



# Advanced Prediction of GBM Recurrence Via Stem Cell Niche Proximity Estimation Coupled SVM for Personalized Radiotherapy

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# Disclosure and Acknowledgement



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## Glioblastoma multiforme (GBM) General Facts



- GBM is the most common primary brain malignancy in adults.
- Patients' response to standard therapies is unsatisfactory with a dismal 5-year survival of only 7%.
- Nearly all GBM patients recur despite aggressive therapies.
- Radiation played a crucial role for GBM patients with demonstrated survival benefit, but therapeutic outcomes continue to be disappointing.

**Algorithms enabling early, and voxel-wise detection of subclinical recurrence are needed for early radiation intervention!**

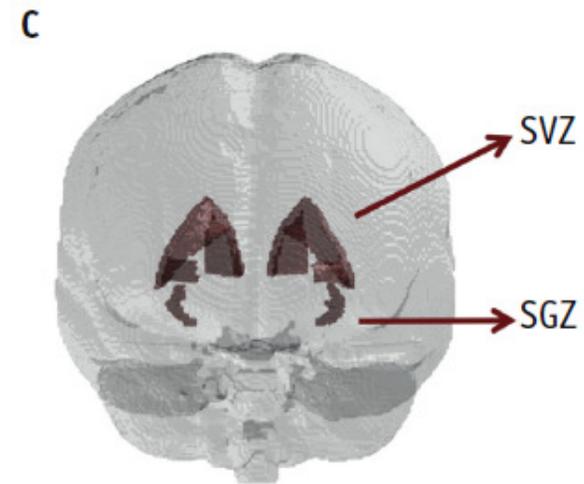
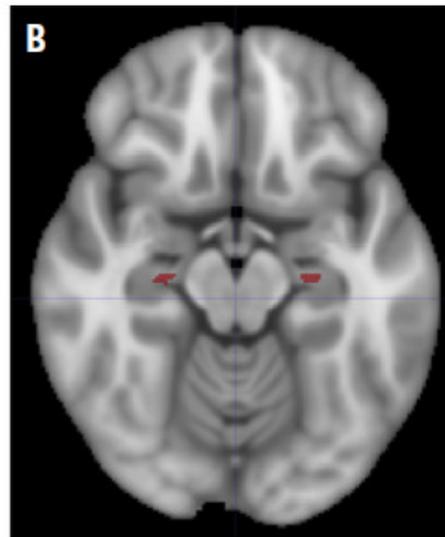
## Machine Learning and Medical Imaging in RT of GBM



- Machine learning integrated with medical imaging has introduced new perspectives in diagnostics of GBM, mainly through radiomics and radio genomics.
- Radiomics features are extracted to build prediction models using classification or regression.
- Prediction of endpoints: survival, genomics, response to therapy, or tumor micro-environment

**However, few studies reported predicting the site of recurrence for GBM, and they are often limited to the recurrence in the peritumoral brain tissues.**

## The Role of Cancer Stem Cells in Glioblastoma

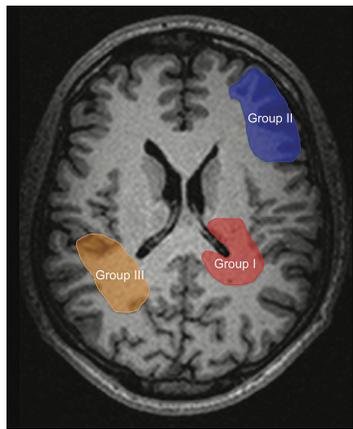


**Can we incorporate cancer stem cell theory into the image analysis for voxel-wise GBM recurrence prediction and RT intervention?**



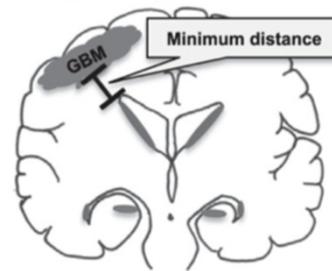
## Radiation of the Stem Cell Niche

- Radiation, in theory, can decrease the number of brain tumor propagating cells in SVZ or SGZ to reduce the likelihood of recurrence or metastasis.
- However, studies in this field reported conflicting results, depending on RT doses and the size of the resection area.



[M Kimura et al., 2013]

Neurogenic region non-contacting



[Linda Chen et al., 2015]

**Coarse characterization of stem cell niche involvement!**

**Need more quantitative metric!**

## Study 1



### Aim

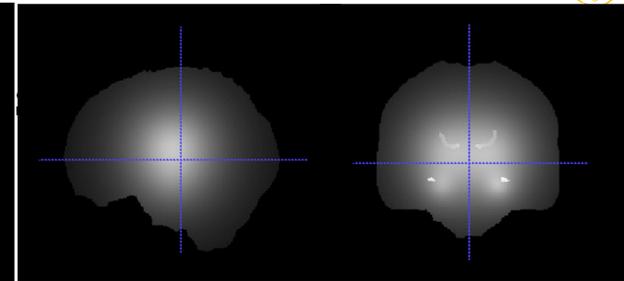
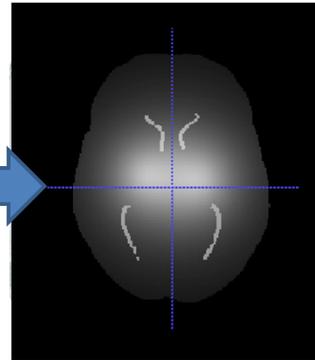
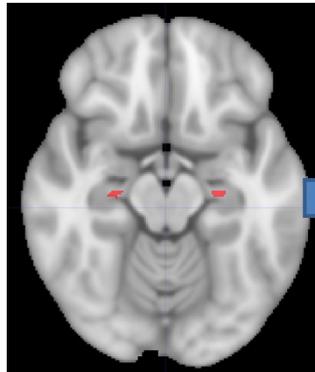
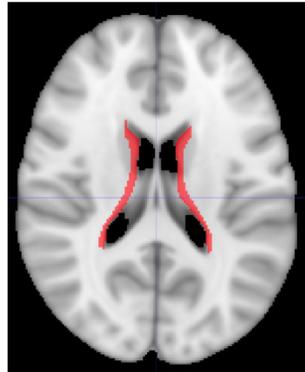
To develop a new inverse distance-based metric, proximity score (PS), to better characterize the geometric relationship of GBM tumors to stem cell niche zones.

### Data

Two T1w MRI datasets were included in the study:

- 102 preoperative scans from the public TCIA dataset for prognostic stratification.
- 65 preoperative and follow-up scan pairs from two institutional databases for recurrent pattern identification.

## Our pipeline



SCN delineation

Quantitative proximity ( $P_S$ ) map

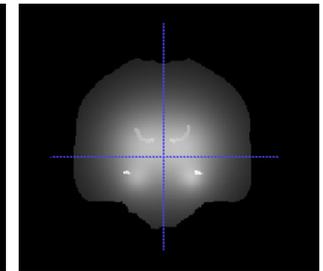
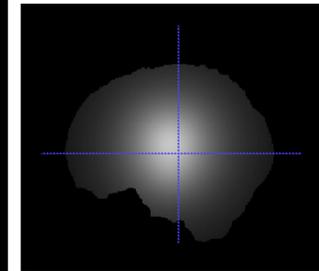
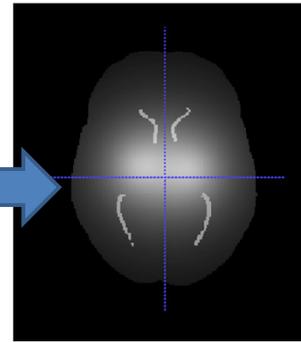
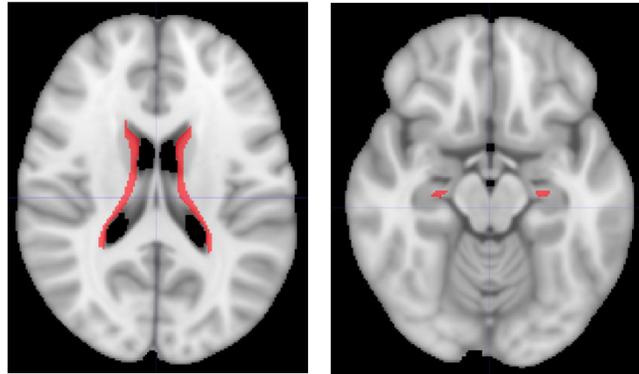
$$P_S(x) = \begin{cases} \frac{ID(x) - ID_{min}}{ID_{max} - ID_{min}}, & \text{if } x \notin S \\ 1, & \text{if } x \in S \end{cases}$$

$$ID(x) = \left( \sum_{i=1}^N \frac{1}{d(x, S_i)^p} \right)^{\frac{1}{p}}$$

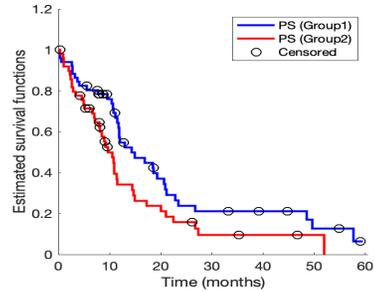
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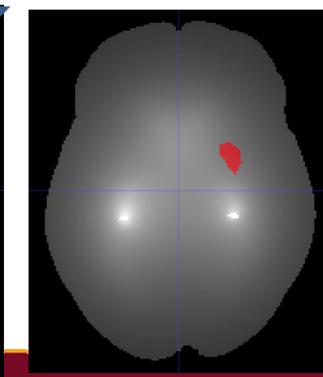
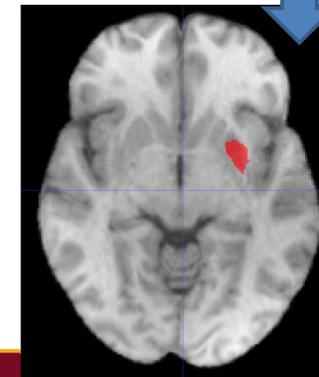
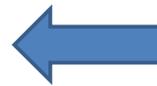
## Our pipeline



Quantitative proximity ( $P_s$ ) map



Statistical analysis



Deformable registration and mean  $P_s$  score

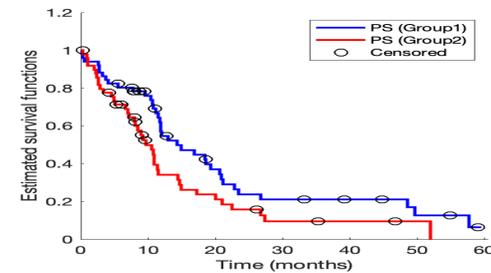
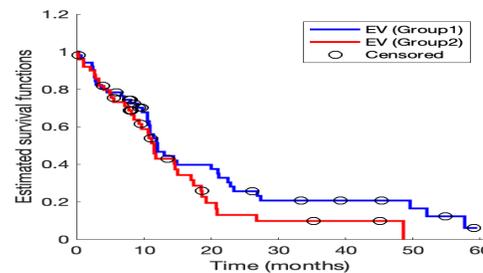
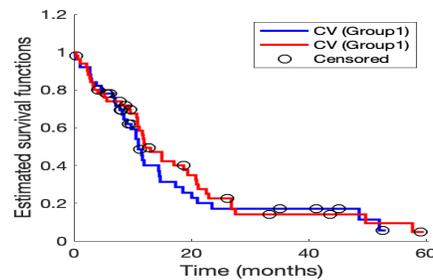
## Results (OS prediction and risk stratification)



- Among 3 SCN features, PS is the only significant predictor of OS (cox regression  $p$ -value = 0.0297)

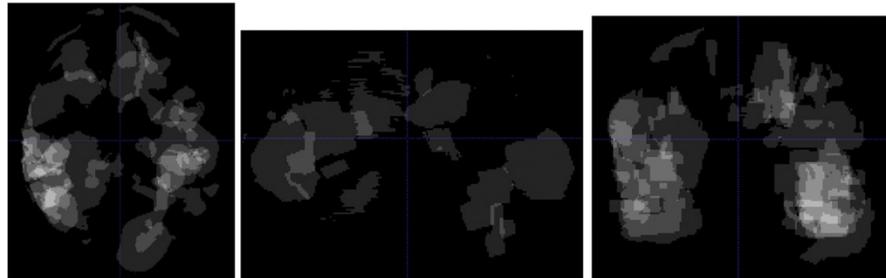
	CV	EV	PS
HR	0.9884	0.9676	4.45
$p$	0.5660	0.7483	0.0297

- PS is the best performer in risk stratification (log-rank  $p = 0.0474$ ).



Kaplan-Meier plots of overall survival for groups of patients stratified by CV (log-rank  $p = 0.5829$ ), EV (log-rank  $p = 0.1486$ ), and PS (log-rank  $p = 0.0474$ ). Censored observations are marked by black circles.

## Results (Primary vs. Recurrence pattern differentiation)

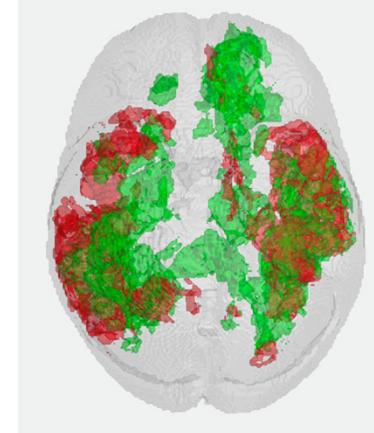


Axial

Sagittal

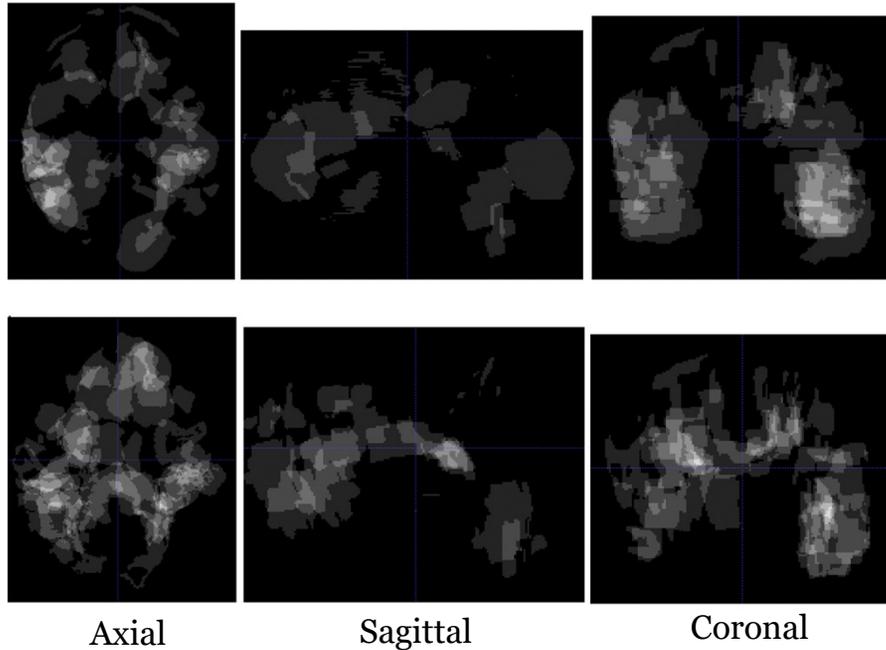
Coronal

Illustrations of overlaid primary (upper row) and recurrent tumor (bottom row) locations from all the subjects.

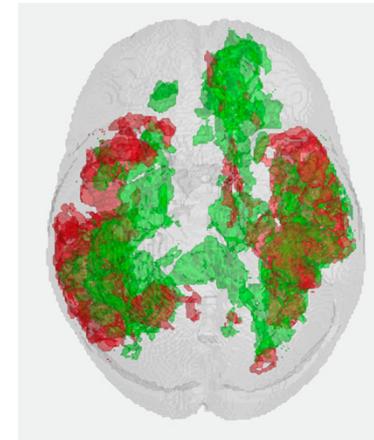


**Red: Original tumors**  
**Green: Recurrence**

## Results (Primary vs. Recurrence)



Illustrations of overlaid primary (upper row) and recurrent tumor (bottom row) locations from all the subjects.



**Red: Original tumors**  
**Green: Recurrence**

	Mean	SD	<i>p</i> -value
Original Tumor	0.1994	0.1083	0.0017*
Recurrence	0.2406	0.1162	

Group comparison of PS between primary and recurrent tumors. ( $p = 0.0101$  for CV and  $p = 0.0051$  for EV.)

## Summary of study 1



- Based on T1 MRI, a novel proximity score metric was developed to quantify tumor proximity to all SCN zones.
- Proximity score-based metrics outperformed traditional edge or center distance-based measurements in survival risk stratification.
- Proximity score best differentiated variations between primary and recurrent tumors in SCN proximities.

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*Quantitative characterization of tumor proximity to stem cell niches: implications on recurrence and survival in GBM patients. 2021 PMID: 33600888*



## Study 2

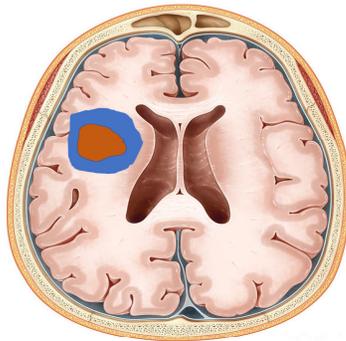
### Advanced prediction of GBM recurrence (**TIME**) for personalized radiotherapy

- Develop voxel-wise GBM recurrence prediction using multi-dimensional support vector machine (SVM) coupling with primary tumor and SCN proximity estimation.
- Demonstrate the radiation dose escalation can be achieved for early predicted recurrence.

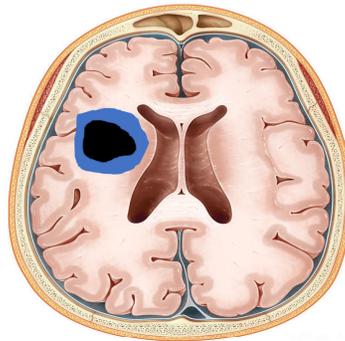


# Motivation to treat subclinical infiltration early

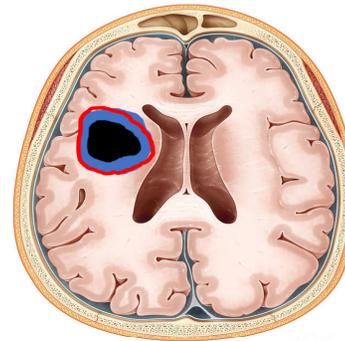
Original GBM



Post surgery

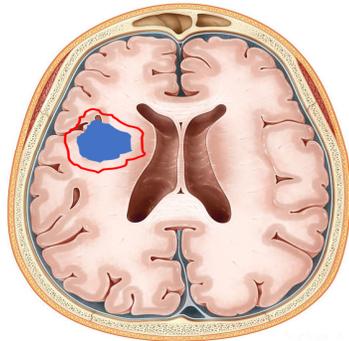


Radiotherapy

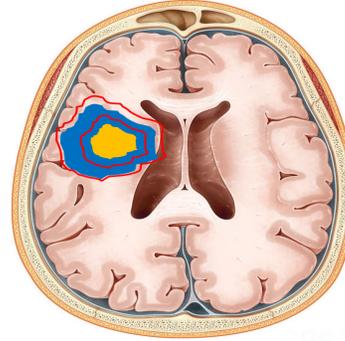


Follow-up MRs

Proposed: early prediction+RT



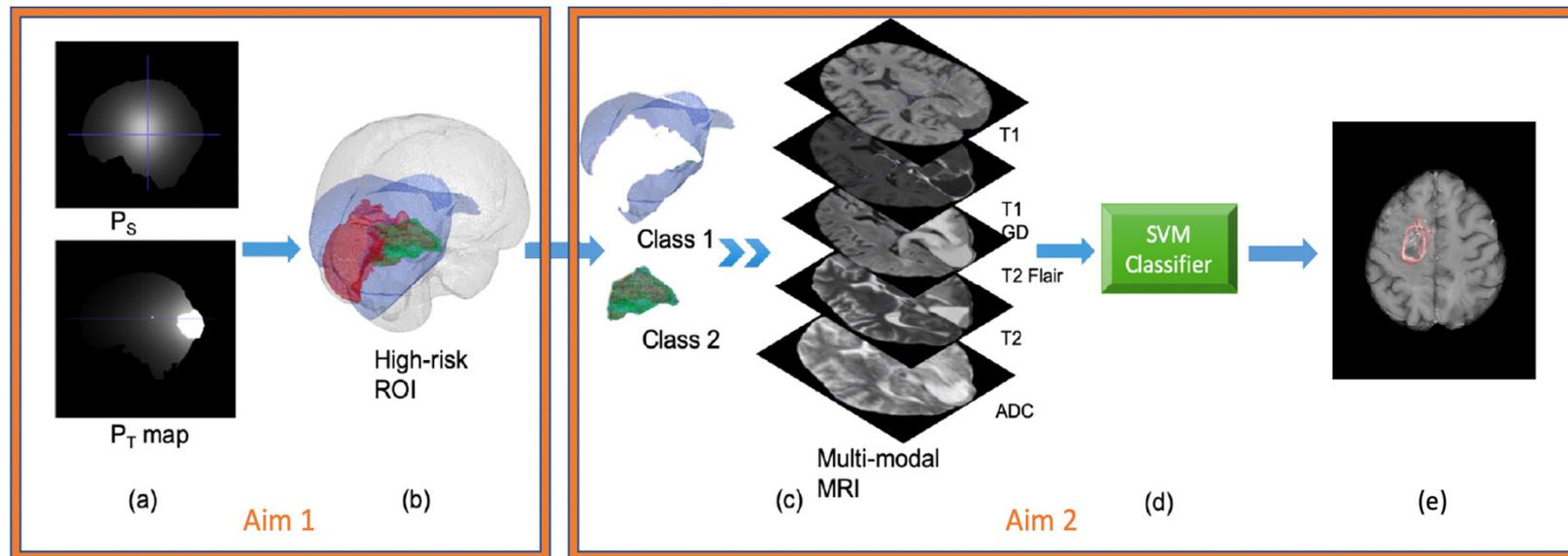
Current: normal detection+RT



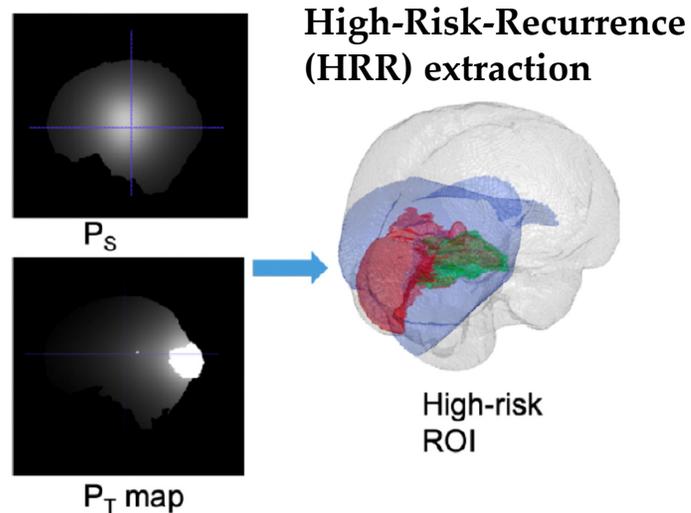
**Blue:** predicted recurrence or subclinical infiltration  
**Yellow:** clinical recurrence  
**Red lines:** Radiation fields for early prediction and actual recurrence, respectively



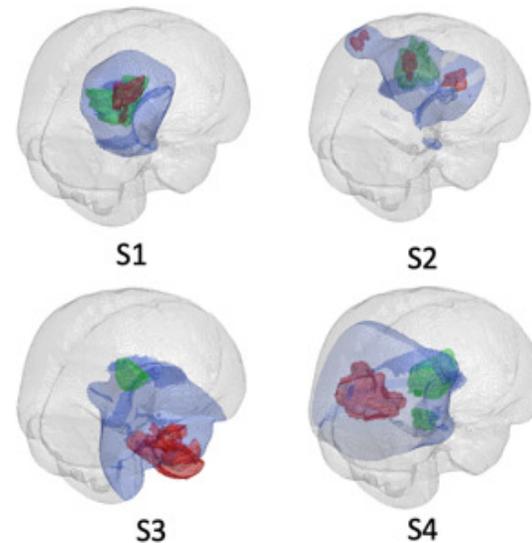
## Our pipeline: overview



# Our pipeline: High Risk of Recurrence (HRR) estimation



**Red: Original tumors**  
**Green: Recurrence**  
**Blue: High Risk of Recurrence**



Four patient examples

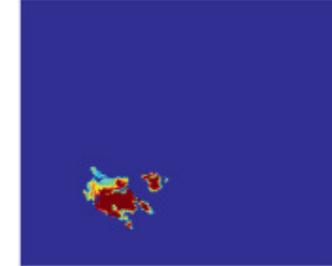
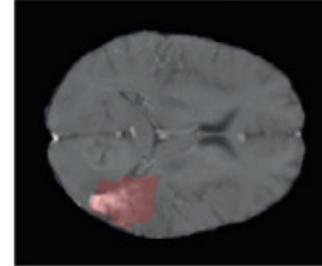
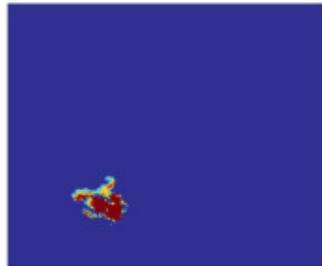
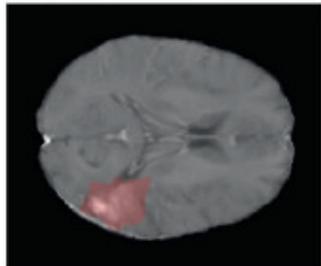
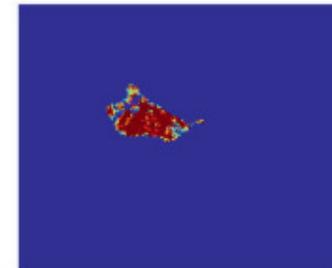
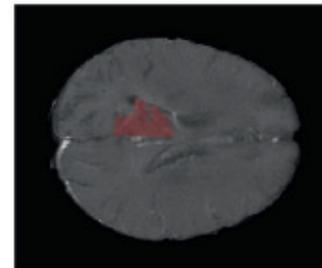
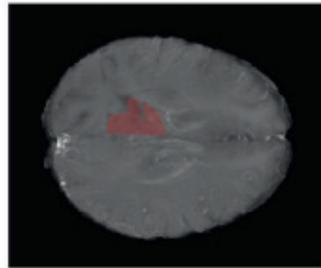


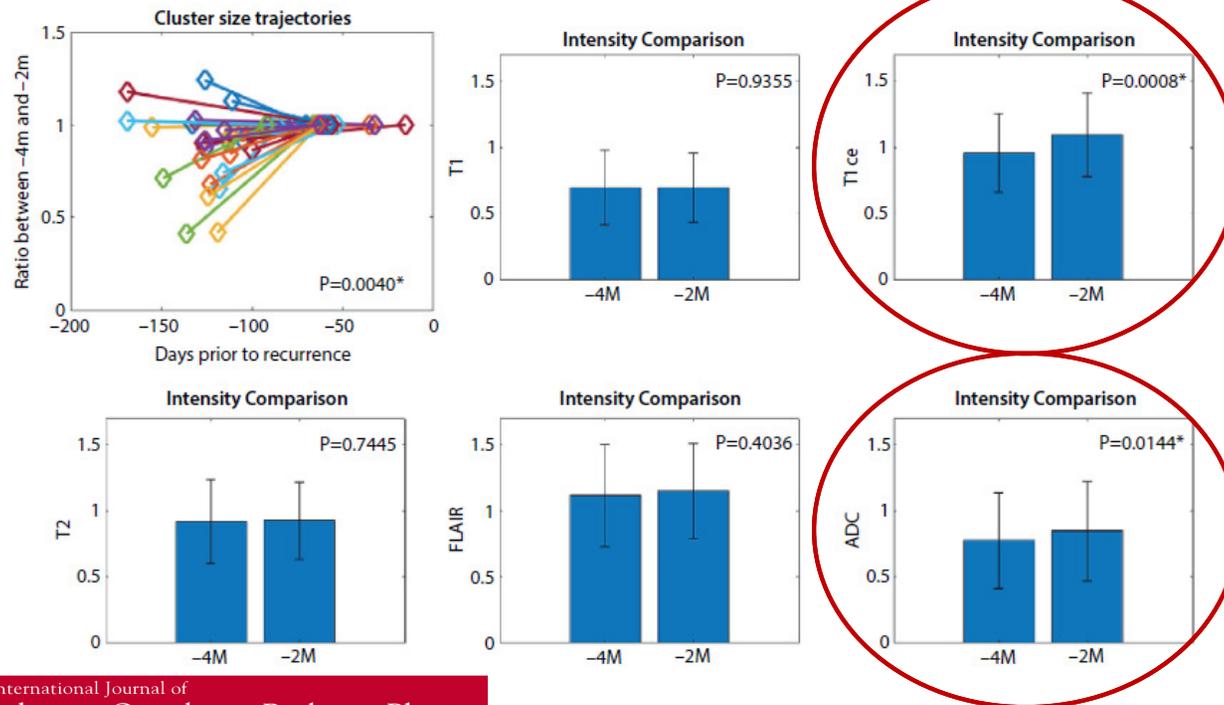
	<u>Training<sup>†</sup></u>		<u>Testing</u>		<i>P</i> values
	Mean	SD	Mean	SD	
Recall	0.81	0.13	0.80	0.10	.591
Precision	0.68	0.14	0.69	0.14	.684
F1	0.73	0.12	0.73	0.10	.978
ABD (mm)	8.14	6.33	7.49	6.19	.722
<p><i>Abbreviations:</i> ABD = average boundary distance; SVM<sub>PE</sub> = proximity estimation–based support vector machine.</p> <p>* For both the training and testing data sets, 4 metrics (recall, precision, F1 score, and ABD) are presented, along with their corresponding groupwise comparison <i>P</i> values. No statistically significant (<math>P &lt; .05</math>) differences were detected on the 4 metrics between the discovery and testing sets.</p> <p><sup>†</sup> For the training data set, performance scores are reported after 10-fold cross-validation.</p>					



- 4 months

- 2 months





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*Voxel-wise Prediction of Recurrent High-Grade Glioma via Proximity Estimation-Coupled  
Multidimensional Support Vector Machine, 2022, PMID: 34963559*

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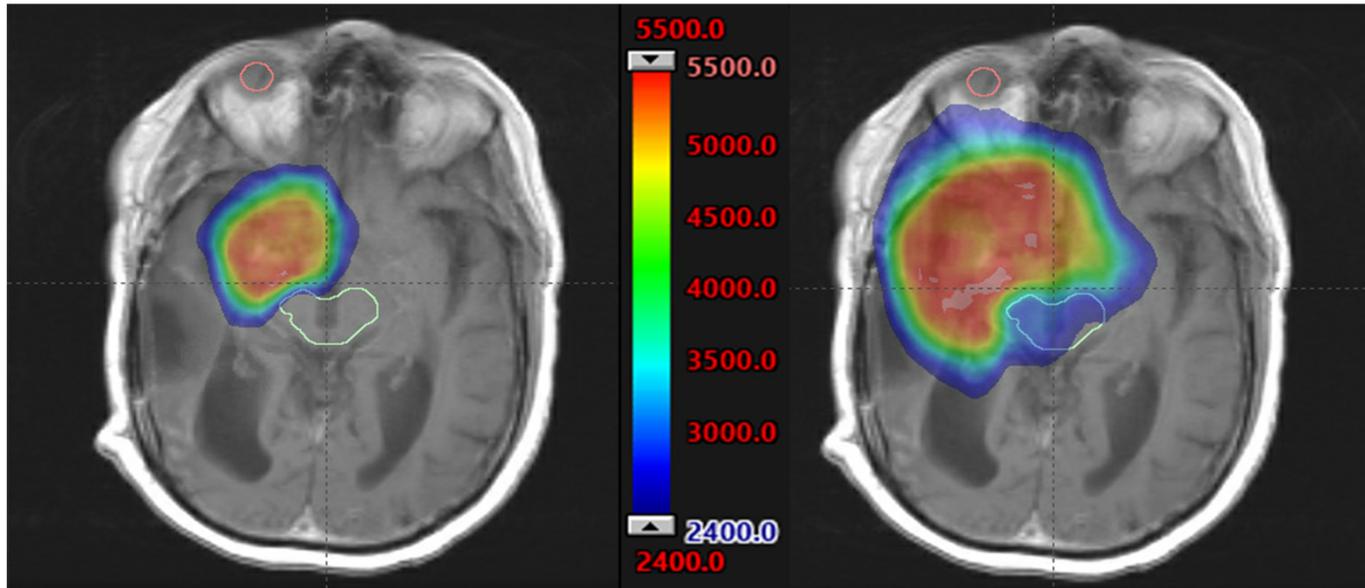
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# Proposed early intervention

**TIME RT plan**

**RT plan of the confirmed recurrence**



## Conclusion



- Tumor stem cell theory was quantitatively incorporated into MR image-based GBM recurrence prediction using proximity maps
- Both local and distant recurrences could be predicted at voxel level
- Virtual dose escalation on predicted clinical target volume shows significantly lower normal tissue doses while achieving higher tumor dose, compared with standard salvage RT
- The **TIME** model provides an advanced prediction tool to support subsequent early radiation interventional trial

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**Thank you!**