Supplementary file

Glioblastoma and Primary Central Nervous System Lymphoma: Differentiation using MRI derived First-order texture analysis- A machine learning study

Texture & Machine learning in Glioblastoma & CNS lymphoma

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Supplementary Table 1: Total number of features used in each modeling approach when fit to full data set

	Whole Tumor			Single Slice		
	Full	**Corr**	**PCA**	**Full**	**Corr**	**PCA**
All other models	36	19	8	36	20	8
ada	31	18	7	29	19	7
enet	34	10	7	6	12	7
gbrm	31	18	7	21	19	7
lasso	17	8	7	6	6	7
rf	35	18	7	35	19	7

Ada: adaboost; enet: elastic net; gbrm: gradient boost regression model; lasso: (least absolute shrinkage and selection operator); rf: random forest' full: full feature set; corr: high correlation filter; pca: principal component analysis

Supplementary Table 2: Prior studies utilizing texture analysis for differentiating glioblastoma from primary CNS lymphoma

Authors	Number of patients	Sequence(s)	2D/3D	Type of Texture parameters	Discriminating features	Machine Learning	Deep Learning/CNN
Priya et al (current study)	GBM: 97 PCNSL: 46	T1W contrast enhanced	2D- all tumor slices (2D volumetric)	Filtration-based first order texture features	LASSO model (high correlation filter) and multilayer perceptron network (high correlation filter performed best for whole (AUC 0.924) and single slice (AUC 0.914) respectively	Yes; three feature selection and 12 machine learning classifier models	No
Kunimatsu et al[24]	GBM-44 PCNSL-16	T1W contrast enhanced	2D-Single slice	First and second order	PCA analysis showed first-order entropy, median, GLRLM-based RLNU, run-percentage (AUC not provided)	No	No
Xiao et al[25]	GBM-60 PCNSL-22	T1W contrast enhanced	2D-Multislice	First and second order and geometric features	First order Skewness, first order Kurtosis, and Ngtdm Busyness showed high discriminatory power (AUC 0.86).	Yes; Naïve Bayes: Best Classifier model (AUC 0.90)	No
Alcaide-Leon et al[26]	GBM-71 PCNSL-35	T1W contrast enhanced	2D-Multislice	First and second order	SVM classifier model is non-inferior to expert human evaluation (p <0.05, mean AUC 0.877)	Yes; SVM	No
Suh et al[27]	GBM-23 PCNSL-54	T1W post contrast, T2W, FLAIR	2D-Multislice (contrast enhancin	First order, second order, wavelet	AUC of the classifier model (0.921) was significantly higher than three radiology readers and ADC	Yes; Random Forest	No

			g portion only)	transformed and shape features	values (p< 0.001 for all).		
Kim et al[21]	GBM- 78 Discovery cohort-49 Validation cohort-29 PCNSL-65 Discovery cohort-37 Validation cohort-28	T1W post contrast, T2W, Diffusion weighted imaging	3D- Contrast enhancing and contrast enhancing plus non-enhancing peritumoral edema	First and second order and shape features	Classifier model using 15 selected features performed well to distinguish between GBM and PCNSL with an AUC OF 0.979 in the discovery cohort with similar performance in the validation cohort (AUC 0.956)	Yes, Logistic regression, SVM, and random forest. Logistic regression had highest AUC in validation cohorts	No
Wang et al[22]	GBM- 81 PCNSL- 28	T2W	2D- Single slice with maximal dimension in axial plane. ROI placed on enhancing segment only	Second order	Angular second momentum, contrast, correlation, inverse difference moment and entropy were significant in differentiating between GBM and PCNSL (p<0.05). Highest AUC 0.752 for second-order texture "Contrast"	No	No
Nakagawa et al[23]	GBM-45 PCNSL-25	T2W, ADC maps, rCBV maps and T1W contrast enhanced	2D- Single slice in maximal axial dimension	Second-order GLCM	Machine learning model based on histogram and texture features (multivariate regression AUC 0.98) was superior to conventional cut-off	Multivariate extreme gradient boosting- XGBoost	No

					method and radiologists (AUC 0.84, and 0.79) (p <0.05)	(AUC 0.980)	
Yun et al[19]	GBM-91 PCNSL-62 Training set: 50 PCNSL, and 73 GBM; Internal validation set: 12 PCNSL, and 18 GBM; External validation set: 14 PCNSL and 28 GBM	T1W contrast enhanced, Diffusion weighted imaging	3D-Contrast enhanced portions only	First order, Second order and wavelet features	Combination of radiomics and MLP network classifier (AUC 0.947) was best in differentiating between two groups while CNN (AUC 0.486) showed the lowest performance in external validation sets. Performance of MPL network highest in external validation set (AUC 0.947), followed by human readers (AUC 0.913 and 0.930) and machine-learning classifier model (AUC 0.811).	Yes, Supervised machine learning	CNN, Multilayer perceptron network (MLP)
Kang et al[20]	Training set: 70 GBM, and 42 PCNSL Internal validation sets:21 GBM, 21 PCNSL; External validation sets: 28 GBM, and 14 PCNSL	Diffusion weighted imaging, T1W contrast enhanced	3D-enhancing portion only	First and second order, shape and wavelet features	Diffusion radiomics model performed better than conventional radiomics (AUC 0.944 versus 0.819) and similar to human readers (AUC 0.896-0.930) in external validation set	Yes, 8 classifier models. ADC model, AUC = 0.983. T1W-CE model AUC = 0.976)	No

Yang et al[28]	GBM-58, PCNSL-37	Multiparametric (T1W, T2W, FLAIR, T1W contrast-enhanced	Key-slices (not volumetric)	Intensity, shape, histogram and texture features	Global accuracy of 96.84% to differentiate GBM and PCNSL	Yes (SVM)	No
Liu et al[2]	GBM-107 PCNSL-60	T1W contrast enhanced	2D, multi-slice	Fractal analysis, Fractal dimension (FD) and lacunarity	PCNSL had lower FD values ($p < 0.001$) and higher lacunarity values ($p < 0.001$) than GBM	No	No
Nguyen et al[29]	Meta-analysis				Machine-learning model lowest AUC 0.878. Machine-learning performed better than radiologists.	Machine-learning performed poorly when applied to external validation datasets	Yes