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# Wasp-Hive Candidate Site Search System Using a Small Drone

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## ABSTRACT

Early detection of wasp hives is crucial for mitigating their impact on native species, preventing agricultural damage, and improving pest control strategies. Traditional detection methods rely on ground surveys and sensor-based tracking of individual insects, which are often labor-intensive, time-consuming, and prone to errors because of environmental constraints. The integration of artificial intelligence and drone-based imaging has the potential to revolutionize ecological monitoring by providing scalable, efficient, and noninvasive methods for detecting wasp hives. However, research on AI-assisted hive detection remains limited, with most studies focusing on large-scale wildlife monitoring rather than small-object localization. Therefore, we propose a system for searching the candidate site of a wasp hive using a small drone. In the proposed system, a small drone is equipped with a camera and takes aerial images of the error range. Subsequently, three-dimensional (3D) modeling is performed on the captured images using a 3D surveying toolkit, and deep learning–based hive detection is performed on the completed 3D model to extract the GPS information of the detected target.

## 1 | Introduction

Artificial intelligence (AI) has progressed rapidly in recent years, driving innovation in various industries (LeCun et al. 2015; Schmidhuber 2015). In particular, the advancement of deep-learning and machine-learning technologies has considerably expanded the applicability of AI in fields such as medicine (Esteva et al. 2017) and manufacturing (Wang et al. 2018). These technologies have demonstrated performance that surpasses human intuition in solving complex problems (Bengio et al. 2017; Silver et al. 2016) and have achieved outstanding results in data analysis (Chui et al. 2018), predictive modeling (Jordan and Mitchell 2015), and automated systems (Jafari et al. 2022).

One promising yet underexplored application of AI is ecosystem management (Han et al. 2024; Maxwell et al. 2016), which remains in its early stages of development (Christin et al. 2019). Ecosystem management is essential for environmental protection and the sustainable use of natural resources, playing a vital role in maintaining the health of the Earth (Mace et al. 2018; Ceballos et al. 2017). However, because of the complexity of ecosystems, data collection and analysis in this field present significant challenges (Farley et al. 2018). Recently, there has been growing interest in leveraging AI for ecosystem monitoring; however, many technical challenges remain (Borowiec et al. 2022). For instance, drone-based monitoring has the potential to provide rapid ecological assessments, yet AI's role in accurately analyzing and interpreting this data requires further investigation (Anderson and Gaston 2013; Linchant et al. 2015).

Searching for wasp hives is a critical task in ecosystem management. Although previous research has focused on tracking individual insects using miniaturized sensors (Walter et al. 2021), this approach has limitations because of tracking errors and sensor weight constraints (Kim, Ju, and Son 2022). However, in many ecological applications, identifying the precise location of hives rather than individual insects is more practical and effective. Early detection of wasp hives can help mitigate ecological imbalances, prevent agricultural damage, and improve biodiversity conservation efforts. Therefore, developing an AI-assisted searching system to efficiently search for wasp hives is necessary to enhance ecosystem monitoring (Mirzaei et al. 2023).

Currently, research utilizing AI in ecosystem management mainly focuses on estimating the population of wild animals and monitoring environmental changes using image recognition and analysis (Tsouros et al. 2019). However, although extensive studies exist on large-scale ecosystem monitoring, research on hive detection remains limited, despite its significance in biodiversity conservation and pest control. Identifying and locating hives, such as wasp, is crucial for effective ecological studies and environmental management. To improve hive localization, more precise and efficient AI-driven solutions are required (Rozenbaum et al. 2024). In particular, integrating drone-based imaging with AI-powered analysis can significantly enhance hive detection from high-resolution aerial images, enabling the development of more accurate ecosystem-management strategies (Tang and Shao 2015).

Our research group has developed a wireless telemetry–based tracking system for ecosystem management that performs aerial tracking using unmanned aerial vehicles (UAVs) equipped with receivers and antennas. Similar to other sensor network–based studies, our tracking strategy includes three steps: capturing the sensor, attaching it to the target, allowing a rest period for recovery, and then performing the actual tracking. Despite these efforts, our system still had a tracking error of approximately 50 m (Kim et al. 2019; Kim, Ju, and Son 2022). Later, we developed and evaluated a multiantenna-based system to reduce the tracking error but found that the tracking error was around 20–40 m (Kim, Pak, et al. 2022). These findings highlight the need for advanced AI-driven methods that can overcome existing tracking limitations and enhance the accuracy of wasp hive search in ecological monitoring.

In this paper, we propose an AI-driven drone system for efficient wasp-hive candidate site search. The system aims to enhance hive localization accuracy by leveraging aerial imagery and deep-learning–based recognition (Figure 1). The proposed system utilizes a small drone equipped with a camera to search for a wasp hive within the identified error range. The camera captures the images of the region of interest (ROI), and the drone provides GPS coordinates for the capture point. These images are then used to create an extensive map, upon which deep learning–based object recognition is performed. Finally, the GPS coordinates of the recognized points are extracted to estimate the precise location of the wasp hive.

## 1.1 | Related Works

### 1.1.1 | AI-Based Ecosystem Management and Monitoring

In recent years, AI technology has begun to play an important role in ecosystem management and monitoring. In particular, the advancement of image recognition and analysis technology has enabled various applications such as wildlife protection, biodiversity monitoring, and environmental change monitoring. Borowiec et al. (2022) conducted an in-depth review of how deep learning technology can be applied in ecological and evolutionary research. They discussed how AI, particularly deep learning, holds the potential to replace traditional manual-based methods currently used in ecosystem management. The study highlighted that deep learning enables the automated analysis of complex ecosystem datasets, facilitating real-time monitoring and rapid responses to environmental changes.

Anderson and Gaston (Anderson and Gaston 2013) emphasized the innovative changes that combining AI with drone technology would bring to spatial ecology research. They explained that the combination of high-resolution image collection using drones and AI-based analysis has enabled a more precise understanding of the spatiotemporal patterns of ecosystems. Linchant et al. (2015) also emphasized the importance of AI in wildlife monitoring using drones and argued that the integration of

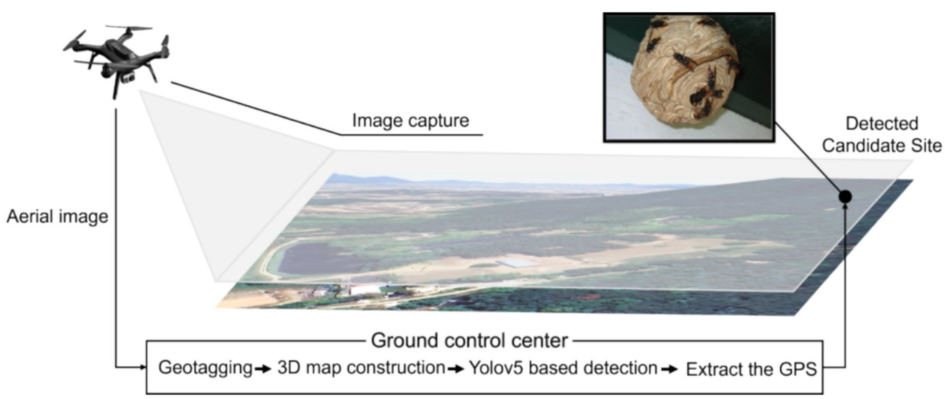


**FIGURE 1** | Concept of a system for searching the candidate site.

drones and AI facilitates a more precise analysis of the distribution and behavior of species.

However, the abovementioned studies mainly focused on monitoring large animals or the ecosystem status of specific areas, and scarce attention was paid to tracking and monitoring small objects such as insects. Rozenbaum et al. (2024) successfully developed an AI-based system to monitor the movements of small organisms, such as insects, utilizing machine learning techniques to analyze their movement paths and behavioral patterns. This advanced technology is particularly effective in tracking the critical roles insects play within ecosystems, enabling real-time detection of their responses to environmental changes. The application of such systems has proven to be instrumental in rapidly assessing insect behavior, providing valuable insights into ecological dynamics and aiding in the management of environmental shifts.

#### 1.1.2 | Sensor Networks and AI for Tracking Small Objects

Tracking the location of small objects such as insects is an important task in ecosystem research, and various studies based on sensor networks are being conducted to solve the problems faced in performing this task. Kim, Ju, and Son (2022) pointed out the limitations of sensor networks in studying the movement patterns of small animals, specifically emphasizing that tracking errors that occur during the miniaturization of sensors can hinder the accuracy of the research.

Walter et al. (2021) review methods for small object detection, emphasizing the shortcomings of current sensor technologies in handling tiny objects and the need for improved AI-driven solutions for real-time tracking. To address these challenges, researchers have proposed combining sensor networks with AI-based image analysis technologies, which offer better accuracy and efficiency in tracking small insects in real-world environments.

Wang et al. (2023) proposed a deep learning–based approach to detect small objects in complex scenes and showed that this method could be effectively used to track small objects such as insects. This study suggests that deep-learning models utilizing high-resolution images can reduce errors that occur in sensor-based approaches. Tsouros et al. (2019) also discussed how the combination of small sensors and AI can be used for crop monitoring in precision agriculture based on UAVs, suggesting that similar technologies can be applied to ecosystem management.

On the basis of existing studies, the present study proposes a technology to search for habitat candidates for small individuals in terms of ecosystem management using a new approach combining drones and AI. This will contribute to the identification of habitat locations of small entities such as insects with greater precision and increase their applicability in ecosystem management.

## 2 | Candidate Site Search System

In this study, we propose a small-drone–based wasp-hive-searching system that comprises two main processes: aerial image–based mapping and wasp hive estimation. This system employs the 3DR Solo drone as an exploration tool, capturing high-resolution aerial images with a GoPro Hero4 Black camera. The acquired images are processed on a computer system for three-dimensional (3D) mapping and object recognition. Drone control and image acquisition are managed by Pix4D Capture software, and location information is obtained from the GPS sensor mounted on the drone (Figure 2). This allows for precise location mapping and efficient data collection, serving as the foundation data for an enhanced object-recognition algorithm.

The wasp hive estimation strategy involves a drone moving to a specific location via sensor network–based tracking. This location is designated as an ROI, considering the error range, and aerial image capture is performed in that region. Captured images are transmitted to the ground control center, where 3D mapping is performed using OpenDroneMap (ODM), an open-source photogrammetry toolkit. The 3D-mapped images are analyzed by a deep learning–based object recognition algorithm. The mapped image is repeatedly rotated, and a recognition task is performed to accurately identify the wasp hive. Yolov5 is used for object recognition, and when the wasp hive is recognized, the GPS information of the location is extracted and used as precise geographical information (Figure 3).

### 2.1 | Capturing Aerial Images

The proposed system uses 3DR Solo and a GoPro HERO4 Black camera to capture aerial images and evaluate habitat candidates. The drone and camera are connected through a dedicated gimbal, which blocks noise caused by disturbance or vibration during flight. When capturing aerial images, the images do not contain geometrical data. Therefore, the drone's GPS information is saved at each shooting time. Additionally, the proposed system performs two flights within one area to prevent distortion during the future map production process. For the first flight, image capture is performed without a set path and separate camera tilting. Subsequently, in the second flight, it flies by rotating 20° compared with the first flight, and images are

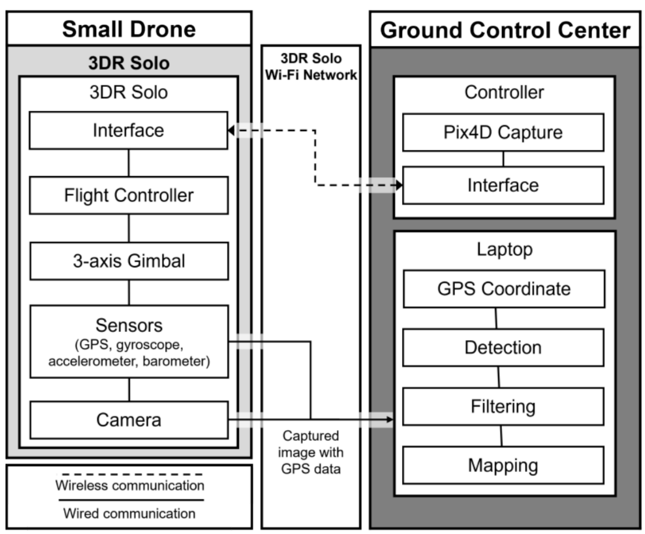


**FIGURE 2** | Architecture of the small-drone–based wasp's hive estimation system.

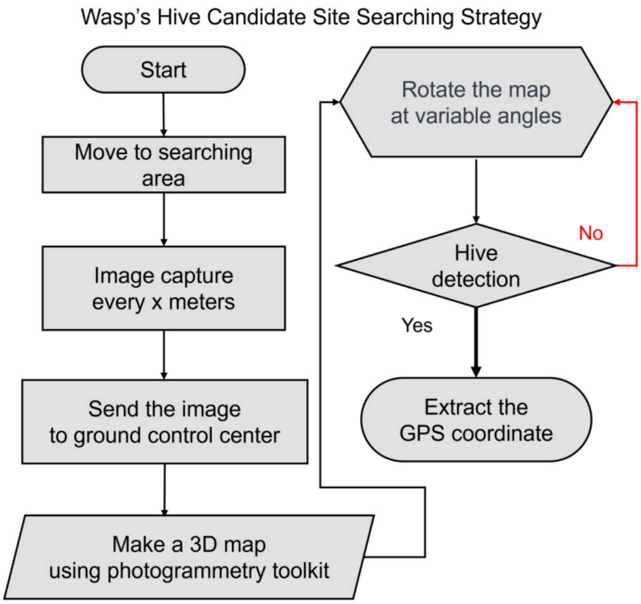


**FIGURE 3** | Flowchart of wasp-hive candidate site searching system.

taken by tilting the camera forward by 5°. The corresponding aerial image capture and flight control are performed using Pix4D Capture.

## 2.2 | Mapping for ROI

Images captured by GoPro HERO4 do not include the exchangeable Image File Format for geographic information. Therefore, geotagging is performed on each image using the drone's GPS sensor data. Each image includes time data at the moment of shooting, and the drone's GPS data also store information at that time. We selected the GPS information of the shooting location by matching the shooting time information of the image with the time of the GPS data and performed geotagging on each image. Next, ODM is used for image-based 3D map production, which includes geographic information. ODM is an open-source photogrammetry toolkit that processes aerial images into maps and 3D models. ODM processes images using the structure-from-motion (SfM) algorithm, estimating the position and orientation of the camera and generating a 3D point cloud. The point cloud data are converted into a mesh, and a textured 3D model is generated via a texturing process. The resulting 3D model is saved in .obj and .ply format. In addition, metadata including geotagging is attached to the model, so that all points in the model contain geographic location information.

## 2.3 | Detection and Extract GPS

The process of capturing images from various angles from a 3D model and recognizing objects in the images using the You Only Look Once (YOLO) algorithm was performed as follows. First, the generated 3D model file was loaded using QGIS software. QGIS is an advanced 3D modeling and rendering tool that provides the ability to visualize 3D models from various angles and capture them as images. After loading the 3D model, the camera viewpoint was set to surround the model in a circular shape to observe and capture the overall structure of the model from various viewpoints. The camera position was expressed as ($x_c$, $y_c$, $z_c$) in the world coordinate system, and the camera direction (rotation matrix $R_c$) was adjusted so that the camera faces the center of the model.

After the camera viewpoint was set, the camera was rotated around the model, and images were captured at regular angular intervals. For example, the camera was moved at 10° intervals during a 360° rotation and a total of 36 images were captured. Each image contained the camera position ($x_c$, $y_c$, $z_c$) and rotation $R_c$ information. This information was later used in the process of conversion into 3D model coordinates. The captured images reflected the structure of the 3D model at each point in time and enabled the detection of objects in the model from various angles.

The YOLOv5 model was used to recognize objects from the captured images. YOLOv5 is a real-time object detection model that shows excellent performance in object recognition and can detect multiple objects in an image simultaneously by a single forward pass. The YOLOv5 model, which was trained by augmenting 147 of wasp-hive images into 514 images, was used to perform object recognition on each image.

The Yolov5 model was applied to each captured image to detect objects. The center point of the $\left(x_{\min}, y_{\min}, x_{\max}, y_{\max}\right)$ coordinates representing the bounding box of the detected object was calculated to extract the two-dimensional (2D) image coordinates $(u, v)$, which are defined as follows:

$$(u, v) = \frac{x_{\min} + x_{\max}}{2}, \frac{y_{\min} + y_{\max}}{2} \tag{1}$$

The process of converting the 2D image coordinates extracted by Yolov5 into the coordinates of the 3D model is performed via the inverse projection process using the camera matrix and external parameters. First, the matrix $K$ of the camera for each viewpoint is defined as follows:

$$K = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where $f_x, f_y$ represent the focal length of the camera and $c_x, c_y$ represent the principal point of the image sensor.

The camera position and orientation at each viewpoint are defined by the rotation vector $R$ and the transformation vector $T$. $R$ represents the rotation in 3D space, and $T$ represents the camera position. These values are defined according to the camera position and rotation information set in QGIS. Afterwards, using the given 2D image coordinates $(u, v)$, camera matrix $K$, and external parameters $R, T$, the 3D model coordinates $X_{\text{target}} = (X, Y, Z)$ are calculated using the following formula:

$$\lambda_i \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} = k\left(R_i \times X_{\text{target}} + T_i\right) \tag{3}$$

where $\lambda$ is a scale vector, which represents the depth in the $Z$-axis direction in 3D coordinates.

## 3 | Experiments and Results

To evaluate the developed system, experiments were designed in two environments: an urban environment and a forest experiment. In the case of wasps, it has been reported that they leave the forest, create hives in urban areas, and cause damage to civilians. Therefore, we evaluate the search performance in the urban environment by considering wasps that had expanded their habitat beyond the forest and into the city center. In the second experiment, a field experiment was conducted in the forest to explore the hives of wasps living in the forest, which is their main habitat.

### 3.1 | Experiment in an Urban Environment

#### 3.1.1 | Experiment Setup

To verify the wasp-hive search performance of the proposed system within the city, an experiment was designed for three wasp-hive models, and the experiment was repeated five times (Figure 4). The experiment location was at Chonnam National University in Gwangju, Korea, and a search was conducted over an area 100 m in width and length. Three wasp-hive models were installed on the roof of the building. The three hive models performed one search and then changed locations to conduct a re-search. To prevent influence from various structures on campus, the drone was maintained at an altitude of 60 m, and if a problem occurred while acquiring image data, it returned to the home base to ensure the quality of the mapping product. After completing aerial image acquisition of the area of interest, the data were transferred to the ground control center to perform mapping and hive detection.

#### 3.1.2 | Experiment Result

The results of five search experiments are presented in Table 1, where "—" indicates cases where target recognition failed, preventing GPS coordinates from being extracted. In the first search, one of the three hive models was recognized, and when the actual GPS coordinates of the recognized model were compared with the extracted GPS coordinates, an error of approximately 23 m was confirmed. In the second search, one of the three hive models was recognized, and when the actual GPS coordinates of the recognized model were compared with the extracted GPS coordinates, an error of around 17 m was observed. In the third experiment, one of the three models was also recognized; when the actual GPS coordinates of the model were compared with the extracted GPS coordinates, an error of about 25 m was found. In the fourth experiment, recognition failed. Finally, in the fifth experiment, one model was recognized, and when the actual GPS coordinates of the model were compared with the extracted GPS coordinates, an error of about 2 m was confirmed.

### 3.2 | Experiment in a Forest Environment

#### 3.2.1 | Experiment Setup

Unlike the experiment in an urban environment, to verify the wasp-hive search performance of the proposed system in the forest, an experiment on two wasp hive models and one actual hive was designed and repeated three times (Figure 5). The experiment location was at Modeungsan Mountain in Gwangju, Korea, and a search was conducted over an area 100 m in width and height. Two wasp hive models and one actual hive were randomly placed within the range of interest. Three targets were searched once; then their locations were changed and searched again. To prevent influence from various structures in the forest, the drone was maintained at an altitude of 60 m, and if a problem occurred while acquiring image data, it returned to the home base to ensure the quality of the mapping product. After completing aerial image acquisition of the area of interest, the data were transferred to the ground control center to perform mapping and hive detection.

#### 3.2.2 | Experiment Result

We conducted a model search experiment in an actual mountainous area using the proposed system. The experiment was designed to evaluate the performance of the system in a complex

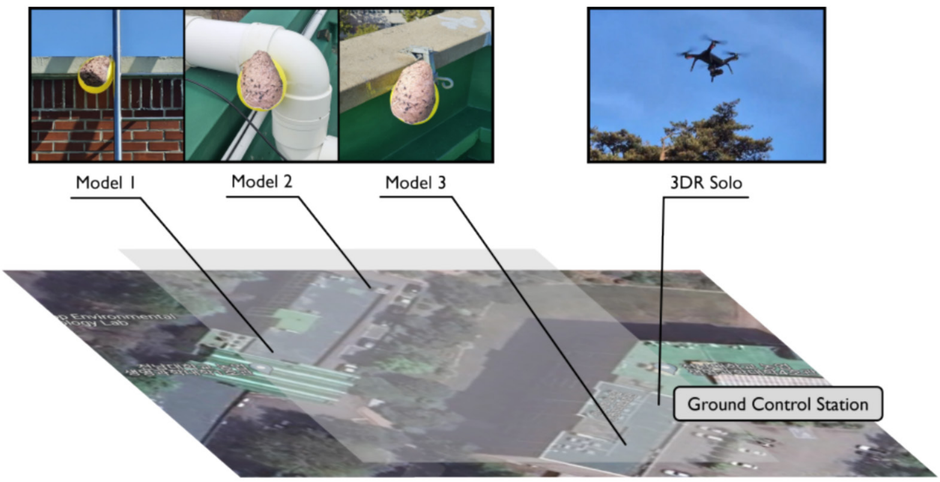


**FIGURE 4** | Experiment setup in an urban environment.

**TABLE 1** | Experimental results for three hive models in an urban environment. GPS refers to the mobile phone–based GPS information at the location where each model was installed. Extracted GPS represents the GPS information obtained using our system.

| Trial 1 | GPS | Extracted GPS |
|---|---|---|
| Model 1 | 35.176152, 126.900629 | 35.17632061997591, 126.9007887008157 |
| Model 2 | 35.175642, 126.900801 | — |
| Model 3 | 35.175567, 126.900933 | — |
| **Trial 2** | **GPS** | **Extracted GPS** |
| Model 1 | 35.176261, 126.900733 | — |
| Model 2 | 35.175688, 126.900900 | — |
| Model 3 | 35.175893, 126.901099 | 35.1759939282907, 126.90124727350667 |
| **Trial 3** | **GPS** | **Extracted GPS** |
| Model 1 | 35.175996, 126.901241 | — |
| Model 2 | 35.175727, 126.901020 | — |
| Model 3 | 35.176349, 126.900734 | 35.176130114698026, 126.90066821109794 |
| **Trial 4** | **GPS** | **Extracted GPS** |
| Model 1 | 35.176344, 126.900913 | — |
| Model 2 | 35.176082, 126.901531 | — |
| Model 3 | 35.176017, 126.901417 | — |
| **Trial 5** | **GPS** | **Extracted GPS** |
| Model 1 | 35.175996, 126.901241 | — |
| Model 2 | 35.175727, 126.901020 | 35.175721299322156, 126.90100218870104 |
| Model 3 | 35.176349, 126.900734 | — |

natural environment, and after randomly placing two models and an actual hive, the search process was repeated. The experiment was conducted three times, where the location of the models was changed each time. The experimental results revealed that the proposed system failed to detect the target model in all three experiments. The mountainous area where the experiment was conducted had a very complex structure with various natural objects such as grass and trees. The diverse appearances and shapes of these natural objects compared with urban environments led to a rapid increase in the number of feature points extracted from images acquired by drones. This apparently had a negative impact on the quality of the 3D model, which in turn led to errors in the object detection process.

## 4 | Discussion

In this study, we developed an AI-driven drone system for wasp hive candidate site search to address the limitations of traditional tracking methods. Unlike previous sensor-based tracking approaches, which often suffer from localization errors and environmental constraints, the proposed system integrates aerial imaging, 3D modeling, and deep learning–based hive detection to enhance accuracy. The results demonstrate that this method significantly improves detection capabilities in controlled urban environments. However, several challenges remain when applying the system to complex real-world scenarios.

One of the main limitations observed in this study is the recognition success rate across different environmental conditions. Although the system performed well in urban settings, as detailed in Section 3.2.2, its detection rate in a real forest environment was considerably lower. Factors such as dense vegetation, lighting variations, and background noise may have impacted the deep learning model's ability to accurately distinguish hives from their surroundings.

To overcome these limitations, future research should focus on enhancing the robustness of the detection model by

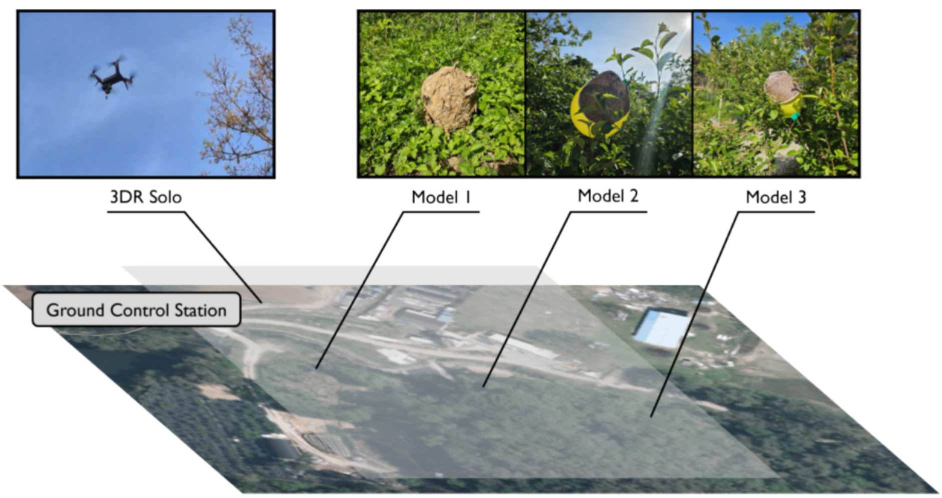


**FIGURE 5** | Experiment setup in a forest environment.

incorporating adaptive algorithms capable of handling diverse environmental conditions. Specifically, integrating LiDAR-based depth perception could enhance detection performance in dense vegetation by providing additional geometric context. Furthermore, thermal imaging could help distinguish wasp hives from their surroundings by leveraging temperature differences, thereby addressing the limitations of conventional RGB-based detection. Additionally, developing more advanced deep learning models trained on a broader range of real-world data could further mitigate recognition errors and improve overall system performance.

Despite these challenges, the proposed system offers a scalable and efficient solution for wasp hive detection, contributing to AI-driven ecological monitoring and pest control strategies. In future work, we plan to improve detection accuracy and tracking success rates by incorporating thermal camera data into the system. Because wasp hives maintain an optimal temperature to support larval development within the colony, leveraging thermal imaging could provide valuable additional features for hive detection. Based on this principle, our goal is to continuously refine and enhance the proposed system to improve its searching performance and contribute to ecosystem management. Future work will focus on further optimizing the system's capabilities for real-world applications, ensuring greater reliability in both urban and natural environments.

## 5 | Conclusion

In this study, we propose a system for searching the candidate site of wasp hives using a small drone and conduct the experiment in two environments. A drone equipped with a camera takes aerial images of the ROI and stores geographical information, and the ground control center geotags and produces an ODM-based 3D model. Then, Yolov5-based wasp-hive recognition is performed, and GPS coordinates of the recognized objects are extracted. Experiments on three models in an urban environment were designed and conducted, and four out of 15 models were recognized and GPS information was confirmed. Afterwards, in a forest environment, two models and one actual hive were tested, where nine models were not recognized. In this process, AI performed precise analysis that could compensate for errors in sensor-based tracking, indicating the potential for a new tool in ecosystem management. Thus, this study will contribute to complementing areas where AI technology has been lacking in ecosystem management, particularly solving the problem of precise location estimation and candidate site selection in small object tracking. Beyond simple technological advancement, this approach could provide practical solutions for ecosystem protection and sustainable environmental management and is expected to be expanded through further research and applications.


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### Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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