# A Study of Automated measurement of fetal head circumference using 2D ultrasound images

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#### 1 Introduction

In this report, I implemented EfficientNetB7 model with loss function Mean Absolute Error (MAE or L1Loss()) to measure the Fetal head circumference using Ultrasound with regression method.

# 2 Data Analysis

The dataset used in this study is the HC18 dataset. The training dataset contains 999 2D ultrasound images of fetal head and the corresponding ground truth masks, whereas the test dataset consists of 335 2D ultrasound images of fetal head with no labels. For training the model, the training dataset will be split into train-valuation-test sets. After thorough examination, the duplicated images are dropped, here is the proportion of the split set: 564-121-121 (806 images). Below is the Histogram plot and the Box plot of the dataset. It demonstrates the pixel's density of the dataset image:

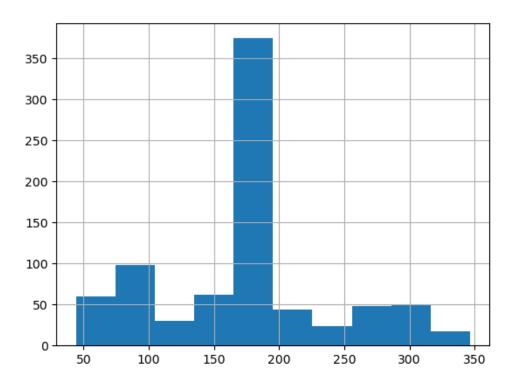


Figure 1: Histogram plot

# 3 Images Transformation

Only for the train set, I applied data augmentation, by flip horizontal randomly, and random rotation with degrees vary from -10 to 10. For all 3 images set, I applied gray scaling, resizing to 224x224 (input format which the model required), blurring using Gaussian's algorithm, cropping the center, and normalizing the pixel density.

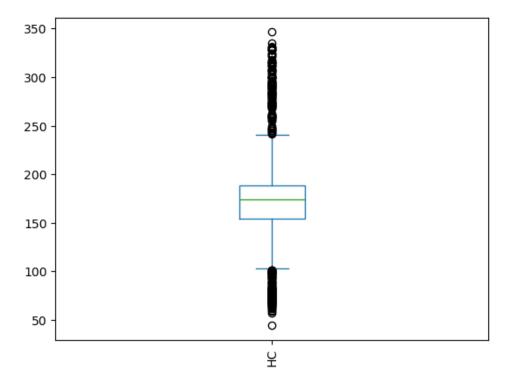


Figure 2: Box plot

# 4 Model

#### 4.1 Transfer Learning

The model I choose is the EfficientNetB7. Originally, this pre-trained model is used for classification tasks with the last layer as softmax activation. In order to transfer learning it into regression task, in the last layer, I get the number of input features (the size of the feature vector extracted by the CNN), then I replace the original classification layer with a new nn.Sequential module. Which means I map the CNN features to a single output neuron, predicting the single continuous value (head circumference) for regression.

#### 4.2 Loss Function

I used the Mean Absolute Error (MAE or L1loss()) in order to evaluate the validation and test set, simply because the teacher required it. The loss function is defined as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

where:

- n is the number of samples.
- $y_i$  is the actual (true) value for the *i*-th sample.
- $\hat{y}_i$  is the predicted value for the *i*-th sample.

# 4.3 Optimizer

I chose the Adam optimizer for training the model. Adam (Adaptive Moment Estimation) is an adaptive learning rate optimization algorithm designed to handle noisy and sparse gradients. It combines the advantages of AdaGrad and RMSProp, providing efficient and effective training. The Adam optimizer updates the network weights based on the first and second moments of the gradients.

## 4.4 Training Details

The model was trained for 150 epochs, with an early stopping criterion set to 20 epochs. This means that if the validation loss did not improve for 20 consecutive epochs, the training process would be terminated to prevent overfitting. The learning rate for the Adam optimizer was set to 0.0001. The batch size used during training was 10.

## 5 Results

# 5.1 Training and Validation Losses

Overall, the training loss and validation loss is quite low.

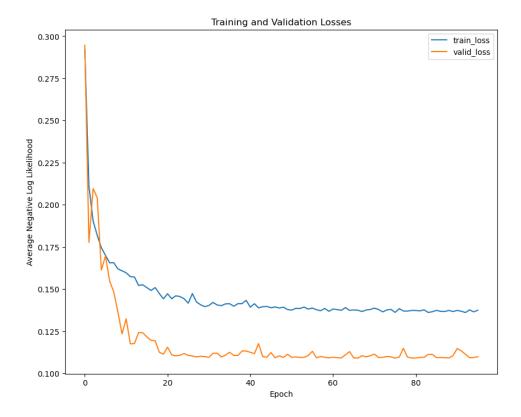


Figure 3: Training and Validation Losses

### 5.2 Evaluation on Test set

Test set MAE loss = 0.1266. Test set standard deviation of HC = 1.9322 mm Test set MAE loss of HC = 43.8687 mm

Filename: 390\_HC.png Actual HC: 177.06 mm Predicted HC: 176.80 mm

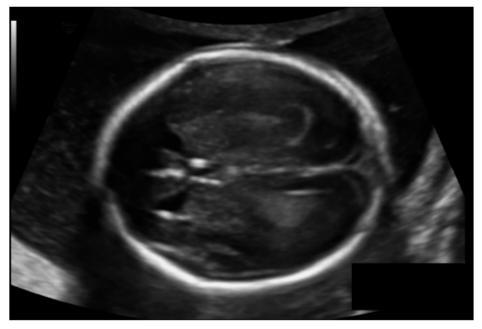


Figure 4: Example 1

Filename: 385\_HC.png Actual HC: 171.12 mm Predicted HC: 179.55 mm

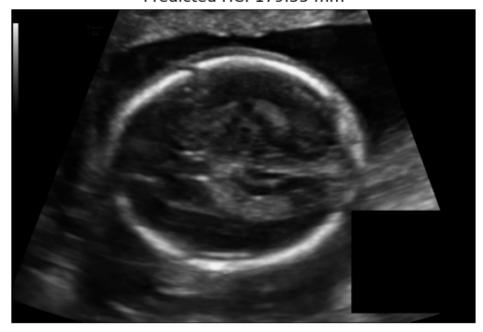


Figure 5: Example 2