Known and Unknown Class Recognition on Plant Species and Diseases

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Presented by **Mingle Xu**

Core Research Institute of Intelligent Robots

Jeonbuk National University, South Korea

Authors: Yao Meng, Mingle Xu, Hyongsuk Kim, Sook Yoon, Yongchae Jeong, Dong Sun Park

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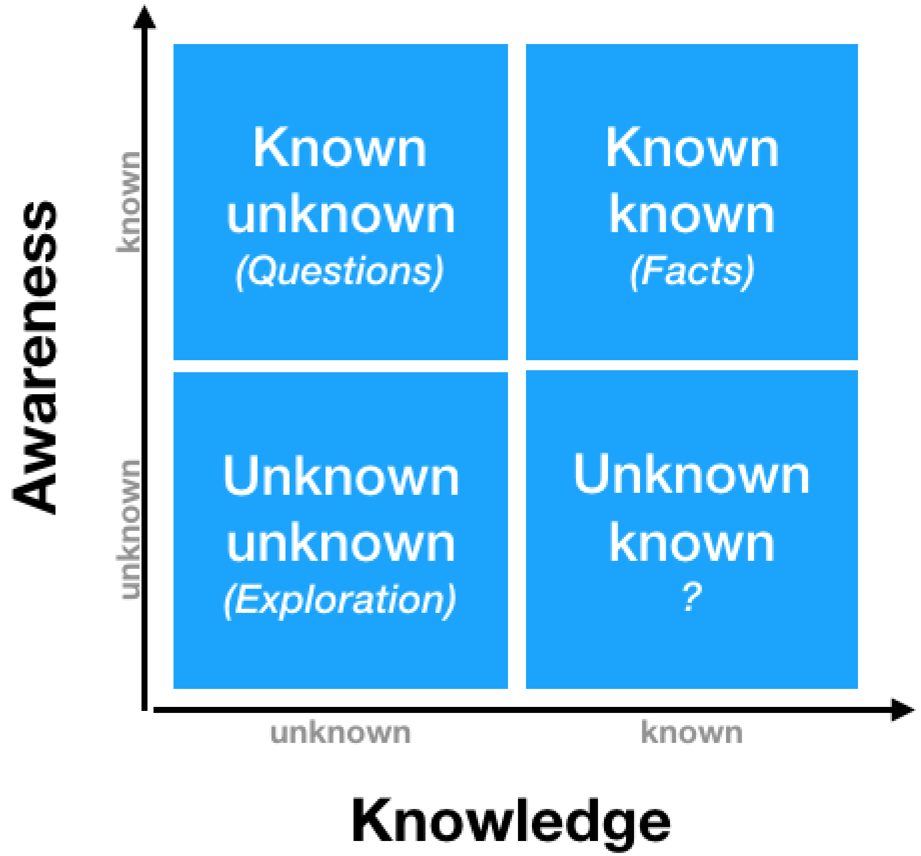
Motivation

Human knowledge and the known unknown are limited.

There are unknown unknowns – Rumsfeld in 2002.



https://en.wikipedia.org/wiki/There_are_unknown_unknowns

https://www.freecodecamp.org/news/how-to-discover-your-unknown-knowns/

Motivation

The world is changing, such as climate change and biodiversity loss.

Dead trees near Iserlohn, Germany, in April 2020 (left) and after felling in June 2021 (right).

"Biodiversity loss and climate extremes—study the feedbacks." *Nature* 612.7938 (2022): 30-32.

Motivation to recognize new classes

Invasive species in China,
Solidago Canadensis L.

Invasive species in USA,
Purple Loosestrife.

https://www.si.edu/stories/escape-invasives

Motivation to recognize new classes

Emergent plant diseases and pests may result in big yield loss.

Mirid bug

What is the problem?

ww

Problem Formalization: POSR Using Deep Learning

Plant-relevant Open Set Recognition (POSR).

Training dataset: only known classes with corresponding labels.

Test dataset: known and unknown.

Task: distinguish the unknown and classify the known.

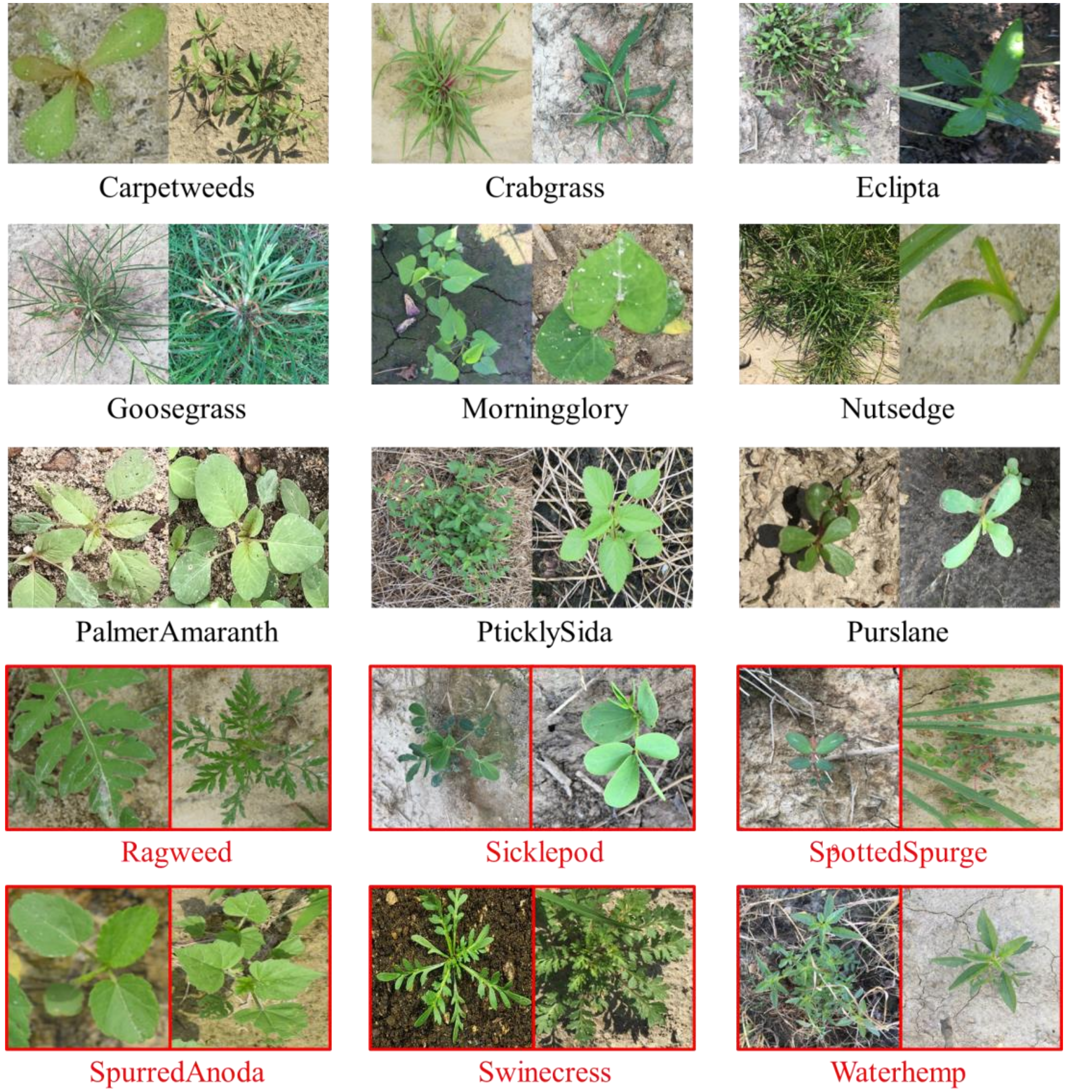
Training Setting Example

The CWD dataset has 15 classes.

Training: 9 known classes.

Test: 9 + 5 unknown classes.

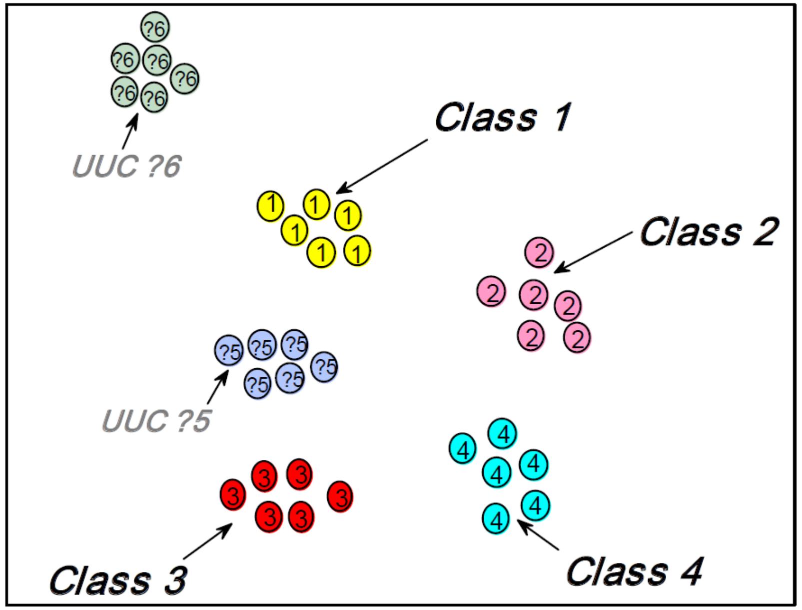
Task example: recognize Ragweed is unknown and classify Carpetweeds.



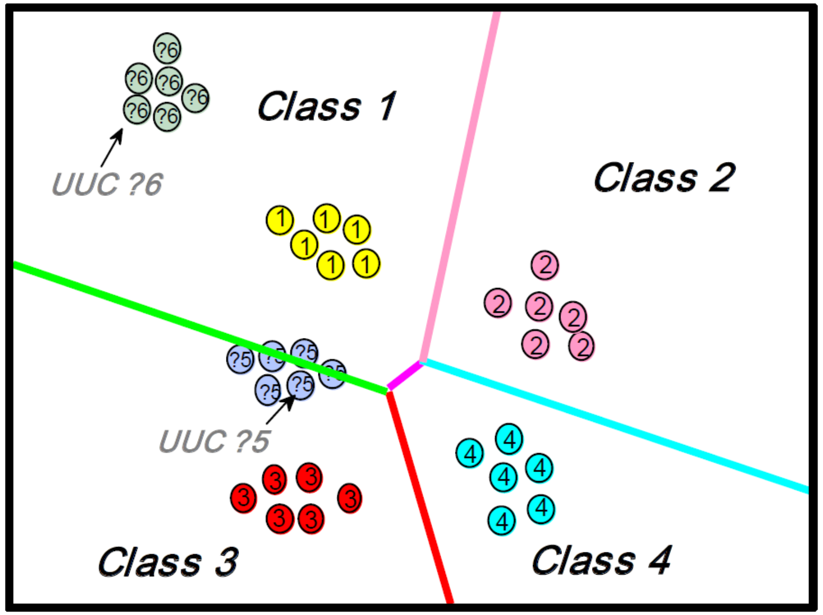
"Performance evaluation of deep transfer learning on multi-class identification of common weed species in cotton production systems." *Computers and Electronics in Agriculture* 198 (2022): 107091.

Basic Understanding of OSR

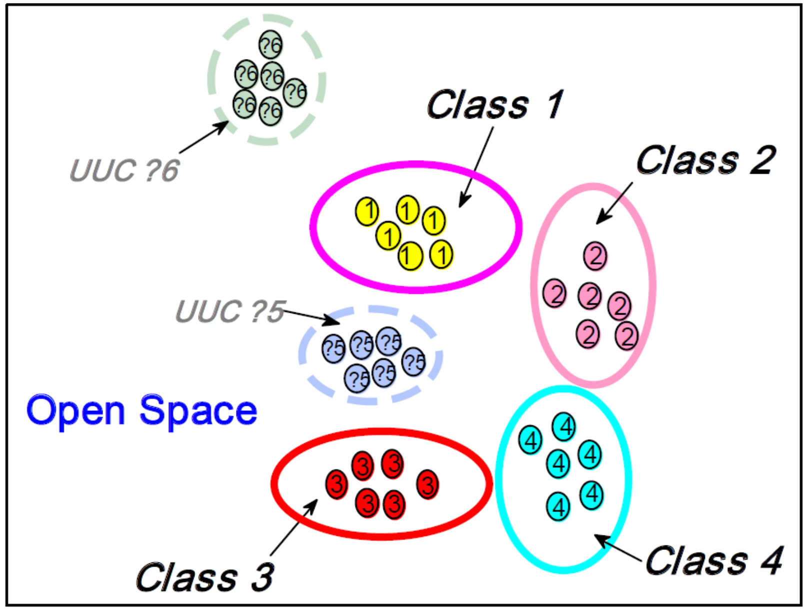
Compare closed-set and open-set.



(a) Distribution of the original data set.



(b) Traditional recognition/classification problem.



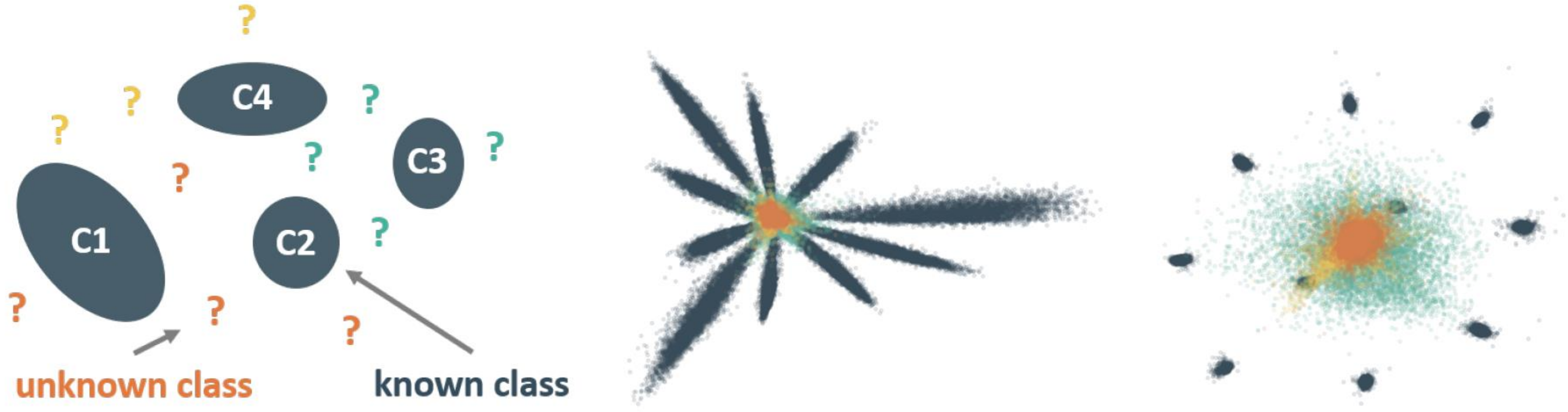
(c) Open set recognition/classification problem.

Basic Understanding of OSR

A basic strategy: protocol.

Learn a centric point (protocol) for every class.

If one image has long distances from all protocols, it will be recognized as unknown.



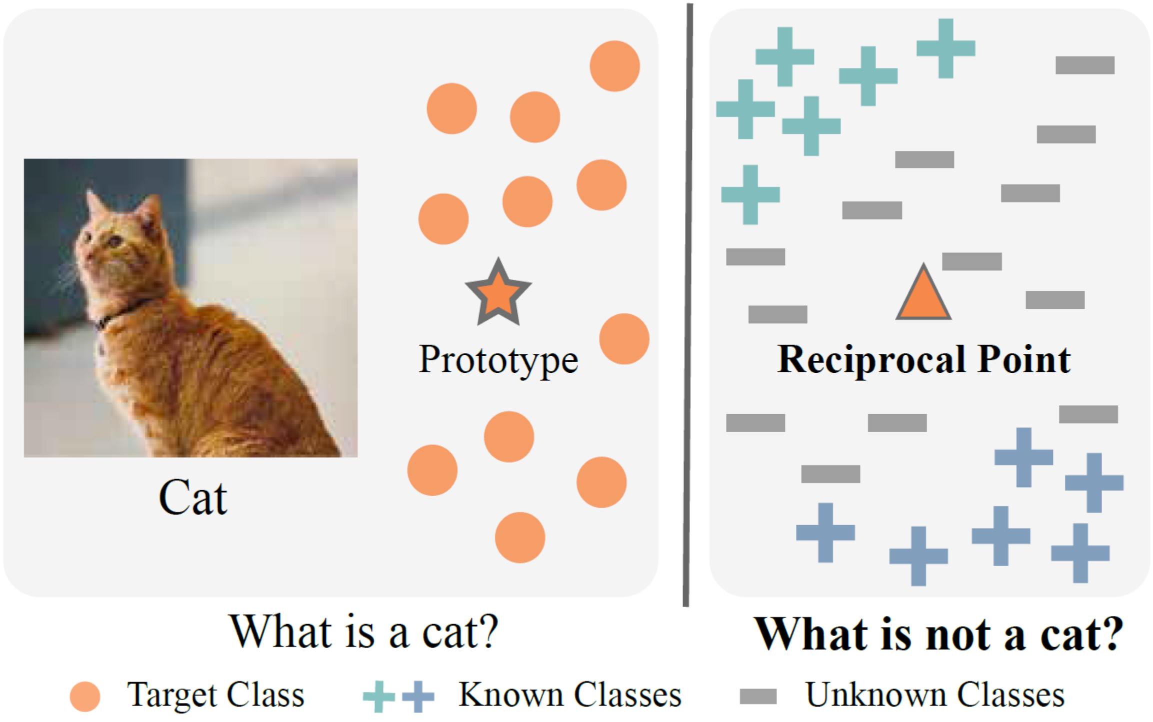
(a) Image-space (b) Softmax (c) Prototype Learning

MNIST: bule, known.
KMNIST: green
SVHN: yellow
CIFAR100: orange

"Adversarial reciprocal points learning for open set recognition." *TPAMI* 44.11 (2021): 8065-8081.

A Stronger Baseline Model: APRL

Use reciprocal points, the opposite of protocol.



MNIST: bule, known.
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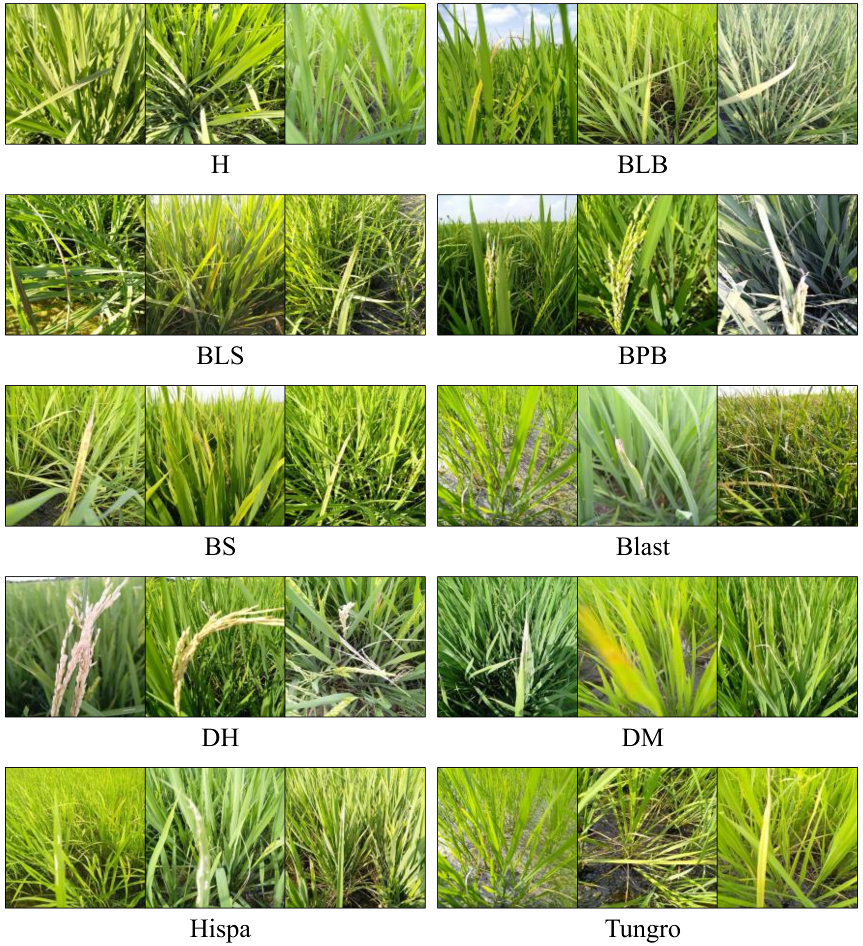
"Adversarial reciprocal points learning for open set recognition." *TPAMI* 44.11 (2021): 8065-8081.

Problem Formulation: POSR

POSR: plant-relevant open set recognition.

POSR is more difficult than generic OSR because the classes are more similar.



"Paddy doctor: A visual image dataset for automated paddy disease classification and benchmarking." *10th ACM IKDD CODS and 28th COMAD*. 2023.

Our Ambition and Objective

Ambition: plant-relevant versatile recognition (PVR)

Objective: POSR in **multiple datasets and multiple targets**.

Plant-relevant Versatile Recognition (PVR)

	Applications	Techniques
Dataset	• **Multi-farm** • **Multi-environment** • **Multi-crop** • …	• Few-shot • **Open set recognition** • Domain adaptation • …
Target	• **Disease recognition** • **Species identification** • Growth-stage recognition • …	• **Image classification** • Object detection • Segmentation • …

Our Strategy 1: Transfer Learning

Source datasets: ImageNet, PlantVillage, PlantCLEF2022

	ImageNet	AI Challenger	PlantCLEF2022
Images	1,281,167	31,718	2,885,052
Classes	1,000	61	80,000
Variations	High	Low	Huge

Multiscale Color Viewpoint

Illumination Background Growth stage

Our Strategy 1: Transfer Learning

Source datasets: ImageNet, PlantVillage, PlantCLEF2022

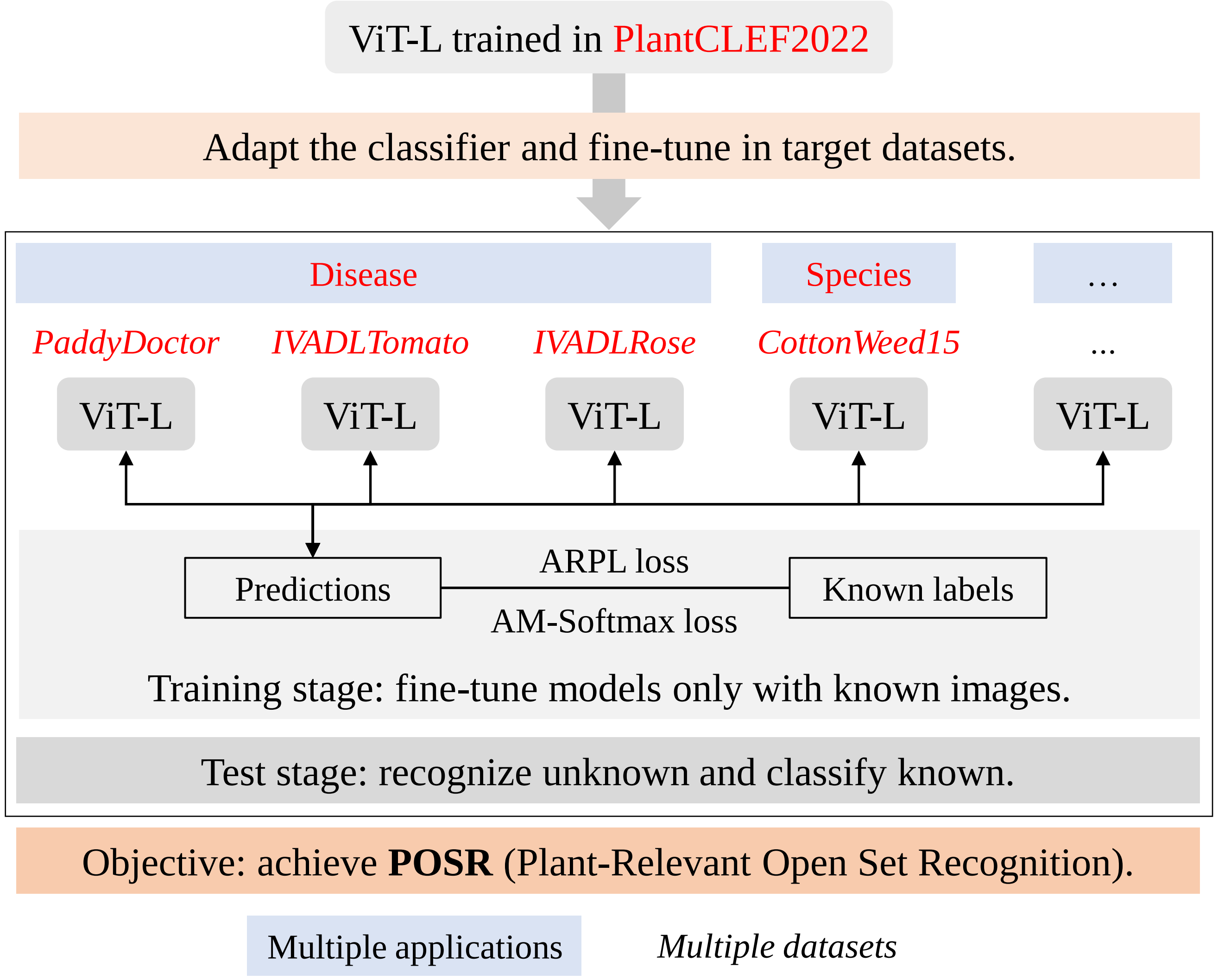
This method is better and faster on 14 datasets.

	1-shot	5-shot	10-shot	20-shot	Ratio20	Ratio40	Ratio60	Ratio80
RN50	20.50	21.75	26.45	35.95	39.90	68.90	66.90	78.25
RN50-IN	45.55	75.95	87.90	87.15	60.85	98.00	98.35	98.55
MoCo-v2	45.65	70.25	84.65	86.05	66.90	96.45	96.20	97.50
ViT	32.70	39.90	44.30	51.45	56.25	65.65	75.40	80.90
ViT-IN	27.20	33.35	43.10	45.25	55.05	68.30	75.50	82.35
MAE	17.45	41.45	59.50	59.20	85.20	97.80	98.35	98.75
Ours	**73.90**	**97.60**	**97.55**	**97.85**	**99.80**	**99.35**	**98.80**	**99.70**

Transfer learning for versatile plant disease recognition with limited data, 2022.

Our Strategy: Transfer Learning

Pretrain a ViT-L model in PlantCLEF2022 for 2 tasks on 4 datasets.



Our Strategy 2: Additive Margin Softmax

To have a compact feature space that gives more space for the unknown.

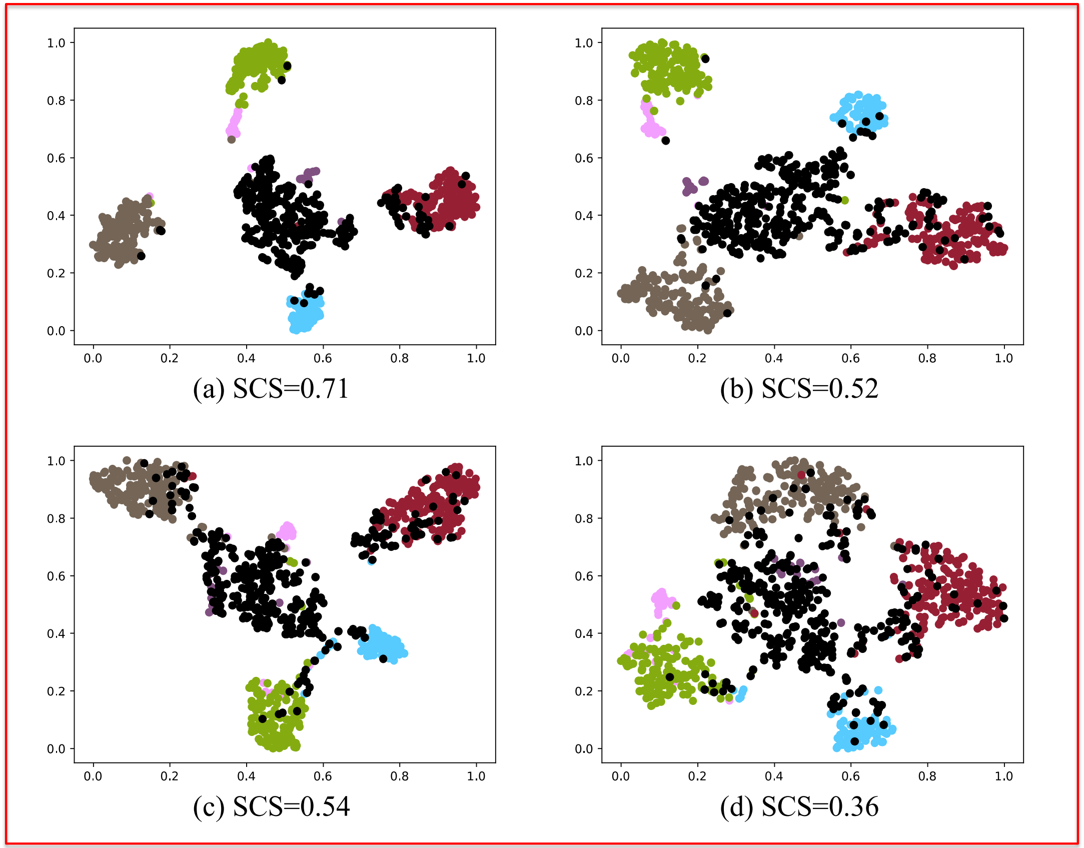
$$p_k = \frac{\exp \boldsymbol{f}^{\mathrm{T}} \boldsymbol{W}_k}{\sum_{c=1}^{C} \exp(\boldsymbol{f}^{\mathrm{T}} \boldsymbol{W}_c)}$$

$$p_k = \begin{cases} \dfrac{\exp(s \cdot (\boldsymbol{f}^{\mathrm{T}} \boldsymbol{W}_k - m))}{\exp(s \cdot (\boldsymbol{f}^{\mathrm{T}} \boldsymbol{W}_k - m)) + \sum_{c=1, c \neq \hat{c}}^{C} \exp(s \cdot \boldsymbol{f}^{\mathrm{T}} \boldsymbol{W}_c)} & \text{if } y_k = 1\,; \\ \dfrac{\exp(s \cdot \boldsymbol{f}^{\mathrm{T}} \boldsymbol{W}_k)}{\exp(s \cdot (\boldsymbol{f}^{\mathrm{T}} \boldsymbol{W}_{\hat{c}} - m)) + \sum_{c=1, c \neq \hat{c}}^{C} \exp(s \cdot \boldsymbol{f}^{\mathrm{T}} \boldsymbol{W}_k)} & \text{otherwise}\,. \end{cases}$$

Additive margin softmax for face verification. IEEE Signal Processing Letters, 25(7):926–930, 2018.

Visualize the learned features with t-SNE.

(a) ViT w. AM Softmax
(b) ViT w.o AM Softmax
(c) ResNet50 w.
(d) ResNet50 w.o



Known classes:
Ulcer
Chlorosis
Yellow_curl
Powdery_mildew
Healthy
Leaf_miner
Unknown classes:
Leaf_fungus
Septoria_spot
Blueworms

s

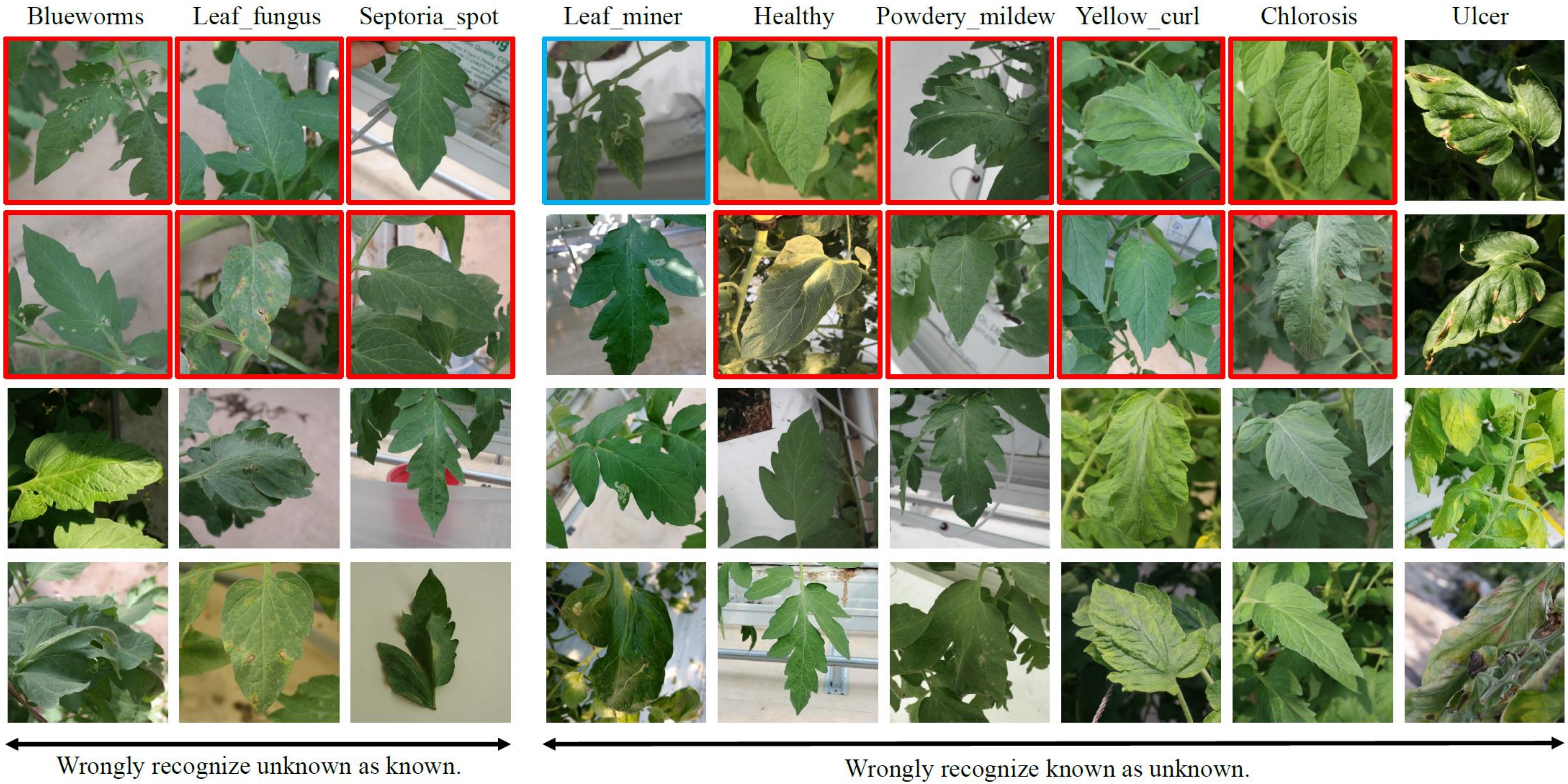
Experimental Results

TDS	Method	Loss	CSA	AUROC	OSCR
PD	RN50	CE	60.97±0.03	60.68±0.06	41.73±0.04
	RN50-IN1k	CE	97.52±0.01	87.57±0.01	86.26±0.01
	RN50-MoCov2	CE	97.97±0.01	90.02±0.01	88.90±0.02
	ViT-L	CE	68.29±0.08	62.15±0.08	47.64±0.09
	ViT-IN1k	CE	97.12±0.01	85.95±0.03	84.53±0.03
	MAE	CE	97.11±0.01	86.28±0.03	84.87±0.03
	MAE-PlantCLEF-CE	CE	98.50±0.01	90.59±0.02	89.73±0.02
	MAE-PlantCLEF-AM	AM	**98.70±0.01**	**91.69±0.01**	**91.07±0.01**
IVADLT	RN50	CE	68.90±0.02	59.83±0.13	47.79±0.11
	RN50-IN1k	CE	95.67±0.00	87.13±0.02	84.74±0.02
	RN50-MoCov2	CE	96.94±0.01	86.17±0.04	84.86±0.04
	ViT-L	CE	68.76±0.01	68.58±0.04	53.34±0.03
	ViT-IN1k	CE	98.81±0.01	91.13±0.03	90.55±0.03
	MAE	CE	93.78±0.02	84.32±0.03	81.46±0.03
	MAE-PlantCLEF-CE	CE	98.62±0.01	90.98±0.04	90.36±0.04
	MAE-PlantCLEF-AM	AM	**99.29±0.00**	**92.02±0.05**	**91.75±0.04**

Experimental Results

IVADLR	RN50	CE	74.97±0.04	58.96±0.08	48.00±0.06
	RN50-IN1k	CE	97.95±0.01	83.98±0.09	83.08±0.09
	RN50-MoCov2	CE	98.69±0.01	81.09±0.10	80.58±0.10
	ViT-L	CE	78.78±0.04	59.65±0.08	52.03±0.07
	ViT-IN1k	CE	99.20±0.01	74.12±0.17	73.75±0.17
	MAE	CE	97.88±0.01	72.04±0.19	71.25±0.19
	MAE-PlantCLEF-CE	CE	99.23±0.01	76.31±0.18	75.93±0.18
	MAE-PlantCLEF-AM	AM	**99.39±0.01**	**91.52±0.09**	**91.14±0.09**
CW	RN50	CE	64.39±0.02	60.12±0.02	43.32±0.02
	RN50-IN1k	CE	97.86±0.01	86.82±0.03	85.69±0.03
	RN50-MoCov2	CE	98.50±0.00	86.61±0.05	85.82±0.05
	ViT-L	CE	69.65±0.03	63.95±0.09	49.27±0.05
	ViT-IN1k	CE	99.12±0.00	94.88±0.01	94.29±0.01
	MAE	CE	98.54±0.00	90.21±0.03	89.46±0.02
	MAE-PlantCLEF-CE	CE	99.75±0.00	**99.51±0.00**	**99.29±0.00**
	MAE-PlantCLEF-AM	AM	**99.80±0.00**	99.26±0.01	99.10±0.01

Wrong Examples



Conclusion

- Propose an ambition, PVR, and an instantiation, POSR for multiple datasets and multiple tasks, plant disease, and species recognition.
- Two strategies to achieve the objective:
  - Transfer learning in the PlantCLEF2022 dataset, plant-related, huge variation, more samples.
  - Additive margin Softmax loss
- However, our model is still risky to deploy in real applications.

Thank you

Questions and Comments

Email: xml@jbnu.ac.kr

Our codes and slides will be public: https://github.com/xml94/POSR