# Patient-Specific Semi-Supervised Learning for Postoperative Brain Tumor Segmentation

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## Abstract

We present a fully-automatic method for segmenting the residual enhancing tumor in postoperative multi-modal MR images. The idea behind our approach is to effectively fuse information from both pre- and post-operative image data of the same patient to improve segmentation of the postoperative image. The method is evaluated on a cohort of 10 high-grade glioma patients, with segmentation performance comparable or superior to a state-of-the-art brain tumor segmentation method.

## Decision Forest

We adopted a semi-supervised decision forest, proposed in [2], for solving our problem of postoperative brain tumor segmentation. The main difference to a standard decision forest lies in the extension of the objective function for handling unlabeled data. In the present case:

$$IG_k(\mathcal{S}_k, \theta_k) = IG_{k,u}(\mathcal{S}_k, \theta_k) + \alpha \cdot IG_{k,s}(\mathcal{S}_{k,\ell}, \theta_k) \qquad (1)$$

with $\alpha$ controlling the influence of the supervised term defined as

$$IG_{k,s}(\mathcal{S}_k, \theta_k) = H(\mathcal{S}_k) - \sum_{i\in\{L,R\}} \frac{|\mathcal{S}_k^i|}{|\mathcal{S}_k|} H(\mathcal{S}_k^i) \qquad (2)$$

where $H(\mathcal{S}_k)$ denotes the entropy, $\mathcal{S}_k^i$ the training data after the split and $\{L, R\}$ index the left and right child node respectively. The unsupervised term is defined as

$$IG_{k,u}(\mathcal{S}_k, \theta_k) = \log(\det \Sigma(\mathcal{S}_k)) - \sum_{i\in\{L,R\}} \frac{|\mathcal{S}_k^i|}{|\mathcal{S}_k|} \log(\det \Sigma(\mathcal{S}_k^i)). \qquad (3)$$

Training corresponds to maximizing eq. (1).

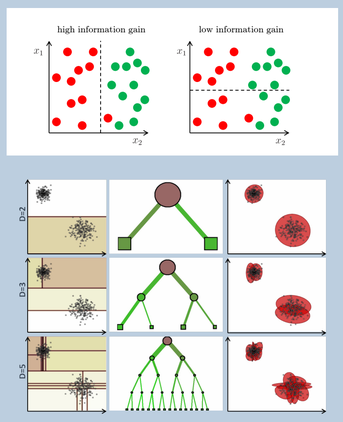


Figure 1: Optimization of supervised (above) and unsupervised information gain (below, image from [2]).

Transduction is performed by propagating leaf statistics via minimizing a geodesic distance (symmetric Mahalanobis distance) between leaf centroids. After this, classification is performed according to the Maximum a posteriori rule, where the posterior is estimated from the forest.

## References

[1] P. L. Kubben, A. a. Postma, A. G. H. Kessels, J. J. van Overbeeke, and H. van Santbrink. Intraobserver and interobserver agreement in volumetric assessment of glioblastoma multiforme resection. *Neurosurgery*, 67(5):1329–34, Dec. 2010.

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[3] S. Bauer, T. Fejes, J. Slotboom, R. Wiest, L.-P. Nolte, and M. Reyes. Segmentation of Brain Tumor Images Based on Integrated Hierarchical Classification and Regularization. In *Proceedings of MICCAI-BRATS 2012*, Jan. 2012.

[4] B. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, et al. The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS).

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## Problem

The current approach for treatment of glioma patients involves primary tumor surgery (resection) followed by combined radio- and chemotherapy. Volumetric analysis of residual enhancing tumor of postoperative images is commonly done in a manual fashion. Lately, it has been shown that manual segmentation of postoperative GBM images is being subject to large interobserver variability [1]. Fully-automatic segmentation methods have the potential to resolve this issue. The segmentation of postoperative brain tumor images is more challenging than segmenting preoperative images for various reasons such as:

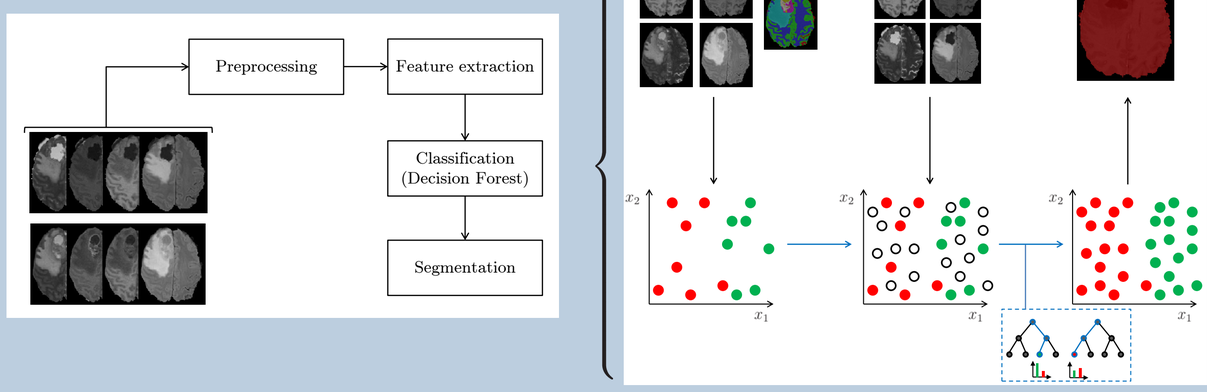
- Hemorrhages (caused by surgery) confound with enhancing tumor.
- Resection cavity confounds with necrosis or edema.
- Curse of dimensionality.


## Patient-specific Semi-Supervised Learning

We consider the problem of postoperative brain tumor segmentation as a classification problem in which we want to map a voxel, represented by a feature vector, to its corresponding binary tissue class label (enhancing tumor/remaining tissue). For every patient we are given a preoperative ($\Omega_{pre}$) and postoperative ($\Omega_{post}$) multimodal image consisting of $T_1$-weighted, $T_1$-weighted post-contrast, $T_2$-weighted and $FLAIR$-weighted MR images.
Our approach is based on two assumptions:

- For every preoperative image $\Omega_{pre}$ a corresponding label map can be generated.
- The enhancing tumor and its residual appear *sufficiently* similar in the pre- and postoperative images (implying proximity in the feature space).

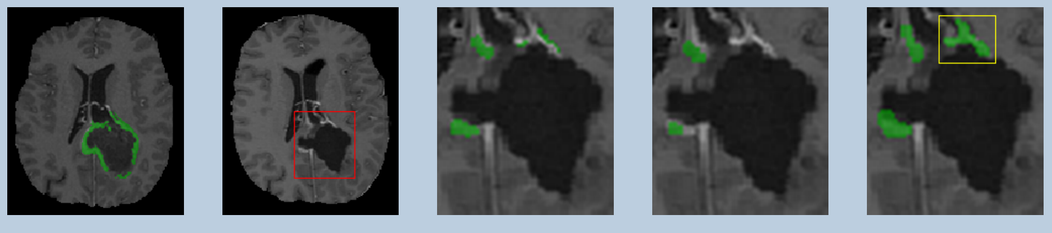
The model is trained both on the labeled preoperative image data as well as on the unlabeled postoperative data of the *same* patient. Since test data (postoperative image) is available during training, we perform classification directly via *transduction*.




## Results

We relied on image data of 10 high-grade glioma patients. For comparison, we chose one of the top-ranked segmentation methods (based on [3]) of the BRATS Challenge [4]. Our method, referred to as *SSDF*, is trained and evaluated on the labeled preoperative and unlabeled postoperative image of one patient at a time. The supervised method is trained either only on pre- (DFPRE) or postoperative (DFPOST) images or on both (DFPREPOST) (using leave-one-out cross validation).

| **Method** | Sensitivity | Specificity | PPV | Abs. volume error $[ml]$ | #MISSED |
|---|---|---|---|---|---|
| SSDF | $(0.16, 0.27)$ | $(0.99, 0.08)$ | $(0.24, 0.93)$ | $(0.24, 4.72)$ | 1 |
| DFPRE | $(0.26, 0.61)$ | $(0.96, 0.26)$ | $(0.15, 0.93)$ | $(2.38, 11.24)$ | 0 |
| DFPOST | $(0, 0.12)$ | $(0.99, 0.01)$ | $(0, 0.92)$ | $(0.15, 6.49)$ | 3 |
| DFPREPOST | $(0.19, 0.26)$ | $(0.99, 0.06)$ | $(0.25, 0.92)$ | $(0.48, 5.87)$ | 1 |



**Conclusion**: *SSDF* does not require postoperative ground truth data, while having performance superior or comparable to inductive models.