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Characterization of Renal Parenchymal Lesions on Computed Tomography Images utilizing higher order texture features

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Abstract:
Background*: Globally, the incidence of renal cell carcinoma (RCC) varies widely from region to region (1), with the highest rates observed in the Czech Republic and North America (2). In the United States, there are approximately 76,000 new cases and almost 14,000 deaths from RCC each year (3). Worldwide, in 2018, there were an estimated 403,000 new cases of RCC and 175,000 deaths due to kidney cancer (4), that makes studies that aids effective diagnosis highly valuable; as the analysis of texture parameters is a useful way of increasing the information obtainable from medical images, hence it has been chosen by the researcher to study renal parenchymal diseases considering that there is only few previous studies considered the method including a recent one conducted by the researcher using first order features ; which guided the researcher to use the current more specific approach.*
Materials and Methods*: In this retrospective case series study, 108 computed tomography axial non-enhanced renal parenchyma images of normal tissue individuals, cyst affected group and renal cell carcinoma patients were chosen; the data afterwards processed using Interactive data language program (IDL) implementing higher order statistics.*
Results*: the classification showed high discrimination power of the textural features:*
Long runs emphasis, Gray Level Non-uniformity, Run Length Non-uniformity, Run Percentage, low Gray Level Run Emphasis, High Gray Level Run Emphasis, Short Run Low Gray Level Emphasis, Long Run Low Gray Level Emphasis.
The accuracy of those features were (93.7%);the sensitivity of discriminating normal renal parenchyma was (94.5%), (96.6%) for renal cysts and (91.6%) for renal cell carcinoma.
Conclusion: *The three chosen groups (normal renal parenchyma, renal cysts and renal cell carcinoma group) were classified accurately by 93.5% by the created model.*
Abbreviations: GLRLM: Gray level run length matrix; LRE: Long Runs Emphasis; SRE: Short Runs Emphasis; GLN: Gray Level Nonuniformaity; RLN: Run Length Non-uniformity; RP: Run Percentage; LGRE: Low Gray Level Run Emphasis; HGRE: High Gray Level Run Emphasis; SRLGE: Short Run Low Gray Level Emphasis; SRHGE: Short Run High Gray Level Emphasis; LRLGE: Long Run low Gray Level Emphasis, LRHGE: Long Run high Gray Level Emphasis(10);PACS: picture archiving and communication system.
Key Word*: texture analysis; renal cell carcinoma; renal cyst; higher order; CT; texture feature model; GLRLM.*

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I. Introduction

In 2018, renal cell carcinoma (RCC) accounted for 403,300 newly diagnosed cancer cases and 175,100 deaths worldwide (4). In the United States alone, RCC is the sixth most common cancer in men and eighth in women, accounting for 5% and 3% of all newly diagnosed cases annually, respectively (5). An increasing incidental detection of renal masses with cross-sectional imaging led to the diagnosis of more asymptomatic, small, and clinically localized renal masses. Small renal masses (SRMs), defined as ≤4 cm in diameter, account for more than 50% of all renal masses, approximately 10–30% of which result in benign histology (7,8). The diagnosis of SRMs carries the risk of subjecting patients to unnecessary procedures and over-treating lesions that may not progress.(6)

The analysis of texture parameters is a useful way of increasing the information obtainable from medical images. It is an ongoing field of research, with applications ranging from the segmentation of specific anatomical structures and the detection of lesions, to differentiation between pathological and healthy tissue in

different organs. Texture analysis uses radiological images obtained in routine diagnostic practice, but involves an ensemble of mathematical computations performed with the data contained within the images. (9). However, texture analysis is most important for those cases in which change cannot be detected by direct inspection of the image. For example, in some conditions the tissue of associated anatomical structures suffers alterations. These can normally be detected by histological examination, but sometimes not by visual inspection of the image of the tissue, whereas they may be demonstrated by statistical analysis of the pixel distribution in the image of the structure. (9)

As texture analysis becomes a highly effective tool in diagnosing medical images and the available data about normal kidneys or renal parenchymal disease is very few this research becomes necessity to provide such valuable data to medical community.

II. Material And Methods

In this retrospective case series study, 108 computed tomography axial non-enhanced renal parenchyma images of normal renal tissue, cystic lesions and renal cell carcinoma affected tissues were chosen; the data afterwards processed using Interactive data language program (IDL) implementing higher order statistics (GLRLM), data collected from August 2020 to December 2020.

Study Design: retrospective case series study.
Study Location: study conducted at two institutions radiology departments.
Study Duration: August 2020 to December 2020.
Sample size: 108 computed tomography images.
Sample size calculation: The sample was convenient random sample.
Subjects & selection method:
Study subjects (CT axial sections) were selected from PACS system of the two selected institutes including all the available images considering the following criteria:

Inclusion criteria:

- Only axial sections from the data set were chosen.
- Non-enhanced CT images (pre-contrast images).
- Images that contain the tissue of interest (renal parenchyma).
- Images that manifested one of the selected classes (normal parenchyma, simple renal cyst, renal cell carcinoma)

Exclusion criteria:

- Non axial sections (coronal or Sagittal).
- After contrast images of the same selected cases.
- Images that don't reveal any of the selected tissue (renal parenchyma) or that demonstrate other pathologies other than the selected (eg. Complicated cysts, benign tumor or renal stone).

Procedure methodology

After written informed consent was obtained with the radiology department staff, CT images for the target sample individuals has taken using CD-roms, then transferred to dedicated CT work station to be processed using RadiAnt DICOM Viewer (32-bit) and then texture features were extracted using interactive data language program (IDL) the quantitive features chosen were (Gray level run length matrix, Long Runs Emphasis, Short Runs Emphasis, Gray Level Nonuniformaity, Run Length Non-uniformity, Run Percentage, Low Gray Level Run Emphasis, High Gray Level Run Emphasis, Short Run Low Gray Level Emphasis, Short Run High Gray Level Emphasis, Run low Gray Level Emphasis, Long Run high Gray Level Emphasis(5)).

Statistical analysis

Data was analyzed using SPSS version 20 (IBM SPSS Statistics 20) stepwise method for fishers discriminant function.

III. Result

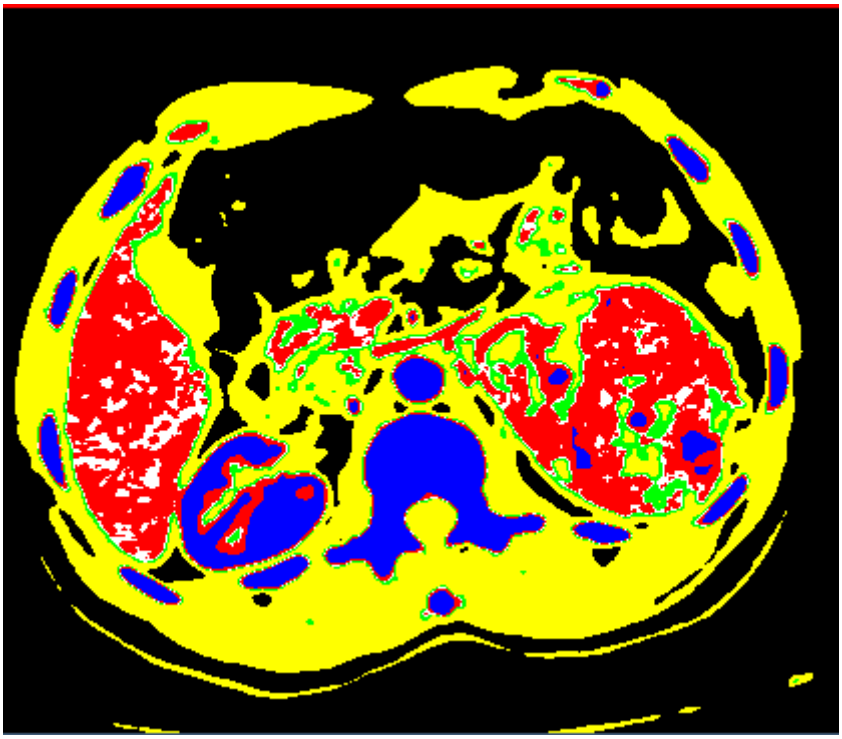

Figure (1): classification map shows discrimination power of the texture features.

Table (1): Cross-tabulation table show the classification results for the three predefined groups (Normal renal parenchyma, renal cyst and renal cell carcinoma) using Fisher's linear discriminant functions.

Classification Results

Classes			Predicted Group Membership			Total
			Normal	cyst	RCC	
Original	%	Normal	94.5	.0	5.5	100.0
		cyst	.0	96.6	3.4	100.0
		RCC	.0	8.4	91.6	100.0

93.7% of original grouped cases correctly classified.

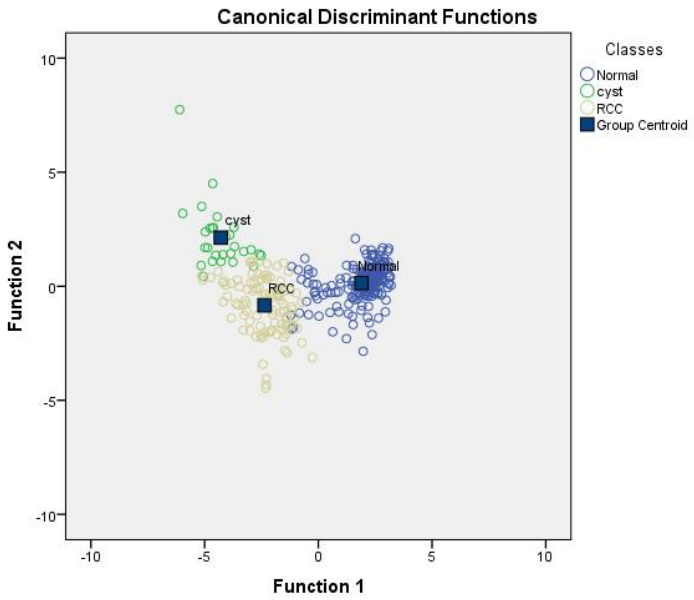

Figure (2): scatter plot shows the discrimination power of the extracted features between the three predefined groups (Normal renal parenchyma, renal cyst and renal cell carcinoma)

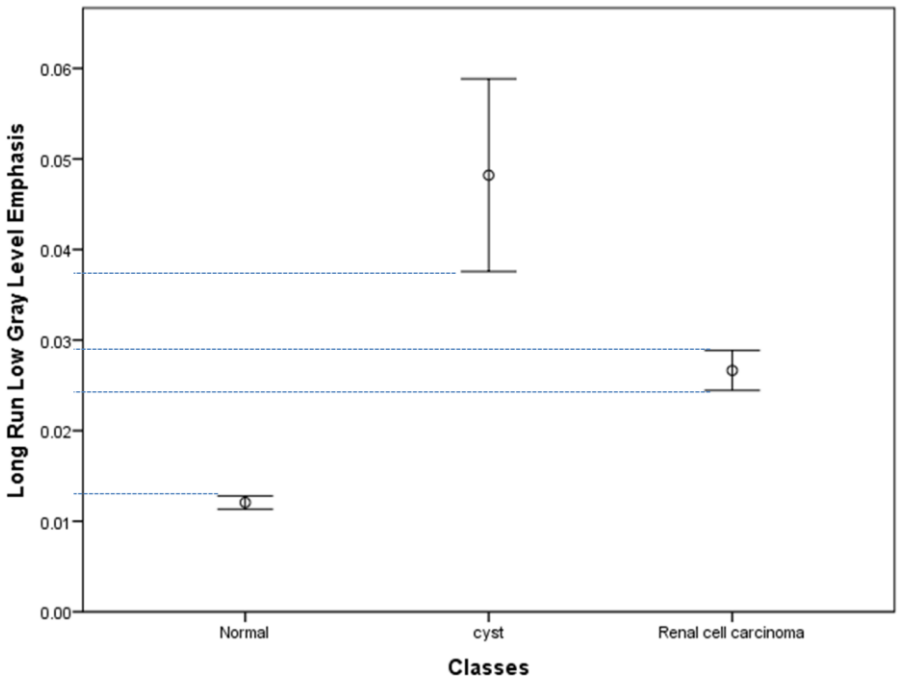

Figure (3): error bar plot shows the discrimination power of (long run low gray level emphasis) textural feature for the selected classes.

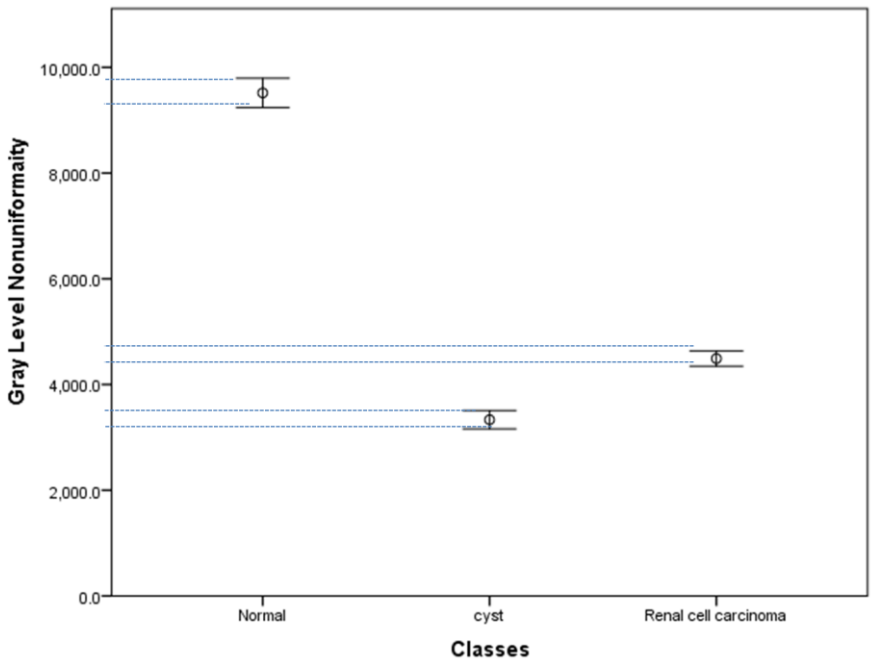

Figure (4): error bar plot shows the discrimination power of (gray level nonuniformaity) textural feature for the selected classes.

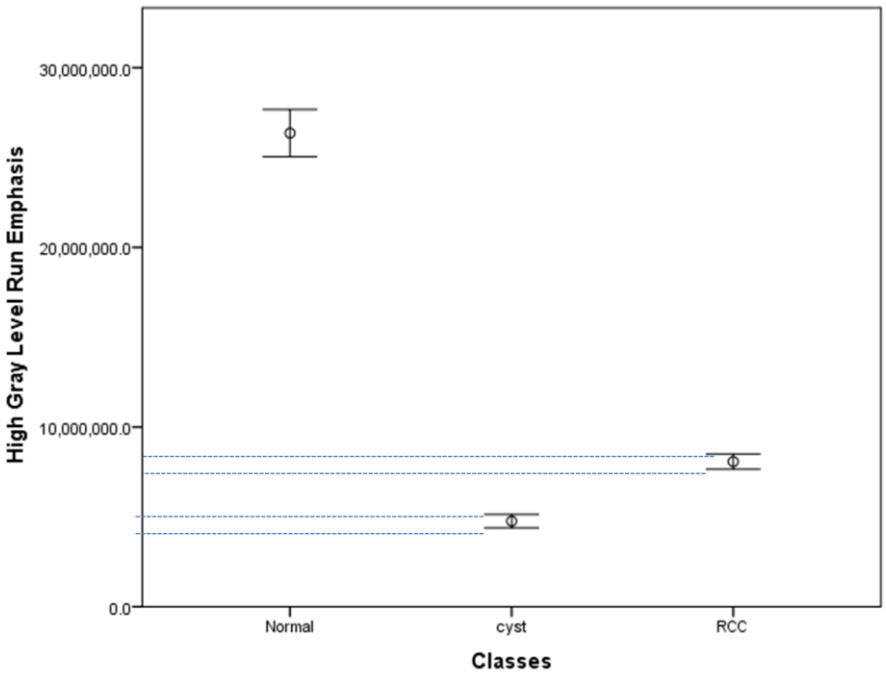

Figure (5): error bar plot shows the discrimination power of (high gray level run emphasis) textural feature for the selected classes.

IV. Discussion

The study primary objective is characterization of renal parenchymal lesions using higher order (***GLRLM***) statistical textural features extraction (Gray level run length matrix, Long Runs Emphasis, Short Runs Emphasis, Gray Level Nonuniformaity, Run Length Non-uniformity, Run Percentage, Low Gray Level Run Emphasis, High Gray Level Run Emphasis, Short Run Low Gray Level Emphasis, Short Run High Gray Level Emphasis, Run low Gray Level Emphasis, Long Run high Gray Level Emphasis (10)).

The first figure **(figure (1))** demonstrating the ability of the classification features in discriminating between different tissue types.

The following (**Table (1)**) conveyed the discrimination power of the textural features (Gray Level Nonuniformaity, Long Runs Emphasis, Run Length Non-uniformity, Run Percentage, Low Gray Level Run Emphasis, High Gray Level Run Emphasis, Short Run Low Gray Level Emphasis, Long Run Low Gray Level Emphasis) which is 93.7% accuracy in defining the groups under-study following these Linear equations extracted from Fisher's linear discriminant functions:

Normal renal parenchyma = (LRE * -11.424470) + (GLN * 0.093014) + (RLN * 41.877870) + (RP *1193.946625) + (LGRE*73.370314) + (HGRE* -0.000020) + (SRLGE*-3353.452193) + (LRLGE*853.723392) -767.560415

Renal cyst = (LRE * -15.937197) + (GLN * 0.078070) + (RLN * 41.8778765.891924) + (RP *1101.304211) + (LGRE *50.693993) + (HGRE * -0.000017) + (SRLGE *-3594.747040) + (LRLGE *1382.857013) -667.064920

Renal cell carcinoma = (LRE * -10.799956) + (GLN * 0.082665) + (RLN * 35.043366) + (RP *1145.442370) + (LGRE *57.256567) + (HGRE * -0.000018) + (SRLGE *-3143.513506) + (LRLGE *925.708968) -670.091648

(**Table (1)**) also showed that the accurately classified normal tissue (94.5%) commencing a high sensitivity with (5.5%) false negatives and high specificity with (0%) false positives, (96.6%) correctly classified cystic lesion with (3.4%) false negatives and (8.4%) false positives, and finally (91.6%) of renal cell carcinoma tissue correctly classified and the sensitivity of the model in predicting this tissue was high with (8.4%) false negatives and (5.5% + 3.4% = 8.9%) false positives indicating high specificity.

Scatter plot for the study groups **(Figure (2))** proved that no interference between cyst and normal tissue in classification with a very minor interference between RCC group and both normal and cystic lesions.

(Figure (3)) conveyed that **LRLGE** as a textural feature has differentiated the three studied groups with no interference and with confidence interval of (95%). The normal tissue showed the minimum **LRLGE**, renal cell carcinoma manifested the middle level and the cystic lesion possessed the highest values.
(Figure (4)) exhibited matching results for **GLN** feature with the cystic lesion possessing the least values of **GLN**, RCC occupying the middle level and the normal owning the highest value.
(Figure (5)) exhibited that no intercession between groups and values arranged from the minimum to the maximum employing **HGRE** as follows: RCC, cystic lesion, Normal renal parenchymal tissue.
This study has provided a more specific approach in describing the normal renal tissue, cystic lesion and RCC lesion conducted using higher order (**GLRLM**) features than the previous work done by the researcher employing the first order textural features (11), as it normally provide higher discrimination indexes.
In comparison to previous study conducted by Siva P. Raman et. al. (12) their work had a similar general objective of creating a model that describe renal lesions with being different in the texture parameters as they employed Random forest method to construct a predictive model to classify lesions, also they used a different texture analysis aiding software (CTTA) and for statistical analysis they employed (S-Plus; TIBCO Software, Palo Alto, CA and R) their elaborated model correctly categorized oncocytomas in 89% of cases (sensitivity = 89%, specificity = 99%), clear cell RCCs in 91% of cases (sensitivity = 91%, specificity = 97%), cysts in 100% of cases (sensitivity = 100%, specificity = 100%), and papillary RCCs in 100% of cases (sensitivity = 100%, specificity = 98%)(12) ; it was slightly less in overall accuracy than the generated model in this study (93.7%) , but in consideration to their pre-classifiction for the data set it gave a more accurate picture of the ability of the texture feature to be valuable in further definition of a cases that very difficult to be differentiated in the qualitative methods.

V. Conclusion

The three chosen groups (normal renal parenchyma, renal cysts and renal cell carcinoma group) were classified accurately by 93.5% by the created model.

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