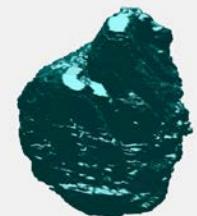
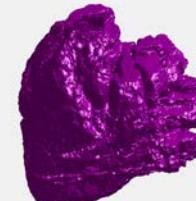
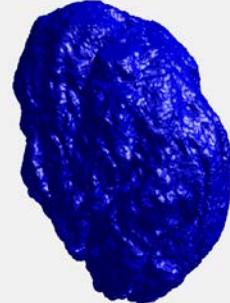


Semantic Segmentation of HeLa Cells:
An Objective Comparison between one Traditional
Algorithm and Four Deep-Learning Architectures

Constantino Carlos Reyes-Aldasoro

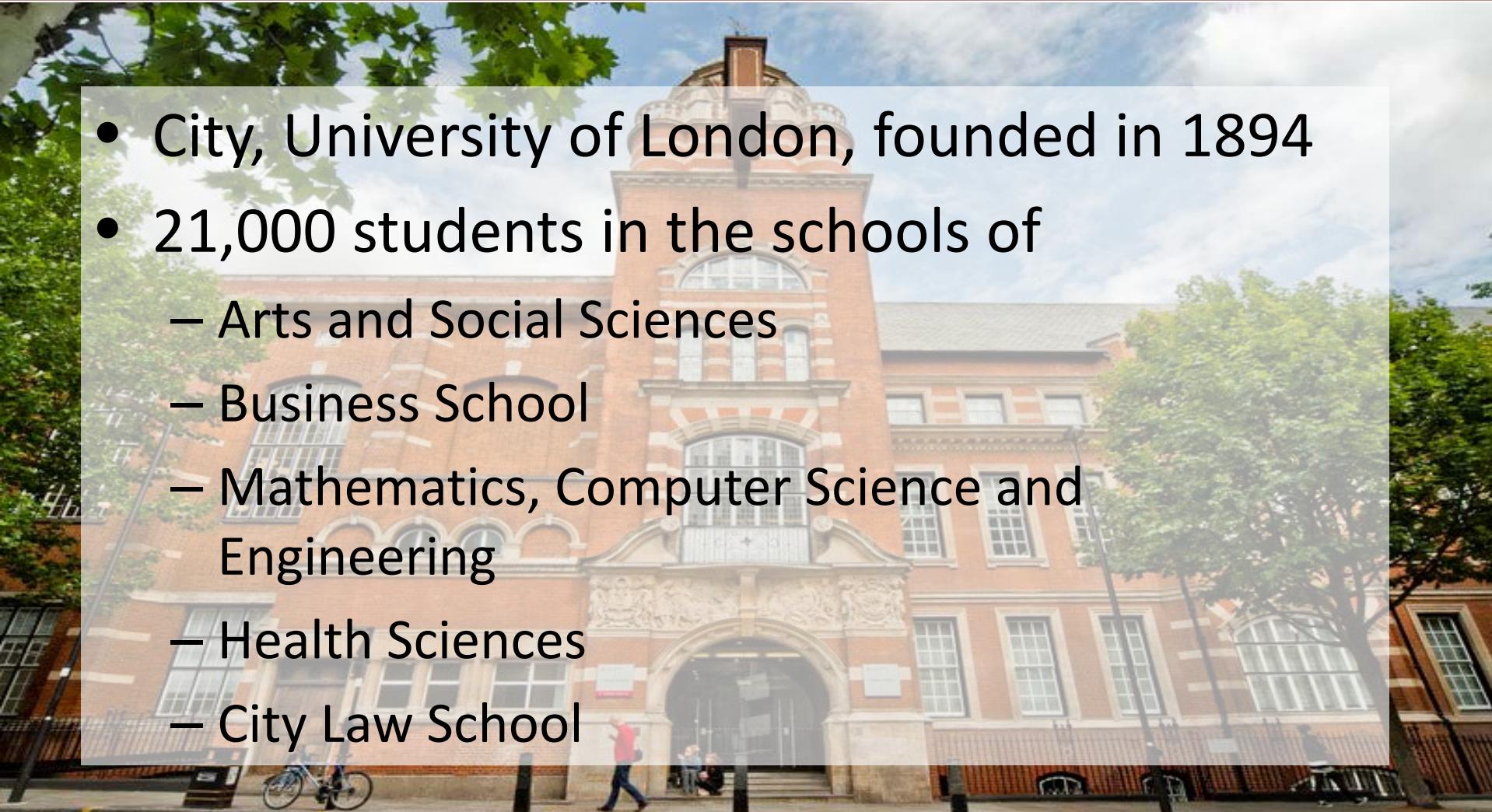
City, University of London, U.K.

reyes@city.ac.uk

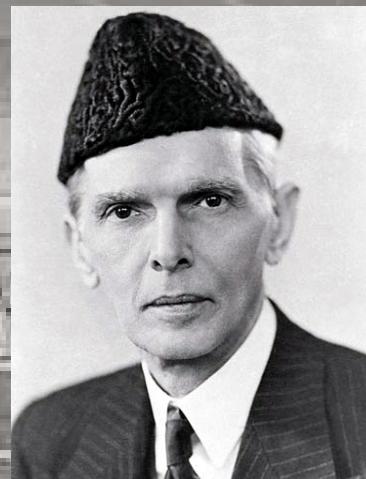
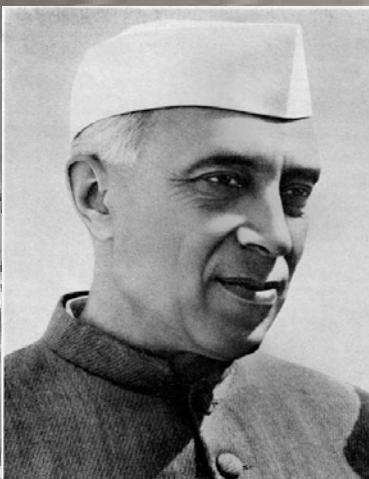
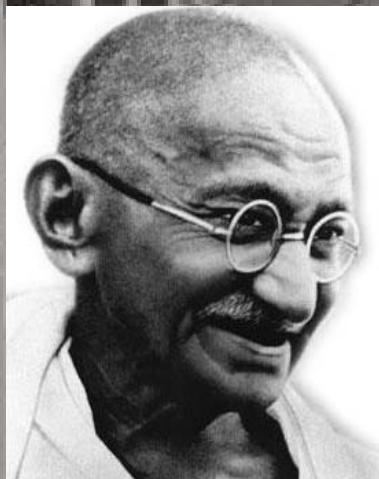


City, University of London

- City, University of London, founded in 1894
- 21,000 students in the schools of
 - Arts and Social Sciences
 - Business School
 - Mathematics, Computer Science and Engineering
 - Health Sciences
 - City Law School

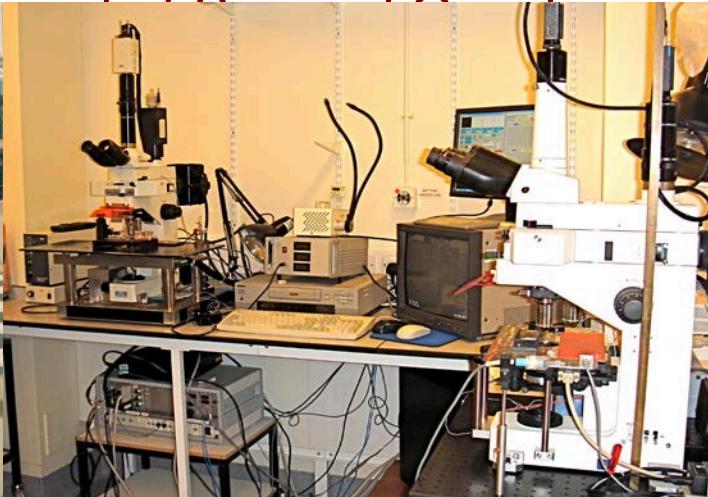
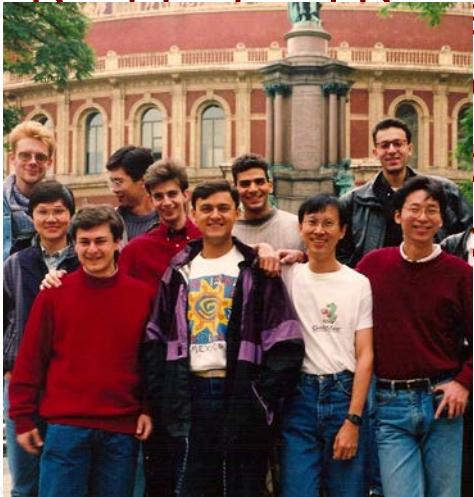


City's Alumni



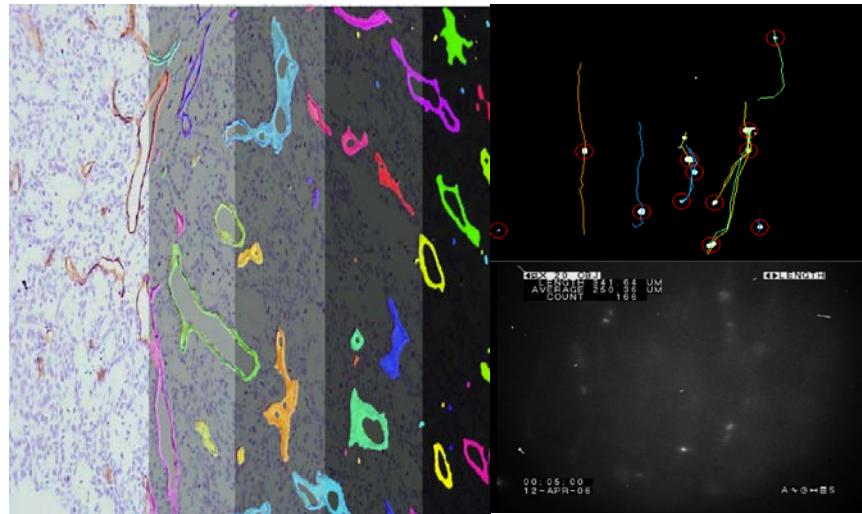
Constantino Carlos Reyes-Aldasoro

- 1987-1992 Mechanical and Electrical Engineering, UNAM
- 1993-1994 MSc Signal Processing, Imperial College
- 2001-2004 PhD Computer Science, Warwick

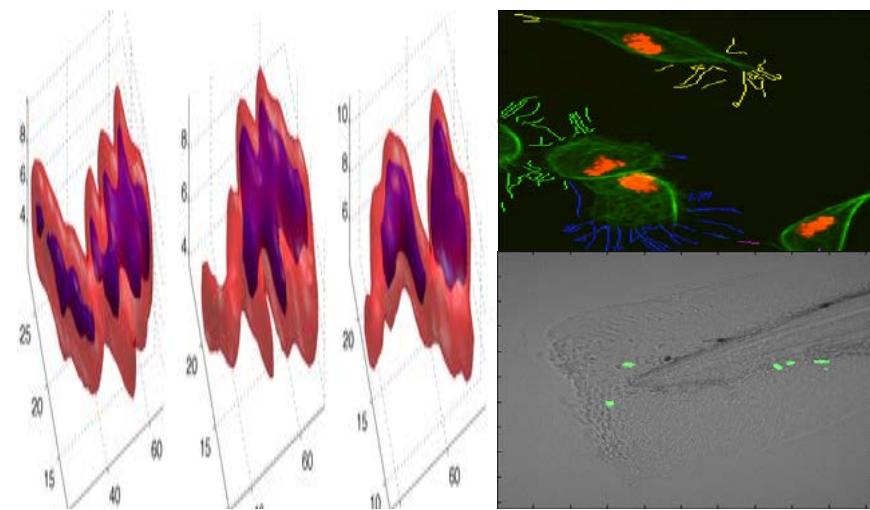


Main areas of interest

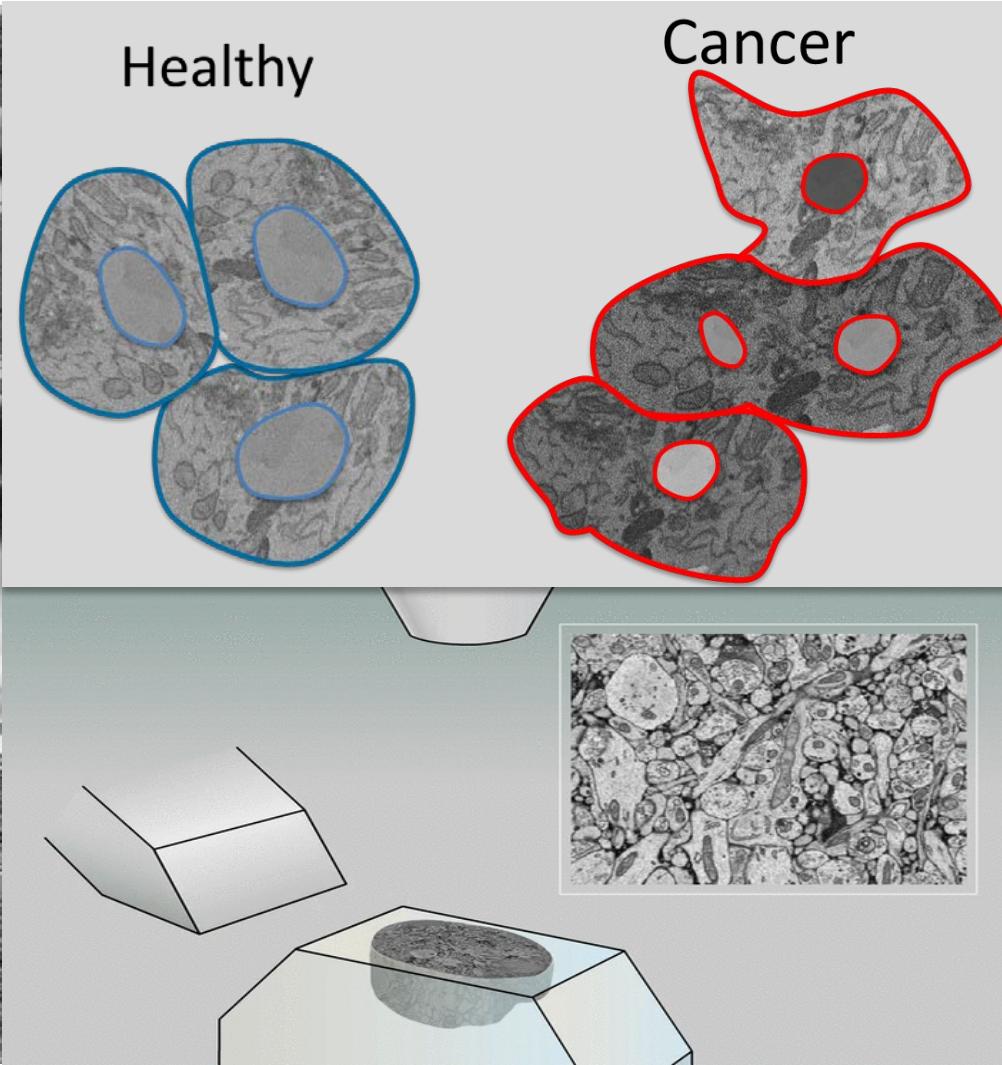
- Cancer



- Immunology



Cancer research



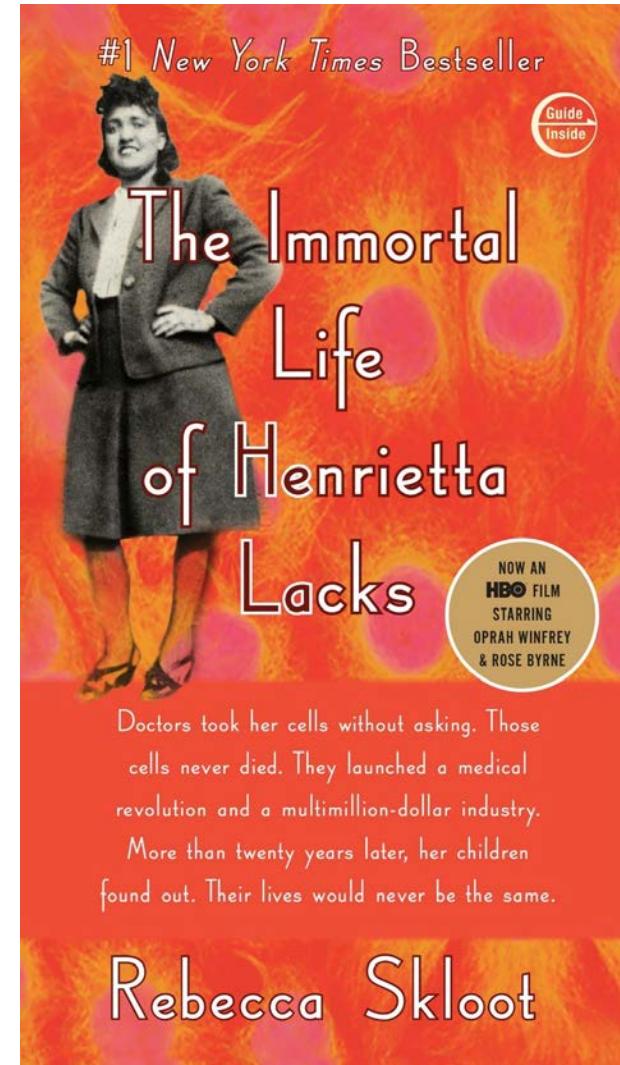
Henrietta Lacks

- In 1951, a young mother of five named Henrietta Lacks visited The Johns Hopkins Hospital complaining of vaginal bleeding.
- Upon examination, the gynaecologist discovered a large, malignant tumour on her cervix.



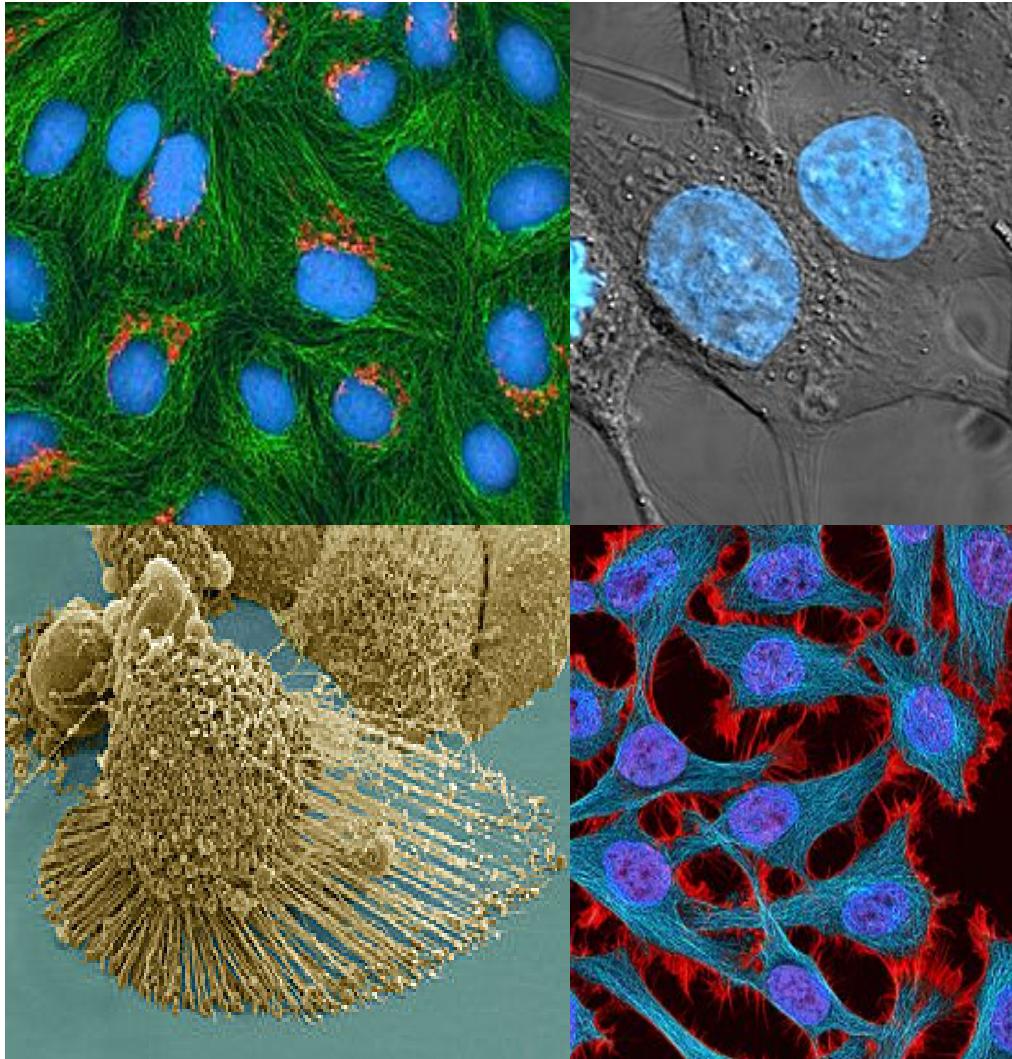
Henrietta Lacks

- *Without her consent*, a sample of her cells were sent to a lab.
- After a few months of radiation treatment, Henrietta died. However, the cells that were extracted followed a different path.

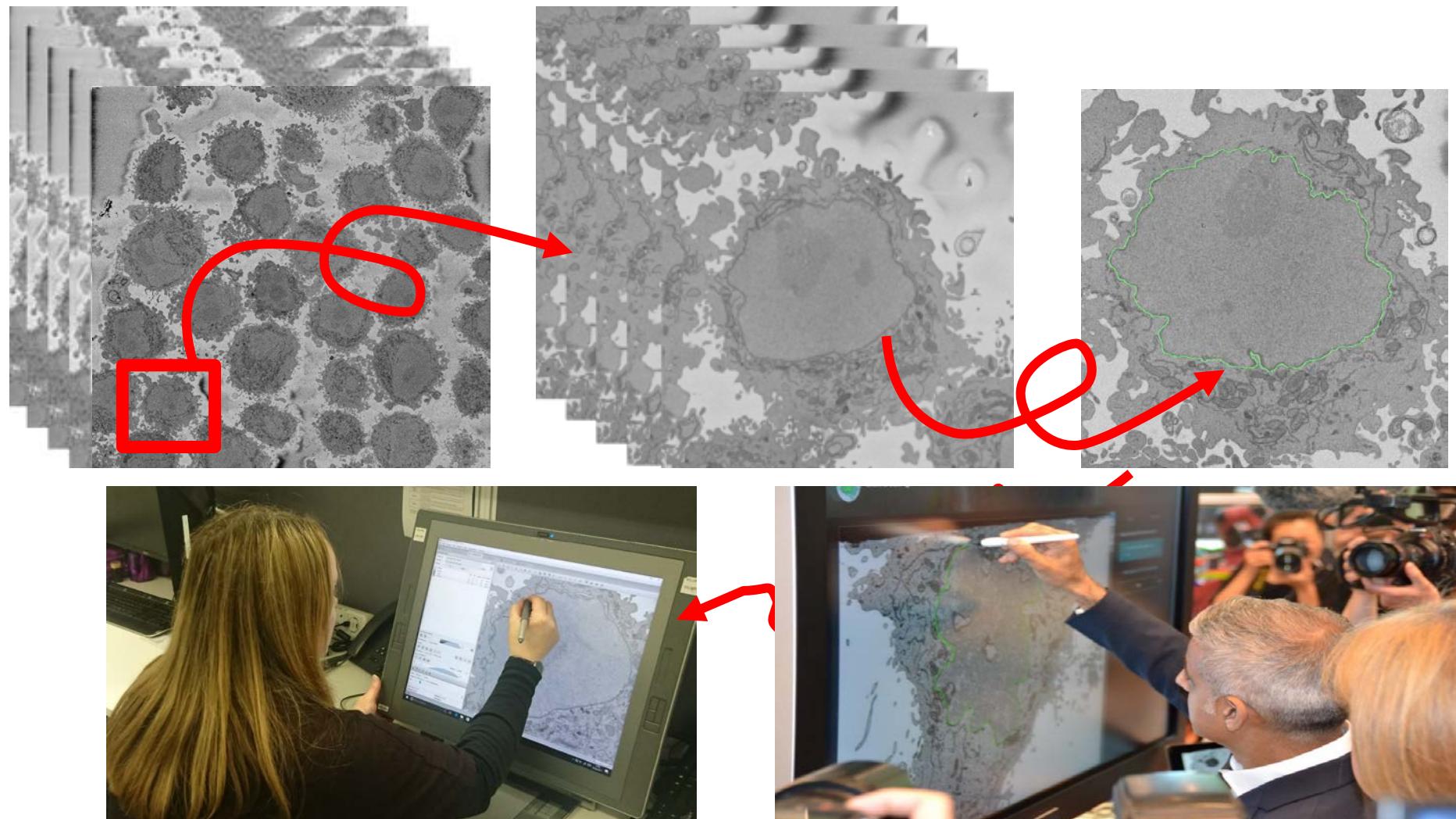


Henrietta Lacks

- At that time, it was not possible to keep cells alive in a lab. Henrietta's cells doubled every 24 hours.
- Those cells are still alive today ... and used in virtually every kind of medical experiment.

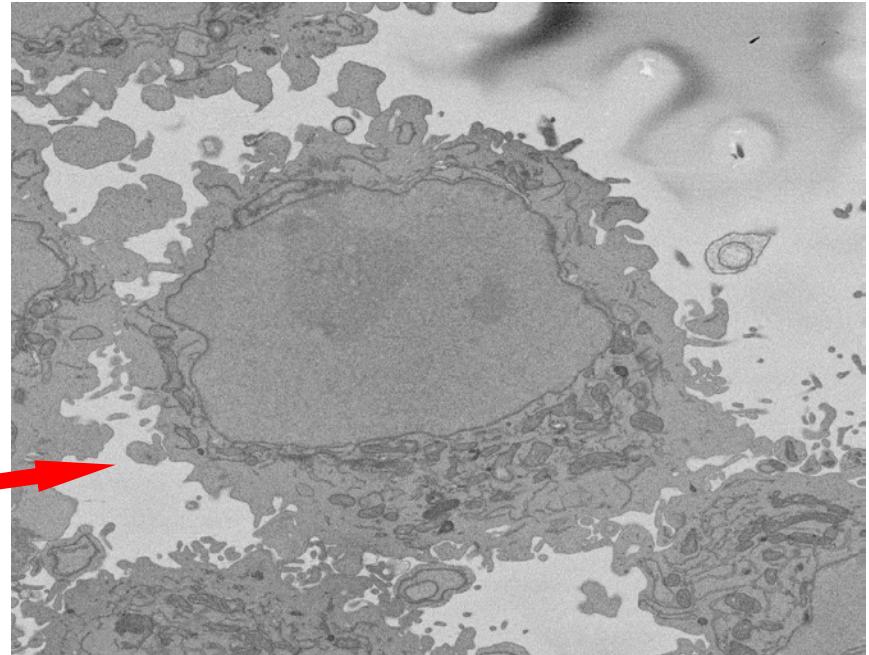
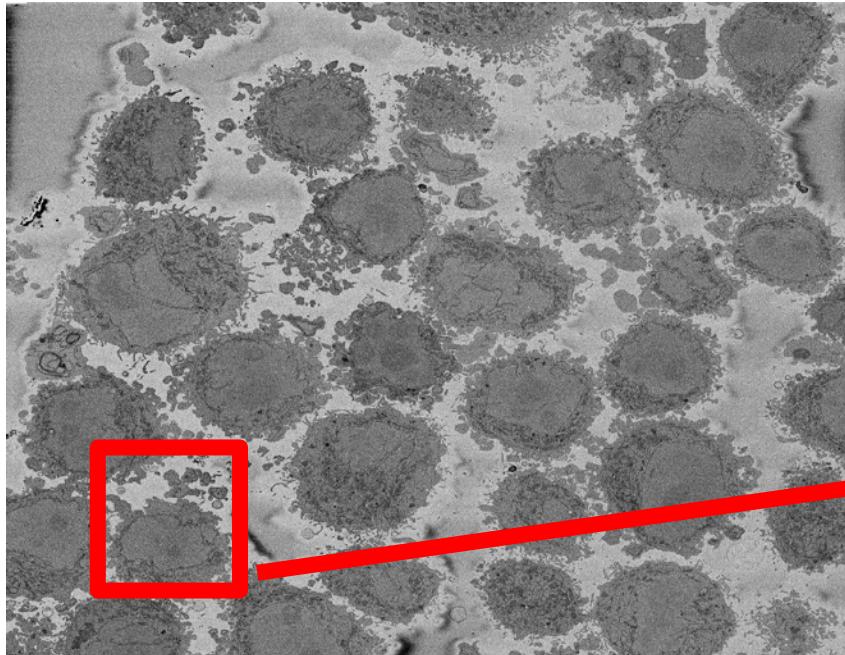


Analyse: slice per slice (by hand)



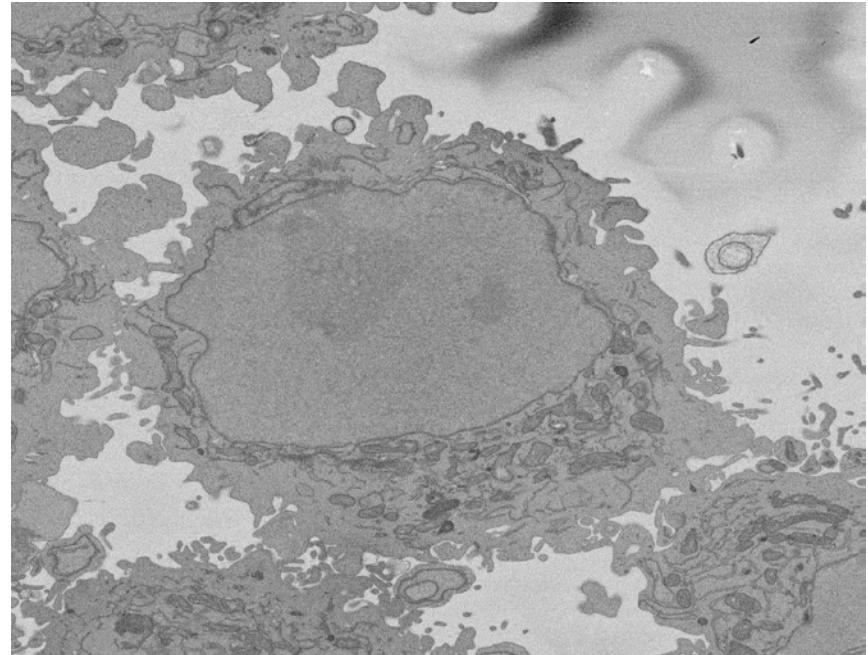
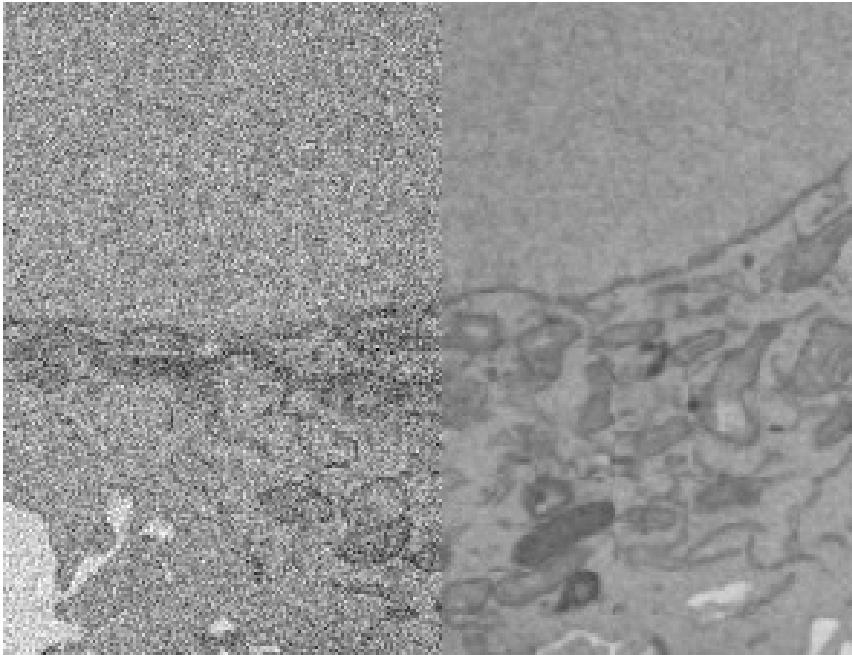
HeLa Segmentation with HI*

* That is, *Human Intelligence* ; -)



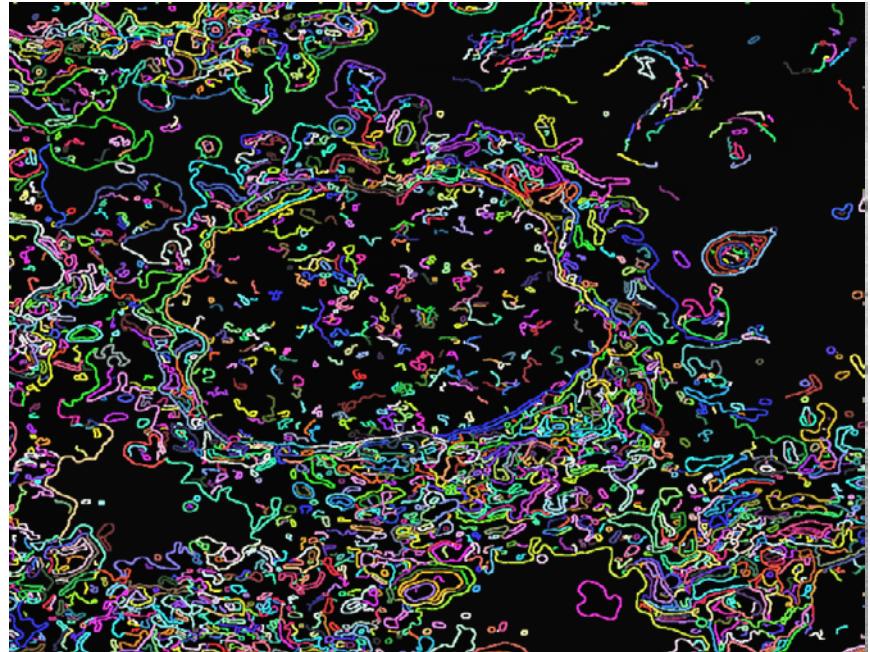
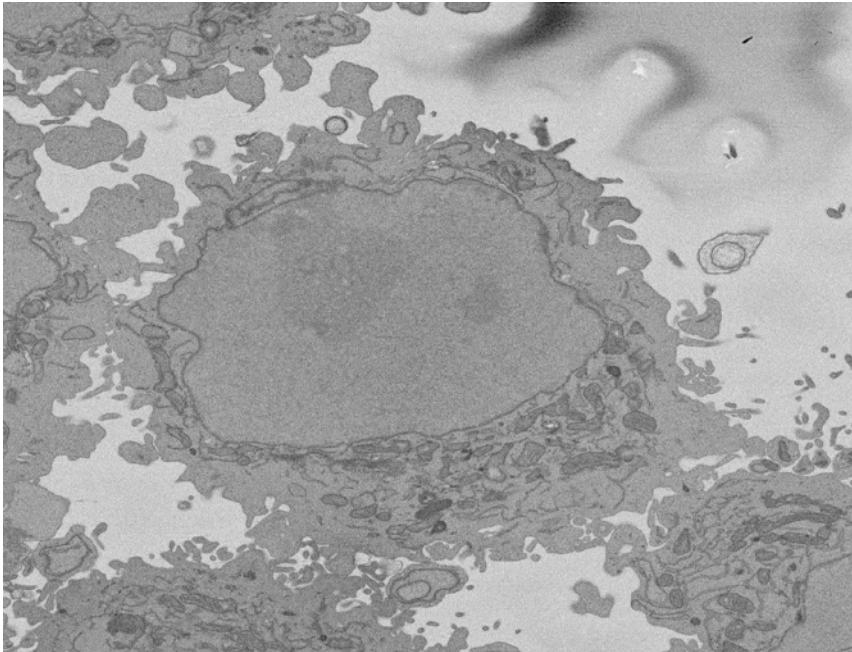
HeLa Segmentation with HI*

- Low pass filter to remove grainy noise



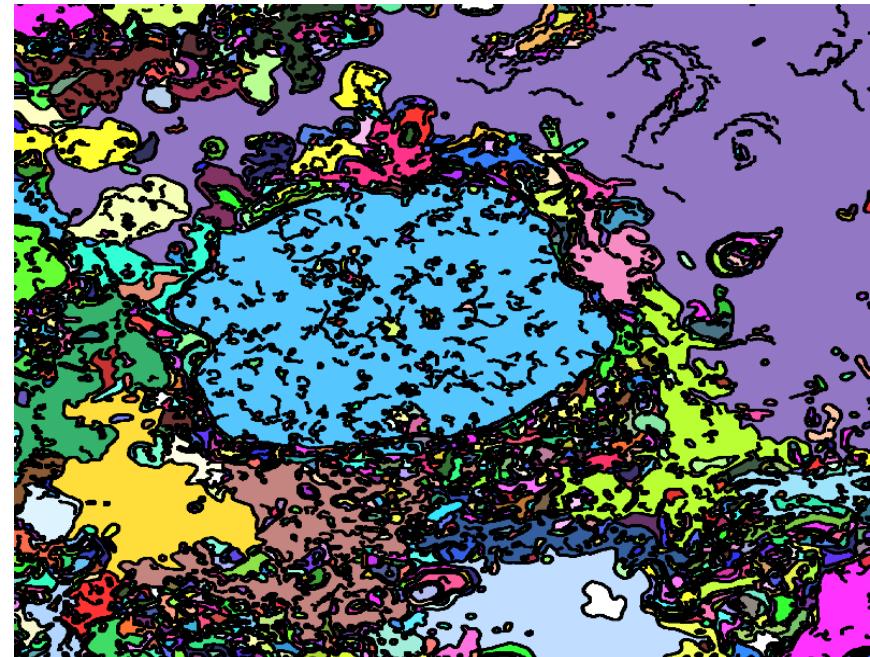
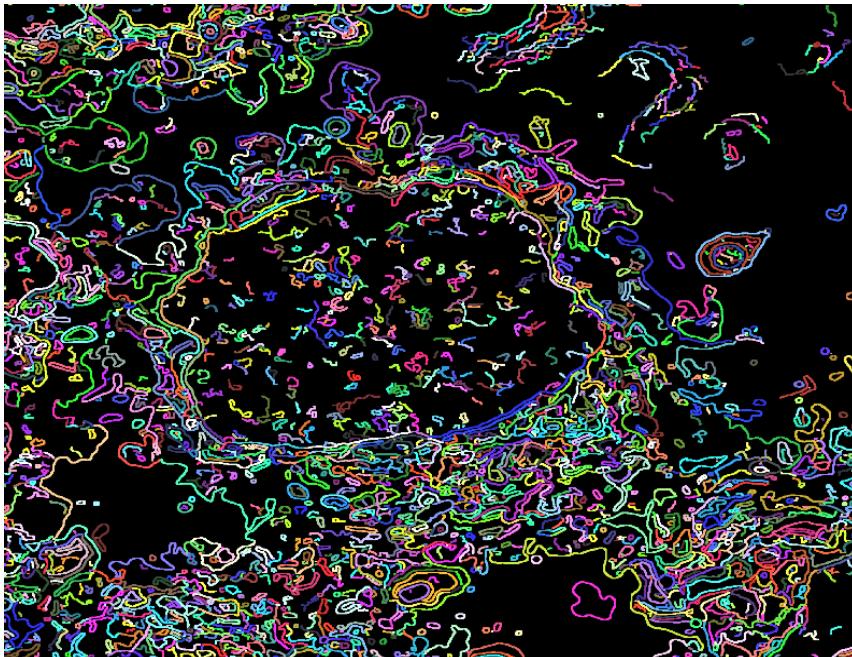
HeLa Segmentation with HI*

- Edge detection between regions of high change of intensity



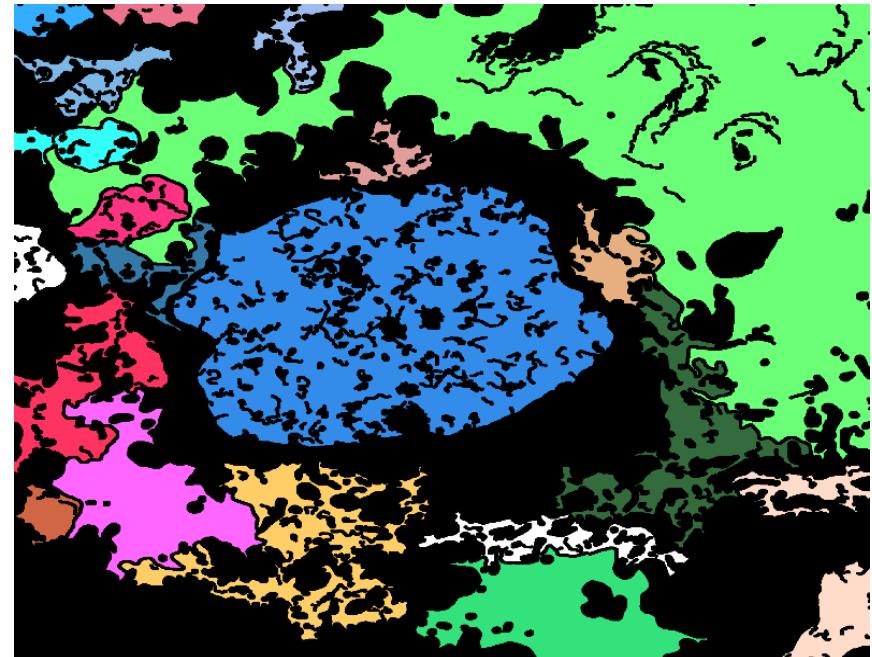
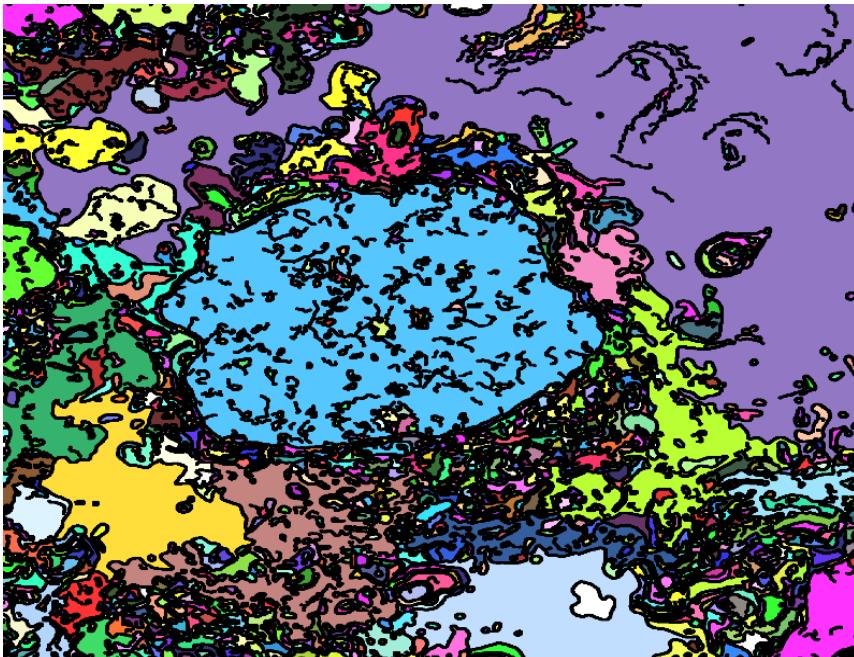
HeLa Segmentation with HI*

- Regions that are not covered by the edges become super-pixels



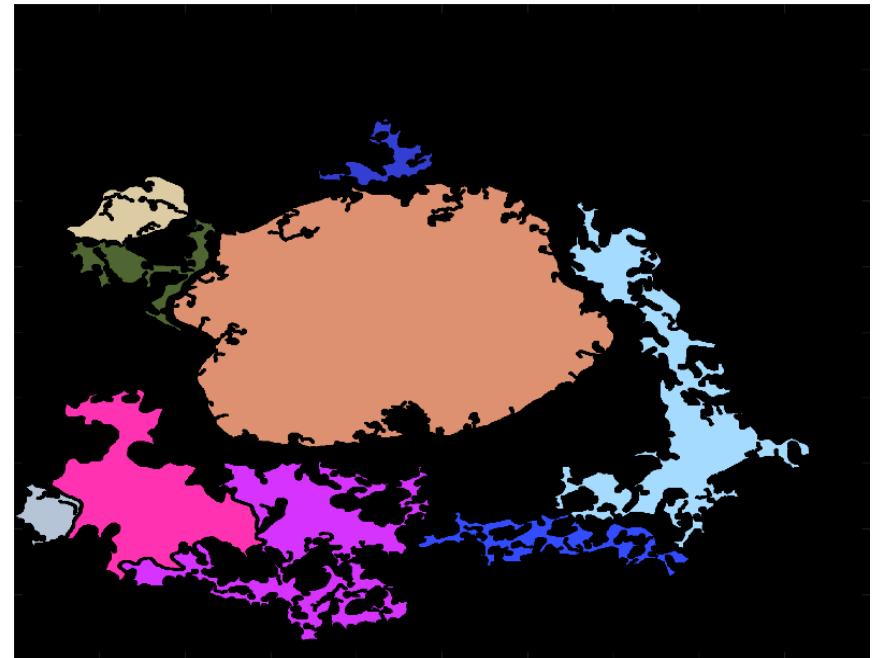
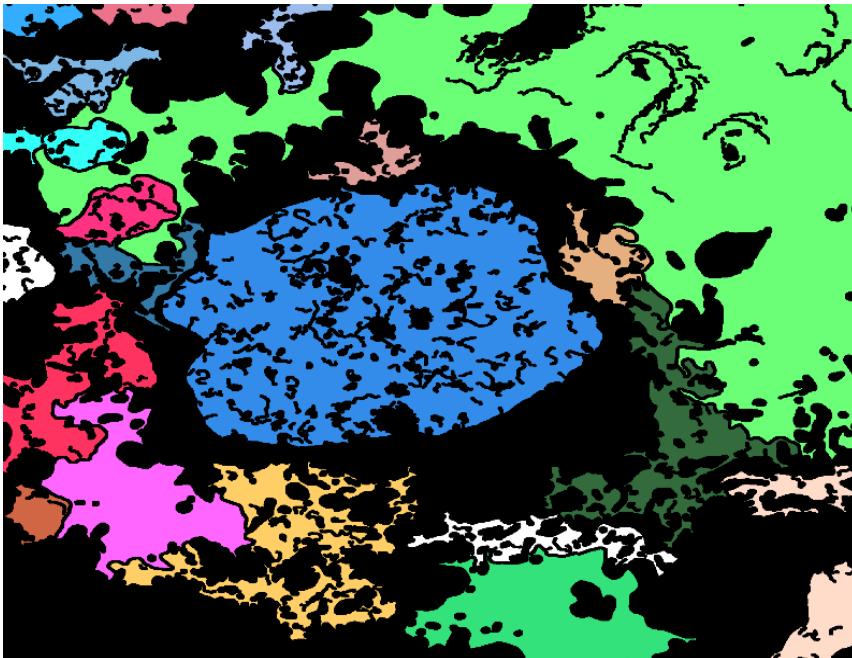
HeLa Segmentation with HI*

- Morphological selection of large super-pixels



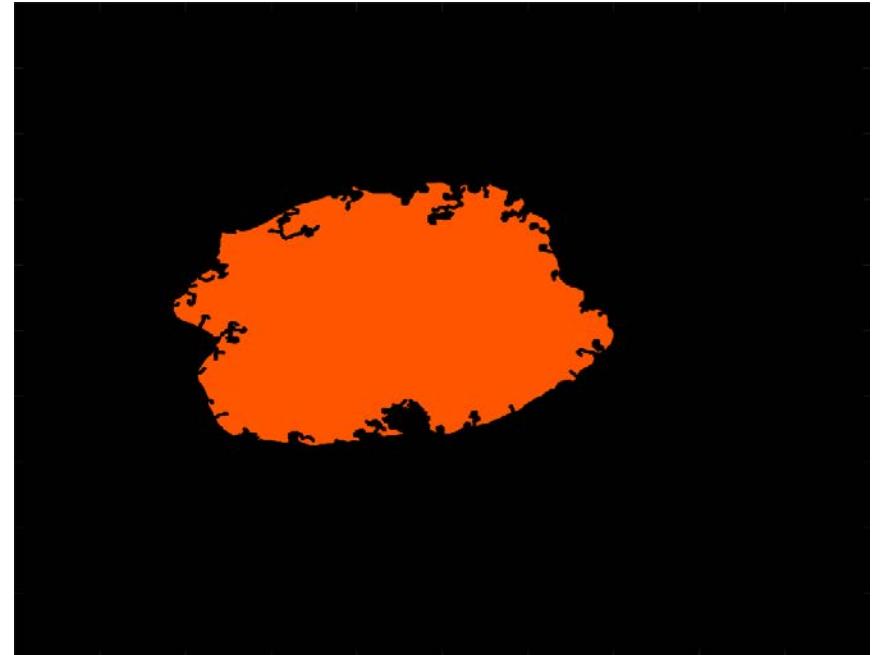
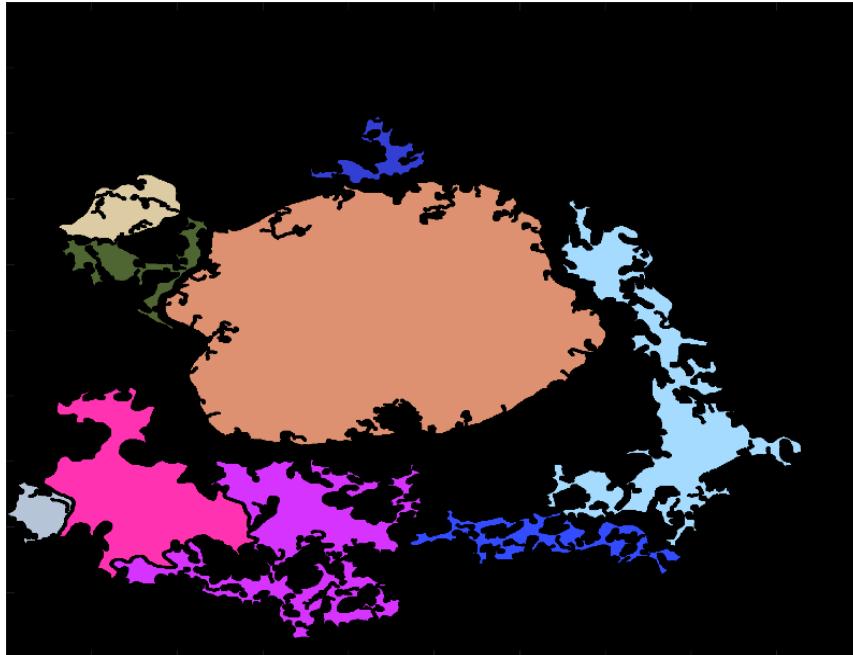
HeLa Segmentation with HI*

- Selection of those pixels that do not touch the boundaries of the image



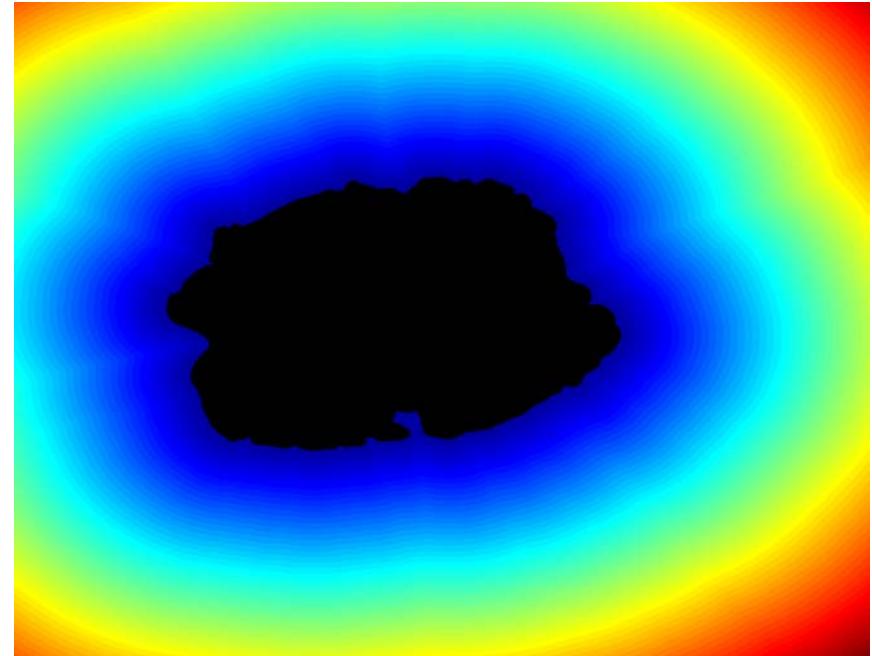
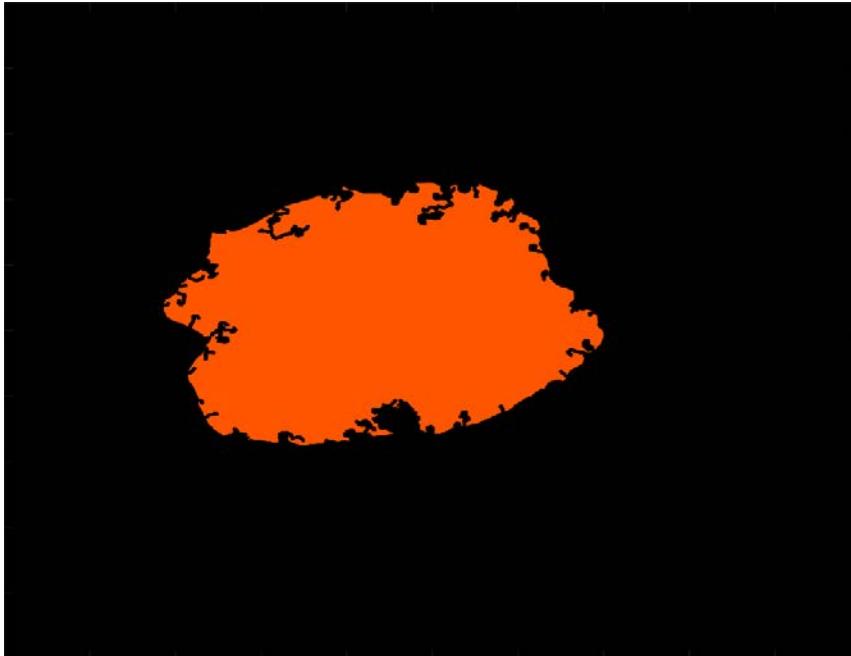
HeLa Segmentation with HI*

- Selection of central super-pixel



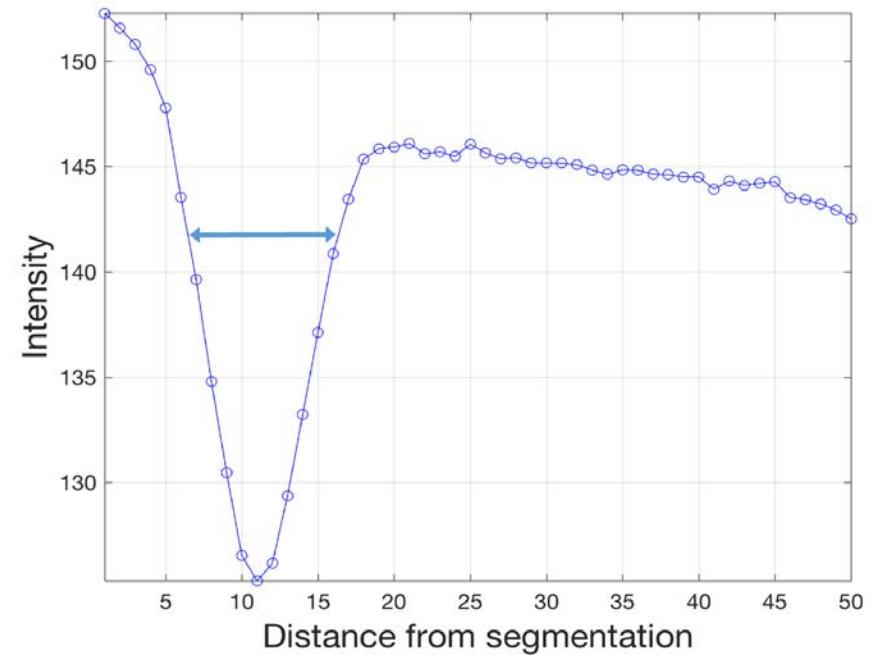
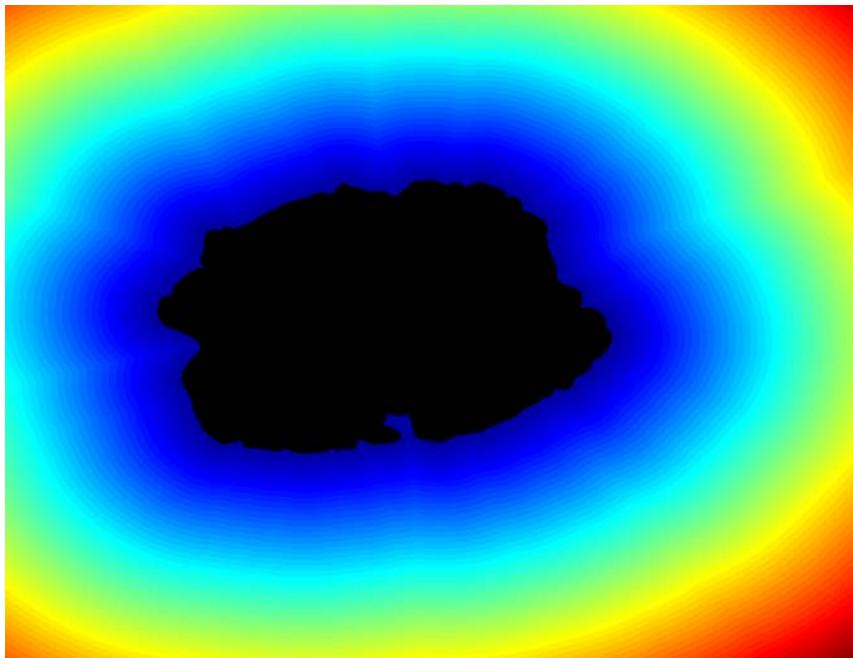
HeLa Segmentation with HI*

- Distance map outside the central super-pixel



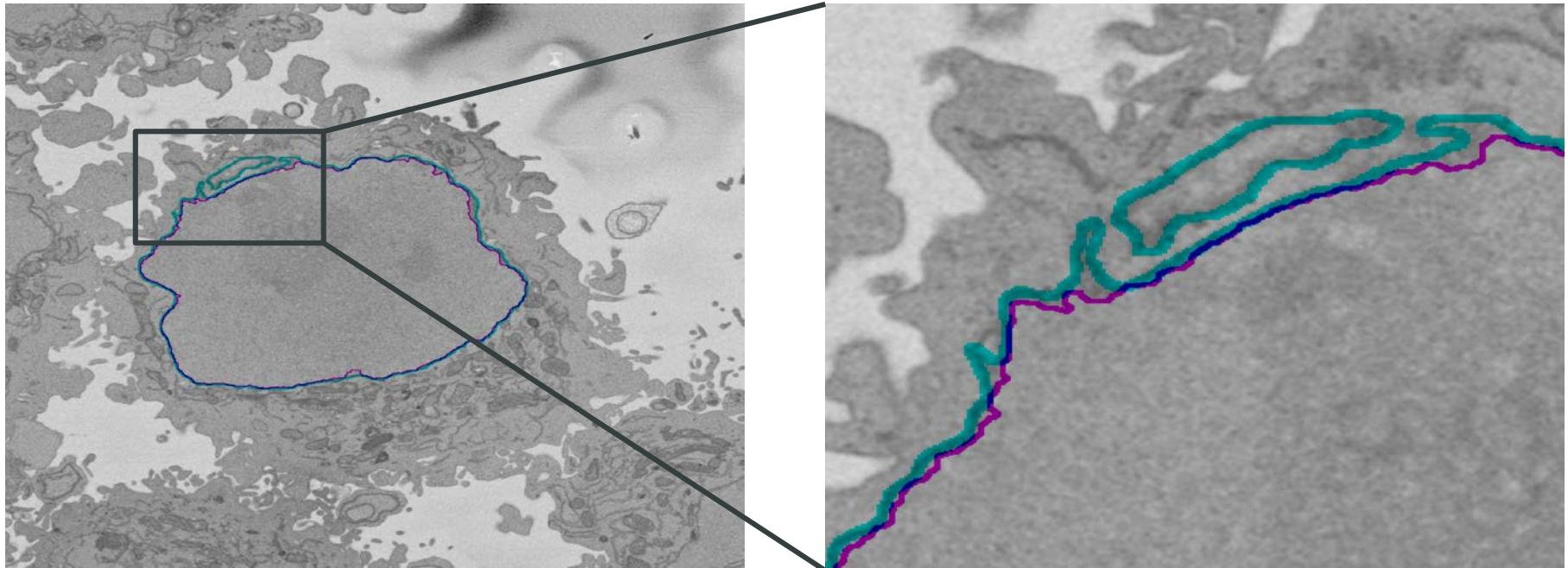
HeLa Segmentation with HI*

- Intensity of the original image at every iso-value region



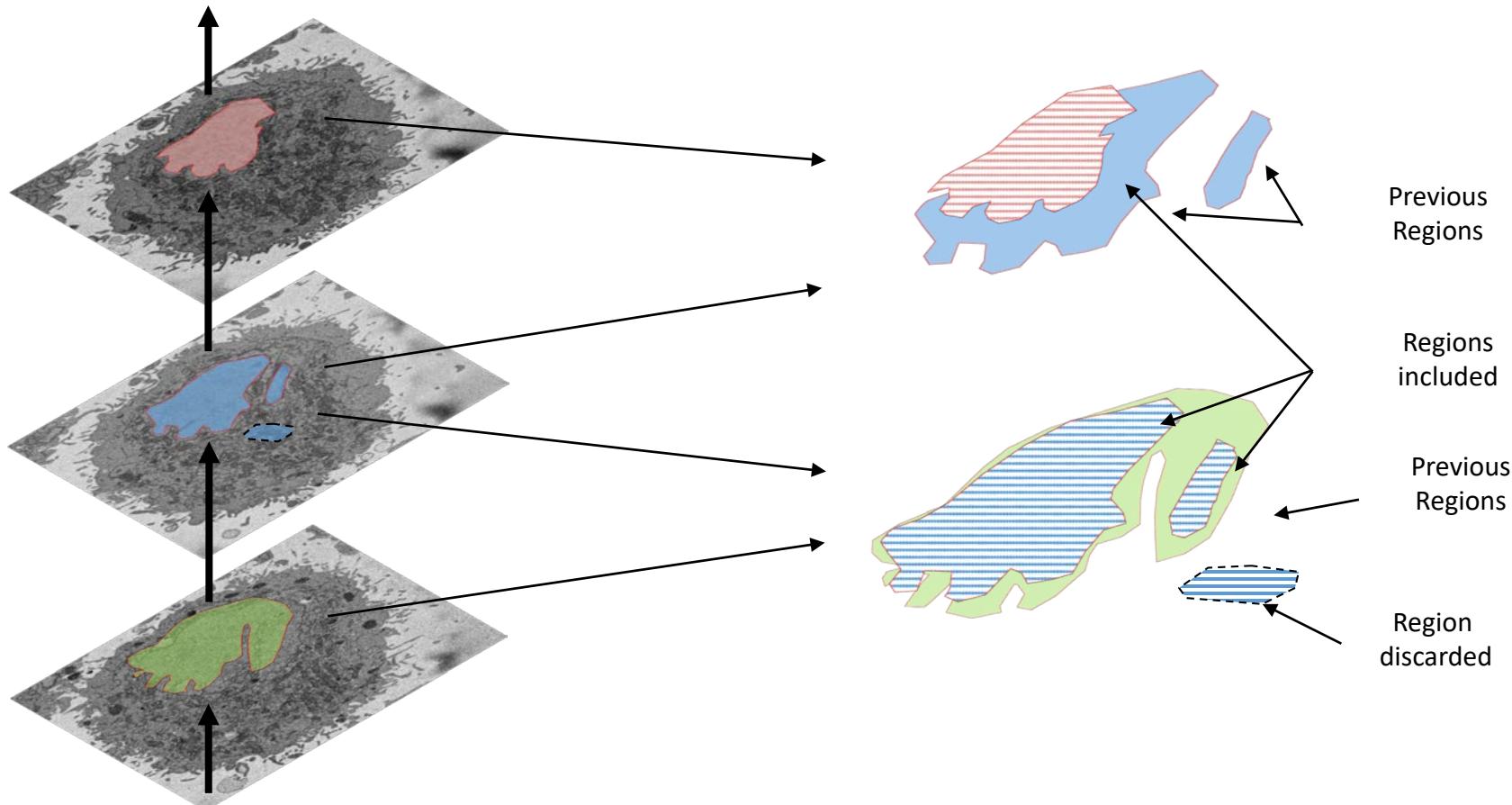
HeLa Segmentation with HI*

- Disconnected regions are not considered (as only one region was selected)



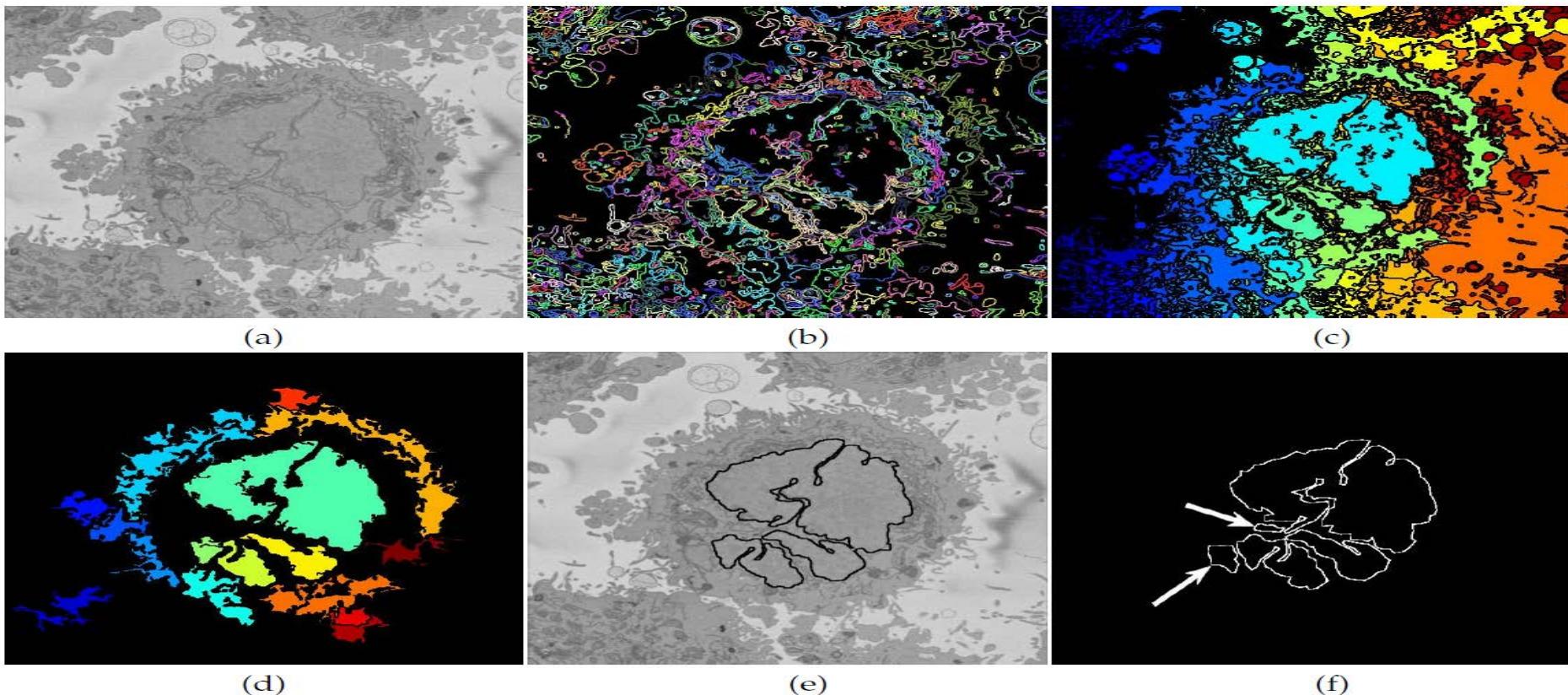
HeLa Segmentation with HI*

- Three-dimensional processing

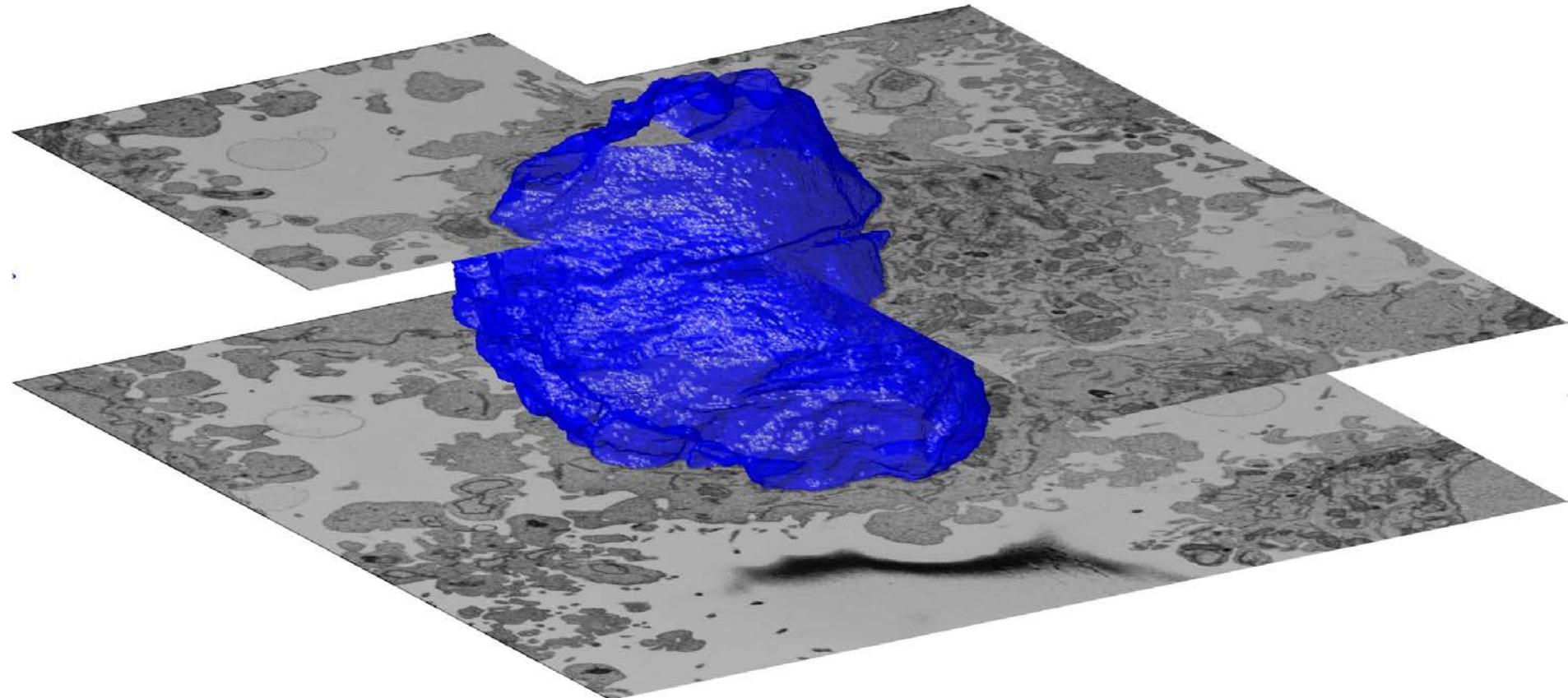


HeLa Segmentation with HI*

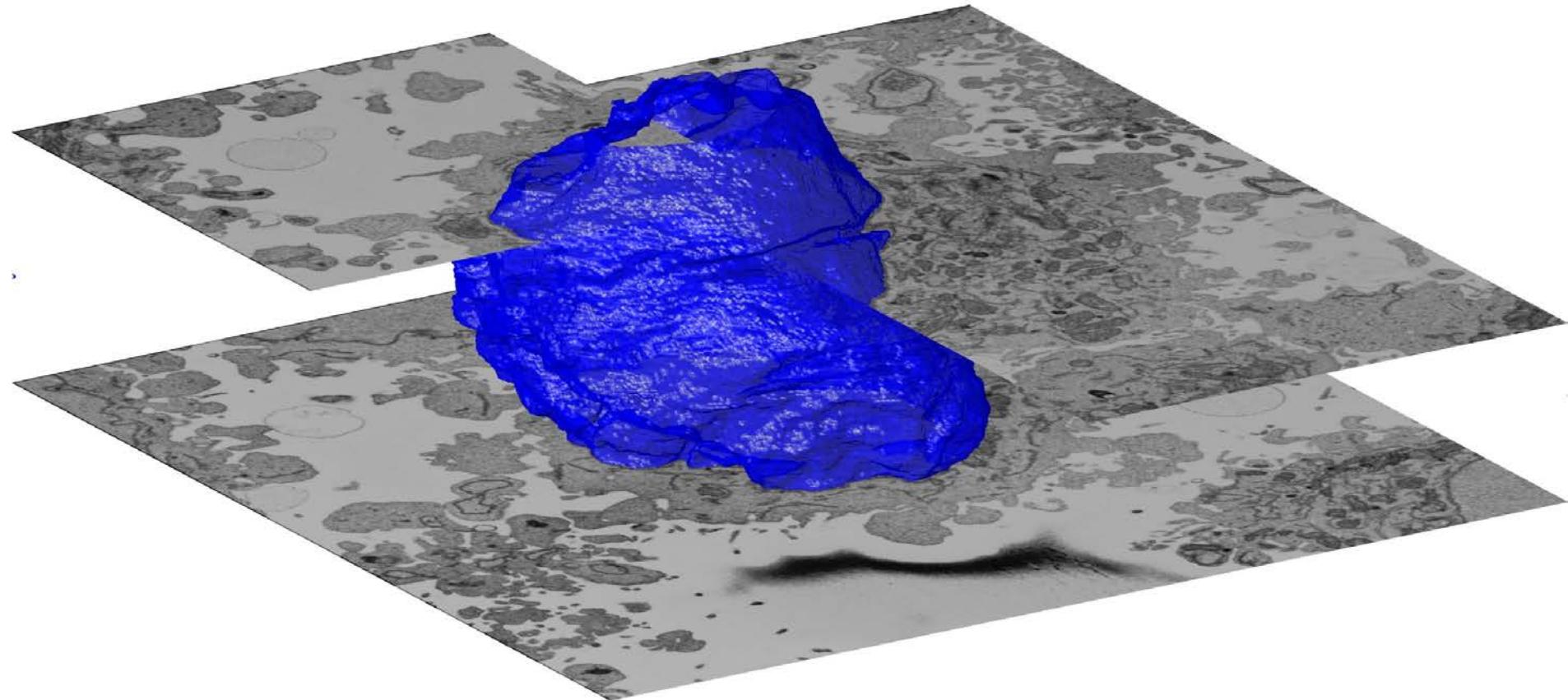
- Summary of the steps



Final Segmentation



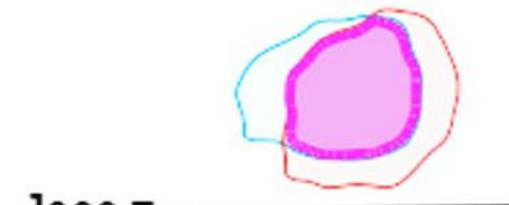
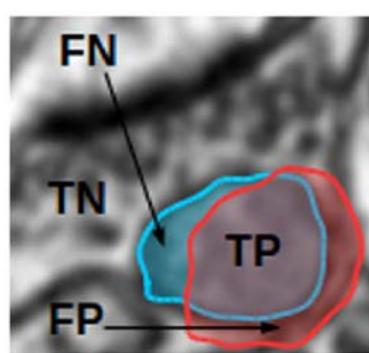
How good is this?



How good is this?

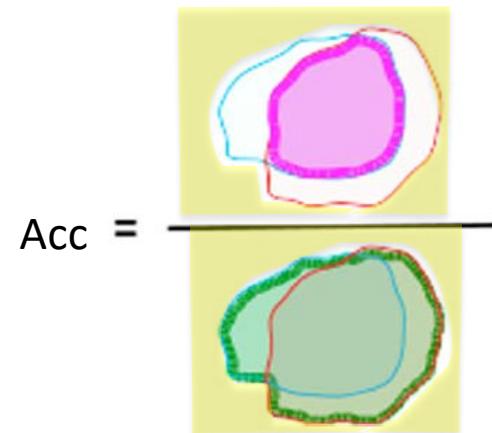
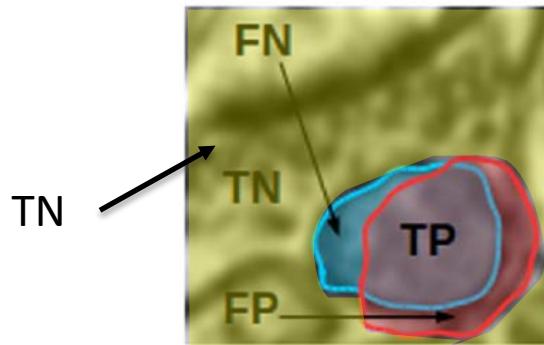
- Jaccard

$$\text{TP} / (\text{TP} + \text{FP} + \text{FN})$$



- Accuracy

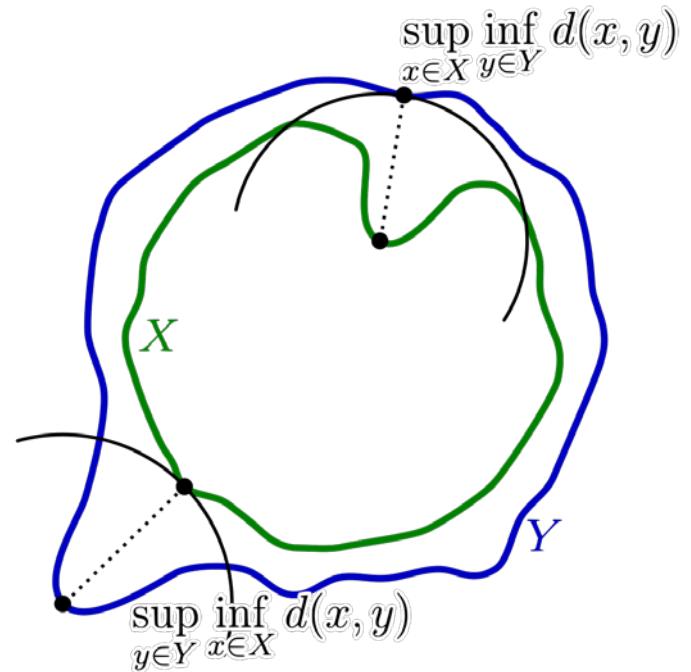
$$(\text{TP} + \text{TN}) / (\text{TP} + \text{FP} + \text{FN} + \text{TN})$$



How good is this?

- Hausdorff Distance

The maximum distance between a point on one curve and its nearest neighbour on the other curve.



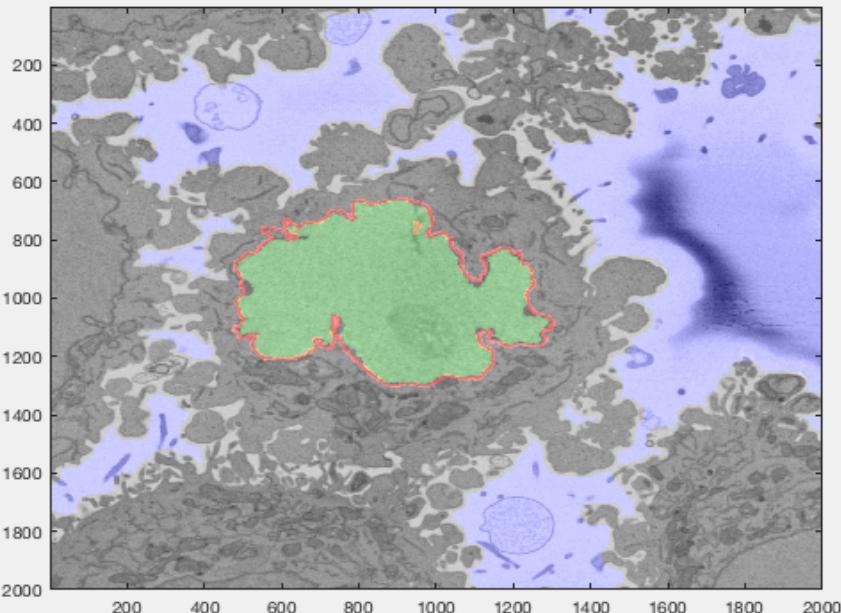
$$d_H(X, Y) = \max\{\sup_{x \in X} \inf_{y \in Y} d(x, y), \sup_{y \in Y} \inf_{x \in X} d(x, y)\}$$

where *sup* represents the supremum (*least upper bound*) and *inf* (*greatest lower bound*) the infimum.

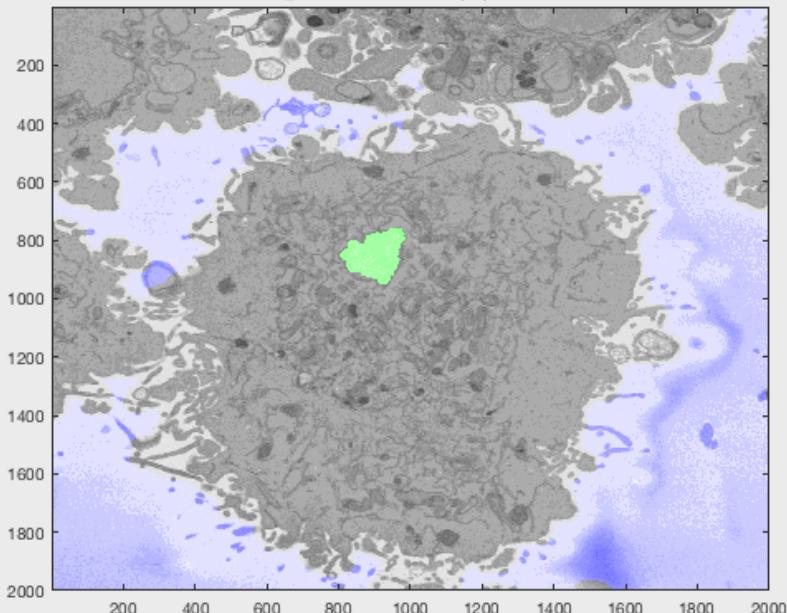
Well, rather good!

- Results per slice, high accuracy, Jaccard index and Hausdorff distance

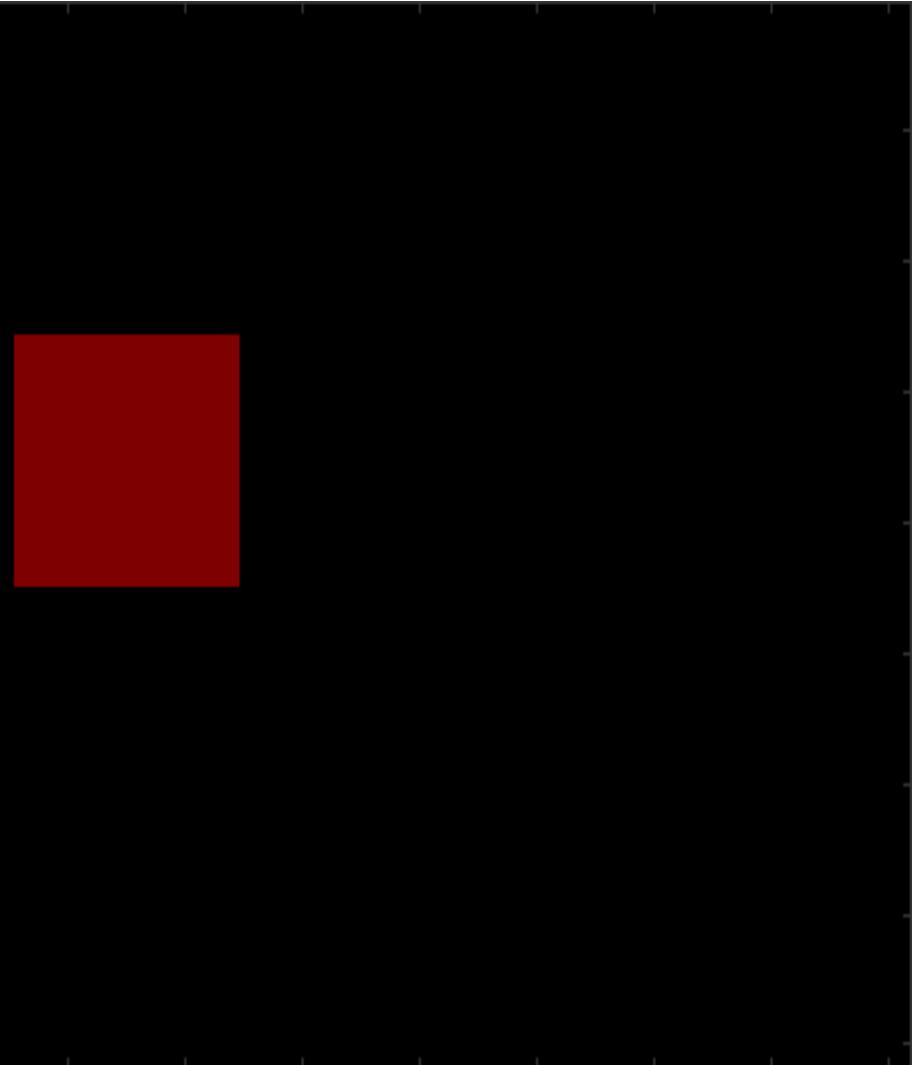
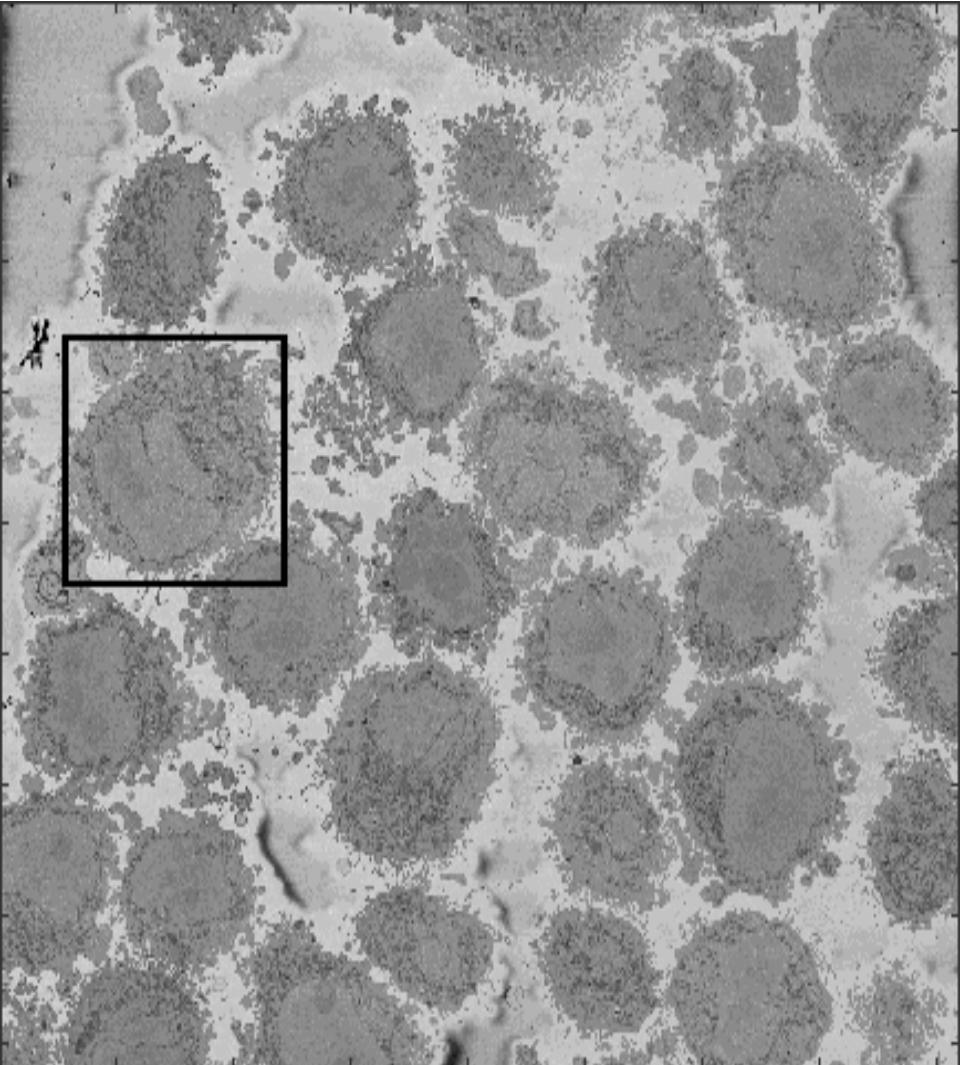
slice =60; jaccard index =0.918



ROI 3516-5712-314.tif (12) -47/300

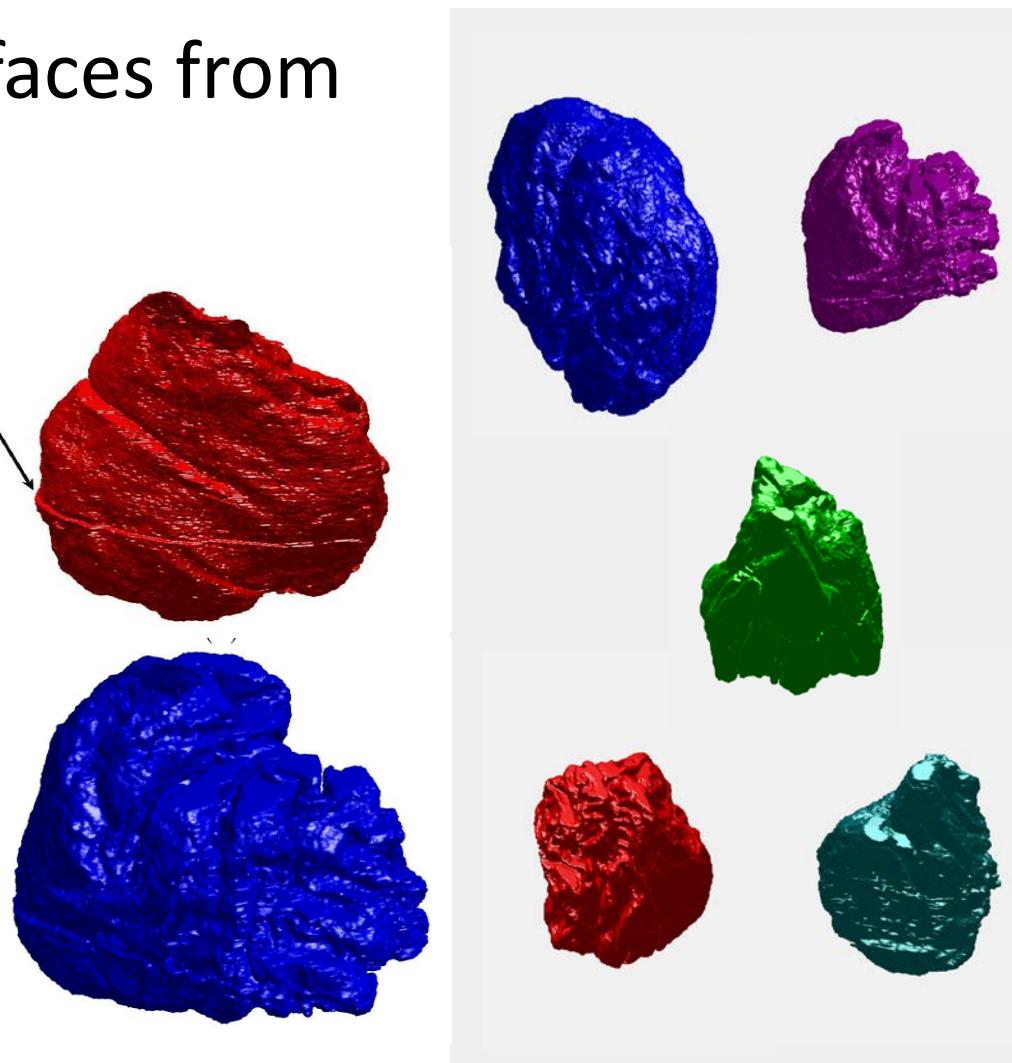
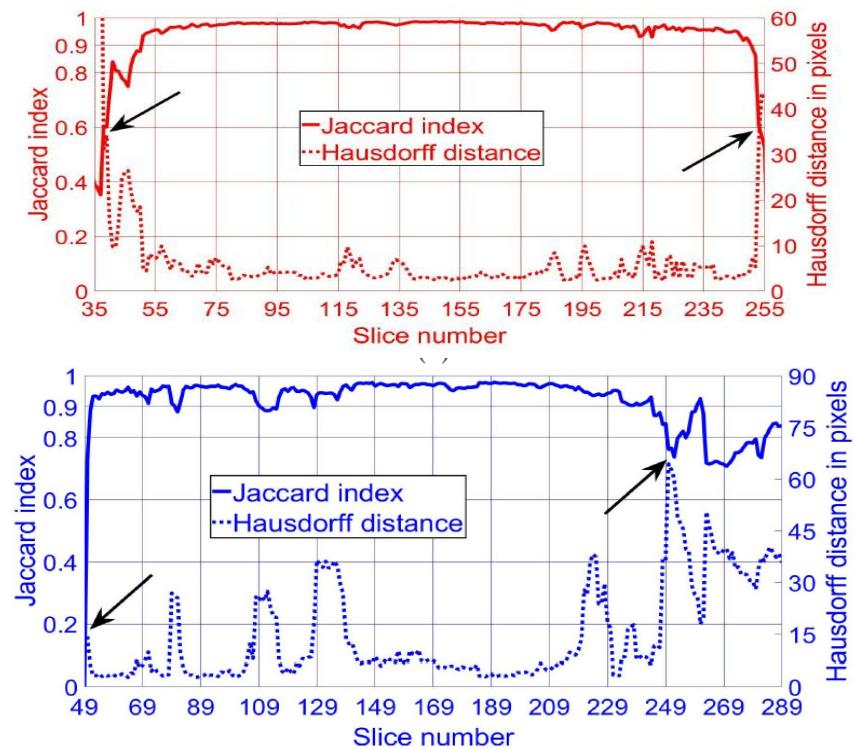


Repeat:
cell per cell and *slice per slice*



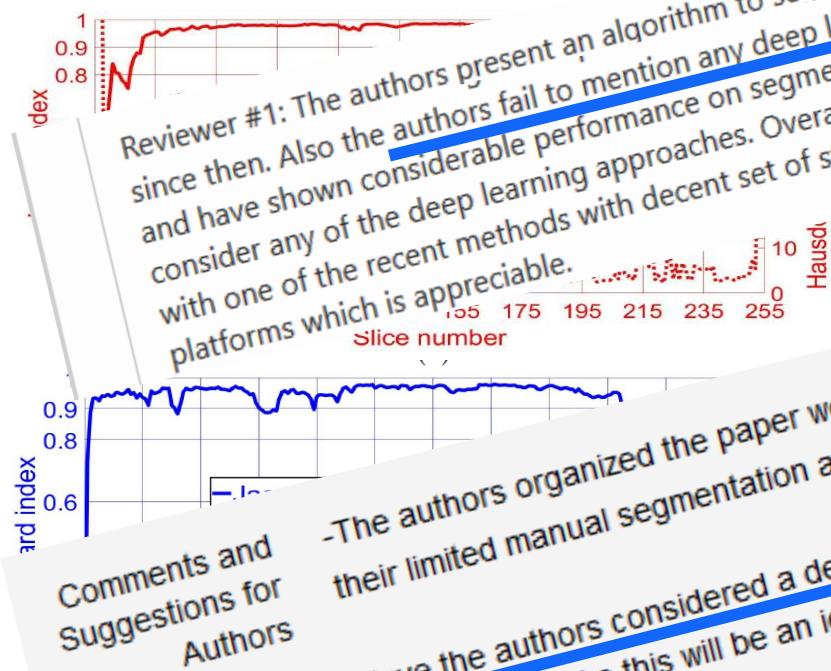
Results

- Three dimensional surfaces from the segmentations



Results

- Three dimensional surfaces from the segmentations



Comments and Suggestions for Authors

Reviewer #1: The authors present an algorithm to segment and model volumetric shape of the nuclear envelope of HeLa since then. Also the authors fail to mention any deep learning approaches which have become popular in the recent past and have shown considerable performance on segmentation for example, U-Net, DCAN, MicroNet ... Did the authors consider any of the deep learning approaches. Overall the paper needs to explain more algorithmic details and comparison with one of the recent methods with decent set of statistical measures. The codes are freely available on open-source platforms which is appreciable.

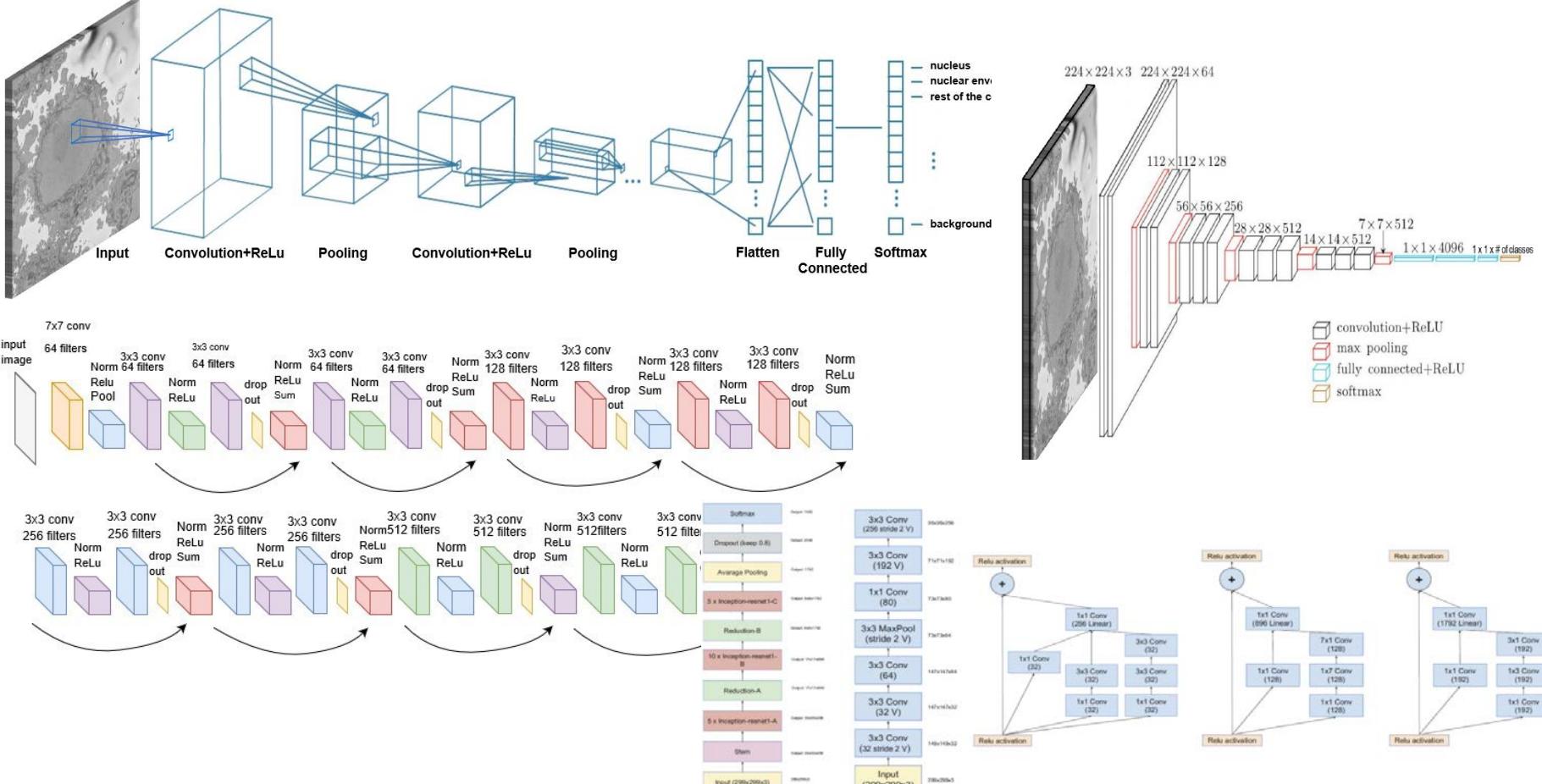
-The authors organized the paper well and they provided results by comparing the work against their limited manual segmentation and also Chan-Vase active contours.

Have the authors considered a deep learning based approach for this problem. Based on the images, I feel like this will be an ideal application for deep learning.

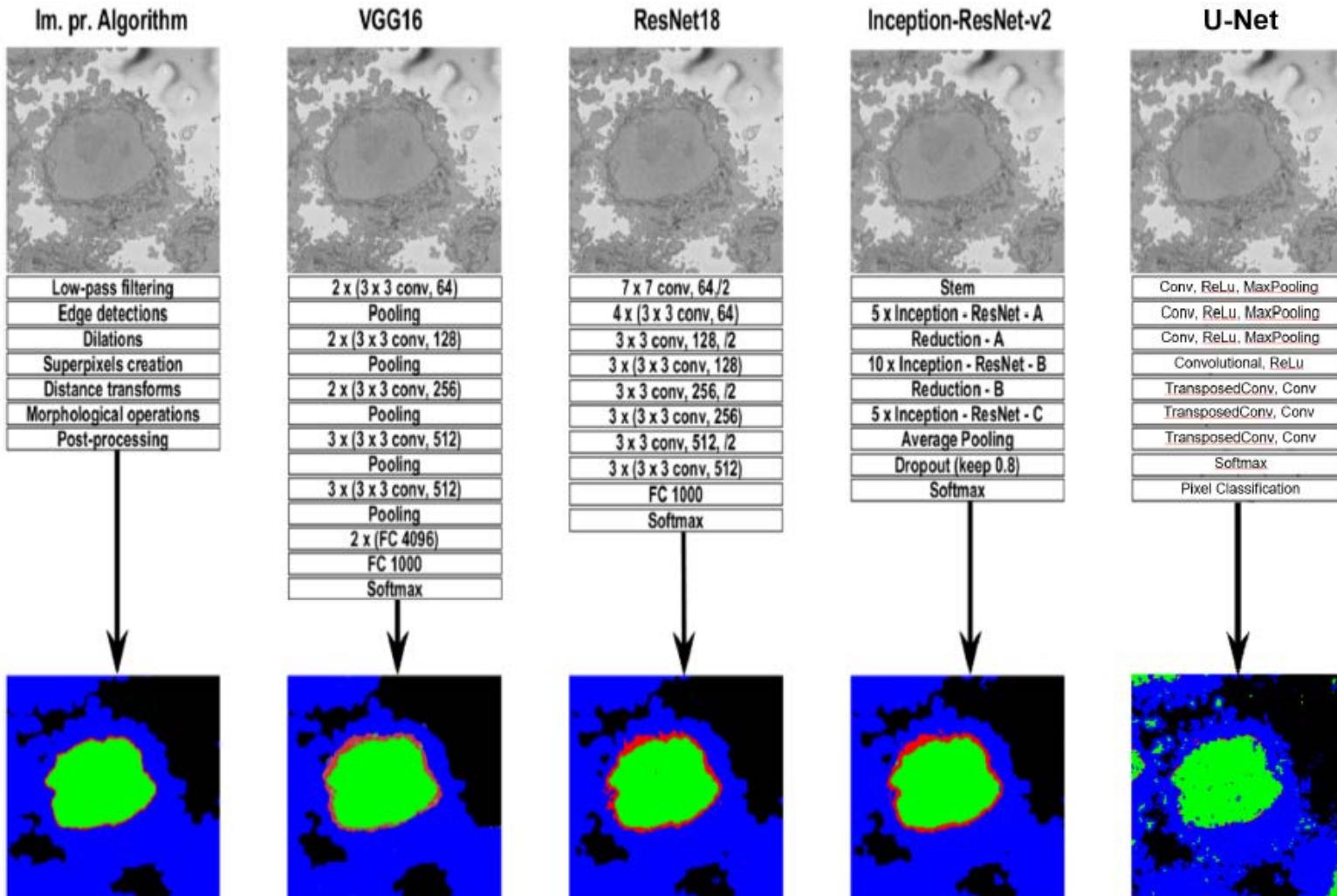
-The performance of the system based on Jaccard Index is somewhat low.

HeLa Segmentation with AI

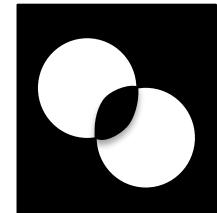
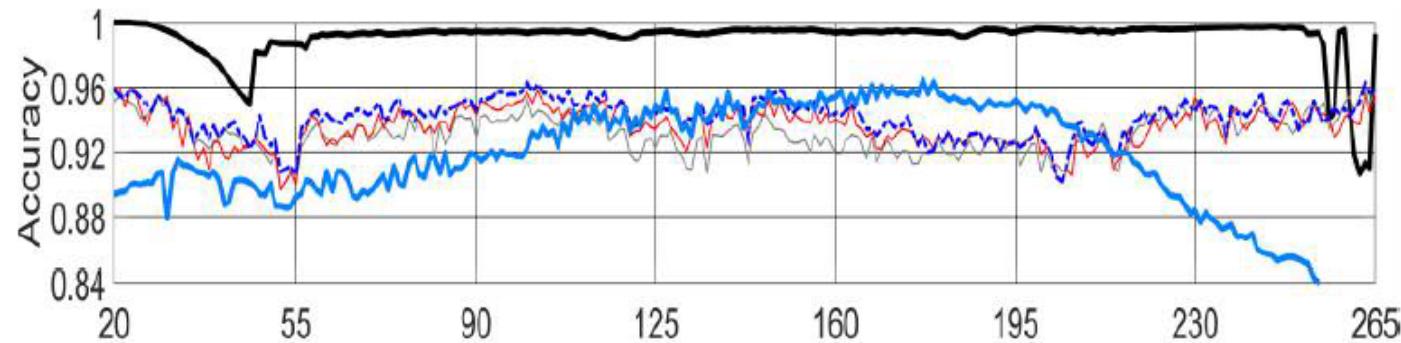
- VGG-16, ResNet, Inception-ResNet, U-Net



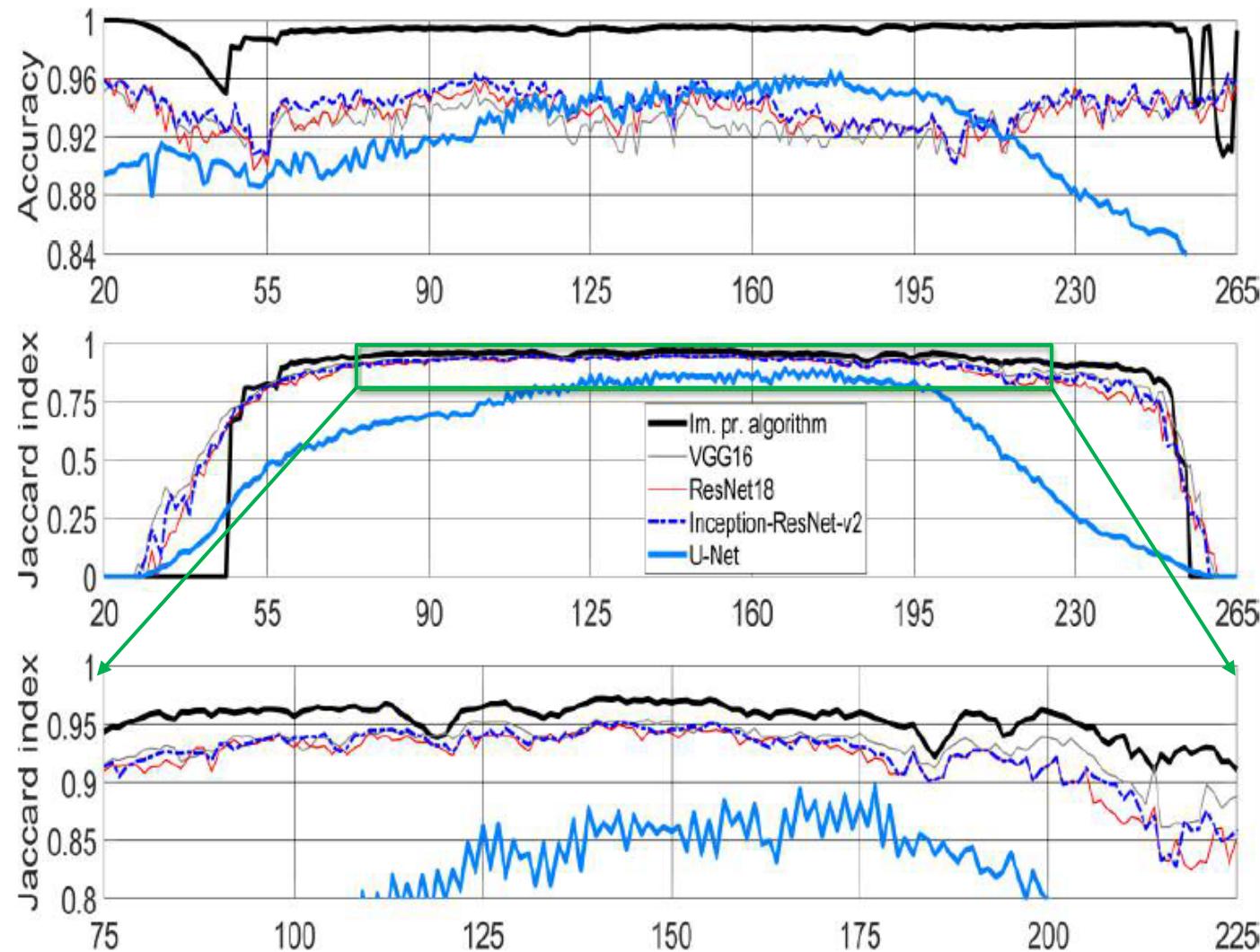
Comparison of Results



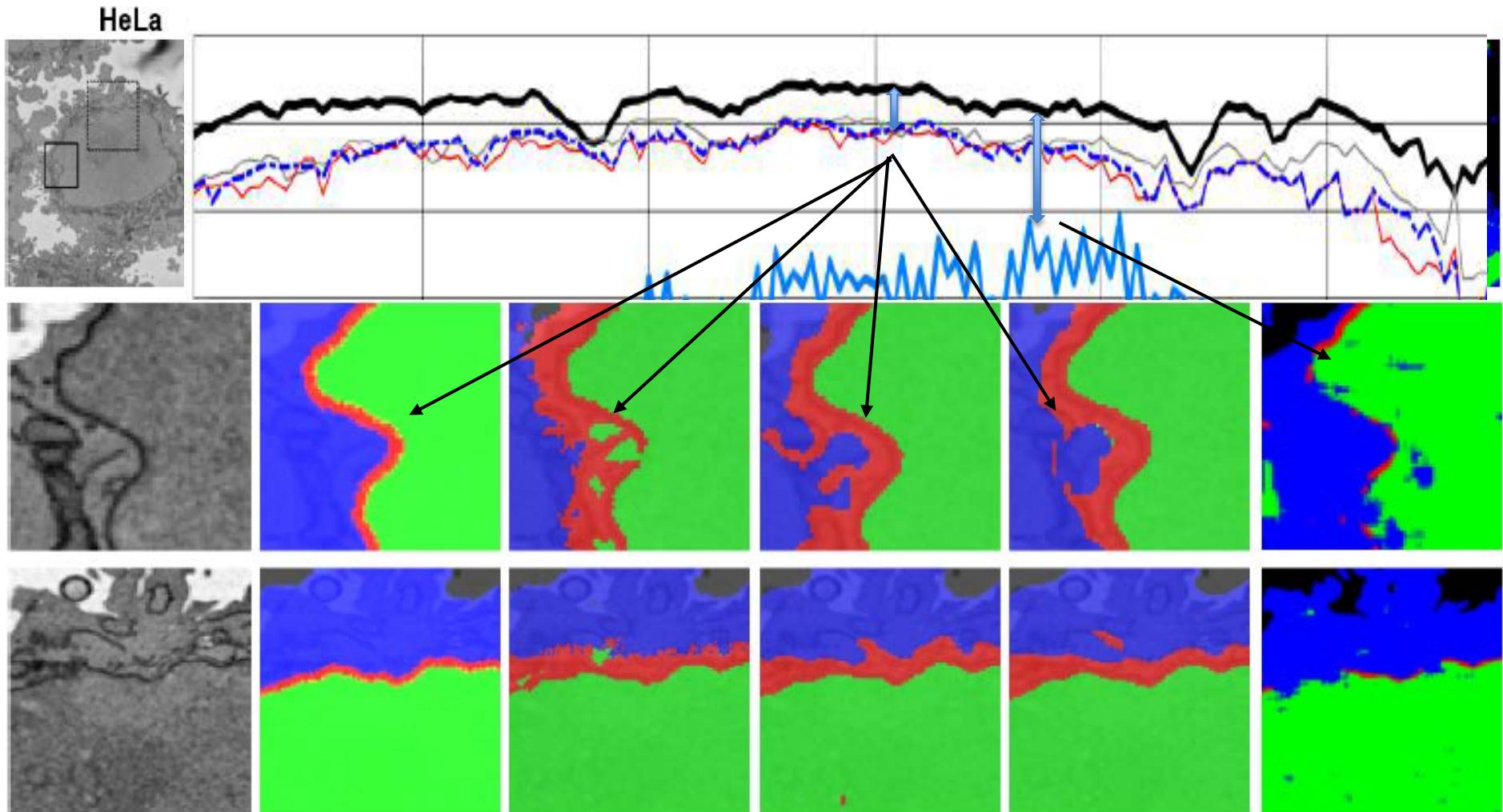
Comparison of Results



Comparison of Results

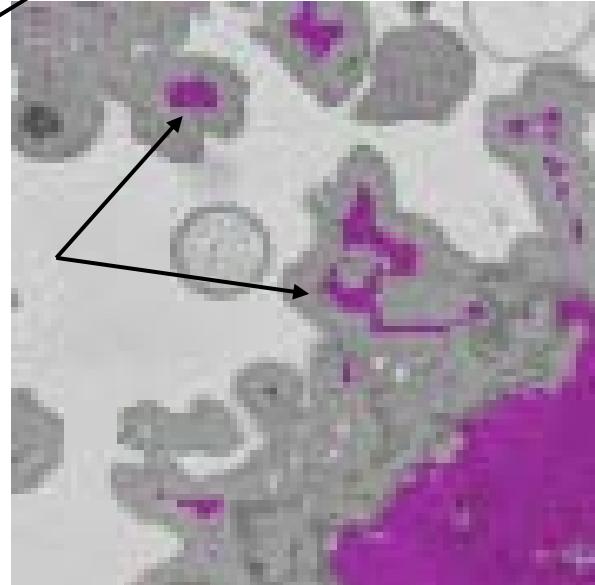
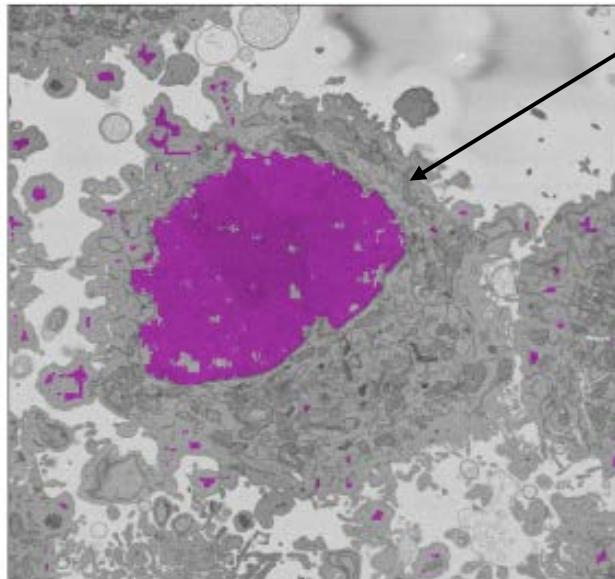
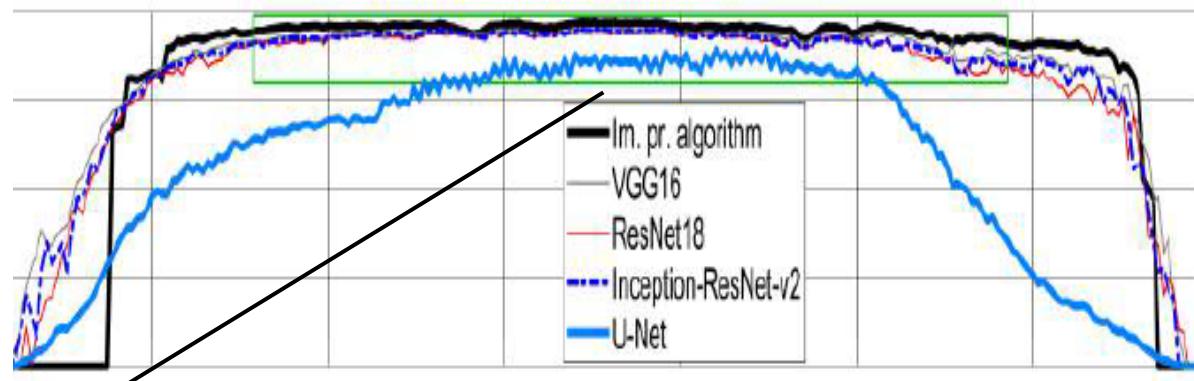


Comparison of Results



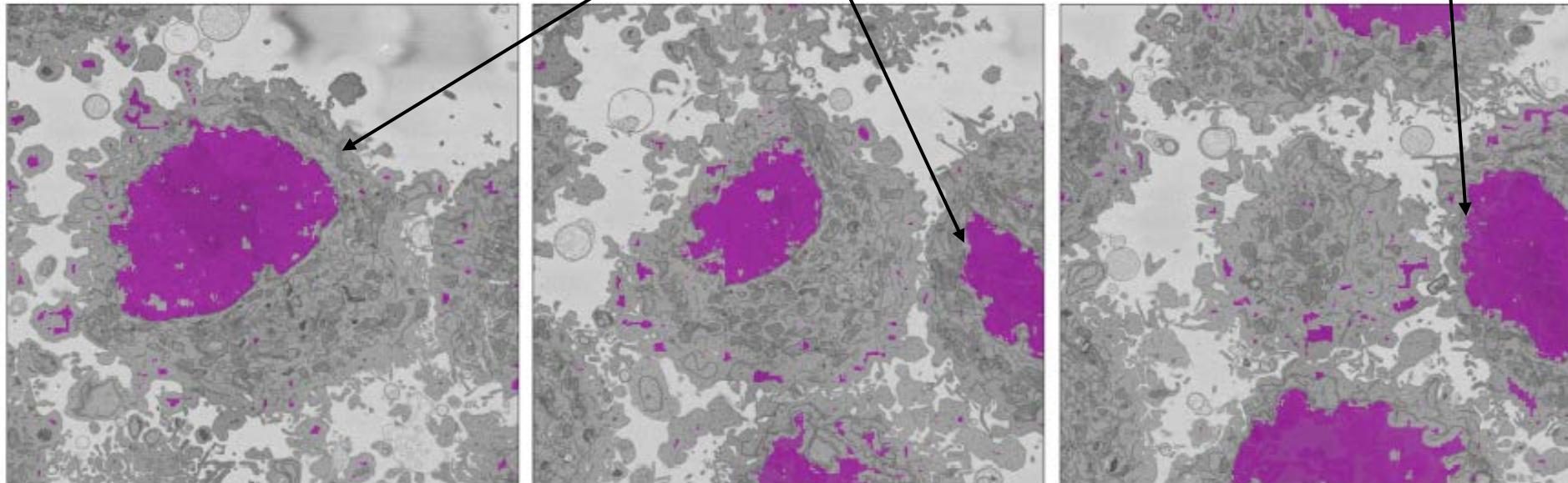
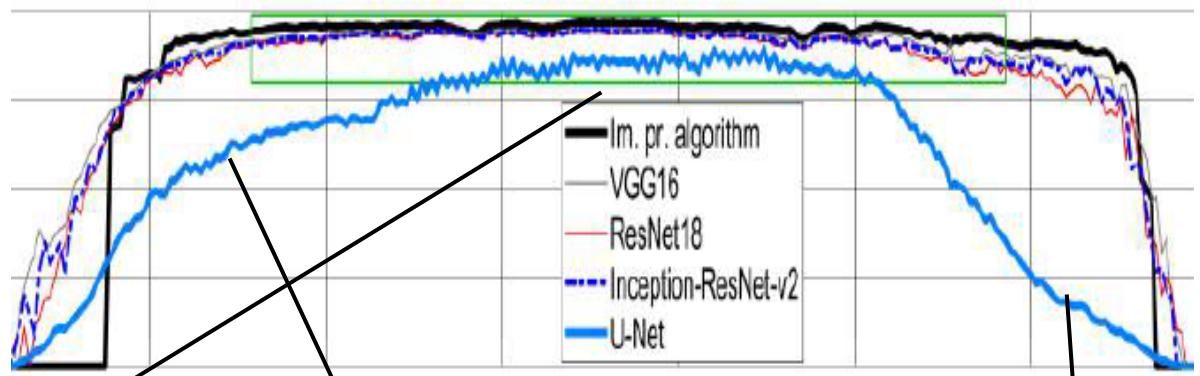
U-Net results

- U-Net presents a very interesting case

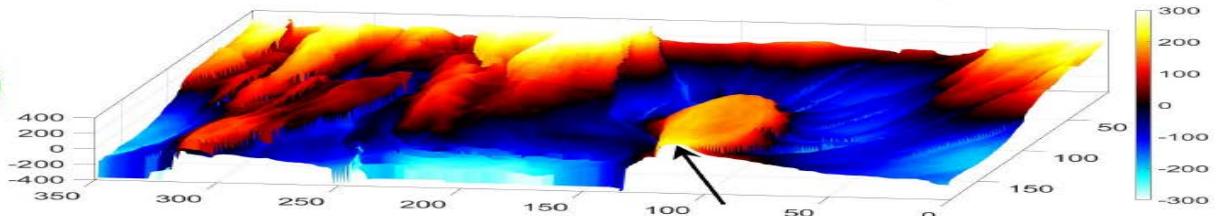
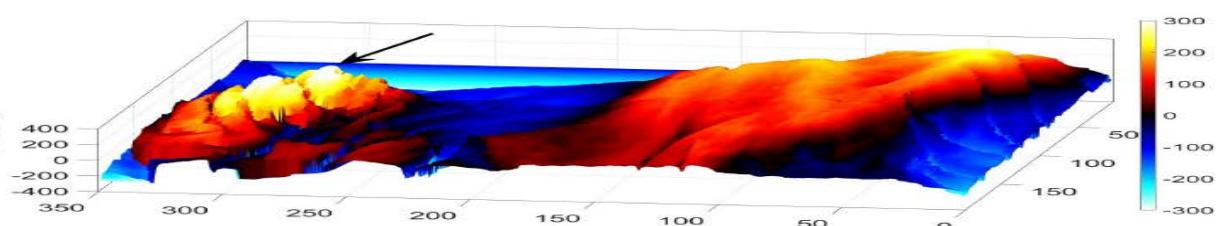
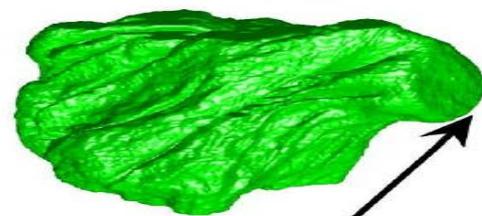
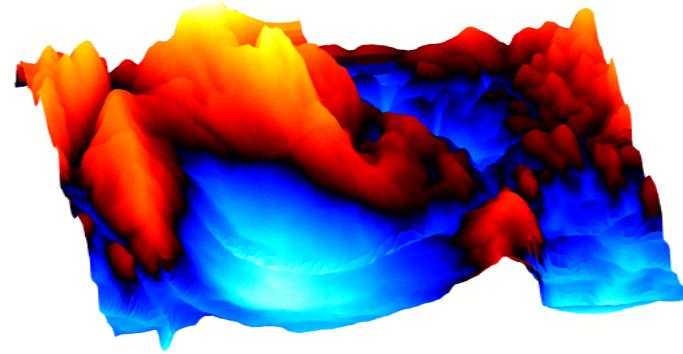
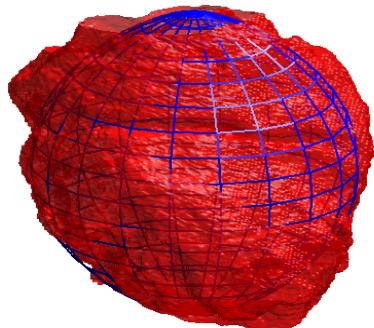
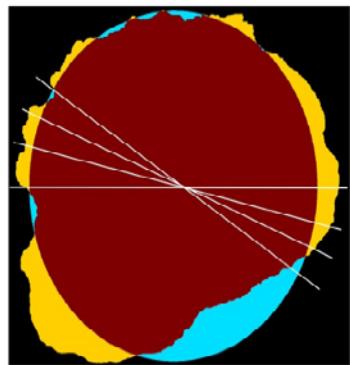


U-Net results

- U-Net presents a very interesting case



Further processing of the surfaces



All code in GitHub

Pull requests Issues Marketplace Explore

reyesaldasoro / HeLa-Cell-Segmentation

Watch 1

Code Issues 0 Pull requests 0 Projects 0 Wiki Security Insights Settings

Branch: master → HeLa-Cell-Segmentation / Code / segmentBackgroundHelaEM.m

CCRA Move Code to separate folder

0 contributors

91 lines (79 sloc) | 4.05 KB

Raw Bla

```
1 function [HeLa_background,Background_intensity,HeLa_intensity] = segmentBackgroundHelaEM(HeLa)
2 %function HeLa_background = segmentBackgroundHelaEM(HeLa)
3 %
4 % Input HeLa      : an image in Matlab format,it can be 2D/3D, double/uint8
5 % Output HeLa_background : a binary image with 1 for background 0 else
6 %
7 %           Background_intensity : average intensity of background (single value)
8 %           HeLa_intensity       : average intensity of cell (single value)
9 %
10 %
11 % This code segments the nuclei of HeLa Cells that have been acquired with Electron
12 % Microscopy at The Crick Institute by Chris Peddie, Anne Weston, Lucy Collinson and
13 % provided to the Data Study Group at the Alan Turing Institute by Martin Jones.
14 %
```

README.md

HeLa-Cell-Segmentation

Segmentation, Measurement and Visualisation of Nuclear Envelope of HeLa Cells observed with Electron Microscope

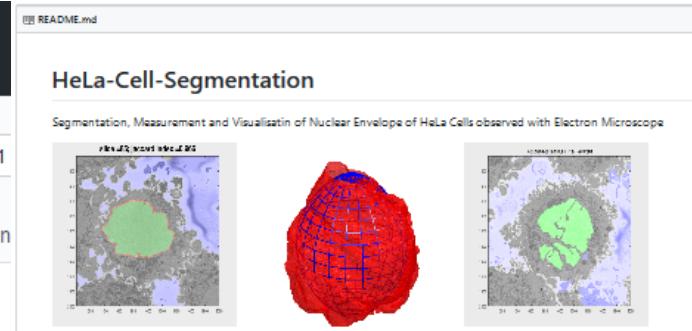


Table of Contents

- HeLa Cells
- Citation
- Brief Description
- Limitations
- Running the code
- Results
- More input parameters
- Region of Interest from 8000 x 8000 images
- Input Options Automatic cropping of multiple Regions of Interest Visual validation of the output
- Automatic cropping of Regions of Interest

Segmentation of Nuclear Envelope of HeLa Cells observed with Electron Microscope

This code contains an image-processing pipeline for the automatic segmentation of the nuclear envelope of (vit HeLa) cells observed through Electron Microscopy. This pipeline has been tested with a 3D stack of 300 images. The intermediate results of neighbouring slices are further combined to improve the final results. Comparison with a hand-segmented ground truth reported Jaccard similarity values between 94-98% on the central slices with a decrease towards the edges of the cell where the structure was considerably more complex. The processing is unsupervised and each 2D Slice is processed in about 5-10 seconds running on a MacBook Pro. No systematic attempt to make the code faster was made.

Citation

This work has been published in the Journal of Imaging, if you find the work or the software interesting or useful, please cite as:

Cefa Karabag, Martin L. Jones, Christopher J. Peddie, Anne E. Weston, Lucy M. Collinson, and Constantino Carlos Reyes-Aldasoro, Segmentation and Modelling the nuclear envelope of HeLa cells, J Imaging (2019), 5(9), 75 <https://doi.org/10.3390/jimaging5090075>

A previous version was accepted as an oral presentation in the conference Medical Image Understanding and Analysis (MIUA) 2018 (<https://miua2018.soton.ac.uk>)

Automated Segmentation of HeLa Nuclear Envelope from Electron Microscopy Images, in Proceedings of Medical Image Understanding and Analysis, 9-11 July 2018, Southampton, UK.

Brief description

Data available in EMPIAR

[EMPIAR home](#)[Deposition](#)[REST API](#)[FAQ](#)[About EMPIAR](#)[Draft policies](#)[Feedback](#)[Share](#)

EMPIAR-10094

Serial Block Face SEM of HeLa cell pellet with 10 nm pixels and 50 nm slices (benchmark dataset)

Publication:

Serial Block Face SEM of HeLa cell pellet with 10 nm pixels and 50 nm slices (benchmark dataset)

Collinson LM

Deposited:

2017-05-02

Released:

2019-05-21

Last modified:

2019-10-25

Dataset size:

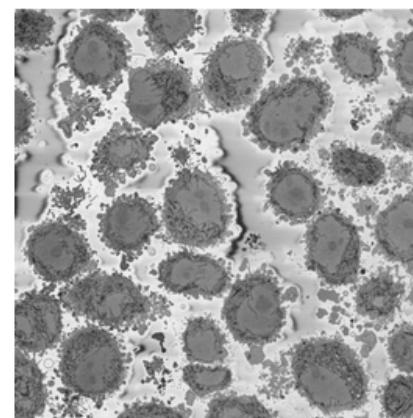
129.8 GB

Dataset DOI:

[10.6019/EMPIAR-10094](https://doi.org/10.6019/EMPIAR-10094)

Contains:

micrographs



Quick links

 [EMDB](#) [PDBe](#) [Biolimage Archive](#) [EMPIAR Quick tour](#) [Download experimental metadata \(xml\)](#)

EMPIAR citations

Differential requirements for cyclase-associated protein (CAP) in actin-dependent processes of *Toxoplasma gondii*.

Hunt A, Russell MRG, Wagener J, Ke

Papers open access



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Segmentation and Modelling of the Nuclear Envelope of HeLa Cells Imaged with Serial Block Face Scanning Electron Microscopy

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Abstract

This paper describes an unsupervised algorithm, which segments the nuclear envelope of HeLa cells imaged by Serial Block Face Scanning Electron Microscopy. The algorithm exploits the variations of pixel intensity in different cellular regions by calculating edges, which are then used to generate superpixels. The superpixels are morphologically processed and those that correspond to the nuclear region are selected through the analysis of size, position, and correspondence with regions detected in neighbouring slices. The nuclear envelope is segmented from the nuclear region. The three-dimensional segmented nuclear envelope is then modelled against a spheroid to create a two-dimensional (2D) surface. The 2D surface summarises the complex 3D shape of the nuclear envelope and allows the extraction of metrics that may be relevant to characterise the nature of cells. The algorithm was developed and validated on a single cell and tested in six separate cells, each with 300 slices of 2000 × 2000 pixels. Ground truth was available for two of these cells, i.e., 600 hand-segmented slices. The accuracy of the algorithm was evaluated with two similarity metrics: Jaccard Similarity Index and Mean Hausdorff distance. Jaccard values of the first/second segmentation were 93%/90% for the whole cell, and 98%/94% between slices 75 and 225, as the central slices of the nucleus are more regular than those on the extremes. Mean Hausdorff distances were 9/17 pixels for the whole cells and 4/13 pixels for central slices. One slice was processed in approximately 8 s and a whole cell in 40 min. The algorithm outperformed active contours in both accuracy and time.

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Semantic segmentation of HeLa cells: An objective comparison between one traditional algorithm and four deep-learning architectures

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Article	Authors	Metrics	Comments	Media Coverage

Abstract

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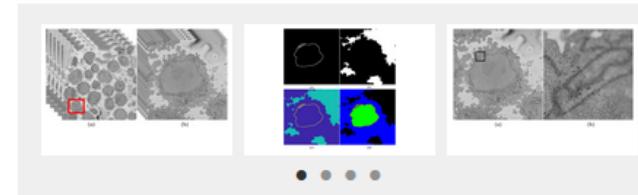
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Abstract

The quantitative study of cell morphology is of great importance as the structure and condition of cells and their structures can be related to conditions of health or disease. The first step towards that, is the accurate segmentation of cell structures. In this work, we compare five approaches, one traditional and four deep-learning, for the semantic segmentation of the nuclear envelope of cervical cancer cells commonly known as HeLa cells. Images of a HeLa cancer cell were semantically segmented with one traditional image-processing algorithm and four three deep learning architectures: VGG16, ResNet18, Inception-ResNet-v2, and U-Net. Three hundred slices, each 2000 × 2000 pixels, of a HeLa Cell were acquired with Serial Block Face Scanning Electron Microscopy. The first three deep learning architectures were pre-trained with ImageNet and then fine-tuned with transfer learning. The U-Net architecture was trained from scratch with 36,000 training images and labels of size 128 × 128. The image-processing algorithm followed a pipeline of several traditional steps like edge detection, dilation and morphological operators. The algorithms were compared by measuring pixel-based segmentation accuracy and Jaccard index against a labelled ground truth. The results indicated a superior performance of the traditional algorithm (Accuracy = 99%, Jaccard = 93%) over the deep learning architectures: VGG16 (93%, 90%), ResNet18 (94%, 88%), Inception-ResNet-v2 (94%, 89%), and U-Net (92%, 56%).

Figures



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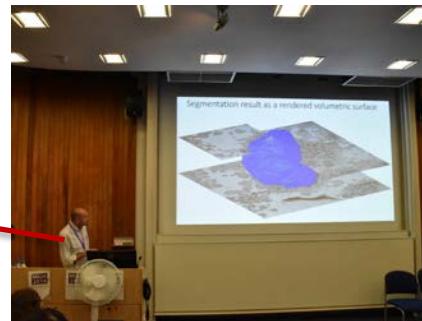
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Cells: Henrietta Lacks

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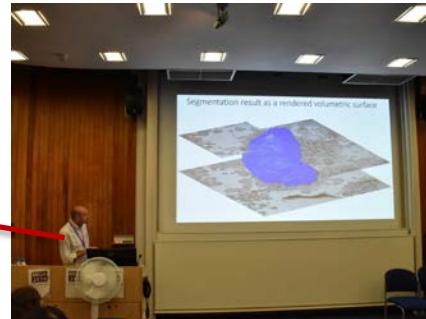
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Questions?

