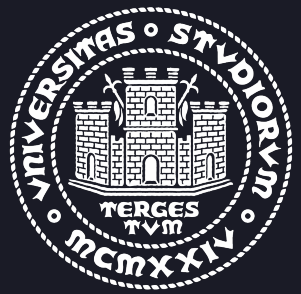
Multi-Model Approach for Brain Tumor Classification and Segmentation

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

October, 2024



Stefano Lusardi Marco Tallone Piero Zappi

Introduction

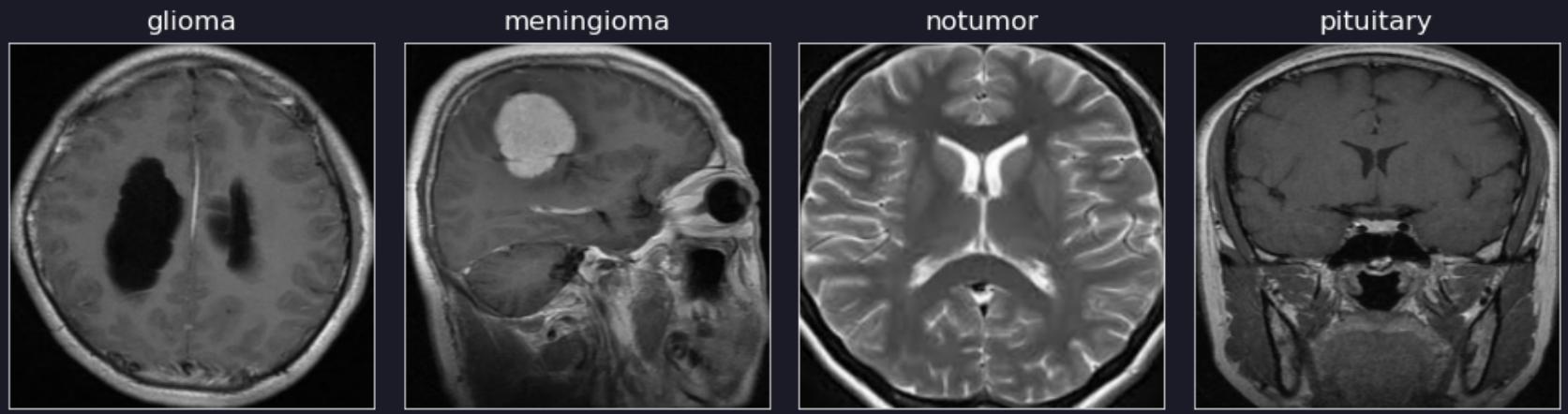
A deep learning project for brain tumor classification and segmentation on MRI images using CNN, U-Net, and VIT models.

1. **Datasets 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**

Brain Tumor MRI Dataset

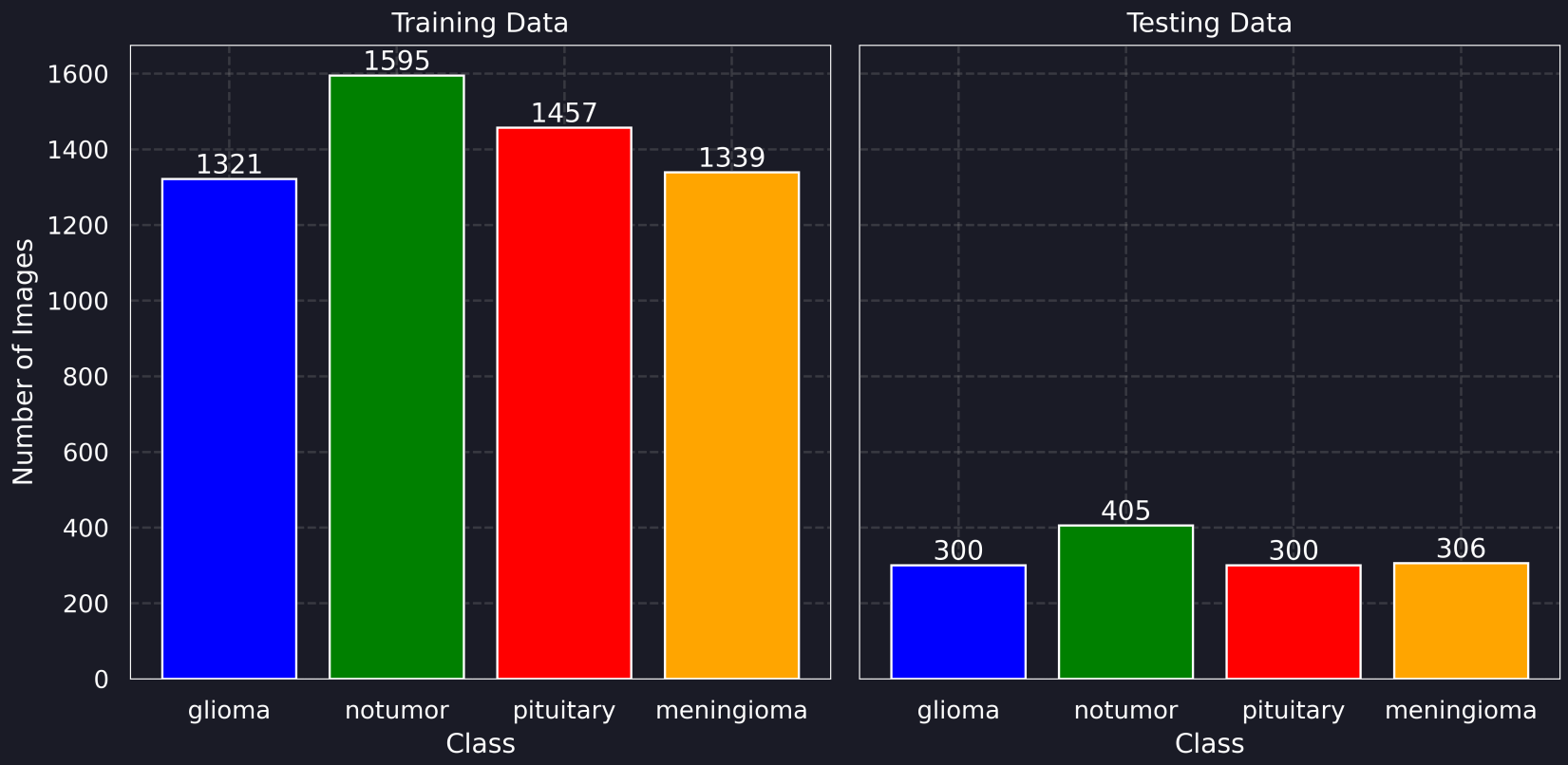
Classification task dataset

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



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

Segmentation task dataset

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

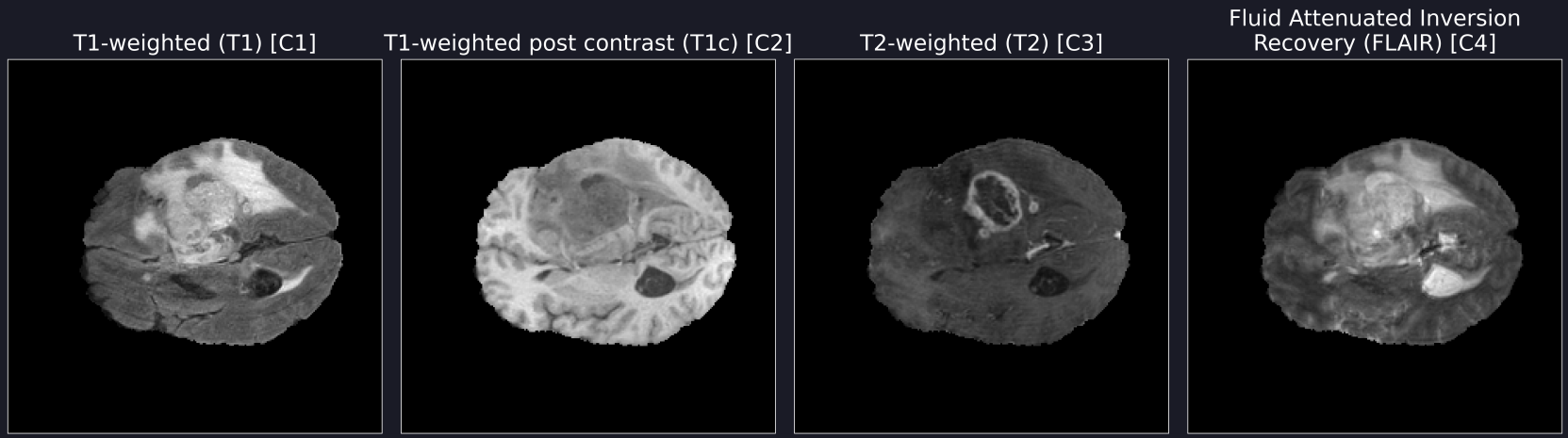
$$155 \cdot 369 = 57195$$

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

BraTS 2020 Dataset

Images have 4 channels:

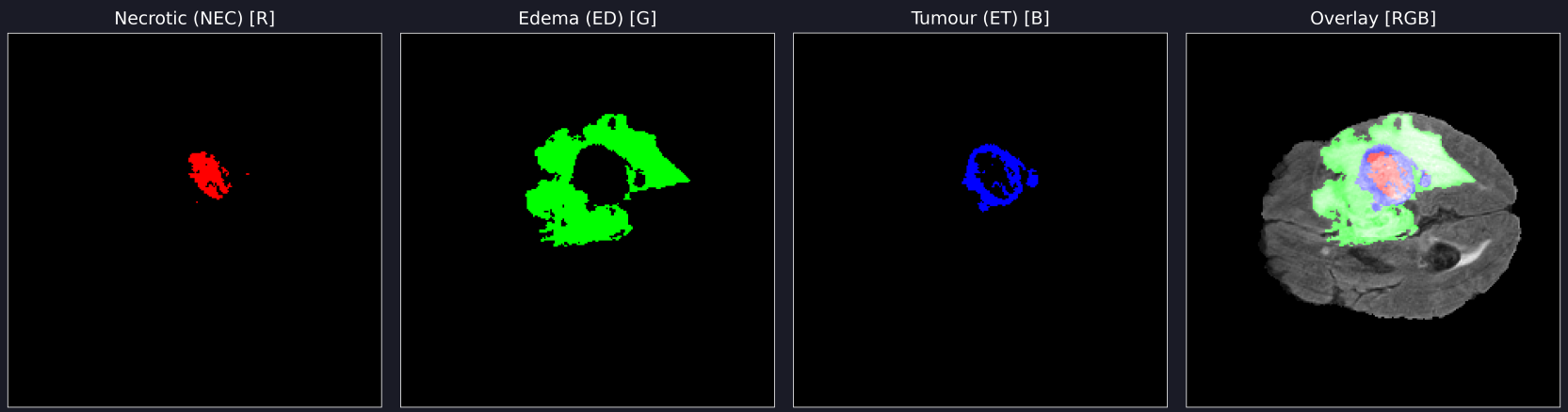
1. **T1 weighted (T1)**: *good for visualizing the brain but not the tumor*
2. **T1 weighted with contrast (T1c)**: *taken with the same technique as T1 but with contrast*
3. **T2 weighted (T2)**: *good for visualizing the edema*
4. **Fluid Attenuated Inversion Recovery (FLAIR)**: *improves the visualization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



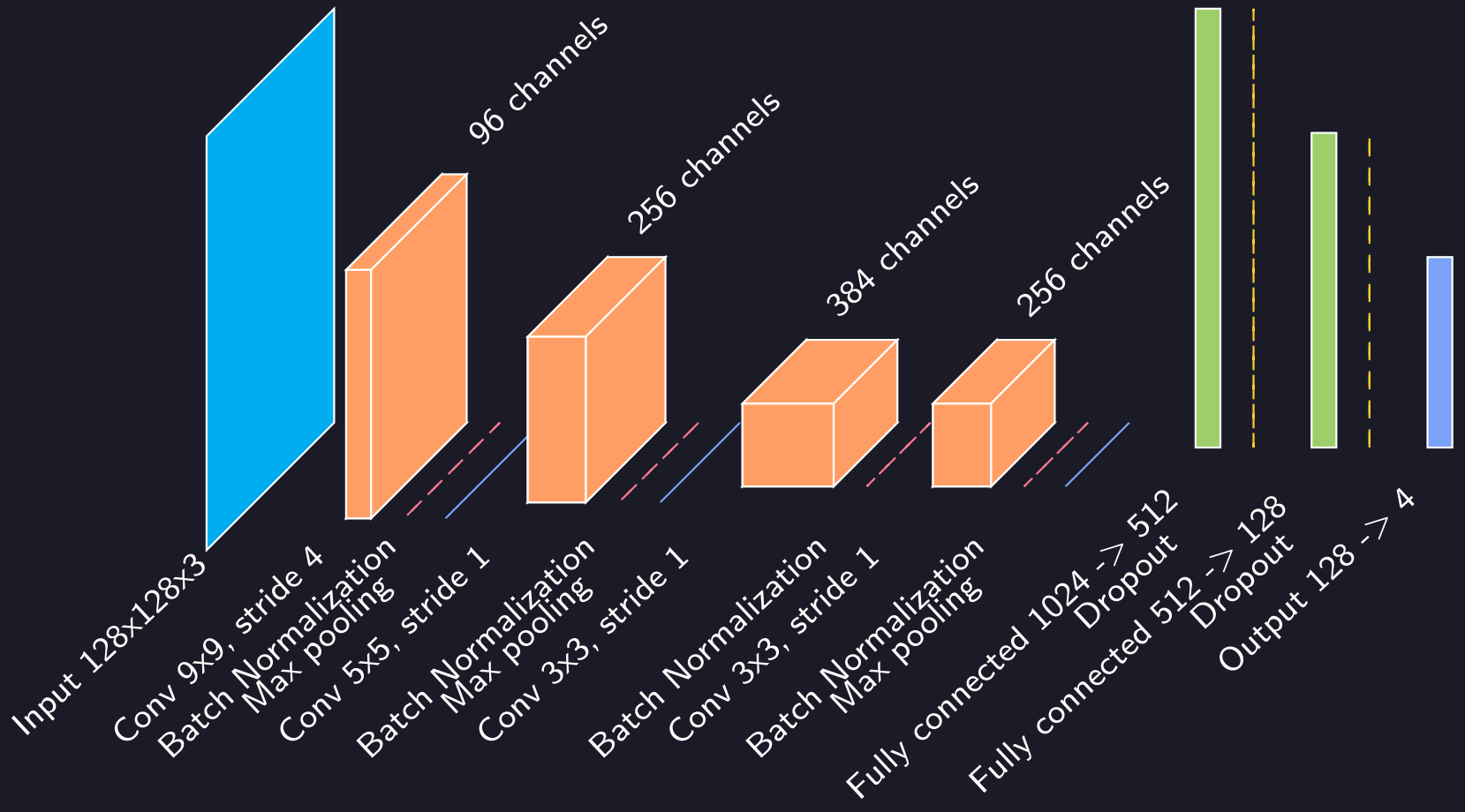
BraTS 2020 Dataset

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)**



Custom CNN Architecture



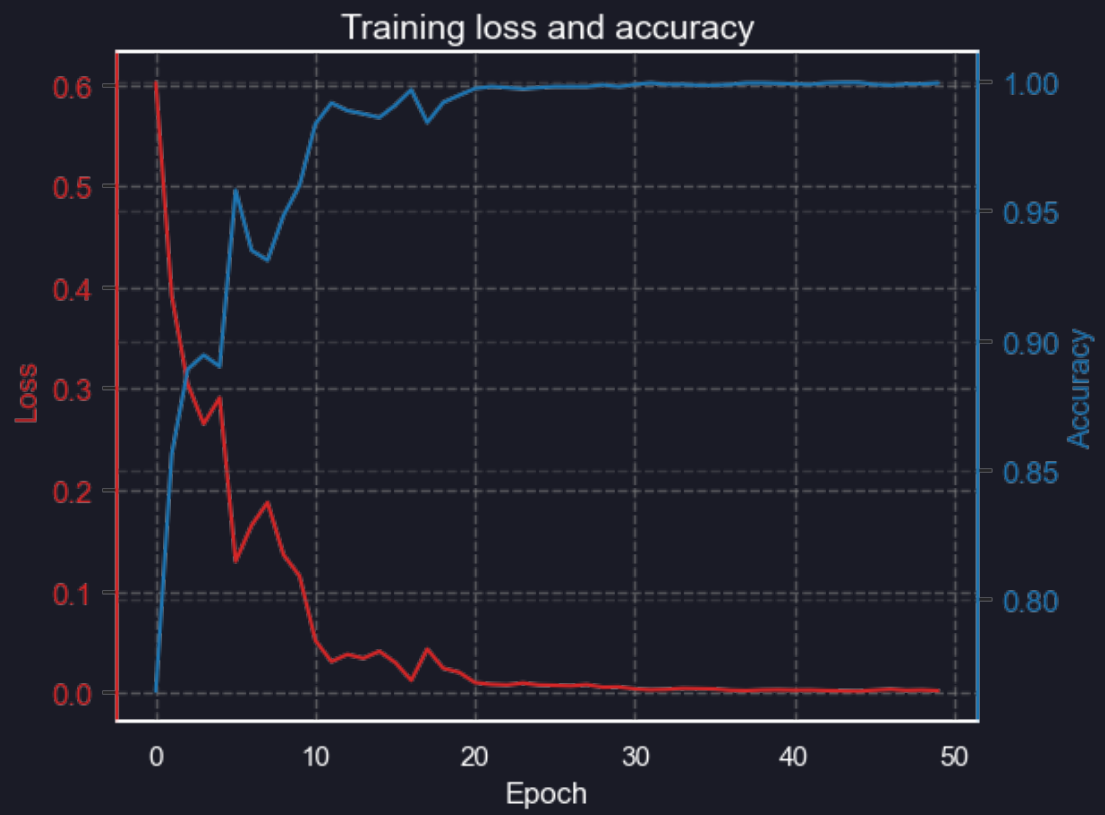
Number of parameters: 3001156

Training Details

Costum CNN model training parameters:

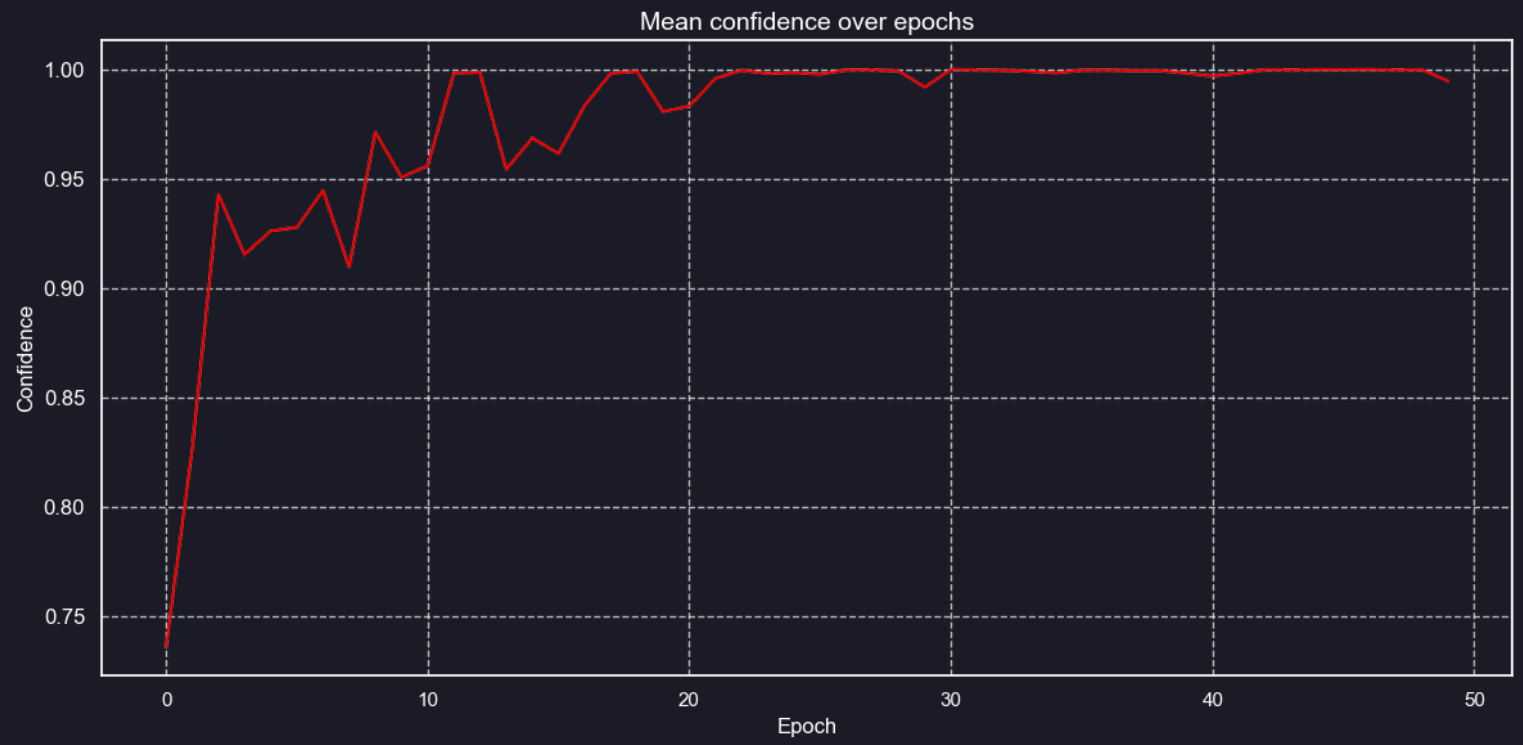
- **Epochs**: 50
- **Optimizer**: Adam (weight decay 1×10^{-5})
- **Scheduler**: stepLR (step size 10, gamma 0.5)
- **Loss function**: Cross-entropy
- **Learning rate**: 1×10^{-4}
- **Batch size**: 64 (both training and validation)
- **Activation function**: Mish
- **Dropout rate**: 0.4
- **Image size**: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

Training Loss and Accuracy



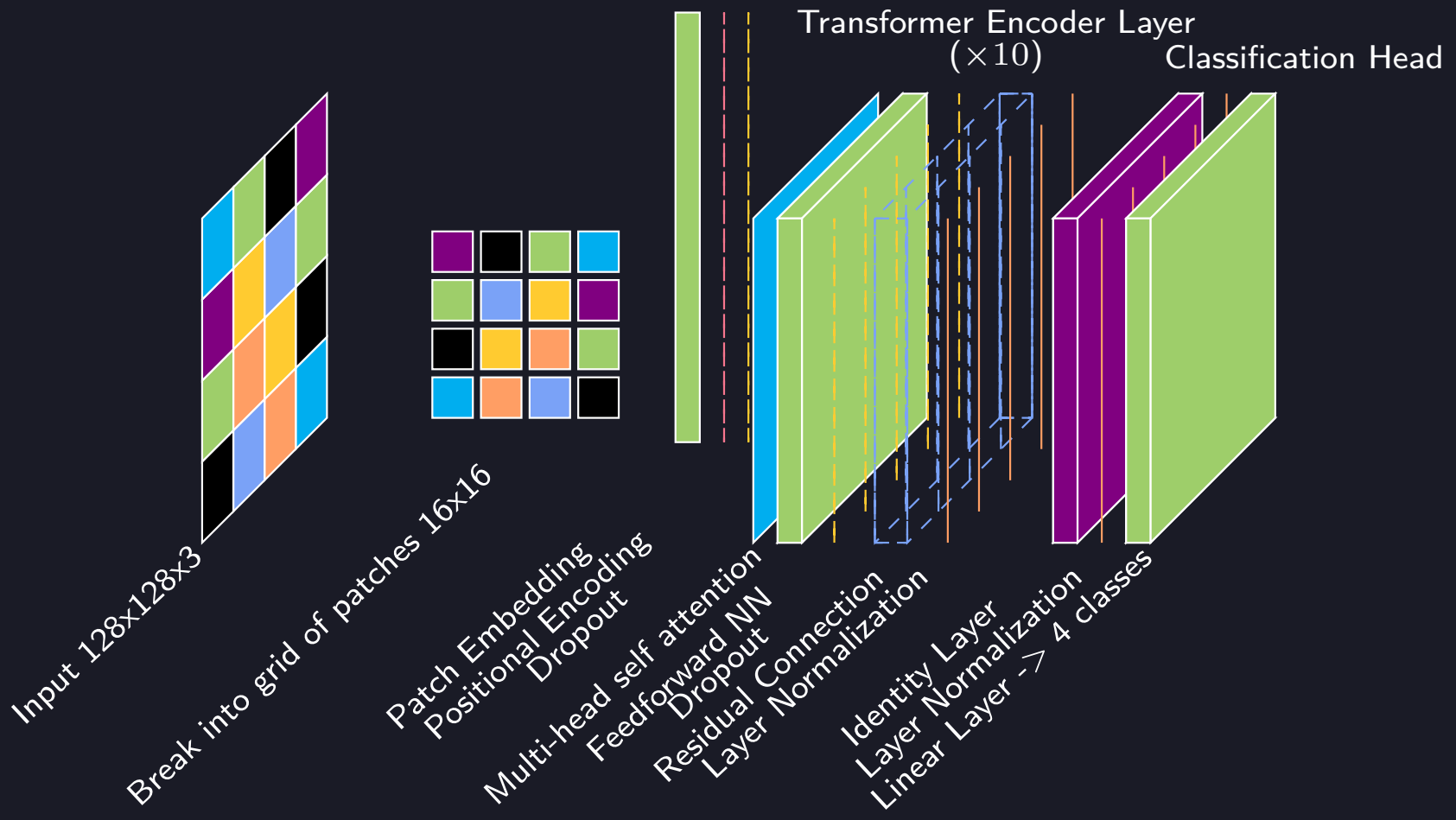
- Final training loss: 1.4×10^{-3}
- Final training accuracy: 99.9%

Confidence and Test Accuracy



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

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

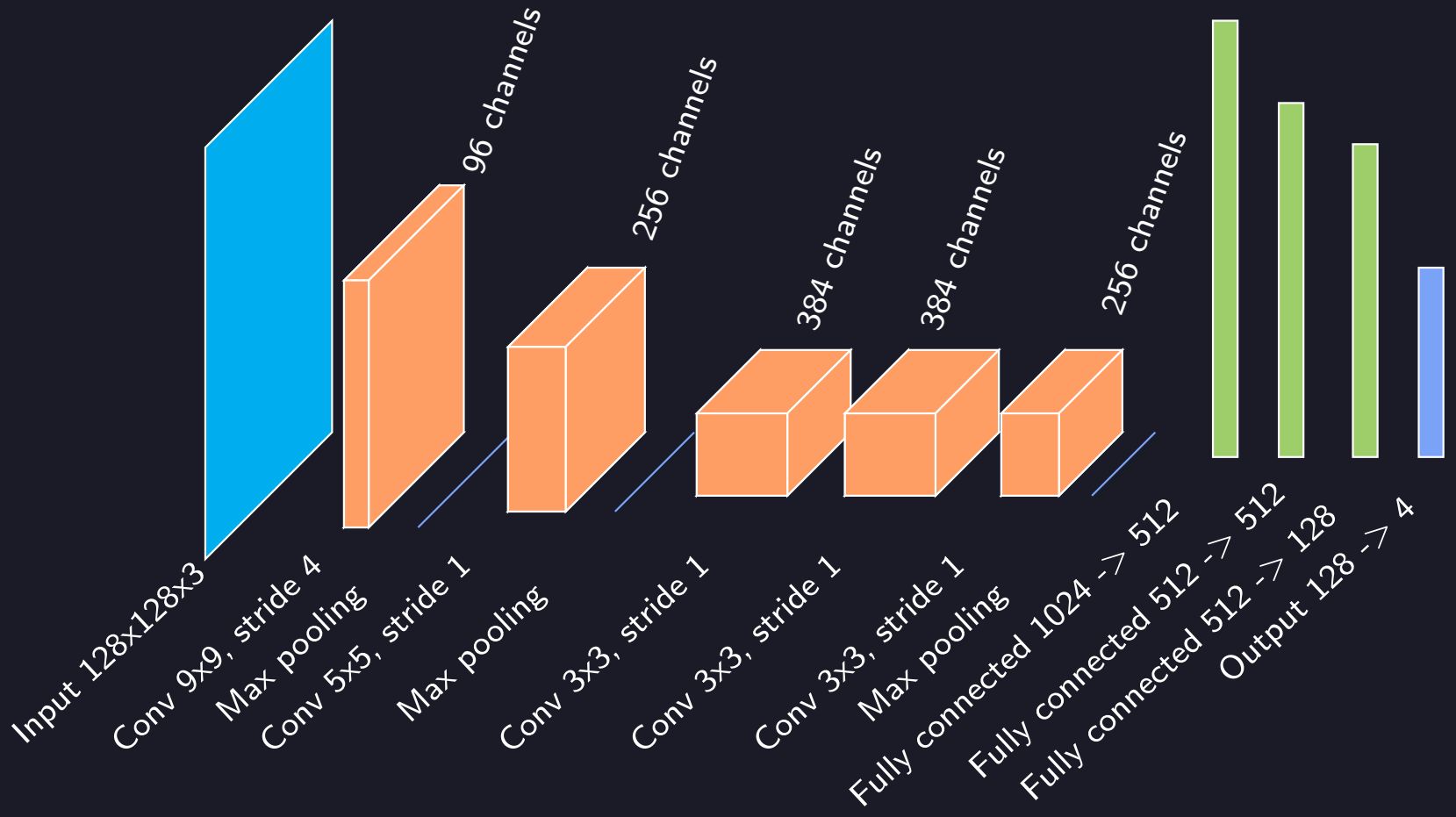
Training Loss and Accuracy

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

Confidence and Test Accuracy

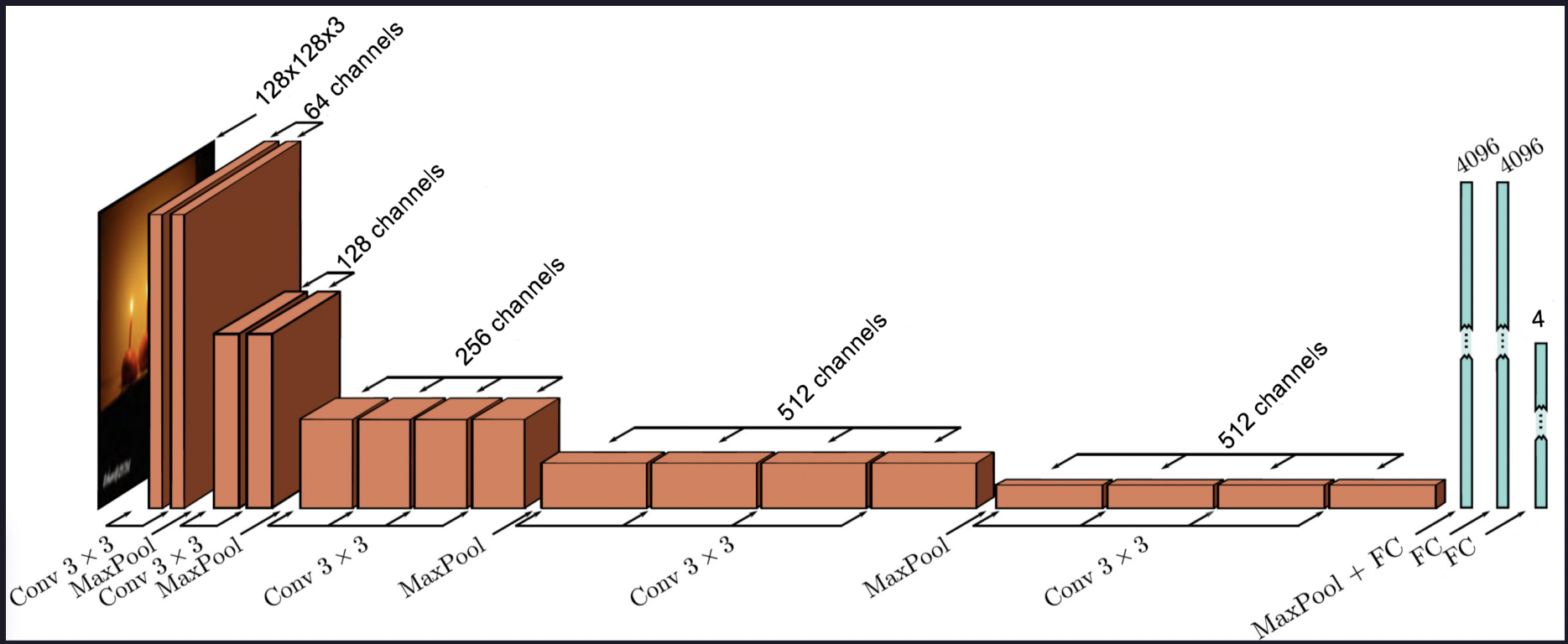
- Final training confidence: 96%
- Final test confidence: 93%
- Final test accuracy: 88%

AlexNet



Number of parameters: 4589316

VGG



Number of parameters: 65070916
Dropout rate: 0.5

Setup Differences

Model	Data augmentation	Scheduler	Activation	L2 regularization
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** also has the highest dropout rate (0.5)

Performance Assessment

Loss Function: Cross-entropy loss

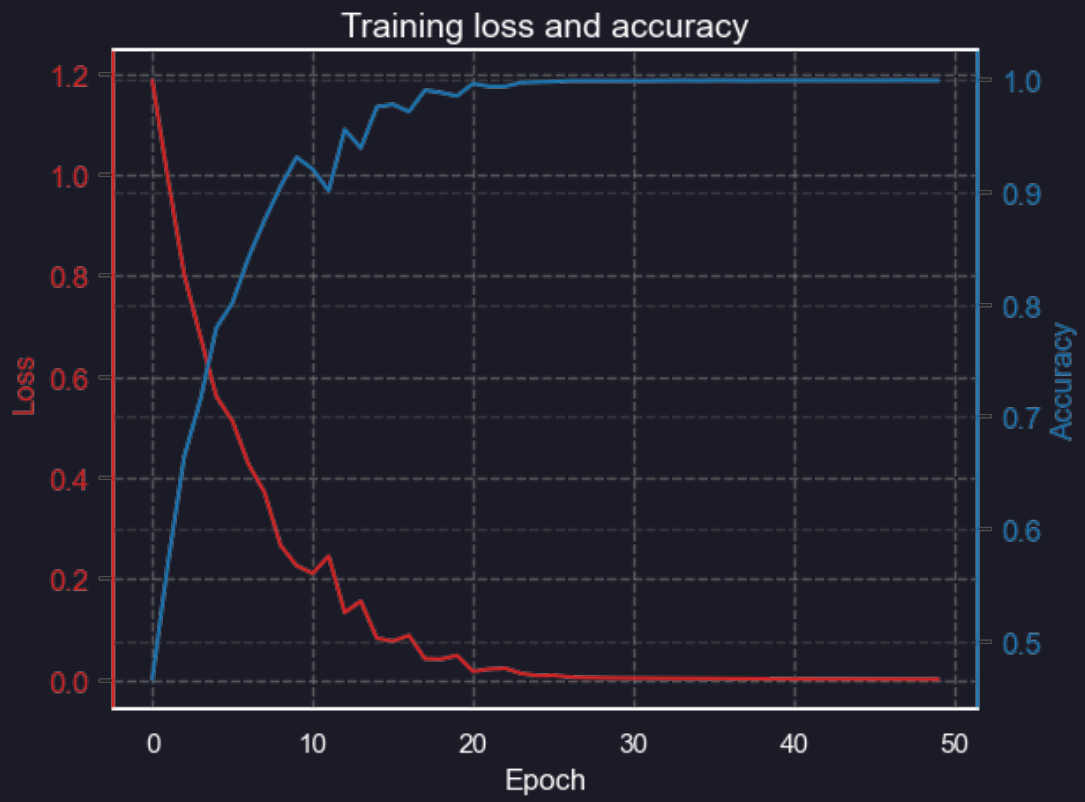
$$L(y, \hat{y}) = -\sum_i y_i \log(\hat{y}_i)$$

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

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

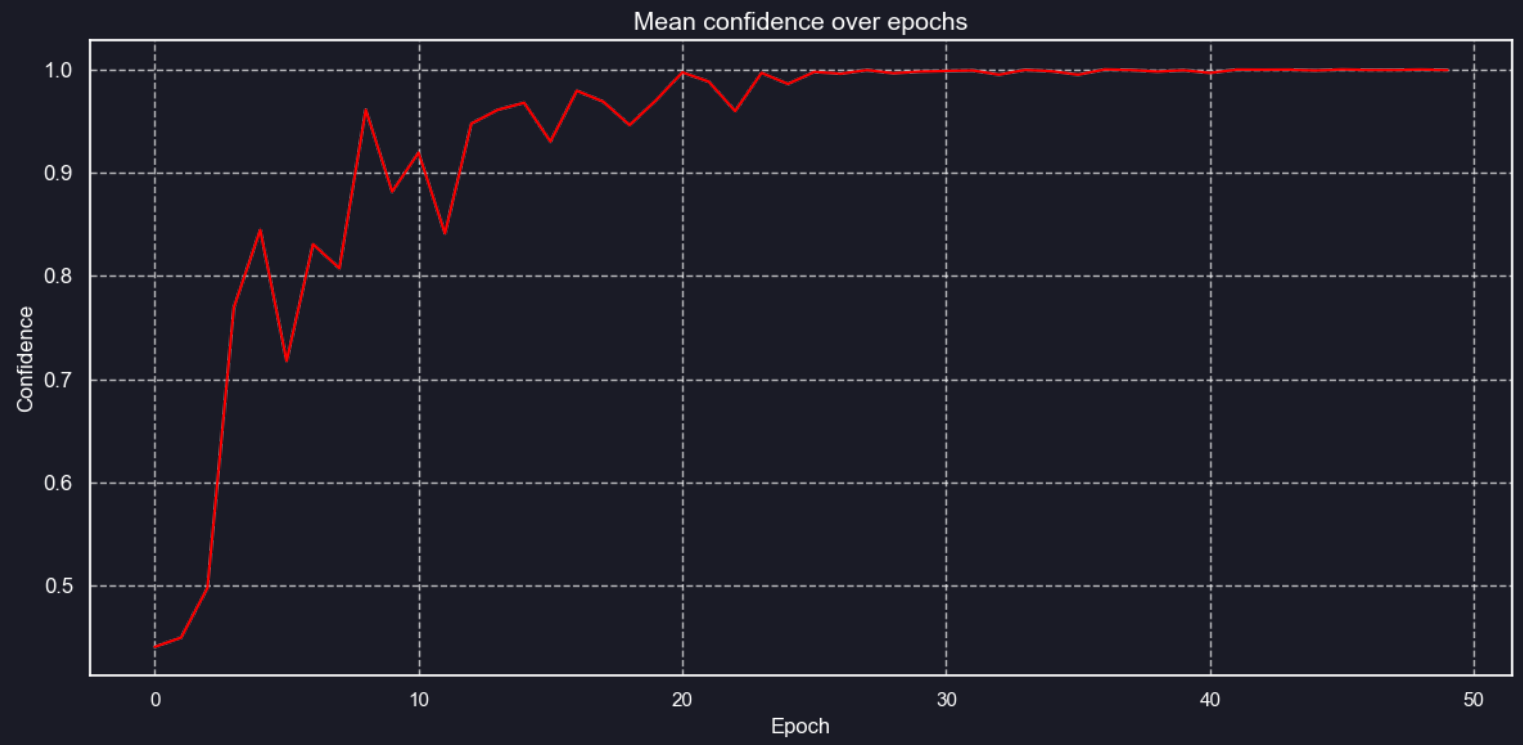
$$S(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

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	$1.4 \cdot 10^{-3}$	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**.

Focus on Accuracy

Test Performance Comparison

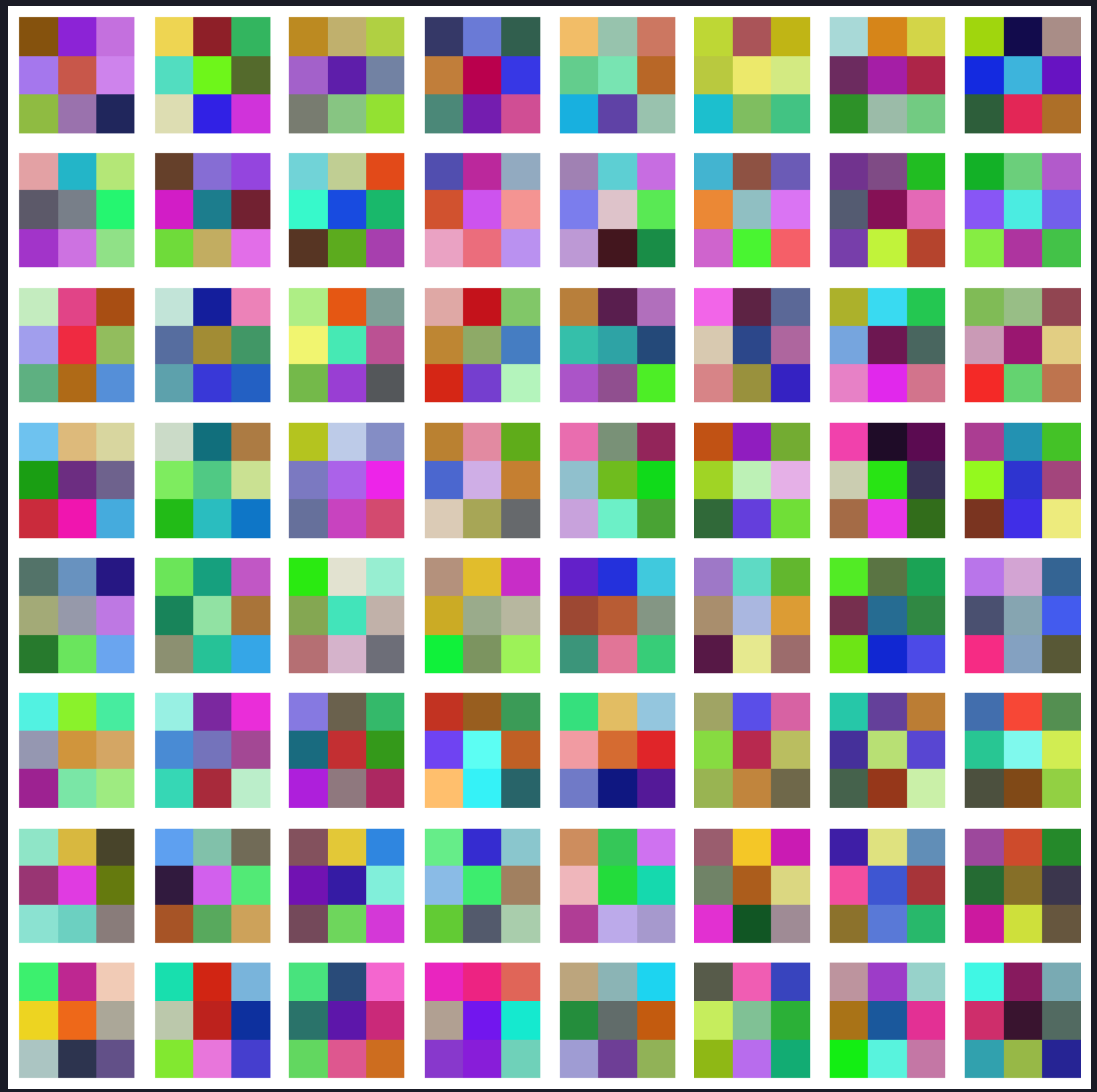
Model	Accuracy	Confidence
CustomCNN	99%	100%
AlexNet	90%	96.5%
VGG16	95%	98.0%
VIT	88%	93.3%

⚠️ 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



U-Net Models

3 models for the segmentation task:

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

U-Net Models

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

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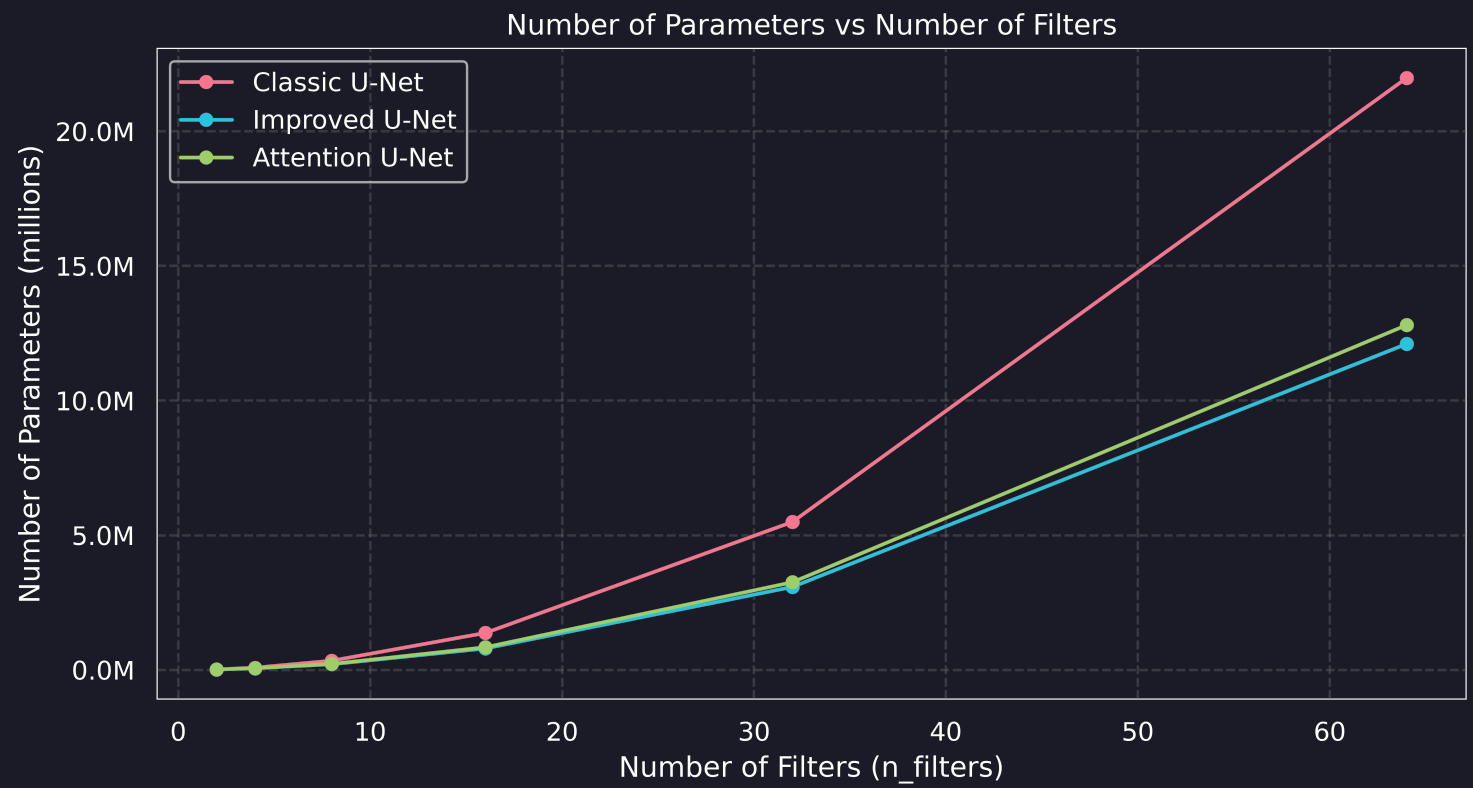
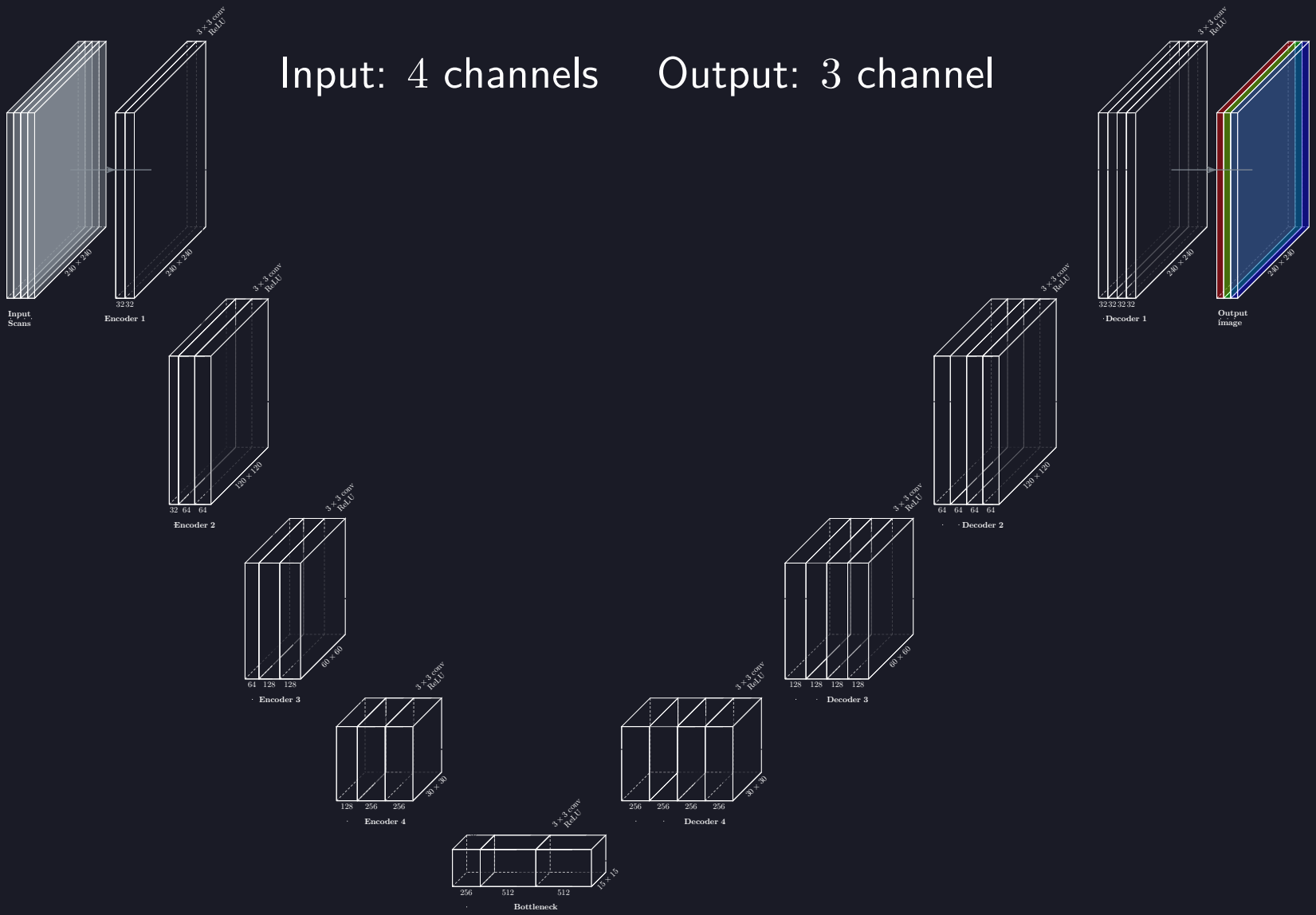
- **Attention U-Net**: *attention mechanism added*



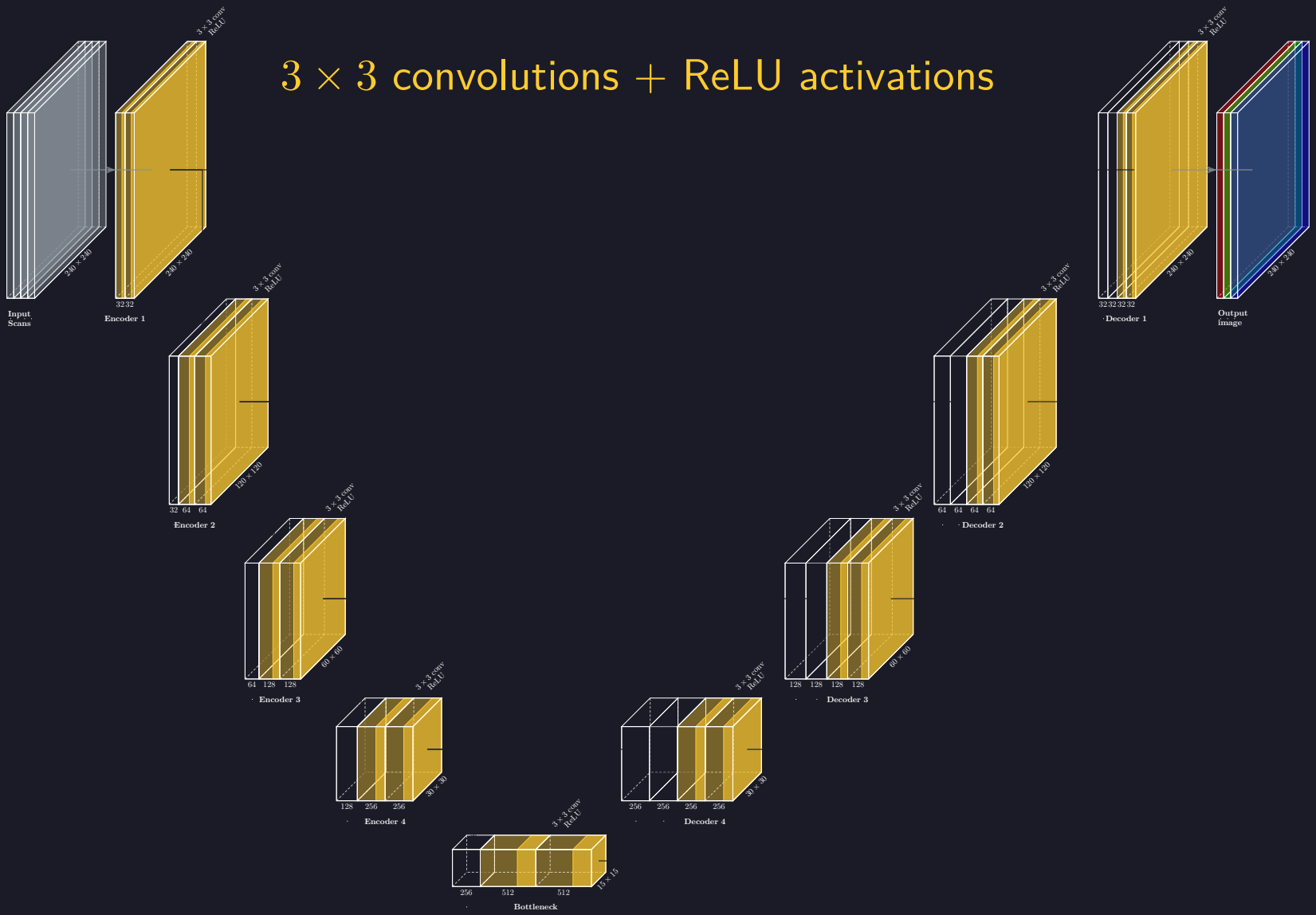
Classic U-Net

Input: 4 channels Output: 3 channel

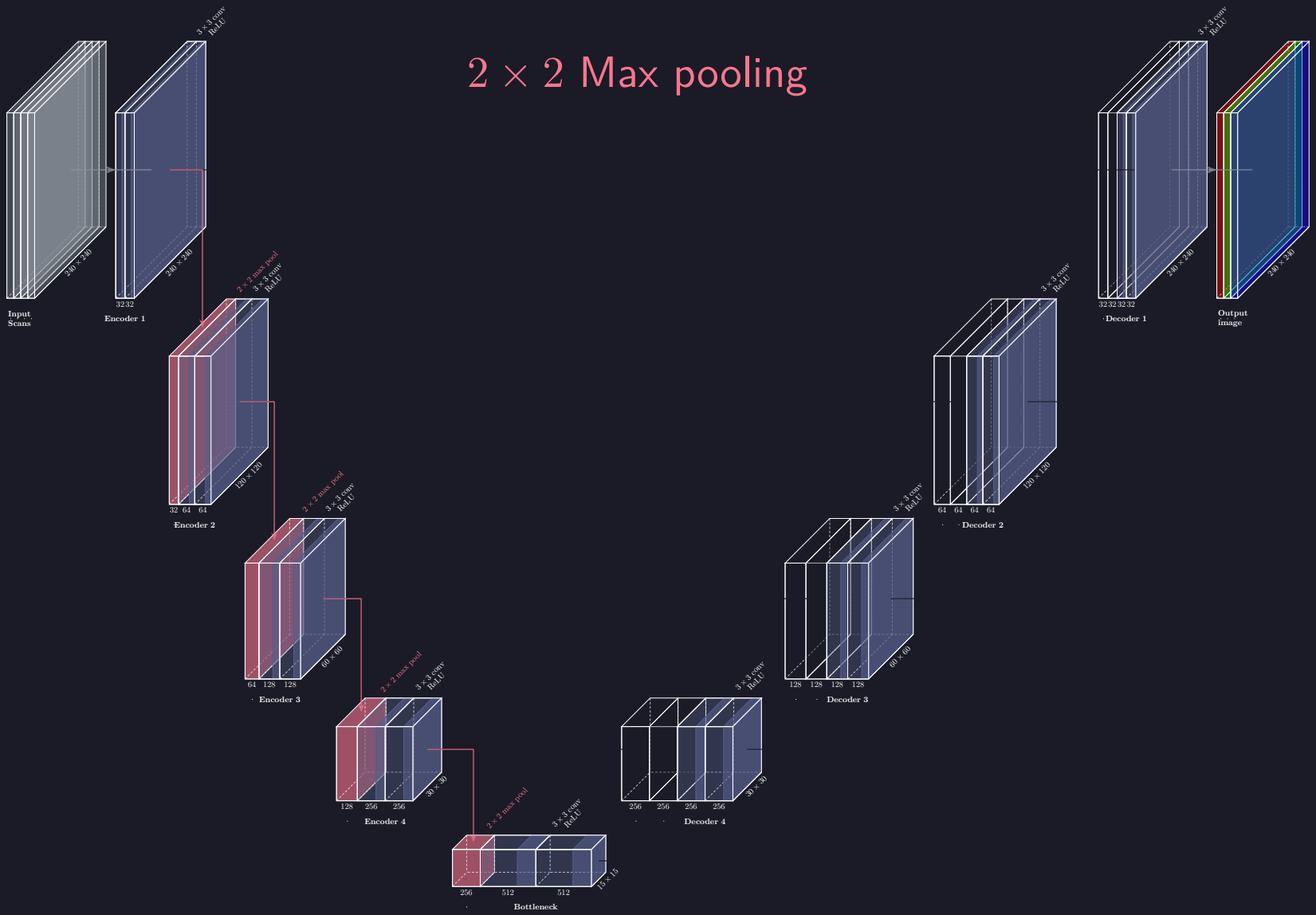


Classic U-Net

3×3 convolutions + ReLU activations



Classic U-Net



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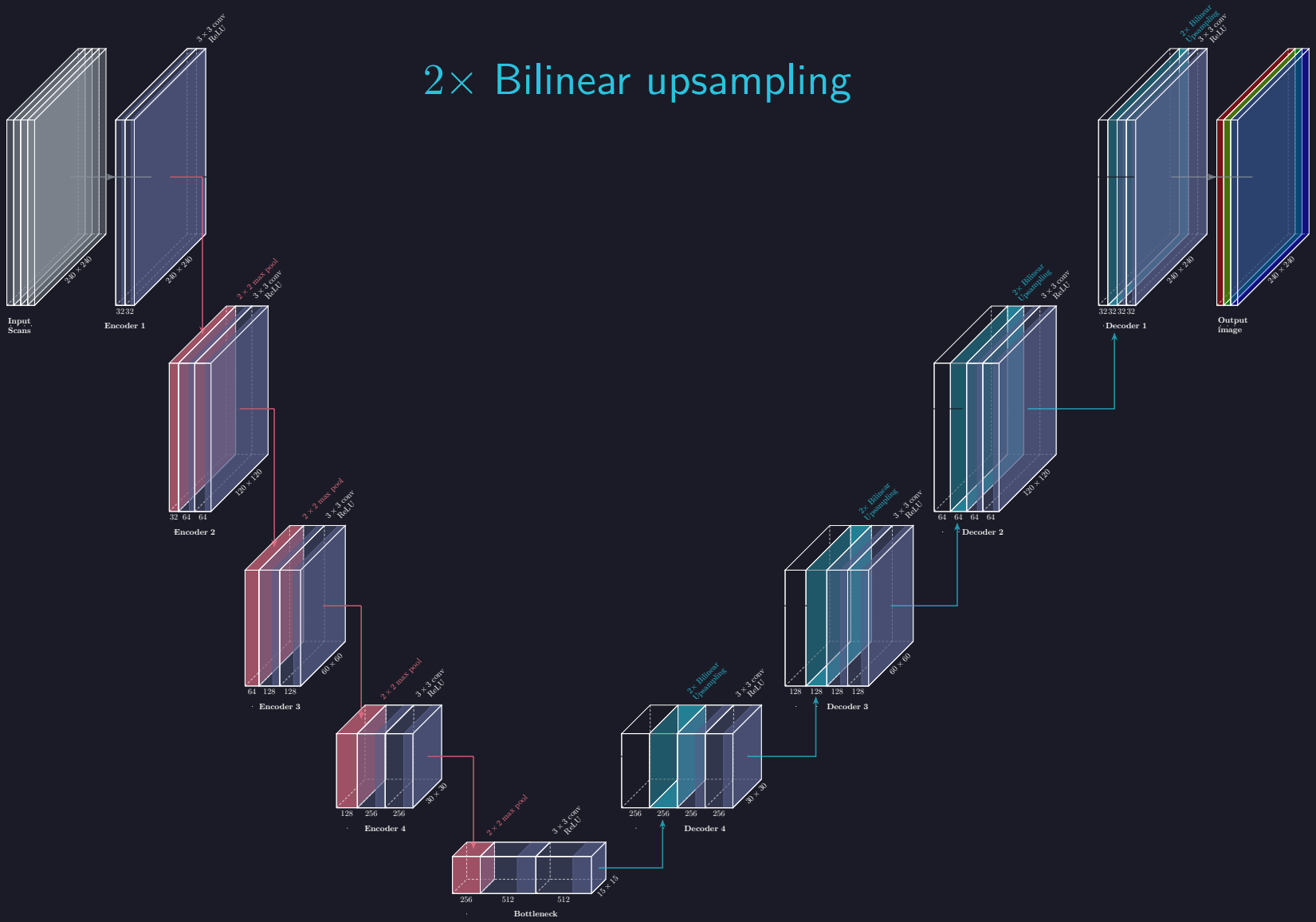

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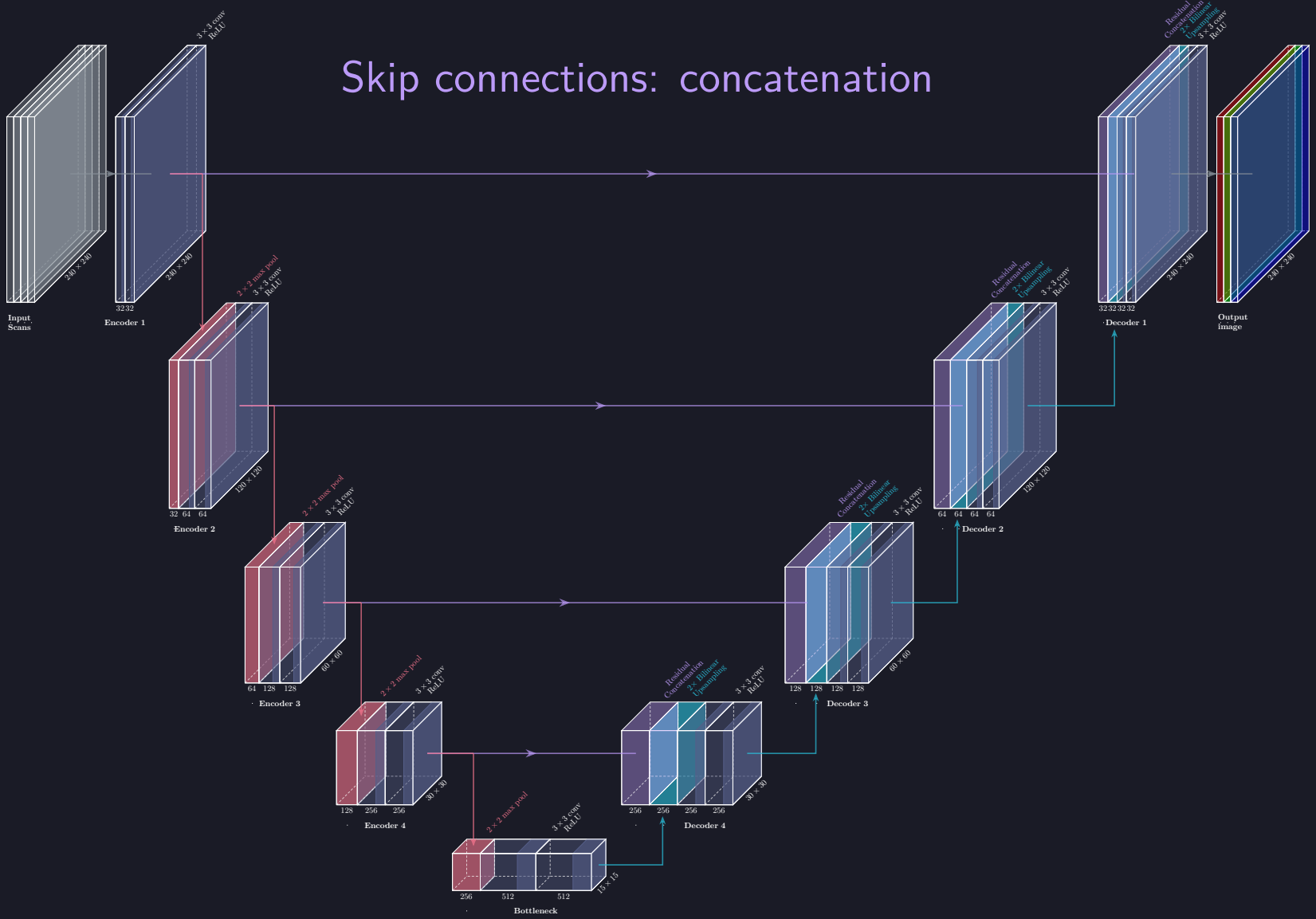
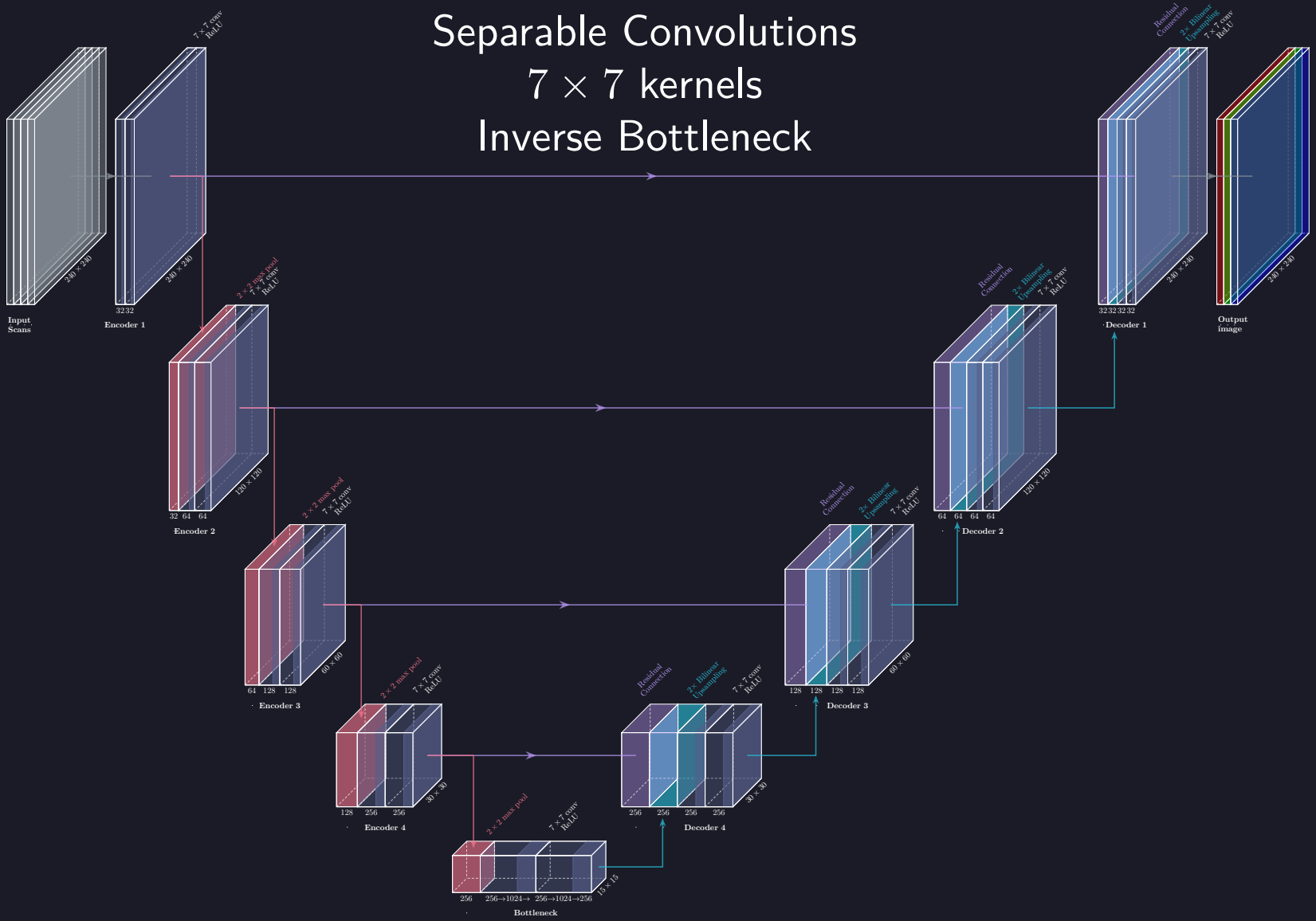


Improved U-Net



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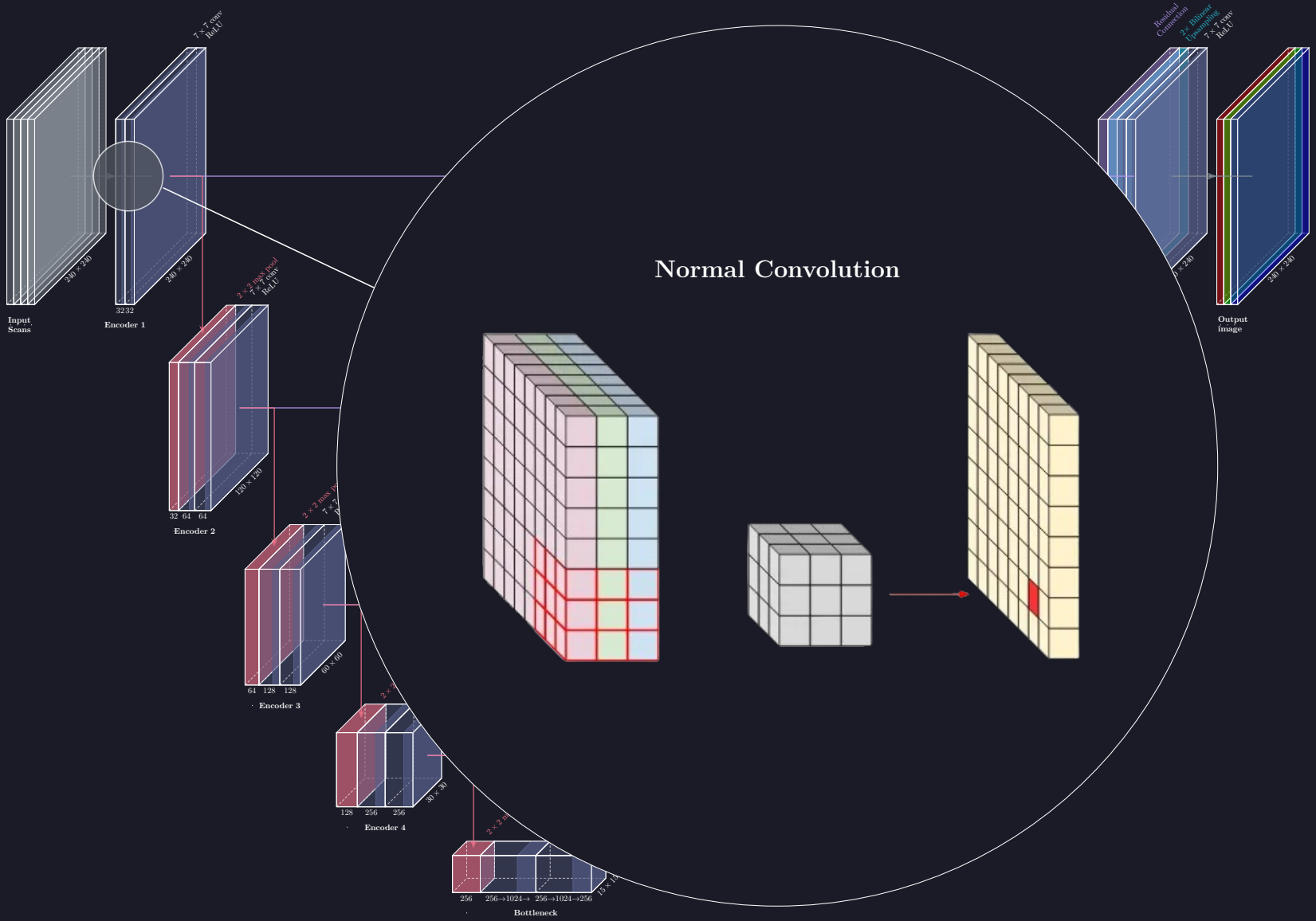

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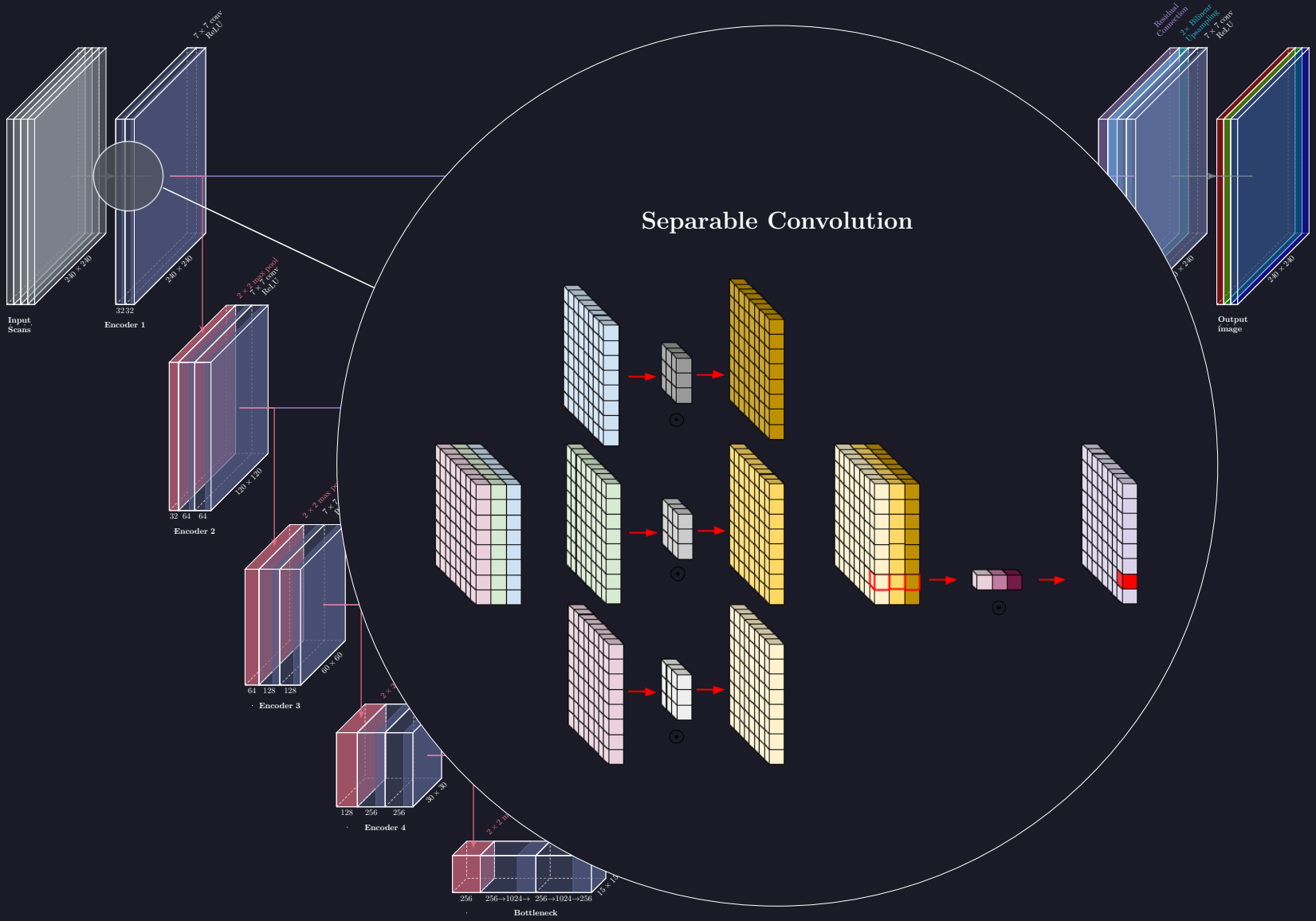

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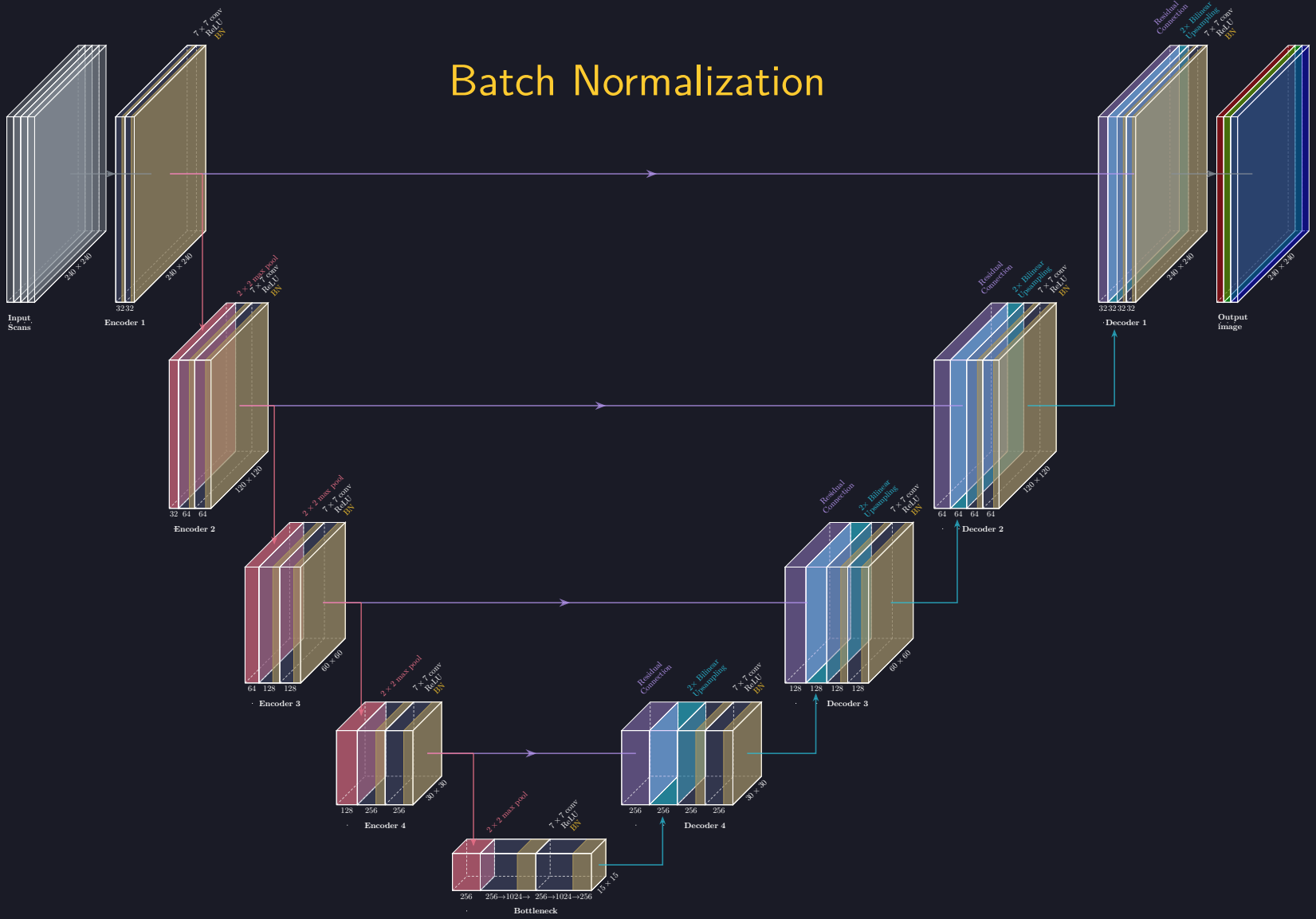

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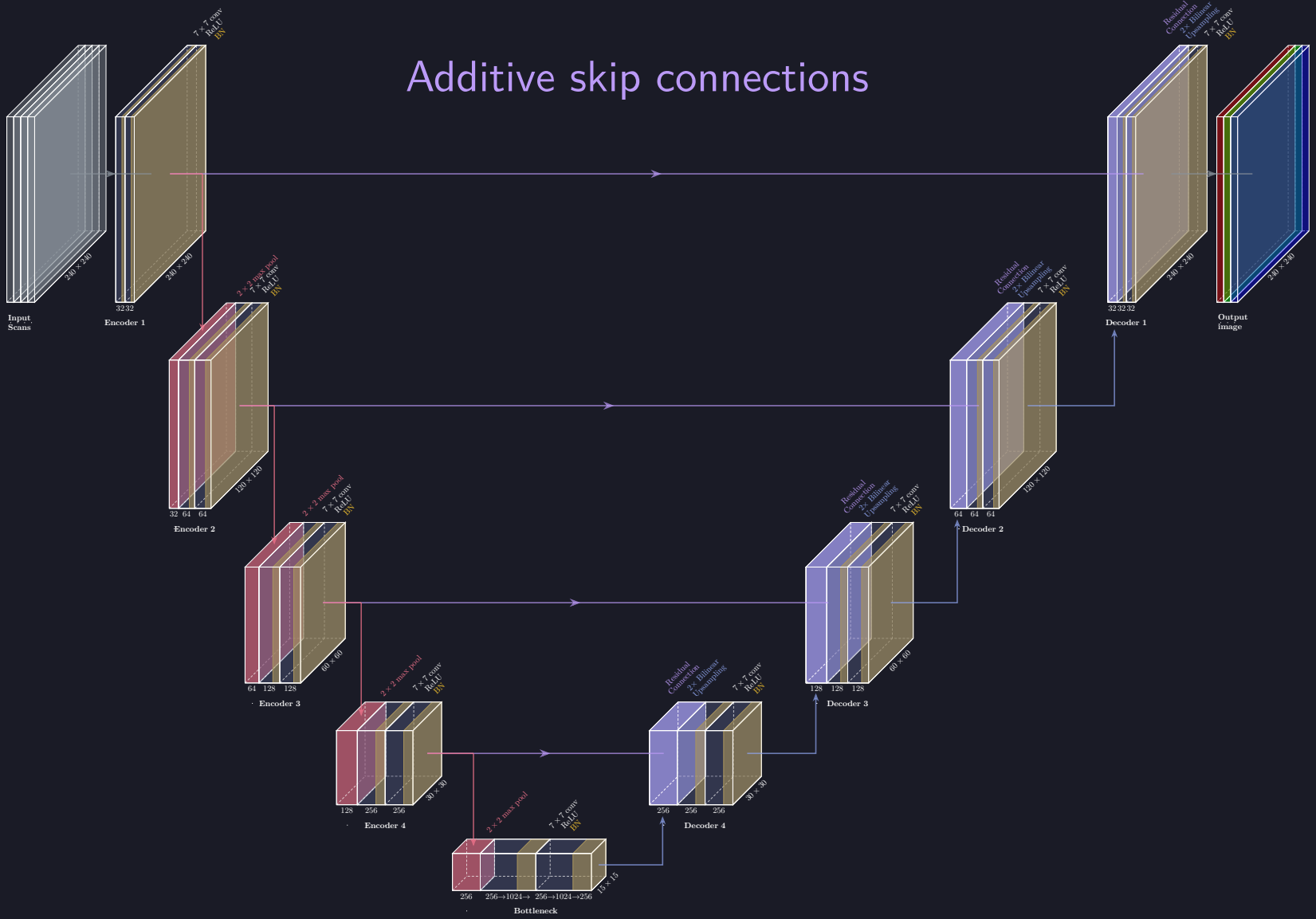
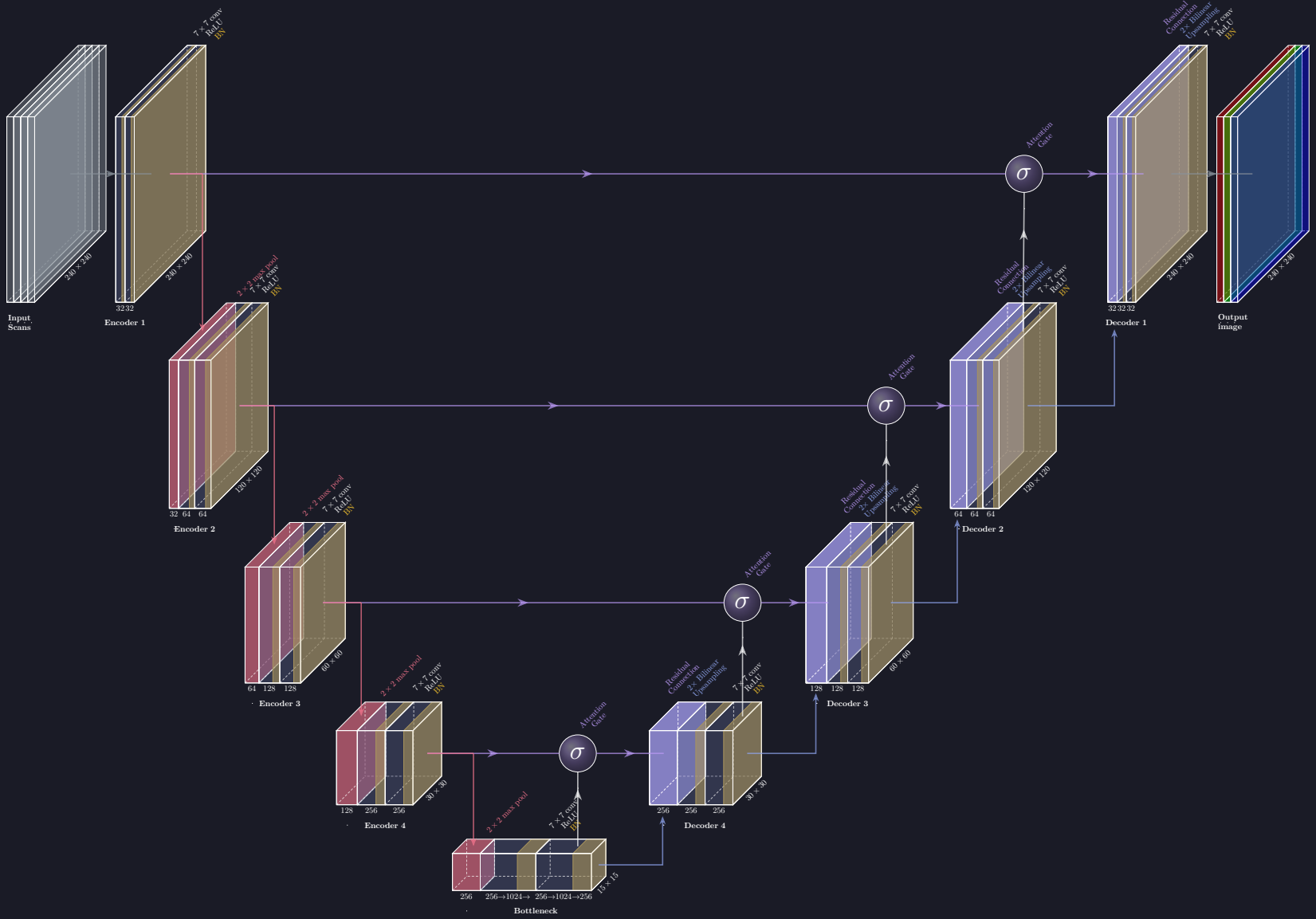


Attention U-Net



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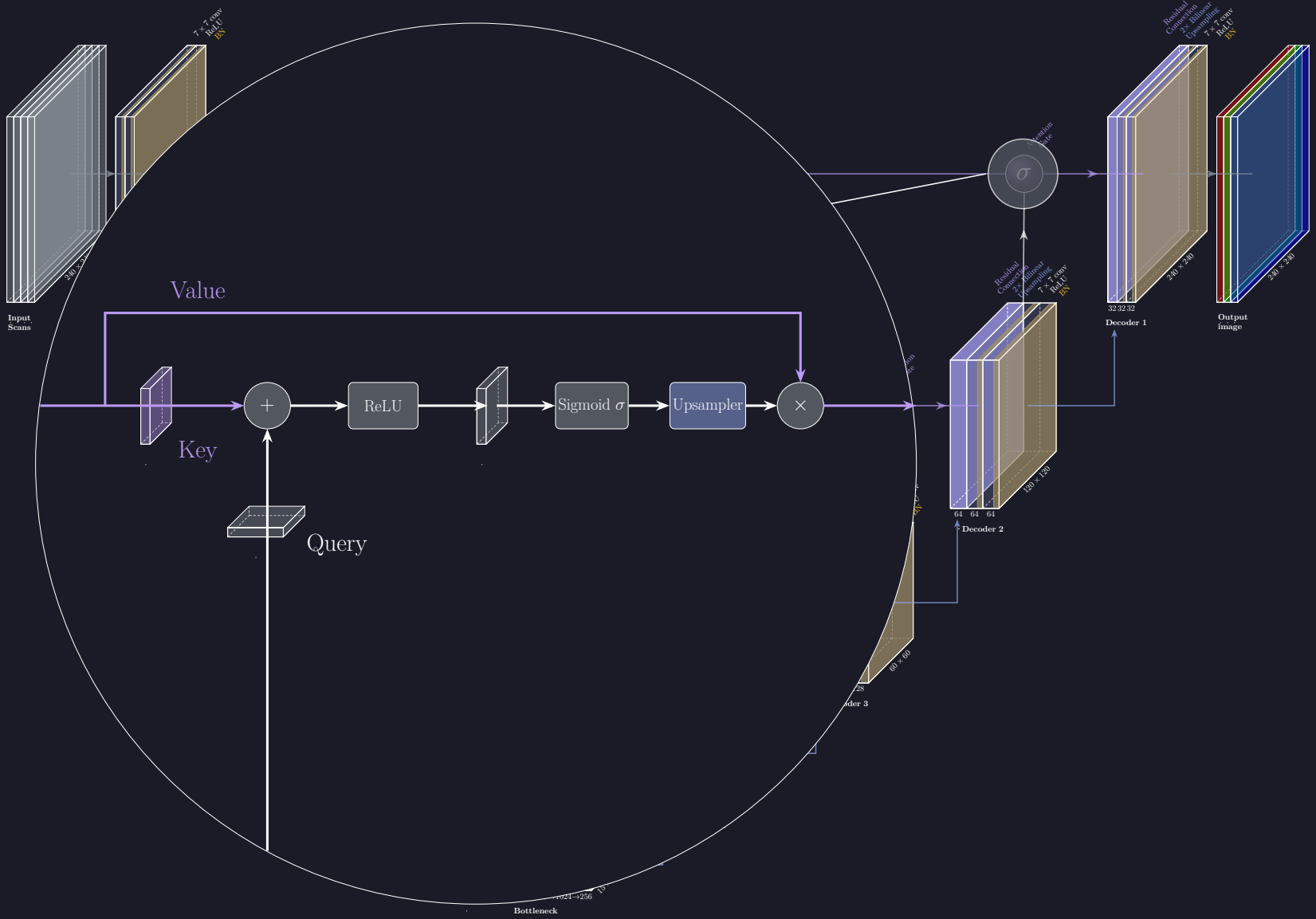


Training Details

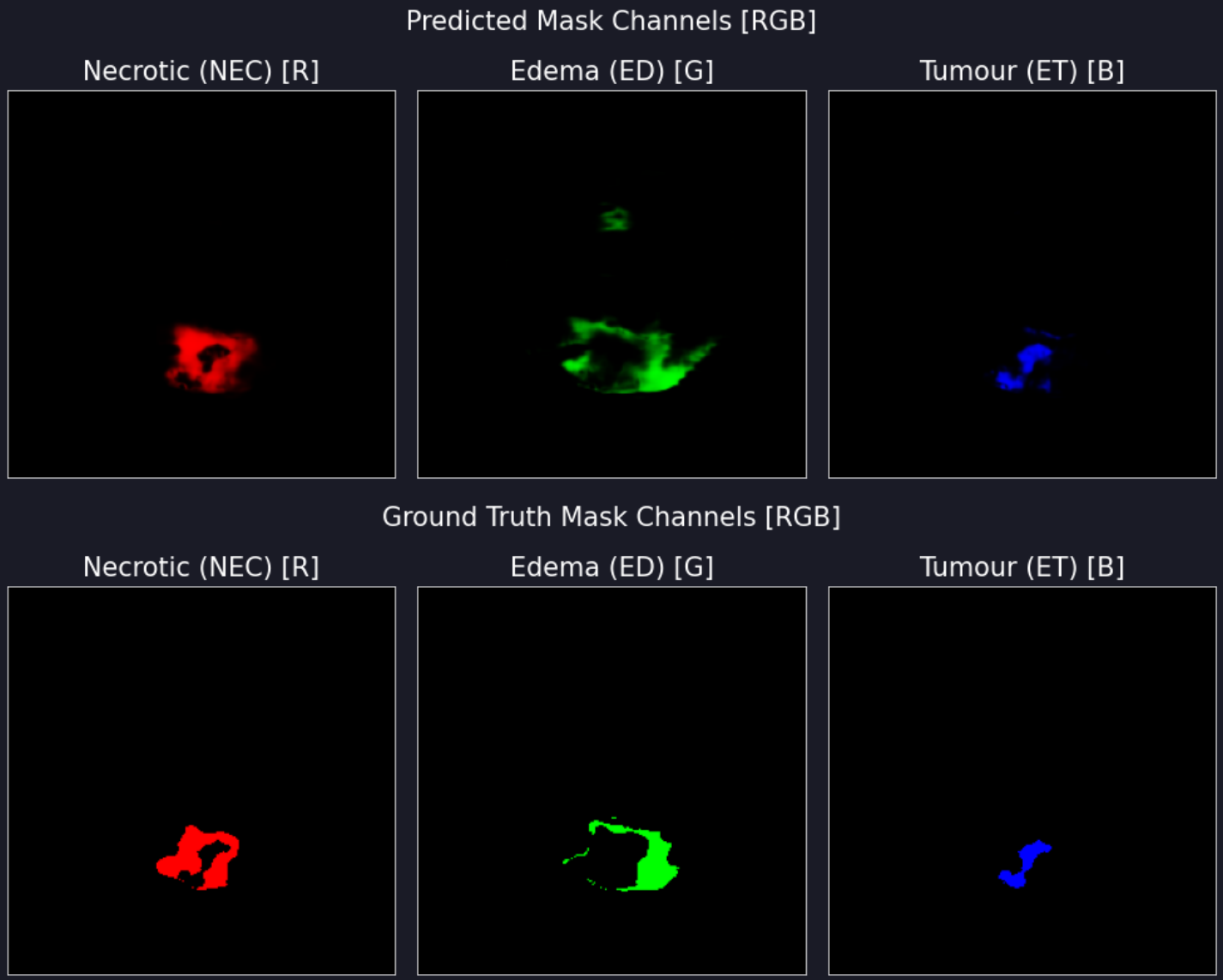
U-Net models training parameters:

- **Epochs**: 20
- **Optimizer**: Adam (with weight decay 1×10^{-2})
- **Scheduler**: Exponential Decay ($\gamma = 0.9$)
- **Loss function**: BCE with Logits Loss:

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

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

Visualizing a prediction



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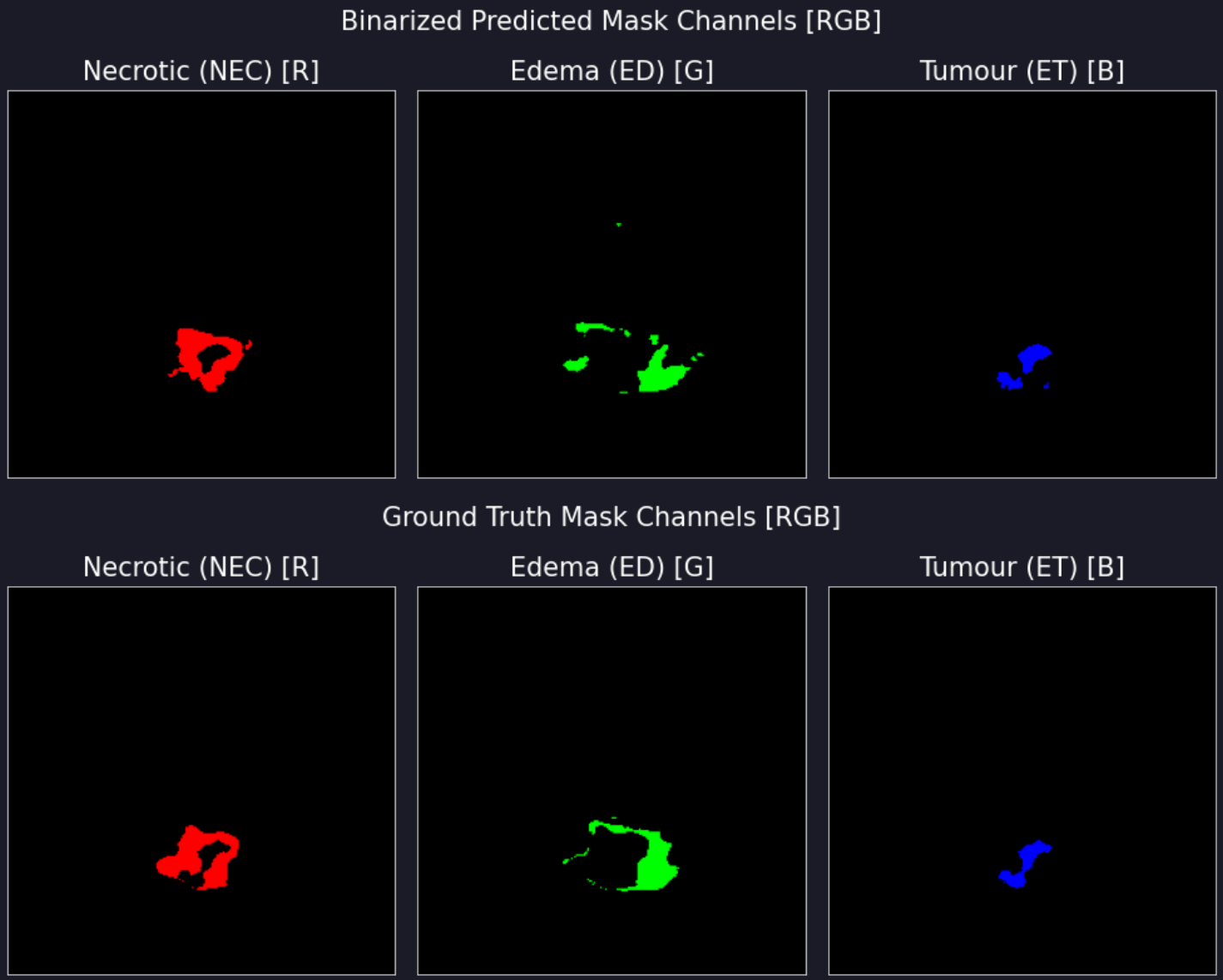


Performance Assessment

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

Dice Coefficient

"overlap" metric

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

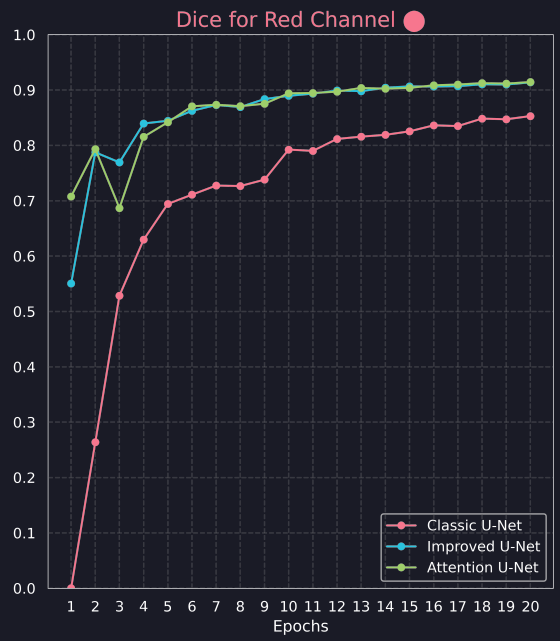
Precision

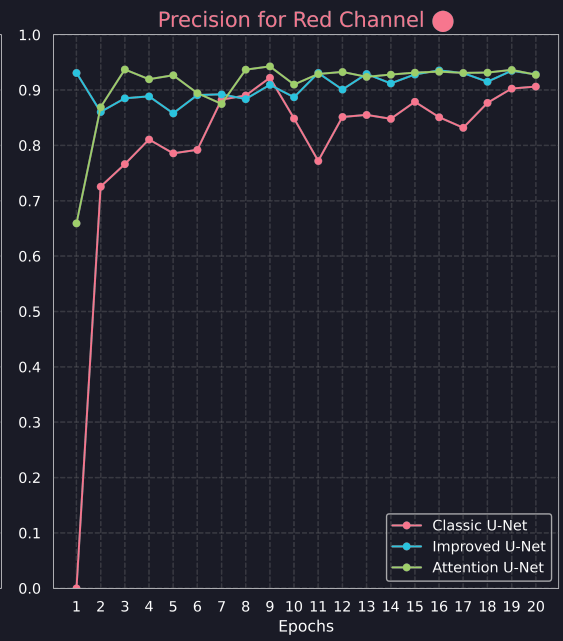
prediction quality

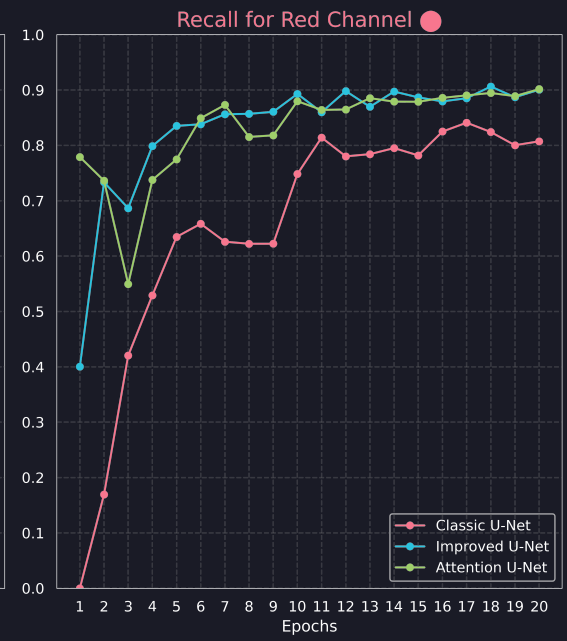
$$\text{Recall} = \frac{TP}{TP + FN}$$

Recall

prediction quantity







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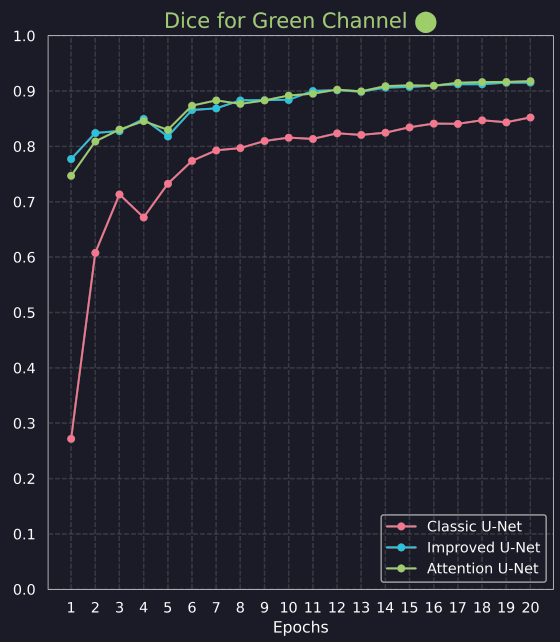

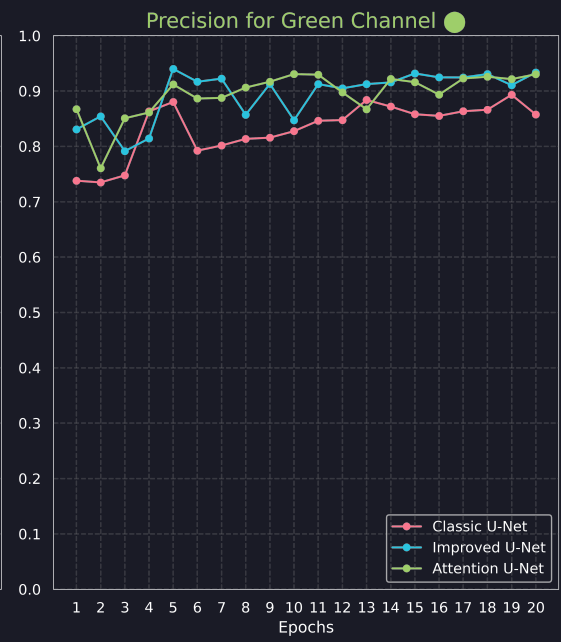

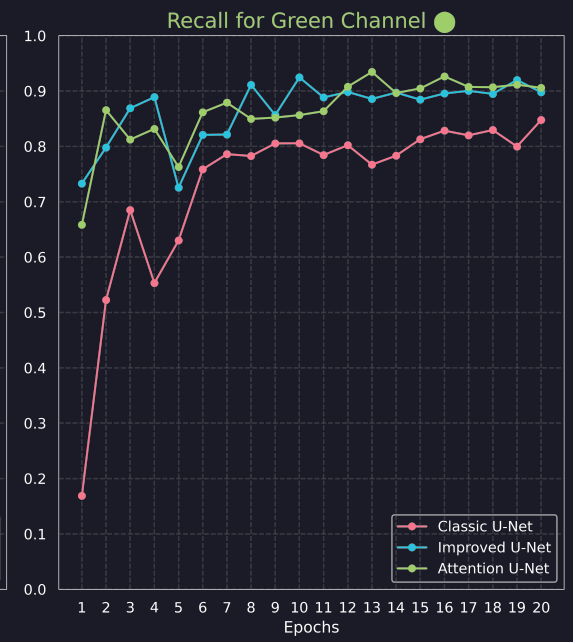

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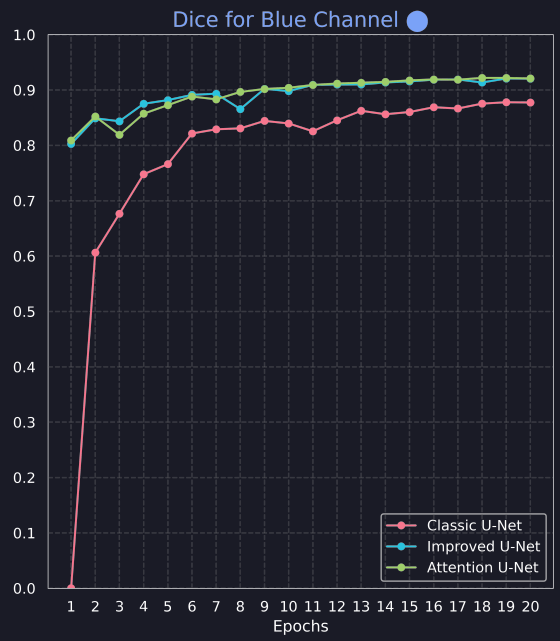
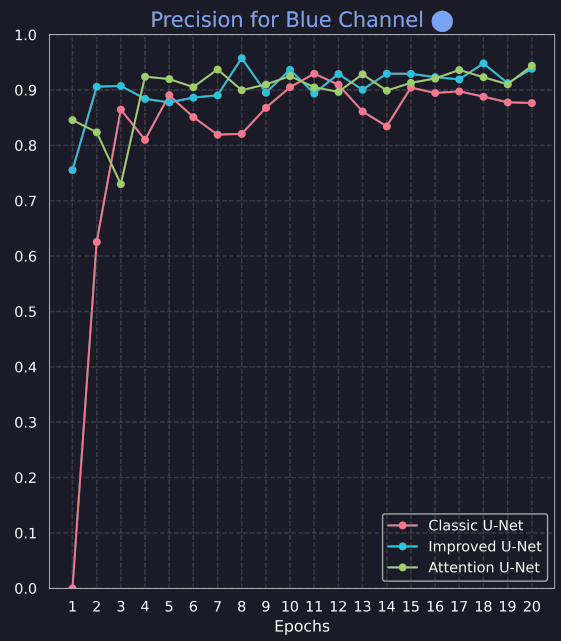
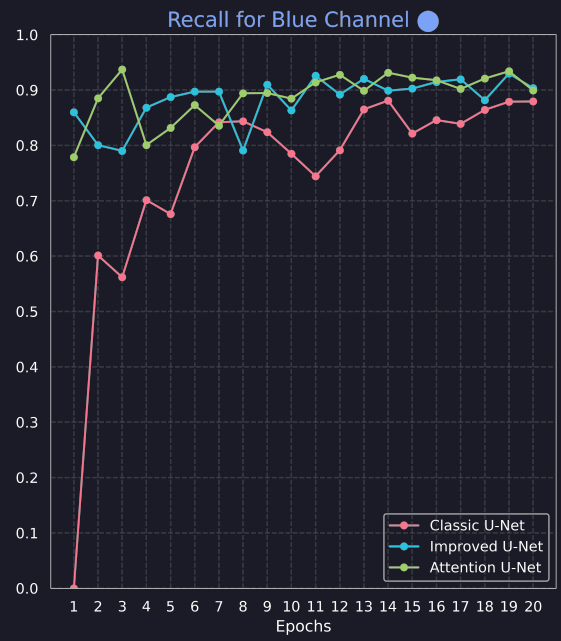






Performance Assessment

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

Dice Coefficient

"overlap" metric

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

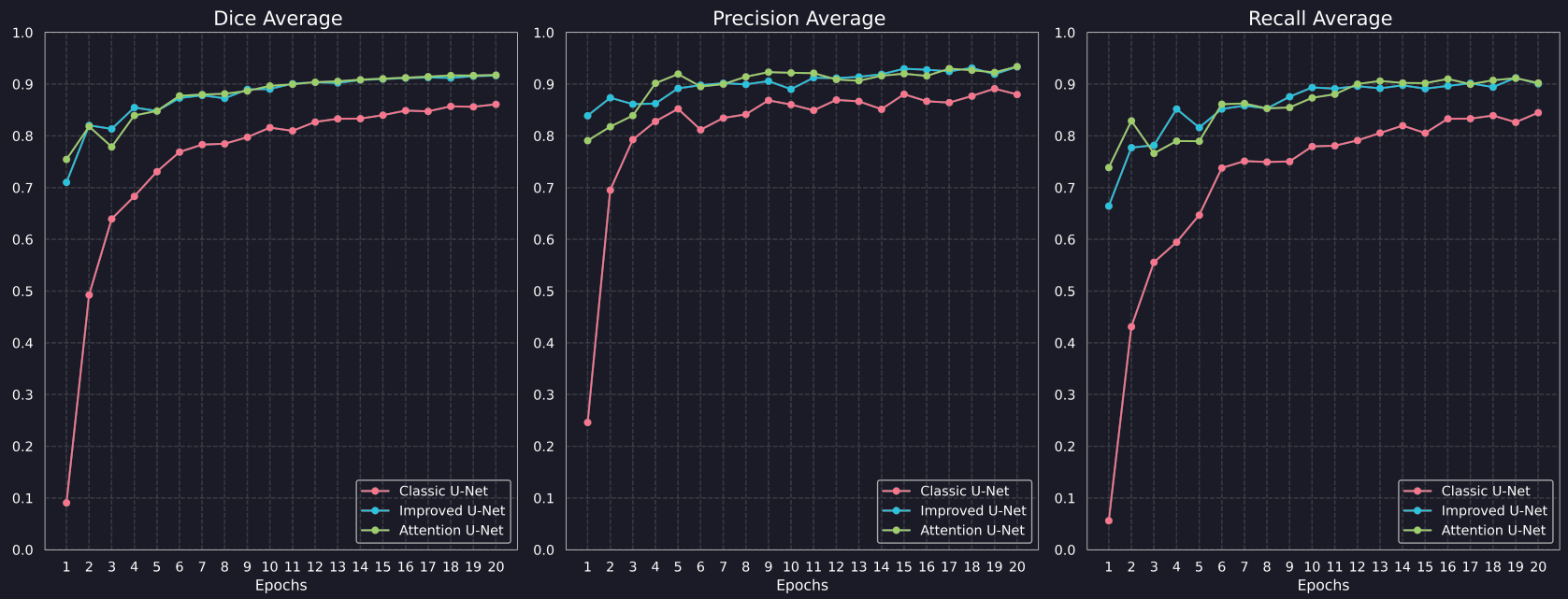
Precision

prediction quality

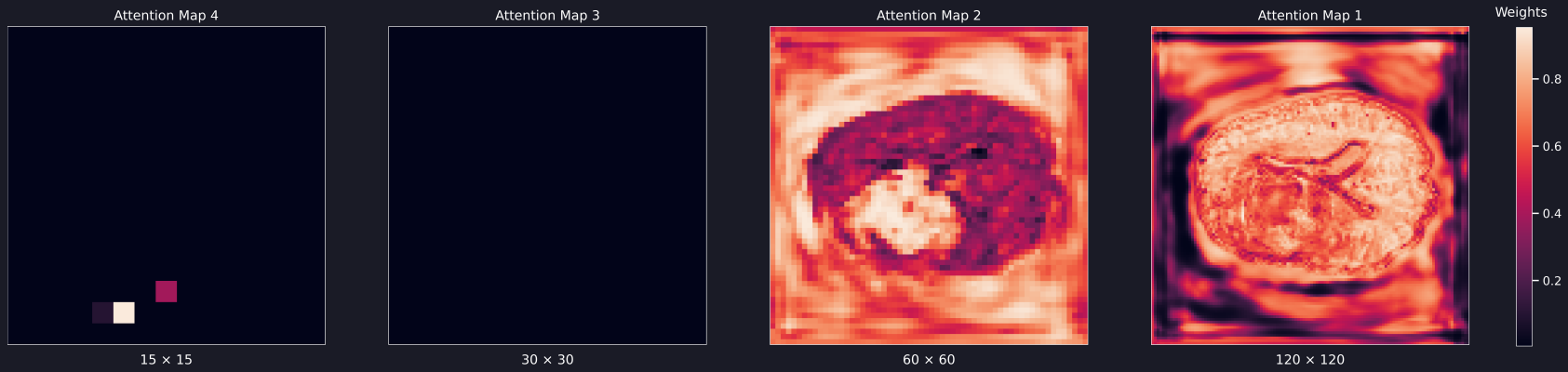
$$\text{Recall} = \frac{TP}{TP + FN}$$

Recall

prediction quantity



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