

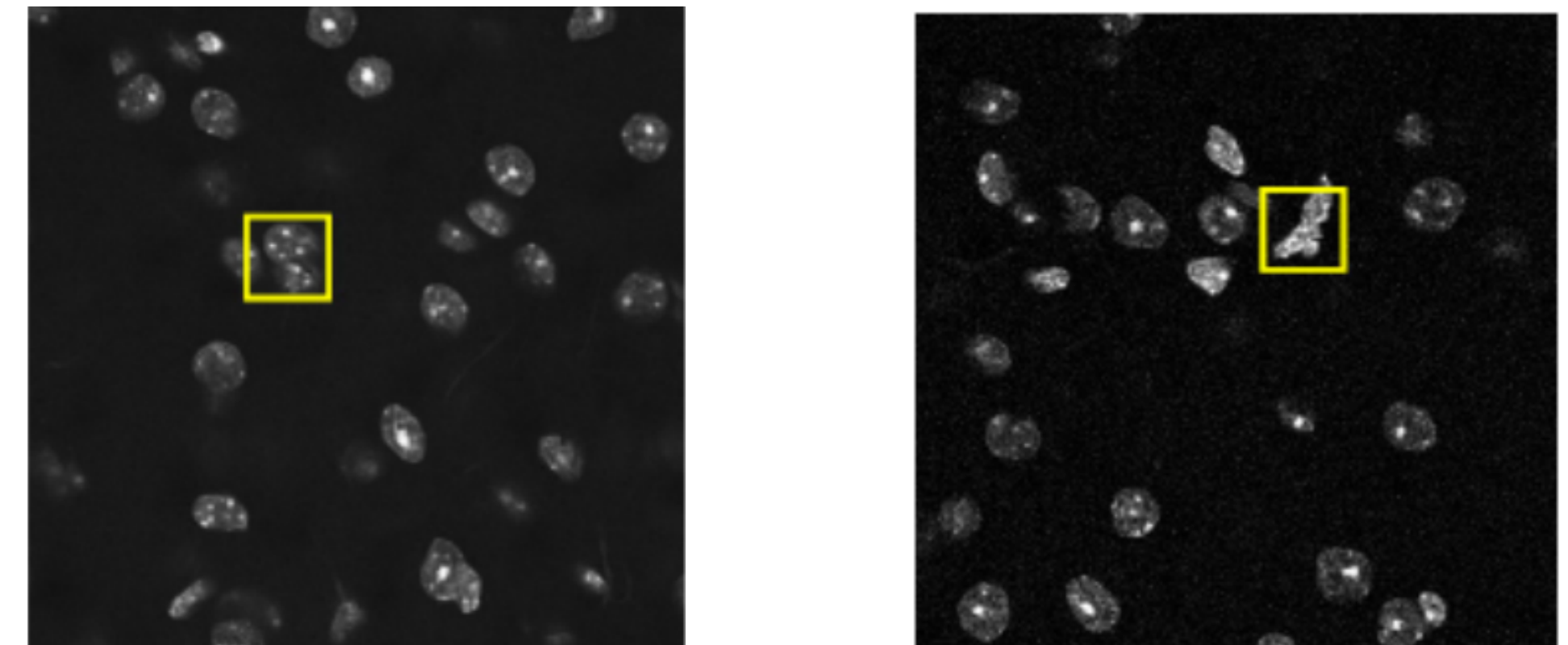
# Exploring the Emergent Abilities of SwinIA for Object Segmentation

Dzvenymyra Yarish  
Yuliia Siur  
Yaroslav Prytula

Institute of Computer Science,  
University of Tartu

## Introduction

In this work, we explore the emergent abilities of the transformer-based model SwinIA [1]. We focus on the semantic segmentation task. We show that the model primarily developed for the denoising task exhibits a promising performance on the image segmentation use case on several cell datasets. We compare the original model with other models, such as Noise2Same on 3 popular cell microscopy datasets.



Example images from FMD Two-photon mice denoising dataset

## Methodology

To perform segmentation, we extract multi-dimensional feature maps before the final projection layer.

Then, we use K-Means clustering algorithm for pixel categorization into two groups: object and background. Clustering is performed on extracted feature maps of shape  $D \times H \times W$  with  $k=2$  for binary segmentation. K-Means is insensitive to class labels, so clusters' correspondence to object or background is determined based on scoring in the evaluation phase.

## Experiments

### 1. Out-of-domain evaluation

We assess adaptability of Noise2Same and SwinIA models (originally trained for denoising on Two-Photon mice dataset [3]) to unseen data.

### 2. Domain specific evaluation

Models undergo self-supervised training on SevenCellLines dataset. Segmentation capabilities are evaluated on the same dataset, offering insights into performance within a familiar domain.

## Results

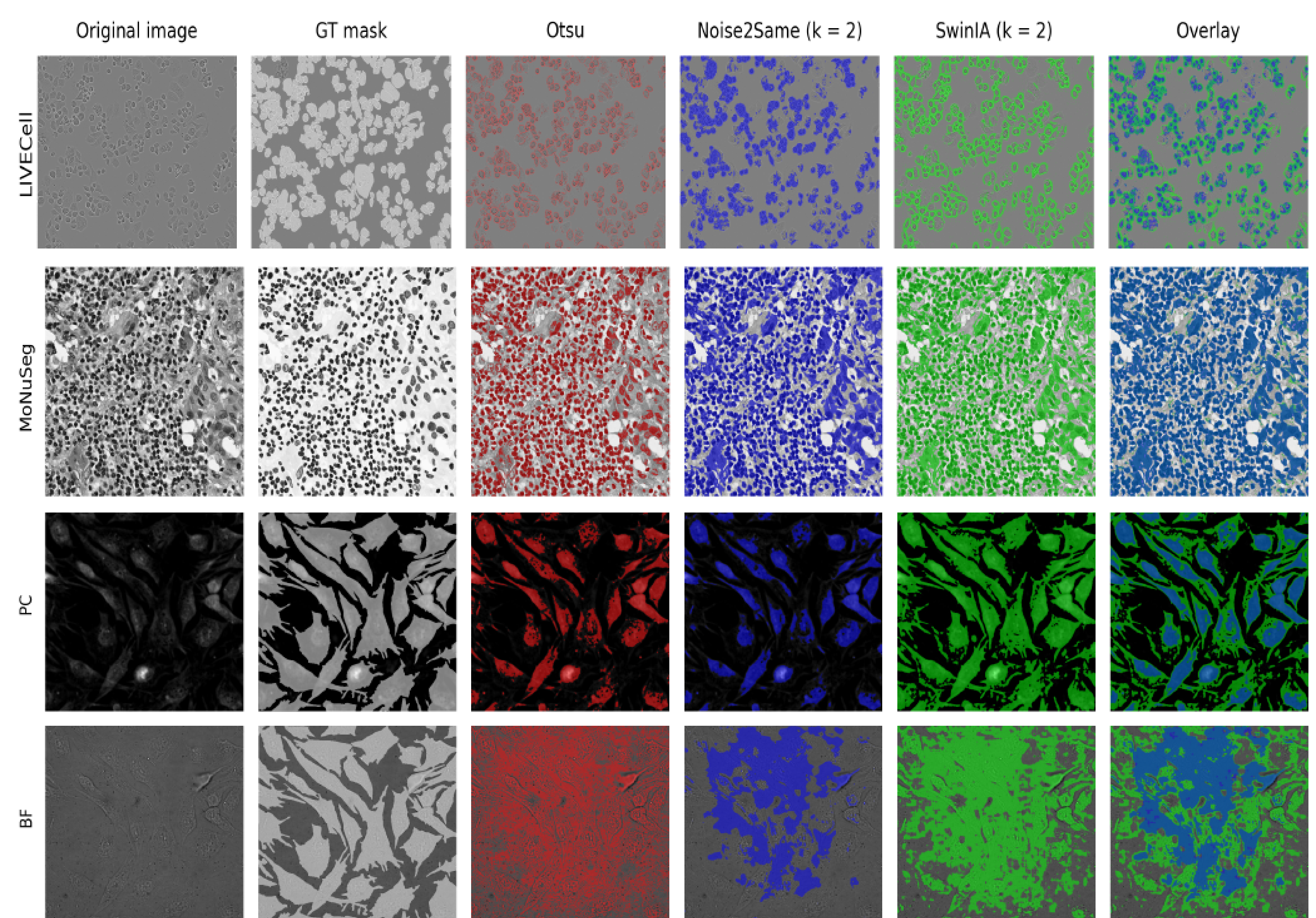
### 1. Out-of-domain

Model	Precision	Recall	F1	IoU
<i>Otsu</i>	<b>0.887</b>	0.834	0.487	0.344
<i>Noise2Same</i>	<u>0.39</u>	<u>0.914</u>	<u>0.497</u>	<u>0.361</u>
<i>SwinIA</i>	0.386	<b>0.987</b>	<b>0.512</b>	<b>0.382</b>
Method	Precision	Recall	F1	IoU
<i>Otsu</i>	0.979	<b>0.578</b>	<b>0.713</b>	<b>0.568</b>
<i>Noise2Same</i>	<b>0.992</b>	0.443	0.601	0.441
<i>SwinIA</i>	<u>0.988</u>	<u>0.467</u>	<u>0.629</u>	<u>0.464</u>

Dataset	Model	Precision	Recall	F1	IoU
<i>PC</i>	<i>Otsu</i>	<u>0.989</u>	0.339	0.503	0.338
	<i>Noise2Same</i>	<b>0.993</b>	<u>0.395</u>	<u>0.563</u>	<u>0.394</u>
	<i>SwinIA</i>	0.931	<b>0.806</b>	<b>0.863</b>	<b>0.761</b>
<i>BF</i>	<i>Otsu</i>	0.511	0.595	0.544	0.375
	<i>Noise2Same</i>	<u>0.542</u>	<u>0.628</u>	<u>0.566</u>	<u>0.405</u>
	<i>SwinIA</i>	<b>0.553</b>	<b>0.648</b>	<b>0.592</b>	<b>0.424</b>

### 2. Domain specific

Model	Precision	Recall	F1	IoU
<i>Noise2Same</i>	0.99	0.32	0.48	0.319
<i>SwinIA</i>	0.976	0.588	0.733	0.58



Binary masks produced from models' final features on different cell modalities from LIVECell, MoNuSeg, and SevenCellLines

## Conclusion

In this work, we evaluated the zero-shot segmentation abilities of SwinIA model. We showed that it exhibits superior performance across 3 datasets in comparison to another popular denoising model, Noise2Same. This confirms that SwinIA learns meaningful features, equally good in global and local contexts. Model's capacity as a universal self-supervised feature extractor and a possible replacement for the existing backbones will be studied in future works.

## References

- [1] Mikhail Papkov and Pavel Chizhov. Swinia: Self-supervised blind-spot image denoising with zero convolutions. ArXiv, abs/2305.05651, 2023.
- [2] Yaochen Xie, Zhengyang Wang, and Shuiwang Ji. Noise2same: Optimizing a self-supervised bound for image denoising. ArXiv, abs/2010.11971, 2020.
- [3] Yide Zhang, Yinhao Zhu, Evan L. Nichols, Qingfei Wang, Siyuan Zhang, Cody J. Smith, and Scott S. Howard. A poisson-gaussian denoising dataset with real fluorescence microscopy images. CVPR, 2018.