2025 Visual Recognition Deep Learning – HW 2

HW2_GithubLink

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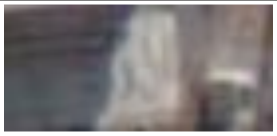
1. Introduction

This assignment focuses on the task of digit recognition, which entails localizing numerical digits within images via bounding boxes and subsequently classifying the digits contained within these regions. The objective is to accurately identify the numerical content present in each image. The dataset comprises 30,062 training images, 3,340 validation images, and 13,068 test images. A notable challenge arises from the fact that some images are of low resolution and small spatial dimensions, thereby rendering the digits difficult to discern. As illustrated in Picture 1, the digit is visually ambiguous, which may hinder both the detection accuracy and overall model performance. This degradation in image quality can adversely affect evaluation metrics such as the mean Average Precision (mAP), potentially leading to missed detections.

To mitigate these limitations, I adopted a more advanced detection framework by leveraging a pre-trained Faster R-CNN model augmented with a Vision Transformer (ViT) backbone, which is based on the paper published in 2021. This architecture has demonstrated superior detection capabilities relative to conventional convolutional counterparts. Furthermore, I introduced architectural modifications to the pre-trained model specifically aimed at enhancing its sensitivity to small-scale digit instances. In addition, a series of experiments were conducted involving hyperparameter tuning and the exploration of various learning rate scheduling strategies, with the goal of further optimizing detection performance. Detailed descriptions of these methodologies and experimental results are presented in the subsequent sections.

Pic 1. Ambiguous images in dataset.

2. Method

This section outlines three key aspects of the methodology: the selected model architecture, the configuration of hyperparameters and data augmentation techniques, and the validation and inference strategies employed in the experiments.

Detailed of Model Architecture

In this work, I adopted the Faster R-CNN architecture with a ResNet-50-FPN v2 backbone for digit detection. The model is implemented using the torchvision.models.detection module and initialized with pre-trained weights (FasterRCNN_ResNet50_FPN_V2_Weights.DEFAULT) to benefit from feature representations learned on large-scale datasets. The backbone consists of a ResNet-50 feature extractor integrated with a Feature Pyramid Network (FPN) to provide rich multi-scale features. All five stages of the backbone are set as trainable (trainable_backbone_layers=5), allowing the network to adapt both low- and high-level features to the digit recognition domain. The Region Proposal Network (RPN), serving as the neck of the model, proposes candidate object regions by predicting objectness scores and bounding box regressions at each pyramid level. To enhance the model's ability to detect small objects, I define a custom anchor generator with anchor sizes of (8, 16, 32, 64, 128) and aspect ratios of (0.5, 1.0, 2.0). This design ensures that smaller receptive fields are considered during proposal generation, which is essential given that many digits in the dataset are small and low-resolution. The region proposals generated by the RPN are refined in the RoI heads, which apply RoI Align followed by fully connected layers for classification and bounding box regression. The default box predictor is replaced with a FastRCNNPredictor that outputs predictions for 11 classes (digits 0-9 and background).

Setting of Hyperparameter and Data Augmentation

To train the model effectively on this task, I use stochastic gradient descent (SGD) with an initial learning rate of 0.005, momentum of 0.9, and weight decay of 5e-4. A step-based learning rate scheduler is employed, decaying the learning rate by a factor of 0.1 every 5 epochs. Training is conducted for 10 epochs with a batch size of 4. Given the low resolution of the input images, I deliberately avoid resizing operations or aggressive geometric transformations that may degrade visual quality. Instead, I apply color-based data augmentations using transforms.ColorJitter with random brightness, contrast, saturation, and hue perturbations (all set to ±0.2). These augmentations improve model generalization without compromising spatial details essential for digit localization. During testing, only normalization is applied to maintain consistency with training input distribution. The model is optimized using the standard Faster R-CNN multi-task loss, combining classification and regression objectives, and is trained using mixed precision to improve computational efficiency.

Pic 2. Data augmentation		

Detailed of Validation and Inference Part

To evaluate model performance, I follow the COCO-style mean Average Precision (mAP) with IoU thresholds ranging from 0.50 to 0.95 in 0.05 increments, using 101-point interpolation. Although the Faster R-CNN model in training mode automatically computes loss values, this loss does not directly reflect detection quality. Therefore, during validation, in addition to monitoring both training and validation loss curves, I compute mAP scores separately on the validation set. The best-performing model checkpoint is selected based on the highest validation mAP score, ensuring that the final model not only fits the training data well but also generalizes effectively.

During inference, I apply a confidence threshold of 0.8 to filter out low-confidence predictions. However, as per the assignment requirements, any image with no confident prediction is assigned a placeholder label of -1. Therefore, while the threshold is intended to suppress unreliable predictions, its practical influence on the final evaluation is limited by this fallback rule, making the model more robust to uncertain outputs without significantly affecting scoring.

3. Final & Additional Experimental Result

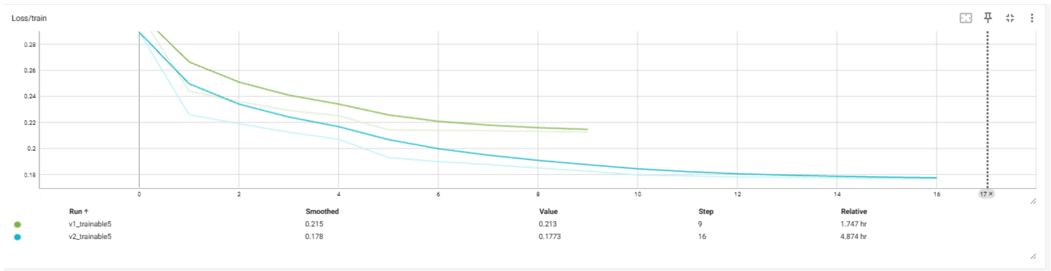
This section presents a comparative analysis of several experimental configurations. The ablation studies focus on five key factors: model architecture selection, the number of trainable backbone layers, anchor size settings in the Region Proposal Network (RPN), the use of a learning rate scheduler, and the effect of data augmentation techniques.

Selection of Training Model

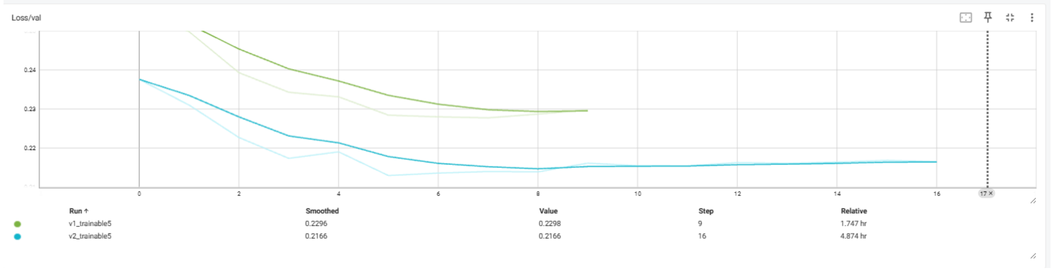
To evaluate model performance, I conducted experiments using different variants of the Faster R-CNN architecture, particularly comparing fasterrcnn_resnet50_fpn (the original paper published in 2015) and fasterrcnn_resnet50_fpn_v2 (the modified paper published in 2021). While both architectures share the same backbone, ResNet-50, the second version incorporates several improvements in its feature pyramid design and normalization strategies. Specifically, v2 replaces the traditional Batch Normalization layers with Frozen Batch Normalization, which improves stability when training on small batch sizes and leads to more consistent feature scaling. Additionally, the improved FPN in v2 facilitates better multi-scale feature fusion, which is particularly beneficial for detecting small digits in this dataset.

Empirically, the v2 model consistently outperformed its predecessor in terms of both training stability and validation accuracy. The training loss curve of the v2 variant showed faster convergence, and its validation mAP achieved a higher score compared to v1 under the same training schedule and data settings. These observations align with my expectations, as the enhanced feature pyramid and frozen normalization layers are designed to address the exact limitations present in v1, especially when dealing with fine-grained object detection tasks.

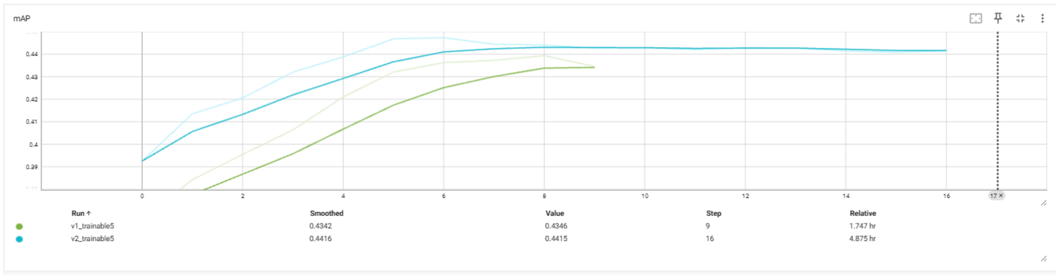
I also considered an alternative architecture using fasterrcnn_mobilenet_v3_large_fpn, which features a significantly lighter backbone. While this model achieved faster inference and lower memory usage, my primary goal is to maximize detection performance rather than reduce computational cost. Therefore, I chose to exclude the MobileNet-based variant from further experiments.



	Run ↑	Smoothed	Value	Step	Relative
●	v1_trainable5	0.215	0.213	9	1.747 hr
●	v2_trainable5	0.178	0.1773	16	4.874 hr



	Run ↑	Smoothed	Value	Step	Relative
●	v1_trainable5	0.2296	0.2298	9	1.747 hr
●	v2_trainable5	0.2166	0.2166	16	4.874 hr



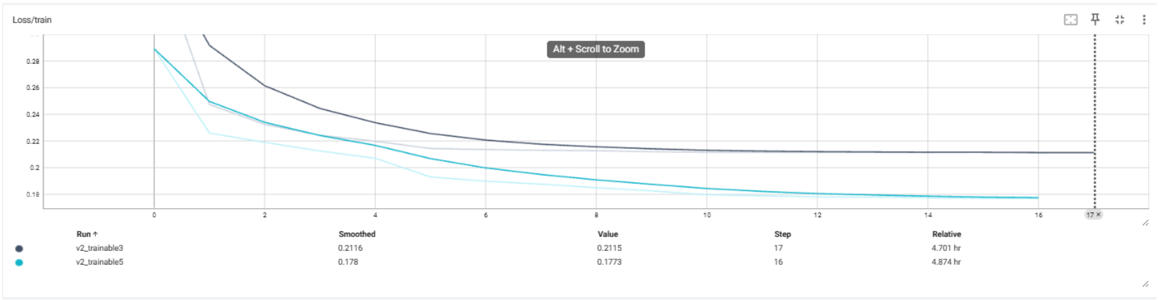
	Run ↑	Smoothed	Value	Step	Relative
●	v1_trainable5	0.4342	0.4346	9	1.747 hr
●	v2_trainable5	0.4416	0.4415	16	4.875 hr

In summary, the architectural enhancements in fasterrcnn_resnet50_fpn_v2 provided measurable benefits in my task, both theoretically and experimentally, which justified its selection as the final model for my system.

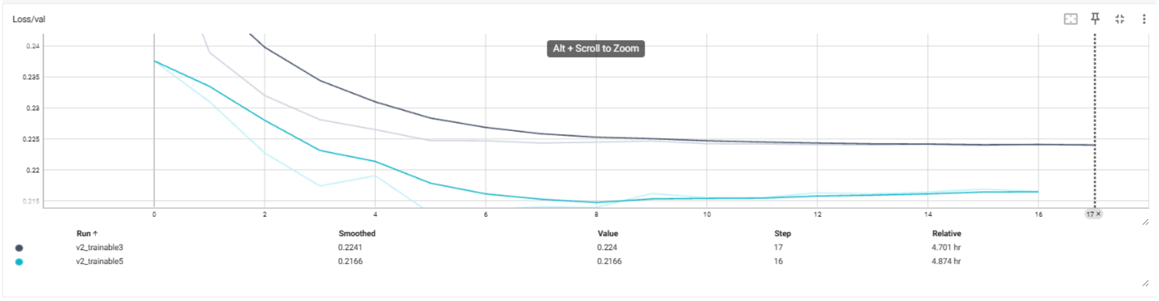
The Number of Trainable Backbone Layers

After selecting fasterrcnn_resnet50_fpn_v2 as the base architecture, I further explored how the number of trainable layers in the backbone affects performance. In torchvision, the trainable_backbone_layers parameter determines how many of the last ResNet stages are unfrozen and updated during training. To investigate this, I compared two settings: trainable backbone layers of 3 and 5. The former allows fine-tuning of the last three stages of the ResNet-50 backbone, while the latter enables training of all five stages.

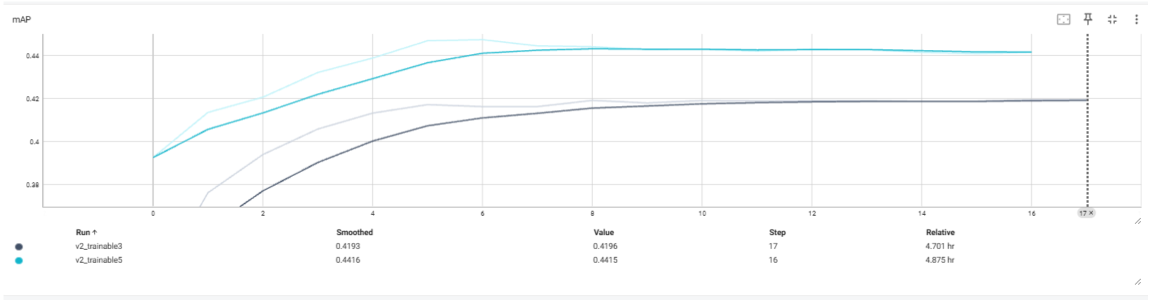
The experimental results are summarized in the figures above. The blue curves correspond to trainable5, while the gray curves represent trainable3. As shown in the training and validation loss plots, the model with more trainable layers (trainable5) achieves consistently lower loss values throughout the training process. Furthermore, the mean Average Precision (mAP) curve clearly demonstrates that trainable5 yields better detection performance, reaching a final smoothed mAP of 0.4415, compared to 0.4196 for trainable3. This suggests that fine-tuning a larger portion of the backbone allows the model to better adapt to the digit detection task, which involves identifying small-scale objects with subtle variations in appearance. Based on these observations, I selected the trainable_backbone_layers=5 configuration for the final model used in subsequent experiments.



	Run	Smoothed	Value	Step	Relative
●	v2_trainable3	0.2116	0.2115	17	4.701 hr
●	v2_trainable5	0.178	0.1773	16	4.874 hr



	Run	Smoothed	Value	Step	Relative
●	v2_trainable3	0.2241	0.224	17	4.701 hr
●	v2_trainable5	0.2166	0.2166	16	4.874 hr



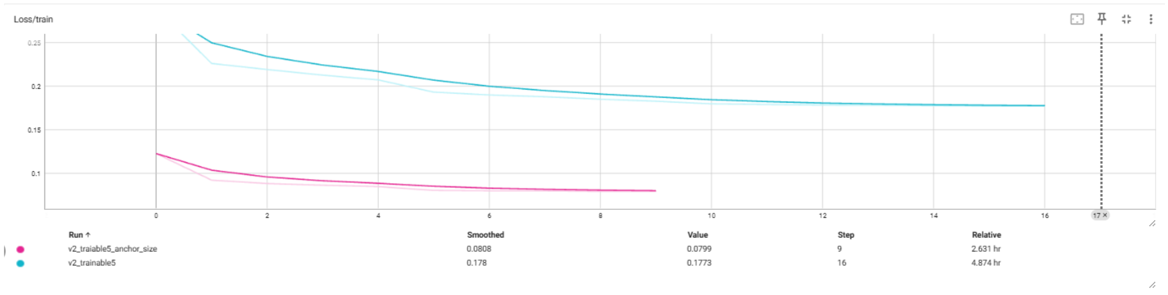
	Run	Smoothed	Value	Step	Relative
●	v2_trainable3	0.4193	0.4196	17	4.701 hr
●	v2_trainable5	0.4416	0.4415	16	4.875 hr

The Impact of Different Anchor Sizes in the Region Proposal Network

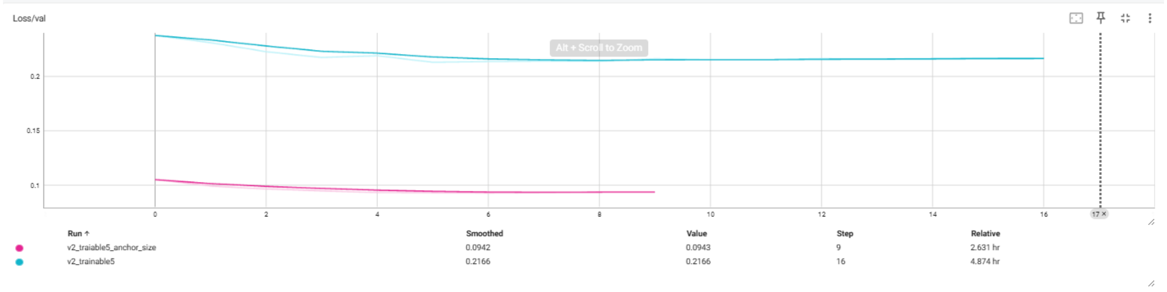
After determining that training all five stages of the backbone (trainable_backbone_layers=5) yields better performance, I further investigated the effect of modifying the anchor sizes in the Region Proposal Network (RPN). As discussed in the methodology section, the images in this dataset are relatively small and low in resolution, leading us to hypothesize that the default anchor sizes may be suboptimal for detecting small digits. To address this, I introduced a customized anchor generator with smaller anchor sizes: (8, 16, 32, 64, 128), covering a broader scale range with finer granularity.

To evaluate this modification, I compared the training behavior and validation performance of two models: one with the default anchor configuration (v2_trainable5) and one with the customized anchors (v2_trainable5_anchor_size). As shown in the loss curves, the model with smaller anchors achieved significantly lower training and validation losses. Specifically, the smoothed training loss dropped to 0.0808, compared to 0.1773 in the baseline, and the validation loss reached 0.0942, improving upon the baseline's 0.2166.

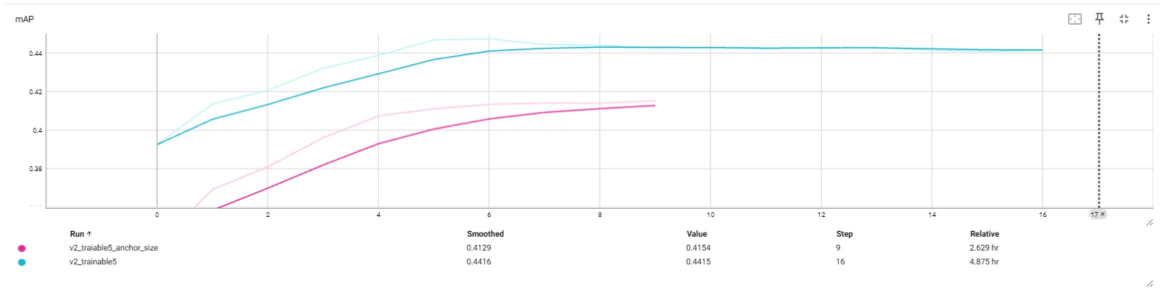
However, despite the improvement in loss values, the actual detection performance measured by COCO-style mAP tells a different story. The model with modified anchor sizes achieved a final mAP of 0.4154, which is slightly lower than the 0.4415 achieved by the model using default anchors. This suggests that while the smaller anchors may lead to easier optimization (i.e., lower loss), they do not necessarily improve detection accuracy on the validation set. One possible explanation is that overly small anchors may have led to an increase in low-quality or redundant proposals, resulting in suboptimal region-of-interest (RoI) selection. Therefore, although modifying the anchor sizes produced lower losses, it did not translate into better overall detection performance. For this reason, I decided to retain the default anchor settings in my final model configuration.



	Run ↑	Smoothed	Value	Step	Relative
●	v2_traiable5_anchor_size	0.0808	0.0799	9	2.631 hr
●	v2_trainable5	0.178	0.1773	16	4.874 hr



	Run ↑	Smoothed	Value	Step	Relative
●	v2_traiable5_anchor_size	0.0942	0.0943	9	2.631 hr
●	v2_trainable5	0.2166	0.2166	16	4.874 hr



	Run ↑	Smoothed	Value	Step	Relative
●	v2_traiable5_anchor_size	0.4129	0.4154	9	2.629 hr
●	v2_trainable5	0.4416	0.4415	16	4.875 hr

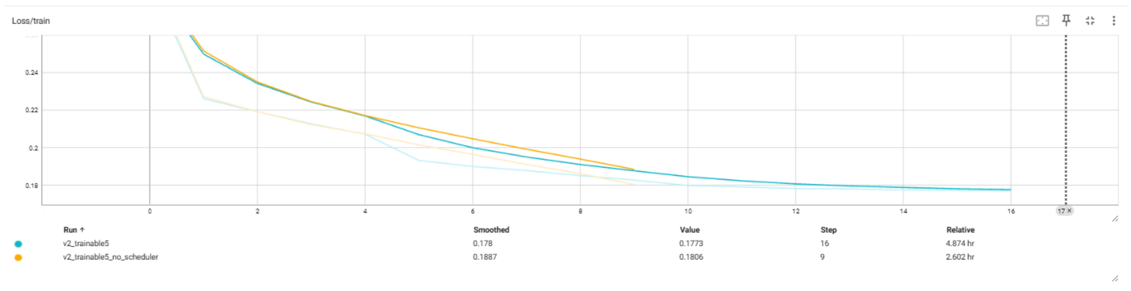
The Impact of Using Learning Rate Scheduler

I further conducted an ablation study to investigate the impact of using a learning rate scheduler during training. Specifically, I compared training the model with and without a StepLR scheduler.

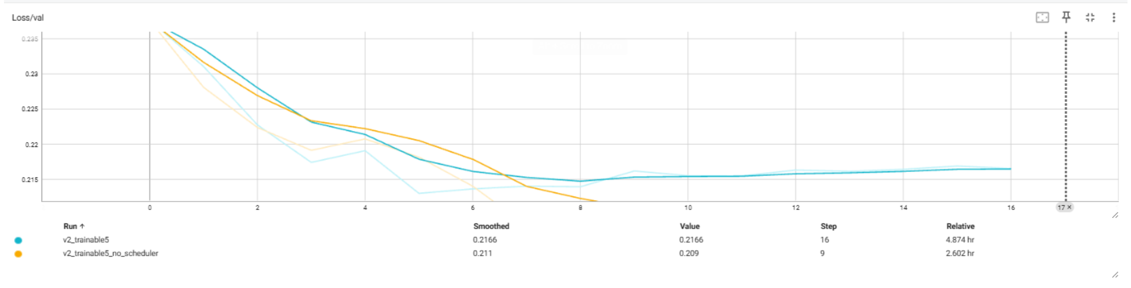
As shown in the training and validation loss plots, the model trained without a scheduler (v2_trainable5_no_scheduler, shown in orange) initially converges at a similar rate but eventually exhibits slightly less stable behavior. While the smoothed training and validation losses are comparable between the two models, the model using the scheduler (v2_trainable5, shown in blue) achieves slightly lower and more consistent losses across later epochs.

More importantly, the mAP curves highlight a more significant difference in detection performance. The model trained with StepLR achieved a final validation mAP of 0.4415, whereas the version without a scheduler plateaued at 0.4191, despite showing similar or lower loss values. This result suggests that dynamically adjusting the learning rate during training helps the model escape shallow local minima and generalize better to the validation set. Additionally, the scheduler likely contributes to more stable convergence in the later training stages, which is especially beneficial for fine-tuning large pre-trained backbones.

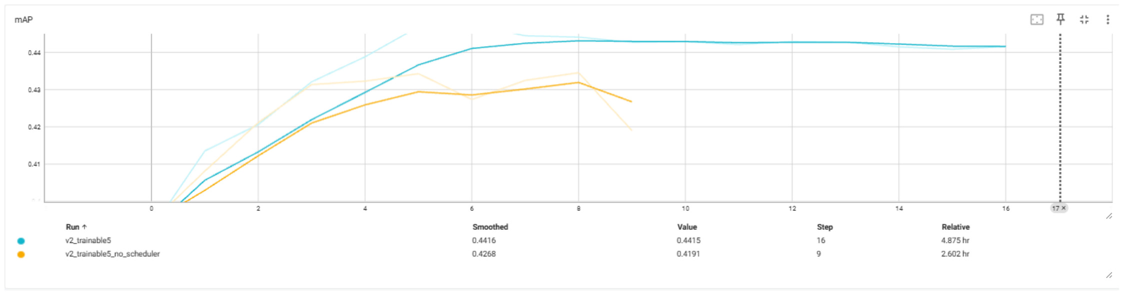
In summary, while both training regimes can achieve reasonable performance, the use of a scheduler provides clear improvements in both detection accuracy and training stability. Therefore, the StepLR scheduler was retained in the final configuration.



	Run ↑	Smoothed	Value	Step	Relative
●	v2_trainable5	0.178	0.1773	16	4.874 hr
●	v2_trainable5_no_scheduler	0.1887	0.1806	9	2.602 hr



	Run ↑	Smoothed	Value	Step	Relative
●	v2_trainable5	0.2166	0.2166	16	4.874 hr
●	v2_trainable5_no_scheduler	0.211	0.209	9	2.602 hr



	Run ↑	Smoothed	Value	Step	Relative
●	v2_trainable5	0.4416	0.4415	16	4.875 hr
●	v2_trainable5_no_scheduler	0.4268	0.4191	9	2.602 hr

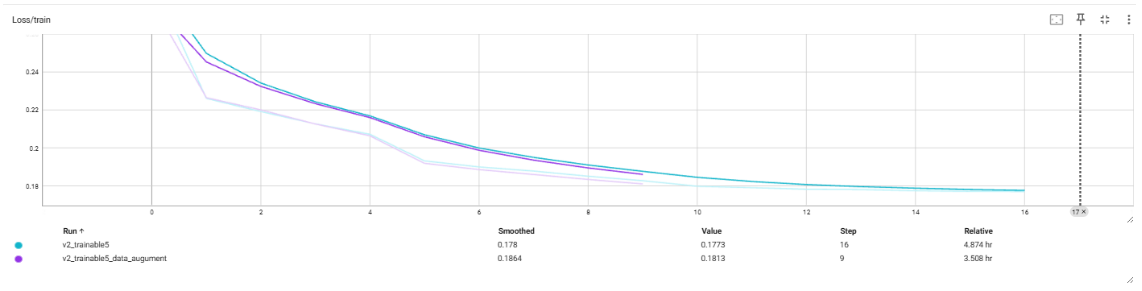
The Impact of Data Augmentation

I also explored the effect of data augmentation on model performance. Given that many of the images in the dataset are small and low in resolution, I opted for lightweight, pixel-level augmentation techniques that would not degrade spatial clarity. Specifically, I applied ColorJitter with randomized adjustments to brightness, contrast, saturation, and hue (each within a range of ±0.2) to increase robustness to color variance and illumination differences.

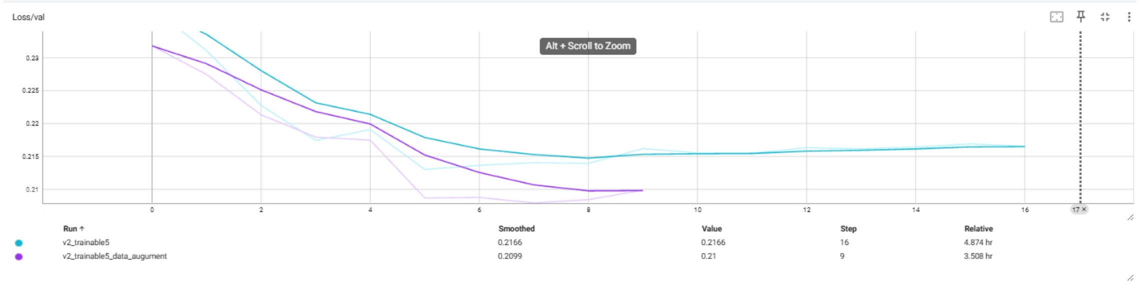
I compared the model trained with ColorJitter-based augmentation (v2_trainable5_data_augment, shown in purple) against the baseline model without augmentation (v2_trainable5, shown in blue). As shown in the training and validation loss plots, the augmented model achieved marginally lower losses. The smoothed training loss dropped to 0.1864 compared to 0.178 in the baseline, and the validation loss improved from 0.2166 to 0.21, indicating better generalization.

However, the difference in detection accuracy, measured by COCO mAP, was relatively minor. The final mAP scores were 0.4415 (baseline) and 0.4414 (with augmentation), showing almost identical performance on the validation set. That said, further testing on the held-out test set revealed that the model trained with augmentation produced slightly better results, suggesting that it may generalize better in unseen conditions.

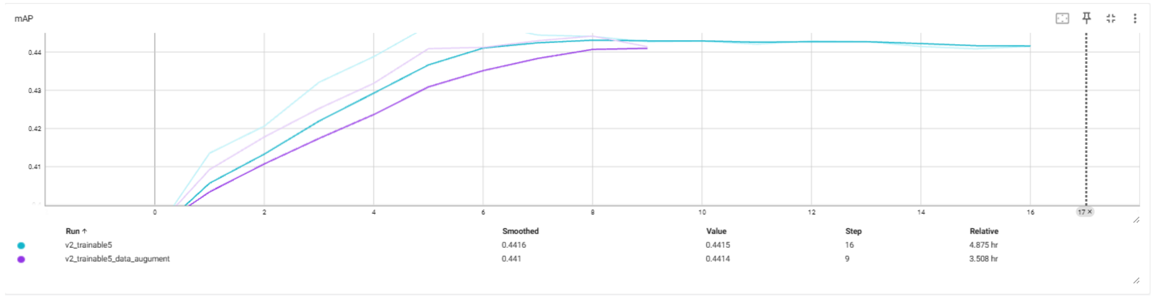
In conclusion, adding color-based augmentation did not significantly change the validation mAP, but it improved training dynamics and generalization behavior, especially on test data. Therefore, I included this augmentation strategy in the final training pipeline.



	Run ↑	Smoothed	Value	Step	Relative
●	v2_trainable5	0.178	0.1773	16	4.874 hr
●	v2_trainable5_data_augument	0.1864	0.1813	9	3.508 hr

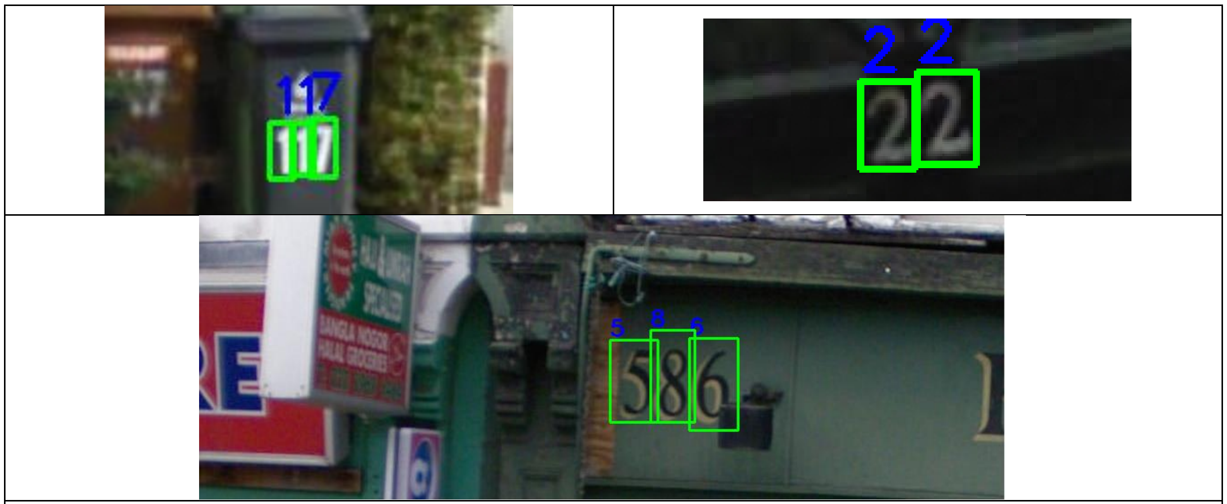


	Run ↑	Smoothed	Value	Step	Relative
●	v2_trainable5	0.2166	0.2166	16	4.874 hr
●	v2_trainable5_data_augument	0.2099	0.21	9	3.508 hr



	Run ↑	Smoothed	Value	Step	Relative
●	v2_trainable5	0.4416	0.4415	16	4.875 hr
●	v2_trainable5_data_augument	0.441	0.4414	9	3.508 hr

Based on the ablation studies, the final configuration adopts the fasterrcnn_resnet50_fpn_v2 model with all five backbone stages set as trainable. In addition, color-based data augmentation is applied to improve generalization. This combination consistently achieved strong performance in both loss reduction and detection accuracy. While the adjustment of anchor sizes did not lead to performance gains in my current setting, I believe that with finer-grained tuning, particularly tailored to the scale distribution of digits in the dataset, it has the potential to yield further improvements.



Pic 2. Results of best weights.

4. References

- PyTorch documentation
- ChatGPT
- Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks
- Benchmarking Detection Transfer Learning with Vision Transformers