YOLO Algorithm Accuracy Analysis in Detecting Amount of Vehicles at the Intersection

N Dewantoro, P N Fernando, Sofyan Tan
Computer Engineering Department, Faculty of Engineering, Bina Nusantara University, Jakarta, Indonesia 11480

*Corresponding author: sofyan@binus.edu

Abstract. The goal of this research is to find out YOLO algorithm’s effectiveness on detecting the number of vehicle on road. Our activity in this research is conduct training using a dataset that we created ourselves and do traffic recording simulation in a lot of scenario using YOLO original datasets and our own datasets. The result of this research is YOLO algorithm successfully detects vehicles as much as 65.3% of the total vehicles passing on the highway and gives the wrong label as much as 20.7% of the total label given if using YOLO original dataset. YOLO algorithm successfully detects vehicles as much as 9.3% of the total vehicles passing on the highway and gives the wrong label as much as 7.4% of the total label given if using our own dataset.

Keywords: YOLO, Deep Learning, Computer Vision

1. Introduction
The problem of congestion has become a common problem that occurs in big cities in the world, like Indonesia, especially in Jakarta. The traffic jams that occur in the Indonesian capital have always been a serious issue to discuss. The congestion that occurred in Jakarta was caused by unbalanced growth in the number of motorized vehicles with inadequate road length growth. On average car drivers in Jakarta waste 90 minutes in traffic. Even-Odd added together for a year, car users spend 22 days per year in a vehicle. [1].

Some of the solutions provided by the DKI Jakarta Provincial Government such as the Even-Odd System have not produced satisfactory results. Most of the people of DKI Jakarta still feel that traffic jams still occur even though the Even-odd rules have been applied. Thus, the DKI Jakarta Provincial Government has not found an effective solution to overcome the problem of congestion in Jakarta [2].

One aspect that can be optimized to reduce congestion is a smart traffic light system that will automatically adjust the time of the red and green lights based on the density of vehicles at the intersection. For example, the smart traffic light system in Pittsburgh succeeded in reducing travel time by 25% and waiting times at intersections by 40% [3].

One study tried to create a smart traffic light algorithm by using VANET to obtain vehicle density data, called Intelligent Traffic Light Control (ITLC) which is able to increase traffic flow by 25% and vehicle output from an intersection by 30% [4].

VANET (Vehicle and Network Adhoc) is a technology that provides communication between vehicles and between vehicles to infrastructure. However, VANET still has several challenges, such as...
the use of IEEE 802.11p, the use of Wireless Access in Vehicular Environment (WAVE), frequency allocation for communication between cars and cars to infrastructure, integration of several different wireless technologies, data transmission security, etc. other [5].

Some researchers also tried to use cameras to detect the number of vehicles to get vehicle density data. One of those studies is to create a vehicle approach algorithm using the Haar-like feature. The result is that the average accuracy obtained for three different road conditions (quiet, normal, solid) is 77.8%, 47.5%, and 28.2%. These results indicate that the Haar-like feature is still not suitable for use in vehicle number detection systems. [6].

One of the object recognition algorithm through image/video that is quite well known is YOLO (You Only Look Once). This algorithm is quite accurate and fast enough in recognizing objects [7]. One study used the YOLO algorithm to detect vehicles at an intersection with satisfactory results[8]. However, other studies use the YOLO algorithm to detect vehicles in an autonomous vehicle system and the results are less satisfactory. [9].

We conducted a study to examine the effectiveness of the YOLO algorithm in detecting the number of vehicles on the highway, so that the YOLO algorithm can be determined, whether it can be used as a congestion detection algorithm in smart traffic systems. The study included how many vehicles could be detected, and how severe the error was in detecting vehicles.

2. Purpose
This study aims to examine the effectiveness of the YOLO algorithm in detecting the number of vehicles on the highway.

3. Method
In this research, we will conduct a vehicle detection simulation on a highway to test the ability of the YOLO algorithm to detect vehicles on a highway in Indonesia. This test is carried out under various conditions that may occur when the vehicle detection system is working. Before conducting the test, we will conduct training in advance by using a dataset containing pictures of vehicles on the Jakarta highway. The goal is that the YOLO algorithm is able to recognize vehicles on the Jakarta highway.

As for the computer specifications that we use are as follows.

- CPU Intel Core i7 8700
- RAM DDR4 2x8GB 2666MHz
- GPU Nvidia Geforce GTX 1080
- M.2 NVMe SSD Samsung 960 Pro
- OS Ubuntu 16.04

To calculate the total accuracy of the YOLO algorithm, we made 2 accuracy calculations, namely Detection Accuracy (% DO) and Recognition Accuracy (% TL). Detection accuracy is the value of how accurate the YOLO algorithm is in detecting a vehicle object. This accuracy can be searched by looking at how accurate the YOLO algorithm is in making boxes of all objects in the image/video. Recognition accuracy is the value of how accurate the YOLO algorithm is in recognizing a vehicle object. This accuracy can be searched by looking at how accurate the YOLO algorithm is in giving the right labels and according to the type of object. The detection accuracy and recognition accuracy formula are:

\[
\text{Detection Accuracy} \, (\% \text{ DO}) = \frac{\text{Number of objects detected}}{\text{Total number of objects}} \times 100 \, (\%) \quad (1)
\]

\[
\text{Recognition Accuracy} \, (\% \text{ TL}) = \frac{\text{The number of correct labels}}{\text{Total number of labels}} \times 100 \, (\%) \quad (2)
\]

To find out the total accuracy as a whole, we do a conversion of each type of vehicle. This is because each type of vehicle will take up a different space on the highway, so the number of vehicles to reach the congestion limit is also different for each vehicle. For example, if on a highway it will be
said to be jammed if it is passed by 20 motorcycles, then that road will also be said to be jammed if it is crossed by 5 cars. We use the Object unit to determine the jam value for each type of vehicle. Here are the values of traffic jams for each type of vehicle:

- 1 Motorcycle = 1 Object
- 1 Car = 4 Objects
- 1 Truck = 8 Objects
- 1 Bus = 8 Objects

The test variables we used in this study were time, density, weather, camera position, and recording angle. The place of our research activity is located on the Slipi Petamburan crossing bridge connecting Slipi Petamburan busway stop with Palmerah Utara Street and Gatot Subroto Street, Jakarta, Indonesia. The vehicle detection trial will use 2 datasets, the original YOLO dataset and an artificial dataset. The original YOLO dataset is a dataset that has been provided by the creators of the YOLO algorithm. An artificial dataset is a dataset that we made ourselves by conducting training.

4. Results and Discussion

Figure 1 shows the overall detection and recognition results for both high and low traffic condition. Error in labeling solid conditions generally occurs in vehicle build up. YOLO algorithm is less able to detect the build up of very dense objects. The YOLO algorithm will sometimes label two objects of the same type. If there are 2 cars that are close together, the YOLO algorithm will provide 3 labels, where the third label is between the cars. In addition, the YOLO algorithm also gives a double-label to an object. The YOLO algorithm often provides a label box that is quite large in size. The box will surround a collection of objects of the same type. For example, if there are a collection of cars that are close together, the YOLO algorithm will provide a label box that surrounds the collection of cars. In addition to labeling errors, the number of motors detected was also small because many motorbikes were blocked by larger vehicles, such as cars, buses, and trucks.

![Detection and Recognition Results](image)

**Figure 1.** Accuracy in detection and recognition at different traffic condition

The overall detection and recognition results for positions and angles are shown in Figure 2. When detecting the position and the angle of the Middle Corner, the YOLO algorithm recognizes the top of
the car as a Cell phone rather than as a car. This is because the original YOLO dataset is the default dataset given by the creator of the YOLO algorithm. This dataset has a large number of objects, not just vehicles. The YOLO algorithm can also recognize motorcyclists as humans, so the YOLO algorithm will label motorbike and people to the motorbike and the rider. In some cases, the YOLO algorithm only labels people. These two things cause the lack of ability to recognize the YOLO algorithm that uses the original dataset. However, the artificial dataset only has data on cars, motorcycles, buses, and trucks. This makes a sharp increase in vehicle recognition by the YOLO algorithm, even though the number of vehicles successfully detected is far less. The problems faced by positions and angle other than Middle Corner is the same as the problems faced by moderate traffic variables.

Figure 2. Accuracy in detection and recognition at different position and sides

Figure 3 shows the overall detection and recognition results for different lighting condition. The accuracy of the YOLO algorithm in detecting vehicles on dark nights is slightly better than in bright daylight if the detection location has sufficient light sources, such as lighting or vehicle lights.
Overall detection and recognition results for different weather conditions are shown in Figure 4. The accuracy of YOLO's algorithm in detecting vehicles in rainy weather is slightly better than in bright daylight if the rain that is happening is not so heavy that it covers the view.

As a whole, the vehicle detection result performed by the YOLO algorithm is illustrated in Figure 5. During the vehicle detection simulation, YOLO's algorithm succeeded in detecting vehicles as much as 65.3% of the total vehicles that passed and gave the wrong label as much as 20.7% of the total
labels he gave when using the original YOLO dataset. If we use the dataset we made, then, YOLO's algorithm can detect vehicles as much as 9.3% of the total vehicles that pass and give the wrong label as much as 7.4% of the total labels.

![Graph showing detection and recognition accuracy of YOLO algorithm](image)

**Figure 5.** Overall Detection and Recognition Accuracy of YOLO algorithm

### 5. Conclusions and Suggestions
Based on the research we have done, the following conclusions can be concluded:

- YOLO's algorithm succeeded in detecting vehicles as much as 65.3% of the total vehicles that passed and gave the wrong label as much as 20.7% of the total labels he gave when using the original YOLO dataset.
- YOLO's algorithm succeeded in detecting vehicles as much as 9.3% of the total vehicles that passed and gave the wrong label as much as 7.4% of the total labels he gave when using the dataset we created.
- Stacking of large, large vehicles in one picture can damage the quality of training results if used in a dataset.
- There was an error labeling when detecting vehicle buildup.
- Position and Front Angles Corners are the most ideal position and angle to detect vehicle buildup.
- Vehicle detection in dark night conditions will be as good as in bright daylight conditions if there are adequate light sources, such as lighting and vehicle lights.
- Detecting vehicles in rainy conditions will be as good as in sunny conditions if the rain is not heavy enough to disturb the view.

### References

[1] Katadata 2017 *Survei Uber: Warga Jakarta Kena Macet 90 Menit Setiap Hari* Accessed from Katadata: [http://katadata.co.id/berita/2017/11/01/survei-uber-warga-jakarta-kena-macet-90-menit-setiap-hari](http://katadata.co.id/berita/2017/11/01/survei-uber-warga-jakarta-kena-macet-90-menit-setiap-hari)

[2] KedaiKOPI 2017 *KedaiKOPI: Ini Respon Publik Jakarta Tentang Ganjil Genap dan Rencana ERP* Accessed from KedaiKOPI: [http://kedaikopii.co/web/index.php/survei/37-kedaikopii-ini](http://kedaikopii.co/web/index.php/survei/37-kedaikopii-ini)
[3] Smith S 2016 *IEEE Spectrum* Accessed from Pittsburgh's AI Traffic Signals Will Make Driving Less Boring: https://spectrum.ieee.org/cars-that-think/robotics/artificial-intelligence/pittsburgh-smart-traffic-signals-will-make-driving-less-boring

[4] Younes M B, and Boukerche A 2014 *An Intelligent Traffic Light scheduling algorithm through VANETs* 39th Annual IEEE Conference on Local Computer Networks Workshops 1-6

[5] Eze E C, Zhang S, and Liu E 2014 *Vehicular ad hoc networks (VANETs): Current state, challenges, potentials and way forward* 2014 20th International Conference on Automation and Computing 1-6

[6] Lazaro A 2017 *Deteksi Jenis Kendaraan di Jalan Menggunakan OpenCV* Undergraduate Thesis 1-6

[7] Redmon J, and Farhadi A 2016 *YOLO9000: Better, Faster, Stronger* Cornell University Library 1-9

[8] Foley K, Frick J, Moccia V, Patel S, and Wheatley K 2017 *AI City Challenge Object Detection Using YOLO* NVIDIA AI City Challenge 1-5

[9] Serrano A S 2017 *YOLO Object Detector for Onboard Driving Images. End of Degree Project in Computer Science, Escolas Enginyeria (EE), Universitat Autonoma de Barcelona (UAB)* 1-11