

باسمه تعالی



## پروژه‌ی درس پردازش تصاویر دیجیتال

استاد درس  
دکتر داوود پوره

دانشکده‌ی مهندسی برق  
دانشگاه صنعتی شریف

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## Introduction

Image processing techniques are used in many applications, nowadays. With developments of deep neural networks in computer vision, the applications are growing at a rapid pace that we may encounter most of them in our daily life. One of the most interesting application is in medical image processing. In this project you will use both classical and deep learning methods that you've learnt for a real-world problem in medical image processing.

## Fetal Health

One of the most important jobs of radiologist is checking the growth of fetus and its health during pregnancy. They use fetal biometric parameters such as head circumference (HC), abdominal circumference (AC), femur length (FL), etc, at each stage of fetus growth to make sure that it's healthy and if not, make decision about it. While it seems to easy, but extracting these parameters could be a time-consuming and prone to operator's error for a radiologist. In order to make this task easier and safer for radiologist and patients, we can use image processing techniques to **extract these parameters** from **ultrasound images**. In this project, you will be given a dataset which comprises of different fetal head images and try to extract the head circumference (HC) from it. We would use multiple methods to improve the validity of our final methods.

## Dataset

The dataset that we're going to use for this project is HC18. First, the data can be downloaded from Zenodo, <https://doi.org/10.5281/zenodo.1322000>. The data is divided into a training set of 999 images and a test set of 335 images. The size of each 2D ultrasound image is 800 by 540 pixels with a **pixel size** ranging from 0.052 to 0.326 mm. The pixel size for each image can be found in the csv files: "training\_set\_pixel\_size\_and\_HC.csv" and "test\_set\_pixel\_size.csv". The training set also includes an image with the manual annotation of the head circumference for each HC, which was made by a trained sonographer. The csv file "training\_set\_pixel\_size\_and\_HC.csv" includes the head circumference measurement (in millimeters) for each annotated HC in the training set. All filenames start with a number. There are 999 images in the training set, but the filenames only go to 805. Some ultrasound images were made during the same echoscopic examination and have therefore a very similar appearance. These images have an additional number in the filename in between "\_" and "HC" (for example 010\_HC.png and 010\_2HC.png). Since the test data images are not annotated, **we would only use the training set**, thus, in different part of the project **divide** the training data into two groups. One for training and the other one for testing. A proportion of **4 to 1** is recommended. Also, in the deep learning part, since the overall size of the training data might be small, try **data augmentation methods** such as rotation to improve your results but don't forget to mention your method precisely in your report document.

## Classical Method

As our first approach, we would use a chain of simple classical operation to extract the fetal head circumference (HC). For this part, you are given a separate example data to implement your processing chain on it. Its name is “example.png” and you can locate it in your project folder.

### Problem 1.

Try to classify the gray-scale version of the image pixels into 3 groups of “bright”, “gray” and “background” using K-means classifier. Depict the bright pixels only in a separate figure. Does it contain the fetal head?

### Problem 2.

Use different morphological transforms to remove small objects from the bright pixels. Specify exactly what kind of morphological transforms have you used. After removing redundant pixels, depict the skeleton image of the remaining pixels.

### Problem 3.

Now, in order to find the best and most prominent ellipse in the image, we would use the iterative randomised Hough transform. First, give a full description of this method in your report.

### Problem 4.

Use the described method to fit the best ellipse in the image. The wanted result should be looking like the following figure. Remember to show the result of some iterations of the iterative randomised Hough transform. (Bonus) Do you have any better idea how to improve this algorithm?

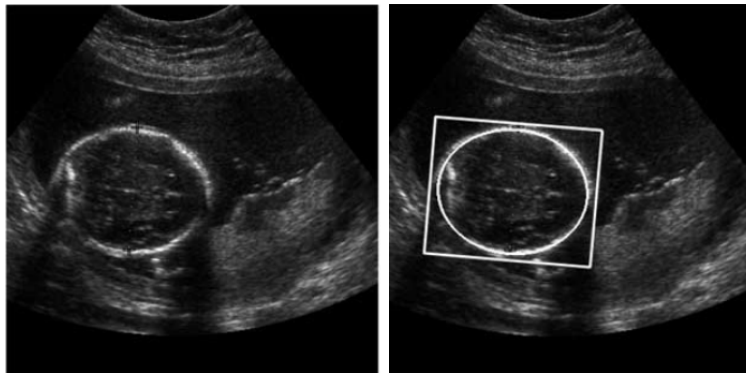


Figure 1: Final result of processing

## Deep learning Methods

Although classical methods are much easier to explainable and more interpretable, but their results are not much acceptable in many applications. On the other hand, with advances in deep learning and their amazing results, the tendency toward using them are growing at a rapid pace. Here, We are going to check the result of some methods based on deep learning with the mentioned classical method. A review of our deep learning approaches are shown in ???. As our first

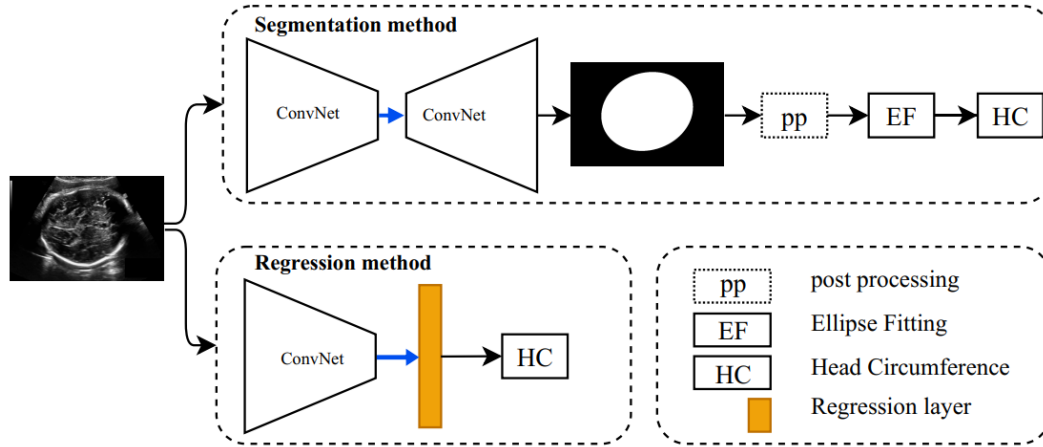


Figure 2: Overview of head circumference estimation process based on either segmentation-based method or regression-based method. HC: Head circumference, pp: Post-processing (the dotted box means is optional), and EF: Ellipse fitting.

approach, we would use a method based on **segmentation of the fetal head** directly from the image. We would use U-Net network for segmentation of the fetal head in the ultrasound images.

### Problem 5.

Give a full description of the structure of the U-Net and its architecture in your report. Also specify the preprocessing methods you would use for improvement of your results.

### Problem 6.

Implement the described U-Net and depict the results of the network on some of your test data images.

### Problem 7.

Now use iterative randomised Hough transform to fit the best ellipse to the segmented images. Depict the result for 1 or 2 images of your test data. As our second approach we want to implement a regression CNN model for estimating the HC parameter. As shown in Figure 2, the regression CNN are composed of a CNN backbone and **regression layer (linear activation function)**, which can learn the features of the input fetus head to estimate the HC value directly. The backbone CNN that we would be state-of-the-art VGG-16 architecture. In order to improve model convergence we suggest to use the network pretrained on ImageNet, and fine-tune them for the task at hand.

**Problem 8.**

Give a full report on your regression CNN model and your preprocessing methods. Implement your model afterwards and give a summary on your results. Note that the HC parameter is calculated using the following equation:

$$HC = \pi(a + b)\left(1 + \frac{3h}{10 + \sqrt{4 - 3h}}\right)$$

Where  $a$  and  $b$  are the long and short axis of the ellipse, respectively. And also,  $h = \frac{(a-b)^2}{(a+b)^2}$ .

**Problem 9.**

Compare the results of the three methods that you've implemented on your test data. Which one is better? Analyse your results in detail.

**Bonus Part**

Generative deep learning models such as GANs are used in recent years for applications such as image-to-image translation. Here we want to implement one of the famous image-to-image network architecture, Pix2Pix.

**Problem 10.**

Give a full description of GANs and Pix2Pix network in your report. Train your Pix2Pix on the [Satellite-Map dataset](#) which consists of satellite map and their corresponding google map translation image.

**Problem 11.**

Fine-tune your network for the fetal head detection and implement the segmentation part process chain on the network result to find the HC parameter. Compare the result with the previous methods.