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Characterization of White Matter Lesions on Brain Magnetic Resonance Images Using Texture Analysis

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Abstract:

Background*: The lesions that affect white matter of the brain could be duo to a variety of causes this study discusses the inflammatory, demyelinating, tumors and lesions found in normal ageing process. The main concept of this study was to use the texture analysis mainly first order features for classification an identification of these lesions which will give quantitative approach for the differential diagnosis between them.*

Materials and Methods*: In this analytical study, the data consist of 98 patients (18MS, 10 SVD and 70 Glioma) age above 18years old. After the images were selected then by using function generated by computer based software Interactive Data language (IDL) in order to extract the predetermined features from gray matter, white matter, Glioma, MS and SVD lesions; then the extracted features were statistically analyzed.*

Results*: The result reveal that the SVD have been differentiated from the rest of the classes by sensitivity equal to 100.0% when using both the first and higher order statistics. In general the best first order textural feature for distinguishing between all classes was the energy. Farther more the best higher order features for differentiation between the three lesions are SRE, LRE, RLN and LGRE on T1+C MR Images.*

Conclusion: *Higher order statistics using linear discriminate analysis on T1+C MR Images for patients with Glioma, MS and SVD have higher discrimination accuracy (equal to 96.%) and with a sensitivity equal to 96.3%, 93.0 and 100.0% respectively than first order statistics.*

Key Word*: White Matter; Magnetic Resonance Imaging; Texture Analysis; Glioma; Multiple Sclerosis; Small Vessels Disease.*

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I. Introduction

The White matter formed of the axons of neurons and conceder the medullary core of the brain; the abnormalities that can affect it are varied; in this study Glioma, Multiple Sclerosis (MS) and Small Vessels Disease (SVD) ware chosen as type of tumor, demyelinating and vascular respectively[1,2]. First Gliomas, conceders the most common malignant brain tumors, reside of glial cells that still have the ability to multiply; they spread by direct extension and can cross from one cerebral hemisphere to the other through connecting white matter tracts[3]. While Multiple sclerosis (MS) is a chronic autoimmune disease that affects the central nervous system (primarily involve the spinal cord, optic nerves, and central white matter of the brain); MS attacks the myelinated axons, destroying the myelin and the axons to varying degrees (most common demyelinating disorder)[3,4]. More over cerebral small vessel disease (SVD) is a generic term that refers to intracranial vascular disease based on various pathological and neurological processes, as well as a syndrome referring to different clinical manifestations and neuroimaging features caused by the structural changes of vascular and brain parenchyma[5]. In neuroradiology the magnetic responses imaging give the best image resolution and give deferent kinds of images according to many physical factors for example: T1, T2 relaxation time and proton density of protons in tissue[6]; 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[7, 8]. The aim of the study is to characterize white matter lesions on brain magnetic resonance images using first order statistics texture features in Sudan.

II. Material And Methods

This analytical study was carried out on Antalya medical center and it was conducted from December 2018 to December 2020.

Study Design: analytical study
Study Location: at radiology department on Antalya medical center, Khartoum –Sudan.
Study Duration: December 2018 to December 2020.
Sample size: 98 patients.
Sample size calculation: convenient sample size
Subjects & selection method: The population of this study includes MR images for patients having: Small Vessels Disease (SVD), Multiple Sclerosis plaque (MS) as demyelinating diseases and Gliomas as a tumor. The MR images viewed by the Radiant, Ant . DICOM viewer in the computer, to select the section of image that have the lesion on it and then this images introduced it into the computer based software Interactive Data language (IDL) and the user then clicks on areas represents the grey matter, white matter, Glioma, MS and SVD lesion plaque.
Inclusion criteria:
1. Glioma, MS and SVD patients
2. Aged >18 years,

Exclusion criteria:
1. Patients having two types of lesions at the same time.

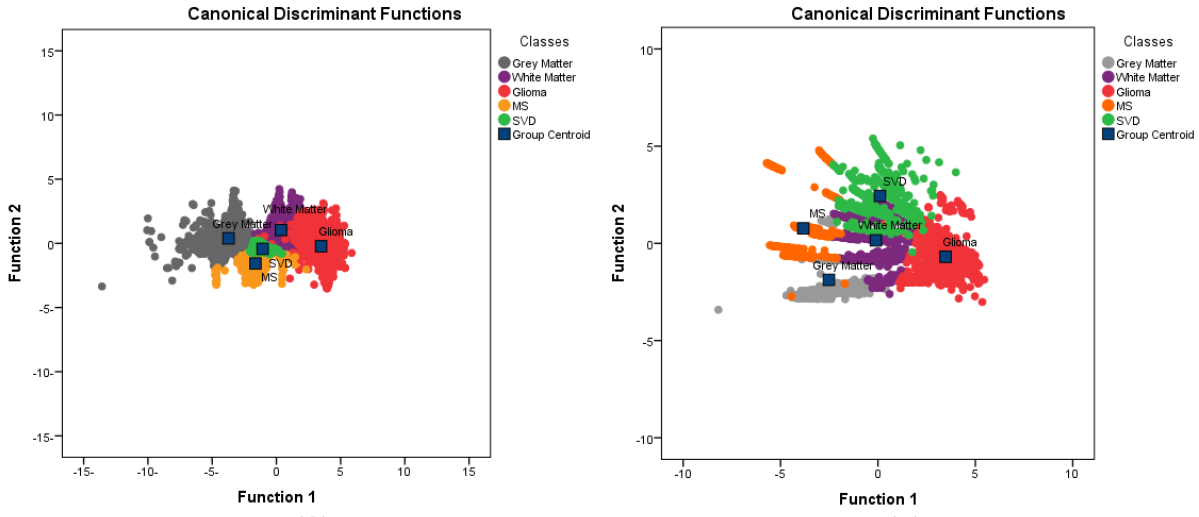
Procedure methodology

The selected images uploaded it into the computer based software Interactive Data language (IDL) and the user then clicks on areas represents the white matter, gray matter, Glioma, MS and SVD lesion plaque. In these areas a window of 3×3 pixel was set for the first order statistics features extraction, and a window of 6×6 pixel was set for the higher order features extraction; for the predetermine classes (white matter, gray matter and lesions). The first order statistical features included are the mean, variance, kurtosis, skewness, energy and entropy. More over the higher order statistical features are: Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray-Level Non-uniformity (GLN), Run-Length Non-uniformity (RLN), Run Percentage (RP), Low Gray Level 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 Gray Level Emphasis (LRHGE). Then these features were entered to SPSS for analysis.

Statistical analysis

Data was analyzed using SPSS version 20, using stepwise linear discriminate analysis to generate a classification score; to select the most discriminate feature that can be used in the classification of the lesions from each other. 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.

III. Result



(A) **(B)**

Figure no1: Scatter plots demonstrate the classification of white matter lesions using linear discriminate analysis on T1+C MR images for patients with Glioma, MS and SVD. 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+C MR Images for patients with Glioma, MS and SVD.

Classes		Predicted Group Membership					Total
		Grey Matter	White Matter	Glioma	MS	SVD	
Original	Grey Matter	89.7	.0	.0	5.4	4.9	100.0
	White Matter	.0	87.3	.0	.0	12.7	100.0
	Glioma	.0	12.2	87.3	.0	.5	100.0
	MS	2.0	.3	.2	80.3	17.3	100.0
	SVD	.0	.0	.0	.0	100.0	100.0
a. 87.2% of original grouped cases correctly classified.							

Table no2: Cross-tabulation shows the classification results of Higher order statistics using linear discriminate analysis on T1+C MR Images for patients with Glioma, MS and SVD.

Classes		Predicted Group Membership					Total
		Grey Matter	White Matter	Glioma	MS	SVD	
Original	Grey Matter	97.5	.0	.1	1.4	1.0	100.0
	White Matter	4.6	93.1	.0	2.3	.0	100.0
	Glioma	.0	3.0	96.3	.0	.6	100.0
	MS	.7	.0	.0	93.0	6.3	100.0
	SVD	.0	.0	.0	.0	100.0	100.0
a. 96.2% of original grouped cases correctly classified.							

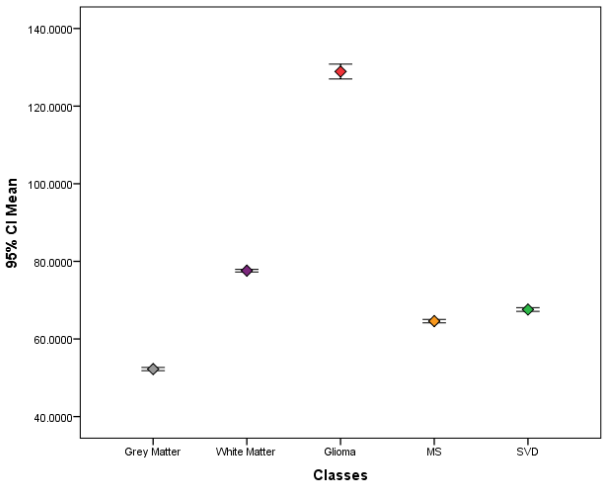


Fig 2: Error bar plot show the discriminate power of the Mean textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

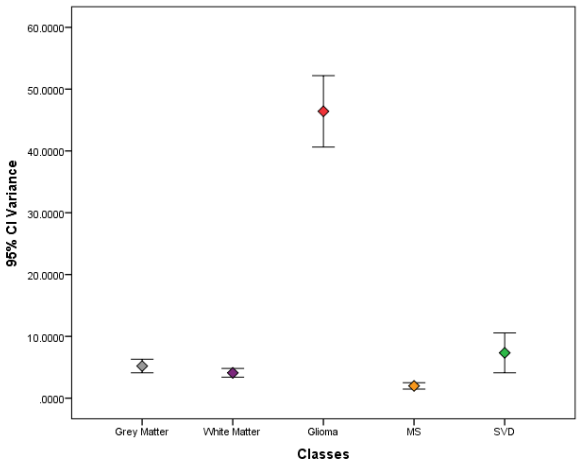


Fig 3: Error bar plot show the discriminate power of the Variance textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

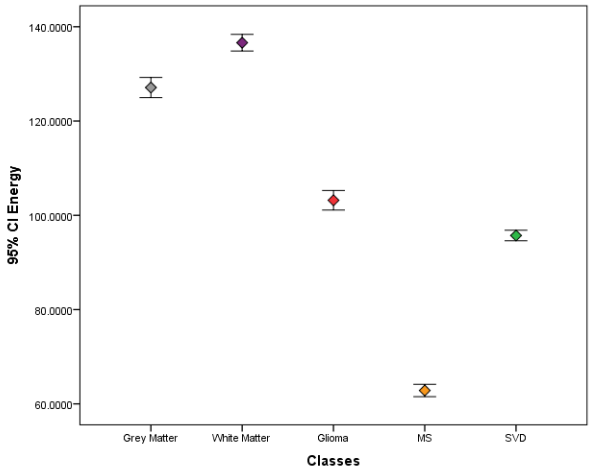


Fig 4: Error bar plot show the discriminate power of the Energy textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

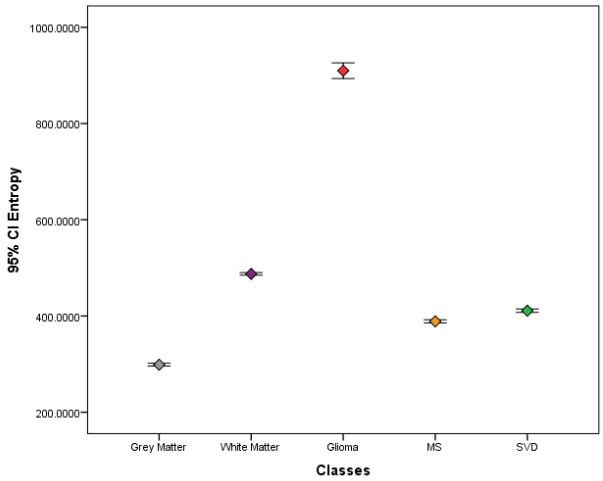


Fig 5: Error bar plot show the discriminate power of the Entropy textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

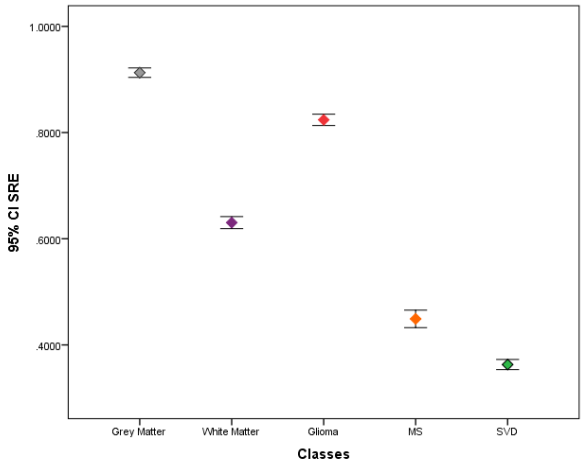


Fig 6: Error bar plot show the discriminate power of the SRE textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

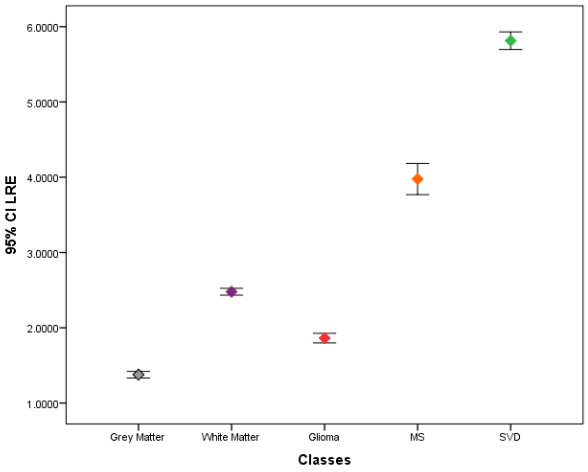


Fig 7: Error bar plot show the discriminate power of the LRE textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

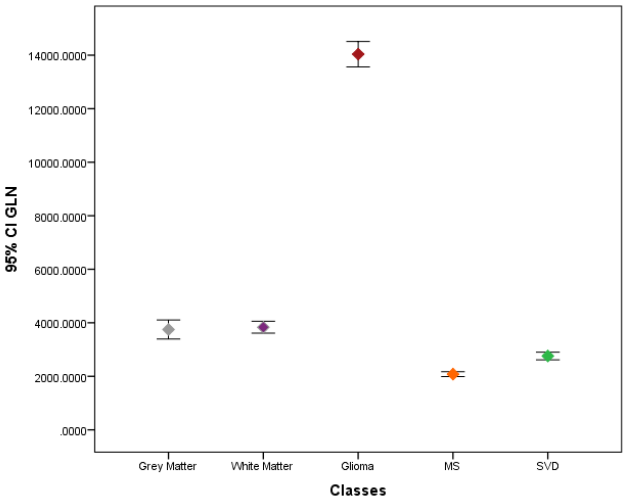


Fig 8: Error bar plot show the discriminate power of the GLN textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

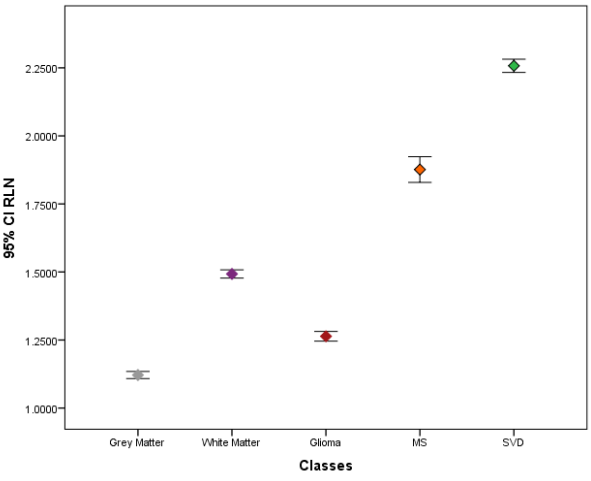


Fig 9: Error bar plot show the discriminate power of the RLN textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

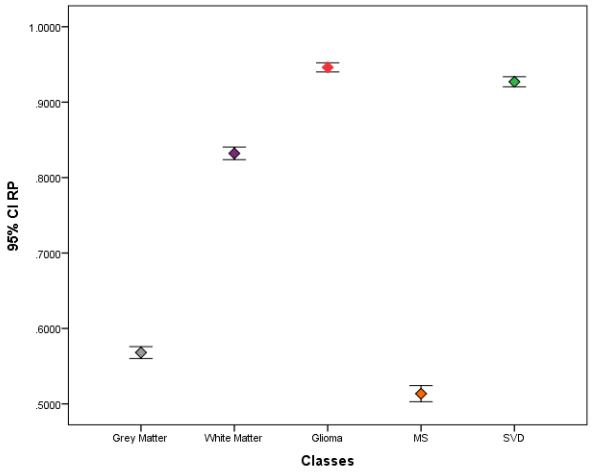


Fig 10: Error bar plot show the discriminate power of the RP textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

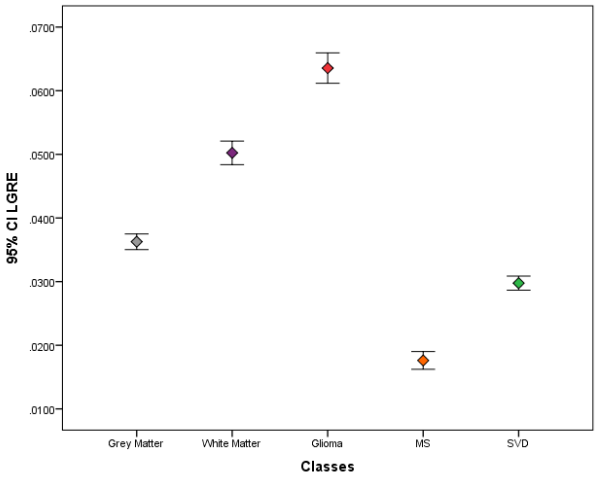


Fig 11: Error bar plot show the discriminate power of the LGRE textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

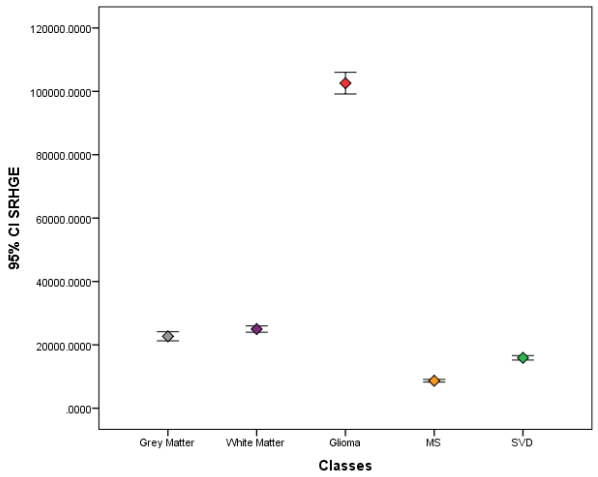


Fig 12: Error bar plot show the discriminate power of the SRHGE textural feature distribution for the selected classes on T1+C MR Images for patients with Glioma, MS and SVD.

IV. Discussion

The main aim of this study is to characterize white matter lesions (Glioma, Multiple Sclerosis (MS) and Small Vassals Disease (SVD)) on contrast enhanced T1waighted images (T1+C). The result of classification using the first order and the higher order statistical features showed that all classes are very different from each other as the center of each class (blue square) is away from the other on T1+C images presented on Fig1; with classification accuracy using the first order textural features equal 87.2%; and the sensitivity of detecting the Glioma, MS and SVD equal 87.3%, 80.3%, 100% respectively, shown from table1. While when using the higher order statistical features the accuracy was on T1+C equal 96.2%; and sensitivity equal 96.3%, 93.0% and 100% for the Glioma, MS and SVD correspondingly, as presented in Table 2

Fig 2 show the excellent discrimination of the mean textural feature between all classes, with the Glioma having the highest mean then white matter then SVD followed by MS and the grey matter have the lowest value. And when using the variance for discrimination presented on fig 3, it provide a well differentiation between the three lesions (Glioma, SVD and MS) with the Glioma having the highest value with showing wide-ranging; also there is interference between the white matter and the gray matter.

Regarding the energy textural feature which shows the best differentiation between all classes among all first order features, with the white matter having the highest energy followed by the grey matter then the Glioma then SVD, finally the MS having the lowest energy, as presented on fig 4. While fig 5 demonstrate that the entropy distinguished well between all classes with the Glioma having the highest value then the white matter, SVD, MS and the grey matter have the lowest value.

Fig6 show the result of the discrimination of the SRE textural feature and reveal that the grey matter have the highest value the Glioma, white matter, MS and SVD in that order with the lowest value. Also the LRE textural feature well differentiate between all classes, with the SVD have the highest value then the MS then the white matter followed by the Glioma and the grey matter have the lowest LRE value as presented in fig 7. Farther more GLN feature distinguished well between the Glioma, SVD and MS but there was interference between the grey matter and the white matter presented at fig 8.

From fig 9 the RLN feature differentiates well between all classes; with the SVD have the highest RLN value then the MS, white matter, Glioma and the grey matter have the lowest value. While regarding the RP feature have discriminate well between all classes, with the Glioma having the highest value while the MS having the lowest value, as presented at fig 10. Farther more the LGRE textural feature on fig 11 which show good differentiation between all classes, also the Glioma having the highest value while the MS having the lowest value.

Finally the SRHGE textural feature at fig 12 show an excellent discrimination between all classes; with the Glioma having the highest value then the white matter followed by grey matter then SVD lastly came MS.

V. Conclusion

In conclusion: the best first order textural feature for distinguishing between the classes is the energy, also the Glioma have the highest value in all first order statistics used on this study while the MS having the lowest vale in all. On the other hand the best higher order features for differentiation between the three lesions are SRE, LRE, RLN and LGRE; more over the best features for discrimination of Glioma from the rest are the GLN, LGRE and the SRHGE; with it having the highest value in each one of them. In case of MS the finest feature that differentiates it from the other lesions is the RP textural feature, as the MS having the lowest RP value among all classes. Finally regarding the SVD the best discrimination features are the LRE and the RLN; with SVD have the highest value on both. And they can be diagnosed quantitatively from normal tissue by using the following equations:

Firstly on the first order statistics with a sensitivity of Glioma, MS and SVD equal to 87.3%, 80.3% and 100.0% respectively on T1+C images using the following equations:

Gray matter = (30.456×mean)+(.004× variance)+(.212×energy)+ (-3.580×entropy) -275.748

White matter = (35.962×mean)+(.004× variance)+(.235×energy)+ (-4.222×entropy) -383.865

Glioma = (38.472×mean)+(.017× variance)+(.203×energy)+ (-4.502×entropy) -444.410

MS = (33.271×mean)+(.002× variance)+(.144×energy)+ (-3.909×entropy) -320.829

SVD = (34.054×mean)+(.005× variance)+(.184×energy)+ (-4.000×entropy) -339.144

Secondly on the higher order statistics with a sensitivity of Glioma, MS and SVD equal to 96.3%, 93.0 and 100.0% respectively on T1+C images using the following equations:

Gray matter = (4206.520× SRE) + (-923.092× LRE) + (.003× GLN) + (5584.293× RLN)+ (291.112× RP) +(-1216.916× LGRE) +(-.001× SRHGE) -4470.826

White matter = (4147.347× SRE) + (-917.456× LRE) + (.004× GLN) + (5544.808× RLN)+ (307.985× RP) +(-1110.208× LGRE) +(-.001× SRHGE) -4405.856

Glioma = (4174.123× SRE) + (-920.189 × LRE) + (.006× GLN) + (5567.667 × RLN)+ (326.898× RP) +(-1035.968× LGRE) +(-.001× SRHGE) -4484.550
MS = (4128.016× SRE) + (-919.006× LRE) + (.002× GLN) + (5550.632 × RLN)+ (258.220× RP) +(-1090.199× LGRE) +(-.001× SRHGE) -4363.774
SVD = (4211.840× SRE) + (-925.650× LRE) + (.004× GLN) + (5612.975× RLN)+ (320.730× RP) +(-1157.571× LGRE) +(-.001× SRHGE) -4540.311

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