Visual Recognition HW3

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Git link: [Link]

1. Introduction

This task involves multi-class cell instance segmentation using the Mask R-CNN framework[1]. To investigate the effect of class-specific modeling, we conduct an ablation study where each semantic category is trained with a dedicated model. The goal is to evaluate whether isolated training improves performance over a shared unified detector. The inference results are then merged to generate the final submission.

2. Method

Data Augmentation:

- Conversion to Tensor.
- **Random Horizontal Flip** with 50% chance.
- **Brightness, Contrast, and Gamma Jittering** applied independently with random parameters:
  - Brightness factor $\in [0.8, 1.2]$
  - Contrast factor $\in [0.8, 1.2]$
  - Gamma factor $\in [0.9, 1.1]$

Model Architecture and Hyperparameters

- **Backbone:** ResNet-50 + FPN, pre-trained on ImageNet (*maskrcnn_resnet50_fpn_v2*).
- **Mask Branch:** 5×5 conv head followed by transposed convolution upsampling.
- **Head:** RoIAlign for feature pooling + class-specific *FastRCNNPredictor* and *MaskRCNNPredictor*.
- **Optimizer**: AdamW[2]
  - lr_backbone = 1e-5
  - lr_heads = 1e-4
  - weight_decay = 1e-4
- **Scheduler**: CosineAnnealingLR [3](min lr = 1e-6)
- **Batch size**: 2
- **Number of epochs**: 300

Backbone Choice: ResNet-50 FPN

PROS:

- Strong feature extraction via residual learning
- Good balance of accuracy and computational cost
- FPN enhances multi-scale detection, beneficial for varying object sizes

CONS:

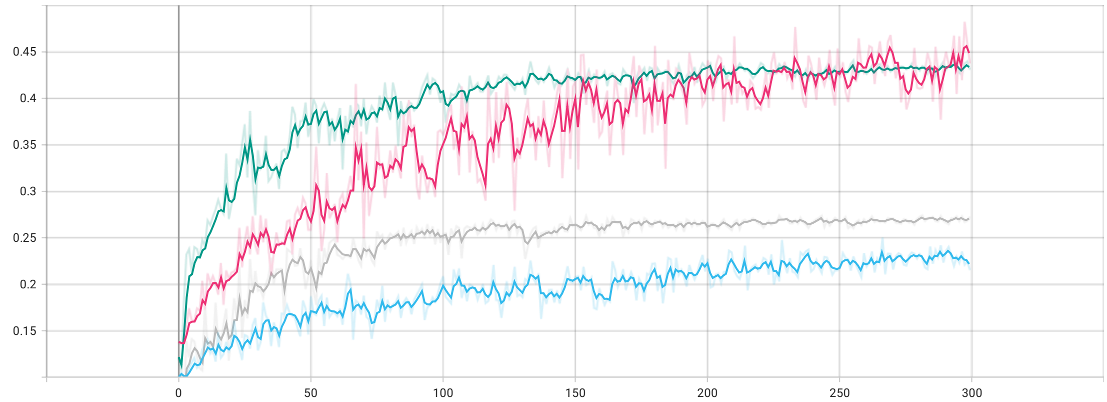
- Heavier than lightweight alternatives (e.g., MobileNet)
- Slower inference compared to shallow networks
- Slightly less accurate than deeper models like ResNet-101 in some cases

Training Strategy

- 4 separate models were trained, each handling **only one semantic class** (class1, class2, class3, class4).
- For each image, instance masks were extracted per class from .tif files, using instance ID > 0 as binary masks.
- When a sample contains **no valid instance** of the target class, a dummy zero-mask and background label is injected to maintain training stability.
- At inference time, four class-specific models were loaded and run independently over each test image.
- For each model, the class-specific label was assigned to all valid predictions (label == 1), and results were filtered based on a minimum score threshold of 0.01. After merging outputs from all models, we applied **NMS** with an IoU threshold of 0.5 to eliminate redundant or spatially overlapping masks across different classes, as commonly practiced in ensemble-based detection pipelines.

3. Results

Training AP50 of each classes shown below.



Color: class-1 – blue, class-2 – pink, class-3 – green, class-4 – gray

The Combined submission score is **32.51%**

4. Additional Experiments

Class-wise Training and Inference:

Hypothesis:

Training a separate Mask R-CNN model for each semantic class allows the network to focus on class-specific visual features without interference from inter-class competition. This may be especially beneficial when objects of different classes have very different shapes or scales.

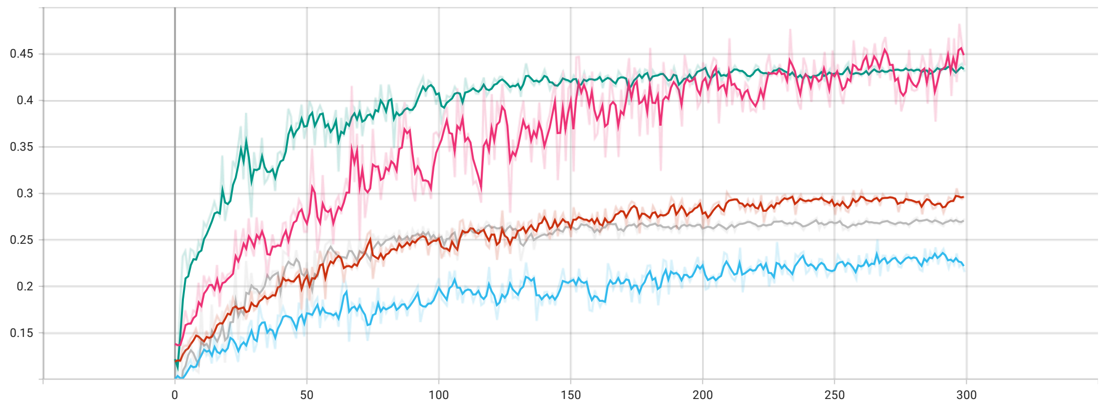
How This May Work:

By isolating training per class, the model simplifies its task into binary instance detection: “object or not” for a given class. This can potentially:

- Improve feature purity for small or rare classes
- Reduce class confusion in overlapping masks
- Allow customized hyperparameters or augmentation for each class

Experiment:

Model	Test AP (%)	Description
class1	**22.18**	Trained exclusively on Class 1
class2	**44.88**	Trained exclusively on Class 2
class3	**43.37**	Trained exclusively on Class 3
class4	**27.07**	Trained exclusively on Class 4
Merged	**32.51**	Combined predictions
Baseline	**31.67**	Standard multi-class Mask R-CNN



*Color: **Baseline** – orange*

The class-wise training strategy yields a **2.65%** relative improvement over the baseline. This supports the claim that separating class training can enhance model accuracy, especially when coupled with proper instance handling and inference fusion.

5. References

[1] K. He, G. Gkioxari, P. Dollár, and R. Girshick, “Mask R-CNN,” in *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 2017, pp. 2961–2969.
[2] I. Loshchilov and F. Hutter, "Decoupled weight decay regularization," *arXiv preprint arXiv:1711.05101*, 2017.
[3] L. N. Smith, "Cyclical learning rates for training neural networks," in *Proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV)*, 2017, pp. 464–472.