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Report Computer vision Lab 2

Abstract

In this paper we explored Detectron2 in depth by preparing a custom dataset and training on it. We train our model using Colab in order to train faster.. Details, instructions have been presented in the paper, including pictures or outputs obtained in each compilation.

1 Part A: Model for instance segmentation

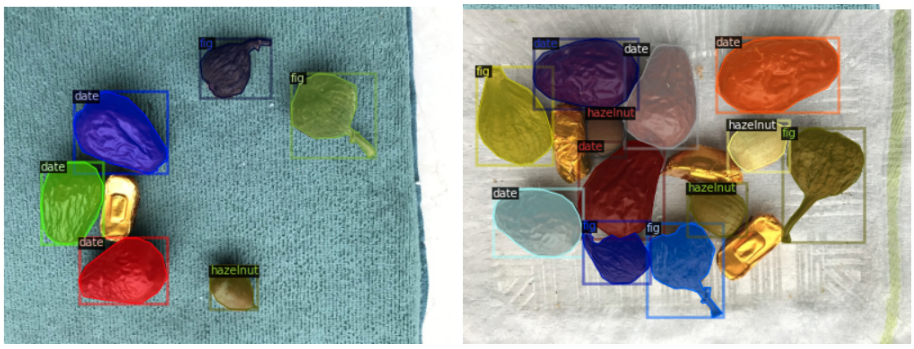
1. Model architecture: We trained a Mask R-CNN model, with a ResNet50 FPN backbone.

   We initialized the model with two initialization schemes, the an existing model pre-trained on the

   * COCO dataset which is an excellent object detection dataset with 80 classes, 80,000 training images and 40,000 validation images annoted and available on detectron2

   * In our study we used a dataset of nuts which has 3 classes: date, fig, and hazelnut, and which is annotated with instance masks. We train the two models, for 300 iterations, a start learning rate of 0.02, 2 images per batch, and 128 regions per batch.

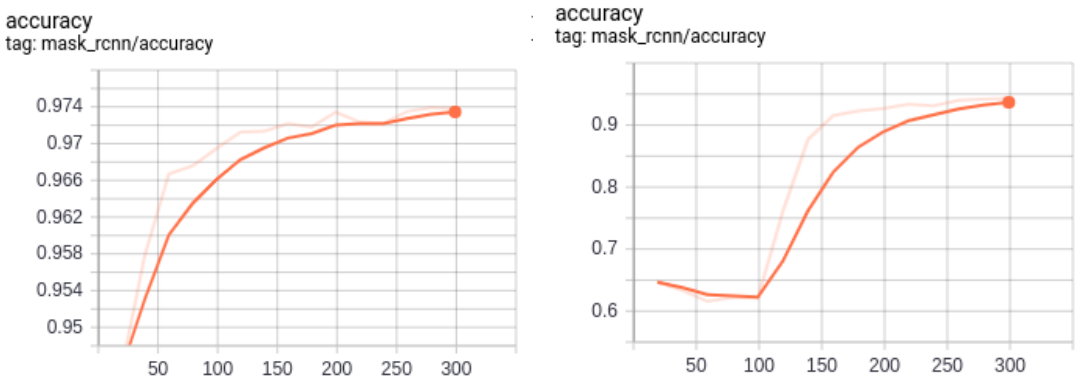
2. Visualization output: The results obtained after training our models have been visualized such that.



(a) COCOinit before training (b) ININit before training

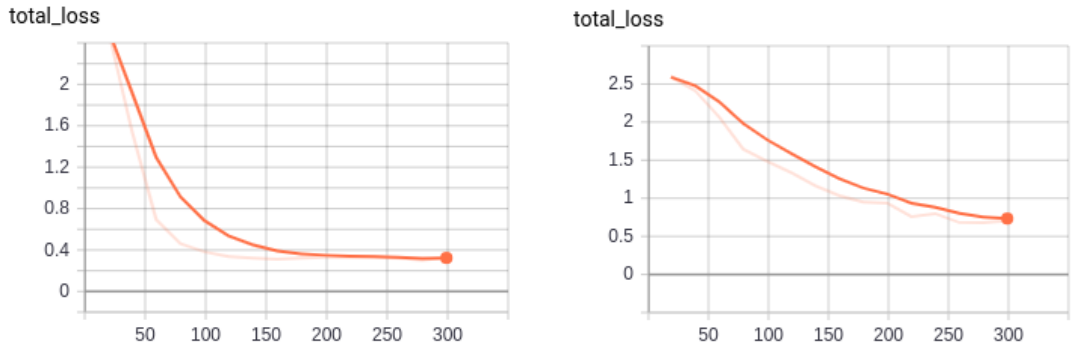
Figure 1: The same model

3. Training curves:



(a) Accuracy with COCOinit (b) Accuracy with ININit

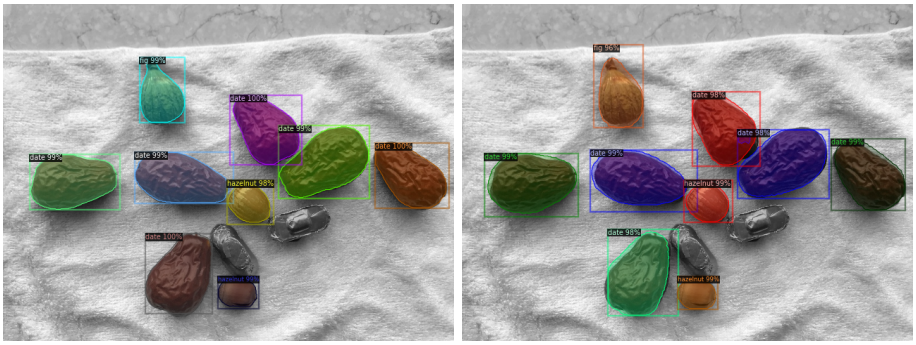
* Accuracy: The accuracy of COCOinit started early before 50 and continue to increased whereas the accuracy with the ININit started late it was decreasing at the beginning and at 100 it started increasing progressively.



(a) Total Loss with COCOinit (b) Total Loss with ININit

* Total loss: The total loss of COCOinit obtained after training is better than the total loss obtained fo the ININit indeed, the loss in COCOinit is less than 0.4 that is better than the loss obtained in case of ININit which is between 0.5 and 1.

4. visualizations of predictions:



(a) Prediction with COCOinit (b) Prediction with ININit

Figure 4

5. Evaluation: The results obtained after training was summuraized in the table depending on COCOinit and ININit respectively such that in each table we have the Average Precision (AP) of the date, fig, hazelnut, Date and the Mean Average .

Table 1: For the case of COCOinit

Category	date	fig	Hazelnut	Mean Average
Bounding Box	83.76	78.15	75.14	79.02
Segmentation	96.22	91.50	88.18	91.97

Table 2: For the case of ININit

Category	date	fig	Hazelnut	Mean Average
Bounding Box	74.86	58.45	68.22	67.18
Segmentation	84.73	66.55	78.61	76.63

2 Conclusion

From the losses of COCOinit and ININit, we got observed that the loss of COCOinit model was better than the loss of ININit model, the same for accuracies and the Bounding box.

We concluded the COCOinit model performs well than the ININit model. COCOinit model used the dataset more specify than ININit model.