



# Direct estimation of fetal head circumference from ultrasound images based on regression CNN

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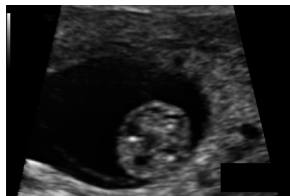
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## Background

Head Circumference (HC)–One of fetal biometrics.

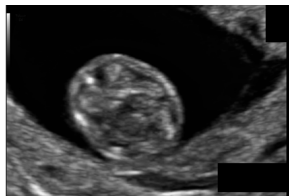
The HC can be used to estimate the gestational age and monitor growth of the fetus.



44.3 mm  
640.7 pixels



69.0 mm  
755.8 pixels

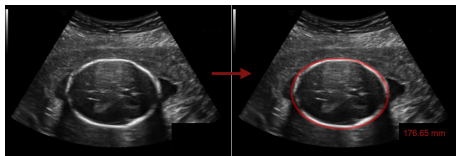


59.8 mm  
976.6 pixels

**Figure:** Ultrasound images of fetal head<sup>1</sup>, corresponding head circumference (HC) is displayed in millimeters and pixels.

<sup>1</sup>Dataset is public in <https://hc18.grand-challenge.org/>

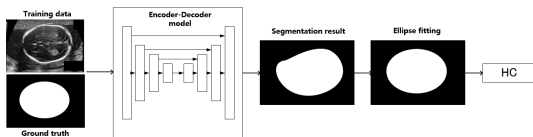
## Related works



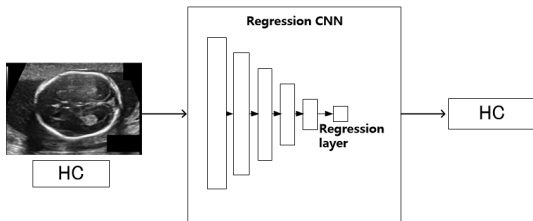
- Manually annotated by an experienced sonographer and a medical researcher(van den Heuvel et al., 2018).
- Automated measurements based on segmentation:
  - Image processing algorithm (Lu, Wei, Jinglu Tan, and Randall Floyd, 2005)
  - Machine learning technique (Feature extraction+ellipse fitting) (van den Heuvel et al.,2018).
  - Deep learning technique (CNN based model to segment and ellipse fitting(Kim et al., 2019)).

# Our method

State of the art:



Our method:



Benefits of our method:

- Doesn't need Ground truth images, no segmentation errors.
- Can estimate the HC value directly by a regression CNN model.

# Regression CNN architecture

2 changes from classic CNN to regression CNN model:

- Last layer: linear regression layer.
- Loss function: regression loss.

$$- MAE = \frac{1}{n} \sum_{i=1}^n |p_i - g_i|$$

$$- MSE = \frac{1}{n} \sum_{i=1}^n (p_i - g_i)^2$$

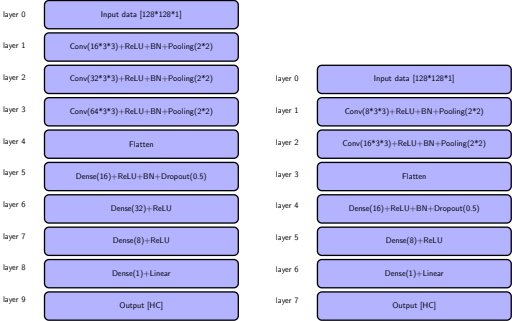
$$- HL = \begin{cases} \frac{1}{n} \sum_{i=1}^n \frac{1}{2} (p_i - g_i)^2, & \text{for } |p_i - g_i| < \delta \\ \frac{1}{n} \sum_{i=1}^n \delta * (|p_i - g_i| - \frac{\delta}{2}), & \text{otherwise} \end{cases}$$

Note: predicted (resp. ground truth) values are denoted  $p_i$  (resp.  $g_i$ ).

# CNN regressors

We tested 4 architectures:

- Custom Regression CNN\_1M
- Custom Regression CNN\_263K
- Regression VGG16
- Regression ResNet50



(a) Regression CNN\_1M (b) Regression CNN\_263K

# Experiment

- The HC18 dataset
  - HC18 training dataset: 999 US images, ground truth HC values range from 439.1 pixels (44.3 mm) to 1786.5 pixels (346.4 mm).
  - Data augmentation: horizontal flipping, translation (5 pixels offset), rotation (10 degrees)
  - Image preprocessing: Resizing(800\*540 to 224\*224).  
Normalization: images:  $\frac{x-\mu}{\sigma}$ . The HC values:  $\frac{HC}{\max(HC)}$ .
- Experimental setup
  - Hyper parameter: 5-fold cross validation,  $\delta = 0.5$  in Huber loss, learning rate  $1e^{-3}$ , Adam optimizer, batch size is 8.
  - Metrics: Mean Absolute Error (mae), percentage of mae (pmae).
  - Implementation: Keras and Tensorflow.

## Performance of 4 CNN regressor models

**Table:** Performance of regression models in terms of mean absolute error (mae) in pixels and %mae ( $\pm$  standard deviation) for three different loss functions: MSE, MAE, HL

	CNN_263K		CNN_1M		Reg-VGG16		Reg-ResNet50	
loss	mae(pixel)	pmae(%)	mae(pixel)	pmae(%)	mae(pixel)	pmae(%)	mae (pixel)	pmae(%)
MSE	90.18 $\pm$ 86.42	8.74 $\pm$ 12.51	50.96 $\pm$ 58.61	4.96 $\pm$ 7.85	<b>38.85</b> $\pm$ 40.31	5.31 $\pm$ 5.63	<b>36.21</b> $\pm$ 35.82	4.62 $\pm$ 4.27
MAE	101.85 $\pm$ 108.51	10.99 $\pm$ 18.48	51.61 $\pm$ 59.96	5.15 $\pm$ 8.66	40.17 $\pm$ 40.99	5.26 $\pm$ 5.79	37.34 $\pm$ 37.46	4.85 $\pm$ 4.93
HL	98.18 $\pm$ 89.77	9.69 $\pm$ 13.9	53.87 $\pm$ 66.46	5.45 $\pm$ 9.08	40.7 $\pm$ 40.07	5.67 $\pm$ 5.19	38.18 $\pm$ 37.32	5.16 $\pm$ 4.84

- The loss MSE performs best among three loss functions.
- The Regression VGG16 and Regression ResNet50 are better than the customized model.



# Performance of CNN regressor based on VGG16 and ResNet50

**Table:** Performance of Reg-Resnet50 vs Reg-VGG16 in terms of mae (pixels and mm). †: significantly different ( $p < 0.05$ ) from all other methods.

	Reg Resnet50		Reg VGG16	
loss	mae (pixels)	mae (mm)	mae (pixels)	mae (mm)
MSE	36.21±35.82†	<b>4.52±4.27†</b>	38.85±40.31	<b>4.87±5.81</b>
MAE	37.34±37.46	4.78±4.41	40.17±40.99	5.46±5.99
HL	38.18±37.32	4.68±4.37	40.7±40.07	5.19±5.42

- The loss MSE with ResNet performs best.
- Room for improve in prediction error (segmentation error is around 2 mm ( (Sobhaninia et al., 2019))).

# Qualitative results

True=744.3, pred=748.3



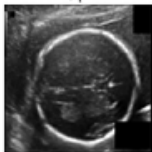
True=1303.3, pred=1298.54



True=1399.5, pred=1399.0



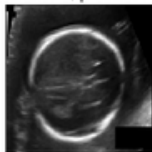
True=1544.1, pred=1542.83



True=663.2, pred=668.15



True=1467.5, pred=1471.59



True=1508.1, pred=1511.96



True=1320.7, pred=1318.84



True=1060.6, pred=1059.69



Figure: Good prediction with Reg-Resnet50-MSE

## Conclusion

- We proposed a regression CNN model that can directly estimate the HC value.
- Encouraging results are obtained according to the experiment results, while room for improvement is left.
- Future work will focus on improving the performance like attention mechanism and multi-task learning.

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Thank you for your attention!