Supplement 1. Search strategies and keywords used across databases for literature retrieval

Scopus

*((TITLE-ABS-KEY(**glioma***) OR TITLE-ABS-KEY("Glial Cell Tumors*") OR TITLE-ABS-KEY(astrocytoma*) OR TITLE-ABS-KEY(astroglioma*) OR TITLE-ABS-KEY(xanthoastrocytoma*) OR TITLE-ABS-KEY(Oligodendroglioma*) OR TITLE-ABS-KEY(Oligodendroblastoma*) OR TITLE-ABS-KEY(Glioblastoma*)) AND (TITLE-ABS-KEY(**"**survival rate") OR TITLE-ABS-KEY("overall survival")) AND (TITLE-ABS-KEY(radiomic*) OR TITLE-ABS-KEY(radiogenomic*) OR TITLE-ABS-KEY(DLR) OR TITLE-ABS-KEY("deep radiomics") OR TITLE-ABS-KEY("deep learning") OR TITLE-ABS-KEY("Hierarchical Learning") OR TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("Transfer Learning") OR TITLE-ABS-KEY("Artificial Intelligence") OR TITLE-ABS-KEY("AI") OR TITLE-ABS-KEY("Machine Intelligence") OR TITLE-ABS-KEY("Computer Vision System*") OR TITLE-ABS-KEY("image processing") OR TITLE-ABS-KEY("Computer-Assisted Image Analysis") OR TITLE-ABS-KEY("image analysis") OR TITLE-ABS-KEY(Nomograms) OR TITLE-ABS-KEY("prognostic model*") OR TITLE-ABS-KEY("prediction prognosis model*")))*

PubMed

((glioma[mesh] OR astrocytoma[mesh] OR oligoastrocytoma[Title/Abstract] OR Oligodendroglioma[mesh] OR Glioblastoma[mesh]) AND ("survival rate"[mesh] OR "overall survival"[Title/Abstract]) AND (radiomic*[Title/Abstract] OR radiogenomic*[Title/Abstract] OR "deep radiomics"[Title/Abstract] OR DLR[Title/Abstract] OR "deep learning"[mesh] OR "Artificial Intelligence"[mesh] OR "machine learning"[mesh] OR "image processing"[mesh] OR Nomograms [mesh] OR "prognostic model*"[Title/Abstract] OR "prediction prognosis model*"[Title/Abstract]))*

Web of Science

*TS = ((**glioma*** OR "Glial Cell Tumors*" OR astrocytoma* OR astroglioma* OR xanthoastrocytoma* OR Oligodendroglioma* OR Oligodendroblastoma* OR Glioblastoma*) AND ("survival rate" OR "overall survival") AND ("Artificial Intelligence " OR "Machine Intelligence" OR AI OR radiomic* OR radiogenomic*OR DLR OR " deep radiomics " OR "deep learning" OR " Hierarchical Learning " OR "machine learning" OR " Computer Vision System*" OR "image processing" OR " Computer-Assisted Image Analysis" OR "image analysis" OR Nomograms OR "prognostic model*" OR "prediction prognosis model*"))*

Supplement 2. A scoping review on the performance of image-based overall survival prediction in glioma: insights into tumor grading, imaging modalities, and machine learning approaches

No.	Author	Title	Country/ Year	Type of study	Sample size	Image specification		Cancer specification		Machine Learning specification				Results	
						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
1	Dong Nie et al. (1)	3D Deep Learning for Multi-modal Imaging-Guided Survival Time	USA/ 2016	Cross-sectional	69	MRI (T1 MRI and DTI modalities)	Not mentionned	High-grade glioma (III or IV)	Preoperative	Whole image	CNN(T1 MRI) And mCNN(fMRI and DTI) - Hand crafted	Principal Component Analysis (PCA) and Sparse	Binary SVM	CNN features - Hand crafted (gender, age at diagnosis, tumor location, size of tumor, and the WHO grade) - SIFT	Accuracy CNN and mCNN =80.12% HF=62.96%

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						Modality	**Quality**	**WHO classification**	**Treatment stage**	**Segmentation Methods**	**Feature extraction Methods**	**Feature selection/reduction Methods**	**The learning algorithm**	**features**	**Metrics for machine learning (their value)**
		Prediction of Brain Tumor Patients									- SIFT[1]	Representation (SR).			HF+ CNN and mCNN=89.58% HF+SIFT=78.35%
2	Rupal Agravat et al. (2)	3D Semantic Segmentation of Brain Tumor for Overall Survival Prediction	India/ 2020	Cross-sectional	369	MRI (T1, T2 , T1c, and FLAIR modalities)	Not mentioned	All grade	Preoperative	3D fully convolutional neural network (FCNN)	Radiomics	Linear regression	Random Forest Regressor(RFR)	Statistical Features(the amount of edema, amount of necrosis, amount of enhancing tumor, the extent of tumor and proportion of tumor) - Age - Radiomic Features for necrosis: Elongation, flatness, minor axis length, primary axis length, 2D diameter row, 2D diameter column, sphericity, surface area, 2D diameter slice, 3D diameter	Accuracy RFR= 51.7%
3	S. Kannan et al. (3)	Advancing Brain Tumor Analysis through Dynamic Hierarchical Attention for Improved Segmentation and Survival Prognosis	India/ 2023	Cross-sectional study	369	MRI (T1-Contrast Enhanced & T1-weighted MRI & T2-weighted MRI& FLAIR)	Not mentioned	All grade	Preoperative	Dynamic Hierarchical Attention for Improved Segmentation and Survival Prognosis (DHA-ISSP) model(combines a three-band 3D convolutional neural network (CNN) U-Net architecture with dynamic hierarchical attention mechanisms)	Radiomics (with Dynamic Hierarchical Attention for Improved Segmentation and Survival Prognosis (DHA-ISSP))	Cross-validation of decision trees	Random forest model	Radiomics features(14 GLDM,5 NGTDM, 22 GLCM) - Clinical data such as patient age and resection status	accuracy of 0.91, precision of 0.84, recall of 0.92, F1 score of 0.88, specificity of 0.94, sensitivity of 0.92, area under the curve (AUC) value of 0.96

[1] scale-invariant transform

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4	Chenan Xu et al. (4)	An automated approach for predicting glioma grade and survival of LGG patients using CNN and radiomics	China/ 2022	Retros-pective	470	MRI	Not mention-ned	Grade I and II(lower-grade glioma)	Preopera-tive	Automated (CNN)	CNN features and radiomics features	Levene's test and least absolute shrinkage and selection operator (LASSO)	The multivariable Cox regres-sion	Radiomics features CNN features	The deep-radiomics signature remained an independent prognostic factor and the integrated nomogram showed significantly better performance than the clinical nomogram in predicting overall survival of LGG patients (C-index: 0.865 vs. 0.796, P=0.005).
5	Alexander F. I. Osman et al. (5)	Automated brain tumor segmentation on magnetic resonance images and patient's overall survival prediction using support vector machines	Lebanon/ 2020	Retrospective	477	MRI (T1-Contrast Enhanced & T1-weighted MRI & T2-weighted MRI& FLAIR)	Not mention-ned	All grade	Preopera-tive	SVM classifier	Radiomics	non-linear classifier with 'Gaussian' kernel	SVM regres-sion	Clinical (age, and segmented tumor's size and its location features) Morphological image feature	For OS prediction, the mean accuracy is 0.49 for the validation dataset and 0.35 for the testing dataset based on regression principle
6	Eric Carver et al. (6)	Automatic Brain Tumor Segmentation and Overall Survival Prediction Using Machine Learning Algorithms	USA/ 2019	Retrospective	77	MRI (T1, T2, FLAIR)	Not mention-ned	High-grade glioma (III or IV)	Preopera-tive	Three different U-nets	Radiomics	Not mention-ned	ELM(Extreme Learning Machine)	age, volume ratio of WT and brain, and 3-D coordinate of the center point of WT	sensitivity for the whole tumor, enhanced tumor, and tumor core contours were 0.887 [0.126], 0.770 [0.245], and 0.750

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															[0.293], respectively. The average [s.d.] specificity was 0. 993 [0.005], 0.998 [0.003], 0.998 [0.002]
7	Shuo Wang et al. (7)	Automatic Brain Tumour Segmentation and Biophysics-Guided Survival Prediction	UK/2019	Retrospective	130	MRI (T1, T2, FLAIR)	Not mention-ned	All grade	Preopera-tive	3D UNet	Radiomics	Re-cursive feature elimination (RFE) scheme with a random forest regressor	Linear regression model-random forest-epsilon-support vector regres-sion	Radiomics features(glcm ClusterShade, glcm MaximumProbability, glcm SumSquares, glszm MaximumProbability, hape center Z), age, Tumour invasiveness model	The accuracy of: Baseline model(Age)=45 % Radiomics model(Age+radiomics)=48% Tumour invasiveness mode=59%
8	Jie Fu et al. (8)	An Automatic Deep Learning–Based Workflow for Glioblastoma Survival Prediction Using Preoperative Multimodal MR Images: A Feasibility Study	USA/ 2021	Retrospective	163	MRI (T1, T2, FLAIR)	Not mention-ned	Grade IV(glioblastoma)	Preopera-tive	VGG-Seg	Radiomics And CNN VGG19 for deep features	univariate C-index	Kaplan-Meier	Radiomics features(50) DL-based features(80)	he DL-based radiomic signature resulted in a numerically higher C-index than the handcrafted signature Radiomics: CI, 0.71-2.91 DL-based signature: CI, 1.26-6.24
9	Varghese Alex et al. ((9)	Automatic segmentation and overall survival prediction in gliomas using fully convolutional neural network and texture analysis	India/ 2017	Retrospective	285	MRI (T1, T2, FLAIR)	Not mention-ned	All grade	Preoperative/ PostOpera-tive	Fully Convolutional Neural Network	Radionics	Not mention-ned	XGBOOST regressor	Texture (Volume, Range, Total Energy, Mean Absolute Deviation, Entropy, Robust Mean Absolute Deviation, Minimum, Root Mean Squared, 10th percentile, Standard Deviation, 90th percentile, Skewness, Maximum, Kurtosis, Mean, Variance,	Accuracy=0.52

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														Median, Uniformity)- Shape(Volume, Maximum 2D diameter (coronal), Surface area, Maximum 2D diameter (sagital), Surface area to Volume Ratio, Major Axis, Sphericity, Minor Axis, Spherical Disproportion, Least Axis, Compactness 1, Elongation, Maximum 3D diameter, Flatness, Maximum 2D diameter (axial), Compactness 2	
9	Suchismita Das et al. (10)	Brain tumor segmentation and overall survival period prediction in glioblastoma multiforme using radiomic features	India/ 2022	Retrospective	210	MRI (T1, T2, FLAIR)	Not mention-ned	All grade	Preopera-tive	U-Net++ architecture	Radiomics And CNN for deep features	PCA	SVM, RF, LGBM, and XgBoost	Radiomics features(9) DL-based features	the method achieves the ACC score of 0.66 using fused feature+SVM+ GA (3-class group) and 0.70 using fused feature+SVM+ PSO (2-class group
10	Mobarakol Islam et al. (11)	Brain Tumor Segmentation and Survival Prediction using 3D Attention UNet	Singa-pore/ 2020	Retrospective	335	MRI (T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	3D attention UNet	Radiomics	Recursive feature eliminatio	XGBoost regression mode	Radiomics((geometry, location, the shape of the segmented tumor) Clinical(Age)	Accuracy: 48.3%
11	Vikas Kumar Anand et al. (12)	Brain Tumor Segmentation and Survival Prediction using Automatic Hard mining in 3D CNN Architecture	India/ 2021	Retrospective	396	MRI (T1, T2, FLAIR)	Not mention-ned	All grade	Preopera-tive	3-D fully convolutional neural networks (CNN)	Radiomics	Forest of trees	Random Forest Regres-sor (RFR	32 Radiomics(first-order radiomic features and second-order features)	Accuracy= 0.452

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12	Songtao Zhang et al. (13)	Brain Tumor Segmentation and Survival Prediction Using Multimodal MRI Scans With Deep Learning	China/ 2019	Retrospective	285	MRI (T1, T2, FLAIR)	Not mentionned	All grade	Preoperative	Ensemble of Models**(CA-CNN, DFKZ Net, 3D U-Net)**	Radiomics	Decision tree and cross validation	Random forest model	Age, glcm_ClusterShade, glcm_Correlation, gldm_LargeDependenceHighGrayLevelEmphasis, glcm_Informational Measure of Correlation, firstorder_Maximum, firstorder_Skewness, glcm_Autocorrelation, gldm_LargeDependenceLowGrayLevelEmphasis, firstorder_Mwtian, glcm_JointEntropy, glcm_ClusterShade, glszm_LargeAreaHighGrayLevelEmphasis, firstorder_10Percentile	Accuracy= 46.4%
13	Xue Feng et al. (14)	Brain Tumor Segmentation using an Ensemble of 3D U-Nets and Overall Survival Prediction using Radiomic Features	USA/ 2020	Retrospective	163	MRI (T1, T2, FLAIR)	Not mentionned	All grade	Preoperative	U-Net and Dense-Net	Radiomics	Correlation coefficients	Multivariate linear regression model	Gross Total Resection (GTR) or Subtotal Resection (STR), Age Radiomics Feature	Accuracy 0.32
14	Jessica Goya-Outi et al. (15)	CAN STRUCTURAL MRI RADIOMICS PREDICT DIPG HISTONE H3 MUTATION AND PATIENT OVERALL SURVIVAL AT DIAGNOSIS TIME?	France/ 2019	Retrospective	38	MRI (T1, T2, FLAIR)	Not mentionned	All grade	Preoperative	Whole Image	Radiomics	Cox proportional hazards (COXPH) combined with inner-LOOCV Least Absolute Shrinkage and Selection Operator (LASSO)	SVM	Imaging feature set (316 features); Clinical feature set composed of age at diagnosis, sex and the globT volume (approximation of tumor volume);	F1-weighted scores= 0.84

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15	Anahita Fathi Kazerooni et al. (16)	Clinical measures, radiomics, and genomics offer synergistic value in AI-based prediction of overall survival in patients with glioblastoma	USA/ 2018	Retrospective	516	MRI (T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	Deep learning brain tumor segmentation module of CaPTk v.1.8.1	Conventional and deep learning methods	Least absolute shrinkage and selection operator (LASSO)	Cox-PH model	Clinical measures[age, gender, and extent of resection (EOR)], MGMT methylation, radiomic signature, and genomics[ARID2, ATRX, BRAF, CDKN2A, CIC, DNMT3A, EGFR, FGFR2, FUBP1, IDH1, IDH2, KDR, KRAS, MDM4, MET, NF1, NOTCH2, NTRK1, PDGFRA, PIK3CA, PIK3R1, PTEN, PTPN11, RB1, SETD2, SMARCB1, TP53]	**c-index (95% CI):** Clinical=0.65 (0.6, 0.7) Clinical + MGMT methylation =0.67 (0.62, 0.72) Clinical + Radiomics=0.70 (0.65, 0.75) Clinical + MGMT methylation + Radiomics=0.72 (0.68, 0.77) Clinical + MGMT methylation + Genomics=0.70 (0.66, 0.75) Clinical + MGMT methylation + Radiomics + Genomics=0.75 (0.72, 0.79)
16	Saima Rathore et al. (17)	Combining MRI and Histologic Imaging Features for Predicting Overall Survival in Patients with Glioma	Switzer-land / 2021	Retrospective	171	MRI (T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	Semiautomated segmentation	Radiomics	Univa-riate feature selection	Cox proportional hazard regression and support vector machine classification (SVC)	14 MRI(Distance,Edema/BS,Tumor cor/BS, ET+NET, ET/TC,Sphericity(ED), Edge sharpness(ET), NGTDM_ coursness, GLCM_homogeneity, GlCM_contrast, GLCM_Entropy, T2_ET, T2_NET, T1CE_NET) and 12 histopathologic features	**Concordance index** MRIcox= 0.70 HistoPathcox= 0.67 MRI1HistoPath = 0.79
17	Di Zhang et al. (18)	Comparison of MRI radiomics-based machine learning survival models in predicting	China/ 2023	Retrospective	131	MRI (T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblastoma)	Preopera-tive	Manually segmented(by two people)	Radiomics	Least absolute shrinkage and selection operator (LASSO) regres-sion	Traditional Cox proportional-hazards (CoxPH), Survival Tree, Random	Morphologic_Eccentricity_Variance, Histogram_bin-2_frequency_Variance, GLSZM_ZoneSizeNoneUniformityNormalized_Min,	**Concordance index:** DeepSurv(0.882 training set/ 0.732 test set), CoxPH (0.663 training set / 0.635 test set), SurvivalTree

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		prognosis of glioblastoma multiforme											survival forest (RSF), DeepSurv, DeepHit	GLRLM_ShortRunLowGrayLeveEmphasis_Office_1_Min, GLRLM_ShortRunLowGrayLeveEmphasis_Office_24_Min, GLCM_Contrast_Variance, Intensity_MeanAbsoluteDeviation_Skewness	(0.702/0.655), RSF (0.735/0.667), DeepHit (0.608/0.560).
18	Ting Sun et al. (19)	Deep learning based on preoperative magnetic resonance (MR) images improves the predictive power of survival models in primary spinal cord astrocytomas	China/ 2023	Retrospective	138	MRI (T1, T2, FLAIR)	Not mentio-ned	All grade(astrocytomas)	Preopera-tive	The CNN with three changes. First, the initial number of feature maps was set to 16. Second, all the convolution kernel shapes were modified from the original 3×3 to 7×3. Third, each concatenation layer in the network structure was followed by a dropout layer with a probability of 0.5	Automatic	Automatic	CNN(like segmentation)	Not mentioned	The 1-year model, 3-year model, and 5-year model had an outstanding performance, with accuracies of 86.0%, 84.0%, and 88.0% and AUCs of 0.881 (95% CI 0.839–0.918), 0.862 (95% CI 0.827–0.901), and 0.905 (95% CI 0.867–0.942), respectively
19	Zhenyu Tang et al. (20)	Deep Learning of Imaging Phenotype and Genotype for Predicting Overall Survival Time of Glioblastoma Patients	USA/ 2020	Retrospective	120	MRI (s T1c MRI and DWI)	3T	Grade IV(glioblastoma)	Preopera-tive	Whole image	Automatic	Automatic	Multi-task CNN	Not mentioned	MSE / CC= 177.0±130.0/0.4695

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						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
20	Ujjwal Baid et al. (21)	Deep learning radiomics algorithm for gliomas (DRAG) model: A novel approach using 3D UNET based deep convolutional neural network for predicting survival in gliomas	India/ 2019	Retrospective	285	MRI (s T1c MRI and DWI)	Not mentioned	All grade(astrocytomas)	Preoperative	Deep Learning Radiomics Algorithm for Gliomas (DRAG) Model based on 3D U-Net network	Radiomics	Spearman's correlation coefficient 0.95	Multi-layer perceptron	Age and 117 radiomics features	Accuracy ,MSE= 0.558 338219.366
21	Jiangwei Lao et al. (22)	A Deep Learning-Based Radiomics Model for Prediction of Survival in Glioblastoma Multiforme	China/ 2017	Retrospective	112	MRI (s T1c MRI and DWI)	Not mentioned	Grade IV(glioblastoma)	Preoperative	Manually by two neurosurgeons	Radimics And CNN_S with five convolution layers and three fully-connected layers	Least absolute shrinkage and selection operator (LASSO) Cox regression model and correlated coefficient	The multivariate Cox analysis	A six-deep-feature signature-age and Karnofsky Performance Score -150 radiomics features	The combined model achieved improved predictive performance (C-index = 0.739)
22	Moona Mazher et al. (23)	Deep learning-based survival prediction of brain tumorpatients using attention-guided 3D convolutional neural-network with	Spain/ 2024	Retrospective	369	MRI (s T1c MRI and DWI)	Not mentioned	All grade(all brain tumor)	Preoperative	Hierarchical channelattention (HAM) module and a multi-scale-aware feature enhancement (MSAFE)	Radiomics-a 3D regressor model based on the 3D convolutional, 3D Batch-Norm, and 3D ReLU layers	Variance-based feature selections	Regression models random forest (RF), 31 regression trees (RT), linear regression (LR), and	Clinical + Radiomics + 3D Latent CNN + 3DDeep Regressor	Combinedfeatures(c-index)= RF= 0.63 XGBR=0.62 DTR=0.61 GBR=0.6 ETR=0.62 BR=0.59

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		radiomics approach from multimoda-lity magnetic resonance imaging											extreme gradient boosting (XGB)		
23	W. Han et al. (24)	Deep Transfer Learning and Radiomics Feature Prediction of Survival of Patients with High-Grade Gliomas	USA/ 2020	Cohorts (retros-pective)	178	MRI	Not mentio-ned	Grade IV (glioblasto-ma)	Preopera-tive	Manually traced by a radiologist	Rediomics and VGG-19 CNN	Median absolute deviation, concorda nce indices (C-indices), and the Pearson coeffi-cient correla-tion	Elastic Net-Cox modeling	Radiomics And deep features	log-rank test P value = .035 (hazard ratio = 1.71; 95% CI, 1.0–2.3)
24	Royyuru Srikanth et al. (25)	Detection and Classification of Brain Tumours from MRI Images with Prediction of the Overall Survival Rate in Glioblastoma Using Machine Learning Techniques	India/ 2024	Retrosp ective	163	MRI (s T1c MRI and DWI)	Not mentio-ned	High-grade glioma (III or IV)	Preopera-tive	U-Net++ CNN	Radiomics And 3D CNN	Principal compo-nent analysis (PCA)	d Random Forest, Support Vector Machines , XgBoost, and the Logistic Regressio n with Boosting Method (LGBM)	Radiomics And deep features	He approach achieves an area under the curve (AUC) score of 0.66 when employing fused features + SVM + GA (3-class group) and 0.70 when employing fused features + SVM + PSO, both of which are better than state-of-the-art methods (2-class group)
25	Xin Chen et al. (26)	Development and Validation of a MRI-Based Radiomics Prognostic	China/ 2019	Retrosp ective	127	MRI(post -T1WI)	Not mentio-ned	High-grade glioma (III or IV)	Preopera-tive	Manually	Radiomics	Mini-mum redun-dancy maxi-mum	Cox propor-tional hazard regres-	Clinical features (gender, age, Karnofsky perfor-mance status, radiation therapy, chemotherapy, and type of resection) VASARI features	AUC of radiomics classifier (training, 0.799; validation,

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		Classifier in Patients with Primary Glioblastoma Multiforme										relevance algorithm	sion model	Radiomics features	0.815 for 12-month) - AUC of clinical risk model(training, 0.749; validation, 0.670 for 12-month) - The predictive accuracy of combined the radiomics classifier with clinical data (training, 0.819; validation: 0.851 for 12-month)
26	Yutao Wang et al. (27)	Development of a nomograph integrating radiomics and deep features based on MRI to predict the prognosis of high grade Gliomas	China/ 2021	Retros-pective	210	MRI (T1, T2, FLAIR)	Not mentio-ned	High-grade glioma (IV)	Preopera-tive	Manually by two radiologist	Radiomics - CNN via transfer learning (3D-ResNet50)	LASSO cox regres-sion model	Kaplan-Meier survival analysis - COX regres-sion	Clinical features - Radiomics features - Deep features	C-index Radiomics signature: 0.688 Deep signature: 0.722 Combined signature: 0.736 Nomogram: 0.741
27	Maria-Fatima Chilaca-Rosas (28)	Diagnostic Performance of Selected MRI-Derived Radiomics Able to Discriminate Progression-Free and Overall Survival in Patients with Midline	Mexico/ 2023	Retrosp ective	91	MRI (T1, T2, FLAIR)	1.5T	All grade	Preopera-tive	Manually by two radiologist	Radiomics	Not mentio-ned	He Mann-Whitney U test, ROC analysis, and calcula-tion of cut-off values	Radiomics(CONVENTIONAL_, peakSphere1mLdiscretizedvolumesought, CONVENTIONAL_RIM_stdev, DISCRETIZED_Q1, DISCRETIZED_, peakSphere1mLdiscretizedvolumesought	Three out of four significant radiomics demonstrated good (80–90%) sensitivity (CONVENTIONAL_peak-Sphere 1mLdiscretized volumesought, CONVENTIONAL_RIM_stdev

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		Glioma and the H3F3AK27M Mutation													and DISCRETIZED _peakSphere 1mLdiscretized volumesought); only the radiomic DISCRETIZED _Q1 showed fair (70–80%) specificity on the performance test
28	Chae Jung Park et at. (29)	Diffusion- and Perfusion-Weighted MRI Radiomics for Survival Prediction in Patients with Lower-Grade Gliomas	Korea/ 2024	Retrosp ective	129	MRI (T1, T2, FLAIR)	Not mentio-ned	: Lower-grade glioma (grades 2 and 3)	Preopera-tive	Not mention	Radionics	Not mention	Multiva-riate Cox regres-sion	Clinical features (age, sex, KPS, postoperative treatment (i.e., chemotherapy or radiation therapy), extent of resection, IDH mutation status, and WHO grade) - Radiomics features	Clinical+ radiomics: 0.83 (0.75–0.92) Clinical: 0.73 (0.65–0.85)
29	Zi Yang et al. (30)	Ensemble learning for glioma patients overall survival prediction using pre-operative MRIs	USA/ 2022	Retrosp ective	235	MRI (T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Post-operative	Manually by one radiologist	ResNet50-based feature extractor	Not mention	Siamese Network - K-NN - Model-Ensemble	Deep feature	The performance is assessed by the accuracy (ACC) and the area under the curve (AUC) of 3-class classification. And the final result achieved an ACC of 65.22% and AUC of 0.81
30	Abdela Ahmed MOSSA et al. (31)	Ensemble learning of multiview CNN models for survival time prediction of brain	Turkey/ 2021	Retrosp ective	163	MRI (T1, T2, FLAIR)	Not mentio-ned	High-grade glioma (IV)	Preopera-tive	Whole image	Single column Mv-CNN	Not mention	Multi column Mv-CNN	Deep feature	Best model achieved an AUC and accuracy values of 0.93 and 92.9%, respectively

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		tumor patients using multimodal MRI scans													
31	Kaoutar Ben Ahmed et al. (32)	Ensembles of Convolutional Neural Networks for Survival Time Estimation of High-Grade Glioma Patients from Multimodal MRI	USA/ 2022	Retrospective	207	MRI (T1, T2, FLAIR)	1.5 T and 3 T	Grade IV (glioblastoma)	Preoperative	Multiview CNN models	3D convolutional neural network	Automatic	Multi-branch 3D convolutional neural network	Deep feature	Accuracy=74%
32	Zeina A. Shboul et al. (33)	Feature-Guided Deep Radiomics for Glioblastoma Patient Survival Prediction	USA/ 2019	Retrospective	163	MRI (T1, T2, FLAIR)	Not mentioned	Grade IV (glioblastoma)	Preoperative	Combines U-Net and FCN based segmentation	Quantitative analysis	Recursive feature selection (RFS)	XGBoost based survival prediction algorithm	Texture, volumetric and area-related features, histogram-graph features, and Euler characteristics	The best accuracy of 0.73 for training datasets and 0.68 for validation datasets
33	Qihua Li et al. (34)	A Fully-Automatic Multiparametric Radiomics Model: Towards Reproducible and Prognostic Imaging Signature for Prediction of Overall Survival in Glioblastoma Multiforme	China/ 2017	Retrospective	92	MRI (T1, T2, FLAIR)	3.0-T	Grade IV (glioblastoma)	Preoperative	Deep learning based automated segmentation	Radionics	Selection operator (LASSO) Cox regression	Univariate C-index	First-order Texture Features, NGTDM Features, GLSZM Features, GLRLM Features, GLCM Features	The multiparametric signature achieved better performance for OS prediction (C-Index = 0.705, 95% CI: 0.672, 0.738)
34	Zhi-Cheng Li et al. (35)	Glioma survival prediction from whole-brain MRI without	China/ 2022	Retrospective	156	MRI (T1, T2, FLAIR)	Not mentioned	All grade(all brain tumor)	Preoperative	m whole-brain MRI	Automatic	Automatic	A deep CNN, named DeepRisk	Deep feature	The IBS and C-index for DeepRisk were 0.14 and 0.83 in external test dataset 1,

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						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
		tumor segmentation using deep attention network: a multicenter study													0.15 and 0.80 in external dataset 2, and 0.16 and 0.77 in TCIA dataset, respectively
35	Luke Macyszyn et al. (36)	Imaging patterns predict patient survival and molecular subtype in glioblastoma via machine learning techniques	USA/ 2016	Retros-pective	105	MRI (T1, T1-Gd, T2, T2-FLAIR, DTI)	3 Tesla	Grade IV (glioblas-toma)	Preopera-tive	The computer-based glioma image segmentation and registration (GLISTR) segmentation algorithm	Quantitative Analysis	Feature selection sequentially selected features that best predicted survival until there was no improvement	Support Vector Machines (SVM)	intensity distributions of various MRI sequences, size and location of the tumor and regions of edema, and parameters extracted from a patient-specific biophysical tumor growth model	The overall, 3-way (long/medium/ short survival) accuracy in the prospective cohort approached 80%
36	Yan Tan et al. (37)	Improving survival prediction of high-grade glioma via machine learning techniques based on MRI radiomic, genetic and clinical risk factors	China/ 2019	Retros-pective	147	MRI(the CE-T1WI and T2FLAIR)	3.0-T	High-grade glioma (III or IV)	Preopera-tive	Manually by one neuroradiologist	Radiomics	He least absolute shrinkage and selection operator (LASSO) Cox regres-sion model	Kaplan Meier survival analysis	11 Radiomics Features(CE-T1WI_Tumor_Mean, CE-T1WI_Tumor_Compactness, CE-T1WI_Tumor_ Angular second moment, CE-T1WI_Tumor_First measure of information correlation, CE-T1WI_Tumor_ Low grey level zone emphasis, CE-T1WI_Tumor_Wavelet P1L2C2, CE-T1WI_Edema_ Number of connected 3D components, CE-T1WI_Edema_ Small zone low grey level emphasis, CE-T1WI_Edema_Mean	The C-Index for OS prediction was 0.707 and 0.711 in training and test cohorts, respectively

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														intensity, T2FLAIR_Edema_Wavelet P1L2C1, T2FLAIR_Edema_ Maximum intensity)	
37	Lina Chato et al. (38)	Machine Learning and Deep Learning Techniques to Predict Overall Survival of Brain Tumor Patients using MRI Images	USA/ 2017	Retros-pective	163	MRI (the CE-T1WI, T2 and FLAIR)	Not mentio-ned	All grade (all brain tumor)	Preopera-tive	Not mentioned	Radiomics and Deep pre-trained AlexNet	PCA	Logistic regres-sion	Volumetric and location features, Statistical and intensity texture features, Histogram, Deep feature	Classification accuracy using volumetric and location features: 68.8%
38	Lina Chato et al. (39)	Machine Learning and Radiomic Features to Predict Overall Survival Time for Glioblastoma Patients	USA/ 2021	Retrospective	212	MRI (the CE-T1WI, T2 and FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Manually by one radiologist	Radiomics	Not mentio-ned	Neural network	Twelve volumetric features	Accuracy of NN (hidden nodes = 40): 53.2%
39	Yoon Seong Choi et al. (40)	Machine learning and radiomic phenotyping of lower grade gliomas: improving survival prediction	South Korea/ 2020	Retrospective	296	MRI (the CE-T1WI and T2FLAIR)	Not mentio-ned	Grade I and II (lower-grade glioma)	Preopera-tive	Manually by a neuroradiologist and confirmed by an independent reviewer	Radiomics	Univa-riate log-rank test and minimal depth	Random survival forest (RSF)	GLCM, GLRLM, GLSZM, Shape, first Order - Non-imaging prognostic factors (age + resection extent + WHO grade + IDH status)	iAUC (95% CI) 1. Radiomic features= 0.620 (0.501–0.756) 2. Non-imaging prognostic factors + radiomic features= 0.709 (0.623–0.843)
40	Yiping Lu et al. (41)	Machine learning-based radiomic, clinical and semantic feature analysis for predicting overall	China/ 2020	Retrospective	181	MRI(the CE-T1WI	3.0T	Grade IV (glioblas-toma)	Preopera-tive	Manually segmented (by two neuroradio-logists)	Radiomics	Not mentio-ned	Random survival forest (RSF)	Clinical, VASARI and CE radiomic features(GLCM, GLRLM, GLSZM, NGTDM)	average iAUC of 96.2 ± 1.7 and C-index of 90.0 ± 0.3

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						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/r eduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
		survival and MGMT promoter methylation status in patients with glioblastoma													
	Jingtao Wang et al (42)	An MRI-based radiomics signature as a pretreatment noninvasive predictor of overall survival and chemotherapeutic benefits in lower-grade gliomas	China/ 2022	Retros-pective	215	MRI (T1, FLAIR)	3.0-T	Lower-grade gliomas	Preopera-tive	Semi-automatically segmented slice by slice using 3D Slicer (by two radiologists)	Radiomics	The LASSO Cox regressio n algorithm	Kaplan-Meier	Not mentioned	C-index: 0.763 CI: 0.639-0.887
	Han Gyul Yoon et al. (43)	Multi-Parametric Deep Learning Model for Prediction of Overall Survival after Postoperative Concurrent Chemoradiot herapy in Glioblastoma Patients	Korea/ 2020	Retro-spectiv e	118	MRI (T1, T2, FLAIR)	3.0-T	Grade IV (glioblas-toma)	Preopera-tive	Whole image	Radiomics	None	CNN	242 readiomics - Clinical(14 clinical features of the included patients, and these features were classified into three categories: (1) “personal” factors (n = 3) – age, sex, and ECOG performance status; (2) “genetic” factors (n = 2) – IDH mutation status and MGMT hypermethylation status; (3) “treatment” factors (n = 9) – resection status)	The model that incorporated clinical and radiomic features showed a higher C-index (0.768 (95% confidence interval (CI): 0.759, 0.776)) and iAUC (0.790 (95% CI: 0.783, 0.797)) than the model using clinical features alone (C-index = 0.693 (95% CI: 0.685, 0.701); iAUC = 0.723 (95% CI: 0.716, 0.731)) and the model using radiomic

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															features alone (C-index = 0.590 (95% CI: 0.579, 0.600); iAUC = 0.614 (95% CI: 0.607, 0.621))
	Xin Jia et al. (44)	A Multiparametric MRI-Based Radiomics Nomogram for Preoperative Prediction of Survival Stratification in Glioblastoma Patients With Standard Treatment	China/ 2022	Cohort	125	MRI (T1, T2, T1C)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Manual using 3D Slicer software separately by two neurosurgeons	Radiomics	T-test and the least absolute shrinkage and selection operator algorithm (LASSO)	Support vector machine (SVM)	LargeAreaLowGrayLevelEmphasis-RootMeanSquared-10Percentile-Maximum-Correlation-Median-Correlation-lmc2-LongRunHighGrayLevelEmphasis-LargeDependenceHighGrayLevelEmphasis-RootMeanSquared-Autocorrelation-SizeZoneNonUniformityNormalized-SmallAreaLowGrayLevelEmphasis-Idmn-90Percentile-ClusterTendency-SmallAreaEmphasis-DifferenceVariance-DependenceVariance	AUCs of 0.877 and 0.919
	Bin Wang et al. (45)	Multiple Survival Outcome Prediction of Glioblastoma Patients Based on Multiparametric MRI	China/ 2021	Retros-pective	134	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Not mentioned	Radiomics	Analysis of variance (ANOVA) and least absolute shrinkage and selection operator (LASSO)	Cox propor-tional hazards model	Wavelet-LLL_glcm_Idmn wavelet-LHH_gldm_SmallDependenceLowGrayLevelEmphasis wavelet-LLL_ngtdm_Contrast original_glcm_Imc1 original_glcm_Imc1 wavelet-HHH_glcm_SumEntropy	The best model achieved C indexes of 0.725, 0.677, and 0.724

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						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
														log-sigma-1-0-mm-3D_firstorder_Skewness original_firstorder_Skewness wavelet-LLH_firstorder_Mean original_firstorder_Kurtosis log-sigma-5-0-mm-3D_firstorder_Kurtosis wavelet-LLH_firstorder_Median wavelet-HHH_gldm_SmallDependenceLowGrayLevelEmphasis wavelet-LHL_glcm_ClusterShade wavelet-LLH_firstorder_Skewness wavelet-LLH_firstorder_Skewness wavelet-HHH_firstorder_Skewness log-sigma-5-0-mm-3D_firstorder_RootMeanSquared wavelet-HHL_glszm_GrayLevelVariance wavelet-HLH_glszm_GrayLevelVariance log-sigma-5-0-mm-3D_firstorder_Mean log-sigma-5-0-mm-3D_glcm_ClusterProminence log-sigma-1-0-mm-3D_glszm_LargeAreaHighGrayLevelEmphasis	

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						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
														wavelet-HHH_glszm_LargeAreaHighGrayLevelEmphasis	
	Jingyu Zhu et al. (46)	Non-invasive prediction of overall survival time for glioblastoma multiforme patients based on multimodal MRI radiomics	China/ 2023	Retros-pective	1305	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	3D UNet	Radionics	Principal Compo-nent Analysis (PCA)	SVR model	Shape (13) First order (18) GLCM (22) GLRLM (16) GLSZM (16) GLDM (14) Interpolated statistic (9)	MSE:121095.8 MAE :173 237.6304 RMSE : 337.3586
	He Huang et al. (47)	Overall Survival Prediction for Gliomas Using a Novel Compound Approach	China/ 2021	Retros-pective	460	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	ReLU	CNN network and Radionics	Random forest model	Random forest model	Shape First order GLCM GLRLM GLSZM GLDM Interpolated statistic	Survival predictive task is as low as 311.5.
	Parita Sanghani et al. (48)	Overall survival prediction in glioblastoma multiforme patients from volumetric, shape and texture features using machine learning	Singa-pore/ 2018	Retros-pective	163	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Whole image	Radionics	SVM-RFE	Linear SVM classifier	Texture features, tumor shape and volumetric features	The 2-class and 3-class OS group prediction accuracy obtained were 98.7% and 88.95% respectively
	Spyridon Bakas et al (49).	Overall survival prediction in glioblastoma patients using structural magnetic resonance imaging (MRI):	USA/ 2020	Retros-pective cohort	101	MRI (T1C, T1, T2, FLAIR, DSC)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	GLISTRboost	Radionics	Support vector machine (SVM)	Multivariate SVM classi-fiers	Radionics features	classification accuracy of 74.26%

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						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
		advanced radiomic features may compensate for lack of advanced MRI modalities													
	Ujjwal Baid et al. (50)	Overall Survival Prediction in Glioblastoma With Radiomic Features Using Machine Learning	India/ 2020	Retros-pective	163	MRI (T1, FLAIR)	Not mentioned	Grade IV (glioblas-toma)	Preopera-tive	3D UNet	Radionics	Pearson's correla-tion coeffi-cient	MLP	First-order Texture Features, NGTDM Features, GLSZM Features, GLRLM Features, GLCM Features	The proposed approach achieved 0.695, 0.571, and 0.558 on BraTS training, validation, and test datasets
	Asma Shaheen et al (51)	Overall Survival Prediction of Glioma Patients With Multiregional Radiomics	USA/ 2022	Retros-pective	369	MRI (T1C, T1, T2, FLAIR)	Not mentioned	All grade	Preopera-tive	Manual	Radionics	No feature selection was perfor-med	CNN	All the radiomics features	the best predictive performance (mean AUC = 0.73)
	Zhenyu Tang et al (52)	Overall survival time prediction for high-grade glioma patients based on large-scale brain functional networks	China/ 2022	Retros-pective	148	MRI (T1-weighted MRI & DTI)	Not mentioned	High-grade glioma (III or IV)	Preopera-tive	Whole image	Radionics	LASSO	Support vector machine (SVM)	16 high-order connectomics features	OS prediction accuracy (86.8%)
	Zhenyu Tang et al (53)	Pre-operative overall survival time prediction for glioblastoma patients using deep learning on both imaging phenotype and genotype	China/ 2019	Retros-pective	120	MRI (T1c, B0, FA and MD)	3T	Grade IV (glioblas-toma)	Preopera-tive	Whole image	CNN	No feature selection was perfor-med	CNN	Not mentioned	OS (RMSE) : 261.0 ± 175.0

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						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
	Golestan Karami et al. (54)	Predicting overall survival time in glioblastoma patients using gradient boosting machines algorithm and recursive feature elimination technique	Italy/ 2021	Cohort	29	MRI (T1, FLAIR)	3T	Grade IV (glioblas-toma)	Preopera-tive	K-mean clustering	Radionics	RF-RFE	Gradient Boosting Machine	Not mentioned	RF-RFE GBoost classifier accuracy: 0.75
	Di Lu et al. (55)	The prognosis prediction of GBM based on high-risk subregion and multi-parametric MR imaging	China/ 2019	Retrospective	104	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	K-means clustering	Radionics	Not mentio-ned	Multiple Instance Learning (MIL)	152 quantitative subregion imaging features	the accuracy, sensitivity, and specificity of 81.82%, 76.92%, and 85.00%, respectively
	Navodini Wijethilake et al. (56)	Radiogeno-mics model for overall survival prediction of glioblastoma	Singa-pore/ 2020	Retros-pective	59	MRI (T1,FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Multi-layer perceptron	Radiomics	RFE	Linear regression (LR), ANN, SVM, random forest (RF), and gradient boosting (GB).	Fractal dimensions of enhancement region • Centroid coordiantes of enhancement region • Second axis length of necrosis	**Acc=** LR (91.67%)- ANN (80%)- SVM (73.33%)- RF (41.67%)- GB (33.33%)
	Sohi Bae et al. (57)	Radiomic MRI Phenotyping of Glioblastoma : Improving Survival Preciction	Korea/ 2018	Retrospective	217	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	ROIs were drawn by a neuroradiologist and were confirmed by another neuroradiologist	Radiomics	The optimal cutoff yielding the most signifi-cant survival differ-rence	RSF model	Among these, 35 features, consisting of 10 ADC histogram parameters from CET, NET, and CET+NET, 20 tumor size parameters from CET, NET, CET+NET, and necrosis, and five tumor volume parameters from CET, NET, CET+NET,	**iAUC=** 0.590 [95% CI: 0.502, 0.689]

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														necrosis, and necrosis+CET+NET	
	Shouchao Wang et al. (58)	Radiomics Analysis Based on Magnetic Resonance Imaging for Preoperative Overall Survival Prediction in Isocitrate Dehydrogenase Wild-Type Glioblastoma	China/ 2022	Retros-pective	142	MRI (T1C, T1, T2, FLAIR)	3.0-T	Grade IV (glioblas-toma)	Preopera-tive	Manually segment the regions of interest (ROIs)	Radiomics	LASSO Cox mode	Kaplan-Meier analysis	45 radiomics features	**C-index = 0.74–0.86**
	Xi Zhang et al. (59)	A radiomics nomogram based on multiparametric MRI might stratify glioblastoma patients according to survival	China/ 2019	Retros-pective	105	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Manual	Radiomics	LASSO regres-sion algorithm	Multiva-riate logistic regres-sion model	25 Radiomic features	C-index= 0.974
	Parita Sanghani et al. (60)	Regression based overall survival prediction of glioblastoma multiforme patients using a single discovery cohort of multi-institutional multi-channel MR images	Singa-pore/ 2019	Retros-pective	163	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Manual	Radiomics	Leave one out cross-valida-tion (LOOCV)	Support vector machine regres-sion	150 Radiomic features	The 3-class prediction accuracy was 80%
	Ruqsar Zaitoon et al. (61)	RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor	India/ 2023	Retros-pective	100	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	RRU-Net2+ model	Radiomics	Not mentio-ned	Multiva-riate time-estimated hazard ratio Cox	18 features	RU-Net2+ algorithm accurately predicts patient survival rates: 85.71% long-

No.	Author	Title	Country/ Year	Type of study	Sample size	Image specification		Cancer specification		Machine Learning specification				Results	
						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
		Segmentation and Survival Rate Prediction											technique with logistic regres-sion CoX-LR		term, 72.72% medium-term, and 61.54% short-term
	Ying Zhuge et al. (62)	Survival Prediction in Glioblastoma Using Combination of Deep Learning and Hand-Crafted Radiomic Features in MRI Images	Turkey/ 2023	Retrospective	369	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	nnU-Net	Hand-crafted feature extraction and DenseNet	LASSO	DeepSurv	120 features	CI of training, validation, and testing sets (0.984, 0.821, and 0.821 18 respectively)
	Xue Fu et al. (63)	Survival prediction of patients suffering from glioblastoma based on two-branch DenseNet using multi-channel features	China/ 2021	Retros-pective	356	MRI (T1, T2)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Manual	Two-branch DenseNet s	-	Kaplan-Meier survival	Not mentioned	Accuracy= 94%
	Ghasem Hajianfar et al. (64)	Time-to-event overall survival prediction in glioblastoma multiforme patients using magnetic resonance imaging radiomics	Switzer-land/ 2023	Retros-pective	119	MRI (T1, T2)	Not mentio-ned	Grade IV(glioblas-toma)	Preopera-tive	Manual	Radiomics	Univariate C-Index (UCI)	Random Survival Forest (RSF)	Radiomics features	The LOG filter with Sigma = 1 mm preprocessing method, MI, GLMB and GLMN achieved significantly higher C-indices than other preprocessing, FS, and ML methods (all p values < 0.05, mean C-indices

No.	Author	Title	Country/ Year	Type of study	Sample size	Image specification		Cancer specification		Machine Learning specification				Results	
						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
															of 0.65, 0.70, and 0.64, respectively)
	Viet Huan Le et al. (65)	A transfer learning approach on MRI-based radiomics signature for overall survival prediction of low-grade and high-grade gliomas	Taiwan/ 2023	Retros-pective	105	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	Manual	Radiomics	LASSO	Multiva-riate logistic regres-sion	17 features	C-index: 0.974
	Jianming Ye et al. (66)	Tumor Grade and Overall Survival Prediction of Gliomas Using Radiomics	China/ 2021	Retros-pective	285	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	Manually by one to four raters,following the same annotation protocol, and experiencedneuroradiologists approved their annotations	Radiomics	PCA, KPCA, ICA, and FA	Random forest (RF)	30 features	AUC=95%
	Li Sun et al. (67)	Tumor segmentation and survival prediction in glioma with deep learning	China/ 2019	Retros-pective	285	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	3D U-Net	Radiomics	Feature imprt-ance	Random forest regressor	14 features	61.0% accuracy
	Shingo Kihira et al. (68)	U-Net Based Segmentation and Characterization of Gliomas	USA/ 2022	Retros-pective	285	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	All grade	Preopera-tive	U-Net	MLP	MLP	MLP	Not mentioned	AUC=75%
	Lina Chato et al. (69)	Wavelet transform to improve accuracy of a prediction model for overall survival time of brain	USA/ 2018	Retros-pective	163	Denoising wavelet transform (DWT)	Not mentio-ned	All grade	Preopera-tive	Whole tumor	Radiomics (histogram features)	All features +age	Support vector machine (SVM)	Histogram features	AUC= 66.7%

No.	Author	Title	Country/ Year	Type of study	Sample size	Image specification		Cancer specification		Machine Learning specification				Results	
						Modality	Quality	WHO classification	Treatment stage	Segmentation Methods	Feature extraction Methods	Feature selection/reduction Methods	The learning algorithm	features	Metrics for machine learning (their value)
		tumor patients based on MRI Images													
	Katharina Ott et al. (70)	Predicting Overall Survival of Glioblastoma Patients Using Deep Learning Classification Based on MRIs	Germany /2024	Retros-pective	1128	MRI (T1C, T1, T2, FLAIR)	Not mentio-ned	Grade IV (glioblas-toma)	Preopera-tive	Whole tumor	CNN(s based on a 3D version of the ResNet50 architecture)	CNN(s based on a 3D version of the ResNet50 architec-ture)	CNN(s based on a 3D version of the ResNet50 architec-ture)	Deep features	F1-score of 0.51 and an accuracy of 0.67

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