MTSFB TR 016:2023

TECHNICAL REPORT

VISION BASED INTELLIGENT TRAFFIC MONITORING SYSTEM (VBITMS)

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Preface

Malaysian Technical Standards Forum Bhd (MTSFB) has awarded Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) the Industry Promotion and Development Grant (IPDG) to implement the Proof of Concept (PoC) of the Vision Based Intelligent Traffic Monitoring System (VBITMS). The duration of this PoC is for 18 months starting March 2021 and was carried out in Cyberjaya.

This Technical Report outlines the objectives, benefits, scope of work, methodology and result analysis.

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Abbreviations

For this Technical Report, the following abbreviations apply.

ADT	Average Daily Traffic
AI	Artificial Intelligent
CCTV	Closed Circuit Television
CO_2	Carbon Dioxide
CPU	Central Processing Unit
FN	False Negative
FP	False Positive
GPU	Graphics Processing Unit
ID	Identity/Identification
IP	Internet Protocol
MCC	Manual Classified Traffic Count
OS	Operating System
PHV	Peak Hour Volume
PoC	Proof of Concept
RAM	Random Access Memory
RTSP	Real-Time Streaming Protocol
TN	True Negative
TP	True Positive
USEPA	United States Environmental Protection Agency
VBITMS	Vision Based Intelligent Traffic Monitoring System
YOLO	You Only Look Once

VISION BASED INTELLIGENT TRAFFIC MONITORING SYSTEM (VBITMS)

Executive summary

This project aims to develop a Proof of Concept (PoC) on a vision-based intelligent traffic monitoring system that classifies and counts vehicles as they move through a fixed detection zone in a CCTV field of view.

The system uses Artificial Intelligent (AI) to classify vehicles into one of three categories: car, motorcycle, and heavy vehicles (vans and trucks). With data trajectory, analysis, and prediction, traffic flow and anomalies condition can be determined in real-time to help authorities and road users make fast decisions.

In addition, historical data on traffic flow can help the city council enforce traffic diversion, revise road planning, develop better access to property and business areas and study the impact of vehicle carbon emissions.

1. Background

Roadside CCTV is widely deployed in many countries to provide remote observation of traffic volumes and flow to a traffic control centre. For example, in Malaysia, the current video analysis is mainly undertaken manually by experienced operators to monitor any abnormalities. With a vast number of screens to monitor, the potential for overlooking and delayed responses is unavoidable.

Automated video data analysis is seen as an increasingly important component of intelligent traffic management, providing the capability to fully exploit the real-time information available from the live video stream of CCTV. Several problems must be solved in measuring individual vehicles, such as real-time detection, tracking and classification while providing feedback on traffic flow analysis and anomalies conditions.

2. Objective

The objectives of the PoC are as follows:

a) To develop real-time vehicle detection, classification, and tracking system.

b) To study the traffic flow pattern based on vehicle counting.

c) To test and implement the proposed system in Cyberjaya,

d) To improve authority responses to traffic conditions.

e) To analyse crucial traffic parameters that are impactful to Cyberjaya road planning and property development.

3. Target groups and benefits

No.	Target groups	Benefits	Description
1.	Community	Timesaving	Display real-time information about traffic conditions during peak hours to assist road users in making informed decisions.
		Safety and health	Monitor carbon emissions produced by vehicles and complied with the limit set by the authority.
2.	Industry	Integration with other smart systems	Provide information to smart traffic lights, smart street lighting and smart parking.
		City blueprint	Quantify the use of communication towers, billboards, road paths and thicknesses, footpaths, and cycleways for better city planning.
		Development	Forecast individuals' purchasing capacity (financial capability) through analysis of vehicle numbers and types, aiming to enhance property and business development strategies.
3.	Authority/council	Surveillance and facilitation	Effectively monitor and manage the flow of vehicles, people and public transport around the area.
		Law enforcement	Enable authority to monitor illegal parking, robbery, or any other malicious activities.

4. Scope of work

The site selected for this PoC is in area Cyber 6, Cyberjaya. This is because there are existing CCTV infrastructures for rapid deployment. This PoC was implemented as part of the “Cyberview Living Lab Pilot” programme, allowing VBITMS to be tested and validated in a real environment. The duration of this PoC is for 18 months, starting March 2021.

The scope of work includes the following.

a) Phase 1

   i) Design the architecture of the system framework.

   ii) Develop the vehicle detection and classification system.

   iii) Test the performance of vehicle detection and classification system using recorded CCTV videos.

b) Phase 2

   i) Develop the vehicle tracking and counting system.

   ii) Test the performance of the vehicle tracking and counting system using real-time CCTV video where video quality and data latency is considered.

d) Phase 3

   i) Set up data server and dashboard.

   ii) Installation of the equipment (AI inference machine) at Cyberview premise.

   iii) Test run and commissioning.

5. Methodology

5.1 System architecture

Figure 1 shows the overall architecture of the VBITMS system implemented in this PoC. There are 4 modules as follows:

a) Video inputs from roadside CCTVs.
b) AI-image processing engine that consists of vehicle detection, classification, tracking, counting, and anomaly detection algorithms.
c) Data handler to manage the output from AI-image engine either to store in the database or send alert when necessary.
d) A dashboard to display analytical data in the type of bar graph, pie chart, table, map and time series line plot.

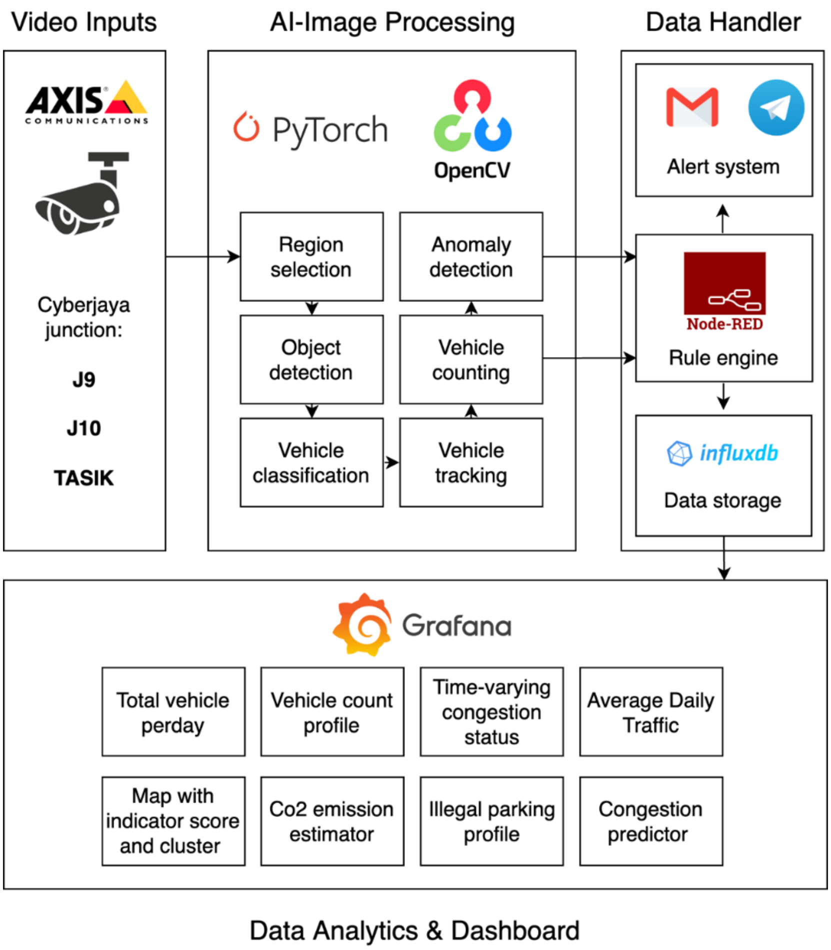


Figure 1. Overall architecture of the VBITMS system

Figure 2 illustrates the CCTV network from the Cyberjaya roadside area to the premise at Cyberview Sdn Bhd. The VBITMS system was installed on the AI inference machine, which uses the Real-Time Streaming Protocol (RTSP) to capture the real-time video feed from Internet Protocol (IP) cameras.

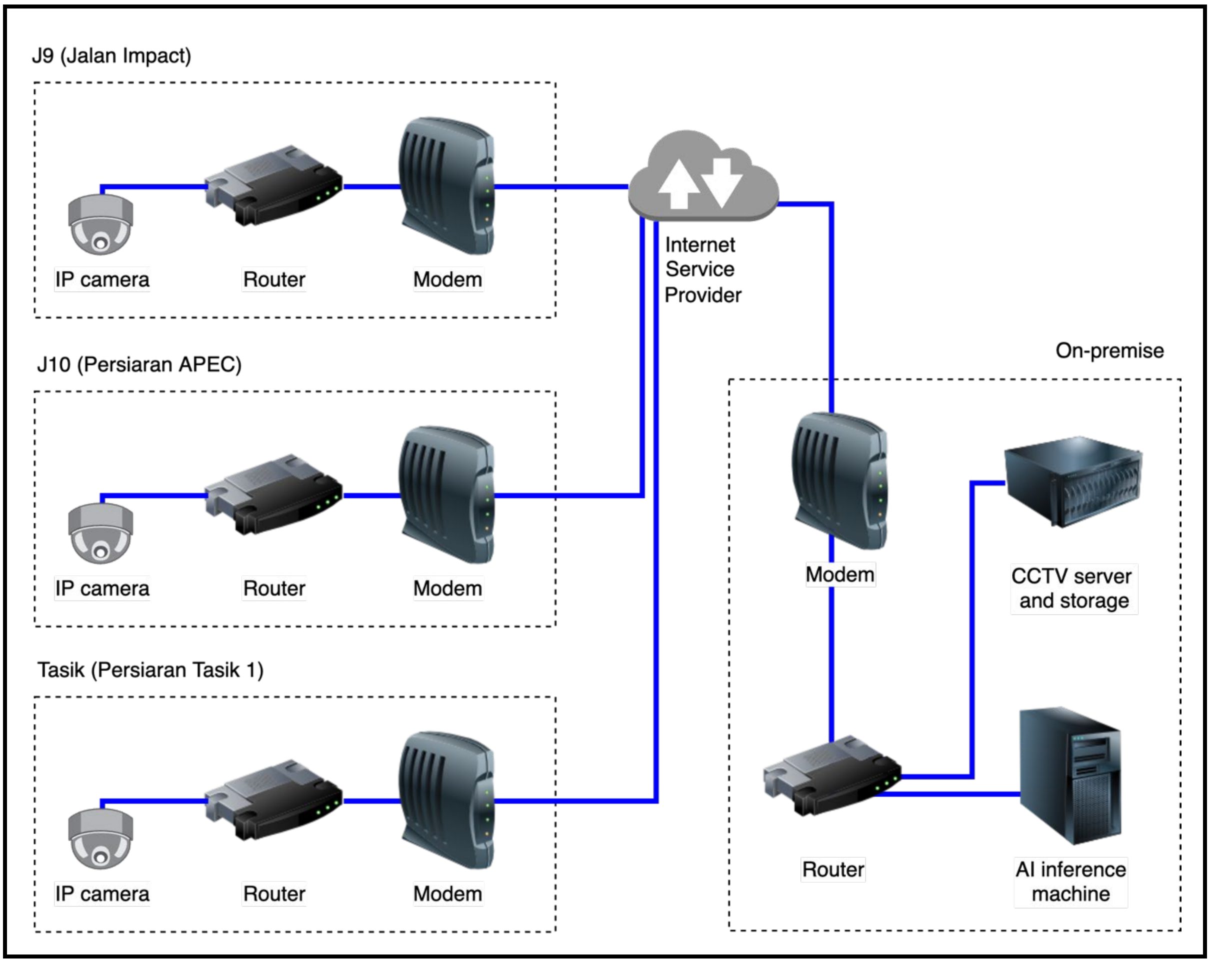


Figure 2. Diagram of CCTV network

Figure 3 shows the hardware placed inside the premise which consists of

a) AI inference machine main unit.

b) AI inference machine backup unit.

c) CCTV server and storage.

Figure 3. Hardware placement inside premise

The specification of the AI inference machine is shown in Annex A.

5.2 Data collection

Figure 4 shows the CCTV locations in Cyberjaya. In this PoC, junction J9 (Jalan Impact), J10 (Persiaran APEC), and Tasik (Persiaran Tasik) were chosen for PoC evaluation as these 3 locations have been identified as the busiest area in Cyberjaya. The reason for selecting these specific locations is based on distinct factors. Junction J9 (Jalan Impact) and J10 (Persiaran APEC) are considered the busiest areas due to high traffic volume and daily commuting. Meanwhile, Tasik (Persiaran Tasik) is a residential area that attracts many visitors with its various attractions. Unfortunately, visitors often park illegally along the roadside, causing disorderly parking.

For phase 1, a total of 30 minutes of video for each junction was recorded and used to verify the performance of the vehicle detection, classification and tracking system. For phase 2 and phase 3, real-time video feed from these CCTVs were used instead.

Figures 5 to 7 show the position of the roadside CCTV in those 3 locations (as shown by the white arrows). All cameras use the same model which is dome network camera type. All cameras are mounted on a single or isolated pole that is far from traffic intersections to reduce vibration or movement coming from vehicles. This can produce a stable visual view with good quality. The pole must be corrosion-resistant and sufficiently robust to withstand both weather conditions and the passage of time.

Figure 4. The chosen locations of Cyberjaya roadside CCTV

Figure 5. CCTV position at J9 (Jalan Impact)

Figure 6. CCTV position at J10 (Persiaran APEC)

Figure 7. CCTV position at Tasik (Persiaran Tasik)

5.3 AI-image processing

The AI image processing combines the object detection unit with the tracking algorithm to count the vehicle traffic data. State-of-the-art You Only Look Once (YOLO) object detection framework is used to recognise the vehicles in video frames, followed by tracking using rudimentary data associated with the Kalman filter estimation technique. The working process of the proposed method is depicted in Figure 8, and a snapshot of its python program is shown in Figure 9.

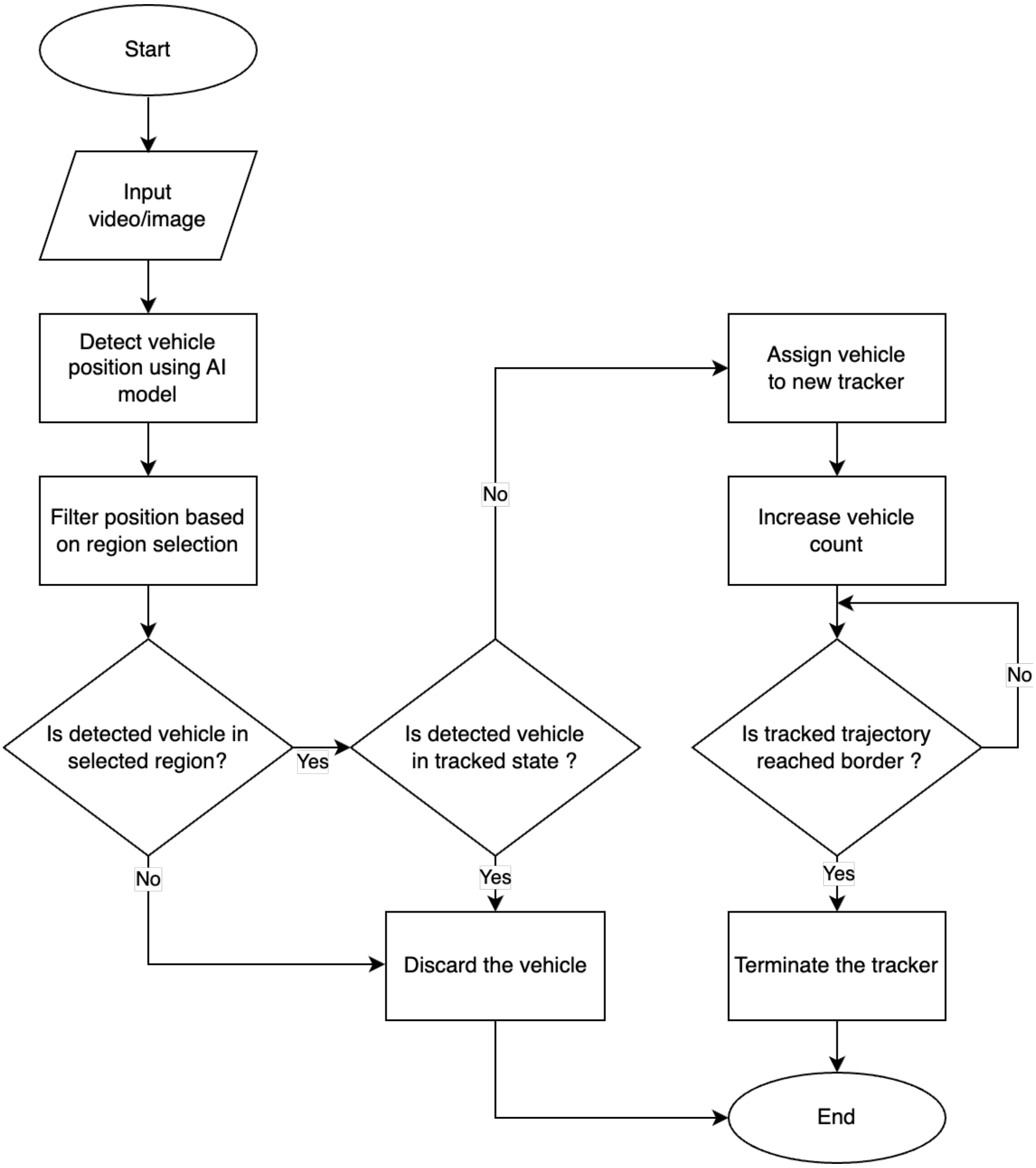


Figure 8. Flowchart of the proposed vehicle counting process

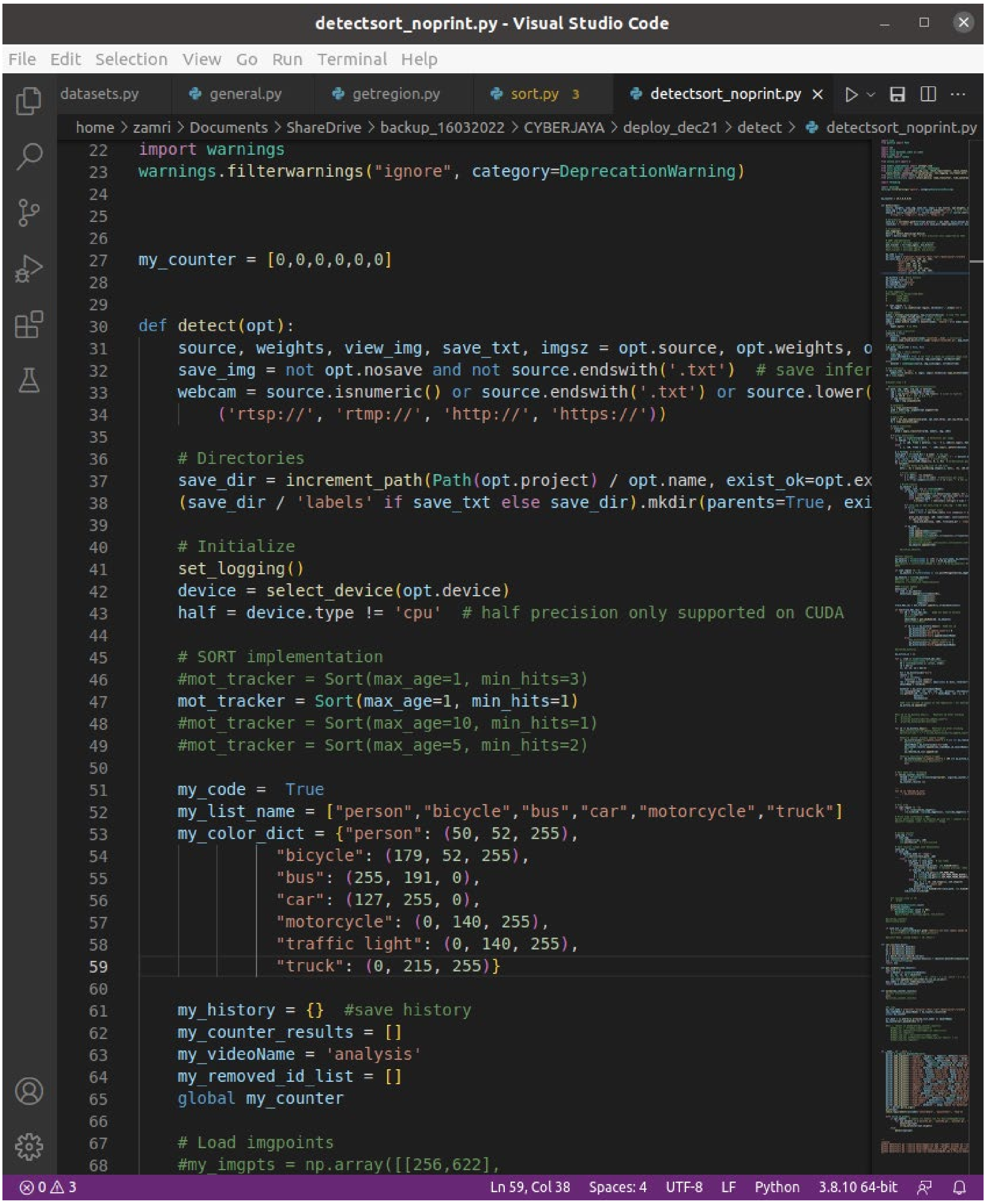


Figure 9. A screenshot of the python program VBITMS

The output of vehicle detection is shown in Figure 10.

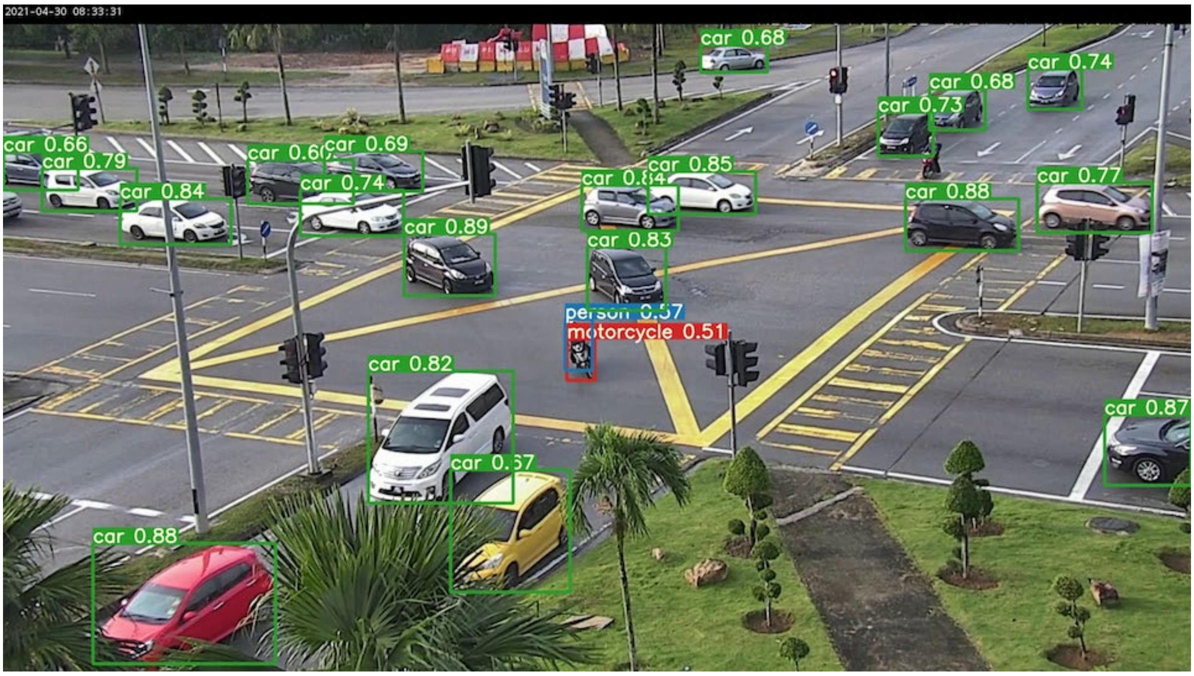


Figure 10. Vehicle detection at J10 (Persiaran APEC)

Figure 11 shows the vehicle tracking in the selected region. The region (red colour) is used as an entry and exit window for each vehicle. To initiate a new track, every detection is validated and then assigned to a tracker based on the Kalman filter. The counting process starts once the tracker is activated. All object classes except “car”, “motorcycle”, “van”, and “truck” are deleted from the detection process.

Figure 11. Vehicle tracking in the selected region

5.4 Data handler

The data handler module has 3 components as follows:

a) Rule engine.

b) Data storage.

c) Alert system.

In VBITMS system, Node-RED was chosen as a rule engine where it can stream the data to event-driven applications by using a flow-based visual programming environment.

Figures 12 and 13 show the flow-based programming on how data been direct from the AI-image processing module to the Influxdb database in a simple way.

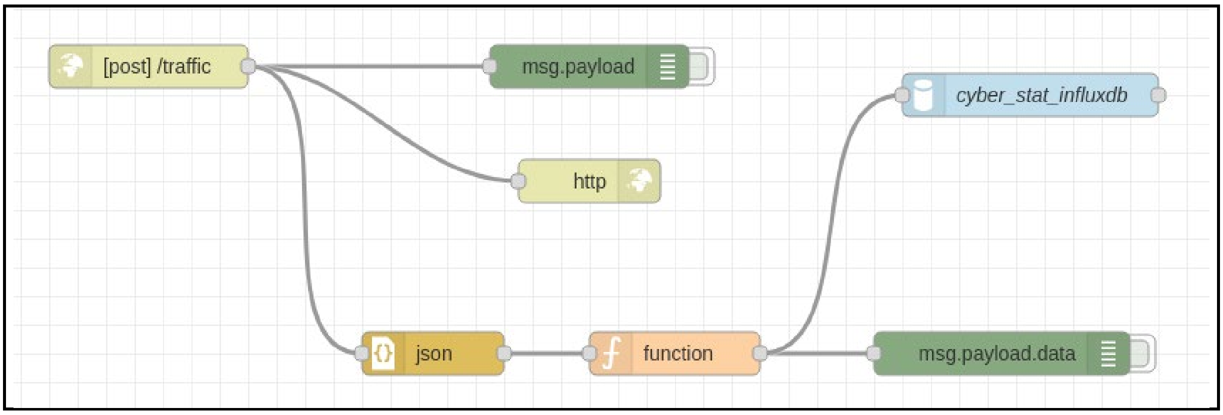


Figure 12. Node-RED flow for traffic data to Influxdb database

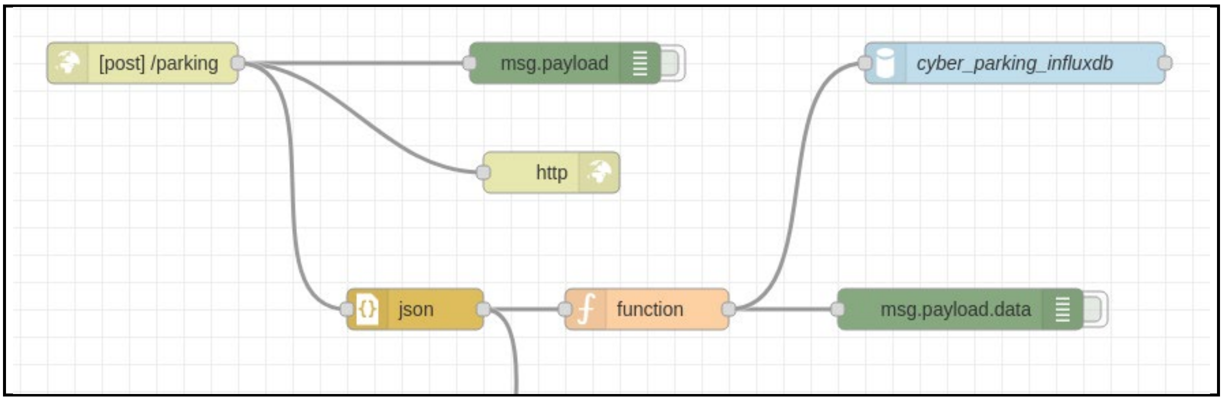


Figure 13. Node-RED flow for parking data to Influxdb database

The advantage of this method is that it can redirect the data to other events-driven applications such as Telegram as shown in Figure 14, or any third-party client that requires the same data for their application without interrupting the real-time video detection process in the AI-image processing module. For example, if user want to create email notifications for illegal parking or daily reports to clients, everything can be simply done in Node-RED rather than modify the code/program in the AI-image processing module. This makes the overall system uninterrupted and scalable.

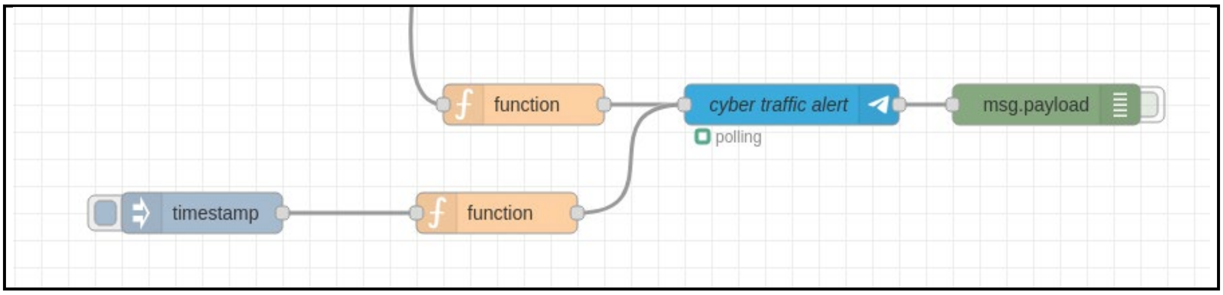


Figure 14. Node-RED flow for parking data to Telegram alert

5.5 Dashboard and data analytics

Data analytics helps individuals and organisations make sense of data. Data analysts typically analyse raw data for insights and trends.

In this PoC, Grafana was used to provide data analytics and insight. Grafana is an open-source solution for data analytics by pulling up metrics from massive amounts of data. In the VBITMS system, the data are stored in Influxdb and analysed information can be viewed with customisable dashboards.

5.6 Performance measurement

Confusion matrix is used to measure the performance of classification models. It is a technique that shows the number of correctly and incorrectly classified examples compared to the actual outcomes (target value) in the test data. A confusion matrix is advantageous for detailed analysis. It helps identify when a model struggles with distinguishing between two classes, unlike accuracy, which can mislead when dealing with imbalanced datasets.

The confusion matrix is n by n, where n is the number of classes. The simplest, binary classifier has only 2 classes: positive/negative or yes/no. The performance of a binary classifier is summarised in a confusion matrix that cross-tabulates predicted and observed examples into 4 options:

a) True Positive (TP): Correctly predicting a label (predicted “yes”, and it’s “yes”).

b) True Negative (TN): Correctly predicting the other label (predicted “no”, and it’s “no”).

c) False Positive (FP): Falsely predicting a label (predicted “yes”, but it’s “no”).

d) False Negative (FN): Missing and incoming label (predicted “no”, but it’s “yes”).

This is a list of rates that are often computed from a confusion matrix for a binary classifier:

a) Accuracy: Overall, how often is the classifier correct?

$$(TP + TN) / (TP + TN + FP + FN)$$

b) Recall: When it’s actually yes, how often does it predict yes?

$$TP / (TP + FN)$$

c) Precision: When it predicts yes, how often is it correct?

$$TP / (TP + FP)$$

d) F1-Score: This is a weighted average of the true positive rate (recall) and precision.

$$2 \times recall \times precision / (recall + precision)$$

6. Findings

6.1 Vehicle detection, classification, tracking and counting

Figures 15 to 17 show some examples of vehicle detection and how it can assign vehicle ID to different vehicles using tracking algorithm in real-time. The ID of the vehicle is unique and always follows the same vehicle. In addition, the region filter is applied to the system so traffic measurement can be focused on specific areas.

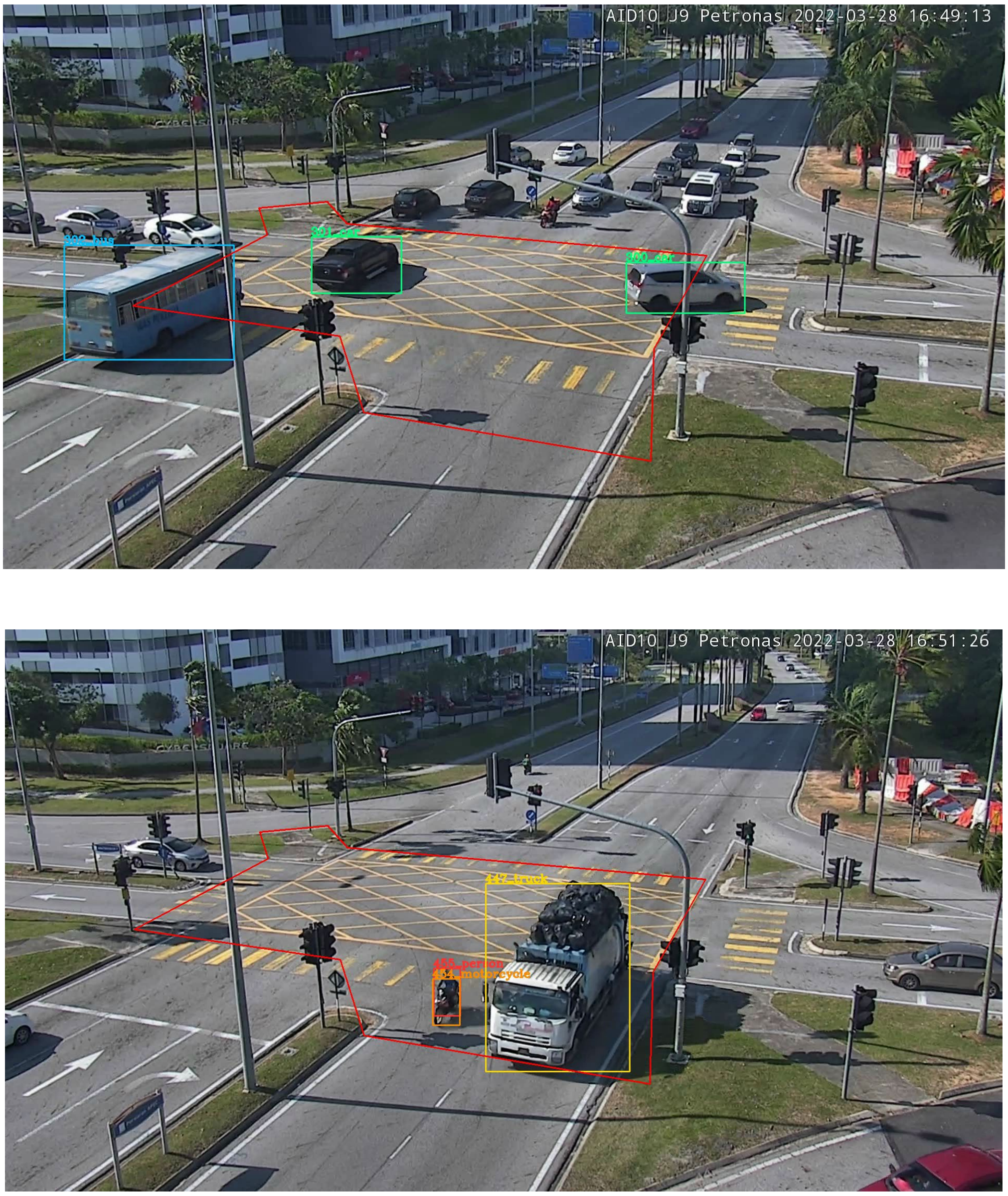


Figure 15. Junction 9 (Jalan Impact)

Figure 16. Junction 10 (Persiaran APEC)

It can be seen in Figures 15 and 16, some vehicle detection examples that include objects other than a car like bus, truck, and motorcycle. It showed that AI algorithm-based detection works well with these vehicle type classifications.

Figure 17 shows 2 region detection systems. The red region is for vehicle detection, tracking, and counting, and the green region is just for illegal parking detection that applies vehicle detection and counting algorithm only. Both works well during the day and night.

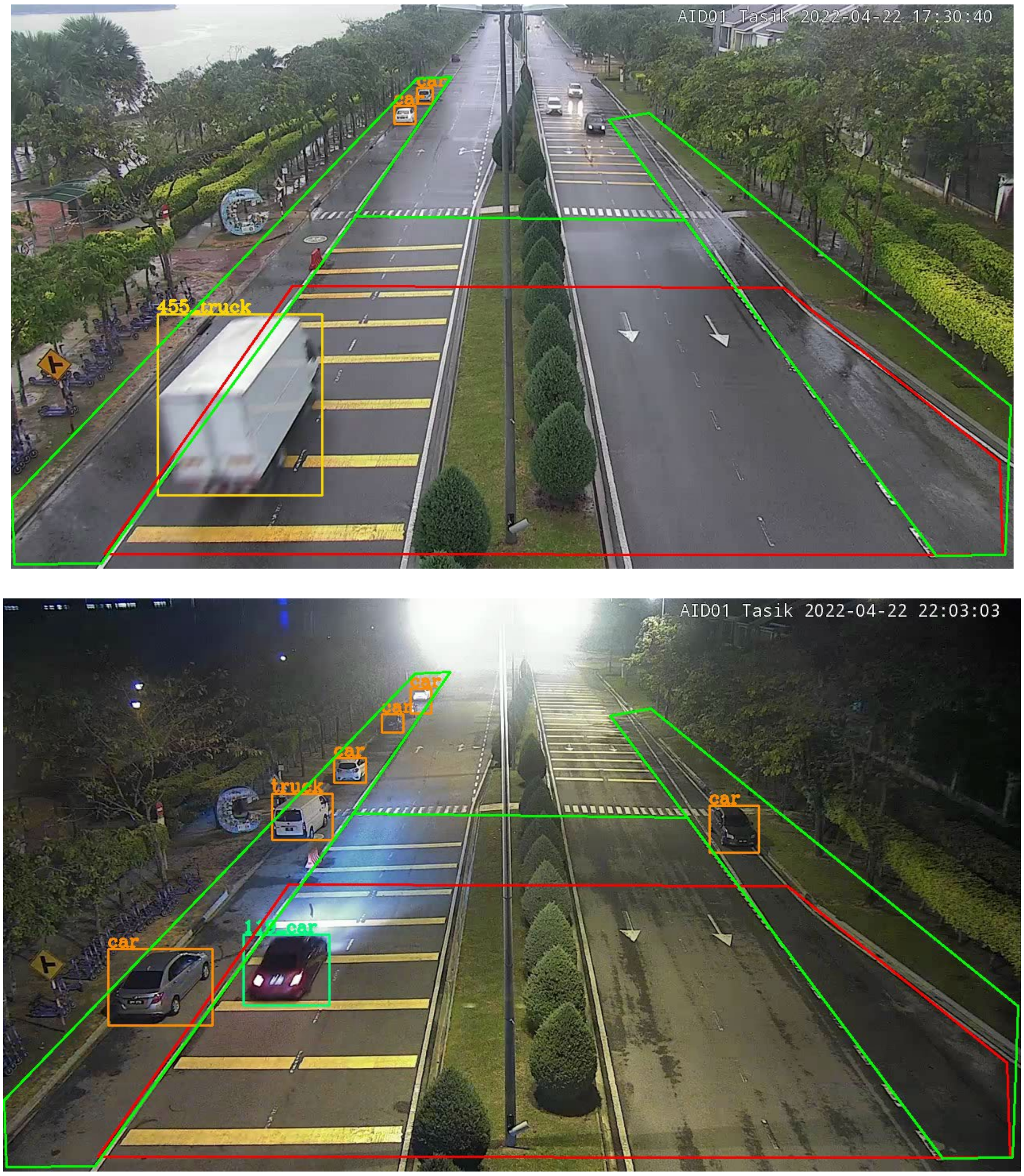


Figure 17. Persiaran Tasik crossroad with illegal parking detection

6.2 Dashboard and data analytics

Below is the list of information displayed on the dashboard:

a) Total vehicle per day.

b) Vehicle count profile.

c) Time-varying congestion status.

d) Map with indicator score and cluster.

e) Congestion predictor.

f) CO_2 emission profile (average daily/monthly).

g) Illegal parking profile.

h) Average daily traffic.

i) Weekly and monthly traffic summary.

Figure 18 shows the snapshot of the dashboard.

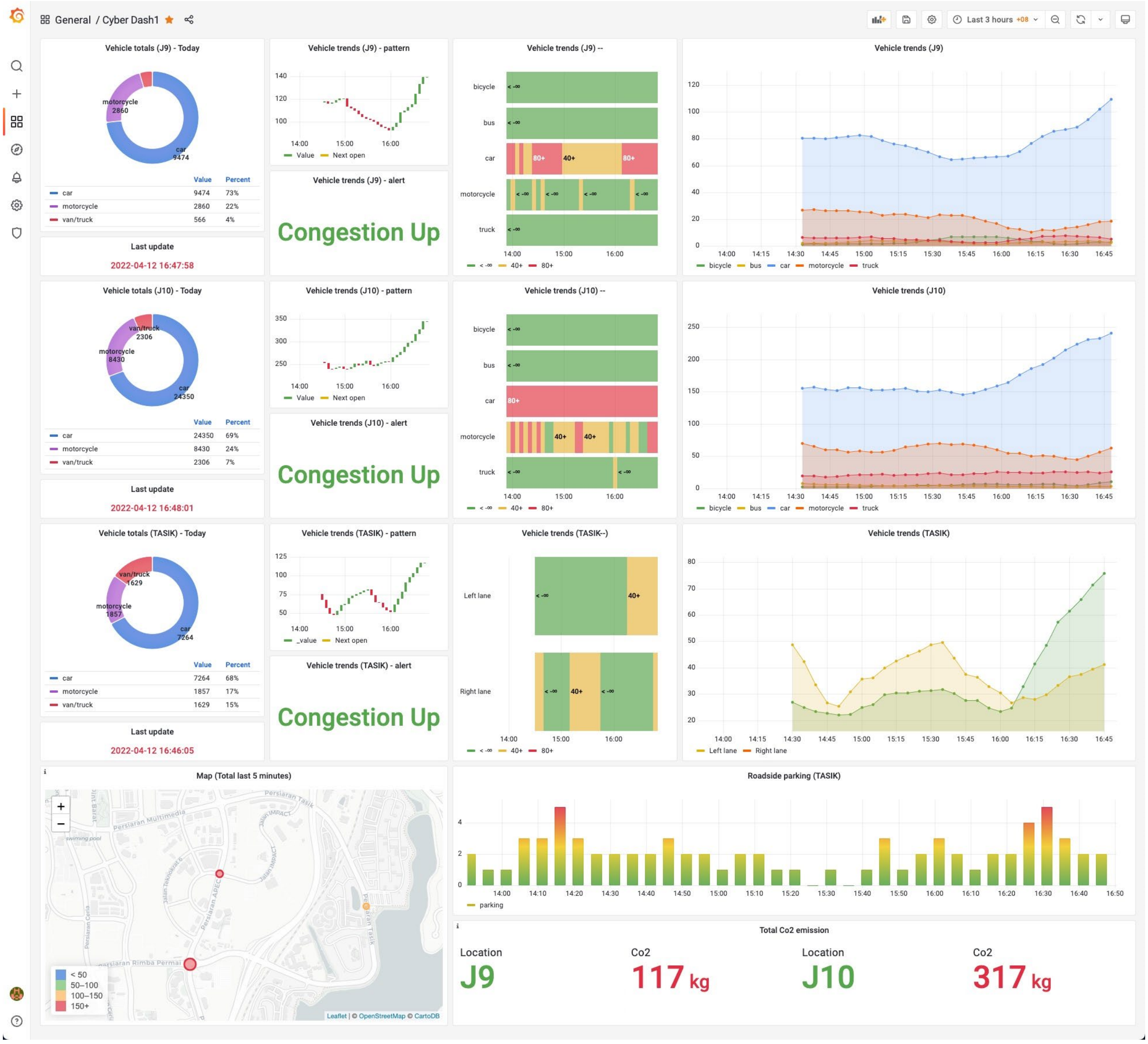
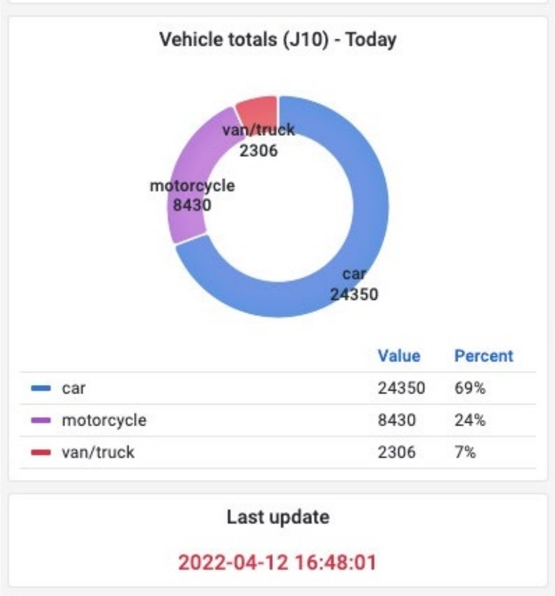


Figure 18. Snapshot of the VBITMS dashboard

Figure 19 shows the total number of vehicles in the current day using a pie chart and table format. Data has been divided into 3 vehicle categories car, motorcycle, and heavy vehicle (van, truck, bus).



	Value	Percent
car	24350	69%
motorcycle	8430	24%
van/truck	2306	7%

Figure 19. Total vehicle per day with last update information

Figure 20 shows the vehicle count profile over a selected time (Monday to Sunday). Each point is plotted with a 5-minute duration. The trend for weekdays (working days) are consistent with each other while trends for weekends (non-working days) are different. The trends also show the traffic reduces during Friday prayer time between 1:00 pm to 2:30 pm.

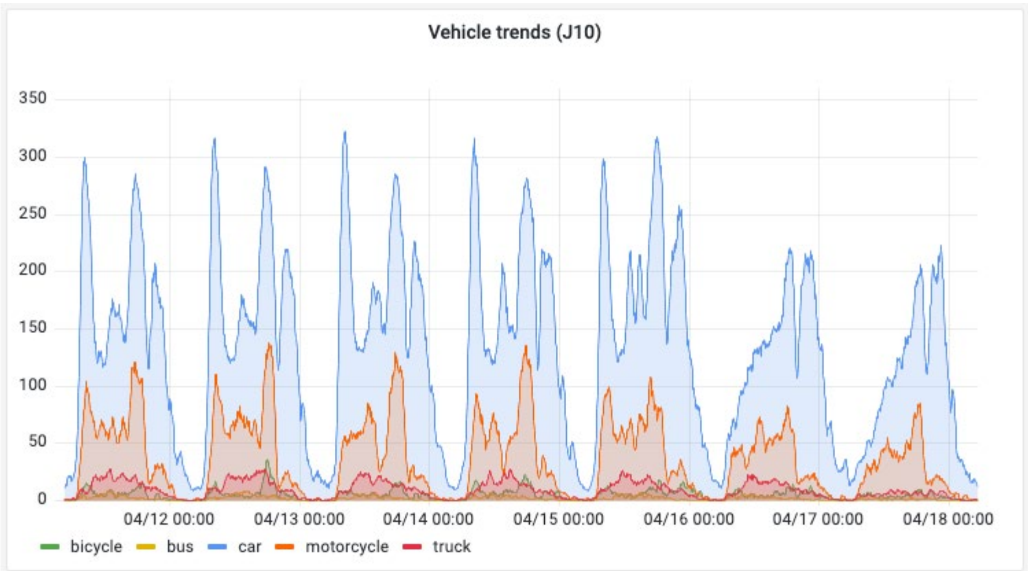


Figure 20. Vehicle count profile over a selected time

Figure 21 shows the time-varying congestion status. Duration of the traffic congestion is based on the threshold criteria (50, 100, and 150) and the example shows a total vehicle higher than 150 counts for 3 hours long from 4:00 pm to 7:00 pm.

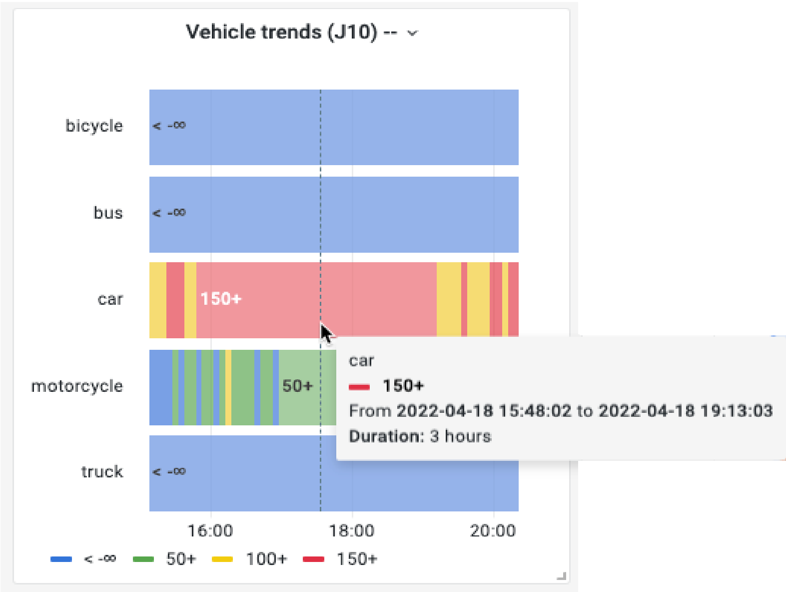


Figure 21. Time-varying congestion status

Figure 22 shows the map indicator with the latest congestion status and cluster size.

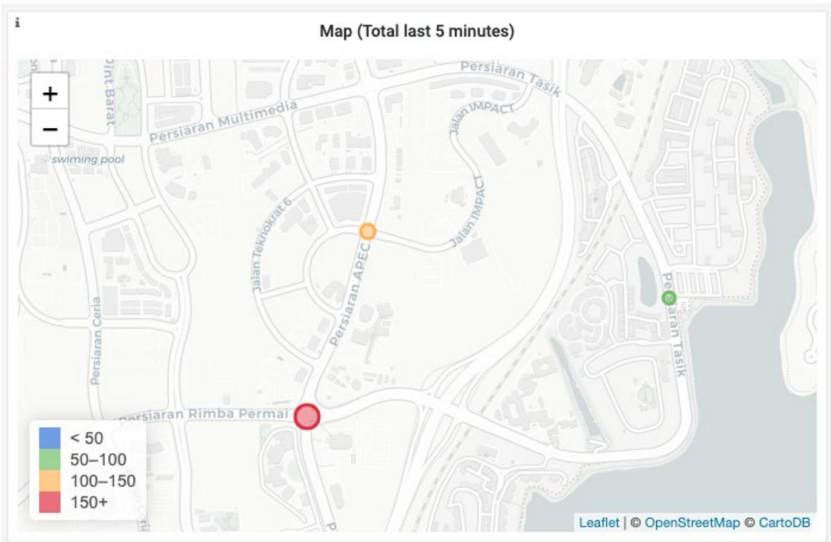


Figure 22. Map with indicator score and cluster

In the VBITMS dashboard, a candlestick chart is used to represent the congestion trend, either up or down. Figure 23 shows the congestion trend with the number of vehicles every 5 minutes (vertical axis) and the congestion trend (horizontal axis). The chart shows that congestion goes up from 12:30 pm to 1:00 pm and goes down from 1:00 pm to 2:00 pm and up again after 2:00 pm. This pattern explains how people use transportation to go out for their lunch break and return to the office later.

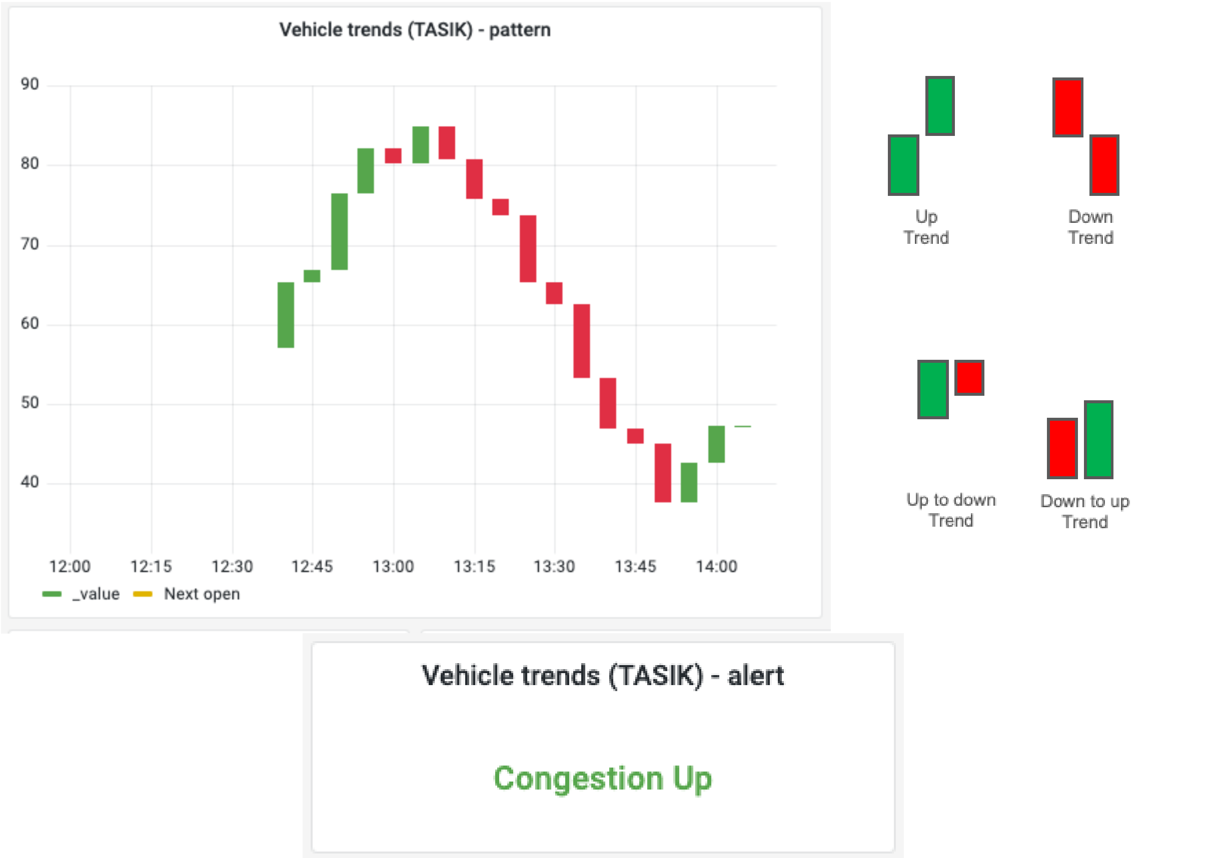


Figure 23. Congestion predictor using Candlestick diagram

Daily activities using vehicles for commuting cause Carbon Dioxide (CO_2) gas emissions. The emission of CO_2 contributes to pollution and thus, global warming. United States Environmental Protection Agency (USEPA) stated that a typical passenger vehicle emits about 4.6 metric tons of carbon dioxide per year. This assumes the average gasoline vehicle on the road today has a fuel economy of approximately 22.0 miles per gallon and drives around 11,500 miles per year. Every gallon of gasoline burned creates about 8,887 grams of CO_2.

This PoC used the standard values recommended by USEPA for CO_2 emission estimation with the assumption one vehicle takes about 60 seconds to cross each intersection including waiting time. CO_2 emission is calculated using the following equation:

$$
\begin{aligned}
CO_2 \text{ (kg) per vehicle} &= 4.6 \times 1000 \times (1/TD) \times (1/TH) \times (1/TM) \\
&= 4.6 \times 1000 \times (1/365) \times (1/24) \times (1/60) \\
&= 0.0087519
\end{aligned}
$$

where

TD = total day per year, 365 days
TH = total hour per day, 24 hours
TM = total minute per hour, 60 minutes

Figure 24 shows the total CO_2 released at each location based on the total number of vehicles per day.

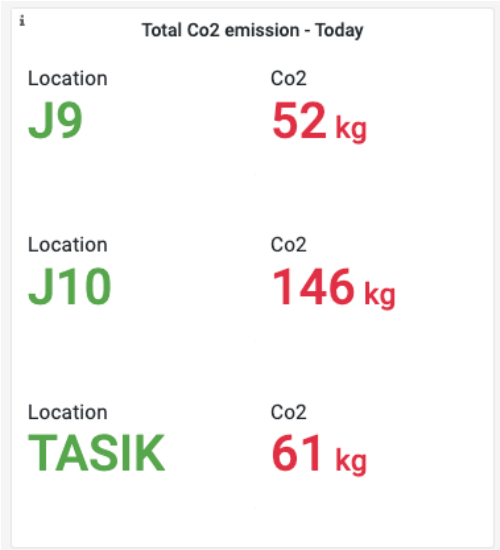


Figure 24. Carbon dioxide (CO_2) gas emissions estimation

In Cyberjaya, the Tasik area is one of the most visited places for sightseeing and exercise. Most car owners park at the roadside and these parking spots are marked illegal by the Cyberjaya authorities.

A parking sensor is one of the solutions to monitor illegal parking but the system suffers from localised wireless area networks, low battery life, and high maintenance costs. Instead of collecting and storing the occupancy and traffic data from this type of sensor, VBITMS uses AI-based image processing technology that utilises existing CCTV infrastructure to detect any vehicles parked in the illegal area. Figure 25 shows how detection has been done at the illegal parking area near Tasik Cyberjaya. Although the image quality is a bit low due to low light sensitivity, vehicle detection algorithm can work well in this situation.

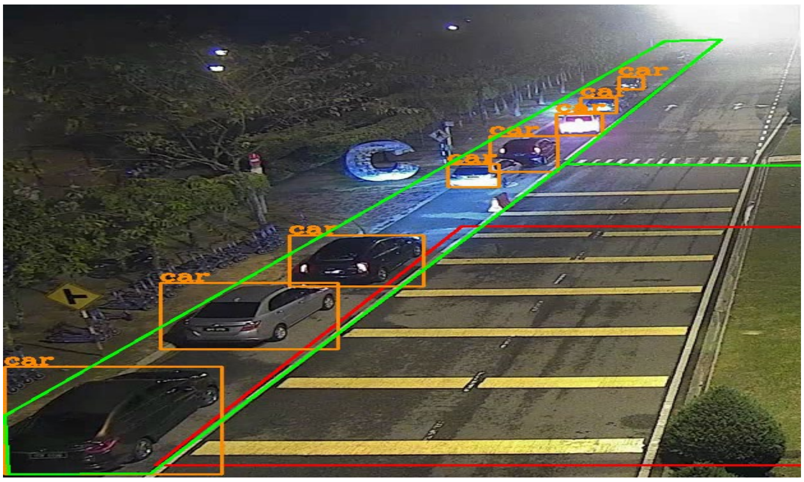


Figure 25. Illegal parking detection at night.

It can be seen the VBITMS system can detect the vehicle and the total number of vehicles parked is plotted over time as in Figure 26.

Figure 26. Illegal parking profile

A threshold is set for 15 vehicles for alert notification. A real-time notification will be sent out to authorities using Telegram if the total counted exceed the threshold set. Figure 27 shows some examples of the message sent.

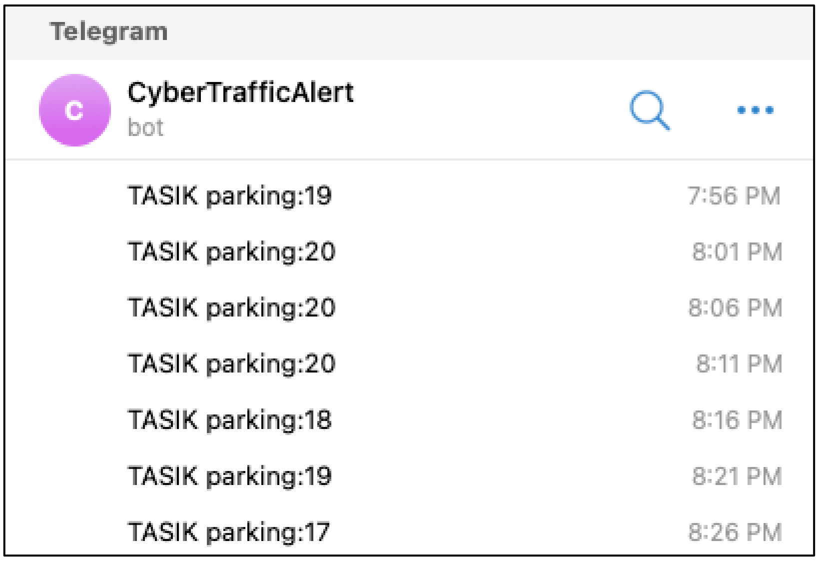


Figure 27. Telegram notification

Average Daily Traffic (ADT) is a key parameter commonly required by traffic engineers and road designers to design and analyse the traffic operational performance of a road segment. In Malaysia, ADT is typically used to forecast traffic volume and design the pavement thickness.

Generally, ADT is obtained from manual classified traffic count (MCC) which is usually carried out twice a year. For each exercise, the counting is done for seven consecutive days at the selected road segment. The second data collection exercise is carried out six months after the first exercise. In cases where ADT is unavailable, the factoring approach based on the Peak Hour Volume (PHV) is used to estimate ADT. Instead of using humans to do the MCC, the proposed VBITMS can produce such data based on vehicle counting using AI technology.

Figure 28 shows the ADT for each vehicle classification.

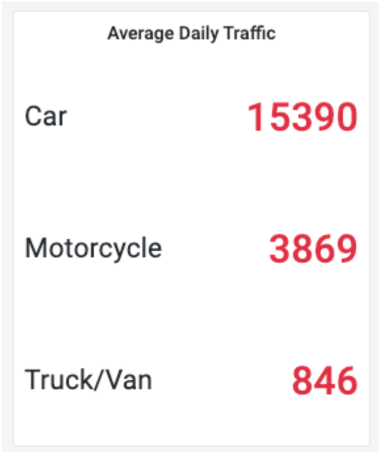


Figure 28. Average Daily Traffic (ADT)

Figures 29 and 30 show the respective weekly and monthly trends. The data shows that the 2 lowest points in weekly traffic data happen in early May and the second week of July due to fewer people traveling in Cyberjaya during the Hari Raya Aidil Fitri and Hari Raya Aidil Adha.

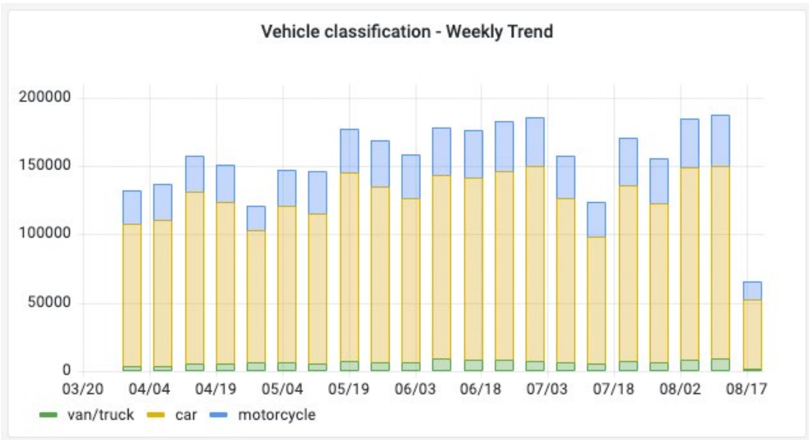


Figure 29. Weekly traffic

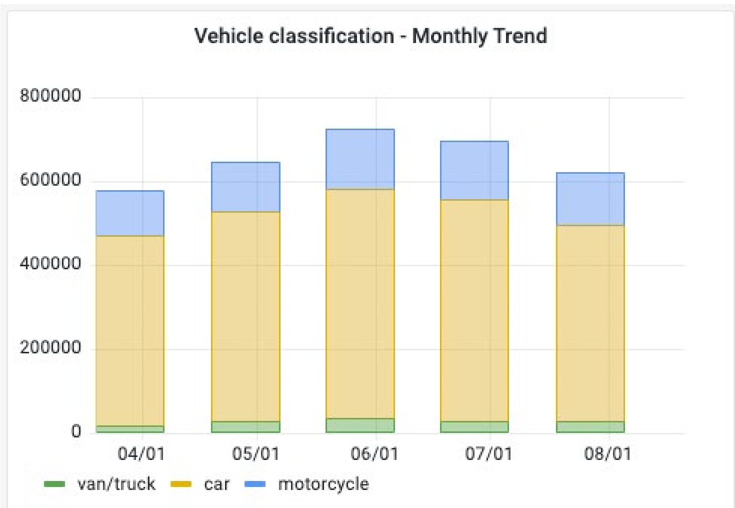


Figure 30. Monthly traffic

7. Results analysis

Tables 1 to 3 show the confusion matrix for vehicle classification at the 3 locations.

Table 1. Confusion matrix for vehicle classification at J9 (Jalan Impact)

		Predicted		
		Car	Motorcycle	Van/Truck
Actual	Car	356	0	5
	Motorcycle	0	63	0
	Van/Truck	3	0	15

Table 2. Confusion matrix for vehicle classification at J10 (Persiaran APEC)

		Predicted		
		Car	Motorcycle	Van/Truck
Actual	Car	184	0	3
	Motorcycle	0	47	0
	Van/Truck	0	0	12

Table 3. Confusion matrix for vehicle classification at Persiaran Tasik

		Predicted		
		Car	Motorcycle	Van/Truck
Actual	Car	192	0	10
	Motorcycle	9	14	0
	Van/Truck	4	0	9

Tables 4 to 6 show its respective classification performance in terms of accuracy, precision, recall and F1-score.

Table 4. Performance on vehicle classification at J9 (Jalan Impact)

Vehicle category	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Car	98.19	99.16	98.61	98.89
Motorcycle	100.00	100.00	100.00	100.00
Van/Truck	98.19	75.00	83.33	78.95

Table 5. Performance on vehicle classification at J10 (Persiaran APEC)

Vehicle category	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Car	98.78	100.00	98.40	99.19
Motorcycle	100.00	100.00	100.00	100.00
Van/Truck	98.78	80.00	100.00	88.89

Table 6. Performance on vehicle classification at Persiaran Tasik

Vehicle category	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Car	90.34	93.66	95.05	94.35
Motorcycle	96.22	100.00	60.87	75.68
Van/Truck	94.12	47.37	69.23	56.25

In general, there are 3 important findings can be concluded from the classification results:

a) The highest classification accuracy is the motorcycle, followed by car and van/truck. The reason is motorcycle has a distinctive shape or features that are unique than a car/truck/van because it has 2 wheels and is small in size.

b) The van/truck tends to be misclassified as a car. The reason is the car and van/truck have similar features like 4 wheels with a box shape.

c) Both J9 and J10 have similar classification performance, while Persiaran Tasik 1 is the lowest among the 3. The reason is the camera position at J9 and J10 have the same view towards the traffic intersections, which have a better view of vehicles (from the side) and vehicles moving at slow speed. In contrast, Persiaran Tasik 1 has a limited view of vehicles (from top) and vehicles moving at high speed.

A common way to measure the performance vehicle counting system is by comparing the results produced by the proposed system with the actual number of vehicles counted manually by humans. A total number of 81,435 frames of images in 3 locations of CCTVs were collected and performed vehicle counting through VBITMS system. Then, the results were compared with manual counting by human eyes. Table 7 shows the comparison between them.

Table 7. Vehicle counting accuracy

<table>
<tr><th>Vehicle category</th><th>Location</th><th>Total number of vehicles in ground-truth (manual counting)</th><th>Total number of vehicles detected using VBITMS</th><th>Counting accuracy (%)</th><th>Average counting accuracy (%)</th></tr>
<tr><td rowspan="3">Car</td><td>J9</td><td>361</td><td>370</td><td>97.51</td><td rowspan="3">96.77</td></tr>
<tr><td>J10</td><td>187</td><td>194</td><td>96.26</td></tr>
<tr><td>Tasik</td><td>202</td><td>209</td><td>96.53</td></tr>
</table>

Table 7. Vehicle counting accuracy *(continued)*

Vehicle category	Location	Total number of vehicles in ground-truth (manual counting)	Total number of vehicles detected using VBITMS	Counting accuracy (%)	Average counting accuracy (%)
Motorcycle	J9	63	68	92.06	91.62
	J10	47	51	91.49	
	Tasik	23	21	91.30	
Van/Truck	J9	18	21	83.33	81.20
	J10	12	14	83.33	
	Tasik	13	16	76.92	
Note: J9 = 32,140 video frames, J10 = 10,008 video frames, Tasik = video 39,287 frames					

The accuracy of the proposed VBITMS system comes close to the actual number of cars with a margin error below 5 %, while motorcycles with a margin error less than 10 %. The accuracy for van/truck is the lowest among the 3 due to misclassification as discussed in Tables 1 to 3.

Another observation is motorcycle has lower counting accuracy compared to the car, while the earlier discussion shows that the motorcycle has a better classification rate than a car as depicted in Tables 4 to 6. The reason is that motorcycle detection regions easily overlap with another motorcycle, thus it tends to disappear and appear again in the video frame with the new tracker counter.

8. Conclusion

The VBITMS has been successfully deployed to monitor traffic conditions in 3 road areas in Cyberjaya located at Jalan Impact, Persiaran APEC and Persiaran Tasik using roadside CCTV. The system used state-of-the-art AI vision technology to detect and classify vehicles in real-time. Vehicle tracking and counting were performed using the state estimation technique and rudimentary data from each image captured in the detection region. Traffic flow studies were conducted based on vehicle counting to understand the road usage pattern by the time of day, weekly, holidays and months.

The principal advantage of using VBITMS is the richness in classifications possible to obtain where vehicle types such as cars, motorcycles, vans and trucks can be easily distinguished and analysed. A second key advantage is that data can be gathered across a wider area of road, typically 30 m square route and behaviour of vehicles can be determined, as well as enabling multiple flow count lines to be placed in the field of view of a single camera. A third key advantage is the traffic information dashboard that visually tracks, analyses, and displays metrics and key data to monitor the traffic in the city. The dashboard allows users to understand the analytics that matter to their needs while authorities can take full advantage to improve traffic conditions. In addition, historical traffic data such as ADT dan CO_2 emission provides crucial input to the city development plan for better road infrastructure, facilities, property, and business development.

Based on this project, there are a few inputs that can contribute toward standardisations:

a) Guidelines to deploy vision-based sensors in IoT fields including data analytics, dashboard and alerts.

b) Terms, definitions and classification of traffic data in Malaysia.

c) Calculation of CO_2 emission based on vehicle counting.

d) Guideline of open data system related to traffic information.

Annex A
(Normative)

The specification of the AI interference machine

A1. Main unit

a) CPU: AMD Ryzen Threadripper 3970X (32 Core/64 Threads/4.5GHz)

b) GPU: 2 x Galax RTX3090 SG 1-CLICK OC 24GB DDR6X

c) RAM: Corsair Vengeance RGB PRO 32GB

d) Motherboard: Asus Prime TRX40-PRO S

e) Power supply: Corsair AX1600i 1600W 80+ Titanium

f) OS: Ubuntu 20.04.4 LTS (Focal Fossa)

A2. Backup unit

a) CPU: AMD Ryzen 7 5800X (8 Core/16 Threads/3.8GHz)

b) GPU: 1 x EVGA RTX3090 FTW3 ULTRA

c) RAM: Corsair Vengeance RGB PRO 32GB

d) Motherboard: Gigabyte X570 AORUS PRO WIFI

e) Power supply: Corsair RM850X 80+ Gold

f) OS: Ubuntu 20.04.4 LTS (Focal Fossa)

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