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Kidney disease detection and segmentation using artificial neural network and multi-kernel k-means clustering for ultrasound images

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The main aim of this paper is to design and develop an approach for kidney disease detection and segmentation using a combination of clustering and classification approach. Nowadays, kidney stone detection and segmentation is one of the crucial procedures in surgical and treatment planning for ultrasound images. However, at present, kidney stone segmentation in ultrasound images is mostly performed manually in clinical practice. Apart from being time-consuming, manual stone delineation is difficult and depends on the individual operator. Therefore, in this work, we proposed a kidney stone detection using artificial neural network and segmentation using multi-kernel k-means clustering algorithm. Normally, the system comprises of four modules like (i) preprocessing, (ii) feature extraction, (iii) classification and (iv) segmentation. Primarily, we eliminate the noise present in the input image using median filter. Then, we extract the important GLCM features from the image. After that, we classify the image as normal or abnormal using neural network classifier. Finally, the abnormal images are given to the segmentation stage to segment the stone and tumor part separately using multi.

Kernel K-means clustering algorithm. The experimentation results show that the proposed system as linear + quadratic based segmentation achieves the maximum accuracy of 99.61%, compare with all other methods.

1. Introduction

Kidney stone illness is one of the real hazardous sicknesses holding on around the world. The stone infections stay unnoticed in the starting stage, which thus harms the kidney as they create. A maximum individual are influenced by kidney failure because of diabetes mellitus, hypertension, glomerulonephritis, etc. Since kidney breaking down can be threatening, diagnosis of the issue in the starting stages is advisable. Ultrasound (US) picture is one of the present accessible strategies [1]. The ultrasound imaging strategy is utilized in the medicinal practices, alongside other imaging strategies, for example, X-ray, CT, and so forth, for creating pictures of live tissue and with the aim of medical diagnosis. Since favorable circumstances of ultrasound imaging strategy, for example, being less expensive, convenience of the gadget, security of the imaging procedure to the patient, and the less measure of real time required for imaging, it has been given more consideration than other imaging techniques [2]. It was likewise revealed that identification of the kidney disease from the US picture is viewed as the challenging task because of characteristic constraints. With the improvement in the picture handling instruments, the characterization of US kidney has turned out to be accurate and preferred. Feature extraction and selection are the important steps for kidney stone detection. There are lot of texture features are available to extract the images namely, GLCM features, statistical features, texture features, region based feature and wavelet features etc. [3]. To extract the features from images lot of methods are available. Similarly, large number of features is a great obstacle for classification [4]. So, the important features are selected. Feature selection process increases the classification accuracy and minimizes the computation complexity. Nowadays, number of optimization algorithms and machine learning algorithms are used for feature selection process [5].

Many machine learning techniques have been applied to classify the tumor, including Fisher linear Discriminant analysis [6], k-nearest neighbor [7] decision tree, multilayer perceptron [8], and support vector machine [9]. A recent comparison of

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classification and feature selection algorithms applied to tumor classification can be found in [10]. Moreover, artificial neural network (ANN) methods provide an attractive approach for a direct multi-category classification problem [11]. The decision tree classification with association rule classification method provides a better option for the physicians classify the benign and malignant images [12]. An encoding techniques are given the better reliability in future that can be found in Radiation in CMC [13], errorencoding [14], ASQED [15], FPGA, 2-Derrorcorrection [16]. Design and implementation of reliable flash ADC for microwave applications, Reliable N sleep shuffled phase damping design for ground bouncing noise mitigation, Which techniques used to develop the result using VLSI chip that can found in [17,18]. Moreover, Ultrasound image segmentation is essential, troublesome and valuable in the medicinal zone. It is vital and helpful as a result of its use in the diagnosis and the treatment applications. For instance, to utilize radiotherapy systems for a kidney stone patient, the initial step is to quantify the volume of the stone from the given medical picture. At that point, as indicated by the size of the stone, the measure of the radiation will be resolved and connected. To segment the stone region from US image Lot of segmentation methods are used namely, k-means clustering, watershed segmentation and clustering methods are used for segmentation. Even though, the accurate kidney disease segmentation is not found out. Therefore in this paper we develop an efficient ultrasound kidney disease segmentation approach.

The main objective of this paper is ultra sound kidney image disease classification and segmentation using artificial neural network and multi-kernel k-means clustering. Basically, the ultrasound image is mainly affected by speckle noise. So the removal of speckle noise is an important process for stone classification and segmentation. For noise removal, in this paper median filter is utilized. After the noise removal, the GLCM features are extracted from each image. To increase the classification accuracy and minimize the complexity of the classification process, we select the important features from extracted features using crow search optimization algorithm (CSOA). Then, the selected features are given to the artificial neural network to classify the given image as normal or abnormal. After the classification process, the abnormal images are selected for segmentation process. In this segmentation, multi-kernel k-means algorithm is used and the performance is analyzed in the result section.

Rest of this paper is organized as follows: Chapter 2 illustrates related works, Chapter 3 illustrates proposed methodology for kidney disease detection system and Chapter 4 gives the result and analysis of proposed work. Finally, Chapter 5 concludes the proposed kidney disease detection work.

2. Related works

Lot of researches has analyzed the kidney disease classification and segmentation using ultrasound images. Among them some of the works are analyzed here; Ravindra et al. [19] have explained a chronic kidney disease (CKD) using support vector machine (SVM). CKD alludes to the disappointment of the renal functionalities that prompts the testimony of squanders, electrolytes and different liquids in the body. It is imperative to perceive the side effects that reason the CKD and neurotic blood and urine test demonstrates the key characteristics. This explicit investigation talks about the grouping of constant and nonchronic kidney illness NCKD utilizing SVM neural systems. To train the SVM in this paper they utilize radial basis kernel. The execution of the proposed plan is assessed as far as the affectability, particularity and order exactness. Moreover, Pawan et al. [20] have explained a Renal Calculi Detection in Ultrasound Images using k-means clustering (KMC). Here, for segmentation fuzzy rule based seed point optimization in KMC is used. The introduced strategy of clustering diminishes the quantity of emphasis for elaborating the area of enthusiasm for entitled pictures. This methodology promising to give an increasingly exact answer for ultrasound pictures and it likewise improves the picture recovery when contrasted with traditional grouping techniques. The test results legitimize the adequacy of introduced approach by diminishing the computational time without affecting the division quality which can be approved by pinnacle flag to commotion proportion esteem.

Similarly, Jyoti et al. [21] have presented a kidney stone detection using Kth nearest neighbour (KNN) and support vector machine (SVM). There are different issue partners with this subject like low goals of picture, comparability of kidney stone and expectation of stone in the new picture of kidney. Ultrasound pictures have low difference and are hard to recognize and separate the locale of intrigue. In this manner, the picture needs to experience the preprocessing which ordinarily contains picture improvement. The point behind this task is to locate the out the best quality, with the goal that the ID ends up simpler. Medicinal imaging is one of the central imaging, since they are utilized in increasingly delicate field which is a restorative field and it must be precise. In this paper, they initially continue for the upgrade of the picture with the assistance of median filter, Gaussian filter and un-sharp filtering. After that they utilize morphological activities like disintegration and expansion and after that entropy based division is utilized to discover the locale of intrigue lastly they use KNN and SVM arrangement systems for the investigation of kidney stone pictures. In [22], Viswanath and Gunasundari have introduced kidney stone detection from US image using level set segmentation and ANN classifier in VLSI implementation. To expel noise in ultrasound pictures preprocessing is applied. Response and dispersion (RD) level set division is connected multiple times, first to the section kidney segment and second to fragment the stone part. The separated area of the kidney stone after division is connected with Symlets, Biorthogonal, and Daubechies lifting plan wavelet subbands with higher vanishing minutes to remove vitality levels. These vitality levels give a sign about the nearness of stone, which essentially fluctuate from that of ordinary vitality level. These vitality levels are prepared by multilayer perceptron (MLP) and back proliferation (BP) ANN to distinguish the kind of stone with a precision of 97.8% and constant usage is finished utilizing Verilog on Vertex-2Pro FPGA. Moreover, Kavitha and Chinna [23] have explained a brain tumor detection using self-adaptive learning PSO. Here, at first ROI region of brain tumor is extracted from original image using modified region growing algorithm. Then GLCM features are extracted. To reduce the complexity important features are extracted using SLPSO algorithm. Then selected features are given to classification process. Here, feed forward neural network is used for classification process.

3. Proposed methodology for kidney disease detection system

The main objective of proposed methodology is kidney disease detection and segmentation using multiple stages. Fig. 1 shows the details of the proposed system. The first stage is the classification of kidney images into normal or abnormal (stone and tumor) image. Ultrasound images are provided to the system for the diagnosis purpose. Initially, the input images are processed for noise removal stage. After the preprocessing stage texture features are extracted from the images. Then, these features are given to the neural network classifier to find out the image as a normal or abnormal image. The last stage of the proposed system is to segmentation; which separate the stone and tumor part from the original image using multi-kernel k-means clustering algorithm.

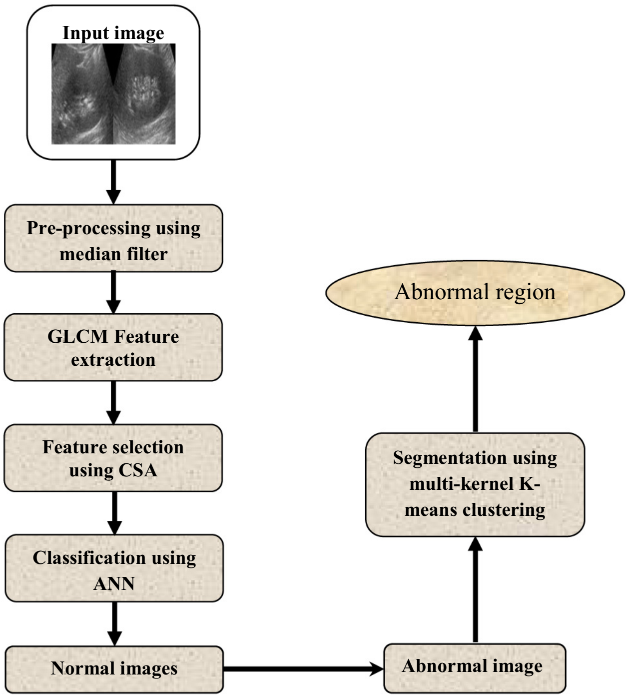

Fig. 1. Overall diagram of proposed methodology.

Finally, it extracts a stone and tumor portion from this ultrasound image.

3.1. Preprocessing

Preprocessing is an imperative procedure of ultrasound pictures because the occurrence of noise is more on Ultrasound picture contrasted with different pictures like CT and MRI. Essentially, the ultrasound pictures are mostly tainted by a speckle noise. Hence, noise removal is a serious procedure in medical ultrasound pictures. In this paper, for noise removal median filter is utilized. Median filter is a non-straight technique used to expel the noise present in the picture. The median is determined by first arranging all the pixel esteems from the window into numerical order, and afterward supplanting the pixel being considered with center pixel value. Middle filter is utilized to evacuate the speckle noise present in the original picture without diminishing the sharpness of the picture. Consider the input image $I(i,j)$ size of $M \times N$ which consist of speckle noise. Then, we split the image into n number of window W and each window has one center value. To remove the noise, we replace the center pixel using median value calculations. The median filter is given in Eq. (1).

$$\hat{I}(i,j) = median_{(s,t)\in C_{xy}}\{G(s,t)\} \tag{1}$$

where C_{xy} is the set of coordinates in a rectangular sub image window, centered at point (x,y) and median represent the median value of the window. This process is repeated for the entire window present in the input image. Finally, in this stage we obtain the noise free image $I^F(i,j)$.

3.2. Feature extraction

After the preprocessing stage, the image $I^F(i,j)$ is given to the feature extraction process. In this paper we extract twenty two types of GLCM features from each image. The features are Angular Second Moment, Contrast, Inverse difference moment, entropy, correlation, Variance, Sum average, Sum variance, Sum entropy, Difference entropy, Inertia, Cluster shade, Cluster prominence, Dissimilarity, homogeneity, energy, Auto correlation, Maximum probability, Inverse difference normalized (INN), Inverse difference moment normalize, Information measure of correlation 1 and Information measure of correlation 2.

3.3. Feature selection

After the feature extraction process, the important features are selected using crow search optimization algorithm (CSA). Because large number of features is affect the performance of classification process and increase the computation complexity. The CSA is depending on the characteristics and intelligence of crows. The step by step process of proposed feature selection process is given below;

Step 1: Initialization

Initialization is a primary stage for the entire optimization problem. In this stage, initially, we randomly select the features from original number of features. If the overall quantity of feature is N, then the length of the crow is N. The solution is denoted as crow. The crows are denoted in the format is as shown in Eq. (1) and solution representation is given in Fig. 2.

$$C_i = \begin{bmatrix} F_{11} & F_{12}\ldots\ldots F_{1D} \\ F_{21} & F_{22}\ldots\ldots F_{2D} \\ F_{n1} & F_{n2}\ldots\ldots F_{nD} \end{bmatrix} \tag{2}$$

Sample solution encoding process is given in Table 1. In this work N = 22 (i.e., number of feature available in one image is 22). The crows are randomly initialized to either 0 or 1. Here, if the ith position of a crow is 0 then it represents that ith attribute does not selected for classification process. Else if it is 1 then the ith attribute is selected for classification process.

Step 2: Fitness calculation

After the solution initialization, the fitness of each crow is calculated. At every iteration, every crow position is evaluated using a specified fitness function. The fitness calculation is a crucial aspect in CSA. It is utilized to measure the aptitude (goodness) of candidate solutions. In this paper, fitness function depends on the accuracy measure. The fitness computation is performed for each crow. For each iteration, the fitness is calculated using Eq. (3),

$$\text{Fitness} = \frac{\text{TP} + \text{TN}}{(\text{TP} + FP + FN + \text{TN})} \tag{3}$$

where TP represents the True positive, FP represents the false positive, TN represents the true negative and FN represents the false negative

Step 3: Updation based on CSA

After fitness calculations, we update the crow positions using CSA. For updating position two cases are available which is given below;

Case 1: The owner crow n of food source B_n^t doesn't realize the cheat crow m follows it so the cheat crow attains to the shroud location of owner crow. The thief crow position updation is provided in Eq. (4).

$$S_m^{t+1} = S_m^t + R_m \times FL_m^t \times (B_n^t - S_m^t) \tag{4}$$

where R_m is a random number in range [0,1], FL_m^t is the flight length of crow m at iteration t.

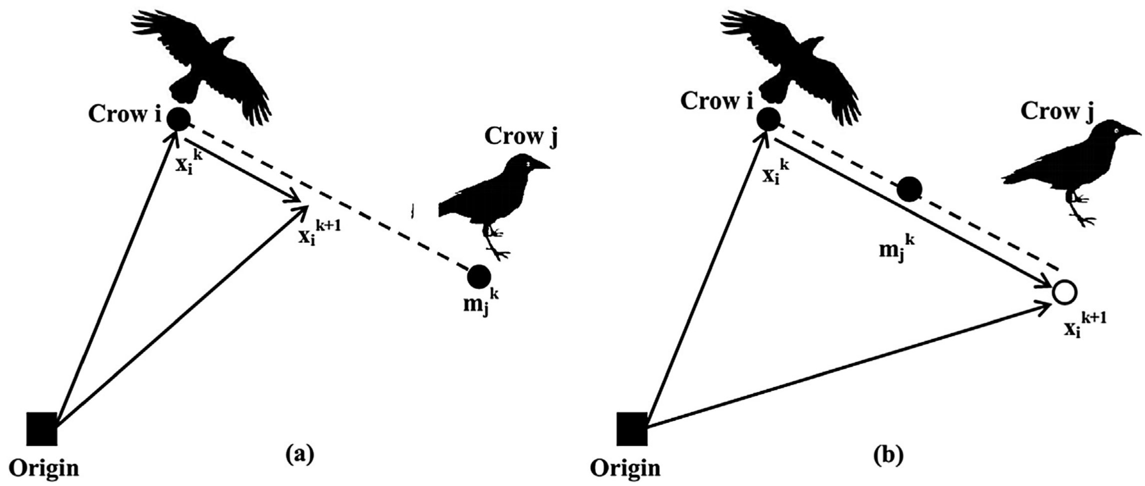

Fig. 2. The effect of the crow flight length on search process (a) if FL < 1 and (b) if FL > 1.

Table 1
Encoding Sample Solutions.

	F_1	F_2	8	F_4		F_{22}
C_1	1	0	1	0	⋯	1
C_2	0	0	1	1	⋯	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
C_u	1	0	1	0		1

Case 2: The owner crow *n* realize that the cheat crow *m* follows it therefore, the owner crow will mislead crow *m* by going to any another location of search space. In this case the position of crow *m* is updated by a randomly. The updation equation is given in Eq. (5).

$$S_m^{t+1} = \begin{cases} \text{if } R_n \geqslant P_n^t & \text{update position by using equation (4)} \\ \text{else} & \text{update to random position} \end{cases} \tag{5}$$

where P_n^t is the probability of awareness of crow *n* at iteration *t*. The positions are updated using Eq. (2) and after that the latest objective function is evaluated, the attained fitness function at iteration *t* is contrasted with earlier one and updating position of flock position is placed.

Step 4: Termination criteria

The optimization process terminates when it achieves the most extreme number of iteration or when the best solution is found. In this work, extreme number of iteration is used. The most extreme number of cycle set in this work is 40. The effect of crow search process is given in Fig. 3.

3.4. Classification stage

After the feature selection process, the selected features are fed to the classification process. In this paper, for classification artificial neural network is used which is classify the given image as three classes namely normal, stone and tumor. ANN consists of three layers namely input layer, hidden layer and output layer. The selected features are fed to the input of the input layer. Then the random weights are assigned to input-hidden w_{jk}^h and hidden-output layer w_{ij}^o. In output layer we obtain the different class. The structure of ANN classifier is given in Fig. 3.

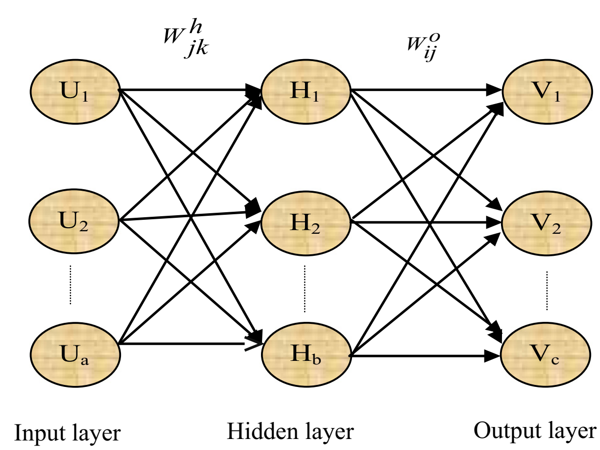

Fig. 3. Structure of artificial neural network.

At first, the each node U_k in the input layer feature value is multiplied with input hidden weights. The hidden node j receives the output H_j is given in Eq. (6).

$$H_j = \alpha_j + \sum_{k=1}^{n} U_k W_{ij}^h \tag{6}$$

Here, α_j is represent the bias value of hidden layer. The activation function is given in Eq. (7).

$$f(H_j) = \frac{1}{1 + e^{-H_j}} \tag{7}$$

After the activation function calculation, we calculate the output value. The output function is described using Eq. (8).

$$O_i = \alpha_i + \sum_{j=1}^{b} W_{ij}^o f(H_j) \tag{8}$$

where α_i is the bias in the output layer. After the output calculation, the error value is measured using Eq. (9).

$$E = \frac{1}{2n} \sum_{i=0}^{h-1} \sqrt{(T_i - Y_i)^2} \tag{9}$$

where n is the number of training parameters, Y_i and T_i are the output value and the target value, respectively. To minimize the error value, in this paper we used the back-propagation algorithm.

In the training process, the minimum error based weight values are stored.

In testing process, the selected features are given to classifier and trained weights are fed to the ANN. Then, ANN gives the feature based corresponding output value. In this paper, three types of class are assigned to the output layer. In each class, we assign different threshold value *TH*. Based on the output value, the given image is found out the corresponding class. The images satisfy the condition which is present in the Eq. (10).

$$output \in \begin{cases} N_1, for\ 0 \leqslant TH < 0.5 \\ N_2, for\ 0.5 \leqslant TH < 0.75 \\ N_3, for\ 0.75 \leqslant TH \end{cases} \tag{10}$$

Here, N_1 represent the normal image, N_2 represent the stone image and N_3 represent the tumor image.

3.5. Segmentation stage

After the image classification process, the abnormal images namely stone and tumor images are given to the segmentation process. For segmentation, multi-kernel k-means algorithm is introduced. In this, the kernel functions are hybrid with k-means clustering algorithm. K-means calculation is a clustering calculation which is utilized to limit the grouping mistake contrast with different algorithms. But this algorithm mainly suffers initial position of cluster center and it only discovers straightly distinct groups. To defeat the issues, in this paper multi kernel k-means clustering is used. In this paper, we utilized hybridization of linear and quadratic kernel.

Let $k_1\, and\, k_2$ be two kernels. The multi kernel K-means algorithm under kernelization of the metric approach is an iterative two steps algorithm that gives a partition $S = \{S_1, ..., S_k\}$ of X into K clusters and their corresponding cluster centroids $Y_k \in R^p\ (K = 1, ..., K)$ which minimizes the objective function;

$$W = \sum_{k=1}^{K} \sum_{x_i \in P_k} \| \Phi(x_i) - \Phi(y_k) \|^2 \tag{11}$$

$$= \sum_{k=1}^{K} \sum_{x_i \in P_k} \{K_{MK}(x_i, x_i) - 2K_{MK}(x_i, y_k) + K_{MK}(y_k, y_k)\} \tag{12}$$

$$K_{MK}(p, q) = K_1(p, q) + K_2(p, q) \tag{13}$$

where K_{MK} represents the hybrid kernel (linear + quadratic). The center updated formula is shown in Eq. (14):

$$y_k = \frac{\sum_{x_i \in p_k} K_{MK}(x_i, y_k)\, x_i}{\sum_{x_i \in p_k} K_{MK}(x_i, y_k)} \tag{14}$$

After the centroids calculation, we calculate the distance between centroids and the data point. This process is repeated until the updated centroids of each cluster are similar in consecutive iterations.

4. Result and discussion

In this section, we discuss the result obtained from the proposed kidney disease classification and segmentation. For implementing the proposed technique, we have used Mat lab version (7.12). This proposed technique is done in windows machine having Intel Core i5 processor with speed 1.6 GHz and 4 GB RAM. The proposed system has been tested on the data set available on the web. We have utilized the size of the image "512 × 512" which images are publicly available (Fig. 4).

4.1. Evaluation metrics

For performance analysis we utilized three measures namely, sensitivity, specificity and accuracy.

4.1.1. Sensitivity

The proportion of actual positives which are correctly identified is the measure of the sensitivity. It relates to the ability of the test to identify positive results.

$$Sensitivity = \frac{T_p}{T_p + F_n} \tag{15}$$

4.1.2. Specificity

The proportion of negatives which are correctly identified is the measure of the specificity. It relates to the ability of the test to identify negative results.

$$Specificity = \frac{T_n}{T_n + F_p} \tag{16}$$

4.1.3. Accuracy

We can compute the measure of accuracy from the measures of sensitivity and specificity as specified below.

$$Accuracy = \frac{T_p + T_n}{T_p + F_p + F_n + T_n} \tag{17}$$

4.2. Dataset description

The kidney images are utilized for segmentation and classification process. We are collecting the dataset into internet sources which are publically available. We collect totally 100 images.

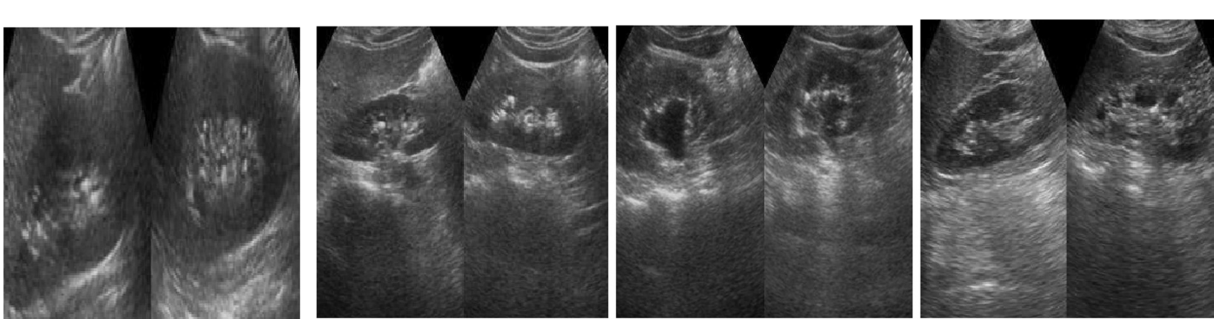

Fig. 4. Input sample images.

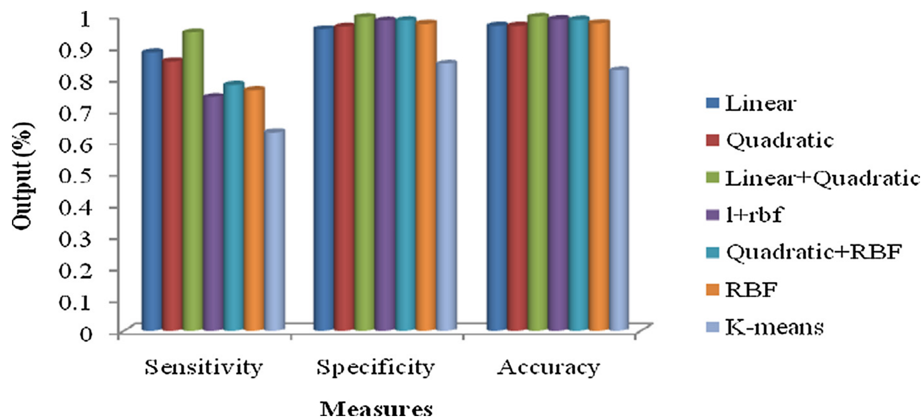

Fig. 5. Comparative analysis for segmentation stage.

Among them 40 images are normal 30 images are tumor and 30 images are stone image. In this we utilize 805 images for training and 20% images for testing process. The sample experimental images are given in Fig. 5.

4.3. Performance analysis on classification stage

In this section, the performance of classification stage is analyzed. For classification we utilized ANN. to improve the performance of the classification stage, we utilize optimal feature selection stage. Performance is analyzed with the help of sensitivity, specificity and accuracy.

From Table 2 the performance evaluation is analyzed by the proposed method by varying the hidden neurons. The sensitivity value is 33.33% when HN = 10, 100% when HN = 20, 66.67% when HN = 30, 33.33% when HN = 40 and 66.67% when HN = 50. The specificity value is 100% when HN = 10, 90% when HN = 20, 80% when HN = 30, 90% when HN = 40 and 90% when HN = 50. The accuracy value is 84.61% when HN = 10, 93.45% when HN = 20, 61.53% when HN = 30, 76.92% when HN = 40 and 84.61% when HN = 50 (Table 3).

To prove the effectiveness of the proposed method, we compare our proposed method with existing classifier. In this we compare our classifier with k-nearest neighbor (KNN) and naïve bias classifier. From Table 2, the evaluation metrics are analyzed for the proposed and existing methods, by which we can observe the efficiency of the proposed kidney stone classification system. When analyzing Table 2, our proposed approach attain the better accuracy of 93.45% which is 84.61% for using KNN and 83.64% for using naïve bias. From the results, we clearly understand our proposed classifier is attaining better results compare to other method.

Table 2
Classification performance by varying number of hidden neurons.

Metrics	HN = 10	HN = 20	HN = 30	HN = 40	HN = 50
Sensitivity	33.33%	100%	66.67%	33.34%	66.67%
Specificity	100%	90%	80%	90%	90%
Accuracy	84.61%	93.45%	61.53%	76.92%	84.61%

Table 3
Comparison of classification result.

Metrics	Proposed ANN	KNN	Existing Naïve bias
Sensitivity (%)	100	66.66	63.57
Specificity (%)	90	90	89.7
Accuracy (%)	93.45	84.61	83.64

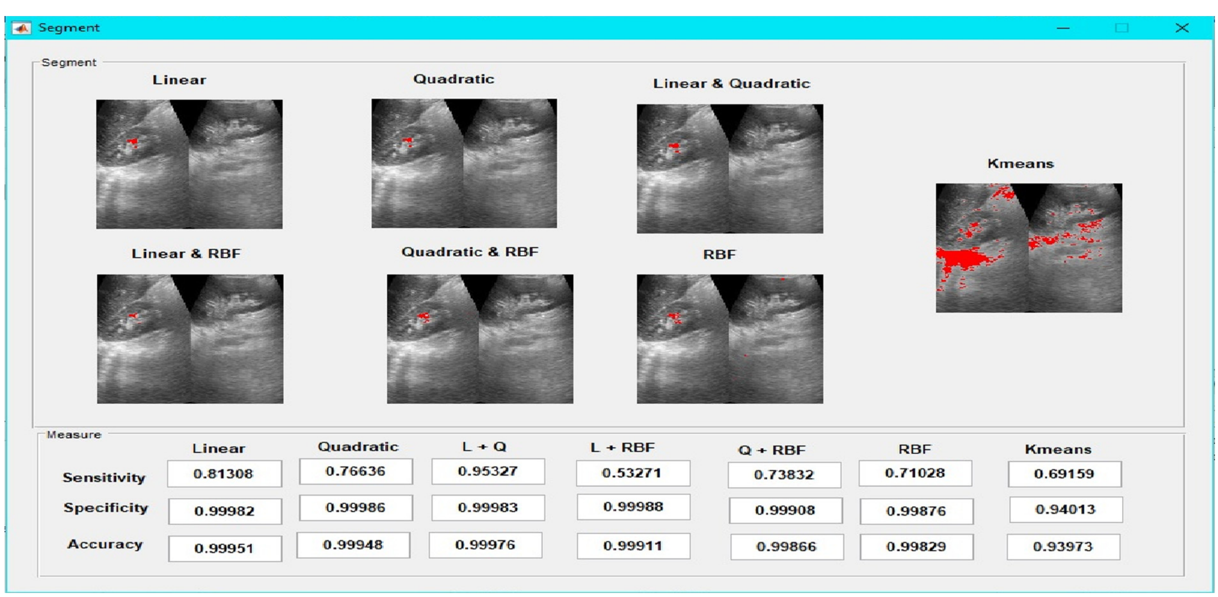

Fig. 6. Performance of segmentation using stone image.

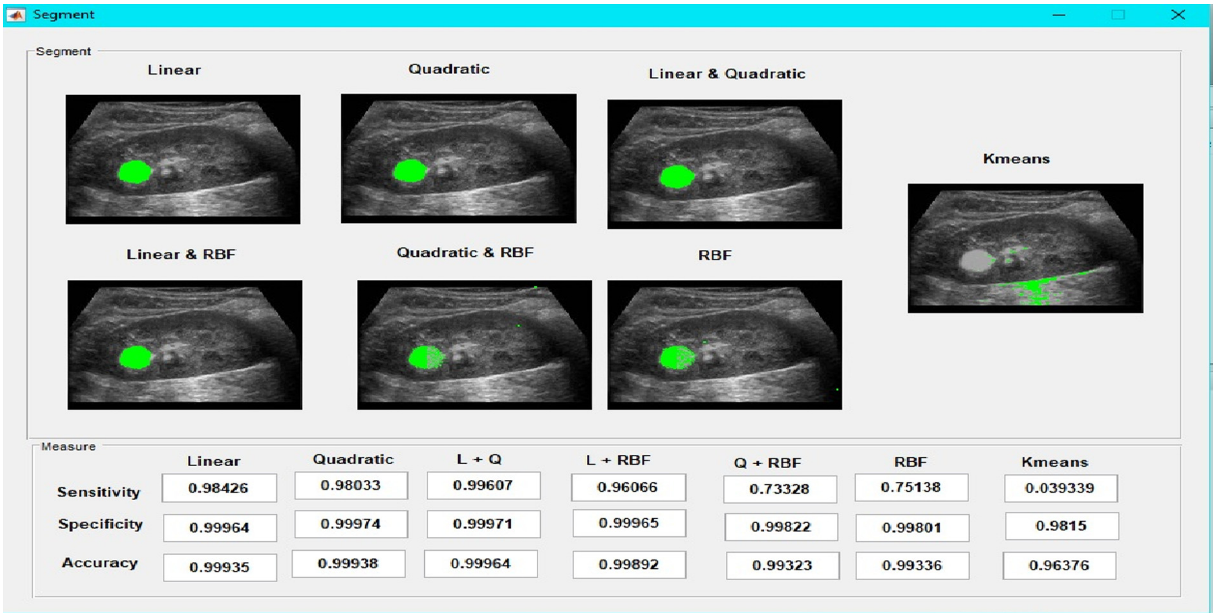

Fig. 7. Performance of segmentation using tumor image.

4.4. Performance analysis on segmentation stage

In this section, we analyze the performance of segmentation stage. For segmentation, to utilize multi kernel k-means algorithm. For multi-kernel, in this paper hybrid linear and quadratic kernel is used. To prove the effectiveness of the proposed work, we compare the proposed multi kernel k-means clustering algorithm (linear + quadratic) with k-means clustering, linear kernel with k-means clustering, quadratic kernel with k-means clustering, RBF kernel with k-means clustering, (linear + radial basis kernel) with k-means clustering, and (quadratic + radial basis kernel) with k-means clustering.

Fig. 6 shows the comparative analyze of segmentation stage. In this segmentation, we proposed a multi kernel k-means clustering algorithm (MKKM). This section, we analyze the performance of segmentation using number of methods such as linear kernel with k-means clustering, quadratic kernel with k-means clustering, RBF kernel with k-means clustering, k-means clustering and three types of multi kernel k-means clustering. When analyzing Fig. 6, linear + quadratic based segmentation achieves the maximum accuracy of 99.61%, Linear kernel based segmentation achieves the accuracy of 96.74%, quadratic kernel based segmentation achieves the accuracy of 96.74%, linear + RBF based segmentation achieves the accuracy of 98.77, quadratic + RBF based segmentation achieves the accuracy of 98.61%, RBF based segmentation achieves the accuracy of 97.53% and k-means algorithm achieves the accuracy of 82.63%. From the result observations the proposed linear + Quadratic kernel based segmentation approach achieves the maximum accuracy compare to other methods. Figs. 6 and 7 shows the GUI results of segmentation for stone and tumor images. The figure indicates the individual results of all the methods. From the results, we clearly understand our proposed multi-kernel k-means clustering algorithm achieves the better result compare to other method.

5. Conclusion

In this paper, multi kernel k-means clustering based kidney abnormal image segmentation, artificial neural network based classification and crow search optimization algorithm based feature selections are explained. The proposed method implemented using MATLAB. The performance of proposed method analyzed using sensitivity, specificity and accuracy measures. To prove the effectiveness of the classification stage, the proposed classifier compared with existing classifier and results are analyzed. Similarly, the multi-kernel k-means clustering based segmentation performance is analyzed different kernel functions. The experimental results clearly showed the proposed method as linear + quadratic based segmentation achieves the maximum accuracy of 99.61% attained the better result. In future, to develop different types of disease segmentation and classification using different algorithm.

Acknowledgement & disclosure

No conflict of interest between authors.

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