Accurate Classification of Brain Gliomas by Discriminate Dictionary Learning based on Projective Dictionary Pair Learning of Proton Magnetic Resonance Spectra

Adebileje Sikiru Afolabi[1, 2,] Ghasemi Keyvan[2,3], Aiyelabegan Hammed Tanimowo[4], Saligheh Rad Hamidreza[1,2,*]

[1]Department of Medical Physics and Biomedical Engineering, Tehran University of Medical Sciences-International Campus (TUMS-IC).
[2]Quantitative MR Imaging and Spectroscopy Group (QMISG), Tehran, Iran.
[3]Department of Chemistry, Imam Khomeini International University, Iran.
[4]Department of Medical Biotechnology, School of Advanced Technologies in Medicine, International Campus, Tehran University of Medical Sciences.

*Corresponding Author

Dr. Saligheh Rad Hamidreza

h-salighehrad@tums.ac.ir

Department of Medical Physics and Biomedical Engineering, Faculty of Medicine, Sina Campus, P.O. Box. 1417613151. Tehran University of Medical Sciences, Tehran, Iran.
+989123141161

ABSTRACT

Proton magnetic resonance spectroscopy is a powerful noninvasive technique that complements the structural images of conventional magnetic resonance imaging, which aids biomedical and clinical researches, by identifying and visualizing the compositions of various metabolites within the tissues of interest. However, accurate classification of proton magnetic resonance spectroscopy is still a challenging issue in clinics due to low signal-to-noise ratio, overlapping peaks of metabolites and the presence of background macromolecules. This paper evaluates the performance of a discriminate dictionary learning classifiers based on projective dictionary pair learning method for brain gliomas proton magnetic resonance spectroscopy spectra classification task and the result were compared to the sub-dictionary learning methods. The proton magnetic resonance spectroscopy data contains a total of 150 spectra (74 healthy, 23 grade II, 23 grade III, 30 grade IV) from two databases. The datasets

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/mrc.4532

This article is protected by copyright. All rights reserved.

from both databases were first coupled together,followed by column normalization. The Kennard-Stone algorithm were used to split the datasets into its training and test sets. Performance comparison based on the overall accuracy, sensitivity, specificity and precision were conducted. Based on the overall accuracy of our classification scheme, the dictionary pair learning method were found to outperform the sub-dictionary learning methods 97.78% compared to 68.89% respectively.

Keywords: Proton magnetic resonance spectroscopy, Brain gliomas, dictionary pair learning, sub-dictionary learning

I. INTRODUCTION

Proton magnetic resonance spectroscopy (^{1}H-MRS) is a powerful noninvasive technique that complements the structural images of conventional magnetic resonance imaging (cMRI) which aids biomedical and clinical applications by identifying and visualizing the compositions of various metabolites within the tissues of interest (brain, heart, etc.)[1,2]. An observed ^{1}H-MRS spectra of the brain is made up of complicated signals corresponding to several overlapping peaks of different metabolites, as well as baseline coming from various macromolecules and lipids coupled with noise and distortions[1,3], an accurate classification of ^{1}H-MRS brain spectra signals is needed for efficient and effective diagnosis of diseases.

With a decision support system for classification[4,5], the ^{1}H-MRS spectra which is a multivariate data can achieve a higher reliability by developing a good statistical model to classify various tumorous ^{1}H-MRS data[6,7]. Several classification methods for ^{1}H-MRS data has been proposed[8–11], but the sparse representation technique is a recent method for classification[12–14].

Sparse representation (SR) is a parsimonious principle that shows the representation of a signal as a linear combination of basis vectors which are chosen from a dictionary[15,16]. The SR method has been found to be robust to noise while its basis vector are non-orthogonal which are sometimes found to be interpretable due to its sparseness property. The SR has achieved a remarkable success in various signal processing, image processing and computer vision applications[17–19].

This article is protected by copyright. All rights reserved.

Dictionary learning (DL) which is a subclass of SR is obtained by finding a desired dictionary that can effectively represent the signal of interest[20,21]. Analysis and synthesis types of dictionaries has been widely studied in literatures and are found to play active roles in signal representation[22]. Synthesis based sparse representation method has been found to allow easy learning of a desired dictionary from a training set and can model complexity better of the local signal structures. However, the synthesis representation coefficient of signals are usually obtained via an lp-norm ($p<1$) sparse coding process which is computationally more expensive than analysis dictionary representation.

The success of DL has been centered mostly on the discrimination capability of the learned dictionary. This simple property has found its applications in most signal restoration problems, and it has also been the bedrock of signal classification task where the main goal of classification problems is to assign correct class label to the test sample.

In literatures, several supervised dictionary learning (SDL) method which promotes the discriminative power of learned dictionary have been proposed. The SDL method works by encoding the test sample over the learned dictionary, where both the coefficients and the residuals of the learned dictionary can be used for classification depending on the DL model employed[23,24].

One of the most popular strategy of discriminative DL model employed in literatures is to learn a shared dictionary of all classes while enforcing the coding coefficients to be discriminative and a classifier based on the coding coefficients can be trained simultaneously to perform the classification task[25,26]. The label consistent KSVD (LC-KSVD) method which was proposed by Jiang et al introduced a binary class label sparse code matrix to encourage samples from the same class to have similar sparse codes[27]. However, Mairal et.al also proposed a task driven dictionary learning (TDDL) framework which minimizes different risk function of the coding coefficients for different tasks where a learned dictionary with their corresponding linear classifier in the coding vector space[28].

The structured DL model is another popular line of research interest which learns a structured dictionary that can promote discrimination between classes while atoms in the structured dictionary have class labels and the class-specific representation residuals that are computed for classification[29,30].

Another exciting discriminative DL model was proposed by Ramirez et al which introduces an incoherence term to encourage the sub-dictionary of different class to be independent[31]. Yang et al proposes a Fisher discrimination dictionary learning (FDDL) method which applies the Fisher criterion to both the representation residual and

This article is protected by copyright. All rights reserved.

representation coefficient[32]. A max-margin dictionary learning (MMDL) algorithm was proposed from the large margin perspective to solve a classification problem[33,34].

Shuhang et.al were the first researchers to propose the projective dictionary pair learning (DPL) which extends the conventional discriminative synthesis DL to discriminative synthesis and analysis DPL, the projective DPL utilizes a coding mechanism that largely improves the efficiency of both the training and testing phase and also achieve a good accuracy[35]. The novelty of this work centers on learning the training dataset with DL which discriminates between classes of the gliomas.

The organization of this paper is as follows: Section II describes materials and methods of ^{1}H-MRS signal with detailed report on discriminate dictionary learning. Section III presents the model evaluation while section IV evaluates the results and discussion of our methods. Section V discusses the conclusions.

II. MATERIALS AND METHODS

^{1}H -MRS samples were collected from 1.5T dataset from INTERPRET EU project[36–38]. This data set consisted of patients with glial tumors and consisted of three classes, defined according to the laid down rules of the World Health Organization (WHO): grade II (15 cases), grade III (18 cases) and high grade gliomas (32 cases). The spectra were validated by an expert panel of spectroscopists, and the histopathological diagnosis of these cases were also available. The datasets were obtained using ^{1}H -MRS scanners of manufacturers (Philips, General Electric and Siemens) from 10 international centers. The acquisition protocols includes Point-Resolved Spectroscopy (PRESS) or Stimulated Echo Acquisition Mode (STEAM) with spectral parameters: TR of 1600-2020 ms, TE of 30-32 ms, spectral width of 1000-2500 Hz and 512 data-points.

The second part is a collection of 51 patients over the range of cancer groups analyzed[39]. This dataset consisted of grade II (11 cases), grade III (6 cases) and high grade gliomas (9 cases). Data related to healthy tissue were acquired from the contralateral brain regions of 25 healthy volunteers. ^{1}H -MRS data of these samples were acquired from patients with glial brain tumors and people with normal brain, according to the medical ethics regulations of Imam Khomeini Hospital, Tehran, Iran. These multi-voxel proton MRS data were acquired on a 3T scanner (Trim Trio, Siemens, Germany), STEM or PRESS pulse sequence on TE of

This article is protected by copyright. All rights reserved.

30 msec, TR=1500ms, spectral width of 500-2500Hz, 1024 data-points and the thickness 10-15 mm for the tissue.

The data from both databases were coupled to create a dataset with 150 spectra. With Kennard-stone algorithm, the spectra data were divided into training and test sets. Therefore, 111 spectra were selected for the training set, and 39 spectra were as an independent test set. The class members for the data analysis were labeled from class I to class IV which shows that the class were from health to grade IV gliomas respectively.

Discriminate Dictionary Learning

Denoting $X = [X_1, ..., X_k, ..., X_K]$ as a set of p-dimensional training samples from K classes, where $X_k \in \Re^{p \times n}$ is the training sample set of class, k and n is the number of samples of each class. Discriminative DL methods aim to learn an effective data representation model from X for the classification task by exploiting the class label information of training data. Most of the state-of-the-art discriminative DL methods can be formulated under the following framework:

$$\min_{D,A} \|X - DA\|_F^2 + \lambda \|A\|_p + \Psi(D, A, Y) \qquad (1)$$

Where $\lambda \geq 0$ is a scalar constant, Y represents the class label matrix of samples in X, D is the synthesis dictionary to be learned, and A is the coding coefficient matrix of X over D.

In the training model (1), the data fidelity term $\|X - DA\|_F^2$ ensures the representation ability of D; $\|A\|_p$ is the l_p-norm regularizer on A; and $\Psi(D, A, Y)$ stands for some discrimination promotion function which ensures the discrimination power of D and A.

Dictionary Pair Learning Model

The DPL model introduced by Shuhang et.al, the model extends the conventional DL model in (1) which learns a discriminative synthesis dictionary, to a novel DPL model, which learns a pair synthesis and analysis dictionaries. The proposed DPL model does not required l_0 or l_1-norm sparsity regularizer, and the coding coefficients can be explicitly obtained by linear projections. However, DPL does not sacrifice the classification accuracy while achieving significance improvement in the efficiency. The formulation of DPL can be expressed as follows:

This article is protected by copyright. All rights reserved.

$$\{P^*, D^*\} = \arg\min_{P,D} \|X - DPX\|_F^2 + \Psi(D, P, X, Y) \qquad (2)$$

Where $\Psi(D, P, X, Y)$ is the discrimination functions, D and P form the synthesis and analysis dictionaries respectively, and both are referred to as the dictionary pair. The analysis of P is used in coding X, and the synthesis dictionary D is used in reconstructing X. However, the optimization of (2) above while ensuring a column normalization of the dictionary with respect to the classes can be expressed as follows:

$$\{P^*, D^*\} = \arg\min_{P,D} \sum_{k=1}^{K} \left\| X_k - D_k P_k X_k \right\|_F^2 + \lambda \left\| P_k X_k \right\|_F^2 \; s.t. \|d_i\|_2^2 \le 1 \quad (3)$$

III. Model evaluation

The most widely used statistics for evaluating a diagnostic test were sensitivity and specificity. These tests are based on the following definitions: true positive (TP)-Sick people correctly diagnosed as sick, false positive (FP) - Healthy people incorrectly identified as sick, true negative (TN) - Healthy people correctly identified as healthy, false negative (FN)-Sick people incorrectly identified as healthy. To evaluate the performance of our method, we report the standard performance measures which includes the sensitivity, specificity, precision and overall accuracy (OA).These measures are defined as follows:

$$Sensitivity = \frac{TP}{TP + FN} \qquad (4)$$

$$Specificity = \frac{TN}{FP + TN} \qquad (5)$$

$$\Pr ecision = \frac{TP}{TP + FP} \qquad (6)$$

$$OA = \frac{TP + TN}{TP + FN + FP + TN} \qquad (7)$$

IV. RESULTS AND DISCUSION

Patient Populations

The group consisted of 26 patient (11 men and 15 women), with ages ranging from 13 to 64 years. We investigated 11 grade II (42.31%), 6 grade III (23.08%) and 9 grade IV gliomas (34.61%).

This article is protected by copyright. All rights reserved.

Conventional MR imaging (cMRI) is a useful tool that provides an excellent information regarding the anatomic imaging of gliomas, contrast material enhancement, distant tumor foci, hemorrhage, necrosis, mass effect, and lots more parameters, which are all important in characterizing tumor grades. However, with good state of the art protocols and sequence optimization techniques, the classification and grading of gliomas with cMRI is sometimes unreliable because contrast material enhancement alone is not always accurate in predicting tumor grade[40–42]. The proton MR spectroscopy as an advanced MR imaging technique is a powerful tool that supports tumor grading. Tumor grading of ^{1}H-MRS gliomas are expressed with metabolites ratios, this ratio has been found to be a reliable indicator of tumor detection.

Before the implementation of DPL and sDL methods on the dataset, Figure.1 shows the class plot of the MR spectra which shows the class of each individual MR spectra. The plot of average scaled dataset of the different profile, classes and MR spectra used in this study against the variance of the spectra distribution are shown in Figure.2 and Figure.3 respectively.

Several pre-processing steps like water suppression to enhance the intrinsic signal of interest, phase correction, zero filling and truncation were perform respectively to enhanced the visibility of the signal. This 1H-MRS signal were arranged into a matrix form and Kennard-Stone algorithm were used in splitting the data into its training and testing sets. Both the training and testing set were l2-norm column normalized.

For sDL, the l_1-nnls sparse coding method, knn predicter and the linear choice of kernel parameters were used, while the DPL method used the following; the dictionary size is set to 30, tau=0.5,lambda=0.03 and gamma=0.001.

Table 1 describes the DPL and sDL classification parameters based on the diagnostic test clinical criterion. The overall accuracy of the sDL model was 68.89% with 40.26% error rate and 59.74% non-error rate. After the evaluation of the model, the sensitivity of the model from healthy to GBM was 81.82%, 14.29%, 42.86% and 100% respectively. This result shows that the sDL is able to extract the correct direction of the grade IV patient, which also shows lower sensitivity and precision value in grade II and grade III respectively. The sDL method of classification denotes inconsistency in model prediction power and unreliable validation results. With the poor prediction power of sDL, the projective DPL method was applied instead of the conventional sDL.

This article is protected by copyright. All rights reserved.

The overall accuracy of projective DPL was 97.78% with 3.57% error rate and 96.43% non-error rate. Table 1 shows the performance values for the projective DPL method, after the evaluation of the model by this set, the sensitivity of the model from health to GBM was 100%, 100%, 85.71% and 100% respectively. The DPL method was able to extract the correct direction of the healthy patient, grade II and grade IV respectively.

In literature, the metabolites of healthy normal tissue is characterized with a higher value of N-acetylaspartate (NAA) peak, higher total creatine (tCr) peak, and a lower peaks for total choline (tCho), Glx, Gly and myo-inositol (Myo) when compared with abnormal spectra. Precisely, the increase in Cho with a decrease in NAA is a good indicator of tumor. There is extensive literature substantiating the metabolite ratios of Cho/ Cr, NAA/Cr, and Myo/Cr and the presence of lipids and lactate to be useful in grading tumors and predicting tumor malignancy[40,43–45].

This study of brain gliomas (grade II-IV) is characterized by a lower value of NAA, and tCr, and a higher value of lactate when compared with healthy tissue. There are compelling evidence from literature that MR spectroscopy provides important supplemental information to that of cMRI[46–49]. The general characteristics of the ^{1}H-MR brain spectra is having a low signal-to-noise ratio (SNR), baseline distortions, large width and asymmetric line shapes as a result of poor shimming. Both sDL and DPL methods are robust to noise, since their formulation is subjected to the difference between the observed and the reconstructed spectra. However, DPL shows better denoising result because of the optimization in the learning methods that involve both the construction of synthesis and analysis dictionaries. As a result, DPL method is a good choice to discriminate between the grades of gliomas class irrespective of the presence of noise in the spectra.

V. CONCLUSION

The application of discriminate dictionary learning for classifying ^{1}H MR Spectra of brain gliomas tumor was investigated. The *in vivo* spectra were known to be noisy with low level of SNR. In this paper, we have compared the performance of discriminate sub-dictionary learning method and projective dictionary pair learning on the classification of brain gliomas. The figure of merits shows that projective DPL performs consistently better than the sub-dictionary learning methods, while both methods were robust to noise.

This article is protected by copyright. All rights reserved.

REFRENCES

[1] Preul MC, Caramanos Z, Collins DL, et al. Accurate, noninvasive diagnosis of human brain tumors by using proton magnetic resonance spectroscopy. *Nat Med* 1996; 2: 323–325.

[2] Z ZRA and W. Proton magnetic resonance spectroscopy. *Crit Rev Neurosurg* 1999; 161–6.

[3] Mountford C E, Stanwell P, Lin A RS and RB. Neurospectroscopy: the past, present and future. *Chem Rev* 2010; 3060–86.

[4] Power D J SR and BF. Decision support systems. *Wiley Online Libr*.

[5] Bonczek R H HCW and WAB. Foundations of decision support systems. *Acad Press*.

[6] Lukas L, Devos A, Suykens JAK, et al. Brain tumor classification based on long echo proton MRS signals. *Artif Intell Med* 2004; 31: 73–89.

[7] Tate a R, Griffiths JR, Martínez-Pérez I, et al. Towards a method for automated classification of 1H MRS spectra from brain tumours. *NMR Biomed* 1998; 11: 177–191.

[8] Simonetti AW, Melssen WJ, Van der Graaf M, et al. A Chemometric Approach for Brain Tumor Classification Using Magnetic Resonance Imaging and Spectroscopy. *Anal Chem* 2003; 75: 5352–5361.

[9] Boguszewicz Ł BS and SM. Brain Edema XIV. *Springer* 2010; 171–5.

[10] L G-NFF and B-M. Using machine learning techniques to explore 1H-MRS data of brain tumors. *Artif Intell 2009 MICAI 2009 Eighth Mex Int Conf IEEE* 2009; 134–9.

[11] Z MJ and S. MRS classification based on independent component analysis and support vector machines. *Hybrid Intell Syst 2005 HIS'05 Fifth Int Conf IEEE)* 2005; 3.

[12] Zhang L, Yang M, Feng X. Sparse representation or collaborative representation: Which helps face recognition? In: *Proceedings of the IEEE International Conference on Computer Vision*. 2011, pp. 471–478.

[13] Chen Y, Nasrabadi NM, Tran TD. Hyperspectral image classification via kernel sparse representation. *IEEE Trans Geosci Remote Sens* 2013; 51: 217–231.

[14] Wright J, Yi Ma, Mairal J, et al. Sparse Representation for Computer Vision and Pattern Recognition. *Proc IEEE* 2010; 98: 1031–1044.

[15] Donoho DL, Elad M. Optimally sparse representation in general (nonorthogonal) dictionaries via l minimization. *Proc Natl Acad Sci U S A* 2003; 100: 2197–2202.

[16] Aharon M, Elad M, Bruckstein A. K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation. *IEEE Trans Signal Process* 2006; 54: 4311–4322.

[17] Lustig M, Donoho D, Pauly JM. Sparse MRI: The application of compressed sensing for rapid MR imaging. *Magn Reson Med* 2007; 58: 1182–1195.

[18] Baraniuk RG, Candes E, Elad M, et al. Applications of sparse representation and

This article is protected by copyright. All rights reserved.

compressive sensing. *Proc IEEE* 2010; 98: 906–909.

[19] Figueiredo MAT, Nowak RD, Wright SJ. Gradient projection for sparse reconstruction: Application to compressed sensing and other inverse problems. *IEEE J Sel Top Signal Process* 2007; 1: 586–597.

[20] Kreutz-Delgado K, Murray JF, Rao BD, et al. Dictionary Learning Algorithms for Sparse Representation. *Neural Comput* 2003; 15: 349–396.

[21] Mairal J, Bach F, Ponce J, et al. Online dictionary learning for sparse coding. *Proc 26th Int Conf Mach Learn* 2009; 1–8.

[22] Rubinstein R, Peleg T, Elad M. Analysis K-SVD: A dictionary-learning algorithm for the analysis sparse model. *IEEE Trans Signal Process* 2013; 61: 661–677.

[23] Mairal J, Bach F, Ponce J, et al. Supervised dictionary learning. *Adv Neural Inf Process Syst* 2008; 1033–1040.

[24] Y-H YC-CM and Y. Supervised dictionary learning for music genre classification. *Proc 2nd ACM Int Conf Multimed Retr ACM)* 2012; 55.

[25] Ma L, Wang C, Xiao B, et al. Sparse representation for face recognition based on discriminative low-rank dictionary learning. In: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. 2012, pp. 2586–2593.

[26] Shrivastava A, Pillai J K PVM and CR. Learning discriminative dictionaries with partially labeled data. *Image Process IEEE Int Conf IEEE* 2012; 3113–6.

[27] Jiang Z, Lin Z, Davis LS. Label consistent K-SVD: Learning a discriminative dictionary for recognition. *IEEE Trans Pattern Anal Mach Intell* 2013; 35: 2651–2664.

[28] Mairal J, Bach F, Ponce J. Task-driven dictionary learning. *IEEE Trans Pattern Anal Mach Intell* 2012; 34: 791–804.

[29] Varoquaux G, Gramfort A, Thirion B, et al. Sparse Structured Dictionary Learning for Brain Resting-State Activity Modeling. In: *NIPS Workshop on Practical Applications of Sparse Modeling: Open Issues and New Directions*. 2010, pp. 1–7.

[30] Zhang Y, Jiang Z, Davis LS. Learning structured low-rank representations for image classification. In: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. 2013, pp. 676–683.

[31] Ramirez I, Sprechmann P, Sapiro G. Classification and clustering via dictionary learning with structured incoherence and shared features. In: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. 2010, pp. 3501–3508.

[32] Yang M, Zhang D, Feng X. Fisher discrimination dictionary learning for sparse representation. *Proc IEEE Int Conf Comput Vis* 2011; 543–550.

[33] Lian X-C, Li Z LB-L and ZL. Computer Vision–ECCV 2010. *Springer* 2010; 157–70.

[34] Wang X, Wang B, Bai X, et al. Max-Margin Multiple-Instance Dictionary Learning. *Icml*; 28.

[35] Gu S, Zhang L ZW and FX. Projective dictionary pair learning for pattern

This article is protected by copyright. All rights reserved.

classification. *Adv Neural Inf Process Syst* 2014; 793–801.

[36] Julià-Sapé M, Acosta D, Mier M AC and WD. A multi-centre, web-accessible and quality control-checked database of in vivo MR spectra of brain tumour patients. *Magn Reson Mater Physics, Biol Med* 2006; 22–33.

[37] Fuster-Garcia E, Navarro C, Vicente J, et al. Compatibility between 3T 1H SV-MRS data and automatic brain tumour diagnosis support systems based on databases of 1.5T 1H SV-MRS spectra. *Magn Reson Mater Physics, Biol Med* 2011; 24: 35–42.

[38] Tate AR, Underwood J, Acosta DM, et al. Development of a decision support system for diagnosis and grading of brain tumours using in vivo magnetic resonance single voxel spectra. *NMR Biomed* 2006; 19: 411–434.

[39] Ghasemi K KM and SRH. Accurate grading of brain gliomas by soft independent modeling of class analogy based on non- negative matrix factorization of proton magnetic resonance spectra. *Magn Reson Chem* 2016; 119–25.

[40] Möller-Hartmann W, Herminghaus S, Krings T, et al. Clinical application of proton magnetic resonance spectroscopy in the diagnosis of intracranial mass lesions. *Neuroradiology* 2002; 44: 371–381.

[41] Watanabe M, Tanaka R, Takeda N. Magnetic resonance imaging and histopathology of cerebral gliomas. *Neuroradiology* 1992; 34: 463–469.

[42] Knopp E a, Cha S, Johnson G, et al. Glial neoplasms: dynamic contrast-enhanced T2*-weighted MR imaging. *Radiology* 1999; 211: 791–798.

[43] Castillo M, Smith JK, Kwock L. Correlation of myo-inositol levels and grading of cerebral astrocytomas. *Am J Neuroradiol* 2000; 21: 1645–1649.

[44] Dowling C, Bollen AW, Noworolski SM, et al. Preoperative proton MR spectroscopic imaging of brain tumors: Correlation with histopathologic analysis of resection specimens. *Am J Neuroradiol* 2001; 22: 604–612.

[45] Maj??s C, Aguilera C, Alonso J, et al. Proton MR spectroscopy improves discrimination between tumor and pseudotumoral lesion in solid brain masses. *Am J Neuroradiol* 2009; 30: 544–551.

[46] Tamiya T, Kinoshita K, Ono Y, et al. Proton magnetic resonance spectroscopy reflects cellular proliferative activity in astrocytomas. *Neuroradiology* 2000; 42: 333–338.

[47] Guillevin R, Menuel C, Duffau H, et al. Proton magnetic resonance spectroscopy predicts proliferative activity in diffuse low-grade gliomas. *J Neurooncol* 2008; 87: 181–187.

[48] Bulik M, Jancalek R, Vanicek J, et al. Potential of MR spectroscopy for assessment of glioma grading. *Clinical Neurology and Neurosurgery* 2013; 115: 146–153.

[49] Shimizu H, Kumabe T, Shirane R, et al. Correlation between choline level measured by proton MR spectroscopy and Ki-67 labeling index in gliomas. *Am J Neuroradiol* 2000; 21: 659–665.

This article is protected by copyright. All rights reserved.

Table 1. The figure of merit table showing the performances of each methods based on the widely used statistics for evaluating diagnostic test

Figure of Merit	DPL Method				sDL Method			
	Healthy	Grade II	Grade III	Grade IV	Healthy	Grade II	Grade III	Grade IV
Sensitivity	100	100	85.71	100	81.82	14.29	42.86	100
Specificity	95.65	100	100	100	95.65	92.11	84.21	88.89
Precision	95.65	100	100	100	94.74	25.00	33.33	69.23

This article is protected by copyright. All rights reserved.

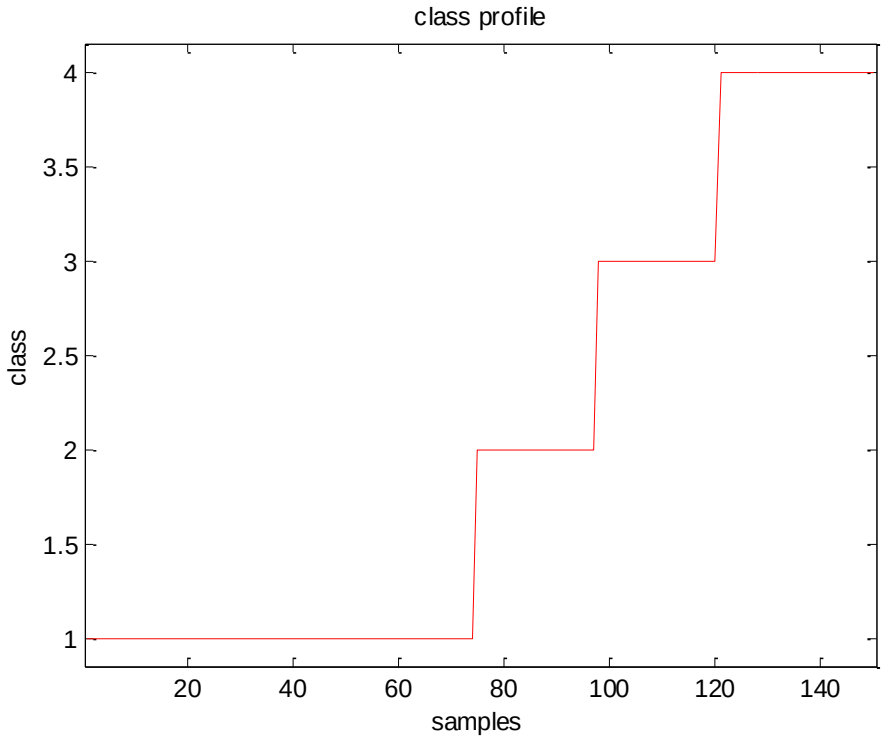

Figure 1: Class distribution of sample used. The figure shows that four classes data were

This article is protected by copyright. All rights reserved.

used.

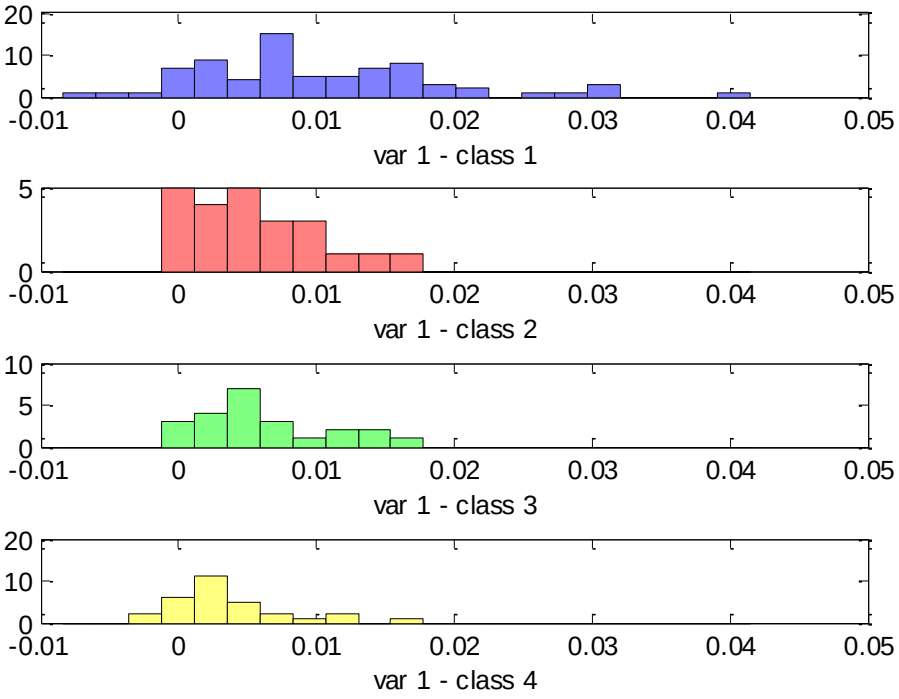

Figure 2: Shows the variance plot of each classes. Class 1=Healthy patient, Class 2= Grade II glioma, Class 3= Grade III glioma, Class 4= Grade IV glioma.

This article is protected by copyright. All rights reserved.

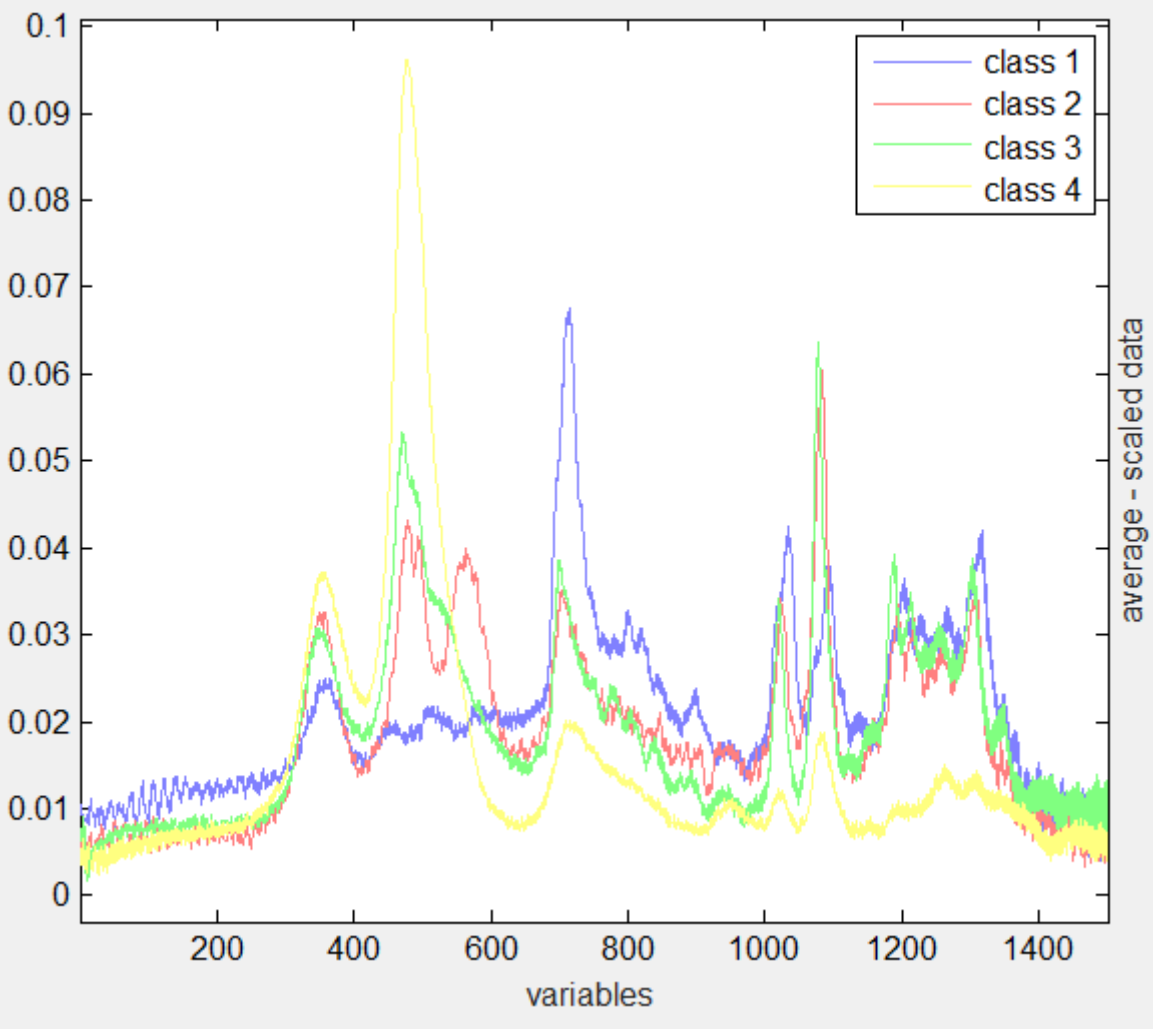

Figure 3: Shows the average-scale of the MR spectra data based on the classes. Class 1=Healthy patient, Class 2= Grade II glioma, Class 3= Grade III glioma, Class 4= Grade IV glioma.

This article is protected by copyright. All rights reserved.