Fetal Brain Segmentation

Basic Approach: Applying a UNet based image segmentation model to ultrasound images.

Input: 3 channel 224*224 ultrasound images   **Model Output:** 6 channel 224*224 segmentation maps

Final Output: 1 channel 224*224 where each pixel represents the segmented class

Downscaling architecture: Pretrained MobileNetv2 (weights are frozen)

Upscaling architecture: 2D Deconvolutional

Loss: SparseCategoricalCrossentropy (since output classes are in int format)

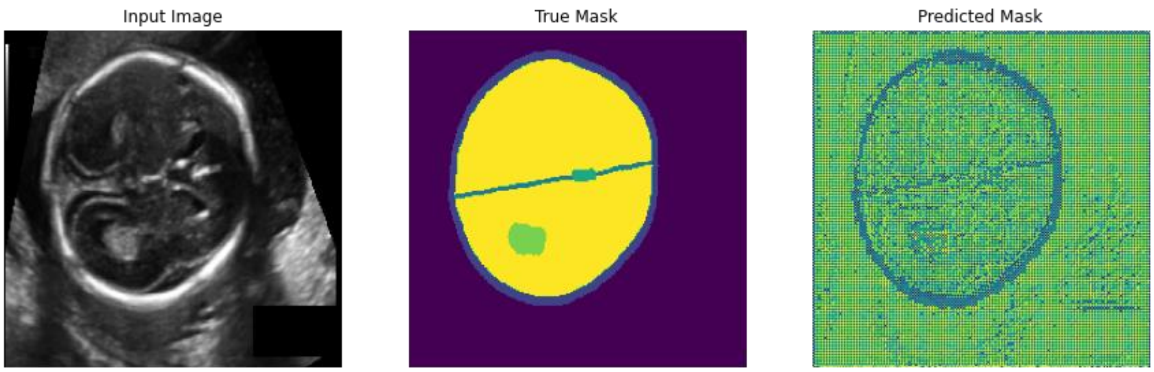

Figure 1: Model output before training.

Model is trained for 10 epochs with validation steps using validation data.

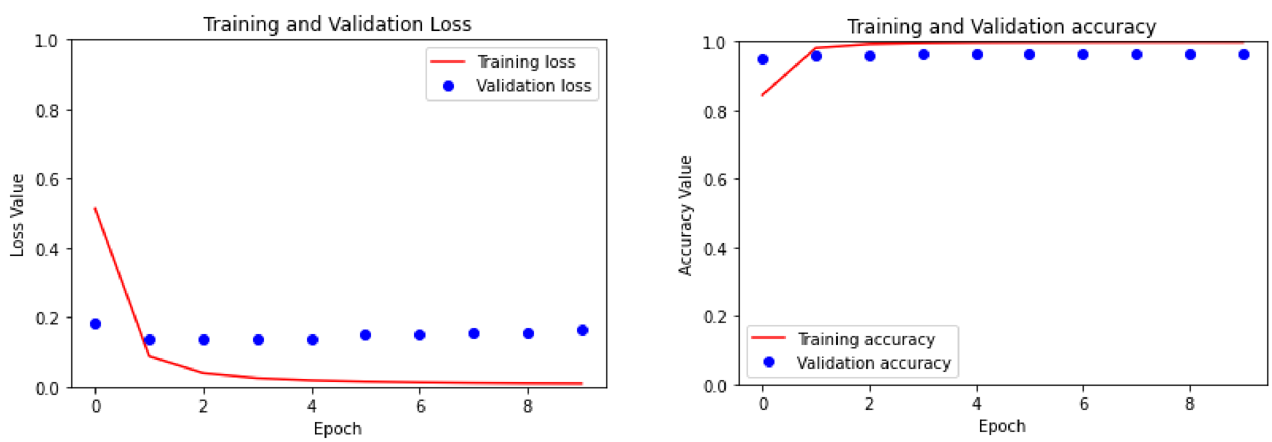

Figure 2: Loss and Accuracy during training.

Dice Score for training set: 0.984

Dice Score for validation set: 0.710

Overall, the resulting class segmentations hold up well, except in cases where certain sections in ultrasound images are not clearly visible or merge into background.

Class Weight Adjustment for improving results

We segment images into 6 different classes, but background and BRAIN_PARENCHYMA nearly takes around 80-90 % of the image. CSP and CHOROID_PLEXUS are small but their relative importance is higher when detecting brain anomaly. So, we try to adjust the weights of the classes by their relative importance in hoped of improving the results.

BACKGROUND : 1 CRANIUM : 2 MIDLINE_FALX : 2 CSP : 3

CHOROID_PLEXUS : 3 BRAIN_PARENCHYMA : 1 (assigned weights)

We have some improvement in Dice score for validation set.

Dice Score for validation set after class weight adjustment: 0.729

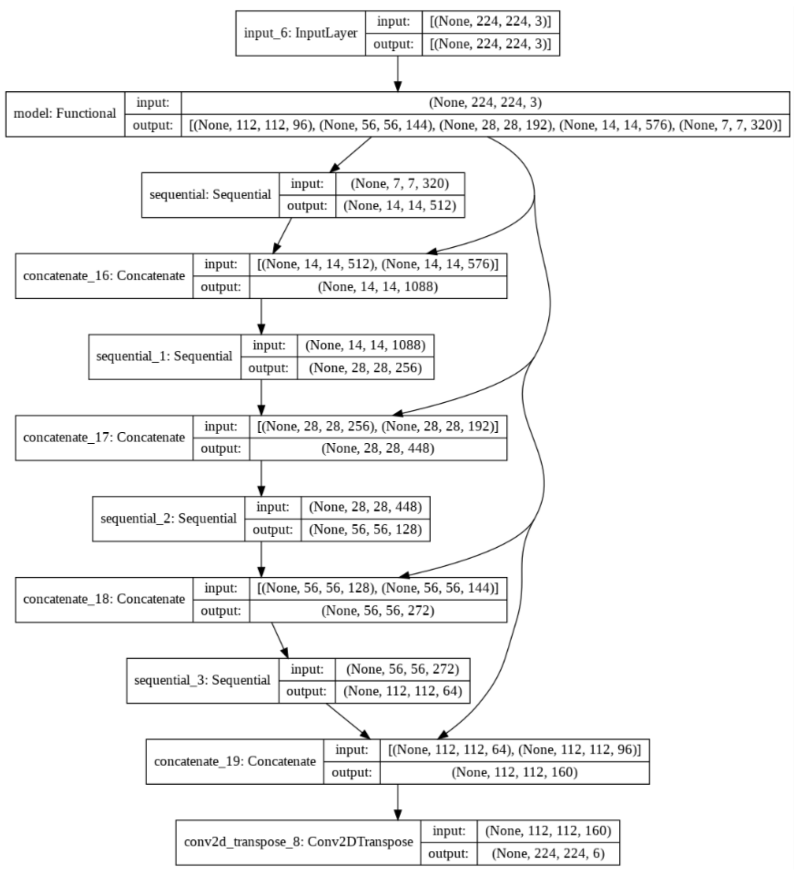

Figure 3: Model Architecture

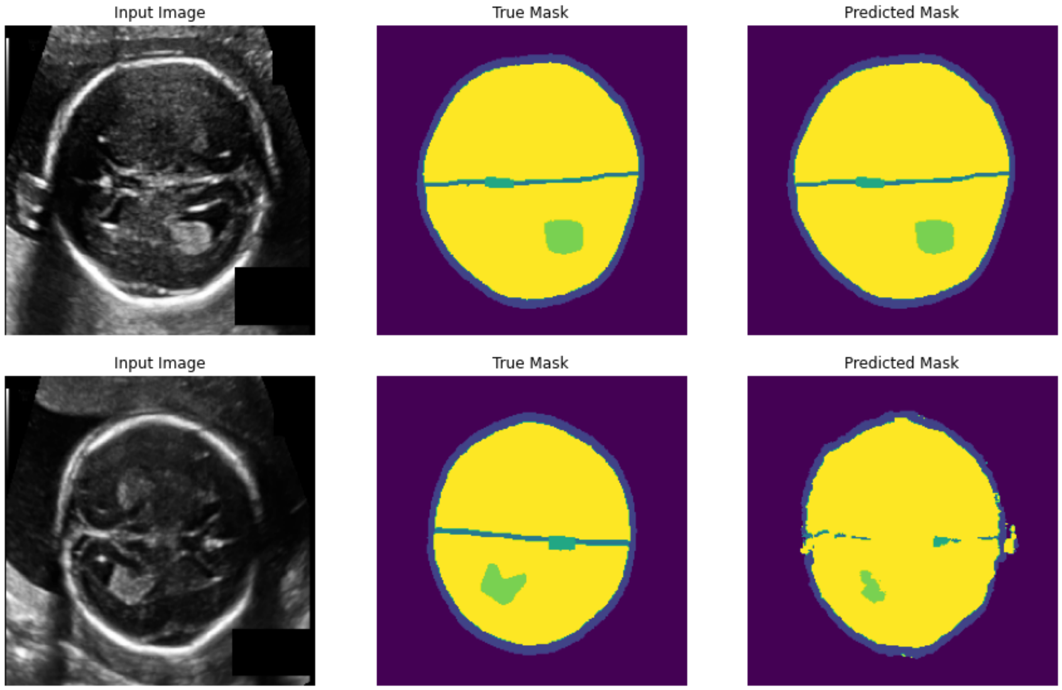

Figure 4: Validation set results