Deep Active Learning for Myelin Segmentation on Histology Data

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Introduction

Context:

Histology data often require segmentation of microstructure (e.g. axons, myelin in spinal cord).

Problem 1:

Manual segmentation is long, tedious, and user-biased.

▶ **Solution**:

Deep learning methods offer highest performance for multi-class segmentation.

Problem 2:

Deep learning requires large amounts of data and labels to train new models (high sample complexity).

▶ **Solution**:

Active Learning [1] enables a learning algorithm to obtain **similar performance** (when compared to pure supervised learning) **with less manual labeling,** by selecting specific data points (uncertainty sampling in this work).

Goal:

Develop an open-source active learning framework for segmenting myelin from histology data based on uncertainty sampling.

Methods

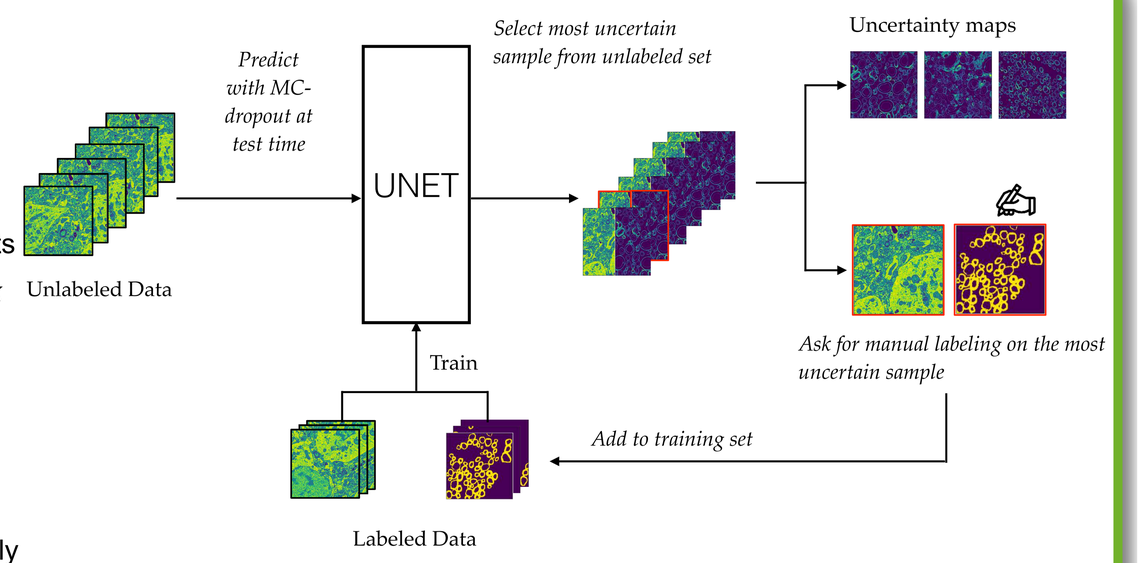
Active Learning framework

Objective:

- Minimize expert's time and effort for data labeling
- Improve a model's performances on small datasets
  - ▶ *Wisely select the samples to train the network*

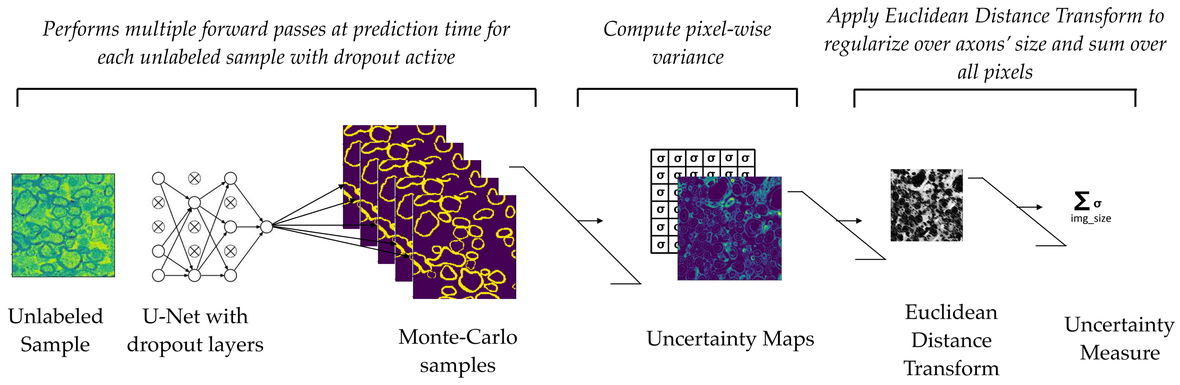
Method: *(Based on CEAL framework [2])*

1. Train U-Net [3] with SMALL initial dataset
2. Use MC-Dropout to compute uncertainty on unlabelled data and RANK it
3. Select MOST UNCERTAIN sample to be manually annotated by an oracle and add to the training set
4. Re-train U-Net from scratch, iterate



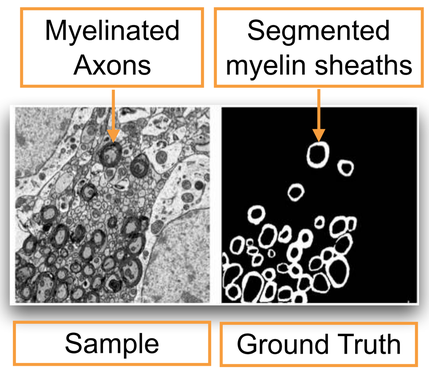
Monte Carlo Dropout

- Easy-to-use, scalable technique to evaluate uncertainty [4] [5]
- Keep dropout layers active at PREDICTION TIME
- Sample predictions to approximate posterior distribution
- Compute pixel-wise standard deviation for multiple predictions.



Results

I. Dataset



Dataset samples

Mouse brain histology observed with Transmission Electron Microscopy (TEM)

II. Myelin segmentation - TEM Dataset [6]

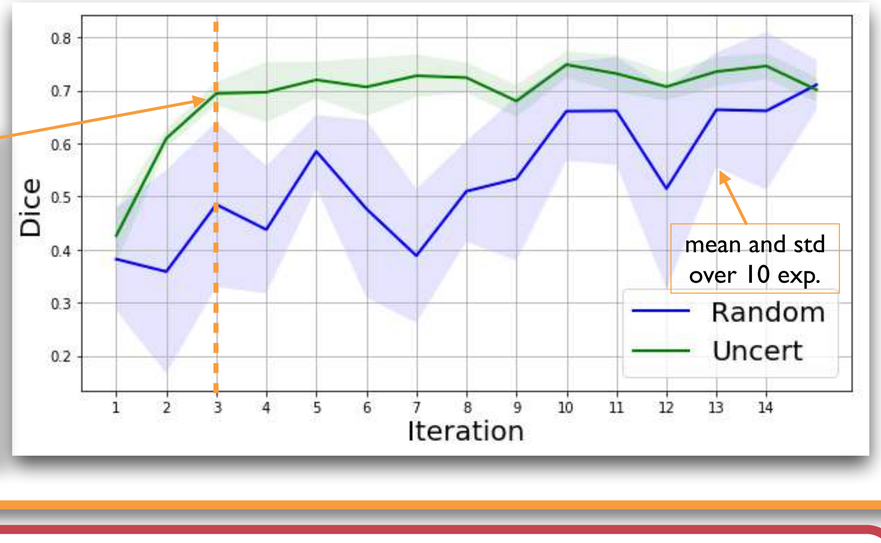
Experimental setting:

- **Initial training set size**: 5 patches (512x512 pixels)
- Adding the **most uncertain sample** (among 26 unlabeled ones) after each iteration
- **Baseline**: Random sampling
- Experiments are repeated 10 times, then averaged
- **Evaluation** with Dice coefficient (the higher the better):

$$\text{Dice} = \frac{2(A \cap B)}{|A| + |B|}$$

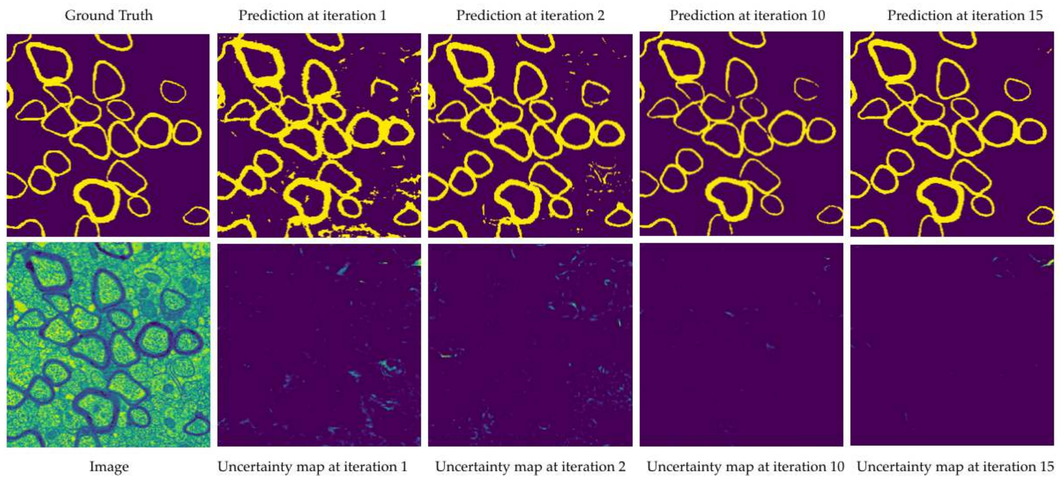
Results: Significant reduction in annotation effort for similar performance.

After only 3 manual patches, the "Uncert" reaches best performance (versus ~15 for the "Random" selection).

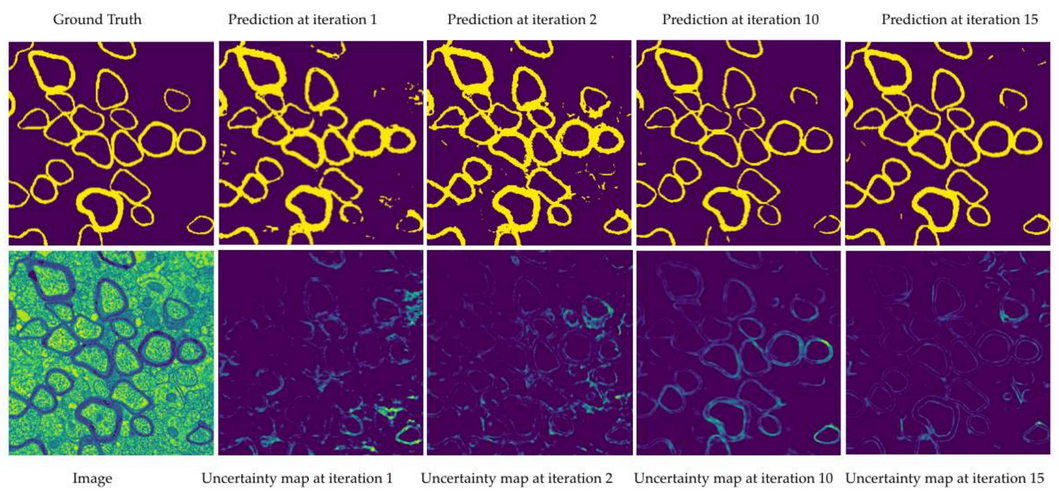


III. Uncertainty Maps

- Each pixel = *variance* of MC-samples' predictions
- Choice of *loss function* impact the *aspect* of the uncertainty maps
- Highlights areas and features on which the model tends to fail
- **Weighted cross-entropy**: uncertainties about the object borders (here: myelin thickness)
- **Dice loss**: uncertainties about other brain microstructures



Evolution of Uncertainty Map when U-Net trained with **Dice Loss**



Evolution of Uncertainty Map when U-Net trained with **Weighted Binary Cross Entropy**

Conclusion

- Active learning can converge to **high performances** with **less data**
- Although it was shown that MC Dropout uncertainty measure [5] doesn't concentrate with more data, the uncertainty metric was proved to yield good results in the active learning context.
- Uncertainty estimation is linked to the **loss function**
- Code is available as open source: https://github.com/neuropoly/deep_active_learning

Future work:

- Explore uncertainty maps benefits
- Explore other uncertainty measurements (such as anchored ensembles)
- Implement method in open-source software package *AxonDeepSeg* [7]

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