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Characterization of Kidney Infection in Ultrasound B-mode Images Using Texture Analysis

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Abstract: ***The general objective of this study was to develop an algorithm that can extracted textural features from ultrasound images of normal and abnormal kidneys in order to classify these images as having normal tissues, glomerulonephritis, or pyelonephritis. Linear discriminant analysis was used to classify the extracted features from the medulla and pelvic calycle system of kidneys ultrasound images. The results of the study showed that the overall accuracy using medulla texture equal to 98% while for those extracted from pelvic calycle system was 95.7. In conclusion linear function was developed to classify other ultrasound images with an error <5%.***

Keywords: B-mode ultrasound, Kidney, Texture Analysis, Feature Extraction.

1. Introduction

Texture analysis is an essential issue in image processing. It comprises a set of mathematical techniques used to quantify the different gray levels within an image in terms of intensity and distribution. Texture represents the spatial arrangement of pixels' gray levels in a region. So, it can be divided into two classes: periodic texture and random texture. Consequently, we can distinguish the structural approaches and the statistic approaches to calculate a number of mathematical parameters that characterize the texture. Structural approaches are more suited to the study of periodic or regular textures. However, statistic approaches are used to characterize fine and non-homogeneous structures without apparent regularity. That is why; this type of method is generally applied in medical imaging [7]. A statistical approach perceives a texture as a quantitative measure of the arrangement of intensities in an area. Statistical methods can be categorized into first order, second-order and higher-order and spectral statistics, based on the number of pixels used to define the feature. [10]

First order statistics measures (FOS) based on the image histogram to calculate texture. The main advantage of this approach is its simplicity through the use of standard descriptors (e.g. mean and variance) to characterize the data. For any surface, or image, grey-levels are in the range $0 \leq i \leq Ng - 1$, where Ng is the total number of distinct grey-levels. If N (i) is the number of pixels with intensity i and M is the total number of pixels in an image, it follows that the histogram, or pixel occurrence probability, is given by,

$$P(i) = \frac{N(i)}{M}.$$

The main image processing discipline in which texture analysis techniques are used are classification, segmentation and synthesis. In image classification the goal is to classify different images or image regions into distinct groups [12]. Texture analysis methods are well suited to this because they provide unique information on the texture, or spatial variation of pixels, of the region where they are applied. In image segmentation problems the aim is to establish boundaries between different image regions. Synthesizing image texture is important in three-dimensional (3D) computer graphics applications where the goal is to generate highly complex and realistic looking surfaces. [13].

In general seven features commonly used to describe the properties of the image histogram, and therefore image texture, are computed. These are: mean; variance; coarseness; skewness; kurtosis; energy; and entropy. [11]

This study was intended to use these feature in classification and characterization of B-mode ultrasound of the kidneys in order to distinguish between the normal and abnormal (Glomerulonephritis, and pyelonephritis) where the infection of the kidney can affect both kidney morphology and image appearance rather than the normal one.

2. Material and Method

The data of this study consisted of 234 patients 106 with normal kidneys, 128 patients had renal infections; 68 diagnosed with glomerulonephritis and 60 with pyelonephritis using ultrasound and medical laboratory tests. Textural features that represent the first order were extracted from the medulla and pelvic calycle system from the three groups, these features include mean, standard deviation, signal to noise ratio, energy and entropy using a window of 3×3 pixel from all data set using medulla and pelvic calycle system as Region of Interest (ROI) through an algorithm written in Interactive Data Language (IDL) software.

The extracted features were classified using stepwise linear discriminant analysis using medulla and pelvic calycle system as separate data set where each include the previous three groups; in order to find the most discriminant textural feature in each set as well as the classification accuracy and sensitivity concerning the characteristics of each set.

3. Results and Discussion

A. Result of Medulla:

The result of the classification concerning the textural feature extracted from the first set (medulla) showed that, the normal kidneys, and those with glomerulonephritis and pyelonephritis were classified with an accuracy of 94.9%, 97.3% and 99.5% (Table and Figure 1); which means there is a heir sensitivity in classification of pyelonephritis, where it make the medulla texture look very different than the result of the groups followed by glomerulonephritis which in some cases falsely classified as pyelonephritis (2.7%), with an overall classification accuracy of 98%. The most discriminant features as shown in Figure 2 (A, B and C) were mean, signal to noise ratio and entropy. The textural feature mean discriminant between the normal and abnormal medulla in the kidney; where the mean signal intensity in the normal medulla were lower than that of the abnormal one; since complexity of the texture were less. Similar essence were exist in case of signal to noise ratio and entropy for the normal medulla while glomerulonephritis scored the higher textual values than that pyelonephritis; which means glomerulonephritis affected medulla more than pyelonephritis hence the textural feature of the glomerulonephritis were different than the rest of the tissues.

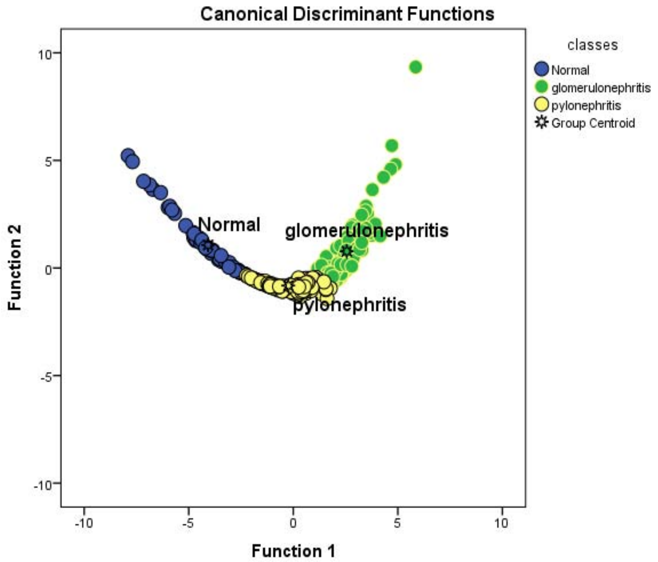
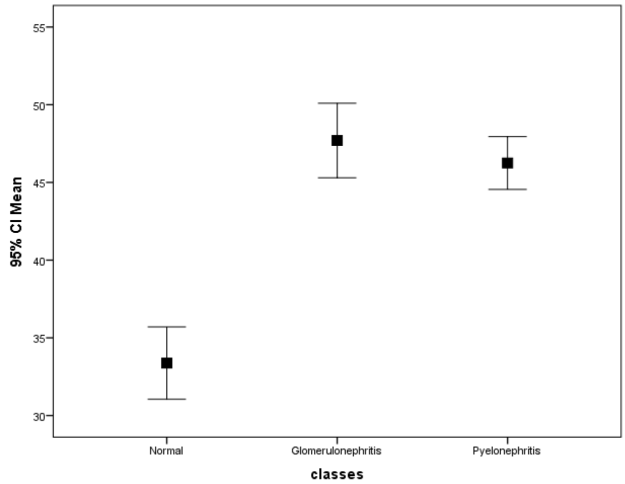


Figure 1: Scatter plot show the classification of textural feature of the kidney medulla classes (normal, glomerulonephritis and pyelonephritis) using linear discriminant analysis

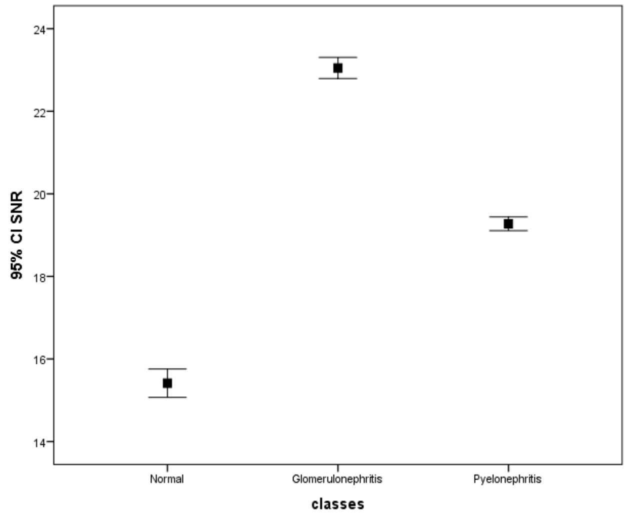
Table 1: A confusion matrix shows the classification accuracy of the selected textural features for the medulla in the normal kidney and glomerulonephritis and pyelonephritis kidneys

Classes	Predicted Group Membership			Total
	NK	GN	PN	
NK	94.9%	4.5%	5.1%	100.0%
GN	0.0	97.3%	2.7%	100.0%
PN	0.0	0.5%	99.5%	100.0%

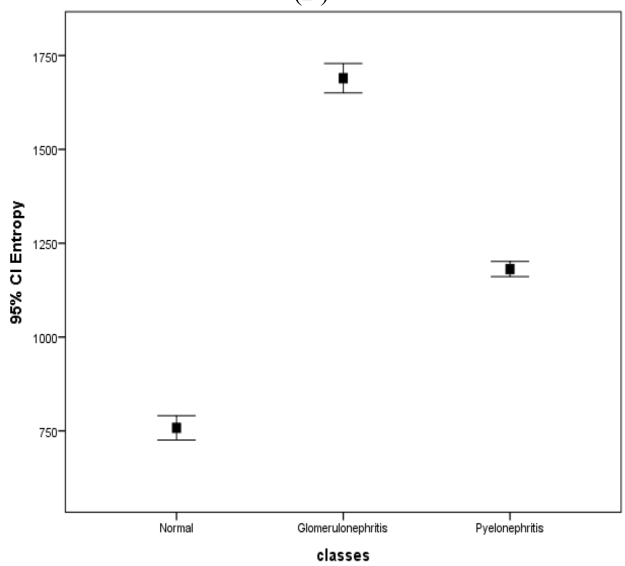
GN: glomerulonephritis
PN: pyelonephritis
NK: normal kidney



(A)



(B)



(C)

Figure 2: An error bar graphs of textural features (A) mean, (B) signal to noise ratio and (C) entropy for the different classes of the normal, glomerulonephritis and pyelonephritis of the medulla of the kidneys

B. Pelvic Calycle System:

The textural features extracted from the pelvic calycle system for the three groups showed overall classification accuracy of 95.7% (Figure 3 and table 2). With a higher sensitivity concerning pyelonephritis which 100% versus 99.5% for those features extracted from the medulla; this confirm that pyelonephritis texturally were very different than the other group textures.

Stepwise linear discriminant analysis selected four texture here as the most discriminant textural features. They include mean, standard deviation, signal to noise ratio and energy (Figure 4-A, B, C and D). Where the mean and signal to noise ratio showed an excellent separation between the three groups, while energy which represent the contrast separated glomerulonephritis from pyelonephritis well with normal pelvic calycle system showed larger variation same as the standard deviation, although the classes showed considerable separation concerning the last feature.

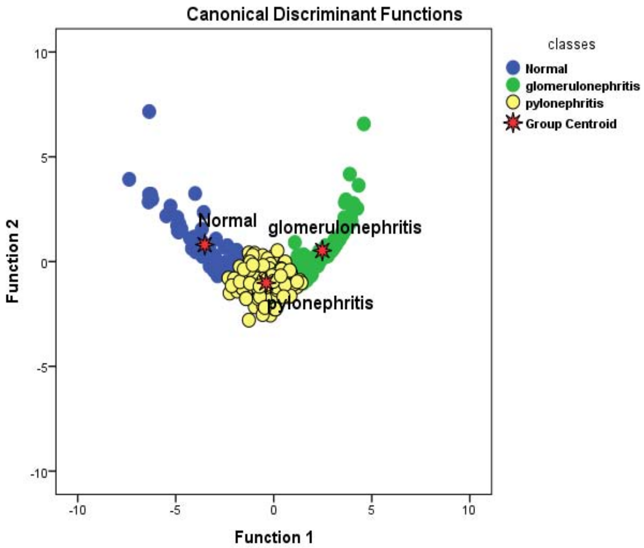
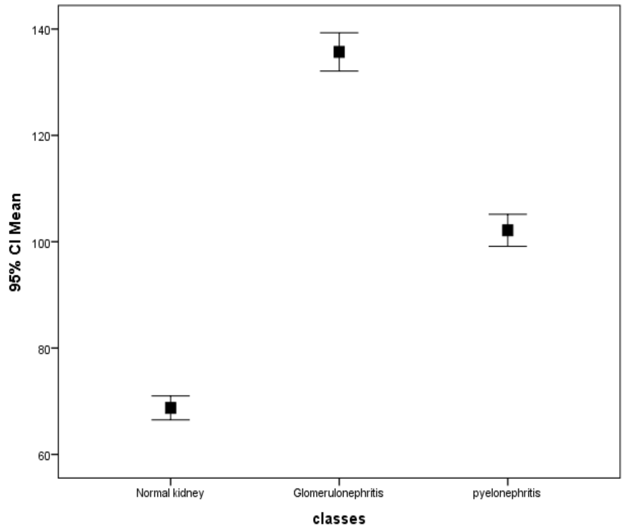


Figure 3: Scatter plot show the classification of textural feature of the kidney medulla classes (normal, glomerulonephritis and pyelonephritis) using linear discriminant analysis.

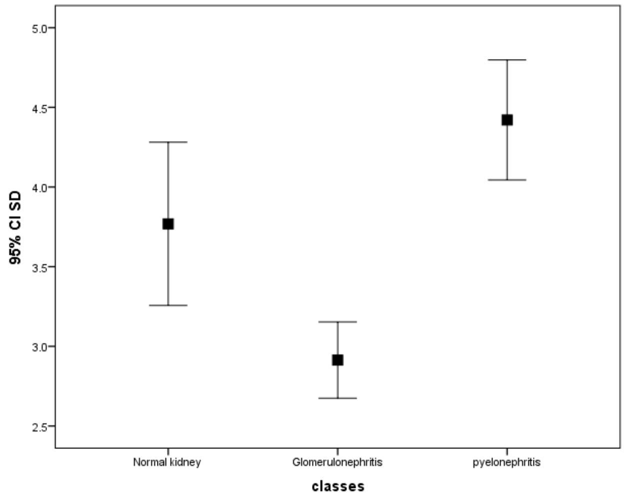
Table 2: A confusion matrix shows the classification accuracy of the selected textural features for the medulla in the normal kidney and normal, glomerulonephritis and pyelonephritis kidneys

Classes	Predicted Group Membership			Total
	NK	GN	PN	
NK	92.6%	0.0%	7.4%	100.0%
GN	0.0	93.4%	6.6%	100.0%
PN	0.0	0.0%	100.0%	100.0%

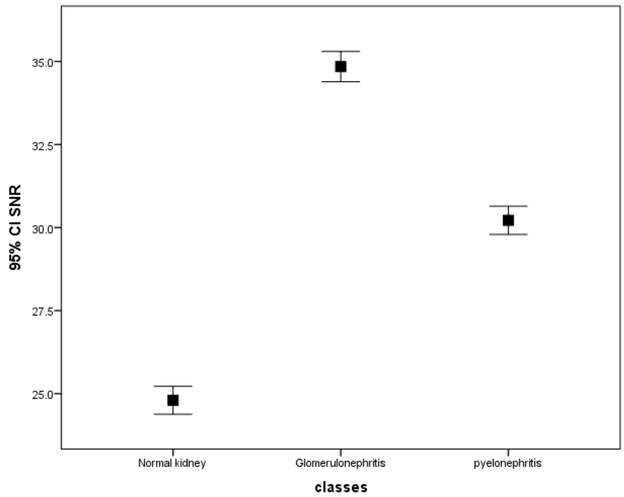
GN: glomerulonephritis
PN: pyelonephritis
NK: normal kidney



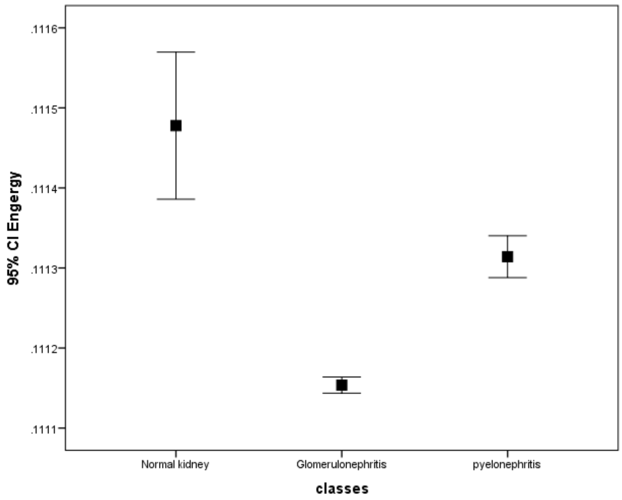
(A)



(B)



(C)



(D)

Figure 4: An error bar graphs of textural features (A) mean, (B) standard deviation,(C) signal to noise ratio and (D) entropy for the different classes of the normal, glomerulonephritis and pyelonephritis pelvic calycle system of the kidneys

4. Conclusion

Glomerulonephritis and pyelonephritis can be identified in an ultrasound image using texture analysis with an overall of accuracy of 98% using multiple linear equation developed using linear discriminant analysis from textural feature extracted from renal medulla, where the vote will be attributed to the highest score as follows:

Normal kidney = (0.099×Mean) + (221.852×SNR) + (-1.654×Entropy) - 1085.580

Glomerulonephritis = (0.263×Mean) + (234.375×SNR) + (-1.712×Entropy) - 1262.280

Pyelonephritis = (0.213×Mean) + (236.449×SNR) + (-1.747×Entropy) - 1252.627

Similarly the same groups can be classified with an overall classification accuracy of 95.7% using texture extracted from Pelvic calycle system as follows:

Normal kidney = (1.085×Mean) + (-901.473×SD) + (271.946×SNR) + (7899815.658×Energy) - 442038.958

Glomerulonephritis= (-.098×Mean) + (-904.525×SD) + (283.403×SNR) + (7907198.703×Energy) - 443071.279

Pyelonephritis= (-.075×Mean) + (-901.782×SD) + (281.429×SNR) + (7895098.465×Energy) - 441673.905

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