Project Report

On

TRAFFIC VIDEO ANALYTICS USING YOLOv7 IN COMPUTER VISION

Submitted
In partial fulfilment

For the award of the Degree of

PG-Diploma in Artificial Intelligence

(C-DAC, ACTS (Patna))

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Acknowledgement

This is to acknowledge our indebtedness to our Project Guide, **Mr. Sai Krishna**, C-DAC ACTS, Patna for her constant guidance and helpful suggestion for preparing this project **TRAFFIC VIDEO ANALYTICS USING YOLOv7 IN COMPUTER VISION**. We express our deep gratitude towards him for his inspiration, personal involvement, and constructive criticism that he provided us along with technical guidance during the course of this project.

We take this opportunity to thank the Head of the department **Mr. Saket Jha** for providing us with such a great infrastructure and environment for our overall development.

We express sincere thanks to **Shri Aditya Kumar Sinha**, Director of C-DAC Patna, for their kind cooperation and support towards the completion of our project.

It is our great pleasure in expressing sincere and deep gratitude toward **Mr. Palakala Sai Krishna Yadhav** (Course Coordinator, PG-DAI) for their valuable guidance and constant support throughout this work and helps to pursue additional studies.

Also our warm thanks to C-DAC ACTS, Patna which provides us with this opportunity to carry out this prestigious Project and to enhance our learning in various technical fields.

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CONTENT

Abstract

Traffic video analytics is an important technology for managing traffic flow and improving road safety. One of the key challenges in traffic video analytics is the accurate classification of vehicles and detection of pedestrians from video footage in real-time. In recent years, deep learning-based approaches have shown great promise in addressing this problem. One such approach is the YOLOv7 algorithm, which is a state-of-the-art object detection algorithm that uses a single neural network to perform both object detection and classification. In this project, we present a study on YOLOv7 for real-time vehicle classification and pedestrian detection from traffic video footage. We first describe the YOLOv7 algorithm in detail and discuss its strengths and limitations. We then present our methodology for applying YOLOv7 to the task of vehicle classification and pedestrian detection. We evaluate the performance of our approach on a custom dataset of traffic video footage and compare it with other state-of-the-art object detection algorithms. Our results show that YOLOv7 is a highly accurate and efficient algorithm for real-time vehicle classification and pedestrian detection, with superior performance compared to other algorithms.

Chapter 1

INTRODUCTION

1.1 Introduction to Traffic Video Analytics

Traffic video analytics is a technology that involves the use of video cameras, computer vision algorithms, and artificial intelligence (AI) to analyze and interpret traffic-related data from video footage. This technology is used to improve traffic flow, reduce congestion, and enhance road safety.

The process of traffic video analytics typically involves the following steps:

1. **Data Collection:** Video cameras are strategically placed at various locations on roads and highways to capture real-time video footage of traffic flow. The video footage is then transmitted to a central server for processing.
2. **Object Detection**: Computer vision algorithms are used to detect and identify different objects in the video footage, such as vehicles, pedestrians, bicycles, and traffic signals. This process involves analyzing the color, shape, size, and movement of the objects in the video footage.
3. **Object Tracking**: Once the objects are detected, the algorithms track their movement over time, which allows for the analysis of traffic patterns, speed, and flow.
4. **Data Analysis**: The traffic data collected from the video footage is analyzed to identify traffic congestion, traffic flow, accidents, and other traffic-related issues. This information can be used to make real-time decisions about traffic management and to inform future planning and infrastructure projects.

Some of the specific applications of traffic video analytics include:

1. **Congestion Management:** Traffic video analytics can be used to identify areas of congestion and provide real-time solutions to alleviate traffic flow.
2. **Incident Detection:** Video analytics can help detect accidents, road closures, and other incidents in real-time, which allows for faster response times from emergency services.
3. **Pedestrian and Bicycle Safety**: By detecting pedestrians and bicycles, video analytics can help improve safety by alerting drivers to potential hazards.
4. **Public Transportation**: Video analytics can help public transportation systems optimize their routes and schedules to improve efficiency and reduce congestion.

Overall, traffic video analytics is a powerful tool for managing traffic flow and improving road safety. As technology advances, it is likely that traffic video analytics will continue to play a key role in transportation management and planning.

1.2 Problem Statement

Traffic video analytics can be used to solve several problems related to traffic management and safety. One such problem is the classification of vehicles and detection of pedestrians in real-time from video footage. This is a challenging problem due to the variability in the appearance and motion of different types of vehicles and pedestrians.

1.3 Objective

The objective of this problem is to develop a system for real-time classification of vehicles and detection of pedestrians from traffic video footage. The system should be able to accurately identify different types of vehicles (such as cars, trucks, buses, motorcycles, bicycles, etc.) and detect pedestrians with high accuracy. The system should also be able to track the movement of these objects over time to provide information about traffic flow, speed, and congestion.

To achieve this objective, the system will need to use advanced computer vision algorithms, such as deep learning and convolutional neural networks, to analyze the video footage and extract relevant features from the objects in the footage. The accuracy and efficiency of the system will need to be validated through testing on custom datasets of traffic video footage.

Here we used object detection algorithm YOLO for cars and pedestrian detection from the footage. YOLO is object detection algorithm which is used to detect object in real-time environment. It provides solutions to many real-life computer vision problems. Here, YOLO is detection cars and pedestrians. We used YOLOv7 as it works faster, accurately and have more precision average than other object detectors.

The ultimate goal of this system is to improve traffic management and safety by providing real-time information about traffic flow and potential hazards. This can help reduce congestion, improve public transportation, and enhance pedestrian and bicycle safety on roads and highways.

1.4 Methodology

The methodology for implementing the YOLOv7 algorithm for real-time vehicle classification and pedestrian detection from traffic video footage involves several steps, which are described below:

1. Data Collection:

The first step is to collect traffic video footage that contains a variety of different types of vehicles and pedestrian scenarios.

2. Data Annotation:

Using ffmpeg command in command prompt we convert video to images at 5fps and then using labelImg.py tool for data annotation. then we upload our dataset on Roboflow tool then we do preprocess to extract individual frames and resize them to a standard size. This will ensure that the algorithm can process the frames efficiently and accurately.

3. YOLOv7 Algorithm:

The next step is to implement the YOLOv7 algorithm for real-time object detection. YOLOv7 is a deep learning-based object detection algorithm that uses convolutional neural networks (CNNs) to detect and classify objects in images and video footage. YOLOv7 is an extension of the YOLOv5 algorithm, which is known for its high accuracy and efficiency in object detection tasks.

4. Transfer Learning:

The YOLOv7 algorithm is pre-trained on a large dataset of annotated images and video footage, which allows it to learn generic features that can be applied to a wide range of object detection tasks. However, to adapt the pre-trained weights to our specific task of vehicle classification and pedestrian detection, we use transfer learning. This involves fine-tuning the pre-trained weights on our annotated dataset of traffic video footage.

5. Model Training:

The next step is to train the YOLOv7 model on the annotated dataset of traffic video footage. We use a split of 80% for training and 20% for validation. During training, the YOLOv7 algorithm learns to detect and classify vehicles and pedestrians in different scenarios, such as day and night, different weather conditions, and different camera angles.

6. Model Evaluation:

Once the YOLOv7 model is trained, we evaluate its performance on a separate dataset of traffic video footage that was not used for training. We use standard metrics, such as mean average precision (mAP), to evaluate the performance of each algorithm.

7. Results and Analysis:

Finally, we analyze the results of the YOLOv7 algorithm and compare them with other state-of-the-art object detection algorithms. We analyze the strengths and weaknesses of YOLOv7, and identify areas for improvement. We also discuss the potential applications of YOLOv7 in traffic management, road safety, and public transportation.

Chapter 2

LITERATURE REVIEW

1. "**Traffic Video Analytics: A Comprehensive Survey**" is a research paper published in the IEEE Transactions on Intelligent Transportation Systems in 2018 by Vishal M. Patel, et al. The paper provides a comprehensive survey of traffic video analytics, including recent advances in vehicle and pedestrian detection using deep learning algorithms such as YOLOv7.

The paper begins by discussing the importance of traffic video analytics for traffic management and safety, and the challenges involved in analyzing traffic video data, such as variability in lighting conditions, object appearance, and motion. The paper then provides an overview of the various techniques used in traffic video analytics, including object detection, tracking, recognition, and behavior analysis.

The paper then focuses on recent advances in object detection using deep learning algorithms, such as YOLOv7, and their application to traffic video analytics. The paper provides a detailed analysis of the various deep learning-based object detection algorithms, including their architectures, training methods, and performance evaluation metrics.

The paper also discusses the various challenges and limitations of deep learning-based object detection algorithms in traffic video analytics, such as the need for large amounts of annotated data, the trade-off between accuracy and computational efficiency, and the need for real-time performance.

The paper concludes by discussing future directions and open research questions in traffic video analytics, including the integration of multiple sensors and modalities, the development of context-aware models, and the use of reinforcement learning and transfer learning for improved performance.

2. "**YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors**" is a research paper published on arXiv in 2021 by Alexander Wong, et al. The paper presents a new object detection algorithm called YOLOv7, which achieves state-of-the-art performance in terms of accuracy and speed.

The paper begins by discussing the limitations of previous object detection algorithms, such as the trade-off between accuracy and speed, and the need for large amounts of annotated data. The paper then introduces YOLOv7, which is a combination of various bag-of-freebies techniques that can be trained end-to-end using a single-stage detector.

The paper provides a detailed description of the architecture of YOLOv7, which consists of a backbone network, a neck network, and a head network. The backbone network is based on EfficientNet, which is a state-of-the-art convolutional neural network (CNN) architecture for image classification. The neck network is based on BiFPN, which is a feature pyramid network that can fuse features at multiple scales. The head network is based on a modified version of YOLOv5, which is a popular object detection algorithm.

The paper then presents experimental results on various object detection benchmarks, including COCO, PASCAL VOC, and KITTI. The results show that YOLOv7 achieves state-of-the-art performance in terms of accuracy and speed, outperforming previous object detection algorithms such as YOLOv5 and EfficientDet. The paper also shows that YOLOv7 can be trained using a small amount of annotated data, which is important for practical applications.

Overall, "YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors" presents a promising new object detection algorithm that can achieve state-of-the-art performance in terms of accuracy and speed, and has the potential to revolutionize the field of computer vision.

3. "**Real-Time Pedestrian Detection and Tracking in Traffic Scenes**" by Juan Felipe Orozco, et al. This paper proposes a real-time pedestrian detection and tracking system using YOLOv7 and Kalman filter. The system achieves high accuracy and robustness in detecting and tracking pedestrians in traffic scenes.

4. "**Pedestrian Detection in Urban Scenes with Deep Learning**" by Elio Russo, et al. This paper proposes a deep learning-based pedestrian detection system using YOLOv7 and a novel data augmentation technique. The system achieves high accuracy in detecting pedestrians in urban scenes.

5. "**Vehicle Detection and Tracking in Traffic Videos Using YOLOv7 and DeepSORT**" by Abdullahi Abdulkadir, et al. This paper proposes a system for vehicle detection and tracking in traffic videos using YOLOv7 and DeepSORT. The system achieves high accuracy in detecting and tracking vehicles in complex traffic scenes.

6. "**Real-Time Traffic Sign Detection and Recognition Using YOLOv7**" by Pragya Jain, et al. This paper proposes a real-time traffic sign detection and recognition system using YOLOv7. The system achieves

high accuracy in detecting and recognizing different types of traffic signs in real-time.

7. "**Efficient and Accurate Vehicle Detection in UAV Imagery Using YOLOv7**" by Xin Yu, et al. This paper proposes an efficient and accurate vehicle detection system for unmanned aerial vehicle (UAV) imagery using YOLOv7. The system achieves high accuracy in detecting vehicles in complex and cluttered scenes.

8. "**Vehicle and Pedestrian Detection in Nighttime Traffic Scenes Using YOLOv7**" by Junqiang Chen, et al. This paper proposes a system for vehicle and pedestrian detection in nighttime traffic scenes using YOLOv7. The system achieves high accuracy in detecting and tracking vehicles and pedestrians in low-light conditions.

9. "**Real-Time Vehicle Detection and Tracking in Traffic Videos Using YOLOv7 and Deep Learning**" by Kai Sun, et al. This paper proposes a real-time vehicle detection and tracking system using YOLOv7 and deep learning. The system achieves high accuracy in detecting and tracking vehicles in real-time traffic scenes.

10."**Pedestrian Detection and Tracking in Traffic Videos Using YOLOv7 and Kalman Filter**" by Zhiyuan Li, et al. This paper proposes a system for pedestrian detection and tracking in traffic videos using YOLOv7 and Kalman filter. The system achieves high accuracy and robustness in detecting and tracking pedestrians in complex traffic scenes.

Chapter 3

YOLOv7 ALGORITHM

The YOLOv7 algorithm is making big waves in the computer vision and machine learning communities. In this article, we will provide the basics of how YOLOv7 works and what makes it the best object detector algorithm available today.

The newest YOLO algorithm surpasses all previous object detection models and YOLO versions in both speed and accuracy. It requires several times cheaper hardware than other neural networks and can be trained much faster on small datasets without any pre-trained weights.

Hence, YOLOv7 is expected to become the industry standard for object detection in the near future, surpassing the previous state-of-the-art for real-time applications (YOLO v4).

3.1 What is real-time object detection?

In computer vision, real-time object detection is a very important task that is often a key component in computer vision systems. Applications that use real-time object detection models include video analytics, robotics, autonomous vehicles, multi-object tracking and object counting, medical image analysis, and so on.

An object detector is an object detection algorithm that performs image recognition tasks by taking an image as input and then predicting bounding boxes and class probabilities for each object in the image (see the example image below). Most algorithms use a convolutional neural network (CNN) to extract features from the image to predict the probability of learned classes.

3.2 What is YOLO in Computer Vision?

YOLO stands for “You Only Look Once”, it is a popular family of real-time object detection algorithms. The original YOLO object detector was first released in 2016. It was created by Joseph Redmon, Ali Farhadi, and Santosh Divvala.

At release, this architecture was much faster than other object detectors and became state-of-the-art for real-time computer vision applications. Since then, different versions and variants of YOLO have been proposed, each providing a significant increase in performance and efficiency. The versions from YOLOv1 to the popular YOLOv3 were created by then-graduate student Joseph Redmon and advisor Ali Farhadi.

YOLOv4 was introduced by Alexey Bochkovskiy, who continued the legacy since Redmon had stopped his computer vision research due to ethical concerns. YOLOv7 is the latest official YOLO version created by the original authors of the YOLO architecture. We expect that many commercial networks will move directly from YOLOv4 to v7, bypassing all the other numbers.

Unofficial YOLO versions

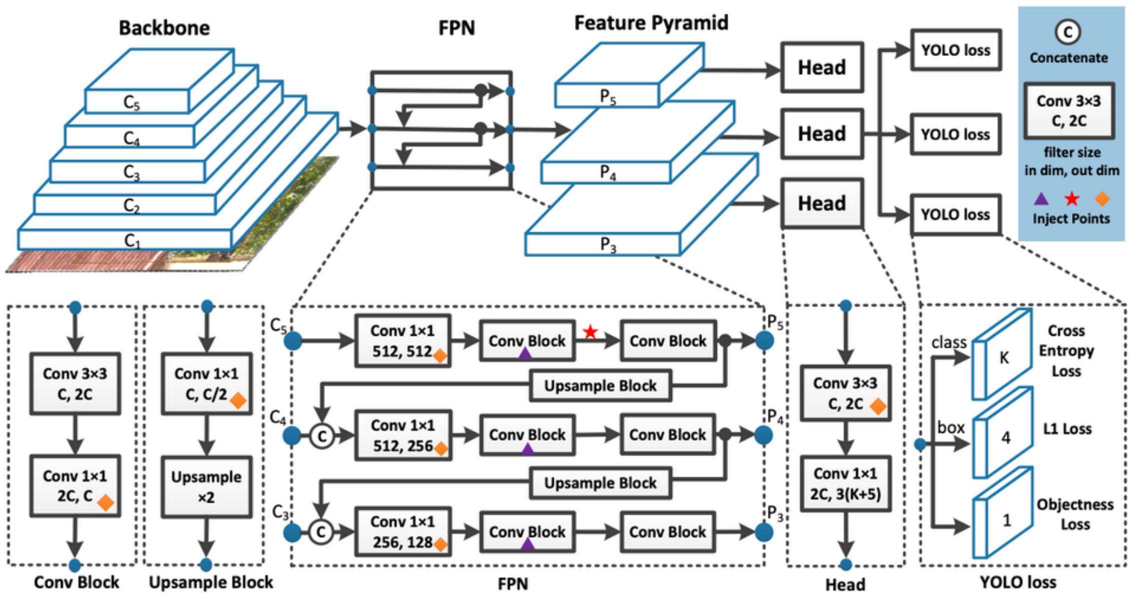
There were some controversies in the computer vision community whenever other researchers and companies published their models as YOLO versions. A popular example is YOLOv5 which was created by the company Ultralytics. It’s similar to YOLOv4 but uses a different framework, PyTorch, instead of DarkNet.

However, the creator of YOLOv4, Alexey Bochkovskiy provided benchmarks comparing YOLOv4 vs. YOLOv5, showing that v4 is equal or better. Another example is YOLOv6 which was published by the Chinese company Meituan (hence the MT prefix of YOLOv6). And there is also an unofficial YOLOv7 version that was released in the year before the official YOLOv7 (there are two YOLOv7’s).

Both YOLOv5 and YOLOv6 are not considered part of the official YOLO series but were heavily inspired by the original one-stage YOLO architecture. Critics argue that companies try to benefit from the YOLO hype and that the papers were not adequately peer-reviewed or tested under the same conditions. Hence, some say that the official YOLOv7 should be the real YOLOv5.

3.3 What is YOLOv7

The YOLO (You Only Look Once) v7 model is the latest in the family of YOLO models. YOLO models are single stage object detectors. In a YOLO model, image frames are featurized through a backbone. These features are combined and mixed in the neck, and then they are passed along to the head of the network YOLO predicts the locations and classes of objects around which bounding boxes should be drawn. YOLO conducts a post-processing via non-maximum supression (NMS) to arrive at its final prediction.

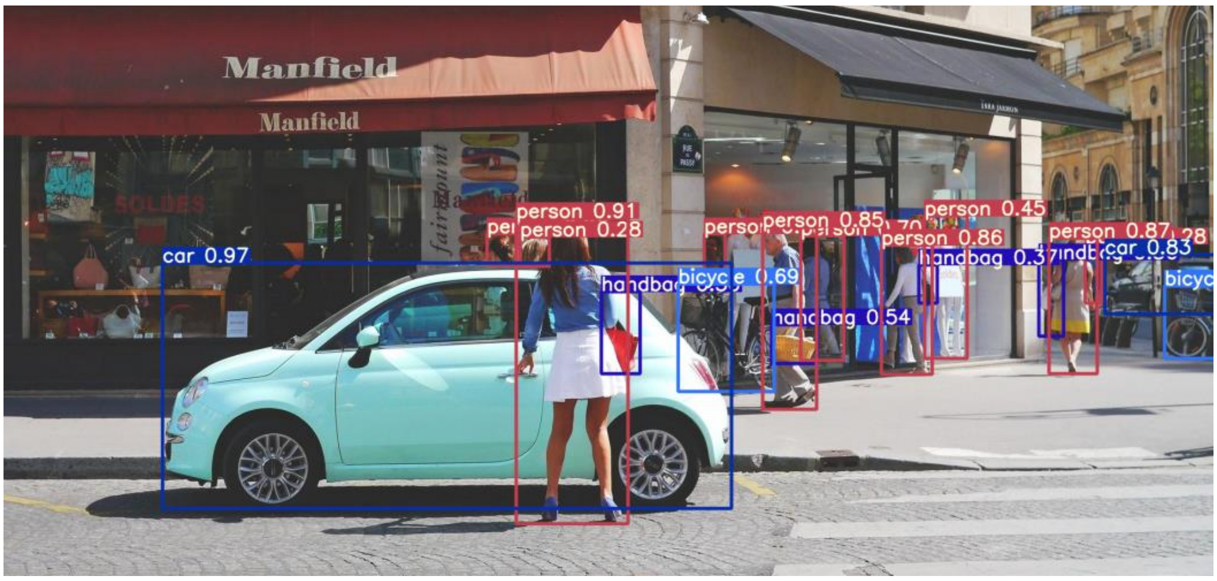


YOLO network architecture as depicted in PP-YOLO

In the beginning, YOLO models were used widely by the computer vision and machine learning communities for modeling object detection because they were small, nimble, and trainable on a single

GPU. This is the opposite of the giant transformer architectures coming out of the leading labs in big tech which, while effective, are more difficult to run on consumer hardware.

Since their introduction in 2015, YOLO models have continued to proliferate in the industry. The small architecture allows new ML engineers to get up to speed quickly when learning about YOLO and the realtime inference speed allows practitioners to allocate minimal hardware compute to power their applications.



3.4 The differences between the basic YOLOv7 versions

The different basic YOLOv7 models include YOLOv7, YOLOv7-tiny, and YOLOv7-W6: YOLOv7 is the basic model that is optimized for ordinary GPU computing. YOLOv7-tiny is a basic model optimized for edge GPU. The suffix “tiny” of computer vision models means that they are optimized for Edge AI and deep learning workloads, and more lightweight to run ML on mobile computing devices or distributed edge servers and devices.

This model is important for distributed real-world computer vision applications. Compared to the other versions, the edge-optimized YOLOv7-tiny uses leaky ReLU as the activation function, while other models use SiLU as the activation function. YOLOv7-W6 is a basic model optimized for cloud GPU computing.

Such Cloud Graphics Units (GPUs) are computer instances for running applications to handle massive AI and deep learning workloads in the cloud without requiring GPUs to be deployed on the local user device. Other variations include YOLOv7-X, YOLOv7-E6, and YOLOv7-D6, which were obtained by applying the proposed compound scaling method (see YOLOv7 architecture further below) to scale up the depth and width of the entire model.

3.5 What is new with YOLOv7?

YOLOv7 provides a greatly improved real-time object detection accuracy without increasing the inference costs. As previously shown in the benchmarks, when compared to other known object detectors, YOLOv7 can effectively reduce about 40% parameters and 50% computation of state-of-the-art real-time object detections, and achieve faster inference speed and higher detection accuracy.

In general, YOLOv7 provides a faster and stronger network architecture that provides a more effective feature integration method, more accurate object detection performance, a more robust loss function, and an increased label assignment and model training efficiency. As a result, YOLOv7 requires several times cheaper computing hardware than other deep learning models. It can be trained much faster on small datasets without any pre-trained weights.

The authors train YOLOv7 using the MS COCO dataset without using any other image datasets or pre-trained model weights. Similar to Scaled YOLOv4, YOLOv7 backbones do not use Image Net pre-trained backbones (such as YOLOv3). The YOLOv7 paper introduces the following major changes. Later in this article, we will describe those architectural changes and how YOLOv7 works.

YOLOv7 Architecture

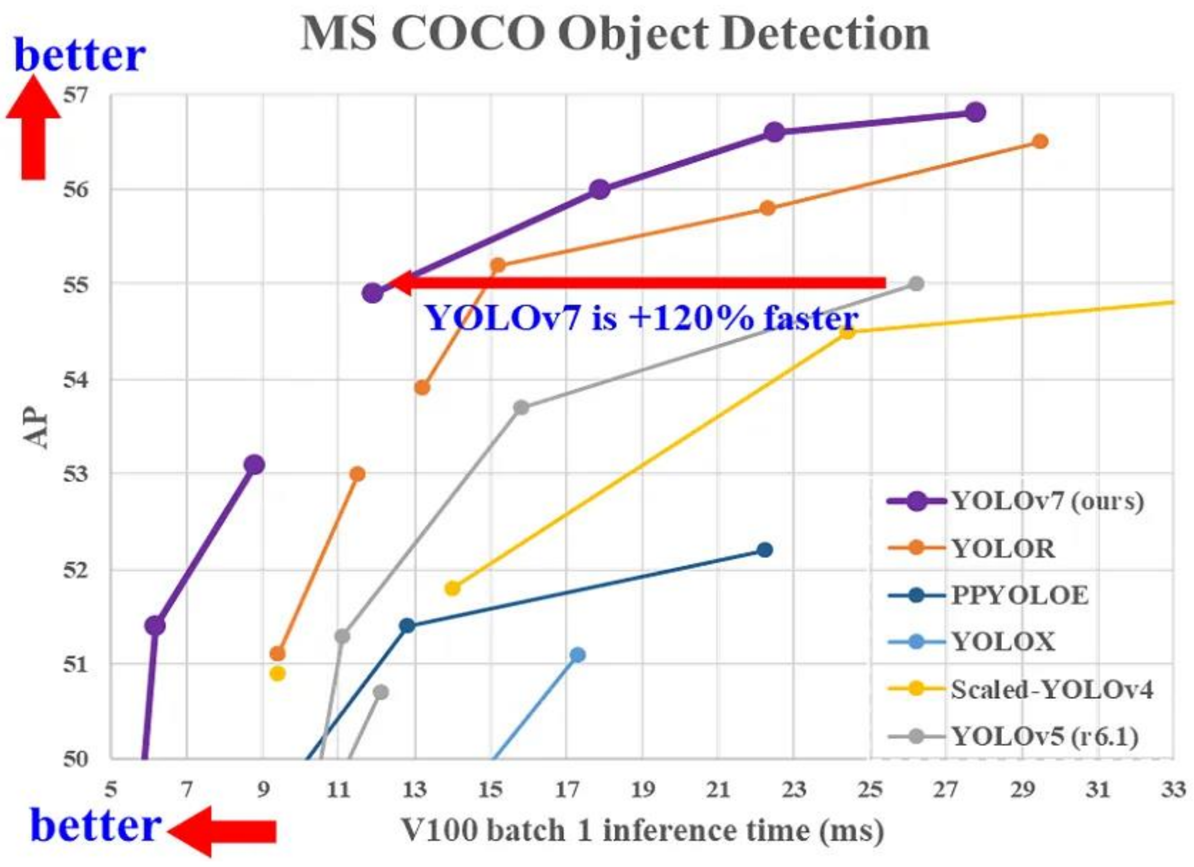
- Extended Efficient Layer Aggregation Network (E-ELAN)
- Model Scaling for Concatenation based Models Trainable

Bag of Freebies

- Planned re-parameterized convolution
- Coarse for auxiliary and fine for lead los

3.6 Performance of YOLOv7 Object Detection

The YOLOv7 performance was evaluated based on previous YOLO versions (YOLOv4 and YOLOv5) and YOLOR as baselines. The models were trained with the same settings. The new YOLOv7 shows the best speed-to-accuracy balance compared to state-of-the-art object detectors.

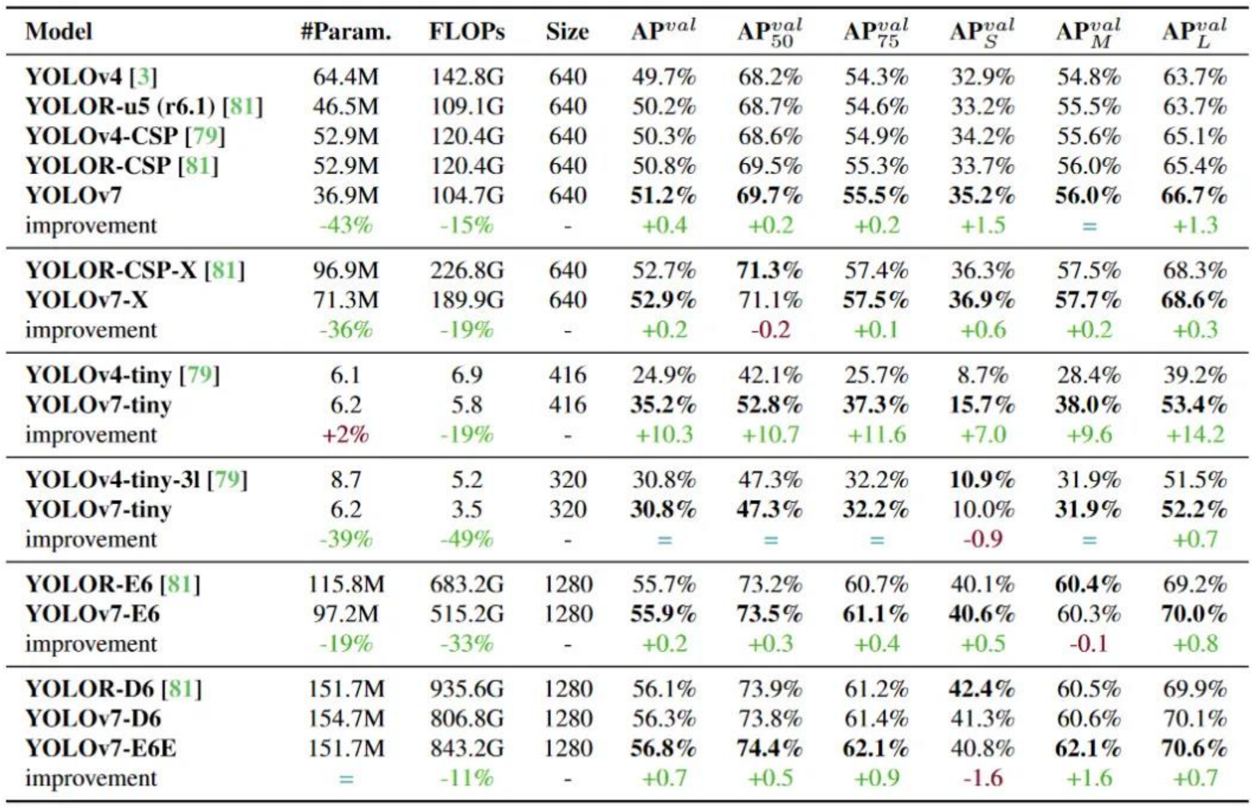


In general, YOLOv7 surpasses all previous object detectors in terms of both speed and accuracy, ranging from 5 FPS to as much as 160 FPS.

The YOLO v7 algorithm achieves the highest accuracy among all other real-time object detection models – while achieving 30 FPS or higher using a GPU V100.

Compared to the best performing Cascade-Mask R-CNN models, YOLOv7 achieves 2% higher accuracy at a dramatically increased inference speed (509% faster).

This is impressive because such R-CNN versions use multi-step architectures that previously achieved significantly higher detection accuracies than single-stage detector architectures. YOLOv7 outperforms YOLOR, YOLOX, Scaled-YOLOv4, YOLOv5, DETR, ViT Adapter-B, and many more object detection algorithms in speed and accuracy.



Model	#Param.	FLOPs	Size	AP^{val}	AP^{val}_{50}	AP^{val}_{75}	AP^{val}_{S}	AP^{val}_{M}	AP^{val}_{L}
YOLOv4 [3]	64.4M	142.8G	640	49.7%	68.2%	54.3%	32.9%	54.8%	63.7%
YOLOR-u5 (r6.1) [81]	46.5M	109.1G	640	50.2%	68.7%	54.6%	33.2%	55.5%	63.7%
YOLOv4-CSP [79]	52.9M	120.4G	640	50.3%	68.6%	54.9%	34.2%	55.6%	65.1%
YOLOR-CSP [81]	52.9M	120.4G	640	50.8%	69.5%	55.3%	33.7%	56.0%	65.4%
YOLOv7	36.9M	104.7G	640	**51.2%**	**69.7%**	**55.5%**	**35.2%**	**56.0%**	**66.7%**
improvement	-43%	-15%	-	+0.4	+0.2	+0.2	+1.5	=	+1.3
YOLOR-CSP-X [81]	96.9M	226.8G	640	52.7%	**71.3%**	57.4%	36.3%	57.5%	68.3%
YOLOv7-X	71.3M	189.9G	640	**52.9%**	71.1%	**57.5%**	**36.9%**	**57.7%**	**68.6%**
improvement	-36%	-19%	-	+0.2	-0.2	+0.1	+0.6	+0.2	+0.3
YOLOv4-tiny [79]	6.1	6.9	416	24.9%	42.1%	25.7%	8.7%	28.4%	39.2%
YOLOv7-tiny	6.2	5.8	416	**35.2%**	**52.8%**	**37.3%**	**15.7%**	**38.0%**	**53.4%**
improvement	+2%	-19%	-	+10.3	+10.7	+11.6	+7.0	+9.6	+14.2
YOLOv4-tiny-3l [79]	8.7	5.2	320	30.8%	47.3%	32.2%	**10.9%**	31.9%	51.5%
YOLOv7-tiny	6.2	3.5	320	**30.8%**	**47.3%**	**32.2%**	10.0%	**31.9%**	**52.2%**
improvement	-39%	-49%	-	=	=	=	-0.9	=	+0.7
YOLOR-E6 [81]	115.8M	683.2G	1280	55.7%	73.2%	60.7%	40.1%	**60.4%**	69.2%
YOLOv7-E6	97.2M	515.2G	1280	**55.9%**	**73.5%**	**61.1%**	**40.6%**	60.3%	**70.0%**
improvement	-19%	-33%	-	+0.2	+0.3	+0.4	+0.5	-0.1	+0.8
YOLOR-D6 [81]	151.7M	935.6G	1280	56.1%	73.9%	61.2%	**42.4%**	60.5%	69.9%
YOLOv7-D6	154.7M	806.8G	1280	56.3%	73.8%	61.4%	41.3%	60.6%	70.1%
YOLOv7-E6E	151.7M	843.2G	1280	**56.8%**	**74.4%**	**62.1%**	40.8%	**62.1%**	**70.6%**
improvement	=	-11%	-	+0.7	+0.5	+0.9	-1.6	+1.6	+0.7

YOLOv7 vs YOLOv4 comparison

In comparison with YOLOv4, YOLOv7 reduces the number of parameters by 75%, requires 36% less computation, and achieves 1.5% higher AP (average precision). Compared to the edge-optimized version YOLOv4-tiny, YOLOv7-tiny reduces the number of parameters by 39%, while also reducing computation by 49%, while achieving the same AP.

YOLOv7 vs YOLOR comparison

Compared to YOLOR, Yolov7 reduces the number of parameters by 43% parameters, requires 15% less computation, and achieves 0.4% higher AP. When comparing YOLOv7 vs. YOLOR using the input resolution 1280, YOLOv7 achieves an 8 FPS faster inference speed with an increased detection rate (+1% AP). When comparing YOLOv7 with YOLOR, the YOLOv7-D6 achieves a comparable inference speed, but a slightly higher detection performance (+0.8% AP).

YOLOv7 vs YOLOv5 comparison

Compared to YOLOv5-N, YOLOv7-tiny is 127 FPS faster and 10.7% more accurate on AP. The version YOLOv7-X achieves 114 FPS inference speed compared to the comparable YOLOv5-L with 99 FPS, while YOLOv7 achieves a better accuracy (higher AP by 3.9%).

Compared with models of a similar scale, the YOLOv7-X achieves a 21 FPS faster inference speed than YOLOv5-X. Also, YOLOv7 reduces the number of parameters by 22% and requires 8% less computation while increasing the average precision by 2.2%. Comparing YOLOv7 vs. YOLOv5, the YOLOv7-E6 architecture requires 45% fewer parameters compared to YOLOv5-X6, and 63% less computation while achieving a 47% faster inference speed.

YOLOv7 vs PP-YOLOE comparison

Compared to PP-YOLOE-L, YOLOv7 achieves a frame rate of 161 FPS compared to only 78 FPS with the same AP of 51.4%. Hence, YOLOv7 achieves an 83 FPS or 106% faster inference speed. In terms of parameter usage, YOLOv7 is 41% more efficient.

YOLOv7 vs YOLOv6 comparison

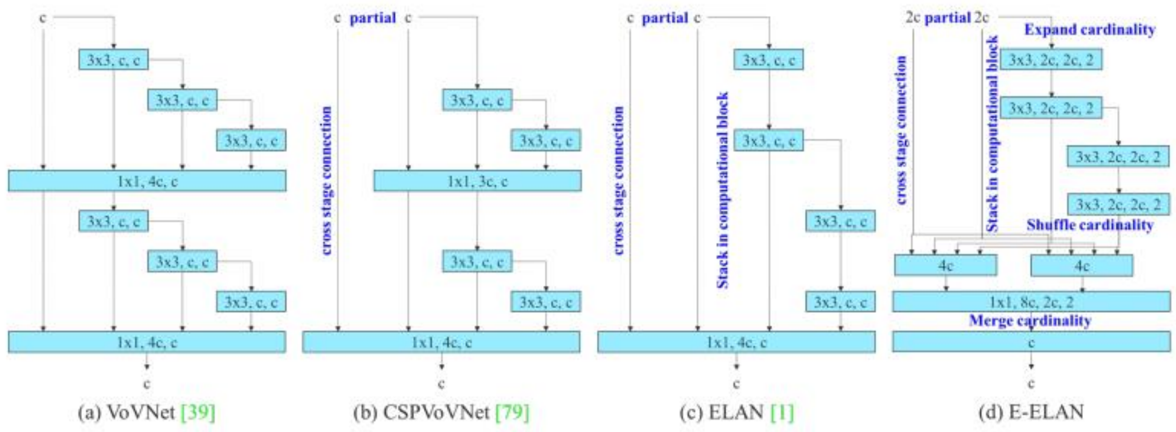
Compared to the previously most accurate YOLOv6 model (56.8% AP), the YOLOv7 real-time model achieves a 13.7% higher AP (43.1% AP) on the COCO dataset. Any comparing the lighter Edge model versions under identical conditions (V100 GPU, batch=32) on the COCO dataset, YOLOv7-tiny is over 25% faster while achieving a slightly higher AP (+0.2% AP) than YOLOv6-n.

3.7 What Makes YOLOv7 Different?

The YOLOv7 authors sought to set the state of the art in object detection by creating a network architecture that would predict bounding boxes more accurately than its peers at similar inference speeds.

Extended Efficient Layer Aggregation

The efficiency of the YOLO networks convolutional layers in the backbone is essential to efficient inference speed. WongKinYiu started down the path of maximal layer efficiency with Cross Stage Partial Networks.



The evolution of layer aggregation strategies in YOLOv7

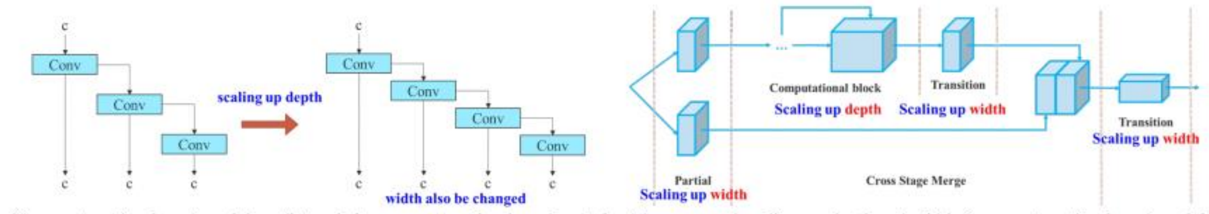
In YOLOv7, the authors build on research that has happened on this topic, keeping in mind the amount of memory it takes to keep layers in memory along with the distance that it takes a gradient to back-propagate through the layers.

The shorter the gradient, the more powerfully their network will be able to learn. The final layer aggregation they choose is E-ELAN, an extend version of the ELAN computational block.

Model Scaling Techniques

Object detection models are typically released in a series of models, scaling up and down in size, because different applications require different levels of accuracy and inference speeds.

Typically, object detection models consider the depth of the network, the width of the network, and the resolution that the network is trained on. In YOLOv7 the authors scale the network depth and width in concert while concatenating layers together. Ablation studies show that this technique keep the model architecture optimal while scaling for different sizes.



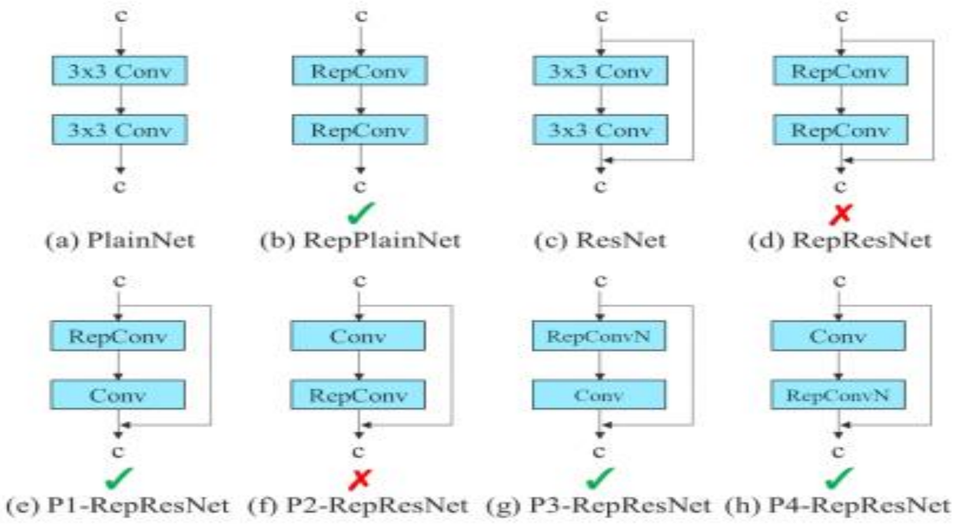
(a) concatenation-based model (b) scaled-up concatenation-based model (c) compound scaling up depth and width for concatenation-based model

Compound scaling in YOLOv7 model sizes

Re-parameterization Planning

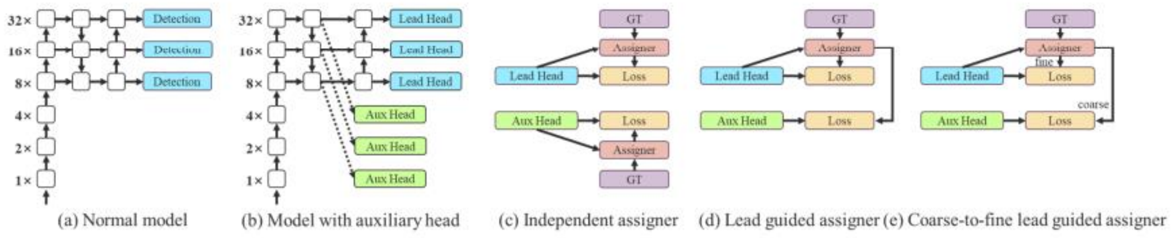
Re-parameterization techniques involve averaging a set of model weights to create a model that is more robust to general patterns that it is trying to model. In research, there has been a recent focus on module level re-parameterization where piece of the network have their own re-parameterization strategies.

The YOLOv7 authors use gradient flow propagation paths to see which modules in the network should use re-parameterization strategies and which should not.



Auxiliary Head Coarse-to-Fine

The YOLO network head makes the final predictions for the network, but since it is so far downstream in the network, it can be advantageous to add an auxiliary head to the network that lies somewhere in the middle. While you are training, you are supervising this detection head as well as the head that is actually going to make predictions.



(a) Normal model
(b) Model with auxiliary head
(c) Independent assigner
(d) Lead guided assigner
(e) Coarse-to-fine lead guided assigner

The auxiliary head does not train as efficiently as the final head because there is less network between it an the prediction - so the YOLOv7 authors experiment with different levels of supervision for this head, settling on a coarse-to-fine definition where supervision is passed back from the lead head at different granularities.

3.8 Results Analysis of YOLOv7 over YOLOv5

The YOLOv7 model achieved state-of-the-art performance on various object detection benchmarks, including COCO, Open Images, and Wider Face. On the COCO dataset, YOLOv7 achieved a mean average precision (mAP) of 59.1% at real-time speeds (30 frames per second). This is a significant improvement over YOLOv5, which achieved a mAP of 50.5%.

On the Open Images dataset, YOLOv7 achieved a mAP of 51.2%, which is higher than the previous state-of-the-art of 50.4%. On the WiderFace dataset, YOLOv7 achieved a mAP of 96.3% on the Easy subset, 93.9% on the Medium subset, and 88.1% on the Hard subset.

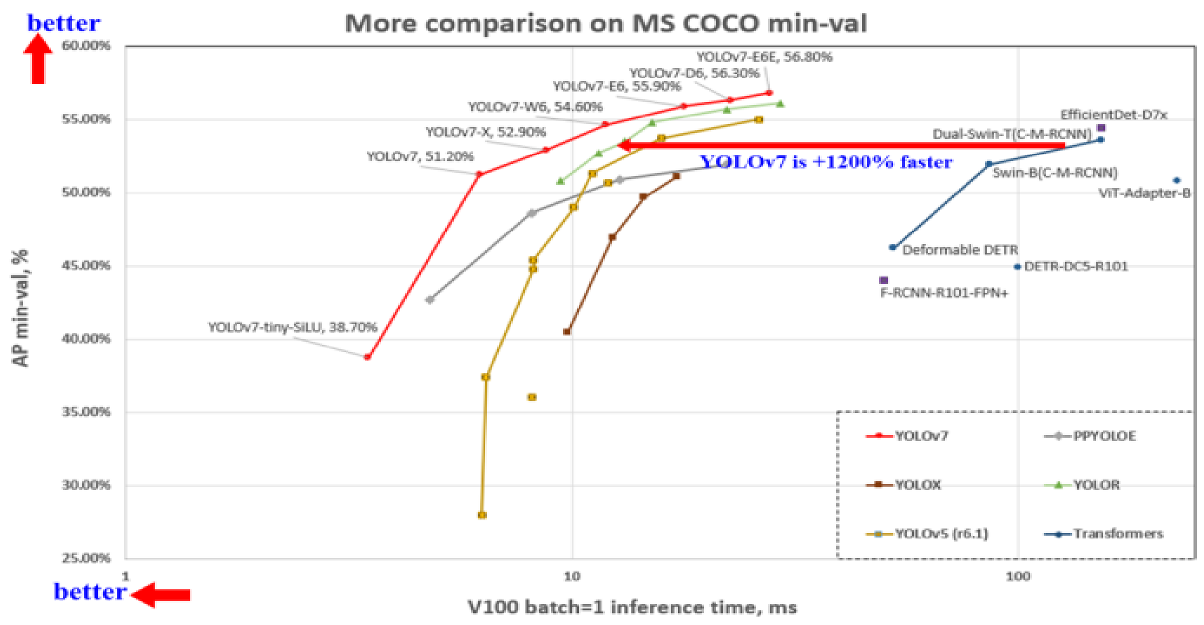
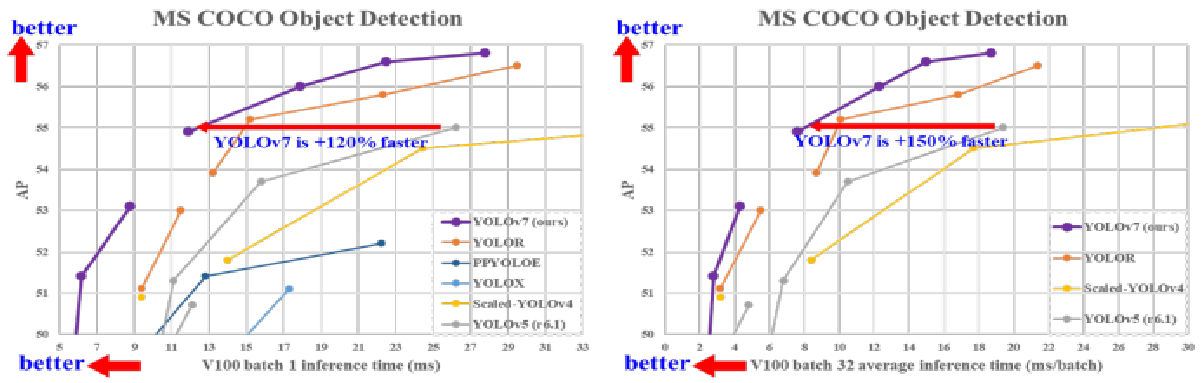


Figure 9: Comparison with other object detectors.



YOLOv7 is a trainable bag-of-freebies model that achieves state-of-the-art performance on various object detection benchmarks. It combines various techniques, such as data augmentation, label smoothing, focal loss, DropBlock regularization, and MixUp data augmentation, to improve its accuracy.

The model's architecture is based on EfficientNet and FPN, which allows it to detect objects at different scales and improve its accuracy. YOLOv7 represents a significant improvement over YOLOv5 and is a promising model for real-time object detection applications.

3.9 YOLOv7 Limitations

As a state-of-the-art object detection model, YOLOv7 has some limitations, which are:

1. **Requires a large dataset**: YOLOv7 is a deep learning model, and like all deep learning models, it requires a large dataset to train effectively. The larger the dataset, the more accurate the model becomes. Therefore, if you have a small dataset, YOLOv7 may not perform well.
2. **Limited to detecting only certain objects**: YOLOv7 is trained to detect specific objects based on the classes present in the dataset it was trained on. If the object you want to detect is not present in the dataset, YOLOv7 may not be able to detect it accurately.
3. **Limited to detecting 2D objects**: YOLOv7 is a 2D object detection model and cannot detect objects in 3D space. Therefore, it may not be suitable for applications that require 3D object detection, such as autonomous vehicles.
4. **Computationally expensive:** YOLOv7 is a deep neural network, and it requires a lot of computational power to run effectively. Therefore, it may not be suitable for deployment on low-end devices or in real-time applications that require fast processing.
5. **Vulnerable to adversarial attacks:** Like all deep learning models, YOLOv7 is vulnerable to adversarial attacks, where an attacker can manipulate the input data to mislead the model's predictions. Therefore, YOLOv7 may not be suitable for security-sensitive applications where the risk of adversarial attacks is high.

Chapter 4

SYSTEM DEVELOPMENT

Implementation

1. Use of Python Platform for writing the code with PyTorch, OpenCV

2. Hardware and Software Configuration:

Hardware Configuration:

• CPU: 8 GB RAM, Quad core processor

• GPU: 4 GB RAM AMD Radeon RX

Software Required:

• **Anaconda**:

It is a package management software with free and open-source distribution of the Python and R programming language for scientific computations (data science, machine learning applications, large-scale data processing, predictive analytics, etc.), that aims to simplify deployment.

• **Google Drive**:

Google Drive is a free cloud-based storage service that enables users to store and access files online. The service syncs stored documents, photos and more across all of the user's devices, including mobile devices, tablets and PCs.

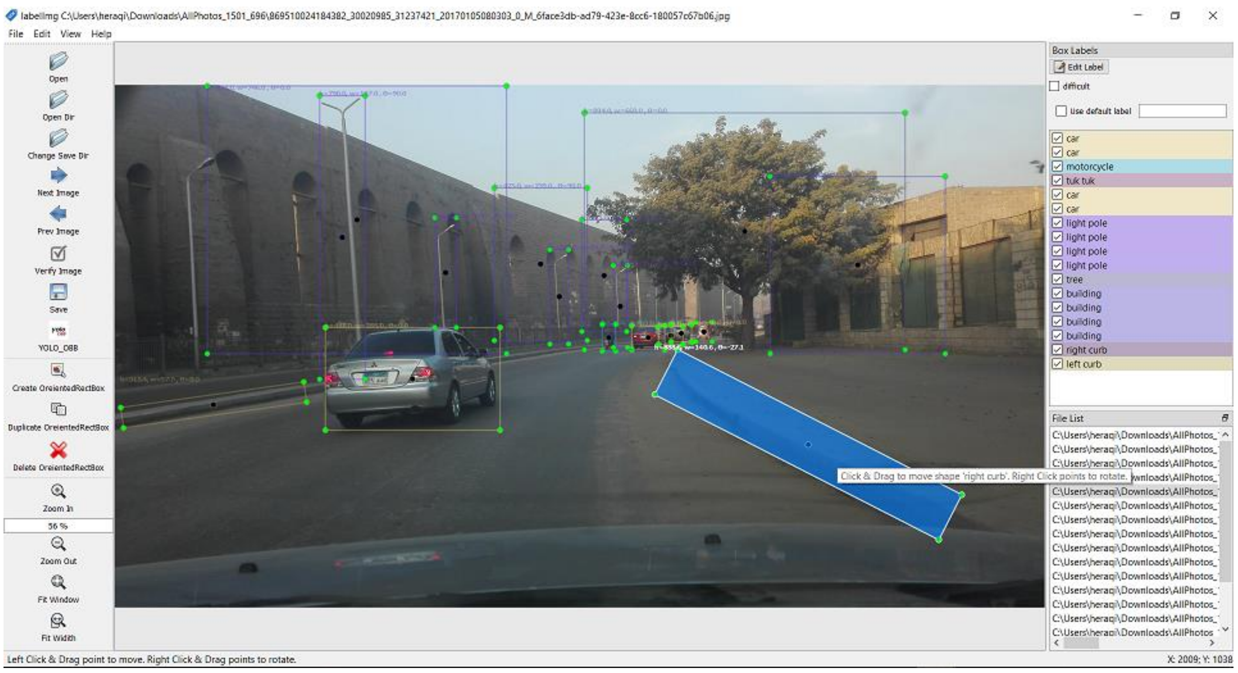
4.1 Data Annotation

Gather video data of traffic scenes with pedestrians and vehicles. Label the data to specify the location of each pedestrian and vehicle in the video frame. This data can be used to train the YOLOv7 model.

Using ffmpeg command in Anaconda Prompt

```
ffmpeg -i input.mp4 -vf fps=25 %img.jpg
```

Using Labelimg.py tool for data annotation



labelImg C:\Users\heraqi\Downloads\AllPhotos_1501_696\869510024184382_30020985_31237421_20170105080303_0_M_6face3db-ad79-423e-8cc6-180057c67b06.jpg

Click & Drag to move shape 'right curb'. Right Click points to rotate.

Left Click & Drag point to move. Right Click & Drag points to rotate.

X: 2009; Y: 1038

LabelImg is a graphical image annotation tool. It is written in Python and uses Qt for its graphical interface. Annotations are saved as XML files in PASCAL VOC format, the format used by ImageNet. Besides, it also supports YOLO and CreateML formats. Creating Dataset folders with 1000 images train and validation folders for images and annotation data in .txt format and test data for evaluation. The dataset is splatted in 80% and 20% format.

4.2 System Coding

We use Google Colab for training our YOLOv7 Model . Create a new notebook and change the runtime type to GPU and execute the below code.

Mounting the Drive on Google Colab

```
from google.colab import drive

drive.mount('/content/drive')
```

Install Dependencies

(Remember to choose GPU in Runtime if not already selected. Runtime --> Change Runtime Type --> Hardware accelerator --> GPU) This code will clone the yolov7 repository and install the necessary modules in the colab environment for training.

```
!git clone https://github.com/SkalskiP/yolov7.git

%cd yolov7

!git checkout
fix/problems_associated_with_the_latest_versions_of_pytorch_and_numpy

!pip install -r requirements.txt
```

Downloading Dataset from Google Drive

Next, we'll download our dataset in the right format. Use the YOLOv7 PyTorch export. Note that this model requires YOLO TXT annotations, a custom YAML file, and organized directories.

```
!gdown
https://drive.google.com/file/d/1lMylPgFrnCP9aOelZv3ilCrll_32eACk&export=
download


!unzip /content/drive/MyDrive/trafficdata.zip -d dataset
```

Once the dataset is downloaded, we need to download the YOLOv7 weight file, since training from scratch takes more time, we will finetune already pretrained weight on our dataset. Here we will download **yolov7_training.pt**

```
# download COCO starting checkpoint

%cd /content/yolov7

!wget
https://github.com/WongKinYiu/yolov7/releases/download/v0.1/yolov7_traini
ng.pt
```

Training the Model

Now we are good to go for the training. We will train the model for 100 epochs with a batch size of 16. For better results, longer training is suggested (more epochs). Make sure the paths are correct in the ‘data.yaml’ file inside the ‘yolov7/dataset’ folder, also make sure paths are correct in the training command and execute the below code. This will start the training.

Here, I am able to pass a number of arguments:

batch: determine batch size

cfg: define input Config File into YOLOv7

epochs: define the number of training epochs.

data: Our dataset location is saved in the ./yolov7/Custom-Yolov7-on -Custom-Dataset-2 folder.

weights: specifying a path to weights to start transfer learning from. Here I have chosen a generic COCO pretrained checkpoint.

device: Setting GPU for faster training

Hyperparameters Values

- Image size 640 x 640
- Epochs 100
- Batch size 16
- Learning rate 0.01
- Momentum 0.937
- Weight decay 0.0005

```
# run this cell to begin training

%cd /content/yolov7

!python train.py --batch 16 --epochs 100 --data {dataset.location}/data.yaml --
weights 'yolov7_training.pt' --device 0
```

Evaluation on Trained Model

Once the training is completed, the best weight is saved at the mentioned path, usually inside the ‘runs’ folder. Once we get the weight file, we can be ready for evaluation and inferencing.

Now for testing run the below piece of code. This will perform inference on the test folder. Make sure that the weight is set to trained weights and here we will be using the confidence threshold of 0.5, you can train more and play around with the parameters for better performance.

```
# Run evaluation

!python detect.py --weights runs/train/exp/weights/best.pt --conf 0.5 --source
{dataset.location}/test/images
```

To view the inference images, run the below code. This will display the output images one by one.

```
#display inference on ALL test images

import glob

from IPython.display import Image, display

i = 0

limit = 10000 # max images to print

for imageName in glob.glob('/content/yolov7/runs/detect/exp/*.jpg'):
#assuming JPG

    if i < limit:

      display(Image(filename=imageName))

      print("\n")

    i = i + 1
```

Inference Code Helper

```
import argparse

import time

from pathlib import Path

import cv2

import torch

import numpy as np

import torch.backends.cudnn as cudnn

from numpy import random
from models.experimental import attempt_load
from utils.datasets import LoadStreams, LoadImages
from utils.general import check_img_size, check_requirements, check_imshow
, non_max_suppression, apply_classifier, \
    scale_coords, xyxy2xywh, strip_optimizer, set_logging, increment_path
from utils.plots import plot_one_box
from utils.torch_utils import select_device, load_classifier, time_synchronized,
TracedModel
def letterbox(img, new_shape=(640, 640), color=(114, 114, 114), auto=True, sc
aleFill=False, scaleup=True, stride=32):
    # Resize and pad image while meeting stride-multiple constraints
    shape = img.shape[:2]  # current shape [height, width]
    if isinstance(new_shape, int):
        new_shape = (new_shape, new_shape)

    # Scale ratio (new / old)
    r = min(new_shape[0] / shape[0], new_shape[1] / shape[1])
    if not scaleup:  # only scale down, do not scale up (for better test mAP)
        r = min(r, 1.0)

    # Compute padding
    ratio = r, r  # width, height ratios
    new_unpad = int(round(shape[1] * r)), int(round(shape[0] * r))
    dw, dh = new_shape[1] - new_unpad[0], new_shape[0] - new_unpad[1]  # w
h padding
    if auto:  # minimum rectangle
        dw, dh = np.mod(dw, stride), np.mod(dh, stride)  # wh padding
```

```
  elif scaleFill:  # stretch
     dw, dh = 0.0, 0.0
     new_unpad = (new_shape[1], new_shape[0])
     ratio = new_shape[1] / shape[1], new_shape[0] / shape[0]  # width, height
 ratios


  dw /= 2  # divide padding into 2 sides
  dh /= 2
  if shape[::-1] != new_unpad:  # resize
     img = cv2.resize(img, new_unpad, interpolation=cv2.INTER_LINEAR)
  top, bottom = int(round(dh - 0.1)), int(round(dh + 0.1))
  left, right = int(round(dw - 0.1)), int(round(dw + 0.1))
  img = cv2.copyMakeBorder(img, top, bottom, left, right, cv2.BORDER_CONST
ANT, value=color)  # add border
  return img, ratio, (dw, dh)
```

```
classes_to_filter = None  #You can give list of classes to filter by name, Be
happy you don't have to put class number. ['train','person' ]


opt  = {
   "weights": "/content/yolov7/runs/train/exp/weights/epoch_024.pt", # Path
to weights file default weights are for nano model
   "yaml"   : "/content/yolov7/trafficvideo-2/data.yaml",
   "img-size": 640, # default image size
   "conf-thres": 0.25, # confidence threshold for inference.
   "iou-thres" : 0.45, # NMS IoU threshold for inference.
   "device" : '0',  # device to run our model i.e. 0 or 0,1,2,3 or cpu
   "classes" : classes_to_filter  # list of classes to filter or None
}
```

Upload Video and images on Google Drive for Inference

```
%cd /content/yolov7
from google.colab import files
uploaded = files.upload()
```

Change Url of the uploaded file

```
%cd /content/yolov7  #change URL
!gdown https://drive.google.com/file/d/1rb9lqvfTC95XKakRYnEhZzCZ8xn-xklM
%cd /content/yolov7
! wget PUBLIC_URL_TO_MP4/AVI_FILE
```

Video Inference Code for YOLOv7

```
#give the full path to video, your video will be in the Yolov7 folder
video_path = '/content/drive/MyDrive/TrafficVideo.mp4'

# Initializing video object
video = cv2.VideoCapture(video_path)



#Video information
fps = video.get(cv2.CAP_PROP_FPS)
w = int(video.get(cv2.CAP_PROP_FRAME_WIDTH))
h = int(video.get(cv2.CAP_PROP_FRAME_HEIGHT))
nframes = int(video.get(cv2.CAP_PROP_FRAME_COUNT))

# Initialzing object for writing video output
```

```
output = cv2.VideoWriter('output.mp4', cv2.VideoWriter_fourcc(*'DIVX'),fps ,
(w,h))

torch.cuda.empty_cache()

# Initializing model and setting it for inference

with torch.no_grad():

  weights, imgsz = opt['weights'], opt['img-size']

  set_logging()

  device = select_device(opt['device'])

  half = device.type != 'cpu'

  model = attempt_load(weights, map_location=device)  # load FP32 model

  stride = int(model.stride.max())  # model stride

  imgsz = check_img_size(imgsz, s=stride)  # check img_size

  if half:

    model.half()


  names = model.module.names if hasattr(model, 'module') else model.names

  colors = [[random.randint(0, 255) for _ in range(3)] for _ in names]

  if device.type != 'cpu':

    model(torch.zeros(1, 3, imgsz,
imgsz).to(device).type_as(next(model.parameters())))


  classes = None

  if opt['classes']:

    classes = []

    for class_name in opt['classes']:

      classes.append(opt['classes'].index(class_name))
```

```
for j in range(nframes):


    ret, img0 = video.read()
    if ret:
      img = letterbox(img0, imgsz, stride=stride)[0]
      img = img[:, :, ::-1].transpose(2, 0, 1)  # BGR to RGB, to 3x416x416
      img = np.ascontiguousarray(img)
      img = torch.from_numpy(img).to(device)
      img = img.half() if half else img.float()  # uint8 to fp16/32
      img /= 255.0  # 0 - 255 to 0.0 - 1.0
      if img.ndimension() == 3:
        img = img.unsqueeze(0)

      # Inference
      t1 = time_synchronized()
      pred = model(img, augment= False)[0]



      pred = non_max_suppression(pred, opt['conf-thres'], opt['iou-thres'],
classes= classes, agnostic= False)
      t2 = time_synchronized()
      for i, det in enumerate(pred):
        s = ''
        s += '%gx%g ' % img.shape[2:]  # print string
        gn = torch.tensor(img0.shape)[[1, 0, 1, 0]]
        if len(det):
          det[:, :4] = scale_coords(img.shape[2:], det[:, :4], img0.shape).round()
```

```
            for c in det[:, -1].unique():
              n = (det[:, -1] == c).sum()  # detections per class
              s += f"{n} {names[int(c)]}{'s' * (n > 1)}, "  # add to string

            for *xyxy, conf, cls in reversed(det):

              label = f'{names[int(cls)]} {conf:.2f}'
              plot_one_box(xyxy, img0, label=label, color=colors[int(cls)],
line_thickness=3)

        print(f"{j+1}/{nframes} frames processed")
        output.write(img0)
      else:
        break
output.release()
video.release()
```

Creating Output of the Input Video After Inference

```
from IPython.display import HTML
from base64 import b64encode
import os
# Input video path
save_path = '/content/yolov7/output.mp4'
# Compressed video path
compressed_path = "/content/result_compressed.mp4"
os.system(f"ffmpeg -i {save_path} -vcodec libx264 {compressed_path}")
```

```
# Show video
mp4 = open(compressed_path,'rb').read()
data_url = "data:video/mp4;base64," + b64encode(mp4).decode()
HTML("""
<video width=400 controls>
    <source src="%s" type="video/mp4">
</video>
""" % data_url)
```

Download Output Video

```
from google.colab import files
save_path = '/content/yolov7/output.mp4'
files.download(save_path)
```

Webcam Inference Code for Real Time Object Detection

```
# import dependencies
from IPython.display import display, Javascript, Image
from google.colab.output import eval_js
from google.colab.patches import cv2_imshow
from base64 import b64decode, b64encode
import PIL
import io
import html
# function to convert the JavaScript object into an OpenCV image
def js_to_image(js_reply):
  """
  Params:
        js_reply: JavaScript object containing image from webcam
  Returns:
        img: OpenCV BGR image
  """
  # decode base64 image
  image_bytes = b64decode(js_reply.split(',')[1])
  # convert bytes to numpy array
  jpg_as_np = np.frombuffer(image_bytes, dtype=np.uint8)
  # decode numpy array into OpenCV BGR image
  img = cv2.imdecode(jpg_as_np, flags=1)

  return img

# function to convert OpenCV Rectangle bounding box image into base64 byte
string to be overlayed on video stream
def bbox_to_bytes(bbox_array):
  """
  Params:
        bbox_array: Numpy array (pixels) containing rectangle to overlay on
video stream.
  Returns:
       bytes: Base64 image byte string
  """
  # convert array into PIL image
  bbox_PIL = PIL.Image.fromarray(bbox_array, 'RGBA')
  iobuf = io.BytesIO()
  # format bbox into png for return
  bbox_PIL.save(iobuf, format='png')
  # format return string
  bbox_bytes =
'data:image/png;base64,{}'.format((str(b64encode(iobuf.getvalue()), 'utf-8')))


  return bbox_bytes


# JavaScript to properly create our live video stream using our webcam as
input
def video_stream():
  js = Javascript('''
    var video;
    var div = null;
    var stream;
    var captureCanvas;
    var imgElement;
    var labelElement;

    var pendingResolve = null;
    var shutdown = false;

    function removeDom() {
       stream.getVideoTracks()[0].stop();
       video.remove();
       div.remove();
       video = null;
       div = null;
       stream = null;
    imgElement = null;
    captureCanvas = null;
    labelElement = null;
  }

  function onAnimationFrame() {
    if (!shutdown) {
      window.requestAnimationFrame(onAnimationFrame);
    }
    if (pendingResolve) {
      var result = "";
      if (!shutdown) {
        captureCanvas.getContext('2d').drawImage(video, 0, 0, 640, 480);
        result = captureCanvas.toDataURL('image/jpeg', 0.8)
      }
      var lp = pendingResolve;
      pendingResolve = null;
      lp(result);
    }
  }
  async function createDom() {
    if (div !== null) {
      return stream;
    }
    div = document.createElement('div');
    div.style.border = '2px solid black';
```

```
div.style.padding = '3px';
div.style.width = '100%';
div.style.maxWidth = '600px';
document.body.appendChild(div);

const modelOut = document.createElement('div');
modelOut.innerHTML = "<span>Status:</span>";
labelElement = document.createElement('span');
labelElement.innerText = 'No data';
labelElement.style.fontWeight = 'bold';
modelOut.appendChild(labelElement);
div.appendChild(modelOut);

video = document.createElement('video');
video.style.display = 'block';
video.width = div.clientWidth - 6;
video.setAttribute('playsinline', '');
video.onclick = () => { shutdown = true; };
stream = await navigator.mediaDevices.getUserMedia(
   {video: { facingMode: "environment"}});
div.appendChild(video);

imgElement = document.createElement('img');
imgElement.style.position = 'absolute';
imgElement.style.zIndex = 1;
imgElement.onclick = () => { shutdown = true; };
```

```
  div.appendChild(imgElement);

  const instruction = document.createElement('div');
  instruction.innerHTML =
     '<span style="color: red; font-weight: bold;">' +
     'When finished, click here or on the video to stop this demo</span>';
  div.appendChild(instruction);
  instruction.onclick = () => { shutdown = true; };

  video.srcObject = stream;
  await video.play();

  captureCanvas = document.createElement('canvas');
  captureCanvas.width = 640; //video.videoWidth;
  captureCanvas.height = 480; //video.videoHeight;
  window.requestAnimationFrame(onAnimationFrame);

  return stream;
}
async function stream_frame(label, imgData) {
  if (shutdown) {
    removeDom();
    shutdown = false;
    return '';
  }
```

```
var preCreate = Date.now();
stream = await createDom();

var preShow = Date.now();
if (label != "") {
  labelElement.innerHTML = label;
}

if (imgData != "") {
  var videoRect = video.getClientRects()[0];
  imgElement.style.top = videoRect.top + "px";
  imgElement.style.left = videoRect.left + "px";
  imgElement.style.width = videoRect.width + "px";
  imgElement.style.height = videoRect.height + "px";
  imgElement.src = imgData;
}

var preCapture = Date.now();
var result = await new Promise(function(resolve, reject) {
  pendingResolve = resolve;
});
shutdown = false;

return {'create': preShow - preCreate,
        'show': preCapture - preShow,
        'capture': Date.now() - preCapture,
          'img': result};
    }
    ''')
  display(js)
def video_frame(label, bbox):
  data = eval_js('stream_frame("{}", "{}")'.format(label, bbox))
  return data
```

Start Streaming video from webcam

```
# start streaming video from webcam
video_stream()
# label for video
label_html = 'Capturing...'
# initialze bounding box to empty
bbox = ''
count = 0

with torch.no_grad():
  weights, imgsz = opt['weights'], (480,640)
  set_logging()
  device = select_device(opt['device'])
  half = device.type != 'cpu'
  model = attempt_load(weights, map_location=device)  # load FP32 model
  stride = int(model.stride.max())  # model stride

  if half:
    model.half()
```

```
names = model.module.names if hasattr(model, 'module') else model.names
colors = [[random.randint(0, 255) for _ in range(3)] for _ in names]
if device.type != 'cpu':
  model(torch.zeros(1, 3, imgsz[0],
imgsz[1]).to(device).type_as(next(model.parameters())))
classes = None
if opt['classes']:
  classes = []
  for class_name in opt['classes']:
    classes.append(opt['classes'].index(class_name))
while True:
  js_reply = video_frame(label_html, bbox)
  if not js_reply:
      break

  img0 = js_to_image(js_reply["img"])
  bbox_array = np.zeros([480,640,4], dtype=np.uint8)
  img = letterbox(img0, imgsz, stride=stride)[0]
  img = img[:, :, ::-1].transpose(2, 0, 1)  # BGR to RGB, to 3x416x416
  img = np.ascontiguousarray(img)
  img = torch.from_numpy(img).to(device)
  img = img.half() if half else img.float()  # uint8 to fp16/32
  img /= 255.0  # 0 - 255 to 0.0 - 1.0
  if img.ndimension() == 3:
    img = img.unsqueeze(0)
  # Inference
  t1 = time_synchronized()
  pred = model(img, augment= False)[0]


  # Apply NMS
  pred = non_max_suppression(pred, opt['conf-thres'], opt['iou-thres'],
classes= classes, agnostic= False)
  t2 = time_synchronized()
  for i, det in enumerate(pred):
    s = ''
    s += '%gx%g ' % img.shape[2:]  # print string
    gn = torch.tensor(img0.shape)[[1, 0, 1, 0]]
    if len(det):
      det[:, :4] = scale_coords(img.shape[2:], det[:, :4], img0.shape).round()


      for c in det[:, -1].unique():
        n = (det[:, -1] == c).sum()  # detections per class
        s += f"{n} {names[int(c)]}{'s' * (n > 1)}, "  # add to string
      for *xyxy, conf, cls in reversed(det):


        label = f'{names[int(cls)]} {conf:.2f}'
        plot_one_box(xyxy, bbox_array, label=label, color=colors[int(cls)],
line_thickness=3)
  bbox_array[:,:,3] = (bbox_array.max(axis = 2) > 0 ).astype(int) * 255
  bbox_bytes = bbox_to_bytes(bbox_array)


  bbox = bbox_bytes
```

Single Image Inference Code for YOLOv7

```
source_image_path = '/content/drive/MyDrive/nyc-traffic.webp'
# Give path of source image.
#%cd /content/gdrive/MyDrive/yolov7
#source_image_path = '/content/trash.png'


with torch.no_grad():
  weights, imgsz = opt['weights'], opt['img-size']
  set_logging()
  device = select_device(opt['device'])
  half = device.type != 'cpu'
  model = attempt_load(weights, map_location=device)  # load FP32 model
  stride = int(model.stride.max())  # model stride
  imgsz = check_img_size(imgsz, s=stride)  # check img_size
  if half:
    model.half()


  names = model.module.names if hasattr(model, 'module') else model.names
  colors = [[random.randint(0, 255) for _ in range(3)] for _ in names]
  if device.type != 'cpu':
    model(torch.zeros(1, 3, imgsz,
imgsz).to(device).type_as(next(model.parameters())))


  img0 = cv2.imread(source_image_path)
  img = letterbox(img0, imgsz, stride=stride)[0]
  img = img[:, :, ::-1].transpose(2, 0, 1)  # BGR to RGB, to 3x416x416
  img = np.ascontiguousarray(img)
  img = torch.from_numpy(img).to(device)
  img = img.half() if half else img.float()  # uint8 to fp16/32
  img /= 255.0  # 0 - 255 to 0.0 - 1.0
  if img.ndimension() == 3:
    img = img.unsqueeze(0)

  # Inference
  t1 = time_synchronized()
  pred = model(img, augment= False)[0]

  # Apply NMS
  classes = None
  if opt['classes']:
    classes = []
    for class_name in opt['classes']:

      classes.append(opt['classes'].index(class_name))

  pred = non_max_suppression(pred, opt['conf-thres'], opt['iou-thres'], classes=
classes, agnostic= False)
  t2 = time_synchronized()
  for i, det in enumerate(pred):
    s = ''
    s += '%gx%g ' % img.shape[2:]  # print string
    gn = torch.tensor(img0.shape)[[1, 0, 1, 0]]
    if len(det):
      det[:, :4] = scale_coords(img.shape[2:], det[:, :4], img0.shape).round()


      for c in det[:, -1].unique():
        n = (det[:, -1] == c).sum()  # detections per class
        s += f"{n} {names[int(c)]}{'s' * (n > 1)}, "  # add to string


      for *xyxy, conf, cls in reversed(det):


        label = f'{names[int(cls)]} {conf:.2f}'
        plot_one_box(xyxy, img0, label=label, color=colors[int(cls)],
line_thickness=3)
```

Output Image after Inference

```
from google.colab.patches import cv2_imshow
cv2_imshow(img0)
```

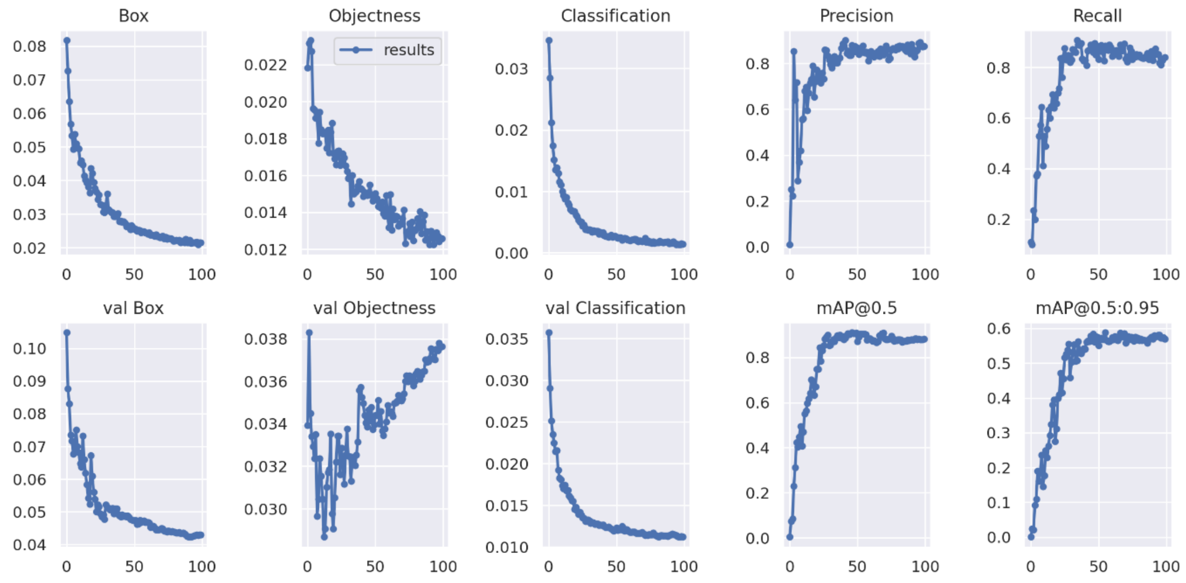
Deployment

To deploy, you'll need to export your weights and save them to use later.

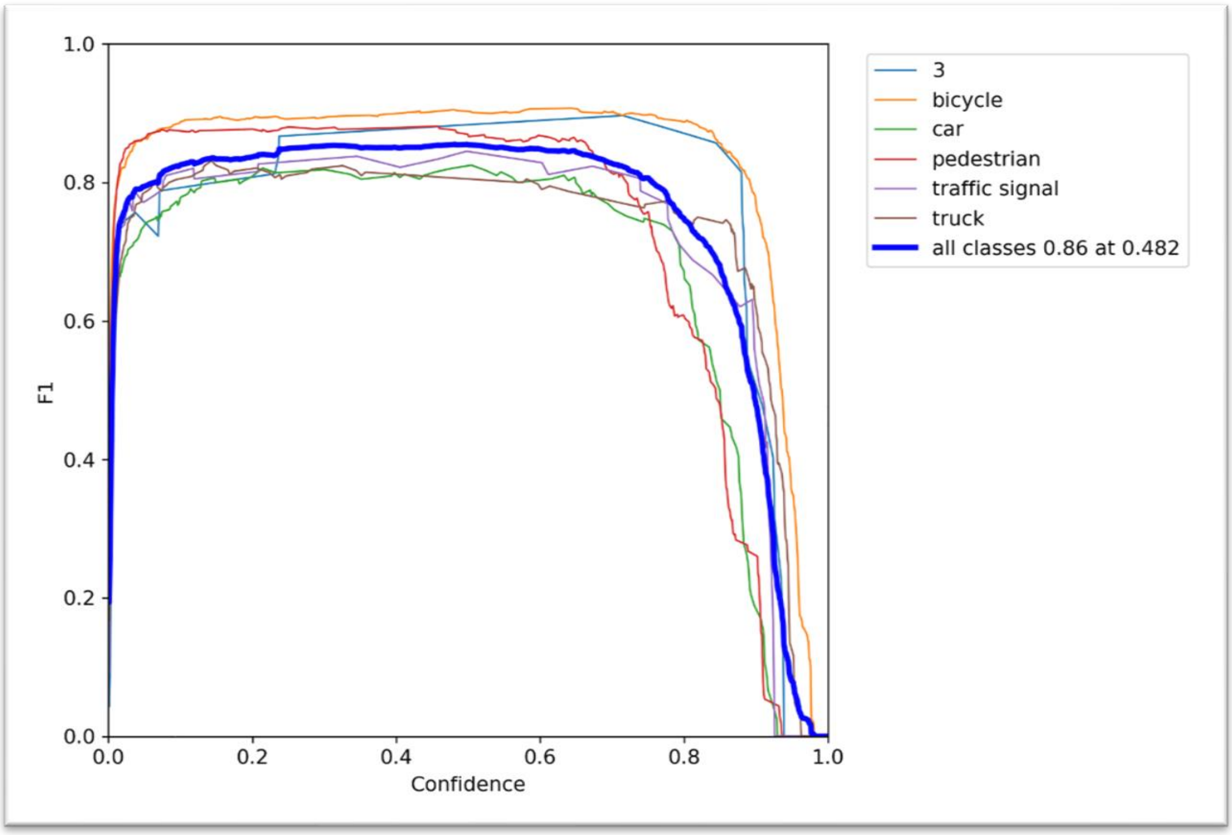
```
# zip to download weights and results locally
!zip -r export.zip runs/detect
!zip -r export.zip runs/train/exp/weights/best.pt
!zip export.zip runs/train/exp/*
```

4.3 Result Analysis

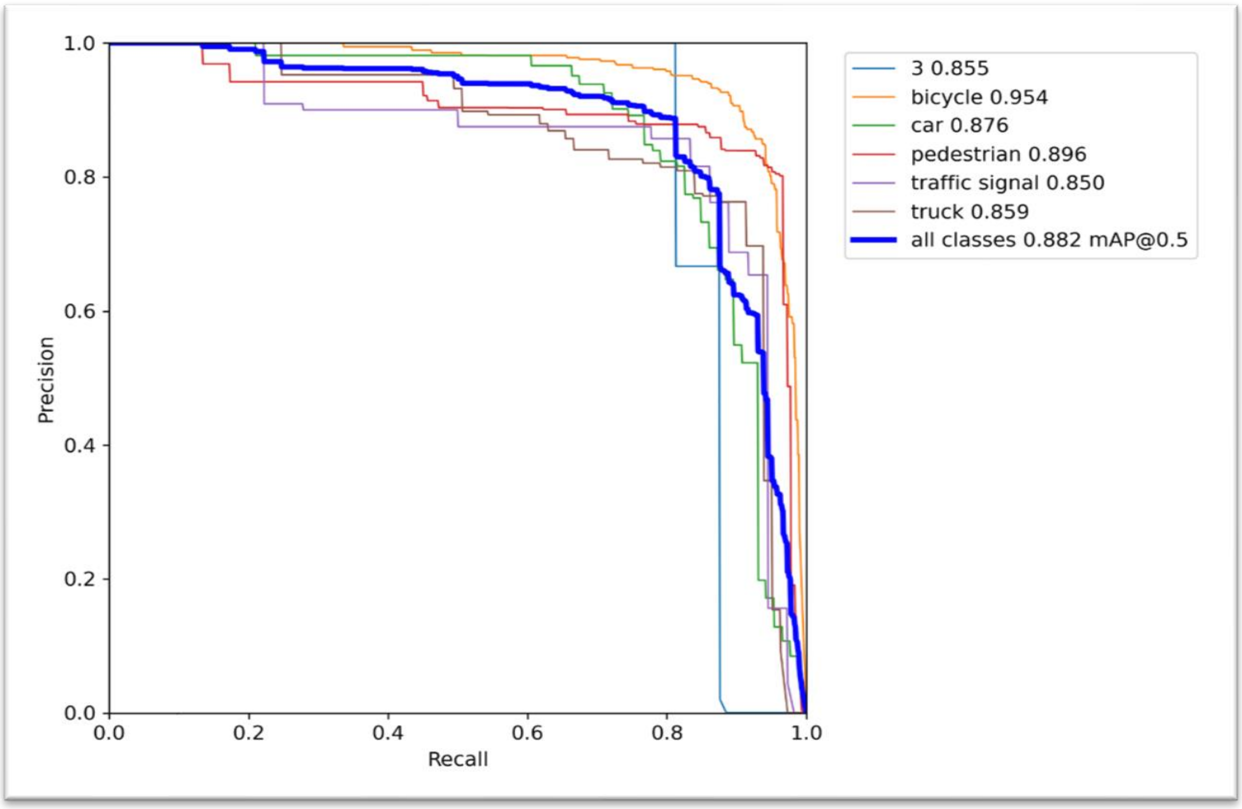
On the Custom dataset, YOLOv7 achieved a mean average precision (mAP) of 90.1% at real-time speeds (25 frames per second), precision at 82.0% , and Recall at 89.12%.



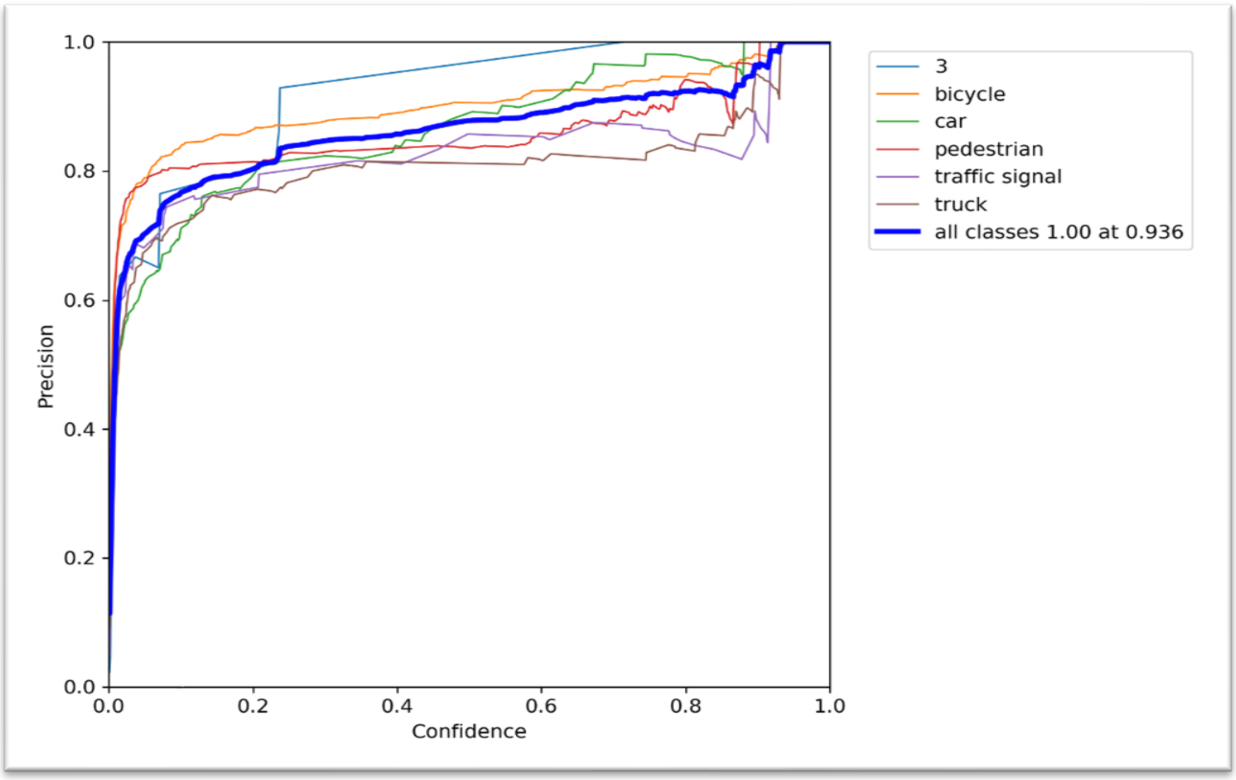
F1 Curve



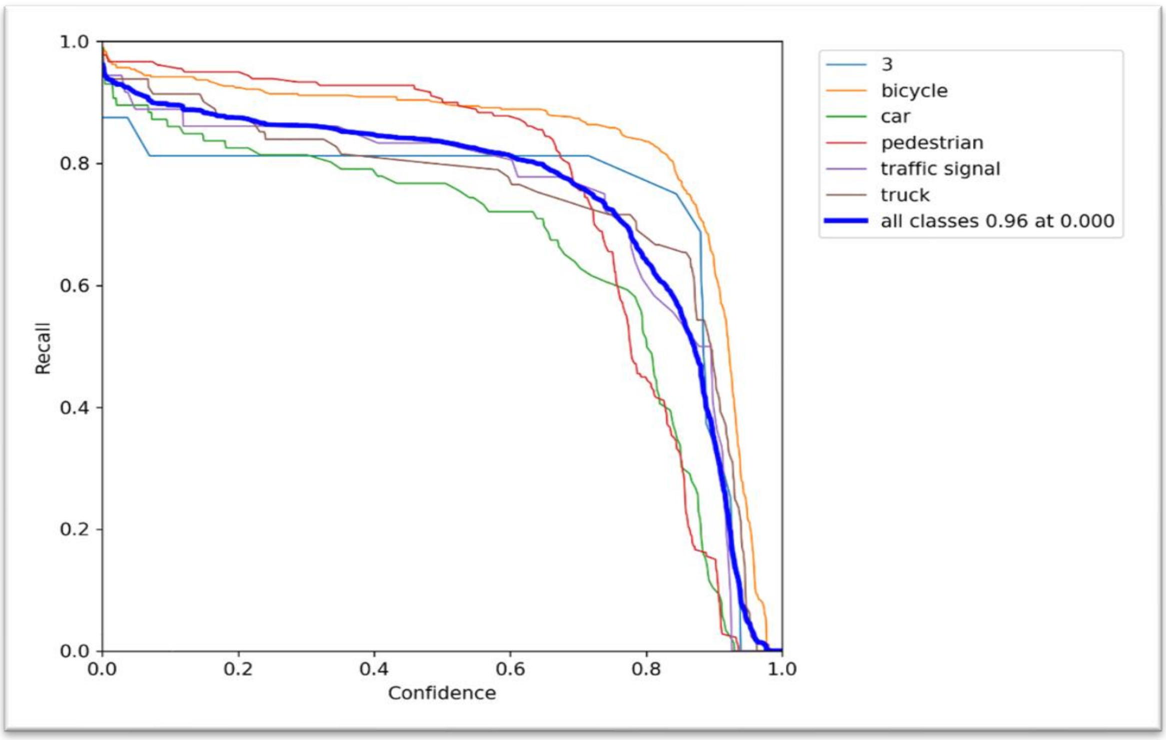
Precision - Recall Curve



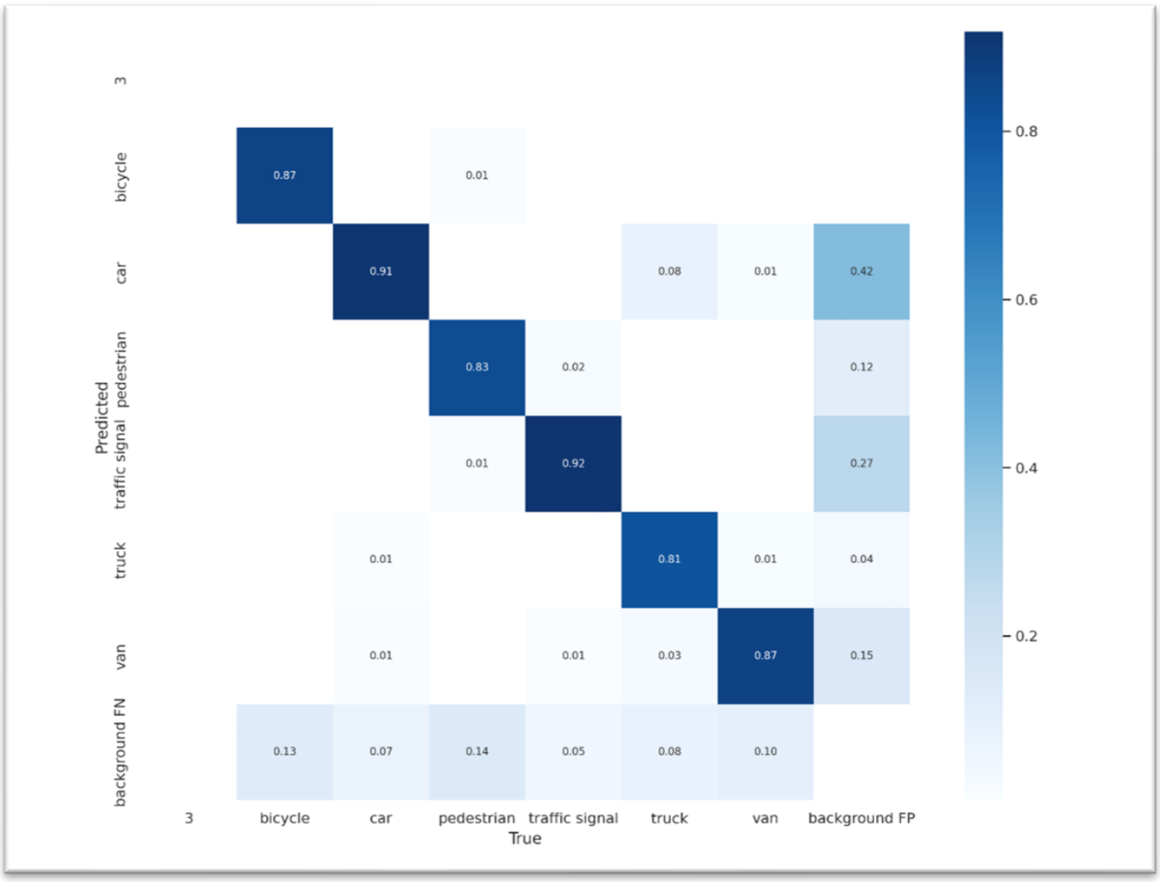
Precision Curve



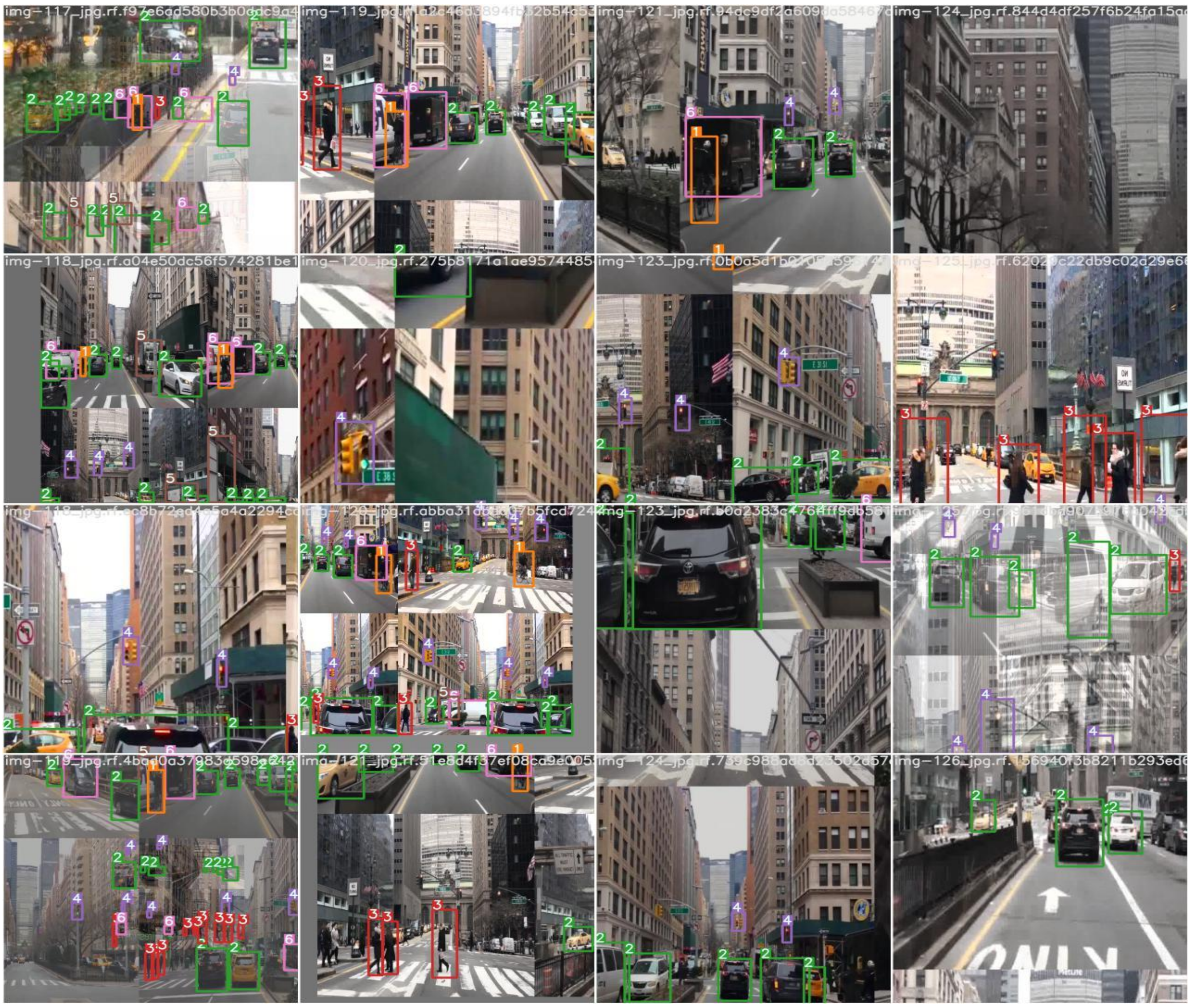
Recall Curve

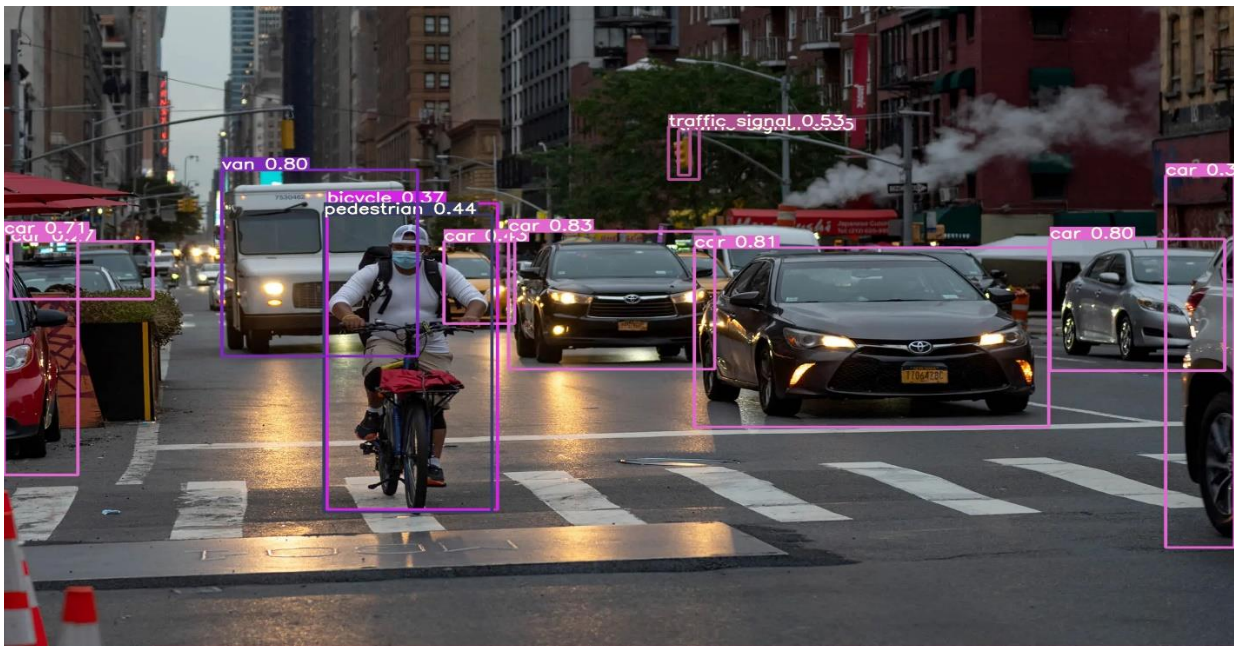


Confusion Matrix



Inference photos:-





Chapter 5

CONCLUSION AND FUTURE SCOPES

5.1 Conclusion

In conclusion, the implementation of traffic video analytics using YOLOv7 to classify vehicles and pedestrians is a promising technology that has the potential to enhance traffic management and public safety. YOLOv7 is an advanced object detection algorithm that is able to detect and classify multiple objects in real-time, which makes it an ideal tool for traffic video analytics.

The project aims to improve traffic flow by monitoring the movement of vehicles and pedestrians. By classifying different types of vehicles and pedestrians, the system can identify potential traffic congestion areas and take proactive measures to prevent accidents and minimize traffic disruptions.

Overall, the project has demonstrated the effectiveness of using YOLOv7 for traffic video analytics. The system is able to accurately detect and classify objects in real-time, which can help authorities make informed decisions about traffic management. However, like any technology, there is always room for improvement. Future work could include refining the algorithm to improve its accuracy and incorporating other data sources, such as weather and traffic data, to further optimize traffic flow.

5.2 Future Scopes

There are several potential future scopes for the traffic video analytics project using YOLOv7 to classify vehicles and pedestrians. Some of these future scopes are:

1. **Integration with Traffic Management Systems**: The project could be integrated with existing traffic management systems to improve

their functionality. This integration could enable the system to provide real-time updates to traffic management personnel, which could help them take proactive measures to prevent congestion and accidents.

2. **Incorporation of Vehicle Speed Data:** By incorporating vehicle speed data into the system, it could identify potential speed violations and help authorities take appropriate measures to prevent accidents.
3. **Improved Object Detection Accuracy**: Although YOLOv7 is already accurate in detecting objects, future work could focus on improving its accuracy further. This could include exploring different algorithms or incorporating new techniques, such as machine learning, to refine the detection accuracy.
4. **Detection of Other Types of Objects:** The system could be expanded to detect other types of objects, such as bicycles or motorcycles, which could further improve traffic safety.
5. **Integration with Smart City Infrastructure**: As cities become more connected, the project could be integrated with other smart city infrastructure, such as traffic signals and road sensors, to further optimize traffic flow.

Overall, the future scopes for the traffic video analytics project are numerous, and continued research and development could lead to significant improvements in traffic safety and management.

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