
VISIONHIVE: An AI-Based Honeybee Entrance Monitoring and Activity Analysis System

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Abstract - Honeybee colonies are essential pollinators, yet traditional colony-health assessment depends on subjective, labour-intensive manual inspection that cannot provide continuous behavioural data. This paper presents VisionHive, a non-invasive, camera-based deep learning system for automated honeybee entrance monitoring. The framework integrates a YOLOv8 object detector with DeepSORT multi-object tracking inside a virtual dual-box Region of Interest (ROI), assigning each detected bee a persistent serial identity and logging direction-independent IN/OUT events with exact timestamps. The model was fine-tuned on 1,416 field-annotated images collected at the Honeybee Research and Training Centre, G.B. Pant University of Agriculture and Technology, Pantnagar, across morning, noon and evening lighting conditions, and evaluated across three time-of-day training cases. The best model, trained on noon-time data, achieved a mAP@0.50 of 0.954, precision of 0.945 and recall of 0.894, while overall counting accuracy reached 93.0% (IN) and 94.6% (OUT) against manual ground truth, with a tracking MOTA of 82.4%. Video-level analysis of processed footage produced annotated output showing live bounding boxes, serial-ID labels and a running IN/OUT counter, with a representative 22.78-second clip recording 10 entries and 12 exits; reproducibility testing across five repeated runs returned identical counts each time, confirming deterministic behaviour. These results confirm that lighting conditions significantly affect detection reliability and demonstrate that the proposed pipeline provides a practical, field-deployable foundation for precision apiculture.

Key Words: Honeybee monitoring, YOLOv8, DeepSORT, object detection, multi-object tracking, precision apiculture

1. INTRODUCTION

Honeybees (*Apis mellifera*) pollinate roughly 75% of the world's flowering plants and nearly a third of the global food supply, with pollination services valued at more than USD 200 billion annually (FAO). In India, apiculture supports over 35,000 registered beekeepers managing about 3.9 million colonies, contributing both directly through honey production and indirectly through crop pollination worth nearly ten times the value of honey itself. Advances in deep learning-based computer vision, particularly the YOLO family of real-time object detectors [1] combined with

multi-object tracking algorithms such as DeepSORT [2] and ByteTrack [3], now make it possible to detect small, fast-moving insects and maintain their identity across frames despite temporary occlusion. Several works have applied YOLO-based detection to hive-entrance monitoring [4]-[7], and a smaller number have paired detection with tracking to obtain entry/exit counts [8],[9]; however, no prior system has unified real-time detection, persistent per-bee identity, direction-independent presence-based counting and timestamped behavioural logging into a single field-deployable pipeline. This paper introduces AI based honeybee entrance monitoring analysis system.

2. PROBLEM STATEMENT

Manual hive inspection remains subjective, labour-intensive and impossible to sustain continuously across large apiaries, while existing sensor-based and detection-only systems cannot identify individual bees, struggle under variable outdoor lighting, and lack persistent identity tracking across video frames, as also highlighted in recent reviews of automated bee-counting technology. Earlier approaches to entrance-traffic estimation relying on omnidirectional motion detection and background subtraction are particularly sensitive to changing outdoor illumination. Consequently, no current system unifies real-time detection, accurate entry/exit tracking and timestamped behavioural logging into a single deployable framework. This research addresses this gap by developing a YOLO-based deep learning model for real-time honeybee detection, a DeepSORT-based entry/exit counting system for live IN/OUT tracking, and a data-driven hive monitoring module for timestamped activity logs.

3. METHODOLOGY

3.1 Dataset

The dataset combines field image/video recorded at HBRTC, Pantnagar, across morning, noon and evening sessions with the Roboflow. After removing bee-free and low-quality frames, 1,416 images were annotated in YOLO format and split 1,239 / 118 / 59 for training, validation and testing (**Table 1**).

3.2 Preprocessing and Augmentation

Images were resized to 432x432 pixels for uniformity. Five augmentation techniques were applied to the training set only: horizontal/vertical flip, up to 20% crop/zoom, +/- 24 degree hue shift, +/-25% brightness adjustment, and up to 1.52% pixel noise, to improve robustness to real-world lighting and orientation variation.

3.3 Detection and Tracking Pipeline

Video is processed through an eight-stage pipeline: video input (OpenCV); **Figure-1** virtual ROI definition - a yellow detection zone with an auto-centred red entrance box, extending earlier entrance-traffic and flight-path monitoring concepts [11]; YOLOv8 detection restricted to the ROI crop at confidence above 0.4; DeepSORT tracking [2] using Kalman-filter motion prediction and 128-dimensional appearance embeddings to assign persistent serial IDs (BEE-01, BEE-02, ..., BEE-n); presence-based IN/OUT logic triggered when a tracked centroid crosses the red box boundary; a six-part validation framework; and output generation as an annotated video with bee_log.csv and bee_timestamps.csv files. DeepSORT's max_age was set to 30 frames (~1 s at 30 FPS) so briefly occluded bees are not dropped from tracking. The annotated output shows YOLOv8-detected honeybees enclosed in blue bounding boxes at the hive entrance, with a live count displayed above each frame, confirming accurate real-time multi-bee detection under varying entrance conditions.

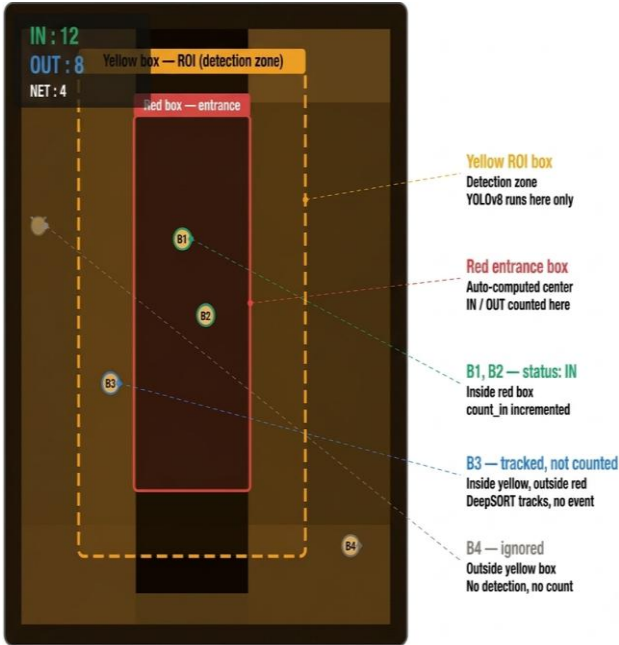


Fig -1: Virtual ROI (Region of Interest) Diagram

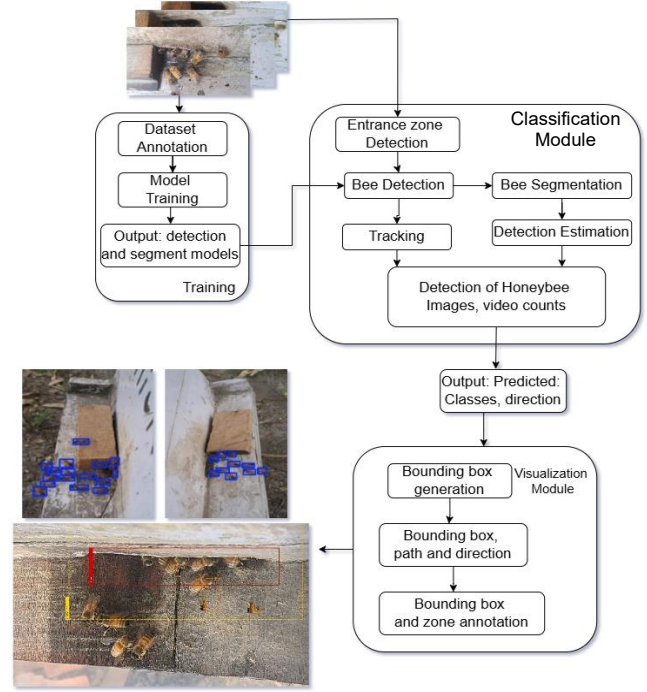


Fig -2: Proposed Model Architecture

3.4 Training Configuration

YOLOv8n was trained separately on morning, noon and evening subsets under identical hyperparameters (**Table 2**) to isolate the effect of lighting on detection performance, using the AdamW optimiser with early stopping (patience of 10-20 epochs).

Class	Train	Test	Valid	Total
Honeybee	1239	59	118	1416

Table -1: Dataset description

Hyperparameter	Value
Classes	1
Batch size	16
Epochs (max)	50
Optimizer	AdamW
Learning rate	0.002

Table -2: Training hyperparameters

4. RESULTS AND DISCUSSION

4.1 Detection Performance Across Lighting Conditions

Three identical YOLOv8n configurations were trained on morning, noon and evening subsets to isolate the effect of natural lighting on detection performance. The noon-time model achieved the best results (**Table 3**): mAP@0.50 of 0.954, mAP@0.50:0.95 of 0.654, precision of 0.945 and recall of 0.894 at epoch 38 of 48. The evening-time model showed the weakest recall (0.854) and highest box loss (1.006), consistent with reduced visual contrast under low light. Precision remained above 0.90 across all three conditions, showing that false positives were well controlled irrespective of time of day, while recall and the

stricter mAP@0.50:0.95 metric were more sensitive to lighting quality.

Metric	Morning	Noon	Evening
mAP@0.50	0.913	0.954	0.923
mAP@0.50:0.95	0.627	0.654	0.605
Precision	0.905	0.945	0.929
Recall	0.871	0.894	0.854

Table -3: Detection performance across time-of-day conditions

4.2 Result for Image Analysis

(Figure -3): YOLOv8 detection output across multiple hive-entrance frames/Images Sample output frames from real apiary footage show YOLOv8-detected honeybees enclosed in blue bounding boxes, with live counts displayed above each image.

4.3 Confusion Matrix Analysis and video analysis chart

Confusion-matrix evaluation mirrored this pattern: noon-time gave the strongest balance (precision 96.2%, recall 85.5%, F1 90.5%), while evening evaluation showed a recall drop to 73.3% (F1 83.5%) with precision remaining high (96.9%) - indicating that missed detections, not false alarms, are the dominant error mode under low-light conditions. On the combined field/public dataset of 4,623 images, the overall best model reached mAP@0.50 of 0.944 (bee: 0.951, pollen-carrier: 0.937), precision 0.953 and recall 0.914 (F1 approx. 0.933).



Bee: 15

Bee: 3



Bee: 16

Bee: 10

Fig -3: Result for Image

Sr. No	Time-stamp (s)	Frame No.	Bee serial ID	Event	Cummulative_In	Cummulative_Out
01	0.3	9	bee_1	OUT	0	1
02	0.93	28	bee_2	OUT	0	2
03	1.33	40	bee_3	IN	1	2
04	2.03	61	bee_4	IN	2	2
05	3.33	100	bee_5	OUT	2	3
06	5	150	bee_6	OUT	2	4
07	6.77	203	bee_7	OUT	2	5
08	6.83	205	bee_8	IN	3	5
09	8.5	255	bee_9	IN	4	5
10	10	300	bee_10	OUT	4	6
11	10.03	301	bee_11	IN	5	6
12	10.33	310	bee_12	IN	6	6
13	11.67	350	bee_13	OUT	6	7
14	13.33	400	bee_14	OUT	6	8
15	13.4	402	bee_15	IN	7	8
16	14.33	430	bee_16	OUT	7	9
17	14.4	432	bee_17	IN	8	9
18	16	480	bee_18	OUT	8	10
19	16.67	500	bee_19	OUT	8	11
20	16.73	502	bee_20	IN	9	11
21	17.33	520	bee_21	OUT	9	12
22	21.03	630	bee_22	IN	10	12

Table -4 Result Chart for Videos Analysis

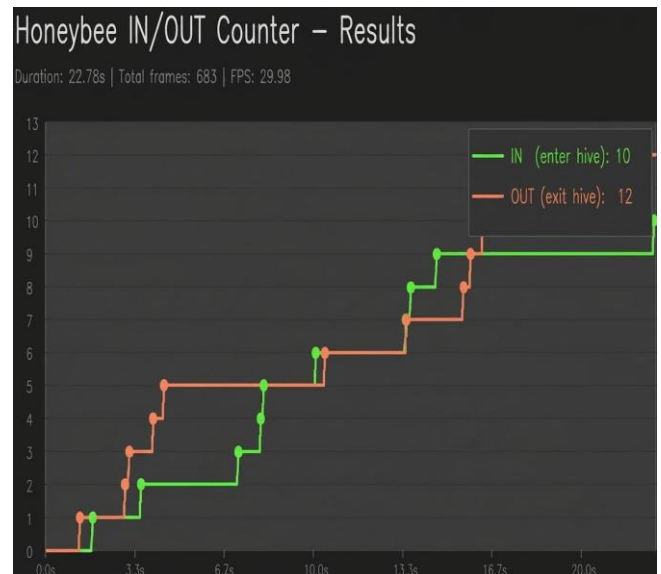


Fig -3 In/Out Counter

4.4 In/Out counter result

(Figure -3) The cumulative IN/OUT plot for a 22.78-second test clip (683 frames, ~30 FPS) shows 10 bees entering and 12 exiting the hive, yielding a net change of -2. The stepped green and orange lines represent real-time entrance and exit events logged by the presence-based counting logic.

4.5 Counting and Tracking Validation

System-level validation against manual ground-truth counts gave an average counting accuracy of 93.0% for IN events and 94.6% for OUT events across all lighting conditions. Tracking evaluation recorded a MOTA score of 82.4% with 14 identity switches across all test videos. Reproducibility testing across five repeated runs of the same video produced identical IN/OUT counts each time (standard deviation of zero), confirming that the counting logic is deterministic. A representative 22.78-second test clip (683 frames) recorded 10 IN and 12 OUT events, illustrating the system's ability to generate session-level behavioural summaries alongside frame-level bounding box and serial-ID overlays.

4.6 Discussion

These results confirm that VisionHive reliably detects, tracks and counts honeybees under real apiary conditions. The consistently high precision across lighting conditions indicates a low false-alarm rate, while the recall gap observed in low light highlights a practical deployment consideration: supplementary lighting or camera adjustment during evening hours could further improve detection consistency. The presence-based, direction-independent counting logic combined with persistent serial-ID tracking distinguishes VisionHive from prior detection-only or aggregate-counting systems [12], enabling genuine per-bee behavioural analysis rather than simple traffic counts, and extends comparative precision-apiculture monitoring studies that contrast traditional and technological methods across different crop settings [13].

5. CONCLUSIONS

This study presented VisionHive, a YOLOv8 and DeepSORT-based deep learning pipeline for non-invasive, automated honeybee entrance monitoring. By combining real-time detection, persistent serial-ID tracking, a virtual dual-box ROI framework and presence-based directional counting, the system addresses a gap left by prior sensor-based and detection-only approaches. Trained and validated on field data from HBRTC Pantnagar, the best model achieved a mAP@0.50 of 0.954 and counting accuracy above 93% against manual ground truth, with noon-time lighting producing the most reliable detections. The proposed framework offers beekeepers, particularly smallholder farmers, an objective, continuous, low-cost tool to shift colony management from reactive to data-driven

practice. Future work will expand the dataset across seasons and hive locations, add a dedicated pollen-carrier detection class building on prior pollen-bearing bee recognition work [14]–[15], integrate ByteTrack[3] for improved occlusion handling, deploy the model on Raspberry Pi hardware for real-time field use in line with existing IoT-based hive-monitoring platforms [12], and build a beekeeper-facing mobile interface for live hive analytics.

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