Learning to Model Pixel-Embedded Affinity for Homogeneous Instance Segmentation

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VIDAR
Visual Information Discovery And Recovery

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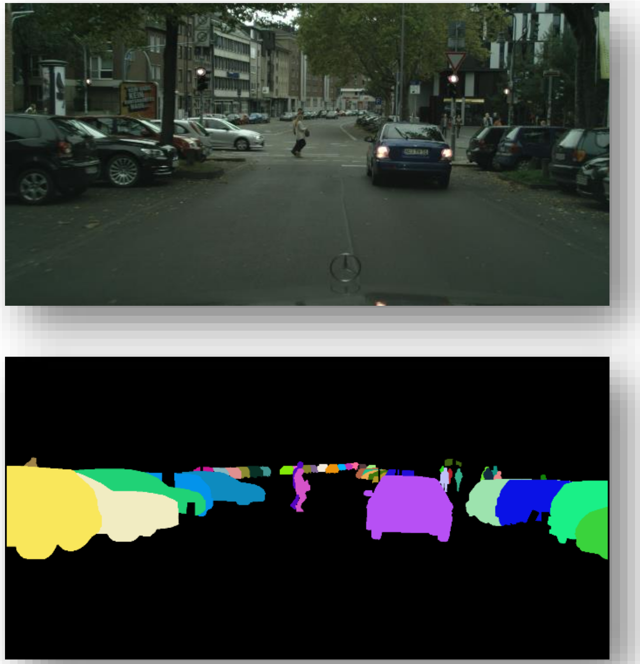
Background

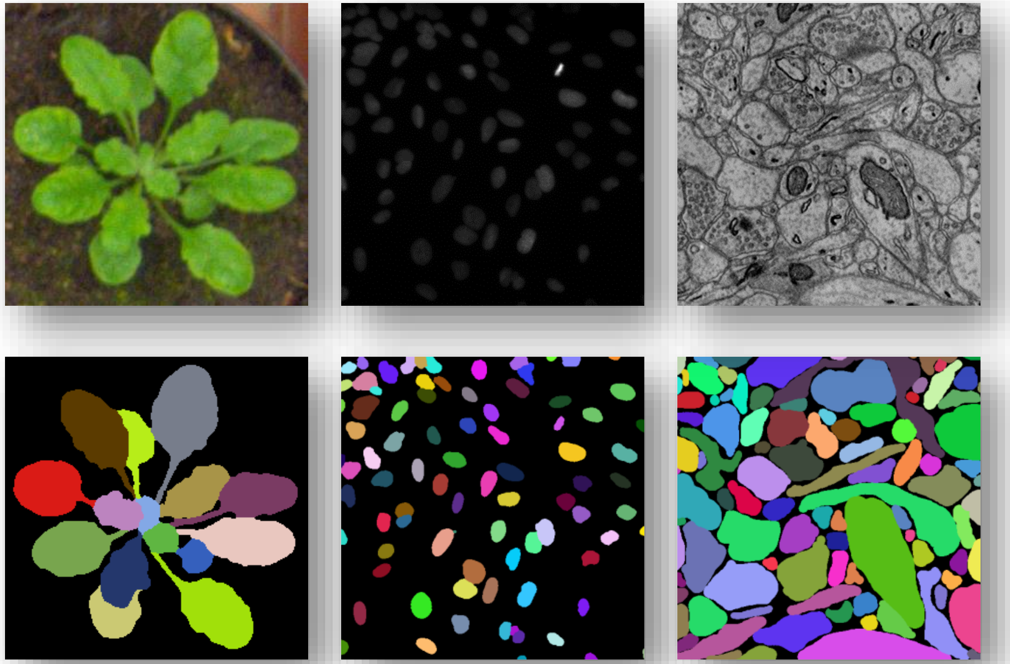
- Instance Segmentation & Homogeneous Instance Segmentation

Instance Segmentation



Persons & Cars

Homogeneous Instance Segmentation

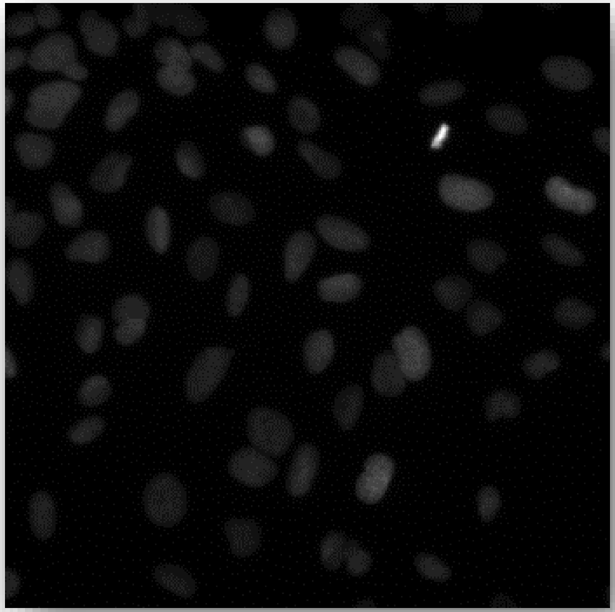


Leaves Nuclei Neurons

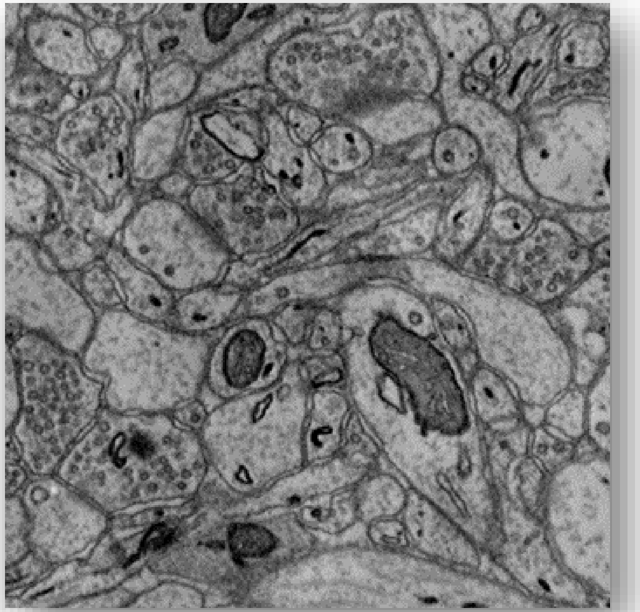
Background

- Challenges
  - Similar appearances
  - Dense distributions
  - Ambiguous boundaries

Leaves



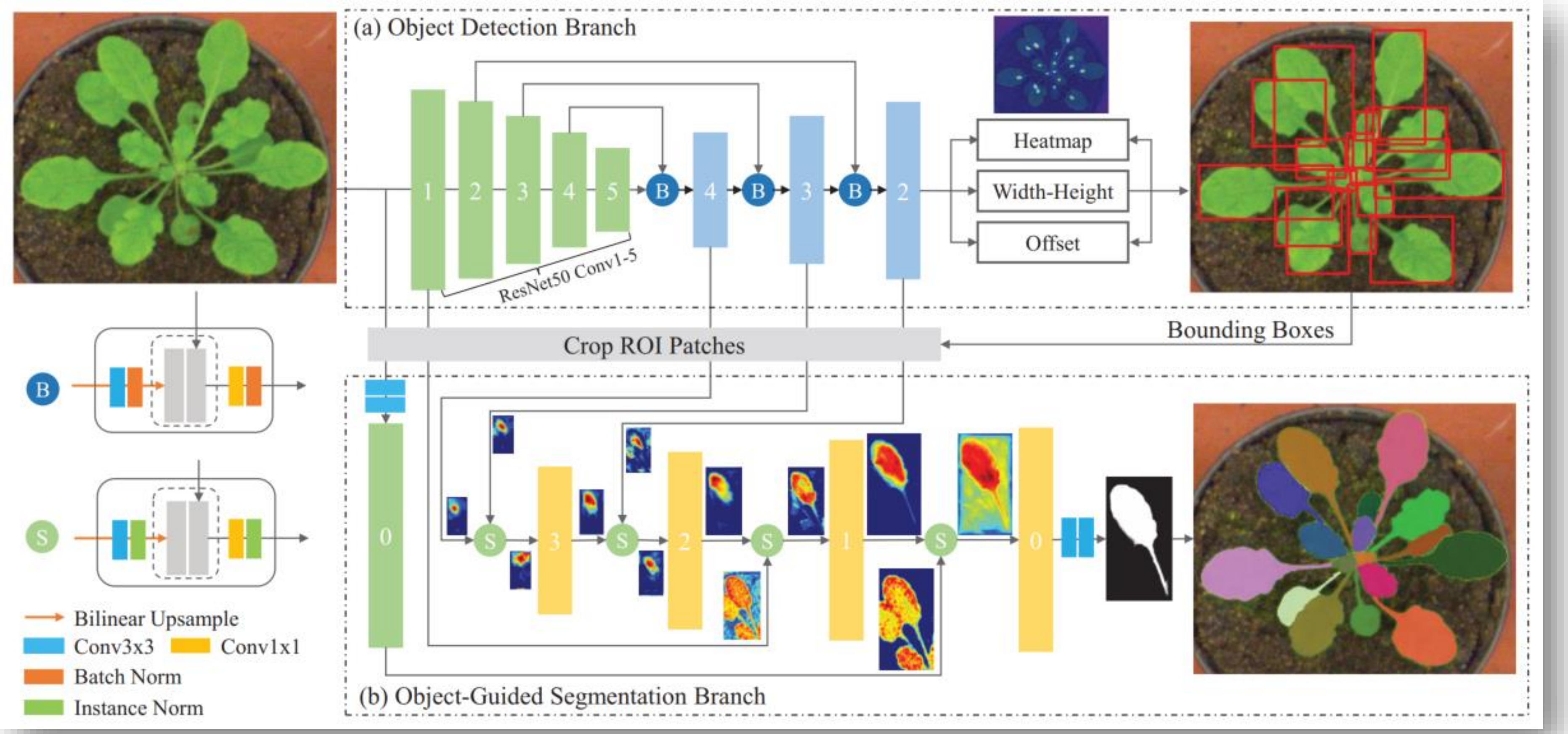
Nuclei



Neurons

Related Work

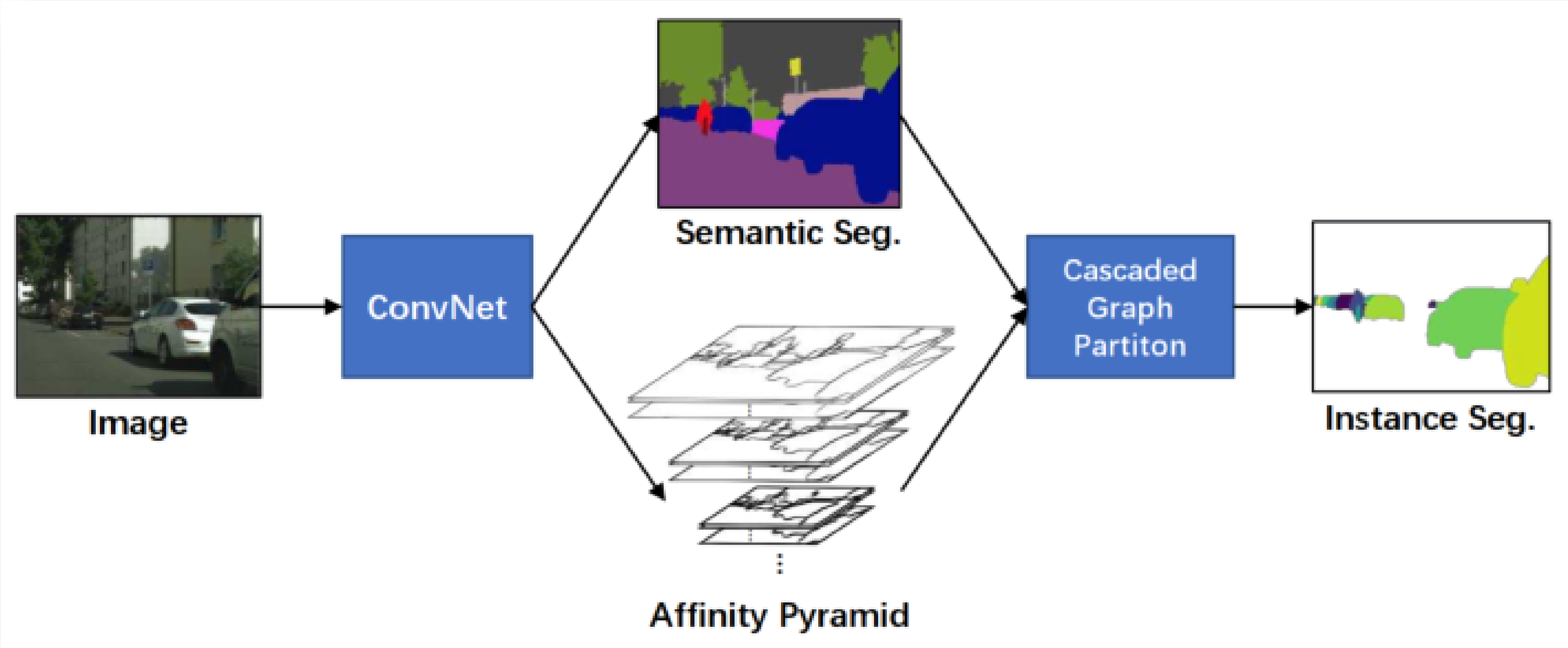
- Proposal-based Instance Segmentation



Jingru Yi, et al. Object-Guided Instance Segmentation for Biological Images. AAAI 2020.

Related Work

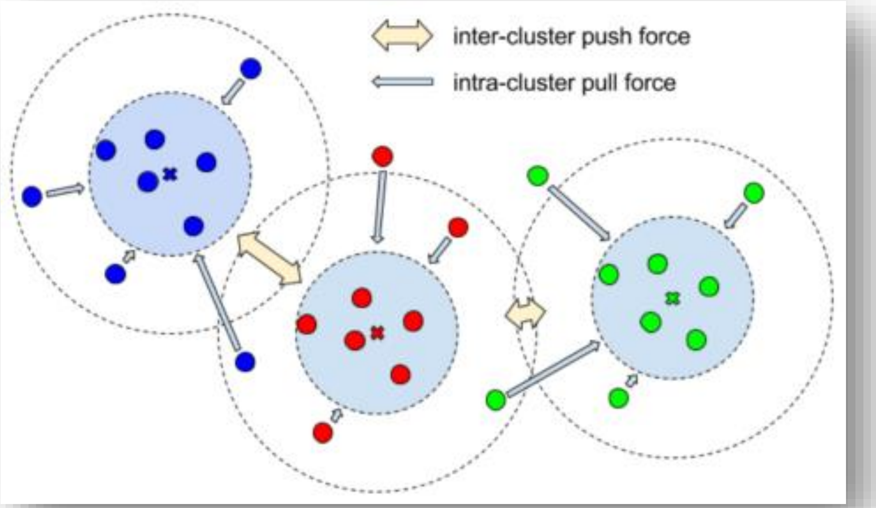
- ➢ Proposal-based Instance Segmentation
- ➢ Proposal-free Instance Segmentation
  - Affinity learning

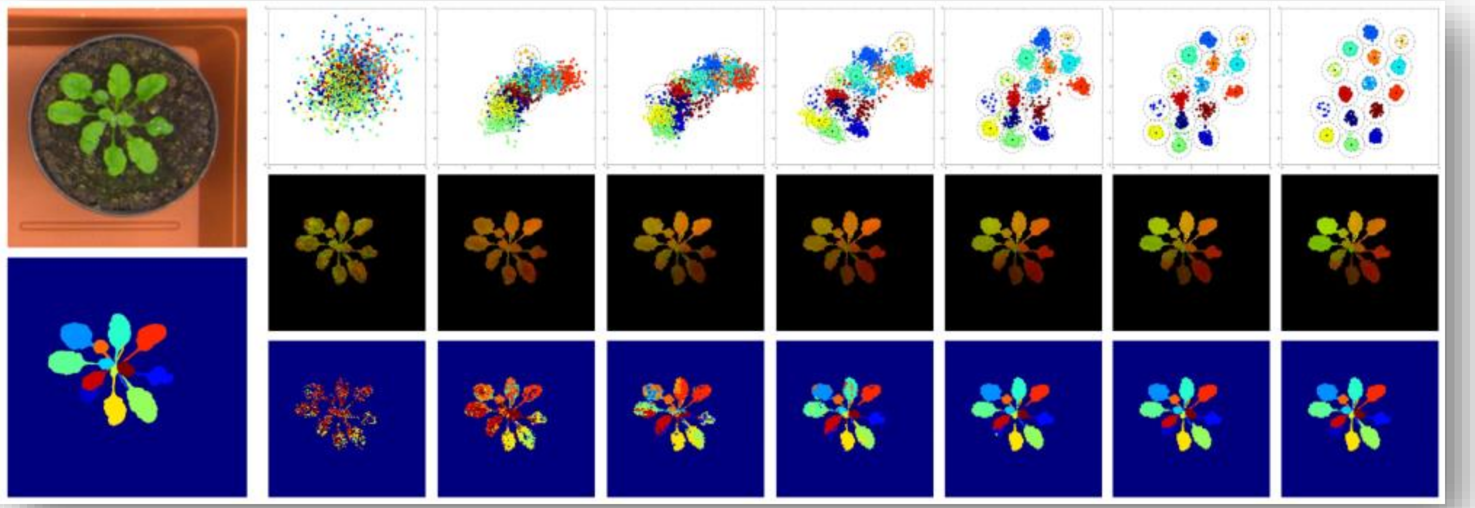


Naiyu Gao, et al. SSAP: Single-Shot Instance Segmentation With Affinity Pyramid. ICCV 2019.

Related Work

- ➢ Proposal-based Instance Segmentation
- ➢ Proposal-free Instance Segmentation
  - Affinity learning
  - Metric learning

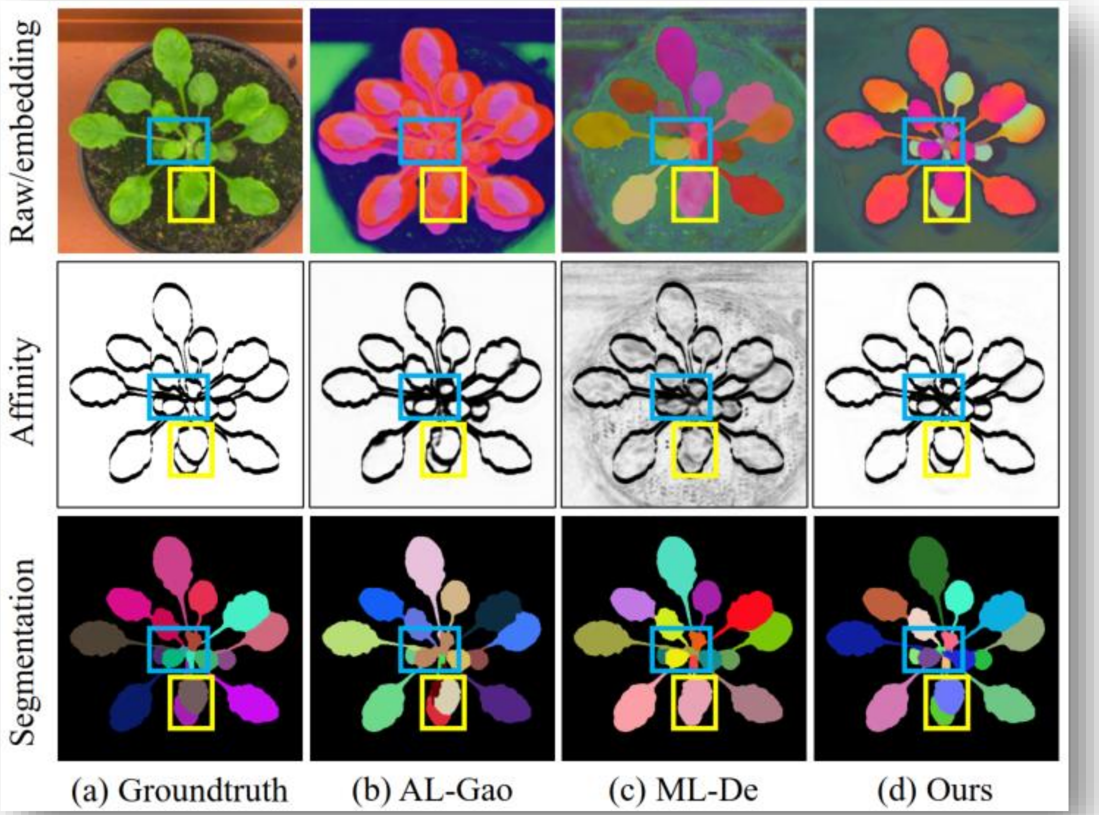




Bert De Brabandere, et al. Semantic Instance Segmentation with a Discriminative Loss Function. arXiv 2017.

Introduction

- Motivations
  - How to preserve the semantic information of instances
  - How to improve the distinguishability of adjacent instances



Introduction

➢ Contributions

Proposed	Operation	Purpose
Self-Correlation Module (SCM)	Explicitly modeling the pairwise relationship between pixels	To preserve the semantic instance information
Cross-Correlation Module (CCM)	Mutually estimating the pairwise relationships under different views and appearances of the input image	To improve the distinguishability of adjacent instances
Embedding Pyramid Module (EPM)	Modeling affinity on different scales	To integrate the global instance information

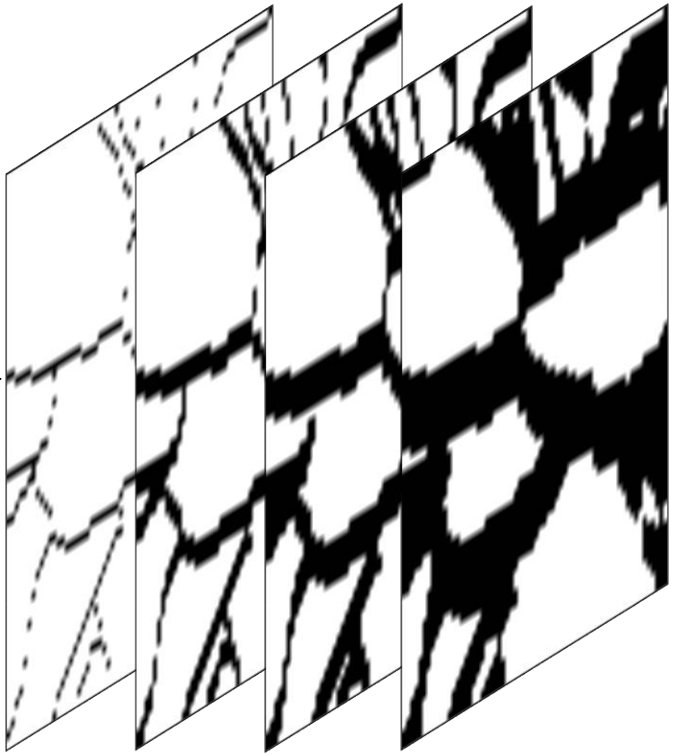
Pixel-Embedded Affinity Modeling

- Affinity Definition

Instance Ground Truth

R={1,3,5,9,…}, N=4

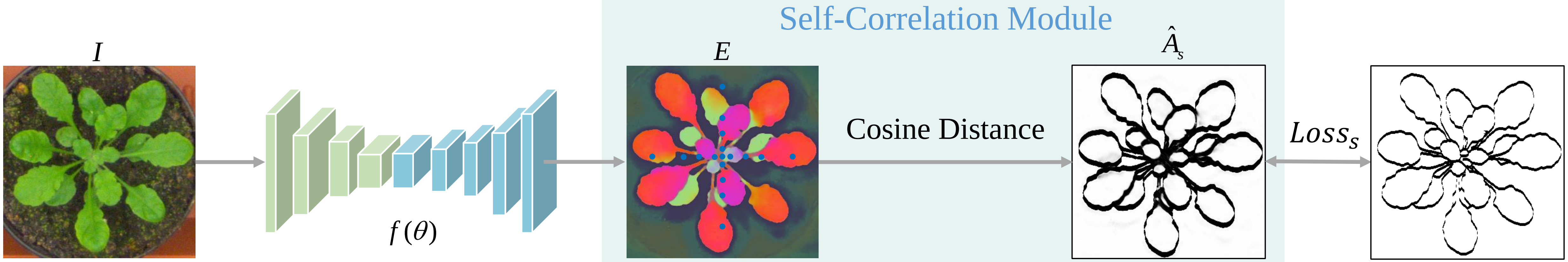
$$a_{n,i} = \begin{cases} 0, & \text{if } y_i \neq y_{i+n} \\ 1, & \text{if } y_i = y_{i+n}, \end{cases}$$



Affinity Ground Truth

Pixel-Embedded Affinity Modeling

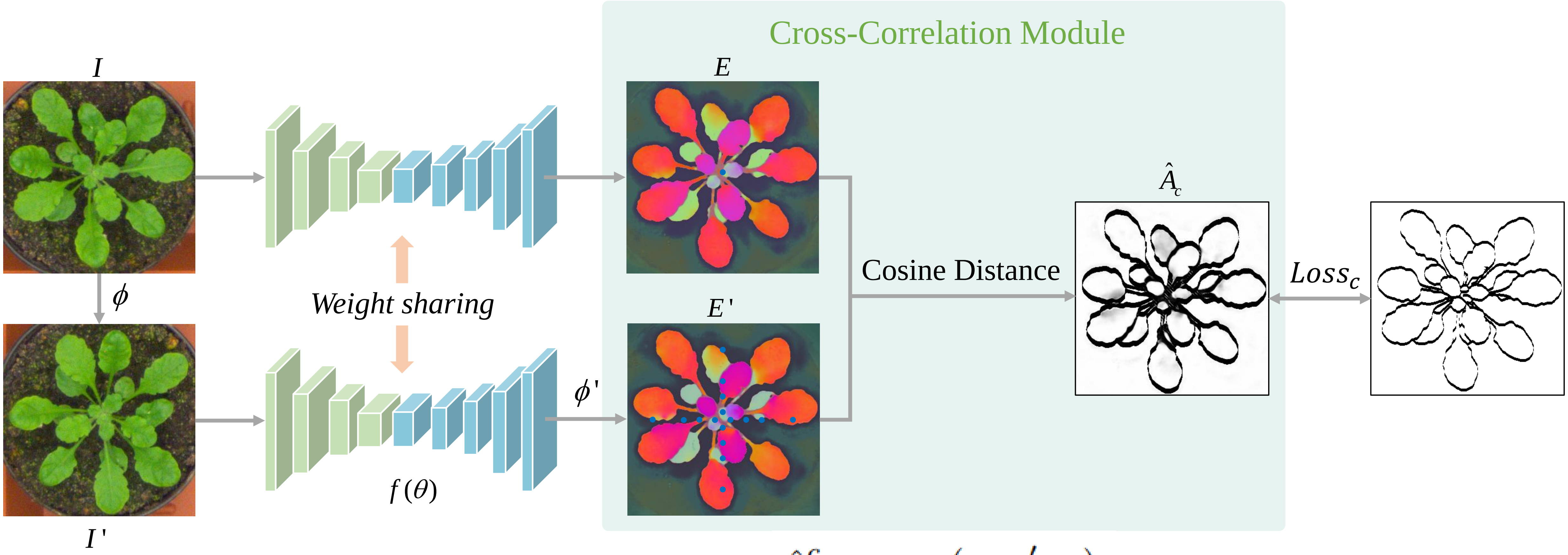
➢ SCM: Modeling Affinity Explicitly



$$\hat{a}^{s}_{n,i} = cos(e_i, e_{i+n}) = \frac{e_i^T e_{i+n}}{||e_i||_2||e_{i+n}||_2},$$

Pixel-Embedded Affinity Modeling

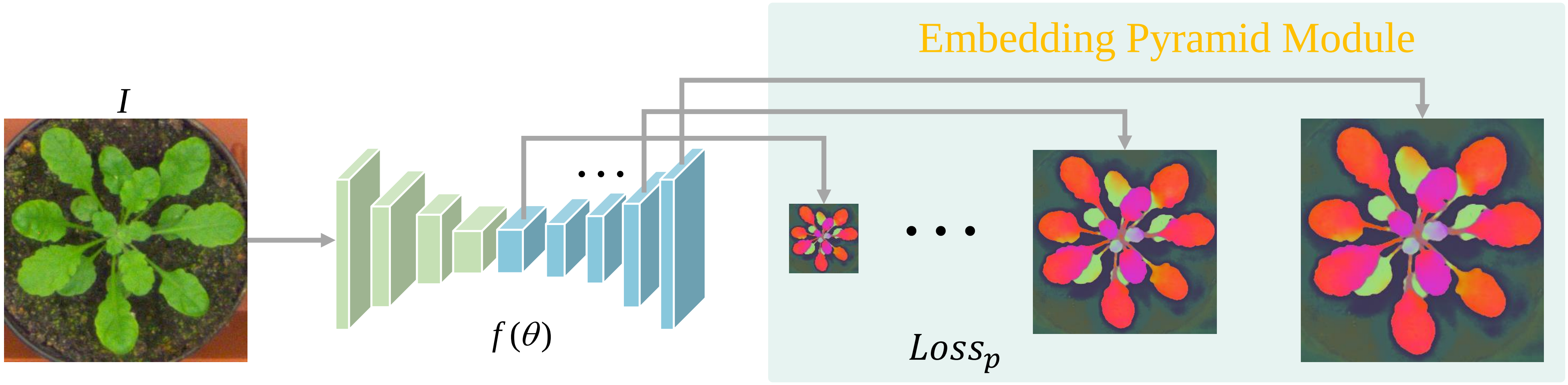
➢ CCM: Distinguishing Adjacent Instances



$$\hat{a}^c_{n,i} = cos(e_i, e'_{i+n}),$$

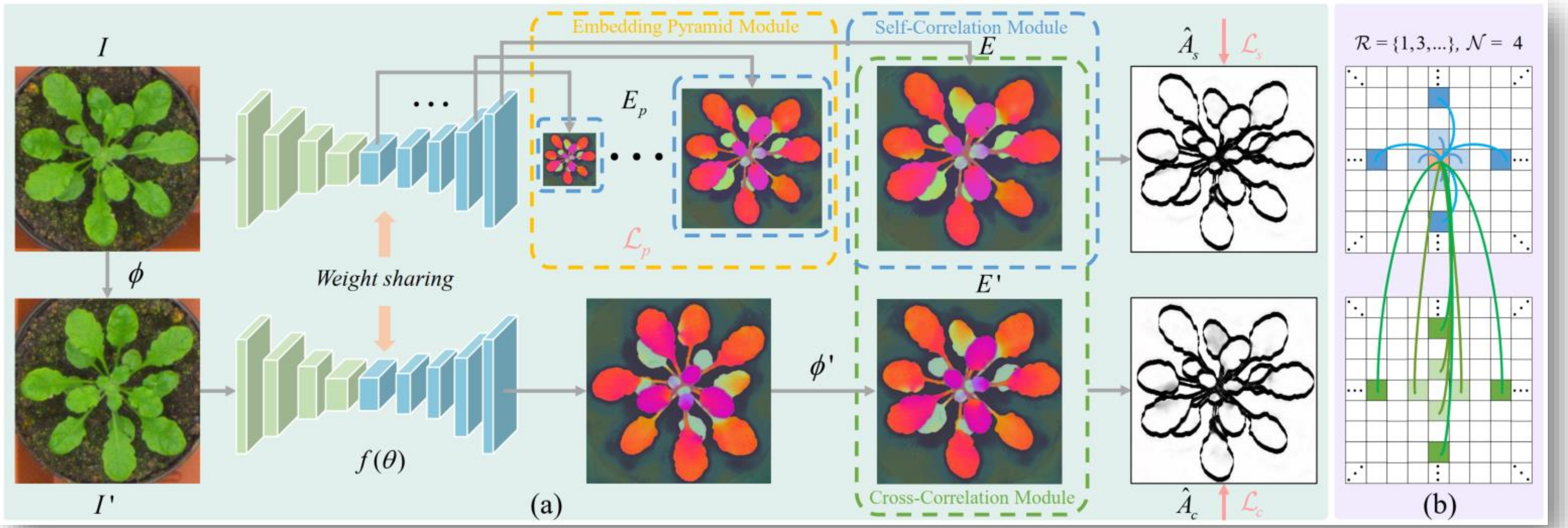
Pixel-Embedded Affinity Modeling

- EPM: Integrating Global Information



Pixel-Embedded Affinity Modeling

➢ Framework



Experiments

- Datasets & Implementation details & Metrics

Dataset	Description	Mode	Training set	Validation set	Test set	Metric
CVPPP [1]	Plant leaves	Consumer-grade camera	108 (530x500)	20 (530x500)	33 (530x500)	SBD, |DiC|
BBBC039V1 [2]	Nuclei of U2OS cells	Fluorescence microscopy	100 (520x696)	50 (520x696)	50 (520x696)	AJI, Dice, PQ
AC3/AC4 [3]	Neurons of mouse brain	Electron microscope	80 (1024x1024)	20 (1024x1024)	100 (1024x1024)	VOI, ARAND

[1]. https://competitions.codalab.org/competitions/18405
[2]. https://bbbc.broadinstitute.org/BBBC039
[3]. https://software.rc.fas.harvard.edu/lichtman/vast/AC3AC4Package.zip

Experiments

➢ Results

- CVPPP

Methods	Param.	SBD	$\|DiC\|$
MSU (Scharr et al. 2016)	-	66.7	2.3
Nottingham (Scharr et al. 2016)	-	68.3	3.8
Wageningen (Yin et al. 2014)	-	71.1	2.2
IPK (Pape and Klukas 2014)	-	74.4	2.6
Coloring (Kulikov et al. 2018)	30.2M	80.4	2.0
ML-De (De Brabandere et al. 2017)	23.1M	84.2	1.0
Recurrent (Ren and Zemel 2017)	-	84.9	**0.8**
Aug. (Kuznichov et al. 2019)	-	88.7	5.3
Harmonic (Kulikov et al. 2020)	43.1M	89.0	3.0
Synthesis (Ward et al. 2018)	105.7M	90.0	-
PFFNet (Liu et al. 2021)	105.7M	91.1	-
Ours w/ ResNet-50	15.3M	91.7	1.5
Ours w/ ResNet-101	34.3M	91.9	1.4
Ours w/ ResUNet	**4.7M**	**92.3**	2.4

Quantitative comparison with state-of-the-art methods on the test set of CVPPP A1.

Dataset	Methods	Clustering	SBD	$\|DiC\|$
A1	AL-Gao	Mutex	87.1	1.25
	ML-De	Mean-shift	87.3	1.45
	ML-De	Mutex	88.5	1.10
	Ours	Mutex	**89.1**	**0.85**
A2	AL-Gao	Mutex	71.1	2.61
	ML-De	Mean-shift	71.2	2.52
	ML-De	Mutex	73.4	2.00
	Ours	Mutex	**76.3**	**1.71**

Quantitative comparison with affinity learning (AL-Gao) and metric learning (ML-De) on the validation sets of CVPPP A1 and A2.

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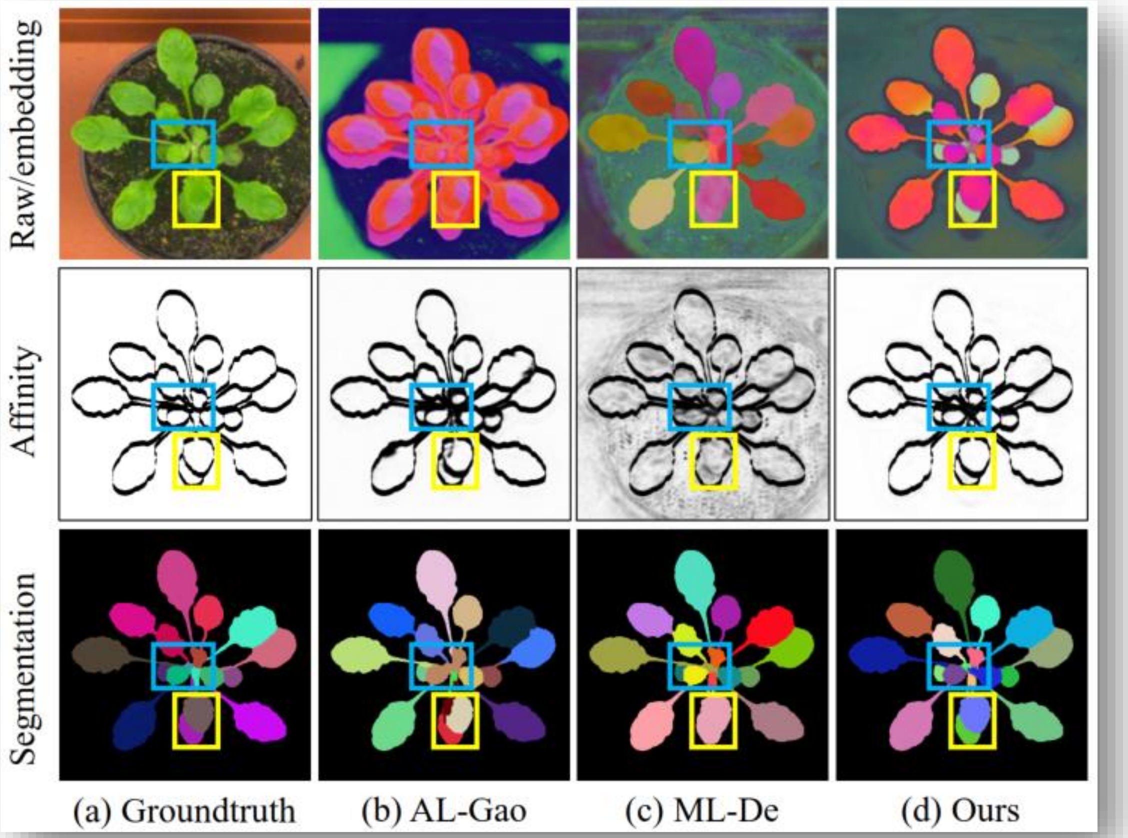
Experiments

- Results
  - CVPPP



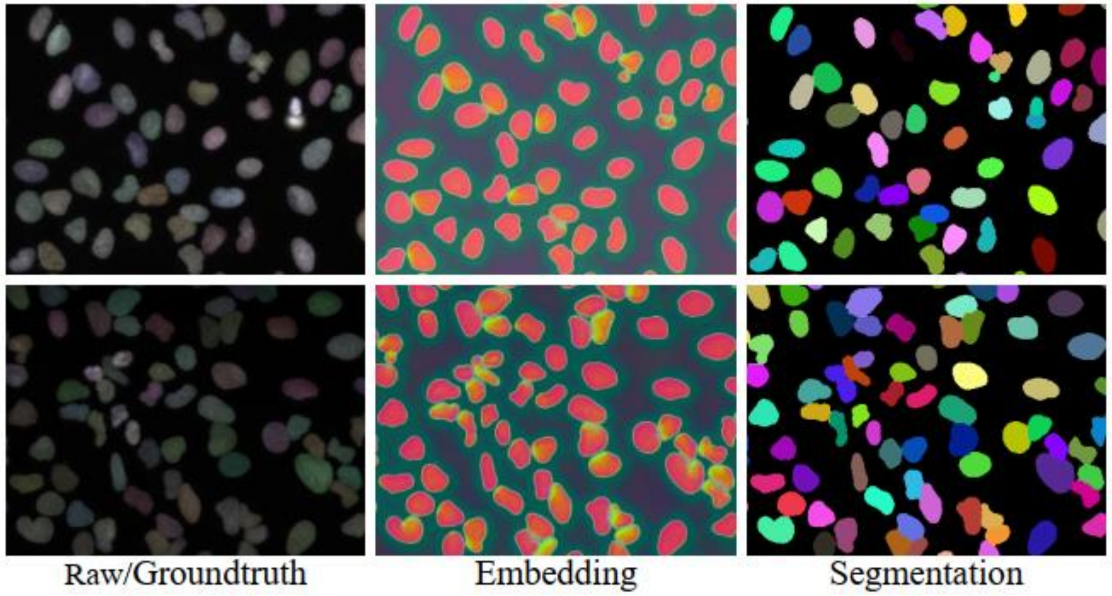
Qualitative comparison with affinity learning (AL-Gao) and metric learning (ML-De).

Experiments

- Results
  - CVPPP
  - BBBC039V1

Methods	*AJI*	*Dice*	*PQ*
Mask R-CNN (He et al. 2017)	0.7983	0.9277	0.7773
Cell R-CNN (Zhang et al. 2018)	0.8070	0.9290	0.7959
UPSNet (Xiong et al. 2019)	0.8128	0.9274	0.7857
JSISNet (De Geus et al. 2018)	0.8134	0.9316	0.7913
PanFPN (Kirillov et al. 2019)	0.8193	0.9320	0.7960
OANet (Liu et al. 2019b)	0.8198	0.9372	0.8085
AUNet (Li et al. 2019)	0.8252	0.9377	0.8090
Cell R-CNN v2 (Liu et al. 2019a)	0.8260	0.9336	0.8010
PFFNet (Liu et al. 2021)	0.8477	0.9478	0.8330
Ours	**0.8674**	**0.9673**	**0.8420**

Quantitative comparison with state-of-the-art methods on the test set of BBBC039V1.



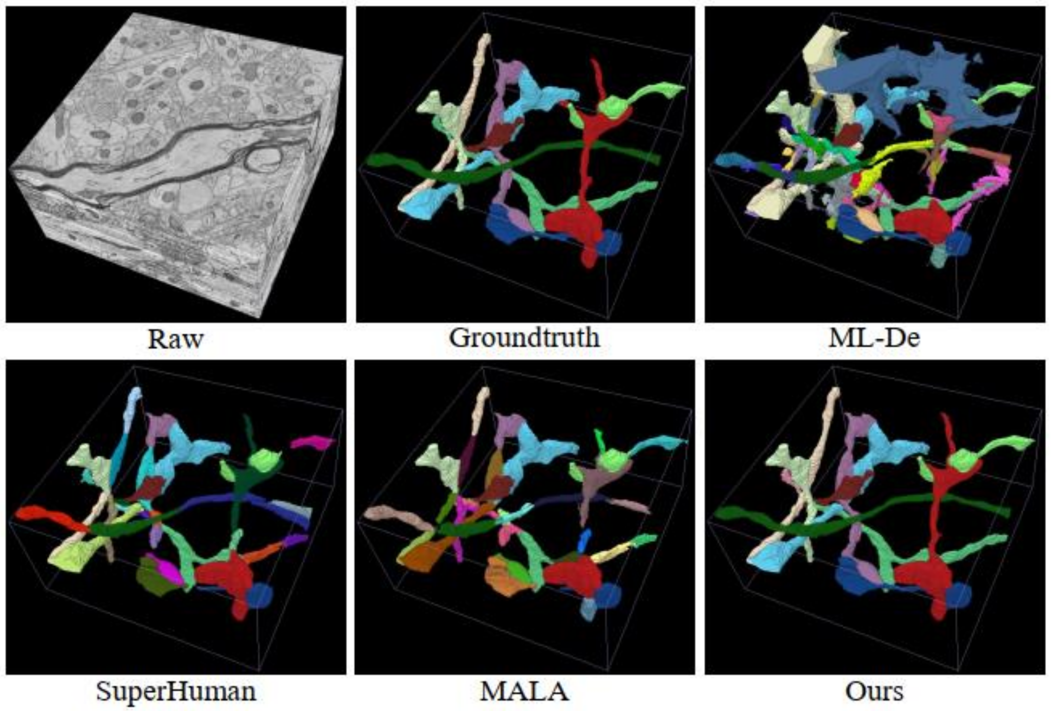
Visual results on the test set of BBBC039V1.

Experiments

- Results
  - CVPPP
  - BBBC039V1
  - AC3/AC4

Methods	VOI_S	VOI_M	VOI	$ARAND$
ML-De	1.5752	0.6151	2.1903	0.1964
SuperHuman	1.1445	0.2630	1.4075	0.1220
MALA	1.3039	0.2423	1.5462	0.1203
Ours	**0.8522**	**0.2322**	**1.0844**	**0.0938**

Quantitative comparison with metric learning (ML-De) and two affinity learning methods (i.e., SuperHuman and MALA) on the test set of AC3/AC4.



Visual comparison on the test set of AC3/AC4.
We select 10 neurons for qualitative comparison.

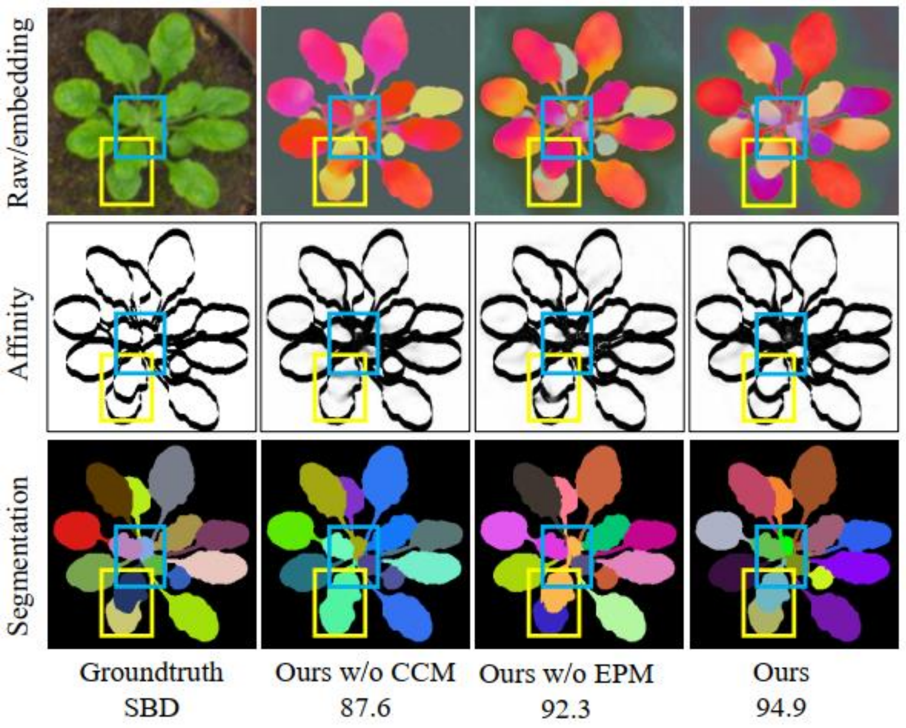
Experiments

➢ Ablation studies

- The effectiveness of modules

SCM	CCM	EPM	*SBD*	|*DiC*|
✓			87.7	1.15
✓		✓	88.1	1.00
✓	✓		88.5	0.95
✓	✓	✓	**89.1**	**0.85**

Ablation results for the effectiveness of modules.



Visual demonstration for the effectiveness of modules on the CVPPP A1 dataset.

Experiments

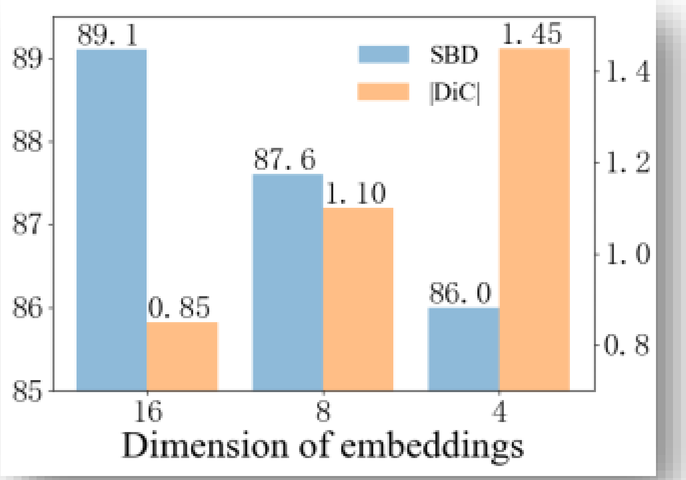
- Ablation studies
  - The effectiveness of modules
  - The effectiveness of transformations

Flip. & Rot.	Cutout	Intensity	SBD	$\|DiC\|$
	✓	✓	86.5	1.35
✓		✓	87.7	1.00
✓	✓		88.6	**0.85**
✓	✓	✓	**89.1**	**0.85**

Ablation results for the effectiveness of transformations.

Experiments

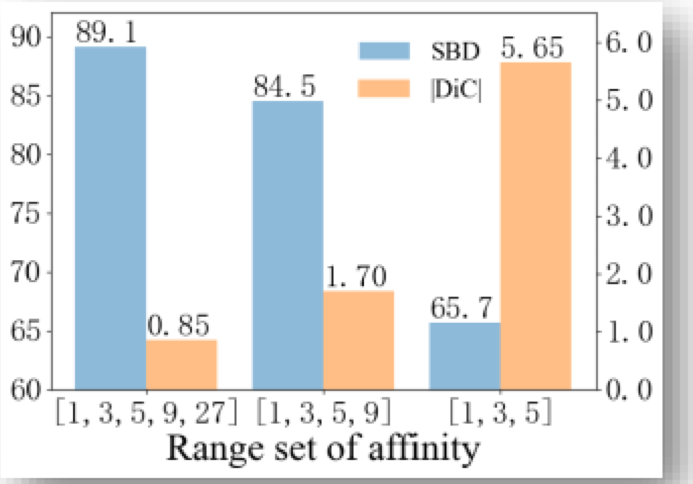
- Ablation studies
  - The effectiveness of modules
  - The effectiveness of transformations
  - Dimension of embeddings



Ablation results for dimension of embeddings

Experiments

- Ablation studies
  - The effectiveness of modules
  - The effectiveness of transformations
  - Dimension of embeddings
  - Range set of affinity



Ablation results for dimension of range set of affinity

Experiments

- Ablation studies
  - The effectiveness of modules
  - The effectiveness of transformations
  - Dimension of embeddings
  - Range set of affinity
  - Adaptive affinity

$\mathcal{R}$	$\mathcal{N}$	SBD	$\lvert DiC \rvert$
$[1, 3, 5, 9, 27]$	4	76.3	1.71
$[1, 3, 5, 9, 27]$	8	77.1	1.68
$[1, 3, 5, 7, 9, 11, 19, 27, 35]$	8	**77.4**	**1.55**

Ablation results for adaptive affinity by extending the ranges and neighborhoods of affinity during inference on the CVPPP A2 dataset.

Conclusion

- A pixel-embedded affinity modeling method for homogeneous instance segmentation, including:
  - A self-correlation module to enable explicit affinity modeling
  - A cross-correlation module to improve the distinguishability of adjacent instances
  - A embedding pyramid module to integrate the global instance information

- Versatile and superior performance on three representative datasets

Thanks for your listening!

Presenter: Wei Huang (weih527@mail.ustc.edu.cn)

https://github.com/weih527/Pixel-Embedded-Affinity

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