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Characterization of Hippocampusin MR Images Using Texture Analysis

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Abstract:*This study concern to characterize the hippocampus were defining to normal, infection, tumor and epilepsy, using texture feature extraction and extract classification features from MR images. The texture analysis technique used to find the gray level variation in CT images. analyzing the image with Interactive Data Language IDL software to measure the grey level variation of images. The results show that texture analysis give classification accuracy of hippocampus to normal 77.8%, tumor 91.8%, infection 99.7%, While the epilepsy tissue showed a classification accuracy 81.4%. The overall classification accuracy of temporal bone area 83.1%.These relationships are stored in a Texture Dictionary that can be later used to automatically annotate new MR images with the appropriate hippocampus area names.*

Keywords*: Hippocampus, Epilepsy, Magnetic Resonance, Texture Analysis*

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I. Introduction

The study of the human hippocampus has traditionally attracted considerable attention from the neuroscience and neuroimaging communities due to its connection with memory [1,2], and an array or neurological disorders, especially Alzheimer's disease (AD) [3-5].

MRI is a diagnostic imaging technique broadcast that has been widespread since the early 80s. It is a method that enables the obtainment of images of organs with high spatial resolution without the use of ionizing radiation. The technique is used extensively in neurology, both for structural and functional evaluations. The versatility of the image capture parameters and the diversity of data processing tools enable its adaptation to a vast array of clinical situations.

The ordinary methods to differentiate between the normal and abnormal tissues largely depending on the radiologist experience [6], using MRI processing by texture analysis, which is being increasingly explored in clinical surveys. This is because histological modifications may be revealed as alterations in the MRI signal detected by this technique. In this case, the statistical parameters of texture of these images may be different from those observed for normal subjects [7-10].

Several studies have specifically focused on the hippocampus for early diagnosis of AD and build predictive models upon anatomical features including volume and shape based measures, and image intensity texture features [11-17].Particularly,promising performance of hippocampus shape [18-20], texture features [21], and 2D convolutional neural networks (CNNs) based features [23] has been demonstrated in AD prediction. However, most of the hippocampus focused pattern classification studies have been relying on the two-category classification techniques.

Recently, following a detailed histological characterization of the human hippocampal head by Ding & Van Hoesen, Dalton and also Berron[22-24] presented a protocol for manually segmenting the subfields of the hippocampal head using geometric rules and descriptions in 2D coronal slices, which captures many key structural features. However, like other protocols limited to 2D slice viewing and geometric rules, these protocols simplify subfield structure in the uncus and cannot easily account for interindividual variability in folding (i.e. digitations) or other differences in morphology (e.g. dysplasias or moreSubtle differences in orientation or position within the medial-temporal lobe), which are issues inIntersubject alignment rather than in defining subfield borders. The application of different approaches of the texture analysis technique to the study of epilepsy is not new. In 2001, Yu et al. found alterations of texture in the hippocampus contralateral to the one that presented atrophy in patients with TLE [25] . In 2003, Bonilha et al. confirmed the efficiency of this technique in detecting hippocampal sclerosis (HS) in cases of mesial temporal lobe epilepsy (MTLE) [26] . As a result, they observed that most of the texture parameters calculated made it possible to distinguish differences

between the sclerotic hippocampal and contralateral tissues of patients and the normal hippocampal tissues of control subjects.

II. Material and Methods

This Study was carried out in the Department of Diagnostic Radiology, Royal Care International Hospital, Sudan. with Toshiba VANTAGE ELAN, SHORT BORE 1.5T MRI system.

Protocol and procedure of patient imaging in MRI: Position for MRI brain Head first supine. Position the head in the head coil and immobilize with cushions. Give cushions under the leg for extra comfort. Center laser beam localizer over the glabella. MRI Brain should be done first axial T1, T2, FLAIR and sagittal images; it is use as screening for presence of mass lesion or other abnormalities. Sagittal image will use as a guide to obtain perpendicular plane to temporal lobe. T2 of coronal 3mm slice thickness, images perpendicular to the long axis of the temporal lobe should be taken.

Statistical Methods

First Order Statistics: FOS can be used as the most basic texture feature extraction methods, which are based on the probability of pixel intensity values occurring in digital images. The parameters in the following statistical formulas are xi, the intensity value of pixel i, N, the total number of pixels, maxV , the maximum intensity value within a patch and Hi, the histogram of an image patch.

Mean: Calculates the mean intensity value of all pixels. In Matlab the function μ= mean2(IP) can be used to compute this feature.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Standard Deviation

The standard deviation of all the intensity values of a patch is used as a texture feature. The corresponding Matlab function is σ= std2(IP).

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Coefficient of variation

The coefficient of variation can be seen as the relative standard deviation. It is calculated by dividing the standard deviation with the mean value.

$$c_v = \frac{\sigma}{\mu}$$

Skewness

Another statistical measure which is used for texture analysis is skewness. It measures the symmetry of a distribution curve of pixel intensity occurrences as seen in a histogram. The function
ϒ1= skewness(IP) can be used to compute the skewness in Matlab.

$$\gamma_1 = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3}{(\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2)^{\frac{3}{2}}}$$

Kurtosis

The kurtosis measures the atness of a histogram relative to a normal distribution. A curve has a high kurtosis when it has a clear peak close to the mean value. The Matlab function for the kurtosis is ϒ2= kurtosis(IP).

$$\gamma_2 = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^4}{(\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2)^2} - 3$$

Entropy

The entropy of a gray-scale image is a measure of intensity value randomness. It is calculated from the histogram counts of an image giving a probability p of certain pixel values occurring in the image.

$$s = -\sum(p. * log2(p))$$

III. Results

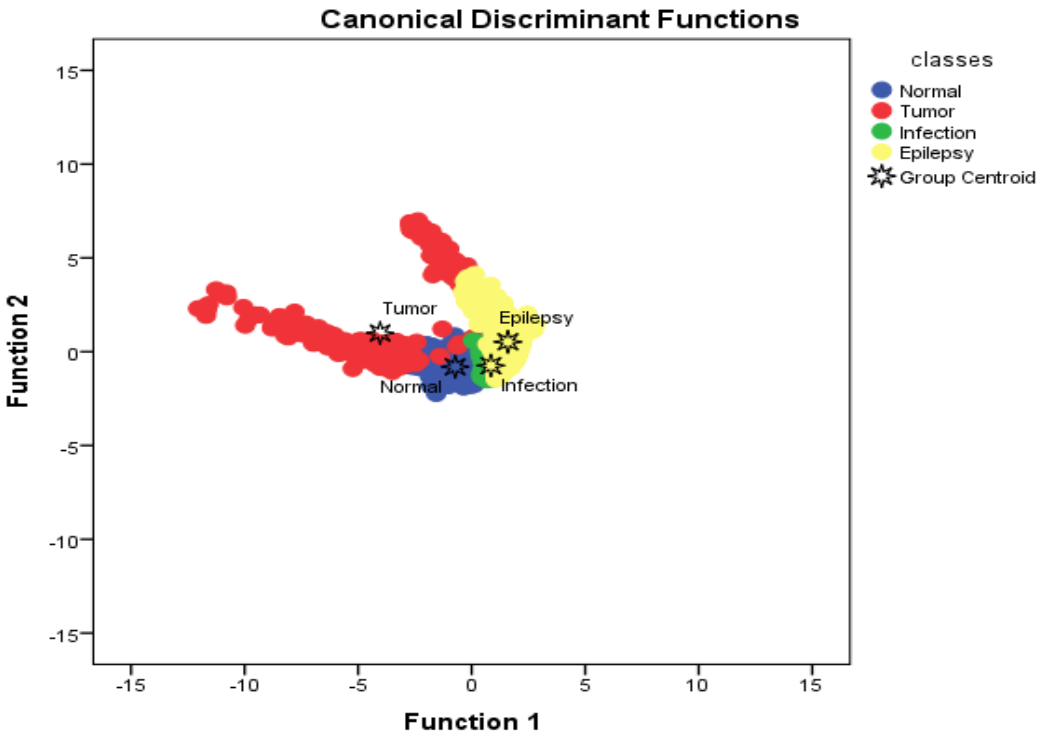

Fig 1. scatter plot demonstrates the distribution of four Classes according to their textural feature using linear discriminate analysis functions

The classification showed that the hippocampus area was classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

Table 4-1. a confusion matrix shows the classification accuracy of the original classes versus the predicted membership according to linear discriminant functions (multiple linear regression equation)

Classes		*Predicted Group Membership %*				*Total*
		Normal	*Tumor*	*Infection*	*Epilepsy*	
Original %	*Normal*	*77.8*	*1.6*	*20.5*	*.1*	*100.0*
	Tumor	*1.0*	*91.8*	*1.0*	*6.3*	*100.0*
	Infection	*0.0*	*0.0*	*99.7*	*.3*	*100.0*
	Epilepsy	*0.0*	*0.0*	*18.6*	*81.4*	*100.0*
83.1% of original grouped cases correctly classified.						

Table .1 show classification score matrix generated by linear discriminate analysis and the overall classification accuracy of hippocampus area 83.1%, were the classification accuracy of epilepsy 81.4%, infection99.7%, tumor 91.8%, While the normal tissue showed a classification accuracy 77.8%.

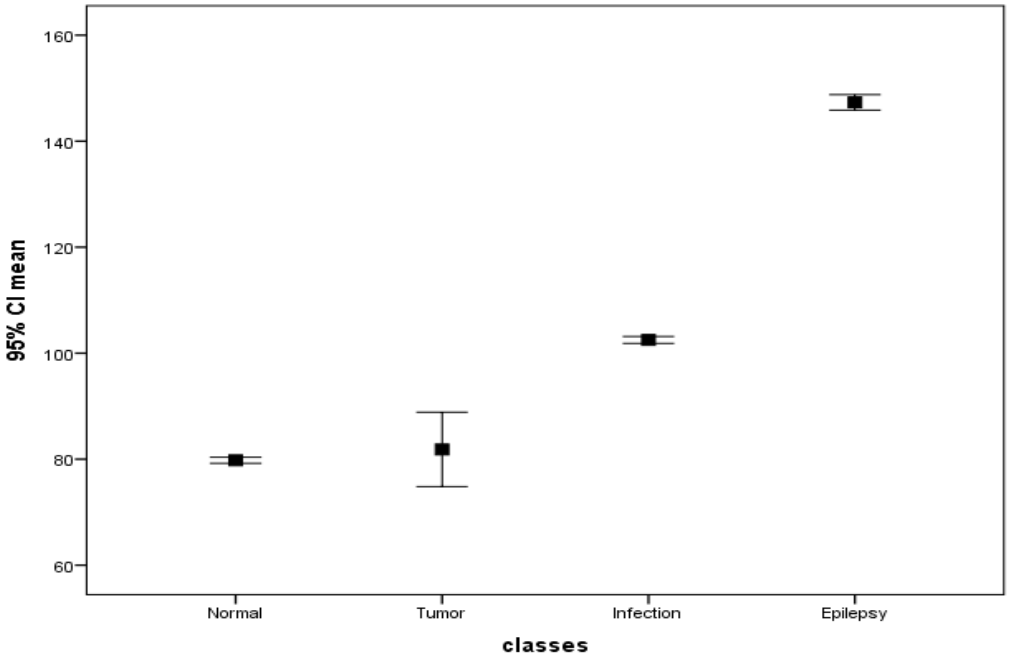

Fig .2 show error bar plot for the CI mean textural features that selected by the linear stepwise as a discriminate feature where it discriminates between all features. From the discriminate power point of view in respect to the applied features the mean can differentiate between all the classes successfully.

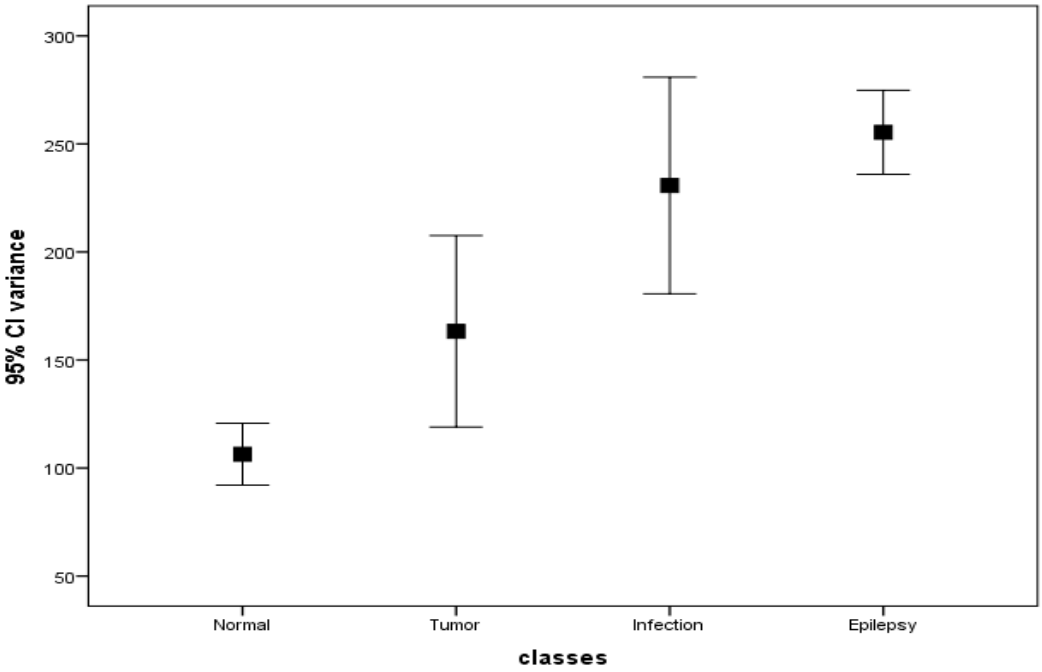

Fig .3 show error bar plot for the CI variance textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.

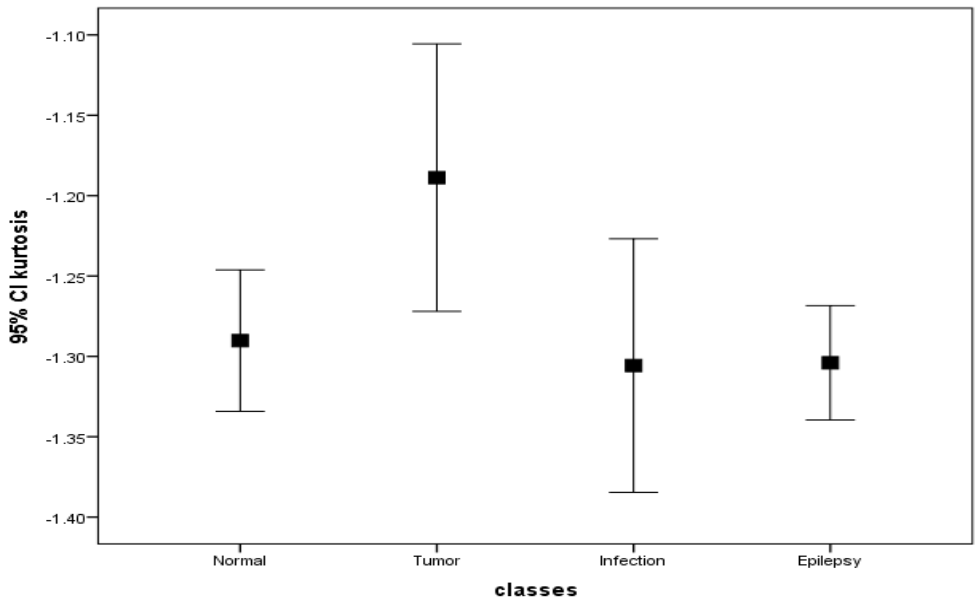

Fig .4 show error bar plot for the CI kurtosis textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.

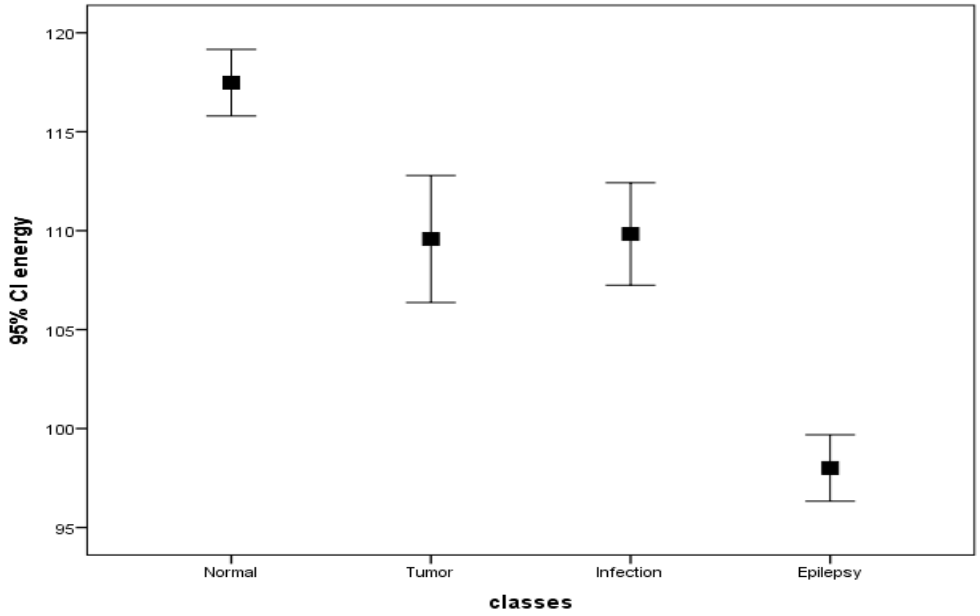

Fig .5 show error bar plot for the CI energy textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.

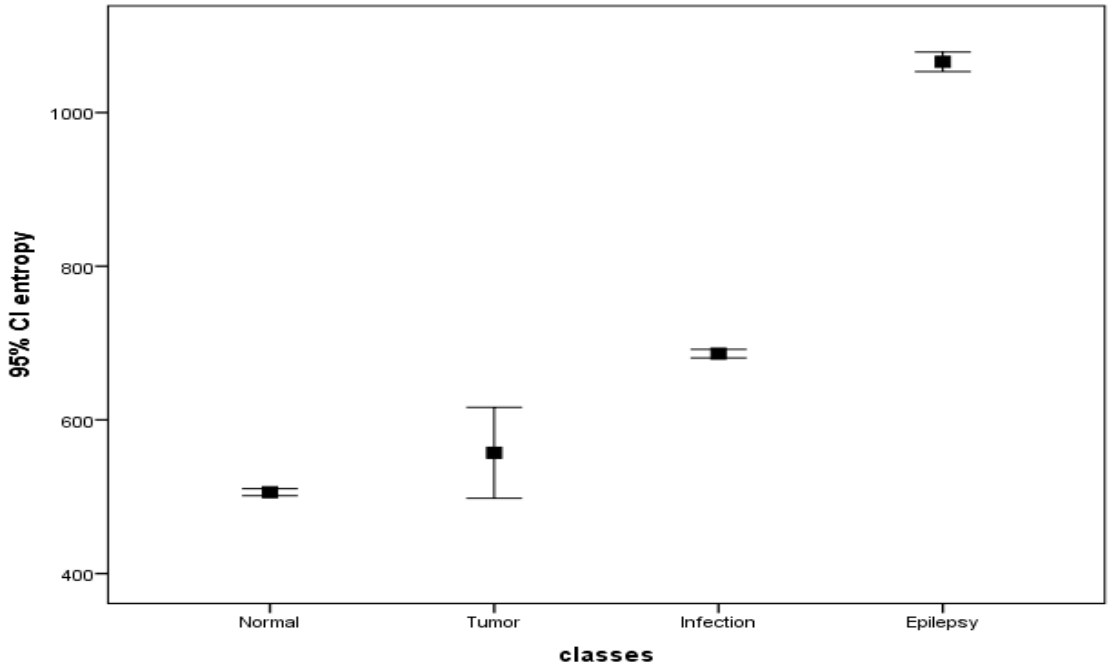

Fig .6 show error bar plot for the CI entropy textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features. From the discriminate power point of view in respect to the applied features the mean can differentiate between all the classes successfully.

IV. Conclusion

The classification processes of MR images for brain defining the hippocampus to normal, tumor, infection and epilepsy, and carried out using Interactive Data Language (IDL) program as platform for the generated codes. The result of the classification showed that the hippocampus areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

Several texture features are introduced from ***FOS*** and the classification score matrix generated by linear discriminate analysis and the overall classification accuracy of hippocampus area classify to normal77.8%, tumor 91.8%, infection99.7%, While the epilepsy tissue showed a classification accuracy 81.4%. The overall classification accuracy of temporal bone area 83.1%.

Using Linear discrimination analysis generated a classification function which can be used to classify other image into the mention classes as using the following multi regression equation;

Normal, infection, tumor and epilepsy:

*Normal = (Mean × 18.019) + (variance * 0.0003) + (kurtosis × -2.5) + (energy × 0.14) + (entropy ×-2.1) - 195.8*

Tumor = (Mean × 14.49) + (variance × 0.00003 + (kurtosis × -2.4 + (energy × 0.125 + (entropy ×1.7) - 130.1

Infection = (Mean × 19.34) + (variance × 0.00034) + (kurtosis × -2.6) + (energy × 0.13) + (entropy × 2.27) - 224.3

Epilepsy = (Mean × 19.47) + (variance × 0.00033) + (kurtosis × -2.89) + (energy × 0.115) + (entropy ×2.28) - 230.6

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