Automated measure of fetal head circumference by means of Distance Field based Mask R-CNN

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Introduction

The measurement of the **circumference of the head of a fetus** can be used to estimate the gestational age of the fetus and to identify growth problems.

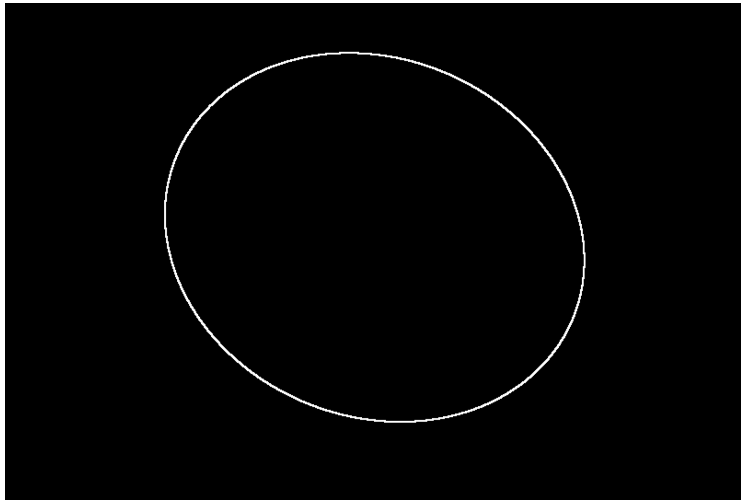
Ultrasound images are widely used for this task because they are low cost, safe and painless

The biometric measurements are obtained manually, which leads to:

- **Inter- and Intra-observer variability**
- **Time consuming operation**

[Loughna et al. 2009]

The **goal** is to provide an **objective basis** for the measures that can be used even where the experts are not there.



State of the art

Model Based Techniques

Reference	Technology	Dataset	Output	Pro	Con
[Rajinikanth et al. 2019]	Pre-processing with Jaya algorithm+Otsu thresholding and Chan-Vase + Level-set for segmentation	HC18: 999 (train) and 335 (test) US Images	Segmentation map: *-Dice: 94.27 %*	Hybrid approach outperform only segmentation approach (CV+LS)	This method uses a threshold and therefore cannot be generalized
[Perez-Gonzalez et al. 2014]	The method incorporate texture map, morphological operations and active contours together with optimal ellipse detection	23 US Images	HC measure: *-DF: 2.73 ± 2.04 mm*	Simple and precise method which can be easily extrapolated to 3D volumes	This method uses a threshold and therefore cannot be generalized

Machine Learning Techniques

Reference	Technology	Dataset	Output	Pro	Con
[Van den Hevel et al. 2018]	Haar-like features and Random Forest Classifier to locate the fetal skull. Head circumference generation using Hough Transform, Dynamic Programming and Ellipse Fitting	HC18	HC measure: *-ADF: 2.8 ± 3.3 mm*	It is the first system that evaluated results for each trimester separately	Needs gestational age for training and uses hand crafted features
[Li et al. 2016]	Random Forest Classifier for ROI Detection, Head circumference generation using Phase Simmetry feature map and ElliFit	524 (train) and 145 (test) US Images	HC measure: *-DF: 1.70 ± 5.29 mm*	Robust method, only six failures (precision < 60%)	RFC is integrated with prior knowledge about gestational age and uses hand crafted features

Deep Learning Techniques

State of the art

Reference	Technology	Dataset	Output	Pro	Con
[Sobhaninia et al., 2019]	Multi-scale input for Multi-task CNN based on **LinkNet**: A Segmentation task and a Regression task for ellipse parameters	HC18	HC measure: *-ADF: 2.12 ± 1.87 mm*	Unique network for Segmentation and Ellipse fitting	No comparision between ellipse regression and an ellipse fitting algorhytm
[Sobhaninia et al., 2020]	Mini-LinkNet based on **LinkNet** with multi-scale input	HC18	HC measure: *-ADF: 2.22 mm*	Comparable to Deep CNNs but require less parameters and less training time	Deep features are not extracted
[Kim et al., 2019]	Image trasformation, **U-Net** for pixel classification and VGGNet19 for ROI Detection, Ellifit for ellipse fitting	102 (train) and 70 (test) US images	Ellipse fit: *-Dice: 95.39 ± 0.02 mm*	Smaller deviations in Dice similarity compared with previous studies	Needs to know the image geometry for image trasformation
[Aji et al., 2019]	CNN based on **U-Net** for segmentation: Fetal Head, Maternal Tissue and Background. Ellifit on Fetal Head segmentation.	HC18	HC measure: *-DF: 41.75 mm*	Does not need ROI Detection	More inaccurate when compared with previous studies and high computational cost
[Desai et al., 2020]	DU-Net based on **U-Net**, Image and Scattering Coefficients used as input. Separate encoders are designed for each of these inputs, outputs are concatenated for a single decoder	HC18	Seg. Map: *-Dice: 97.33 ± 1.41 %*	Perform close to state of the art despite no augmentation and use of a simpler network	Deep features are not extracted
[Irene et al., 2019]	**YOLO** for ROI detection and compare Hough Transform and DoGell for ellipse detection	326 US Images	HC measure: *-ADF: 5.93 mm*	DoGell performs better than Hough Transform and is also faster	The CNN is used only to locate the ROI
[Zhang et al., 2020]	Regression CNNs for HC measure without segmentation. CNNs used: **CNN_263K, CNN_1M, VGG16 and Resnet50.**	HC18	HC measure: *-ADF: 4.52 +- 4.27 mm*	Less computational time compared to segmentation methods	The error obtained with CNN regressor is doubled w.r.t. that of segmentation-based approaches

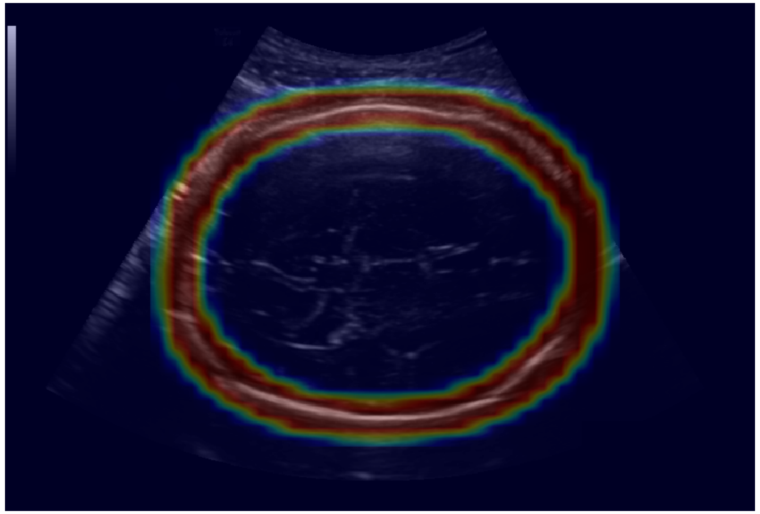
Aim of the work

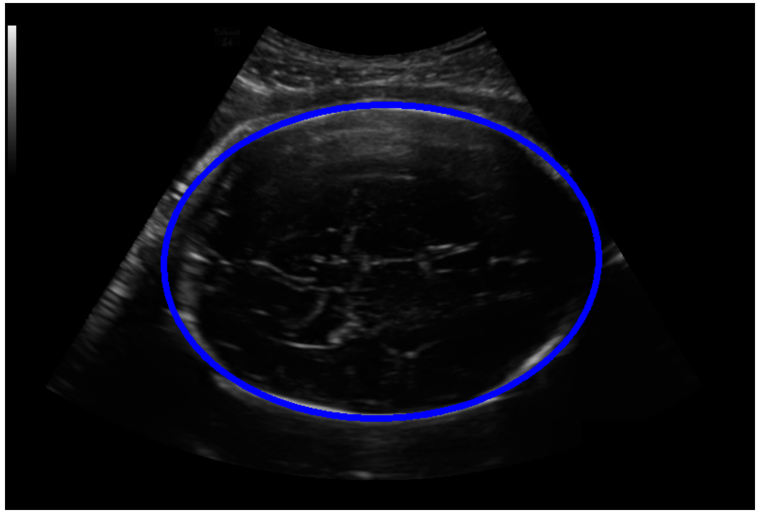
The goal of our project is to obtain the **measurement of the head circumference** from the ultrasounds of fetuses.

Combination of Detection and Regression may bring good results in an **Edge Detection task.**

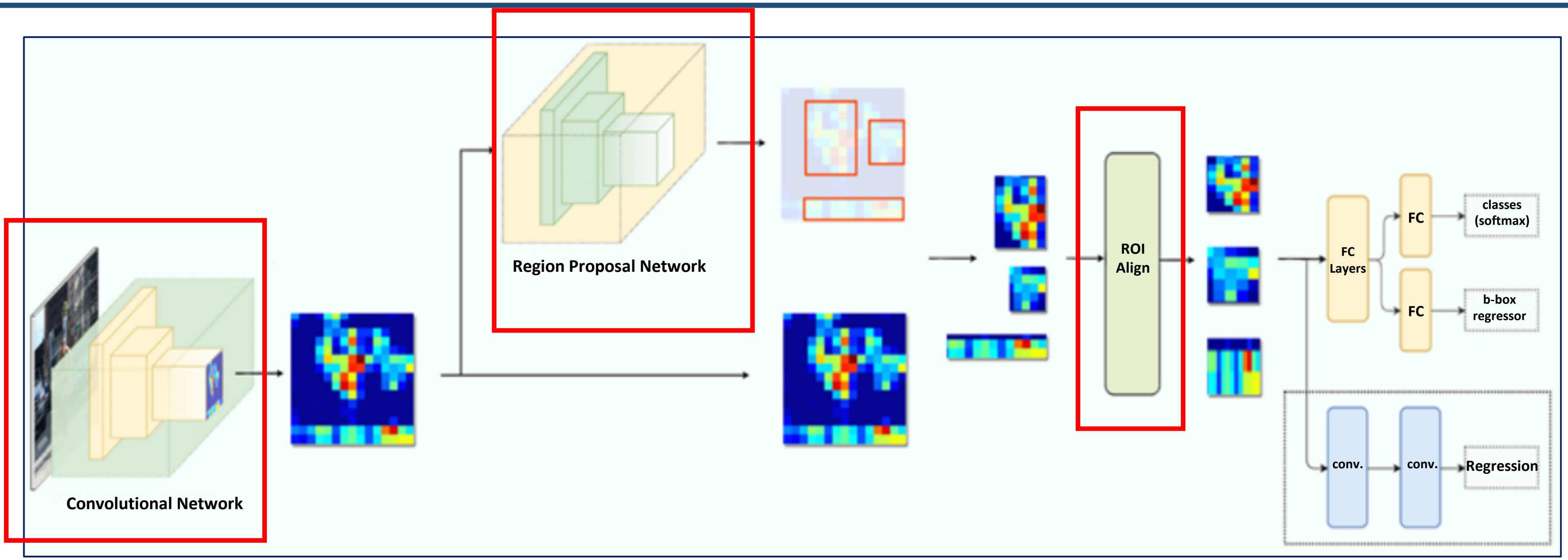
For this reason it has been chosen to use a **Mask R-CNN** *[He et al. 2018]* where the segmentation branch was replaced with a **Regression Branch**.

Once the **Distance Field** has been obtained a threshold is applied, the ellipse is calculated through **Ellipse Fitting**.





Materials and Methods



Convolutional Network Backbone

- Use **ResNet101**
- **FPN** to build pyramid of features

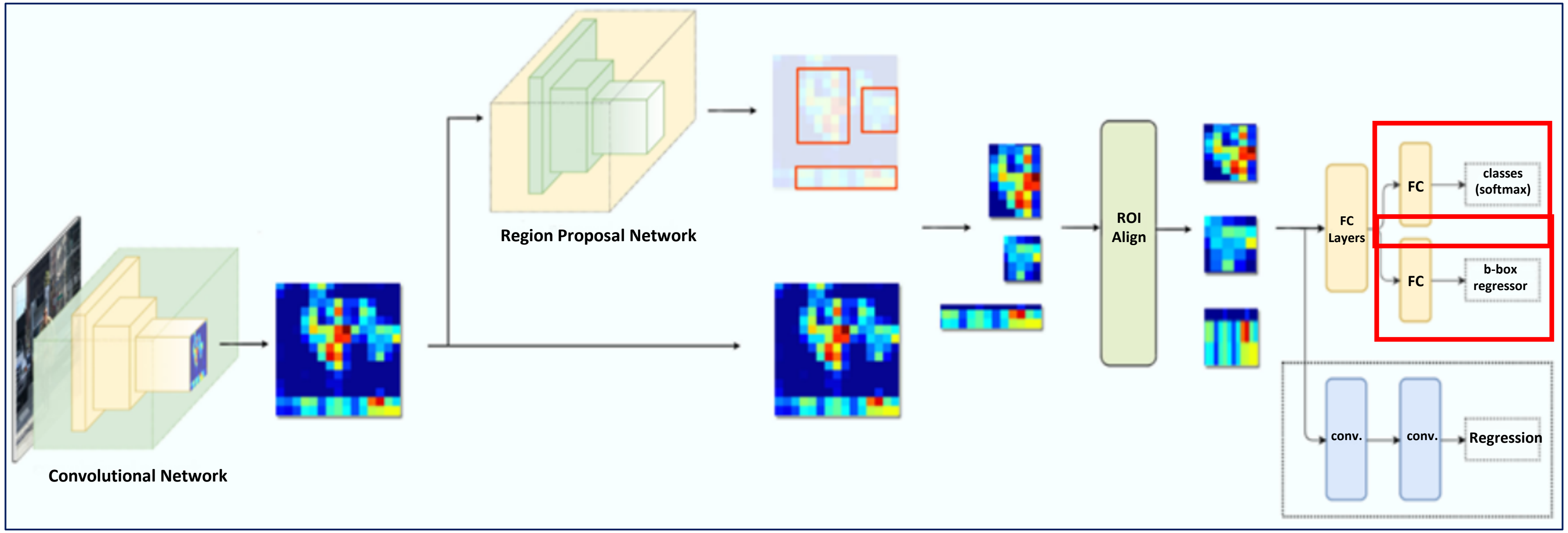
Region Proposal Network

- CNN **proposing bounding boxes**
- Learn BG and FG from the backbone feature maps

ROI align

- Extract a **feature map from each ROI**
- Final values are obtained through **bilinear interpolation**

Materials and Methods



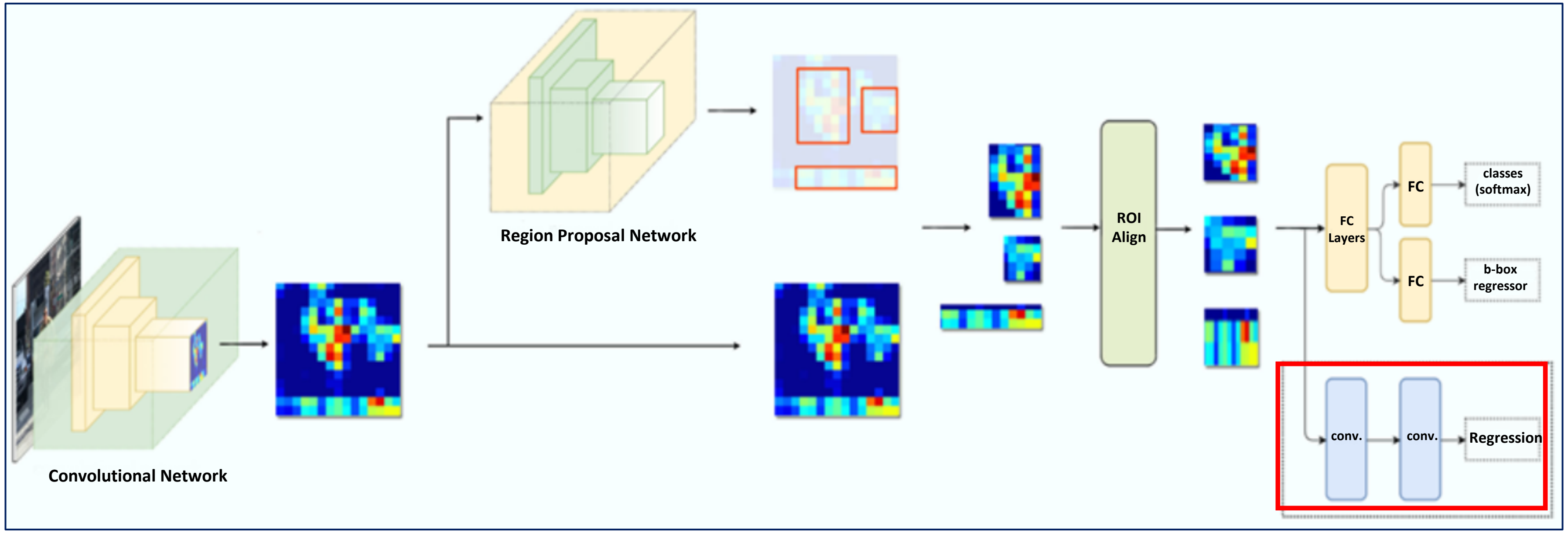
Class Branch

- Class prediction via softmax

B-Box Regressor Branch

- Regression of Bounding Box values

Materials and Methods



Mask RCNN:
Mask Branch

- **Loss:** Binary Cross Entropy
- **Output:** Binary Mask

Distance Field Mask RCNN:
Regression Branch

- **Loss:** Mean Squared Error
- **Output:** Distance Field

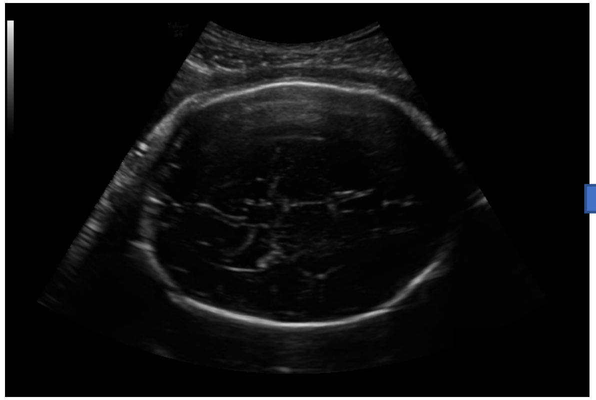
Materials and Methods

After we have obtained the **fetal head Distance Field** from the modified Mask RCNN:

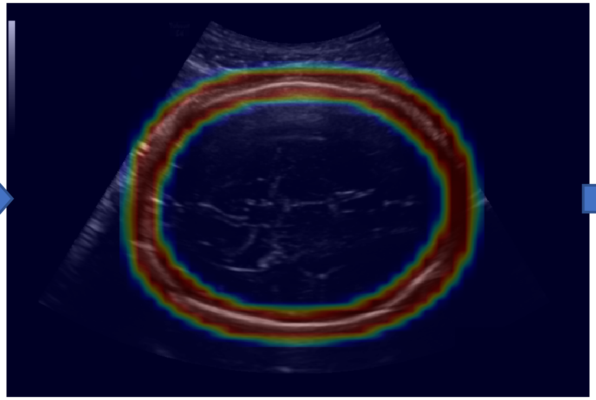
- We use a **threshold** to obtain a binary mask
- Than an Ellipse Fitting method to find the **ellipse that approximates the head**

Ellipse Fitting Method

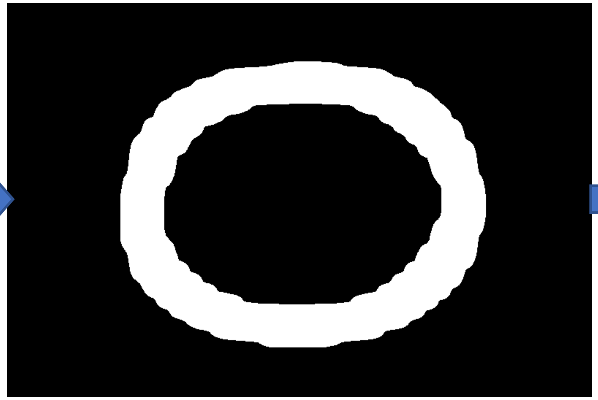
Models the non-linear problem of ellipse fitting. The algorythm calculates the ellipse parameters: certer coordinates, axes length and rotation angle. *[Prasad et al. 2013]*



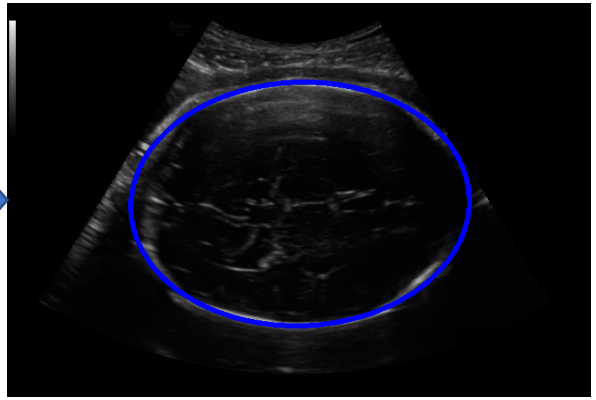
US image



Distance Field



Binary mask



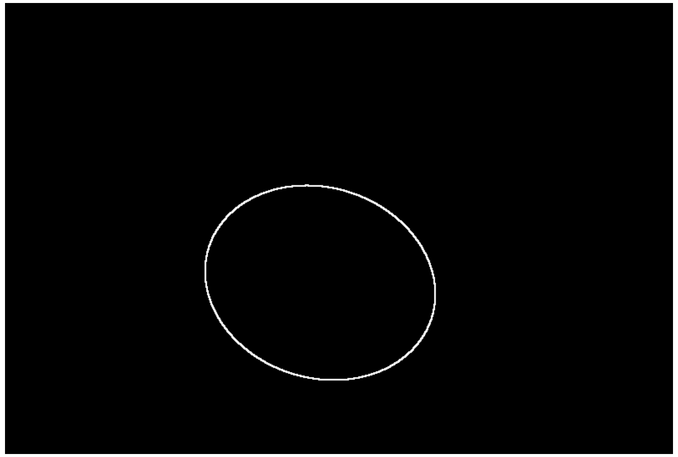
Ellipse

Dataset description and its challenges

HC18 Grand Challenge Dataset *[Van den Hevel et al. 2018]*

- **999** ultrasound images and their annotation for training
- **335** ultrasound for testing

Ultrasound images are related to **all gestational trimesters**.



Challeges of the Dataset

- Head size variability
- Artifacts
- Attenuation
- Shadows
- Speckle Noise
- Missing Boundaries
- Low signal-to-noise ratio

Dataset description and its challenges

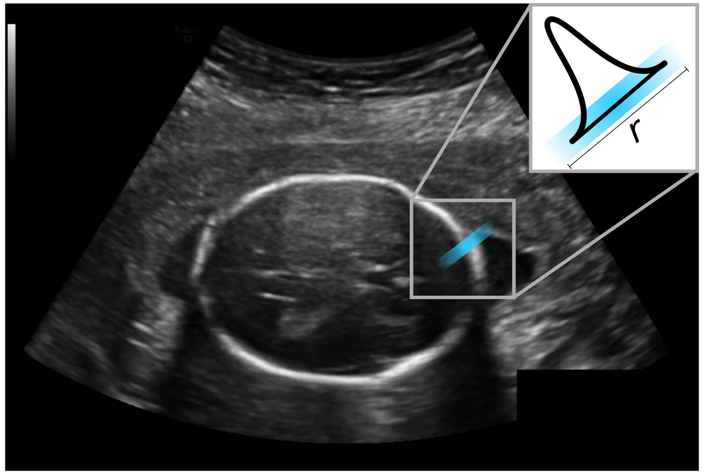
Regression Masks were used in regression phase.

Hold Out is performed to divide the training dataset in two parts:

- **80% Training set**
- **20% Validation set**

We used a stratified split to obtain two balanced set on the trimester.

Data Augmentation on the fly is performed: images and mask in the training set are scaled, translated and rotated.



Regression Mask

Experimental Protocol

The **Distance Field Mask RCNN** was trained with the following settings, starting with **coco weights**:

- **Backbone:** ResNet 101
- **Optimizer:** Mini Batch Gradient Descent
- **Learning rate:** 0.001
- **Momentum:** 0.9
- **Batch size:** 4
- **Epochs:** 10 Head layers + 12 All layers

Performance Metrics:

DC: $\frac{2*|\mathrm{Area_p} \cap \mathrm{Area_{gt}}|}{|\mathrm{Area_p}|+|\mathrm{Area_{gt}}|}$

DF (mm): $HC_p - HC_{gt}$

ADF (mm): $|HC_p - HC_{gt}|$

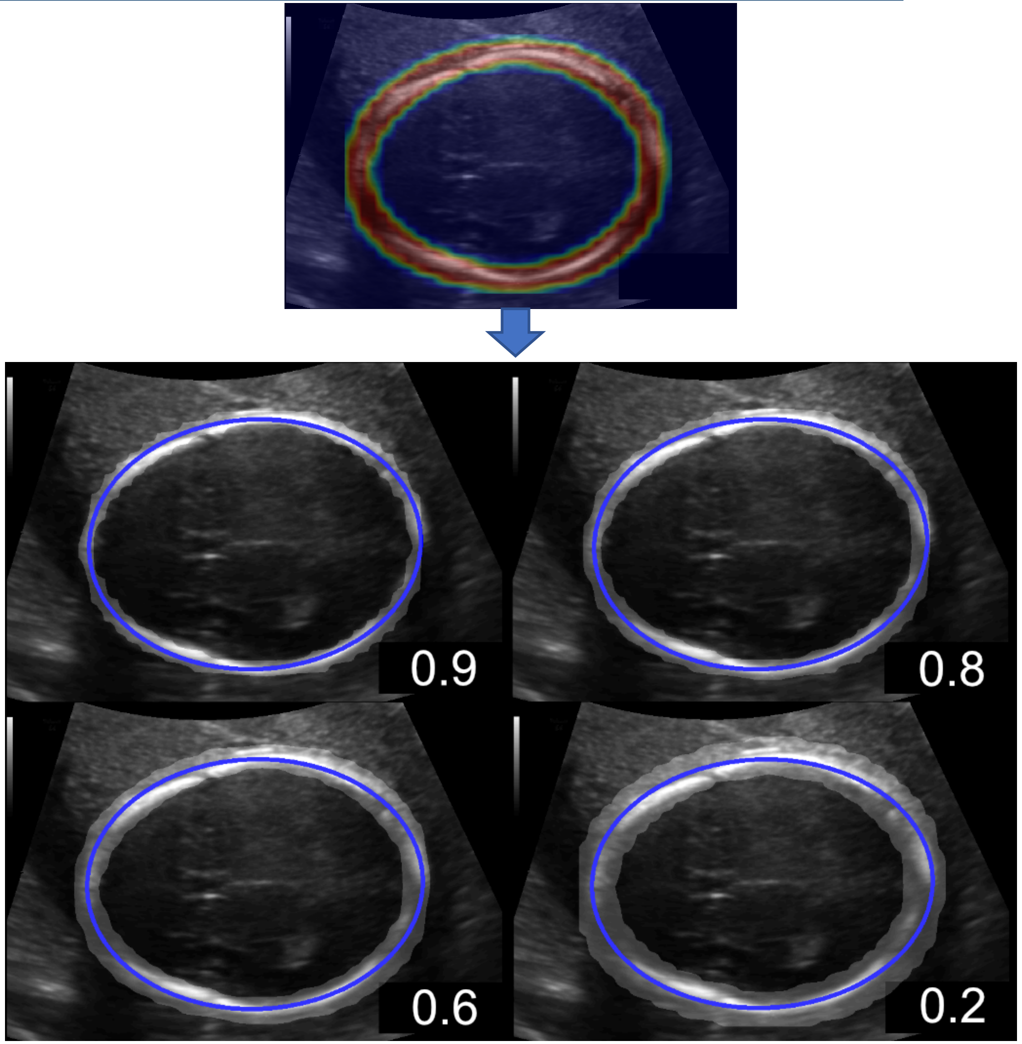
HD (mm): $\max(h(P,G), h(G,P))$

$$h(P,G) = \max_{p \in P} \min_{g \in G} \|p - g\|$$

Results

The table below shows the results obtained with the varius **thresholds applied to the Distance Fields**

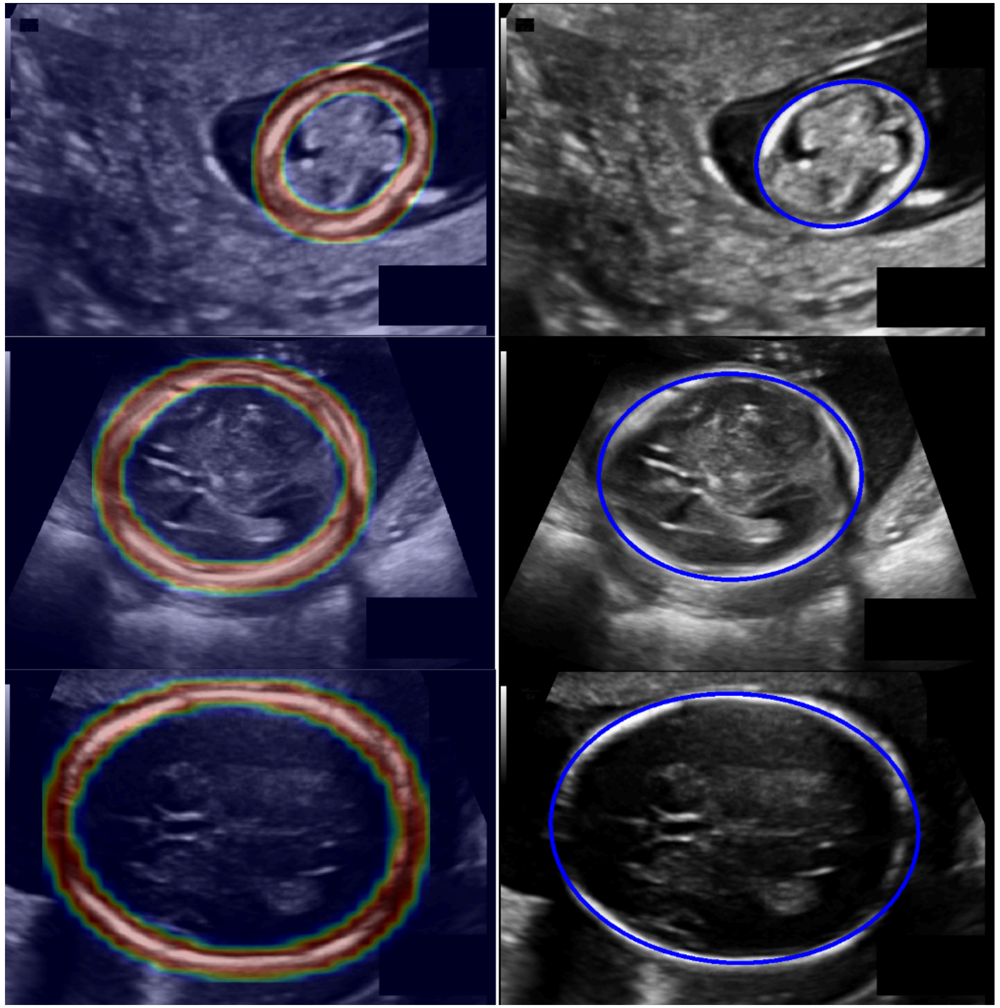
Threshold	DC	DF (mm)	ADF (mm)	HD (mm)
0.9	97.30 $\pm$ 1.22	-2.88 $\pm$ 3.04	3.29 $\pm$ 2.59	1.53 $\pm$ 0.84
0.8	97.29 $\pm$ 1.27	-2.47 $\pm$ 3.01	3.00 $\pm$ 2.48	1.52 $\pm$ 0.82
0.6	97.25 $\pm$ 1.39	-1.65 $\pm$ 2.94	2.50 $\pm$ 2.27	1.54 $\pm$ 0.82
0.2	**96.83 $\pm$ 1.73**	**0.22 $\pm$ 2.96**	**2.10 $\pm$ 2.10**	**1.80 $\pm$ 0.96**



Results

The table below shows the results obtained with the **threshold = 0.2 diveded by trimester**

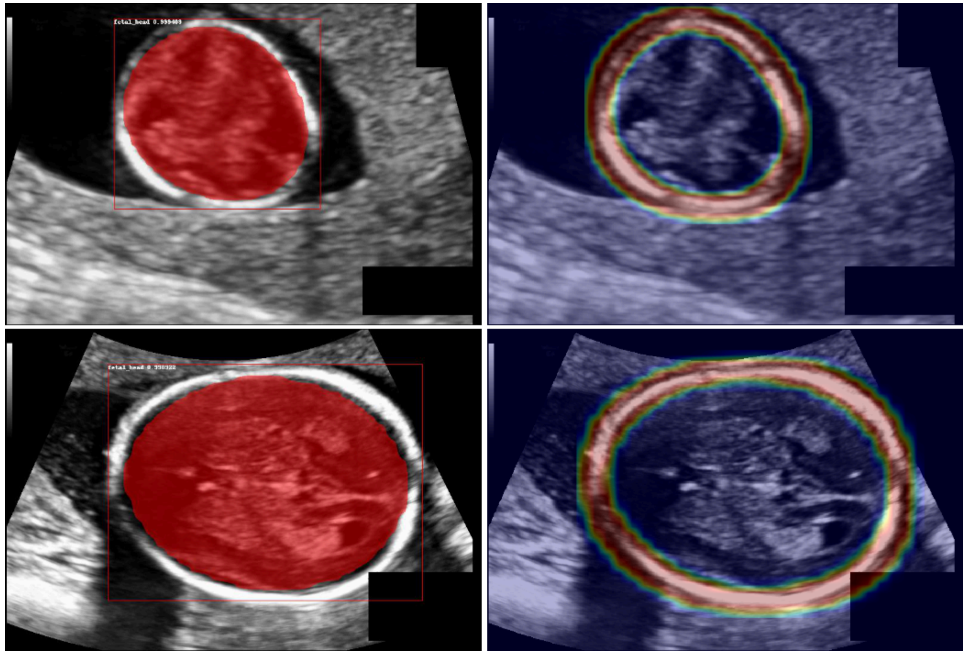
Trimester	DC	DF (mm)	ADF (mm)	HD (mm)
1	95.17 $\pm$ 2.97	1.39 $\pm$ 2.72	1.96 $\pm$ 2.33	1.35 $\pm$ 0.91
2	97.16 $\pm$ 1.15	0.13 $\pm$ 2.56	1.83 $\pm$ 1.79	1.69 $\pm$ 0.83
3	97.16 $\pm$ 0.85	-0.68 $\pm$ 4.44	3.61 $\pm$ 2.62	2.88 $\pm$ 0.90



Results

We compared the best results obtained with the **Distance Field Mask RCNN** with the best results obtained with the **original Mask RCNN.**
Mask RCNN fails in the segmetation of the head contourn.

Method	DC	DF (mm)	ADF (mm)	HD (mm)
Mask RCNN	89.25 $\pm$ 1.59	-18.11 $\pm$ 7.56	18.13 $\pm$ 7.52	3.85 $\pm$ 1.58
DF Mask RCNN	**96.83 $\pm$ 1.73**	**0.22 $\pm$ 2.96**	**2.10 $\pm$ 2.10**	**1.80 $\pm$ 0.96**



On the left column the output of the original Mask RCNN, on the right column the output of the Distance Field Mask RCNN

Results

We also compared our best results with those presented in literature.
Our method shows comparable results to the other systems.

Method	DC	DF (mm)	ADF (mm)	HD (mm)
DF Mask RCNN (ours)	**96.83 $\pm$ 1.73**	**0.22 $\pm$ 2.96**	**2.10 $\pm$ 2.10**	**1.80 $\pm$ 0.96**
Rajinikanth et al. 2019	94.27 $\pm$ -	-	-	-
Van den Hevel et al. 2018	97.0 $\pm$ 2.8	0.6 $\pm$ 4.3	2.8 $\pm$ 3.3	2.0 $\pm$ 1.6
Desai et al., 2020	97.33 $\pm$ 1.41	-	-	1.58 $\pm$ 0.97
Sobhaninia et al., 2019	96.84 $\pm$ 2.89	1.13 $\pm$ 2.69	2.12 $\pm$ 1.87	1.72 $\pm$ 1.39
Sobhaninia et al., 2020	92.46 $\pm$ -	1.19 $\pm$ -	2.22 $\pm$ -	3.40 $\pm$ -
Sobhaninia et al., 2020	-	-	4.52 $\pm$ 4.27	-
Aji et al., 2019	-	41.75 $\pm$ -	-	-

Future work

Future improvements for the proposed method:

- A **larger dataset** with more ultrasound images
- Add Convolutional Layers to **directly regress the parameters of the ellipse**

Thank you

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