

Multi-Model Approach for Brain Tumor Classification and Segmentation

Deep Learning Course Exam Project
SDIC Master Degree, University of Trieste (UniTS)

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Stefano Lusardi

Marco Tallone

Piero Zappi

Introduction

Introduction

A deep learning project for brain tumor classification and segmentation on MRI images using CNN, U-Net, and VIT models.

1. Datasets

- ▶ Brain Tumor MRI Dataset (*classification*)
- ▶ BraTS 2020 Dataset (*segmentation*)

2. Classification

- ▶ Custom CNN
- ▶ VIT
- ▶ AlexNet
- ▶ VGG16

3. Segmentation

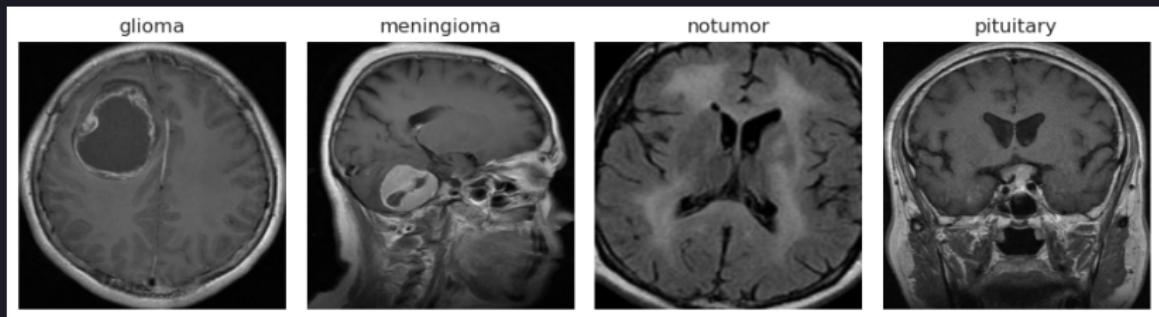
- ▶ U-Net Models

4. Conclusion

Datasets

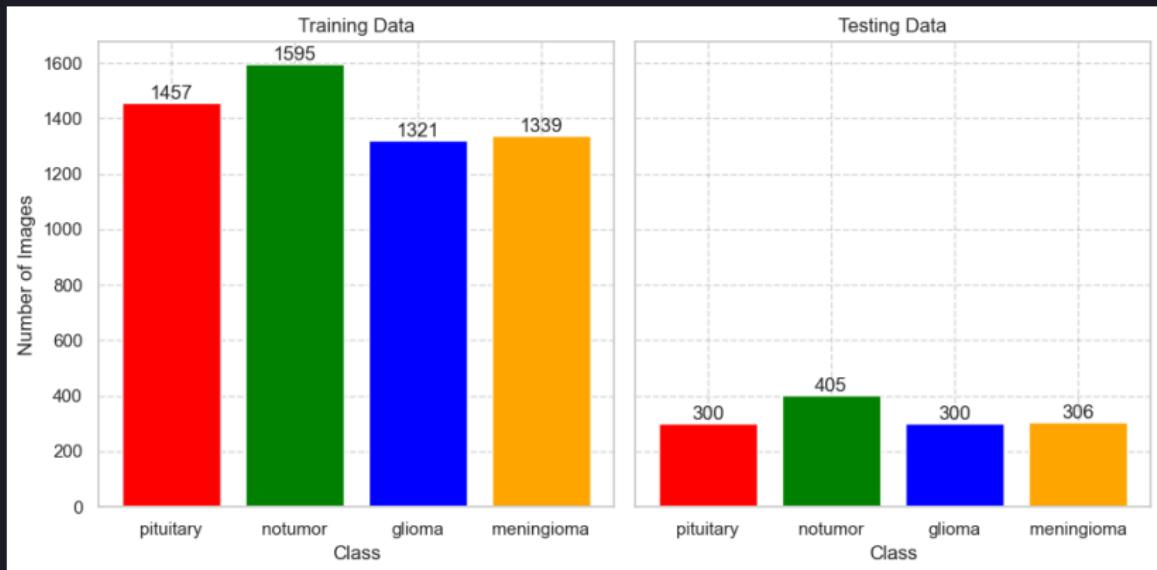
Brain Tumor MRI Dataset

- Combination of three datasets
- 7023 images of human brain MRI images
- Four classes: glioma, meningioma, no-tumor and pituitary



Brain Tumor MRI Dataset

The dataset is separated into training and testing sets with a ratio of 80% and 20% respectively



Resizing and Data Augmentation

- Images are resized to 128×128 pixels

Transformations applied to the images at each epoch:

- Random horizontal flip
- Random rotation up to 10 degrees
- Random change in brightness, contrast, saturation, and hue

These transformations add variability to the dataset and help the model generalize better

BraTS 2020 Dataset

- BraTS stands for Brain Tumor Segmentation
- it is composed by 155 horizontal "slices" of brain MRI images for 369 patients (volumes)

$$155 \cdot 369 = 57195$$

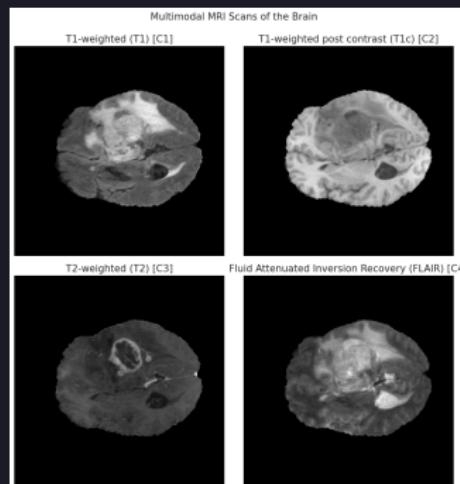
- we used the 50% most significant slices of the dataset
- we used 90% of the dataset for training and 10% for testing

Datasets

BraTS 2020 Dataset

Images have 4 channels:

1. **T1 weighted (T1)** good for visualizing the brain but not the tumor
2. **T1 weighted with contrast (T1c)** taken with the same technique as T1 but with contrast
3. **T2 weighted (T2)** good for visualizing the edema
4. **Fluid Attenuated Inversion Recovery (FLAIR)** improves the visualization of the edema



Datasets

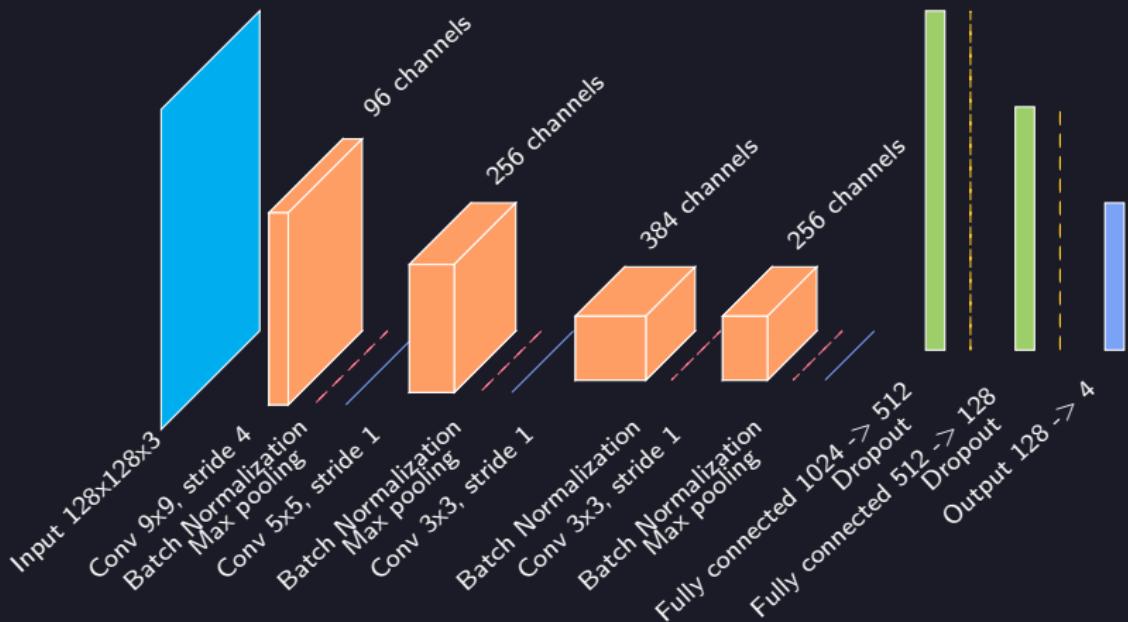
BraTS 2020 Dataset

Each slice has (eventually) 3 mask labels:

1. Necrotic and Non-Enhancing Tumour Core (NCR/NET)
2. Edema (ED)
3. Enhancing Tumour (ET)



Custom CNN Architecture



Number of parameters: 3001156

Training Details

Training parameters:

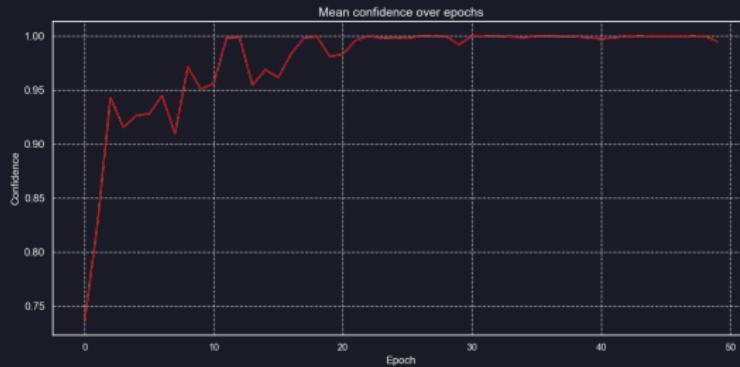
- **Epochs:** 50
- **Batch size:** 64
- **Learning rate:** 1×10^{-4}
- **Optimizer:** Adam (weight decay 1×10^{-5})
- **Scheduler:** stepLR (step size 10, gamma 0.5)
- **Loss function:** Cross-entropy
- **Activation function:** Mish
- **Dropout rate:** 0.4
- **Image size:** 128×128

Training Loss and Accuracy



- Final training loss: 1.4×10^{-3}
- Final training accuracy: 99.9%

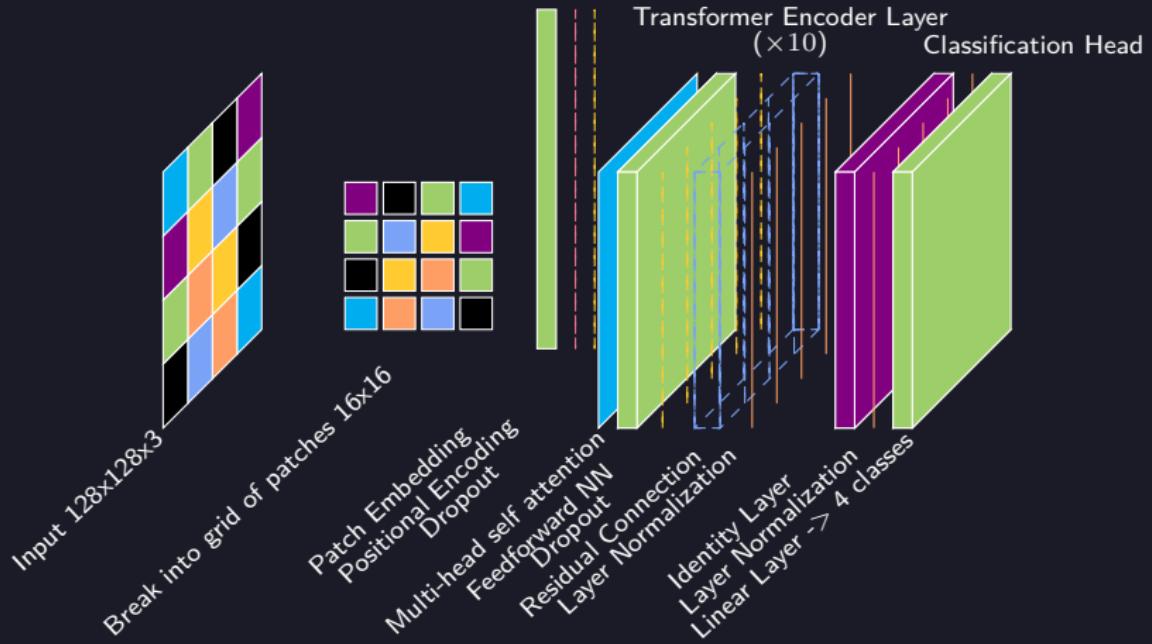
Confidence and Test Accuracy



- Final training confidence: 99.9%
- Final test confidence: 99.9%
- Final test accuracy: 99%

Classification

VIT Architecture



Number of parameters: 21459460

Training Details

Training and model parameters:

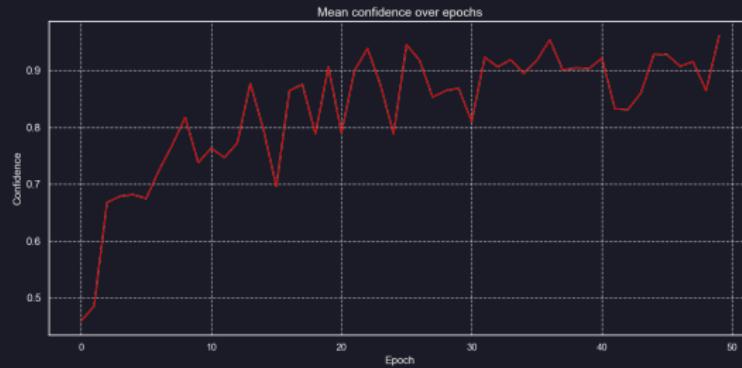
- **Epochs:** 50
- **Batch size:** 64
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- **Optimizer:** Adam (weight decay 1×10^{-5})
- **Scheduler:** stepLR (step size 10, gamma 0.5)
- **Loss function:** Cross-entropy
- **Activation function:** Mish
- **Dropout rate:** 0.2
- **Image size and Patch size:** 128×128 , 16×16
- **Number of heads:** 8
- **Number of layers:** 10
- **Patch embedding dimension:** 512
- **Feedforward dimension:** 1024

Training Loss and Accuracy



- Final training loss: 0.27
- Final training accuracy: 90%

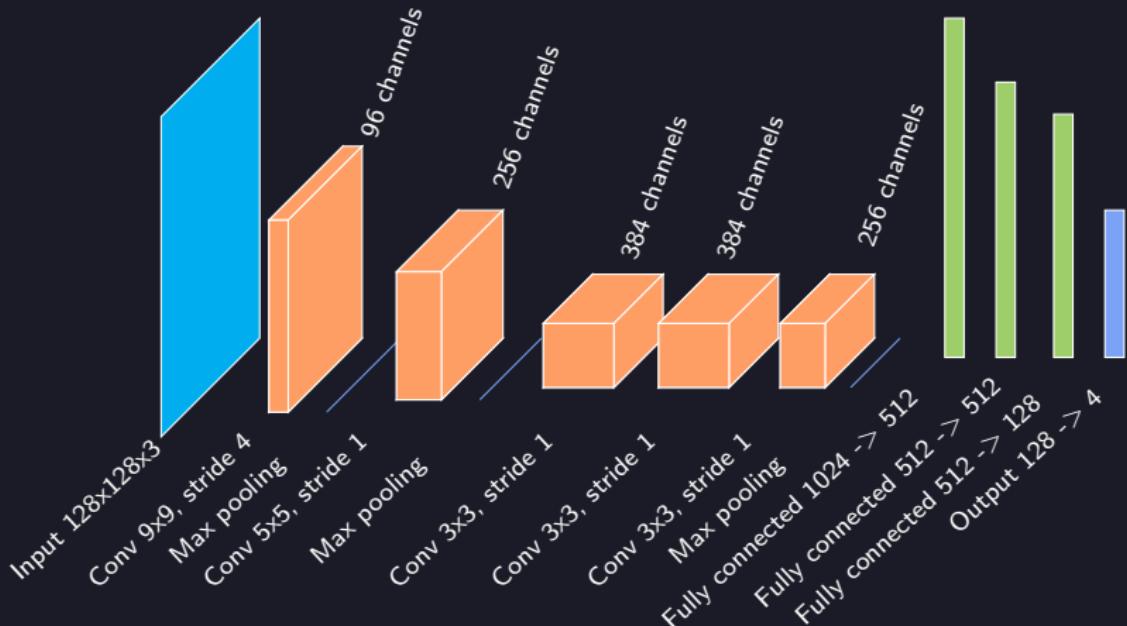
Confidence and Test Accuracy



- Final training confidence: 96%
- Final test confidence: 93%
- Final test accuracy: 88%

Classification

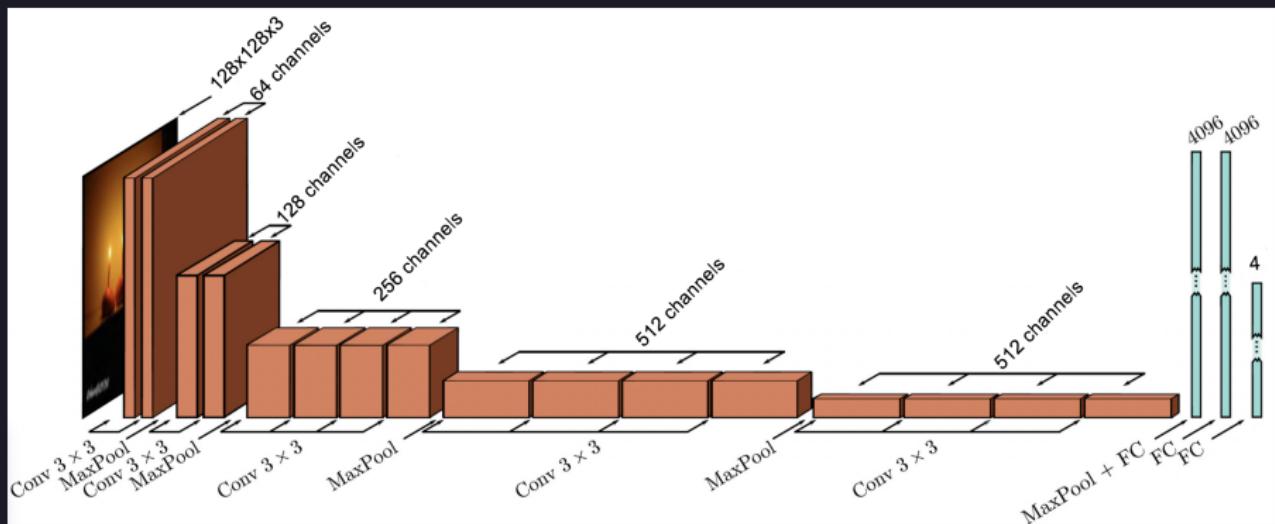
AlexNet



Number of parameters: 4589316

Classification

VGG



Number of parameters: 65070916

Dropout rate: 0.5

Setup Differences

Model	Data augmentation	LR Scheduler	Activation	L2 reg.
CustomCNN	Yes	Yes	<i>Mish</i>	Yes
AlexNet	No	Yes	<i>ReLU</i>	Yes
VGG16	No	No	<i>ReLU</i>	No
VIT	Yes	Yes	<i>Mish</i>	Yes

- All the other hyperparameters and settings are the same for all models(batch size, optimizer, epochs, etc)
- Note that the **CustomCNN** is the one with less parameters (3,001,156) while **VGG16** is the one with more parameters(65,070,916)
- **VGG16** is also the one with the highest dropout rate (0.5)

Performance Assessment

- **Loss function:** Cross-entropy loss $L(y, \hat{y}) = -\sum_i y_i \log(\hat{y}_i)$
- **Accuracy:** Number of correct predictions divided by the total number of predictions
- **Confidence:** Given by the Softmax function applied to the net output $S(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$

Training Loss and Accuracy for AlexNet



- Final training loss: $1.2 \cdot 10^{-3}$
- Final training accuracy: 99.9%

Confidence and Test Accuracy for AlexNet



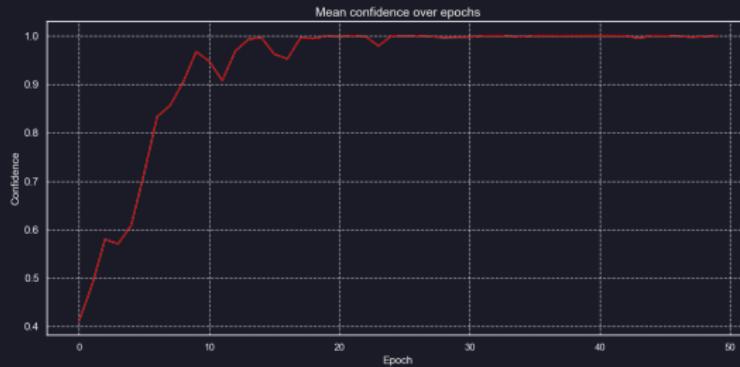
- Final training confidence: 99.9%
- Final test confidence: 96.5%
- Final test accuracy: 90%

Training Loss and Accuracy for VGG16



- Final training loss: $8.9 \cdot 10^{-6}$
- Final training accuracy: 99.9%

Confidence and Test Accuracy for VGG16



- Final training confidence: 100%
- Final test confidence: 98%
- Final test accuracy: 95%

Training Performance Comparison

Model	Loss	Accuracy	Confidence
CustomCNN	$1.4 \cdot 10^{-3}$	0.99	100%
AlexNet	$1.2 \cdot 10^{-3}$	0.99	99.9%
VGG16	$8.9 \cdot 10^{-6}$	0.99	100%
VIT	0.27	0.90	96.1%

Note that these are the values reached during the last epoch.

Classification

Focus on Accuracy



Test Performance Comparison

Model	Accuracy	Confidence
CustomCNN	0.99	100%
AlexNet	0.90	96.5%
VGG16	0.95	98.0%
VIT	0.88	93.3%

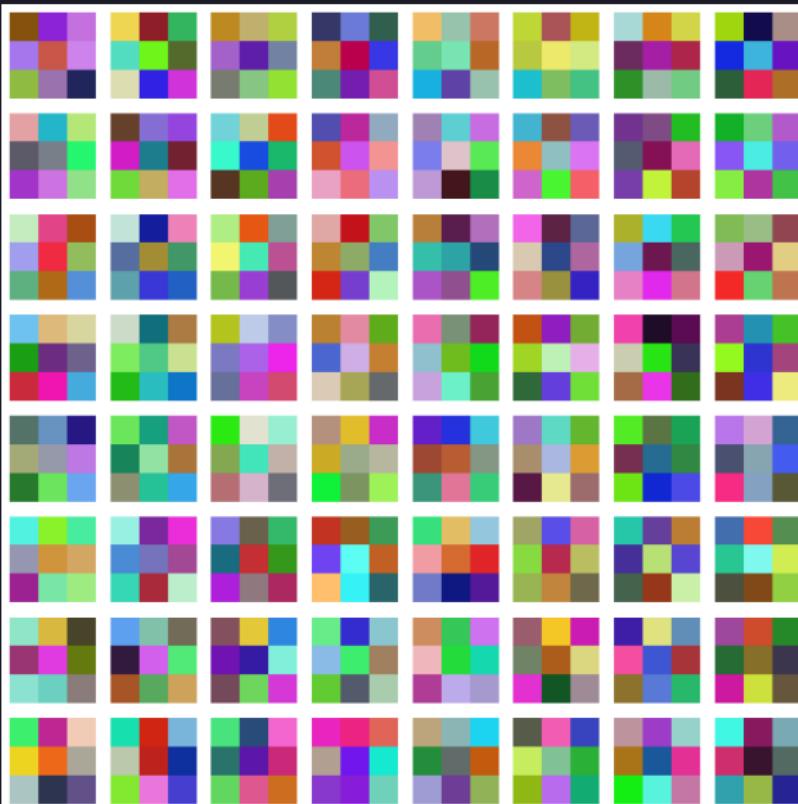
Visualizing the first layer filters, CustomCNN



Visualizing the first layer filters, AlexNet



Visualizing the first layer filters, VGG16



U-Net Models

3 models for the segmentation task:

- **Classic U-Net:** *baseline U-Net model architecture*

U-Net Models

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U-Net Models

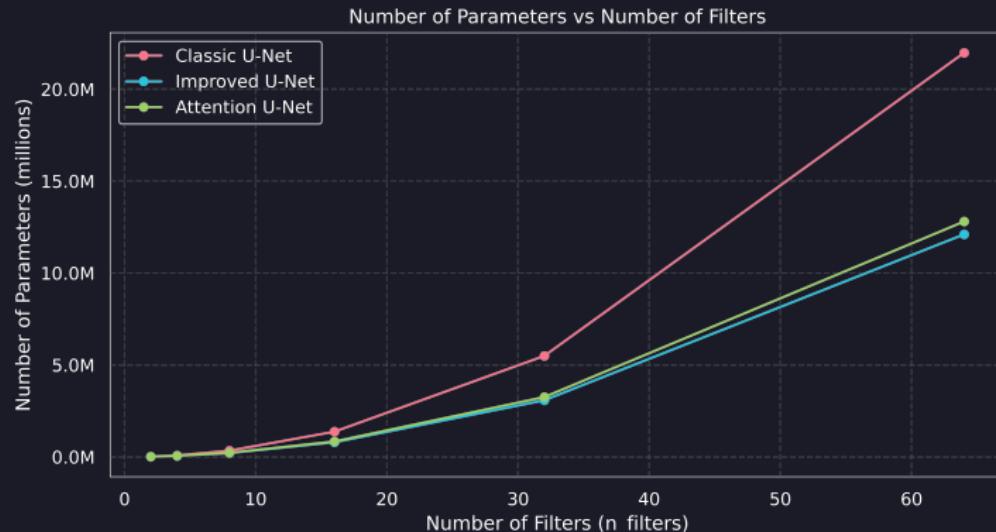
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U-Net Models

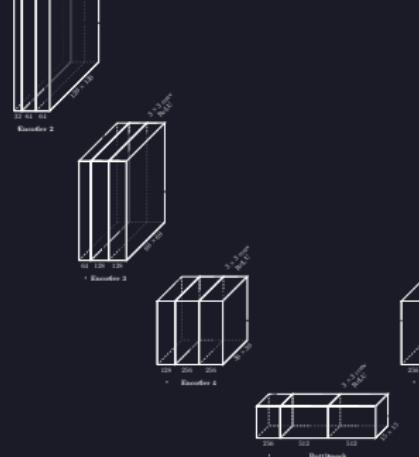
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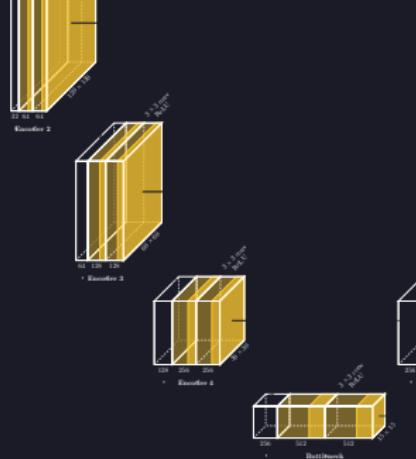
Segmentation Models

Classic U-Net



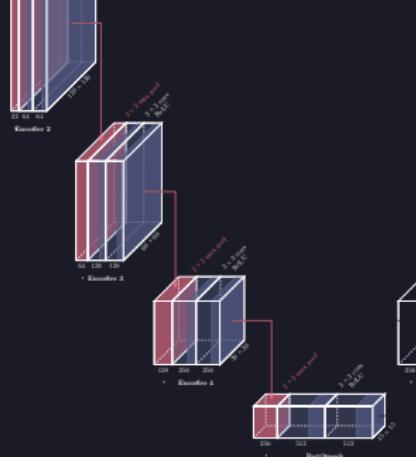
Segmentation Models

Classic U-Net



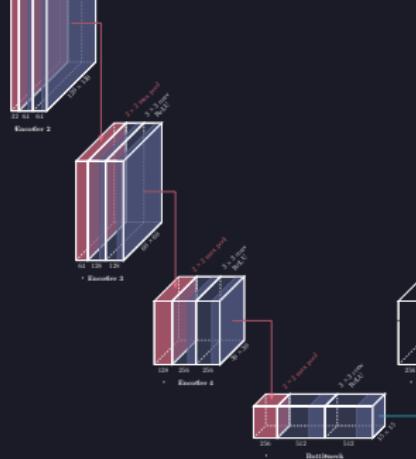
Segmentation Models

Classic U-Net



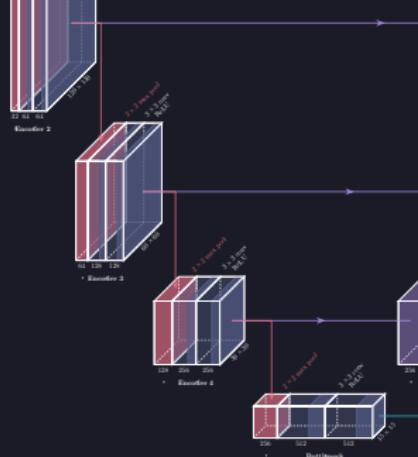
Segmentation Models

Classic U-Net



Segmentation Models

Classic U-Net



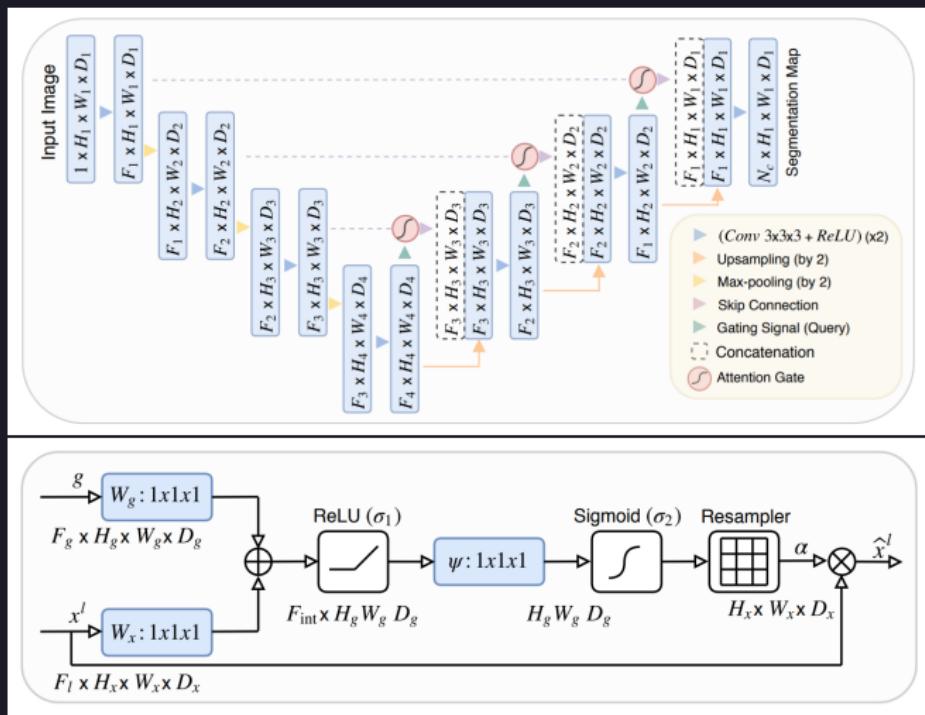
Improved U-Net

Small improvements from previous → to reduce n^o of parameters and improve performance:

- **Separable Convolutions:** depthwise + pointwise convolutions
- **Batch Normalization:** to improve training and generalization
- **Larger Kernel Size:** 7×7 kernels instead of 3×3
- **Inverse Bottleneck:** expands + compresses channels
- **Additive Skip Connections:** instead of concatenated ones

Segmentation Models

Attention U-Net



Training Details

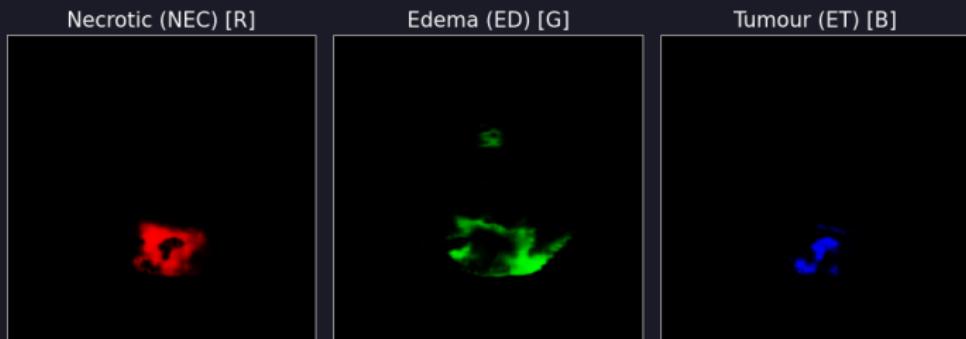
U-Net Models training parameters:

- **epochs:** 20
- **Optimizer:** Adam (with weight decay (1×10^{-2}))
- **Scheduler:** Exponential Decay ($\gamma = 0.9$)
- **Loss Function:** BCE with Logits Loss
- **learning rate:** 2×10^{-3}
- **batch size:** 32 (both training and validation)
- **image size:** 240×240
- **first encoder filters:** 32

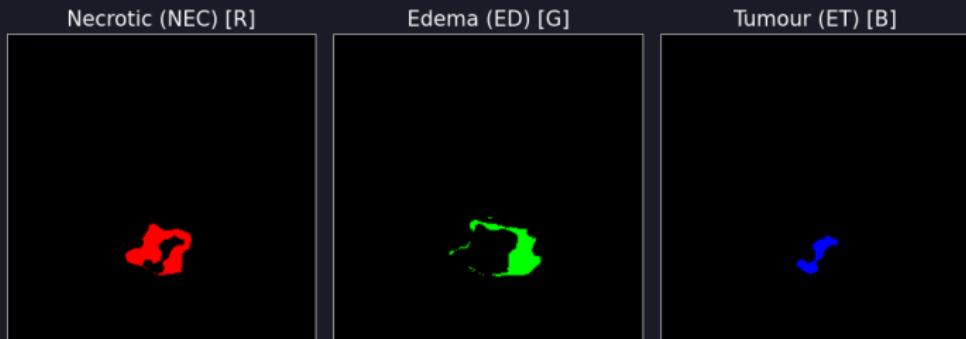
Segmentation Models

Visualizing a prediction

Predicted Mask Channels [RGB]



Ground Truth Mask Channels [RGB]



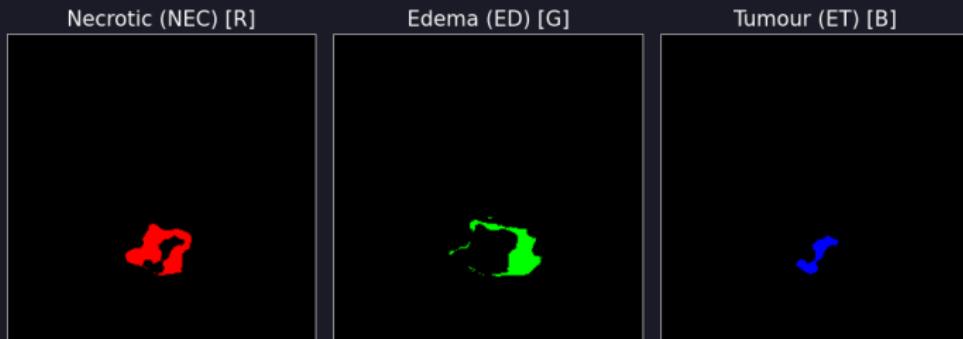
Segmentation Models

Visualizing a prediction

Binarized Predicted Mask Channels [RGB]



Ground Truth Mask Channels [RGB]



Segmentation Models

Performance Assessment

$$\text{Dice} = \frac{2 \times |X \cap Y|}{|X| + |Y|}$$

Dice Coefficient

"overlap" metric

$$\text{Precision} = \frac{TP}{TP + FP}$$

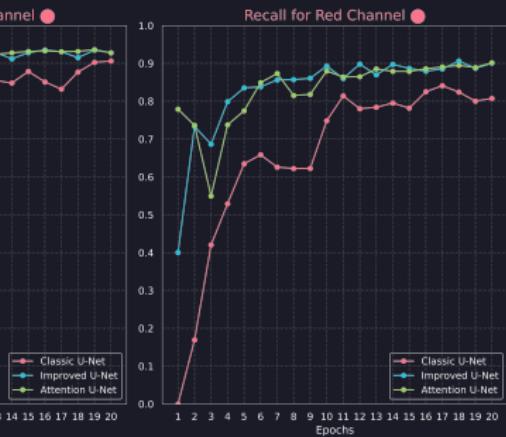
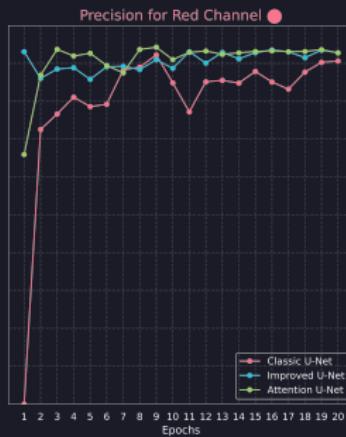
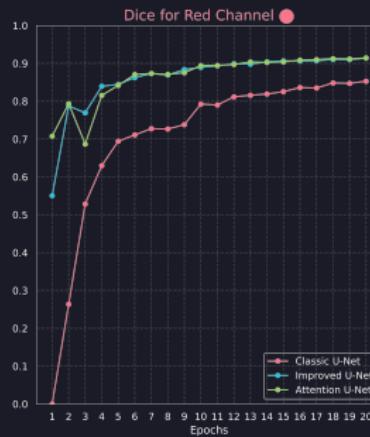
Precision

prediction quality

$$\text{Recall} = \frac{TP}{TP + FN}$$

Recall

prediction quantity



Segmentation Models

Performance Assessment

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Dice Coefficient

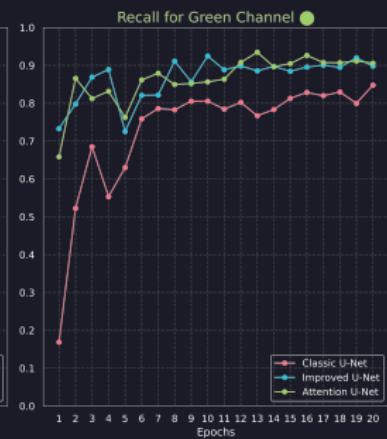
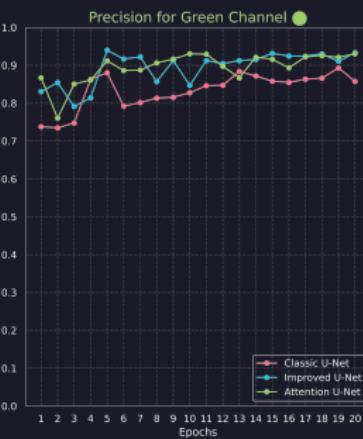
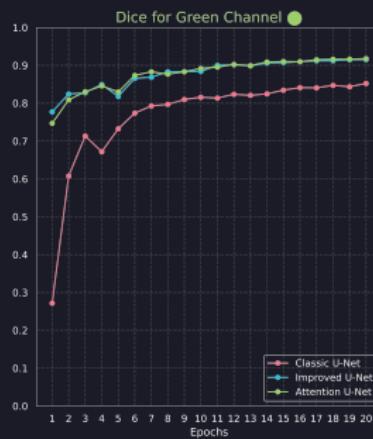
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Segmentation Models

Performance Assessment

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Dice Coefficient

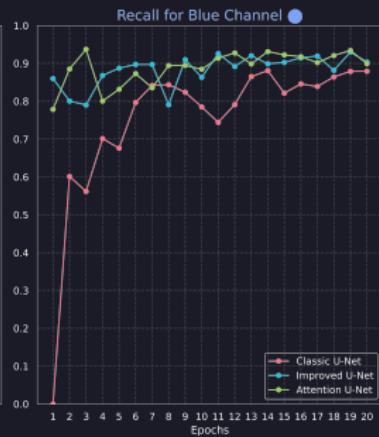
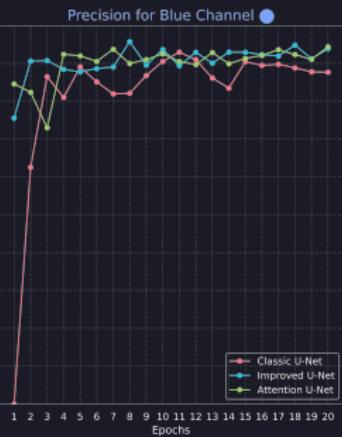
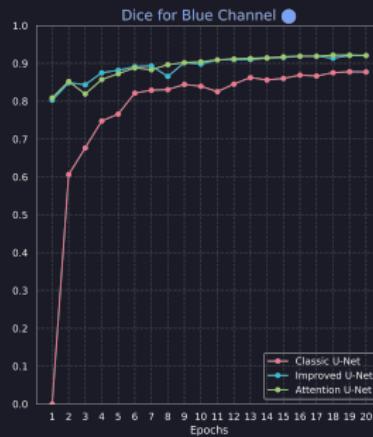
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Segmentation Models

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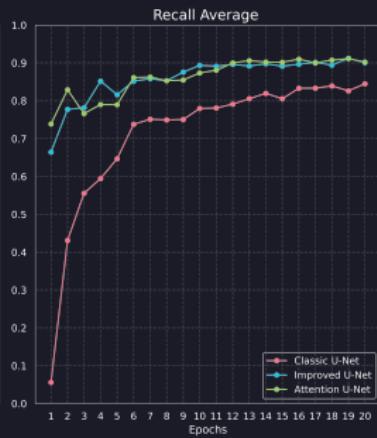
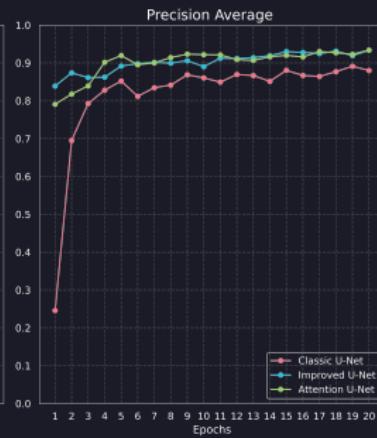
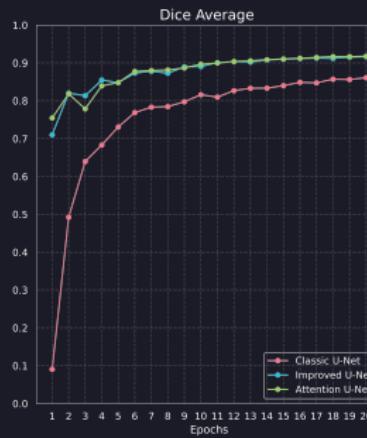
Dice Coefficient
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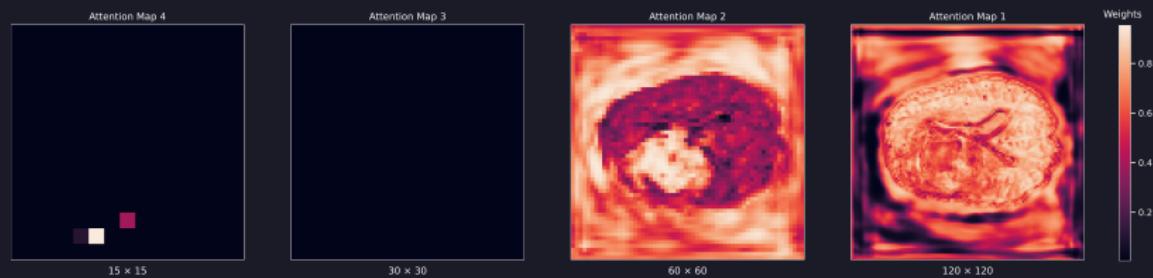
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Recall
prediction quantity



Segmentation Models

Visualizing Attention Maps



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 rate