On-line Table 1: MRTA glioma grade

Author, Year of Publication	No. of Patients Analyzed (HGG/LGG)	Magnet Strength/ MRI Sequences	Segmentation Manual/Automatic	Texture Software	Type of Texture Analysis	Best Discriminating Texture Feature	Classification Models	Results
Kang et al,[2] 2011	27 (21/6)	1.5T/ADC	Manual 2D-VOI (stacks of images)	In-house	Histogram	Fifth percentile	No	5th Percentile of cumulative ADC histogram at a higher b-value (3000) was more significant ($P < .05$) to distinguish HGGs from LGGs
Ryu et al,[27] 2014	40 (32/8)	1.5T/ADC	Manual 2D	Medical Imaging Solutions[a]	Histogram GLCM	Fifth percentile entropy	No	Entropy, skewness, and 5th percentile significantly differentiated grade II and III gliomas and only entropy between grades III and IV gliomas; entropy had higher accuracy (80%) than 5th percentile (65%) in distinguishing HGGs from LGGs ($P < .05$).
Kinoshita et al,[28] 2016	50 (28/22)	1.5T–3T/T2WI	Manual 3D	Matlab[b]	Gradient GLCM	Entropy	No	Lower entropy in homogeneous lesions and *IDH1* wild-type gliomas (AUC = 0.73); high-edge mean (AUC = 0.81) and median values (AUC = 0.83) in homogeneous lesions
Skogen et al,[29] 2016	95 (68/27)	3T/T1-CE	Manual 2D	TexRAD[c]	Histogram	Fine texture scale	No	LGGs and HGGs were best discriminated using SD at fine-texture scale, with a sensitivity and specificity of 93% and 81% (AUC = 0.910, $P < .0001$)
Raja et al,[10] 2016	53 (34/19)	3T/DWI/DKI	Manual 2D	Matlab	Histogram	Entropy Busyness	No	Entropy and Busyness had highest discriminability between grades II and III ($P = .029$) and grades III and IV gliomas ($P = .0312$)
Tian et al,[30] 2016	153 (111/42)	3T/Multiparametric (T1WI, T2WI, DWI, ASL, T1-CE)	Manual 2D-VOI (stack of slices)	Matlab	GLCM, GLGCM histogram mean	30 and 28 Optimal features (of 420 texture and 90 histogram features)	SVM-RFE	Texture features were statistically significant over histogram parameters for glioma grading; accuracy of classifying LGGs versus HGGs was 96.8%, while it was 98.1% for grade III–IV gliomas
Xie et al,[31] 2018	42 (27/15)	3T/dynamic contrast-enhanced	Manual 2D	OmniKinetics[d]	GLCM	Entropy and IDM	No	Entropy and IDM efficiently differentiated grade IV from grade III gliomas as well as grade II from grade III gliomas; no feature was able to distinguish subtypes of grade II and grade III gliomas; entropy (AUC = 0.885) and IDM (AUC = 0.901) of extended Tofts- and Patlak-based vp (extended Tofts) showed highest AUC in discriminating grade III and IV gliomas
Qi et al,[32] 2018	39 (26/13)	3T/DWI/DKI	Manual 2D	ImageJ[e]	Histogram	All 12 parameters calculated	No	Histogram parameters on DKI were significant in differentiating high- (grade III and IV) from low-grade (II) gliomas ($P < .05$); mean kurtosis was the best independent predictor of differentiating glioma grades with AUC = 0.925

Note:—DKI indicates diffusional kurtosis imaging; ASL, arterial spin-labeling; GLGCM, gray-level gradient co-occurrence matrix; vp, blood plasma volume; RFE, recursive feature elimination.

[a] https://medicalimaginggroup.com/.

[b] MathWorks, Natick, Massachusetts.

[c] https://imagingendpoints.com/texrad-software/.

[d] http://www.omnikinetics.com/.

[e] National Institutes of Health, Bethesda, Maryland.

On-line Table 2: MRTA glioma survival

Author, Year of Publication	No. of Patients (HGG)	Magnet Strength/ MRI Sequence	Segmentation	Texture Software	Type of Texture Analysis	Best Discriminating Texture Feature	Classification Models	Results
Brynolfsson et al,[34] 2014	23	1.5T/ADC maps	Manual 2D (volume extracted in 3 orthogonal directions)	Matlab	GLCM	1st, 3rd, and 5th component of PCA of 60 texture features	PCA	1st, 3rd, and 5th components of PCA were strongly correlated with longer survival times ($P < .05$) in patients with grade III and IV gliomas
Upadhaya et al,[35] 2015	40 (TCIA)	T1WI, T2WI, FLAIR, T1-CE	Automatic 2D	–	Histogram GLCM, GLRLM, GLSZM	Single sequence (cluster shade, HGLZE, LHGLE, GLNSH, SZNU); combination of T1 pre- (HGLZE, variance) and T1 postcontrast (cluster prominence, SHGLE, SZNU, sum)	SVM	Highest accuracy was extracted from T1-CE using a combination of 5 texture features with an accuracy of 82.5%
Yang et al,[36] 2015	82 (TCGA)	T1-CE, T2WI, FLAIR	Manual 3D (stack of slices)	Matlab using the NIfTI toolbox	SFTA, RLM, LBP, HOG Haralick texture features	–	Random forest model	Several texture features were predictive of molecular subtypes and 12-mo survival; SFTA features on T1-CE were most predictive of survival and proneural subtype (AUC = 0.82); Haralick features on T1-CE for classic (AUC = 0.72); HOG features on T2WI, FLAIR axial for mesenchymal (AUC = 0.70); RLM features on T2 FLAIR axial for neural (AUC = 0.75)
Chaddad,[37] 2016	40 (TCIA)	3T/T1-CE, FLAIR	Manual 3D	Matlab	GLCM	All 22 texture features derived	Discriminant analysis, Naïve Bayes, decision trees, SVM	Discriminant analysis provided maximum accuracy (79.31%); texture features from contrast-enhanced segment were most statistically significant to predict survival; of 22 features selected, 3 features (difference entropy, information measure of correlation, and inverse difference) of active enhancing tumor phenotype were statistically significant
Lee et al,[38] 2016	24 (TCGA)	DSCE, rCBV maps	Manual 2D	Matlab	Histogram GLCM kinetic texture analysis	CEL (homogeneity, ASM, IDM, entropy) NEL (skewness, variance) kinetic (Haralick correlation)	No	Homogeneity (AUC = 0.83), ASM (AUC = 0.76), IDM (AUC = 0.81), and entropy (AUC = 0.80) from contrast-enhancing regions were significant in predicting survival; for non-contrast-enhancing regions, skewness (AUC = 0.80) and variance ratios predicted survival; in kinetic texture analysis; Haralick correlation feature was significant ($P < .05$)
Molina et al,[39] 2016	79	1.5–3T/T1-CE	Manual 3D	Matlab	GLCM, GLRLM	GLCM (entropy, homogeneity, contrast, dissimilarity) GLRLM (LRE, HGLRE, LRHGE, RPC)	No	Patients had better prognosis when high LRHGE, low RPC, low entropy, high homogeneity, and low dissimilarity were present ($P < .05$)
Kickingereder et al,[40] 2016	119	3T/T1-CE, FLAIR	Manual 3D	Medical Imaging Toolkit[a]	Histogram volume and shape features; texture features; wavelet analysis	11 Features of 12, 190 features	SPC analysis	SPC analysis performed better than clinical (age and Karnofsky Performance Score) and radiologic (rCBV and ADC) parameters
Grossmann et al,[41] 2017	165	1.5/3T/T1-CE, FLAIR	Semi-automatic 3D	Matlab	Histogram GLCM GLRLM	Information correlation	PCA	Texture features derived from T1-CE resulted in higher prognostic power compared with FLAIR imaging; information correlation from T1-CE had significantly high score in patients progressing within 3 mo
Chaddad et al,[42] 2019	73 (TCIA)	T1-CE, FLAIR	Semi-automatic 2D	–	GLCM JIM	JIM (entropy, inverse-variance) in necrosis region and (entropy, contrast) in edema region	No	JIM of T1-CE and FLAIR images significantly predicted survival outcomes with moderate correlation; 9 features were found to be associated with glioblastoma survival, $P < .05$, accuracy of 68%–70%
Bahrami et al,[43] 2018	33	3T/FLAIR	Semi-automatic 3D	–	EC	–	No	Post-bevacizumab therapy, low EC of FLAIR hyperintense signal predicted poor progression-free survival ($P = .009$) and overall survival ($P = .022$)
Liu et al,[44] 2018	119 (TCGA)	T1WI, T2WI, FLAIR, T1-CE	Manual 2D	–	Histogram GLCM GLRLM	13 Textural features	SVM-RFE	T1-CE sequence performed best, with AUC of 0.7915 and accuracy of 80.67%

Note:—DSCE indicates dynamic susceptibility contrast-enhanced MRI; rCBV, relative cerebral blood volume; JIM, joint intensity matrices; RLM, run-length matrix; TCGA, The Cancer Genome Atlas; TCIA, The Cancer Imaging Archive; ASM, angular second moment; LRE, long-run emphasis; HGLRE, high gray-level run emphasis; LRHGE, long-run high gray-level emphasis; RPC, run percentage; HGLZE, high gray-level zone emphasis; LHGLE, large zone high gray-level emphasis; GLNSH, gray-level nonuniform spectral homogeneity; SZNU, size-zone nonuniformity; SRHGLE, short-run high gray-level emphasis; EC, edge contrast; RFE, recursive feature elimination; –, not available; SFTA, segmentation-based fractal texture analysis; LBP, local binary pattern; HOG, histogram-oriented gradient; NEL, Non-enhancing lesion region; SPC, supervised principal component; CEL, contrast enhancing lesion region; GLSZM, gray-level size-zone matrix; SHGLE, short zone high gray-level emphasis.

[a] http://www.mitk.org/wiki/The_Medical_Imaging_Interaction_Toolkit_(MITK).

On-line Table 3: MRTA glioma molecular status

Author, Year of Publication	No. of Patients (*IDH* Mutant/Wild-Type)	No. of *IDH* Mutant Tumors with 1p/19q Codeletion/Intact	Magnet Strength/MRI Sequences	Segmentation	Texture Software	Type of Texture Analysis	Best Discriminating Texture Feature	Classification Models	Results
Zhang et al,[48] 2017	152 (92/60); TCIA	–	1.5T–3T/T1-CE, T1WI, T2WI, FLAIR	Manual 3D	Matlab-based	GLCM GLGCM	15 Optimal features from 168 Haralick features	SVM-REF	AUC 0.841 for noninvasively discriminating *IDH* mutation of patients with glioma
Hsieh et al,[49] 2017	39 (7/32); TCGA	–	1.5T–3T/T1-CE	Manual 2D	CAD system	Morphologic, intensity-GLCM	14 GLCM	Binary logistic regression classifier	Textural features describing local patterns yielded an accuracy of 85% in detecting the *IDH* status
Eichinger et al,[50] 2017	79 (50/19)	–	3T/DTI (B_0, FA maps)	Semi-automatic 3D	3D-LBP	100 (50 LBP textures in B_0 and FA)	100 (50 LBP textures in B_0 and FA)	Neural network classifier using R package "nnet"[a]	*IDH*-mutation prediction accuracy of the training model 92% (AUC = 0.921); and validation cohort 95% (AUC = 0.952)
Bahrami et al,[51] 2018	61 (43/11; 7 unknown)	24/19 MGMT, methylated, 23, unmethylated, 9	3T/Pre- and post-T1-CE, FLAIR	Semi-automatic 3D	3D-co-occurrence matrix	Histogram, GLCM	Homogeneity, pixel correlation, EC	Logistic regression with LASSO regularization	Greater signal heterogeneity and lower EC noted in *IDH* wild-type tumors; *IDH*-mutant tumors with 1p/19q-codeleted status;. lower EC in MGMT-methylated tumors
Shofty et al,[52] 2018	47 LGGs	26/21	1.5T–3T/FLAIR, T2, T1-CE	Automatic using FSL,[b] 3D	Matlab	Histogram, contrast, correlation, energy, entropy, homogeneity	39 of 152 Textural features	17 Classifiers	Ensemble of bagged trees classifier achieved the best performance (87% accuracy) for the detection of 1p/19q codeletion; majority of differences detected for T2 and T1-CE and only a few for FLAIR
Jakola et al,[53] 2018	25 (20/5)	11/9	3T/3D-FLAIR	Semiautomatic 3D	ImageJ	Homogeneity, energy, entropy, correlation, inertia	Homogeneity	–	Homogeneity discriminated patients with LGG in *IDH* mutant and *IDH* wild-type ($P = .005$); authors could not separate *IDH*-mutant tumors on the basis of 1p/19q-codeletion status
Rui et al,[54] 2018	54	34/20	3T/T2 FLAIR	Manual 2D	OmniKinetics	1st Order, GLCM	1st Order, energy, entropy, mean deviation, 2nd order HGLRE, cluster shade, sum average	–	True oligodendrogliomas with *IDH* mutation and 1p/19q codeletion rather than gliomas with *IDH*-mutation and 1p/19q-intact status showed lower energy and higher entropy ($P = .008$) and high sum average, high HGLRE, and lower cluster shade; 2nd order texture features showed high Sn and Sp compared with 1st order
Han et al,[55] 2019	42 (21/21)	–	3T/T1WI, T2WI, 3D-T1-CE	Manual 3D	OmniKinetics	29 Texture features from first order and GLCM	Inertia, cluster prominence, GLCM entropy	–	According to logistic regression model, the contrast-enhanced T1WI features model had the highest accuracy (95.2%) and the best diagnostic efficiency (Sn, 100%; Sp, 95.2%) followed by T1WI (85.7%) and T2WI (73.8%)

Note:—MGMT indicates methylguanine methyltransferase; FA, fractional anisotropy; Sn, sensitivity; Sp, specificity; –, not available; LASSO, least absolute shrinkage and selection operator; CAD, computer-aided diagnosis; TCGA, The Cancer Genome Atlas; TCIA, The Cancer Imaging Archive; LBP, local binary pattern; GLGCM, gray-level gradient co-occurrence matrix; EC, edge contrast; HGLRE, high gray-level run emphasis; REF, recursive-feature elimination.

[a] R statistical and computing software (http://www.r-project.org).

[b] FSL (http://www.fmrib.ox.ac.uk/fsl).

On-line Table 4: Miscellaneous applications

Author, Year of Publication	No. of Patients (Gliomas/PCNSLs)	Magnet Strength/MRI Sequences	Segmentation	Texture Software	Type of Texture Analysis	Best Discriminating Texture Feature	Classification Model	ROC Results of Combined First- and Second-Order Texture Features for 1p/19q Genotyping (AUC) (*P* Value)
Kunimatsu et al,[60] 2019; Kunimatsu et al,[61] 2018	Training set, 60 (44/16); test data, 76 (55/21)	3T/T1-CE	2D	Radiomic Image-Processing Toolbox[a]	Histogram, GLCM, GLRLM, GLSZM, mGLSZM	1st Order, entropy, median; GLRLM- RLNU, run percentage	SVM; SVM, linear and Gaussian	Entropy and RLNU higher in glioblastomas; median and run percentage lower in glioblastomas; SVM-based classifiers demonstrated accuracies of 66%–82% for glioblastoma and 75%–81% for PCNSL; AUC on the training data was 0.99 for the SVM-based Gaussian kernel classifier and 0.87 for the linear kernel classifier; both classifiers showed prediction accuracy of 75%
Suh et al,[59] 2018	77 (23/54)	3T/T1-CE, T2, FLAIR	2D	Python package, PyRadiomics 1.2.0[b]	Shape, volume, 1st order, GLCM, GLRLM, mGLSZM, and wavelet transform	A total of 6366 radiomics features subjected to recursive feature elimination and random forest analysis with nested cross-validation	SVM	In comparing diagnostic performances, the AUC (0.921) and accuracy (90%) of the radiomics classifier was significantly higher than those of the 3 radiologists ($P < .001$)
Xiao et al,[62] 2018	82 (60/22)	1.5T–3T /T1-CE, T2, FLAIR	3D	PyRadiomics and Python	1st Order, GLCM	1st Order skewness > kurtosis > Ngtdm Busyness[c]	Logistic regression, Naïve Bayes, SVM	Skewness was the best selected predictor for classification (AUC = 0.86), followed by Ngtdm Busyness (AUC = 0.83) and 1st order kurtosis (AUC = 0.80); among 3 classification models, the Naïve Bayes classifier was superior overall, with a high AUC (0.90) and the best specificity (0.91); the SVM model provided the best sensitivity (92%) and accuracy (88%)
Alcaide-Leon et al,[63] 2017	106 (71/35)	3T/T1-CE	Manual 3D	In-house	1st and 2nd order	153 Features	SVM	Mean AUC of the SVM classifier (0.877) was significantly superior to the mean AUC of readers
Verma et al,[66] 2017	20 (15/5)	DSCE	Manual 2D	In-house, dynamic texture parameter analysis	Histogram	Mean, SD, variance	–	Most significant differences are obtained during the earliest phase of contrast passage rather than in later phase
Bahrami et al,[43] 2018	105 Glioblastomas	T1-CE, T2WI/FLAIR	Manual 2D	–	30 Shape features	Top 2 most discriminative features	–	3D shape attributes from the lesion habitat can be differentially expressed across pseudoprogression and tumor progression and could be used to distinguish these radiographically similar pathologies
Grossmann et al,[41] 2017	126	Baseline and follow-up MRI (1 and 6 wks), T1WI, T2WI, FLAIR, T1-CE	Semi-automatically with Slicer 3D[d]	Radiomics pipeline	1) 1st Order statistics of the voxel intensity histogram, 2) tumor shape, and 3) tumor texture	Information correlation	PCA	Radiomics provides prognostic value for survival and progression in patients with recurrent glioblastoma receiving bevacizumab treatment; features derived from postcontrast T1WI yielded higher prognostic power compared with pre-contrast-enhancing T2WI

Note:—mGLSZM indicates multiple gray-level size-zone matrix, RLNU, run-length nonuniformity; –, not available; DSCE, dynamic susceptibility contrast-enhanced MRI; GLSZM, gray-level size-zone matrix.

[a] https://www.mathworks.com/products/image.html.

[b] https://github.com/Radiomics/pyradiomics/commit/fd8abd4be501587f45abb04a67cc6fd20bbf0df6.

[c] https://pyradiomics.readthedocs.io/en/latest/_modules/radiomics/ngtdm.html.

[d] http://www.slicer.org.