# **Object Detection and Autopilot Safety analysis**

# Part 1: Object Detection

#### **Import libraries**

```
import torch
import os
import shutil
import pathlib
from glob import glob
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import cv2
import numpy as np
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

### Define the data paths

```
# For colab execution

zip_file_path = '/content/drive/MyDrive/DL/od.zip'

data_root_colab = '/content/drive/MyDrive/DL/Object Detection'
image_data_path_colab = '/content/drive/MyDrive/DL/Object Detection/Images'
labels_path_colab = f'{data_root_colab}/labels.csv'

#for Kaggle execution
```

```
image data path kaggle = '/kaggle/input/object-detection/Object Detection/Images'
labels_path_kaggle = '/kaggle/input/object-detection/Object Detection/labels.csv'
data root kaggle = '.'
image data path = None
data root = None
labels path = None
if os.path.exists(image data path kaggle):
    image data path = image data path kaggle
    data root = data root kaggle
   labels path = labels path kaggle
    print(f'Using Kaggle data ')
else:
   print('Not on kaggle')
   from google.colab import drive
   drive.mount('/content/drive')
   data root = data root colab
   image data path = image data path colab
   labels path = labels path colab
   if not os.path.exists(image data path):
         from zipfile import ZipFile
         zip ref = ZipFile(zip file path, 'r')
         zip ref.extractall('/content/drive/MyDrive/DL/')
         zip ref.close()
   print(f'Using Google Drive data')
print(f'image data path is {image data path}')
print(f'labels path is at {labels path}')
Not on kaggle
Mounted at /content/drive
Using Google Drive data
```

## Create the directory structure for yolo training

image data path is /content/drive/MyDrive/DL/Object Detection/Images
labels path is at /content/drive/MyDrive/DL/Object Detection/labels.csv

```
# create train , validation and test image directories
train label path = 'datasets/train/labels'
val labels path = 'datasets/val/labels'
train image path = 'datasets/train/images'
val image path = 'datasets/val/images'
test image path = 'datasets/test/images'
dirs = [train label path,val labels path,train image path,val image path,test image path]
for d in dirs:
    if os.path.exists(d):
        shutil.rmtree(d)
    os.makedirs(d)
    print(f'created {d}')
if not os.path.exists('datasets/data.yaml'):
    pathlib.Path.touch('datasets/data.yaml')
created datasets/train/labels
created datasets/val/labels
created datasets/train/images
created datasets/val/images
created datasets/test/images
%ls datasets
data.yaml test/ train/ val/
```

#### Load the labels csv file

```
import pandas as pd

label_data = pd.read_csv(labels_path,names=['id','name','x_min','y_min','x_max','y_max'])
label_data = label_data.drop_duplicates('id')
label_data['id'] = label_data['id'].astype(str).str.zfill(8)
label_data = label_data.iloc[0:len(os.listdir(image_data_path))]
label_data['image'] = sorted(os.listdir(image_data_path))
```

```
print(label_data.shape)
label_data.head()
```

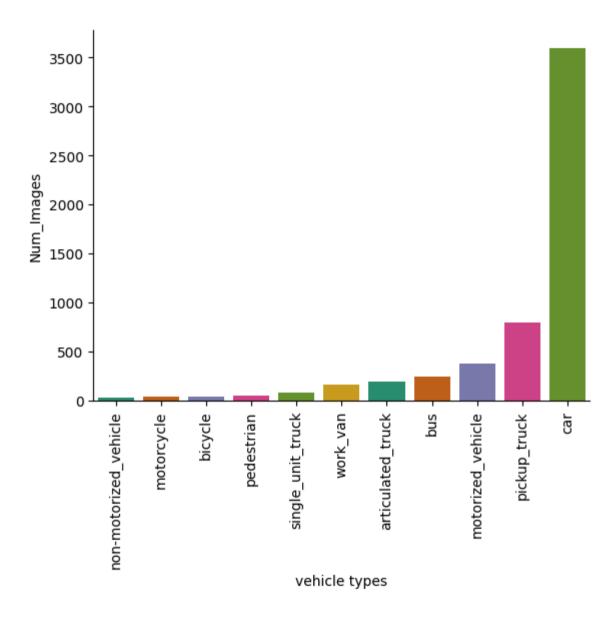
(5626, 7)

	id	name	x_min	y_min	x_max	y_max	image
0	00000000	pickup_truck	213	34	255	50	00000000.jpg
5	00000001	bus	205	155	568	314	00000001.jpg
11	00000002	motorized_vehicle	334	362	603	479	00000002.jpg
12	00000003	car	480	99	511	120	00000003.jpg
14	00000004	bus	439	32	719	171	00000004.jpg

#### **Estimate Vehicle numbers**

```
Plots the number of images in each class
:param directory: the directory containing the images
:param title: the title of the plot
:return: a dataframe containing the number of images in each class
sub dirs = get subdirectories(directory)
images = {}
image class = []
num images = []
class dict = {}
for d in sub dirs:
    image class.append(d)
    num images.append(len(os.listdir(str(directory)+'/'+d)))
df = pd.DataFrame({'Image Class':image class,'Num Images':num images})
df = df.sort values(by='Num Images',ascending=True).reset index()
indices = sorted(df['index'].values.tolist())
class names = df['Image Class'].values
for i in indices:
  class dict[i] = class names[i]
sns.barplot(data=df,x='Image Class',y='Num Images',palette=sns.mpl palette('Dark2'))
plt.xlabel('vehicle types')
plt.title(f' {title}')
plt.xticks(rotation = 90)
plt.gca().spines[['top', 'right',]].set visible(False)
plt.show()
return df
```

```
plot_class_numbers(f'{data_root}/image_root','')
```



	index	Image_Class	Num_Images
0	6	non-motorized_vehicle	32
1	10	motorcycle	38
2	3	bicycle	43
3	5	pedestrian	56
4	9	single_unit_truck	80
5	7	work_van	161
6	1	articulated_truck	195
7	4	bus	244
8	8	motorized_vehicle	383
9	0	pickup_truck	801
10	2	car	3593

There is substantial class imbalance

# Create a map of vehicle types to index

```
import pprint
class_names = label_data.name.unique().tolist()
d = {}
for i in range(len(class_names)):
   d[class_names[i]] = i
pprint.pprint(d)
```

```
{'articulated_truck': 4,
  'bicycle': 8,
  'bus': 1,
  'car': 3,
  'motorcycle': 10,
  'motorized_vehicle': 2,
  'non-motorized_vehicle': 7,
  'pedestrian': 6,
  'pickup_truck': 0,
  'single_unit_truck': 9,
  'work van': 5}
```

## Create labels for training and validation

```
import cv2
import numpy as np
import pathlib
def get label filename(row):
   return row['id']+'.txt'
def normalize bb(x min,y min,x max,y max,id):
   img path = f'{image data path}/{id}.jpg'
  if os.path.exists(img path):
     img = cv2.imread(img_path)
      image height,image width, = img.shape
     x center = (x min + x max)/2
     y center = (y min + y max)/2
     width = x \max - x \min
     height = y max - y min
     normalized x center = x center / image width
     normalized y center = y center / image height
      normalized width = width / image width
      normalized height = height / image height
      return normalized x center, normalized y center, normalized width , normalized height
def get label data(row):
  dims = normalize bb(row['x min'], row['y min'], row['x max'], row['y max'], row['id'])
  class id = d.get(row['name'])
```

```
yolo annotaion = f'{class id} {dims[0]:.3f} {dims[1]:.3f} {dims[2]:.3f} {dims[0]:.3f}'
  return yolo annotaion
def get image width(row):
    img path = f"{image data path}/{row['id']}.jpg"
    img = cv2.imread(img path)
     return img.shape[1]
def get image height(row):
    img_path = f"{image_data_path}/{row['id']}.jpg"
    img = cv2.imread(img path)
     return img.shape[0]
def create yaml():
  file path = 'datasets/data.yaml'
  if os.path.exists(file path):
    os.remove(file path)
  train = 'train: train'
  val = 'val: val'
  nc = "nc: 11"
  names = f"names: {str(class names)}"
  lines to append = [train,val,nc,names]
  try:
    with open(file path, 'a') as file:
     for line in lines to append:
          file.write(f'{line}\n')
    print('data.yaml created')
  except Exception as e:
    print(f"An error occurred: {e}")
```

## Create data.yaml for training

```
create_yaml()
data.yaml created
```

```
%cat datasets/data.yaml

train: train
val: val
nc: 11
names: ['pickup_truck', 'bus', 'motorized_vehicle', 'car', 'articulated_truck', 'work_van', 'pedestrian', 'non-motorized_vehicle', 'bicy cle', 'single_unit_truck', 'motorcycle']
```

#### Create annotations in YOLO5 format

```
from glob import glob
import warnings
warnings.filterwarnings('ignore')
num images = len(glob(f'{image data path}/*.jpg'))
num train images = int(num images*0.8)
num test images = 60
num val images = num images - num train images - num test images
print(f'total :{num images}, train : {num train images}, val :{num val images}, test:{num test images}')
labels train = label data.iloc[0:num train images]
labels val = label data.iloc[num train images:num images-num test images]
print(f'train shape : {labels train.shape}, val shape: {labels val.shape}')
total :5626, train : 4500, val :1066, test:60
train shape: (4500, 7), val shape: (1066, 7)
labels train['filename'] = labels train.apply(get label filename.axis=1)
labels train['text'] = labels train.apply(get label data,axis=1)
labels train['image width'] = labels train.apply( get image width,axis=1)
labels train['image height'] = labels train.apply( get image height,axis=1)
labels val['filename'] = labels val.apply( get label filename,axis=1)
labels val['text'] = labels val.apply( get label data,axis=1)
labels val['image width'] = labels val.apply( get image width,axis=1)
labels val['image height'] = labels val.apply( get image height,axis=1)
```

print(f'train shape : {labels\_train.shape}, val shape: {labels\_val.shape}')
labels\_train.sample(10)

train shape : (4500, 11), val shape: (1066, 11)

	id	name	x_min	y_min	x_max	y_max	image	filename	text	image_width	image_height
13607	00004345	car	135	259	192	348	00004345.jpg	00004345.txt	3 0.227 0.632 0.079 0.227	720	480
3157	00001001	car	607	147	654	172	00001001.jpg	00001001.txt	3 0.876 0.332 0.065 0.876	720	480
9668	00003069	car	129	62	203	97	00003069.jpg	00003069.txt	3 0.485 0.349 0.216 0.485	342	228
8476	00002708	car	120	94	198	144	00002708.jpg	00002708.txt	3 0.465 0.522 0.228 0.465	342	228
5320	00001672	car	150	172	225	219	00001672.jpg	00001672.txt	3 0.260 0.407 0.104 0.260	720	480
5781	00001828	bicycle	357	136	394	236	00001828.jpg	00001828.txt	8 0.522 0.388 0.051 0.522	720	480
684	00000211	motorized_vehicle	0	244	72	351	00000211.jpg	00000211.txt	2 0.050 0.620 0.100 0.050	720	480
7226	00002261	car	514	159	715	292	00002261.jpg	00002261.txt	3 0.853 0.470 0.279 0.853	720	480
6702	00002114	car	70	130	219	201	00002114.jpg	00002114.txt	3 0.201 0.345 0.207 0.201	720	480
4456	00001412	pickup_truck	42	47	144	91	00001412.jpg	00001412.txt	0 0.272 0.303 0.298 0.272	342	228

# Define function to create the yolo label file

```
from pathlib import Path

# create the label file
def create_label_file(label_path,file_name,text):

f = Path(f'{label_path}/{file_name}')
f.write_text(text)
```

### Create label files for train and validation images

```
labels_train.apply(lambda row: create_label_file(train_label_path,row['filename'],row['text']) , axis =1)
_=labels_val.apply(lambda row: create_label_file(val_labels_path,row['filename'],row['text']) , axis =1)
```

### Copy the images to train, val and test folders

### install ultralytics

```
!pip install ultralytics > install.txt
```

#### Train the model

```
from ultralytics import YOLO
data_yaml_kaggle = "/kaggle/working/datasets/data.yaml"
data_yaml_colab = "/content/datasets/data.yaml"
epochs = 100
patience = 10
data_yaml = data_yaml_kaggle if os.path.exists(data_yaml_kaggle) else data_yaml_colab
model = YOLO("yolov5su.pt")
train_results=model.train(data=data_yaml, epochs=epochs, patience = patience,imgsz=640)
```

Ultralytics 8.3.107 

✓ Python-3.11.11 torch-2.5.1+cu124 CUDA:0 (Tesla T4, 15095MiB)

engine/trainer: task=detect, mode=train, model=yolov5su.pt, data=/kaggle/working/datasets/data.yaml, epochs=100, time=None, patience=10, batch=16, imgsz=640, save=True, save\_period=-1, cache=False, device=None, workers=8, project=None, name=train3, exist\_ok=False, pretrain ed=True, optimizer=auto, verbose=True, seed=0, deterministic=True, single\_cls=False, rect=False, cos\_lr=False, close\_mosaic=10, resume=F alse, amp=True, fraction=1.0, profile=False, freeze=None, multi\_scale=False, overlap\_mask=True, mask\_ratio=4, dropout=0.0, val=True, spl it=val, save\_json=False, conf=None, iou=0.7, max\_det=300, half=False, dnn=False, plots=True, source=None, vid\_stride=1, stream\_buffer=False, visualize=False, augment=False, agnostic\_nms=False, classes=None, retina\_masks=False, embed=None, show=False, save\_frames=False, save\_txt=False, save\_conf=False, save\_crop=False, show\_labels=True, show\_conf=True, show\_boxes=True, line\_width=None, format=torchscript, keras=False, optimize=False, int8=False, dynamic=False, simplify=True, opset=None, workspace=None, nms=False, lr0=0.01, lrf=0.01, moment um=0.937, weight\_decay=0.0005, warmup\_epochs=3.0, warmup\_momentum=0.8, warmup\_bias\_lr=0.1, box=7.5, cls=0.5, dfl=1.5, pose=12.0, kobj=1.0, nbs=64, hsv\_h=0.015, hsv\_s=0.7, hsv\_v=0.4, degrees=0.0, translate=0.1, scale=0.5, shear=0.0, perspective=0.0, flipud=0.0, fliplr=0.5, bgr=0.0, mosaic=1.0, mixup=0.0, copy\_paste=0.0, copy\_paste\_mode=flip, auto\_augment=randaugment, erasing=0.4, crop\_fraction=1.0, cfg=None, tracker=botsort.yaml, save\_dir=runs/detect/train3
Overriding model.yaml nc=80 with nc=11

	from	n	params	module	arguments
0	-1	1	3520	ultralytics.nn.modules.conv.Conv	[3, 32, 6, 2, 2]
1	-1	1	18560	ultralytics.nn.modules.conv.Conv	[32, 64, 3, 2]
2	-1	1	18816	ultralytics.nn.modules.block.C3	[64, 64, 1]
3	-1	1	73984	ultralytics.nn.modules.conv.Conv	[64, 128, 3, 2]
4	-1	2	115712	ultralytics.nn.modules.block.C3	[128, 128, 2]
5	-1	1	295424	ultralytics.nn.modules.conv.Conv	[128, 256, 3, 2]
6	-1	3	625152	ultralytics.nn.modules.block.C3	[256, 256, 3]
7	-1	1	1180672	ultralytics.nn.modules.conv.Conv	[256, 512, 3, 2]
8	-1	1	1182720	ultralytics.nn.modules.block.C3	[512, 512, 1]
9	-1	1	656896	ultralytics.nn.modules.block.SPPF	[512, 512, 5]
10	-1	1	131584	ultralytics.nn.modules.conv.Conv	[512, 256, 1, 1]
11	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
12	[-1, 6]	1	0	ultralytics.nn.modules.conv.Concat	[1]
13	-1	1	361984	ultralytics.nn.modules.block.C3	[512, 256, 1, False]
14	-1	1	33024	ultralytics.nn.modules.conv.Conv	[256, 128, 1, 1]
15	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
16	[-1, 4]	1	0	ultralytics.nn.modules.conv.Concat	[1]
17	-1	1	90880	ultralytics.nn.modules.block.C3	[256, 128, 1, False]
18	-1	1	147712	ultralytics.nn.modules.conv.Conv	[128, 128, 3, 2]
19	[-1, 14]	1	0	ultralytics.nn.modules.conv.Concat	[1]
20	-1	1	296448	ultralytics.nn.modules.block.C3	[256, 256, 1, False]
21	-1	1	590336	ultralytics.nn.modules.conv.Conv	[256, 256, 3, 2]
22	[-1, 10]	1	0	ultralytics.nn.modules.conv.Concat	[1]
23	-1	1	1182720	ultralytics.nn.modules.block.C3	[512, 512, 1, False]
24	[17, 20, 23]	1	2120305	ultralytics.nn.modules.head.Detect	[11, [128, 256, 512]]

YOLOv5s summary: 153 layers, 9,126,449 parameters, 9,126,433 gradients, 24.1 GFLOPs

Transferred 421/427 items from pretrained weights

TensorBoard: Start with 'tensorboard --logdir runs/detect/train3', view at http://localhost:6006/

Freezing layer 'model.24.dfl.conv.weight'

AMP: running Automatic Mixed Precision (AMP) checks...

AMP: checks passed ✓

train: Scanning /kaggle/working/datasets/train/labels.cache... 4500 images, 0 backgrounds, 0 corrupt: 100%| 4500/4500 [00:00 <?, ?it/s]

albumentations: Blur(p=0.01, blur\_limit=(3, 7)), MedianBlur(p=0.01, blur\_limit=(3, 7)), ToGray(p=0.01, num\_output\_channels=3, method='we ighted\_average'), CLAHE(p=0.01, clip\_limit=(1.0, 4.0), tile\_grid\_size=(8, 8))

val: Scanning /kaggle/working/datasets/val/labels.cache... 1066 images, 0 backgrounds, 0 corrupt: 100%| 1066/1066 [00:00<?, ?
it/s]</pre>

Plotting labels to runs/detect/train3/labels.jpg...

optimizer: 'optimizer=auto' found, ignoring 'lr0=0.01' and 'momentum=0.937' and determining best 'optimizer', 'lr0' and 'momentum' autom
atically...

optimizer: AdamW(lr=0.000667, momentum=0.9) with parameter groups 69 weight(decay=0.0), 76 weight(decay=0.0005), 75 bias(decay=0.0)

TensorBoard: model graph visualization added ✓

Image sizes 640 train, 640 val

Using 2 dataloader workers

Logging results to  ${\it runs/detect/train3}$ 

Starting training for 100 epochs...

	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
s]	1/100	6.65G Class	1.887 Images	4.267 Instances	1.829 Box(P	12 R		100%  <b>               </b>	282/282 [01:13<00:00, 3.83it/s] 100%  34/34 [00:06<00:00, 5.28it/
-		all	1066	1066	0.683	0.14	0.0755	0.0385	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
s]	2/100	6.67G Class	1.631 Images	2.714 Instances	1.666 Box(P	11 R		100%  mAP50-95):	282/282 [01:11<00:00, 3.97it/s] 100%  34/34 [00:06<00:00, 5.30it/
		all	1066	1066	0.615	0.0942	0.0654	0.0354	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
s]	3/100	6.67G Class	1.605 Images	2.582 Instances	1.647 Box(P	<b>11</b> R		100%  <b>  100%</b>   mAP50-95):	282/282 [01:11<00:00, 3.97it/s] 100%  34/34 [00:06<00:00, 5.19it/

		all	1066	1066	0.606	0.0992	0.0592	0.0328	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	4/100	6.67G Class	1.548	2.476 Instances	1.614 Box(P	9 R	640: mAP50		282/282 [01:10<00:00, 4.03it/s] 100%  34/34 [00:06<00:00, 5.22it/
s]		Class	Illiages	Tilscalices	DOX(F	IX.	IIIAF JO	IIIAF 30-93).	100%  3.2211/
		all	1066	1066	0.522	0.136	0.0906	0.051	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	5/100	6.67G	1.481	2.368	1.554	9			282/282 [01:10<00:00, 4.02it/s]
s]		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.12it/
2]		all	1066	1066	0.716	0.112	0.0891	0.0574	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	6/100	6.67G	1.422	2.242	1.52	9	640:	100%	282/282 [01:10<00:00, 4.02it/s]
,		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.24it/
s]		all	1066	1066	0.733	0.114	0.124	0.0804	
	Epoch	GPU_mem	box_loss			Instances	Size	0,000	
	7/100	6.67G	1.376	2.219	1.488	8		100%	282/282 [01:10<00:00, 4.02it/s]
	,, ===	Class		Instances	Box(P	R			100%  34/34 [00:06<00:00, 5.24it/
s]									
		all	1066	1066	0.624	0.126	0.107	0.07	
	Epoch	GPU_mem	box_loss	_		Instances	Size		
	8/100	6.67G	1.338	2.132	1.459	5 B			282/282 [01:10<00:00, 4.02it/s]
s]		Class	Images	Instances	Box(P	R	MAPSO	IIIAPSU-95);	100%  34/34 [00:06<00:00, 5.18it/
		all	1066	1066	0.69	0.196	0.156	0.0965	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	9/100	6.67G	1.293	2.081	1.428	11	640:	100%	282/282 [01:10<00:00, 4.01it/s]
,		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.29it/
s]		all	1066	1066	0.395	0.187	0.14	0.092	
	Epoch	GPU_mem	box_loss	cls_loss		Instances	Size	3.032	
	10/100	6.67G	1.265	2.039	1.412	8		100%	282/282 [01:10<00:00, 4.02it/s]
	10, 100	Class		Instances	Box(P	R			100%  34/34 [00:06<00:00, 5.18it/
s]									
		all	1066	1066	0.461	0.248	0.174	0.119	

	Epoch	GPU_mem	box_loss	cls_loss	dfl loss	Instances	Size		
	11/100	6.67G	1.247	2.026	1.392	12		100%	282/282 [01:10<00:00, 4.02it/s]
	11/100	Class		Instances	Box(P	R			100%  34/34 [00:06<00:00, 5.24it/
s]			- 0		- (				, , , , , , , , , , , , , , , , , , , ,
		all	1066	1066	0.725	0.149	0.181	0.126	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	12/100	6.67G	1.219	1.952	1.373	12	640:	100%	282/282 [01:09<00:00, 4.03it/s]
_		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.22it/
s]		all	1066	1066	0.412	0.257	0.171	0.121	
	C a a a la							0.121	
	Epoch	GPU_mem		cls_loss		Instances	Size	1000/1	1 000 (000 [04 40 00 00 4 00]) / 1
	13/100	6.67G Class	1.219	1.929 Instances	1.364 Box(P	7 R			282/282 [01:10<00:00, 4.02it/s] 100%  34/34 [00:06<00:00, 5.25it/
s]		CIass	Tillages	Tils calices	DOX(F	IX.	IIIAF JO	IIIAF 30-33).	34/34 [00.00000.00, 3.2311/
•		all	1066	1066	0.499	0.287	0.197	0.133	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	14/100	6.67G	1.169	1.855	1.33	6	640:	100%	282/282 [01:10<00:00, 4.00it/s]
		Class	Images	Instances	Box(P	R			100%  34/34 [00:06<00:00, 5.28it/
s]		11	4055	4044	2 425	0.046	0.404	0.420	
		all	1066	1066	0.405	0.216	0.196	0.139	
	Epoch	GPU_mem		cls_loss		Instances	Size		
	15/100	6.67G	1.175	1.862	1.333	8			282/282 [01:10<00:00, 4.02it/s]
s]		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.19it/
2]		all	1066	1066	0.347	0.304	0.217	0.16	
	Epoch	GPU mem	box loss	cls loss	dfl loss	Instances	Size		
	16/100	6.67G	1.145	1.827	1.311	5		100%	282/282 [01:10<00:00, 4.02it/s]
	10, 100	Class		Instances	Box(P	R			100%  34/34 [00:06<00:00, 5.27it/
s]					·			·	
		all	1066	1066	0.386	0.331	0.235	0.154	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	17/100	6.67G	1.132	1.801	1.305	10			282/282 [01:10<00:00, 4.03it/s]
,		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.21it/
s]		all	1066	1066	0.33	0.35	0.243	0.169	
	Enoch						Size	0.103	
	Epoch	GPU_mem	box_loss	cls_loss	uT1_1055	Instances	2126		

	18/100	6.67G	1.124	1.775	1.294 Box(P	7 R		100%	282/282 [01:10<00:00, 4.02it/s]   100%    34/34 [00:06<00:00, 5.32it/
s]		Class	Images	Instances	BOX (P	ĸ	IIIAPSØ	MAP30-93):	100%  34/34 [00:00<00:00, 5:3211/
_		all	1066	1066	0.421	0.282	0.238	0.16	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	19/100	6.67G	1.113	1.762	1.285	9	640:	100%	282/282 [01:10<00:00, 4.02it/s]
		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.30it/
s]		11	1066	1055	0.200	0.227	0.246	0.475	
		all	1066	1066	0.288	0.337	0.246	0.175	
	Epoch	GPU_mem	box_loss	cls_loss	_	Instances	Size		
	20/100	6.67G	1.089	1.743	1.27	9		100%	
s]		Class	Images	Instances	Box(P	R	mAP50	MAP50-95):	100%  34/34 [00:06<00:00, 5.25it/
٦٦		all	1066	1066	0.49	0.339	0.24	0.168	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	21/100	6.67G	1.07	1.725	1.256	11	640:	100%	282/282 [01:10<00:00, 4.03it/s]
		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.41it/
s]									
		all	1066	1066	0.575	0.243	0.248	0.168	
	Epoch	GPU_mem	box_loss	cls_loss	_	Instances	Size		_
	22/100	6.67G	1.085	1.695	1.268	12		100%	282/282 [01:09<00:00, 4.03it/s]
c 1		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.26it/
s]		all	1066						
			ממשד	1066	0.443	0.278	0.268	0.189	
	Fnoch	GPU mem		1066	0.443	0.278	0.268 Size	0.189	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		202/202 [01:10:00:00 / 02i+/c]
	Epoch 23/100	6.67G	box_loss 1.041	cls_loss 1.673	dfl_loss 1.244	Instances	Size 640:	100%	282/282 [01:10<00:00, 4.02it/s]   100%    34/34 [00:06<00:00, 5.40it/
s]			box_loss 1.041	cls_loss	dfl_loss	Instances	Size 640:	100%	282/282 [01:10<00:00, 4.02it/s]   100%    34/34 [00:06<00:00, 5.40it/
s]		6.67G	box_loss 1.041	cls_loss 1.673	dfl_loss 1.244	Instances	Size 640:	100%	
s]		6.67G Class	box_loss 1.041 Images	cls_loss 1.673 Instances	dfl_loss 1.244 Box(P 0.321	Instances 4 R	Size 640: mAP50	100%  MAP50-95):	
s]	23/100	6.67G Class	box_loss 1.041 Images 1066	cls_loss 1.673 Instances	dfl_loss 1.244 Box(P 0.321	Instances 4 R 0.381	Size 640: mAP50 0.258 Size 640:	100%  MAP50-95):  0.184	100%  34/34 [00:06<00:00, 5.40it/
	23/100 Epoch	6.67G Class all GPU_mem	box_loss 1.041 Images 1066 box_loss 1.058	cls_loss 1.673 Instances 1066 cls_loss	dfl_loss 1.244 Box(P 0.321 dfl_loss	Instances  4  R  0.381  Instances	Size 640: mAP50 0.258 Size 640:	100%  MAP50-95):  0.184	100%  34/34 [00:06<00:00, 5.40it/
s]	23/100 Epoch	GPU_mem 6.67G Class	box_loss 1.041 Images 1066 box_loss 1.058 Images	cls_loss 1.673 Instances 1066 cls_loss 1.684 Instances	dfl_loss 1.244 Box(P 0.321 dfl_loss 1.248 Box(P	Instances  4 R  0.381  Instances  10 R	Size 640: mAP50 0.258 Size 640: mAP50	100%  MAP50-95):  0.184  100%  MAP50-95):	100%  34/34 [00:06<00:00, 5.40it/
	23/100 Epoch	6.67G Class all GPU_mem 6.67G	box_loss 1.041 Images 1066 box_loss 1.058	cls_loss 1.673 Instances 1066 cls_loss 1.684	dfl_loss 1.244 Box(P 0.321 dfl_loss 1.248 Box(P	Instances  4 R  0.381  Instances 10	Size 640: mAP50 0.258 Size 640:	100%  MAP50-95):  0.184	100%  34/34 [00:06<00:00, 5.40it/

	25/100	6.67G Class	1.043 Images	1.65 Instances	1.239 Box(P	9 R		100%  mAP50-95):	282/282 [01:10<00:00, 4.00it/s] 100%  34/34 [00:06<00:00, 5.27it/
s]									
		all	1066	1066	0.243	0.376	0.267	0.2	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
s]	26/100	6.67G Class	1.004 Images	1.594 Instances	1.215 Box(P	9 R			282/282 [01:09<00:00, 4.03it/s] 100%  34/34 [00:06<00:00, 5.44it/
		all	1066	1066	0.338	0.375	0.302	0.213	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
s]	27/100	6.67G Class	1.024 Images	1.646 Instances	1.223 Box(P	7 R	640: mAP50		282/282 [01:10<00:00, 4.03it/s] 100%  34/34 [00:06<00:00, 5.31it/
		all	1066	1066	0.386	0.281	0.289	0.199	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
s]	28/100	6.67G Class	0.9985 Images	1.607 Instances	1.21 Box(P	9 R		100%  <b>             </b>	282/282 [01:10<00:00, 4.01it/s] 100%  34/34 [00:06<00:00, 5.35it/
		all	1066	1066	0.466	0.349	0.293	0.211	
	Epoch	GPU mem	box loss	cls loss	dfl loss	Instances	Size		
s]	29/100	6.67G Class	0.9956 Images	1.588 Instances	1.206 Box(P	11 R		100%  MAP50_95):	282/282 [01:10<00:00, 4.02it/s]   100%    34/34 [00:06<00:00, 5.20it/
								IIIAF 30-33).	34/34 [00.00000.00, 3.2010/
		all	1066	1066	0.425	0.374	0.296	0.214	100%
	Epoch	all GPU_mem		1066 cls_loss		0.374 Instances			100%  34/34 [00.0000.00, 3.2010)
s]	Epoch 30/100		box_loss 0.994				0.296 Size 640:	0.214	282/282 [01:10<00:00, 4.02it/s]   100%  34/34 [00:06<00:00, 5.14it/
s]		GPU_mem 6.67G	box_loss 0.994	cls_loss 1.59	dfl_loss 1.206	Instances	0.296 Size 640:	0.214	282/282 [01:10<00:00, 4.02it/s]
s]		GPU_mem 6.67G Class	box_loss 0.994 Images	cls_loss 1.59 Instances	dfl_loss 1.206 Box(P 0.341	Instances 9 R	0.296 Size 640: mAP50	0.214 100%  MAP50-95):	282/282 [01:10<00:00, 4.02it/s]
	30/100	GPU_mem 6.67G Class all	box_loss 0.994 Images 1066 box_loss 0.9869	cls_loss 1.59 Instances 1066	dfl_loss 1.206 Box(P 0.341	Instances 9 R 0.389	0.296 Size 640: mAP50 0.299 Size 640:	0.214  100%  MAP50-95):  0.207	282/282 [01:10<00:00, 4.02it/s]
s]	30/100 Epoch	GPU_mem 6.67G Class all GPU_mem 6.67G	box_loss 0.994 Images 1066 box_loss 0.9869	cls_loss 1.59 Instances 1066 cls_loss 1.575	dfl_loss 1.206 Box(P 0.341 dfl_loss 1.195	Instances 9 R 0.389 Instances 8	0.296 Size 640: mAP50 0.299 Size 640:	0.214  100%  MAP50-95):  0.207	282/282 [01:10<00:00, 4.02it/s]   100%    34/34 [00:06<00:00, 5.14it/

	32/100	6.67G	0.9588	1.529	1.179	9	640:	100%	28	32/282 [01:10<00:00, 4.02it/s]	
s]		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%	34/34 [00:06<00:00, 5	.30it/
٦٦		all	1066	1066	0.242	0.39	0.28	0.216			
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size				
	33/100	6.67G	0.9705	1.541	1.185	5	640:	100%	28	32/282 [01:10<00:00, 4.01it/s]	
		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%	34/34 [00:06<00:00, 5	.24it/
s]		all	1066	1066	0.396	0.389	0.322	0.245			
	F. a. a. la						Size	0.245			
	Epoch	GPU_mem	box_loss	cls_loss		Instances		100%	1 20	22/202 [04:40:00:00 4 02:+/-]	
	34/100	6.67G Class	0.958 Tmages	1.517 Instances	1.183 Box(P	6 R	640: mAP50			32/282 [01:10<00:00, 4.02it/s] 34/34 [00:06<00:00, 5	.36it/
s]		61433	10863	2113 carrees	20%(1				200/01	3.73. [00.00.00.00, 3	.5010,
		all	1066	1066	0.347	0.383	0.311	0.244			
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size				
	35/100	6.67G	0.9581	1.541	1.184	10				82/282 [01:10<00:00, 4.02it/s]	
-1		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%	34/34 [00:06<00:00, 5	.21it/
s]											
		all	1066	1066	0.331	0.41	0.29	0.221			
	Epoch				0.331 dfl loss		0.29 Size	0.221			
	Epoch 36/100	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		28	32/282 [01:10<00:00. 4.02it/s]	
	Epoch 36/100		box_loss 0.9421				Size 640:	100%		32/282 [01:10<00:00, 4.02it/s]	.34it/
s]		GPU_mem 6.67G Class	box_loss 0.9421 Images	cls_loss 1.508 Instances	dfl_loss 1.171 Box(P	Instances 5 R	Size 640: mAP50	100%  MAP50-95):			.34it/
s]	36/100	GPU_mem 6.67G Class	box_loss 0.9421 Images 1066	cls_loss 1.508 Instances	dfl_loss 1.171 Box(P 0.26	Instances 5 R 0.417	Size 640: mAP50 0.3	100%			.34it/
s]	36/100 Epoch	GPU_mem 6.67G Class all GPU_mem	box_loss 0.9421 Images 1066 box_loss	cls_loss 1.508 Instances 1066 cls_loss	dfl_loss 1.171 Box(P 0.26 dfl_loss	Instances 5 R 0.417 Instances	Size 640: mAP50 0.3 Size	100%  MAP50-95): 0.234	100%	34/34 [00:06<00:00, 5	.34it/
s]	36/100	GPU_mem 6.67G Class all GPU_mem 6.67G	box_loss 0.9421 Images 1066 box_loss 0.9267	cls_loss 1.508 Instances 1066 cls_loss 1.483	dfl_loss 1.171 Box(P 0.26 dfl_loss 1.158	Instances 5 R 0.417 Instances 7	Size 640: mAP50 0.3 Size 640:	100%  MAP50-95):  0.234	100%	34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s]	
	36/100 Epoch	GPU_mem 6.67G Class all GPU_mem	box_loss 0.9421 Images 1066 box_loss 0.9267	cls_loss 1.508 Instances 1066 cls_loss	dfl_loss 1.171 Box(P 0.26 dfl_loss	Instances 5 R 0.417 Instances	Size 640: mAP50 0.3 Size 640:	100%  MAP50-95):  0.234	100%	34/34 [00:06<00:00, 5	
s]	36/100 Epoch	GPU_mem 6.67G Class all GPU_mem 6.67G	box_loss 0.9421 Images 1066 box_loss 0.9267	cls_loss 1.508 Instances 1066 cls_loss 1.483	dfl_loss 1.171 Box(P 0.26 dfl_loss 1.158	Instances 5 R 0.417 Instances 7	Size 640: mAP50 0.3 Size 640:	100%  MAP50-95):  0.234	100%	34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s]	
	36/100 Epoch	GPU_mem 6.67G Class all GPU_mem 6.67G Class	box_loss 0.9421 Images 1066 box_loss 0.9267 Images	cls_loss 1.508 Instances 1066 cls_loss 1.483 Instances	dfl_loss 1.171 Box(P 0.26 dfl_loss 1.158 Box(P	Instances 5 R 0.417 Instances 7 R	Size 640: mAP50 0.3 Size 640: mAP50	100%  MAP50-95):  0.234  100%  MAP50-95):	100%	34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s]	
	36/100 Epoch 37/100	GPU_mem 6.67G Class all GPU_mem 6.67G Class all	box_loss 0.9421 Images 1066 box_loss 0.9267 Images	cls_loss 1.508 Instances 1066 cls_loss 1.483 Instances	dfl_loss 1.171 Box(P 0.26 dfl_loss 1.158 Box(P	Instances 5 R 0.417 Instances 7 R 0.356	Size 640: mAP50 0.3 Size 640: mAP50 0.308 Size	100%  MAP50-95):  0.234  100%  MAP50-95):	100%  28	34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s]	
s]	36/100 Epoch 37/100 Epoch	GPU_mem 6.67G Class all GPU_mem 6.67G Class all GPU_mem	box_loss 0.9421 Images 1066 box_loss 0.9267 Images 1066 box_loss 0.9275	cls_loss 1.508 Instances 1066 cls_loss 1.483 Instances 1066 cls_loss	dfl_loss 1.171 Box(P 0.26 dfl_loss 1.158 Box(P 0.478 dfl_loss	Instances 5 R 0.417 Instances 7 R 0.356 Instances	Size 640: mAP50 0.3 Size 640: mAP50 0.308 Size 640:	100%  MAP50-95):  0.234  100%  MAP50-95):  0.24	100%  28	34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s] 34/34 [00:06<00:00, 5	.32it/
	36/100 Epoch 37/100 Epoch	GPU_mem 6.67G Class all GPU_mem 6.67G Class all GPU_mem 6.67G Class	box_loss 0.9421 Images 1066 box_loss 0.9267 Images 1066 box_loss 0.9275 Images	cls_loss 1.508 Instances 1066 cls_loss 1.483 Instances 1066 cls_loss 1.468 Instances	dfl_loss 1.171 Box(P 0.26 dfl_loss 1.158 Box(P 0.478 dfl_loss 1.157 Box(P	Instances 5 R 0.417 Instances 7 R 0.356 Instances 10 R	Size 640: mAP50 0.3 Size 640: mAP50 0.308 Size 640: mAP50	100%  MAP50-95):  0.234  100%  MAP50-95):  0.24  100%  MAP50-95):	100%  28	34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s] 34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s]	.32it/
s]	36/100 Epoch 37/100 Epoch	GPU_mem 6.67G Class all GPU_mem 6.67G Class all GPU_mem 6.67G	box_loss 0.9421 Images 1066 box_loss 0.9267 Images 1066 box_loss 0.9275	cls_loss 1.508 Instances 1066 cls_loss 1.483 Instances 1066 cls_loss 1.468	dfl_loss 1.171 Box(P 0.26 dfl_loss 1.158 Box(P 0.478 dfl_loss 1.157 Box(P	Instances 5 R 0.417 Instances 7 R 0.356 Instances 10	Size 640: mAP50 0.3 Size 640: mAP50 0.308 Size 640:	100%  MAP50-95):  0.234  100%  MAP50-95):  0.24	100%  28	34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s] 34/34 [00:06<00:00, 5 32/282 [01:10<00:00, 4.02it/s]	.32it/

	39/100	6.67G	0.929	1.482	1.156	7	640:	100%	282/282 [01:10<00:00, 4.02it/s]
		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.36it
s]			4044	1055	0.404		0.004	0.044	
		all	1066	1066	0.434	0.39	0.326	0.241	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	40/100	6.67G	0.9107	1.433	1.147	5			282/282 [01:10<00:00, 4.02it/s]
-		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.20it
s]		all	1066	1066	0.352	0.418	0.311	0.238	
								0.230	
	Epoch	GPU_mem	_	cls_loss	_	Instances	Size		
	41/100	6.67G	0.9006	1.426	1.141	9			282/282 [01:10<00:00, 4.02it/s]
c 1		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.35it,
s]		all	1066	1066	0.285	0.382	0.321	0.254	
	Epoch	GPU_mem		cls_loss		Instances	Size	0,120	
	42/100	_	_	1.436	_			100%	202/202 [01:00:00:00 4 02:+/-]
	42/100	6.67G Class	0.9028	Instances	1.14 Box(P	8 R			282/282 [01:09<00:00, 4.03it/s] 100%  34/34 [00:06<00:00, 5.44it/s]
s]		CIASS	Illiages	Tilscalices	DOX(I	K	IIIAI 30	IIIAI JU-JJ).	100%
		all	1066	1066	0.372	0.356	0.334	0.262	
	Epoch	GPU mem	box loss	cls_loss	dfl loss	Instances	Size		
	43/100	6.67G	0.8907	1.418	1.135	7	640:	100%	282/282 [01:09<00:00, 4.03it/s]
	13, 200	Class		Instances	Box(P	R			100% 34/34 [00:06<00:00, 5.29it,
s]			Ü		`			,	
		all	1066	1066	0.411	0.459	0.341	0.265	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	44/100	6.67G	0.8859	1.416	1.128	5	640:	100%	282/282 [01:09<00:00, 4.03it/s]
		Class	Images	Instances	Box(P	R			100%  34/34 [00:06<00:00, 5.43it,
s]									
		all	1066	1066	0.347	0.452	0.354	0.275	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	45/100	6.67G	0.8805	1.381	1.13	7			282/282 [01:09<00:00, 4.03it/s]
		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.25it
s]		_11	1000	1000	0.202	0 447	0.224	0.257	
		all	1066	1066	0.288	0.447	0.331	0.257	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		

	46/100	6.67G	0.8838	1.387	1.126	6			282/282 [01:10<00:00, 4.01it/s]
_		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.32it/
s]		all	1066	1066	0.448	0.343	0.305	0.236	
	- 1							0.230	
	Epoch	GPU_mem	_	cls_loss		Instances	Size		
	47/100	6.67G	0.8759	1.373	1.119	5			282/282 [01:10<00:00, 4.02it/s]
s]		Class	Images	Instances	Box(P	R	MAP50	MAP50-95):	100%  34/34 [00:06<00:00, 5.49it/
٦]		all	1066	1066	0.393	0.357	0.329	0.257	
	Epoch	GPU_mem	box loss	cls_loss		Instances	Size		
	48/100	6.67G	0.8776	1.393	1.124	6		100%	282/282 [01:10<00:00, 4.02it/s]
	.0, 200	Class		Instances	Box(P	R			100% 34/34 [00:06<00:00, 5.47it/
s]			· ·		`			,	
		all	1066	1066	0.274	0.456	0.323	0.254	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	49/100	6.67G	0.8612	1.352	1.115	11	640:	100%	282/282 [01:10<00:00, 4.03it/s]
		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.31it/
s]		11	1000	1066	0.403	0.454	0.26	0.004	
		all	1066	1066	0.403	0.451	0.36	0.281	
	Epoch	GPU_mem	_	cls_loss		Instances	Size		
	50/100	6.67G	0.8492	1.337	1.105	8			282/282 [01:09<00:00, 4.03it/s]
c 1		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.28it/
s]		all	1066	1066	0.325	0.422	0.353	0.271	
	Epoch	GPU mem		cls_loss		Instances	Size	0.272	
	51/100	6.67G	0.8587	1.326	1.116	1113 carices		100%	282/282 [01:09<00:00, 4.03it/s]
	51/100	Class		Instances	Box(P	R			100%  100%  34/34 [00:06<00:00, 5.36it/
s]		CIUSS	Tillages	instances	DOX(I		iliAi 50	IIIAI 30 33).	134/34 [00.000.00, 3.3011/
-		all	1066	1066	0.452	0.379	0.353	0.283	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	52/100	6.67G	0.8389	1.334	1.099	9	640:	100%	282/282 [01:09<00:00, 4.03it/s]
		Class	Images	Instances	Box(P	R			100%  34/34 [00:06<00:00, 5.43it/
s]									
		all	1066	1066	0.435	0.39	0.339	0.269	
	Epoch	GPU_mem	box loss	cls_loss	dfl loss	Instances	Size		

	53/100	6.67G	0.8477	1.309	1.107	4	640:	100%	282/282 [01:10<00:00, 4.03it/s]
		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.46it
s]			1000	1055	0.245	0.444	0.254	0.074	
		all	1066	1066	0.365	0.411	0.354	0.276	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	54/100	6.67G	0.8392	1.309	1.107	4			282/282 [01:10<00:00, 4.03it/s]
		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.40it
s]		-11	1000	1000	0.264	0.4	0.254	0.270	
		all	1066	1066	0.364	0.4	0.354	0.278	
	Epoch	GPU_mem		cls_loss	_	Instances	Size		
	55/100	6.67G	0.8323	1.305	1.095	5			282/282 [01:09<00:00, 4.03it/s]
,		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.27it
s]		all	1066	1066	0.276	0.427	0.327	0.253	
	- 1							0.255	
	Epoch	GPU_mem	_	cls_loss	_	Instances	Size		
	56/100	6.67G	0.8401	1.293	1.095	6			282/282 [01:09<00:00, 4.03it/s]
<b>6</b> 1		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.09it
s]		all	1066	1066	0.469	0.346	0.337	0.269	
	Epoch	GPU mem		cls_loss		Instances	Size	0.203	
			_	_	_			10001	
	57/100	6.67G	0.8336	1.29	1.089	6			282/282 [01:10<00:00, 4.02it/s] 100%  34/34 [00:06<00:00, 5.33it
s]		Class	Images	Instances	Box(P	R	IIIAP50	MAP30-93):	100%  34/34 [00:00<00:00, 5:3310]
2]		all	1066	1066	0.288	0.417	0.348	0.275	
	Epoch	GPU mem		cls_loss		Instances	Size		
	58/100	6.67G	0.8166	1.266	1.087	11		100%	282/282 [01:10<00:00, 4.03it/s]
	58/100	Class		Instances	1.087 Box(P	R			100%  34/34 [00:06<00:00, 4.031t/s]
s]		CIASS	Illiages	Tils calices	DOX(I	K	IIIAI 30	MAI 30-33).	34/34 [00.00000.00; 3.4410]
- ]		all	1066	1066	0.341	0.431	0.349	0.271	
	Epoch	GPU mem	box loss	cls loss	dfl loss	Instances	Size		
	59/100	6.67G	0.8017	1.245	1.073	9		100%	282/282 [01:10<00:00, 4.02it/s]
	33/ 100	Class		Instances	Box(P	R			100%  34/34 [00:06<00:00, 5.35it
s]			863		20//(1		50		1 3 ./ 3 . [20:00:00, 3:3510]
		all	1066	1066	0.477	0.39	0.353	0.268	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	-poc.,	3. 0	201-1033	213_1033	w. 1_1000		3120		

s]	60/100	6.67G Class	0.808 Images	1.234 Instances	1.079 Box(P	7 R		100%  <b>             </b>	282/282 [01:10<00:00, 4.02it/s] 100%  34/34 [00:06<00:00, 5.23it/
		all	1066	1066	0.307	0.404	0.336	0.264	
	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size		
	61/100	6.67G	0.7981	1.24	1.076	4		100%	282/282 [01:10<00:00, 4.00it/s]
c 1		Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%  34/34 [00:06<00:00, 5.28it/
s]		all	1066	1066	0.498	0.362	0.347	0.268	

EarlyStopping: Training stopped early as no improvement observed in last 10 epochs. Best results observed at epoch 51, best model saved as best.pt.

To update EarlyStopping(patience=10) pass a new patience value, i.e. `patience=300` or use `patience=0` to disable EarlyStopping.

61 epochs completed in 1.307 hours.

Optimizer stripped from runs/detect/train3/weights/last.pt, 18.5MB Optimizer stripped from runs/detect/train3/weights/best.pt, 18.5MB

Validating runs/detect/train3/weights/best.pt...

Ultralytics 8.3.107 

✓ Python-3.11.11 torch-2.5.1+cu124 CUDA:0 (Tesla T4, 15095MiB)

YOLOv5s summary (fused): 84 layers, 9,115,793 parameters, 0 gradients, 23.8 GFLOPs

Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100%	34/34 [00:06<00:00,	4.93it/
all	1066	1066	0.452	0.378	0.353	0.283			
pickup_truck	154	154	0.436	0.558	0.488	0.424			
bus	51	51	0.573	0.784	0.63	0.519			
<pre>motorized_vehicle</pre>	74	74	0.181	0.0811	0.0714	0.0482			
car	667	667	0.444	0.594	0.518	0.428			
articulated_truck	28	28	0.367	0.56	0.465	0.37			
work_van	39	39	0.491	0.308	0.359	0.305			
pedestrian	13	13	0.293	0.154	0.136	0.0641			
non-motorized_vehicle	6	6	1	0	0.00137	0.000683			
bicycle	8	8	0.418	0.272	0.382	0.294			
single_unit_truck	18	18	0.356	0.222	0.173	0.134			
motorcycle	8	8	0.419	0.625	0.663	0.527			
C 0 1	2 ( : (		- 1 1 0						

Speed: 0.1ms preprocess, 2.6ms inference, 0.0ms loss, 1.0ms postprocess per image Results saved to runs/detect/train3

```
from glob import glob
def get_res_dir():
    res_dir_count = len(glob('runs/detect/*'))
```

```
# print(f'current number of result directories : {res_dir_count}')
res_dir = f'runs/detect/train{res_dir_count}'
# print(f"result dir : {res_dir}")
return res_dir
```

# Precision, Recall, Accuracy curves

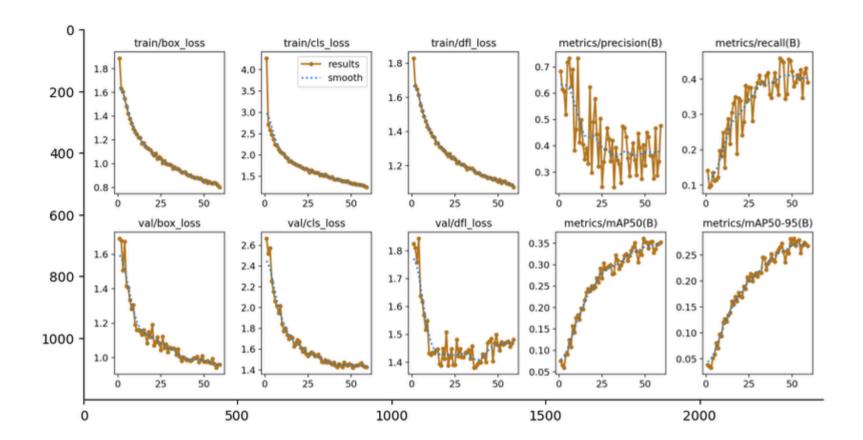
```
import cv2

plt.figure(figsize = (10,10))

res_dir = get_res_dir()

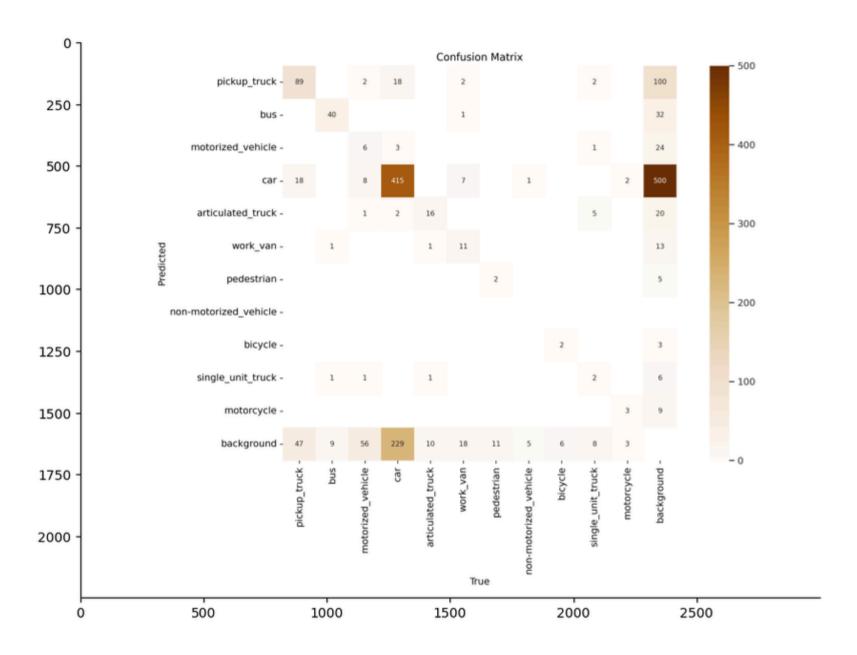
img = cv2.imread(f'{res_dir}/results.png')

plt.gca().spines[['top', 'right',]].set_visible(False)
    _=plt.imshow(img)
```



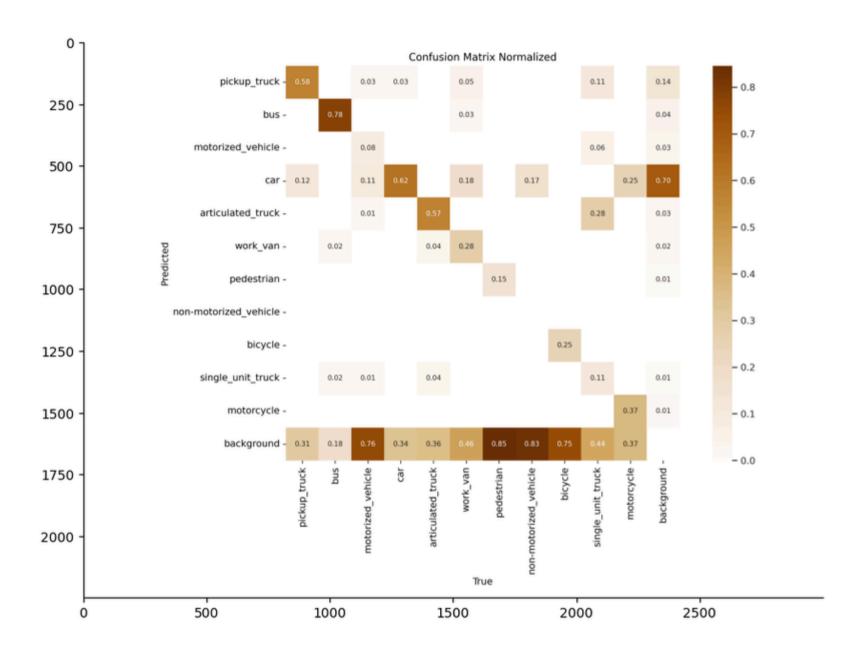
### **Confusion Matrix**

```
plt.figure(figsize = (10,10))
img = cv2.imread(f'{res_dir}/confusion_matrix.png')
plt.gca().spines[['top', 'right',]].set_visible(False)
_=plt.imshow(img)
```



**Confusion Matrix Normalized** 

```
plt.figure(figsize = (10,10))
img = cv2.imread(f'{res_dir}/confusion_matrix_normalized.png')
plt.gca().spines[['top', 'right',]].set_visible(False)
_=plt.imshow(img)
```



**Derive predictions** 

results = model.predict(test\_image\_path)

```
image 1/60 /kaggle/working/datasets/test/images/00005598.jpg: 448x640 1 work van, 11.9ms
image 2/60 /kaggle/working/datasets/test/images/00005599.jpg: 448x640 1 bus, 11.8ms
image 3/60 /kaggle/working/datasets/test/images/00005600.jpg: 448x640 1 car, 11.7ms
image 4/60 /kaggle/working/datasets/test/images/00005601.jpg: 448x640 (no detections), 11.7ms
image 5/60 /kaggle/working/datasets/test/images/00005602.jpg: 448x640 1 car, 11.8ms
image 6/60 /kaggle/working/datasets/test/images/00005603.jpg: 448x640 (no detections), 11.8ms
image 7/60 /kaggle/working/datasets/test/images/00005604.jpg: 448x640 1 pickup truck, 1 car, 11.7ms
image 8/60 /kaggle/working/datasets/test/images/00005605.jpg: 448x640 1 pickup truck, 11.8ms
image 9/60 /kaggle/working/datasets/test/images/00005606.jpg: 448x640 1 car, 11.8ms
image 10/60 /kaggle/working/datasets/test/images/00005607.jpg: 448x640 2 cars, 9.2ms
image 11/60 /kaggle/working/datasets/test/images/00005608.jpg: 448x640 (no detections), 9.2ms
image 12/60 /kaggle/working/datasets/test/images/00005609.jpg: 448x640 1 bus, 9.2ms
image 13/60 /kaggle/working/datasets/test/images/00005610.jpg: 448x640 1 car, 9.3ms
image 14/60 /kaggle/working/datasets/test/images/00005611.jpg: 448x640 1 pickup truck, 3 cars, 1 work van, 9.2ms
image 15/60 /kaggle/working/datasets/test/images/00005612.jpg: 448x640 2 pickup trucks, 9.2ms
image 16/60 /kaggle/working/datasets/test/images/00005613.jpg: 448x640 2 cars, 9.2ms
image 17/60 /kaggle/working/datasets/test/images/00005614.jpg: 448x640 (no detections), 9.2ms
image 18/60 /kaggle/working/datasets/test/images/00005615.jpg: 448x640 1 motorized vehicle, 2 cars, 9.2ms
image 19/60 /kaggle/working/datasets/test/images/00005616.jpg: 448x640 1 car, 9.2ms
image 20/60 /kaggle/working/datasets/test/images/00005617.jpg: 448x640 1 pickup truck, 1 car, 9.2ms
image 21/60 /kaggle/working/datasets/test/images/00005618.jpg: 448x640 (no detections), 9.3ms
image 22/60 /kaggle/working/datasets/test/images/00005619.jpg: 448x640 1 car, 9.2ms
image 23/60 /kaggle/working/datasets/test/images/00005620.jpg: 448x640 1 car, 9.2ms
image 24/60 /kaggle/working/datasets/test/images/00005621.jpg: 448x640 (no detections), 6.6ms
image 25/60 /kaggle/working/datasets/test/images/00005622.jpg: 448x640 2 cars, 6.6ms
image 26/60 /kaggle/working/datasets/test/images/00005623.jpg: 448x640 1 car, 6.5ms
image 27/60 /kaggle/working/datasets/test/images/00005624.jpg: 448x640 2 cars, 6.4ms
image 28/60 /kaggle/working/datasets/test/images/00005625.jpg: 448x640 1 car, 6.4ms
image 29/60 /kaggle/working/datasets/test/images/00005626.jpg: 448x640 1 bus, 6.3ms
image 30/60 /kaggle/working/datasets/test/images/00005627.jpg: 448x640 (no detections), 6.2ms
image 31/60 /kaggle/working/datasets/test/images/00005628.jpg: 448x640 2 cars, 1 pedestrian, 6.4ms
image 32/60 /kaggle/working/datasets/test/images/00005629.jpg: 448x640 3 cars, 6.3ms
image 33/60 /kaggle/working/datasets/test/images/00005630.jpg: 448x640 1 pickup truck, 6.4ms
image 34/60 /kaggle/working/datasets/test/images/00005631.jpg: 448x640 1 pickup truck, 1 car, 7.0ms
image 35/60 /kaggle/working/datasets/test/images/00005632.jpg: 448x640 (no detections), 6.5ms
image 36/60 /kaggle/working/datasets/test/images/00005633.jpg: 448x640 1 car, 6.9ms
image 37/60 /kaggle/working/datasets/test/images/00005634.jpg: 448x640 1 car, 6.6ms
image 38/60 /kaggle/working/datasets/test/images/00005635.jpg: 448x640 1 car, 6.5ms
image 39/60 /kaggle/working/datasets/test/images/00005636.jpg: 448x640 1 bus, 2 cars, 6.5ms
image 40/60 /kaggle/working/datasets/test/images/00005637.jpg: 448x640 (no detections), 6.7ms
image 41/60 /kaggle/working/datasets/test/images/00005638.jpg: 448x640 2 articulated trucks, 6.7ms
```

```
image 42/60 /kaggle/working/datasets/test/images/00005639.jpg: 448x640 (no detections), 6.8ms
image 43/60 /kaggle/working/datasets/test/images/00005640.jpg: 448x640 4 cars, 6.7ms
image 44/60 /kaggle/working/datasets/test/images/00005641.jpg: 448x640 1 bus, 6.5ms
image 45/60 /kaggle/working/datasets/test/images/00005642.jpg: 448x640 2 cars, 6.4ms
image 46/60 /kaggle/working/datasets/test/images/00005643.jpg: 448x640 2 cars, 6.7ms
image 47/60 /kaggle/working/datasets/test/images/00005644.jpg: 448x640 2 cars, 6.5ms
image 48/60 /kaggle/working/datasets/test/images/00005645.jpg: 448x640 1 car, 6.4ms
image 49/60 /kaggle/working/datasets/test/images/00005646.jpg: 448x640 1 pickup truck, 2 cars, 6.5ms
image 50/60 /kaggle/working/datasets/test/images/00005647.jpg: 448x640 1 pickup truck, 6.5ms
image 51/60 /kaggle/working/datasets/test/images/00005648.jpg: 448x640 1 car, 6.7ms
image 52/60 /kaggle/working/datasets/test/images/00005649.jpg: 448x640 1 pickup truck, 1 bus, 6.3ms
image 53/60 /kaggle/working/datasets/test/images/00005650.jpg: 448x640 1 car, 6.6ms
image 54/60 /kaggle/working/datasets/test/images/00005651.jpg: 448x640 (no detections), 6.4ms
image 55/60 /kaggle/working/datasets/test/images/00005652.jpg: 448x640 (no detections), 6.7ms
image 56/60 /kaggle/working/datasets/test/images/00005653.jpg: 448x640 2 cars, 6.5ms
image 57/60 /kaggle/working/datasets/test/images/00005654.jpg: 448x640 (no detections), 6.5ms
image 58/60 /kaggle/working/datasets/test/images/00005655.jpg: 448x640 1 car, 6.8ms
image 59/60 /kaggle/working/datasets/test/images/00005656.jpg: 448x640 2 cars, 6.3ms
image 60/60 /kaggle/working/datasets/test/images/00005657.jpg: 448x640 2 cars, 6.5ms
Speed: 1.7ms preprocess, 8.0ms inference, 0.9ms postprocess per image at shape (1, 3, 448, 640)
def plot box(image,boxes,labels):
    h, w, = image.shape
    for box num,box in enumerate(boxes):
        xyxy = box.xyxy.int().tolist()
        xmin, ymin, xmax, ymax = xyxy[0][0], xyxy[0][1], xyxy[0][2], xyxy[0][3]
        width = xmax-xmin
        height = ymax-ymin
        class name = class names[int(labels[box num])]
        color = COLORS[int(labels[box num])]
        cv2.rectangle(image,(xmin,ymin),(xmax,ymax),color,5)
        font scale = 1 \# min(1, max(3, int(w/500)))
        font thickness = 2\#min(2, max(10, int(w/50)))
        font = cv2.FONT HERSHEY SIMPLEX
        # p1,p1 = (int(xmin+1.5*width),ymin), (int(xmin+width),ymin-int(1.5*height))
        text width = cv2.getTextSize(class name, font, font scale, font thickness)[0][0]
        text height = cv2.getTextSize(class name,font,font scale,font thickness)[0][1]
        cv2.putText(image,class name,(xmin,ymin+20),font,font scale,color,font thickness)
    names[path] = temp
    return image
```

```
def get identified names(image,boxes,labels):
    h,w, = image.shape
   temp = []
   for box num,box in enumerate(boxes):
        xyxy = box.xyxy.int().tolist()
        xmin, ymin, xmax, ymax = xyxy[0][0], xyxy[0][1], xyxy[0][2], xyxy[0][3]
        width = xmax-xmin
        height = ymax-ymin
        class name = class names[int(labels[box num])]
        temp.append(class_name)
    return temp
COLORS = np.random.uniform(0,255,size=(len(class names),3))
slices = []
count = 0
d = list()
images per row = 5
for j,res in enumerate(results):
    d.append(res)
   if len(d) == images per row:
     slices.append(d)
     d = list()
```

fig,axes = plt.subplots(nrows=1,ncols=images per row,figsize=(20,10),constrained layout=True)

for i in (range(len(slices))):

for j in range(len(results )):

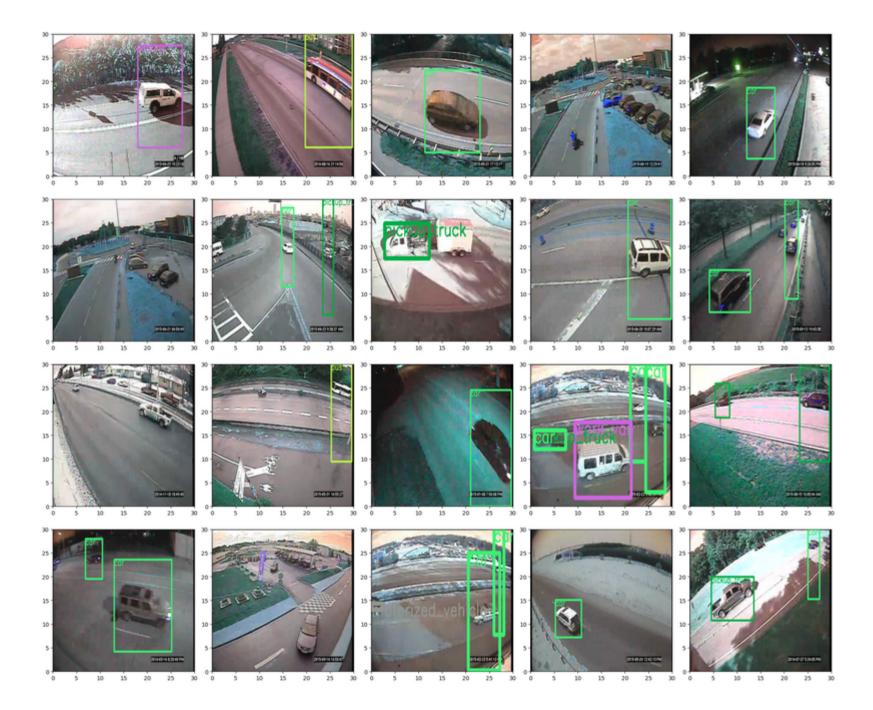
confidences = boxes.conf
classes = boxes.cls
path = res.path

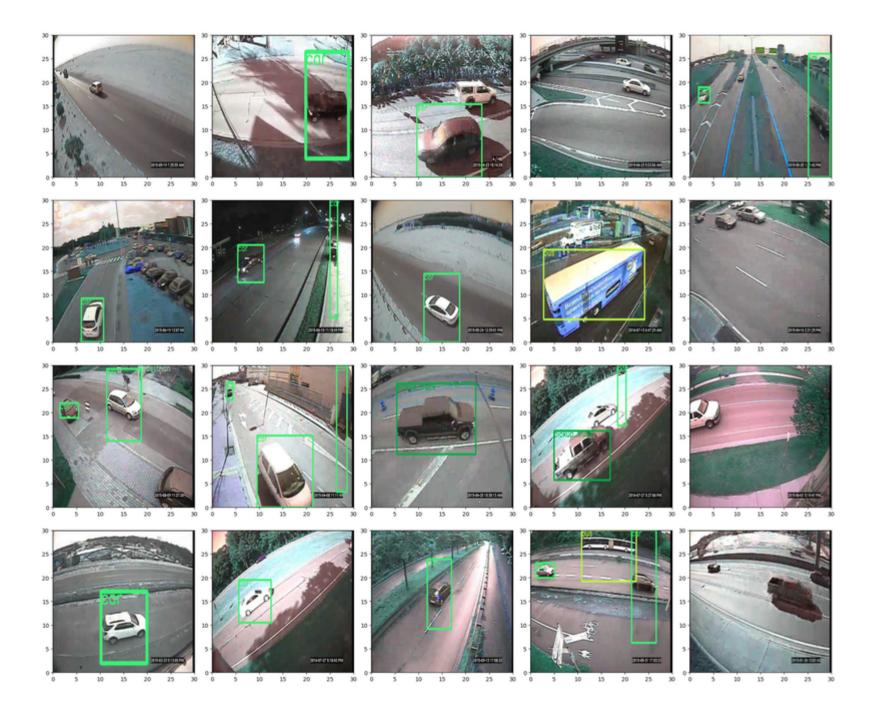
box img = plot box(image,boxes,classes)

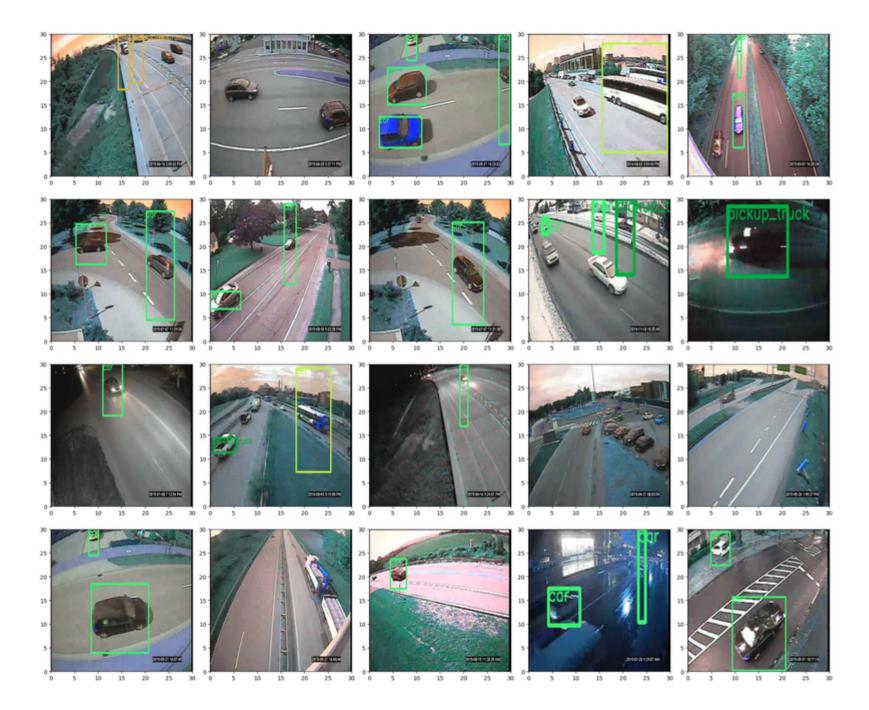
axes[j].imshow(box img, extent=[0, 30, 0, 30])

results = slices[i]

res = results\_[j]
image = res.orig\_img
boxes = res.boxes







## Part 2: Tesla Auto pilot and Road Safety

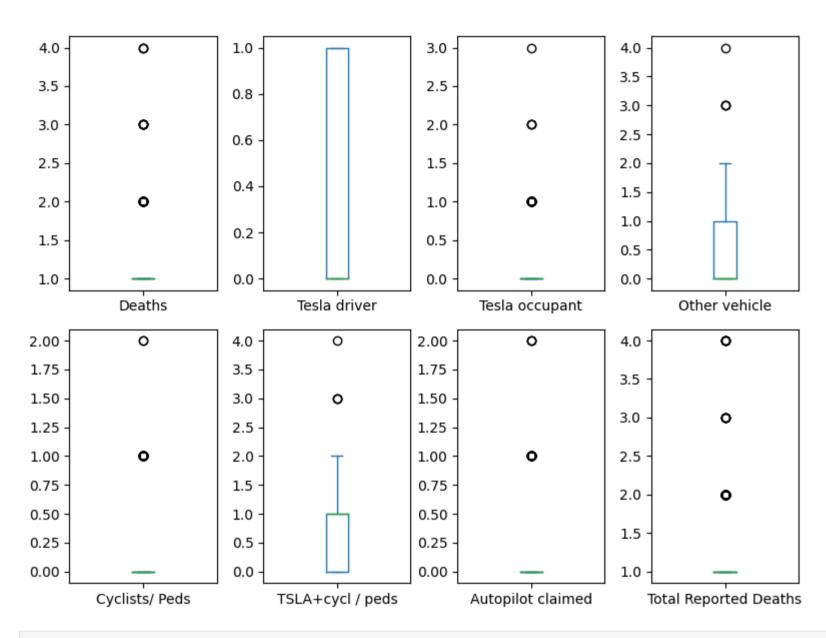
#### Data wrangling

```
import pandas as pd
import torch
torch.device('cpu')
url = 'https://raw.githubusercontent.com/tksundar/autonomous driving/refs/heads/master/Tesla%20-%20Deaths.csv'
data = pd.read csv(url, skip blank lines=True, skipinitialspace=True)
data.isna().sum()
data.columns = data.columns.str.rstrip()
nan counts = data.isna().sum()
columns to drop = ['Unnamed: 16','Unnamed: 17','Source','State']
columns to drop.extend(nan counts[nan counts >= 220].index)
data.drop(columns to drop,axis=1,inplace=True)
# Remove rows that does not have a case number
# The values in these rows are outliers
data = data.dropna(subset=['Case #'])
print(data.shape)
print(data.isna().sum())
```

```
(294, 15)
Case #
                                                                        0
                                                                        0
Year
Date
                                                                        0
Country
Description
                                                                        0
Deaths
Tesla driver
Tesla occupant
                                                                        9
Other vehicle
Cyclists/ Peds
                                                                        3
TSLA+cycl / peds
                                                                        2
Model
Autopilot claimed
                                                                      18
Verified Tesla Autopilot Deaths
                                                                       4
Verified Tesla Autopilot Deaths + All Deaths Reported to NHTSA SGO
                                                                       1
dtype: int64
import numpy as np
import matplotlib.pyplot as plt
columns = ['Deaths','Tesla driver', 'Tesla occupant', 'Other vehicle', 'Cyclists/ Peds',
       'TSLA+cycl / peds', 'Model', 'Autopilot claimed',
       'Verified Tesla Autopilot Deaths',
       'Verified Tesla Autopilot Deaths + All Deaths Reported to NHTSA SGO']
for col in columns:
  data[col] = data[col].apply(lambda x : '0' if x in ['-',','] else x)
  data[col] = pd.to numeric(data[col], errors='coerce')
  data[col] = data[col].fillna(0)
year mode = data['Year'].mode()[0]
data['Year'] = data['Year'].apply(lambda x: year mode if np.isnan(x) else x)
data['Year'] = data['Year'].apply(lambda x: year mode if x == 202 else x)
data['Year'] = data['Year'].astype(int)
print(data.isna().sum())
```

```
Case #
                                                                       0
Year
Date
                                                                       0
Country
                                                                       0
Description
                                                                       0
Deaths
                                                                       0
Tesla driver
                                                                       0
Tesla occupant
Other vehicle
Cyclists/ Peds
                                                                       0
TSLA+cvcl / peds
Model
                                                                       0
Autopilot claimed
                                                                       0
Verified Tesla Autopilot Deaths
Verified Tesla Autopilot Deaths + All Deaths Reported to NHTSA SGO
dtype: int64
```

#### Distribution of numeric columns



data.head()

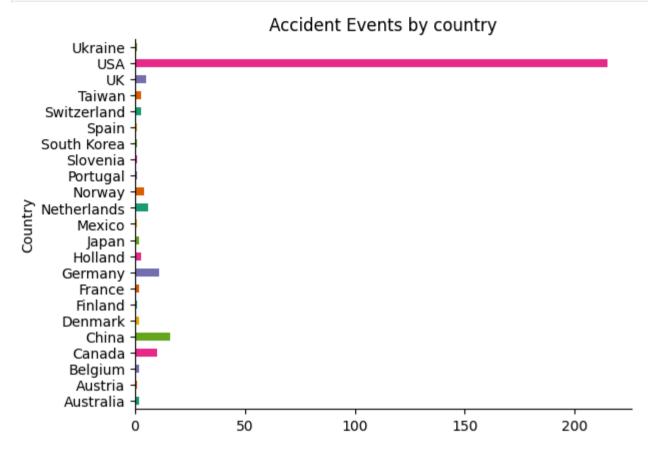
	Case #	Year	Date	Country	Description	Deaths	Tesla driver	Tesla occupant	Other vehicle	Cyclists/ Peds	TSLA+cycl / peds	Model	Autopilot claimed	Verified Tesla Autopilot Deaths	Tesla Autopilot Deaths + All Deaths Reported to NHTSA SGO	To Report Deat
0	294.0	2022	2023- 01-17	USA	Tesla crashes into back of semi	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
1	293.0	2022	2023- 01-07	Canada	Tesla crashes	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
2	292.0	2022	2023- 01-07	USA	Tesla hits pole, catches on fire	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
3	291.0	2022	2022- 12-22	USA	Tesla crashes and burns	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
4	290.0	2022	2022- 12-19	Canada	Tesla crashes into storefront	1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	
4																

Verified

# **Accident Events by country**

```
from matplotlib import pyplot as plt
import seaborn as sns
data.groupby('Country').size().plot(kind='barh', color=sns.palettes.mpl_palette('Dark2'))
```

```
plt.gca().spines[['top', 'right',]].set_visible(False)
_=plt.title('Accident Events by country')
```

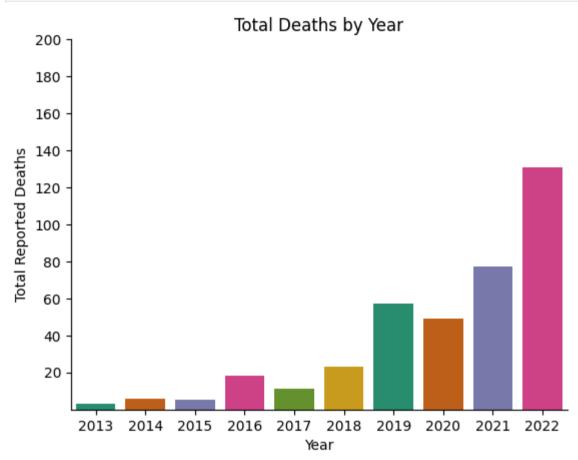


### Deaths by year

```
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
deaths_by_year = pd.DataFrame(data.groupby('Year')['Total Reported Deaths'].sum()).reset_index()
plt.gca().spines[['top', 'right',]].set_visible(False)

fig=sns.barplot(data = deaths_by_year, x='Year', y='Total Reported Deaths' , palette = sns.mpl_palette('Dark2'))
plt.title('Total Deaths by Year')
```

```
plt.yticks(np.arange(20,220,20))
plt.show()
```

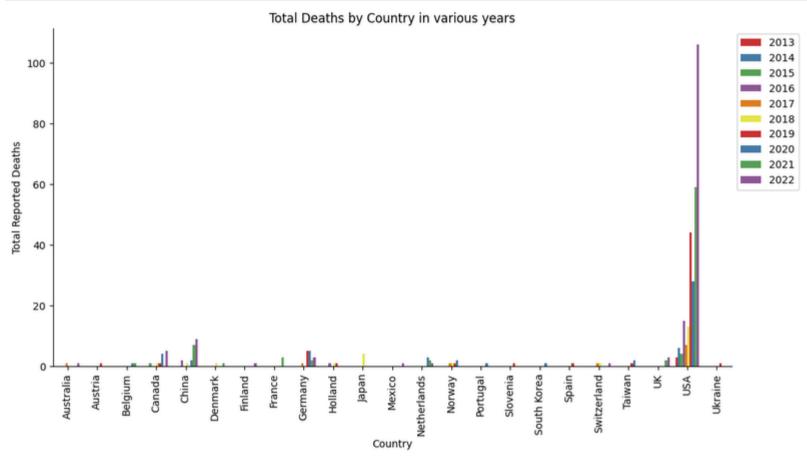


#### Deaths by country and year

```
deaths_by_year = pd.DataFrame(data.groupby(['Country','Year'])['Total Reported Deaths'].sum()).reset_index()

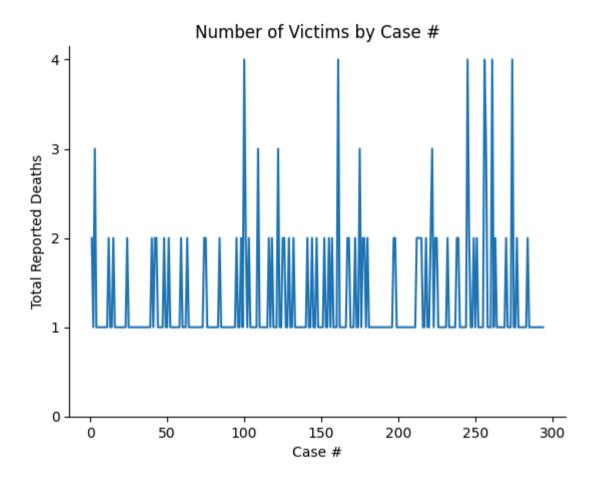
plt.figure(figsize = (12,6))
fig=sns.barplot(data = deaths_by_year, x='Country', hue = "Year", y='Total Reported Deaths', palette = sns.mpl_palette('Set1'))
plt.title('Total Deaths by Country in various years')
plt.xticks(rotation=90)
plt.legend(bbox_to_anchor=(1, 1), loc="upper left")
```

```
plt.gca().spines[['top', 'right',]].set_visible(False)
plt.show()
```



#### Number of victims per accident

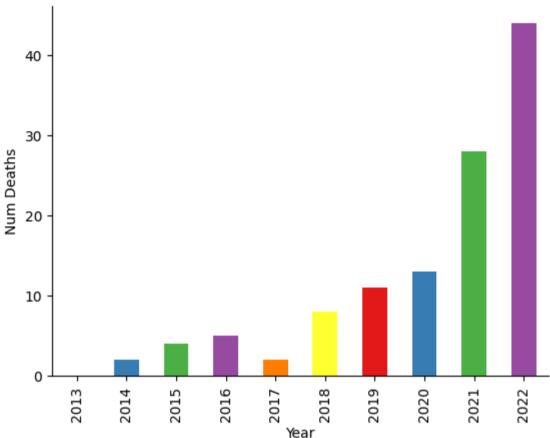
```
df = data [['Case #','Total Reported Deaths']].sort_values(by='Case #')
sns.lineplot(data=df , x= 'Case #', y='Total Reported Deaths')
plt.gca().spines[['top', 'right',]].set_visible(False)
plt.yticks(np.arange(0,5))
    _=plt.title('Number of Victims by Case #')
```



#### Instances of Tesla driver deaths

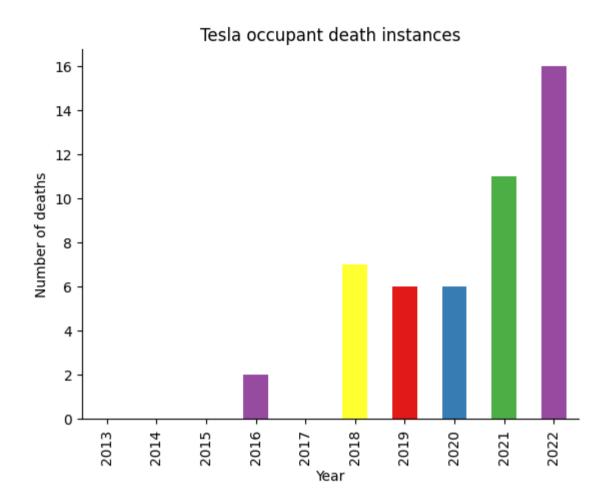
```
_=data.groupby('Year')['Tesla driver'].sum().plot(kind='bar', color = sns.mpl_palette('Set1'))
plt.title('Tesla driver death instances')
plt.xlabel('Year')
plt.ylabel('Num Deaths')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

# Tesla driver death instances



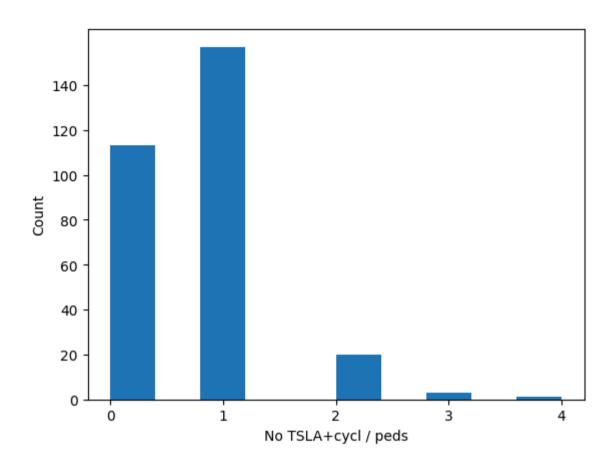
### Instances of Tesla occupant deaths

```
data.groupby('Year')['Tesla occupant'].sum().plot(kind='bar', color = sns.mpl_palette('Set1'))
plt.title('Tesla occupant death instances')
plt.ylabel('Number of deaths')
plt.gca().spines[['top', 'right',]].set_visible(False)
```



# Distribution of events in which the vehicle hit a cyclist or a pedestrian

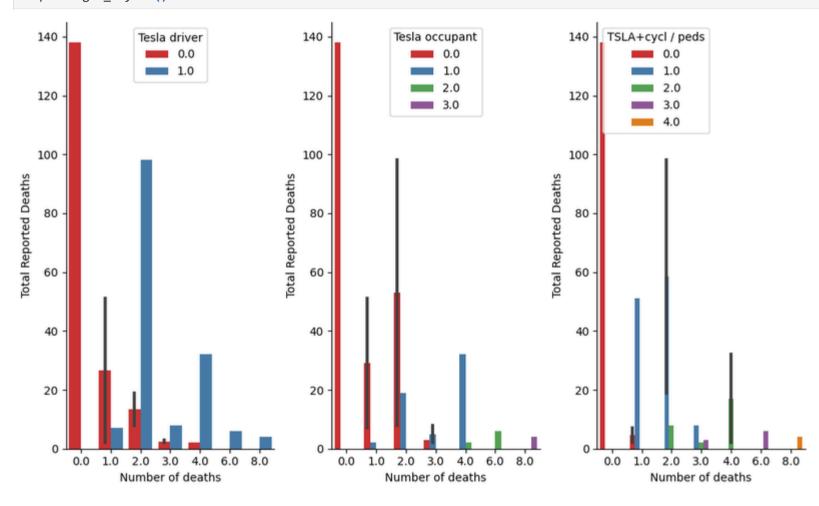
```
_=data['TSLA+cycl / peds'].hist(bins=10,grid=False)
_=plt.xlabel('No TSLA+cycl / peds')
_=plt.xticks(np.arange(0,5,1))
_=plt.ylabel('Count')
_=plt.yticks(np.arange(0,160,20))
```



#### Deaths of occupant, driver of a Tesla along with a cyclist or pedestrian

```
columns = ['Tesla driver','Tesla occupant','TSLA+cycl / peds']
grp = pd.DataFrame(data.groupby(columns)['Total Reported Deaths'].sum()).reset_index()
grp['Cumulative'] = grp.apply(lambda row: row['Tesla driver'] + row['Tesla occupant'] + row['TSLA+cycl / peds'],axis = 1)
plt.figure(figsize=(10,6))
for i,col in enumerate(columns):
    plt.subplot(1,3,i+1)
    _=sns.barplot(data = grp , x = 'Cumulative',y='Total Reported Deaths',hue=col,palette = sns.mpl_palette('Set1'))
    _=plt.xlabel('Number of deaths')
    plt.gca().spines[['top', 'right',]].set_visible(False)
```

```
plt.tight_layout()
```



```
def check_for_two__vehicles(description):
    vehicles = []
    count = 0
    description_lower = description.lower() # For case-insensitive matching
    temp = []
    for object__ in objects:
        if object__.lower() in description_lower:
            temp.append(object_)
```

```
if(len(temp)>= 2):
    return 1
return 0

url_labels = 'https://raw.githubusercontent.com/tksundar/autonomous_driving/refs/heads/master/labels.csv'
labels = pd.read_csv(url_labels, names = ['id', 'name', 'xmin', 'ymin', 'xmax', 'ymax'])

objects = labels['name'].unique().tolist()
objects.remove('pedestrian')
objects.append('Tesla')
objects.append('Semi')
```

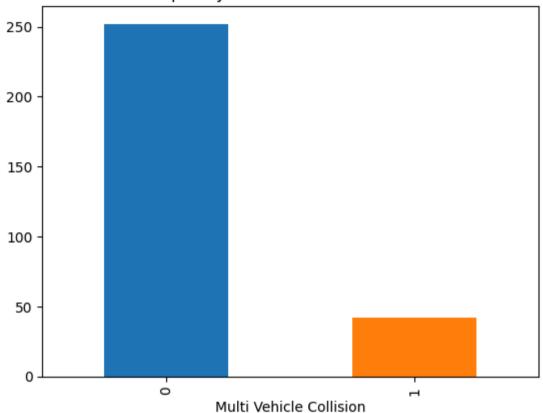
#### Frequency of Tesla colliding with other vehicles

```
data['Multi Vehicle Collision'] = data.apply(lambda row: check_for_two__vehicles(row['Description']),axis=1)
    _=data.groupby(['Multi Vehicle Collision']).size().plot(kind = 'bar', color = sns.mpl_palette('tab10'))
plt.title('Frequency of multi vehicle collisions')

print(f"Total multi vehicle collisions : {data['Multi Vehicle Collision'].sum()}\n")
```

Total multi vehicle collisions : 42

#### Frequency of multi vehicle collisions



```
_=pd.crosstab(data['Other vehicle'],data['Multi Vehicle Collision']).plot(kind='bar')
plt.ylabel('Number of multi vehicle collisions')
_=pd.crosstab(data['Cyclists/ Peds'],data['Multi Vehicle Collision']).plot(kind='bar')
_=plt.ylabel('Number of multi vehicle collisions')
```

