AUTOMATED SMART TRAFFIC JUNCTION OVERHEAD POLE CAMERA ANALYTICS WITH DEEP NEURAL NETWORK

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This report is submitted in partial fulfilment of the requirements for the degree of Bachelor of Electronic Engineering with Honours

Faculty of Electronic and Computer Engineering
Universiti Teknikal Malaysia Melaka

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DECLARATION

I declare that this report entitled "Automated Smart Traffic Junction Overhead Pole Camera Analytics with Deep Neural Network" is the result of my own work except for quotes as cited in the references.

Signature : ....

Author : Ong Chen Yan

Date : 25 June 2021

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Bachelor of Electronic Engineering with Honours.

Signature : ……………………………………

Supervisor Name : Associate Professor Dr. Lim Kim Chuan

Date : 25 June 2021

DEDICATION

I would like to dedicate this study to my project supervisor, Associate Professor Dr. Lim Kim Chuan who had given me a fully support and encouragement in accomplishing this study.

ABSTRACT

As current trend in Industrial Revolution 4.0, the use of artificial intelligent technology provides a better alternative method in traffic data collection. Deep Neural Network is applied for vehicle recognition with OpenVINO toolkit in this study. Meanwhile, algorithm has been implemented for lane detection and vehicle counting based on each detected lane region. The main goal of this study is to provide reliable traffic data for traffic management system. Experiment has been carried out for 15 pre-recorded traffic videos with different time, angle view, number of lanes and weather. The performances of algorithm are then analysed and optimised based on the computation time of algorithm per frame and accuracy of algorithm. According to the results obtained, the performance of algorithm during clear sunny day is the best where it achieves 100% accuracy for lane detection algorithm and 70.62% to 87.97% accuracy for vehicle lane count algorithm. The overall performance of algorithm after optimisation has improved and all traffic videos obtained mean computation time of algorithm below than the frame rate of input traffic videos. Besides, all traffic videos had no deterioration in accuracy of optimised lane detection algorithm. At the same time, the deterioration in accuracy of optimised vehicle lane count algorithm for all traffic videos are less than 10%.

ABSTRAK

Dengan Revolusi Perindustrian 4.0 sebagai trend semasa, pengenalan teknologi kepintaran buatan telah membekalkan cara alternatif yang bermanfaat dalam pengumpulan data trafik. "Deep Neural Network" telah digunakan dalam projek ini bagi pengiktirafan kenderaan dengan peralatan "OpenVINO". Pada masa yang sama, algoritma juga dilaksanakan bagi mengira bilangan jalan dan jumlah kenderaan dalam setiap jalan tersebut. Tujuan utama projek ini adalah untuk memberikan data trafik yang tepat bagi pengurusan sistem trafik. Eksperimen telah dilaksanakan dengan melibatkan 15 video trafik dari masa, sudut, jumlah jalan dan cuaca yang berbeza. Kemudian, prestasi algoritma telah dianalisis berdasarkan masa pelaksanaan algoritma bagi setiap bingkai video dan ketepatan algoritma. Berdasarkan keputusan, waktu pagi membekalkan keputusan yang terbaik di mana ketepatan algoritma dalam pengiraan bilangan jalan adalah 100% dan ketepatan pengiraan kenderaan adalah antara 70.62% hingga 87.97%. Prestasi algoritma mencatatkan peningkatan dan masa pelaksanaan algoritma bagi semua video adalah kurang daripada kadar bingkainya. Selain itu, tiada video menghadapi penurunan dalam ketepatan pengiraan jalan manakala semua video menghadapi penurunan kurang daripada 10% bagi pengiraan kenderaan selepas permudahan.

ACKNOWLEDGEMENTS

I felt so grateful that I had met a lot of wonderful people and professionals in guiding me throughout my final year project. Hence, I would like to grab this chance to thank those who had given me a helping hand.

First and foremost, I would like to express my special thanks of gratitude to my project supervisor, Associate Professor Dr. Lim Kim Chuan for sharing his knowledge and suggesting me a lot of useful ideas with patient. Despite of being extraordinary busy with his duty, he still willing to sacrifice his time in guiding me and correcting my mistake from time to time without any complaint.

Next, I would also like to thank to my panels, Dr. Siva Kumar a/l Subramaniam and Dr. Yusmarnita binti Yusop for their valuable advice and suggestion during seminar session in leading me towards a better improvement. Also, thanks to Universiti Teknikal Malaysia Melaka (UTeM) for providing me a comfortable environment to explore knowledge.

Last but not least, I would like to express my deepest appreciation to my beloved parents who had given me an unconditional support and encouragement in my study.

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LIST OF SYMBOLS AND ABBREVIATIONS

AI	:	Artificial Intelligence
DNN	:	Deep Neural Network
TOPS	:	Trillion of Operation Per Second
IR 4.0	:	Industrial Revolution 4.0
OpenVINO	:	Open Visual Inference and Neural Network Optimisation
IoT	:	Internet of Things
ITS	:	Intelligent Transport System
DBKL	:	Dewan Bandaraya Kuala Lumpur
LiDAR	:	Light Detection and Ranging
GPS	:	Global Positioning System
HSV	:	Hue, Saturation, Value
STSC	:	Smart Traffic Signal Control
RSU	:	Roadside Unit
OBU	:	On Board Unit
EVSP	:	Emergency Vehicle Signal Pre-emption
TSP	:	Transit Signal Priority
ATSC	:	Adaptive Traffic Signal Control
IR	:	Infrared

KNN		K Nearest Neighbours
RFID	:	Radio Frequency Identification
CCTV	:	Closed-Circuit Television
OS	:	Operating System
CLI	:	Command Line Interface
ROI	:	Region of Interest
CO_2	:	Carbon Dioxide

CHAPTER 1

INTRODUCTION

This chapter presents the overview of this project including project background on traffic data collection method, problem statement, objectives, scope of work, project significance and thesis outline.

1.1 Project Background

Traffic data collection is the backbone for the creation of traffic management system. It helps to reflect the real world traffic situation [1] where traffic engineers and road engineers require these data for the implementation of traffic signal timing plan and road planning [2]. The development of technology has contributed to the evolution of traffic data collection method from time to time. Traffic data collection method begins with manual counting then followed by sensors detection method and recently artificial intelligence technology is introduced.

1.1.1 Manual Counting Method

In the past, manual counting is one of the common methods for traffic data collection [3]. This method is carried out by assigning human surveyors to distinguish between couple of vehicle categories and the direction of the vehicles in a pre-selected time interval [1]. The main disadvantage of this method is it required high demand on manpower meanwhile the accuracy of the collected data is not guaranteed.

Figure 1.1: Manual Counting Method

1.1.2 Sensor Detection Method

Sensors such as pneumatic tube, induction loop, weigh-in-motion sensor and micro-millimetre wave radar detector have been introduced to replace manual counting method for traffic data collection in order to solve resources intensive problem in manual counting method. These sensors often installed near the traffic light to detect the presence of vehicles and control the traffic signal.

Figure 1.2: Sensor Detection Method

Sensor detection has automated vehicle detection process but it is expensive and lack of flexibility due to only specific parameter can be detected. A lot of different sensors need to be interfaced to provide an all-round traffic data.

1.1.3 Artificial Intelligence Data Collection

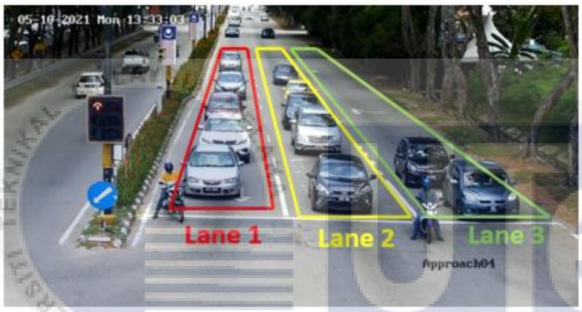
Artificial Intelligence (AI) technology has blossomed to be the latest trend of technology in the development of system that required human intelligent to be performed. This technology has been implemented in traffic data collection where traffic camera is used to capture the real time traffic situation and AI technology is used for vehicle recognition with the combination of camera analytics to analyse the traffic data for vehicle counting and license plate recognition. Usually, this traffic camera is installed at overhead pole to provide a wide viewing angle for capturing the real time traffic conditions.

Figure 1.3: Overhead Pole Traffic Camera

Figure 1.4: Artificial Intelligence Data Collection

1.2 Problem Statement

Traffic data is the fundamental element for the development of traffic management system. It always a challenging process for traffic engineers to collect reliable traffic data [4]. Manpower is required to manually segment the lane region, observe and count the number of vehicles through the traffic camera deployed at traffic junction. This scenario had made traffic data collection to be resource-intensive. As a result, camera analytics with deep neural network is required to improve the traffic data collection method.



Count the Number of Vehicles Based on Each Lane

Lane 1	Lane 2	Lane 3
5	5	2

Figure 1.5: Manual Segment Lane Region and Vehicle Counting

1.3 Objectives

This study aims to provide a reliable data for traffic management system with the introduction of Deep Neural Network and camera analytics. The study embarks on the following objectives:

i. To develop an automated system which capable to identify the number of lanes for the deep learning traffic camera deployed at traffic junction.
ii. To implement algorithm which able to automate the vehicle lane count of deep learning traffic camera.
iii. To analyse and optimise the performance of algorithm based on computation time of algorithm per frame and accuracy of algorithm.

1.4 Scope of Work

This project is a software-based project that only covered on the development of an automated system which capable to identify number of lanes at traffic junction and count the number of vehicles on each detected lane region. Linux is chosen as main operating system while Python is selected as the programming language for this project. Meanwhile, Open Visual Inference and Neural Network Optimisation (OpenVINO) is applied for vehicle recognition by enabling deep learning interference.

An experiment has been carried out in this study using 15 pre-recorded traffic videos with duration of 5 minutes and different time, angle view, number of lanes as well as weather to verify the functionality of algorithm. The performances of algorithm for each video are then analysed and optimised based on computational time of algorithm per frame and accuracy of algorithm.

1.5 Project Significance

Previously, manpower is required to segment the lane region and count the number of vehicles based on each lane region for traffic data collection. It is resource-intensive and inaccurate. This project introduced AI technology with camera analytics to provide automatic lane detection and vehicle lane counting via the deployment of deep learning camera. The capability to capture and analyse a long distance of traffic data in this project has helped to avoid the problem of integration of multiple sensors in traffic data collection.

Besides, the real time vehicle lane counting contributed by this project is helpful in reflecting the real time traffic density which is vital in traffic signal control system. The synchronisation of traffic density with traffic signal has allowed the flexible changes on the waiting time of traffic light which is useful in reducing traffic congestion in the city especially during peak hour.

1.6 Thesis Outline

This thesis comprises of five main chapters. Chapter 1 introduces the project background on traffic data collection method, problem statement, objectives, scope of work and project significance. Chapter 2 presents the overview of deep learning and deep neural network, deployment of smart traffic system in Malaysia, existing method in vehicle detection and application of camera analytics in traffic data collection. The review of previous works related to lane detection, smart traffic system and vehicle recognition with neural network are also discussed in this chapter. Chapter 3 discusses on the overall project flow planning for implementation, verification, analysis, and optimisation of algorithm with illustration of flow charts. Chapter 4 involves all the results for each video with the discussion on the performance of algorithm based on computation time of algorithm per frame and accuracy of algorithm. The comparison on the performance of the algorithm before and after optimisation are also discussed in this chapter. Last but not least, the achievement of project and proposed method for the improvement of project in the future is presented in Chapter 5.

CHAPTER 2

BACKGROUND STUDY

This chapter involves the overview of deep learning and deep neural network, deployment of smart traffic system in Malaysia, existing method in vehicle detection and application of camera analytics in traffic data collection. The review of previous work related to lane detection, smart traffic system and vehicle recognition with neural network are also discussed in this chapter.

2.1 Overview of Deep Learning and Deep Neural Network

Deep learning is defined as a subset of machine learning which based on neural networks that permit a machine to train itself and perform task [5]. Yann Le Cun *et al.* (2015) mentioned that deep learning allows computational models to learn representation of data with multiple levels of abstraction through discovery of intricate structure in large data sets via backpropagation algorithm [6]. The breakthrough of deep learning has boosted its application in various field including recognition, targeted advertisement, natural language assistant and prototype self-driving vehicle systems [7].

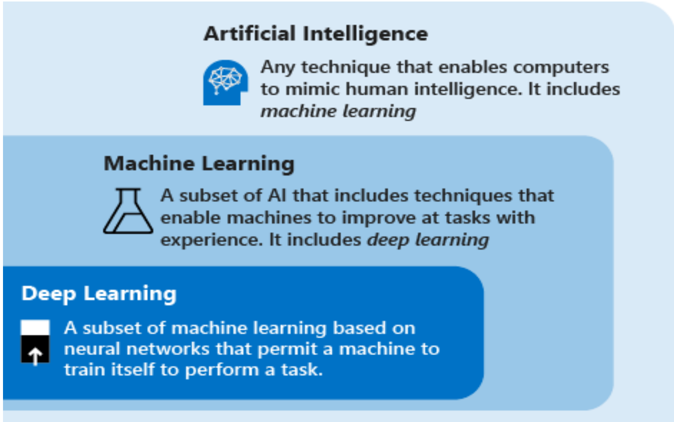


Figure 2.1: Artificial Intelligence, Machine Learning and Deep Learning [5]

Alternatively, Deep Neural Network is one of the most essential tools in the broader area of deep learning. It processes input information in a hierarchy way where each subsequent level of processing extracts more abstract features [8]. Generally, there are two key processes involved in deep learning which are training and inference. Training is used for the creation of deep learning model whereas inference is used for application of trained deep learning model in making prediction [9].

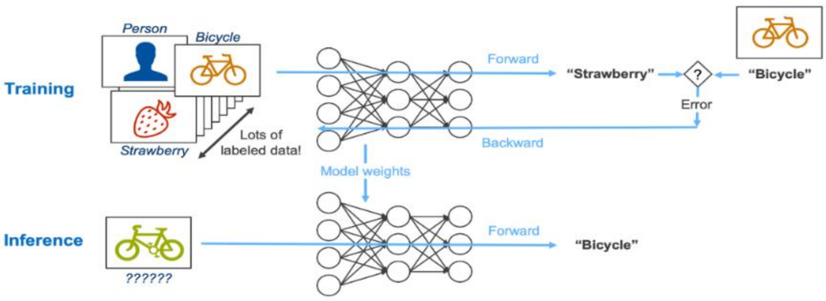


Figure 2.2: Training and Inference of Deep Learning [9]

2.2 Deployment of Smart Traffic System in Malaysia

In recent years, IR 4.0 is transforming economy, job and society. Physical and digital technology are combining through analytics, AI, cognitive technologies as well as Internet of Things (IoT) to provide a more informed decision-making [10]. All these technologies have also become the key elements in building a smart city.

Figure 2.3: Smart City [11]

As stated in Eleventh Malaysia Plan (2016-2020), Malaysia had started to embrace smart city with the vision of becoming a fully developed country along various dimensions including economics, political, social, spiritual, psychological, and cultural [12]. One of the biggest efforts that can be proved is Malaysia had run a trial of smart city technologies by building a smart traffic management system in Cyberjaya town [13]. In this project, cameras were applied to analyse the traffic situation and intelligently direct traffic at the intersection to reduce waiting time of traffic lights. Besides, data collected by each of the camera were also connected wireless via cloud to a Central Traffic Management Command Centre for direct access to traffic light controller. As a result, this project has made effectively contribution in reducing traffic congestion meanwhile providing a more systematic traffic management.

Due to rapid urbanisation, traffic congestion has become part of daily life for Malaysians. Therefore, The Ministry of Works Malaysia had proposed Intelligent Transport System (ITS) (2019) [10] to tackle this problem with the main goal to foster Big Data analytics in planning, implementation and operation of transportation, mobility and logistics movement. In this blueprint, the need of multiple agencies collaboration in ITS deployment had been accentuated and classified into nine sectors which acts as a benchmark for the way forward of ITS in Malaysia.

Figure 2.4: ITS Sectors [10]

Moreover, the collaboration of Sena Traffic System Sdn. Bhd. and Alibaba Cloud had also started the development of smart traffic solution in the year of 2019 to ease traffic congestion [14]. In May 2019, Kuala Lumpur City Hall (DBKL) had begun a pilot test of an intelligent traffic management system and data from the pilot project had revealed that travel times could be reduced by 12% with proper implementation of the system [15][16]. These data collected has proven that the proliferation of AI and cloud computing has contributed beneficially in providing an efficient solution for the improvement of traffic system and should be widely implemented in Malaysia.

2.3 Applications of Camera Analytics in Traffic Data Collection

Camera analytics or image processing refers to the technology that processes a digital video signal or image which captured by camera with the use of algorithm to transform them into intelligent data which assist in making decisions [17]. This technology has been typically used in traffic data collection in retrieving useful traffic information since it helps to keep track of everything that is going on without high manpower requirement.

2.3.1 Vehicle Counting

Edge detection and background subtraction are both commonly used camera analytics in vehicle detection and counting. In traffic management system, vehicle counting is very helpful in reflecting real time traffic density and providing input data for the creation of traffic signal timing plan. The synchronisation of real time traffic density and traffic signal timing plan helps to provide an accurate prediction in waiting time of traffic light and play an important role in reducing traffic congestion.

Figure 2.5: Vehicle Counting [18]

2.3.2 License Plate Recognition

Character segmentation is the main camera analytics applied for license plate recognition. License plate recognition plays an important role in vehicle tracking. It assists law enforcement officers to identify stolen vehicles and capture vehicle information from those that violate traffic laws instantly [19][20]. Besides, this method has also been widely applied in automated parking system and access control system in guarded residence area to avoid unauthorised vehicles from entering.

Figure 2.6: License Plate Recognition

2.4 Existing Method in Vehicle Detection

2.4.1 Background Subtraction

Background subtraction is a process of extracting moving foreground objects from a background image [21]. The rationale behind this approach is detecting the moving objects by performing a subtraction between the current frame and a background model [22].

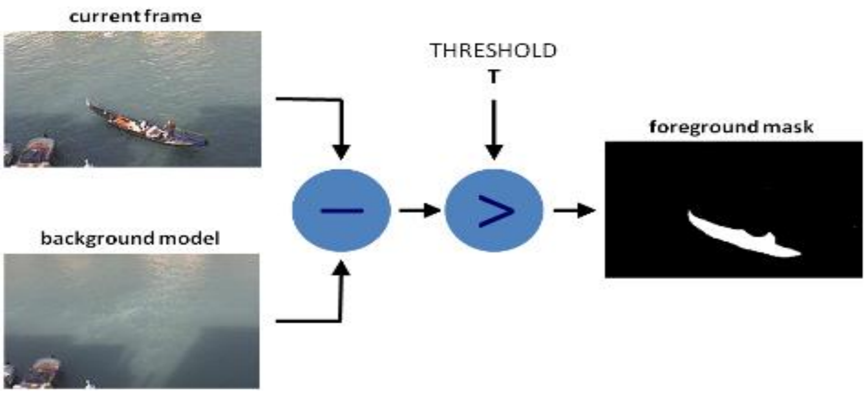


Figure 2.7: Concept of Background Subtraction [22]

This approach had been widely used in detecting vehicles in a video frame. However, this approach has a weakness which it detects all moving objects including some noise and traffic light which might lead to false detection. Therefore, filtering process is often used together with background subtraction to improve the detection results.

Figure 2.8: Weakness of Background Subtraction

2.4.2 Induction Loop Detector

Since early 1960s, induction loop detector technology had been introduced for detecting vehicles passing or arriving at a certain point [23]. This induction loop sensor mainly consists of a loop of wire and an electronic detection unit. There are often buried in the roadway to detect vehicles for traffic signal control.

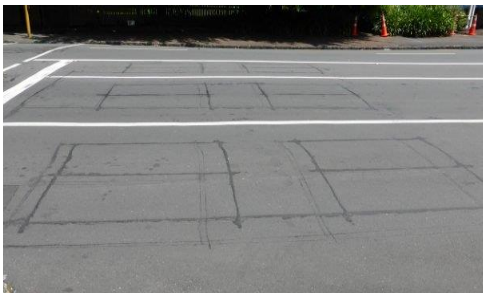


Figure 2.9: Induction Loop Buried in The Roadway

When there is a vehicle passing over the loop, the inductance in the wire loop starts to decrease due to eddy current induced by the vehicle. The decrement of inductance in the wire loop actuates the electronic unit output relay to send a pulse to the traffic signal controller for the presence of vehicle [23]. This method has a limitation on the detection region so it is often used to detect presence of vehicle instead of vehicle counting.

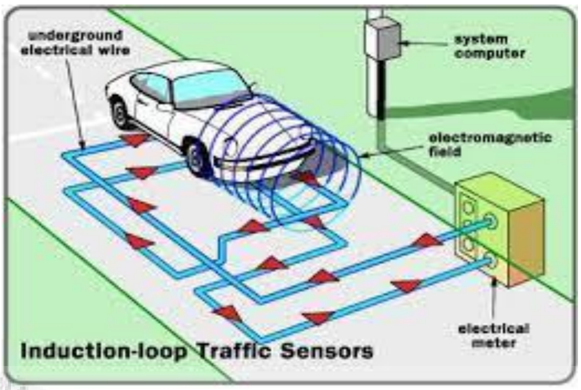


Figure 2.10: Operation of Induction Loop Sensor

2.4.3 Deep Neural Network

Deep Neural Network is basically one of the most essential tools in the broader area of deep learning. It allows computational models to learn representation of data with multiple levels of abstraction through discovery of intricate structure in large data sets via backpropagation algorithm [6].

This approach is carried out by training the deep learning model with a huge amount of data set so that it can extract the useful information from the data set independently and provide deep learning model which is ready for inference process. For vehicle detection and recognition, a large amount of vehicle image is required to train the deep learning model. After the training process, the deep learning model is then ready to make decision in detecting and classifying the vehicles.

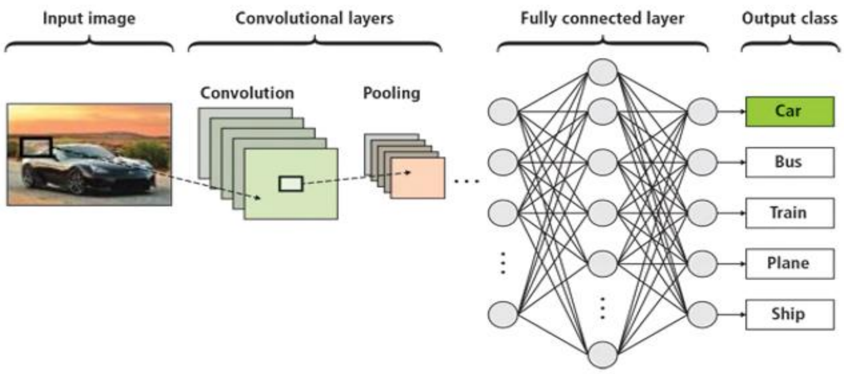


Figure 2.11: Vehicle Detection with Deep Neural Network [24]

2.5 Review of Previous Works

Generally, the review of previous works is classified into three main parts which are lane detection, smart traffic system and vehicle recognition with neural network. The concept of review is based on the research goal and its methodology.

2.5.1 Lane Detection

2.5.1.1 Lane Detection in Driving Assistant System

L.Araya *et.al* (2018) [25] had proposed image processing in lane detection with the intention to reduce road accidents caused by reckless driving. The proposed method comprised of four stages which were edge enhancement, potential lanes detection, post-processing and colour lane estimation. The data collected were then process for risk condition detection such as presence of obstacles and incorrect lane changes.

Besides, V.Nguyen *et.al* (2018) [26] had also implemented camera analytics for providing driver assistant system that capable to monitor lane change of vehicles. In this proposed paper, line detection was used for lane region detection whereas horizontal edge filter, Otsu thresholding, and vertical edge was used for vehicle detection. Meanwhile, Kalman filter was also utilised for vehicle tracking.

Figure 2.12: Vehicle Lane Change Monitoring [26]

2.5.1.2 Lane Detection in Autonomous Driving Vehicles

J. Jung *et.al* (2018) [27] had applied LiDAR data for real time lane detection in urban areas. In this paper, a real time working prototype was developed with LiDAR sensor for road lane detection and drivable region categorisation also GPS sensor for lane level digital map generation. The aim of this research paper was to provide useful data for the development of autonomous driving vehicles.

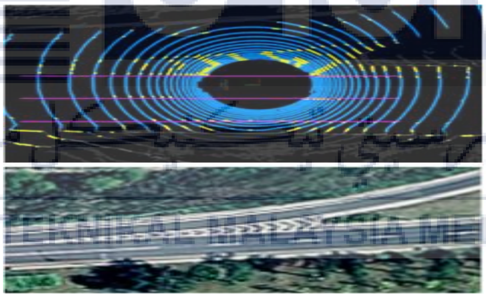


Figure 2.13: Lane Detection via LiDAR data [27]

2.5.1.3 Lane Detection in Road Line Identification

M. Li *et.al* (2018) [28] had proposed lane detection using various feature extraction methods to improve the efficiency and accuracy of real time lane detection. In the proposed system, it divided into two main processes. For pre-processing, it used HSV colour transformation to extract the white features and add preliminary edge feature detection. For lane detection, Canny operator was used for edge detection of road line while Hough transform was used to identify the road line.

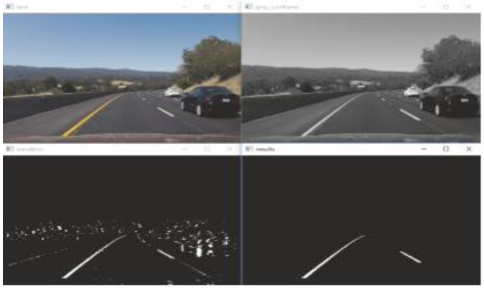


Figure 2.14: Road Line Detection [28]

2.5.1.4 Lane Detection in Road Lane Identification

J. Ren *et.al* (2014) [29] had proposed a novel method in detecting the lane region via rapid extraction and high accuracy clustering of vehicle motion trajectories in order to overcome the weakness of bad flexibility of traditional lane position detection system. In this paper, vehicle feature points were clustered and extracted.

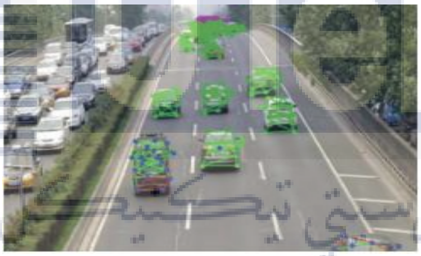


Figure 2.15: Clustering and Extraction of Vehicle Feature Point [29]

Vehicle motion trajectories were then be obtained by sparse feature point tracking with Kalman filter. Finally, the lane regions were identified through the vehicle motion trajectory with a rough k-means incremental clustering.

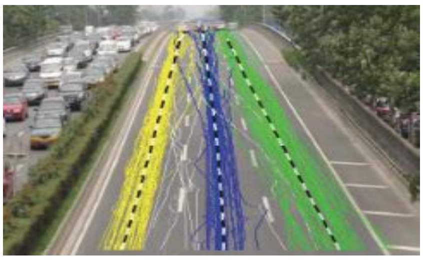


Figure 2.16: Lane Detection using Vehicle Motion Trajectory [29]

2.5.2 Smart Traffic System

2.5.2.1 Smart Traffic System via Cloud Centre or IoT Platform

W. Lee and C. Chiu (2020) [30] had designed a Smart Traffic Signal Control (STSC) system which comprises of Roadside Unit (RSU) controller, On Board Unit (OBU), signal controller and cloud centre to provide a smart transportation service. The designed system was capable to support various ITS applications including Emergency Vehicle Signal Pre-emption (EVSP), Transit Signal Priority (TSP), Adaptive Traffic Signal Control (ATSC), eco-driving and pre-time signal control.

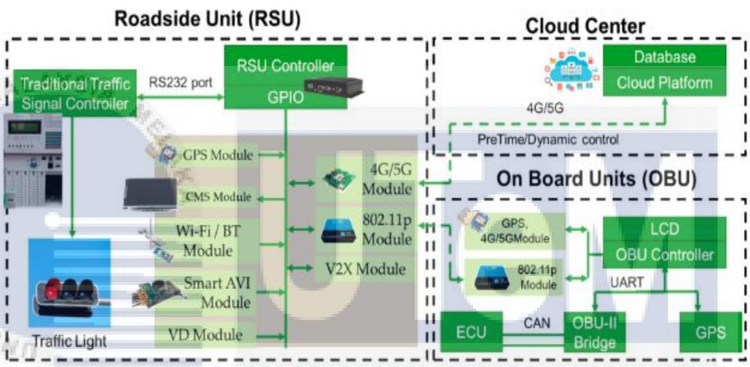


Figure 2.17: Block Diagram of STSC System [30]

S. Jahanan *et.al* (2018) [31] had proposed a model which consist of multiple IR sensors and a IoT platform with the intention to optimise the timing interval of traffic signal. In the proposed model, multiple IR sensors were used for vehicle counting whereas IoT platform was used for traffic signal monitoring. Moreover, K-Nearest Neighbours (KNN) algorithm was also applied to determine expected signal timing based on the vehicle count.

Besides, S. Javaid *et.al* (2018) [32] had also developed an IoT-based system to improve traffic management system by optimise the traffic flow on road. In this paper, a prototype had been proposed with sensors and surveillance camera for traffic data collection, AI-based algorithm for traffic density prediction, IoT platform for user interface and real time traffic monitoring as well as Radio Frequency Identification (RFID) for prioritising emergency vehicles during traffic jam.

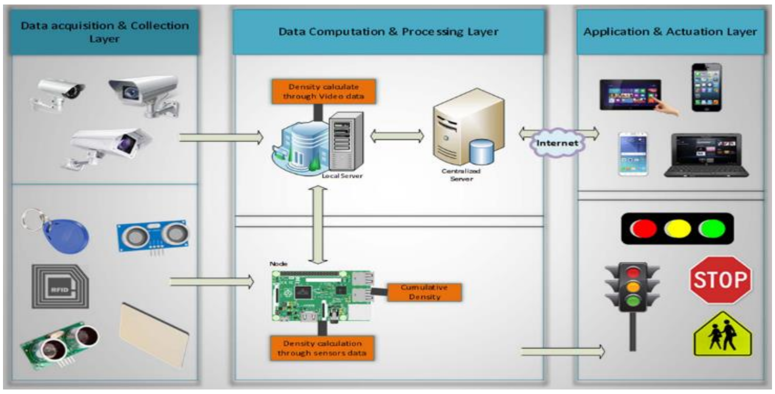


Figure 2.18: IoT Platform in Smart Traffic Management System [32]

Furthermore, P. Rizwan *et.al* (2016) [33] had also applied IoT and Big Data for the development of real time smart traffic management system with the main purpose of providing better service in updating traffic details. In the proposed system, IoT was being used to acquire traffic data collected by sensors and transmitted it for processing while Big Data analytics was used to analyse traffic density and provide solution through predictive analytics.

2.5.2.2 Smart Traffic System via Image Processing

J. Nodado *et.al* (2019) [34] had applied image processing technique of segmentation and feature extraction in the development of smart transportation system. This research was aimed to regulate the traffic system. The proposed system included Closed-Circuit Television (CCTV) for capturing traffic images, image processing for traffic density identification and also mobile application for traffic signal controlling and monitoring.

Besides, K. Senthilkumar *et.al* (2017) [35] had introduced traffic analysis and control with image processing to reduce the traffic stoppage on traffic lights. In this paper, background subtraction and Prewitt algorithm were used for vehicle detection. The traffic data was then be analysed based detected vehicles. At the same time, traffic signal timings were controlled and adjusted according to the traffic density and real time demands.

Moreover, P. Jadhav *et.al* (2016) [36] had also implemented a smart traffic project using image processing via MATLAB software to prevent heavy traffic congestion. In this paper, the researchers had proposed an image processing module pipeline which consist of background subtraction, blob detection, blob analysis, blob tracking and vehicle counting to analyse the traffic density based on the traffic condition captured through the deployed traffic camera.

In addition, M. Hasan *et.al* (2014) [37] had also developed image processing technique in determining traffic congestion on road. In this paper, background subtraction was introduced to detect the foreground objects which are vehicles. The traffic density was then measured from the total area of the vehicles occupied which was the total number of white pixels in the image. This traffic density collected is then used for providing traffic signal timing plan that synchronous with the real time traffic situation.

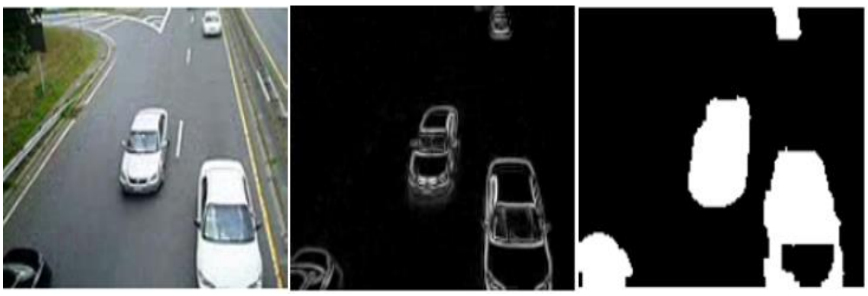


Figure 2.19: Image Processing in Determining Traffic Density [37]

2.5.3 Vehicle Recognition with Neural Network

G. Lingani *et.al* (2019) [38] had proposed neural network in enhancing the traffic management system. The researchers applied Convolution Neural Network to detect, classify, track and compute moving object velocity and direction. Counting and classifying was also carried out to provide reliable data for traffic monitoring system.

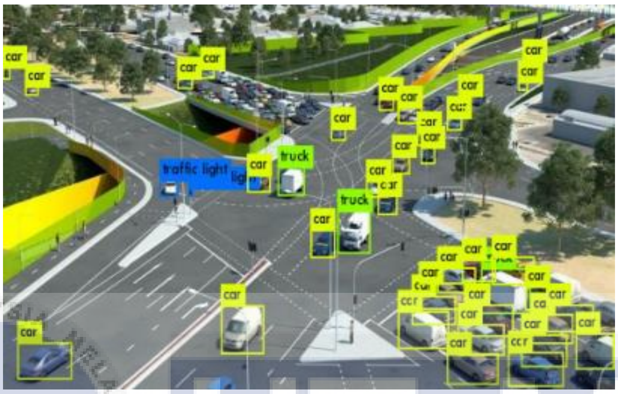


Figure 2.20: Vehicle Recognition with Neural Network [38]

I. Ullah and H. Lee (2017) [39] had introduced Deep Neural Network in vehicle detection and extraction of vehicle information. This research was aimed to extract vehicle information including their make, model and type for aiding traffic monitoring system such as law enforcement officers can use this information to identify stolen vehicles.

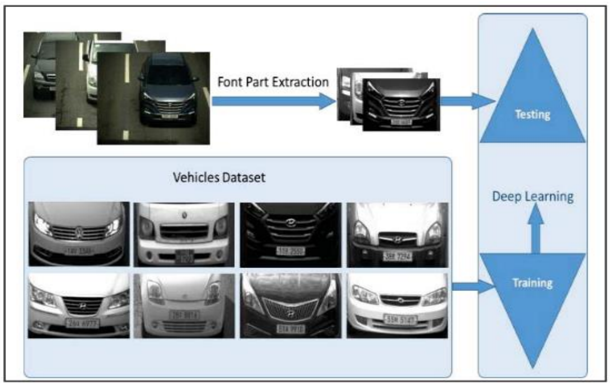


Figure 2.21: Extraction of Vehicle Information via DNN [39]

Y. Zhou *et.al* (2016) [40] had conducted a study on image-based vehicle analysis using Deep Neural Network. In this study, YOLO model had been used for vehicle detection whereas AlexNet model had been applied for vehicle classification. The two models were also trained and tested on a limited size dataset and extreme lighting condition.

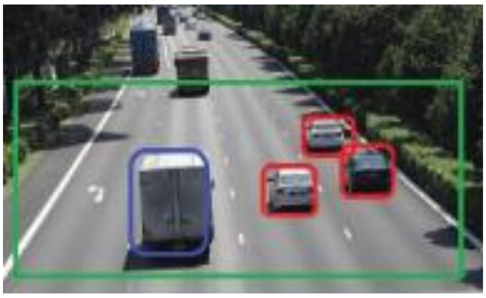


Figure 2.22: Vehicle Detection via YOLO Model [40]

Table 2.1: Comparison Table of Previous Works

Study	Research Field	Type of System	Research Goal
[25]	Lane Detection in Drive Assistant	Camera Analytics System	Reduce Road Accident
[26]	Lane Detection in Drive Assistant	Camera Analytics System	Reduce Road Accident
[27]	Lane Detection in Autonomous Vehicle	Sensor Based System	Provide Data for Autonomous Vehicle
[28]	Lane Detection in Road Line Identification	Camera Analytics System	Provide Real Time Lane Detection
[29]	Lane Detection in Road Region Identification	Camera Analytics System	Improve Traditional Lane Position Detection System
[30]	Smart Traffic Signal Control System via Cloud Centre	Sensor with Cloud Centre Based System	Provide Smart Transportation Service
[31]	Smart Traffic Signal Monitoring System via IoT Platform	Sensor with IoT Based System	Optimise Timing Interval of Traffic Signal
[32]	Smart Traffic Management System via IoT Platform	Sensor with IoT Based System	Optimise Traffic Flow on Road
[33]	Smart Traffic Management System via IoT Platform and Big Data Analytics	Sensor with IoT Based System	Provide Better Service in Updating Traffic Details

[34]	Smart Traffic Light via Image Processing	Camera Analytics System	Regulate Traffic Light System
[35]	Smart Traffic Analysis and Control via Image Processing	Camera Analytics System	Reduce Traffic Stoppage on Traffic Lights
[36]	Smart Traffic Control System via Image Processing	Camera Analytics System	Prevent Heavy Traffic Congestion
[37]	Smart Traffic Control System via Image Processing	Camera Analytics System	Reduce Traffic Congestion on Road
[38]	Smart Traffic Management System via Neural Network	CNN Based System	Provide Reliable Data for Traffic Monitoring System
[39]	Vehicle Detection via Neural Network	DNN Based System	Extract Vehicle Information
[40]	Vehicle Analysis via Neural Network	DNN Based System	Detect and Classify Vehicle with Limited Data Set and Extreme Lightning Condition

2.6 Summary

From the background study, it showed that many researchers have actively proposed variety of methods including camera analytics, IoT as well as neural network in enhancing the existing traffic system by reducing the traffic congestion and road accidents. The idea of background subtraction is used for the development of this project with the combination of Deep Neural Network for vehicle recognition in order to prevent false detection. Furthermore, this project also referred the idea proposed in the study of [29] which make use of vehicle trajectories in lane detection.

CHAPTER 3

METHODOLOGY

This chapter discusses on the overall project planning for implementation, verification, analysation and optimisation of lane detection and vehicle lane count algorithm. Flow charts are included for the illustration of project flow.

3.1 Introduction

The project is started with some background studies on lane detection method, smart traffic system and also vehicle recognition via neural network. From the reference of relevant journal and online resources, the idea for the implementation of algorithm is planned and developed.

The implementation of algorithm is divided into two parts which are lane detection and vehicle lane count. After completing the project development, the algorithm is tested with 15 pre-recorded traffic videos with duration of 5 minutes and different time, angle view, number of lanes as well as weather. The performances of algorithm are then analysed and optimised based on computation time of algorithm per frame and accuracy of algorithm.

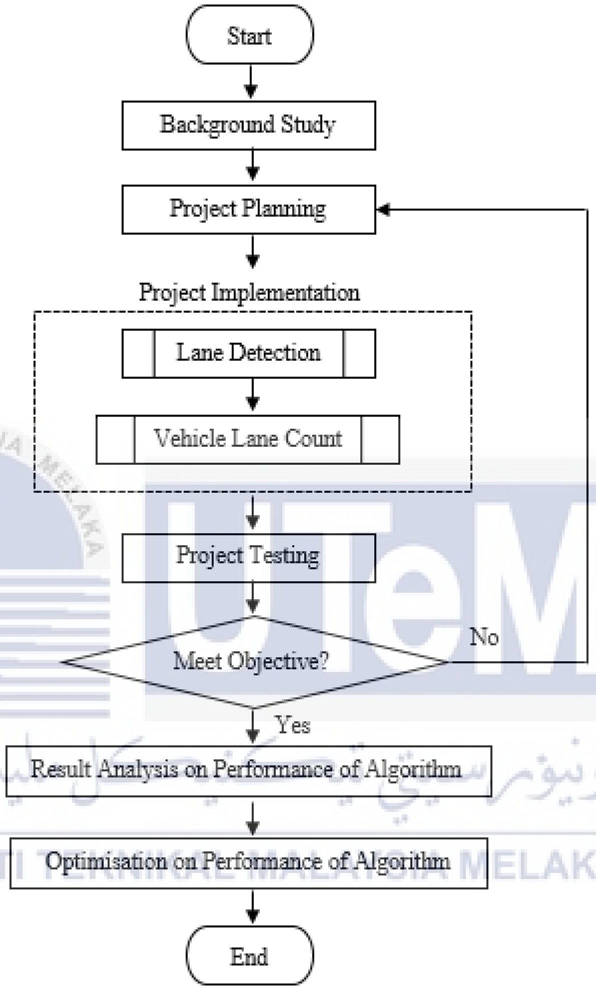


Figure 3.1: Overall Project Flow Chart

This project is a software-based project that focused on implementing algorithm with Deep Neural Network and camera analytics to provide reliable traffic data for traffic management system. The project involved automatic identify number of lanes at traffic junction via vehicle trajectories and vehicle counting according to each detected lane region.

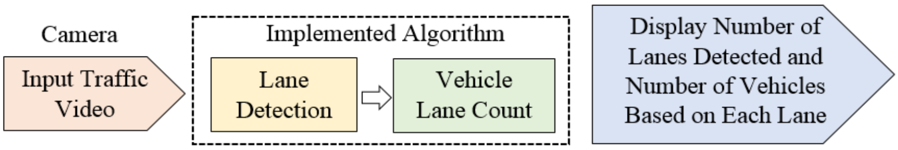


Figure 3.2: Project Block Diagram

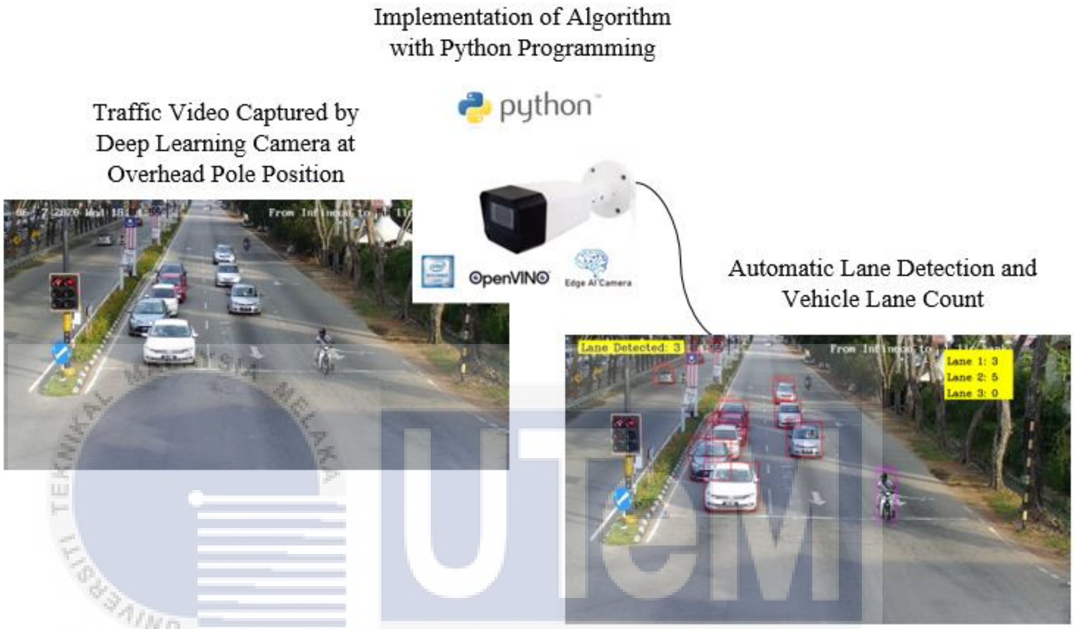


Figure 3.3: Project Overview

The software tools involved in this project included Linux as main operating system, Python as programming language for the implementation of algorithm and OpenVINO toolkit for vehicle recognition by enabling deep learning inference.

3.1.1 Linux Operating System

Linux OS is chosen as the main operating system in this project since it is an open-source operating system which allow modification of source codes and customisation of desktop environment. In this project, Command Line Interface (CLI) or Linux Command has been used to execute the implemented algorithm in the OpenVINO environment.

3.1.2 Python Programming

Python is a general-purpose high level programming language which is widely used for software development. In this project, Python version 3.6.9 is applied for the implementation of algorithm. Python library of Numpy and OpenCV is used for creating vehicle mask image via vehicle trajectories and vehicle counting based on each detected lane. Besides, time module and statistics module are also applied for results analysis in determining the computation time of algorithm per frame.

3.1.3 OpenVINO Toolkit

OpenVINO toolkit is a deep learning and vision tools which developed by Intel company for enabling deep learning interference from edge to cloud [41]. In this project, OpenVINO toolkit version 2020.2.120 is implemented for vehicle recognition with a pre-trained deep learning model. The vehicle recognition in this project is classified into six classes which are car, lorry, van, bus, motorcycle and bicycle.

3.2 Project Implementation

The project implementation is divided into two main parts. The algorithm started with lane detection through the votes in vehicle mask image to identify the lane region. Then, the number of lanes detected at traffic junction is identified. Finally, the vehicles at the detected lane region are started to be counted after the lane region is being detected.

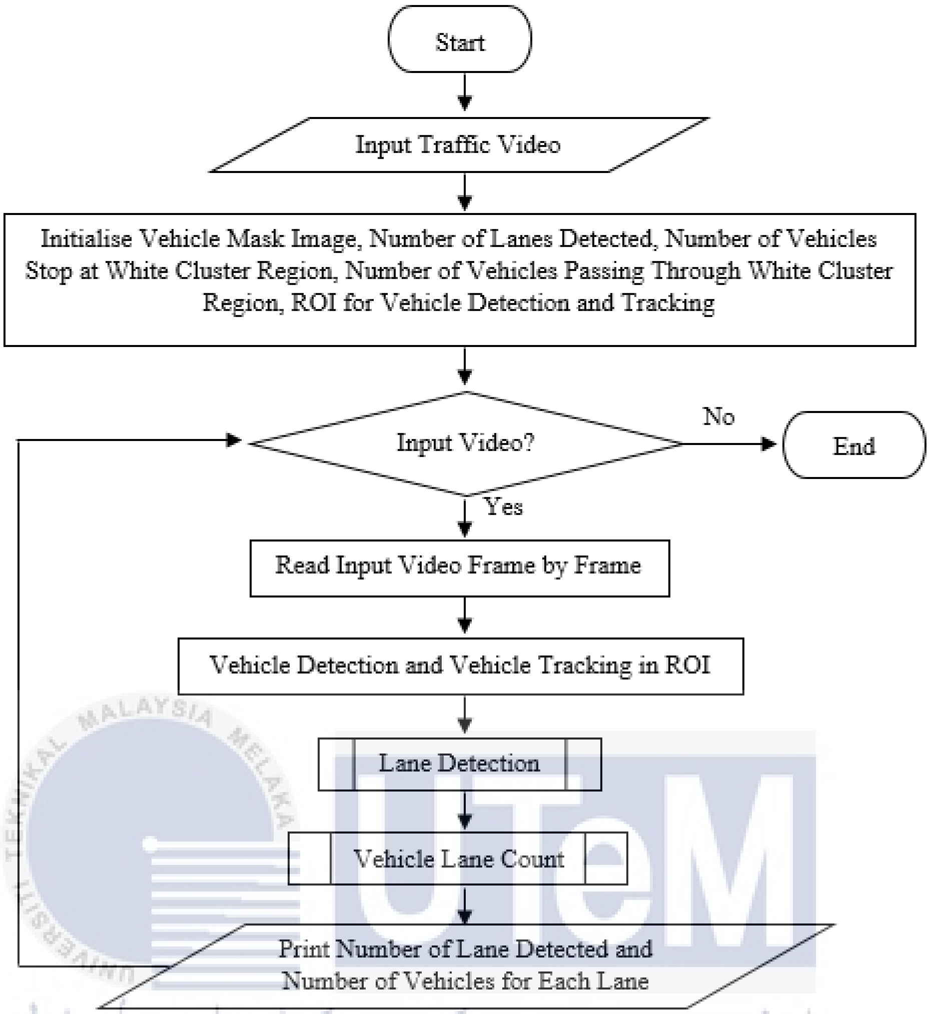


Figure 3.4: Project Implementation Flow Chart

3.2.1 Lane Detection Algorithm

The lane detection algorithm started with turn on the car detection only. This mainly because the trajectory of car is the best representation of lane region as motorcyclist that do not ride according to lane may contribute to false detection. Next, the vehicle moving angle is calculated using dot product by comparing the position of the vehicle from the previous frame and current frame. The calculation of vehicle moving angle enable us to reduce the effect of false detection caused by vehicles when crossing lane meanwhile ensure that only vehicles moving towards the camera direction is considered for the detection.

$$\boldsymbol{a} \cdot \boldsymbol{b} = |\boldsymbol{a}|\,|\boldsymbol{b}|\cos\boldsymbol{\theta}$$

$$\theta = \cos^{-1}\left(\frac{\boldsymbol{a} \cdot \boldsymbol{b}}{|\boldsymbol{a}|\,|\boldsymbol{b}|}\right)$$

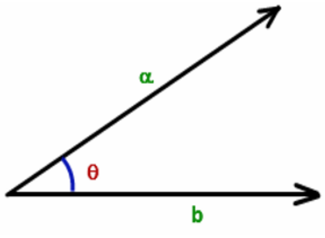


Figure 3.5: Concept of Dot Product

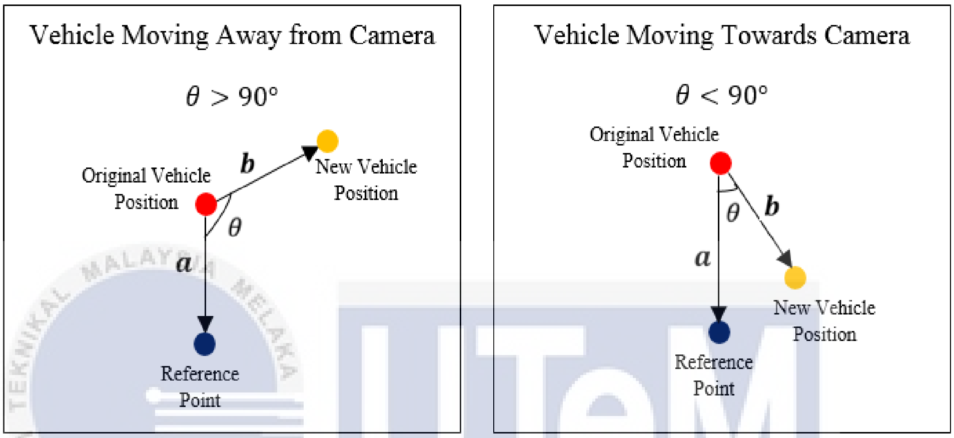


Figure 3.6: Vehicle Moving Angle

If the angle is smaller than 60°, the pre-defined piecewise linear function is applied to vote the detected vehicles in vehicle mask image.

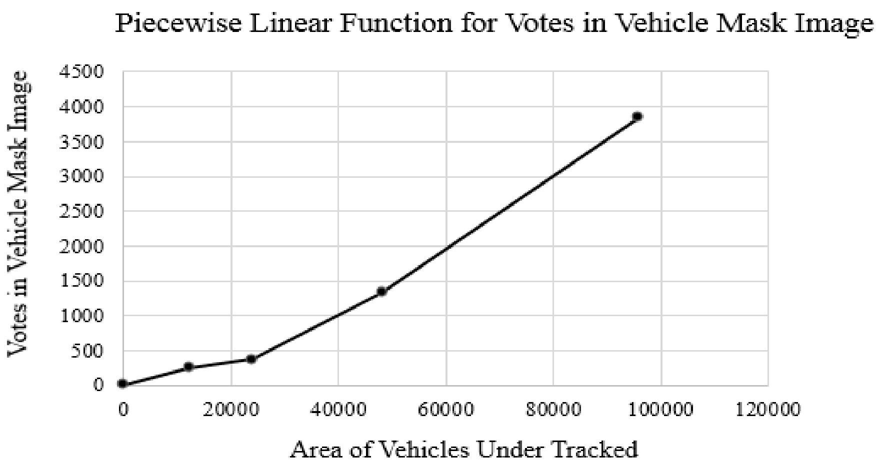


Figure 3.7: Pre-Defined Piecewise Linear Function

The votes in the vehicle mask image are introduced to collect vehicle trajectories for the representation of lane region. Basically, an image is represented by pixel values in camera analytics where the pixel values indicate the brightness of a pixel. The higher the value of pixel, the brighter the specific pixel. Since this project using grey scale image for vehicle mask image, hence the maximum value of pixel is 255 which is white colour. The rationale behind the vote concept is when there are more vehicles passing through the same region, the pixel values on the specific region will increases and become brighter.

After collecting the vehicle trajectories through vehicle mask image, the binary vehicle mask image is obtained with threshold value of 200. This method is applied mainly to minimise the effect of vehicles that do not drive according to lane region during the detection process.

Figure 3.8: Vehicle Mask Image in Collecting Vehicle Trajectories

After obtaining the binary vehicle mask image, the size of white cluster region presented in it is obtained through OpenCV contour module. If the size of the white cluster is more than 10000 pixels, the number of vehicles stop and passing through white cluster region is found. If both the number of vehicles stop and pass through the region more than 4, then the number of lanes detected is increased by 1. The number of vehicles passing through white cluster region is mainly used to confirm the detected lane region, while the number of vehicles stop at white cluster region is use to ensure that only the number of lanes at traffic junction is focussed.

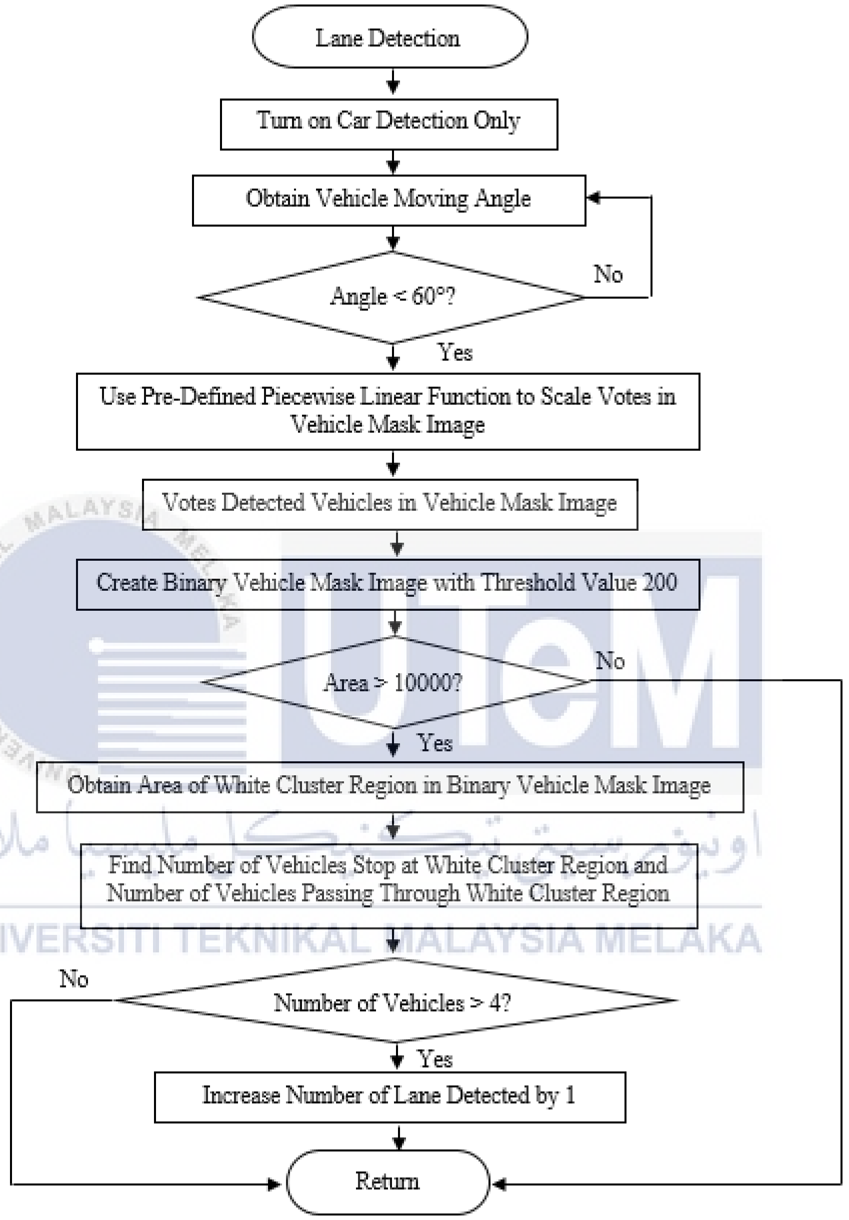


Figure 3.9: Flow Chart of Lane Detection Algorithm

3.2.2 Vehicle Lane Count Algorithm

The vehicle lane count algorithm is started once the lane region is detected. First, the number of vehicles for each lane is initialise into zero for every frame. Then, find the position of each vehicle under tracked. If the vehicle is in lane 1, then number of vehicles in lane 1 is increased by 1. The same concept is applied for other lane regions. This counting process is focussed on the vehicles at the traffic junction and will execute continually except when there is no input video frame.

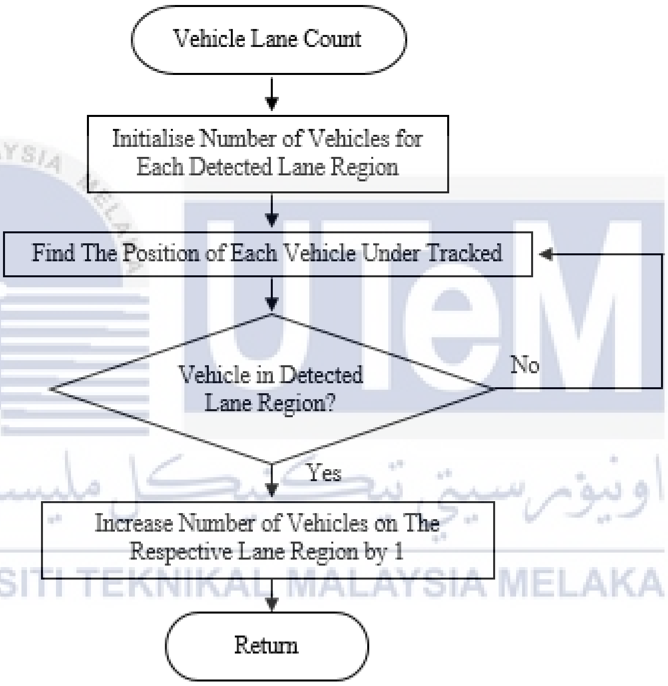
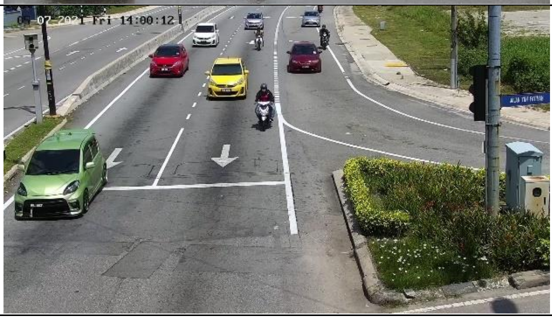


Figure 3.10: Flow Chart of Vehicle Lane Count Algorithm

3.3 Verification of Algorithm

The implemented algorithm is tested using 15 pre-recorded videos with 5 minutes duration and different time, angle view, number of lanes as well as weather. These 15 pre-recorded videos are basically obtained from 5 different traffic cameras deployed at the traffic junction under 3 different conditions which are clear sunny day, at night and rainy day.

Table 3.1: Characteristics of Traffic Videos

Traffic Camera	Angle of View	Number of Lane	Traffic Video
Camera 1	Front View	3	
Camera 2	Side View	3	
Camera 3	Front View	2	
Camera 4	Side View	1	
Camera 5	Side View	2	

3.4 Analysis on Performance of Algorithm

The performance of the lane detection and vehicle lane count algorithm are analysed based on computation time of algorithm per frame and accuracy of algorithm. The computation time of algorithm per frame is referred to the time taken for each frame to complete the execution of lane detection and vehicle lane count algorithm. Alternatively, accuracy of algorithm is referred to the closeness of number of lanes identified or vehicles counted via algorithm when compared to ground truth value.

3.4.1 Computation Time of Algorithm Per Frame

The time module in Python programming is used to measure the time taken for each frame to complete the execution of the implemented algorithm. The results of the recorded time for each frame are then stored in a list. After that, statistics module is then utilised to obtain the mean and standard deviation of the computation time per frame for the 5 minutes traffic video.

3.4.2 Accuracy of Algorithm

The accuracy of algorithm is classified into two parts which are accuracy of lane detection algorithm and vehicle lane count algorithm.

3.4.2.1 Accuracy of Lane Detection Algorithm

The accuracy of lane detection algorithm is referred to the closeness of number of lanes identified via algorithm with the ground truth value which is the number of lanes we observed. It is calculated using equation (**3.1**) by comparing the number of lanes identified by algorithm at the last video frame and the number of lanes observed.

$$\text{Accuracy} = \left(1 - \frac{|\text{Lane Observed} - \text{Lane Identified}|}{\text{Lane Observed}}\right) \times 100\% \qquad (3.1)$$

3.4.2.2 Accuracy of Vehicle Lane Count Algorithm

The accuracy of vehicle lane count algorithm is referred to the percentage of correctness of algorithm in counting the number of vehicles based on each detected lane region. The video frame is captured for every 10 seconds after the number of lanes identified is greater than 0. The number of vehicles for each of the lane is observed and recorded manually in a given Region of Interest (ROI). The results of vehicle count for each detected lane region is then compared with the observed value that we recorded manually. The equation (**3.2**) is used to calculated the accuracy of vehicle lane count algorithm.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% \qquad (3.2)$$

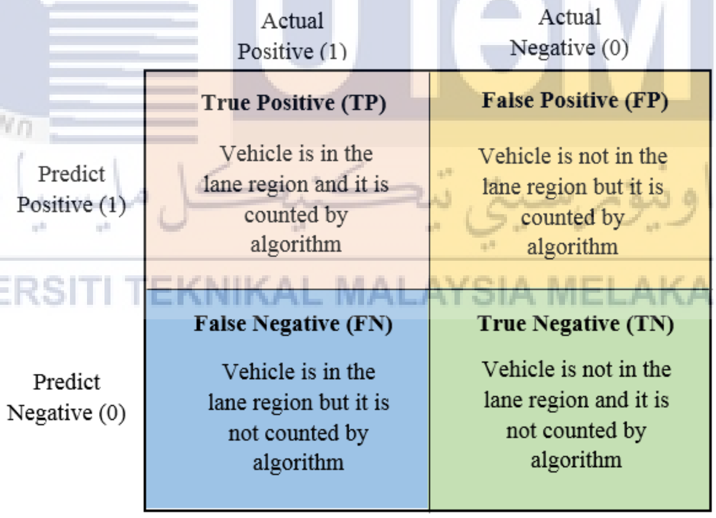


Figure 3.11: Confusion Matrix in Accuracy Analysis of Algorithm

3.5 Optimisation on Performance of Algorithm

The optimisation process is vital to ensure that the computation time of algorithm per frame is almost same or less than frame rate of the recorded traffic video. For real time development, it is essential to reduce latency so that the data collected is synchronous with the real time traffic condition. In this project, a scale factor of 1/5 is applied to reduce the size of the vehicle mask image and its image during the detection process.

After optimisation, the performance of algorithm is analysed by comparing the improvement in mean computation time of algorithm per frame and deterioration in accuracy of algorithm. The improvement in mean computation time of algorithm is calculated using equation (**3.3**) whereas the deterioration in accuracy of algorithm is calculated using equation (**3.4**).

$$\text{Improvement} = \left(\frac{\text{Time}_{\text{original}} - \text{Time}_{\text{optimised}}}{\text{Time}_{\text{original}}}\right) \times 100\% \tag{3.3}$$

$$\text{Deterioration} = \left(\frac{\text{Accuracy}_{\text{original}} - \text{Accuracy}_{\text{optimised}}}{\text{Accuracy}_{\text{original}}}\right) \times 100\% \tag{3.4}$$

3.6 Summary

In summary, this project mainly utilised the vehicle trajectories in identifying the lane region at traffic junction. Vehicle moving angle and votes in vehicle mask image has been introduced to reduce the effect caused by vehicles during crossing lane meanwhile ensure that only vehicles moving towards the direction of camera is considered for the detection. The number of lanes is increased by 1 only if the area of white cluster is greater than 10000 pixels and both the number of vehicles stop and passing through white cluster is more than 4. The vehicle counting process are only focussed on the lane at traffic junction. Lastly, the algorithm is optimised with reduction of size of vehicle mask image and detection image by scale factor 1/5 to avoid latency during real-time implementation.

CHAPTER 4

RESULTS AND DISCUSSION

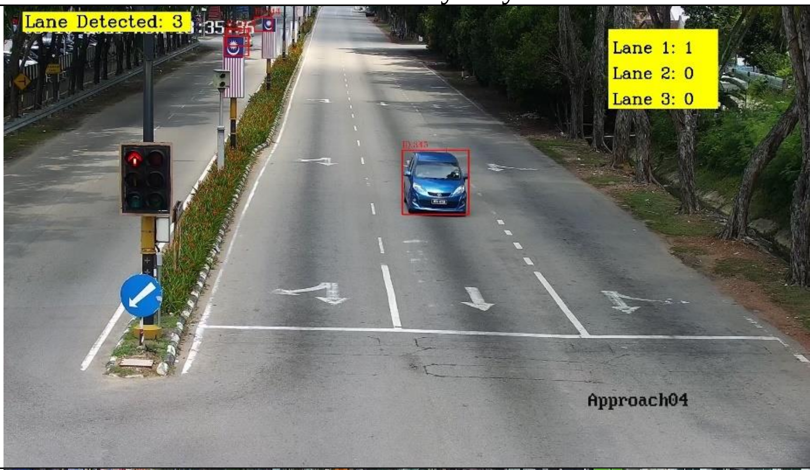
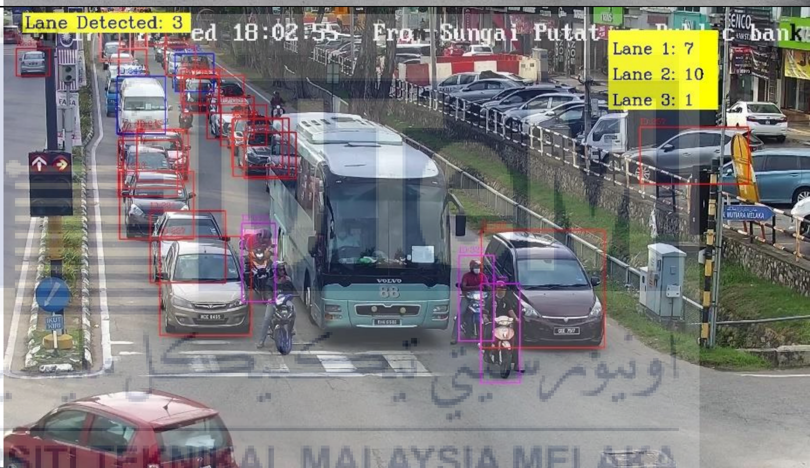
This chapter presents and discusses the testing results that carried out for lane detection and vehicle lane count algorithm using 15 pre-recorded traffic videos with different time, angle view, number of lanes and weather. The performances of algorithm are analysed and optimised based on computation time and standard deviation of algorithm, accuracy of lane detection algorithm and accuracy of vehicle lane count algorithm.

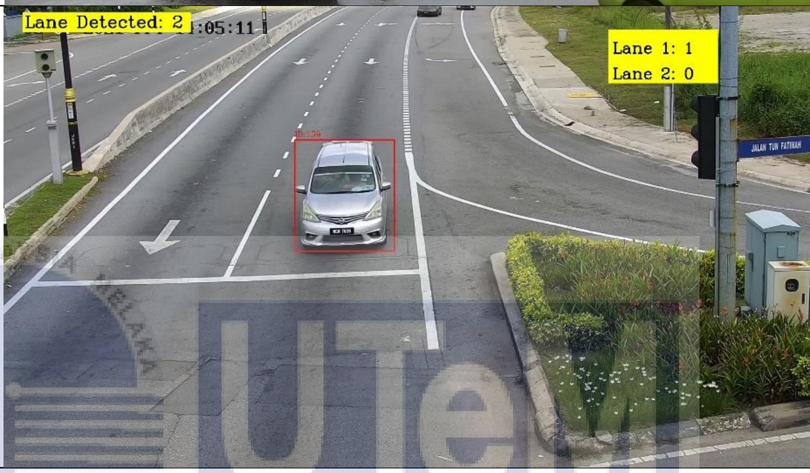
4.1 Testing on Developed Lane Detection and Vehicle Lane Count Algorithm

The implemented lane detection and vehicle lane count algorithm was tested with 15 traffic videos obtained from 5 different traffic cameras deployed at the traffic junction under 3 different conditions which are clear sunny day, at night and rainy day. The results are showed in Table 4.1, Table 4.2 and Table 4.3.

4.1.1 Testing with Recorded Traffic Video During Clear Sunny Day

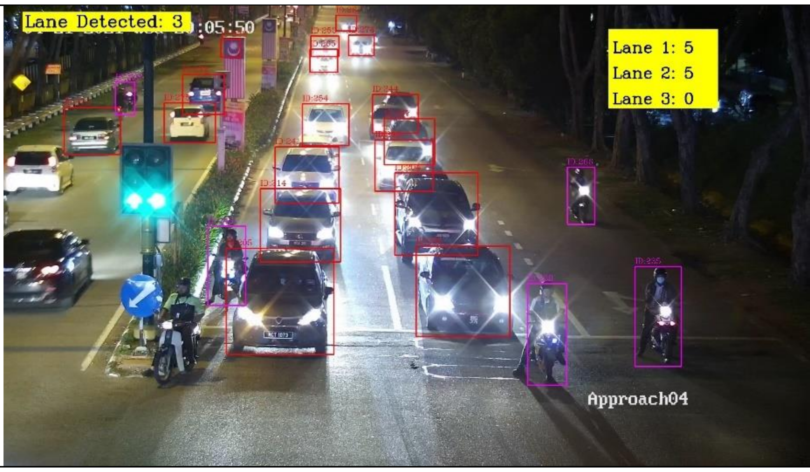
Table 4.1: Testing Results of Traffic Video During Clear Sunny Day

Traffic Camera	Testing Result of Traffic Video with Developed Algorithm During Clear Sunny Day
Camera 1	
Camera 2	
Camera 3	

Camera 4	
Camera 5	

4.1.2 Testing with Recorded Traffic Videos at Night

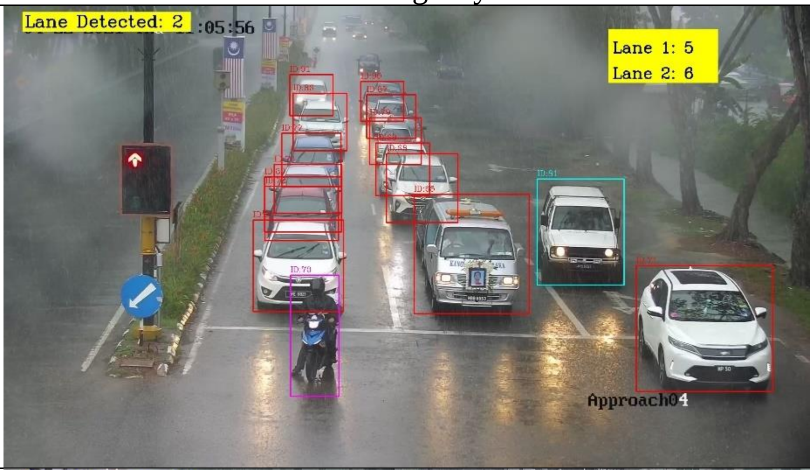
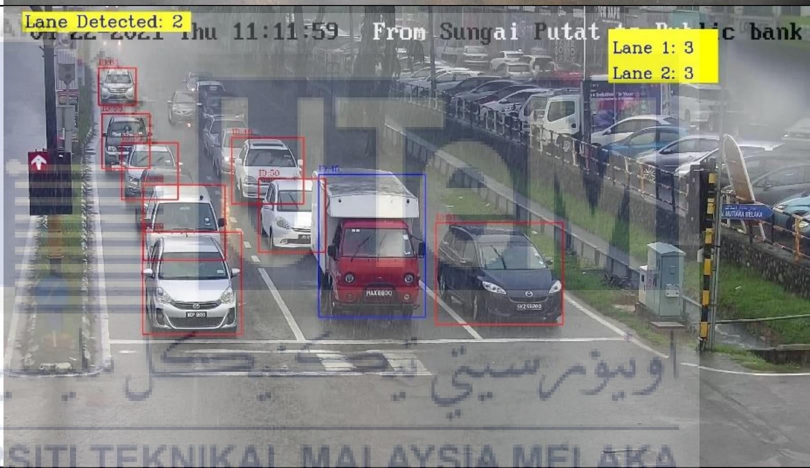
Table 4.2: Testing Results of Traffic Video at Night

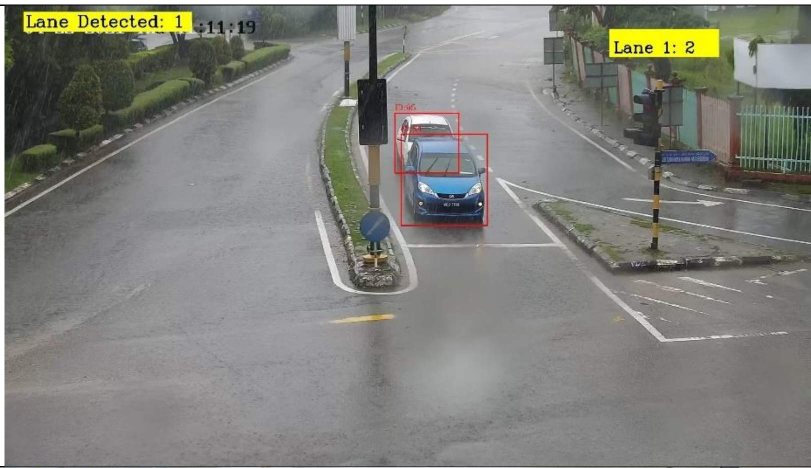
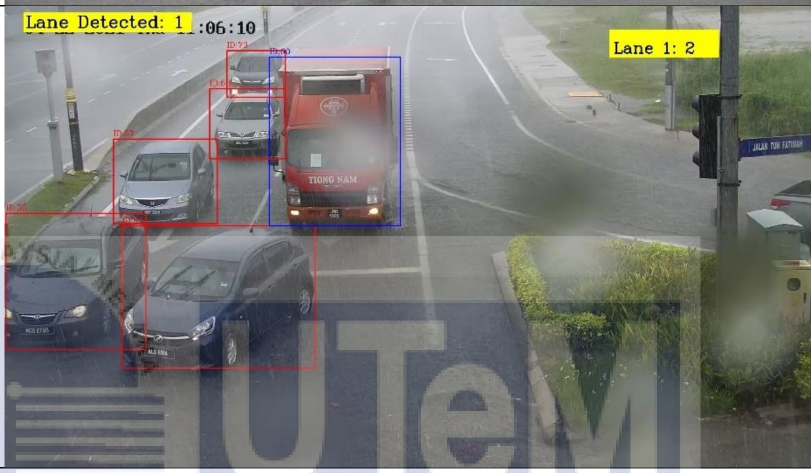
Traffic Camera	Testing Result of Traffic Video with Developed Algorithm at Night
Camera 1	

Camera 2		
Camera 3		
Camera 4		
Camera 5		

4.1.3 Testing with Recorded Traffic Video During Rainy Day

Table 4.3: Testing Results of Traffic Video During Rainy Day

Traffic Camera	Testing Result of Traffic Video with Developed Algorithm During Raining Day
Camera 1	
Camera 2	
Camera 3	

Camera 4		
Camera 5		

4.2 Performance Analysis of Algorithm of Developed Lane Detection and Vehicle Lane Count Algorithm

4.2.1 Computation Time of Algorithm Per Frame

The computation time of algorithm per frame are showed in Table 4.4, Table 4.5 and Table 4.6. The mean computation time of algorithm is highly depending on the number of vehicles in the traffic video. When there are more vehicles presented in the video, longer time is required to detect and track the vehicles in the frame, check for its moving angle, vote it in vehicle mask image as well as count it based on the detected lane region. According to Figure 4.1, mean computation time of algorithm during clear sunny day is the highest as compared to mean computation time of algorithm at night and rainy day due to plenty of vehicles presented in the traffic videos.

Alternatively, the standard deviation is referred to the variation in computation time of algorithm per frame. When the vehicle lane count algorithm began, it required longer computation time. Therefore, the standard deviation will be large when the vehicle counting started at the last few video frames due to the sudden increment in computation time. Besides, the number of vehicles that varied significantly between subsequent frame will also increase the standard deviation of computation time.

Table 4.4: Computation Time of Algorithm Per Frame During Clear Sunny Day

Traffic Camera	Mean Computation Time Per Frame, μ_{ori}	Standard Deviation of Computation Time Per Frame, σ_{ori}
Camera 1	150.37 ms	11.02 ms
Camera 2	153.13 ms	10.08 ms
Camera 3	147.94 ms	8.95 ms
Camera 4	127.78 ms	10.15 ms
Camera 5	143.50 ms	11.95 ms

Table 4.5: Computation Time of Algorithm Per Frame at Night

Traffic Camera	Mean Computation Time Per Frame, μ_{ori}	Standard Deviation of Computation Time Per Frame, σ_{ori}
Camera 1	144.30 ms	12.63 ms
Camera 2	126.57 ms	13.09 ms
Camera 3	139.68 ms	10.83 ms
Camera 4	117.99 ms	7.28 ms
Camera 5	124.12 ms	13.71 ms

Table 4.6: Computation Time of Algorithm Per Frame During Rainy Day

Traffic Camera	Mean Computation Time Per Frame, μ_{ori}	Standard Deviation of Computation Time Per Frame, σ_{ori}
Camera 1	141.07 ms	10.26 ms
Camera 2	144.28 ms	13.82 ms
Camera 3	145.29 ms	15.31 ms
Camera 4	116.83 ms	6.66 ms
Camera 5	126.41 ms	11.04 ms

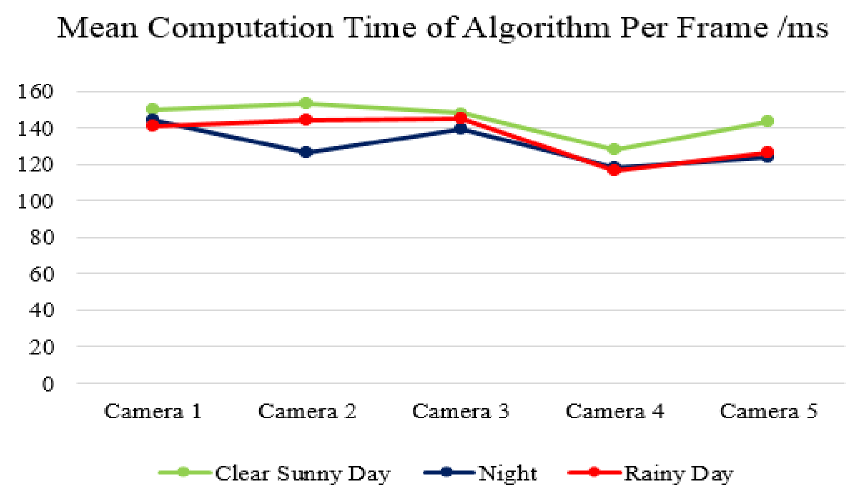


Figure 4.1: Mean Computation Time of Algorithm Per Frame

4.2.2 Accuracy of Lane Detection Algorithm

The accuracy of lane detection algorithm for each traffic video are showed in Table 4.7, Table 4.8 and Table 4.9. According to Table 4.7, the accuracy of lane detection algorithm for clear sunny is the highest where all traffic videos successfully identified the number of lanes due to a clear camera sight view and plenty of vehicles presented in the video which helped to provide a better vehicle mask image in reflecting the lane region.

Table 4.7: Accuracy of Lane Detection Algorithm During Clear Sunny Day

Traffic Camera	Number of Lanes Observed, L_o	Number of Lanes Identified via Algorithm, L_i	Accuracy of Lane Detection Algorithm, AL_{ori} $\left(1-\frac{\lvert L_o-L_i\rvert}{L_o}\right)\times 100\%$
Camera 1	3	3	100%
Camera 2	3	3	100%
Camera 3	2	2	100%
Camera 4	1	1	100%
Camera 5	2	2	100%

The accuracy of lane detection algorithm at night is low where only two traffic videos successfully identified the number of lanes. This is because the low light intensity at night is challenging for vehicle recognition. On the other hand, less vehicles in the traffic video also caused the collection of vehicle trajectories process become challenging in identify the lane region.

Table 4.8: Accuracy of Lane Detection Algorithm at Night

Traffic Camera	Number of Lanes Observed, L_o	Number of Lanes Identified via Algorithm, L_i	Accuracy of Lane Detection Algorithm, AL_{ori} $\left(1-\frac{\lvert L_o-L_i\rvert}{L_o}\right)\times 100\%$
Camera 1	3	3	100%
Camera 2	3	2	66.67%
Camera 3	2	3	66.67%
Camera 4	1	1	100%
Camera 5	2	1	50%

Alternatively, the accuracy of lane detection algorithm during rainy day is also low as water droplet fall on the camera reduced the capability in vehicle recognition and affect the collection of vehicle trajectories. Therefore, it is not suggested to carry out lane detection during rainy day as it possesses high risk to provide inaccurate result.

Table 4.9: Accuracy of Lane Detection Algorithm During Rainy Day

Traffic Camera	Number of Lanes Observed, L_o	Number of Lanes Identified via Algorithm, L_i	Accuracy of Lane Detection Algorithm, AL_{ori} $\left(1-\frac{\lvert L_o-L_i\rvert}{L_o}\right)\times 100\%$
Camera 1	3	2	66.67%
Camera 2	3	2	66.67%
Camera 3	2	2	100%
Camera 4	1	1	100%
Camera 5	2	1	50%

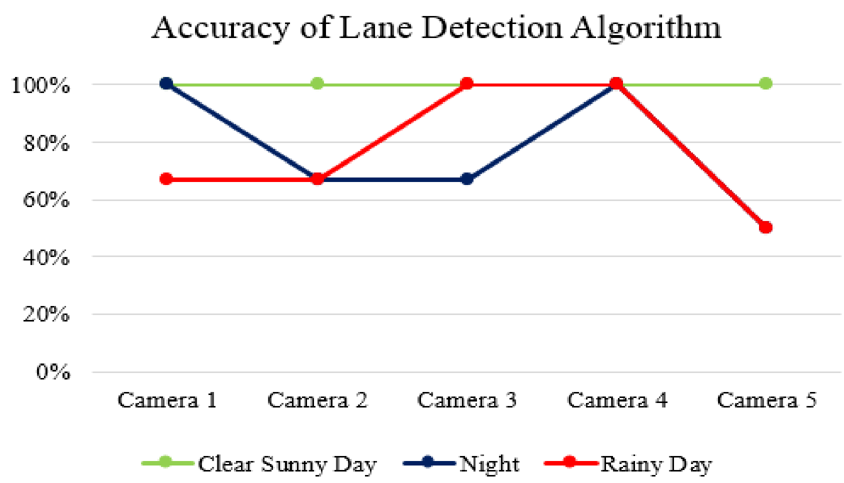


Figure 4.2: Accuracy of Lane Detection Algorithm

4.2.3 Accuracy of Vehicle Lane Count Algorithm

The accuracy of vehicle lane count algorithm for each traffic video are showed in Table 4.10, Table 4.11 and Table 4.12. The accuracy of vehicle lane count algorithm is depending on the white cluster identify by the binary vehicle mask image. According to the results, the accuracy of vehicle lane count algorithm is the highest during clear sunny day except for camera 5. During clear sunny day, the camera has clear sight view for vehicle recognition which ease the counting process. Moreover, plenty of vehicles in the video also helped to provide a better of vehicle mask image in reflecting the lane region at traffic junction.

Table 4.10: Accuracy of Vehicle Lane Count Algorithm During Clear Sunny Day

Traffic Camera	TP	TN	FP	FN	Accuracy, AC_{ori} $\frac{TP+TN}{TP+TN+FP+FN} \times 100\%$
Camera 1	178	21	1	75	72.36%
Camera 2	182	6	21	27	79.66%
Camera 3	135	14	0	62	70.62%
Camera 4	117	0	2	14	87.97%
Camera 5	39	0	0	13	75.00%

The accuracy of vehicle lane count algorithm for camera 3 during night time is the lowest among all traffic videos which is 47.27% due to its lane structure and low light intensity that limit the vehicle recognition. Camera 3 consist of small turning region. The vehicle counting process which started before the consideration of whole lane region has led to false detection. As a result, camera 3 has lowest accuracy at night.

Table 4.11: Accuracy of Vehicle Lane Count Algorithm at Night

Traffic Camera	TP	TN	FP	FN	Accuracy, AC_{ori} $\frac{TP+TN}{TP+TN+FP+FN} \times 100\%$
Camera 1	62	8	0	35	66.67%
Camera 2	59	8	4	41	59.82%
Camera 3	26	0	7	22	47.27%
Camera 4	9	0	0	4	69.23%
Camera 5	4	0	0	1	80.00%

During rainy day, camera has blur sight view and water droplet fall on the camera might blocked and inhibited the vehicle recognition process. This condition had caused the collection of vehicle trajectories that reflect the lane region become challenging. Although the accuracy of algorithm in counting vehicles for the detected lane region is still higher than at night, but it is not suggested for application of implemented algorithm as it possesses high risk in providing an inaccurate result.

Table 4.12: Accuracy of Vehicle Lane Count Algorithm During Rainy Day

Traffic Camera	TP	TN	FP	FN	Accuracy, AC_{ori} $\frac{TP+TN}{TP+TN+FP+FN} \times 100\%$
Camera 1	29	10	2	14	70.91%
Camera 2	43	19	0	31	66.67%
Camera 3	48	25	0	60	54.89%
Camera 4	11	0	0	8	57.89%
Camera 5	4	0	0	2	66.67%

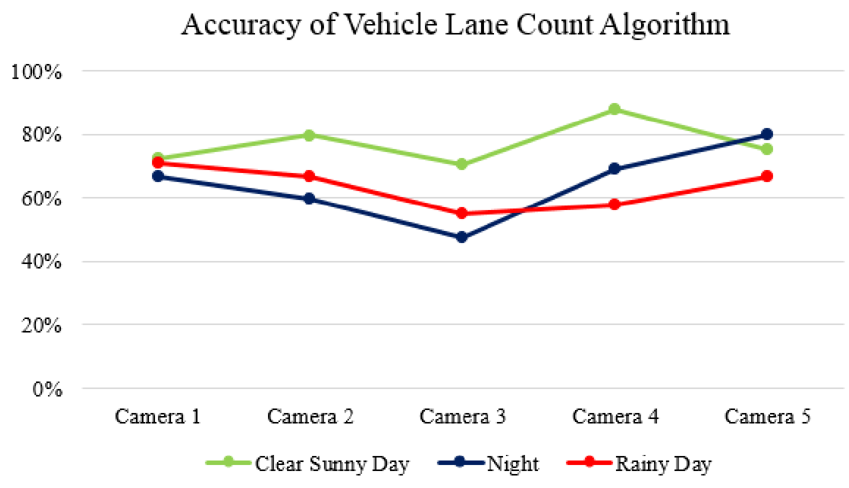


Figure 4.3: Accuracy of Vehicle Lane Count Algorithm

4.3 Performance Analysis on Optimised Lane Detection and Vehicle Lane Count Algorithm

The scale factor of 1/5 is used to reduce the size of the vehicle mask image and its binary image for optimisation process. There is a trade-off between computation time and accuracy of algorithm during optimisation process. Thus, the performance of optimised algorithm is analysed based on the improvement in computation time and deterioration in accuracy of algorithm by using equation (**3.3**) and (**3.4**).

4.3.1 Computation Time of Optimised Algorithm Per Frame

The results for computation time of optimised algorithm are showed in Table 4.13, Table 4.14 and Table 4.15. The mean computation time of optimised algorithm had improved significantly which is between 41.53% to 53.51%. Besides, all the computation time of optimised algorithm is below 100ms which is lowered than the frame rate of the traffic video. Hence, the optimised algorithm will not cause latency during real time implementation.

Table 4.13: Computation Time of Optimised Algorithm Per Frame During Clear Sunny Day

Traffic Camera	Mean Computation Time Per Frame, μ_{op}	Standard Deviation of Computation Time Per Frame, σ_{op}	Improvement in Mean Computation Time $\frac{\mu_{ori} - \mu_{op}}{\mu_{ori}} \times 100\%$
Camera 1	79.93 ms	9.07 ms	46.84%
Camera 2	83.47 ms	7.29 ms	45.49%
Camera 3	68.78 ms	8.95 ms	53.51%
Camera 4	74.71 ms	4.63 ms	41.53%
Camera 5	73.76 ms	4.16 ms	48.60%

Table 4.14: Computation Time of Optimised Algorithm Per Frame at Night

Traffic Camera	Mean Computation Time Per Frame, μ_{op}	Standard Deviation of Computation Time Per Frame, σ_{op}	Improvement in Mean Computation Time $\frac{\mu_{ori} - \mu_{op}}{\mu_{ori}} \times 100\%$
Camera 1	75.61 ms	7.00 ms	47.60%
Camera 2	73.60 ms	6.04 ms	41.85%
Camera 3	71.26 ms	5.15 ms	48.98%
Camera 4	68.55 ms	3.42 ms	41.90%
Camera 5	69.05 ms	3.85 ms	44.37%

Table 4.15: Computation Time of Optimised Algorithm Per Frame During Rainy Day

Traffic Camera	Mean Computation Time Per Frame, μ_{op}	Standard Deviation of Computation Time Per Frame, σ_{op}	Improvement in Mean Computation Time $\frac{\mu_{ori} - \mu_{op}}{\mu_{ori}} \times 100\%$
Camera 1	71.22 ms	4.96 ms	49.51%
Camera 2	73.97 ms	2.83 ms	48.73%
Camera 3	83.71 ms	11.69 ms	42.38%
Camera 4	67.07 ms	2.91 ms	42.59%
Camera 5	72.06 ms	3.68 ms	43.00%

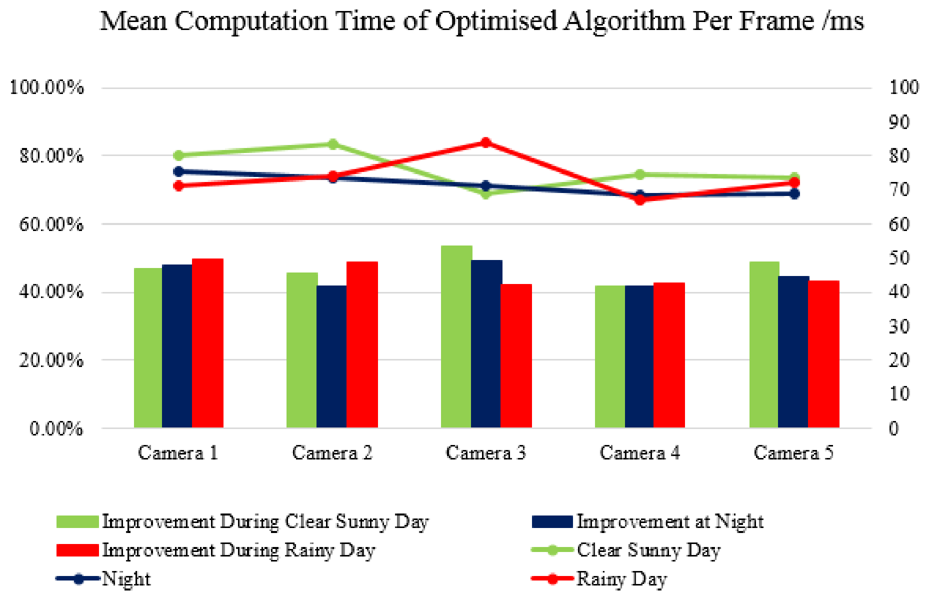


Figure 4.4: Mean Computation Time of Optimised Algorithm Per Frame

4.3.2 Accuracy of Optimised Lane Detection Algorithm

The accuracy of the optimised lane detection algorithm is as showed in Table 4.16, Table 4.17 and Table 4.18. According to the result obtained, there is no deterioration for the accuracy of lane detection algorithm after optimisation. This proved that the optimised lane detection algorithm had good performance in identifying the number of lanes with low possibility of deterioration.

Table 4.16: Accuracy of Optimised Lane Detection Algorithm During Clear Sunny Day

Traffic Camera	Number of Lanes Observed, L_o	Number of Lanes Identified via Algorithm, L_{op}	Accuracy, AL_{op} $\left(1 - \frac{\lvert L_o - L_{op}\rvert}{L_o}\right) \times 100\%$	Deterioration in Accuracy $\frac{AL_{ori} - AL_{op}}{AL_{ori}} \times 100\%$
Camera 1	3	3	100%	0%
Camera 2	3	3	100%	0%
Camera 3	2	1	100%	0%
Camera 4	1	2	100%	0%
Camera 5	2	2	100%	0%

Table 4.17: Accuracy of Optimised Lane Detection Algorithm at Night

Traffic Camera	Number of Lanes Observed, L_o	Number of Lanes Identified via Algorithm, L_{op}	Accuracy, AL_{op} $\left(1-\frac{\lvert L_o - L_{op}\rvert}{L_o}\right)\times 100\%$	Deterioration in Accuracy $\frac{AL_{ori} - AL_{op}}{AL_{ori}} \times 100\%$
Camera 1	3	3	100%	0%
Camera 2	3	2	66.67%	0%
Camera 3	2	3	66.67%	0%
Camera 4	1	1	100%	0%
Camera 5	2	1	50%	0%

Table 4.18: Accuracy of Optimised Lane Detection Algorithm During Rainy Day

Traffic Camera	Number of Lanes Observed, L_o	Number of Lanes Identified via Algorithm, L_{op}	Accuracy, AL_{op} $\left(1-\frac{\lvert L_o - L_{op}\rvert}{L_o}\right)\times 100\%$	Deterioration in Accuracy $\frac{AL_{ori} - AL_{op}}{AL_{ori}} \times 100\%$
Camera 1	3	2	66.67%	0%
Camera 2	3	2	66.67%	0%
Camera 3	2	2	100%	0%
Camera 4	1	1	100%	0%
Camera 5	2	1	50%	0%

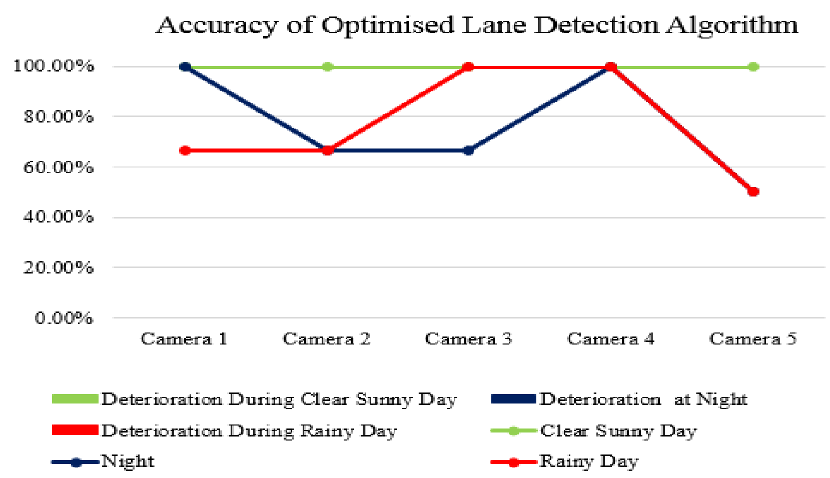


Figure 4.5: Accuracy of Optimised Lane Detection Algorithm

4.3.3 Accuracy of Optimised Vehicle Lane Count Algorithm

The accuracy of optimised vehicle lane count algorithm is as showed in Table 4.19, Table 4.20 and Table 4.21. The accuracy of vehicle lane count algorithm during clear sunny day is still the highest except camera 5. Besides, the accuracy of vehicle lane count algorithm before and after optimisation process do not show significant changes where the accuracy of optimised vehicle lane algorithm only decreased below than 10%. The deterioration in accuracy algorithm mainly because of the reduction on the size of vehicle mask image had made the process of obtaining the position of vehicles from the labelled connected component image become challenging.

Table 4.19: Accuracy of Optimised Vehicle Lane Count Algorithm During Clear Sunny Day

Traffic Camera	TP	TN	FP	FN	Accuracy, AC_{op} $\frac{TP+TN}{TP+TN+FP+FN} \times 100\%$	Deterioration in Accuracy $\frac{AC_{ori} - AC_{op}}{AC_{ori}} \times 100\%$
Camera 1	136	54	0	83	69.60%	3.81%
Camera 2	167	2	10	38	77.88%	2.23%
Camera 3	135	14	0	62	70.62%	0.00%
Camera 4	117	0	2	14	87.97%	0.00%
Camera 5	39	0	1	13	73.58%	1.89%

Table 4.20: Accuracy of Optimised Vehicle Lane Count Algorithm at Night

Traffic Camera	TP	TN	FP	FN	Accuracy, AC_{op} $\frac{TP+TN}{TP+TN+FP+FN} \times 100\%$	Deterioration in Accuracy $\frac{AC_{ori} - AC_{op}}{AC_{ori}} \times 100\%$
Camera 1	66	7	0	37	66.36%	0.46%
Camera 2	64	5	6	42	58.97%	1.42%
Camera 3	24	0	7	24	43.64%	7.60%
Camera 4	9	0	0	4	69.23%	0%
Camera 5	4	0	0	1	80.00%	0%

Table 4.21: Accuracy of Optimised Vehicle Lane Count Algorithm During Rainy Day

Traffic Camera	TP	TP	FP	FN	Accuracy, AC_{op} $\frac{TP+TN}{TP+TN+FP+FN} \times 100\%$	Deterioration in Accuracy $\frac{AC_{ori} - AC_{op}}{AC_{ori}} \times 100\%$
Camera 1	25	11	1	17	66.67%	5.98%
Camera 2	42	33	0	42	64.10%	3.85%
Camera 3	55	15	0	66	51.47%	6.23%
Camera 4	11	0	0	8	57.89%	0%
Camera 5	4	0	0	2	66.67%	0%

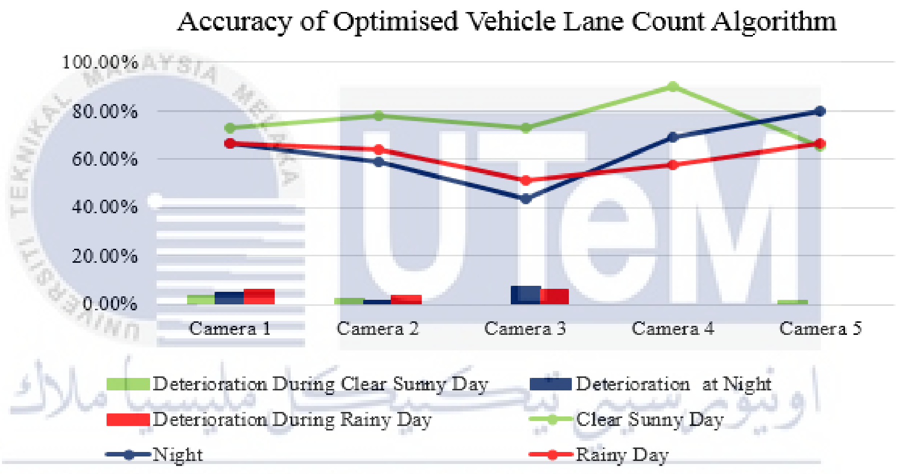


Figure 4.6: Accuracy of Optimised Vehicle Lane Count Algorithm

4.4 Environment and Sustainability

This project has applied Deep Neural Network which is the latest technology for vehicle recognition and implemented the algorithm with camera analytics to provide vehicle counting based on each detected lane at traffic junction. The vehicle counting provided by this project is useful to reflect the real time traffic density which is the fundamental element for the creation of traffic signal timing plan. The synchronisation of traffic density and traffic signal helped to reduce the traffic congestion.

According to Malaysia Stocktaking Report on Sustainable Transport and Climate Change (2016) [42], the emission of harmful gases mainly Carbon Dioxide (CO_2) from vehicles on road has resulted air pollution issues. Hence, the real time traffic data provided by this project which can helps to accurately predict traffic light waiting time is useful in minimising the vehicle journey time and indirectly decrease the emission of harmful gases. Finally, provide an environment friendly country.

4.5 Summary

In summary, the implemented algorithm is highly dependent on the vehicle trajectories. When there is insufficient of vehicle in the traffic video, the algorithm will fail to identify the number of lanes present and count the number of vehicles at each lane. For traffic video with less vehicles, longer time is required to obtain an accurate result. Clear sunny day is among the best condition to apply the implemented algorithm as it consists of plenty of vehicles and a clear camera view which ease the process of collecting vehicle trajectories in identifying lane region. On the other hand, the algorithm is crucial to be optimised in order to reduce its computation time so that the algorithm can be used for real time implementation without any latency.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

This chapter concludes all the achievement of project and proposed method for the improvement of project in the future.

5.1 Conclusion

In conclusion, clear sunny day is the best condition for the implementation of algorithm as it recorded the highest accuracy of detection which is 70.62% to 87.97%. This mainly due to camera has a clear sight view which capable to provide vehicle recognition for a longer distance during day time and plenty of moving vehicles which benefits the lane detection process. The night time is not recommended for lane detection due to its low light intensity that limit the vehicle recognition. It may require longer time for detection in order to provide accurate results. Besides, rainy day is not suggested lane detection as the water droplet falls on the camera may block the camera view for vehicle recognition and caused the lane region failed to be connected due to the blocking region. The algorithm is urged to be optimised in order to avoid latency during real time implementation. Although there is a trade-off between the computation time of algorithm and the accuracy of algorithm, but the overall performance of the algorithm still showed improvement after optimisation as the improvement in computation time is significant than the deterioration in accuracy.

5.2 Future Work

The implemented algorithm in this project has a weakness when the moving vehicles on the road lane is unequal, the lane with less moving vehicles will face difficulty to obtain its lane region in a fix time interval. Besides, the lane structure which consists of small turning region will also require larger threshold area to verify the lane region before the vehicle counting process. In future work, a function fitting algorithm can be proposed to improve the limitation of this project. The lane region can be obtained by kept on finding the line of best fit to represent the lane region through centre of the vehicles under tracked. This idea not only helps to minimise the possibility of false detection caused by vehicles crossing lanes but also fix the problem of unequal number of moving vehicles at traffic junction.

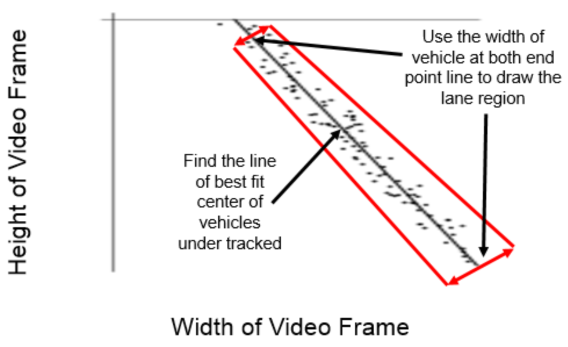


Figure 5.1: Future Work Proposed

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