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Traffic light counter detection comparison using you only look oncev3 and you only look oncev5 for version 3 and 5

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ABSTRACT

This project aims to develop a vision system that can detect traffic light counter and to recognise the numbers shown on it. The system used you only look once version 3 (YOLOv3) algorithm because of its robust performance and reliability and able to be implemented in Nvidia Jetson nano kit. A total of 2204 images consisting of numbers from 0-9 green and 0-9 red. Another 80% (1764) from the images are used for training and 20% (440) are used for testing. The results obtained from the training demonstrated Total precision=89%, Recall=99.2%, F1 score=70%, intersection over union (IoU)=70.49%, mean average precision (mAp)=87.89%, Accuracy=99.2% and the estimate total confidence rate for red and green are 98.4% and 99.3% respectively. The results were compared with the previous YOLOv5 algorithm, and the results are substantially close to each other as the YOLOv5 accuracy and recall at 97.5% and 97.5% respectively.

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1. INTRODUCTION

Road safety is globally recognised as one of the most significant problems that need to be appropriately addressed. Driving through the red light is one of the most common causes for accidents that occur at intersections. According to a research conducted by the insurance institute for highway safety (IIHS), violations of traffic lights resulted in around 928 fatalities and 115,741 injuries on the highways of the United States in 2020 [1]. Regrettably, most of the victims in the fatality or those with serious injuries were in good health prior to the accidents. Hence, traffic lights are critical in ensuring the safety of especially urban roads. Several studies on traffic safety have been conducted that looked into the different components of the system [2]–[4].

The detection of traffic light counters on the road is critical for the safety of drivers, whether it is autonomous vehicles or standard cars. The perception system, which gives the vehicle the ability to observe and comprehend its surroundings, is a fundamental part of an autonomous automobile. It is possible to remark that the development of autonomous vehicles has been motivated by a desire to cut down on the number of accidents that take place worldwide. The detection of traffic light counter by an autonomous vehicle is an essential kind of perception since it is critical for the control that the autonomous vehicle must perform, whether it is to reduce the speed and stop at the traffic light junction or continue driving and cross the intersection. Furthermore, if the driver is unfamiliar with the traffic light signals, a system that aids them in seeing the details of traffic light signals or helps them to take actions based on the remaining time that is shown on the counter of the traffic light which in turn is very important and might be crucial in a sensitive driving manoeuvre (for instance, crossing an intersection) [5].

The aim of this research is to design and develop a system that detects the traffic light counter and classifies the numbers (0-9) and their colour (red or green) on the counter, and to compare the results of the you only look once version 3 (YOLOv3) algorithm with the YOLOv5 algorithm in different aspects such as accuracy and confidence rate. Moreover, this research is focused on the classification of the traffic light counter from zero to nine only. The classification is only for the numbers with colours which are (red and green) and lastly, the detection system for the traffic light counter is performed in daytime only.

2. RELATED WORK

This section will review related literature on traffic light counter detection. Although autonomous vehicles have been profoundly studied, most of the research conducted focussed on road signs and traffic lights without including the traffic light counter. The study by Bascón *et al.* [6] focused on road signs where the detection and recognition were based on support vector machines (SVMs) and the system proved to be accurate and reliable. Furthermore, in [7], the process for detection and recognition utilised the illumination conditions and multi-exposure images and it was also based on an SVM classifier. Although the results of the system were accurate and reliable, the SVM classifier is however quite old and not very useful for current detection and classification. Therefore, convolutional neural networks (CNN) [8] is more relevant for contemporary conditions and has been used for applications in traffic lights, traffic signals and traffic light counter detection.

Meanwhile, Muller and Dietmayer [9], and Li and Zhou [10] have used single-shot multibox detection (SSD) for traffic light detection. They utilized the DriveU traffic light dataset [11] and results from the research were at 95% recall for small objects and up to 98% recall for larger objects while the false positive rates were between 0.1 and 1. It was also demonstrated by Jensen *et al.* [12] that using YOLO [13]–[15] with the laboratory for intelligent and safe automobiles (LISA) traffic light dataset [16] and logistic activity recognition challenge (LARa) traffic light dataset [17] had produced 96.38% recall for YOLOv3, 68.06% recall for YOLOv2 and 42.3% recall for YOLOv1. Another research [18] used faster region based convolutional neural networks (R-CNN) [19] and LISA traffic light dataset [16] and Bosch small traffic light dataset [20] and the results achieved were 56.31% mean average precision (mAP) on the Bosch dataset and 76.37% mAP on the LISA dataset.

All the mentioned studies did not include the traffic light counter but rather the traffic light signals only. Other research had used deep learning and YOLO for different purposes [21]–[38]. However, the study by Chand *et al.* [5] used mask R-CNN [29] and was specifically for the countdown timer of the traffic light. The dataset used were microsoft common objects in context (MS COCO) [30] and street view house numbers dataset (SVHN) [31] with the acquired result of 82.2% precision and 82.78% recall. Based on the review of past research, it is clear that multiple researchers had worked on traffic light detection and recognition systems [32] and compared multiple algorithms to decide the best method for traffic light detection and classification [33]. Nevertheless, this does not happen to the detection and classification of the timer counter on the traffic light. Therefore, this paper will present the method to do the detection and classification of the counter, and subsequently compare the performance of the results with two different algorithms which are the YOLOv3 and YOLOv5.

3. METHOD

This project employed deep learning method with the YOLOv3 algorithm. When a photo is taken, this algorithm identifies and recognises the numerous items in the image (in real-time). Object detection in YOLO is accomplished using a regression problem, which results in the generation of class probabilities for the pictures that were discovered. CNN are used in the YOLO method to recognise objects in real-time. When it comes to object detection, the approach just needs a single forward propagation through a neural network, as implied by the name. This indicates that a single algorithm run is sufficient to anticipate the content of the whole image. It is used to forecast several class probabilities and bounding boxes simultaneously using a CNN algorithm.

The dataset is a video collection of traffic lights with counter taken via a smartphone camera around the city of Melaka, Malaysia and the videos were split into multiple frames per second to acquire a total of 2,204 frames with 1,764 (80%) were used for training. Another 440 (20%) were used for testing. The flow chart of the system building and training process is illustrated in Figure 1.

The dataset was labelled manually and individually via computer vision annotation tool (CVAT) which is an online platform. The dataset was then set into 20 classes (0-9 red and 0-9 green). Consequently, the YOLOv3 algorithm was trained on Google Colab platform using Python. For the training process, the maximum batch value was set to 40,000 and the filters to 75. Figure 2 shows a sample of the used dataset for training.

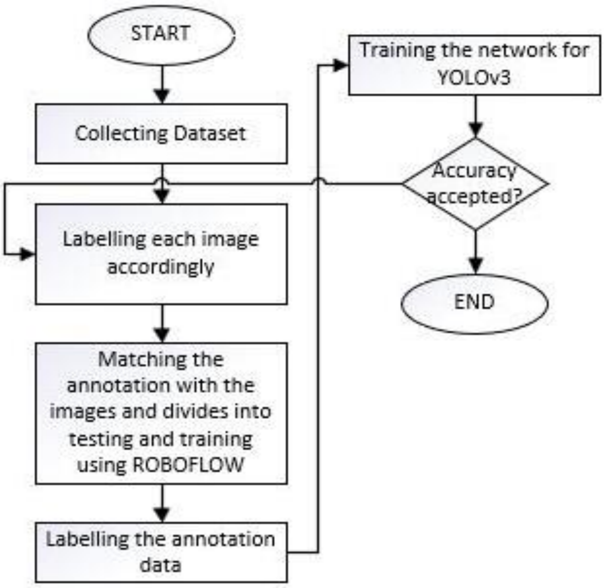

Figure 1. Flowchart of the module building process

Figure 2. Sample of the dataset

4. RESULTS AND DISCUSSION

4.1. Training output

Upon completion of the training process, some results can be obtained automatically using Google Colab that will make the trained module tests itself on the testing dataset. Table 1 shows some results obtained after the completion of the training process. The Precision and Recall were calculated by using (1) and (2).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

Table 1. Results from YOLOv3 algorithm

		Colour					
		RED			Green		
		True positive	False positive	Precision%	True positive	False positive	Precision%
Number	1	14	8	63.63	41	4	91.1
	2	16	0	100	19	5	79.1
	3	16	0	100	19	0	100
	4	16	0	100	19	5	79.1
	5	19	0	100	13	0	100
	6	34	0	100	19	5	79.1
	7	28	0	100	14	0	100
	8	20	8	71.4	21	5	80.07
	9	10	0	100	9	1	90
	0	20	5	80	9	5	64
		Average precision%		91.5	Average precision		86.247
		z		Recall %		F1 score %	
		89		83		70	
		IoU %		mAp %		Iteration	
		70.49		87.89		40,000	

4.2. Testing evaluation for classification

The trained module was then manually tested over 2,000 images for the classification and the results are compared. Tables 2 and 3 show the confusion matrix of YOLOv3 and YOLOv5 algorithms. YOLOv3 algorithm was trained on 20 classes (0-9 red and 0-9 green) while the YOLOv5 algorithm was trained on 12 classes (0-9 without specifying the colour and then red and green from the colour of the traffic light bulb or arrow). The accuracy can be obtained using (3).

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

Table 2. YOLOv3 confusion matrix for red and green numbers

		Colour							
		Red				Green			
		True positive	False negative	Recall%	Accuracy%	True positive	False negative	Recall%	Accuracy%
Number	1	100	0	100	100	100	0	100	100
	2	100	0	100	100	100	0	100	100
	3	97	3	97	97	100	0	100	100
	4	100	0	100	100	100	0	100	100
	5	98	2	98	98	95	5	95	95
	6	100	0	100	100	100	0	100	100
	7	99	1	99	99	100	0	100	100
	8	100	0	100	100	100	0	100	100
	9	100	0	100	100	100	0	100	100
	0	98	2	92	92	97	3	97	97
			Total true positive				Total false negative		
			1,984				16		
			Average recall%				Average accuracy%		
			99.2				99.2		

Table 3. YOLOv5 confusion matrix

		Parameters			
		True positive	False negative	Recall%	Accuracy%
Object	1	93	7	93	93
	2	97	3	97	97
	3	91	9	91	91
	4	96	4	96	96
	5	93	7	93	93
	6	100	0	100	100
	7	100	0	100	100
	8	100	0	100	100
	9	100	0	100	100
	0	100	0	100	100
	Green	100	0	100	100
	Red	100	0	100	100
		Total true positive		Total false negative	
		1,170		30	
		Average recall%		Average accuracy%	
		97.5		97.5	

4.3. Traffic light counter with bounding box

The module was then tested for the detection of the numbers shown on the traffic light counter to obtain the average confidence rate of the system. A sample of some images with bounding boxes and the confidence rates are given in Figure 3. Meanwhile, Figures 4 and 5 show the average confidence rate of the trained YOLOv3 algorithm after testing 200 images (10 images for each class) with good result of detection and confidence rate. Consequently, the module was tested on a Nvidia Jetson Nano Kit (JN) to evaluate the frames per second performance of both the JN and the algorithm. Additionally, Table 4 and Figure 6 show the average frames per second on the Nvidia Jetson Nano Kit versus the Tesla T4 cloud GPU by Google Colab.

Figure 3. Examples of the detection module for YOLOv3

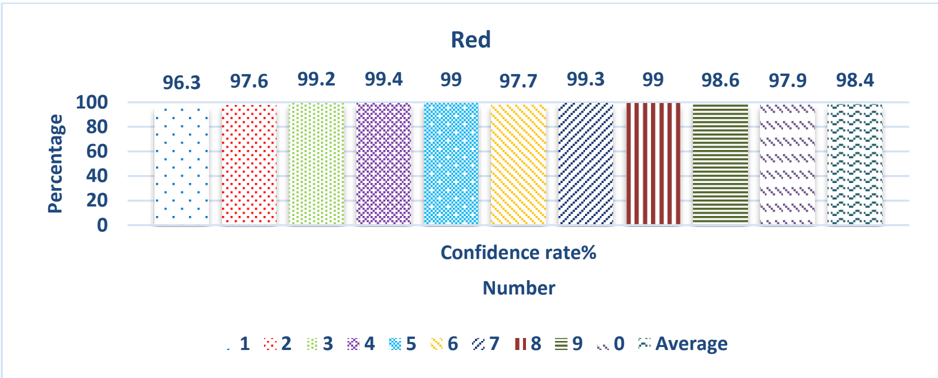

Figure 4. Confidence rate for red numbers for YOLOv3

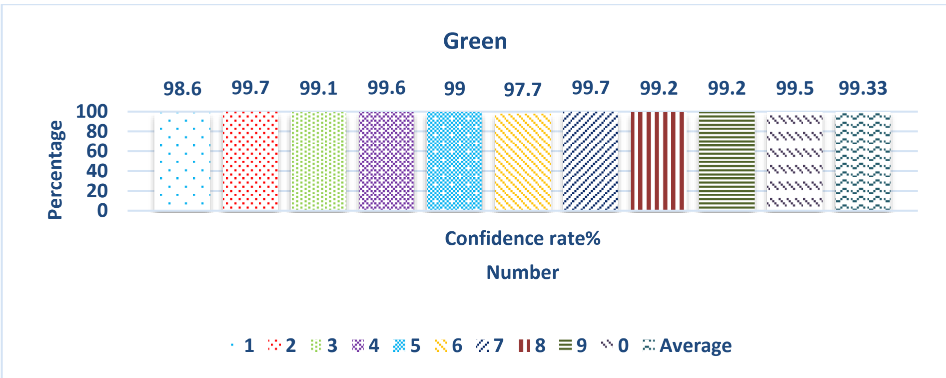

Figure 5. Confidence rate for green numbers for YOLOv3

Table 4. Average frames per second

GPU algorithm	Tesla T4	Nvidia Jetson Nano
YOLOv3	12 Frames per second	2.5 Frames per second

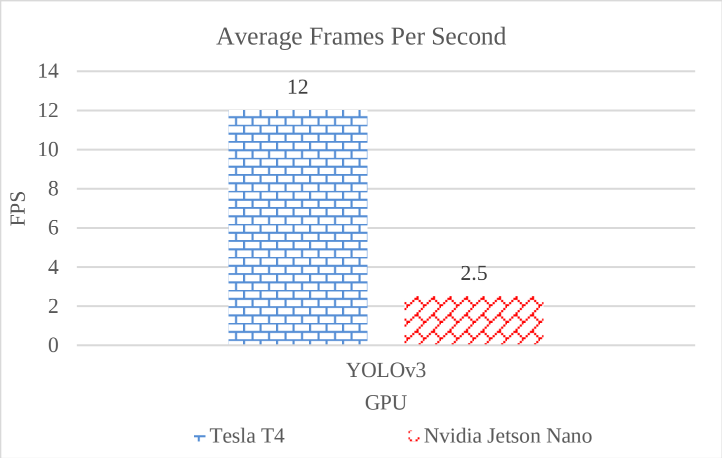

Figure 6. YOLOv3 FPS on different GPUs

5. CONCLUSION

In conclusion, the YOLOv3 algorithm was successfully tested with the dataset collected around the city of Melaka Malaysia. A total of 2204 images were split into 80% for training and 20% for testing and have been labelled via CVAT and trained via Google Colab. The system was able to detect traffic light counter and classifies the numbers (0-9) and its colour (red or green). The results for accuracy and recall are at 99.2%, precision is at 89% intersection over union (IoU) is at 70.49% and mAp is at 87.89%. The YOLOv5 had been tested and compared with the results shown are not very far from each other in terms of accuracy and reliability. However, YOLOv5 has some limitations in terms of compatibility with the Nvidia Jetson Nano Kit as it cannot be deployed on it. Moreover, YOLOv3 is lighter and has fewer layers; thus, it should have better FPS results in both the Jetson Nano and personal computer.

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