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Machine Learning based Differentiation of Glioblastoma from Brain Metastasis using MRI derived Radiomics

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Type of manuscript: Original research

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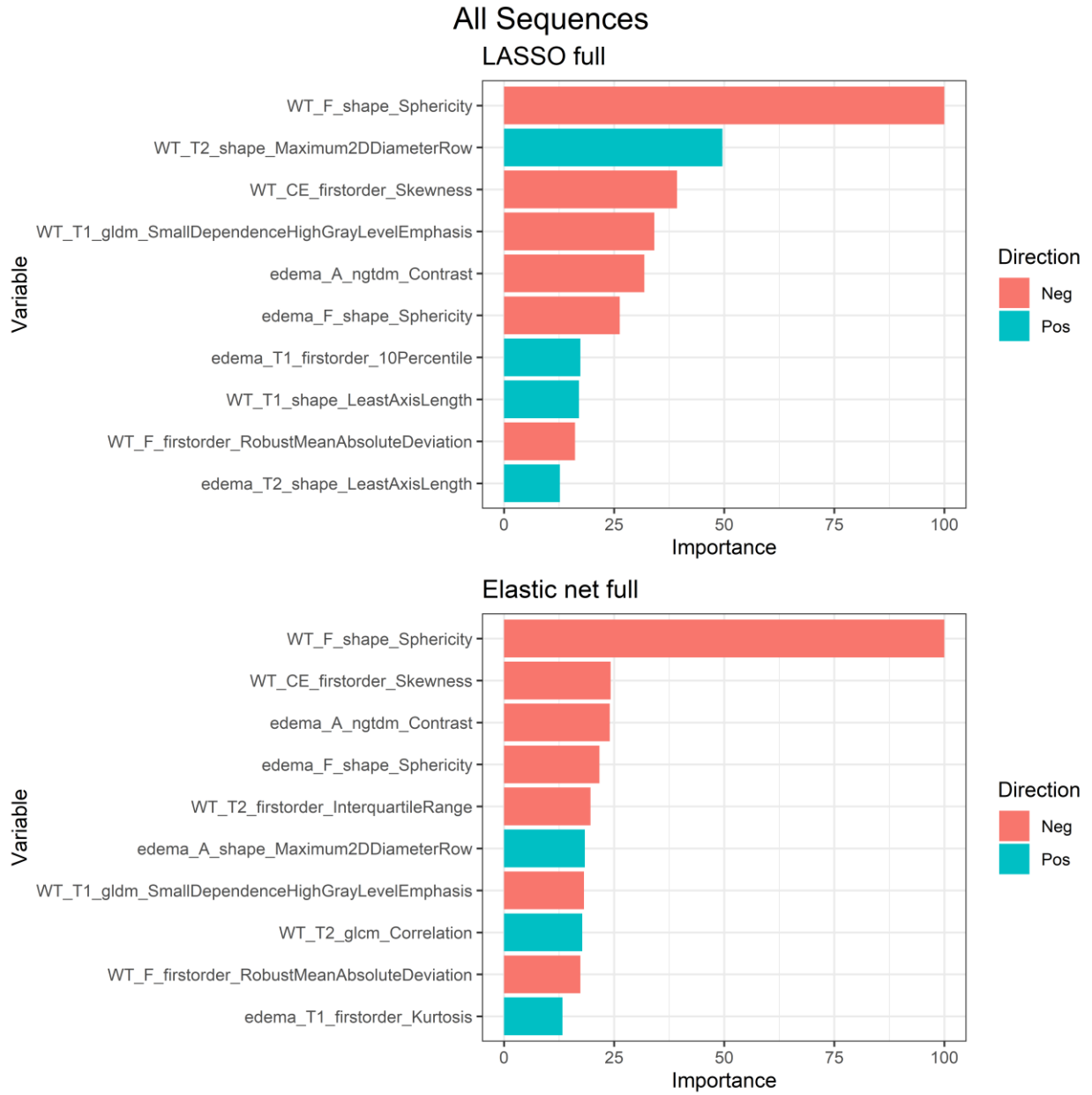
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Supplementary Table S1: Ranking by variable Importance for the 10 most important features in the two best models fit using all sequences

LASSO Full Feature set				
Rank	Mask	Seq	Feature	Relative Importance
1	WT	F	shape_Sphericity	100.00
2	WT	T2	Maximum2DDiameterRow	49.63
3	WT	CE	firstorder_Skewness	39.31
4	WT	T1	gldm_SmallDependenceHighGrayLevelEmphasis	34.16
5	Edema	A	ngtdm_Contrast	31.87
6	Edema	F	shape_Sphericity	26.28
7	Edema	T1	firstorder_10Percentile	17.36
8	WT	T1	shape_LeastAxisLength	17.04
9	WT	F	firstorder_RobustMeanAbsoluteDeviation	16.14
10	Edema	T2	shape_LeastAxisLength	12.70
Elastic Net Full Feature set				
Rank	Mask	Seq	Feature	Relative Importance
1	WT	F	shape_Sphericity	100.00
2	WT	CE	firstorder_Skewness	24.24
3	Edema	A	ngtdm_Contrast	24.02
4	Edema	F	shape_Sphericity	21.67
5	WT	T2	firstorder_InterquartileRange	19.66
6	Edema	A	Maximum2DDiameterRow	18.36
7	WT	T1	gldm_SmallDependenceHighGrayLevelEmphasis	18.16
8	WT	T2	glcm_Correlation	17.79
9	WT	F	firstorder_RobustMeanAbsoluteDeviation	17.35
10	Edema	T1	firstorder_Kurtosis	13.28

WT: Whole tumor mask; A: ADC; F: FLAIR; CE: T1-CE

Supplementary Figure 1: Feature ranking for the 10 most important features in the two best models fit using all sequences



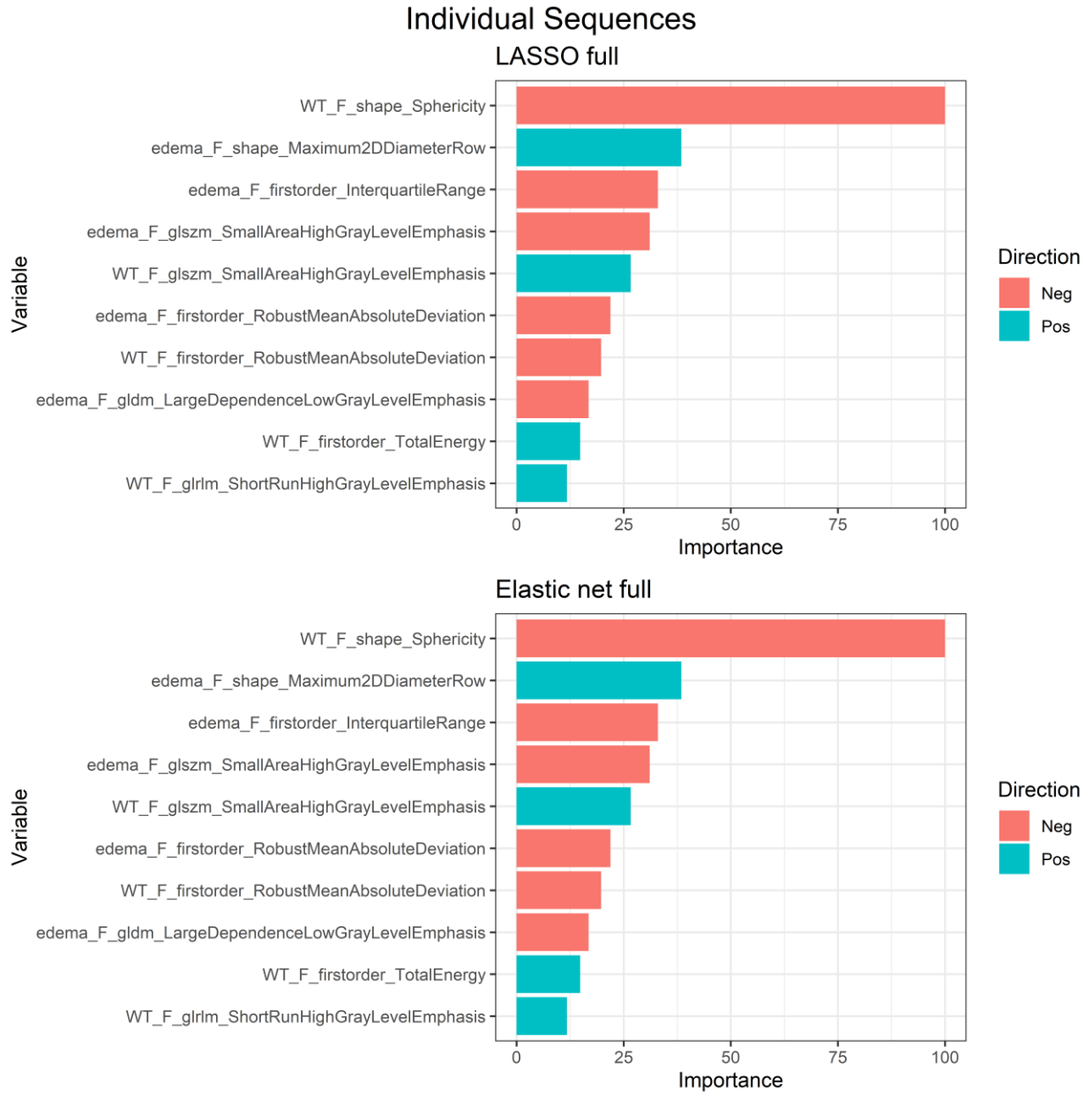
Positive (Pos) association indicates that larger value of that feature is associated with GBM and a negative (Neg) value indicates that smaller values of that feature are associated with GBM (i.e. larger values are associated with metastasis).

Supplementary Table S2: Ranking by variable Importance for the 10 most important features in the two best models fit using individual sequences

LASSO Full Feature set FLAIR			
Rank	Mask	Feature	Relative Importance
1	WT	shape_Sphericity	100.00
2	Edema	Maximum2DDiameterRow	38.46
3	Edema	firstorder_InterquartileRange	33.00
4	Edema	glszm_SmallAreaHighGrayLevelEmphasis	31.07
5	WT	glszm_SmallAreaHighGrayLevelEmphasis	26.64
6	Edema	firstorder_RobustMeanAbsoluteDeviation	21.92
7	WT	firstorder_RobustMeanAbsoluteDeviation	19.74
8	Edema	gldm_LargeDependenceLowGrayLevelEmphasis	16.80
9	WT	firstorder_TotalEnergy	14.84
10	WT	glrlm_ShortRunHighGrayLevelEmphasis	11.75
Elastic Net Full Feature set FLAIR			
Rank	Mask	Feature	Relative Importance
1	WT	shape_Sphericity	100.00
2	Edema	Maximum2DDiameterRow	38.46
3	Edema	firstorder_InterquartileRange	33.00
4	Edema	glszm_SmallAreaHighGrayLevelEmphasis	31.07
5	WT	glszm_SmallAreaHighGrayLevelEmphasis	26.64
6	Edema	firstorder_RobustMeanAbsoluteDeviation	21.92
7	WT	firstorder_RobustMeanAbsoluteDeviation	19.74
8	Edema	gldm_LargeDependenceLowGrayLevelEmphasis	16.80
9	WT	firstorder_TotalEnergy	14.84
10	WT	glrlm_ShortRunHighGrayLevelEmphasis	11.75

WT: Whole tumor mask

Supplementary Figure 2: Feature ranking for the 10 most important features in the two best models fit using individual sequences



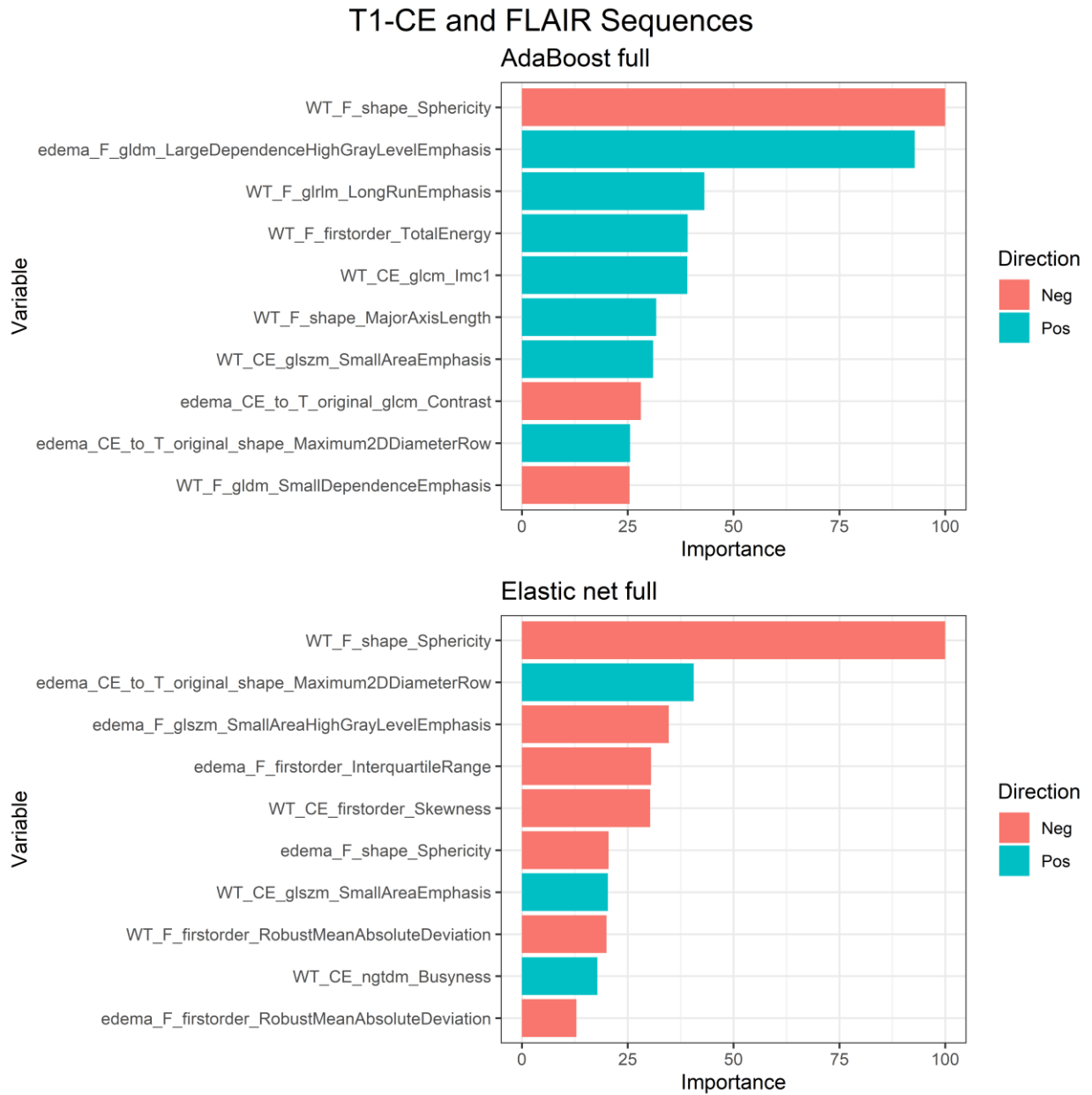
Positive (Pos) association indicates that larger value of that feature is associated with GBM and a negative (Neg) value indicates that smaller values of that feature are associated with GBM (i.e. larger values are associated with metastasis).

Supplementary Table S3: Ranking by variable Importance for the 10 most important features in the two best models fit using T1-CE and FLAIR sequences

adaBoost Full T1 CE+F				
Rank	Mask	Seq	Feature	Relative Importance
1	WT	F	shape_Sphericity	100.00
2	Edema	F	gldm_LargeDependenceHighGrayLevelEmphasis	92.81
3	WT	F	glrlm_LongRunEmphasis	43.11
4	WT	F	firstorder_TotalEnergy	39.19
5	WT	CE	glcm_Imc1	39.11
6	WT	F	shape_MajorAxisLength	31.76
7	WT	CE	glszm_SmallAreaEmphasis	31.03
8	Edema	CE	glcm_Contrast	28.13
9	Edema	CE	shape_Maximum2DDiameterRow	25.58
10	WT	F	gldm_SmallDependenceEmphasis	25.44
LASSO Full T1 CE+F				
Rank	Mask	Seq	Feature	Relative Importance
1	WT	F	shape_Sphericity	100.00
2	Edema	CE	shape_Maximum2DDiameterRow	40.61
3	Edema	F	glszm_SmallAreaHighGrayLevelEmphasis	34.69
4	Edema	F	firstorder_InterquartileRange	30.52
5	WT	CE	firstorder_Skewness	30.31
6	Edema	F	shape_Sphericity	20.48
7	WT	CE	glszm_SmallAreaEmphasis	20.34
8	WT	F	firstorder_RobustMeanAbsoluteDeviation	19.99
9	WT	CE	ngtdm_Busyness	17.83
10	Edema	F	firstorder_RobustMeanAbsoluteDeviation	12.91

WT: Whole tumor mask; A: ADC; F: FLAIR; CE: T1-CE

Supplementary Figure 3: Feature ranking for the 10 most important features in the two best models fit using T1-CE and FLAIR sequences

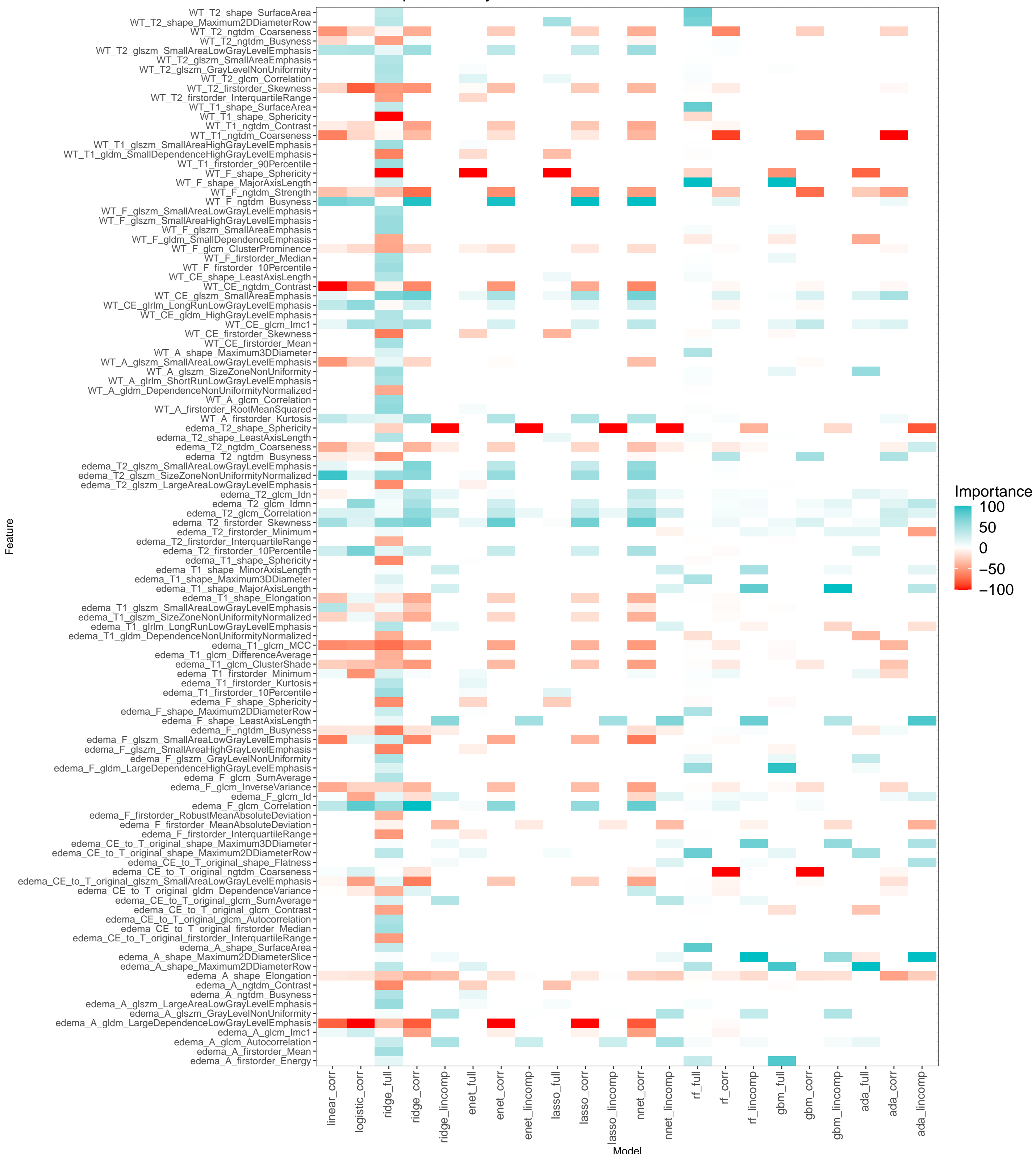


Positive (Pos) association indicates that larger value of that feature is associated with GBM and a negative (Neg) value indicates that smaller values of that feature are associated with GBM (i.e. larger values are associated with metastasis).

Supplementary Figure 4: Heatmap for feature importance for multiparametric MRI models

Red (positive) is indicative that larger values are associated with Glioblastoma and the blue (negative) is indicative that smaller values are associated with Glioblastoma (i.e. larger values are associated with metastasis).

Variable Importance by Model/Feature Selection



Supplementary Table S4: Comparison with prior radiomic studies differentiating glioblastoma from metastatic brain lesions

Authors	Patients	Scanner/sequences/Masks	Texture	ML/DL	Accuracy
Priya et al (Current study)	120 (GBM-60, Metastasis 60)	1.5 T; volumetric 3D segmentation; whole tumor and edema mask;	107 radiomics features	12 machine learning models and three feature selection methods	LASSO (using full feature set); AUC 0.953
Dong et al 2020 ¹	120 (GBM-60, Metastasis 60)	1.5t/3t; 2-D; T1 CE, T2W, T1W; edema mask	321 features	Boruta algorithm, 5 classifiers	Highest accuracy (77%)- achieved after combining all 5 ML classifiers
Ortiz et al 2020 ²	100 (GBM-50, Metastasis 50)	1.5T; 2-D; T1 CE coronal; only largest tumor segmented; enhancing mask	88 rotation invariant features	5 classifier models, 3 feature selection methods	MLP model- Accuracy (82%); AUC- 0.912
Bae et al 2020 ³	248 (GBM-159, Metastasis 89)	3-T; 2-D; T1 CE; T2W; enhancing, edema masks, enhancing plus edema combined	265	5 methods for feature selection; 7 machine learning classifiers; Deep learning- Deep neural network (DNN)	DNN- Highest accuracy from combined mask (89%); AUC (0.956); Best ML model – from combined masks (adaptive boosting combined with tree-based feature selection- AUC- 0.890; Accuracy 83%)
Csutak et al 2020 ⁴	42 (High grade glioma-16, Metastasis 26)	1.5 T, T2W, peritumoral texture	First, second order, wavelet texture features	Fisher selection method	Perc01 texture feature yielded highest AUC (0.858)

Tateishi et al 2020 ⁵	126 (GBM-73, Metastasis 53)	3T, T1CE, T2W, ADC	36 Features	SVM	AUC 0.920
Dastmalchian et al 2020 ⁶	31 (GBM-17, Low grade glioma-6, Metastasis-8)	3T, T1 and T2 maps, MRI fingerprinting	39 Texture features	Log rank test	AUC 0.877 (GBM versus metastasis)
Artzi et al 2019 ⁷	439 (GBM-212, IMD- 227)	1.5T/3T; 2-D; T1 CE; Three tumor slices selected; enhancing mask	First, Second-order, morphological, wavelet features	Supervised learning-4 ML classifiers- Unsupervised learning- Bag of features (BoF) extraction	Supervised-SVM- 85% (AUC-0.940) Unsupervised - BoF Accuracy- 75%
Qian et al 2019 ⁸	412 (GBM 242, Metastasis 170)	3T; 2-D; T1 CE; volumetric segmentation	1303 radiomic features	12 feature selection methods; 7 supervised machine-learning classifiers	LASSO-SVM- Accuracy- 83% (AUC 0.900)
Zhang et al 2019 ⁹	62 (GBM-36, Metastasis 26)	3T; 2-D; ADC; largest cross-section only; whole tumor mask (enhancing plus necrotic); enhancing mask only	5 GLCM parameters	No	Whole tumor mask- AUC 0.682 (Homogeneity texture); enhancing only mask (AUC 0.886; Homogeneity texture)
Skogen et al 2019 ¹⁰	43 (GBM-22, Metastasis 21)	3T; 2-D; ADC, FA maps; largest cross-section only segmented;	5 first-order texture features at different filters	No	FA plus ADC unfiltered image- AUC- 0.911
Petrujkić et al 2019 ¹¹	55 (GBM-30, Metastasis 25)	3T, R2W, Susceptibility weighted imaging, T1 CE	Fractal and texture analysis	No	AUC 0.908
Mouthuy et al 2012 ¹²	50 (GBM-41, Metastasis 14)	1.5 T, peritumoral texture from washout phase of the perfusion sequence	9 texture features	k-means clustering	Highest AUC 0.75 from correlation texture

					feature
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ML- machine learning; DL: deep learning; LASSO: least absolute shrinkage and selection operator; SVM: support vector machine; MLP: multilayer perceptron; FA: fractional anisotropy

Supplementary Table S5: Typical scanning parameters for various sequences at the authors institute:

T1W (TR/TE/TI: 1950/10/840, NEX: 2, slice thickness: 5 mm, matrix: 320×256 , field of view (FOV) 240 mm, pixel size 0.75 mm)

T2W (TR/TE: 4000/90, NEX: 2, slice thickness: 5 mm, matrix: 512×408 , FOV 240 mm, pixel size 0.5 mm);

FLAIR (TR/TE/TI: 9000/105/2500, NEX: 1, slice thickness: 5 mm, matrix: 384×308 , FOV 240 mm, pixel size 0.6 mm)

DWI (TR/TE: 4000/74, NEX: 3, slice thickness: 5 mm, matrix: 128×128 , FOV 240 mm, pixel size 1.8 mm)

T1W-CE (TR/TE/TI: 570/13, NEX: 2, slice thickness: 5 mm, matrix: 384×312 , field of view (FOV) 240 mm, pixel size 0.62 mm)

T1 W contrast-enhanced images were acquired after administration of gadobenate dimeglumine (Multihance; Bayer Healthcare Pharma) or gadobutrol (Gadavist; Bayer Healthcare Pharma, Berlin, Germany) injected at the rate of 0.1 ml/kg body weight.

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