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PATTERN ANALYSIS OF KIDNEY DISEASES FOR DETECTION AND CLASSIFICATION USING ULTRASOUND B - MODE IMAGES

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ABSTARCT

Ultrasound imaging techniques play a crucial role in emergency diagnostic method. It is widely used due to its non invasive inexpensive availability and non radiation exposure. The main intention of this work is the automatic detection and classification of various diseases such as stone, cyst and cancer masses present in the pelvic region of the kidney. For this research work three main methods are proposed. The first method employs the detection of kidney diseases using Viola Jones incorporated with HOG, Haar, and LBP features. The second method is feature extraction using scale Invariant Feature Transform (SIFT) and Speeded- up Robust Feature (SURF). The final method is the modeling of various kidney diseases using Support Vector Machine (SVM). The overall detection rate of detected kidney diseases using HOG with Adaboost classifier is 96.67%. The performance accuracy for the kidney disease classification using SVM with SIFT feature is 82.5% and SVM with SURF feature is 89.3 %.

Related keywords: Ultrasound B-Mode, Ada-boost, Scale Invariant Feature Transform, Speeded up Robust Feature, Support Vector Machine.

1. Introduction

The kidney diseases can be grouped into two main stages namely chronic kidney diseases (CKD) and acute kidney injury (AKI). The prevalence of chronic kidney diseases will gradually increase if they are not properly treated. It may initiate serious health hazards namely diabetes, blood pressure, pulmonary hypertension, and other cardiovascular diseases. According to the statistics of National Centre for Biotechnology Information (NCBI) there is 30 percent increase in the prevalence of chronic kidney diseases in United States, In India 40% to 60% of diabetic and hypertension cases are due to CKD. It is more necessary to diagnose the kidney diseases at early stages which can prevent us from the several serious diseases. Ultrasound modality is one of the best imaging diagnostic techniques when compared to other imaging modalities such as Magnetic resonance imaging (MRI), Computed tomography (CT) and X-ray, because of it is available at less expense with no harmful radiation exposure and its smart portability.

This paper concentrates on the most significant chronic kidney diseases such as kidney stone, cyst and cancer. Each malformation is diagnosed through US images having distinct echogenic properties. These echogenicity properties may be hyper echogenic or anechogenic depending on the reflection of sound waves during movement of the transducer. Various kinds of stones

calcium, uric, cystine and struvite are identified in the region of kidney. The echogenicity associated with posterior acoustic shadow may indicate the kidney stones. The kidney cyst is characterized as by bag of fluid which causes the echo properties. It has dark lesion (anechoic) sac surrounded by well-bounded thin wall. Likewise renal cell carcinoma generally has less visualization than renal parenchyma on ultrasound findings. Based on intensity level of the cavity ablation and the parenchymal tissues, the renal cell carcinoma is to be considered.

1.1 Related work

Speckle reduction is the major task on ultrasound images due to high multiplicative noises created by back scattered waves. A cluster based anisotropic diffusion filtering technique for reducing the multiplicative noises in ultrasound images which have the significant outcomes [1]. An edge based anisotropic diffusion filter which concentrated on both edge preservation and noise reduction [2]. The Adaboost learning by integrating various feature sets for the classification of pathological prostate images and to detect micro calcification in breast cancer images [4] [5]. The automatic detection of kidney diseases using Viola Jones method incorporated with different features is used in smart phone [6]. David G Lowe [7] proposed a techniques using local scale invariant features by computing its difference of Gaussian, orientations and Hough transform for object recognition. SIFT algorithm along with CLAHE in order to recognize the night pattern object [8]. The learning algorithm based on the SIFT features for multiple learning instance would produced the significant results on learning [9]. The technique speeded up robust features [10] was inspired by SIFT features was propose and its time consumption for this technique is too low when compared to SIFT. The SURF [11] feature for annotating the medical images which has less false negative results with SVM when compared to SIFT feature.

1.3 Contribution of the work

The proposed work consists of framework with feature extraction and modeling techniques to detect and classify the kidney diseases. Adaboost classifier is used for detecting the diseases and SIFT and SURF features are extracted for classification. For modeling SVM is used to categorize the different kinds of diseases

2. PREPROCESSING

2.1 Image acquisition

For this work, Ultrasound B-mode images are acquired from ultrasound scanner. At first the acquired dicom images are converted into jpeg format for processing. Each the images has the size of 1024x768 pixel dimension.

2.2 Speckle reduction

Preprocessing always yields better results for further processing. Usually the ultrasound images have speckle noise due the high frequency backscattered waves on transducer. Anisotropic diffusion filter produces better noise reduction results and preserves edge without much loss of information, when compared to other filtering techniques. A novel fast oriented anisotropic diffusion filter [12] which yields the best image performance metrics. The memory based anisotropic diffusion filter [13] that reduces progressive loss of information in US images. In this work, the speckle reducing filter based on the Perona Malik model [14] has been used for noise reduction using equation (1) and (2).

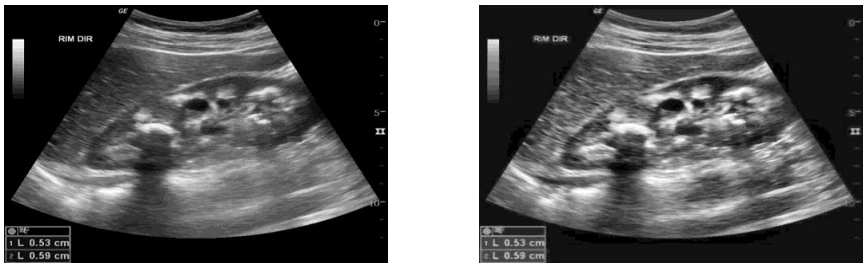
$$\mathrm{I}_t = div\,(d_{coeff}\,\Delta I + \nabla d_{coeff}\,.\nabla I) \tag{1}$$

where I denotes Input image, t represents time physical evolution parameter for diffusion, d_{coeff} denotes diffusion coefficient, Δ represents change of divergence and ∇ denotes the gradient of that image.

$$\frac{\partial u}{\partial t} = (div(d_{coeff})q\nabla u) \tag{2}$$

where $(d_{coeff})q$ denotes diffusion function.

The speckle reduced ultrasound kidney Image is shown in Fig. 1(a) for the input image Fig. 1(b)



(a) (b)

Fig. 1: Speckle Reduction. (a) Input US kidney Image. (b) Speckle reduced US kidney Image.

3. Detection of Kidney Diseases

Various types of kidney diseases are listed under chronic Kidney diseases which may cause severe health problem. This work emphasizes the most prevalent diseases occurring in the kidney region for detection. It mainly emphasized on kidney stone, kidney cyst and renal cell cancer. The proposed detection part has been carried out by two methods. First, Feature extraction using Histogram of Oriented Gradients (HOG) method was employed and it was compared to Haar and Local Binary Pattern (LBP). Second, bounding box was drawn over the detected disease using Ada-boost classifier.

3.1. Feature Extraction for Kidney Disease Detection

Three types of features extraction techniques were used for this work namely Haar, LBP and HOG. Among these three techniques, HOG produced the best detection rate on cascade classifier. LBP features [15] are used to find the level of the cells taken from US spectroscopy. A comparative study [16] with the various types of LBP features was analyzed. LBP computes the histogram by replacing neighboring pixel values with binary values for feature extraction. Meanwhile

3.1.1. HOG Features

HOG is the vision based feature based on image gradient, magnitude and direction. This feature is widely applied for several medical imaging detection and recognition problems. HOG feature [17] is utilized for segmenting tissue deformation using US images. Split up the image into boxy region called cells. Calculate the gradient magnitude and edge orientations for each pixel within cells. Input images are preprocessed by applying Gaussian smoothing and one dimensional centered mask on both vertical and horizontal direction. The angular bins were created based on gradient magnitude and orientations. The normalization of histogram can be derived by grouping adjacent cells as a spatial block. Each pixel of the cells possess the weighted gradients are moved to corresponding angular bin. The 9 histogram bins with respect to different angles from 0 to 160 degrees are created by comparing the values of magnitude and orientation of the image subset. Finally the 4x4 subset of an image with 9 bins of histogram produces 144 feature vectors.

The gradient magnitude is computed by using the equation

$$G = \sqrt{G_x^2 + G_y^2} \tag{3}$$

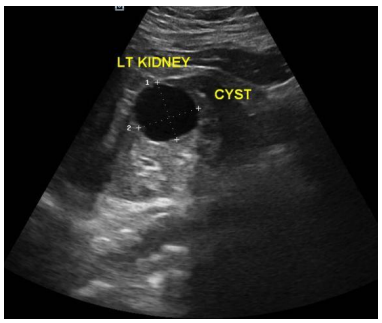
$$where \;\; G_x = I * Gm_x$$

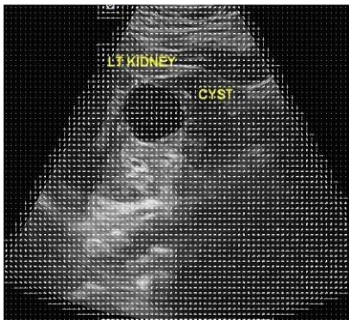
$$and \quad G_y = I * Gm_x$$

The orientation of an image is calculated by using the equation

$$\theta = \tan^{-1}\left(\frac{G_x}{G_y}\right) \tag{4}$$

The HOG features are shown in Fig. 2. (b) for the given ultrasound image shown in Fig. 2. (b)





(a) **(b)**

Fig. 2: a) Ultrasound Image. b) HOG feature extracted image.

3.1.2. Haar Features

The Haar wavelet based features [18] set adapted by Viola Jones is named as Haar–like features, features provides the deep image representation which provides effective learning. Haar This transform uses different weighted monochromatic integral images in both vertical and horizontal positions. Four types of rectangles with two different gray levels are used to compute the Haar features. The size of rectangles determines the features set. The difference of the sum of the pixels lies within the two gray leveled rectangles. These rectangles have the primitives with vertical, horizontal and diagonal variations of the pixels in the image. The variations of the primitives are shown in Fig. 3. The fourth variation is the skew-symmetrical variation. With these variations the integral image $II(x, y)$ is calculated. The integral image is stuffed with sum of all pixels located on the up left region of the original images. This position permits to compute the sum of pixels at any scale on four lookups. The Haar-like features of normal and abnormal kidney Ultrasound image are shown in Figs. 4(a) and 4(b) respectively. The four types of Haar – like rectangular feature is shown in Fig. 3

The integral image is calculated by using equation

$$I_{img}(x, y) = \sum_{x' \leq x,\, y' \leq y} I(x', y') \qquad (4)$$

Where $I_{img}(x, y)$ and $I(x', y')$ is the original image

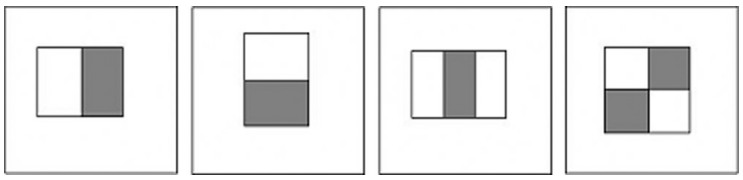
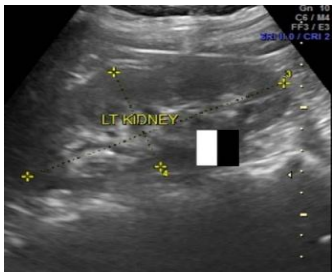
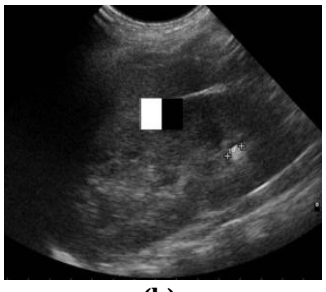


Fig. 3: Variations of Haar-like rectangular feature



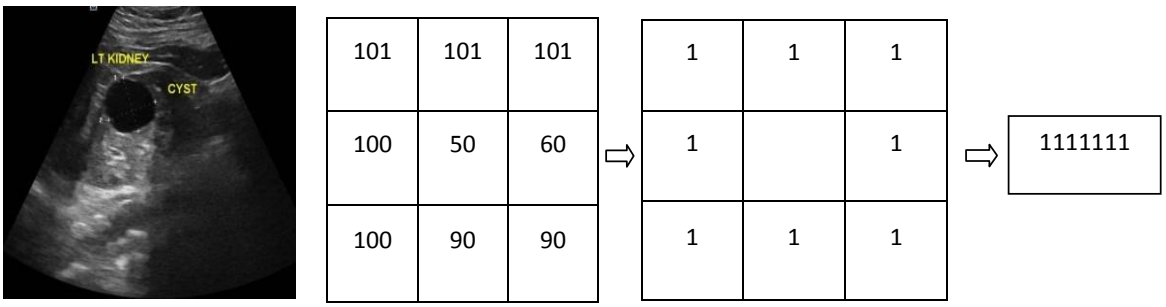


(a) **(b)**

Fig. 4: a) Horizontal variation from Normal kidney image. b) Horizontal variation from diseases kidney.

3.1.3 Local Binary Pattern

LBP [19] is recognized as a kind of the visual descriptor for binary texture classification. It produces the significant detection performance on some datasets. The Local Binary Pattern in [20] is used for segmenting Liver US images with significant results. Splitting up the window into cells containing 8x8 pixel, compare the neighbor pixel with the center pixel by either clockwise or anticlockwise direction, if the center pixel is greater than neighbor pixel, put 0 otherwise 1 The consecutive feature binary pattern obtained from the cells is referred as feature vector. The LBP Feature extracted is shown in Fig. 5



(a) (b) (c) (d)

Fig.5: a) Ultrasound image with Cyst. b) LBP Feature extracted from Cyst. c) Binary thresholding. d) Feature vector.

3.2 Detection of Kidney Diseases Using Adaboost Classifier

Adaboost classifier [21] consists of number of stages to identify the strong learner among the weak learners by loading the positive samples (i.e. diseased window) through multiple stages, If there is a negative feature (i.e. non diseased), it would be rejected in each stage. The training phase of the cascade object detector needs to be trained using group of diseased images and non diseased images. The positive images with the region of interest should be trained to the classifier. Meanwhile the negative images do not contain any malformation as like positive samples. Fig. 6 shows that the cascade object detector accepts only the positive samples and rejects the negative samples.

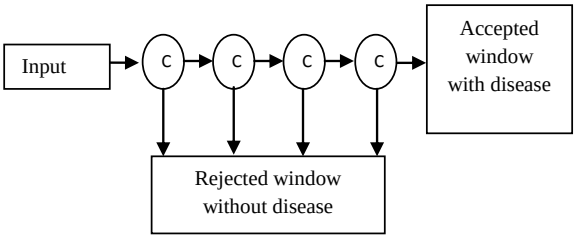
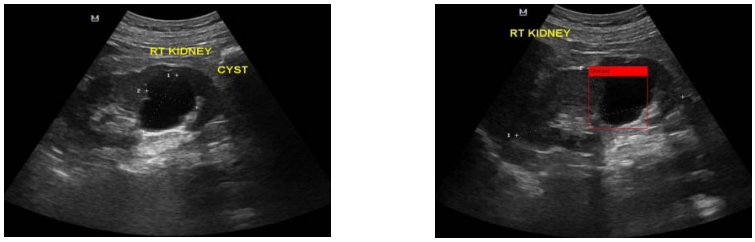


Fig. 6: Adaboost classifier

The detected diseased window (i.e., strong classifier) is given by

$$h(x) = \begin{cases} 1, if \sum_{t=1}^{T} \propto_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \propto_t \\ -1, \quad otherwise \end{cases} \tag{5}$$

Adaboost Algorithm is an iteratively ordering calculation to build a strong classifier utilizing just a preparation set and it is a weak learning calculation. It changes the weak classifiers into strong classifiers. A weak classifier with the base arrangement mistake is chosen by the examining calculation at every emphasis. There are 30 positive images and 20 negative images were subjected to different feature vectors with the cascade object detector. Among these three different feature vectors, the HOG feature gives better performance on detecting kidney diseases.



(a) (b)

Fig. 7: Input ultrasound image. b) Detected cyst image.

4. Recognition Of Kidney Diseases

Kidney stones are recognized using different types of features and classification methods. This work aims at effective features extraction with particular samples of input image and classification with that features.

4.1 Feature Extraction from Detected Kidney Diseases

4.1.1 SIFT features:

Scale Invariant Feature Transform (SIFT) [22] provides the unique pattern of features such as edges, blobs, and corners intensity of an image at particular interest point. It provides the group of features which has no difficulties that are experienced by any other techniques. SIFT works better even if more number of images is captured at the same location with the different positions. Each feature vectors are invariant to scaling, translation or rotation. The SIFT feature is perceived by refining methods. Scale Space Extrema Detection can be obtained by getting the extreme values from the Gaussian convolution. The key point localization is achieved by eliminating poor edges and low contrast points. It removes the large curvature across edge and small curvature in the

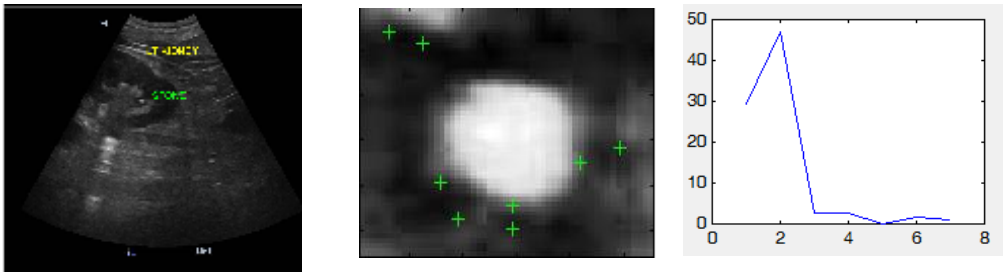
perpendicular direction. The gradient magnitude and orientation is calculated for each key point. Gradient magnitude $m(x,y)$ can be calculated by using the equation

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + \big(L(x,y+1) - L(x,y-1)\big)^2} \quad (6)$$

and the orientation can be

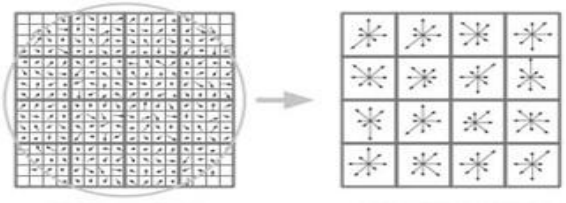
$$\theta(x,y) = \tan^{-1}\left[\frac{(L(x,y+1)-L(x,y-1)}{(L(x+1,y)-L(x-1,y)}\right] \quad (7)$$

A histogram of orientation with 360 degree for an image has been created. Histogram is further divided into 36 bins with respect to 10 degrees. For example if the orientation value is 15 degree, then this value is placed at 10 to 19 degree histogram bin. Key point descriptor is computed for the local image region that is as distinctive as possible at each key point. Gradient magnitude and key points are sampled around the key point location. Here the final most descriptor at any key point with the distinctiveness for an image has been calculated. The histogram of 4x4 sub region with 7 orientations of pixels of is weighted by Gaussian function with varianceσ. From that, the 4x4x7 histogram 112 distinctive descriptors have to be obtained. The 112 distinctive descriptors are used as feature vector.



(a) (b) (c)

Fig. 8: Ultrasound image. b) SIFT key points. c) SIFT Features



(a) (b)

Fig. 9: a) SIFT Gradient, b) SIFT descriptor

4.1.2 Speeded Up Robust Features (SURF)

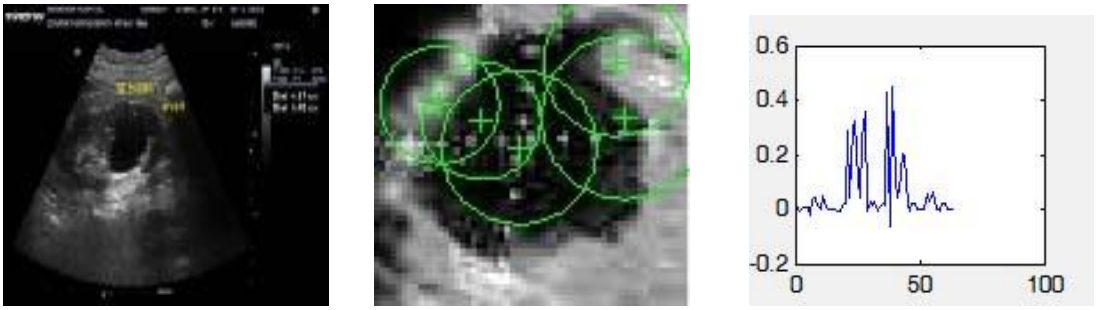
Speeded up robust feature (SURF) [23] is the vision based feature vector that is computed from the local elements of an image. The standard version of the SURF is much faster than SIFT. SURF technique is slightly inspired by Scale Invariant transform method. SURF uses Hessian based blob detector to find interest points. Octaves have to be initialized with difference of Gaussian (DoG) square shaped filters. The scale can be represented by hessian matrix convoluted second order Gaussian derivative function with 9x9 image.

$$h(p,\sigma) = \begin{pmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{yx}(x,\sigma) & L_{yy}(x,\sigma) \end{pmatrix} \tag{7}$$

Given a point x=(x, y) in an image (I) $L_{xx}(x,\sigma)$ is the convolution of image with the second order derivative of the Gaussian. Determinant of hessian matrix is given by

$$\det(h_{approx}) = D_{xx}D_{yy} - (0.9D_{xy})^2 \tag{8}$$

where $\det(h_{approx})$ is the determinant of hessian matrix computed for selecting the interest point detector. Interest point descriptor can be detected with the haar kernel filter (i.e. integral image) taken from the input image. From that image, the existing intensity values and their absolutes at both horizontal and vertical position are summed. $\sum d_x$ is the horizontal orientation, $\sum d_y$ is vertical orientation $|\sum d_z|\left|\sum d_y\right|$ are absolutes of the horizontal and vertical orientations. Finally the summed value of 4x4 sub region of gives the 64 feature vector. Ultrasound kidney image and its SURF key points and surf features shown in the Fig. 10. a, b and c respectively



(a) (b) (c)

Fig. 10: a) Ultrasound Kidney Image. b) SURF Key points. c) SURF features.

4.2 Recognition of Kidney Diseases Using SVM

Support vector machine [24] classifies the detected object using SVM with SIFT features which gives the best results. It is a classification mechanism which relies on structural risk minimization (SRM) with reduced error rate and generalization. It separates the set of data points by decision plane that defines the boundary between two classes. Support vectors are the training samples used to define the optimal margin hyper plane. It mainly gives better results for pattern

classification and non-linear regression. It maps input space into higher dimensional feature space. In this work support vector machines are chosen for classifying the kidney diseases. Kidney stone, cyst, and cancer are recognized using SIFT and SURF features. The architecture of SVM is shown in the Fig.11. The kernel function of SVM is given in the table 1.

Table 1: kernel types of SVM

Types of kernels	Inner products of kernel $K(x^T, x_i)$	Description
Polynomial	$(x^t . x_{i+1})^n$	Where x is the input image patterns and x_i is support vectors σ is the variance Ns is the support vectors β_0, β_1 are the contants p is the degree of polynomial.
Gaussian	$exp\left[\frac{-\|x^T - x_i\|^2}{2\sigma^2}\right]$	
Sigmoid	$\tanh(\beta_0(x^T x_i) +)\beta_1$	

SVM Principle

The Architecture of the SVM is given in Fig. 11. Let X be the unique pattern of vector where $X = (x_1, x_2, x_3 \ldots . x_n)$ and Y be the class label such r is that $y = +1, -1$. It indicates the given training samples belong to the two class problem.

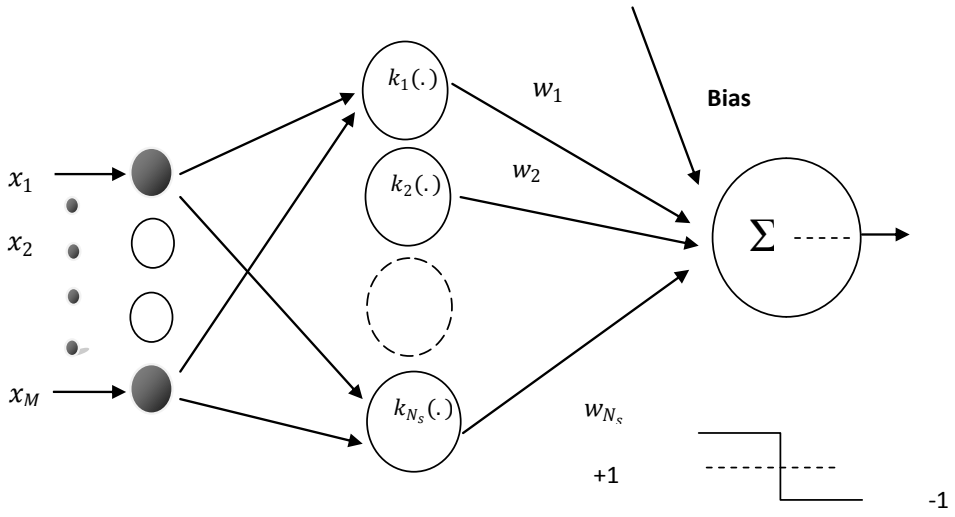


FIG. 11: Architecture of SVM

The positive and negative kidney ultrasound images were trained to the machine using SVM. During testing the cluster y possesses the pattern of x which is given by the equation

$$y = \begin{cases} n, if\, d_n(x) + t > 1 \\ 0, if\, d_n(x) + t \leq 0 \end{cases} \quad (9)$$

where t denotes the classification threshold and $d_n(x)$ denotes max dist(x) =1 the distance between support vectors and the hyper plane corresponding to diseased image i and the $y = 1$ denotes support vectors other than the class.

5. Experimental Results

The performance of the detection and classification of kidney diseases is assessed using ultrasound B mode image dataset collected from various hospitals and kidney research centers. The input images were resized into 640x 480 pixels resolution and could be converted from RGB to gray scale format. Then speckle noises were reduced using anisotropic diffusion filter.

5.1. Detection of kidney diseases using Adaboost Classifier

During training phase, the cascade classifier trains the n-stage of filtered patterns with set of positive and negative images. The Adaboost algorithm is used to learn a strong classifier by reweighting the training samples with set of weak classifiers. The binary thresholding decision or a small classification and regression tree (CART) is applied to the features for getting weak classifier. The classifier that best classifies the sample based on feature is added to each round of the boosting. Half of the negative pattern is rejected during each stage of the training.

For HOG the training phase, 144 dimensional HOG features are extracted from the set of positive images and it is given as training sample to the Adaboost classifier. This cascade classifier has 8 stages for training. For testing 640 X 480 dimension ultrasound images are given to the test classifier. The detected diseases has visualized by placed a bounding box over the disease portion. For Haar feature the standard 24x24 sub window with 162336 features are from the set of positive images. The extracted Haar features are given as input to the Adaboost classifier. Number of stages used for the cascade classifier training is 8 stages. When testing 640 X 480 dimension ultrasound images are given to the test classifier. The bounding box placed over the image shows the detection of disease. For LBP, the binary patterned features selected from the 8x8 window are inputted to Adaboost classifier. It used 9 stages of cascade classifier for the training .For testing 640 X 480 dimension image is used as input to the test classifier.

5.2. Recognition of Kidney Diseases using SVM

SIFT with SVM

In training phase 112 dimension SIFT features are extracted from kidney disease detected image constructed with 4x4 grids and 7 orientation bin. The extracted features are labelled and trained using SVM with corresponding disease category. During the testing phase SIFT features of the test samples are extracted and applied as input to the SVM, Decisively the SVM classifies the image is whether stone, cyst, or cancerous mass. Fig. 12 shows the classification of kidney disease using SIFT with cancerous mass.

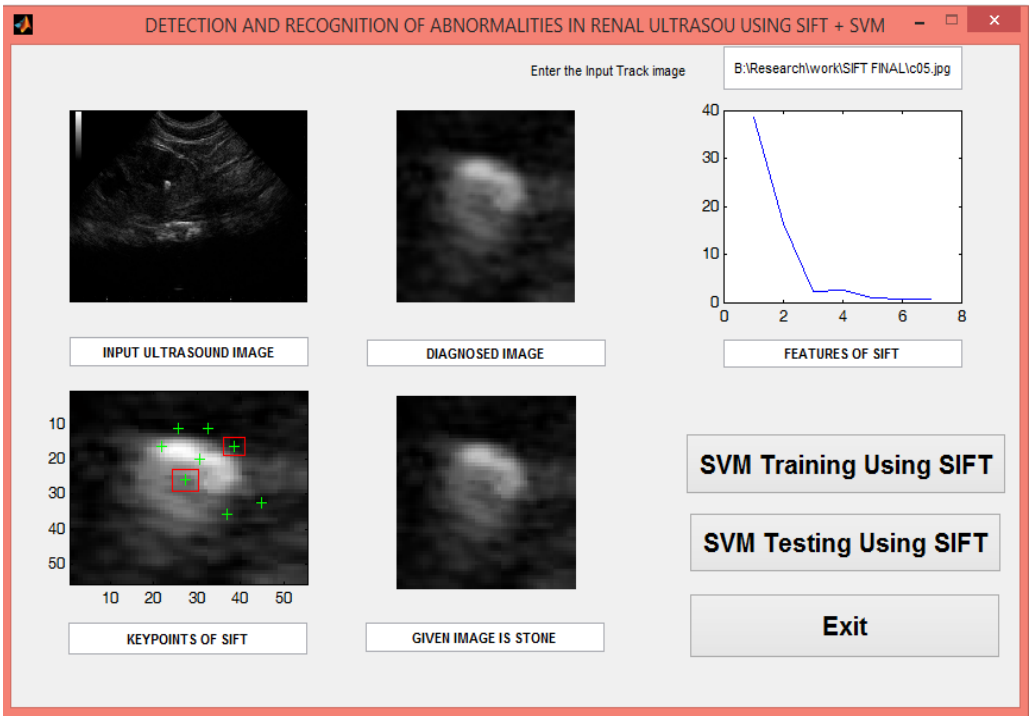


Fig. 12: Kidney Stone Recognized Using SIFT with SVM

SURF with SVM

In training phase 64 dimension features are extracted from the kidney disease detected image processed with 4x4 grid and 4 orientation bins. The extracted features from the training samples are labelled and trained using SURF with corresponding category. During the testing phase the SURF Features are extracted from the training samples are given as input to the SVM. Finally SVM classifies the given sample is either stone cyst or cancerous mass. SURF produces the

better results than SIFT. Fig. 13 shows the classification of kidney disease using SURF with kidney stone,

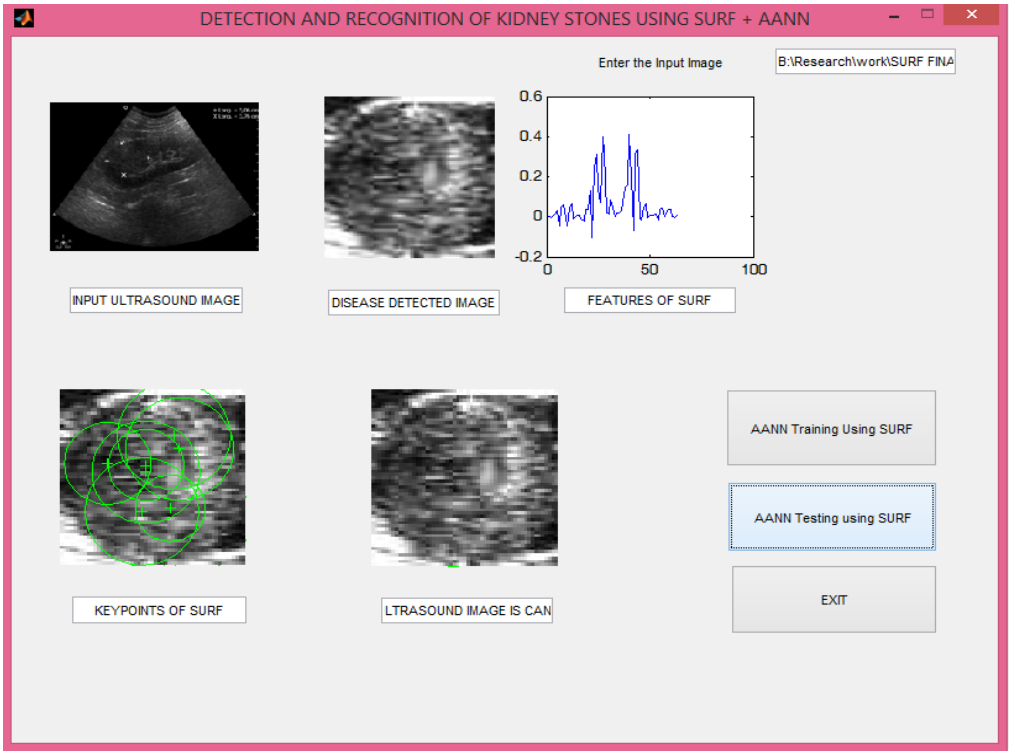


Fig 13: Kidney Cancerous Mass Recognized Using SIFT with SVM.

5.2 Performance Measures

The performance measure for the detection of kidney diseases would be calculated by the total detection rate with the total images of each category. Overall detection rate will be given in the Table 2.

Feature extraction method	Overall Detection rate of various kidney diseases
Histogram of Oriented gradients(HOG)	96.7%
Haar	93.3%
LBP	90.0%

Table. 2: Overall Detection Rate for Various Kidney Diseases

The performance measures for the classification of SIFT and SURF with SVM will computed using Confusion matrix and it is given in Table. 3 (a) and 3 (b).

Testing Samples (%)	Training Samples(%)		
	70	20	10
	0	80	20
	30	0	70

(a)

Testing Samples(%)	Training Samples (%)		
	90	0	10
	10	80	10
	0	20	80

(b)

Table . 3: a) Confusion matrix for SIFT with SVM. b) Confusion matrix for SURF with SVM.

The overall performance accuracy for classification of SIFT and SURF with SVM will be given in Table. 4.

Feature extraction techniques	MODEL	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
SIFT	SVM	82.5	73.8	73.8	73.8
SURF		89.3	83.8	83.8	83.8

Table. 4: Overall Results Feature Extraction Techniques SIFT and SURF with SVM

6. CONCLUSION AND FUTURE ENHANCEMENT

In this work two important operations such as detection and classification of various kidney diseases have been experimented. Hundred ultrasound B-mode images with unique size collected from various centers were used for this study. The quality measures were taken for both detection and classification. Experimental results for the detection of various types of kidney diseases using HOG features show better performance. The performance measure for classification was done with two featuring techniques with SVM such that SIFT and SURF.

SURF would produce better performance than SIFT. For future implementation, this feature will be subjected to some other neural network method to gain a improved accuracy. The improvements will be examined by applying neuro genetic method

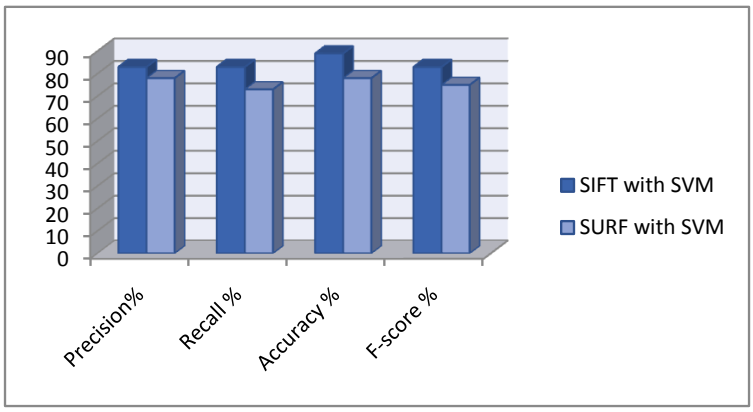


Fig: 7 Performance Chart for Diseases Classification Using SIFT SURF WITH SVM

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