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Evaluating and Optimizing Training and Interference Performances Between Variations of UNET Models for Nuclei Detection and Segmentation

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Presented by
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Temerty Medicine

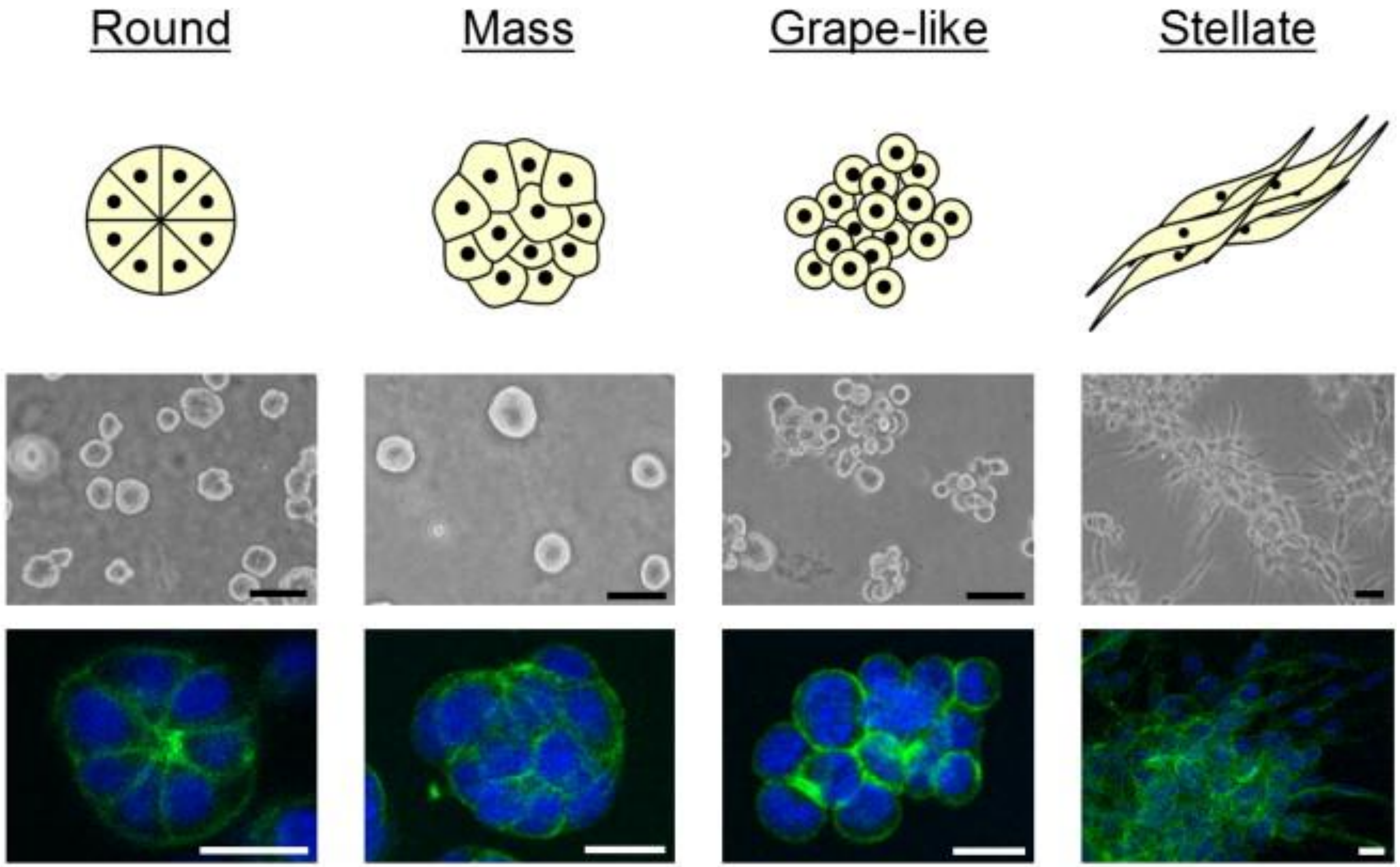
Sunnybrook RESEARCH INSTITUTE

Princess Margaret Cancer Centre UHN

Introduction

Why do we need cell segmentation?

Cell morphology is highly related to cancer research



- Organized nuclei
- Robust cell-cell adhesion

- Disorganized nuclei
- Robust cell-cell adhesion

- Disorganized nuclei
- Poor cell-cell adhesion

- Disorganized nuclei
- Elongated cell body with invasive processes

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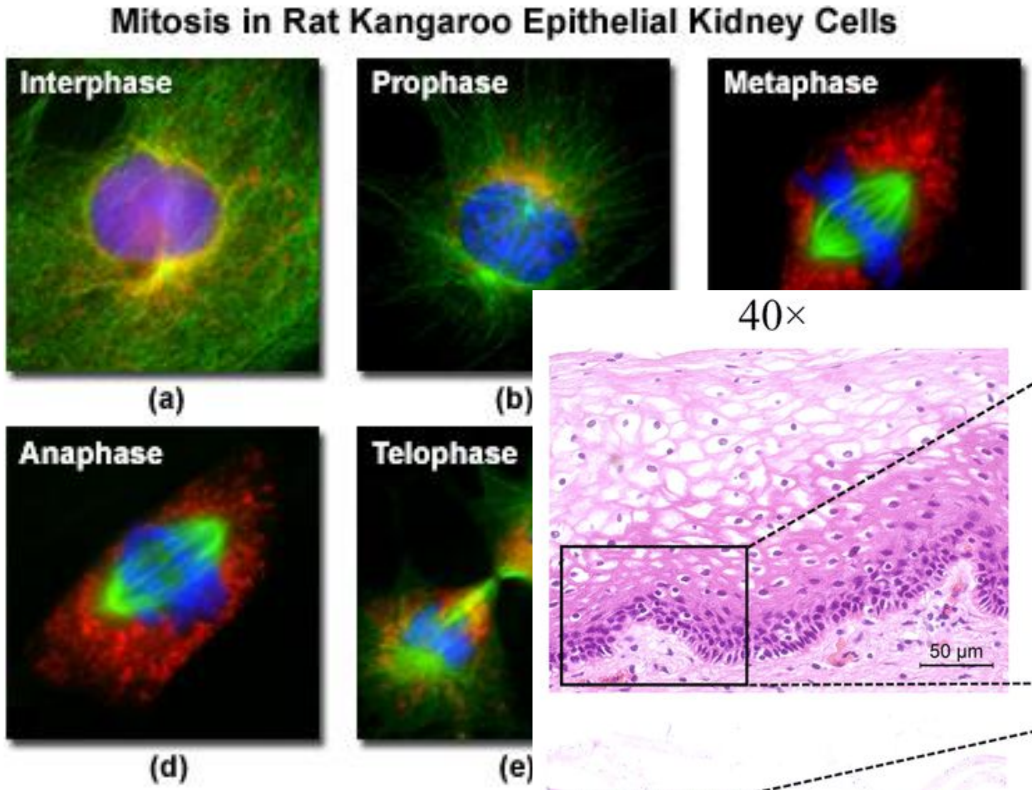
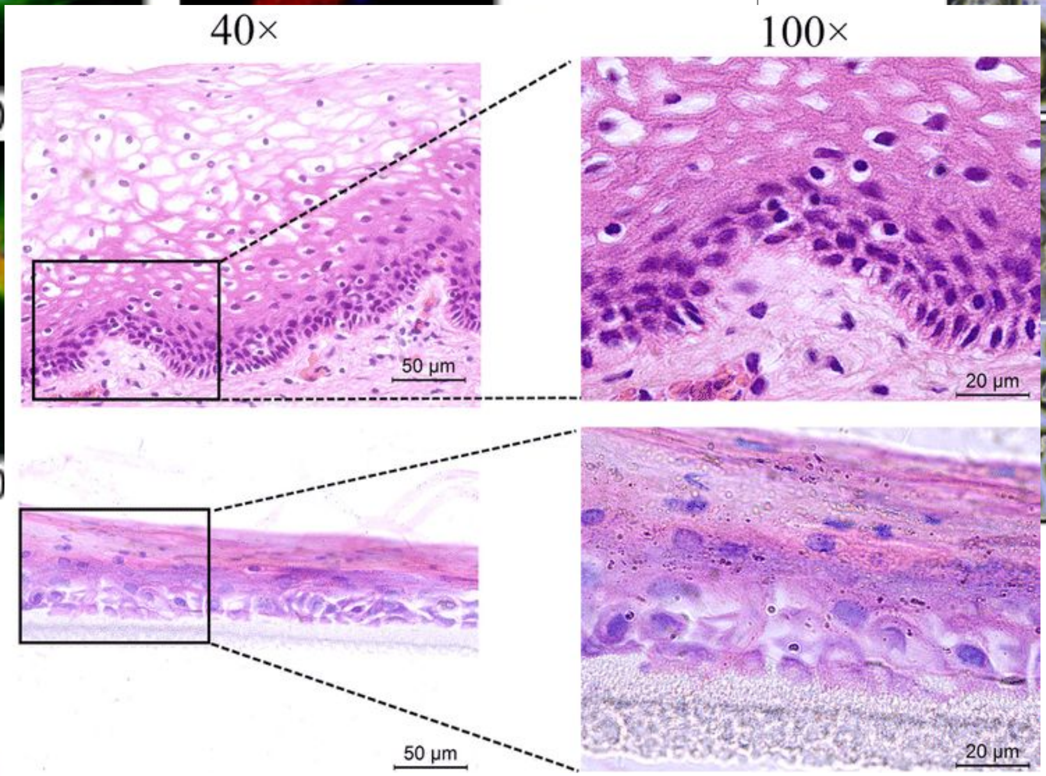
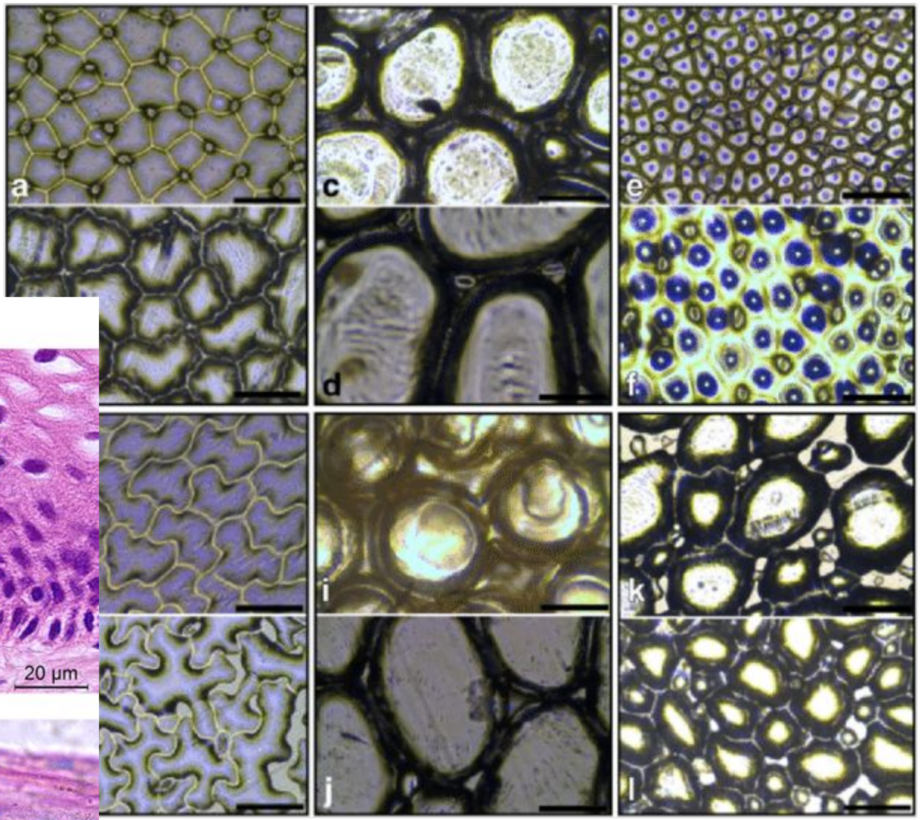
Kenney et al. (2007)*Molecular Oncology*

Microscope is the major contributor for cell visualization







National High Magnetic field library (2015)
Jooste et al. (2016) *BMC Evolutionary Biology*
Zhu et al. (2017) *Oncotarget*

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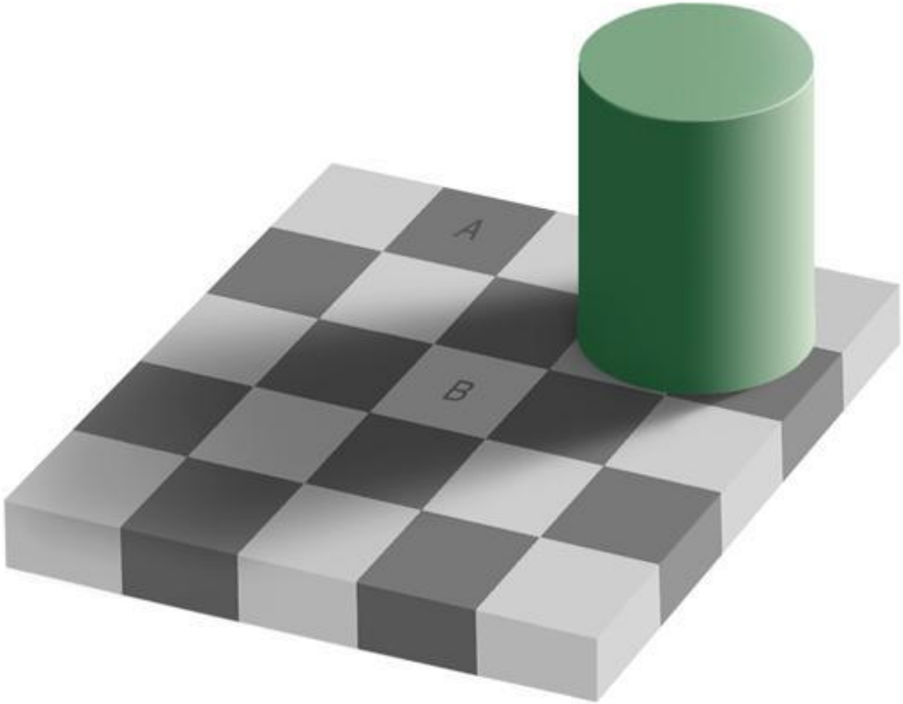
Problems

- Hard to analyze large volume of data **manually**
- **Human vision** might not identify some characteristics of cell edges and background efficiently



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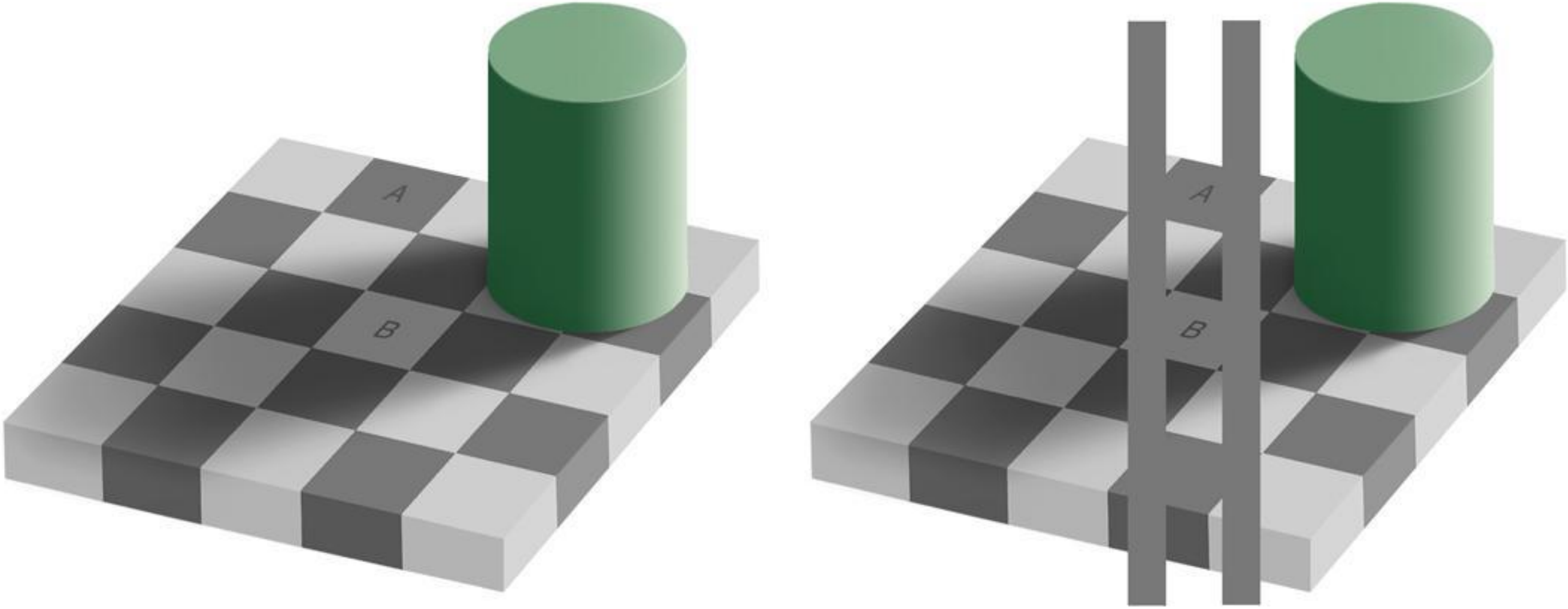
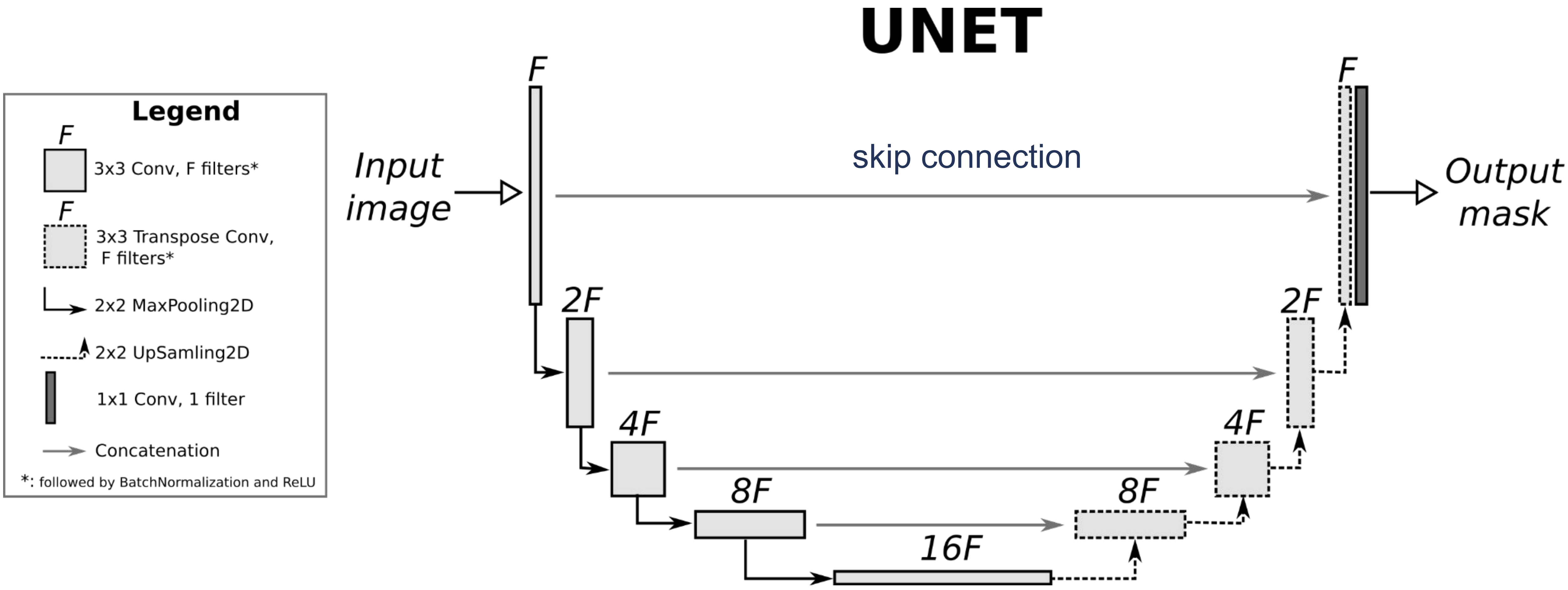


UNET and UNETR (transformer)



Keras_UNET_segmentation(2019)Github

Optimizer and learning rate scheduler

- Optimizer -

An algorithm used to adjust the parameters of a model during training to minimize the loss function

update actual parameters based on gradients and other additional parameters

- Learning rate scheduler -

A technique used to adjust learning rate based on predefined schedule

modify the learning rate over the course of training to improve convergence / stability / performance

Goal of this presentation

- Provide a practical guide for choosing **the most suited model architecture** for future researchers who wish to train their own **cell segmentation model**.

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Aims of this study

- Evaluate cell segmentation performance of **UNET and UNETR**
- Compare the performances of models **with and without** the use of a learning rate scheduler and models with Adam/SGD

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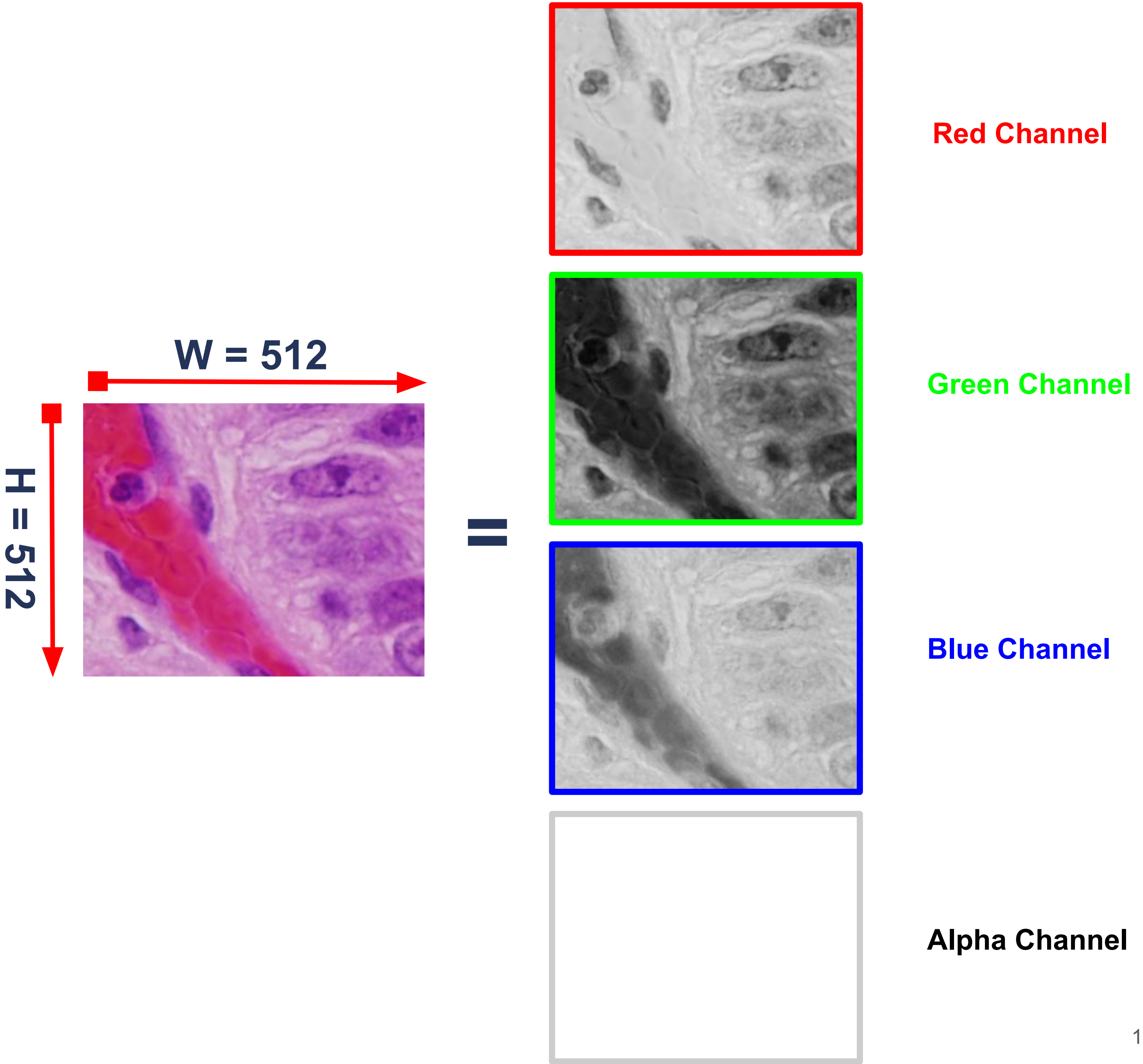
Materials and Methods

Dataset, Model Design, and Training Details

Data Preprocessing

- Define Channel
  - Image: 4 channels (RGBA)
  - Mask: 1 channel (grayscale)
- Unify Data Dimension (512 x 512)
  - Image => linear interpolation
  - Mask => nearest interpolation
- Intensity Normalization
  - Min-max normalization
  - Scale the intensity within [0,1]



Network Design

- UNET
  - Layers: [16, 32, 64, 128, 256, 512]
  - Strides: 2
  - Kernel: 3 x 3
  - Activation: LeakyRelu
  - Normalization: batch
  - Dropout ratio: 0.2

- UNETR
  - Feature size: 16
  - Hidden layers: 768
  - Number of attention heads: 12
  - Activation: LeakyRelu
  - Normalization: batch
  - Dropout ratio: 0.2

Optimizer and LR Scheduler

- Adam Gradient Descent
  - Weight decay: 3e-5
  - Learning rate: 0.005
- Stochastic Gradient Descent (nesterov momentum)
  - Weight decay: 3e-5
  - Learning rate: 0.005
  - Momentum factor: 0.99
- Polynomial Learning Rate Decay
  - Decrease every epoch with an exponential power 0.9

Evaluations

- Dice + Focal Loss

$$\mathrm{FL}(p_t) = -(1 - p_t)^{\gamma} \log(p_t)$$

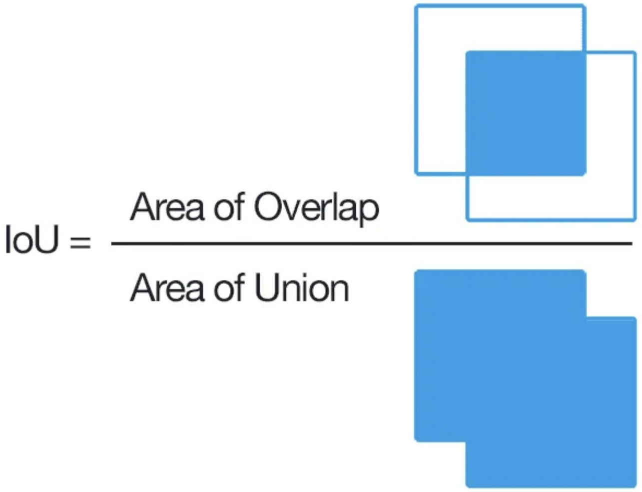
$$DC = \frac{2\left|\hat{Y} \cap Y\right|}{\left|\hat{Y}\right| + |Y|} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

$$DL(Y, \hat{Y}) = 1 - DC$$

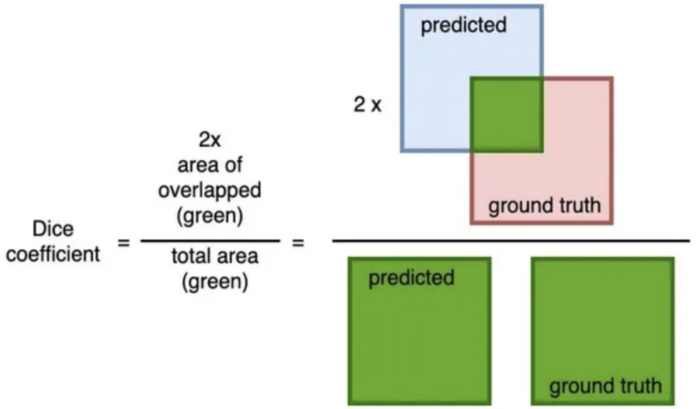
$$\boxed{Loss = W_{FL} \times FL + W_{DL} \times DL}$$

p_t: estimated probability for the class
$\hat{Y}$: network output
Y: ground truth
TP: true positive
FP: false positive
FN: false negative

- Intersection over Union (IoU)



- Dice Coefficient (DC)



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Results & Discussion

Comparison of various model performances

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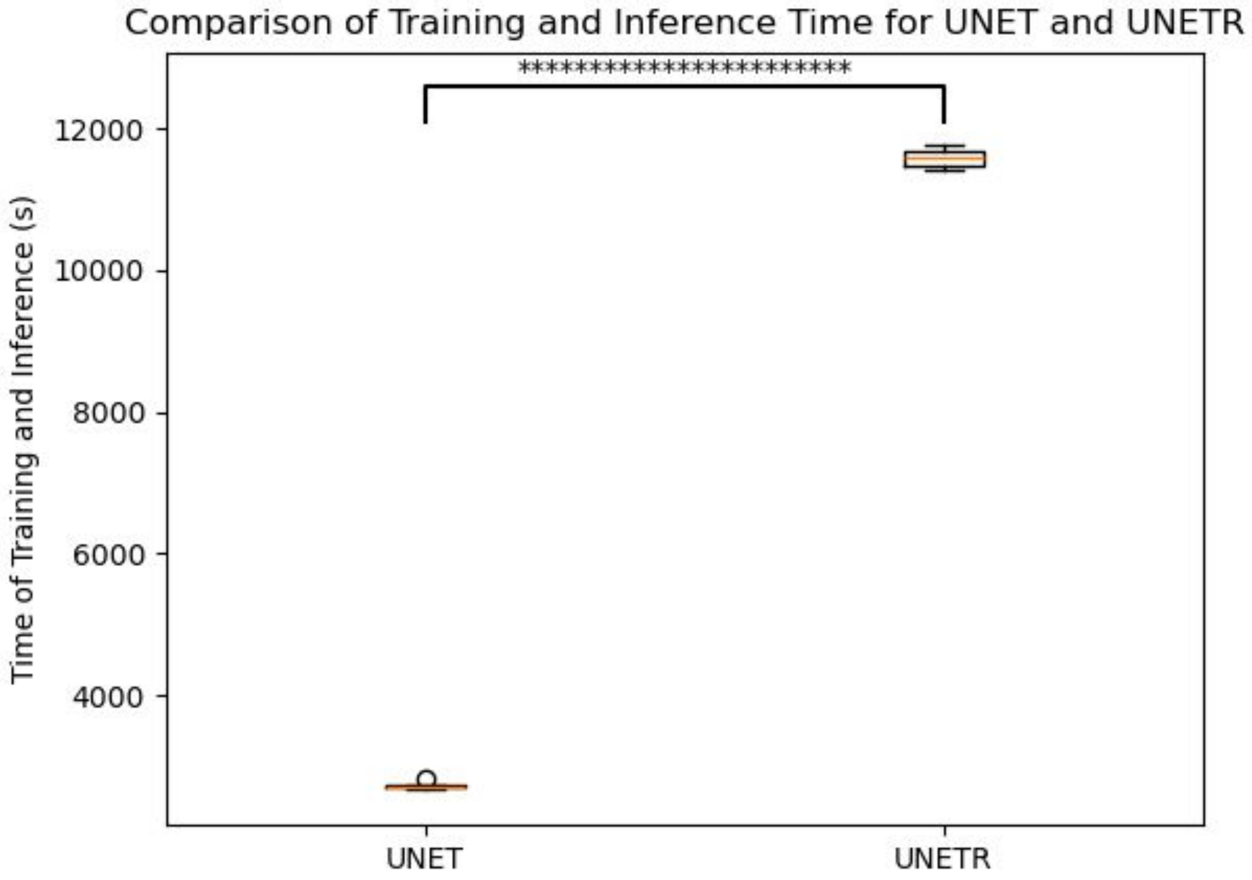
UNET requires significantly less time for training



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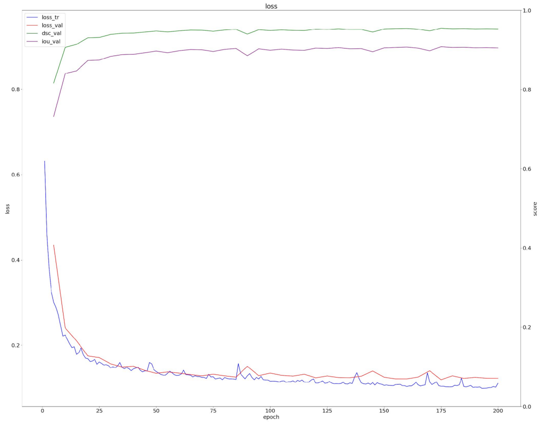
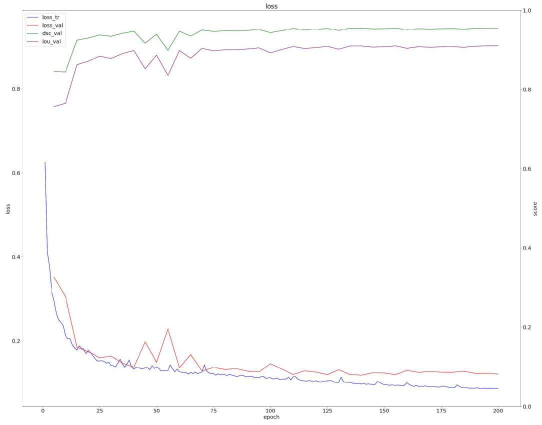
Adam converges faster for UNET but does not improve testing metrics

(a) Original

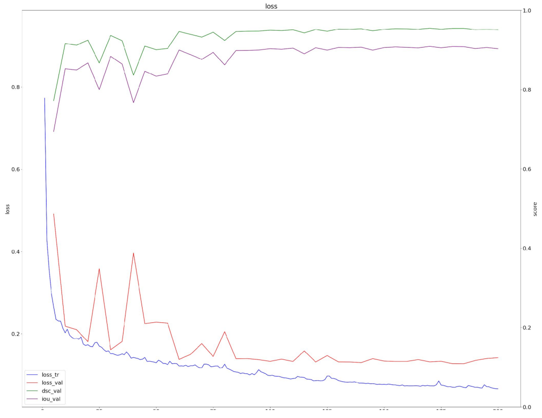


(b) Learning rate scheduler

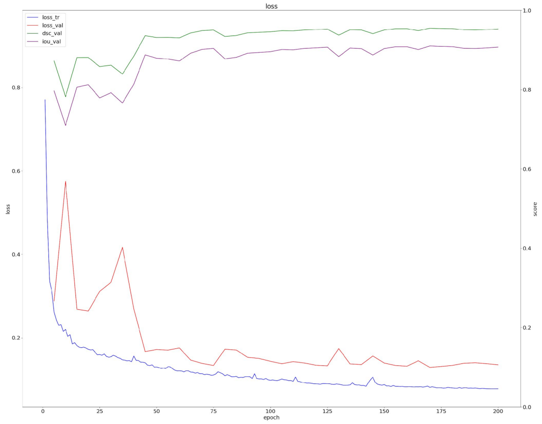


Adam

(c)



(d)



SGD

Table 1: Summary of the performance metrics (average Dice and IoU scores) of variations of UNET and UNETR models on the testing dataset. Sche indicates that the model used a learning rate scheduler during training.

		Adam	Adam + Sche	SGD	SGD + Sche
UNET	Dice	0.82	0.81	0.82	0.82
	IoU	0.73	0.72	0.73	0.71
UNETR	Dice	0.72	0.73	0.79	0.78
	IoU	0.59	0.60	0.68	0.68

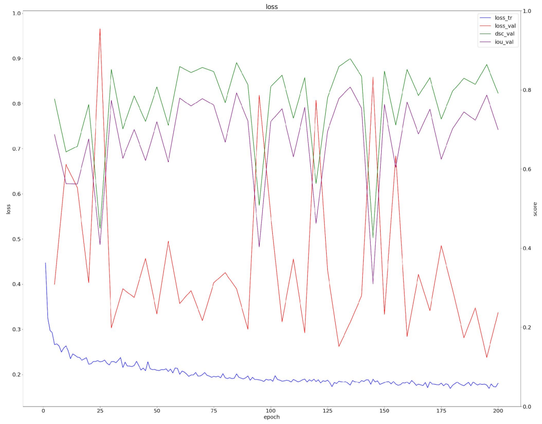
SGD makes training more stable for UNETR models and allows for better testing performance

Original

Learning rate scheduler

Adam

(a)



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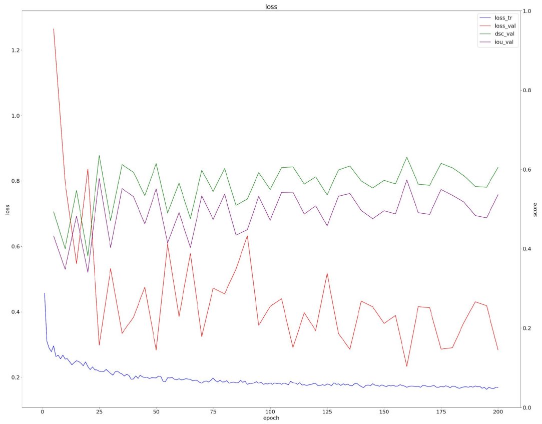

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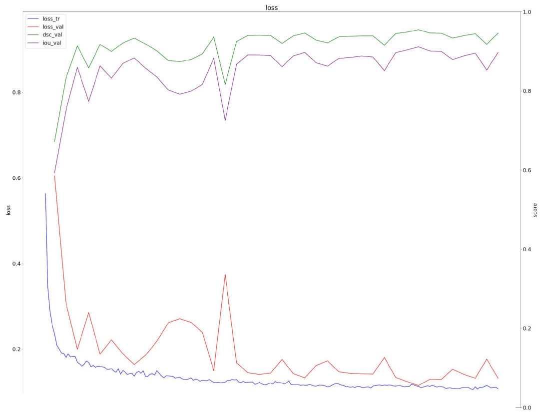

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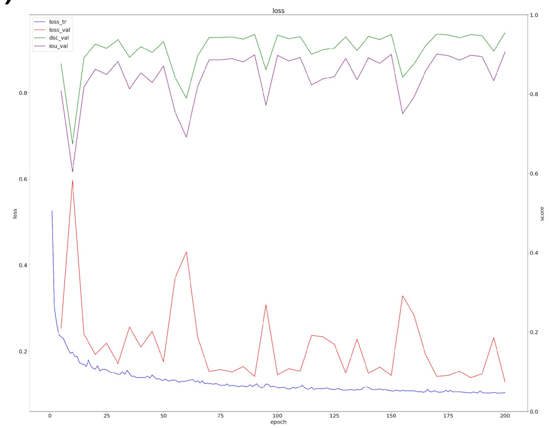

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Learning rate scheduler has limited if not negative impact on model testing performance

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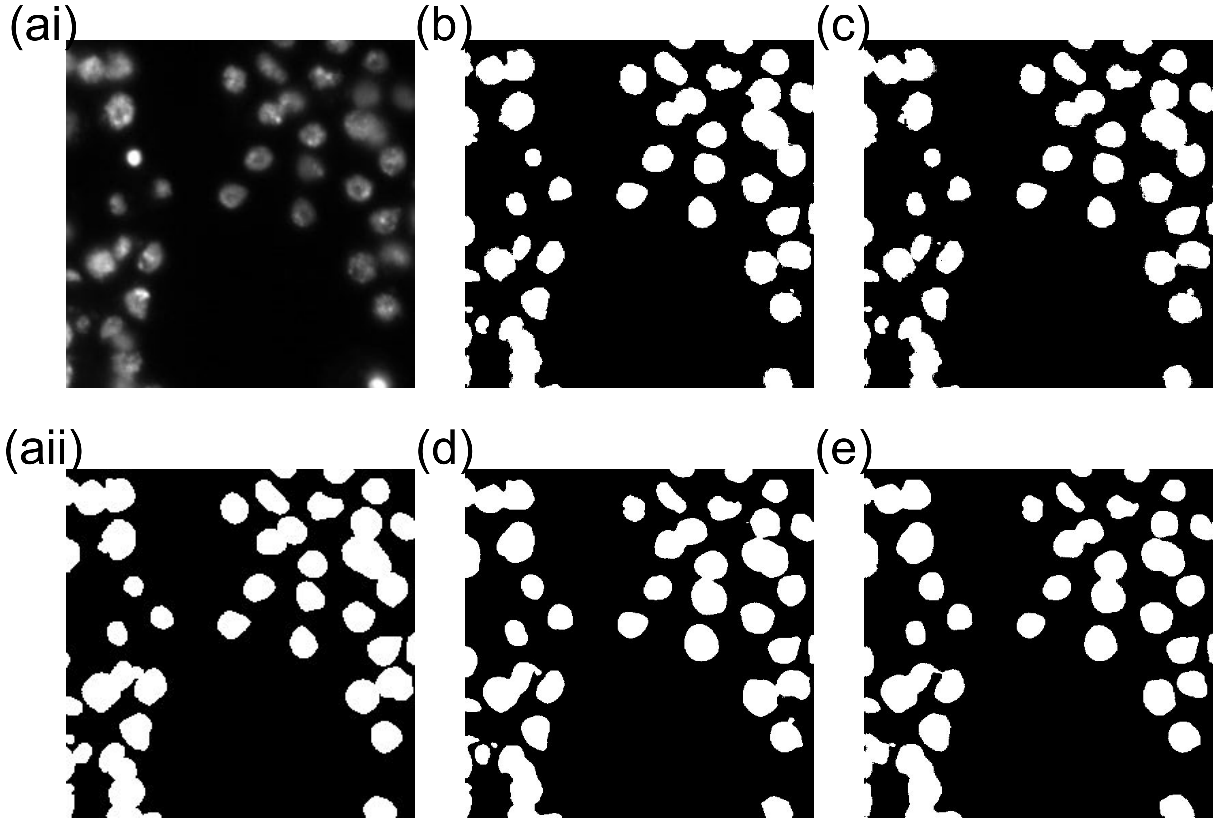
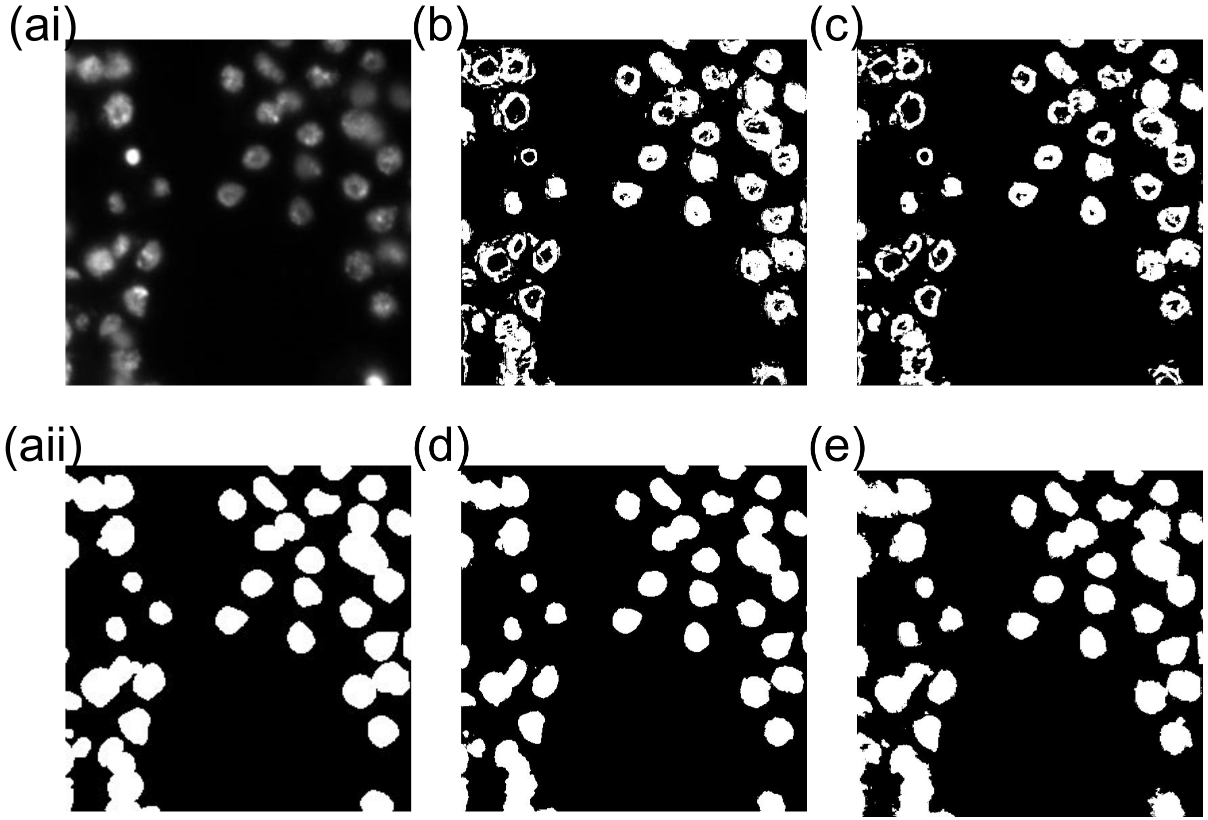
UNET has overall better performance than UNETR



UNET



UNETR

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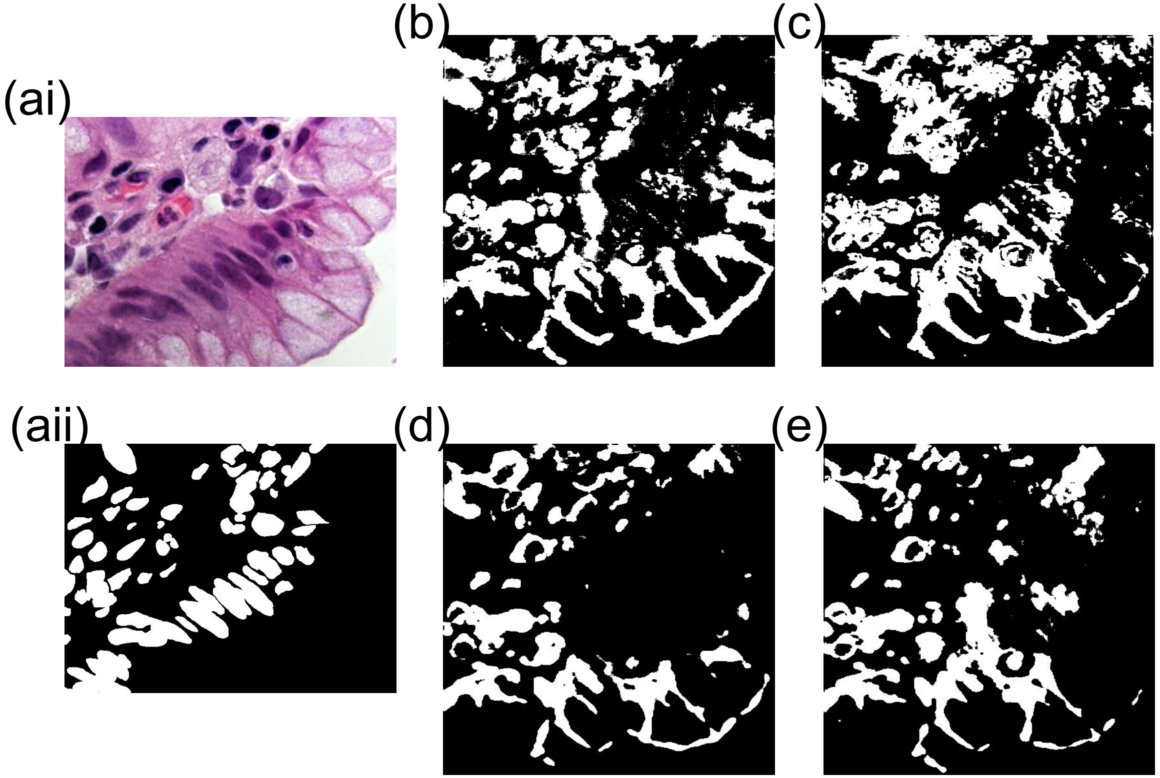
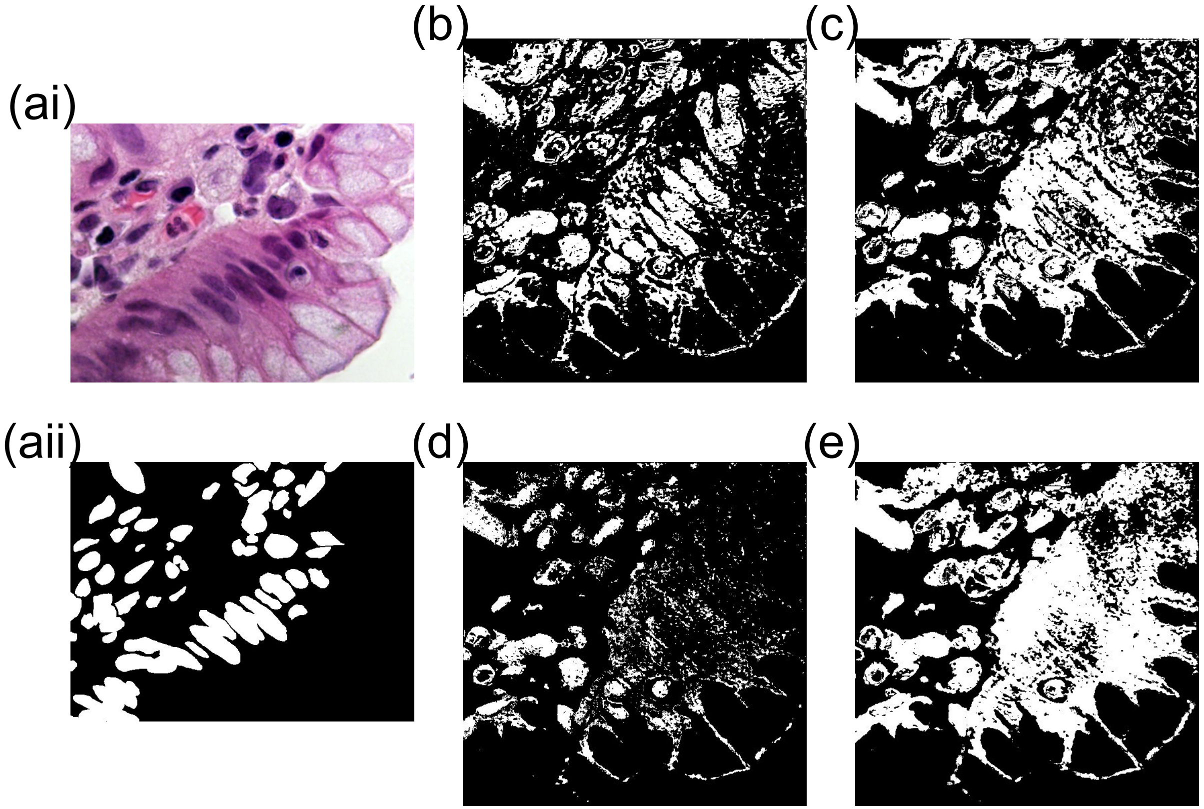
Both models did not do well with stained images



UNET



UNETR

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Conclusion

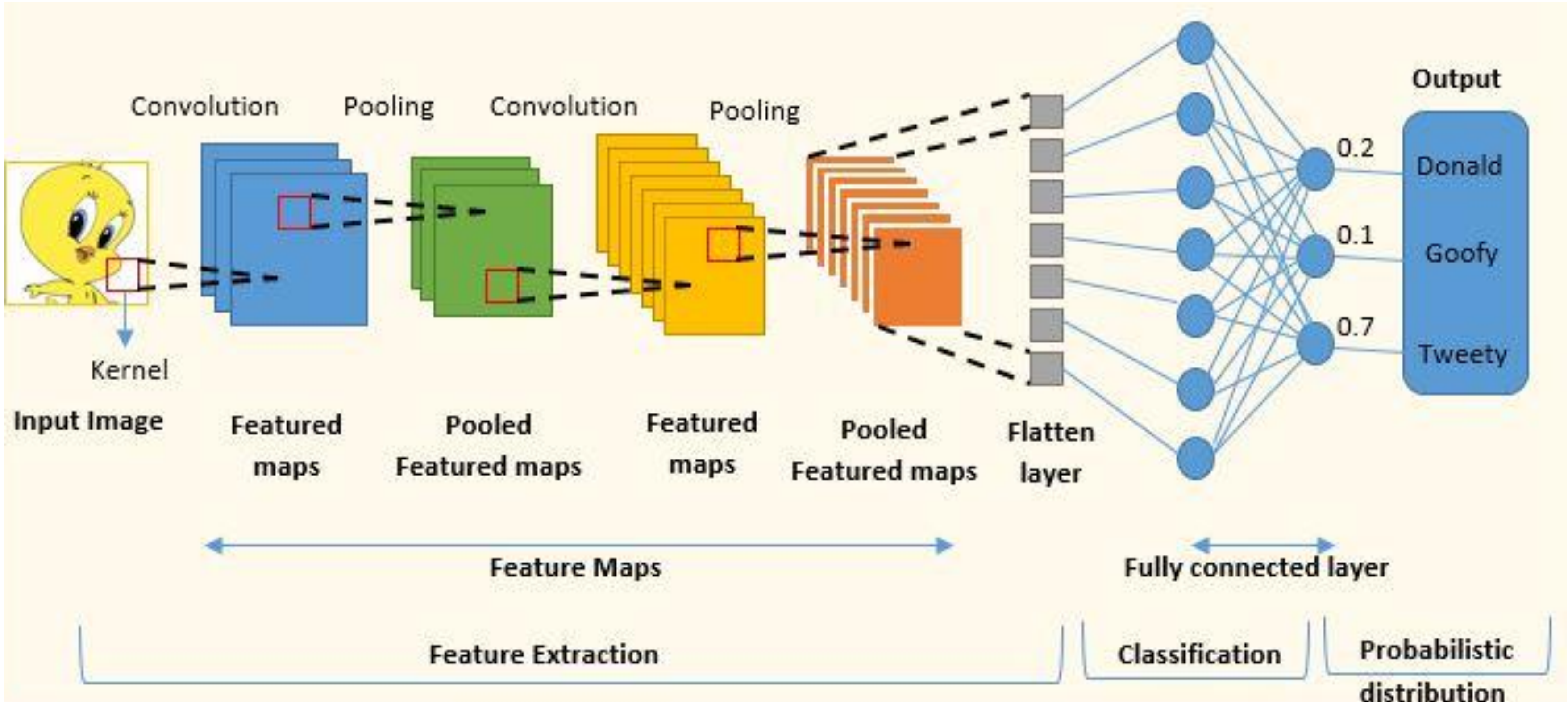
How can future researchers design cell segmentation models?

With a small and unbalanced dataset…

- UNET with SGD has the best performance while also require relatively low training resources
- LR scheduler can be helpful if it is tuned properly
- A bigger and more balanced dataset is always welcomed!
- Dataset should be exclaimed closely to choose the best tools for training

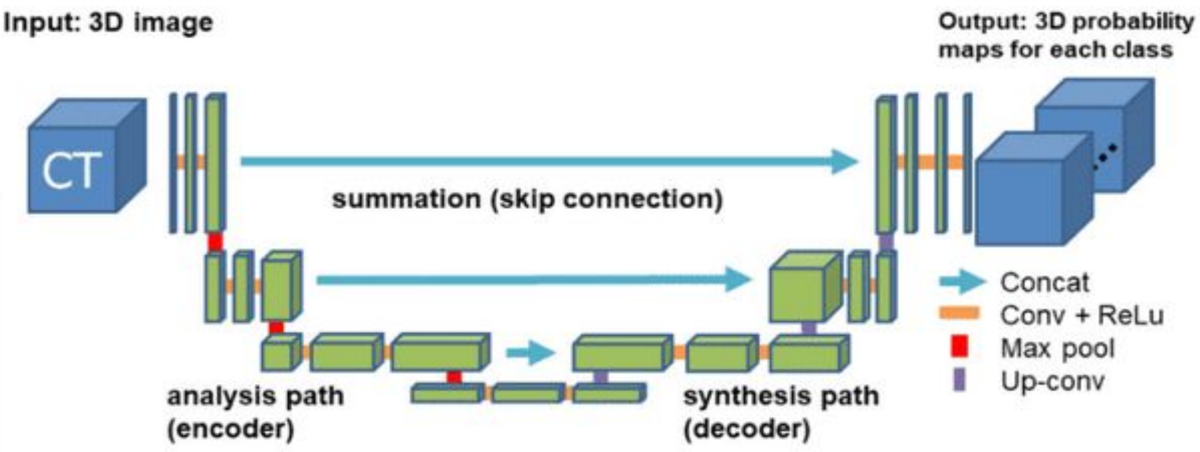
Thank you!

Convolutional Neural Network (CNN)

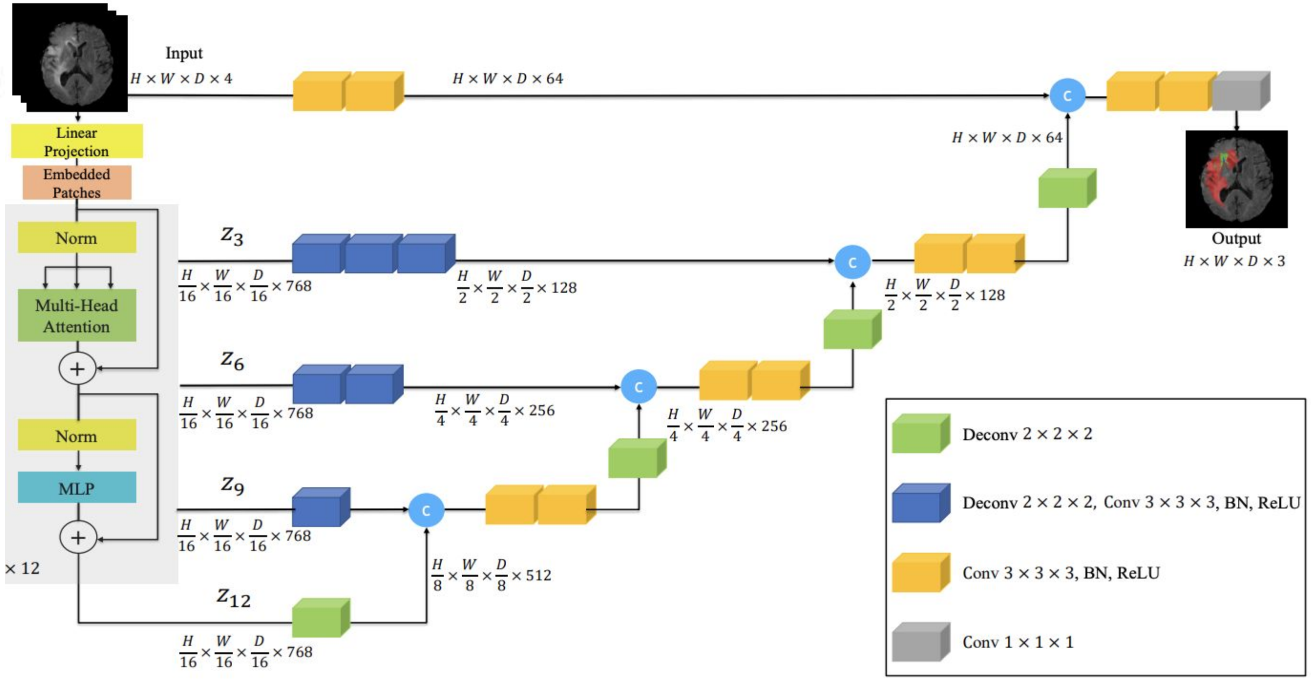


UNET and UNETR

UNET



UNET transformer (UNETR)



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