A COMPREHENSIVE REVIEW OF KIDNEY STONE SEGMENTATION AND CLASSIFICATION

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Abstract

The kidney is an important organ of humans for balancing fluid levels, removing waste and cleaning the blood. The primary function of the kidney is to maintain blood pressure normal with acid balance. Due to the modern life cycle and food habits, stones are developed in the kidney.Persons who are susceptible to kidney stones have a higher risk of other kidney complications. Different techniques have been followed to diagnose stones in the kidney. Among these, image-processing based diagnose offer the best solution in terms of accuracy. But, the varied structure of stones makes the detection complex. So, more effective computer-aided models are essential to support health care persons in making accurate conclusions. This work reviews image processing steps, preprocessing filters,and previously proposed machine learning and deep learning models for the detection of kidney stones. Also, the performance metric for evaluation and data set details for further processing are discussed.

1 INTRODUCTION

Kidney stone is a deposition of salt or minerals in the urinary tract of the human-caused by some medical conditions or excessive weight [1]. The major symptoms of kidney stones are blood in urine, severe pain and vomiting. The types of kidney stones include Calcium stones, Struvite stones,Uric acid stones and Cystine stones [2]. Based on the size or volume of the stones, there are two ways followed by health care professionals to cure the pain: the stones with minimum stones can be shifted and passed by medicines and the stones with larger sizes can be removed only by surgery [3]. The early diagnosis of kidney stones supports people to prevent surgery. Health care experts may use lab or imaging to identify kidney stones. Lab test uses Urinalysis and blood tests to detect the presence of stones kidney. But the sample-based approach fails to detect accurately and is not used for type classification and further treatments. The imaging system uses x-ray , Computed tomography (CT) and Ultrasound to identify the stones in the kidney[4]. Compared to the sample-based approach, imaging-based detection offers higher accuracy in detection. It allows experts to locate the position of the stones precisely with their size [5].

The manual detection and classificationstones are complex tasks and time-consuming. the concept of Computer-aided detection (CAD) can be used to identify and locate the stones accurately andefficiency [6]. CAD model applies artificial intelligence (AI) algorithms to reduce human error. AI applies computer algorithms and programs to process the image for the identification of patterns. It has two parts machine learning and deep learning. This technique processes the images into three stages: preprocessing, features extraction or segmentation and classification. the preprocessing stage of image processing includes filtering (noise removal), image conversion and resizing. The features extraction technique applies segmentation algorithms to extract animportant feature for classification. The classification stages follow either supervises or un supervised learning to classify the image. The overall image-based kidney stone detection steps are shown in Figure 1.

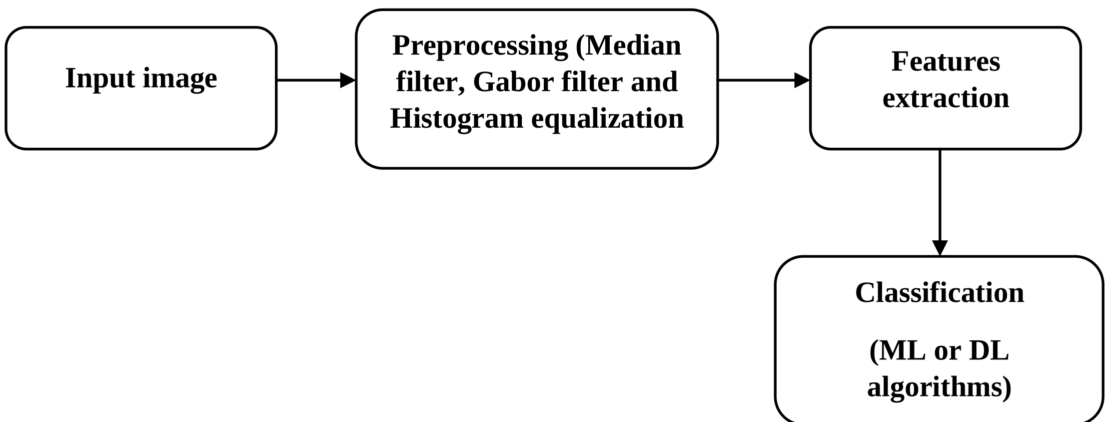

Fig. 1. Kidney image processing

In machine learning algorithms feature extraction and classificationare performed separately. It requires manual feature selection algorithms. Conversely, deep learning (DL) algorithms perform feature extraction, selection and classification in the model itself with higher accuracy. DL approaches are improving the quality of the images with higher accuracy
The rest of this paper is structured as follows. Section IISummarizes the Related Works in kidney image preprocessing and classificationtechniques, Section III discusses the data set availability and performance metrics, Section IV presents the future work, and finally, this paper is concluded in Section V.

2 RELATED WORKS

The ultra-sound image is mostly affected by Speckle noise. This noise disturbs edges and fine patterns of stones and the detection process more difficult. So, careful consideration is given to speckle noise removal before further processing. The common methods followed to remove speckle noises are Multiple-look processing, Adaptive and Non-Adaptive Filters, Filtering Techniques, Texture Analysis and Wavelet-based speckle reduction methods. The Wavelet-based speckle reduction methods include Thresholding Method, Coefficients correlation method and Bayesian estimation methods. The well-known filters used for speckle noise removal are Median Filter, Wiener Filter and Gaussian Low-pass Filters. similarly, the CT images are affected by the noise sources of Random noise, Statistical noise, electronic noise and Roundoff errors. This noise also can be handled by filtering techniques used for ultrasound images.

Different filtering techniques have been proposed for preprocessing kidney stone images. Wan M et al [7] proposed modified filter techniques to remove a speckle noise in the ultra sound image. T.Ratha Jeyalakshmi et al [8] proposed preprocessing technique based on morphological image cleaning to remove speckle noises. S.Sudha et al [9] analyze the effect of wavelet transform for preprocessing the ultra sound image. Theauthors of [10][11][12] designed anadaptive filter for handling noise in ultrasound images. The authors of [13][14][15] studied the effect of denoising filters in CT images.

The works related segmentation and classification of kidney stones are summarized as follows:Merve Karaman et al [16] proposed an ML algorithm of ada boost classifier-based kidney stone detection technique. Also, it uses aggregate channel features for the classification. This feature is extracted directly as pixel values in extended channels without calculating rectangular sums at different locations and scales.

Rahman, et al [17] developeda region-based segmentation model for detecting stones in ultra sound kidney images. For preprocessing, the Gabor filter is used. Region-based segmentation uses a seed point with the nearest clustering to separate a stone from the boundaries.

Marsousi et al [18] developed a probabilistic kidney stone detection model in 3d ultrasound images. Anisotropic Diffusion Filter is used to remove the speckle noises in the preprocessing stage. Then, the level set segmentation is applied to detect a stone. The proposed model achieved a detection rate of 92.68% for different data set images.GLCM (Gray Level Co-Occurrence Matrix) based features extraction technique is used by M Ranjitha et al. [19]. A total of thirty-six features are extracted and selected using Principal Component Analysis. The increasing number of features increases the classification accuracy of the model

Hafizah et al [20] [21] proposed an artificial neural network (ANN) based stone classification method with a multiple feature extraction approach. The proposed classifier is trained using histogram features and GLCM features. The histogram features are Mean, Variance, Skewness, Kurtosis and Entropy. The GLSM features are Homogeneity, Entropy, Energy, Cluster Shade, Informative Measure of Correlation -0.851 -0.784 -0.836 -0.834 Inverse Diff, Inverse Difference Moment and Cluster Prominence.

The hybrid model of wavelet and ANN is proposed by Viswanath et al [22-25] for-kidney stone segmentation. The energy levels are extracted using wavelet analysis and trained to the ANN model for classification. For preprocessing, contrast enhancement and histogram equalization have been used.The ML algorithm of Support Vector Machine (SVM) based stone severity calculation is proposed Akanksha et al [26-30] It involves three stages: histogram equalization, embossing and SVM classification. Embossing is performed to extract features vertically and horizontally in CT images and SVM is used to classify the severity of stones by comparing extracted features.

Thein et al [31] [32]proposed a threefold thresholding algorithm for stone segmentation. Initially, intensity thresholding is used to remove soft portions. Then, the portions of the bony skeleton are removed by applying area thresholding. Finally, area thresholding is performed to remove bet-mat regions. This thresholding process removes unwanted parts effectively and supports more accurate segmentation [33].

Akshaya et al proposed a kidney stone classification model by combing Fuzzy C-Mean (FCM) clustering with a back propagation network algorithm. The GLCM features are extracted using FCM-based segmentation and a neural network is used for classification. The proposed hybrid model shows higher accuracy than other models.

An ensemble learning-based kidney stone types classification model has been proposed Kazemi Y et al It involves four different classifiers of SVM, ANN, decision tree and Bayesian model to increase classification accuracy. The proposed model reaches an accuracy of 95.64%.Nithya, A et al developed a multi–Kernel K-means clustering algorithm for the detection of stones in the ultrasound image. Initially, the median filter is used for preprocessing. Then, multi–Kernel K-means are applied for segmentation. Also, the crow search optimization algorithm is used to select the best feature from extracted features.

The hybrid KNN and SVM model is proposed by Verma et al [28] For preprocessing, gaussian filtering and un-sharp masking are applied. Then, the morphological operation of erosion and dilation is applied to find a region of interest. The types of stones are identified using a combined KNN and SVM model.Kolhe, et al [29] proposed a morphological segmentation model for detecting stones in ultrasound images. Adaptive histogram equalization is performed in preprocessing stages for contrast enhancement. For segmentation, a morphological segmentation model is developed. The accuracy achieved is 90%.

Rudenko et al [30] constructed a DL model with a self-attention mechanism for kidney stone calcification classification. Also, the volumetric analysis is performed to classify the stone types. Işıl AKSAKALLI et al [31] developed a CNN model with re sampling process for classifying stones in X-ray images. The proposed model outperforms other models like SVM, NN and AdaBoost in terms of accuracy and sensitivity. Elias Villalvazo-Avila et al [32] developed a Multiview model for stone detection. It combines different features with an attention mechanism to increase detection accuracy. The accuracy of detection is improved by 4.5% when using the attention mechanism. The methods and results achieved by different researchers are summarized in Table 1.

Table 1. Summary of literature

Author	**Image modality**	**Technique**	**Results**
Merve Karaman et al	CT image	AdaBoost classifier and Aggregate Channel Features (ACF) algorithm	Accuracy -94%
Rahman et al	Ultrasound Image	Region based segmentation	Accuracy of 89.96%
Marsousi et al	Ultrasound Image	Shape-based segmentation	Detection rate 92.68%
M Ranjithaet al	Ultrasound Image	GLCM and k-means	Accuracy -93.45%
Hafizah et al	Ultrasound Image	Artificial neural network (ANN) or fuzzy	-
Viswanath et al	Ultrasound Image	Wavelet and ANN	-
Akanksha et al	CT	Support Vector Machine	98.71% accuracy by testing 156 CT samples

Thein et al	CT	Intensity,area and location based thresholding	s 95.24% sensitivity as the evaluation parameter
Akshaya et al	CT	Fuzzy C-Mean (FCM) clustering	-
Kazemi Y et al	CT	Ensemble leaning	Accuracy of 97.1%
Nithya, A et al	Ultrasound Image	Multi Kernel K-means clustering algorithm	The maximum accuracy of 99.61%
Yildirim K et al	Cross-sectional CT images	Convolutional neural network	Accuracy of 96.82%
Verma et al	Ultrasound Image	KNN and SVM classification	The accuracy of KNN was found 89% and that of SVM was 84%.
Kolhe, et al	Ultrasound Image	Morphological segmentation	Accuracy of classification system is around 90%
Işıl AKSAKALLI et al	X-ray	S+U sampling method.	Success rate of 85.3%
Elias Villalvazo-Avila	X-ray	Multi view model	An overall accuracy of 0.996±0.005

3 PROPOSED METHOD

Future , the two DL models such as AlexNet and gated Recurrent Unit (GRU) are hybrid to perform a feature extraction and classification. These two models are combined and performed to provide an accurate training parameter performance. The optimised AlexNet-GRU model is proposed for a kidney stone detection to perform a feature extraction and classification. The Elephant Herding Optimizer (EHO) is used for finetuning the hyperparameter of AlexNet-GRU model

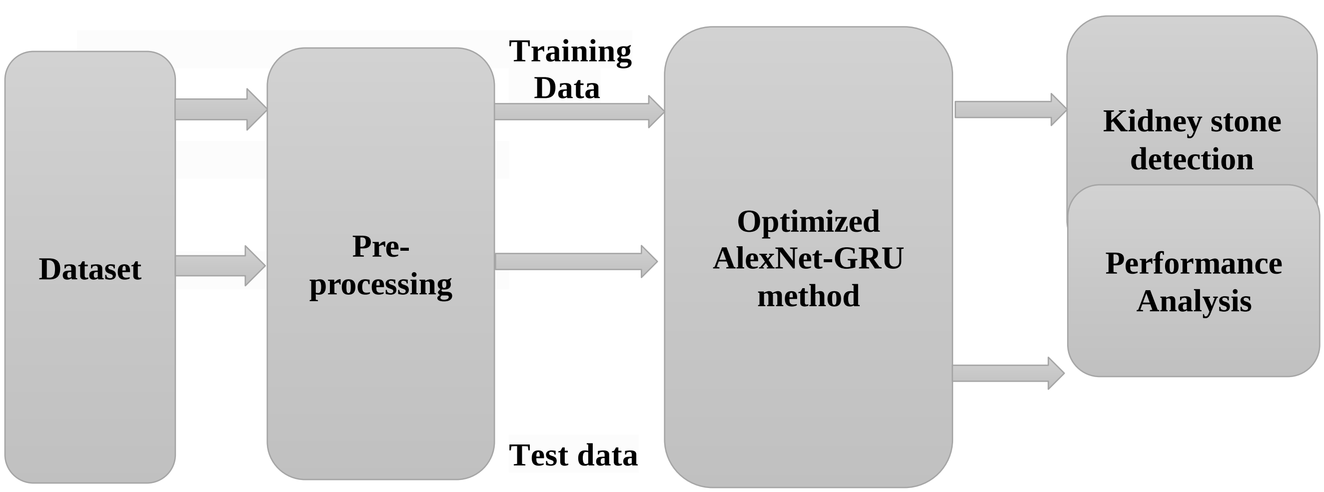

Fig.2. Proposed Method

4 DATA SETS AND PERFORMANCE MEASURES

The data set for kidney image processing can be downloaded from websites(http://splab.cz/en/download/databaze/ultrasound and https://www.medicaldata.cloud/data-sets/kidney-ct-dataset/) . the sample images are shown in Figure

Fig.3. Kidney images a) ultra sound b) X-ray c) CT image

The performance of segmentation and classification in ML and DL can beevaluated using the following parameters:

$$\text{Sensitivity} = \frac{\text{TP}}{TP+FN} \quad (1)$$

$$\text{Specificity} = \frac{\text{TN}}{TN+FP} \quad (2)$$

$$\text{Accuracy} = \frac{\text{TP+FN}}{TP+FP+TN+FN} \quad (3)$$

$$\text{F1Score} = \frac{\text{2TP}}{2TP+FP+FN} \quad (4)$$

$$\text{Precision} = \frac{\text{TP}}{TP+FP} \quad (5)$$

$$\text{Recall} = \frac{\text{TP}}{TP+FN} \quad (6)$$

$$\text{HD} = \max\{\sup_{r\in\partial R} \text{dm(s,r)}, \sup_{s\in\partial S} \text{dm(s,r)},\} \quad (7)$$

Where, TP is the True Positive rate, FN is the False Negative, FP is the False Positive and TN is the True Negative. For evaluation,atotal of 80% of images are used for training the DL models and the remaining 20% will be used for testing.

5 CHALLENGES AND FUTURE WORK

Based on the survey, the challenges in kidney stone detection are as follows

- The poor quality of images due to noises like speckle noise
- Due to the gap present in the kidney boundary
- The shadows created by the stones make a segmentation error

- By the probe miss-alignment, the structure of stones is not fully visible

The above reasons cause processing stone images more complex. Infuture, hybrid models will be introduced to solve the above difficulties faced in kidney image processing. Further, the meta-heuristic algorithms will be used to tune the hybrid model parameters to achieve higher accuracy,precision and recall rates.

6CONCLUSIONS

This paper reviews different techniques for the detection of stones in kidney images. The detection approaches need multiple stages of filtering, feature extraction and classification models *f2010.jjjjjjjjjjjjjjjj45;lorhigher accuracy. The proper selection classifier leads to more accuracy. ‘;-/Further, the suitable filtering technique also supports improving the classification performance. Future, the TL-based hybrid model is proposed to solve the issues in existing approaches.

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