KIDNEY NEPHROLITHIASIS DETECTION AND CLASSIFICATION IN COMPUTED TOMOGRAPHY IMAGES

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ABSTRACT

As the research of the Kidney International Research center shows that the population of the chronic kidney disease (CKD) is beyond 3.8 hundred million and still increase rapidly. Kidney stone problem also called as nephrolithiasis is a common type of urological disease with a high recurrence rate of 20 % after one year, 50 % over a period of 5-10 years and 75 % over a period of 20 years. Over the last 20 years (1999-2019),the prevalence rate of kidney nephrolithiasis disease in India has increased nearly twice from 5.95 % to 10.63 % which has been documented in India. Kidney stone disease is a progressive disease that damage the kidneys leading to be permanent damage and undone problem. Some Low level classification techniques are not efficient due to their low accuracy level. Therefore, this project plays a vital role to identify and to cure kidney stone disease before the permanent damage is done with efficient techniques with high accuracy results. This project propose a high efficiency classification framework to detect and to classify the kidney nephrolithiasis in Computed Tomography images using machine and deep learning classifiers. To segment and to extract the features of detected kidney nephrolithiasis with the size of stone using clustering algorithm.

Keywords: *Kidney Nephrolithiasis, Fuzzy C Logic, K-Means Clustering algorithm, Convolutional Neural Network (CNN), support vector machine (SVM).*

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1. INTRODUCTION

Kidney nephrolithiasis is formed when sodium chloride and certain minerals such as Calcium Acetate and uric acid are accumulated in urine. It mainly occurs when the human body lacks fluid and accumulates a lot of waste in urinary bladder. Diabetes mellitus, high blood pressure and obesity are some of the major causes of kidney nephrolithiasis in an individual. Kidney stones can affect any part of the urinary tract from the kidneys to bladder. Often, stones form when the urine becomes concentrated, allowing minerals to crystallize and stick together. Passing kidney stones can be quite painful, but the stones usually cause no permanent damage if they're recognized in a timely fashion. Depending on the situation, one may need to take pain medication and drink lots of water to pass a kidney stone. : Most kidney stones are calcium stones, usually in the form of calcium oxalate. Oxalate is a substance made daily by liver or absorbed from diet. Certain fruits and vegetables, as well as nuts and chocolate, have high oxalate content. Automatic kidney nephrolithiasis segmentation from abdominal Computed tomography images is challenging on the aspects of segmentation accuracy due to its variety of size, shape and location. Deep Learning models for CT-related tasks, such as nephrolithiasis detection, that are trained on CT images may exhibit better g rationalization, where rationalization is defined as the accuracy of a model trained on images in one model and tested on images acquired from another model.

2.LITERATURE SURVEY

Jiawen yang et al.,(2018) [1] proposed the region average pooling (RAPooling) method which makes a feature extraction that focus on the parts of region of interest. Finally, a linear classifier RankOpt based on the area under the ROC curve is used for optimization and an accuracy of 82% is achieved.Marwan Ali Albahar et al.,(2019) [2] given the brief introduction about the new prediction model that classifies kidney stones based on a novel regulizer technique. Hence, this is a binary classifier that discriminates the presence of kidney stones. The proposed model achieved an average accuracy of 91.49%, which in turns into superiority over other state of the art methods. The performance of the CNN in terms of ROC with an embedded novel regulizer is tested on multiple use cases.Jeremy Kawahara et al.,(2019) [3] provided the neural network architecture which uses interpolated feature maps from several intermediate network layers, and addresses imbalanced labels by minimizing a negative multi-label Dice-F1 score, where the score is computed across the mini-batch for each label. In this, fuzzy Jaccard Index method is incorporated. The results of classification of clinical dermoscopic features can be effectively approached for the segmentation problem and the current metrics used to rank models may not well capture the efficiency of the model. Finally, a linear classifier RankOpt based on the area under the ROC curve is used for optimization and an accuracy of 84% is achieved.Fangzhou et al., (2019) [4] given the deep neural network in which the Local Binary Pattern (LBP) is used to provide Region Of Interest (ROI). The Convolutional Neural Network (CNN) is used to score these ROI and choose one ROI with highest score. Finally a Hyper Column Fully Convolutional Network (FCN) is implemented to classify the kidney stone presence.Sultana Bano et al.,(2018) [5] proposed various image preprocessing technique for the input images to enhance the image properties. Statistical region merging algorithm is based on region growing and merging. Two neural networks are used as classifier such as back propagation neural network and auto associative neural network. The Alexnet architecture is used and the validation accuracy of 75% is obtained. Li Kuo et al., (2017) [6] given the introduction for Regression Neural Network (RNN) containing two neural nets that performs center point localization and detection of kidney stone borders. Image preprocessing followed by segmentation and feature extraction. Classification is carried out based on the extracted features.Zewen et al., (2017) [7] proposed a technique in which FCN is used to segment the kidney stone images . This is followed by an active contour technique to obtain precise edges. Also tensor voting is employed to fill its missing parts. It provided a six layer Convolutional Neural Network(CNN) which is used for feature extraction. This CNN includes a softmax fully connected layer for classification of pathological cases. Finally a Hyper Column Fully Convolutional Network (FCN) is implemented to classify the kidney stone presence. Zhen Yu et al.,(2019) [8] proposed deep learning and local descriptor encoding strategy. The local deep descriptors are aggregated by order less visual statistic features based on fisher vector (FV) encoding to build a global image representation. Finally, the FV encoded representations are used to classify stone images using a support vector machine (SVM) with a Chi-squared kernel. The proposed method can generate more discriminative features to deal with large variations within stone classes as well as small variations between presence and absence classes with limited training data.Balazs Harangi., (2018).

3.METHODOLOGY

The Methodology section explains about the process that are involved in the Kidney stone detection.

3.1 Image Acquisition

The Image samples for the experimentation of the kidney Nephrolithiasis classification are taken from the Harley Acevedo database.The database has a collection of normal kidney and kidney with Nephrolithiasis images Totally, Harley Acevedo consists of 263 samples among which 131 are normal kidney and 132 are kidney with Nephrolithiasis.

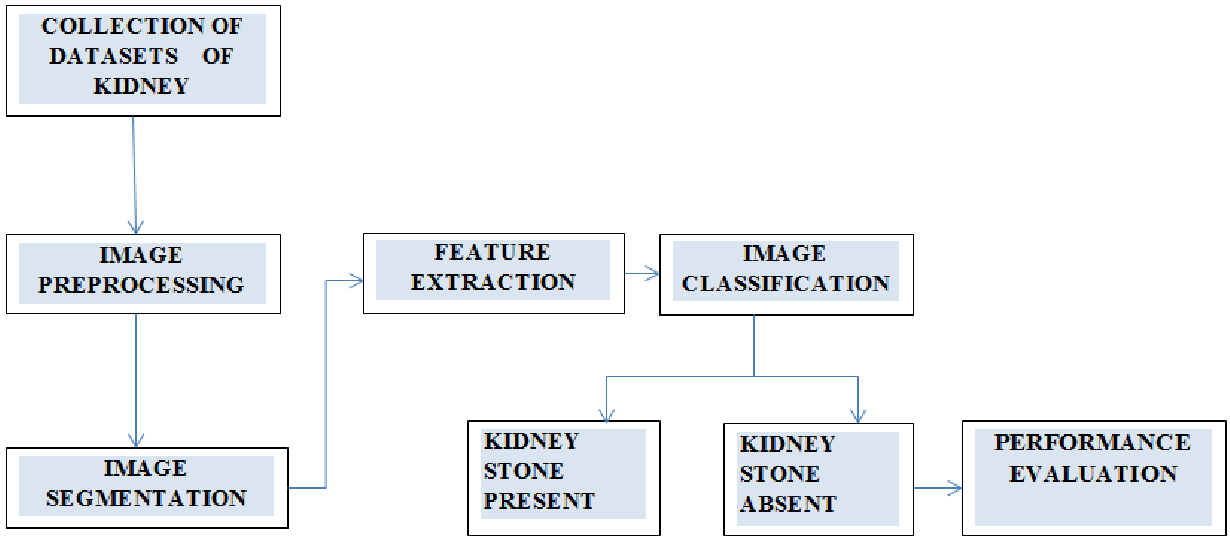


Fig – 1: Block diagram of kidney Nephrolithiasis Detection Module

Figure 1 shows complete process of kidney Nephrolithiasis detection. In the first stage, the images are get resized which is then followed by segmentation. Then the features that are extracted from segmented images is fed into the CNN and SVM where it detect the kidney with Nephrolithiasis and the kidney without Nephrolithiasis images.

3.2 Pre- Processing

The images in the database are exposed to the pre-processing stage where the resizing task is carried out to maintain the uniform dimensions among the images.

3.3 Image Segmentation

After pre-processing, it is necessary to identify Nephrolithiasis regions. For that, the pre-processed image has to undergo segmentation process. For segmentation process, two algorithms namely K means clustering algorithm and Fuzzy C logic algorithm is developed. Based on the performance of the algorithm, final segmented images will be selected.

3.4 K-means clustering algorithm

K-means algorithm is an iterative method that allows to partition the dataset into *K* predefined distinct non overlapping subgroups also called as clusters where each data point belongs to only one group. It consists of two separate phases. In the first phase algorithm calculates the k centroid and in the second phase it calculates each point to the cluster which has a nearest centroid from the respective data point. The method used to define the distance of the nearest centroid is Euclidean distance. Calculating the Euclidean distance d, between the center and each pixel of an image by,

$$d = \| p(x, y) - c_k \| \quad \textbf{(1)}$$

Where p(x, y) be an input pixels to be cluster and ck be the cluster centers. ck is calculated by,

$$c_k = \frac{1}{k} \sum_{y \in c_k} \sum_{x \in c_k} p(x, y) \quad \textbf{(2)}$$

Once the grouping is made it recalculate the new centroid of each cluster and based on that newly calculated centroid, a new Euclidean distance is calculated between each center of clusters and each data point and assigns the points in the cluster which have minimum Euclidean distance.

3.5 Fuzzy C-Means Clustering Algorithm

Fuzzy C-means (FCM) algorithm is a method of clustering algorithm which allow one piece of data belongs to two or more clusters. C-means is fuzzy also called as soft but k-means is hard each point is belonging to a centroid in K-means algorithm, but in fuzzy c-means each point can be belonging to two centroids but with different quality of an image.

3.6 Performance metrics

Parameter	**formula**
Accuracy	$\text{Accuracy} = \dfrac{TP + TN}{TP + TN + FP + FN}$

Based the performance metrics such as accuracy, the efficient segmentation model is selected and the segmented images is forwarded to further processing.

3.7 Feature Extraction

Feature Extraction describes the most relevant information of an image. While working with the large dataset, it helps to obtain the important details from the original content. The features that are going to be extracted are statistical features which represents texture based features. The mathematical information is extracted by computing mean, variance, standard deviation, skewness , kurtosis, contrast, correlation, energy, homogeneity, RMS and entropy.

3.8 Classification: CNN

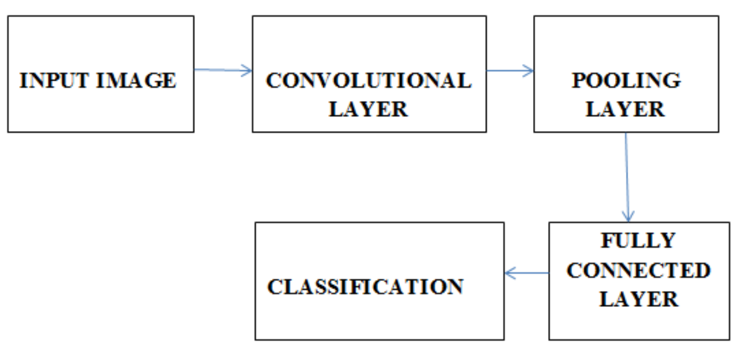


Fig -2 : Architecture of Deep CNN

Figure 2, explains about the classification process. The features that are extracted are given to the convolutional layer which is then forwarded to the pooling layer with the help of Activation function. Finally all the neuron is linked to the fully connected layer which classifies the image samples. Initially the convolutional layer forms the feature map with the help of the weight parameters and the feature vector. Then the feature map is forwarded to the pooling layer with the help of the Rectified Linear Unit (ReLU). The results of the pooling layer are given to the fully connected layer where the final classification will be occurs. The final expression is given as:

$$(D_d^v) = (B_d^v) + \sum_{e=1}^{J_1^{e-1}} \sum_{r=1}^{n_1^j} \sum_{s=1}^{n_2^j} U_{d,e,r,s}^v * D_e^{v-1} \quad \textbf{(3)}$$

Where,

$U_{d,e,r,s}^v$ – indicate interconnection of weight with the feature map.

The weight which is used in each layer plays a significant role in classification. It can be identified by using proper optimizing algorithm.

3.9 Support vector machine

The features that are extracted are given to the SVM to classify the kidney images. Support Vector Machine is a supervised machine learning algorithm not a deep learning algorithm but it can be used for both classification or regression challenges. The algorithm creates a line or a hyper plane which separates the data into classes.Hyper planes are decision boundaries that helps to classify the data points. Calculated data points falling on either side of the hyper plane can be attributed to different classes of SVM.

4.RESULTS AND DISCUSSIONS

4.1 Inputs and Pre-Processing

The input images are taken from Harley Acevedo database.It totally has 263 images. Among them 131 images are normal kidney and 132 are kidney with Nephrolithiasis. Initial stage of the detection module is pre-processing where the images are get resized to the dimensions of 256 X 256.

(a)

(b)

Fig- 3: (a) Normal kidney (b) kidney with Nephrolithiasis

In Figure 3, the kidney images are presented. Figure (a) represents normal kidney and Figure (b) represents kidney with Nephrolithiasis.

4.2 Grey scale conversion

Fig - 4 : Gray scale conversion

This process removes all color information, leaving only the luminance of each pixel as shown in Figure 4.

4.3 Segmentation: K-Means clustering algorithm and Fuzzy C logic algorithm

Table 1. Segmentation Results

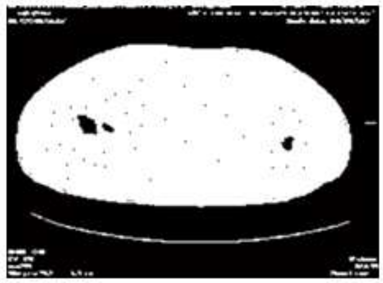
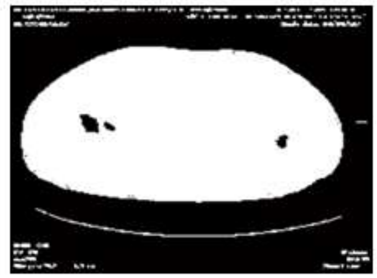
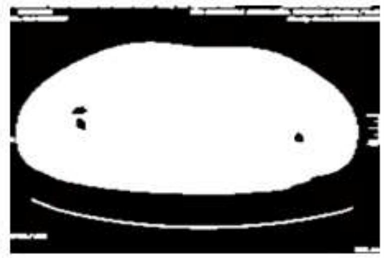
INPUT IMAGE	K-MEANS CLUSTERING SEGMENTED OUTPUT IMAGE	FUZZY C MEANS CLUSTERING SEGMENTED OUTPUT IMAGE
		
		

Table 1 shows the segmented results of K-Means clustering algorithm and Fuzzy C logic algorithm Model. First column of the table represents the resized input images. The second column shows the K-Means clustering segmented output image .The Third column shows the results of Fuzzy C logic algorithm segmented output image.

4.4 Performance Metrics

Table 2. Performance Metrics

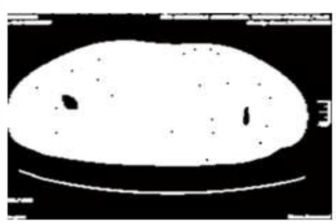
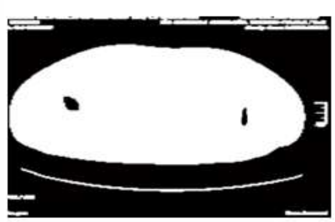
K MEANS CLUSTERING ALGORITHM		Accuracy = 83%
FUZZY C MEANS CLUSTERING ALGORITHM		Accuracy = 92%

Table 2 shows the Accuracy for both K-Means clustering algorithm and Fuzzy C logic algorithm. Fuzzy C logic algorithm provides higher Accuracy of about 92%.

4.5 Features Extraction

Mean=0.0052824
Standard Deviation=0.0896592
Variance=0.0080360
Smoothness=0.951576
Kurtosis=6.73182
Skewness=0.42588
Contrast=0.22386
Correlation=0.0996916
Energy=0.753798
Homogeneity=0.931285
RMS=0.0898027
Entropy=3.19429

(a) **(b)**

Fig- 5 : (a) Segmented kidney stone image (b) Extracted features

In Figure 5, the kidney images are presented. Figure (a) represents Segmented kidney stone image and Figure (b) Extracted features of kidney stone.

4.6 CNN Classification

Table 3. CNN classification

Kidney with stone	Kidney with stone	Kidney with stone
		
Kidney without stone	Kidney without stone	Kidney without stone
		

Table 3 shows the CNN classification of kidney with stone and kidney without stone.

4.7 SVM Classification

Table 4. SVM classification

INPUT IMAGE	CLASSIFICATION OUTPUT
	Kidney without stone
	Kidney with stone
	Kidney with stone

Table 4 shows the SVM classification of kidney with stone and kidney without stone.

4.8 Comparison

Table 5. Comparison on different models

MODELS	ACCURACY	PRECISION	RECALL
CLASSIFICATION BY CNN	94%	93%	92%
CLASSIFICATION BY SVM	90%	89%	91%

Table 6. Comparison on Optimizers

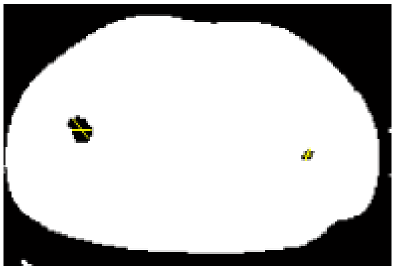
Optimizers	Classification Using CNN and SVM			
	Accuracy	Precision	Recall	F1 Score
SCA	83.99	82.64	85.09	81.63
Adam	93.84	91.89	96.35	94.24
RMSProp	78.66	78.45	81.24	77.38

Table 5 and 6 shows the comparison on different models and classification using CNN and SVM depends on optimizer.

4.9 Size of Stone

Stone surface area was calculated using the formula of spatial calibration.

Stone surface area=maximum diameter of stone $\times$ width $\times$ π $\times$ 0.25



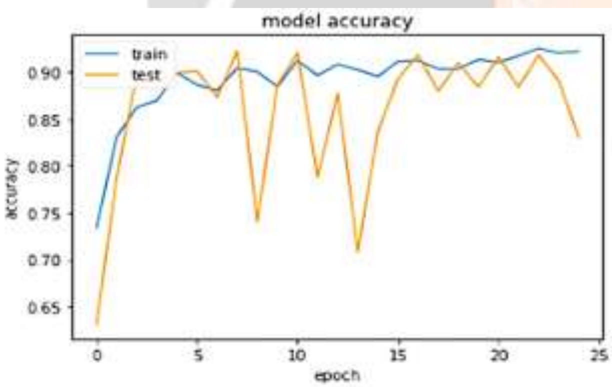
```
Maximum diameter of stone 1 = 11.2 mm
Width of stone 1 = 7.6 mm
Area = 66.8 sq.mm
Maximum diameter of stone 2 = 3.3 mm
Width of stone 2 = 5 mm
Area = 12.9 sq.mm
```

(a) **(b)**

Fig-6 : (a) Segmented kidney stone image (b) size of kidney stone

In Figure 6, the kidney images are presented. Figure (a) represents Segmented kidney stone image and Figure (b) size of kidney stone.

4.10 ADAM Optimization and Performance Metrics




```
Confusion matrix :
 [[105  25]
 [ 17 113]]
tn,fp,fn,tp : 105 25 17 113
Accuracy: 0.9384615384615385
precision: 91.88405797101449
recall: 96.92307692307692
f1score: 94.32835820895522
```

(a) **(b)**

Fig- 7 : ADAM Optimization and Performance Metrics

Figure 7(a) shows the adam Optimization graph which explains about the comparison of worst weight solutions with the best weight solutions and it is observed that the best solutions are more converged to zero than the worst solutions. Figure 7(b) shows the performance metrics of the CNN model. Based on the TP, TN, FP and FN, the Precision, Recall and F1 Score are calculated.

5. CONCLUSION

Convolutional neural network and Support vector machine have been used to detect and to classify the kidney stone with its size. The usage of GLCM feature extraction and CNN neural network is efficiently done. Comparing with Gabor filters, Canny Edge Detection lifting schemes GLCM has shown notable potential for spotting the giant features for accurate categorization of kidney stone. GLCM feature extraction is a statistical technique. Fuzzy C means algorithm plays better than K-means clustering in case of overlapped information. In Fuzzy C approach a statistics factor may belong to a couple of cluster mid-value not like k-means wherein data factor must completely belong to 1 cluster center.

Finally, the optimization techniques are used and accuracy has been analyzed. The validation accuracy for testing of the input images depends on the learning rate provided for optimization. The comparison is made based on the validation or testing accuracy. From the results, it is concluded that CNN performs better with the accuracy of 93% for Kidney Stone classification other than SVM.

6. REFERENCES

(1) S. Hu et al., "*Towards quantification of kidney stones using X-ray dark-field tomography*," 2018 IEEE 14th International Symposium on Biomedical Imaging in 2017.

(2) Y. Xie, B. Bowe, H. A. Mokdad, H. Xian, Y. Yan, T. Li, et al., "*Automatic Kidney Lesion Detection for CT Images Using Morphological Cascade Neural Networks*", IEEE Journal on Biologically inspired image processing vol. 94, pp. 567-581, June 2019.

(3) M. Shehata, F. Khalifa, A. Soliman, M. Ghazal, F. Taher, M. A. El-Ghar, et al., "*Computer-aided diagnostic system for early detection of acute renal transplant rejection using diffusion-weighted MRI*", *IEEE Transaction Biomedical Engineering.*, vol. 66, no. 2, pp. 539-552, Feb. 2019.

(4) J. Jiang, P. Trundle and J. Ren, "*Medical dissolution therapy for kidney stone with low density on non contrast computed tomography.*", *Comput. Med. Imag. Graph.*, vol. 34, no. 8, pp. 617-631, Dec. 2018.

(5) S. Asadi, H. Hassanpour, and A. Pouyan, “Texture based image contrast enhancement using gamma correction and kidney stone detection”, Middle-East Journal of Scientific Research, vol. 6, no. 6, pp. 569-574, 2010.

(6) R. C. Gonzalez and R. E. Woods,“Digital Image Processing”, 2nd ed., 1992, ch. 2, pp. 47-51 and ch. 10, pp. 568-611.

(7) D. Y. Kim and J. W. Park, “Computer-Aided detection of kidney tumor on abdominal computed tomography scans”, vol. 45, no. 7, pp. 791-795, 2004.

(8) D. T. Lin, C. C. Lei, and S. W. Hung, “Computer-Aided kidney segmentation on abdominal CT images”, IEEE Trans. on Information Technology in Biomedicine, vol. 10, no. 1, pp. 59-65, Jan. 2006.