INTELLIGENT TRAFFIC MANAGEMENT SYSTEM USING YOLO MACHINE LEARING MODEL

PHASE II REPORT

Submitted by

ANANDHAKUMAR.P	**(Reg. No. 17110009)**
ASHWIN.G	**(Reg. No. 17110013)**
AVINASH.V	**(Reg. No. 17110014)**
DINAKARAN.K. P	**(Reg. No. 17110027)**

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BONAFIDE CERTIFICATE

Certified that this Phase-II Project Report "**INTELLIGENT TRAFFIC MANAGEMENT SYSTEM USING YOLO MACHINE LEARING MODEL**" is the bonafide work of "**ASHWIN.G, ANANDHAKUMAR.P, AVINASH.V, DINAKARAN.K. P**" who carried out the project work under my supervision.

SUPERVISOR

Dr.B. Gomathi, Ph.D.,
Associate Professor,
Department of Information Technology,
Hindusthan College of Engineering and Technology,
Coimbatore – 641032.

HEAD OF THE DEPARTMENT

Dr.N. Rajkumar, Ph.D.,
Professor and Head,
Department of Information Technology,
Hindusthan College of Engineering and Technology,
Coimbatore – 641032.

Submitted for the Phase-II Project VIVA-VOCE exam conducted on ……

INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

We, hereby jointly declare that the project work entitled "**INTELLIGENT TRAFFIC MANAGEMENT SYSTEM USING YOLO MACHINE LEARING**" submitted to the Autonomous Institute, in partial fulfilment for the award of the degree of **BACHELOR OF TECHNOLOGY** in **INFORMATION TECHNOLOGY**, is report of the original project work done under the guidance of Dr GOMATHI B, Associate Professor, Department of Information Technology, Hindusthan College of Engineering and Technology, Coimbatore.

NAME	**SIGNATURE**
ASHWIN.G	……..
ANANDHAKUMAR.P	……..
AVINASH.V	……..
DINAKARAN.K.P	……..

Place : Coimbatore

Date :

ABSTRACT

People in today's era usually have the tendency of using their own private vehicles for commutation rather than using public transit and this result in large number of private vehicles on road. It leads to traffic congestion at every roads. In such scenario one cannot restrict individual to limit the usage of their private vehicles but we can able to manage traffic flow in a way that it doesn't alleviate congestion issues. The traditional traffic management approach works efficiently only if the traffic is less, but if the density of vehicles on a particular side of road increases on one side than other side, this approach fails. Hence, we aim to redesign the traffic signal system from static switching to dynamic signal switching, which can perform instant-time signal monitoring and handling. There are many projects emerging in order to convert the current transport system of cities to 'Smart system', by introducing Intelligent Transport System. Many initiatives are taken to design a system that can perform instant monitoring of traffic signals i.e., the traffic signal switching time will depend on the count of vehicles on each side of the road instead of predefined switching time. The switching time of signal will be decided based on vehicle detection in day-to-day traffic scenarios with good accuracy. This practice can prove its effectiveness in releasing the congested traffic at an efficient and faster rate.

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ABBREVIATION

YOLO	-	YouOnlyLookOnce Machine Learning Model
GMM	-	Gaussian Mixture Model
R-CNN	-	Region Based Convolutional Neural Network
F-RCNN	-	Fast Region Based Convolutional Neural Network
ML	-	Machine Learning
OpenCV	-	Open-source Computer Vision Library
CCTV	-	Closed-Circuit Television
ITS	-	Intelligent Traffic System
DPM	-	Deformable Part Models
CUDA	-	Compute Unified Device Architecture
cuDNN	-	CUDA Deep Neural Network library
IDD	-	India Driving Dataset
IoU	-	Intersection Over Union

CHAPTER 1

INTRODUCTION

1.1 TRAFFIC MANAGEMENT SYSTEM

The history of Traffic Management System started in 1972 to centrally control the freeway system in the Twin Cities metro area. The Traffic Management System aims to provide motorists with a faster, safer trip on metro area freeways by optimizing the use of available freeway capacity, efficiently managing incidents and special events, providing traveller information, and providing incentives for ride sharing. Cities and traffic have developed hand-in-hand since the earliest large human settlements. The same forces that draw inhabitants to congregate in large urban areas also lead to sometimes intolerable levels of traffic congestion on urban streets. Cities are the powerhouses of economic growth for any country. Transportation system provides the way for movements and medium for reaching destinations. Inadequate transportation system hampers economic activities and creates hindrances for development.

In most of the developing countries which are overburdened by rising population and extreme poverty, increasing economic activities and opportunities in the cities result in rapid increase in urban population and consequent need for transportation facilities. Authorities in these countries often fail to cope with the pressure of increasing population growth and economic activities in the cities, causing uncontrolled expansion of the cities, urban sprawl, traffic congestion and environmental degradation. Transportation and property are important in physical and economic development of towns and cities all over the world. Property and land values tend to increase in areas with expanding transportation networks, and increase less rapidly in areas without such improvements. Rapid and continued rise in housing and land prices are expected in cities with transportation improvements, rapid economic and population growth. The world would be

severely limited in development without transportation, which is a key factor for physical and economic growth.

The transportation route is part of distinct development pattern or road network and mostly described by regular street patterns as an indispensable factor of human existence, development and civilization. The route network coupled with increased transport investment result in changed levels of accessibility reflected through Cost-benefit analysis, savings in travel time and other benefits. These benefits are noticeable in increased catchment areas for services and facilities like shops, schools, offices, banks, and leisure activities. Road networks are observed in terms of its components of accessibility, connectivity and Traffic density, level of service, compactness and density of particular roads. Level of service is a measure by which the quality of service on transportation devices or infrastructure is determined, and it is a holistic approach considering several factors regarded as measures of traffic density and congestion rather than overall speed of the journey. Access to major roads provides relative advantages consequent upon which commercial users locate to enjoy the advantages. Modern businesses, industries, trades and general activities depend on transport and transport infrastructure, with movement of goods and services from place to place becoming vital and inseparable aspects of global and urban economic survival.

Developments of various transportation modes have become pivotal to physical and economic developments. Such modes include human porterage, railways, ropeways and cableways, pipelines, inland waterways, sea, air, and roads. Transport is critical to economic development, both low volume/rural roads and major arterials, and there is a direct relationship between a country's economic prosperity audiometers of paved roads. Since, traffic congestion creates quite an obstruction for smooth functioning of public transports, thus leading to avoidance of those by common people. According to a survey, an

average person spends about 300 hours every year, waiting on traffic signals, which boils down approximately to an hour daily. Thus, traffic is an important part of our lives, not only having an impact on our transportation but also have a significant effect on our urban environment. Thus, it is a necessity to have a better functioning traffic control system implementation. Generally, the traffic system is controlled by three signal lights- green, red and yellow. The reason for the traffic congestion (commonly termed as traffic jams) is increasing number of vehicles and poor management of traffic algorithms. There is no fixed infrastructure for every junction, street and road which lead to loopholes in construction of fixed timing algorithms. Previously, human administrated or automated offline software were used for computation of time slots given to each signal at traffic signals. But these timings used to fail at specific times of the day or particular days (festivals etc.), which led to the development of self-automated online system in our project that continuously sense the environment and compute the timings to be given to traffic signal at a particular instant. The purpose of Traffic Management System is to improve transport operations and transport services profitability, reduce traffic jams and fatalities, provide sufficient driving, training, maintain road infrastructure, and maintain traffic law enforcement using the help of Machine Learning.

1.2 Machine Learning :

Machine learning (ML) means that the computer can figure out a solution without being specifically programmed. That is, machines are able to continuously learn and deal with huge datasets using classifier algorithms. Classifiers, which categorize observations, are considered the backbone of ML. Meanwhile, other ML algorithms are built models of behaviors and use those models as a basis for making future predictions based on new input data. The power of machine learning tools lies in detecting and analyzing network attacks without having to accurately describe them as previously defined. Machine

learning can aid in solving the most common tasks including regression, prediction, and classification in the era of extremely large amount of data and cybersecurity talent shortage. Machine-learning techniques have been applied in many aspects of network operation and management, where the system performance can be optimized and resources can be better utilized. Moreover, clustering and classification extract patterns out of data packets which can be used in many applications such as security analysis and user profiling. Furthermore, there are many applications for analyzing traffic based on the ML algorithms such as identifying anomalies through discovery-based workbooks or features that describe user behavior.

There are four steps of machine learning model that is useful for prediction for the prediction process.

1. Identify classes from training data.
2. Create a model using the training dataset that is being trained by ML algorithm.
3. During test phase, use the trained model to classify the unknown data and makes a prediction.
4. The prediction is evaluated for accuracy.

If the accuracy is not acceptable, the Machine Learning algorithm is trained repeatedly with an augmented training data set.

There are two main types of ML approaches, which are supervised and unsupervised.

- Supervised learning:

  It is a classification method, which trains the labeled data set to produce new prediction outputs, given input variables and output variables.

In Supervised learning, learning continues until the algorithm reaches an acceptable level of performance. The algorithm constantly predicts outcomes based on training data, and it is constantly corrected.

- Unsupervised Learning:

This technique is called clustering method, where dataset does not need to be labeled; only input data will be given. The aim of unsupervised learning is to learn more about data by modeling infrastructure or basic distribution of data.

In our project, the supervised learning approach is used for traffic analysis purpose. We can create labeled data set and pre-train the model to produce the prediction outputs.

1.3 Intelligent Traffic Management System using Machine Learning:

With the highly rising traffic congestion all around the world, and it's management by traditional approach are not efficient for smooth commutation purpose. Hence, there is a need to come up with a solution which can be globally accepted and would lead for the better management of traffic. In today's traditional approach the signal switches at its predefined regular interval, but the density of vehicles of the road at every signal doesn't remains the same, hence the static approach fails. Under such scenario, if the signal remains the same to switch at its regular interval then the side of road which is densely populated will always remain completely packed. As mentioned in above systems, till date they are to getting vehicle count only, so that comparative study and analysis of traffic can be done.

There are many projects emerging in order to convert the current transport system of cities to 'Smart system' and there are many initiatives under this, one of this is Intelligent Transport System. Many initiatives were taken to design a

system that can perform real-time monitoring of traffic signals i.e., the traffic signal switching time will not be predefined one, instead the switching time will depend on the count of vehicles on each side of the road. This process of getting the count of vehicle on the road can be achieved using various detection techniques. Techniques like Vehicle detection using sensors may fail at circumstances when the traffic gets denser at peak timings.

Our aim is to design and develop a miniature to depict the current road situation along with monitoring and handling the traffic issues. Hence to proceed with this project we are using a pre-trained YOLO Machine Learning Model to perform the task of object detection.

YOLO (You Only Look Once), is a network for object detection. It is the one of the most powerful pretrained model to give utmost accuracy. Yolo is a combined version of RCNN (Region-based Convolutional Neural Networks) and SSD (Single Shot Detector), both make YOLO much faster, efficient and powerful algorithm. By applying object detection algorithm in YOLO, one will not only be able to determine what is in an image, but also where a given object is placed i.e., the location. Also, the model is trained using huge dataset hence it can detect image placed in any random manner i.e., it can detect object even if they are rotated in 360 degree. YOLO is an efficient model by distinguishing between two very closely placed objects. Unlike traditional approach of applying classifier on each image and making prediction, YOLO look at the image once and but in a clever way. It divides the image into N numbers of partitions and into MxM grid. Now YOLO applies its algorithm one by one in partitions and predict confidence score/ Confidence score is the score that tells us whether object is present or not. On the basis of the confidence score, YOLO detects an object.

YOLO can process many frames with less execution time as compared to other pretrained models. YOLO computes its prediction in terms of precision and

recall, precision measures how accurate the predictions are and recall measures how good we find all the positives i.e., how correctly the objects are classified. To increase its performance factor YOLO uses IoU, Intersection over Union is an evaluation metric used to measure the accuracy of an object detector on a particular dataset. IoU defines how two closely place objects can be easily detected without hampering the accuracy of the model. YOLO consist of two core components. One of the YOLO's component R_CNN uses selective search algorithm and proposes accurate bounding box that definitely contains objects whereas the other component SSD that helps to speed up the processing of an image. Compared to other region proposal classification networks (fast RCNN) which perform detection on various region proposals and thus end up performing prediction multiple times for various regions in an image, YOLO architecture is more like FCNN (fully convolutional neural network) and passes the image size NxN once through the FCNN and output size is MxM prediction. This architecture is splitting the input image size as MxM grid and for each grid generation 2 bounding boxes and class probabilities for those bounding boxes is done.

YOLO uses OpenCV for object detection along with multiple foreground and background subtraction and removal of noise from the input image. The CCTV cameras that are being used for surveillance purpose can be made use to capturing the footage of the road, this image will be passed to the pretrained model as input image. To do so each side of the road will be divided into particular frames of same height and width for capturing the image. The count obtained from the image is passed into a pre-defined Python program. As per the count obtained, switching time will be assigned for each side of road. The program will initially check if the count of vehicle in all lanes and then the signal switching will happen dynamically where the lane with higher vehicle count will be opened first.

CHAPTER 2

LITERATURE SURVEY

Vehicle Detection and Tracking using Gaussian Mixture Model and Kalman Filter [1]

Recently, the technological advance in various fields is growing rapidly, particularly in the field of transport, namely Intelligent Transport System (ITS). ITS was a method used traffic arrangements to make efficient road-based transport system and it was applied in the developed countries. Example of ITS application is the use of CCTV cameras for surveillance. The transportation authority and decision-makers can easily obtain data to be used in traffic engineering, such as data on the number of vehicles and vehicle speed. To obtain data on the number of vehicles and vehicle speed through CCTV, the first thing to be done is to detect vehicle object. There are several methods that can be used for vehicles detection such as Histogram of Oriented Gradient (HOG), Viola Jones and GMM (Gaussian Mixture Model). Object detection through CCTV is done by distinguishing between object to be detected with other objects. HOG and Viola Jones are detection methods that relying on existed database in detection process. This database consists of two forms of data i.e., positive and negative database. Positive database is collection of data that contain the object to be detected, while the negative database is collection of data that does not contain the object to be detected. This scenario of data distinction is usually applied to detect objects from image. GMM method is a detection method that compares between foreground object (moving object) and background object (stationary object). This approach is usually applied for detecting object within a video. The second thing beside the vehicle detection is tracking the object in traffic surveillance using CCTV. One of the methods that can be used in object tracking is Kalman Filter method. In this research, vehicle detection is conducted

using GMM method combined with object tracking with Kalman Filter. Combining those techniques are expected to achieve higher accuracy in system detection.

Vehicle Detection, Tracking and Counting [2]

Detection of vehicles in a sequence of frames is an active field of research in computer vision which helps in overcoming an ever-growing complication in traffic surveillance and security. Computer vision deals highly with the automatic extraction, understanding and analysis of the useful information from a single image or from a sequence of images. It implicates the theoretical and algorithmic based steps to achieve visual understanding automatically. In this work, computer vision-based vehicle detection, counting and tracking method were proposed that uses a Gaussian mixture model for background subtraction which yields a foreground mask (binary mask). The foreground mask thus obtained is then processed using the morphological operators (e.g., dilation, erosion, opening and closing) to eliminate noise. The BLOB (Binary Large Object) analysis technique then helps in clearly discerning the vehicles from the background. It basically detects the cluster of connected pixels which may correspond to moving objects. Afterwards, a binary classifier helps in discerning a vehicle from pedestrians. This classifier makes use of the fact that the width to height ratio of vehicles is always greater than 1 and that for pedestrians is always less than 1. Kalman filter then helps predict the locations of vehicles during the next update interval. Hungarian algorithm is then exploited for associating labels to the tracked vehicles. In order to increase the computational speed, all of this processing is done within a region of interest (ROI) which is set in our video frames such that only those vehicles are detected which enters the ROI. Thus, the vehicle counter is incremented only when a vehicle enters the ROI.

Extraction of vehicles in frames of a video given as an input in the first step is achieved using Gaussian Mixture Model. After the extraction of vehicles, noise is removed from the processed binary image obtained as a result of second step. This noise filtering is taken care of using morphological operators. After the removal of noise, BLOB analysis is used to highlight the detected vehicles and counter is employed to achieve the counting of vehicles depending upon the highlighting of vehicles, basically refers to cost estimation which is achieved in this frame work using a Hungarian model. This cost estimation model helps in assigning tracks to the corresponding associations.

Automated Traffic Monitoring Using Image Vision [3]

The most common way of maintaining an automated traffic monitoring system is by means of using CCTV cameras having a frame rate of 15 frames per second placed at strategic locations. Modern cities have been making use of this facility ever since the inception of IoT based cameras. To improve the method, certain specific algorithms need to be applied to reduce the complexity of the method. This is extremely important in order to produce results as quickly as possible. Currently, the traffic information is available in real-time from multiple systems by means of using inductive loop detectors, infra-red detectors, radar detectors and video-based systems. Intelligent traffic monitoring system is the need of the hour. The method applied in our country is to make use of manual traffic control. Although, it is a very commonly applied as well as reliable method, it has a lot of shortcomings including the pressure of man power. Another problem is the inability to rationally count the number of vehicles in a particular road and reduce traffic congestion by prioritizing the roads having the greatest number of vehicles. To count the number of vehicles automatically pressure plates may be used and applying the concept of RFID placed on the vehicle number plates. The other approach is by traffic video surveillance. A very common practice of traffic monitoring is performed semi manually by traffic police sitting in a control room

while monitoring the different traffic cameras. This is also not a very efficient method because the process involves man power. Thus, in this paper we are proposing a method to apply the concepts of Digital Image Processing (DIP) to identify the number of vehicles in each road at the traffic cross-section and thereby providing inputs to apply any method to schedule the traffic control. Our method does not emphasize on using high resolution video quality but applies a simplified edge detection followed by closed figure identification to count the number of vehicles in the least complexity possible. This paper proposes a two-step process to count the number of vehicles in each road at the cross-section followed by a Traffic Scheduling Algorithm to ease the traffic congestion at heavily populated road cross-sections. The output obtained from the Vehicle Identification Algorithm is used as input for the Traffic Scheduling Algorithm. The second involves the use of choosing from the most suitable scenario out of in 12 possible traffic scenarios in case of traffic junctions of 4 roads have 3 dedicated lanes for Left, Straight, and Right.

Intelligent Traffic Light System Using Computer Vision with Android Monitoring and Control [4]

Traffic congestion have always been one of the major unsettled crises primarily faced by the residents and the industry sectors of the Philippines for decades and is becoming worst every year. This is becoming a worldwide phenomenon as the number of vehicles increases. This traffic issue adversely affects the productivity and economy of a country. In fact, in U.S. alone nearly $300 billion were spent in gas and time and almost $70 million per year lost due to traffic congestion in the business sector. Moreover, according to Boston Consulting Group, by 2022 traffic in Manila, Philippines will hit “standstill levels”, this means that vehicles will have an average speed of 5 mph or less during peak hours. A study by Japan International Cooperating Agency (JICA) cites that Metro Manila, Philippines is experiencing 3.5 billion in work hours and business opportunities lost per day,

due to the worsening traffic congestion. Numerous efforts have been implemented in the country to regulate traffic problem including highway and road expansion, and the implementation of several traffic schemes. One of the research thrusts being studied is the solution to the limitation of traditional traffic light systems. The improvement of traffic efficiency has been the key goal of why intelligent transportation system (ITS) is introduced as a suggested substitute for conventional traffic light system. To further optimized traffic efficiency, the traffic lights (or traffic signals) is used by altering signal lights for traffic flow control at road intersections, pedestrian crossings, and other places. Conventional traffic light system, also known as the traditional traffic light system, are usually fixed-timed cycles which means that the signaling light switches from one another thru regular intervals. It is inefficient given that traffic situation is a variable event that is constantly changing due to different circumstances, i.e., peak hours, accidents or collision, rally, roadshow, etc. Due to these certain limitations, ITS is introduced. ITS is designed to adaptively control traffic flow operation based on real-time traffic situation. Typical class of intelligent traffic light system is a traffic signaling system that can measure and calculate the traffic densities of each lane using either sensors, or cameras placed on the intersections, and prioritize lanes which are more congested and needed attention. However, a huge amount of human intervention is required for these types of system to become fully functional and thus automated computer vision-based approaches were proposed. In the research used a rotary camera placed at the center of the intersection to capture images from different lanes then process the image captured using image processing techniques based on edge detection. Traffic density and timing were computed for operation and control of traffic signal lights. Another research used a webcam mounted on a DC motor placed at the road junction for capturing images. Image processing techniques included were image cropping, image enhancement, thresholding, edge detection and object counting. However, computer vision-based system used in traffic lights is still a

challenging task since most of these systems were not designed for extreme weather conditions (stormy, foggy and rainy) that influence vehicle detection accuracy. Also, some studies that uses camera for image processing have difficulty measuring the traffic density at nighttime and controls were usually thru a computer or microcontroller with limited mobility and access. This research proposes to develop an intelligent traffic light system using computer vision to measure the traffic density which can operate regardless of the time of day. The system employs CCTV cameras stationed at each lane of the intersection for the capturing of traffic images which will then be sent to the Raspberry Pi 3 microcontroller for traffic density calculation using image processing. Automated and manual control of traffic lights via an android application is provided for added mobility and access.

CHAPTER 3

SYSTEM ANALYSIS AND SPECIFICATION

3.1 SYSTEM ANALYSIS

3.1.1 Existing System

With the highly rising traffic congestion all around the world, and it's management by traditional approach are not efficient for smooth commutation purpose hence there is a need to come up with a solution which can be globally accepted and would lead for the better management of traffic. In today's world where technology has transcended all barriers it has now become easy to solve most human problems and one of these problems include Traffic Congestion. Traffic congestion has increased drastically over the years and has had negative impacts that include road rage, accidents, air pollution, wastage of fuel and most importantly unnecessary delays. The fact that encouraged proposing new solution is that in many cities of the world, the traffic signal allocation is still based on timer.

The Timer Approach has a drawback that even when there is a less traffic in one of the roads, green signal is still allocated to the road till its timer value falls to 0, whereas the traffic on another road is comparably more faces red signal at that time. This causes congestion and time loss to commutators. Most of the present systems are not automated and are prone to human errors. There are many projects emerging in order to convert the current transport system of cities to 'Smart system' and there are many initiatives under this, one of this is Intelligent Transport System. Many initiatives were taken to design a system that can perform real-time monitoring of traffic signals i.e., the traffic signal switching time will not be predefined one, instead the switching time will depend on the count of vehicles on each side of the road.

3.1.2 PROPOSED SYSTEM

Our aim is to design and develop a machine learning model to handle the traffic signal switching by depicting the number of vehicles present in a road along with detection of different types of vehicles present in the road. The proposed system helps to develop a solution that analyses the presence of vehicles on the road and handles the traffic congestion issues, resulting in a better managed, more coordinated and smarter use of traffic networks. This can be done using the analysis of vehicle count data obtained from source like CCTV Cameras present in highways or in traffic signals, using a trained machine learning model called **YOLO**. YOLO is an OpenCV based machine learning model which does the Object Detection and counts the number of vehicles in a lane. The recorded data is then sent into the predefined python program where the machine learning model is already written and based on the obtained vehicle count data – we can dynamically switch the signal among the lanes. Thereby, round the clock safety and hassle-free traffic management can be obtained using Proposed Intelligent Traffic Management System. Implementation of our project will eliminate the need for traffic personnel at various junctions for regulating traffic. Thus, the use of this technology is valuable for the analysis and performance improvement of road traffic. Also, priority to emergency vehicles has been the topic of some research in the past which can be enabled with further training of our machine learning of our model.

3.2 SYSTEM REQUIREMENTS

3.2.1 Hardware Requirements:

- High-end Graphics Processing Unit
    - NVIDIA CUDA Powered GPU
    - Google Colab Cloud Environment

High-end Graphics Processing Unit:

Machine learning models require a lot of computational power to run on. For any neural network, the training phase of the deep learning model is the most resource-intensive task. Traditionally, the training phase of the deep learning pipeline takes the longest to achieve. This is not only a time-consuming process, but an expensive one. While training, a neural network takes in inputs, which are then processed in hidden layers using weights that are adjusted during training and the model then spits out a prediction. Weights are adjusted to find patterns in order to make better predictions. To significantly reduce training time, we can use machine learning GPUs, which enable us to perform AI computing operations in parallel. GPUs are optimized for training artificial intelligence and deep learning models as they can process multiple computations simultaneously.

GPUs are parallel processors designed to accelerate portions of a program, but not to replace CPU computing. The main program is executed on the CPU, but some code fragments, called kernels, are executed on the GPU. These Graphical processing units (GPUs) can reduce these costs, enabling us to run models with massive numbers of parameters quickly and efficiently. This is because GPUs enable us to parallelize the training tasks, distributing tasks over clusters of processors and performing compute operations simultaneously.

GPUs are also optimized to perform target tasks, finishing computations faster than non-specialized hardware. These processors process the same tasks faster and free the CPUs for other tasks. This eliminates bottlenecks created by compute limitations.

Selecting the right GPU for our project:

Selecting the GPUs for the implementation has significant budget and performance implications. We need to select GPUs that can support the project in the long run and have the ability to scale through integration and clustering. For large-scale projects, this means selecting production-grade or data center

GPUs. In the GPU market, there are two main players i.e AMD and Nvidia. Nvidia GPUs are widely used for machine learning because they have extensive support in the forum software, drivers, CUDA, and cuDNN. So, in terms of AI and machine learning, NVIDIA is the pioneer for a long time.

NVIDIA GPUs are the best supported in terms of machine learning libraries and integration with common frameworks, such as PyTorch or TensorFlow. The NVIDIA CUDA toolkit includes GPU-accelerated libraries, a C and C++ compiler and runtime, and optimization and debugging tools. It enables us to get started right away without worrying about building custom integrations.

NVIDIA CUDA Powered GPUs:

CUDA stands for 'Compute Unified Device Architecture' which was launched in the year 2007, it's a way in which we can achieve parallel computing and yield most out of GPU power in an optimized way, which results in much better performance while executing tasks. The CUDA toolkit is a complete package that consists of a development environment that is used to build applications that make use of GPUs. Also, the CUDA runtime has its drivers so that it can communicate with the GPU.

cuDNN is a neural network library that is GPU optimized and can take full advantage of Nvidia GPU. This library consists of the implementation of convolution, forward and backward propagation, activation functions, and pooling. It is a must library without which we cannot use GPU for training neural networks.

The main difference between GPUs and CPUs is that GPUs devote proportionally more transistors to arithmetic logic units and fewer to caches and flow control as compared to CPUs. A GPU is smaller than a CPU but tends to have more logical cores (arithmetic logic units, control units and memory cache) than the latter.

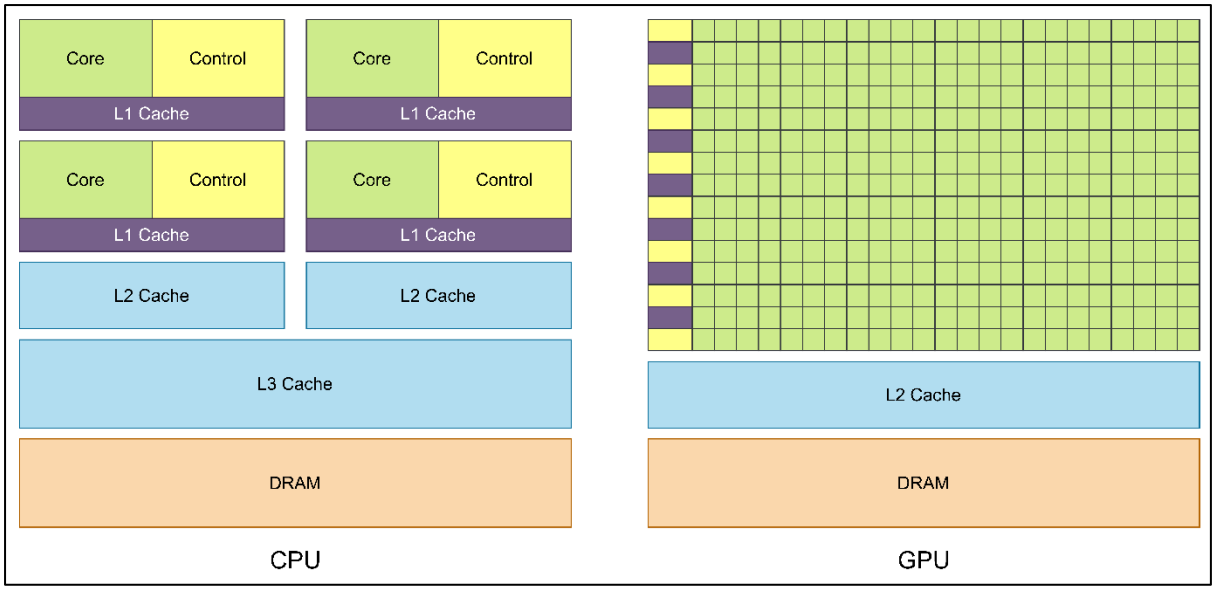

Fig 3.1 CPU vs GPU – The Architecture Difference

Google Colab Cloud Environment:

Google Colaboratory is an online cloud-based platform based on the Jupyter Notebook framework, designed mainly for use in machine learning operations. There are many distinguishing features that set it apart from any other coding environment.

Reason for choosing Google Colab over PC:

One of the main benefits of using Colab is that it has most of the common libraries that are needed for machine learning like TensorFlow, Keras, Scikit Learn, OpenCV, numpy, pandas, etc. pre-installed. Having all of these dependencies means that we can just open a notebook and start coding without having to set up anything at all. Any libraries that are not pre-installed can also be installed using standard terminal commands. While the syntax for executing terminal commands remains the same, one must add an exclamation mark (!) at the start of the command so that the compiler can identify it as a terminal command. Another feature is that the Colab environment is independent of the computing power of the computer itself. Since it is a cloud-based system, as long

as there is an internet connectivity, even heavy machine learning operations can be run from a relatively old computer that ordinarily wouldn't be able to handle the load of executing those operations locally. Additionally, Google also offers a GPU (Graphics Processing Unit) and a TPU (Tensor Processing Unit) for free. These hardware accelerators can run heavy machine learning operations on large datasets much faster than any local environment. While Colab allows uploading local files onto the runtime each time it is loaded, uploading and re-uploading large training datasets each time the runtime is restarted can be frustrating. Colab also offers data versatility, a simple alternative 'mount' Google Drive onto the Colab notebook. This operation requires just two lines of code that Colab inserts a file with the click of a button and this enables access to read files that is uploaded into Google Drive. This means that we don't have to reupload local files after every runtime restart. Simply uploading them once and access them simply by mounting the Google Drive solves the issue. Like the rest of Google's online document editing platforms like Google docs, Google Slides, Google Sheets, etc., Colab too offers similar sharing options allows to seamlessly collaborate with others on joint coding projects. One thing to keep in mind is that when a notebook is shared, other users cannot see the output and results from code that one has executed. Also, if one uploads some files from their computer to the notebook, other collaborators will not be able to see them so it is better to upload those files to Google Drive and then access them from there so everyone can see and use the files.

Limitations of Google Colab:

1. Google Colab has a 'maximum lifetime' limit of running notebooks that is 12 hours with the browser open, and the 'Idle' notebook instance is interrupted after 90 minutes. In addition, a Google Account on Colab can run a maximum of 2 notebooks simultaneously.

2. GPUs and TPUs are sometimes prioritized for users who use Colab interactively rather than for long-running computations, or for users who have recently used3 less resources in Colab. As a result, users who use Colab for long-running computations, or users who have recently used more resources in Colab, are more likely to run into usage limits and have their access to GPUs and TPUs temporarily restricted
3. Resources present in a Colab session's Storage will be automatically deleted once the session gets restarted, so we cannot access the files that are stored during the previous session after recycling it.

3.2.2 Software Requirements:

Software requirements deal with defining software resource requirements and prerequisites that need to be installed on a computer to provide optimal functioning of an application. These requirements or prerequisites are generally not included in the software installation package and need to be installed separately before the software is installed. Some of the software requirements for our project are,

1. Operating System
2. Python (Programming Language)
3. Darknet (Neural-network framework)

Operating System

An operating system is system software that manages computer hardware, software resources and provides common services for computer programs. Since we are using Google Colab Cloud Environment for our project, we will be using the services of Debian Linux Operating System.

Reason for Debian to be the default operating system in Google Colab is because the Debian Family of Linux has official support for CUDA, Kubernetes,

TensorFlow and Keras by default. So, it becomes easy for users to work around our cloud environment with basic Linux commands.

Python

Our machine learning model is written with Python programming language as it is the most preferred language for developing machine learning models. Python is a very useful programming language that has an easy-to-read syntax, and allows programmers to use fewer lines of code than would be possible in languages such as assembly, C, or Java.

Reasons for choosing Python :

One of the key reasons for using Python for Machine Learning is its great library ecosystem. A library is a module or a group of modules published by different sources like 'PyPi' which include a pre-written piece of code that allows users to reach some functionality or perform different actions. Python libraries provide base level items so developers don't have to code them from the very beginning every time.

Machine Learning requires continuous data processing, and Python's libraries let users access, handle and transform data. These are some of the most widespread libraries namely,

- Scikit-learn : For handling basic ML algorithms like clustering, linear and logistic regressions, regression, classification, and others.
- Pandas : For high-level data structures and analysis. It allows merging and filtering of data, as well as gathering it from other external sources like Excel, for instance.
- Keras : It allows fast calculations and prototyping, as it uses the GPU in addition to the CPU of the computer.

- TensorFlow : For working with deep learning by setting up, training, and utilizing artificial neural networks with massive datasets..

Python for machine learning is a great choice, as it is very flexible. The flexibility factor decreases the possibility of errors, as programmers have a chance to take the situation under control and work in a comfortable environment.

- It offers an option to choose either to use OOPs or scripting.
- There's also no need to recompile the source code, developers can implement any changes and quickly see the results.
- Programmers can combine Python and other languages to reach their goals.

Moreover, its flexibility allows developers to choose the programming styles which they are fully comfortable with or even combine these styles to solve different types of problems in the most efficient way.

Darknet Framework:

Darknet is an open-source neural network framework like Keras, PyTorch and TensorFlow. Darknet is written in C and CUDA. It is fast, easy to install, and supports CPU and GPU computation. Darknet is installed with only two optional dependencies: OpenCV if users want a wider variety of supported image types or CUDA if they want GPU computation.

The framework features You Only Look Once (YOLO) Machine Learning Algorithm, a state-of-the-art, real-time object detection system. On a Titan X it processes images at 40-90 FPS and has a mAP on VOC 2007 of 78.6% and a mAP of 44.0% on COCO test-dev. Darknet displays information as it loads the config file and weights then it can be enabled to classify the image and print the top-10 classes for the image. Moreover, the framework can be enabled to run neural networks backward in a feature appropriately named Darknet Nightmare.

Recurrent neural networks are powerful models for representing data that changes over time and Darknet can handle them without making use of CUDA or OpenCV. The framework also allows its users to venture into game-playing neural networks. It features a neural network that predicts the most likely next moves in a game of Go. Users can play along with professional games and see what moves are likely to happen next, make it play itself, or try to play against it.

Reason for choosing Darknet over the rest:

Darknet is mainly for Object Detection, and have different architecture, features than other deep learning frameworks. It is faster than many other NN architectures and approaches like FasterRCNN etc. One have to be in C if one needs speed, and most of the deep NN frameworks are written in c. TensorFlow has a broader scope in Machine Learning, but Darknet architecture & YOLO is a specialized framework, and it is in top of its game in speed and accuracy. YOLO can run on CPU but one can get 500 times more speed on GPU as it leverages CUDA and cuDNN.

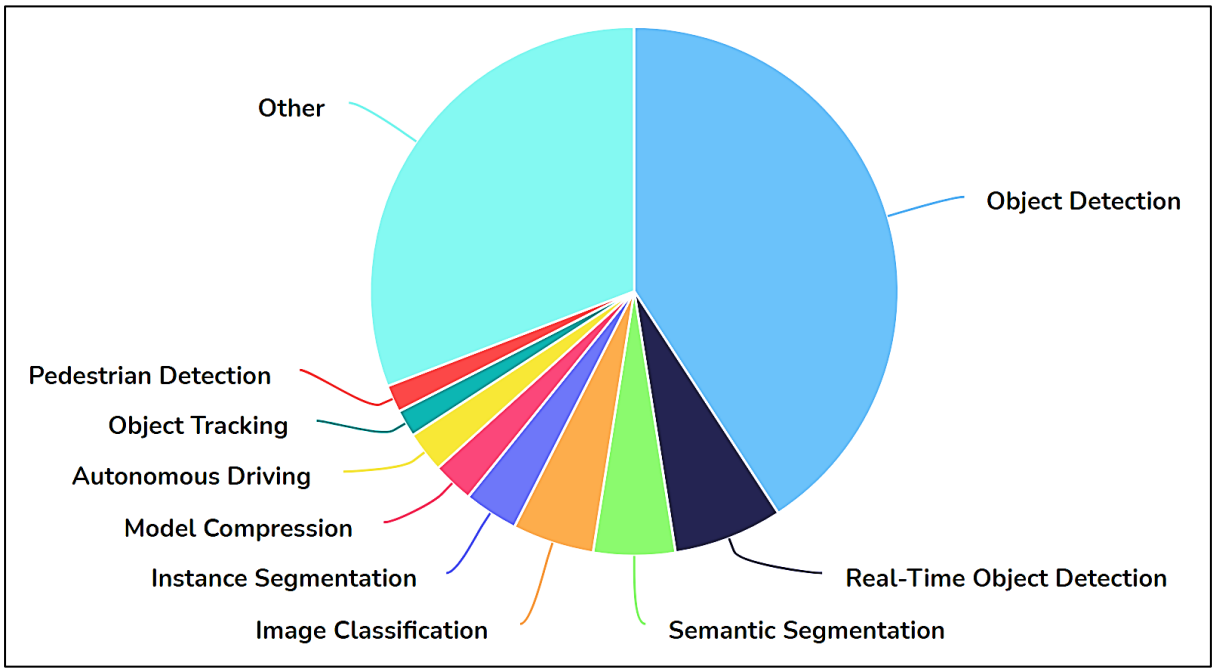

Fig: 3.2 Use of Darknet Framework in various fields

3.3 SYSTEM ARCHITECTURE

Our proposed system implements Intelligent Traffic Management System using YOLO Machine Learning Model. Applying Machine Learning model will result in a very efficient management of the traffic, since the machine learning models get better as it learns over the period after its implementation. Current work focuses on training the machine learning model and deploying it to get the traffic count for better management of the traffic. Current detection systems repurpose classifiers to perform detection. To detect an object, these systems take a classifier for that object and evaluate it at various locations and scales in a test image. Systems like deformable parts models (DPM) use a sliding window approach where the classifier is run at evenly spaced locations over the entire image [10]. More recent approaches like R-CNN use region proposal methods to first generate potential bounding boxes in an image and then run a classifier on these proposed boxes. After classification, post-processing is used to refine the bounding boxes, eliminate duplicate detections, and rescore the boxes based on other objects in the scene [13]. These complex pipelines are slow and hard to optimize because each individual component must be trained separately. We reframe object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. So, we are using a machine learning model called YOLO – (YouLookOnlyOnce).

Principle of YOLO :

YOLO is refreshingly simple, single convolutional network model that simultaneously predicts multiple bounding boxes and class probabilities for those boxes. YOLO trains on full images and directly optimizes detection performance. This unified model has several benefits over traditional methods of object detection. First, YOLO is extremely fast. Since we frame detection as a regression problem we don’t need a complex pipeline. We simply run our neural network on a new image at test time to predict detections. Our base network runs at 45 frames

per second with no batch processing on a Titan X GPU and a fast version runs at more than 150 fps. This means we can process streaming video in real-time with less than 25 milliseconds of latency Compared to other region proposal classification networks (fast RCNN) which perform detection on various region proposals and thus end up performing prediction multiple times for various regions in an image, Yolo architecture is more like FCNN (fully convolutional neural network) and passes the image of size NxN once through the FCNN and output of size MxM prediction. YOLO architecture is splitting the input image in MxM grid and for each grid generation 2 bounding boxes and class probabilities for those bounding boxes. We reframe object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. A single convolutional network simultaneously predicts multiple bounding boxes and class probabilities for those boxes. YOLO trains on full images and directly optimizes detection performance. This unified model has several benefits over traditional methods of object detection. First, YOLO is extremely fast. Since we frame detection as a regression problem, we don't need a complex pipeline. We simply run our neural network on a new image at test time to predict detections. Our base network runs at 45 frames per second with no batch processing on a Titan X GPU and a fast version runs at more than 150 fps. This means we can process streaming video in real-time with less than 25 milliseconds of latency.

Second, YOLO reasons globally about the image when making predictions. Unlike sliding window and region proposal-based techniques, YOLO sees the entire image during training and test time so it implicitly encodes contextual information about classes as well as their appearance. Fast R-CNN, a top detection method, mistakes background patches in an image for objects because it can't see the larger context. YOLO makes less than half the number of background errors compared to Fast R-CNN.

Third, YOLO learns generalizable representations of objects. When trained on natural images and tested on artwork, YOLO outperforms top detection methods like DPM and R-CNN by a wide margin. Since YOLO is highly generalizable it is less likely to break down when applied to new domains or unexpected inputs.

Our network uses features from the entire image to predict each bounding box. It also predicts all bounding boxes across all classes for an image simultaneously. This means our network reasons globally about the full image and all the objects in the image. The YOLO design enables end-to-end training and real-time speeds while maintaining high average precision.

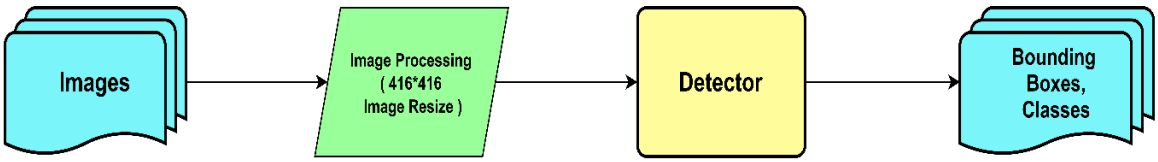

Fig: 3.3 YOLO - Simplified Network Architecture

At first, the captured image from the input source is sent to the model and then the YOLO model detects the objects, and the model in-turn increments the count of the object. This process is repeated for each road and the signal switching takes place.

Why YOLO is preferred for our system instead of others?

- Biggest advantage of YOLO Model, when compared to the rest of the algorithms is, it's speed (45 frames per second).
- Network understands generalized object representation (This allowed them to train the network on real world images and predictions on artwork was still fairly accurate).
- Faster version (with smaller architecture) — 155 frames per sec but is less accurate.

- Open-Source Machine Learning Model

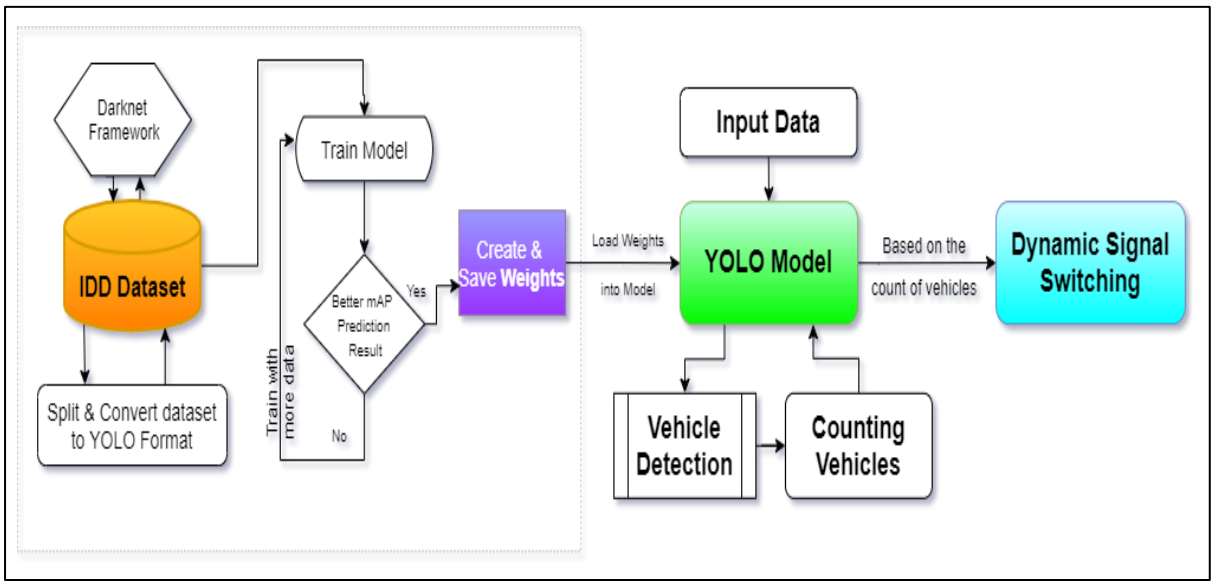

Fig. 3.4 ITMS - Architecture Diagram

As the base for our proposed system lies in the use of YOLO Machine Learning Model, the development of YOLO Model plays a major role in the development of our project. After installing the Darknet Framework, we will be using IDD Dataset for training, validation and testing of our machine learning model, the dataset is initially split into those three parts, if not divided by default. Since every machine learning model has proprietary format of understanding training labels, so does YOLO. We will need to convert the IDD Dataset into YOLO Compatible Format for training it. i.e., YOLO requires the image to be trained with annotation details present on the same file name as the training image with After successful completion of the training and validation, the model can be now tested and ready to be deployed. The traffic input source can be now passed into our developed YOLO Model, which does the job of Vehicle Counting after successful completion of Object Detection. The count of vehicles is then passed into a pre-programmed python function which then determines to dynamically switch the traffic signal for each lane.

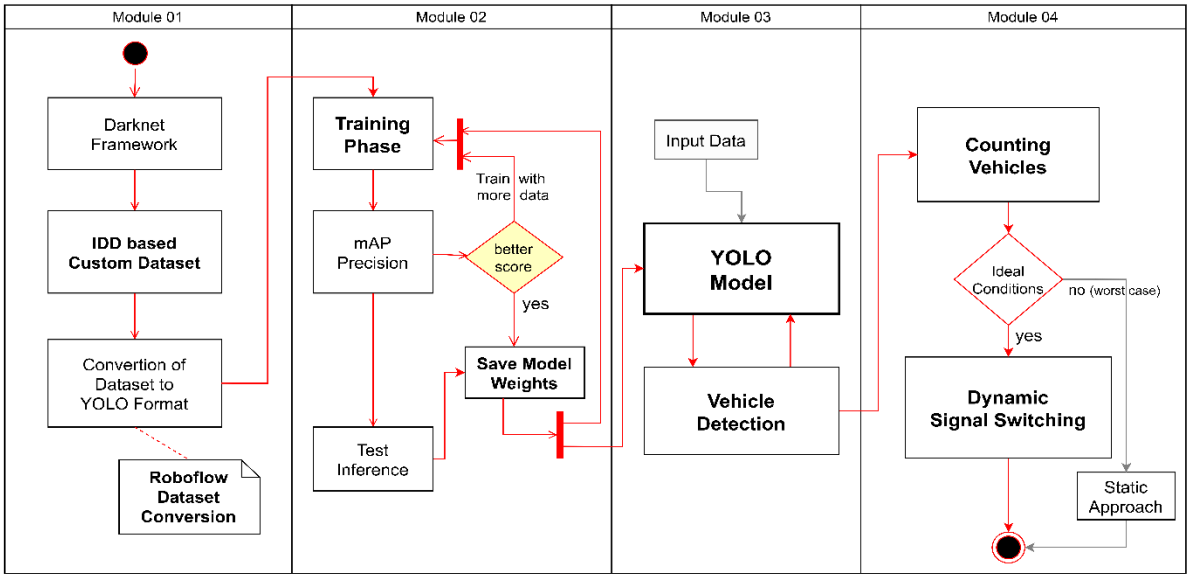

Fig 3.5 ITMS - UML Diagram

As our project is divided into 4 modules, the traffic data input is passed into the YOLO Machine Learning Model which was already trained and deployed by us during the development stages. The model now detects the image based on the classifiers and the confidence score. The detected objects are counted by the model, so that the vehicle count data is later used for dynamic signal switching in the traffic signals based on the pre-defined threshold value condition. If the model passes the validation and testing part successfully, it can be deployed. Else more training data must be passed into the model for better accuracy in object detection.

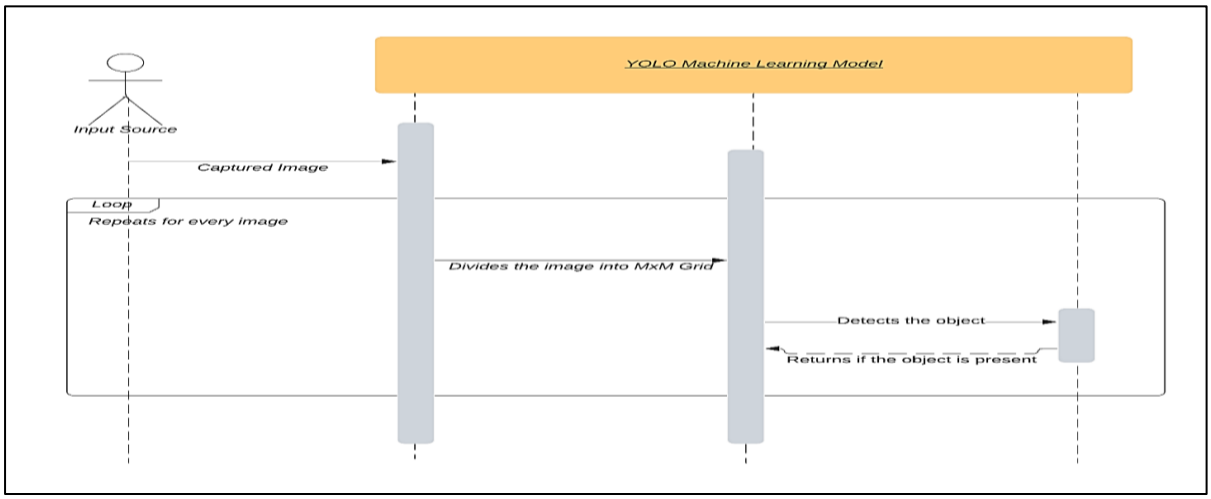

Fig 3.6 ITMS – Sequence Diagram

From the Input Source, the captured data is now transferred to our developed machine learning model, which divides the image into MxM grids and the classification is applied by our YOLO Model for each grid were based on the confidence score, the machine learning model detects the one or more objects present in our YOLO Machine Learning Model. This process is done during the first phase of our project. The obtained data contains the object detection data in addition with the number of vehicles present in the captured data. This process repeats in a loop for each input data that is passed into our model. In the second phase of our project, these data can be used to calculate the threshold value for each lane, so that the pre-developed python program decides which lane to open at first. Based on the threshold value, the dynamic signal switching happens.

CHAPTER 4

SYSTEM IMPLEMENTATION

4. MODULE DESCRIPTION

Our proposed system consists of 4 modules and divided into 2 phases. The modules are namely,

1. Machine Learning Model Setup and Development
2. YOLO Machine Learning Model Training & Weight Creation
3. Vehicle Detection and Counting of Vehicles by YOLO Model
4. Dynamic Signal Switching

4.1 Machine Learning Model Setup and Development:

Before starting to develop our machine learning model with our own dataset, we must prepare the suitable environment for our model to develop it in a faster way – because creation of a machine learning model is a tedious process and it takes huge computation power to develop it.

So, we are developing our machine learning model in Google Colab, which will drastically save our computation time and helps us to develop comparably faster than what it might actually take to develop in our personal computer. Google Colab Environment's automatically provisioned computation power is arguably 100x faster than the computation capability of our local host.

4.1.1 Setting up the Google Colab Environment:

As we knew already, Google Colab Cloud Environment will dynamically provision resources for each session based on our computations. Since we are need to train the dataset for developing a fully-functioning YOLO Machine Learning Model, we must change the Runtime Instance of our current Google Colab Session into GPU/TPU Runtime.

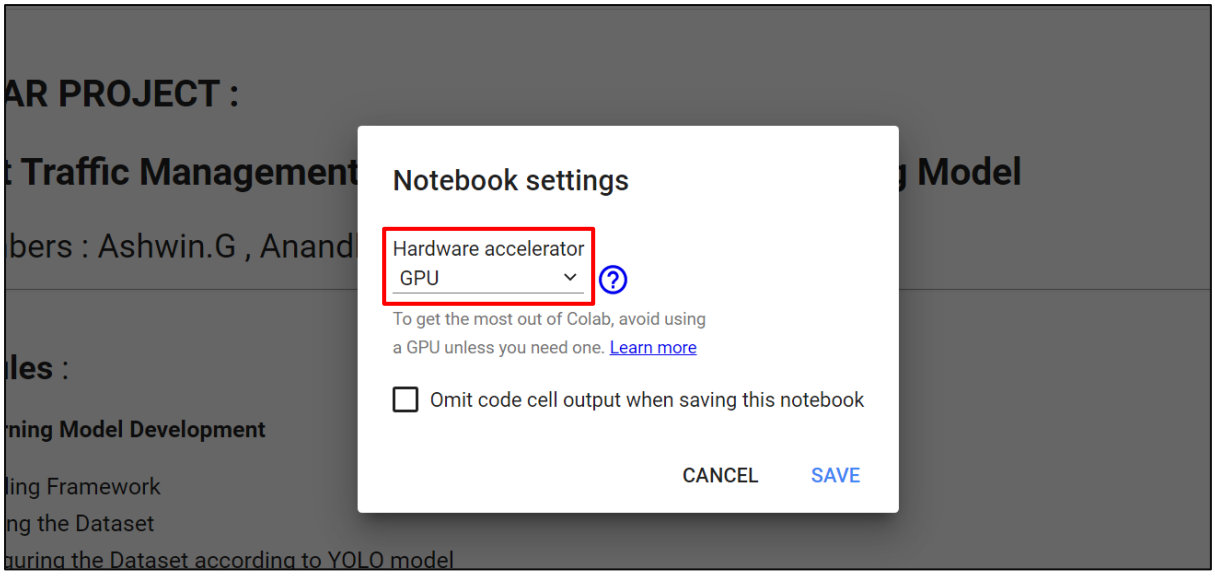

Fig: 4.1 Enabling the "Hardware Acceleration" to "GPU"

Once the GPU Runtime is provisioned and connected, we must now check the name of the underlying GPU to make it compatible with Darknet Framework accordingly with NVIDIA SMI Utility. The NVIDIA System Management Interface (nvidia-smi) is a command line utility intended to aid in the management and monitoring of NVIDIA GPU devices.

```
!nvidia-smi

Mon Jan 11 19:59:33 2021
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 460.27.04    Driver Version: 418.67       CUDA Version: 10.1     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla K80           Off  | 00000000:00:04.0 Off |                    0 |
| N/A   69C    P0    60W / 149W |      0MiB / 11441MiB |      0%      Default |
|                               |                      |                 ERR! |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

Fig: 4.2 NVIDIA Tesla K80 – Runtime Environment provisioned by Google Colab

4.1.2 Installing Darknet and Overwriting Makefile:

Makefile is a program building tool which runs on Unix, Linux, and their flavors. It aids in simplifying building program executables that may need various modules. To determine how the modules need to be compiled or recompiled together, **make** takes the help of user-defined makefile. As we knew that NVIDIA Tesla K80 is the GPU present in our runtime environment, we can now install the darknet neural-network framework now by creating a folder called "darknet" and cloning the GitHub repository of Darknet. Once after cloning the darknet framework into our environment, start creating the configuration file for our darknet framework inside the darknet folder. We must modify and overwrite the "make file" (configuration) for our Darknet framework which is compatible with the computations that will be required for training our machine learning model using this framework. Compute capability of a GPU determines its general specifications and available features. Since our GPU is NVIDIA Tesla K80, the compute capability of our GPU is 30, which needs to be set in the 'Make File' of Darknet Framework. Since the Colab's GPU dependencies shift from time to time automatically, we need to run the makefile after checking the actual dependency to which our Colab Notebook is currently connected to. Currently, our Colab Notebook is connected to NVIDIA Tesla K80 GPU. If the GPU is shifted to another GPU, we need to tweak the 'Make File' accordingly.

4.1.3 Dataset Collection:

For developing a machine learning model, one need to create an image dataset first. A dataset assembles a collection of images that are labeled and used as references for objects that are used by the developers to test, train and evaluate the performance of their algorithms. Algorithms trained with larger datasets perform significantly better than those trained on smaller ones. With more data come more variations and the algorithm can learn from the myriads of differences

of the visual world. The quality of the model depends on the quality of the data set input. Creating a dataset is not always a simple matter. We must collect, annotate, convert into model supported format and then insert the dataset into the model for training the data which might take hours to several days.

4.1.3.1 Dataset used in our model:

While several datasets are already available to develop machine learning models, they tend to focus on neatly structured driving environments. This usually corresponds to well-delineated infrastructure such as lanes, a small number of well-defined categories for traffic participants, low variation in object or background appearance and strict adherence to traffic rules. We chose **IDD – India Driving Dataset** as a main source of training images for our project. IDD is a novel dataset for road scene understanding in unstructured environments where the above assumptions are largely not satisfied. It consists of 10,004 images, finely annotated with 34 classes collected from 182 drive sequences on Indian roads. The label set is expanded in comparison to popular benchmarks such as Cityscapes, to account for new classes. It also reflects label distributions of road scenes significantly different from existing datasets, with most classes displaying greater within-class diversity.

Our dataset annotations have unique labels like billboard, auto-rickshaw, animal etc. We also focus on identifying probable safe driving areas beside the road. The labels for the dataset are organized as a 4-level hierarchy. Unique integer identifiers are given for each of these levels. The histogram bellow gives:

1. Pixel counts for each label in the y axis.
2. The four-level label hierarchy and the label ids for intermediate levels (level 2, level 3).

3. The color coding used for the prediction and ground truth masks are given to the corresponding masks.

For example, with the Cityscape dataset is one of the most widely adapted for developing the object detection algorithms, but for India, where traffic violations are rampant, these datasets can't be inculcated to ensure safer road travel.

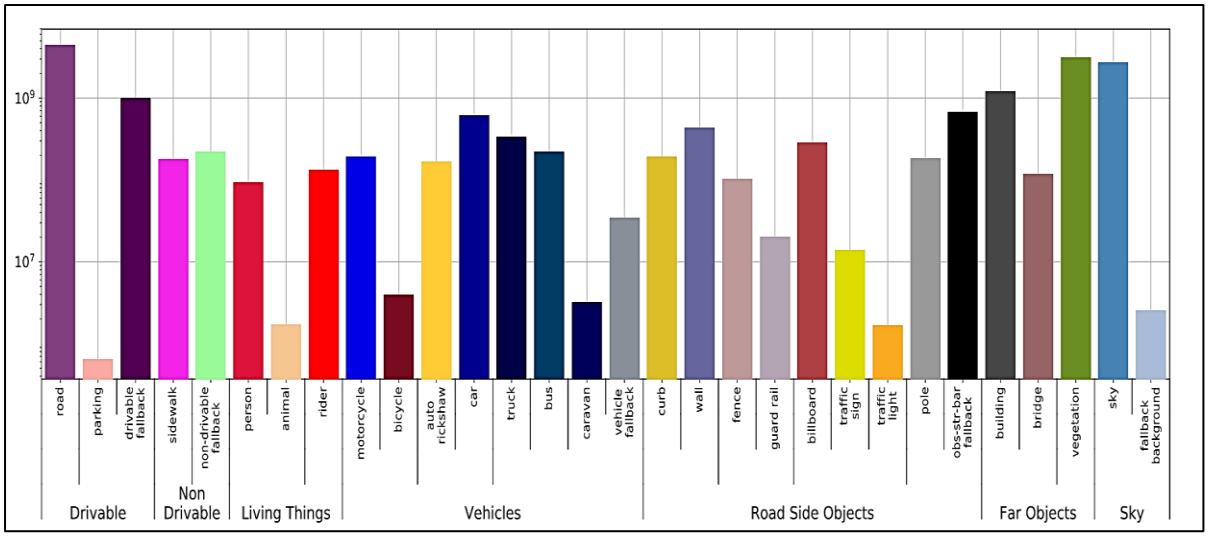

Fig 4.3 IDD Dataset – Labels Available

The dataset consists of images obtained from a front facing camera attached to a car. The car was driven around Hyderabad, Bangalore cities and their outskirts. The images are mostly of 1080p resolution, but there are also some images with 720p and other resolutions.

Dataset	Nearby frames/Video	Distortion /Night	Images/ Sequences	Labels Train/Total	Average Resolution
Cityscapes	✓		5K/50	19/34	2048x1024
IDD	✓		10K/180	30/34	1678x968
Beijing Driving Dataset	✓	✓	10K/10K	19/30	1280x720

Fig 4.4 Comparison of Segmented Datasets

We will also be using images from Google Open-Images Dataset and images obtained from manual search results in Google Images to collect more images for training our model. So, our dataset will be a custom dataset largely supported by images from IDD Dataset. We will be using the same dataset both training and testing of our YOLO – Machine Learning Model, as the IDD Dataset is so large that it can comfortably divided into 3 parts as train, validation and test.

Type	Images
Full	2,588
Train	1,294
Validation	862
Testing	432

Fig 4.5 Images used for Training and Testing Phase from our Dataset

So, as mentioned in the figure 4.3 – we will be using 67% of the IDD Dataset for training our YOLO Machine Learning Model, whereas 22% of the dataset is used for Validation where the rest 11% is used for testing our developed machine learning model.

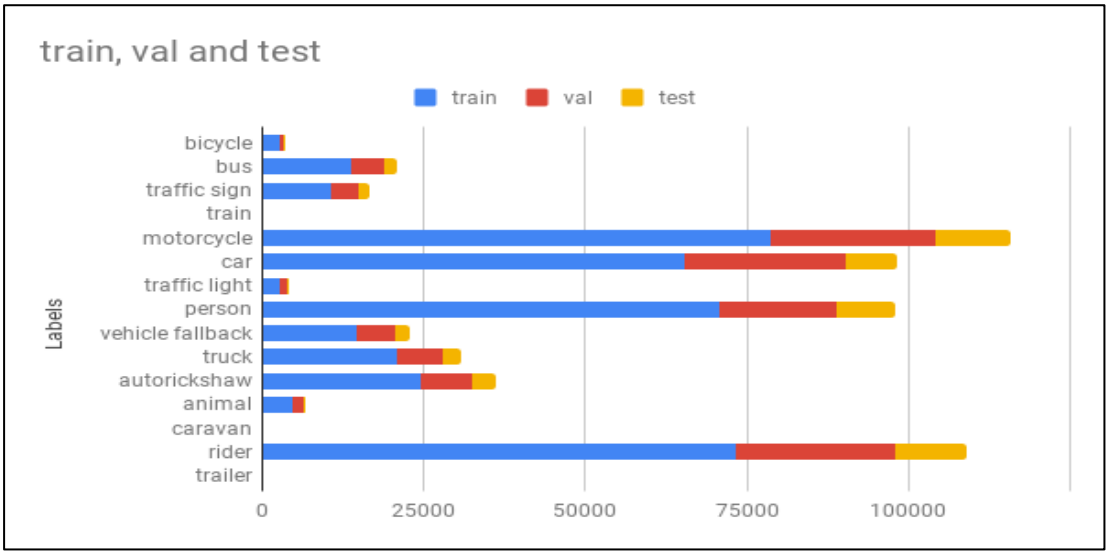

Fig 4.6 Label Distribution for each phase

4.1.3.2 Downloading the Dataset:

Under India Driving Dataset, there are several types of dataset available open to use for different applications. Some of them are,

1. IDD Segmentation – 18.5 GB
2. IDD Multimodal – 17.1 GB
3. IDD Temporal Train – 58 GB
4. IDD Detection – 22.8 GB

Since we are training our machine learning model for Object Detection, we will be selecting the "IDD Detection" Dataset for training our machine learning model. IDD Detection Dataset consists of more than 40,000 finely annotated images with 30+ labels with an average resolution over 720p.

4.2 YOLO Machine Learning Model Training & Weight Creation:

Weight Creation is the ultimate aim of second module of our project. Weight is the parameter within a neural network that transforms input data within the network's hidden layers. A neural network is a series of nodes, or neurons. Within each node is a set of inputs, weight, and a bias value. As an input enters the node, it gets multiplied by a weight value and the resulting output is either observed, or passed to the next layer in the neural network. Often the weights of a neural network are contained within the hidden layers of the network. As we have collected our dataset and it is ready to be trained, we must now start training the dataset after converting it to YOLO Compatible Format.

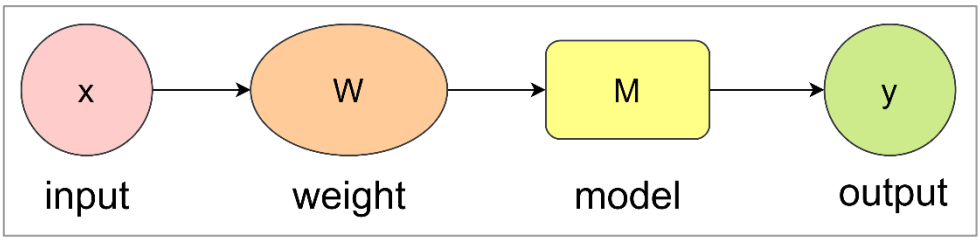

Fig: 4.7 Machine Learning Model – Simplified Sequence Diagram.

4.2.1 Dataset Conversion:

Since the format of each machine learning model differs, so does YOLO's. As YOLO divides an image/frame into 13x13 grids, and predicts atleast 5 bounding boxes on each grid – we must convert any dataset into our YOLO Format.

We, here use Roboflow - a web service to convert our dataset into YOLO Format and we will be now ready to use our own dataset into our YOLO Detector Machine Learning Model.

Roboflow is a Computer Vision developer framework for better data collection to preprocessing, and model training techniques. Roboflow has public datasets readily available to users and has access for users to upload their own custom data also. Roboflow accepts various annotation formats. In data pre-processing, there are steps involved such as image orientations, resizing, contrasting, and data augmentations.

We can manually convert our customized IDD Dataset to the YOLO Model's Format, but it is a serious time-consuming process which might take us days depending on the quantity of dataset files.

1. To do so, we first need to a create a free Roboflow account.
2. Upload our images and their annotations (in any format: VOC XML, COCO JSON, TensorFlow CSV, etc).
3. Roboflow also provides a free annotating tool with which we can easily annotate images with missing annotations
4. Apply preprocessing and augmentation steps as our wish
5. Few processes like auto-orient and a resize to 416x416 is welcomed for better result.
6. Once everything is done, click Generate.

7. Export our dataset in the **YOLO Darknet format**.

8. Copy our **API** download link, and paste it in the Colab Notebook

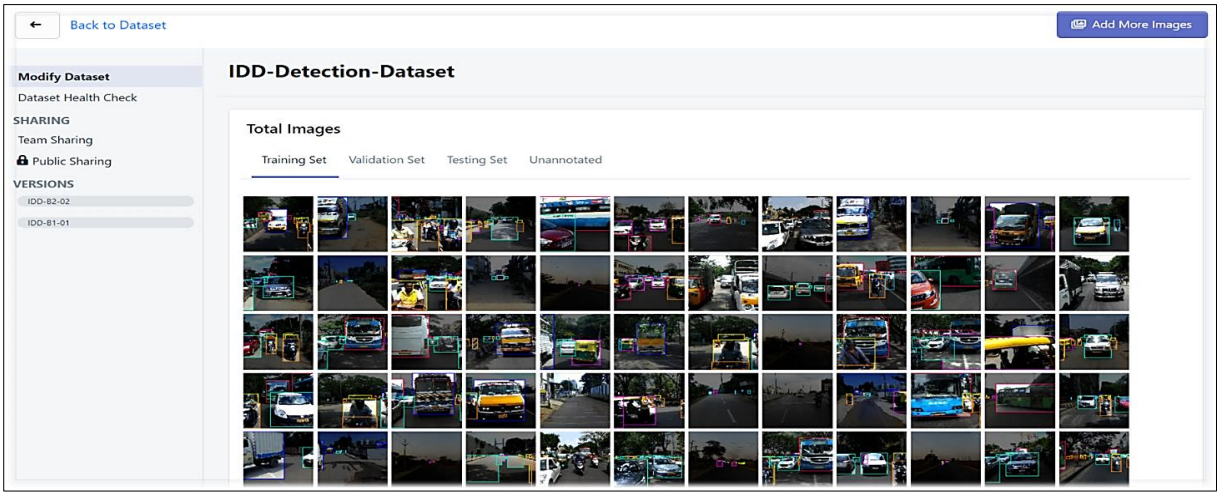

Fig:4.8 Sample from IDD Dataset uploaded in our Roboflow account.

Roboflow accepts images along with its XML files where we have the details of our annotation. As IDD Dataset comes pre-annotated with the help of XML files with them, we can upload the image as well as it's XML file into Roboflow which largely conserves our preparation time for pre-annotated dataset images. In addition to that, we can use the existing dataset as a part of custom dataset that we are planning to create. Like in our case where we are creating a dataset with IDD Dataset as a main contributor and vehicle images from web search as part of our dataset. Here, only the images from IDD Dataset are already annotated and the files that we have uploaded from sources like Google Open-Images Dataset and Google Search might be missing the annotation for them. Roboflow even offers free annotation tool which filters the images in our custom dataset with missing annotation and helps us annotate those images.

During the Dataset Generation process in Roboflow, we can split the dataset as training , validation and testing set which might help us validate how well the model gets trained with this dataset. We can also upload images as batches and save different versions of same dataset in Roboflow.

Roboflow offers various other image pre-processing services like Auto-Orient Images, resizing all the dataset images, merging color channels to make our model faster and insensitive to subject color. Boosting contrasts based on the image's histogram to improve normalization and line detection in varying lighting conditions. Roboflow just like Google Colab is a freemium service where we have to pay for using it above limited service. So, we can opt for premium option if we wish to scale up the size of our dataset.

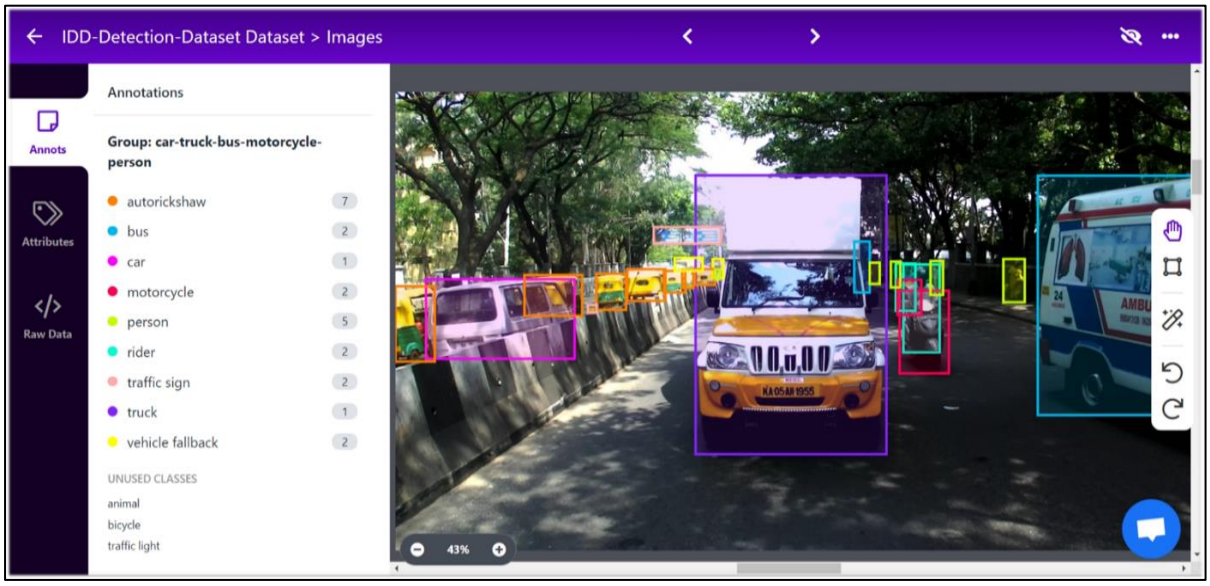

Fig:4.9 Example of Annotation Process at Roboflow service.

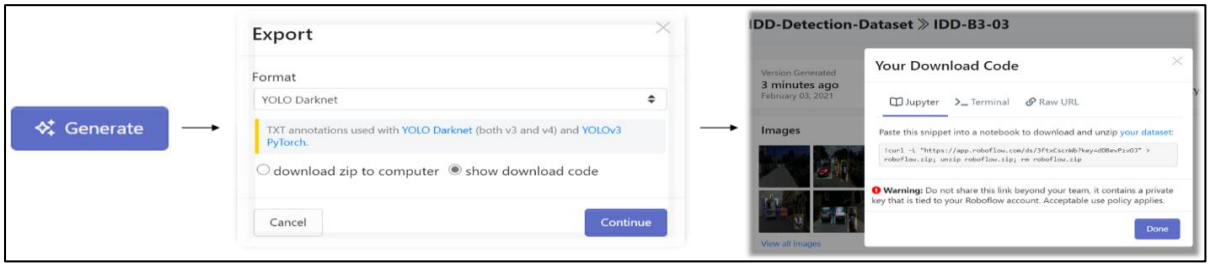

Fig:4.10 Roboflow Conversion Process and API Key.

4.2.2 Dataset Extraction:

Using the API Key obtained at the end of conversion of dataset by Roboflow, we can now the same to unzip the dataset in our Google Colab Cloud

Environment Notebook. After unzipping process, we can now start setting up the directory path for our YOLO – Darknet Framework to detect the extracted data.

Once the extraction process is done, we must write the configuration file for our model based on the number of classes available in our dataset used for training. We build the configuration file iteratively from the base configuration file available on the Darknet Framework's cloned open-source repository. Soon after setting up the configuration file's variables, we can now know that the file is written in our runtime with the help of output displayed at the end of execution.

Now, the model can be started to train. The model runs on the configuration file that we have created moments ago.

4.2.3. Dataset Training & Weight Creation:

Now, we will be using the YOLO Darknet Detector to train the model. When the mAP for first 1000 iterations are done, now the mAP score is calculated and then mAP score will be calculated after further 100 iterations at 1100 iterations. At 1100 iterations - the mAP(mean Average Precision) Score is calculated and compared with the previous mAP score and the training continues for 1200 iterations. This process continues for hours/days according to the size of the dataset and the files that are present.

```
[ ]  1 !./darknet detector train data/obj.data cfg/custom-yolov4-detector.cfg yolov4.conv.137 -dont_show -map

 (next mAP calculation at 1500 iterations)
 Last accuracy mAP@0.5 = 26.17 %, best = 26.62 %
 1406: 11.163265, 8.878999 avg loss, 0.001000 rate, 18.338339 seconds, 67488 images, 82.571598 hours left
Loaded: 0.000047 seconds
^C
```

Fig:4.11 Training our dataset along with mAP Score displayed

Currently, our project's training was done until 1406 iterations - which nearly took 5 hours with 82 hours of training left and 67488 images getting trained. Here the 67488 images are not the actual 67488 images, because a single image can be divided into N*N grid, so the actual set of images trained is unclear currently.

At the end of training, we will be able to notice the “weights” necessary for functioning of our machine learning model.

To test whether the trained weight is able to detect objects present in a sample image, we can pass that image into the detector present in Darknet framework.

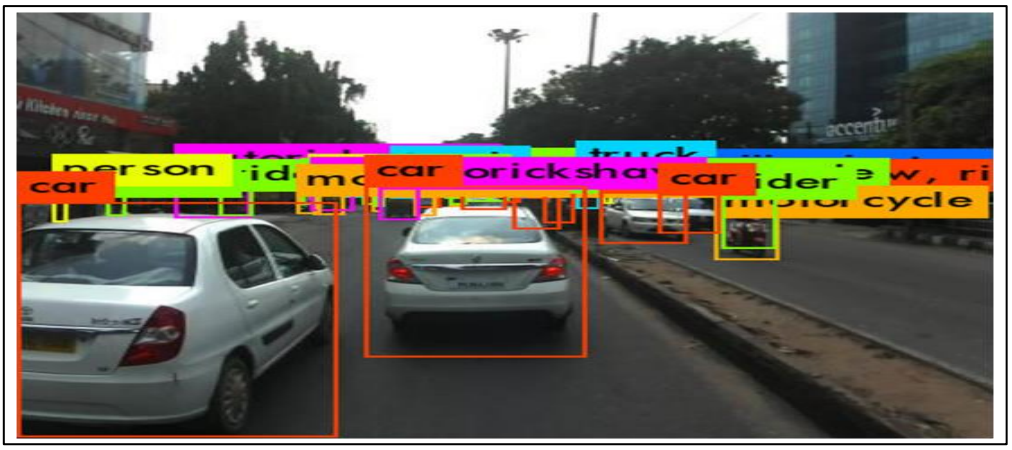

Fig:4.12 Detected Image with trained weights of our Dataset

With our testing results, we conclude that our weights are good to go for Vehicle Detection with our YOLO Machine Learning Model. The Weights can be extended with further training of the model with additional training data and the weights will continue to with better accuracy in extensive training.

4.3 YOLO Machine Learning Model and Vehicle Detection:

The YOLO(YouLookOnlyOnce) model is a combined version of RCNN and SSD for object detection which gives utmost accuracy and also it is a much faster, efficient and powerful algorithm. The YOLO framework (You Only Look Once) takes the entire image in a single instance and predicts the bounding box coordinates and class probabilities for these boxes. The biggest advantage of using YOLO is its superb speed – it’s incredibly fast and can process 45 frames per second. It outperforms other detection methods, including DPM (Deformable Parts Models) and R-CNN. YOLO reframes object detection as a single regression problem instead of a classification problem. This system only looks at

the image once to detect what objects are present and where they are, hence the name YOLO(YouLookOnlyOnce). Also, the model can be trained using huge dataset hence it can detect image placed in any random manner. i.e., it can detect object even if they are rotated in 360 degree. Unlike traditional approach of applying classifier on each image and making prediction, YOLO first takes an input data, and then divides the input data grids. Image classification and localization are applied on each grid. YOLO then predicts the bounding boxes and their corresponding class probabilities for objects if present. Now YOLO applies its algorithm one by one in partitions and predict confidence score, confidence score is the scores that tells us whether object is present or not. On the basis of the confidence score YOLO detects an object.

4.3.1 YOLO Model - Network Architecture:

Our YOLO model has 24 convolutional layers followed by 2 fully connected layers. It uses 1 x 1 reduction layers followed by a 3 x 3 convolutional layer. The 7x7 layer(rightmost) is one of the many bounding boxes that is classified by our YOLO Model. Our model applies its algorithm in each of these many bounding boxes that our model has already classified. The entire process is explained below [5].

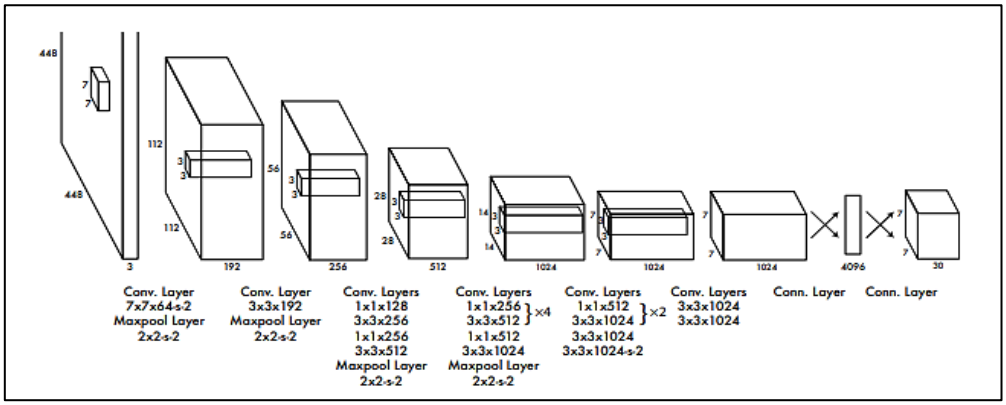

Fig:4.13 YOLO Model – Convolution Layers

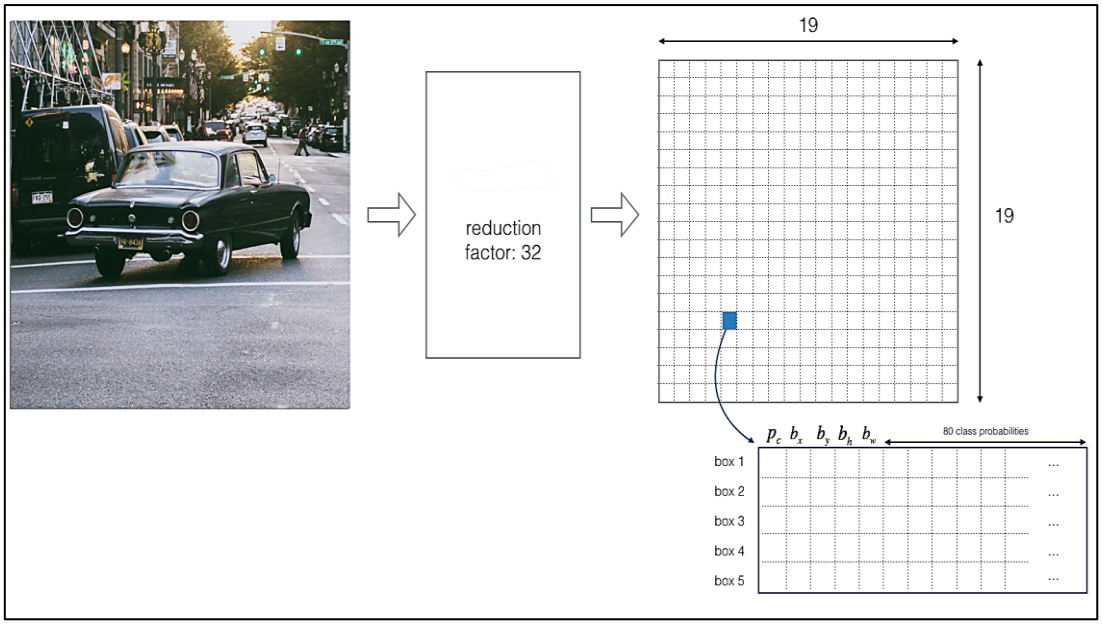

Fig 4.14 Example of How YOLO divides an input image

The system here divides the input image received, into an S x S grid. Each of these grid cells predicts B bounding boxes and confidence scores for these boxes. The confidence score indicates how sure the model is that the box contains an object and also how accurate it thinks the box is that predicts. The confidence score can be calculated using the formula:

$$C = Pr(object) * IoU$$

IoU: Intersection over Union between the predicted box and the ground truth. If no object exists in a cell, its confidence score should be zero.

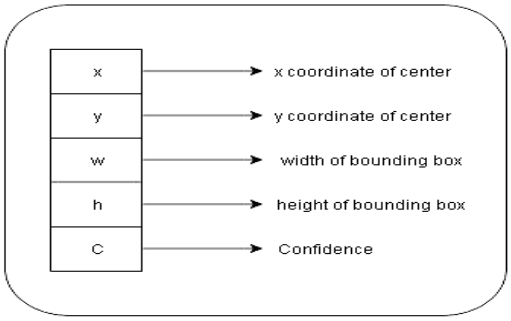

Fig 4.15 YOLO – Bounding Box Prediction

Each bounding box consists of five predictions: **B** = **x, y, w, h**, and confidence where,

1. **(x, y):** Coordinates representing the center of the box. These coordinates are calculated with respect to the bounds of the grid cells.
2. **w:** Width of the bounding box.
3. **h:** Height of the bounding box.

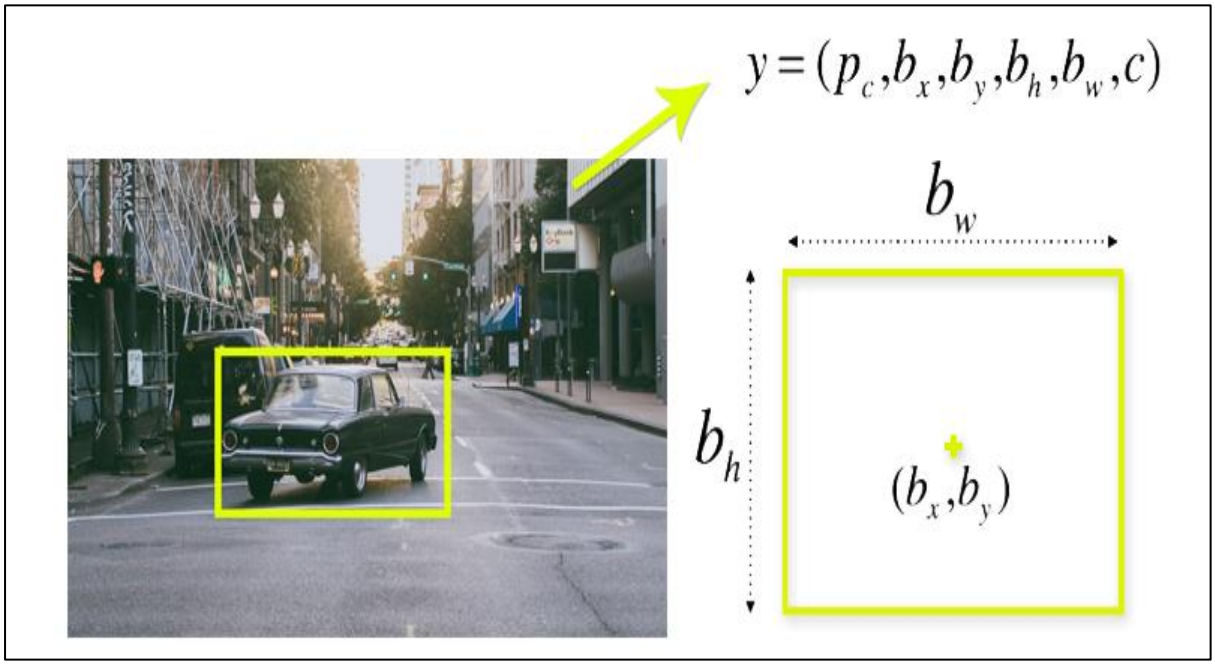

Fig 4.16 Example of YOLO - Bounding Box Prediction

Each grid cell also predicts C conditional class probabilities *Pr (Class i | Object).* It only predicts one set of class probabilities per grid cell, regardless of the number of boxes B. During testing, these conditional class probabilities are multiplied by individual box confidence predictions which give class-specific confidence scores for each box. These scores show both the probability of that class and how well the box fits the object.

*Pr (Class i| Object) *Pr (Object)*IoU = Pr (Class i) *IoU.*

The final predictions of a confidence score are encoded as, **S x S x (B*5 + C).**

Intersection Over Union (IoU):

Intersection Over Union (IoU) is used to evaluate the object detection algorithm. It is the overlap between the ground truth and the predicted bounding box.

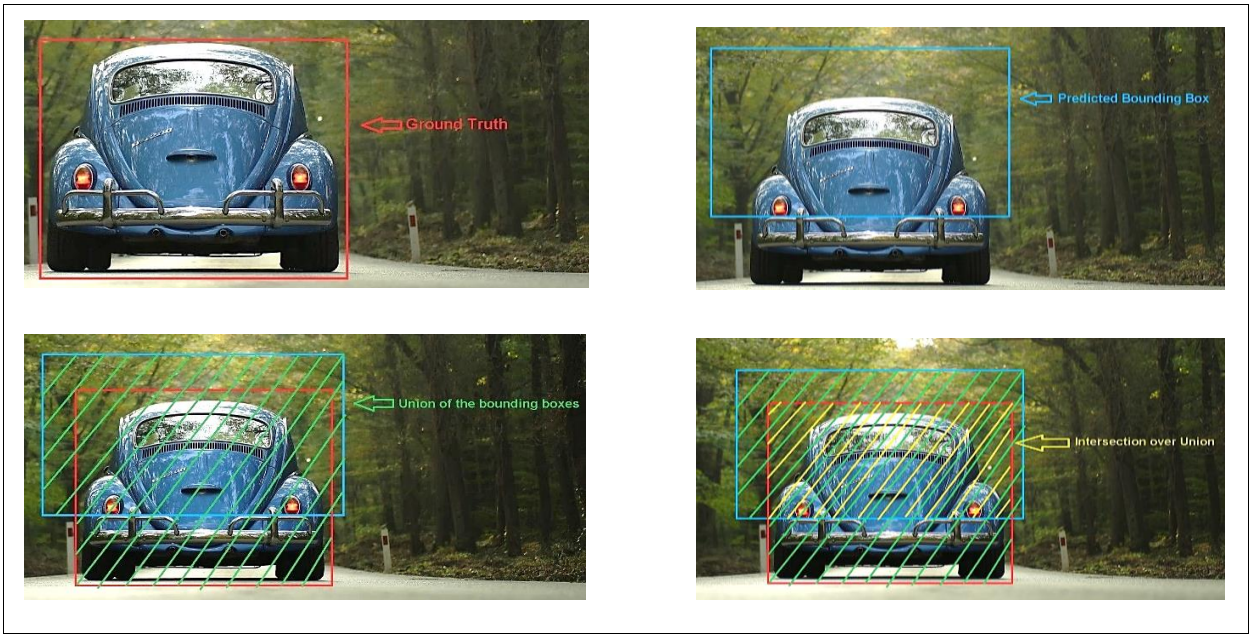

Fig 4.17 Demonstration of IoU used for YOLO Confidence Score

Usually, the threshold for IoU is kept as greater than 0.5. Although many researchers apply a much more stringent threshold like 0.6 or 0.7. If a bounding box has an IoU less than the specified threshold, that bounding box is not taken into consideration.

Looking at the boxes, someone may visually feel it is good enough to conclude that the model detected the car object. Someone else may feel the model is not yet accurate as the predicted box does not fit the ground-truth box well.

To objectively judge whether the model predicted the box location correctly or not, a threshold is used. If the model predicts a box with an IoU score greater than or equal to the threshold, then there is a high overlap between the predicted box and one of the ground-truth boxes. This means the model was able to detect an object successfully. The detected region is classified as Positive (i.e., contains an

object). On the other hand, when the IoU score is smaller than the threshold, then the model made a bad prediction as the predicted box does not overlap with the ground-truth box. This means the detected region is classified as Negative (i.e., does not contain an object).

$$class(IoU) = \begin{cases} Positive \rightarrow IoU \geq Threshold \\ Negative \rightarrow IoU < Threshold \end{cases}$$

Fig:4.18 IoU and the use of Threshold Value

Non-Maximum Suppression:

The algorithm may find multiple detections of the same object. Non-max suppression is a technique by which the algorithm detects the object only once. Consider an example where the algorithm detected three bounding boxes for the same object.

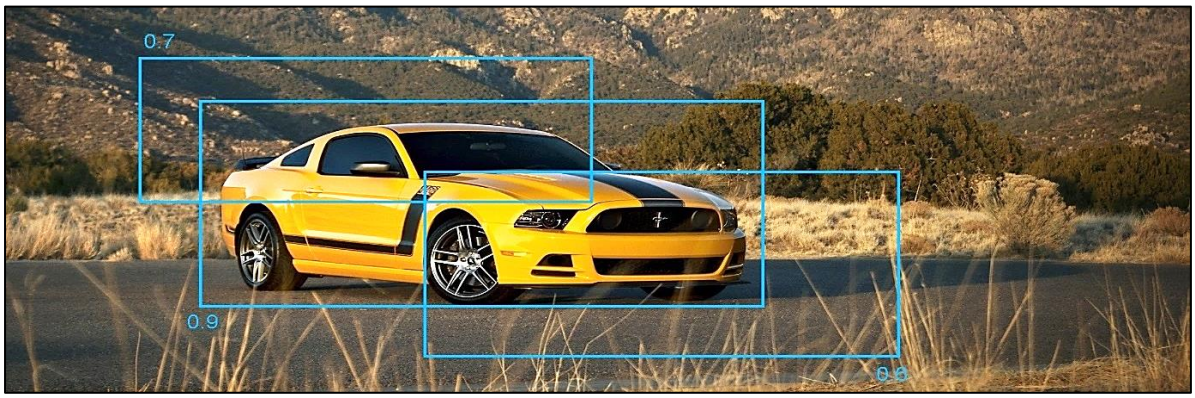

Fig 4.19 Multiple Bounding Boxes of the Same Object

The probabilities of the boxes are 0.7, 0.9, and 0.6 respectively. To remove the duplicates, we are first going to select the box with the highest probability and output that as a prediction. Then eliminate any bounding box with IoU > 0.5 (or any threshold value) with the predicted output. The result will be:

Fig 4.20 Bounding Box Selected After Non-Max Suppression

4.3.2 Vehicle Detection:

After the development of the model, we must pass an input image into the model as an argument to the startup program. The python program will initially start importing necessary libraries required for running the program along with packages from other directories. After importing all necessary libraries and packages. With loading the input from the arguments passed into the model, the model loads the ‘weights’ file for the model which was saved by us earlier from the second module of our project. Along with the weights the model loads the directories of configuration file and the names file containing the dataset label names. Then, the model checks if a GPU is present in the local runtime to boost the speed of the machine learning model. Now the model enters the vehicle detection phase. The model once again checks for if the image is present from the passes input argument path. Now the image enters the image processing phase. The input image is now resized into 416*416 resolution, which helps in better performance of the model to detect inputs. This configuration is built-in already in YOLO’s configuration file. The resized image is then returned as a tensor variable into the model. Now the model uses the neural network weights to detect the input with bounding boxes initially and then perform non-max suppression and the detected output is displayed as result.

```
[ ]  1 !python /content/FYP-ITMS/images3.py --images /content/drive/MyDrive/FYP-ITMS/YOLO-Model/test-images/0012840.jpg

Kickstarting YOLO...

Input Data Passed Into YOLO Model...✓
YOLO Neural Network Successfully Loaded...✓

Performing Vehicle Detection...✓

------------------------------------------------------------------------------------------------------------------------
SUMMARY
------------------------------------------------------------------------------------------------------------------------
Task                                    : Time Taken (in seconds)

Detecting Input File Passed into YOLO Model  :  1.350 seconds
------------------------------------------------------------------------------------------------------------------------
Loading batch                           : 0.035
Average time for detecting an image     : 1.385
------------------------------------------------------------------------------------------------------------------------
Total Number of Objects Detected        : 12
Types of Objects detected with count    : [('car', 6), ('person', 3), ('motorbike', 3)]
------------------------------------------------------------------------------------------------------------------------
Number of Vehicles detected in total    : 9
------------------------------------------------------------------------------------------------------------------------
Vehicle Type    Count

car             6
motorbike       3
```

Fig 4.21 Vehicle Detection Output with YOLO Model

4.4 Vehicle Count & Dynamic Signal Switching:

As we have developed the YOLO model to count the number of vehicles present from an input source, the model detects the vehicles from the image and then counts the number of vehicles present in the given source. The count obtained from the source can now be passed into the python program for determining the threshold value of each lane which we have predefined already. The python program now compares the count of vehicles from each lane and executes further steps in the next module. The obtained data is then sent to the computer system in which we have written a python program that processes the input information and we have already predefined a threshold value based on the count of vehicles. So that the system determines the priority of each lane to open the signal. If all model detects no vehicles or same number of vehicles on each lane, the model will automatically switch to static signal switching approach.

```
[ ]  1 !python /content/FYP-ITMS/itms-yolo-m4-01.py --images /content/FYP-ITMS/vehicles-on-lanes/

Kickstarting YOLO...

Input Data Passed Into YOLO Model...✓
YOLO Neural Network Successfully Loaded...✓

Performing Vehicle Detection with YOLO Neural Network...✓

--------------------------------------------------------------------------------------------------------------------------------
SUMMARY
--------------------------------------------------------------------------------------------------------------------------------

Detected  (4 inputs)    :

Lane : 1 - Number of Vehicles detected :       16
           Vehicle Type    Count
            car             16
Lane : 2 - Number of Vehicles detected :       20
           Vehicle Type    Count
            car             19
            truck           1
Lane : 3 - Number of Vehicles detected :       23
           Vehicle Type    Count
            car             17
            motorbike       3
            truck           3
Lane : 4 - Number of Vehicles detected :       22
           Vehicle Type    Count
            car             21
            motorbike       1
--------------------------------------------------------------------------------------------------------------------------------
🚦 Lane with denser traffic is : Lane 3
```

Fig:4.22 Vehicle Detection and Count Data – Output

The input from 4 lanes are detected and the lane with higher vehicle count is determined by our system. From Fig: 4.22 the lane with denser traffic is Lane-3. System will open the signal of Lane-3 for 30 seconds and close after 30 seconds.

```
--------------------------------------------------------------------------------------------------------------------------------
🚦 Lane with denser traffic is : Lane 3


OPENING LANE-3:
--------------------------------------------------------------------------------
Lane 1              Lane 2              Lane 3              Lane 4
  🔴                  🔴                  🟢                  🔴
  ⚫                  ⚫                  ⚫                  ⚫
  ⚫                  ⚫                  ⚫                  ⚫

LANE-3 is now OPEN and will CLOSE after 5 seconds .....

CLOSING LANE-3:
--------------------------------------------------------------------------------

Lane 1              Lane 2              Lane 3              Lane 4
  🔴                  🔴                  🔴                  🔴
  ⚫                  ⚫                  ⚫                  ⚫
  ⚫                  ⚫                  ⚫                  ⚫

LANE-3 is now CLOSED
--------------------------------------------------------------------------------------------------------------------------------
```

Fig:4.23 Dynamic Signal Switching - Output

This can be repeated for every interval by connecting the system with the existing Traffic Management System's CCTV Cameras as inputs and the dynamic signal switching approach will continue to work wonders with time to time since our model learns from time to time. Thereby, round the clock safety and hassle-free traffic management can be obtained using Proposed Intelligent Traffic Management System.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 CONCLUSION:

The main objective of Intelligent Traffic Management system is founded to fix the problem of traffic which most of the cities in urban as well as rural areas are facing with the help of this project wherein the focus would be to minimize the vehicular congestion. The setup requires traffic data as input which will then be used with our machine learning model for efficient traffic flow without creating much chaos on the road. The model may take comparatively more training time but the response time will be less. The model is prepared in such a way that it decides smart switching timing for the signal on all sides of the road so the no one has to wait for longer interval of time on the road and flow of traffic is smooth on the road. Since the system learns from time to time, the system can be updated in future to become fully-autonomous with training and learning.

5.2 FUTURE WORK

The timer-approach can be enabled to come into existence when the model fails to detect at crucial times like bad weather and low visibility initially. The system can be added with cloud computation support in the future so that the system can log the traffic of respective lanes with date and time which will be highly effective in analyzing the traffic data for further improvement of roads This scenario can be vastly minimized with extended use of our model, since the machine learning models can learn to adapt to different scenarios with continuous use. Our model is able to add even more custom-functions to the program like closing signal for pedestrians crossing, priority for lane with ambulance and vehicle monitoring etc,.

APPENDIX

PROGRAM CODE:

ML MODEL – YOLO:

model.py:

```
from collections import defaultdict

import numpy as np
import torch
from torch import nn

from .parser import parse_model_configuration
from .moduler import modules_creator

class Darknet(nn.Module):
    """YOLOv3 object detection model"""
    def __init__(self, config_path, img_size=416):

        super(Darknet, self).__init__()
        self.blocks = parse_model_configuration(config_path)
        self.hyperparams, self.module_list ,self.num_classes =
modules_creator(self.blocks)
        self.img_size = img_size
        self.seen = 0
        self.header_info = np.array([0, 0, 0, self.seen, 0])
        self.loss_names = ["x", "y", "w", "h", "conf", "cls", "recall",
"precision"]

    def forward(self, x, targets=None):
        is_training = targets is not None
        output = []
        self.losses = defaultdict(float)
        layer_outputs = []
        for i, (block, module) in enumerate(zip(self.blocks,
self.module_list)):
            if block["type"] in ["convolutional", "upsample", "maxpool"]:
                x = module(x)
            elif block["type"] == "route":
                layer_i = [int(x) for x in block["layers"].split(",")]
                x = torch.cat([layer_outputs[i] for i in layer_i], 1)
            elif block["type"] == "shortcut":
                layer_i = int(block["from"])
                x = layer_outputs[-1] + layer_outputs[layer_i]
            elif block["type"] == "yolo":
                # Train phase: get loss
                if is_training:
                    x, *losses = module[0](x, targets)
                    for name, loss in zip(self.loss_names, losses):
```

```
                        self.losses[name] += loss
                # Test phase: Get detections
                else:
                    x = module(x)
                output.append(x)
            layer_outputs.append(x)

        self.losses["recall"] /= 3
        self.losses["precision"] /= 3
        return sum(output) if is_training else torch.cat(output, 1)

    def load_weights(self, weights_path):
        # Open the weights file
        fp = open(weights_path, "rb")
        header = np.fromfile(fp, dtype=np.int32, count=5)  # First five are
header values

        # Needed to write header when saving weights
        self.header_info = header

        self.seen = header[3]
        weights = np.fromfile(fp, dtype=np.float32)  # The rest are weights
        fp.close()

        ptr = 0
        for i, (block, module) in enumerate(zip(self.blocks,
self.module_list)):
            if block["type"] == "convolutional":
                conv_layer = module[0]
                try:
                    block["batch_normalize"]
                except:
                    block["batch_normalize"] = 0
                if block["batch_normalize"]:
                    # Load BN bias, weights, running mean and running
variance
                    bn_layer = module[1]
                    num_b = bn_layer.bias.numel()  # Number of biases
                    # Bias
                    bn_b = torch.from_numpy(weights[ptr : ptr +
num_b]).view_as(bn_layer.bias)
                    bn_layer.bias.data.copy_(bn_b)
                    ptr += num_b
                    # Weight
                    bn_w = torch.from_numpy(weights[ptr : ptr +
num_b]).view_as(bn_layer.weight)
                    bn_layer.weight.data.copy_(bn_w)
                    ptr += num_b
                    # Running Mean
                    bn_rm = torch.from_numpy(weights[ptr : ptr +
num_b]).view_as(bn_layer.running_mean)
                    bn_layer.running_mean.data.copy_(bn_rm)
                    ptr += num_b
```

```
                    # Running Var
                    bn_rv = torch.from_numpy(weights[ptr : ptr +
num_b]).view_as(bn_layer.running_var)
                    bn_layer.running_var.data.copy_(bn_rv)
                    ptr += num_b
                else:
                    # Load conv. bias
                    num_b = conv_layer.bias.numel()
                    conv_b = torch.from_numpy(weights[ptr : ptr +
num_b]).view_as(conv_layer.bias)
                    conv_layer.bias.data.copy_(conv_b)
                    ptr += num_b
                # Load conv. weights
                num_w = conv_layer.weight.numel()
                conv_w = torch.from_numpy(weights[ptr : ptr +
num_w]).view_as(conv_layer.weight)
                conv_layer.weight.data.copy_(conv_w)
                ptr += num_w

    def save_weights(self, path, cutoff=-1):

        fp = open(path, "wb")
        self.header_info[3] = self.seen
        self.header_info.tofile(fp)

        # Iterate through layers
        for i, (block, module) in enumerate(zip(self.blocks[:cutoff],
self.module_list[:cutoff])):
            if block["type"] == "convolutional":
                conv_layer = module[0]
                # If batch norm, load bn first
                if block["batch_normalize"]:
                    bn_layer = module[1]
                    bn_layer.bias.data.cpu().numpy().tofile(fp)
                    bn_layer.weight.data.cpu().numpy().tofile(fp)
                    bn_layer.running_mean.data.cpu().numpy().tofile(fp)
                    bn_layer.running_var.data.cpu().numpy().tofile(fp)
                # Load conv bias
                else:
                    conv_layer.bias.data.cpu().numpy().tofile(fp)
                # Load conv weights
                conv_layer.weight.data.cpu().numpy().tofile(fp)
        fp.close()
```

image_processor.py:

```
import numpy as np
import cv2
import torch

def letterbox_image(image, input_dimension):
    image_width, image_height = image.shape[1], image.shape[0]
```

```
    width, height = input_dimension
    new_width = int(image_width * min(width/image_width,
height/image_height))
    new_height = int(image_height * min(width/image_width,
height/image_height))
    resized_image = cv2.resize(image, (new_width,new_height), interpolation
= cv2.INTER_CUBIC)

    image_as_tensor = np.full((input_dimension[1], input_dimension[0], 3),
128)
    image_as_tensor[(height-new_height)//2:(height-new_height)//2 +
new_height,(width-new_width)//2:(width-new_width)//2 + new_width,  :] =
resized_image

    return image_as_tensor

def preparing_image(image, input_dimension):
    image = (letterbox_image(image, (input_dimension, input_dimension)))
    image = image[:,:,::-1].transpose((2,0,1)).copy()
    image = torch.from_numpy(image).float().div(255.0).unsqueeze(0)

    return image
```

utils.py:

```
import math
import numpy as np
import torch

def bbox_iou(box1, box2, x1y1x2y2=True):
    """
    Function:
        Calculate intersection over union between two bboxes

    Arguments:
       box1 -- first bbox
       box2 -- second bbox
       x1y1x2y2 -- bool value
    Return:
        iou --  the IoU of two bounding boxes
    """
    if not x1y1x2y2:
        # Transform from center and width to exact coordinates
        b1_x1, b1_x2 = box1[:, 0] - box1[:, 2] / 2, box1[:, 0] + box1[:, 2]
/ 2
        b1_y1, b1_y2 = box1[:, 1] - box1[:, 3] / 2, box1[:, 1] + box1[:, 3]
/ 2
        b2_x1, b2_x2 = box2[:, 0] - box2[:, 2] / 2, box2[:, 0] + box2[:, 2]
/ 2
        b2_y1, b2_y2 = box2[:, 1] - box2[:, 3] / 2, box2[:, 1] + box2[:, 3]
/ 2
    else:
        # Get the coordinates of bounding boxes
```

```
        b1_x1, b1_y1, b1_x2, b1_y2 = box1[:, 0], box1[:, 1], box1[:, 2],
box1[:, 3]
        b2_x1, b2_y1, b2_x2, b2_y2 = box2[:, 0], box2[:, 1], box2[:, 2],
box2[:, 3]

    # get the corrdinates of the intersection rectangle
    inter_rect_x1 = torch.max(b1_x1, b2_x1)
    inter_rect_y1 = torch.max(b1_y1, b2_y1)
    inter_rect_x2 = torch.min(b1_x2, b2_x2)
    inter_rect_y2 = torch.min(b1_y2, b2_y2)
    # Intersection area
    inter_area = torch.clamp(inter_rect_x2 - inter_rect_x1 + 1, min=0) *
torch.clamp(
        inter_rect_y2 - inter_rect_y1 + 1, min=0
    )
    # Union Area
    b1_area = (b1_x2 - b1_x1 + 1) * (b1_y2 - b1_y1 + 1)
    b2_area = (b2_x2 - b2_x1 + 1) * (b2_y2 - b2_y1 + 1)

    iou = inter_area / (b1_area + b2_area - inter_area + 1e-16)

    return iou

def unique(tensor):
    """
    Function:
        Get the various classes detected in the image

    Arguments:
        tensor -- torch tensor

    Return:
        tensor_res -- torch tensor after preparing
    """
    tensor_np = tensor.detach().cpu().numpy()
    unique_np = np.unique(tensor_np)
    unique_tensor = torch.from_numpy(unique_np)

    tensor_res = tensor.new(unique_tensor.shape)
    tensor_res.copy_(unique_tensor)
    return tensor_res


def non_max_suppression(prediction, confidence, num_classes, nms_conf =
0.4):
    """
    Function:
        Removes detections with lower object confidence score than
'conf_thres' and performs
        Non-Maximum Suppression to further filter detections.

    Arguments:
        prediction -- tensor of yolo model prediction
```

```
        confidence -- float value to remove all prediction has confidence
value low than the confidence
        num_classes -- number of class
        nms_conf -- float value (non max suppression) to remove bbox it's
iou larger than nms_conf

    Return:
        output -- tuple (x1, y1, x2, y2, object_conf, class_score,
class_pred)
    """
    conf_mask = (prediction[:,:,4] > confidence).float().unsqueeze(2)
    prediction = prediction*conf_mask

    box_corner = prediction.new(prediction.shape)
    box_corner[:,:,0] = (prediction[:,:,0] - prediction[:,:,2]/2)
    box_corner[:,:,1] = (prediction[:,:,1] - prediction[:,:,3]/2)
    box_corner[:,:,2] = (prediction[:,:,0] + prediction[:,:,2]/2)
    box_corner[:,:,3] = (prediction[:,:,1] + prediction[:,:,3]/2)
    prediction[:,:,:4] = box_corner[:,:,:4]

    batch_size = prediction.size(0)

    write = False



    for ind in range(batch_size):
        image_pred = prediction[ind]          #image Tensor
       #confidence threshholding
       #NMS

        max_conf, max_conf_score = torch.max(image_pred[:,5:5+
num_classes], 1)
        max_conf = max_conf.float().unsqueeze(1)
        max_conf_score = max_conf_score.float().unsqueeze(1)
        seq = (image_pred[:,:5], max_conf, max_conf_score)
        image_pred = torch.cat(seq, 1)

        non_zero_ind =  (torch.nonzero(image_pred[:,4]))
        try:
            image_pred_ = image_pred[non_zero_ind.squeeze(),:].view(-1,7)
        except:
            continue

        if image_pred_.shape[0] == 0:
            continue
#

        #Get the various classes detected in the image
        img_classes = unique(image_pred_[:,-1])  # -1 index holds the class
index
```

```
        for cls in img_classes:
            #perform NMS


            #get the detections with one particular class
            cls_mask = image_pred_*(image_pred_[:,-1] ==
cls).float().unsqueeze(1)
            class_mask_ind = torch.nonzero(cls_mask[:,-2]).squeeze()
            image_pred_class = image_pred_[class_mask_ind].view(-1,7)

            #sort the detections such that the entry with the maximum
objectness
            #confidence is at the top
            conf_sort_index = torch.sort(image_pred_class[:,4], descending
= True )[1]
            image_pred_class = image_pred_class[conf_sort_index]
            idx = image_pred_class.size(0)   #Number of detections

            for i in range(idx):
                #Get the IOUs of all boxes that come after the one we are
looking at
                #in the loop
                try:
                    ious = bbox_iou(image_pred_class[i].unsqueeze(0),
image_pred_class[i+1:])
                except ValueError:
                    break

                except IndexError:
                    break

                #Zero out all the detections that have IoU > treshhold
                iou_mask = (ious < nms_conf).float().unsqueeze(1)
                image_pred_class[i+1:] *= iou_mask

                #Remove the non-zero entries
                non_zero_ind =
torch.nonzero(image_pred_class[:,4]).squeeze()
                image_pred_class = image_pred_class[non_zero_ind].view(-
1,7)

            batch_ind = image_pred_class.new(image_pred_class.size(0),
1).fill_(ind)      #Repeat the batch_id for as many detections of the class
cls in the image
            seq = batch_ind, image_pred_class

            if not write:
                output = torch.cat(seq,1)
                write = True
            else:
                out = torch.cat(seq,1)
                output = torch.cat((output,out))
```

```
    try:
        return output
    except:
        return 0


def build_targets(pred_boxes, pred_conf, pred_cls, target, anchors,
num_anchors,
                  num_classes, grid_size, ignore_thres, img_dim):
    """
    Function:
        build the target values for training process
    Arguments:
       pred_boxes -- predicted bboxes
       pred_conf -- predicted confidence of bbox
       pred_cls -- predicted class of bbox
       target -- target value
       anchors -- list of anchors boxs' dimensions
       num_anchors -- number of anchor boxes
       num_classes -- number of classes
       grid_size -- grid size
       ignore_thres -- confidence thres
       img_dim -- input image dimension

    Return:
        nGT -- total number of predictions
        n_correct -- number of correct predictions
        mask -- mask
        conf_mask -- confidence mask
        tx -- xs of bboxes
        ty -- ys of bboxs
        tw -- width of bbox
        th -- height of bbox
        tconf -- confidence
        tcls  -- class prediction
    """


    batch_size = target.size(0)
    num_anchors = num_anchors
    num_classes = num_classes
    n_grid = grid_size

    mask = torch.zeros(batch_size, num_anchors, n_grid, n_grid)
    conf_mask = torch.ones(batch_size, num_anchors, n_grid, n_grid)

    tx = torch.zeros(batch_size, num_anchors, n_grid, n_grid)
    ty = torch.zeros(batch_size, num_anchors, n_grid, n_grid)
    tw = torch.zeros(batch_size, num_anchors, n_grid, n_grid)
    th = torch.zeros(batch_size, num_anchors, n_grid, n_grid)

    tconf = torch.ByteTensor(batch_size, num_anchors, n_grid,
n_grid).fill_(0)
```

```
    tcls = torch.ByteTensor(batch_size, num_anchors, n_grid, n_grid,
num_classes).fill_(0)

    nGT = 0
    n_correct = 0

    for b in range(batch_size):
        for t in range(target.shape[1]):
            if target[b, t].sum == 0:
                continue

            nGT += 1

            # Convert to position relative to box
            gx = target[b, t, 1] * n_grid
            gy = target[b, t, 2] * n_grid
            gw = target[b, t, 3] * n_grid
            gh = target[b, t, 4] * n_grid

            # Get grid box indices
            gi = int(gx)
            gj = int(gy)

            # Get shape of gt box
            gt_box = torch.FloatTensor(np.array([0, 0, gw,
gh])).unsqueeze(0)

            # Get shape of anchor box
            anchor_shapes =
torch.FloatTensor(np.concatenate((np.zeros((len(anchors), 2)),
np.array(anchors)), 1))

            # Calculate iou between gt and anchor shapes
            anch_ious = bbox_iou(gt_box, anchor_shapes)

            # Where the overlap is larger than threshold set mask to zero
(ignore)
            conf_mask[b, anch_ious > ignore_thres, gj, gi] = 0

            # Find the best matching anchor box
            best_n = np.argmax(anch_ious)

            # Get ground truth box
            gt_box = torch.FloatTensor(np.array([gx, gy, gw,
gh])).unsqueeze(0)

            # Get the best prediction
            pred_box = pred_boxes[b, best_n, gj, gi].unsqueeze(0)

            # Masks
            mask[b, best_n, gj, gi] = 1
            conf_mask[b, best_n, gj, gi] = 1
```

```
            # Coordinates
            tx[b, best_n, gj, gi] = gx - gi
            ty[b, best_n, gj, gi] = gy - gj

            # Width and height
            tw[b, best_n, gj, gi] = math.log(gw / anchors[best_n][0] + 1e-
16)
            th[b, best_n, gj, gi] = math.log(gh / anchors[best_n][1] + 1e-
16)

            # One-hot encoding of label
            target_label = int(target[b, t, 0])
            tcls[b, best_n, gj, gi, target_label] = 1
            tconf[b, best_n, gj, gi] = 1

            iou = bbox_iou(gt_box, pred_box, x1y1x2y2=False)
            pred_label = torch.argmax(pred_cls[b, best_n, gj, gi])
            score = pred_conf[b, best_n, gj, gi]
            if iou > 0.5 and pred_label == target_label and score > 0.5:
                n_correct += 1

    return nGT, n_correct, mask, conf_mask, tx, ty, tw, th, tconf, tcls



def weights_init_normal(m):
    """
    Function:
        Initialize weights

    Arguments:
       m -- module
    """
    classname = m.__class__.__name__
    if classname.find("Conv") != -1:
        torch.nn.init.normal_(m.weight.data, 0.0, 0.02)
    elif classname.find("BatchNorm2d") != -1:
        torch.nn.init.normal_(m.weight.data, 1.0, 0.02)
        torch.nn.init.constant_(m.bias.data, 0.0)
```

main.py:

```
'''*** Import Section ***'''

from __future__ import
from collections import Counter
import argparse
import os
import os.path as osp
import pickle as pkl
import pandas as
import time
```

```
import sys
import torch
from torch.autograd import Variable
import cv2
import emoji
import warnings
warnings.filterwarnings(
    'ignore')
print('\033[1m' + '\033[91m' + "Kickstarting YOLO...\n")
from util.parser import load_classes
from util.model import Darknet
from util.image_processor import preparing_image
from util.utils import non_max_suppression
from util.signal_switching import countdown
from util.signal_lights import switch_signal


#*** Parsing Arguments to YOLO Model ***
def arg_parse():
    parser = argparse.ArgumentParser(
        description=
        'YOLO Vehicle Detection Model for Intelligent Traffic Management
System'
    )
    parser.add_argument(
        "--images",
        dest='images',
        help="Image / Directory containing images to  vehicle detection
upon",
        default="/content/Model/test-images",
        type=str)
    '''parser.add_argument("--outputs",dest='outputs',help="Image /
Directory to store detections",default="/content/output/",type=str)'''
    parser.add_argument("--bs", dest="bs", help="Batch size", default=1)
    parser.add_argument("--confidence_score",
                        dest="confidence",
                        help="Confidence Score to filter Vehicle
Prediction",
                        default=0.3)
    parser.add_argument("--nms_thresh",
                        dest="nms_thresh",
                        help="NMS Threshhold",
                        default=0.3)
    parser.add_argument("--cfg",
                        dest='cfgfile',
                        help="Config file",
                        default="config/yolov3.cfg",
                        type=str)
    parser.add_argument("--weights",
                        dest='weightsfile',
                        help="weightsfile",
                        default="weights/yolov3.weights",
                        type=str)
```

```
    parser.add_argument(
        "--reso",
        dest='reso',
        help=
        "Input resolution of the network. Increase to increase accuracy.
Decrease to increase speed",
        default="416",
        type=str)
    return parser.parse_args()


args = arg_parse()
images = args.images
batch_size = int(args.bs)
confidence = float(args.confidence)
nms_thesh = float(args.nms_thresh)
start = 0
CUDA = torch.cuda.is_available()

#***Loading Dataset Class File***
classes = load_classes("data/idd.names")

#***Setting up the neural network***
model = Darknet(args.cfgfile)
print('\033[0m' + "Input Data Passed into YOLO Model..." + u'\N{check
mark}')
model.load_weights(args.weightsfile)
print('\033[0m' + "YOLO Neural Network Successfully Loaded..." +
      u'\N{check mark}')
print('\033[0m')
model.hyperparams["height"] = args.reso
inp_dim = int(model.hyperparams["height"])
assert inp_dim % 32 == 0
assert inp_dim > 32
num_classes = model.num_classes
print('\033[1m' + '\033[92m' +
      "Performing Vehicle Detection with YOLO Neural Network..." +
'\033[0m' +
      u'\N{check mark}')
#Putting YOLO Model into GPU:
if CUDA:
    model.cuda()
model.eval()
read_dir = time.time()

#***Vehicle Detection Phase***
try:
    imlist = [
        osp.join(osp.realpath('.'), images, img) for img in
os.listdir(images)
    ]
except NotADirectoryError:
    imlist = []
```

```
    imlist.append(osp.join(osp.realpath('.'), images))
except FileNotFoundError:
    print("No Input with the name {}".format(images))
    print("Model failed to load your input.  ")
    exit()

load_batch = time.time()
loaded_ims = [cv2.imread(x) for x in imlist]

im_batches = list(
    map(preparing_image, loaded_ims, [inp_dim for x in
range(len(imlist))]))
im_dim_list = [(x.shape[1], x.shape[0]) for x in loaded_ims]
im_dim_list = torch.FloatTensor(im_dim_list).repeat(1, 2)

leftover = 0

if (len(im_dim_list) % batch_size):
    leftover = 1

if batch_size != 1:
    num_batches = len(imlist) // batch_size + leftover
    im_batches = [
        torch.cat(
            (im_batches[i * batch_size:min((i + 1) *
                                           batch_size, len(im_batches))]))
        for i in range(num_batches)
    ]

write = 0

if CUDA:
    im_dim_list = im_dim_list.cuda()
start_outputs_loop = time.time()

input_image_count = 0
denser_lane = 0
lane_with_higher_count = 0
print()
print('\033[1m' + "SUMMARY")
)
print('\033[1m' +
      "{:25s}: ".format("\nDetected  (" + str(len(imlist)) + " inputs)"))
print('\033[0m')
#Loading the image, if present :
for i, batch in enumerate(im_batches):
    #load the image
    vehicle_count = 0
    start = time.time()
    if CUDA:
        batch = batch.cuda()
    with torch.no_grad():
        prediction = model(Variable(batch))
```

```
    prediction = non_max_suppression(prediction,
                                     confidence,
                                     num_classes,
                                     nms_conf=nms_thesh)

    end = time.time()

    if type(prediction) == int:
        for im_num, image in enumerate(
                imlist[i * batch_size:min((i + 1) * batch_size,
len(imlist))]):
            im_id = i * batch_size + im_num
            print("{0:20s} predicted in {1:6.3f} seconds".format(
                image.split("/")[-1], (end - start) / batch_size))
            print("{0:20s} {1:s}".format("Objects detected:", ""))

        continue

    prediction[:,
               0] += i * batch_size  # transform the atribute from index in
batch to index in imlist

    if not write:  # If we have't initialised output
        output = prediction
        write = 1
    else:
        output = torch.cat((output, prediction))

    for im_num, image in enumerate(
            imlist[i * batch_size:min((i + 1) * batch_size, len(imlist))]):
        vehicle_count = 0
        input_image_count += 1
        #denser_lane =
        im_id = i * batch_size + im_num
        objs = [classes[int(x[-1])] for x in output if int(x[0]) == im_id]
        vc = Counter(objs)
        for i in objs:
            if i == "car" or i == "motorbike" or i == "truck" or i ==
"bicycle" or i == "autorickshaw":
                vehicle_count += 1

        print('\033[1m' + "Lane : {} - {} : {:5s} {}".format(
            input_image_count, "Number of Vehicles detected", "",
            vehicle_count))
        if vehicle_count > lane_with_higher_count:
            lane_with_higher_count = vehicle_count
            denser_lane = input_image_count
        print(
            '\033[0m' +
            "           File Name:     {0:20s}.".format(image.split("/")[-
1]))
        print('\033[0m' +
```

```
              "           {:15} {}".format("Vehicle Type", "Count"))
        for key, value in sorted(vc.items()):
            if key == "car" or key == "motorbike" or key == "truck" or key
== "bicycle":
                print('\033[0m' + "           {:15s} {}".format(key,
value))

    if CUDA:
        torch.cuda.synchronize()
    if vehicle_count == 0:
        print(
            '\033[1m' +
            "There are no vehicles present from the input that was passed
into our YOLO Model."
        )

print(
    emoji.emojize(':vertical_traffic_light:') + '\033[1m' + '\033[94m' +
    " Lane with denser traffic is : Lane " + str(denser_lane) +'\033[30m'+
"\n")

switch_signal(1, 5)
try:
    output
except NameError:
    print("No detections were made | No Objects were found from the input")
    exit()

torch.cuda.empty_cache()
```

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