

IAUNet: Instance-Aware U-Net

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UNIVERSITY OF TARTU

Institute of Computer Science



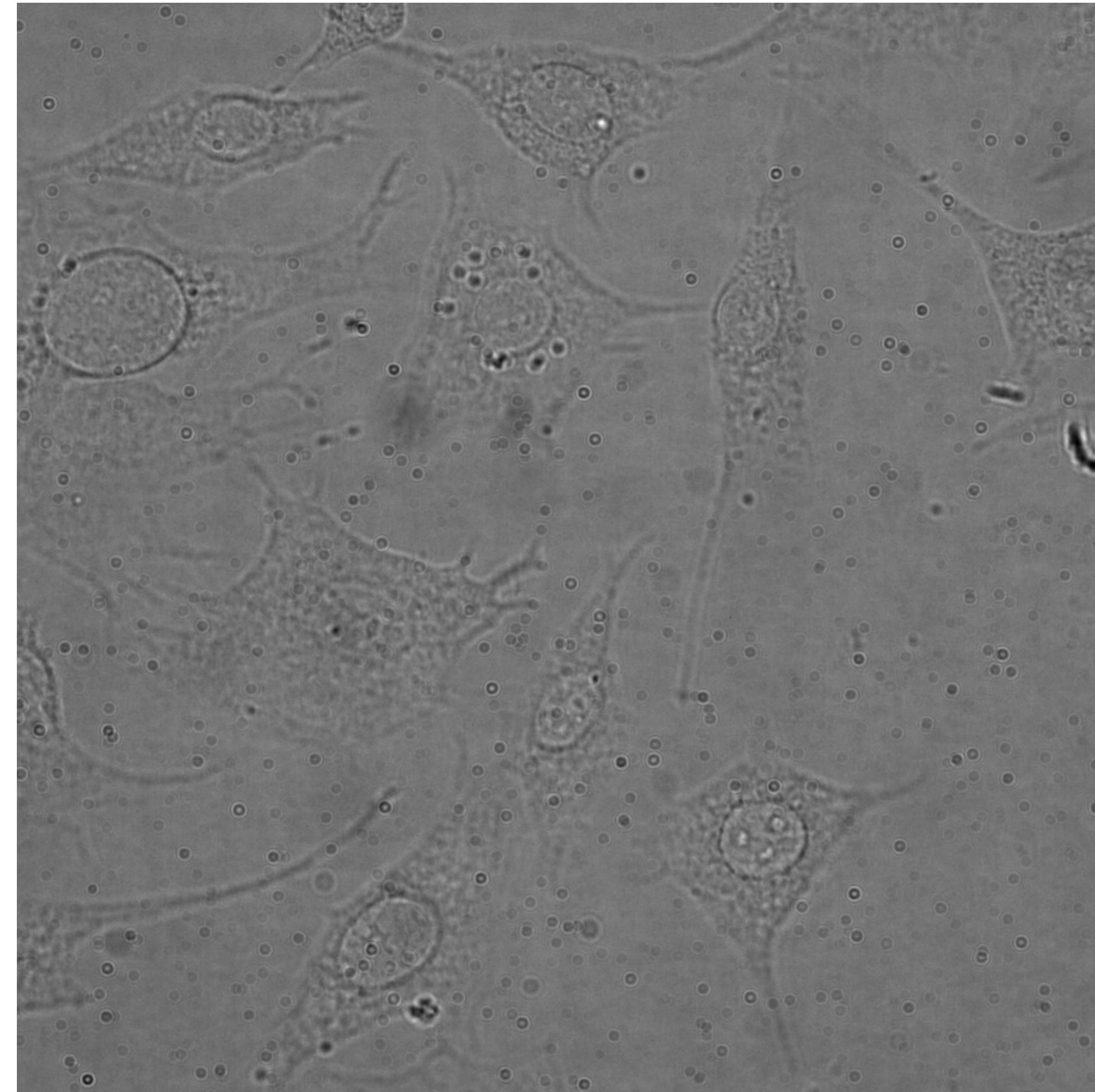
revvity



BCV Lab



Brightfield



Microscopy Image

Brightfield

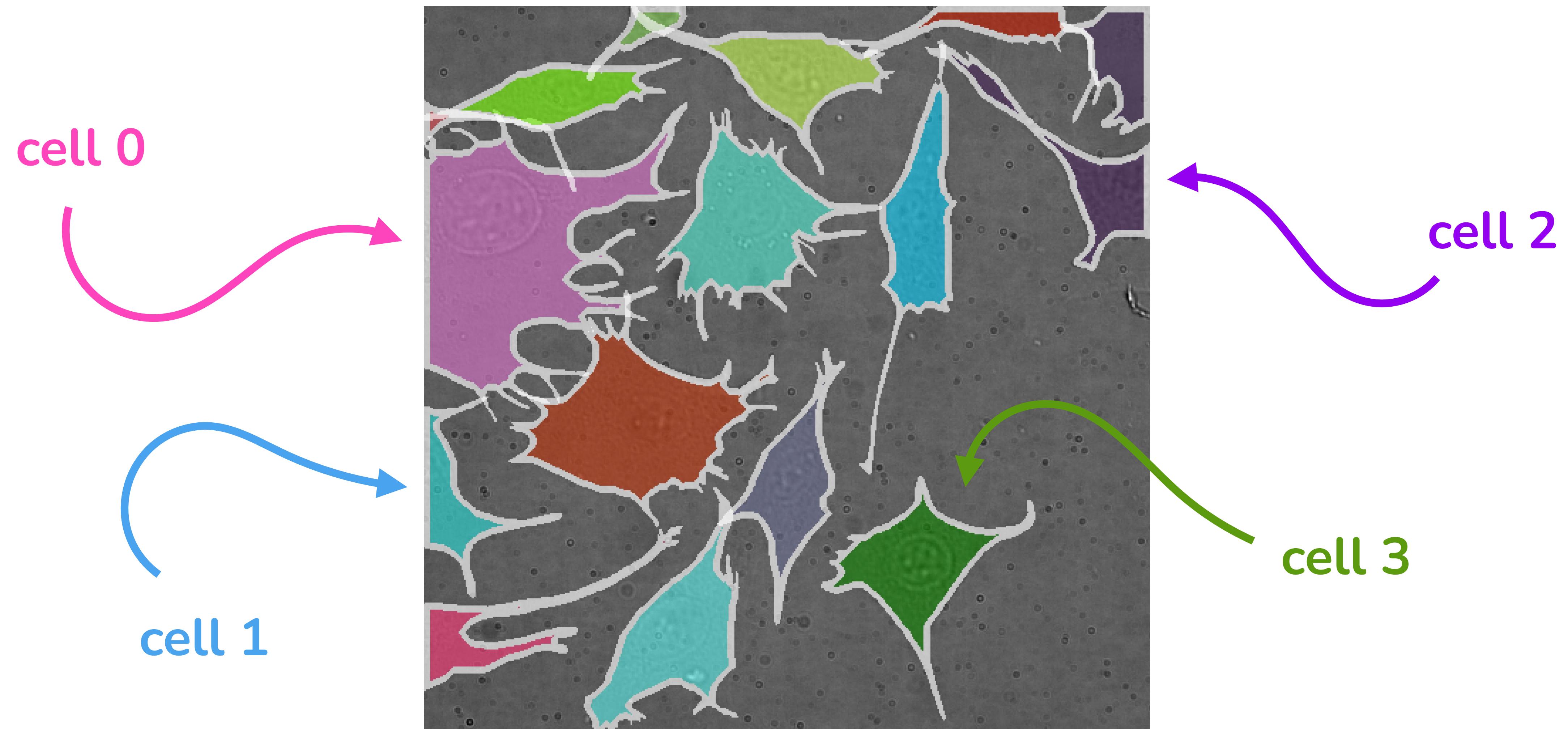


Pixels of class
“cell”

Pixels of class
“cell”

Semantic Segmentation

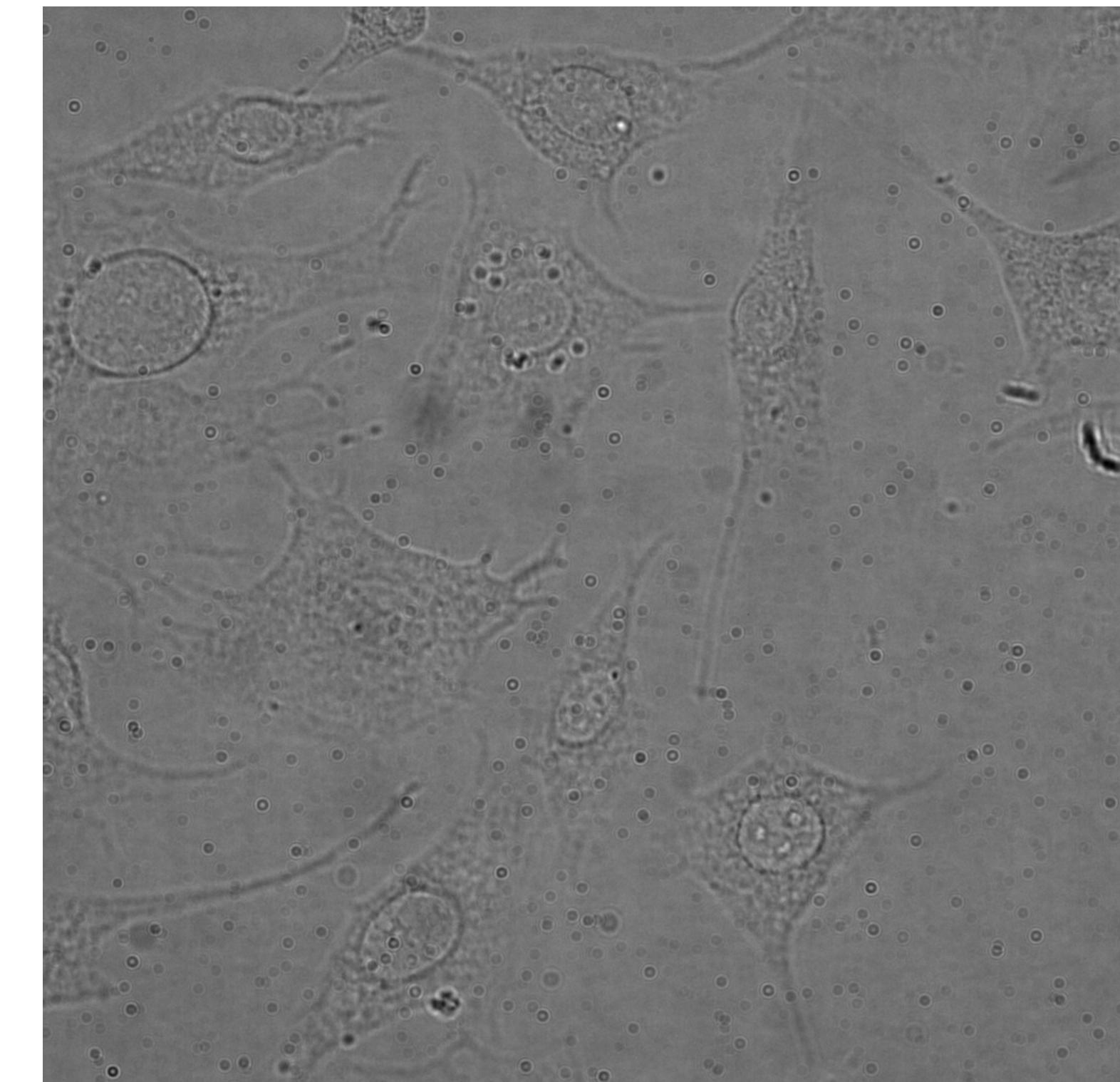
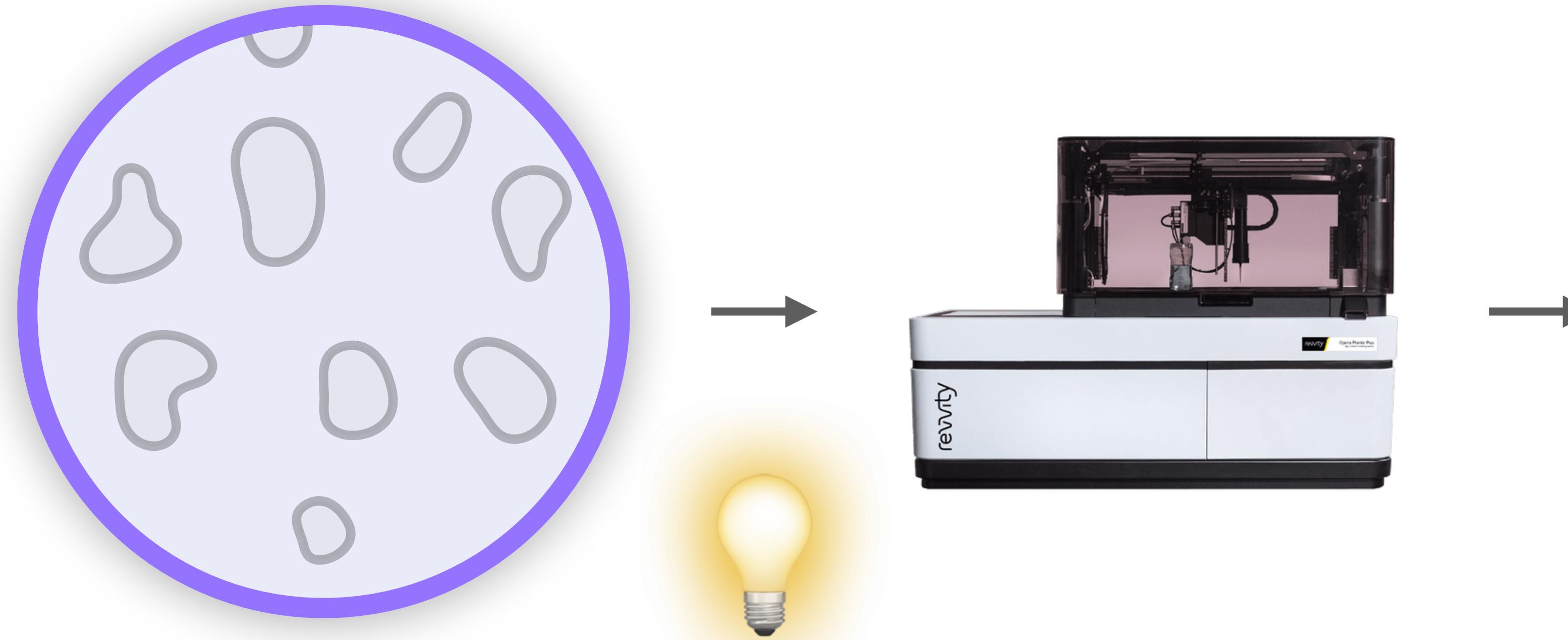
Brightfield



Instance Segmentation

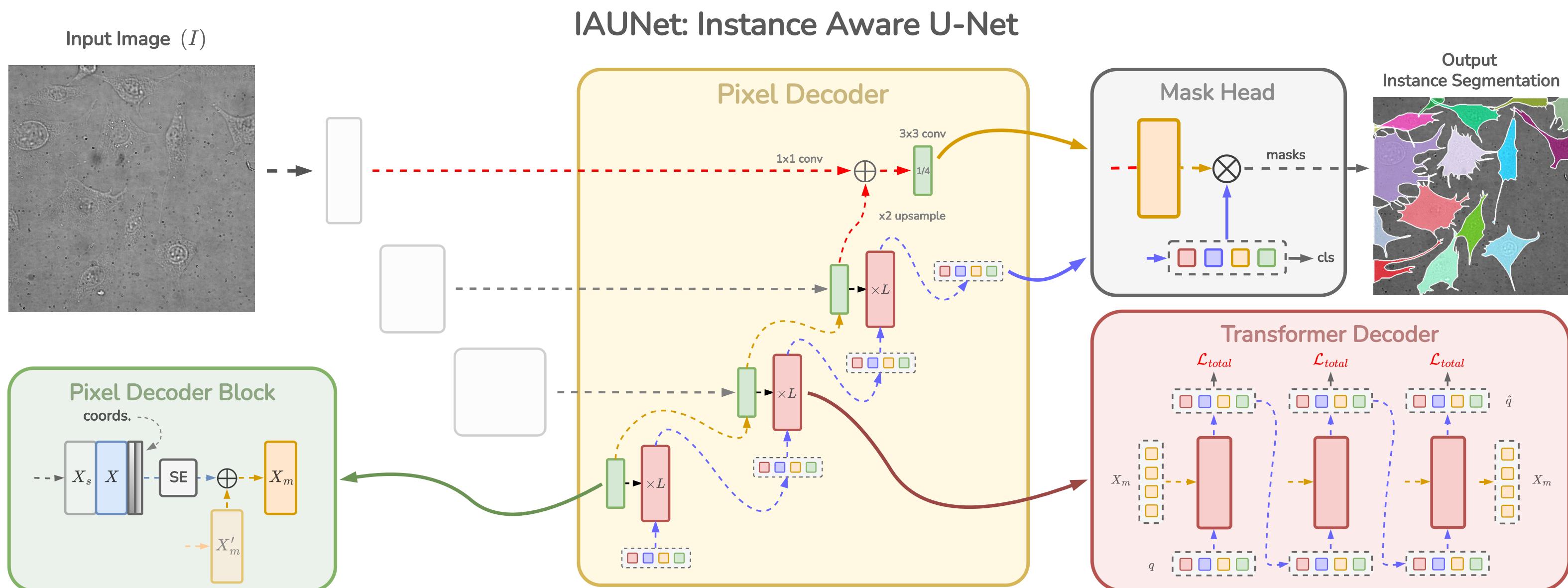
Motivation

Brightfield captures images by transmitting standard white light through the sample



Contributions

IAUNet

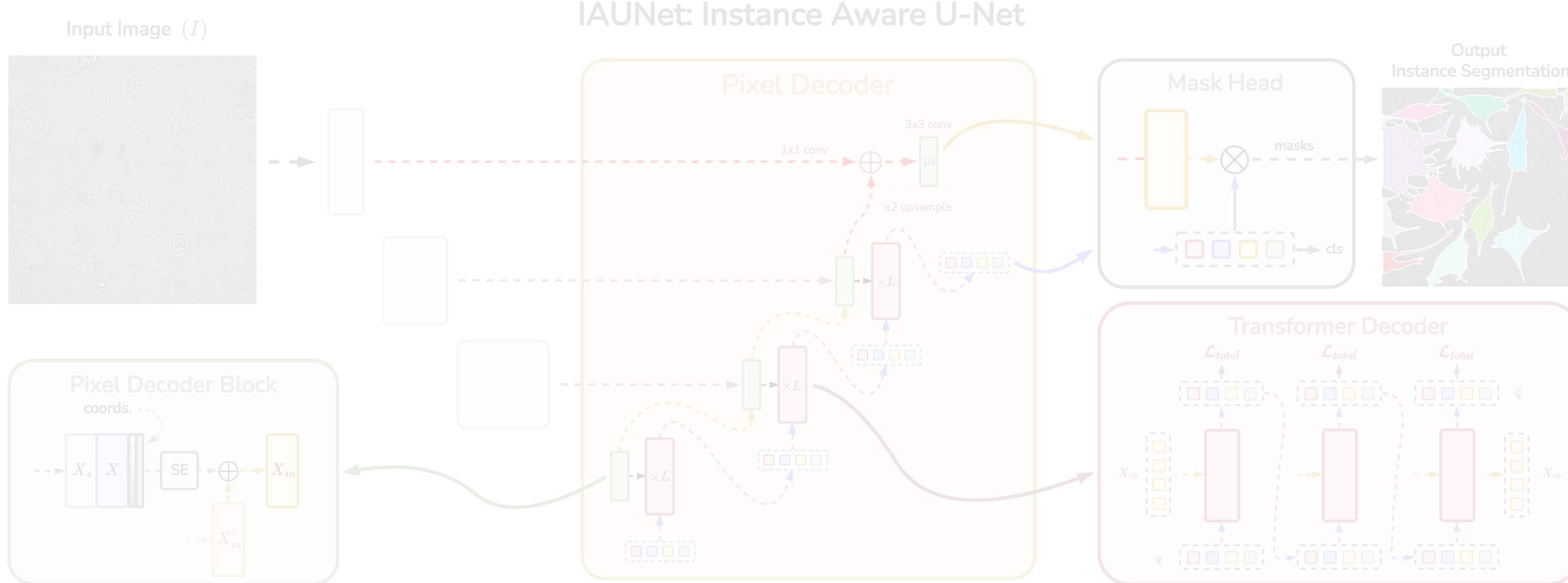


Revvity-25

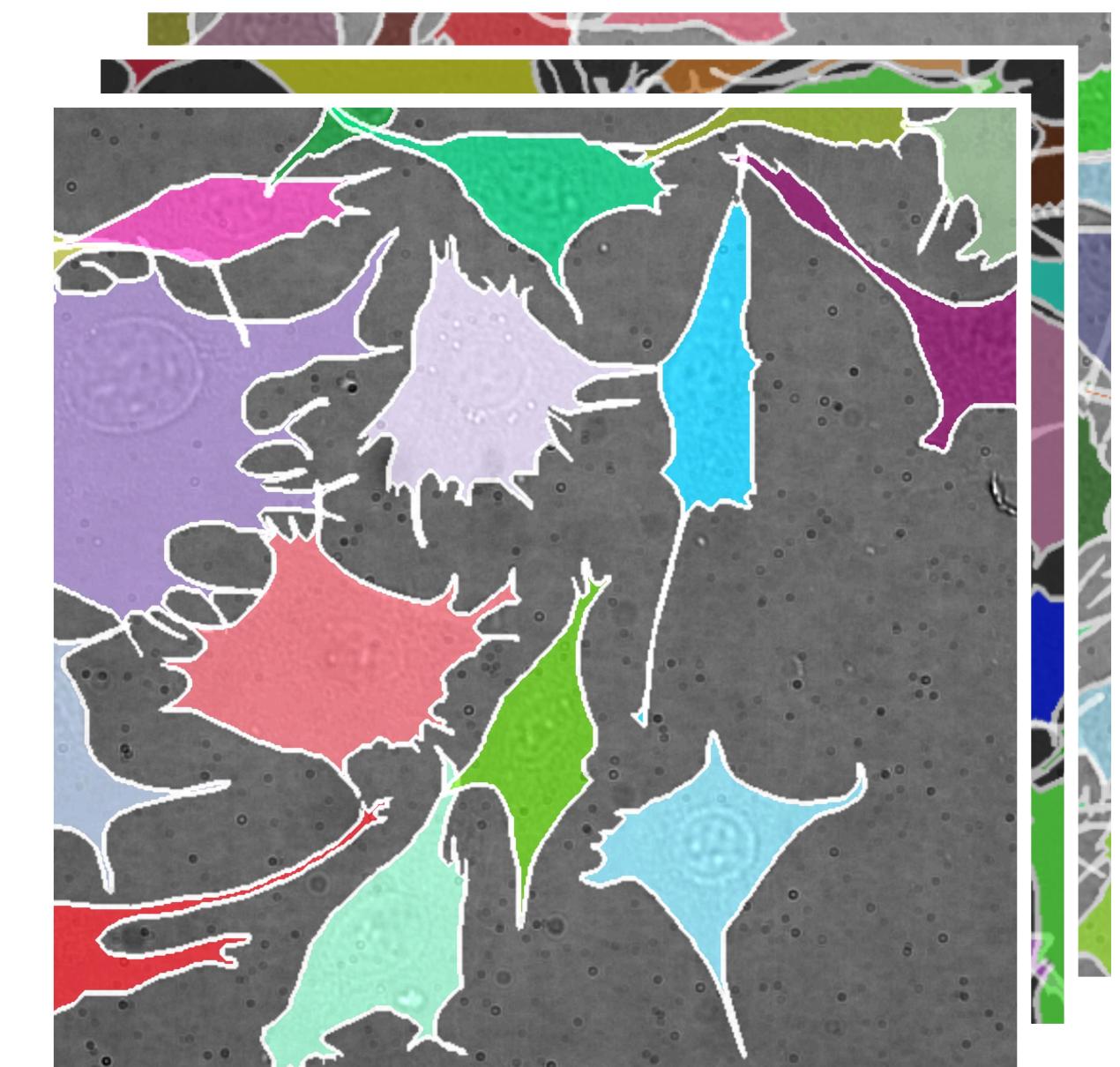


Contributions

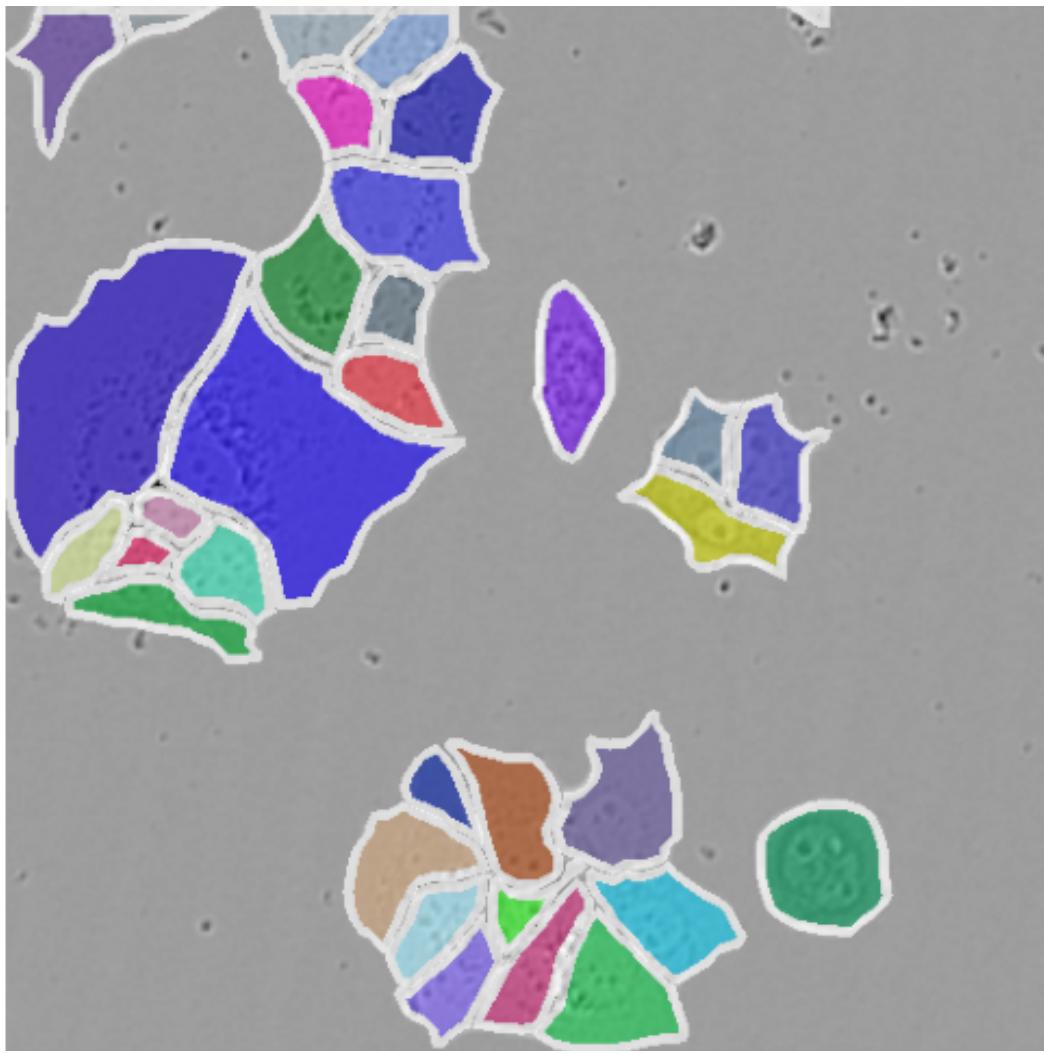
IAUNet



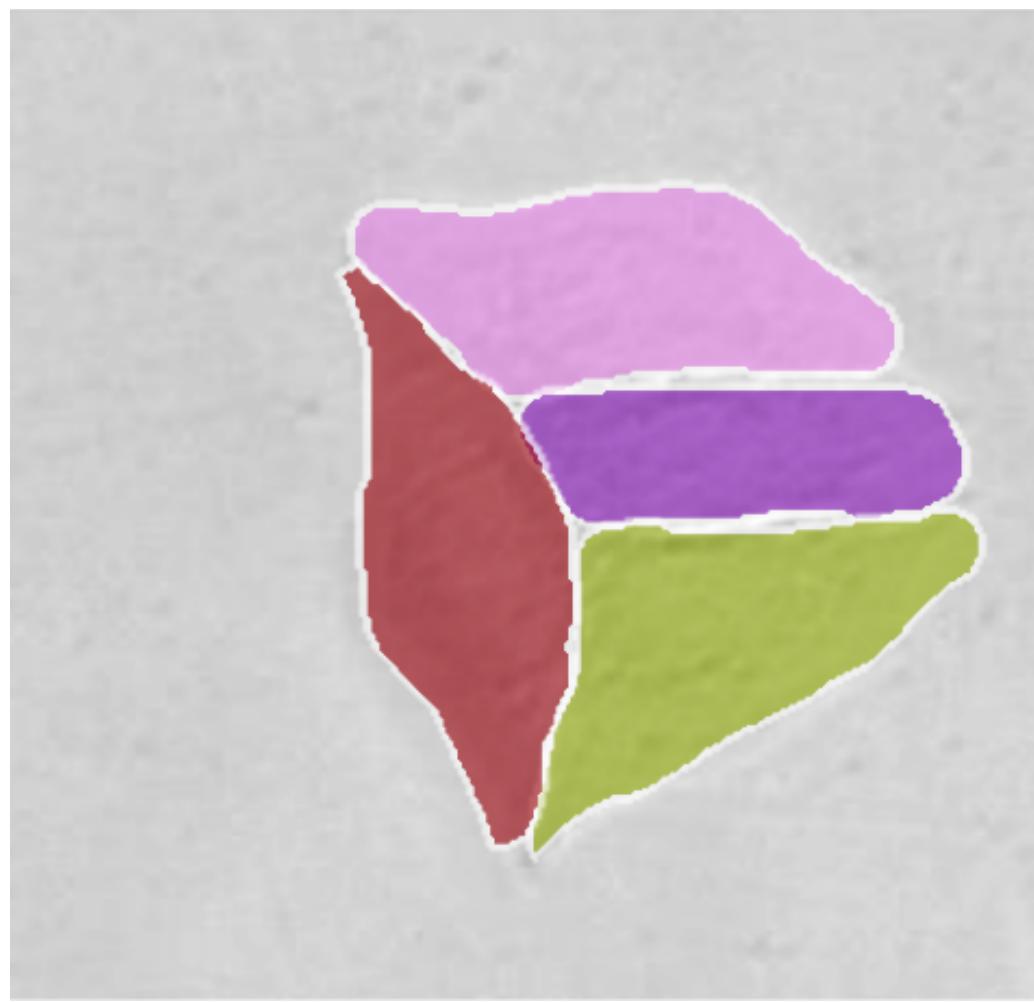
Revvity-25



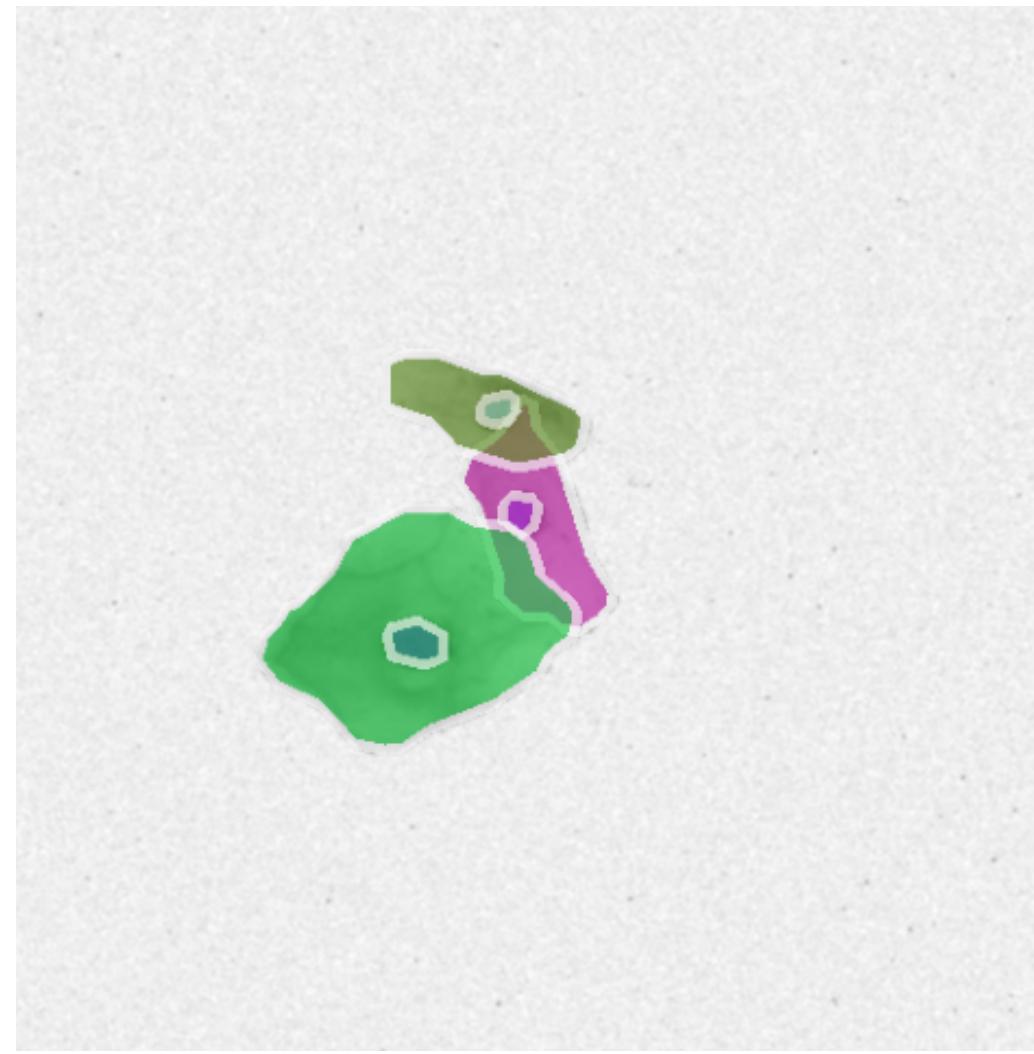
LIVECell



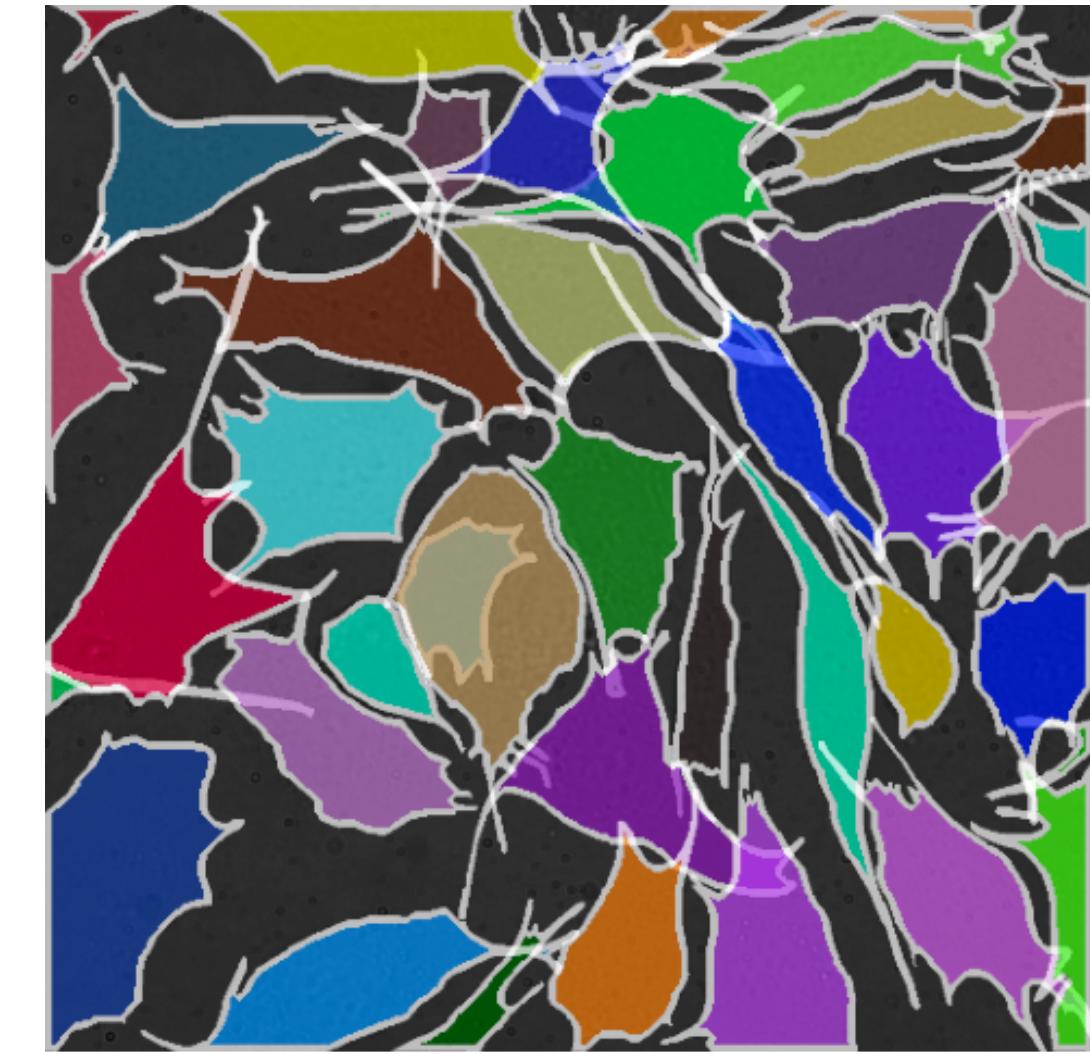
EVICAN



ISBI2014



Revvity-25



✗ No overlaps

✗ Missing annotations

✓ Many instances

✓ Large Dataset

✓ High visual complexity

✗ No overlaps

✗ Coarse annotations

✗ Few instances

✓ Large Dataset

✗ Low visual complexity

✓ Overlaps

✗ Simple annotations

✗ Few instances

✗ Small Dataset

✗ Low visual complexity

✓ Overlaps

✓ Precise annotations

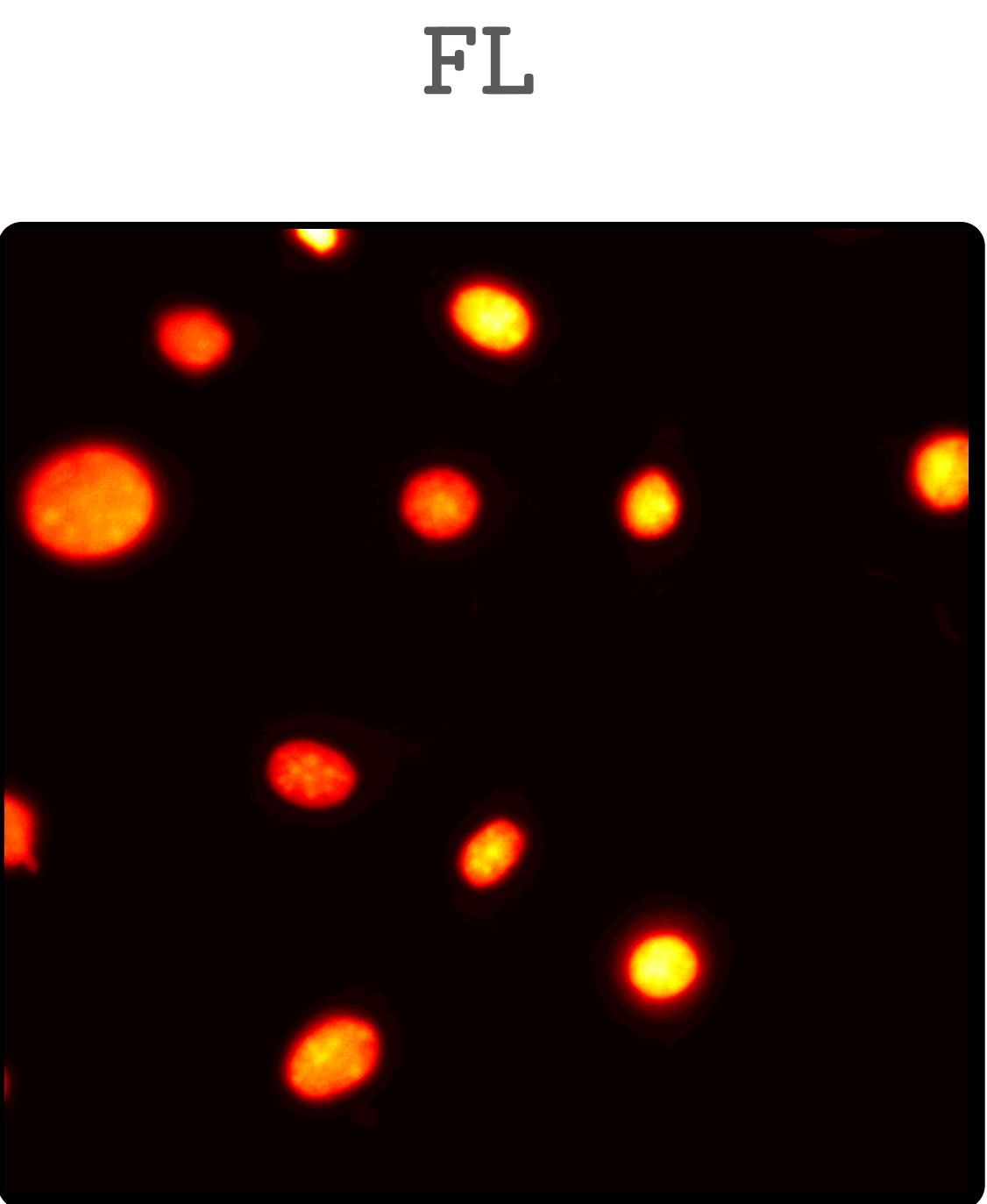
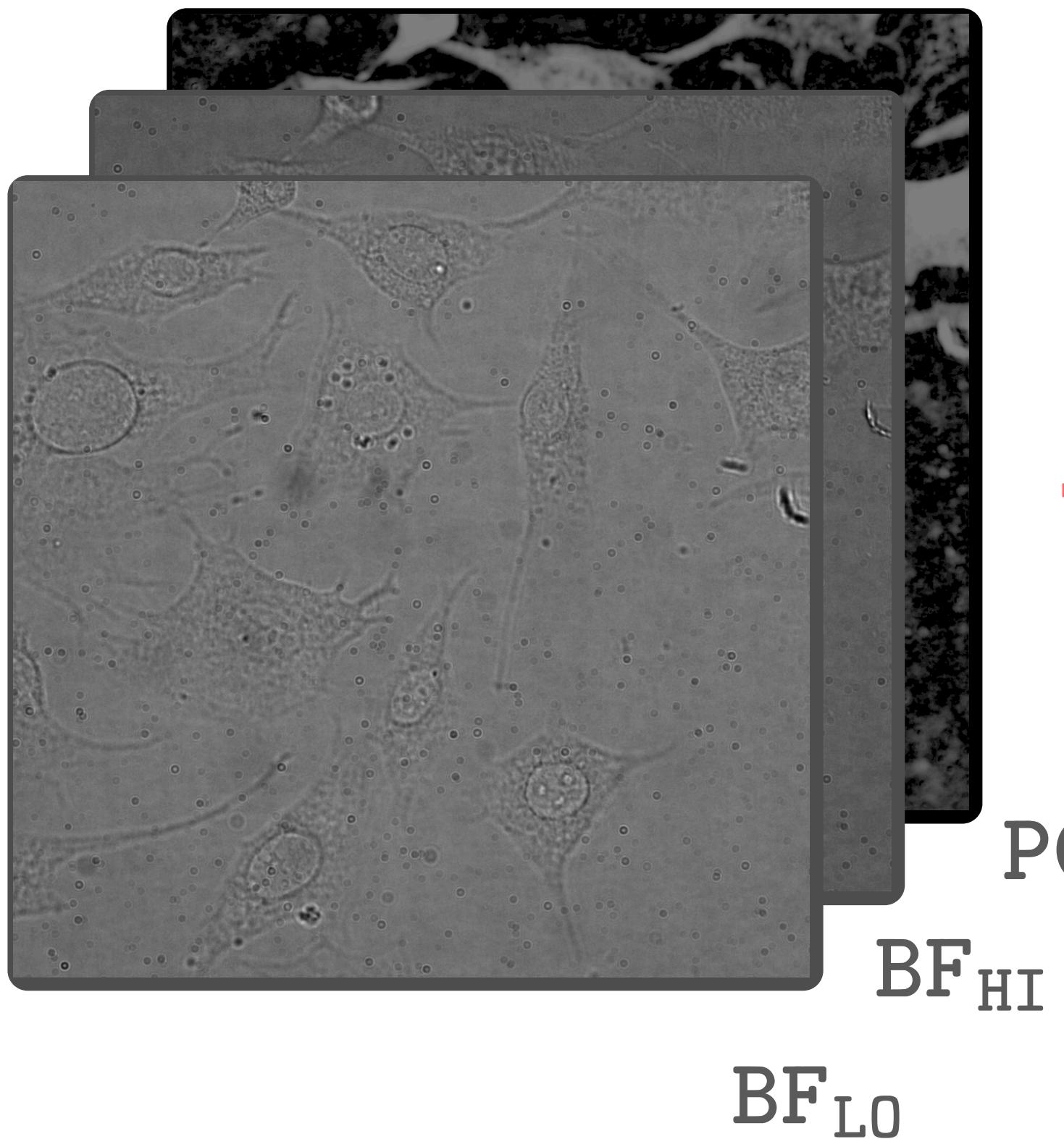
✓ Many instances

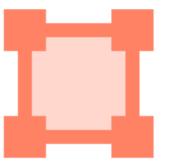
✗ Small Dataset

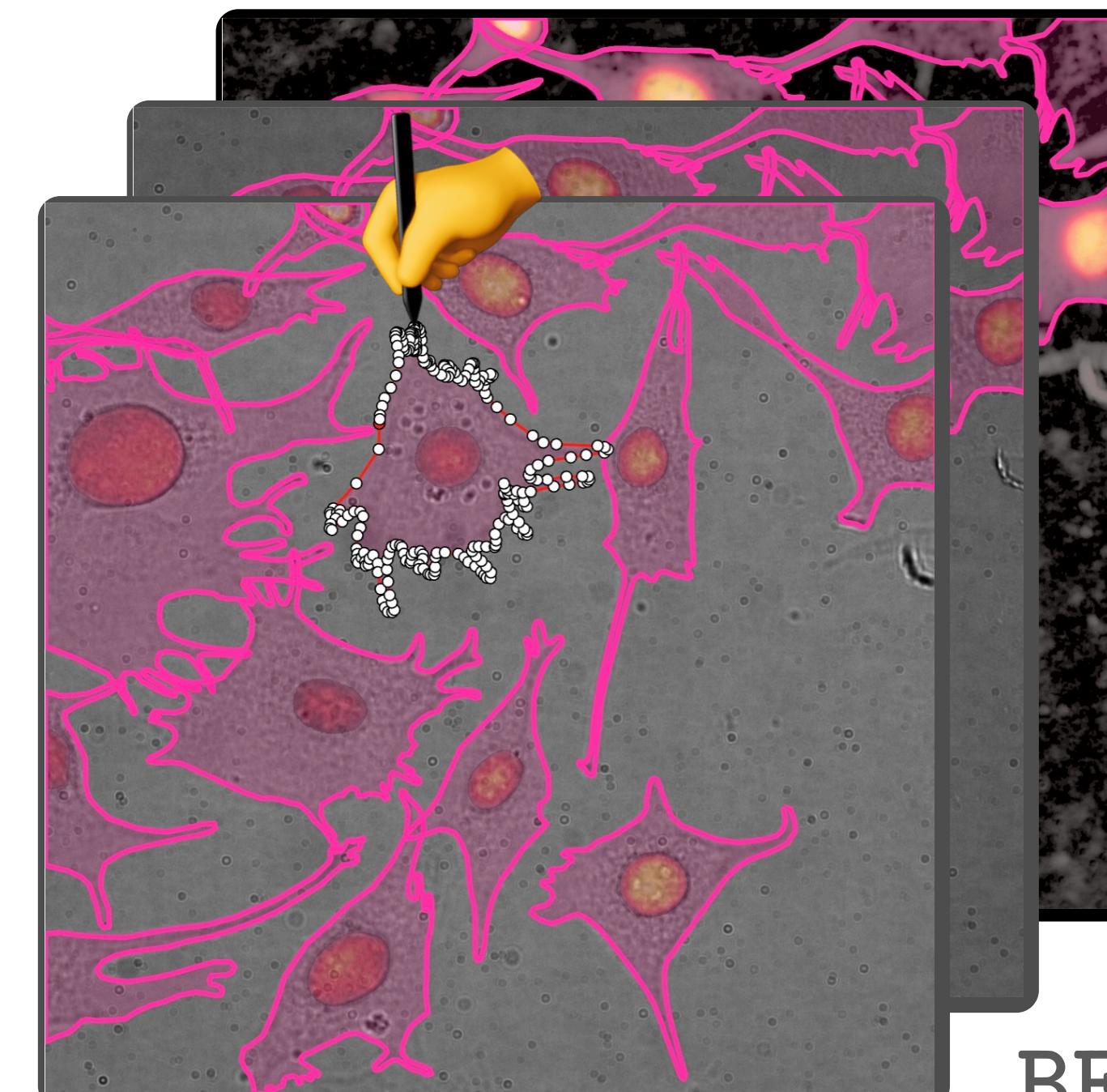
✓ High visual complexity

Revvity-25

Raw Images



 Label Studio



Revvity-25

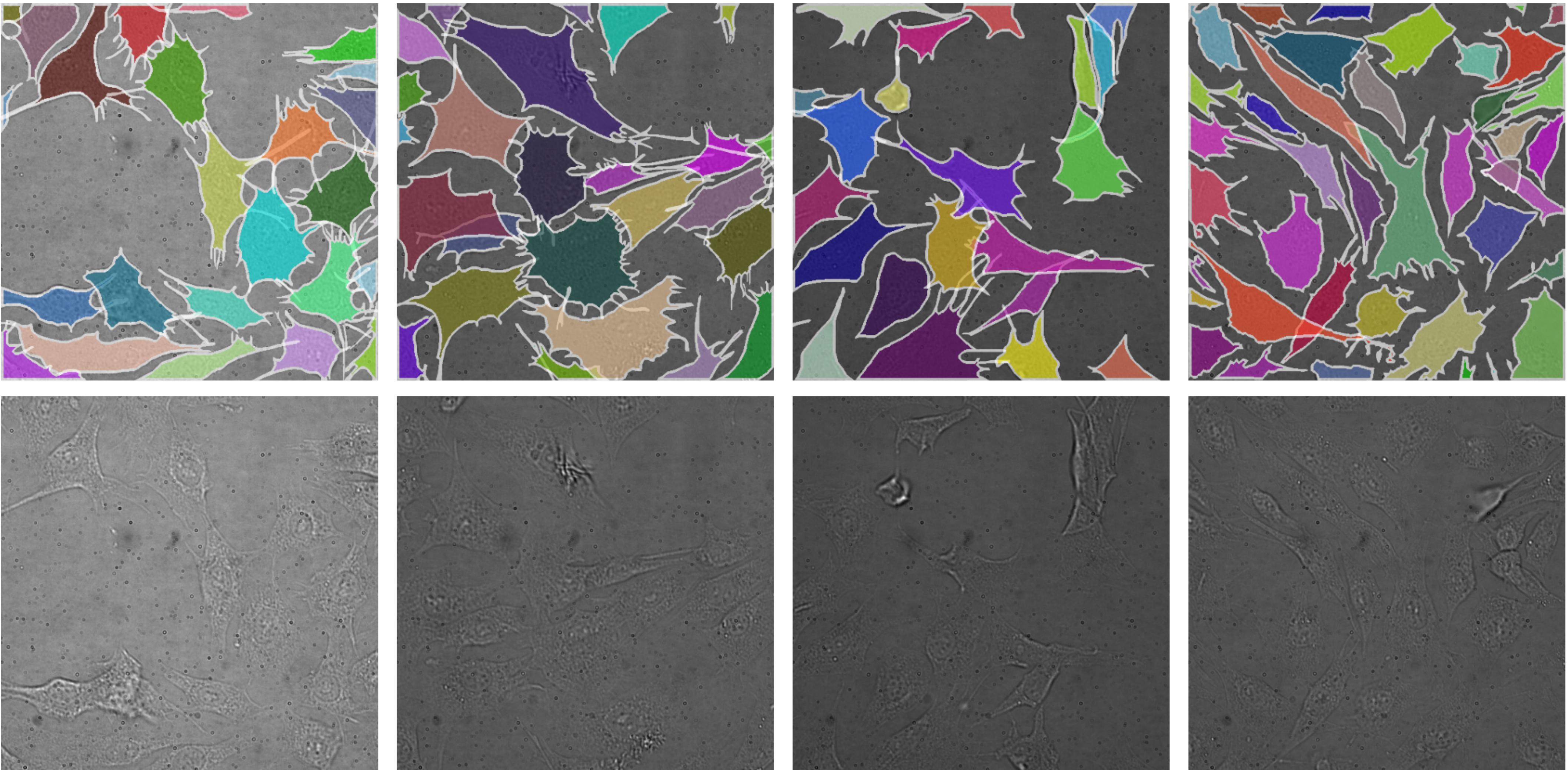
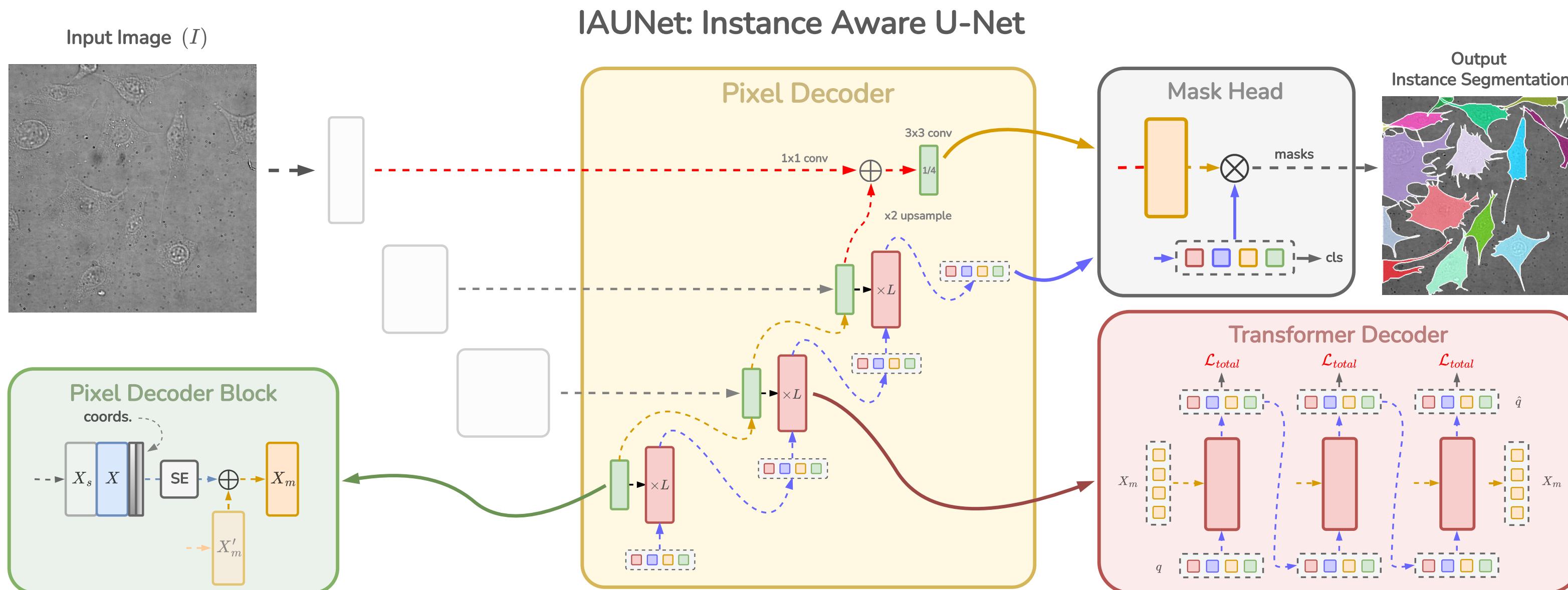


Figure 1. Revvity-25 Dataset.

Contributions

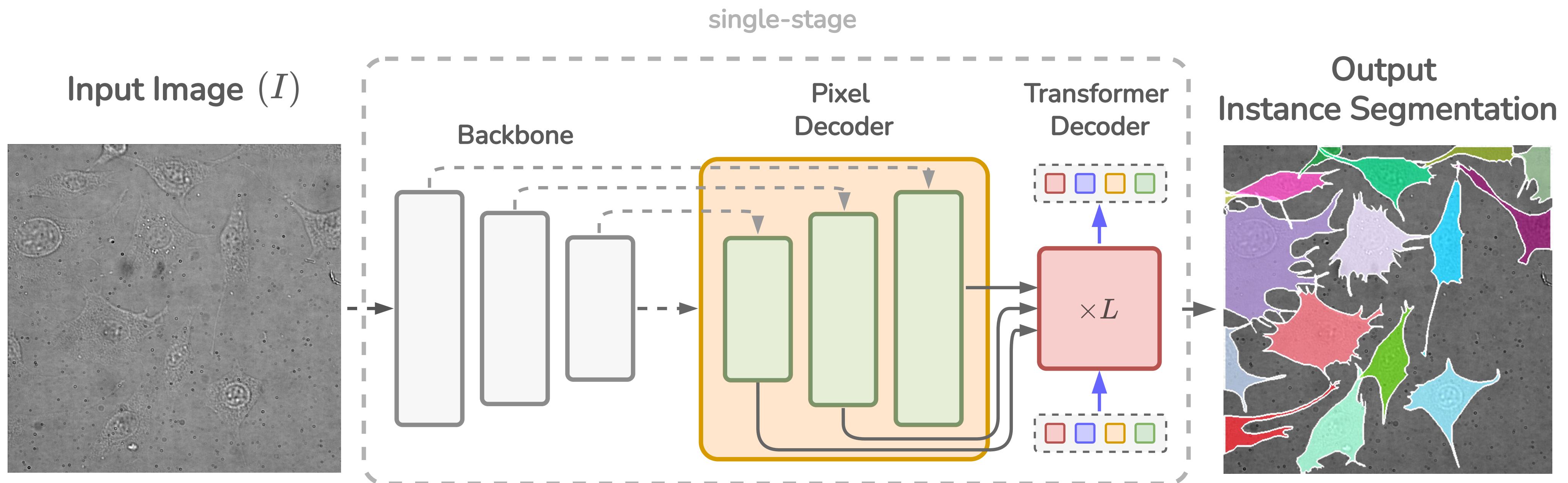
IAUNet

Revvity-25



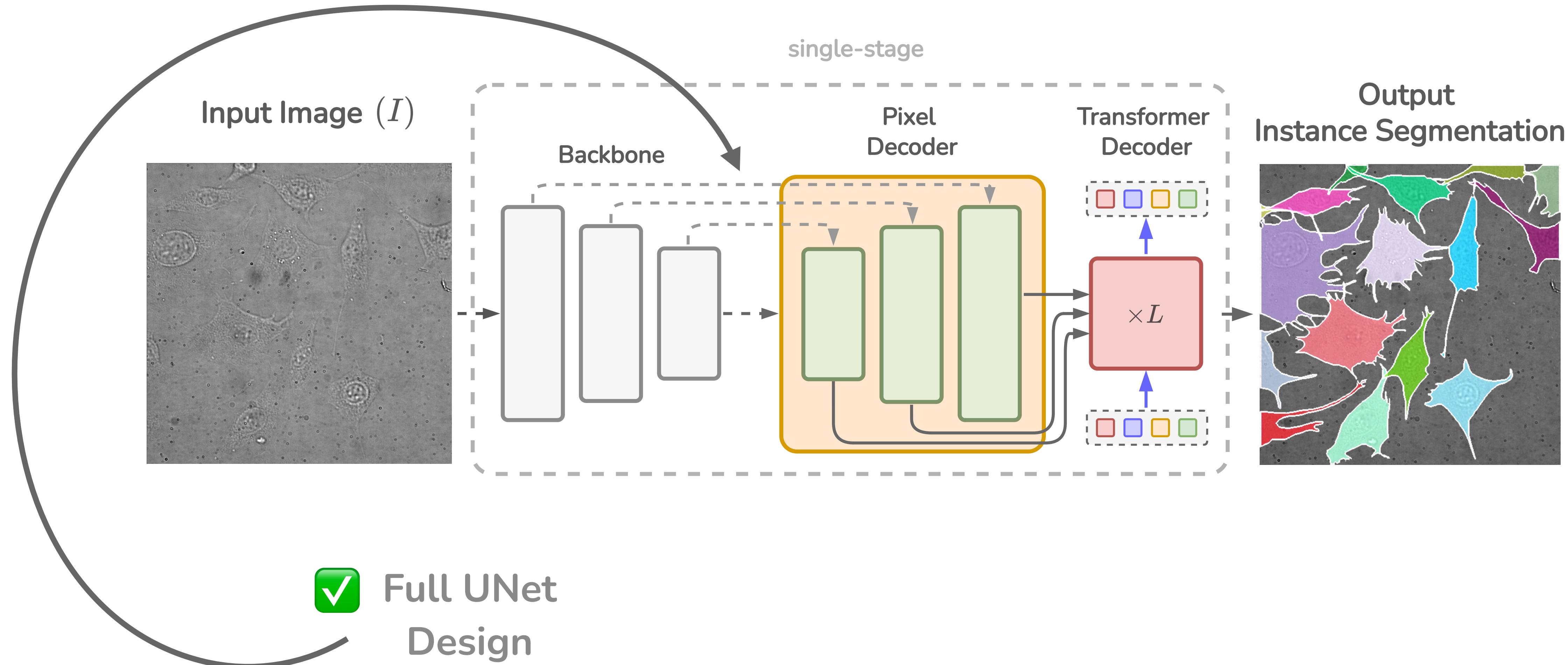
Instance-Aware UNet (IAUNet)

(Query-Based)



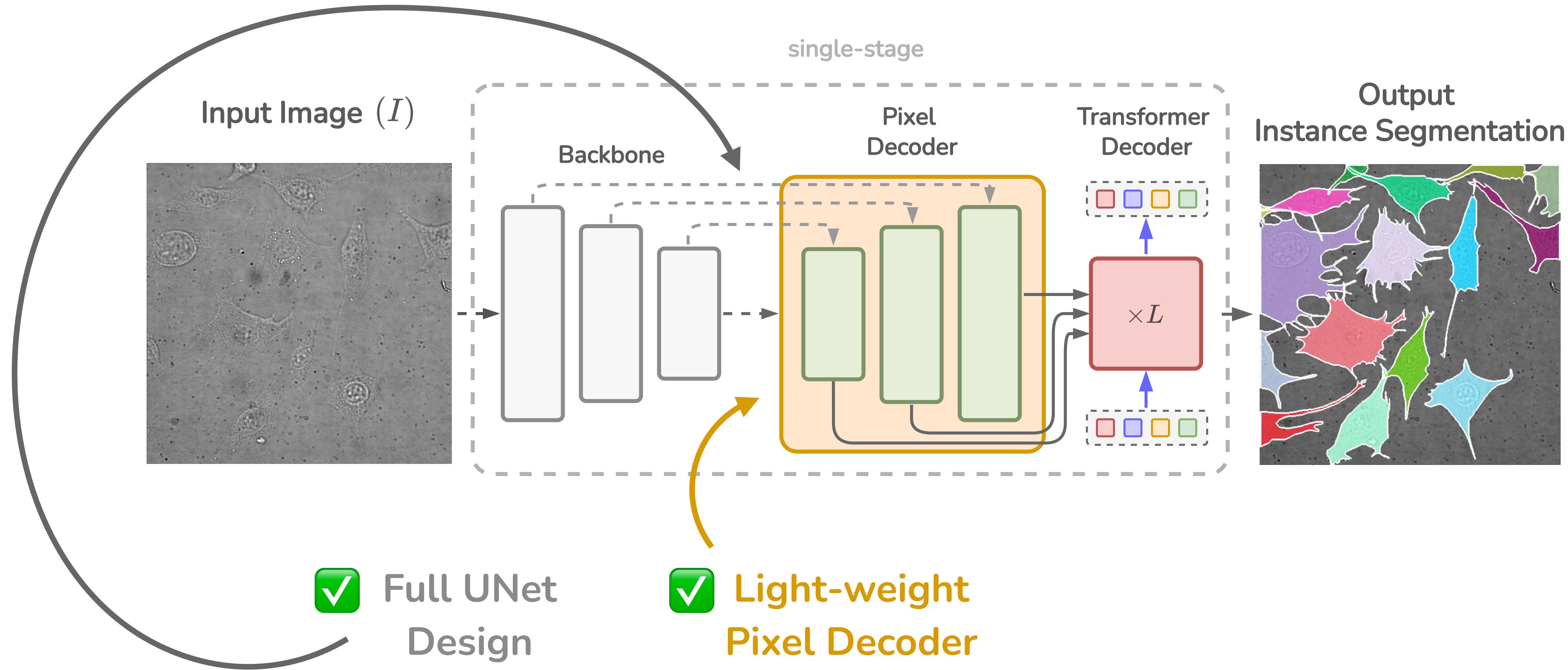
Instance-Aware UNet (IAUNet)

(Query-Based)



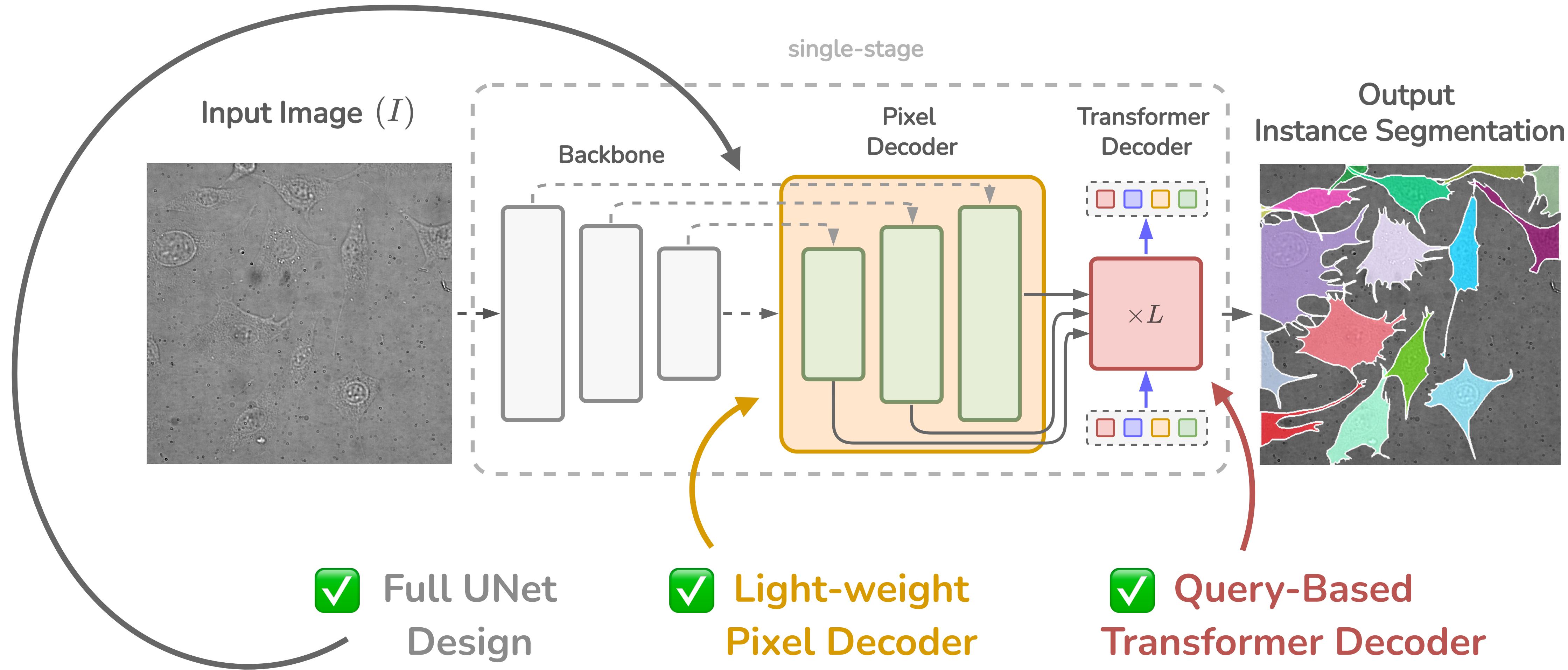
Instance-Aware UNet (IAUNet)

(Query-Based)



Instance-Aware UNet (IAUNet)

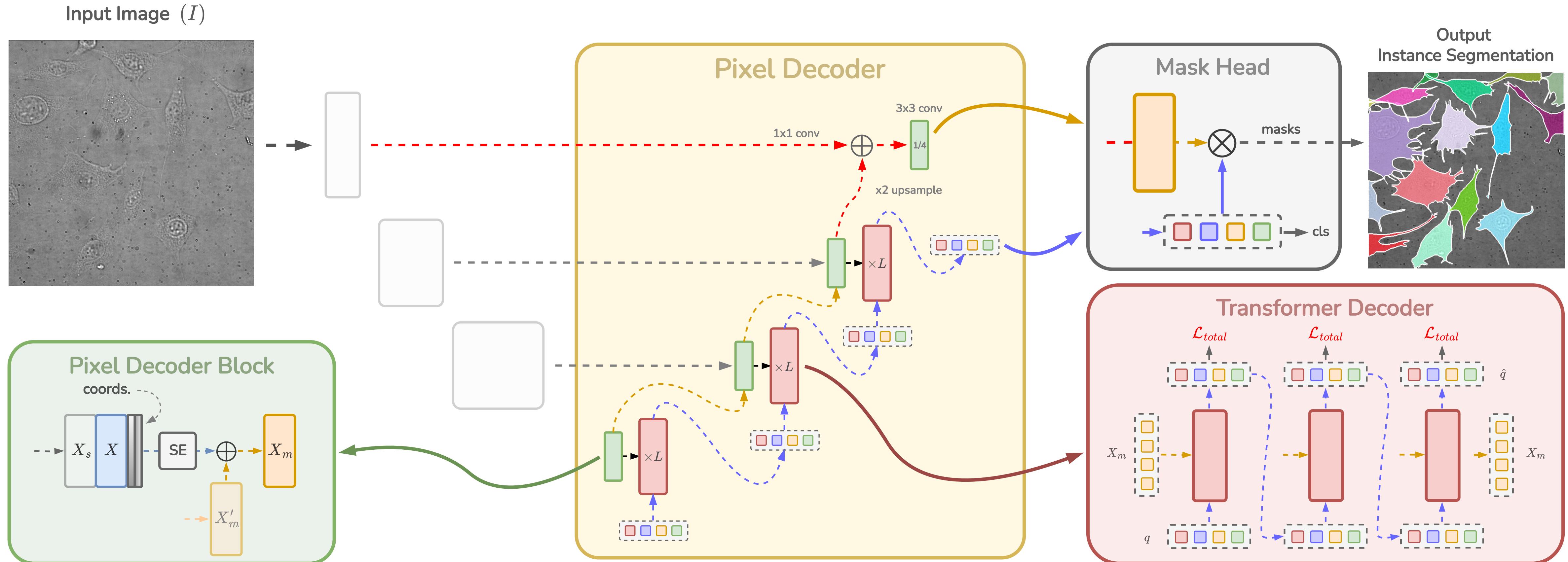
(Query-Based)



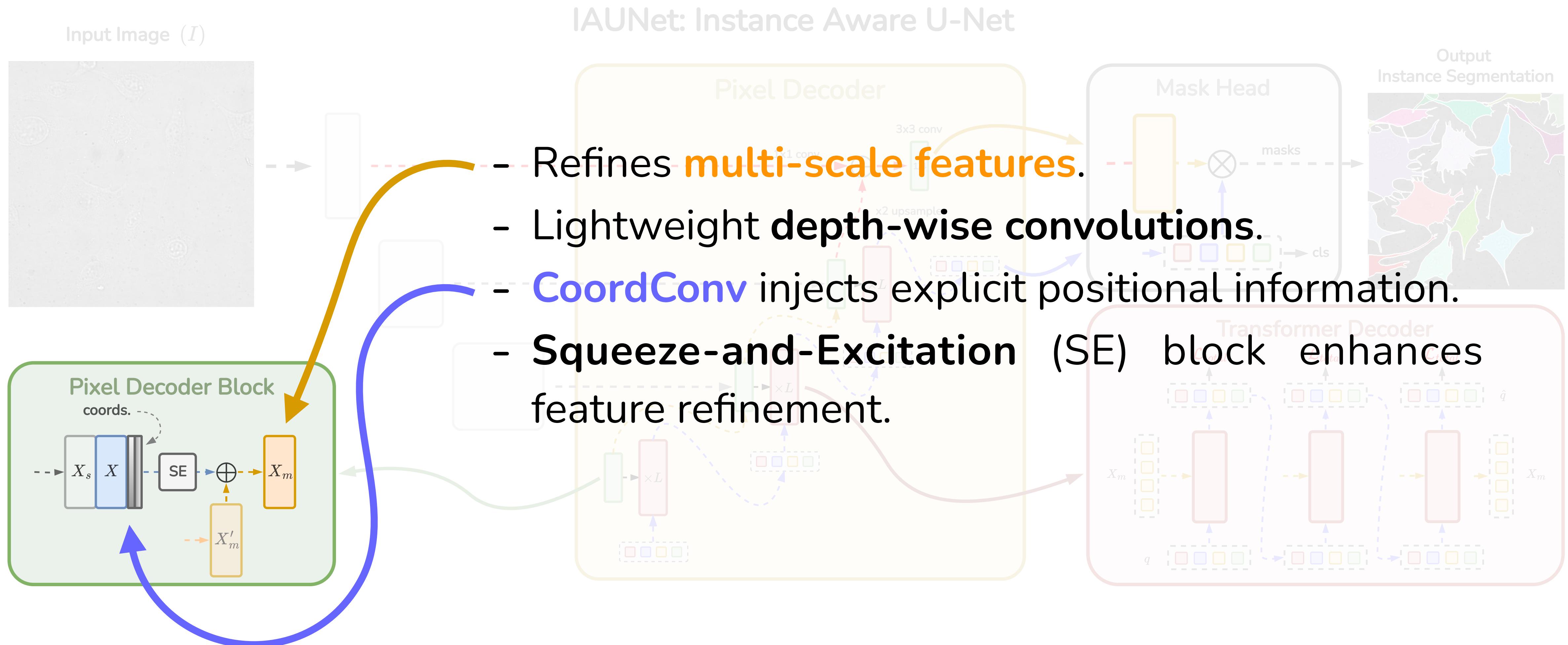
Related Works

	U-Net	Mask R-CNN	Mask2Former	MaskDINO	Cellpose	IAUNet
Instance segmentation						
Overlaps						
Single-stage						
No NMS	-					
U-Net Pixel Decoder						
Query selection	-	-			-	

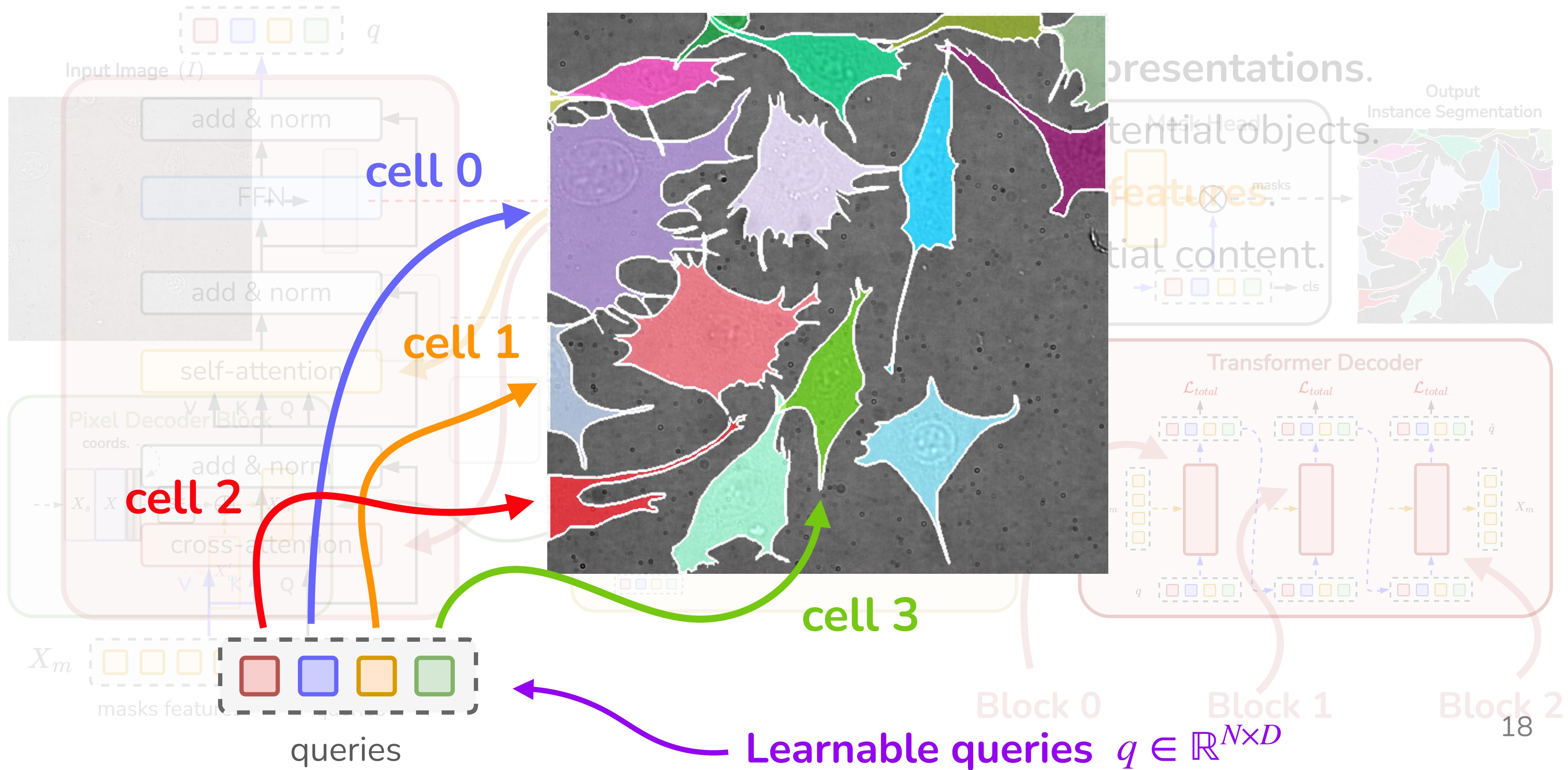
Instance-Aware UNet (IAUNet)



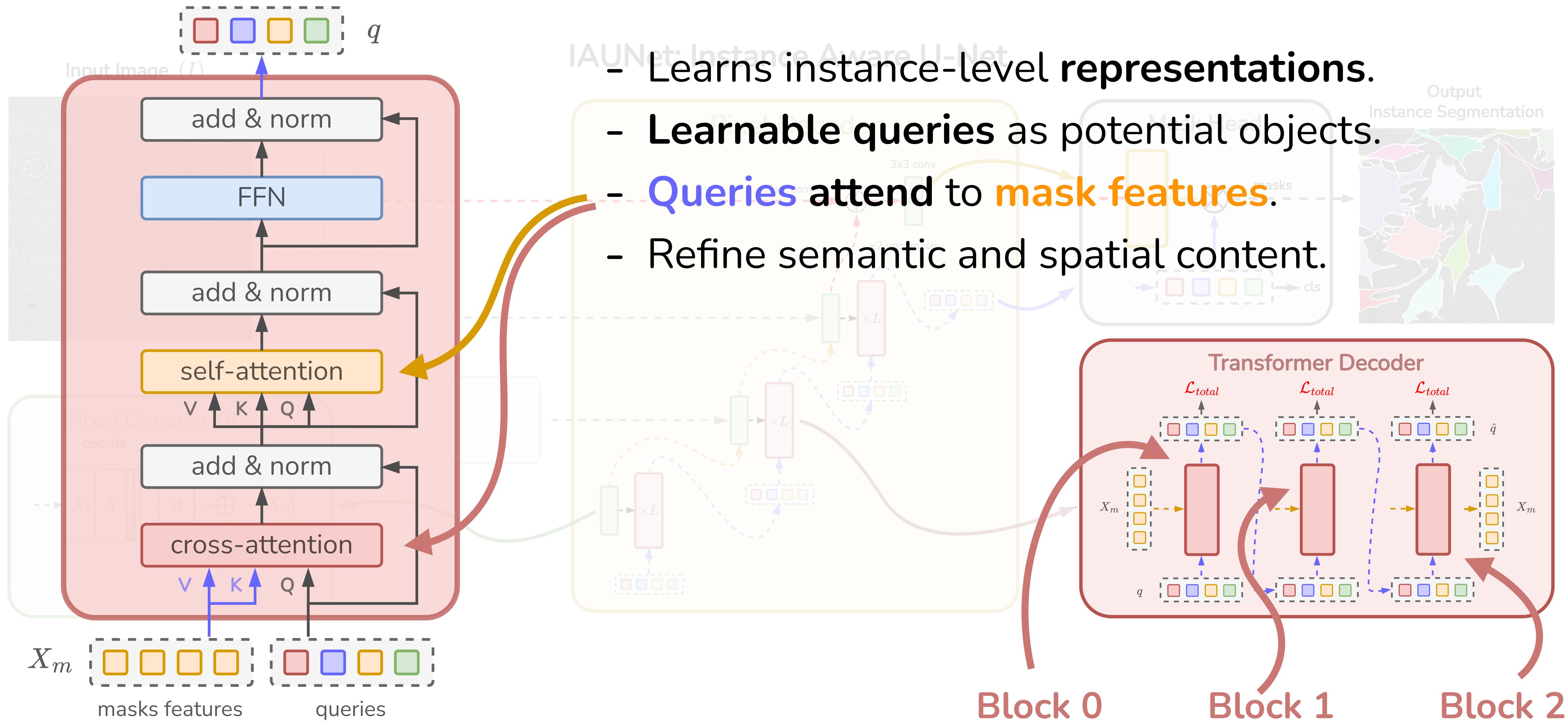
Pixel Decoder Block



Each query encodes features about a potential object

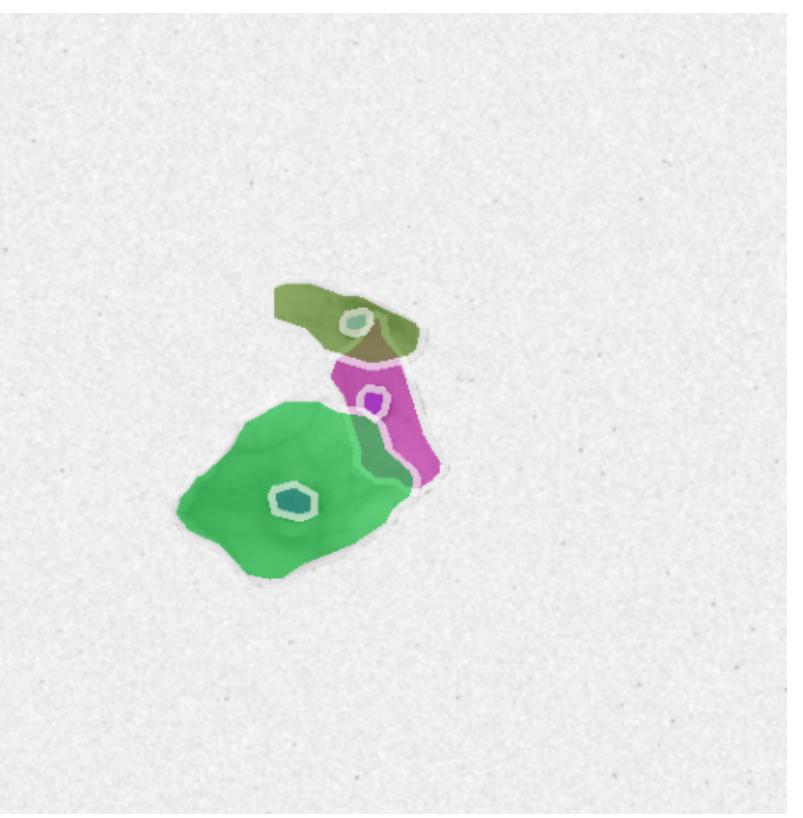
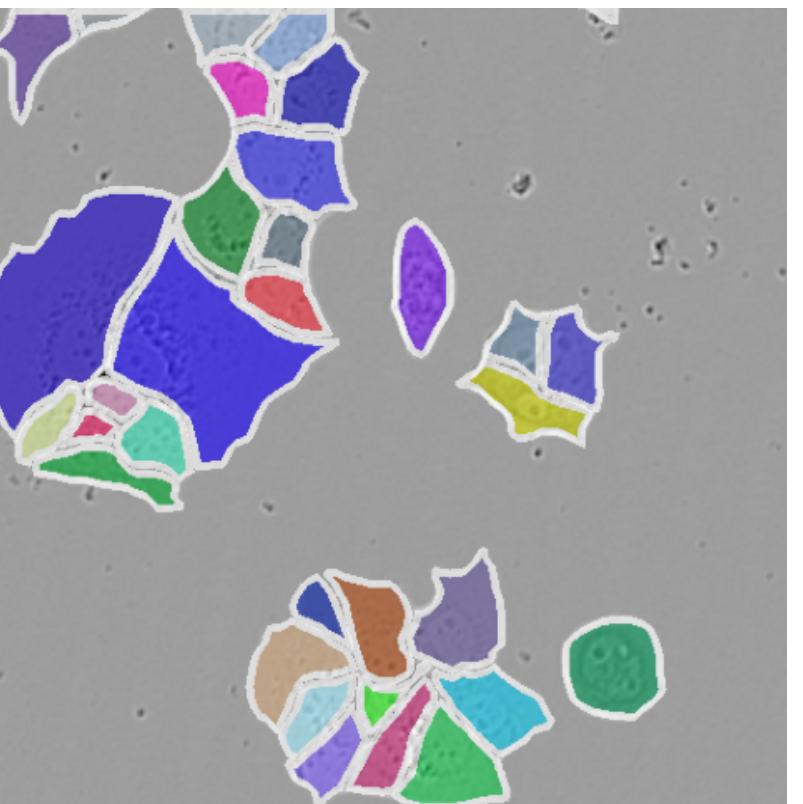


Transformer Decoder Block



Models	backbones	num_queries	LIVECell		EVICAN2 _E		EVICAN2 _M		EVICAN2 _D		ISBI2014		#params.	FLOPs
			AP	AP ₅₀	AP	AP ₅₀	AP	AP ₅₀	AP	AP ₅₀	AP	AP ₅₀		
Models with Convolution-Based Backbones														
Mask R-CNN [14]	R50	100	44.7	74.2	48.1	75.9	20.7	42.5	19.1	39.8	58.9	88.7	44M	115G
PointRend [34]	R50	100	44.0	73.5	26.6	47.9	18.0	38.5	13.4	28.3	60.0	88.7	56M	66G
Mask2Former [19]	R50	100	43.7	73.8	53.4	89.1	29.1	54.9	24.2	50.4	58.5	87.5	44M	67G
MaskDINO [20]	R50	100	43.3	73.5	50.7	83.9	29.3	57.9	22.0	41.9	55.4	86.8	44M	64G
IAUNet (ours)	R50	100	45.3	75.3	58.0	91.8	32.1	59.0	24.9	45.4	56.0	85.0	39M	49G
Mask R-CNN [14]	R101	100	44.2	73.2	41.5	69.9	23.3	46.9	17.8	36.7	60.7	88.8	63M	134G
PointRend [34]	R101	100	44.0	73.7	41.3	65.2	20.2	39.3	14.8	32.1	60.3	89.2	75M	86G
Mask2Former [19]	R101	100	44.0	73.5	54.4	87.8	27.1	51.7	20.4	42.4	59.5	88.6	63M	86G
MaskDINO [20]	R101	100	43.4	73.6	53.7	85.0	31.8	59.2	27.1	51.3	55.7	87.4	63M	84G
IAUNet (ours)	R101	100	45.4	75.5	58.3	92.7	32.9	59.6	26.9	50.0	56.5	87.1	58M	69G
Models with Transformer-Based Backbones														
Mask R-CNN [14]	Swin-S	100	44.3	73.3	52.6	91.7	27.0	59.2	20.2	50.2	61.9	90.7	69M	141G
PointRend [34]	Swin-S	100	43.9	73.5	55.1	89.2	30.1	61.6	24.4	54.6	62.1	91.0	81M	93G
Mask2Former [19]	Swin-S	100	44.6	74.3	65.2	96.8	36.2	66.7	30.9	62.7	57.1	87.3	69M	93G
MaskDINO [20]	Swin-S	100	43.9	73.8	57.0	86.9	33.6	64.9	27.6	56.9	52.7	85.3	71M	181G
MaskDINO [20]	Swin-S	300	44.8	75.1	56.5	91.8	35.0	70.7	30.2	64.3	51.2	83.4	71M	187G
IAUNet (ours)	Swin-S	100	45.4	75.4	58.8	93.1	32.2	61.9	27.7	54.1	61.1	90.1	64M	76G
IAUNet (ours)	Swin-S	300	45.6	76.4	60.9	93.6	33.2	62.0	29.6	58.0	61.8	89.8	64M	87G
Mask R-CNN [14]	Swin-B	100	44.2	73.1	52.0	89.0	26.7	60.3	24.8	55.5	62.4	91.5	107M	186G
PointRend [34]	Swin-B	100	44.0	73.7	58.6	91.0	34.1	64.6	25.8	52.0	62.7	91.5	119M	137G
Mask2Former [19]	Swin-B	100	44.9	74.7	55.0	92.5	31.4	60.9	27.7	56.6	58.1	88.4	107M	138G
MaskDINO [20]	Swin-B	100	44.3	74.1	57.3	91.1	37.3	75.7	30.1	65.6	53.5	86.6	110M	226G
MaskDINO [20]	Swin-B	300	45.2	75.8	57.9	91.6	39.1	78.8	34.0	72.3	53.3	84.8	110M	232G
IAUNet (ours)	Swin-B	100	45.5	75.6	59.6	93.5	34.2	65.7	28.9	56.9	61.5	90.8	102M	120G
IAUNet (ours)	Swin-B	300	45.8	76.7	61.2	94.8	38.0	69.6	30.7	59.9	63.0	91.5	102M	132G

Table 1. Instance segmentation on LIVECell, EVICAN2 (Easy, Medium, Difficult test subsets), and ISBI2014.



LIVECell

EVICAN

ISBI2014

Models	backbones	num_queries	LIVECell		EVICAN2 _E		EVICAN2 _M		EVICAN2 _D		ISBI2014		#params.	FLOPs
			AP	AP ₅₀	AP	AP ₅₀	AP	AP ₅₀	AP	AP ₅₀	AP	AP ₅₀		
Models with Convolution-Based Backbones														
Mask R-CNN [14]	R50	100	44.7	74.2	48.1	75.9	20.7	42.5	19.1	39.8	58.9	88.7	44M	115G
PointRend [34]	R50	100	44.0	73.5	26.6	47.9	18.0	38.5	13.4	28.3	60.0	88.7	56M	66G
Mask2Former [19]	R50	100	43.7	73.8	53.4	89.1	29.1	54.9	24.2	50.4	58.5	87.5	44M	67G
MaskDINO [20]	R50	100	43.3	73.5	50.7	83.9	29.3	57.9	22.0	41.9	55.4	86.8	44M	64G
IAUNet (ours)	R50	100	45.3	75.3	58.0	91.8	32.1	59.0	24.9	45.4	56.0	85.0	39M	49G
Mask R-CNN [14]	R101	100	44.2	73.2	41.5	69.9	23.3	46.9	17.8	36.7	60.7	88.8	63M	134G
PointRend [34]	R101	100	44.0	73.7	41.3	65.2	20.2	39.3	14.8	32.1	60.3	89.2	75M	86G
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MaskDINO [20]	R101	100	43.4	73.6	53.7	85.0	31.8	59.2	27.1	51.3	55.7	87.4	63M	84G
IAUNet (ours)	R101	100	45.4	75.5	58.3	92.7	32.9	59.6	26.9	50.0	56.5	87.1	58M	69G
Models with Transformer-Based Backbones														
Mask R-CNN [14]	Swin-S	100	44.3	73.3	52.6	91.7	27.0	59.2	20.2	50.2	61.9	90.7	69M	141G
PointRend [34]	Swin-S	100	43.9	73.5	55.1	89.2	30.1	61.6	24.4	54.6	62.1	91.0	81M	93G
Mask2Former [19]	Swin-S	100	44.6	74.3	65.2	96.8	36.2	<u>66.7</u>	30.9	<u>62.7</u>	57.1	87.3	69M	93G
MaskDINO [20]	Swin-S	100	43.9	73.8	57.0	86.9	33.6	64.9	27.6	56.9	52.7	85.3	71M	181G
MaskDINO [20]	Swin-S	300	44.8	75.1	56.5	91.8	<u>35.0</u>	70.7	<u>30.2</u>	64.3	51.2	83.4	71M	187G
IAUNet (ours)	Swin-S	100	<u>45.4</u>	<u>75.4</u>	58.8	93.1	32.2	61.9	27.7	54.1	61.1	90.1	64M	76G
IAUNet (ours)	Swin-S	300	45.6	76.4	<u>60.9</u>	<u>93.6</u>	33.2	62.0	29.6	58.0	61.8	89.8	64M	87G
Mask R-CNN [14]	Swin-B	100	44.2	73.1	52.0	89.0	26.7	60.3	24.8	55.5	62.4	91.5	107M	186G
PointRend [34]	Swin-B	100	44.0	73.7	58.6	91.0	34.1	64.6	25.8	52.0	<u>62.7</u>	91.5	119M	137G
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MaskDINO [20]	Swin-B	300	45.2	<u>75.8</u>	57.9	91.6	39.1	78.8	34.0	72.3	53.3	84.8	110M	232G
IAUNet (ours)	Swin-B	100	<u>45.5</u>	75.6	<u>59.6</u>	<u>93.5</u>	34.2	65.7	28.9	56.9	61.5	<u>90.8</u>	102M	120G
IAUNet (ours)	Swin-B	300	45.8	76.7	61.2	94.8	<u>38.0</u>	69.6	<u>30.7</u>	59.9	63.0	91.5	102M	132G

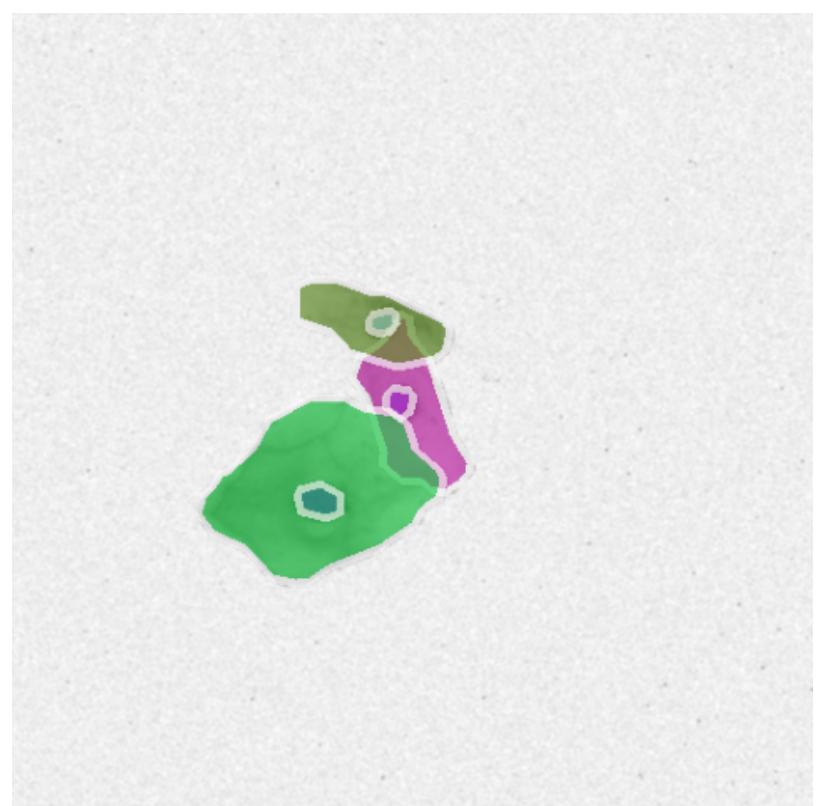
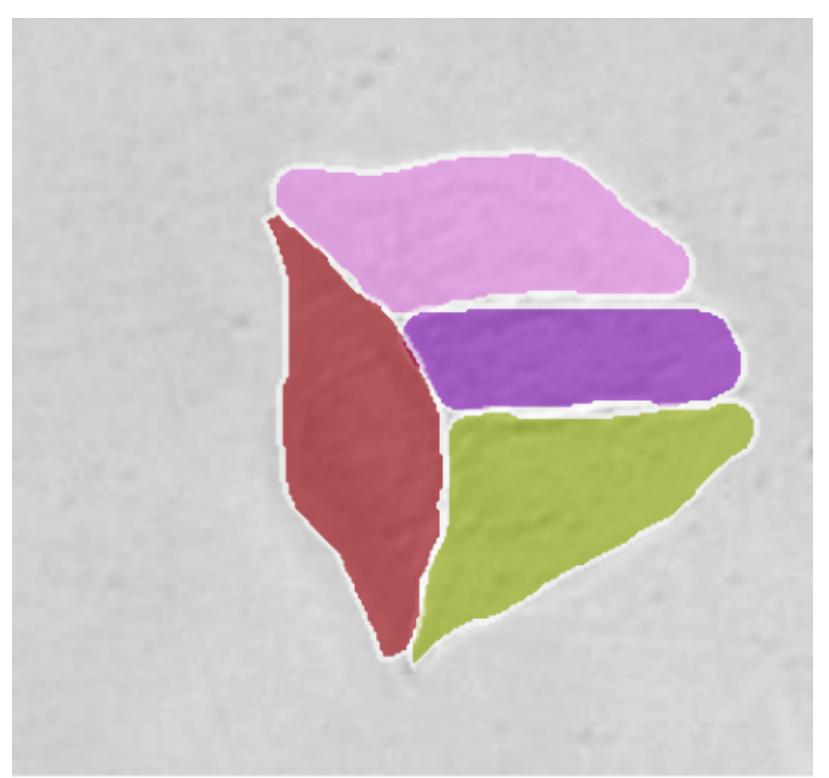
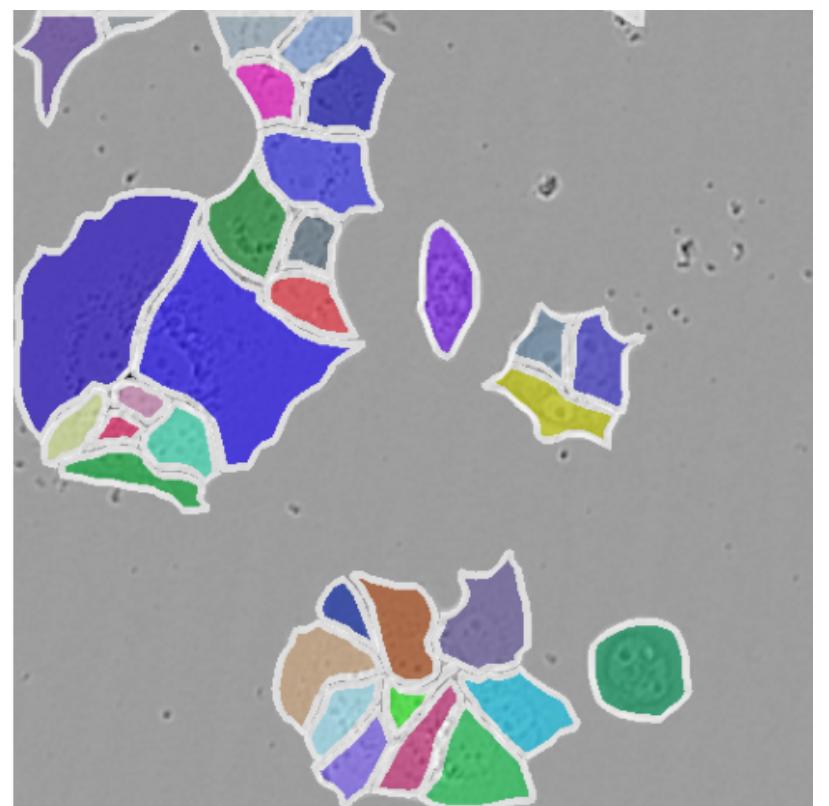


Table 1. Instance segmentation on LIVECell, EVICAN2 (Easy, Medium, Difficult test subsets), and ISBI2014.

Models	backbones	num_queries	AP	AP ₅₀	AP ₇₅	AP _S	AP _M	AP _L	#params.	FLOPs
Models with Convolution-Based Backbones										
Mask R-CNN [14]	R50	100	39.7	77.2	37.4	0.6	19.0	44.6	44M	115G
PointRend [34]	R50	100	42.2	79.4	40.9	0.4	21.7	47.3	56M	66G
Mask2Former [19]	R50	100	<u>46.4</u>	79.8	<u>49.9</u>	<u>0.7</u>	<u>25.7</u>	<u>52.8</u>	44M	67G
MaskDINO [20]	R50	100	45.6	80.4	48.2	1.8	22.3	51.8	44M	64G
IAUNet (ours)	R50	100	49.7	82.1	54.8	0.6	27.3	56.0	39M	49G
Mask R-CNN [14]	R101	100	40.7	77.5	39.9	0.4	20.1	45.8	63M	134G
PointRend [34]	R101	100	42.9	79.3	42.5	0.0	18.4	48.9	75M	86G
Mask2Former [19]	R101	100	47.2	80.1	<u>51.8</u>	1.7	<u>25.7</u>	53.3	63M	86G
MaskDINO [20]	R101	100	<u>47.3</u>	<u>81.0</u>	50.4	<u>0.9</u>	23.0	<u>53.5</u>	63M	84G
IAUNet (ours)	R101	100	51.5	84.7	56.1	1.7	29.2	57.8	58M	69G
Models with Transformer-Based Backbones										
Mask R-CNN [14]	Swin-S	100	24.7	63.4	12.5	0.0	7.3	28.9	69M	141G
PointRend [34]	Swin-S	100	43.6	80.0	43.0	0.5	21.5	48.9	81M	93G
Mask2Former [19]	Swin-S	100	51.2	83.3	56.4	2.7	27.7	58.0	69M	93G
MaskDINO [20]	Swin-S	100	50.3	83.2	53.9	4.7	27.6	56.1	71M	181G
MaskDINO [20]	Swin-S	300	49.4	83.6	53.3	2.9	25.8	55.3	71M	187G
IAUNet (ours)	Swin-S	100	<u>53.0</u>	<u>85.7</u>	<u>57.0</u>	1.3	29.7	<u>59.1</u>	64M	76G
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IAUNet (ours)	Swin-B	100	<u>53.5</u>	<u>86.1</u>	59.4	0.8	30.5	<u>59.7</u>	102M	120G
IAUNet (ours)	Swin-B	300	53.7	86.5	59.4	1.0	<u>30.0</u>	60.3	102M	132G

Revvity-25

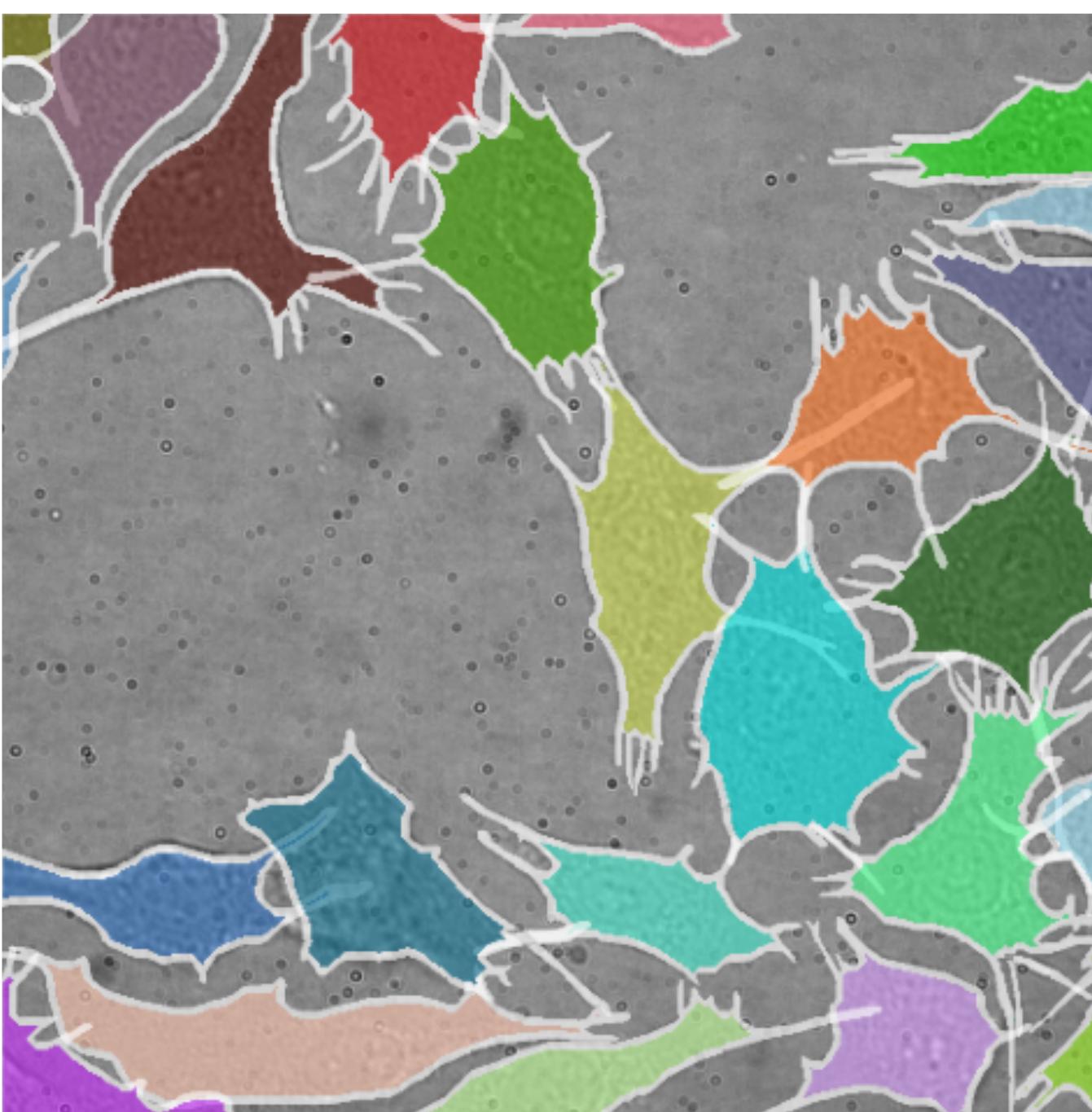


Table 2. Instance segmentation on our Revvity-25 dataset. IAUNet outperforms strong query-based baselines as well as other state-of-the-art models when training with fewer parameters

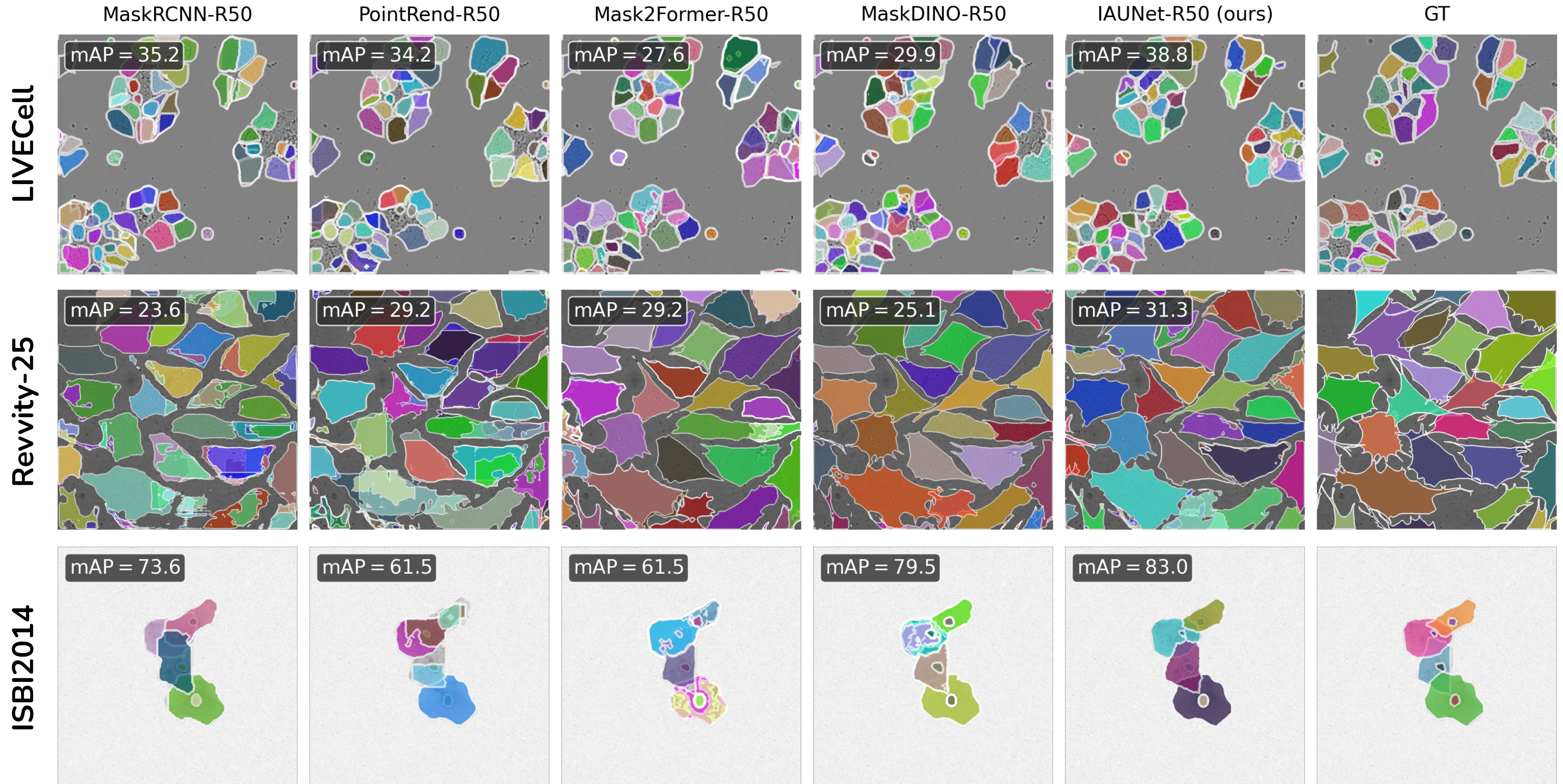


Figure 2. Visualization of instance segmentation predictions across different state-of-the-art models (using ResNet50 backbone). We also report per-image AP score.

Conclusions



- We introduce **IAUNet**, a novel model for cell instance segmentation that integrates a **lightweight convolutional Pixel decoder** and a **Transformer decoder** for efficient multi-scale object query refinement.

Conclusions



- We introduce **IAUNet**, a novel model for cell instance segmentation that integrates a **lightweight convolutional Pixel decoder** and a **Transformer decoder** for efficient multi-scale object query refinement.
- We present the **2025 Revvity Full Cell Segmentation Dataset**, featuring detailed and validated annotations for evaluating segmentation models on brightfield images.

Thank you! ❤



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Institute of Computer Science

revvity BCV Lab



Armed Forces
of Ukraine



Dzyga's
Paw



APPLIED
SCIENCES
FACULTY

Appendix

Ablations

We investigate the **benefit** of adding different **decoder components**.
Adding **CoordConv** improves object localization.

Decoder	AP	AP ₅₀	AP ₇₅	#params.	FLOPs
IAUNet (R50)	43.8	73.1	47.4	34M	42G
+ mask branch X_m	44.0	73.2	47.9	34M	42G
+ FFN (2048 → 1024)	44.1	73.2	48.0	32M	42G
+ SE block [68]	44.2	73.3	48.1	32M	42G
+ CoordConv [67]	44.7	74.1	<u>48.7</u>	32M	42G
+ L (1 → 3) (round-robin.)	44.3	74.0	48.1	39M	49G
+ L (1 → 3) (seq.)	<u>45.1</u>	<u>74.4</u>	49.4	39M	49G
+ deep_supervision	45.3	75.3	49.4	39M	49G

Figure <>. Visualization of instance segmentation predictions across different state-of-the-art models (using ResNet50 backbone). We also report per-image AP score.

Ablations

We observe consistent gains when increasing
the query count from 100 to 300 and 500

num_queries	AP	AP ₅₀	AP ₇₅	FLOPs
100	45.3	75.3	49.4	49G
300	<u>45.9</u>	<u>76.5</u>	<u>50.4</u>	61G
500	46.1	76.8	50.8	73G
1000	45.3	76.3	50.0	104G

Figure <>. Scaling the number of object queries benefits the model

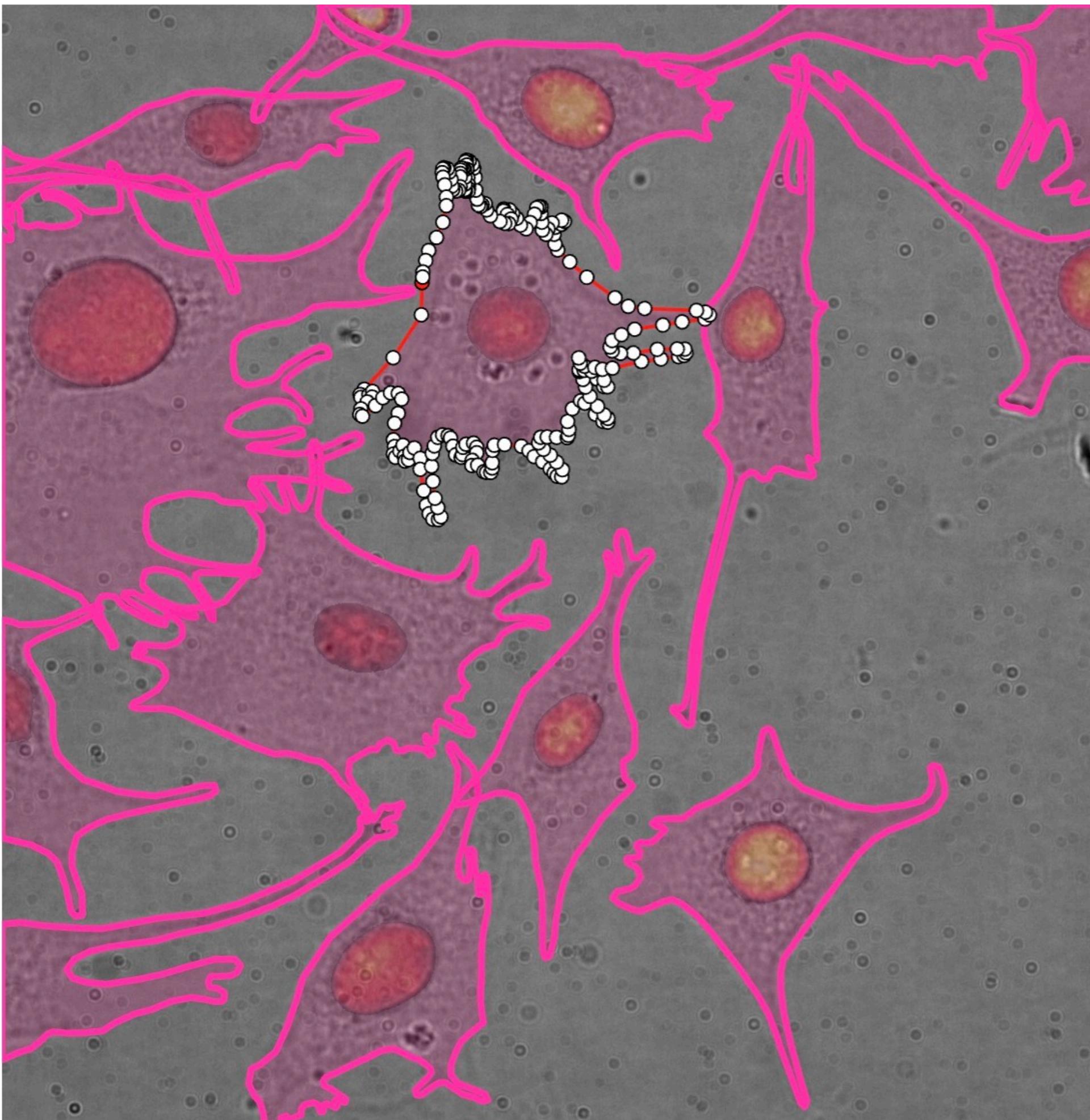
Ablations

We observe consistent gains when increasing
the query count from 100 to 300 and 500

Pixel Decoder	AP	AP ₅₀	AP ₇₅	FLOPs
+ full skip	44.7	73.9	48.9	146G
+ 1 × 1 skip concat	44.2	<u>73.8</u>	<u>48.3</u>	135G
+ 1 × 1 skip add	<u>44.3</u>	73.3	48.2	132G
+ light mask head	43.8	73.1	47.4	42G

Figure <>. Scaling the number of object queries benefits the model

Revvity-25



- **High-resolution** (1080×1080)
- **110** brightfield images
- **2,937** expert-validated cell instances
- average of **60** points per cell and up to **400** points for cells with complex morphology
- On average **27** manually labeled
- **7** cell lines

mouse fibroblasts (**NIH/3T3**)
canine kidney epithelial cells (**MDCK**)
human cervical adenocarcinoma (**HeLa**)
human breast adenocarcinoma (**MCF7**)
human lung carcinoma (**A549**)
human hepatocellular carcinoma (**HepG2**)
human fibrosarcoma (**HT1080**)