Image Segmentation with PCUNet

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Introduction

Image segmentation plays a vital role in healthcare for extracting key information from complex images of tissues and organs . Our focus is on a specific paper in this field, which provides an innovative method for extracting information from ovarian tissues. The paper chosen is Orian Tumor Ultrasound Image Segmentation with Deep Neural Networks.

Existing Technology in the Field

The U-Net already exist and has demonstrated remarkable success in the field of medical image computing. However due to its small receptive field, U-Net faces challenges in extracting global context information. This paper presents a U-Net based network named PCU-Net for segmentation of ovarian tumors incorporating ConvMixer and Pyramid Dilated Convolution (PDC modules)

The UNet

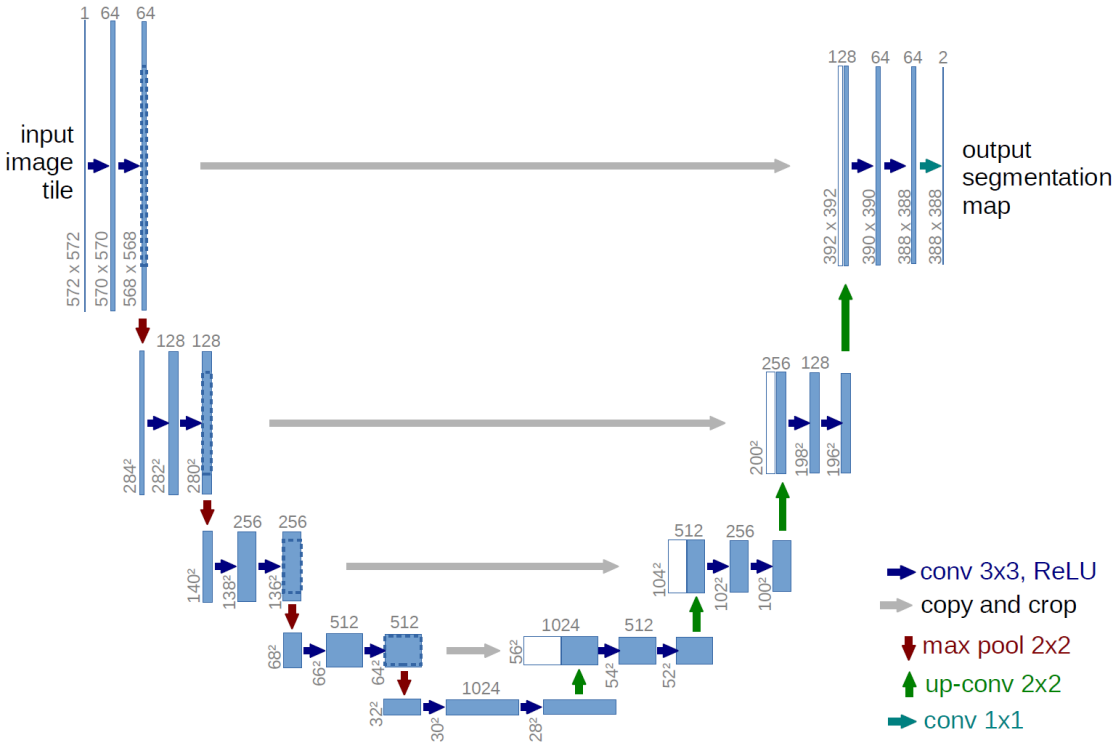


Figure: The U-Net

The Conv Mixer and PDC Layer

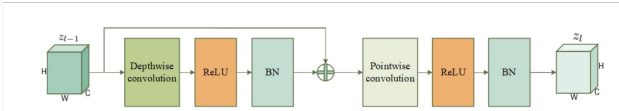


Figure: ConvMixer

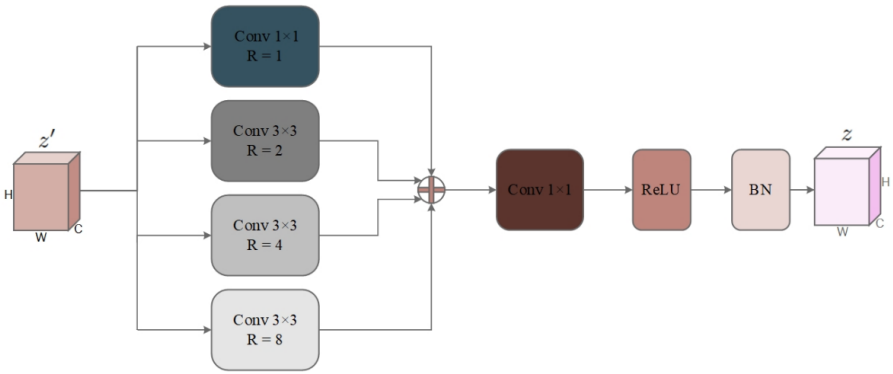


Fig. 2. Pyramid Dilated Convolution (PDC) module structure.

Figure: PDC Layer

The CUNet

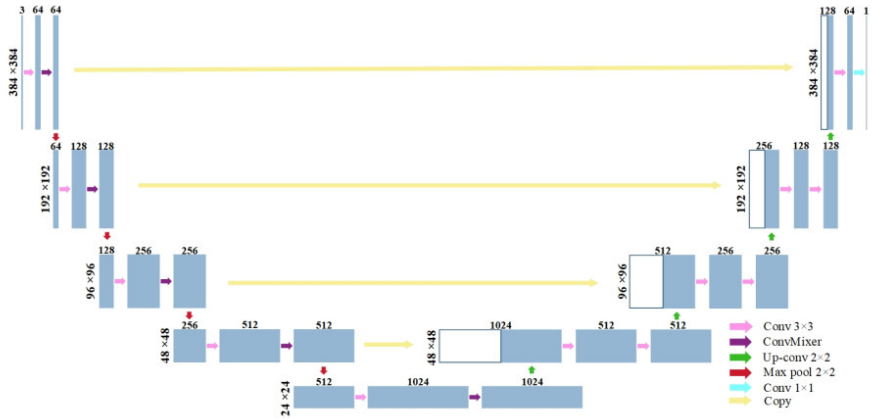


Fig. 3. Overview of the proposed CU-Net architecture.

Figure: The CU-Net

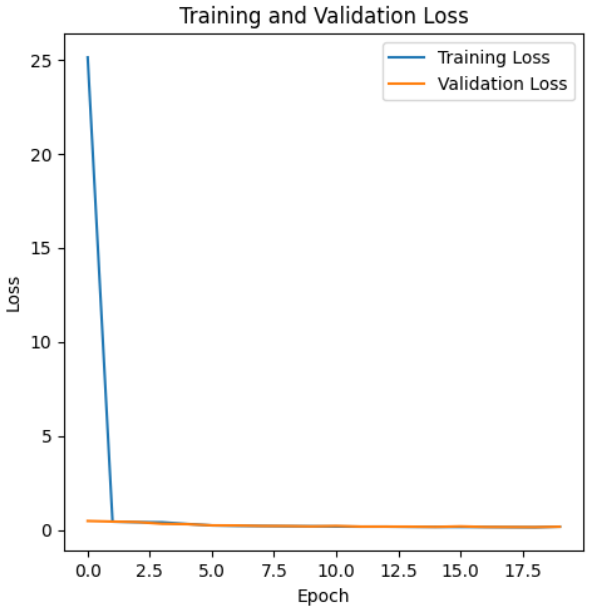
Architecture of UNet

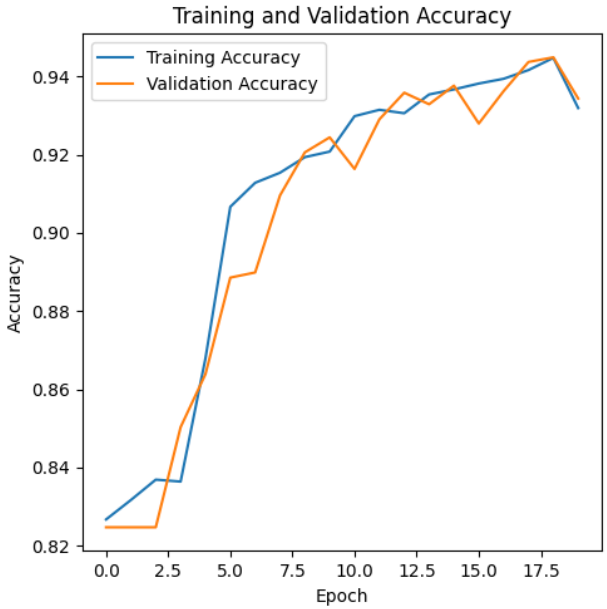
1. UNet consists of a contracting path (encoder) and an expansive path (decoder) with skip connections.
2. In the encoder section, the goal is to receive the ultrasound image as input and achieve a condensed representation of the input image.
3. The decoder section decodes the information extracted from the encoder stage to the size of the input image.
4. In U-Net, skip connections are direct connections between corresponding layers in the contracting path (encoder) and the expanding path (decoder), facilitating the seamless flow of high-resolution spatial information to the decoding layers and aiding in the precise localization of features, thereby improving the segmentation accuracy.

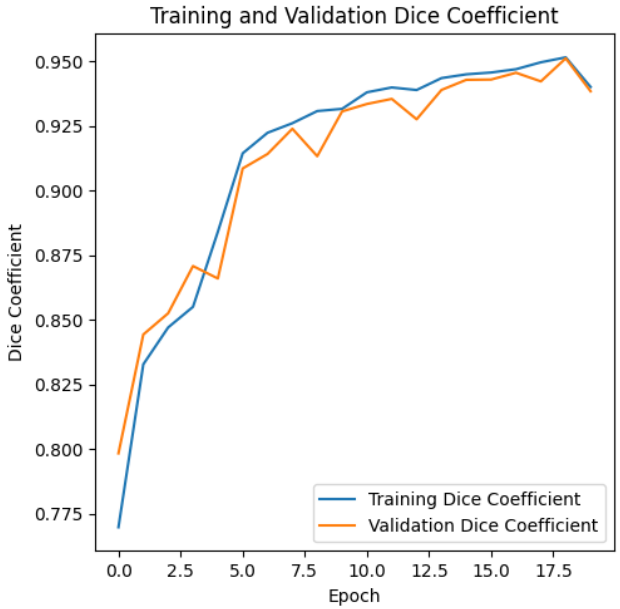
Why PCUNet?

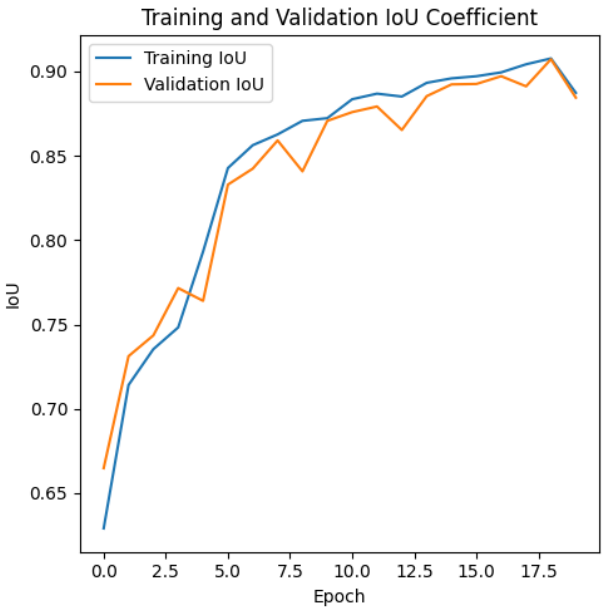
- The CUNet differs from the UNet in that is has a ConvMixer block instead of the convolutional layer of the UNet for each of the encoder blocks except the last one.
- The PCUNet has a PDC layer in the place of a ConvMixer block in the last encoder block.
- The ConvMixer module captures global context information by utilizing large-size kernels. The PDC module integrates local and global contextual patterns through utilization of parallel dilated convolution with different dilation rate. Furthermore, this model has fewer parameters than U-Net. We have replicated the results of the paper on the dataset Multi-Modality Ovarian Tumor Ultrasound (MMOTU)which includes two subsets with two modes, OUT 2d and OUT CEUS, containing 1469 2D ultrasound images and 170 CEUS images, respectively. We have worked on the OUT 2d subset.

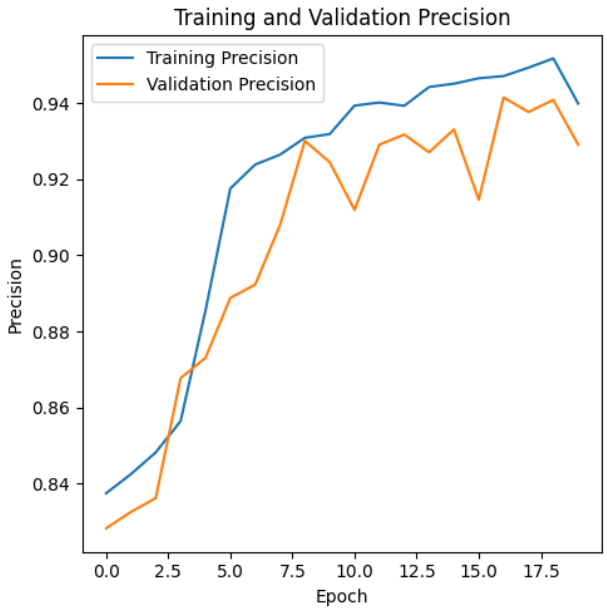
Results : UNet

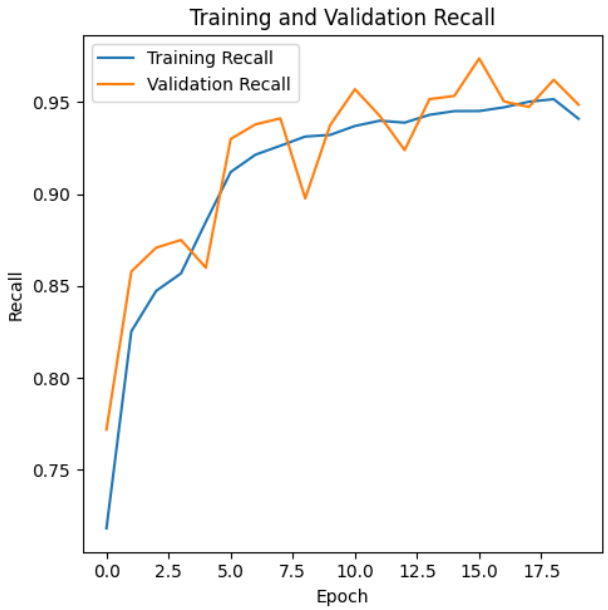




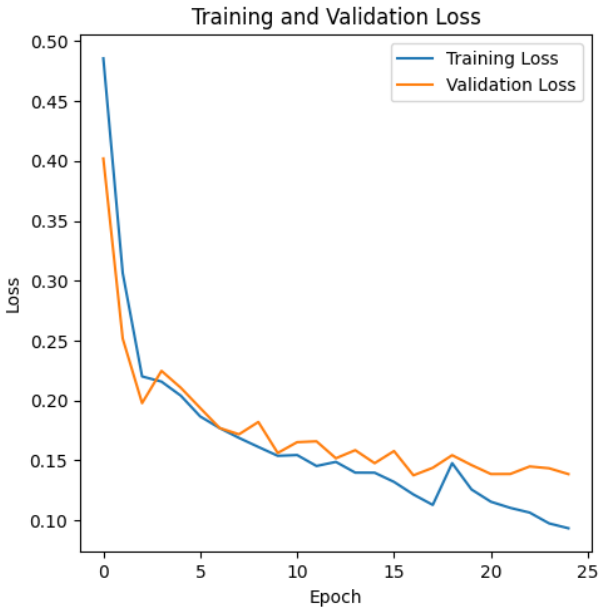


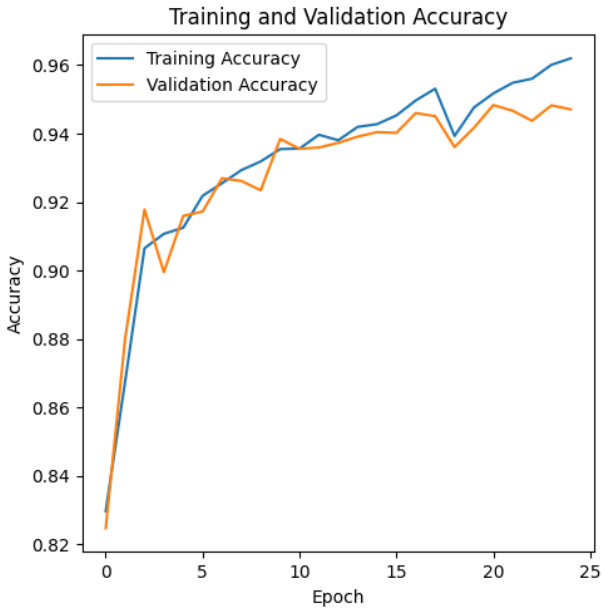


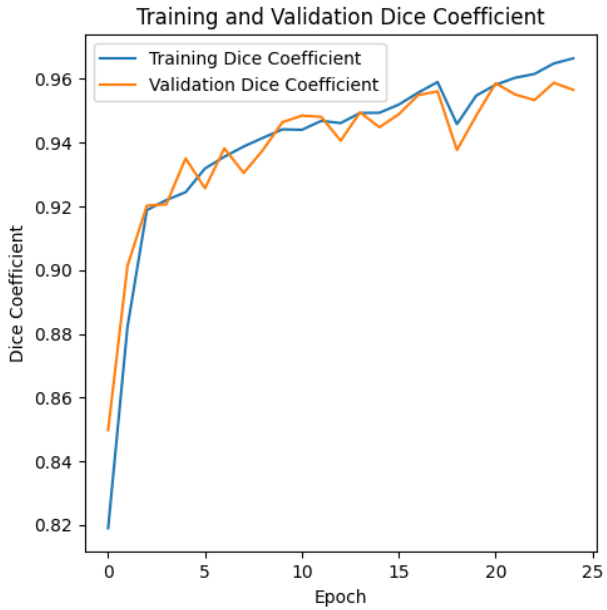


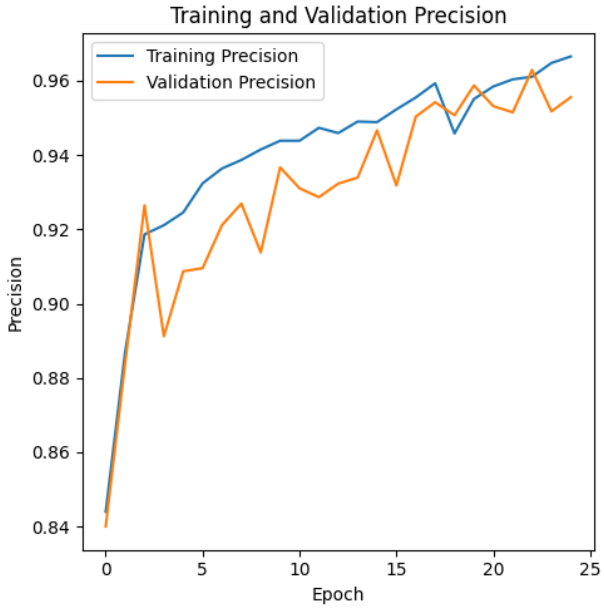


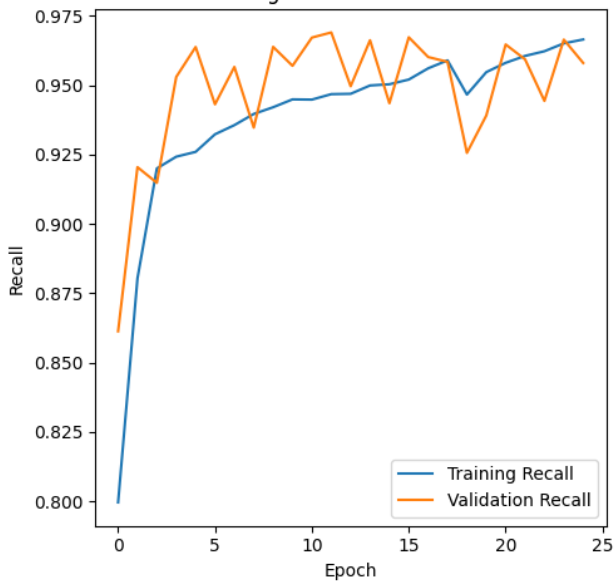
Results : CUNet



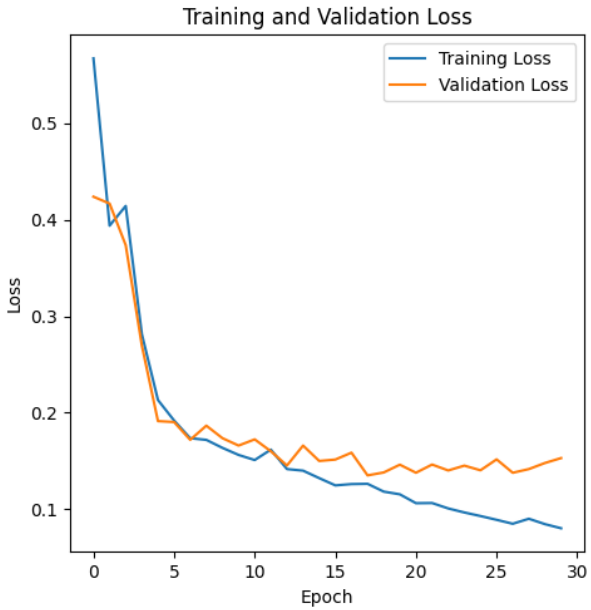


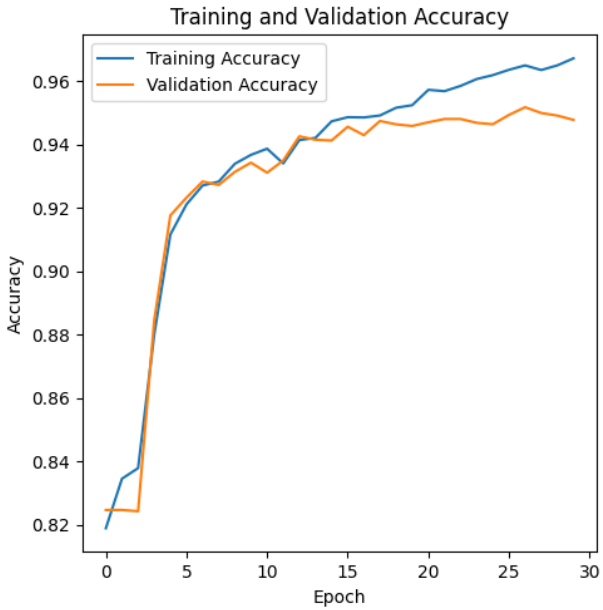


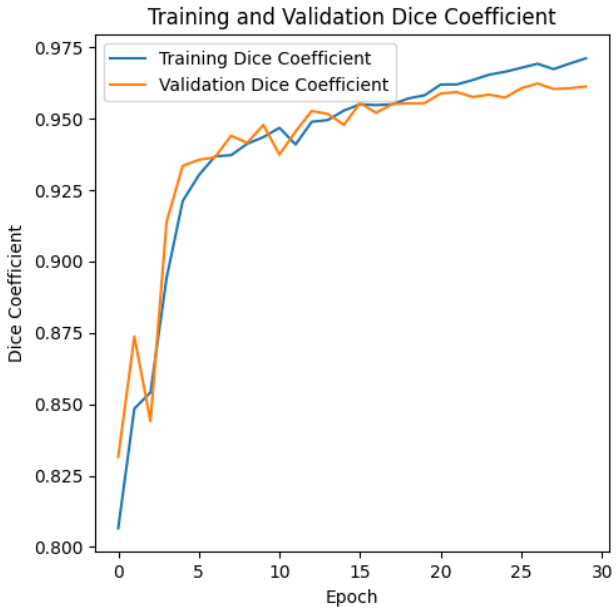


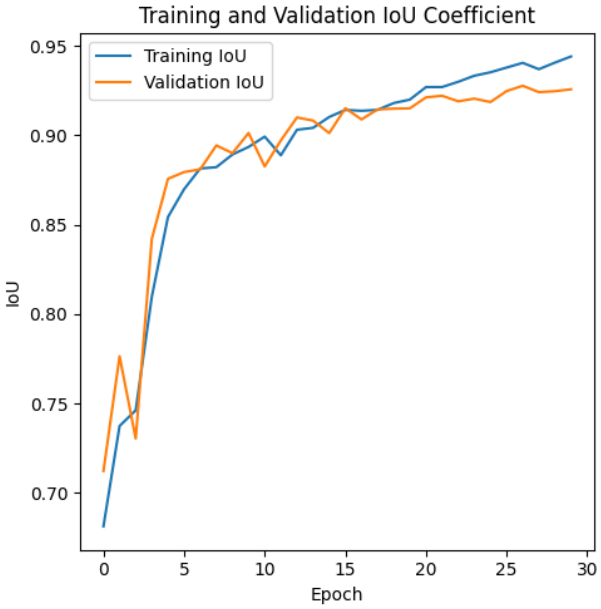


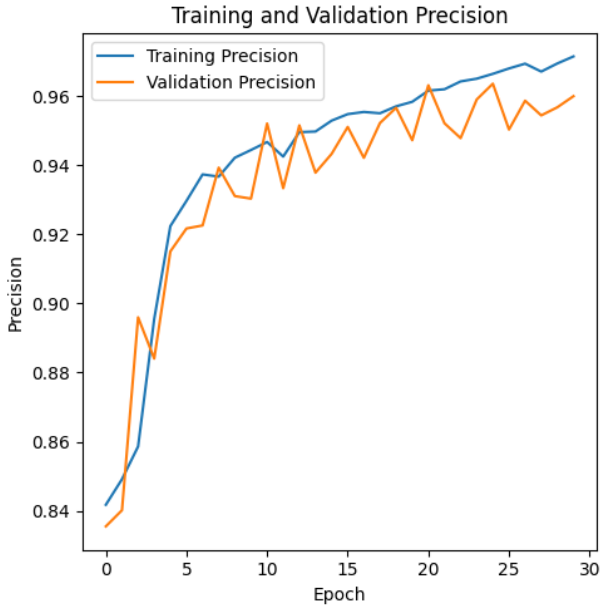
Results : PCUNet

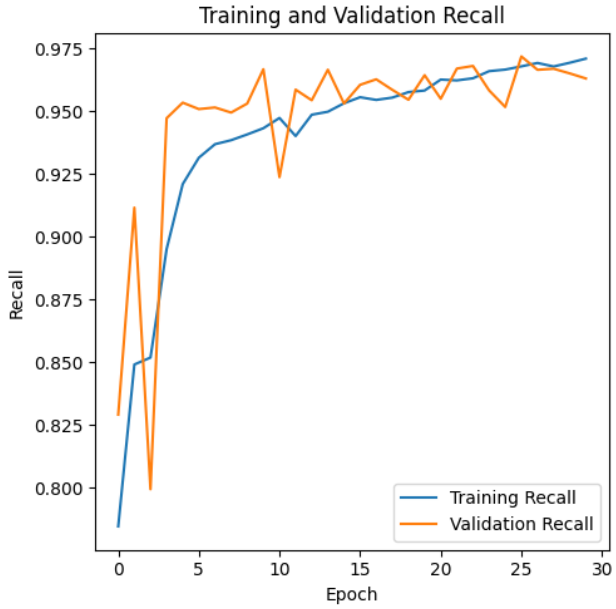












Summary

Method	U-Net	CU-Net	PCU-Net
IoU	0.8868	0.9352	0.9440
DSC	0.9399	0.9665	0.9712
Precision	0.9401	0.9666	0.9715
Recall	0.9399	0.9665	0.9710
Accuracy	0.9319	0.9620	0.9673

Table: Performance Comparison

Clearly the PCUNet has better performance metrics than the CUNet and UNet models.

References

1. The paper https://ieeexplore.ieee.org/document/10491156
2. Reference code https://towardsdatascience.com/cook-your-first-u-net-in-pytorch-b3297a844cf3