

Artificial Intelligence Identification of Key Sonographic Landmarks in the Fetal Brain

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Introduction

Artificial intelligence in medical imaging is commonly applied through convolutional neural networks (CNNs) - a type of machine learning designed to process information in the same way as a human brain¹. Multiple studies have shown good reproducibility of fetal biometry parameters (such as head circumference, biparietal diameter et cetera) by artificial intelligence models when compared to expert sonographers²⁻⁴.

In this study, we trained CNNs to detect important landmarks in fetal brain ultrasonography and evaluated its diagnostic accuracy through validation against a set of new unannotated images.

Fetal central nervous system (CNS) abnormalities

- A major cause of intrauterine mortality and postnatal morbidity⁵
- Prominent example of ventriculomegaly which may be isolated or associated with conditions such as infections, chromosomal or structural defects⁶
- For isolated severe ventriculomegaly (above 15mm), a meta-analysis showed a survival rate of 88% in babies (after excluding cases of termination of pregnancy), with a disability-free rate of 42%⁷
- Early initiation of prenatal care and counselling is paramount in managing fetal abnormalities⁸

Fetal ultrasonography	
Strengths	Limitations
• Widely regarded as safe • Relatively accessible	• Lack of trained operators • Time-consuming • Steep learning curve

Given the abovementioned strengths and limitations of fetal ultrasonography, there is a need to explore methods to improve scanning processes for timely and appropriate delivery of care.

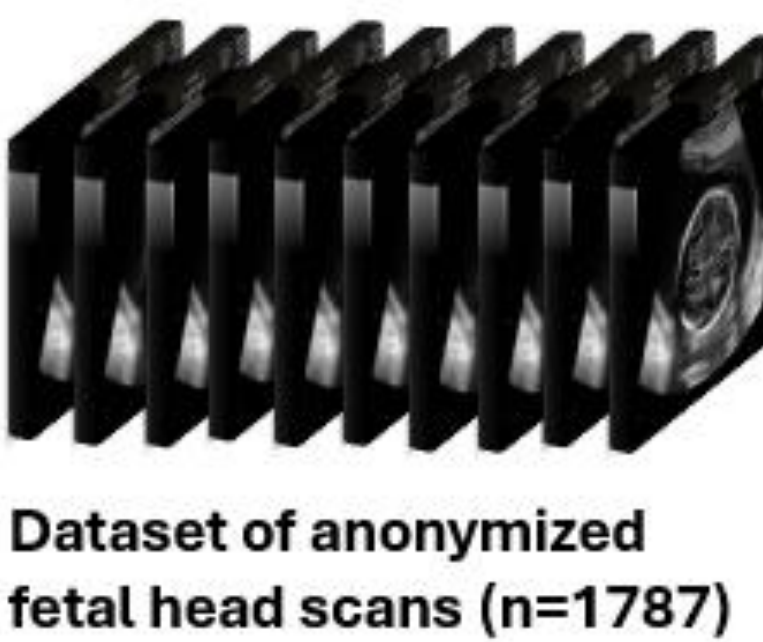
Objective

To train and develop a convolutional neural network (CNN) for identification of fetal CNS parameters that aims to increase scanning efficiency whilst maintaining diagnostic accuracy.

Methodology

1787 sets of fetal head ultrasound images were obtained via routine screening at a specialist fetal ultrasound unit. The data was divided in a 7:2:1 ratio for training, testing and validation, respectively.

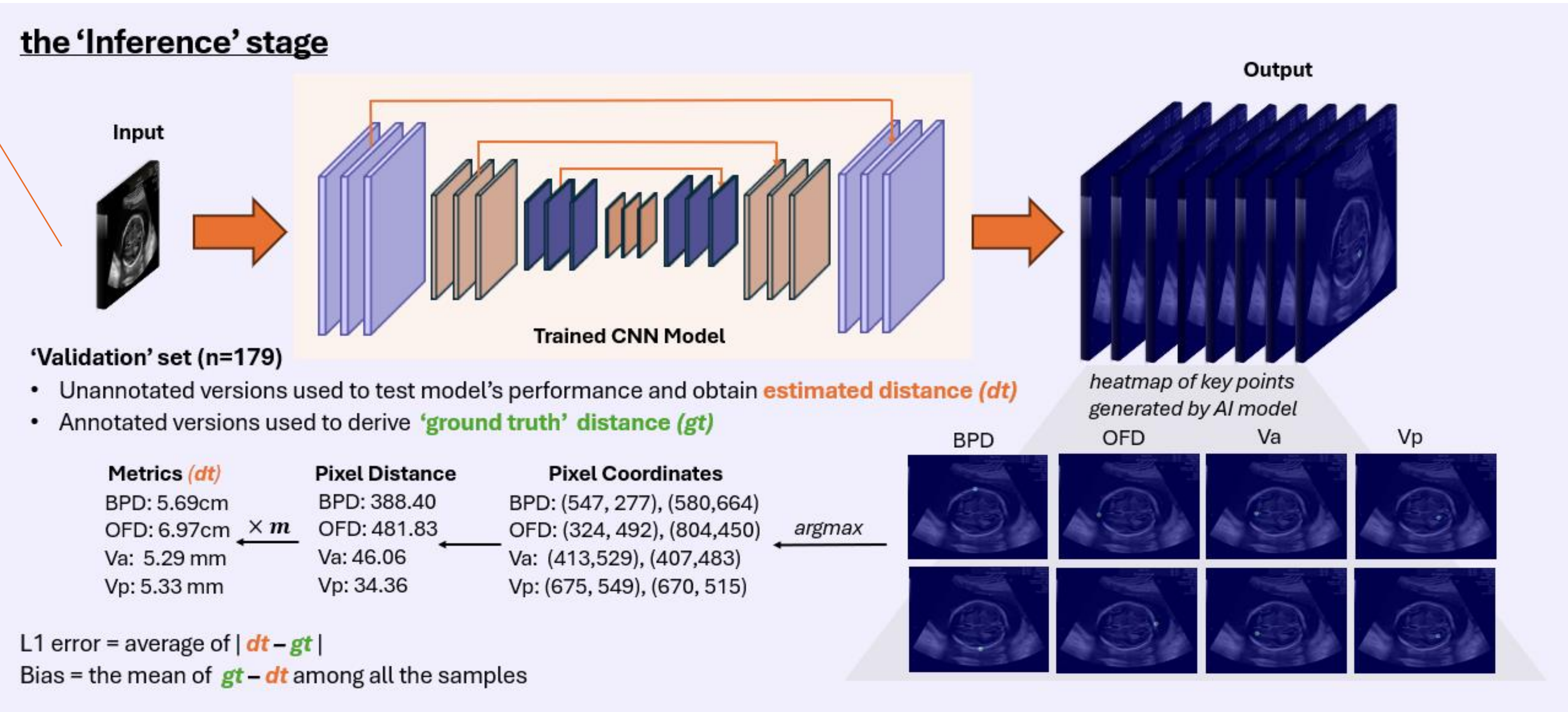
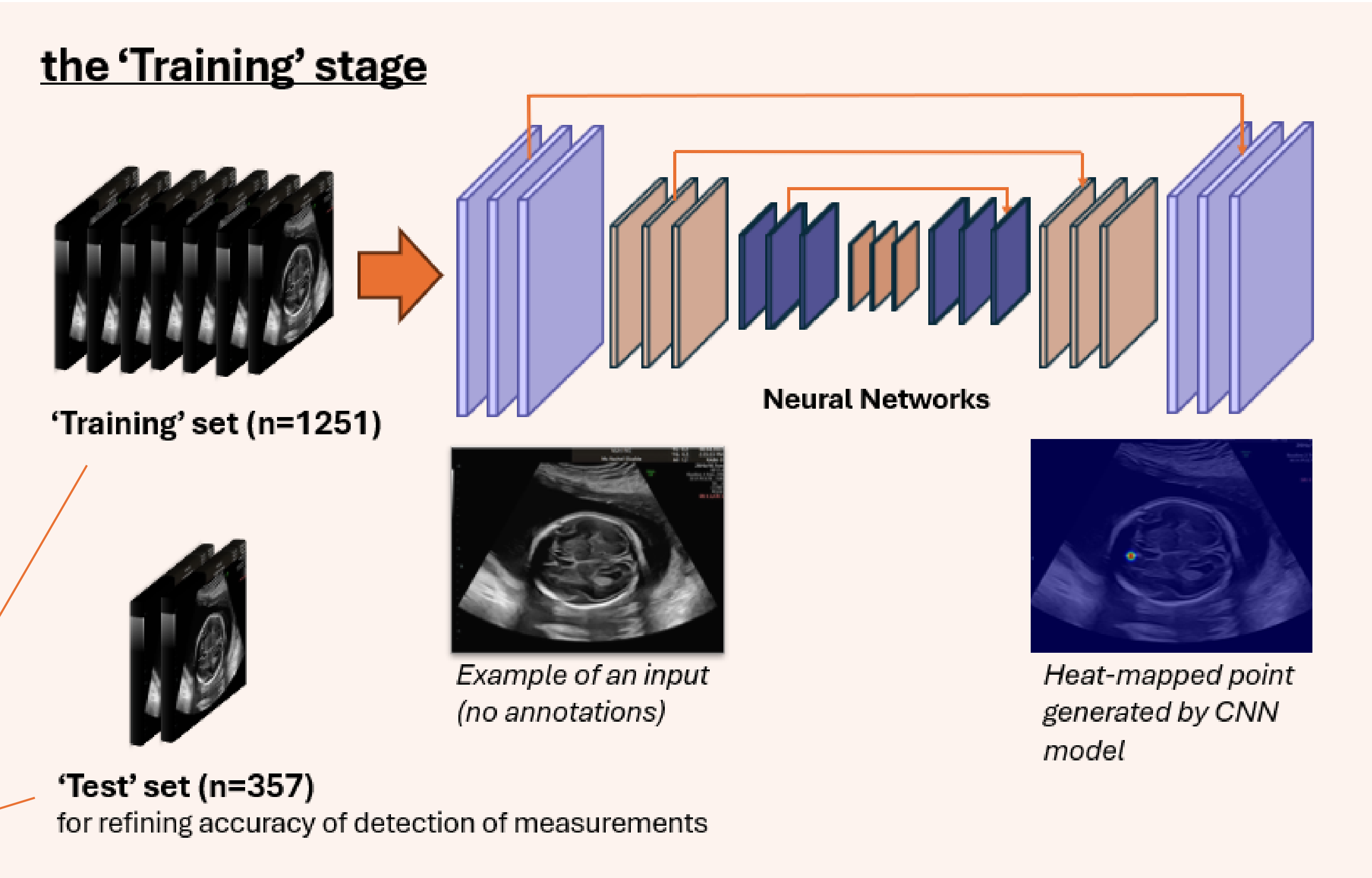
We utilised HRNet-w32 and UNet-50 (public-accessible CNNs) to detect key landmarks and measure fetal head parameters.



The accuracy of parameter measurements made by the CNNs was determined using the following calculations:

- **L1 error**, also known as **mean absolute error**, measures the average absolute difference between **predicted values** and **actual values**
- **Bias** calculates the mean difference between **ground truth distance** and **estimated distance** for all measurements (not the absolute value), providing an indication of how robust the estimation is

Example of biparietal diameter (BPD) measured using points identified by an expert sonographer (left image; **ground truth gt**) and the CNN model (right image; **estimated distance dt**)



Convolutional neural networks explained

CNNs are a type of deep learning model which work via matrix manipulation to build layers for image recognition⁹

Supervised training utilises annotated versions of the scans to generate a 'true' heatmap for comparison against the model-generated heatmap, aiming to reduce error via an optimisation algorithm

Backpropagation is an algorithm used to train neural networks which entails prediction (forward pass) and adjustment for error (backward pass)¹⁰

Skip connections (represented by the thin orange arrows) facilitate flow of information between layers during backpropagation, bypassing intermediate layers to allow effective training of deep neural networks¹¹

Results

Our research showed that HRNet-32 was useful for our task, achieving a more accurate detection of fetal parameters biparietal diameter (BPD) and occipito-frontal diameter (OFD), with L1 values of 0.0454mm and 0.0874mm respectively. The detection of measurements of the anterior (Va) and posterior (Vp) horns of lateral ventricles were less accurate than that of BPD and OFD, scoring an L1 error of 0.6901mm and 0.6658mm respectively. Detection of nuchal fold (NF) and cisterna magna (CM), with L1 errors 0.6125mm and 0.6928mm respectively, were less accurate than that of cerebellar diameter (Cereb), which produced an L1 error of 0.1127mm.

(a) Trans-thalamic plane

	BPD (cm)		OFD (cm)		Va (mm)		Vp (mm)	
	L1	Bias	L1	Bias	L1	Bias	L1	Bias
HRNet-w32	0.0454	0.0008	0.0874	0.0217	0.6901	-0.1409	0.6658	0.3263
Unet-50	0.0541	-0.0164	0.2521	-0.1076	1.2317	0.8123	2.1031	1.3457

(b) Trans-ventricular plane

	NF (mm)		CM (mm)		Cereb (cm)	
	L1	Bias	L1	Bias	L1	Bias
HRNet-w32	0.6125	-0.0767	0.6928	-0.0673	0.1127	-0.0436
Unet-50	2.5797	1.5818	2.5797	0.0192	0.1829	-0.0434

Discussion

Further development of convolutional neural networks with larger datasets¹² is necessary to reduce error and improve accurate detection of fetal landmarks. With smaller measurements being technically challenging even for experienced sonographers, the CNNs should aim towards accurate detection of such measurements to value-add to existing processes¹³. Subsequent application of trained CNNs to a real-time imaging detection software¹⁴ is a potential way to ensure sustained benefit to clinical practice.

Conclusion

The findings demonstrate that public-accessible CNNs can be trained to accurately measure biometric components of the fetal brain such as BPD and OFD. While parameters involving less distinct landmarks were less accurate, the CNNs still had a low level of error comparable to standard sonographer interobserver variability. Error can be potentially lowered with larger training sets. Application of other DLMs to our datasets as well as to other landmarks is needed to further demonstrate the efficacy of these CNNs in the fetal neurosonogram, which can potentially improve efficiency¹⁵ in busy scan centers and help less experienced sonographers.

Fetal head parameters studied

- BPD: Biparietal diameter
- OFD: Occipito-frontal diameter
- Cereb: Cerebellar diameter
- Va: Anterior horn of the lateral ventricle
- Vp: Posterior horn of the lateral ventricle
- CM: Cisterna Magna
- NF: Nuchal fold

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