



RESEARCH ARTICLE - BEES

Edge-computing and Deep Learning Integration for Real-time, High-resolution Monitoring of *Apis cerana cerana* Fabricius Entrance Traffic

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Abstract

Continuous monitoring of honey bee (*Apis cerana cerana* Fabricius) entrance traffic is essential for evaluating colony health and foraging dynamics in precision apiculture. Existing vision-based systems struggle to balance high spatiotemporal resolution, real-time processing capabilities, and cost-effective field deployment. We developed a low-cost, standalone edge-computing framework that integrates a 60-fps global-shutter camera with an Orange Pi 5B single-board computer. Using a PP-YOLOE+ object detection model (mean Average Precision at IoU threshold 0.5 of 0.95) coupled with the ByteTrack algorithm, the system performs robust, real-time multi-object tracking and directional counting locally at 35 fps. A 30-day continuous field deployment across three colonies successfully processed over two million entry and exit events, yielding a Multiple Object Tracking Accuracy of 77.8%. Subsequent biological analysis of this dataset revealed synchronized bimodal diurnal foraging rhythms across multiple colonies, indicating that shared environmental factors strongly influenced foraging behaviors. By maintaining stable analytical accuracy on affordable hardware without relying on continuous cloud processing, this system provides a scalable, non-invasive solution for automated colony assessment and data-driven precision apiculture.

Introduction

Accurate monitoring of hive-entrance traffic serves as a fundamental indicator of foraging dynamics and colony health in precision apiculture (Hadjur et al., 2022). Traditional monitoring methods often rely on infrared sensor systems. While these sensors offer a non-invasive approach to bee counting (Chen et al., 2015), they lack sufficient spatial resolution and typically provide only aggregate entrance and exit statistics. As a result, conventional sensor-based hive monitors cannot capture fine-grained traits such as pollen payload, individual identity, social interactions, gait, and detailed flight trajectories (Rodriguez et al., 2022).

Video-based computer-vision monitoring has emerged as a viable alternative to extract richer details regarding colony activity. However, existing visual monitoring systems often involve trade-offs among accuracy, cost, and computational

burden in field deployments (Ratnayake et al., 2021). Processing high-resolution, high-framerate video streams demands substantial computational resources, causing traditional computer vision architectures to rely on expensive cloud-computing infrastructure. Due to limited communication bandwidth and stringent power constraints in the field, these systems are restricted to controlled laboratory settings or offline data analysis (Kimura et al., 2014), limiting their practical utility and scalability.

To address these technical bottlenecks, we developed a highly integrated, low-cost edge-computing system specifically tailored for monitoring the entrance traffic of *Apis cerana cerana* Fabricius. Our objective is to demonstrate a scalable, high-resolution framework for automated colony assessment that functions reliably under complex field conditions. Unlike existing commercial or cloud-reliant alternatives, our framework improves cost-efficiency, processing latency, and deployment



scalability. By leveraging affordable edge-computing hardware to perform deep learning inference locally, the system achieves the 30-fps benchmark required for real-time traffic analysis without exceeding typical hardware budgets. Additionally, the platform features a native Linux environment and a built-in Wi-Fi module, which facilitates the continuous, low-power transmission of ecological data and ensures high adaptability for future algorithm enhancements and multi-hive scaling operations.

Materials and Methods

Study Site and Monitoring Setup

Continuous monitoring was conducted over 30 days (6 February to 6 March 2024) in an apiary located in central Hainan Island, China (109°41'15.6717"E, 19°02'11.1329"N). Three colonies were selected to represent the full ecological spectrum of local population dynamics: a strong colony (Beehive 3, five combs), a weak colony (Beehive 2, one comb), and an intermediate colony (Beehive 1, two combs). During deployment, the system logged and processed over two million entry and exit events, validating the stability of the edge-computing framework.

Entrance traffic was recorded using a custom video-monitoring assembly combining a high-speed global-shutter camera (GZ60, Shenzhen Jierui Weitong Electronic Technology Co., Ltd.) with an 8 GB Orange Pi 5B single-board computer (Shenzhen Xunlong Software Co., Ltd.). The camera captured monochrome images at 60 fps and was mounted 32 cm above the hive entrance to maximize the field of view and minimize perspective distortion. System power was supplied by a regulated 5 V, 4 A DC source. All components were securely enclosed in weather-resistant housings to ensure continuous operational stability under variable field conditions.

Edge Computing Hardware Platform and Real-Time Data Pipeline

The Orange Pi 5B was selected for its cost-effectiveness (~800 RMB) and robust Rockchip RK3588 architecture. Running

a native Linux operating system, the board features an integrated Neural Processing Unit capable of 6 Tera Operations Per Second. This provides dedicated computational power to sustain real-time deep learning inference without frame loss. Operating at 1080p resolution, the pipeline achieved a practical inference speed of 35 fps, which is sufficient to capture continuous and high-speed bee trajectories.

Dataset Preparation and Model Training

To train the vision model, a 90-minute video segment (approximately 324,000 frames at 60 fps) was recorded at the hive entrance. We extracted 10,000 frames displaying clearly visible bee morphology and manually annotated them via the Roboflow platform, yielding approximately 120,000 labeled bee instances. This ground-truth dataset was randomly partitioned into independent training (80%), validation (10%), and testing (10%) sets. Image augmentation techniques including RandomDistort, RandomCrop, and RandomFlip were applied to enhance model generalization under variable field illumination.

The PP-YOLOE+ object detection framework (https://github.com/PaddlePaddle/PaddleDetection/blob/release/2.8.1/configs/pp yoloe/README_cn.md) was trained over 300 epochs using two NVIDIA GeForce RTX 2080 Ti GPUs. Optimization utilized a Momentum optimizer (momentum = 0.9, L2 regularizer = 0.0005) with a base learning rate of 0.01, governed by a cosine decay schedule. During the object detection inference phase, a Non-Maximum Suppression IoU threshold of 0.5 was applied to filter overlapping bounding boxes.

Following object detection, the ByteTrack algorithm (<https://github.com/FoundationVision/ByteTrack>; auxiliary utilities: <https://github.com/roboflow/supervision>) was integrated to perform multi-object tracking by assigning persistent numerical identifiers to individual bee centroids across consecutive frames. To quantify directional traffic, the camera's field of view was digitally divided into two spatial zones separated by a horizontal virtual baseline (Fig 1). Entry events were recorded when a tracked trajectory crossed from the upper region (Region A) to Region B.

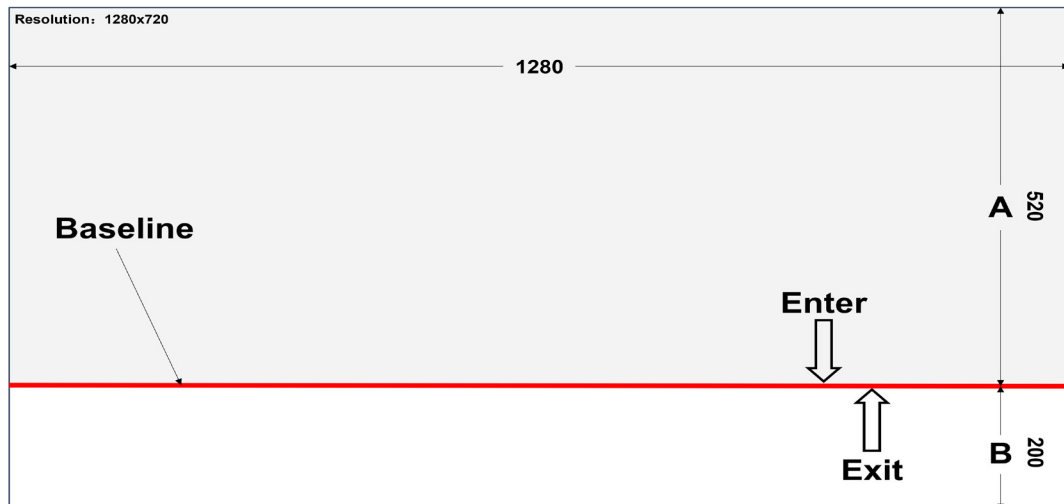


Fig 1. Schematic of the video monitoring setup showing the horizontal baseline that divides the camera field of view into Region A (above the baseline) and Region B (below the baseline). Crossings from Region A to Region B are logged as entries; crossings from Region B to Region A are logged as exits.

to the lower region (Region B). Exit events were logged for trajectories moving in the reverse direction. Tracking outputs and cumulative event counters were continuously overlaid on the video stream to visualize temporal progression and verify counting accuracy (Fig 2). To validate the automated tracking

counts, a total of 30 distinct video segments were manually annotated to establish a ground-truth baseline (Supplementary Table 1). The automated edge-computing system achieved an overall counting accuracy of 93.80% compared to the manual baseline.

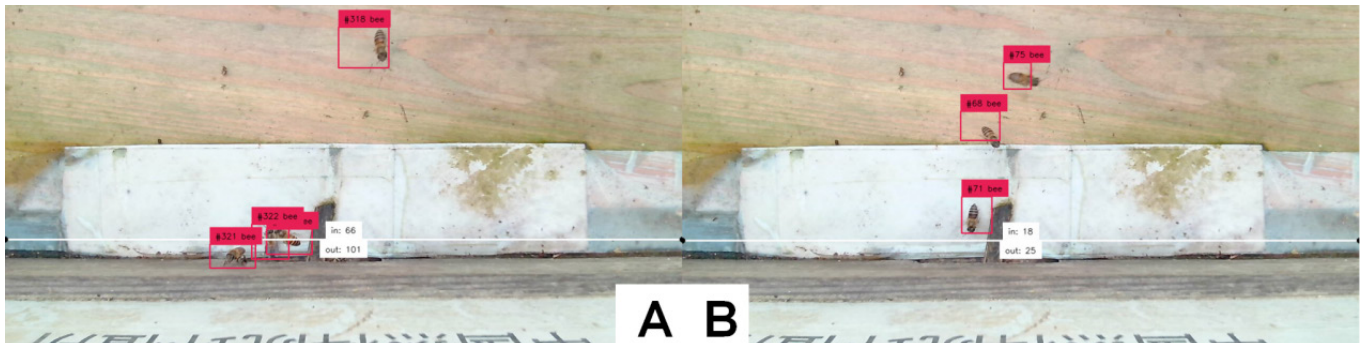


Fig 2. Example frames from the live monitoring stream illustrating AI detections and tracking overlays. Red bounding boxes indicate detected individuals; numerical IDs show persistent tracks assigned by ByteTrack. The embedded counters (e.g., “in: 88” and “out: 101”) display cumulative entries and exits during the current recording session. Panels A and B represent two different moments in time to illustrate typical trajectories and short-term occlusions.

Table 1. Average 5-minute entry and exit counts for colonies over a 30-day monitoring period.

Day	Beehive 1		Beehive 2		Beehive 3	
	Mean/bee (SD)	Median/bee [Min, Max]	Mean/bee (SD)	Median/bee [Min, Max]	Mean/bee (SD)	Median/bee [Min, Max]
1	155 (95)	135 [24, 446]	49 (35)	41 [3, 290]	134 (61)	123 [3, 553]
2	143 (80)	138 [17, 312]	40 (48)	36 [20, 308]	81 (59)	69 [0, 465]
3	124 (64)	123 [1, 263]	41 (41)	33 [0, 351]	70 (43)	62 [0, 354]
4	106 (107)	80.5 [18, 617]	23 (29)	16 [0, 203]	97 (79)	92 [3, 625]
5	106 (64)	94.5 [6, 454]	36 (34)	28 [1, 242]	136 (77)	124 [3, 508]
6	131 (75)	127 [22, 474]	40 (28)	33 [1, 204]	136 (75)	117 [35, 488]
7	123 (55)	131 [29, 291]	40 (24)	37 [1, 197]	137 (56)	130 [26, 372]
8	123 (55)	131 [29, 291]	42 (28)	37 [4, 183]	132 (49)	129 [49, 274]
9	151 (84)	149 [29, 495]	44 (32)	35 [9, 308]	147 (73)	132 [2, 482]
10	136 (78)	136 [25, 347]	43 (30)	37 [5, 282]	128 (57)	124 [45, 291]
11	139 (82)	125 [28, 367]	40 (37)	31 [3, 302]	131 (76)	123 [40, 443]
12	135 (108)	110 [28, 572]	39 (44)	28 [2, 434]	128 (102)	99.5 [32, 509]
13	130 (106)	107 [5, 565]	37 (40)	29 [7, 301]	128 (94)	119 [3, 556]
14	122 (106)	98 [12, 576]	42 (50)	29 [5, 487]	125 (89)	116 [13, 512]
15	122 (85)	104 [21, 518]	11 (22)	1 [0, 123]	122 (85)	110 [8, 506]
16	106 (121)	47.5 [20, 673]	42 (48)	25 [7, 416]	132 (84)	115 [18, 387]
17	102 (61)	83 [12, 349]	57 (36)	48 [15, 229]	151 (76)	149 [10, 388]
18	93 (56)	76 [14, 468]	56 (40)	41 [17, 315]	158 (87)	151 [19, 481]
19	87 (43)	81 [5, 256]	78 (35)	72 [8, 187]	139 (72)	119 [2, 577]
20	55 (41)	46 [0, 189]	68 (31)	59 [1, 159]	131 (73)	105 [12, 452]
21	73 (32)	67 [14, 165]	42 (36)	36 [0, 185]	114 (65)	122 [0, 278]
22	90 (152)	45 [5, 860]	40 (36)	31 [5, 226]	135 (87)	131 [29, 339]
23	50 (18)	50 [14, 112]	42 (31)	35 [9, 197]	128 (89)	120 [2, 521]
24	66 (25)	66 [3, 184]	46 (29)	39 [7, 175]	83 (95)	55 [0, 584]
25	68 (43)	67 [8, 452]	40 (30)	38 [0, 204]	22 (30)	8 [0, 267]
26	83 (40)	80 [9, 454]	44 (30)	40 [0, 146]	126 (59)	120 [17, 284]
27	83 (50)	71 [15, 423]	39 (23)	34 [3, 149]	131 (78)	123 [6, 398]
28	74 (49)	70 [14, 450]	45 (32)	37 [1, 125]	124 (73)	102 [23, 363]
29	88 (53)	80 [13, 536]	30 (19)	28 [1, 184]	133 (58)	132 [2, 333]
30	99 (54)	95 [14, 536]	23 (29)	16 [0, 203]	122 (77)	106 [13, 445]

Statistical Analysis

All data processing and statistical analyses were conducted using R software (version 4.3.3). The tidyverse package was utilized for preliminary data cleaning and wrangling. Descriptive statistics were calculated to capture the variability of daily traffic activity across the three colonies. Inter-group correlation analyses (Pearson correlation matrices) and statistical significance testing were conducted to evaluate behavioral synchronization. Entrance and exit flight activities were quantified at 5-minute intervals and summarized as daily totals throughout the 30-day monitoring period. All data are expressed as the mean $\pm$ standard deviation. To assess significant differences across the colonies, the non-parametric Kruskal-Wallis H test was applied because the data deviated significantly from a normal distribution.

Results

Temporal Dynamics of Colony Traffic

Over the 30-day monitoring period, the three colonies exhibited distinct traffic patterns at the hive entrance (Table 1). Beehive 3 recorded the highest overall activity, with 5-minute mean counts fluctuating between 22 and 158 bees. Beehive 1 displayed intermediate activity levels (5-minute mean counts ranging from 50 to 155 bees); its maximum traffic occurred on Day 1 (mean = 155 bees), and the minimum was observed on Day 23 (mean = 50 bees). Beehive 2 maintained the lowest throughput, with interval means ranging from 11 bees (Day 15) to 78 bees (Day 19).

Significant variations in flight activity were observed among the three hives (Table 2; daily total: Kruskal-Wallis $\chi^2 = 57.101$, $df = 2$, $p < 0.001$; 5-min interval: Kruskal-Wallis $\chi^2 = 4045.409$, $df = 2$, $p < 0.001$). Beehive 3 consistently demonstrated the highest activity levels at both the 5-minute interval (121 ± 79 bees/5 min) and daily total ($17,668 \pm 3,920$ bees/day). Beehive 1 showed intermediate activity levels (104 ± 81 bees/5 min; $14,836 \pm 4,154$ bees/day), while Beehive 2 recorded the lowest flight activity.

Correlation analysis of the 30-day, 5-minute traffic series (Fig 3) revealed strong synchronization among the three colonies. Beehive 1 and Beehive 3 showed a very strong positive correlation ($r = 0.93$, $p < 0.01$), and Beehive 3 and Beehive 2 were similarly correlated ($r = 0.90$, $p < 0.01$). The relationship between Beehive 1 and Beehive 2 was also

robust ($r = 0.80$, $p < 0.01$). These high correlation coefficients suggest that shared environmental factors strongly influence flight activity across colonies.

Diurnal Traffic Patterns in *A. cerana cerana* Colonies

All monitored colonies exhibited a bimodal diurnal rhythm, with peak activity occurring at dawn and in the early afternoon (Fig 4). In Beehive 1, an early-morning surge marked the onset of foraging, followed by a gradual decline and a smaller midday peak (Fig 4A). Beehive 2 exhibited a similar bimodal pattern (Fig 4B). In Beehive 3, traffic magnitudes were highest and rhythmical oscillations were most pronounced (Fig 4C).

Specifically, Beehive 1 demonstrated an initial peak of 188 bees at 07:40, a secondary peak of 110 bees at 13:35, and activity decreased to near-zero activity by 19:40. Beehive 2 initiated activity at 06:55 and reached its first modest peak by 07:40, averaging 87 combined entries and exits. After a midday lull, a secondary peak culminated at 14:15 (117 bees) before counts declined to zero by 19:30. Beehive 3 exhibited an early surge to a peak of 244 bees at 07:30, followed by a lower second peak of 163 bees at 14:20; activity tapered off by 19:35.

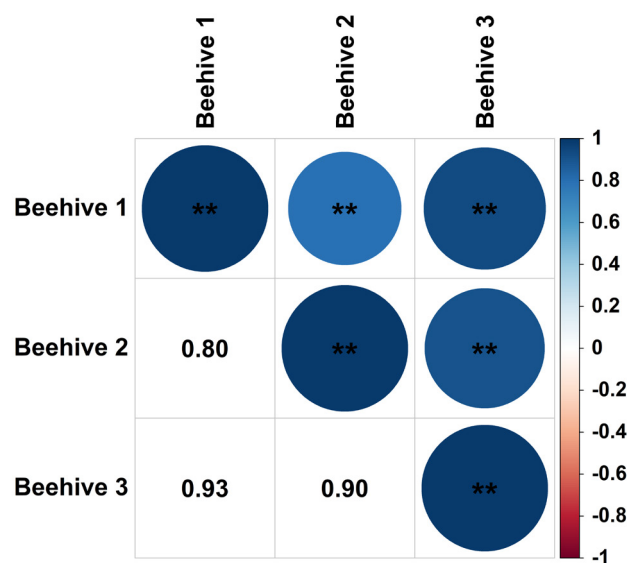


Fig 3. Pearson correlation matrix of 30-day average hive throughput at 5-minute intervals among three colonies.

Note: **represents significant correlation ($p < 0.01$).

Table 2. Statistical summary of entrance and exit flight activity (Mean $\pm$ standard deviation) for *A. cerana cerana* colonies over a 30-day monitoring period.

Temporal Scale	Beehive 1 (bee)	Beehive 2 (bee)	Beehive 3 (bee)
5-min Interval	104 $\pm$ 81a	42 $\pm$ 37b	121 $\pm$ 79c
Daily Total	14,836 $\pm$ 4,154a	6,056 $\pm$ 1,779b	17,668 $\pm$ 3,920c

Note: Different lowercase letters within a row denote significant differences ($p < 0.05$), whereas identical letters indicate no significant difference.

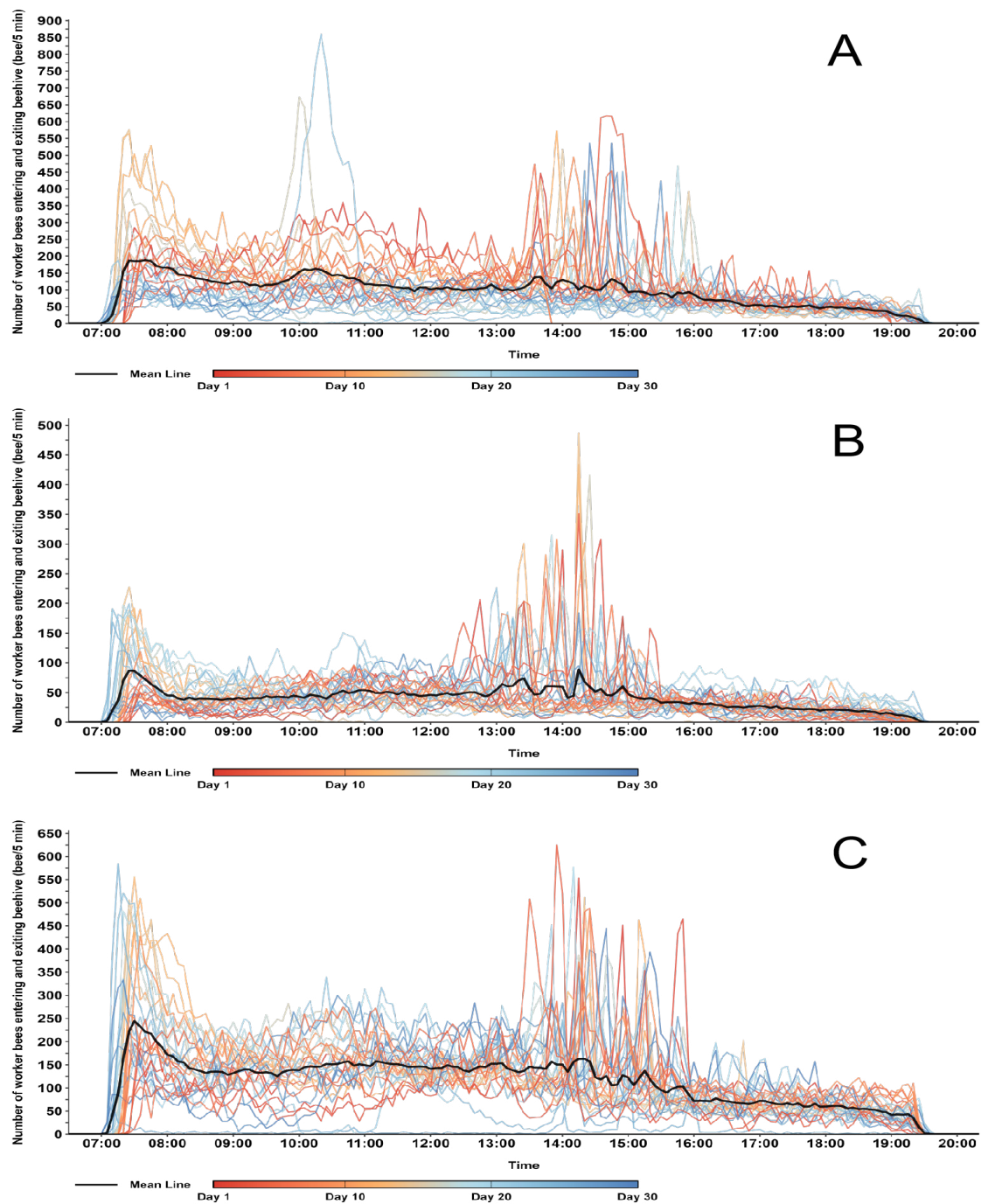


Fig 4. Five-minute interval traffic dynamics for three monitored colonies over a continuous 30-day period (6 February–6 March 2024). Panels A–C show per-hive time series (entries and exits aggregated per 5-minute interval) for Beehives 1–3, respectively. The black curve in each panel represents the overall mean for each individual colony. The recording window spans 04:30–20:00 daily (186 intervals per day).

Discussion

This study demonstrates a methodological advance in automated hive monitoring by validating a cost-effective, edge-computing vision system. Using our independent testing dataset, the PP-YOLOE+ model achieved a mean Average Precision at IoU threshold 0.5 of 0.95, a Precision of 0.91, a Recall of 0.82, and an F1-score of 0.86. Integrated with

the ByteTrack multi-object tracking algorithm, the pipeline achieved a Multiple Object Tracking Accuracy (MOTA) of 77.8%, an ID F1 Score (IDF1) of 75.2%, and a Higher Order Tracking Accuracy (HOTA) of 61.3%.

A key physical factor contributing to this algorithmic stability is the natural constraint of the hive entrance, which restricts bees to a nearly single-layered passage. This physical bottleneck mitigates severe occlusion, allowing tracking

algorithms to maintain consistent identity assignments during peak traffic periods. While recent studies report that deep-learning-based detection and tracking approaches have been widely applied to automated bee monitoring, ranging from whole-colony tracking on the comb to individual bee detection and counting at the hive entrance and in the wild (Alex et al., 2025; Zheng et al., 2024; Bozek et al., 2021), our pipeline provides practical, stable accuracy optimized specifically for low-power edge hardware. A comprehensive comparison of our framework with existing bee-monitoring approaches is summarized in Supplementary Table 2.

Compared to infrared counters or single-sensor methods, our vision-based pipeline offers distinct biological and economic advantages. Infrared sensors frequently miscount due to occlusion or changing illumination (Borlinghaus et al., 2022) and primarily capture thermal signatures rather than detailed morphological features. This limitation makes it exceedingly difficult to differentiate between bee castes, such as distinguishing a queen from worker bees. In contrast, the high-resolution optical camera preserves these physical features. It reduces hardware costs compared to high-resolution thermal alternatives, fulfilling the objective of scalable, economically feasible deployment for smart apiary operations.

To ensure the biological validity of such automated metrics, rigorous calibration against independent ground truth, such as manually annotated video frames or auxiliary sensors, remains essential (Kulyukin & Kulyukin, 2023). Because training high-quality detectors requires substantial labeled data, manual annotation poses a bottleneck due to its labor-intensive and costly nature. Integrating semi-automated workflows, such as active learning and assisted annotation, will be critical strategies for scaling datasets while minimizing labeling effort and error rates (Amin et al., 2023).

Despite reliable uptime during the continuous 30-day deployment, the system's long-term hardware durability and algorithmic stability under varying environmental conditions require further validation. Future work should focus on extended, cross-site validations to ensure the generalizability of the edge-computing pipeline. Additionally, while the reported tracking metrics inherently account for detection and tracking errors, the raw statistical counts of these errors were not independently extracted. Reporting these granular statistics alongside composite metrics in future studies could enhance the transparency of the tracking performance.

Integrating this vision-based system with broader environmental metadata presents strong potential for future research. Multimodal fusion, combining video trajectories with meteorological records, floral resource mapping, and acoustic diagnostics, can improve predictive modeling of colony behavior and health. By mapping individual trajectories alongside ambient temperature, humidity, and internal hive acoustics, future iterations of this platform could enable automated, early detection of colony stressors, directly supporting data-driven yield forecasting in precision apiculture.

Author's Contribution

J-X. W.: writing-original draft, visualization, validation, software, methodology, investigation, formal analysis, data curation, conceptualization.

H-Y. H.: visualization, validation, software, methodology, formal analysis, investigation.

H-J. L.: supervision, project administration, methodology, funding acquisition, conceptualization.

Y-X. G.: visualization, validation, software, methodology.

J-L. G.: supervision, conceptualization.

S. Z.: investigation, resources.

S-J. W.: writing-review & editing, supervision, project administration, funding acquisition, conceptualization.

Data Availability Statement

The datasets generated or analyzed during the current study are available from the corresponding author on reasonable request.

Disclosure Statement

The authors declare that they have no conflict of interest.

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