IMAGE SEGMENTATION OF BREAST ULTRASOUND IMAGES

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CONTENT

AIM:

To Identify and segment the breast tumor tissue from the breast Ultrasound images.

Image segmentation in breast cancer detection:

- Histopathology is the branch of pathology that involves the examination of tissues and cells at a microscopic level in order to diagnose disease. It involves the study of changes in tissue structure and function caused by disease or injury.
- Example: Breast Cancer Detection
- Breast cancer is a serious health issue affecting millions of women worldwide. Early detection is critical in reducing mortality rates.

Image segmentation in breast cancer detection:

- Image segmentation is a technique that involves dividing an image into multiple segments to extract meaningful information or to analyze the image further.
- Image segmentation can be used in the detection of breast cancer to isolate and identify suspicious breast tissue regions, such as lumps or other anomalies that might be cancerous.

About the Dataset:

The data collected at baseline include breast ultrasound images among women in ages between 25 and 75 years old.

*This data was collected in 2018. The number of patients is 600 female patients. The dataset consists of 780 images with an average image size of 500*500 pixels. The images are in PNG format.*

The ground truth images are presented with original images. The images are categorized into three classes, which are normal, benign, and malignant

Models Implemented

01

PSPNet

02

DEEPLab V3+

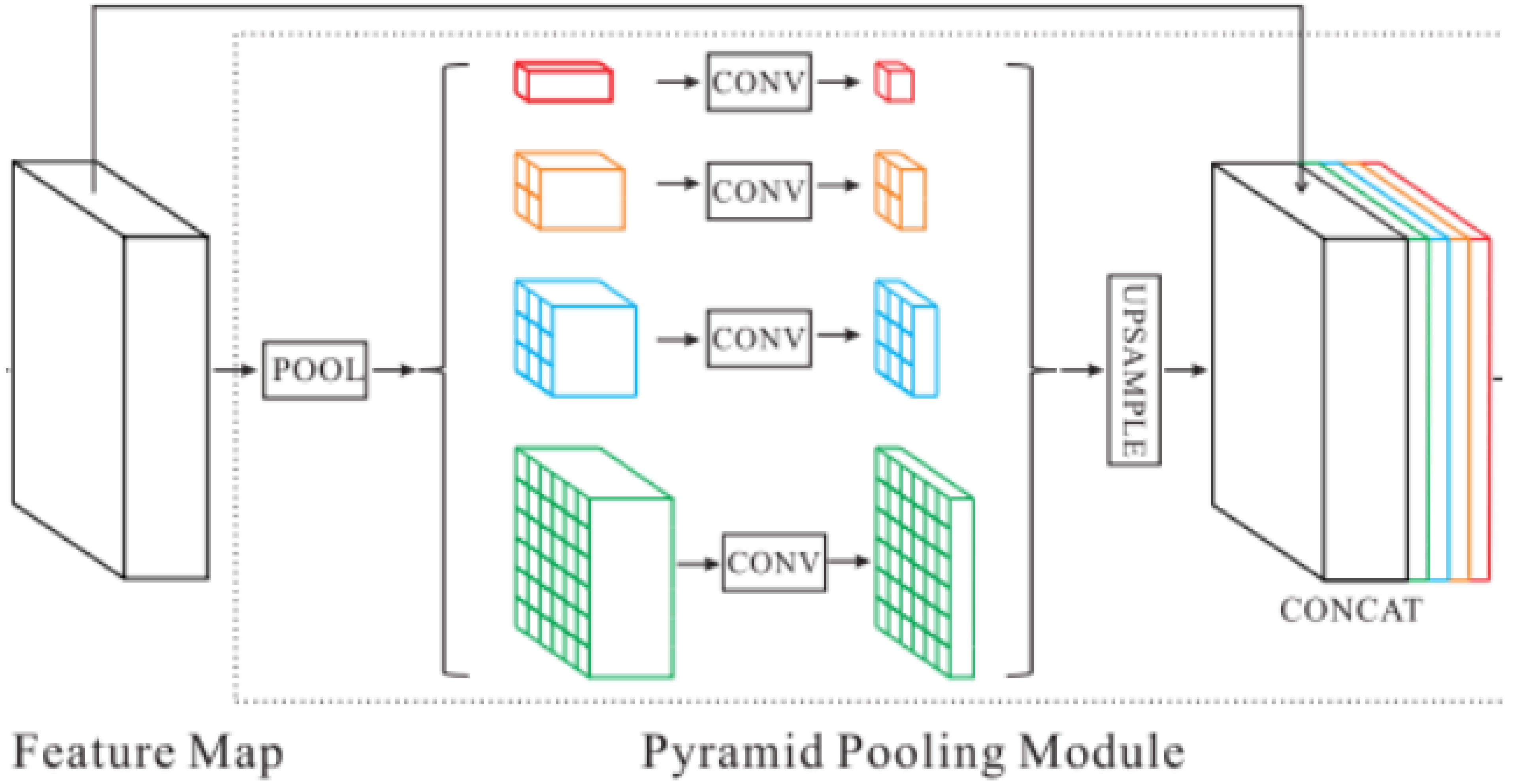
03

FPN

PSPNet

- Pyramid Scene Parsing Network, is a semantic segmentation model that utilises a pyramid parsing module to capture contextual information at multiple scales.

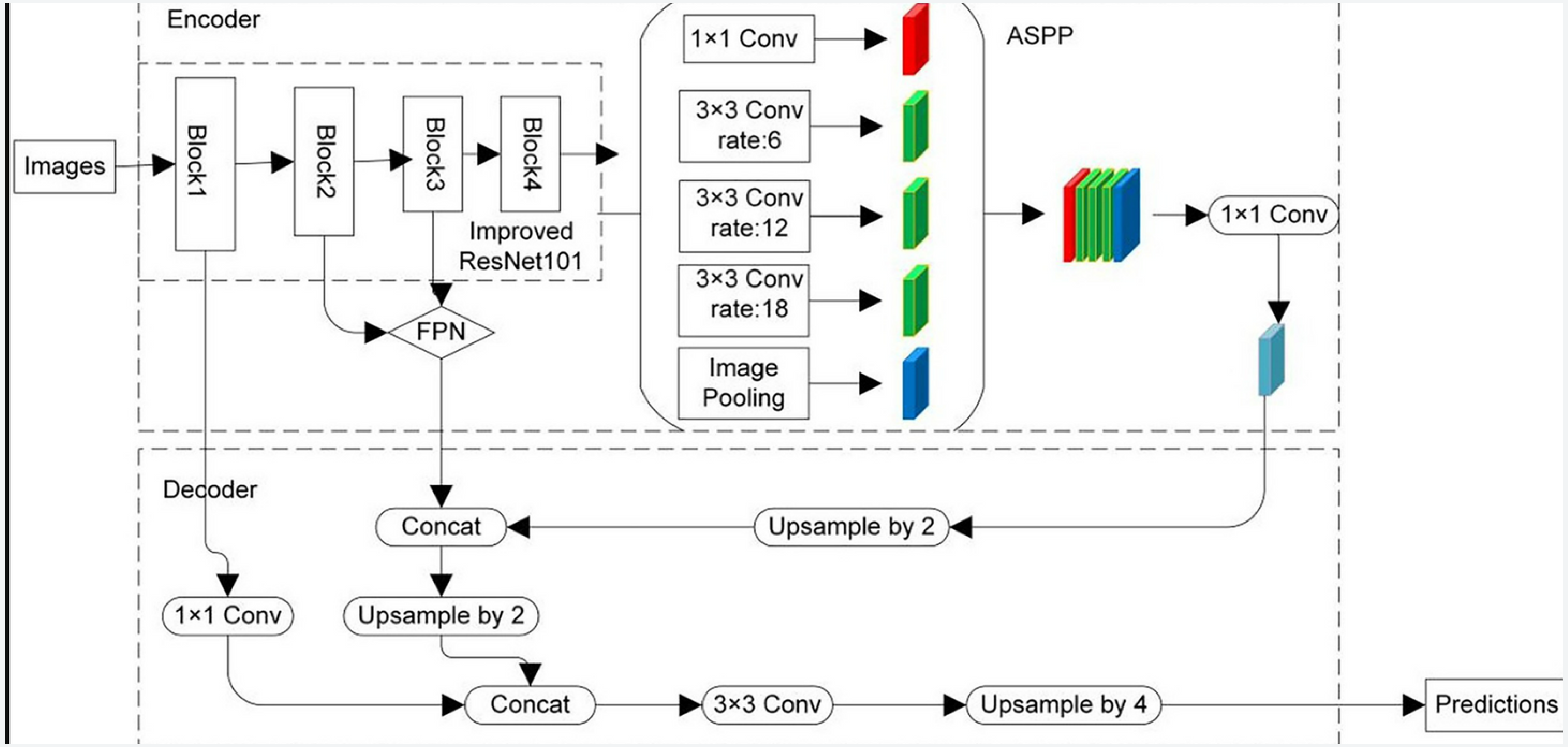
- The input image is first passed through a convolutional neural network (CNN) to extract features, which are then fed into the pyramid pooling module.



- The pyramid pooling module applies pooling operations at different scales and resolutions, and then concatenates the resulting feature maps to form a multi-scale representation of the image. This multi-scale representation is then passed through another CNN for further processing and segmentation.

DeepLabV3+

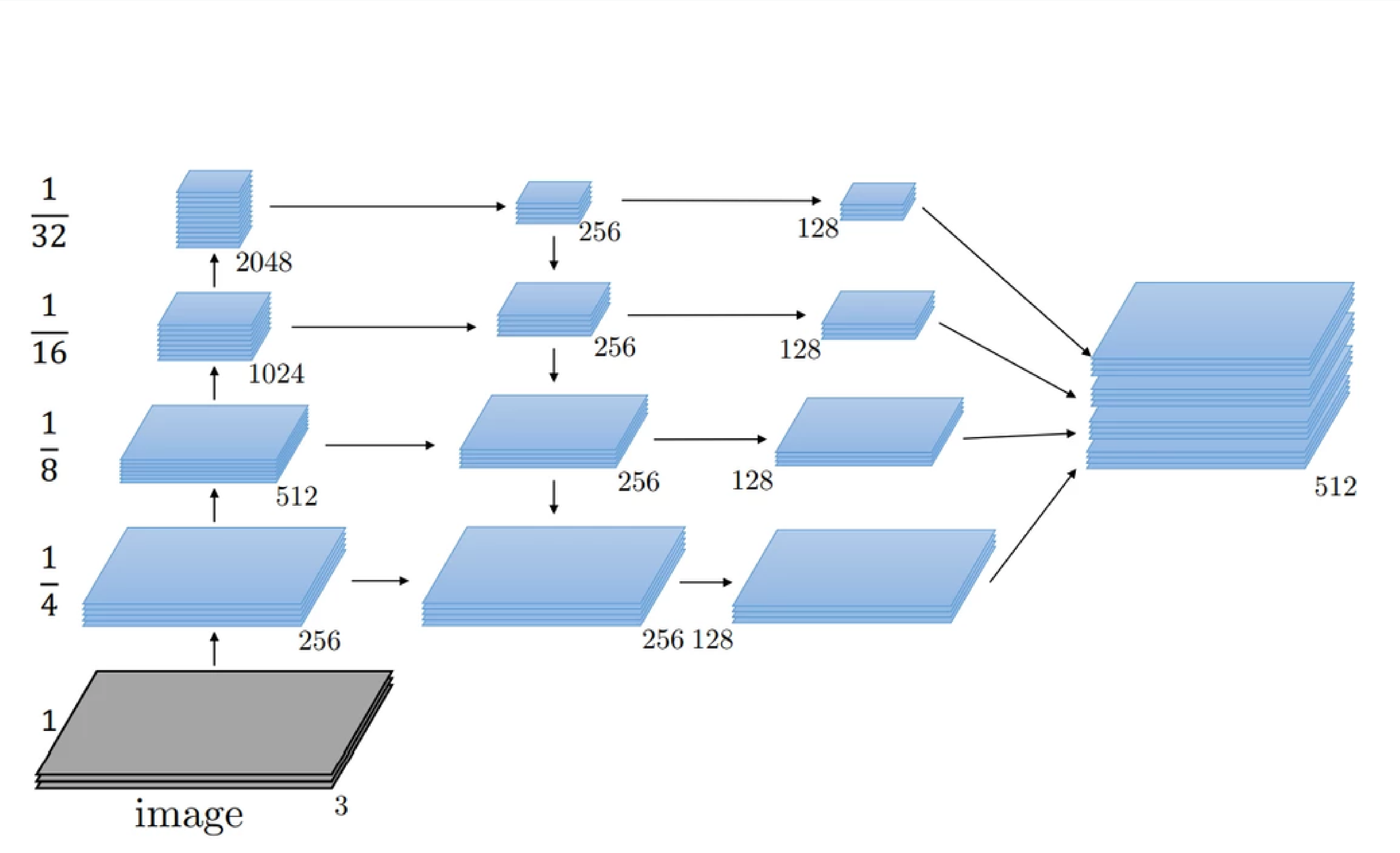
- DeepLabv3+ is a semantic segmentation architecture that builds on DeepLabv3 by adding a simple yet effective decoder module to enhance segmentation results.



- Multiple downsampling of a CNN will lead the feature map resolution to become smaller, resulting in lower prediction accuracy and loss of boundary information in semantic segmentation. Similarly, aggregating context around a feature helps in segmenting it better, which is accomplished with the atrous convolutions. DeepLabv3+ helps in solving these issues.

FPN:

- A Feature Pyramid Network is a feature extractor that takes a single-scale image of an arbitrary size as input, and outputs proportionally sized feature maps at multiple levels, in a fully convolutional network.



- The FPN architecture consists of a bottom-up pathway and a top-down pathway. The bottom-up pathway is a series of convolutional layers that extract features from the input image at different scales. The top-down pathway is a series of upsampling and lateral connections that combine the low-level features from the bottom-up pathway with the high-level features from the top-down pathway.

WORK DONE:

- The images of normal, malignant and benign classes are merged into one dataset.
- Then the obtained dataset is divided into train, validation and test datasets in the ratio of 70:10:20.
- The Augmentations were applied to increase variability and decrease overfitting, which includes:
- ->Horizontal or Vertical Flip or Random Rotation on half of the dataset.
- ->Adding Gauss Noise on half of the dataset

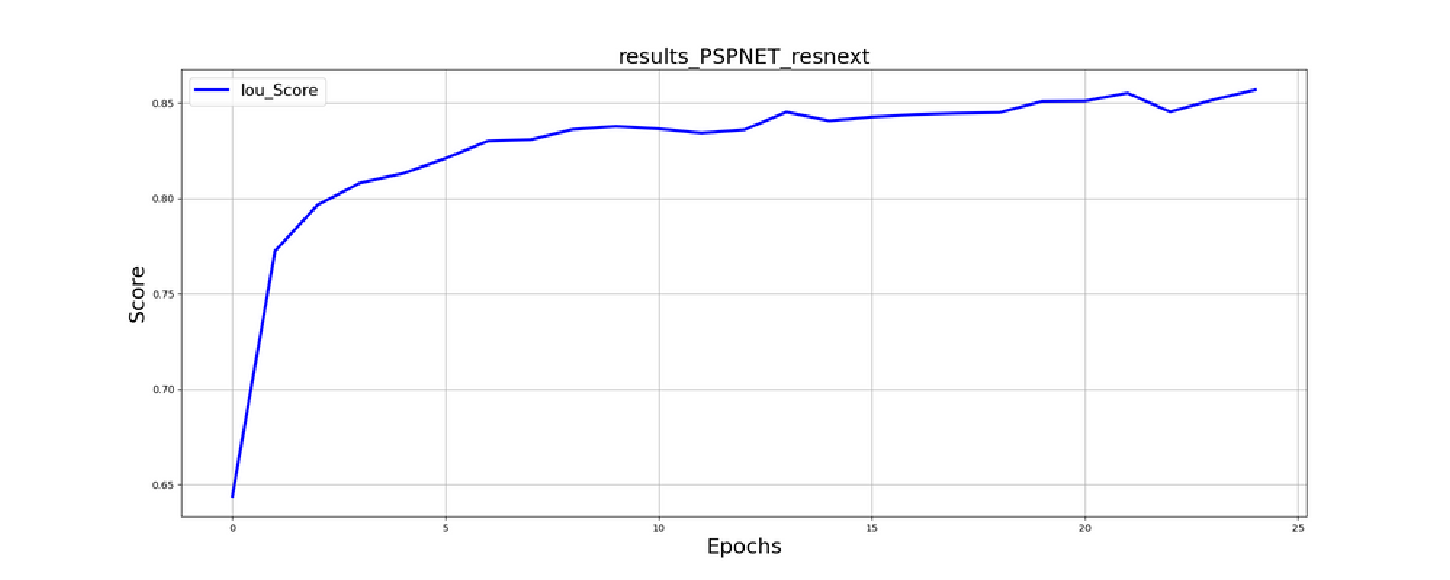
WORK DONE:

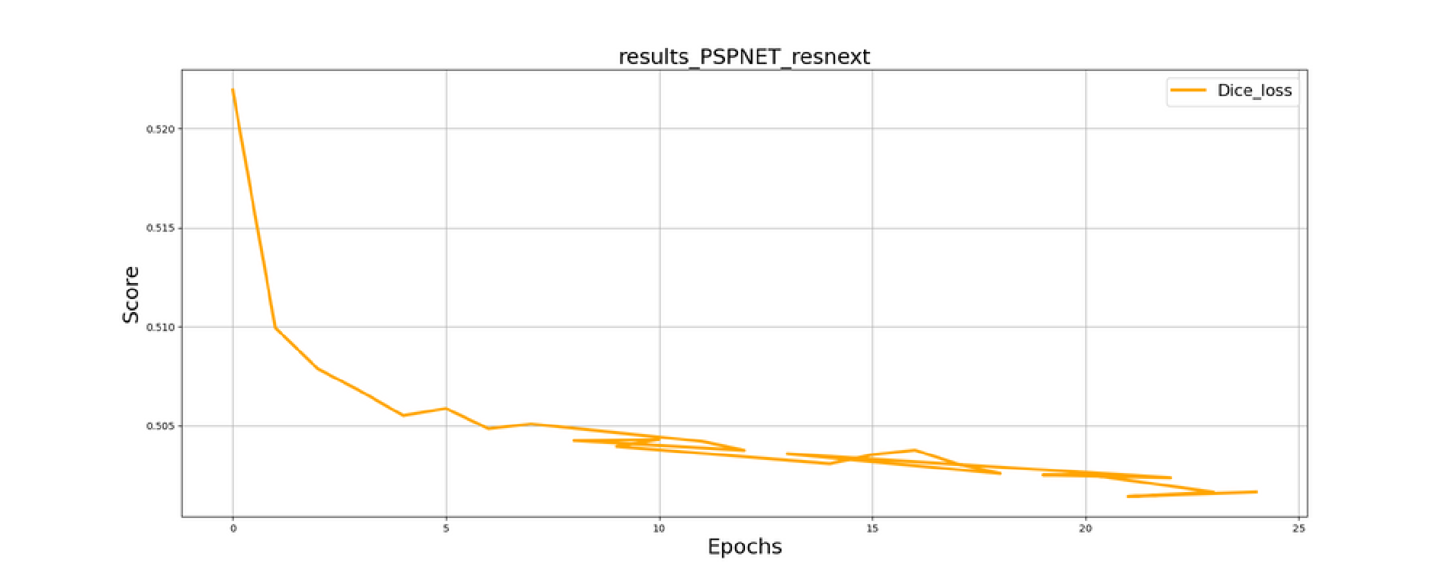
- Preprocessing was done according to corresponding to encoder and encoder weights.
- The dataset is trained on three models : [PSPNet, FPN, DeepLabV3+] along with changing the encoders [efficient-net-b3, resnet50, renext50_32xd, vgg16].
- In this step, the training was done upto 25 epochs for each combination
- Metrics used Iou_score with Loss function- Dice loss.

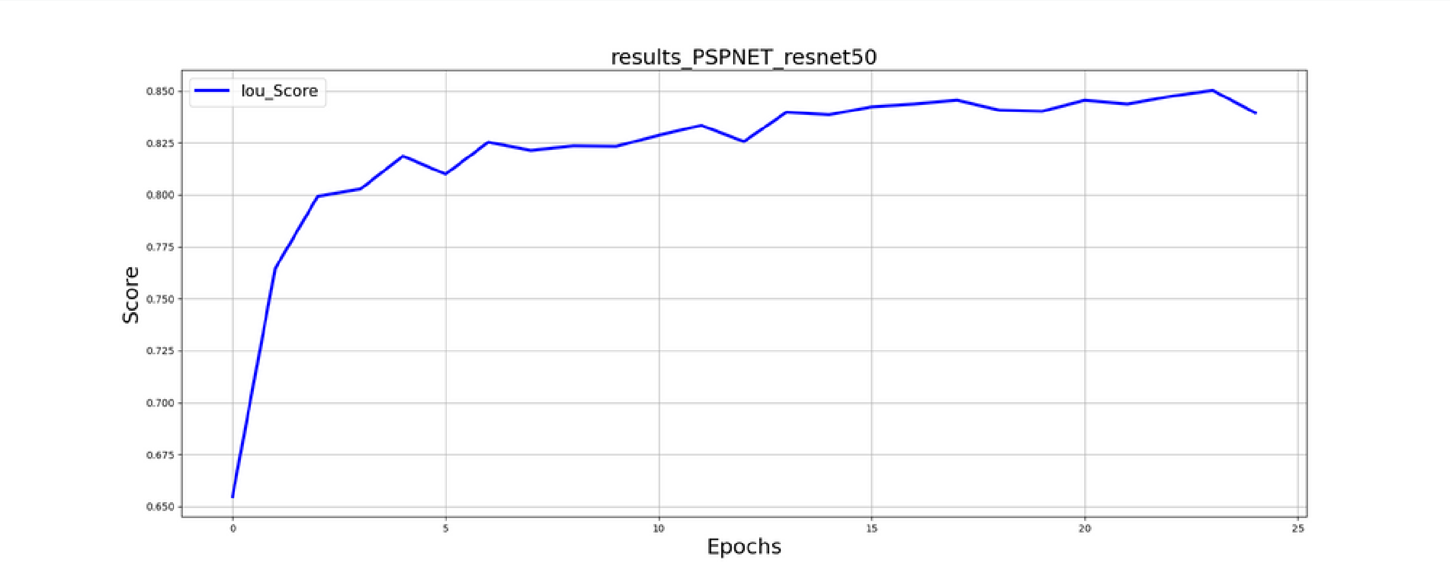
Results and Analysis

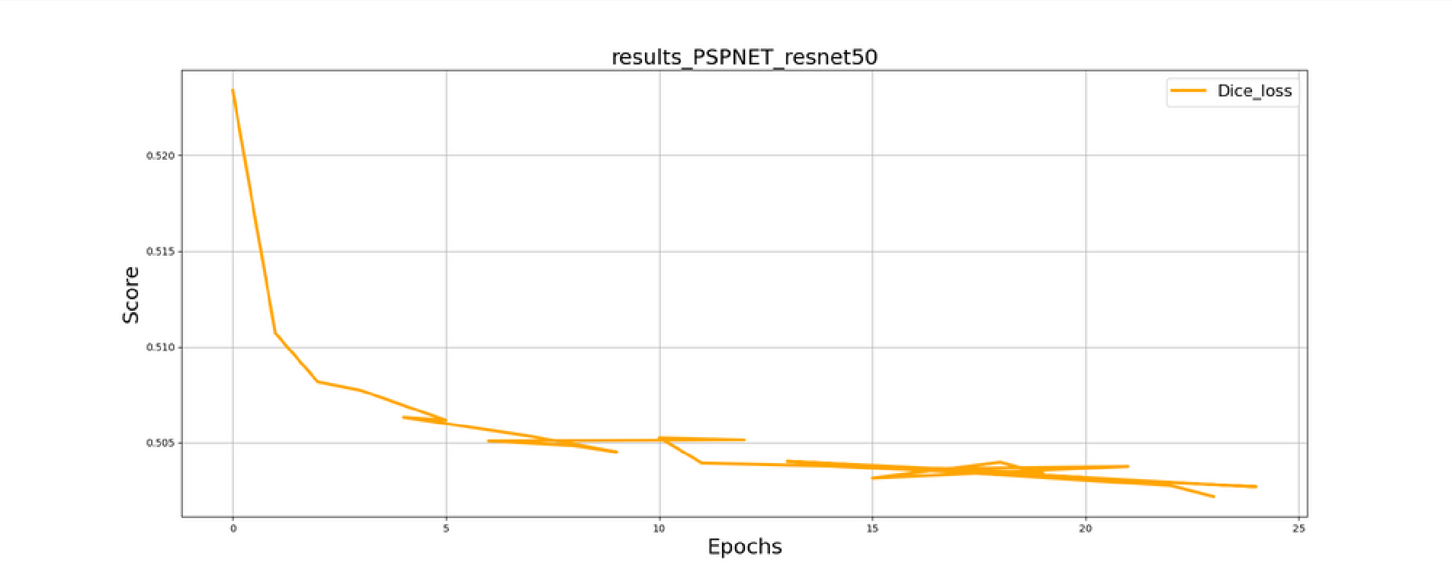
Encoder	Decoder	Epoch	Iou_score	Dice_loss
resnext50_32x4d	PSPNet	25	0.8570179052	0.5016670983
resnet50	PSPNet	24	0.8502235232	0.5021890637
efficientnet-b3	PSPNet	24	0.8081085779	0.5067316148
vgg16	PSPNet	23	0.9124910873	0.4989029834
resnext50_32x4d	FPN	23	0.8905694873	0.5005438411
resnet50	FPN	24	0.9441646629	0.4973984236
resnext50_32x4d	DeepLabV3+	21	0.9537335981	0.498601298
resnet50	DeepLabV3+	24	0.9464840473	0.4985954581

Plots for models run:









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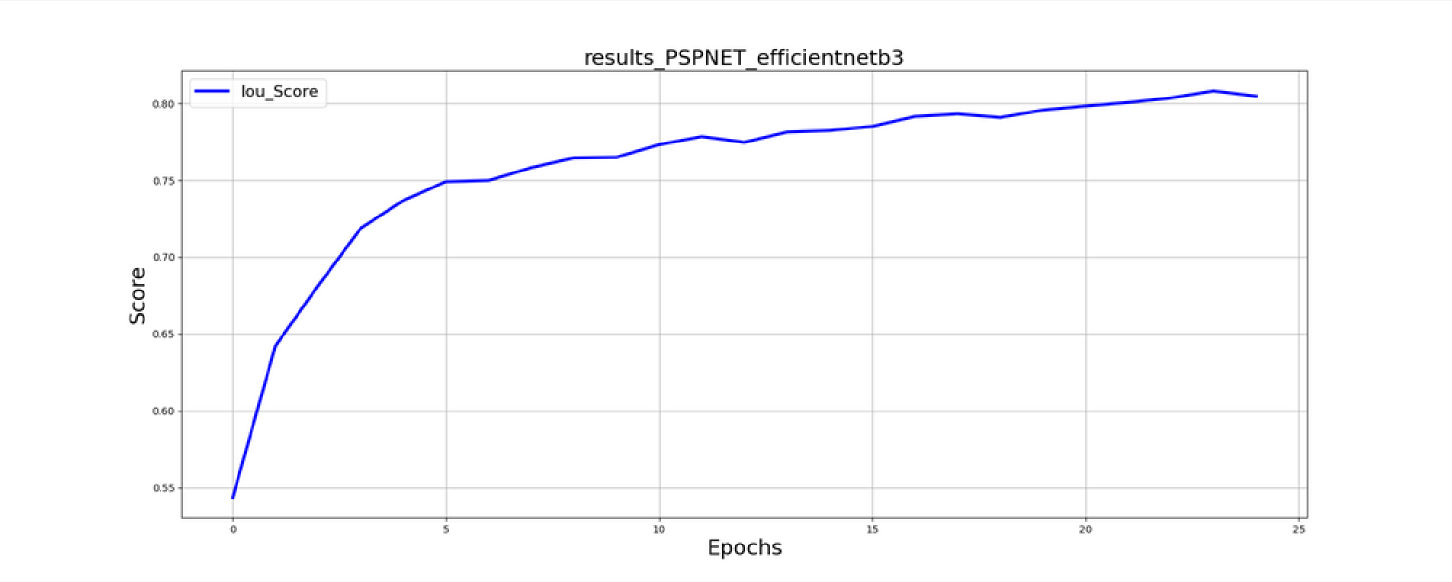

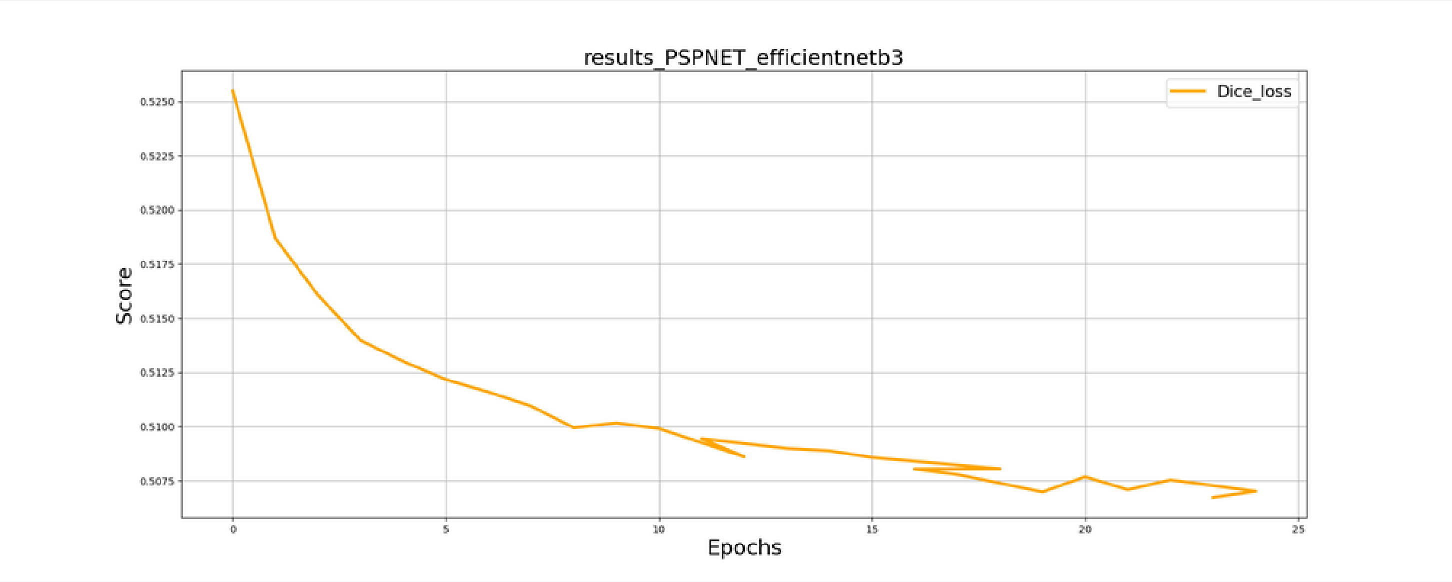

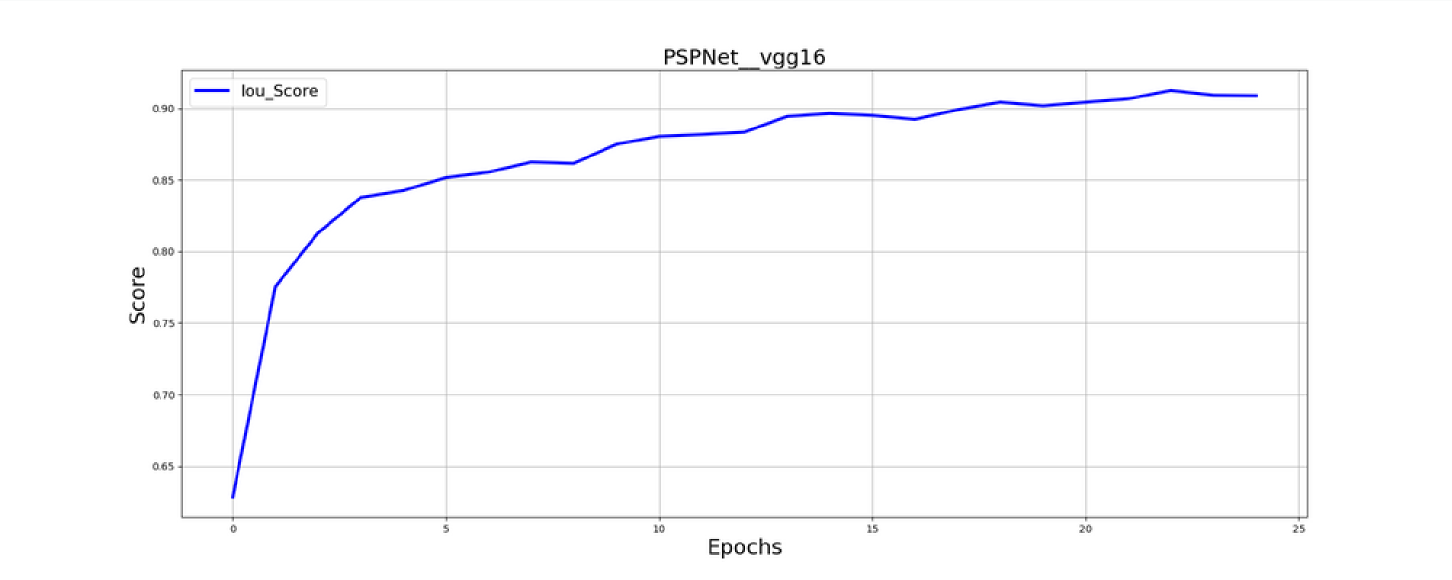

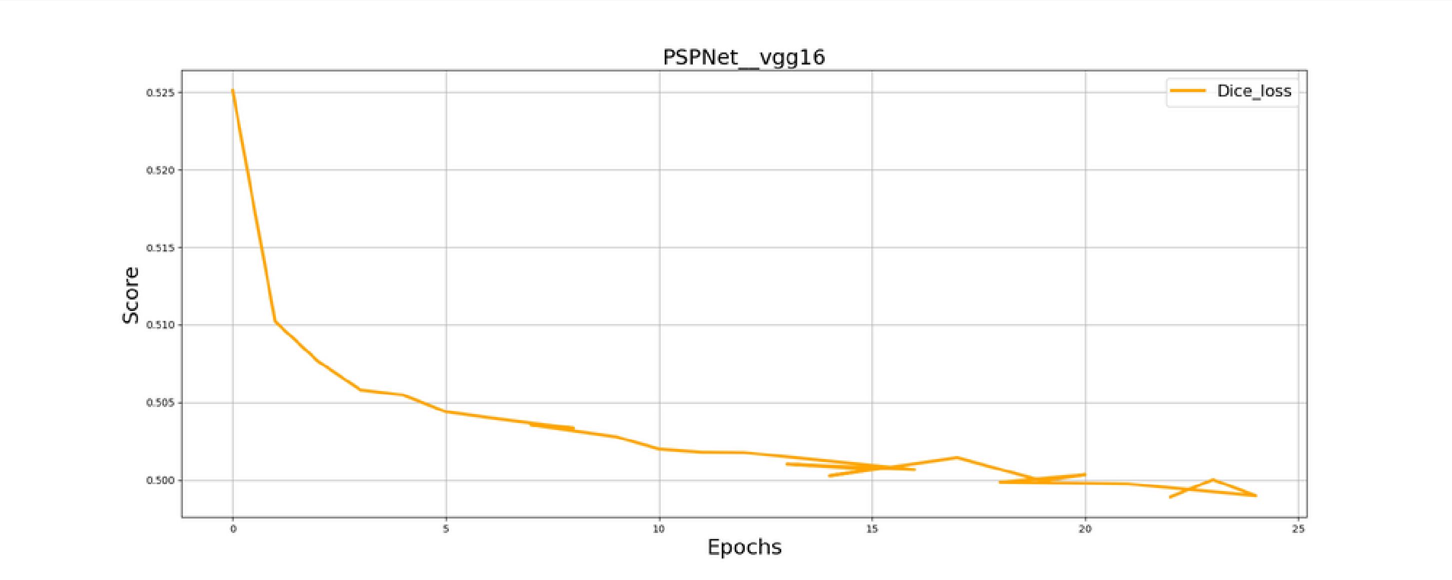

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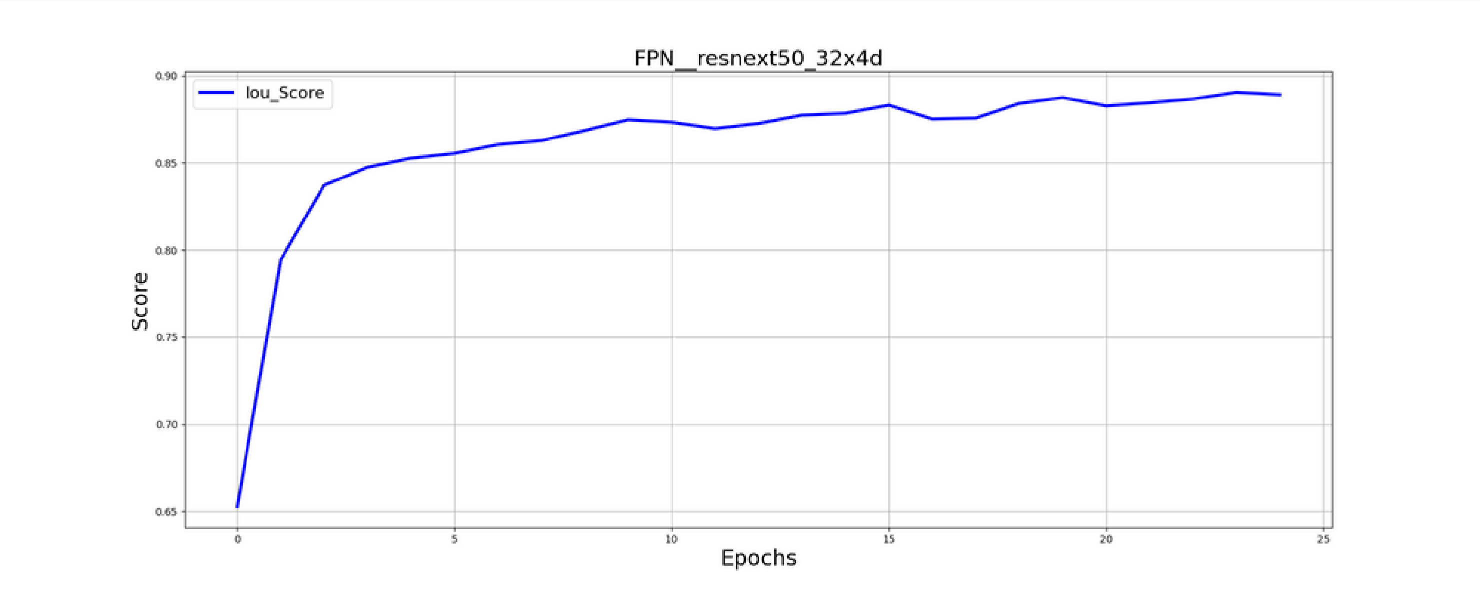
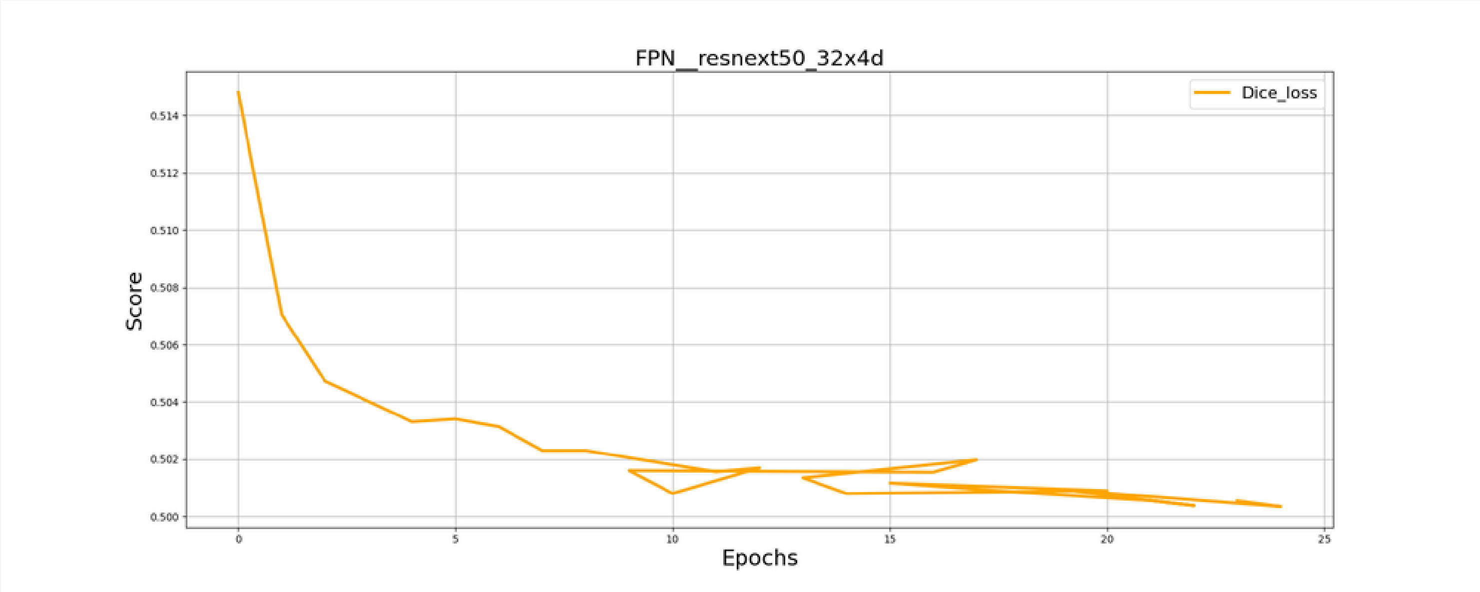
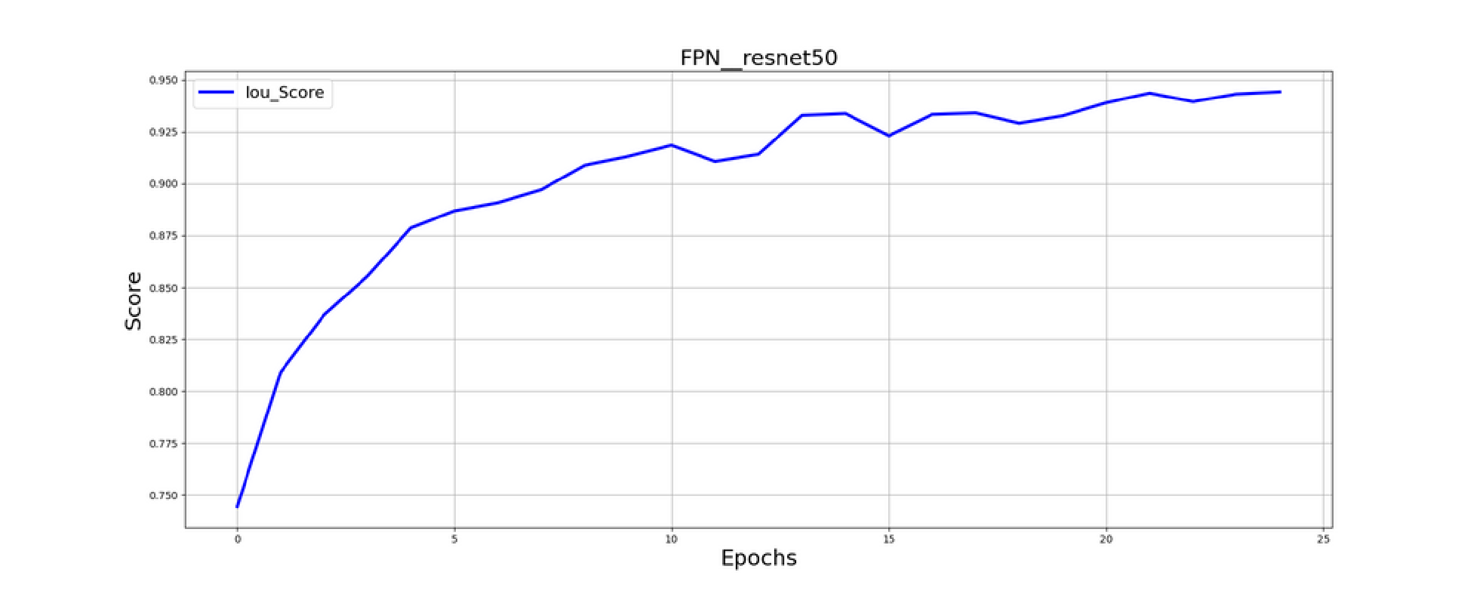
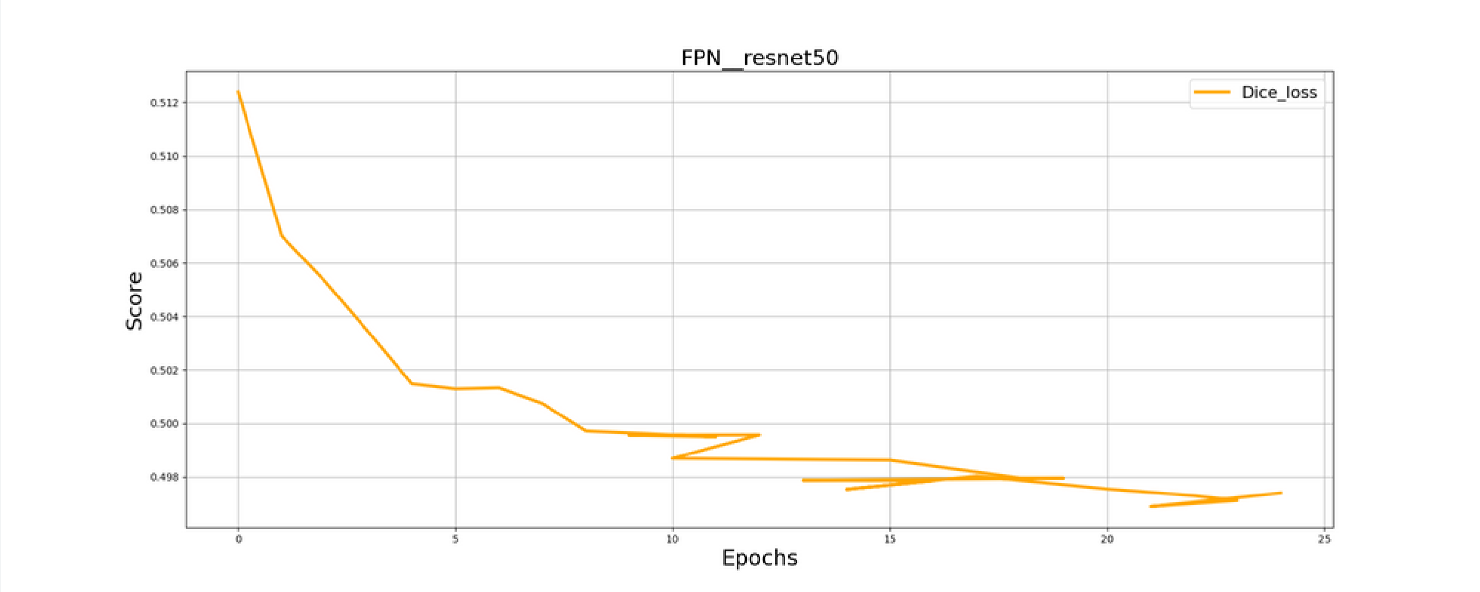
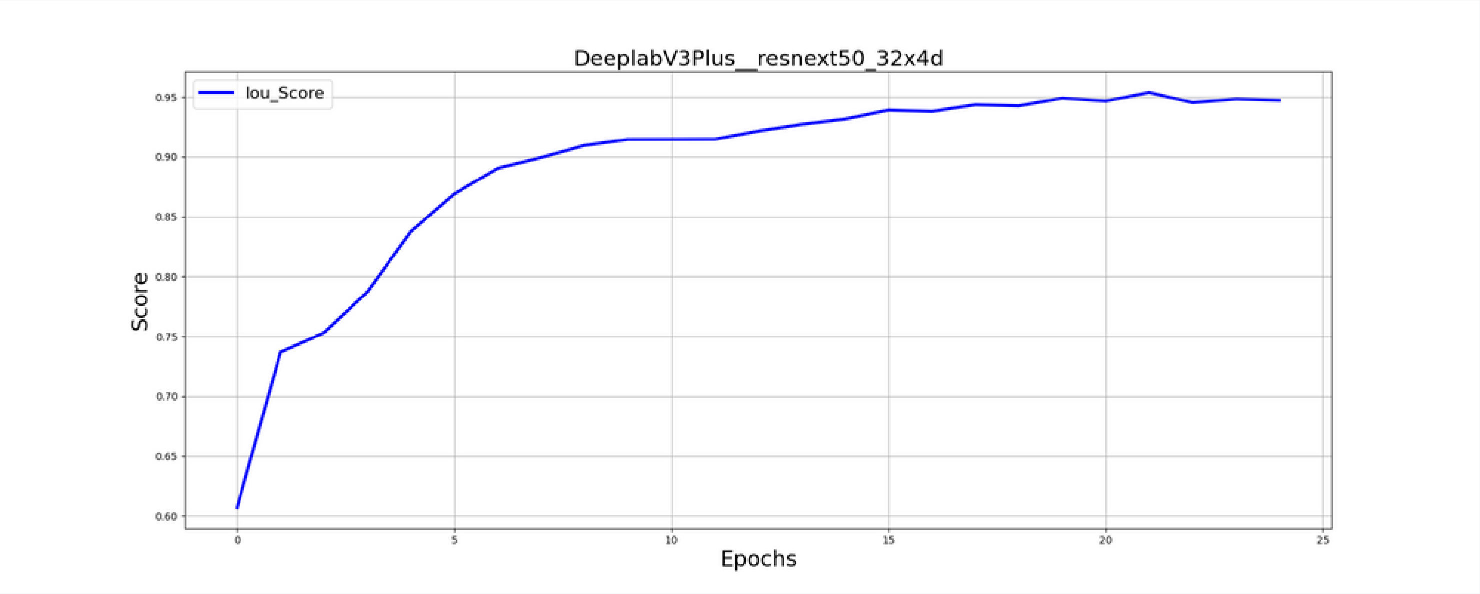


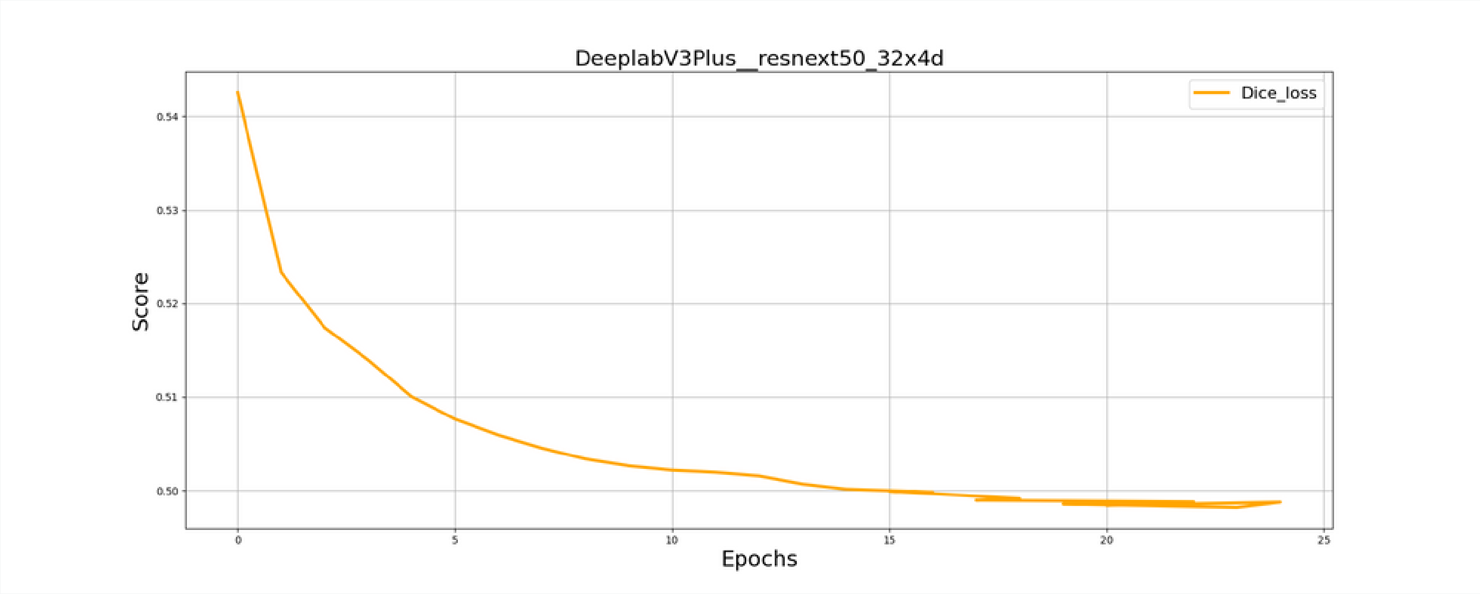


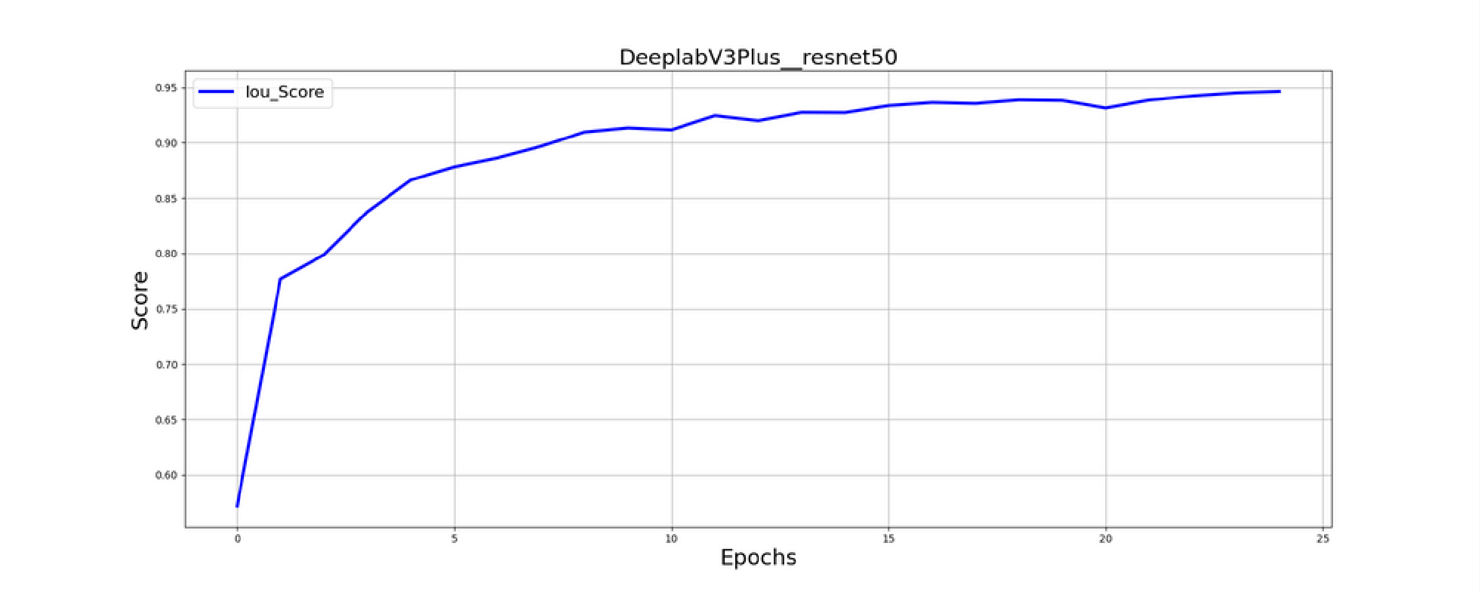


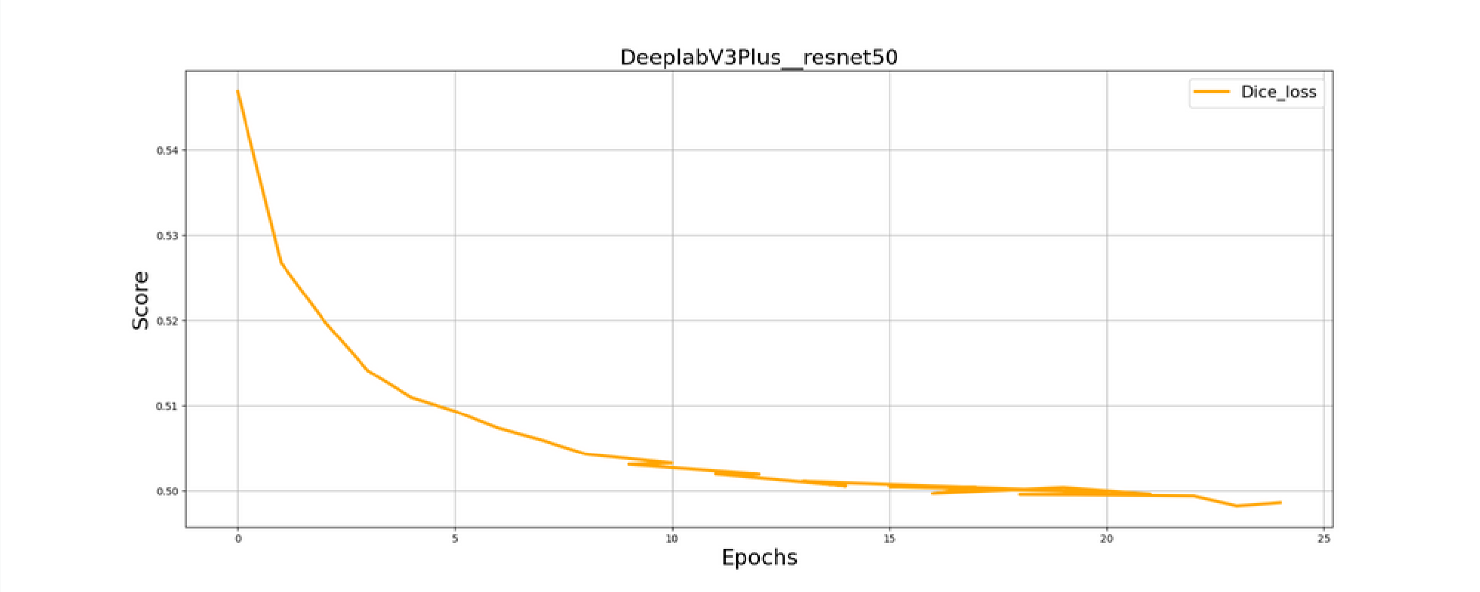


Plots for models run:







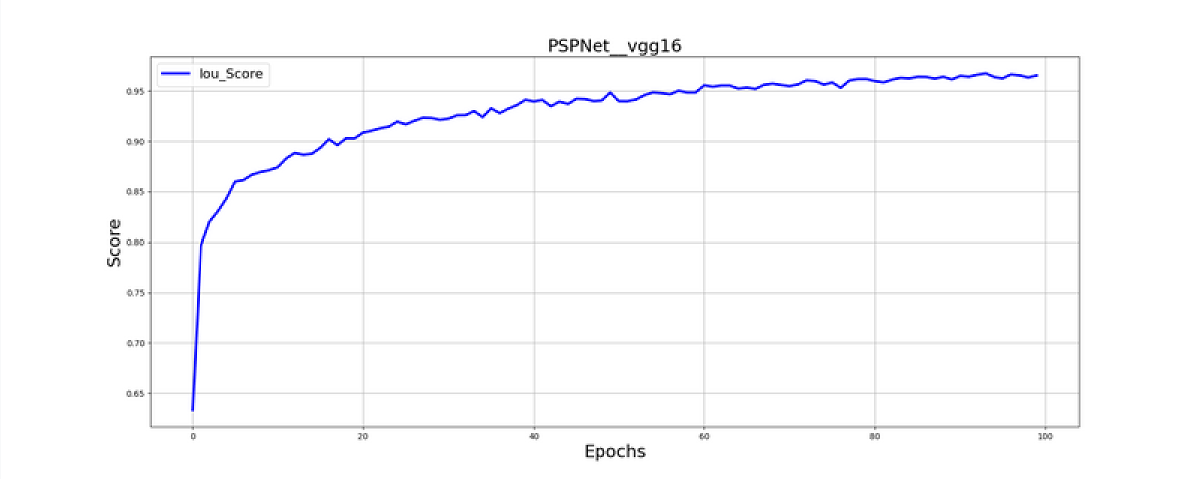


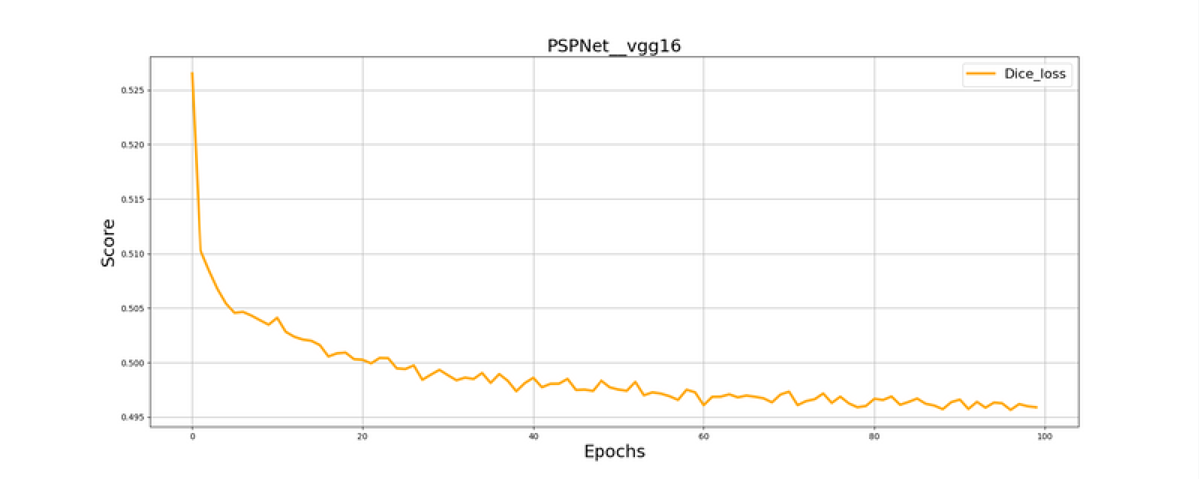
- Then, three of the combinations which performed well are taken and run for hundred epochs
- Then the testing is done on trained models and predictions are made.

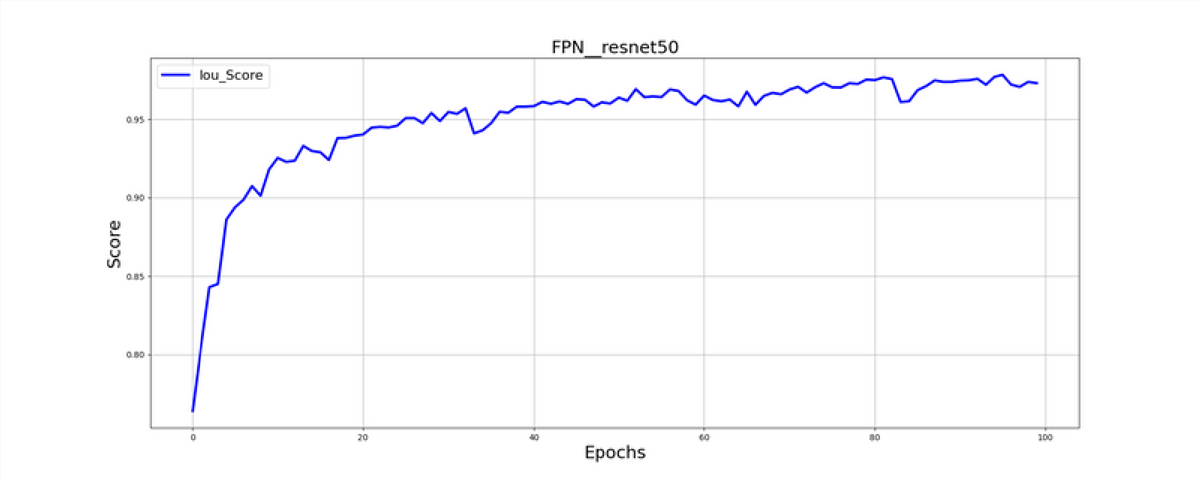
Results

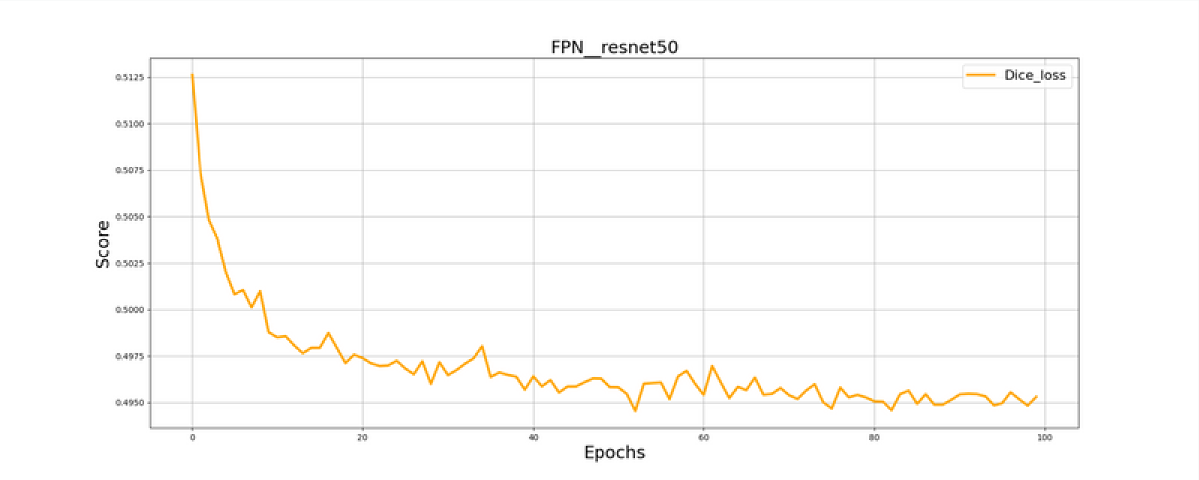
Encoder	Decoder	Epoch	IoU Score	Dice loss
vgg16	PSPNet	94	0.9675501031	0.4958592154
resnet	FPN	96	0.9785133184	0.4949562397
resnext50_32x4d	DeepLabV3+	97	0.9796665838	0.4953152988

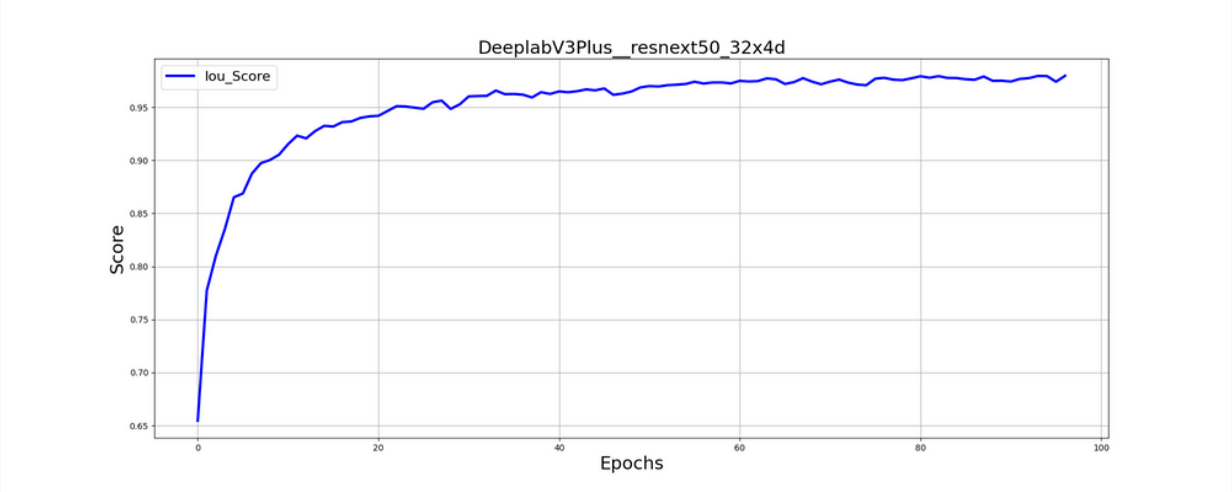
Plots

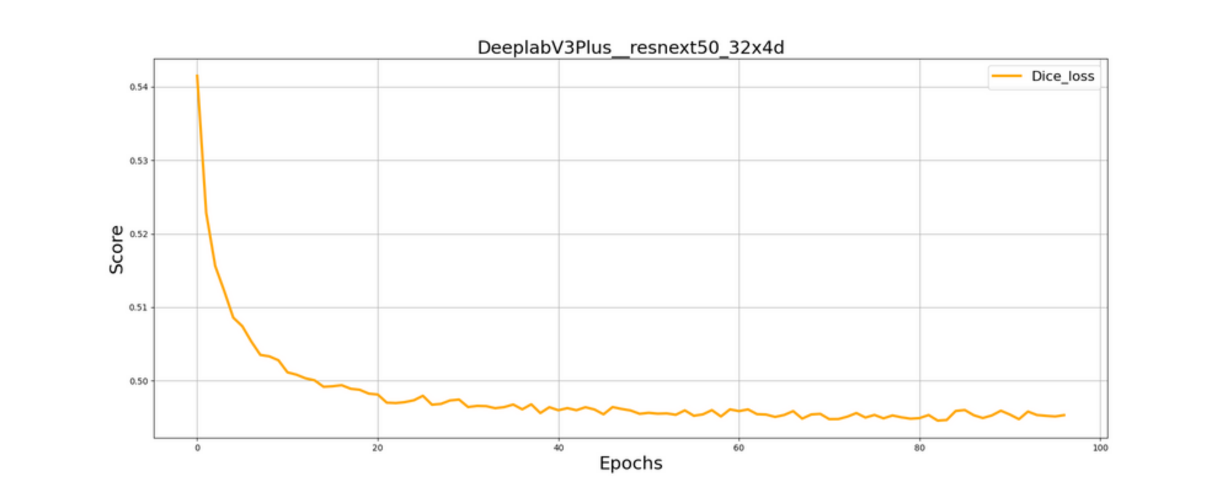

PSPNet__vgg16
Iou_Score
Score
Epochs


PSPNet__vgg16
Dice_loss
Score
Epochs

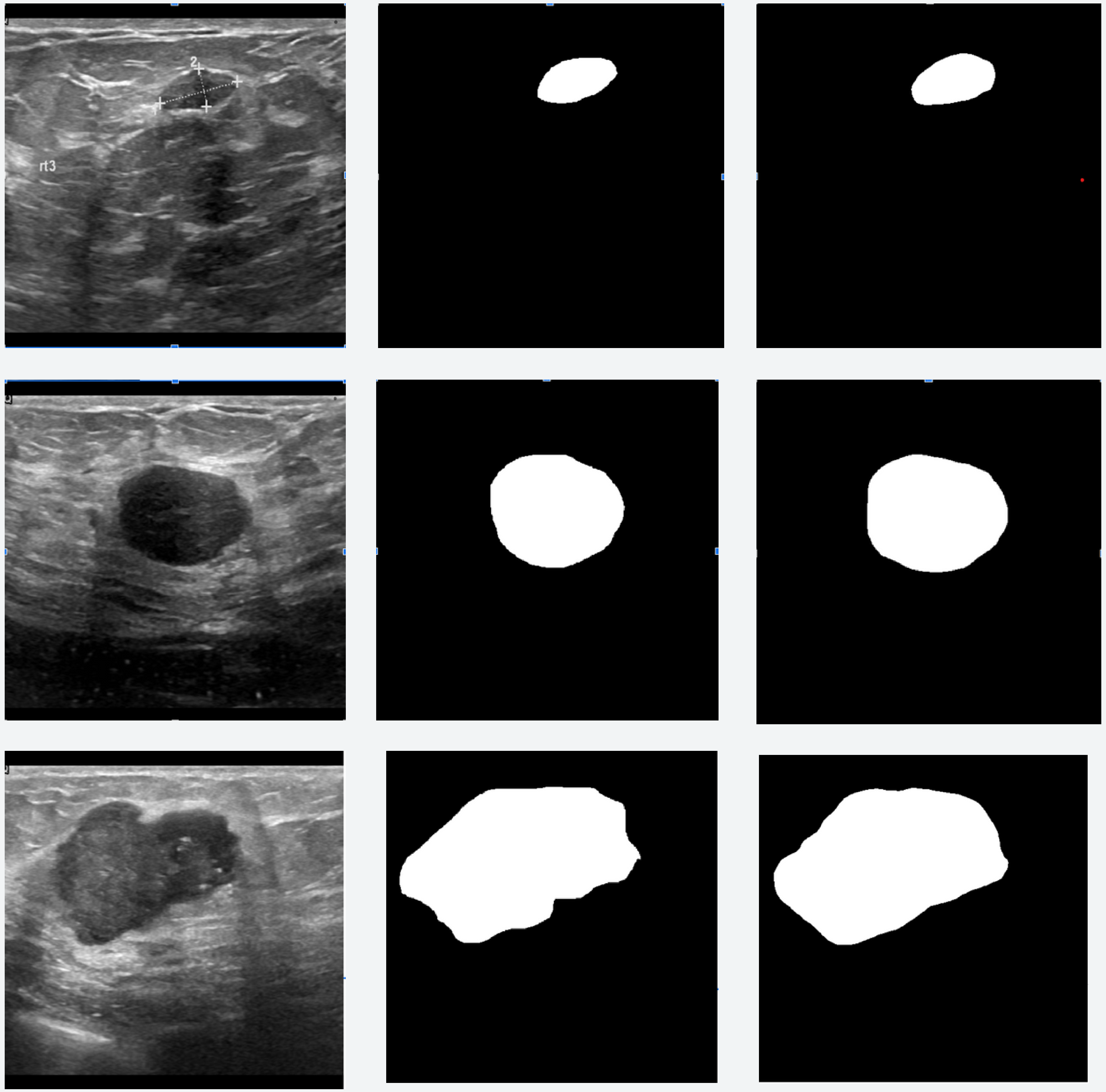

FPN__resnet50
Iou_Score
Score
Epochs


FPN__resnet50
Dice_loss
Score
Epochs

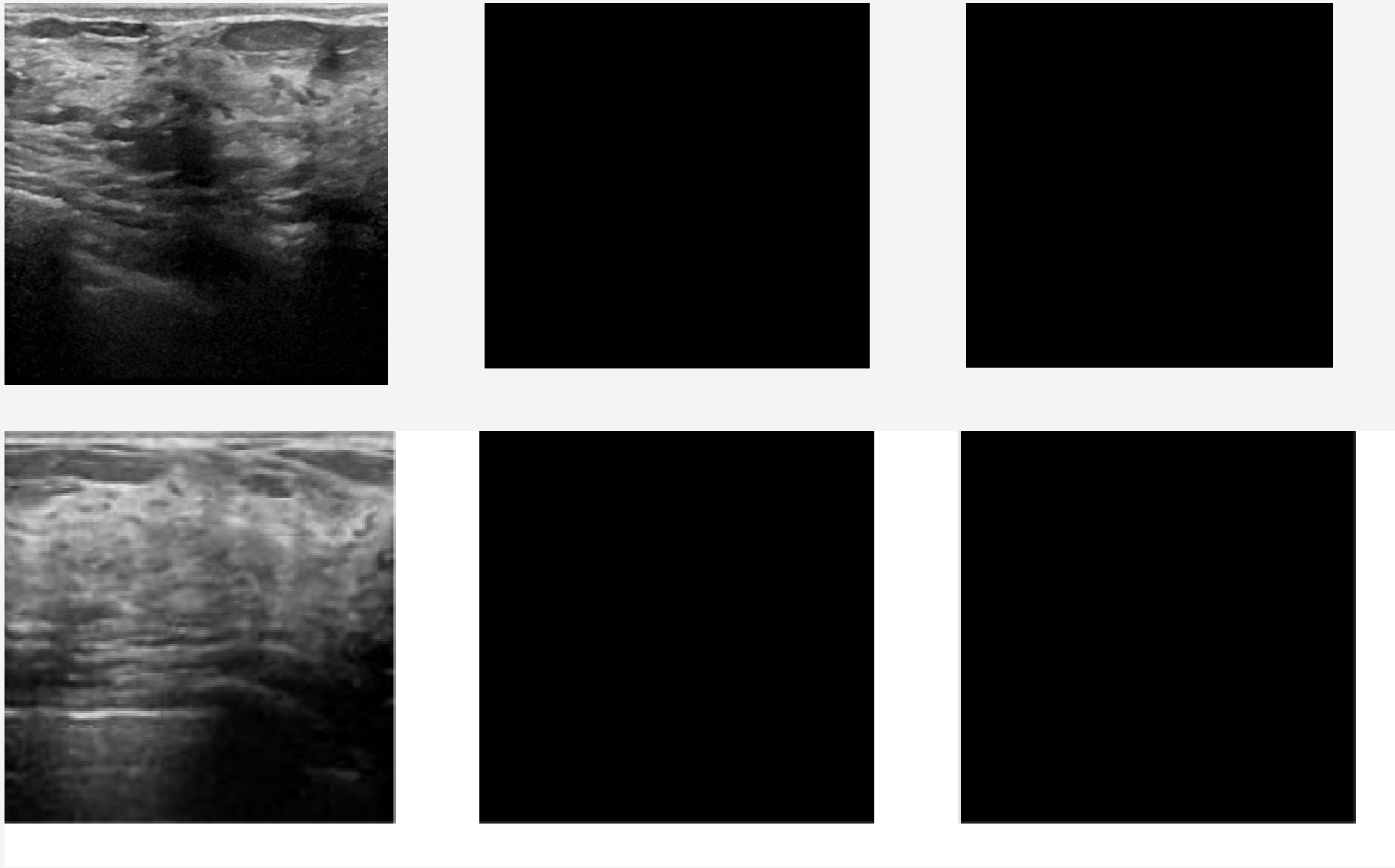

DeeplabV3Plus__resnext50_32x4d
Iou_Score
Score
Epochs


DeeplabV3Plus__resnext50_32x4d
Dice_loss
Score
Epochs

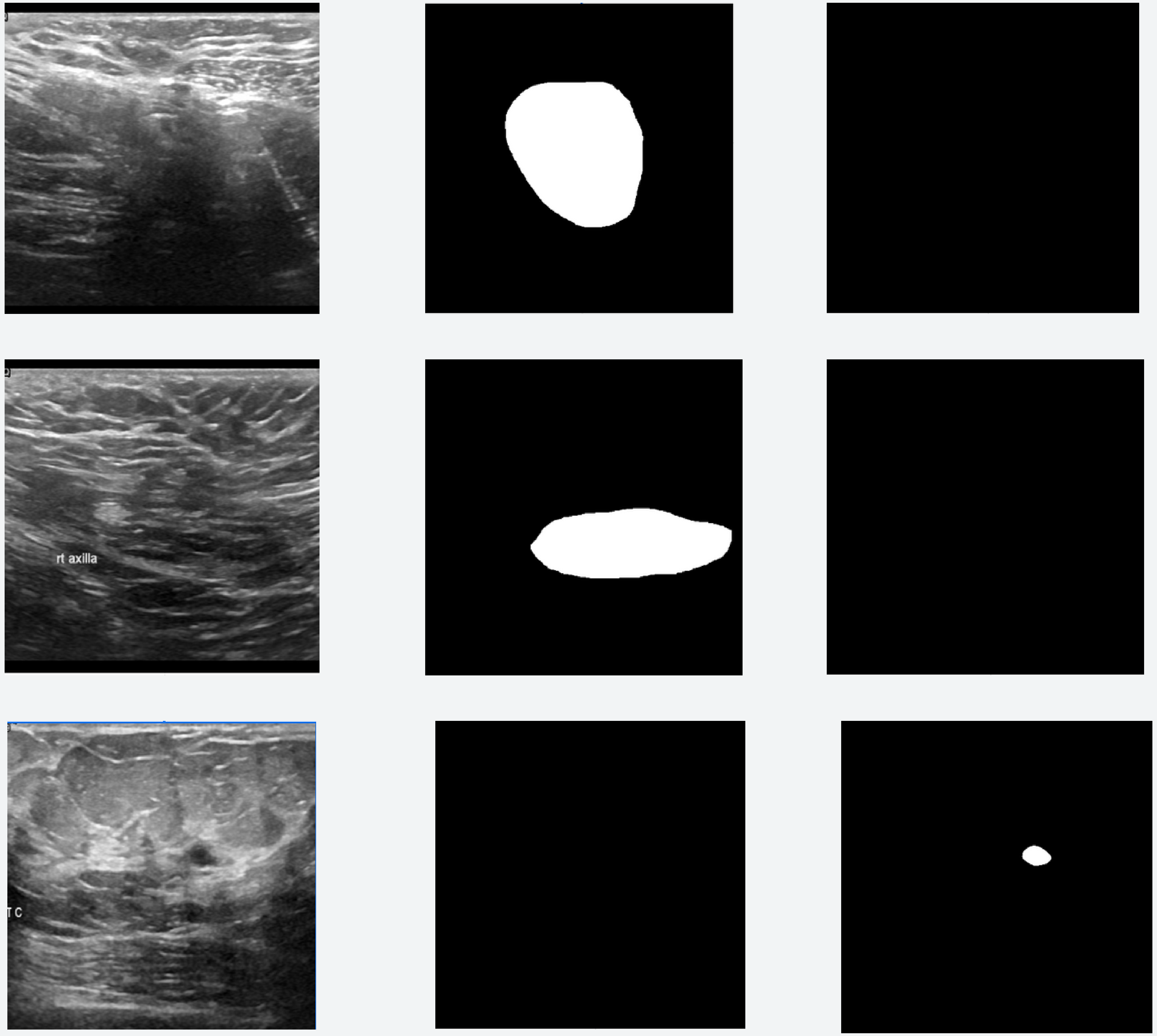
Predictions



Predictions



Wrong Predictions



Observations:

- We can observe that DeepLabV3+ model resulted in the highest validation score.
- Though the segmentation of the images is performed well by it, there are few errors such as predicting the image to be non-cancerous even when it is cancerous.

THANK YOU !!