

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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Introduction

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

1. Datasets Description

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

2. Classification Task

- Custom CNN
- ViT
- AlexNet
- VGG16

3. Segmentation Task

- U-Net Models

4. Conclusion

Datasets

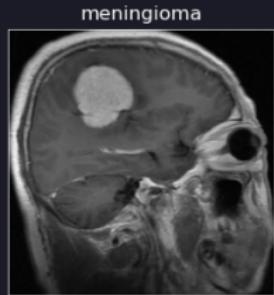
Brain Tumor MRI Dataset

Classification task dataset

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



glioma



meningioma



notumor

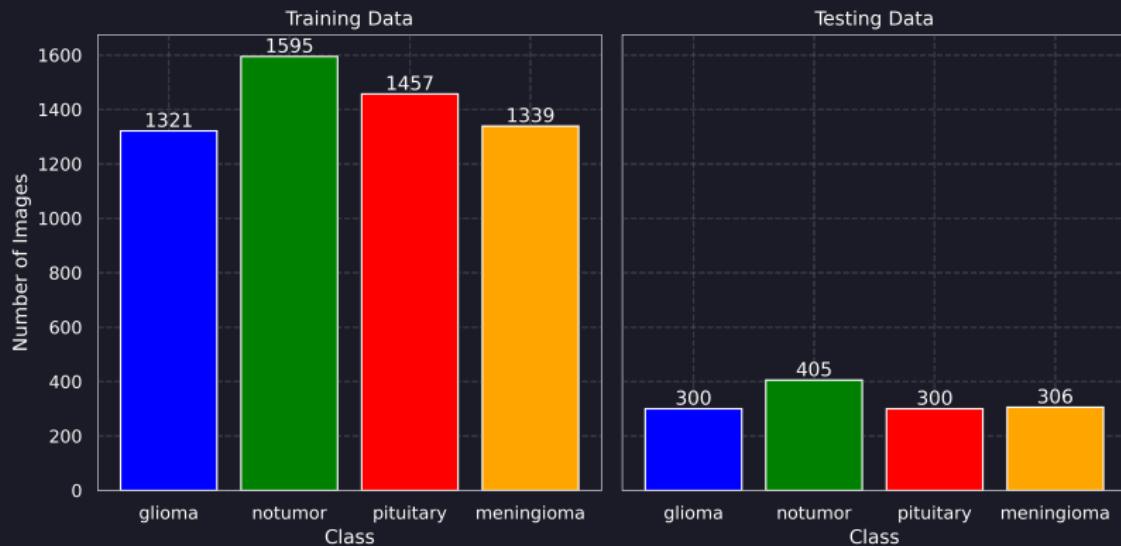


pituitary

Datasets

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

Segmentation task dataset

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

$$155 \cdot 369 = 57195$$

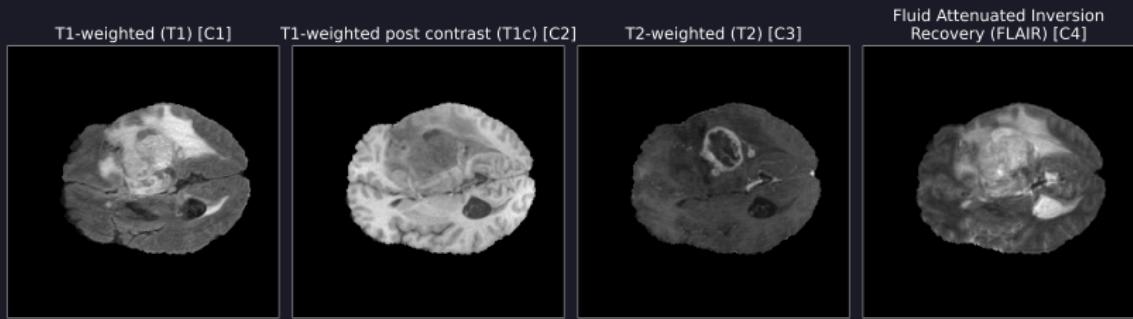
- we used the 50% “*most significant*” slices of the dataset
- we used 90% of data for **training** and 10% for testing

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*

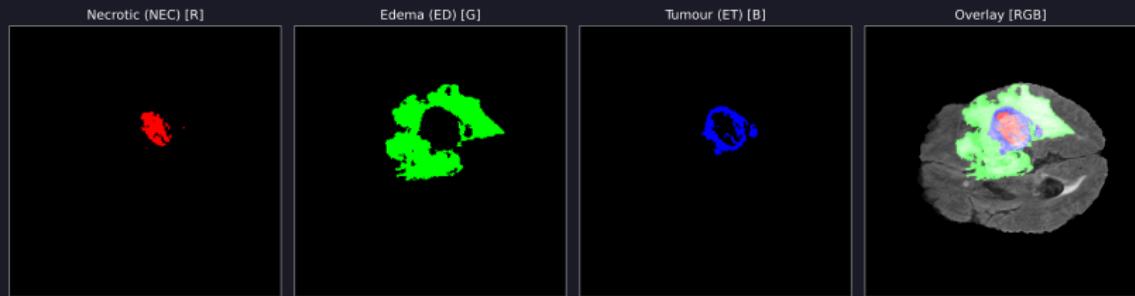


Datasets

BraTS 2020 Dataset

Each slice has 3 mask labels (*some might be empty*):

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



Classification

Performance Assessment

Loss Function: Cross-entropy loss

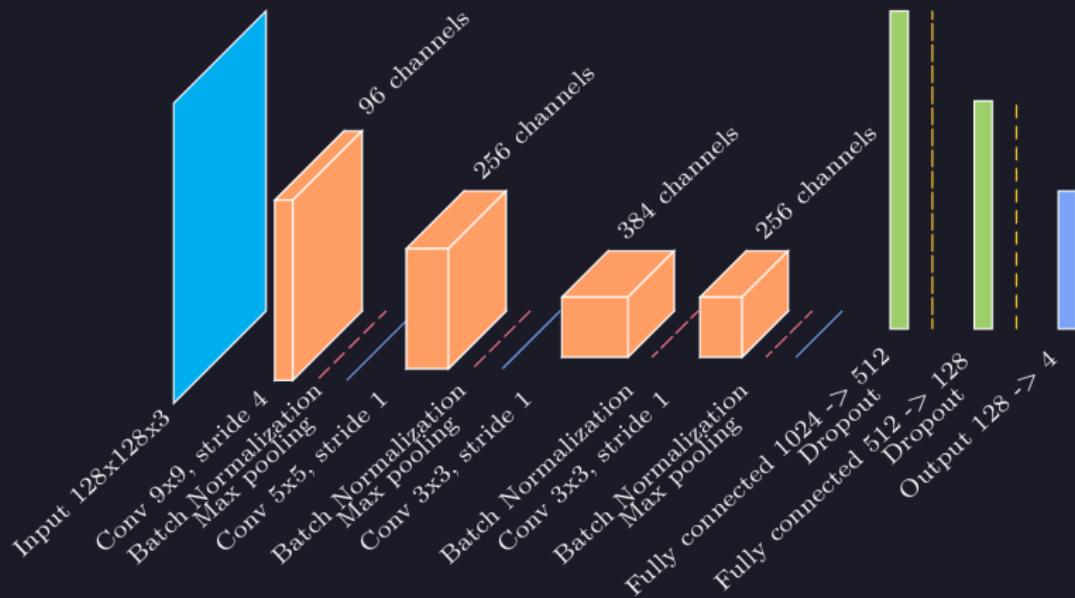
$$L(y, \hat{y}) = - \sum_i y_i \log(\hat{y}_i)$$

Accuracy: Number of correct predictions divided by the total number of predictions

Confidence: Given by the Softmax function applied to the net output

$$S(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

Custom CNN Architecture



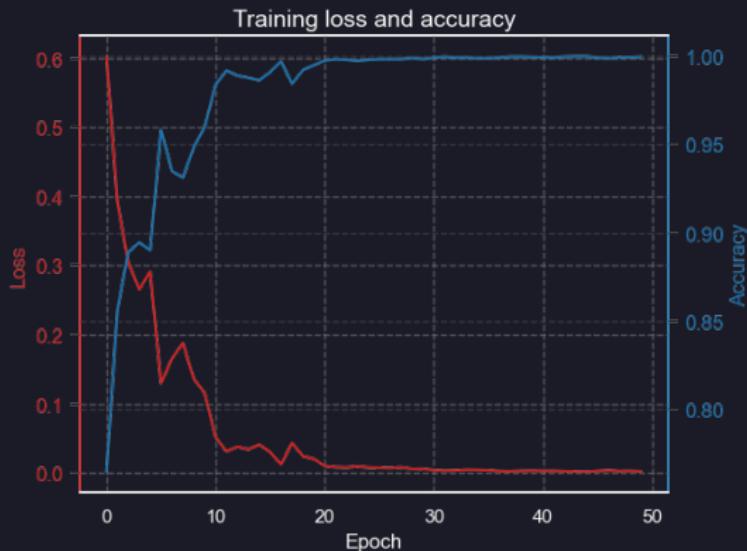
Number of parameters: 3001156

Training Details

Costum CNN model training parameters:

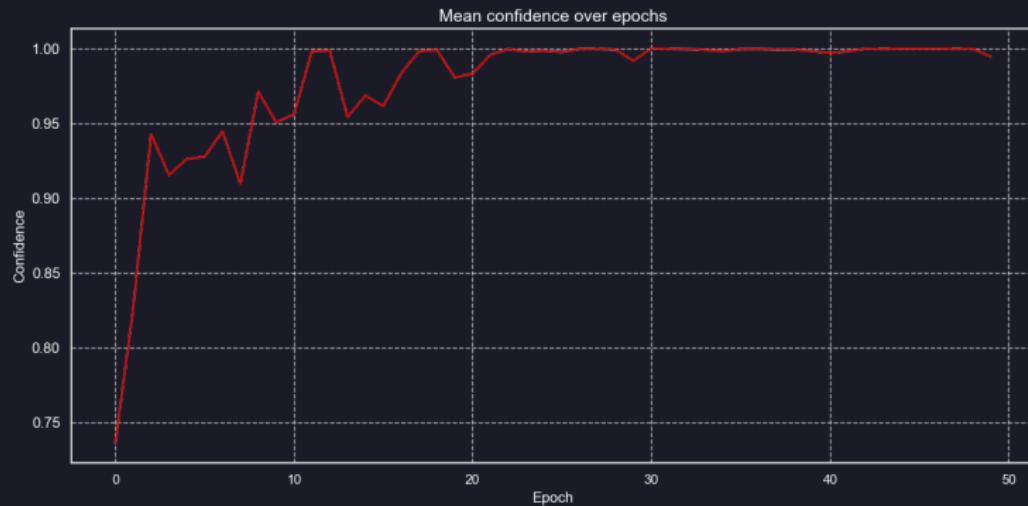
- **Epochs:** 50
- **Optimizer:** Adam (weight decay 1×10^{-5})
- **Scheduler:** stepLR (step size 10, gamma 0.5)
- **Loss function:** Cross-entropy
- **Learning rate:** 1×10^{-4}
- **Batch size:** 64 (both training and validation)
- **Activation function:** Mish
- **Dropout rate:** 0.4
- **Image size:**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

Training Loss and Accuracy



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

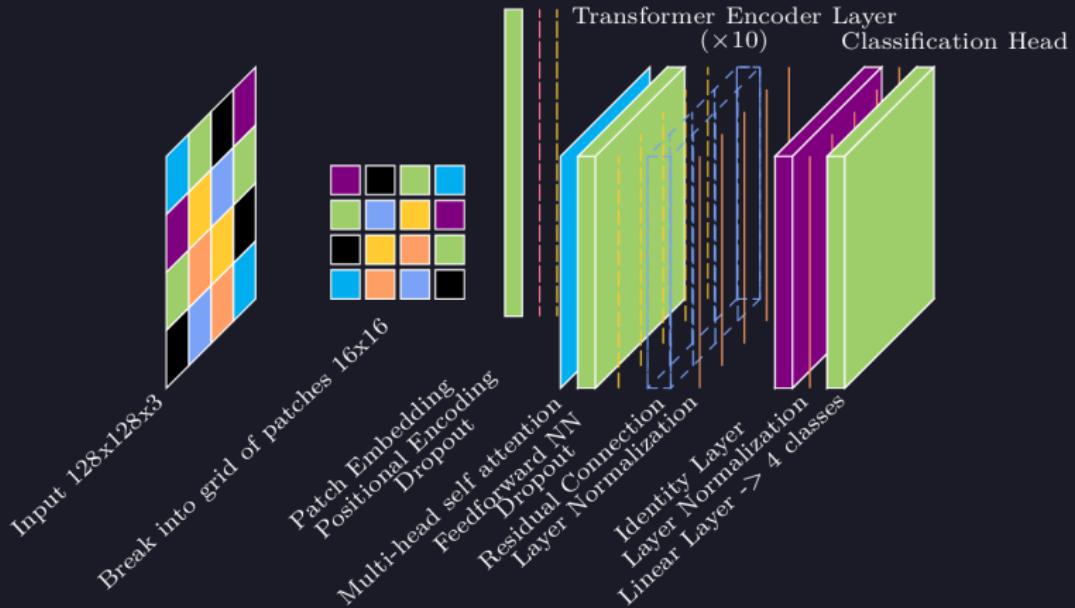
Confidence and Test Accuracy



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

Classification

VIT Architecture



Number of parameters: 21459460

Training Details

VIT training and model parameters:

- **Epochs:** 50
- **Optimizer:** Adam (weight decay 1×10^{-5})
- **Scheduler:** stepLR (step size 10, gamma 0.5)
- **Loss function:** Cross-entropy
- **Learning rate:** 1×10^{-4}
- **Batch size:** 64 (both training and validation)
- **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%

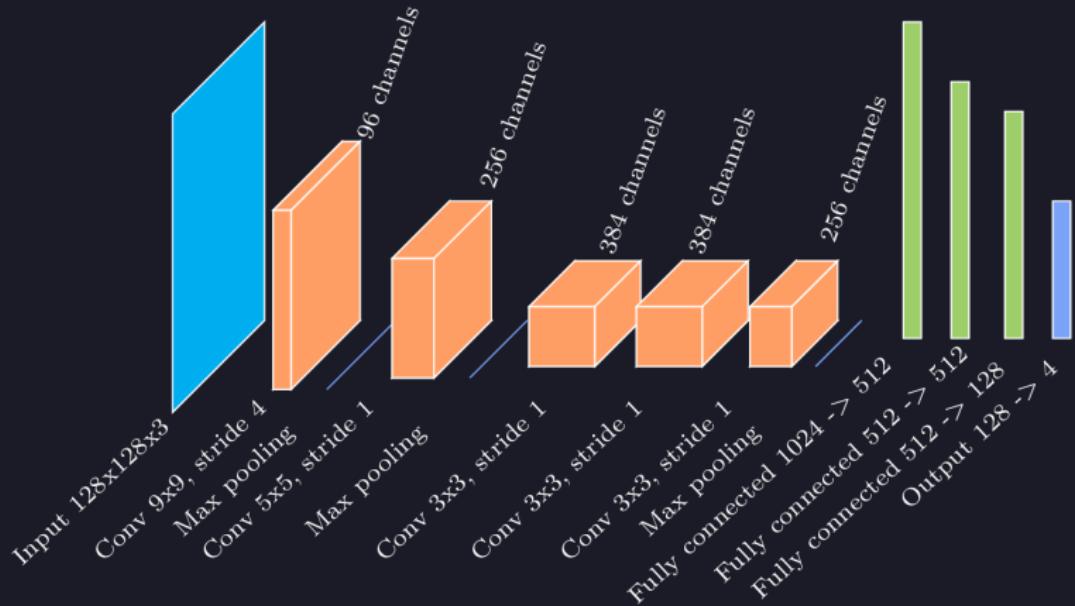
Confidence and Test Accuracy



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

Classification

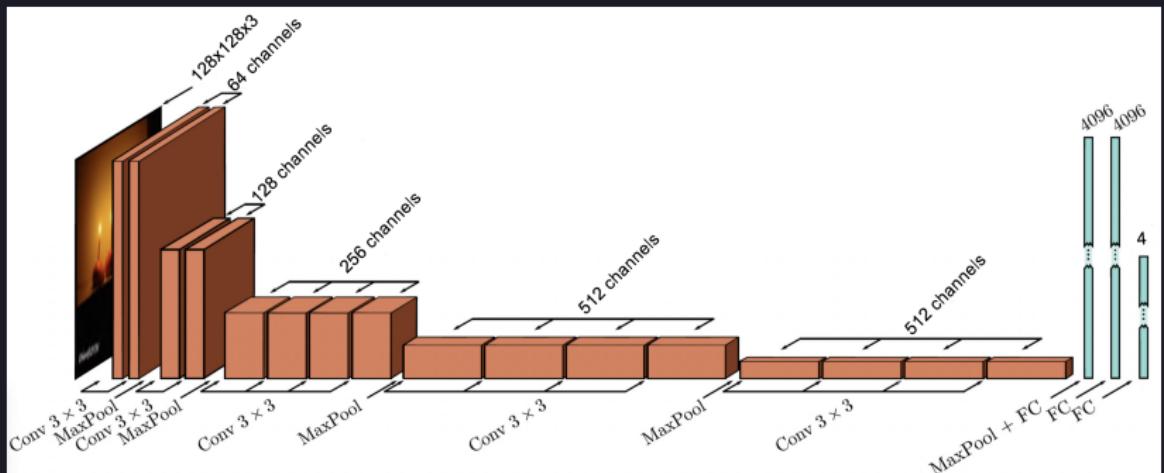
AlexNet



Number of parameters: 4589316

Classification

VGG



Number of parameters: 65070916

Dropout rate: 0.5

Setup Differences

| Model | Data augmentation | Scheduler | Activation | L2 regularization |
|-----------|-------------------|-----------|-------------|-------------------|
| 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 ✓ |

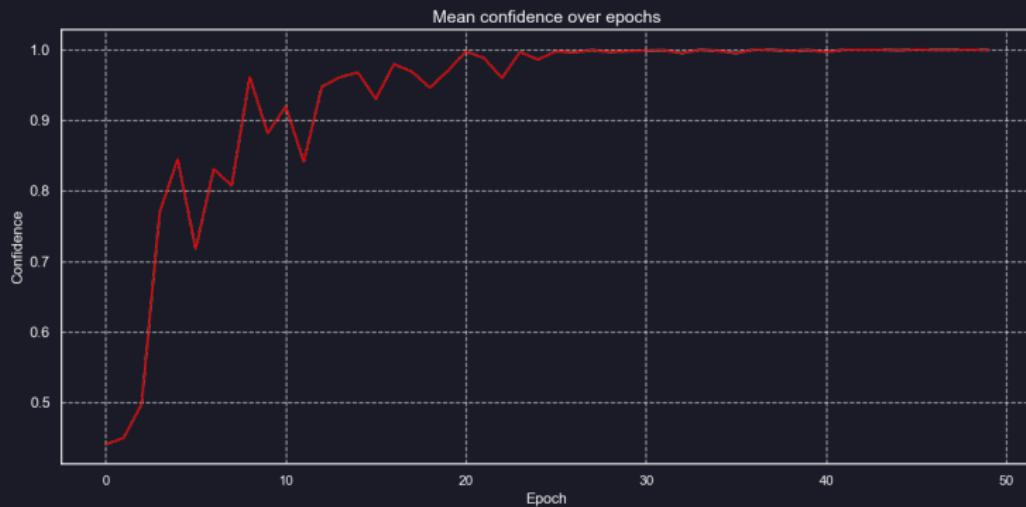
- All the other hyperparameters and settings are the same for all models (*batch size, optimizer, epochs, etc...*)
- Note that the **CustomCNN** is the one with less parameters (3,001,156) while **VGG16** is the one with more parameters(65,070,916)
- **VGG16** also has the highest dropout rate (0.5)

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 | $1.4 \cdot 10^{-3}$ | 99% | 100% |
| AlexNet | $1.2 \cdot 10^{-3}$ | 99% | 99.9% |
| VGG16 | $8.9 \cdot 10^{-6}$ | 99% | 100% |
| VIT | 0.27 | 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 | 99% | 100% |
| AlexNet | 90% | 96.5% |
| VGG16 | 95% | 98.0% |
| VIT | 88% | 93.3% |



Note that these are the values reached after the **last epoch**.

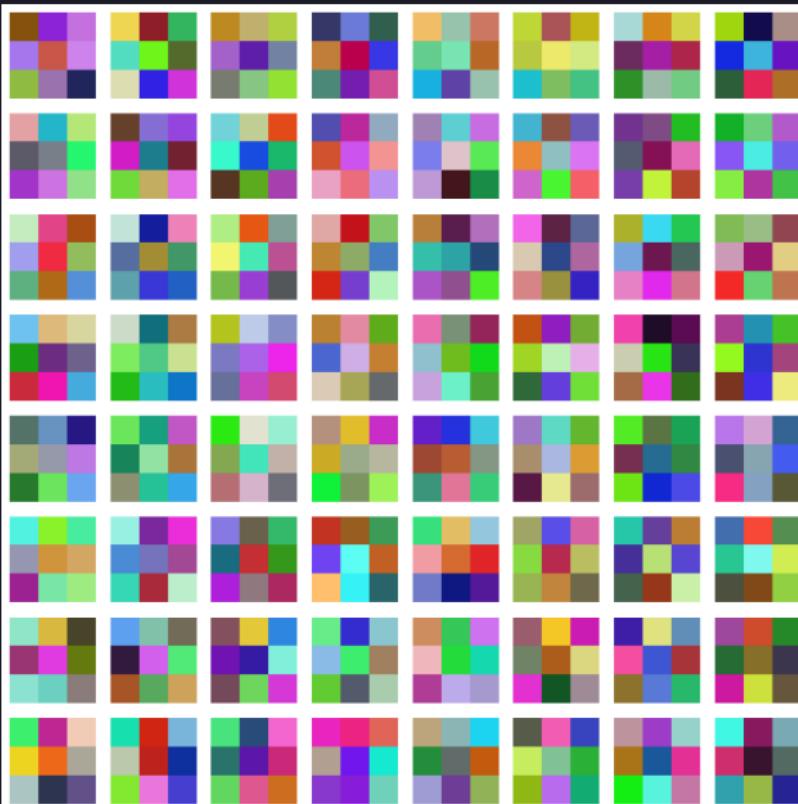
Visualizing the first layer filters, CustomCNN



Visualizing the first layer filters, AlexNet



Visualizing the first layer filters, VGG16



Segmentation

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

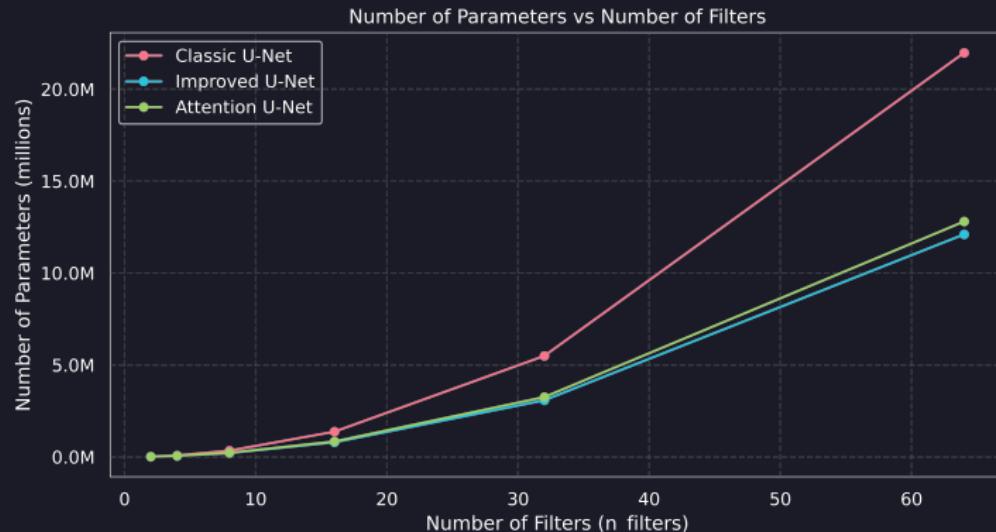
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U-Net Models

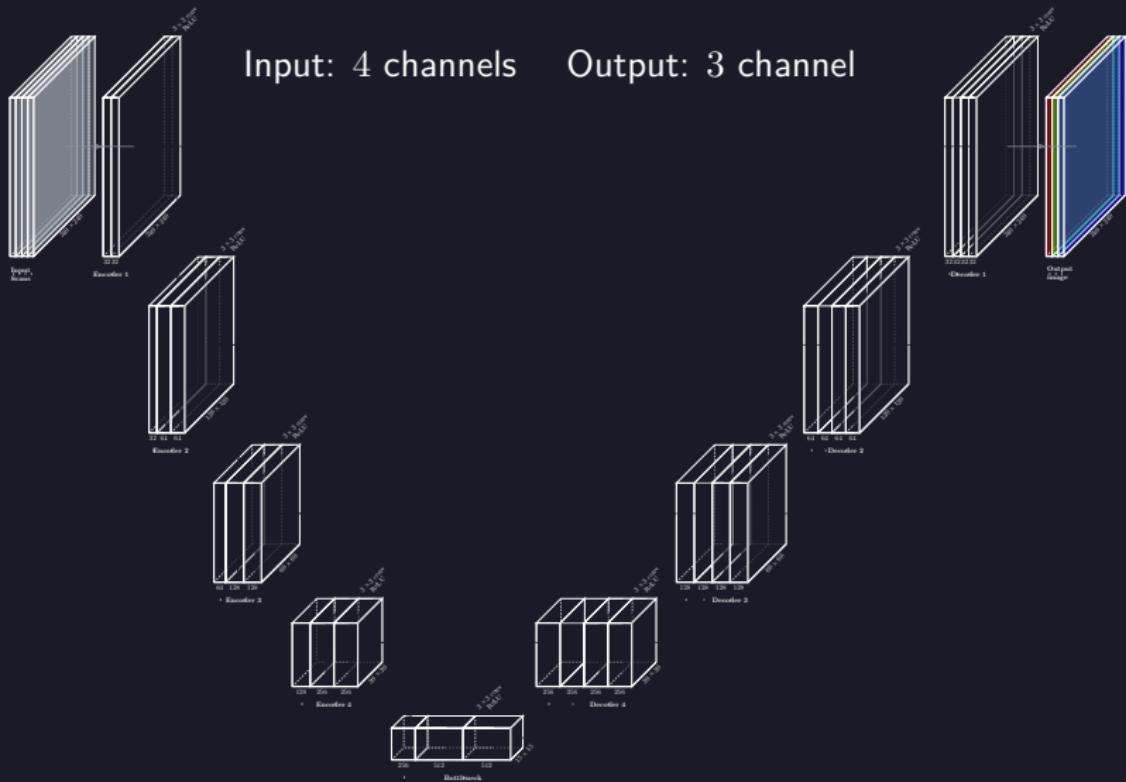
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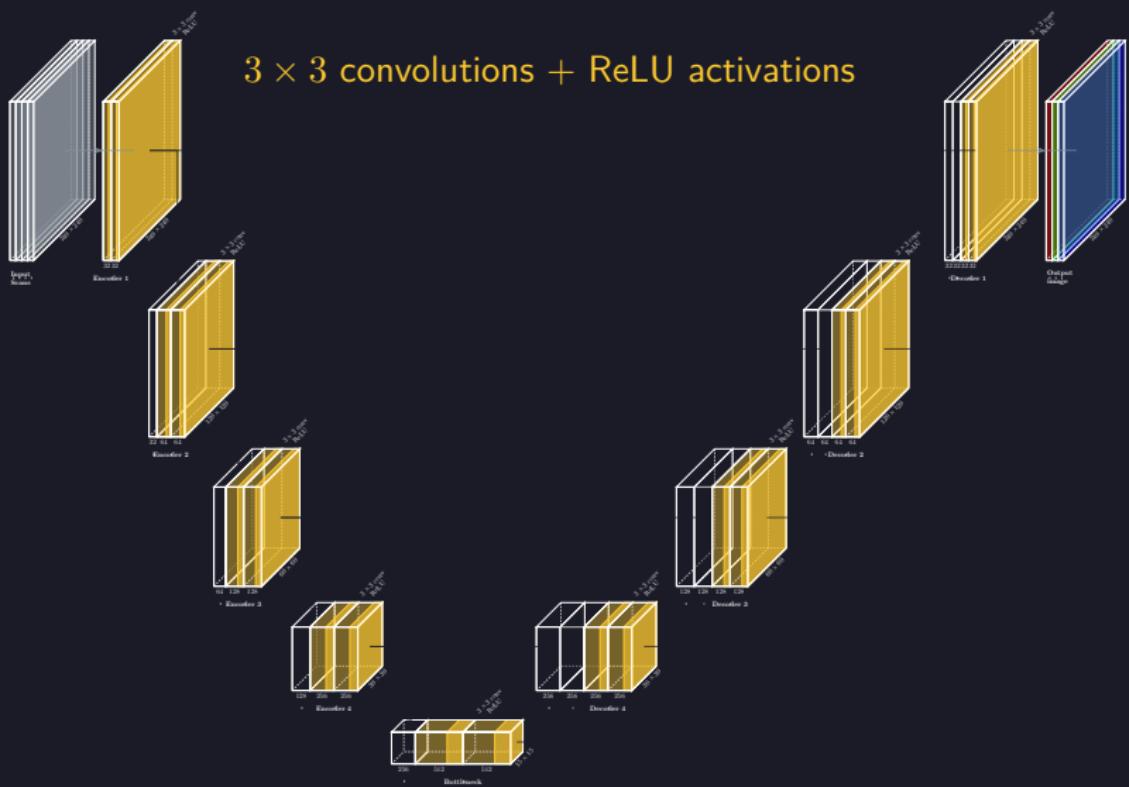
Segmentation

Classic U-Net



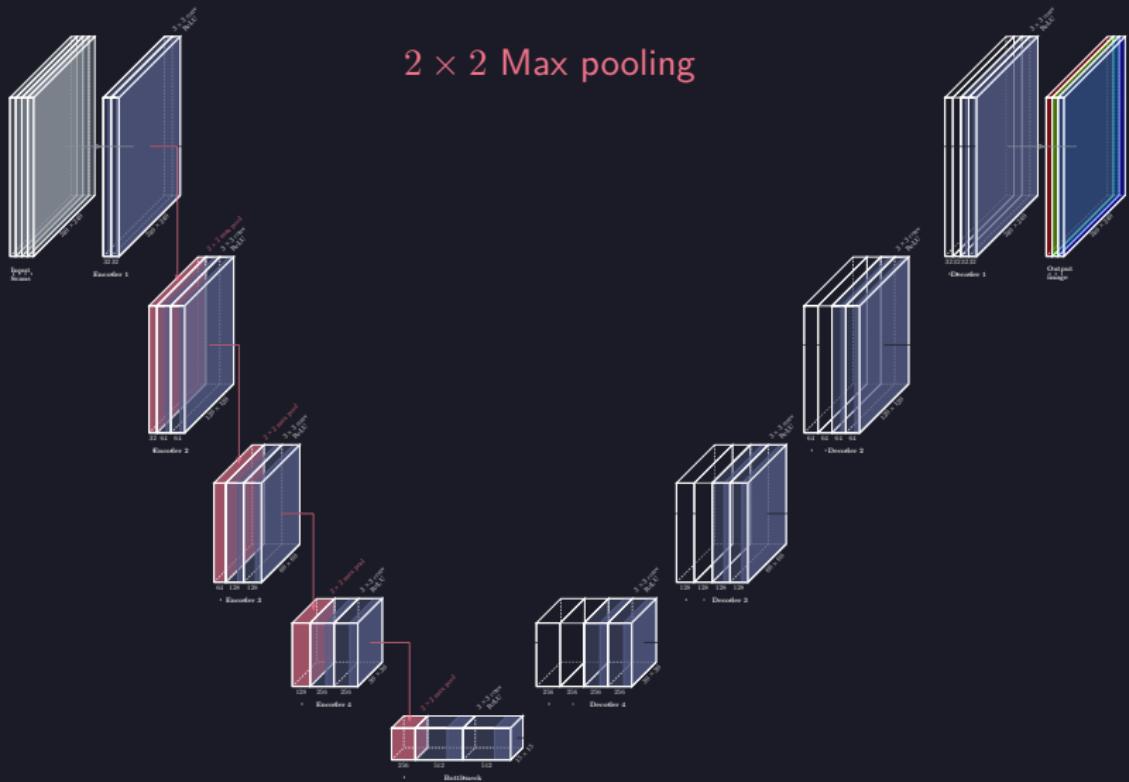
Segmentation

Classic U-Net



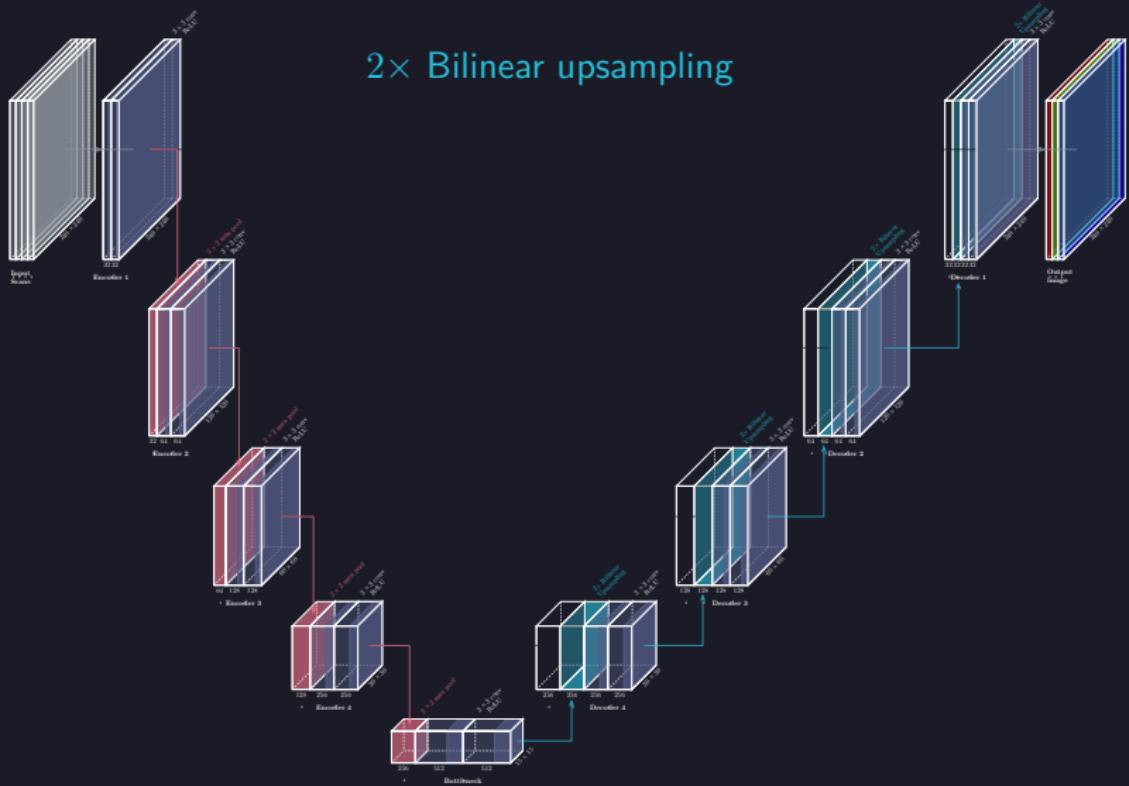
Segmentation

Classic U-Net



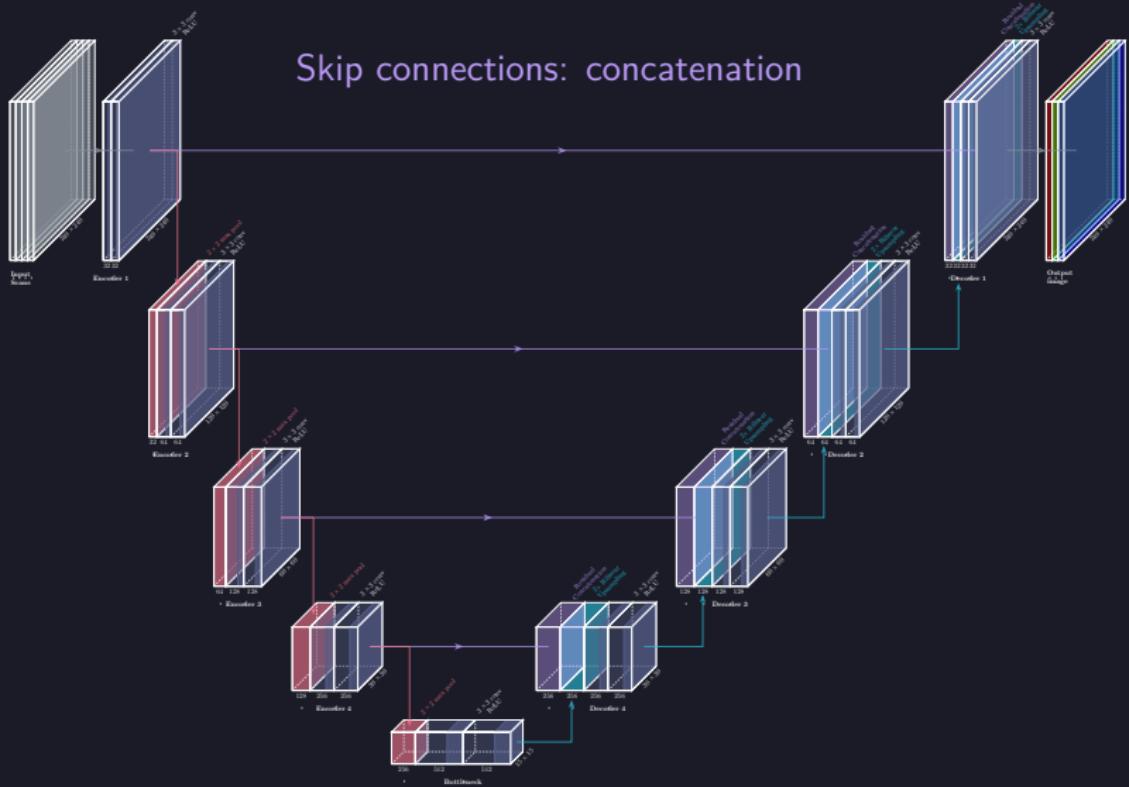
Segmentation

Classic U-Net



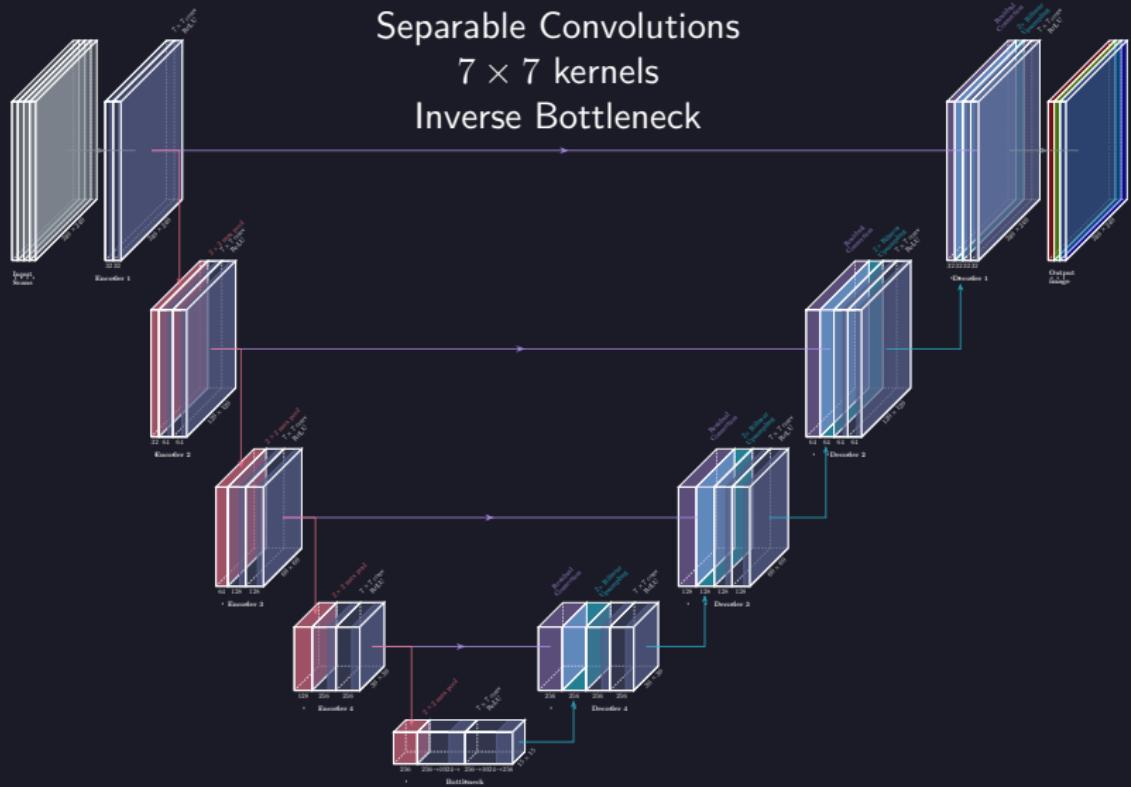
Segmentation

Classic U-Net



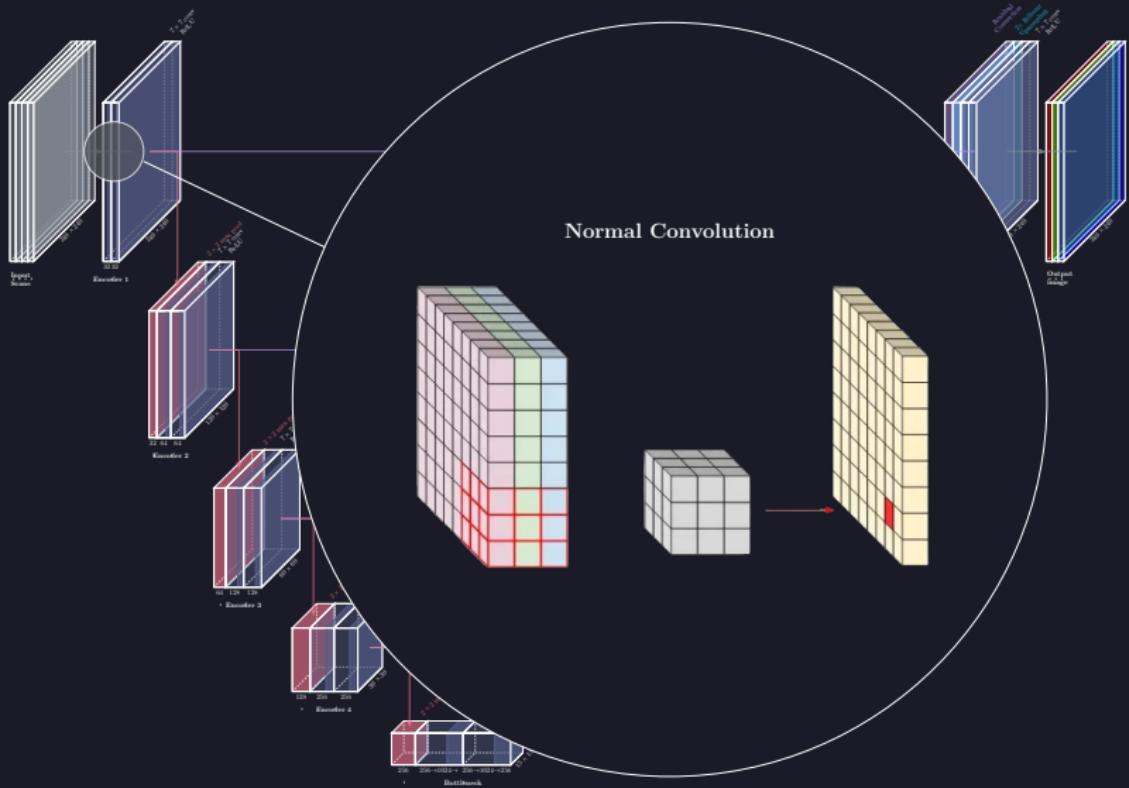
Segmentation

Improved U-Net



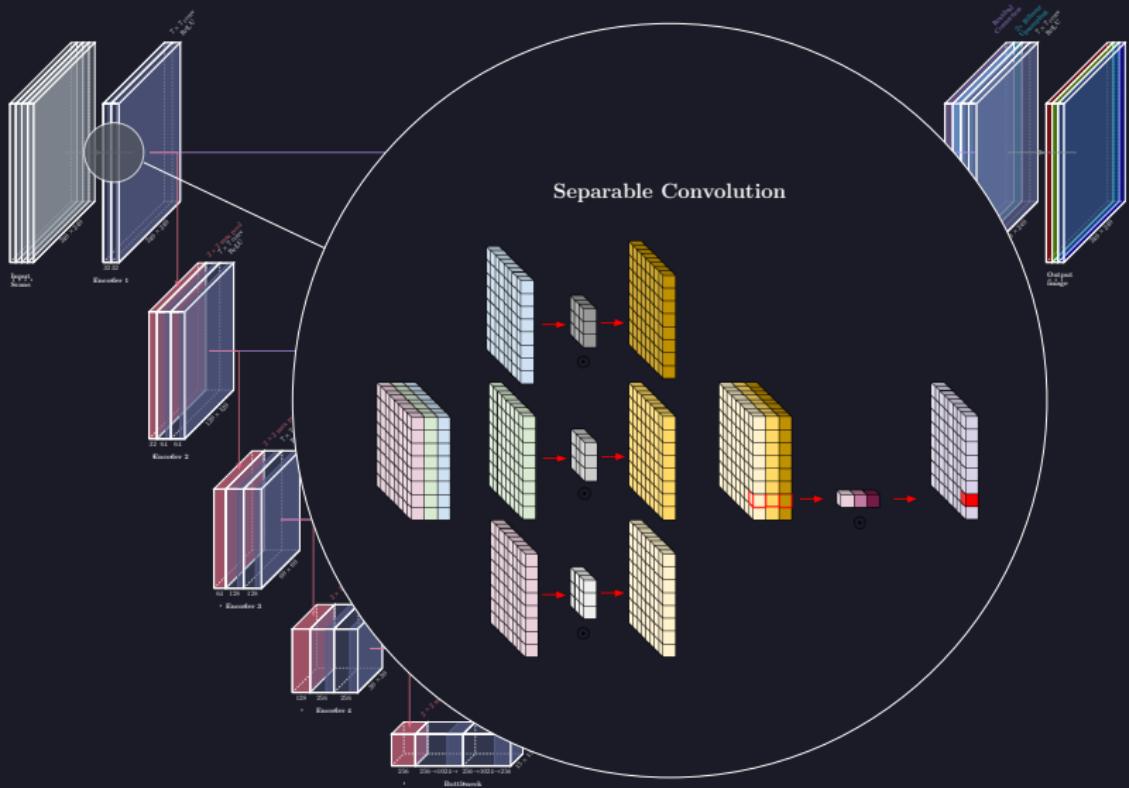
Segmentation

Improved U-Net



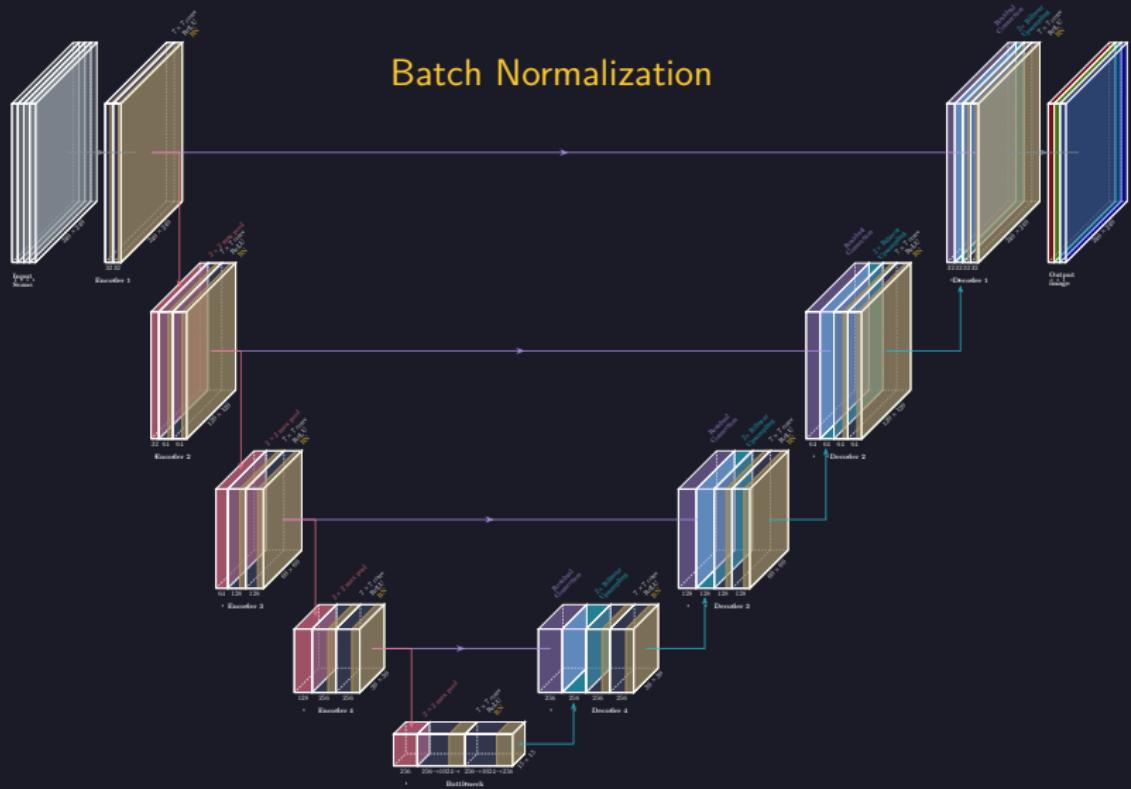
Segmentation

Improved U-Net



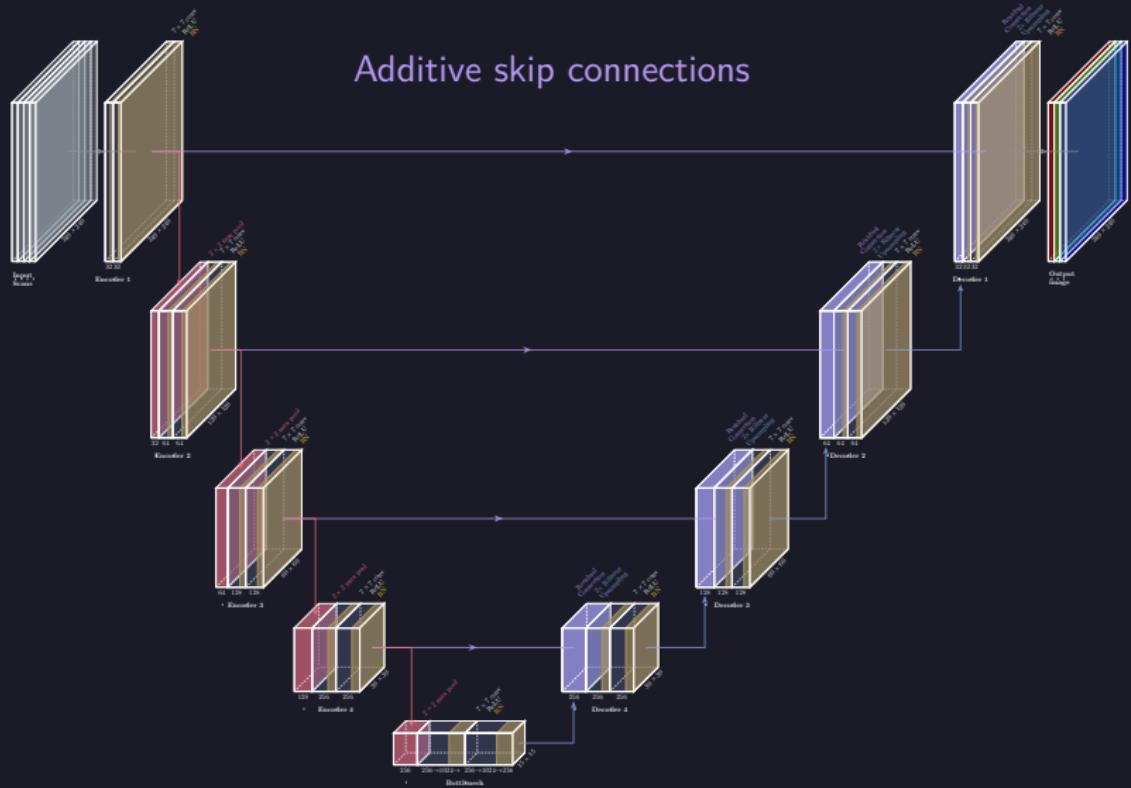
Segmentation

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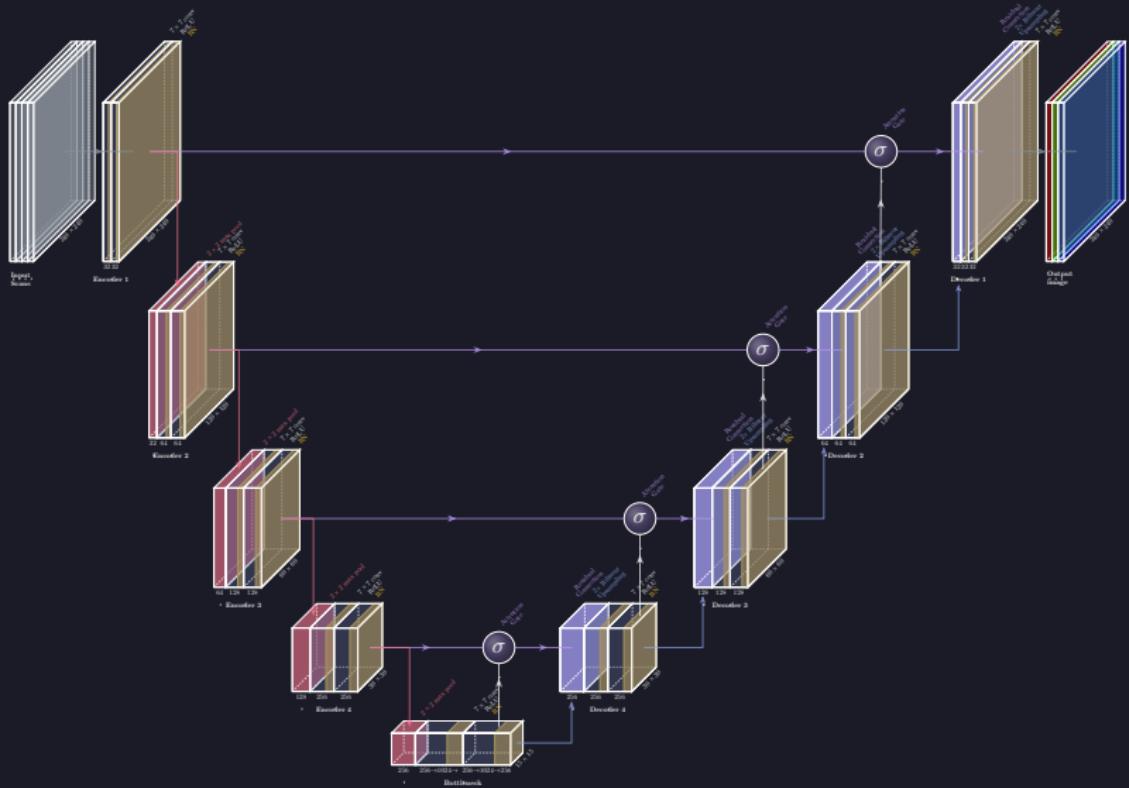
Segmentation

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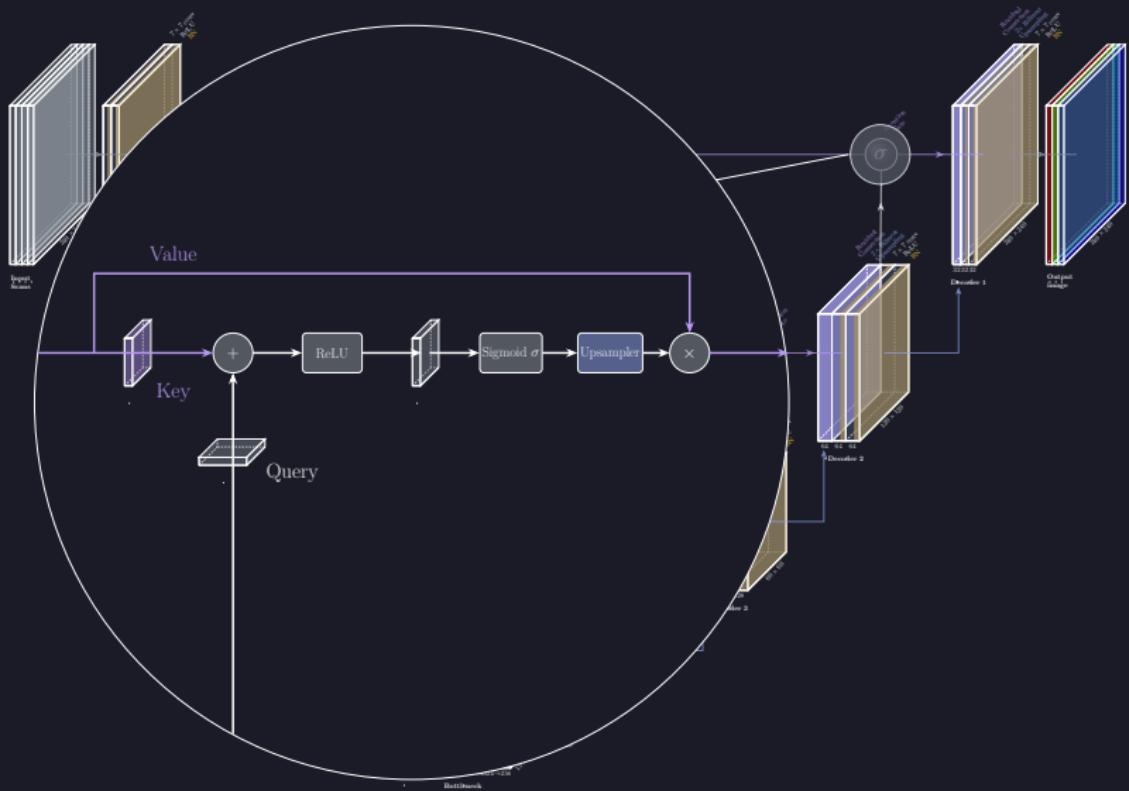
Segmentation

Attention U-Net



Segmentation

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:

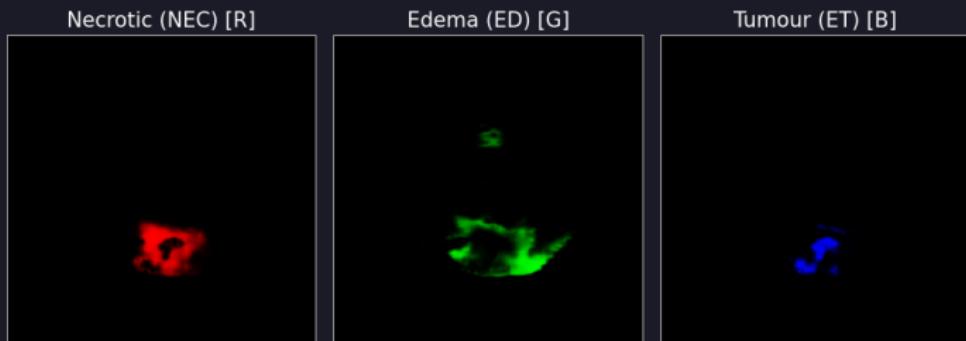
$$\ell(y, \hat{y}) = -[y \log(\sigma(\hat{y})) + (1 - y) \log(1 - \sigma(\hat{y}))]$$

- **Learning rate:** 2×10^{-3}
- **Batch size:** 32 (both training and validation)
- **First encoder filters:** 32
- **Image size:** 240×240

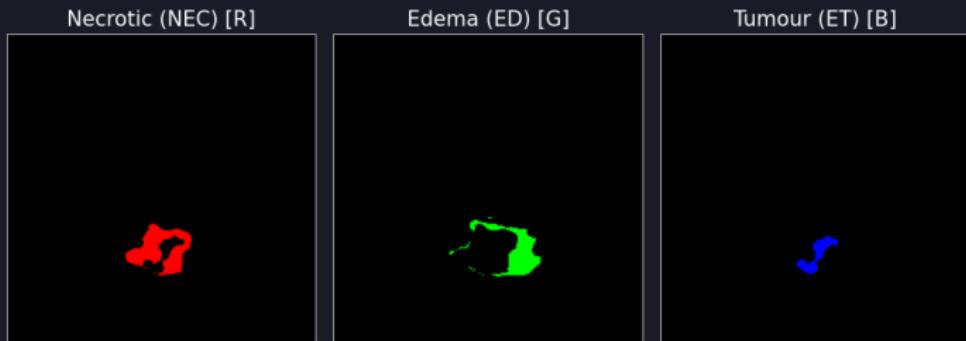
Segmentation

Visualizing a prediction

Predicted Mask Channels [RGB]



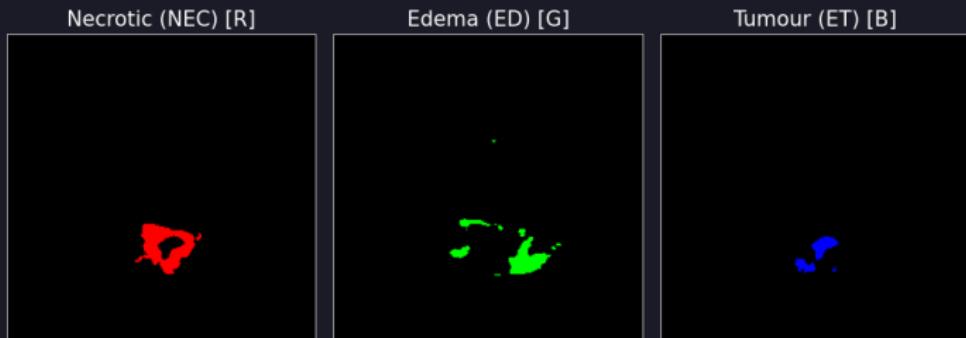
Ground Truth Mask Channels [RGB]



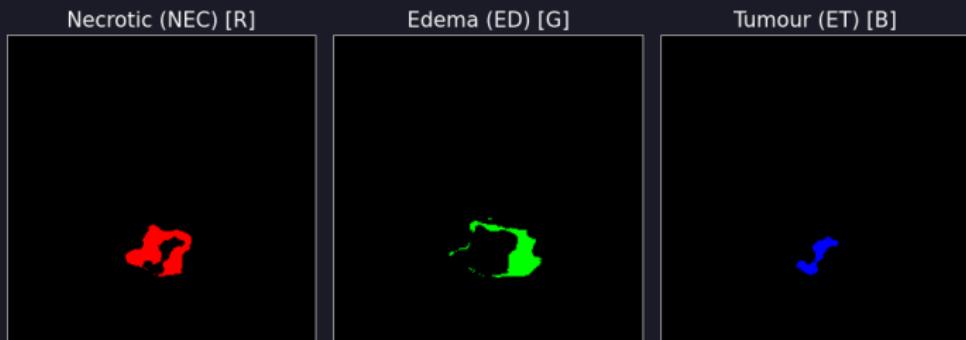
Segmentation

Visualizing a prediction

Binarized Predicted Mask Channels [RGB]



Ground Truth Mask Channels [RGB]



Segmentation

Performance Assessment

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

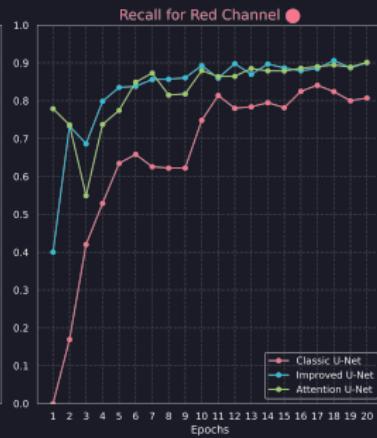
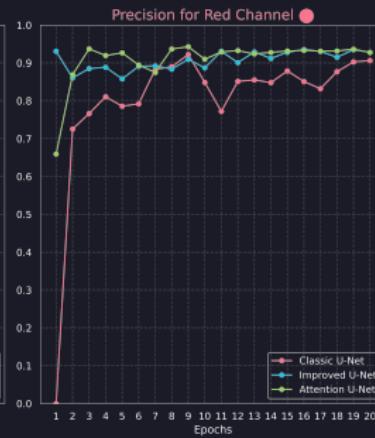
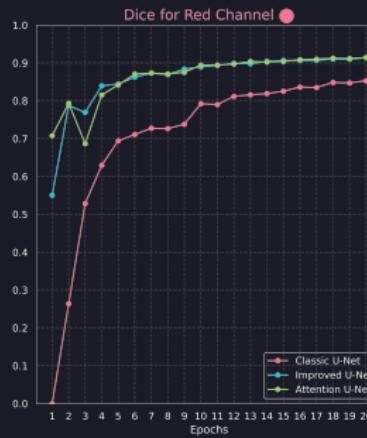
Dice Coefficient
"overlap" metric

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

Precision
prediction quality

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

Recall
prediction quantity



Segmentation

Performance Assessment

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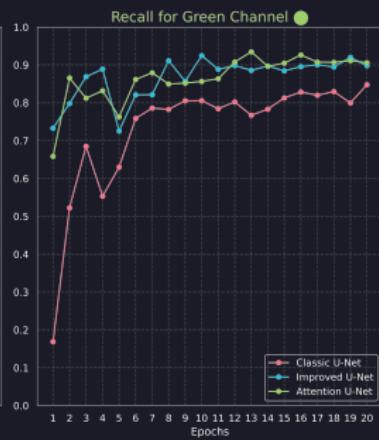
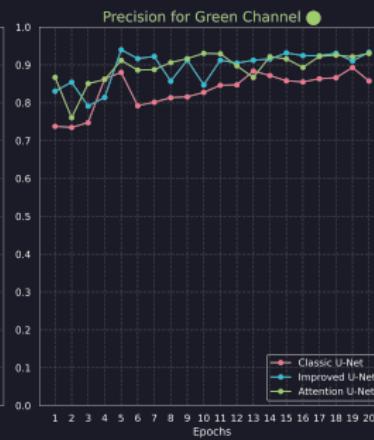
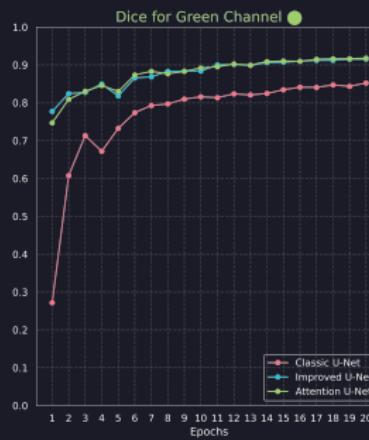
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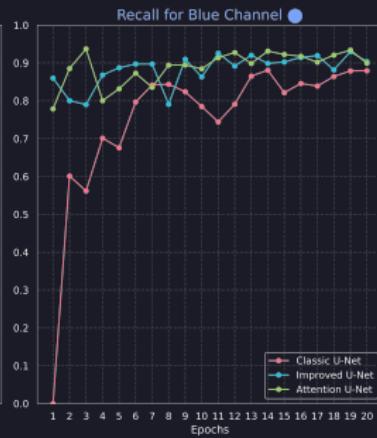
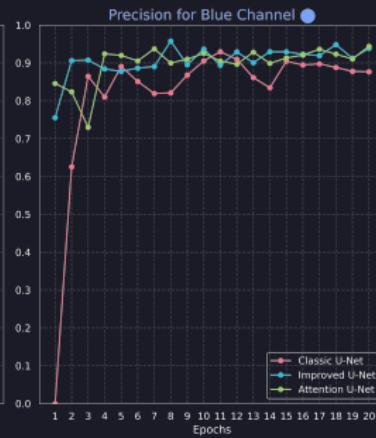
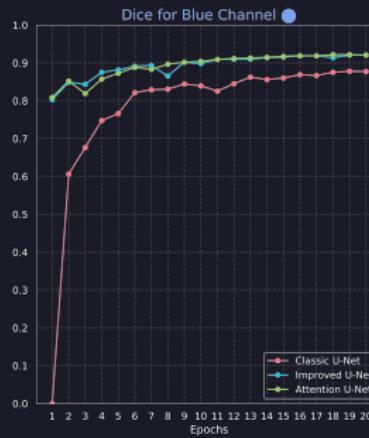
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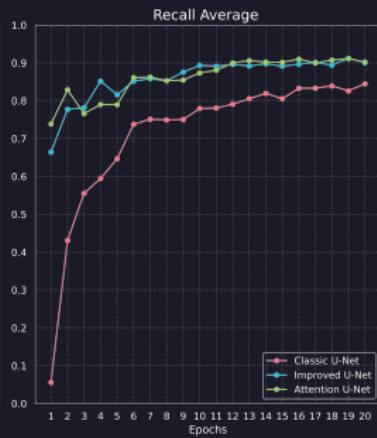
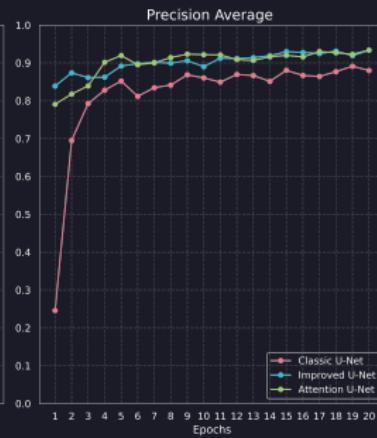
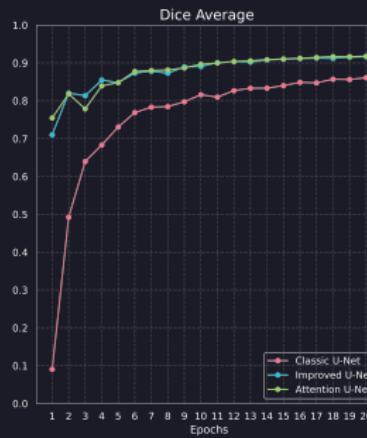
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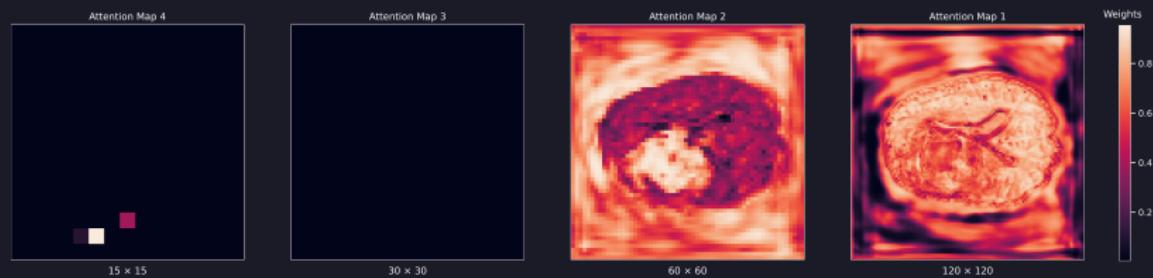
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Recall
prediction quantity



Segmentation

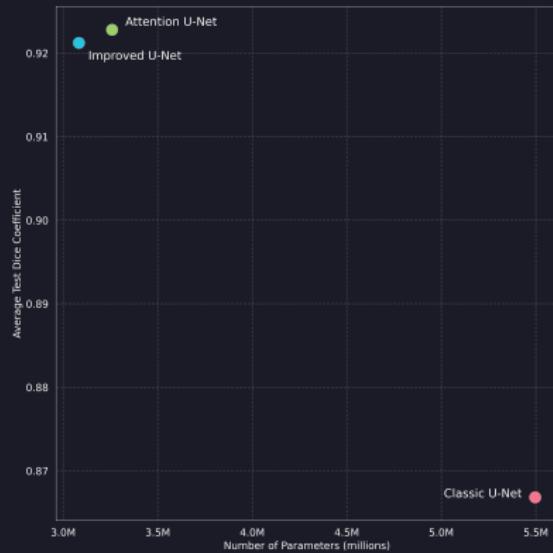
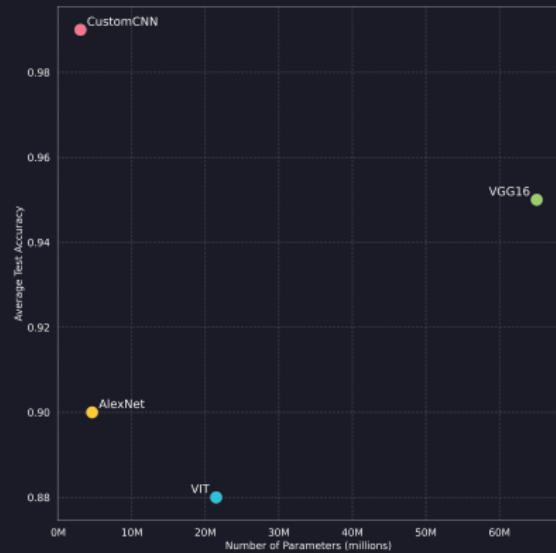
Visualizing Attention Maps



Conclusion

Conclusion

Conclusion



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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<http://arxiv.org/abs/1801.04381>
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