

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

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Presented by  
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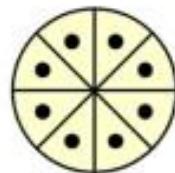


# Introduction

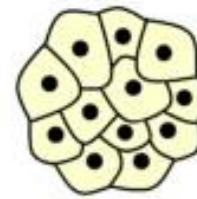
Why do we need cell segmentation?

# Cell morphology is highly related to cancer research

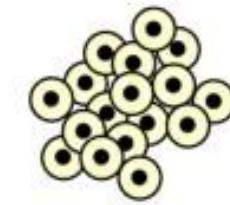
Round



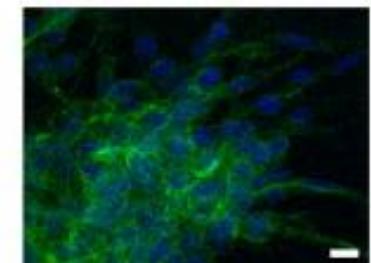
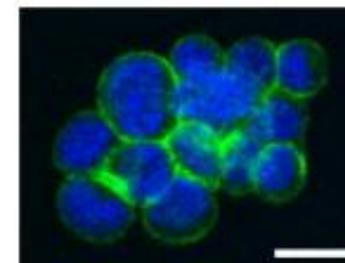
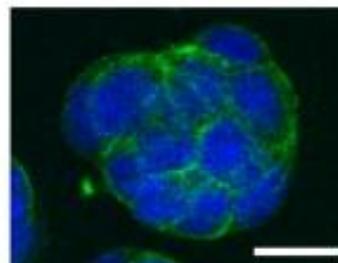
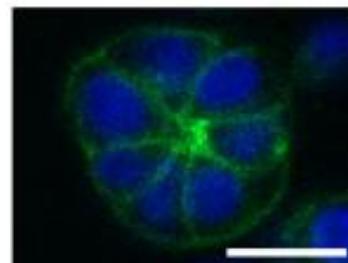
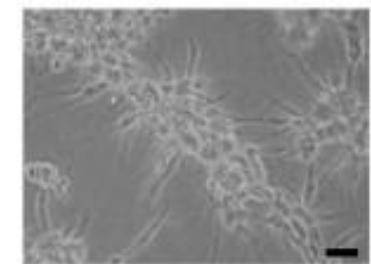
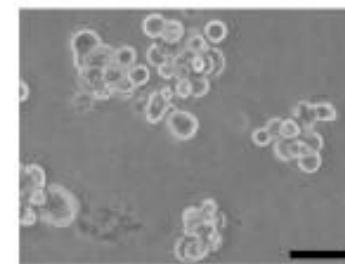
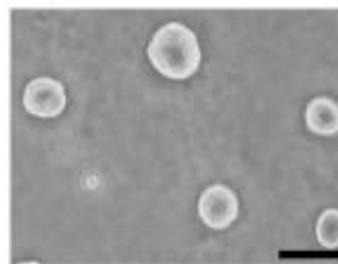
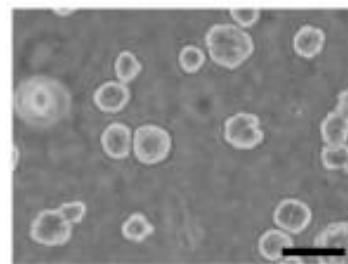
Mass



Grape-like



Stellate



- Organized nuclei
- Robust cell-cell adhesion

- Disorganized nuclei
- Robust cell-cell adhesion

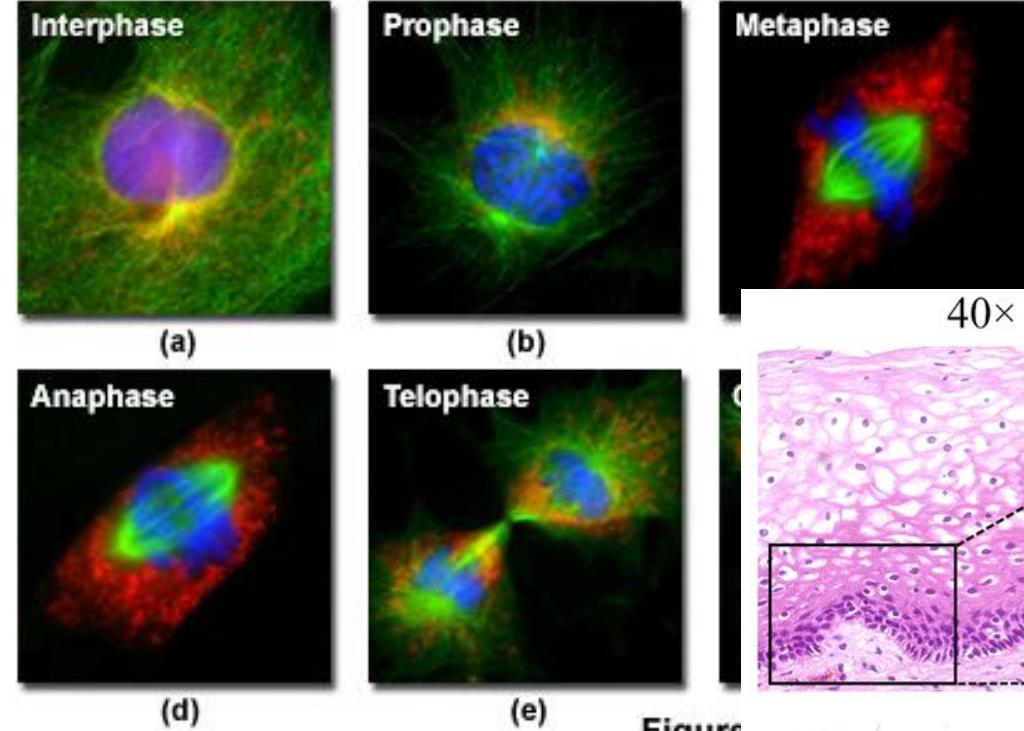
- Disorganized nuclei
- Poor cell-cell adhesion

- Disorganized nuclei
- Elongated cell body with invasive processes



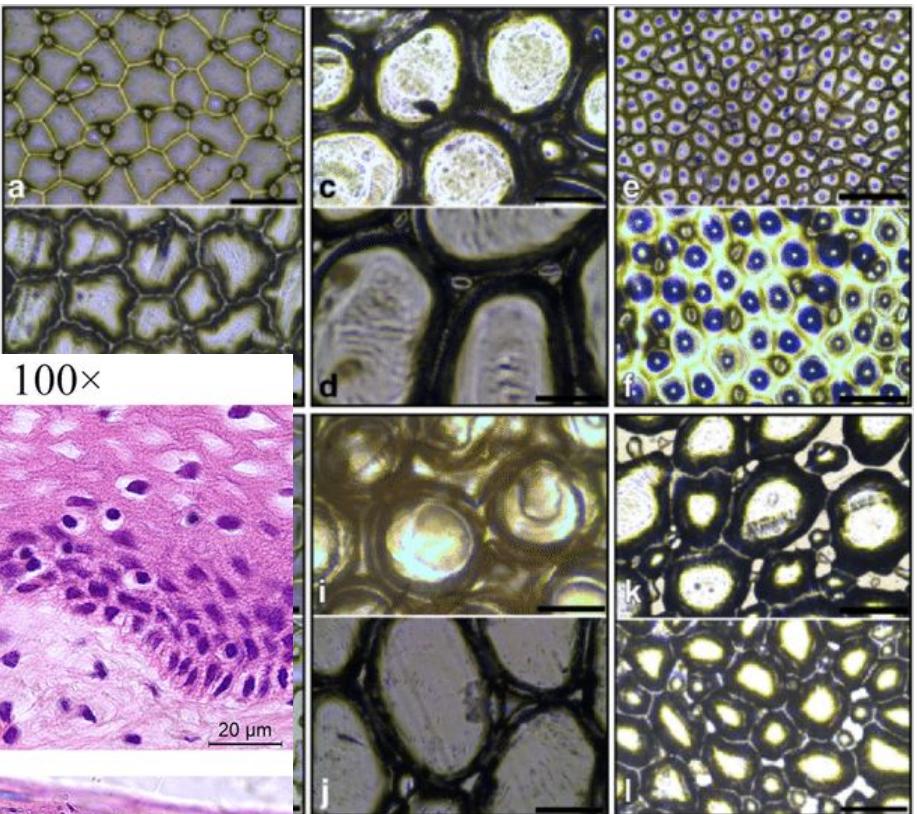
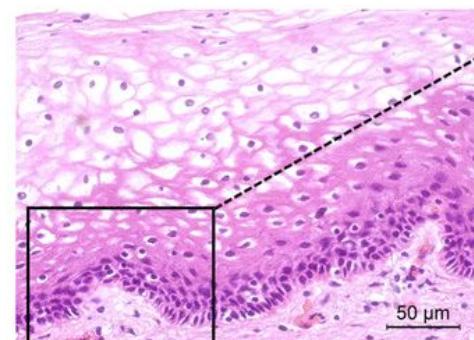
# Microscope is the major contributor for cell visualization

Mitosis in Rat Kangaroo Epithelial Kidney Cells



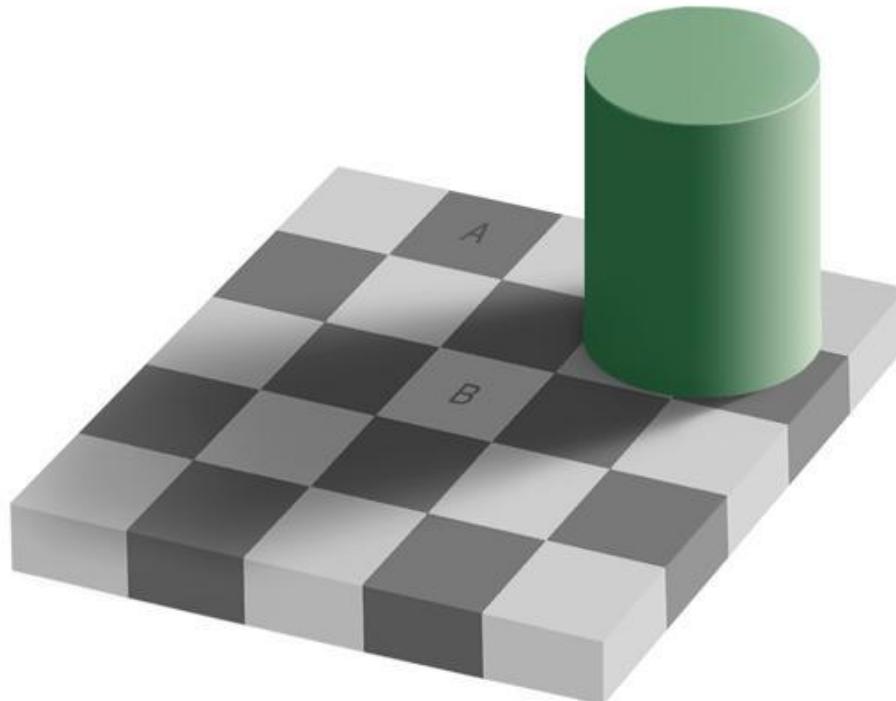
Figure

40×



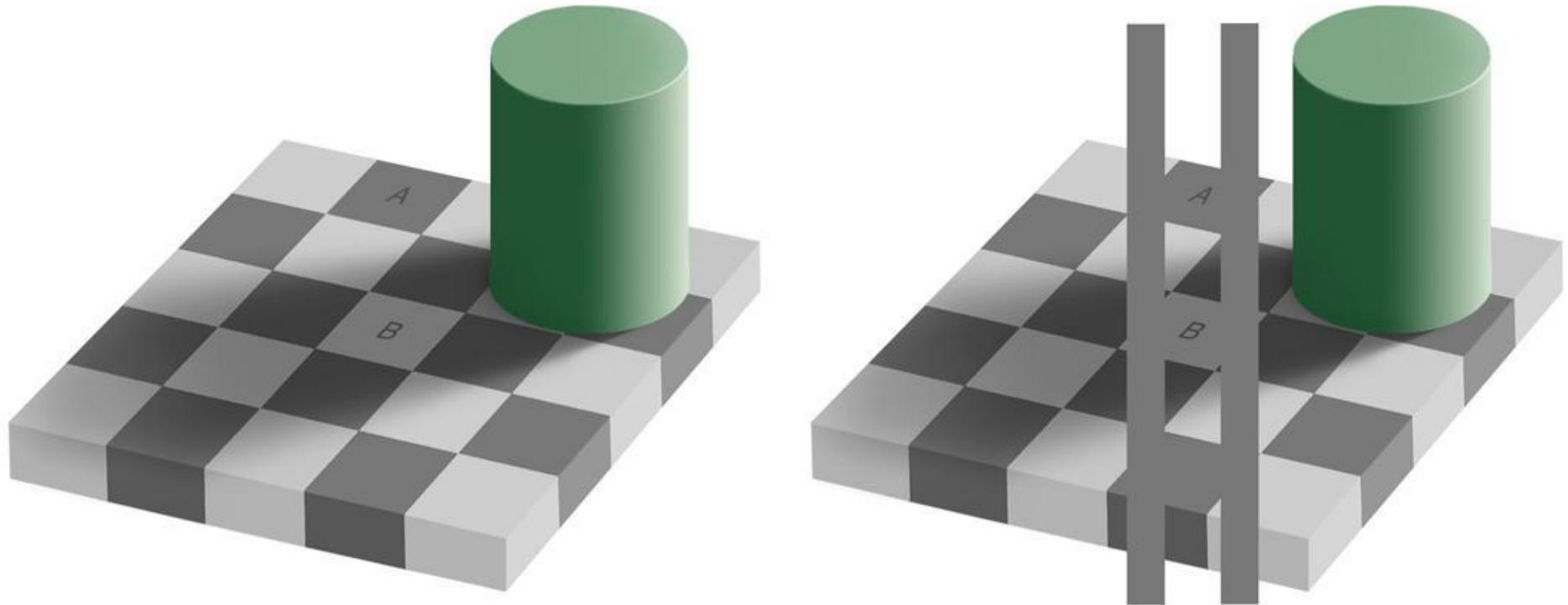
# Problems

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



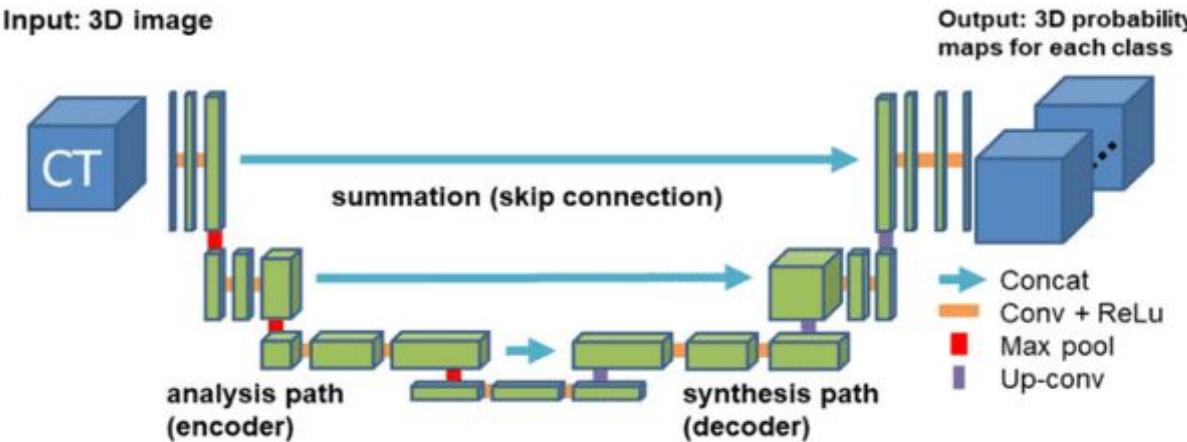
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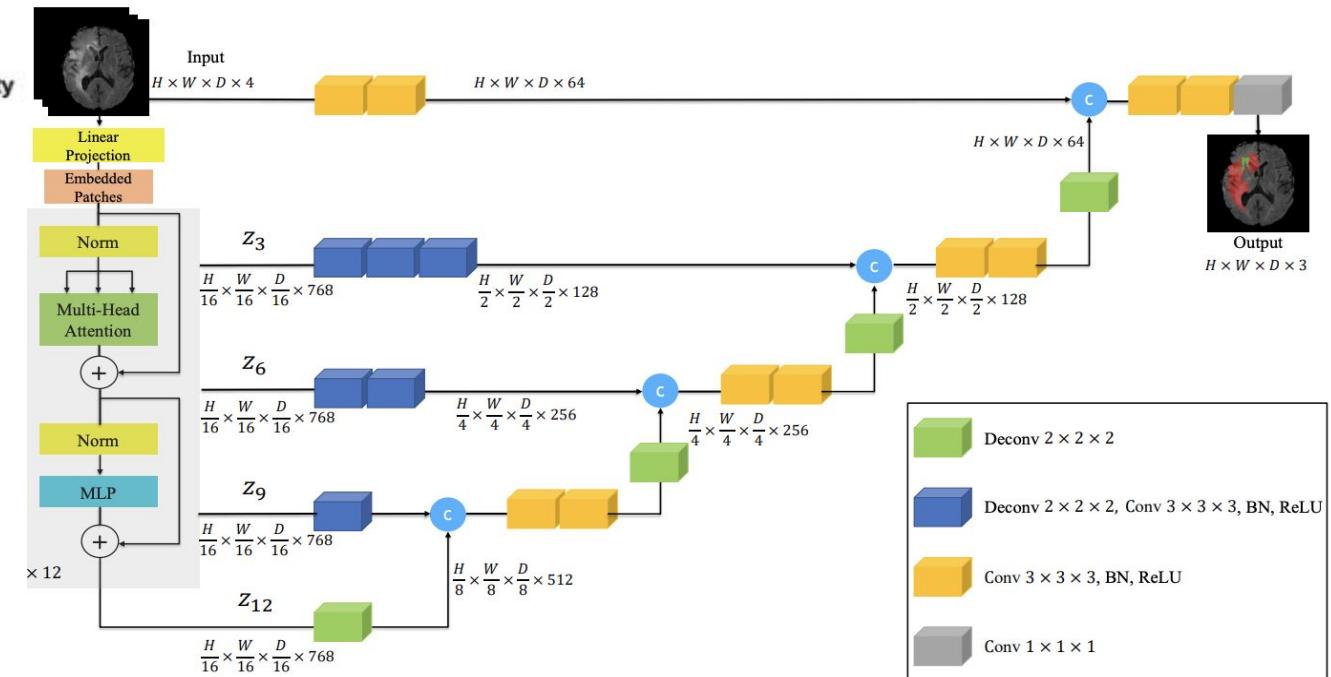


# UNET and UNETR

## UNET



## UNET transformer (UNETR)



# 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

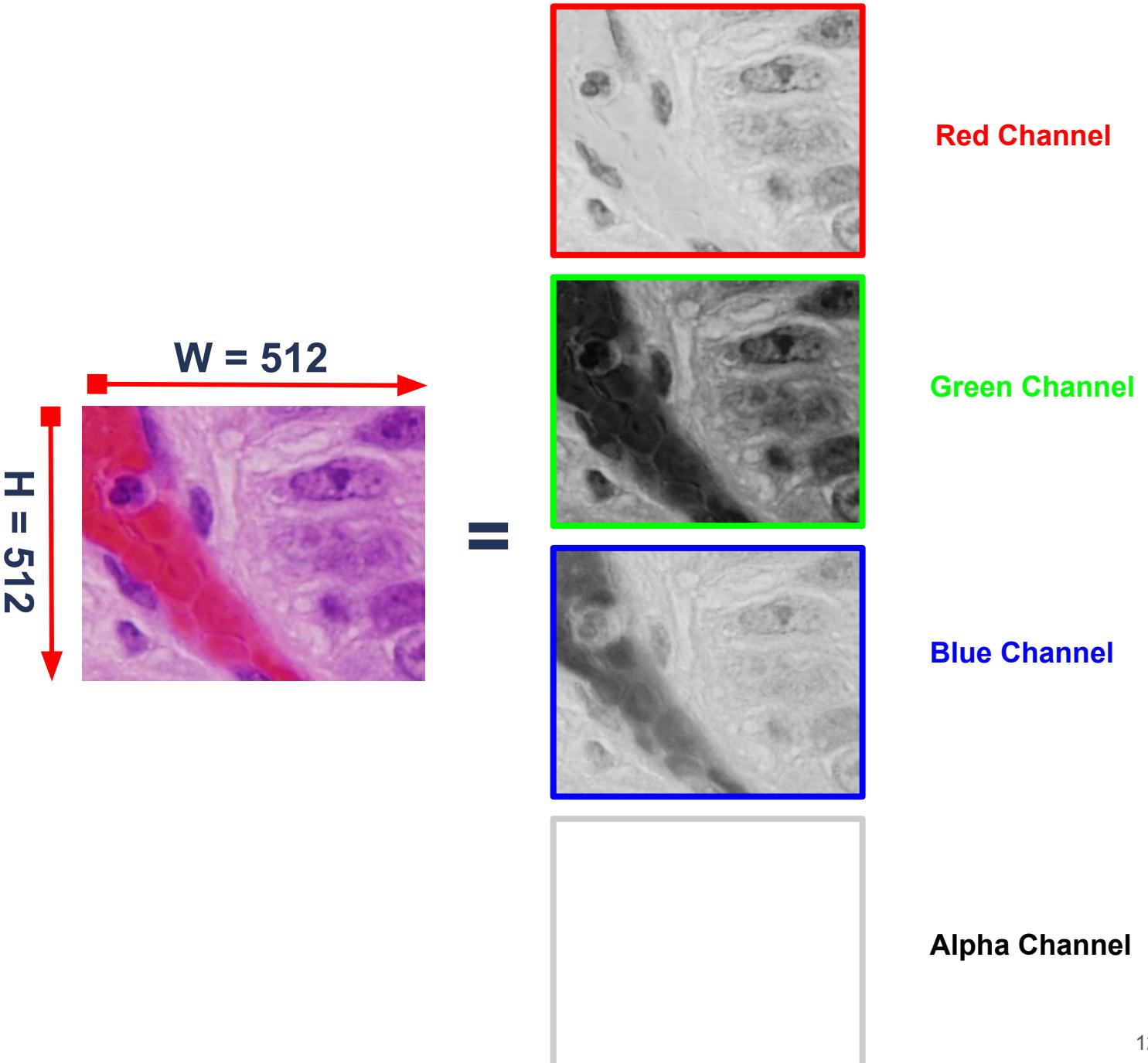


# Materials and Methods

## 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

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

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

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

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

$p_t$ : estimated probability for the class

$\hat{Y}$ : network output

$Y$ : ground truth

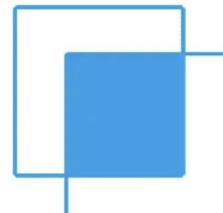
$TP$ : true positive

$FP$ : false positive

$FN$ : false negative

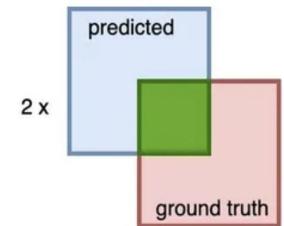
- Intersection over Union (IoU)

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



- Dice Coefficient (DC)

$$\text{Dice coefficient} = \frac{2x \text{ area of overlapped (green)}}{\text{total area (green)}} = \frac{2x \text{ area of overlapped (green)}}{\text{predicted} + \text{ground truth}}$$



# Results & Discussion

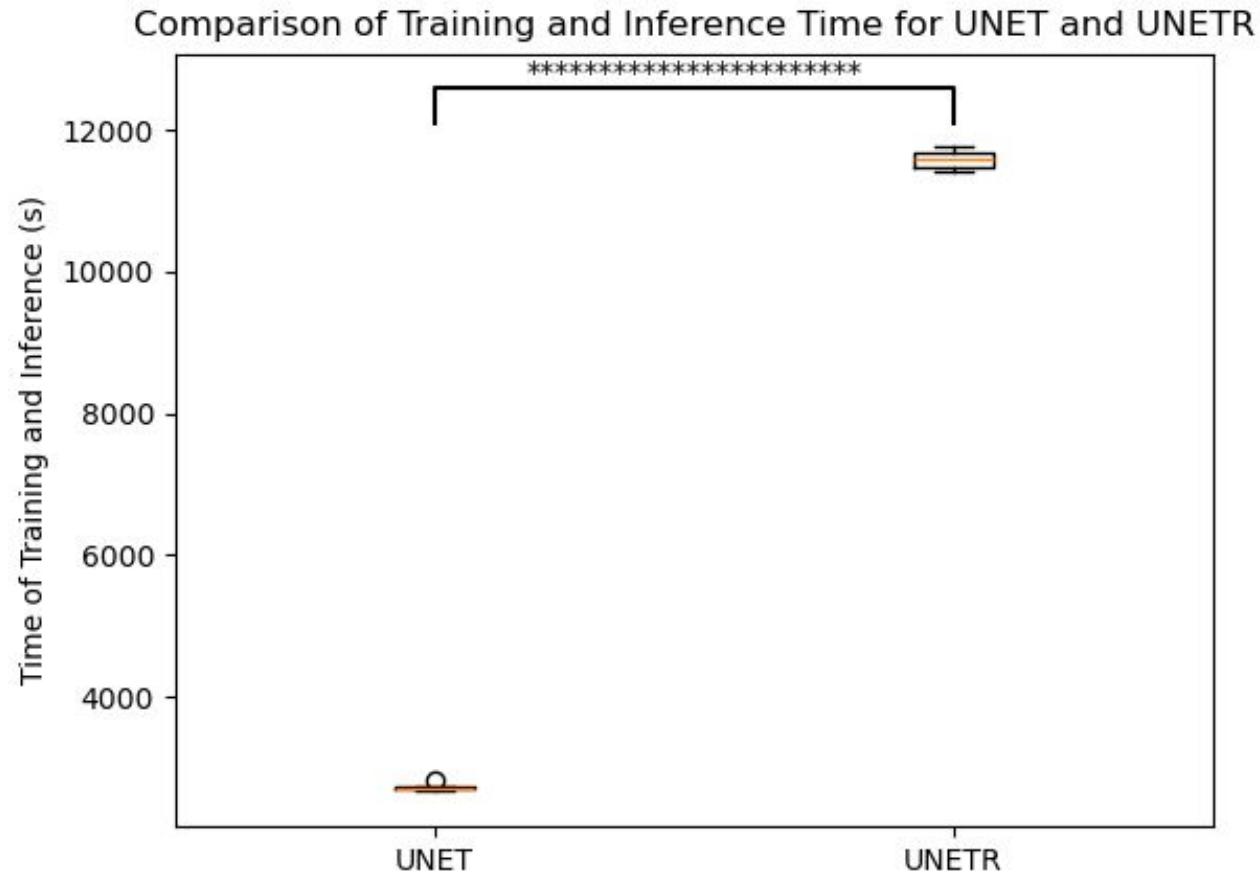
Comparison of various model performances



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# UNET requires significantly less time for training



# Adam converges faster for UNET but does not improve testing metrics

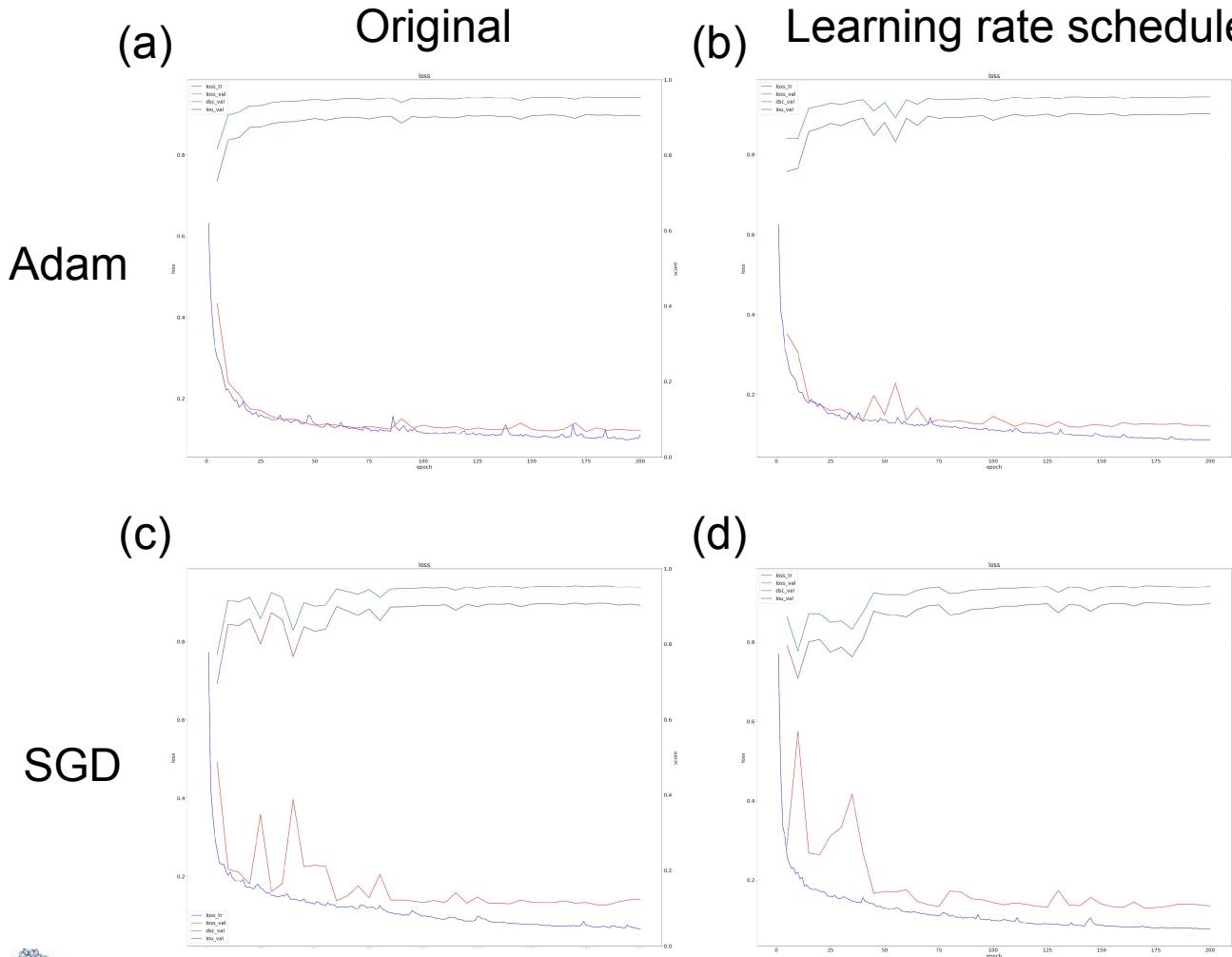


Table 1: Summary of the performance metrics (average Dice and IoU scores) of variations of UNET and UNETR models on the testing dataset. Sche indicates that the model used a learning rate scheduler during training.

		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

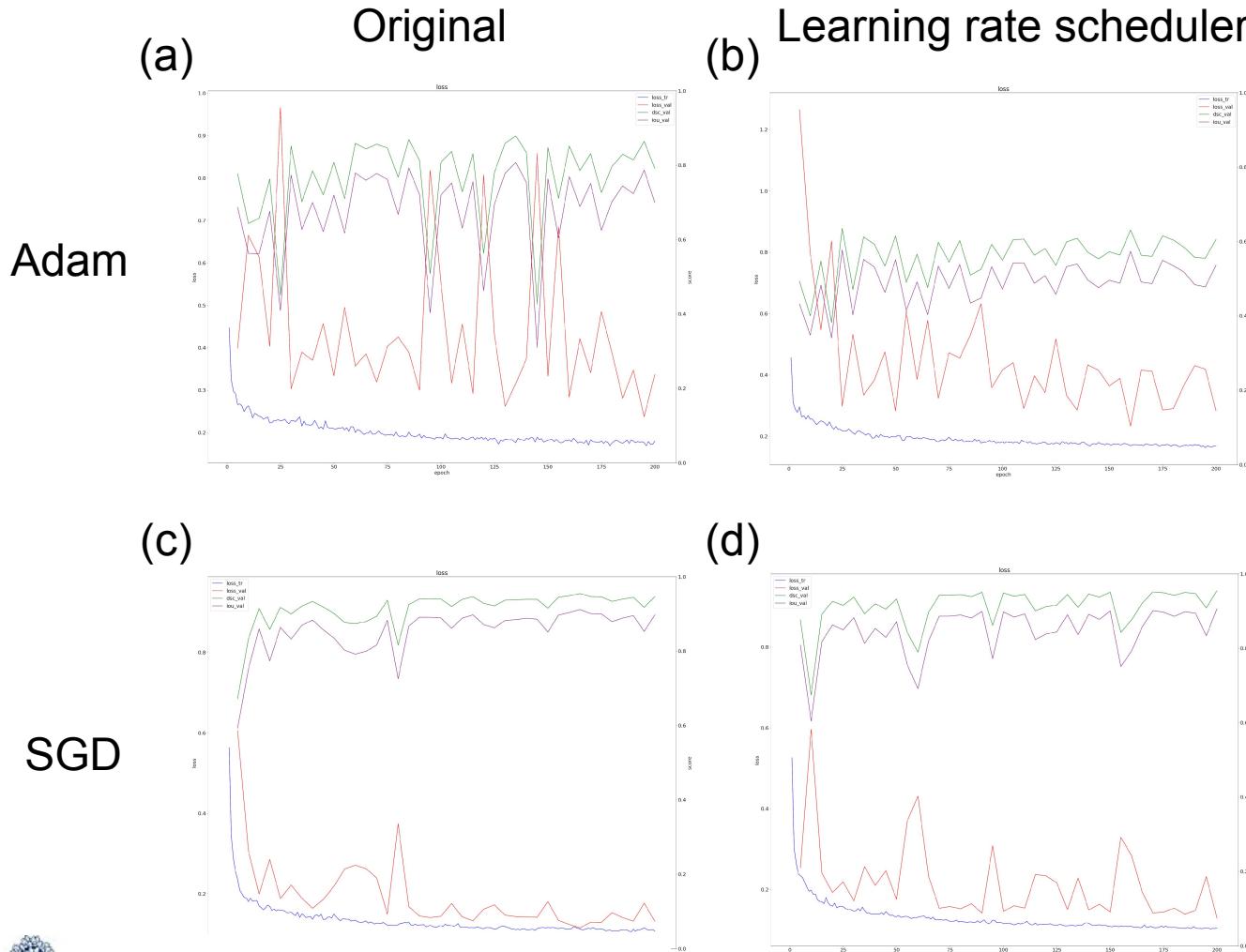


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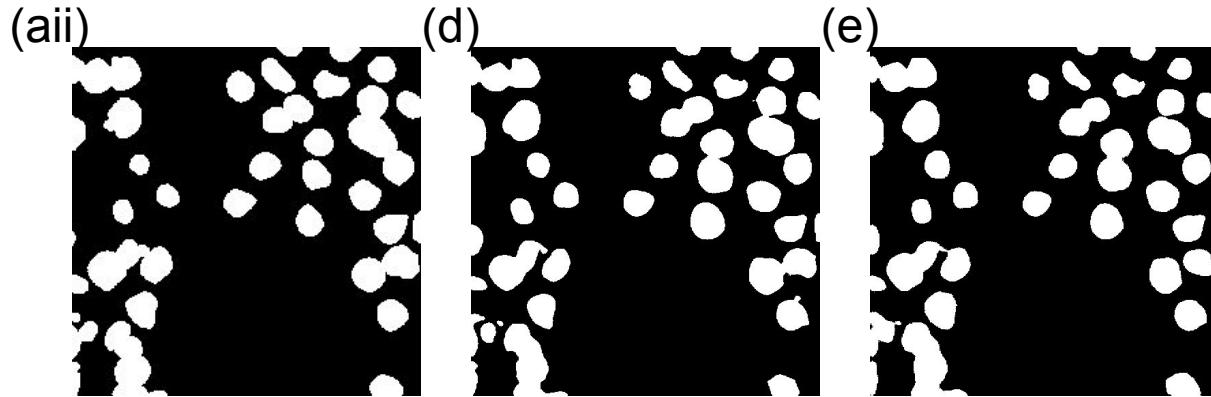
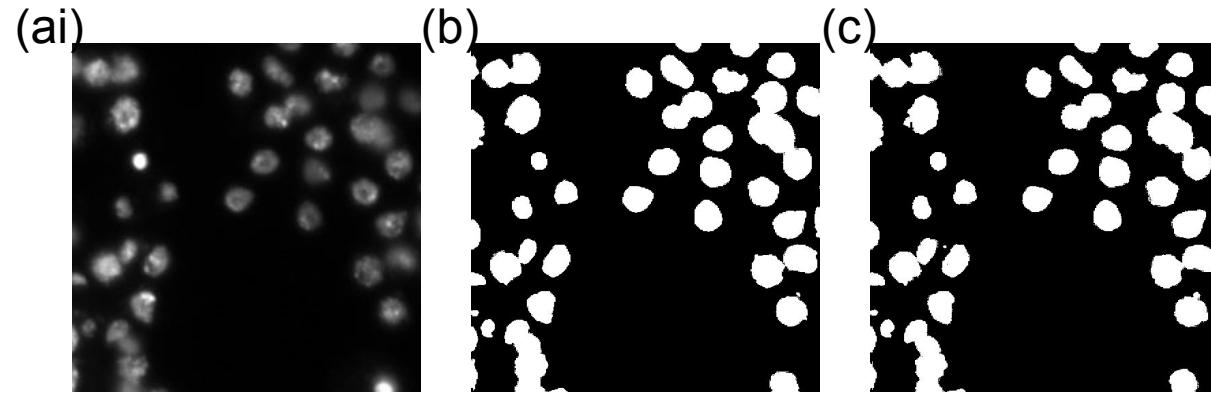
# Learning rate scheduler has limited if not negative impact on model testing performance

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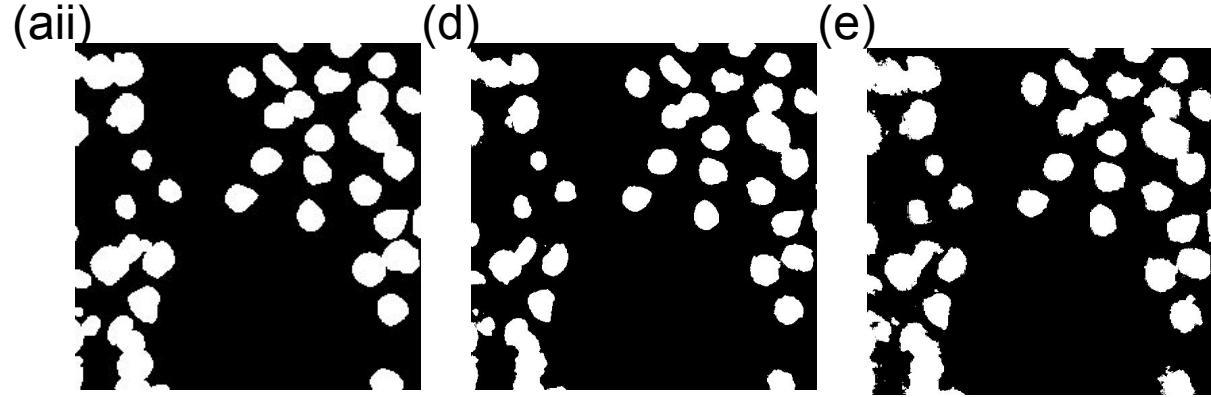
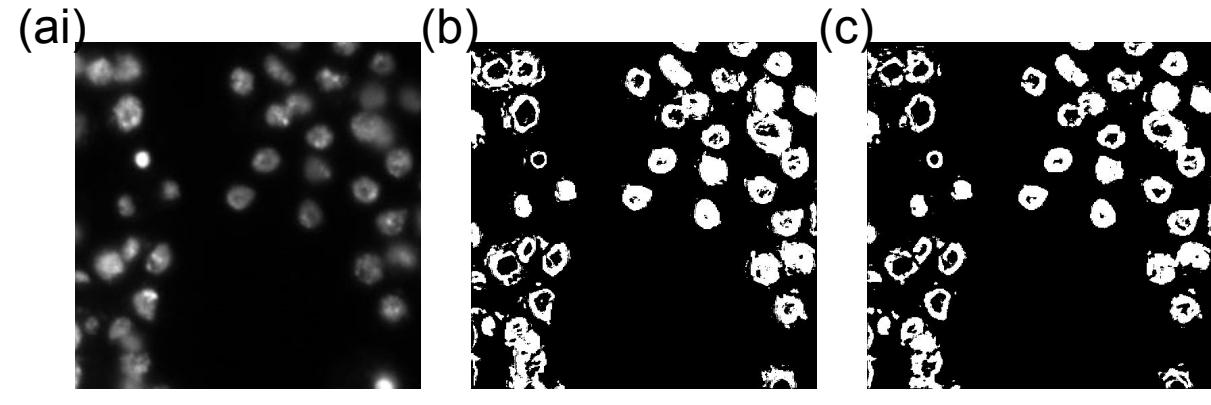
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# UNET has overall better performance than UNETR



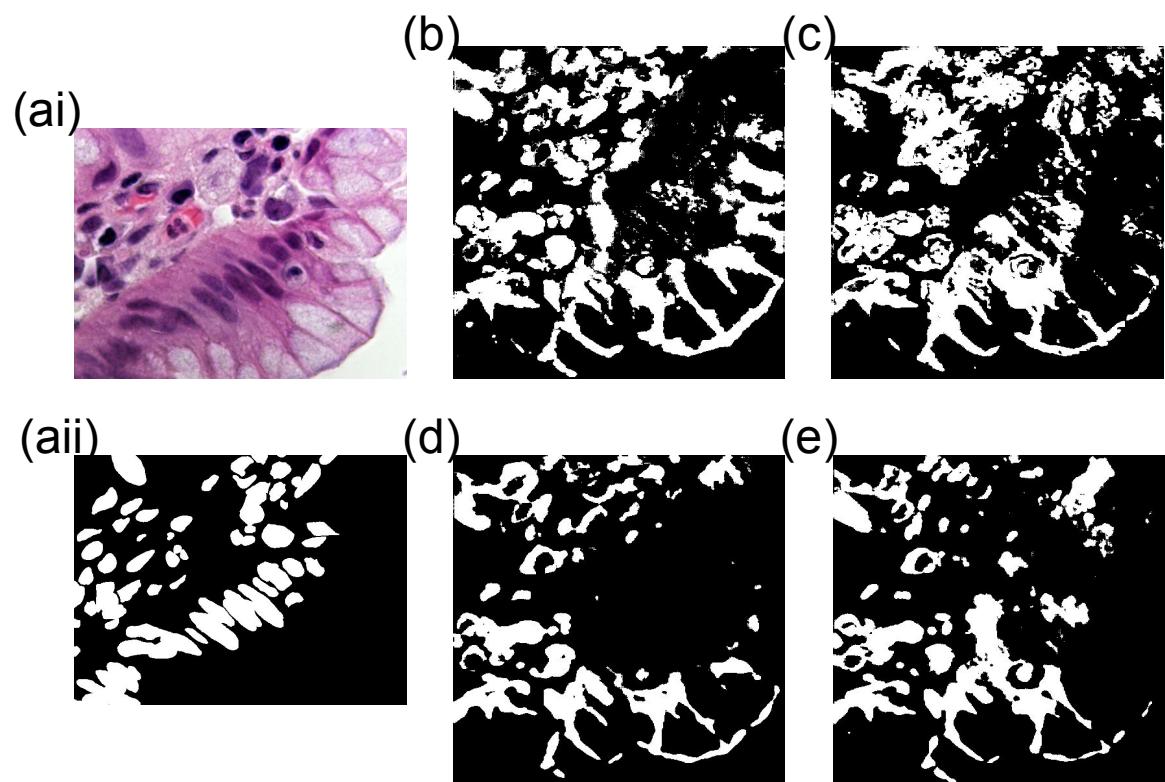
UNET



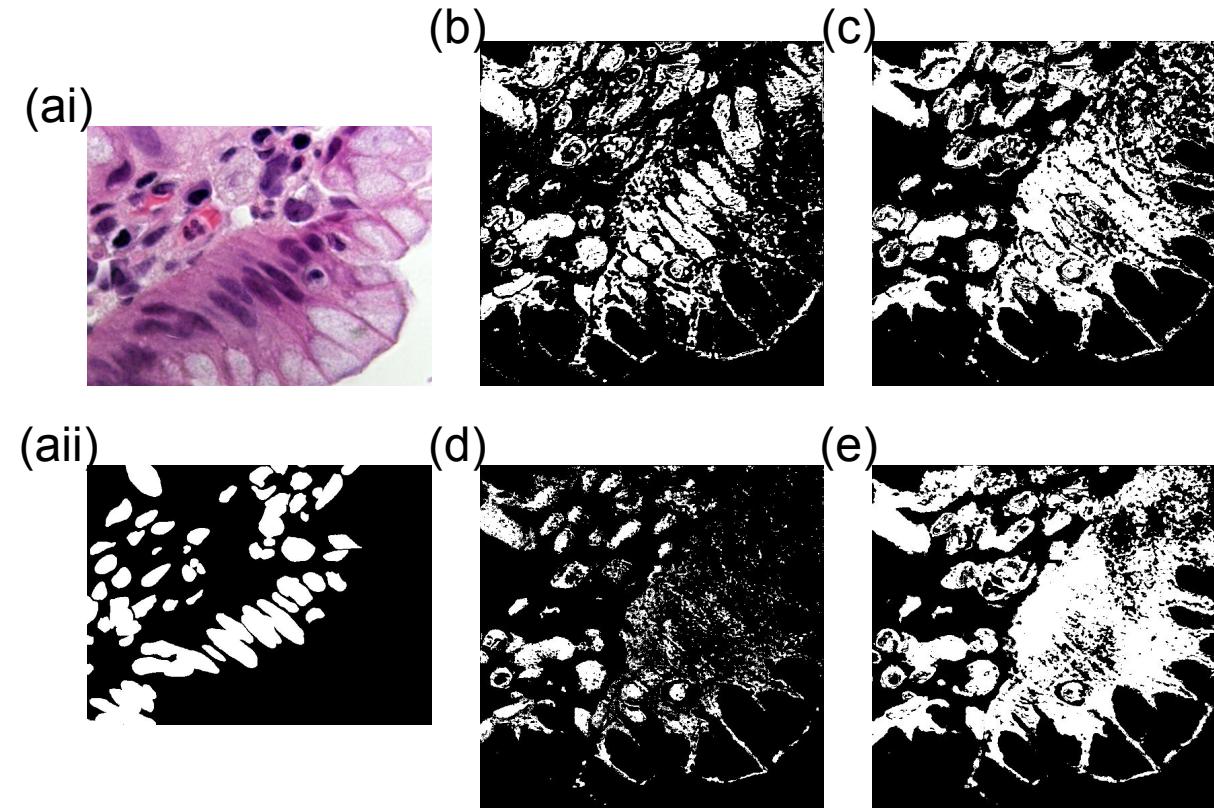
UNETR



# Both models did not do well with stained images



UNET



UNETR



# Conclusion

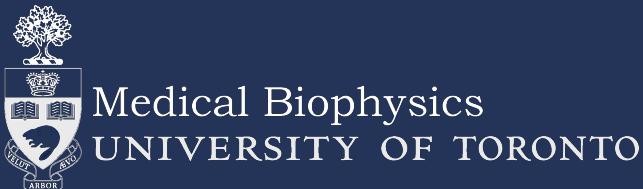
How can future researchers design cell segmentation models?

# 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 examined closely to choose the best tools for training



# Thank you!



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# Convolutional Neural Network (CNN)

