Task: You are given a dataset of aerial images containing six classes: 'car', 'house', 'road', 'swimming pool', 'tree', and 'yard'. Your objectives are as follows:

FAQ

- How to access the best.pt of YOLOv9?

> Unzip the ZIP which contains all the files from trained modules , predicted images from test,val and drone images

> Inside train\weights you can find the `best.pt` and `last.pt` which are useful for the API and the prediction

- How to see the contents of YOLOv8?

> Similar to YOLOv9 the contents can be found at ZIP *Check email for this*

- Where is the solution to the written test?

> File

- How to validate the API?

> Simply run the folder inside api ; treat it as a notebook and make sure the ngrok configuration is built upon and use the postman as instructed below

Explanation

1. Train a Model: Develop and train a machine learning model to detect and classify objects into the six specified classes Creating a virtual environment

```
py -3.11 -m venv yolo
yolo\Scripts\activate
python -m pip install --upgrade pip
pip install ultralytics
```

Importing Library

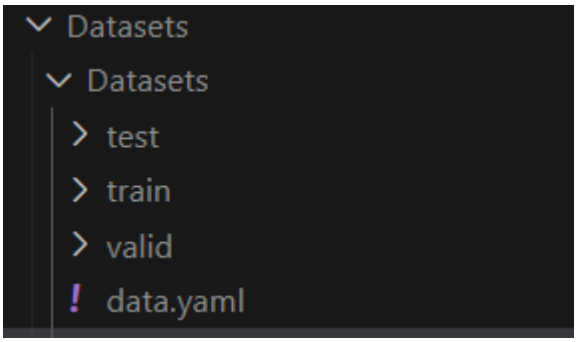
```
import matplotlib.pyplot as plt
import os
from collections import Counter
import matplotlib.pyplot as plt
import matplotlib.patches as patches

from IPython.display import display

# display.clear_output()
```

```
from PIL import Image
import ultralytics
ultralytics.checks()
from ultralytics import YOLO
```

Configuring the data.yaml to use it for google drive as I need to use it for colab

```
train: /content/drive/MyDrive/datasets/datasets/train/images/
val: /content/drive/MyDrive/datasets/datasets/valid/images/
test: /content/drive/MyDrive/datasets/datasets/test/images/

nc: 6
names: ['car', 'house', 'road', 'swimming pool', 'tree', 'yard']
```

File Structure

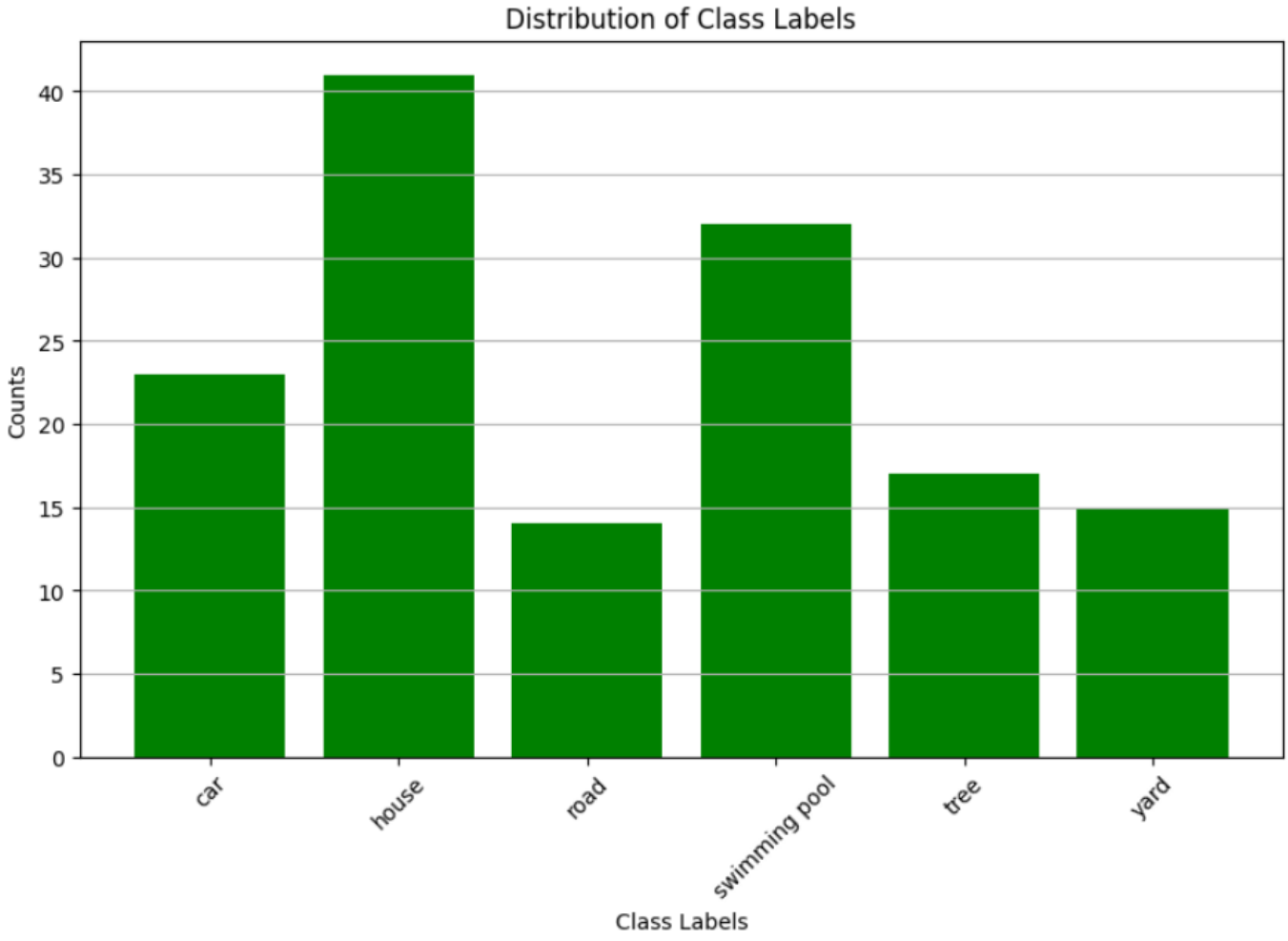


Data Visualization & Preprocessing

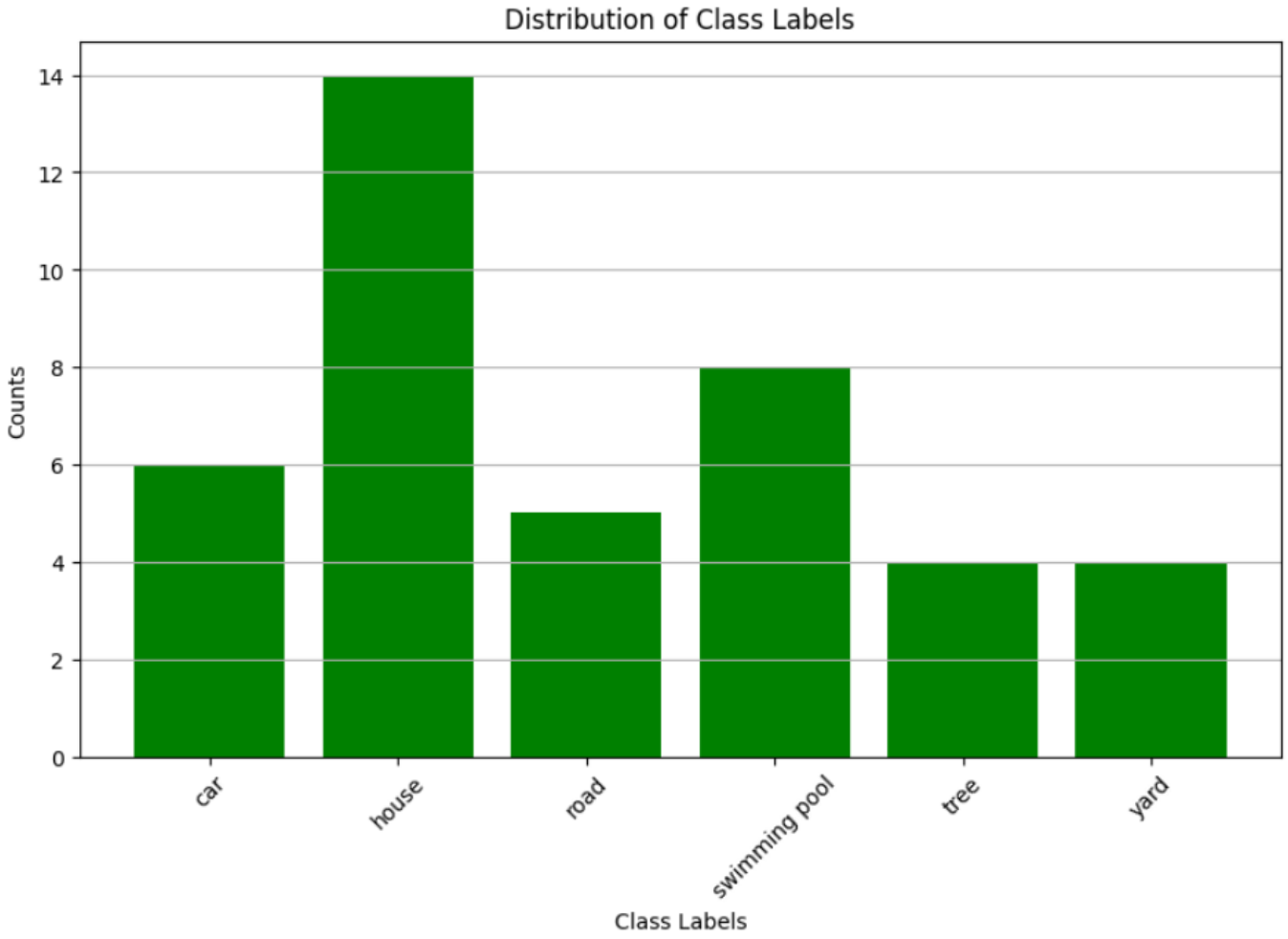
```
def load_labels_from_directory(label_dir):
    labels = []
    for label_file in os.listdir(label_dir):
        if label_file.endswith('.txt'):
            with open(os.path.join(label_dir, label_file), 'r') as f:
                label = f.readline().strip()
                labels.append(label)
    return labels


def extract_labels(annotations):
    labels = []
    for annotation in annotations:
        label = annotation.split()[0]
        labels.append(label)
    return labels

def count_classes(labels):
    return Counter(labels)
```

```
train_label_dir = '/content/drive/MyDrive/datasets/datasets/train/labels'
valid_label_dir = '/content/drive/MyDrive/datasets/datasets/valid/labels'
test_label_dir = '/content/drive/MyDrive/datasets/datasets/test/labels'
train_labels = load_labels_from_directory(train_label_dir)
valid_labels = load_labels_from_directory(valid_label_dir)
test_labels = load_labels_from_directory(test_label_dir)
```

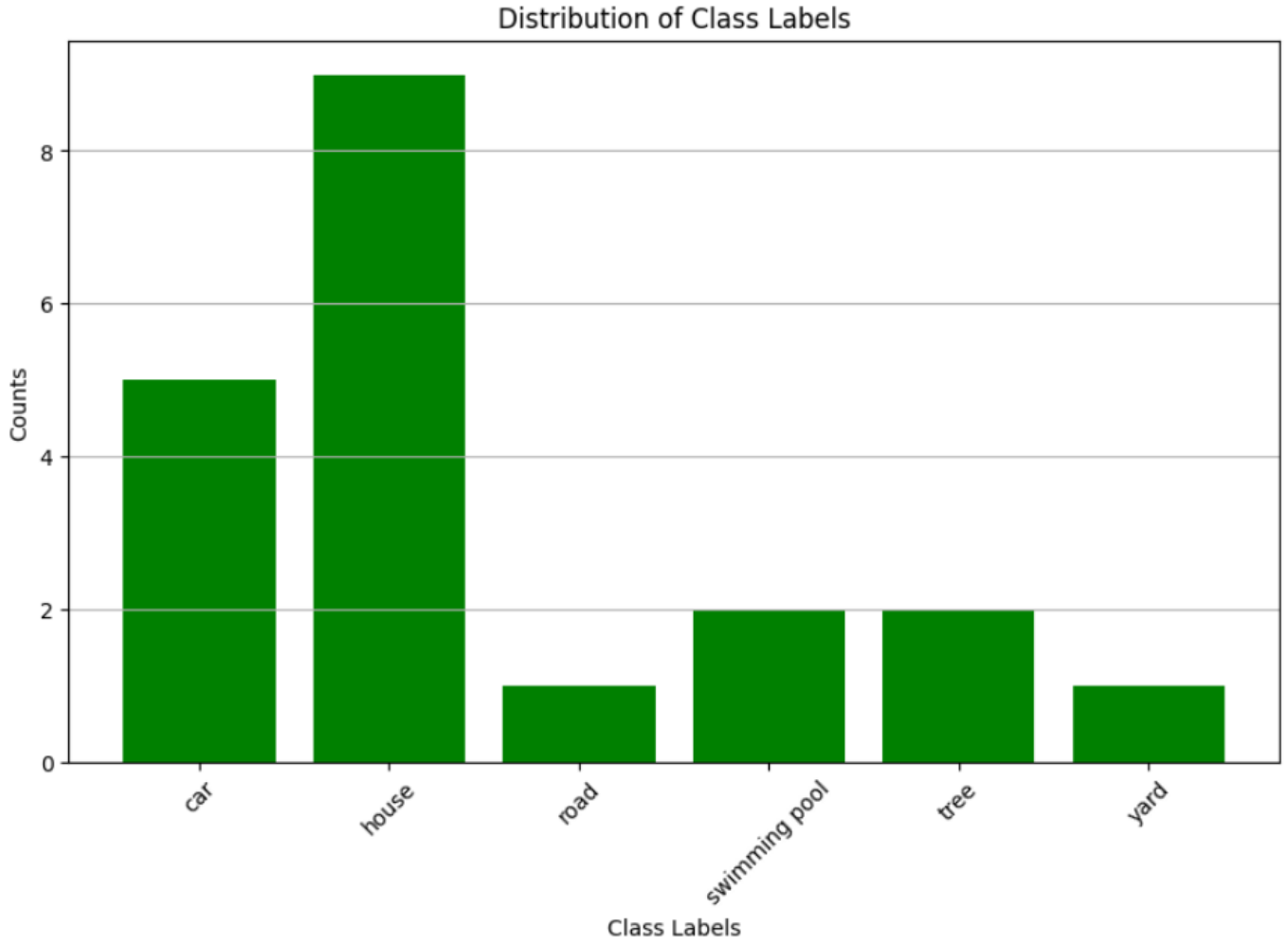
Distribution of class counts in train test and val: Train:



Val:


Distribution of Class Labels
Counts
0
2
4
6
8
10
12
14
car
house
road
swimming pool
tree
yard
Class Labels

Test:



The image size provided is : `(640,640)` whereas of the high dimensional drone image is of `(6000,4000)`

The images to be tested are of huge size and it is advised to ensure the consistency in the image size

```
folder_path = "/content/drive/MyDrive/datasets/Drone Images Test"
```

```
output_folder = "/content/drive/MyDrive/resized_drone_test_images"
os.makedirs(output_folder, exist_ok=True)
for filename in os.listdir(folder_path):
    if filename.endswith(".JPG") :
        img = Image.open(os.path.join(folder_path, filename))
        print(filename)
        resized_img = img.resize((640,640))
        resized_img.save(os.path.join(output_folder, filename))
        print(f"Resized and saved {filename}")

print("All images resized and saved successfully.")
```

The another approach could have been fragmenting the image into smaller fragments such that the desired height and width could have been acheived.

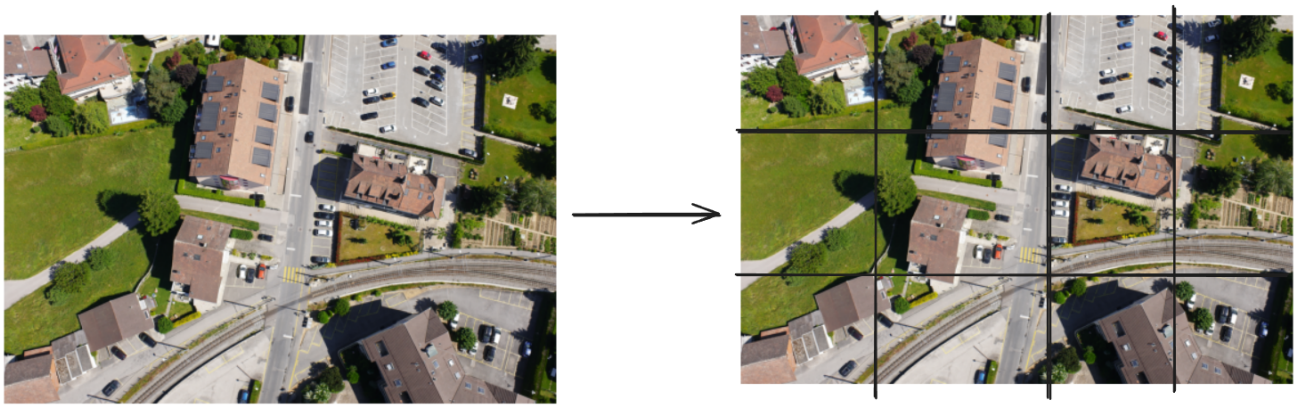
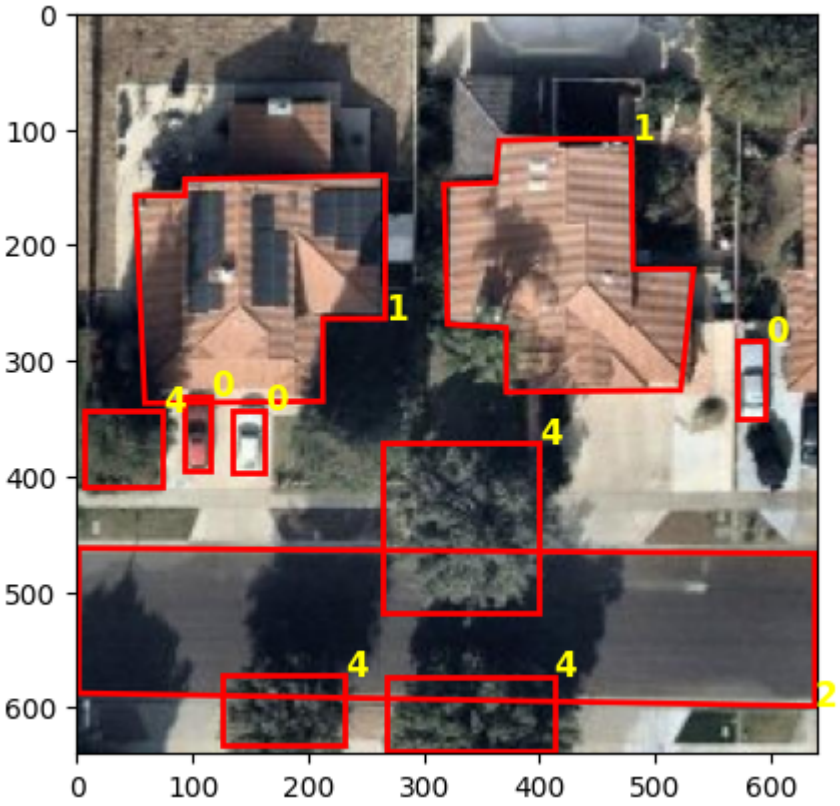


Image with annotations

The annotation provided in the labels are `class x1 y1 x2 y2 x3 y3 ...`

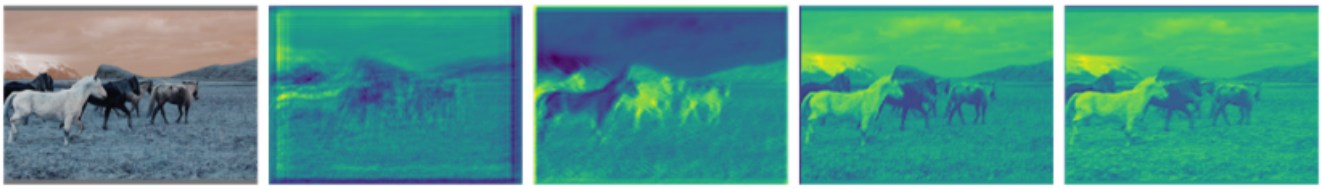
```
def load_image(image_path):
    return Image.open(image_path)


def parse_annotation(annotation):
    parts = annotation.strip().split()
    label = parts[0]
    coordinates = [float(x) for x in parts[1:]]
    return label, coordinates


def unnormalize_coordinates(coordinates, image_width, image_height):
    unnormalized_coordinates = []
    for i in range(0, len(coordinates), 2):
        x = coordinates[i] * image_width
        y = coordinates[i + 1] * image_height
        unnormalized_coordinates.extend([x, y])
    return unnormalized_coordinates
```

```
def plot_annotations(image_path, label_path):
      # Load image
    image = load_image(image_path)

    # Load annotations
    with open(label_path, 'r') as file:
        annotations = file.readlines()

    fig, ax = plt.subplots(1)
    ax.imshow(image)

    image_width, image_height = image.size
    print(f"Image size is {image.size}")
    for annotation in annotations:
        label, coordinates = parse_annotation(annotation)
        coordinates = unnormalize_coordinates(coordinates, image_width,
                                              image_height)
        polygon = [(coordinates[i], coordinates[i + 1])
                   for i in range(0, len(coordinates), 2)]
        polygon.append(polygon[0])  # Close the polygon

        poly = patches.Polygon(polygon,
                               closed=True,
                               fill=False,
                               edgecolor='red',
                               linewidth=2)
        ax.add_patch(poly)
        ax.text(polygon[0][0],
                polygon[0][1],
                label,
                color='yellow',
                fontsize=12,
                weight='bold')

    plt.show()
```

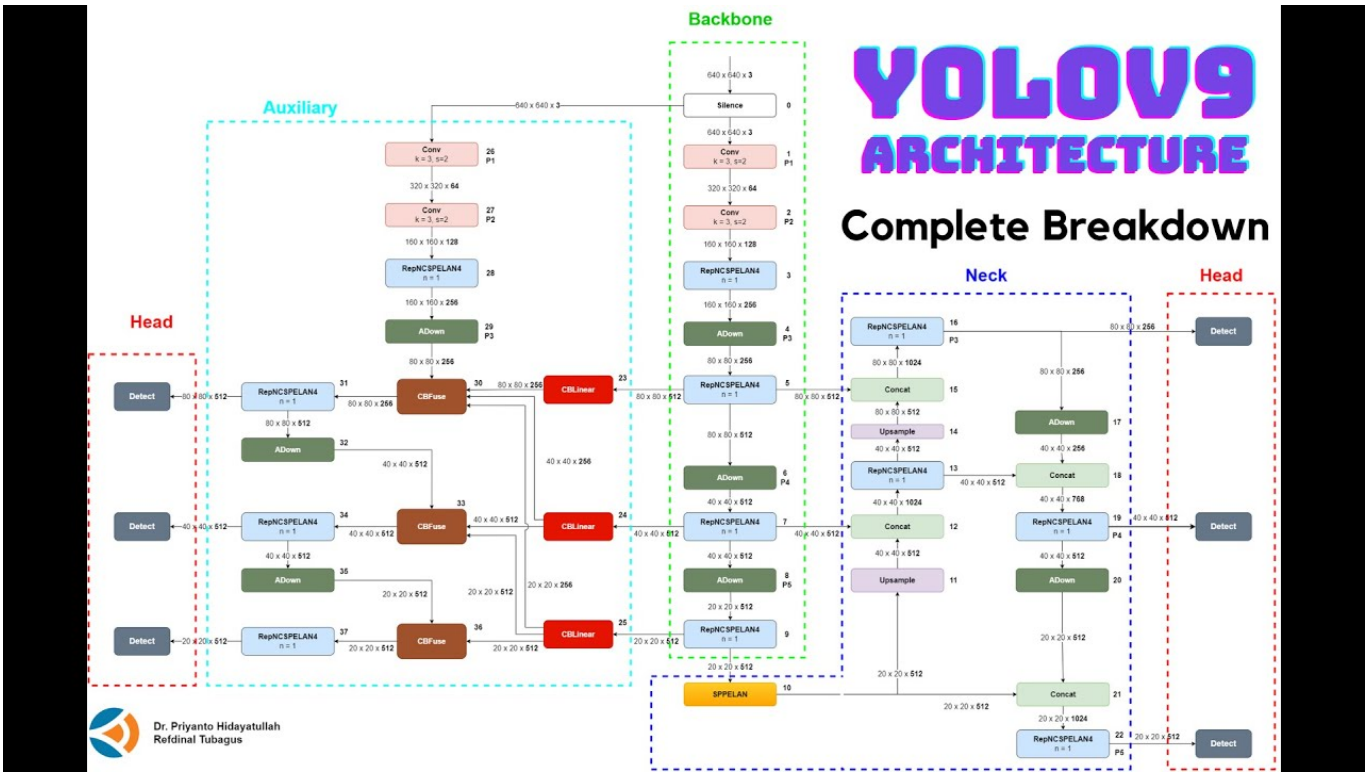


YOLO algorithm

yolov9 was proposed in the paper YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information



This is the most recent deep learning techniques concentrate on creating objective functions that are optimally suited to produce model predictions that are as near to the actual data as possible. In the interim, it is necessary to create a suitable architecture that can make it easier to gather sufficient data for prediction. Current approaches overlook the fact that a significant amount of information is lost during layer-by-layer feature extraction and spatial translation of incoming data. Information bottlenecks and reversible functions—two significant causes of data loss during data transmission across deep networks—will be covered in detail in this presentation. To address the several modifications that deep networks need to make in order to accomplish several goals, we introduced the idea of programmable gradient information (PGI). On working out the YOLOv9 was found to be one of the best algorithms for the development test. The architecture it uses is :



	from	n	params	module	arguments
0	-1	1	1856	ultralytics.nn.modules.conv.Conv	[3, 64, 3, 2]
1	-1	1	73984	ultralytics.nn.modules.conv.Conv	[64, 128, 3, 2]
2	-1	1	212864	ultralytics.nn.modules.block.RepNCSPELAN4	[128, 256, 128, 64, 1]
3	-1	1	164352	ultralytics.nn.modules.block.ADown	[256, 256]
4	-1	1	847616	ultralytics.nn.modules.block.RepNCSPELAN4	[256, 512, 256, 128, 1]
5	-1	1	656384	ultralytics.nn.modules.block.ADown	[512, 512]
6	-1	1	2857472	ultralytics.nn.modules.block.RepNCSPELAN4	[512, 512, 512, 256, 1]
7	-1	1	656384	ultralytics.nn.modules.block.ADown	[512, 512]
8	-1	1	2857472	ultralytics.nn.modules.block.RepNCSPELAN4	[512, 512, 512, 256, 1]
9	-1	1	656896	ultralytics.nn.modules.block.SPPELAN	[512, 512, 256]
10	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
11	[-1, 6]	1	0	ultralytics.nn.modules.conv.Concat	[1]
12	-1	1	3119616	ultralytics.nn.modules.block.RepNCSPELAN4	[1024, 512, 512, 256, 1]
13	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
14	[-1, 4]	1	0	ultralytics.nn.modules.conv.Concat	[1]
15	-1	1	912640	ultralytics.nn.modules.block.RepNCSPELAN4	[1024, 256, 256, 128, 1]
16	-1	1	164352	ultralytics.nn.modules.block.ADown	[256, 256]
17	[-1, 12]	1	0	ultralytics.nn.modules.conv.Concat	[1]
18	-1	1	2988544	ultralytics.nn.modules.block.RepNCSPELAN4	[768, 512, 512, 256, 1]
19	-1	1	656384	ultralytics.nn.modules.block.ADown	[512, 512]
20	[-1, 9]	1	0	ultralytics.nn.modules.conv.Concat	[1]
21	-1	1	3119616	ultralytics.nn.modules.block.RepNCSPELAN4	[1024, 512, 512, 256, 1]
22	[15, 18, 21]	1	7893634	ultralytics.nn.modules.head.Segment	[6, 32, 256, [256, 512, 512]]

YOLOv9c-seg summary: 654 layers, 27840066 parameters, 27840050 gradients, 159.1 GFLOPs

Data augmentation supported: `Blur(p=0.01, blur_limit=(3, 7)), MedianBlur(p=0.01, blur_limit=(3, 7)), ToGray(p=0.01), CLAHE(p=0.01, clip_limit=(1, 4.0), tile_grid_size=(8, 8))`

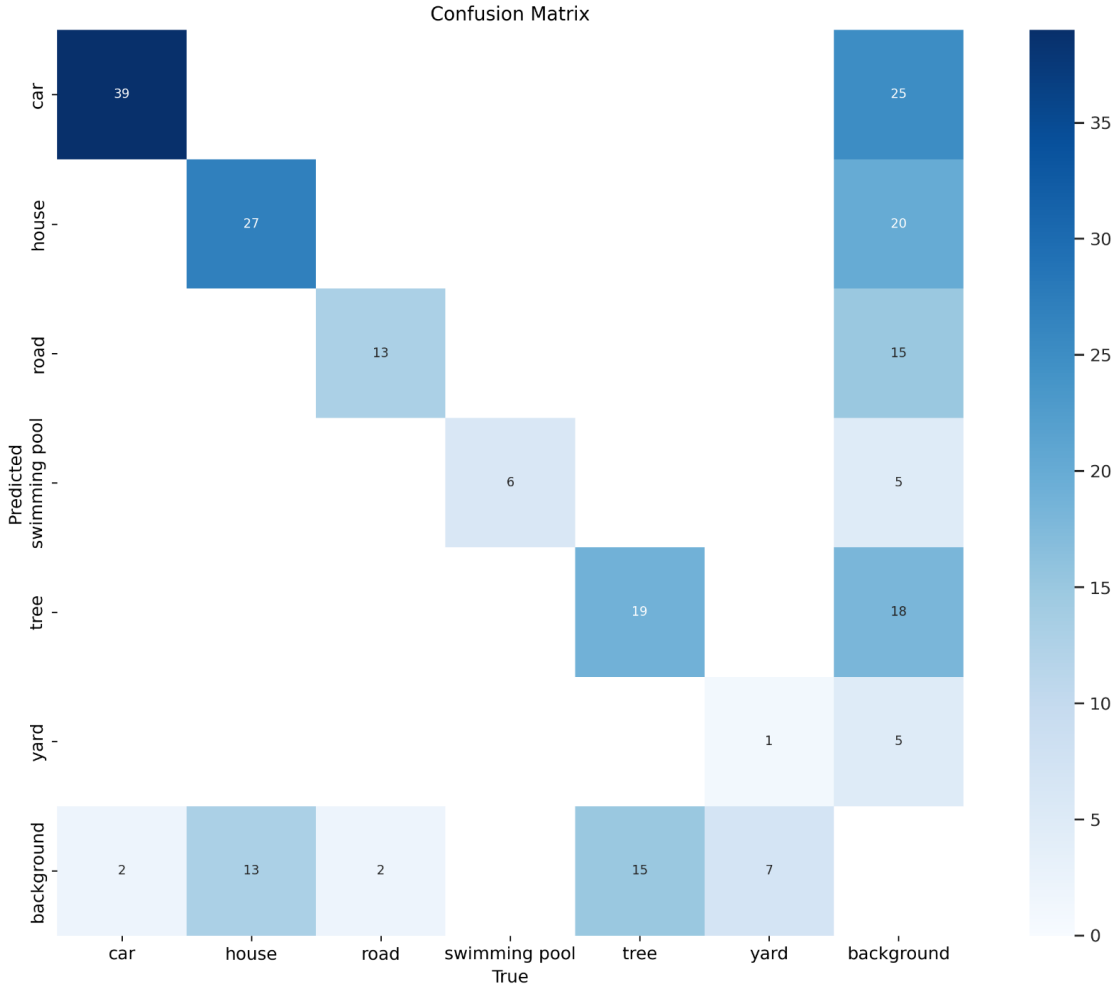
Training

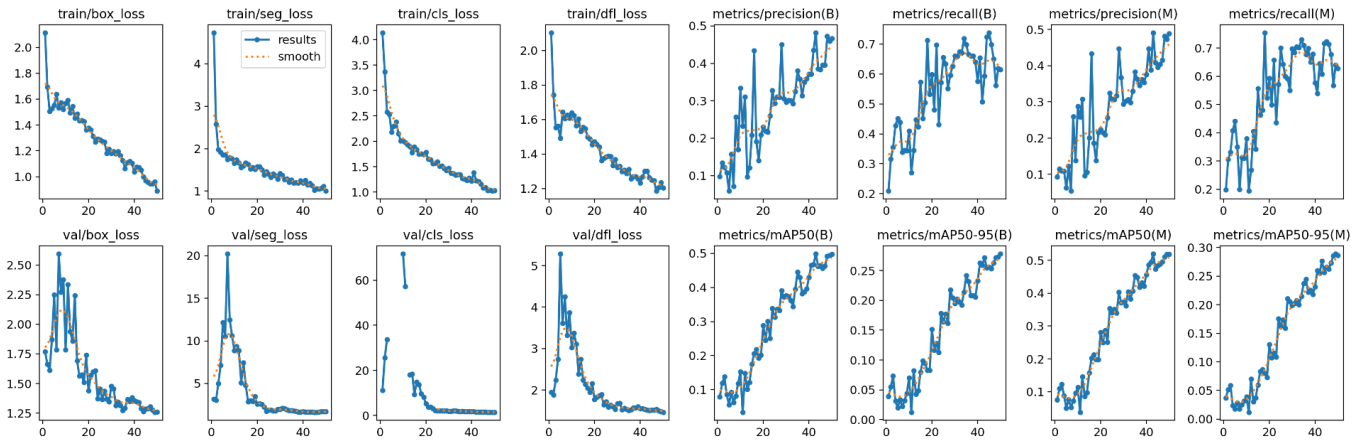
```
HOME = '/content/drive/MyDrive/yolov9c-seg'
%cd {HOME}
!yolo task=segment mode=train model=yolov9c-seg.pt data='{DATA_DIR}/data.yaml'
epochs=50 imgsz=640
```

Summary

```
YOLOv9c-seg summary (fused): 411 layers, 27629154 parameters, 0 gradients, 157.7 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95)     Mask(P          R      mAP50  mAP50-95): 100% 2/2 [00:01<00:
                   all         41        144      0.463      0.615      0.497      0.278      0.488      0.629      0.518      0.286
                   car         18         41      0.545      0.805        0.7      0.305      0.544       0.78      0.668      0.257
                 house         27         40      0.521      0.624      0.531      0.419      0.515       0.61      0.531      0.414
                  road         15         15      0.518      0.667       0.55      0.329       0.63        0.8      0.706      0.454
         swimming pool          5          6      0.457          1      0.543      0.329      0.465          1      0.543      0.285
                  tree         14         34      0.614      0.471      0.526      0.209      0.634      0.459      0.526       0.23
                  yard          6          8      0.125      0.125      0.135     0.0759      0.138      0.125      0.135     0.0734
```

Confusion Matrix

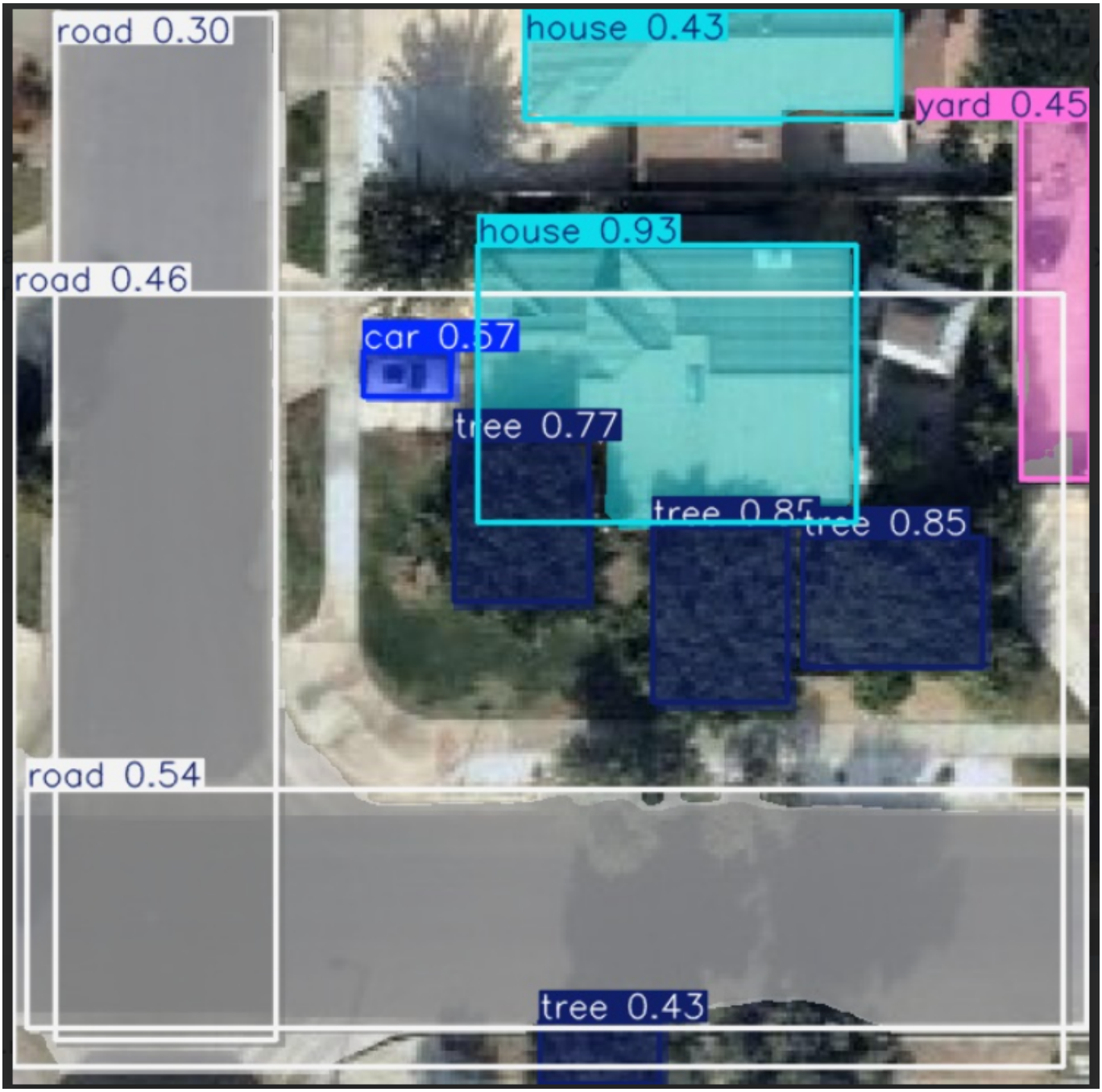


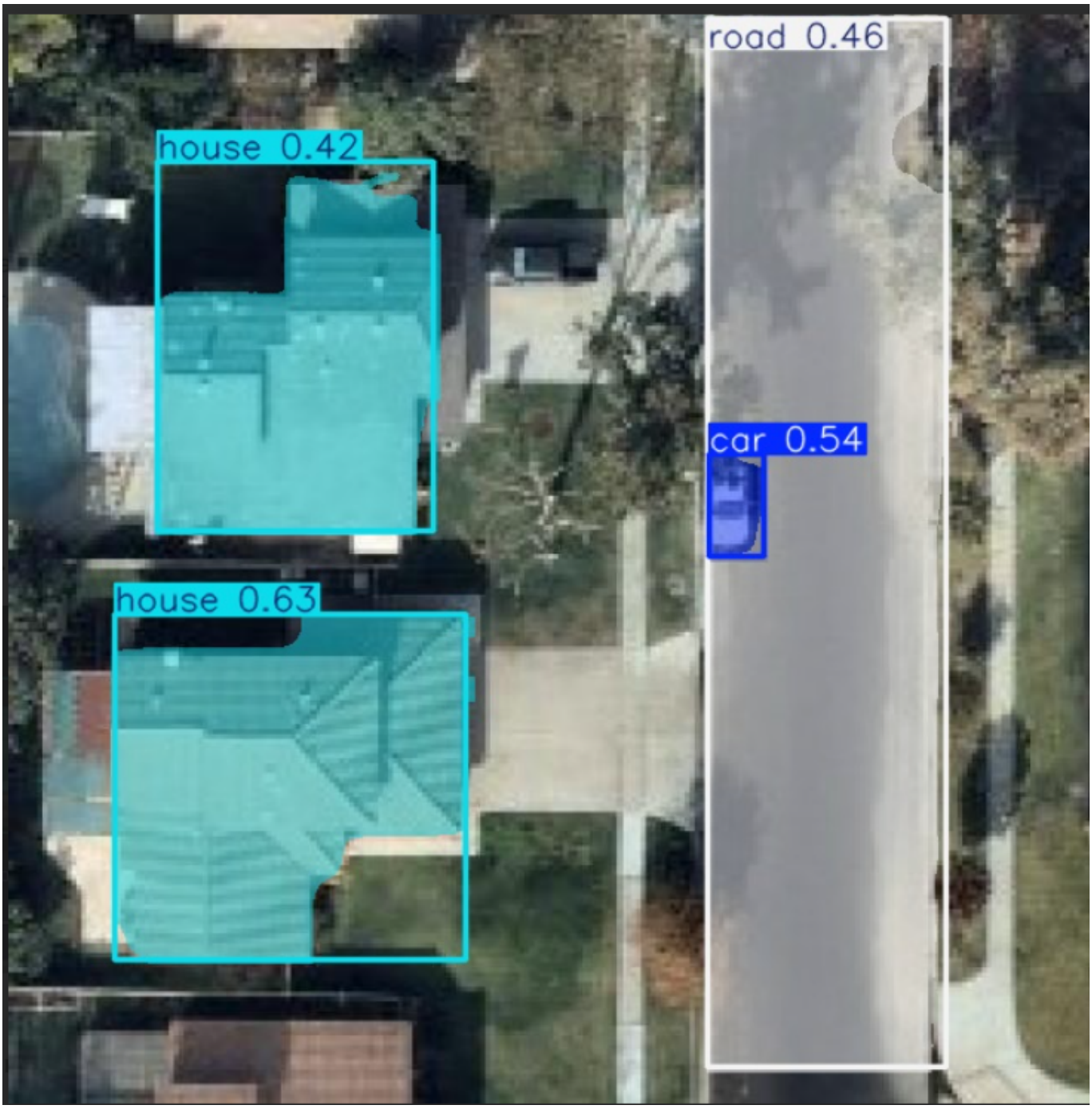


The chart suggests that loss is decreasing on each epoch and due to time and resource constraints I was limited to 50 epochs but could have increased to 100-200 epochs. -The confusion matrix shows that cars are shown to be quite mistaken as the background and the yard is greatly mistaken as the background by the model *In validation set,*

```
%cd {HOME}
!yolo task=segment mode=val model='{HOME}/runs/segment/train/weights/best.pt'
data='{DATA_DIR}/data.yaml'
```

```
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95)     Mask(P          R      mAP50  mAP50-95):   0% 0/3 [00:00<?, ?it/
self.pid = os.fork()
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95)     Mask(P          R      mAP50  mAP50-95): 100% 3/3 [00:05<00:00,
                   all         41        144      0.42      0.741      0.523      0.325       0.43      0.709      0.536      0.327
                   car         41         41      0.511      0.789       0.71      0.328      0.529      0.732       0.69      0.276
                 house         41         40      0.472      0.848      0.567      0.438      0.472      0.825      0.567      0.414
                  road         41         15      0.612          1      0.823      0.594      0.612      0.933      0.863      0.666
          swimming pool        41          6      0.386          1      0.412      0.232      0.395          1      0.412       0.25
                  tree         41         34      0.396      0.558      0.405      0.181       0.42      0.511      0.432      0.178
                  yard         41          8      0.143       0.25      0.223      0.176      0.155       0.25      0.252      0.176
Speed: 3.7ms pre-process, 35.9ms inference, 0.0ms loss, 20.2ms post-process per image
```





Similarly for the test set

```
%cd {HOME}
!yolo task=segment mode=predict model='{HOME}/runs/segment/train/weights/best.pt'
conf=0.25 source='/content/drive/MyDrive/datasets/datasets/test/images' save=true
name='test_predictions'
```

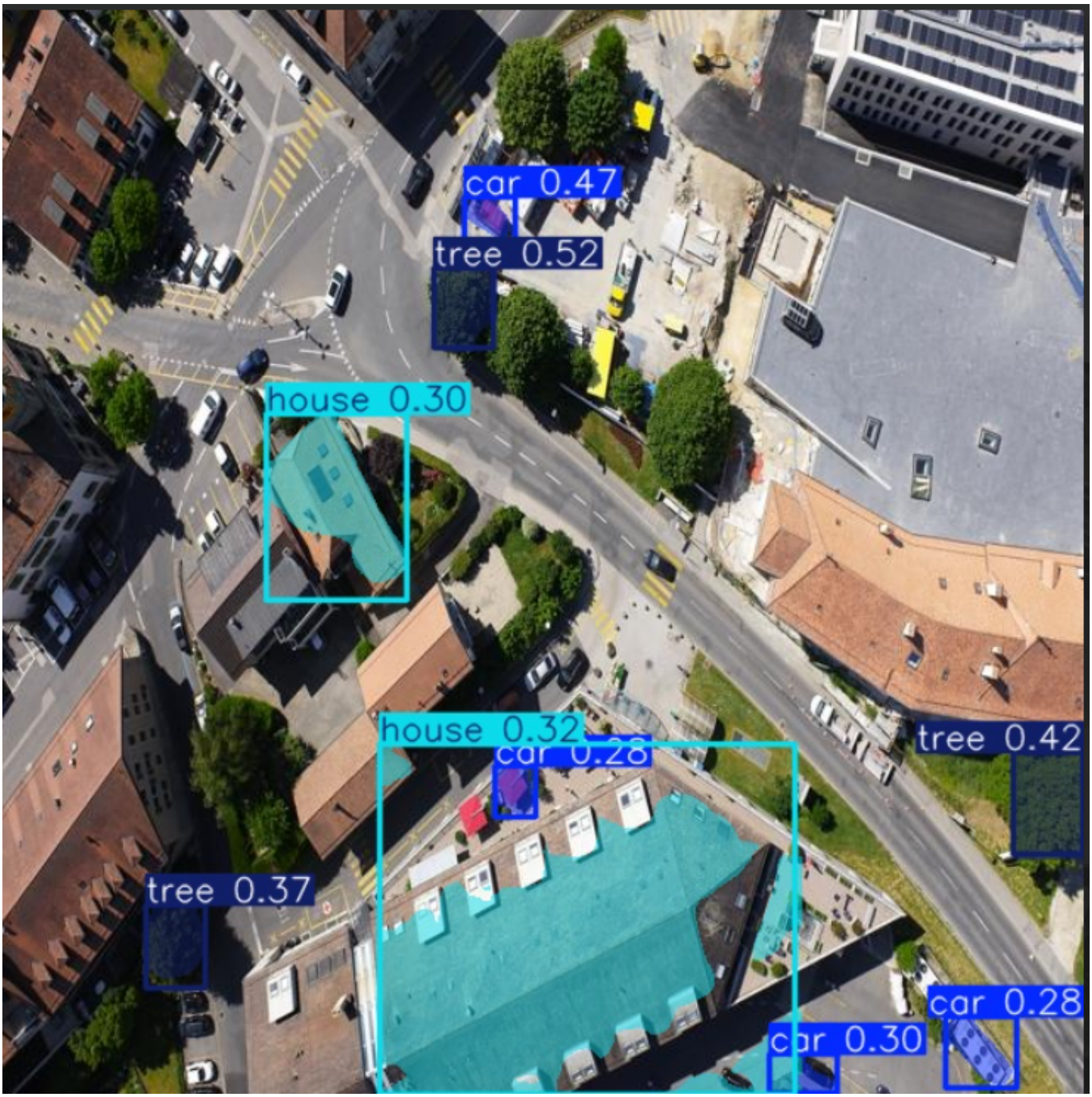

road 0.36
car 0.39
house 0.67
car 0.39


house 0.31
car 0.45
house 0.86

High Quality Drone Images

Resized High Quality Drone Images


```
%cd {HOME}
!yolo task=segment mode=predict model='{HOME}/runs/segment/train/weights/best.pt'
conf=0.25 source='/content/drive/MyDrive/resized_drone_test_images' save=true
name='drone_images_predictions'
```



However on trying to work with `yolov9e-seg.pt` memory error was detected

```
    return F.silu(input, inplace=self.inplace)
  File "/usr/local/lib/python3.10/dist-packages/torch/nn/functional.py", line 2101, in silu
    return torch._C._nn.silu_(input)
torch.cuda.OutOfMemoryError: CUDA out of memory. Tried to allocate 50.00 MiB. GPU
```

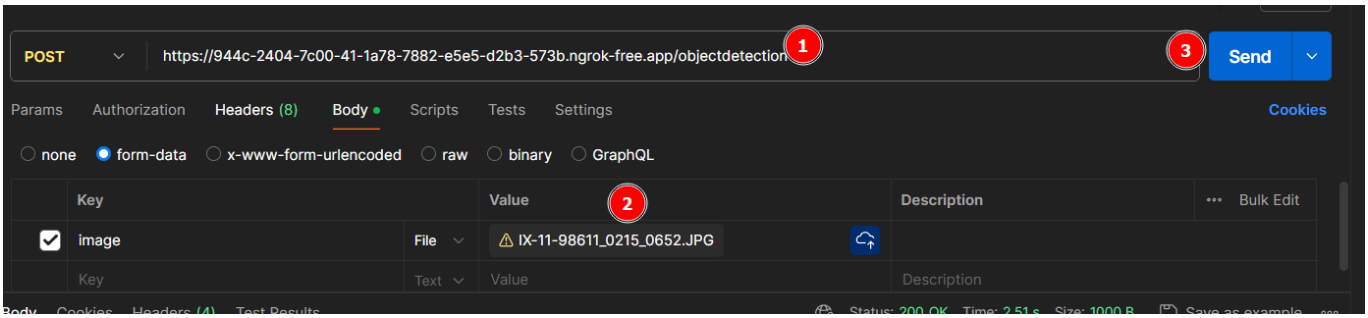
2. □□Create an API□ Develop an API that can accept an image, detect and classify objects, and return the predictions along with bounding box coordinates for each detected object. This image is a high-quality drone image with geolocation data EXIF, XMP

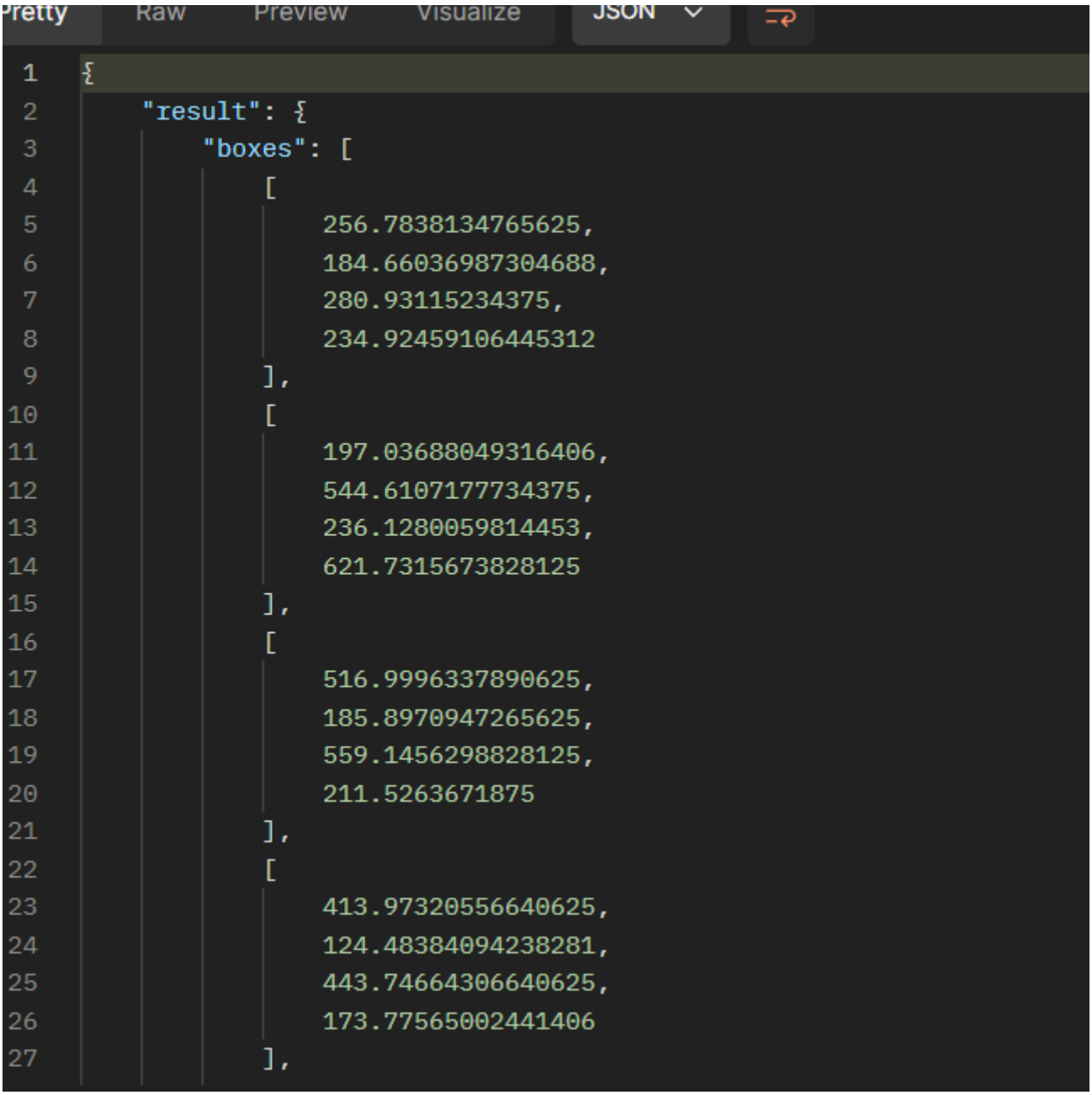
```
import io
from PIL import Image
from flask import Flask, request
import nest_asyncio
from pyngrok import ngrok
import torch
```

```
from ultralytics import YOLO

app = Flask(__name__)
model = YOLO('best.pt')


@app.route("/objectdetection/", methods=["POST"])
def predict():
    if not request.method == "POST":
        return

    if request.files.get("image"):
        image_file = request.files["image"]
        image_bytes = image_file.read()
        img = Image.open(io.BytesIO(image_bytes))
        img = img.reshape(640,640)
        results = model(img)
        class_indices = results[0].boxes.cls
        indices = class_indices.to(dtype=torch.int).tolist()
        names = ['car', 'house', 'road', 'swimming pool', 'tree', 'yard']
        mapped_names = [names[idx] for idx in indices]
        results_json = {
            "boxes": results[0].boxes.xyxy.tolist(),
            "classes": mapped_names,
            "confidence":results[0].boxes.conf.tolist()
        }
        return {"result": results_json}


ngrok_tunnel = ngrok.connect(5000)
print('Public URL:', ngrok_tunnel.public_url)
nest_asyncio.apply()
app.run(host="0.0.0.0", port=5000)
```

I hope the ngrok is configured in this term

```
Public URL: https://944c-2404-7c00-41-1a78-7882-e5e5-d2b3-573b.ngrok-free.app
 * Serving Flask app '__main__'
 * Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on all addresses (0.0.0.0)
 * Running on http://127.0.0.1:8000
 * Running on http://192.168.101.11:8000
Press CTRL+C to quit
127.0.0.1 - - [10/Jul/2024 20:48:50] "POST /objectdetection HTTP/1.1" 308 -

0: 640x640 2 cars, 1 tree, 1019.9ms
Speed: 8.0ms preprocess, 1019.9ms inference, 16.0ms postprocess per image at shape (1, 3, 640, 640)
127.0.0.1 - - [10/Jul/2024 20:49:00] "POST /objectdetection/ HTTP/1.1" 200 -
127.0.0.1 - - [10/Jul/2024 20:49:31] "POST /objectdetection HTTP/1.1" 308 -

0: 640x640 5 cars, 1 house, 1 tree, 1 yard, 1024.0ms
Speed: 9.3ms preprocess, 1024.0ms inference, 13.8ms postprocess per image at shape (1, 3, 640, 640)
127.0.0.1 - - [10/Jul/2024 20:49:33] "POST /objectdetection/ HTTP/1.1" 200 -
```

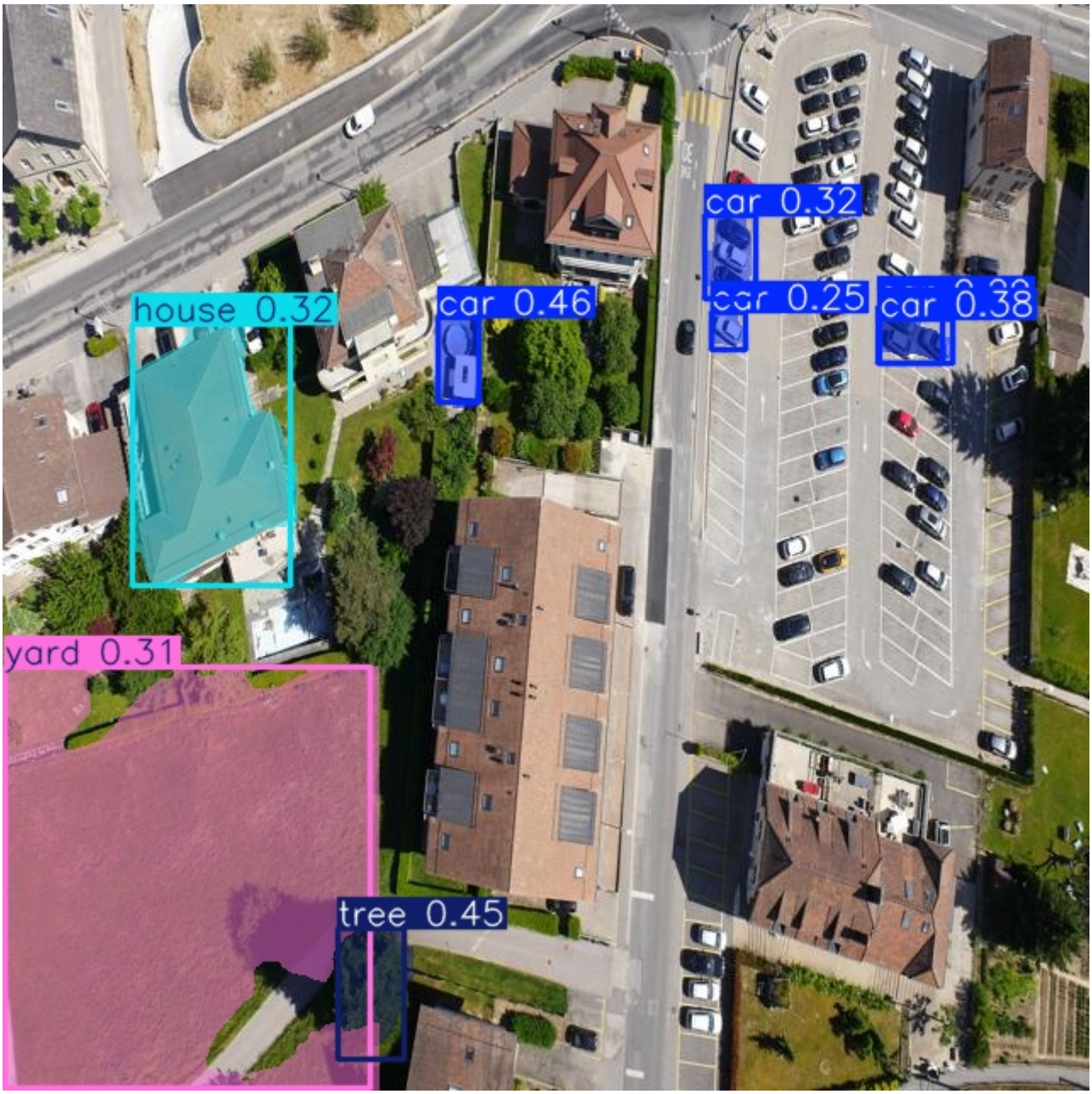





```
{
    "result": {
        "boxes": [
            [
                256.7838134765625,
                184.66036987304688,
                280.93115234375,
                234.92459106445312
            ],
```

```
            [
                197.03688049316406,
                544.6107177734375,
                236.1280059814453,
                621.7315673828125
            ],
            [
                516.9996337890625,
                185.8970947265625,
                559.1456298828125,
                211.5263671875
            ],
            [
                413.97320556640625,
                124.48384094238281,
                443.74664306640625,
                173.77565002441406
            ],
            [
                76.98167419433594,
                188.19851684570312,
                169.49618530273438,
                342.4807434082031
            ],
            [
                1.717864990234375,
                390.8797302246094,
                216.53475952148438,
                638.1531982421875
            ],
            [
                515.683837890625,
                178.48582458496094,
                553.950927734375,
                211.6399688720703
            ],
            [
                417.0240478515625,
                181.49562072753906,
                437.6375732421875,
                203.02882385253906
            ]
        ],
        "classes": [
            "car",
            "tree",
            "car",
            "car",
            "house",
            "yard",
            "car",
            "car"
        ],
        "confidence": [
```

```
                0.4641158878803253,
                0.4473479688167572,
                0.3838241696357727,
                0.3237011134624481,
                0.3161289095878601,
                0.31437838077545166,
                0.286126971244812,
                0.25324496626853943
            ]
        }
    }
```

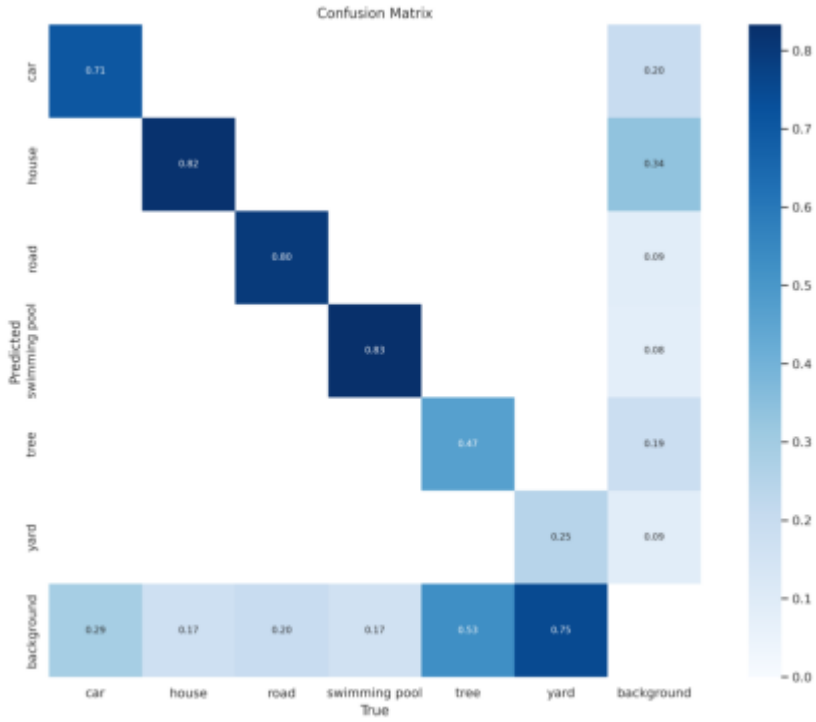


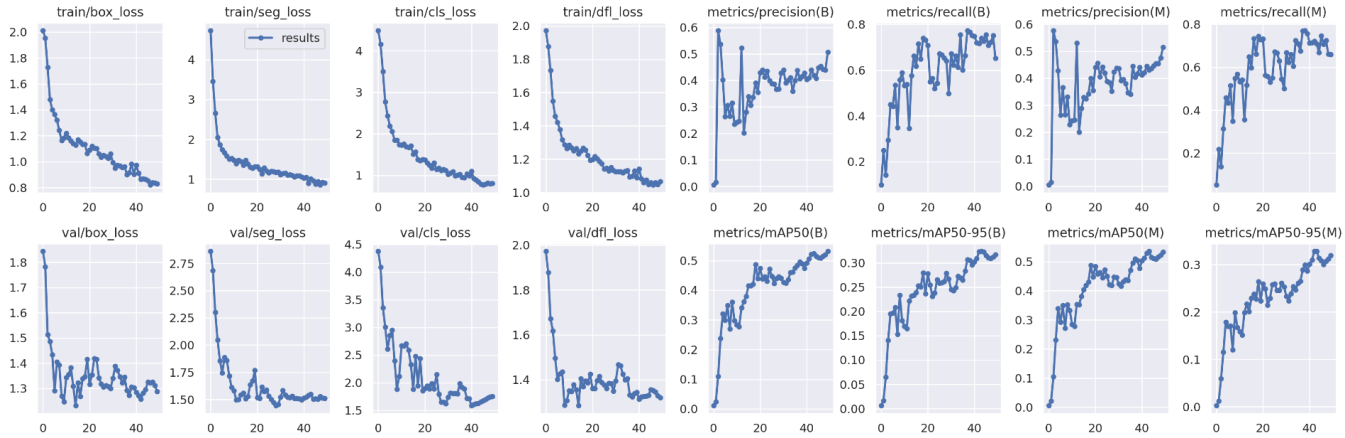
Further the API can be used to host it using AWS Sagemaker to deploy on the cloud

Comparision with other models

yolov8m-seg

```
YOLOv8m-seg summary (fused): 245 layers, 27225858 parameters, 0 gradients, 110.0 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95)     Mask(P          R      mAP50  mAP50-95):   0% 0
  self.pid = os.fork()
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95)     Mask(P          R      mAP50  mAP50-95): 100% 2
                   all         41        144       0.42      0.741      0.524      0.325       0.43      0.709      0.536      0.329
                   car         41         41      0.511      0.789      0.713      0.328      0.528      0.732      0.693       0.28
                 house         41         40      0.472      0.848      0.567      0.437      0.471      0.825      0.567      0.415
                  road         41         15      0.612          1      0.823      0.594      0.612      0.933      0.863      0.667
           swimming pool         41          6      0.386          1      0.412      0.232      0.394          1      0.412       0.25
                  tree         41         34      0.396      0.559      0.405      0.181      0.421      0.513      0.432      0.187
                  yard         41          8      0.143       0.25      0.223      0.176      0.155       0.25       0.25      0.176
Speed: 0.2ms pre-process, 14.4ms inference, 0.0ms loss, 1.4ms post-process per image
```





In comparision, yolov9 is far better than yolov8

Conclusion

The problem I see with this test set is the lack of data.Open-source training datasets such as COCO (Common Objects in Context) dataset and pre-trained models are predominantly available for non-ortho images Ref .YOLO is not properly built for the drone image. The limited details add the burden to the model. The domain shift is another problem with the dataset as well. The high pixels drone images mostly have the cars and houses.This difference has somewhat affected the performance of machine learning models trained on the

training set and then tested on the test set, because the model may not generalize well to the test data due to the domain shift.