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Deep ensemble model for segmenting microscopy images in the presence of limited labeled data

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Introduction

- Supervised Learning assumption = data is ***i.i.d***
- Small dataset are mostly not ***i.i.d***
- Current ensemble models focus more on differences in the ***models*** than ***data***
- Class imbalance/various annotators → multiple data ***modes***

Objective:

Creating deep ensemble model which takes advantage of different modes in the data therefore being able to perform efficient 2D segmentation.

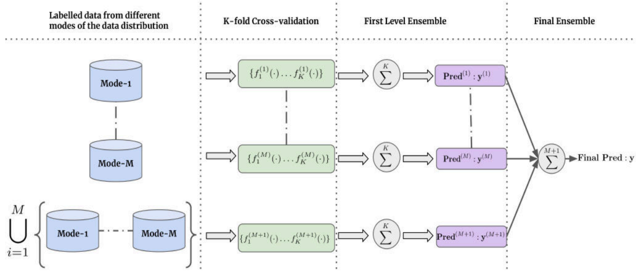
METHOD

Training data partitioning:

- **Partitioning of data into M modes performed based on expert knowledge or non-overlapping different raters**
- **Complete dataset as additional mode**

Deep ensemble model

- **k-fold cross-validation for each data mode**
- **(M+1)*K identically structured segmentation models**
- **First level ensemble is a combined segmentation for each mode**
- **Final ensemble is combined from all mode-level predictions with (M+1)*K discrete prediction levels**

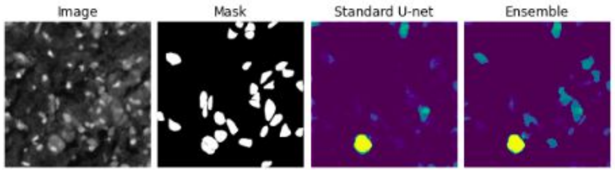


$$\mathbf{y}^{(m)} = \frac{1}{K}\sum_{k=1}^{K}[f_k^{(m)}(\mathbf{x}) > 0.5] \qquad \mathbf{y} = \frac{1}{(M+1)}\sum_{m=1}^{M+1}\mathbf{y}^{(m)}$$

Pipeline for the proposed Deep Ensemble model. The training dataset is split into M partitions; an additional combined dataset is obtained comprising all M partitions (last row). Each of these M + 1 partitions are trained in a K-fold cross validation setting. Predictions from each cross-validation are aggregated to obtain the first level ensemble prediction. Finally, the M + 1 predictions are combined to output the final model prediction.

Data & Experiments

- High-resolution, greyscale mice spinal cord microscopy images
  - acquired at 2 different timepoints; 1st- (P1) and 28th-(P28) postnatal day
  - images divided into patches of size 512x512;
  - 52 training patches with sparse labels; 2% of dataset
  - 4 test images fully annotated
- Standard U-net and Seeded Region Growing (SRG) for baseline
- 2 data modes and 15 separate U-nets trained in the ensemble
- DICE loss and F1 score as metrics



Example of a test image with the corresponding mask, standard U-net segmentation result and ensemble segmentation result.

Method	F1 score
Ensemble model	$\mathbf{0.64 \pm 0.10}$
Standard U-net	0.53 ± 0.02
SRG	0.59 ± 0.18

Average F1 score obtain over test data for the ensemble model, Standard U-net and SRG with threshold of t=0.06.

Conclusions

- The proposed ensemble improves the F1 score by ≈0.1 compared to standard U-net
- Best F1 score obtained with threshold of 0.06 implies that all models are usefull
- We hypothesise that proposed model is most useful under the non i.i.d data regime; the diversity is achieved by learning on different modes of data distribution

References
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