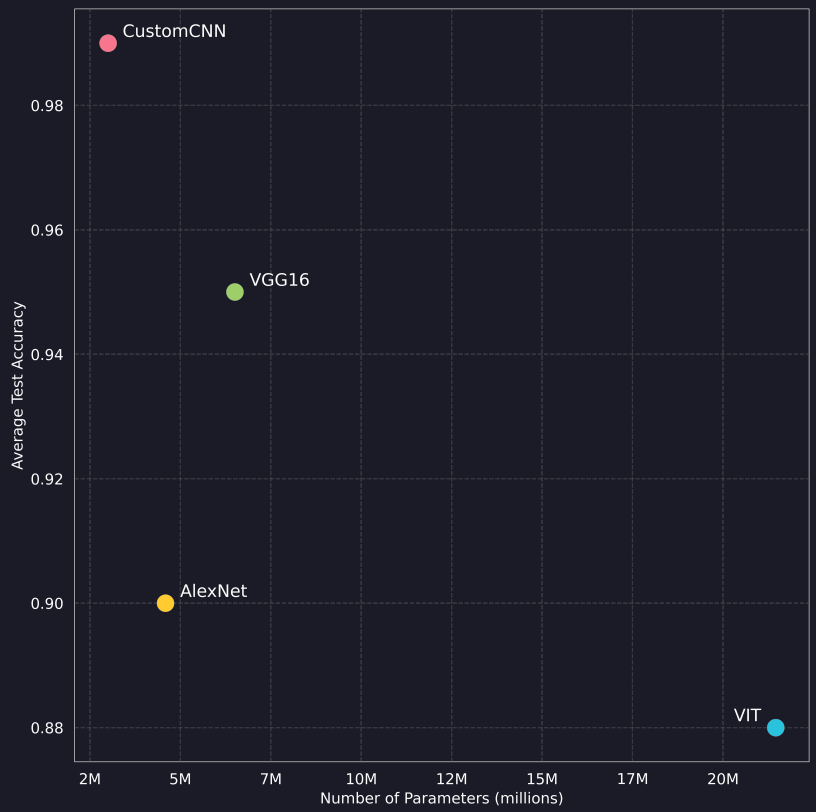
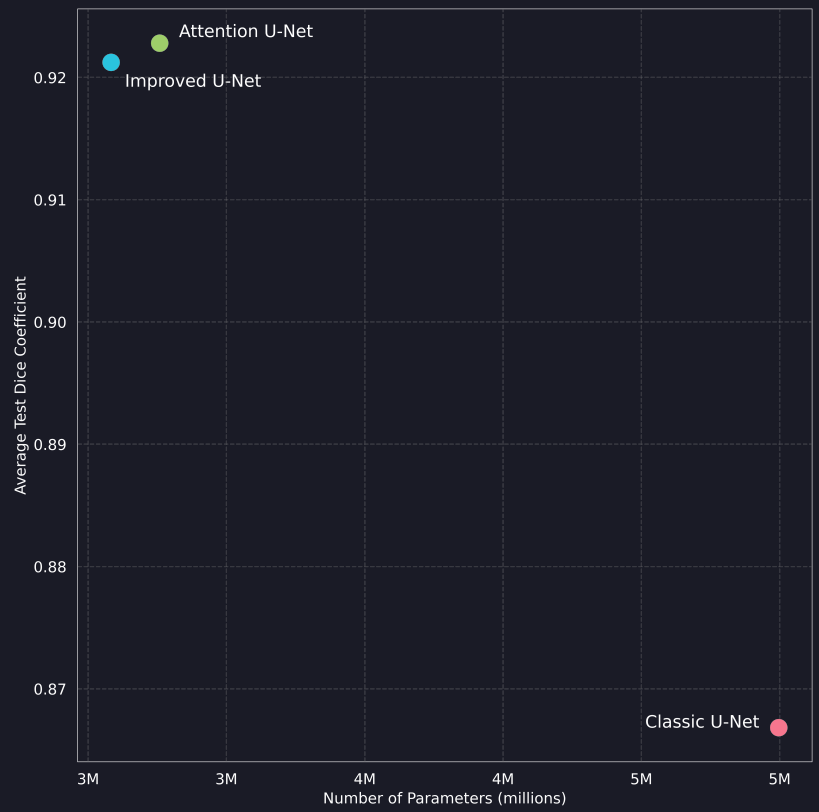
Conclusion

Conclusion


CustomCNN
VGG16
AlexNet
VIT
0.98
0.96
0.94
0.92
0.90
0.88
Average Test Accuracy
2M
5M
7M
10M
12M
15M
17M
20M
Number of Parameters (millions)


Attention U-Net
Improved U-Net
Classic U-Net
0.92
0.91
0.90
0.89
0.88
0.87
Average Test Dice Coefficient
3M
3M
4M
4M
5M
5M
Number of Parameters (millions)

Conclusion

Possible improvements:

- Use original image size for better classification results
- Use larger dataset to train the VIT model
- Enlarge the VIT model for better performance
- Attempt transfer learning with VIT model
- Test different architectures for the segmentation task
- Fully exploit segmentation dataset
- Perform complete hyperparameter search for the segmentation models
- Use metadata information to predict patient's survival days

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