Domain Generalization for Crop Segmentation with Knowledge Distillation

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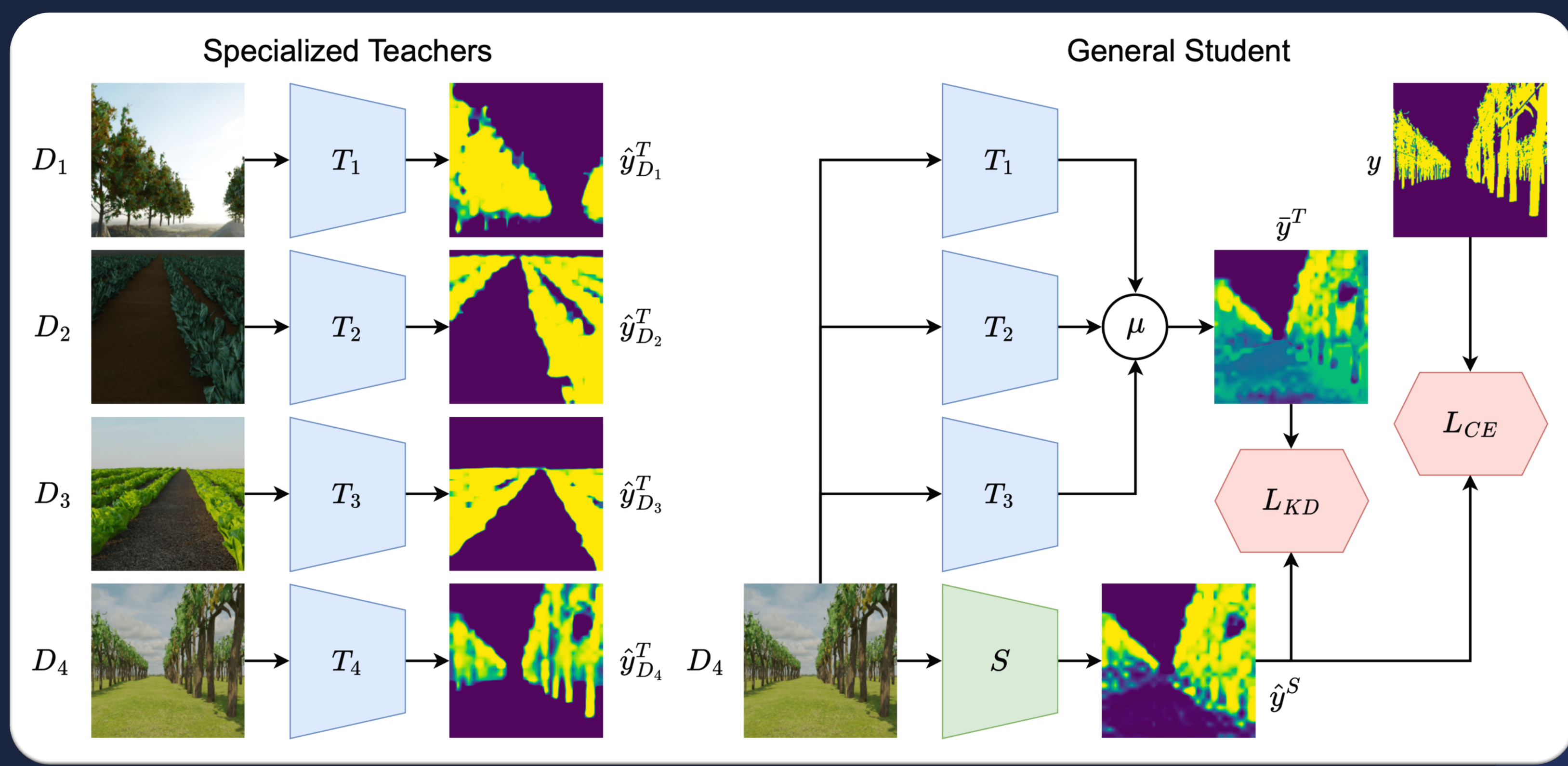
We propose a novel approach to enhance domain generalization by transferring knowledge from an ensemble of teachers trained on different source domains.



Dataset and Architecture

- We build **AgriSeg**, a **multi-domain** dataset for crop segmentation, to have a **real-world** benchmark for our method.
- **Agriseg** contains **11** synthetic and real **domains** with different lighting and background conditions and more than **46,500 samples**.
- We use the **LR-ASPP** real-time segmentation model.

The AgriSeg dataset (models and rendering)

Distillation Method

- Inspired by [1], we train each teacher as a **single-domain expert**.
- We generate the teacher's output by **averaging** the output **logits** of the single-domain experts.
- That yields a more **informative** mask which can be further smoothened using a **temperature** factor.
- **Softmax** is applied along the flattened **spatial dimension** instead of channels as suggested by [2].

$$L = L_{CE}(y, \hat{y}^S) + \lambda L_{KD}(\bar{y}^T, \hat{y}^S), \qquad \bar{y}^T = \frac{1}{D}\sum_{d=1}^{D} \hat{y}^T_d$$

$$L_{KD} = \frac{\tau^2}{C}\sum_{c=1}^{C}\sum_{i=1}^{W\cdot H} \phi(\bar{y}^T_{c,i}) \cdot \log\left(\frac{\phi(\bar{y}^T_{c,i})}{\phi(\hat{y}^S_{c,i})}\right), \qquad \phi(y) = \frac{\exp\left(\frac{y}{\tau}\right)}{\sum_{i=1}^{W\cdot H}\exp\left(\frac{y_i}{\tau}\right)}$$

Proposed training loss

Results

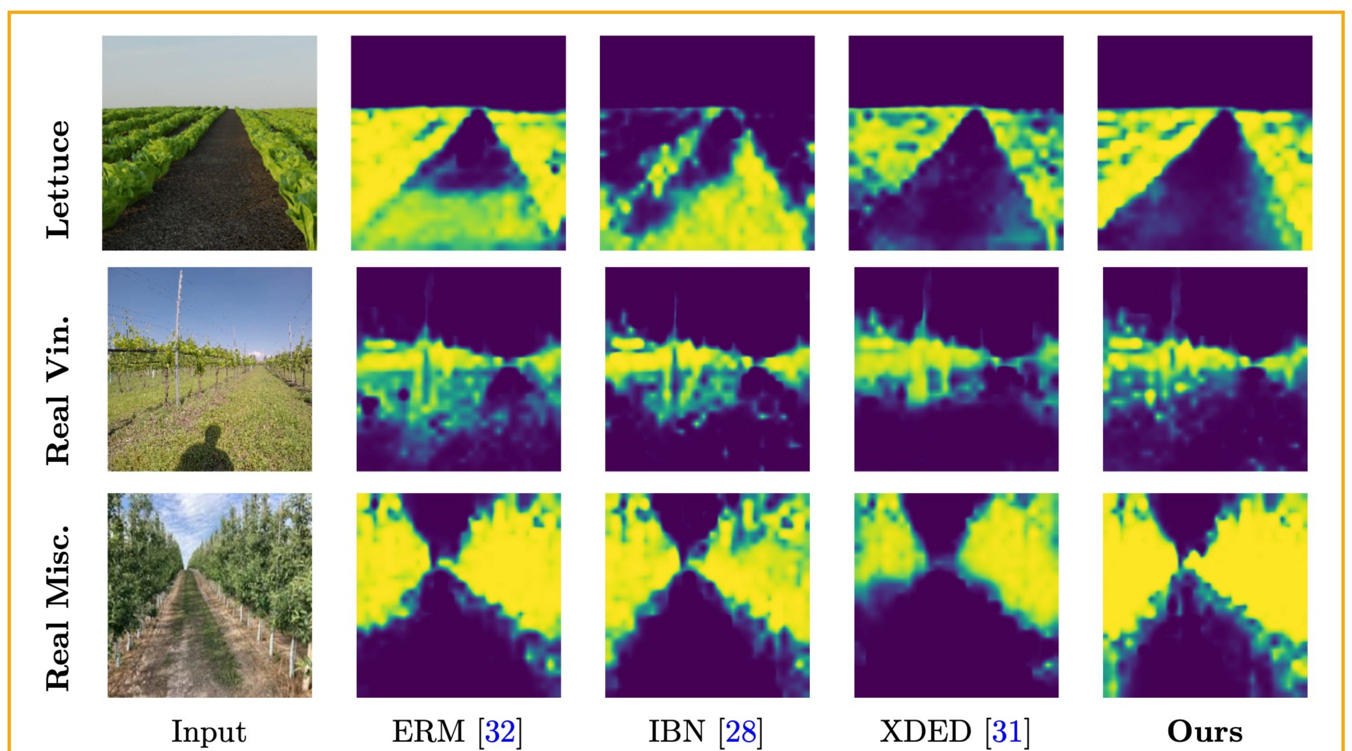
- We compare our method with other state-of-the-art DG algorithms and report the **Intersection-over-Union** (in %).

Leave-one-out DG evaluation

Method	Generic Tree 2	Chard	Lettuce	Vineyard	Average
ERM[32]	38.38 ± 12.10	83.22 ± 5.50	$\underline{33.45 \pm 13.34}$	46.69 ± 9.69	50.44 ± 10.15
IBN[28]	26.92 ± 12.61	83.52 ± 1.97	33.14 ± 22.82	47.72 ± 2.96	47.83 ± 10.09
ISW[22]	$\mathbf{65.72 \pm 8.47}$	$\underline{86.05 \pm 3.87}$	25.72 ± 12.89	51.34 ± 2.36	$\underline{57.21 \pm 6.00}$
pAdaIN[29]	42.27 ± 12.80	79.93 ± 1.65	13.22 ± 8.30	45.73 ± 4.81	45.29 ± 6.89
XDED[31]	38.79 ± 17.26	84.35 ± 5.11	29.99 ± 14.80	47.63 ± 6.27	50.19 ± 10.86
WildNet[23]	45.76 ± 2.17	82.45 ± 0.78	22.20 ± 0.73	$\mathbf{59.78 \pm 0.48}$	52.55 ± 1.04
Ours	$\underline{50.02 \pm 06.80}$	$\mathbf{86.17 \pm 1.79}$	$\mathbf{58.01 \pm 12.74}$	$\underline{53.26 \pm 3.59}$	$\mathbf{61.86 \pm 6.23}$

Sim2Real test domains

Method	Pear Tree	Zucchini	Real Vineyard	Real Misc.	Average
ERM[32]	$\underline{78.37 \pm 2.51}$	$\underline{86.51 \pm 1.71}$	42.76 ± 11.38	$\underline{64.40 \pm 3.10}$	$\underline{68.01 \pm 4.68}$
IBN[28]	73.80 ± 4.21	86.21 ± 3.23	42.23 ± 11.32	63.36 ± 9.47	66.40 ± 7.13
ISW[22]	73.49 ± 1.81	$\mathbf{87.47 \pm 0.77}$	33.80 ± 23.85	48.36 ± 7.30	60.78 ± 8.43
pAdaIN[29]	74.53 ± 2.53	81.83 ± 4.82	41.16 ± 10.23	60.32 ± 9.09	64.46 ± 6.67
XDED[31]	76.82 ± 3.02	86.34 ± 1.07	$\underline{46.38 \pm 10.07}$	57.24 ± 8.89	66.69 ± 5.76
WildNet[23]	75.31 ± 3.50	81.88 ± 2.37	31.11 ± 1.35	46.57 ± 3.09	58.72 ± 2.58
Ours	$\mathbf{80.18 \pm 2.65}$	86.25 ± 1.42	$\mathbf{52.01 \pm 4.68}$	$\mathbf{66.69 \pm 3.18}$	$\mathbf{71.28 \pm 2.98}$



Qualitative Comparison with state-of-the-art solutions

Our method extends the **generalization** of segmentation models to **unseen real-world scenarios** through **knowledge distillation**.

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References

*[1] Lee, K., Kim, S., & Kwak, S. (2022). **Cross-domain ensemble distillation for domain generalization**, ECCV.*

*[2] Shu, C., Liu, Y., Gao, J., Yan, Z., & Shen, C. (2021). **Channel-wise knowledge distillation for dense prediction**, CVPR.*

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