

# Joint Class-Affinity Loss Correction for Robust Medical Image Segmentation with Noisy Labels

**Xiaoqing Guo**

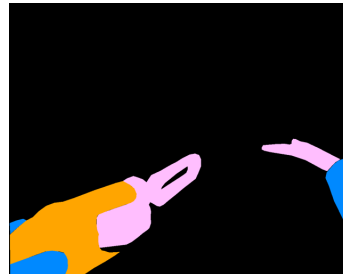
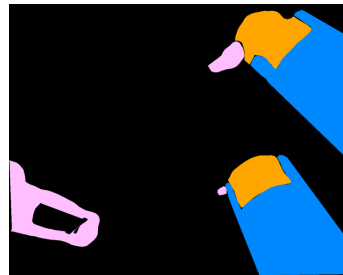
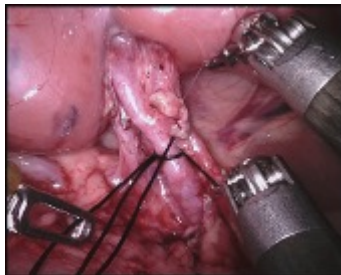
**Yixuan Yuan<sup>†</sup>**

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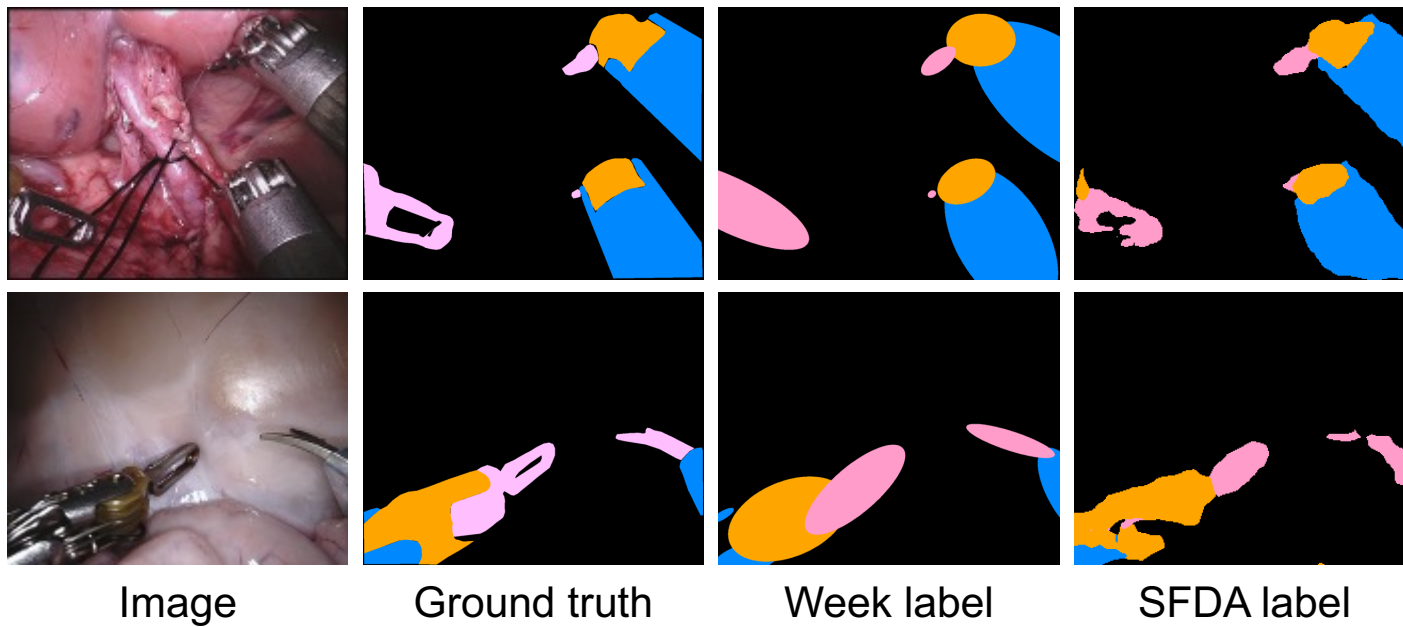
- **Background:**



Image

Ground truth

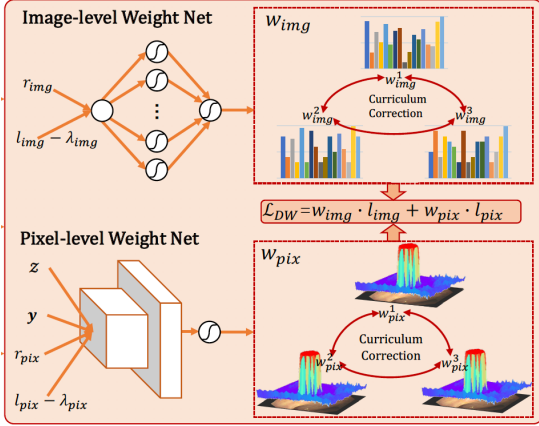
- Background:



*SFDA: source-free domain adaptation*

- Existing approaches:

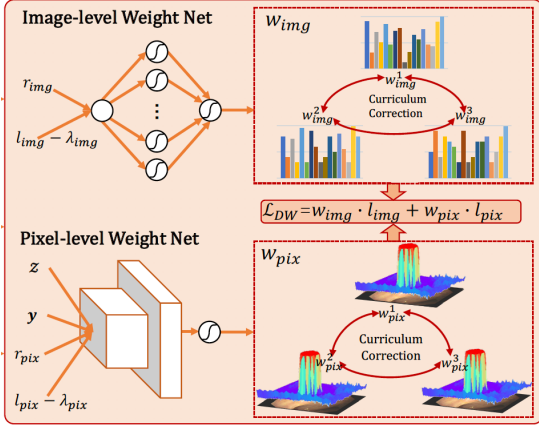
## Existing approaches:



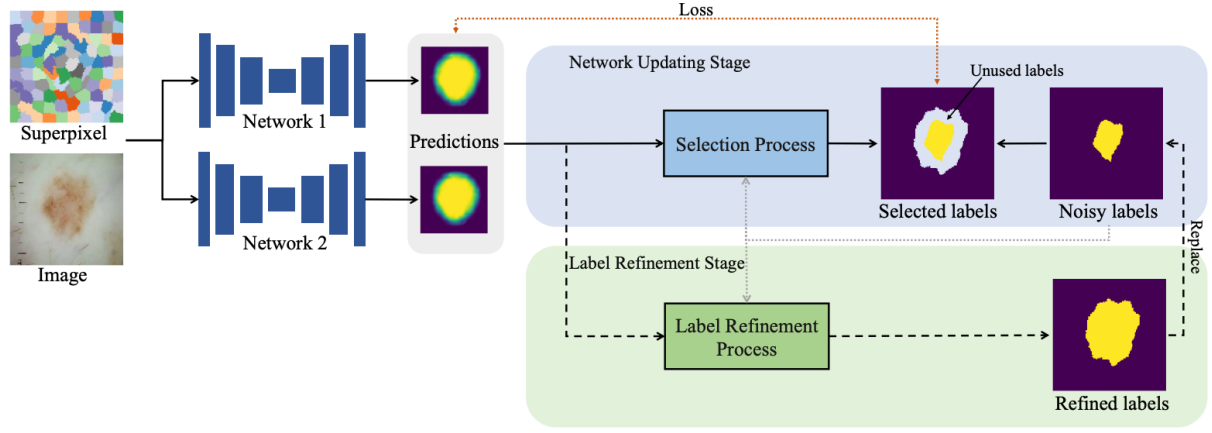
Resampling and reweighting strategy [1]

[1] Guo, X., Chen, Z., Liu, J., Yuan, Y. Non-equivalent images and pixels: Confidence-aware resampling with meta-learning mixup for polyp segmentation. Medical Image Analysis, 78, 102394, (2022).

## Existing approaches:



Resampling and reweighting strategy [1]

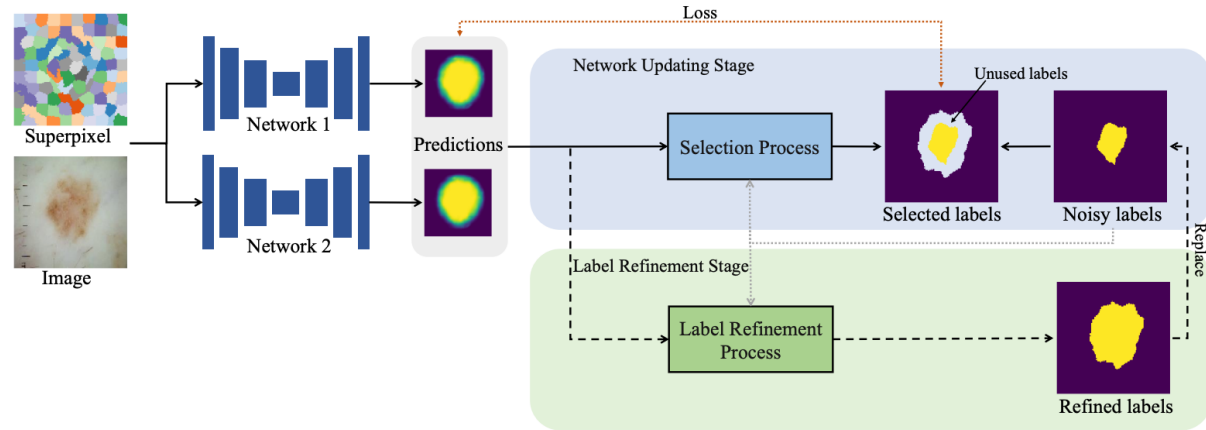
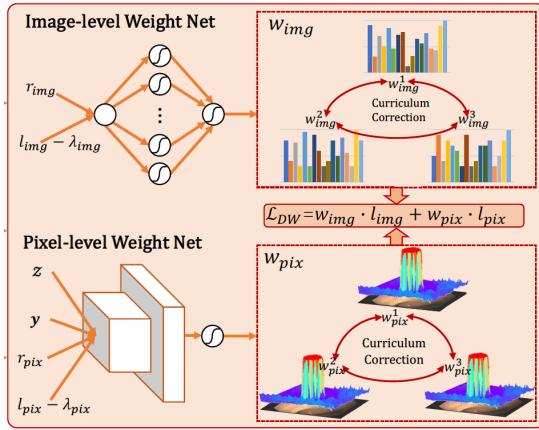


Label Correction [2]

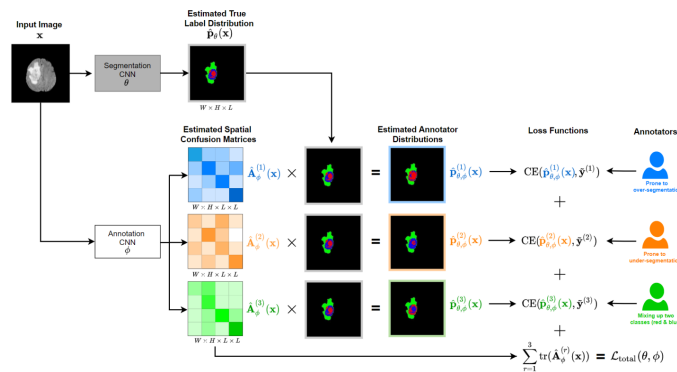
[1] Guo, X., Chen, Z., Liu, J., Yuan, Y. Non-equivalent images and pixels: Confidence-aware resampling with meta-learning mixup for polyp segmentation. Medical Image Analysis, 78, 102394, (2022).  
[2] Li, S., Gao, Z., He, X.: Superpixel-guided iterative learning from noisy labels for medical image segmentation. In: MICCAI. pp. 525–535. Springer (2021)

# Introduction

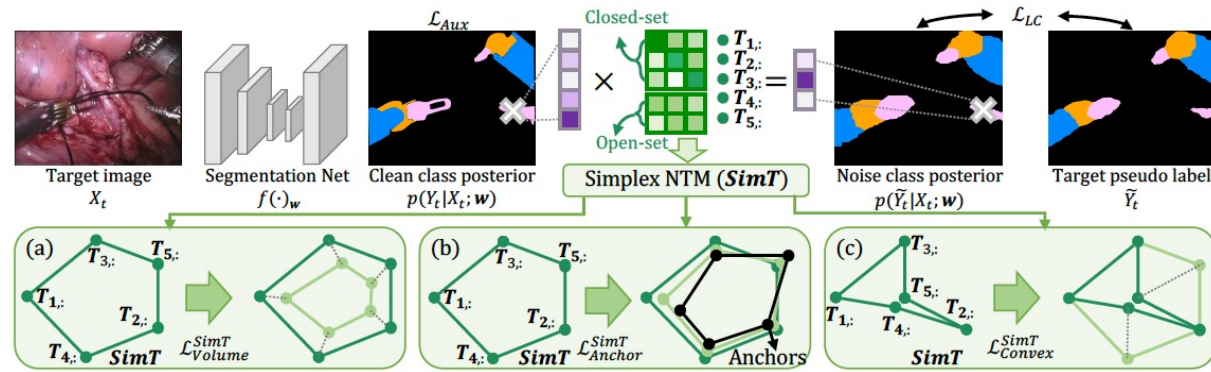
## Existing approaches:



## Resampling and reweighting strategy [1]



## Label Correction [2]



## Loss correction w/ confusion matrix [3]

## Loss correction w/ noise transition matrix (NTM) [4]

- [1] Guo, X., Chen, Z., Liu, J., Yuan, Y. Non-equivalent images and pixels: Confidence-aware resampling with meta-learning mixup for polyp segmentation. *Medical Image Analysis*, 78, 102394, (2022).  
 [2] Li, S., Gao, Z., He, X.: Superpixel-guided iterative learning from noisy labels for medical image segmentation. In: MICCAI. pp. 525–535. Springer (2021)  
 [3] Zhang, L., Tanno, et al., Alexander, D.: Disentangling human error from ground truth in segmentation of medical images. *NeurIPS* 33, 15750–15762 (2020)  
 [4] Guo, X., Liu, J., Liu, T., Yuan, Y.: Simt: Handling open-set noise for domain adaptive semantic segmentation. In: CVPR (2022)

# Motivation

## • Motivation

- The pair-wise manner reduces label noise rate

0	0	1
1	2	2
3	3	0

Clean label

0	1	1
2	2	3
3	0	0

Noisy label

2/3			1/3
	1/2	1/2	
		1/2	1/2
			1/2

Class-level NTM

$T_C$

1	1	0	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	0	1
0	0	1	1	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	0
0	0	0	0	1	1	0	0	0	0
0	0	0	0	1	1	0	0	0	0
0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	1	1	0	0
1	1	0	0	0	0	0	0	0	1

Clean affinity label

1	0	0	0	0	0	0	0	1	1
0	1	1	0	0	0	0	0	0	0
0	1	1	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	1	1	0	0	0
1	0	0	0	0	0	0	0	1	1
1	0	0	0	0	0	0	0	1	1

Noisy affinity label

11/20	9/20
10/61	50/61

Affinity-level NTM

$T_A$



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		1/2	1/2
			1/2

Class-level NTM

$T_C$

1	1	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	1
0	0	1	1	0	0	0	0	0
0	0	1	1	0	0	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	1	1	0
1	1	0	0	0	0	0	0	1

Clean affinity label

1	0	0	0	0	0	0	1	1
0	1	1	0	0	0	0	0	0
0	1	1	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0
0	0	0	1	1	0	0	0	0
0	0	0	0	0	1	1	0	0
0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	1	1	0
1	0	0	0	0	0	0	1	1
1	0	0	0	0	0	0	1	1

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		1/2	1/2
			1/2

Class-level NTM

$T_C$

1	1	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	1
0	0	1	1	0	0	0	0	0
0	0	1	1	0	0	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	1	1	0
1	1	0	0	0	0	0	0	1

Clean affinity label

1	0	0	0	0	0	0	1	1
0	1	1	0	0	0	0	0	0
0	1	1	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0
0	0	0	1	1	0	0	0	0
0	0	0	0	0	1	1	0	0
0	0	0	0	0	1	1	0	0
1	0	0	0	0	0	0	1	1
1	0	0	0	0	0	0	1	1

Noisy affinity label

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Class-level NTM

$T_C$

Noise rate:  
**44%**

11/20	9/20
10/61	50/61

Affinity-level NTM

$T_A$

Noise rate:  
**23%**

1	1	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	1
0	0	1	1	0	0	0	0	0
0	0	1	1	0	0	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	1	1	0
1	1	0	0	0	0	0	0	1

Clean affinity label

1	0	0	0	0	0	0	1	1
0	1	1	0	0	0	0	0	0
0	1	1	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0
0	0	0	1	1	0	0	0	0
0	0	0	0	0	1	1	0	0
0	0	0	0	0	1	1	0	0
1	0	0	0	0	0	0	1	1
1	0	0	0	0	0	0	1	1

Noisy affinity label

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	1/2	1/2	
		1/2	1/2
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Class-level NTM

$T_C$

$$\mathbf{T}_{C \rightarrow A}(0, 1) = \frac{\sum_m [N_m \sum_n \mathbf{T}_C(m, n)]^2 - \sum_m (N_m)^2 \|\mathbf{T}_C\|_2^2}{\sum_m [N_m (\sum_m N_m - N_m)]}$$

$$\mathbf{T}_{C \rightarrow A}(0, 0) = 1 - \mathbf{T}_{C \rightarrow A}(0, 1),$$

$$\mathbf{T}_{C \rightarrow A}(1, 1) = \frac{\sum_m (N_m)^2 \|\mathbf{T}_C\|_2^2}{\sum_m (N_m)^2},$$

$$\mathbf{T}_{C \rightarrow A}(1, 0) = 1 - \mathbf{T}_{C \rightarrow A}(1, 1).$$

Noise rate:  
44%

11/20	9/20
10/61	50/61

Affinity-level NTM

$T_A$

Noise rate:  
23%

1	1	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	1
0	0	1	1	0	0	0	0	0
0	0	1	1	0	0	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	1	1	0
1	1	0	0	0	0	0	0	1

Clean affinity label

1	0	0	0	0	0	0	0	1	1
0	1	1	0	0	0	0	0	0	0
0	1	1	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	1	1	0	0	0
1	0	0	0	0	0	0	1	1	1
1	0	0	0	0	0	0	0	1	1

Noisy affinity label

# Motivation

## • Motivation

- The pair-wise manner reduces label noise rate
- Unify the pixel-wise and pair-wise manners

0	0	1
1	2	2
3	3	0

Clean label

0	1	1
2	2	3
3	0	0

Noisy label

2/3			1/3
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Class-level NTM

$T_C$

$$T_{C \rightarrow A}(0, 1) = \frac{\sum_m [N_m \sum_n T_C(m, n)]^2 - \sum_m (N_m)^2 \|T_C\|_2^2}{\sum_m [N_m (\sum_m N_m - N_m)]}$$

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$$T_{C \rightarrow A}(1, 0) = 1 - T_{C \rightarrow A}(1, 1).$$

Noise rate:  
44%

11/20	9/20
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Affinity-level NTM

$T_A$

Noise rate:  
23%

1	1	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	1
0	0	1	1	0	0	0	0	0
0	0	1	1	0	0	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	1	1	0
1	1	0	0	0	0	0	0	1

Clean affinity label

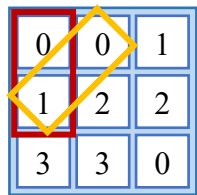
1	0	0	0	0	0	0	0	1	1
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0	1	1	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	1	1	0	0	0
1	0	0	0	0	0	0	1	1	1
1	0	0	0	0	0	0	0	1	1

Noisy affinity label

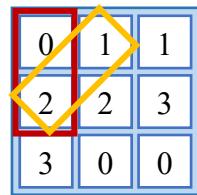
# Motivation

## • Motivation

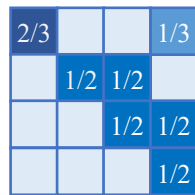
- The pair-wise manner reduces label noise rate
- Unify the pixel-wise and pair-wise manners
- The first effort in exploiting the affinity relation between pixels within an image for noisy mitigation



Clean label



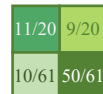
Noisy label



Class-level NTM

$T_C$

Noise rate:  
**44%**



Affinity-level NTM

$T_A$

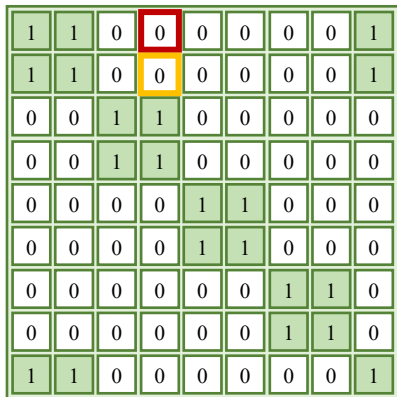
Noise rate:  
**23%**

$$T_{C \rightarrow A}(0, 1) = \frac{\sum_m [N_m \sum_n T_C(m, n)]^2 - \sum_m (N_m)^2 \|T_C\|_2^2}{\sum_m [N_m (\sum_m N_m - N_m)]}$$

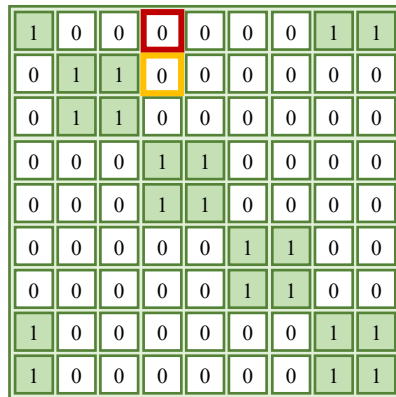
$$T_{C \rightarrow A}(0, 0) = 1 - T_{C \rightarrow A}(0, 1),$$

$$T_{C \rightarrow A}(1, 1) = \frac{\sum_m (N_m)^2 \|T_C\|_2^2}{\sum_m (N_m)^2},$$

$$T_{C \rightarrow A}(1, 0) = 1 - T_{C \rightarrow A}(1, 1).$$



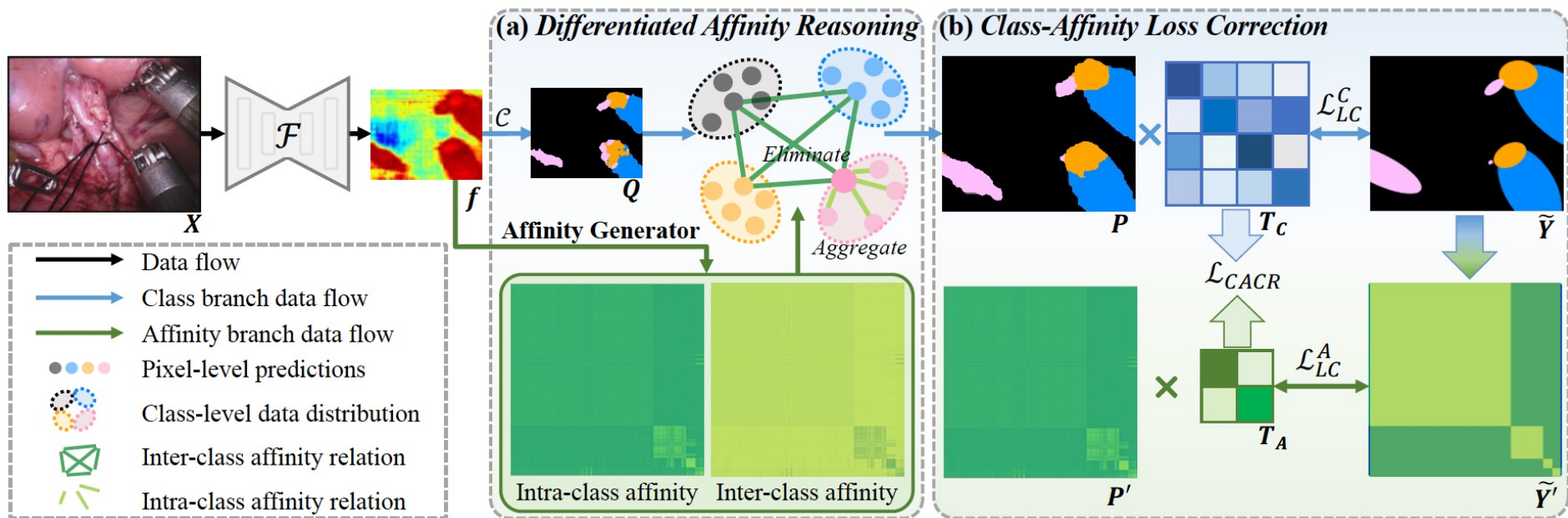
Clean affinity label



Noisy affinity label

## • Our approach: Joint Class-Affinity Loss Correction (JCAS)

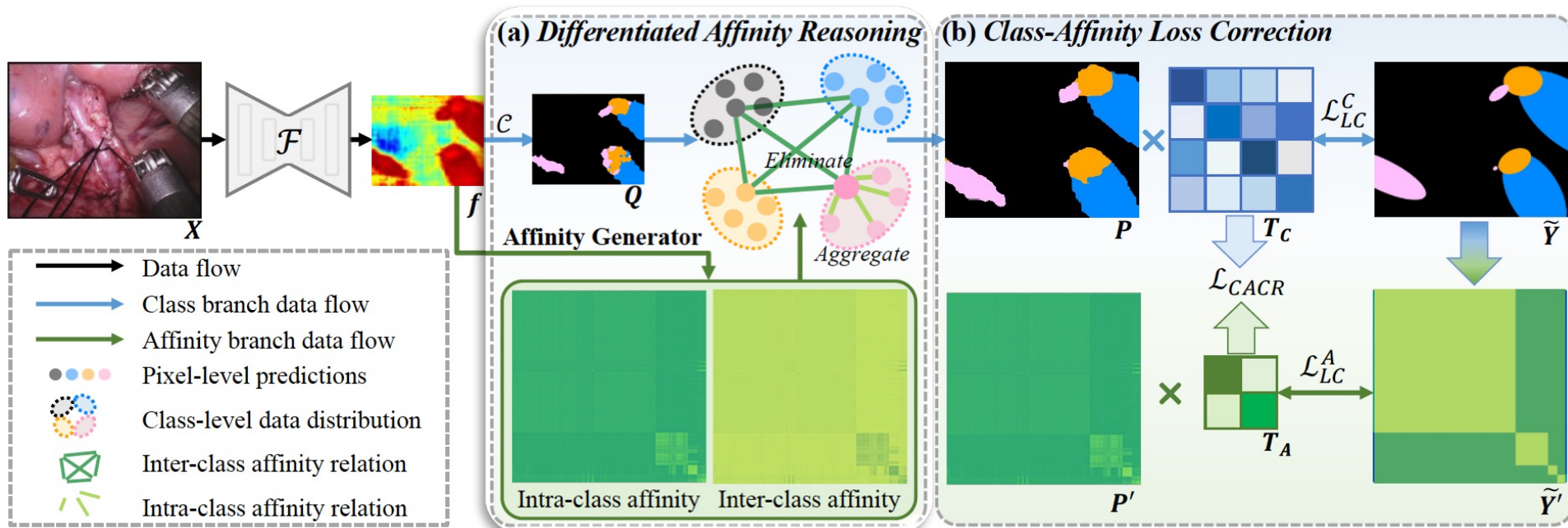
- Pixel-wise supervision signal derived from class label preserves semantics
- Pair-wise supervision signal derived from affinity label reduces noise rate



## • Our approach: Joint Class-Affinity Loss Correction (JCAS)

- Pixel-wise supervision signal derived from class label preserves semantics
- Pair-wise supervision signal derived from affinity label reduces noise rate
- Differentiated affinity reasoning (DAR) module

$$P_{intra}(k_1) = P(k_1) + \sum_{k_2}^n P'(k_1, k_2)Q(k_2); P_{inter}(k_1) = P(k_1) - \sum_{k_2}^n P'_{re}(k_1, k_2)Q(k_2)$$



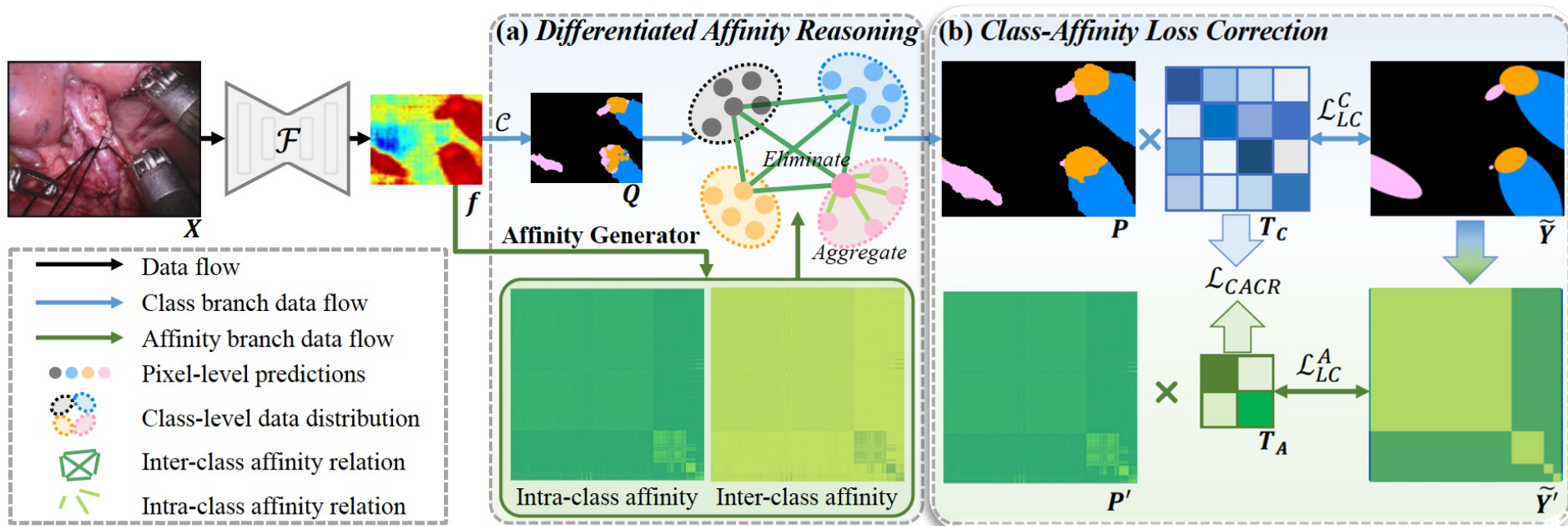


## • Our approach: Joint Class-Affinity Loss Correction (JCAS)

- Pixel-wise supervision signal derived from class label preserves semantics
- Pair-wise supervision signal derived from affinity label reduces noise rate
- Differentiated affinity reasoning (DAR) module

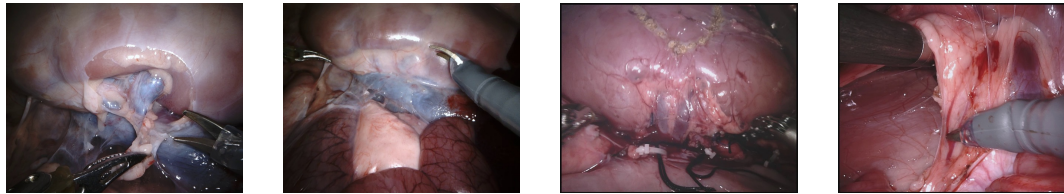
$$P_{intra}(k_1) = P(k_1) + \sum_{k_2}^n P'(k_1, k_2)Q(k_2); P_{inter}(k_1) = P(k_1) - \sum_{k_2}^n P'_{re}(k_1, k_2)Q(k_2)$$

- Class-affinity loss correction (CALC) strategy  $\mathcal{L}_{CACR} = \|T_{C \rightarrow A} - T_A\|_2$



- **Datasets:**

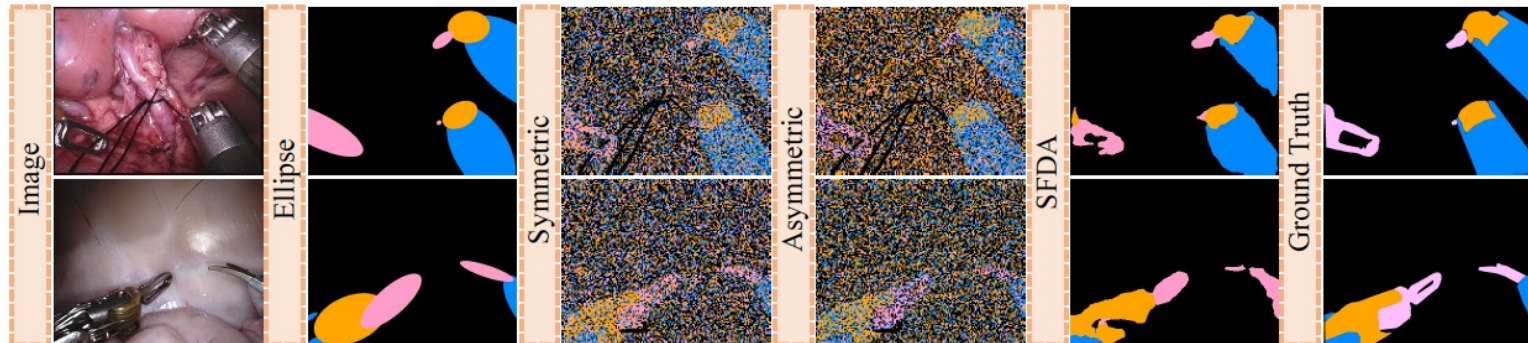
- Endovis18: 2235 images (1639 training images & 596 test images)  
3 instrument part classes (shaft, wrist and clasper classes)



- Noise patterns:

synthetic label noise (ellipse, symmetric and asymmetric noises)

real-world label noise (noisy pseudo labels in source-free domain adaptation (SFDA))

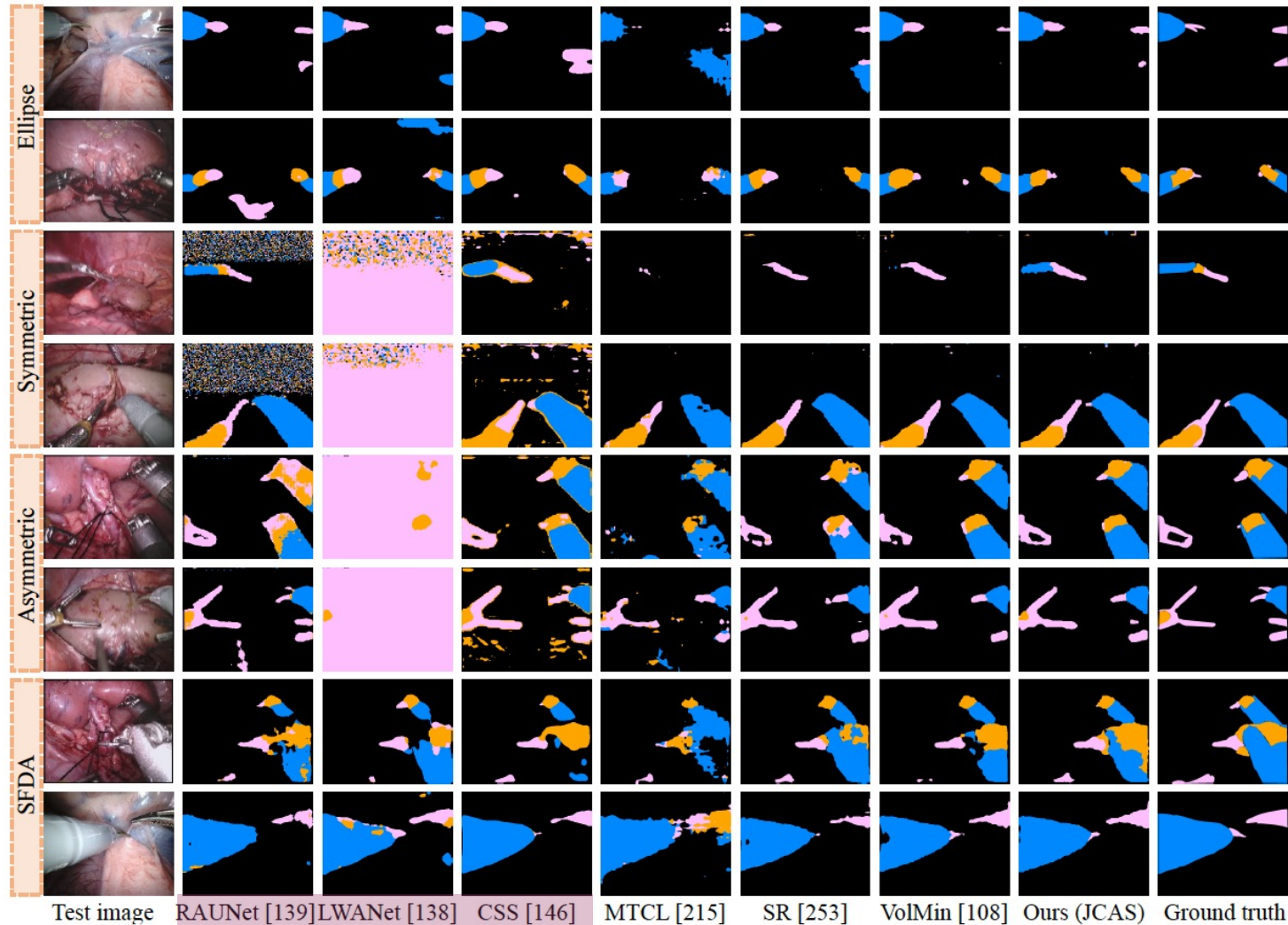


- **Evaluation metrics:**

*Dice, Jac* per class

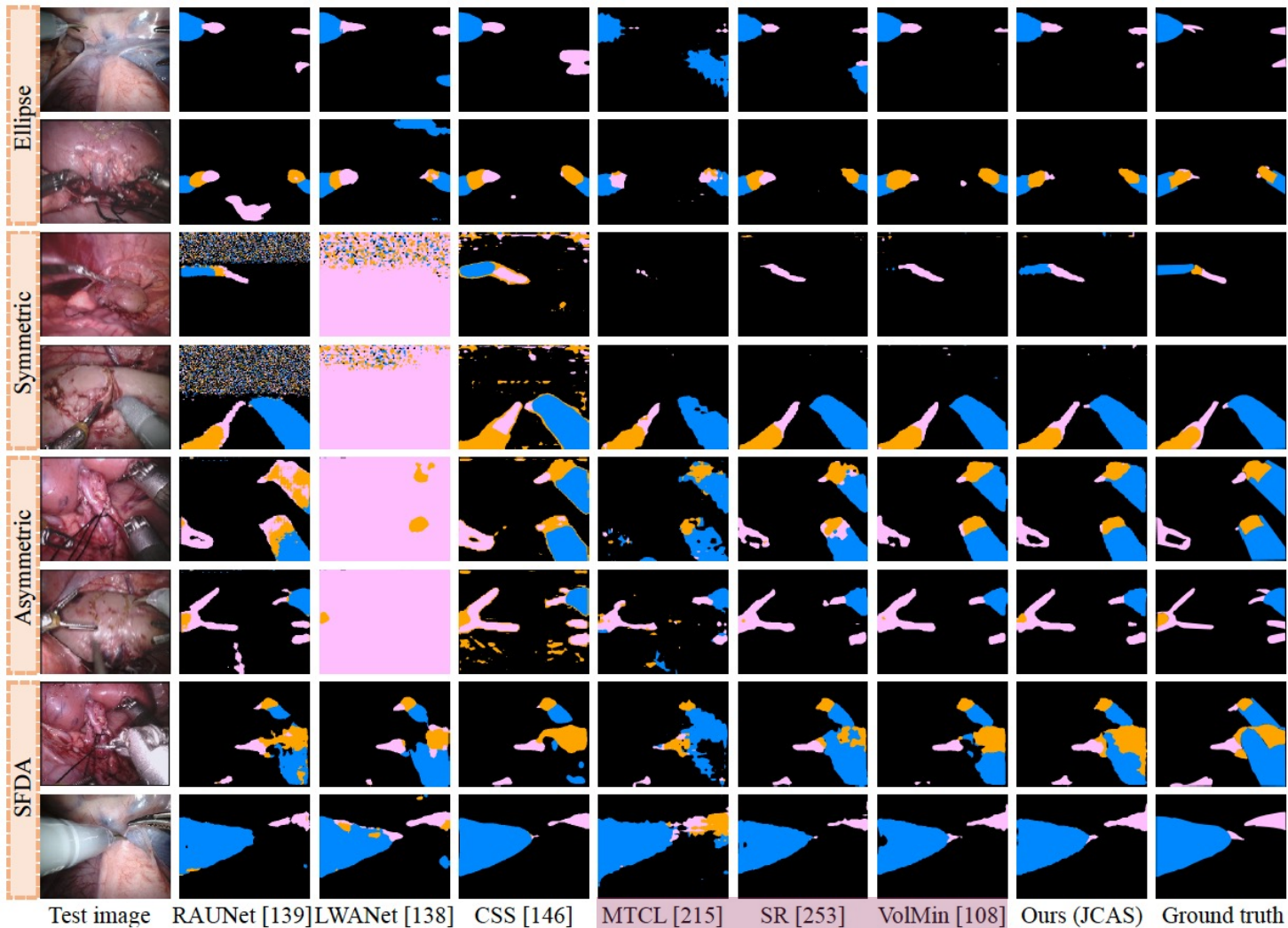
- Experimental results

- Superior to state-of-the-art methods



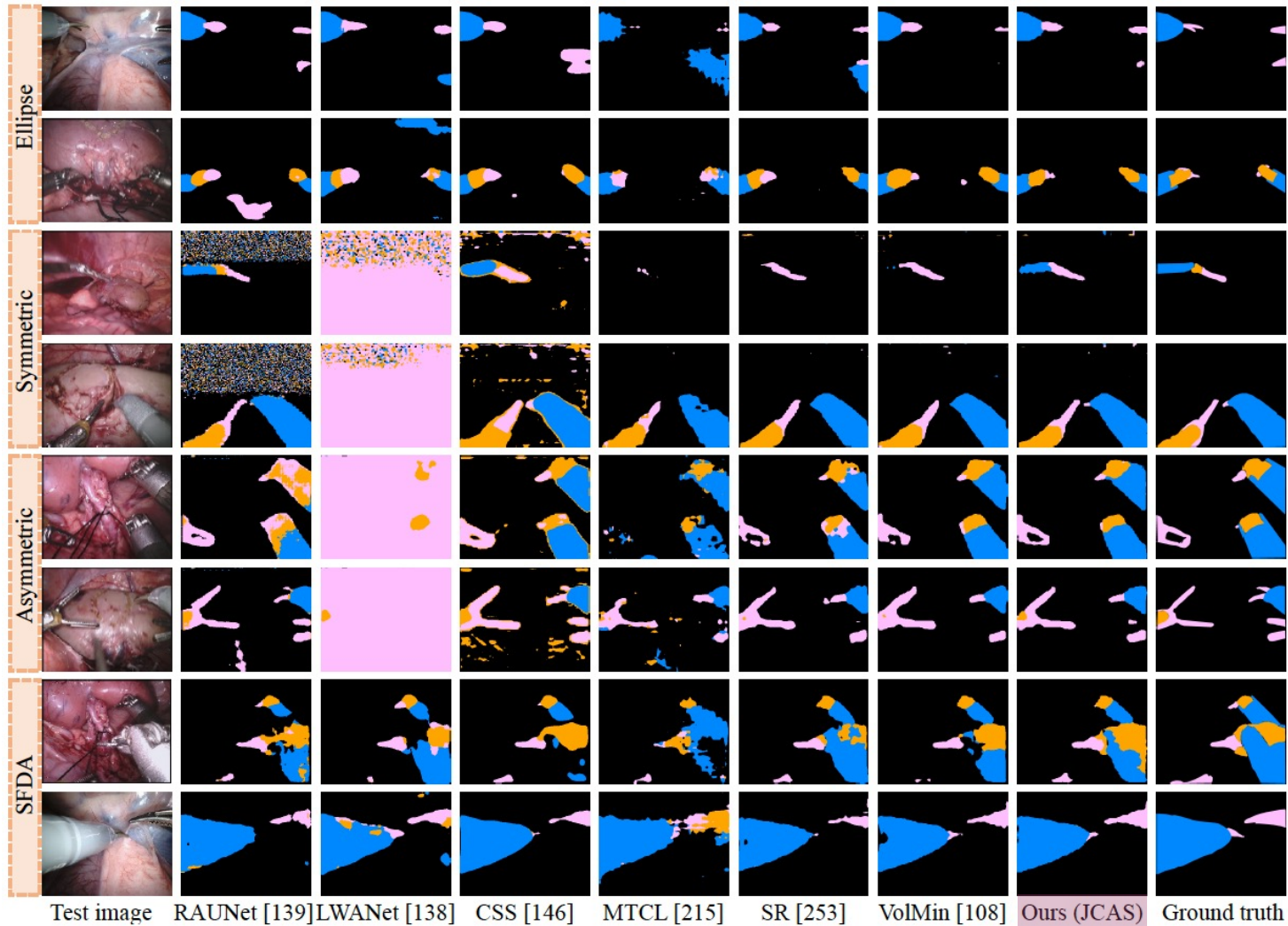
- Experimental results

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- Experimental results

- Superior to state-of-the-art methods



- **Experimental results**
  - Ablation study under ellipse label noise

Method	Shaft		Wrist		Clasper		Average	
	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>
Upper bound	88.740	81.699	65.045	52.627	70.531	56.618	74.772	63.648
Baseline [18]	79.021	68.097	42.069	29.582	55.489	40.175	58.860	45.951
w/ Affinity	82.158	72.339	49.128	35.455	58.933	43.594	63.406	50.463
w/ DAR	82.698	72.992	52.207	38.442	61.544	46.027	65.483	52.487
w/ CALC	82.973	73.126	<u>61.885</u>	<u>47.527</u>	60.416	44.821	68.425	55.158
Ours (JCAS)	<b>84.683</b>	<u>75.378</u>	<b>65.599</b>	<b>51.623</b>	<u>63.871</u>	<u>48.356</u>	<b>71.384</b>	<b>58.452</b>

- **Experimental results**
  - Ablation study under ellipse label noise

Method	Shaft		Wrist		Clasper		Average	
	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>
Upper bound	88.740	81.699	65.045	52.627	70.531	56.618	74.772	63.648
Baseline [18]	79.021	68.097	42.069	29.582	55.489	40.175	58.860	45.951
w/ Affinity	82.158	72.339	49.128	35.455	58.933	43.594	63.406	50.463
w/ DAR	82.698	72.992	52.207	38.442	61.544	46.027	65.483	52.487
w/ CALC	82.973	73.126	<u>61.885</u>	<u>47.527</u>	60.416	44.821	68.425	55.158
Ours (JCAS)	<b>84.683</b>	<u>75.378</u>	<b>65.599</b>	<b>51.623</b>	<u>63.871</u>	<u>48.356</u>	<b>71.384</b>	<b>58.452</b>

- Curve of test *Jac* vs. epoch with four different types of noise labels

- **Experimental results**
  - Ablation study under ellipse label noise

Method	Shaft		Wrist		Clasper		Average	
	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>	<i>Dice (%)</i>	<i>Jac (%)</i>
Upper bound	88.740	81.699	65.045	52.627	70.531	56.618	74.772	63.648
Baseline [18]	79.021	68.097	42.069	29.582	55.489	40.175	58.860	45.951
w/ Affinity	82.158	72.339	49.128	35.455	58.933	43.594	63.406	50.463
w/ DAR	82.698	72.992	52.207	38.442	61.544	46.027	65.483	52.487
w/ CALC	82.973	73.126	<u>61.885</u>	<u>47.527</u>	60.416	44.821	68.425	55.158
Ours (JCAS)	<b>84.683</b>	<u>75.378</u>	<b>65.599</b>	<b>51.623</b>	<u>63.871</u>	<u>48.356</u>	<b>71.384</b>	<b>58.452</b>



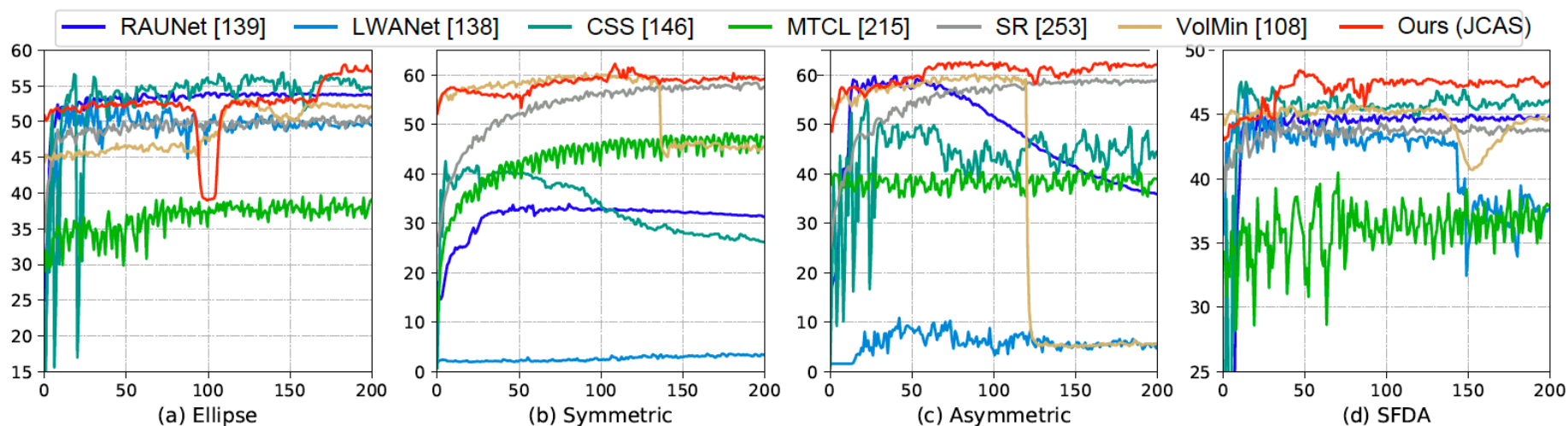
- Experimental results
  - Ablation study under ellipse label noise

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- Experimental results
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- Curve of test *Jac* vs. epoch with four different types of noise labels



# Thanks!

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Paper



Code