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Non-Invasive Technique to Classify Cirrhotic Liver Using Texture Parameters

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ABSTRACT

Texture analysis is an outstanding and fundamental task being used in many medical and computer vision applications. Malfunctioning of the human liver upsets almost all the other organs in the human body. Usually liver infections are difficult to analyze because of inconclusive side effects. More often, the liver could be confronting critically but it may not be significantly unveiled. The main objective of this research work is to provide some standard liver diagnostic measures to minimize the risk factors, as better diagnosis is essential requirement in radiology. The Computerized Tomography (CT) contributes important information to the clinical evaluation of diffuse liver diseases. Haralick texture parameters have been computed on the selected Regions of Interest. B11 is used for discrimination and interpretation of normal and cirrhotic liver diseases. Normal and diseased Liver CT images were collected from Bahawal Victoria Hospital. Normal and cirrhotic liver samples of clinically verified patients were obtained and total 900 Regions of Interest (ROIs) were taken from the selected data. Training of the classes was next step after texture parameter computation. In this work, supervised classification method was used to classify the selected images. In this way, the classes were trained in a supervised manner. The maximum accuracy obtained during this research work was 100%, linear dimensionality was 1 and the linear separability was 0.99%. Results of this research work suggested that texture parameters have high degree of reliability to automatically discriminate similar tissue textures, when regions are obvious. This framework separates benign from malignant liver tumors with moderately high precision and is therefore link up the psychophysics with machine vision to outline, recognize, categorize or discriminate textures.

Keywords: Cirrhotic Liver Disorders, Texture Analysis, Computed Tomography, Computer Diagnosis

1. INTRODUCTION

The liver is the most essential organ responsible for digestion of supplements and discharge of waste metabolites. Any imperfection in the function of normal liver exhibits the liver's incredible significance [1]. Cirrhotic Liver is one of the main sources of death in developing countries. To decrease the liver malignancy, the most helpful approach is to treat the sickness on early stages. Early treatment requires early finding, precise and absolute indicative analysis. This requires a technique that enables doctors to timely diagnose the liver malignancy. The most widely recognized therapeutic imaging techniques for

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early identification and finding of liver tumors are: Ultrasonography (US), Computerized Tomography (CT), Magnetic Resonance (MR) imaging and angiography [2]. These imaging techniques can be utilized separately or in combination, contingent upon the tumor type, site, and clinical requirements. The interpretation to the images obtained by any modality mainly is dependent upon visual procedure. However, there are some features which cannot be perceived by naked eye. Besides, when images are examined in an increasingly quantitative way, Standard region of interests investigation may give a mean parameter esteem, e.g., Hounsfield Unit (HU) on CT, signal force on MRI, or institutionalized take-up worth on PET, yet does not regularly depict the basic spatial transmission [3]. Chronic Liver Diseases (CLDs) are real reasons for mortality around the world [4]. In this examination work we bound our self for the texture investigation of infections brought about by Space Occupying Lesions (SOL) of liver [5]. Sometimes there are unusual findings for liver cysts, lesions *etc*. Probability of this condition ought to be remembered when there is scarcest uncertainty on clinical or image findings.

2. TEXTURE ANALYSIS

Texture is one of the most important property of a visible surface, and provides useful information to describe or characterize it. Texture analysis plays a significant role in pattern recognition (human and machine vision) *e.g.* biomedical imaging, remote sensing, industrial automation, quality control *etc*. [6, 7]. Liu *et al.* [8] in their work offered the novel approach for the classification of different textures based on features selection methods. Haralick *et al.* [9] have given the primary concept of grey level and texture. According to this concept, grey level and texture are essential parts of any image. Texture Analysis is a methodology for evaluating heterogeneity that may not be valued by unaided eye. In human visual system, two dimensional Fourier Transform of spatial frequency content is important to recognize and discriminate various visual objects, verified by the experimental findings as well as from relevant literature available in the field of psychophysics. Spatial variation in pixel intensities for an image is used to describe the region of interest through texture analysis. Fletcher *et al.* [10] performed an experimental work and concluded the dependency of visual textures on spatial frequency by investigating the relationship between them. In texture study of hepatic tumors and colorectal malignant growth patients, CT images have advantage over different assessment techniques as it measures spatial variation in intensities.

Texture analysis is used to quantify the pixel variation on portal venous phase in Liver CT scans [11]. In CT images, with some adjustments in entropy and consistency, some of texture features can highlight the possible separation between with and without colorectal liver metastases stages in patients [12]. Texture Analysis provides the improved assessment method far beyond the direct visual analysis in radiology [3]. Ganeshan *et al*. [13] discussed the relationship between micro metastasis formation and texture entropy of CT images of colorectal cancer patients with normal seeming liver. Sometimes, obesity, alcoholic consumption and physical disturbance are the major causes of Liver Cirrhosis [14]. In cirrhotic liver, there is diffused surface irregularity [15]. Haralick texture features computed from Gray level co-occurrence matrix are mostly used due to their simple interpretation and successful outcomes [16]. The way radiologists attempt to separate the anatomical structure of liver tissues is abstract. Now it is very basic and necessary to provide the understanding outcomes of tomographic images by texture analytical methods using statistical techniques.

3. EXPERIMENTAL TOOLS AND MATERIALS

Gray-Level Co-occurrence Matrices (GLCM) were used in texture analysis to describe and characterize the statistical variation of pixel's spatial relationships in parenchymal regions. This approach has become very common and works well to describe a large classes of textures when their primitive shapes are undefinable and small, comparable to the size of a pixel. In this research work, co-occurrence matrices were constructed from the selected ROI of window size 16 by 16 at four angles (0^0, 45^0, 90^0 and 135^0) and displacement d = 1. Then the constructed matrices were normalized and their average values were used to compute thirteen Haralick texture parameters (1-13

mentioned in Table 2) for each sample. The details of these parameters are as under:

1) Angular Second Moment

$$f_1 = \sum_i \sum_j \{ p(i,j)\}^2$$

2) Contrast

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p\ (i,j) \right\}$$

3) Correlation

$$f_3 = \frac{\sum_i \sum_j (ij) p(i,j) - \mu_x \mu_y}{\delta_x \delta_y}$$

4) Variance

$$f_4 = \sum_i \sum_j (1-\mu)^2\ p(i,j)$$

5) Inverse Difference Moment

$$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^2}\ p(i,j)$$

6) Sum Average

$$f_6 = \sum_{i=2}^{2N_g} i\ p_{x+y}\ (i)$$

7) Sum Variance

$$f_7 = \sum_{i=2}^{2N_g} (i - f_8)^2 p_{x+y}\ (i)$$

8) Sum Entropy

$$f_8 = -\sum_{i=2}^{2N_g} p_{x+y}\ (i)\ \log\{ p_{x+y}\ (i)\}$$

9) Entropy

$$f_9 = -\sum_i \sum_j p(i,j) \log(p(i,j))$$

10) Difference Variance

$$f_{10} = \text{variance of } p_{x-y}$$

11) Difference Entropy

$$f_{11} = -\sum_{i=2}^{2N_g} p_{x-y}\ (i)\ \log\{ p_{x-y}\ (i)\}$$

12), 13) Information Measures of Correlation

$$f_{12} = \frac{HXY - HXY1}{\max\{HX,\ HY\}}$$

$$f_{13} = (1 - \exp[-2.0\ (HXY2 - HXY)])$$

$$HXY = -\sum_i \sum_j p(i,j)\ \log(p(i,j))$$

For feature analysis and classification, B11 is an effective, reliable and efficient software program. B11 tool for analysis is developed by the COST. In this research work B11 and the Image processing software (developed by Ahmad [19]) has been used for texture analysis of CT Liver images. Following techniques are implemented in B11 for feature extraction or projection and classification [17-19].

(i) Principal Component Analysis (PCA)
(ii) Linear Discriminant Analysis (LDA)
(iii) Non-Linear Discriminant Analysis (NLDA)

4. METHODOLOGY

The research work was performed with the collaboration of Bahawal Victoria Hospital, Radiology Department with CT diagnostic experts as to complete the analysis part and to understand experimental work. Steps followed during experimental work are as under:

(a) Patients data was collected on DVDs

(b) 'DICOM Viewer' was used to retrieve patient's data and CT-Images were then converted to BMP image file format.

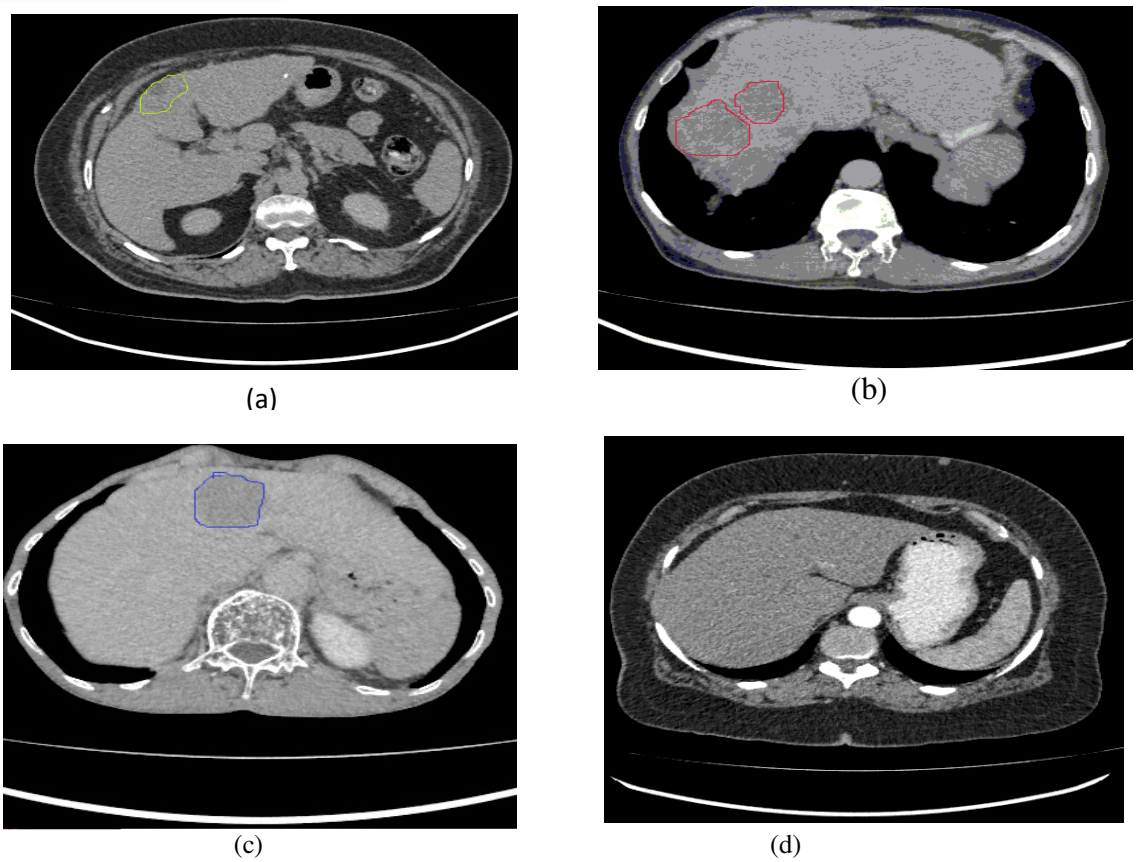
(c) This research work used CT images of 90 clinically verified samples with help of expert radiologists for normal and cirrhotic liver classification, as shown in Fig. 1. Before classification process, the four different groups were created from selected CT images and the samples of groups were labelled as Necrosis lesion, Mixed lesion, Solid lesion and Normal liver. Patient's images were then accessed to compute 13 Haralick texture parameters on the selected 900 ROIs of 16 by 16 dimensions to search out characteristics texture element (Texel) of each texture class during this research work (See Fig. 2). Assessment of texture element of each texture is made by analyzing the classification rate of each image class. In this perspective infected part of the image was divided into number of sub images of same sizes which is evidence and sound confirmation of all samples belongs to same category. The utilization of ROIS and the total number of ROIS in samples are shown in Table 1 and computed Haralick texture parameters are listed in Table 2.

(d) 'B11' [20] software and Image processing system were used during Normal and Pathological liver-tissue classes training and testing. Final classification task was also performed using the same software.

Selected Liver CT-images were divided into following three Categories to perform research work:
Category 1: Necrotic lesion (Necrosis is the death of cells in living tissue caused by external factors such as infection, trauma, or toxins) versus normal liver.

Category 2: Mixed lesions with both solid and cystic component versus normal liver.

Category 3: Solid Lesion (An abnormal mass of tissue that usually does not contain cysts or liquid areas) versus normal liver.
The categorization was based on the study of the classification/quantification of cirrhotic liver from normal liver.



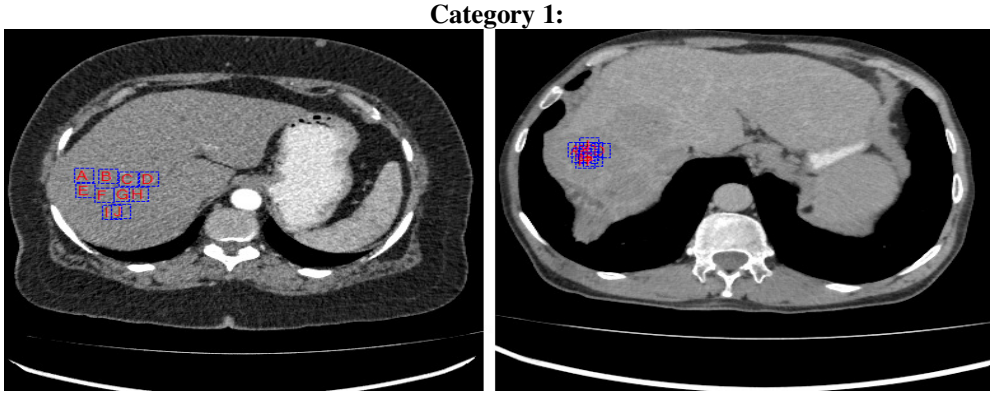
(a) (b) (c) (d)

Fig 1: (a, b, c) Marked infected regions of CLD patients by radiologists (manually) (d) Normal Human Liver

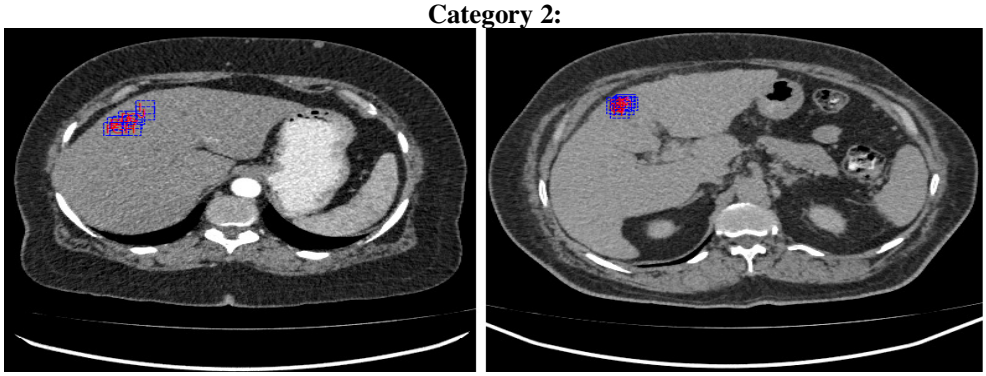
Table 1: Utilized ROIs and total number of ROIs in samples

Category No.	Patient's description	Selected Samples	ROIs	Patient's description	Selected Samples	ROIs	Total ROIs in each sample
1	Patient with SOL in right lobe, Cirrhotic Liver	15	150	Patient with Normal Liver	15	150	300
2	Patient with SOL in right and left lobe, Cirrhotic Liver	15	150	Patient with Normal Liver	15	150	300
3	Patient with SOL in right lobe, Cirrhotic Liver	15	150	Patient with Normal Liver	15	150	300
Total	45 cases	45	450		45	450	900

Category 1:



Category 2:



Category 3:

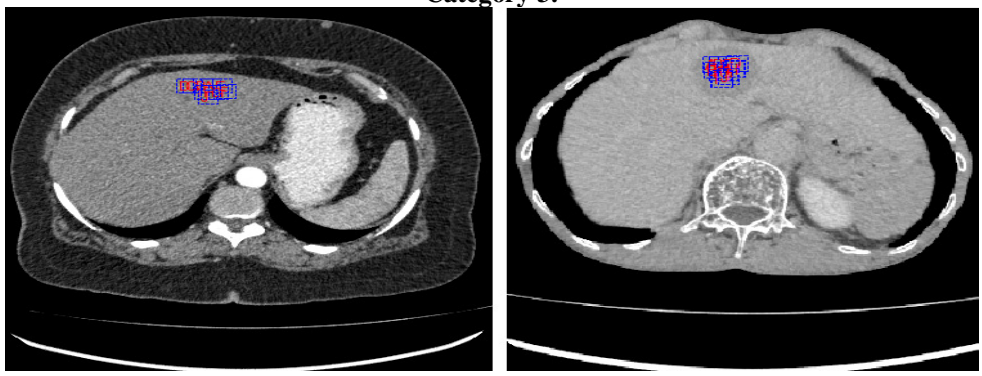
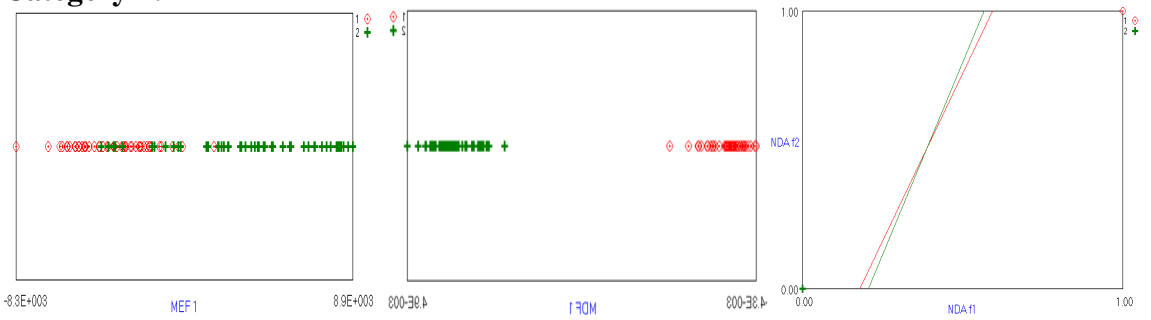


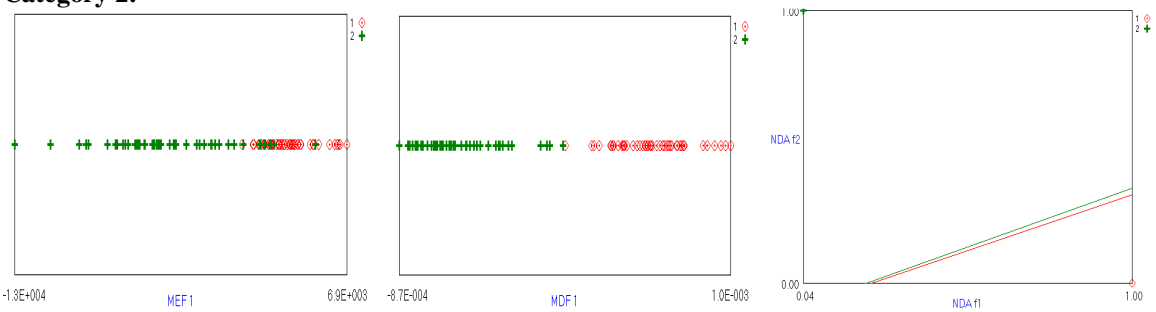
Fig 2: Developed ROIs Size (16×16)

Table 2: Computed Parameters			
No.	Haralick Texure Parameters	No.	Haralick Second Parameters
1	Angular Second Moment	8	Sum Enropy
2	Contrast	9	Entropy
3	Correlation	10	Difference Variance
4	Variance	11	Difference Entropy
5	Inverse Difference Moment	12	Info_measur_corr1
6	Sum Average	13	Info_measur_corr2
7	Sum Variance		

Category 1:



Category 2:



Category 3:

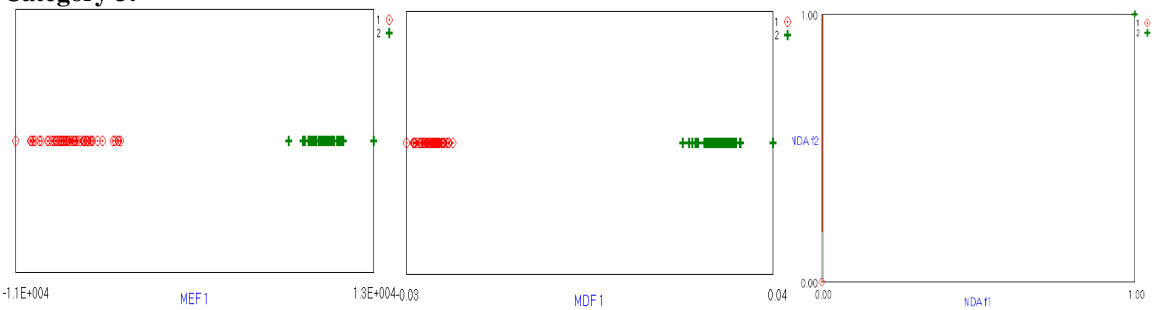


Fig 3: Scattered Plot of pattern with 13 statistical features for PCA, LDA and NDA

Table 3: System Output results for the classification of selected data with 13 statistical features

Features Analysis Statistics	Category I (%)			Category II (%)			Category III (%)		
	PCA	LDA	NDA	PCA	LDA	NDA	PCA	LDA	NDA
Classification Rate	87	100	100	92.52	98.06	100	100	100	100
Fisher's Coefficient	5.1	202.9	---	5.6	27.4	---	161	520.3	---
Linear Dimensionality	1	1	---	1	1	---	1	1	---
Linear Separability	---	0.98	---	---	0.87	---	----	0.99	---

5. RESULTS AND DISCUSSION

More than 900 samples were taken from the selected data of the clinically verified selected patients for the cases that included normal liver samples and cirrhotic liver samples. System Output results for the classification of selected data with 13 statistical Texture features are discussed in Table 3.

In Category 1 when all texture parameters are selected, the higher classification rate is 87% for PCA, 100% for LDA and 100% for NDA. In Category 2 the classification rate is 92.52% for PCA, 98.06% for LDA and 100% for NDA. While in Category 3 the classification rate is 100% for PCA, 100% for LDA and 100% for NDA. Results of this research work concludes that texture parameters have high degree of trustworthiness for automatically discriminate similar tissue textures when regions are marked correctly with perfection. The scattered plot of patterns in Fig 3 for

PCA, LDA, and NDA significantly differentiate the diseased and normal ROIs. The ROIs of normal and Cirrhotic liver are clearly showing the variation of intensity of the gray levels in images.

6. CONCLUSION

Obtained results of this research work concludes the misclassification rate for first category was 13% or 0.13 for PCA and 0% for LDA and NDA, for second category it was 7.48% or 0.0748 for PCA, 1.94% or 0.0194 for LDA and 0% for NDA, and finally for third category misclassification rate for PCA was 0% for PCA, LDA and NDA. This indicates that trustworthy results may be achieved from the proposed automated technique for discrimination of similar tissue textures if regions are marked with precision. In this investigation, a technique employing these integrative ways was proposed to differentiate normal and cirrhotic CT Liver images. Haralick Texture parameters *i.e.* contrast, variance, entropy *etc.* were examined which assured the quality of quantification for diagnostic imaging.

System's performance may increase and be more accurate, by increasing the strength of training data sets/classes. This classification system will provide more fine results if there is variability in the input data. The proposed method with minor changes can meet the requirements for the classification of other anatomies of the human body images obtained from different imaging modalities. Some infections, or malignancies at early stages might be curable through this technique.

These advanced procedures and system can be incorporated in hospitals and other research centers as well. In this study, the small number of cirrhotic patients may be difficult on generalization of the results. But examining more ROI samples confirm use of discrimination methods. It has been shown that, automated texture analysis successfully discriminates progressive cirrhosis from normal liver.

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