

Supplementary Information

1. Methodology used to extract handcrafted features and textured extraction parameters.

1.1 Handcrafted feature extraction

The handcrafted features extracted from the tumor region were divided into non-textured and textured features. In total, four non-textured features were drawn from the tumor of each patient: (1) Volume (number of voxels in the tumor region multiplied by the dimension of voxels), (2) size (longest diameter of the tumor region), (3) solidity (ratio of the number of voxels in the tumor region to the number of voxels in the 3D convex hull of the tumor region (smallest polyhedron containing the tumor region)), and (4) eccentricity. Note that eccentricity refers to the ellipsoid that best fits the tumor region; it is calculated by $\left[1 - \frac{axb}{c^2}\right]^{\frac{1}{2}}$, where c is the longest semi-principal axes of the ellipsoid and a and b are the second and third longest semi-principal axes of the ellipsoid, respectively. The textured features were divided into two parts. The first part is based on the intensity histogram features of the tumor region. A total of three intensity histogram features were drawn, namely, variance, skewness, and kurtosis. The second part is based on the matrix features, and a total of 40 features, including 9 gray-level co-occurrence matrix features, 13 GLRLM features, 13 GLSZM features, and 5 neighborhood gray-tone difference matrix features, were extracted. The 43 textured features are shown in Table 1. In this research, data of images of the four modalities were used. Therefore, 172 (43 features are extracted from each image of each MRI modality) textured features were involved in this

study.

Table 1. Forty-three textural features.

Texture type	References	Texture name
Global	—	Variance
		Skewness
		Kurtosis
GLCM	(Haralick <i>et al</i> 1973)	Energy
(Grey-level co-occurrence matrix)		Contrast
		Correlation
		Homogeneity
		Variance
		Sum Average
		Entropy
	—	Dissimilarity
	—	AutoCorrelation
GLRLM	(Galloway 1975)	Short Run Emphasis (SRE)
(Grey-level run-length matrix)		Long Run Emphasis (LRE)
		Grey-Level Non-uniformity (GLN)
		Run-Length Non-uniformity (RLN)
		Run Percentage (RP)
	(Chu <i>et al</i> 1990)	Low Grey-Level Run Emphasis (LGRE)
		High Grey-Level Run Emphasis (HGRE)

(Dassarathy and Holder 1991)	Short Run Low Grey-Level Emphasis (SRLGE)
	Short Run High Grey-Level Emphasis (SRHGE)
	Long Run Low Grey-Level Emphasis (LRLGE)
	Long Run High Grey-Level Emphasis (LRHGE)
(Thibault et al 2009)	Grey-Level Variance (GLV) Run-Length Variance (RLV)
GLSZM (Grey-level size zone matrix)	Small Zone Emphasis (SZE) Large Zone Emphasis (LZE) Grey-Level Non-uniformity (GLN) Zone-Size Non-uniformity (ZSN) Zone Percentage (ZP)
(Chu et al 1990, Thibault <i>et al</i> 2009)	Low Grey-Level Zone Emphasis (LGZE) High Grey-Level Zone Emphasis (HGZE)
(Dasarathy and Holder 1991, Thibault <i>et al</i> 2009)	Small Zone Low Grey-Level Emphasis (SZLGE) Small Zone High Grey-Level Emphasis (SHZGE) Large Zone Low Grey-Level Emphasis

	(LZLGE)
Large Zone High Grey-Level Emphasis	
	(LZHGE)
(Thibault <i>et al</i> 2009)	Grey-Level Variance (GLV)
Zone-Size Variance (ZSV)	
NGTDM	Coarseness
(Neighbourhood grey-tone difference matrix)	Contrast Busyness Complexity Strength

1.2 Textured feature extraction parameters

In this study, the influence of the following extraction parameters on the predictive value of textures was investigated.

(1) **Wavelet band-pass filtering:** The wavelet basis function ‘sym8’ in matlab was used in our study. The wavelet basis function first decomposes the tumor region into low-frequency sub-bands (LLL), band-pass sub-bands (LHL, LHH, LLH, HLL, HHL and HLH) and high-frequency sub-bands (HHH). Different weights ($\frac{1}{2}, \frac{2}{3}, 1, \frac{3}{2}$, or 2) were used to the eight different frequency sub-bands. The eight sub-bands with different weights were then formed a full frequency tumor region images through inverse wavelet transform. The purpose of this operation was to highlight the tumor information of different frequency sub-bands and help the local preservation of spatial characteristics of tumor region. We used R to denote the weight value, and used N_R to denote the number of the R values, and thus $N_R = 5$.

(2) **Isotropic voxel size:** Before computing the textured features, the neighbouring properties of voxels had to be considered. All volumes were resampled to an isotropic voxel size set to a desired resolution using cubic interpolation. The isotropic voxel size that determined the resolution was denoted as “Scale.” The scale values of 1mm, 2mm, 3mm, 4mm, 5mm, and initial in-plane resolution (denoted as “in-pR”) were tested. For example, the voxel size of an MRI volume is $0.45\text{mm} \times 0.45\text{mm} \times 7\text{mm}$. If the scale is set to 5 mm, the voxel size could be isotropically resampled to $5\text{mm} \times 5\text{mm} \times 5\text{mm}$. We used N_{scale} to denote the number of the scale values, and thus $N_{scale} = 6$.

(3) **Gray-level quantization:** The full intensity range of the tumor region was quantized to a small number of grey levels. Two extraction parameters were related to the quantization :

(i) Quantitative algorithms: Two quantitative algorithms (equal-probability and Lloyd-Max) were implemented using the *histeq* and *lloyds* functions of MATLAB. We used N_{algo} to denote the number of quantitative algorithms, and thus $N_{algo} = 2$.

(ii) Number of gray levels: Number of gray levels in the quantized volume was tested on 8, 16, 32, and 64. We used N_{gl} to denote the number of gray levels, and thus $N_{gl} = 4$.

Considering the full set of texture extraction parameters, there are 240 combinations $(N_R \times N_{scale} \times N_{algo} \times N_{gl} = 5 \times 6 \times 2 \times 4 = 240)$. Under these combinations of parameters, 10,320 textured parameter features were extracted from single-modality MRI images (43 textured features and each textured feature has 240 textured combination parameters, $43 \times 240 = 10320$), and 41,280 textured parameter features were drawn from multi-modalities (T1, T1C, T2, and T2-FLAIR) MRI images.

The feature reduction and selection processes were repeated for all possible combinations of textured extraction parameter types, thereby allowing variation. Thus, for experiments in which specific extraction parameters were not allowed to vary,

baseline parameters were defined. In this study, the baseline textured extraction parameters used for the four different types of scans were $R = 1$, scale = in-pR, algo = Lloyd, and $N = 32$.

2. Outline of the AlexNet and Inception v3 network architectures as shown in Tables 2 and 3, respectively.

Table 2. Outline of the AlexNet network architecture. The tumor region is used as the input. Features are extracted from the second full connection layer (FC7).

Type	Input	Output
Input	$3 \times 227 \times 227$	$3 \times 227 \times 227$
Convolution	$3 \times 227 \times 227$	$96 \times 55 \times 55$
Max pooling	$96 \times 55 \times 55$	$96 \times 27 \times 27$
Convolution	$96 \times 27 \times 27$	$256 \times 27 \times 27$
Max pooling	$256 \times 27 \times 27$	$256 \times 13 \times 13$
Convolution	$256 \times 13 \times 13$	$384 \times 13 \times 13$
Convolution	$384 \times 13 \times 13$	$384 \times 13 \times 13$
Convolution	$384 \times 13 \times 13$	$256 \times 13 \times 13$
Max pooling	$256 \times 13 \times 13$	$256 \times 6 \times 6$
Fully connected (FC6)	$256 \times 6 \times 6$	4096×1
Fully connected (FC7)	4096×1	4096×1
Fully connected (FC8)	4096×1	1000×1

Table 3. Outline of the Inception v3 network architecture. The tumor region is used as the input. Features are drawn from the avg_pool layer.

Type	Input	Output
Input	$3 \times 299 \times 299$	$3 \times 299 \times 299$
Conv	$3 \times 299 \times 299$	$32 \times 149 \times 149$
Conv	$32 \times 149 \times 149$	$32 \times 147 \times 147$
Conv padded	$32 \times 147 \times 147$	$64 \times 147 \times 147$
Pool	$64 \times 147 \times 147$	$64 \times 73 \times 73$
Conv	$64 \times 73 \times 73$	$80 \times 71 \times 71$
Conv	$80 \times 71 \times 71$	$192 \times 35 \times 35$
Conv	$192 \times 35 \times 35$	$288 \times 35 \times 35$
$3 \times$ Inception	$288 \times 35 \times 35$	$768 \times 17 \times 17$
$5 \times$ Inception	$768 \times 17 \times 17$	$1280 \times 8 \times 8$
$2 \times$ Inception	$1280 \times 8 \times 8$	$2048 \times 8 \times 8$
Avg_pool	$2048 \times 8 \times 8$	$2048 \times 1 \times 1$
Linear	$2048 \times 1 \times 1$	$1000 \times 1 \times 1$
Softmax	$1000 \times 1 \times 1$	1000×1

3. The sensitivity and specificity of handcrafted and deep feature sets can be defined as follows:

$$\left[\hat{S} \right]_{0.632+} = \frac{1}{B} \sum_{b=1}^B \left[(1 - \alpha(b)) \cdot S(x, x) + \alpha(b) \cdot S(x^{*b}, x^{*b}(0)) \right]$$

where $\alpha(b) = \frac{0.632}{1 - 0.368 \cdot R(b)}$

and

$$R(b) = \begin{cases} \frac{S(x, x) - S(x^{*b}, x^{*b}(0))}{S(x, x)} & \text{if } \frac{S(x, x)}{S(x^{*b}, x^{*b}(0))} > 1 \\ 0 & \text{otherwise,} \end{cases}$$

for

S:Sensitivity, Specificity

4. Table 4 presents the r_s between handcrafted features and glioma recurrence versus necrosis, along with their corresponding p values.

Type	Feature	Modality	r_s	P value
Non-Texture	Volume	T1		
		T2	0.0373	0.7949
		FLAIR		
		T1C		
Size		T1		
		T2	0.0172	0.9045
		FLAIR		
		T1C		
Solidity		T1		
		T2	0.0115	0.9363
		FLAIR		
		T1C		
Eccentricity		T1		
		T2	-0.0172	0.9045
		FLAIR		
		T1C		

Global	Variance	T1	-0.2067	0.1455
		T2	-0.2240	0.1141
		FLAIR	-0.1034	0.4704
		T1C	-0.1608	0.2597
	Skewness	T1	-0.0689	0.6309
		T2	-0.2326	0.1005
		FLAIR	0.3158	0.0240
		T1C	0.2240	0.1141
	Kurtosis	T1	0.1378	0.3348
		T2	0.2613	0.0640
		FLAIR	0.1866	0.1897
		T1C	-0.2383	0.0922
LCM	Energy	T1	-0.2756	0.0503
		T2	-0.3532	0.0110
		FLAIR	-0.2900	0.0390
		T1C	-0.3761	0.0065
	Contrast	T1	0.2986	0.0333
		T2	0.3101	0.0268
		FLAIR	-0.1694	0.2347
		T1C	-0.3187	0.0226
	Entropy	T1	0.2900	0.0390
		T2	0.3388	0.0150

	FLAIR	0.2412	0.0882
	T1C	0.3962	0.0040
Homogeneity	T1	-0.2642	0.0610
	T2	0.2699	0.0554
	FLAIR	-0.1292	0.3662
	T1C	-0.2441	0.0844
Correlation	T1	-0.2756	0.0503
	T2	-0.2240	0.1141
	FLAIR	0.1378	0.3348
	T1C	0.1120	0.4340
Sum Average	T1	-0.2326	0.1005
	T2	0.3532	0.0110
	FLAIR	-0.3331	0.0169
	T1C	-0.4049	0.0032
Variance	T1	0.2153	0.1291
	T2	-0.2929	0.0370
	FLAIR	-0.2986	0.0333
	T1C	0.4020	0.0035
Dissimilarity	T1	0.2843	0.0432
	T2	0.3359	0.0159
	FLAIR	0.1751	0.2189

		T1C	0.2670	0.0582
	Auto Correlaion	T1	-0.3044	0.0299
		T2	0.3417	0.0141
		FLAIR	-0.3647	0.0085
		T1C	-0.4135	0.0026
GLRLM	SRE	T1	-0.2010	0.1573
		T2	-0.2957	0.0351
		FLAIR	-0.1895	0.1829
		T1C	0.1952	0.1697
LRE		T1	-0.2182	0.1240
		T2	0.2957	0.0351
		FLAIR	0.1838	0.1968
		T1C	0.1694	0.2347
GLN		T1	0.1895	0.1829
		T2	0.1924	0.1762
		FLAIR	0.1838	0.1968
		T1C	0.1838	0.1968
RLN		T1	0.2469	0.0807
		T2	0.2211	0.1190
		FLAIR	0.1866	0.1897
		T1C	0.1952	0.1697
RP		T1	0.2297	0.1049

	T2	-0.3015	0.0316
	FLAIR	-0.1924	0.1762
	T1C	0.1780	0.2114
LGRE	T1	-0.3876	0.0049
	T2	-0.4192	0.0022
	FLAIR	-0.3647	0.0085
	T1C	-0.3876	0.0049
HGRE	T1	0.3273	0.0190
	T2	-0.3331	0.0169
	FLAIR	-0.3187	0.0226
	T1C	0.4594	0.0007
SRLGE	T1	-0.3848	0.0053
	T2	-0.4163	0.0024
	FLAIR	-0.3790	0.0061
	T1C	-0.3474	0.0125
SRHGE	T1	0.2814	0.0455
	T2	0.2814	0.0455
	FLAIR	-0.2498	0.0771
	T1C	0.4049	0.0032
LRLGE	T1	-0.3819	0.0057
	T2	-4192	0.0022
	FLAIR	0.3618	0.0091

		T1C	0.3130	0.0253
LRHGE		T1	0.2010	0.1573
		T2	0.3503	0.0117
		FLAIR	-0.2527	0.0736
		T1C	-0.3331	0.0169
GLV		T1	-0.2354	0.0963
		T2	-2756	0.0503
		FLAIR	-0.3187	0.0226
		T1C	-0.3158	0.0240
RLV		T1	-0.3158	0.0240
		T2	-2871	0.0411
		FLAIR	-0.3072	0.0283
		T1C	-0.3245	0.0202
GLSZM	SZE	T1	0.4135	0.0026
		T2	-3176	0.0065
		FLAIR	-0.3790	0.0061
		T1C	-0.3733	0.0070
LZE		T1	0.2096	0.1399
		T2	0.2871	0.0411
		FLAIR	0.2441	0.0844
		T1C	0.1694	0.2347
GLN		T1	0.3216	0.0214

	T2	0.2785	0.0478
	FLAIR	0.1924	0.1762
	T1C	0.2182	0.1240
ZSN	T1	0.3589	0.0097
	T2	0.2527	0.0736
	FLAIR	0.1809	0.2040
	T1C	0.2613	0.0640
ZP	T1	-0.2498	0.0771
	T2	-0.2900	0.0390
	FLAIR	-0.3072	0.0283
	T1C	0.2584	0.0671
LGZE	T1	-0.4020	0.0035
	T2	-0.4192	0.0022
	FLAIR	-0.4422	0.0012
	T1C	-0.3273	0.0190
HGZE	T1	0.3790	0.0061
	T2	-0.4508	0.0009
	FLAIR	-0.4852	0.0003
	T1C	0.4738	0.0004
SZLGE	T1	0.3876	0.0049
	T2	-0.3790	0.0061
	FLAIR	-0.4652	0.0006

	T1C	-0.3962	0.0040
SZHGE	T1	0.4163	0.0024
	T2	-0.3446	0.0133
	FLAIR	-0.4738	0.0004
	T1C	0.3618	0.0091
LZLGE	T1	-0.2584	0.0671
	T2	-0.3618	0.0091
	FLAIR	0.3072	0.0283
	T1C	-0.2843	0.0432
LZHGE	T1	0.2182	0.1240
	T2	0.2756	0.0503
	FLAIR	0.2441	0.0844
	T1C	-0.2240	0.1141
GLV	T1	-0.2527	0.0736
	T2	-0.2326	0.1005
	FLAIR	-0.2670	0.0582
	T1C	-0.2010	0.1573
ZSV	T1	-0.4049	0.0032
	T2	-0.3503	0.0117
	FLAIR	0.2642	0.0610
	T1C	-0.3302	0.0180
NGTDM	Coarseness	T1	-0.2326
			0.1005

	T2	-0.2297	0.1049
	FLAIR	-0.1924	0.1762
	T1C	-0.2039	0.1513
Contrast	T1	0.3675	0.0080
	T2	0.3015	0.0316
	FLAIR	0.2699	0.0554
	T1C	0.4192	0.0022
Busyness	T1	0.2527	0.0736
	T2	0.2153	0.1291
	FLAIR	0.2900	0.0390
	T1C	0.2441	0.0844
Complexity	T1	0.3273	0.0190
	T2	0.3273	0.0190
	FLAIR	0.2469	0.0807
	T1C	0.2555	0.0703
Strength	T1	-0.2642	0.0610
	T2	-0.2153	0.1291
	FLAIR	-0.1809	0.2040
	T1C	-0.2153	0.1291

$$p = \frac{\alpha}{K} = \frac{0.05}{176}$$

5. Probability of developing glioma recurrent (*R*) or necrotic (*N*) as a function of the response of the multivariable model proposed in this

work

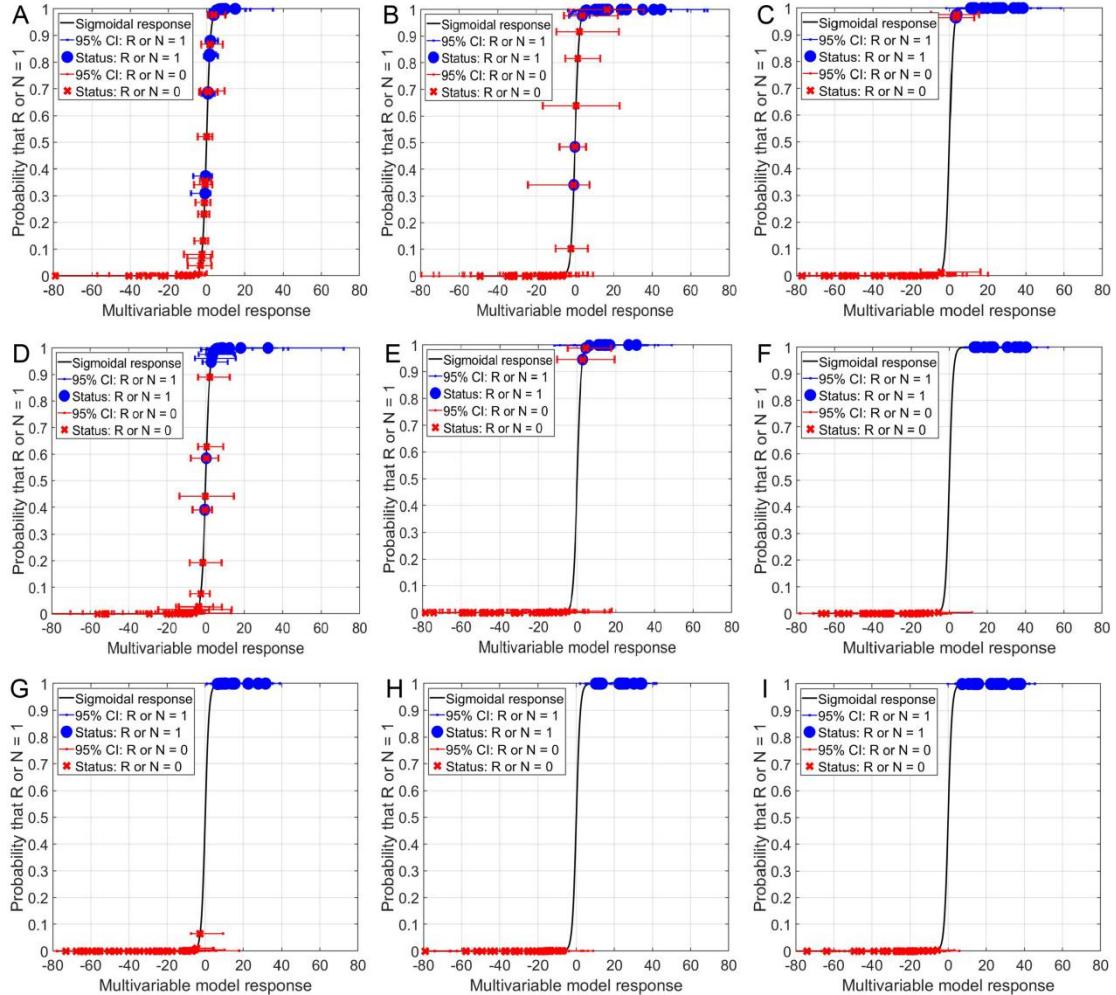


Fig. 1 A–I respectively refer to the responses from T1C, T2, T1, T2-FLAIR, multi-modality, AlexNet, Inception v3, fusion AlexNet, and fusion Inception v3 features. The red crosses represent patients with glioma recurrence, and the blue dots refer to patients with glioma necrosis. The red crosses or blue dots between the two horizontal lines represent patients with uncertainty or misclassification.

6. Imaging features of the best model constructed from individual data sets

Textural features extracted from T1 images

Model:

$(-170.7) \times T1(R=2.00, Scale=5, Quant.algo=Lloyd, Ng=64)--GLSZM-GLV$

$+ 445.5 \times T1(R=1.50, Scale=3, Quant.algo=Lloyd, Ng=8) -- GLSZM-SZLGE$
 $+ 4.558 \times T1(R=1.50, Scale=4, Quant.algo=Lloyd, Ng=8) -- GLSZM-HGZE$
 $+ (-63.22) \times T1(R=1.50, Scale=pixelW, Quant.algo=Lloyd, Ng=64) -- GLCM-Homogeneity$
 $+ (-0.06402) \times T1(R=2.00, Scale=pixelW, Quant.algo=Lloyd, Ng=32) -- GLSZM-GLN$
 $+ 689.1 \times T1(R=0.67, Scale=pixelW, Quant.algo=Lloyd, Ng=64) -- NGTDM-Contrast$
 $+ (-733.6) \times T1(R=2.00, Scale=pixelW, Quant.algo=Equal, Ng=16) -- GLCM-Correlation$
 $+ 574.2$

Textural features extracted from T1C images

Model:

$0.07604 \times T1C(R=1.50, Scale=4, Quant.algo=Equal, Ng=64) -- GLRLM-HGRE$
 $+ (-0.01174) \times T1C(R=2.00, Scale=pixelW, Quant.algo=Lloyd, Ng=64) -- GLRLM-LRHGE$
 $+ (-2.078) \times T1C(R=0.50, Scale=2, Quant.algo=Equal, Ng=16) -- GLCM-AutoCorrelation$
 $+ (-5.527) \times T1C(R=1.00, Scale=1, Quant.algo=Equal, Ng=8) -- Global-Kurtosis$
 $+ 74.54 \times T1C(R=0.67, Scale=3, Quant.algo=Equal, Ng=16) -- GLSZM-LGZE$
 $+ 4721 \times T1C(R=0.67, Scale=1, Quant.algo=Equal, Ng=16) -- GLCM-SumAverage$
 -60.2

Textural features extracted from T2 images

Model:

$(-1519000) \times T2(R=1.50, Scale=pixelW, Quant.algo=Equal, Ng=64) -- GLSZM-ZSV$
 $+ (-1.911) \times T2(R=0.67, Scale=pixelW, Quant.algo=Equal, Ng=8) -- GLSZM-HGZE$
 $+ 7.548 \times T2(R=0.50, Scale=5, Quant.algo=Equal, Ng=8) -- Global-Kurtosis$
 $+ 0.08183 \times T2(R=1.50, Scale=4, Quant.algo=Lloyd, Ng=32) -- GLRLM-LRHGE$

$+ (-3.318) \times T2(R=0.67, Scale=pixelW, Quant.algo=Equal, Ng=8) -- GLRLM-HGRE$
 $+ 161 \times T2(R=2.00, Scale=pixelW, Quant.algo=Equal, Ng=64) -- NGTDM-Contrast$
 $+ 45.25$

Textural features extracted from FLAIR images

Model:

$29.09 \times FLAIR(R=2.00, Scale=4, Quant.algo=Equal, Ng=32) -- GLCM-Entropy$
 $+ (-0.5803) \times FLAIR(R=1.50, Scale=1, Quant.algo=Equal, Ng=16) -- GLSZM-SZHGE$
 $+ (-1125) \times FLAIR(R=0.67, Scale=4, Quant.algo=Equal, Ng=64) -- GLSZM-SZLGE$
 $+ (-638) \times FLAIR(R=0.67, Scale=5, Quant.algo=Equal, Ng=8) -- GLCM-Variance$
 $+ 245.5 \times FLAIR(R=1.50, Scale=4, Quant.algo=Lloyd, Ng=8) -- GLSZM-ZSV$
 $+ 292.7 \times FLAIR(R=2.00, Scale=pixelW, Quant.algo=Lloyd, Ng=64) -- NGTDM-Contrast$
 -221.8

Textural features extracted from multi-modalities images

Model:

$247.4 \times T1C(R=1.50, Scale=pixelW, Quant.algo=Lloyd, Ng=64) -- GLSZM-SZE$
 $+ (-550.8) \times T2(R=1.50, Scale=pixelW, Quant.algo=Lloyd, Ng=8) -- GLRLM-LGRE$
 $+ (-3.995) \times T2(R=0.67, Scale=pixelW, Quant.algo=Equal, Ng=8) -- GLSZM-HGZE$
 $+ 2.66 \times T1(R=0.50, Scale=pixelW, Quant.algo=Lloyd, Ng=8) -- GLSZM-HGZE$
 $+ 253.7 \times T1(R=1.50, Scale=pixelW, Quant.algo=Lloyd, Ng=64) -- NGTDM-Contrast$
 $+ 14.65 \times T2(R=2.00, Scale=pixelW, Quant.algo=Lloyd, Ng=64) -- GLCM-Dissimilarity$
 $+ (-0.1769) \times FLAIR(R=1.00, Scale=pixelW, Quant.algo=Equal, Ng=32) -- GLSZM-SZHGE$
 -77.43

Alexnet features extracted from multi-modalities images

Model:

$4.834 \times T2_F7_3501$

$+ (-5.983) \times T1C_F7_783 + 5.518 \times FLAIR_F7_647 + (-7.081) \times T2_F7_2703 + 4.844 \times T1_F7_1421$

$+ 6.404 \times FLAIR_F7_598$

$+ 2.477 \times T1_F7_1394 + 13.51$

Inceptionv3 features extracted from multi-modalities images

Model:

$(-65.41) \times T1_avg_pool_1268 + (-124.1) \times T2_avg_pool_1732 + (-62.1) \times T1C_avg_pool_172 +$

$(-49.23) \times T1C_avg_pool_1930 + (-38.36) \times T1C_avg_pool_1857 + (-24.96) \times T1C_avg_pool_1153 +$

37.98

Fusion alexnet features extracted from multi-modalities images

Model:

$(-5.119) \times T1C_F7_2133 + (-10.51) \times T2_F7_2703 + 5.291 \times FLAIR_F7_598 + 4.764 \times$

$T1C_F7_2535 + (-1.241) \times FLAIR (R=1.50, Scale=1, Quant.algo=Equal, Ng=16) -- GLSZM-SZHGE$

$+ 1.076 \times T1 (R=1.50, Scale=4, Quant.algo=Lloyd, Ng=8) -- GLSZM-HGZE - 11.31$

Fusion inceptionv3 features extracted from multi-modalities images

Model:

$(-0.4733) \times FLAIR (R=1.00, Scale=pixelW, Quant.algo=Equal, Ng=16) -- GLSZM-HGZE + (-152.7) \times$

$T1C_avg_pool_1930 + 86.65 \times T1C_avg_pool_1759 + 2.819 \times$

$T1 (R=1.50, Scale=4, Quant.algo=Lloyd, Ng=8) -- GLSZM-HGZE$

$+ (-1181) \times FLAIR (R=0.67, Scale=4, Quant.algo=Equal, Ng=64) -- GLSZM-SZLGE + (-52.88) \times$

T2_avg_pool_1732 - 14.91