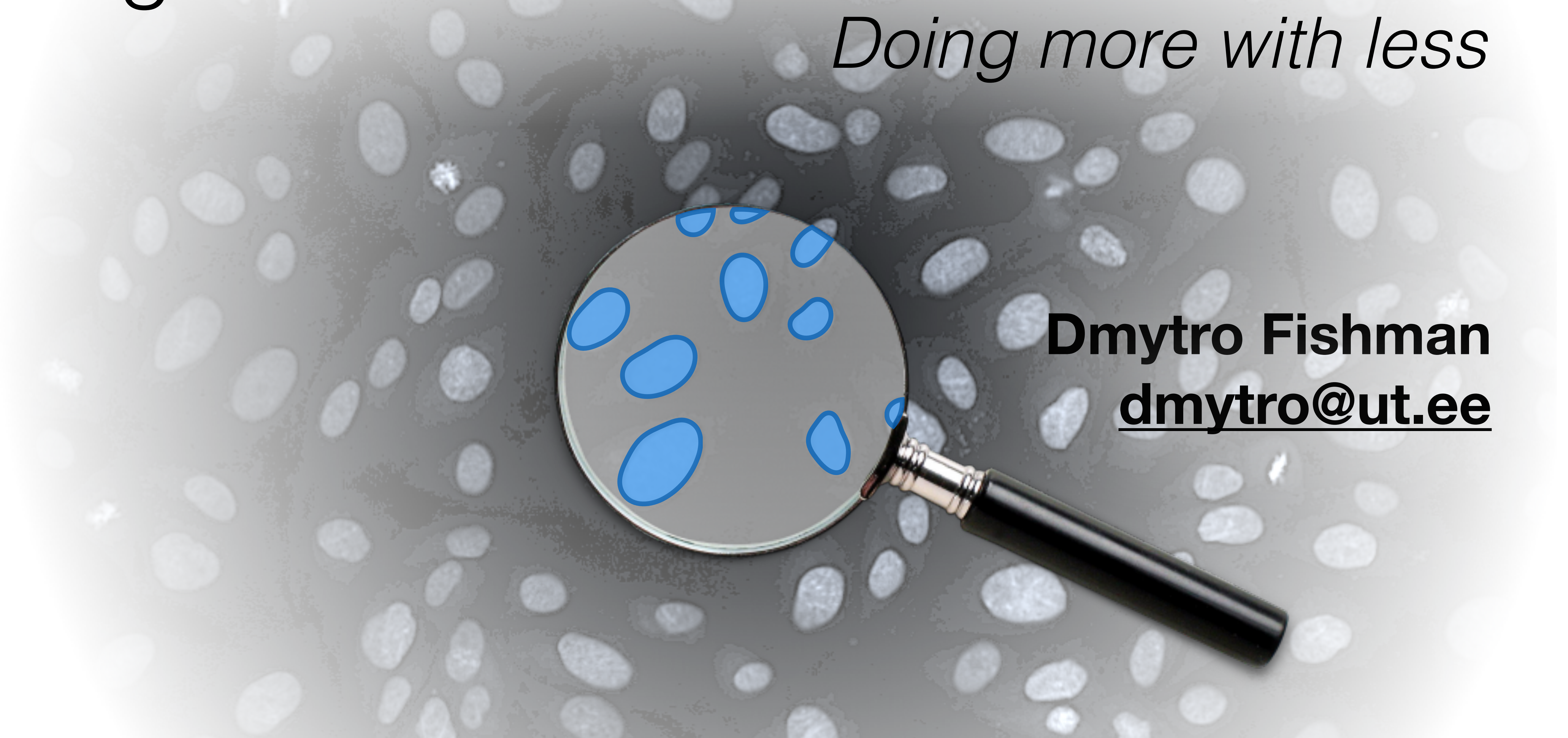
Under supervised semantic segmentation

Doing more with less



Dmytro Fishman
dmytro@ut.ee

Biomedical Image Analysis Group

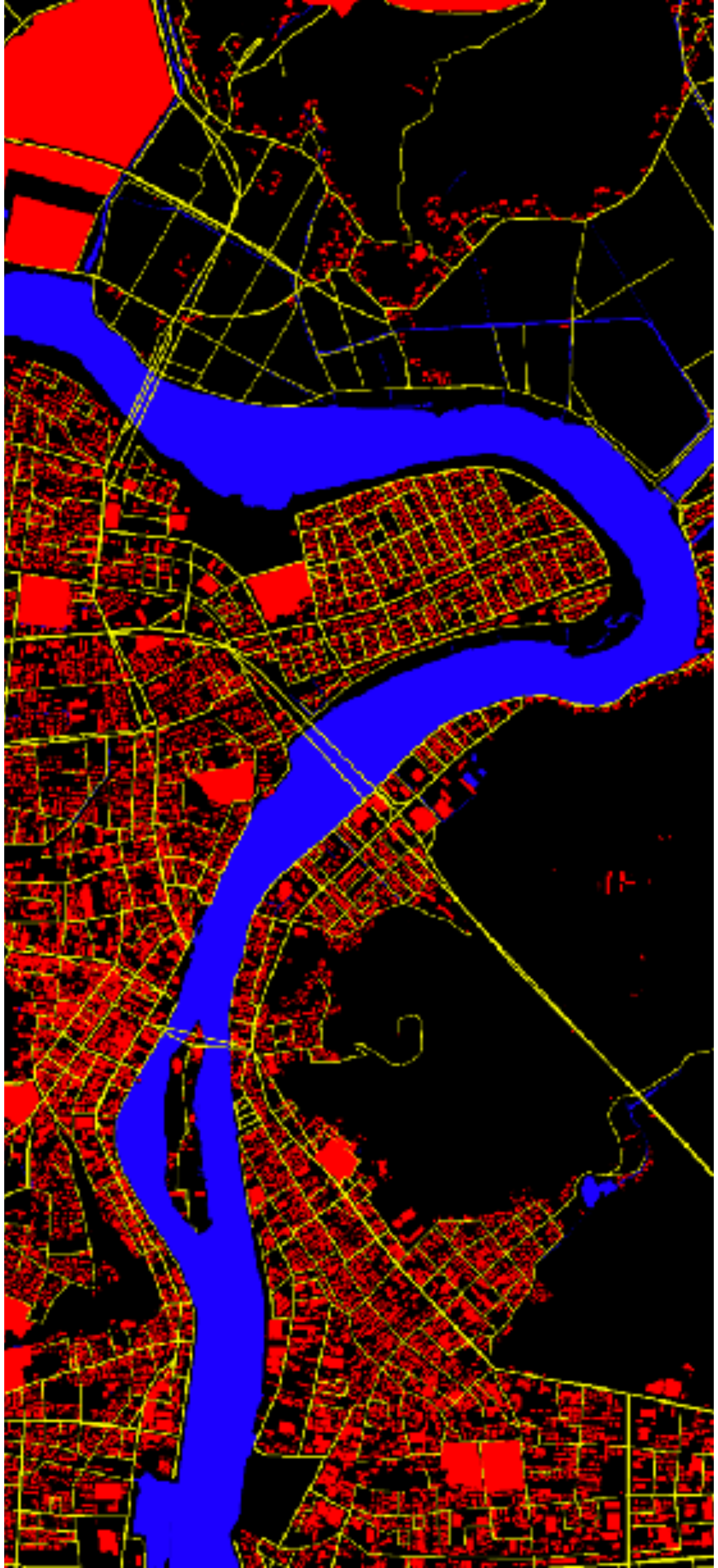
TARTU ÜLIKOOL
UNIVERSITAS TARTUENSIS
1632

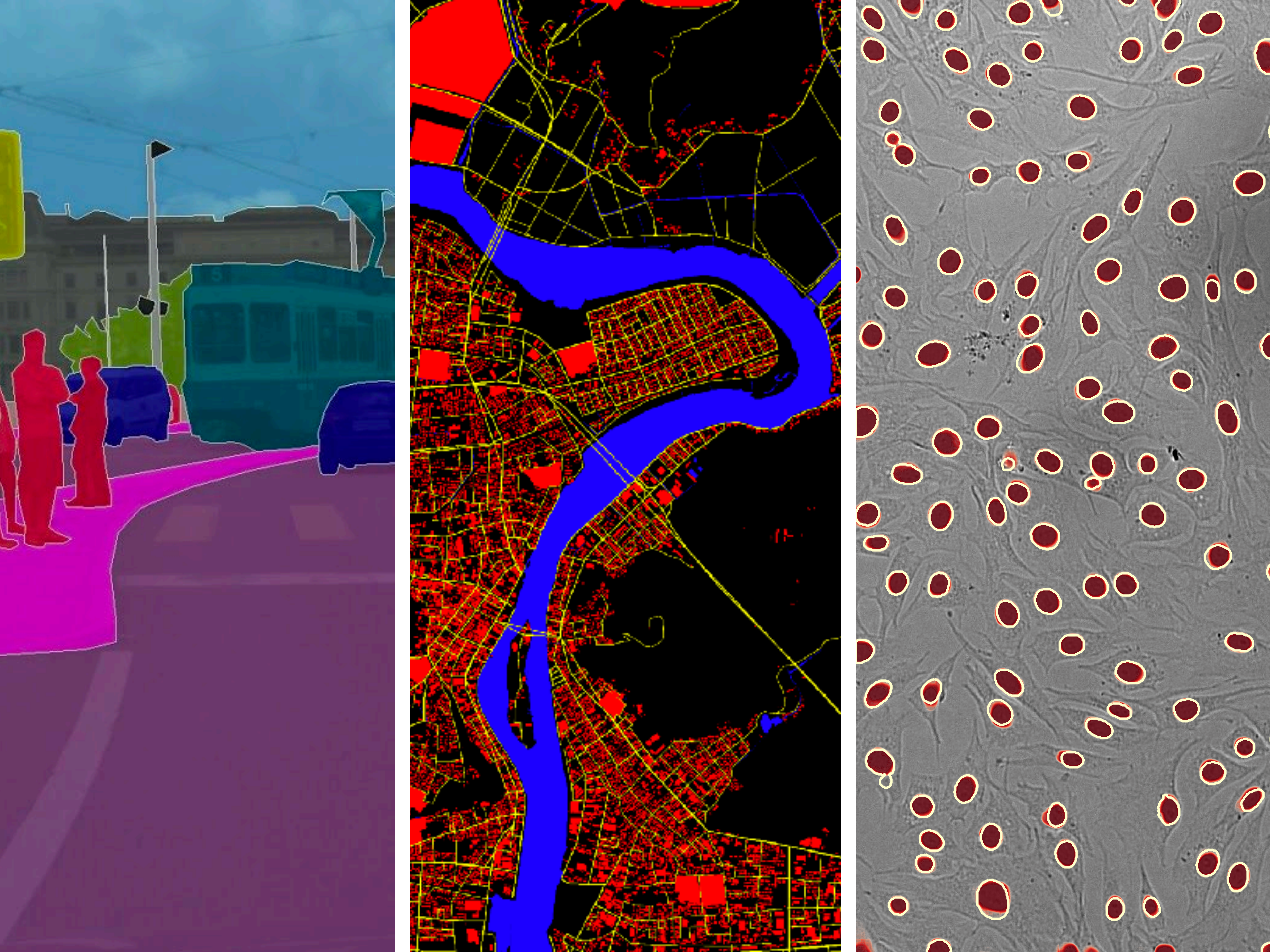
PerkinElmer
For the Better

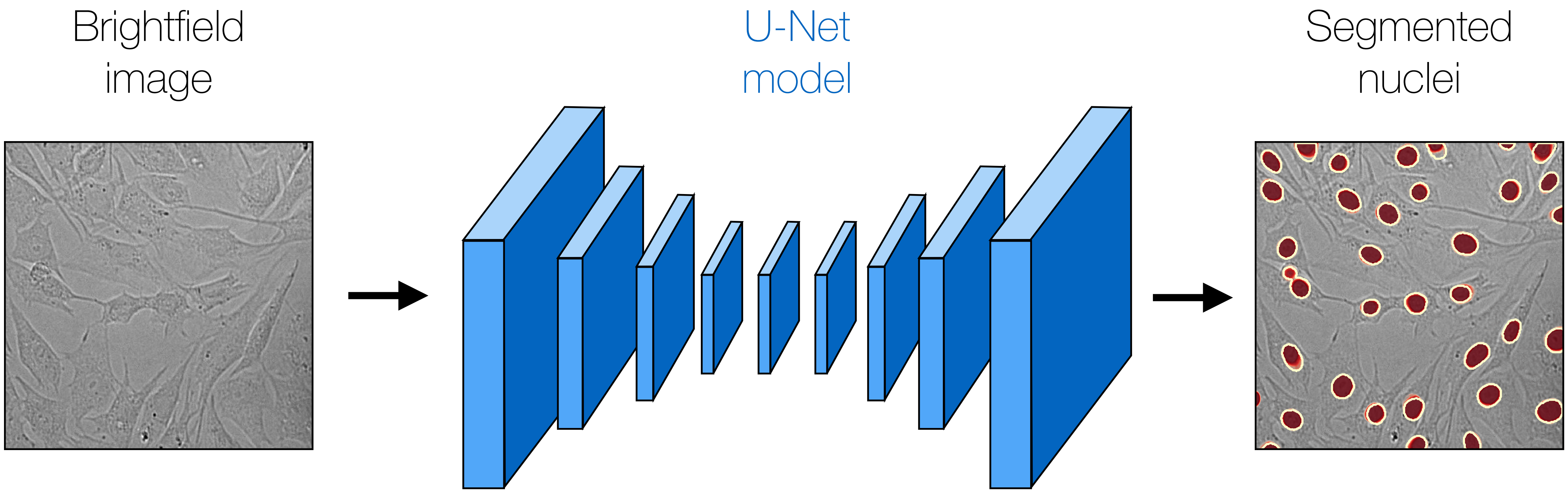
Segmentation problem - predicting **class** for each pixel in the image (in this case **pedestrian** and **background**)

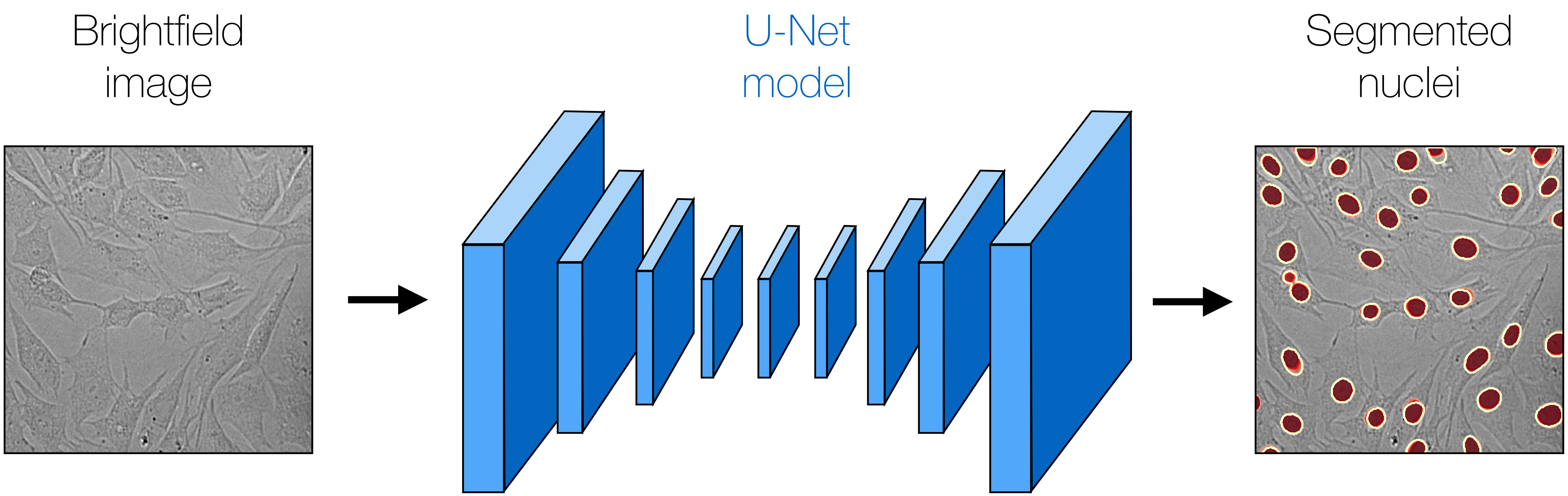
Segmentation problem - predicting **class** for each pixel in the image (in this case **pedestrian** and **background**)

Segmentation problem - predicting **class** for each pixel in the image (in this case **pedestrian** and **background**)

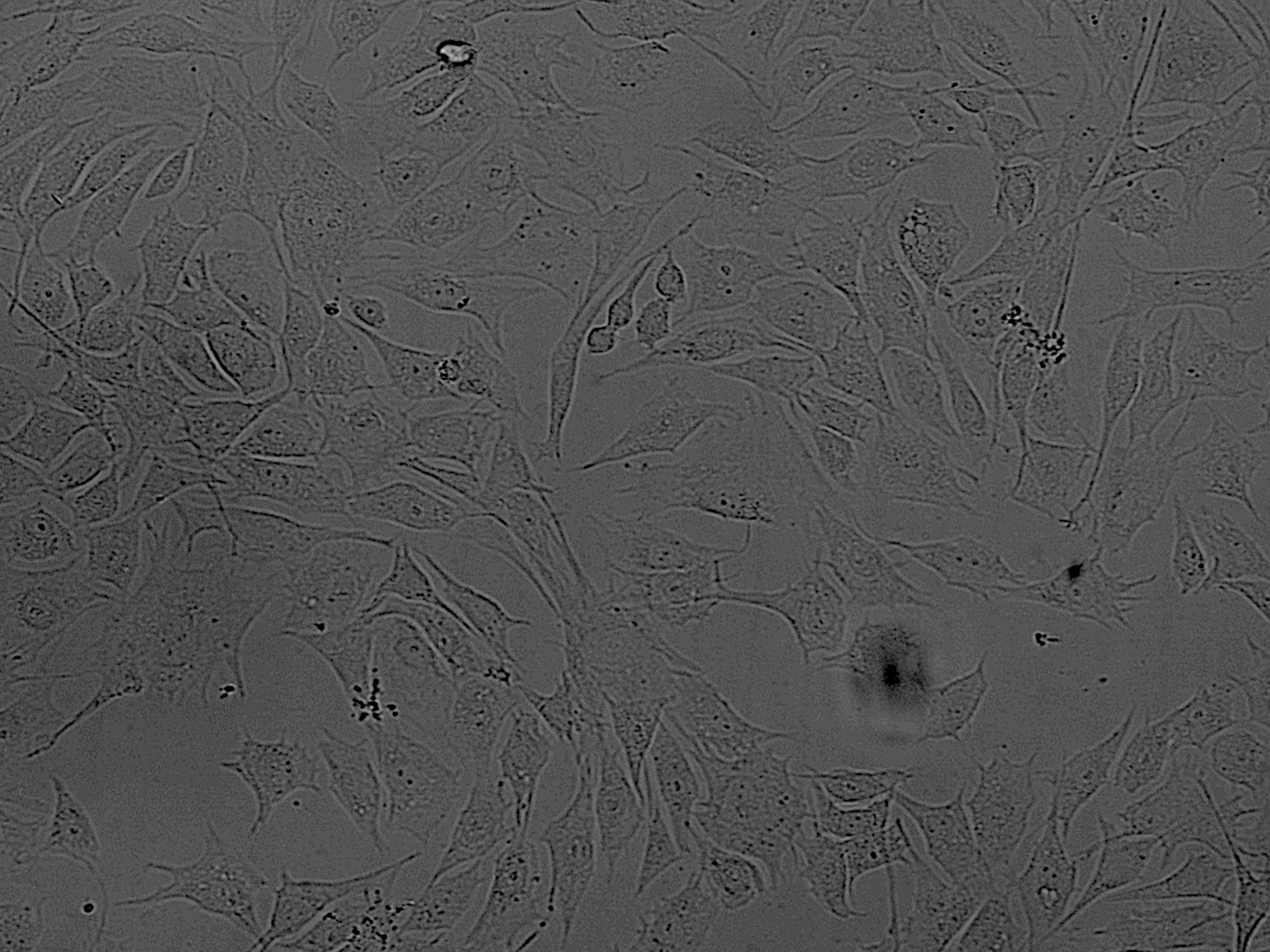


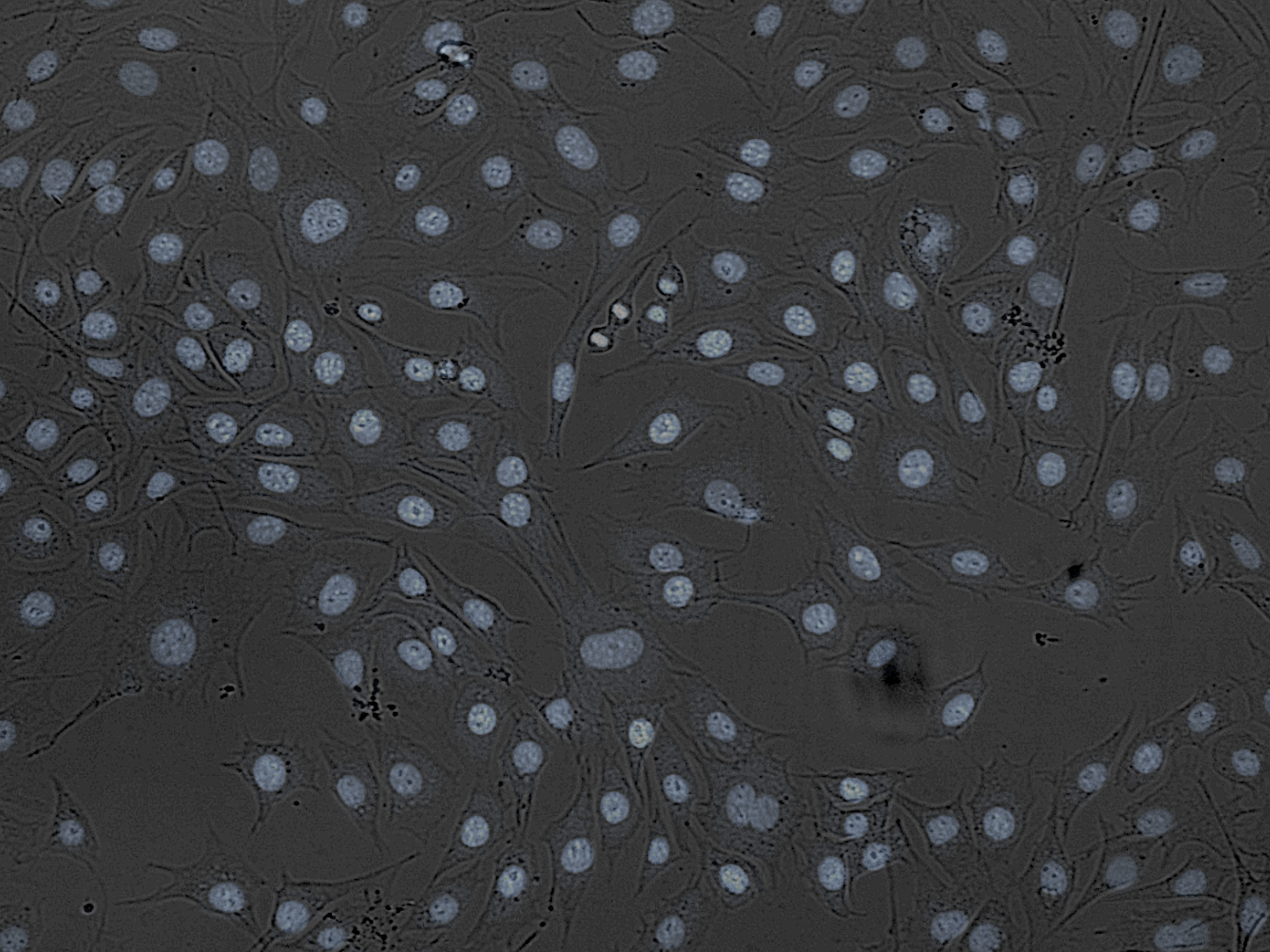


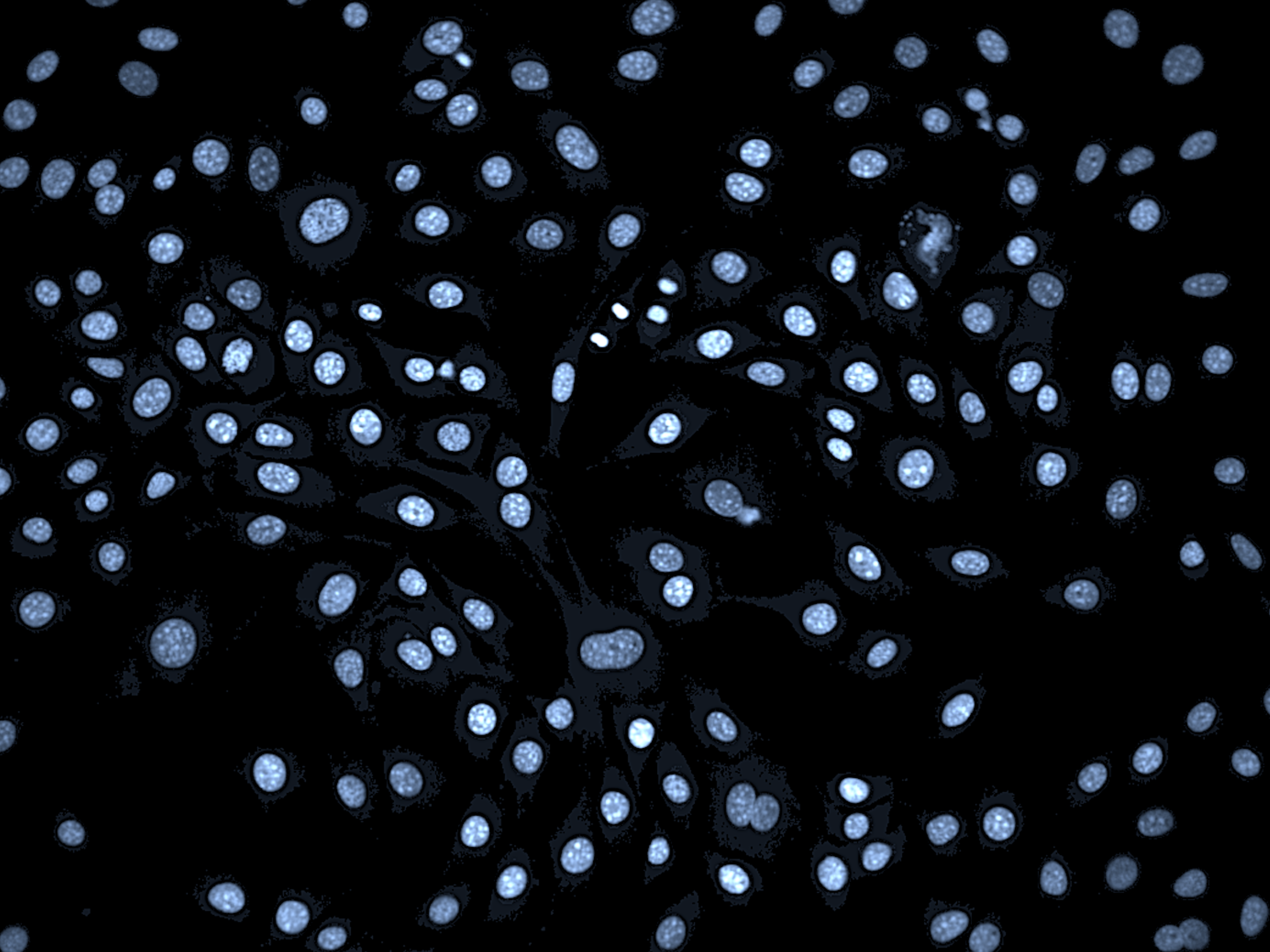

Brightfield
image
U-Net
model
Segmented
nuclei



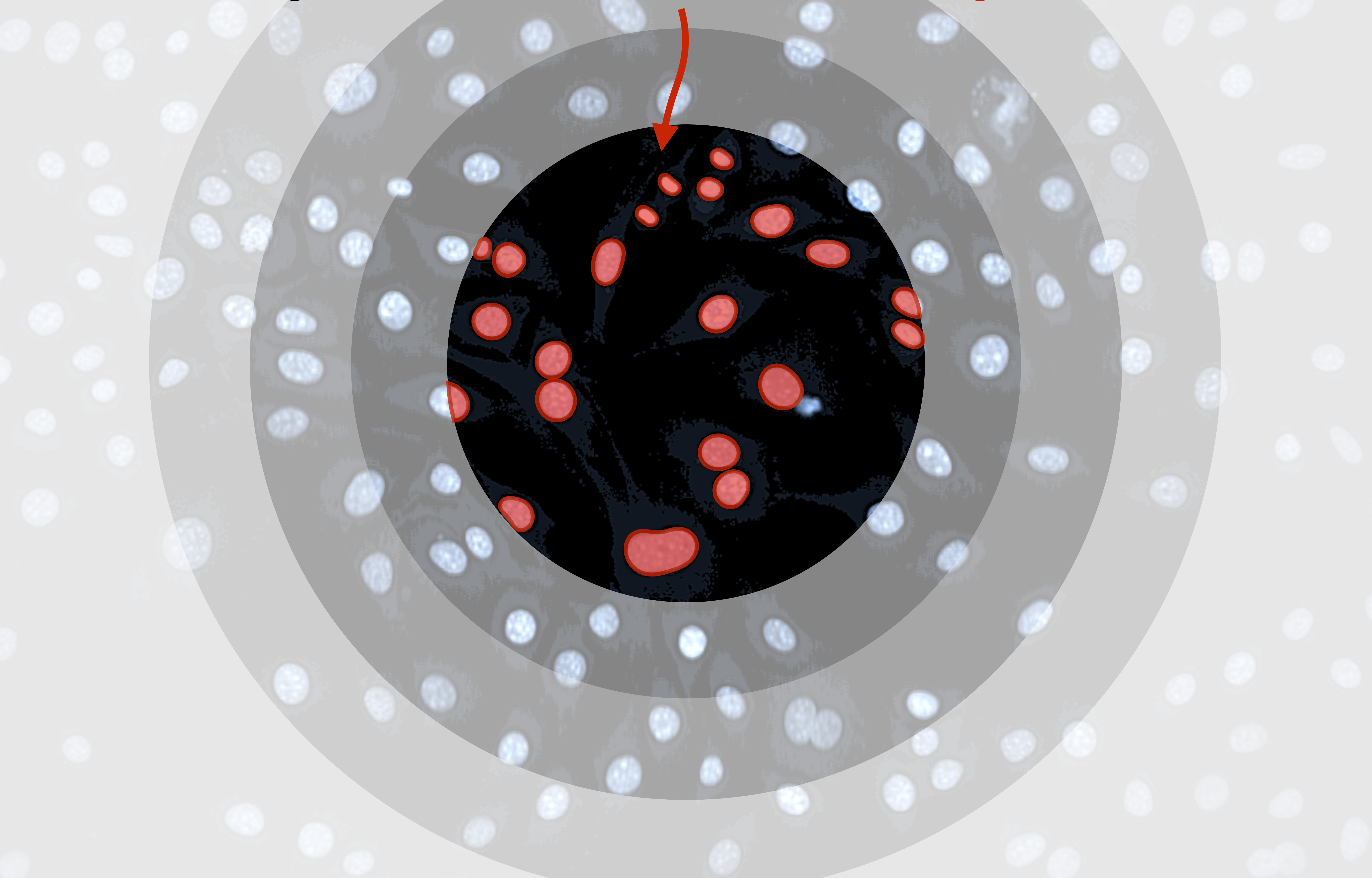
Where **training masks** come from?

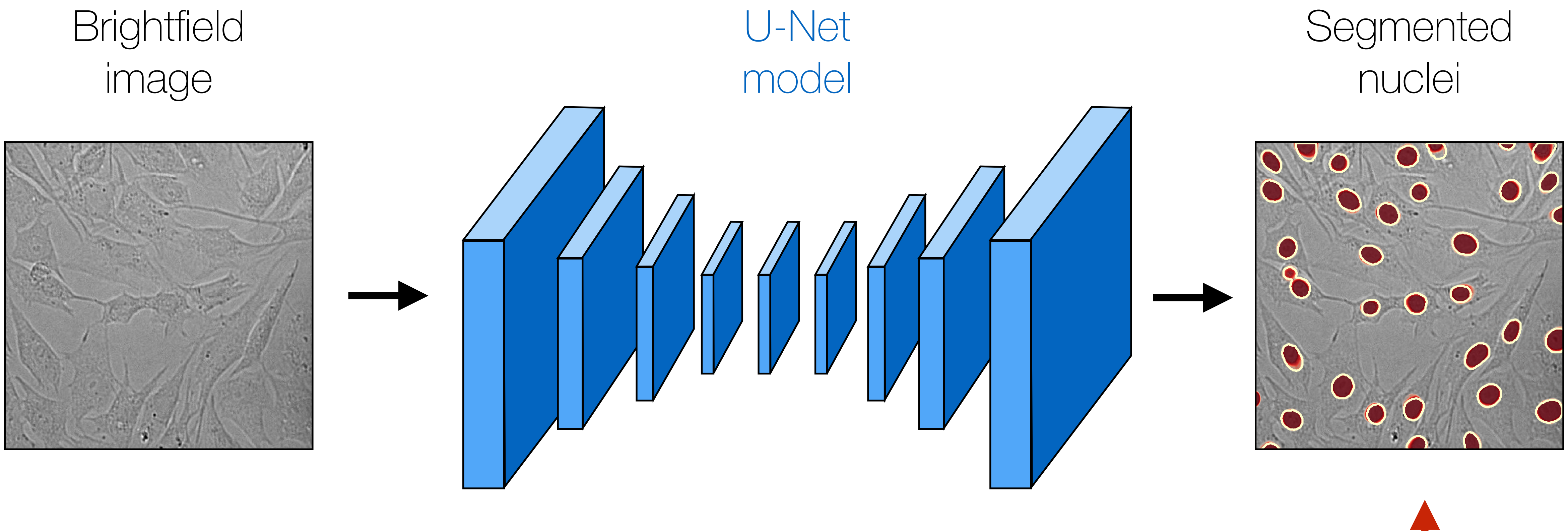






Fluorescent images are relatively easy* to segment using **semi-automated classical algorithms**





Training masks come from fluorescent images

Practical segmentation of nuclei in brightfield cell images with neural networks trained on fluorescently labelled samples

Authors: **Dmytro Fishman**, **Sten-Oliver Salumaa**, Daniel Majoral, Tõnis Laasfeld, Samantha Peel, Jan Wildenhain, Alexander Schreiner, Kaupo Palo, Leopold Parts.

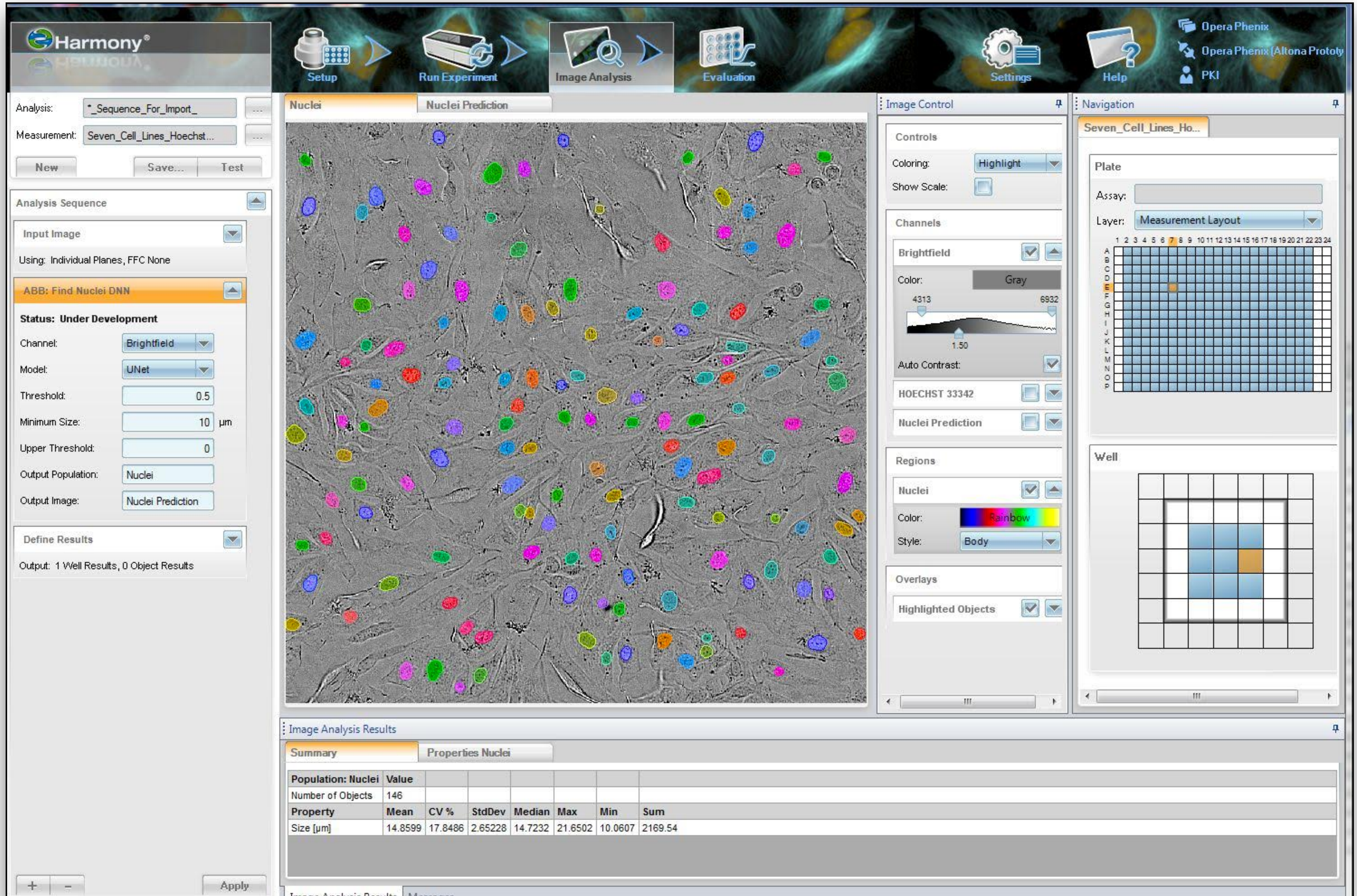
DOI: https://doi.org/10.1111/jmi.13038

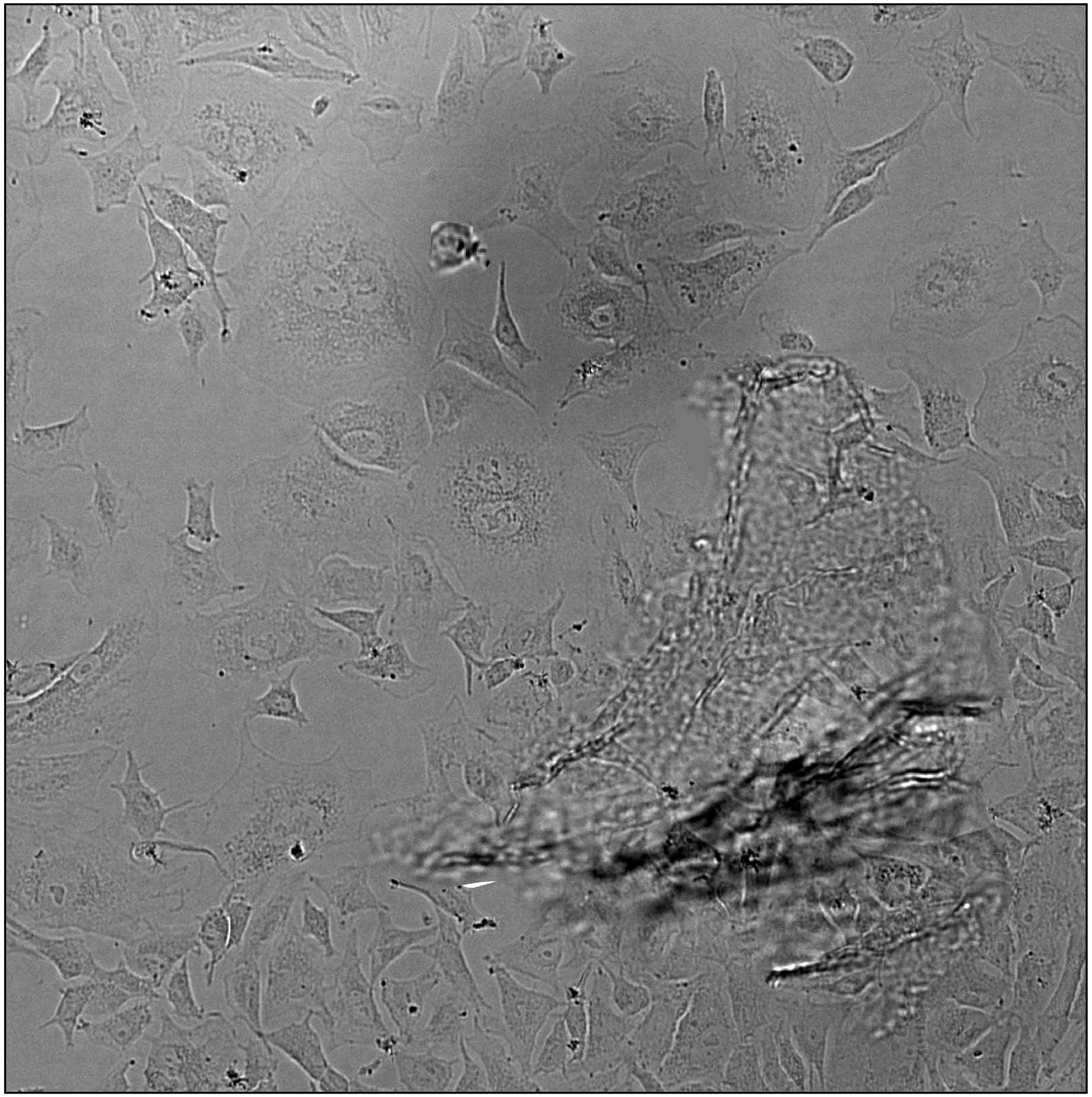
Evaluating Very Deep Convolutional Neural Networks for Nucleus Segmentation from Brightfield Cell Microscopy Images

Authors: **Mohammed A. S. Ali**, Oleg Misko, Sten-Oliver Salumaa, Mikhail Papkov, Kaupo Palo, Dmytro Fishman, Leopold Parts

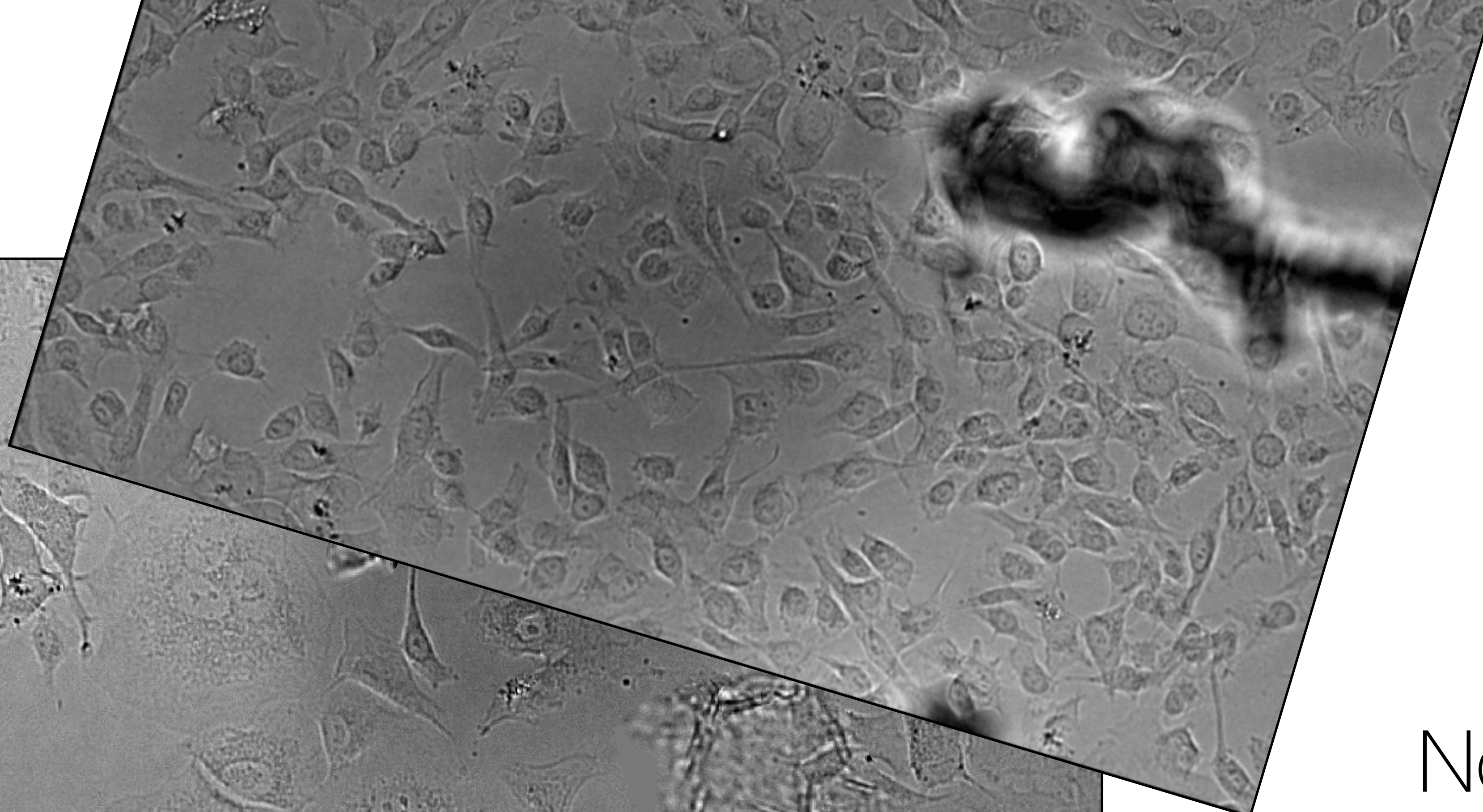
DOI: https://doi.org/10.1177/24725552211023214

The results of this research is **used outside our group**

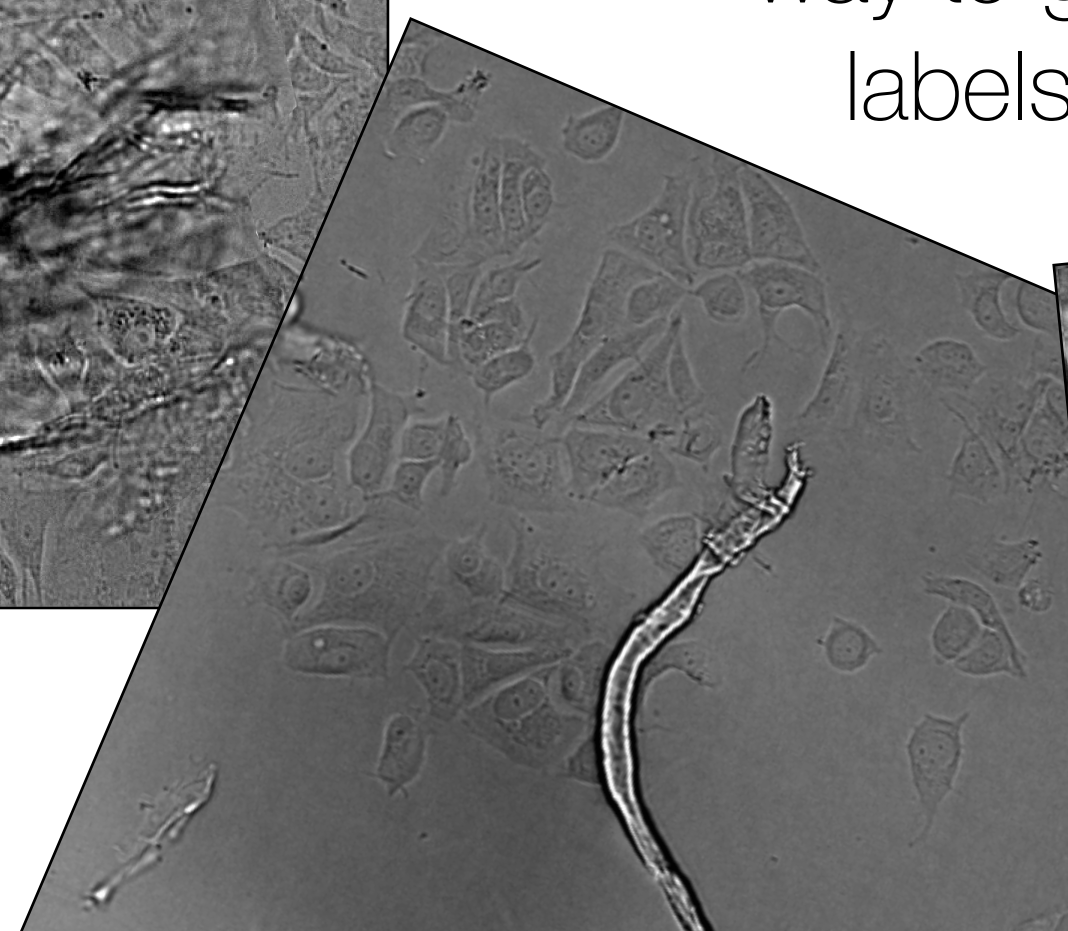


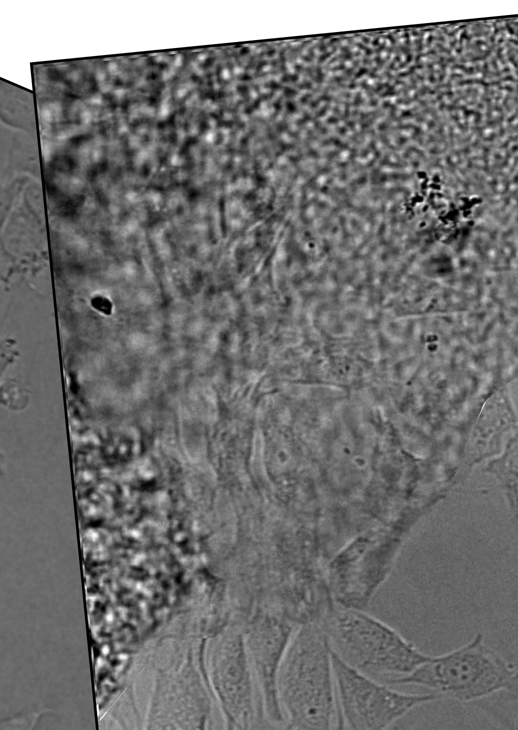


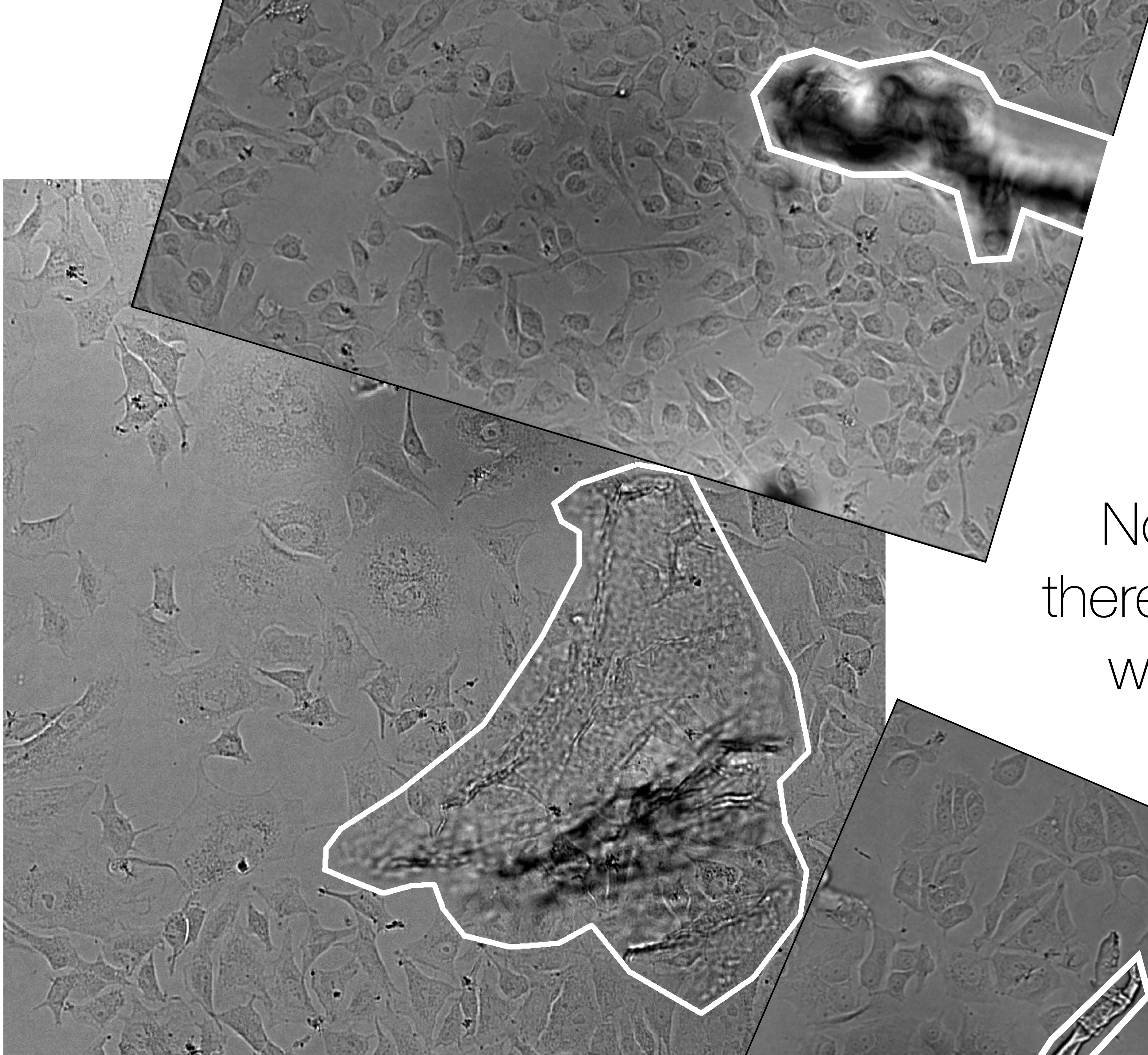
Not always there is an easy way to get labels



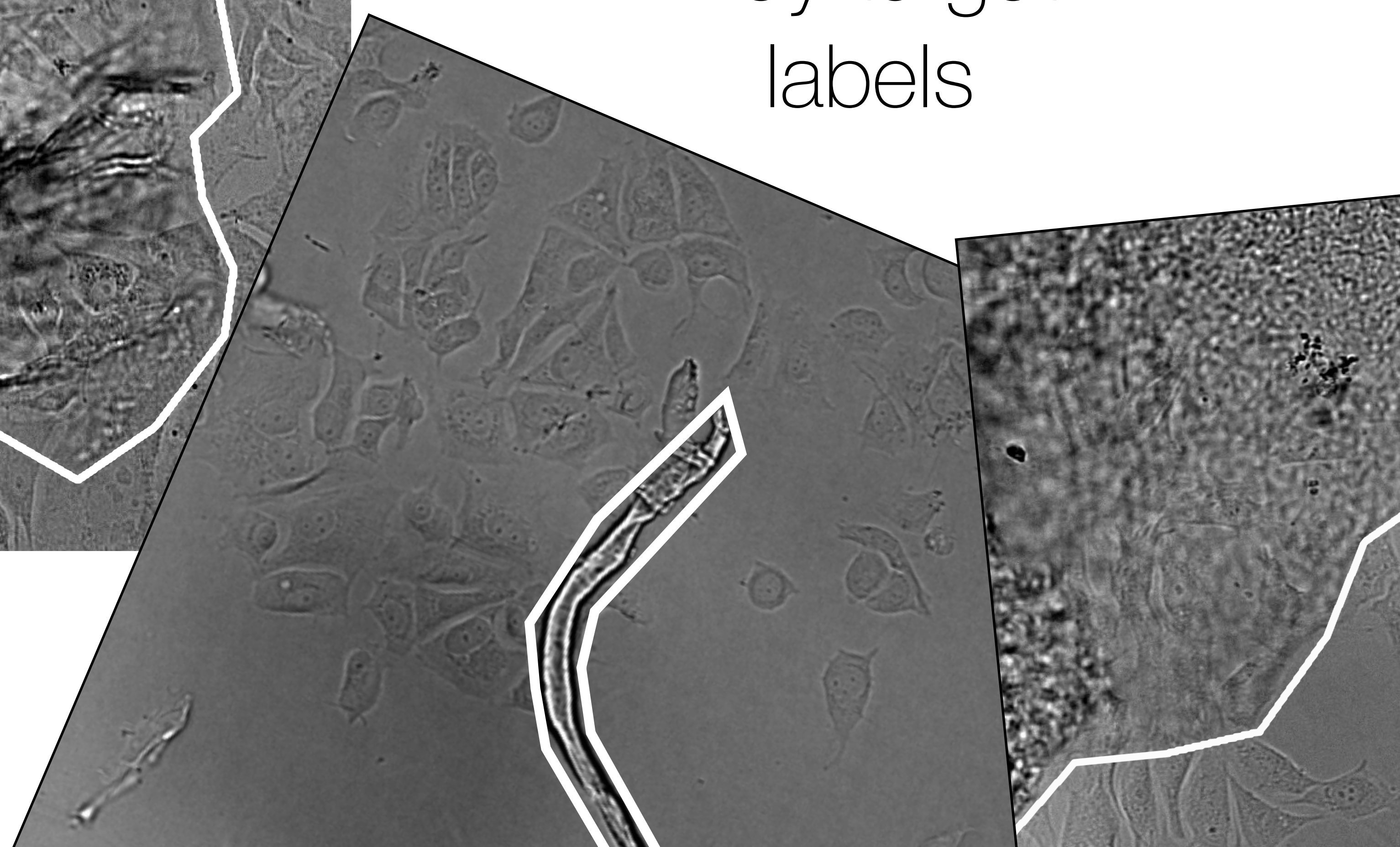
Not always there is an easy way to get labels



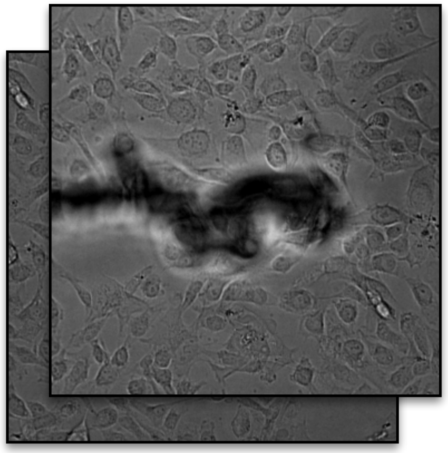




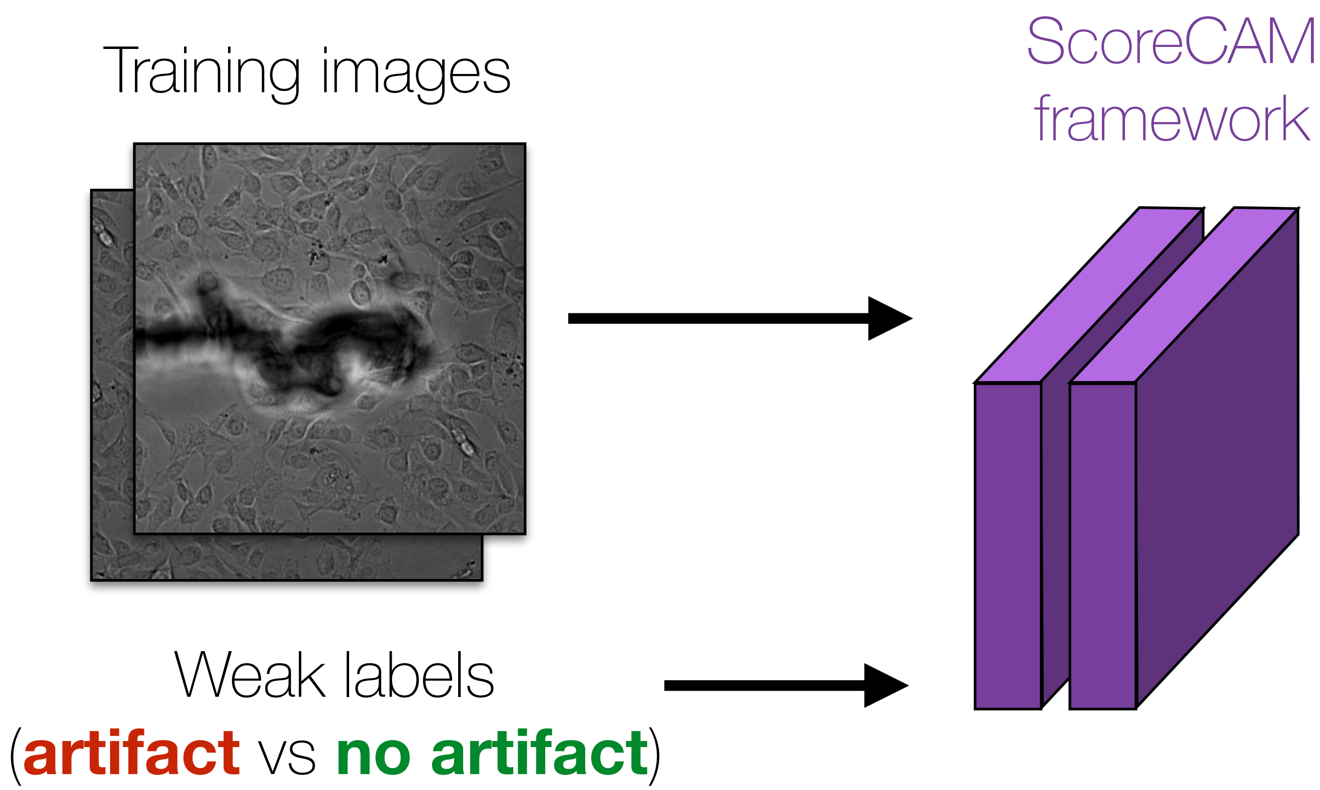
Not always
there is an easy
way to get
labels

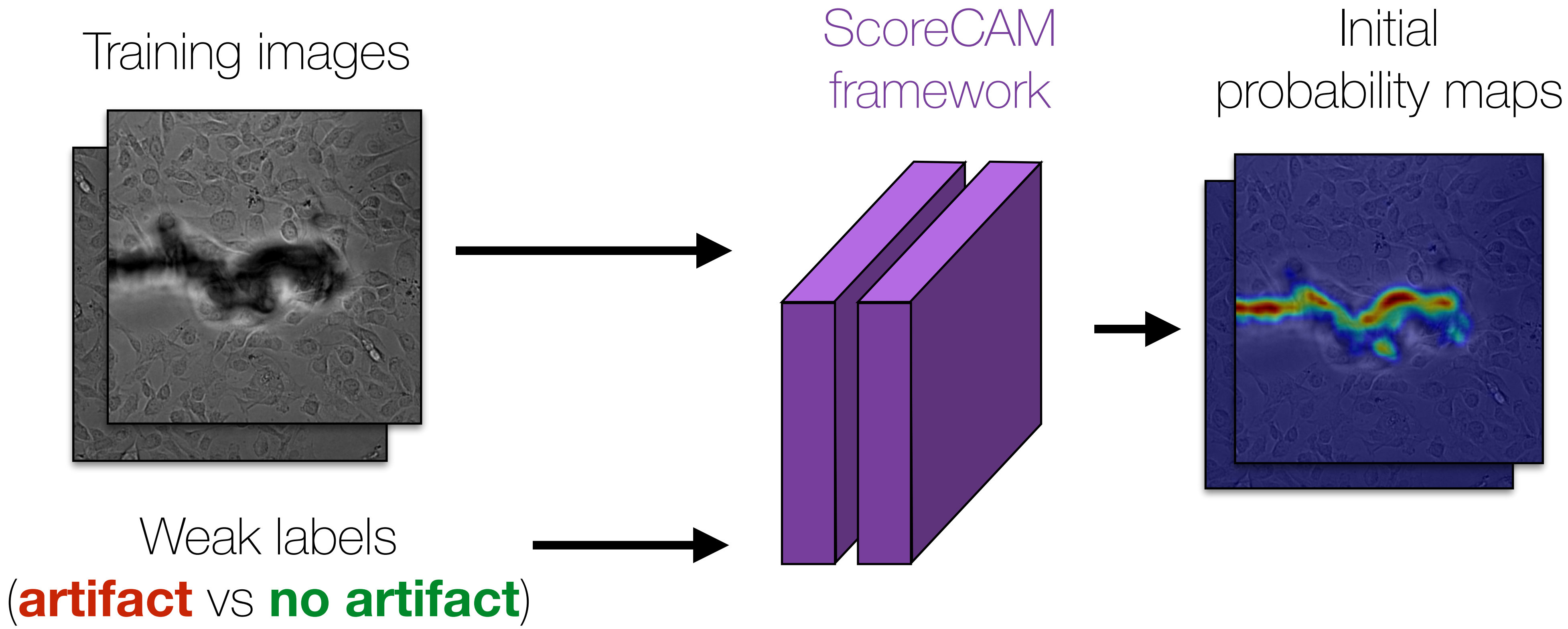


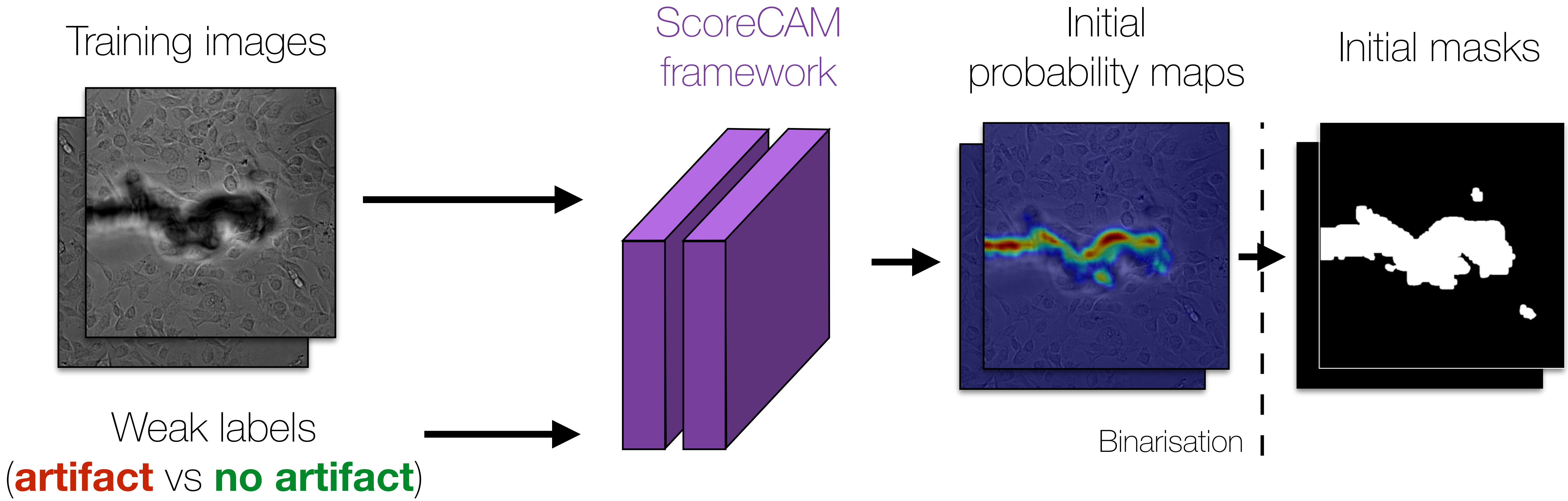
Training images



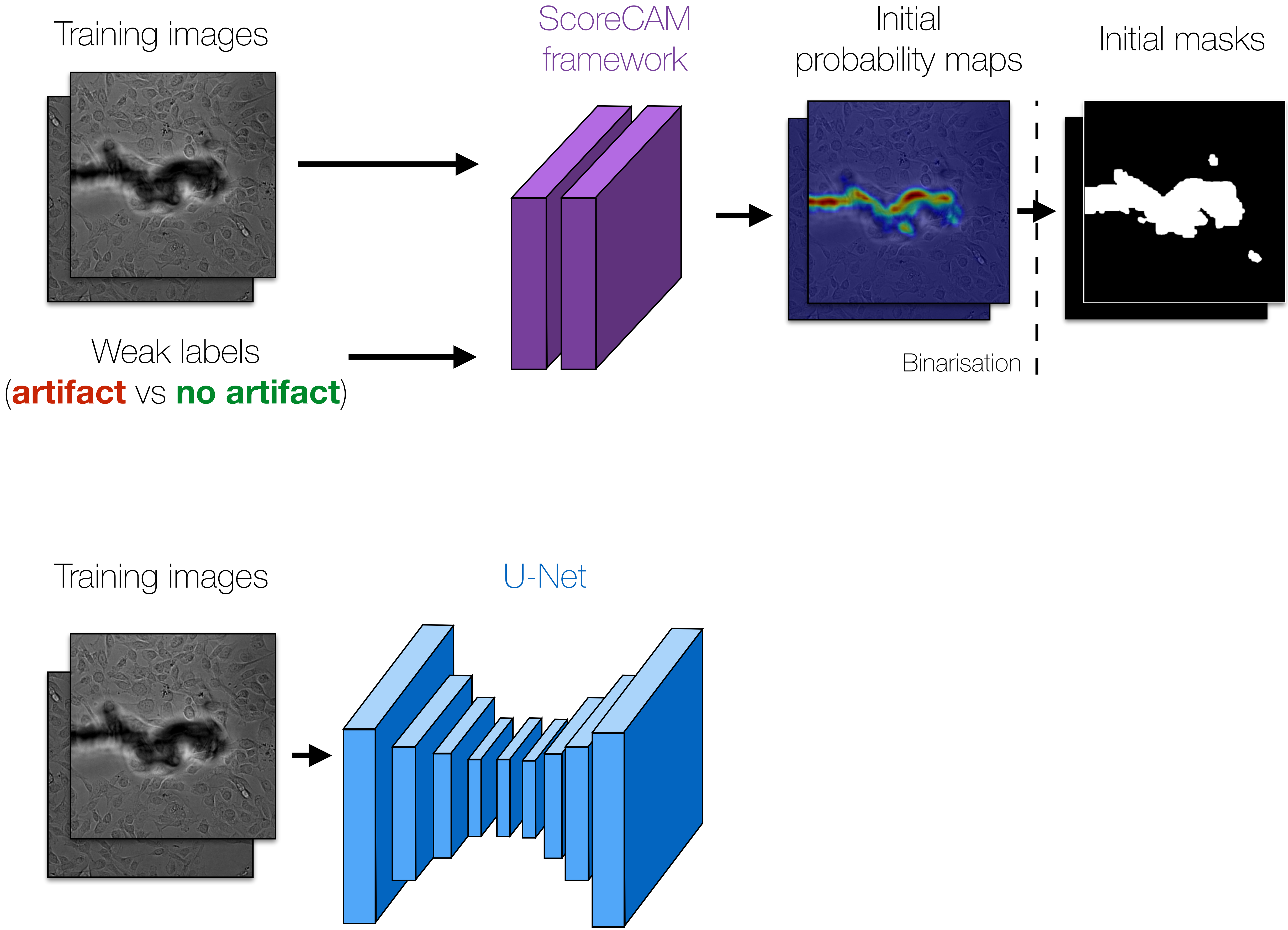
Weak labels
(**artifact** vs **no artifact**)


Training images
ScoreCAM framework
Weak labels
(artifact vs no artifact)

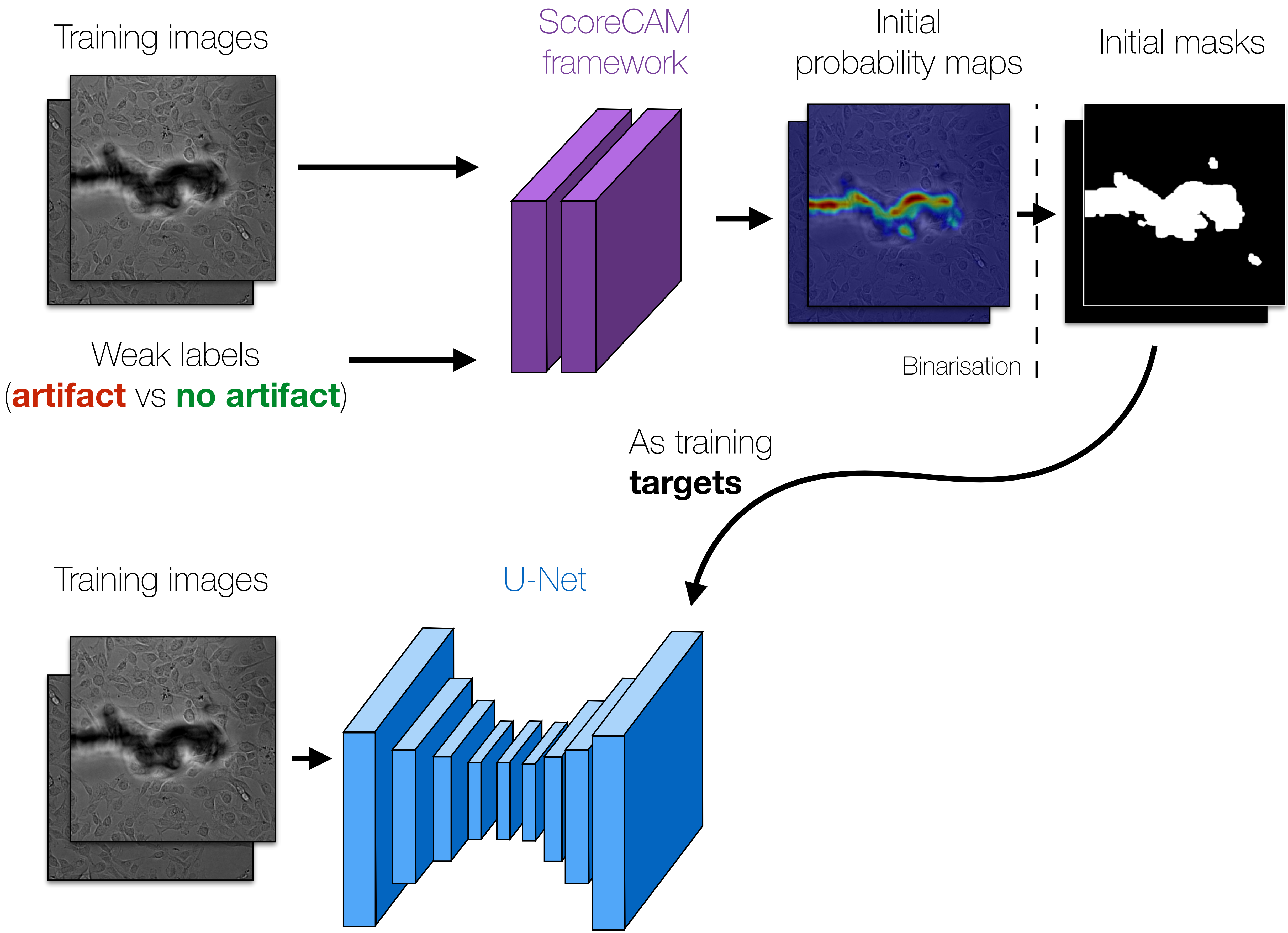

Training images
ScoreCAM
framework
Initial
probability maps
Weak labels
(artifact vs no artifact)

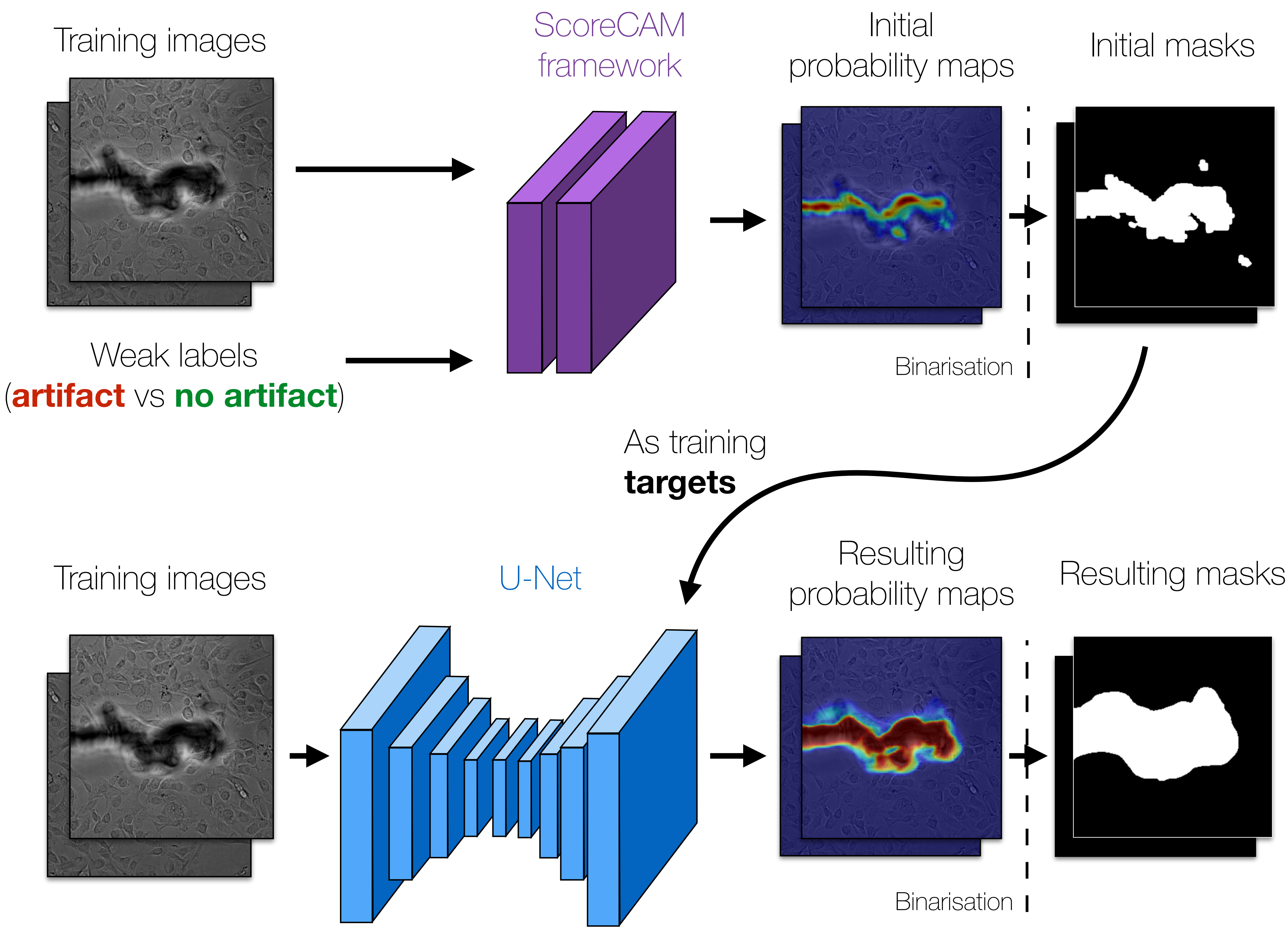


Training images
ScoreCAM framework
Initial probability maps
Initial masks
Weak labels
(artifact vs no artifact)
Binarisation



Training images
ScoreCAM framework
Initial probability maps
Initial masks
Weak labels
(artifact vs no artifact)
Binarisation
Training images
U-Net


Training images
ScoreCAM
framework
Initial
probability maps
Initial masks
Weak labels
(artifact vs no artifact)
Binarisation
As training
targets
Training images
U-Net



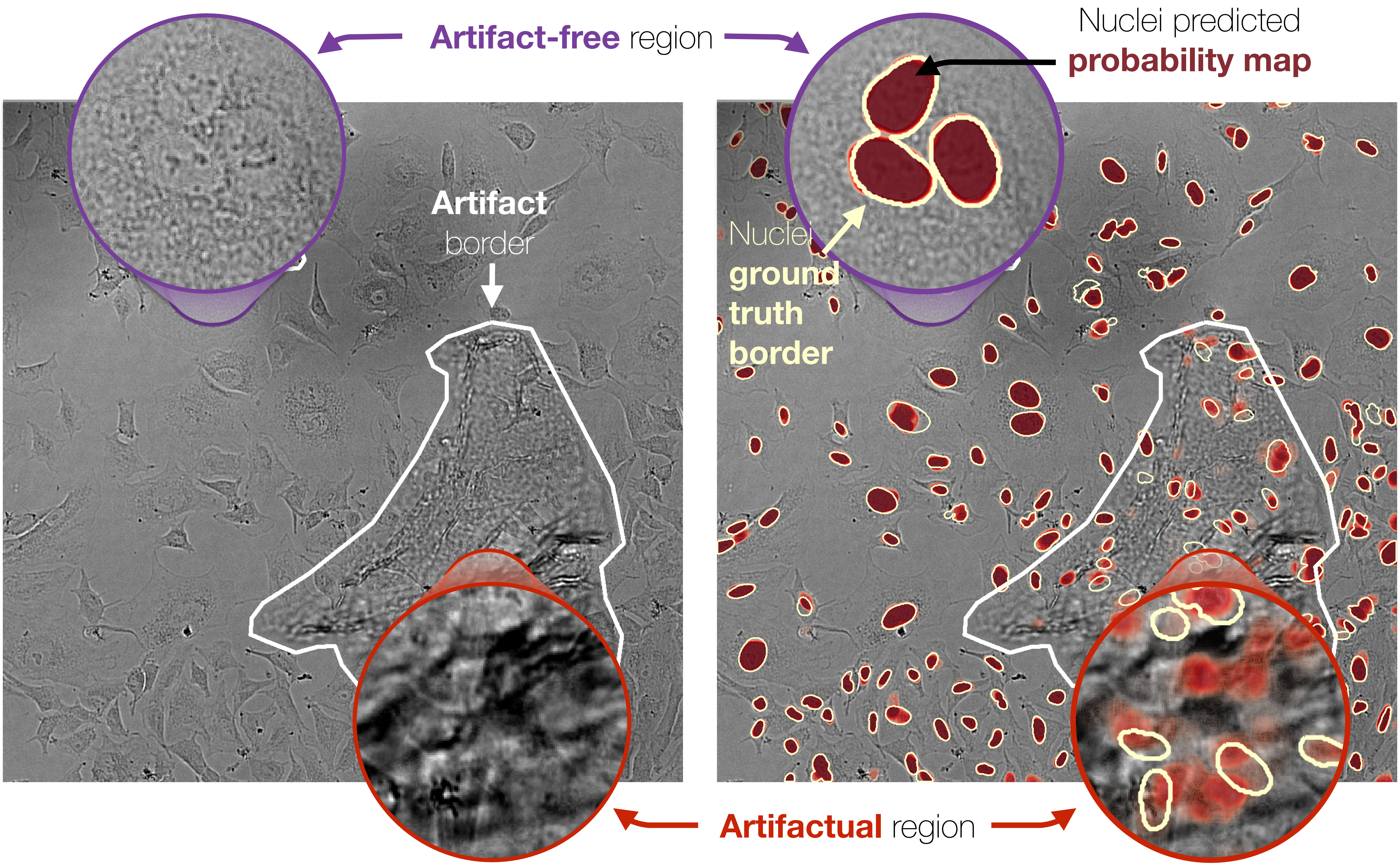
Training images
ScoreCAM framework
Initial probability maps
Initial masks
Weak labels
(artifact vs no artifact)
Binarisation
As training targets
Training images
U-Net
Resulting probability maps
Resulting masks
Binarisation

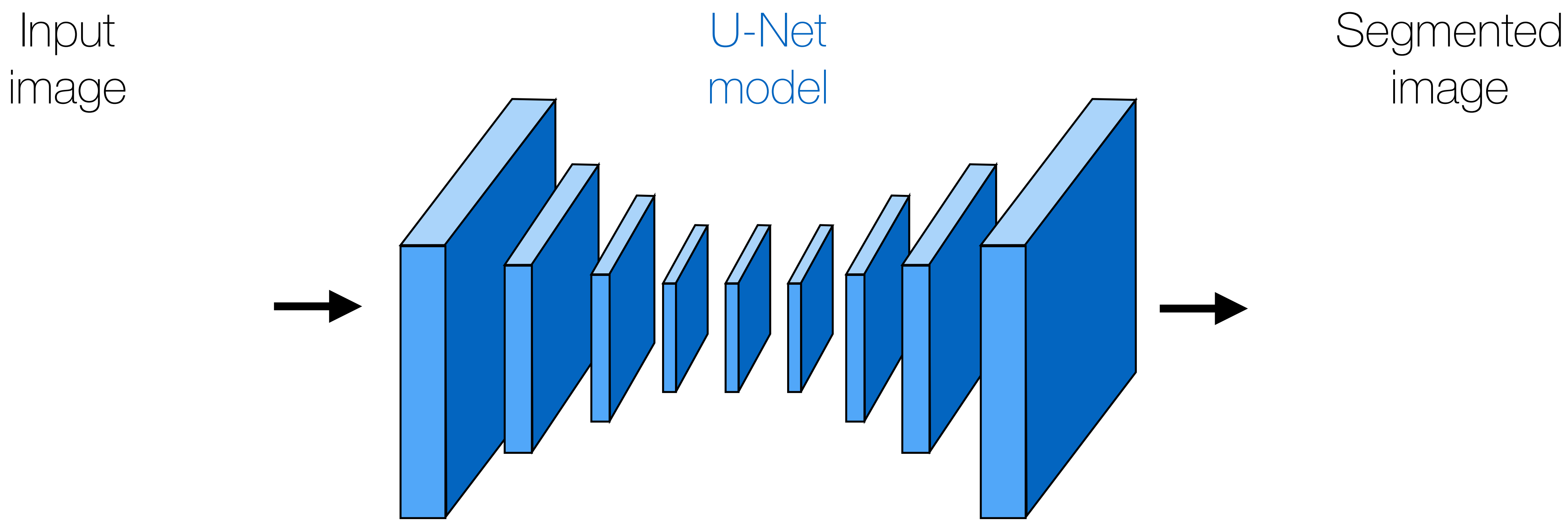
ArtSeg: Rapid Artifact Segmentation and Removal in Brightfield Cell Microscopy Images

Authors: **Mohammed A. S. Ali**, **Kaspar Hollo**, Tõnis Laasfeld, Jane Torp, Maris-Johanna Tahk, Ago Rinken, Kaupo Palo, Leopold Parts, Dmytro Fishman

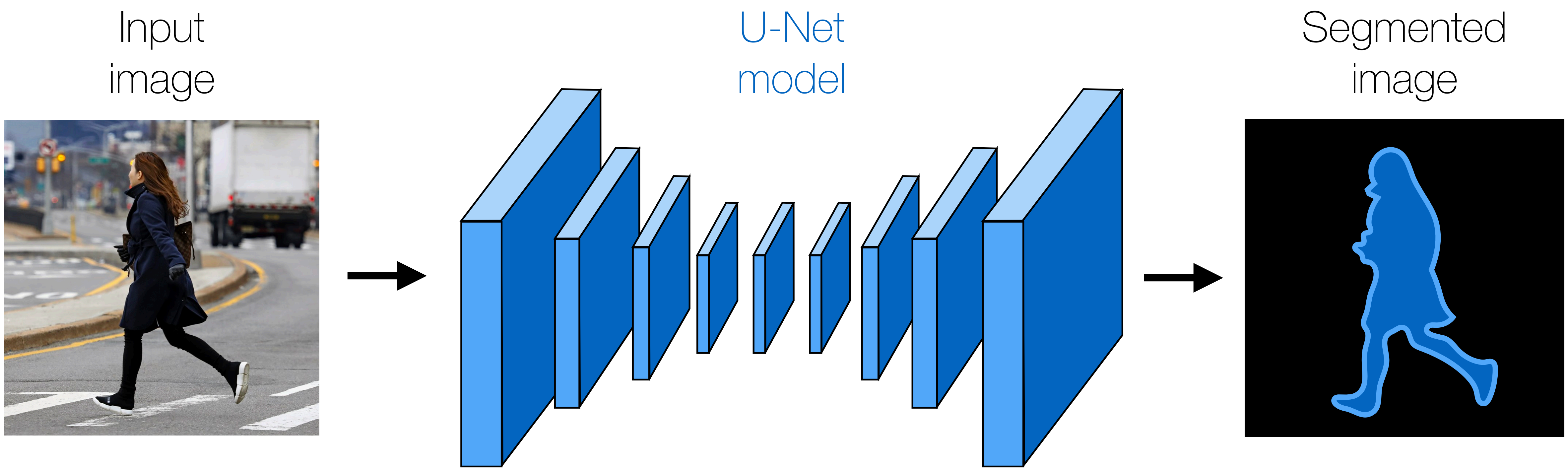
DOI: https://doi.org/10.1101/2022.01.24.477467

Under review in SCIENTIFIC REPORTS

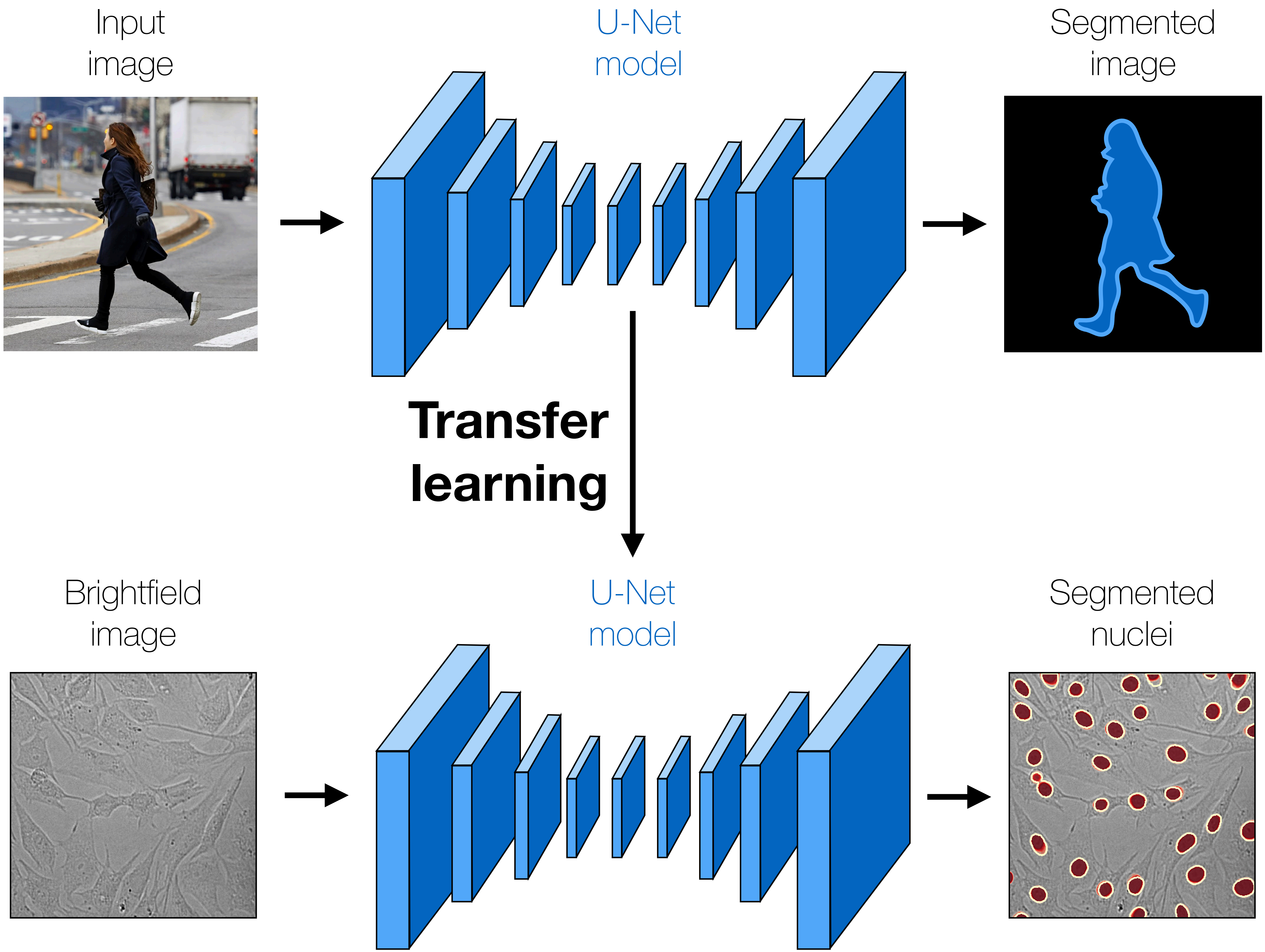

Artifact-free region
Nuclei predicted
probability map
Artifact
border
Nuclei
ground
truth
border
Artifactual region

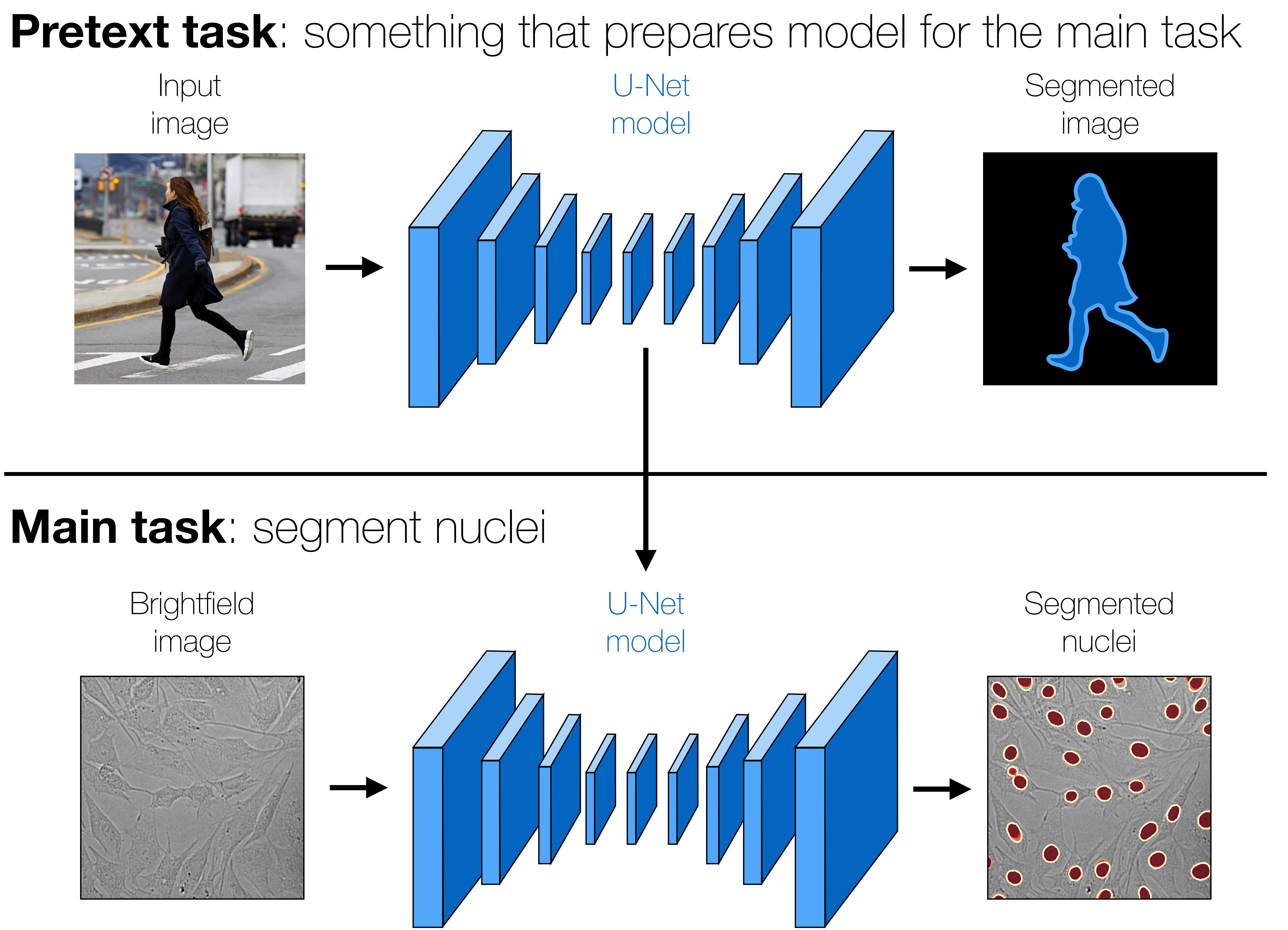


It has been shown before that one can reduce the need for training data via **transfer learning**

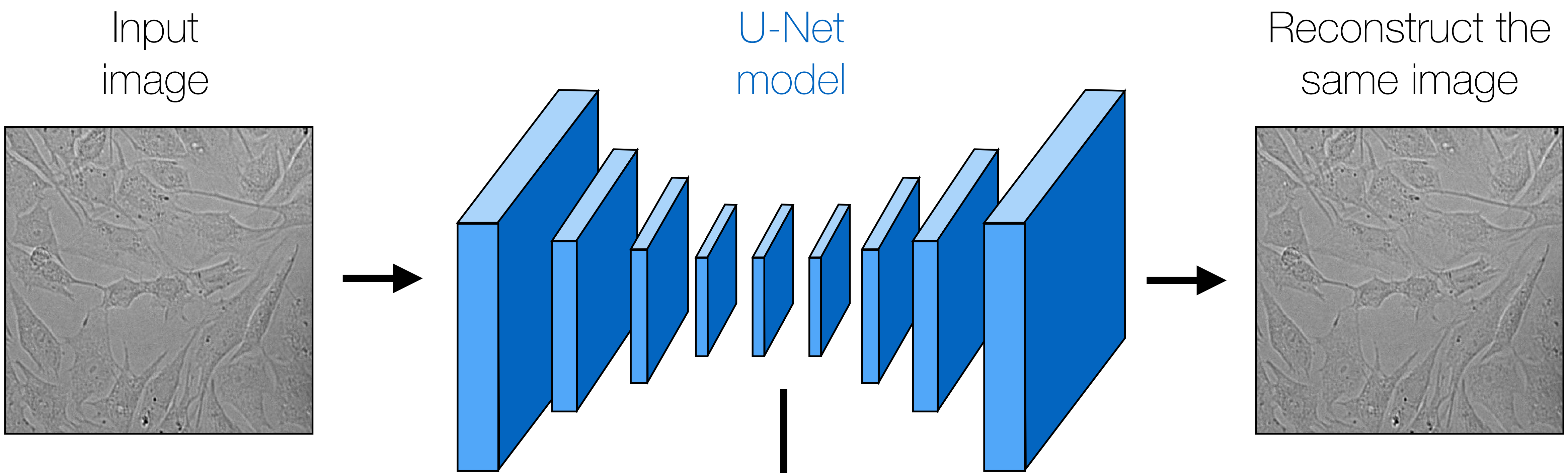


It has been shown before that one can reduce the need for training data via **transfer learning**

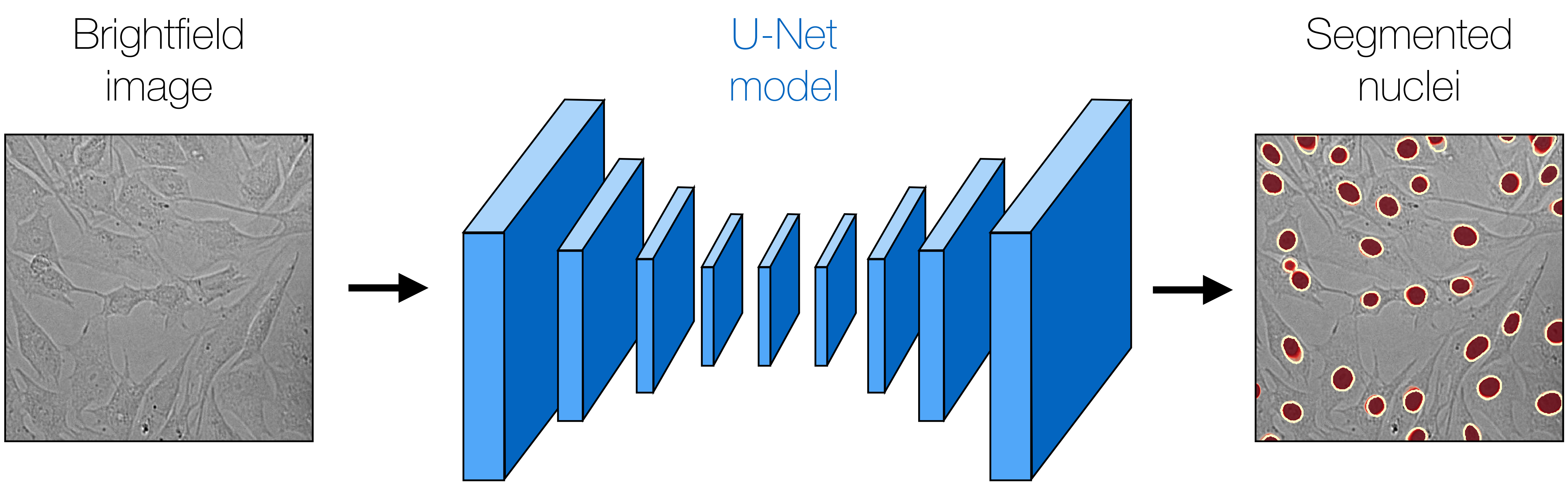

Input
image
U-Net
model
Segmented
image
Transfer
learning
Brightfield
image
U-Net
model
Segmented
nuclei


Pretext task: something that prepares model for the main task
Input image
U-Net model
Segmented image
Main task: segment nuclei
Brightfield image
U-Net model
Segmented nuclei

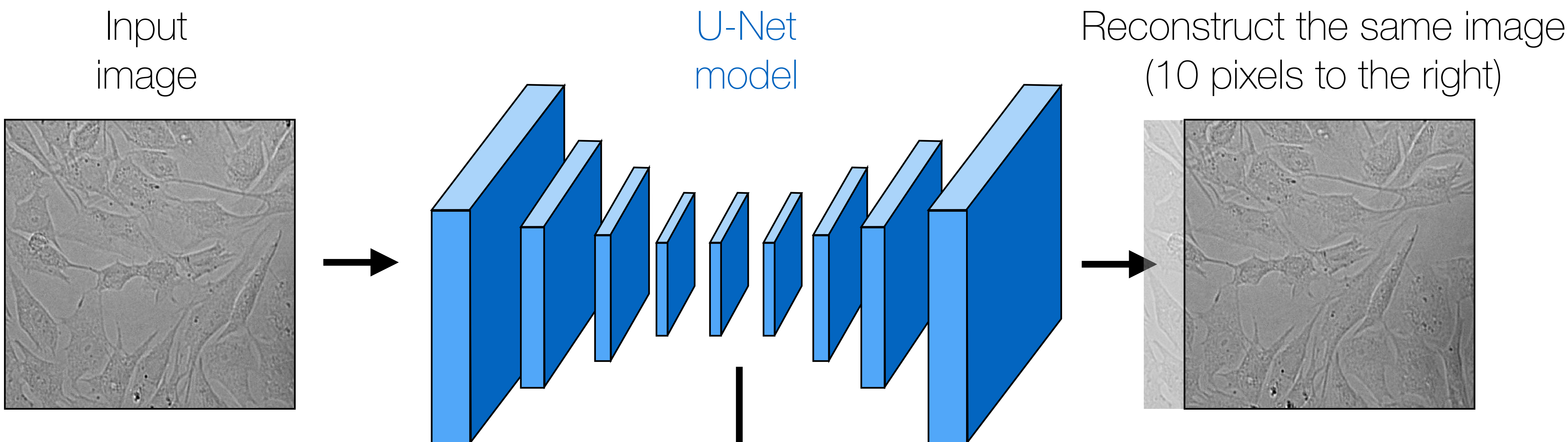
Pretext task: something that prepares model for the main task



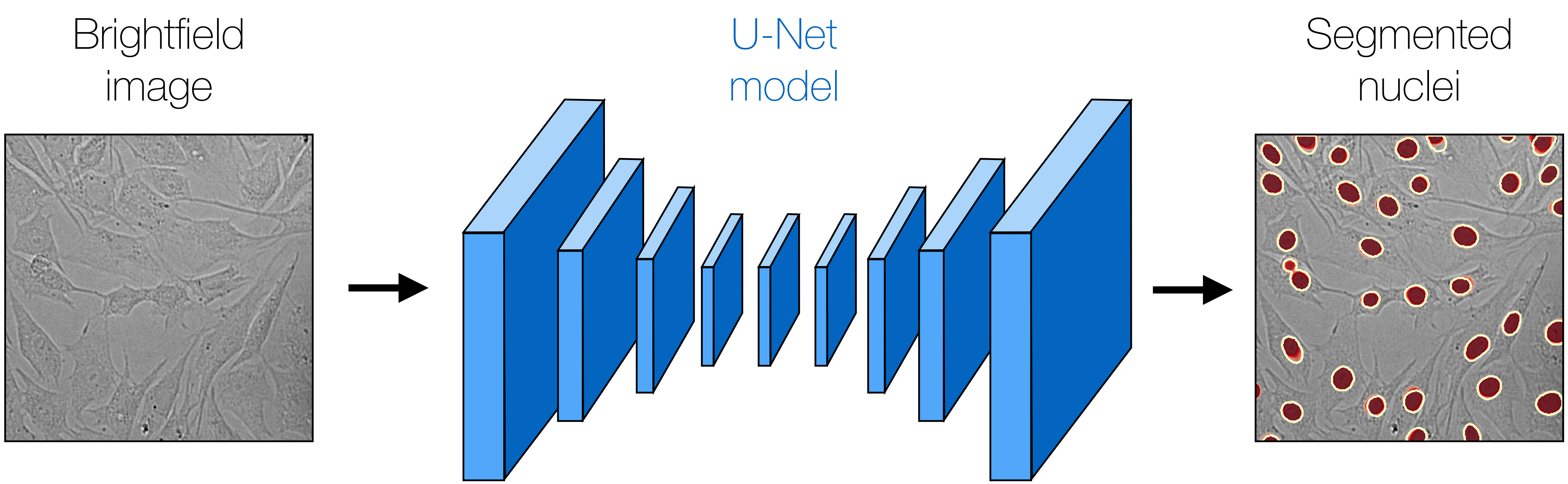
Main task: segment nuclei



Pretext task: something that prepares model for the main task



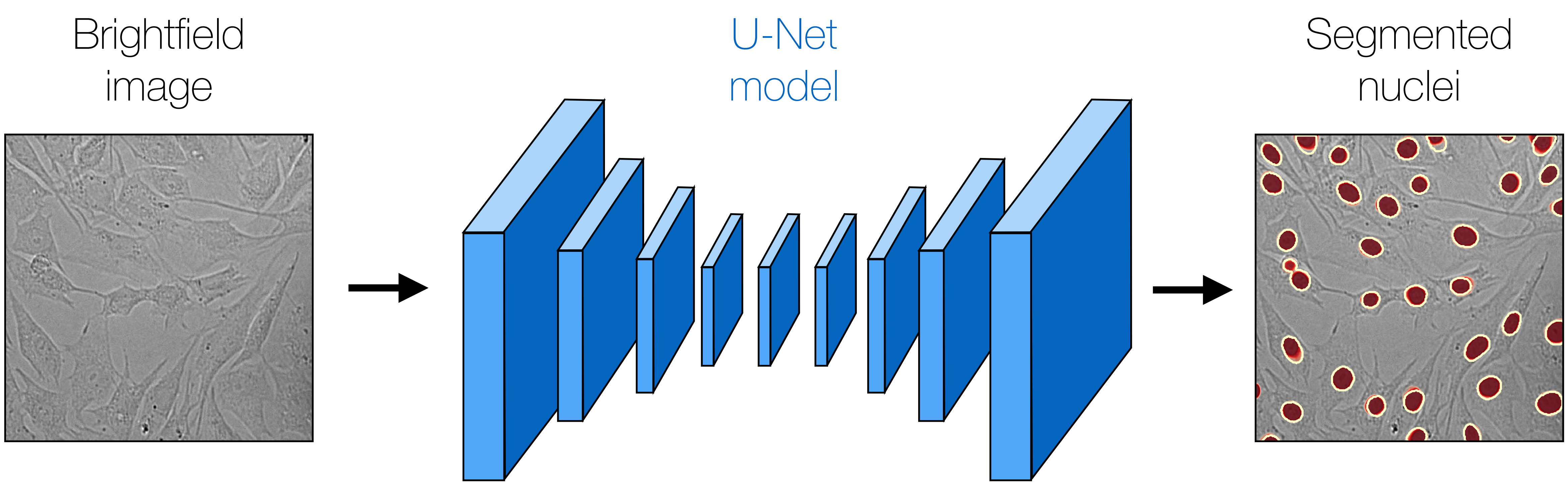
Main task: segment nuclei



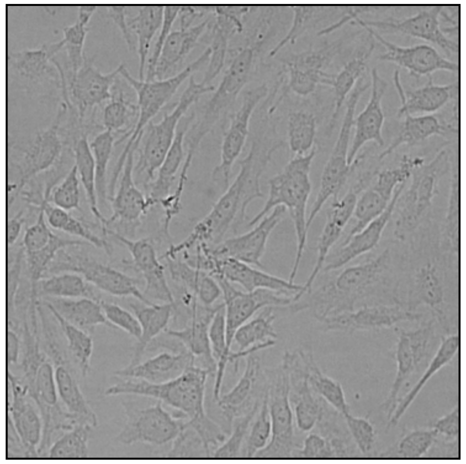
Self-supervised learning

Pretext task: useful pretext is highly domain dependent and needs effort to figure out. Jury is out to evaluate various approaches.

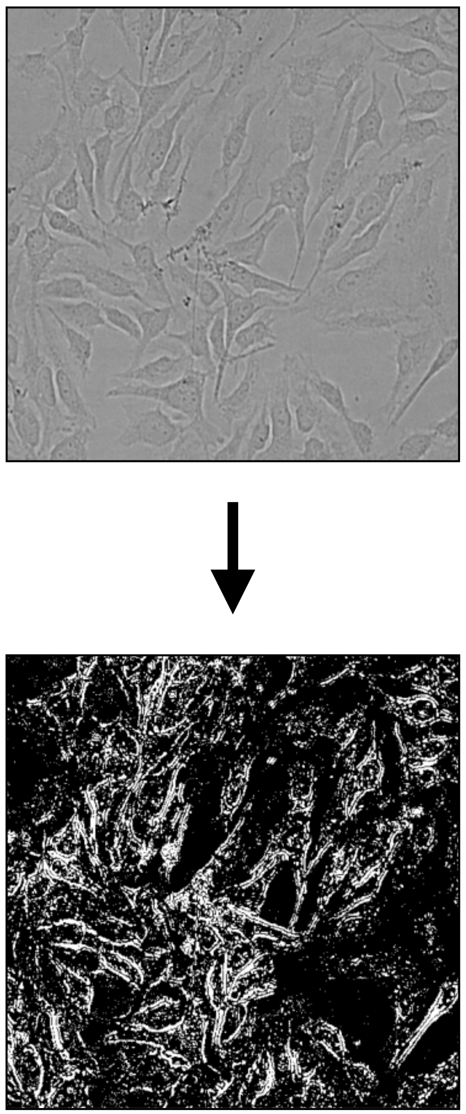
Main task: segment nuclei



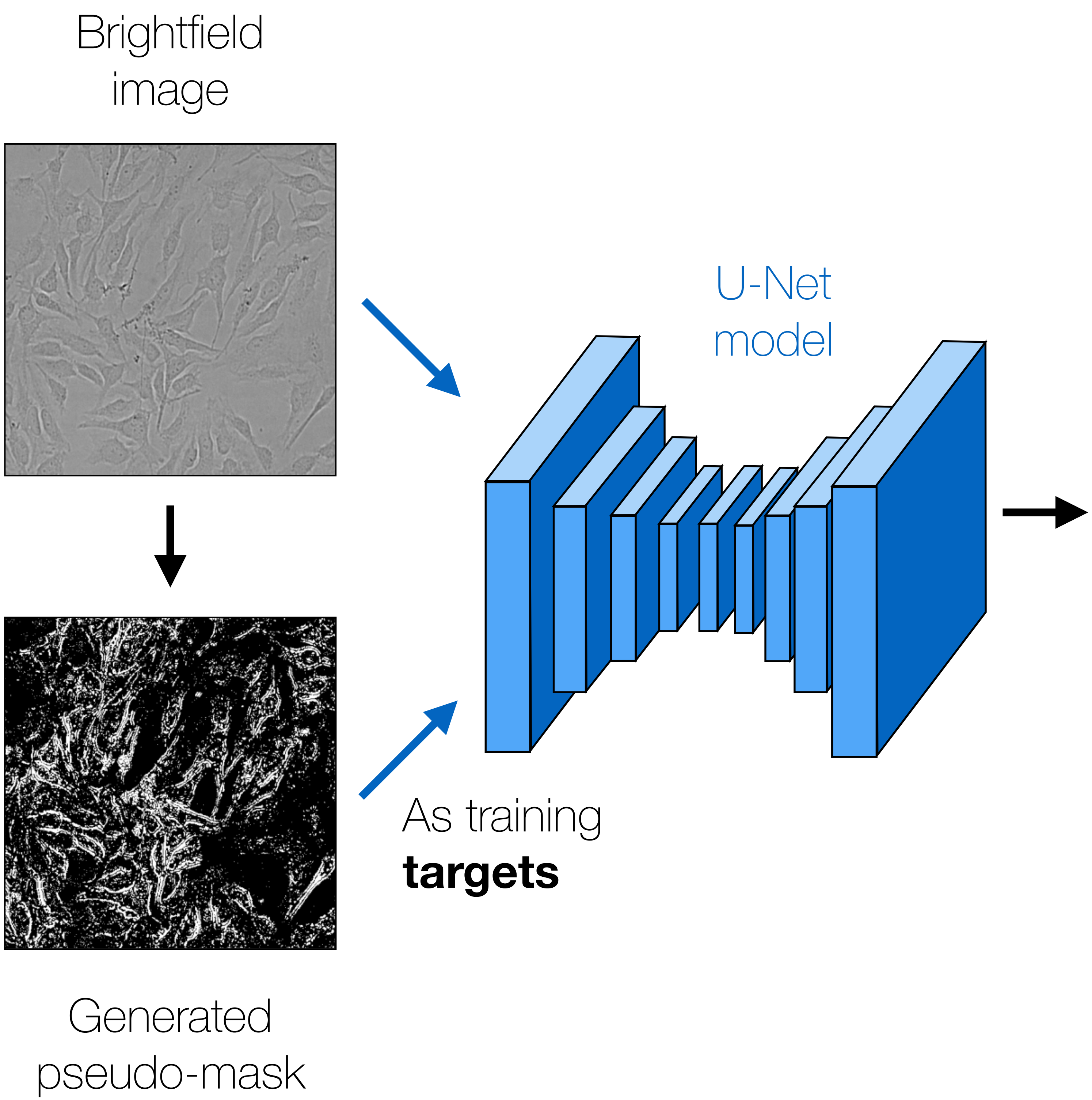
Brightfield
image

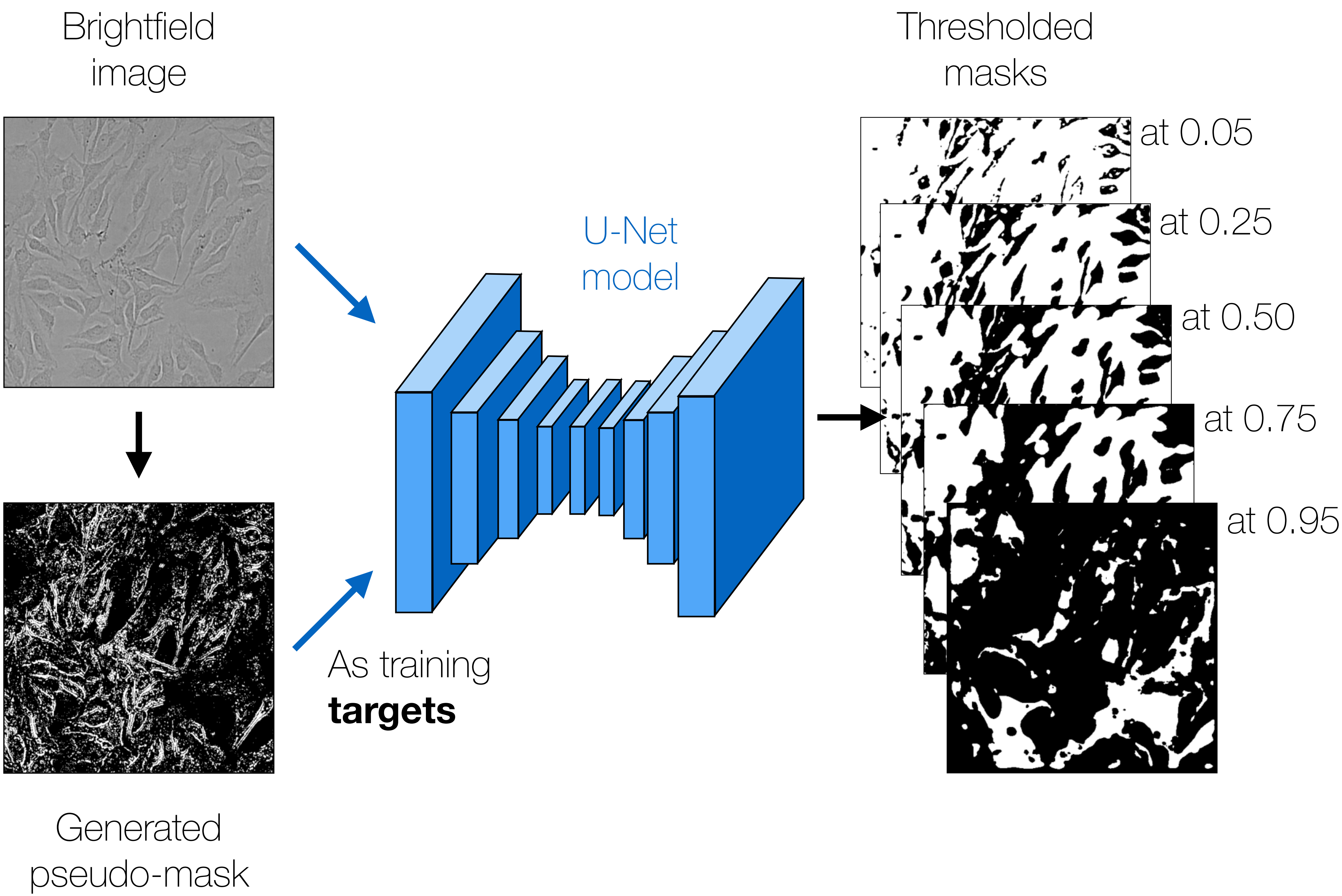


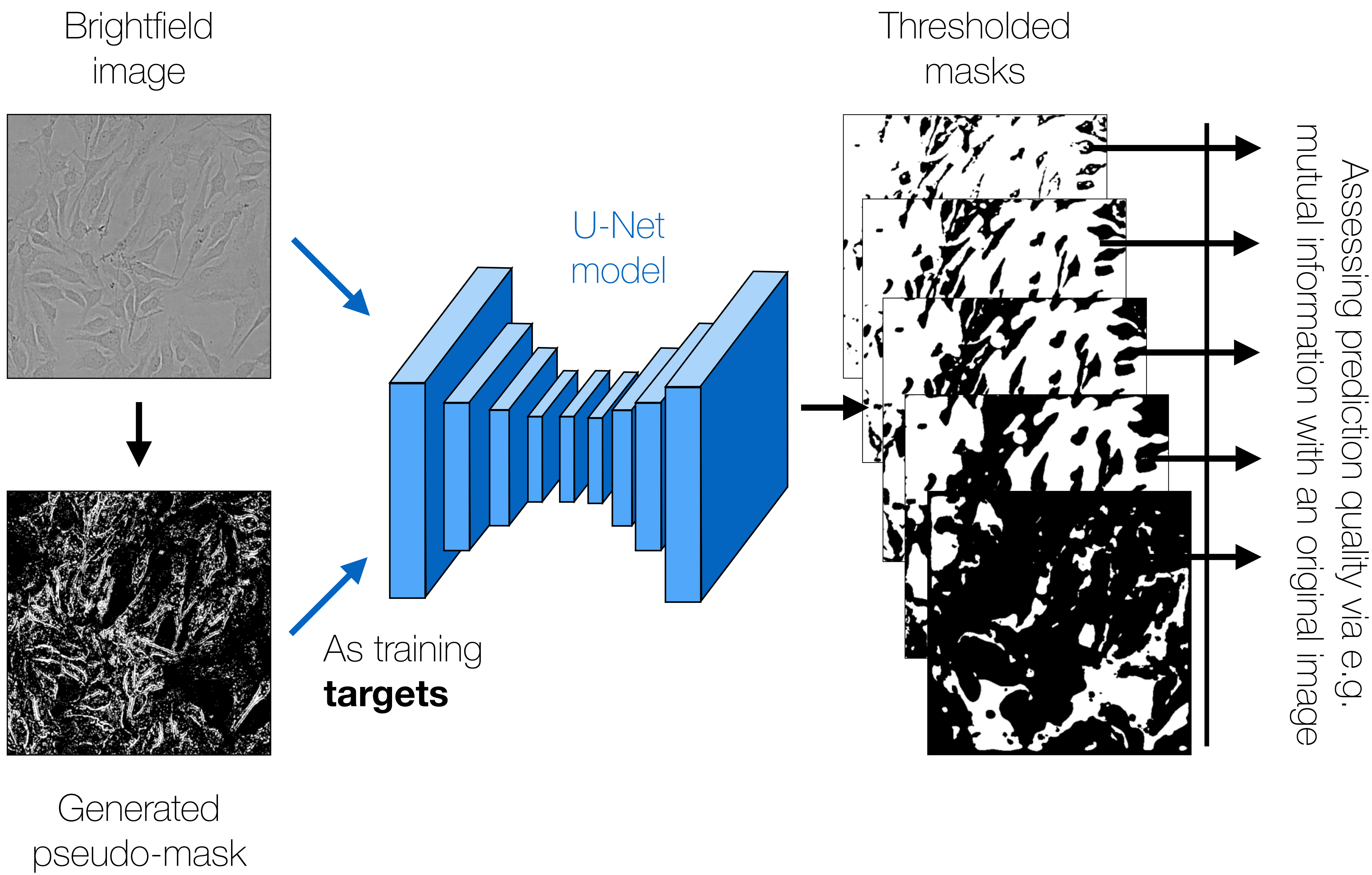
Brightfield image



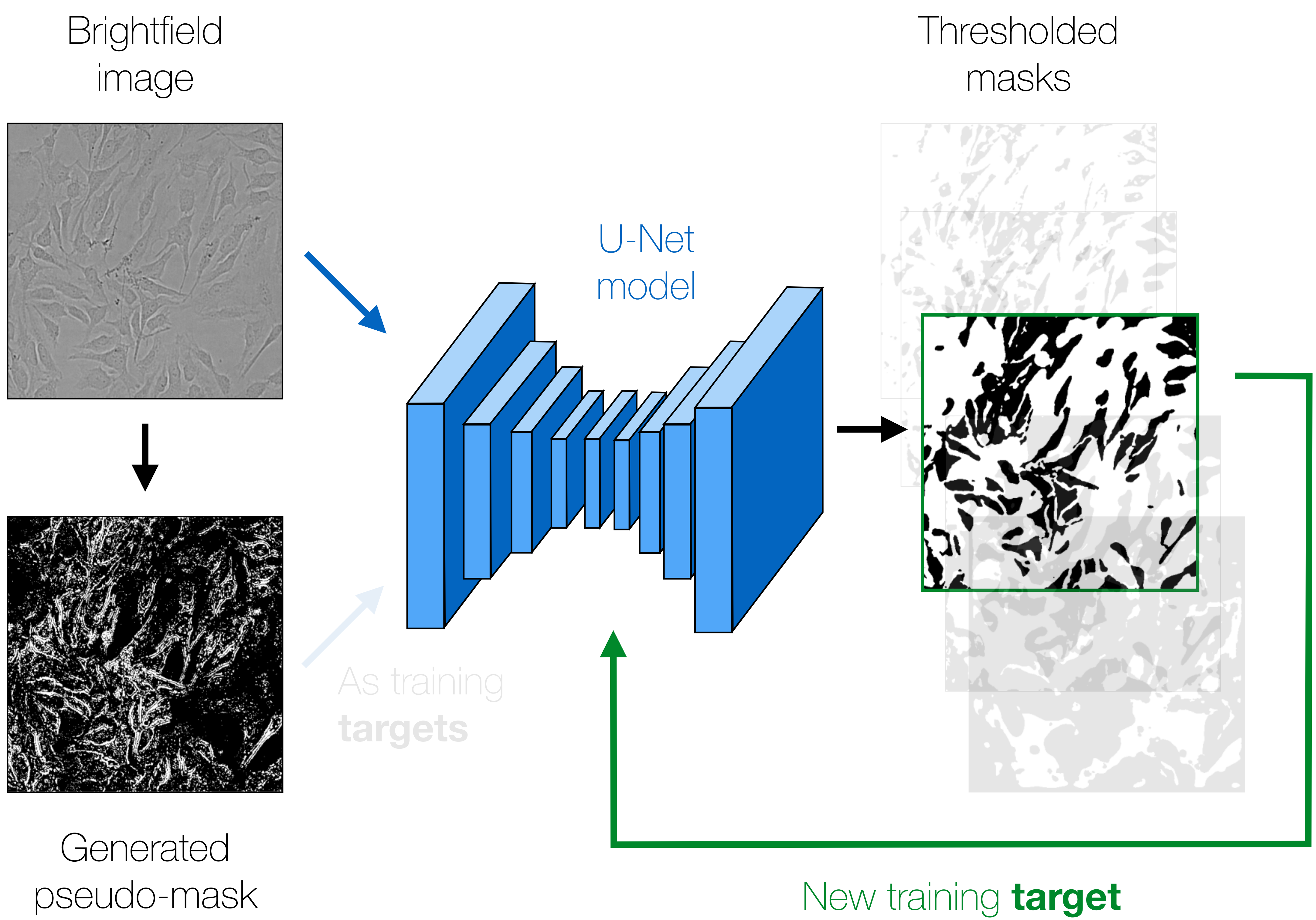
Generated pseudo-mask


Brightfield
image
U-Net
model
As training
targets
Generated
pseudo-mask


Brightfield
image
Generated
pseudo-mask
As training
targets
U-Net
model
Thresholded
masks
at 0.05
at 0.25
at 0.50
at 0.75
at 0.95

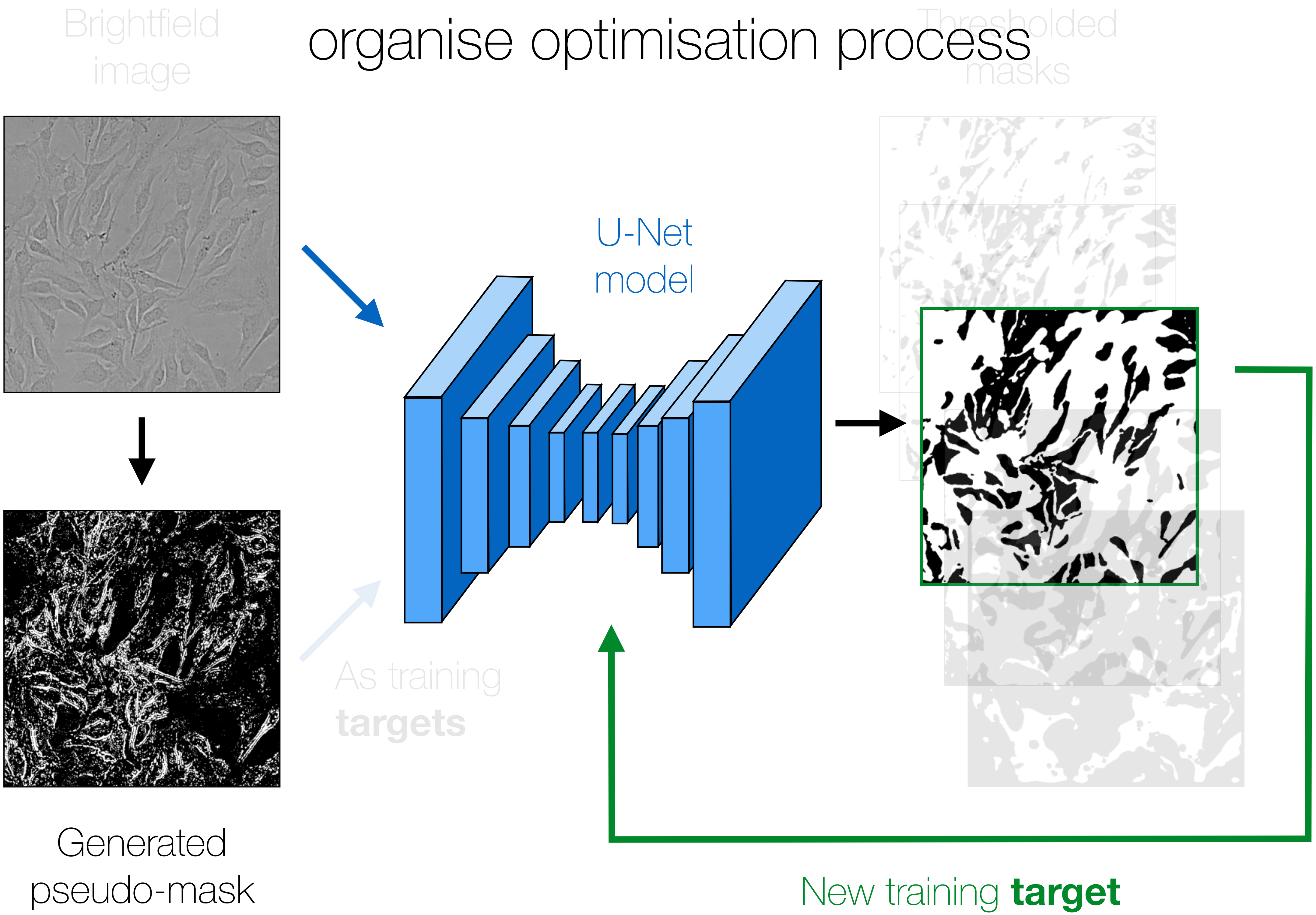


Brightfield image
Generated pseudo-mask
As training
targets
U-Net model
Thresholded masks
Assessing prediction quality via e.g. mutual information with an original image


Brightfield
image
Generated
pseudo-mask
U-Net
model
As training
targets
Thresholded
masks
New training target

Unsupervised segmentation

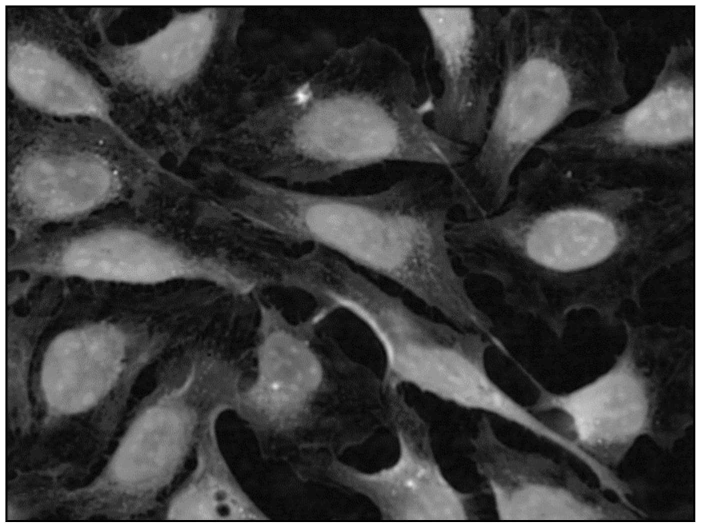
Did not work in our case, as it turned out to be hard to organise optimisation process



by **Tetiana Rabiichuk**

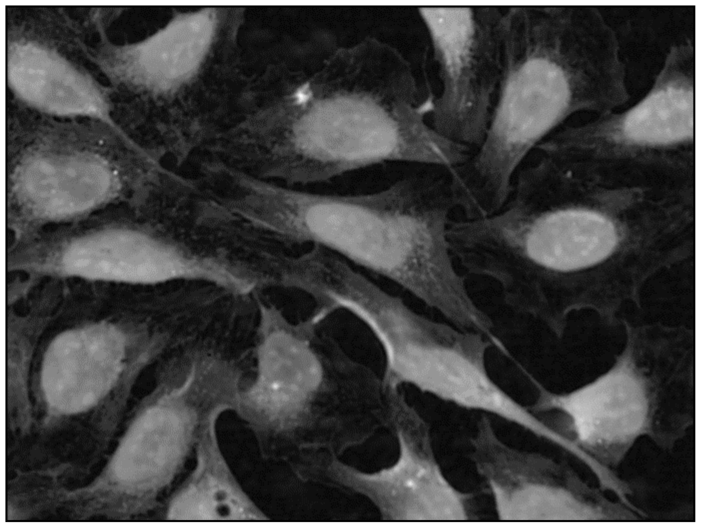
After battling with **unsupervised learning**, we come to appreciate **manual labelling**

Phase image

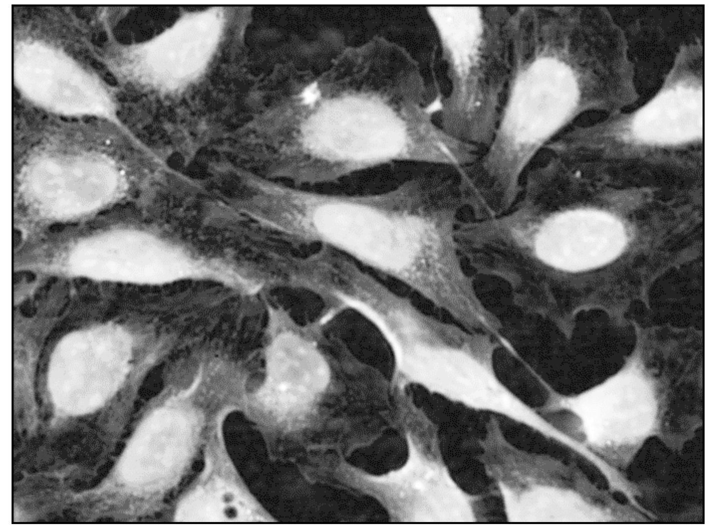


After battling with **unsupervised learning**, we come to appreciate **manual labelling**

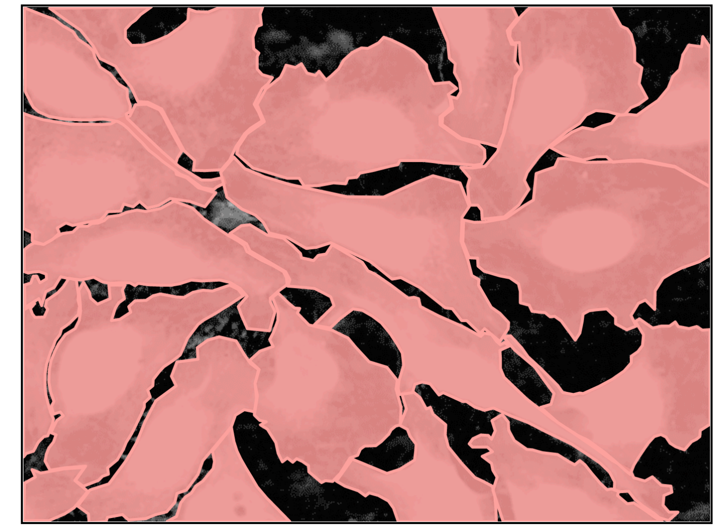
Phase image



High contrast

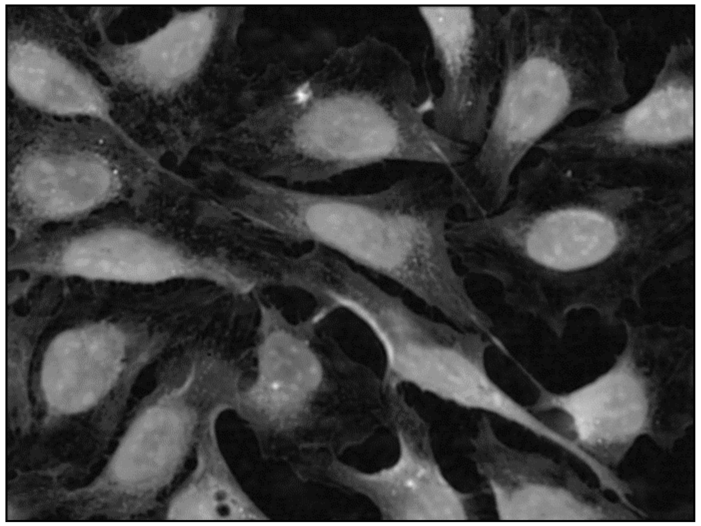


Manual annotation in **LabelStudio**

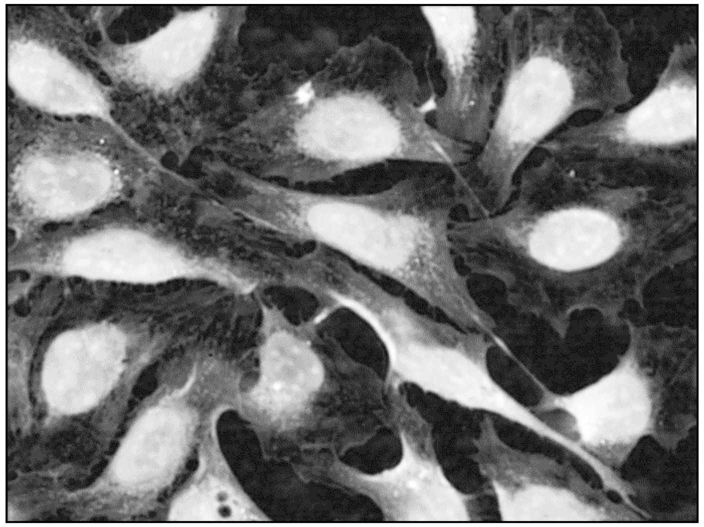


After battling with **unsupervised learning**, we come to appreciate **manual labelling**

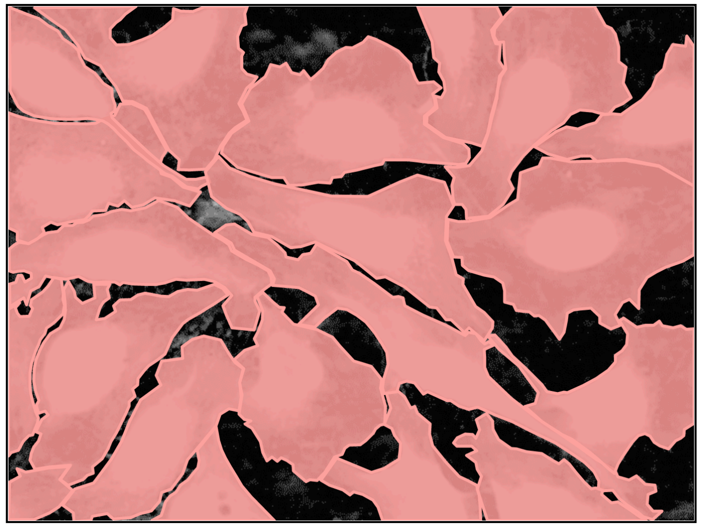
Phase image



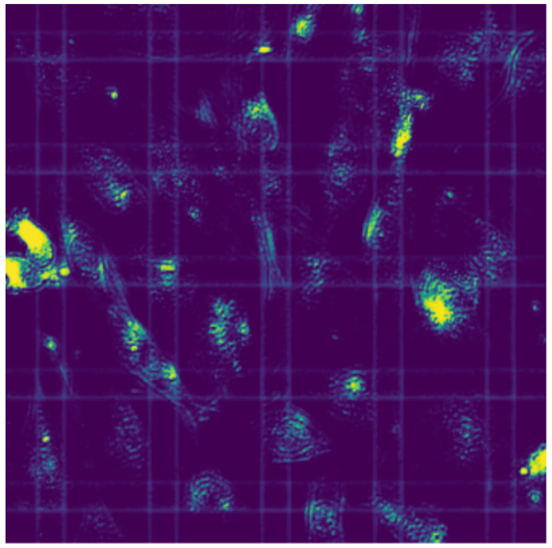
High contrast



Manual annotation in **LabelStudio**



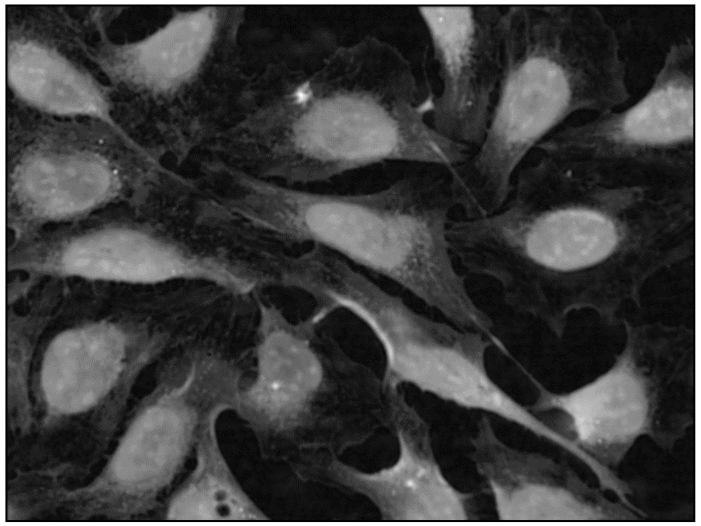
1 training image



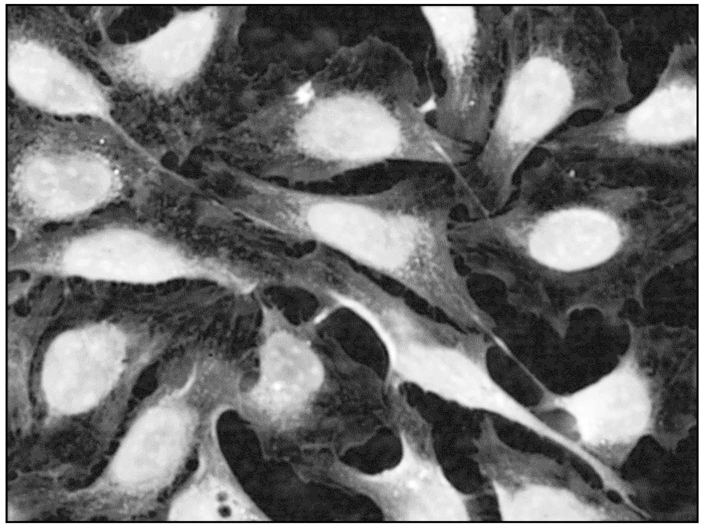
PW F1 score **0.48**

After battling with **unsupervised learning**, we come to appreciate **manual labelling**

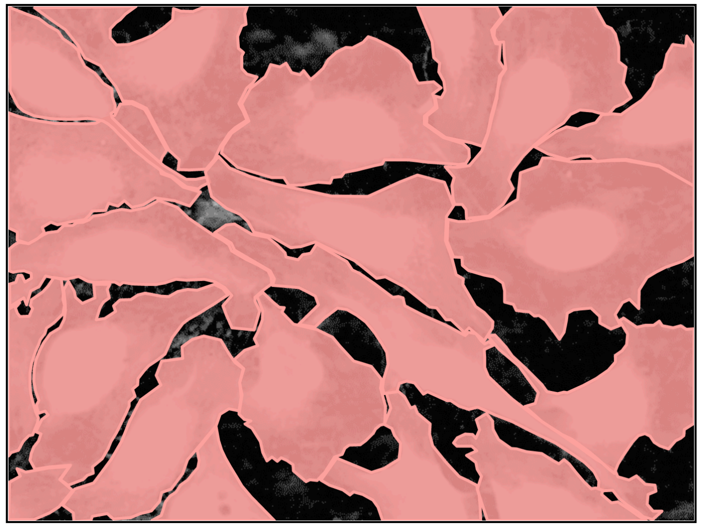
Phase image



High contrast

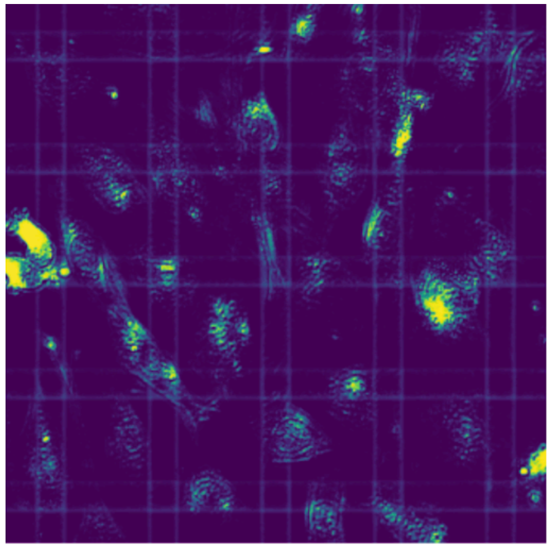


Manual annotation in **LabelStudio**



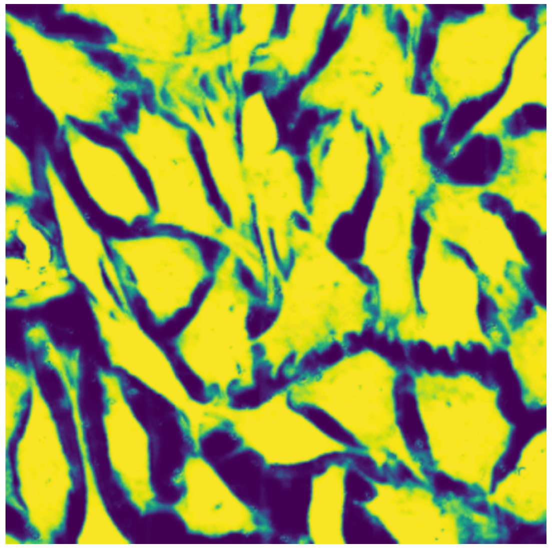
---

1 training image



PW F1 score **0.48**

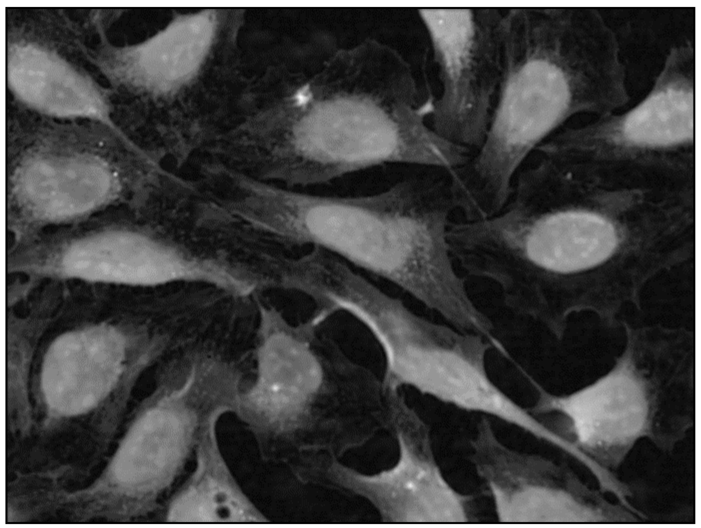
4 training images



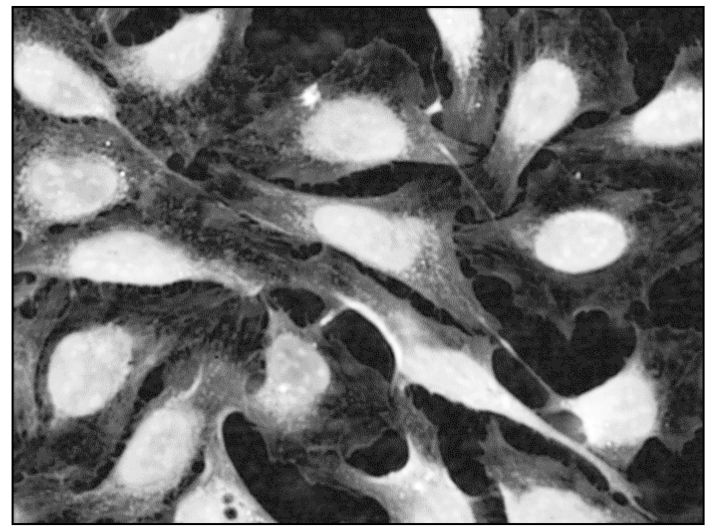
+ 0.34 PW F1

After battling with **unsupervised learning**, we come to appreciate **manual labelling**

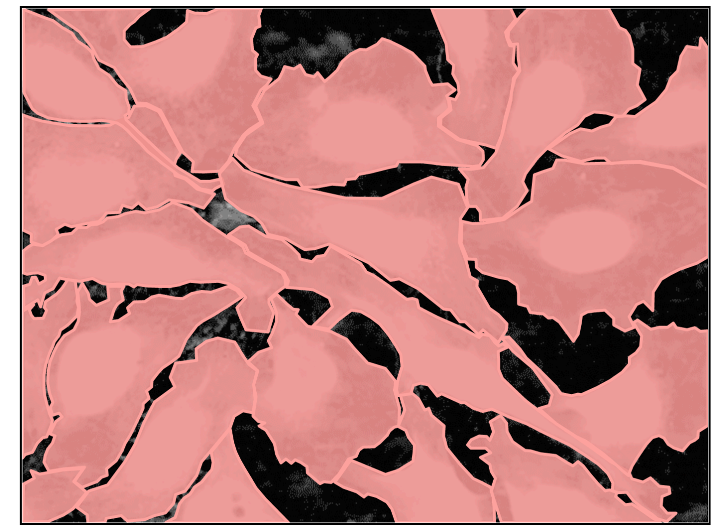
Phase image



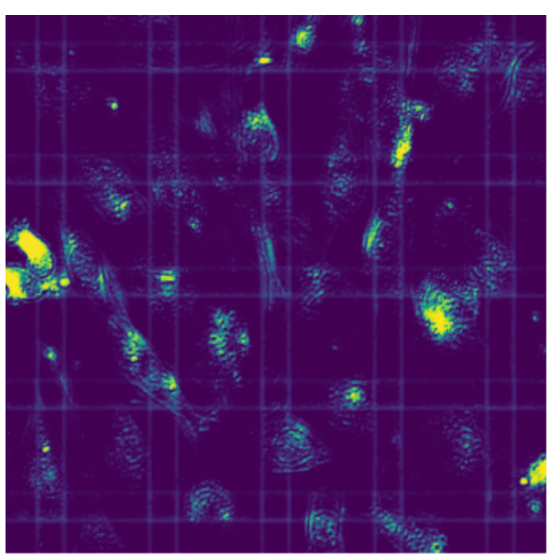
High contrast



Manual annotation in **LabelStudio**

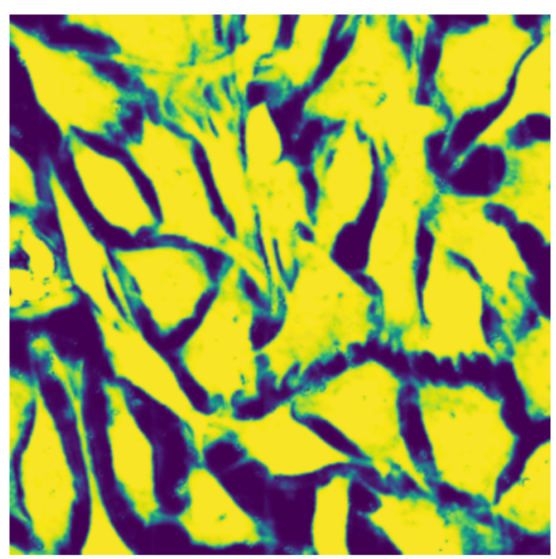


1 training image



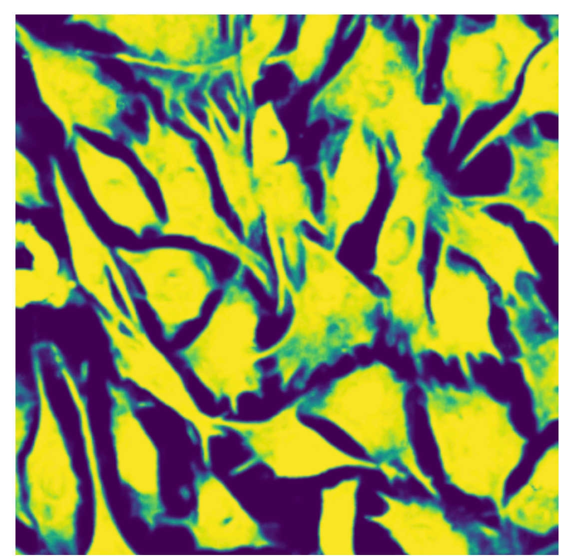
PW F1 score **0.48**

4 training images



+ 0.34 PW F1

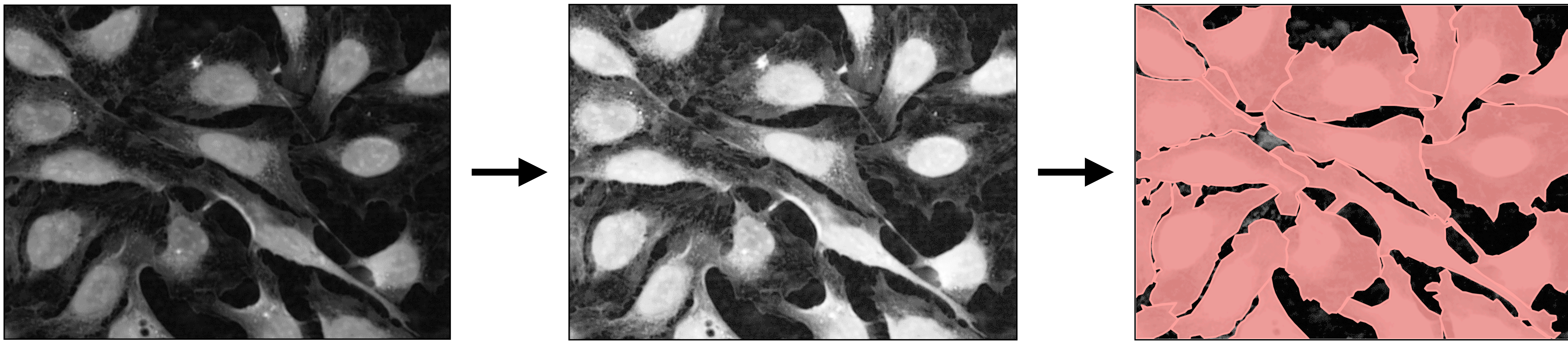
8 training images



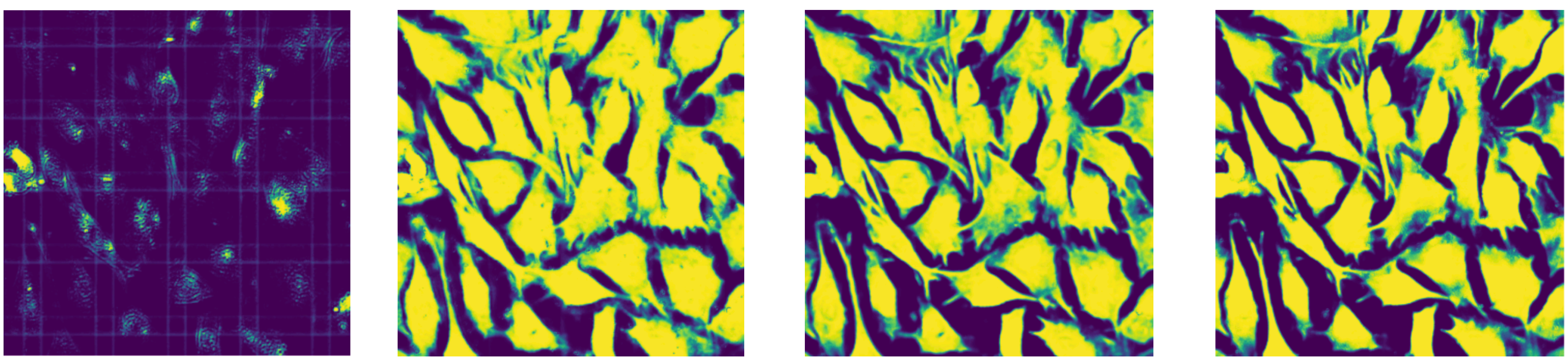
+ 0.07 PW F1

After battling with **unsupervised learning**, we come to appreciate **manual labelling**

Phase image | High contrast | Manual annotation in **LabelStudio**



1 training image | 4 training images | 8 training images | 16 training images



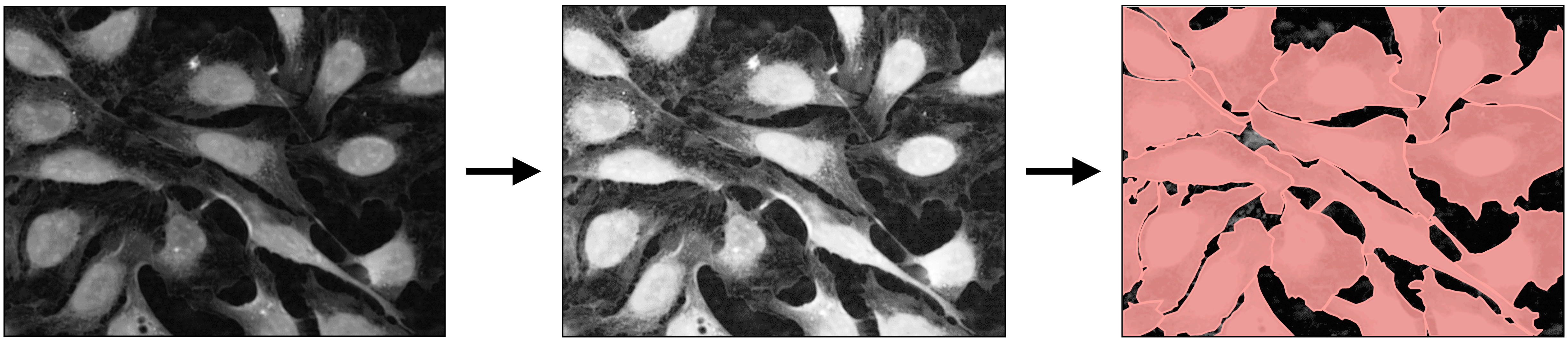
PW F1 score **0.48** | **+ 0.34** PW F1 | **+ 0.07** PW F1 | **+ 0.03** PW F1

After battling with **unsupervised learning**, we come to appreciate **manual labelling**

Phase image

High contrast

Manual annotation in **LabelStudio**

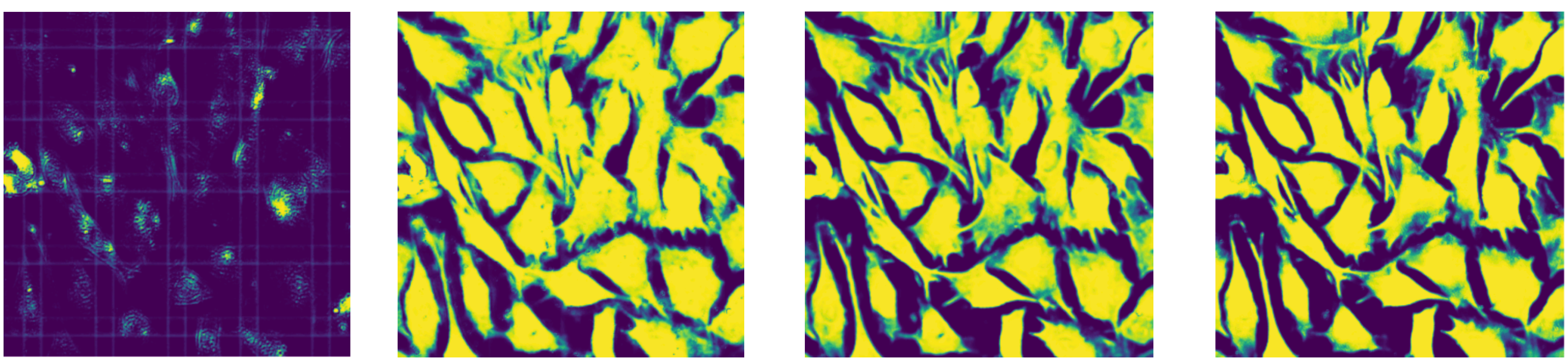


1 training image

4 training images

8 training images

16 training images



PW F1 score **0.48**

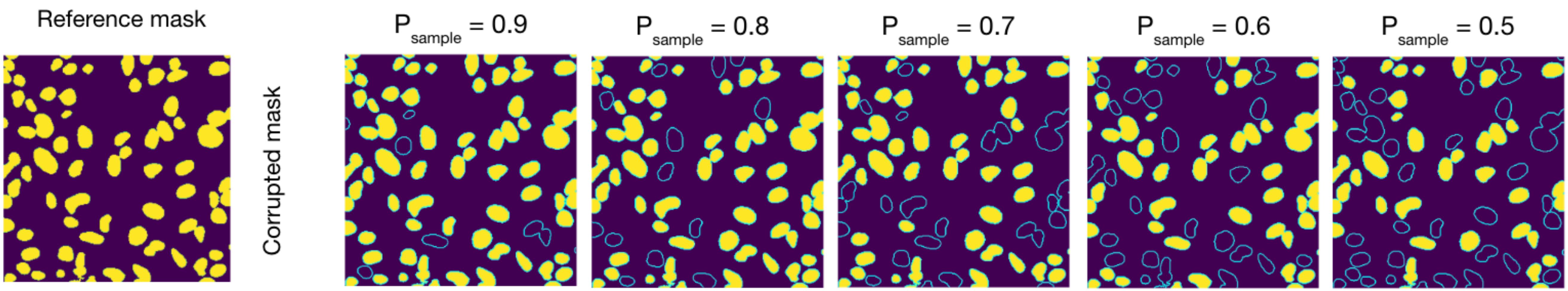
+ 0.34 PW F1

+ 0.07 PW F1

+ 0.03 PW F1

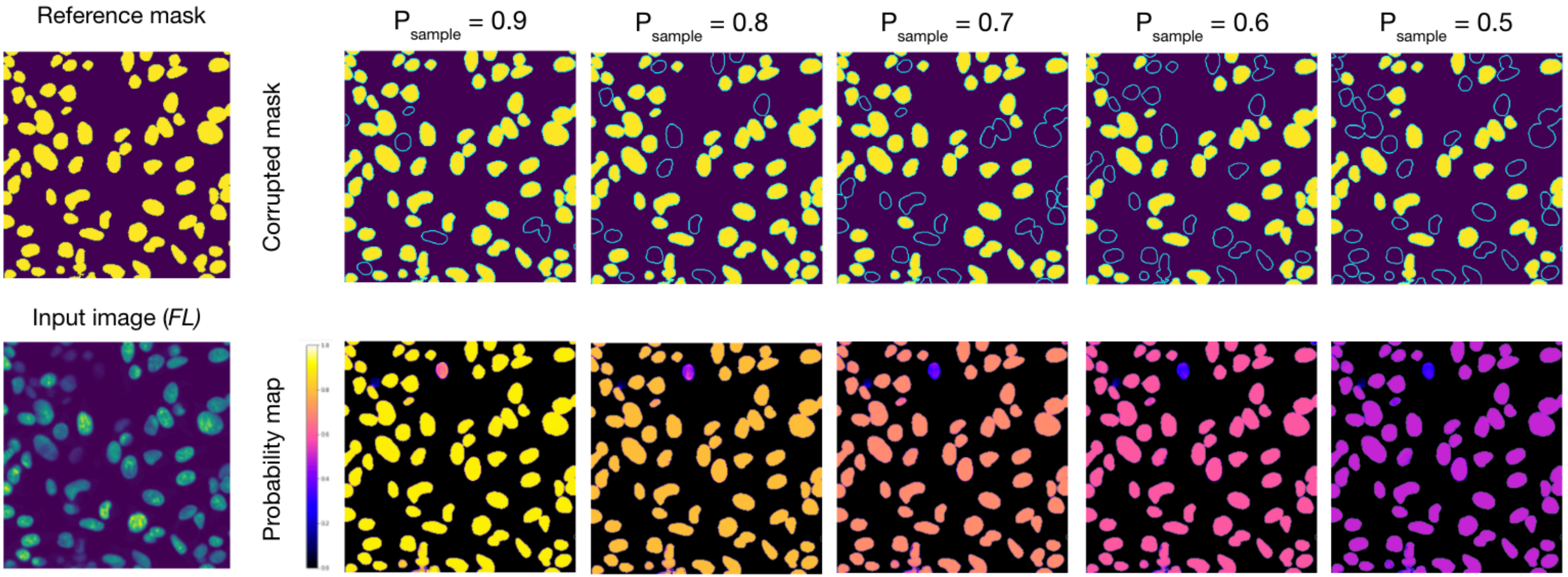
by **Yaroslav Prytula**

Complete annotations can be impossible to get using manual annotation, but even incomplete or noisy annotations would do.



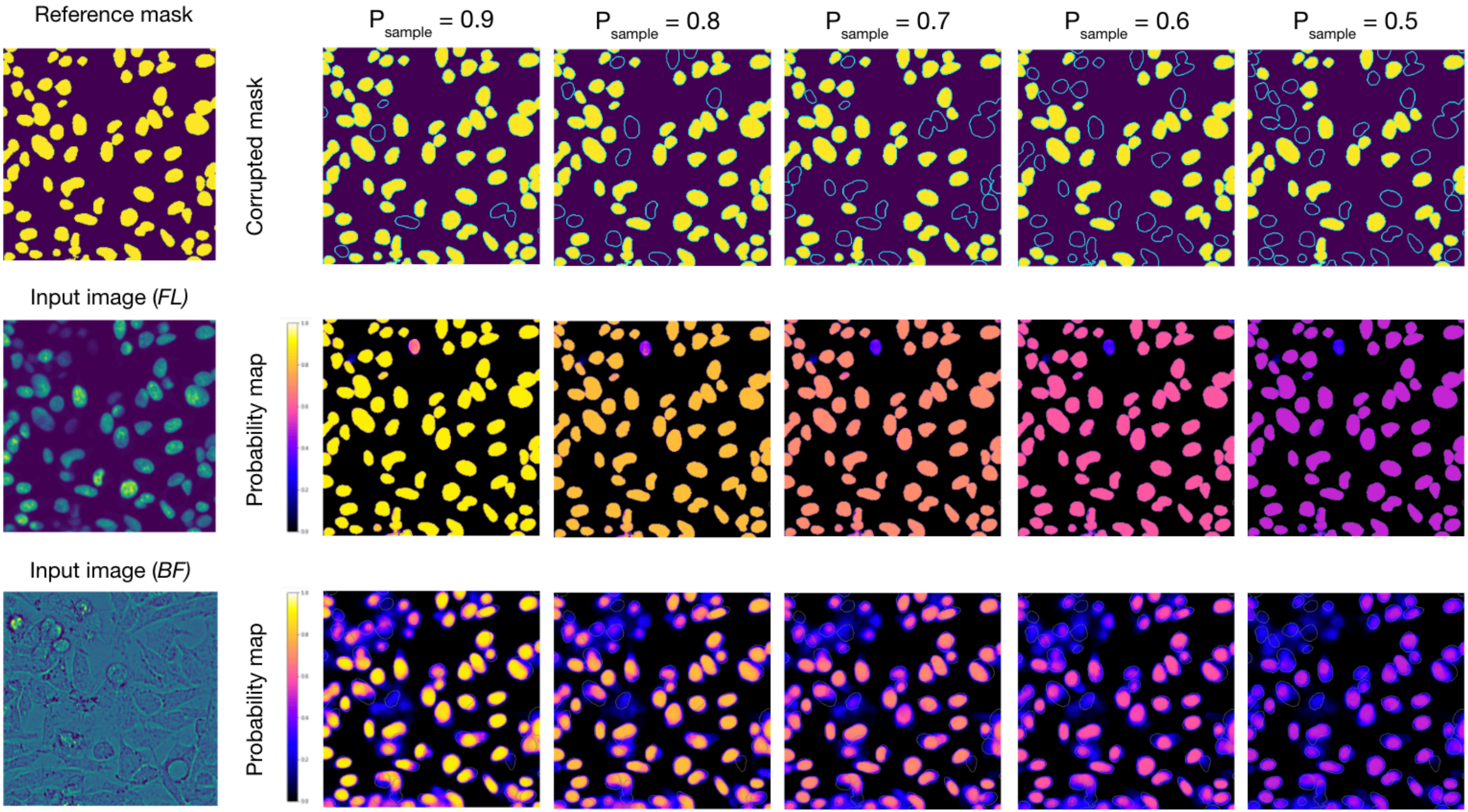
by **Aleksandr Krylov**

Complete annotations can be impossible to get using manual annotation, but even incomplete or noisy annotations would do.



by **Aleksandr Krylov**

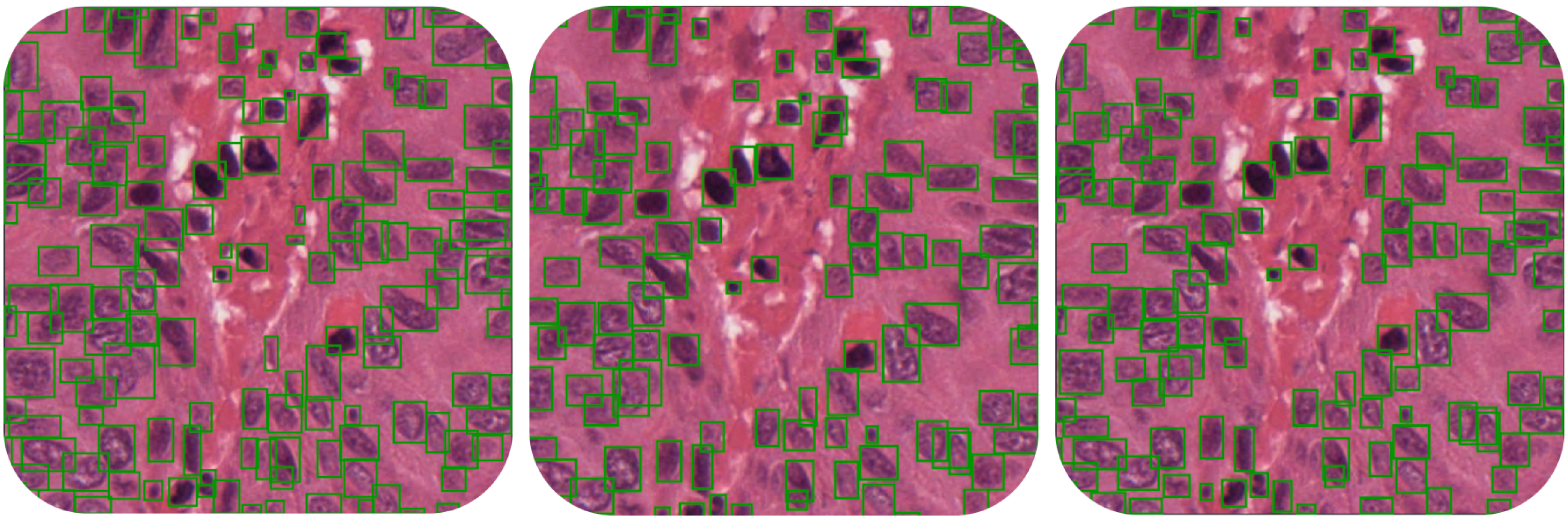
Complete annotations can be impossible to get using manual annotation, but even incomplete or noisy annotations would do.



by **Aleksandr Krylov**

Complete annotations can be impossible to get using manual annotation, but even incomplete or noisy annotations would do.

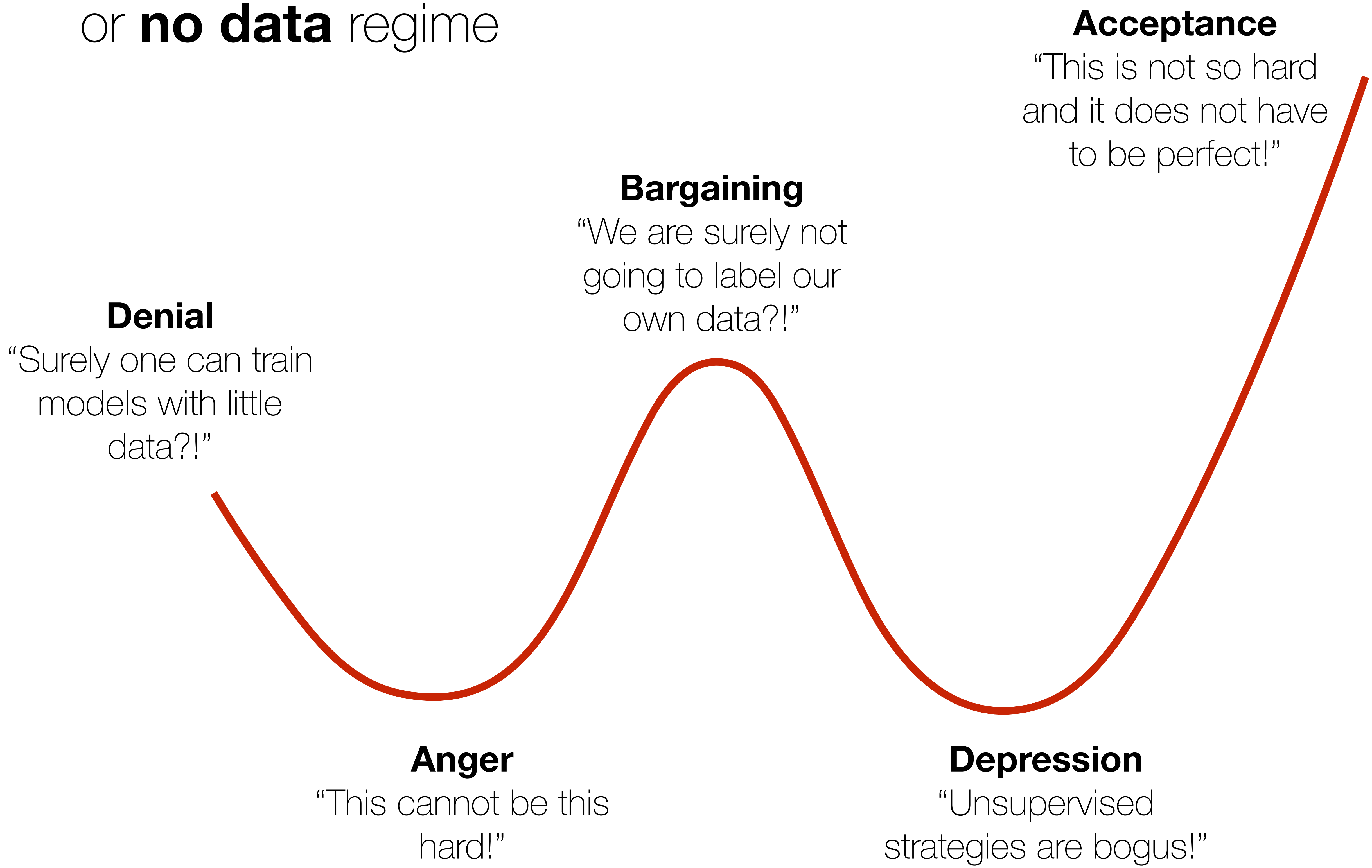
Ground truth objects | **100% of training data** model predictions | **50% of training data** model predictions



YOLOv5 was used in these experiments

by **Denys Kaliuzhnyi**, **Farid Hasanov** & **Mikhail Papkov**

Five stages of working in a **small** or **no data** regime

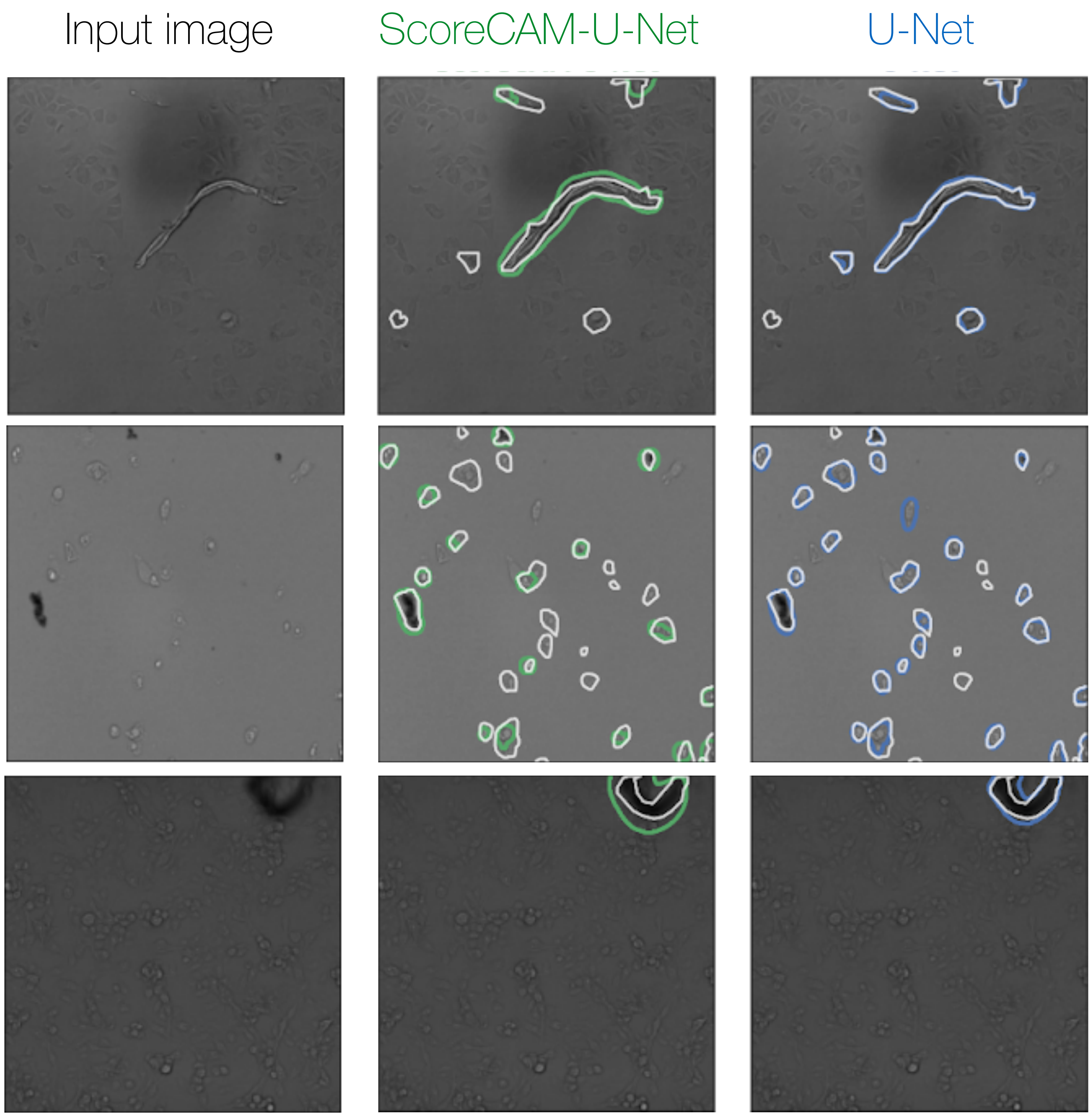


+ Tõnis Laasfeld, Dmytro Urukov, Kaspar Hollo, Joonas Ariva,
Farid Hasanov, Leopold Parts

TARTU ÜLIKOOL 1632 UNIVERSITAS TARTUENSIS

PerkinElmer® *For the Better*

Drop me an email
dmytro@ut.ee


Input image
ScoreCAM-U-Net
U-Net