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Object Detection with YOLO v7: Unveiling the Future of Real-Time Image Analysis

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Abstract: ***In the rapidly evolving field of object detection, the YOLO (You Only Look Once) series has consistently set benchmarks for speed and accuracy. The latest iteration, YOLO v7, introduces groundbreaking enhancements that significantly improve upon its predecessors and competing models. This paper presents a comprehensive analysis of YOLO v7, focusing on its innovative architecture, training methodologies, and performance metrics. Through rigorous evaluation on standard datasets, YOLO v7 demonstrates superior detection accuracy and real-time processing capabilities, addressing the critical challenges of scale variation, object occlusion, and real-time inference requirements. Key innovations include an optimized network architecture that balances computational efficiency with detection precision, advanced data augmentation techniques, and refined training strategies that collectively contribute to its state-of-the-art performance. Comparative analysis with previous YOLO versions and other leading object detection frameworks highlights YOLO v7's advancements in mean Average Precision (mAP) and inference speed, establishing it as a leading solution for applications requiring fast and reliable object detection. This study not only underscores YOLO v7's contributions to the field but also sets the stage for future research directions, emphasizing the potential for further improvements and application-specific adaptations.***

Keywords: YOLO v7, Image Analysis

1. Introduction

Object detection stands as a cornerstone technology in computer vision, powering a myriad of applications from autonomous driving to surveillance and industrial automation. Despite significant advancements, the quest for models that combine high accuracy with real-time processing capabilities remains paramount. Enter the YOLO (You Only Look Once) series, a lineage of object detection models renowned for their efficiency and speed. YOLO v7, the latest installment, promises to push the boundaries further, offering unparalleled performance. This paper delves into YOLO v7, dissecting its methodology, implementation, and the strides it makes in object detection. The evolution of the YOLO series has been marked by continuous improvement in handling real-world challenges such as object scale variation, occlusion, and the need for swift inference. YOLO v7 introduces novel architectural enhancements and training techniques, setting new benchmarks in detection accuracy and computational efficiency. By conducting an exhaustive analysis and comparison with preceding versions and other state-of-the-art models, this study aims to illuminate the advancements YOLO v7 brings to the field. Our exploration is not just a testament to the ongoing innovation in object detection but also a pointer towards future avenues of research that could benefit from YOLO v7's contributions.

2. Literature Review

The field of object detection has significantly evolved with the advent of deep learning, marking substantial advancements in models that enhance both speed and accuracy. Among these, the YOLO (You Only Look Once) series has been particularly influential, beginning with the groundbreaking introduction of the original YOLO model by [1] **Redmon et al. in 2018**, which revolutionized real-time object detection by processing images in a single evaluation step. Subsequent iterations, including YOLOv2 by [2] **Bochkovskiy et al. in 2020**, and YOLOv3 in 2018, introduced notable improvements such as anchor boxes and refined detection across various object sizes. YOLOv4, presented by [3] **an, M., & Le, Q. (2020)**, further optimized these models for speed and accuracy, especially in production environments.

Parallel to the YOLO series, other frameworks like SSD (Single Shot Detector) by[4]**Carion et al. in 2020**, and Faster R-CNN by [5] **Liu et al. in 2016**, have contributed to the field by balancing accuracy with processing speed and enhancing detection through region proposal networks, respectively. However, YOLO's continuous evolution, including the more recent YOLOv5 and YOLOv6 models, which introduced enhancements like transformer networks and advanced data augmentation, underscores the series' commitment to pushing the boundaries of object detection technology.

The introduction of YOLOv7 represents the culmination of these efforts, integrating novel architectural enhancements and training techniques to set new benchmarks in detection accuracy and computational efficiency. This evolution mirrors broader trends in the field, where models like Mask R-CNN, EfficientDet, and transformer-based DETR have sought to address the perennial challenges of object detection, including scale variation, occlusion, and real-time inference requirements. Recent reviews, such as that by [6] **Ren et al. in 2015**, encapsulate these developments, highlighting deep learning's role in driving forward object detection capabilities.

In comparing YOLO with other models, it's evident that the series not only excels in speed and efficiency but also in adaptability to real-world applications, reflecting a significant contribution to the field. The trajectory of YOLO, from its inception to YOLOv7, illustrates a broader narrative of innovation and improvement in object detection technologies, suggesting a promising direction for future research and application in this dynamic domain

3. Methodology

3.1 Architecture

The YOLO v7 architecture is an innovative design that incorporates advancements in deep learning for object detection. We detail the network's structure, focusing on the backbone for feature extraction, the additional modules for feature integration, and the prediction heads for detecting objects. The architecture is optimized for both speed and accuracy, with specific enhancements aimed at improving performance on diverse object scales and complex scenes.

Just like a human body, our algorithm also has a head, neck, and backbone. YOLOv7 uses the Cross-Stage Partial Networks (CSPNet) architecture as its backbone. This provides improved accuracy and lowers the processing time. The Feature Pyramid Network (FPN) is employed to extract features at different scales. The neck is responsible for ensuring the accurate detection of objects of all sizes, that may be in the background of the image. YOLOv7 utilizes a single detection head for both classification and localization tasks. This simplifies its architecture and improves inference speed (testing time).

Here's a quick look at how YOLOv7 works:

- **Single-stage detection:** Usually, models require multiple stages of processing as in the case of CNNs. But true to its name, YOLOv7 performs object detection by passing the image just once. This is why it is much faster than its competitors.
- **Focuses on relevant regions:** YOLOv7 employs a novel attention mechanism that directs its focus towards areas most likely to contain object. This optimizes and reduces the model would actually need.
- **Resource efficient training:** This innovative approach combines various techniques like data augmentation and model distillation to enhance performance without additional computational costs. Data augmentation is the method of creating new data from your existing images through some modifications like rotation, cropping, etc.

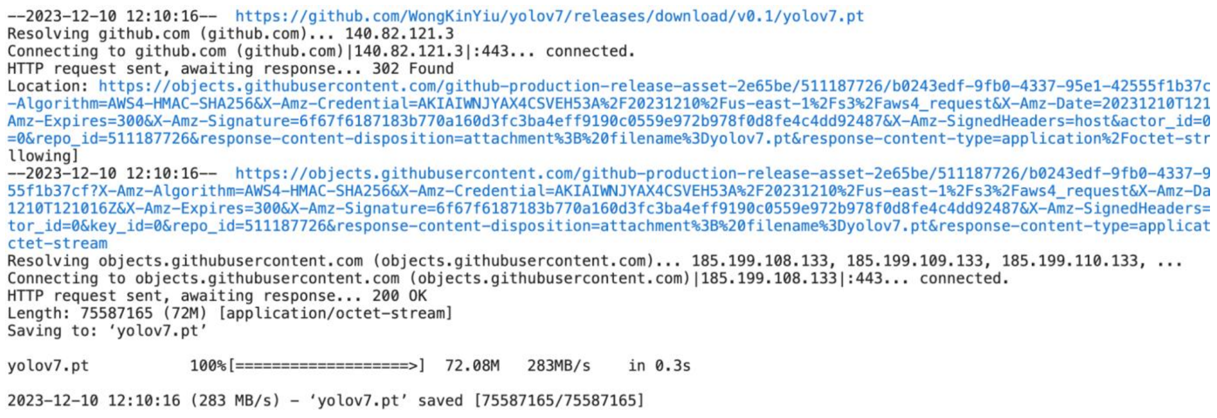
3.2 Environment Setup

The first step of any machine learning project is installing all the packages and modules required. For our case, we will be using the cv2 package to read and process images, matplolib for visualization, and pandas, numpy for processing CSV files.

```
import numpy as np
import pandas as pd
import os
import random
import cv2
from matplotlib import pyplot as plt
```

The next important task is to download the YOLOv7 model and install its requirements. As it is a pre-trained model, we can download the pre-trained weights and use them to finetune the model on our custom dataset. Follow the below code snippet.

```
!git clone
https://github.com/WongKinYiu/yolov7
!pip install -qr ./yolov7/requirements.txt
!wget
"https://github.com/WongKinYiu/yolov7/releas
es/download/v0.1/yolov7.pt"
```



```
--2023-12-10 12:10:16--  https://github.com/WongKinYiu/yolov7/releases/download/v0.1/yolov7.pt
Resolving github.com (github.com)... 140.82.121.3
Connecting to github.com (github.com)|140.82.121.3|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://objects.githubusercontent.com/github-production-release-asset-2e65be/511187726/b0243edf-9fb0-4337-95e1-42555f1b37c
-Algorithm=AWS4-HMAC-SHA256&X-Amz-Credential=AKIAIWNJYAX4CSVEH53A%2F20231210%2Fus-east-1%2Fs3%2Faws4_request&X-Amz-Date=20231210T121
Amz-Expires=300&X-Amz-Signature=6f67f6187183b770a160d3fc3ba4eff9190c0559e972b978f0d8fe4c4dd92487&X-Amz-SignedHeaders=host&actor_id=0
=0&repo_id=511187726&response-content-disposition=attachment%3B%20filename%3Dyolov7.pt&response-content-type=application%2Foctet-str
llowing]
--2023-12-10 12:10:16--  https://objects.githubusercontent.com/github-production-release-asset-2e65be/511187726/b0243edf-9fb0-4337-9
55f1b37cf?X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Credential=AKIAIWNJYAX4CSVEH53A%2F20231210%2Fus-east-1%2Fs3%2Faws4_request&X-Amz-Da
1210T121016Z&X-Amz-Expires=300&X-Amz-Signature=6f67f6187183b770a160d3fc3ba4eff9190c0559e972b978f0d8fe4c4dd92487&X-Amz-SignedHeaders=
tor_id=0&key_id=0&repo_id=511187726&response-content-disposition=attachment%3B%20filename%3Dyolov7.pt&response-content-type=applicat
ctet-stream
Resolving objects.githubusercontent.com (objects.githubusercontent.com)... 185.199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to objects.githubusercontent.com (objects.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 75587165 (72M) [application/octet-stream]
Saving to: ‘yolov7.pt’

yolov7.pt           100%[===================>]  72.08M   283MB/s    in 0.3s

2023-12-10 12:10:16 (283 MB/s) - ‘yolov7.pt’ saved [75587165/75587165]
```

There should be an output like the above when the weights are downloaded.

Next, let’s move on to our dataset of interest. We’ll be working on the Car images dataset, which contains image stills from traffic. Let’s read the CSV file into the pandas data frame. You can see that in each row there is an image in JPG format and the bounding box coordinates of the car in the image. Bounding boxes in object detection are rectangular frames drawn around identified objects within an image or video.

```
df = pd.read_csv('../input/car-object-
detection/data/train_solution_bounding_boxes
.csv')
df.head()
```

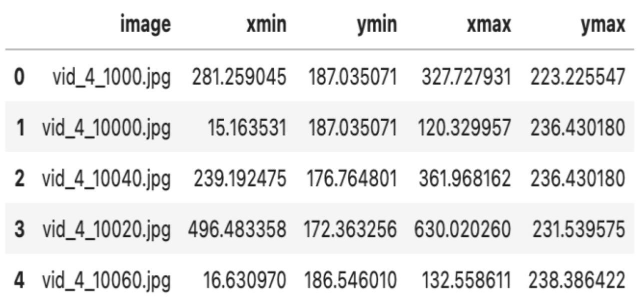


	image	xmin	ymin	xmax	ymax
0	vid_4_1000.jpg	281.259045	187.035071	327.727931	223.225547
1	vid_4_10000.jpg	15.163531	187.035071	120.329957	236.430180
2	vid_4_10040.jpg	239.192475	176.764801	361.968162	236.430180
3	vid_4_10020.jpg	496.483358	172.363256	630.020260	231.539575
4	vid_4_10060.jpg	16.630970	186.546010	132.558611	238.386422

The Xmin and xmax correspond to the lower and upper coordinates of the bounding box in the axis, and similarly in the Y-axis. Let's read one random image and plot the bounding box using the below code:

```
# Read the image in RGB
sample_image = cv2.imread(f"../input/car-object-detection/data/training_images/vid_5_xxxx}.jpg")
sample_image = cv2.cvtColor(img, cv2.COLOR_BGRA2RGB)

# Plot the image with the box
fig, ax = plt.subplots(figsize=(10,10))
min_point = (df.iloc[image_idx]["xmin"], df.iloc[image_idx]["ymin"])
width = df.iloc[image_idx]["xmax"] - min_point[0]
height = df.iloc[image_idx]["ymax"] - min_point[1]
bbox = patches.Rectangle(min_point, width, height, linewidth=1)
ax.add_patch(rect)
```

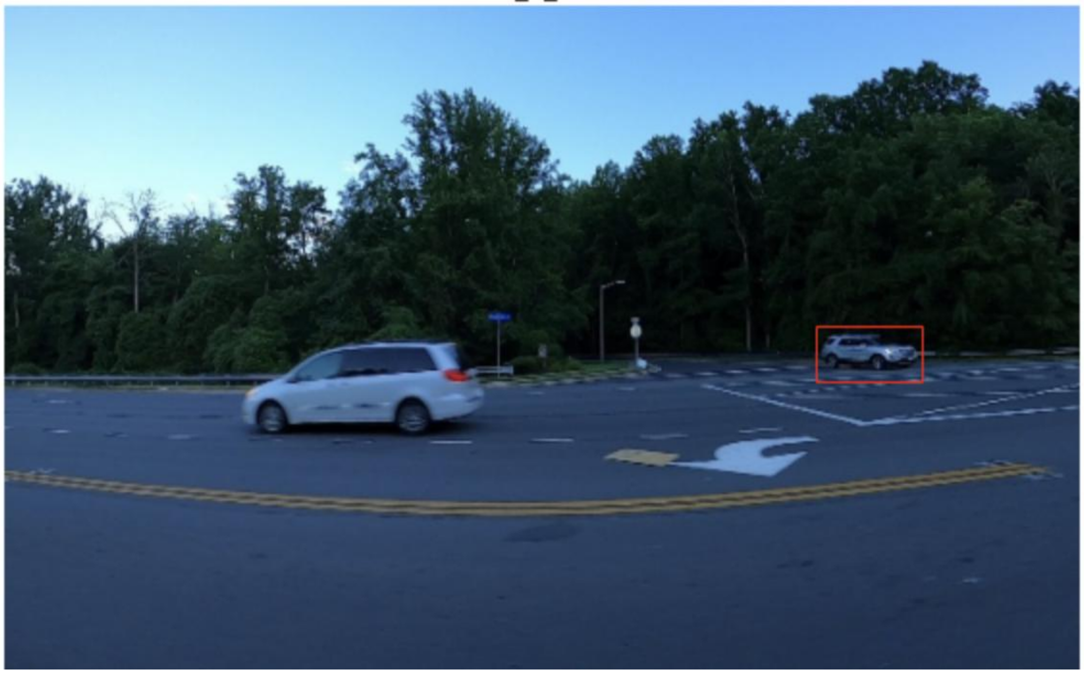


Figure 1: Model Input

The red bounding box is the label and the image is the input. We want to try YOLOv7 on our images to predict the car(bounding box coordinates) in any new input image.

4. Data Pre-processing for YoLO

4.1 Data Preparation

Prior to the fine-tuning of the YOLO model with our specialized dataset, it is imperative to format the training data according to the specifications mandated by YOLO.

In the case of YOLOv7, the framework necessitates a unique format for the annotation of bounding boxes. The representation of each bounding box is delineated by a set of four normalized values, as follows:

x_center: This value signifies the normalized x-coordinate of the bounding box's center.
y_center: Similarly, this represents the normalized y-coordinate of the center of the bounding box.
width: This indicates the normalized width of the bounding box.
height: Lastly, this value denotes the normalized height of the bounding box.

These parameters are essential for accurately defining the location and size of objects within an image, facilitating the YOLOv7 model's learning and detection capabilities.

Below code shows how to do it

```
df['x_center'] = (df['xmin'] + df['xmax'])/2
df['y_center'] = (df['ymin'] + df['ymax'])/2
df['width'] = df['xmax'] - df['xmin']
df['height'] = df['ymax'] - df['ymin']
df['classes'] = 0
df.head()
```

- height: Normalized height of the bounding box.

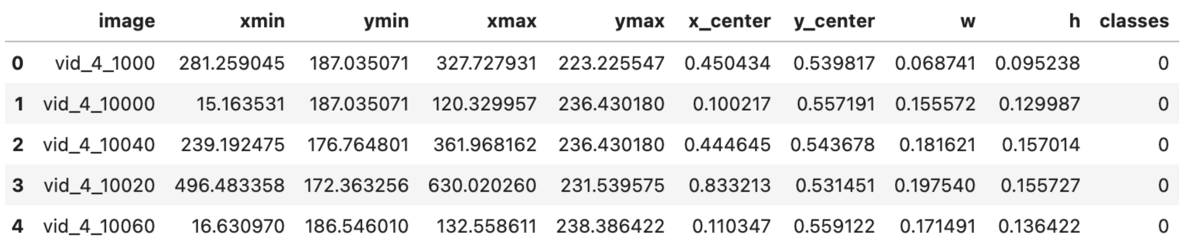


	image	xmin	ymin	xmax	ymax	x_center	y_center	w	h	classes
0	vid_4_1000	281.259045	187.035071	327.727931	223.225547	0.450434	0.539817	0.068741	0.095238	0
1	vid_4_10000	15.163531	187.035071	120.329957	236.430180	0.100217	0.557191	0.155572	0.129987	0
2	vid_4_10040	239.192475	176.764801	361.968162	236.430180	0.444645	0.543678	0.181621	0.157014	0
3	vid_4_10020	496.483358	172.363256	630.020260	231.539575	0.833213	0.531451	0.197540	0.155727	0
4	vid_4_10060	16.630970	186.546010	132.558611	238.386422	0.110347	0.559122	0.171491	0.136422	0

Figure 2: Testing dataset

4.2 Modelling Data

The subsequent step involves organizing the data for modeling. This requires dividing our dataset into two distinct subsets: training and validation. The rationale behind this division is straightforward but critical. The model undergoes training using the training set, while the validation set serves as a tool to evaluate the model's performance. It's crucial that the images within the validation dataset are entirely new to the model, providing a reliable measure of the model's capacity to generalize beyond the training data.

For this purpose, I have allocated 25% of the dataset to serve as the validation set. In the following procedure, I employ a random selection process to designate 25% of the images as validation samples. These images are then segregated into separate directories, specifically created for this validation subset.

```
validation_size = 0.25
val_index = list(df.index)[df.shape[0] -
int(df.shape[0]*validation_ratio):]
val_paths =
df.iloc[val_index]["image"].values

train_label_dir =
"preprocessed_dataset/train/labels/"
val_label_dir =
"preprocessed_dataset/val/labels/"
```

The concluding step in this process involves creating a configuration file for YOLO that includes the custom paths to our training and validation directories.

```
config = {'path': 'preprocessed_dataset',
         'train':
'preprocessed_dataset/train',
          'val': 'preprocessed_dataset/val',
        'nc': len(classes),
         'names': classes}

with open("data.yaml", "w") as file:
yaml.dump(config, file,
default_flow_style=False)
```

5. Testing and Results

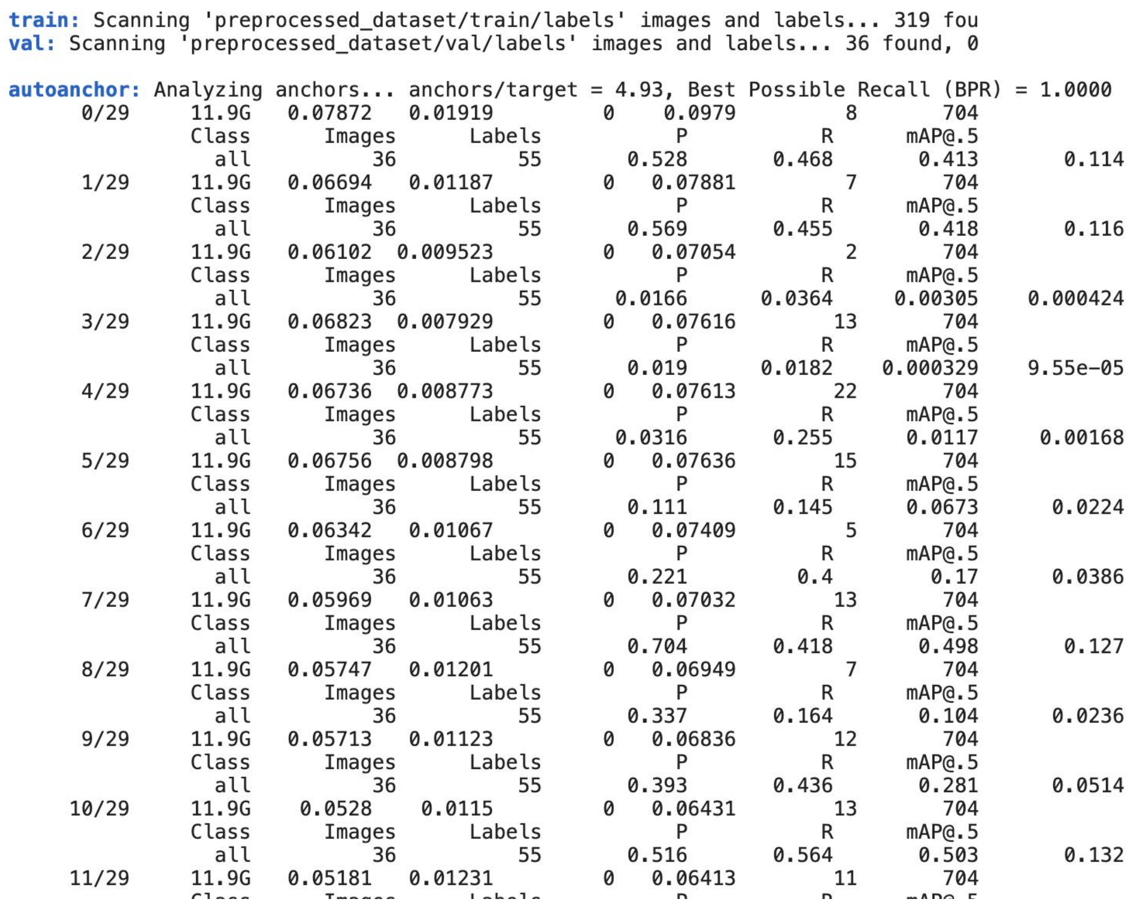
At this juncture, our datasets are properly prepared and ready for use. The next step is to specify the parameters necessary for fine-tuning the model. The 'SIZE' parameter denotes the resolution or input size of the images that will be fed into the YOLOv7 model for training. The batch size refers to the quantity of training examples processed in a single iteration. For our purposes, the model will handle a batch consisting of 12 images during each iteration. An epoch represents a full cycle through the entire training dataset. Conceptually, an epoch can be equated to a single iteration. In our setup, we have specified 30 epochs, indicating that the model will be exposed to the full dataset 30 times, allowing it ample opportunity to learn and recognize patterns.

```
Define paramaters
SIZE = 676

BATCH_SIZE = 12
EPOCHS = 30
MODEL = "yolov7"
WORKERS = 4
PROJECT = "yolo_object_detection"
RUN_NAME =
f"{MODEL}_size{SIZE}_epochs{EPOCHS}_batch{BA
TCH_SIZE}"
```

Once this is defined, use the below command to finetune YOLOv7 on the training data.

```
import torch
torch.cuda.empty_cache()

!python ./yolov7/train.py --img {SIZE} --
batch {BATCH_SIZE} --epochs {EPOCHS} --data
./data.yaml --weights {MODEL}.pt --device 0
--workers {WORKERS} --project {PROJECT} --
name {RUN_NAME} --exist-ok
```

The image displayed below showcases the outcomes of the test.



```
train: Scanning 'preprocessed_dataset/train/labels' images and labels... 319 fou
val: Scanning 'preprocessed_dataset/val/labels' images and labels... 36 found, 0

autoanchor: Analyzing anchors... anchors/target = 4.93, Best Possible Recall (BPR) = 1.0000
      0/29     11.9G   0.07872   0.01919         0    0.0979         8       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.528       0.468       0.413       0.114
      1/29     11.9G   0.06694   0.01187         0   0.07881         7       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.569       0.455       0.418       0.116
      2/29     11.9G   0.06102  0.009523         0   0.07054         2       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55      0.0166      0.0364     0.00305    0.000424
      3/29     11.9G   0.06823  0.007929         0   0.07616        13       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.019      0.0182    0.000329    9.55e-05
      4/29     11.9G   0.06736  0.008773         0   0.07613        22       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55      0.0316       0.255      0.0117     0.00168
      5/29     11.9G   0.06756  0.008798         0   0.07636        15       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.111       0.145      0.0673      0.0224
      6/29     11.9G   0.06342   0.01067         0   0.07409         5       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.221         0.4        0.17      0.0386
      7/29     11.9G   0.05969   0.01063         0   0.07032        13       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.704       0.418       0.498       0.127
      8/29     11.9G   0.05747   0.01201         0   0.06949         7       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.337       0.164       0.104      0.0236
      9/29     11.9G   0.05713   0.01123         0   0.06836        12       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.393       0.436       0.281      0.0514
     10/29     11.9G    0.0528    0.0115         0   0.06431        13       704
               Class      Images      Labels           P           R      mAP@.5
                 all          36          55       0.516       0.564       0.503       0.132
     11/29     11.9G   0.05181   0.01231         0   0.06413        11       704
```

Figure 3: Testing Result

Upon completing the training, proceed to integrate the model with the updated weights, as demonstrated in the subsequent steps.

```
model = torch.hub.load("./yolov7",
                        'custom',

"./car_detection/yolov7_size676_epochs30_batch4/weights/best.pt",
                        source='local',
force_reload=True)
```

Select an image from the test dataset and input it into the model to observe the outcome. The model will generate predictions, including the coordinates of bounding boxes around cars within the image, accompanied by a confidence score indicating the likelihood of accuracy. To illustrate the model's capability, let's conduct a test using a randomly chosen image from the dataset and visually represent the results by plotting them. This exercise aims to demonstrate the practical application of the model in identifying and locating objects within a given image, showcasing its effectiveness in real-world scenarios.

```
from PIL import Image, ImageDraw
```

```
img_path= '../input/car-object-detection/data/testing_images/vid_5_26740.jpg'

img= cv2.imread(img_path)
img= cv2.cvtColor(img, cv2.COLOR_BGRA2RGB)

results = model(img, size=676)
prediction =results.pandas().xyxy[0]

foriin range(len(result_pd)):
xmin, ymin= int(result_pd['xmin'][i]), int(result_pd['ymin'][i])
xmax, ymax= int(result_pd['xmax'][i]), int(result_pd['ymax'][i])
   confidence =result_pd['confidence'][i]
   name = prediction['name'][i]
img= cv2.rectangle(img, (xmin, ymin), (xmax, ymax), (36,255,12), 1)
   cv2.putText(img, f"{name} :{confidence:0.2f}", (xmin, ymin-10), 0.9, (36,255,12), 2)

plt.imshow(img)
plt.show()
```

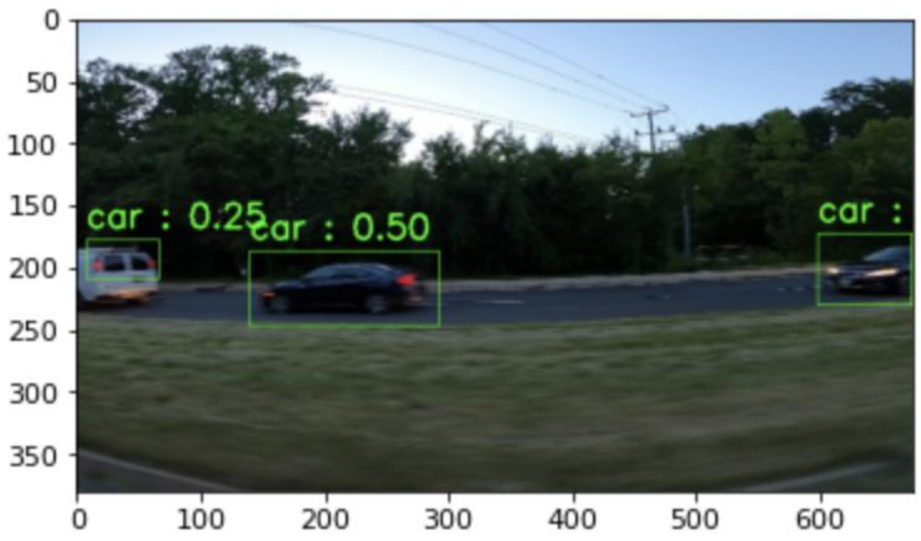


Figure 3: Model Output

The performance of our model is commendable, as it successfully identifies all cars in the image, including those that are partially obscured. This outcome is promising and indicates the model's proficiency in object detection within complex visual contexts. To enhance the model's accuracy and robustness further, incorporating a wider variety of images into the training set, fine-tuning the hyperparameters, and implementing data augmentation techniques are recommended strategies. These steps will likely improve the model's ability to generalize and perform reliably across a broader range of scenarios, elevating its effectiveness in real-world applications.

6. Advantage and Limitation

YOLOv7 stands out for several key reasons:

- **Enhanced Speed:** Markedly outpacing its predecessors, YOLOv7 can process images at over 160 FPS on a single GPU in certain configurations, making it ideal for time-sensitive tasks such as real-time crowd monitoring.
- **Remarkable Accuracy**: With a performance exceeding 51.4% AP on the COCO dataset, YOLOv7 sets a new standard for detection precision.
- **Versatile Scalability:** Whether it's running on a smartphone or a high-powered computing setup, YOLOv7 offers a version that fits the bill, showcasing its adaptability across different hardware capabilities.
- **Efficient Use of Resources:** YOLOv7 employs innovative strategies like data augmentation and model distillation, boosting its efficiency and performance without necessitating extra computing power.
- **Accessibility of Source Code:** The open-source nature of YOLOv7, with its code available on GitHub, ensures transparency and facilitates easy customization and integration into diverse projects, aligning with various user requirements.

Despite its strengths, YOLOv7 faces certain limitations:

Difficulty with Small Objects: In intricate environments, especially with the smaller versions of the model, YOLOv7 may find it challenging to accurately detect tiny objects.

Limited to Detection and Localization: While excelling in identifying and locating objects, YOLOv7 does not perform as well in fine-grained classification, making it less suitable for tasks needing precise differentiation among very similar objects.

Opacity of Model Mechanics: YOLOv7, akin to many advanced deep learning models, operates as a "black box," making it hard to interpret how it arrives at specific predictions.

Dependence on Data Quality: The effectiveness of YOLOv7 heavily relies on the availability of vast quantities of accurately labeled data for training, presenting a significant hurdle in terms of data collection and preparation.

7. Conclusion

YOLOv7 stands out as a formidable force in the realm of object detection, redefining expectations for speed and precision in this field. Its advanced architecture and the integration of cutting-edge techniques such as the trainable bag-of-freebies underscore its revolutionary impact. While YOLOv7 offers remarkable capabilities, it operates within a competitive landscape that includes other high-performing models like EfficientDet and DETR, each bringing its own strengths to the table. The choice of an object detection model hinges on specific requirements, whether that be the necessity for real-time processing capabilities or the demand for high precision in critical applications such as medical imaging. YOLOv7's versatility opens up a plethora of practical applications, exemplified by the potential to develop a real-time supply tracker for inventory management. This application could revolutionize inventory practices by monitoring stock levels, identifying replenishment needs, and facilitating proactive restocking decisions, thereby enhancing operational efficiency and preventing supply shortages. YOLOv7 not only pushes the boundaries of technological capabilities in object detection but also paves the way for innovative solutions to everyday challenges.

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