MEDICAL IMAGE SEGMENTATION ; CHEST X-RAYS AND ULTRA SOUND IMAGES OF FOETAL HEADS

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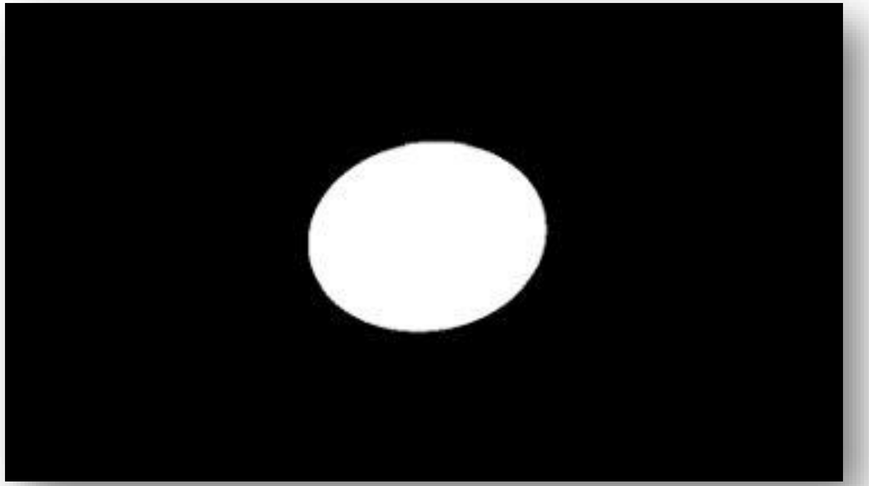
DATASETS USED

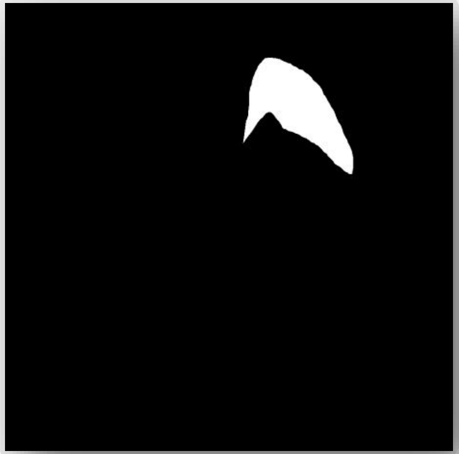
1) HC18 Dataset (Ultra sound images)
   - Given Information
     - Images (800 X 540)
     - Masks
     - Train-set 999 images
     - Test-set 335 images

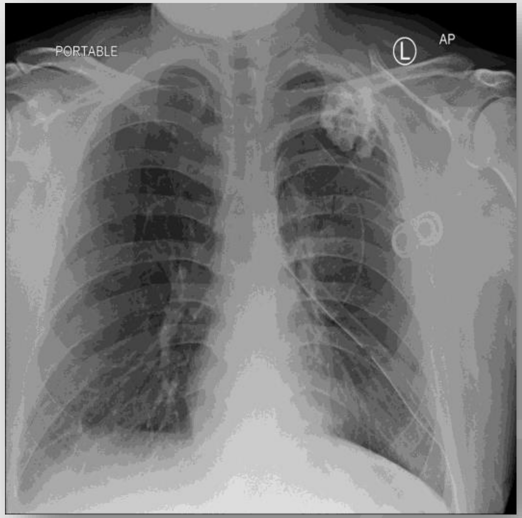


2) Chest X-ray dataset (SIIM Dataset)

- Given Information
  - Images (1024 X 1024)
  - Masks
  - Labels (0 or 1)
  - 12,047 images

im_path	label
0.jpg	0
1.jpg	1
2.jpg	0





PRE-PROCESSING:

1) GAUSSIAN BLUR + THRESHOLDING

Gaussian blurring followed by a combination of Otsu's and binary thresholding is done to remove noise components and smoothen the image

2) CLAHE

CLAHE is a variant of *Adaptive histogram equalization (AHE)* which takes care of over-amplification of the contrast.

CLAHE operates on small regions in the image, called tiles, rather than the entire image. The neighbouring tiles are then combined using bilinear interpolation to remove the artificial boundaries.

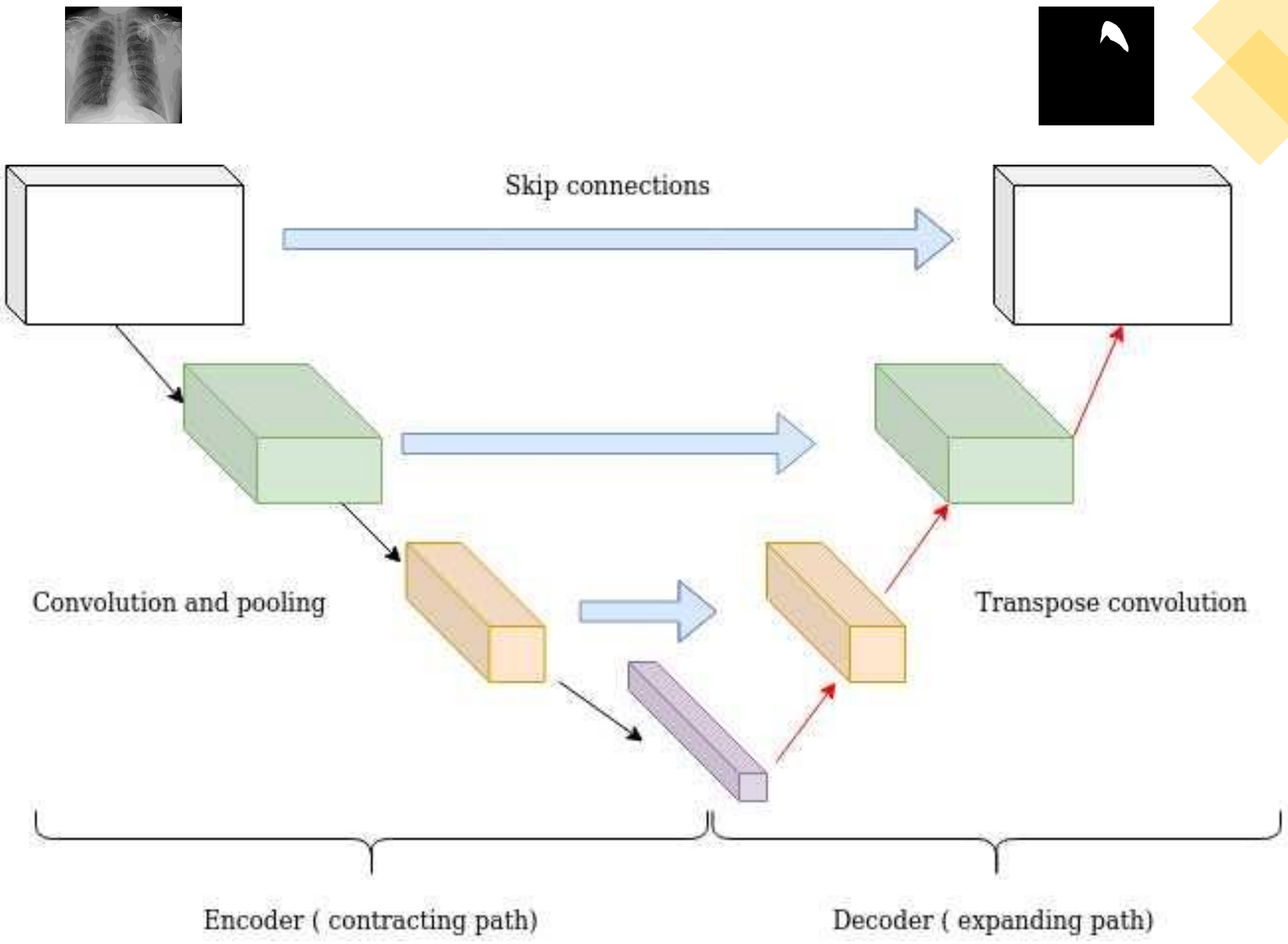
3) MEDIAN BLUR + CLAHE

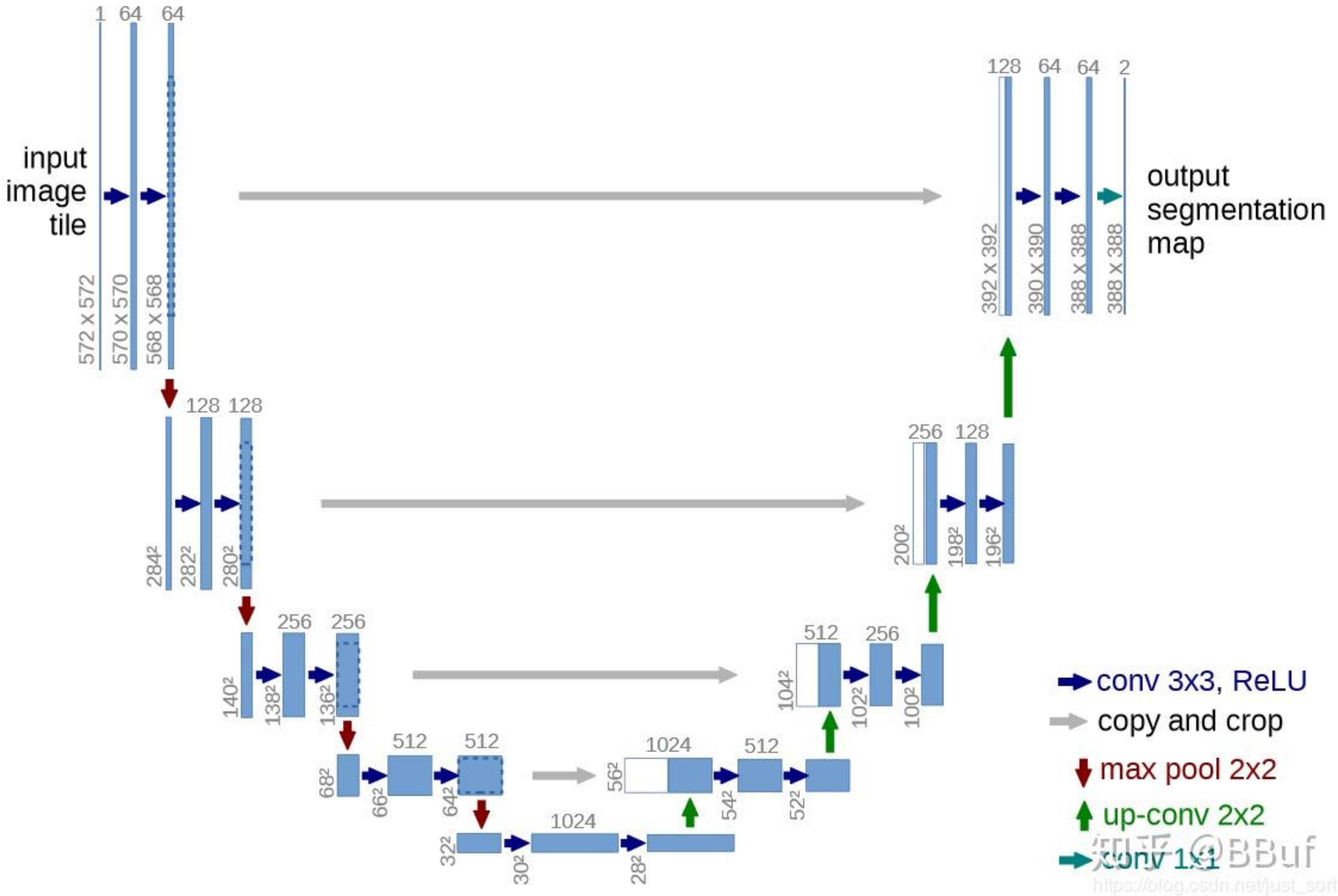
The Median filter is a non-linear filter. Unlike linear filters, median filters replace the pixel values with the median value available in the local neighborhood (say, 5x5 or 3x3 pixels around the central pixel value). Also, median filter is edge preserving (the median value must actually be the value of one of the pixels in the neighborhood).

MODELS USED

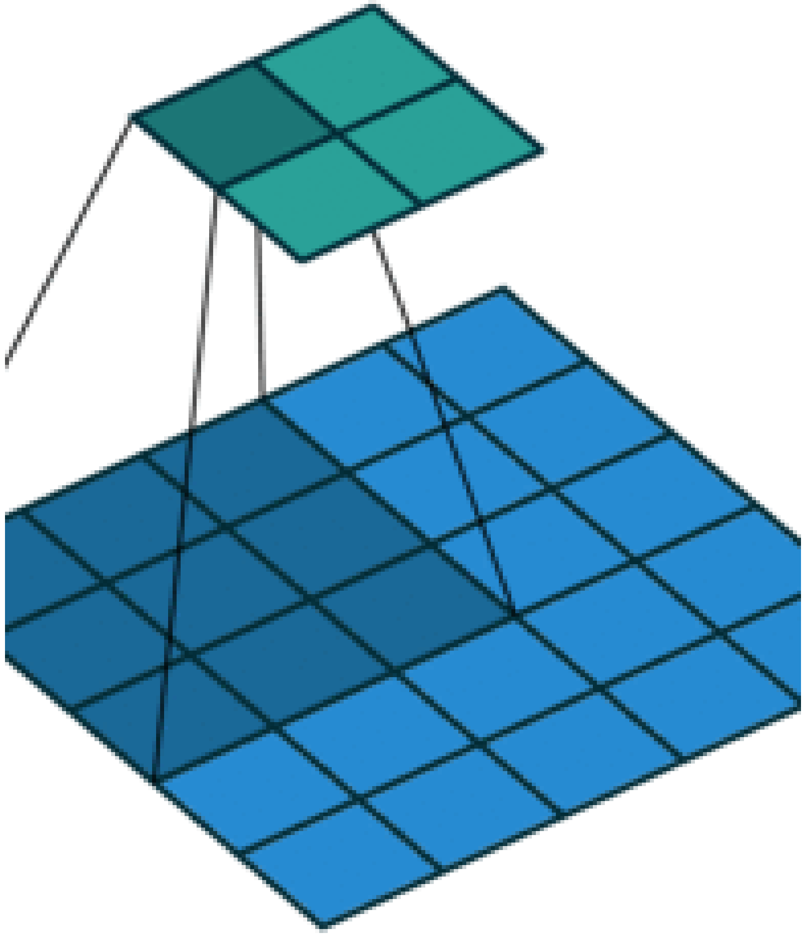
1) U-Net

- Encoder
  - Resnet 34 without fully connected layer and the global average pooling layer at the end.
- Decoder
  - Five blocks, each consisting of a 2 × 2 up-sampling layer followed by two sets of layers, each set has
    - Convolution
    - Batch normalization
    - ReLu Activation
- Skip Connections
  - First four blocks of the decoder and encoder are concatenated (the feature maps after up-sampling are concatenated with the feature maps)





input
image
tile
output
segmentation
map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1
1
64
64
572 x 572
570 x 570
568 x 568
128
128
284^2
282^2
280^2
256
256
140^2
138^2
136^2
512
512
68^2
66^2
64^2
1024
32^2
30^2
28^2
1024
512
56^2
54^2
52^2
512
256
104^2
102^2
100^2
256
128
200^2
198^2
196^2
128
64
64
2
392 x 392
390 x 390
388 x 388
388 x 388
知乎 @BBuf
https://blog.csdn.net/just_sort

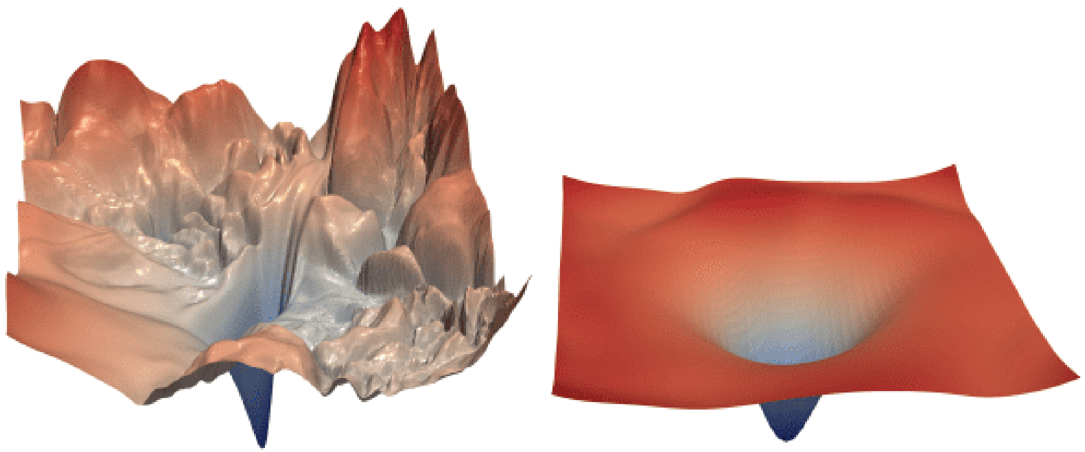


Unet :

- Unet is a fully Convolutional Neural Network.
- The architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization.
- UNet breaks the images down with the Convolution operations and re-creates the mask as the same size that of the image with De-convolution operations.
- Convolution :
  - Down-samples the image by convolution. Convolution in its core, reduces the dimensionality of the image by applying the various filters. On different levels of convolutions, we get images that are more fine-grained. Image becomes more and more fine grained with the level of convolution
- Deconvolution Network
  - Upsamples the image by de-convolution operations – transposed convolution
  - The transposed convolution operation forms the same connectivity as the normal convolution but in the backward direction. We can use it to conduct up-sampling.

Skip Connections Between Encoder and Decoder :

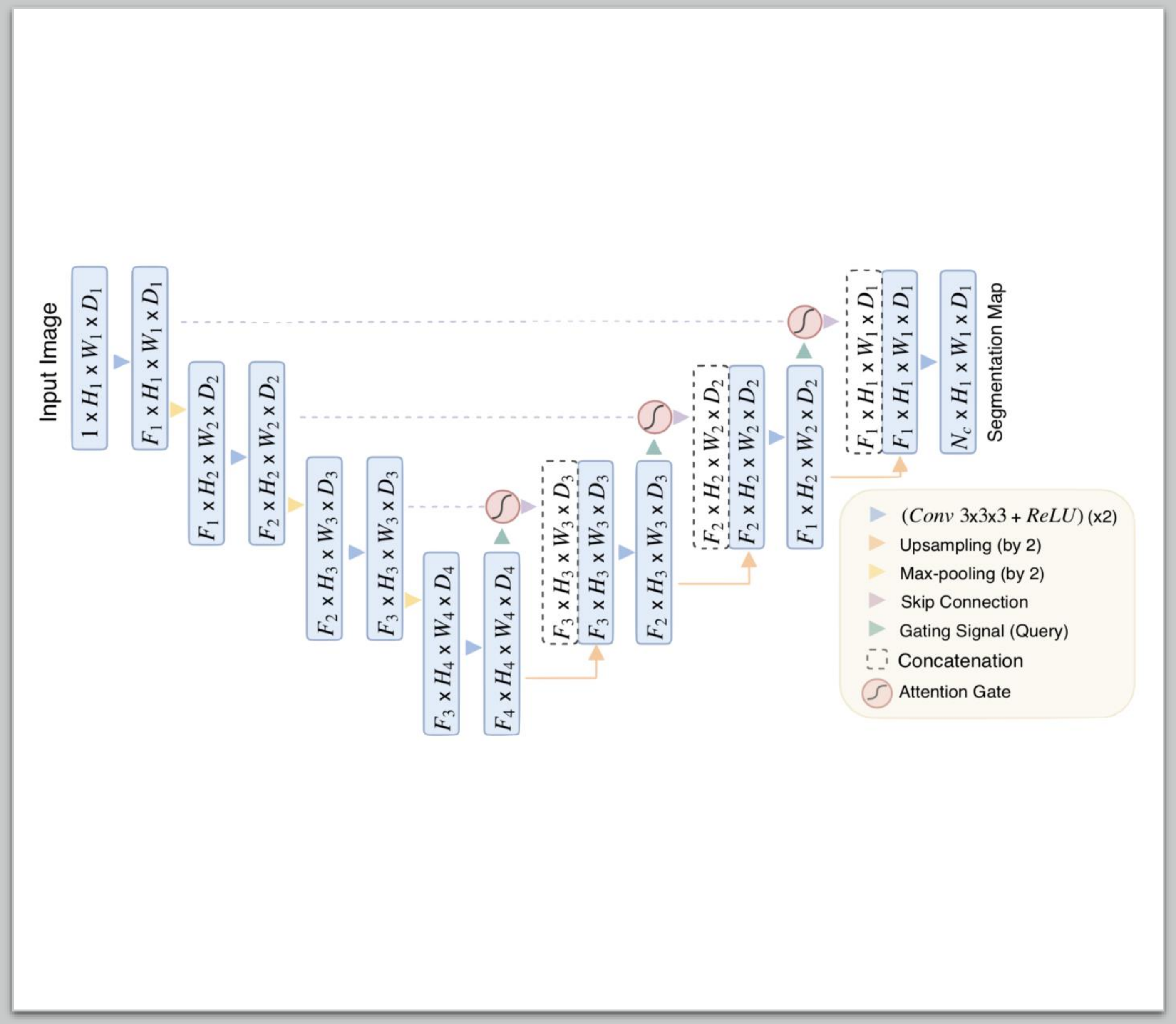
- At every step of the decoder we use skip connections by concatenating the output of the transposed convolution layers with the feature maps from the Encoder at the same level
- During upsampling in the expanding path, spatial information recreated is imprecise.
- To counteract this problem, the U-Net uses large skip connections that combine spatial information from the downsampling path with the upsampling path.
- the gradient becomes very small as we approach the earlier layers in a deep architecture, smaller skip connnections will help us overcome this.
- This brings across many redundant low-level feature extractions, as feature representation is poor in the initial layers.



(a) without skip connections (b) with skip connections

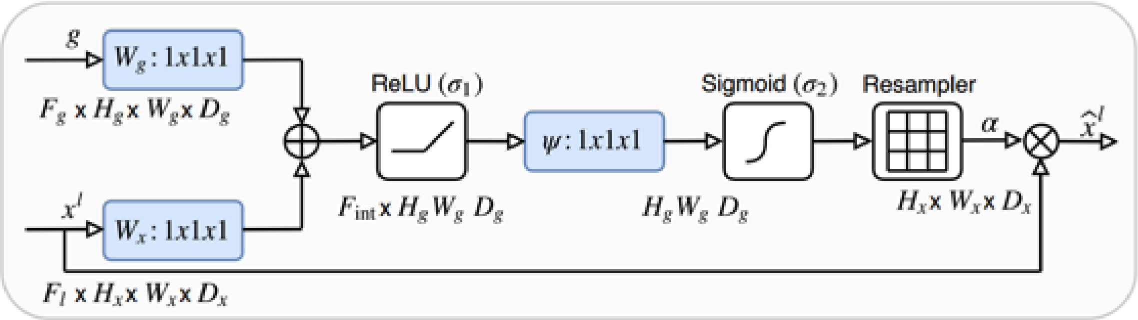
2) U-NET WITH ATTENTION (SMP)

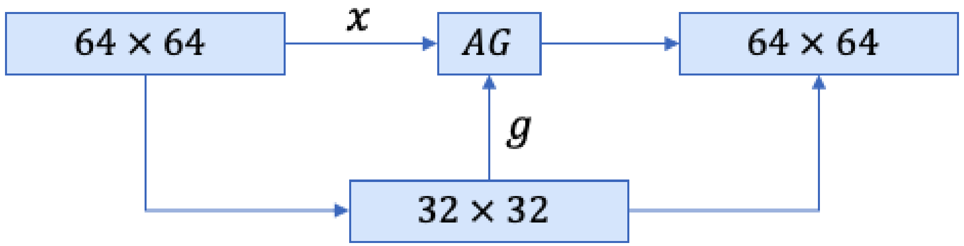
- U-Net with added Attention

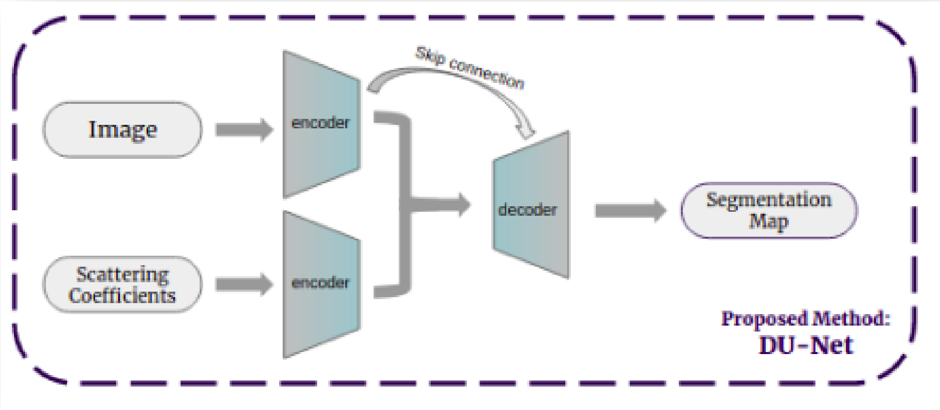


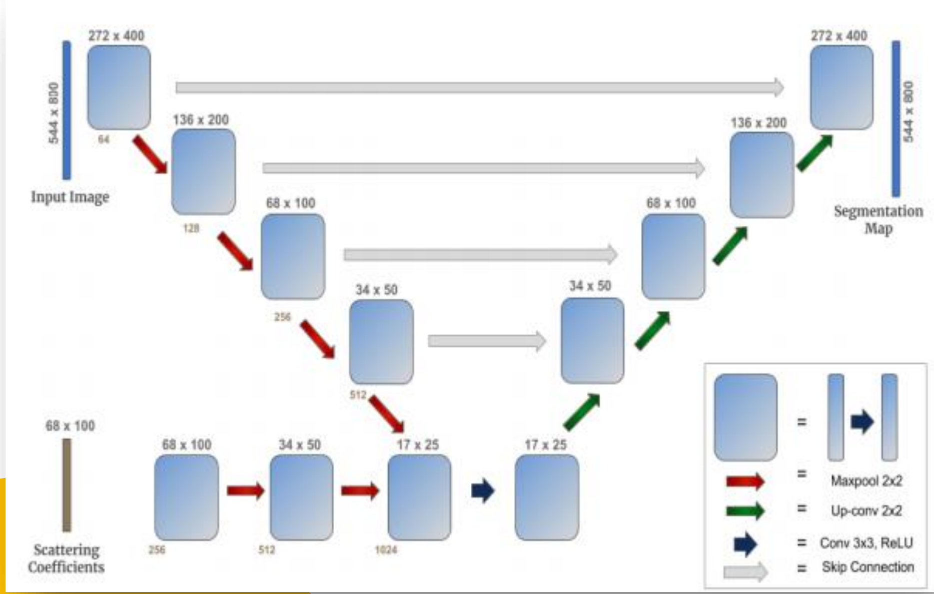
Unet with Attention :

- **Soft** attention implemented at the skip connections in UNet with attention model.
- This soft attention will actively suppress activations in irrelevant regions, reducing the number of redundant features brought across.









3) DU-NET

- Lighter network
- Attains good segmentation results
  - Encoder
    - Resnet 34 without fully connected layer and the global average pooling layer at the end
  - Scattering Coefficients
    - SC are lipschitz continous to deformations and are invariant to translations
    - Scattering coefficients of input images were derived from kymatio.torch library.
    - Encoder: Two blocks, each consisting of 3 x 3 convolution followed by 2 x 2 max-pool
  - Decoder
    - Five blocks, each consisting of a 2 × 2 up-sampling layer followed by two sets of layers, each set has
      - Convolution
      - Batch normalization
      - ReLu Activation

TRAINING

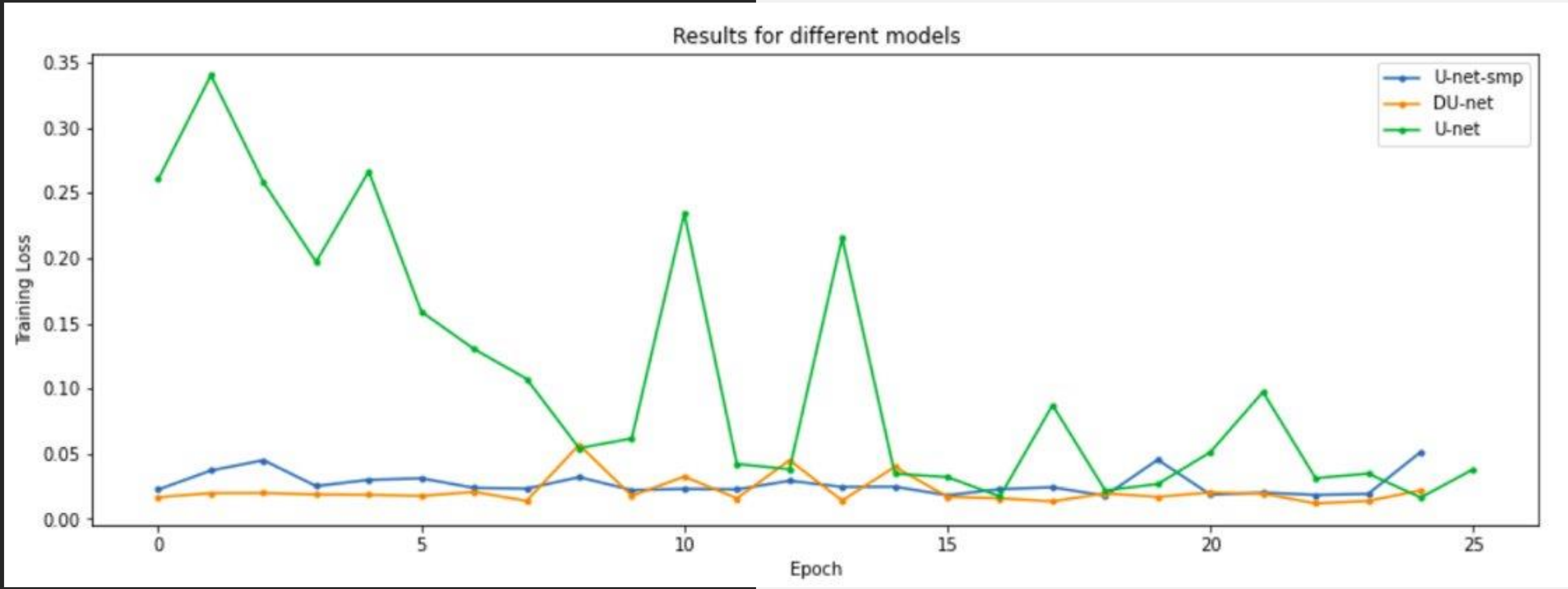
- 3 Models
  - Unet, SMP, DUnet
    - Training Criteria: Dice loss
    - Epochs: 25
    - Optimiser: ADAM optimiser
- Evaluation Criteria: IoU Score

$$\mathrm{DSCL} = 1 - \frac{2 \times |\mathrm{X} \bigcap \mathrm{Y}|}{|\mathrm{X}| + |\mathrm{Y}|}$$

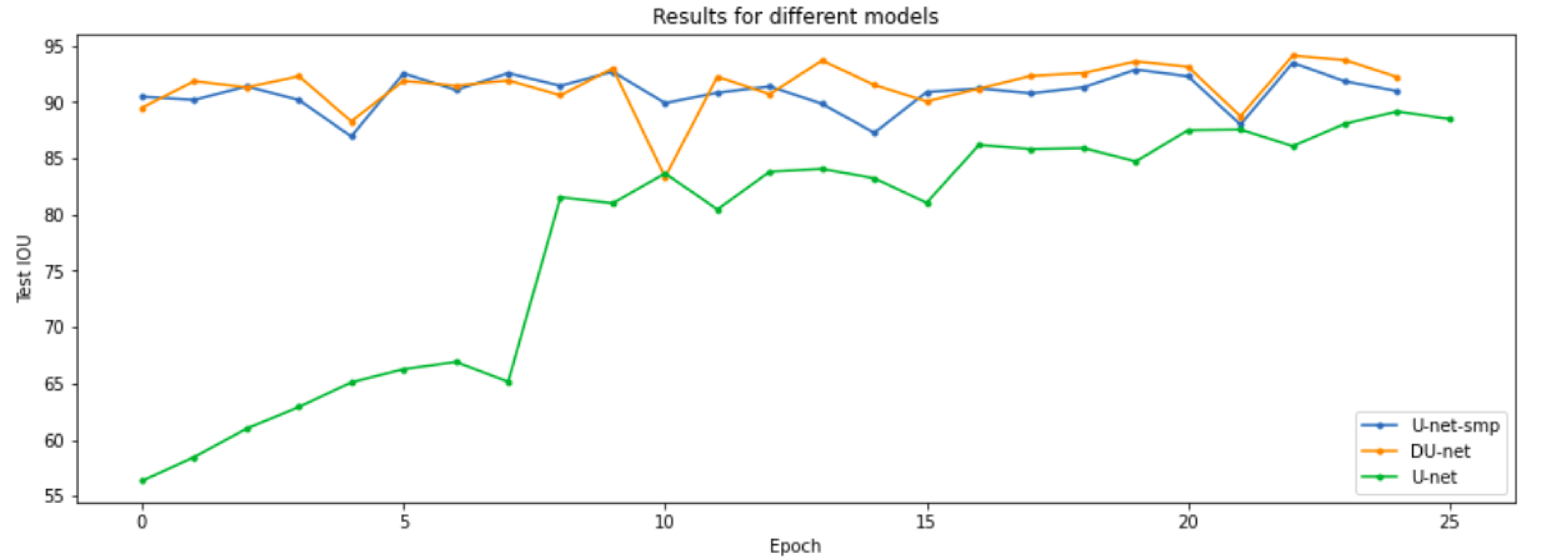
$$\mathrm{IoU}(P_{\text{true}}, P_{\text{predicted}}) = \frac{P_{\text{true}} \bigcap P_{\text{predicted}}}{P_{\text{true}} \bigcup P_{\text{predicted}}}$$

Model comparison

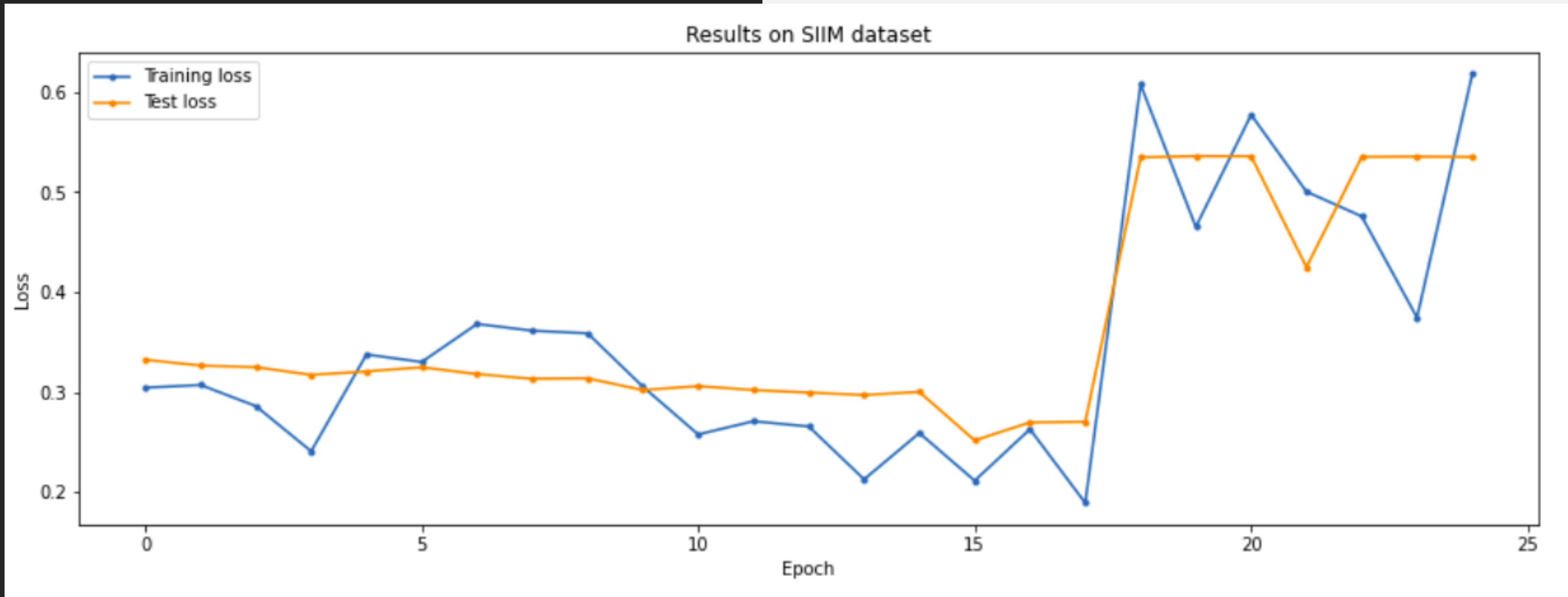
- Train results of 3 models
    - HC-18 dataset
    - Epoch Vs Loss



- Test results of 3 models
  - HC-18 dataset
  - Epoch Vs IoU Score



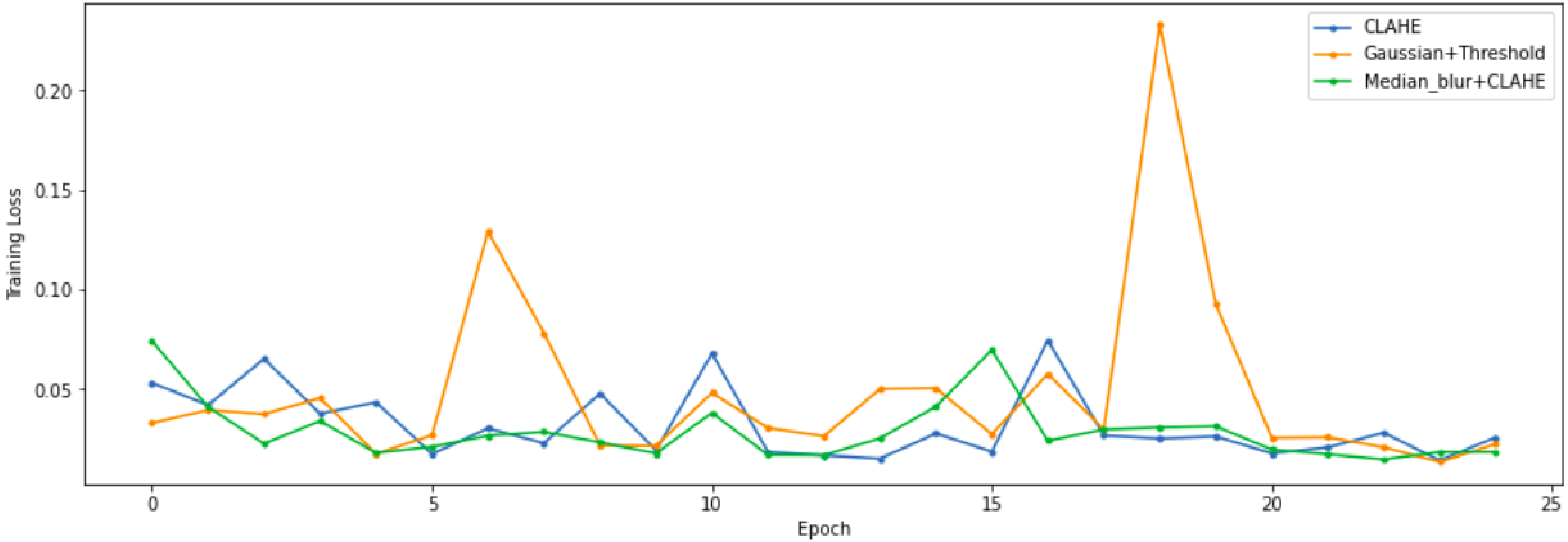
- Train results
    - SIIM dataset
    - Epoch Vs Loss



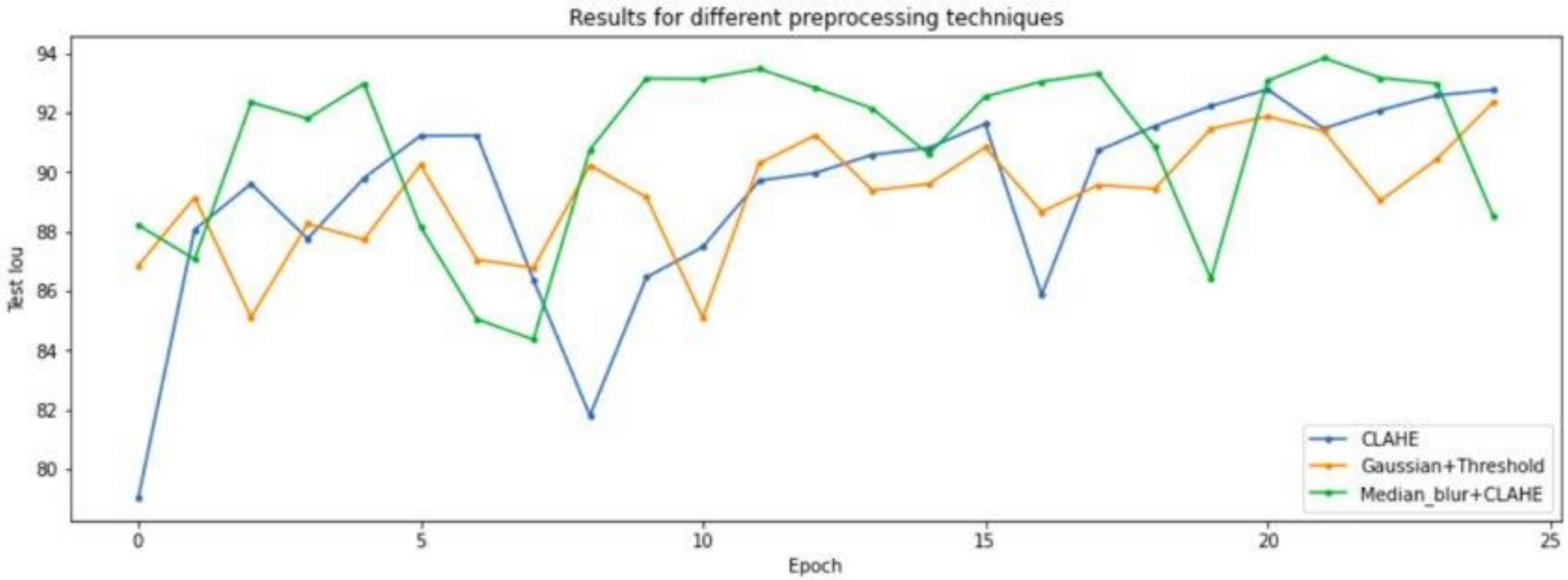
- Test results
  - SIIM dataset
  - Epoch Vs IoU Score

With pre-processing

- Train results
    - Model: UNet-SMP
    - HC-18 dataset with 3 different preprocessing techniques
    - Epoch Vs Loss graph



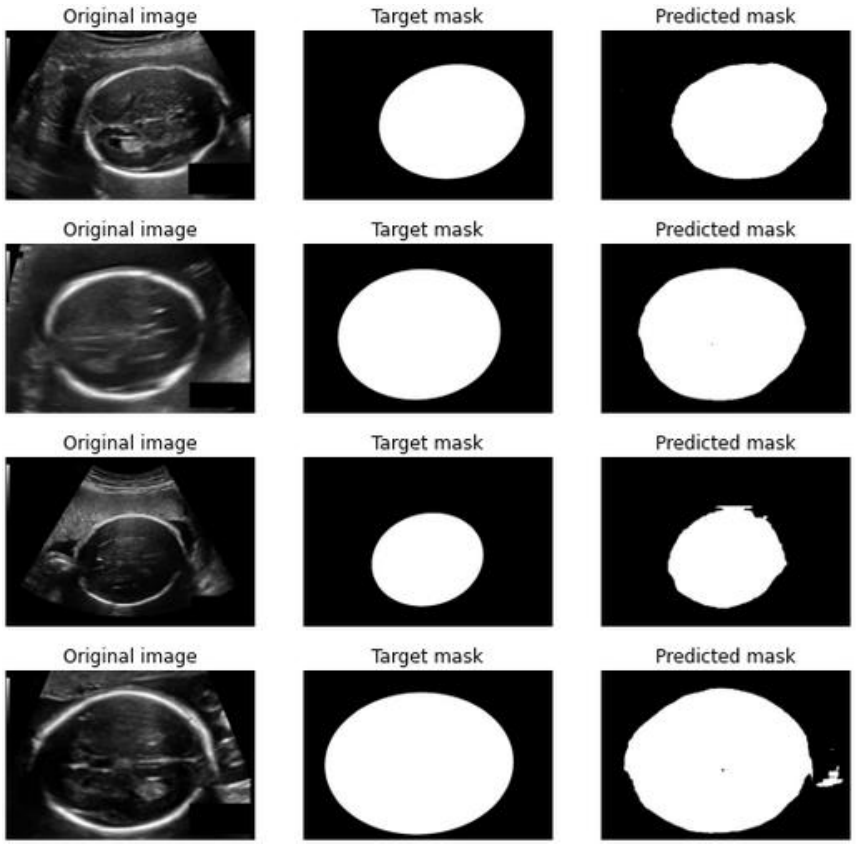
- Test results
  - Model: Unet-SMP
  - HC18 dataset with different preprocessing techniques
  - Epoch vs test IoU score

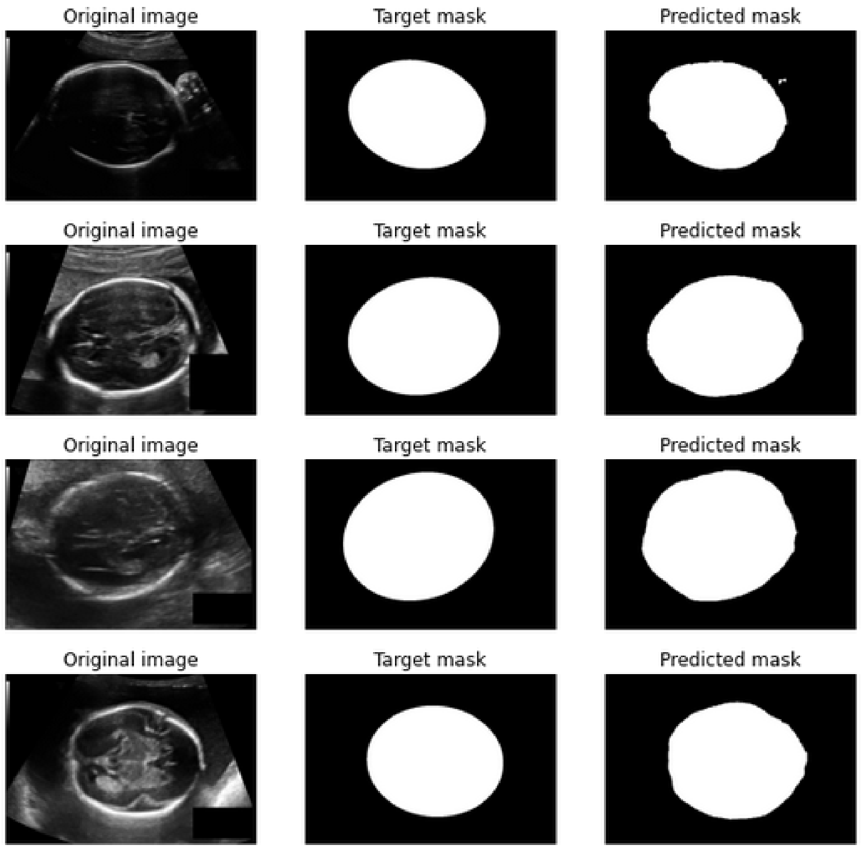


RESULTS

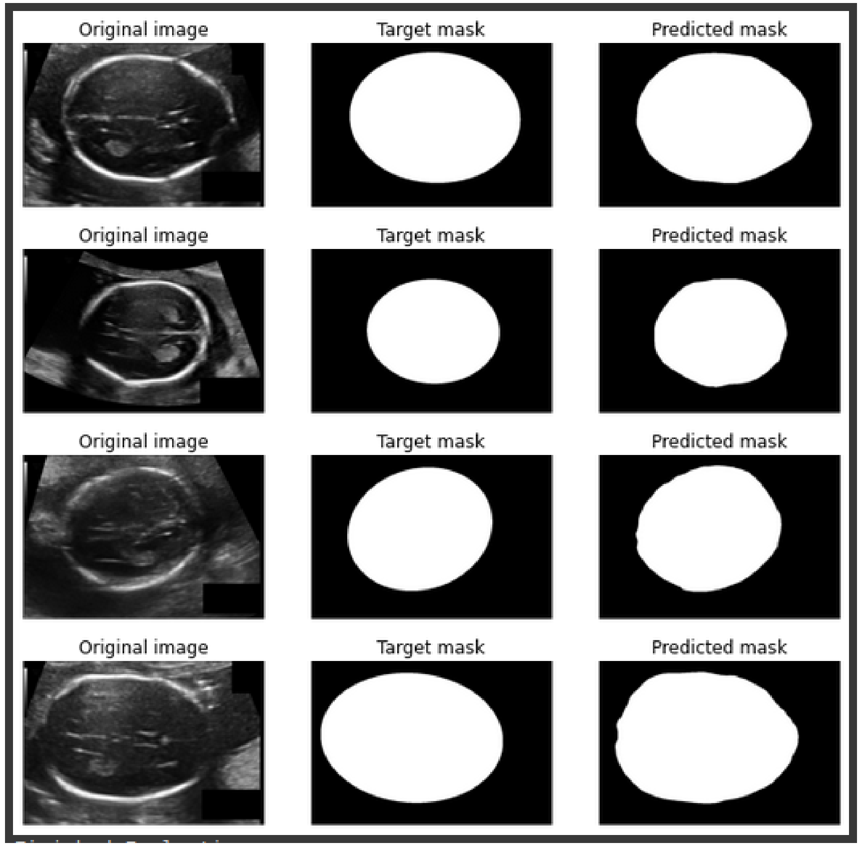
Model	Test-IoU
UNet(SMP)	**93.483**
UNet(SMP) with Median Blur + Clahe	**93.848**
UNet(SMP) with Gaussian Threshold	92.367
UNet(SMP) with Clahe	92.793
UNET	89.168
DU-NET	**94.137**
SIIM dataset	53.867

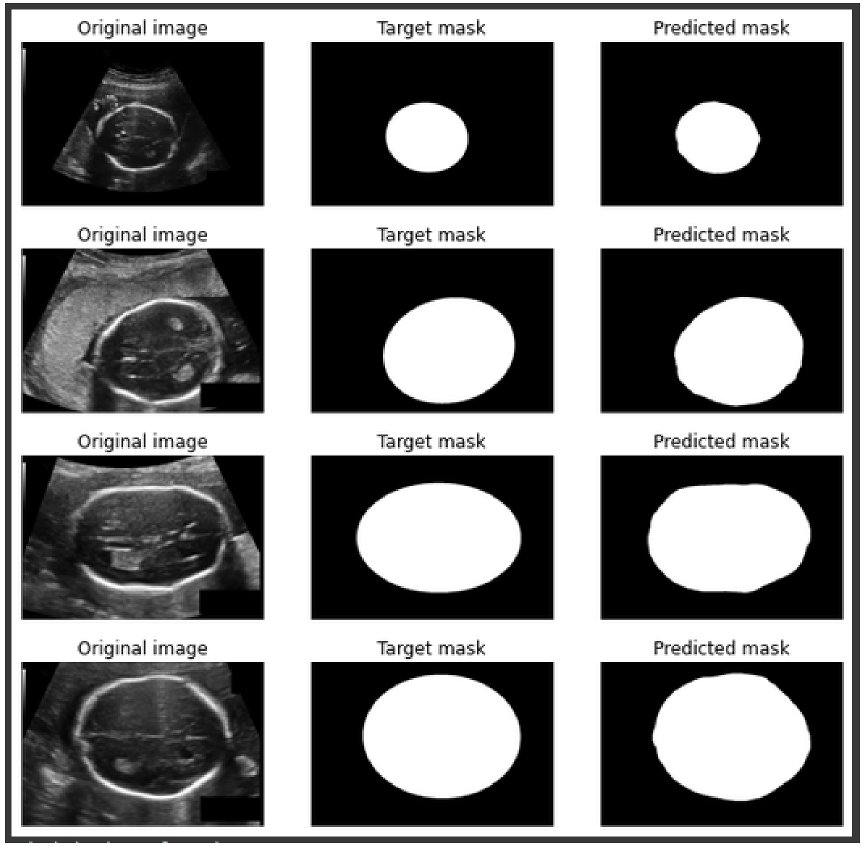
Unet - HC18


Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask

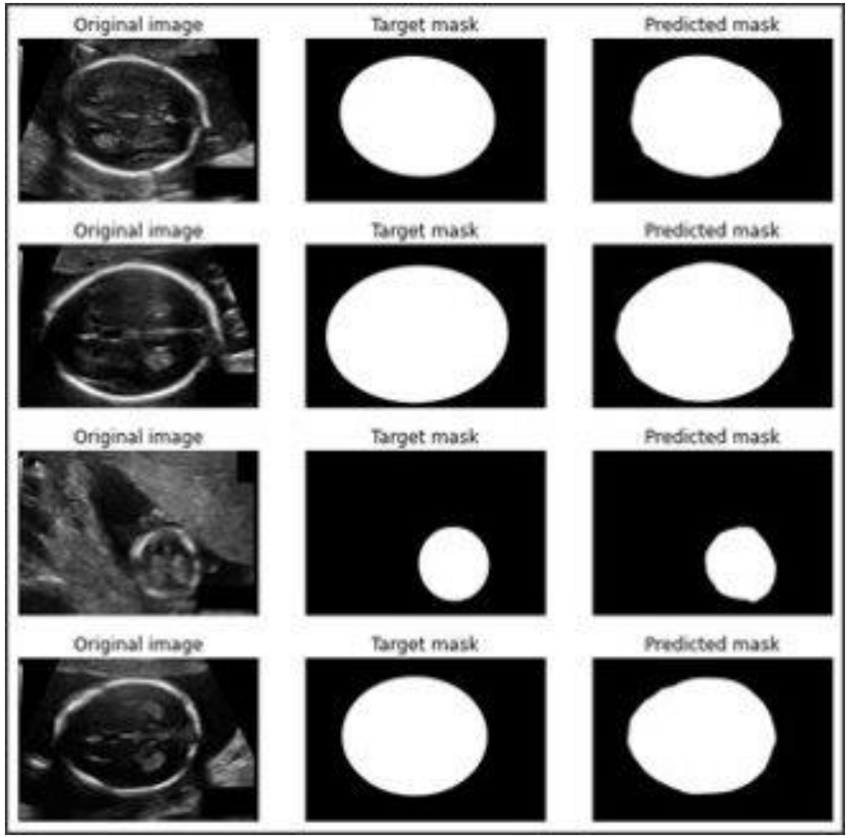

Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask

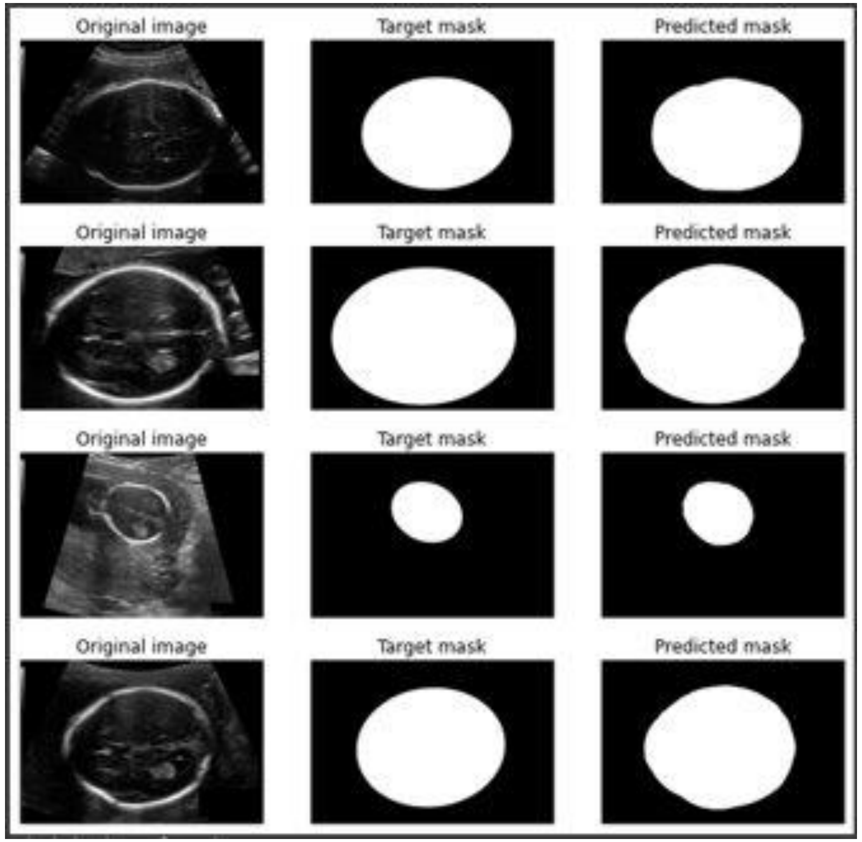
Unet SMP - HC18



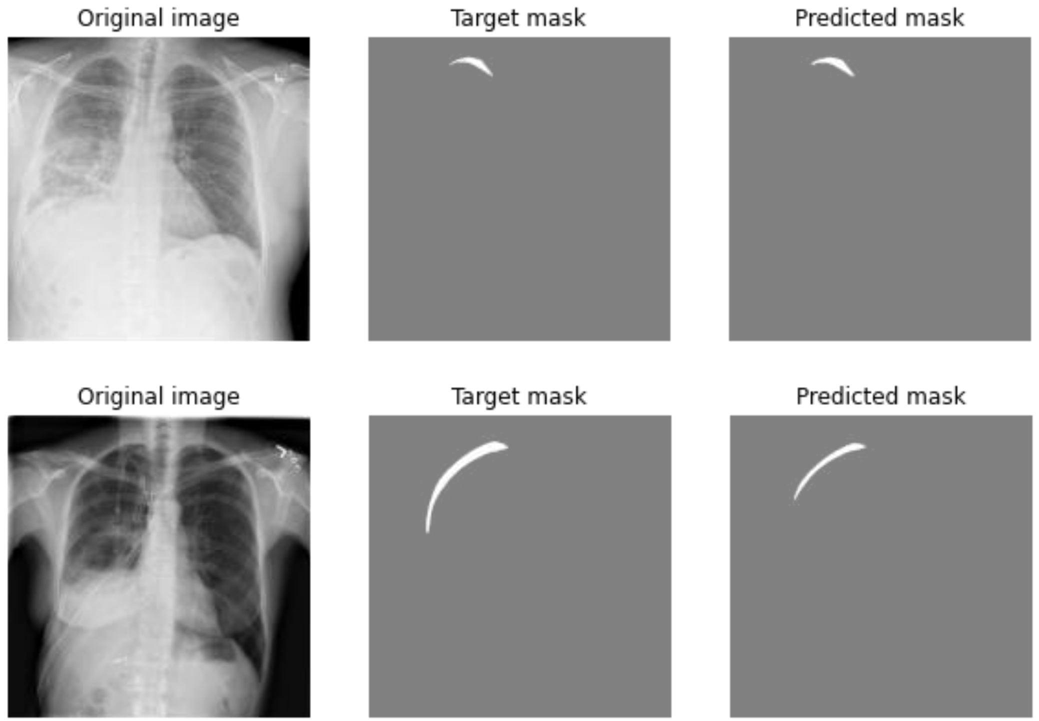


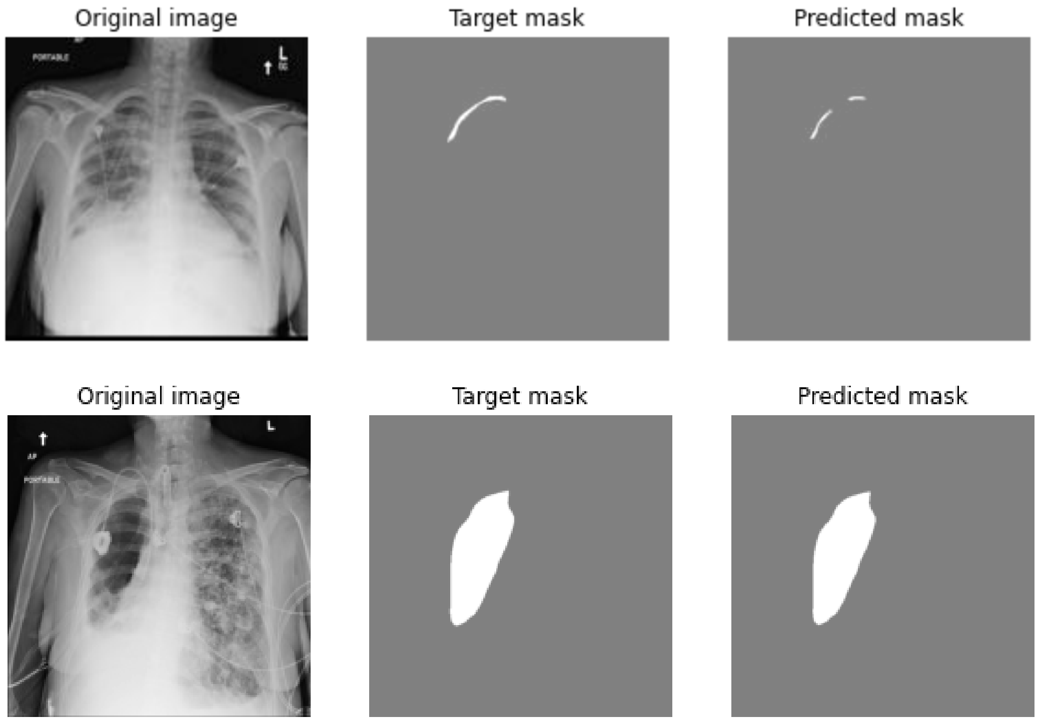
DUnet – HC18


Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask

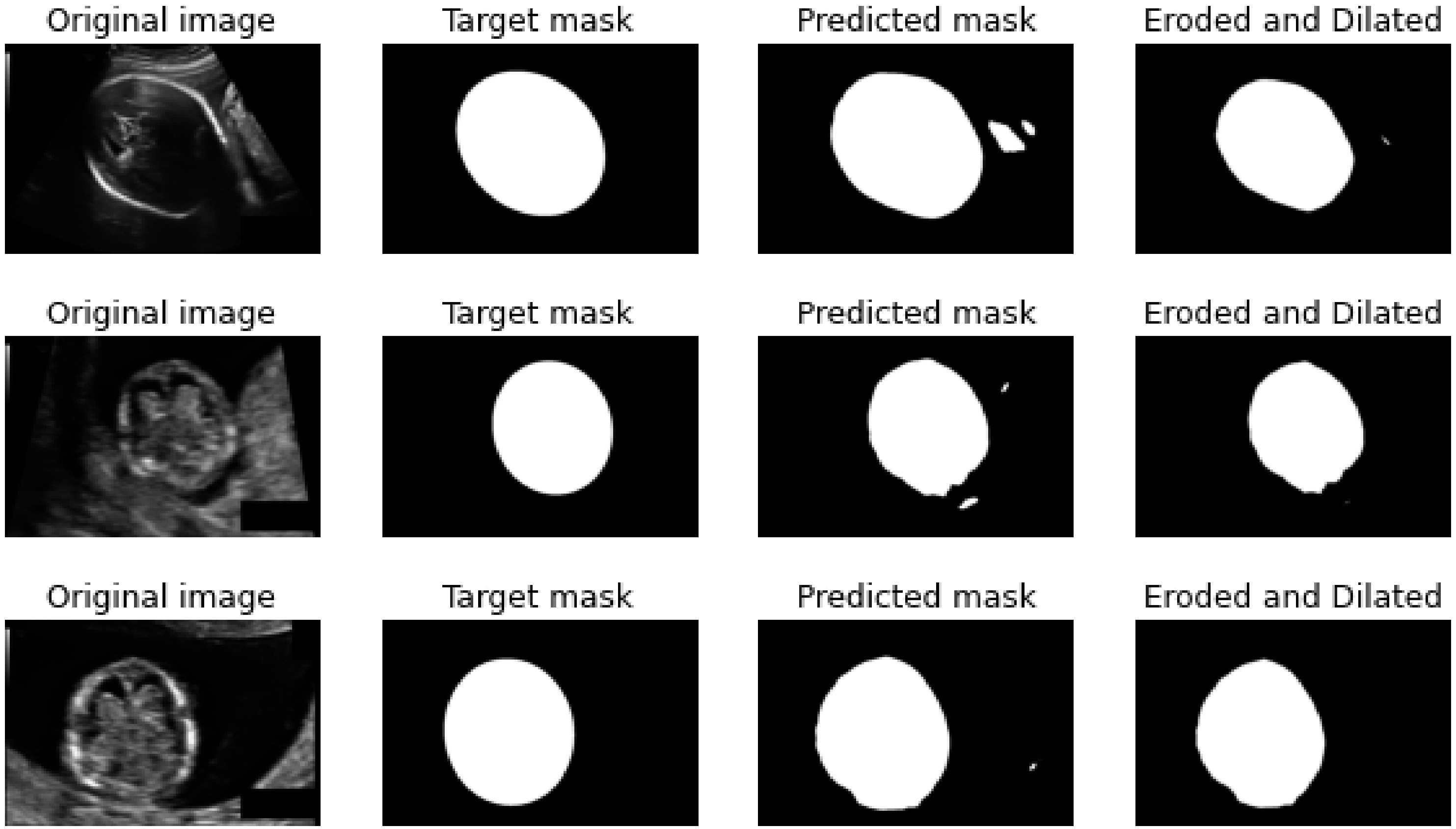

Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask
Original image
Target mask
Predicted mask

Unet SMP - SIIM





EROSION AND DILATION:



Future work

The model was pretrained on the Imagenet dataset. Better performance can be obtained on pretraining with a medical image dataset.

We would like to further explore different models like Densenet, ResNext in the encoder part in the proposed models.

We would like to explore different loss functions and their combinations.

Following the usage of hand-crafted features in DU-net, we would like to experiment with others such as wavelets.

Timeline

Understanding the paper, literature survey, and having a clear view on the tasks to be completed and the corresponding timelines

Feb 15th

Feb 25th

Data-augmentation and required pre-processing

Implementation of the model

March 14

April 7th

Completing the training, testing, evaluation. (Mid-evals)

Experiment with parameters and additional pre-processing techniques mentioned.

Final Evals (April 24th)

Thank you!