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Detecting Greenhouses from the Planetscope Satellite Imagery Using the YOLO Algorithm*

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YOLO 알고리즘을 활용한 Planetscope 위성영상 기반 비닐하우스 탐지*

김성수[1] · 정연인[2] · 정윤재[3※]

ABSTRACT

Detecting greenhouses from the remote sensing datasets is useful in identifying the illegal agricultural facilities and predicting the agricultural output of the greenhouses. This research proposed a methodology for automatically detecting greenhouses from a given Planetscope satellite imagery acquired in the areas of Gimje City using the deep learning technique through a series of steps. First, multiple training images with a fixed size that contain the greenhouse features were generated from the five training Planetscope satellite imagery. Next, the YOLO(You Only Look Once) model was trained using the generated training images. Finally, the greenhouse features were detected from the input Planetscope satellite image. Statistical results showed that the 76.4% of the greenhouse features were detected from the input Planetscope satellite imagery by using the trained YOLO model. In future research, the high-resolution satellite imagery with a spatial resolution less than 1m should be used to detect more greenhouse features.

KEYWORDS : Greenhouse, Planetscope satellite image, YOLO, Deep learning

요 약

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원격탐사 자료 기반 비닐하우스 탐지 기술 개발은 불법 농경 시설물의 현황 파악과 비닐하우스에서 재배되는 농작물 수량 예측을 위해 중요하다. 본 연구에서는 딥러닝 알고리즘을 활용하여 김제시 지역을 촬영한 Planetscope 위성영상들로부터 비닐하우스를 탐지하기 위한 방법을 제안하였다. 우선, 5장의 Planetscope 위성영상을 기반으로 비닐하우스 객체를 포함한 훈련 영상들을 제작하였다. 그리고, 훈련 영상들을 이용하여 YOLO(You Only Look Once) 모델을 학습시킨다. 학습시킨 YOLO 모델을 테스트 Planetscope 위성영상에 적용하여 비닐하우스 객체들을 탐지한다. 본 연구에서 제안한 방법을 적용한 결과, 주어진 Planetscope 위성영상으로부터 총 76.4%의 비닐하우스가 탐지되었다. 추후 연구에서는 공간해상도 1m 이하의 고해상도 위성영상에서 더 많은 비닐하우스 객체를 탐지하기 위한 기술을 개발할 계획이다.

주요어 : 비닐하우스, Planetscope 위성영상, YOLO 알고리즘, 딥러닝

INTRODUCTION

In the agricultural industry, a greenhouse is defined as “frames of inflated structure covered with a transparent material in which crops are grown under controlled environment conditions” (ScienceDirect, 2023). In general, a greenhouse is built for protecting out-of-season plants against extreme cold or hot weather(Britannica, 2023). A basic structure of greenhouses includes side walls, end walls, side posts and a rafter. The appropriate structure of a greenhouse depends on your local climate, types of cultivated crops and the size of your operation(Prospiant, 2023). Most greenhouses in South Korea have plastic covers and arched roofs that are suitable for growing cucumbers, melons, watermelons, pumpkins, strawberries and etc(Agroberichten Buitenland, 2023). Figure 1 shows examples of the greenhouses with plastic covers and arched roofs in South Korea.

Identifying the greenhouse locations is important in assessing the sun exposure,

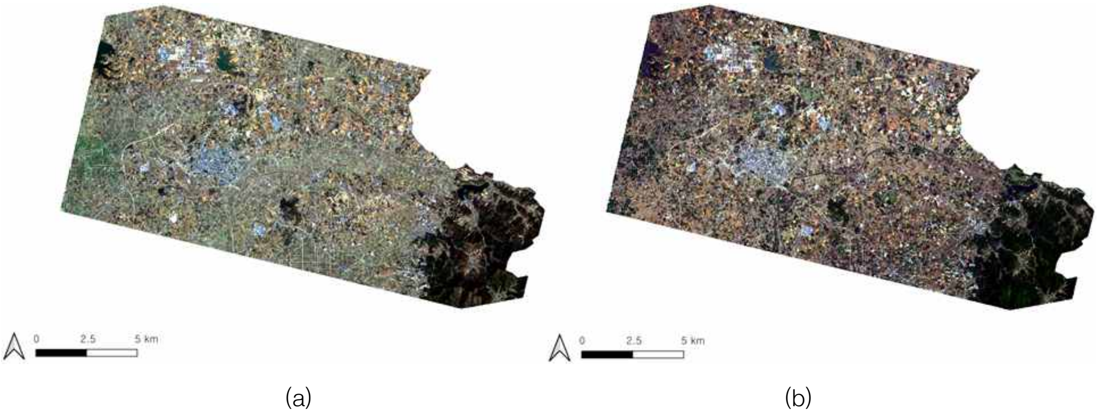
FIGURE 1. Examples of the greenhouses with plastic covers and arched roofs in South Korea (a figure captured from http://www.newsfarm.co.kr/news/articleView.html?idxno=49997)

wind exposure, drainage, slope and direction of the greenhouse, which is important in its operation(NIP Group, 2023). In general, remote sensing datasets such as the multispectral imagery acquired by the optical sensors of satellites or drones are useful in sustainably monitoring the croplands(Choung, 2015; Ham *et al.*, 2019; Lee and Choi, 2019). Recently, these remote sensing datasets have been used in detecting the greenhouses in agricultural areas. Sun *et al.*(2021) developed a method of mapping greenhouses from the two-temporal Sentinel-2 images and the pixel-based classifier. Yoon *et al.*(2023b) detected the greenhouses from the Planetscope satellite imagery using the image segmentation technique. Yoon *et al.*(2023a) also detected the greenhouse from the aerial orthoimage using the deep learning model.

Detecting the greenhouse from the remotely sensed imagery is challenging because the shapes of some greenhouses are not visually distinguished from the other structures such as buildings. In previous research, the greenhouse features were detected from the high-resolution imagery where these features were well visually identified. In this research, the object detection technique, was employed for automatically detecting the greenhouses in the low-resolution satellite imagery through the following steps. First, the training images that contains the greenhouse features were generated from the training Planetscope satellite imagery. Then, the YOLO model was trained using the training images. Finally, the greenhouse features were detected from the input Planetscope satellite image.

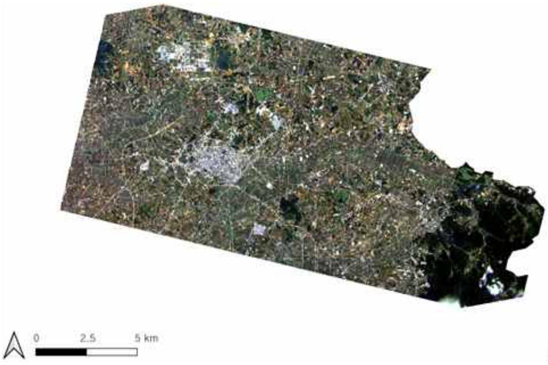
DATA AND STUDY AREA

FIGURE 2 shows the five scenes of the training Planetscope satellite imagery taken on 9 February 2020, 6 May 2020, 19 June 2020, 21 November 2020 and 22 May 2021 as acquired in the areas of Gimje City(approximately, 230㎢) used for generating the training images of greenhouse features. Also shown is the one scene of the input Planetscope satellite image taken on 4

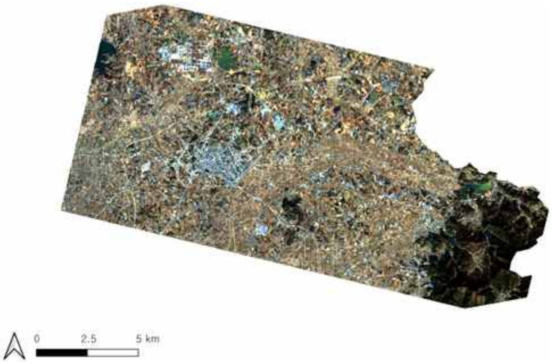


(a) (b)

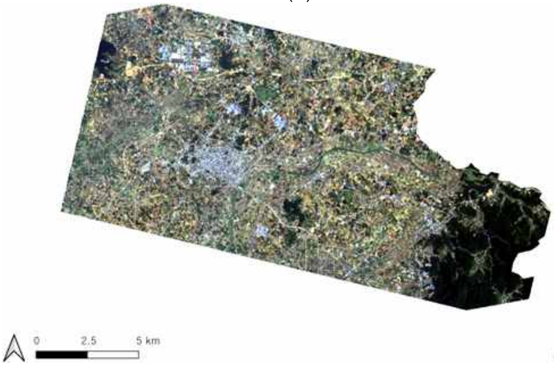
FIGURE 2. Planetscope satellite imagery used for generating the training images ((a) 9 February 2020; (b) 6 May 2020, (c) 19 June 2020; (d) 21 November 2020; (e) 22 May 2021) and detecting the greenhouse features ((f) 4 November 2022)



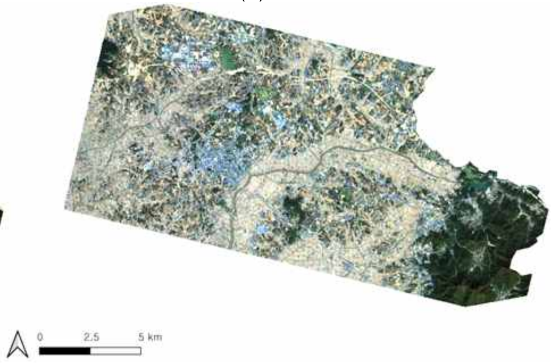
(c)



(d)



(e)



(f)

FIGURE 2. Continued

November 2022 used as the input image for detecting the greenhouse features. The given Planetscope satellite imagery have the 3 multispectral bands including blue, green and red bands, and their wavelengths are 465−515nm, 513−549nm and 650−680nm, respectively(SentinelHub, 2023).

The greenhouse features were generally visualized in the high-resolution satellite imagery such as the Google Satellite Map (FIGURE 3(a)), while they were not easily identified in the Planetscope satellite image (FIGURE 3(b)) due to its low spatial resolution(3m). We used the farm map data provided by the Ministry of Agriculture, Food and Rural Affairs to identify the locations of the greenhouse features in the given five Planetscope satellite imagery (see FIGURE 3(c)). Based on the farm map, the bounding box that contains the greenhouse feature was generated(see FIGURE 3(d)). FIGURE 3(e) represents the location of the bounding boxes for the greenhouse features in the entire Planetscope satellite image.

METHODOLOGY

This section illustrates the procedure for detecting the greenhouses in the given Planetscope satellite imagery. Deep learning is useful in detecting and localizing the specific objects in images, because it is superior in learning the hierarchical

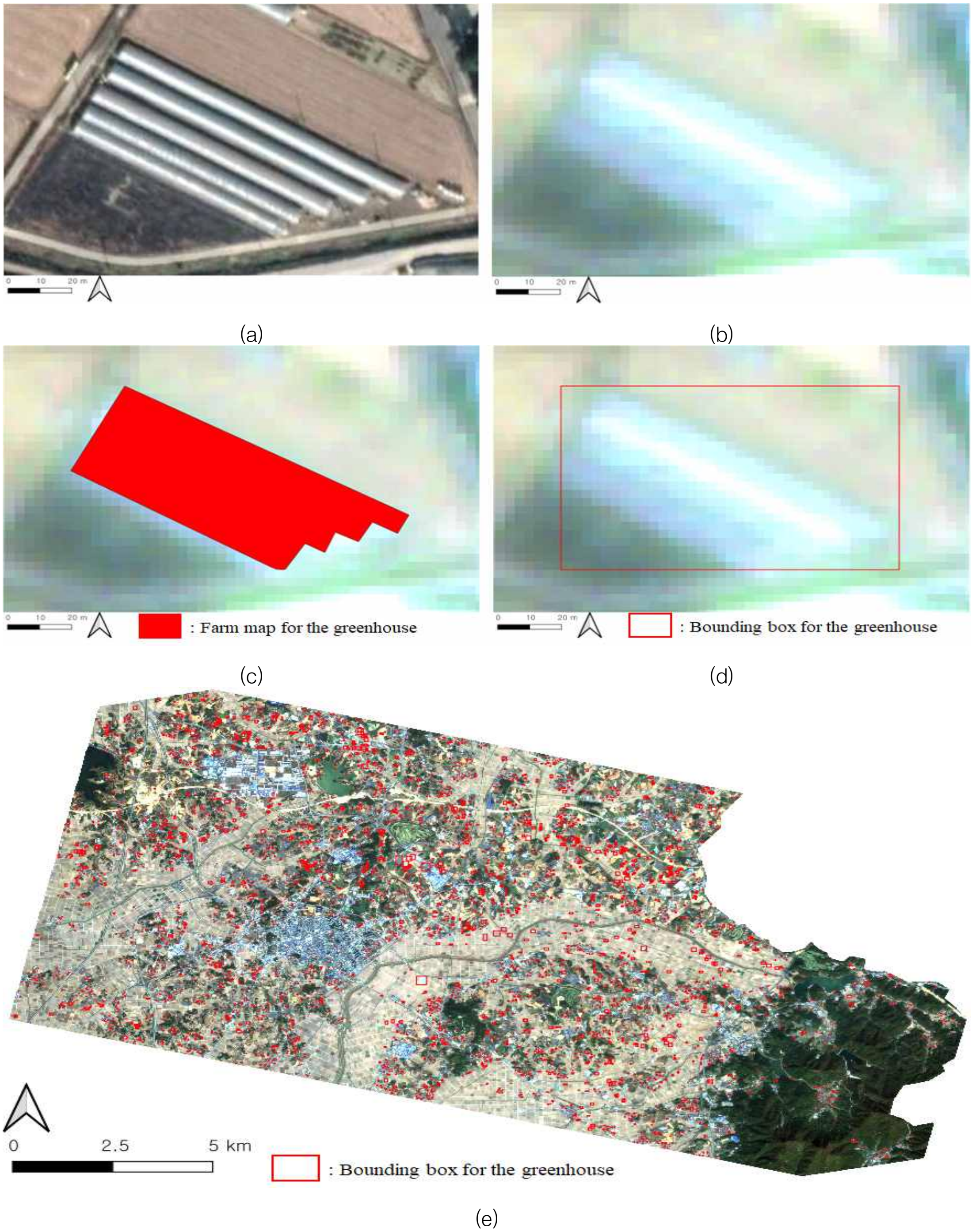


FIGURE 3. Greenhouse features shown in the Google Satellite Map(a), in the Planetscope satellite image (b), the farm map (c), the bounding box for the greenhouse feature (d), and the locations of all bounding boxes in the entire Planetscope satellite image (e)

representations of the features from the images and extract the meaningful features from the images(Wu *et al*., 2020). YOLO (You Only Look Once) is a widely used deep learning technique for detecting objects in images due to its high speed and accuracy. It uses an end-to-end neural network for making predictions of bounding boxes and class probability at once(Redmon *et al*., 2016). YOLO calculates the positions and the boundaries of the objects in the given image without the complex pipeline, while other algorithms such as R-CNN (Convolutional neural network) have the process of predicting the potential positions and extracting the boundaries of the objects in the given image using the convolution nets(Redmon *et al*., 2016; Datahunt, 2023). The objects in the images can be detected by using the YOLO algorithm through a series of steps. First, the input image is resized to match the neural network' s input dimension. Then, the employed deep convolutional neural network processes the entire image in a single forward pass and extracts hierarchical features from the input image. Next, the output feature map is divided into a grid and the size of this grid depends on the input image and the neural network' s architecture. Each grid predicts the multiple bounding boxes and class probabilities for the different object categories. Non-Maximum Suppression(NMS) is then applied to delete the redundant and overlapping detections. Finally, the remaining boxes after NMS are defined as the final detected objects(see FIGURE 4).

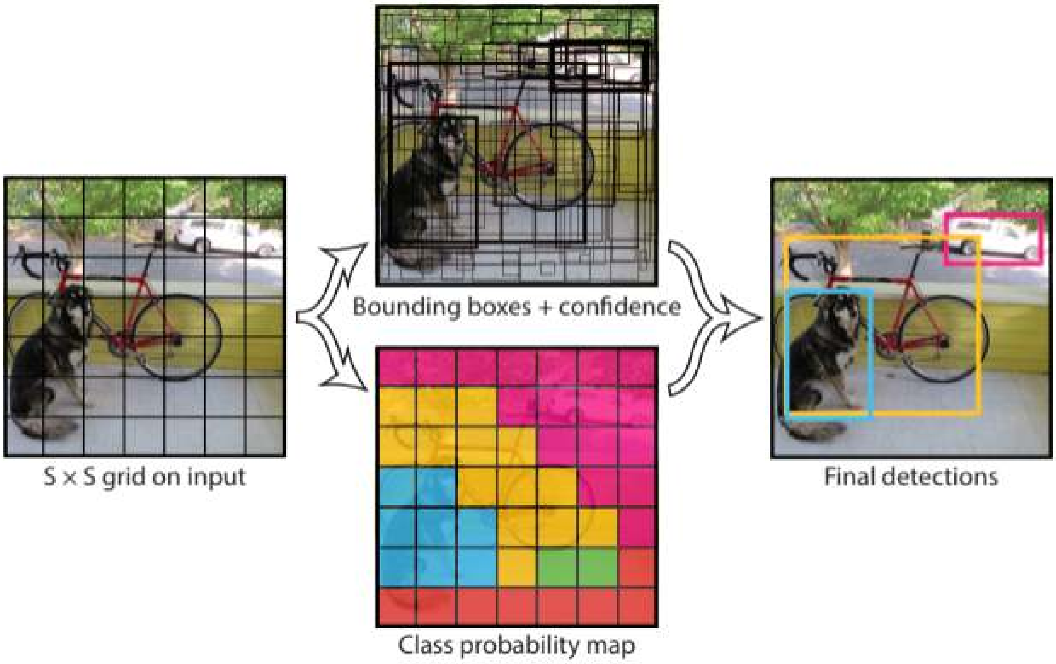


FIGURE 4. A figure showing the objects detected from the image using the YOLO algorithm (captured from Redmon *et al.*, 2016)

FIGURE 5. Examples of the training images that contain the greenhouse features

Since the YOLO algorithm was first introduced in 2016, it has undergone several iterations(V7, 2023), the latest being YOLO−v8 that was used in this research. The size of the training images that contain the greenhouse features was set at 640*640, the default input size of YOLO−v8 architecture. We also employed the bounding box augmentations for generating the 10,376 training images that contain the 62,108 greenhouse features with the labels. FIGURE 5 shows examples of training images that contain the greenhouse features with the red colored bounding boxes.

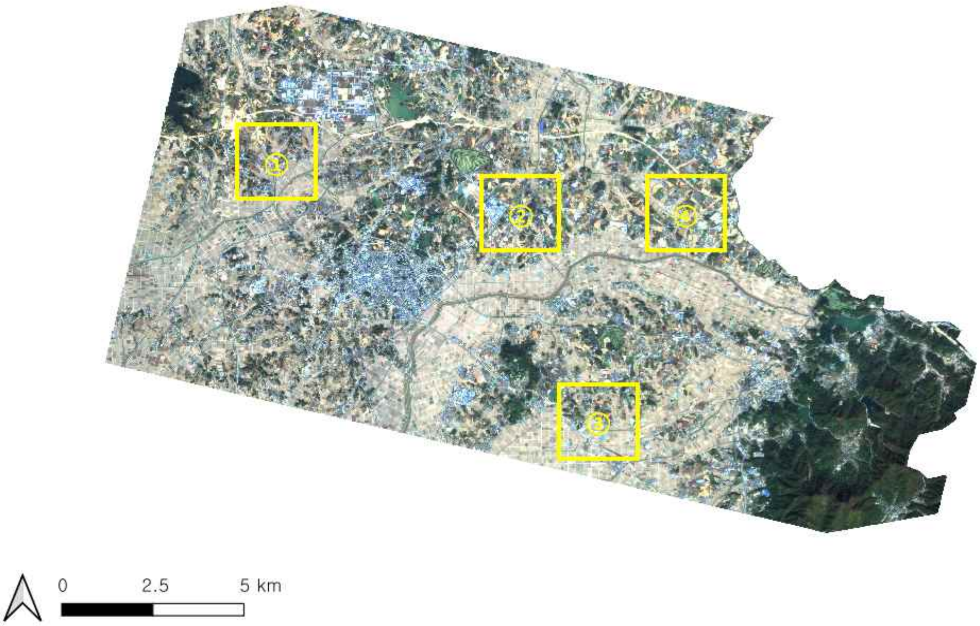
We trained the YOLO−v8 model using the training images with the 8−bit intensity values, and then the trained YOLO model was applied into the input Planetscope satellite image with the Red, Gree and Blue bands to generate the output image that contains the detected greenhouse features with the bounding boxes.

Results and Discussion

FIGURE 6 shows the output image that contains the detected greenhouse features with the bounding boxes.

After the greenhouses were detected, we calculated the detection rate of the greenhouses features with the single or multiple structures from the given Planetscope satellite image. The greenhouse feature was counted to be detected when the farm map polygon for the greenhouse features was visually contained in the generated bounding box. TABLE 1 Statistical results of the detection rate of the greenhouses from the given Planetscope satellite image.

As can be seen in TABLE 1, the detection rate of the greenhouse features from the input Planetscope image was 76.4%, which means that some greenhouse features were not detected from the input Planetscope satellite image due to a number



(a)

(b)

FIGURE 6. Output image that contains the detected greenhouse features with the bounding boxes: In the entire area (a), in the area ① (b), in the area ② (c), in the area ③ (d), in the area ④ (e), respectively.

(c)

(d)

FIGURE 6. Continued

(e)

FIGURE 6. Continued

TABLE 1. Statistical results of the detection rate of the greenhouses from the given Planetscope satellite image

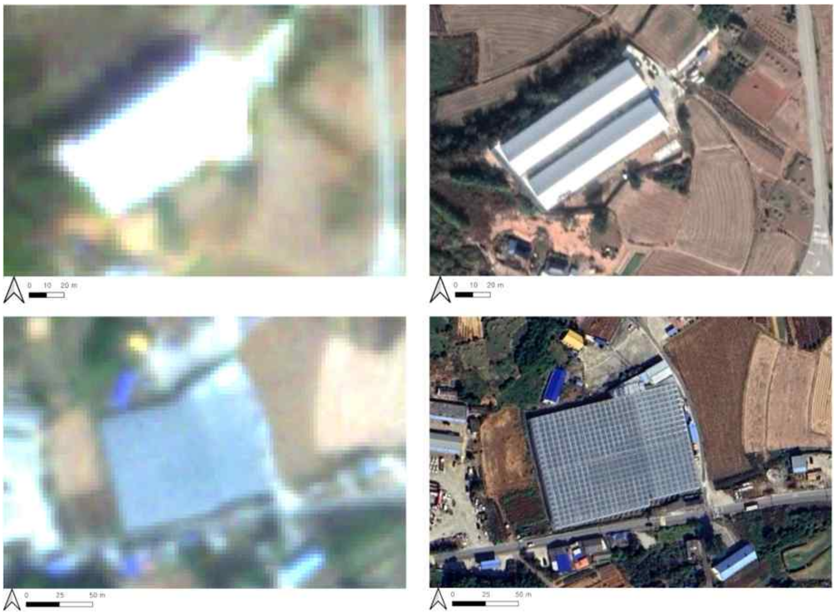
Number of the greenhouse features visually identified	Number of the greenhouse features detected using the trained YOLO model	Detection rate of the greenhouse features using the trained YOLO model
1,000	764	76.4%

of reasons. First, the original size of the training images that contain the greenhouse features was 640*640, resulting in non-detection of the greenhouse features that were not contained in the training images with the bounding boxes. Second, the greenhouse features that have different shapes, colors, directions from the greenhouses in the training images with the bounding boxes were not detected. FIGURES 7 and 8 show examples of the undetected greenhouse features and the detected greenshouse features shown in the input Planetscope satellite image and Google Satellite Map.

As can be seen in FIGURES 7 and 8, the greenhouses with the arched roof structures were well detected, while the greenhouses with the other roof structures were not detected from the input Planetscope satellite image using the trained YOLO model.

Conclusion

In this research, we proposed a methodology



(left) (right)

FIGURE 7. Examples of the undetected greenhouse features from the input Planetscope satellite image using the trained YOLO model: Planetscope satellite image (left) and Google Satellite Map (right)

(left) (right)

FIGURE 8. Examples of the detected greenhouse features from the input Planetscope satellite image using the trained YOLO model: Planetscope satellite image(left) and Google Satellite Map(right)

for detecting the greenhouse features in a given Planetscope satellite imagery using the YOLO model. Results showed that 76.4% of the greenhouse features were detected from the input Planetscope satellite image, which means that the proposed methodology can contribute significantly to the management of crop production greenhouses. However, some greenhouse features with different structures from the greenhouse features in the training images were not detected using the proposed methodology. In future research, research on detecting the various types of greenhouses from the remote sensing datasets should be carried out by using the other object detection models. In addition, the use of the high-resolution satellite image with the less than 1m and the more training images is recommended for visually identifying the locations of the greenhouse features and enhancing the detection rates of the greenhouse features from the image sources. KAGIS

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