposed method is obtained by combining the slice classification, kidney segmentation and the post-processing step to reduce false positives. To validate the proposed method, we use the public database KiTS19, which is quite heterogeneous and complex. Despite failing to improve some of the classification performance metrics, the kidney slice recovery step was of great importance in the proposed method. It helped to improve the accuracy of the kidney segmentation step, which resulted in better qualitative results. This was possible due to an improvement in the sensitivity rate. The combination of the techniques above-mentioned was able to obtain optimal kidney segmentation results, using a CNN based on U-Net. In general, our method demonstrated great robustness in the face of such a diverse and complex database, presenting promising results and standing out among the best works found in the literature. Therefore, we believe that the proposed method represents a great contribution to the scientific environment, despite its limitations

Sabarinathan, et.al,…[8] Motivated by the superior performance of Convolutional Neural Networks, in this paper, a Hyper vision Net architecture is presented to segment the kidney and tumor region which is automatic and accurate. This challenge is carried out using KiTs19 dataset. The performance of our method is reported quantitatively and qualitatively for the given type of training and validation images. Our method achieved a maximum Dice score of 0.9633 for the training set and 0.9535 for the validation set. Comparatively the proposed Hyper vision Net reported best segmentation results in terms of Dice score. A dataset consists of real arterial phase abdominal CT scans of 300 patients, including 45964 images has been provided from KiTs19 for training and validation of the proposed model. Compared with the state-of-the-art segmentation methods, the results demonstrate the superiority of our approach on training dice value score of 0.9552 and 0.9633 in tumor region and kidney region, respectively

Omid Bazgir, et.al,…[9] address the issue of the background effect, we incorporated a derived MRI contrast mechanism for the localization step prior to learned segmentation. Second, we modified the 3D U-Net to reduce the number of parameters and incorporated a Dice loss function for the segmentation. Third, we incorporated augmentation and MRI histogram matching to increase the number of training datasets. We also applied our method on super resolved images of our dataset to determine whether enhanced images can improve segmentation performance. These methods were implemented on preclinical MRI using an animal model of lupus nephritis. In vivo imaging modalities offer unique strengths and limitations. MRI, in particular, does not have ionizing radiation, is not operator dependent, and has good tissue contrast that enables kidney segmentation and volume related information. Traditional methods have been used to evaluate the kidney more locally, such as manual tracing, stereology, or general image processing. These methods can be labor intensive or inconsistent. To address these issues, we propose to use an integrated deep learning model to segment the kidney.

Yuliia Kamkova, et.al,…[10] proposed a novel combined approach for kidney and tumor segmentation. Our approach combine 2D and 3D methods, and include two deep learning methods for kidney detection and segmentation. With the use of Faster R-CNN with ResNet50, we were able to obtain fast and high recall results for kidney detection. Also, this network created 3D cropping boxes to extract only region of interests. Followed by V-Net with these 3D volumes, resulted in our accurate segmentation of kidney and tumor. This paper presents our method for automatic segmentation for kidney and tumor as part of the Kidney Tumor Segmentation Challenge (KiTS19). The KiTS19 Challenge had released a dataset of 300 unique kidney cancer patients, with manual annotations done by Climb 4 Kidney Cancer (C4KC). Here we have proposed our new combined cascade deep learning (DL) approach for solving the tasks of the challenge. We used deep learning-based detection for localising kidney with the tumor, followed by deep learning-based segmentation to create the labels for kidney and tumor locally.

3. BACKGROUND OF THE WORK

In existing system, implemented kidney segmentation in abdominal computed tomography (CT) sequences is an essential and crucial task for surgical planning and navigation in kidney tumor ablation and a coarse-to-fine method was applied to segment kidney from CT images, which consists two stages including rough segmentation and refined segmentation. The SKFCM algorithm introduces a kernel function and spatial constraint into fuzzy c-means clustering (FCM) algorithm [17][18]. The FCM algorithm makes good use of the continuity of CT sequences in space which can automatically generate the seed labels and improve the efficiency of segmentation. The experimental results performed on the whole dataset of abdominal CT images have shown that the proposed method is accurate and efficient. And described kidney image requires proper motion correction and it produce less accuracy and loss of reproducibility. It is not available in clinical modelling due to loss of reliability. The proposed method is to attain accuracy and to efficiently detect kidney disease using DCE-MRI kidney image from the MRI moving kidneys and edge detection algorithm are used to detect edges from MRI kidney image.

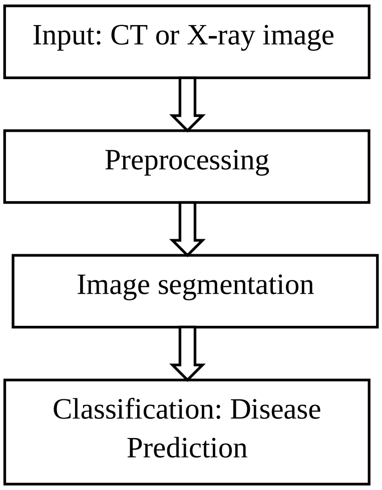

Fig 2: Existing block diagram

The existing system is experimentally evaluated using real time input image from MRI moving kidneys and it is very useful to analyse doctors to know patient's prostate disease and related treatments. Keywords - Glomerular Filtration Rate, segmentation, magnetic resonance imaging. The problem of registration of MRI kidney image requires proper motion correction for combined registration and segmentation, applicable to DCE-MRI acquisitions of the moving human kidney images. They conclude that our segmentation driven registration approach has a great potential for further development into a full-blown pharmacokinetic Glomerular filtration rate (GFR) modeldriven segmentation of the kidneys and its useful method to detect kidney diseases in medical image processing.

4. PROPOSED MODEL

Kidney failure can be a life-threatening situation. As a result, early diagnosis of kidney diseases are critical. It is critical to accurately identify kidney diseases in order to assure the effectiveness of surgical procedures. The ultrasound images of the kidney contain speckle noise and have low contrast, making it difficult to detect kidney problems. As a result, doctors may find identifying small kidney stones and their nature difficult and complicated. Soft computing approaches, such as neural networks, have shown considerable potential to be used in the advancement of medical diagnosis because medical diagnosis is by nature a complicated and fuzzy cognitive process [19]. When time and knowledge are limited, learning and detecting incomplete disease can be useful in disease diagnosis. As a result, artificial neural networks are a useful tool for partial diagnosis. Deep learning technology aids in the classification of kidney disease patients, and this technique aids in the identification of prospective patients by evaluating a data set derived from a scanned image. The goal is to automate this procedure so that kidney diseases diagnostics may be done efficiently and quickly using deep learning technology. In this paper proposed Convolutional neural network algorithm to identify kidney stone diseases [20]. VGGNet is a CNN jointly developed by the Visual Geometry Group at the University of Oxford and Google DeepMind. VGGNet architecture can be considered an extended AlexNet, characterized by 3 × 3 convolutional kernels and 2 × 2 pooling layers, and the network architecture can be deepened by using smaller convolutional layers to enhance feature learning. The two most common current VGGNet versions are VGGNet-16 and VGGNet-19.The network architecture consists of 16 layers deep: 13 convolutions 4 max-pooling and 3 fully connected layers. The convolutional input layer has a shape of 224 × 224 × 3; this layer determines the input dimensions and shape. Max-pooling minimizes the dimensionality of images by reducing the number of pixels from the previous convolutional layer. In addition, a fully connected ANN has an input layer that reflects the size of max-pooling output data and a hidden layer with the Relu activation function, also an output layer with a softmax output classifier that performs the prediction percentages for each class.

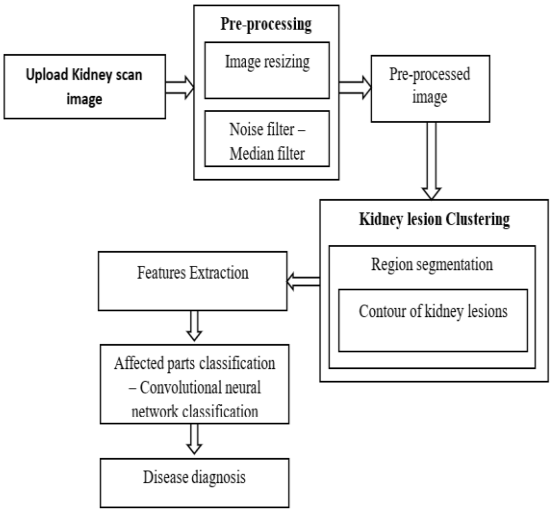

Fig 3: Proposed framework

IMAGE ACQUISITION: Kidney diseases are on rise throughout the world and majority people with kidney disease do not notice the disease as it damages the organ slowly before showing symptoms. The increasing number of patients with kidney diseases leads to a high demand of early detection and prevention of kidney diseases. In this module, we can upload the Scan images with any type and any size

PREPROCESSING: Pre-processing is a common name for operations with images at the lowest level of abstraction — both input and output are intensity images. These iconic images are of the same kind as the original data captured by the sensor, with an intensity image usually represented by a matrix of image function values (brightness's). Image pre-processing methods are classified into four categories according to the size of the pixel neighbourhood that is used for the calculation of new pixel brightness. The aim of pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing, although geometric transformations of images (e.g. rotation, scaling, translation) are classified among pre-processing methods here since similar techniques are used. The user has to select the required kidney image for further processing. Then each image is resized to 256*256. Then implement median filter to remove noises from kidney images. The median filter is a nonlinear digital filtering technique, often used to remove noise from an image or signal.

SEGMENTATION

Guided active contour algorithm is one of the well-known unsupervised clustering techniques used for segmentation. Clustering of data is a method by which image large sets of data are grouped into clusters of smaller sets of similar data. It is a method of clustering which allows one piece of data to belong to two or more clusters. It is frequently used in pattern recognition. The process of detection of edge stone in particular image appears very dark on the image which is very confusing. In this module implement features extraction algorithm to extract colour, shape and texture features from the pre-processed image. The output image will have all gray values in equal proportion. It is used to detect the kidney stone in ultrasound scan image.

CLASSIFICATION: Neural networks have achieved a greater in the field of medical image analysis. The concept of neural network is combined with wavelets to develop a CAD system for kidney stone feature detection. Disease is classified using Back propagation neural network algorithm. BPNNs represent feed-forward neural networks which encompass diverse combos of the hidden layers, max pooling layers, and completely related layers and Take advantage of spatially neighbourhood correlation by way of way of imposing a nearby connectivity pattern among neurons of adjacent layers. Hidden layers alternate with max pooling layers mimicking the individual of complex and clean cells in mammalian seen cortex. A CNN includes one or extra pairs of perceptron and max pooling layers and ultimately ends with completely related neural networks. The hierarchical structure of CNNs is steadily proved to be the most efficient and successful manner to analyse visible representations. The fundamental challenge in such visual tasks is to model the intra-class appearance and shape variation of objects. The image data with hundreds of spectral channels can be illustrated as 2D curves. We can see that the curve of every class has its own visual shape which is different from other classes, although it is relatively difficult to distinguish some classes with human eye (e.g., gravel and self-blocking bricks). We know that CNNs can accomplish competitive and even better performance than human being in some visual problems, and its capability inspires us to study the possibility of applying CNNs for classify the coal features. The CNN varies in how the convolutional and max pooling layers are realized and how the nets are trained. This network varies affording to the spectral channel size and the number of output classes of input image data.

DISEASE PREDICTION

In this module, identify the multiple kidney diseases using Back propagation neural network algorithm. Basic kidney diseases are cyst, stone, tumour and normal.

Kidney cysts are round pouches of fluid that form on or in the kidneys. Kidney cysts can be associated with serious disorders that may impair kidney function

Kidney stones (also called renal calculi, nephrolithiasis or urolithiasis) are hard deposits made of minerals and salts that form inside kidneys.

A kidney mass, or tumor, is an abnormal growth in the kidney. Some kidney masses are benign (not cancerous) and some are malignant (cancerous). One in four kidney masses are benign. Smaller masses are more likely to be benign.

Based on the CNN classification, we can identify the kidney diseases and provide the diagnosis information based on affected kidney disease.

5. EXPERIMETNAL RESULTS

In this study, we can input the kidney datasets that are collected from KAGGLE sources. And implemented using Python framework. The performance of the system evaluated using sensitivity parameter.

Sensitivity (SN) is found as the fraction of number of perfect positive predictions to the total number of positive predictions. The finest possible sensitivity is 1.0, whereas the very worst is 0.0.

$$SN = \frac{TP}{TP + TN}$$

ALGORITHM	SENSITIVITY
DECISION TREE	0.75
RANDOM FOREST	0.85
CNN CLASSIFICATION	0.94

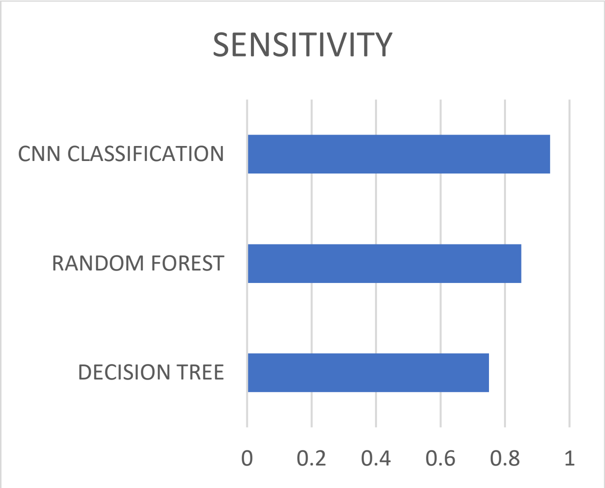

Fig 4: Performance evaluation

From the above figure, proposed system provide improved efficiency than the existing algorithms.

6. CONCLUSION

The diagnosis of nephrolithiasis is based on CT-scan features is a complex task for physicians due to the cause that the CT-scan images will not be alike for all populace instead it varies from person to person. Therefore, the Systems can be used by a physician to automatically extract CT-scan features and to perform the prediction of stone automatically based on the extracted features. The developed System decreases the diagnosis time and improves the accuracy of the diagnosis. The results obtained show that the texture features could be used to classify multiple kidney diseases. The results obtained further show that there is a possibility of developing CAD and computer aided classification of kidney stones by texture analysis method and framing a suitable decision rule. By analysing many more images by Guided active contour method and classification algorithm using Convolutional neural network algorithm to identify the affected regions with improved accuracy.

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