Using Deep Learning to Segment the Developing Cortical Plate from 3D Fetal Ultrasound.

Madeleine K. Wyburd [1], Mark Jenkinson [2,3,4] and Ana I. L. Namburete [1]

Madeleine.wyburd@hertford.ox.ac.uk

[1] Institute of Biomedical Engineering, Department of Engineering Science, University of Oxford, Oxford, UK
[2] Wellcome Centre for Integrative Neuroimaging, FMRIB,University of Oxford, Oxford, UK
[3] Australian Institute for Machine Learning (AIML), Department of Computer Science, University of Adelaide
[4] South Australian Health and Medical Research Institute (SAHMRI), North Terrace, Adelaide, Australia

DEPARTMENT OF ENGINEERING SCIENCE

UNIVERSITY OF OXFORD

1. Purpose:

Analysis of cortical folding can be predictive of healthy development. We have designed an automated method using deep learning to segment the developing cortical plate from 3D ultrasound volumes which is needed for analysis.

Background:

- **Abnormal cortical folding** in new-borns, adolescents and adults is commonly **linked to disease**.
- There is a growing amount of evidence that such **variations** are **identifiable *in-utero*** [1].
- Studying cortical plate development could therefore be used as an **early biomarker for diseased or at-risk pregnancies.**
- In order to study cortical folding the developing cortical plate must first be segmented.
- Manual annotations are time consuming and expensive so there is a need for an automated method
- Recent work has shown **automated cortical plate delineation** using deep learning from **MRI volumes** [2], however, **not from challenging ultrasound data**: the modality of choice in prenatal care.

2. Methods:

Data:

Throughout this work we used **307** 3D ultrasound volumes **between 126 to 160 days of gestation**, obtained as part of INTERGROWTH-21st's Fetal Growth Longitudinal Study (FGLS) [3].

Generate Cortical Plate Labels:

To generate the labels for training we used atlas-based label propagation. An average weekly atlas was generated by registering the individuals scans together [4], the atlas was then manually labelled and the inverse registration was used to propagate the labels back to individuals, shown in Fig 1.

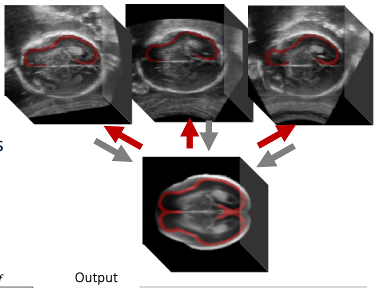

Fig 1) Atlas-based Label Propagation: Ultrasound volumes were registered together, shown in grey arrows. The labels then propagated backwards to individuals, red arrows.

Convolution Neural Network:

An encoder-decoder network was trained with 90% of the dataset to segment the cortical plate from inputted brain volumes. The architecture is shown in Fig 2.

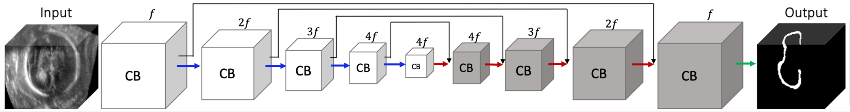

Fig 2) Deep Learning Architecture: A schematic of the 3D convolutional neural network based on the U-Net [5]. Where f is the number of feature maps, CB is a convolutional block.

3. Results:

Evaluation:

The network was evaluated on the unseen volumes, achieving:

- Cortical plate segmentation in **0.2 seconds.**
- **81.0±0.4%** dice overlap between the ground truths and network predictions, shown in Fig 3.

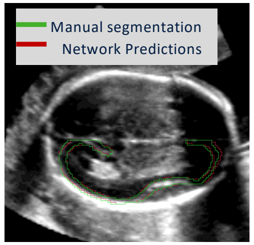

Fig 3) Network Predictions: The outline of the manually annotated cortical plate compared the the network predictions

Analysis:

The Sylvian fissure depth was measured from the network predictions, shown in Fig 4. The results were compared to known measurements recorded in [6] and followed the expected trend of increasing with gestational age. The depth of the outer cortical plate surface from the skull was measured, shown in Fig 5. Visual inspection of the surface maps shows that for each hemisphere, the Sylvain fissure (SF) is the deepest structure, becoming wider and deeper with age as expected (a process called operculization).

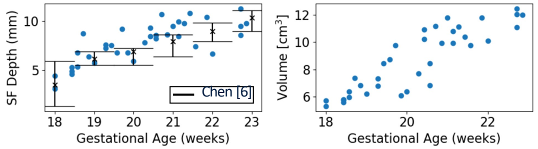

Fig 4) SF and Volume: The SF depth and cortical volume increasing with gestational age, following the expected trend as shown in [6]

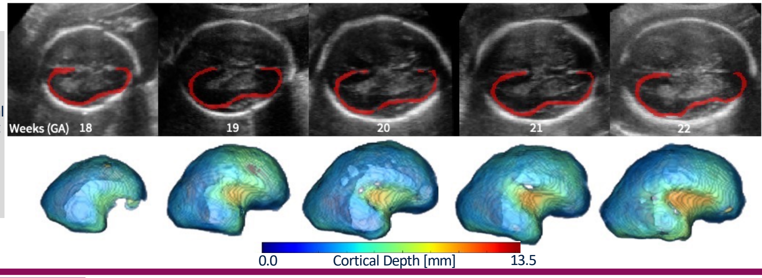

Fig 5) Cortical Plate and Depths: The top row shows the predicted cortical plate at different gestational ages. The bottom row shows the corresponding cortical depth.

4. Conclusion:

We have shown that deep learning architectures can be used for **high quality cortical plate delineation** from challenging 3D ultrasound volumes, achieving **quick, accurate** and parameter-free results.

[1] Thomason, Moriah E., et al. *Scientific reports* 7.1 (2017): 1-10.
[2] Fetit, Ahmed E., et al. *Medical Imaging with Deep Learning.* 2020
[3] Papageorghiou, Aris T., et al *The Lancet* 384.9946 (2014): 869-879.
[4] Namburete, Ana IL, et al. *Data Driven Treatment Response Assessment and Preterm, Perinatal, and Paediatric Image Analysis.*
[5] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. *International Conference on Medical image computing and computer-assisted intervention.* 2015
[6] Chen, Xi, et al. *Chinese medical journal* 130.8 (2017): 92