DOI: 10.24996/ijs.2023.64.4.41

ISSN: 0067-2904

Using K-mean Clustering to Classify the Kidney Images

Enass Hammadi Hassan[1]*, Alyaa Hussein Ali[2], Russul Mohammad Shehab [3], Walaa Ahmad Abd Alrida[4], Mohammad Salih Mahdi[5]

[1]Department Radiology&SonarTechniques., AL-Esraa University College, Baghdad, Iraq
[2] Department of Physics, College of the Science for women, University of Baghdad, Baghdad, Iraq
[3]Department Radiology&SonarTechniques., AL-Esraa University College, Baghdad, Iraq
[4]Department Prothodontics Techniques., AL-Esraa University College, Baghdad, Iraq
[5]BIT Department Business Information College, University of Information Technology and Communication, Baghdad, Iraq

Received: 28/2/2022 Accepted: 4/8/2022 Published: 30/4/2023

Abstract

This study has applied digital image processing on three-dimensional C.T. images to detect and diagnose kidney diseases. Medical images of different cases of kidney diseases were compared with those of healthy cases. Four different kidneys disorders, such as stones, tumors (cancer), cysts, and renal fibrosis were considered in additional to healthy tissues. This method helps in differentiating between the healthy and diseased kidney tissues. It can detect tumors in its very early stages, before they grow large enough to be seen by the human eye. The method used for segmentation and texture analysis was the k-means with co-occurrence matrix. The k-means separates the healthy classes and the tumor classes, and the affected parts were isolated from the healthy parts. To isolate the kidney from the other anatomical parts in a CT image, a mask must be generated, which is a binary image (0s or 1s). This mask was also utilized to remove undesired characteristics from the images. Density slicing was utilized to color the image based on its texture density. A slice is considered a band of neighboring gray levels in a gray scale image seen through monocular color. The gray scale band of (0-255) is transformed into a variety of color slices; it is the conversion of a gray scale image to a colored image that efficiently displays symmetric and diverse regions. Density slicing is a property process for segmentation. The unsupervised classification process, the K-Mean clustering, is used the application of K-mean on C.T. images to detect and classify the type of tumor in the kidney. The K-mean clustering separates each class depending on the texture properties and the distance from each class and color. This method of segmentation was used to separate the affected part from the healthy part of the tissue; the K-mean with Co-occurrence matrices gives statistical properties such as energy, homogeneity, contrast, and correlation. These give an indication of the nature of the tissues that are different in density. The standard deviation for the cancer was higher than the stone, so was the mean, the contrast and the correlation. This means that the texture of the cancer was brighter and has a none of grey level more than the stone and this can be seen from the energy value; the texture of the cancer was highly correlated. This method proved to be a good method for the early diagnosis.

Keywords- Computed Tomography (C.T.), K-Mean (K.M.), Image Classification, Gray-Level Co-occurrence Matrices (GLCM), Red Green Blue (RGB).

*Email: enasshammadi@gmail.com

استخدام *K-mean Clustering* لتصنيف امراض الكلى من الصور الطبية

ايناس حمادي حسن[1]*, علياء حسين علي[2], رسل محمد شهاب[3], ولاء احمد عبد الرض[4], محمد صالح مهدي[5]

[1]قسم تقنيات الاشعة والسونار , كلية الاسراء الجامعة, بغداد, العراق

[2]قسم الفيزياء, كلية العلوم للبنات, جامعة بغداد, بغداد, العراق

[3]قسم تقنيات الاشعة والسونار , كلية الاسراء الجامعة, بغداد, العراق

[4]قسم تقنيات صناعة الاسنان, كلية الاسراء الجامعة, بغداد, العراق

[5]قسم تكنولوجيا معلومات الاعمال ,لكلية معلوماتية الاعمال, جامعة تكنلوجيا المعلومات والاتصالات, بغداد, العراق

الخلاصة

في هذه الورقة البحثية سيتم تحديد وتشخيص امراض الكلى تطبق على الصور الطبية المقطعية المحوسبة باستخدام تطبيقات معالجة الصور الرقمية , الاشعة المقطعية هي تقنية الصور الطبية الخاصة وتكون ثلاثية الابعاد تتضمن الكثير من المعلومات عن هيكيلية وتركيب الجسم المتكونة من العظام والاعضاء الداخلية في الجسم. تم اخذ صور طبية لحالات مختلفة من امراض الكلى مع حالة سليمة لمقارنتها ب غير السليمة نذكرها هي تتضمن الحالة السليمة, الحصى, الاورام الخبيثة, التكيس والتليف. الاشعة المقطعية جهاز ال CT scan تجهز صورة عن الجسم سوف تعطي للطبيب المختص التصور الكامل والمعلومات التي يحتاجها لتشخيص الحالة باستخدام الاشعة السينية وجهاز الحاسوب, في هذا البحث تم عمل دراسة للحالات المرضية التالية لصور الكلى , لمساعدة وتسمح للشعاعي والطبيب المختص لتحديد الاجزاء المتضررة في الكلى وكيفية حماية الاجزاء السليمة من التعرض للاشعاع قدر الامكان بهذه التقنية يمكن تحديد الاورام قبل ان يزداد بالنمو ويكبر حجمه. الطريقة التي استخدمت في التقطيع والتحليل النسيجي هي k-mean مع مصفوفة co-occurence طريقة k-mean تفصل المناطق السليمة ومنطقة الورم والاجزاء المتضررة التي تحيط بالسليمة في بادىء الامر يتم فصل الكلى من بقية الاعضاء والاجزاء الموجودة من الجسم الظاهرة في الصورة ليتم عمل الدراسة على جزء الكلى فقط وتحديد الاجزاء المتضررة منها يتم من خلال معالجة الصور الرقمية في برنامج (ROI) Reign of Interest المنطقة المهمة او الرئيسية تحديد الكلى البرنامج يعمل لها المرشح ويقطعها يفصلها من باقي الاجزاء الاخرى, هذا المرشح ضروري لاستخلاص الاجزاء الغير مرغوب بها. الخطوة التالية هو استخدام طريقة التلوين Density Slicing لتلوين الصورة اعتمادا على كثافة النسيج سوف تقسم الى حزم كل حزمة تاخذ لون احادي معين وهي عملية تهيأة لعملية التقطيع التي هي الخطوة التالية بعدها لفصل الاجزاء بطريقة K-Mean clustering يستخدم هذا التطبيق لتصنيف وتحديد نوع الورم في الكلى. K-mean هي طريقة لفصل كل صنف عن الاخر اعتمادا على خصائص النسيج والمسافة المحددة مابين صنف واخر واعتمادا على اللون. هذه الطريقة من التقطيع استخدمت لفصل الاجزاء المتضررة من الاجزاء السليمة في النسيج. تم استخدام مصفوفة Co-occurence مع K-mean اعطت نتائج عن الخصائص الاحصائية للنسيج منها الطاقة, التجانس مابين النسيج, التباين , الارتباط والتي تكون مختلفة بالكثافة كثافة النسيج, والانحراف المعياري. الانحراف المعياري للاورام الخبيثة يكون قيمته اعلى من الحصوة وكذلك بالنسبة للتباين والارتباط, بهذه الخصائص تم معرفة ان نسيج الورم كان اكثر سطوعا ولايملك مستويات الرمادي من حالة الحصى وتم مشاهدة هذا بوضوح من خلال قيمة طاقة نسيج الورم طاقته اعلى من خاصية الارتباط في نسيجه. هذه الخصائص الاحصائية تعطي انطباع عن طبيعة النسيج مثل الطاقة والتجانس تكون عالية في الاجزاء السليمة من النسيج بينما قيمهم تكون قليلة في الاجزاء المتضررة من الكلى اعتمادا على عدد مستويات الرمادي النسيج السليم يكون اكثر منتظم من النسيج المتضرر (الورم). واخيرا تم تحديد وتشخيص اورام الكلى وحصى الكلى من صور الاشعة المقطعية باستخدام برامج معالجة الصور الرقمية , الطريقة التي استخدمت للتقطيع وتحليل النسيج هي K-mean مع مصفوفة Co-occurence التي فصلت الاجزاء السليمة عن المصابة الى اصناف وكانت طريقة جيدة جدا في التشخيص المبكر للمرض وبالتالي العلاج المبكر.

1. INTRODUCTION:

Medical imaging produces images that contain information regarding the anatomical structure being examined, which helps to establish accurate diagnosis, choose the appropriate treatment, monitor the treatment's progression, and so on. Physicians have always visually completed medical image analysis. Yet, in the past 20 years, automated systems capable of assisting physicians in such tasks were developed, primarily since they want to quantify some functional and anatomical parameters that are useful for diagnosis and treatment, which have previously been evaluated qualitatively by humans [1]. Medical research was extremely open to image processing in applications such as computed tomography(CT) scans. The image of the patient's body obtained by such a technique allows the physician to diagnose and evaluate the patient condition without the necessity for surgery [2]. Early detection and suitable treatment depending on a precise diagnosis are critical stages in improving disease outcomes.Unsupervised classification process, the K-Mean clustering, can be applied on CT images. It is a method of separating healthy tissues from tumor tissues in a CT image, depending on tissue texture properties, distance between tissues and color[3]. It can be applied on CT images to detect and classify the type of tumor in kidneys.

Statistical features as well as geometrical features, which represent the area and perimeter, are calculated for tumor or stone in the kidneys, which are separated by the k-mean cluster analysis process. It is very important to estimate the irregularity of the tumor or stone which indicates the tumor and stone shape. The study aim is to use digital image processing on CT images to diagnose kidney diseases. The unsupervised classification process, the K-Mean clustering was used. This was done through many steps. First, the kidney in the selected CT images was isolated from the other anatomical features in the image. The K-mean algorithm was used on the CT images of the kidneys to diagnose the disease and isolate the damaged parts from the healthy parts. Statistical properties of the kidneys were calculated for both the right and the left kidneys and of the damaged and healthy parts through the co-occurrence matrices; the geometrical features of the affected parts(tumor or stone) were then calculated. In this method, a color was given to each area of the kidneys, depending on the density of the area, by selecting it with boundaries. Then based on the color, the parts were separated to easily identify the tumor and the affected part[3].

2. Methodology

2.1 Mathematics and Methods

2.2 SEGMENTATION: Segmentation separates the structures or subjects of interest from the background and one another. C.T. segmentation separates the critical data required to investigate its ROI Reign of Interest from the background data [3].

$$f(x, y) = \begin{cases} 1 \; if & f(x, y) > \mathrm{T} \\ 0 \; if & f(x, y) \leq \mathrm{T} \end{cases} \qquad (1)$$

T represents the threshold value. x, y represents the coordinates of the threshold value point. $f(x, y)$ represents the points of the gray level image pixels.

$f(x, y)$ represents the intensity value of the pixel at (x, y) [4].

2.3 DENSITY SLICING

It is the process of converting a gray scale image to a false-color image, which is an effective way of displaying symmetric and diverse regions with an image [5]. Density slicing is the monocular color band of neighbouring gray levels in a gray scale image. A 'slice' is defined as a band of nearby gray levels. Various color parts have been created from the gray scale band (0-255). In addition, color density slicing uses gray levels to limit the number of image colors. The human eye might just distinguish between about 16 shades of gray in an image, yet it can differentiate between hundreds of colors. As a result, an image improvement approach changes limit color to customize digital number values, which raises the variance of a particular D.N. (Density Neighbouring of pixels) value compared to the image's nearby pixels. Parts of an image that yield a given D.N. value of the benefit can be colored, or the entire image can be converted from gray to color. Furthermore, density slicing is performed by dividing a band's brightness band into periods, assigning a color to each one of the periods [5].

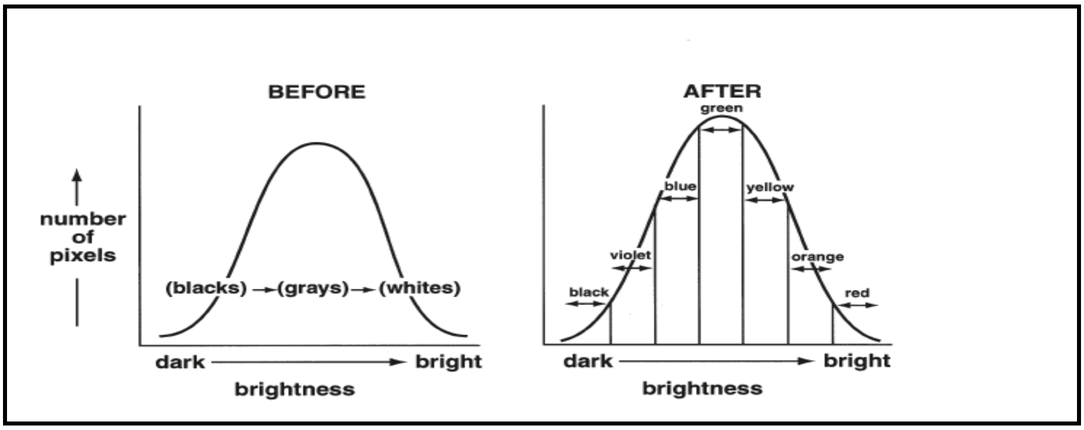


Figure 1: Density slicing customizes colors to limit brightness values periods [5].

2.4 K-MEANS CLUSTERING ALGORITHM:

K-means clustering can be defined as an algorithm that separates regions of an image based on the image's attributes and quality,

where K is a positive number representing the number of groups. The distance between the relevant cluster centroid and the data is minimized during grouping (clustering) [6]. K-means clustering is considered a cluster analysis approach that aims to isolate or separate each color based on the number of clusters to which each part belongs.

The following steps indicate the K-means clustering approach employed[6]:

1) The gray scale data points were fragmented into random choice centroids, one for each cluster.
2) The mean values regarding all cluster elements were calculated to find other cluster centroids.
3) New clusters were specified to obtain the area between the cluster elements and cluster centroid.
4) Step 1 was repeated till the centroids do not move or till a certain number of repetitions have been completed.
5)

The K-means technique is used to find the smallest value of an objective function:\

$$H = \sum_{a=1}^{A} \sum_{g=1}^{G} |d_g^a - c_a|^2 \quad (1)$$

Where: d_g^a represents data points and C_a means the center of the cluster. K-means clustering technique produces a cluster image [7], which consists of a number of clusters. It is worth noting that the K-mean can be defined as an unsupervised classification procedure whose main goal is to segment images depending on each pixel's color value. In RGB (Red,Green and Blue) color space, the CT Image is displayed. The original image is displayed in RGB color space and then transformed into a new color space for the segmentation of the image using the K-means clustering technique

2.5 CO-OCCURRENCE MATRICES:

The gray level co-occurrence matrix (GLCM) is crucial in texture classification. The gray level co-occurrence matrix (GLCM) is typically represented as (θ, d), where (θ) stands for the angle between them (which is in general restricted to values (45±; 90±; 135±)) while (d) represents linear distance in the pixels. The GLCM is used to generate various textural metrics that aid in understanding the overall image content [7]. Also, it provides visual features linked to second-order statistics, which considers the relationship between pixels or groups of pixels (typically two). GLCM was suggested by Bino Sebastian et al., and have since become one of the commonly used and most well-known texture properties; they defined the GLCM as a square matrix [8]. The combined prospect distributions of pairs of pixels were used in this approach. GLCM shows how frequently each gray level occurs when the pixel is placed in a fixed geometric position for each subsequent pixel [9]. Averaging the texture features of the four directional co-occurrence matrices [9]. Depending on the gray level, Figure (2) depicts a 3*3 image and the four GLCMs that go with it [9].

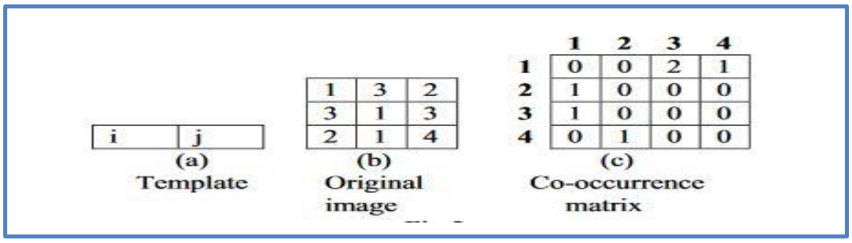


Figure 2: shows 3*3 images and 4 gray-level co-occurrence matrices [9].

3. RESULT AND DISCUSSION

The statistical characteristics are energy, contrast, homogeneity, correlation, mean, and standard deviation and geometrical characteristic like area and perimeter, those characteristics shown in Tables (1,2,3,4,5,6,7 and 8). The spatial gray dependence matrices are used to construct the co- occurrence texture features. The relative frequency with which 2 pixels (one with gray level value (i) and the other with gray level (j), separated by distance d at a specific degree of an angle, which appears in the image are contained in the matrix (p). It is worth noting that using all possible discrete signal levels when computing co-occurrence features from images with a large number of potential pixel intensity values (e.g.) is not a good idea. If all of the original intensity levels have been used, a noise in the image might readily blur the derived texture information. As a result, it is desirable to use a quantization approach to convert the original values of the intensity into a reduced number of potential levels.

Contrast: The contrast between the reference pixel and the surrounding pixels measures intensity or gray-level differences [10].

$$C = \sum_{i=0}^{Ng-1} \sum_{i=0}^{Ng-1} (i-j)^2 \; p(i,j) \tag{2}$$

Correlation: The linear dependency of the gray level values in the co-occurrence matrix is calculated using correlation [11].

$$cor = \frac{1}{\sigma_x \sigma_y \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i,j) p \quad (i,j)} - \mu_x \mu_y \tag{3}$$

Entropy (ENT): It is a measure of randomness; it is one of the statistical characteristics by which the nature of the texture image input is identified. H measures the randomness of a gray level distribution.[11]:

$$H = -\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} p(i,j)log\big(p(i,j)\big) \tag{4}$$

Energy: The energy refers to how the image's gray levels are distributed [12]:

$$Energy = \sum_{i=0}^{Ng-1}\sum_{i=0}^{Ng-1}[p(i,j)]^2 \tag{5}$$

Homogeneity: homogeneity of an image is characterized by including just some gray levels, GLCM gives only a few but fairly high values of $p(i,j)$. [12].

$$Hom = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} \frac{\mathbf{p(i,j)}}{\mathbf{1}} + |i-j| \tag{6}$$

Where: $\mu_x, \mu_y, \sigma_x, and\ \sigma_y$ Are the means and standard deviation of $p_x\ and\ p_y$.

1- Healthy case:

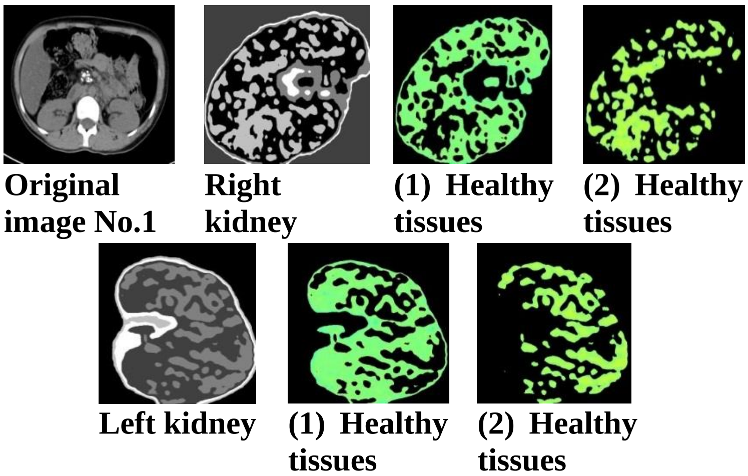
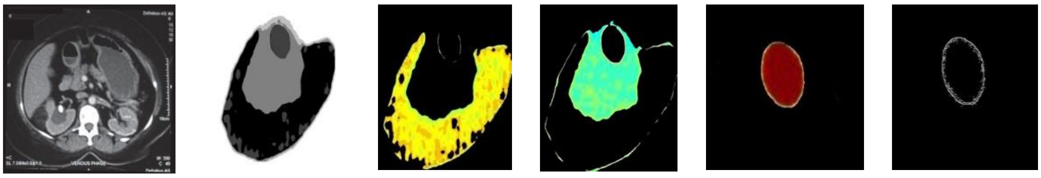
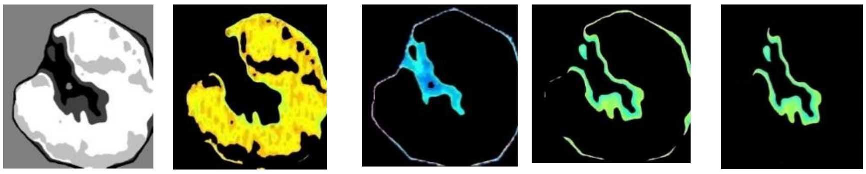


Figure 3: The original image of right and left kidneys with healthy tissues using K-mean Clustering.

2- Stones cases (two cases)



Original image No.3 **Right kidney** **Healthy tissues** **Stone pressure area on the tissue** **(c1) Stone** **Boundary of Stone**



Left kidney **Healthy tissues** **(c2) Cancer** **Boundary the tumor** **Boundary of tumor**

Figure 4: The original image with stone and cancer part using K-mean Clustering for kidney stones.

Table 1: texture features for the abnormal part for left and right side of kidney.

Image No3	Standard Deviation	Mean	Contrast	Correlation	Energy	Homogeneity	Area in pixels
c1	18.77	5.0497	0.2217	0.8702	0.8393	0.9794	**76788**
c2	43.1086	13.6327	0.2780	0.9027	0.8017	0.9707	**104599**

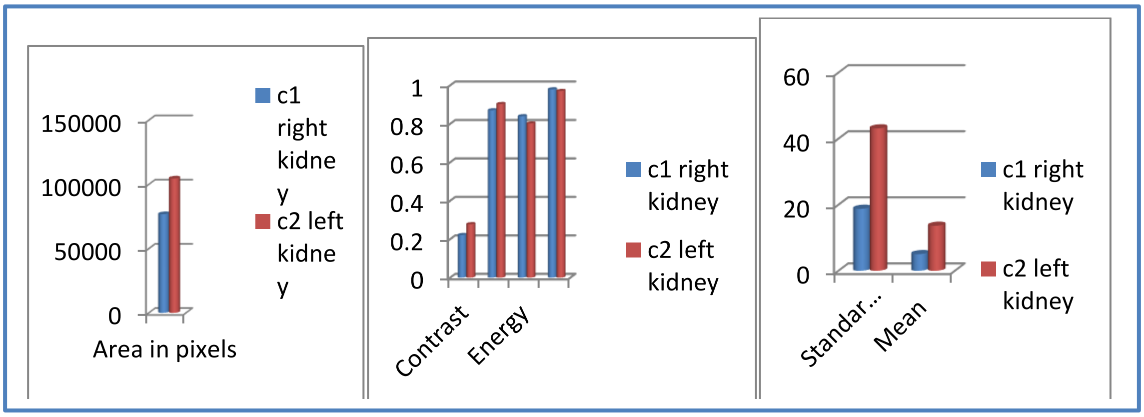
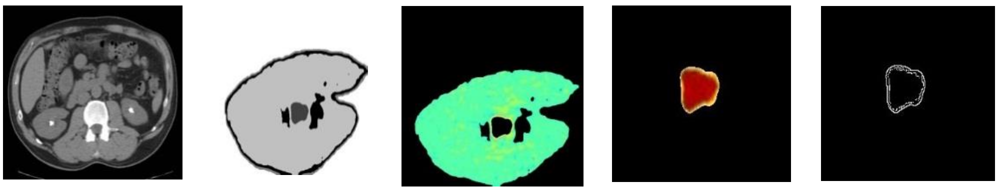
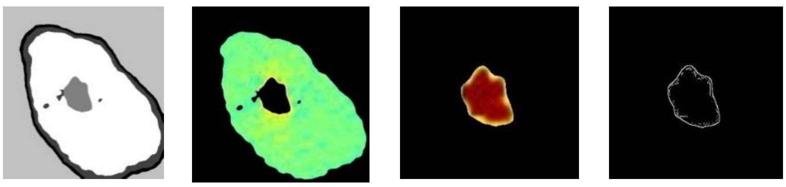


Figure 5: Graphs of the statistical features listed in Table (1).



Original image No.4 **Right kidney** **Healthy tissues** **(d1) Stone** **Boundary of stone**



Left kidney **Healthy tissues** **(d2) Stone** **Stone Boundary**

Figure 6: The original image with stones part utilizing the K-mean Clustering for kidney stones.

Table 2: texture features for the abnormal part of both left and right kidney.

Image No.4	Standard Dev.	Mean	Contrast	Correlation	Energy	Homogeneity	Area in pixels
d1	22.1559	4.2896	0.0475	0.9365	0.9073	0.9917	**13121**
d2	26.4011	6.2119	0.0637	0.9389	0.8588	0.9907	**26701**

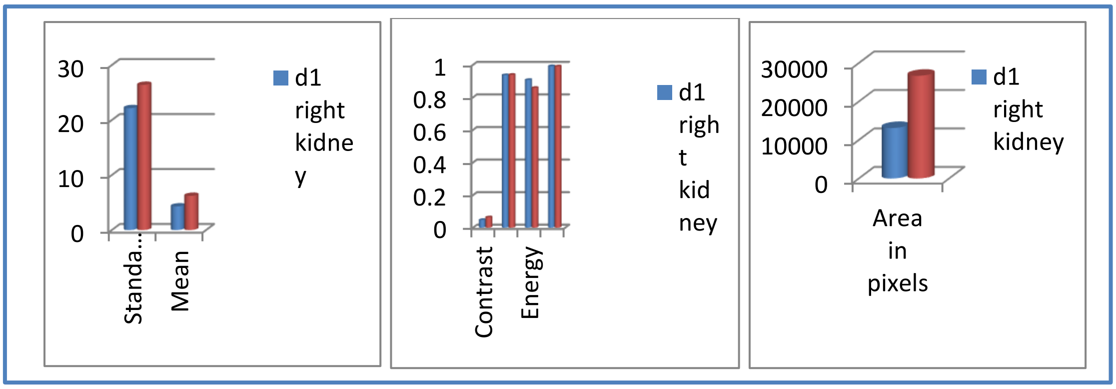
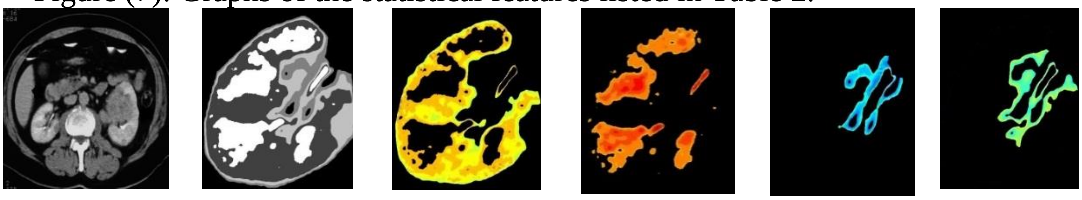


Figure 7: Graphs of the statistical features listed in Table 2.

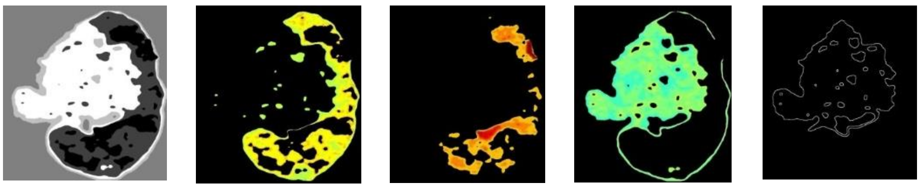
3- Cancer case (two cases)

Figure (7) and Table (3) show the cancer case for both kidneys, the healthy and the cancer tissue, Table (3) gives the statistical features calculated from the co-occurrence matrix.

Figure (7): Graphs of the statistical features listed in Table 2.



Original image No.9 **Right kidney** **(1) Healthy tissues** **(2) Healthy tissues** **(i1) Cancer** **Boundary of cancer**



Left kidney **(3) Healthy tissues** **(4) Healthy tissue** **(i2) Cancer** **Cancer Boundary**

Figure 8: The original image with (cancer case) using K-mean Clustering.

Table 3: texture features for the abnormal part left and right of the kidney.

Image No.9	Standard Dev.	Mean	Contrast	Correlation	Energy	Homogeneity	Area in pixels
i1	34.2714	8.3379	0.1421	0.9213	0.8819	0.9848	**69583**
i2	89.0099	57.5087	0.7013	0.9417	0.5019	0.9456	**285053**

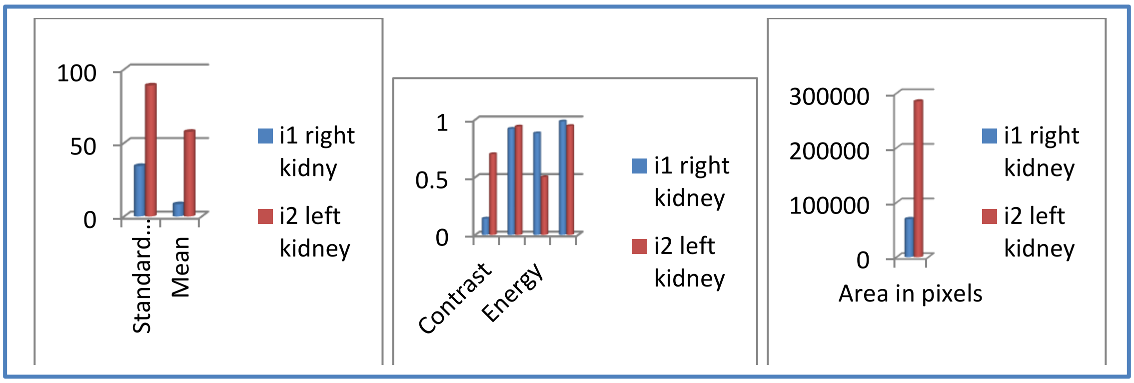


Figure 9: Graphs of the statistical features shown in Table 3.

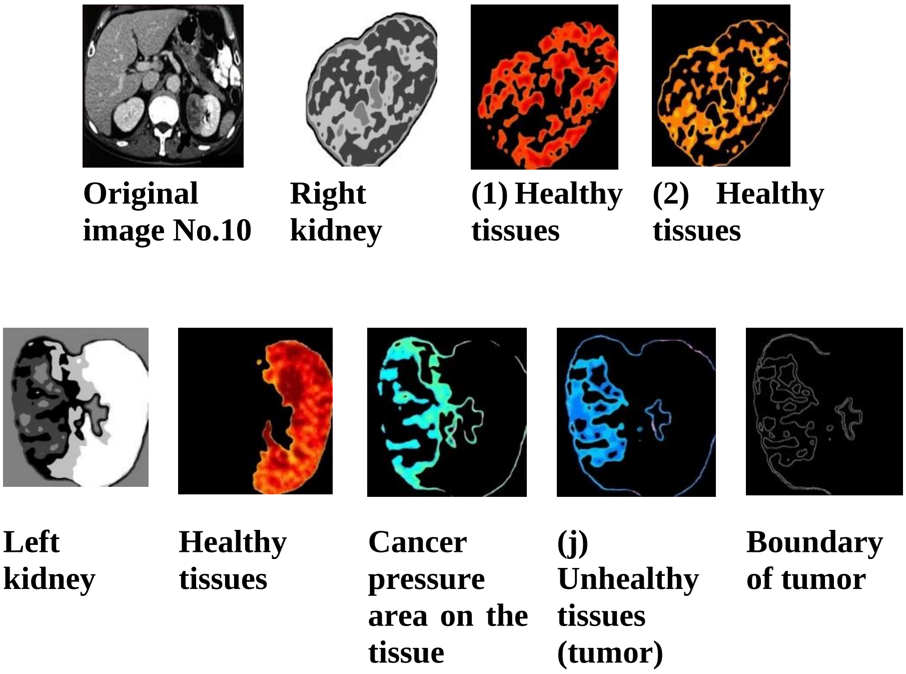


Figure 10: The original image with (cancer case) using K-mean Clustering.

Table 4: texture features for the abnormal part of the left kidney.

Image No.10	Standard Dev.	Mean	Contrast	Correlation	Energy	Homogeneity	Area in pixels
j	89.0099	57.5087	0.7013	0.9417	0.5019	0.9456	**223094**

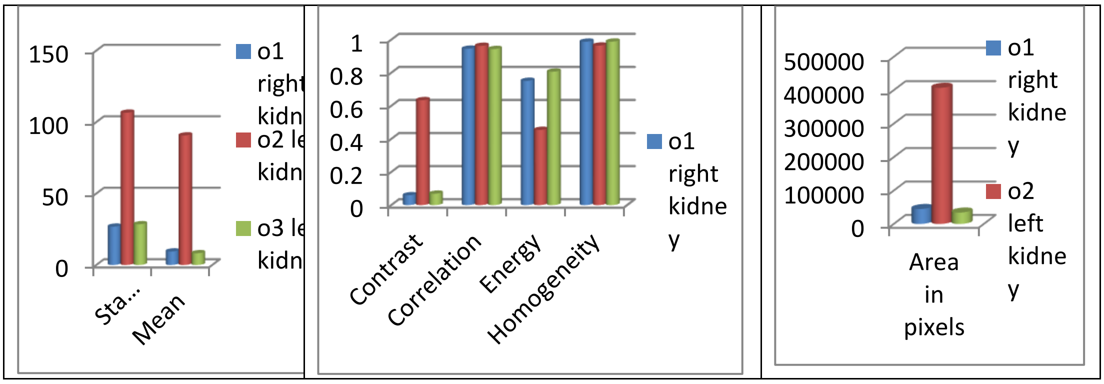
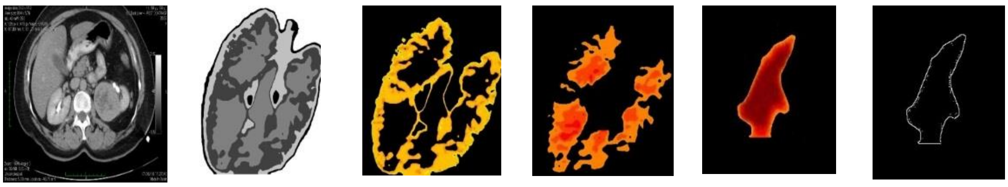
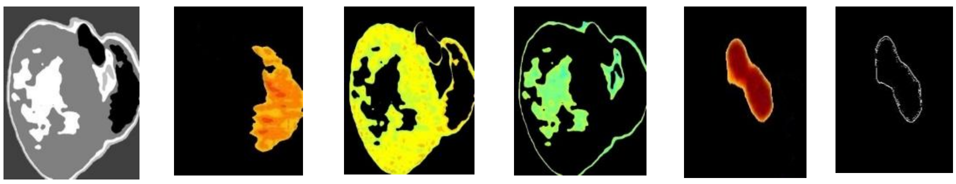


Figure 11: Graphs of the statistical features of Table 5.

4- Cysts case (two cases): Figure (10) shows the right kidney with a stone while the left kidney has stone and cyst. Table (5) shows that the value of mean for the cyst is very high compared with that of stone; so is the standard deviation, the contrast, and the correlation while its energy and homogeneity are low compared with the stone case. The homogeneity measures the purity of texture, while, a low energy value means that there is a large number of gray level values in the image.



Original image No.15 | **Right kidney** | **(1) Healthy tissues** | **(2) Healthy tissues** | **(o1) Stone** | **Boundary of stone**



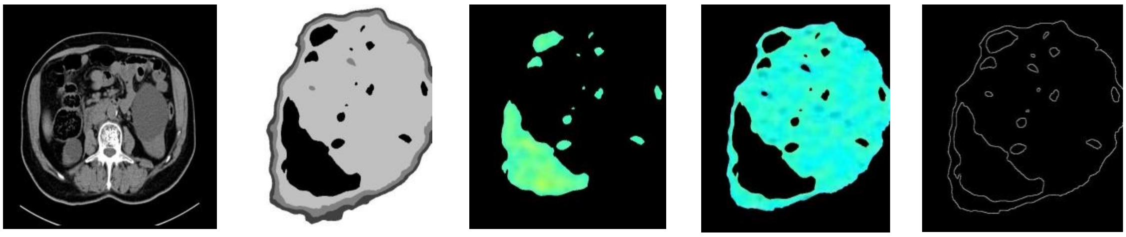
Left kidney | **(1) Healthy tissues** | **(o2) cyst** | **Unhealthy tissues** | **(o3) Stone** | **Boundary of stone**

Figure 12: The original image using K-mean Clustering (cysts case).

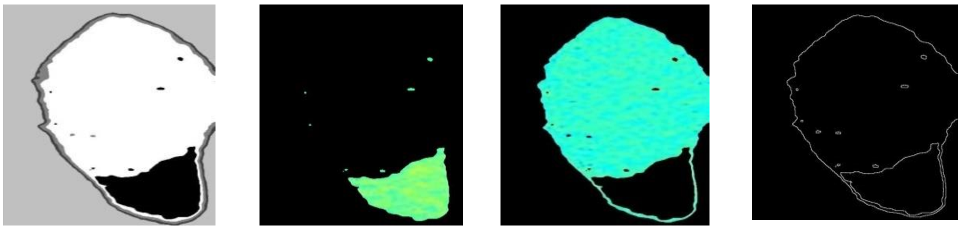
Table 5: texture features for the abnormal part left and right of the kidney.

Image No.15	Standard Dev.	Mean	Contrast	Correlation	Energy	Homogeneity	Area in pixels
O1	26.8282	9.4676	0.0593	0.9452	0.7512	0.9878	**44688**
O2	106.5509	90.6314	0.6342	0.9627	0.4548	0.9642	**407040**
O3	28.4950	8.2222	0.0690	0.9435	0.8066	0.9883	**34058**

Figure (12) shows the cyst case for both right and left kidneys; as it can be seen from Table (6), the texture feature for the cyst, the value of mean and standard deviation are high compared with other cases.



Original image No.16 **Right kidney** **Healthy tissues** **(p1) Cyst** **Boundary of cyst**



Left kidney **Healthy tissues** **(p2) Cyst** **Boundary of cyst**

Figure 13: The original image with (cyst case) using K-mean Clustering.

Table 6: texture features for the abnormal part left and right of the kidney.

Image No.16	Standard Dev.	Mean	Contrast	Correlation	Energy	Homogeneity	Area in pixels
p1	89.9727	80.1624	0.3542	0.9709	0.4638	0.9745	392437
p2	91.5982	84.5029	0.2783	0.9775	0.4747	0.9818	396978

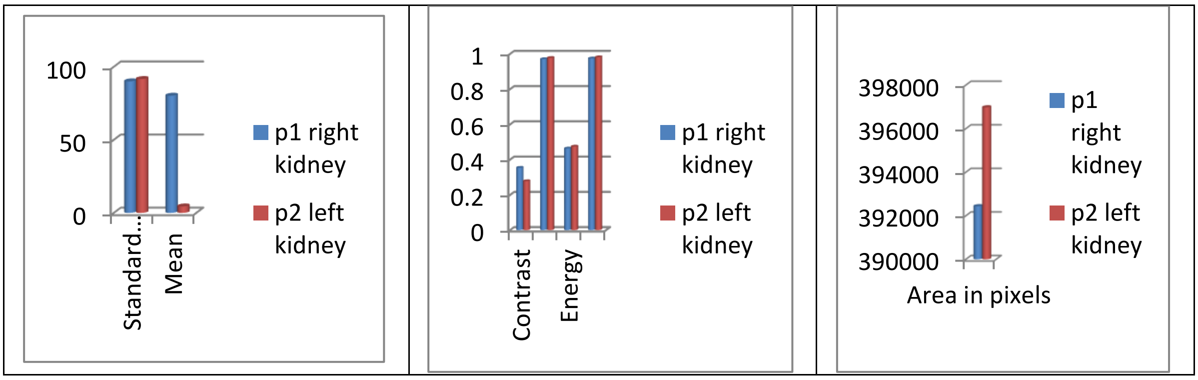


Figure 14: Graphs of the statistical features listed in Table 6.

5- Kidney failure cases (kidney fibrosis) (two cases):

Figures (15) and (17) shows fibrosis cases for the two kidneys; Tables (7) and (8) exhibits the statistical features of both kidneys. The features for (1,2,3,4,5,6) tables are nearly equel.

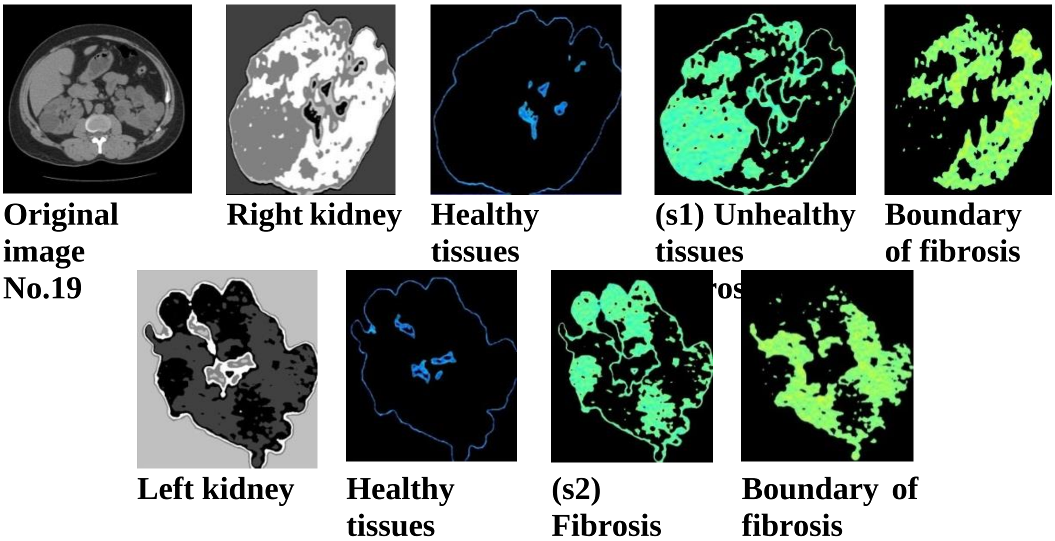


Figure 15: The original image with (fibrosis case) using K-mean Clustering.

Table 7: texture features for the abnormal part both left and right of the kidney.

Image No.19	Standard Dev.	Mean	Contrast	Correlation	Energy	Homogeneity	Area in pixels
S1	86.8426	60.1378	0.8994	0.9172	0.4851	0.9379	398314
S2	89.0009	60.8671	0.2083	0.8383	0.8742	0.9746	334036

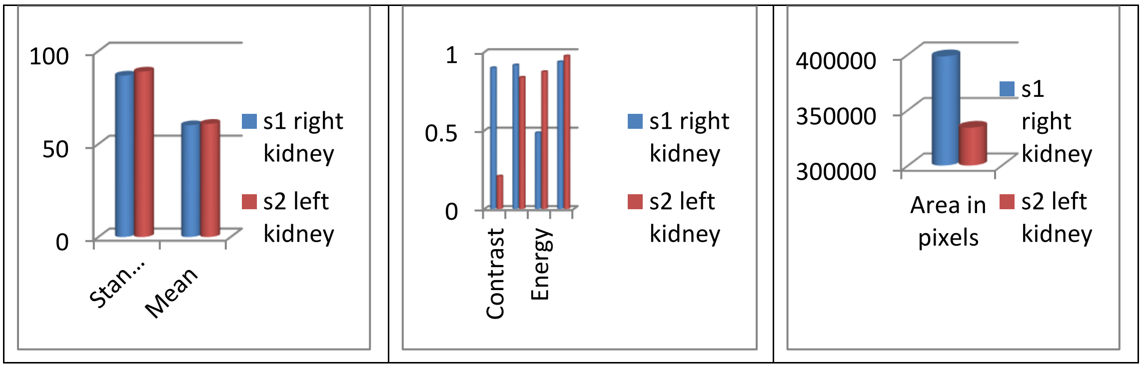
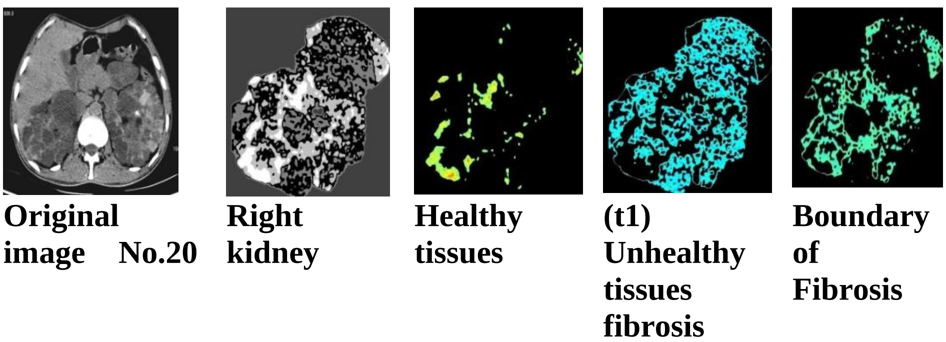
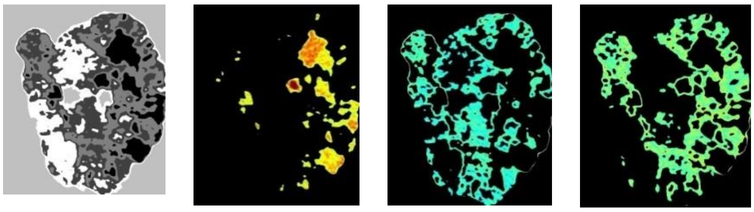


Figure 16: Graphs of the statistical features in Table 7.





Left kidney **Healthy tissues** **(t2) Unhealthy tissues fibrosis** **Boundary of fibrosis**

Figure 17: The original image with (fibrosis case) using K-mean Clustering.

Table 8: texture features for the abnormal part both left and right of the kidney.

Image No.20	Standard Dev.	Mean	Contrast	Correlation	Energy	Homogeneity	Area in pixels
t1	74.9210	49.9382	1.4784	0.8327	0.4368	0.8795	399220
t2	75.0933	42.8303	1.2793	0.8491	0.5417	0.9171	351146

Table (8) shows the value of each side fibrosis cases. The values of the statistical features are nearly equal.

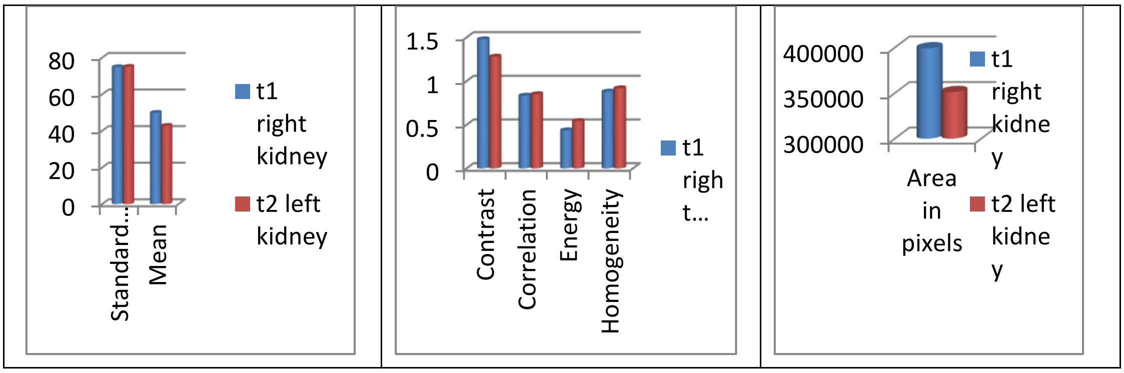


Figure 18: Graphs of the statistical features shown in Table 8.

4. GEOMETRICAL FEATURES

The geometrical features are very important in the tumor area and its surroundings. The area calculation was based on determining the edge (perimeter), orientation length, width, diameter of the tumor or kidney stone, and then irregularities account [13]. Geometrical features such as the diameter, area, perimeter, and irregularity can be calculated by isolating the kidney tumor or stone. If the number of pixels is equal to the one in the image, this indicates the region of interest(ROI) white area of the tumor or kidney stone separate from the kidneys; if the value of the pixels is equal to zero, this gives the background Black The irregularities in the tumor or stone are computed by [13]:

$$I = \frac{4\pi A}{P^2} \tag{7}$$

Where: **p** represents the perimeter of the tumor, and **A** represents the area of tumor in units called pixels. The index of the irregularity equals 1 only for a circular shape, and it is < 1 for all other shapes [14].

$$\mathbf{A} = \sum white\ pixel\ in\ the\ image \tag{8}$$

The area of segmented stones or tumor is calculated by counting the number of pixels in the image array with the value 1. Binary images are employed in the computing domain [14].

Geometrical features for K-mean clustering

Table (9) and Table (10) shows the values of the area and the perimeter for the stones, cancer, cysts, and fibrosis for the right and left kidneys as calculated by the K-mean clustering method

Table 9: The values of the perimeter, area, and irregularity index of the right kidney

Image No.	Area (A) in pixels	Perimeter (P) in pixel	Irregularity Index (I)
3(c1)	76788	17790	**0.00304115**
4(d1)	13121	8235	**0.0024301292**
9(i1)	69583	140208	**0.0000444577**
15(o1)	44688	20289	**0.001363513**
16(p1)	392437	81789	**0.0007368342**
19(s1)	398314	330836	**0.0000457077**
20(t1)	399220	303788	**0.0000543326**

Table 10: The values of the perimeter, area, and irregularity index of the left kidney

Image No.	Area (A) in pixels	Perimeter (P) in pixel	Irregularity Index (I)
3(c2)	104599	124424	**0.0000848611**
4(d2)	26701	16788	**0.0011899241**
9(i2)	285053	78279	**0.000584285**
10(j2)	223094	116040	**0.0002080952**
15(o2)	407040	122781	**0.0003391285**
15(o3)	34058	14538	**0.0020239485**
16(p2)	396978	66111	**0.0011407977**
19(s2)	334036	298466	**0.0000470969**
20(t2)	351146	282044	**0.0000554426**

5. CONCLUSIONS

Through this research, the correct method for early detection of kidney disease was reached, and it was a good and clear method through the use of K-mean clustering is an excellent process of segmentation used to classify textures and separate the affected part from the healthy part. By this way, segmentation gives the right solution for diagnosis, and it allows radiologists and physicians to identify the damaged parts of the kidney for protecting the normal parts from radiation exposure during the treatement stage. This technique can detect tumors before they grow large enough to be seen by the human eye. Through the use of the density slicing method, each part was separated by color depending on the density of the texture. The transformation of a greyscale image to colored image is an efficient method of showing various and symmetric regions within an image. K-mean clustering is a method of separating each class depending on the texture properties and the distance between each class and tissues. This method of segmentation was used to separate the affected part from the healthy part of the tissue, the statistical features which are calculated from co-occurrence matrix for both the right and left kidney such as energy, homogeneity, contrast, correlation, standard deviation, and mean each feature indicates the texture properties so classification of diseases. The texture of the fibrous tissue had more variation in its grey level value while the cyst texture was regular in its shape, so its variation was small; the healthy kidney was more correlated in its texture than the other cases, the lower correlation was in the cancer case. The energy value was the highest for the cyst case in which energy was high; when the number of grey levels in the image was low the texture was regular, while it has its lower value for the the fibrous tissue which had a large number of grey level values and its texture was non-regular. The last feature is the homogeneity, the healthy kidney had the highest value of homogeneity in which this feature gives in for motion about the purity of healthy texture, so is the stone case the lowest homogeneity is for the fibrosis case, the fibrosis has the highest contrast, while the stone and healthy had the lowest value, this means that the texture of fibrosis has great variation compared with stone and healthy cases. The energy of the fibrosis was the lowest one among the other cases, while the stone had the highest value, the healthy and the cyst had the highest homogeneity value, while the stone carried the lowest homogeneity. The statistical features and area of the tumor and the calculation of the area are important in the case of cancer because it helps the physician decide the appropriate radiation dose to be given to the patient and not affecting the healthy tissues. It can be concluded that k-mean clustering is a successful way to classify tissues into affected and healthy parts.

6. REFERENCES

[1] R. Dobrescu, M. Dobrescu, S. Mocanu, D. Popescu, "Medical images classification for skin cancer diagnosis based on combined texture and fractal analysis," International Journal of Wseas Transaction on Biology and Biomedicine, *" WSEAS Transactions on Biology and Biomedicine* , vol. 7, no. 3, pp. 223-232, 2010

[2] E. Kohilavani, E. Thangaselvi, and O. Revathy, "Analysis and Classification of Ultrasound Kidney Images Using Texture Properties Based on Logical Operators," *International Journal of Engineering and Technology (IJET)*, vol. 2, no. 5, 2012.

[3] E. H. Hassan, "Classification and Analysis of Kidney Images Using Texture Properties," M.Sc. thesis, University of Baghdad, 2016.

[4] D. Gadkari, "Image Quality Analysis Using GLCM," M.Sc. thesis, University of Central Florida Orlando, Florida, 2004.

[5] V. R. Patil and R. R. Manza,"A Method of Feature Extraction from Leaf Architecture," International Journal of Advanced Research in Computer Science and Software Engineering, vol. 5, no. 7, pp. 1025-1029, 2015.

[6] A. R. Raja and J. R. Ranjani, "Segment based Detection and Quantification of Kidney Stones and its Symmetric Analysis using Texture Properties based on Logical Operators with Ultra Sound Scanning," IJCA proceedings on International conference on Computing and information Technolgy, IC2IT, no. 1, pp. 8-15, 2013.

[7] R.N. Maysaa, "A Study the Change Detection in Mysan Province Using Remote Sensing Image between 2000 and 2013" M.Sc. thesis, Universtiy of Baghdad, 2015.

[8] A. Jose, S. Ravi, M. Sambath, "Brain Tumor Segmentation Using K-Means Clustering and Fuzzy C-Means Algorithms and its Area Calculation," International Journal of Innovative Research in Computer and Communication Engineering, vol.2, no. 3, pp. 2320-9801, 2014. ISSN pp:2320-9801.

[9] V. Bino Sebastian, A. Unnikrishnan, K. Balakrishnan,"Gray Level Co-occurrence Matrices:Generalisation and Some New Features,", *International Journal of Computer Science Engineering and Information Technology (IJCSEIT)*, vol. 2, no. 2, pp. 151-157, 2012.

[10] G. N. Srinivasan and G. Shobha, "Statistical Texture Analysis," *Proceedings of World Academy of Science, Engineering and Technology*, vol. 36, pp. 1264-1269, 2008.

[11] Sh. I. Abdulsalam, "Detection and Classification of Stroke Using Textural Analysis on Brain CT Digital Images," M.Sc. Thesis, University of Baghdad, 2015.

[12] K. A. Khalaph, "Detection of Brain Tumor from M.R. Images Based on Co-occurrence Matrix," M.Sc. Thesis, University of Baghdad, 2014.

[13] E. M. Hadi, "Diagnosis of Liver Tumor from C.T. Images using Digital Images Processing," M.Sc. Thesis, University of Baghdad, 2015.

[14] M. S. Mahdi, Y. M. Abid, A. H. Omran, & G. H. Abdul-Majeed, “A Novel Aided diagnosis schema for covid 19 using convolution neural network,” *IOP Conference Series: Materials Science and Engineering*, vol. 1051, no. 1, p. 012007, 2021.