



Detection of Renal Calculi in Ultrasound Image Using Meta-Heuristic Support Vector Machine

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Abstract

Typically, the acquired renal ultrasound image includes a course of speckle noises. This paper primarily investigates an approach for the detection of renal calculi by processing those raw US images with the help of a meta-heuristic SVM classifier. One of the major downsides of involving Ultrasound images in medical analysis is the prevalence of Speckle Noises. An Adaptive Mean Median Filter approach has been introduced in the work to get rid of the speckle noises to the maximum extent ever in the literature. Segmentation is performed by employing conventional K-Means and GLCM features were extracted for classification using a meta-heuristic SVM classifier. The proposed methodology investigates with a Real-time Acquired Dataset of Mithra Scans, Tamilnadu, India comprises of 250 clinical Ultra-Sound Kidney Images of which 150 are having Calculi and the rest are Healthy. With the experimental results, the proposed meta-heuristic SVM classifier have performed better in noisy images while comparing with other conventional methods considered in the literature. It exhibits an Accuracy of 98.8% with a FAR rate of 1.8 for FRR as high as 3.3. The results clearly proposed that the novel AMM-PSO-SVM could be a promising technique for object or foreign body detection in a medical imaging application that uses ultrasound imaging.

Keywords Ultrasonic imaging · Renal calculi · Speckle noise · K means segmentation · Meta · Heuristic support vector machines

Introduction

Ultra Sound imaging technique has been extensively used in the field of Medical Imaging and the diagnosis of various diseases. It has an upper-hand of real-time easiness with low-cost implementation than other modalities like computed tomography (CT), X-ray and magnetic resonance imaging (MRI). With its wide variance in contrast levels, the segmentation of foreign bodies becomes more sensible in ultrasound imaging in its applications than processing CT and MRI images. However, the main drawback of medical ultrasonography is its average quality of images that are prone to

be affected by non-Gaussian and speckle noises. Since the underlying structures of Kidney are usually too small to be resolved by such large ultrasound wavelengths, the presence of such noises is highly undesirable as it deteriorates the image and thus makes the tasks of human interpretation and diagnosis a tougher one. The scientific contribution of the work is unveiling the Adaptive Mean-Median Filter to de-noise a non-Gaussian fine coarse speckle noises and a divisive hierarchical k means segmentation methodology. In this context, renal calculi detection had been formulated as a supervised-learning binary-classification problem and a meta-heuristic PSO inspired SVM algorithm has been designed to detect whether a Calculi is present or not at each pixel of the given image.

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Related works

Ultrasound imaging is one of the widely used imaging modality for the detection and diagnosis of renal calculus. Despite having advantages of being cost effective to implement and less toiling to use, the acquired ultrasound images are characterized as relatively poorer and noisy [1].

These speckle noises and other high intensity fine grained lights in the raw US images makes the process of identifying the underlying kidney stones which possess similar physical properties to the above said noises and some artefacts as a more complex and an arduous task. Therefore, the process of de-speckling the ultrasound images becomes an inevitable stage of the preprocessing.

In the work, it is accomplished by de-noising with the application of Wavelet threshold methodology. Here, the wavelet decomposition is performed on the de-speckled images and the extracted wavelet energy features are classified. Furthermore, these energy features are used by a feed-forward back propagated artificial neural network to classify the input kidney ultrasound image to suggest whether it had renal calculi or a healthy one. Also, with respect to the results, it is clearly established that the approach is suitable and effective for de-noised images. [2]

The strategy of SVM learning approach has been inspired by the core idea of minimization of the structural risk. The role of evaluation function while training the classifier provides the discriminating ability to determine in terms of support vectors that were identified as positive. In addition, the proposed SEL model has been designed so as to improve the performance of the trained SVM classifier. The discouraging result is that the SVM classifier achieves low generalization error when it is used to classify samples that were not trained and of little bit noisy. While analyzing the obtained results closely, it evidently reveals that the framework put-forth seems significantly insensitive and the model is also unresponsive to the choice of several model parameters for various features. [3]

Kidney-Urine-Belly computed tomography (KUB CT) is one of the widely used imaging modalities that have the ability to improve the identification and isolation of kidney stone. This study had initiated and investigated the design of a semi-automated diagnosis model by making use of various image processing techniques and its underlying geometry principles. In the literature, it sets a new benchmark results and it successfully defines the boundary and segmentation of the kidney area. It manifests the detected kidney stones and the output that not only just identifies the size and it also generalizes location of the kidney based on pixel count which is very helpful for finding ROI for other related researches.

The performance of the proposed approach was analyzed with kidney images of 39 subjects at Imam Reza Hospital in Iran. They were further classified into two criterions with respect to the availability of formation of kidney stones in their hospital diagnosis records. Of these, the proposed approach has generated inconsistent results due to the poor quality of the original CT scans. Results had evidently showed that the proposed approach possess of about 84.61% accuracy. Besides lot of good results in identifying ROI, the work also fails to fix the speckle noises that pull down the accuracy significantly. [4]

In the work, ultrasound kidney images from 28 subjects have been collected those includes 10 normal subjects and 18 abnormal. In this work, to remove the speckle noise from the acquired kidney images, they were filtered using wiener and median filter. It is followed by the segmentation process so as to find the suitable ROI in the processed Images. It is a important step, since it decreases the time taken to extract the desired features. To assess the quality of image preprocessing, the quality indicators such as Peak to Signal Noise Ratio (PSNR) and Mean Squared Error (MSE) were computed. The main contribution of the paper is the attempts of extracting the local SIFT features and texture features to classify the renal abnormalities. [5]

Methodology

In this paper, proposed methodology is used to identify the presence of nephrolithiasis (kidney stone) in the ultrasound images of the kidney. Our methodology consists of pre-processing, segmentation, and feature extraction and classification as shown in the below Fig. 1.

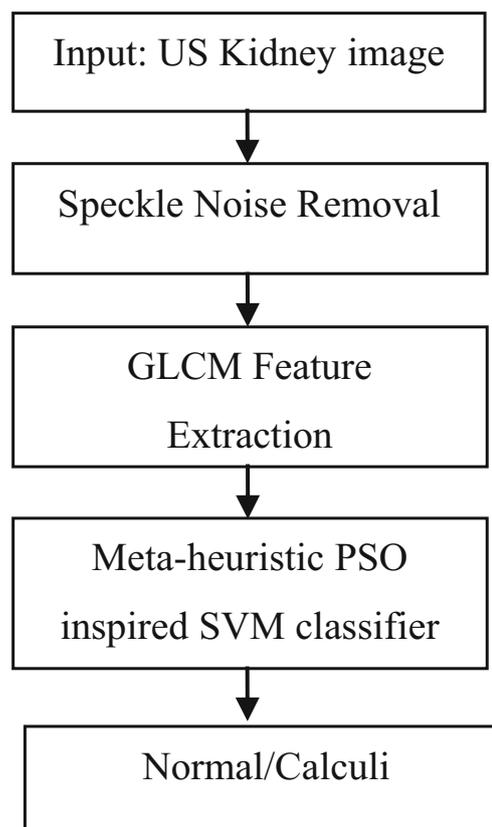


Fig. 1 Flowchart of Methodology

Dataset

The input used is the work fetched from the self-generated database of real-time ultra sound kidney images collected from Mithra Scan Centre, Tamil Nadu, India. The samples of kidney images are used to analyze the features and characteristics of renal calculi to enable computer vision. In the dataset, the size of the images is of 1024×768 pixel dimension.

Preprocessing

The idea behind the preprocessing stage is to normalize the local intensity in order to get rid of background noise which is usually characterized by lower order frequency of the image. In order to remove the reflections, it is needed to mask those slices of images. The preprocessing of the work particularly attempts to fix the non-Gaussian and multiplicative-speckle noise thereby enhancing the quality of the input image that shows significant improvements in the feature extraction and the classification eventually detects the presence of calculi with improved accuracy.

With the intention of improving the speed and accuracy of classification process further, the region of interest (ROI) has been determined by selecting only the kidney area and neglecting unwanted details like patient and scan information. In the proposed work, the morphological operations such as dilation and erosion were done to eliminate the undesired and irrelevant parts of the image. Smaller bright intensities were left out to make subsequent holes that can be re-filled by performing the erosion and dilation operations simultaneously. To ensure that every unwanted pixel in the image gets processed, the image is subdivided with 80×80 sections with focus as center since the kidney has been usually found almost at the focus of the image in the training cases. Finally, a rectangular ROI of range 256×256 pixels has been automatically generated by creating a small pattern called structuring element translated over the image. Only the regions that intersect with this window will be remaining as seed point candidates, and the rest will be deleted.

Adaptive mean-median filter

Due to the presence of coarse speckle noise, the image contrast gets affected significantly. Hence, it becomes an essential step to fix these speckle noise so as to enhance the contrast of the kidney. It should be cautiously performed without much significant tunings in the actual pixels, since every pixel of an image might carry vital information that will affect the performance of the classifier greatly.

The scope is to hold the original pixel values of the input image data while suppressing the linear fine-grained salt and pepper noises and other distortions encountered in the image. In the proposed methodology, an adaptive Mean- Median

Filter is deployed to remove noise and enhance the quality of the image for further usage.

The mean filter works by replacing every pixel of the image with the average value of its neighbors by including the current pixel also. The reason for choosing the filter model is, it eliminates the indifferent pixel values to its neighbors.

The mean filter operation on an image includes removing short tailed uniform and Gaussian noises from the image at the expense of blurring the image. The speckle noises are normally fine grained and sometimes it is similar to its neighboring pixels and few pixels length. Thus it entails a spatial filtering operation that computes the current value by considering at least a 2D mask that is applied to each pixel in the input image that effectively removes an blur in mean filtering. [6] In median filtering, the pixel value is replaced by the median of the pixel values in the 3×3 neighborhood. Median filter attempts to reduce the variance of the intensities in the image. The algorithm for adaptive Mean-Median filter is as follows:

Algorithm AMM-Filter

Input: Mean-filtered image $P_m(x, y)$

Output: De-noised Image

Initialize a 3×3 window and center

Sort the pixel values ascending order in a vector $v []$

Assign $v [0] \rightarrow \text{Min}$

$v [n] \rightarrow \text{Max}$

$v [n/2] \rightarrow \text{Mid}$

For every pixel in $P_m(x, y)$,

do

If ($\text{Min} < P(x, y) < \text{Max}$ and $\text{Min} > 0$ & $\text{Max} < 255$)

Label $P(x, y)$ as normal and $P(x, y) ++$

Else Label as Corrupted

For all Corrupted $P(x, y)$

do

If ($\text{Min} < \text{Mid} < \text{Max}$) && ($0 < \text{Mid} < 255$)

Replace $P(x, y)$ with Mid

Else $P_{\text{mid}} \rightarrow \text{Noise}$

Compute $V_{\text{dif}} []$

For all V_i where $i: 0$ to $n-1$ do

$V_{\text{dif}_i} = V_{i+1} - V_i$

Find $V_{\text{dif}_{\text{max}}} = \text{Maximum}(V_{\text{dif}_0} \text{ to } V_{\text{dif}_n})$

Assign $j \leftarrow \text{Index}[V_{\text{dif}_{\text{max}}}]$

Replace V_j with $V_{\text{dif}_{\text{max}}}$

Mean Squared Error (MSE) and the Peak Signal to Noise Ratio (PSNR) are two widely adapted error metrics used to analyze how good the image has been processed with respect to its original image. It is to be noted that the image should be acquired devoid of artefacts. In the work, the estimator is an unbiased the MSE measure denotes the cumulative squared error that is invariance between the processed and the actual image, whereas the PSNR represents the peak error ratio.

A lower value for MSE means lesser variance. Since PSNR is inversely related to MSE, for a better processed image, it is seen that as MSE approaches to 0 the PSNR will be approaching to infinite, at least for higher values. From the above Table 1, the AMM filtering possesses the least MSE and highest PSNR which is applied in this work to remove speckle noises from the acquired US kidney images. The inclusion of mean filtering before Median filtering significantly improves the performance of the conventional Median filter which is portrayed by the results in Table 1.

Segmentation

Many of the researches have been done in the past with various segmentation algorithms but still, it is a challenging task to isolate an accurate feature in the US images. The result of segmentation process of image greatly depends on the quality of the pre-processed image and the accuracy of feature measurement. [7]

In the segmentation process, the divisive Hierarchical K-Means segmentation algorithm has been deployed. Divisive methods are usually following top-down strategy. In this method, the complete image has been considered as the root of the hierarchical tree and then with reference to the current threshold evaluation, the tree has been progressively growing itself into its subsequent leaf nodes towards a maximum level. In this work, the divisive hierarchical method has been designed as a recursive procedure which iterates the k-means algorithm as many times the linkage-criterion at each node holds for every node that were generated in the hierarchical tree. One of the significant tasks is the calculation of the suitable parameter value for k in the current k-means algorithm. Since it is a binary classification problem, the criterion is initialized as k = 2. The algorithm of the hierarchical divisive K means clustering is inspired from the work of Jose Antonio [8] and is implemented as below:

Table 1 Performance analysis AMM filtering of renal calculi images

Image	Mean		Median [5]		AMM	
	MSE	PSNR	MSE	PSNR	MSE	PSNR
Normal	0.06	138.7	0.08	148.9	0.01	165.8
Renal	1.2	69.5	1	78.4	0.08	121.8

1. Initially, with a value for $k = 1$ and $k = 2$, the entire image I has been undergone a k-means clustering.
2. For every $k \geq 2$, increment $k = k + 1$ then perform clustering.
3. Compute the performance indexes $J(k)$ and $J(k - 1)$, if $J(k) \geq J(k - 1)$ holds, perform an increment $k = k + 1$.
4. Else if $J(k) < J(k + 1)$, for all $k - 1$ classes: perform the algorithm for each class generated.

As suggested by the algorithm, the clustering performance index J splits the image at the maximal point by maximizing their inter-class scattering(\mathbf{B}) and thereby minimizing the intra-scattering (\mathbf{W}). The index J is computed by using the following formulae:

$$B(k) = \sqrt{\frac{\sum_{i=1}^k (m_i - \mu)^2}{k-1}}, \text{ for } k \geq 2 \tag{1}$$

where μ is the computed mean of all possible the k centroids and m_i are the i^{th} centroid vector.

Here $\mathbf{B}(\mathbf{k})$ is calculated by taking square root of the centroids over all the clusters. It can also be considered as the vector of centroidal standard deviations of all the generated k-clusters.

$$W(k) = \frac{\sum_{i=1}^k \sqrt{\frac{\sum_{j=1}^{n_i} (x_{ij} - m_i)^2}{n_i - 1}}}{k} \tag{2}$$

where x_{ij} is the j th vector of the i th generated cluster, m_i is the centroid of the cluster I and n_i is the total number of elements grouped under the current cluster i .

Here, $\mathbf{W}(\mathbf{k})$ is computed by calculating $\mathbf{B}(\mathbf{K})$ for every feature comprises in the k cluster. Thus, it is also known as the mean vector of the standard deviation of each feature vector of each cluster.

$$J(k) = \frac{1}{W^T} \cdot B \tag{3}$$

This ratio is widely branded as the Fisher’s ratio that stands as an important measure to bring out the quality of a clustering. Since the acquired methodology is divisive and hierarchical, J has been maximized by evaluating $J(k)$ for $k = 1 \dots N$ for all the generated clusters to achieve a global optimum value for J . One of the major abilities of the method is that once a binary problem that usually have only two classes has been clustered, the entire focus is to classify the rest of the data into either of the two classes leaving noises generated by other irrelevant classes.

Support Vector Machine

SVM plots training data to a high dimensional features space through mapping of $\varphi(x)$ so as to construct a hyper-plane that is separating with maximal margin resulting in nonlinear decision boundary in original input space. To maximize x , the distance between the nearest point on the hyper-plane to the origin has been used. Furthermore, for the other side points, the same procedure is applied to find its corresponding distance.

By assuming the following linear function: $f(x) = w^T x_i + b$ such that training examples from the two different classes are successfully separated by the hyper-plane $f(x) = w^T x_i + b = 0$. The idea of SVM is to find a largest hyper-plane that separates the decision function values of the binary class problem with respect to the corresponding features. [9]

The hyper-plane can be mathematically computed by minimizing the following cost function:

$$J(w) = \frac{1}{2} (w^T \cdot w) = \frac{1}{2} \|w\|^2 \tag{4}$$

Subject to the bounded separability constraints for

$$\begin{aligned} w^T x_i + b &\geq +1, y_i = +1 \\ \text{or} \\ w^T x_i + b &\leq -1, y_i = -1 \\ \forall i &= 1, 2, 3, \dots, l \end{aligned} \tag{5}$$

These constraints can also be rewritten more efficiently as

$$y_i (w^T x_i + b) \geq +1, i = 1, 2, 3, \dots, l \tag{6}$$

Usually the hyper-planes were selected such that there are no points between the linearly separable training data and the obtained equation of the hyper-plane that has been maximized [10] In the current work, a normalized cross-correlation (NCC) similarity measure has been used to determine whether a reference feature vector was similar to the current vector from a series of training set images from the Mithra Dataset. The Segmented features in the reference vector provide the foundation for the confined block matching to fix the feature locations in the current frame vector.

Such hyper-plane is learned from training data using an optimization procedure that aims to maximize the margin. We employed a soft-margin SVM with a radial kernel. So as to determine the optimal values of SVM tuning parameter C and radial kernel tuning parameter γ with respect to this dataset. A 10-fold cross-validation methodology has been applied to the training data. The resulting cross-validated values for these parameters were $\gamma = 0.0188$ and $C = 31$.

Meta-heuristic support vector machine

The aim of applying Particle Swarm Optimization as meta-heuristic is to find the optimal hyper-plane. PSO is

one among the popular stochastic optimization techniques that is inspired by the natural behavior of its populations i.e., birds within a flight in the general case. It is based on the allegory of how a swarm of birds flying through the various ranges of landscape which is considered as fitness ranges thereby to pick the appropriate landscape that provides the optimum value of the corresponding fitness function. The basic idea of the algorithm is inspired by the following unique phenomenon in which every other particle could mutually exchange their individual fitness values in a manner that every single swarm has been well aware of the overall fitness of the entire swarm. This gives the ability of the swarm to explore the most advantageous areas of the entire search landscape. The learning factor signifies the attraction that a swarm/particle possessed to fetch a better peak that ensures its own success which is called as cognitive learning factor (represented as C1) or that of its neighbor's success which is known as social learning factor (represented as C2). Here, in general both C1 and C2 are considered as constants. Finally, the neighborhood organization and flying fashion determines the set of swarms that can contribute to the local best value of a particular particle [11].

Algorithm: Feature selection using PSO-SVM

Initialize parameters: V_{max} , V_{min} , inertia, correction factor,

Read input data from trained linear SVM

Randomize the initial position of particles to (p, q)

Initialize: Repetition = 0, recurrence = 0

do

For all the particles in the swarm do

Update current location (x, y) to position (p, q)

Fetch SVM's result for this position

Update l best

End-for

Update g best's index with current l best

Update velocities V_{max} , V_{min} for each particle

Repetition++

If g best's position has not changed and repetition > K then

Repeat++

End-if

End-while recurrence > R

G best's position = current particle positions

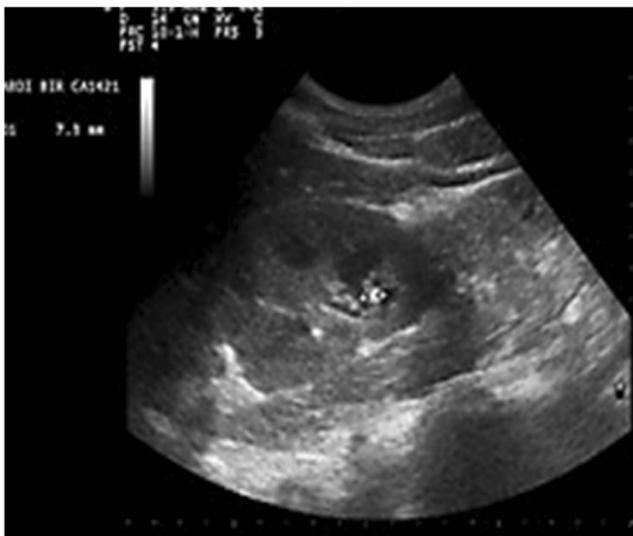


Fig. 2 Input image

Here, the swarm is perceived as a population of all the particles in the state space in which every particle epitomizes a probable resolution to the problem. The particle-best (p best) represents the position in which the maximum value of the particle can be computed by the SVM for the particular feature. For the current particle, the local best (l best) can defines the position of the best neighborhood particle member of the flock. The current position of the best-known particle of the current swarm considered has been called as the global best (g best). The particle that is used by SVM to drive the search space to find other better particles from the current state space is known as Leader of the search or the current swarms. The velocity is a vector that conveys and guides a particle in which direction it needs to explore or fly so as to refine its current position towards the success. The purpose of the inclusion of inertia weight (W) is to regulate the influence

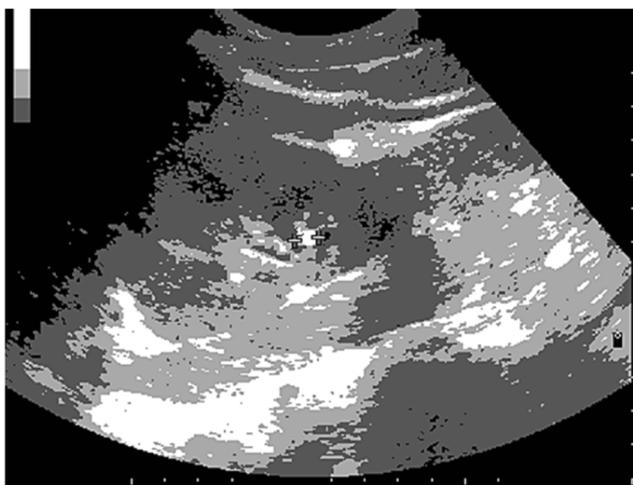


Fig. 3 Preprocessed Image

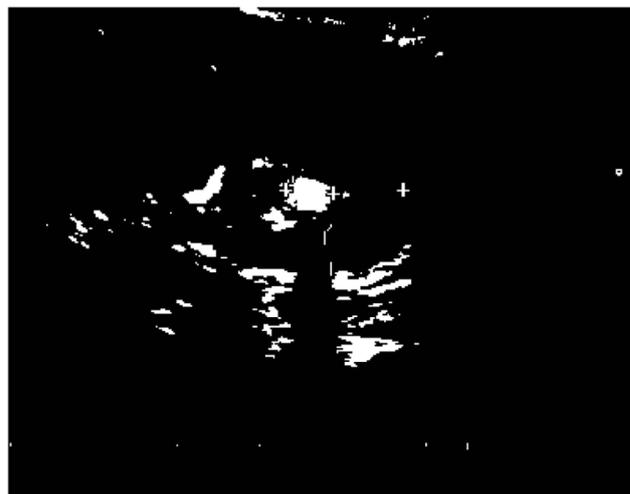


Fig. 4 K-Means Segmented Image

of the former history of velocities on the existing velocity of that particular feature.

Results and discussions

In this context, the meta-heuristic SVM classifier is introduced to deal with the bi-classification problem to find whether the kidney stone is present or not. The accuracy of similar models in the literature study has been used to analyze the performance of the proposed meta-heuristic SVM along with accuracy, Sensitivity and Specificity has also been taken into account for the comparative analysis.

The following figure will show the output of kidney with & without kidney stone image using K-means clustering algorithm in MATLAB. In the input image Median filtering is

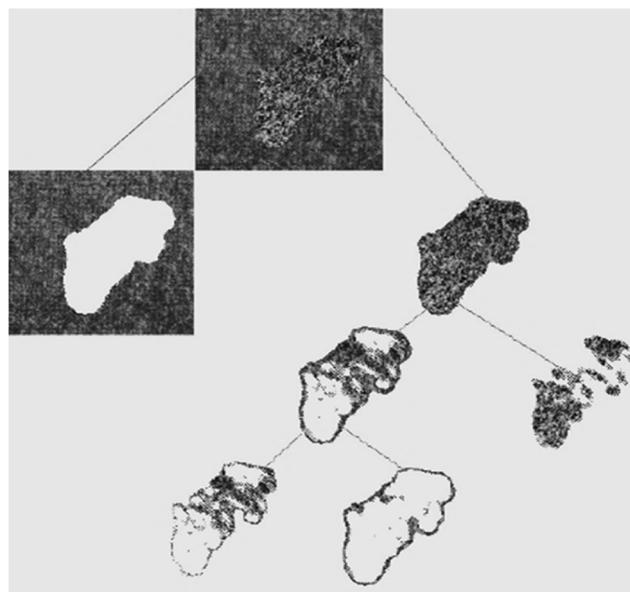


Fig. 5 HDK-Means Segmented Image

Fig. 6 Feature values of Normal kidney using PSO-SVM

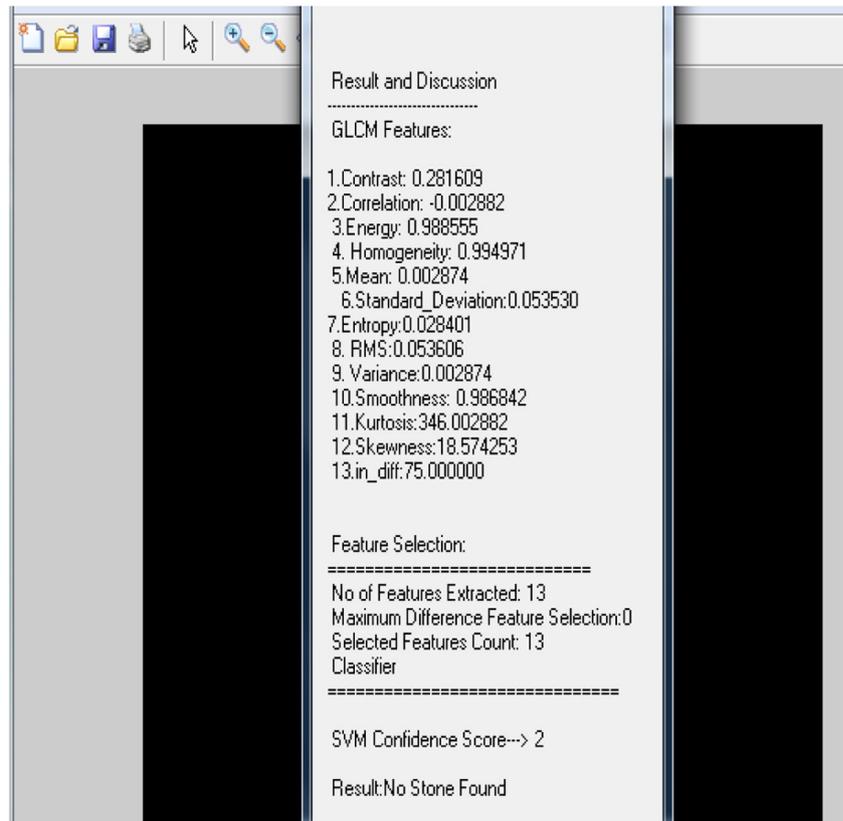
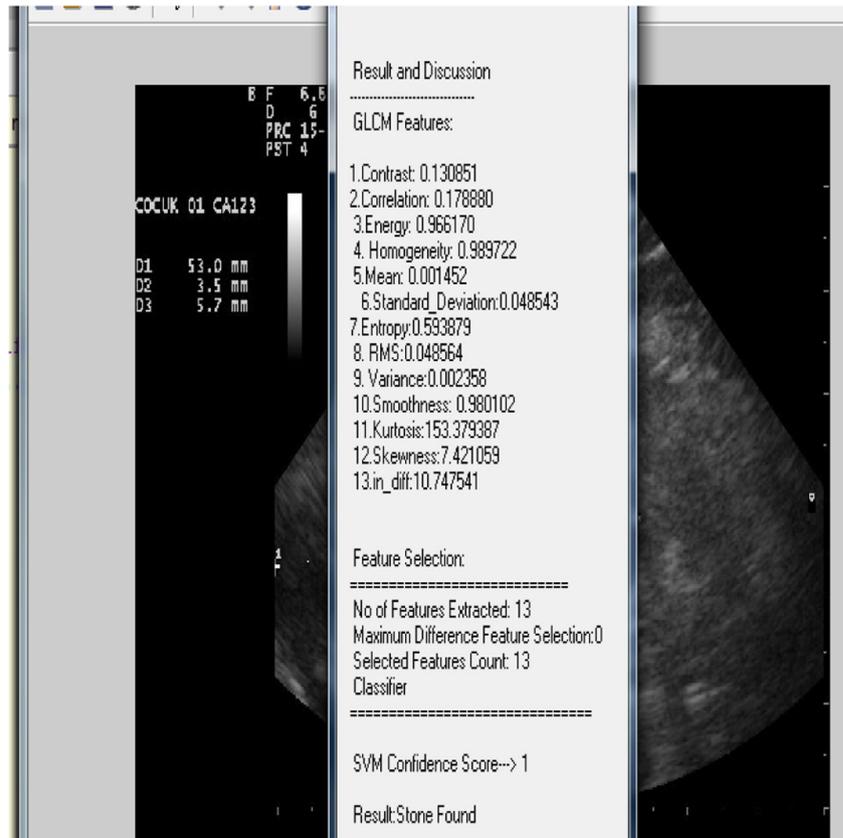


Fig. 7 Detected Kidney Stone Features using PSO-SVM



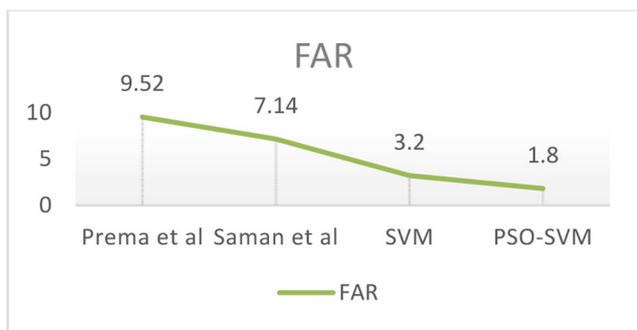


Fig. 8 Comparison of FAR

applied in order to remove the noise in that image. The following Fig. 2 shows the sample calculi image and Fig. 3 shows the preprocessed input.

And the above Fig. 4 shows the Segmentation using K-Means Segmentation Algorithm and Fig. 5 shows the Segmentation using Hierarchical divisive K-Means Segmentation Algorithm.

And the above Figs. 6 and 7 shows the Extracted GLCM feature values of the given sample of kidney with no stone and with stone respectively.

Performance analysis

The performance of the proposed method has been evaluated by comparing the obtained experimental results with ground-truth images. The performance of proposed meta-heuristic SVM algorithm to identify the kidney stone area has been compared to that of the conventional SVM and other literature works. The GLCM statistical feature measures were extracted for 100 sample US images (50 normal and 50 stone images) using 10-fold approach for training the SVM.

For the binary classification problem, the results are commonly categorized as positive (p) or negative (n). The feasible results with respect to the classification skeleton used in this context is often well-portrayed in some statistical measures such as false positive (FP), true positive (TP), true negative

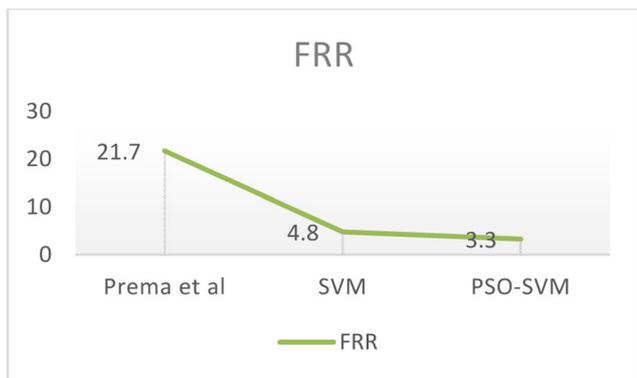


Fig. 9 Comparison of FRR

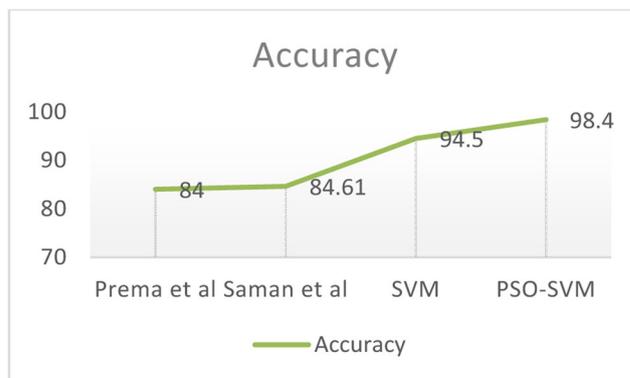


Fig. 10 Comparison of Accuracy

(TN) and false negative (FN) respectively. These analytical metrics are widely considered and accepted to exhibit the performance of the proposed method in this work measured quantitatively by Accuracy, False Acceptance Rate (FAR) and False Rejection Rate (FRR).

Accuracy portrays the class discrimination ability of the classifier that represents the percentage of test samples that are correctly identified by the system.

$$ACC = \frac{TP + TN}{p + n}$$

$$FAR = \frac{FP}{(FP + TN)}$$

$$FRR = \frac{FN}{(FN + TP)}$$

Where.

- FP False positive,
- FN False negative,
- TN True negative,
- TP True positive

In this context, the exploitation of contour significantly diminishes the relative error in between the segmented calculi images from the proposed method and to that of expert radiologist at the scanning centre. And hence, the obtained errors such as FAR and FRR are minimized that leads to high efficiency. [12]

Table 2 Performance analysis of proposed method

Method / Measures	FAR (%)	FRR (%)	ACC (%)
Prema et al., [2]	9.52	21.7	84
Saman Ebrahimi et al., [4]	7.14	NA	84.61
Conventional SVM	6.2	12.8	90.5
AMM -SVM	3.2	4.8	96.5
Proposed PSO-SVM	2.6	3.9	97.4
Proposed AMM-PSO-SVM	1.8	3.3	98.8

From the Figs. 8 and 9, it is clearly seen that the FAR and FRR of the proposed PSO optimized SVM outperforms the other techniques in the literature. The lower FAR and FRR indicate that the proposed model has the minimal misclassification significantly. Since both the Type-1 and Type-2 Errors of the model has been greatly reduced, the Accuracy has been at its peak which can be clearly seen in the Fig. 10.

Conclusion

This work is primarily concerned with the application of the SVM in order to considerably improve the prediction capacity for the detection of renal calculi. The non-Gaussian speckle noises that acts as a predominant performance spoiler of many literature works has been addressed greatly in this work. From the Table 1, it is clear that the AMM filtered image possess better results in terms of MSE and SNR. The Table 2 suggests clearly that the AMM-PSO-SVM outperforms the other methodologies significantly. Also, the proposed methodology possesses the highest accuracy of over 98.8% with lowest FAR and FRR that makes it readily usable after the clinical observations. The new results create a significant impact from a clinical perspective, as they maintain the lower FAR rate while significantly improving the FRR which is the precious contribution in terms of medical image diagnosis as one false prediction may cost a wrong diagnosis. This model also is readily showcased to the physicians to get the clinical feedbacks so as to tune the classifier to the finest quality.

The process of finding the optimal values for SVM regularization parameters obviously involves a 10-fold training runs in the work that is computationally a complex process. Even though, the parameter values had been fine-tuned so that the classifier exhibits a better accuracy only limited for the trained dataset, in real time applications, the classifier may undergo processing real time acquired subjects that are not trained and are naturally dynamic as well. This demands a fast and effective SVM parameter optimization method.

Future scope

In future, Local features such as LBP, SURF and SIFT features will be considered and experimented with some advanced classifiers like Deep Learning. The future scope of the work is perceived to address this issue. Also, the works will also be carried out to translate these algorithms into a software toolbox that could finally be distributed among physicians for their fieldwork and feedbacks.

Compliance with ethical standards

Conflict of Interest Selvarani S declares that she has no conflict of interest. Rajendran P declares that she has no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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