



# **Instance Segmentation for Campus Waste Detection Using Mask R-CNN**

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# Dataset Overview

- Task:** Detect and segment waste items on UNH campus images
- Data source:** COCO-format annotations (remapped from original LabelMe)
- Number of samples:** 200 images (512×512 px each)
- Classes:** 2 (recyclable\_container, food\_packaging)
- Partition:**
  - Train: 160 (80 %)
  - Val: 20 (10 %)
  - Test: 20 (10 %)
- Normalization:** Images normalized using ImageNet mean [0.485, 0.456, 0.406] and std [0.229, 0.224, 0.225] (Detectron2 defaults)
- Augmentation (training):** Random horizontal flips; resize shortest edge to 800 px; other default FPN augmentations from Mask R-CNN config

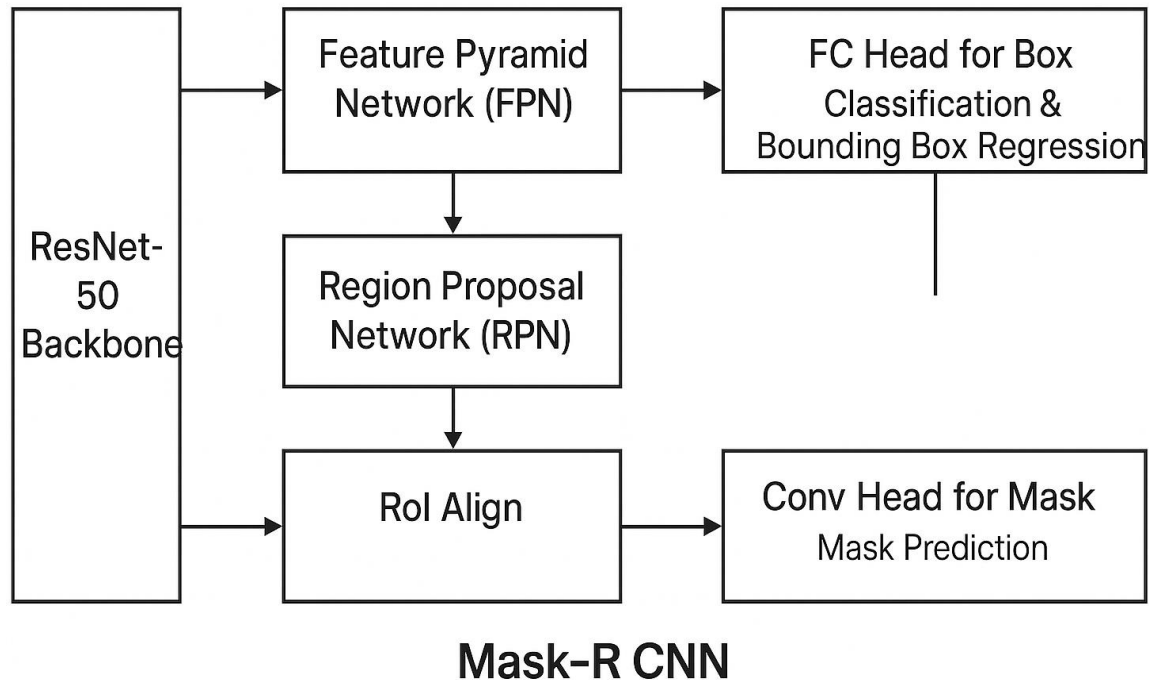
XFMT4614.jpg



DYYQ2405.jpg



# Model Architecture



- Base network:** Mask R-CNN with ResNet-50 backbone + Feature Pyramid Network (FPN)

- Pretrained weights:** COCO-InstanceSegmentation/mask\_rcnn\_R\_50\_FPN\_3x

- ROI Heads:**

- Box head → classification + bbox regression

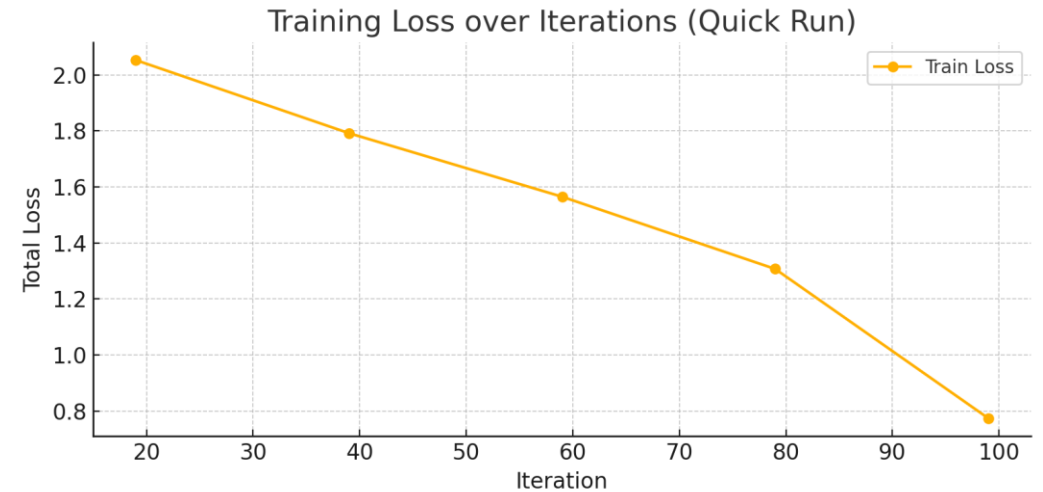
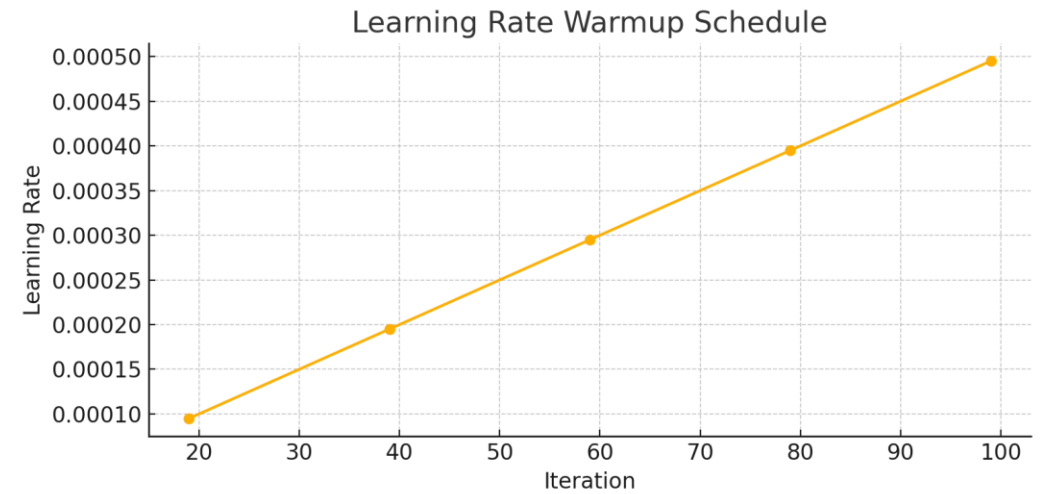
- Mask head → per-pixel segmentation

- Num classes:** 2

- Losses:** Cross-entropy for class, smooth L1 for boxes, binary cross-entropy for masks

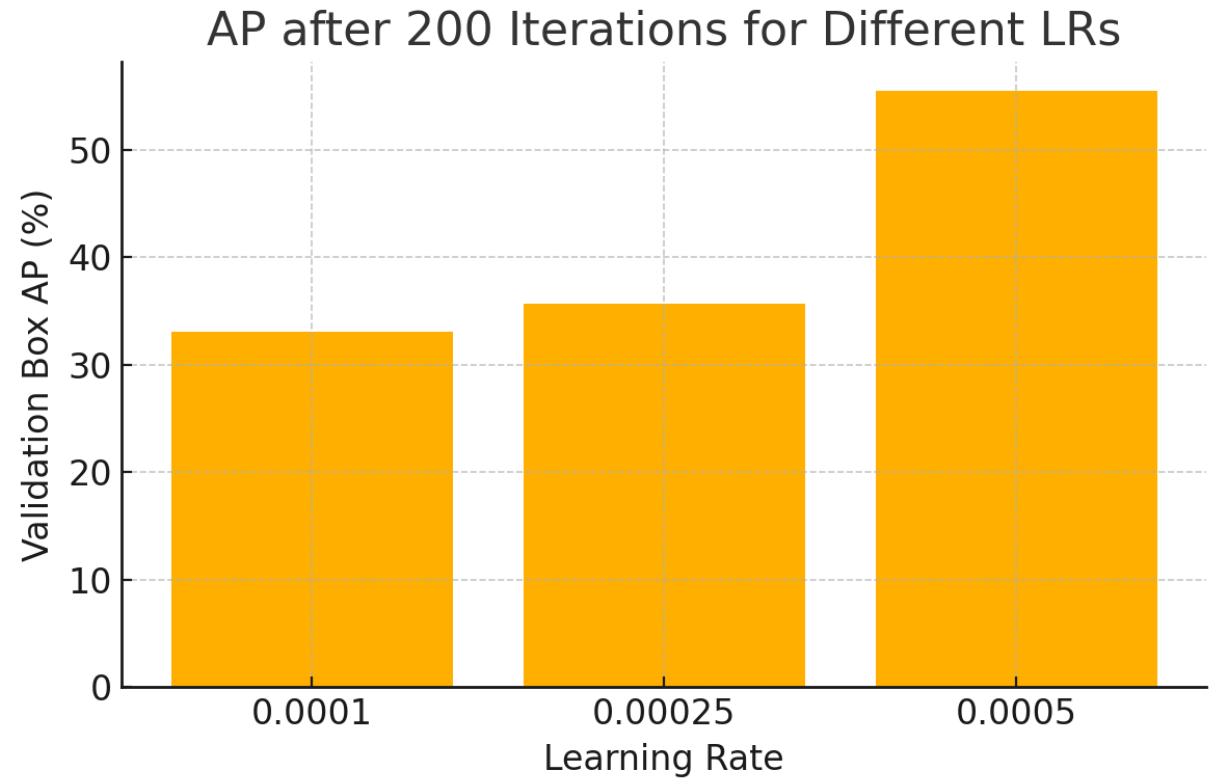
# Training Setup

- Framework:** Detectron2 DefaultTrainer
- Initial hyperparameter grid search over learning rates [ $1\text{e-}4$ ,  $2.5\text{e-}4$ ,  $5\text{e-}4$ ]
- Short runs: batch size 4 images/GPU for 200 iterations
- Selected best LR ( $5 \times 10^{-4}$ ), then merged train+val (180 images) for fine-tuning
- Final run:** 1,000 iterations, SGD optimizer (momentum 0.9, weight decay  $1 \times 10^{-4}$ )



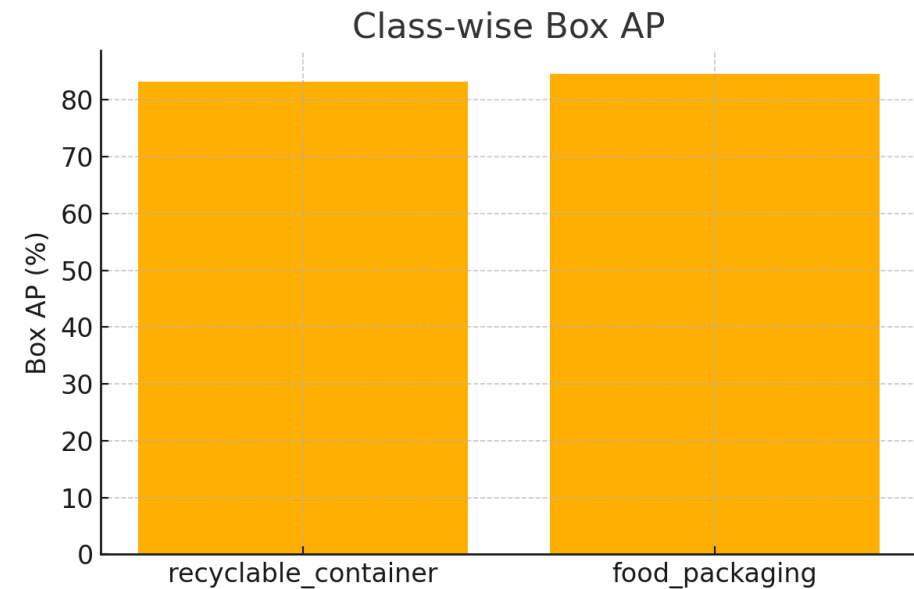
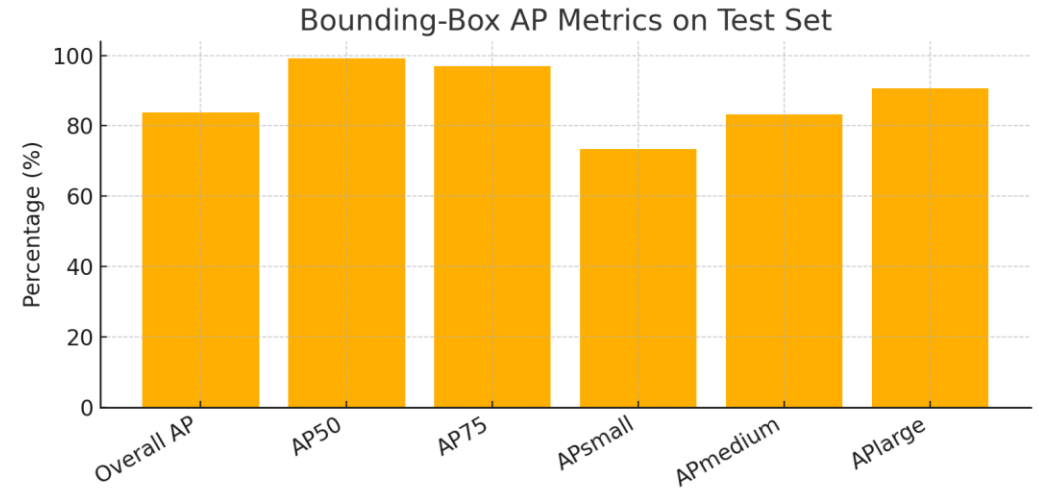
# Hyperparameter Tuning Results

- $\text{LR} = 1 \times 10^{-4} \rightarrow \text{box AP} \approx 33\%$  after 200 iterations
- $\text{LR} = 2.5 \times 10^{-4} \rightarrow \text{box AP} \approx 36\%$  after 200 iterations
- $\text{LR} = 5 \times 10^{-4} \rightarrow \text{box AP} \approx 55\%$  after 200 iterations
- Clear performance boost at higher learning rate, indicating under-learning at lower rates



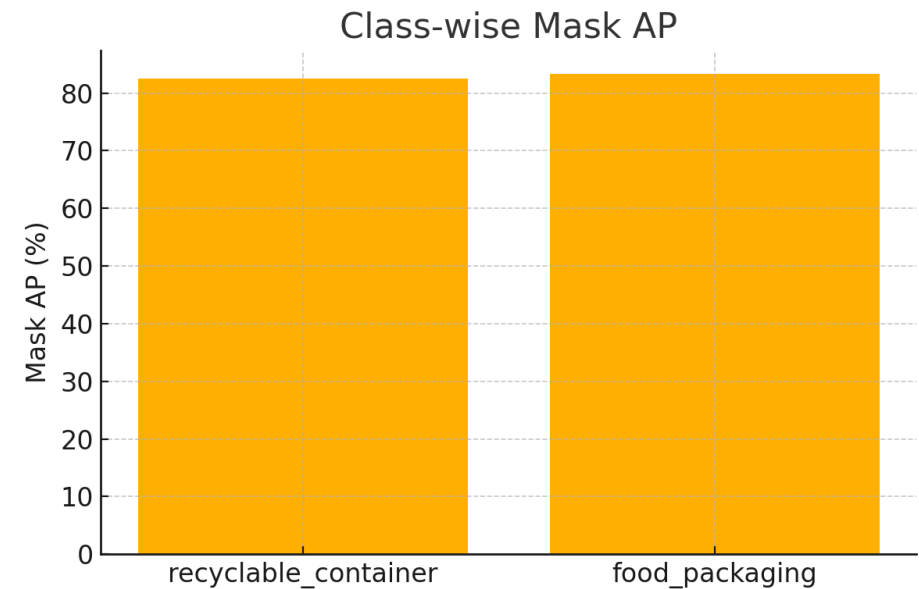
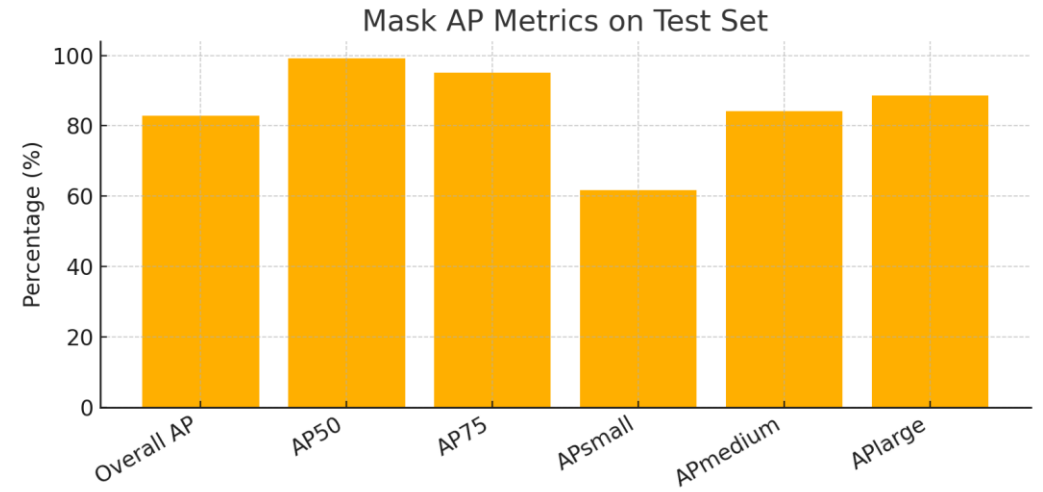
# Final Test-Set Performance (Bounding Boxes)

- Overall AP: 83.9 %
- AP50: 99.1 % | AP75: 97.1 %
- APsmall/APmedium/APlarge: 73.4 % / 83.3 % / 90.7 %
- Class-wise box AP:
  - recyclable\_container: 83.2 %
  - food\_packaging: 84.5 %



# Final Test-Set Performance (Segmentation Masks)

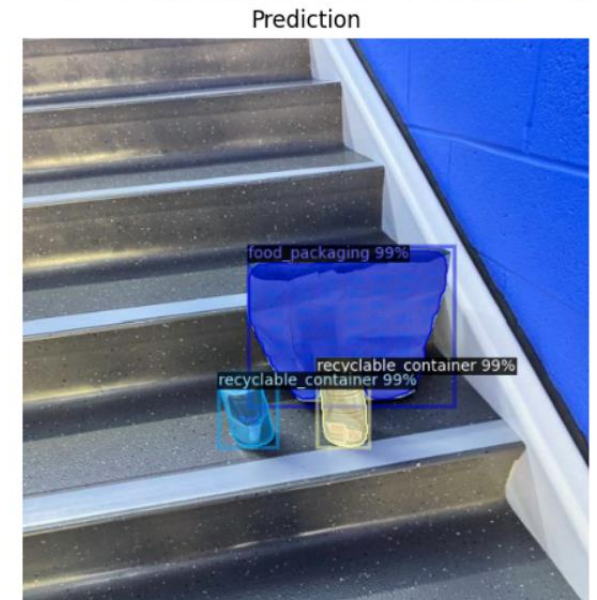
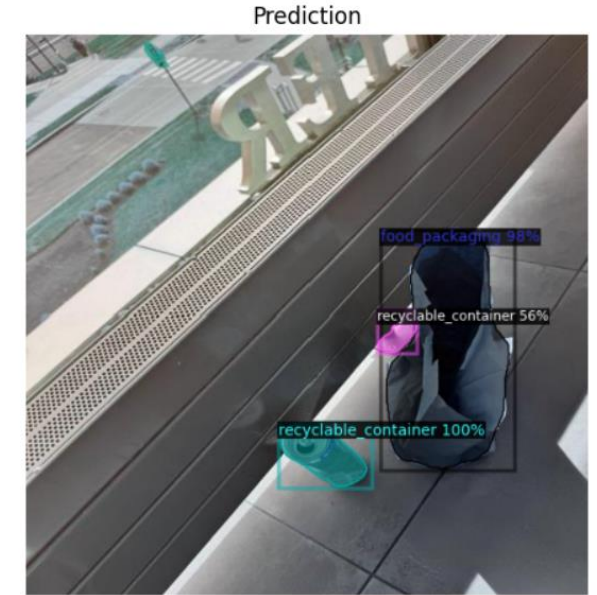
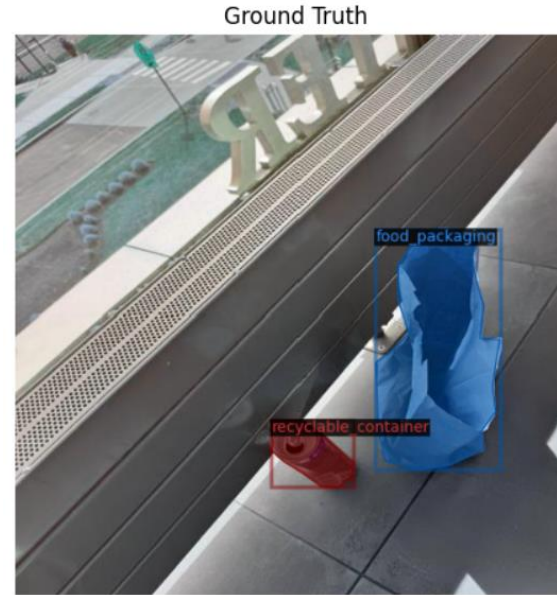
- Overall mask AP: 82.9 %
- AP50: 99.1 % | AP75: 95.2 %
- APsmall/APmedium/APlarge: 61.8 % / 84.1 % / 88.6 %
- Class-wise mask AP:
  - recyclable\_container: 82.6 %
  - food\_packaging: 83.3 %





# Qualitative Results

- Display side-by-side: ground-truth vs. predicted masks
- High-quality boundary delineation even under occlusion and varied lighting
- Rare misclassifications; model reliably ignores background clutter





# Conclusions & Future Work

- Demonstrated effective transfer learning with just 200 annotated images
- Achieved  $> 80\%$  AP on both detection and segmentation tasks
- Future plans:
  - Expand to additional waste categories (paper, metal, etc.)
  - Deploy optimized model on edge devices for real-time campus monitoring
  - Integrate alerts into campus recycling management system