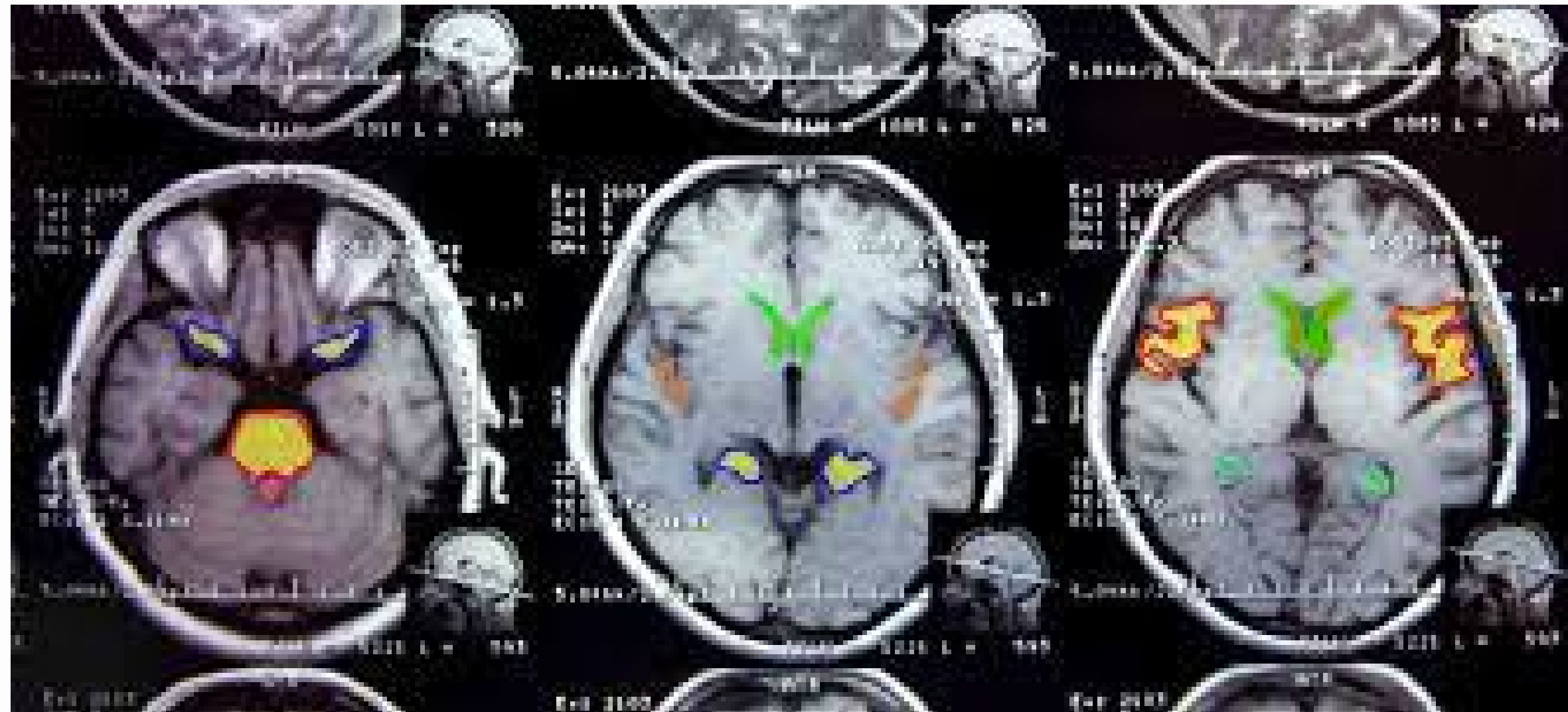
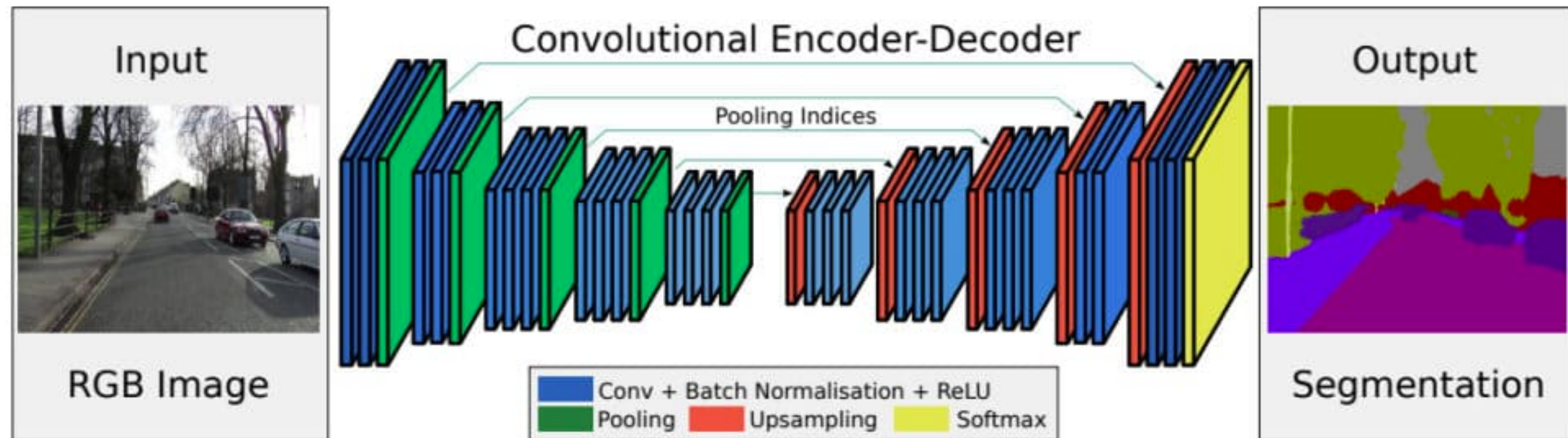


# BRAIN MRI SEGMENTATION

WITH DIFFERENT ENCODERS



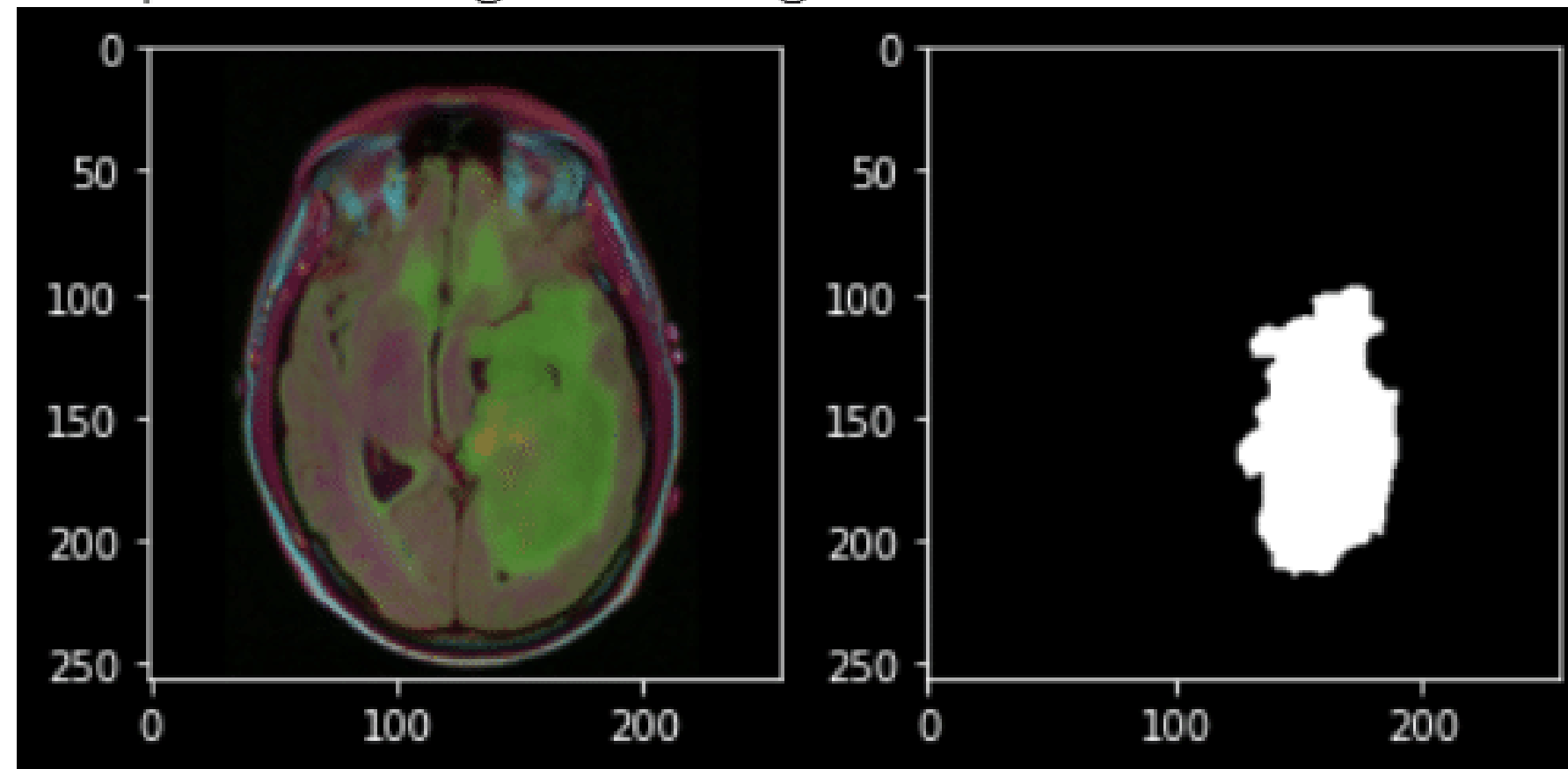
# Semantic Segmentation



Assigns a class label to each pixel in an image

# Brain MRI Semantic Segmentation

Data source: <https://www.kaggle.com/datasets/mateuszbeda/lgg-mri-segmentation>



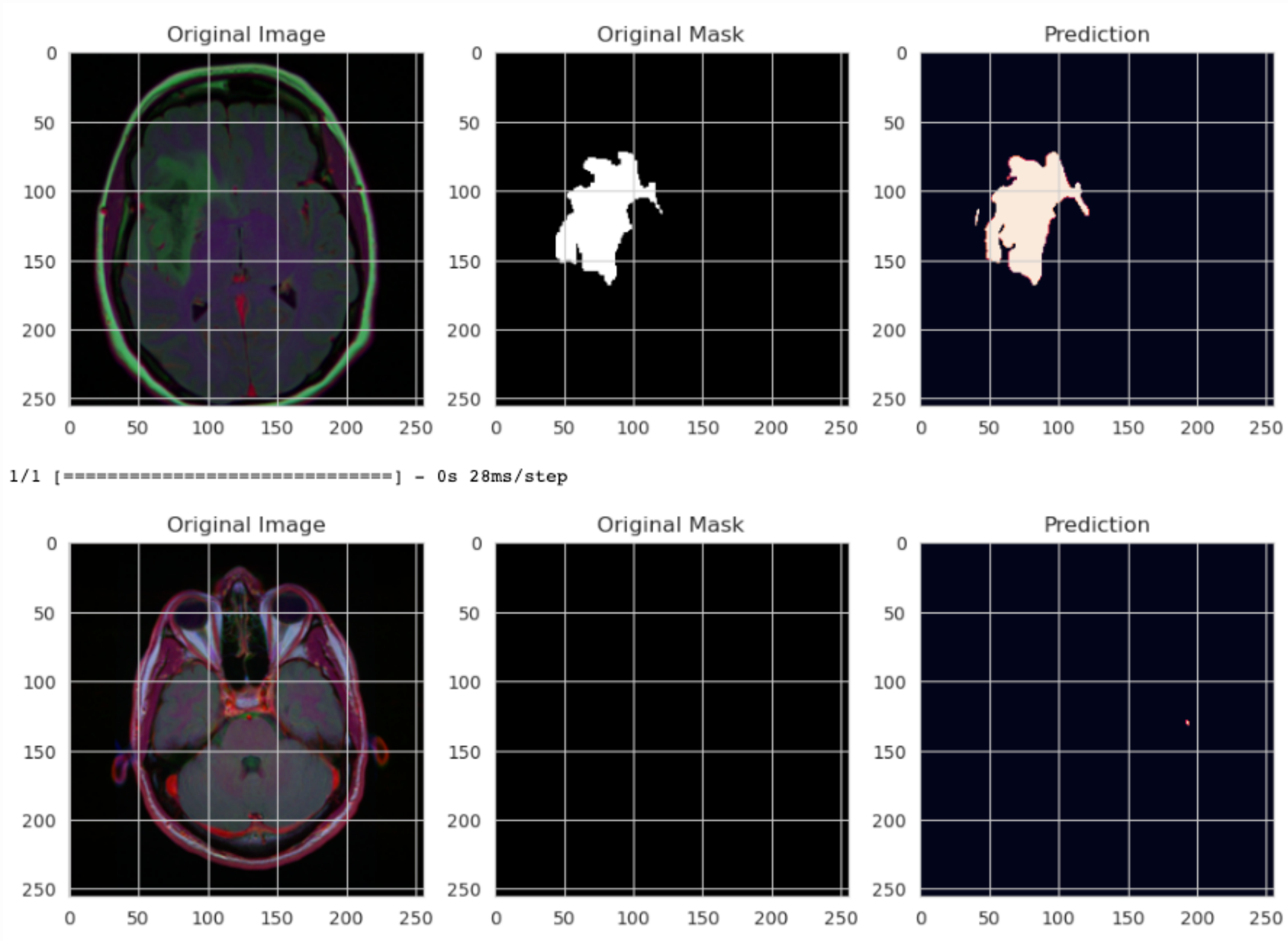
This dataset contains brain MR images together with manual FLAIR abnormality segmentation masks.

<b>Training set:</b>	<b>2828</b>
<b>Validation set:</b>	<b>393</b>
<b>Test set:</b>	<b>708</b>

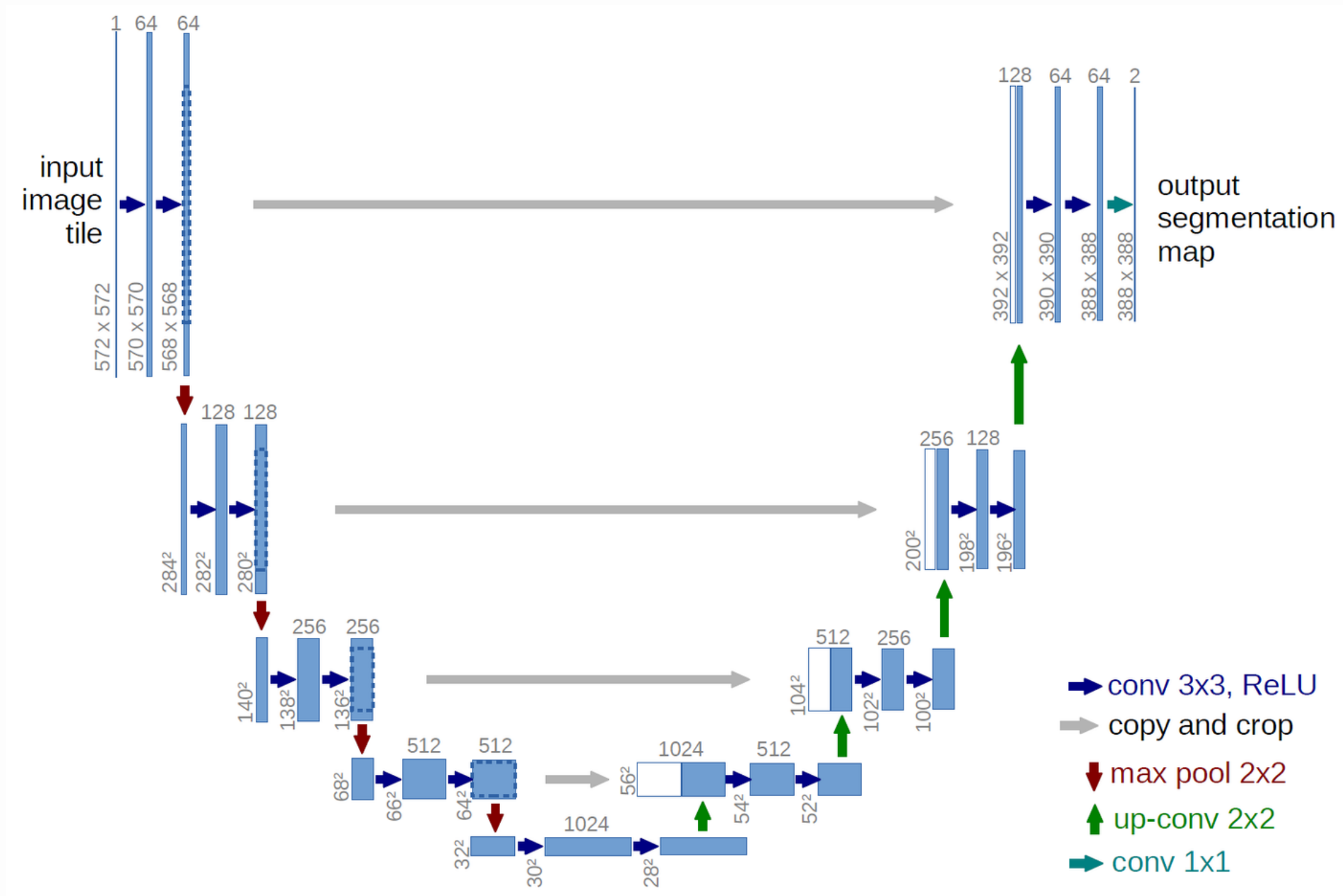
<b>Total:</b>	<b>3929</b>
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# Brain MRI

## 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

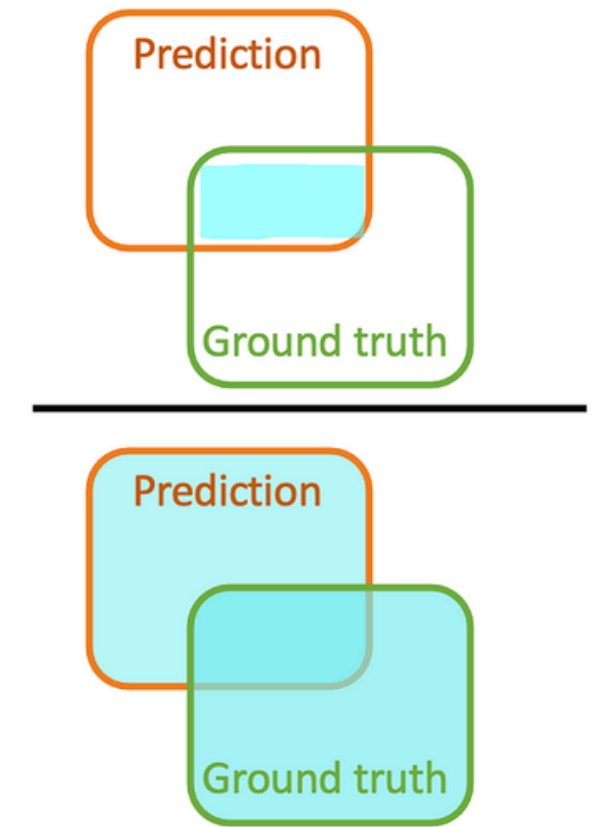
- **Generic Unet(no pretrained encoders)**
- **VGG16 (retrain all layer)**
- **ResNet50 (retrain all layer)**
- **ResNet50 (freeze first two conv blocks)**



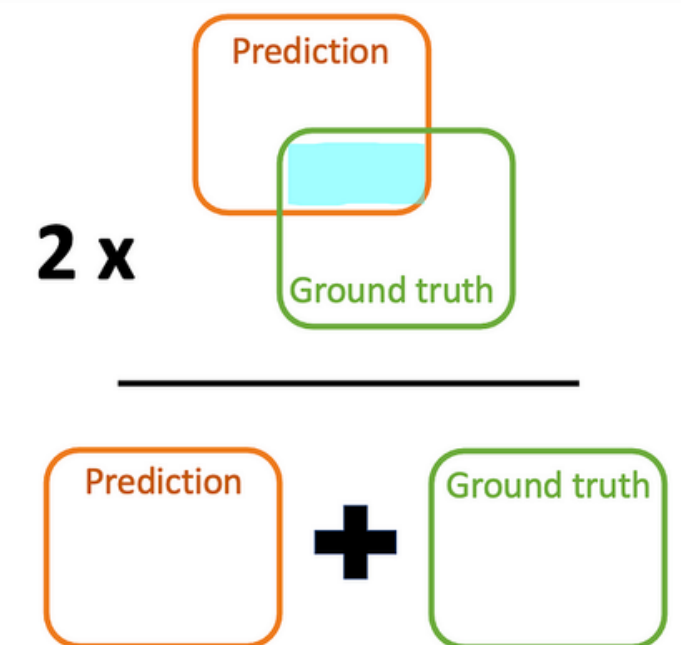
# Metrics

- 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.

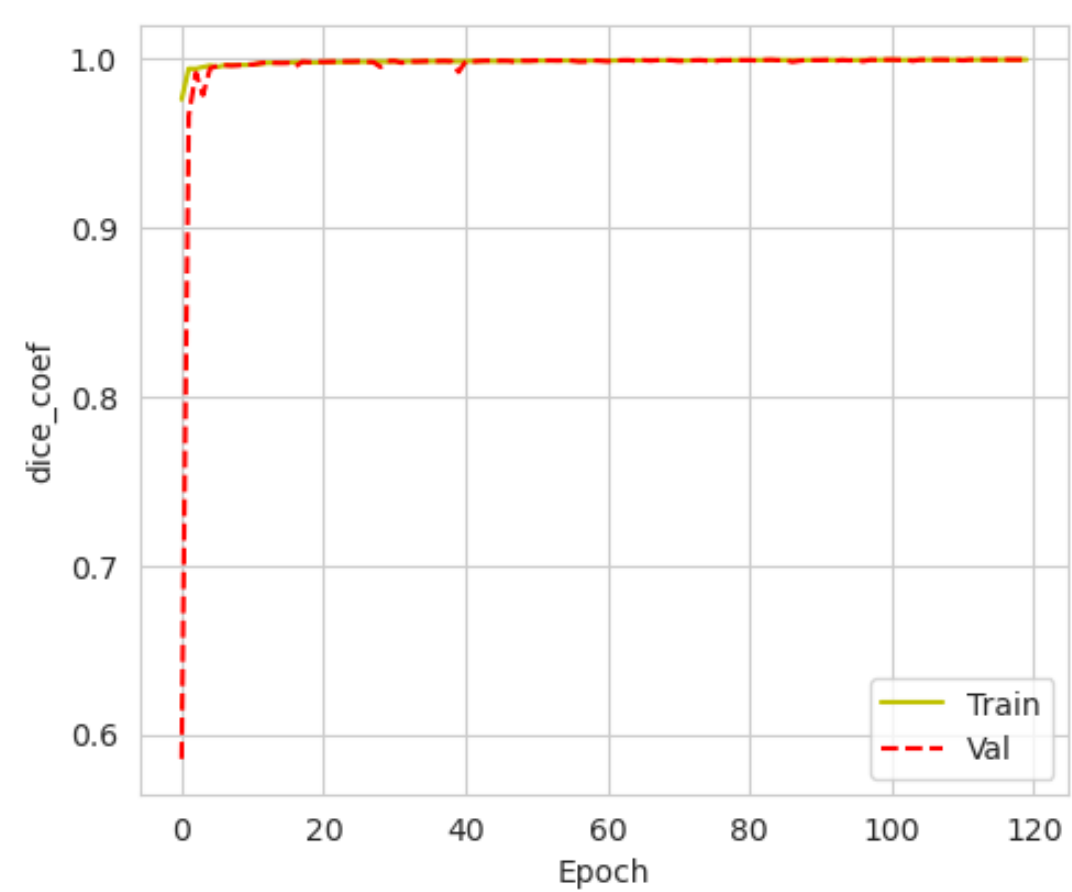
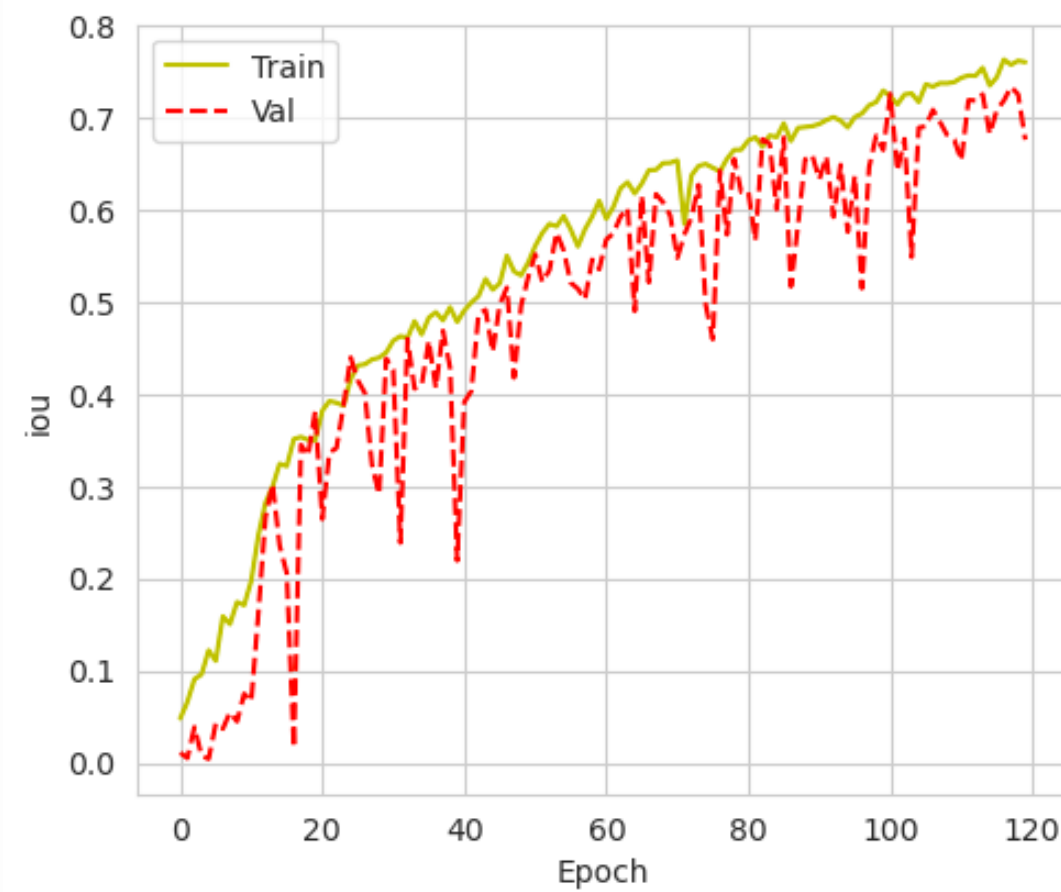
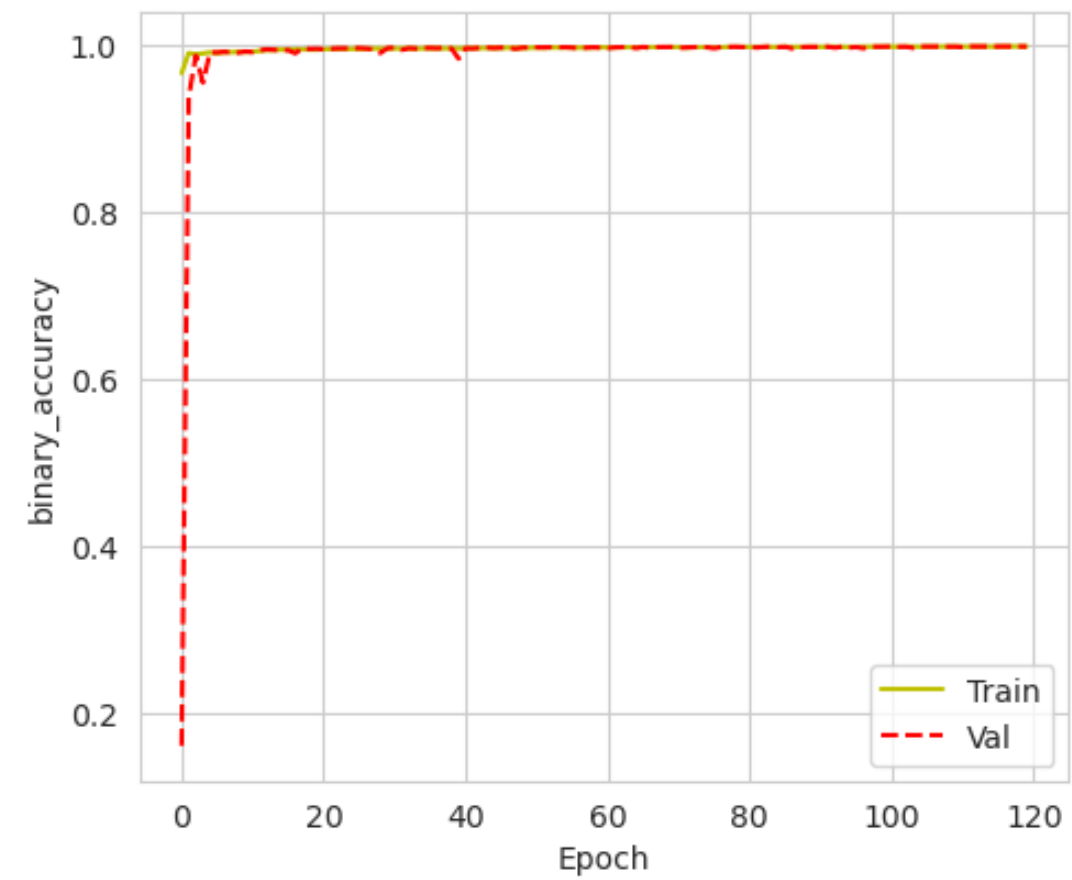
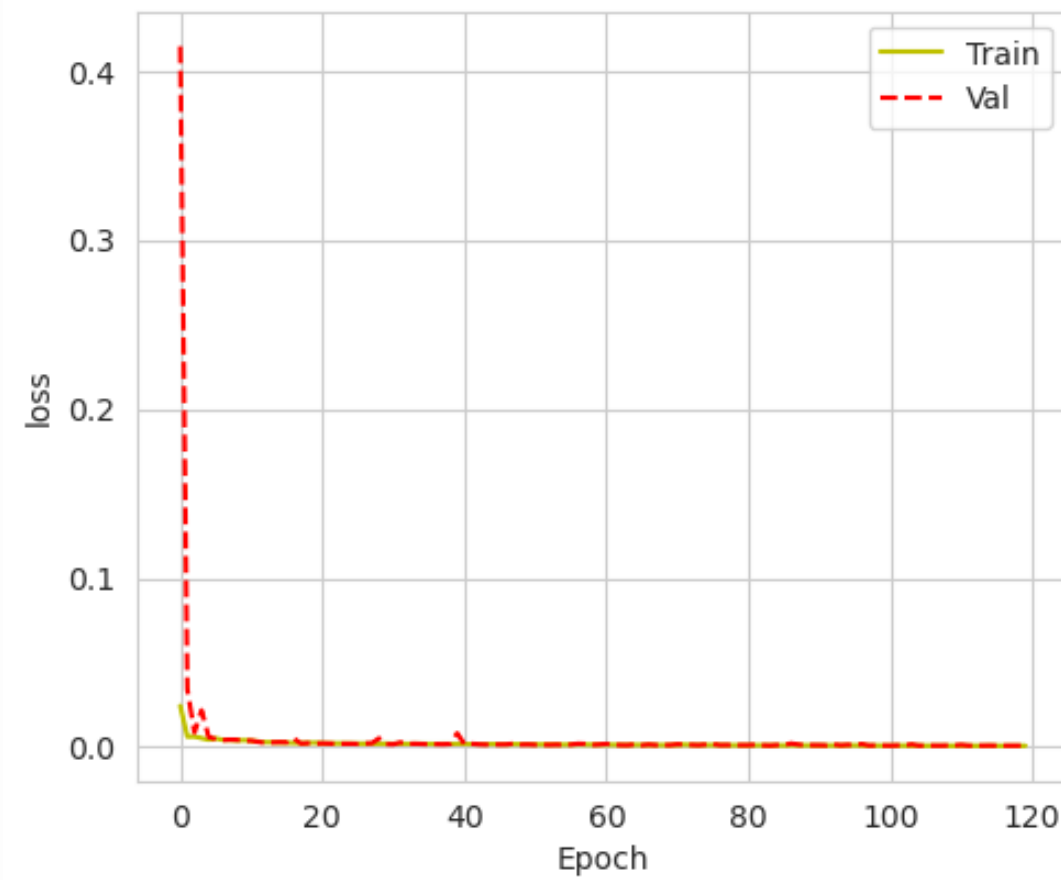
$$\text{IoU} = \frac{\text{Area of overlap}}{\text{Area of union}} =$$



$$\text{Dice} = \frac{2 \times \text{Area of overlap}}{\text{Total area}} =$$

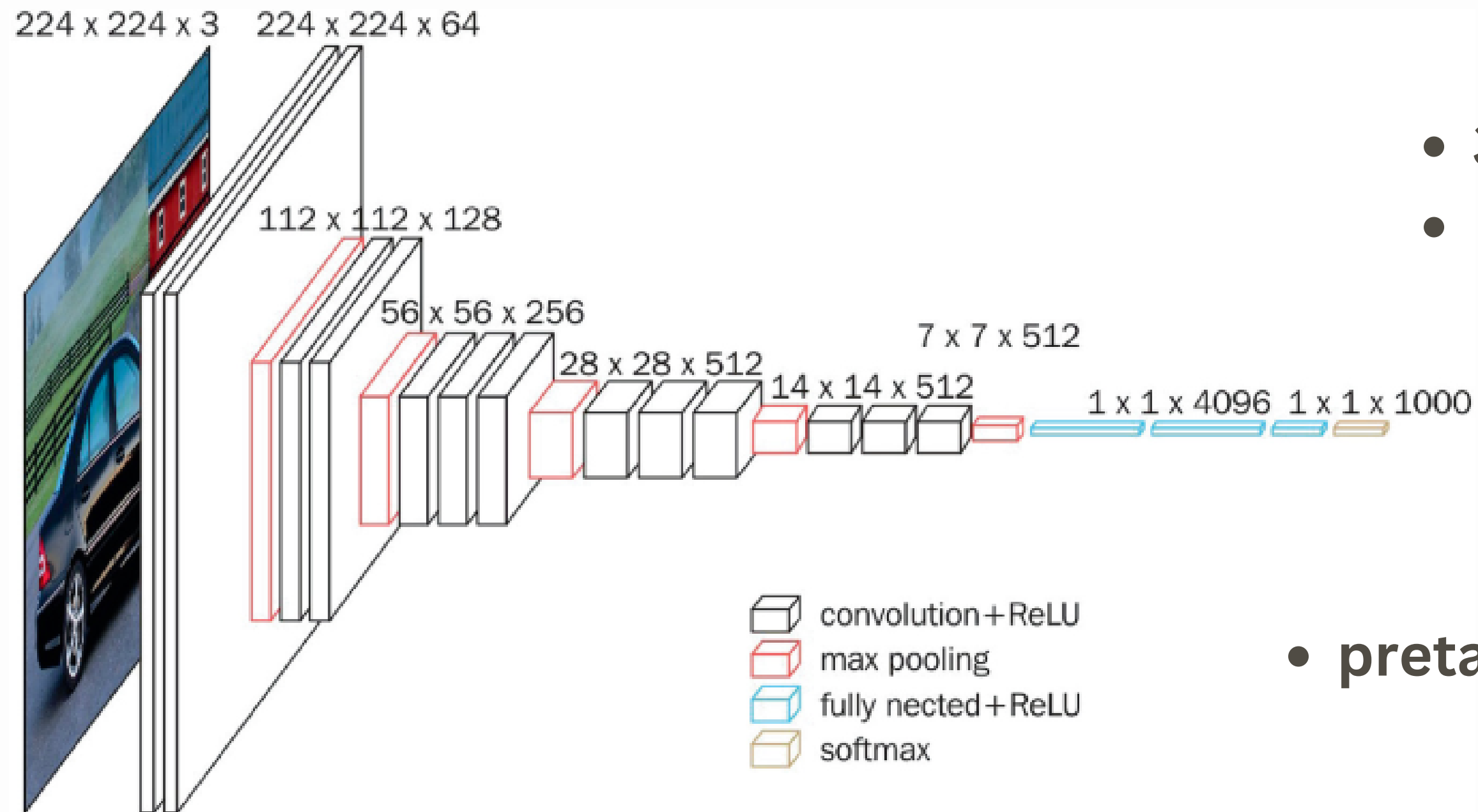


# Unet





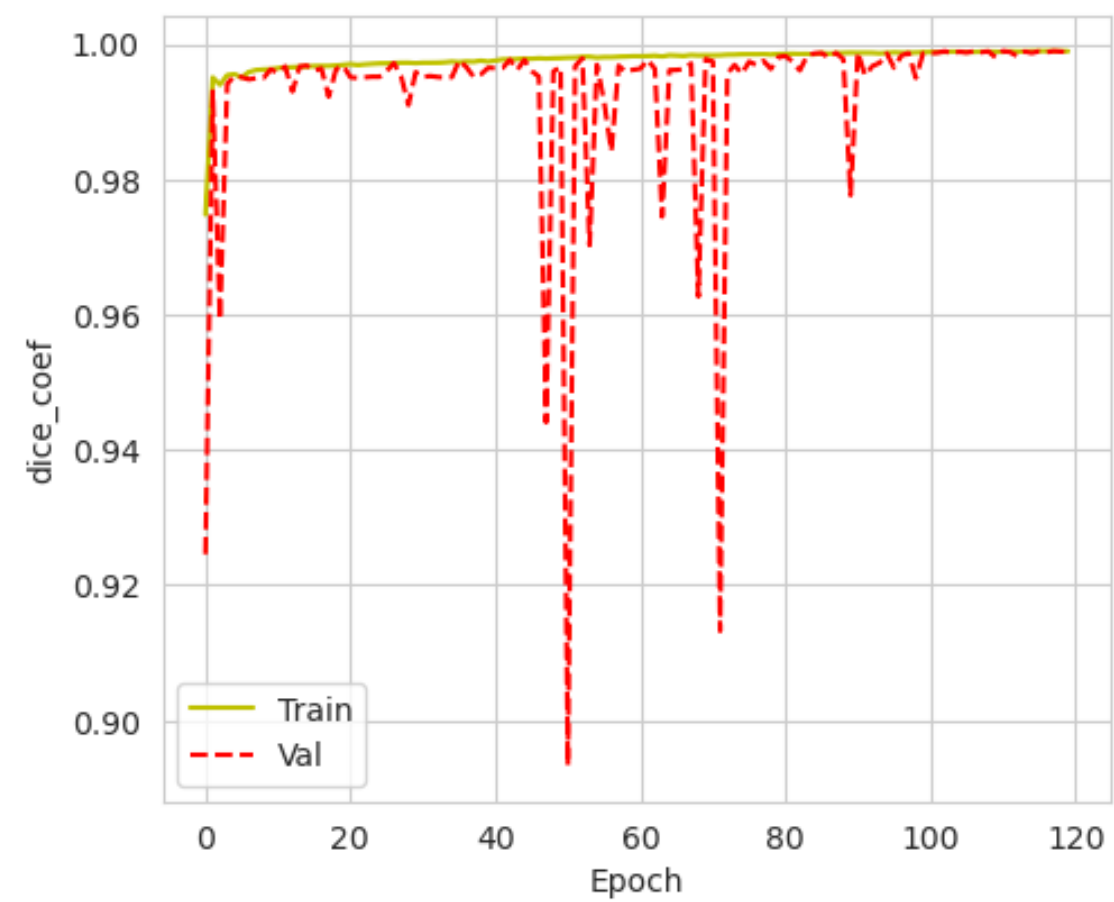
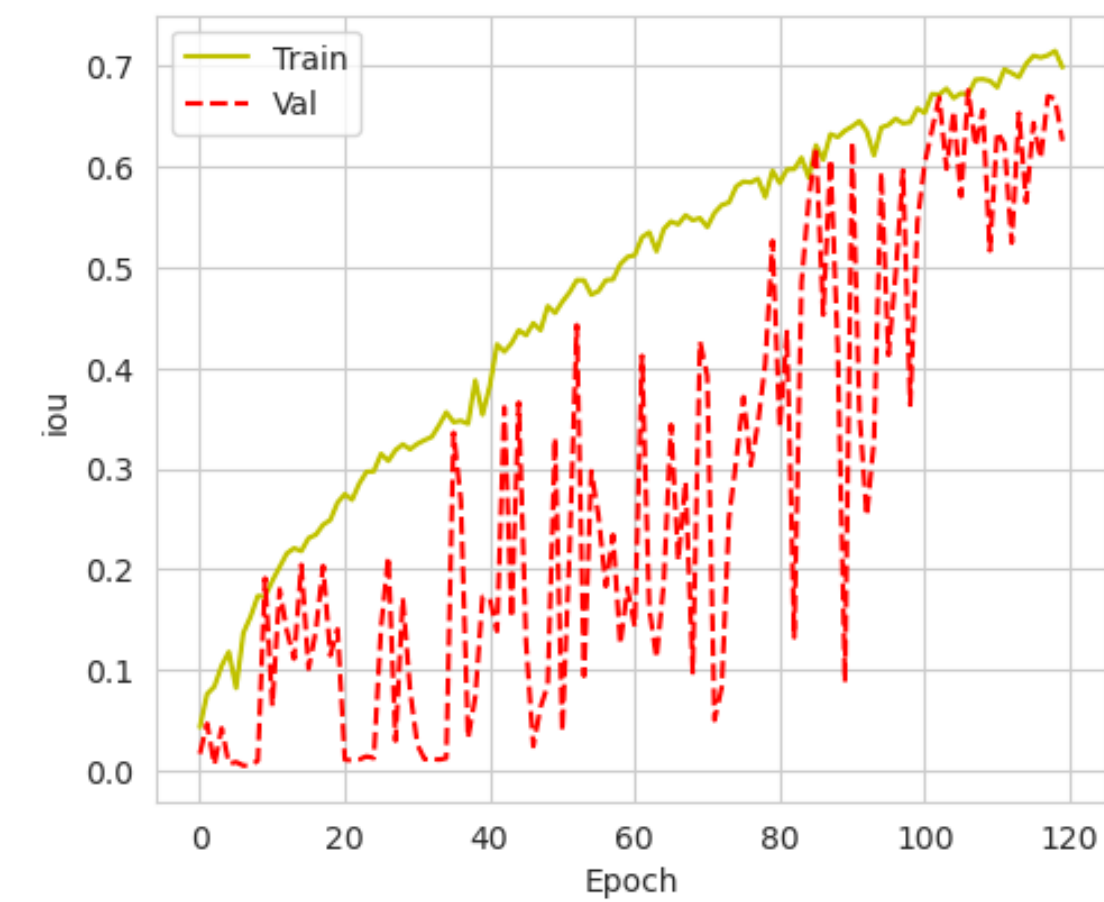
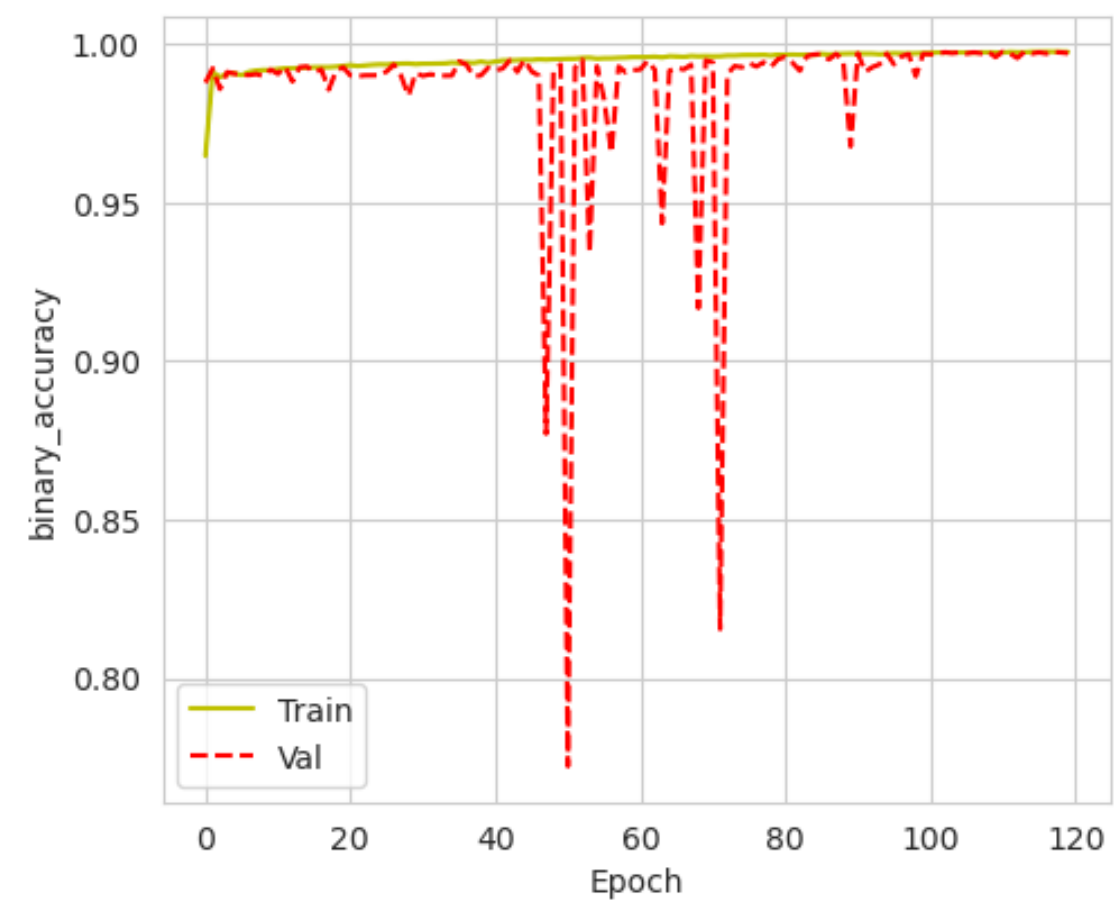
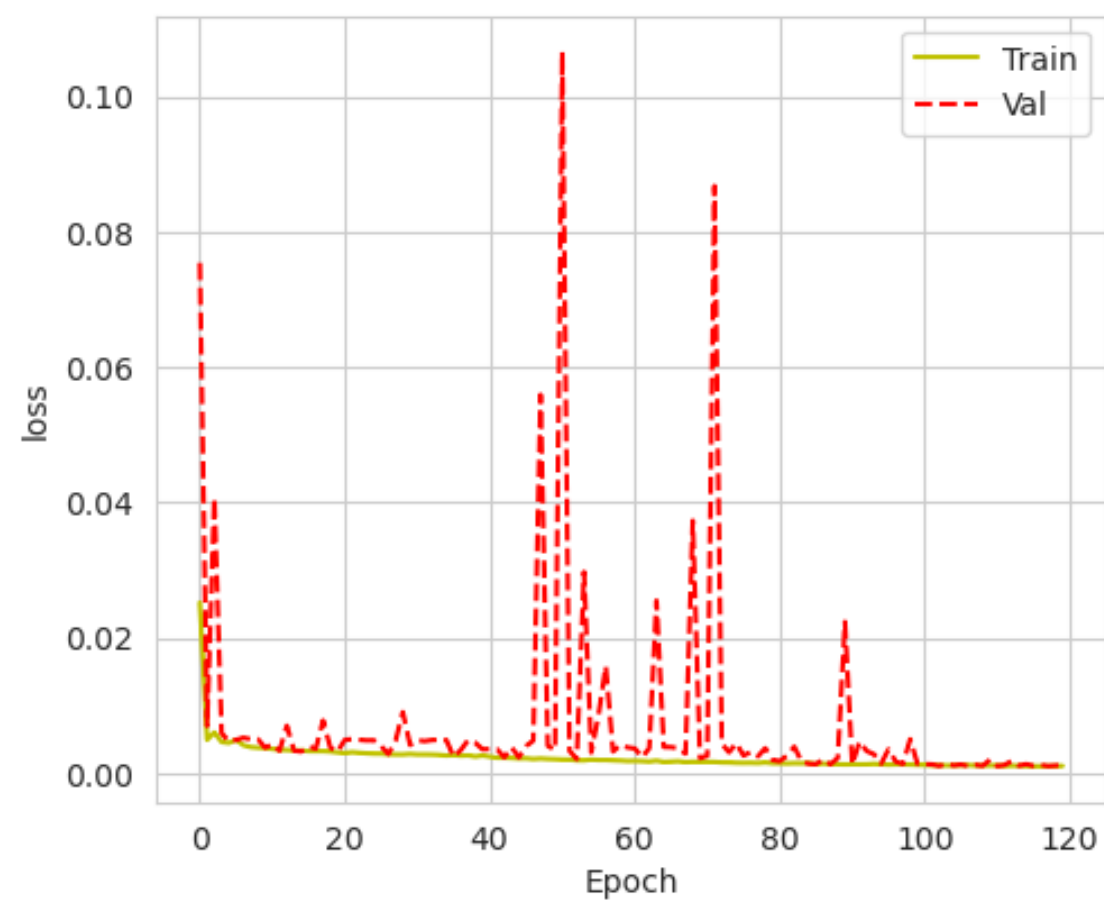
# VGG 16



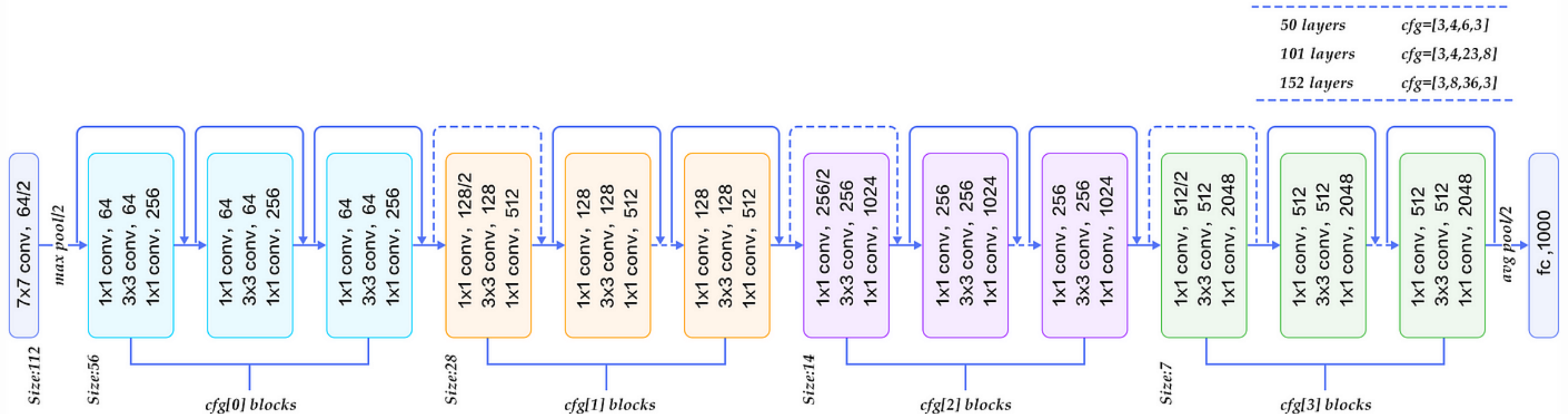
- 3x3 convolutional filters
- Deeper networks

- pretrained weights on ImageNet

# VGG 16

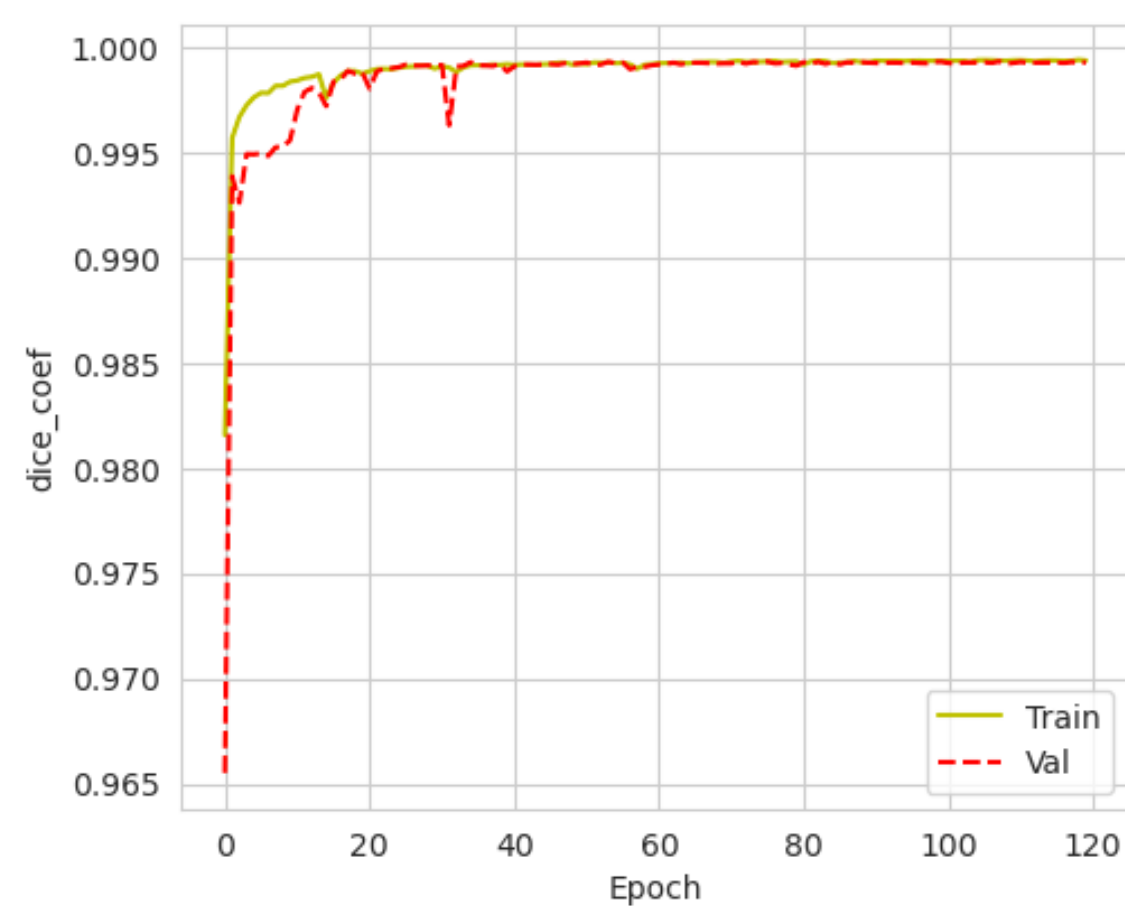
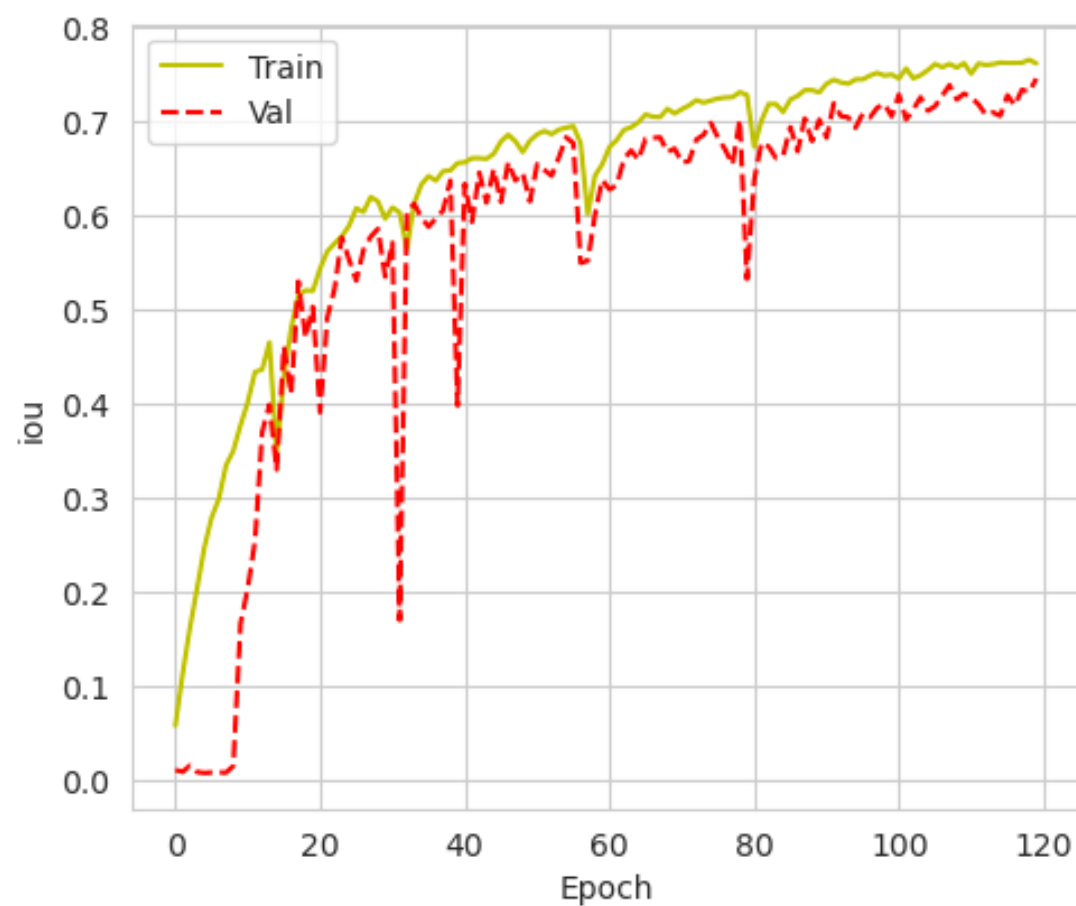
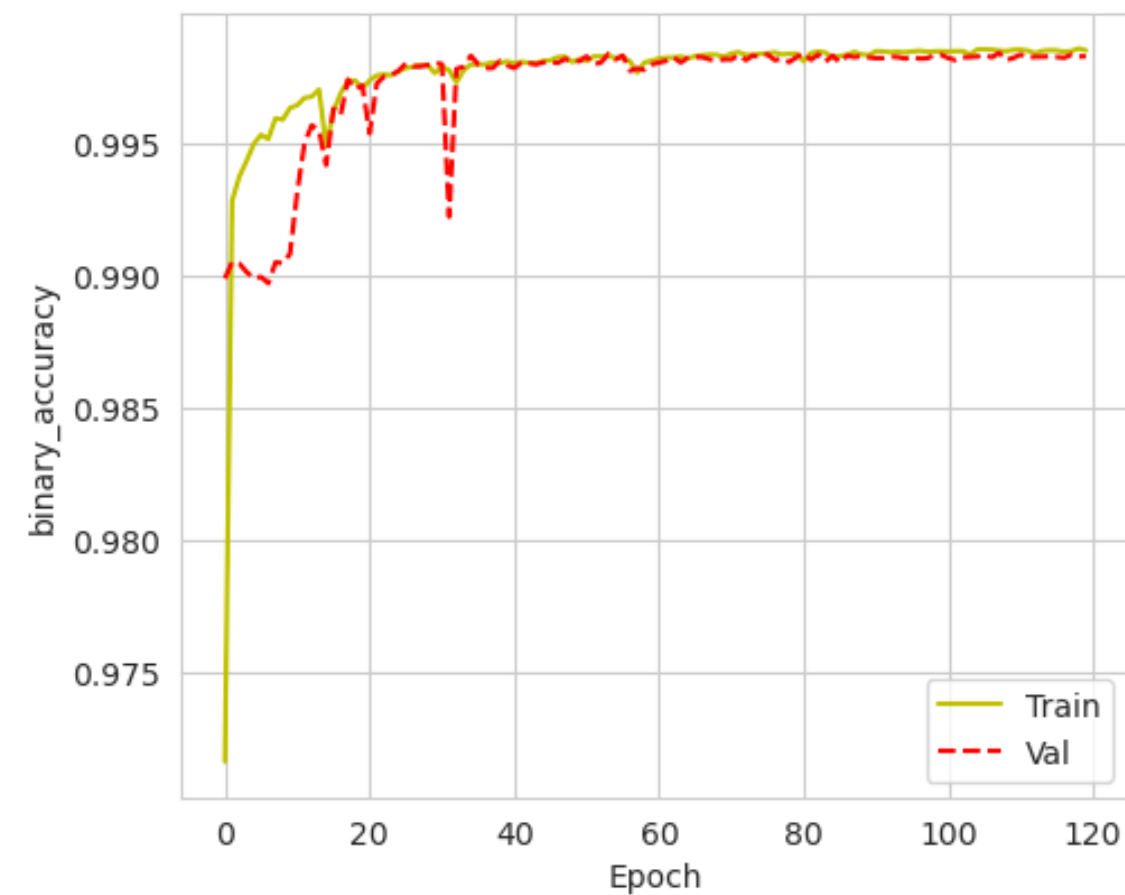
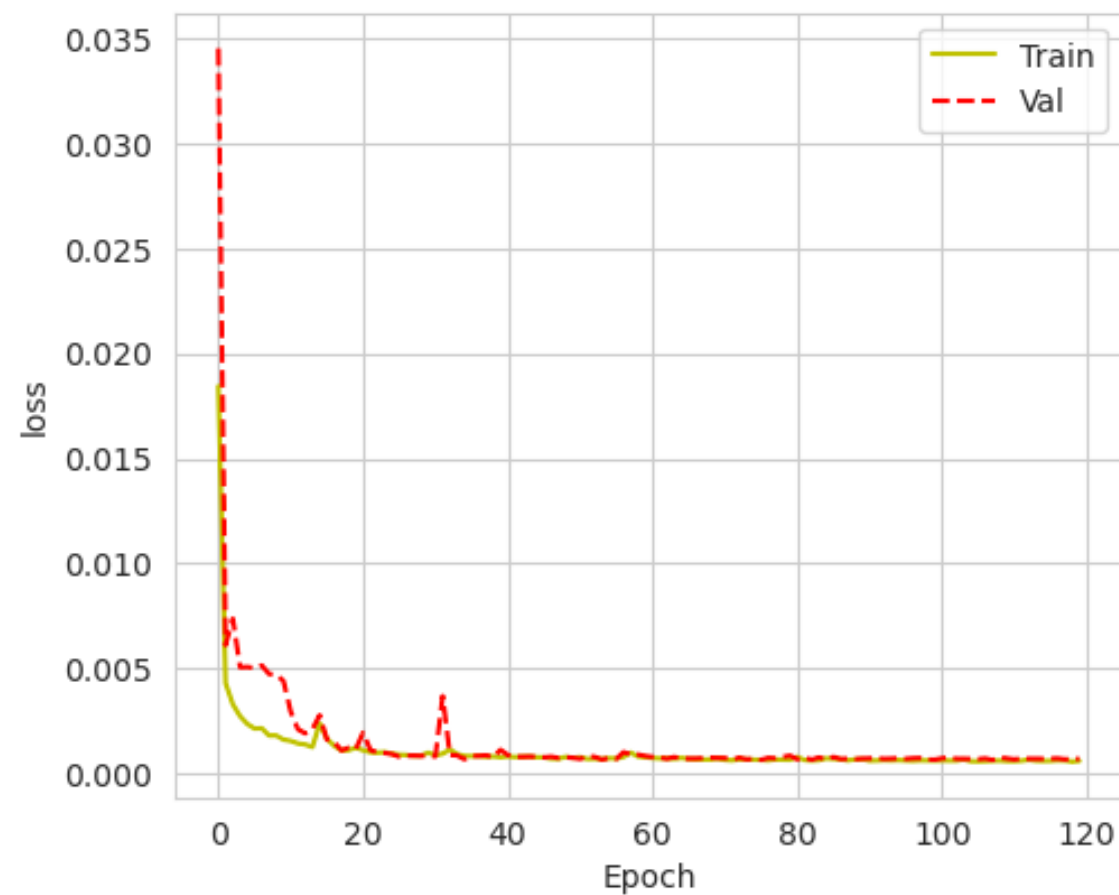


# ResNet 50



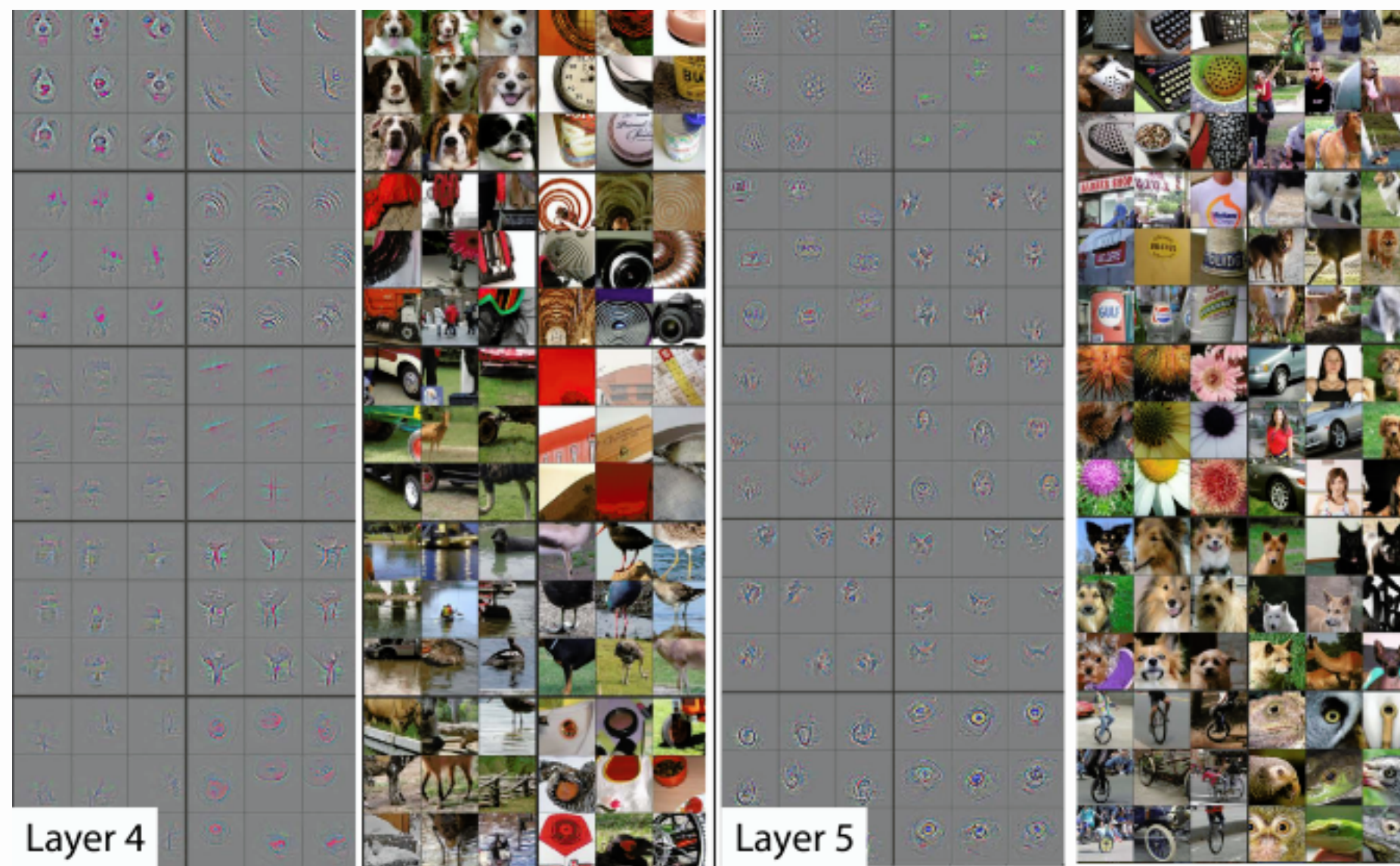
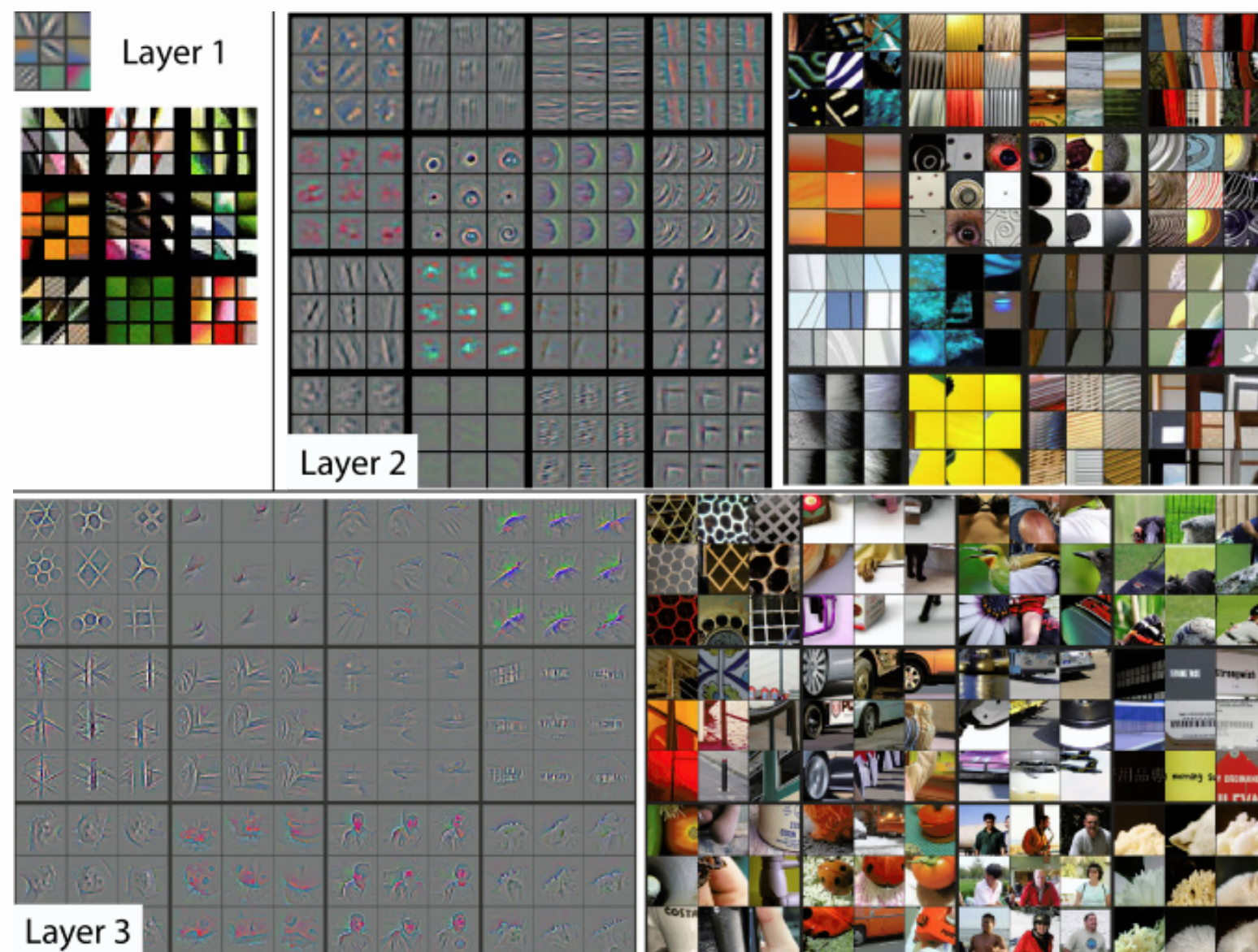
- Has residual connections (also known as skip connections)
- residual connections allow the network to learn residual mappings, bypassing certain layers and enabling the flow of gradients throughout the network.
- Allows for much deeper networks without a decrease in accuracy

# ResNet50 fine tuning



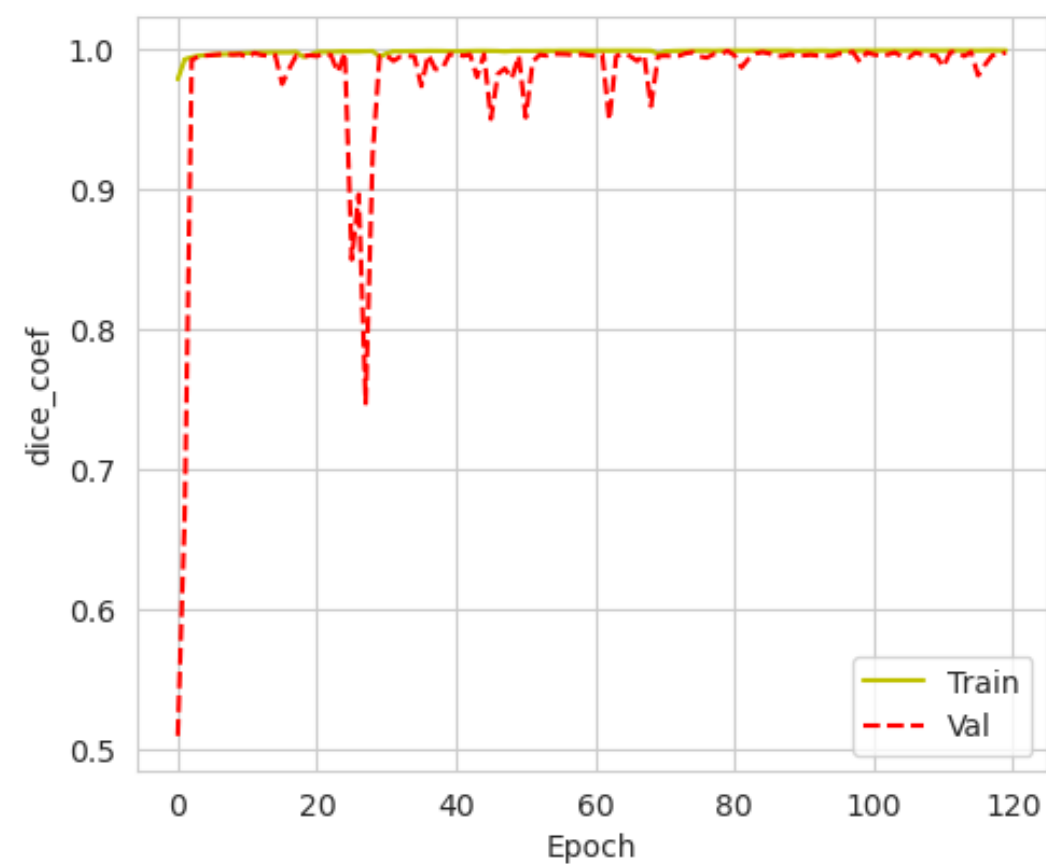
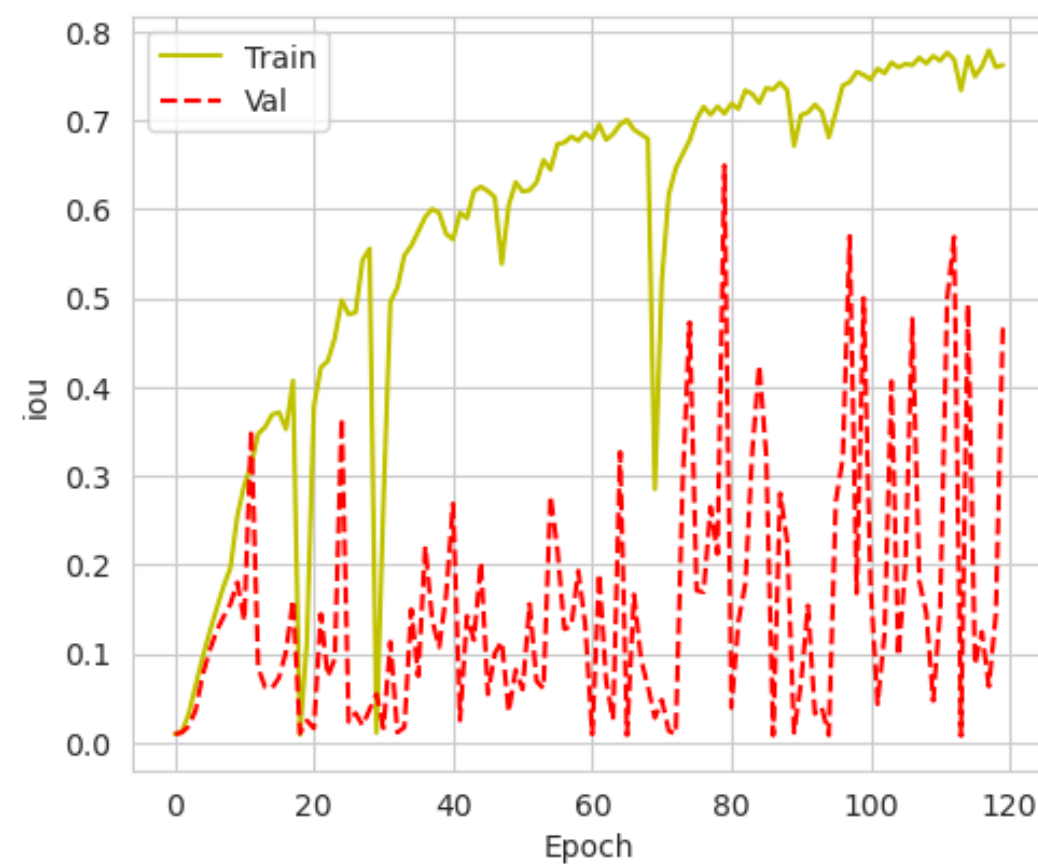
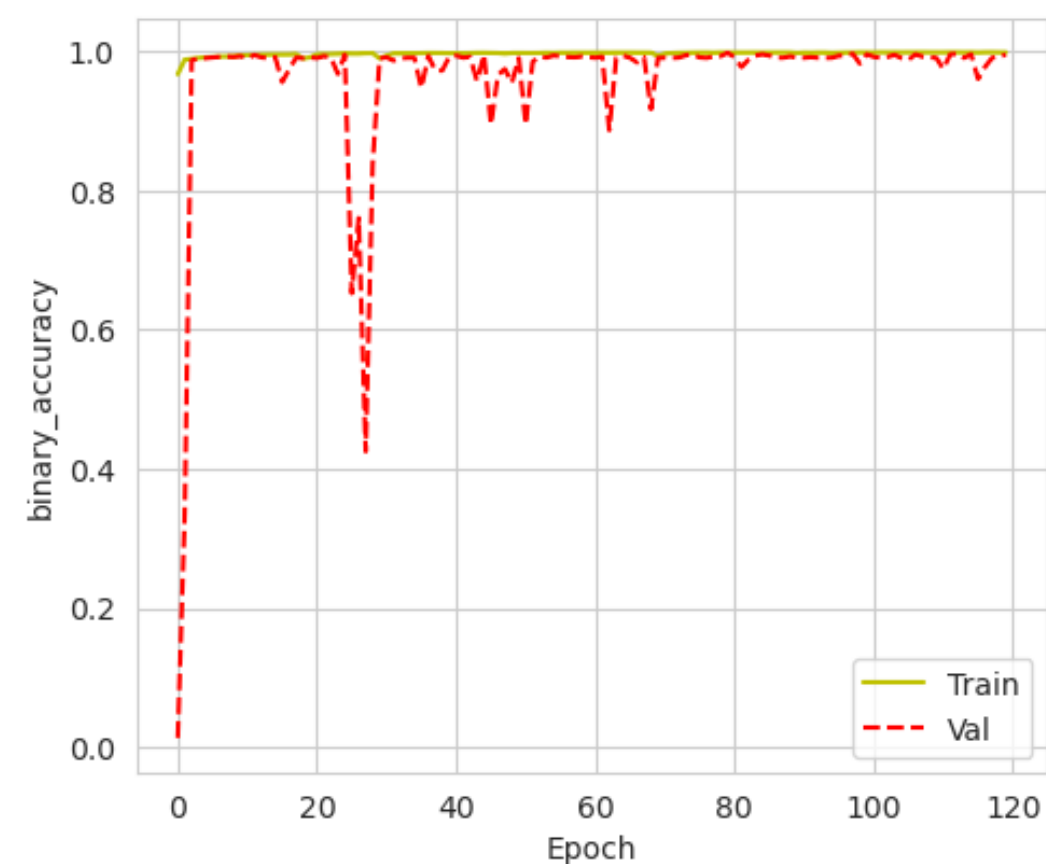
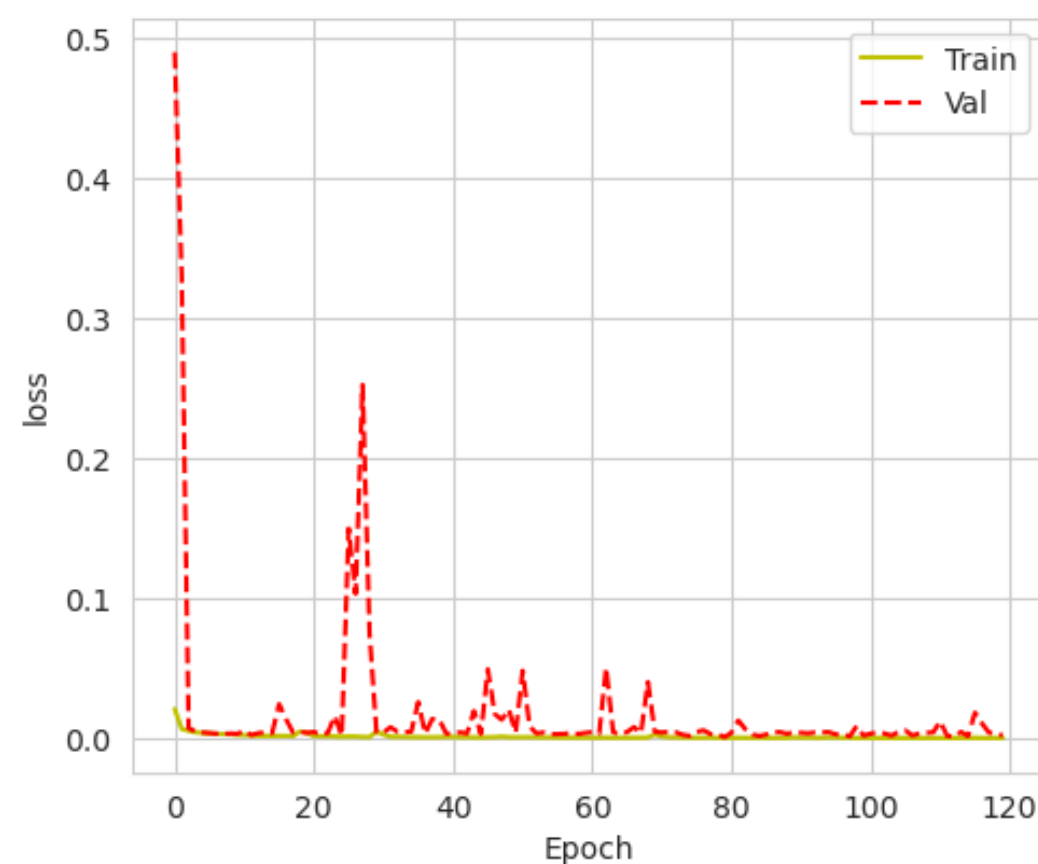


# Feature Maps





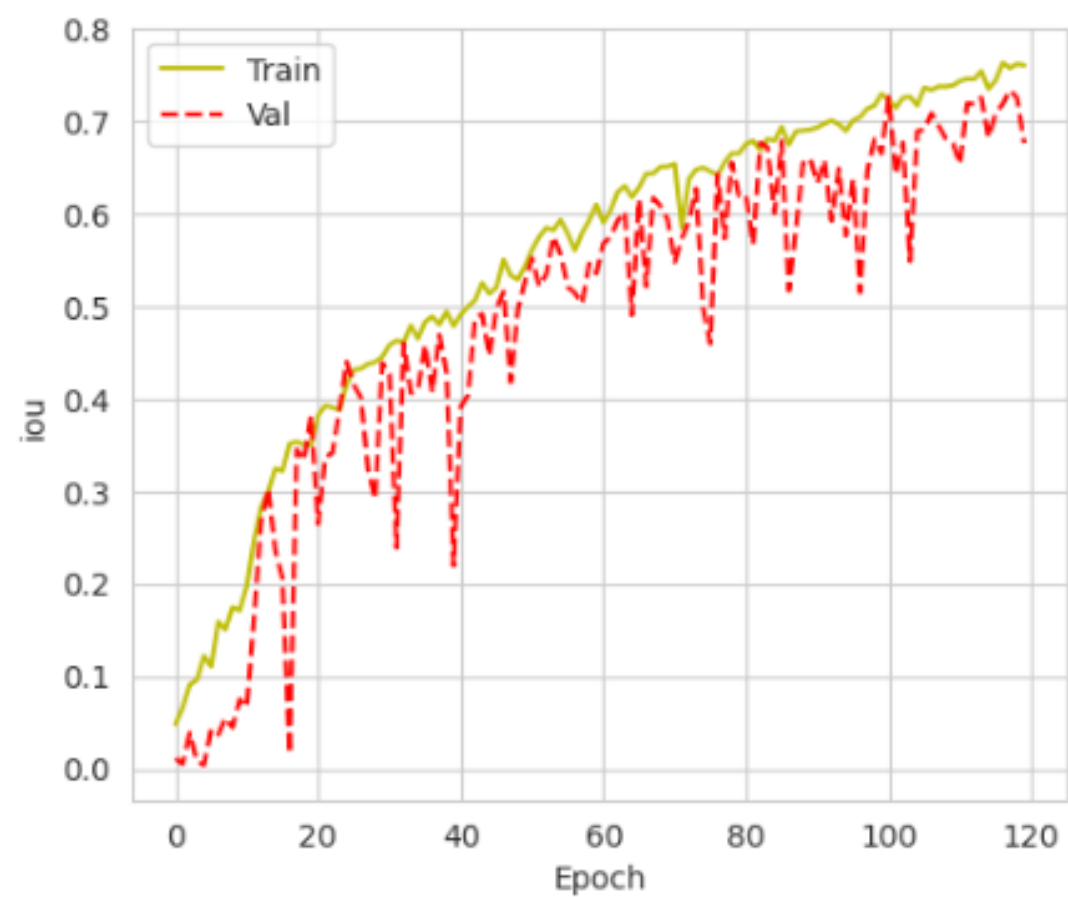
# ResNet50 freeze first two conv blocks



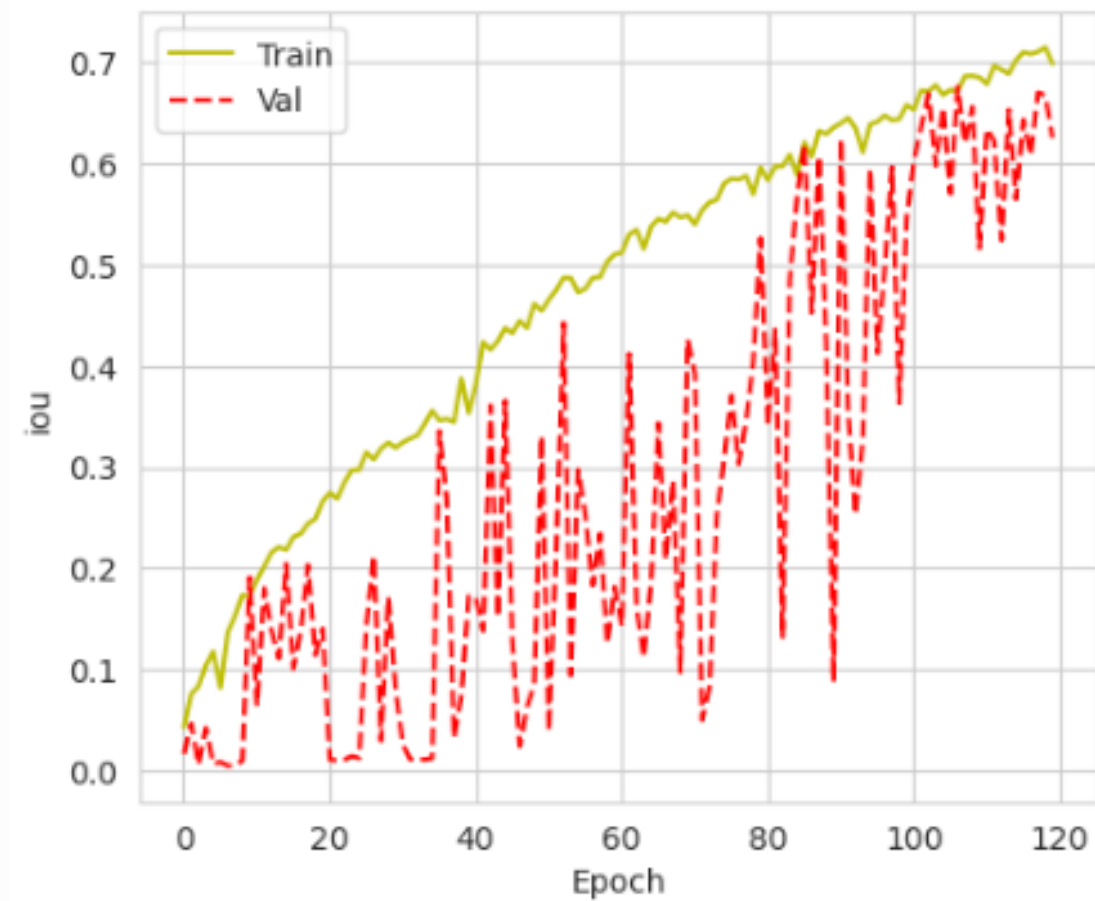


# IoU Comparision

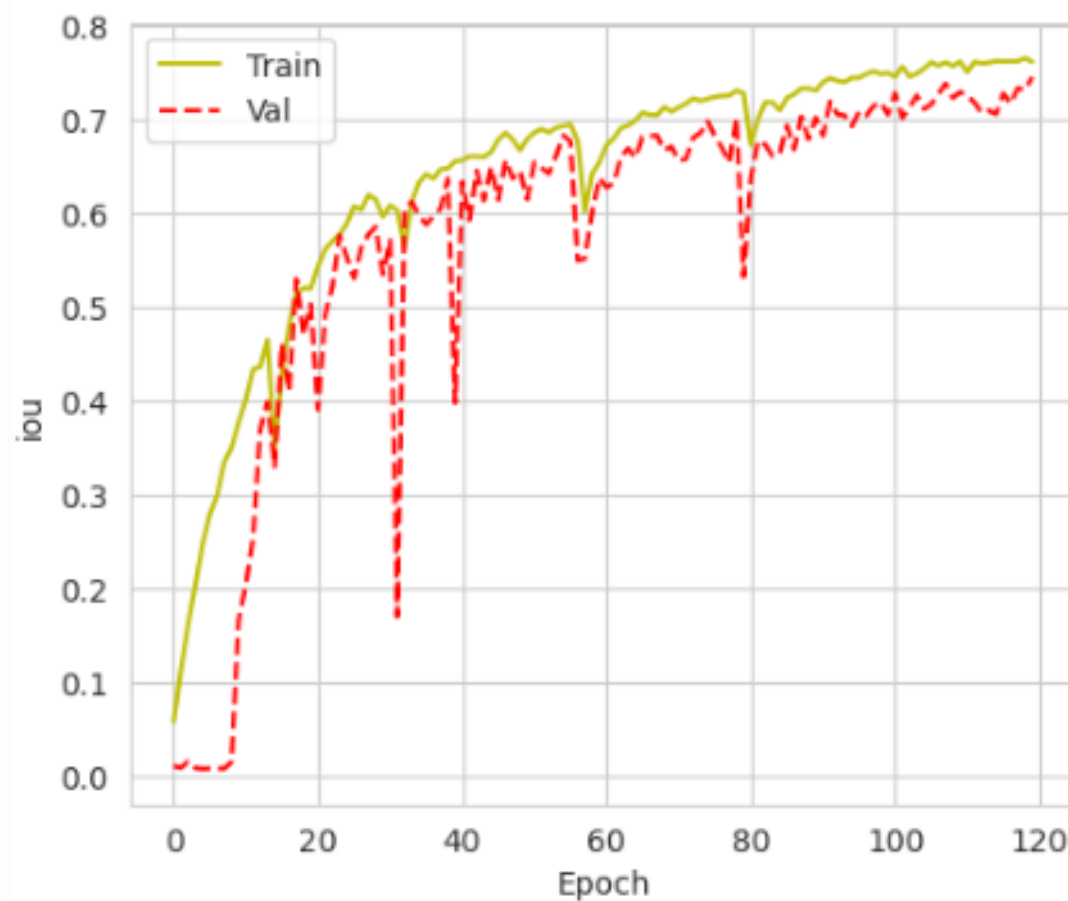
Unet



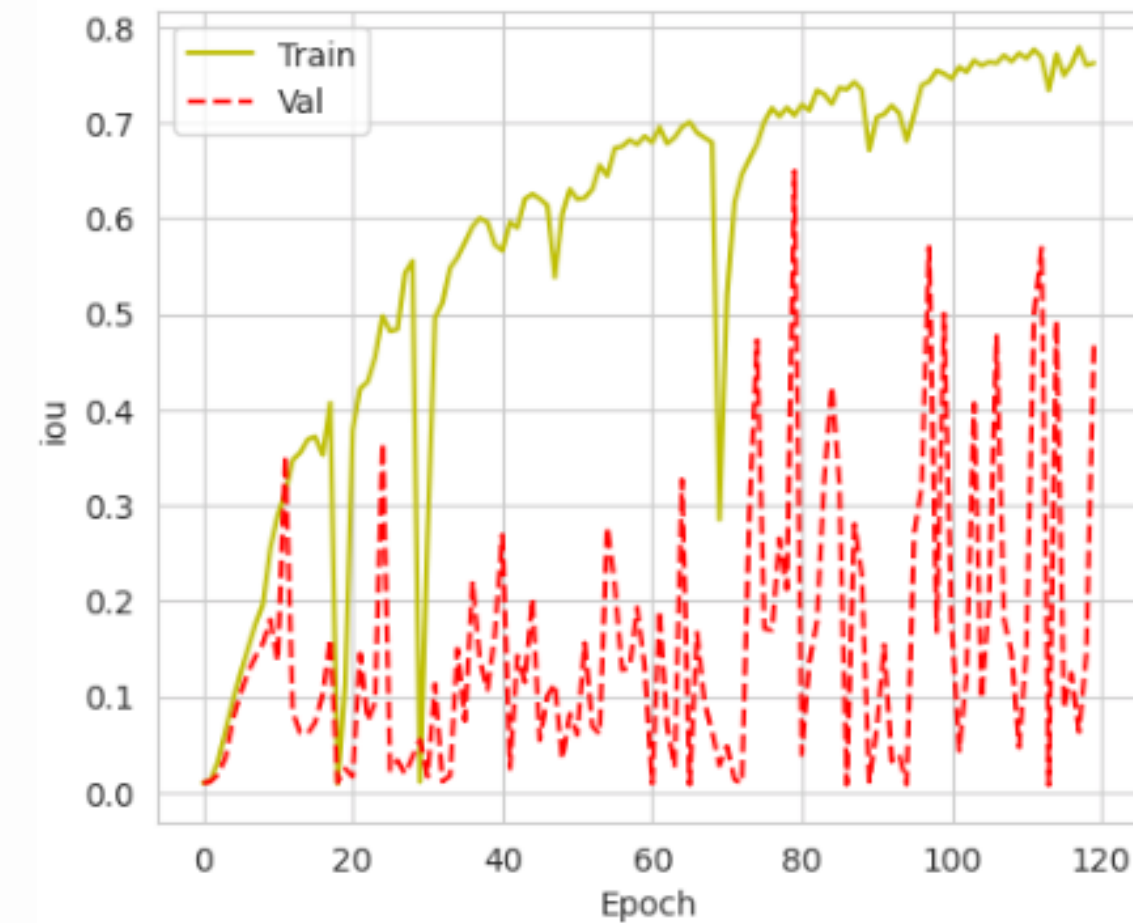
VGG



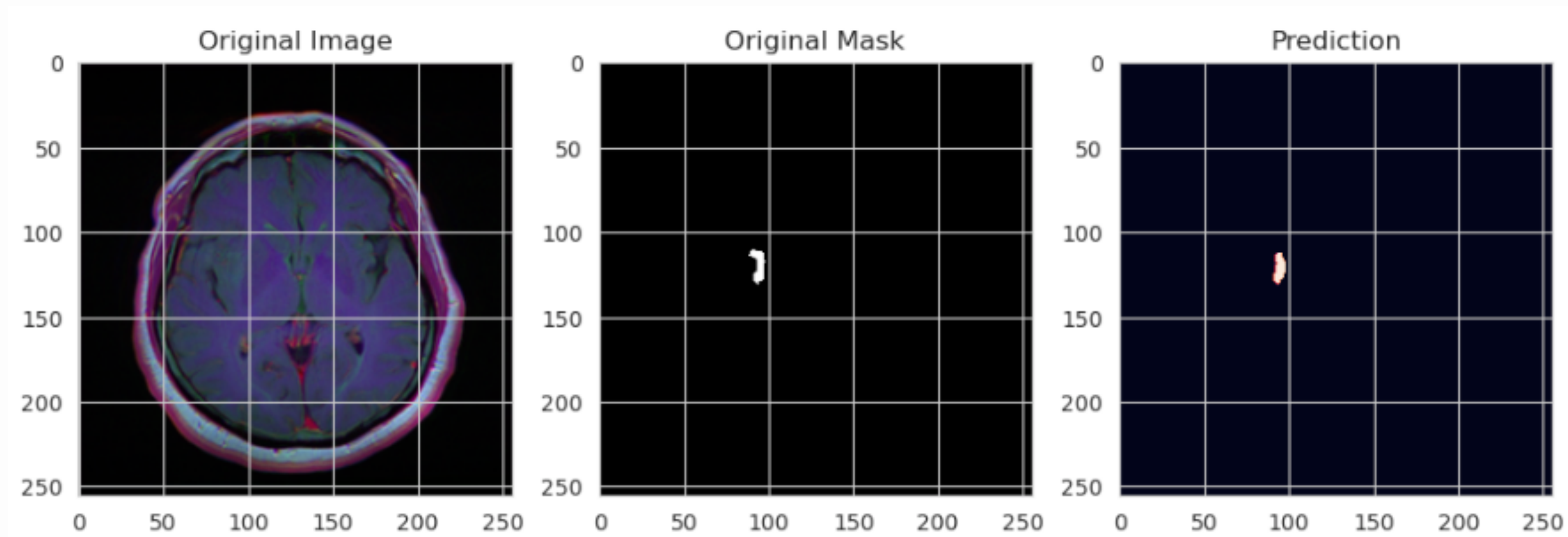
ResNet50  
finetuning



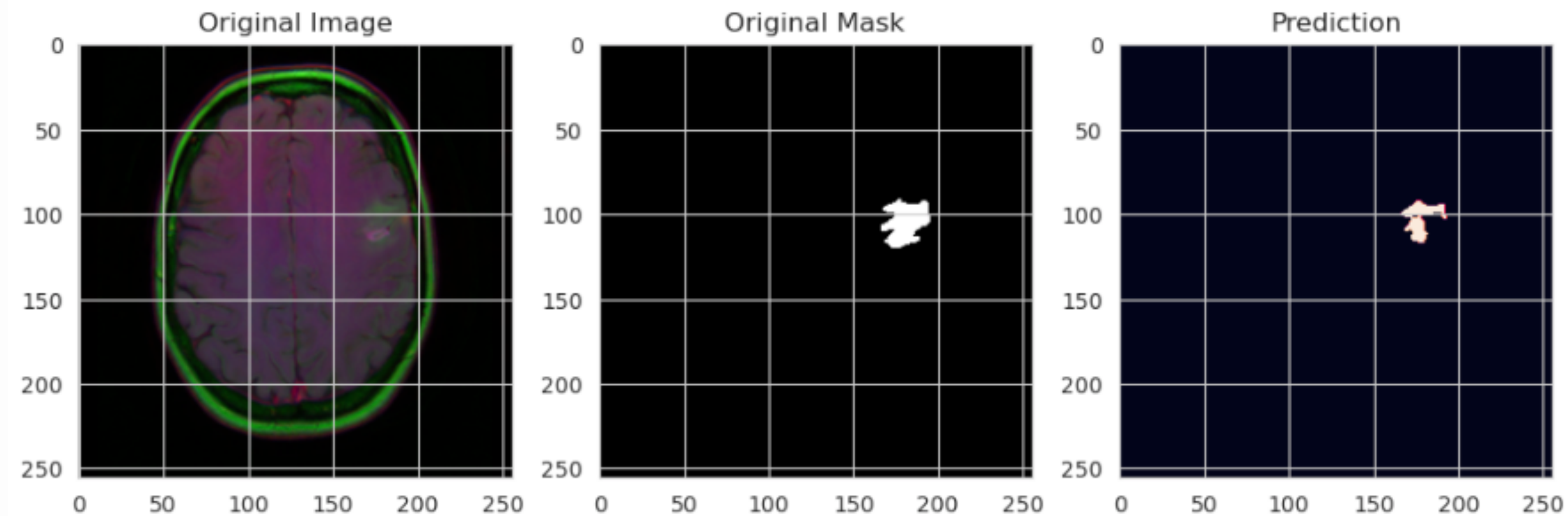
ResNet50  
freeze



# Mask Visualization



1/1 [=====] - 0s 29ms/step



# Conclusion

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

# What's next

- **Increase training epochs of Unet and ResNet50 (retrain all layer) to improve the results**
- **Try cyclical learning 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**