International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Characterization of Colorectal Cancer Gross Target Volume with 18F-FDG PET/CT Image using the Second-Order Statistical Texture Analysis

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Abstract: ***The aim of this study is to characterize the colorectal region, including the rectum, tumor, and submucosal, using the Gray Level Co-occurrence Matrix (GLCM) and extract classification features from PET/CT with fluorine-18 fluorodeoxyglucose images. The GLCM technique was applied to identify variations in gray levels in the PET/CT images, which complements the features extracted from the images by estimating the distribution of sub-patterns using the Interactive Data Language (IDL) software. The results indicate that the combination of the Gray Level Co-occurrence Matrix and the extracted features achieved a classification accuracy of 100.0% for the rectum, 96.2% for the tumor, and 97.0% for the sub-mucosal, with an overall classification accuracy of 97.4 % for the colorectal area. These relationships are stored in a Texture Dictionary, which can be used in the future to automatically annotate new PET/CT images with the appropriate names for the colorectal regions.***

Keywords: Colorectal cancer, 18F-FDG, PET/CT, Texture analysis

1. Introduction

Colorectal cancer is one of the most common types of cancer according to worldwide incidences statistics. The conventional treatment strategy for colorectal cancer typically involves a combination of surgery, chemotherapy, and radiation therapy. The specific treatment plan depends on several factors, including the stage of cancer, the location of the tumor, and the overall health of the patient (1, 2). The correct diagnosis of colorectal cancer leads to the indication of the most adequate treatments for cancer-affected patients. The diagnosis is made through the visual analysis of tissue samples by pathologists. However, this analysis is susceptible to intra-and inter-pathologists' variability in addition to being a complex and time-consuming task (3).

Fluorine-18 fluorodeoxyglucose (FDG) is commonly used in Positron Emission Tomography (PET) imaging for the evaluation of colorectal cancer (4).

The 18F-FDG PET is a non-invasive imaging technique that allows for the visualization of metabolic activity within the body.18F-FDG PET is usually performed in conjunction with a CT scan, which provides detailed anatomic information about the body. The combined information from the FDG PET and CT scans can provide a more complete picture of cancer and help guide the treatment plan.18-FDG PET/CT can be used for staging, monitoring treatment response, detecting recurrence, and differentiating colorectal cancer from other conditions such as inflammatory bowel disease.

SUV max (maximum standardized uptake value) is a commonly used parameter in 18F-FDG PET imaging to quantify the level of 18F-FDG uptake in a particular region of interest within the body. In colorectal cancer, higher SUVmax values in the affected area are generally associated with higher levels of metabolic activity, which can indicate the presence of cancer (5).

Higher SUV max values have been found to be associated with higher histologic grades, larger tumor size, and more advanced stages of the disease. Some studies have even shown that SUVmax can be used as a predictor of malignancy in colorectal cancer and can help to distinguish between benign and malignant lesions. Numerous studies have examined the correlation between SUV max measurements obtained from 18F-FDG PET scans and histopathological diagnosis in colorectal cancer, yielding predominantly favorable outcomes (6).

Second-order statistical texture analysis is a method used to quantify the spatial variations in the gray-level intensity of medical images, including 18F-FDG PET images. The goal of texture analysis in 18F-FDG PET is to extract features that can help differentiate normal tissue from diseased tissue and to improve the accuracy of diagnosis and treatment planning.

The gray-level co-occurrence matrix (GLCM), also known as grey-tone spatial dependence matrices (GTSDM) is a commonly used tool in second-order statistical texture analysis. The GLCM measures the spatial relationship between pairs of pixels with similar gray-level intensities. The use of GLCM for texture analysis was suggested by Haralick (7).

The GLCM of an image is created based on the correlations between image pixels. For a k bit image with $L=2k$ brightness levels, an $L \times L$ matrix is created whose elements are the number of occurrences of a pair of pixels with brightness of **a. b** separated by **d** pixels in a certain direction.

For example, in Fig (1), a 3-bit image with 8 levels of intensity is shown and its GLCM has 8 rows and 8 columns. The elements of this matrix are the number of pixel occurrences with gray levels ($i. j$) which are represented by a displacement of 1 pixel in the direction of zero degrees.

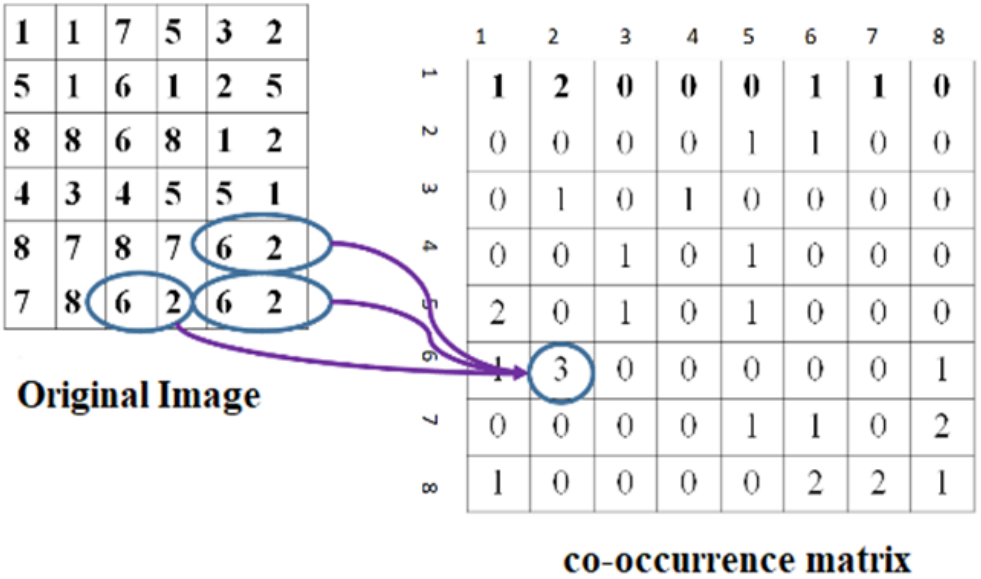

Figure 1: An Example of How to Extract a Co-Occurrence Matrix with 8 Brightness Levels

Typically, the co-occurrence matrix is defined for the four main directions (0, 45, 90, and 135). In Fig (2), four possible angles between two pixels with angles (0, 45, 90 and 135) degrees are represented with a displacement of 3 between two pixels. The resulting matrix is then used to calculate various statistical measures, which can be used as features for diagnosis and treatment planning (8).

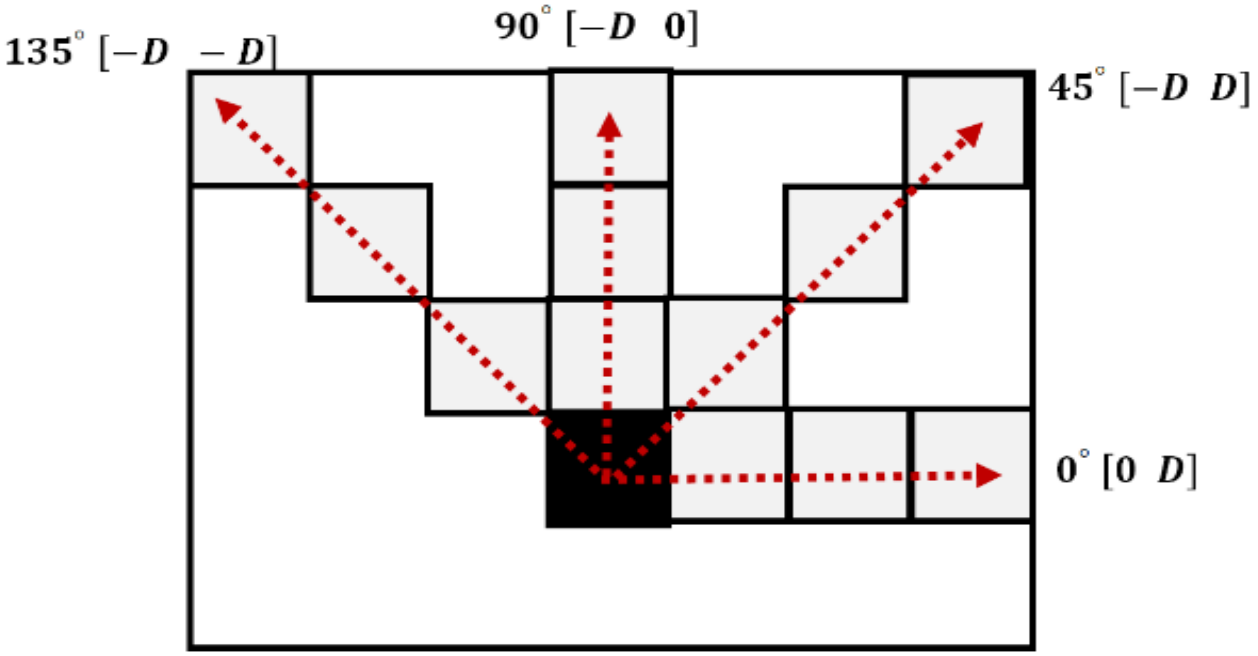

Figure 2: Four different directions with displacement

In practice the information provided by certain features may be highly correlated or of limited practical use. A feature selection strategy is therefore useful with this approach to take account of redundant, or irrelevant, information.

It is also interesting to note that prior to any processing the GTSDMs, which are symmetric, can provide some useful information on the characteristics of the image being studied. For example, the co-occurrence matrix entries for a coarse texture will be heavily focused along the diagonals relative to the distance d between the pixels studied. Texture analysis, as an image post-processing technique, has been more and more utilized in the field of oncologic imaging (9). Characterizing tumor heterogeneity using texture indices derived from 18F-FDG PET images has shown promise in predicting treatment response and patient survival in some types of cancer. The relationship between PET-derived texture indices, precise tracer distribution, and biologic heterogeneity was clarified using PET images, autoradiographic images, and histologic images (10).

The aim of present study was to characterize the colorectal cancer region, including the rectum, tumor, and submucosal, using the Gray Level Co-occurrence Matrix (GLCM) and extract classification features from PET/CT with fluorine-18 fluorodeoxyglucose images.

2. Material and Method

PET/CT study for 127 patients was examined in Kuwait Cancer Control Center by 18F-FDG Whole-Body PET/CT. The patients were scanned using GE Discovery 710 consists of a fully integrated 3D Positron Emission Tomography and multi-slice Computed Tomography scanner with all available CT diagnostic applications, except gantry tilt. Due to the PET/CT length, the patient table sits on a unique base that drives the table between the PET and CT portions of the gantry. The PET/CT table is rated for a patient weight of 227 Kg (500 pounds) and the cradle travels up to 170 cm on standard systems or up 2 meters on systems with the 2m scan range option.

All patients received an intravenous injection of 0.06 mCi/Kg of 18F-FDG. Patient's plasma glucose is 6.2 (±1.5) mmol/l. After an initial uptake phase of an approximately 60 minutes, a CT-Scan without oral or IV contrast, without breath holding at low mA level was acquired for attenuation correction and localization purposes only. Subsequently, PET images from vertex to mid-thigh were obtained using 2.0 min/bed acquisition (6 to 10 bed positions in total). A scout scan was performed at 10mA prior to a CT scan for gross anatomical visualization. CT, PET, and fused images were reconstructed in trans-axial, coronal, and sagittal projections and interpreted from a workstation.

In this study, Interactive Data Language IDL Version 6.1 was used to extract features from the 18F-FDG PET/CT images using GLCM Second-order statistics techniques, and IBM SPSS Statistics Version 26 was employed for statistical analysis.

3. Results and Discussion

The GLCM Second order statistics technique was used to extract texture features, including mean, variance, skewness, kurtosis, energy, and entropy from all PET/CT images. Stepwise linear regression was then employed to identify the most significant feature for classifying rectum cells in the PET/CT images.

Linear Discriminant Analysis (LDA) was utilized for classification, where LDA creates a classification function by determining linear combinations of features that optimally differentiate the classes. The classification outcomes produced by LDA are summarized in Table (1).

The results indicate that the overall accuracy of classifying colorectal cells was 99.0%, with a rectum classification accuracy of 99.8%, tumor classification accuracy of 96.4%, and submucosal classification accuracy of 97.7%.

Table 1: Classification results generated by linear discriminate analysis (LDA)

Classes		Predicted Group Membership			Total
	Original Groups	Rectum	Submucosal	Tumor	
%	Rectum	100.0	0.0	0.0	100
	Submucosal	2.1	97.0	0.9	100
	Tumor	0.0	3.8	96.2	100

The classification showed that the rectum cells were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

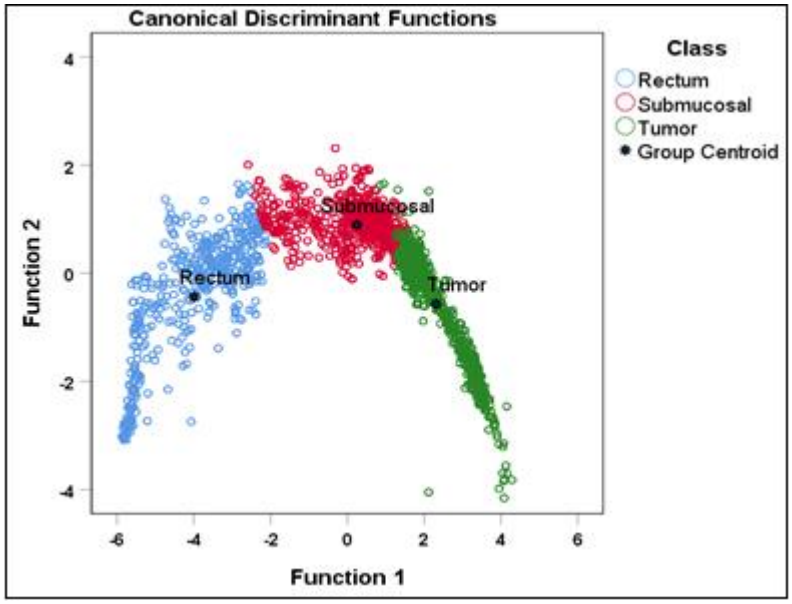

Figure 3: Scatter plot generated LDA classification function for three classes represents: rectum, tumor and submucosal

Figures 4, 5, 6, 7, and 8 display error bar plots for the 95% Confidence Interval (CI) of mean, skewness, kurtosis, energy, and entropy textural features, respectively. These features were selected by the linear stepwise discriminate function as discriminate features, and they effectively differentiate between all the features.

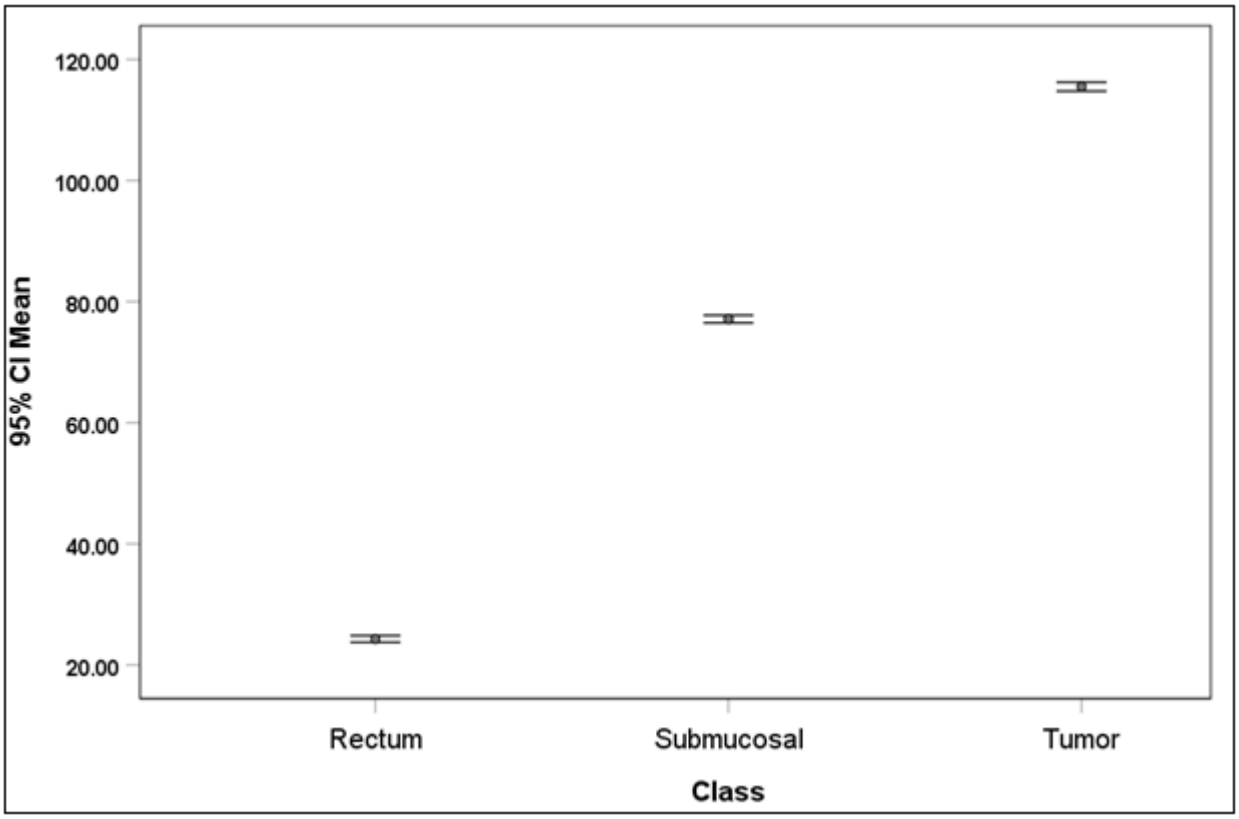

Figure 4: Error bar plot for the CI mean textural features

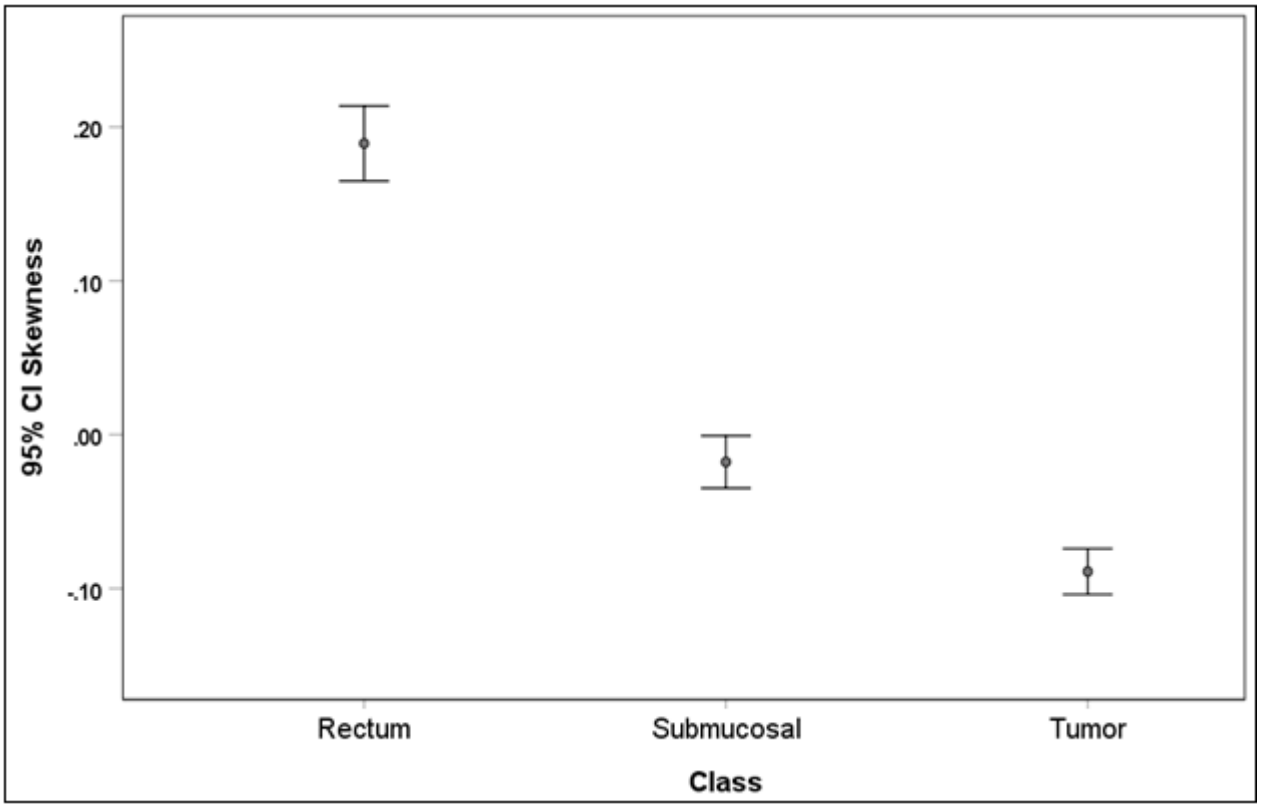

Figure 5: Error bar plot for the CI skewness textural feature

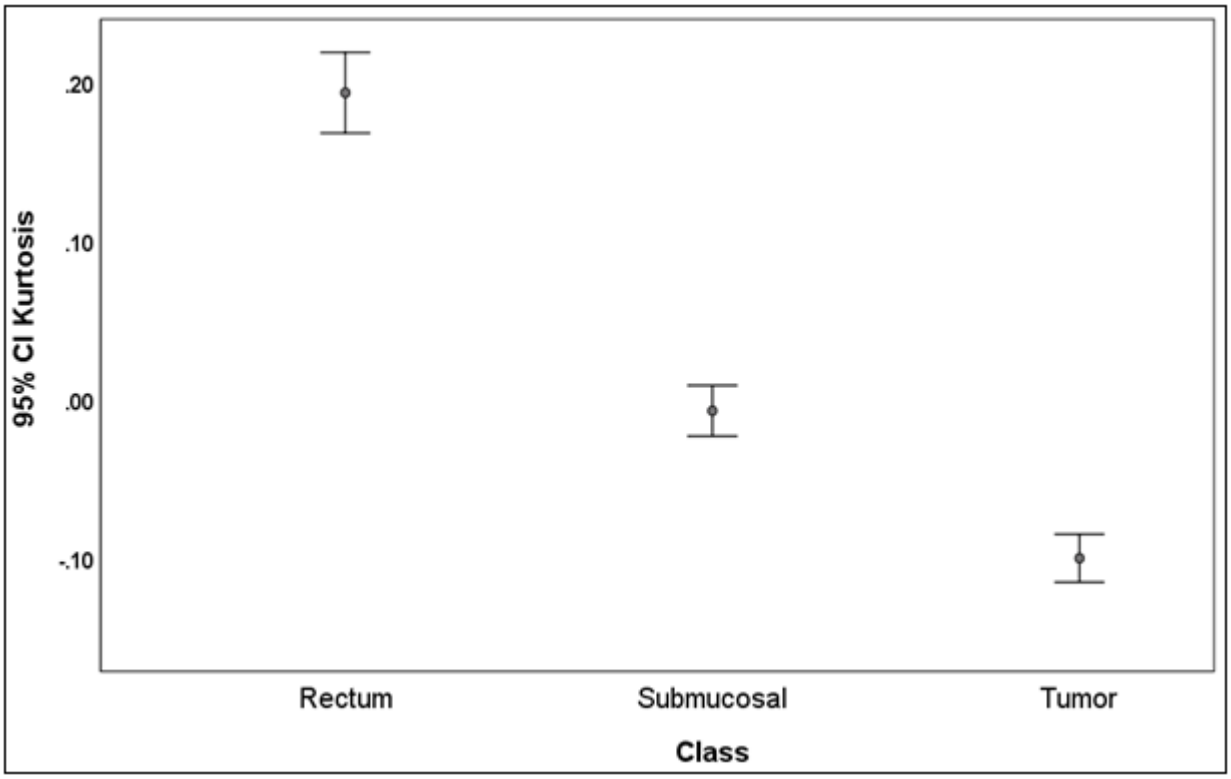

Figure 6: Error bar plot for the CI kurtosis textural features

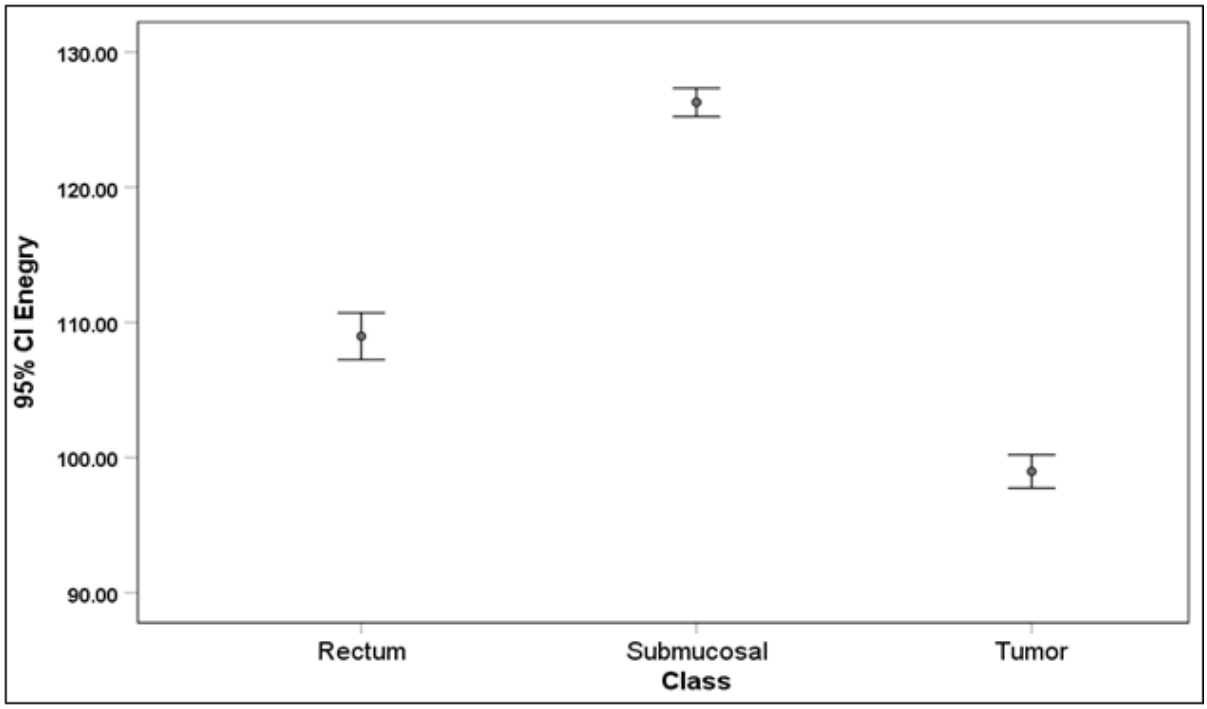

Figure 7: Error bar plot for the CI% energy textural features

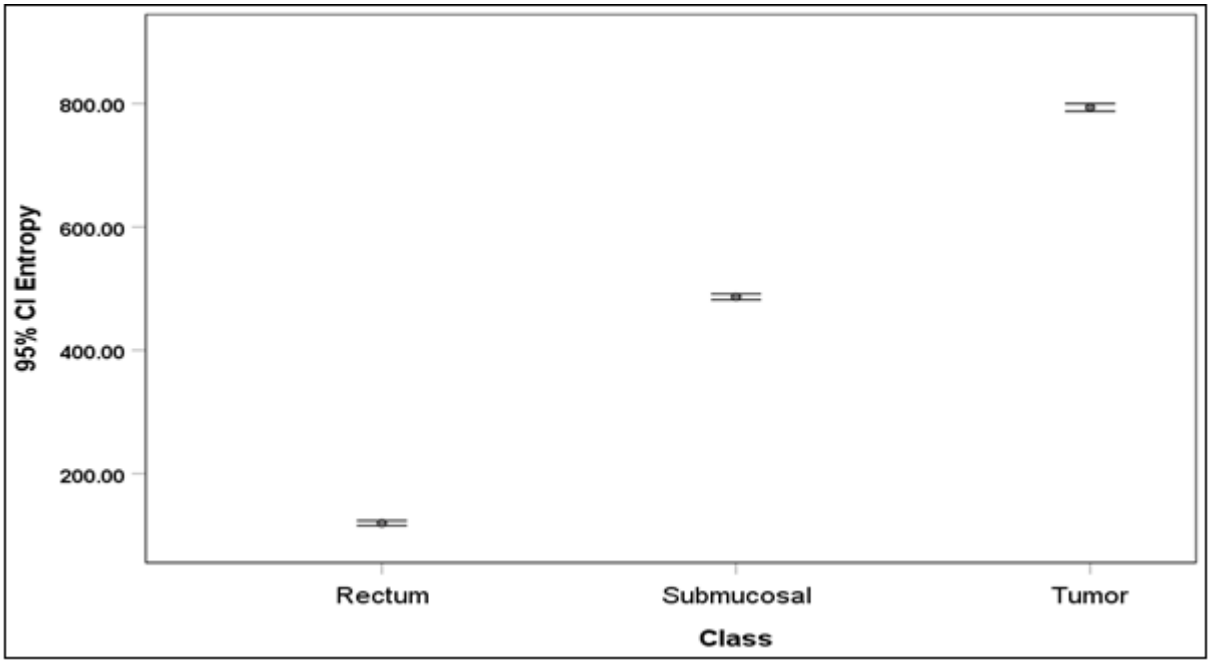

Figure 8: Error bar plot for the CI entropy textural features

Regarding their discriminatory power, both mean and entropy features are capable of successfully differentiating between all the classes. These findings are in line with previous studies on texture analysis using GLCM for extracting classification features from 18F-FDG PET/CT images, demonstrating good agreement with those results (12).

4. Conclusions

The use of GLCM second-order statistical texture analysis is a valuable technique for analyzing 18F-FDG PET images, as it provides important information about the image texture that can enhance diagnosis and treatment planning. Linear discriminate analysis (LDA) can be applied to generate a classification function that separates images into different classes by identifying linear combinations of features that maximize class separation.

In this study, several texture features were extracted from Gray Level Co-occurrence Matrix (GLCM), and the resulting classification score matrix from LDA achieved an overall classification accuracy of 97.4% for image regions. The accuracy of rectum classification was 100%, while tumor classification accuracy was 96.2% and submucosal accuracy was 97.0%.

The classification function generated by linear discrimination analysis can be used to classify other images into the mentioned classes using the following multi-regression equation:

Tumor =-8.310+ (Mean*0.361) + (Skewness*-0.126) + (Energy*-0.006) +Entropy*-0.039)
Submucosal =-7.992+ (Mean*0.363) + (Skewness*-0.099) + (Energy*-0.007) +Entropy*-0.039)
Rectum =-4.914+ (Mean*0.207) + (Skewness*-0.096) + (Energy*-0.006) +Entropy*-0.019)

The results of texture analysis can be used to generate a texture dictionary, which can be used to automatically annotate new FDG PET images with the appropriate diagnosis or treatment information for the colorectal regions. It is important to note that texture analysis is just one of many tools used to evaluate FDG PET images, and should be used in conjunction with other imaging modalities and clinical information to ensure the most accurate and comprehensive evaluation of the patient.

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