Traffic Density Estimation System using Deep Learning Technique for Vehicle Detection

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ABSTRACT

Nowadays driving a car is necessary to travel to places. The benefits of a car to travel are comfortable and fast. Since the increasing number of cars are being driven every day, the number of on-site parking spaces is insufficient to park cars. Therefore, this work is created to help us know how many parking spaces are left inside the facility. The equipment used in the experiment was a camera and a laptop. The camera was installed at an electricity post near the dormitory. After the video of cars entering and exiting the road have been recorded, they were processed by YOLOv4 techniques. The images of the cars were analyzed. Which has been experimented with two forms: The first form is a separate type of car. The result is sedan car has the highest detection accuracy of 100%, while the van has the lowest detection accuracy of 66.7%. The second form was the accuracy of vehicle detection at times intervals. The result of the highest detection accuracy is 94.8% in the evening and the lowest detection accuracy is 68.4% at night. Finally, the number of cars entering and exiting has been counted automatically and stored in the database. Not only the number of cars entering, exiting, and remaining in a place have been shown on the web page in real-time, but also the statistics of the total number of cars that enter each day has been stored. This project will help to make it easier to see how many parking spaces are left to be able to park. Which our web page, the part that received the most satisfaction score is contact at an excellent level.

Keywords: *YOLOv4, YOLOv4-tiny, Vehicle detection, Vehicle counting*

INTRODUCTION

There are numerous methods for detecting vehicles. including the development of computer vision software to aid in the performance of tasks These technologies have been developed a plethora of times. And there are many people who are still experimenting in this field. Detecting objects can be accomplished using a variety of algorithms.

There are many different techniques for detecting vehicles. including computer vision development that facilitates work These technologies have been developed countless times. And a lot of people are still experimenting in this field. A variety of algorithms can be used to detect objects.

Using Faster R-CCN algorithms in experiments. (Tariq et al., 2021) has previously proposed solutions for vehicle detection and vehicle color classification.

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The proposed method is based on the modified qualities of Faster R-CNN. His experiments have created good results as compared to current techniques. This method is also highly efficient with 95.31% exactness. (Boyuk et al., 2020) use images in UAVs to detect vehicles. A graphics card has been used with a lot of processing capacity. This research will add YOLOv3-Tiny and SSD algorithms to the proposed system. As a result, the location of vehicles driving in traffic will be discovered automatically. (Qiao et al., 2021) compared the detection capabilities of several vehicles. YOLOV4 and Faster R-CNN models have been applied. They are both efficient and accurate at detecting objects within a specific distance. To measure the distance between other cars, a vision-based distance estimation technique has been. proposed. On two-way highways, the results of YOLOV4 and Faster R-CNN had average accuracy of 99.16 % and 95.47% respectively. The F1 result in identifying vehicles within 100 meters distance are 79.36 % and 85.54% respectively. The detection speed for YOLOV4 and Faster R-CNN are 68 fps and 14 fps, respectively.

Using YOLO algorithms in experiments. (Bin & Kamaru, 2021) uses TensorFlow and YOLO4 in vehicle detection. This vehicle detection also uses the DeepSORT algorithm to help effectively count the number of vehicles passing in the video. Which achieved state-of-the-art results with an AP50 of 82.08% and it used a49 custom dataset with real-time speeds of approximately 14 fps on the GTX 1660ti. (Du et al., 2021) proposed the heavily obscured vehicles detection by YOLOV4 in the complicated background of weak infrared camera aerial images. By transferring data from the visible to the infrared dataset, they used the secondary transfer learning system. The model has a high level of average accuracy (AP). The model have been trained in the UCAS-AOD visible dataset, and then transferred to the VIVID visible dataset. Finally, it has been trained to theVIVID infrared dataset. Meanwhile, the second time YOLOV4 model was modified to include a negative sample mining block, which reduced the false detection rate even more. The average accuracy increased from 90.34 % to 91.92% in the lab. The F1 score improved from 87.5 % to 87.98%.

Using classification algorithms in experiments. (Satyanarayana et al.,2021) experimented with different traffic and channel-free by extracting binary data from a separate sensor array. The binary images are generated with logic 1 or 0. This image is being used to determine the width and length of a car. It is retrieved from virtual loops in recording video and classify vehicles. The width and height data are obtained through the use of micro- LIDAR arrays and vehicle classification. By adjusting the distance between the observation zones, the proposed method can be automatically adapted to high or low traffic situations. When retrieving video, the detection accuracy was 98%, and when using micro-LiDAR, the detection accuracy was 91.3%. (Jagannathan et al., 2021) proposed the image-based vehicle detection and categorization of vehicles such as buses, cars, and pickup trucks. The information was obtained from the Beijing Institute of Technology vehicle dataset and the MIOvision traffic camera dataset. To improve the quality of the collected vehicle images and to detect vehicles from the cropped images, the adaptive histograms and Gaussian composite models have been applied. The feature vectors from the detected vehicles are then extracted using the Maneuverable Pyramid Transformation and the Weber Local Descriptor. On the MIOvision traffic camera dataset, all proposed deep learning techniques achieved 99.13 % and 99.28 % classification accuracy. (Fawzy et al., 2021) proposed the vehicle detection algorithms based on triangulation and frame differential background removal, as well as a Kalman Filter (KF). The proposed method for the vehicle detection and recognition is carried out on videos that classified based on the lighting conditions, the resolution of the camera and the density of car. The average absolute error between the predicted and detected vehicles was used to evaluate which vehicle detection and tracking experimental results. They were relevant in three separate surveillance videos with highly accurate 95.51 %, 94.714 %, and 95.719 %, respectively.

Another algorithm for vehicle detection proposed by (Shan et al., 2021) is based on the YOLACT one-step algorithm on the MS COCO 2017 dataset. In vehicle detection regression, the P-CIOU (accurate) loss was used to predict the regression region. A cross-computational NMS mechanism that combines the IoU threshold y and the standard center distance method was proposed to select the final candidate boundary. This mechanism is capable of accurately discussing similar occlusion issues. The results show that the task increased quality by almost 2% without sacrificing inference efficiency at all. (Lin et al., 2020) using AugGAN, a GAN-enhanced data tool to convert the road traffic images into desired domains, while the visible object has been well preserved. This work consists of three parts: (1) create an unrivaled image-to-image translation network that can realize the structure, (2) quantitatively proves that the domain scaling capability of the vehicle detector is not limited by training data, and (3) object healing networks. The method was also evaluated by training Faster R-CNN and YOLO on datasets generated from converted results. In our work, we proposed the vehicle detection based on the YOLOv4 algorithm. It has better detection accuracy than YOLOv3 algorithm. This paper is structured as follows. Section 2 describes the methods and materials. The results and conclusion will be in the sections3 and 4 respectively.

METHODS AND MATERIALS

System Overview

This paper presents a vehicle detection system based on image processing. The input vehicle footages are captured from the camera mounted at a high angle. We fetched videos via a laptop by OpenCV and processed by YOLOv4. If the YOLOv4 algorithm detects the vehicle images, the counter will be increased then the data will be sent to store in the database. Later, the web application displays the number of detected vehicles entering and exiting the particular point. It can show data in real time and also provide historical data. The proposed system is shown in Figure 1.

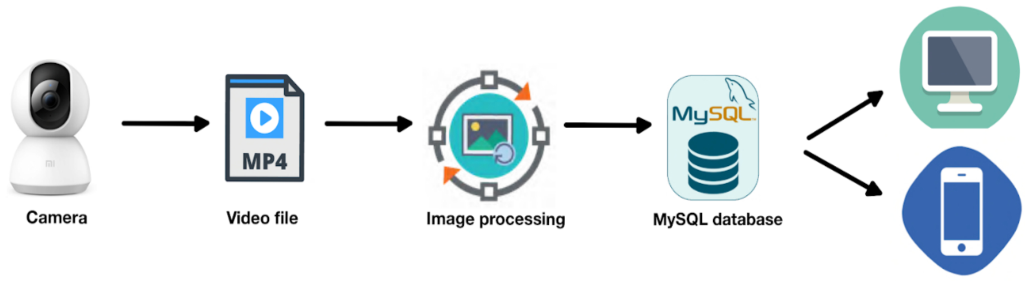


Figure 1 System Overview Diagram.

Flowchart diagram

The workflow for this project is after the videos have been taken form the camera, they are sent to process using OpenCV. Next YOLO4 algorithm is the key to detect the vehicle more efficiently and accurately. Once the vehicle was detected, a bounding box and it center will be highlighted on vehicle in the image as shown in Figure 2. Whenever the center of the vehicle (center point) passes by the designed horizontal line, the counter will be increased. This line has been set up at the middle of the frame. The offset value of our proposed is 15 pixels above and below the line. If the vehicle moving from top to bottom position of image and the center of vehicle passes the line within the offset range, the enter counter is increased. This flow chart represents in the same manner in both directions (vehicle enters to and exit from the horizontal line). The counter will update the database and finally display on the web page.

Figure 2 Car detecting image from video.

YOLOv4 flowchart

The type of object detection model of YOLOv4 is a one-stage model, capable of detecting objects without the need for a preliminary step. The advantage of a one-stage detector is the speed. It is able to make predictions quickly allowing real-time use. Three main steps of the model are illustrated in Figure 3 as Backbone, Neck (detector) and Head (detector).

First, the Backbone will extract the essential features from the input video. The YoloV4 backbone architecture is composed of three parts. Bag of freebies increases the cost of training or changed the training strategy while leaving the cost of inference low. The followings are 7 methods used in the bag of freebies: Photometric distortion, Geometric distortion, MixUp, CutMix, Focal Loss, Label smoothing and IoU loss. Bag of specials increases inference cost by a small amount but can significantly improve the accuracy of object detection. Mish activation is used in the bag of specials to eliminates by designing the necessary preconditions for the Dying ReLU phenomenon. Its properties help in better expressivity and information flow. CSPDarknet53 uses the previous input and concatenates it with the current input before moving into the dense layer.

Next, Neck (detector) collects the feature maps from different stages. The followings are 2 elements that make up the neck. Spatial Pyramid Pooling Layer (SSP) generates a fixed-length output regardless of the input size. It can pool features extracted at variable scales to the flexibility of input scales. PaNet for aggregating different backbone levels allows the better propagation of layer information from bottom to top or top to bottom.

Last, Head (detector) performs the dense prediction. It composes of a vector containing the coordinates of the predicted bounding box (center, height, width), the confidence score of the prediction and the label. The followings are 10 components of Bag of freebies (BoF): CIoU-loss, CmBN (Cross mini Batch Normalization), Drop Block regularization, Mosaic data augmentation, Self-Adversarial Training (SAT), Eliminate grid sensitivity, Multiple anchors for a single ground truth, Cosine annealing scheduler, Optimal hyper-parameters and Random training shape. Bag of specials (BoS) consists of 3 components are as follows: Mish activation, SAM-block consists of applying two separate and DIoU-NMS. Finally, the output is a detected image.

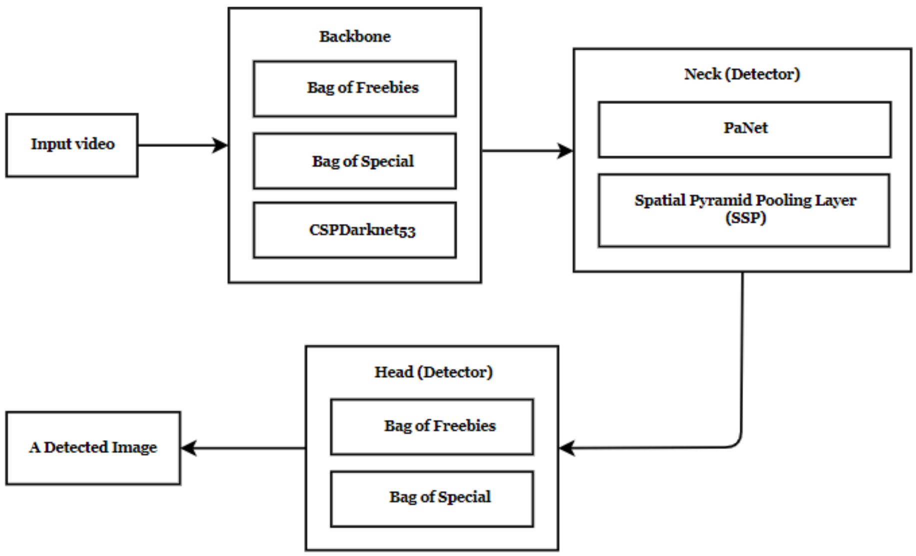


Figure 3 Flowchart YOLOv4

RESULTS

Detection by vehicle type

The observation and experiment are placed at two area. Figure 4 shows the location of the camera which installed in front of the dormitory. The example of video frame has been recorded as an image as illustrated in Figure 5. During the experiment, we found that the number of vehicles in front of the dormitory is very small. Therefore, the experiment was conducted from a single overpass in front of the university. The camera has been set up at the overpass (Figure 6). In this area, many vehicles have been detected as depicted in Figure 7. The designed horizontal line is located as the blue line in both Figure 5 and Figure 7. Whenever the center of vehicle (red point) passes the line within the offset range, the counter is activated. The experiment has been tested by the category of vehicle such as sedan cars, pickup cars and van cars. Equation (1) is the formula for the percentage of the detection accuracy calculation.

$$accuracy\% = \frac{Number\ of\ cars\ detection}{Total\ number\ of\ car} \times 100 \quad (1)$$

Figure 4 Install the camera at the post.

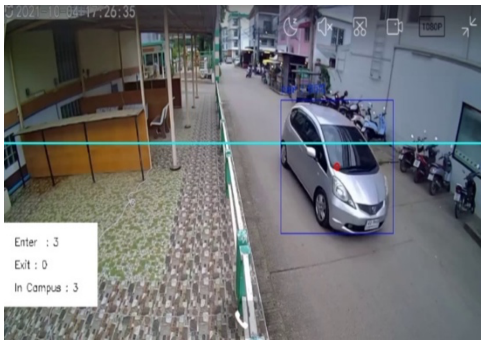


Figure 5 Cars detection in front of the dormitory.

Figure 6 Take a video clip on the overpass.

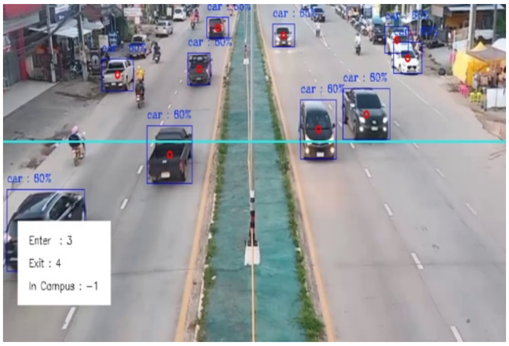


Figure 7 Cars detection from the overpass.

Table 1 Types of vehicle detection information

Types of vehicles	Number of cars	Number of detected cars	Accuracy of cars
Sedan cars	39	39	100%
Pickup cars	22	20	90.9%
Van cars	3	2	66.7%
Total	64	61	95.3%

In Table 1, it is observed that the proposed work produces the highest detection accuracy of 100% when tested on sedan cars. Meanwhile, the detection of vans has the lowest accuracy of 66.7%. The total average accuracy of all vehicle is still high (more than 90%).

From the evaluation results, the confusion matrix shown in Figure 8 is the result of vehicle detection of 64 vehicles. We recorded the car detection and the undetectable car of the mobile camera sample test. True Positive (TP) achieving 61, the vehicle can be correctly detected with the YOLOv4 model. False Positive (FP) where the YOLOv4 model detects objects other than the sample vehicle taken to be equal to 0. False Negative (FN) where the YOLOv4 model cannot be detect the vehicle even if the vehicle is still within the video frame of 3. The last column is True Negative (TN) where models strongly can detect vehicles equal to 0.

Actual Values

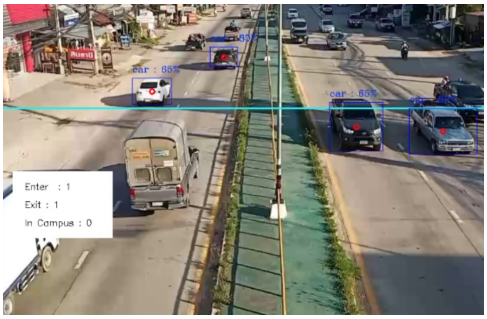
Predicted Values		
	TP = 61	FP = 0
	FN = 3	TN = 0

Figure 8 Confusion matrix.

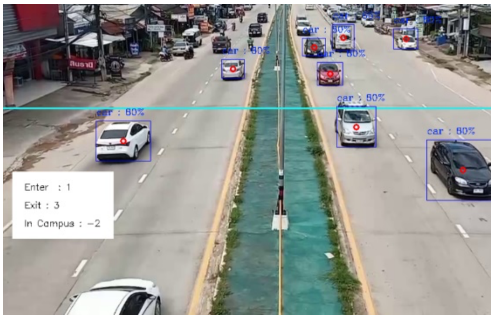
Detection at each time interval

In addition, the experiments in different period of time had been evaluated the proposed system. The test durations are 8:00-8:20 a.m., 1:00-1:20 p.m., 5:50-6:10 p.m. and 9:00-9:20 p.m. In each duration, the experiment is designed to evaluate the system in every 20 minutes.

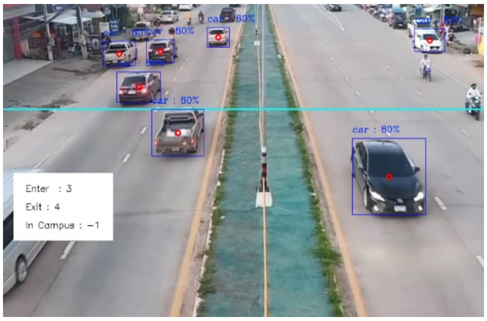
The images in Figure 9 show the results of detection performance. It can be seen that different types of vehicles at different times have different detection accuracy as shown in Table 2. Different time returns different results. Even though, the accuracy is reached 80.9% in the 8:00-8:20 interval time and increase to 87.1% during 1:00-1:20p.m. But the highest vehicle detection accuracy percentage was 94.8% in the evening time (5:50-6:10 p.m.). It is almost 30% different compared with the lowest accuracy percentage 68.4%) at the 9:00-9:20 p.m. interval. It can be seen that the light, shadow and clarity at that time are more visible than other times. It may cause by the dark area and the unwanted interference of the headlight of vehicle being too bright. Therefore, the image in the video is not clear vision.



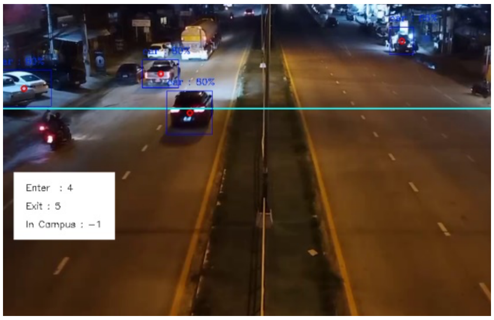
(a)



(b)



(c)



(d)

Figure 10 Example results in difference time.
a) 8:00-8:20 a.m., b) 1:00-1:20 p.m., c) 5:50-6:10 p.m., d) 9:00-9:20 p.m.

Table 2 Vehicle detection which compared between 4-time intervals

Time	Number of vehicles			Total of detected cars by system	Total of cars by human	Accuracy
	Sedan cars	**Pickup cars**	**Vans**			
8:00-8:20 a.m.	15	16	3	34	42	80.9%
1:00-1:20 p.m.	17	15	2	34	39	87.1%
5:50-6:10p.m.	30	21	4	55	58	94.8%
9:00-9:20p.m.	6	6	1	13	19	68.4%

Web page satisfaction

After the vehicles are detected, the data of the incoming and outgoing vehicles are stored in the database. The web page links to a database to retrieve that information and display it on the web page. Our web page has only one main page and divided into 3 parts. The first part of web page (Figure 10) shows the number of cars entering, exiting and remaining inside the university. This figure shows the example data at each parking area. Next, the second part presents the total number of parking spaces in each area inside the campus as shown in Figure 11. The last part of web page, the statistic of the total number of vehicles entering each day has been reported as a graph in Figure 12.

Figure 11 The first part shows the number of cars entering-exiting and the remaining cars.

Total Parking Spaces: 3018

Building	Parking Space
D1 building	68
E1 building	70
E3 building	57
C4 building	70
M-Square building	34

Figure 12 The second part shows the total number of parking spaces on campus.

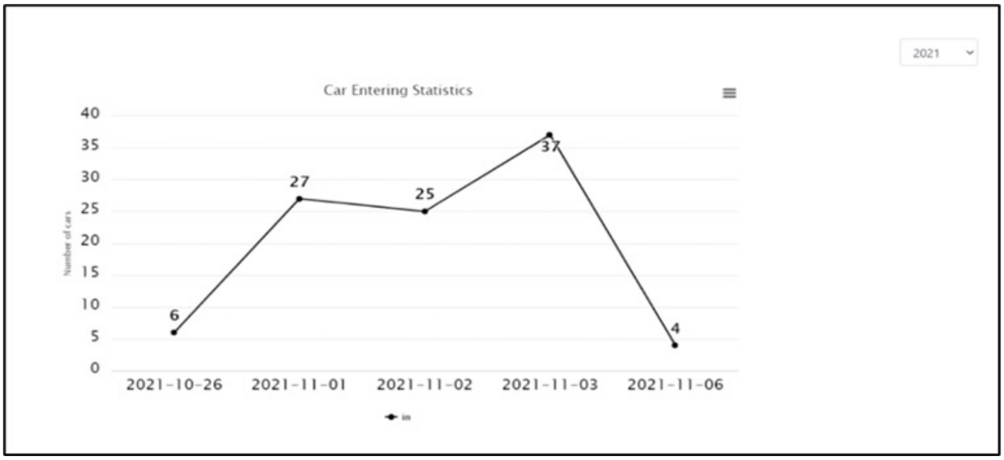


Figure 13 The last part shows the statistics of the total number of cars entering each day.

Table 3 Results of the satisfaction study of web pages.

Assessment topic	$\bar{x}$	S.D.	Satisfaction level
1. Simplicity, easy to understand	4.23	0.67	Good
2. Outstanding and unique	3.53	0.91	Good
3. The content on the web is good and complete.	4.33	0.72	Good
4. The navigation system is easy to use.	3.97	0.77	Good
5. Web page quality	3.67	0.84	Good
6. Content is useful to users.	3.73	0.78	Good
7. Pictures, colors and designs are appropriate.	4.03	0.77	Good
8. The language is easy to understand and concise.	4.27	0.70	Good
9. There is a way to contact and suggest.	4.53	0.64	Excellence
Average	4.03	0.76	Good

The web page had been tested by 15 undergraduate students who study the web programming and web application course. The results of the satisfaction study of this work is shown in Table3. By considering each topic, it was found that the assessment topic 9 has the highest average value. Followed by topic 3 about the content on the web, the mean is 4.33 and the standard deviation is 0.72. The assessment topic 2 (outstanding and unique) has the lowest average at 3.53 with a standard deviation of 0.91. Finally, it was found that the overall satisfaction of the study was at a good level with a 4.03-average value and 0.76-standard deviation.

CONCLUSION

In this article, the vehicle detection and counting the number of cars entering and exiting system has been proposed. The framework was developed by considering both type of vehicle and the testing period of time.

The experimental results showed that the system obtained good performance. According to the experiment, sedans have the highest detection accuracy of 100 %. Van cars have the lowest detection accuracy of 66.7%. The most accurate time to detect vehicles entering and exiting is 5:50-6:10 p.m. which the 94.8% accuracy. Although, in terms of counting number of cars in and out. The velocity of vehicle may have been affected on the accuracy. But overall, the system works well and satisfies all testing conditions. In addition, many testers generally agree with our method and web page application. They agreed that web page had impacted their decisions for planning to find the available parking space in daily life. In future work, the authors plan to implement this proposed work to other parking space in the university. Therefore, all data may make people the easier decision to finding parking space. All resources such as time and fuel will be managed efficiently.

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