Active Contour Texture Analysis: A Cutting-Edge Technique for Renal Mass Characterization

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Abstract

Objective: The number of incidental detections of solid renal masses has significantly increased in the modern period due to the growing trend of cross-section imaging. Early identification of small renal cell carcinomas influences prognosis, patient care, and medical expenses since it allows for prompt detection. Our aim is to distinguish benign and malignant renal masses by a feature extraction technique in computed tomography scan.

Methods: A retrospective study was conducted at our institution from December 2021 to December 2023 using the CT images of 100 patients. The 100 patients were categorized into two groups of 50 patients each. Group 1 had patients with benign and malignant renal masses. Group 2 served as the control group, which included kidneys from healthy individuals. The 12 gray level Co-occurrence matrix features were compared between the 2 groups and analyzed.

Results: Out of 12 parameters analyzed, six parameters (entropy, energy, inertia, sum variance, sum average, and low gray level emphasis) revealed statistically significant difference between benign and malignant renal masses ($p<0.05$). The other six parameters did not show significant difference between benign and malignant groups.

Conclusion: The study concludes by saying that fine texture features like entropy, energy, sum average, sum variance, inertia and low gray level emphasis were associated with a higher probability of diagnosis of malignant renal tumours. This study can be extended for other renal diseases such as pyelonephritis, calculus, and metastasis as well.

Keywords: Texture analysis, Active contour, Benign, Malignant, Renal mass

1. Introduction

Globally, the prevalence of renal masses is increasing overall. Solid renal masses are increasingly being detected in the first stage, particularly when the mass is tiny, thanks to improved imaging modalities and rising public health awareness. Tumours smaller than 4 cm are referred to as small kidney masses. Bells rule, though unreliable states that tumors less than 3 cm are said to be benign in nature. Around 30% of small renal masses are benign. Renal cell carcinoma (RCC) constitutes 85% of kidney tumours and 3% of all adult cancers [1, 2]. RCC usually manifests in the sixth and seventh decades of life and is largely a disease of the elderly. Race-dependent incidence rates have been observed to be 10–20% higher among African Americans for unidentified causes [3]. Men are more likely than women to develop renal cell carcinoma (RCC), with a 1.6:1 ratio. Two percent of kidney tumours are bilateral, despite the fact that the majority are unilateral. Because it is particularly challenging to figure out whether renal tumours are benign or malignant prior to surgery, managing them is more complicated. We have been able to distinguish between benign and malignant kidney tumours and make pre-operative diagnosis with the help of advanced Computed Tomography (CT)- aided categorization methods.

A common method for confirming the diagnosis of renal masses is the CT scan. Malignant tumours make for about 85% of solid kidney masses. However, there will occasionally be a diagnostic conundrum when using these CT scans to make a firm diagnosis. In these cases, several image processing techniques can be used to improve the quality to better interpret hidden information and extract certain features which helps in arriving at a conclusive diagnosis.

Texture analysis is one of the feature extraction techniques like edge detection, blob detection and transform-based features, used in image processing. Renal tumour, normal parenchyma, and surrounding organs are all often segmented using computer-aided diagnostic (CAD) systems. The red, green, and blue input image is transformed into a grayscale image that aids in the identification of anomalies and lesions and offers anatomical information. Our goal is to find whether different criteria can help differentiate between benign and malignant renal tumours in CT by using the texture analysis feature extraction method.

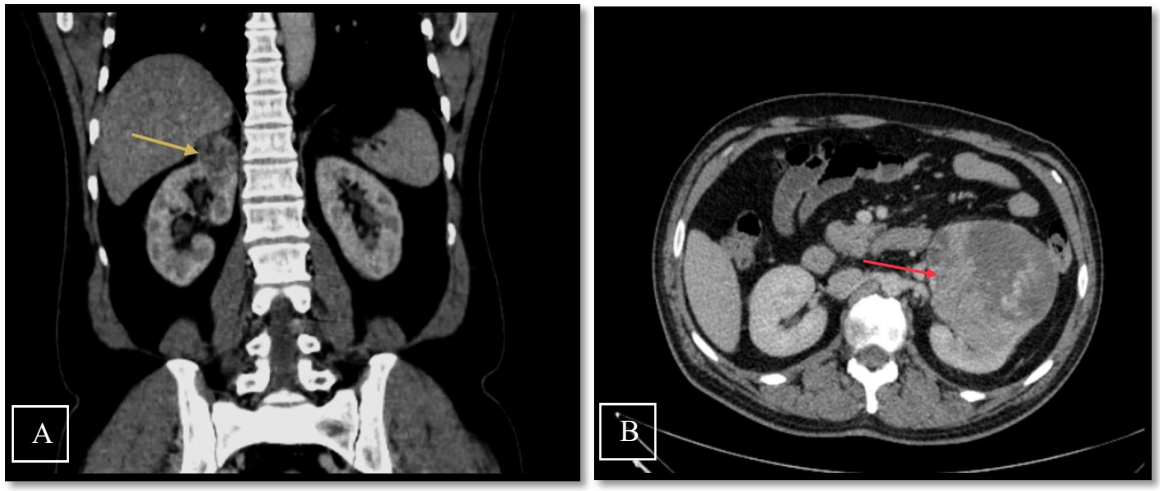
2. Materials and Methods

2.1. Study design

This was a retrospective study conducted at our institution from December 2021 to December 2023 using the CT images of patients. The study was approved by the Institutional Ethics committee. Our study includes around 100 contrast-enhanced abdomen CT scans. Two groups of 50 patients each were formed from the 100 patients.

Of the individuals with renal masses in Group 1, 11 were benign and 39 were malignant. In almost all of the cases, renal cell carcinoma was the histology of the malignant group. It was discovered that the 11 patients with benign tumours had either oncocytoma, adenomas, or angiomyolipoma. Group 2 served as the control group, and kidneys from healthy individuals who had been screened for other conditions were compared. Figure 1 illustrates CT abdomen depicting a large left malignant renal mass. Figure 2 illustrates CT abdomen depicting a small right benign renal mass.

Fig. 1: A) CT abdomen image of a patient with right benign renal mass (red arrow). **B)** CT abdomen image of a patient with left malignant renal mass (yellow arrow).



2.2. Inclusion criteria

All benign and malignant solid renal masses, confirmed on CT image.

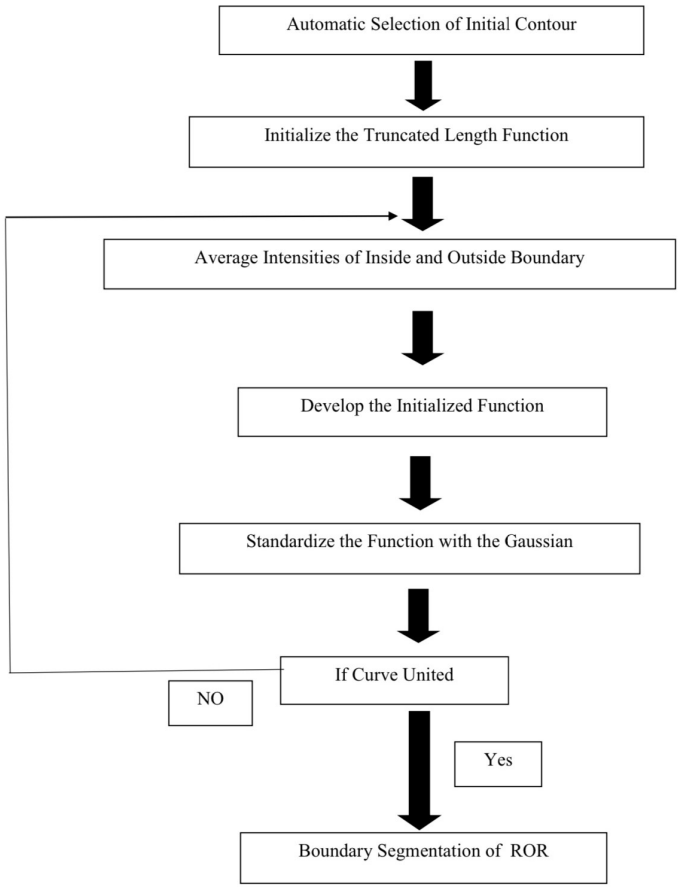
2.3. Exclusion criteria

1.All cystic renal masses

2.Neither a nephrectomy nor a percutaneous biopsy produced tissue confirmation.

There is an inherent error in how the human eye interprets CT scans. There are numerous enhancing benign masses and non-enhancing malignant masses that can seriously confuse the interpretation of the naked eye, even though enhancement is thought to be an entity that strongly favours malignancy. An improved automatic renal segmentation is therefore required because this could result in a misdiagnosis.

Fig. 2: Illustration of current workflow.



2.4 Technique

The active contour method is a technique that uses contour segmentation of the same pixels to create a boundary shape that resembles a snake. The snake model will display the curve's

beginning and ending points. With a signed pressure force, the snake model produced an approximate boundary form. The following are the different elements of the active contour method

2.4.1 Preprocessing

Despite their widespread use, deformable model-based techniques are ineffective when dealing with diffused boundaries, high picture noise, or low image resolution. Certain preprocessing approaches must be used to evacuate noise from such medical images. Through contrast enhancement and noise reduction, the Weiner filter is used to develop the image's character.

2.4.2 Segmentation

Simplifying the image to make it easier to analyze and more meaningful is the aim of segmentation. Technically, image segmentation is used to identify boundaries (lines, curves, etc.), objects of interest, and the infiltration of nearby organs.

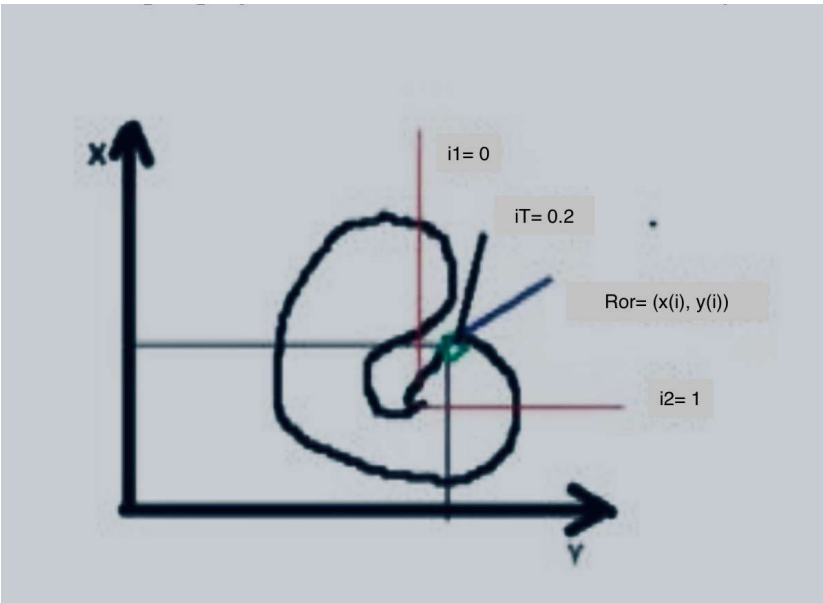
2.4.3 The Active Contour Approach

The energy-minimizing spline known as the "active contour method" finds the necessary features in an image. It is a bendable curve that can be actively reshaped to fit the necessary edges or objects in a picture. There are 4 processes in active contour method.

i). Basic curve form of active contour -

With the signed pressure force of the default iteration, Figure 3 shows the curve's beginning point at i1=0 and its extension to the same pixel region with threshold iT=0.2. The curve within the function of x(i), y(i) defines the contour. The value ranges from 0 to 1 is represented by the character "i." It reduces the energy, where E (energy) = Eint + Eext, where Eext is the curve's propagation towards the object edges and Eint is the internal energy of the curve that expands or contracts in the contour and smooths the curve.

Fig. 3: Curve form of active contour in XY axis



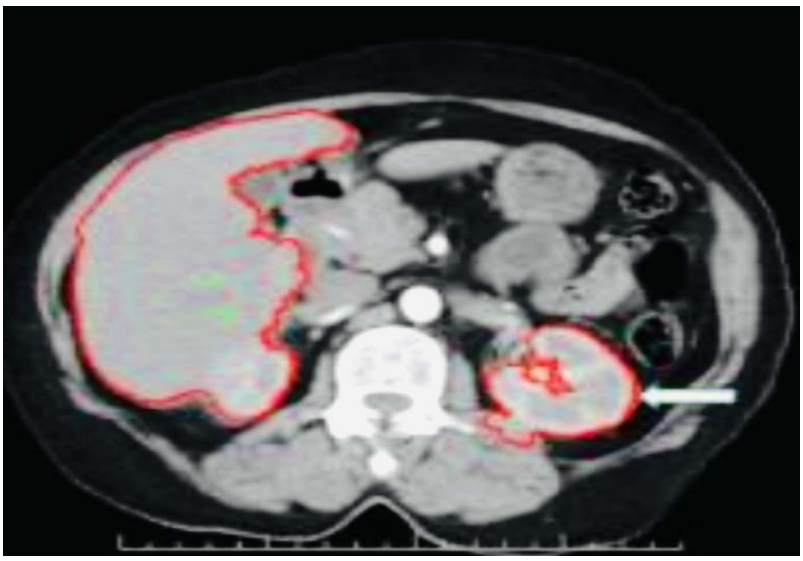
ii). Seed point selection –

Uncontrolled cells in the control region protrude into nearby organs that share characteristics with the renal lesion location. The test's lesion region was retained while the control regions were eliminated based on the K-Nearest Neighbours Algorithm (KNN) classification [23]. Effective seed sites should be chosen in this regard to eliminate the control region.

iii). Region increasing segmentation –

The snake model detection roaming approach yields a smooth border. The filtered image's closed curve contour, which represented the estimated mass's border, was extracted using the active contour approach. Every image has a defined zone of interest with the same pixel intensity. Accurate classification of benign and malignant images is achieved. Nonetheless, the seed points serve as the active contour's initial contour. The minimal fitting length affects the active contour method's accuracy. A quick balloon tracking system of a boundary is used because the minimum fitting length results in high pressure of the optimal threshold with a closed curve of lesion. An illustration of the suggested contour method's overview is shown in Figure 4.

Fig. 4: Overview of proposed contour method.



iv). Extraction of Features –

One popular study metric linked to spatial texture is the Gray Level Co-occurrence Matrix (GLCM). When compared to other texture characters, the results from the co-occurrence matrices are of extremely high quality. The statistical parameters are entropy, energy, inertia, sum variance, sum average, low gray level emphasis, kurtosis, run emphasis (short and long), run percentage, homogeneity, and correlation of the sample textures. Entropy is the measure of randomness of intensity image. Energy is the texture uniformity. Inertia is the intensity contrast between a pixel and its neighbourhood. Sum variance measures the texture heterogeneity. Kurtosis is the peakness of the distribution of values in the image region of interest. Short run emphasis measures the texture sharpness and long rum emphasis measures the texture roughness. Run percentage measures the texture sharpness homogeneity. Correlation is the relation of the pixel to its neighbourhood. Texture analysis, image segmentation, retrieval, analysis, and classification can all benefit from the usage of GLCM. Only six of the twelve GLCM parameters were chosen for our investigation since they were shown to be statistically significant. The factors that often differentiate the control group from the benign and malignant groups were analyzed.

2.5. Statistical analysis

Data analysis of significant difference ($p<0.05$) for each parameter was individually formulated with the help of Sigma Stats 4.0 software. The test of hypothesis was conducted to identify the significant difference between the parameters of benign and malignant lesion. The p-value of less than 0.05 is said to be statistically significant.

3. Results

3.1. Number of patients

100 patients were included which were divided into two groups (tumour group and control group) of 50 patients each. Tumour group had 39 patients (78%) with malignant renal mass and 11 patients (22%) with benign renal mass.

3.2. Age

The mean age in tumour and control group was 53.56 and 45.56 years, respectively.

3.3. Gender

Out of 50 patients in control group, 28 were female (56%) and 22 were male (44%). Out of 50 patients of tumour group, 14 were female (28%) and 36 were male (72%).

3.4. CT imaging features

For the study, 12 CT imaging characteristics were taken into account. These 12 measures were used in the study of all 50 patients with renal masses and the remaining 50 patients in the control group. These parameters are compared between the benign, control, and malignant groups in Table 1. Table 1 made it clear that the first six parameters displayed statistically significant data, which aids a clinician in distinguishing benign from malignant renal masses.

1) Entropy

2) Energy

3) Sum average

4) Sum variance

5) Inertia

6) Low gray level emphasis

To distinguish between benign and malignant renal masses, the remaining six indicators (7–12) were not as useful. This shows unequivocally that, the first six criteria are important enough to imply that benign kidney masses can be easily distinguished from malignant ones using a non-invasive CT imaging.

Table 1: Parameters extracted by texture analysis in control, benign, and malignant group.

S. no	Parameters (No. Of Subjects)	Control (50) Mean ± S.D	Benign (11) Mean ± S.D	P-value	Malignant (39) Mean ± S.D	Control (50) Mean ± S.D	P-value	Benign (11) Mean ± S.D	Malignant (39) Mean ± S.D	P-value
1	Entropy	0.670 ±0.14	0.61 ±0.13	0.002	0.9638 ±0.46	0.670 ±0.14	0.021	0.61 ±0.13	0.9638 ±0.46	0.022
2	Energy	1.0005 ±0.001	1.0041 ±0.0002	0.01	1.0040 ±0.005	1.0005 ±0.001	0.01	1.0041 ±0.0002	1.0040 ±0.005	0.004
3	Sum Average	0.389 ±0.18	0.337 ±0.13	0.042	0.4031 ±0.25	0.389 ±0.18	0.004	0.337 ±0.13	0.4031 ±0.25	0.036
4	Sum variance	2.602 ±2.23	1.8863 ±0.86	0.014	2.9512 ±0.6	2.602 ±2.23	0.028	1.8863 ±0.86	2.9512 ±0.6	0.001
5	Inertia	0.1595 ±0.077	0.1412 ±0.04	0.026	0.16827 ±0.05	0.1595 ±0.077	0.04	1.1412 ±0.04	0.16827 ±0.05	0.002
6	Low Gray level Run Emphasis	142.71 ±3.80	134.62 ±19.56	0.038	139.71 ±35.41	142.71 ±3.80	0.03	134.62 ±19.56	139.71 ±35.41	0.026
7	Kurtosis	1.0623 ±0.03	1.1163 ±0.61	0.407	1.0470 ±0.015	1.0623 ±0.03	0.068	1.1163 ±0.61	1.0470 ±0.015	0.470
8	Short Run Emphasis	0.480 ±0.014	0.4814 ±0.04	1.00	0.4983 ±0.05	0.480 ±0.014	0.156	0.4814 ±0.04	0.4983 ±0.05	0.362
9	Run percentage	0.1216 ±0.007	0.1244 ±0.04	0.359	0.3367 ±0.27	0.1216 ±0.007	0.303	0.1244 ±0.04	0.3367 ±0.27	0.39
10	Long run Emphasis	4054 ±288	4443 ±274	0.992	2713 ±1098	4054 ±288	0.490	4443 ±274	2713 ±1098	0.92
11	Correlation	0.883 ±0.052	0.8371 ±0.03	0.454	0.9101 ±0.05	0.8883 ±0.052	0.618	0.8371 ±0.03	0.9101 ±0.05	0.14
12	Homogeneity	0.9624 ±0.004	0.9513 ±0.01	0.646	0.9839 ±0.004	0.9624 ±0.004	1.00	0.9513 ±0.01	0.9839 ±0.004	0.202

4. Discussion

Malignant renal neoplasms account for 1-2% of all visceral cancers. They are usually seen in older individuals, above sixth decade. RCC shows a male predominance with a ratio of 3:1 [4]. The major risk factors are smoking, obesity, family history of the disease and hypertension [5]. Most common presentation of RCC is asymptomatic, with the tumour being diagnosed incidentally on CT abdomen imaging done for other complaints [6]. Plain and contrast enhanced CT abdomen is the confirmatory imaging for detection of the renal masses. They can be performed from every 3 to 6 months to annually or every two years based on the size of the tumour, family history and its associated syndromes. Jayson et al described that, due to the availability of advanced imaging techniques and improved health cognizance among the population, solid renal masses are easily diagnosed in the initial stages,

particularly when the size of the tumour is less [7]. Contrast CT abdomen usually shows the tumour and its associated characteristics, presence of other tumour(s) in the affected and contralateral kidney, periureteric and perinephric events, renal vein and IVC status, presence of tumor thrombus, lymph node status, and suspicious metastatic lesions elsewhere in the body.

Region of interest (ROI) is the origin of boundary segmentation followed by feature extraction, which helps in catching the visual content of the images for identification and retrieval. Tony Chan & Luminita Vese made a contemporary design for active contours to find objects in an image, relying on the methods of curve evolution [8]. It is not necessary to smooth the initial image, despite being noisy, as the boundary locations are well detected and maintained. Automatically detected interior contours start with only one initial curve. The location of the initial curve can be anywhere in the image and not needed to surround the objects to be identified. In 2010, Gao et al. Suggested renal segmentation from CT films, and it is done manually or semi-automatically due to the gray-levels similarities of adjacent organs, contrast media effect and high variation of organ's positions and shapes in abdominal CT images [9]. The methodology used in this work combines two distinct steps of image processing techniques with anatomical information. First, the predicted kidney position is extracted using an enhanced connected component labelling technique based on the intensity value. This method uses the location of the kidney and spine to work with abdomen CT scans of varying sizes. In the second step, fine kidney areas are extracted using a unique region-growing technique based on the labeling algorithms.

Kobashi and Shapiro et al. described a knowledge-based method for detecting and extracting kidney organs from normal CT images [10]. The developed method explained the anatomical information, detection, and extraction of kidney from normal CT image. Hetal and Astha Baxi proposed Otsu segmentation method for image processing for the evaluation of maximum criteria between class variance to enhance the contrast by applying threshold [11]. Kim et al. proposed a kidney segmentation method depending on the pixel value distribution of the internal organs and the operation is purely of the mesh form [12]. In 2017, Hang sang lee et al. Found a method for the detection and segmentation of Small Renal Masses (SRMs) in contrast-enhanced CT images. An active contour method segmented the SRM with texture sensitivity and specificity of 89.91% and 98.96%, respectively. Kim proposed a gray level threshold method to detect and segment the tumor in kidney using CT film digitizer of transverse images [13]. The region growing method is applied to merge the neighbouring as

the kidney tumor boundary and the segmented tumor obtained the sensitivity of 85% and no false positive ratings. Rao explained the GLCM that enumerates the statistical parameters shown on gray level intensities of the image [14]. Such a characteristic of the GLCM is helpful in the texture recognition, image segmentation, image retrieval, colour image analysis, image classification, object recognition and texture analysis methods. Haralick derived a set of 14 GLCM texture features with the help of gray-tone spatial-dependence matrices, essential for the 2D gray-level displacement vectors [15]. Hamida et al. in 2021 developed the Spatial Gray-Level Dependence Matrices (SGDLM) using active contour method to segment the solid renal masses. This method's output performs with a well-defined threshold for the classification of renal lesions.

In 2009, Lunt and Nelson et al conducted a whole- tumour volumetric textural analysis using GLCM and shown that tumours exhibiting more heterogeneity had increased chances of being malignant [16]. Cui et al. proposed several studies suggesting that malignant tumours display heterogeneity [17]. In 2010, Ganeshan et al. did a study on non–small cell lung cancer and described that, in the CT texture analysis without enhancement, there was also a negative correlation between the tumor stage and coarse texture uniformity. [18]. Ruchi Luhadiya & Anagha Khedhar in 2016 proposed iris segmentation with the preprocessing steps, and the gray level run length matrix (GLRLM) features are extracted given as input to the KNN classifier [19]. The smoothing operation is carried out by the Gaussian filter using 2D convolution operator to remove the blurring noise. The run length matrices gave the maximum accuracy of 92.66%. Mohanaiah et al. explained an application of GLCM to extract second order texture features for the evaluation of motion images [20]. The extracted texture features having high discrimination accuracy and computation time were reduced to only four features extracted. The extracted features are useful in various applications of real time pattern assessment. Jicksy Susan Jose et al. explains the implementation of Computer-Aided Diagnosis (CAD) for diagnosis and classification of kidney images using association rule-mining method, which is preprocessed to enhance and extract the features for the diagnosis of US kidney images [21]. The earlier works focused on manual segmentation of solid renal masses in CT and only histopathology parameters are shared for the accuracy. This novel approach could be helpful in boundary detecting and classification of renal lesions accurately.

5. Conclusion

There is an ever-increasing awareness amongst the medical fraternity that a substantial proportion of small and solid renal masses may be benign. Though imaging can diagnose most of them, some are mistakenly believed to be renal cell carcinoma landing up in doing unnecessary surgeries. With recent advances in medical imaging techniques and progress in the field of molecular biology, it is convincing that renal imaging may be considered for selected patients with small renal masses in whom it might impact the clinical management. Our study concludes that parameters like entropy, energy, sum average, sum variance, inertia and low gray level emphasis were linked to an increased likelihood of diagnosing malignant tumours. In future, this study can be extended for other renal diseases such as pyelonephritis, calculus, necrosis, and metastasis etc. because this method is based on the characteristics of CT imaging and can be easily adjustable for other images as well.

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Author contributions

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