



# TOWARDS ADVANCED ULTRASOUND IMAGE ANALYSIS BY COMBINING RADIOMICS AND ARTIFICIAL INTELLIGENCE IN BRAIN TUMORS

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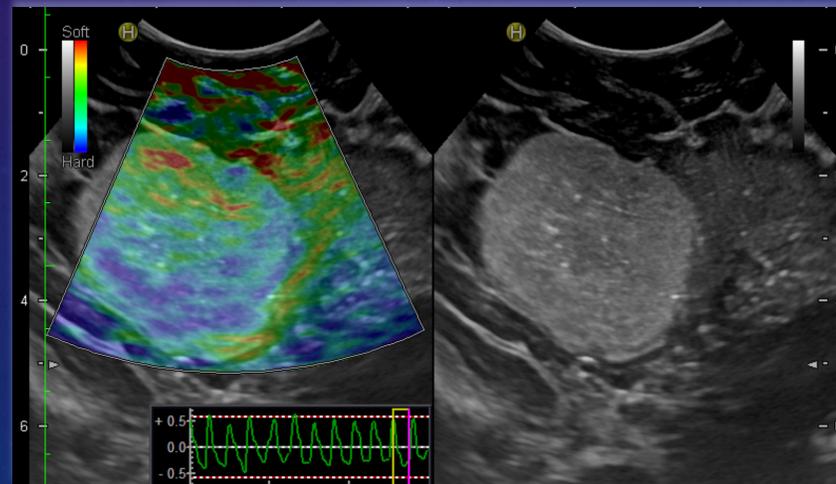
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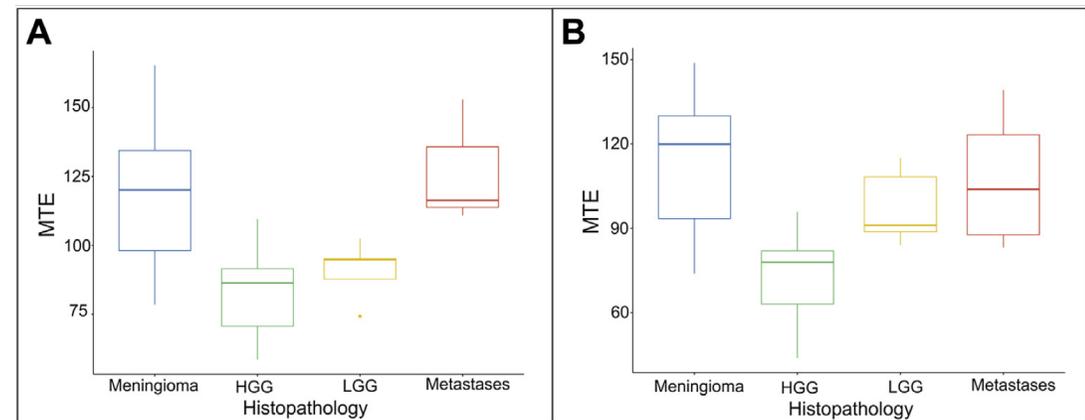
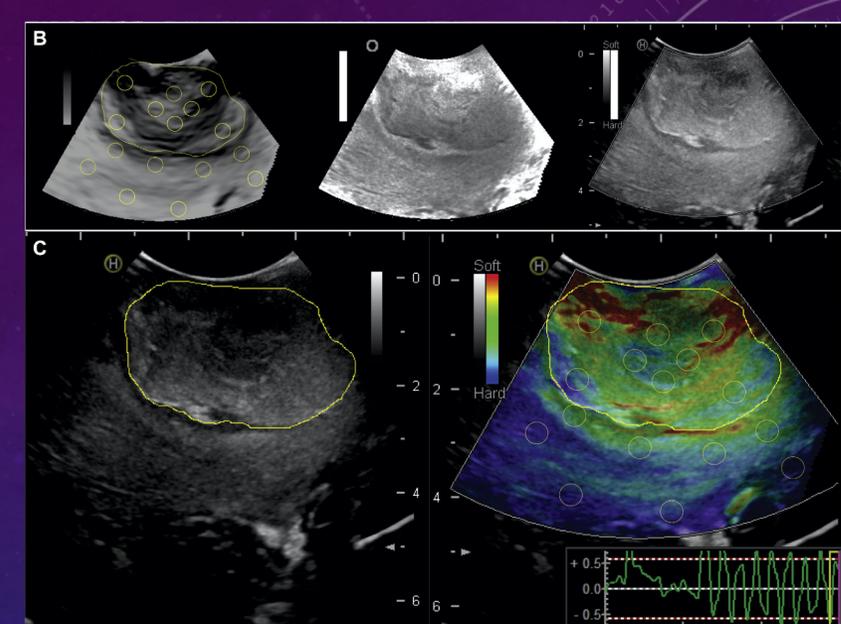
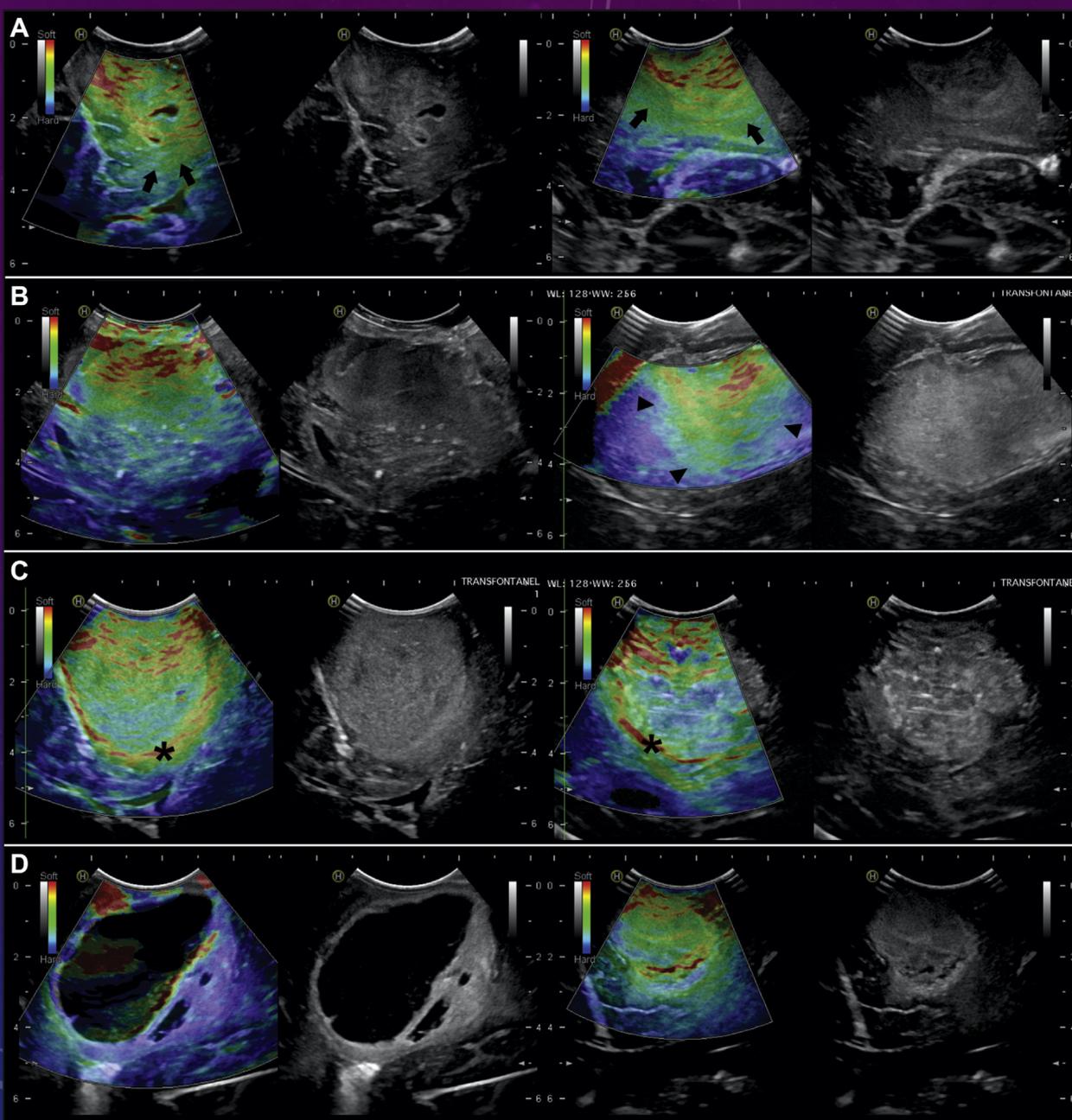
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# BACKGROUND

- Intraoperative ultrasound (ioUS) images of brain tumors contain information that has not yet been exploited.
- The present work aims to analyze images in both B-mode and strain-elastography using techniques based on artificial intelligence and radiomics.
- We pretend to assess the capacity for differentiating glioblastomas (GBM) from solitary brain metastases (SBM) and also to assess the ability to predict the overall survival (OS) in GBM.



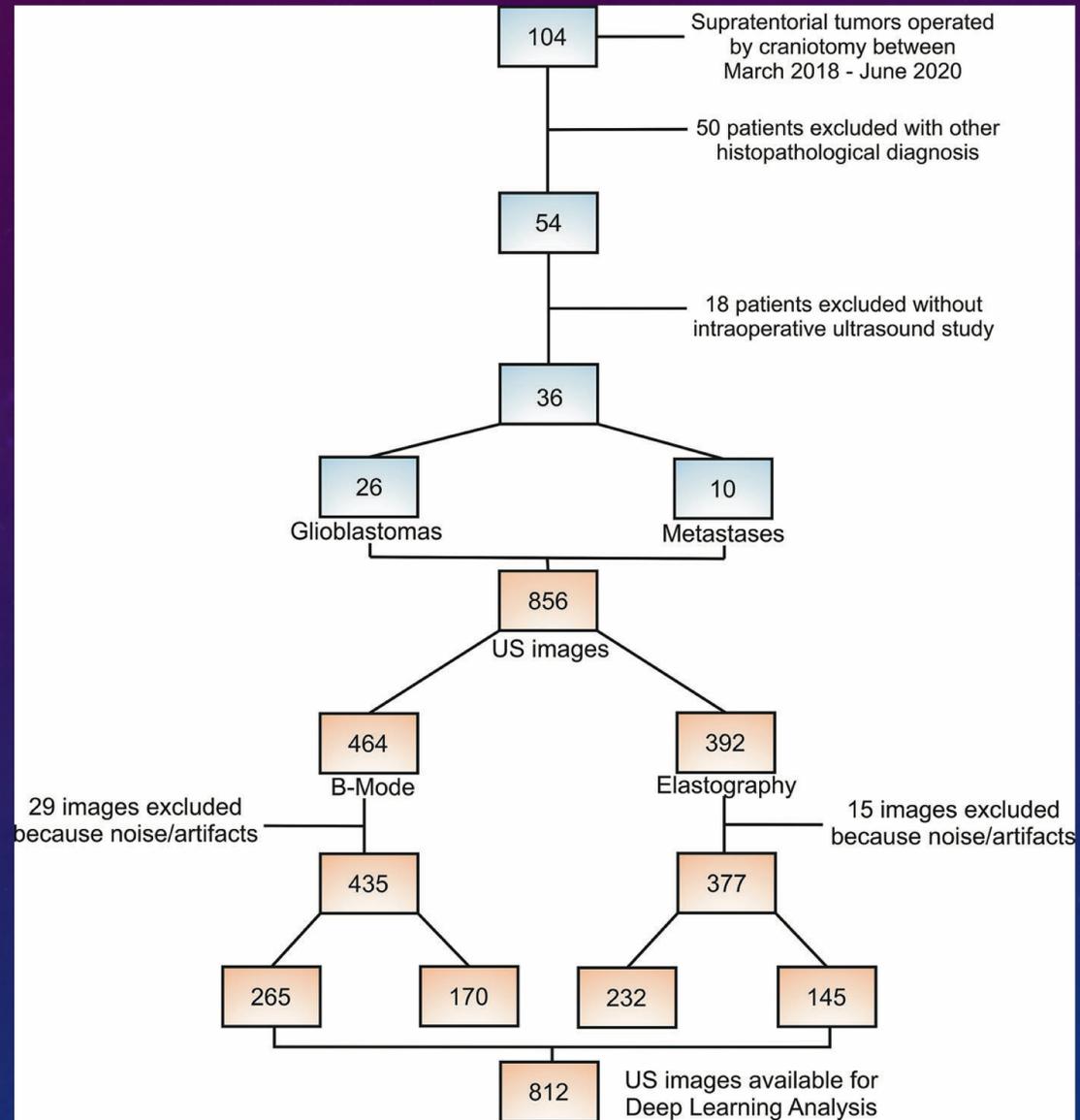


Cepeda S, Barrena C, Arrese I, Fernández-Pérez G, Sarabia R. Intraoperative ultrasonographic elastography: a semi-quantitative analysis of brain tumor elasticity patterns and peritumoral region. *World Neurosurg.* 2020;135:e258–e270.

# METHODS

- We performed a retrospective analysis of patients who underwent craniotomy between March 2018 to June 2020 with GBM and SBM diagnoses.
- Cases with an ioUS study were included.
- In the first group of patients, an analysis based on deep learning was performed. An existing neural network (Inception V3) was used to classify tumors into GBM and SBM. The models were evaluated using the area under the curve (AUC), classification accuracy, and precision.
- In the second group, radiomic features from the tumor region were extracted. Radiomic features associated with OS were selected employing univariate correlations. Then, a survival analysis was conducted using Cox regression.

# RESULTS



**TABLE 2** | Diagnostic performance of classification algorithms based on Ultrasound B-mode images.

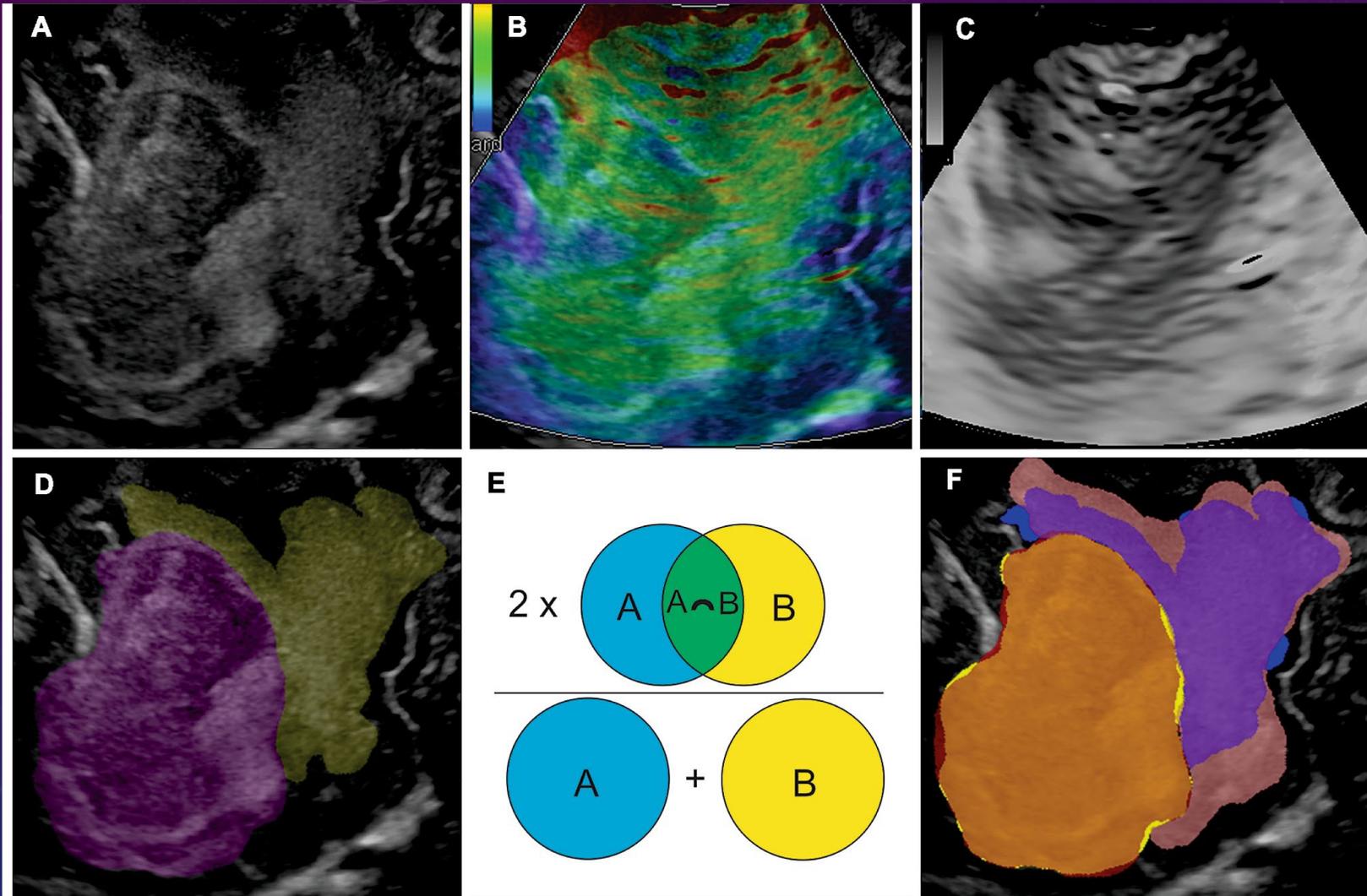
<b>Classifier</b>	<b>AUC</b>	<b>CA</b>	<b>F1-Score</b>	<b>Precision</b>	<b>Recall</b>
kNN	0.938	0.897	0.897	0.898	0.897
Logistic Regression	0.915	0.871	0.871	0.871	0.871
Neural Network	0.945	0.876	0.877	0.879	0.876
Random Forest	0.791	0.749	0.724	0.779	0.749
SVM	0.944	0.887	0.887	0.887	0.887

*AUC, Area Under the Curve; CA, Classification Accuracy; kNN, k-Nearest Neighbor; SVM, Support Vector Machine.*

**TABLE 3** | Diagnostic performance of classification algorithms based on Ultrasound Elastography images.

<b>Classifier</b>	<b>AUC</b>	<b>CA</b>	<b>F1-Score</b>	<b>Precision</b>	<b>Recall</b>
kNN	0.983	0.947	0.947	0.947	0.947
Logistic Regression	0.960	0.889	0.888	0.888	0.889
Neural Network	0.985	0.918	0.918	0.922	0.918
Random Forest	0.861	0.796	0.786	0.803	0.796
SVM	0.985	0.941	0.941	0.942	0.942

*AUC, Area Under the Curve; CA, Classification Accuracy; kNN, k-Nearest Neighbor; SVM, Support Vector Machine.*



**Table 1** Univariate Cox regression for overall survival

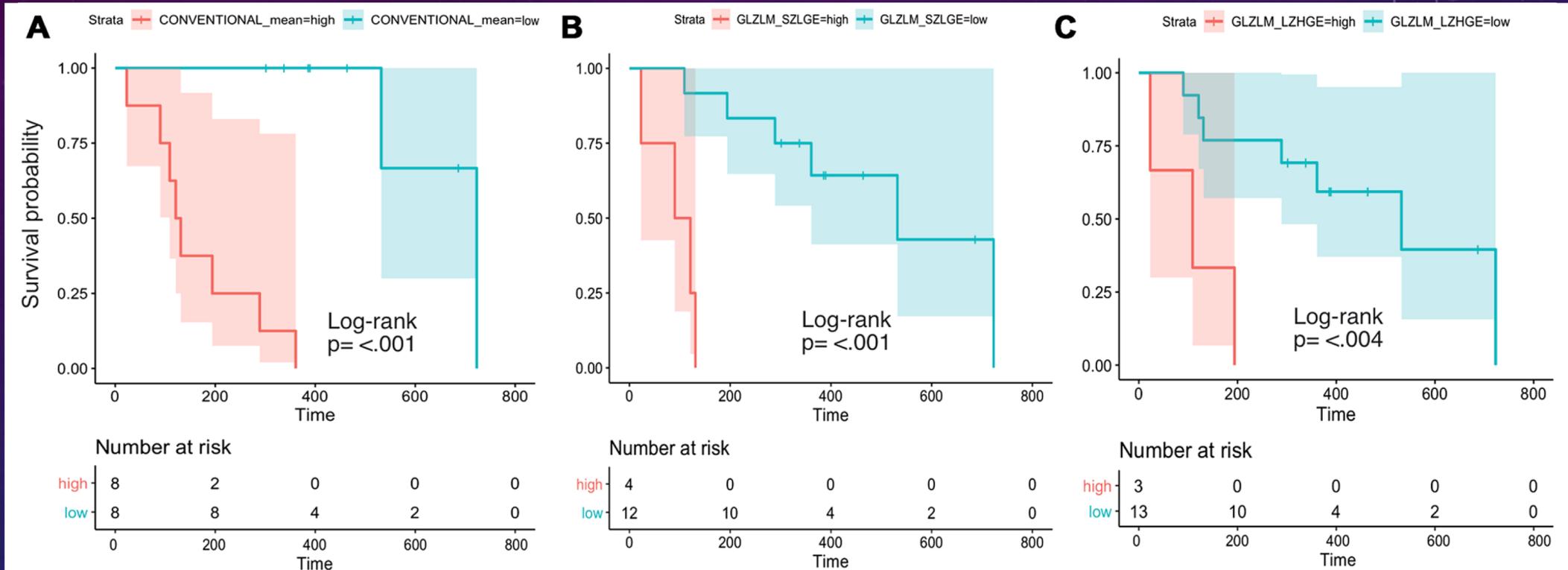
Variable	$\beta$	HR	95% CI	<i>p</i>	Likelihood ratio test	C-index
Age	0.01	1.01	0.94–1.08	0.77	$\chi^2 = 0.08, df = 1, p = 0.8$	0.46
KPS	−0.05	0.95	0.85–1.06	0.333	$\chi^2 = 0.97, df = 1, p = 0.3$	0.58
Initial tumor volume	0.06	1.06	1.02–1.10	0.003	$\chi^2 = 10.62, df = 1, p = 0.001$	0.80
B-mode						
Conventional mean	1.04	2.84	1.42–5.69	0.003	$\chi^2 = 9.31, df = 1, p = 0.002$	0.85
GLZLM_SZLGE	1.28	3.59	1.48–8.69	0.005	$\chi^2 = 0.48, df = 1, p = 0.002$	0.75
Strain elastography						
GLZLM_LZHGE	0.84	2.31	1.16–4.58	0.017	$\chi^2 = 5.02, df = 1, p = 0.02$	0.61

HR hazard ratio, KPS Karnofsky Performance Score, GLZLM\_SZLGE conventional intensity mean and the grey-level zone length matrix/short-zone low gray-level emphasis, GLZLM\_LZHGE grey-level zone length matrix/long-zone high gray-level emphasis

**Table 2** Kaplan–Meier analysis for overall survival and texture-based groups

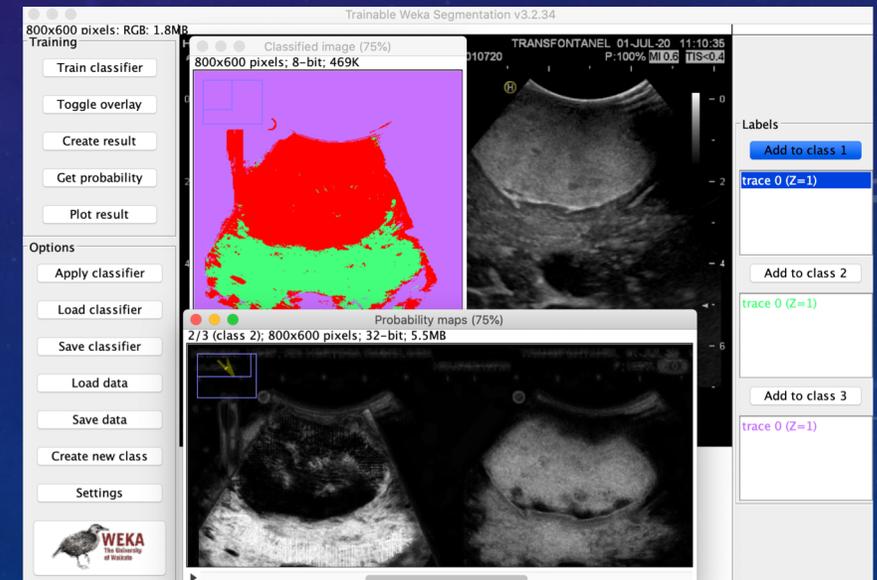
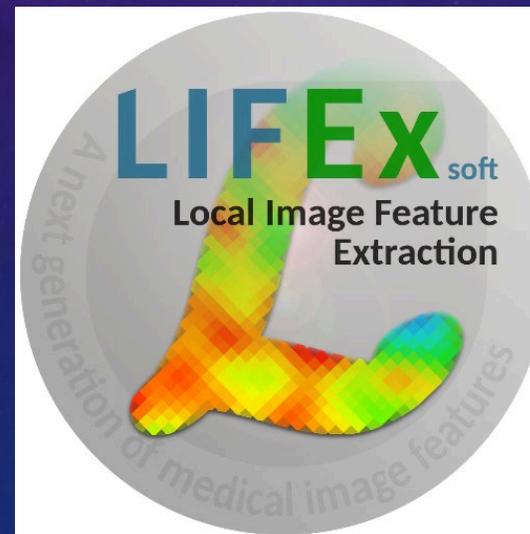
Radiomic feature	Cutpoint	Risk groups and number of cases	Median OS (IQR)	Log-rank test	
				$\chi^2$	<i>p</i>
Conventional mean	−0.1824347	Low = 8	427 (197)	16.5	<0.001
		High = 8	126 (114)		
GLZLM_SZLGE	−0.1300415	Low = 12	374 (182)	14.9	<0.001
		High = 4	106 (50)		
GLZLM_LZHGE	0.2890771	Low = 13	361 (175)	8.4	0.004
		High = 3	109 (86)		

OS overall survival, IQR interquartile range, GLZLM\_SZLGE conventional intensity mean and the grey-level zone length matrix/short-zone low gray-level emphasis, GLZLM\_LZHGE grey-level zone length matrix/long-zone high gray-level emphasis



# WHAT'S NEXT ?

- Automatic segmentation methods (Trainable Weka Segmentation)
- Open-source software
- Multicenter ultrasound database. The “**BraTioUS-DB initiative**” (Brain Tumor intraoperative ultrasound database)



# CONCLUSIONS

- Automated processing of ioUS images through deep learning can generate high-precision classification algorithms.
- Radiomic tumor region features in B-mode and elastography appear to be significantly associated with OS in GBM.

THANK YOU

