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An Automated Kidney Segmentation and Abnormality Detection Using Hybrid Model of FCM and Adaboost Classifier

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ABSTRACT: Diagnosing a disease using medical images is an important task for patient care and disease cure.The aim of the work is to detect the abnormality in ultrasound-based kidney images using machine learning techniques such as fuzzy c means clustering and adaptive boosting classifier.This system consists of four modules like (i) pre-processing, (ii) segmentation, (iii) feature extraction and feature selection, and (iv) classification.First, we eliminate the noise present in the ultrasound images using pre-processing techniques: histogram equalization, median filtering, background subtraction.Then the kidney region from the pre-processed ultrasound image is segmented using fuzzy c means clustering. After segmentation process, the gray level co-occurrence matrix features from the segmented image is extracted and then the selection of features using an ant lion optimizer method. Finally, the kidney images are classified as normal and abnormal by means of an adaptive boosting classifier. The experimentation result shows that the proposed system as achieves the maximum accuracy compare with all other methods.

KEYWORDS: Kidney segmentation, Fuzzy c means clustering, Ant lion optimizer, Adaboost classifier.

I.INTRODUCTION

Kidneys are essential to having a healthy body.They are mainly responsible for filtering waste products, excess water, and other impurities out of the blood.These toxins are stored in the bladder and then removed during urination. The kidneys also regulate pH, salt, and potassium levels in the body.Ultrasound is one of the non-invasive low-cost imaging techniques. It can follow anatomical deformations in real time during biopsy and treatment, and it is noninvasive and does not require ionizing radiation. However, ultrasound images produced by this technique contain to echo perturbations and speckle noise that can affect the diagnosis result for a patient. Therefore, the appropriate kidney region detection in the ultrasound image may involve segmentation method and image enhancement to suppress the speckle noise.

Machine learning approaches are increasingly successful in image-based diagnosis, disease prognosis and risk assessment.Nowadays, many techniques have made use of digital pre-processing of coherent echo signals to enhance the quality and information content of ultrasonic images of the body. Example of these methods consists of resolution enhancement, contrast enhancement to suppress speckles and imaging of spectral parameters. Contrast enhancement is a technique that able to suppress speckle in kidney ultrasound image.One of the popular methods in contrast enhancement is histogram equalization. Histogram Equalization is a technique for recovering some of apparently lost contrast in an image by remapping the brightness values in such a way as to equalize and distribute its brightness values.

Segmentation is a process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves etc.,) in images. Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image.

Feature extraction aims to reduce the number of features in a dataset by creating new features from the existing ones. Feature selection process increases the classification accuracy and minimizes the computation complexity.Image classification plays an important role in medical image analysis. Image classification accepts given input image and produces output classification for identifying whether the disease is present or not.

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II.LITERATURE SURVEY

AlirezaOsareh et al (2011) proposed a concept on "A computer aided diagnosis system for breast cancer". A computer-aided diagnosis (CAD) framework for breast cancer is developed using application of supervised machine learning techniques to the classification of cancerous and non-cancerous data. Three classifiers such as support vector machine, k-nearest neighbour, probabilistic neural network was combined with feature ranking method to classify breast tumor. It improves the evaluation performance of the prognostic risk of recrudescence and metastasis. This system is not suitable for large data sets and not perform very well when data set has more noise.

Amitha Raj et al (2015) proposed a concept on "Automated liver tumor detection using markov random field segmentation". Early detection of liver cancer helps to improve life expectancy. Also need to know the tumor status during treatment stages. Computer aided diagnosis of liver tumors from CT images. Initially liver is segmented using markov random field method. It provides robustness to noise and fast segmentation. The shape ambiguities of the segmented liver are found out by shape analysis methods which uses training set for correction. From the corrected liver segmentation, hepatic tumors are detected by graph cut method and feature extraction is done to classify them using SVM classifier. It helps radiologists and surgeons to have easy and convenient access to organ measurements.

Bikesh Kumar Singh et al (2015) proposed a concept on "Adaptive gradient descent backpropagation for classification of breast tumors in ultrasound imaging". The ultrasound images were pre-processed by wavelet filters for reducing speckle noise. Fifty-seven texture and shape attributes were extracted from filtered breast ultrasound images to classify breast tumors. Gradient descent Backpropagation artificial neural network has been used for classification of breast tumors. The convergence time of the classification process highly depends on the learning algorithm and learning. This method has highest capability in classifying benign and malignant tumors. This algorithm suffers from time complexity.

Dharani Devi et al (2017) proposed a concept on "Kidney abcess segmentation and detection on computed tomography data". The segmentation process is based on hybrid level set method with elliptical shape constraints. Identification of the kidney tumor and vascular tree is based on RUSBoost and the decision tree techniques. This approach enables to resolve main problems connected with region classification: class imbalance and the number of voxels to classify. The proposed feature selection algorithm is the combination of cuttle fish feature selection algorithm and extended chi-square algorithm. It requires more time to process.

Jilian Su et al (2020) proposed a concept on "Ultrasound image assisted diagnosis of hydronephrosis based on CNN neural network". To improve the ultrasound diagnosis of hydronephrosis, based on CNN neural network technology, it analyses the traditional image resolution processing algorithm by contrast analysis method, and proposes a fast image super-resolution reconstruction algorithm. The method improves the image processing efficiency and combines the CNN neural network to effectively treat the hydronephrosis ultrasound image. Diffusion tensor tracking imaging was used to image the medullary tubule structure at the central level of bilateral kidneys.

NilarThein et al (2018) proposed a concept on "An image pre-processing method for kidney stone segmentation in CT scan images". Automatic kidney stone segmentation from abdominal CT images is challenging on the aspects of segmentation accuracy due to its variety of size, shape and location. It develops reader independent pre-processing algorithm for kidney stone detection and segmentation in CT images. Three thresholding algorithms based on intensity, size and location are applied for unwanted regions removing such as soft-organ removing, bony skeleton removing, bed-mat removing. So, it can reduce the noise and unwanted regions with good detection. This method weak in robustness and it has low accuracy.

NurettinAcir et al (2006) proposed a concept on "Automatic classification of auditory brainstem responses using SVM-based feature selection algorithm for threshold detection". A novel system for automatic recognition of auditory brainstem responses to detect hearing threshold. It consists of two stages. In the first stage, for feature extraction, a set of raw amplitude values, a set of discrete cosines transform and a set of discrete wavelets transform coefficients are calculated and extracted from signals. In the second stage, the feature vectors are classified by a support vector machine for solving classification problems. It gives good accuracy and sensitivity. This system has poor directionality and not perform very well.

PankajSapra et al (2013) proposed a concept on "Brain tumor detection using neural network". The modified image segmentation techniques were applied on MRI scan images in order to detect brain tumors. Also modified probabilistic

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neural network model that is based on learning vector quantization with image and data analysis and manipulation techniques is proposed to carry out an automated brain tumor classification using MRI scans. It gives accurate classification compared with the image processing and conventional probabilistic neural network techniques. This method can be used to filter out non-suspecting brain scans as well as to point out suspicious regions that have similar property as the tumor regions. It requires more memory space to store the model.

SabanOzturk et al (2018) proposed a concept on "Effects of histopathological images pre-processing on convolutional neural networks". The images are classified into four pre-processing classes are original, normal pre-processing, other normal pre-processing and over pre-processing. Histopathological images of these four classes include cancerous and non-cancerous image patches. Cancer patch classification is done using convolutional neural network. For the normal pre-processing algorithm, background noise reduction and cell enhancement are applied. For over re-processing, thresholding and morphological operations are applied in addition to normal pre-processing operations. At the end of the experiments, the most successful classification results are produced. If pre-processing is excessive, success cannot reach the desired level.

III.PROPOSED METHODOLOGY

In this work, we proposed a kidney abnormality detection using machine learning techniques using fuzzy c means clustering (FCM) algorithm and adaboost classifier. Normally, the system comprises of four modules like (i) pre-processing, (ii) segmentation (ii) feature extraction and feature selection, (iv) classification. Primarily, we eliminate the noise present in the input US image using Pre-processing techniques: histogram equalization, median filtering and background subtraction. Then the kidney region from the pre-processed image is segmented using fuzzy c means clustering. Then, we extract the important GLCM features from that image. After that, the feature is selected using ant lion optimizer. Finally, the abnormality in the kidney images are classified as normal and abnormal using adaboost classifier.

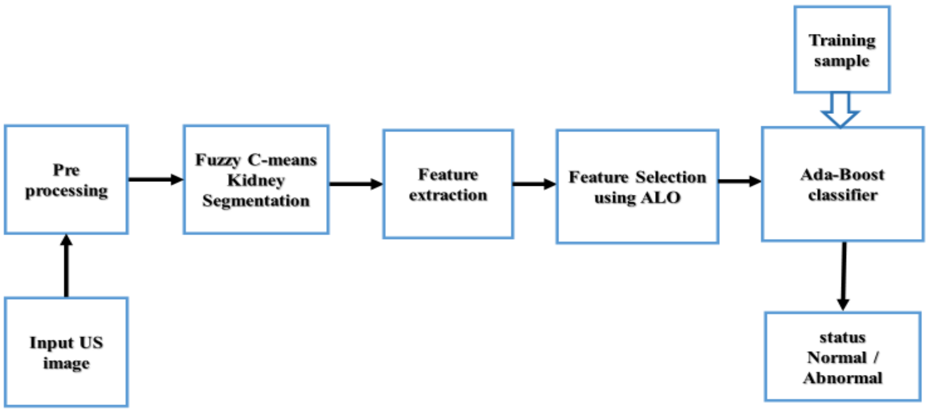

Figure 1: Proposed system block diagram

A. PREPROCESSING

In the pre-processing of US image, the noise will be removed by utilising the non-local median filter which does not update a pixel's value with an average of the pixels around it, instead updates it using a weighted average of the pixels judged to be most kinded. The weight of each pixel depends on the distance between its intensity grey level vector and that of the target pixel. De-noised image of each pixel i of the non-local means is computed with the following equation

$$N(i,j) = \sum_{j \in D} w(i,j) D(i,j)$$

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Where, j is the noisy image and N is the de-noised image, and weights w (i, j) meet the following conditions $0 \leq w(i, j) \leq 1$. Each pixel is a weighted average of all the pixels in the image which is based on the similarity between the neighbourhoods of pixels i and j.

B. FUZZY C MEANS SEGMENTATION

Fuzzy c means clustering algorithm is used to segment the kidney region from the ultrasound image. The system utilizes the authentic size of the image to perform high quality image segmentation which causes high-resolution image data points to be clustered. Therefore, utilize the FCM algorithm for clustering image data by considering that it has ability to cluster immensely clossed data and additionally outliers' payments are utilized expeditiously and efficiently. The FCM algorithm is

Let x_i be a vector of values for data point g_i.

1. Initialize membership $U^{(0)} = [u_{ij}]$ for data point g_i of cluster $cl_j$by random
2. At the *k*-th step, compute the fuzzy centroid $C^{(k)} = [c_j]$ for $j = 1,.., nc$, where nc is the number of clusters, using

$$c_j = \frac{\sum_{i=1}^{n} (u_{ij})^m x_i}{\sum_{i=1}^{n} (u_{ij})^m}$$

where m is the fuzzy parameter and n is the number of data points.

3. Update the fuzzy membership $U^{(k)} = [u_{ij}]$, using

$$u_{ij} = \frac{\left(\frac{1}{\left\| x_i - c_j \right\|} \right)^{\frac{1}{(m-1)}}}{\sum_{j=1}^{n_c} \left(\frac{1}{\left\| x_i - c_j \right\|} \right)^{\frac{1}{(m-1)}}}$$

3. If $\|U^{(k)} - U^{(k-1)}\| < \varepsilon$, then STOP, else return to step 2.
4. Determine membership cutoff
   - For each data point g_i, assign g_i to cluster cl_j if u_{ij} of $U^{(k)} > \alpha$

C. FEATURE EXTRACTION

The features are the key points of the pattern recognition techniques and the extraction of the feature is to be carefully conducted because the whole accuracy is depending upon the features. This work accommodates two features namely texture features and shape/geometrical features. The process of feature extraction is useful when you need to reduce the number of resources needed for processing without losing important or relevant information. Feature extraction can also reduce the amount of redundant data for a given analysis. Feature extraction aims to reduce the number of features in a dataset by creating new features from the existing ones. These new reduced set of features should be able to summarize most of the information contained in the original set of features. The GLCM features are extracted from the kidney segmented image. A co-occurrence matrix or co-occurrence distribution also referred to as gray-level co-occurrence matrices GLCM is a matrix that is defined over an image to be the distribution of co-occurring pixel values (grayscale values or colors) at a given offset. It is used as an approach to texture analysis with various applications especially in medical image analysis.The features are area, perimeter, orientation, maximum axis length, correlation, homogeneity and energy among the gray pixels.

D. FEATURE SELECTION

Antlion optimizer method is used for feature selection. Feature selection becomes a must to remove irrelevant features and enhances classificationThe Ant Lion Optimizer, known as ALO or Antlion Optimizer, is a recent meta-heuristic

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that mathematically models the interaction of ants and antlions in nature. Ant lion optimizer is a feature selection method. An optimization algorithm has been developed to solve optimization problems considering random walk of ants, building traps, entrapment of ants in traps, catching preys, and re-building traps are implemented. The selected features are correlation, contrast and homogeneity.

E. ADABOOST CLASSIFIER

Adaboost or Adaptive Boosting is one of ensemble boosting classifier proposed by Yoav Freund and Robert Schapire in 1996. It combines multible classifiers to increase the accuracy of classifiers. Adaboost is an iterative ensemble method. Adaboost classifier builds a strong classifier by combining multible poorly performing classifiers so that you will get high accuracy strong classifier. The Basic concept behind Adaboost is to set the weights of classifiersand training the data sample in each iteration such that it ensures the accurate predictions of unusual observations. Any machine learning algorithm can be used as base classifier if it accepts weights on the training set.

An Adaboost classifier is a meta-estimator that begins by fitting a classifier on the original dataset and then fits additional copies of the classifier on the same dataset but where the weights of incorrectly classified instances are adjusted such that subsequent classifiers focus more on difficult cases. Adaboost classifier classifies the kidney image as normal or abnormal. The abnormality in the kidney is detected as tumor or any other disease.

Given: $(x_1, y_1), \ldots, (x_m, y_m)$ where $x_i \in \mathscr{X}$, $y_i \in \{-1, +1\}$.
Initialize: $D_1(i) = 1/m$ for $i = 1, \ldots, m$.
For $t = 1, \ldots, T$:

- Train weak learner using distribution D_t.
- Get weak hypothesis $h_t : \mathscr{X} \to \{-1, +1\}$.
- Aim: select h_t with low weighted error:

$$\varepsilon_t = \Pr_{i \sim D_t}\left[h_t(x_i) \neq y_i\right].$$

- Choose $\alpha_t = \frac{1}{2} \ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$.
- Update, for $i = 1, \ldots, m$:

$$D_{t+1}(i) = \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution).

Output the final hypothesis:

$$H(x) = \operatorname{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right).$$

Figure 2: Adaboost algorithm

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IV. RESULT AND DISCUSSION

The ultrasound original image is shown in figure 3 and this image is RGB (Red, Green and Blue) mode and converted in to grayscale (Black, White and Gray) images.

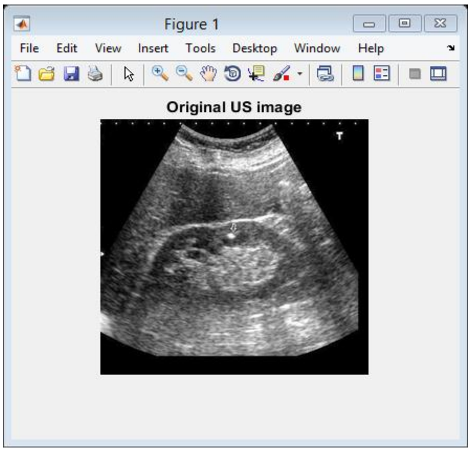

Figure 3: Original US image

The grayscale image is shown in figure 4 and the grayscale image has some noise.

Figure 4: US gray image

The noisy image is shown in figure 5 it consists of some speckle noise and it is removed by median filter.

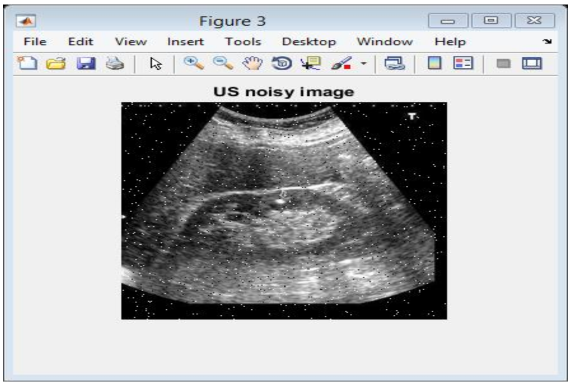

Figure 5: US noisy image

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The median filtered image is shown in figure 6.

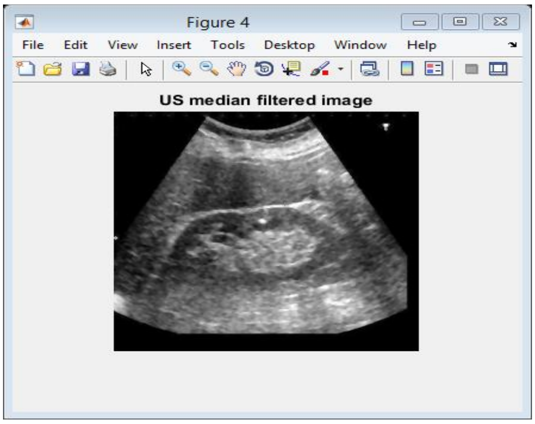

Figure 6: US median filtered image

Thefuzzy c means clustering was applied to the median filtered image for segmentation shown in figure 7.

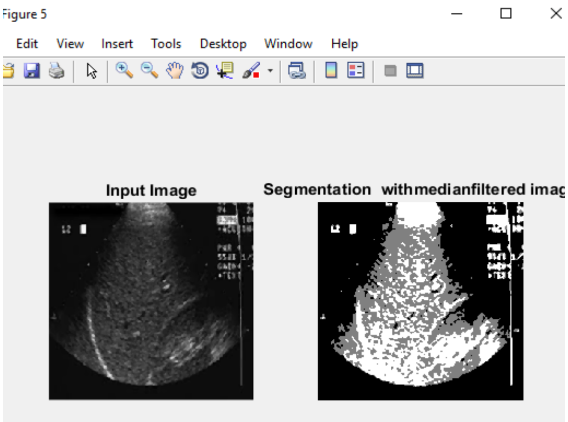

Figure 7: Noise removed input image and segmentation image

The unsupervised clustering of the pixels is producing the result as clustering 1 background pixels shown in figure 8 and the background pixels image is represented in black colour.

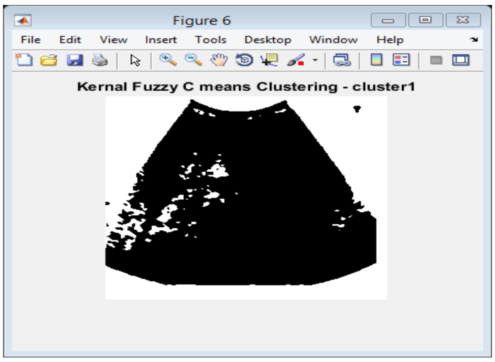

Figure 8: FCM clustering 1-background pixels

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The unsupervised clustering of the pixels is producing the result as clustering 2 foreground pixels shown in figure 9and foreground pixels image is represented in white colour.

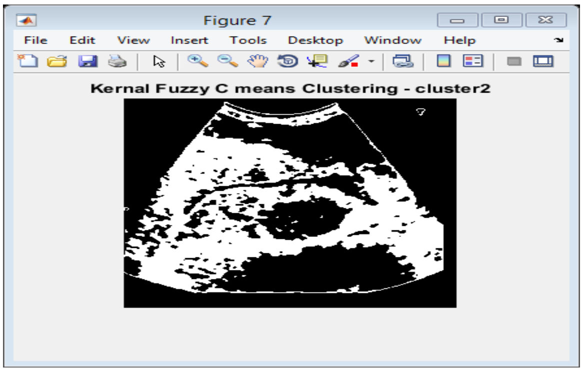

Figure 9: FCM clustering 2-foreground pixels

The unsupervised clustering of the pixels is producing the result as clustering 3 segmented kidney region shown in figure 10 and it is represented as gray colour.

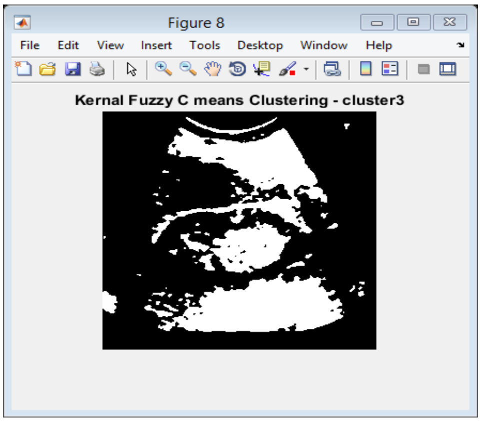

Figure 10: FCM clustering 3-foreground segmented kidney region

Feature extraction aims to reduce the number of features in a dataset and it summarize most of the information contained in the original set of features. The GLCM features are extracted as contrast, correlation, Homogeneity, energy, entropy and the values are given in table1.

Images	Contrast	Correlation	Homogeneity	Energy	Entropy
Sample 1	1.12007874	0.86033242	0.8850832	0.48568073	2.6855415
Sample2	0.33203125	0.87872427	0.93899584	0.62344236	1.95997133
Sample3	0.4415908	0.90697036	0.92931542	0.45790809	2.89924311
Sample4	0.57532603	0.83667329	0.94235848	0.5907839	1.96462187
Sample5	1.12007874	0.86033242	0.8850832	0.48568073	2.6855415

Table 1:Samples of US based kidney Image feature values

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The abnormality in the kidney region is detected using adaboost classifier and the tumor is present in kidney area, here the highlighting area is a tumor region and the tumor is present in the kidney shown in figure 11.

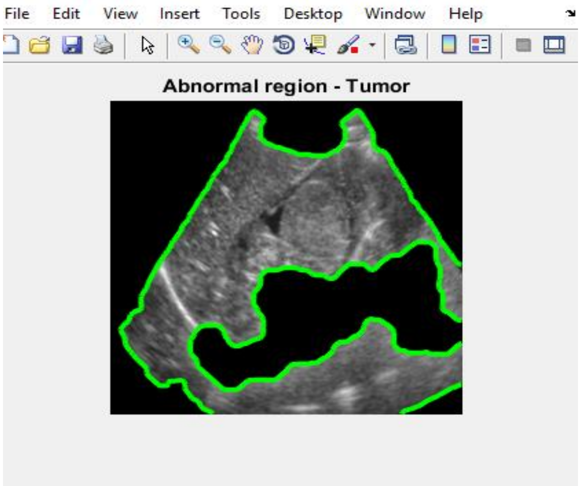

Figure 11: Abnormal region in kidney

V. CONCLUSION

The aim of the present study was to segment the kidney and detect the abnormality. This proposed segmentation and classification methods provides good support in detecting tumour region. The image is pre-processed and noise is removed by median filter. Thefuzzy c means clustering was applied to the images for segmentation of kidney region. The unsupervised clustering of the pixels is producing the result as background image, foreground pixels and kidney areas as 3 clusters. The glcm features from the cluster parts are extracted and feature is selected for classification of normal and abnormal part in kidney. Adaboost classifier detected the abnormality in kidney region and this method gives good accuracy and easy to understand the disease. This work is very helpful for physicians.

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