



Debiased Learning from Naturally Imbalanced xView Data

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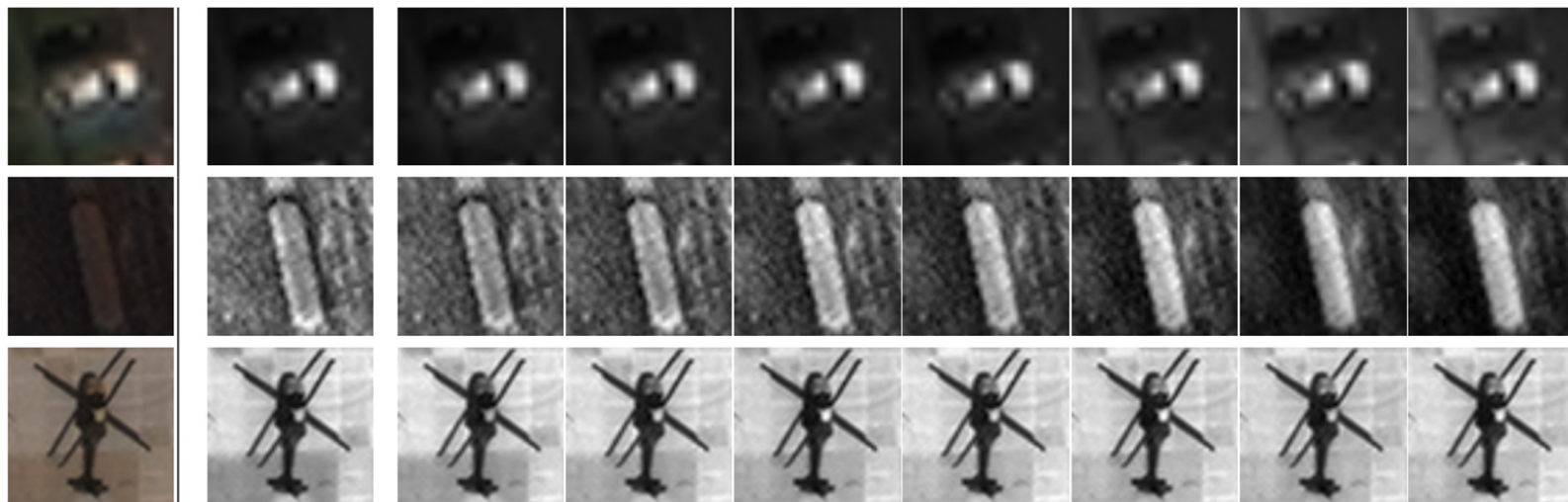
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06/19/2023

**This work was supported, in part, by the National Geospatial Intelligence
Agency / Etegent Technologies Ltd. contract HMD47620C0063.**

Our Task: Remote Sensing Data

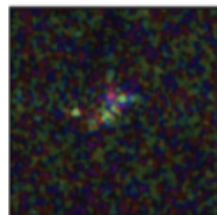
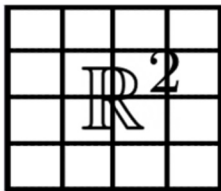
8-Band Images (xView Dataset) Classification



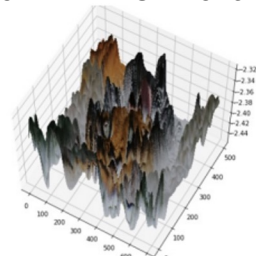
color RGB | 1.coastal blue 2.blue 3.green 4.yellow 5.red 6.red edge 7.near-IR1 8.near-IR2

An Image is a Function from Domain to Co-Domain

Domain: Pixel Locations (x,y)

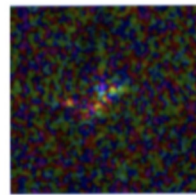
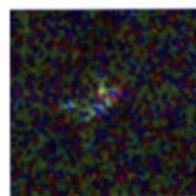


Co-Domain: Pixel Values (RGB)



scaling

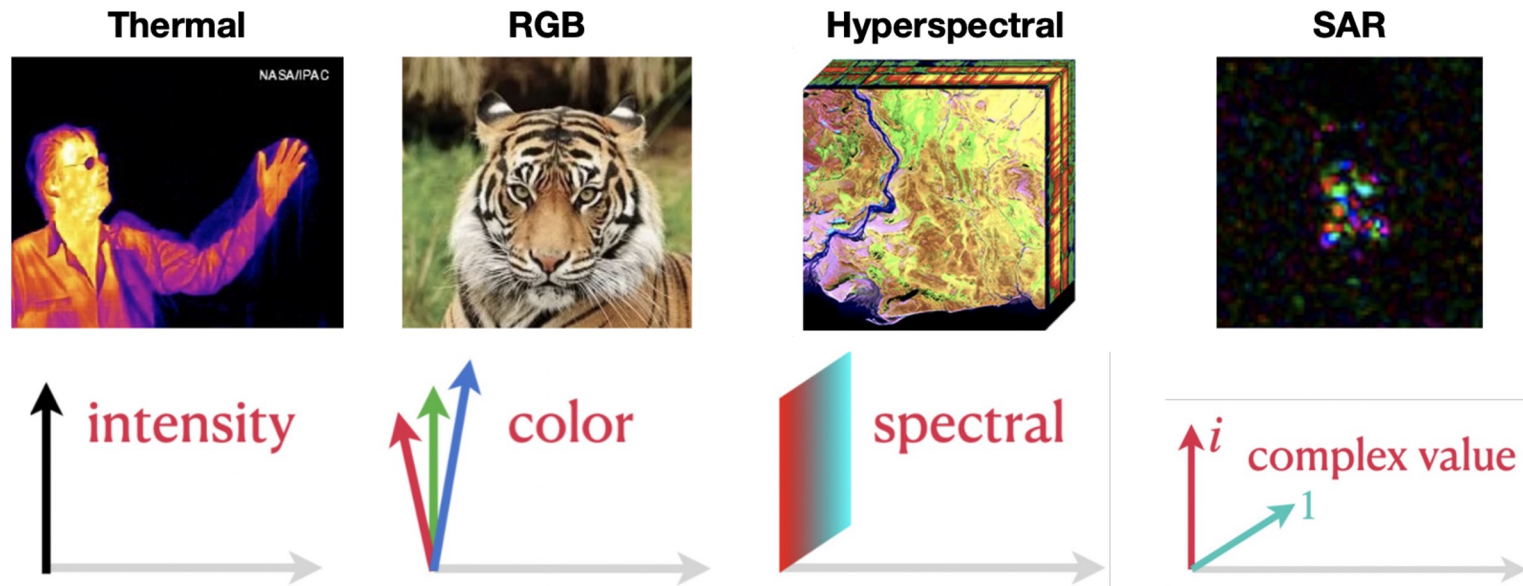
rotation



color

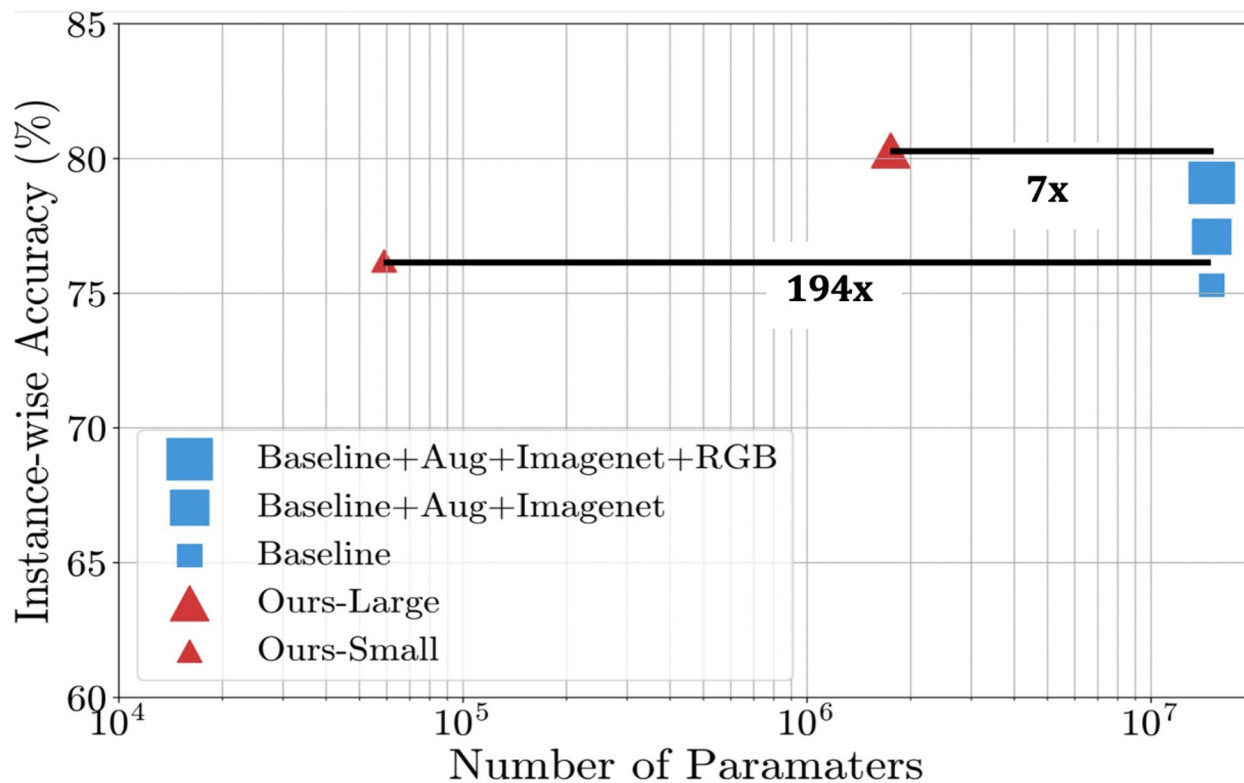
C-scaling

Co-Domain is Related to Diversity of Image Types



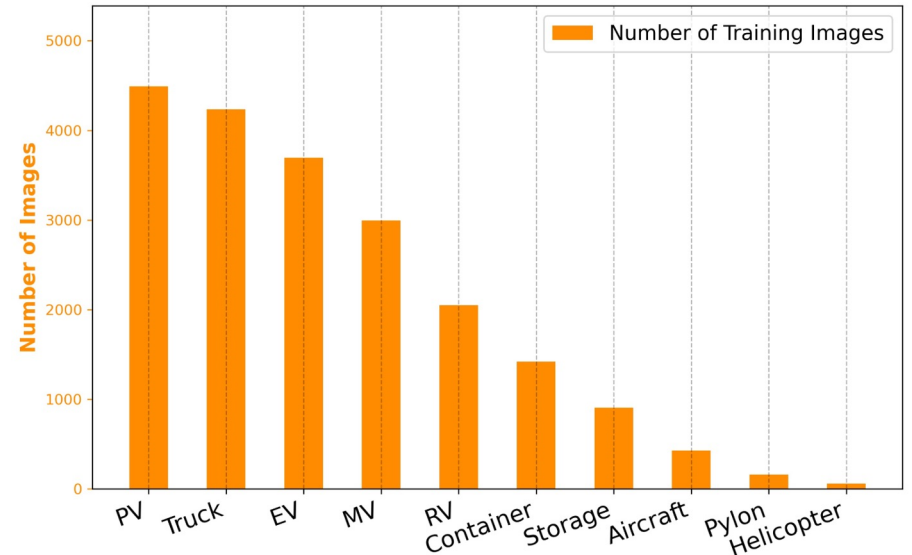
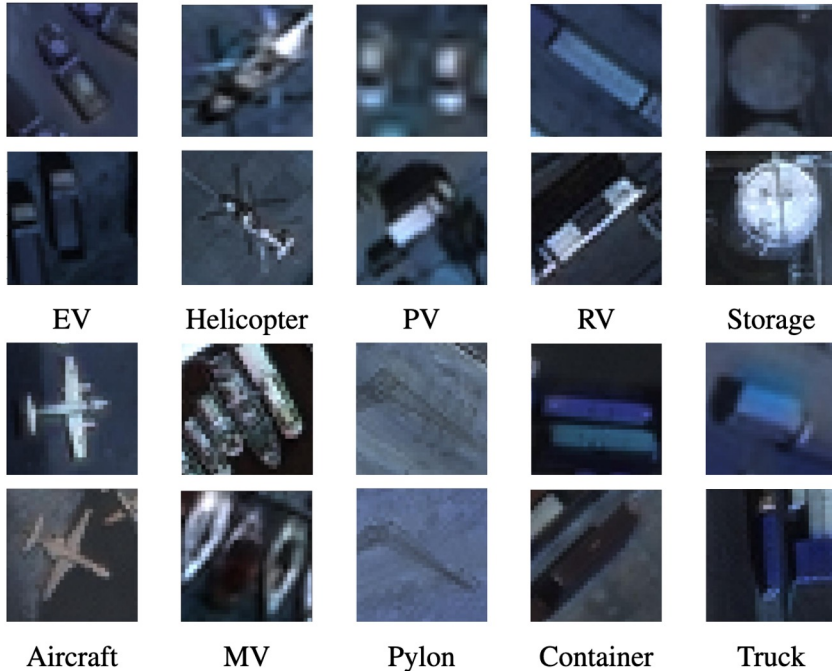
Singhal, Utkarsh, Yifei Xing, and Stella X. Yu. "Co-domain symmetry for complex-valued deep learning." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.

xView Results: Simpler and Better Ultra-lean

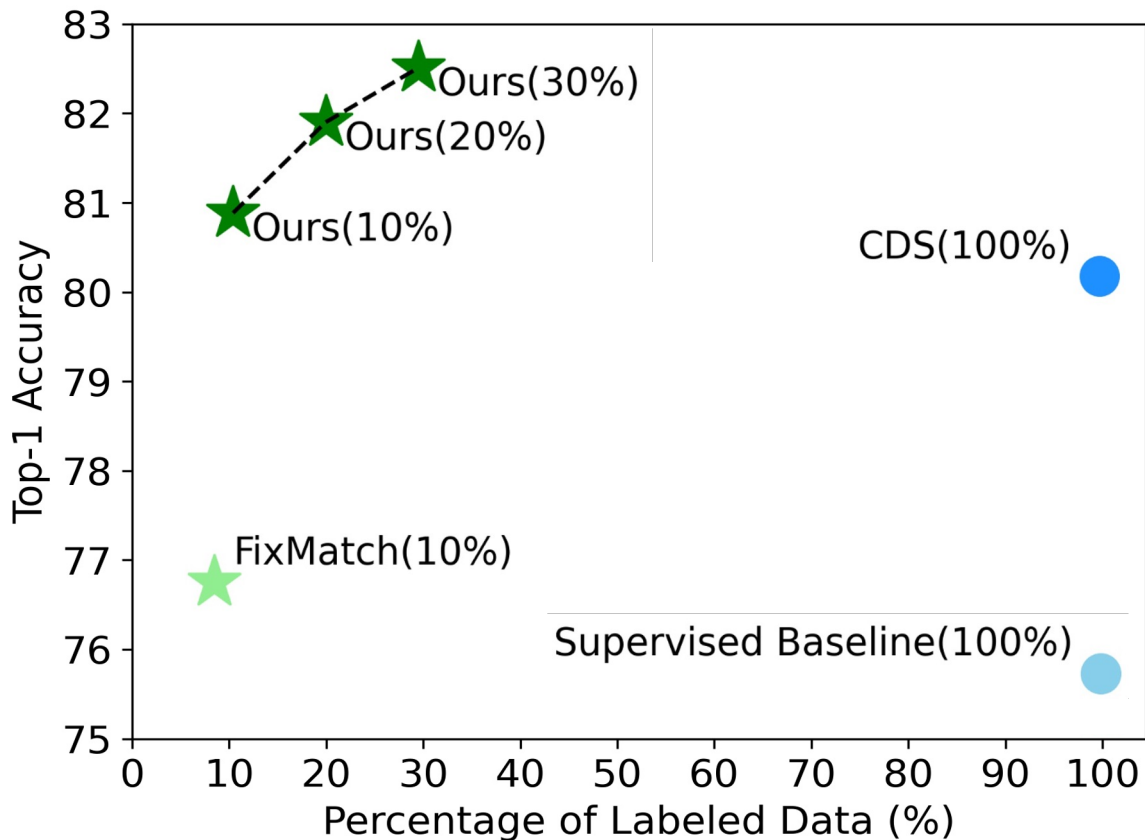


Our Task: Remote Sensing Data Classification

xView Dataset

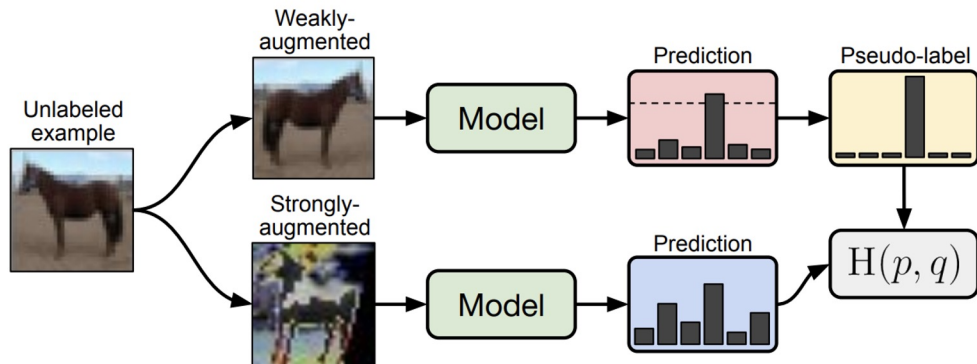


Our Task: Remote Sensing Data

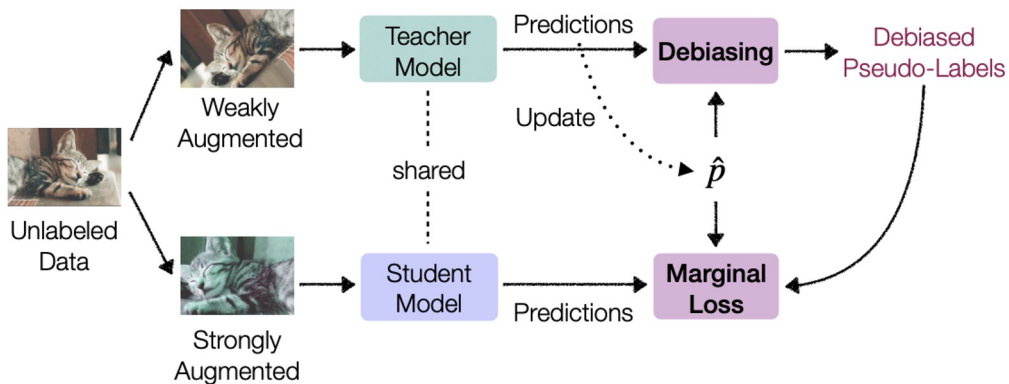


Related Semi-Supervised Learning Methods

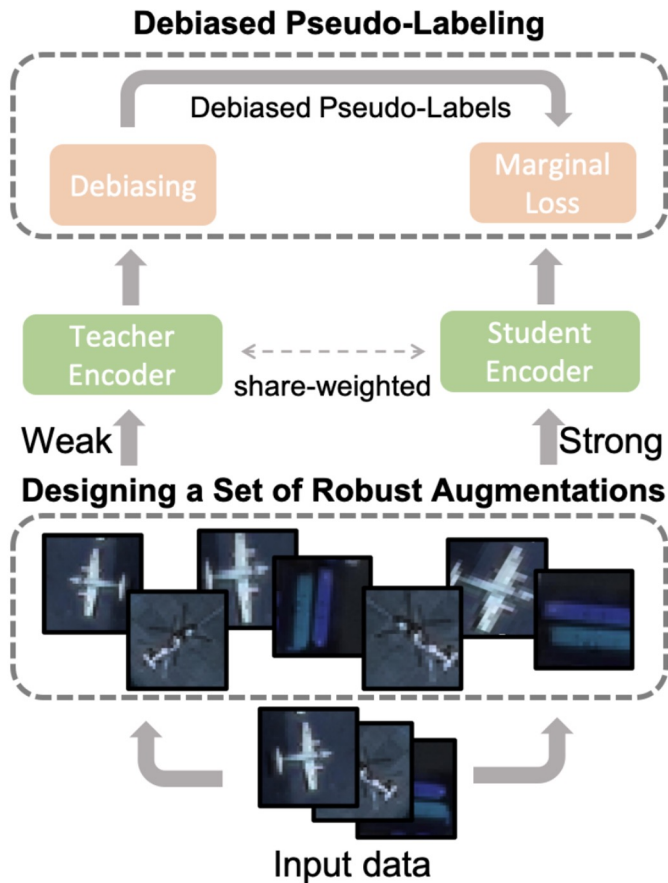
**FixMatch
(NeurIPS'20)**



**DebiasedPL
(CVPR'22)**



Our Semi-Supervised Learning Framework



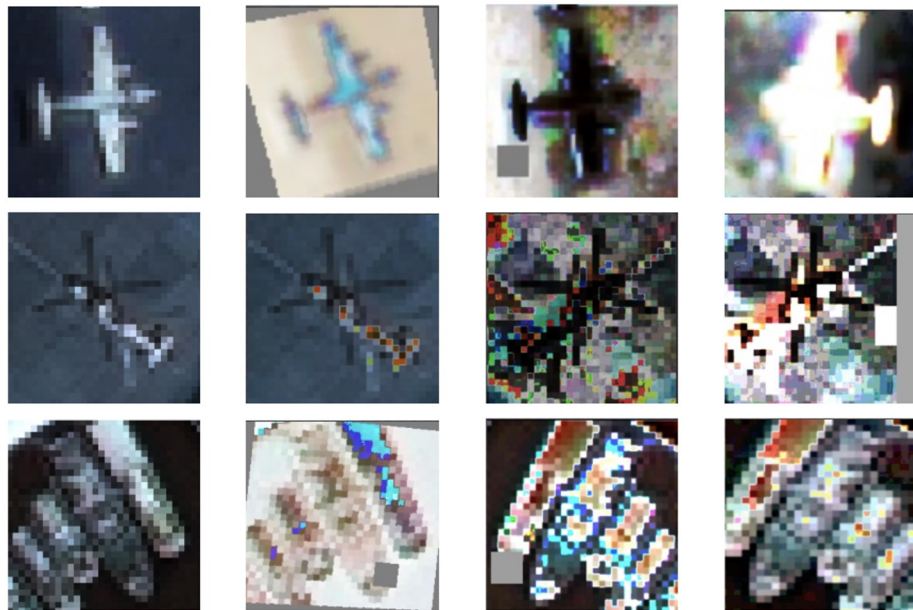
Contribution #1: Robust Augmentations

Design a set of robust strong and weak augmentations suitable for remote sensing data.

Contribution #2: Debiased Pseudo-Labeling

Leverage DebiasedPL to mitigate the bias in pseudo-labeling.

RandAugment Appears to be too Complicated for Remote Sensing Data



Original

RandAugment
($m = 6$)

RandAugment
($m = 8$)

RandAugment
($m = 10$)

Our New Findings: Data Augmentations for Remote Sensing Data

Augmentations	Used	Reason
<i>RandAugment</i> [8]	×	The use of RandAugment with high intensity of transformations may result in overfitting to the training set, which can be detrimental for generalization on remote sensing data.
<i>Rotation</i>	✓	random rotation (± 10 degrees) can simulate variations in remote sensing imaging angles.
<i>Scaling</i>	✓	scaling(0.8, 1.2) can simulate variations in ground sampling distances, which is important for generalization on remote sensing data.
<i>Horizontal Flip</i>	✓	horizontal flipping simulates mirror-reflected scenes in remote sensing data

Weak augmentation

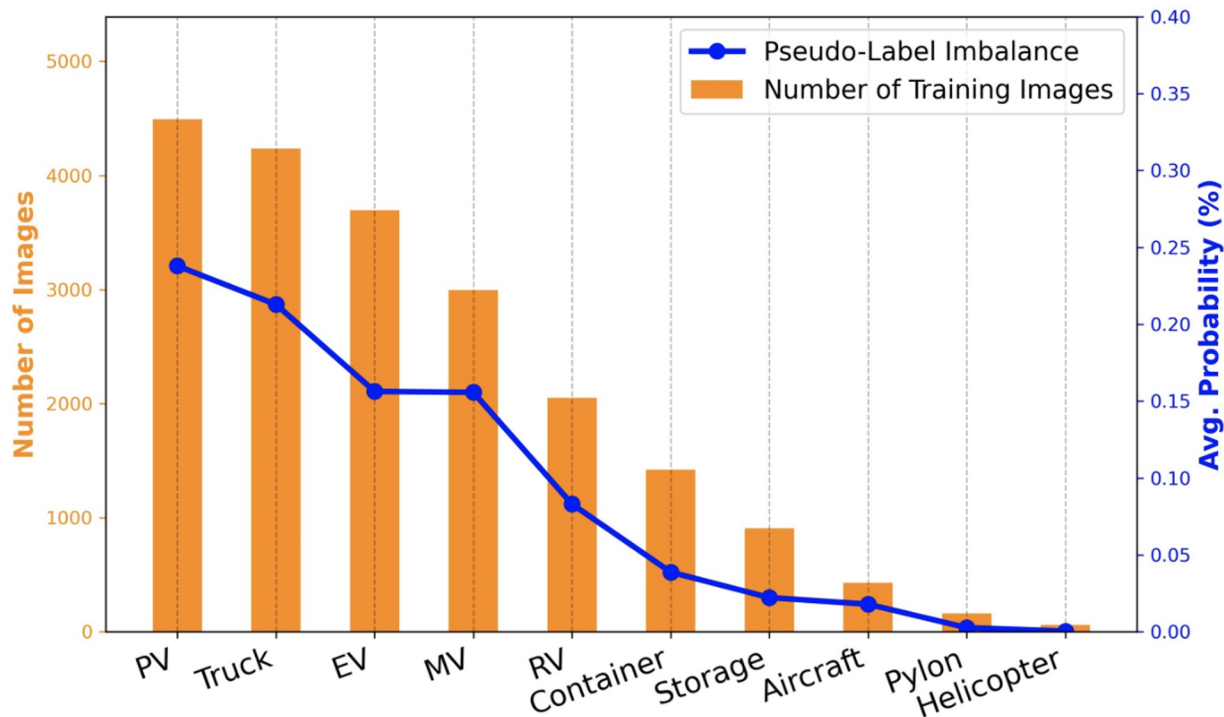
<i>None</i>	✓	×	×	✓	×	×
<i>Random Resize Cropping</i>	×	✓	✓	×	✓	✓
<i>Horizontal flipping</i>	×	✓	✓	×	✓	✓

Strong augmentation

<i>ResizeCropping + Horizontal flipping</i>	✓	✓	✓	✓	✓	✓
<i>Rotation(± 10 degrees)</i>	×	×	×	✓	✓	✓
<i>Scaling(0.8, 1.2)</i>	×	×	×	✓	×	✓
<i>RandAugment(m=10)</i>	✓	✓	×	×	×	×
<i>RandAugment(m=5)</i>	×	×	✓	×	×	×

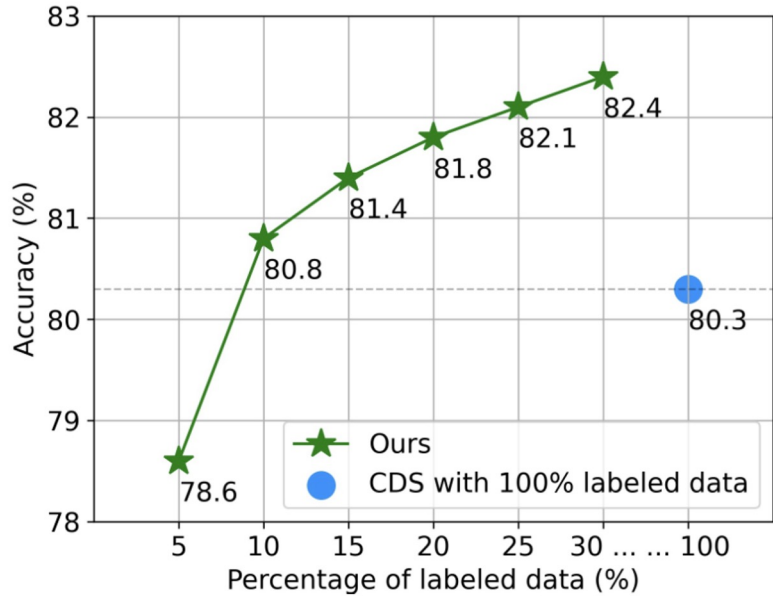
Top-1 accuracy (%)	69.8	75.6	76.3	79.4	79.7	80.8
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Two Sources of Imbalance (Training Label & Pseudo-Label)



Quantitative Results

Increasing the amount of labeled data



Class-wise accuracy

