CMPT 412

Project 3

Object Detection, Semantic Segmentation, and Instance Segmentation

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Note: Use 3 free late-day

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Part 1: Object Detection

1. Configs and Modifications:

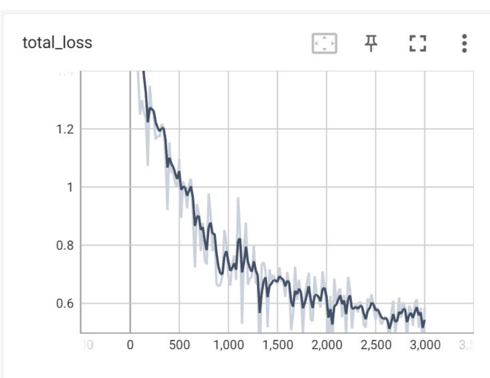
The learning rate and the number of iterations have been modified:

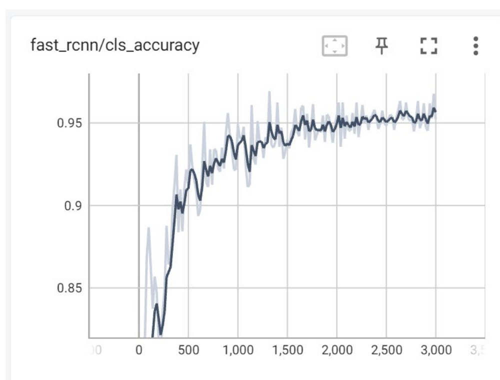
```
cfg.merge_from_file(model_zoo.get_config_file("COCO-Detection/faster_rcnn_R_101_FPN_3x.yaml"))
cfg.DATASETS.TRAIN = ("plane_train",)
cfg.DATASETS.TEST = ()
cfg.DATALOADER.NUM_WORKERS = 2
cfg.MODEL.WEIGHTS = model_zoo.get_checkpoint_url("COCO-Detection/faster_rcnn_R_101_FPN_3x.yaml")
cfg.SOLVER.IMS_PER_BATCH = 2  # batch size
cfg.SOLVER.BASE_LR = 0.0003  # LR
cfg.SOLVER.MAX_ITER = 3000
cfg.MODEL.ROI_HEADS.BATCH_SIZE_PER_IMAGE = 512
cfg.MODEL.ROI_HEADS.NUM_CLASSES = 1  # only have plane
```

2. Factors:

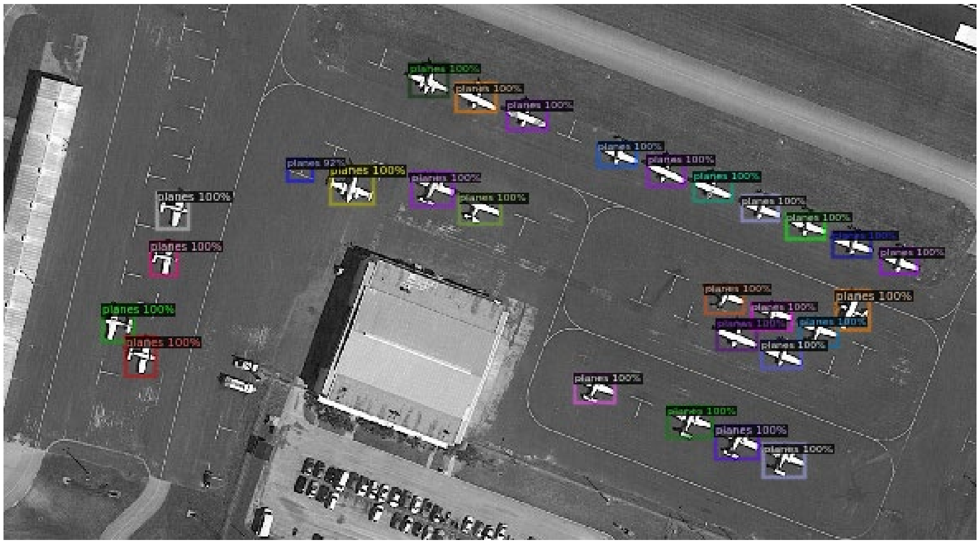
I first set the number of iterations at 500, and then set the learning rate at 0.0003 through several tests. Then I adjusted the number of iterations and found that the best accuracy could be achieved at 3000 without wasting training cost. At the end, get AP50 = 62.564

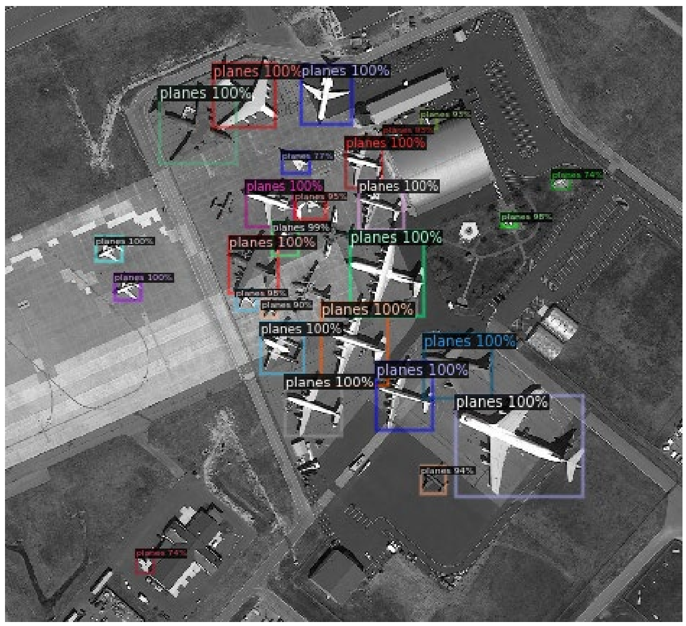
3. Final plot





4. Visualization






planes 99%
planes 100%
planes 100%

5. Ablation study:

I performed ablation study on the number of iterations. I leave all other parameters unchanged and adjust only the number of iterations.

- MAX_ITER = 500

AP	AP50	AP75	APs	APm	APl
25.631	47.240	25.758	17.370	33.062	52.314

- MAX_ITER = 2000

AP	AP50	AP75	APs	APm	APl
37.804	58.323	42.507	26.755	45.778	71.471

- MAX_ITER = 3000

AP	AP50	AP75	APs	APm	APl
39.560	62.564	44.099	29.556	47.392	71.334

- MAX_ITER = 3500

AP	AP50	AP75	APs	APm	APl
40.053	62.700	44.476	29.529	48.045	72.047

Figure 1 Iter 500

Figure 2 Iter 2000

Figure 3 Iter 3000

Figure 4 Iter 3500

The data andthe visualization results show that the increase in the number of iterations has a positive effect on the training effect. Each of Figures 1, 2, and 4 has a part of the body of the plane that is also recognized as a separate plane. In contrast, Figure 3, which used a number of 3000 iterations, identified exactly the best results.

Part 2: Semantic Segmentation

1. Hyperparameter settings:

After a series of adjustments, my parameters were set as follows:

```
batch_size = 4
learning_rate = 0.003
num_epochs = 150
```

2. Final architecture:

I have made changes to the default "down" class and "up" class:

For "down" class: To increase the degree of training, I added an extra layer of "conv".

For "up" class: To increase efficiency, I added an extra layer of "nn.BatchNorm2d".

MyModel code:

```
def forward(self, input):
    y = self.input_conv(input)
    y = self.down1(y)
    y = self.down2(y)
    y = self.down3(y)
    y = self.down4(y)
    y = self.down5(y)
    y = self.down6(y)
    y = self.up1(y)
    y = self.up2(y)
    y = self.up3(y)
    y = self.up4(y)
    y = self.up5(y)
    y = self.up6(y)
    output = self.output_conv(y)
```

Torchsummary:

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 4, 128, 128]             112
       BatchNorm2d-2         [-1, 4, 128, 128]               8
              ReLU-3         [-1, 4, 128, 128]               0
              conv-4         [-1, 4, 128, 128]               0
            Conv2d-5         [-1, 8, 128, 128]             296
       BatchNorm2d-6         [-1, 8, 128, 128]              16
              ReLU-7         [-1, 8, 128, 128]               0
              conv-8         [-1, 8, 128, 128]               0
            Conv2d-9         [-1, 8, 128, 128]             584
      BatchNorm2d-10         [-1, 8, 128, 128]              16
             ReLU-11         [-1, 8, 128, 128]               0
             conv-12         [-1, 8, 128, 128]               0
        MaxPool2d-13           [-1, 8, 64, 64]               0
             down-14           [-1, 8, 64, 64]               0
           Conv2d-15          [-1, 16, 64, 64]           1,168
      BatchNorm2d-16          [-1, 16, 64, 64]              32
             ReLU-17          [-1, 16, 64, 64]               0
             conv-18          [-1, 16, 64, 64]               0
           Conv2d-19          [-1, 16, 64, 64]           2,320
      BatchNorm2d-20          [-1, 16, 64, 64]              32
             ReLU-21          [-1, 16, 64, 64]               0
             conv-22          [-1, 16, 64, 64]               0
        MaxPool2d-23          [-1, 16, 32, 32]               0
             down-24          [-1, 16, 32, 32]               0
           Conv2d-25          [-1, 32, 32, 32]           4,640
      BatchNorm2d-26          [-1, 32, 32, 32]              64
             ReLU-27          [-1, 32, 32, 32]               0
             conv-28          [-1, 32, 32, 32]               0
           Conv2d-29          [-1, 32, 32, 32]           9,248
      BatchNorm2d-30          [-1, 32, 32, 32]              64
             ReLU-31          [-1, 32, 32, 32]               0
             conv-32          [-1, 32, 32, 32]               0
        MaxPool2d-33          [-1, 32, 16, 16]               0
             down-34          [-1, 32, 16, 16]               0
           Conv2d-35          [-1, 64, 16, 16]          18,496
      BatchNorm2d-36          [-1, 64, 16, 16]             128
             ReLU-37          [-1, 64, 16, 16]               0
             conv-38          [-1, 64, 16, 16]               0
           Conv2d-39          [-1, 64, 16, 16]          36,928
      BatchNorm2d-40          [-1, 64, 16, 16]             128
             ReLU-41          [-1, 64, 16, 16]               0
             conv-42          [-1, 64, 16, 16]               0
        MaxPool2d-43            [-1, 64, 8, 8]               0
             down-44            [-1, 64, 8, 8]               0
           Conv2d-45           [-1, 128, 8, 8]          73,856
      BatchNorm2d-46           [-1, 128, 8, 8]             256
             ReLU-47           [-1, 128, 8, 8]               0
             conv-48           [-1, 128, 8, 8]               0
           Conv2d-49           [-1, 128, 8, 8]         147,584
      BatchNorm2d-50           [-1, 128, 8, 8]             256
             ReLU-51           [-1, 128, 8, 8]               0
             conv-52           [-1, 128, 8, 8]               0
        MaxPool2d-53           [-1, 128, 4, 4]               0
             down-54           [-1, 128, 4, 4]               0
           Conv2d-55           [-1, 256, 4, 4]         295,168
      BatchNorm2d-56           [-1, 256, 4, 4]             512
             ReLU-57           [-1, 256, 4, 4]               0
             conv-58           [-1, 256, 4, 4]               0
           Conv2d-59           [-1, 256, 4, 4]         590,080
      BatchNorm2d-60           [-1, 256, 4, 4]             512
             ReLU-61           [-1, 256, 4, 4]               0
             conv-62           [-1, 256, 4, 4]               0
        MaxPool2d-63           [-1, 256, 2, 2]               0
             down-64           [-1, 256, 2, 2]               0
  ConvTranspose2d-65           [-1, 256, 4, 4]         262,400
           Conv2d-66           [-1, 128, 4, 4]         295,040
      BatchNorm2d-67           [-1, 128, 4, 4]             256
             ReLU-68           [-1, 128, 4, 4]               0
             conv-69           [-1, 128, 4, 4]               0
      BatchNorm2d-70           [-1, 128, 4, 4]             256
               up-71           [-1, 128, 4, 4]               0
  ConvTranspose2d-72           [-1, 128, 8, 8]          65,664
           Conv2d-73            [-1, 64, 8, 8]          73,792
      BatchNorm2d-74            [-1, 64, 8, 8]             128
             ReLU-75            [-1, 64, 8, 8]               0
             conv-76            [-1, 64, 8, 8]               0
      BatchNorm2d-77            [-1, 64, 8, 8]             128
               up-78            [-1, 64, 8, 8]               0
  ConvTranspose2d-79          [-1, 64, 16, 16]          16,448
           Conv2d-80          [-1, 32, 16, 16]          18,464
      BatchNorm2d-81          [-1, 32, 16, 16]              64
             ReLU-82          [-1, 32, 16, 16]               0
             conv-83          [-1, 32, 16, 16]               0
      BatchNorm2d-84          [-1, 32, 16, 16]              64
               up-85          [-1, 32, 16, 16]               0
  ConvTranspose2d-86          [-1, 32, 32, 32]           4,128
           Conv2d-87          [-1, 16, 32, 32]           4,624
      BatchNorm2d-88          [-1, 16, 32, 32]              32
             ReLU-89          [-1, 16, 32, 32]               0
             conv-90          [-1, 16, 32, 32]               0
      BatchNorm2d-91          [-1, 16, 32, 32]              32
               up-92          [-1, 16, 32, 32]               0
  ConvTranspose2d-93          [-1, 16, 64, 64]           1,040
           Conv2d-94           [-1, 8, 64, 64]           1,160
      BatchNorm2d-95           [-1, 8, 64, 64]              16
             ReLU-96           [-1, 8, 64, 64]               0
             conv-97           [-1, 8, 64, 64]               0
      BatchNorm2d-98           [-1, 8, 64, 64]              16
               up-99           [-1, 8, 64, 64]               0
ConvTranspose2d-100         [-1, 8, 128, 128]             264
          Conv2d-101         [-1, 4, 128, 128]             292
     BatchNorm2d-102         [-1, 4, 128, 128]               8
            ReLU-103         [-1, 4, 128, 128]               0
            conv-104         [-1, 4, 128, 128]               0
     BatchNorm2d-105         [-1, 4, 128, 128]               8
              up-106         [-1, 4, 128, 128]               0
          Conv2d-107         [-1, 1, 128, 128]              37
            conv-108         [-1, 1, 128, 128]               0
================================================================
```

3. Loss functions:

The loss functions I used is the default loss function:

```
crit = nn.BCEWithLogitsLoss() # Define the loss function
```

Epoch	Loss	Epoch	Loss
0	0.548725962638855	74	0.10606835782527924
1	0.35738807916641235	75	0.10531891882419586
2	0.29464346170425415	76	0.1045506969094276
3	0.2662748098373413	77	0.10415859520435333
4	0.24825114011764526	78	0.10370544344186783
…	…	…	…
…	…	…	…
…	…	…	…
69	0.10856733471155167	145	0.08330231159925461
70	0.10829269886016846	146	0.08313968032598495
71	0.10713459551334381	147	0.08315932005643845
72	0.10693884640932083	148	0.08290217071771622
73	0.10650912672281265	149	0.08267544955015182

4. IoU:

The final mean IoU of my model is:

```
Mean IoU: 0.8916377923312807
```

5. Visualize:

Part 3: Instance Segmentation

1. Kaggle Group Name: ChengH.

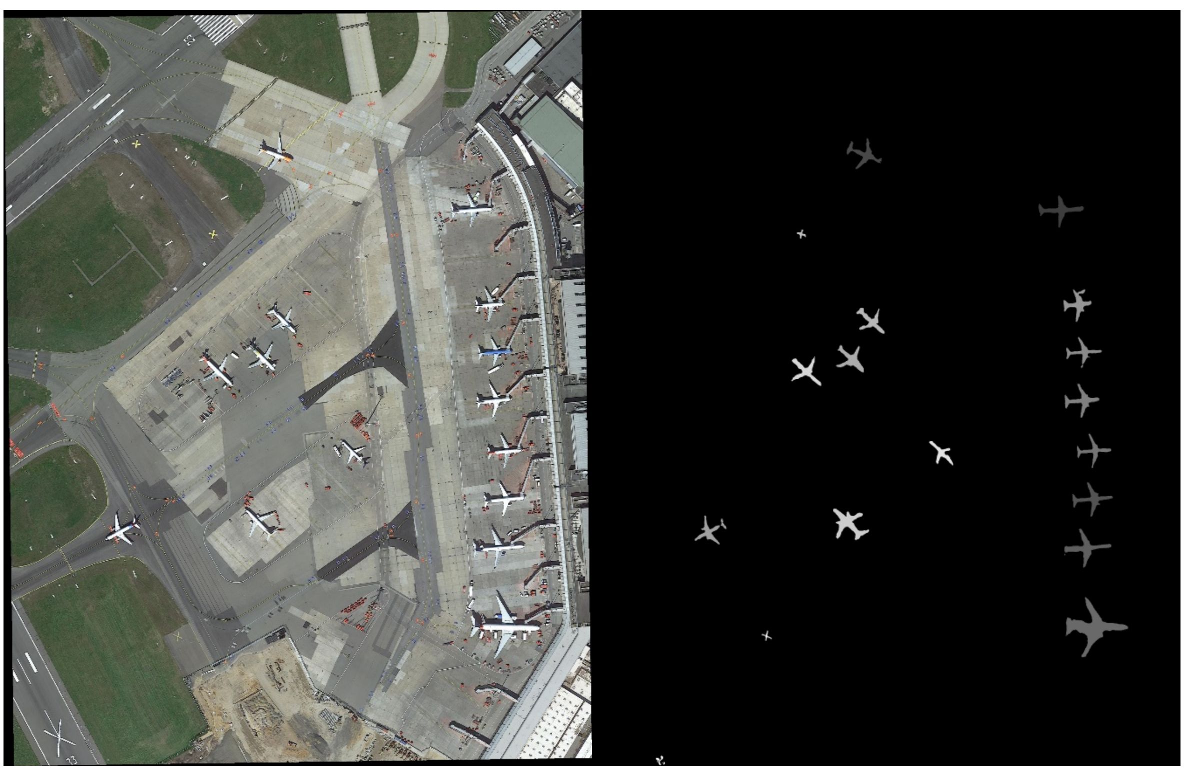
Members: Cheng Hu (301435966), Kaikun Fang (301416542)

2. Best accuracy:

The highest score of our group on Kaggle is 0.83098

3.Visualization:

My best result:



Part4: Mask R-CNN

1. Config:

```
cfg.merge_from_file(model_zoo.get_config_file("COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x.yaml"))
cfg.DATASETS.TRAIN = ("plane_train",)
cfg.DATASETS.TEST = ()
cfg.DATALOADER.NUM_WORKERS = 2
cfg.MODEL.WEIGHTS = model_zoo.get_checkpoint_url("COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x.yaml")
cfg.SOLVER.IMS_PER_BATCH = 2  # batch size
cfg.SOLVER.BASE_LR = 0.0003  # LR
cfg.SOLVER.MAX_ITER = 3000
cfg.MODEL.ROI_HEADS.BATCH_SIZE_PER_IMAGE = 512
cfg.MODEL.ROI_HEADS.NUM_CLASSES = 1  # only have plane
```

2.Visualization:

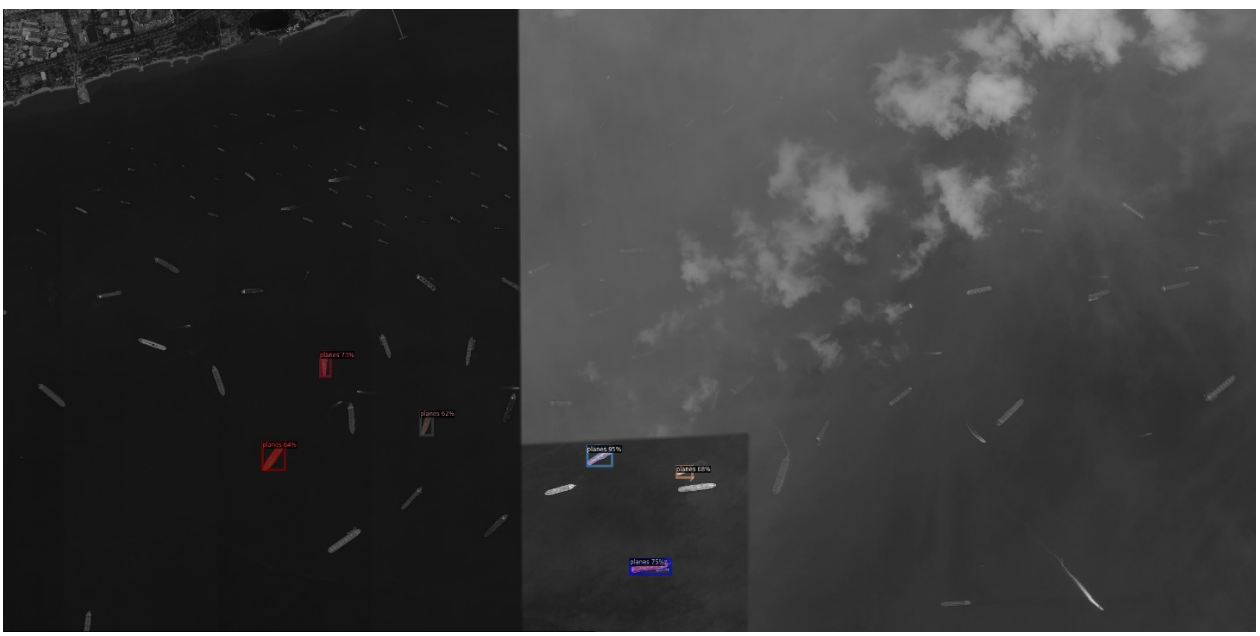


Figure 5


planes 99%
planes 100%
planes 99%
planes 81%
planes 100%
planes 99%
planes 99%
planes 99%
planes 100%
planes 64%
planes 100%
planes 99%

Figure 6

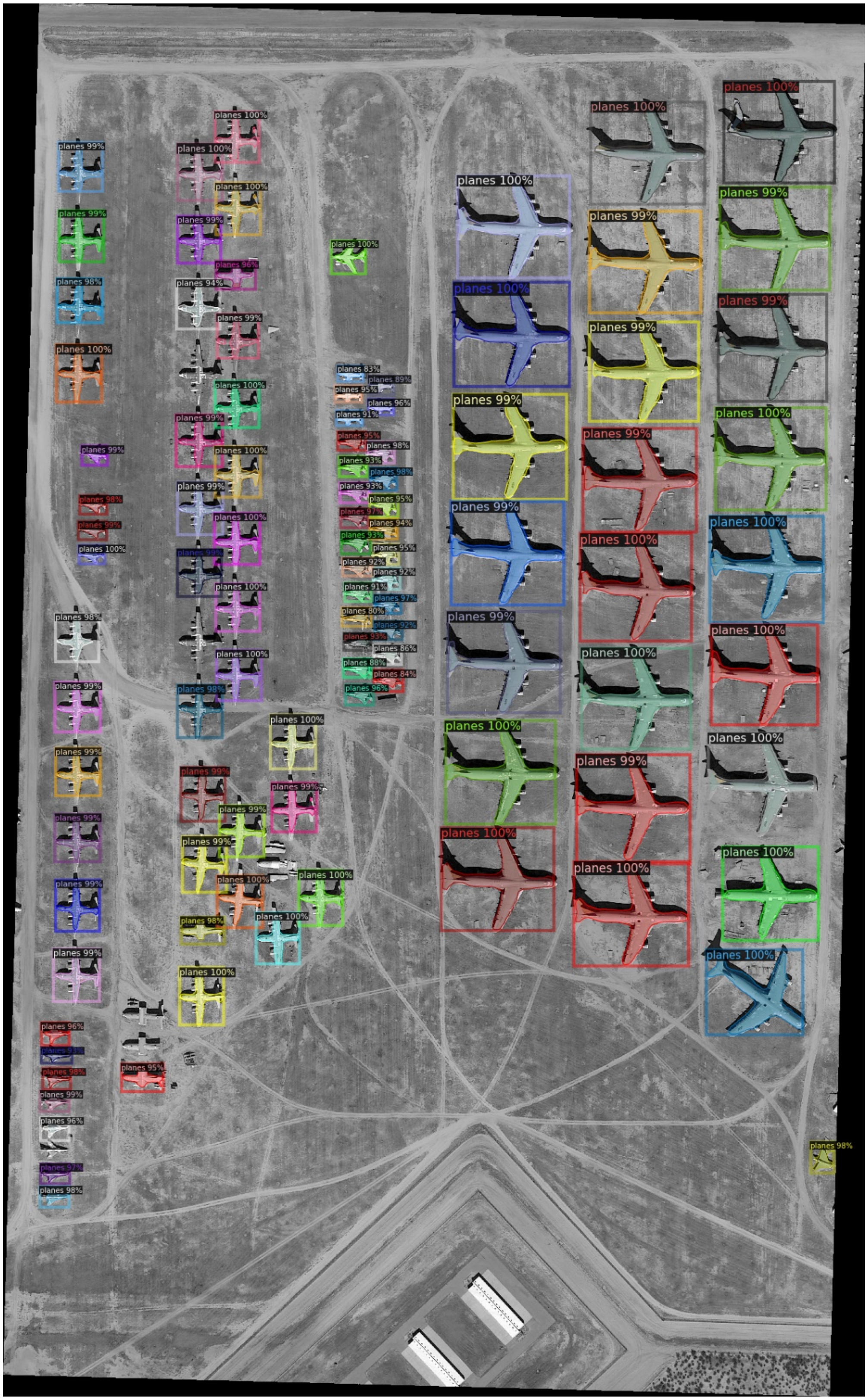


Figure 7

2. Evaluation:

Con: The segmentation of the planes fuselage is not accurate enough. In some results, other objects next to the plane are incorrectly counted as part of the plane. And In Figure 5, the number of ships incorrectly identified as planes is relatively high, this is not as good as part1's performance.

Pro: The trained model is able to find the vast majority of planes in the picture. And faster.

3. Difference between Part 3 and Part 4:

The comparison of the results revealed that. In the detection of the number of planes, part4 is higher than the number detected by part3. But in the partitioning of the airplane fuselage and background, part3 is more accurate in partitioning the fuselage. part4 will incorrectly partition some things near the fuselage as part of the fuselage as well.