Brain Tumor Segmentation with Random Forest and U-Net

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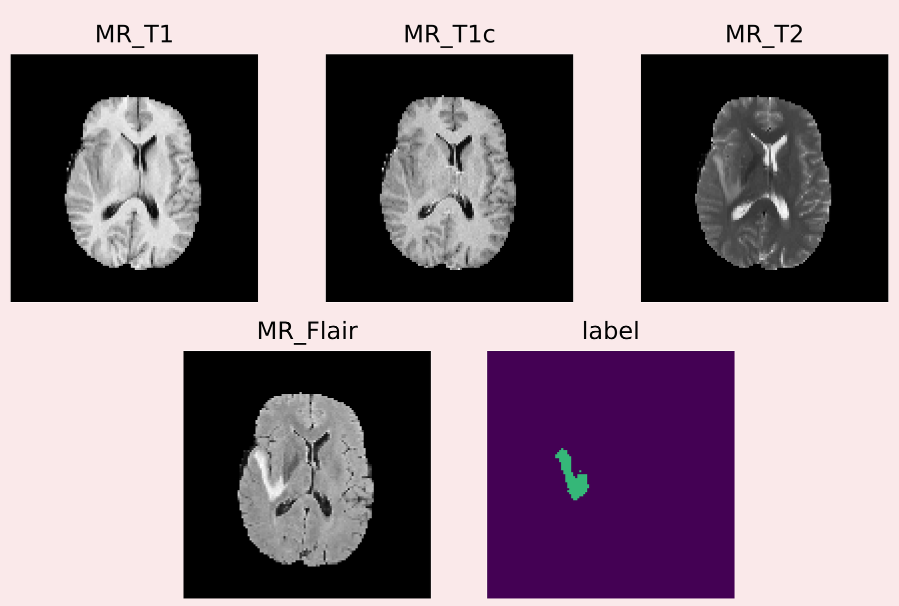
Motivation

- Brain tumors need immediate treatment
- Even experts can not segment perfectly
- Takes time to go through a complete MR scan

Efficiently and automatically segmenting tumors improves treatment planing

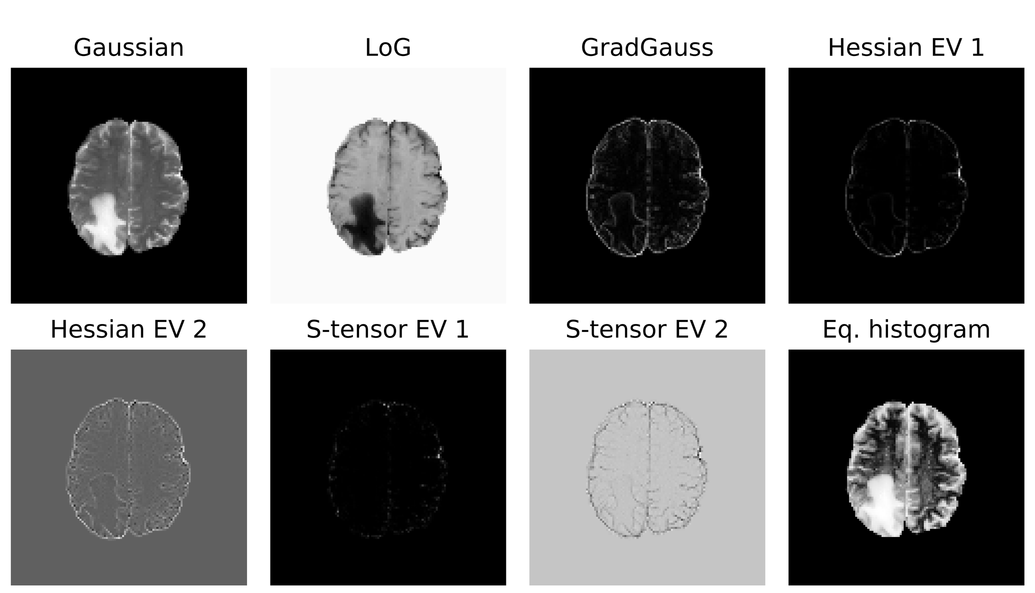
Dataset

- 3D MR scans of 275 human brains
- 4 scan types, T1, T1c, T2 and Flair
- $\text{depth} = 155$, $\text{height} = 240$, $\text{width} = 240$
- $\Rightarrow 170500$ images
- 5 classes (we only use 2: tumor/background)
- center-cropped to 80% of their size



Features

- Gaussian, LoG, Gaussian gradient
- Hessian and structure tensor eigenvalues
- equalized histogram
- 29 features in total
- 1k images + features ≈ 30 GB of memory



Random Forest [1]

- default settings of scikit-learn implementation
- trained in batch-mode
- 100 estimators per batch, 3 batches of 1k images

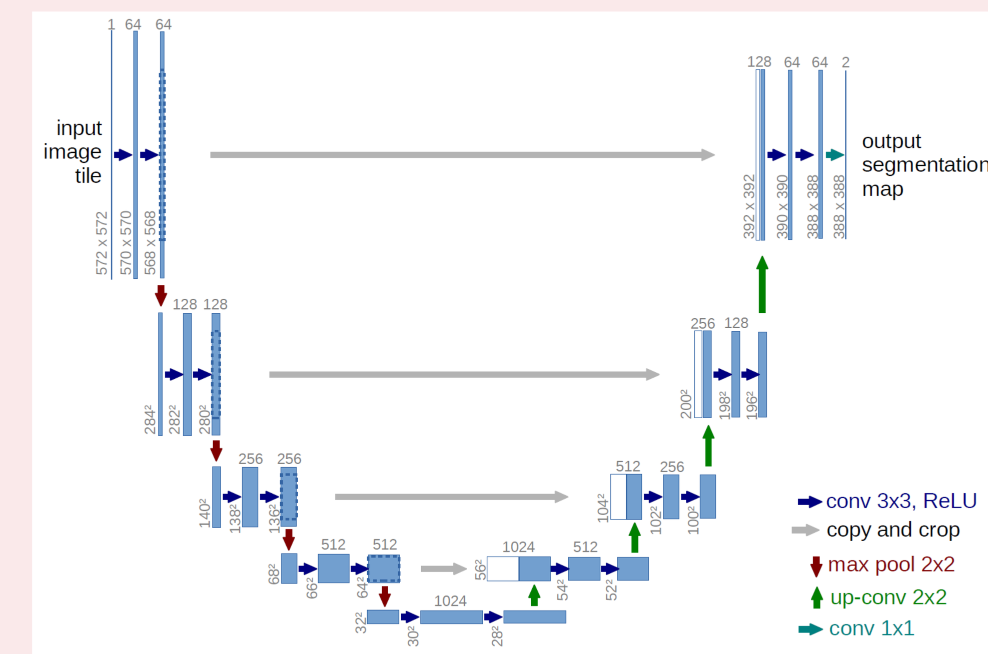
Advantages and disadvantages

- \+ Simple
- \+ Rarely overfits
- \+ Variable image input size
- \+ Optimized implementation available
- − No GPU training
- − No incremental training (for vanilla RF)
- − Features have to be hand-selected

U-Net [2]

modifications: depth = 4, loss = 1 - Dice, padding

Training: 10 images/batch, 30 epochs

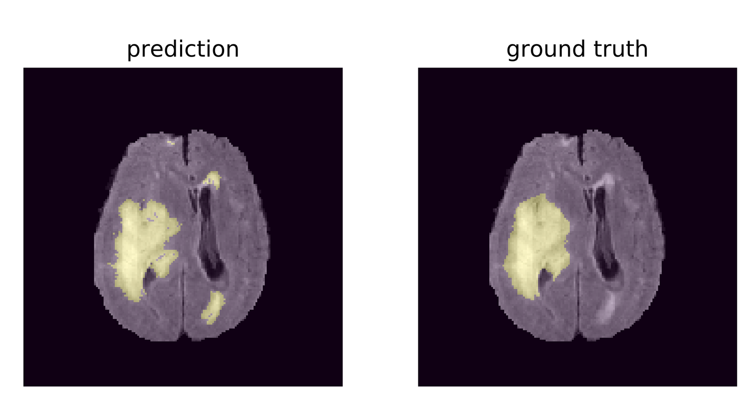


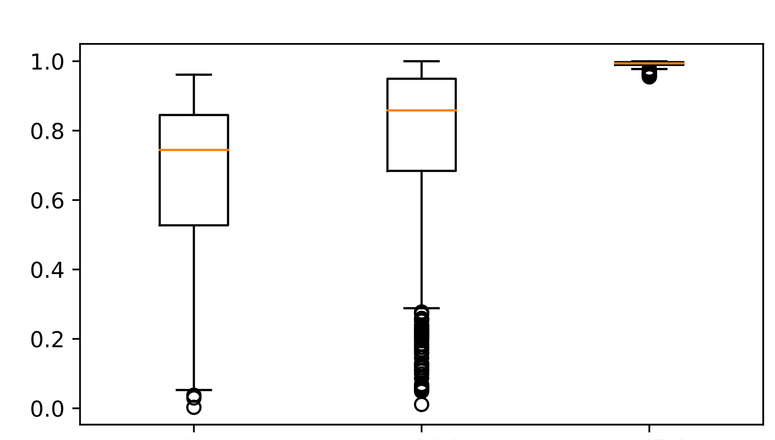
Final Scores

	Dice [%]	Sensitivity [%]	Specificity [%]
Random Forest	65.9	77.1	99.1
U-Net	69.3	73.1	99.4
winner 2017 [3]	90.1	89.5	-

RF: Results

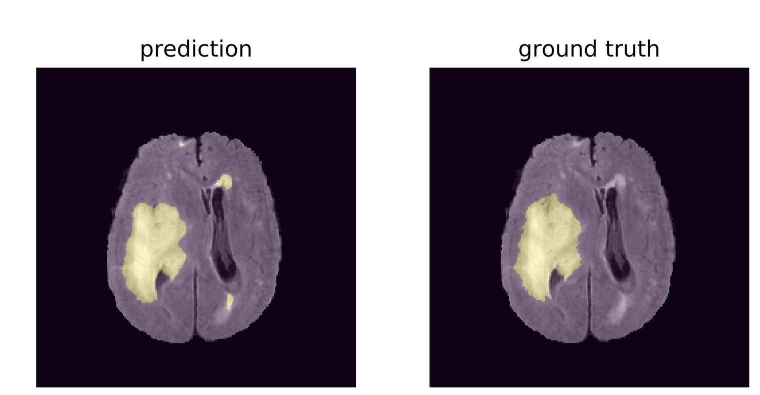
- training time ≈ 13 h
- inference time $\approx 2 - 20s$ per image
- load time $\approx 310s$
- disk space ≈ 15 GB (pickled)
- memory space during inference ≈ 20 GB

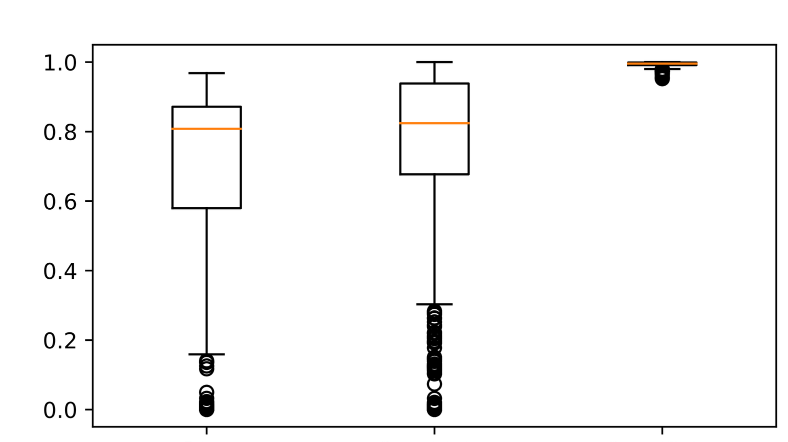




U-Net: Results

- training time ≈ 1.5 h
- inference time ≈ 0.5 s per image
- load time $\approx 20s$
- disk space ≈ 0.3 GB
- memory space during inference ≈ 0.7 GB



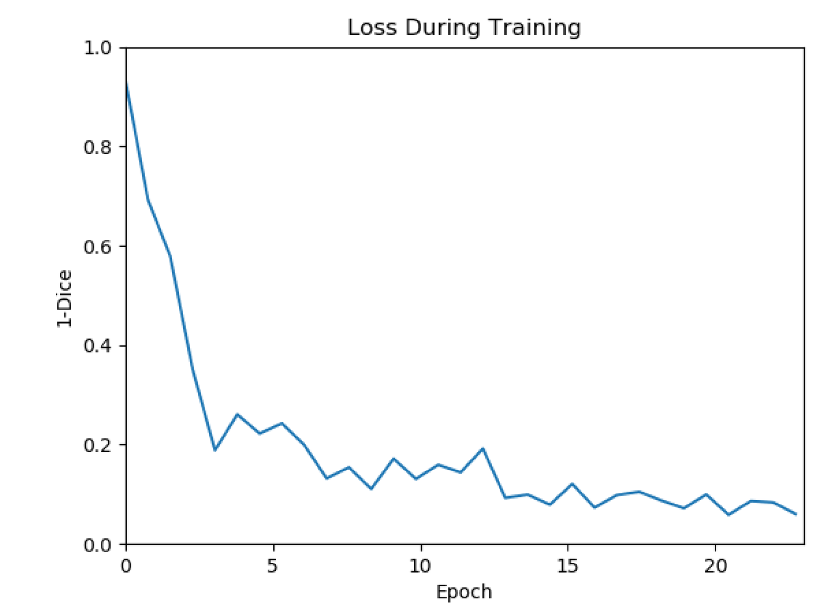


Loss

Dice score: $2\frac{|P_1 \cap T_1|}{|P_1|+|T_1|}$

P_1: tumor area of the prediction

T_1: tumor area of the ground truth



Conclusion

- Both methods achieve similar results regarding the scores
- Random Forest is easier to set up
- U-Net is easier and faster to train
- None of the two methods could achieve state-of-the-art results out of the box

References

[1] M. Ristin, M. Guillaumin, J. Gall, and L. Van Gool. Incremental learning of random forests for large-scale image classification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 38(3):490–503, March 2016.

[2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[3] Konstantinos Kamnitsas et. al. Ensembles of multiple models and architectures for robust brain tumour segmentation. *CoRR*, abs/1711.01468, 2017.

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