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Characterization of Glioma on Brain Magnetic Resonance Images Using Texture Analysis

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Abstract:
Background*: Texture analysis studies have been produced more often in oncology on the recent years; As it can increase the information that we can get from the radio-diagnostic images; here we took Glioma as it considered the most common malignant tumor of the brain; The study main concept is to use the texture analysis first order features for characterization of the Glioma which will give quantitative approach for the diagnosis.*
Materials and Methods*: In this cross sectional analytical study, the data was collected from Antalya medical center; it consists of 300 MR images for Glioma patients (50 T1, 100 T2, 100 FLAIR and 50 T1+C) age above 18years. After the images were selected the introduced to the it into the computer based software Interactive Data language (IDL) to extract the textural features (first order and higher order statistics) for gray matter, white matter and the Glioma; then the extracted features were entered to SPSS for analysis.*
Results*: For the first order statistics features the T2 weighted images shows the best differentiation of the glioma from normal brain tissues among all imaging sequences with accuracy = 99%, farther more the entropy texture feature in particular, demonstrated the best differentiation between the Glioma and the rest of classes; and it has the highest entropy in all imaging sequences. On the other hand the when using the higher order statistical features the MR imaging sequence that show the greatest discrimination accuracy is T1+C imaging sequence equal 93.6%, and the best higher order feature for classification of Glioma CLN textural feature which discriminates highly all classes in all imaging sequences; with the Glioma having the highest CLN in all imaging sequences.*
Conclusion: *Glioma were most different from the rest of brain tissues on T2 weighted images than the rest imaging sequences and with classification accuracy of 99% and sensitivity equal 98.2% when using first order statistical features and it can be diagnosed quantitatively from normal tissue by using the following equation:*
Glioma = (19.977×mean) + (-.100× variance) + (1.830× Kurtosis)+(.053×energy)+ (-2.363×entropy) - 217.467.
And when using the higher order statistical features the best discrimination was on T1+C images with accuracy = 94.8% and sensitivity equal 93.6% and it can be diagnosed quantitatively from normal tissue by using the following equation:
Glioma=(94.305× SRE)+(11.117× LRE)+(.009× GLN)+(79.843× RP)+(157.989× LGRE)+(-77.437× SRLGE)-112.462
Key Word*: Texture Analysis; Glioma; Magnetic Resonance Images; First Order Statistics; Higher order statistic.*

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I. Introduction

In neuroradiology the magnetic responses (MR) imaging give the best image resolution, soft-tissue differentiation and tumor delineation; also provide deferent kinds of images according to many physical factors for example: T1, T2 relaxation time and proton density of protons in tissue[1,2]; then radiologists diagnosis this images according to their knowledge and experience; texture analysis increases the information that obtained from the images as it evaluate and computed the inter-relationships of the pixels[3,4]; Texture analysis has many types on of them is the statistical based method which is depends on the pixel values, distribution, and spatial interrelationship in the defined region of interest; and it consist of First-order statistical texture analysis which is a histogram representation of image intensities in a predefined region of interest and calculates mean, variance, energy, skewness, entropy, uniformity, and kurtosis; While higher order statistical texture analysis

quantifies the image pattern on the basis of the spatial relationship or co-occurrence of the pixel value [5,6]. Gliomas appears on magnetic resonance images as heterogeneous mass ,as it represent a mixture of solid tumor portions, necrosis and surrounding edema; the tumor portion have low signal intensity on T1-weighted images and as high signal intensity on T2/fluid attenuated inversion recovery (FLAIR) weighted images[1,7]. The aim of the study is to characterize Glioma on brain magnetic resonance images using first order statistics texture features in Sudan.

II. Material And Methods

This analytical study of a case control type where normal T1, T2,T1+C and FLAIR MR Images of the brain taken as a reference was carried out at Antalya medical center and it was conducted from December 2018 to December 2020.

Study Design: Retrospective cross sectional analytical study

Study Location: At radiology department on Antalya medical center, Khartoum–Sudan.

Study Duration: December 2018 to December 2020.

Sample size: it consists of 300 MR images for Glioma patients (50 T1, 100 T2, 100 FLAIR and 50 T1 with contrast weighted images (T1+C))

Sample size calculation: convenient sample size

Subjects & selection method: The population of this study includes MR images for patients having Gliomas. The MR images were drawn from the picture archiving and communicating system (PACS) of Antalya medical center minutely and stored on computed disc the they was viewed by the Radiant, Ant- digital imaging and communication in medicine (DICOM) viewer in computer, to select the section of image that have the lesion on it and then this images uploaded it into the computer based software Interactive Data language (IDL) where the DICOM image converted to tagged image file format (TIFF) and the user then clicks on areas represents the white matter and lesion plaque.

Inclusion criteria:

1. Glioma patients
2. Either sex
3. Aged >18 years.

Exclusion criteria:

1. Patients having pathology other than Glioma..

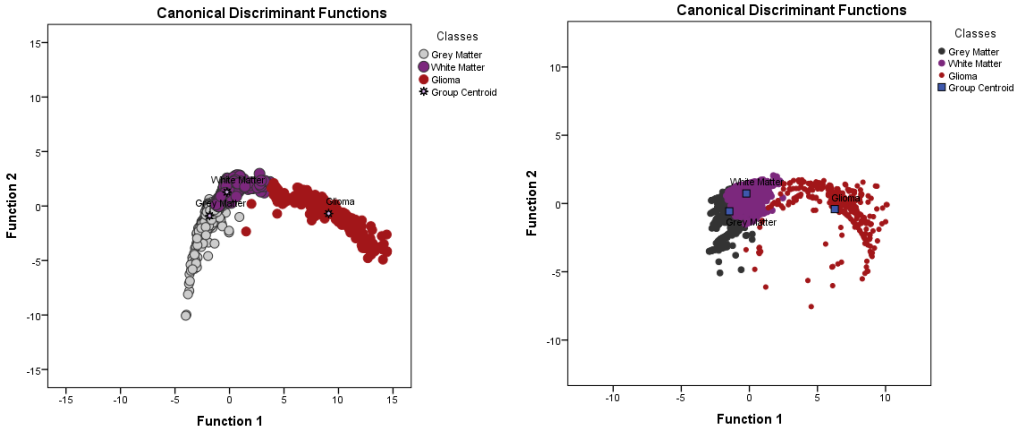
Procedure methodology

The selected images uploaded it into the computer based software Interactive Data language (IDL) where the DICOM image converted to TIFF format and the user then clicks on areas represents the white matter, gray matter and Glioma . In these areas a window of 3×3 pixel was set and the first order statistics were extracted. Including the first order statistics features: mean, variance, skewness, kurtosis, energy and entropy. And a window of 6×6 pixel was set for higher order statistical features extraction which are Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray-Level Nonuniformity (GLN), Run-Length Nonuniformity (RLN), Run Percentage (RP), Low GrayLevel Run Emphasis (LGRE), High Gray-Level Run Emphasis (HGRE), Short Run Low Gray-Level Emphasis (SRLGE), Short Run High Gray-Level Emphasis (SRHGE), Long Run Low Gray-Level Emphasis (LRLGE), Long Run High GrayLevel Emphasis (LRHGE), These features were extracted for the predetermine classes (white matter, gray matter and lesion) for all lesion individually; then entered to SPSS for analysis.

Statistical analysis

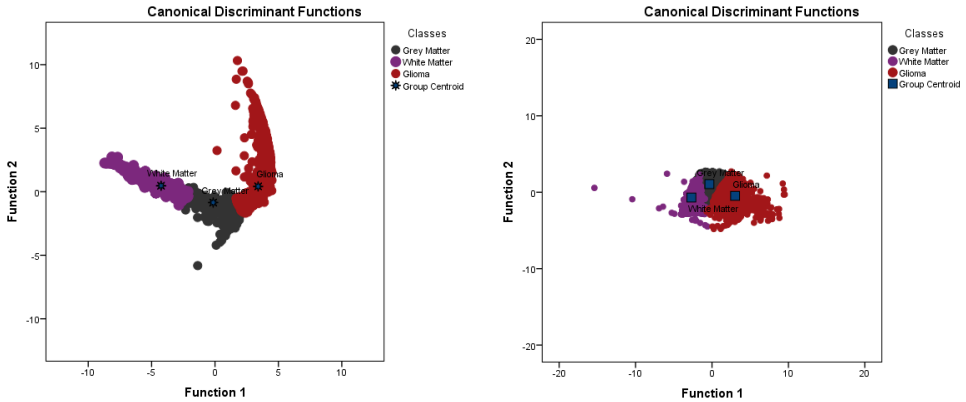
Data was entered into SPSS version 20 (SPSS Inc., Chicago, IL) to generate a classification score using stepwise linear discriminate analysis; to select the most discriminate feature that can be used in the classification of white matter pathologies. Fisher exact tests were performed to test for differences in proportions of categorical variables between the groups; then scatter plot using discriminate function was generated as well as classification accuracy and linear discriminate function equation to differentiate between classes for unseen images.

III. Result



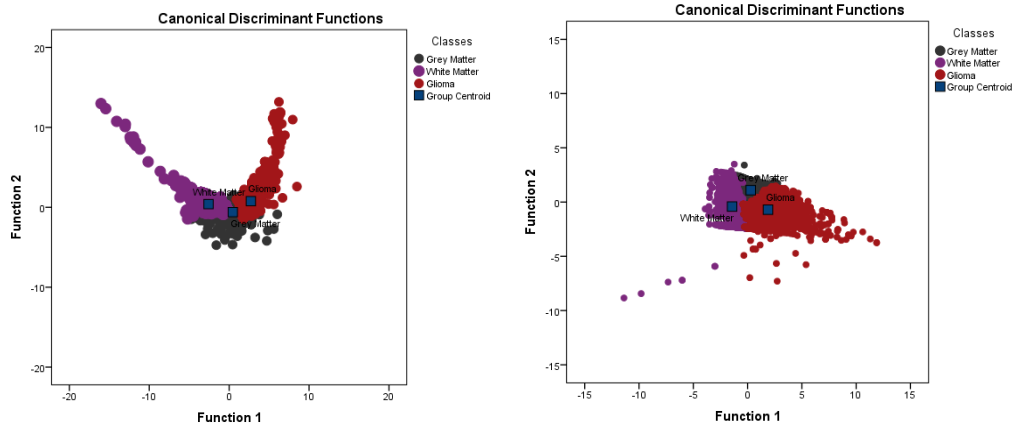
(A) (B)

Figure no1: Scatter plot demonstrate the classification of brain tissues using linear discriminate analysis on T1 images for Glioma patients. First order features (A) and higher order features (B)



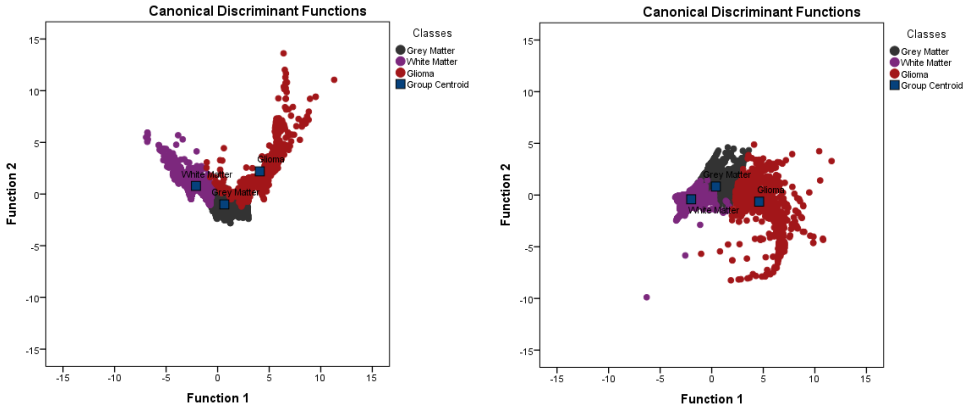
(A) (B)

Figure no2: Scatter plot demonstrate the classification of brain tissues using linear discriminate analysis on T2 images for Glioma patients. First order features (A) and higher order features (B)



(A) (B)

Figure no3: Scatter plot demonstrate the classification of brain tissues using linear discriminate analysis on FLAIR images for Glioma patients. First order features (A) and higher order features (B)



(A) (B)

Figure no4: Scatter plot demonstrate the classification of brain tissues using linear discriminate analysis on T1+ C images for Glioma patients. First order features (A) and higher order features (B)

Table no1: Cross-tabulation shows the classification results of first order statistics using linear discriminate analysis on T1 images for Glioma patients.

Classes		Predicted Group Membership			Total
		Grey Matter	White Matter	Glioma	
Original	Grey Matter	99.8	.2	.0	100.0
	White Matter	6.5	93.5	.0	100.0
	Glioma	.4	4.0	95.6	100.0
a. 96.9% of original grouped cases correctly classified.					

Table no2: Cross-tabulation shows the classification results of first order statistics using linear discriminate analysis on T2 images for Glioma patients.

Classes		Predicted Group Membership			Total
		Grey Matter	White Matter	Glioma	
Original	Grey Matter	99.6	.4	.0	100.0
	White Matter	.9	99.1	.0	100.0
	Glioma	1.8	.0	98.2	100.0
a. 99.0% of original grouped cases correctly classified.					

Table no3: Cross-tabulation shows the classification results of first order statistics using linear discriminate analysis on FLAIR images for Glioma patients.

Classes		Predicted Group Membership			Total
		Grey Matter	White Matter	Glioma	
Original	Grey Matter	98.8	.8	.4	100.0
	White Matter	11.5	88.5	.0	100.0
	Glioma	16.9	.0	83.1	100.0
a. 92.2% of original grouped cases correctly classified.					

Table no4: Cross-tabulation shows the classification results of first order statistics using linear discriminate analysis on T1+C images for Glioma patients.

Classes		Predicted Group Membership			Total
		Grey Matter	White Matter	Glioma	
Original	Grey Matter	98.7	1.3	.0	100.0
	White Matter	7.7	92.3	.0	100.0
	Glioma	14.7	1.5	83.8	100.0
a. 94.8% of original grouped cases correctly classified.					

Table no5: Cross-tabulation shows the classification results of higher order statistics using linear discriminate analysis on T1 images for Glioma patients.

Classes		Predicted Group Membership			Total
		Grey Matter	White Matter	Glioma	
Original	Grey Matter	83.8	16.2	.0	100.0
	White Matter	11.5	88.5	.0	100.0
	Glioma	2.9	8.7	88.3	100.0
a. 86.3% of original grouped cases correctly classified.					

Table no6: Cross-tabulation shows the classification results of higher order statistics using linear discriminate analysis on T2 images for Glioma patients.

Classes		Predicted Group Membership			Total
		Grey Matter	White Matter	Glioma	
Original	Grey Matter	93.7	6.3	.0	100.0
	White Matter	7.3	92.7	.0	100.0
	Glioma	7.9	.9	91.3	100.0
a. 92.6% of original grouped cases correctly classified.					

Table no7: Cross-tabulation shows the classification results of higher order statistics using linear discriminate analysis on FLAIR images for Glioma patients.

Classes		Predicted Group Membership			Total
		Grey Matter	White Matter	Glioma	
Original	Grey Matter	93.7	4.8	1.5	100.0
	White Matter	8.9	91.0	.1	100.0
	Glioma	7.9	10.7	81.4	100.0
a. 89.4% of original grouped cases correctly classified.					

Table no8: Cross-tabulation shows the classification results tissues using linear discriminate analysis on T1+C images for Glioma patients.

Classes		Predicted Group Membership			Total
		Grey Matter	White Matter	Glioma	
Original	Grey Matter	92.4	7.6	.0	100.0
	White Matter	5.6	94.4	.0	100.0
	Glioma	6.2	.1	93.6	100.0
a. 93.6% of original grouped cases correctly classified.					

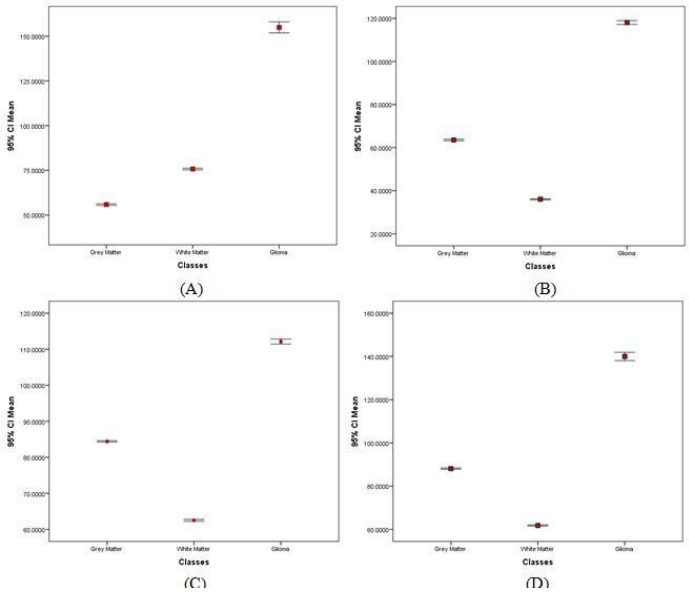


Fig 5: Error bar plot show the discriminate power of the Mean textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

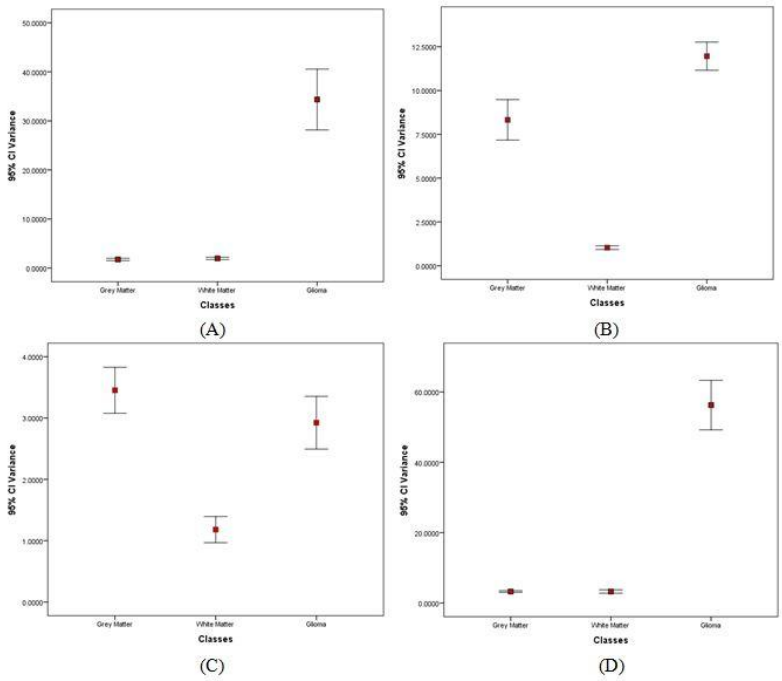


Fig 6: Error bar plot show the discriminate power of the Variance textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

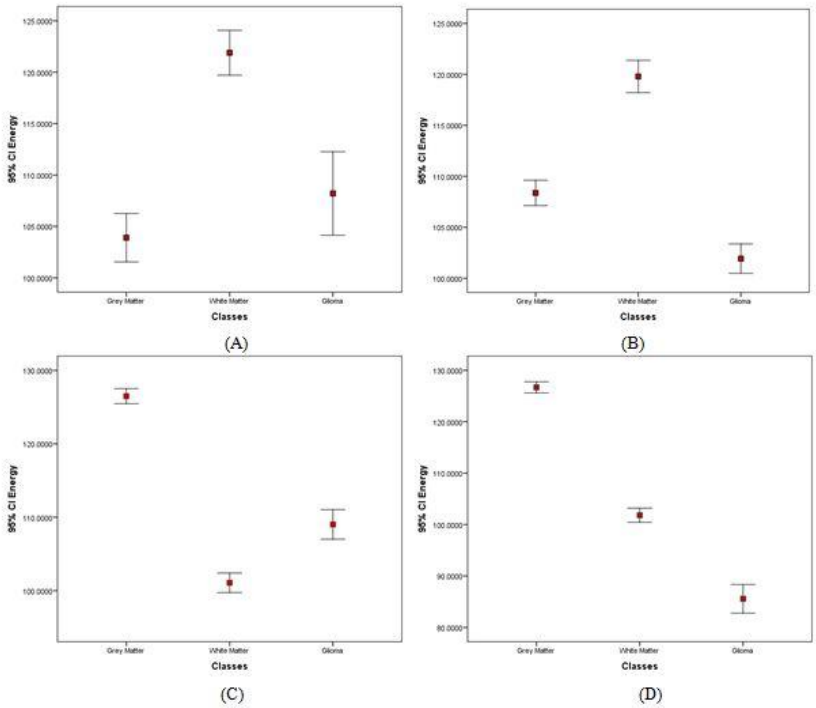


Fig 7: Error bar plot show the discriminate power of the Energy textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

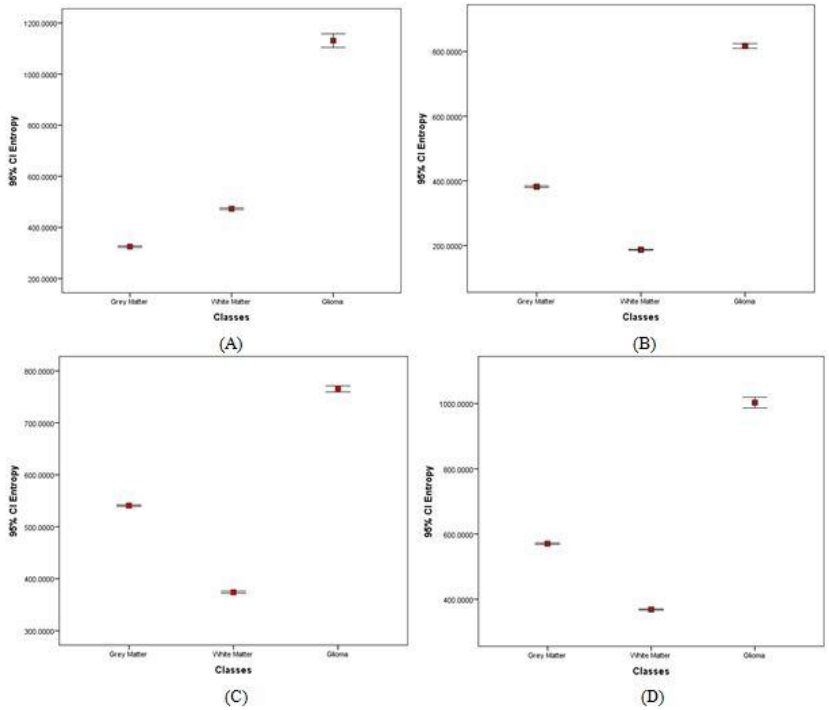


Fig 8: Error bar plot show the discriminate power of the Entropy textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

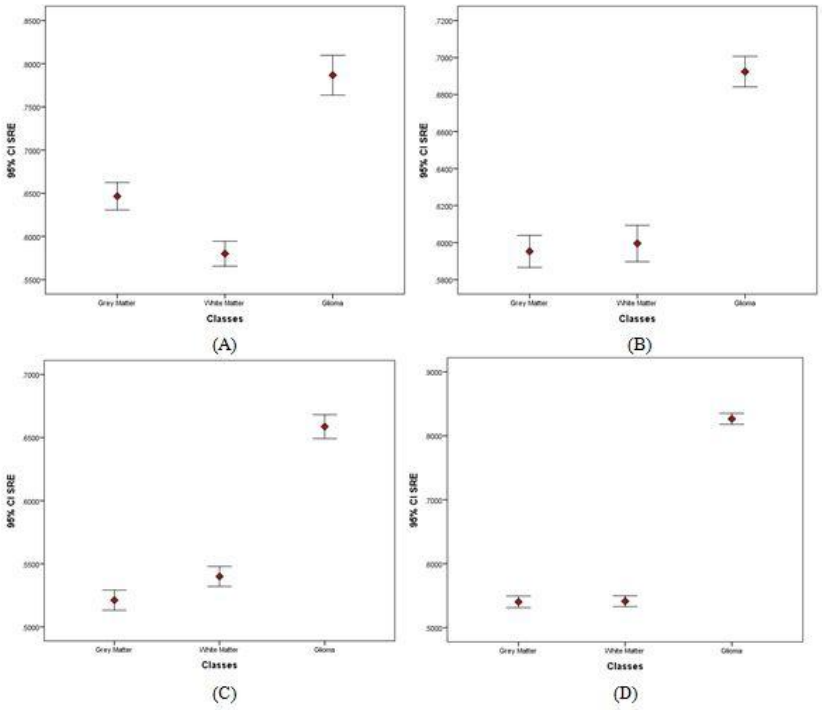


Fig 9: Error bar plot show the discriminate power of the SRE textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

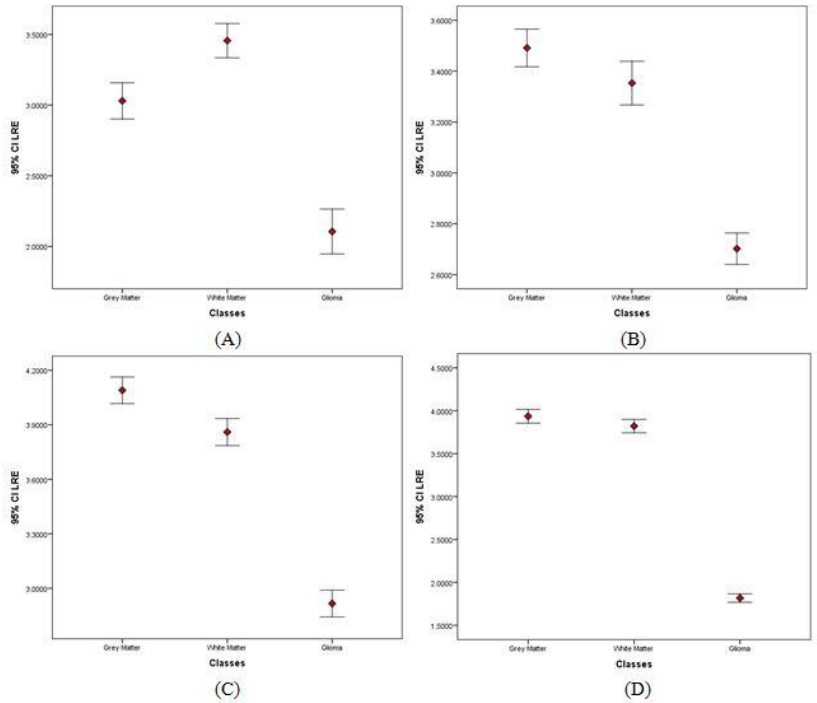


Fig 10: Error bar plot show the discriminate power of the LRE textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

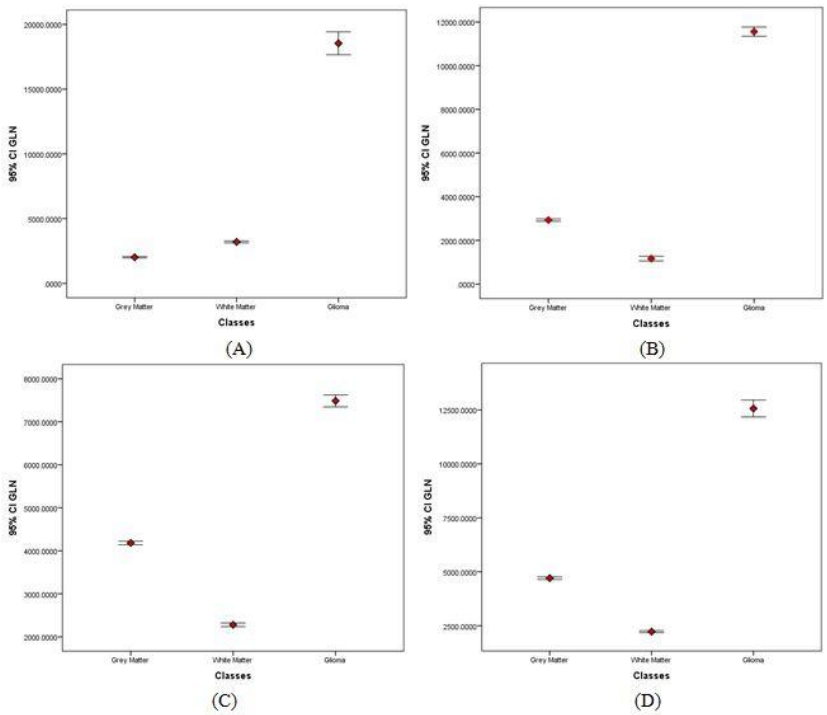


Fig 11: Error bar plot show the discriminate power of the GLN textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

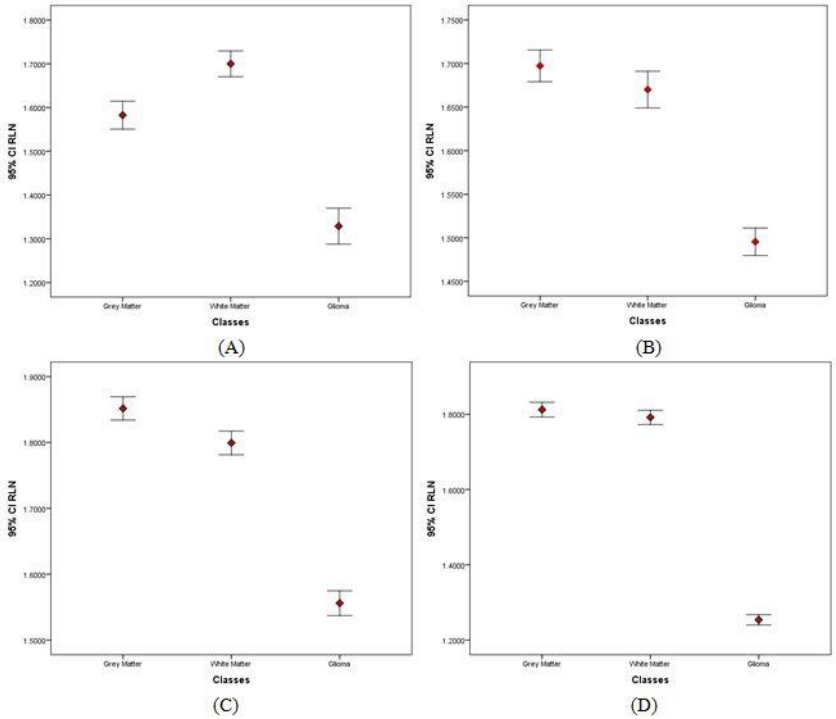


Fig 12: Error bar plot show the discriminate power of the RLN textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

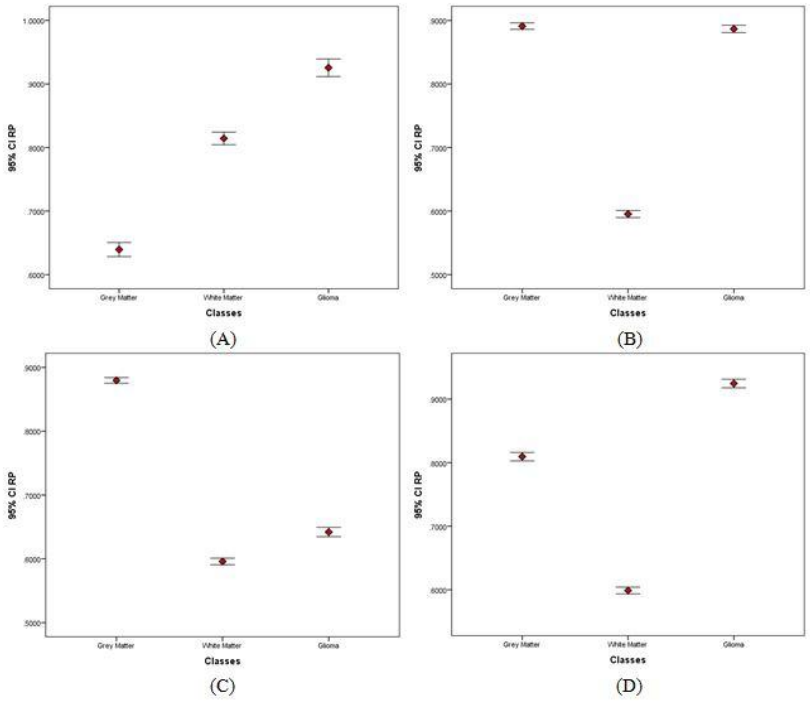


Fig 13: Error bar plot show the discriminate power of the RP textural feature distribution for the selected classes on T1(A), T2(B), FLAIR(C) and T1+C(D) images for Glioma patients

IV. Discussion

In this study there were three classes: gray matter, white matter and Glioma; from each one the First order statistical features and the higher order statistical features were extracted using IDL program; To classify the Glioma from normal brain tissue using linear discriminate analysis.

The result of classification using the first order and the higher order statistical features showed that Glioma is very different from the grey matter and white matter of the brain on T1, T2, T1+C and FLAIR images presented on Fig1 to Fig4; with classification accuracy using the first order textural features equal 99.0%, 96.9%, 94.8% and 92.2% on T2,T1,T1+C and FLAIR images respectively; and the sensitivity of detecting the Glioma in that order equal 98.2%, 95.6%, 83.8% and 83.1% shown from table1 to table4. While when using the higher order statistical features the highest accuracy was on T1+C then T2, FLAIR and lastly T1 images (=93.6%, 92.6%, 89.4% and 86.4% respectively); and sensitivity = 93.6%, 91.3%, 81.4% and 88.3% correspondingly. Table 5 to Table 8. Furthermore Tian et al also found that the T1+C was the best single sequence for glioma grading in MR texture analysis.

Firstly first order statistical features:

From fig5 when using the mean texture feature; the Glioma has the highest intensity in all imaging sequences; fallowed by grey matter then the white matter on T2, FLAIR and T1+C, while on T1 weighted images the white matter has higher intensity than the grey matter (as it contain fat).

Fig6 regarding the variance; Glioma had the highest variance on T2 weighted images fallowed by the grey matter and then the white matter; even though on T1 and T1+C have the highest variance, but there is an interference between the grey matter and white matter. While on FLAIR images the white matter has the highest variance and there is interference between the grey matter and the Glioma. Moreover Ditmer et al perform a study about detecting the accuracy grading the gliomas on MRI texture analysis and found that using the statistical parameter standard deviation at fine texture scale is the best to discriminate the gliomas grads with high a sensitivity and specificity on T1+C images. Also Skogen et al performed texture analysis using first order statistics using contrast enhancing MR images and found standard deviation parameters at a fine texture highly significant in distinguishing low grad gliomas from high grad gliomas

From fig7 When using the energy texture feature (contrast); on T2 images the Glioma has the highest energy (as a result to the presence of edema); and after the fluid attenuation on FLAIR images the Glioma has energy in between the grey matter highest and the white matter lowest than it. While on T1 images the white matter has the highest contrast, then then Glioma then the grey matter, and there is interference Glioma and the gray matter; after introducing contrast media to the patient on T1+C images the interference has gone; and the energy textural feature has discriminate well between the classes (the white matter has the highest energy followed grey matter and finally the Glioma which had the lowest energy).

Regarding the entropy texture feature, it highly differentiate between the Glioma and the rest of classes; it has the highest entropy followed by grey matter then the white matter on T2, FLAIR and T1+C images, but on T1 weighted images the white matter has entropy greater than the grey matter from fig8. Comparable Xie et al perform a study on dynamic contrast enhanced MRI texture analysis for glioma grading and observed that the entropy was able to differentiate glioma grades on T1+C images, same as declared by Soni et al that entropy values consistently exhibited promising results for differentiating low-grade gliomas from high-grade gliomas.

The skewness discriminate the Glioma in T1 and FLAIR images; on the T1 images the Glioma had the lowest skewness, while on FLAIR images the white matter had lowest skewness than the Glioma and the grey matter which had the highest skewness.

Secondly higher order statistical features:

SRE highly distinguished between the Glioma from the other classes in all MR imaging sequences and had the highest SRE value, followed by the grey matter then the white matter on the T1 and FLAIR images; but on the T1+C and T2 images there interference between the grey matter and white matter presented on fig9.

From fig10 LRG textural feature also differentiate well the Glioma from the remnant classes in all imaging sequences and it had the lowest LRG; moreover there is interference between the grey matter and the white matter on T2 and T1+C images.

CLN discriminates highly between all classes in all imaging sequences; and the Glioma had the highest CLN in all imaging sequences followed by the grey matter then the white matter on T2, T1+C and FLAIR images, but on T1 images followed by the white matter then the grey matter as presented in fig 11.

From fig 12 regarding RLN textural feature it discriminates the Glioma from the grey matter and the white matter in all imaging sequences, and it had the lowest value from all classes in all imaging sequences; but on T2 and T1+C images there interference the grey matter and white matter.

RP firstly for T1 and T1+C images it differentiates well between the Glioma and the rest of the classes, and the Glioma had the highest RP in both imaging sequences. While on FLAIR images the grey matter had the highest RP then the Glioma and then the white matter which has the lowest RP. Finally on the T2 images the white matter had the highest RP and there interference between the Glioma and the grey matter as presented on fig13.

Finally the LGRE textural feature it differentiate the Glioma from the normal tissue on T1 an T1+C images only, and it had the highest LGRE on both sequences, but the Glioma in the T1 images shows wide dispersion .

V. Conclusion

In conclusion Glioma can be diagnosed quantitatively from normal tissue by:

Firstly on the first order statistics:

*sensitivity equal to **98.2%** on **T2** images using the following equations:

Glioma = (19.977×mean) + (-.100× variance) + (1.830× Kurtosis)+(.053×energy)+ (-2.363×entropy) -217.467

White matter = (13.668×mean)+ (-.053× variance)+ (1.059× Kurtosis)+(.061×energy)+ (-1.635×entropy) - 98.053

Grey matter = (17.800×mean)+ (-.067× variance) + (1.781× Kurtosis)+(.053×energy) + (-2.123×entropy) - 163.923

*sensitivity equal to **95.6%** on **TI** images using the following equations:

Glioma = (20.230×mean) + (.277× variance) + (-5.500×skewness)+(.206×energy)+ (-2.321×entropy) -275.570

White matter = (23.640×mean)+ (-.103× variance)+ (-5.337×skewness)+(.219×energy)+ (-2.851×entropy) - 238.220

Grey matter = (21.471×mean)+ (-.129× variance) + (-4.689×skewness)+(.192×energy) + (-2.605×entropy) - 189.823

*sensitivity equal to **83.8%** on **T1+C** images using the following equations:

Glioma = (33.284×mean) + (.047× variance) +(.265×energy)+ (-3.955×entropy) -360.222

White matter = (31.523×mean)+ (-.013× variance)+ (.259×energy)+ (-3.796×entropy) -288.834

Grey matter = (35.007×mean)+ (-.010× variance) + (.298×energy) + (-4.202×entropy) -364.053

*sensitivity equal to **83.1%** on **FLAIR** images using the following equations:

Glioma = (43.313×mean) + (.456× variance) + (-1.354×skewness)+(.209×energy) + (-5.206×entropy) -449.781

White matter = (39.778×mean)+ (.426× variance)+ (-1.425×skewness)+(.165×energy)+ (-4.830×entropy) - 351.069

Grey matter = (43.227×mean)+ (.471× variance) + (-1.642×skewness)+(.201×energy) + (-5.227×entropy) - 427.022

Secondly on the higher order statistics:

*sensitivity equal to **93.6%** on **T1+C** images using the following equations:

Glioma=(94.305× SRE)+(11.117× LRE)+(.009× GLN)+(79.843× RP)+(157.989× LGRE)+(-77.437× SRLGE)-112.462

White matter=(98.729× SRE)+(10.535× LRE)+(.005× GLN)+(71.341× RP)+(-183.077× LGRE)+(-104.702× SRLGE)- 68.796

Grey matter=(99.810× SRE)+(10.712× LRE)+(.007× GLN)+(79.136× RP)+(-87.865× LGRE)+(-143.967×SRLGE)- 84.798

*sensitivity equal to **91.3%** on **T2** images using the following equations:

Glioma = (3018.801× SRE) + (-735.729× LRE) + (.010× GLN) +(4323.954×RLN) + (125.574× RP) - 3355.977

White matter = (3010.589× SRE) + (-734.551× LRE) + (.006× GLN)+(4315.083×RLN)+ (105.704× RP) - 3307.723

Grey matter = (3024.061× SRE) + (-735.840×LRE) + (.008× GLN) +(4325.909×RLN) + (126.052× RP) - 3347.503

*sensitivity equal to **81.4%** on **FLAIR** images using the following equations:

Glioma = (204.564× SRE) + (.008× GLN) + (102.857× RLN)+(71.911× RP) -181.097

White matter = (208.547× SRE) + (.005× GLN) + (103.777× RLN)+(73.037× RP) -172.733

Grey matter = (210.897× SRE) + (.007× GLN) + (104.680× RLN)+(83.014× RP) -187.687

*sensitivity equal to **88.3%** on **T1** images using the following equations:

Glioma = (91.169× SRE) + (8.573 × LRE) + (.007× GLN) + (83.018× RP) +(-151.252× LGRE) -108.927

White matter = (102.659× SRE) + (9.108× LRE) + (.004× GLN) + (85.814× RP) +(-273.059× LGRE) -76.855

Grey matter = (102.199× SRE) + (9.358×LRE) + (.003× GLN) + (74.818× RP) +(-246.055× LGRE) -67.418

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