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AI vehicle detection and recognition for effective traffic management

Abstract

As cars become more and more affordable, traffic congestion is a hard nut to crack for traffic authorities around the world. At present, there is still no perfect solution to it.

The goal of our assignment and project is to reduce traffic congestion and jams in congested areas in primarily Singapore and potentially in other countries in the world with AI technology. The focus is on reducing traffic congestion by researching, studying, and changing the control timings of when the traffic lights turn red, yellow and green. Hence, we are trying to build an AI enabled traffic management system, the focus on changing the length of traffic light signals.

Beyond that, our AI solution may create other possible benefits, through detection of type of vehicles and vehicle counting. This report will be divided into 3 sections: 1) Introduction; 2) Problem assessment; 3) Data and knowledge acquisition; 4) Prototype.

Introduction

Traffic congestion is a serious problem in modern cities around the world. For the traveller, traffic congestion results in longer travelling times and commuters' frustration (Wen, 2008). Time wasted during travel reduces the travellers' quality of life and may sometimes incur more financial costs. This is especially true in times of changing situations, for example, in the recent post-pandemic world, where there is a surge in commuter numbers in Singapore daily due to more people coming back to work in office. Traffic congestion would mean delivery delays and lost worker productivity (Wen, 2008). In metropolitan cities such as Singapore, there are possibly thousands of vehicles on the roads, roads could be more prone to fatal accidents (Joy et al., 2018).

Furthermore, there is an impact of traffic congestion on air pollution and fuel consumption, which affects health and the environment. A recent study has determined that Singapore is one of the best places for motorists (Tan, 2023). However, this comes at the cost to vehicle-owners, due to the measures implemented by the Singapore government to curb traffic congestion and the number of vehicles on the roads. These costs include higher High Additional Registration Fees for vehicles, requirement of obtaining "*Certificate of Entitlement*" for purchase of cars (Meng et al., 2015), and increasing ERP charges. These costs may be unnecessary if there is a better traffic management solution or the ability to manage traffic, at the same time to allow more motorists on roads. Detection of the number of vehicles and collecting this data could be useful to understand and plan future traffic policies and in better managing traffic.

Problem Description

Currently, there are three main standard methods widely adopted in the world to manage traffic at intersections (Gandhi et al., 2020; Zaid et al., 2017):

- Manual controlling: It requires traffic police to carry out the duties of directing traffic at the intersection by using signs or a whistle. This method is a bit outdated and only used when the traffic lights malfunction. A skilled person is required and is not accurate. This is almost not used in modern parts of the world.
- Fixed-time traffic light: This is a conventional method controlled by static timers. The lights are changed at a fixed interval which is predetermined by the historical data. This could be the most common approach in most parts of the world.
- Dynamic control system: This method adapts to the traffic conditions by detectors that are installed on the road surface or above the road. This approach is often taken in smart cities.
    - Automatic controlling via sensor based (Tubaishat et al., 2009; Yousef et al., 2010).

      Uses sensor network to detect cars such as the use of infrared radar sensor, magnetic loop detectors. These are costly and require infrastructure with maintenance to ensure accuracy of results.

- Automatic controlling through image processing based (Michalopoulos, 1991).

  Images are extracted from videos or captured by CCTV from cameras on traffic lights or expressways, the number of cars on each traffic light can be computed and the traffic light is controlled. This is deemed as a more efficient and reliable method compared to previously described methods.

However, the first two methods were not able to solve the sophisticated traffic flows at the interactions with the increasing number of vehicles on the roads at metropolitan societies.

They have some drawbacks certainly. For instance, fixed-time traffic lights would turn red and delay the vehicles' movement even though there are no pedestrians crossing the road. This is not adaptive to the current traffic condition. In addition, dynamic control systems heavily rely on sensors which are expensive to install and maintain. At the same time, the results are not very accurate in terms of the number of cars counting when the space between the vehicles on the road is small (Lakshmi & Kalpana, 2017). Instead, it could be more cost-efficient to first utilise the current technologies available in Singapore, such as CCTV cameras installed at the traffic junctions, rather than installing expensive sensors to collect data. There are "Junction Electronic Eyes" (J-Eyes) system of some 400 cameras (mounted on traffic light posts, lampposts, etc.) located at major traffic junctions in Singapore that monitor traffic conditions and verifies real-time incidents.

In Singapore, there are other intelligent transport systems implemented by the Land Transport Authority (LTA) such as:

1. Green Link Determining System

   Adjacent traffic signals are linked to allow vehicles to travel from one junction to another with minimal stops.

In recent years, artificial intelligence is getting popular in integration into traffic control systems as it has achieved better throughput in urban traffic areas (Vogel et al., 2018). In Singapore, many CCTV cameras are installed on the road network for incident management, which can facilitate traffic condition management at the intersections as well. Our plan is to detect, count and identify the type of vehicles at the traffic light junctions and the number of people waiting at the traffic light junction through the use of cameras or CCTVs.

There are a set of possible commonly used vehicles in Singapore, such as cars, trucks, buses, and lorries. These vehicles are either transporting humans, goods, delivery packages or other dangerous items. Our AI project aims to detect whether the incoming vehicles are either of the above types of vehicles. This data will be reprocessed to adjust the traffic light in response to the road conditions to alleviate the traffic problems.

Data and knowledge acquisition

There are traffic camera images of major expressways across the entire Singapore that are available from the Land Transport Authority website, that is updated at every five minutes intervals, found at https://onemotoring.lta.gov.sg/content/onemotoring/home/driving/traffic_information/traffic-cameras.html. A program can be written to download the images periodically from all the traffic cameras or for a specific traffic camera over a specified period of time. A video demonstration is found here: https://www.youtube.com/watch?v=HVymH2Uv_I0.

Our solution highly relies on the image data fed by the traffic cameras. Therefore, the quality of the data may affect the effectiveness of our solution.

Below are common issues when or after acquisition of traffic data.

Issue 1: Traffic images at traffic junctions are difficult to obtain

Although most of the road networks are installed with CCTV cameras, not all of them are of high definition. Traffic junction images are not publicly available, however, this problem be circumvented with the use of publicly available traffic images to infer the traffic conditions leading up to the traffic junctions (see Figure 5 for illustration). The image captured for incident management may not be suitable for object detection.

Issue 2: Incompatible data

There could be issues with the incompatible image formats being used for analysis. Traffic cameras may output data to incompatible formats. This applies even for image data, formats may vary, conversion of data formats from one image format to other image formats may result in loss of data. Some image photos may not be compatible for use in prediction.

Issue 3: Missing data

When traffic cameras are under maintenance, there could be a period of downtime, whereby the density of the traffic cannot be predicted. There are some occurrences of these, in future, our project may account for this problem by detecting this earlier.

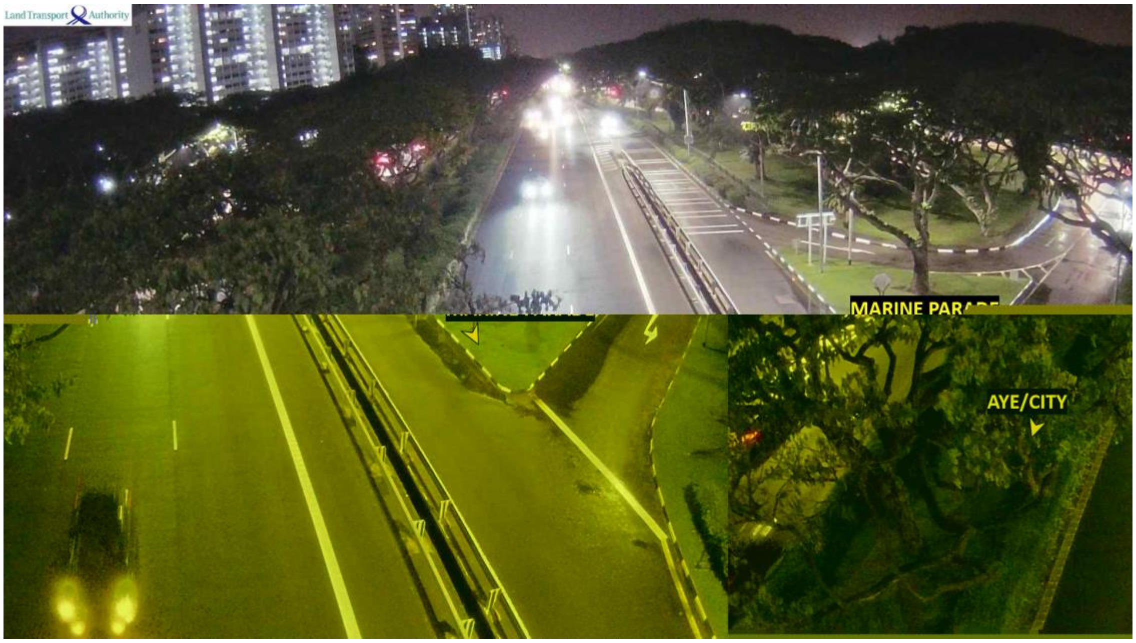
Issue 4: Data corruption

Since traffic image data are being downloaded from a network, there could be issues with data corruption. Image data are smaller than video feed used in some projects, hence this problem may be considered as minor.

Issue 5: Poor quality of data

There are some traffic camera images that are of poorer quality than others or could have been subjected to unexpected changes not previously specified.

For example, the traffic camera view from Marine Parade Flyover taken at 03/03/2023 23:21 PM:



Differs from usual images collected and this could be unexpected.

Bright light leads to inability to detect moving vehicles.

Examples of images collected from daily CCTV traffic images:

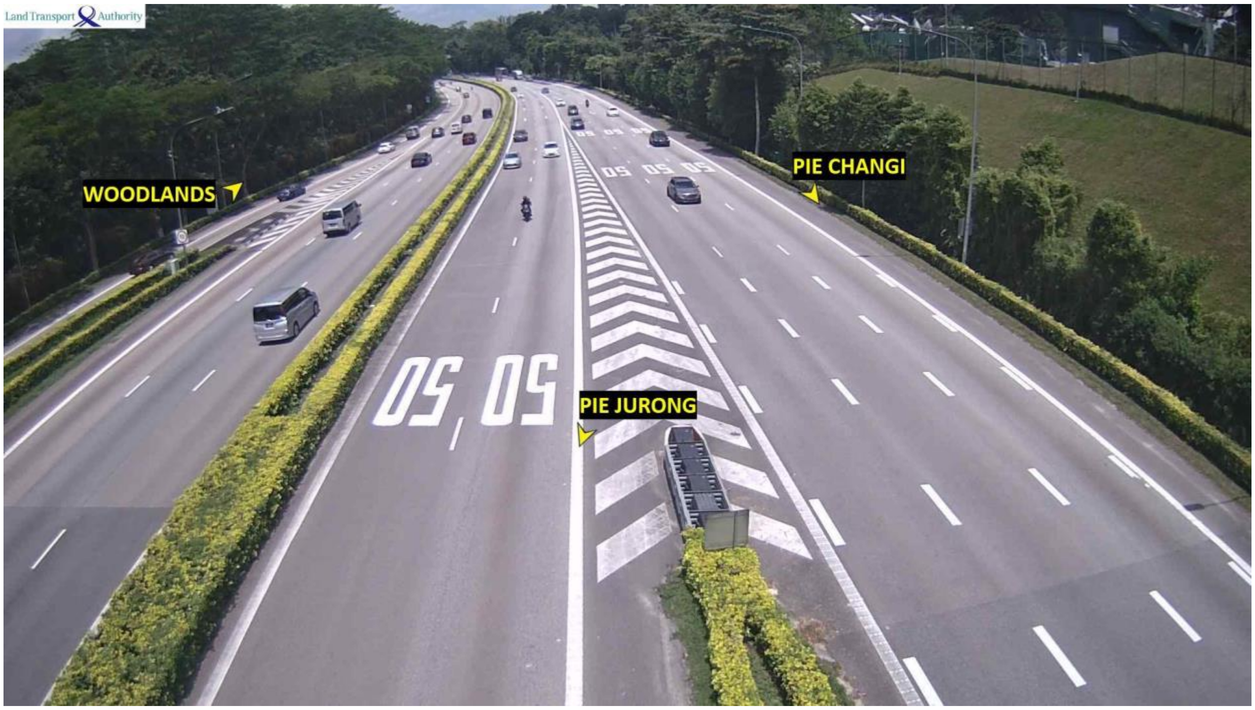


Figure 1 - Image collected at 19 Feb 2023 at 12.40pm (Camera ID 2703) - _2023-02-19_12-40_2703_1238_20230219124108_529752.jpg

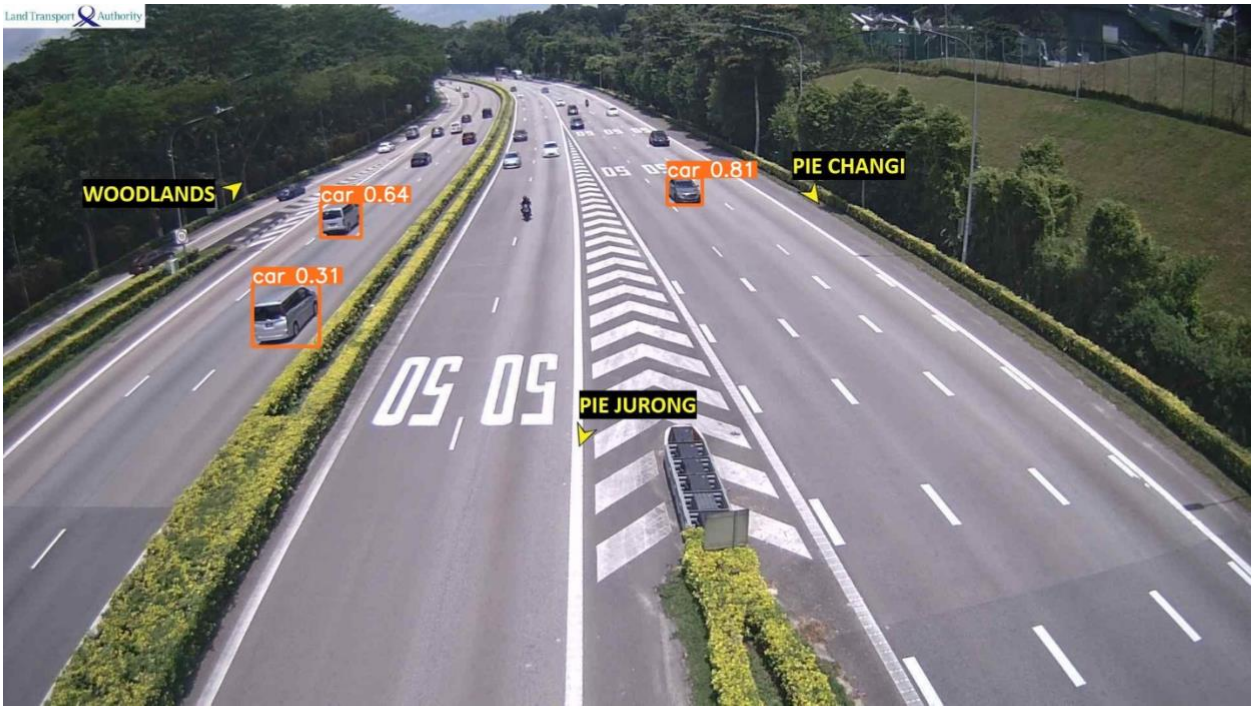


Figure 2 - Predicted on available pre-trained model

As seen in Figure 2, small vehicles cannot be detected with the pre-trained model being applied to the image directly. Hence, this may result in under-counting the number of vehicles in the traffic.

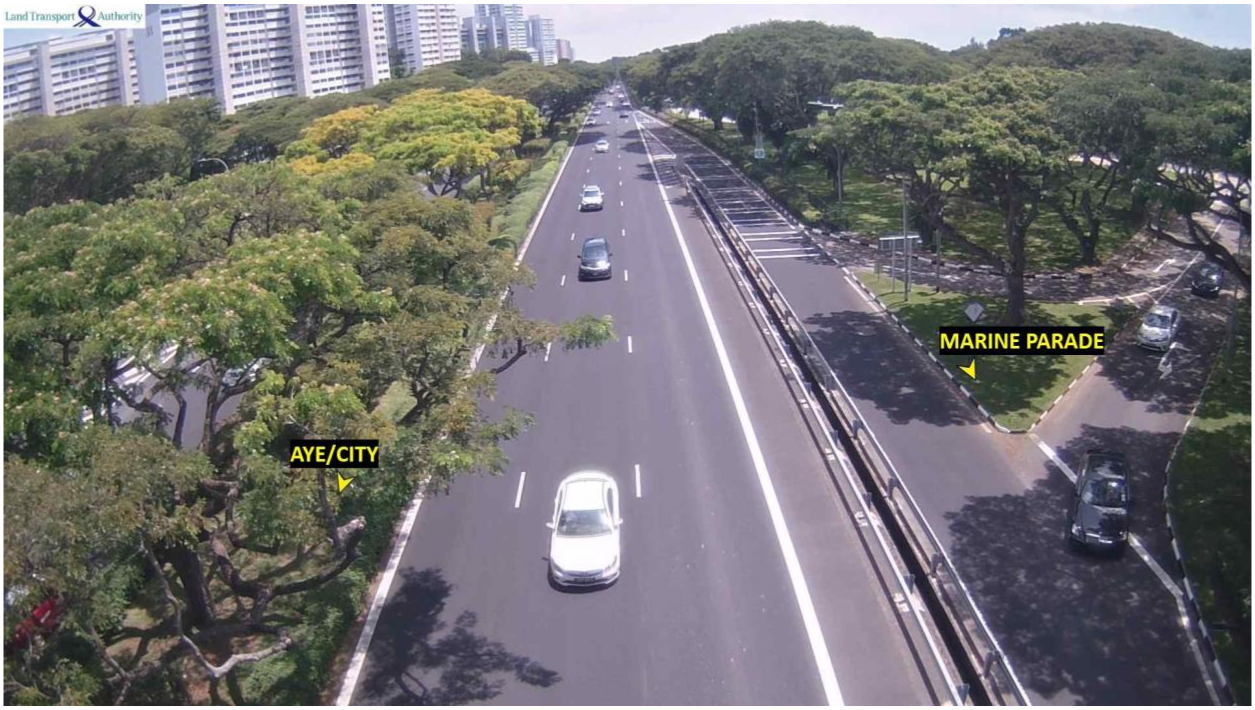


Figure 3 - Image collected at 19 Feb 2023 at 12.40pm (Camera ID 3795) - _2023-02-19_12-40_3795_1239_20230219124021_504899.jpg

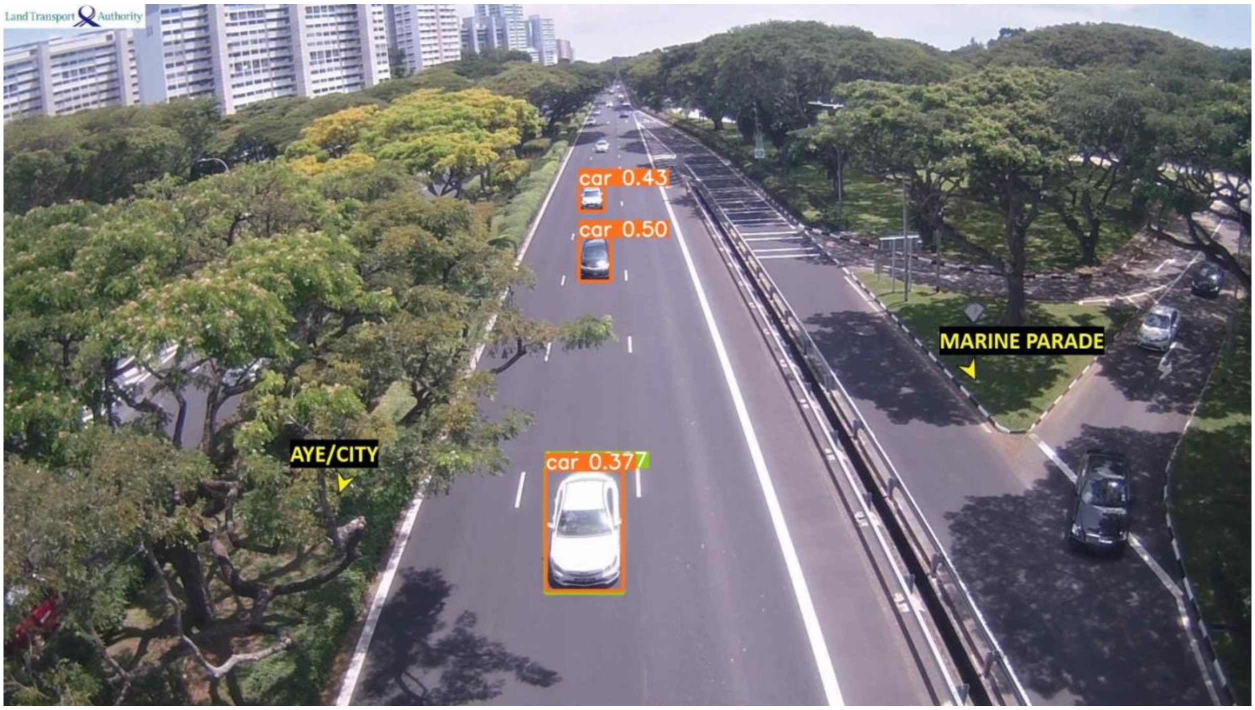


Figure 4 - _2023-02-19_12-40_3795_1239_20230219124021_504899.jpg (Predicted on available pre-trained model)

As seen in Figure 4, some vehicles on darker regions or shadows cannot be detected as cars using the pretrained model directly applied to the earlier image. Furthermore, the car (0.37) is being detected as something else at the same time.

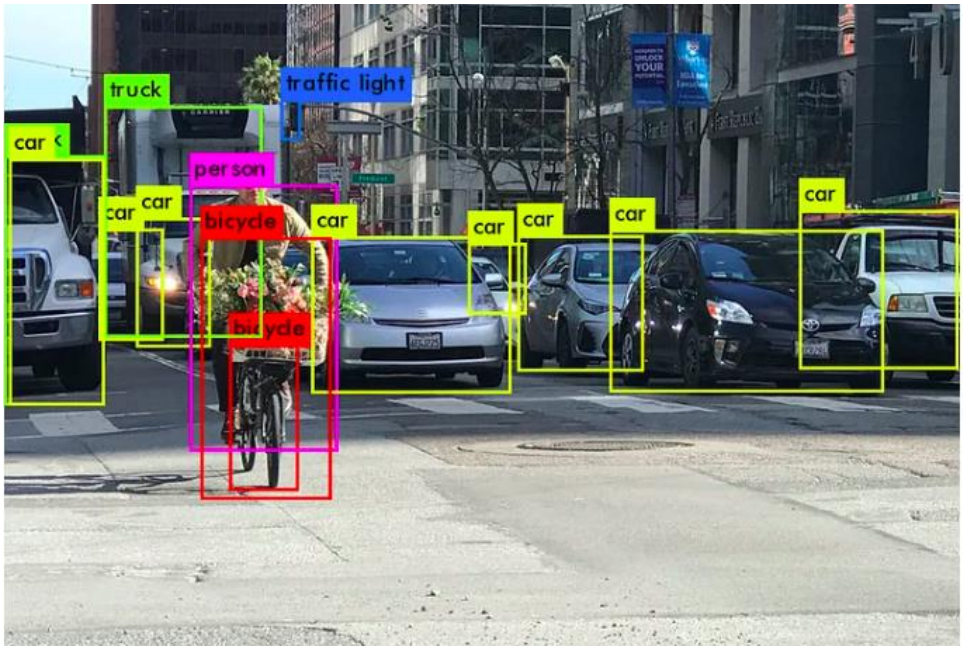
In this project, we aim to select one of the CCTV camera images collected over a period of time. The collection of CCTV images can be configured to collect images at an interval of around 10 minutes. The above images are samples of the CCTV traffic images at certain regions in Singapore collected on 19 Feb 2023 at 12:39 PM. The location of the CCTV is approximately at the location shown on Google Maps below, which is at the Marine Parade Flyover (how this is determined is demonstrated here: https://www.youtube.com/watch?v=z3ipUt8BgOE):

Figure 5 - Traffic camera location (Google Maps)

Issue 6: Differences in data across different countries and regions

Even within Singapore, there are differences in the image data being collected, such as different designs of buses, cars and other vehicles. The variations in how the traffic system works vary even more across different countries although the variation within a small Singapore like Singapore can be assumed to be minimal.

There may be some traffic regulations that I may not be aware of, since I am not an expert in road traffic, including all the traffic regulations in many countries will be too lengthy in our project or report.



Objection detection by YOLO - Source: (www.medium.com)

Data preparation

The image data can be cropped to focus on just the road that we are interested in detecting the number of vehicles. This may increase the accuracy of the detection and counting of vehicles on the roads.

Image captured from CCTV camera at intersections can be used as input for real time traffic density calculation through image processing and object detection.

Investigation of suitable AI technique or solution for suggested AI product

AI techniques used for vehicle detection and time prediction

YOLO Objection Detection

The detection of vehicle numbers leads to the period of green light allocation. In another word, the failure on the accuracy of vehicle detection will lead to miscalculation of the period of green light for them. Hence, we recommend YOLO (You only look once). YOLO is an object detection system that can handle real-time processing. As it is run based on a convolutional neural network (CNN) which predicts multiple bounding boxes and classes simultaneously. Moreover, it is highly accurate. It was reported that YOLO achieves 72% top-1 accuracy and 91.2% top-4 on ImageNet respectively (Hui, 2018). With the release of YOLO8, it is perceived to be higher accuracy and flexibility (Bhalerao, 2023).

Rule-based AI Technique

In many countries, Rule-based AI is used for adaptive traffic management systems. It was considered effective in reducing traffic congestion. However, this method has difficulty in distinguishing between regular objects like billboards, poles and trees with vehicles as they were converted to black and white. Moreover, it fails to detect emergency vehicle (Gandhi & Daptardar, 2020).

Artificial Neural Network (ANN)

This is used to detect the number of moving vehicles and the vehicle types

An Artificial Neural Network (ANN) is the imitation of a biological neuron. It could consist of many inputs and one output. There are many simple processing elements that are intertwined with each other and at different layers (Mishra & Srivastava, 2014).

There have been some problems with ANN described (Mishra & Srivastava, 2014):

1. No structured methodology available in ANN
2. No single standardised paradigm for the development of ANN
3. Output quality of ANN may be unpredictable
4. ANN systems do not describe how they solve problems
5. High computational burden

In this case, ANN will process the image capture to determine what class of the vehicles belong to for further analysis. As a result, the output of this method will heavily depend on tuning positive and negative training data using the sliding window method (Zaid et al., 2017) and the prediction was only on whether it was a car or not. A study by Soman and Radhakrishnan (2018) also found that there is an error rate of 2% with execution of 1.5 seconds.

Fuzzy logic

This is used for estimating the traffic light timings (to turn green, red or orange).

A fuzzy system is built upon membership functions (MFs). It comprises several fuzzy sets. Generally, there are three codification shapes to choose from for MFs inputs. They are triangular, trapezoidal and Gauss respectively and trapezoidal is commonly used (Akhtar & Moridpour, 2021).

In our case, fuzzy logic is used to determine a suitable period for the red and green light at traffic junctions. When the number of vehicles increases, the period of green light will increase.

Generally, after the completion of vehicles detection by YOLO, fuzzy logic will be applied on the data output of the YOLO algorithm to estimate the period needed to allow those vehicles to pass the traffic junction.

Deep reinforcement learning approaches

A number of studies were conducted and applied deep reinforcement learning techniques but have been unfeasible for practical intelligent traffic control system due to continuous action spaces (Ning et al., 2021). Most of these systems ignore vehicles' mobilities on computation and caching resource allocation.

Constraint programming

This is based on techniques used to represent constraints to allow for propagation of values among variables. A set of elements that is to be interpreted and arranged as a network of elements with possible values and a set of constraints among arranged elements restrict value assignment. A constraint satisfaction mechanism tries to achieve assignment of values to these elements according to the constraints. The set of elements could be the intersections in the traffic process and the constraints could be the structural knowledge of the network such as acquired traffic data (Bielli et al., 1991).

Prototype

Image detection using YOLO algorithm

Image detection is being applied to traffic camera images either at traffic junctions or at readily available traffic images that can be extracted from the Singapore's Land Transport Authority website. The number of vehicles and the type of vehicles are being predicted, after the image is being fed to the model for prediction.

Table 1 - Table of types of vehicles found in Singapore and their importance

Vehicle type	**Number of passengers**	**Importance**
Car	1	1
Bus	35 (varies)	35
Truck	10	10
Ambulance	3	500
Motorbike	1	1
Rickshaw	3	3

A demonstration is performed here: https://www.youtube.com/watch?v=leNAv8qYlqo on how the script works and the computation of the volume-importance metric is being shown in the video.

The output from the prototype Python script (which is attached to this report) will be the volume-importance metric (variable volume_*imp*) which will be the input of the fuzzy system below as "*vehicleCount*".

```
In [81]: volume_imp = car_w * car_no + bus_w * bus_no + truck_w * truck_no

         volume_imp

Out[81]: 35
```

The importance value (termed by me as volume-importance vehicle metric) can be tuned or modified by a subject-matter expert or through further research with machine learning (e.g., using linear regression, etc.). The importance value can be adjusted by the expert on a separate configuration file. This volume-importance of vehicles metric is important and this value will be sent to the fuzzy rule-based system as an input.

The number of people waiting at the traffic junctions can be also fed to the fuzzy system as an input, and the traffic from intersecting roads. These inputs (or more, in our project) will determine the duration of the traffic light showing red or green, as an improvement to the traditional traffic control system.

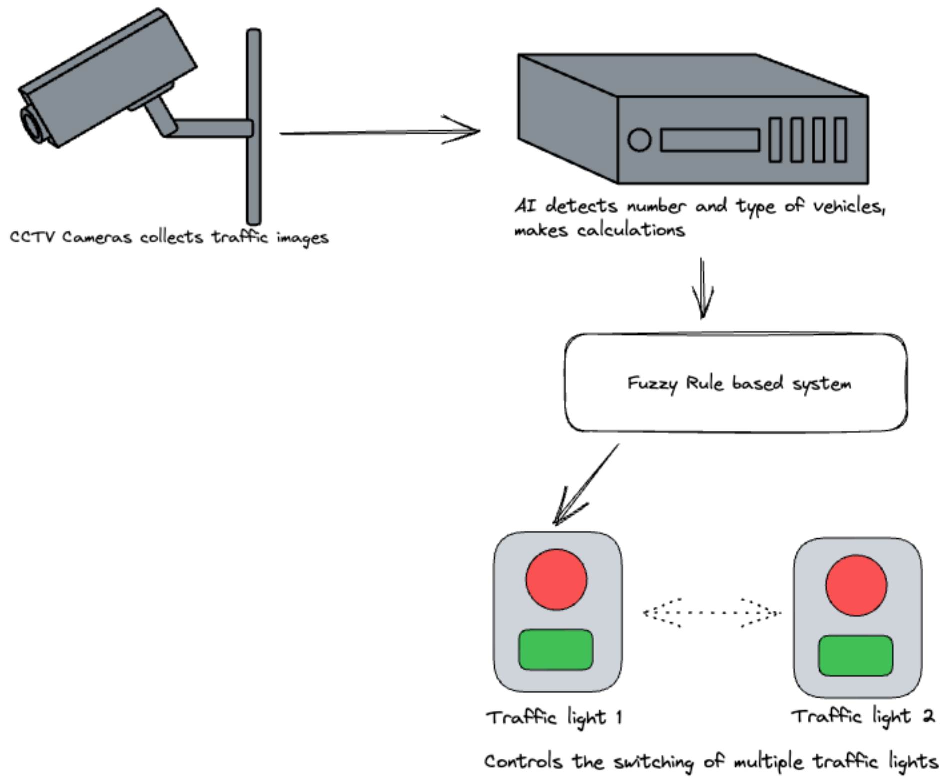


Figure 6 - General idea of the prototype

Fuzzy logic system to determine the traffic green light duration

A demo of the traffic green light duration obtained from the fuzzy rule-based system to control the traffic light from the point-of-view of the vehicles at the traffic junction can be seen in the video I have created here: https://www.youtube.com/watch?v=3xeNdoAVezc

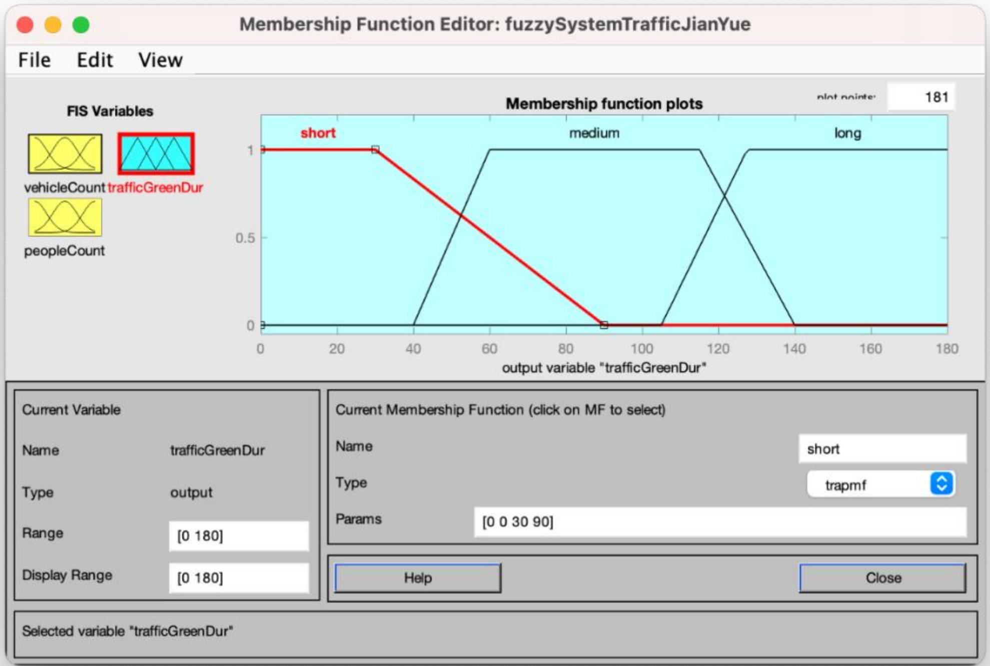


Figure 7 - Example of membership function indicating the linguistic variable, names used are "short", "medium" and "long".

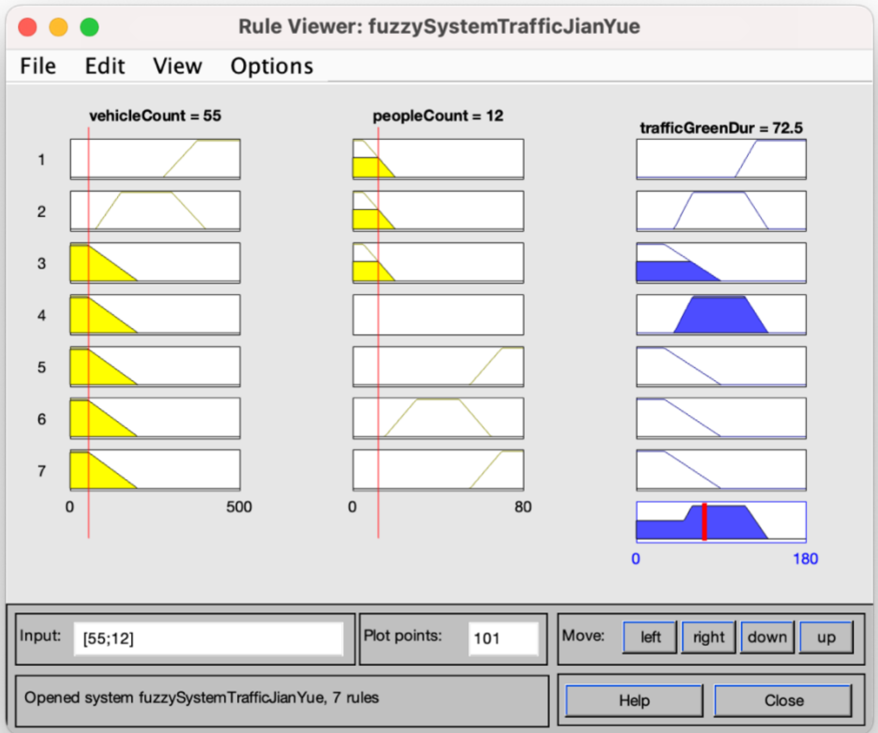


Figure 8 - Fuzzy rule viewer example

For example, for relatively low volume-importance of vehicles (vehicleCount), and few number of people (peopleCount), the traffic green light duration is determined to be 72.5 seconds.

The output can be obtained from the MATLAB interface and the output (in number of seconds) may be fed back to the traffic light controller system.

```
>> greenLightTime = evalfis(fuzzySystemTrafficJianYue, [200,70])

greenLightTime =

    65.4804
```

Generally, there is only a need to control the duration of the green light on a traffic light, the time it takes from green to amber and to red is generally standardised based on the roads and country in question and there is rarely a need to adjust. The intersecting traffic light will be the negation of the traffic light in control, even though the traffic conditions on the intersecting traffic light could influence the traffic light duration, which could be explored further in our project.

Conclusion

No other project that I could find has used the new metric introduced called the volume-importance metric and the plan to detect vehicles customised to Singapore may be new. Furthermore, Singapore has been using sensors which is usually more expensive to install and maintain, with lesser reliance on the availability of traffic cameras. This project could integrate with existing technologies to provide smoother and better travellers' experiences.

Other than the problems as described earlier, our project could further include more functionalities which are not limited to:

2. Vehicles violating traffic rules: If we engage experts in road safety and laws in our system across multiple countries, vehicles violating traffic laws could be identified by high-speed photo and video capture. This is important as to potentially reduce the road traffic accidents which causes longer travelling times. This may require involvement in image processing techniques (Gandhi et al., 2020).
3. Better methods by combining different sources of data and testing to find the optimal green light duration in different situations such as combining existing technologies already implemented and discussed above. However, this could be an issue as many of such data are not publicly available.
4. Model shall include more vehicles that are not found in the available pre-trained model, this will involve possible training on annotated and labelled images.

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