O A T M L

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Uncertainty Evaluation Metric for Brain Tumour Segmentation

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@QUBraTS (Quantification of Uncertainty in Brain Tumour Segmentation)

MIDL 2020

Brain Tumour Segmentation

- Automatic tumour segmentation is of clinical importance
  - Diagnose and staging
  - Outcome prediction
  - Surgical planning

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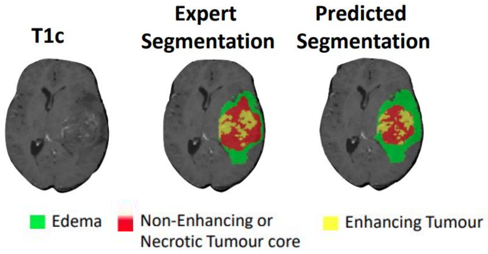

Ronneberger et. al., MICCAI 2015; Cicek et. al., MICCAI 2016; Kamnitsas et. al., MedIA 2016, BrainLes 2016; Isensee et. al., BrainLes 2018; Havaei et. al., MedIA 2017

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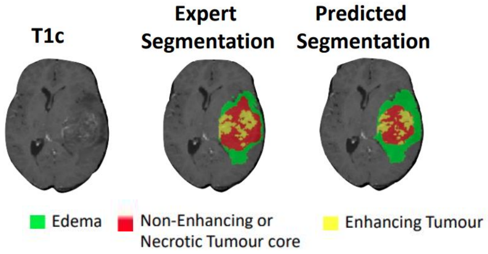

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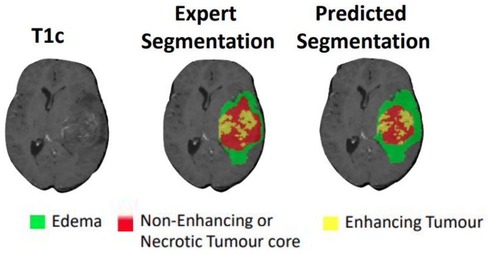

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- Tumour Segmentation problem is hard:
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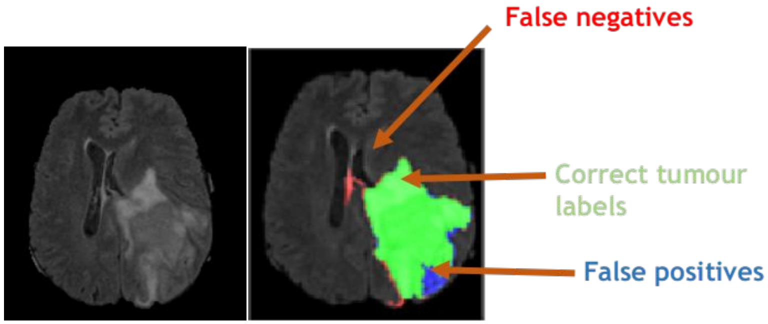
- **Deep learning models can make mistakes!**



Whole Tumour Segmentation

Ronneberger et. al., MICCAI 2015; Cicek et. al., MICCAI 2016; Kamnitsas et. al., MedIA 2016, BrainLes 2016; Isensee et. al., BrainLes 2018; Havaei et. al., MedIA 2017

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Segmentation of Brain Tumours - Uncertainty

- **Errors in** results of **machine learning** algorithms for segmentation of brain tumours can lead to
  - distrust by clinicians,
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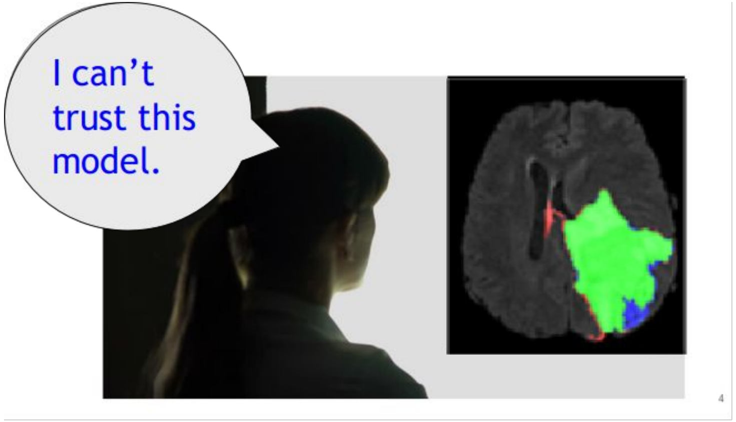

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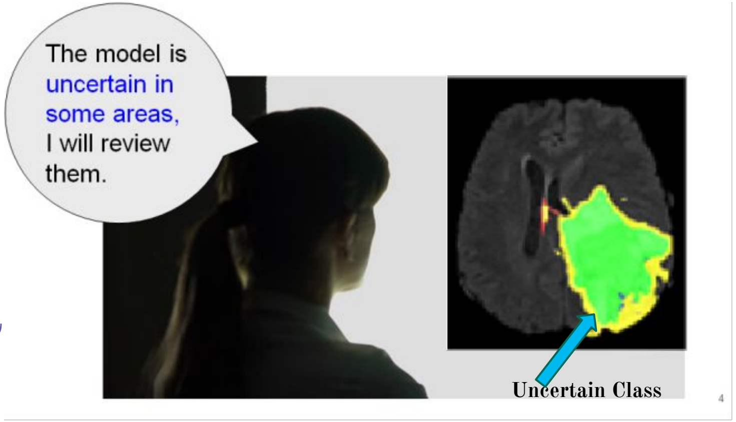

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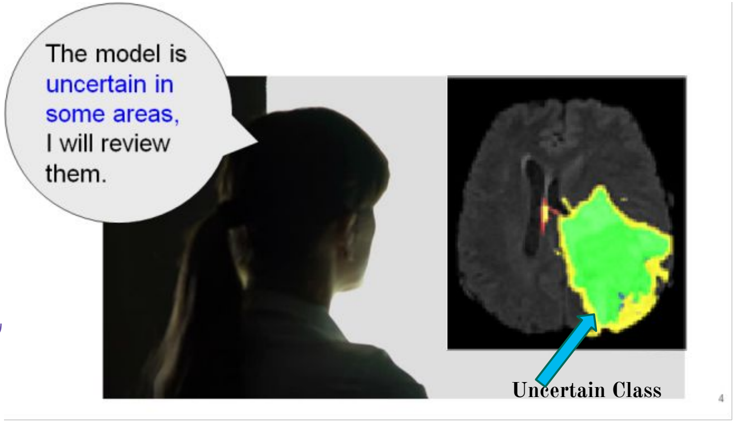
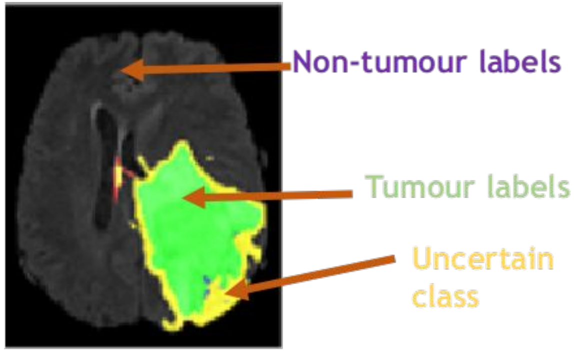
- **Bayesian Deep Learning** is useful for getting uncertainty [1,2,3]



[1] Gal and Ghahramani, "Dropout as a Bayesian approximation: Representing model uncertainty in deep learning.", ICML 2016.
[2] Kohl et al., "A probabilistic u-net for segmentation of ambiguous images.", NeurIPS 2018.
[3] Lakshminarayanan et al., "Simple and scalable predictive uncertainty estimation using deep ensembles.", NeurIPS 2017.

Uncertainty Analysis: Clinical Adoption

Goal: Uncertainty to enable clinicians, radiologists, surgeons to focus on **reviewing the most uncertain predictions** and **trusting the most confident predictions**



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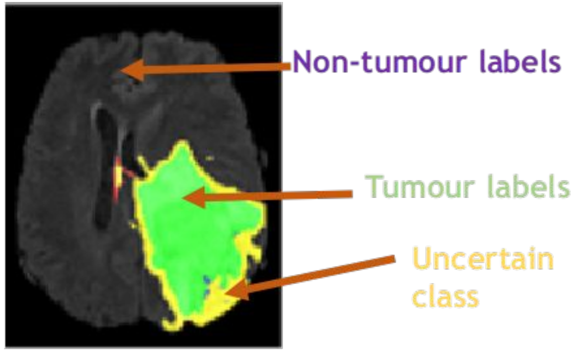
- Uncertainty metric **must** have the following properties:

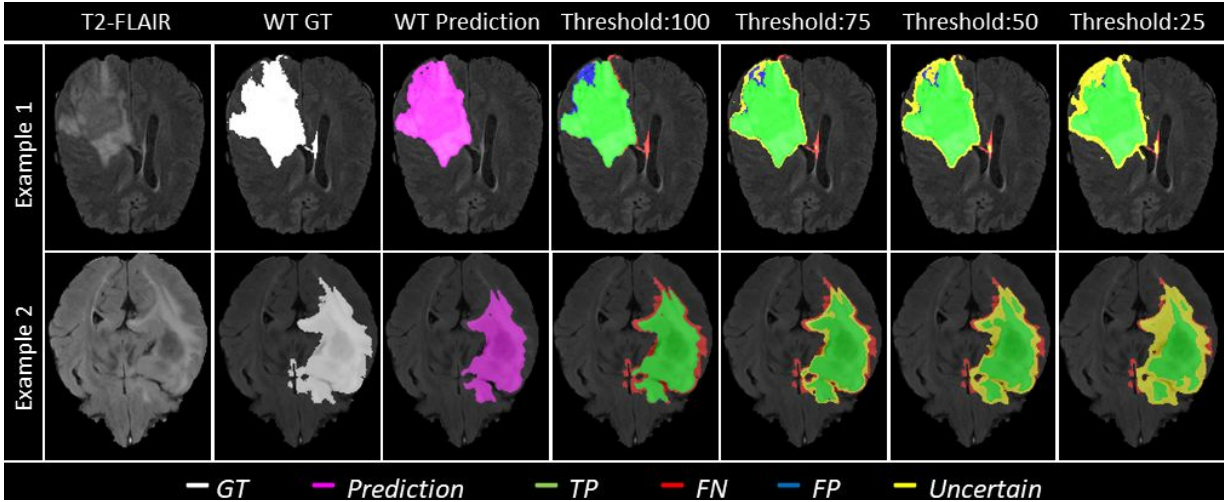
Confident predictions → Correct predictions

Incorrect predictions → Higher Uncertainties



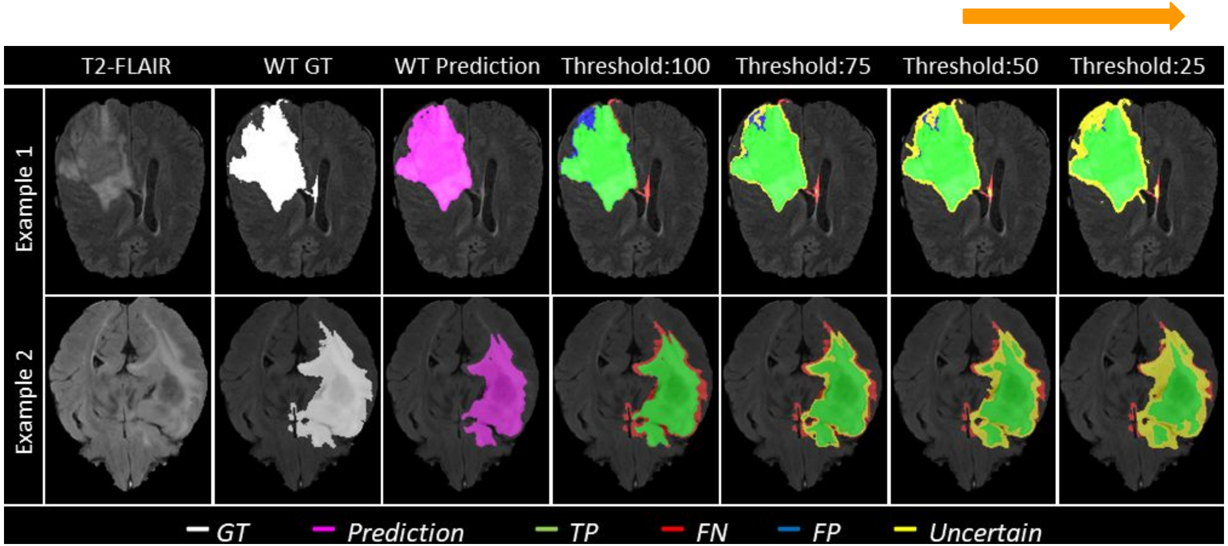
Quantification of Uncertainty for BraTS

- Compute the **uncertainty** of a model **at each voxel**



Quantification of Uncertainty for BraTS

- Compute the **uncertainty** of a model **at each voxel**
- Filter most uncertain voxels, calculate the metric of interest (e.g. **Dice**) on the remaining one. **Should Improve!**



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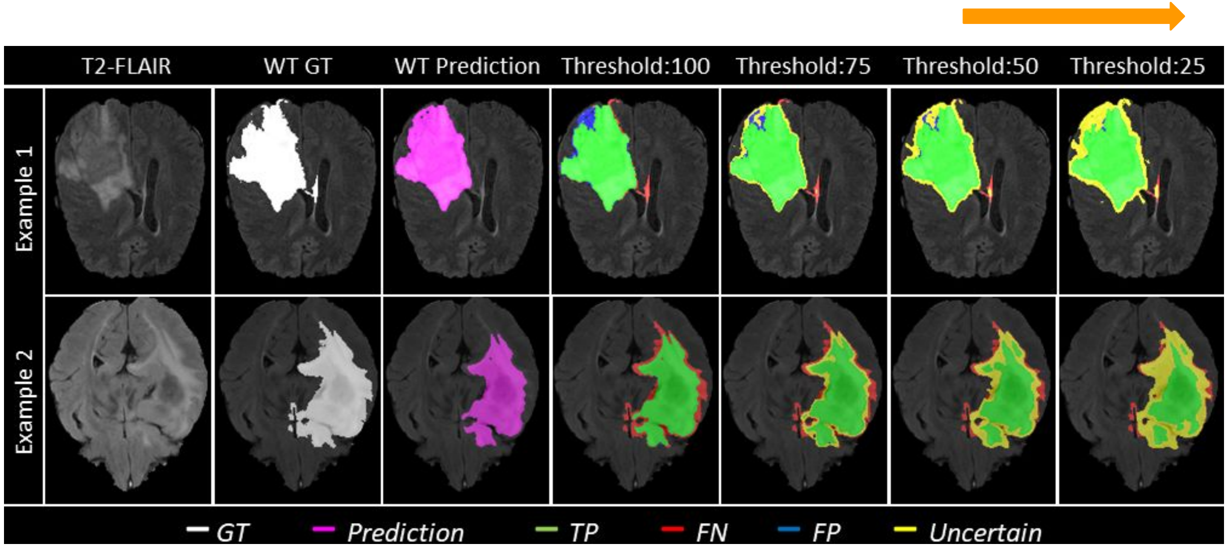
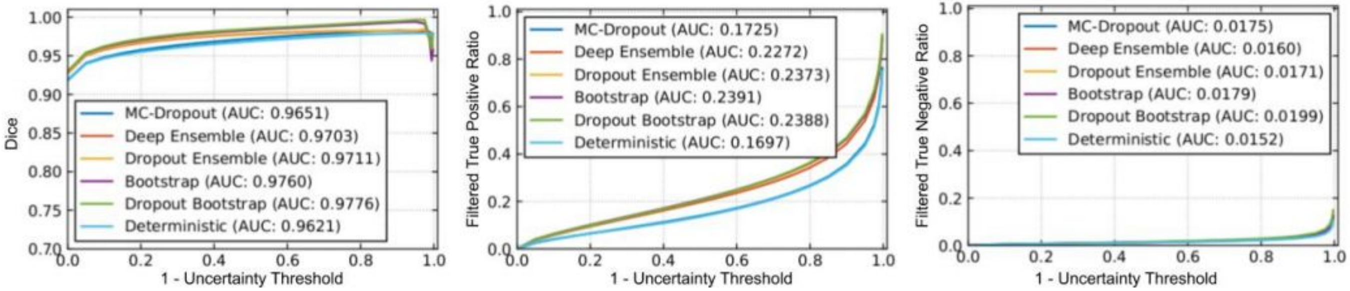
- Not at the **expense of filtering out correct predictions!**
  - Penalize methods for higher filtering of correct predictions.



Benchmark Results (Entropy - whole tumour)

- 3D U-Net architecture [1]
- Brain Tumour Segmentation (BraTS) 2019 [2] Training set (335):
- Performances of whole tumour segmentation with the Entropy uncertainty measure [3]
- Comparison of various uncertainty generation methods:
  - MC-Dropout [4]
  - Deep Ensemble [5]
  - Dropout Ensemble [6]
  - Bootstrap
  - Bootstrap Ensemble



1. Cicek et al., MICCAI 2016
2. Bakas et al., arXiv:1811.02629, 2018
3. Gal et al., ICML 2017
4. Gal and Ghahramani, ICML 2016
5. Lakshminarayanan et al., NeurIPS 2017
6. Smith and Gal, arXiv:1803.08533

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Thank You

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