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Evaluating the Performance of a Visual Support System for Driving Assistance using a Deep Learning Algorithm

Mohammad Sojon Beg[1], Muhammad Yusri Ismail[1,*], Md. Saef Ullah Miah[2]

[1] Faculty of Mechanical and Automotive Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA), Pekan, 26600, Malaysia
[2] Department of Computer Science, American International University Bangladesh (AIUB), Dhaka, Bangladesh

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ABSTRACT

The issue of road accidents endangering human life has become a global concern due to the rise in traffic volumes. This article presents the evaluation of an object detection model for University of Malaysia Pahang (UMP) roadside conditions, focusing on the detection of vehicles, motorcycles, and traffic lamps. The dataset consists of the driving distance from Hospital Pekan to the University of Malaysia Pahang. Around one thousand images were selected in Roboflow for the train dataset. The model utilises the YOLO V8 deep learning algorithm in the Google Colab environment and is trained using a custom dataset managed by the Roboflow dataset manager. The dataset comprises a diverse set of training and validation images, capturing the unique characteristics of Malaysian roads. The train model's performance was assessed using the F1 score, precision, and recall, with results of 71%, 88.2%, and 84%, respectively. A comprehensive comparison with validation results has shown the efficacy of the proposed model in accurately detecting vehicles, motorcycles, and traffic lamps in real-world Malaysian road scenarios. This study contributes to the improvement of intelligent transportation systems and road safety in Malaysia.

1. Introduction

Road safety has been a growing concern in recent years, particularly in developing countries where the infrastructure and traffic management systems are still evolving. In Malaysia, the increasing number of vehicles on the roads has led to significant challenges in terms of traffic congestion and accident rates [1]. The World Health Organization’s Global Status Report on Road Safety (2018) identified Malaysia as having one of Southeast Asia's highest road traffic fatalities, with over 7,000 fatalities annually [2]. To address these issues, the implementation of advanced driver assistance systems (ADAS) based on object and vehicle detection technologies is essential for improving road safety and reducing accidents [1-3].

* *Corresponding author.*
E-mail address: yusriismail@ump.edu.my

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Object and vehicle detection is a critical component of ADAS, which enables vehicles to identify and track other vehicles, pedestrians, cyclists, and various obstacles on the road [4]. These technologies have gained considerable attention in recent years due to the rapid advancements in computer vision, machine learning, and artificial intelligence (AI) [5]. They have been proven effective in enhancing road safety in various countries with advanced transportation systems [6]. However, the application of these technologies in the context of Malaysian road conditions presents unique challenges and opportunities that warrant further investigation [7].

Malaysian road conditions are characterized by diverse driving environments, such as urban and rural areas, highways, and narrow roads [8]. Furthermore, the tropical climate often results in heavy rainfall and flooding, which can significantly impact visibility and road conditions [9]. Additionally, Malaysia is a multicultural country with various road users, including pedestrians, cyclists, motorcyclists, and drivers of various types of vehicles, all adhering to different road etiquette and behaviours [10]. These factors make object and vehicle detection in Malaysian road conditions a complex and challenging task [11].

Machine learning-based approaches, including Support Vector Machines (SVM) and Decision Trees, have been used for vehicle detection and classification. These methods usually rely on handcrafted features, such as Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP), which may not be robust enough for diverse Malaysian road scenarios [12].

Deep learning-based techniques, particularly Convolutional Neural Networks (CNNs), have been widely adopted in recent years. Popular frameworks, such as YOLO, Faster R-CNN and SSD have demonstrated superior performance in vehicle and object detection [13].

Azizi Abdullah has utilized various datasets for evaluating object and vehicle detection algorithms, including international benchmarks like PASCAL VOC, KITTI, and COCO. However, there is a need for locally relevant datasets that capture the unique characteristics of Malaysian roads [14]. Moreover, commonly used evaluation metrics, such as mean Average Precision (mAP) and Intersection over Union (IoU), should be employed to assess the performance of detection algorithms [15].

One such work is the use of convolutional neural networks (CNNs) for object detection in real-world images [16]. Some researchers have adopted transfer learning and fine-tuning to train their CNN model on a large annotated dataset. Their results demonstrated that their approach outperformed traditional object detection methods in terms of both accuracy and processing speed [17-19].

Reinforcement learning has also been explored for object detection in previous works. A novel approach was proposed, utilising reinforcement learning to optimise the parameters of a deep neural network for object detection [20]. Another author demonstrated that their approach achieved competitive results compared to state-of-the-art object detection methods [21]. Some previous studies based on semi-supervised learning have investigated it as an alternative approach for object detection. These studies have shown that the incorporation of unlabelled data into the training process can significantly improve the performance of object detection systems [22,23].

The aforementioned previous works highlight the significance of incorporating advanced techniques and algorithms in the field of object detection and image annotation [24]. The proposed system model in this study incorporates the strengths of various techniques to achieve improved performance in object detection [25].

This article aims to examine the current state of object and vehicle detection technologies, specifically focusing on their applicability in University of Malaysia Pahang, including the effectiveness of the YOLO v8 deep learning algorithm for detecting vehicles, motorcycles, and traffic lamps. The implementation of these technologies in University of Malaysia Pahang will be explored, including the impact of climate, road infrastructure, and cultural factors on their performance.

Additionally, the latest advancements in AI and machine learning techniques that can potentially address these challenges and enhance the effectiveness of object and vehicle detection systems will be discussed. Ultimately, the goal is to highlight the potential opportunities and benefits that these technologies, particularly the YOLO v8 deep learning algorithm to Malaysian road safety, traffic management, and the broader transportation ecosystem.

2. Methodology

This research experiment used YOLO v8 deep learning algorithm for object and vehicle detection. The objective was to obtain precision, recall, and F1-score metrics for object and vehicle detection in Malaysian road conditions. A visual camera sensor captured videos from Pekan hospital to UMP pekan campus road. Approximately 1,000 images were extracted from these videos and managed using the Roboflow dataset manager. Figure 1 illustrates the workflow process of the proposed system model. The process begins with recording on-road videos in Pekan hospital to UMP road. Then the videos were converted to images. Subsequently, the recorded images are annotated using the Roboflow to generate a dataset. The next step involves setting up a Google Colab environment to train the dataset and importing the YOLO v8 deep learning algorithm. Finally, the performance of the system model is evaluated by testing it on some custom images.

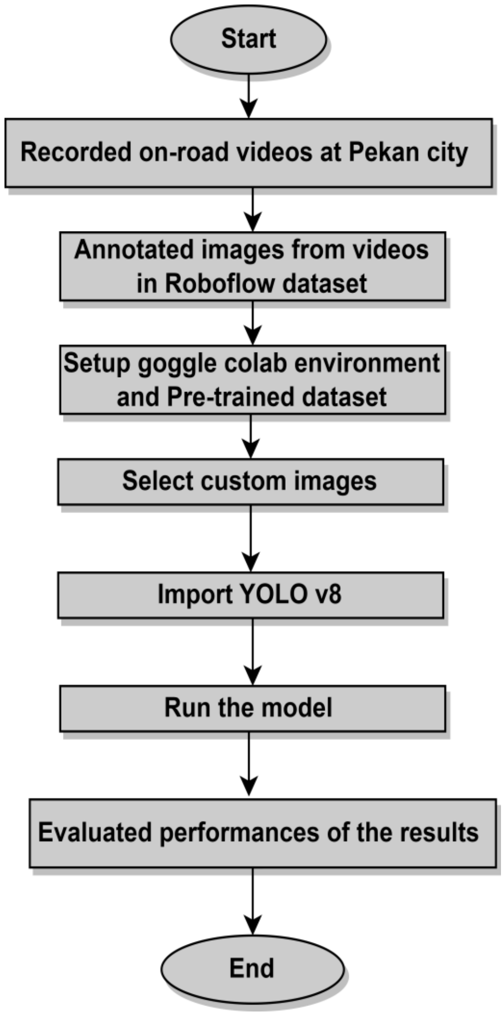

Fig. 1. Flow-chart of the model

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The images were labelled with objects such as vehicles, motorcycles, and traffic lamps. Figure 2 demonstrates the dataset's total number of annotated objects, with approximately 3700 traffic lamps, 900 motorcycles and 10,000 vehicles. The total number of labelled boxes for each class is also displayed.

For the purpose of training and evaluating the model, the dataset was partitioned into 70% for training and 20% for testing and 10% for validation. In addition, several independent images were collected for model validation. In the Google Colab environment notebook is utilized to execute the program and obtain results.

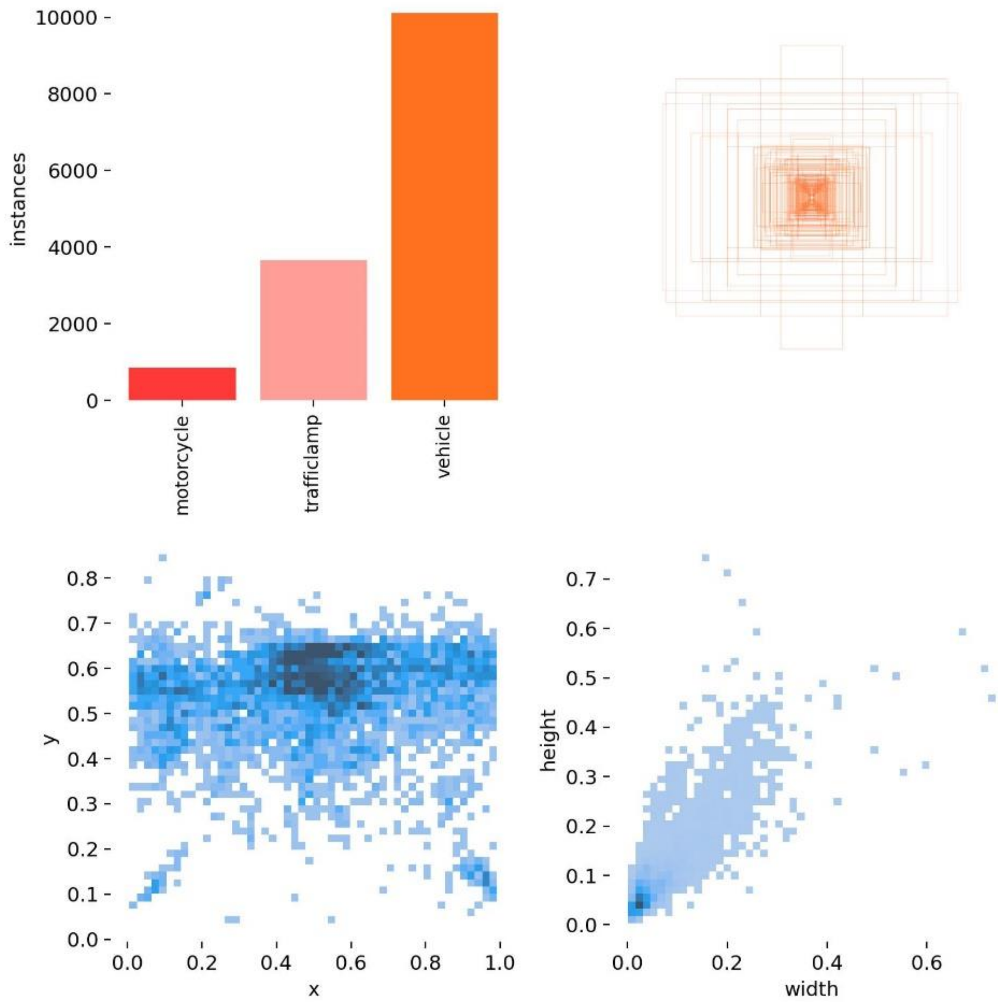

Fig. 2. The total number of detected objects inside dataset images

Figure 3 illustrates the areas in which the system detected the most objects. By combining a scatter plot and bar graphs, the diagram effectively highlights the regions of the frame with a higher concentration of objects. Detailed information about the objects' positions is provided along the axes, indicating their specific height and width coordinates.

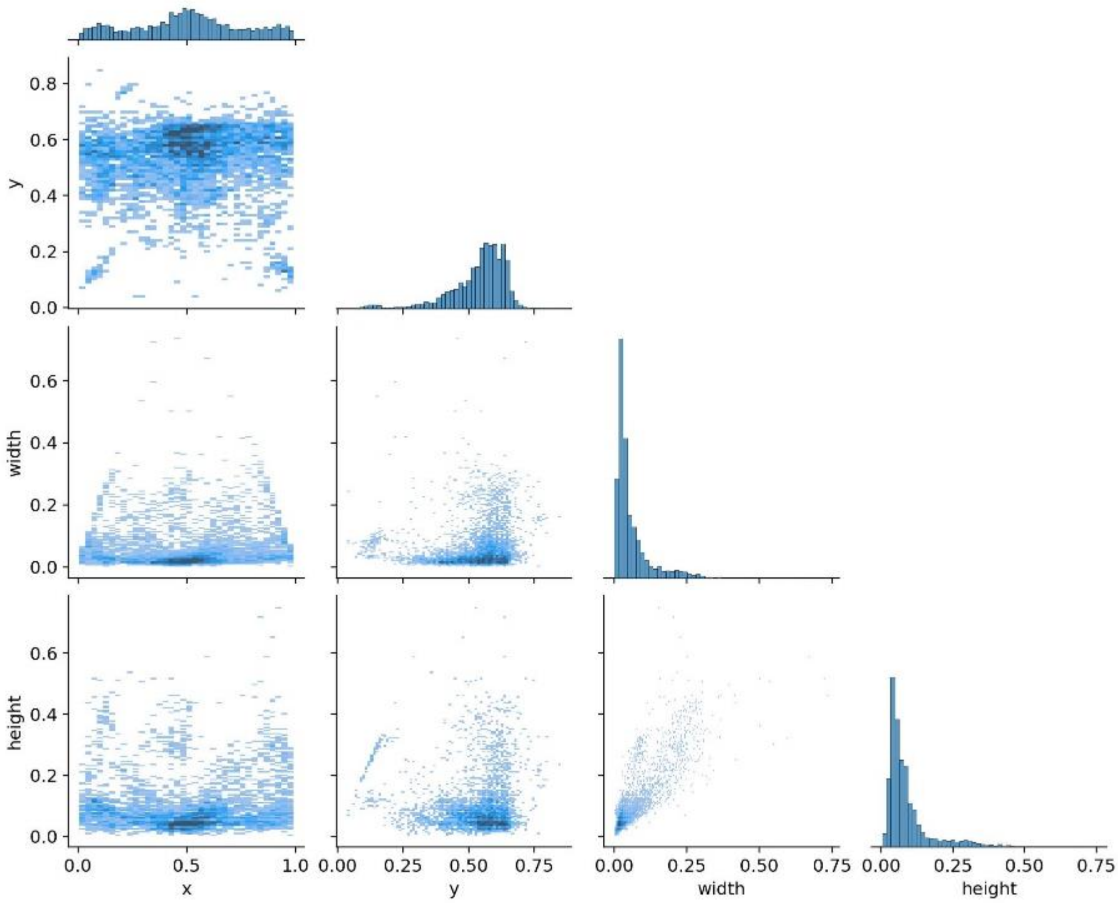

Fig. 3. The density of object detecting area in the frame

The figure above presents a comprehensive overview of the total number of vehicles, motorcycles, and traffic lights in the given scene. It effectively highlights the areas with the highest density of detected objects, demonstrating where these items are most commonly found. This visualization allows for a deeper understanding of the spatial distribution and concentration of various elements within the traffic environment.

3. Results

In this study, the performance of YOLO V8 in object and vehicle detection is assessed through a thorough examination of its training and validation results. Essential evaluation metrics, including F1 score, precision, recall, and the Precision-Recall curve, are utilized to provide a comprehensive comparison of the model's performance across both phases.

The first section of the analysis investigates the performance of the YOLO V8 during the training phase. By evaluating the F1 score, precision, and recall values, insights into the model's ability to learn the detection of objects and vehicles are gained. Furthermore, an in-depth analysis of the Precision-Recall curve facilitates an understanding of the trade-offs between precision and recall at various thresholds, offering a detailed overview of the model's overall performance during the training process.

In the subsequent section, the focus shifts to an evaluation of the validation results. By juxtaposing the validation metrics with the training metrics, the model's generalization capabilities can be inferred. Ideally, the model should demonstrate comparable performance levels in both training and validation, indicative of its effective learning and ability to generalize to new, unseen data. A considerable disparity between the two sets of results might imply overfitting or other potential concerns.

3.1 Results for Training Images

The initial step in the analysis involved training all the images from the dataset. During this session, the performance of the model was evaluated using various metrics such as F1, Precision, and Recall. Figure 4 presents the F1 performance of the model on the train dataset images. The F1 score is a crucial metric in assessing how effectively an object detection model can detect and classify objects in an image. The model performed well across all three classes, namely motorcycle, traffic lamp, and vehicle, during the training session.

Figure 4 highlights that the traffic light F1 score was higher than the other classes, with a score of more than 0.83 at 40% confidence. The vehicle and motorcycle classes achieved scores of 0.765 and 0.57, respectively. The overall performance score for all classes was 0.71 at 32% confidence. The analysis suggests that the model exhibits robust object detection capabilities for the three classes, with the traffic light class performing exceptionally well.

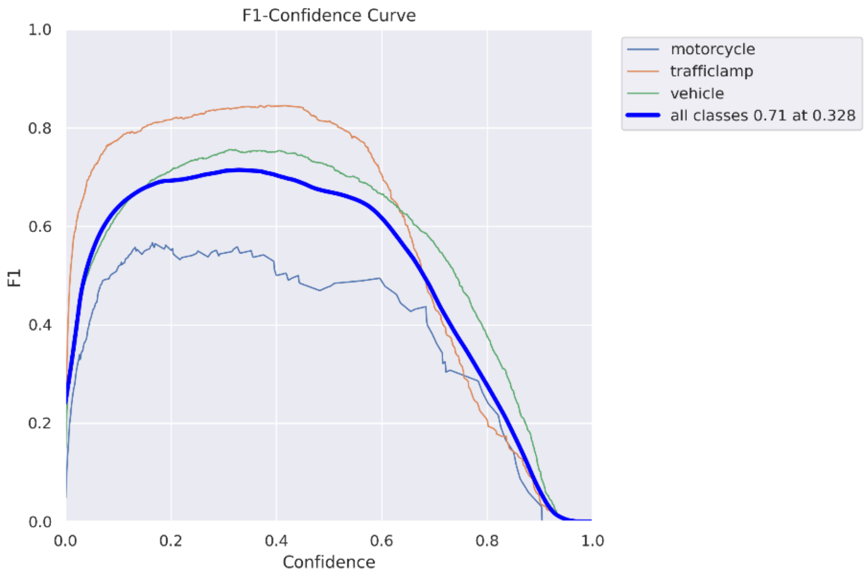

Fig. 4. F1 result for train results

The precision-confidence curve is a graphical representation of the precision and confidence scores for a given object detection task. It shows how precision changes as the confidence threshold is increased, and can be used to evaluate the trade-off between precision and recall for a detection system. The curve can help in selecting an optimal confidence threshold that maximizes precision while maintaining an acceptable recall level, and is a useful tool for evaluating and optimizing the performance of object detection systems. Figure 5 shows that all classes gained a perfect precision score of 1.00 at the 88% confidence level.

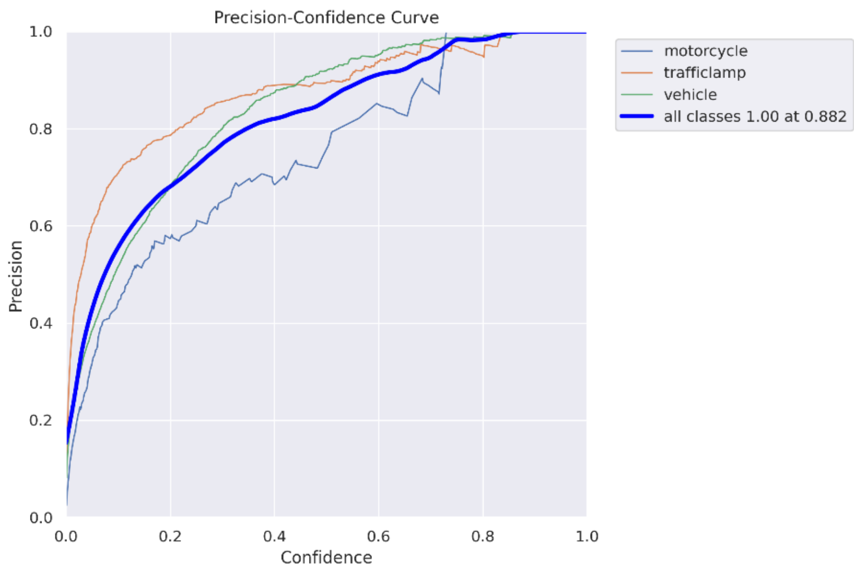

Fig. 5. Precision curve for training results

The precision-recall curve shows the model's ability to detect and distinguish specific objects, such as vehicles, traffic lamps, and motorcycles, from other objects in the scene. It demonstrates how the model's precision and recall values change as the detection threshold is varied. A high-precision, high-recall model is desirable for accurate and comprehensive object detection, but achieving both can be challenging. The curve helps identify the optimal trade-off between precision and recall for a given model and application.

The Figure 6 depicts the precision-recall values for the classes of motorcycle, traffic lamp, and vehicle, which are 0.523, 0.844, and 0.776, respectively. The mean average precision for all classes was 0.715 at the 50% confidence.

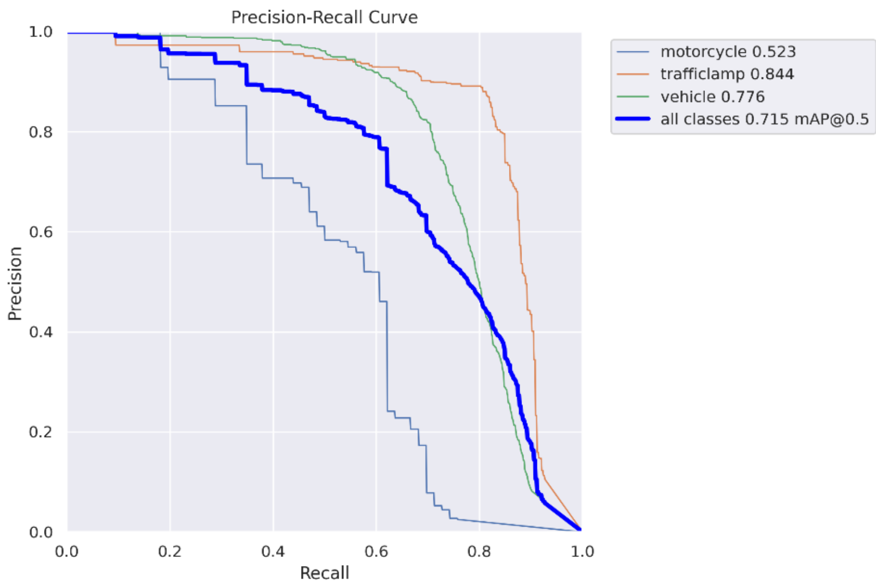

Fig. 6. Precision curve for training results

The recall-confidence curve is a tool used to evaluate the performance of object and vehicle detection systems. It shows the relationship between the recall and confidence scores for a given detection task, allowing for the analysis of the system's ability to correctly identify positive instances at different confidence thresholds. The curve can be used to find an optimal threshold that balances the detection rate and false positive rate, and to compare the performance of different detection algorithms. Ultimately, the recall-confidence curve helps to optimize the parameters of the detection system for the best possible performance.

The Figure 7 displays the performance of the object detection system for various classes, including motorcycle, traffic lamp, and vehicle, with corresponding recall values of 0.78, 0.9, and 0.889, respectively. Furthermore, the overall performance of the system across all classes at a confidence threshold of 0.000 is 0.84.

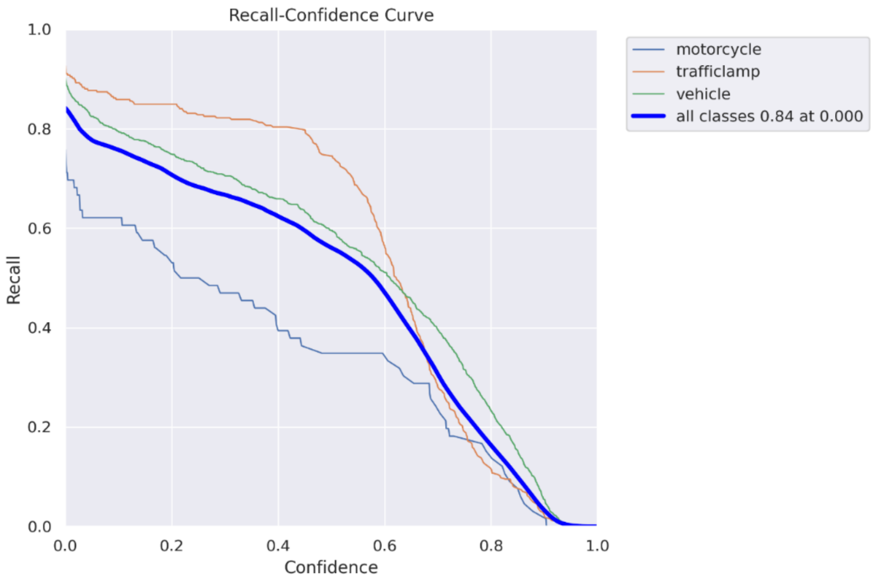

Fig. 7. Precision curve for training results

3.2 Results for Validation Images

In this section some independent images have taken for evaluating the performances of the model. Then this performance results will be compared with train results.

Figure 8 shows F1 score for validation data. It has seen all classes averages score 0.72 at 32.7 % confidence where trained result F1 score was 0.71. it performed bit better than train images.

Figure 9 showing the precision curve for validation images. From the figure, it can be seen that average precision for all the classes are 1.00 at 88.3% confidence where training result also exhibited the same trend.

The precision-recall curve for the validation images is depicted in the Figure 10. Notably, the precision scores for the classes motorcycle and traffic lamp are 0.846 and the precision score for vehicle is 0.772, which deviate slightly from the corresponding scores in the train output results. Across all classes, the mean average precision at 50% confidence is 0.715, whereas in the train output, the mean average precision was the same for all classes.

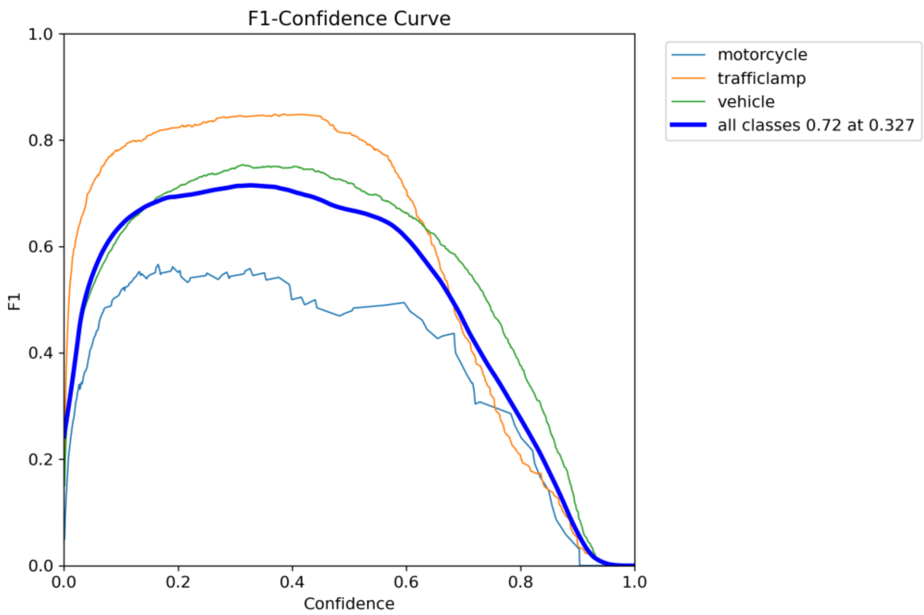

Fig. 8. F1 for Validation results

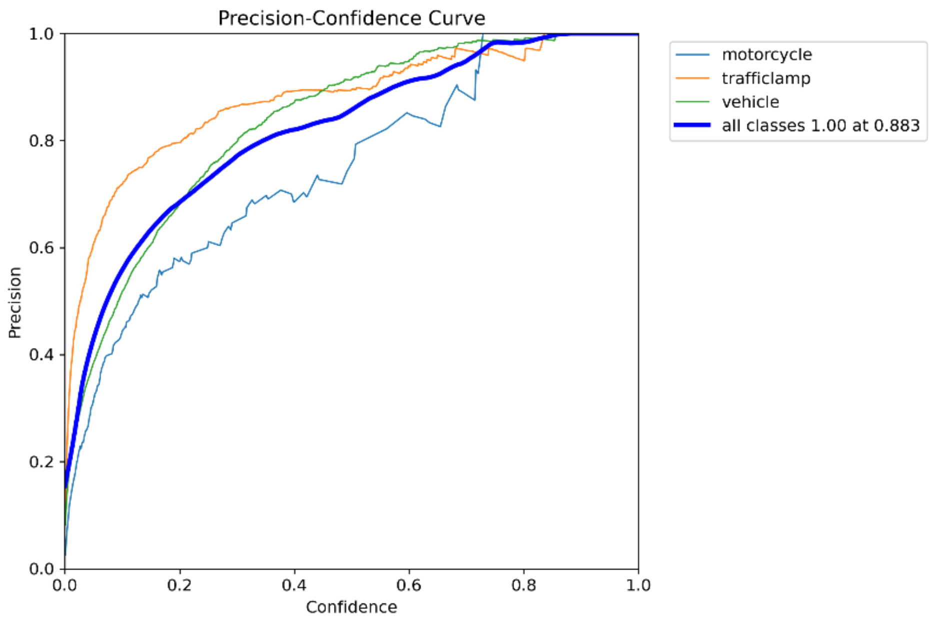

Fig. 9. Precision curve for validation result

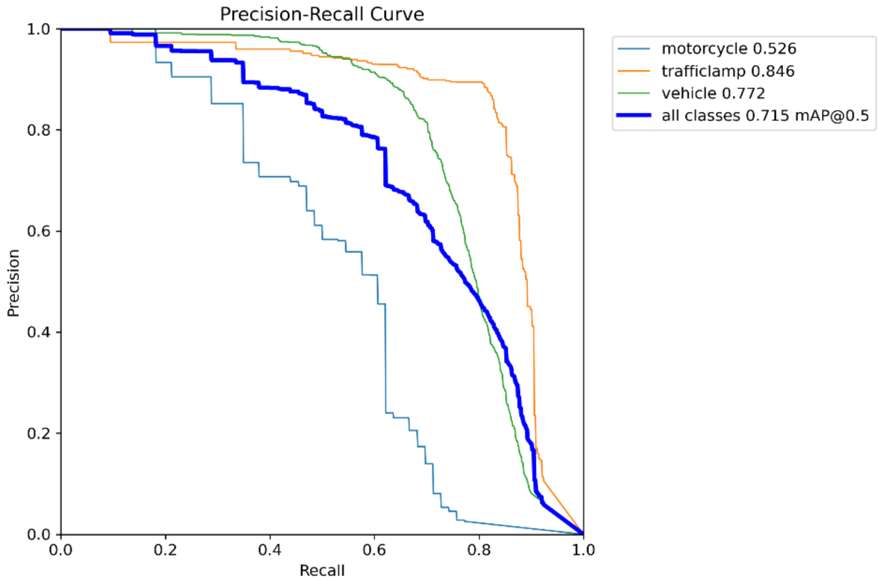

Fig. 10. Precision-Recall curve for validation results

Figure 11 illustrates the recall rates for the validation images. Remarkably, the average recall rate across all classes was 0.84 at position 0% confidence, which is a slight improvement from the corresponding rate of 0.83 observed for the training images. This suggests that the model's ability to identify true positive instances improved slightly when presented with the validation data, indicating that the model is generalizing well to new data.

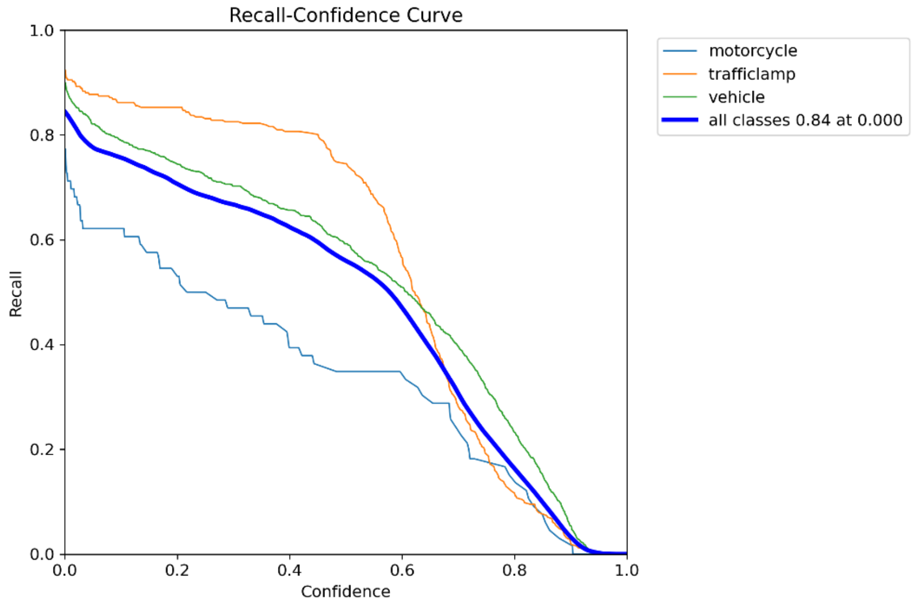

Fig. 11. Recall-Confidence curve for validation results

Figure 12 and 13 illustrate two states of the images which are plain image and object detected image. Figure 12 shows the raw images, which were captured at a straight road and a traffic junction, prior to being fed into the system model.

Fig. 12. Images before detection

Figure 13 depicts the same images after the model detected and identified various vehicles and objects present in the scene. These figures provide valuable insight into the effectiveness and accuracy of the system model in detecting and localizing objects in real-world scenarios.

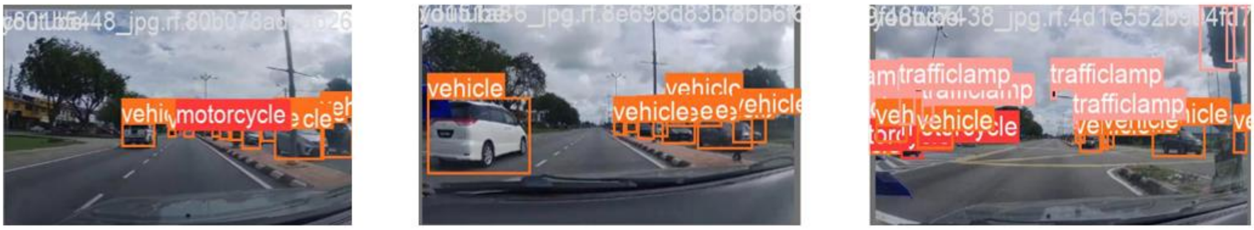

Fig. 13. Images after detection

The experimental findings indicate that the performance of the model on the training dataset was almost identical to that on the validation dataset. However, slight differences were observed due to variations in the number of images present in each dataset. Notably, the training dataset contained a significantly larger number of images, while the validation dataset only included a few. Consequently, the precision, recall, and F1 scores exhibited some differences between the two datasets. These findings highlight the importance of carefully selecting and curating datasets for training and validation purposes to ensure optimal model performance in real-world scenarios.

4. Conclusions

This study presents the implementation and evaluation of vehicle and object detection using YOLO V8 and the Roboflow dataset manager in Malaysian road conditions, focusing on straight and junction scenarios. The primary aim was to detect vehicles, motorcycles, and traffic lamps with the experimented model.

The experimental results demonstrated that the proposed model achieved satisfactory performance, with an F1 score of 71%, a precision of 88.2%, and a recall of 84%. When comparing the performance across different object categories, motorcycles obtained a mAP of 0.523, traffic lamps achieved a mAP of 0.844, and vehicles reached a mAP of 0.776 at an Intersection over Union (IoU) threshold of 0.5. These results indicate that the model is more efficient at detecting traffic lamps and vehicles than motorcycles.

In summary, the YOLO V8-based model has shown promising vehicle and object detection results in Malaysian road conditions. However, there is room for improvement, particularly in detecting motorcycles. Future research could focus on enhancing the model's performance for this category and exploring additional object classes and road scenarios for a more comprehensive traffic monitoring system.

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