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# OCELOT: Overlapped Cell on Tissue Dataset for Histopathology

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## Paper Review

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Jan, 24, 2025

# Abstract/Conclusion

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## Context & Motivation

- Traditional cell detection focuses on high-magnification patches **only**
- Paper introduces **OCELOT**, a new dataset with overlapping patches for cell detection and tissue segmentation

## Key Contributions

- Multi-organ coverage with both cell and tissue annotations
- Multi-task learning approach improves F1-score by **up to 6.79%** over single-task baseline

# Abstract/Conclusion

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## Core Finding

- Exploiting **cell-tissue relationships** significantly boosts cell detection performance

## Broader Impact

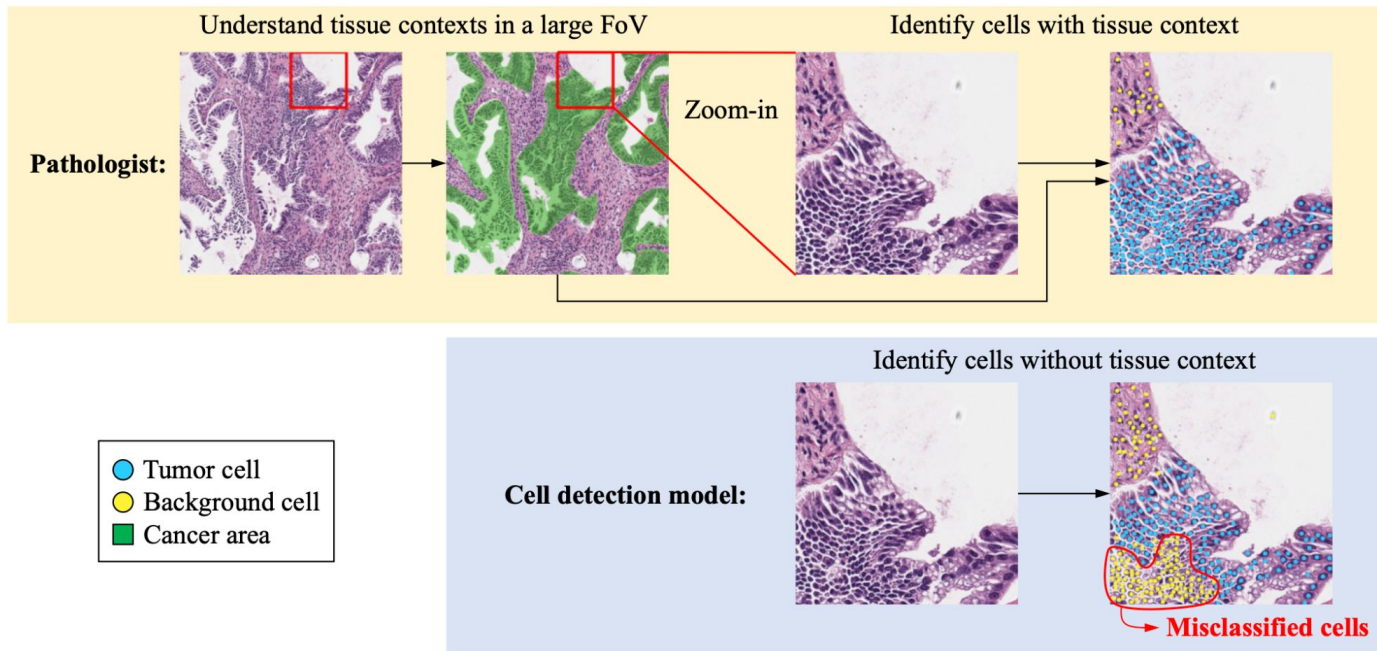
- Validate across multiple datasets, indicating **robust, generalizable improvements**
- Encourage further research on combining tissue context with cell-level analysis

## Future Direction

- Investigate two-way interaction (how **cell** information aids **tissue** segmentation)
- Explore larger-scale datasets

# Introduction

Pathologist examine **large FoV** first to understand tissue architecture, then **zoom in** to classify individual cells.



# Related Works

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## Cell Detection Datasets

- Many existing sets focus on **single organs** or **multiple organs**.

## Tissue Segmentation Datasets

- Proposed for various organs (e.g., prostate [7,23,33], colorectal [50], brain [1]).
- Often do **not overlap** with cell annotations, making **joint training** infeasible.

## Lack of Overlapping Annotations

- A few datasets have both tasks, but **no overlapping** between cell and tissue subsets.
- **TIGER** has overlapping cell/tissue annotations, but **no further attempts** at joint cell-tissue modeling.

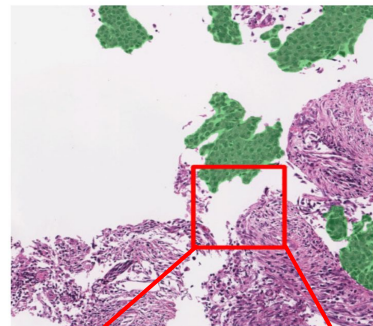
# OCELOT Dataset

## Data Composition

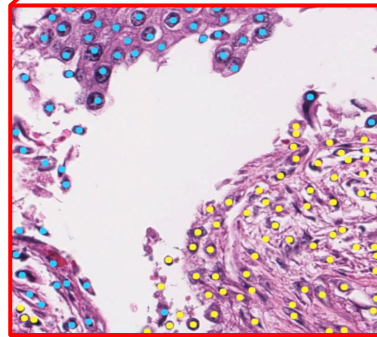
$$\mathcal{D} = \left\{ (x_s, y_s^c, x_l, y_l^t, c_x, c_y)_i \right\}_{i=1}^N$$

1.  $x_s$ : Small FoV patch
2.  $y_s^c$ : Cell annotations
3.  $x_l$ : Large FoV patch
4.  $y_l^t$ : Tissue segmentation
5.  $c_x, c_y$ : Relative coordinates of  $x_s$  within  $x_l$

- WSIs from **6** different organs.
- Patch configuration of **1024 X 1024** pixels and **4096 X 4096** pixels.



$(x_l, y_l^t)$



$(x_s, y_s^c)$

# OCELOT Dataset

## Annotation

### Cell Annotations/Small FoV Patch

- Two classes: Tumor Cell (TC) vs. Background Cell (BC).
- TC 35.01% | BC 64.99%.

### Tissue Annotations/Large FoV Patch

- Pixel-wise segmentation: Cancer Area (CA), Background (BG).
- BG 55.77% | CA 40.17% | UNK 4.06%.

### Dataset Splits

- Train, Val, Test in a **6:2:2 ratio**

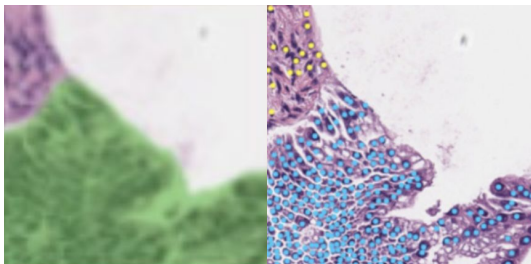
Organs	# Slides			# Patch Pairs		
	Train	Val	Test	Train	Val	Test
Kidney	48	15	18	125	41	41
Head-neck	13	5	6	27	9	10
Prostate	26	12	10	50	17	16
Stomach	15	6	5	36	12	12
Endometrium	38	13	13	86	29	25
Bladder	35	14	14	82	29	26
<b>Total</b>	175	65	66	406	137	130

Table 2. **Dataset size per organ and data subset.**

# Empirical Analysis

## Interrelation between cell and tissue classes

- This insights are further corroborated by two main empirical observations
- Verified that in OCELOT, around 93% of TC are located within CA



Cell	Tissue	
	CA	non-CA
TC	67.7K	5.4K
BC	6.4K	35.2K

(a) OCELOT

Cell	Tissue	
	ST	non-ST
LC	45.4K	5.4K

(b) TIGER

Table 3. **Cell counts based on the tissue class.** Each value stands for the number of cells located inside the tissue area. *TC*, *BC*, *LC*, *CA*, and *ST* stand for Tumor Cell, Background Cell, Lymphocyte Cell, Cancer Area tissue, and Stroma tissue, respectively.

CA	non-CA
40.17%	59.83%

(a) OCELOT

ST	non-ST
30.79%	69.21%

(b) TIGER

Table 4. **Pixel ratio among tissue classes.** *CA*, and *ST* stand for Cancer Area tissue, and Stroma tissue, respectively.

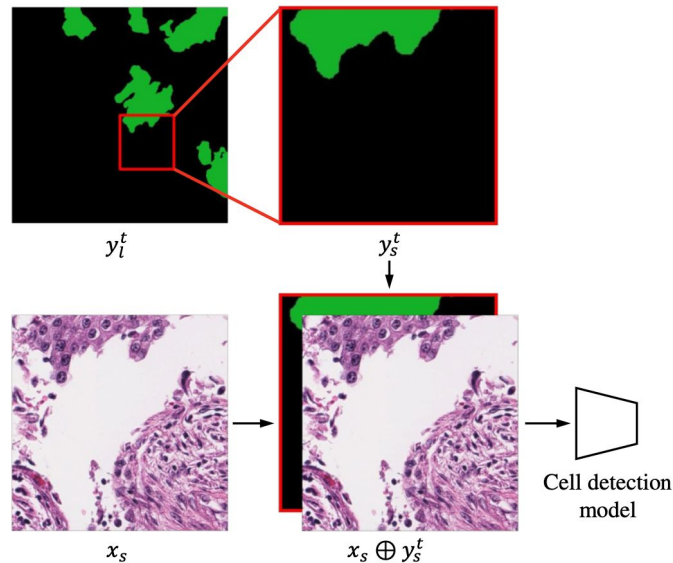


# Tissue-label Leaking Model

**Exploratory experiment** to see how using tissue labels affects cell detection.

- Tissue-label Leaking Model improves F1-score on OCELOT by +7.69% and +9.76%.
- Not feasible in real-world use, because true tissue labels are unknown at inference.

1. **Crop & Upsample** the tissue annotation ( $y_l^t$ ) to match the small patch size ( $x_s$ ).
2. **Concatenate** ( $x_s \oplus y_s^t$ ) along the channel dimension.
3. **Train** a cell detection model with this combined input.

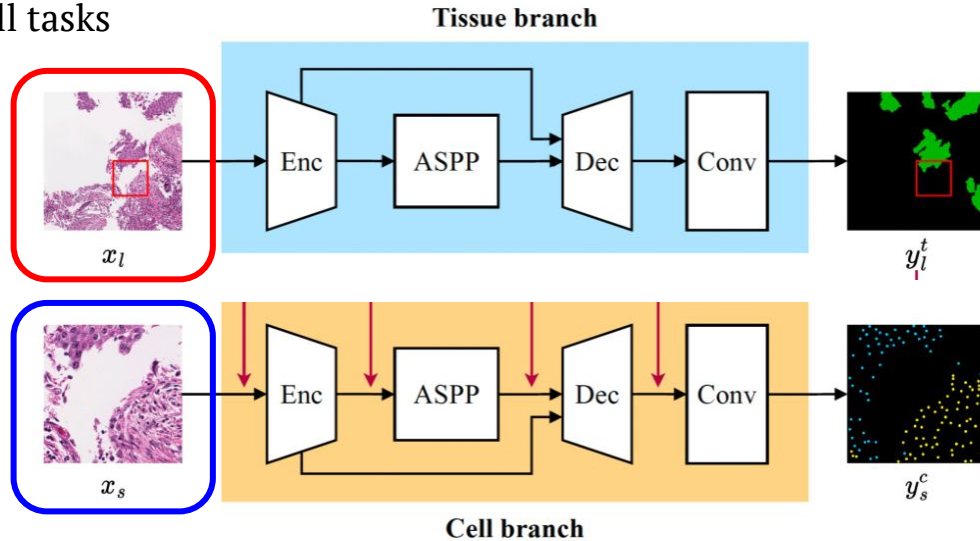


# Method

## Dual Branch Architecture

- Simple U-net segmentation architectures
- Separated corresponding to tissue and cell tasks

$$\mathcal{D} = \left\{ \left( \boxed{x_s, y_s^c}, \boxed{x_l, y_l^t}, c_x, c_y \right)_i \right\}_{i=1}^N$$

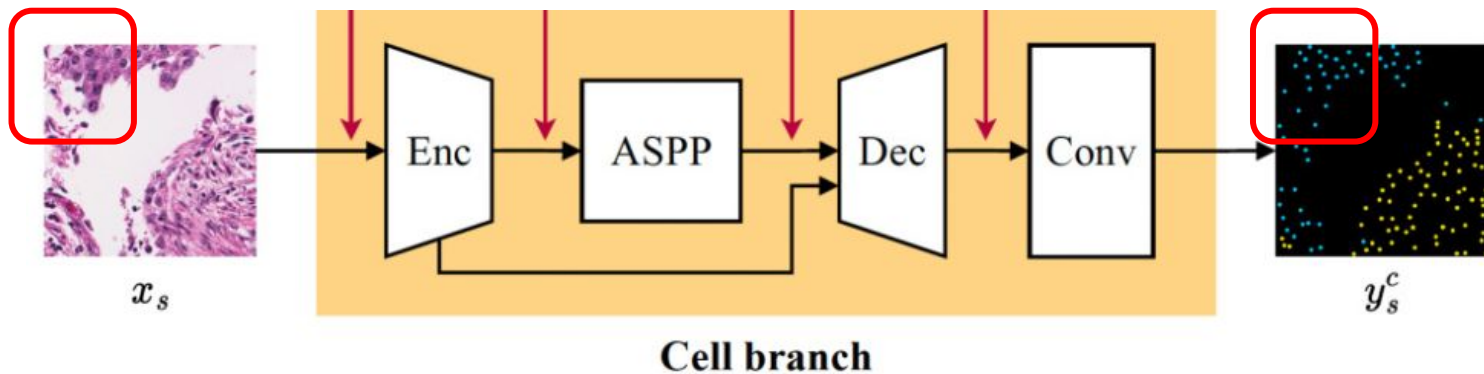


# Method

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## Dual Branch Architecture

- Especially **cell segmentation branch**, make the fixed-radius annotation centered on cell point
- Inference, output as point prediction using predicted **cell probability maps**



# Method

## Tissue-prediction injection model

- Simple extensions of Tissue label leaking model
- Injection is considered in **four possible points**

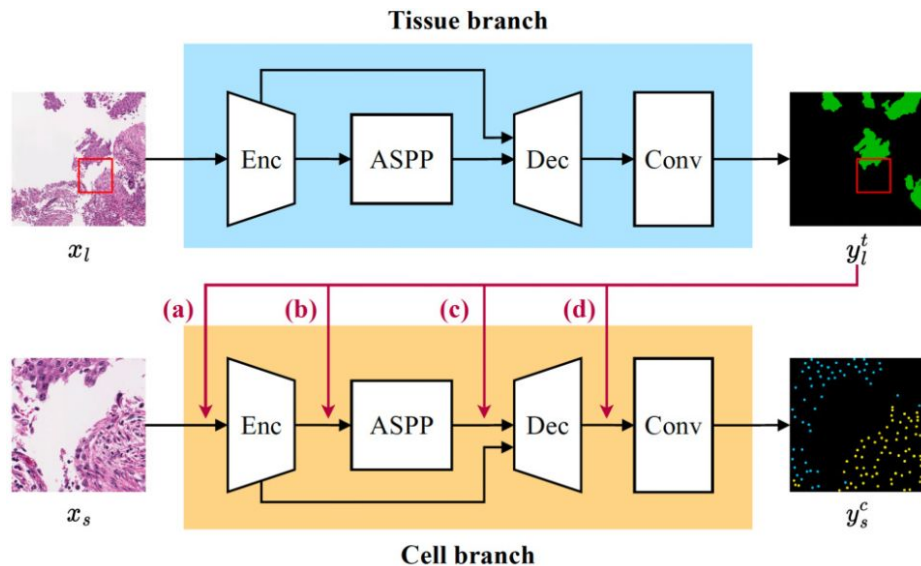
*a. Pred-to-input*

*b. Pred-to-afterEnc*

*c. Pred-to-afterASPP*

*d. Pred-to-afterDec*

- **Align the cell and tissue contents then, just concatenate them** in the channel dimensions

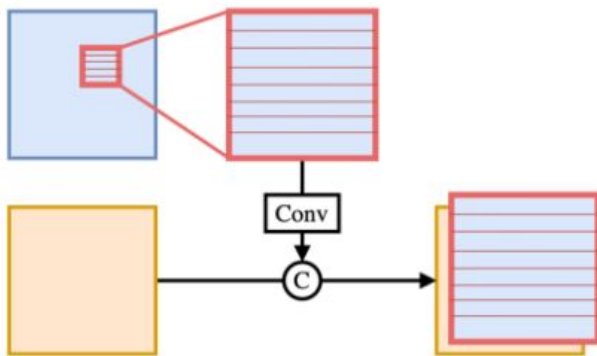


# Method

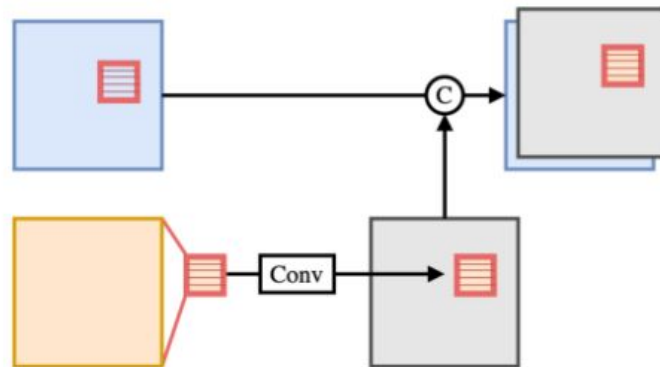
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## Cell-Tissue Feature Sharing Model

- Simplify the **Bi-directional injection logic**
- Each corresponding region go through the shallow 3x3 conv and **concatenated**



(a) Tissue to Cell

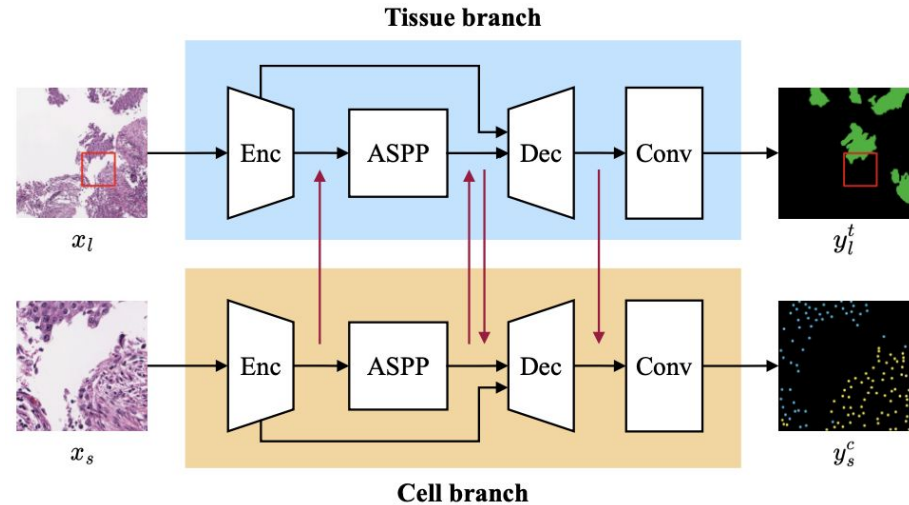
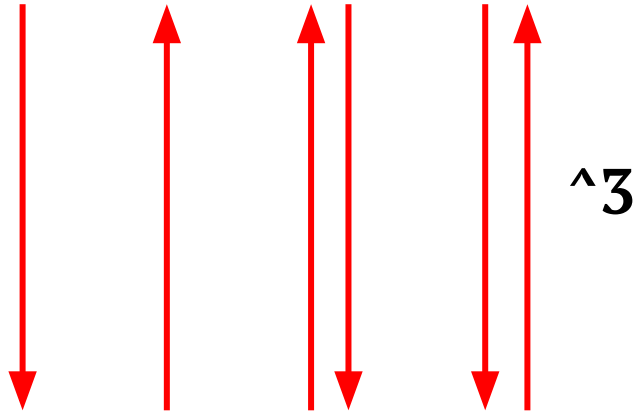


(b) Cell to Tissue

# Method

## Cell-Tissue Feature Sharing Model

- Found the best performing model within  $4^3$  experiments
- Denominated Cell-Tissue Feature Sharing Model



# Experiments and Results

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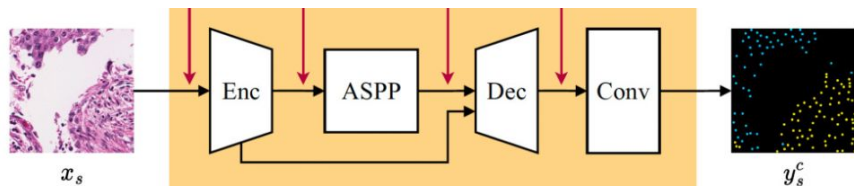
## Implementation Details

Aspect	Details
Model Architecture	Both cell and tissue branches based on DeepLabV3+ with a ResNet-34 encoder
Datasets	OCELOT, TIGER, CARP
Training Epochs	300 (OCELOT), 150 (TIGER), 100 (CARP)
Optimizer	Adam
Learning Rate Range	$[5 \times 10^{-5}, 2 \times 10^{-3}]$
Model Selection	Best-performing model on the validation set is used for test set evaluation
Repetitions	All experiments repeated 5 times
Metrics Reporting	Mean and 95% confidence interval of performance metrics
Additional Details	More implementation details available in the supplementary material

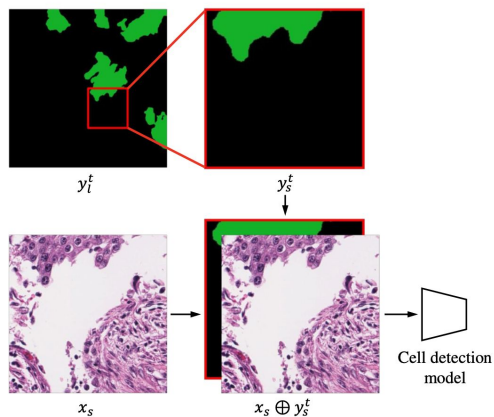
# Experiments and Results

## Approached Models

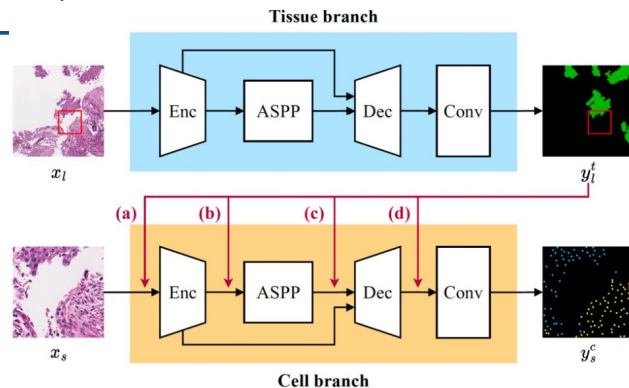
### Cell-Only



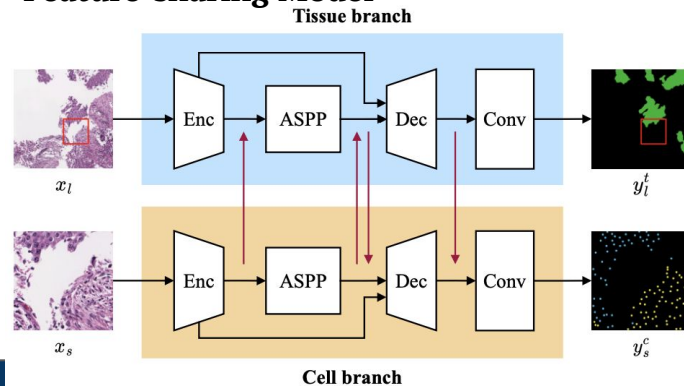
### Tissue-label Leaking



## Injection Models



## Feature-sharing Model





# Experiments and Results

## Main Results

### F1 scores per Cell detection models

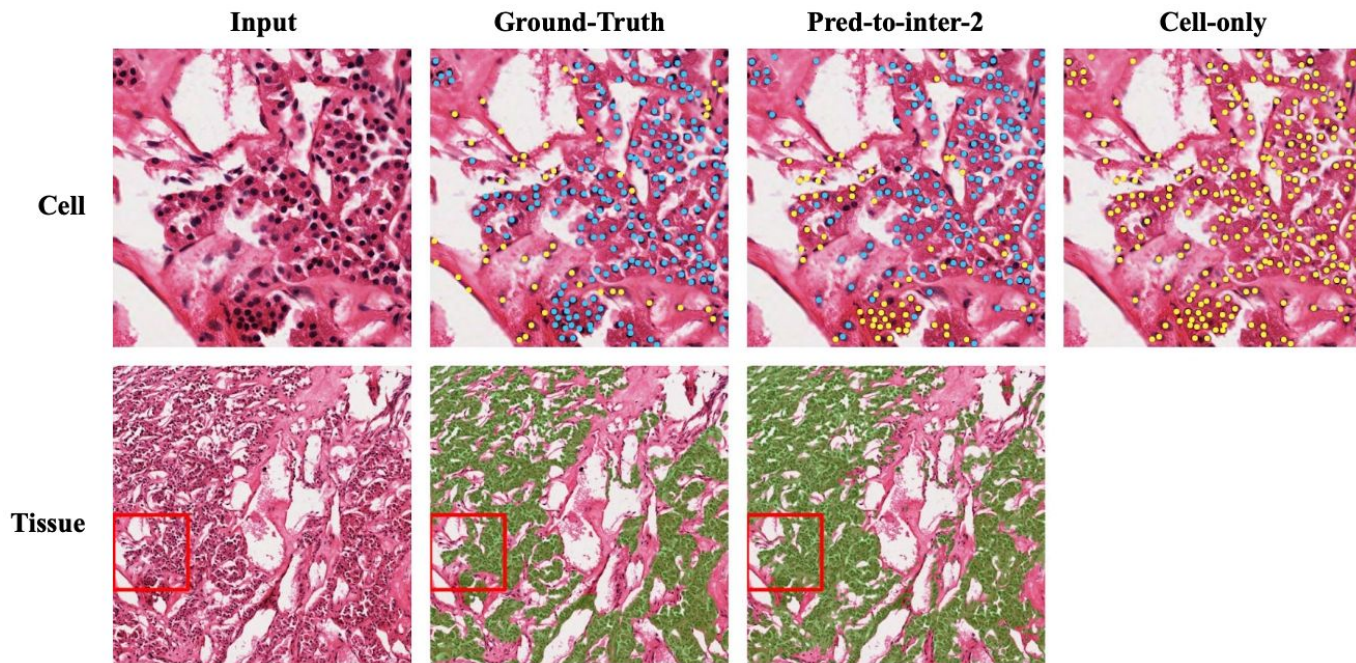
Method	OCELOT		TIGER		CARP	
	Val	Test	Val	Test	Val	Test
<i>Cell-only</i>	68.87 $\pm$ 1.76	64.44 $\pm$ 1.82	63.89 $\pm$ 1.39	53.82 $\pm$ 1.23	78.48 $\pm$ 0.69	70.96 $\pm$ 1.47
<i>Pred-to-input</i>	<b>73.36<math>\pm</math>0.59</b>	69.65 $\pm$ 3.93	<u>66.00<math>\pm</math>2.00</u>	53.29 $\pm$ 1.30	79.46 $\pm$ 0.79	72.98 $\pm$ 0.82
<i>Pred-to-inter-1</i>	<u>72.74<math>\pm</math>0.50</u>	<u>70.54<math>\pm</math>2.20</u>	<b>66.19<math>\pm</math>1.02</b>	<b>55.87<math>\pm</math>1.78</b>	<u>79.74<math>\pm</math>0.80</u>	<u>73.05<math>\pm</math>0.69</u>
<i>Pred-to-inter-2</i>	72.68 $\pm$ 1.58	<b>71.23<math>\pm</math>0.96</b>	65.43 $\pm$ 1.14	<u>54.75<math>\pm</math>2.25</u>	<b>79.87<math>\pm</math>0.78</b>	<b>73.14<math>\pm</math>1.53</b>
<i>Pred-to-output</i>	66.85 $\pm$ 5.62	65.05 $\pm$ 3.72	63.02 $\pm$ 0.16	53.32 $\pm$ 0.42	78.92 $\pm$ 0.60	72.61 $\pm$ 0.95
<i>Feature-sharing</i>	72.30 $\pm$ 0.73	68.91 $\pm$ 2.52	65.64 $\pm$ 1.07	55.10 $\pm$ 2.18	79.38 $\pm$ 0.74	73.00 $\pm$ 0.33
<i>Tissue-label leaking</i>	76.56 $\pm$ 0.80	74.20 $\pm$ 0.91	69.71 $\pm$ 0.61	61.66 $\pm$ 1.16	80.13 $\pm$ 1.04	72.97 $\pm$ 0.49

Assume that it's too late

# Experiments and Results

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## Main Results



# Experiments and Results

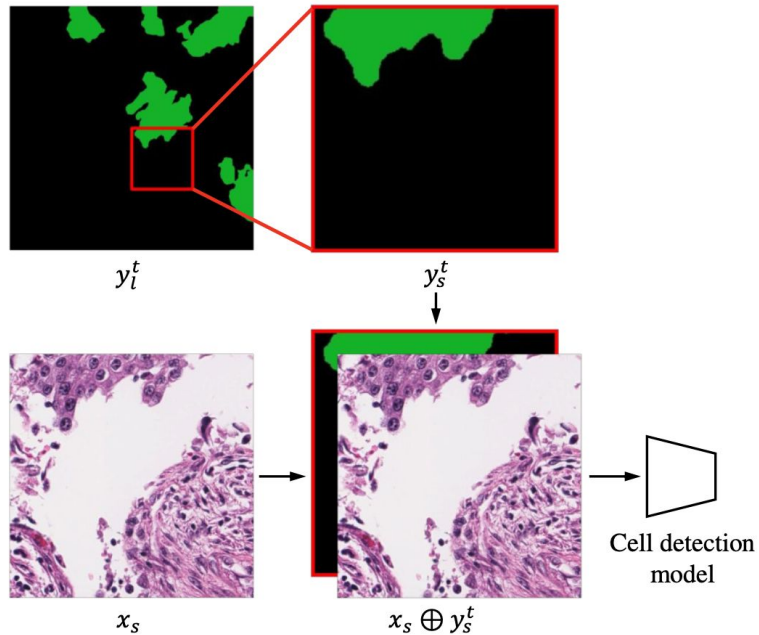
## Main Results

### F1 scores per Cell detection models within the Organs

Method	population (130)	kidney (41)	endometrium (25)	bladder (26)	prostate (16)	stomach (12)	head-neck (10)
<i>Cell-only</i>	64.44 $\pm$ 1.82	64.12 $\pm$ 3.41	66.88 $\pm$ 3.71	59.42 $\pm$ 5.61	65.46 $\pm$ 1.64	66.19 $\pm$ 8.93	59.24 $\pm$ 5.04
<i>Pred-to-input</i>	69.65 $\pm$ 3.93	63.37 $\pm$ 3.27	73.31 $\pm$ 6.35	63.61 $\pm$ 4.55	68.36 $\pm$ 8.61	69.34 $\pm$ 7.15	<b>75.28<math>\pm</math>0.82</b>
<i>Pred-to-inter-1</i>	70.54 $\pm$ 2.20	66.62 $\pm$ 7.30	73.05 $\pm$ 4.14	64.35 $\pm$ 3.59	<b>70.20<math>\pm</math>2.56</b>	<b>71.55<math>\pm</math>5.21</b>	74.50 $\pm$ 1.52
<i>Pred-to-inter-2</i>	<b>71.23<math>\pm</math>0.96</b>	<b>68.94<math>\pm</math>5.65</b>	<b>75.15<math>\pm</math>2.70</b>	<b>64.94<math>\pm</math>2.34</b>	68.35 $\pm$ 8.83	70.29 $\pm$ 0.81	73.74 $\pm$ 1.72
<i>Pred-to-output</i>	65.05 $\pm$ 3.72	63.38 $\pm$ 4.48	68.21 $\pm$ 4.11	59.81 $\pm$ 3.96	64.18 $\pm$ 8.41	67.51 $\pm$ 6.39	60.88 $\pm$ 6.77
<i>Feature-sharing</i>	68.91 $\pm$ 2.52	64.97 $\pm$ 5.33	71.28 $\pm$ 5.30	63.21 $\pm$ 5.31	66.25 $\pm$ 9.52	69.79 $\pm$ 2.25	73.88 $\pm$ 4.39
<i>Tissue-label leaking</i>	74.20 $\pm$ 0.91	75.75 $\pm$ 1.97	72.71 $\pm$ 1.12	71.18 $\pm$ 0.93	74.56 $\pm$ 1.25	75.24 $\pm$ 1.71	75.78 $\pm$ 0.46

# Discussions

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Think Backward..

- The most of cells were on the tissues
- Tissue area can be defined as the associations of cells?
- Reverse Cell-Tissue leaking model!

**QnA**