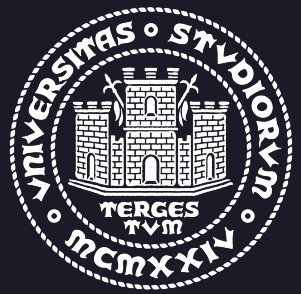
Multi-Model Approach for Brain Tumor Classification and Segmentation

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

October, 2024



Stefano Lusardi Marco Tallone Piero Zappi

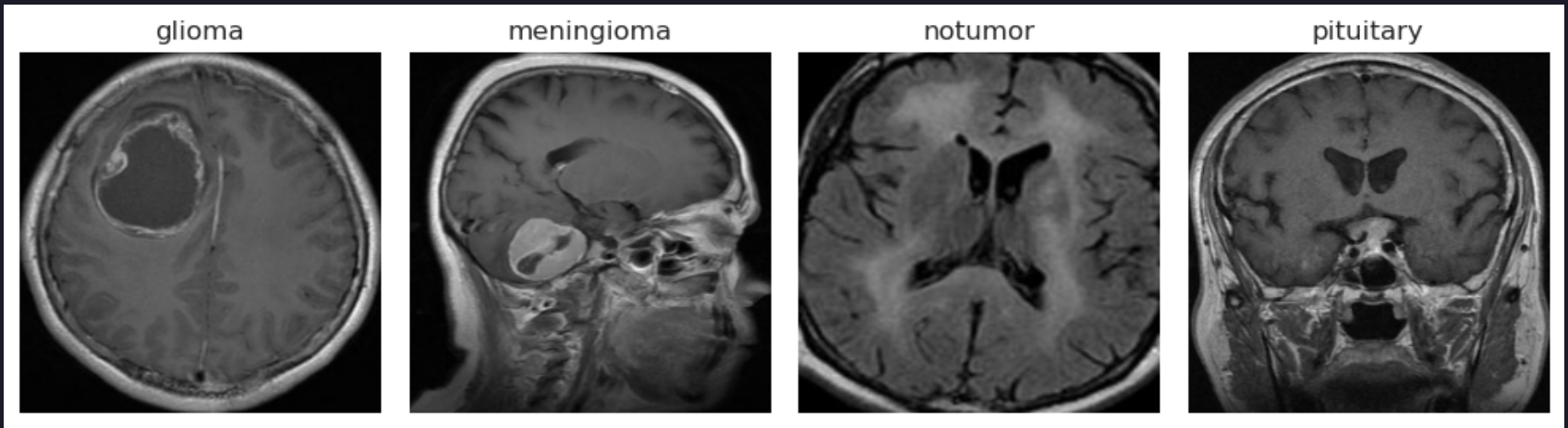
Introduction

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
   - AlexNet
   - VGG16
   - Custom CNN
   - VIT
3. Segmentation
   - U-Net Models

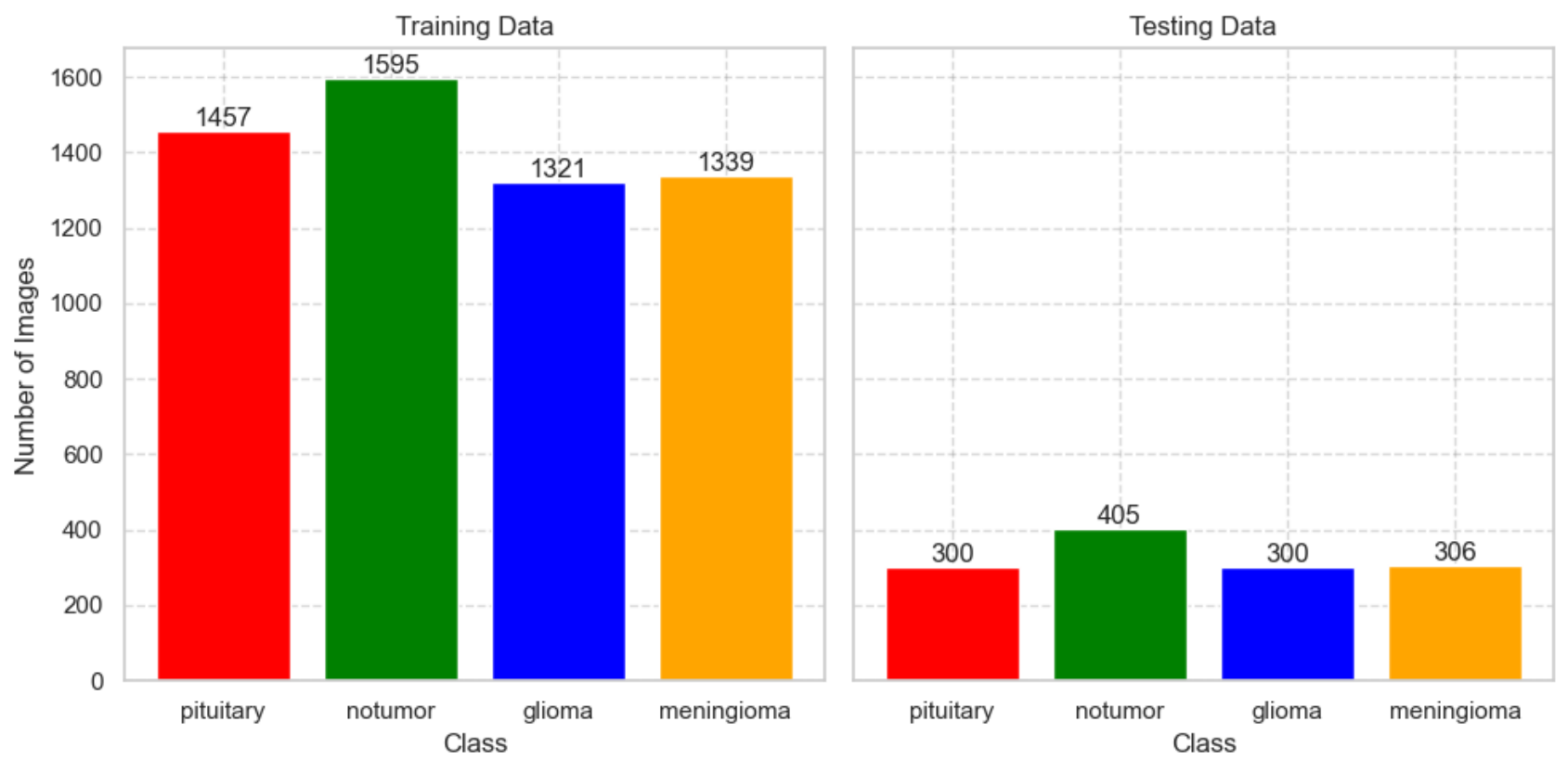
Brain Tumor MRI Dataset

- 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

Theses 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)

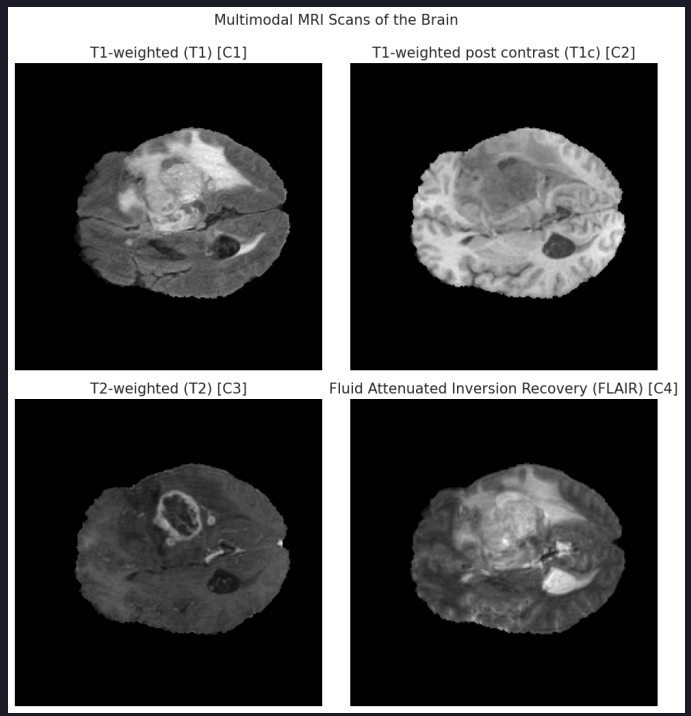
$$155 \cdot 369 = 57195$$

- we used 90% of the dataset for training and 10% for testing

BraTS 2020 Dataset

Images have 4 channels:

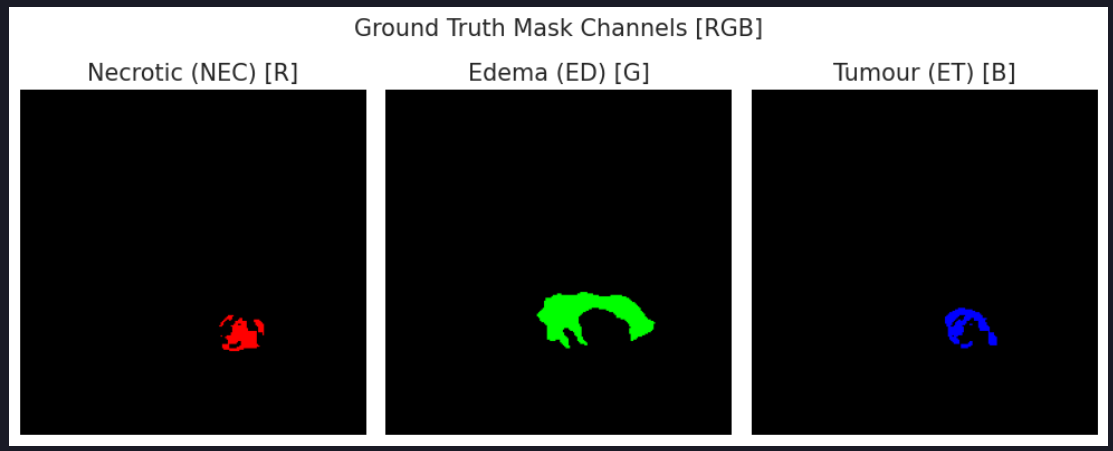
1. **T1 weighted (T1)** good for visualizing the brain but not the tumor
2. **T1 weighted with contrast (T1c)** taken with the same tecnique as T1 but with contrast
3. **T2 weighted (T2)** good for visualizing the edema
4. **Fluid Attenuated Inversion Recovery (FLAIR)** improves the visualization of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



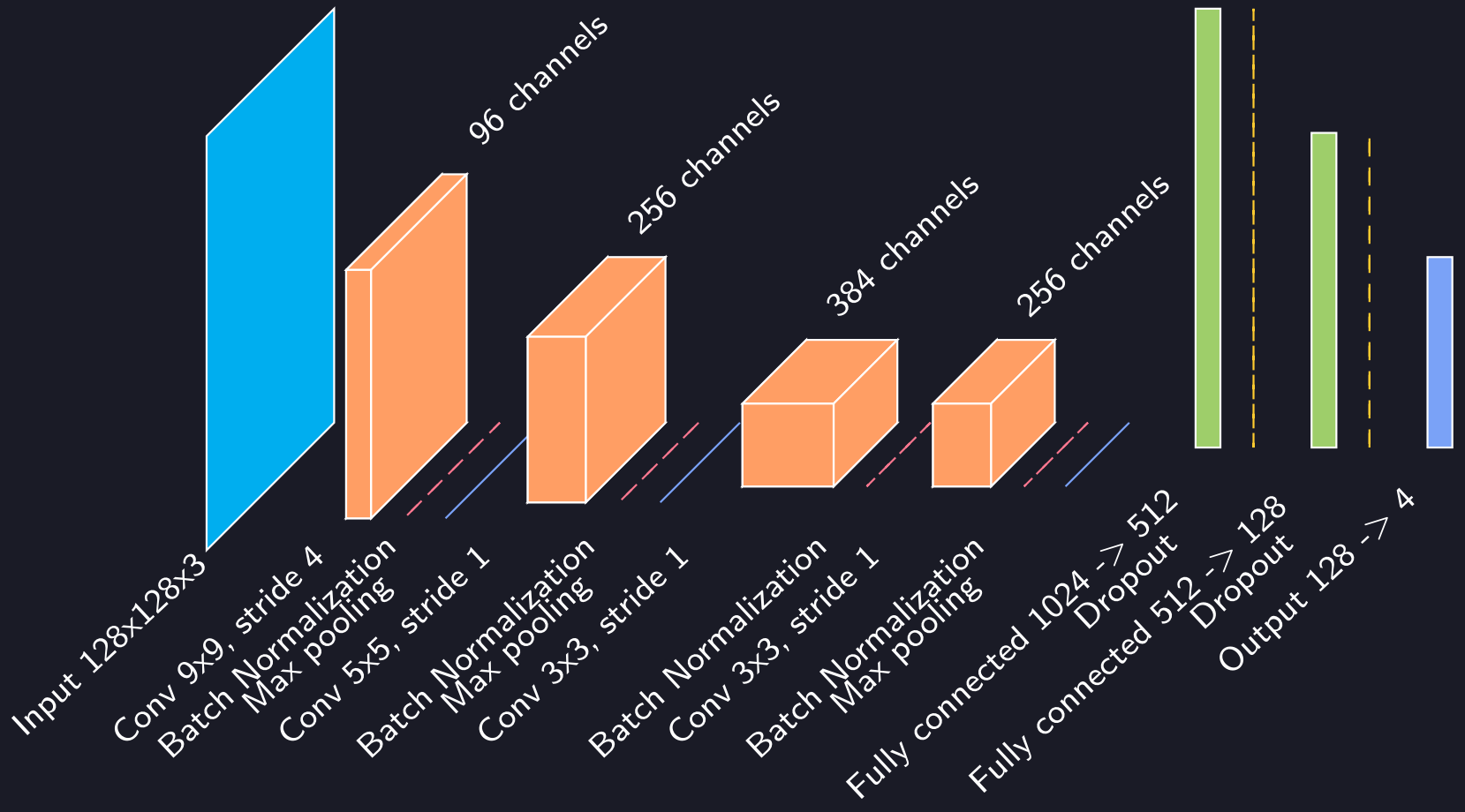
BraTS 2020 Dataset

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



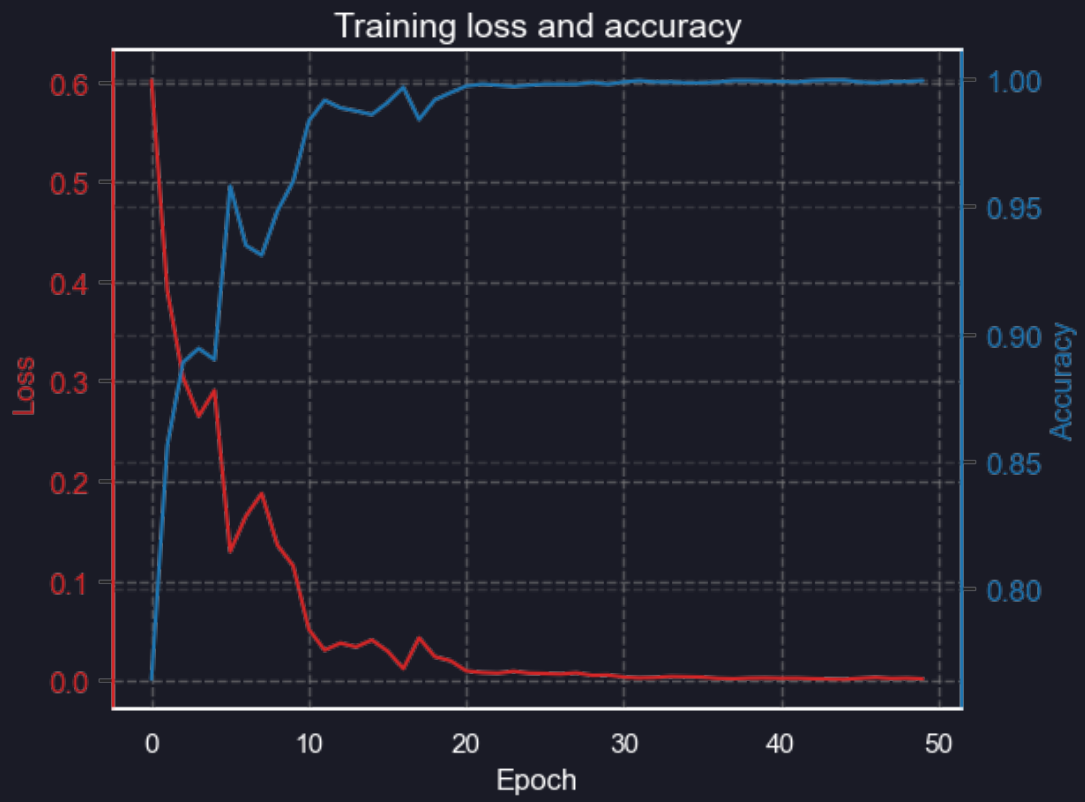
Number of parameters: 3001156

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

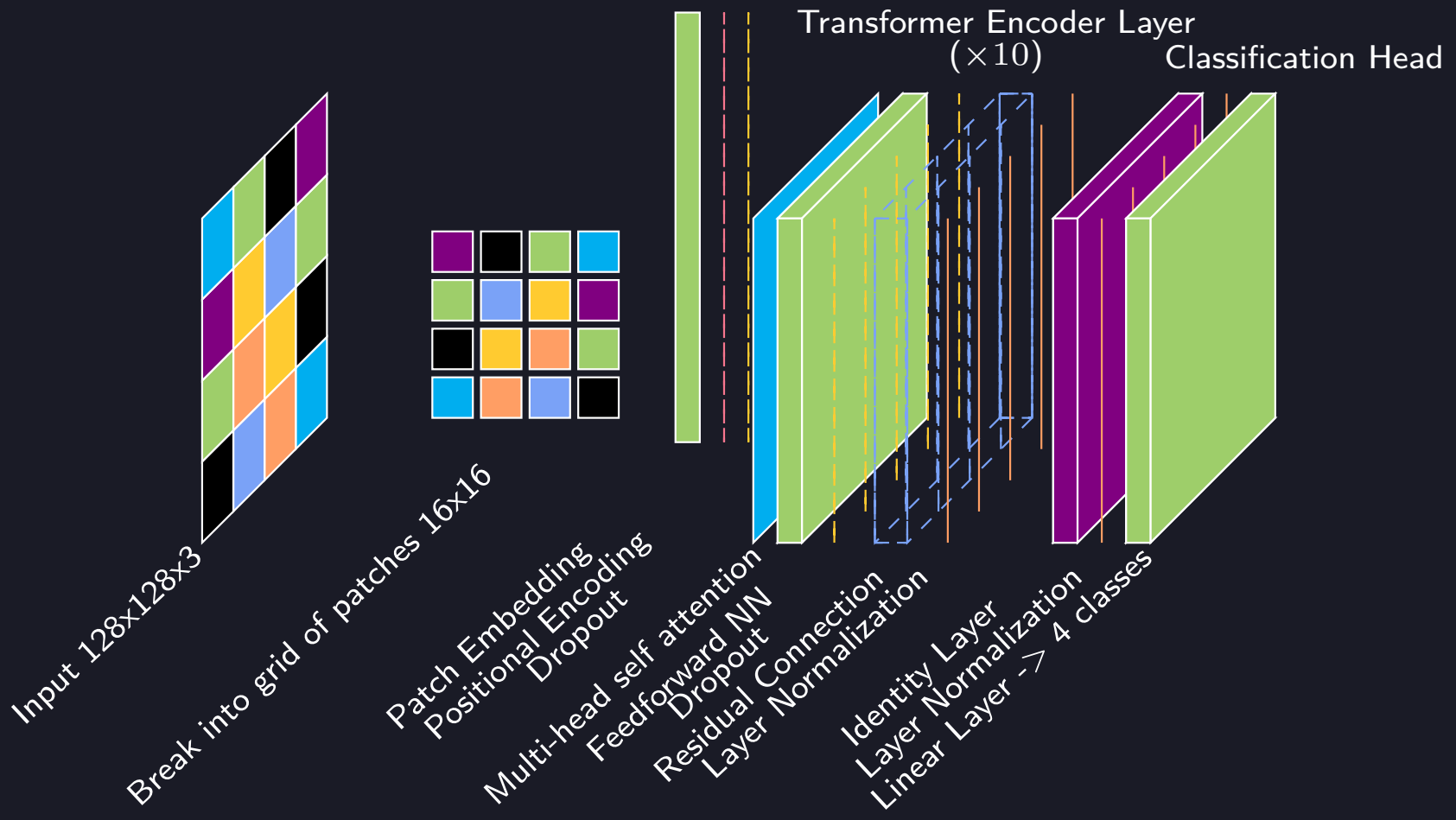


- Final training loss: 1.4×10^{-3}
- Final training accuracy: 99.9%

Confidence and Test Accuracy

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

VIT Architecture



Number of parameters: 21459460

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- **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

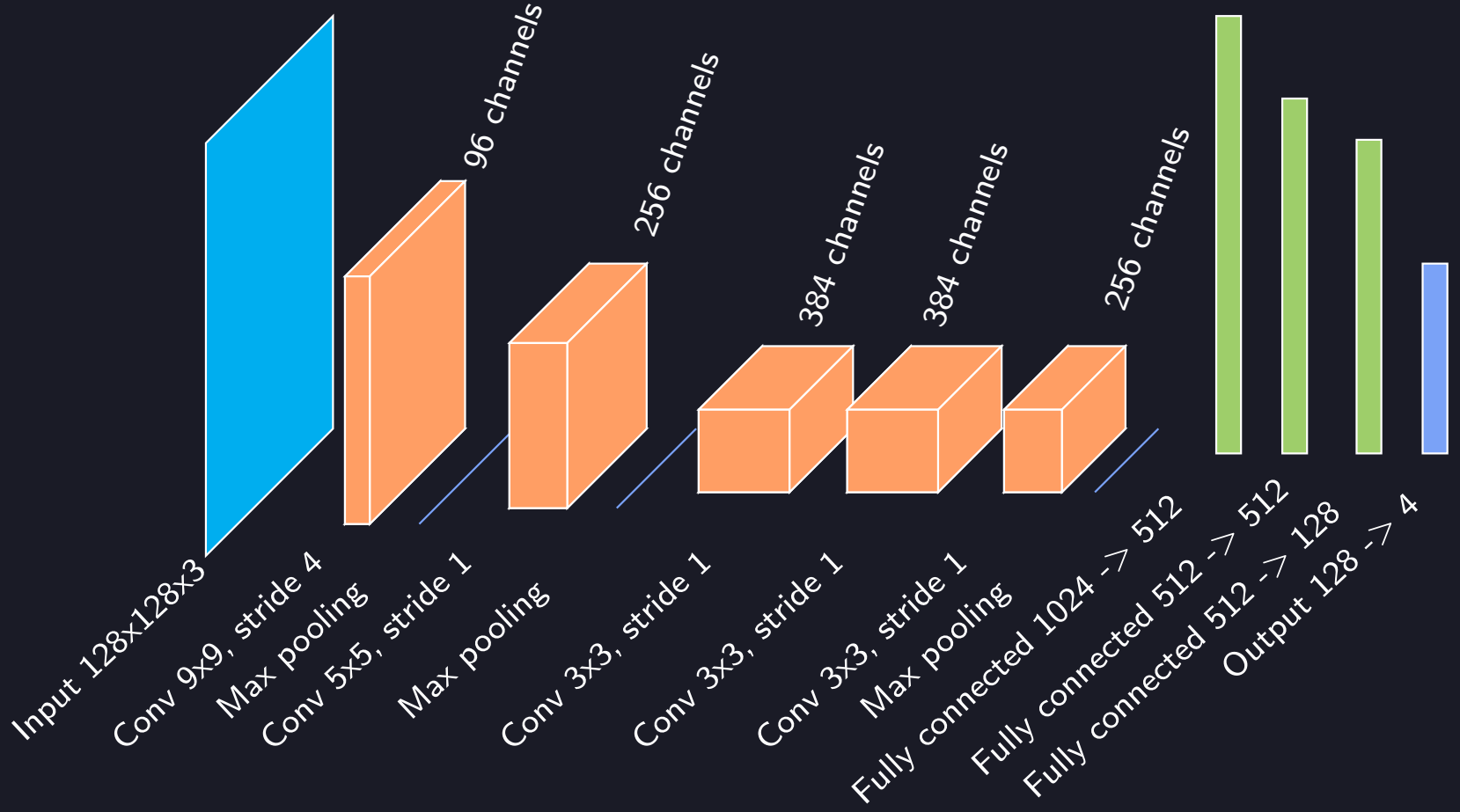
Training Loss and Accuracy

- 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%

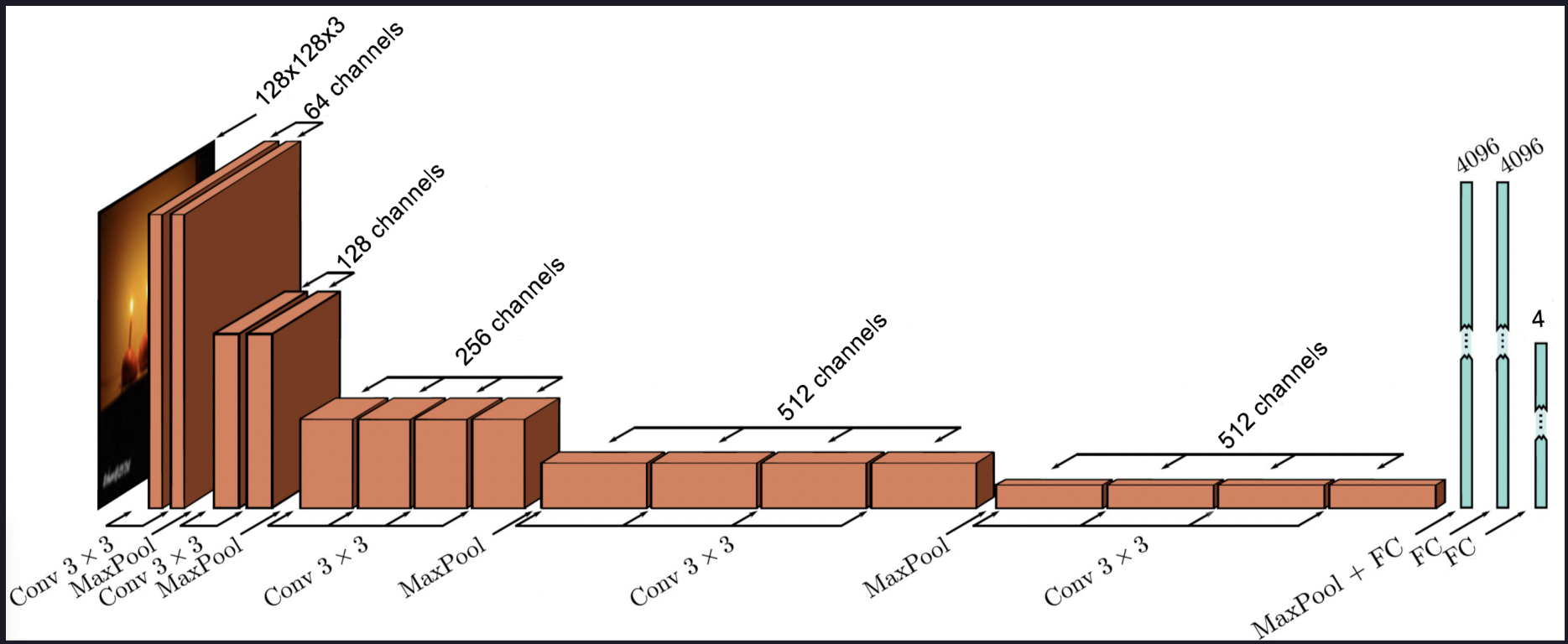
AlexNet



Number of parameters: 4589316

Dropout rate: 0.4

VGG



Number of parameters: 65070916
Dropout rate: 0.5

Setup Differences

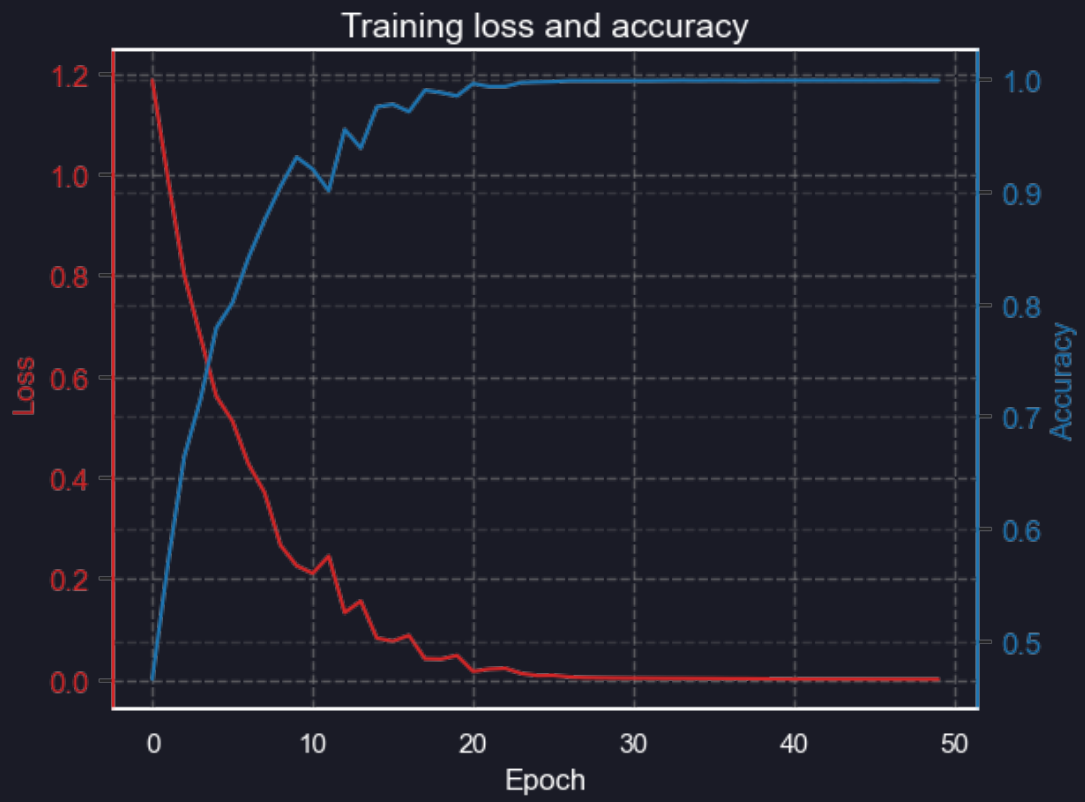
Model	Data augmentation	LR Scheduler	Activation	L2 reg.
CustomCNN	Yes	Yes	*Mish*	Yes
AlexNet	No	Yes	*ReLU*	Yes
VGG16	No	No	*ReLU*	No
VIT	Yes	Yes	*Mish*	Yes

- 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

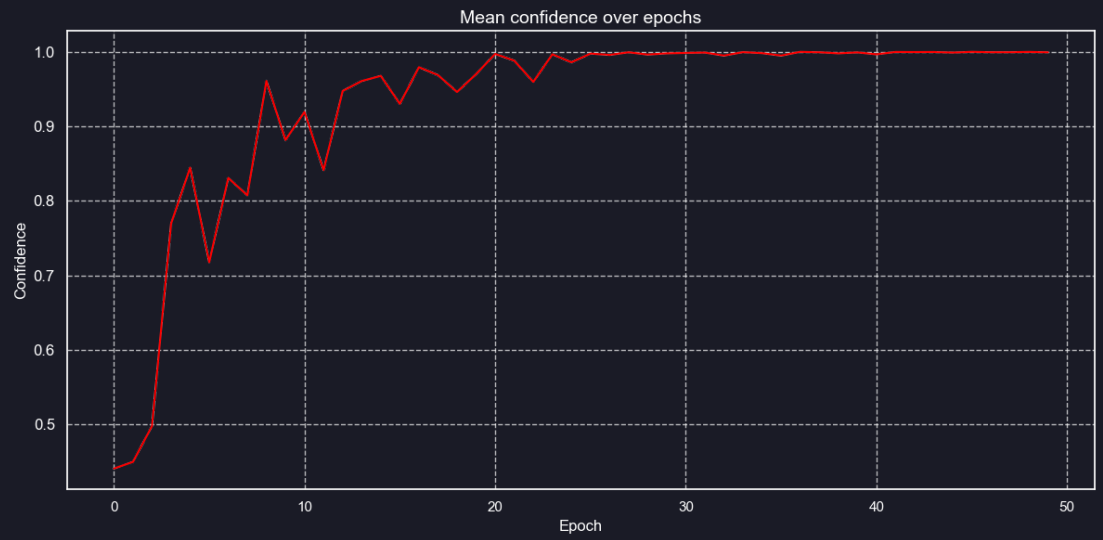
- **Loss function**: Cross-entropy loss $L(y, \hat{y}) = -\sum_i y_i \log(\hat{y}_i)$
- **Accuracy**: Number of correct predictions divided by the total number of predictions
- **Confidence**: Given by the Softmax function applied to the net output $S(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$

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%

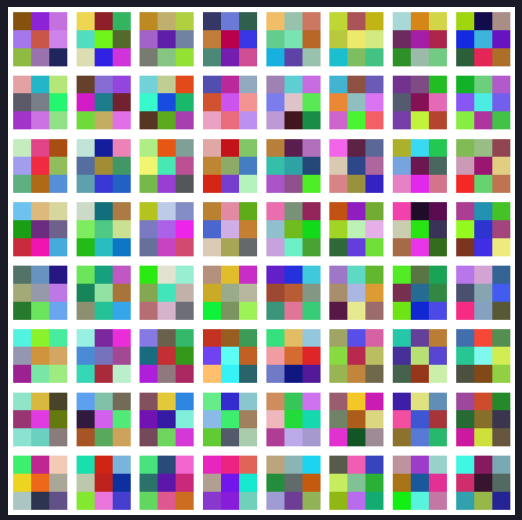
Note that these are the values reached during the last epoch.

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



U-Net Models

3 models for the segmentation task:

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

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- **Attention U-Net**: *attention mechanism added*

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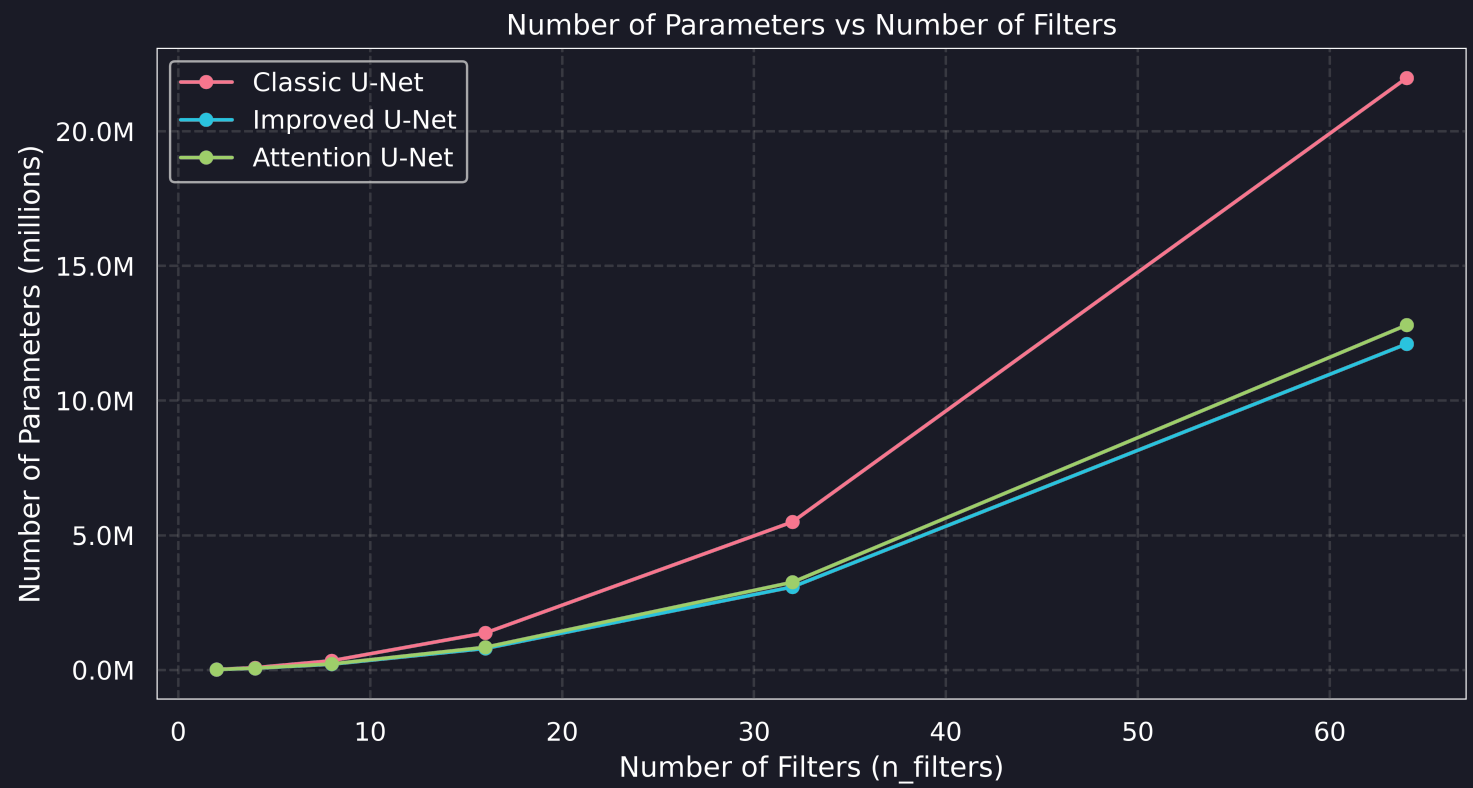
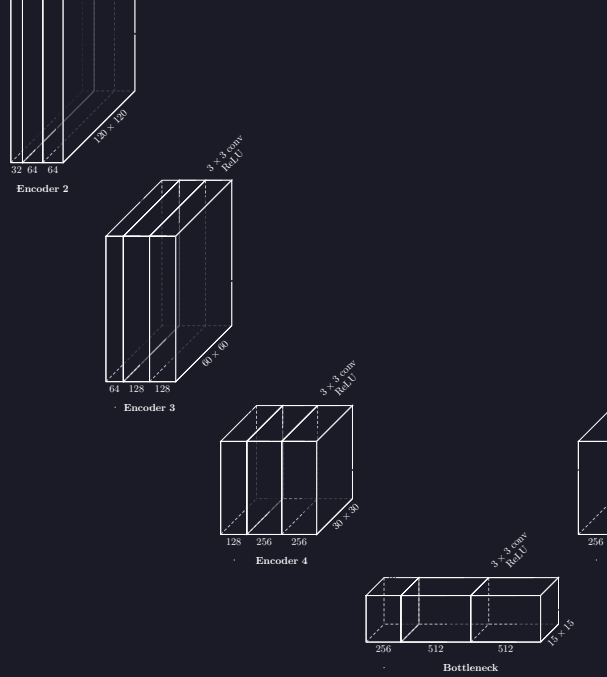
- **Classic U-Net**: *baseline U-Net model architecture*
- **Improved U-Net**: *small improvements, fewer parameters*
- **Attention U-Net**: *attention mechanism added*



Classic U-Net



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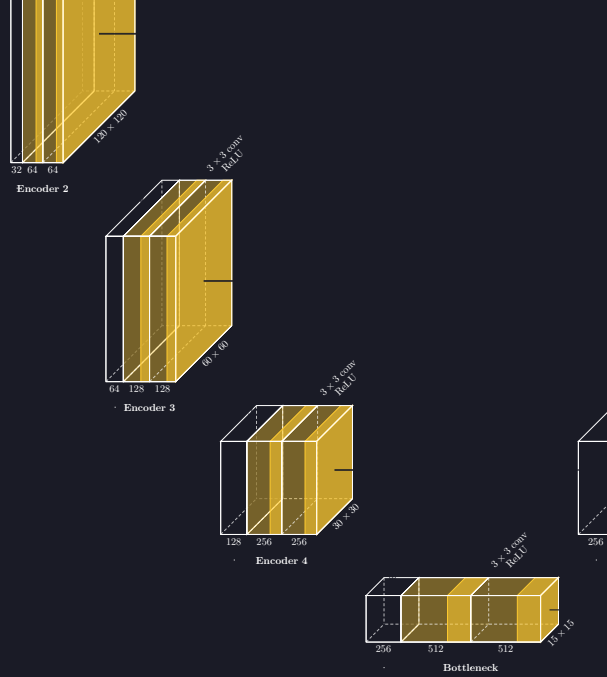

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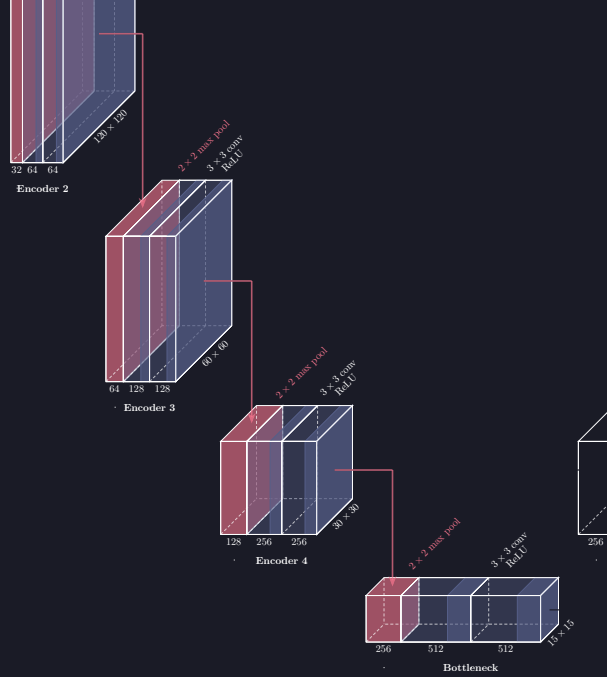
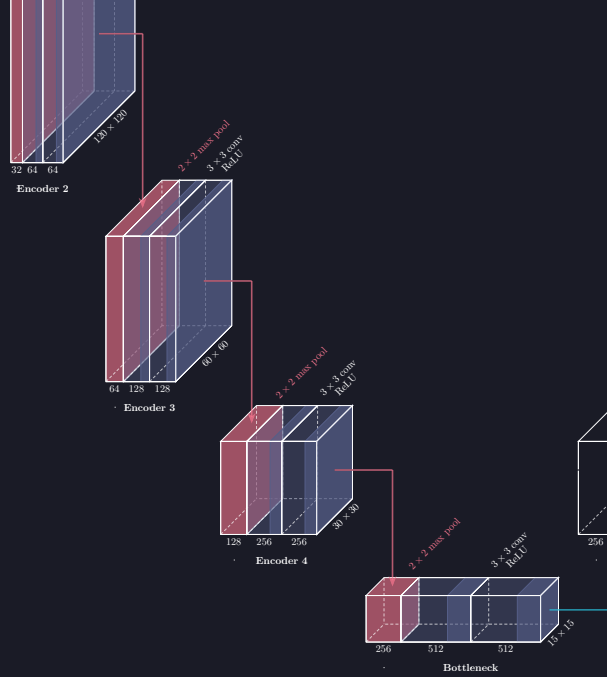
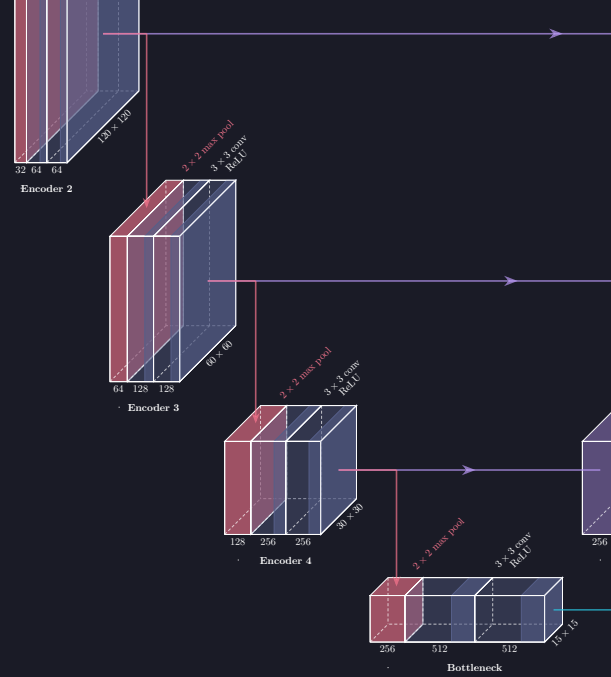


Classic U-Net



Classic U-Net

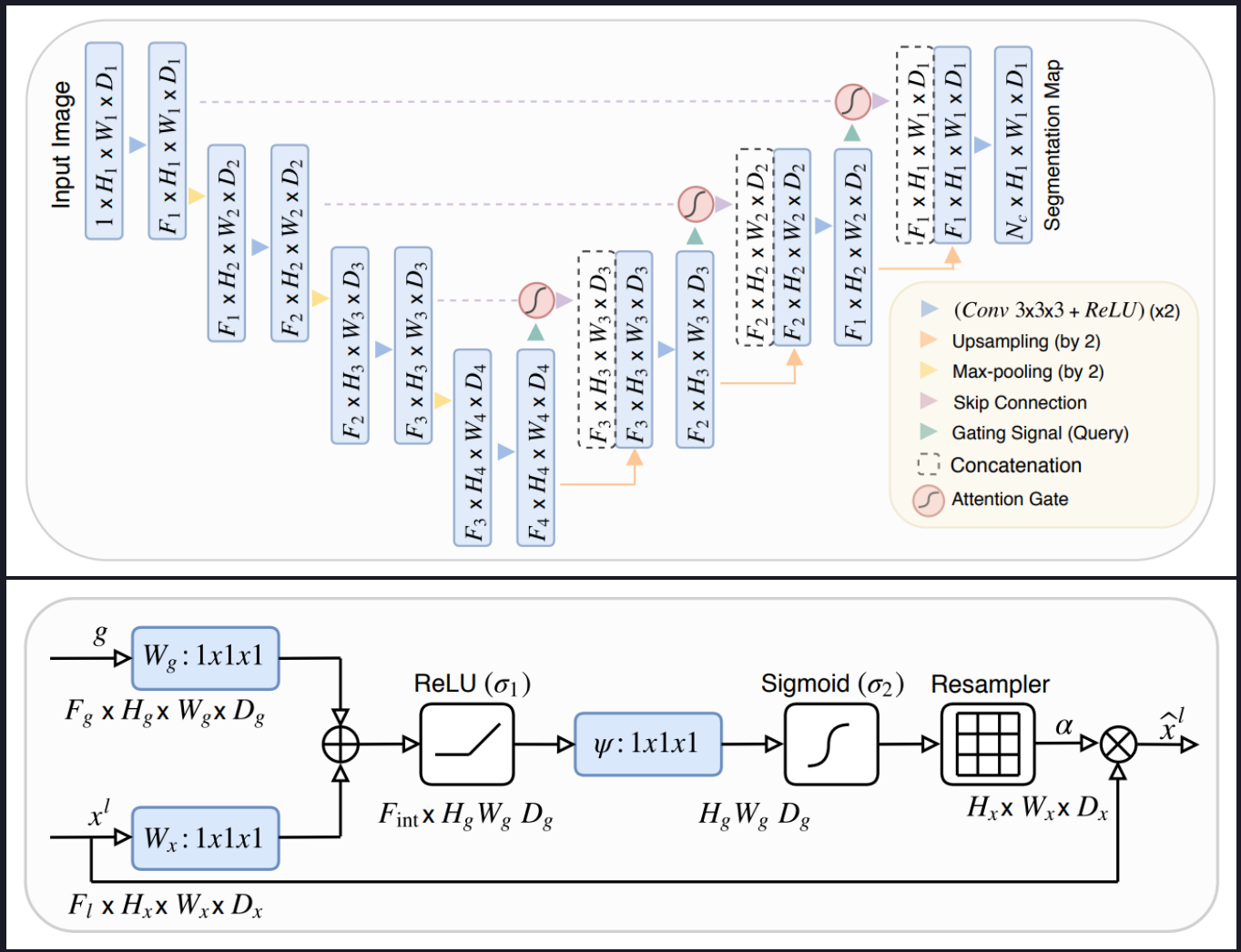


Improved U-Net

Small improvements from previous $\rightarrow$ to reduce n° 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

Attention U-Net

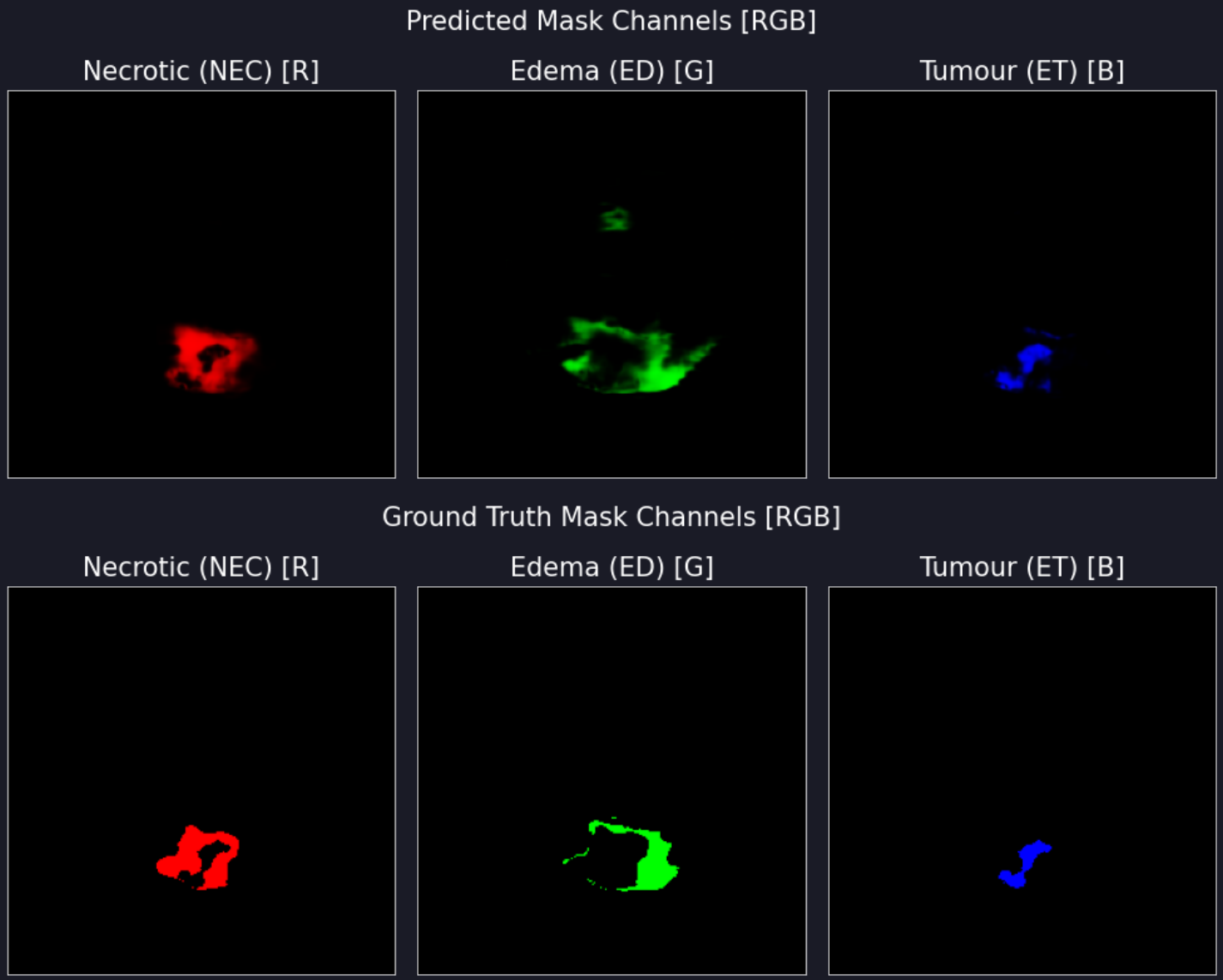


Training Details

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

Visualizing a prediction



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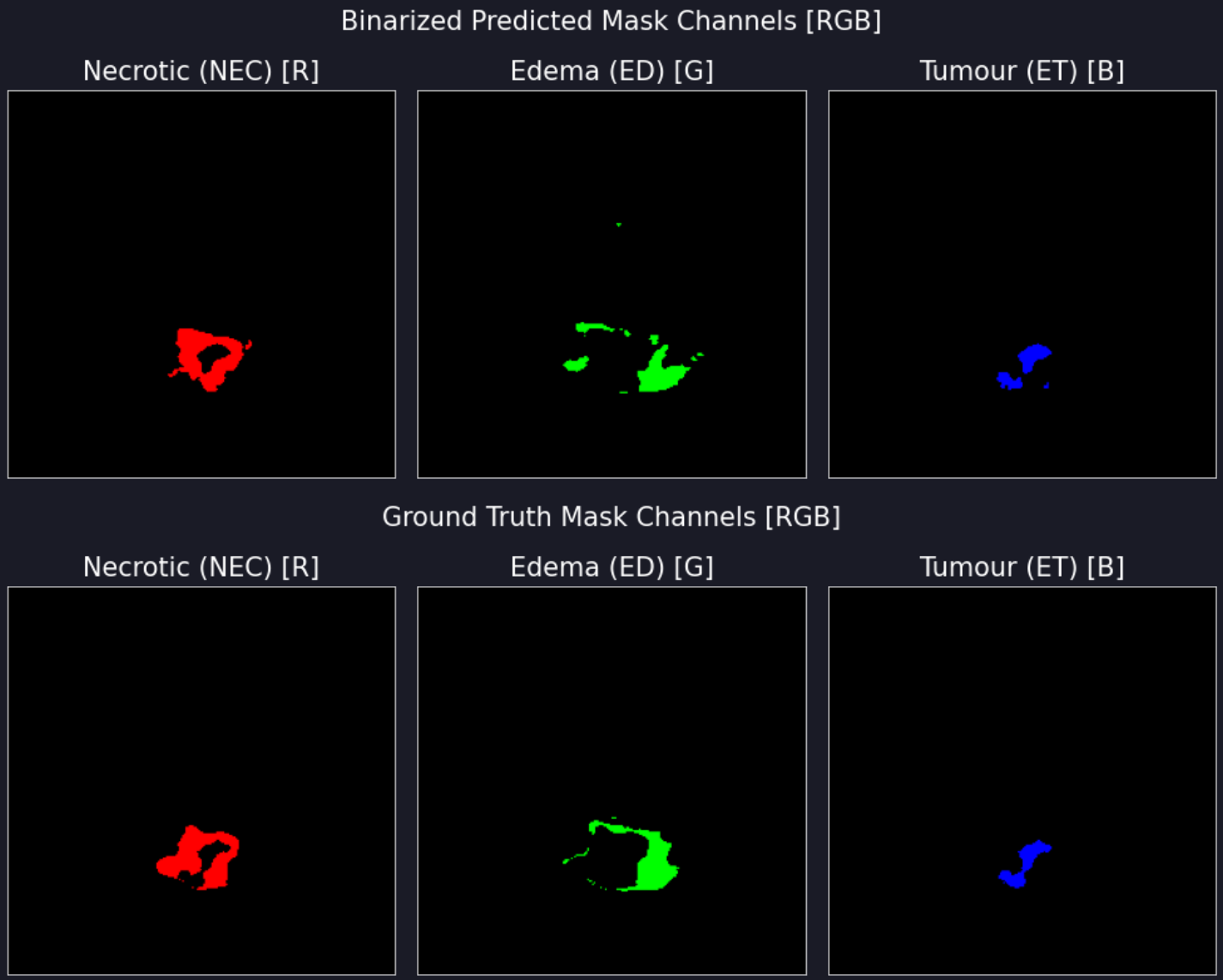


Performance Assessment

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

Dice Coefficient

"overlap" metric

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

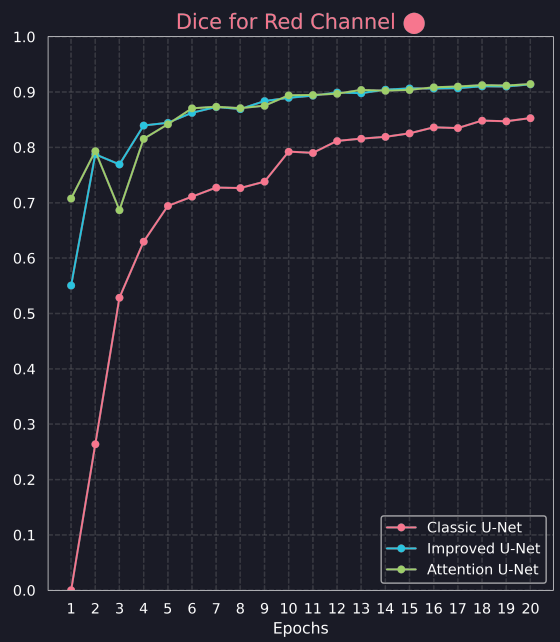
Precision

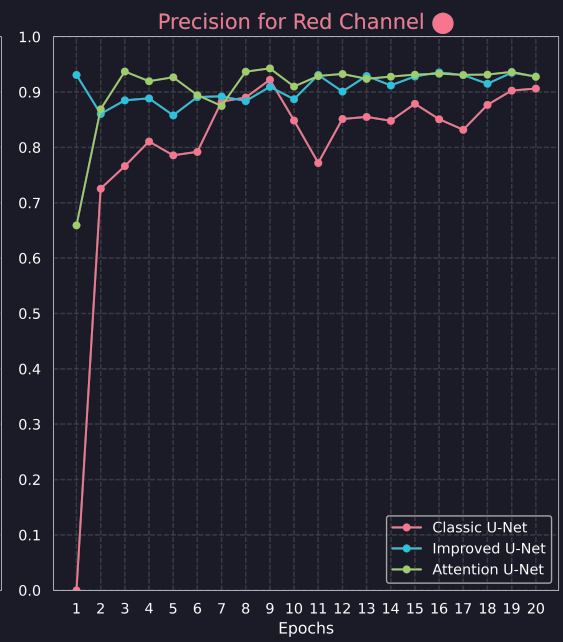
prediction quality

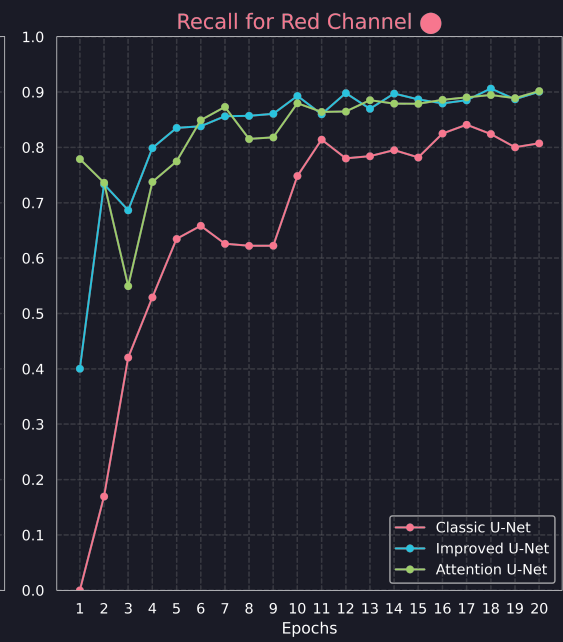
$$\text{Recall} = \frac{TP}{TP+FN}$$

Recall

prediction quantity







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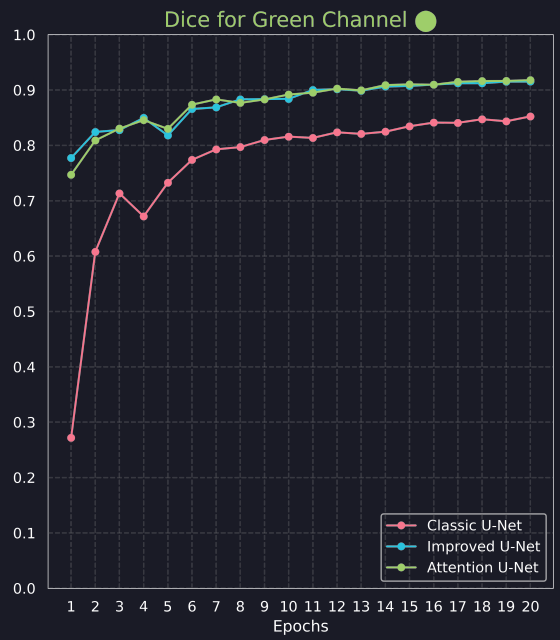

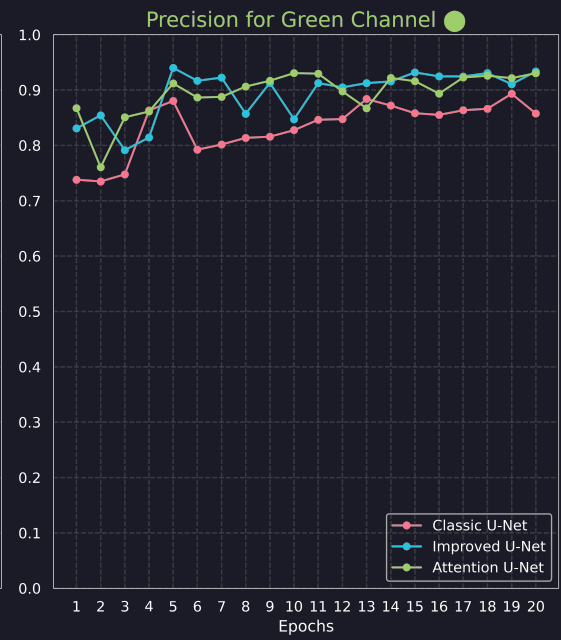

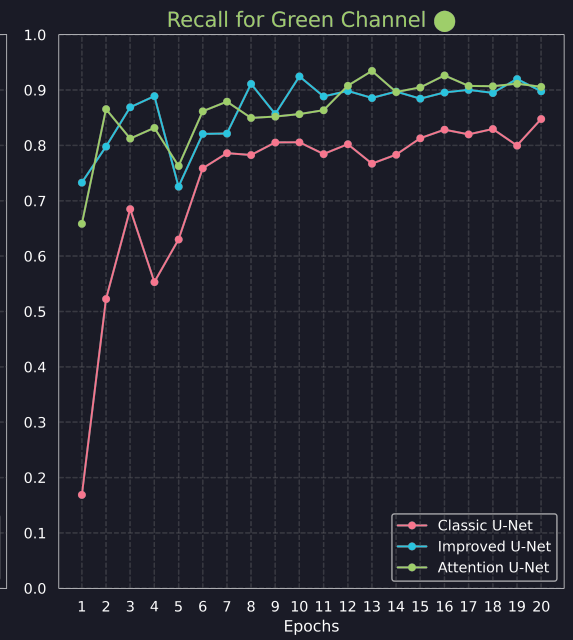

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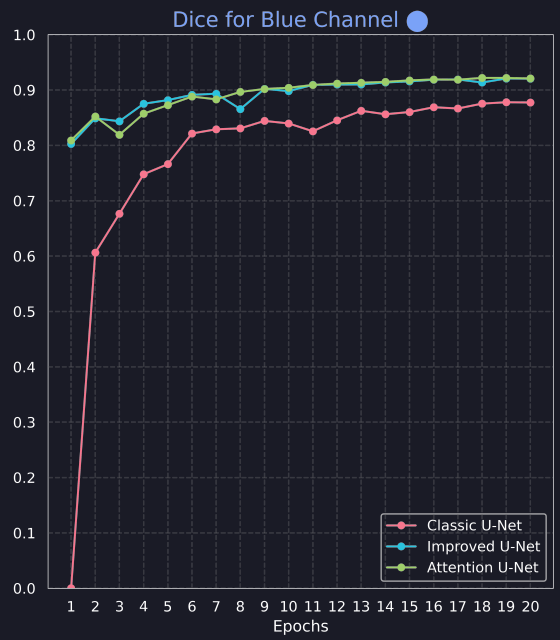

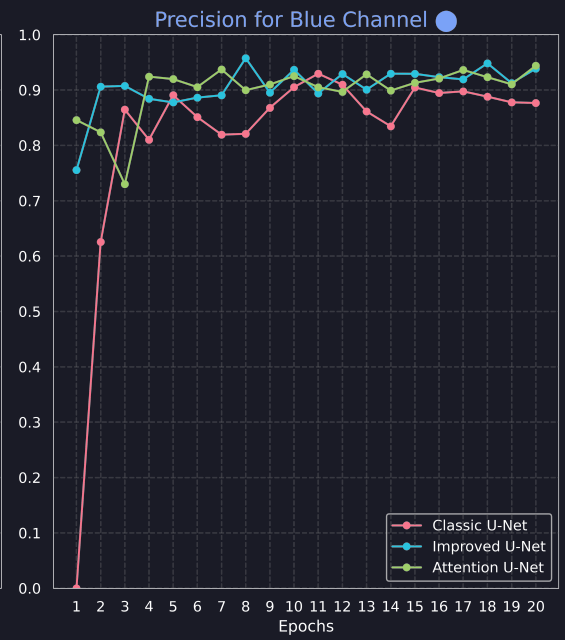

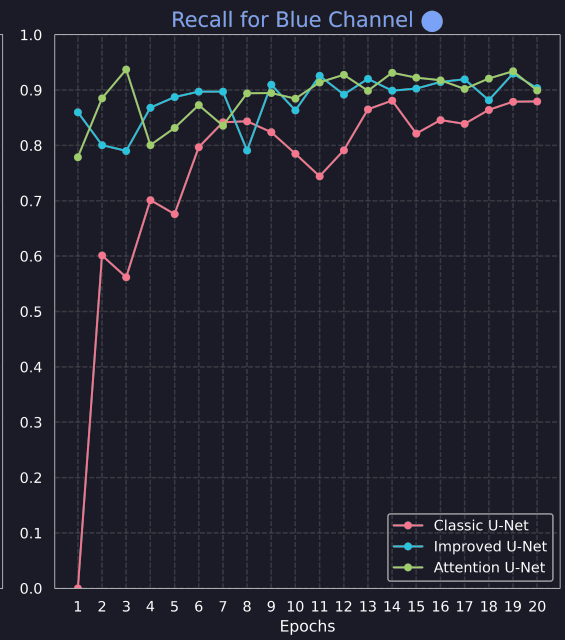

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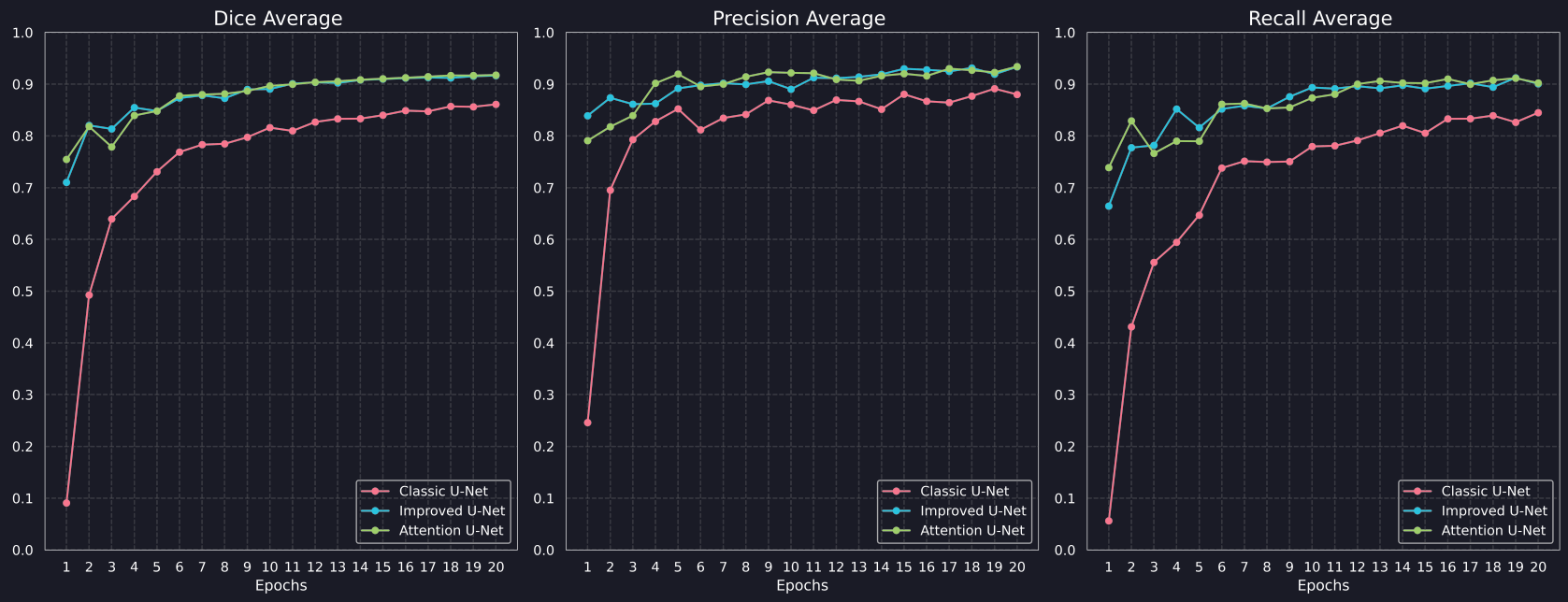

Visualizing Attention Maps