

# VEHICLE DETECTION USING A DEEP LEARNING METHOD

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This Thesis report has been submitted in fulfillment of the requirements for the Degree of Bachelor of Science in Software Engineering

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## **APPROVAL**

This thesis titled on "VEHICLE DETECTION USING A DEEP LEARNING METHOD", submitted by Rifat Abdullah (ID: 191-35-2730) to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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# THESIS DECLARATION

I announce hereby that I am rendering this study document under Md. Rittique Alam, Lecturer, Department of Software Engineering, Daffodil International University. I therefore state that this work or any portion of it was not proposed here therefore for Bachelor's degree or any graduation.

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I would wish to thank Mr. Md. Rittique Alam, a lecturer in the Daffodil International University department of software engineering who served as my honorary supervisor, for his appropriate guidance, assistance, support, and collaboration. someone without whom I couldn't have done my thesis. His unwavering patience, intellectual leadership, relentless encouragement, constant and forceful supervision, constructive criticism, astute advice, reading multiple poor versions, and improving them at every level made this endeavor possible.

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Finally, I want to thank my parents for always being there for me. They continually offer my suggestions and motivation top importance.

Rifat Abdullah

#### ABSTRACT

The use of deep learning-based object detection methods in computer vision is covered in this thesis. The primary objective is the real-time detection and identification of various types of vehicles found in Bangladesh.In the present One of the key prerequisites for monitoring and applications like traffic autonomous vehicles is vehicle detection.Bangladesh presents extra difficulties because to the unpredictable traffic, the wide variety of vehicles, and the dearth of a robust dataset. On the "Vehicle Detection System Dataset, "various neural networks were trained utilizing YOLOV5, YOLOV6, and YOLOV7 for the Detection. The model was trained using Google Colaboratory, a cloudbased platform, using YOLOV5, YOLOV6, and YOLOV7. Written with Python 3.10.4, the codes. The dataset for training was organized using Roboflow, an online-based computer vision technology. Using a smartphone camera, data was collected. The model with the most effective performance and the most promising results was YOLOV7. YOLOV7 has an extremely remarkable recall rate and precision. which is sufficient to find vehicles. In comparison to the other two models, it was also able to detect vehicles with greater accuracy. This study has a lot of potential and can be seen as a development for autonomous vehicles and smart traffic systems in Bangladesh.

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# **CHAPTER 1**

# INTRODUCTION

#### **1.1 BACKGROUND**

As the population and transportation network both grow daily, so does the need for management of both. The planet is rapidly becoming populous. As a result, the number of machinery of all kinds, including automobiles, increased concurrently. In light of this, it is necessary to manage new subjects like traffic, accidents, and numerous other problems. New trends and technologies have been discovered and created to handle each and every milestone that humankind is aiming to attain because managing them using the outdated approaches is difficult. Highway and city traffic is one of these difficulties. To deal with this phenomenon, numerous options such as traffic lights, signs, etc. have been implemented. These choices alone seem to be insufficient or ineffective. A decision-making process can use data produced by automated camera surveillance to generate new technologies like object detection. With the ability to recognize and classify vehicles, we can enhance how traffic moves along roadways, prevent accidents, and keep track of traffic infractions and crimes.

Vehicles may be easily identified by humans in pictures or movies, as well as in different vehicle types. The sorts of data that are used in computer algorithms and programs have a significant impact. The weather and light have a significant impact in determining how easy or difficult a task is. We currently have a variety of vehicle kinds and shapes. In addition, a new challenge may be to recognize moving objects in a video that are diverse in size and shape in real time.

Vehicle detection and classification use a variety of approaches and procedures.Deep learning method is also among of them.In Bangladesh,there are different types of vehicles like Bus,Cars,Bike,Cng Auto-rickshaw,Heavy vehicles,Emergency vehicles and others.Also,there are a huge traffic problem in Bangladesh.Using Deep learning method it is very easy to detect different vehicles also this can be use in automatic traffic detection and autonomous driving vehicles that is a big need for our country.

Vehicle Name	Туре	Class Name
Bike	Image	Bike
Bus	Image	Bus
Car	Image	Car
Ambulance,police Car	Image	Emergency Vehicle
Truck,Pickup,Tanker	Image	Heavy Transport
Leguna	Image	Public Transport
Rickshaw	Image	Rickshaw
Cng Auto-rickshaw	Image	cng

Table 1: STANDARD CLASSIFICATION OF VEHICLES AND CLASSES

In my work, I utilize a classified dataset. I tried to identify the automobiles from the photo data using three different sorts of models. In order to count the vehicles from the images, I had to find them.

#### **1.2 MOTIVATION OF THE RESEARCH**

Now a days, most of the countries around the world uses automatic traffic system for reducing traffic jam and other problems. The human trafficking system is quite old and not suitable in this modern era. Also when it is human based system, it can suffer a lot sometimes. But when the traffic system will be fully autometic then there are not any chance for suffering. The vehicle drivers of our country aren't much concern about the traffic law. If The total traffic system can be automated it will be a great help for all the drivers. Also, Autonomous vehicle is a good invention of human being. In here the vehicle don't need any human driver for drive it. It drives itself by detecting vehicles of its nearby. Also in Bangladesh many traffic related crimes happening here. They ought to be resolved quickly. Otherwise, the number of accidents and fatalities won't go down. On the other hand, we observe that numerous foreign nations have already made significant progress on these. However, there isn't much research or effort being done on it in our country.

Other nations use their own data to complete their work. In our nation, there are no such data. We should use our own data, which is why we wish to do it. It takes a lot of effort and money to detect vehicles. It is being developed in various areas of other nations. Whereas nothing has occurred in our nation, they are spotting this issue very early and in less time. We

need to think about acquiring information through taking inspiration from them, and it was very challenging for us. As a result, a technique was created to make it simpler for the traffic to detect automobiles. Thus, the study's objective is to develop a low-cost system that will enable our country to achieve the best results possible in accordance with the available data.

## **1.3 PROBLEM STATEMENT**

Recently, the research sector has been more interested in object detection. Vehicle detection has already received a lot of attention. Many of the authors of the study make use of many types of algorithms, such as Deep Convolutional Neural Networks, CNN, R-CNN, embedded systems, and many others. Modern techniques are also used in some schemes. There are a few techniques for detecting vehicles. To categorize the many types of autos, they employed SVM, Random Forest, decision trees, and numerous other classification approaches. To obtain an acceptable degree of accuracy, researchers are attempting to investigate the subject. Object detection is done via deep learning. They collected the data using a number of systems. Some used customized datasets, while others used widely available worldwide data. In other nations, people use their own data for their automobiles' operations. However, Bangladesh's environment and circumstances are totally unique compared to those of other nations. Therefore, the study has application to their own country. There are numerous methods for doing this task, however in order to choose the best model from the offered models, this thesis will examine the problem of object detection while evaluating three different methods and recommending the one that provides the best accuracy and performance.There are Eight classes in our dataset.They are:Bike,Bus,Car,Emergency Vehicle,Heavy Transport,Public Transport,Rickshaw and cng.

## **1.4 RESEARCH OBJECTIVE**

The main objective of my paper is to locate various autos at a reasonable cost from various areas. To make our concept more applicable, we also worked toward a better result. In support of our argument. We contend:

- Creating a computerized system.
- For creating a low-cost system that a developing country like Bangladesh might manage.
- More Accurate for autonomous driving.
- Can be install on any traffic management system.

## **1.5 RESEARCH SCOPE**

#### The following are the primary research areas:

- In order to collect data, a technique based on the many vehicle types in Bangladesh needs to be developed that can recognize cars, bikes, buses, rickshaws, CNGs, heavy vehicles, public transportation, and emergency vehicles from photos.
- Will swiftly recognize various vehicle kinds and will be advantageous for Bangladesh's traffic system. The Bangladeshi Road Traffic System will see a significant improvement as a result. As a result, accident rate will be decreased with the effective traffic management.
- How many automobiles are on the road and how many are damaging the air can both be easily determined.
- This system will be very helpful to the traffic police. It will significantly lessen their suffering because they will be able to identify any criminal or excessively fast car and immediately file cases.
- We will attempt to create an alarm system so that the message reaches the driver who is driving too quickly.
- This technique makes it very simple to identify any car, which will be beneficial for traffic management.

## **1.6 THESIS ORGANIZATION**

The first chapter of the study goes into great detail on the vehicle detection system and its use, as well as the background of the study, the justification for the research, the issue description, the research questions, and the research aim. The further elements of our study are listed below.

In the second chapter, I'll discuss the review of the literature, which enables us to see past research on vehicle detection, the methodology used, any gaps, and a comparison of my work and that of other researchers depending on how we both interpret their findings.

The third chapter will go over our research methods. The methodology component of my study will go into data collecting, data preprocessing, and work analysis. The approaches' workings are also discussed.

The methodology's results and all other forms of result accuracy numerous scores will be covered in chapter 4. We can readily comprehend this document for the sake of this debate, including all accuracy and vehicle detection data.

The conclusion is found in the last chapter. I'll give my conclusion right here, along with a thorough account of everything I've done. I've discussed the work I'll do moving ahead to enhance the work here.

# CHAPTER 2 LITERATURE REVIEW

#### **2.1 INTRODUCTION**

A researcher looks at earlier work, research, conference papers, books, journals, etc. in a literature study. With the help of this data, one may find out what research has already been conducted on the problem, summarize it, and pinpoint any gaps in the knowledge. After investigation, they may concentrate on restrictions and discover workarounds to acquire better outcomes.

# **2.2 PREVIOUS LITERATURE**

Vehicle detection is a concept that emerged mostly as a result of the high number of fatalities in traffic accidents and the daily rise in vehicle-related crimes. Driving is not recommended on many of Bangladesh's roads. Additionally, the traffic laws are not well known by drivers and other road users. Numerous researchers began their work on it. I had excellent outcomes from doing this. Again, many of them were unable to reach their principal objective effectively. Using a variety of models, numerous researchers have conducted detection classification. I want to complete my work to more accurately identify and classify while also attempting to do it at a reasonable cost. This work has undergone many reviews of related papers.

Ke Li,Rongchun Deng,Yongkang Cheng,Rongqun Hu,Keyong Shen [1] Worked on vehicle detection and classification. To find vehicles, they extract features from infrared images. Here, machine learning is used for vehicle detection and classification. They get their data using infrared CCD. However, they are not accurate enough to detect automobiles.

Raad Ahmed Hadi,Ghazali Sulong and Loay Edwar George [2] worked on vehicle detection and tracking.They use Background Subtraction Methods,Feature Based Methods and Frame Differencing and Motion Based methods for detecting and tracking.They also ©Daffodil International University use many techniques and algorithm to detect and track any vehicle more accurately.But the outcome of their study is much good to detech and track vehicle.

Anik Datta,Tamara Islam Meghla,Tania Khatun,Mehedi Hasan Bhuiya,Shakilur Rahman Shuvo,Md. Mahfujur Rahman [3] worked on Road Object Detection in Bangladesh using Faster R-CNN.In here they use deep learning and machine learning both model.But sometimes their model mistakenly detected wrong vehicle.To reduce this they use very high performance machine and GPU which are quite expensive.Also The model accuracy and detection rate are not very impressive.

Wencan Mao [4] worked on vision based vehicle detection. He publish his paper on 2021. In his research he worked on Intelligent Transportation System, Computer Vision, YOLO neural network and others. His model is very much fast. But it is not much accurate compare to its speed. His research limitation is the collected must have to be very quality full it is not low cost.

Sriashika Addala [5] worked for vehicle detection and recognition. In 2020 she published this research paper. She use HAAR, AdaBoost and these type of techniques for detecting the vehicle. She also use Gabor's waveslet for detecting vehicles. But, this system can be used only in private area and not in road. Also the precision and the recall rate are very impressive for this model.

# CHAPTER 3 RESEARCH METHODOLOGY

## 3.1 RESEARCH METHODOLOGY

We used YOLOv5,YOLOv6 and YOLOv7 on a dataset that was taken from our own dataset.

# **3.2 DATA COLLECTION**

The gathering of data is the first step in every research effort. Therefore, we carefully gathered all of the data.Data collection has several uses, including corporate and academic research by some governments and businesses.

My information primarily relates to various types of vehicles.So,i went to many places inside Dhaka city and there are also some data which is collected from outside of Dhaka.So that,the detection result can be more accurate.

All the images of this collection are captured from smartphone camera. Which picture quality was good for detection system. Some data were collect in low light in night, some data were collected in the evening , some collected from a running vehicle and so on. There are Eight types of data in our dataset. We think these data will be a good choice for us for training and detecting vehicle.



Figure 1: All the type of vehicle sample pictures.

# **3.3 DATA PREPROCESSING**

Data preparation is a crucial step in the process of converting the data into a format that can be used. Data preparation is a step in data mining. I have gathered information from numerous locations in Bangladesh. There are 700 photos of various sorts of automobiles in the dataset. This data has additional annotations. I use Roboflow platform for lebeling. This file accurately describes the labels on the objects in the corresponding image. The files with annotations were exported in YOLO format.

We are choosing eight classes for annotation. Those classes are cars, bikes, buses, rickshaws, cng, heavy vehicles, public transportation, and emergency vehicles. We sorted those photos into 3 folders after preprocessing and data collection. To prepare the data for training, validation, and testing. I divided it into 3 sets. 70% of the data are in the training dataset, 20% are in the validation set, and 10% are in the testing set. The train folder contains 490 photos, the validation folder 140 images, and the test folder 70 images after the dataset has been divided.

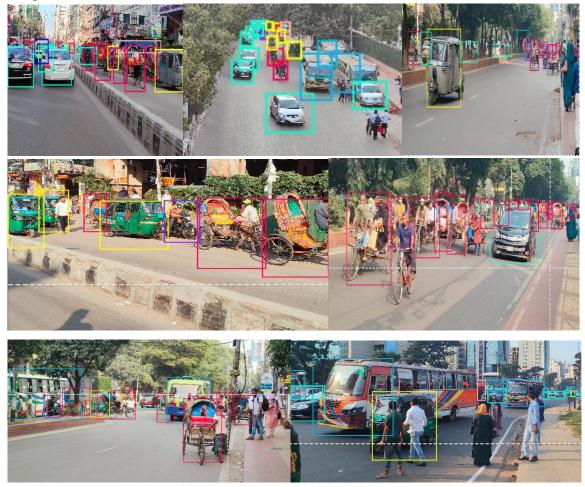


Figure 2: Type dataset sample

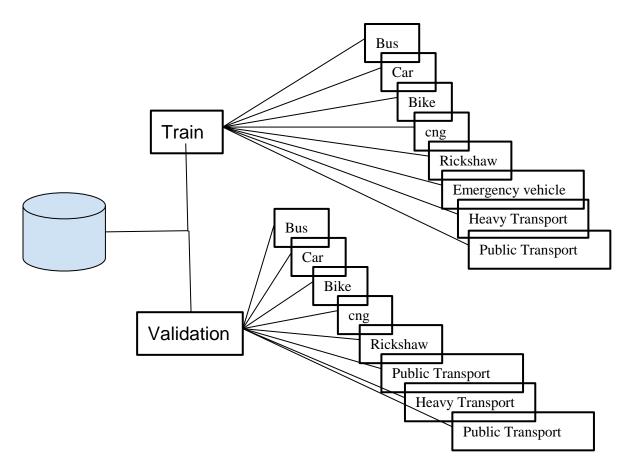


Figure 3 : Dataset Labeling

#### 3.4 YOLOv5

Joseph Redmon first proposed YOLO (You Only Look Once) as a model for object detection issues in 2015. The term was derived from the fact that the network was single-shot, meaning that bounding box and class predictions were obtained by inferring only once via the network.

The You Only Look Once (YOLO) family of computer vision models includes the model known as YOLOv5. YOLOv5 is frequently employed for object detection. YOLOv5 is available in several variations.Offering increasingly greater accuracy rates with each variation. A variable amount of time is required to train for each type.

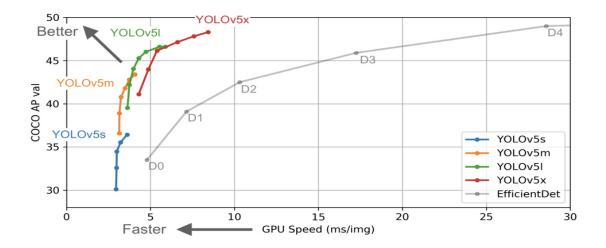


Figure 4 : Variations of YOLOv5

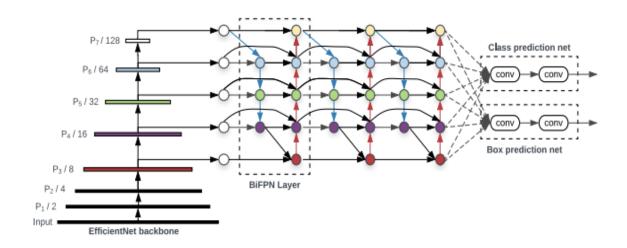


Figure 5 : Architecture of YOLOv5

In YOLOv5 the detection accuracy and the precision,recall rate are good.In 2020, a company called Ultralytics published YOLOv5. Glenn Jocher, the founder and CEO of Ultralytics, placed it in a GitHub repository, and it quickly gained popularity after that.

# 3.5 YOLOv6

YOLOv6 (also known as MT-YOLOv6) is a single-stage object detection model based on the YOLO architecture. The YOLOv6 model was developed by researchers at Meituan. YOLOv6 achieves stronger performance than YOLOv5 when benchmarked against the MS COCO dataset.

YOLOv6 models take an input image and pass it through a series of convolutional layers in the backbone. YOLO models then feed those backbone features through the neck. YOLO models then pass the neck features through to three heads, where the predict objectness, class, and box regression.

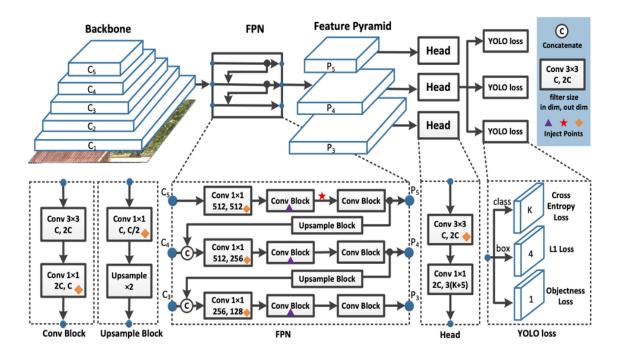


Figure 6 : Architecture of YOLOv6

The YOLO backbone and neck are redesigned in YOLOv6 to take advantage of the hardware. The model introduces an EfficientRep Backbone and a Rep-PAN Neck, according to the authors. The classification and box regression heads in YOLO models up to and including YOLOv5 share the same attributes.

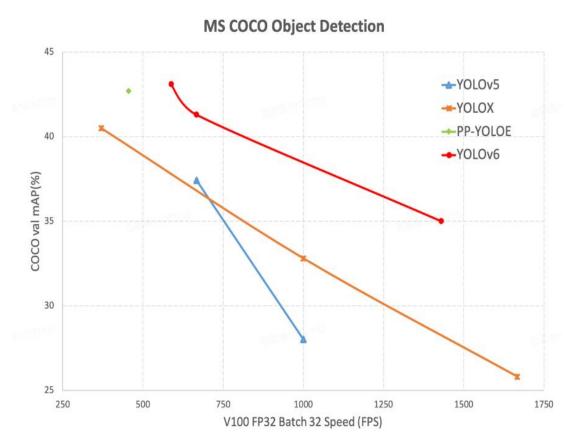
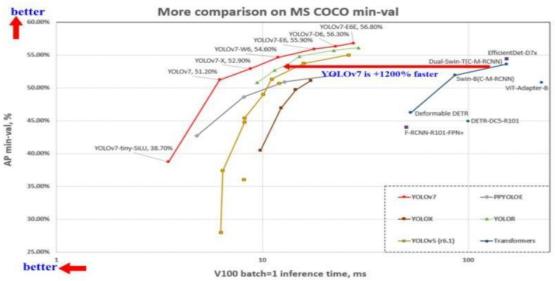


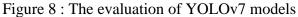
Figure 7 : The comparison between YOLOv5 and YOLOv6

#### 3.6 YOLOv7

In 2016, the YOLO model was first made available. The new YOLO model is 10 times faster than the older variants. Version 7 of YOLO is the most recent release. It is significantly faster than the previous models, and its batch average duration is less than before. Its batch frame rate is also significantly higher.

The official YOLOv7 article, titled "YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors," was published in July 2022 by Chien-Yao Wang, Alexey Bochkovskiy, and Hong-Yuan Mark Liao. The official YOLOv7 GitHub repository is where we can readily find YOLOv7. In the upper left, YOLOv7 evaluates faster and more accurately than it does according to the network diagram, YOLOv7 network architecture diagram, and flowchart for YOLO training.





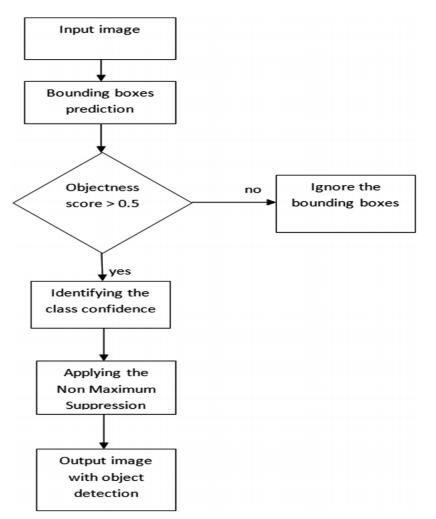


Figure 9 : The training flowchart for YOLO

#### **3.7 Evaluation Methods**

I plotted the confusion matrix to evaluate the results. Evaluation requires both true positive and negative results as well as false positive and false negative values. This is a real plus because the actual amount was as predicted. Correct rejection of true-negative values where the value is actually a false positive when expected to be positive False-negative is wrongfully disregarded.

#### 3.7.1 Accuracy

The accuracy of the model determines how well a computer can predict outcomes. Something is significant when each class is equally important. For me, every course is equally important to my work. In order to assess the model's accuracy, accuracy is essential. For binary classification, accuracy can also be assessed in terms of positives and negatives, as shown below:

$$Accuracy = rac{TP + TN}{TP + TN + FP + FN}$$

Where TP = "True Positives", TN = "True Negatives", FP = "False Positives", and FN = "True Negatives,".

#### 3.7.2 Precision

The number of predictions from the positive class that really fall under it is measured by precision. The genuine positive value is subtracted from the total positive value to compute precision.

Following is a definition of precision:

$$Precision = \frac{TP}{TP + FP}$$

Where TP = "True Positives", and FP = "False Positives".

#### 3.7.3 Recall

A measurement for determining the precise real positive identification is recall. The recall is calculated by dividing the true positive value by the total number of pertinent documents that are currently in existence.

The definition of recall is as follows:

$$ext{Recall} = rac{TP}{TP + FN}$$

Where TP = "True Positives", and FP = "False Negatives".

#### 3.7.4 F1 Score

The F1 Score is calculated by combining precision and recall. Therefore, this score takes into account both false positives and false negatives. Despite being less intuitively straightforward to understand, F1 is frequently more advantageous than accuracy, especially if you have an unequal class distribution. For accuracy to work optimally, false positives and false negatives should approximately cost the same. If the costs of false positives and false negatives differ significantly, it is desirable to take into account both Precision and Recall.

The definition of an F1 score is as follows:

$$F_1 = 2 * \frac{precision * recall}{precision + recall}$$

I've showed the mAP and model correctness for models using the YOLOv7 approach. Both training accuracy and validation accuracy are used when calculating model accuracy using mAP.

#### 3.7.5 Mean Average Precision (mAP)

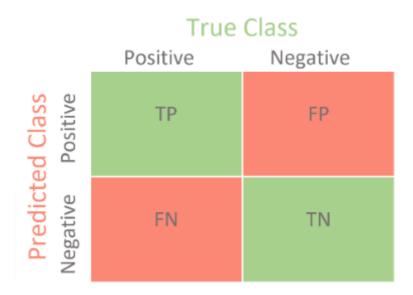
The YOLO object detection models are evaluated using the mean average precision (mAP). By comparing the detected box to the ground-truth bounding box, the mAP determines a score. The more points, the more trustworthy the model's detections are. The mean values of the average accuracy (AP) are calculated over recall levels ranging from 0 to 1.

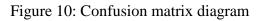
The mAP formula is made up of the following sub-metrics:

- Confusion Matrix,
- Intersection over Union (IoU),
- Recall,
- Precision

#### 3.7.5.1 Confusion Matrix

To evaluate a classifier's performance, it is much better to look at the confusion matrix. The major objective is to ascertain the frequency with which examples of class A are classified as class B examples. To create a confusion matrix, we require the following four characteristics:





- True Positives (TP): Matches when both the label and the ground truth were correctly predicted by the model.
- True Negatives (TN): The label is not predicted by the model, and it is not based on the truth.
- False Positives (FP): when a model predicts a label but the label isn't actually present in the data (Type I Error).
- False Negatives (FN): are labels that are accurate in reality but which the model does not predict ( Error type II).

#### 3.7.5.2 Intersection over Union (IoU)

The phrase "Intersection over Union" calculates how much of two boxes overlap (IoU). IoU evaluates the overlap between the Ground Truth and Prediction areas in the context of object segmentation and identification.

You've undoubtedly heard it a lot if you work in computer vision or are just interested in it. It acts as the first evaluation to see if a model is reliable. It's a statistic that allows us to evaluate how accurate a forecast is, to put it simply.

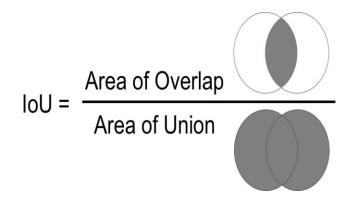


Figure 11: Intersection over Union diagram

# **CHAPTER 4**

## **RESULTS AND DISCUSSION**

#### **4.1 INTRODUCTION**

The techniques and models for detecting various vehicles. I described the models I used for the detection strategy after the data collection and preparation phase. I utilize three different models and contrast their results. There, the results of the models I employed will be discussed.

#### 4.2 **RESULT DISCUSSION**

Following model implementation, our dataset yields a large number of outcomes. To detect vehicles, we used YOLOv5, YOLOv6, and YOLOv7. We find several weights for our dataset, F1 score, Precision, Recall, and mAP value for various models. We also discover the loss plotting graph for the model. Training and validation accuracy are compared to produce a graph displaying the accuracy and loss of each model.

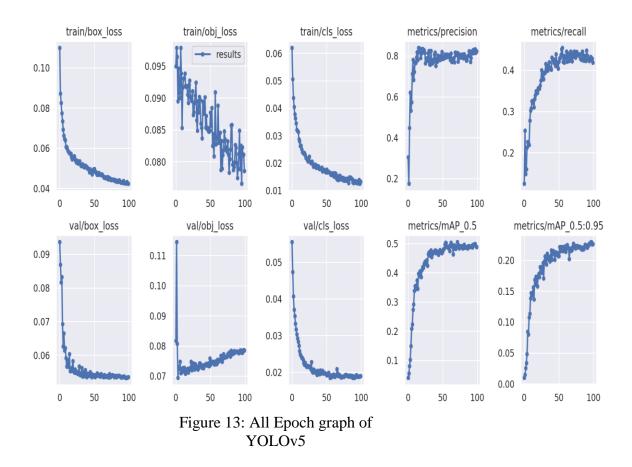
#### 4.2.1 YOLOv5

According to the YOLOv5 output, a total of 100 epochs were performed on 490 pieces of data, 8 of which were classified into classes. There were 138 photographs distributed to each class. The accuracy, recall, and map values sum up to 83%, 43%, and 50% of all classes when we look at the complete output, respectively. It's not what you would anticipate getting for that sum. If we compute based on the different classifications, we can see that there is a sizable variation in the data. With an accuracy value of 88%, a recall value of 67%, and a map value of 77%, the Bus class has the most data.Having a precision value of 64.5%, a recall value of 41%, and a map value of 44.5%, it has the least quantity of data is for the Heavy Transport class. As a result, it is obvious how much both less and more data have affected the output. If the data is bigger or smaller, we can't get amazing precision. For the best results, we will thus use the alternative model.

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Epoch 118/119	gpu_mem 11.4G Class all	box 0.03147 Images 138	obj 0.02624 0.005 Labels 2055	cls total 237 0.06295 P 0.754	labels 68 R 0.564	img_size 640: mAP@.5 0.577	: 100% 31/31 [00:38<00:00, 1.23s/it] mAP@.5:.95: 100% 5/5 [00:03<00:00, 1.33it/s] 0.266
Epoch	gpu_mem	box	obj	cls total	Tapels	img_size	
119/119	11.4G	0.03199	0.02669 0.005	778 0.06445	80	640:	: 100% 31/31 [00:35<00:00, 1.15s/it]
	Class	Images	Labels	Р	R	mAP@.5	mAP@.5:.95: 100% 5/5 [00:06<00:00, 1.32s/it]
	all	138	2055	0.766	0.55	0.569	0.264
	Bike	138	280	0.772	0.618	0.673	0.29
	Bus	138	252	0.825	0.784	0.807	0.429
	Car	138	618	0.73	0.667	0.692	0.295
Emergency	/ vehicle	138	26	0.673	0.423	0.482	0.223
Heavy 1	ransport	138	70	0.673	0.528	0.553	0.269
Public t	ransport	138		1	0	0.00175	0.000721
	Rickshaw	138	554	0.696	0.682	0.66	0.296
	cng	138	250	0.761	0.7	0.685	0.306
120 epochs o	completed	in 1.455 hou	irs.				

Figure 12: Mapping of YOLOv5



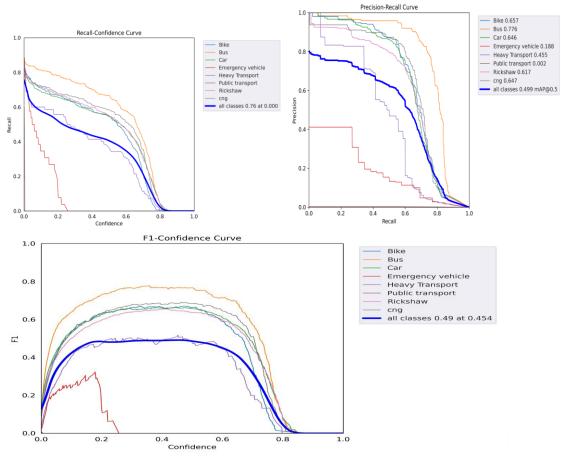


Figure 14: Precision, Recall, Pricision-Recall and F1 graph of YOLOv5

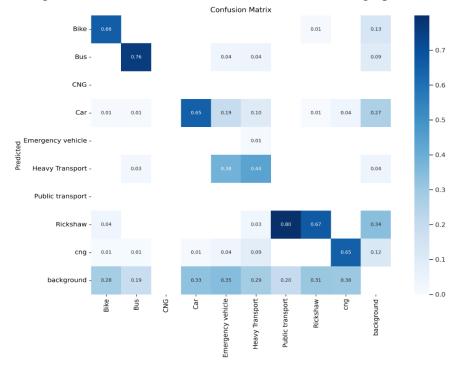


Figure 15: Confusion Matrix of YOLOv5



Figure 16: Output of YOLOv5

## 4.2.2 YOLOv6

According to the YOLOv6 output, a total of 100 epochs were performed on 490 pieces of data, 8 of which were classified into classes. There were 138 photographs distributed to each class. With an accuracy value of 14%, a recall value of 24%, and a map value of 50%, the Bus class has the most data. Having a precision value of 2%, a recall value of 8%, and a map value of 44.5%, it has the least quantity of data is for the Heavy Transport class. As a result, it is obvious how much both less and more data have affected the output. If the data is bigger or smaller, we can't get amazing precision. So we can see the accuracy of this model is very low from the previous model. Also the recall and the map values are very low. But in this model we can see this model is more faster than the previous YOLOv5 model. But, after all we need the accuracy from the model. So, we can see this model is not accurate for detection type system through the model is very fast. But the accuracy is very low to count. And it can not detect vehicles correctly. So, for the best results, we will thus use the alternative model.

```
Epoch iou_loss dfl_loss cls_loss
         99/99
                        0.8664
                                                                1.081: 100% 15/15 [00:10<00:00, 1.37it/s]
                                                       0
Inferencing model in train datasets.: 100% 3/3 [00:09<00:00, 3.32s/it]
Evaluating speed.
Evaluating mAP by pycocotools.
Saving runs/train/exp/predictions.json...
loading annotations into memory ...
Done (t=0.01s)
creating index.
index created!
Loading and preparing results...
DONE (t=0.42s)
creating index...
index created!
Running per image evaluation ...
Evaluate annotation type *bbox*
DONE (t=4.80s).
Accumulating evaluation results...
DONE (t=0.39s).

      Average Precision
      (AP) @[ IoU=0.50:0.95 | area= all | maxDets=100 ] = 0.053

      Average Precision
      (AP) @[ IoU=0.50 | area= all | maxDets=100 ] = 0.147

      Average Precision
      (AP) @[ IoU=0.75 | area= all | maxDets=100 ] = 0.020

      Average Precision
      (AP) @[ IoU=0.50:0.95 | area= all | maxDets=100 ] = 0.020

      Average Precision
      (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.015

      Average Precision
      (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.064

      Average Precision
      (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.064

      Average Recall
      (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.097

      Average Recall
      (AR) @[ IoU=0.50:0.95 | area= all | maxDets= 1 ] = 0.046

      Average Recall
      (AR) @[ IoU=0.50:0.95 | area= all | maxDets= 10 ] = 0.137

      Average Recall
      (AR) @[ IoU=0.50:0.95 | area= all | maxDets=100 ] = 0.137

 Average Recall
                                     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.084
                                    (AR) @[ IOU=0.50:0.95 | area=medium | maxDets=100 ] = 0.222
(AR) @[ IOU=0.50:0.95 | area= large | maxDets=100 ] = 0.247
 Average Recall
 Average Recall
Results saved to runs/train/exp
Epoch: 99 | mAP@0.5: 0.14657100687448946 | mAP@0.50:0.95: 0.05317952252074942
Training completed in 0.711 hours.
```

```
Figure 17: Training of YOLOv6
```

```
Evaluating mAP by pycocotools.
Saving runs/val/exp/predictions.json...
loading annotations into memory...
Done (t=0.01s)
creating index...
index created!
Loading and preparing results ...
DONE (t=0.16s)
creating index...
index created!
Running per image evaluation ...
Evaluate annotation type *bbox*
DONE (t=3.21s).
Accumulating evaluation results...
DONE (t=0.38s).
Average Precision (AP) @[ IoU=0.50:0.95 | area= all | maxDets=100 ] = 0.053
Average Precision (AP) @[IoU=0.50 | area= all | maxDets=100 ] = 0.147
                                         | area= all | maxDets=100 ] = 0.020
Average Precision (AP) @[ IoU=0.75
                   (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.015
Average Precision
Average Precision (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.064
Average Precision (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.097
                   (AR) @[ IoU=0.50:0.95 | area= all | maxDets= 1 ] = 0.046
Average Recall
                                                   all | maxDets= 10 ] = 0.137
Average Recall
                   (AR) @[ IoU=0.50:0.95 | area=
                   (AR) @[ IOU=0.50:0.95 | area= all | maxDets=100 ] = 0.188
Average Recall
Average Recall
                   (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.083
                   (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.222
Average Recall
                   (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.248
Average Recall
Results saved to runs/val/exp
```

Figure 18: Precision-Recall of YOLOv6



Figure 19: Output of YOLOv6

## 4.2.3 YOLOv7

According to the Yolov7 output, a total of 120 epochs were performed on 490 pieces of data, 8 of which were classified into classes. There were 138 photographs distributed to each class. The accuracy, recall, and map values sum up to 78%, 55%, and 57% of all classes when we look at the complete output, respectively. It's not what you would anticipate getting for that sum. If we compute based on the different classifications, we can see that there is a sizable variation in the data. With an accuracy value of 83%, a recall value of 78%, and a map value of 80%, the Bus class has the most data. Having a precision value of 67.3%, a recall value of 42.8%, and a map value of 48%, it has the least quantity of data is for the Heavy Transport class. As a result, it is obvious how much both less and more data have affected the output. If the data is bigger or smaller, we can't get amazing precision. From this model we can see the accuracy rate, recall and map values are much higher than the previous YOLOv5 and YOLOv6 model.For that, this model can detect vehicles more accurately and more correctly.So,We can see this is the suitable model for detecting vehicle accurately and correctly.

Epo	ch GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size					
99/	99 4.66G	0.04229	0.07856	0.01317	78	640:	100% 31/31	[00:09<00	:00, 3.22it/s	5]	
	Class	Images	Instances	P	R	mAP50	mAP50-95:	100% 5/5	[00:01<00:00,	2.92it/s]	
	all	138	2055	0.822	0.418	0.488	0.226		-	-	
Optimizer	s completed in stripped from stripped from	runs/train	/exp/weight:								
	g runs/train/e	xp/weights/	ʻbest.pt								
Fusing la	yers										
Model sum	mary: 157 laye	rs, 7034398	} parameters	, 0 gradien	ts, 15.8 GF	LOPs					
	Class	Тладос	Instanzos	D	P	mADEQ	mADEQ_QE ·	100% 5/5	[00.05/00.00	1 10c/it1	

Class	Images	Instances	Р	R	mAP50	mAP50-95:	100% 5/5	[00:05<00:00,	1.10s/it]
all	138	2055	0.833	0.425	0.499	0.229			
Bike	138	280	0.807	0.564	0.657	0.268			
Bus	138	252	0.881	0.676	0.776	0.409			
Car	138	618	0.801	0.565	0.646	0.294			
Emergency vehicle	138	26	1	0	0.188	0.0734			
Heavy Transport	138	70	0.645	0.414	0.455	0.229			
Public transport	138	5	1	0	0.00247	0.000885			
Rickshaw	138	554	0.735	0.579	0.617	0.277			
cng	138	250	0.798	0.602	0.647	0.285			
Results saved to runs/tra	ain/exp								

#### Figure 20: Mapping of YOLOv7.



Figure 21: Output of YOLOv7.

# **CHAPTER 5**

# **CONCLUSION AND LIMITATIONS**

# 5.1 CONCLUSION

The data clearly shows that YOLOv7 object detection was successful in accurately classifying and localizing all item kinds, and that it is well suited for real-time processing. The proposed end-to-end architecture has all the components needed for deployment and automation for monitoring, and it was successfully developed. The edge point of the vehicle can be determined using a variety of techniques. Because they are entirely open source, the libraries and software used in our project are very adaptable and reasonably priced. The fundamental issue that plagued traffic management was its lack of effectiveness. We can infer from this that, if adopted by any traffic management body, it would make their work easier and more effective.

# **5.2 LIMITATIONS**

The work's outcome is not particularly good. It can be as a result of the image data's angle, which is based on Dhaka and other roadways. The amplification of all photos is another factor. Maybe paper accuracy would improve if we used augmentation photographs. I'll also make an effort to snap photos at the best angles possible to acquire a higher mAP. Along with this work, I'll also make an effort to determine each vehicle's flow individually and compare the mAP using various models. Additionally, I'll try to put it into practice as an automatic case-closing system to make it simple to catch sped-up drivers who break traffic laws.

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