

# SEGMENTATION OF THE ORGANS AT RISK IN BRAIN CANCER THROUGH A DEEP LEARNING ARCHITECTURE: CLINICAL APPLICATION

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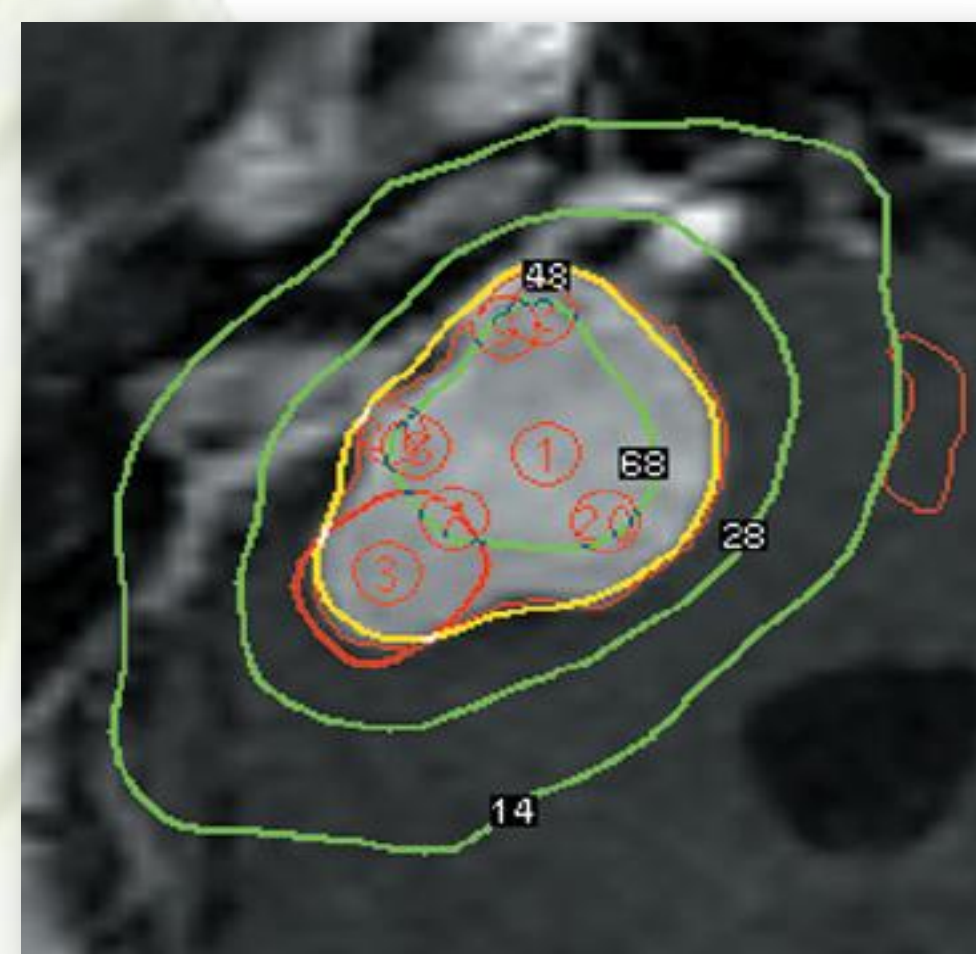
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**Introduction:** Cancer is a leading cause of death and disability worldwide, accounting for 14.1 million of new cancer cases and 8.2 million deaths in 2012. Radiotherapy and radio surgery have become often the selected treatment to treat brain cancers. To constrain the risk of severe toxicity of critical brain structures –organs at risk (OARs)- during radiation treatment planning (RTP), volume measurements of these structures are required.

OARs segmentation is mostly performed manually. This makes the process highly time-consuming and operator dependent. To assist during the task, a variety of techniques have been presented to segment brain structures [1]. However:

- OARs involved in the RTP are rarely included in the evaluations.
- When included, limited success has been reported.
- Most of the proposed techniques often require a deformable registration step and long processing times.
- The presence of tumors may deform the structures and appear together with edema that changes intensity properties of the nearby region, leading to failure of many approaches.

We propose the use of a classification scheme based on deep learning, as alternative, to segment the OARs in brain cancer.



Radiation treatment planning with the gamma knife

## Method and Materials:

Features used in the classification:

- The most influencing factor in realizing a classifier with high generalization ability is the set of features used.
- Features typically employed in medical image segmentation are:
  - Image Intensity
  - Probabilistic information
  - Location knowledge
- Additionally to classical features, we propose the use of some other features, which are sometimes organ-dependent:
  - Geodesic Distance Transform Map.
  - 3D Local Binary Patterns.
  - Geometrical properties (distance, angles, etc...) [2]

## Method and Materials:

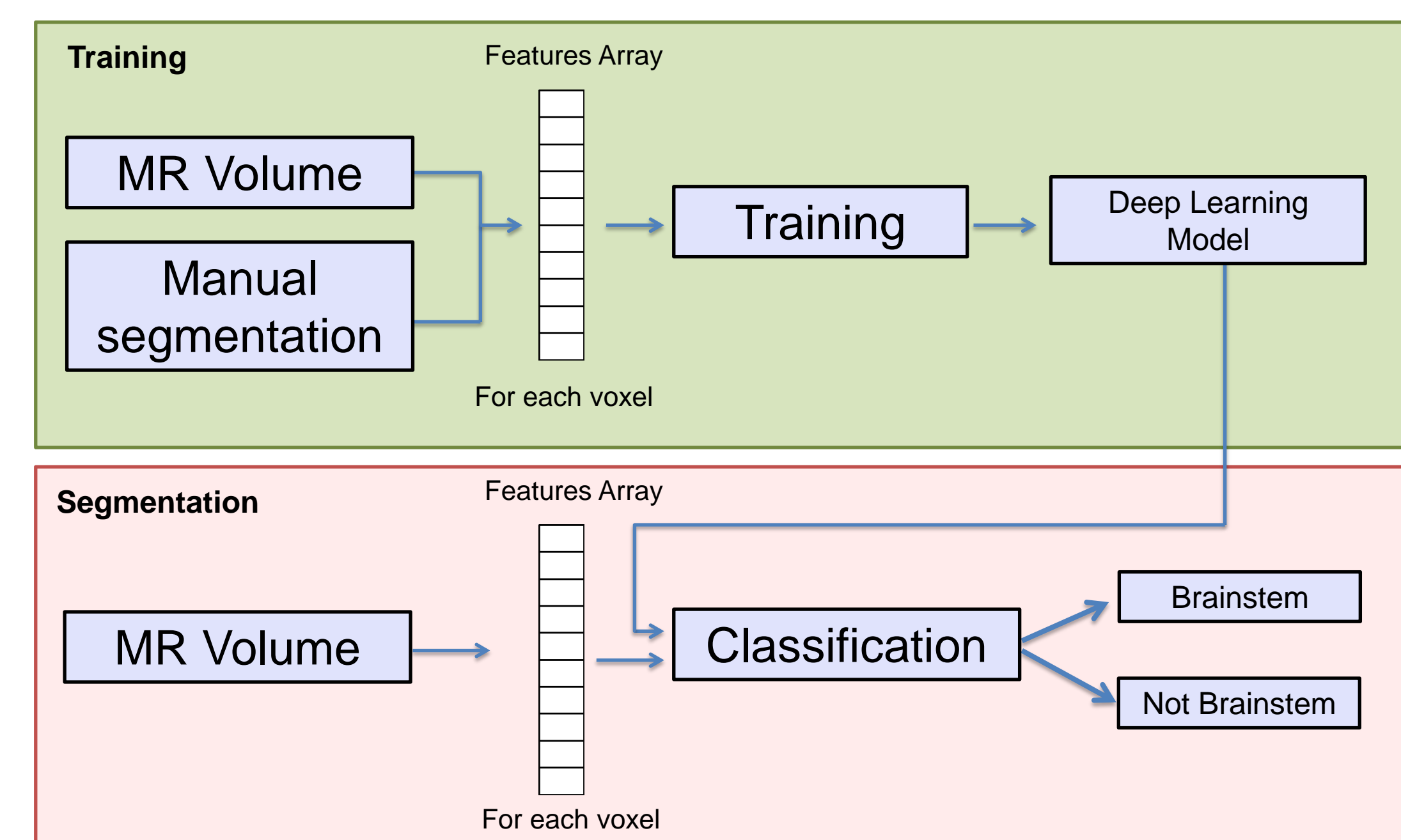
### Brainstem segmentation example

Features vector composition (per voxel) [3]:

- MR T1 intensity values (of voxel under examination and its vicinity).
- Probability Map value.
- Geodesic Distant Transform Map (GDTM) value.
- Image Gradient value.
- Spherical coordinates.
- 3D Local binary pattern (LBP) characterization.

Evaluation:

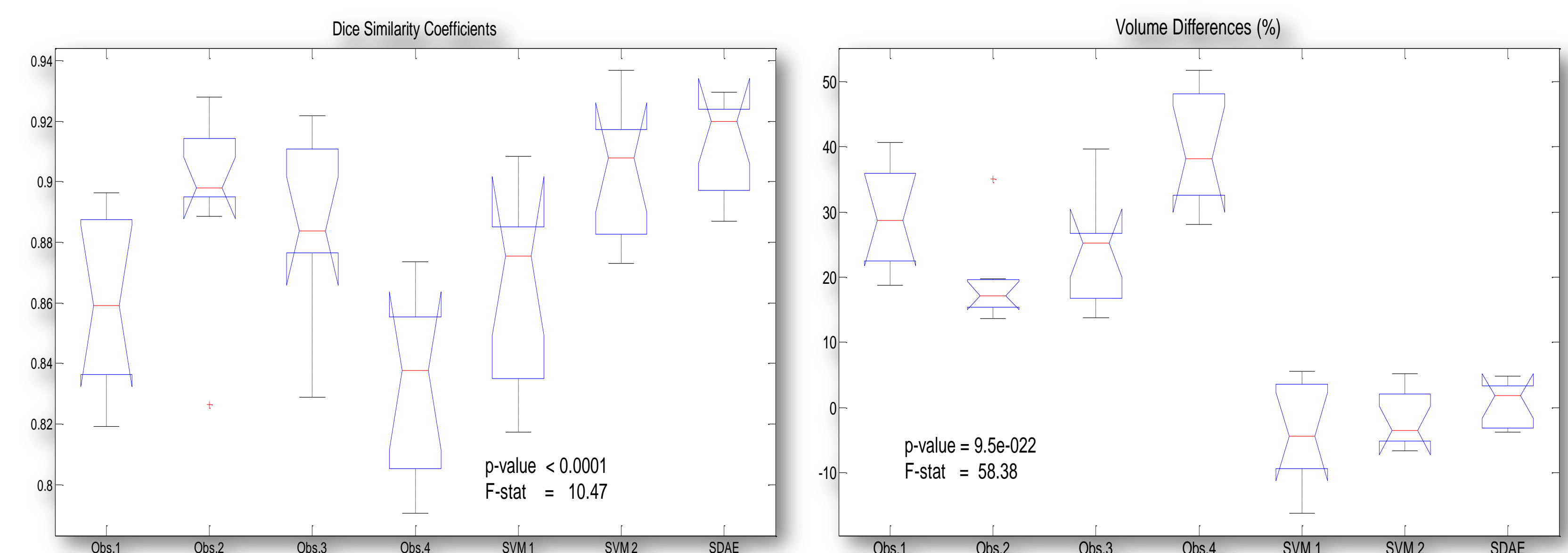
- MR T1 images from 9 brain cancer patients.
- Manual contours from 4 clinicians.
- Ground Truth (GT) generated from the manual contours.
- Support Vector Machines (SVM) and Stacked Denoising Auto-Encoders (SDAE) are the learning algorithms employed.



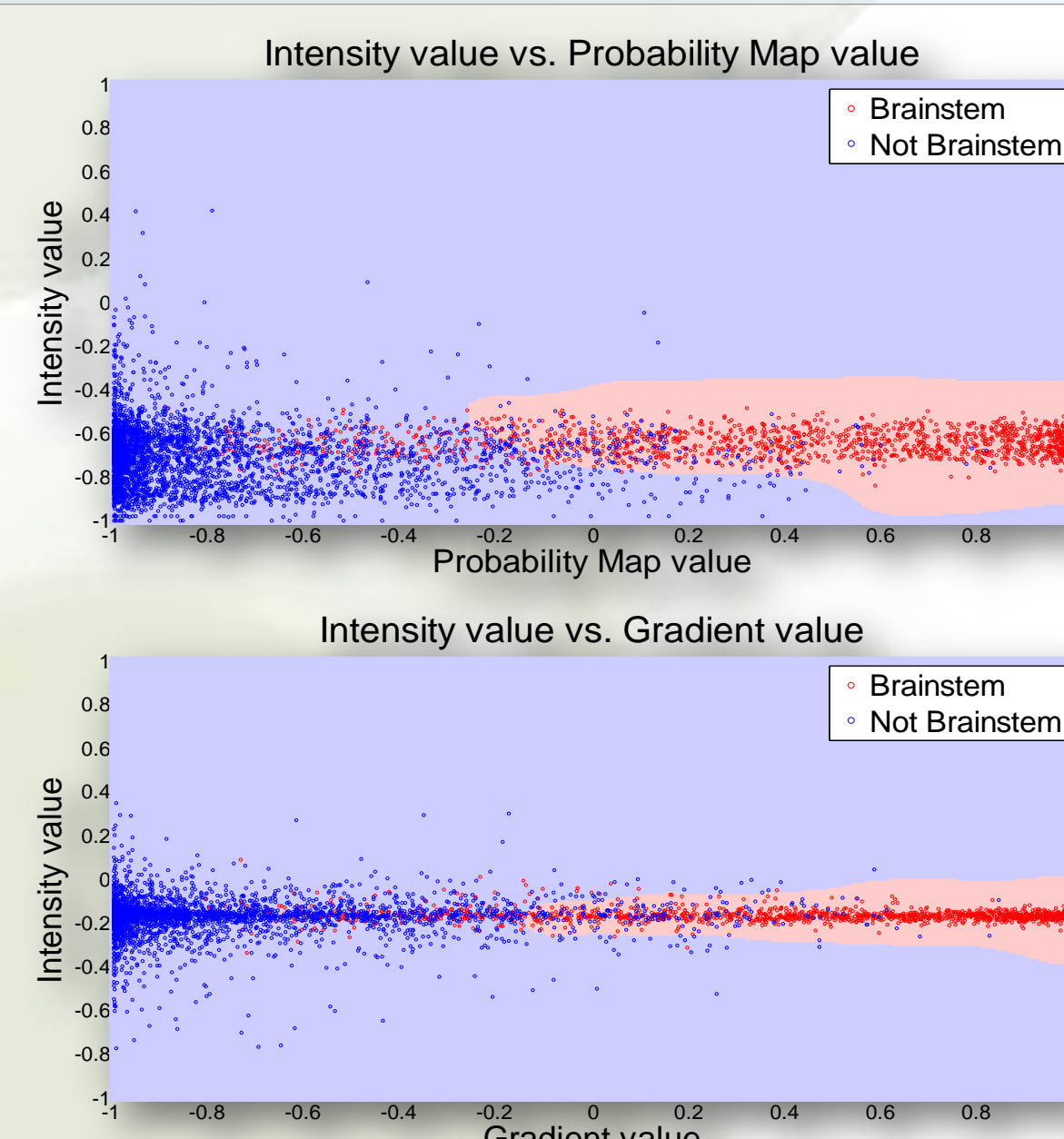
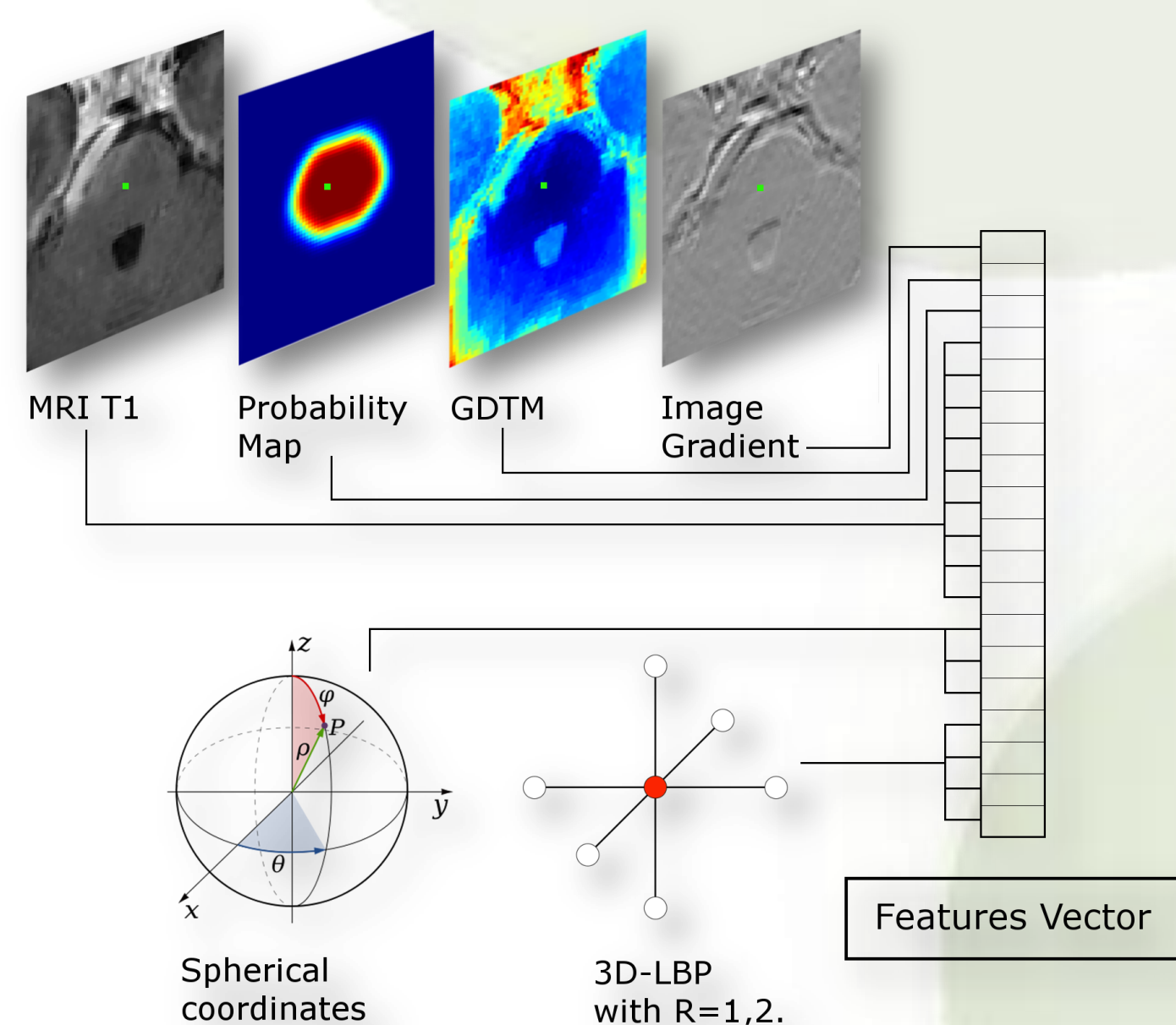
Workflow of the classification process.

**Results:** Approaches including the proposed features (SVM2 and SDAE) performed significantly better ( $p < 0.05$ ) than SVM with classical features (SVM1) and manual contours, both in:

- Dice Similarity Coefficient (DSC)
- Volume differences (%).
- In terms of speed, while SVM approaches took nearly 25 seconds to segment a whole volume, SDAE performed the task in 0.36 seconds as average.



Segmentation results (DSC and volume differences) of the four observers and the three automatic methods in comparison with the ground truth.



Pair to pair correlation of some of the features employed.

Composition of the features vector for each voxel in the case of brainstem segmentation

**Conclusion:** In this thesis, we propose the use of a deep learning technique -SDAE- as alternative to classical segmentation approaches to segment brain structures. Particularly, segmentation of OARs in brain cancer is assessed by the proposed scheme. In addition to features commonly employed in machine learning to segment medical images, novel features are also proposed. Results on analyzed structures show that our segmentation results lie on the variability of the observers. Furthermore, segmentation times are highly reduced, achieving acceptable results in less than a second.

## References:

- [1] J. Dolz *et al.*, "Segmentation algorithms of subcortical brain structures on MRI for radiotherapy and radiosurgery: a survey", IRBM. 36,200-212. (2015).
- [2] J. Dolz *et al.*, "A fast and fully automated approach to segment optic nerves on MRI and its application to radiosurgery" IEEE International Symposium on Biomedical Imaging (ISBI), April 2015, New York (pp. 1102-1105).
- [3] J. Dolz *et al.*, "Supervised machine learning-based classification scheme to segment the brainstem on MRI in multicenter brain tumor treatment context" International Journal of Computer Assisted Radiology and Surgery (IJCARs), 2015, 1-9.