Vehicle Detection and Accuracy Verification Using YOLOv8

Seungchan L. [1], Chansol K. [2], Cheonggil J. [3] and Chuluong C. [4*]

[1]Master's student, Division of Earth and Environmental System Science, Pukyong National University, Republic of Korea

[2]Master's student, Division of Earth and Environmental System Science (Major of Spatial Information Engineering), Pukyong National University, Republic of Korea

[3]PhD, Division of Earth and Environmental System Science (Major of Spatial Information Engineering), Pukyong National University, Republic of Korea

[4] Prof., Division of Earth and Environmental System Science (Major of Spatial Information Engineering), Pukyong National University, Republic of Korea

*cuchoi@pknu.ac.kr

1. Introduction

In recent years, machine learning technology has made rapid advances and is being used in a variety of fields. One of the main applications of machine learning is object detection. It is a technology that identifies specific objects within images or videos and estimates their location.

YOLO(You Only Look Once) is an algorithm that has introduced a revolutionary approach to object detection and has attracted attention for its real-time detection capabilities. YOLO uses a single neural network to analyze images at once, which gives it a huge advantage in terms of speed and accuracy.

Similarly, advances in drone technology have made it possible to capture high-resolution images from various angles and altitudes. However, object detection using drone images present challenges, as detection accuracy can vary depending on the altitude and angle.

The objective of this research is to evaluate the performance of the YOLOv8 algorithm for vehicle detection in drone images at different distances. And we also analyze the results and accuracy of vehicle detection using YOLOv8.

2. MATERIALS AND METHODS

2.1 Materials

In this research, the data was collected using a DJI Phantom 4 Pro drone. It can take high-resolution photos. The drone used in this research is shown in Figure 1(a). The photos used in this research were taken between 10:42 a.m. and 10:50 a.m. on Wednesday, 1 November

2023. And 246 photos were taken at 2-second intervals for about 8 minutes at an altitude of 10m. The research was conducted at Pukyong National University in Nam-gu, Busan. The images used in this research are shown in Figure 1(b).

(a) DJI Phantom 4 Pro (b) Research area

Figure 1. DJI Phantom 4 Pro & Research area

2.2 Methods

First, we set the research objectives and then determined the scope of the research. The photos were used as input to pre-trained model using the COCO128 dataset. Object detection was performed through the model, and the result post-processing was performed. This is the process of extracting the bounding boxes of the detection results. Next, the results were saved as image files which became image segments in the process of saving and visualizing the results. Finally, the results were analysed and conclusions were drawn. YOLOv8 is the latest version, released in January 2023. It was chosen for this research due to its high accuracy and efficiency, achieved with fewer parameters compared to previous versions. It incorporates an anchor-free detection mechanism, which allows for more flexible bounding box predictions while reducing computational overhead. In addition, YOLOv8 has improved loss functions and a new architecture that improves both speed and accuracy, making it particularly effective in real-time detection tasks.

YOLOv8 is available in five models: Nano (YOLOv8n), Small (YOLOv8s), Medium (YOLOv8m), Large (YOLOv8l), and XLarge (YOLOv8x), which have the same backbone and head but differing in performance. In this research, we used the x model to maximize detection accuracy.

3. Results

3.1 YOLOv8-based vehicle detection results

In this research, we analysed vehicle images taken by drone using the x model of YOLOv8. A total of 246 images were used, of which 143 images contained vehicles and 103 images did not contain vehicles. In each image, the distance was measured relative to trees and terrain features. Vehicle detection was based on vehicles moving on the road; parked vehicles were excluded from the analysis. Based on the location of the objects, they were categorized into 20m, 27m, 37m, 44m, 51m, 58m, 65m, 72m, 79m, 86m, and 93m. The altitude of the drone is fixed at 10m, which is not considered when calculating the distance to the target. A total of 193 vehicles were detected at a certain distance, of which 171 were cars and 22 were trucks. The number of cars and trucks detected at a certain distance is shown in Table 1.

Table 1. Number of vehicles detected at a certain distance

	20m	**27m**	**37m**	**44m**	**51m**	**58m**
Car&Truck	39	25	21	8	16	11
Car	35	22	19	7	15	9
Truck	4	3	2	1	1	2
	65m	**72m**	**79m**	**86m**	**93m**	**Total**
Car&Truck	9	10	12	15	27	193
Car	8	9	11	13	23	171
Truck	1	1	1	2	4	22

3.2 Vehicle detection accuracy analysis

In this research, we evaluated the accuracy from two perspectives. The first perspective is "Was the vehicle recognized at a certain distance?", i.e., whether the vehicle was detected correctly. The second perspective is "What is the confidence of the YOLO model in the machine's own evaluation of the results?".

3.2.1 Vehicle detection rate analysis

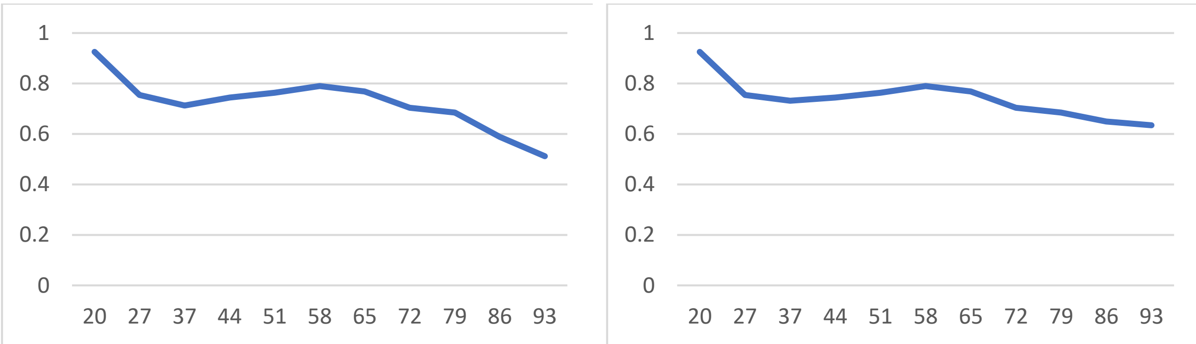
As the vehicle detection rate analysis looks at whether a vehicle is recognized or not, false positives and false negatives were analyzed to assess this. False positives are when an object that is not a vehicle is incorrectly detected as a vehicle. False negatives are when a real vehicle is not detected. According to the detection results, there were no false positives and false negatives at distances of 20m, 27m, 44m, and 51m. However, there were false positives and false negatives at distances of 37m, 58m, 65m, 72m, 86m, and 93m. The ratio of false positives and false negatives by vehicle type showed that cars were detected with an accuracy of about 97.66%, with 4 false positives and 4 false negatives. And trucks were detected with an accuracy of 50%, with 11 false positives and 11 false negatives. Figure 2(a) shows a case of a false positive where a truck was falsely detected as a bus, and Figure 2(b) shows a case of a false negative where a car was not detected at 93m.

(a) False positive (b) False negative

Figure 2. False positive & False negative

3.2.2 Vehicle detection analysis based on confidence

We evaluated what percentage probability the YOLOv8 model has confidence in a vehicle at a certain distance. We calculated the average confidence of the detected vehicle at a certain distance. The average confidence at certain distance for only car excluding false positives and false negatives is shown in Figure 3(a). Trucks were excluded due to their low number of passes and small sample size. Values with a confidence of less than 0.5 were considered outliers, removed, and a new confidence average was calculated. And the result of calculation is shown in Figure 3(b).



(a) Average confidence of cars (b) Average confidence of car after removing confidence < 0.5

Figure 3. Average confidence of car & after removing confidence below 0.5 (X: Distance, Y: Confidence)

In Figure 3(a), the confidence was highest at 20m, around 0.925, and lowest at a 93m, with a confidence of 0.512. The confidences were relatively high between 44m and 65m. However, an unexpected drop in confidence was observed at 27m and 37m, which we attribute to the presence of crosswalks and speed bumps affecting the vehicle detection process. In Figure 3(b), the average confidence after removing less than 0.5 increased overall, especially at 93m, from 0.512 to 0.635.

4. Conclusion

In this research, we evaluated the performance of the YOLOv8 algorithm for vehicle detection using drone images. Our results showed that YOLOv8 achieved high accuracy in detecting vehicles, especially for cars, with an accuracy of approximately 97.66%. However, the accuracy for trucks was significantly lower at 50%. Vehicle detection was almost flawless at close distances, although accuracy decreased at longer distances, especially for trucks. Analysis of the confidence value also showed that the model's performance declined as the distance increased, indicating a challenge in detecting vehicles at longer distances.
The results suggest that while YOLOv8 is highly effective for real-time vehicle detection in drone images, its accuracy may be affected by factors such as distance and object type. Future research could focus on improving detection of larger vehicles, such as trucks, and reducing false negatives at longer distances. In addition, optimising the algorithm to increase detection confidence under varying conditions could further improve its applicability in real-world scenarios, such as traffic monitoring or disaster management.

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