Few-shot subcortical brain structure segmentation in 3D fetal brain ultrasound

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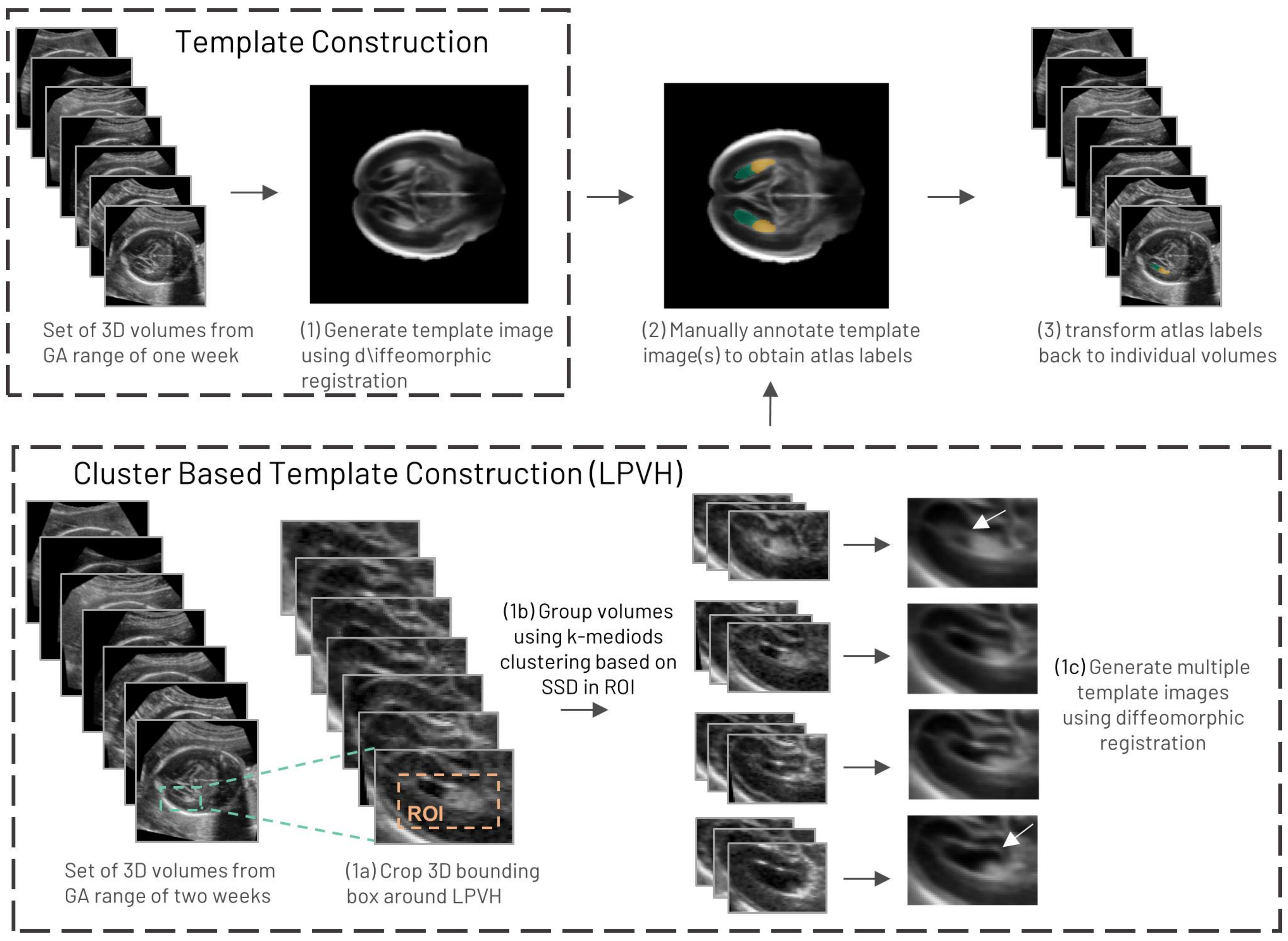
https://lindehesse.github.io/FetalSubcortSegm

1. Motivation

- Quantifying subcortical volumes during gestation can provide diagnostic information indicative of central nervous system abnormalities or delayed growth.
- Ultrasound (US) is routinely used in prenatal care, but manually segmenting subcortical structures in 3D US volumes is time-consuming and challenging due to low soft tissue contrast and speckle.
- In this study, we developed a convolutional neural network (CNN) to segment the choroid plexus (CP), lateral posterior ventricle horn (LPVH), cavum septum pellucidum et vergae (CSPV) and cerebellum (CB) from 3D US using only few manual annotations for training.

2. Methods

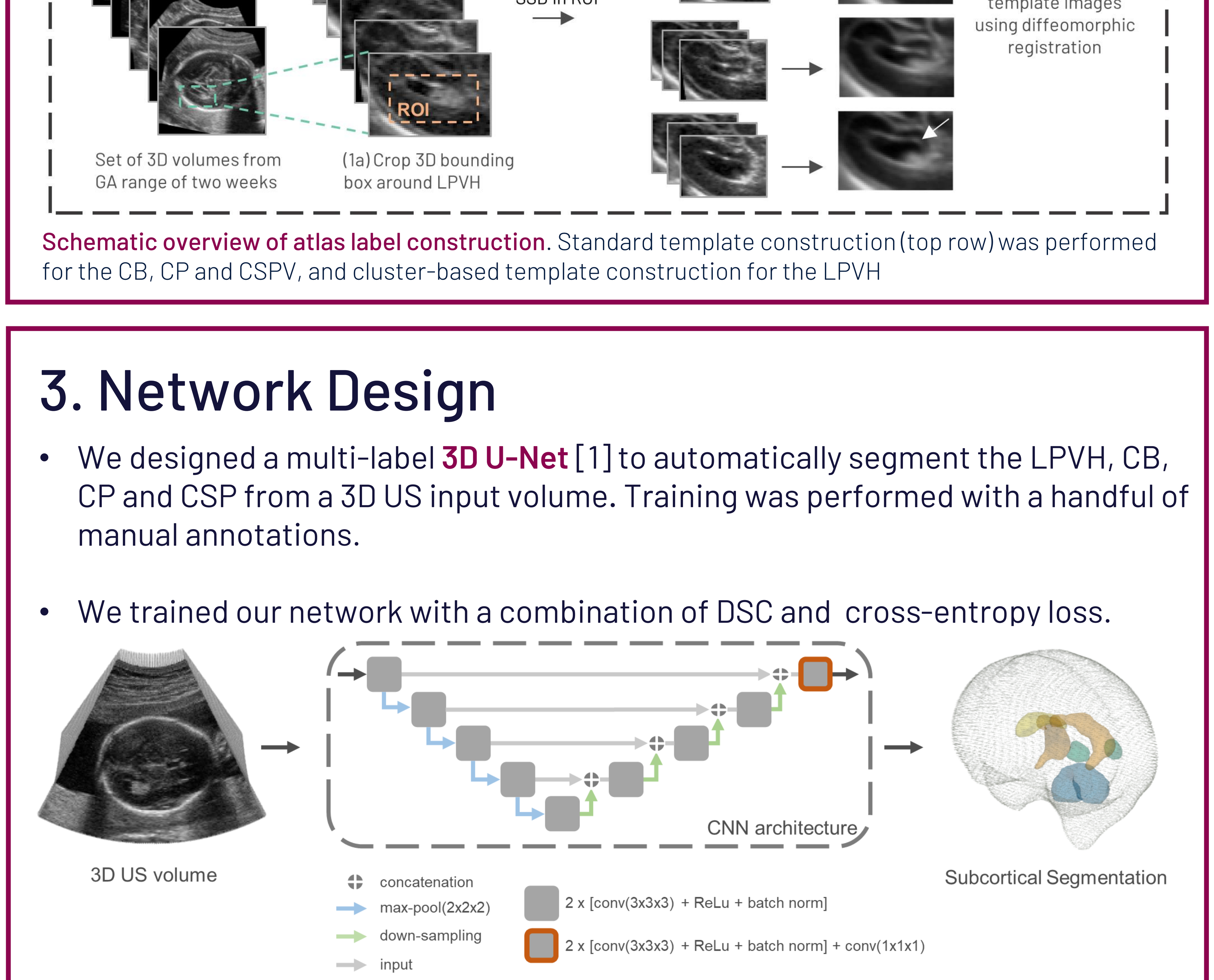
- We compared the segmentation performance of using a small number (N = 9) of individually annotated volumes (expert labels) for training versus using many (N = 256) weakly labelled volumes obtained from annotating an equivalent number of template images (atlas labels).
- We used 512 3D US volumes with a gestational age (GA) between 18 and 27 weeks from the INTERGROWTH-21st study [2] containing US volumes from healthy women (256 for training, 40 for validation, 25 for testing and 216 for growth analysis).



Schematic overview of atlas label construction. Standard template construction (top row) was performed for the CB, CP and CSPV, and cluster-based template construction for the LPVH

3. Network Design

- We designed a multi-label **3D U-Net** [1] to automatically segment the LPVH, CB, CP and CSP from a 3D US input volume. Training was performed with a handful of manual annotations.
- We trained our network with a combination of DSC and cross-entropy loss.



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4. Segmentation Performance

- We compared DSC segmentation performance between the naïve propagated atlas masks, our CNN trained with 256 atlas labels and our CNN trained with 9 expert labels. We also compared our performance to previous work.
- Competitive segmentation performance is obtained for all structures. Best performance is obtained by training our CNN with only 9 annotated volumes.

	CP	LPVH	CSP	Cerebellum
Guitierez-Becker et al. [3]				0.80 (0.05)
Yaqub et al. [4]*	0.79 (0.09)	**0.82 (0.10)**	0.74 (0.11)	0.63 (0.15)
Huang et al. [5]**	0.76 (0.08)		**0.81 (0.06)**	
Venturini et al. [6]				0.76 (0.01)
This work				
Propagated Atlas labels	0.79 (0.07)	0.68 (0.01)	0.72 (0.10)	0.80 (0.09)
CNN (atlas labels)	0.84 (0.04)	0.76 (0.08)	0.76 (0.08)	0.85 (0.03)
CNN (expert labels)	**0.85 (0.05)**	0.81 (0.06)	0.80 (0.07)	**0.89 (0.02)**
Intra-Observer variability	0.86 (0.03)	0.85 (0.03)	0.86 (0.04)	0.90 (0.02)

* Search region limited to cuboid around ground-truth annotation
** Segmentation only in 2D standard planes

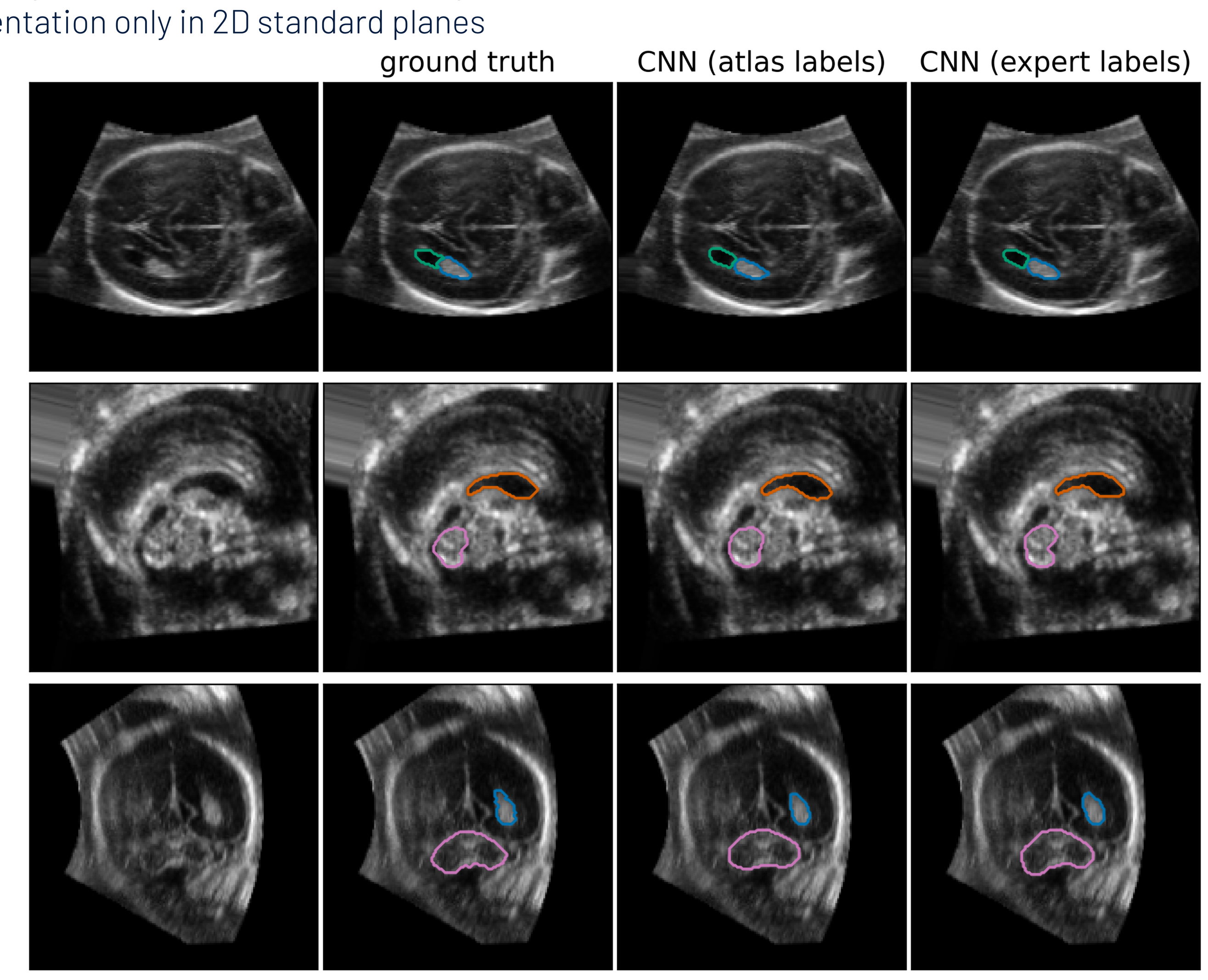
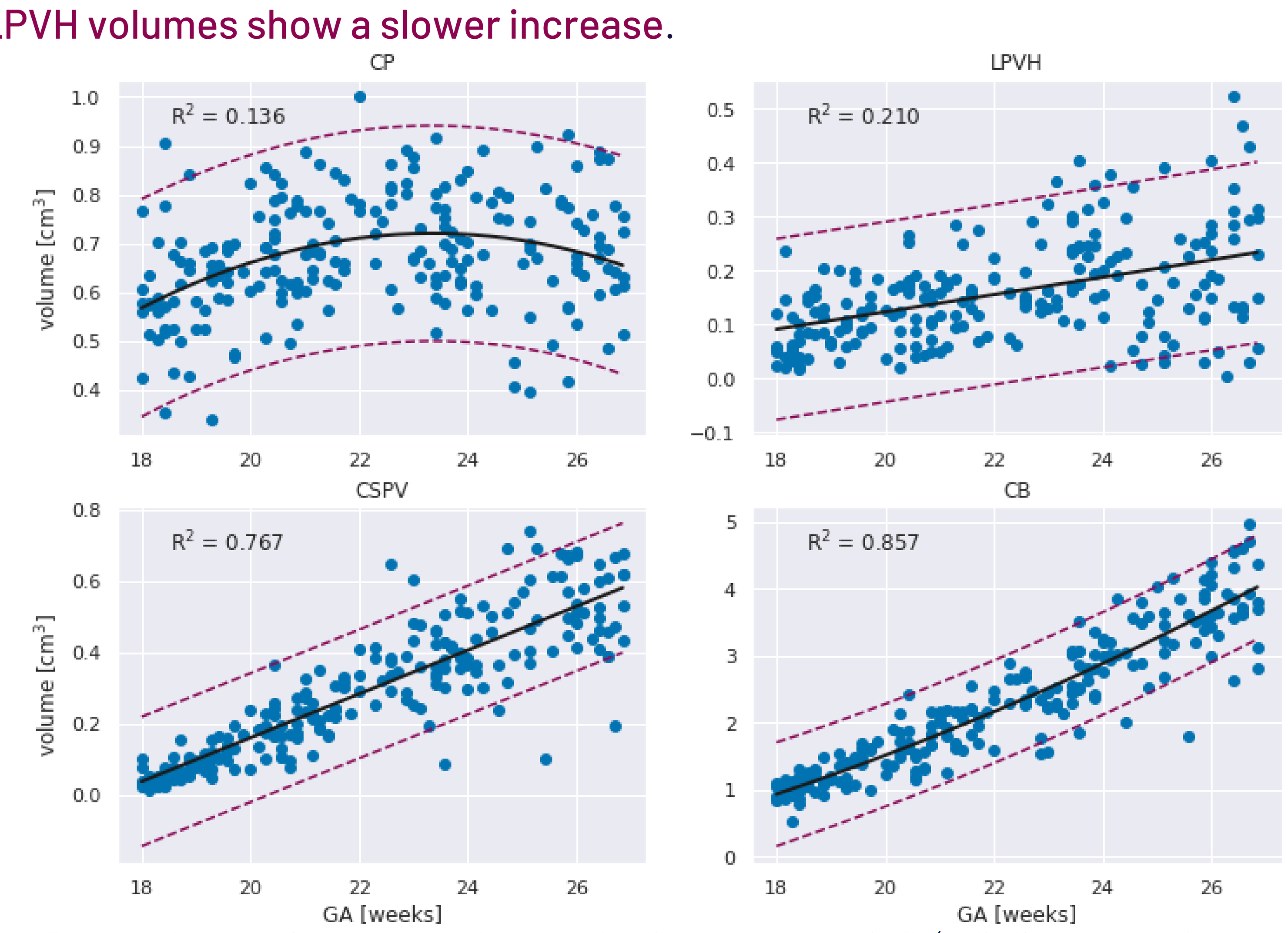


Fig. 2 Qualitative results from the subcortical segmentation. Delineated structures are the cerebellum (pink), CSPV (orange), LPVH (green) and CP (blue). It can be observed that accurate predictions are produced for both trained CNN models.

5. Growth Curves

- We used the best-performing CNN (trained with expert labels) to predict subcortical volumes during the second trimester for a healthy fetal cohort (N=216).
- CSPV and CB volumes strongly increase during gestation whereas the CP and LPVH volumes show a slower increase.



Predicted subcortical volumes shown with a linear or quadratic fit (solid line, quadratic term was added if significant) and 95% prediction intervals (dashed lines).

References

[1] Malinger et al (2020)
[1] Ronneberger et al (2015)
[2] Papageorghiou et al (2014)
[3] Gutierez-Becker et al (2013)
[4] Yaqub et al (2013)
[5] Huang et al (2018)
[6] Venturini et al (2019)