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Enhancing Driving Assistance System with YOLO V8-Based Normal Visual Camera Sensor

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ABSTRACT

One of the safety features that can alert drivers to the presence of other vehicles and reduce the risk of collisions is vehicle detection. In this study, the objective is to setup a driving support system for detecting vehicles, motorcycles, and traffic signals on the roads near to Universiti Malaysia Pahang using object detection techniques. The video was taken through a direct camera to capture video footage of traffic objects on the roads in the district, which was then analysed using the YOLO-V8 deep learning algorithm. The system was trained on a primary dataset of 1,068 images, with 70% of the dataset used for training, 20% for testing and 10% for validation. After conducting a performance validation, the system achieved a mean average precision (mAP) of 88.2% on train dataset and was able to detect different types of vehicles such as cars, motorcycles, and traffic lights. The results of this study could be beneficial for road safety authorities and researchers interested in developing intelligent transportation systems.

1. Introduction

Malaysia is a Southeast Asian country that has experienced significant growth and development in recent decades. A well-functioning transportation system is crucial for maintaining and improving this growth, and the country has made significant investments in its transportation infrastructure [1]. Transportation is also a key driver of economic growth in Malaysia. By facilitating trade and commerce, transportation helps to support the growth of businesses and industries, boosting the country's overall economy [2].

Figure 1 shows the road fatalities that involve in Malaysia since 2010 to 2019 based on the different types of vehicles used for this transportation. Heavy-duty, medium-duty, and light-duty vehicles play essential roles in various industries and sectors, including transportation, construction, agriculture, and more [3]. Heavy-duty vehicles, such as Class 8 trucks, tractor-trailers, and concrete

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mixers, are used to transport large loads and heavy cargo over long distances, while medium-duty vehicles, such as box trucks and delivery vans, are used for local and regional transportation of goods and equipment [4]. Light-duty vehicles, such as passenger cars and pick-up trucks, are used for personal transportation and light-duty work and deliveries. Each type of vehicle is designed to meet the specific needs and requirements of its intended use, and all are critical components of the transportation and logistics system [5].

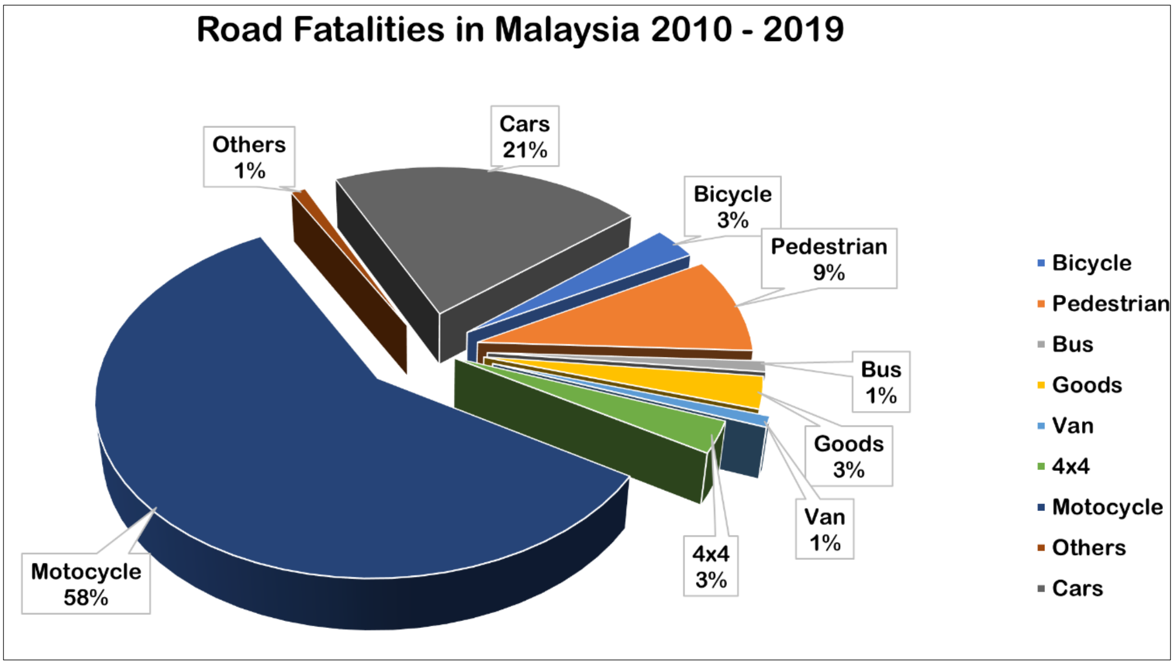

Fig. 1. Road fatalities in Malaysia 2010 – 2019 (source: ministry of transport Malaysia)

As the number of vehicles engaged in traffic accidents increases, the danger of injury and death continues to rise. According to the Road Transport Department of Malaysia, the country has a high rate of road accidents, with an average of over 20,000 accidents per year [6]. The leading causes of accidents in Malaysia are reckless driving, speeding, and failure to obey traffic laws [7]. The government has implemented various measures to reduce the number of road accidents, including increasing the enforcement of traffic laws, improving the road infrastructure, and promoting road safety education to reduce road accident deaths [8-9].

Apart from the government implementation, the need to look at the car crash safety features is also required. This is to assist the driver and alert them of the danger surrounding the car, especially in the junction, roundabout and straight lane [10-11]. These three types of driving scenarios commonly involve multiple vehicle car crashes, head-on collisions, and side impacts. The factors that lead up to automobile collisions have been the subject of a significant amount of written work [12]. Gu *et al.,* investigated geographical random forest analysis to predict the intersection crash frequency using the extracted data that focused on speed, acceleration, and yaw rate in Ann Arbor, Michigan. The model acquired approximately 2800 connected cars on the road over 70 miles of streets between October 2012 and April 2013. Based on their findings, compared to large roads, the probability of a rear-end collision occurring at a junction linking two smaller roads is much higher [13].

To further examine the role of machine learning analysis, Kong *et al.,* carried out modelling in predicting the severity of car crashes in Korea. The collected data focused on 1417 patients enrolled in the Korean motor vehicle crashes study database from 2011 to 2021. A confusion matrix and F-measures were used to analyse the likelihood of the predictive performance of a few different models namely, XGBoost, multilayer perceptron, and logistic regression. The findings revealed that the data-balanced XGBoost model successfully achieved a dependable performance on the injury severity categorization of patients presenting to the emergency department [14].

The process of recognising the sort of target objects and locating them on a video frame is referred to as vehicle detection [11]. Generally speaking, object identification algorithms may be broken down into two categories: traditional machine learning and deep learning [15]. On highways, the Kalman and Particle Filter tracking algorithms have problems tracking items that move extremely quickly and when there are over 30 objects in a single frame [16]. In addition, recognising and tracking cars have been difficult problems for conventional computer vision and image processing research because to obstacles such as partial or complete occlusion of objects, camera shake, variable image quality, and weather conditions such as rain, snow, and wind [17]. These obstacles make it difficult to reliably identify and track cars, and in certain circumstances such systems may not function at all [18].

Jahongir Azimjonov developed a method for the extraction of real-time traffic flow data that employs vehicle recognition and tracking algorithms to interpret conventional camera photos. Using two vehicle counting technologies, the category and total number of vehicles in four highway movies were estimated [19]. Using vehicle detection 1 and 2, the vehicle counting 1 and 2 were constructed. Vehicle detection 1 relied on Yolo's general-purpose weight model, while vehicle detection 2 integrated Yolo with a CNN-based classifier. Due to misclassification and detection issues, Vehicle Counting 1 failed for trucks and buses. Overall, vehicle counting 2 (Yolo + the CNN-based classifier + the bounding-box-based tracker) estimated the classified and total number of cars across all four highway films with the greatest degree of precision [20].

Chen has suggested YOLO v3-live, an enhancement to the YOLO v3-tiny network structure that allows real-time vehicle detection on embedded devices. YOLO v3-live employs multi-scale receptive fields to extract more exhaustive and detailed data [21]. In addition, the original network structure's down sampling process is changed by delaying the down sampling of feature maps and by replacing certain pooling layers with convolutional layers with a step size of 2. This reduces the loss of features during down sampling. Despite a decrease in mAP upon quantification, the detection accuracy remains at 69.79% [22]. Nonetheless, there is still opportunity for increase in accuracy while retaining detection speed, and this will be the primary challenge of future research. of deep learning algorithms in intelligent transportation systems in Malaysia and other countries with similar road conditions [23].

On the research gap related to the impact of local road infrastructure and signage on algorithm performance, it is important to consider how these factors can affect the accuracy of object detection algorithms like YOLO V8 when deployed in diverse road environments such as those in Malaysia. The differences in traffic rules, signage, and infrastructure between Malaysia and the regions where YOLO V8 was trained can present a significant challenge in accurately detecting and tracking objects on Malaysian roads.

For example, road markings and signage may be unique or different in Malaysia, and the algorithm may not recognize them. This could lead to object detection and tracking errors, resulting in lower accuracy and potentially unsafe driving conditions for autonomous vehicles. Additionally, the road surfaces in Malaysia may differ from those in the regions where YOLO V8 was trained, which can affect the algorithm's performance in accurately detecting objects.

Therefore, further research is needed to explore the impact of local road infrastructure and signage on the accuracy of object detection algorithms like YOLO V8 when deployed in diverse road environments like Malaysia. This research could include fine-tuning the algorithm to incorporate local knowledge, evaluating its performance in various scenarios, and identifying any areas for improvement. Ultimately, addressing this research gap is critical for optimizing the performance of object detection algorithms in autonomous vehicles and ensuring safe and reliable driving in diverse road environments.

2. Methodology

This experiment setup involved using a camera sensor in a car dash-cam position to investigate the accuracy of the algorithm to detect the motorcycles, traffic lamp and vehicles. The map that the tested roadside object detection was as shown as in Figure 2. A single driver operated the car with (60 to 80 km/h speed) and the camera, adhering to all traffic and objects throughout the experiment. The camera captured video footage of the road ahead and recorded the duration of the journey.

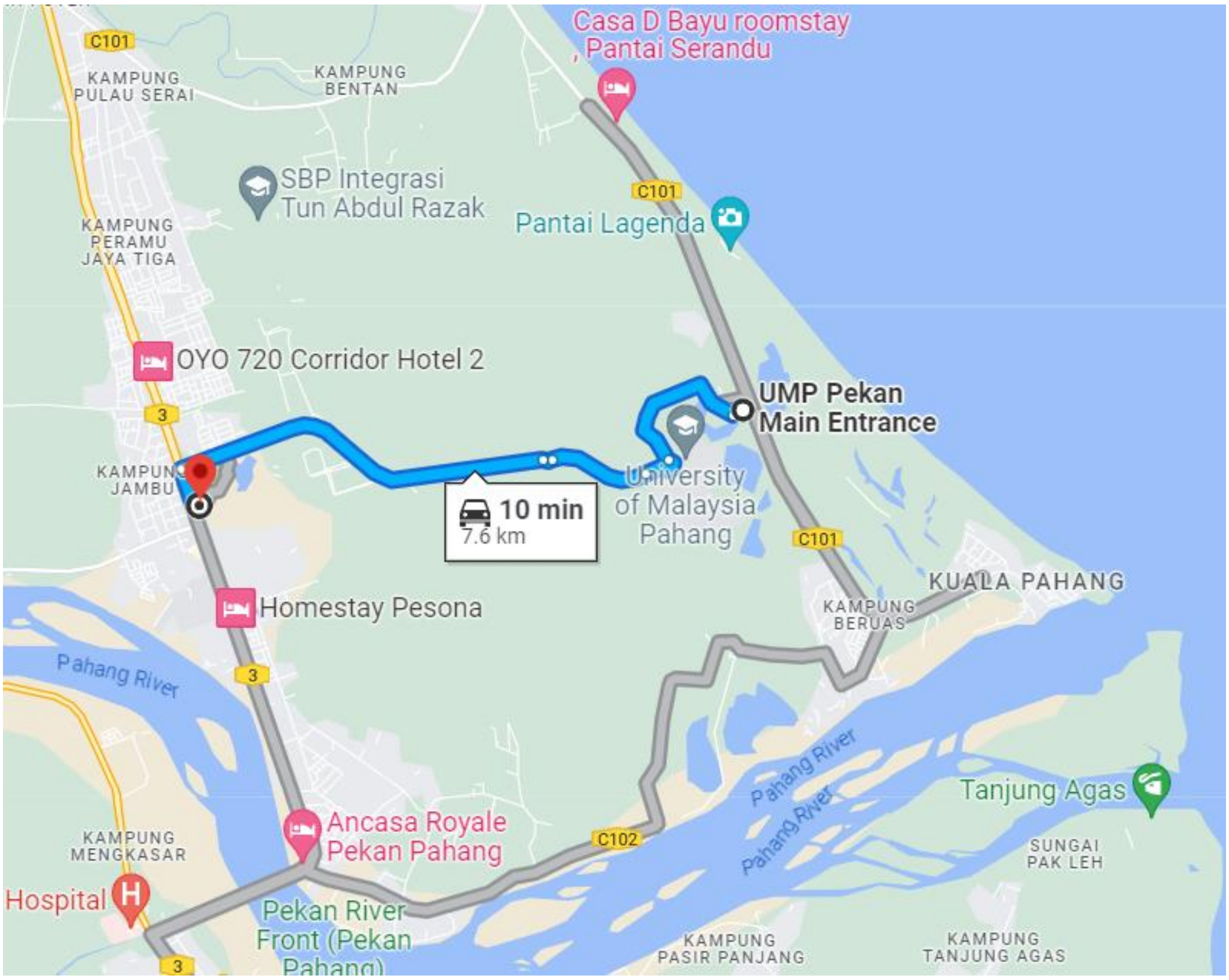

Fig. 2. The experimental road planning from UMP Pekan campus to Pekan- Kuantan main road junction

The research experiment employed the YOLO- V8 deep learning algorithm for object and vehicle detection in Malaysian road conditions. The study focused on identifying three objects: vehicles, traffic lamps, and motorcycles. The pre-train dataset consisted of 1,068 images labelled using the Roboflow dataset manager. The dataset was split into training (70%), testing (20%) and validation (10%) images. Figure 3, the flowchart of the system models is listed in several key stages. The first stage is image pre-processing, then passed through a convolutional neural network (CNN) is trained to recognize the features of different objects. YOLO v8 uses anchor boxes to predict the bounding boxes of objects in an image.

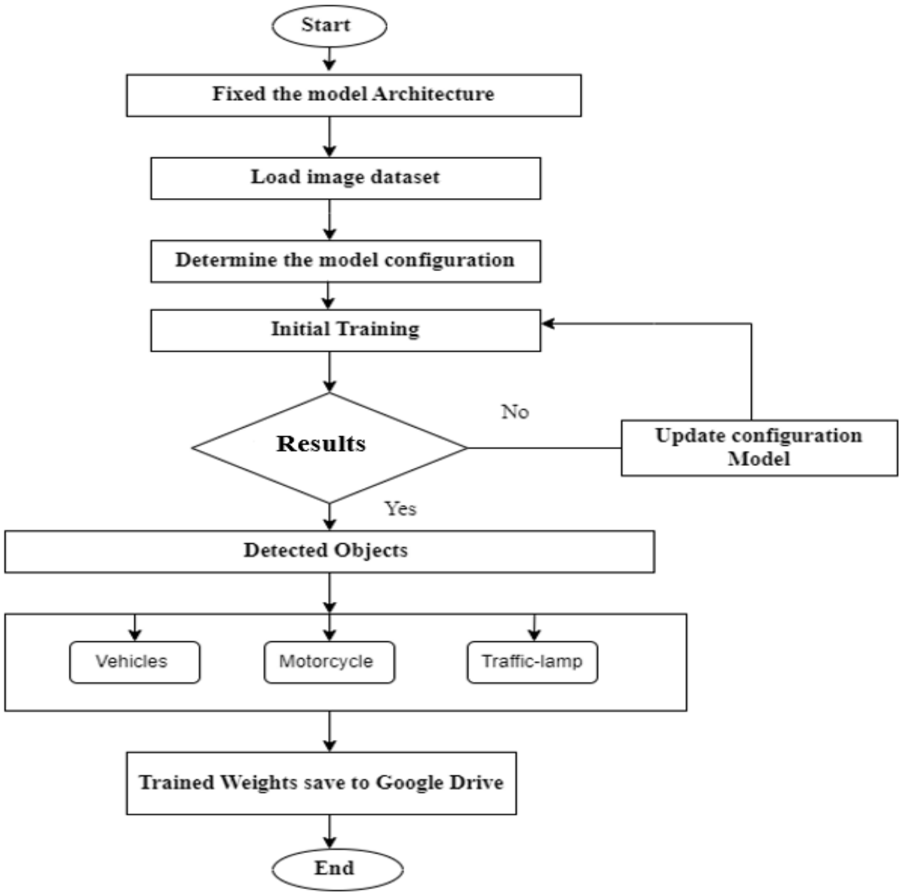

Fig. 3. Flow-chart of the model

A large dataset of annotated images with bounding boxes and class labels for the objects and vehicles that must be detected. The next step is to train a deep neural network-based object detector. The model is trained to predict objects and vehicles' bounding boxes and class labels in an image Figure 4, illustrates the process flow. Then move to set up Google colab environment for the YOLO V8 object-detecting algorithm. In Google colab tested the performance of the primary dataset, then imported some custom images to compare the performance.

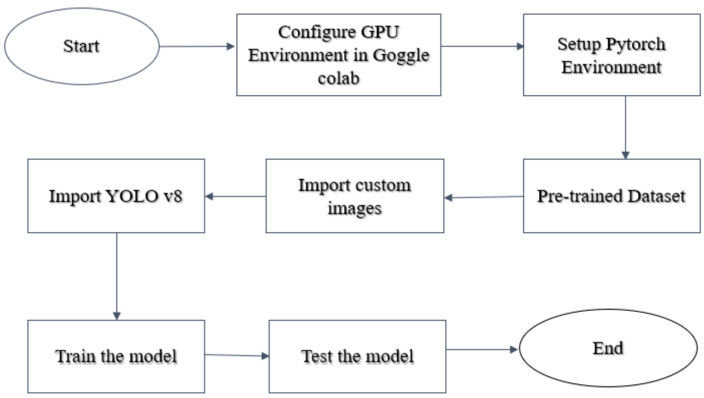

Fig. 4. Works flow diagram of the system

The model's performance was evaluated by calculating the mean average precision and recall for the train and validation results. These metrics were analysed using specific parameters, and the overall performance score was calculated based on this analysis in Figure 5.

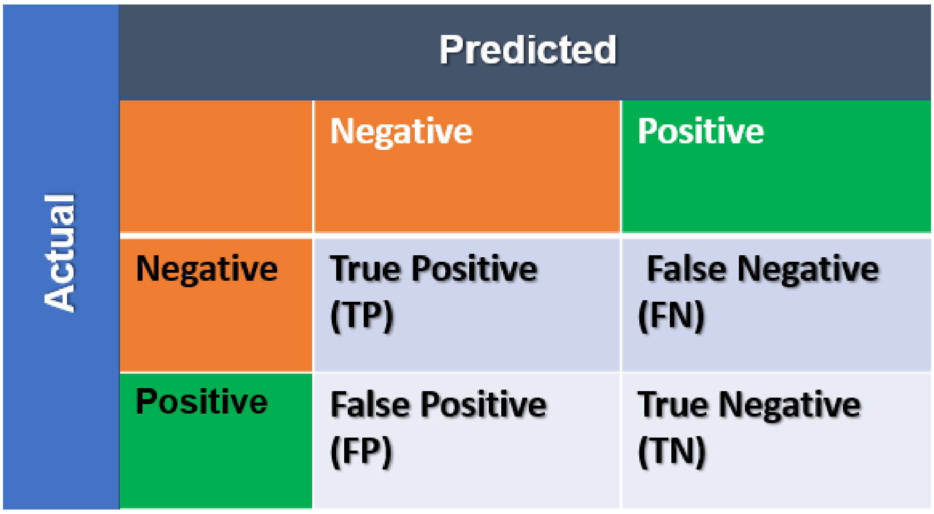

Fig. 5. Performance measurement parameters for object detection result analysis

The terms True Positive (TP), False Positive (FP), and False Negative (FN) describe the number of correct and incorrect predictions made by a model. TP refers to the number of correct positive predictions, FP represents the number of incorrect positive predictions, and FN refers to incorrect negative predictions. Precision is a metric that assesses the accuracy of positive predictions, while recall gauges the completeness of positive predictions.

3. Result and Discussion

Evaluating the performance of YOLO v8 involves measuring several key metrics, including box loss, classification loss, objectness (differentiable focal) loss, precision, and recall. These metrics are typically measured on both the training and validation data to assess the model's performance in both scenarios. Comparing the performance provided insights into the model's generalization ability. The model is not overfitting as it performs similarly on training and validation data. Low box loss on both sets indicates accurate bounding box predictions.

The classification loss indicates accurate class predictions by the model. Validation classification loss should be comparable or slightly higher than training classification loss. Figure 6, shows that training class loss is close to zero, while validation class loss is slightly higher. Low objectness (dfl_ loss) on both training and validation data indicates accurate object presence predictions by the model. Validation dfl_ loss should be comparable and slightly higher than training loss. As for precision and recall, a higher value on both the training and validation data demonstrates that the model makes fewer false positive predictions and detects a higher proportion of positive instances.

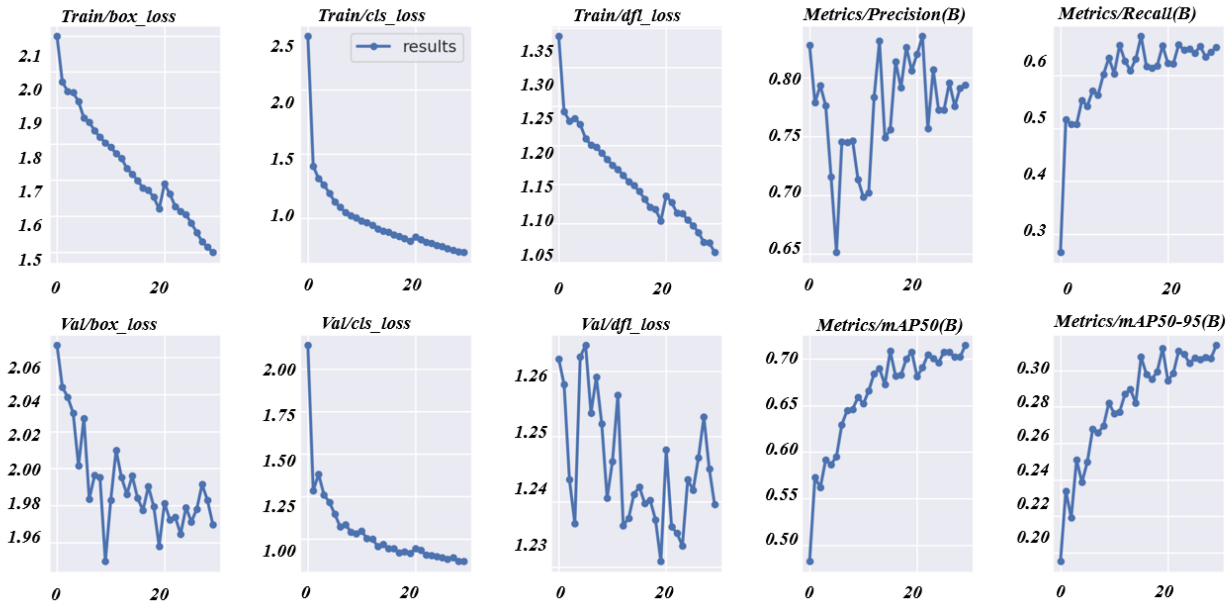

Fig. 6. Result of the experiment test

In this work, the performance of the YOLO v8 object detection algorithm was evaluated and compared with the results of previous research in the field. The evaluation showed that YOLO v8 achieved a mean average precision (mAP) of 88.2% and 71 % recall for tarin result. In a recent experiment conducted by Ji *et al.,* various versions of the YOLO object detection algorithm were tested for their mean average precision (mAP) scores. The results showed that YOLO v4 achieved 81.33% mAP, YOLO v3 achieved 72.1% mAP, YOLO-X achieved 82.25% mAP, and YOLO v5 achieved 82.18% mAP.

For validation result analysis, the mAP50 is a specific type of mAP calculated using an NMS (non-maximum suppression) overlap threshold of 50%. It is commonly used as a benchmark for object detection algorithms, and a higher mAP50 score indicates better algorithm performance. mAP50-95 is a comprehensive metric range from 50% to 95%. A higher mAP value indicates a better performance of the algorithm in detecting objects and accurately placing bounding boxes around them. The Figure 6 clearly illustrates that 70.1% and 30.5% are the values for mAP50 and mAP50-95.

In order to gain a comprehensive understanding of the model's performance, raw images were obtained prior to running them through the system. These images were then compared with the results obtained after object detection. As depicted in Figure 7, images were taken from various road conditions, including junctions and straight roads to evaluate the model's capability. The comparison of the raw and processed images was performed to assess the performance of the system.

(a) (b)

(c)

Fig. 7. Images before testing

The implementation of a deep learning approach in the model resulted in effective detection of various types of vehicles, motorcycles, and traffic lamps in both the training and validation sets. The experiment was successful in achieving its objectives. Figure 8, depicts the results of the object detection scenario, with the number of specific objects displayed in the images.

(a) (b)

(c)

Fig. 8. After the experiment test the detected objects and vehicles

Successfully detecting these objects in the training and validation sets can improve and optimize the model's performance. Fine-tuning the model and incorporating additional data can lead to more accurate detections in future experiments.

The results of the object detection experiment are presented in the table above. The model performed well in detecting various objects, including motorcycles, traffic lamps, and vehicles. The number of images and instances for each class is also provided.

The present study examined the performance of an object detection model by analysing confusion matrix results. Specifically, the model's ability to accurately classify motorcycles, traffic lamps, and vehicles were assessed based on actual prediction rates and false prediction rates at Figure 9.

The analysis revealed that the object detection model performed exceptionally well in classifying motorcycles, with an actual prediction rate of 0.50 and a low false prediction rate of 0.05. For the class Traffic-lamp, the model demonstrated a high actual prediction rate of 0.85, albeit with a relatively higher false prediction rate of 0.17. Additionally, the model's performance in classifying vehicles was notable, with an actual prediction rate of 0.75 and a false prediction rate of 0.06.

the confusion matrices of the train and validation datasets showed similar trends in terms of true positives, false positives, false negatives, and true negatives for all object classes except the background class. The background class values differed due to the relative proportion of images assigned to the train and validation datasets.

Fig. 9. Confusion matrices result for train and validation

4. Conclusion

The present study aimed to propose a deep learning-based object detection model for road conditions in Malaysia with the objective of driving supporting system. The proposed model was designed to detect vehicles, motorcycles, and traffic lamps. A primary dataset was created using over 1000 images processed through Roboflow workflows. The images were collected from Pekan City and represented a variety of road conditions including junctions and straight roads. The YOLO v8 deep learning algorithm was integrated with the Roboflow dataset and the experiments were conducted in a Google Colab environment.

The YOLO-v8 object and vehicle detection model successfully detected vehicles, motorcycles, and traffic lamps from those videos. The model achieved results with an 88.2% mAP for train and 88.3% for validation, indicating a high level of accuracy in its predictions. Detection speed 2.3ms preprocess, 4.3ms inference, 0.0ms loss, 8.5ms postprocess per image. The system's ability to accurately detect objects and vehicles demonstrates the power of deep learning models in computer vision applications. Overall, the YOLO-v8 object and vehicle detection model shows great promise in improving safety and efficiency in transportation systems.

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