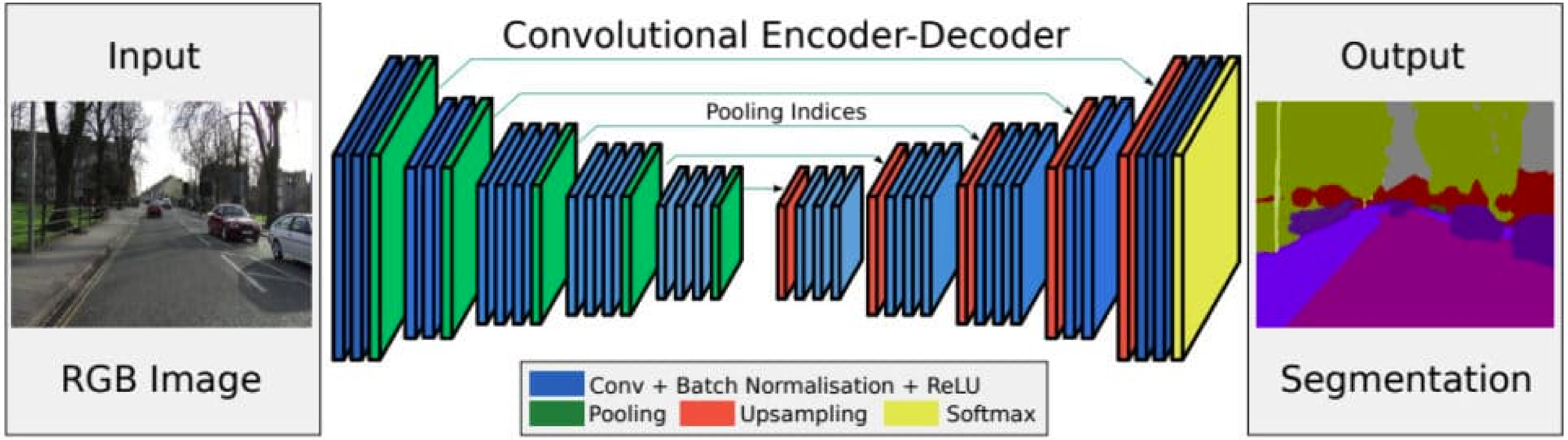
BRIAN MRI SEGEMENTATION

WITH DIFFERRENT ENCODERS

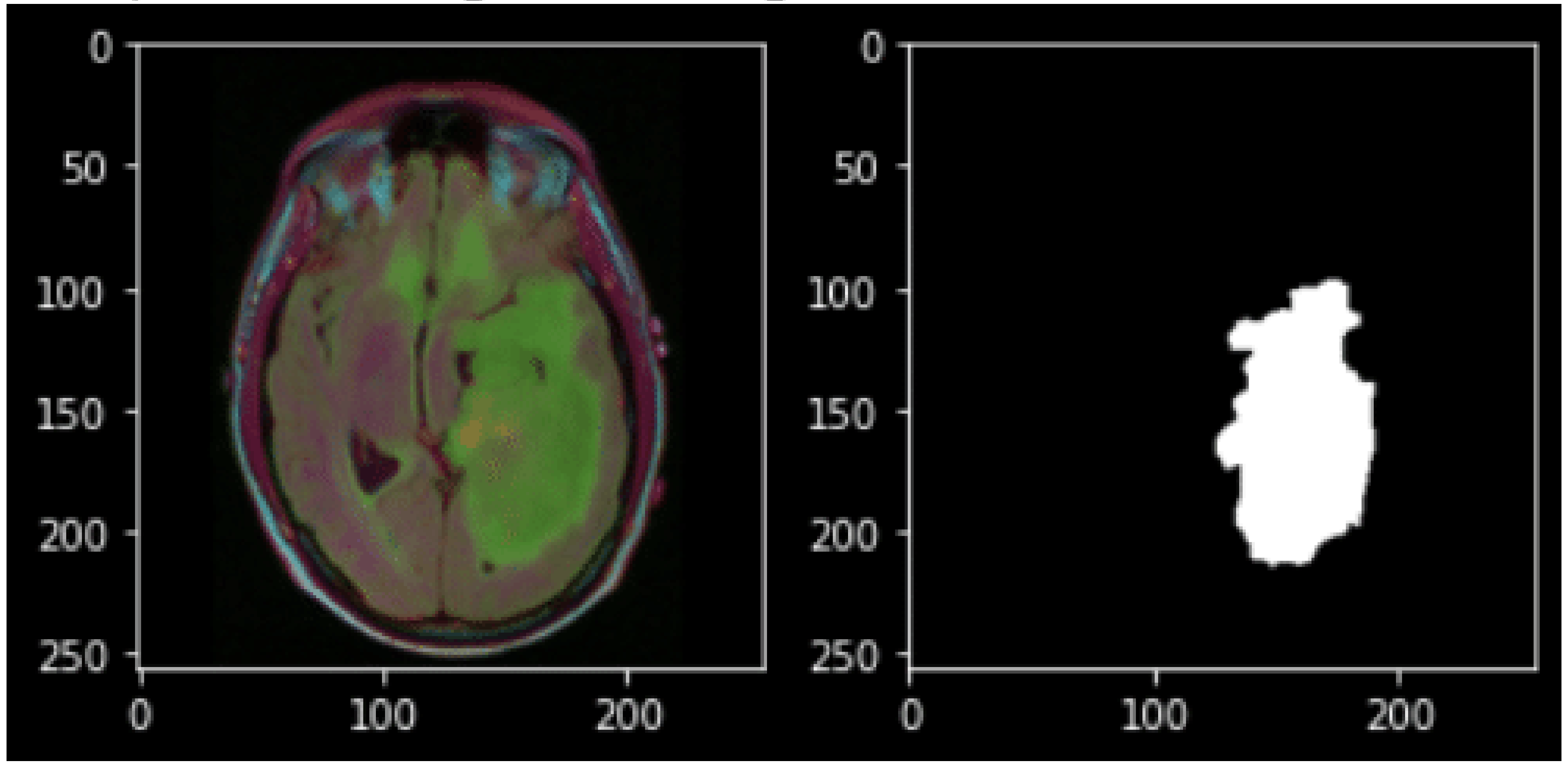
Semantic Segmentation



Assigns a class label to each pixel in an image

Brain MRI Semantic Segmentation

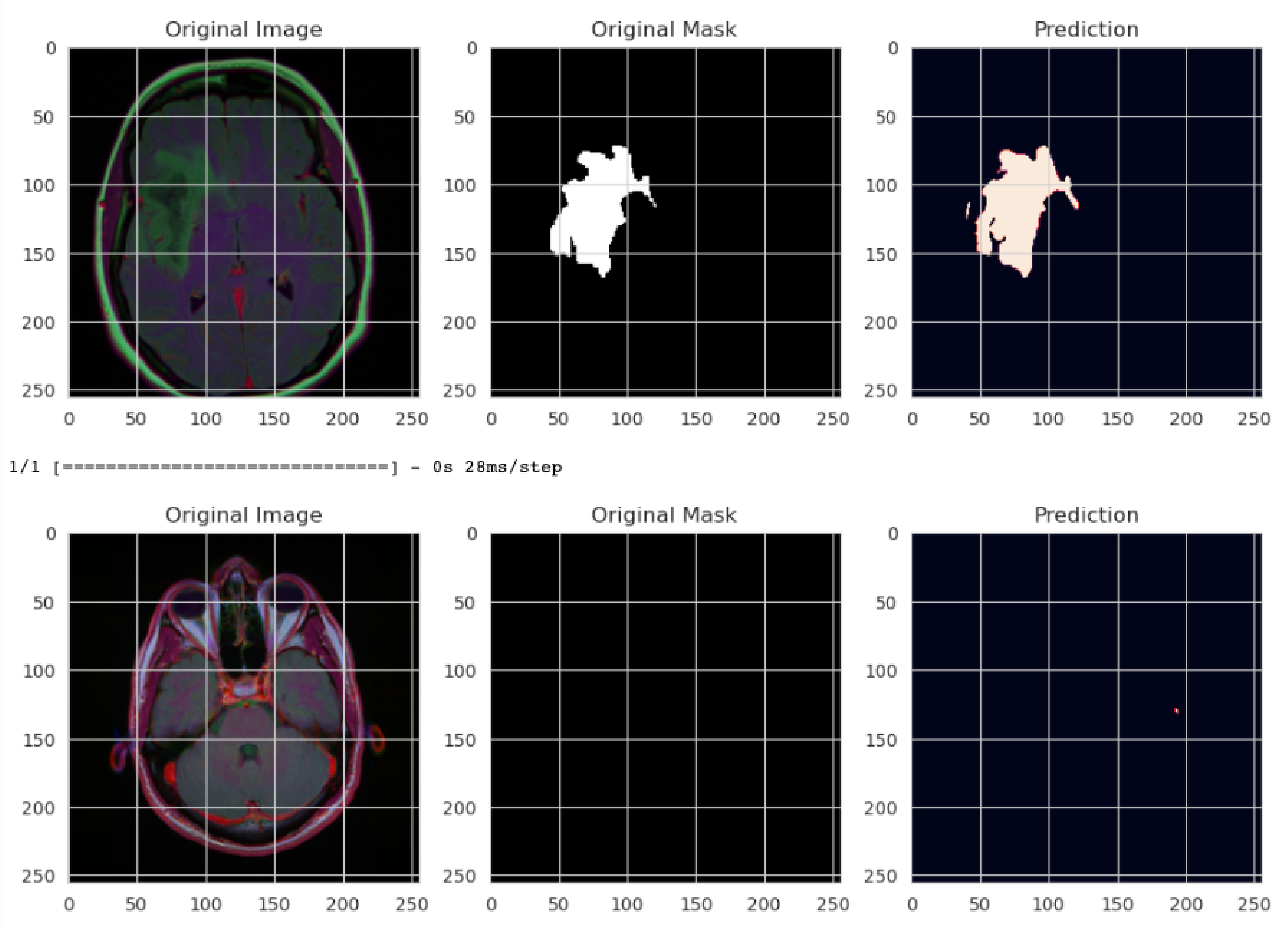
Data source:https://www.kaggle.com/datasets/mateuszbuda/lgg-mri-segmentation



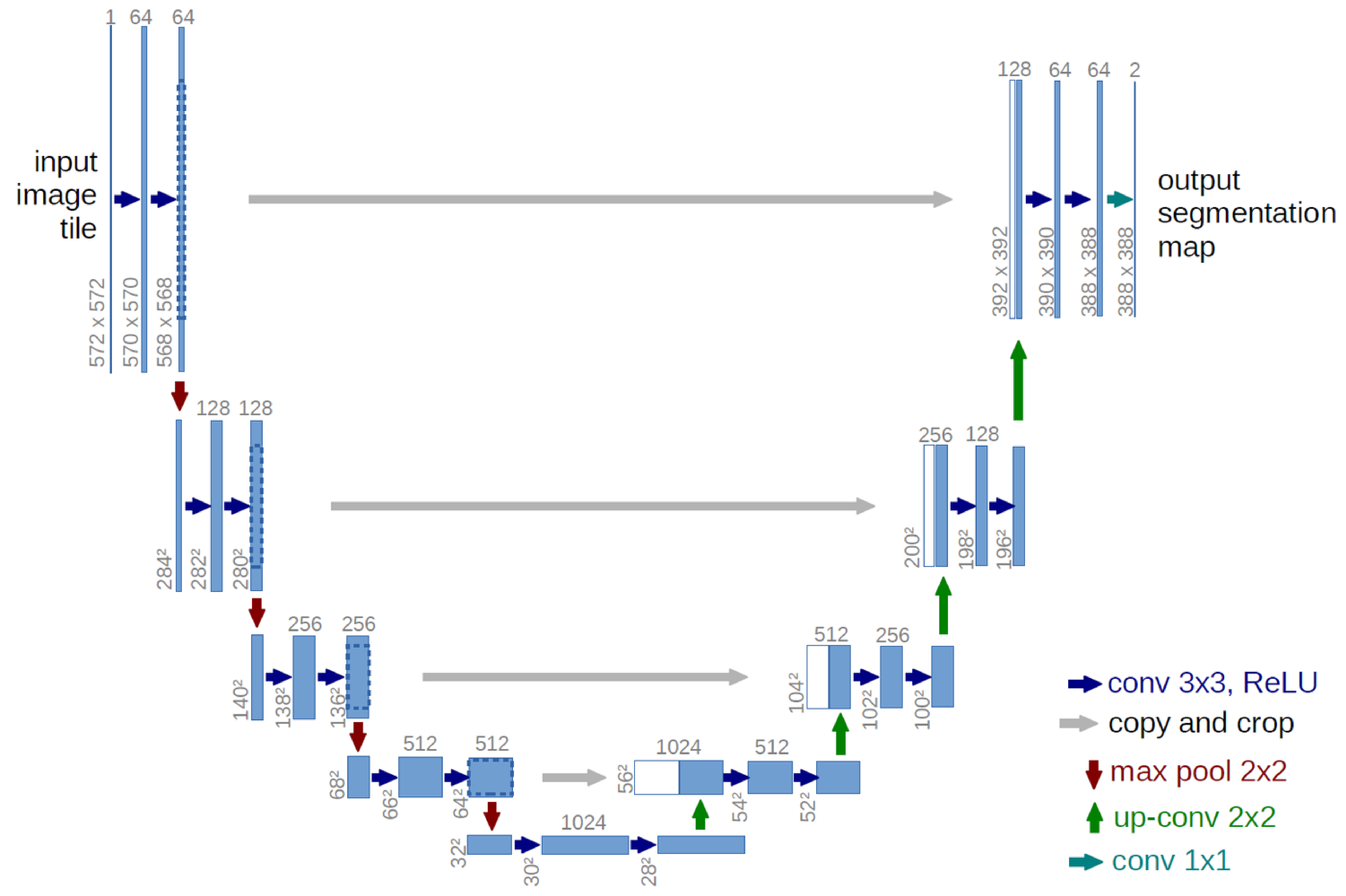
Training set:	**2828**
Validation set:	**393**
Test set:	**708**
Total:	**3929**

This dataset contains brain MRI images together with manual FLAIR abnormality segmentation masks.

Brain MRI
Semantic Segmentation



Unet



- A CNN architecture specifically designed for biomedical image segmentation
- Symmetric U-shaped structure with contracting and expanding paths
- Enable precise localization and high-resolution feature mapping

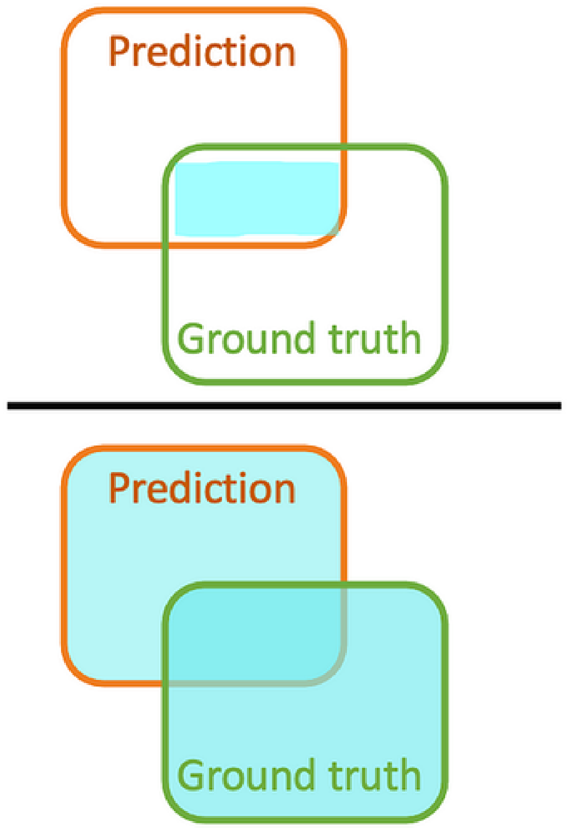
Different encoders

- Generic Unet(no pretained encoders)
- VGG16 (retrain all layer)
- ResNet50 (retrain all layer)
- ResNet50 (freeze first two conv blocks)

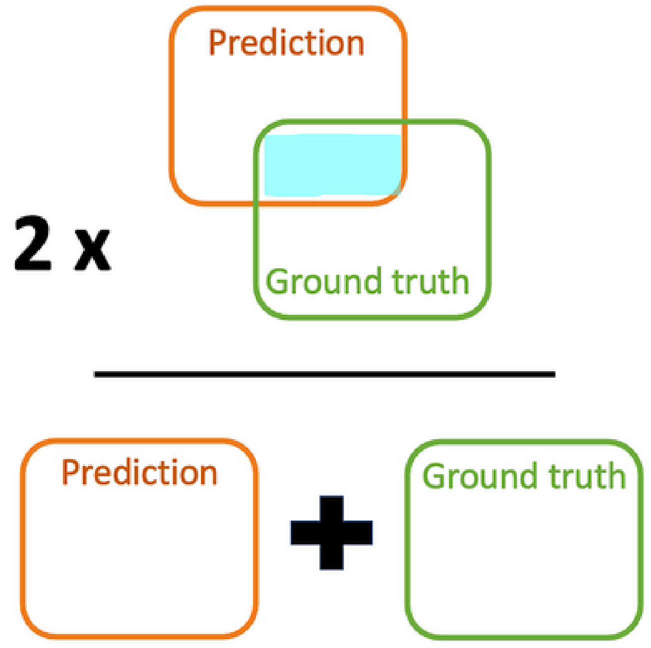
Metrics

- Both metrics have values between 0 and 1, where a score of 1 indicates a perfect match between the predicted and ground truth masks.
- The subtle difference between them is that the dice score tends to veer towards the average performance. Whereas the IOU helps one understand worst case performance.
- In practice, they're often both used.

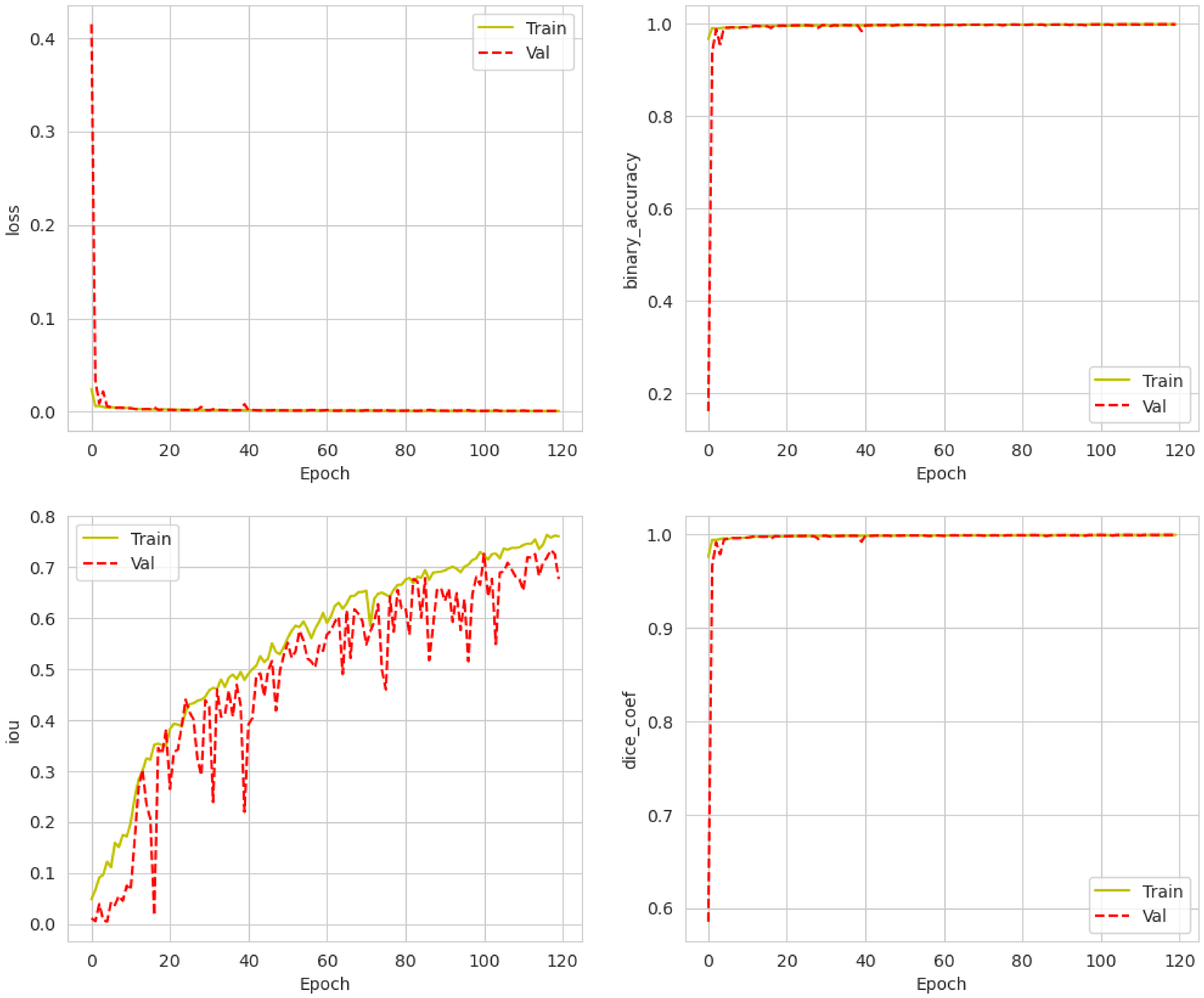
$$\mathrm{IoU} = \frac{\textit{Area of overlap}}{\textit{Area of union}} =$$



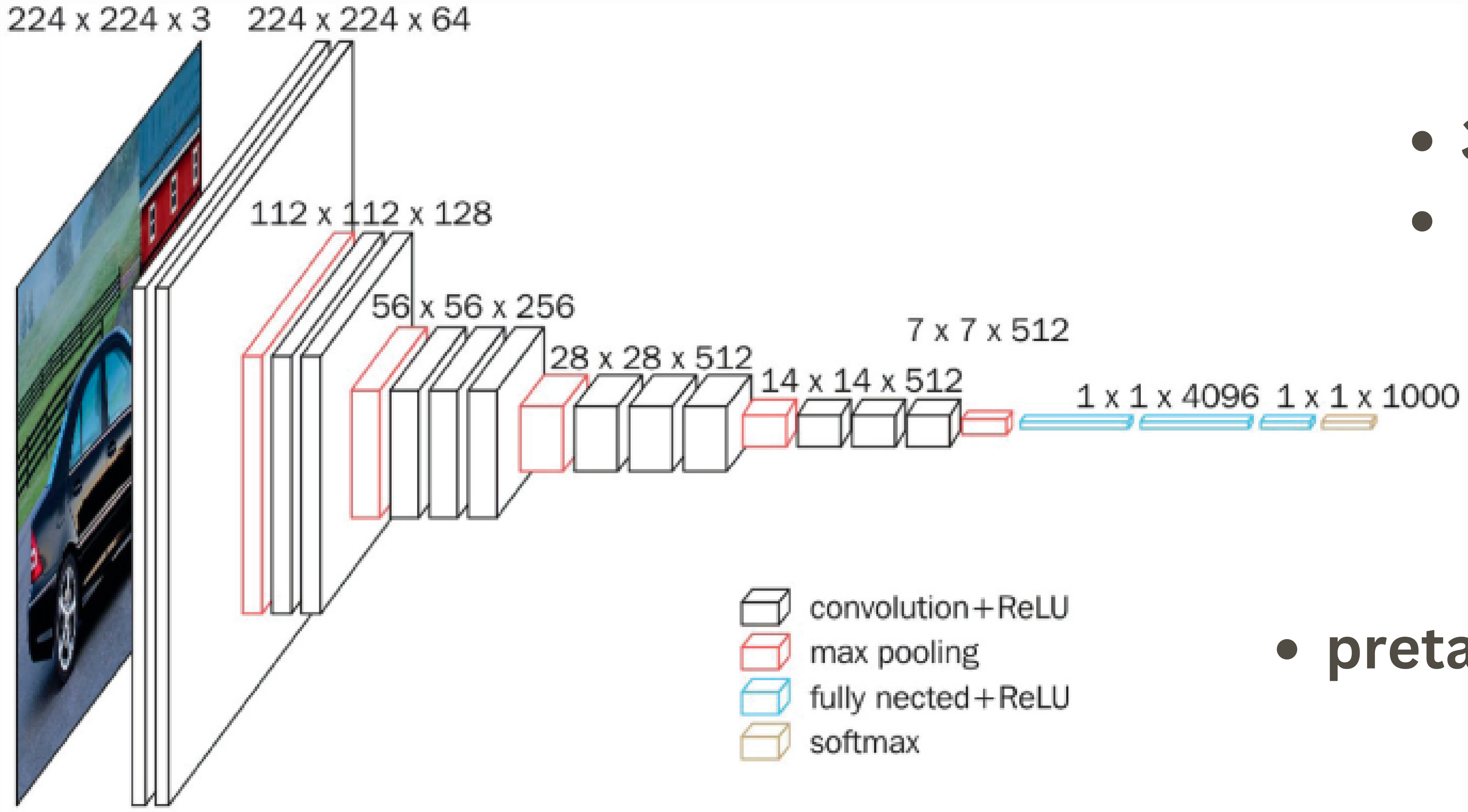
$$\mathrm{Dice} = \frac{2\ X\ \textit{Area of overlap}}{\textit{Total area}} =$$



Unet



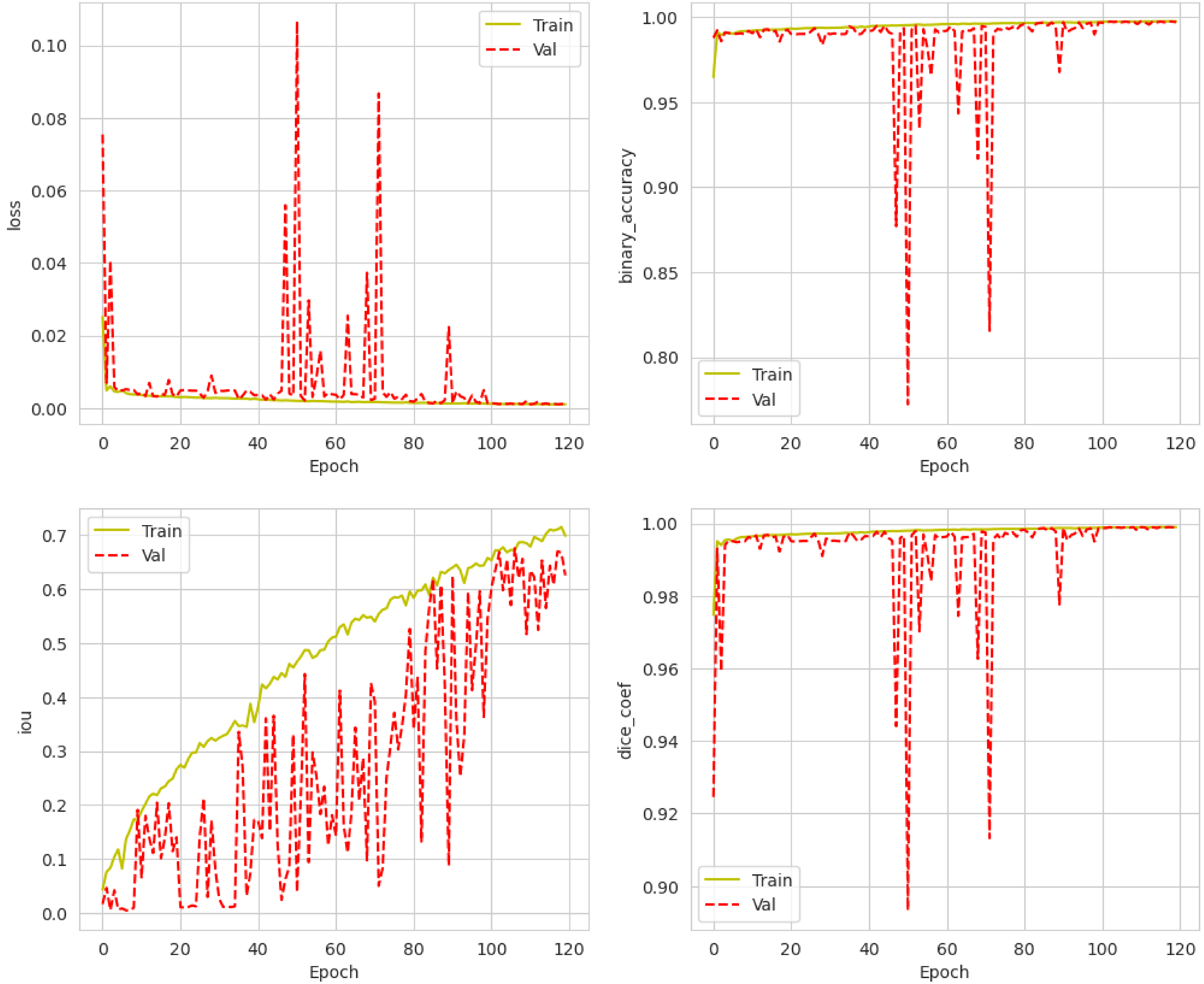
VGG 16



- 3x3 convolutional filters
- Deeper networks

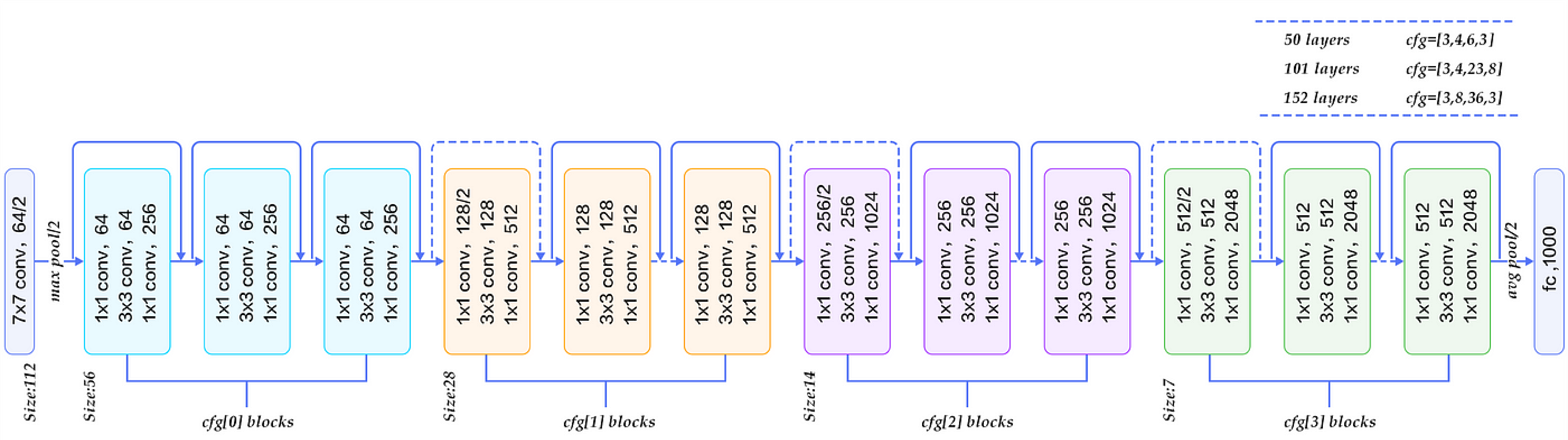
- pretained weights on ImageNet

VGG 16



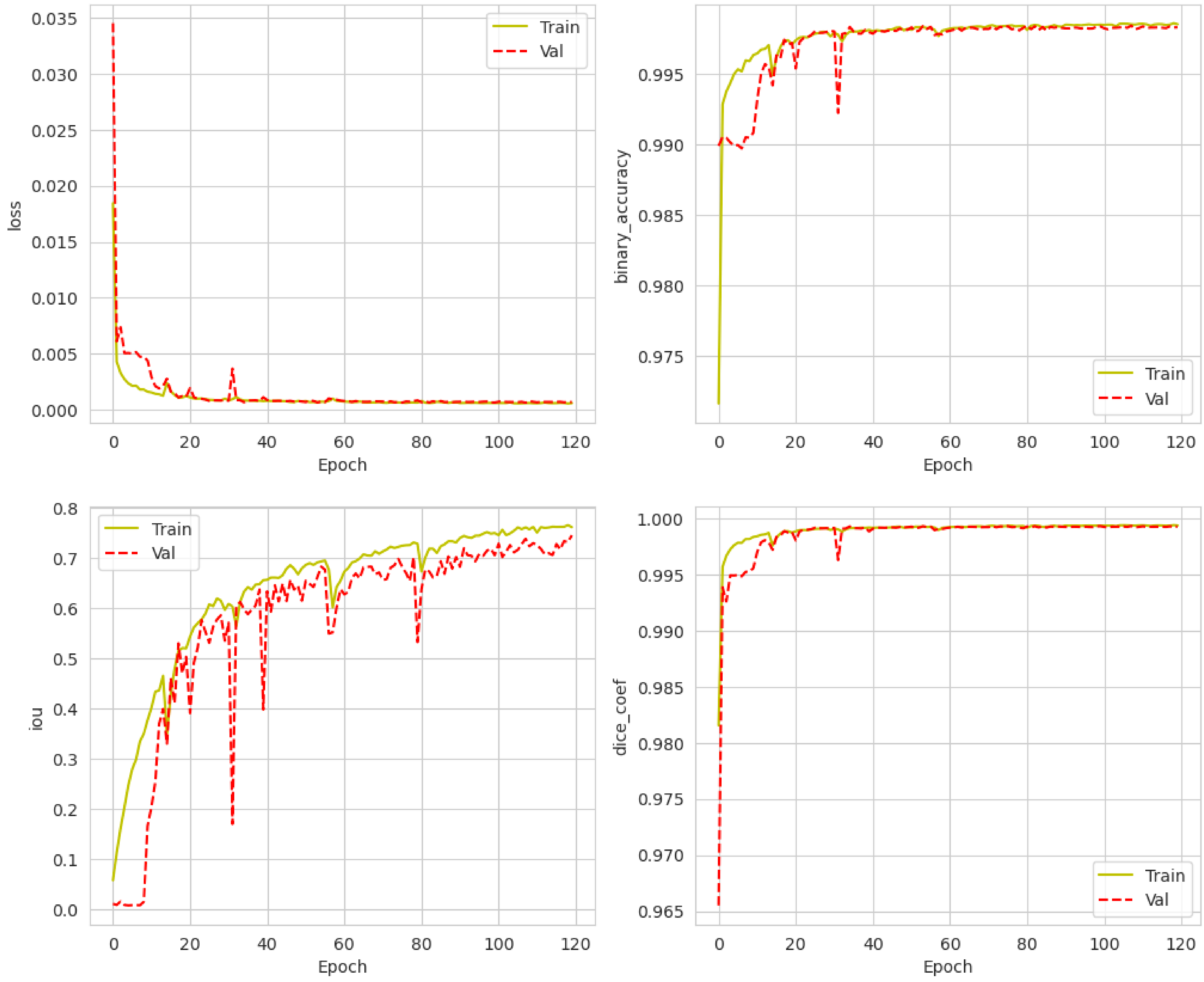
loss
Epoch
Train
Val
binary_accuracy
iou
dice_coef
0.00
0.02
0.04
0.06
0.08
0.10
0.80
0.85
0.90
0.95
1.00
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.90
0.92
0.94
0.96
0.98
0
20
40
60
80
100
120

ResNet 50

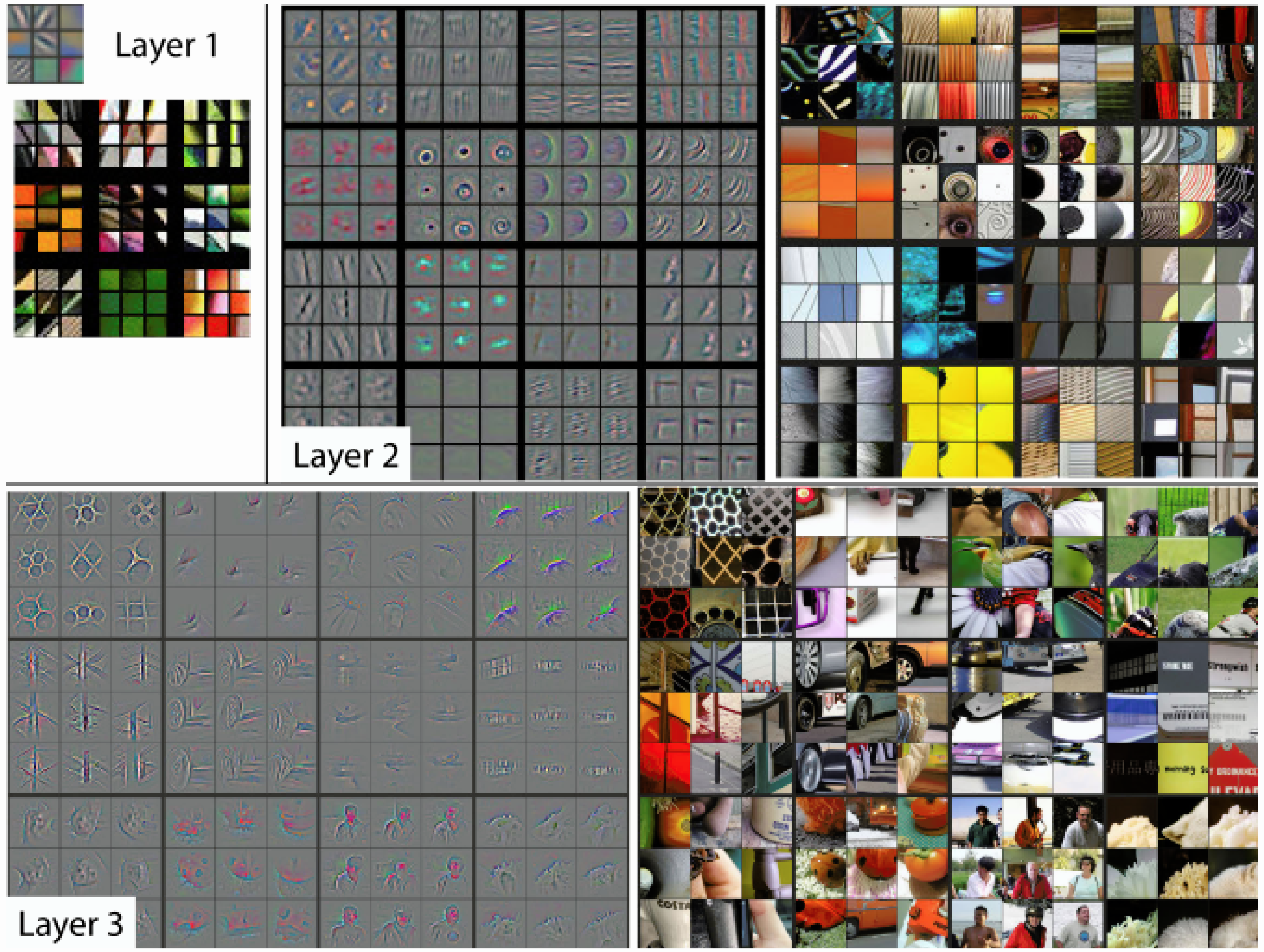


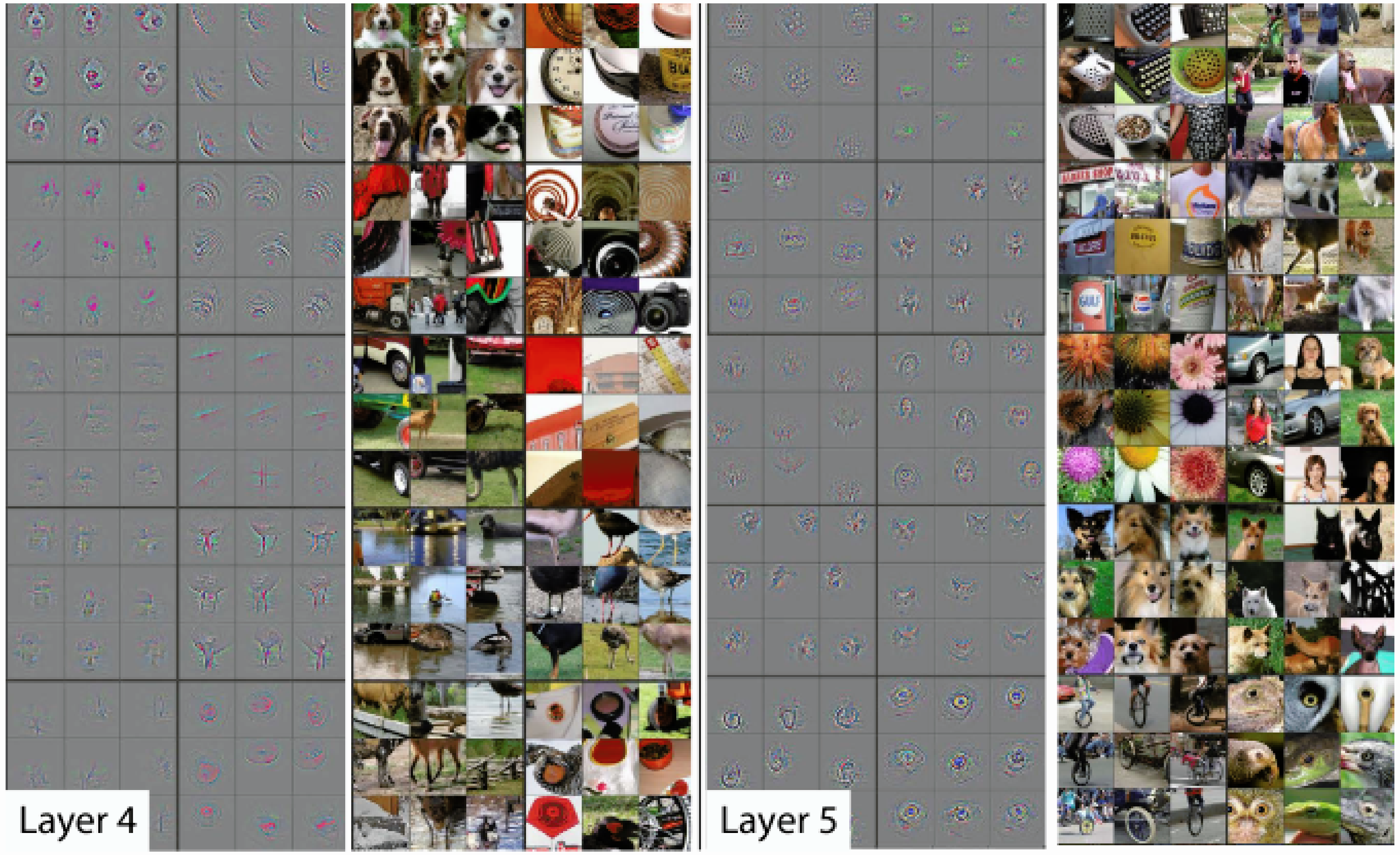
- Has residual connections (also known as skip connections)
- residual connections allow the network to learn residual mappings, bypassing certain layers and enabling the flow of gradients throughout the network.
- Allows for much deeper networks without a decrease in accuracy

ResNet50 fine tuning

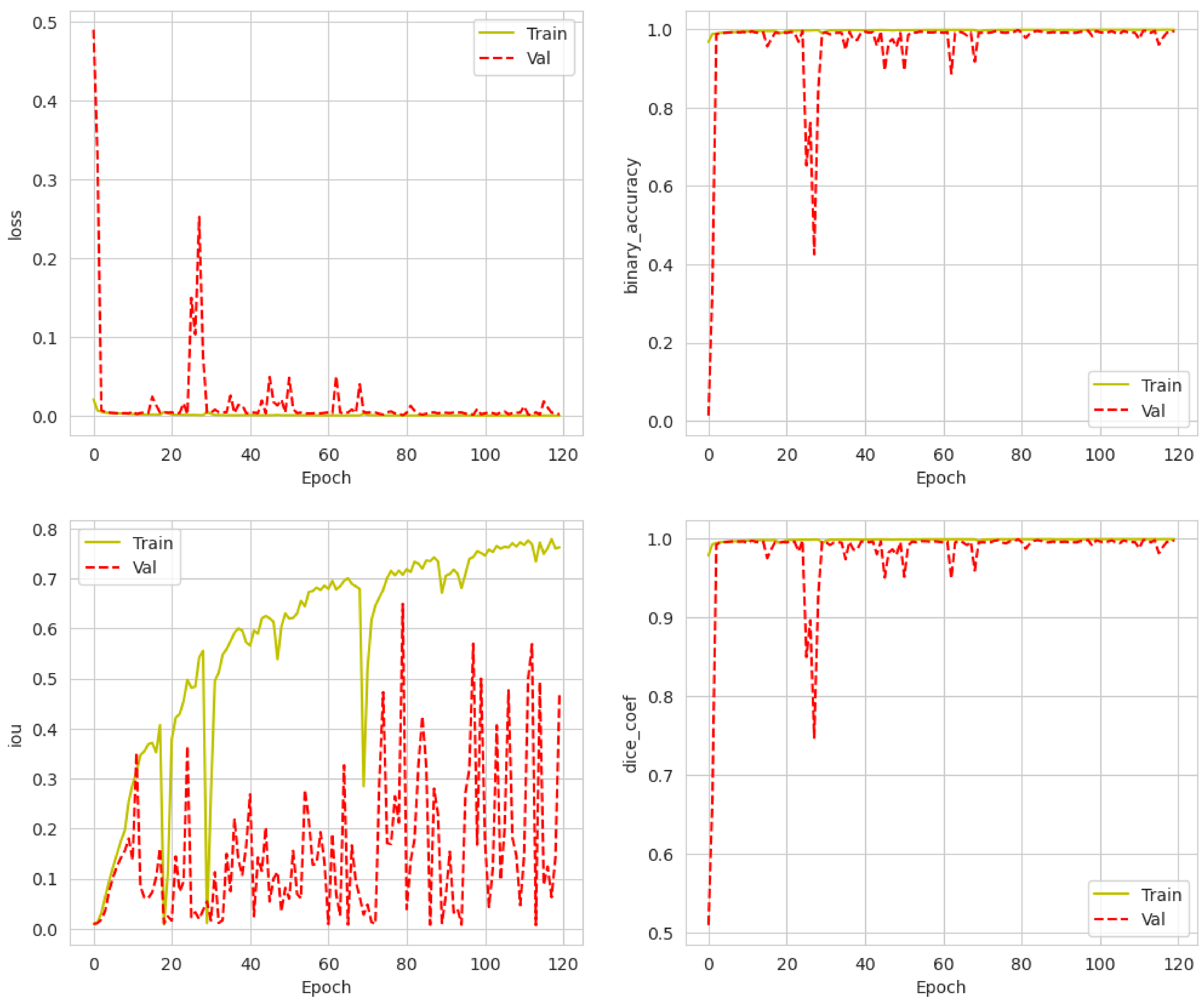


Feature Maps



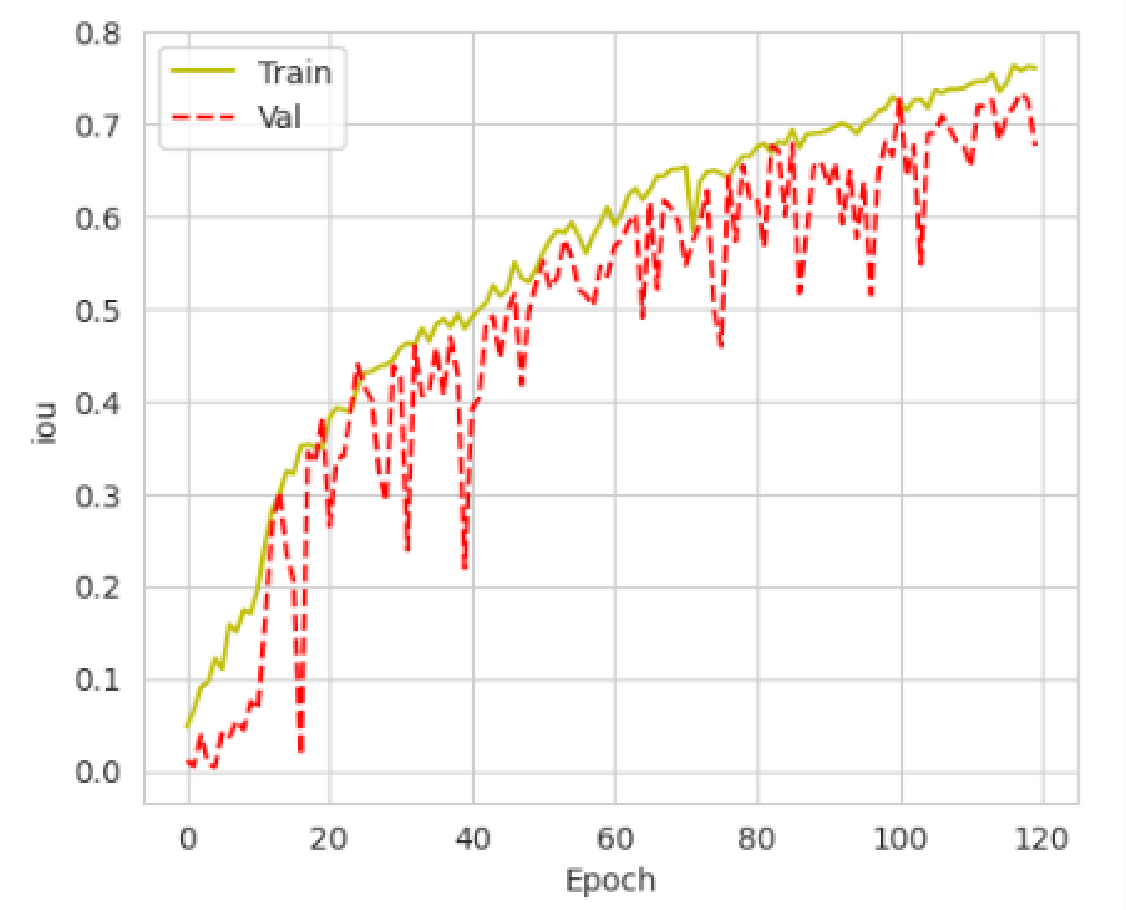


ResNet50 frezee first two conv blocks

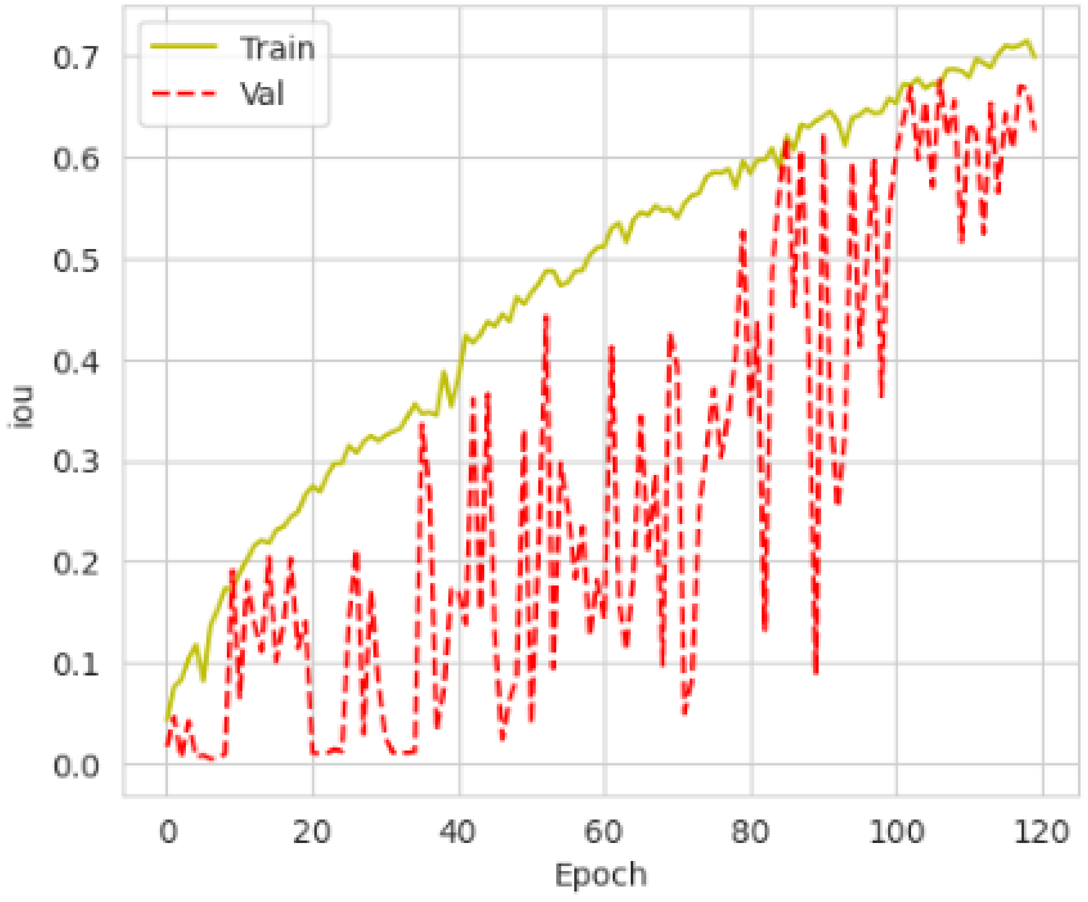


IoU Comparision

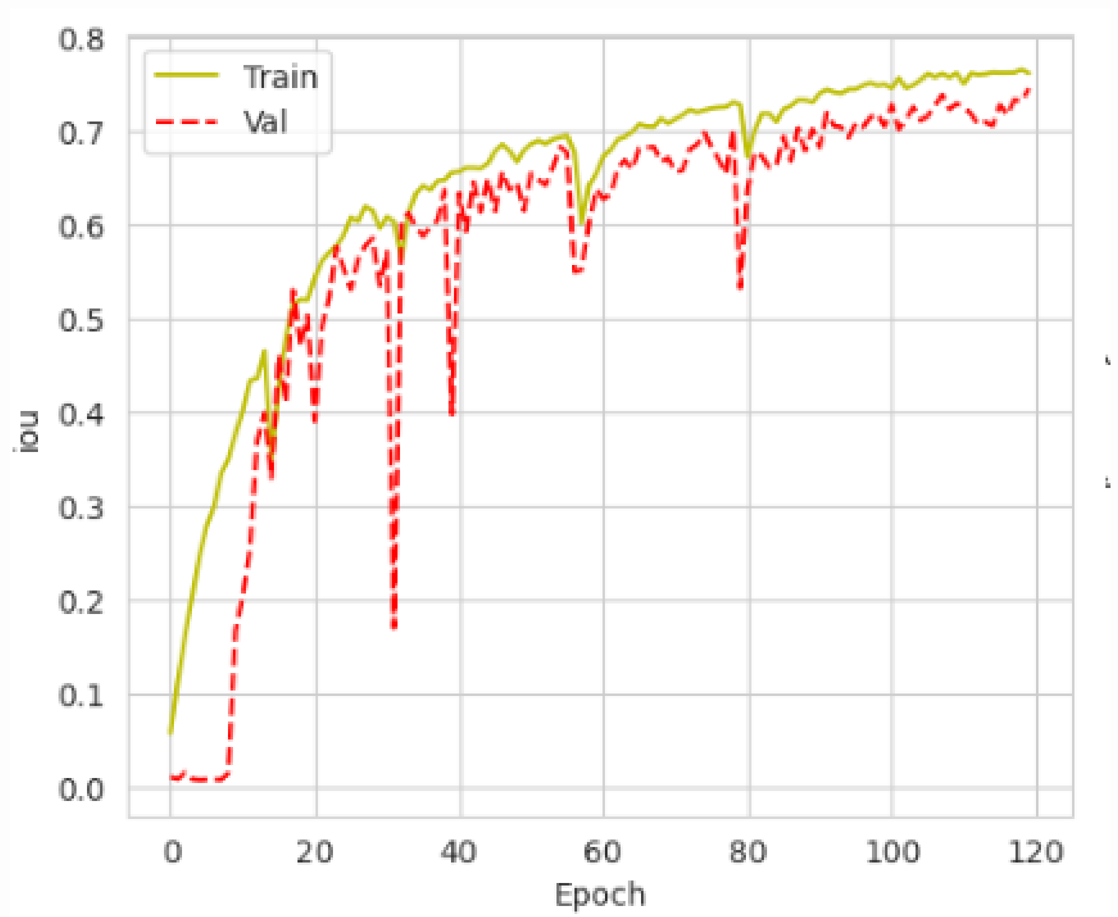
Unet



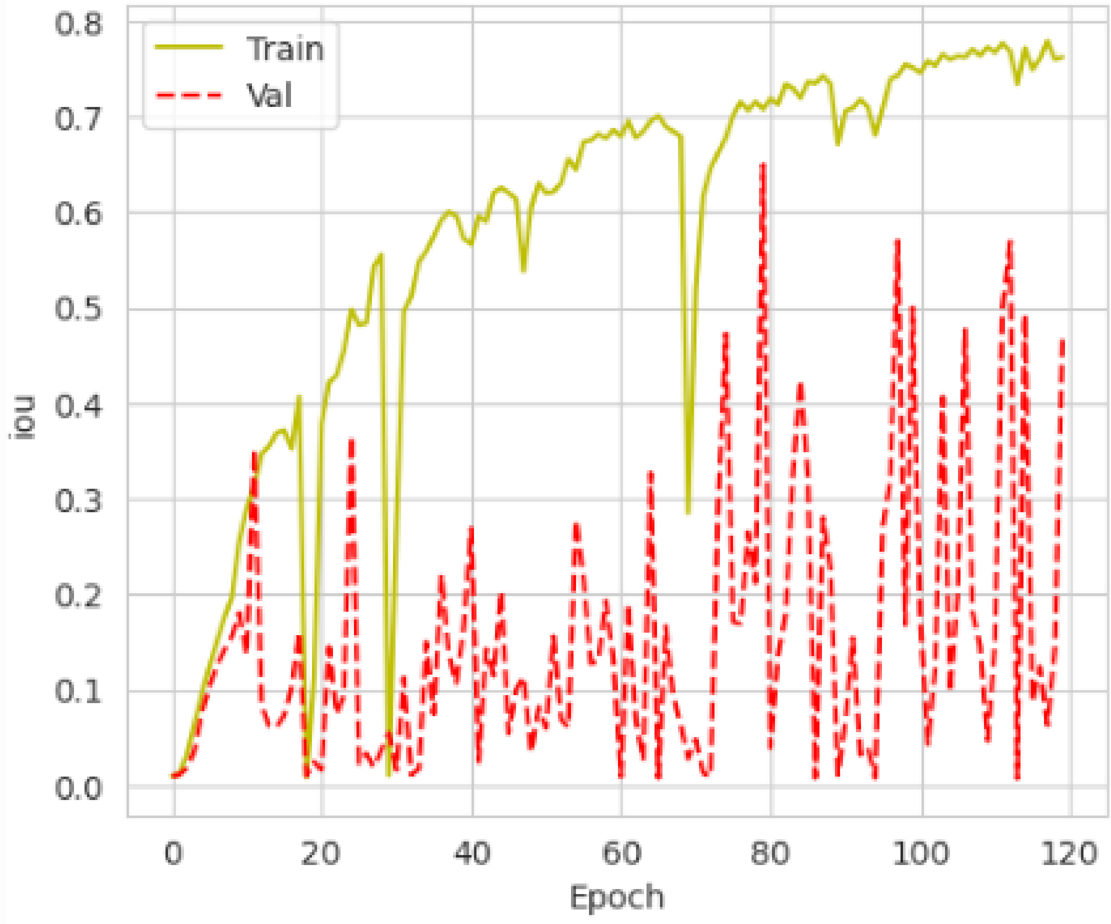
VGG



ResNet50 finetuning



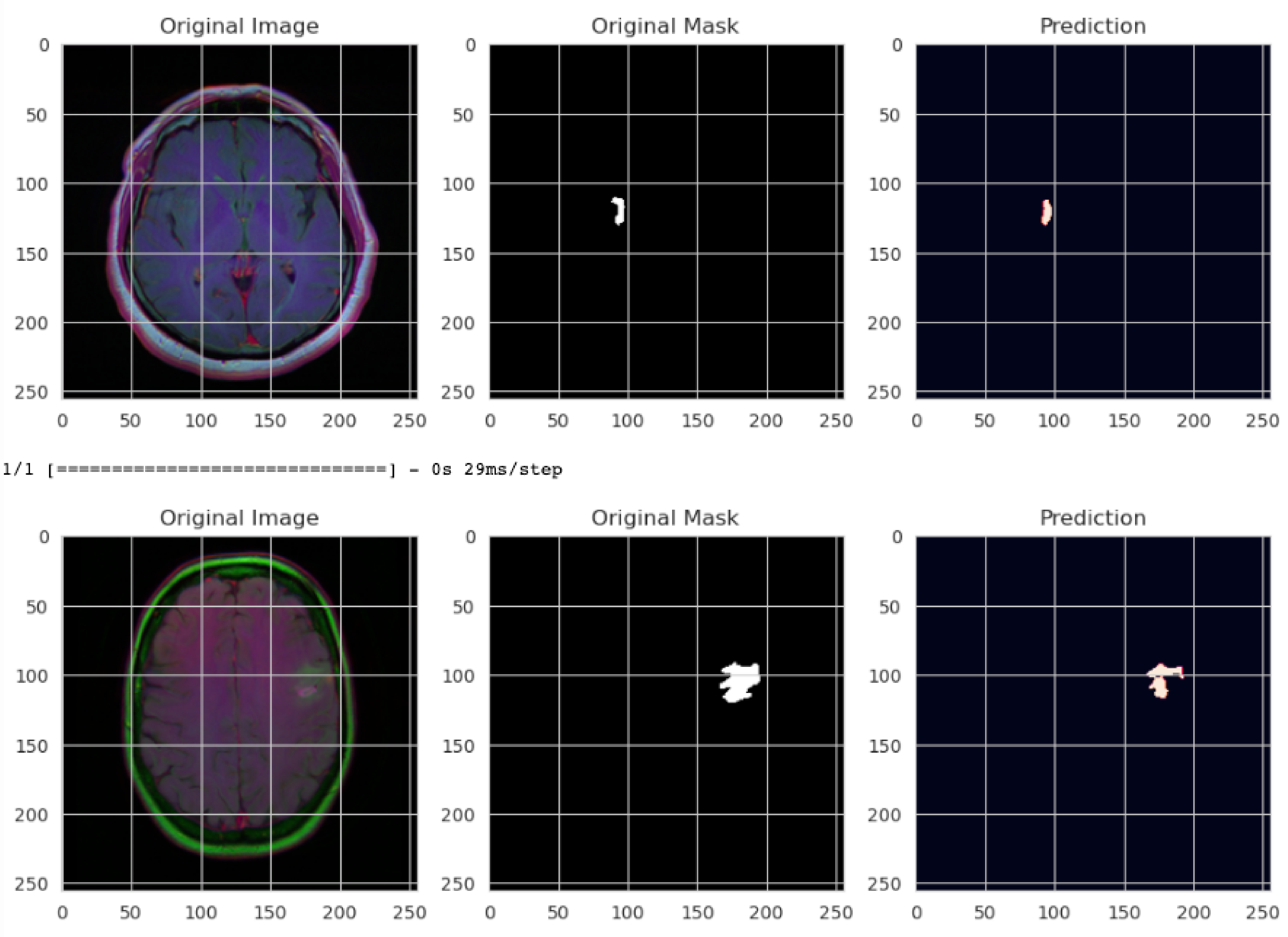
ResNet50 freeze



Performance Comparision

	unet	vgg16	resnet50	partial_resnet50
Loss	0.000714	0.001196	0.000690	0.002926
Binary_Accuracy	0.998279	0.997081	0.998334	0.993751
IoU	0.703022	0.639999	0.732958	0.468088
Dice_Coefficient	0.999286	0.998804	0.999310	0.997074

Mask Visualization



Conclusion

- Unet and ResNet50 (retrain all layer) gave better results
- ResNet50 (retrain all layer) converge faster then Unet, so the pretrained weights helped
- ResNet50 (freeze first two conv blocks) gave the worst result, so the pretrained weights that was trained on ImageNet classification task didn't work well on medical image segmentation.

What's next

- Increse training epoches of Unet and ResNet50 (retrain all layer) to improve the results
- Try cyclical leanring rate to fasten training and improve model performance
- Find pretrained models that were trained on medical images, then use the pretrained weights to do transfer learning