PERSONAL MOBILITY DETECTION USING YOLO DEEP LEARNING ALGORITHM

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ABSTRACT: Recently, the utilization rate of Personal Mobility (PM) and its users have been rapidly increasing as a short-distance transportation option. As the consumption patterns shifted towards the sharing economy, various shared mobility platforms have been developed, leading to the emergence of PM in the form of shared electric scooters. Consequently, there has been a simultaneous increase in companies providing shared PM services. However, due to the diversity of shared PM offered by different service providers and variations in the number of providers across regions, the comprehensive management of PMs has become more challenging. Therefore, this paper aims to evaluate the feasibility of utilizing the YOLOv3 algorithm to detect shared PM objects from images collected by drones. The detection accuracy was evaluated to verify the potential for integrated management of PMs. PM objects within the experimental area were collected by drones, and labeling was performed to train a deep learning model for PM detection. The experimental results demonstrated a detection accuracy of 87.38% and an AP(average precision) value of 0.73, indicating high viability of utilizing the YOLOv3 algorithm on drone images to detect shared PMs.

1. INTRODUCTION

Personal Mobility (PM), a personal mobility device, is attracting attention as a new means of transportation due to its easy accessibility and economical and convenient use. With the recent active sharing economy, the use of shared personal mobility devices has dramatically increased in society (Choi, 2022). According to the Korea Transport Institute, the current usage of PMs in Korea surged to 60,000 in 2016, 75,000 in 2017, 90,000 in 2021, and 200,000 in 2022, resulting in various safety accidents and urban appearance problems (Korea Transport Institute, 2017). Since PM is a relatively recently developed transportation service and the business size is small, there are no companies with a significant advantage in market share. For this reason, various service providers exist. Currently, there are 16 shared PM service companies in Seoul, Korea. The facts that service-available companies varies from region to region and there are many service providers make it more challenging to manage integrated transportation system. Therefore, this study attempted to detect PMs using drone images. Finding the location from the GNSS receiver installed in the PM is a basic method. However, PM detection was performed using drone images and YOLOv3 deep learning algorithms because there are GNSS equipment damage and loss problems, GNSS signal reception problems depending on the parking and mounting conditions of the PM. As a related study, Park *et al*. (2020) classified and detected vehicles in drone images into passenger cars, trucks, and buses using the YOLOv3 algorithm and confirmed the possibility of real-time traffic analysis through vehicle detection and accuracy evaluation according to vehicle type. Wael and Lee (2022) tracked vehicles using the YOLOv5 algorithm based on drone vehicle detection results and analyzed the degree of air pollution on pedestrian roads. Kim *et al*. (2022) used the YOLOv5 algorithm to subdivide the returned PM into three parts according to the shooting angle. They suggested a technique to recognize the image in which the PM exists more accurately. In addition, users using PM in ground photos were detected through the YOLOv3 algorithm (Gilory et al, 2022). As such, a few studies have been conducted to detect vehicles using drones, and PM detection studies using ground photos have also been conducted. However, no studies have detected PM using drones to locate and manage PMs. Therefore, in this study, the images containing PMs were collected from drones. Then, the possibility of PM detection using drones was analyzed through accuracy verification

2. METHODS

In this study, PM detection was performed using the YOLOv3, an object detection algorithm based on deep learning. The drone image was acquired, and the acquired image was standardized to 512 by 512 pixels for training the deep learning model. A total of 1,528 PM objects were manually labeled using the resized images to train the model, detect PMs, and verify the usability.

2.1. Experimental area and data collection

A university campus consisting of flatland with high PM usage, Gyeongsang National University in Korea, was selected as an experimental area. The used drone is DJI's Phantom 4 RTK and drone images were taken four times. The drone was manually flown and hovered at an altitude of 50 m to obtain images, and the acquired image was standardized by dividing it into 512 by 512 pixels.

2.2. Model training

For model training, we used 'imageLabeler', the tool of Matlab software Computer Vision Toolbox, to label PM objects in the standardized images. A total of 1,528 PM objects were manually labeled in 353 standardized images. The YOLOv3 algorithm used for PM detection was implemented through Matlab software, and 353 images were randomly divided into 60% for training and 40% for testing. The network input size larger than the input size was required which is set to [227 227 3]. As a training set, the PM detection model was learned by setting Epochs 80 to go through 80 learning times for the entire dataset, Minibatchesize 8 to save learning time by dividing the entire dataset into 10 equal parts, and LearningRate 0.001, which means how much learning should be done once.

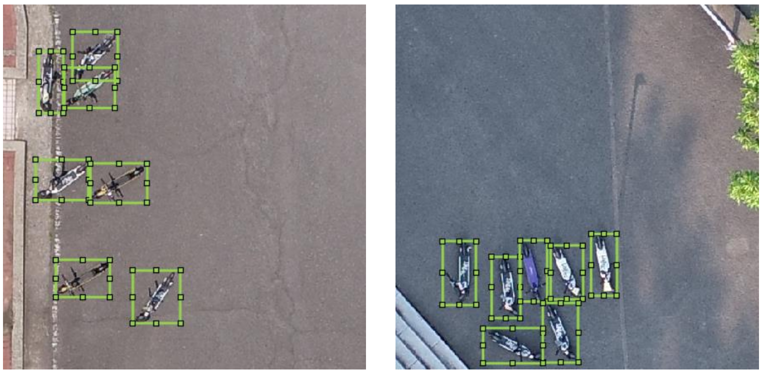

Figure 1. PM object labeling

3. RESULTS AND DISCUSSION

3.1. Detection results

As a result of detecting PM based on our model, a total of 618 PMs were detected. From the 618 PM detection results, 540 PMs were successfully detected. The number of misdetection was 78 and 135 were omission. The PM detection results according to different companies are shown in Table 1.

Table 1**.** PM detection results

Company	Correct detection	Misdetection	Omission
All PMs	540	40	135
A	315	29	21
B	55	1	41
C	40	2	14
D	50	4	18
E	80	4	41

3.2. Accuracy assessment

For accuracy assessment, evaluation indicators used in machine learning object detection were used. The representative way to check the performance of object detection is to investigate varying recall and precision rates using Precision-Recall (PR) graph. Average Precision (AP) is a comprehensive evaluation index as a representative value of a PR graph by averaging the value of precision for each unit. The figure 2 shows the PR graph when recall and precision change in this study. The performance of the PM detection model showed an AP value of 0.73.

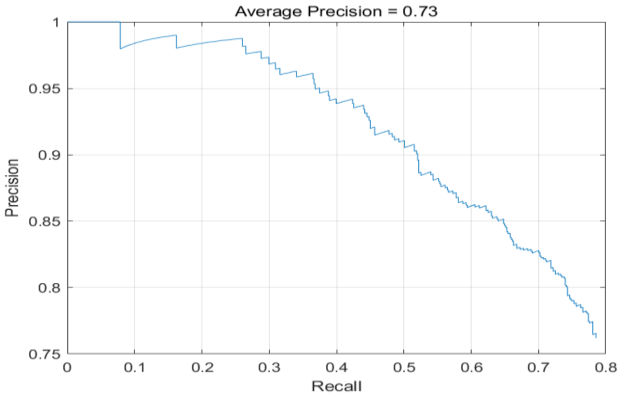

Figure 2. PR curve result

4. CONCLUSION

This paper detected shared PMs by applying a fast and accurate YOLOv3 deep learning model to drone images. Through this, we analyzed the possibility of detecting shared PMs in drone images. Images of parked PMs were collected using drones at an altitude of 50 m, and PMs were detected by training the YOLOv3 algorithm model, and accuracy evaluation was conducted. As a result of the experiment, it was confirmed that PM detection could be performed through drone images with a detection accuracy of 0.73 AP. However, when the PMs were parked closely, the many omissions in PM detection occured, and the PM detection results of Company B and E were more likely to be omitted than that of other companies. To resolve the problem, we plan to collect data for various filming angles and conduct additional experiments by enhancing training data for high density PM detection.

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