Student Intern Presentation (NeuroIm Lab)

Milton O. Candela-Leal

Fetal-Neonatal Neuroimaging and Developmental Science Center (FNNDSC)

Milton.CandelaLeal@childrens.harvard.edu
milton_candela@hotmail.com

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Overview

Section 1

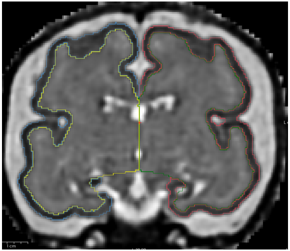
Fetal MRI

Manual MRI segmentation correction

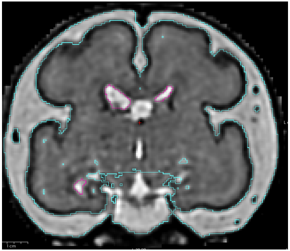
Dataset	n	Year
Placenta/CHD	20	'23
dHCP	31	'23
High-res CP	15+2	'23
VM	30+10	'23
CSF	19	'24
Ventricle	19	'24
High-res SP	63	'24
Coordinated high-res SP	(68)	'24
	209 (277)	

Examples

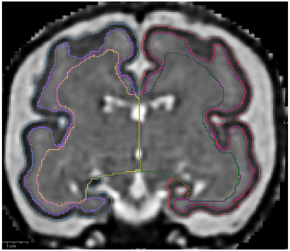
Cortical Plate



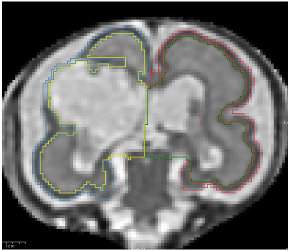
CSF & Ventricle



Subplate



Ventriculomegaly

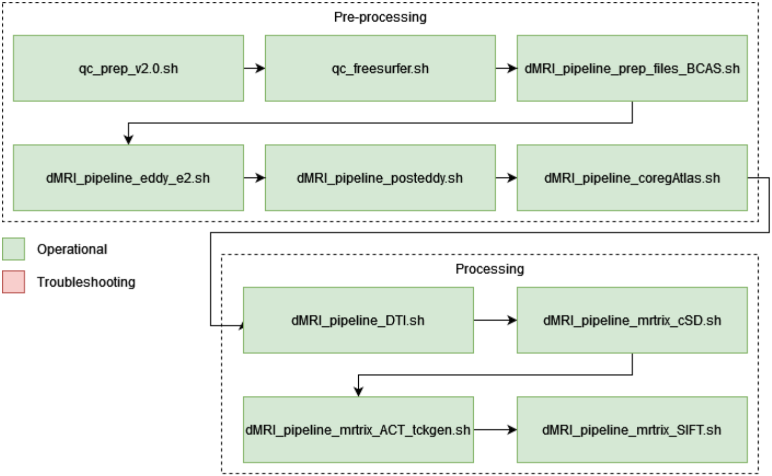


Section 2

Fetal dMRI

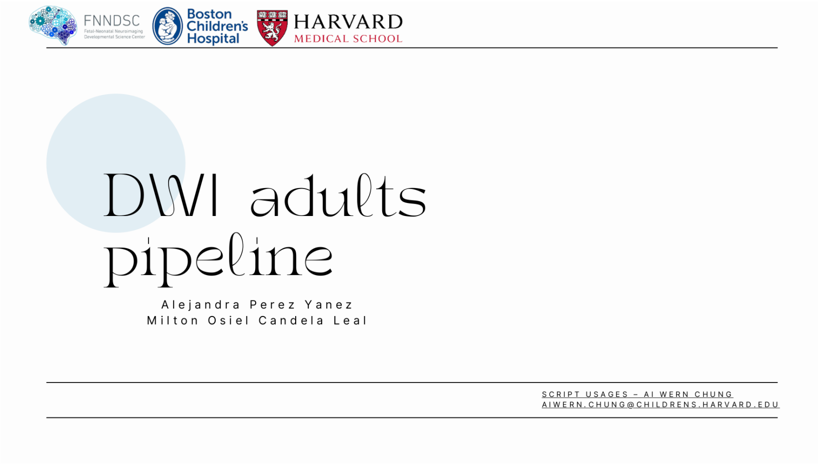
In collaboration with Alejandra Pérez Yañez (BSc)
Supervised by Kiho Im (PhD)

Flow diagram



- Ran Ai Wern Chung (PhD) pipeline for adult dMRI.
- Consolidated requirements in a single *conda* environment (/MRI_processing/fetal_dMRI/dMRI_env) activated by dMRI_pkg.

Manual



Documented inputs and outputs of Chung's pipeline in a 56-slides presentation. (github.com/miltoncandela/miltoncandela.github.io/fetaldmri_pipeline.pdf)

Issues on fetal dMRI

The DTI pipeline need further testing in fetal dMRI data due to:

- bvals and bvecs being different in:
  - Range: [0, 1000, 2000, 3000] in adults, [0, 500] in fetus
  - Size: 60 in adults, 12 in fetus
- Fetal DWI being noiser.

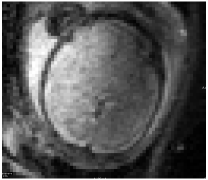


Figure: BRAIN

Figure: TRACEW

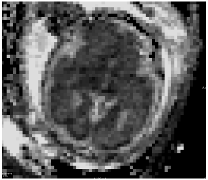


Figure: ADC

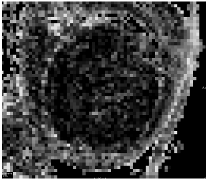
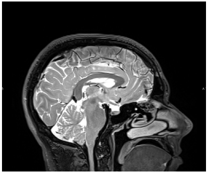
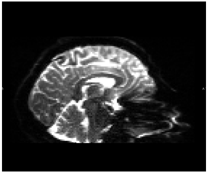


Figure: FA





Section 3

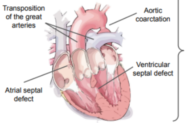
qMRI CHD Classification

In collaboration with Samantha A. Esparza Esparza (BSc)
Supervised by Sungmin You (PhD)

Introduction

Congenital Heart Disease (CHD)

Examples



- Reduced oxygen supply
- Altered blood flow dynamics
- Neuroinflamation

[1]

Early detection relevance

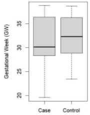
Enhanced Prenatal Counseling

Potential for discovery of **unique biomarkers** indicative of CHD impact on fetal brain

Non-linear Combined qMRI Features Generation and Selection

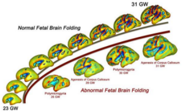
Cohort composed of:

- 96 CHD MRI (mean = 31.38 weeks, sd = 4.80)
- 62 TD MRI (mean = 32.38 weeks, sd = 4.17)



Age-adjusted qMRI features

As Gestational Weeks (GW) is a cofounding variable in fetal MRI

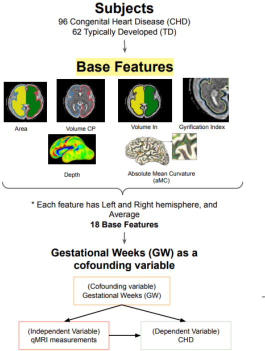


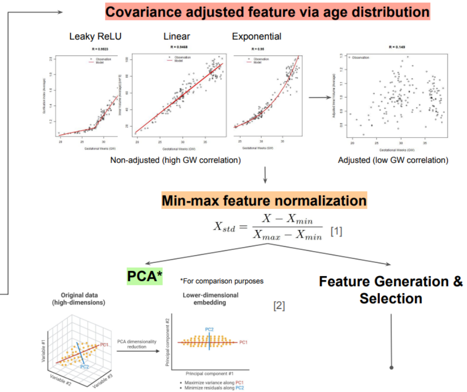
[2]

[1] Khalil et al ., *Ultrasound Obstet Gynecol.*, 2016
[2] Im., Advances in Magnetic Resonance Technology and Applications., 2021

Presented by Samantha last week.
Symposium slides: miltoncandela.github.io/chd_slides.pdf

Data pre-processing





[1] Candela-Leal et al., *Appl. Sci.*, 2022
[2] Blanco-Rios and Candela-Leal et al., *Front. Hum. Neurosci.*, 2024

Data processing

Non-linear feature transformations [1]

Name	Quadratic	Cube	Inverse	Logarithm	Inter-hemisphere	Intra-hemisphere	Difference
Description	F^2	F^3	$\frac{1}{F+1}$	$ln\|F + 1\|$	$\frac{F_L}{F_R+1} \| \frac{F_R}{F_L+1}$	$\frac{F_{VolCP_L}}{F_{VolIn_L}+1}, \frac{F_{VolIn_L}}{F_{VolCP_L}+1}, \frac{F_{VolCP_R}}{F_{VolIn_R}+1} \| \frac{F_{VolIn_R}}{F_{VolCP_R}}$	$F_L - F_R \| F_R - F_L$
Left/Right Hemisphere	×	×	×	×	×	×	×
Average	×	×	×	×			
Volume CP or In only						×	

+ 100 NL Features

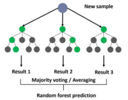
Combined Feature Creations

Division → 13, 806 [2]	*Multiplication* → 6, 647 [3]
Pairwise combinations with order	Non-repeating pairwise combinations with repetition
$(n \cdot (n-1))$	$\frac{(n \cdot (n-1))}{2}$

+ 20,453 Combined Features

= 20,571 Total Features

Random Forest (RF) Feature Selection [4]



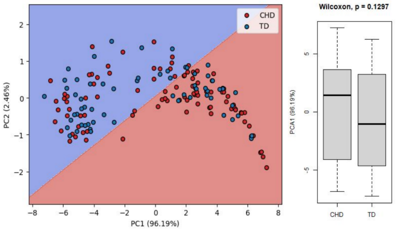
Best 14 Features

kNN model fitting [5]

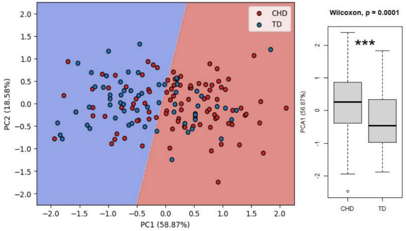
[1] Aguilar-Herrera et al., *ML-DT Edu. Innovation Workshop*, 2021
[2] Ramírez-Moreno et al., *Int. J. Environ. Res. Public Health*, 2021
[3] Olivas-Martínez et al., *ML-DT Edu. Innovation Workshop*, 2021
[4] Candela-Leal et al., *IEOM-NA VI*, 2021
[5] Shon et al., *Int. J. Environ. Res. Public Health*, 2018

Better differentiation at PCA components

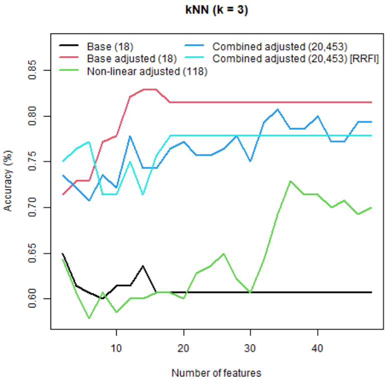
Base features

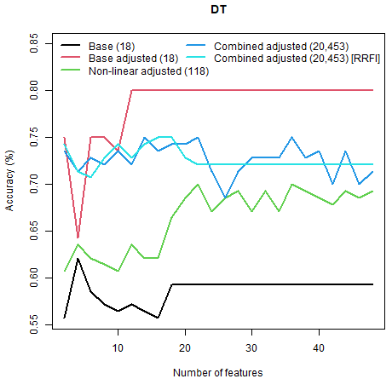


Adjusted features



Increase in model's performance



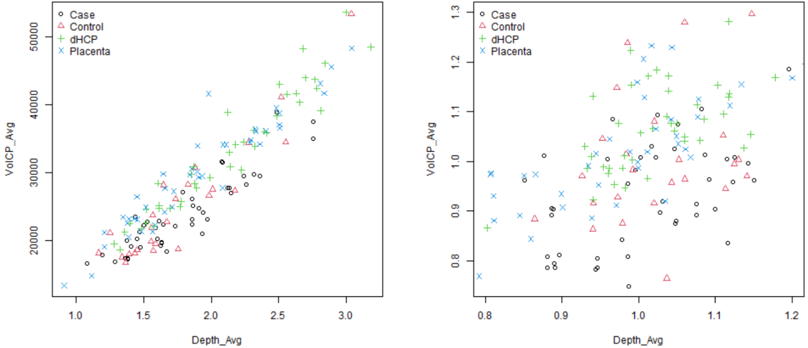


Adjusted features:

- Significantly outperformed non-adjusted features (+20% accuracy).
- Greatly outperformed combined adjusted features (+5% accuracy).

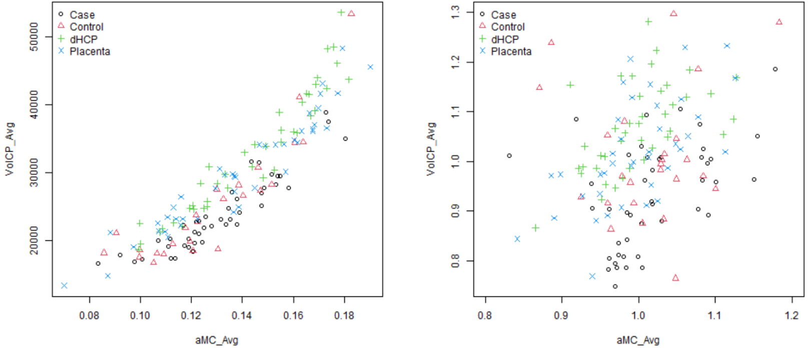
Adjusting only the right features (VolCP, Depth)

(Left) Non-adjusted, (Right) Adjusted



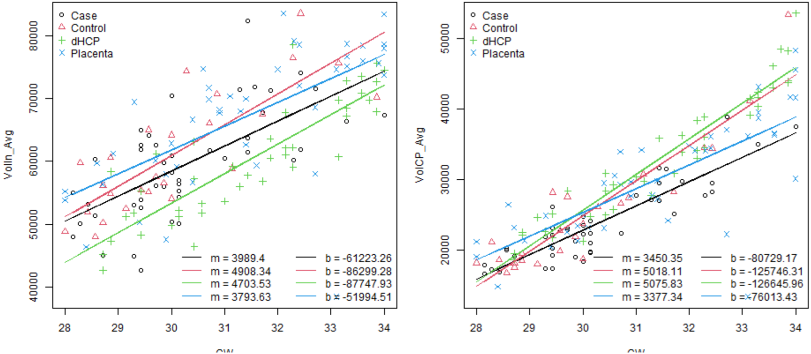
Adjusting only the right features (VolCP, aMC)

(Left) Non-adjusted, (Right) Adjusted



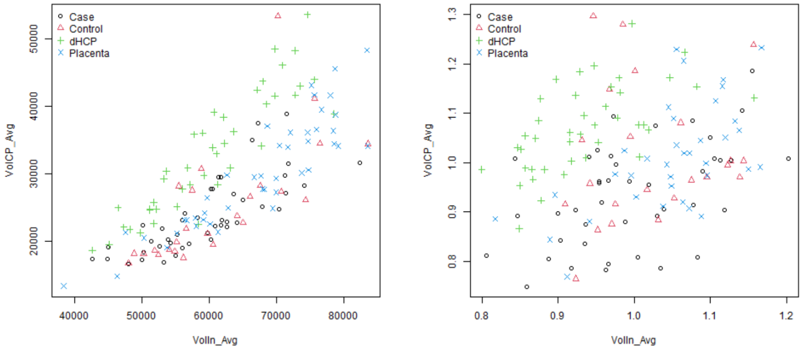
Which features shouldn't be adjusted?

VolIn: Different b across datasets.



Clusterized behavior when adjusting VolIn

(Left) Non-adjusted, (Right) Adjusted



Section 4

High-resolution Subplate

Supervised by HyukJin Yun (PhD)

Overview

Subplate (SP) in fetal brain is a **transitory** compartment[1,2] that lasts until 31 weeks of gestational age (GA)[3,4], and it is critical for **brain development**[5], **cortical circuitry** and **structure**[2,6].

Objective

- **Upsample** and **auto-smooth** existing low-resolution (0.86 mm) SP dataset (n=82) to high-resolution (0.5 mm), via IRTK and **Gaussian Smoothing**
- **Train** a high-resolution **U-Net model** for **automatic** SP, cortical plate (CP), and inner part (IP) **segmentation**

Benefits

- More **detailed delineation** of brain tissues such as the SP, CP, and IP
- More accurate SP **volume & thickness**

[1] Serati et al., *Neuroscience*, 2019
[2] Kostovic et al., *Int. J. Dev. Neurosci.*, 2010
[3] Vasung et al., *Cereb. Cortex*, 2020
[4] Rados et al., *Eur. J. Radiol.*, 2006
[5] Allendoefer and Shatz, *Annu. Rev. Neurosci.*, 1994
[6] Luhmann et al., *Front. Neural Circuits*, 2016

Procedure

First

1. De-anonymize SP data (n=51) [BCH_XXXX_s1]
2. Search for their native files in Placenta, Normative, CHD, and TMC folders
3. Make a reconstruction in 0.5 mm using NeSVoR
4. Upsample, align, and apply BGS to the SP data
5. Train pre-initial model (n=40) by proposing the usage of transfer-learning on the high-res CP model (n=114)

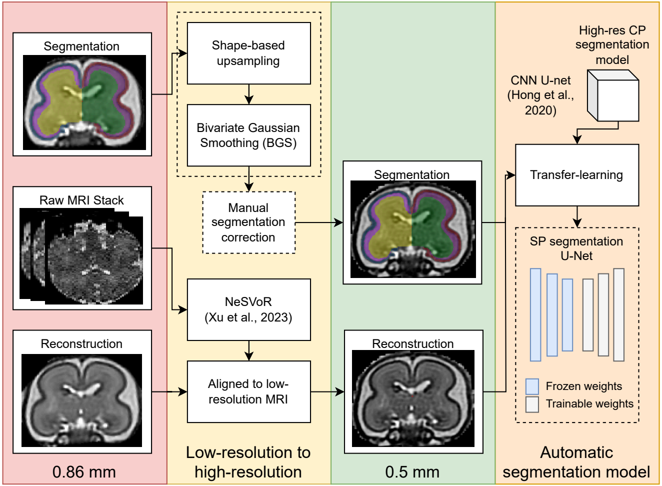
Then

1. Predict and correct the segmentation of low-quality subjects (n=9)
2. Train transfer-learning initial model (n=49), and predict on misaligned (n=14) and high-res CP data (n=71) to distribute to other interns

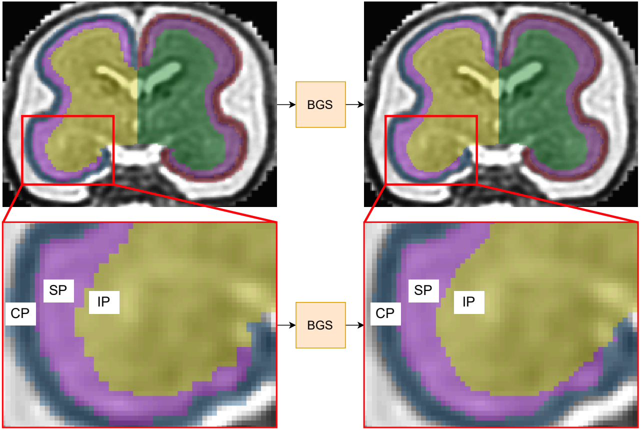
Finally

1. Correct misaligned (n=14) while supervising interns' manual corrections
2. Train final model (n=120) and test on a multi-site hold-out dataset

Flow diagram



Bivariate Gaussian Smoothing (BGS)



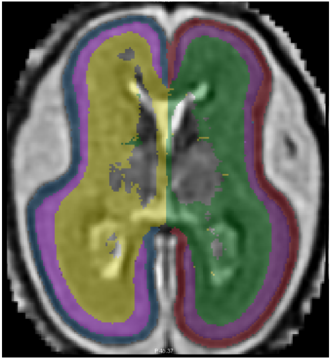
Univariate GS for IP mask **(dilatation)**

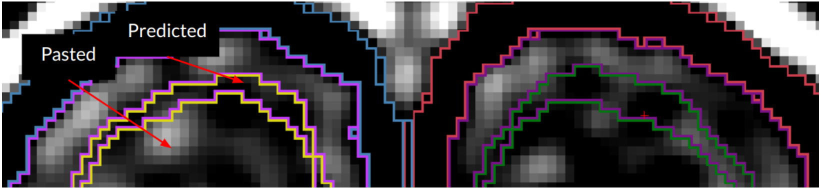
$$G(x, y, \sigma)_{ip} = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Univariate GS for -IP mask **(erosion)**

$$G(x, y, \tau)_{-ip} = \frac{1}{2\pi\tau^2} e^{-\frac{x^2+y^2}{2\tau^2}} \quad (2)$$

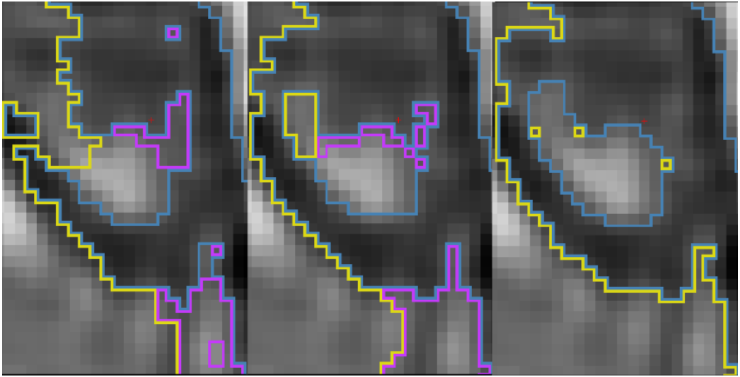
Misaligned & bad quality data prediction (n=40)

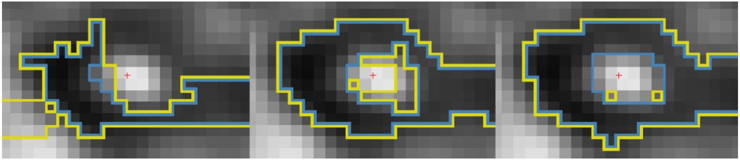




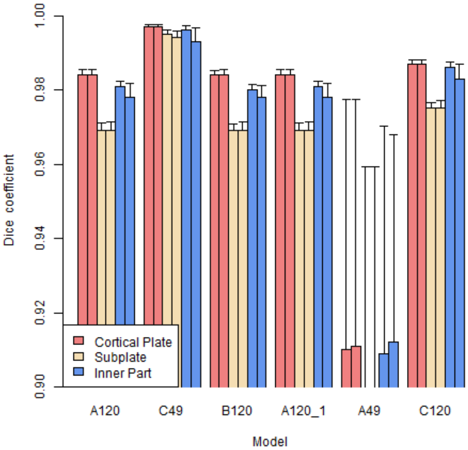
Better initial segmentation when using transfer-learning

No transfer-learning (n=40), transfer-learning (n=40), CP model (n=114)





Model's performance on multi-site testing dataset (n=14)



- A: No transfer-learning
- B: Without low-quality subjects
- C: Encoder & decoder pre-trained

C models (transfer-learning) outperformed A & B (no transfer-learning) at SP labels

Transfer-learning still having benefit in CSF areas

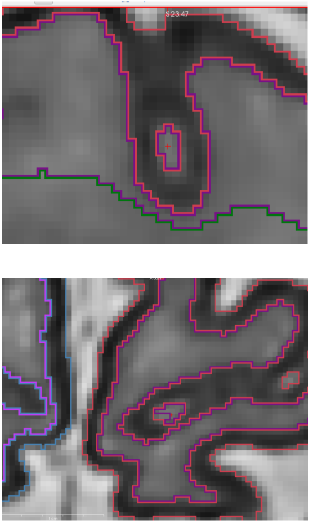


Figure: A120

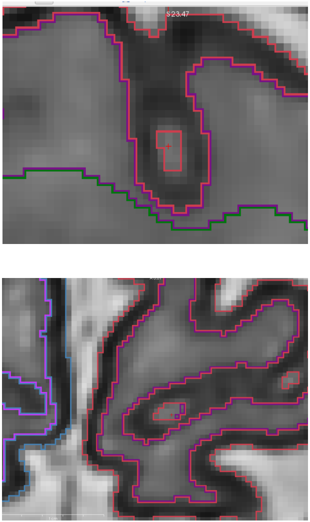
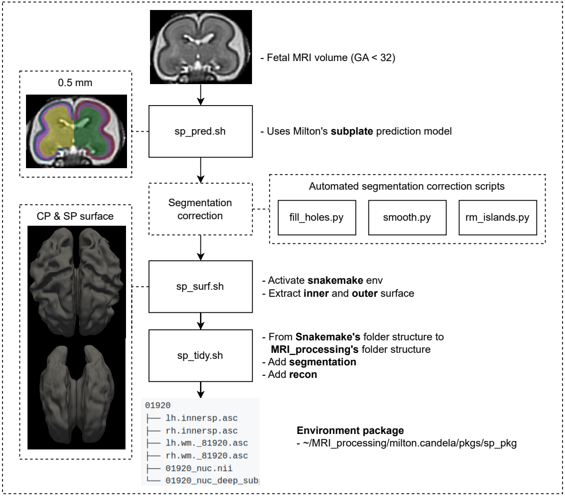


Figure: C49

Automatic subplate segmentation prediction and surface extraction



Subplate surface extraction

Surfaces look similar, but high-resolution SP thickness should be more accurate.

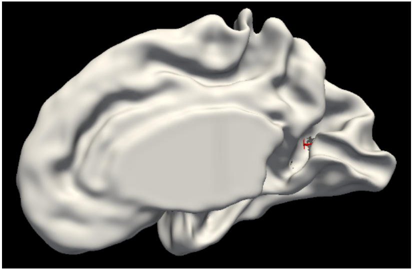


Figure: Low-resolution (0.86 mm)

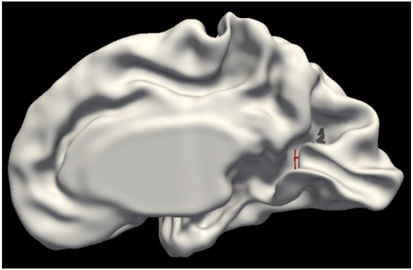


Figure: High-resolution (0.5 mm)

Section 5

FeTA Challenge @ MICCAI 2024

In collaboration with Andrea Gonová (PhD)
Supervised by Sungmin You (PhD)

Overview

I did tissue segmentation while Andrea did biometry measurements. Segmentation consisted in creating a model that predicted 7 labels:

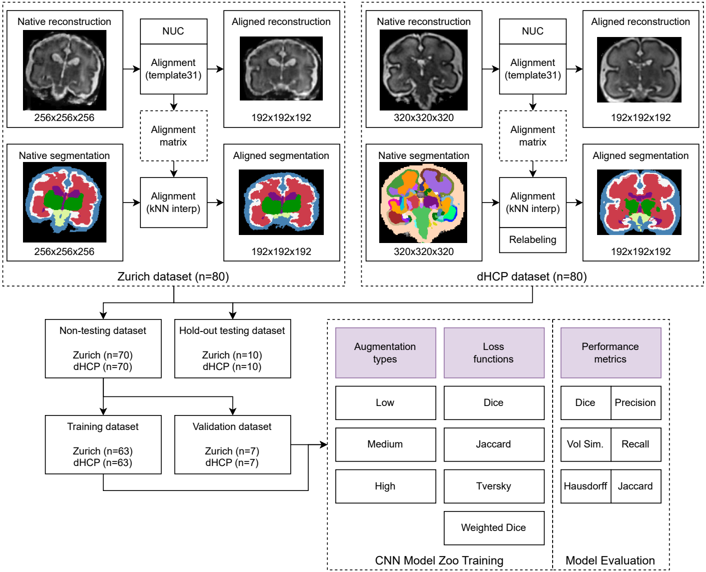
1. External Cerebrospinal Fluid
2. Grey Matter
3. White Matter
4. Ventricles
5. Cerebellum
6. Deep Grey Matter
7. Brainstem

Main issue

Site, Vendor & Field strength			Training	Testing
UNIVERSITÄTS-KINDERSPITAL ZÜRICH		3T, 1.5T	x 80	x 40
MEDIZINISCHE UNIVERSITÄT WIEN	PHILIPS	3T, 1.5T	x 40	x 40
CHUV Centre hospitalier universitaire vaudois	SIEMENS Healthineers	3T, 1.5T	x 0	x 40
UCSF Benioff Children's Hospitals		3T, 1.5T	x 0	x 40
KING'S College LONDON	SIEMENS Healthineers	0.55T	x 0	x 20

Testing dataset is composed of multi-site unseen data.

Flow diagram



Fetal MRI data augmentation

Augmentation	Low	Medium	High
rotation_range	15	**30**	30
width_shift_range	0.1	**0.2**	0.2
height_shift_range	0.1	**0.2**	0.2
vertical_flip	True	True	True
horizontal_flip	True	True	True
zoom_range	0.1	**0.2**	**0.3**
brightness_range	[0.8, 1.2]	**[0.7, 1.3]**	**[0.6, 1.4]**
gaussian_noise*	[0, 0.1]	**[0, 0.2]**	**[0, 0.3]**
gaussian_blur*	1	**2**	**3**

* not in Tensorflow's *ImageDataGenerator*

Adding the right amount of augmentation

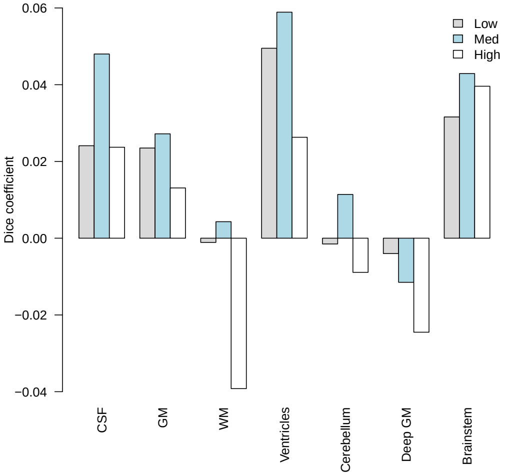


Figure: Dice difference when including augmentation at testing Zurich dataset (n=10)

- Med increased CSF, GM, ventricles, and brainstem differentiation.
- High augmentation saturated the model, making it incapable of learning.

Loss functions

Dice

$$1 - \frac{2|A \cap B|}{|A| + |B|} \tag{3}$$

Jaccard

$$1 - \frac{|A \cap B|}{|A \cup B|} \tag{4}$$

Tversky

$$1 - \frac{|A \cap B|}{|A \cap B| + \alpha|A \setminus B| + (1-\alpha)|B \setminus A|} \tag{5}$$

Weighted Dice

$$1 - \frac{2\sum_{i=1}^{n} w_i \cdot (A_i \cap B_i)}{\sum_{i=1}^{n} w_i \cdot (A_i + B_i)} \tag{6}$$

Where w_i is the label i inverse:

- Volume
- Posterior performance

W were **softmaxed**, based on:

$$\sigma(W)_k = \frac{e^{\frac{W_k}{\gamma}}}{\sum_{j=1}^{K} e^{\frac{W_j}{\gamma}}} \tag{7}$$

Where a high γ would lead to a more uniform distribution (low weight effect).

Performance metrics

Challenge-specific

Dice

$$DSC(A, B) = \frac{2|A \cap B|}{|A| + |B|} \tag{8}$$

Volume Similarity

$$VS(V_1, V_2) = 1 - \frac{|V_1 - V_2|}{V_1 + V_2} \tag{9}$$

Hausdorff Distance

$$d_H(A, B) = \max\{\sup_{a \in A} d(a, B), \sup_{b \in B} d(A, b)\} \tag{10}$$

Other

Jaccard

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \tag{11}$$

Precision

$$P(TP, FP) = \frac{TP}{TP + FP} \tag{12}$$

Recall

$$R(TP, FN) = \frac{TP}{TP + FN} \tag{13}$$

Loss functions' performance

All 2D CNN models trained using a single 90:10 random split with axial view data, 150 epochs, medium augmentation, and no callbacks.
Performance measured on a hold-out stratified dataset (anomaly and GW).

Loss function	Dice	Vol S.	Hausd	Jacc.	Precis.	Recall	Rank
hybrid	0.7614	0.8980	**6.7119**	0.6479	0.7711	0.7929	3
whyb (γ=5)	0.6700	0.8223	6.7405	0.5347	0.7478	0.6619	7.16
whyb (γ=10)	0.7355	0.8765	7.3656	0.6136	0.7695	0.7458	6.83
whyb (γ=15)	0.7548	0.8912	7.8590	0.6317	0.7727	0.7704	5.16
thyb (α=0.7)	**0.7662**	0.8896	7.1658	0.6437	0.7586	**0.7997**	3.66
jhyb	0.7503	0.8842	7.2448	0.6308	0.7794	0.7591	5.33
whyb (Jacc.)	**0.7662**	**0.9067**	7.4884	**0.6512**	0.7747	0.7853	2.66
whyb (Dice)	0.7654	0.8999	7.1133	0.6483	**0.7847**	0.7771	**2.5**

1. whyb (Jacc.) with the highest **Dice** and **Vol S.**, but a low **Hausd**
2. whyb (Dice) overall superior performance than hybrid
3. Or should we stick to the naïve hybrid loss?

Naïve hybrid loss' output was more stable

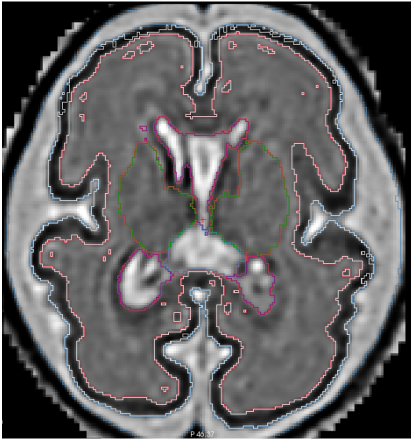


Figure: hyb

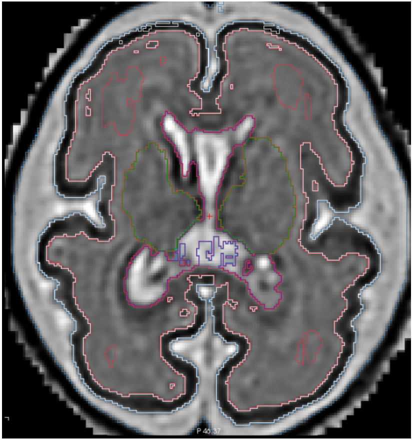


Figure: whyb

Internal dataset validation (hold-out test, Zurich)

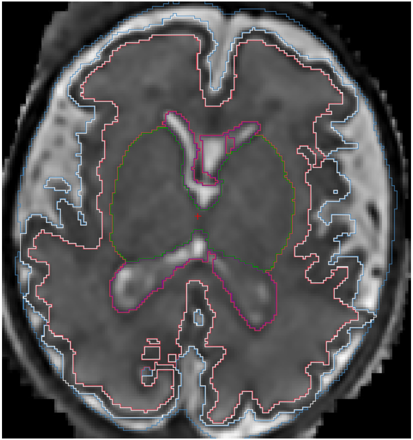


Figure: Ground truth

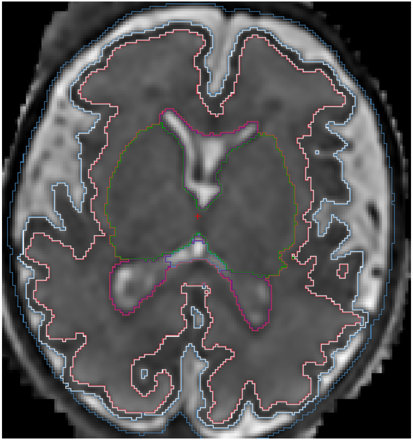


Figure: Model's prediction

External dataset validation (HBCD, TMC)

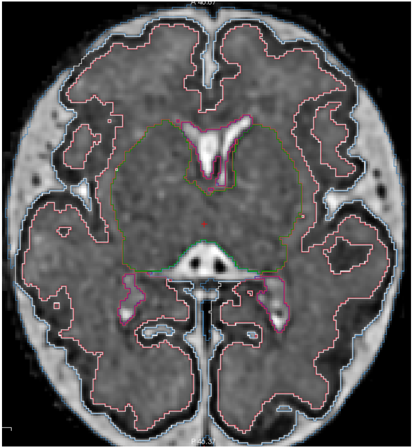


Figure: 100_005_1, GW = 31.14

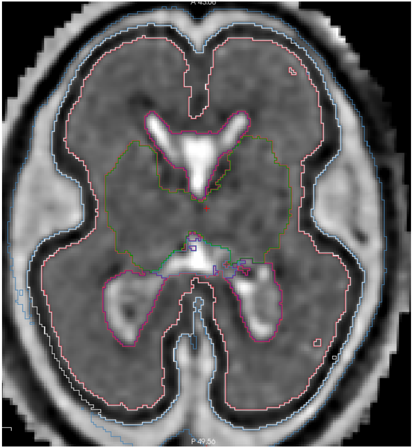


Figure: BM47, GW = 24.71

External dataset validation (Placenta, CHD)

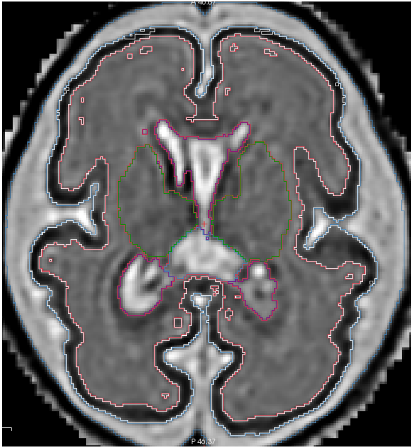


Figure: 5437941, GW = 29.7

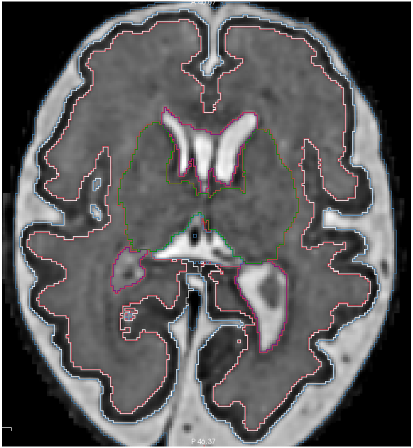


Figure: FCB147, GW = 30.7

Difference when including augmentation in BCH data

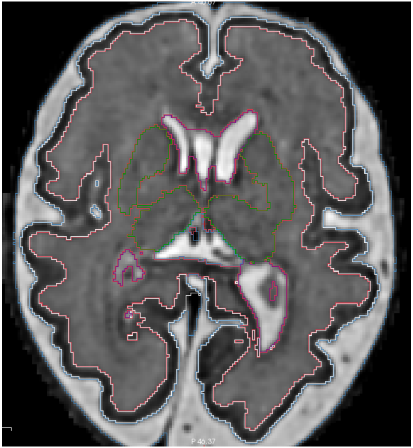


Figure: No augmentation

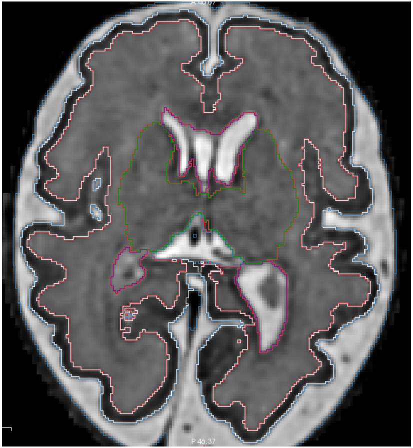


Figure: Medium augmentation

Thank you!

Thank you!

Center Director: P. Ellen Grant

Principal investigator: Kiho Im

Supervising instructors/post-docs: Andrea Gonová, Sungmin You, Ai Wern Chung, HyukJin Yun

Program Coordinator: Winona Bruce-Baiden

RAs: Seungyoon Jeong, Enrique Mondragon Estrada, Jennings Zhang

Interns: Guillermo Tafoya Milo, Samantha A. Esparza Esparza, Alejandra Pérez Yañez, Melquisideth Lagunas Barroso, C. Simón Amador Izaguirre, Alan J. Rivas Muñoz, Alberto Martinez Hernandez, Servando Rodríguez Quiroz, José A. Martínez Negrete, Pablo Jaquez Vergara