# Brain Tumor Segmentation with Random Forest and U-Net

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### Motivation

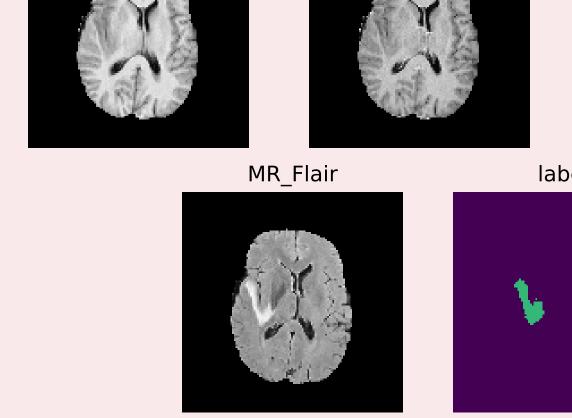
Brain tumors need immediate treatment Even experts can not segment perfectly

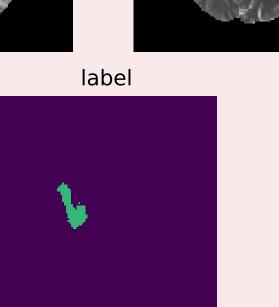
Takes time to go through a complete MR scan

Efficiently segmenting tumors automatically improves treatment planing

# Dataset

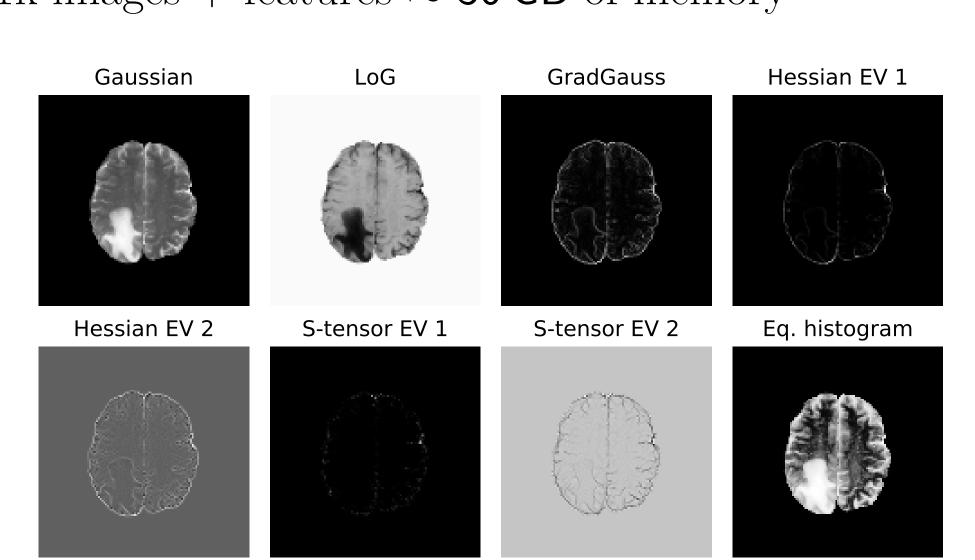
3D MR scans of 275 human brains 4 scan types, T1, T1c, T2 and Flair depth = 155, height = 240, width = 240 $\Rightarrow 170500 \text{ images}$ 5 classes (we only use 2) center-cropped to 80% of their size MR\_T1c MR\_T2





#### **Features**

Gaussian, LoG, Gaussian gradient Hessian and structure tensor eigenvalues equalized histogram 29 features in total 1k images + features  $\approx 30 \, \text{GB}$  of memory



#### Random Forest

trained in batch-mode [1] 100 estimators per batch, 3 batches of 1k images

Advantages and disadvantages

- + Easier to understand
- + Rarely overfits
- + Single pixel training
- No GPU training
- No incremental training (for vanilla RF)
- Features have to be hand-selected

## Methods

Results

# Additional Information

Conclusion

#### 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.

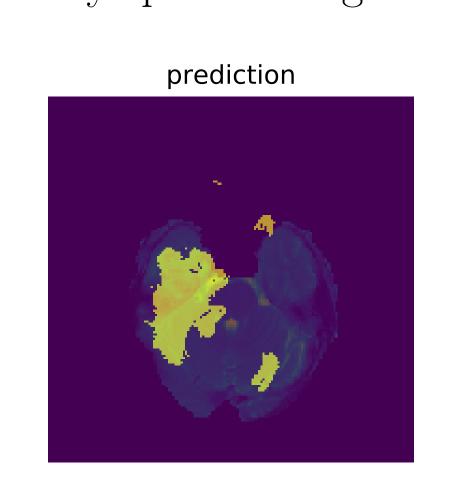
# Comparison

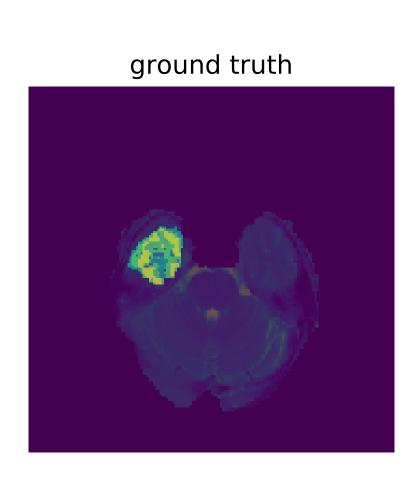
Dice [%] Sensitivity [%] Specificity [%] Random Forest 99.1 65.977.1

U-Net

#### RF: Results

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





### Acknowledgements

