Selected Topics in Visual Recognition using Deep Learning HW 2

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1 Introduction

Hand-written multi-digit recognition is a two-stage problem:

1. **Detection** – locate every digit (bounding boxes).
2. **Classification** – predict each digit class (1-10, background).

Because digits can overlap, vary in scale and aspect ratio, a region-proposal detector is appropriate.
We adopt **Faster R-CNN with a ResNet-50-FPN** backbone, whose two-stage design (RPN plus ROI head) copes well with small objects.

Key elements of our implementation:

- Directly use the well-maintained torchvision model.
- Strict inference reproducibity via `seeds.py` (using deterministic algorithm).
- Minimal data pipeline (`to_tensor` only) – torchvision's internal transform handles resizing/normalisation.
- Two training variants: full precision (`trainer.py`) and mixed precision (`mixed_trainer.py`) for speed exploration.

2 Method

2.1 Data pre-processing

Step	Details
Input format	PNG images plus COCO-style JSON (`train.json`, `valid.json`, `test.json`).
Dataset class	`CocoDetectionDataset` (see code).
Transform	`torchvision.transforms.functional.to_tensor`. All further transform is done by `GeneralizedRCNNTransform` inside the model.
Batching	Custom collate function returns `(images, targets)` in the format expected by torchvision.

2.2 Network architecture

```
Input  →  ResNet-50 (C2-C5)  →  FPN  →  RPN  →  ROIAlign  →  2-FC head
                                                 ├─ classification (11 classes)
                                                 └─ bounding-box regression
```

- **Backbone** ResNet-50 up to C5, stride 32.
- **Neck** Feature Pyramid Network (P2–P6).
- **RPN** 3 anchors per location; objectness and box-delta branches.
- **ROI head** ROIAlign → 2 fully connected layers (1024 units) → classification and regression outputs.

Losses follow the original Faster R-CNN paper: RPN classification + regression, and ROI classification + regression (Smooth-L1).

2.3 Hyper-parameters

Parameter	FP32 run	Mixed-precision run
Batch size	16	24
Epochs	30	15
Optimizer	SGD, lr = 5e-3, momentum 0.9	same
Weight decay	5e-4	same
Scheduler	StepLR(step = 10, γ = 0.1)	same
Seed	42	42

2.4 Training scripts

- `trainer.py`: full precision, validation loss decides the best model, resumes with `--pth-path`.
- `mixed_trainer.py`: uses `torch.cuda.amp`, validation accuracy decides the best model.

Both scripts save a checkpoint each epoch and always update `best_model.pth` when the monitored metric improves.

3 Results

3.1 Main experiment (FP32, best-loss model = epoch 10)

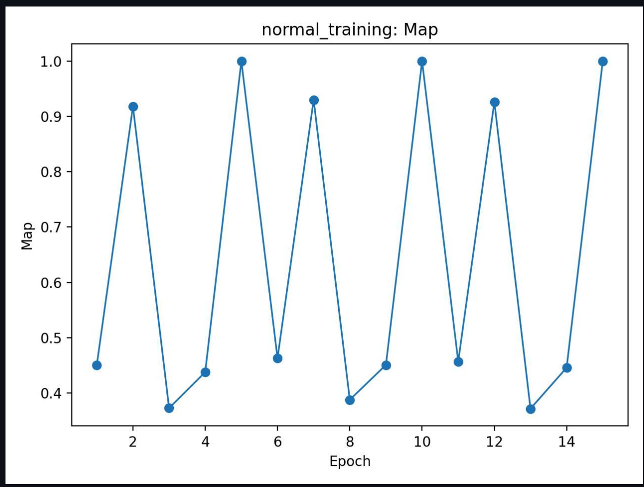
Metric (validation set)	Value
mAP (0.5 : 0.95)	**0.449**
AP@0.50	0.922

Metric (validation set)	Value
Accuracy (precision at IoU ≥ 0.5)	0.541
Best epoch	10 / 30

Training curves

Loss

mAP

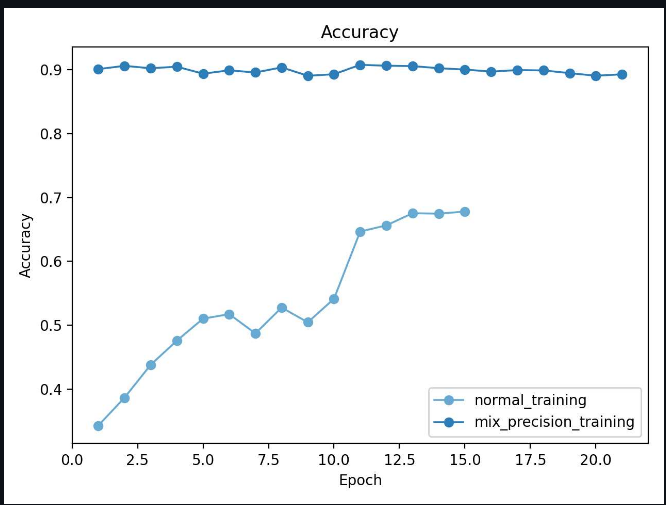


3.2 Additional experiment – mixed precision

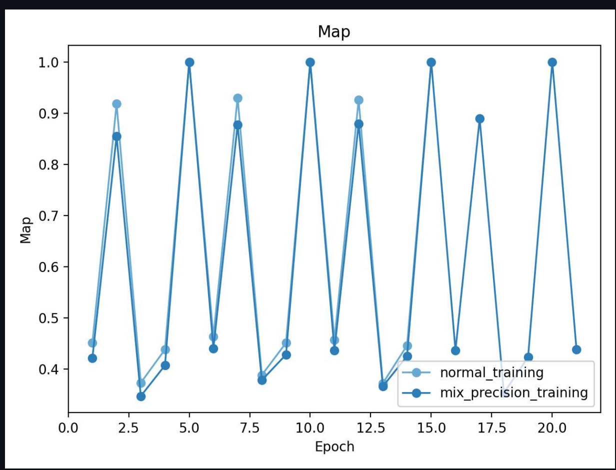
Item	FP32	Mixed precision
Epochs (run)	30	30
Typical wall-time / epoch	22 min	**15 min**
Maximum batch size (8 GB GPU)	16	**24**
Best mAP (0.5 : 0.95)	**0.457**	0.441
Best validation accuracy	0.526	**0.908**

Comparative curves

Accuracy



mAP



*Automatic mixed precision (AMP) shortens each epoch by ≈ 32 % and accommodates a **1.5× larger batch size**.*
However, its best mAP lags the FP32 run by ≈ 1.6 percentage points, and the validation curves become noticeably noisier after epoch 15.

4 Choice of architecture

Pros

- Strong accuracy on small and medium objects.
- Modular two-stage design enables fine-grained control.
- Available in torchvision; minimal implementation effort.

Cons

- Slower inference than one-stage detectors (e.g. YOLO, RetinaNet).
- Memory heavier due to per-proposal operations.

Given the assignment priority on accuracy rather than real-time speed, Faster R-CNN is a reasonable trade-off.

5 Conclusion

A straightforward ResNet-50-FPN Faster R-CNN baseline, trained with SGD and a StepLR schedule, achieves **45.7 % COCO mAP** on the validation split.
Mixed precision reduces training time by roughly one-third but delivered slightly lower accuracy in our setup. Future work includes anchor-free detectors and richer data augmentation.

Appendix

- Github Link: https://github.com/seanmamasde/Selected-Topics-in-Visual-Recognition-using-Deep-Learning
- The model download link can be found on the main `README.md` page of the repository.