

# Female Cancer Control Diagnosis by Decision Making using Image Processing - A Prospective Study

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**Abstract:** In this paper, an effective method is implemented for the feature extraction of renal tumor. Image segmentation is vital in many medical image diagnostic applications. It identifies the region of interest in a data. The outline of semi-programmed division contains the following stages, (i) Initial one is the Region of Renal interest(ROI); (ii) the Second one is automatize iterative method.(iii) the third is a novel work to select the best classifier for female optimal features. This is an optimal method to shun the CT guided Biopsy. An optimum method is chosen for overcoming the limitations seen in the morphological operation method and getting the degree of correspondence. Boundary segmentation of renal tumor extends to feature extraction of images and classification. The high specificity of Fuzzy is 99.5% for the left and 99.4% for the right tumor. The qualitative examination done on 37 out of 67 subjects indicates the average comparison of accuracy 95.7% and 94.7% (Left and Right region) respectively between the successive classifiers.

**Keywords:** Renal, Tumor, Active contour method, segmentation, Boundary Detection, Feature Extraction, Classifier, Statistical Analysis, Accuracy, Sensitivity, specificity

## 1. Introduction

The main aim of renal segmentation is to diagnose the presence of tumor. The neighboring organs like liver, lungs, and Pancreas are affected by the tumor. Axial computed tomography (ACT) scans can form an input to Computer aided diagnostic (CAD) systems for the segmentation of renal structure along with its neighboring organs. The input RGB image (Sudhakar M.S., 2016) is converted into gray scale image and resized the image into 512 X 512 pixels. The purpose of gray scale image is to provide clear anatomical information, illumination of the abnormalities and lesions. Segmentation methods are classified as: (1) image-based, (2) model-based, and (3) hybrid methods. Usually, statistical snake models (Kobashi M, 1995) are developed on the basis of a training iteration method and implemented in the specialized region of interest. Ultrasound imaging test is a screening test with speckles noise. Noise free scanning CT images have high Signal-to-noise ratio (SNR) and provide an accurate anatomical structure. The quality of noble image, and the advanced Digital image technique, inspires the researchers to develop computerized methods for anatomical automatic renal tumor segmentation analysis. (Kobashi et al, 1995) have described the anatomic information, identification and extraction of renal from normal CT image. The detection result was rated 85% grade A from the testing of 78 images. The feature extraction of image in the basic of digital radiography (Giger and Doi et al, 1988). A proposed a deformable model approach for automatic renal segmentation. They have used a deformable model represented by the gray level appearance of renal and its statistical information of the shape (Tsagaan et al., 2002). They have used a deformable model represented by the gray level appearance of the kidney and statistical information of its shape (86.9%). Semi-automatically produced images were used considering the similarities between the gray levels in adjacent organs, contrast media effect and relatively high variation of the organ positions and shapes in abdominal CT images and uses labeling method (Campadelli et al, 2004 & Shi et al, 2004). Medical image segmentation is done through tissue surface analysis and maximum dispersal directions (85%) (Mavromatis et al, 2004 & Saitoh

et al, 2002). A deformable model approach for automatic kidney segmentation, the automatic extraction technique of a kidney region which use Q-Learning method. This was proposed as a pretreatment for the automatic detection of the kidney diseases (Hetzheim et al, 1993). Feature classification is one of classical problems of concern in image processing.

The goal of feature classification is to found the best categories of the input image using Active contour method. There are different types of feature extraction via Gray-level co-occurrence matrix (GLCM), Zernike moments (American cancer society, 1993) and Texture and moments order of features. There are various approaches for the selection of the best classifier, such as k nearest neighbor (KNN), Membership Function Rules applying Fuzzy (MFRF) Artificial Neural Network (ANN), and Support Vector Machine (SVM) from the best features.

## 2. Materials and Method

Automatic image segmentation system is one of the stimulating tasks for the researcher to design the computerized diagnosis in the medical image field. Different medical imaging Modalities available are Radiography X-ray, Ultrasound (US), Axial computed Tomography (ACT), Magnetic Resonance Imaging (MRI), etc. for the guidance of the diagnostics. The computed Tomography is selected from the above list as the best Modality for the feature extraction of renal (Yoshiki et al, 2004). In renal, Normal and abnormal cells fight each other, providing the result of Necrotic patient. Hence the Hounsfield value more than 100 is tumor. The normal cell always merges with benign whereas it does not occur in tumor. Based on human eye interpretation of a large number of CT Normal/Abnormal images may lead to misclassification. Hence there is a compulsion of automated renal segmentation, with the best features for a good differentiation. The proposed flow of work is illustrated in figure.1. In this article, research examination has used different features of renal cell carcinoma and GLCM and textural features of tumor are extracted.

## 2.1 Morphological Method

The mathematical morphology method is used for renal segmentation and feature extraction of renal image, added to check whether the diseased renal disturbs the neighboring organs or not. The representation and description of region shape, neighboring pixels, boundaries, tumor lesions (Gao L et al, 1996) have been implemented. The morphological method includes operations that include dilation and erosion. This method has failed to segment the region of interest, renal. Some of the features are extracted remaining or not obtained. Now we decided pass on to Active contour method.

## 2.2 Active Contour Segmentation

The origin of the snake style boundary is located by the contour segmentation of grouping the same pixels. Snakes model shows the origin of the curve and ends at the same point of the curve, just like point-to-point pixel connectivity. The approximate shape of boundary (Campadelli et al, 2007) is obtained using the snake model. Based on the human interpretation, the occurrence of boundary has a curve like structure. The objective of utilizing the optimum method is recouping the diversion occurred in the limit, dispersion in neighboring organs and accumulation of missing image data. Ignorance of the missing boundary information has been obtained by the deceptive contour (Abdul Kadir Jumaat et al, 2012).

## 2.3 Axial Computed Tomography

Computed Tomography scanner is used for taking slices of images for the diagnosis of Diseases. These machines use a distinct X-RAY kit for generating the rays exposed to human body whole the visualized pictures or scanned interior area of interest are obtained in the Human anatomy. It is also called Axial computed tomography (ACT) and is computerized axial Tomography (CAT). CT or CAT scan is a non-invasive method of diagnostic technique. It uses the input source as x-rays and produces the digitized images of human structure such as Bones, blood vessels, and lymph nodes, or organs such as the brain, lungs or liver as the Scanner rotates with the x-ray beam around the body. This scanner enables obtaining images from the different views like Axial, Sagittal and Coronal of the interior organs of the body. The CT images produced provide a detailed interior information, apart from the Conventional x-ray method. They are presented as black and white pixels, just like in digital Electronics ZEROS and ONES are represented as switch ON & OFF respectively.

This helps the Radiology expert in gathering clear information on normal and lesions of the internal organs of the body. CT scanner is not utilized in the screening test whereas, in ultrasound, it is. The solid mass or fluid type of appearance is scanned in the renal and diagnosed as tumor. The fluid type of cell obtained is benign and the solid mass type is tumor. Before scanning the internal organs of the body, a contrast dye is fed into the human in order to obtain the clear images of slices.

## 2.4 Tumor Tissues

Mostly 90 out of 45 patients are affected by tumor in today's life. The area of tumor tissue size extends from 4cm to 7cm in metastasis stages of renal and finally confirms the occurrence of tumor of a fully bulged form of solid type of masses inside it. The tumor tissues spread whereas the benign tissues compress. The tumor cells spread to the neighboring organs. The indeterminate form of lesion is found in the renal. There are three types of therapy for curing tumor. The first is chemotherapy, the second is radiotherapy and the third is Surgery. Before going to the surgery, CT guided Biopsy can be done before going in for surgery to get confirmation of the clear existence of tumour.

## 3. Datasets

Based on the radiologist interpretation, differentiation of renal image into hypo/hyper dense in CT imaging is done. Hyper dense means white pixels of tumor while hypo dense means black pixels of benign and hypo dense means gray scale pixels i.e., intermediate in imaging. Clicking the mouse at lesion place results in each pixels giving attenuation of Hounsfield Unit for doctors identification (Campadelli et al, 2007). Basically, the images consist of voxel and pixel. Each set of 50 samples of the Benign, Tumor and Normal pictures accumulated concerning the HU of clinical masters respectively. Totally more than 209 example Images have been gathered. Each photo is resized into 512 X 512 pixels in the venous stage of significant view. 67 out of 209 were taken as tumor and remaining as benign and normal images for feature extraction. 37 out of 67 were separated as female renal tumor. Classification is followed by segmentation for feature extraction.

### 3.1 Hounsfield Unit

Despite the coverage of tumor being small / large, there is no variation in the HU and it has a constant value. Mouse clicking the position of white pixel denotes the tumor while black pixel denotes the benign. As per the clinical practice the value is given and displayed. The range of Hounsfield value determines the strength of tumor cells. As per expert Radiologist advice, range of values from 100-300 HU for Tumor (Gonzales R C, 1993) shown in figure 2(a) and 3(a).

### 3.2 Tumor Images

Typical cell proliferation in abnormal fashion results in the tumor solid mass lesion of various boundary are visualized as the images in figure 4 below. The tumor extends to the neighboring region which yielding low dice similarity coefficient. The tumor cells divide without count and invade the nearby tissues. The Hounsfield unit starting from 98 and greater is clearly clinically represented in the figure. 2 (b) and 3(b). The cortex medulla is fully dispersed by the solid mass lesion.

### 3.3 Benign Images

A typical cell proliferation in an abnormal fashion results in benign lesions, with ranging values from 20-100 HU as shown in figure 5. The cystic images shows the compression

of renal masses. The normal and benign images are the same in identification in most cases. There is variation in the cortex medulla thickness due to shrinkage. The fatty acids form the strands around the kidney.

### 3.4 Normal Images

No change occurs in the Cortex medulla thickness, this illustrates the normal images of renal. The Hounsfield unit of normal stands between 10-20 values in numeric. The extracted best features of the normal and abnormal images are shown in Table 1 with the *P* - value.

## 4. Image Segmentation

The goal of segmentation is to simplify the image into something meaningful and easy to analyze. Image segmentation is technically used to locate interested objects and boundaries (lines, curves, etc.). Segmentation of a particular portion of an image is done for better diagnostic therapy. Exact image segmentation (Nader H. Abdelmassieh et al, 2010) is considered as the process of conveying a label to each pixel in an image. Pixels with the same label portion visual the noble. Technically speaking, image segmentation refers to the rot of an image into different pixel and grouping the same pixel components. Scientifically speaking, theoretical based segmentation between low level and high level task of boundary areas. Medical image analysis (Marius George Linguraru et al, 2012) can be used as an initial screening test for the renal lesion treatment.

### 4.1 Preprocessing

Obscure and noise evacuation of any medical picture requires the preprocessing of ventures in division. The Weiner filter of high SNR (signal to noise ratio) is selected for building the nature of the Image by noise concealment. Much consideration is required in picture investigation to assemble the data and to enhance the nature of pictures.

### 4.2 Active contour Method

Active contour method provides the required image information on renal by through use of the iterative detection method. The irregular curvature form of boundary is obtained using the snake model detection region growing method. Active contour method is used for extraction of a closed curve contour of filtered image which is the boundary of the speculated mass. The region of interest is fixed for the same pixel intensity of each image. The Active contour method processing self-time of each image is 0.929secs compared to Morphological method which is 1.023secs (slow). Differentiation of Benign and Tumor images is accurately classified. In Morphological operation, the ROI (Xing Zhang et al, 2011) is dead, unable to identify feature extraction. 50 out of 15 images only are segmented and the remaining are unsegment.

### 4.3 Extraction of Features

Gray Level Co-occurrence Matrix (GLCM) is a widely used texture characteristic and the results obtained from the co-

occurrence matrices are of high quality than the other texture Parameters. The second order statistical parameters are contrast, energy, homogeneity and Correlation of the sample textures (Lin D T et al, 2006) are handled using software. It computes the statistical features based on image gray level intensity. The application of GLCM (Kanchana R et al, 2017) is a useful in texture analysis; image segmentation; retrieval; analysis; image classification. etc. Each element in the resultant is represented as (I, j) in vector form of pixel, of the input image, I. A GLCM is a matrix representation of rows and columns in a vector form of gray levels. The matrix element GLCM (i, j | x, y) is the comparative related frequency separated by a pixel distance (x, y) co-ordinates. Totally 40 features of GLCM for each are obtained for each image. 10 out of 40 is selected for optimal classification. Texture and shape feature are also found using the GLCM (Nader H et al, 2010 & Hetzheim M. H. 1993) and Contour Signature methods respectively.

### 4.4 Classification

Carcinoma Identification & Classification: The identification and classification of carcinoma consist of two parts, namely training and classification. The four classifiers chosen for the best performance are KNN (k-Nearest Neighbor), ANN (Artificial Neural Network) and SVM (Support Vector Machine) and FIS (Fuzzy Inference System) classifiers; the classifier which gives the best result is FIS.

### 4.5 Fuzzy Inference System

In this classifier, three triangular membership functions are taken and the range of values is given for each membership function (Yan G et al, 2010) as LOW, Medium and High of input and output. For each input the value range is assumed also from low to high. Similarly the values are assigned for the output as per the parameters obtained. The selected 10 optimal input parameters are divided into 2 divisions for each fuzzy logic controller (FLC). For each FLC five inputs are taken, such that  $2^5$  i.e., 32 rules are framed for two FLCs. The next step is to continue the output of two FLC to obtain the percentages of accuracy, sensitivity and specificity. The output gives 100% specificity. In Fuzzy (Sugeno, 1974) based applications there are two types of FLC algorithm, the first is Mamdani (use only range of values) and second one Sugeno constant values. In this work of classifier, mamdani is implemented for the range of values to get the best classification.

## 5. Results and Discussion

The CT Images were collected and the visual appearances of human renal CT images was stored in Brilliance 16 / Light Speed VCT machine as DICOM images on W350×L150 window size.

The image and results shown are noble and consistent segmentation by snake method as shown in Table 2 below. The table leads to the understanding that the p value failed to satisfy the parameter info\_correlation1, whose p value has been statistically analyzed for 37 subjects of left / right region of interest of kidney. There is a standard hike in the

parameters of sum variance and the standard deviation of images of random collection ages between 30-70 yrs. this is shown in figures 6 & 7.

The real use of a medicinal picture division is to identify the tumor. In all 40 GLCM –Gray level co-occurrence features are extracted. These observations indicate that among the extracted forty features, with respect to statistical analysis, ten features provide the optimum significance of the degree between normal and abnormal regions. The energy, entropy, Homogeneity and correlation parameters are in the same range of values for both sexes. The statistical significant value  $p < 0.050$  is passed for the most of the parameters. The area obtained for each image is based on the invasion of cells nearby neighboring organs. The extent of cells to neighboring organs gives high value of area like 145589 whereas the area within the kidney is around 4668 as shown in Table 3. The selected five parameters of contrast, Homogeneity, correlation, Difference average and difference entropy provide the same comparison values of random images of  $p$  value,  $P < 0.050$  as represented in figures 8 & 9. The contrast value of the left renal is very high compared to the right renal, since most of the left side male renal is affected, mainly due to the symptoms of smoking, race, hematuria and overuse of certain medications. The accuracy comparison of female sex renal (Fasquel J. B et al. 2006) indicates the origin of artificial neural network. In ANN, the testing data and training data are separated. The training data and testing data is selected 15% each, whereas the validation data is 70%. The input left and right region are separately trained. The output is given as the training data for performing the training. The data can be trained to reach the ROC (Region of Convergence), till the goal is reached. A similar process is followed in KNN and SVM. The performance of a classifier is done separately for female left/right renal; this is shown in figure 10. In medical diagnosis, the accuracy of a test is the ability to differentiate between the patient and a Normal (healthy) person correctly. Sensitivity test is the ability of a test to correctly identify those with the Tumor disease (true positive rate), whereas specificity test is the ability of the test for correct identification of those without the tumor disease (true negative rate).

**Accuracy:** Of the 140 cases that have been tried, the test could decide 58 patients and 72 solid cases effectively. Thus, the exactness of the test is equivalent to 130 isolated by 140 or 93%.

**Sensitivity:** From the 73 patients, the analysis of test was done for 45. In this way, its affectability is 45 separated by 73 or 33%.

**Specificity:** From the 67 diseased subjects, the test has effectively brought up every one of the 67. Accordingly, its specificity is 67 separated by 67 or 100%.

According to these statistical characteristics, this test is not appropriate for screening purposes; but rather it is suited for the final assertion of a disease.

The female of both left/female renal tumor obtained more or less equivalent values of accuracy, sensitivity and specificity

as shown in figure 11. The 40yr normal renal image of both left and right female of features is shown in figure 12. The Fuzzy classifier is trained with three membership function of 52 rules to get higher specificity. The specificity percentages obtained for the left and right renal tumor are 99.8% & 99.4% respectively.

## 6. Conclusions

An effective Fuzzy Inference System (FIS) classifier indicates the significance of best  $p$ -value parameters extracted by the active contour method of segmentation. First, the renal tumor is segmented and the number of features is extracted. Among them the significant  $p$ -value features from among them are selected for classification. Four types classifier were selected to train the optimal parameter and for getting high positive disease data. The fuzzy inference system shows the higher specificity value among all. The data shows GLCM parameters are as crucial tools for the determination of the composition solid mass of tumor. When comparing with the previous research work, it is easy and inexpensive and has a high rate of efficient results. However, to formulate a correct diagnosis and establish a correct therapy, parallel pre-operative Biopsy analysis is highly recommended to avoid the CT guided Biopsy in day today life. The authors have planned to take (67 tumor + 73 normal) 140 patients for separation from lesions and comparison of accuracy of left/ right renal to segment tumor from Axial CT image is done using Active contour snake model which provides an efficient result in %. The ten optimal extracted features are the same for female left /right renal out of forty parameters and selected for the best classifier performance of fuzzy 99.5% left and 99.4% female. The results show a significant accuracy in real time recognition

## References

- [1] Abdul Kadir Jumaat, Ummu Mardhiah Abdul Jalil. (2012) 'Seed Point Selection for Seed-Based Region Growing in Segmenting Micro calcifications', *International Conference of the IEEE SSBE Langkawi, Sep 10–12*.
- [2] American Cancer Society (2013) 'Cancer facts & figure', *Atlanta, GA: Am Cancer Soc.*
- [3] Campadelli P., Casiraghi E., Lombardi G. (2007) 'Automatic Liver Segmentation from Abdominal CT Scans', *14th International Conference on Image Analysis and Processing-ICIAP 2007, IEEE Computer Society, pp. 731–736*.
- [4] Fasquel J. B., Agnus V., Moreau J., Soler L. and Marescaux J (2006) 'An Interactive Medical Image Segmentation System Based on the Optimal Management of Regions of Interest Using Topological Medical Knowledge', *Computer Methods and Programs in Biomedicine, vol. 82, pp. 216–230*.
- [5] Gao L., Heath D. G., Kuszyk B. S., Fishman E. K. (1996) 'Automatic Liver Segmentation Technique for Three dimensional Visualization of CT Data', *Radiology, vol. 201, pp. 359–364*.
- [6] Giger M. L., Doi K., Mac Mahon H., Metz C. E., and Yin F. F. (1988) 'Image feature analysis and computer

aided diagnosis in digital radiography’, *Medical Physics.*, vol. 15, pp.158–166.

[7] Gonzalez R. C., Woods R.E. ‘Digital Image Processing. Addison Wesley, 1993.

[8] Hetzheim H. Anwendung der (1993) ‘Fuzzy-Logic in der Bildverarbeitung. Vision Jahrbuch’, *Coburg: Sprechsaal Pub.*, pp. 47–53, 1993.

[9] Hetzheim M. H.(1993) ‘Detection of stochastic structures in Images by Fuzzy and Choquet Integrals’, *ACCV’95, Second Asian Conference on Computer Vision*, vol.3, pp. 116–120.

[10] Kanchana R and Menaka R.(2017) ‘A novel approach for characterisation of ischaemic stroke lesion using histogram bin-based segmentation and gray level co-occurrence Matrix features’, *The Imaging Sci. J.*, vol.65, No.2,pp.124-136.

[11] Kobashi M. and Shapiro L. G.(1995) ‘Knowledge-based organ identification from CT images’, *Pattern Recognition*, vol. 28, p.475–491.

[12] Lin, D. T., Lei, C. C., & Hung, S. W. (2006) ‘Computer-aided kidney segmentation on Abdominal CT images’, *IEEE Transactions on Information Technology in Biomedicine*, vol.10, No.1, pp.59-65.

[13] Marius George Linguraru, William J. Richbourg, Jianfei Liu, Jeremy M. Watt, Vivek Pamulapati, Shijun Wang, and Ronald M. Summers. (2012), ‘Tumour Burden Analysis on Computed Tomography by Automated Liver and Tumour Segmentation’, *IEEE Transaction on Medical Imaging*, vol. 31, November 10, October

[14] Mavromatis S., Bo J. M., and Sequeira J.(2001) ‘Medical image segmentation using texture directional features’, *Presented in IEEE 23rd Annul. Int. Conf. Eng. Med. Biol. Soc., Istanbul, Turkey. Issue 3.*

[15] Nader H. Abdel-massieh, Mohiy M. Hadhoud, Khalid M. Amin (2010) ‘Fully Automatic Liver Tumour Segmentation from Abdominal CT Scans’, *IEEE, The 2010 International Conference on Computer Engineering & Systems*

[16] Saitoh T., Tamura Y., Kaneko T. (2004) ‘Automatic Segmentation of Liver Region Based on Extracted Blood Vessels’, *Systems and Computers in Japan*, vol. 35, pp. 1–10.

[17] Sudhakar M. S. (2016) ‘Biomedical image query in Gaussian-modeled feature space Employing GeoSOM with enhanced inverted indexing’, *The Imaging Sci. J.*, vol.64, No.4, pp.179-195.

[18] Shi, J., and Tomasi, C. (2004), ‘Good features to track’, *In Computer Vision and Pattern Recognition, 1994. Proceedings CVPR’94*, pp. 593-600..

[19] Sugeno. (1974) ‘Theory of fuzzy integrals and its application. Doctoral Thesis’, *Tokyo Institute of Technology.*

[20] Tsagaan B., Shimizu A., Kobatake H., and Miyakawa K.(2002) ‘An automated segmentation Method of renal using statistical information’, *In Proc. Medical Image Computing and Computer Assisted Intervention. vol. 1*, pp. 556– 563.

[21] Xing Zhang, Jie Tian, Dehui Xing, Xiuli Li and Keindeng.(2011) ‘Interactive Liver Tumour

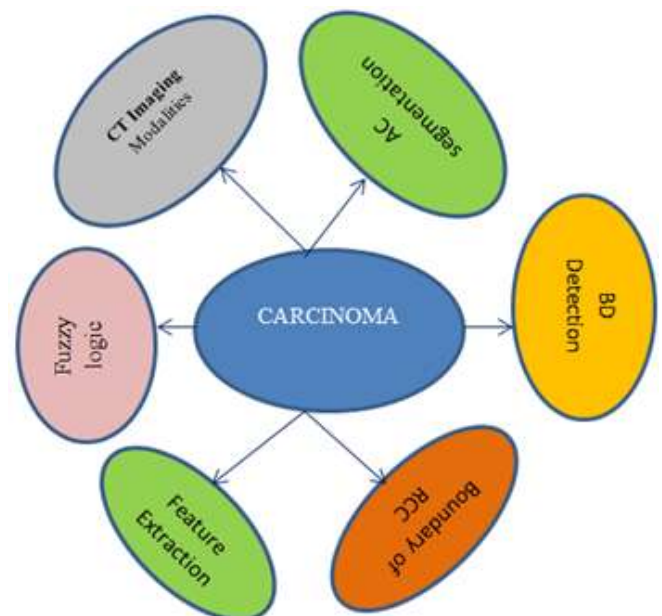
Segmentation from CT Scans Using Support Vector Classification with Watershed’, *33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, August 30–September 3.*

[22] Yan G. and Wang B. (2010). Automatic kidney segmentation from abdominal CT Images. *Intelligent Computing and Intelligent Systems (ICIS)*, *IEEE International Conference on Xiamen*, pp.280–284.

[23] Yoshiki K., Mitsukura Y., Fukumi M., Akamatsu N., and Yasutomo M. (2004) ‘Automatic extraction of a kidney region by using the Q-learning’, *In Ko S. J. (Ed.), Proceedings of 2004 International Symposium on Intelligent Signal Processing and Communication Systems, ISPACS.*, pp. 536–540.

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**Figure 1:** Concept of Malignant features

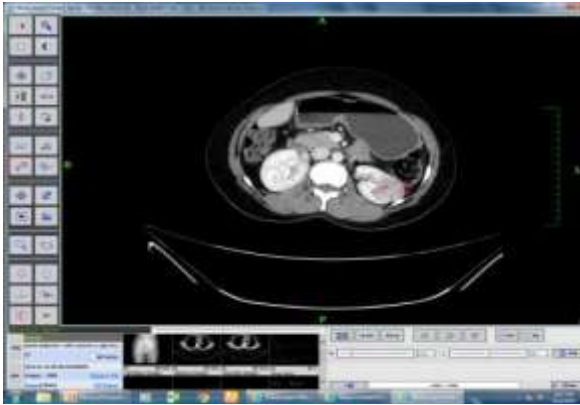


Figure 2: (a) Med synapse patient Left image

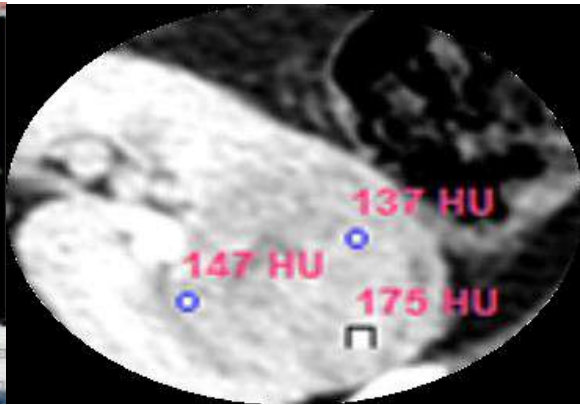


Figure 2(b): HU of Female Left Renal

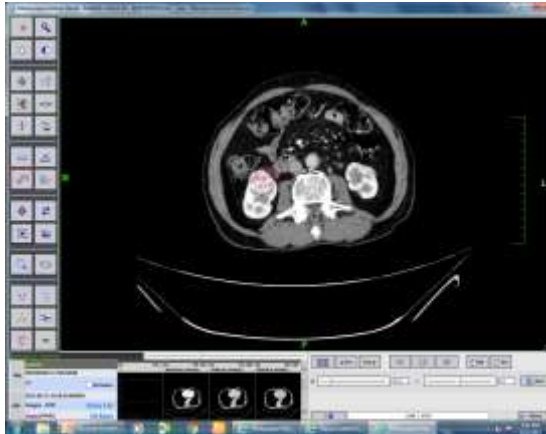


Figure 3(a): Med synapse patient Right image

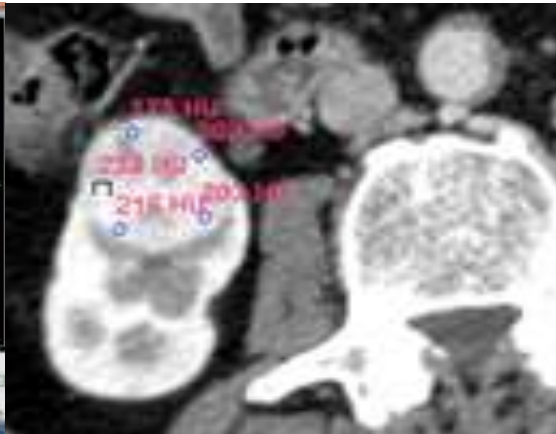


Figure 3(b): HU of Female Right Renal

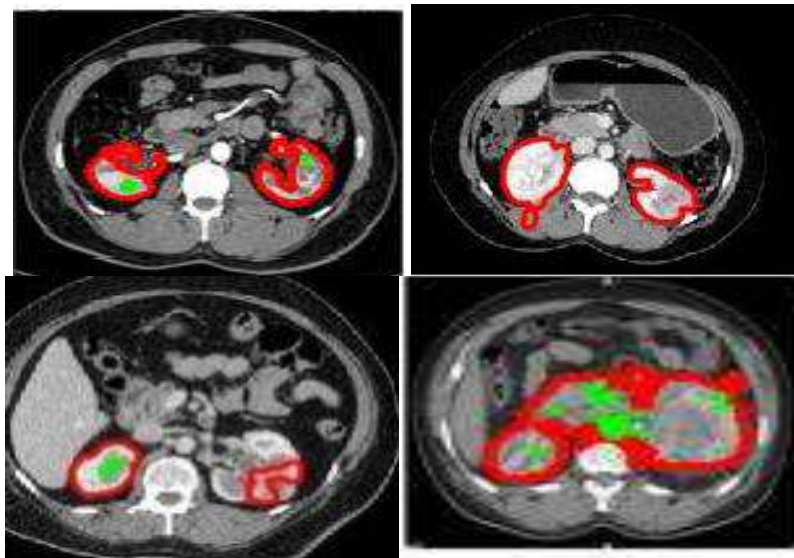
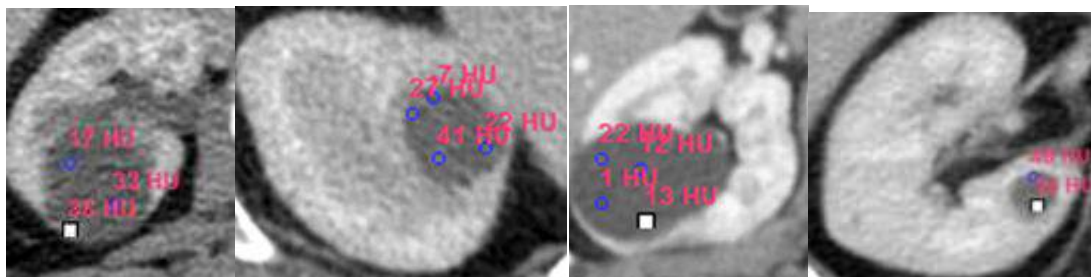
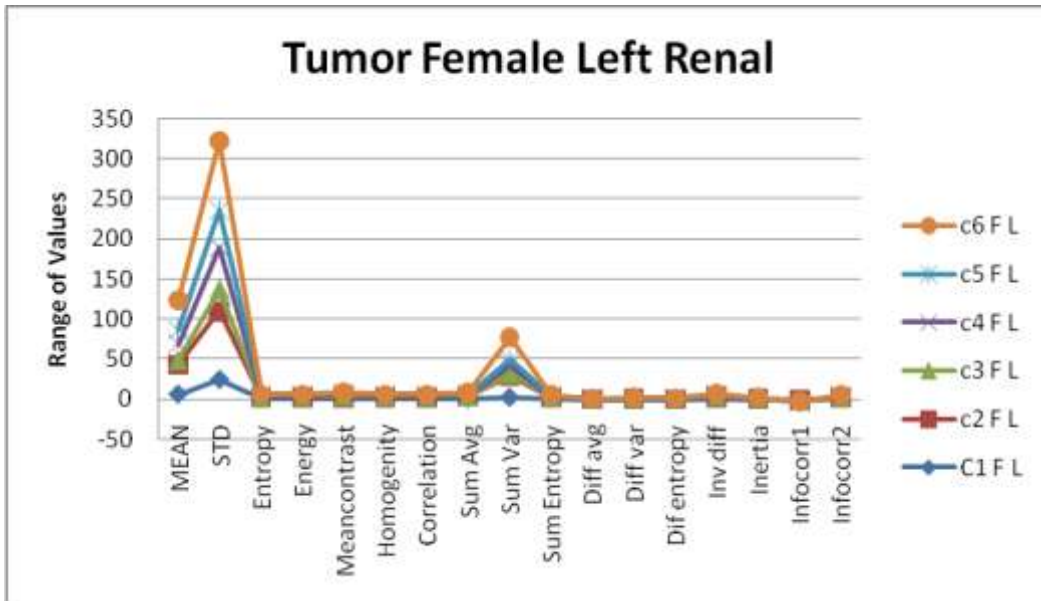


Figure 4: Boundary segmentation of tumor

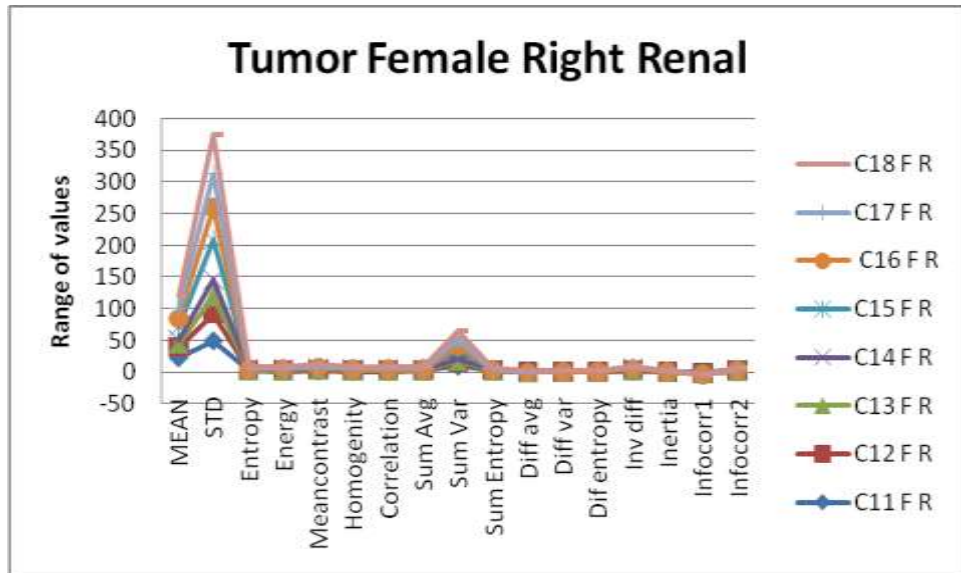


54 F/R 33-38 50 M/L 20-47 57 F/R 20-22 60 M/R 20-48

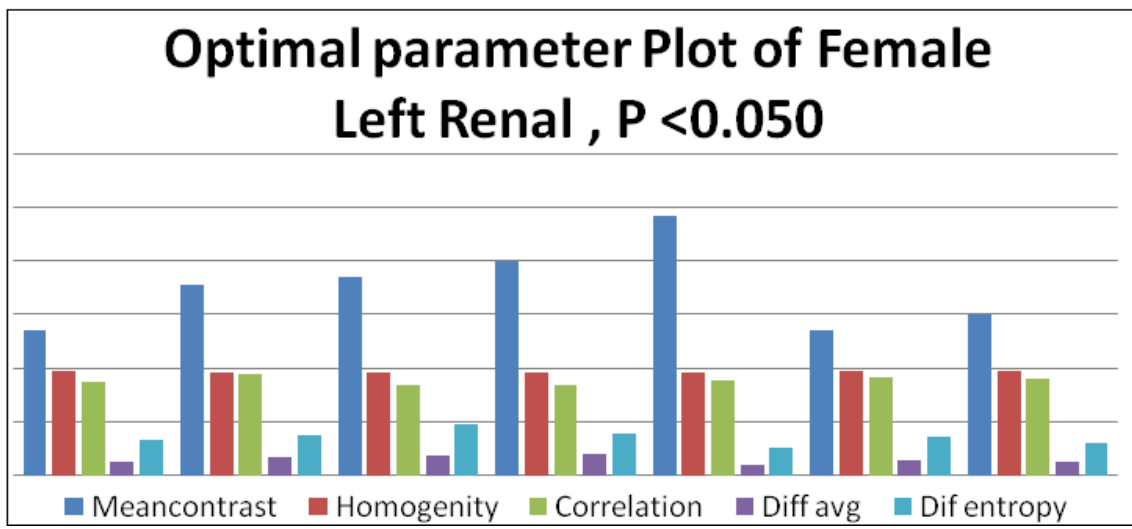
Figure 5: illustrated the Hounsfield unit of Benign cells



C1-C6 is subjects, F L-Female Left  
**Figure 6:** Performance of Female Left Renal Tumor



C11-C18 is subjects ,FR-Female Right  
**Figure 7:** Performance of Female Right Renal Tumor



**Figure 8:** Performance of Female Left Renal Tumor,  $P < 0.050$

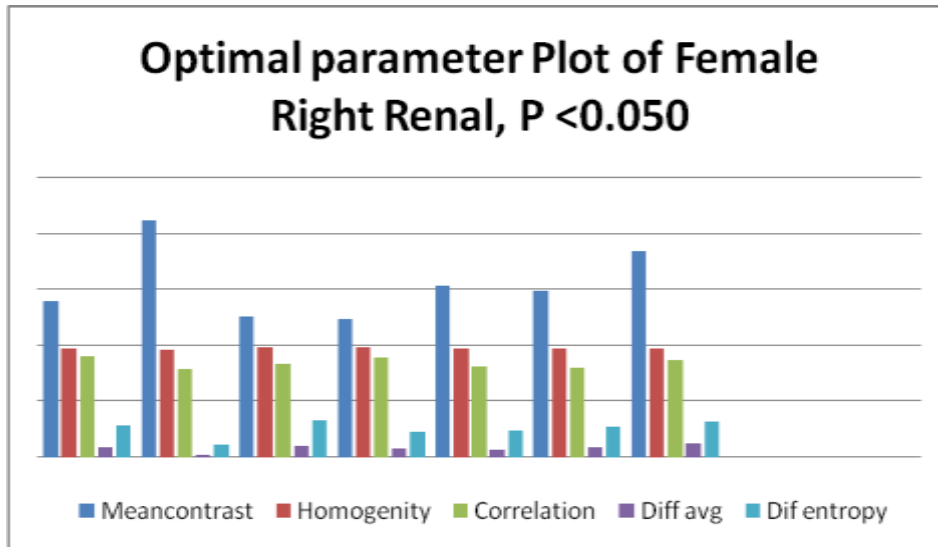


Figure 9: Performance of Female Right Renal Tumor, P<0.050

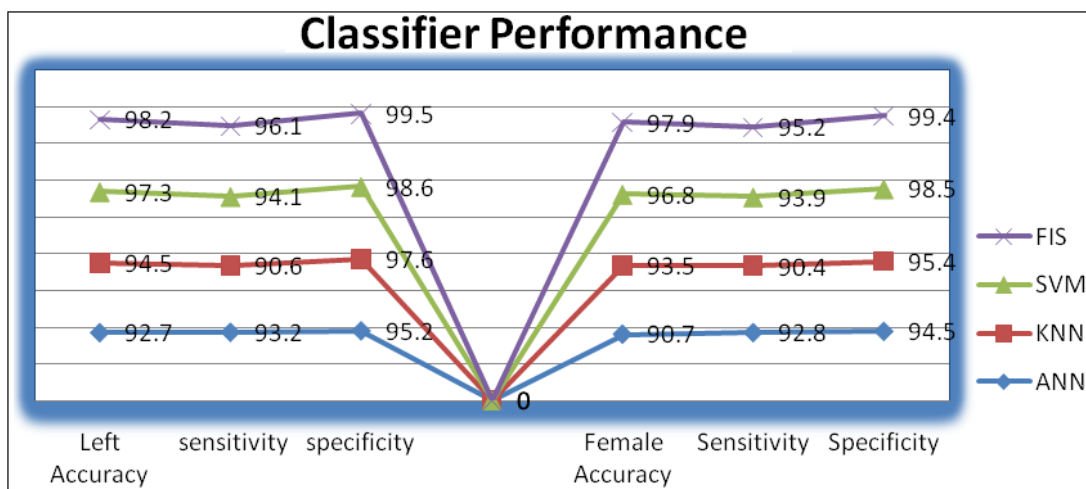


Figure 10: Classifier Performance of Tumor

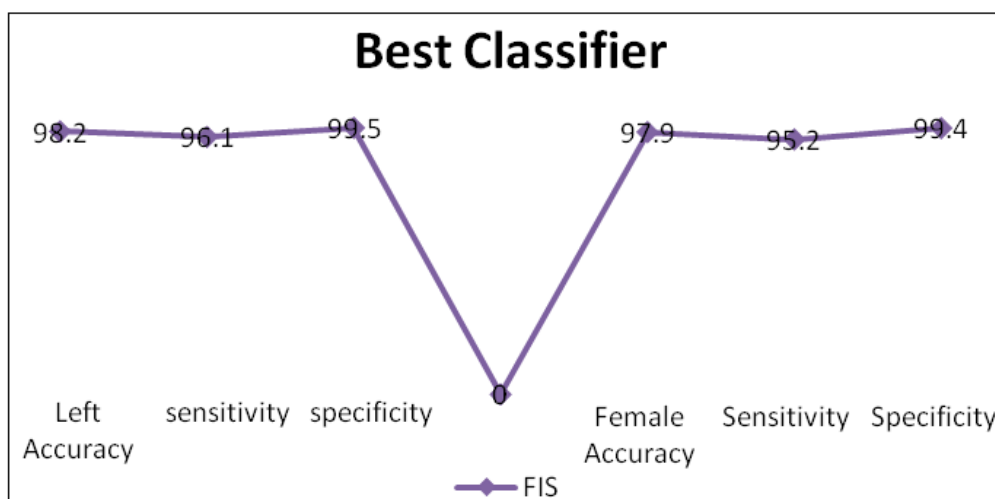
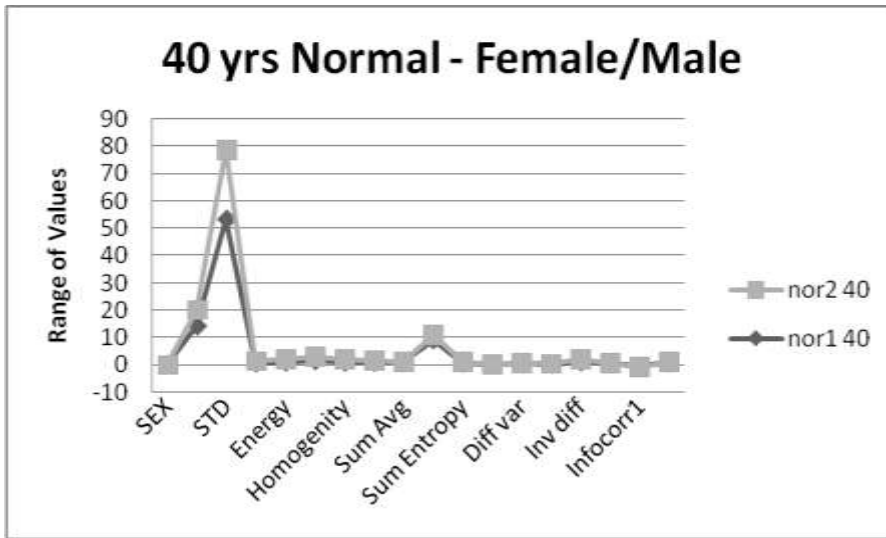


Figure 11: Performance of Best Classifier of Tumor





Nor1,nor2 –Normal subject 1 &2 and 40yrs  
**Figure 12:** Performance of 40yrs normal Renal of Female/Male