The Be-Hive Project—Counting Bee Traffic Based on Deep Learning and Pose Estimation

Chirag Padubidri[1,2](✉), Andreas Kamilaris[1,3], Alexis Charalambous[1], Andreas Lanitis[1,2], and Marios Constantinides[1]

[1] CYENS Centre of Excellence, Nicosia, Cyprus
[2] Cyprus University of Technology, Limassol, Cyprus
c.padubidri@cyens.org.cy
[3] University of Twente, Enschede, Netherlands

Abstract. Beekeeping is an important practice for ensuring the abundance of pollinators and for honey production. Traditionally, beekeepers inspect hives regularly to monitor their bees' populations, but this method is invasive and can cause stress to the bees. It is also impractical, for beekeepers having hundreds or thousands of beehives. In recent decades, various attempts have been made to automate the monitoring of bee colonies using emerging technologies. These technologies include sensors that collect micro-climate parameters, photos, video and audio from inside the hives and the nearby environment, which are then analyzed using automatic or manual methods. The beehive project aims a range of sensing technologies (image, sound, temperature, humidity, weight), together with state-of-the-art computer vision technologies and remote-sensing imagery to create a smart beehive system and monitor beehive on real-time. In this paper, we present the preliminary results of the BE-HIVE, a smart beehive monitoring system. We present the monitoring system developed and the deep learning algorithm used to count bee traffic using the image from the camera placed at the entrance of the hive. For bee traffic estimation, we employ a counting algorithm that predicts the pose of individual bees and tracks them in subsequent frames. To reduce the annotation overhead of the key-points for pose estimation, we generate synthetic data to train our algorithm. The results show that the key-point detection model achieves an Intersection Over Union (IOU) of 86% when trained only on synthetic data and a traffic count mean absolute error of 5.7. These results indicate that the proposed approach can be used to monitor the bee activity remotely, increasing convenience and productivity.

Keywords: Smart beehive · IoT · Deep learning · Bees' traffic counting

1 Introduction

Honey bees and pollinators in general constitute a key component of our planet's ecosystem and an essential actor in the global food production. With their pollination services, bees facilitate the growth of more than one-third of the world's

K. Arai (Ed.): IntelliSys 2023, LNNS 823, pp. 531–545, 2024.
https://doi.org/10.1007/978-3-031-47724-9_35

crops, which is crucial for the agricultural industry [15] and for feeding the human population and animals. In the United States alone [8], honey bees are estimated between 21.22 and 54.75 billion. However, the population of honey bees has experienced a drastic decline in recent years, primarily due to Colony Collapse Disorder (CCD) [19], as well as factors like climate change, pesticides, and diseases [17]. This decline in honey bee populations has a significant impact on global food security and ecosystem stability. Monitoring honey bee populations is essential to understand their health and well-being, which is critical for preventing colonies' collapse. Traditionally, beekeepers visually inspect their hives to assess the bees' health, manually looking around the hive for potential threats. However, this method is time-consuming, inefficient, impractical and stressful for the bees.

Recent advances in technology have led to the development of automated beehive monitoring systems that use cameras, microphones, and other sensors to monitor and analyze hive health remotely [4,21]. By enabling beekeepers to remotely evaluate the health of their hives, these systems can monitor the honey bee populations with less manual effort, reducing the stress on bees. Other important factors that determine the health of bee populations include weather conditions, micro-climate near the colony, plant species in the surrounding environment and the timing of their flowering [7,11]. Correlating the behavior of bees with these external factors can provide a better understanding of how the ambient environment affects the overall health of the bee colony. This knowledge can help beekeepers make informed decisions about the placement of their hives, predict their productivity in honey and ensure that bees are operating in a healthy environment. Remote sensing and aerial imagery are essential tools that can aid in collecting data on external factors such as weather, land cover and nearby vegetation. Via such a multi-modal sensing approach, valuable insights about the complex relationship between bees and their environment can be derived, leading to the development of smarter decisions to ensure productivity of each colony at local scale, as well as effective conservation strategies to protect bee populations at large scale.

The Be-Hive project aims to develop a multi-modal sensing system, which uses multiple sensors to collect a range of different types of data, employing various AI-based techniques to analyze and observe the bee colony's health in real-time. The proposed system constitutes a low-cost, DIY solution, which allows beekeepers to understand the well-being of their bee colonies, be notified about the current internal and external threats to the colony in real-time, and reduce human labour by facilitating remote observations and analytic. This paper provides an overview of the Be-Hive system, covering hardware and software components of the proposed smart beehive. The key features of the system are presented, explaining how these features work together to offer a complete solution for monitoring bees' activity. In the second part, we present the results of the bee traffic estimation based on bee pose estimation using the images captured by the smart beehive system.

The main contributions of this paper are listed below:

- A system design which is based on various interviews with actual beekeepers in the East Mediterranean region, recording their needs and requirements, translated into hardware and software design;
- A novel approach to bees' key-point detection based on the use of synthetic data during training to minimize the annotation overhead for training a deep learning (DL) algorithm. This approach significantly reduces the time and effort required for manual annotation, while still achieving high levels of accuracy for bees' pose estimation, which can be used for bees' tracking and counting;
- A tracking algorithm based on the Hungarian algorithm [10], which allows for efficient and accurate tracking bee key-points.

2 Related Work

Related work is divided in two parts: smart beehive systems based on emerging sensing technologies and bees' traffic monitoring algorithms using images and/or video as input.

2.1 Smart Beehive Systems

The use of technology to collect data that may be harnessed to investigate the behavior and health of bee hives has taken many forms over the years. Earlier studies in the field depended on manually-written records to gather data, which is time-consuming and error-prone. The human labour required restricts the ability to scale to many hives and to monitor beehives at scale. The concept of using emerging sensory technology and concepts of the Internet of Things (IoT) for monitoring bee colonies has gained popularity due to its non-invasive nature, increased automation and ability to provide data and create alerts in real-time. Numerous studies have been conducted utilizing automatic sensors to collect and analyze visual [2,4], audio [14,21] and other sensory data [9,18] to get important insights about bees, such as how individual bees behave, how many bees enter and exit the hive (in- and out-fluxes), or how the hive is performing overall in terms of productivity of honey, well-being of its bees, especially of the queen. In addition to the audio and video data, auxiliary data like temperature, humidity, and weight could give more insights. Previous work has demonstrated that monitoring the activity of bees around the hive's entrance, such as counting the number of bees entering and leaving the hive or watching for signs of swarming behaviour, provides valuable data on the hives' health and growth status.

In regards to sound recordings, the noise made by bees denote certain aspects of their status. Analysis of the sounds made by honey bees is an area of research that has seen significant progress, since it can help identify the various stressors for honeybee colonies. Microphones or accelerometers placed inside or outside a hive can be used to collect the sound generated by the bees. For example, Frings and Little [5] observed that bees react to different sounds. A certain sound at a particular frequency and amplitude causes the whole hive to come to a halt of its operations (i.e., freeze). Wenner [20] used a spectrograph and a microphone placed inside the colony to perform one of the first spectral analyses on the honey bees sound.

2.2 Bees' Traffic Monitoring

Research using video to track and analyze honey bees' behaviour is mostly limited to the past two decades, as video recording devices and storage systems became available at the market at rational prices. Some attempts aimed to track bees inside the hive using a marker placed on each individual bee [1,6]. These techniques are effective for tracking individual bees, but they require the manual labeling of each bee, which is an invasive technique that needs considerable human effort. Other manual and semi-automatic techniques use the camera placed at the entrance of the beehive to count the bee traffic [13,23]. In [13], background subtraction and ellipse approximation techniques are combined to segment and track individual bees at the hive's entrance.

More recent techniques based on pose estimation employ deep learning to detect the bees' pose based on image data. In [16], Rodriguez et al. used a VGG model to detect six key-points of a bee (tail, abdomen, head, and tentacles) and estimate the bee's pose. Castro et al. [4] demonstrate an experimental setup involving inexpensive color charge-coupled device cameras, mounted in waterproof boxes, along with a battery power source. These cameras are placed in an orchard, positioned to capture video of bees visiting flowers when blooming. Videos are captured at a resolution of 320×240 pixels at 24 frames per second (FPS), with one minute of video captured at ten minute intervals. As the authors note, their results are limited by the quality of the video, as well as the battery power source, which prevent them from capturing more frequent recordings. Despite the challenges, image-based techniques have the potential to provide valuable insights into honey bees' behaviour analysis and could ultimately lead to improved hive management and conservation efforts. Future research in this area could focus on developing more advanced deep learning based techniques for tracking and analyzing honey bee behaviour using video/image data.

In relation to related work, our system differs in that it integrates audio, camera, and sensor data to provide a more comprehensive view of bee hive activity. This multi-modal approach enables us to capture and analyze a wider range of data, including visual cues such as bee traffic and movement patterns, audio cues such as the sounds made by the bees, and auxiliary data such as temperature, humidity, and weight. By combining these different data streams, our system can provide a more accurate and holistic picture of the hive's health and behavior than the system discussed above. Additionally, the proposed system utilizes a deep learning approach for pose estimation to track individual bees in video data. Specifically, we use key-point detection to estimate the positions of critical body parts such as the head, abdomen, and tail. This approach has several advantages over other image-based techniques, including the ability to track individual bees even when they are partially occluded by other bees or objects in the frame. This can provide more accurate data on individual bee behavior and interactions, which can ultimately lead to improved hive management.

3 Methodology

3.1 Requirements for BE-HIVE System

Bees are the primary pollinators of local flora, so it is critical to preserve the bee population (and its diversity) healthy and safe across the world. Based on various interviews with local beekeepers, the major problems which bee colonies face in East Mediterranean region include the following:

1. Parasites e.g. the Varroa Destructor and Apocephalus Borealis parasite);
2. Pesticides i.e. chemical fertilizers sprayed on plants, which are lethal to bees;
3. Land use change which is responsible for reducing the bees' food sources (i.e. plants, flowers), reducing the potential space for settling their base (colony); and
4. Competition with other bee colonies, wild bees and wasps.

According to Zacepins et al. [22], it is crucial to effectively identify and measure potential threats to bee colonies using indicators such as the swarming/pre-swarming state, extreme nectar flow, queenless state, broodless state, declining colony, and starving at early stage is very important to smartly manage the bee colonies. Some behavioural cues of the bees are indicator of abnormal behaviour, anomaly and threats. Such cues can be derived from observations such as bees' flying out at different time of the day and different duration, covering varied flying distances, flying out uncoordinated in different directions each time, walking in circles on the ground, etc. Abnormality can be derived from noise inside the hive (captured by the audio sensors), bee traffic at the entrance (captured by cameras and computer vision), direction in which they fly and distance traveled (captured by camera traps strategically located near significant sources of food identified using drones).

Considering the above, an important requirement of the BE-HIVE system is to become an end-to-end monitoring ecosystem which can record and characterize behavioural cues from the bee colony using multi-modal data, allowing to derive anomalies or abnormal behaviour. The system will work in a non-intrusive way, to avoid stressing the bees and to increase the convenience for beekeepers.

To achieve the above, the proposed BE-HIVE system needs to include:

- A camera installed at the entrance of the hive to capture the bees entering and exiting;
- An audio microphone placed inside the hive to capture the bees' buzz/noise;
- Temperature, humidity and weight sensors placed inside the hive to measure the hive's micro-climate and mass of the honey produced;
- A land cover map of plants/flowers in the surrounding environment;
- Auxiliary camera traps, placed near flowering plants to identify bees' visiting sites, distance traveled and visit time during the day. Positioning of the traps will be based on the land cover map.

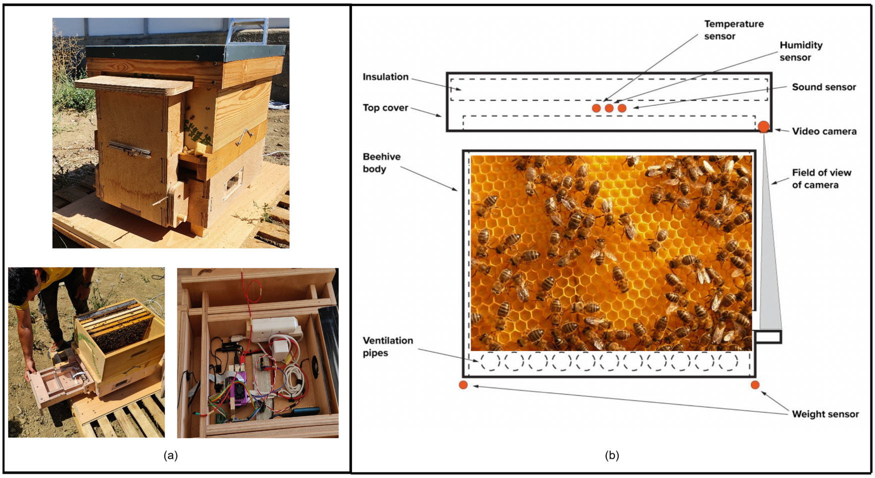

Fig. 1. Smart bee hive monitoring system overview. The system consist of a camera, microphone, humidity sensor, temperature sensor, and weight sensor (**b**). Image from actual site (**a**)

3.2 Design of BE-HIVE System

Hardware The first step in creating a reliable hive monitoring system is to develop the system for gathering high-quality data. This system is unavoidably exposed to elements that can harm most electronics, such as rain, sunshine, wind, cold, bee attacks, and disturbances. Additionally, the interior components must be positioned in a way that prevents bees from covering them in propolis or wax [18].

The structure of the system was developed through digital fabrication, considering guidelines provided by local beekeepers. A 3D model of the entire structure was designed using Rhinoceros 6 software, which allowed to identify issues that could hinder both the user experience and the device's performance.

Figure 1 illustrates the design and development of the BE-HIVE system, using Raspberry Pi (RP) as the basis to connect the sensory equipment used. The current version of the BE-HIVE system consists of:

1. A camera placed at the entrance of the bee hive, capturing the bees flying in and out. The camera can capture images at a maximum resolution of 3280×2464 pixels;
2. A USB microphone (35 Hz–18 kHz);
3. Temperature, humidity and weight sensors, all of which are connected through the built-in 40-pin GPIO of the RP. Due to harsh weather conditions, namely intense sun irradiation and high ambient air temperature, the sensor package was installed in the middle of the beehive.

Software A multi-process Python-based data collection system (DCS) was developed. The system consists of multiple processes, i.e. the controller, the camera handler, the microphone handler and the sensor handler. Each sensor is controlled based on a separate process. Additionally, the DCS system was designed to automatically execute the code on boot time, making it user-friendly when deployed in the field and easily handled by beekeepers. This enables users to simply connect the system to the electricity network and then DCS automatically initiates. The open-source DCS system created for the BE-HIVE system is available to the public and can be found on Github.[1]

3.3 Bees' Traffic Counting

Data Preparation Image data was collected using a camera installed at the entrance of the beehive. The images were captured at a rate of 3–6 frames per second with a resolution of 640 × 480. For this experiment, approximately 4,000 images were collected over the course of three consecutive days. Figure 2a shows a raw image captured by the system's camera. To reduce unneeded info, we carefully selected a region of interest and used a mask to remove the irrelevant areas. Then, to standardize the image size and make them more computationally efficient, we resized the images to a uniform size of 256 × 256 (Fig. 2b).

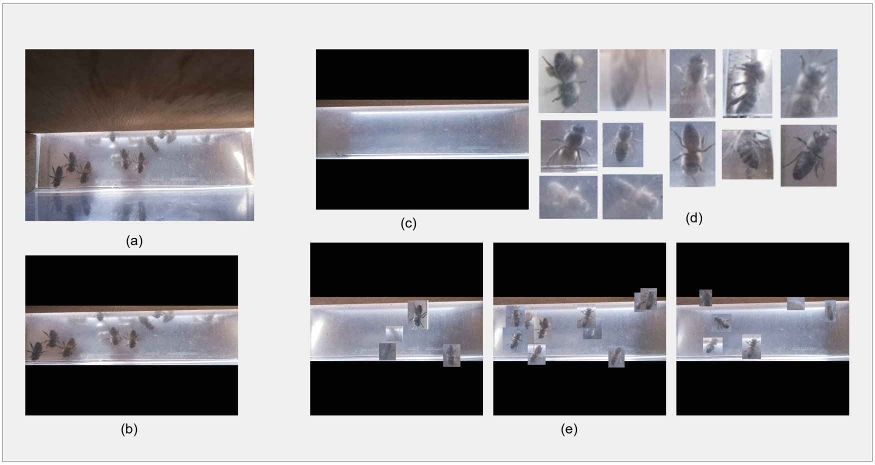

Fig. 2. Image data collected from the BE-HIVE camera and synthetic data generated. **a** Raw image collected from the camera installed at the entrance of the beehive, 640 × 480. **b** The region selected, resized to 256 × 256. **c** A sample of a background image used to generate synthetic data. **d** Samples of cropped images showing honey bees with different sizes, poses and lighting conditions. **e** Synthetically generated images using the background image (**c**) and bees' real images (**d**)

To train the key-point detection model, we annotated the key-points of individual bees, i.e. the head, abdomen, and tail. However, annotating pixel-level

[1] https://github.com/superworld-cyens/BE-HIVE.

key-points for a large dataset can be tedious and time-consuming. To overcome this challenge, we adopted a synthetic data approach to generate artificial data about bees.

To do this, we first cropped 287 individual bees (Fig. 2c) and 165 background images (Fig. 2d) from our original dataset, compassing a wide range of poses, lighting conditions and sizes. Each bee was manually annotated with its corresponding key-points. We then developed a Python-based synthetic data generator which takes an empty background image and populates it with a random number of bees at various locations. We set the number of bees in each image to be between 2 and 16 to simulate a range of realistic scenarios, based on our observations at the experimental bee hive. Figure 2b shows an example of a synthetically generated bee image, illustrating the diversity of poses and locations captured via this approach. In total, 1646 synthetic images were generated for training and validation (Fig. 2e).

Key-Point Detection and Pose Estimation An end-to-end key-point detection model (see Fig. 3), inspired by FPN [12], was used to predict the bees' key-points. We employed a methodology similar to the one proposed by OpenPose [3] for human pose estimation using a key-point confidence map and part affinity field. In our implementation, instead of a part affinity field, we predict part affinity confidence masks, which encode the line connecting the head, abdomen and tail parts of the bee. The key-point detection model takes a color image of size $256 \times 256 \times 3$ as input and produces an output map ($256 \times 256 \times 4$) of 2D locations of anatomical key-points (head, abdomen, and tail) for each bee and a part affinity confidence mask. First, a feed-forward network predicts a set of 2D confidence masks S of each body part location and a 2D part affinity confidence mask C, which encodes the connection between the key-points. The set $S = (S_1, S_2, \ldots, S_j)$ has $J = 3$ confidence masks, $S_j \in \mathbb{R}^{w \times h}$.

During inference, the key-point confidence masks and the part affinity confidence mask are parsed by greedy inference to connect the head, abdomen and tail key-points, associating them with each bee [3]. This is done by computing the line integral over the corresponding part locations. In other words, we measure the alignment of the predicted part affinity confidence mask with the possible connection formed by connecting the detected key-points. For example, for two candidate part locations d_{head} and d_{tail}, we sample the predicted part affinity confidence mask, C, along the line segment to measure the confidence in their association.

The equation that measures the confidence is given by:

$$E = \int_{u=1}^{u=0} C(p(u)) \cdot \frac{\mathbf{d_{head}} - \mathbf{d_{tail}}}{|\mathbf{d_{head}} - \mathbf{d_{tail}}|^2} du$$

Here, $p(u)$ interpolates the position of the two body parts d_{head} and d_{tail}, $p(u) = (1-u)d_{head} + ud_{tail}$. In practice, we approximate the integral by sampling

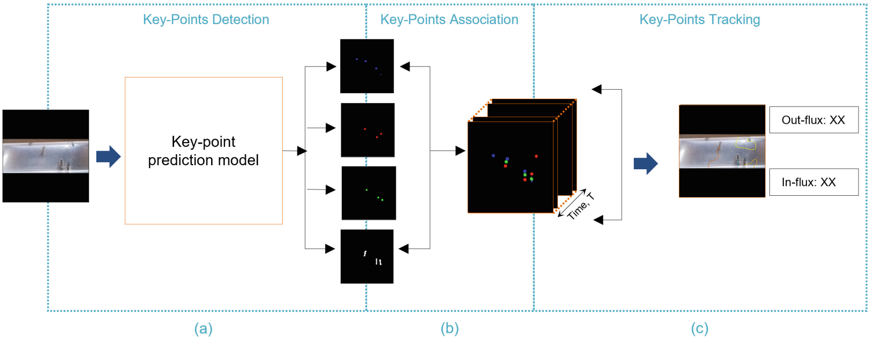

Fig. 3. Block diagram: the proposed key-point detection model and tracking algorithm. Given an RGB image, we feed it into our DL architecture to produce a key-point confidence mask (One mask per key point) and a part affinity confidence mask. The part-affinity confidence mask is used to associate the head, abdomen and tail key-points to individual bees. Finally the key-points are tracked using tracker algorithm

and summing uniformly spaced values of u.

Key-Point Tracking Once the key-point is detected and each key-point is associated with its corresponding body part, the next step is to track the individual bees in the consecutive frames and count the in-flux and out-flux of the bees. For simplicity, we considered only the head and tail key-points for tracking. Instead of tracking two points, we calculated the midpoint of the line joining the key-points and the angle of orientation of the line (here, we consider the x-axis as the zero-degree line). Thus, each bee is associated with a midpoint location and an angle of orientation in each frame.

The proposed multi-object tracker proposed utilizes the Hungarian algorithm [10] to associate detections of bees across consecutive frames. When a new frame is processed, the algorithm calculates the Euclidean distance between midpoints and cosine similarity score for the angle of orientation of the detected bees in the current and previous frames. Using the Hungarian algorithm, it then assigns the most likely detected bee in the current frame to the bee in the previous frame, forming a *"track"* of the bee's trajectory across the frames. The assignment is determined by the lowest cost for both distance and angle. In this context, a "track" refers to the trajectory of a single bee object in consecutive frames, represented by a series of detections associated over time. If the cost between a track and detection is greater than a threshold distance and threshold angle, the track is marked as lost. If a track has been lost for too many frames, it is deleted. The threshold distance and angle are determined by the bee's velocity and camera FPS.

$$\text{Average bee movement (in Pixel)} = \frac{bee_{disp}}{(W_{actual}/W_{pixel})} \times \frac{bee_{disp}}{(H_{actual}/H_{pixel})}$$
$$= 25 \times 25$$
$$\text{Average angle of rotation (in Pixel)} = \cos^{-1}\left(\frac{bee_{len}^2 - bee_{disp}^2}{2 * bee_{len}^2}\right)$$
$$= 60^\circ$$

where bee_{disp} is the average walking speed per frame, which is 30 mm/6, i.e., 5 mm/frame, $W_{actual} \times H_{actual}$ represents the actual dimensions of the walking board (Fig. 2b), which are 140×100 mm. $W_{pixel} \times H_{pixel}$ is the image resolution, which is 640×480 pixels, and bee_{len} is the average bee length, which is 15 mm. Based on our calculations and adding a slight buffer, we have set the threshold distance at 35 pixels, and the threshold angle at $\pm 45^\circ$.

The tracker maintains a list of tracks, where each track represents the movement of an individual bee over time. The track contains the current location of the bee as well as its past locations. When a track cannot be achieved, it means that the bee has left the frame of the camera. If the track ends at the top of the walking board, it means that the bee has left the area being monitored and has flown out. In this case, the out-flux count is incremented, indicating that one more bee has flown out. On the other hand, if the track ends at the bottom of the walking board, it means that the bee has entered the monitored area from outside. In this case, the in-flux count is incremented, indicating that one more bee has entered the area being monitored. Overall, the tracker keeps track of the movements of bees and uses this information to determine the number of bees entering and leaving the monitored area. The key-point detection model, and tracking algorithm is available here.[2]

4 Results and Discussion

Key-Point Detection and Pose Estimation: The key-point detection model was exclusively trained on generated synthetic data, utilizing the Adam optimizer for 1000 epochs. The model exhibited impressive performance, achieving an IoU of 97% and an F1-score of 98% during training. To evaluate its real-world effectiveness, the trained model was tested on 75 manually annotated images, each containing an average of 6 bees. The test images yielded an IoU of 86.2% and an F1-score of 88%, which represents a slight decrease from the training results.

The observed decline in algorithm performance can be attributed to several factors. Firstly, the changing lighting conditions during the day resulted in overexposed images in the afternoon, as evident from the visual depiction in Fig. 4. This issue could be addressed by covering the hive entrance with a dark film

[2] https://github.com/superworld-cyens/BE-HIVE/tree/main/BEE_ANALYSIS.

(a)

(b)

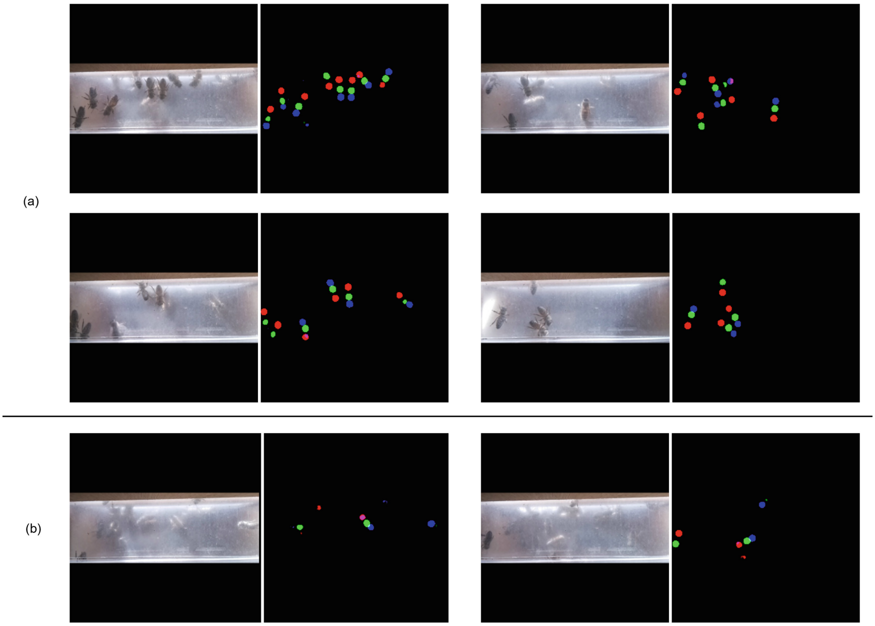

Fig. 4. The sample output from the Keypoint detection model is shown in the figure, with the input image on the left and the predicted keypoints on the right. The Image (**a**) show few examples that the predicted key-points matches with actual bee location, Image (**b**) are few examples where key-point detection model performance decrease due to over-exposure of light

to limit the exposure of sunlight, which will be explored in future works. Secondly, the model encountered difficulties in accurately predicting the position of bees when only one key-point was visible in the frame. This was primarily due to the structural similarities of bees on both sides, leading to the model's confusion between the head and tail positions. However, this problem was mitigated when at least two points (head-abdomen, tail-abdomen) were visible in the frame, resulting in improved model accuracy. Further research could focus on optimizing the identification and tracking of bees in such scenarios, thereby enhancing the overall performance of the algorithm.

Key-Points Tracking The tracking algorithm relies exclusively on the key-point predictions generated by the detection model. To evaluate the performance of the algorithm, we conducted experiments on five different video datasets captured at different times of the day. These datasets were manually analyzed, and the total number of in-bee and out-bee events were recorded for each video. Each dataset comprised an average of 150 frames, with an average of 20 bee tracks in each frame.

The key-point detection model was applied to each frame, and the detected key-points were tracked using the developed tracker algorithm. The performance of the algorithm was evaluated based on its ability to accurately track individual bees and correctly measure their in-flux and out-flux. The results, as shown in the Table 1, demonstrate that the algorithm achieved good accuracy in all 6 sets of videos, with a mean absolute error of 5.7 for in-flux/out-flux measurement. This could be used as bench mark for bee traffic counting using images. To test the robustness of the proposed algorithm we ran the algorithm on 2 hours of video capture between 9:30 AM and 03:50 PM. The results showed that there were 6857 in-flux and 7165 out-flux. These results have not been verified due to the unavailability of ground truth, but they were used to demonstrate the robustness of the proposed model. Figure 5 shows a snapshot of the bee traffic count for the analyzed video. The data was taken at the beginning of the foraging season when the number of bees is slightly less than during peak foraging season. It is expected that the traffic will increase in the coming months which will be ideal time to test the algorithm on site. In the graph it is noted that the out-flux

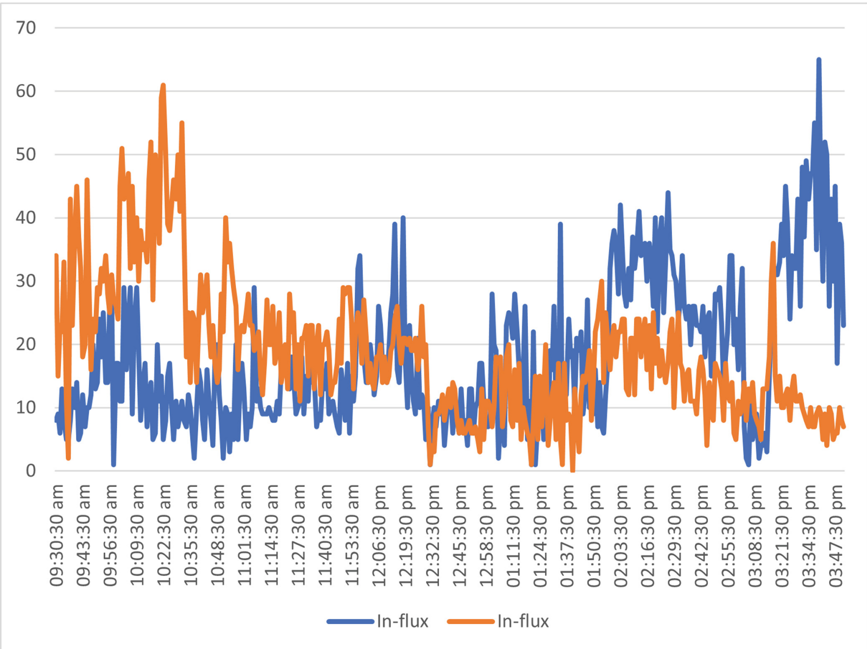

Fig. 5. The graph shows the inflow and outflow of bee traffic between 9:30 AM and 03:50 PM on a typical day. The x-axis represents time, and the y-axis represents count. The orange line shows the influx count, and the blue line shows the outflux count. Since this is the start of the day, the bees tend to leave the beehive for foraging activities to collect nectar and pollen. So the out-flux is slightly more then the in-flux

Table 1. Tracking results

Video	Actual value (In count)	Actual value (Out count)	Predicted value (In count)	Predicted value (Out count)	Average MAE
Video 1	21	23	27	29	6
Video 2	5	6	7	8	2
Video 3	7	4	7	5	0.5
Video 4	28	19	35	24	6
Video 5	12	11	18	18	6.5
Video 6	34	44	39	54	7.5
					MAE: 5.7

is slightly higher then the in-flux, this is mainly because at this time of the day the bees tends to leave their hive for forging activity to collect nectar and pollen.

The results of our analysis indicate that the proposed tracking algorithm tended to overestimate bee counts due to the bees' tendency to congregate near the hive entrance and cross the walking board multiple times. The counter was incremented every time a bee approached the entry and exit line, irrespective of its actual direction of movement. To address this issue, we plan to incorporate tracking IDs along with the trajectory in the next version of the algorithm. This will allow for more precise identification and tracking of individual bees and enable us to accurately differentiate between inbound and outbound movement, leading to more accurate bee counts. We believe this enhancement will substantially improve the algorithm's effectiveness in accurately tracking bee activity and provide more reliable data for monitoring hive behavior (Table 1).

5 Future Work

As a future research direction, we will deploy the proposed tracking algorithm on beehives in real-time to evaluate its efficacy in practical settings. This will entail testing the algorithm on annotated longer video captures from the beehive to ensure its ability to handle extended tracking periods. As previously discussed, the current counter utilizes the position of the trajectory to count the in/out-flux. However, in the updated version, the counter will increment only when a bee leaves the walking board, taking into account both the position of the trajectory and the bee ID, resulting in more precise measurements of bee activity.

Furthermore, we aim to direct attention to other objectives of the Beehive project, including audio data analysis, classification of behavior based on bee trajectory, and detection of anomalies. To achieve this, we intend to develop a dashboard for beekeepers and researchers to monitor the hive's vitals, such as temperature, humidity, and weight, and provide a live video feed from the hive entrance, as well as statistics on bee population. Moreover, the dashboard will include a heat map of recent bee visits, enabling beekeepers to manage the hive with minimal intrusion. Our future research directions will focus on enhancing the proposed tracking algorithm's accuracy and effectiveness and expanding the Beehive project's objectives to include a broader range of bee monitoring and management capabilities.

6 Conclusion

The smart beehive system presented in this paper is an inexpensive, do-it-yourself Raspberry Pi system that can be quickly deployed and can collect high-quality data. The system offers various levels of calibration at both the hardware and software levels, and is easy to expand and upgrade. The paper introduces a novel approach to bee key-point detection that employs synthetic data during training to reduce the need for manual annotation. By doing so, the proposed model has the potential to significantly reduce the time and effort required for manual annotation while still achieving high levels of accuracy. The bee traffic counting model developed in this study demonstrates the robustness of the collected data. In the future, the use of artificial intelligence with the collected data will allow beekeepers and researchers to monitor the hive remotely with minimal intrusion.

Funding This project received funding from the European Unions Horizon 2020 Research and Innovation Programme under Grant Agreement No. 739578 and the Government of the Republic of Cyprus through the Deputy Ministry of Research, Innovation and Digital Policy.

References

1. Boenisch, F., Rosemann, B., Wild, B., Dormagen, D., Wario, F., Landgraf, T.: Tracking all members of a honey bee colony over their lifetime using learned models of correspondence. Front. Robot. AI **5**, 35 (2018)
2. Campbell, J., Mummert, L., Sukthankar, R.: Video monitoring of honey bee colonies at the hive entrance. Vis. Observ. Anal. Anim. Insect Behav. ICPR **8**, 1–4 (2008)
3. Cao, Z., Simon, T., Wei, S.-E., Sheikh, Y.: Realtime multi-person 2d pose estimation using part affinity fields. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 7291–7299 (2017)
4. Estivill-Castro, V., Lattin, D., Suraweera, F., Vithanage, V.: Tracking bees—A 3d, outdoor small object environment. In: IEEE International Conference on Image Processing, vol. 3, pp. III–1021 (2003)
5. Frings, H., Little, F.: Reactions of honey bees in the hive to simple sounds. Science **125**(3238), 122–122 (1957)
6. Gernat, T., Rao, V.D., Middendorf, M., Dankowicz, H., Goldenfeld, N., Robinson, G.E.: Automated monitoring of behavior reveals bursty interaction patterns and rapid spreading dynamics in honeybee social networks. Proc. Natl. Acad. Sci. **115**(7), 1433–1438 (2018)

7. Goulson, D., Nicholls, E., Botías, C., Rotheray, E.L.: Bee declines driven by combined stress from parasites, pesticides, and lack of flowers. Science **347**(6229), 1255957 (2015)
8. Kim, S., Kim, K., Lee, J.H., Han, S.H., Lee, S.H.: Differential expression of acetylcholinesterase 1 in response to various stress factors in honey bee workers. Sci. Rep. **9** (2019)
9. Andreas König. IndusBee 4.0-integrated intelligent sensory systems for advanced bee hive instrumentation and hive keepers' assistance systems. Sens. Transducers **237**(9/10), 109–121 (2019)
10. Kuhn, H.W.: The Hungarian method for the assignment problem. Naval Res. Logist. Q. **2**(1–2), 83–97 (1955)
11. Le Conte, Y., Navajas, M.: Climate change: impact on honey bee populations and diseases. Revue Sci. Tech.-Office Int. des Epizooties **27**(2), 499–510 (2008)
12. Lin, T.-Y., Dollár, P., Girshick, R., He, K., Hariharan, B., Belongie, S.: Feature pyramid networks for object detection. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 2117–2125 (2017)
13. Magnier, B., Ekszterowicz, G., Laurent, J., Rival, M., Pfister, F.: Bee hive traffic monitoring by tracking bee flight paths. In: 13th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications, pp. 563–571, Funchal, Madeira, Portugal (2018)
14. Mezquida, D., Martínez, J.: Short communication.: Platform for bee-hives monitoring based on sound analysis. A perpetual warehouse for swarms daily activity. Spanish J. Agricul. Res. **7**(4), 824–828 (2009). ISSN: 1695-971X
15. Potts, S.G., Biesmeijer, J.C., Kremen, C., Neumann, P., Schweiger, O., Kunin, W.E.: Global pollinator declines: trends, impacts and drivers. Trends Ecol. Evol. **25**(6), 345–353 (2010)
16. Rodríguez, I.F., Branson, K., Acuña, E., Agosto-Rivera, J.L., Giray, T., Mégret, R.: Honeybee detection and pose estimation using convolutional neural networks. In: Congres Reconnaissance des Formes, Image, Apprentissage et Perception (RFIAP) (2018)
17. Soroye, P., Newbold, T., Kerr, J.: Climate change contributes to widespread declines among bumble bees across continents. Science **367**, 685–688 (2020)
18. Tashakkori, R., Hamza, A.S., Crawford, M.B.: Beemon: an IoT-based beehive monitoring system. Comput. Electron. Agric. **190**, 106427 (2021)
19. VanEngelsdorp, D., Evans, J.D., Saegerman, C., Mullin, C., Haubruge, E., Nguyen, B.K., Frazier, M., Frazier, J., Cox-Foster, D., Chen, Y., Underwood, R.: Colony collapse disorder: a descriptive study. PloS One **4**, e6481 (2009)
20. Wenner, A.: Sound communication in honeybees. Sci. Am. SCI AMER **210**, 116–122 (1964)
21. Woods, E.: Electronic prediction of swarming in bees. Nature **184**, 842–844 (1959)
22. Zacepins, A., Brusbardis, V., Meitalovs, J., Stalidzans, E.: Challenges in the development of precision beekeeping. Biosys. Eng. **130**, 60–71 (2015)
23. Zhong, Y., Gao, J., Lei, Q., Zhou, Y.: A vision-based counting and recognition system for flying insects in intelligent agriculture. Sensors **18**(5), 1489 (2018)