Automated fetal brain segmentation of 2D magnetic resonance images: transfer learning and 3D topology correction

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BACKGROUND

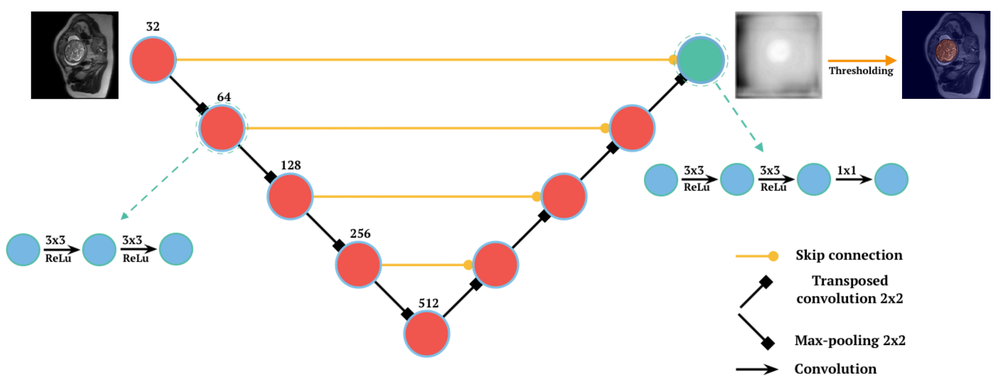
- **Fetal brain extraction in MRI**: first step for further processing (super-resolution reconstruction, tissue segmentation, etc.)
- Manual annotations are cumbersome and time consuming, and hence inappropriate to automated analysis and large-scale studies.
- **Deep learning** is an *Artificial Intelligence* branch that has proven to be very successful in image processing, including fetal brain segmentation[1-3].

Automated brain segmentation of a fetus of 26 gestational weeks

- Deep learning limitations:
  - Need of a **large amount of labeled data**
  - Highly **specialized models**
- **Transfer learning** can partially help to overcome these caveats.
- ***Aim:*** To evaluate transfer learning for segmenting the fetal brain from one dataset (Lausanne University Hospital, **CHUV**) using the pre-trained parameters of a larger dataset (Boston Children Hospital's, **BCH** [1]).

MATERIALS AND METHODS

- 2D convolutional neural network U-Net[4].



Network

- U-Net architecture[4] with ~8 million parameters
- Weighted-cross entropy loss function
- Trained with Adam optimiser for ~200 epochs

- Model evaluation in a **leave-four-out cross-validation** using an average of *precision* and *recall*

Our dataset (CHUV)

- 39 subjects
- From 20 to 36 weeks of gestation
- Orthogonal T2-weighted HASTE at **1.5T**
- 227 series totalling **4,767 slices**
- 1.125 mm in-plane isotropic
- 3 to 5 mm slice thickness

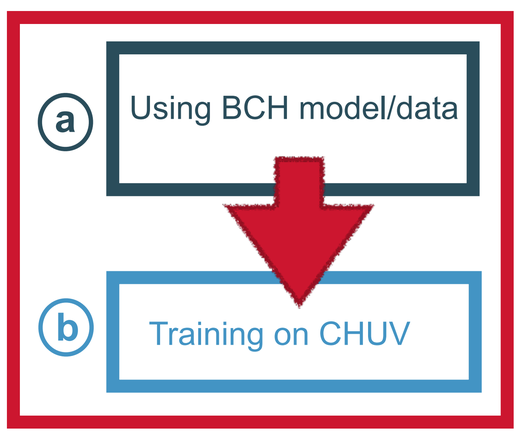
BCH dataset

- 41 subjects
- From 22 to 38 weeks of gestation
- Orthogonal T2-weighted SSFSE at **3T**
- 385 series totalling **~13,000 slices**
- 1 to 1.125 mm in-plane isotropic
- 2 to 3 mm slice thickness

- We evaluate **three scenarios**:

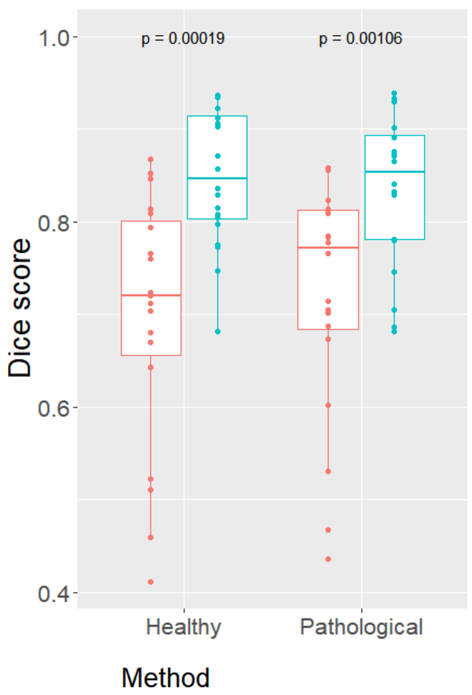
a. Using BCH pre-trained parameters[1] to test on CHUV dataset;
b. Solely training on CHUV data, with **random initialization**;
c. Fine-tuning the network with the **pre-trained** parameters of [1].

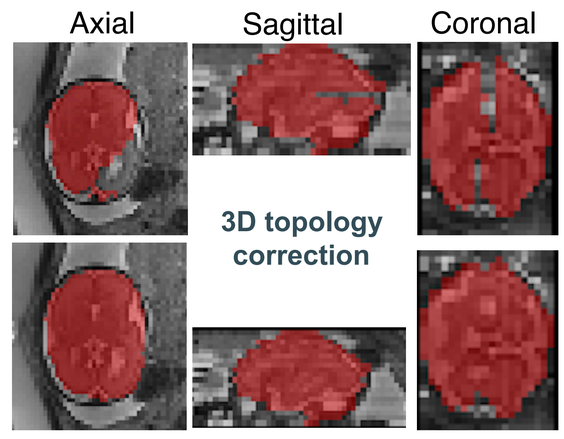
- Post-processing: **3D continuity** of the brain to refine the predictions by **morphological operations** such as closing, opening and connected components.



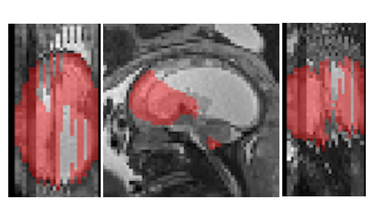
RESULTS

- Directly applying the pre-trained weights (a) from [1] to our dataset generated non plausible segmentations.
- The pre-trained network (c) significantly outperforms the randomly initialized (b) network in both healthy and pathological subjects (Wilcoxon test, $p<0.05$).
- Remaining errors: 1) at extremities of the brain, 2) slices containing the temporal lobe.
- The 3D topology correction did help qualitatively but not quantitatively.

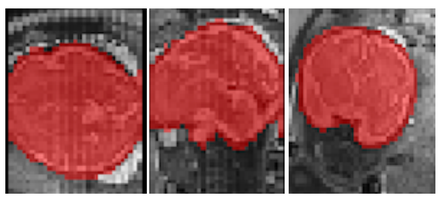




Underperformance (ventriculomegaly)



Good performance (healthy)



CONCLUSION

- Feasibility of using a different scanner/magnetic field strength through transfer learning.
- Hospitals lacking of a large amount of data can benefit from pre-trained parameters from other hospitals to boost their models.

REFERENCES: [1] Salehi et al., ISBI 2018; [2] Lou et al., MLMI 2019; [3] Rutherford et al., bioRxiv 2019; [4] Ronneberger et al., MICCAI 2015.
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