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Characterization of Breast Masses in Mammography using Image Texture Analysis

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ABSTRACT: Mammogram–breast x-ray is considered the most effective, low cost, and reliable method in early detection of breast cancer, several texture features are introduced from a proposed higher-order statistical matrix, the gray level run length matrix GLRLM, The sample is 155 patients and the data collected randomly from X-ray department at cancer diagnostic medical center. The patient under examination must perform x-ray mammography, and FNAC of breast mass in order to identify the tumor feature and type, determine tumor site and size then the patient image will be analyzed by using of IDL program for textural analysis.

Several texture features are introduced from (GLRLM) and the classification accuracy of breast masses 91.5%, were the classification accuracy of gland 98.9%, fat 86.3%, connective tissue 91.9%, While the tumor showed a classification accuracy 88.9%. These relationships are stored in a Texture Dictionary that can be later used to automatically annotate new CT images with the appropriate organ names.

Keywords:- breast masses, connective tissue, Gray Level Run Length, Texture Classification, Mammogram

I. INTRODUCTION:

Mammography is the most effective modality to early detect of breast cancer [1] However, the positive predictive value of mammographic diagnosis is only about 15%–30% [2]. As the number of patients undergoing mammography increases, it will be increasingly important to improve the positive predictive value of this procedure in order to decrease patient discomfort and costs [3]. Recent studies have shown that mammography is sensitive in diagnosis and screening of breast cancer, but with a high false-positive rate [4]. According to the traumatic nature and high cost of histopathology, can be results in develop computer-based methods to accurately differentiate the benign masses from malignant tumors. this computerized algorithm can assist radiologists in classification of mammographic abnormalities that can decrease benign biopsies [3] , all this can be helpful in the primary or secondary screening of mammograms, and provide objective tools to assist radiologists in analyzing difficult cases and in deciding on biopsy recommendations. It is known that a small but significant number of cancer cases detected in screening programs have prompts visible in earlier screening examinations [5]. benign masses are more homogeneous as compared to malignant tumors in terms of density distribution[6]. Most benign masses have well-defined and clear boundaries, in contrast to irregular or ill-defined boundaries of malignant tumors. However, some benign masses like fibroadenomas and cystic masses may also have ill-defined boundaries [7].

Texture analysis refers to the branch of imaging science that is concerned with the description of characteristic image properties by textural features. However, there is no universally agreed-upon definition of what image texture is and in general different researchers use different definitions depending upon the particular area of application [8] texture is defined as the spatial variation of pixel intensities, which is a definition that is widely used and accepted in the field. The main image processing disciplines 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 [9]. 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 [10]. By applying texture analysis methods to an image, and determining the precise location where texture feature values change significantly, boundaries between regions can be established. The proposed texture parameters are generally derived from simple (e. g. first order and gradient-based) statistics or more sophisticated (for example, based on co-occurrence matrices [11] or run-length matrices [12]) statistical properties of the image.

Traditional Run-Length Features

From the original run-length matrix p(i; j), many numerical texture measures can be computed. The five original features of run length statistics derived by Galloway [13] are as follows.

Short Run Emphasis (SRE):

$$\text{SRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{j^2} = \frac{1}{n_r} \sum_{j=1}^{N} \frac{p_r(j)}{j^2}.$$

Long Run Emphasis (LRE)

$$\text{LRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i, j) \cdot j^2 = \frac{1}{n_r} \sum_{j=1}^{N} p_r(j) \cdot j^2.$$

Gray-Level Nonuniformity (GLN)

$$\text{GLN} = \frac{1}{n_r} \sum_{i=1}^{M} \left(\sum_{j=1}^{N} p(i, j) \right)^2 = \frac{1}{n_r} \sum_{i=1}^{M} p_g(i)^2.$$

Run Length Nonuniformity (RLN)

$$\text{RLN} = \frac{1}{n_r} \sum_{j=1}^{N} \left(\sum_{i=1}^{M} p(i, j) \right)^2 = \frac{1}{n_r} \sum_{j=1}^{N} p_r(i)^2.$$

Run Percentage (RP):

$$\text{RP} = \frac{n_r}{n_p}.$$

In the above, n_r is the total number of runs and np is the number of pixels in the image. Based on the observation that most features are only functions of p_r (j), without considering the gray level information contained in p_g (i), Chu et al.[14] proposed two new features, as follows, to extract gray level information in the matrix.

Low Gray-Level Run Emphasis (LGRE)

$$\text{LGRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{i^2} = \frac{1}{n_r} \sum_{i=1}^{M} \frac{p_g(i)}{i^2}.$$

High Gray-Level Run Emphasis (HGRE):

$$\text{HGRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i, j) \cdot i^2 = \frac{1}{n_r} \sum_{i=1}^{M} p_g(i) \cdot i^2.$$

In a more recent study, Dasarathy and Holder [15] described another four feature extraction functions following the idea of joint statistical measure of gray level and run length, as follows.

Short Run Low Gray-Level Emphasis (SRLGE

$$\text{SRLGE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{i^2 \cdot j^2}.$$

Short Run High Gray-Level Emphasis (SRHGE)

$$\text{SRHGE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j) \cdot i^2}{j^2}.$$

Long Run Low Gray-Level Emphasis (LRLGE)

$$\mathrm{LRLGE} = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)\cdot j^2}{i^2}.$$

Long Run High Gray-Level Emphasis (LRHGE)

$$\mathrm{LRLGE} = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}p(i,\,j)\cdot i^2\cdot j^2.$$

Dasarathy and Holder [15] tested all eleven features on the classification of a set of cell images and showed that the last four features gave better performance. These features are all based on intuitive reasoning, in an attempt to capture some apparent properties of run-length distribution. For example, the eight features illustrated in Fig. 2 are weighted-sum measures of the run-length concentration in the eight directions, i.e., the positive and negative 0 ,45,90, and 135 directions. Two drawbacks of this approach are: there is no theoretical proof that, given a certain number of features, maximum texture information can be extracted from the run-length matrix, and many of these features are highly correlated with each other.

II. METHODOLOGY:

This study carried out to evaluate the role of texture analysis technique in detection of and outlining the breast masses related to its textural feature. The sample is 155 patients and the data collected randomly from X-ray department at cancer diagnostic medical center. The patient under examination must perform x-ray mammography, and FNAC of breast mass in order to identify the tumor feature and type, determine tumor site and size then the patient image will analyzed by using of IDL program for textural analysis.
once we need faster and accurate diagnostic modalities in this situation in order to have high diagnostic accuracy in assessing breast tumors and therefore using this scan to plan patient for treatment which need Avery accurate delineation of tumor edges in case of CTV and planning target volume in order to deliver sufficient dose in case of radiation to the both volumes and increase therapeutic and diagnostic radio.

III. RESULTS:

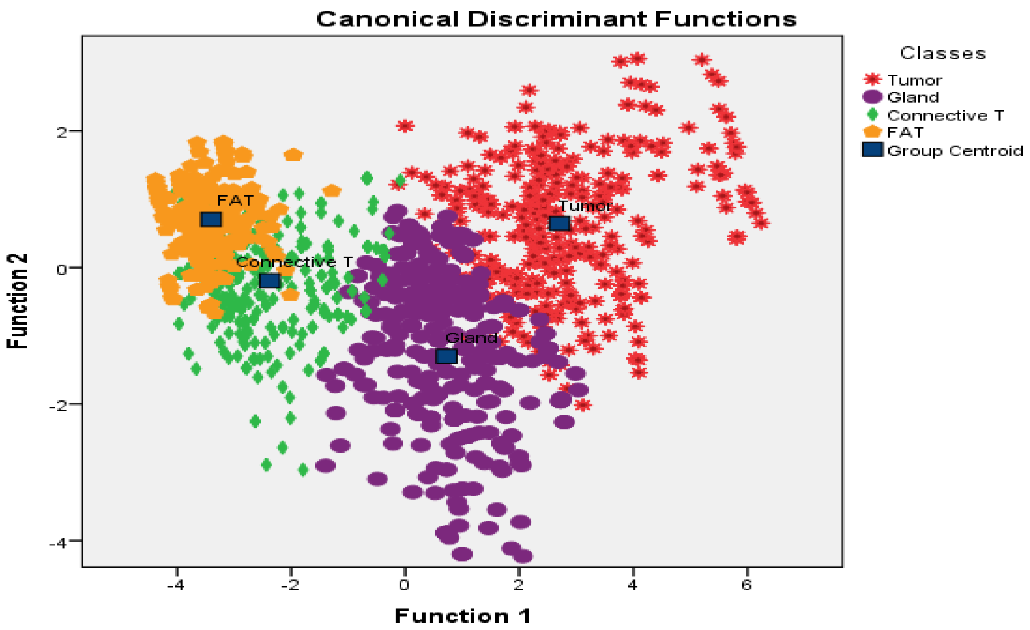

Fig 1. Show Scatter plot generated using discriminate analysis function for four lasses represents: Tumor, gland, connective tissues and fat.

To classify the breast tumor, gland, connective tissues and fat the features classified regions of the whole images (as raw data) were classified furthers using linear discriminate analysis. The result of the classification showed that the tumor areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

Classes	Predicted Group Membership				Total
	Tumor	Gland	Connective T	FAT	
Tumor	88.9	11.1	0.0	0.0	100.0
Gland	0.8	98.9	0.3	0.0	100.0
Connective T	0.0	3.2	91.9	4.9	100.0
FAT	0.0	0.0	13.7	86.3	100.0
91.5% of original grouped cases correctly classified.					

Table 1. Show classification score matrix generated by linear discriminate analysis and classification accuracy of 91.5%.

The classification accuracy of tumor 88.9%, gland 98.9%, connective tissues 91.9% and the fat showed a classification accuracy of 86.3%.

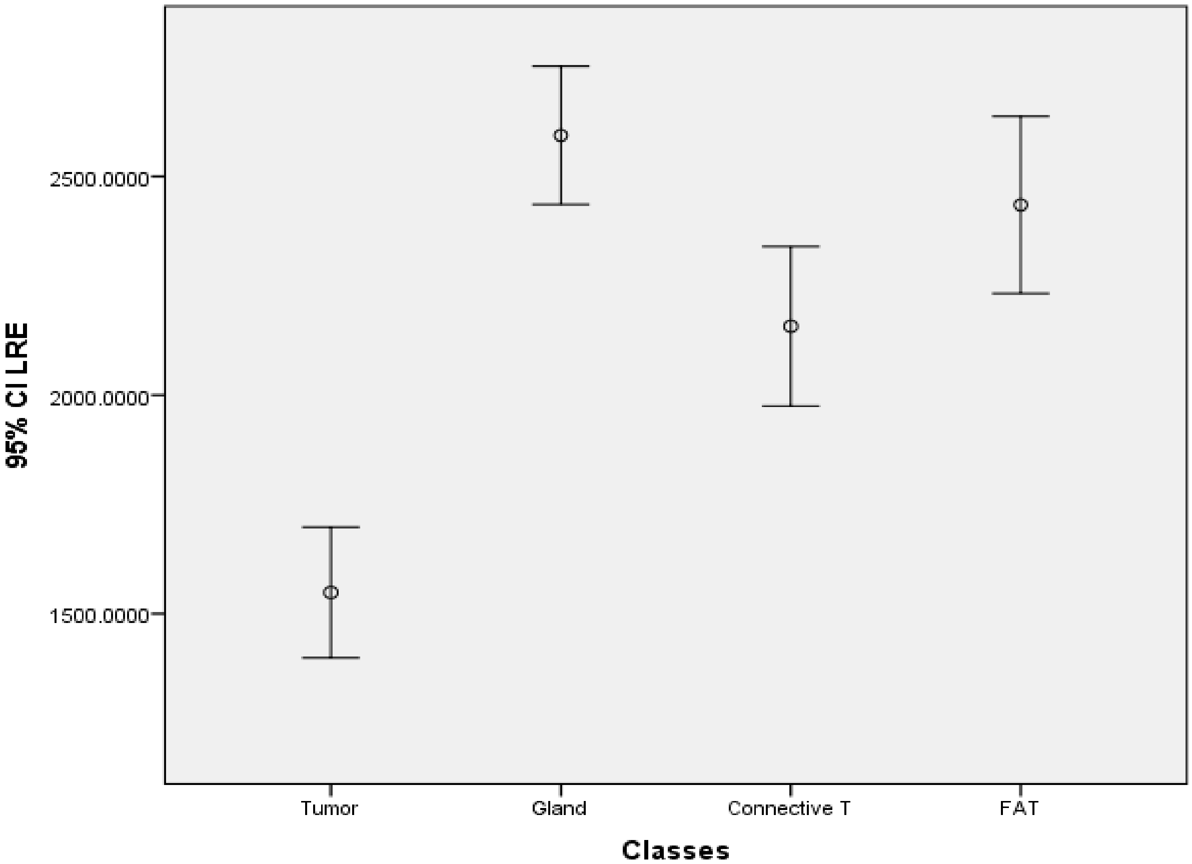

Fig 2. Show error bar plot for the Long Run Emphasis (LRE) textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.
From the discriminante power point of view in respect to the applied features the Long Run Emphasis (LRE) can differentiate between all the classes successfully.

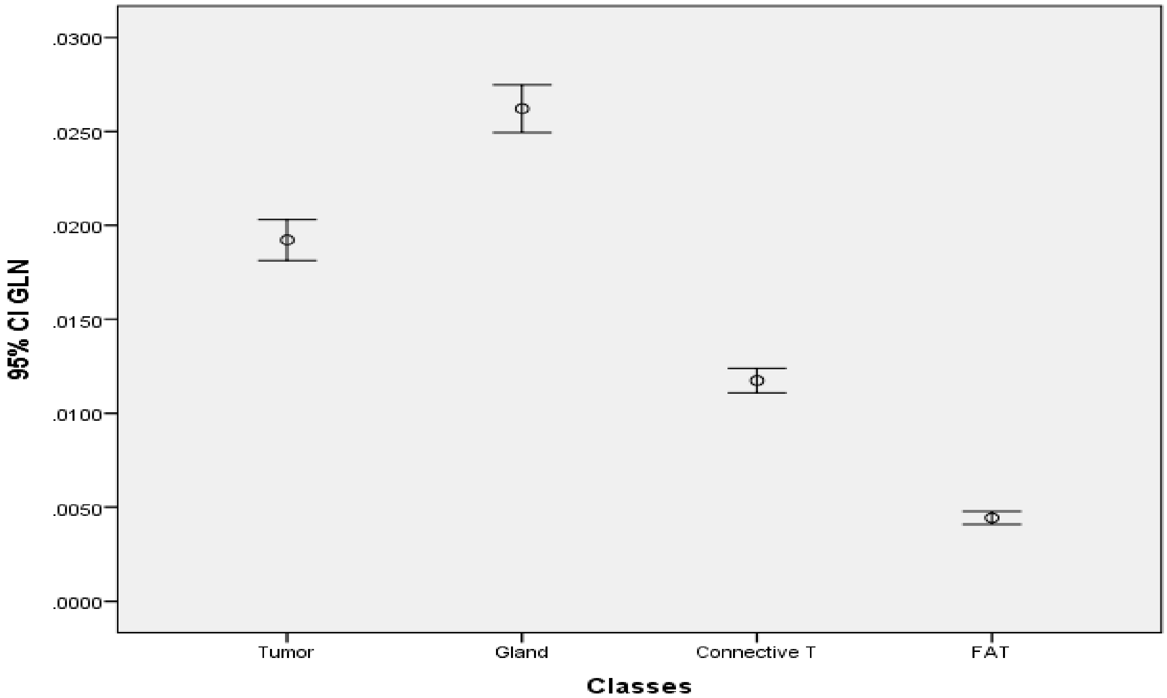

Fig 3. Show error bar plot for the Gray Level Non-uniformity (GLN) textural features that selected by the linear stepwise discriminante function as a discriminante feature where it discriminate between all features.

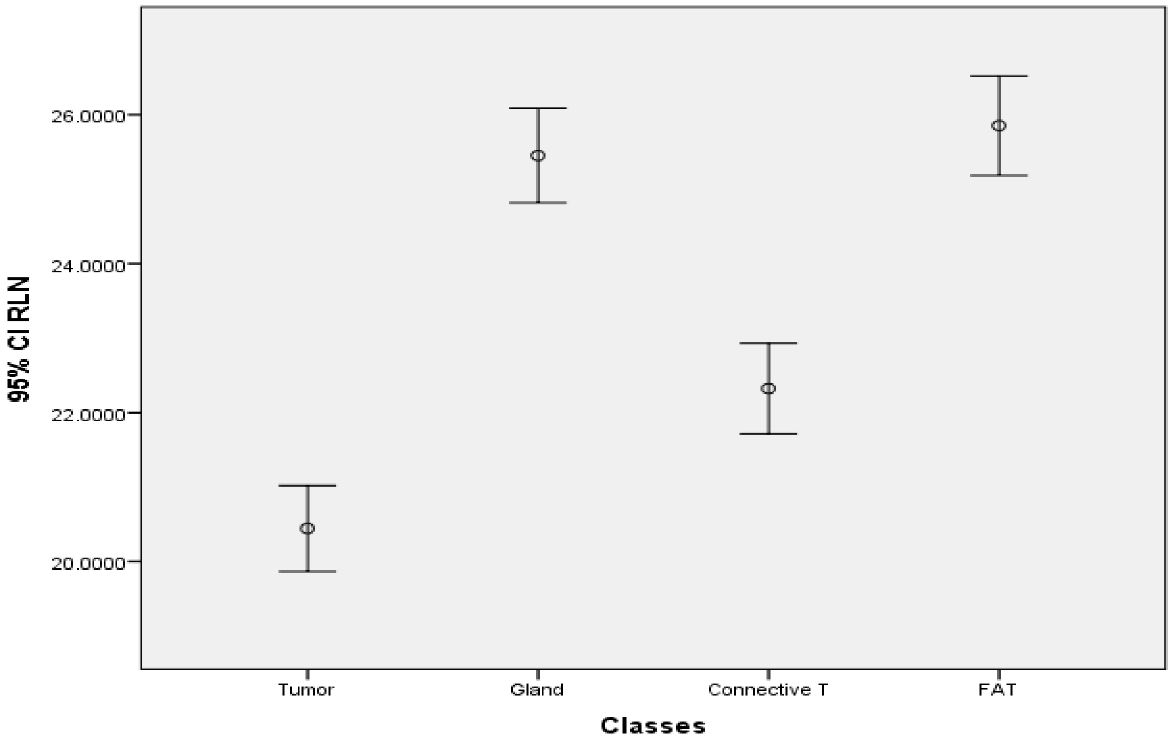

Fig 4. Show error bar plot for the (RLN) textural features that selected by the linear stepwise discriminante function as a discriminante feature where it discriminate between all features.

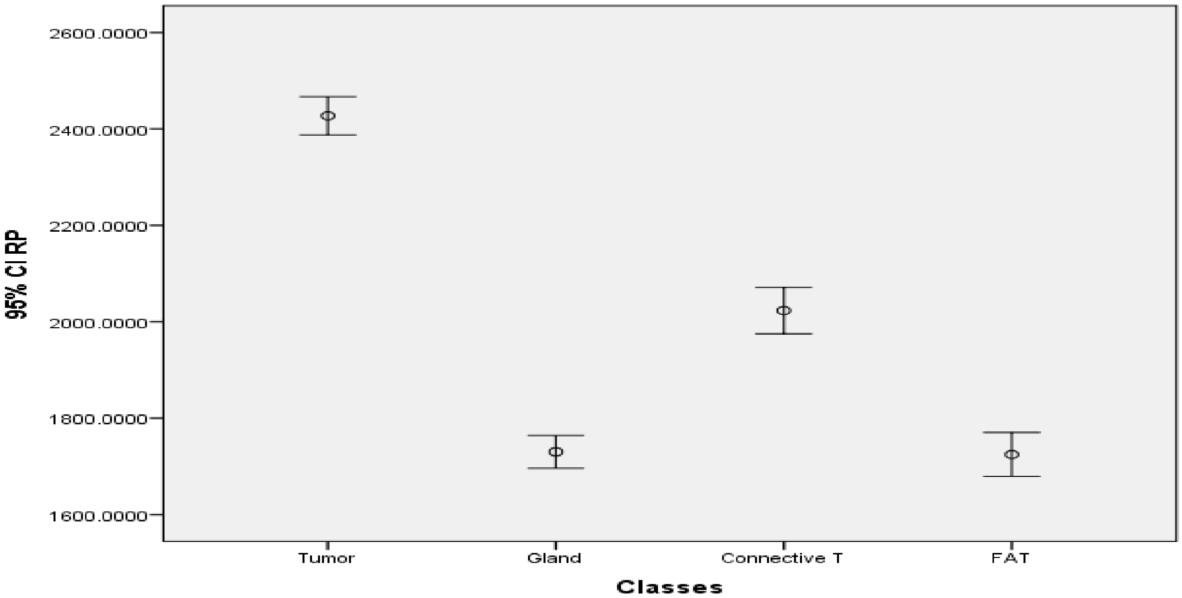

Fig 5. Show error bar plot for the RP textural features that selected by the linear stepwise discriminante function as a discriminante feature where it discriminate between all features.

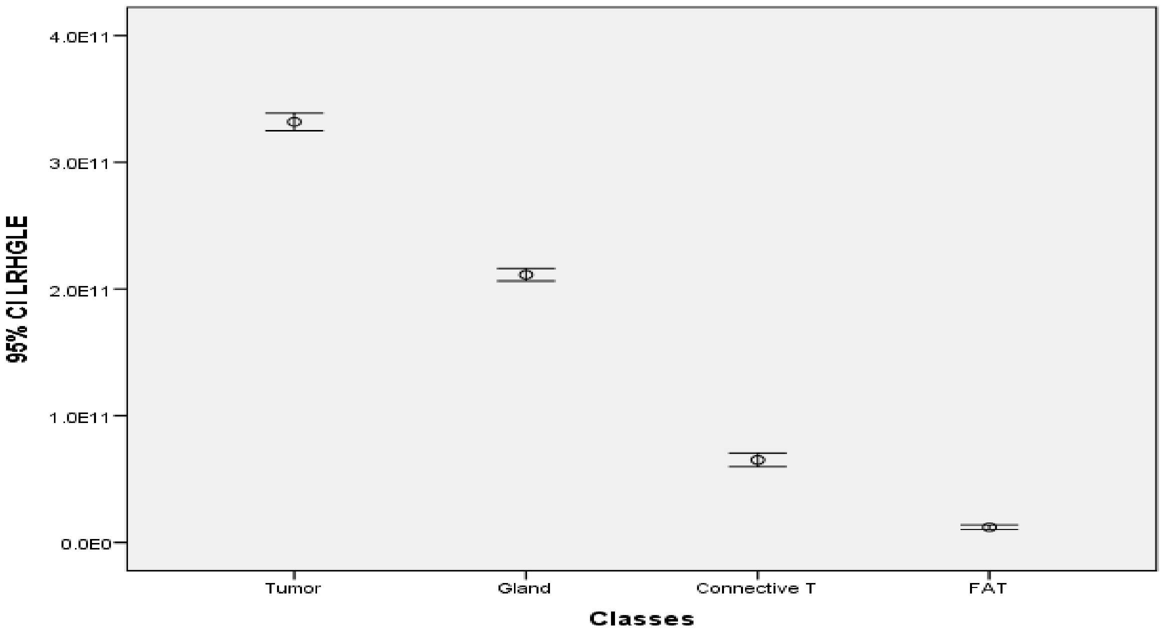

Fig 6. Show error bar plot for the Long Run High Gray Level Emphasis (LRHGE) textural features that selected by the linear stepwise discriminante function as a discriminante feature where it discriminates between all features.

IV. CONCLUSION:

Mammogram–breast x-ray is considered the most effective, low cost, and reliable method in early detection of breast cancer, several texture features are introduced from a proposed higher-order statistical matrix, the gray level run length matrix GLRLM, The sample is 155 patients and the data collected randomly from X-ray department at cancer diagnostic medical center. Several texture features are introduced from (GLRLM). The GLRLM measures the gray level variations in an image. It complements the gray level run length matrix (GLRLM) Features extracted from the weighted GLRLM can be used to estimate the size distribution of the sub-patterns. It works much faster than the commonly used K statistic based on gray level cooccurrence matrices. The GLRLM and its features seem very useful in texture classification, and the classification accuracy of breast masses 91.5%, were the classification accuracy of gland 98.9%, fat 86.3%, connective tissue 91.9%, While the tumor showed a classification accuracy 88.9%. These relationships are stored in a Texture Dictionary that can be later used to automatically annotate new CT images with the appropriate organ names.

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