

A YOLOv8-Based Two-Stage Framework for Non-Destructive Detection of *Varroa destructor* Infestations in *Apis mellifera* Colonies

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[Abstract]

The European honeybee (*Apis mellifera*) is an important pollinator threatened by colony collapse disorder (CCD), primarily due to infestation by the Varroa mite (*Varroa destructor*). Traditional detection methods are invasive and time-consuming, often causing additional stress to colonies. We propose a two-stage framework using the You Only Look Once version 8 (YOLOv8) model for non-destructive and rapid detection of Varroa mite infestation. The framework uses comb light images from inside the hives. In the first stage, a YOLOv8-n model detects bees and extracts individual bee images. In the second stage, a YOLOv8-cls model classifies the infestation status of each bee. Our object detection model achieved a mAP@0.5 of 0.701, and the classification model achieved an average accuracy of 91%. These results demonstrate the effectiveness of the framework as a non-destructive method for Varroa mite detection. Based on this research, we expect to provide beekeepers with an efficient tool for early detection and management of Varroa mite infestations, potentially reducing the incidence of CCD and supporting the sustainability of apiculture.

▶ **Key words:** Small Object Detection, Smart Beekeeping, Colony Collapse Disorder (CCD), YOLOv8, *Varroa destructor*, Non-Destructive Inspection

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[요 약]

유럽 꿀벌(*Apis mellifera*)은 중요한 화분매개자로서 군집 붕괴 현상(CCD)으로 위협받고 있으며, 이는 주로 바로아 응애(*Varroa destructor*) 감염에 기인한다. 기존의 감염 검사는 침습적이고 시간이 많이 소요되어 벌통에 추가적인 스트레스를 준다. 본 논문에서는 YOLOv8 모델을 활용한 비파괴적이고 신속한 바로아 응애 감염 검사를 위한 2단계 프레임워크를 제안한다. 프레임워크는 벌통 내부에서 촬영한 소초광 이미지를 사용한다. 첫 번째 단계에서 YOLOv8-n 모델로 벌 객체를 탐지하고 개별 벌 이미지를 추출한다. 두 번째 단계에서 YOLOv8-cls 모델로 각 벌의 감염 여부를 판별한다. 제안한 모델은 객체 탐지에서 mAP@0.5 0.701, 감염 분류에서 평균 정확도 91%를 달성하여 효과적인 비파괴적 검사 방법임을 입증한다. 본 연구를 바탕으로 양봉가들에게 바로아 응애 감염의 조기 발견과 관리를 위한 효율적인 도구를 제공하여 CCD 발생을 감소시키고 양봉업의 지속 가능성을 지원할 수 있을 것으로 기대한다.

▶ **주제어:** 소형 객체 탐지, 스마트 양봉, 군집 붕괴 현상, YOLOv8, 바로아 응애, 비파괴 검사

I. Introduction

Bees are the most economically valuable pollinators on Earth, playing a crucial role in maintaining biodiversity and supporting agricultural productivity [1]. Among them, the European honey bee (*Apis mellifera*) is found on every continent except Antarctica [2]. However, beekeepers worldwide are currently facing a serious challenge known as colony collapse disorder (CCD), in which entire colonies suddenly disappear [3]. While several factors contribute to CCD, pests and diseases have been identified as the most significant causes [4]. Notably, approximately 43% of CCD incidents in the United States from April 2019 to April 2020 were attributed to infestations of the Varroa mite (*Varroa destructor*), a parasitic mite that is detrimental to bee populations [5].

Accurate and efficient detection of *Varroa destructor* infestations is essential for the timely management and preservation of bee colonies. Without timely intervention, these parasitic mites can rapidly multiply and devastate entire hives, exacerbating the global decline in bee populations [6]. Traditional detection methods, such as uncapping brood, sugar powder tests, and bottom board inspections, are not only time-consuming but also invasive, potentially adding stress to

already vulnerable colonies [7]. These methods often require physical disturbance of the hive structure and the bees, which can disrupt their natural behaviors and increase the risk of harming the queen or brood [8]. As a result, there is an urgent need for non-destructive, rapid, and accurate diagnostic methods that allow beekeepers to effectively monitor and manage *Varroa destructor* infestations without causing additional harm [9].

Advances in deep learning technologies have led to significant progress in computer vision, particularly in the processing and analysis of image data [10]. The You Only Look Once (YOLO) object detection algorithm has received considerable attention for its ability to quickly and accurately detect object locations and categories within images [11]. Unlike traditional object detection methods that repeatedly analyze multiple regions of an image, YOLO takes an innovative approach by making predictions over the entire image in a single pass through a neural network [12]. This efficiency makes YOLO highly suitable for real-time applications and has led to its integration with various technologies to solve diverse object detection challenges [13].

In this paper, we propose an accurate and

non-destructive two-stage framework for inspecting *Varroa destructor* infestation in apiaries using the YOLO algorithm. The proposed framework uses comb-light images captured from inside the hives. In the first stage, we input these images into a pre-trained YOLOv8-n model to detect individual bees and obtain bounding box coordinates for each bee. In the second stage, we pass the cropped images of individual bees through a pre-trained YOLOv8-cls model to classify the infestation status. This method allows efficient, non-destructive monitoring of bee colonies and helps beekeepers in early detection and management of infestations [14].

The rest of this paper is organized as follows: In Section II, we review related work on deep learning applications in insect detection and beehive monitoring. Section III details our proposed methodology, including the framework architecture, the image processing models, and the datasets used. Section IV presents the experimental results, comparing the performance of different YOLO models in the object detection stage and evaluating the classification accuracy in the infestation detection stage. Finally, Section V concludes the paper and discusses future research directions.

II. Related Work

Kwon et al. [15] proposed an improved structure of the YOLO version X (YOLOX) model to improve the accuracy of hornet detection. They replaced the cross-stage partial layer (CSPLayer) in each stage of the existing YOLOX backbone with a shuffle layer. This modification reduced the parameter size by approximately 91%, thereby increasing the processing speed. Experimental results showed that the proposed method achieved a mean average precision (mAP) of 87.35%, which is an increase of 1.114% compared to the standard YOLOX.

Gwak et al. [16] compared the accuracy of deep learning models for wasp detection based on different training datasets. The base dataset consisted of typical training images where objects occupy a large portion of the image. In addition, they created a training dataset to improve the detection performance for small objects. This dataset was modified so that the object area was 0.3% of the total image area, similar to the proportion of wasps in real camera footage. Experimental results showed that the YOLO version 7 (YOLOv7) model trained solely on the created dataset achieved the best mAP@0.5 of 95.4%.

Berkaya et al. [17] proposed a hive monitoring system to classify the state of bee colonies using deep learning technology. They trained their models using three datasets: a *Varroa* dataset, a bee image dataset, and a pollen-carrying dataset. They developed several deep learning-based classification models by extracting features from the image data using transfer-learned deep neural network (DNN) models and then classifying the extracted features using a support vector machine (SVM) model. The types of DNN models and the methods used for feature extraction are shown in Table 1.

In their experiments, the transfer-learned Visual Geometry Group network 19 (VGGNet-19) model achieved the highest accuracy of 93.22% on the *Varroa destructor* dataset. On the bee image dataset, the SVM model using both deep and shallow features extracted from the GoogLeNet model achieved the highest accuracy of 98.2%. For the pollen-carrying dataset, the transfer-learned GoogLeNet model achieved the highest accuracy of 99.07%. To avoid possible misunderstandings, it is important to note that for each DNN model listed in Table 1, multiple feature extraction methods were applied:

- Transfer learning only: The DNN model was used as is, with its pre-trained weights, to perform classification.
- Deep features: Features were extracted from the deeper layers of the DNN model and then

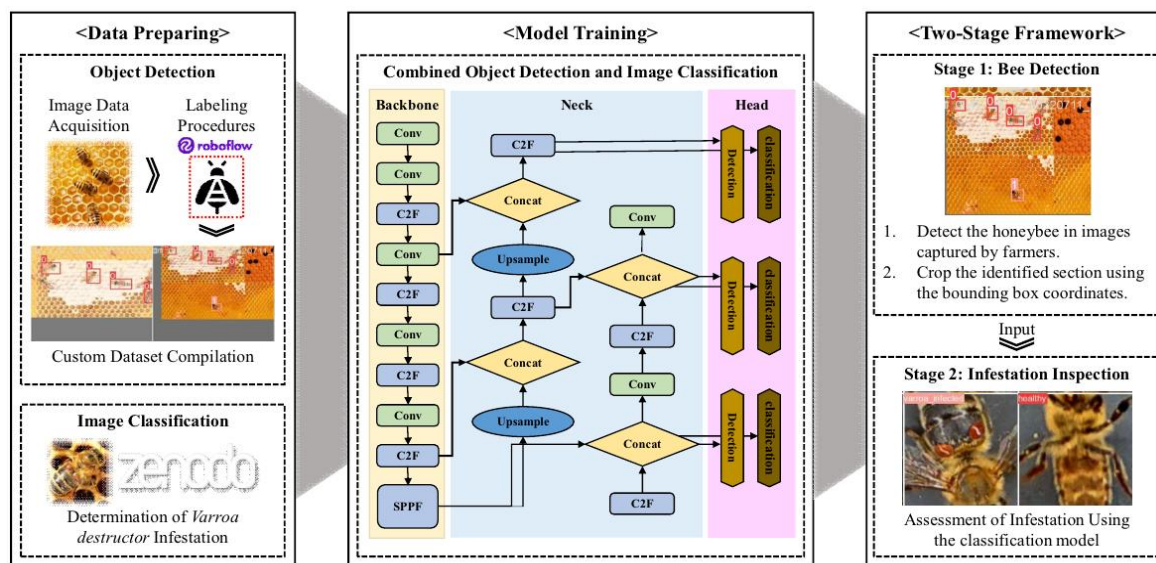


Fig. 1. Framework for Object Detection and Classification

used as input to the SVM classifier.

- **Shallow features:** Features were extracted from the shallower layers of the DNN model and then used as input to the SVM classifier.

By experimenting with different combinations of DNN models and feature extraction methods, the researchers aimed to determine the most effective approach for classifying the state of bee colonies.

Table 1. Types of Deep Neural Network Models and Feature Extraction Methods

| Model | Feature Extraction Methods |
|--------------|---|
| AlexNet | Transfer learning only Deep features Shallow features |
| DenseNet-201 | Transfer learning only Deep features Shallow features |
| GoogLeNet | Transfer learning only Deep features Shallow features |
| ResNet-101 | Transfer learning only Deep features Shallow features |
| ResNet-18 | Transfer learning only Deep features Shallow features |
| VGG-16 | Transfer learning only Deep features Shallow features |
| VGG-19 | Transfer learning only Deep features Shallow features |

III. Datasets and Preprocessing

This section details the datasets employed in the development of the proposed framework and the preprocessing steps undertaken to prepare the data for modeling. Figure 1 provides an overview of the workflow, and this section elaborates on the preprocessing procedures.

1. Dataset Description

1.1 Bee Object Detection Dataset

To construct the bee object detection model, we used a publicly available dataset [18] of images taken inside honeycombs. The dataset contains images of bees at different life stages and from different subspecies, providing a diverse set of scenarios for model training. Specifically, we selected 2,500 images each of worker bees and queen bees of the species *Apis mellifera*. The images depict bees in their natural hive environment, providing realistic backgrounds and lighting conditions that enhance the robustness of the detection model.

1.2 Varroa Mite Infestation Classification Dataset

For the Varroa mite infestation classification model, we used a dataset [19] containing images of bees either infested with *Varroa destructor* mites or

uninfested. The dataset consists of 10,000 images, evenly distributed between the two classes to avoid bias in the classification results. The images capture bees in a variety of positions and lighting conditions, reflecting real-world variability and enhancing the generalization capabilities of the model.

2. Data Preprocessing Methods

Data preprocessing is crucial to improving the quality of the input data and the performance of the models. The following preprocessing steps were applied to both datasets:

- (1) Data Splitting: Each dataset was split into training and validation sets with a ratio of 8:2. This split ensures that the models have enough data to learn while maintaining a separate set for unbiased performance evaluation.
- (2) Image Augmentation: To increase the diversity of the training data and to avoid overfitting, several data augmentation techniques were applied:
 - Random Flipping: Images were randomly flipped horizontally and/or vertically.
 - Rotation: Images were rotated at random angles within a specified range.
 - Scaling and Cropping: Randomly scaled and cropped images to simulate different distances and perspectives.
 - Brightness and Contrast Adjustment: Random brightness and contrast changes were made to simulate different lighting conditions.
- (3) Image Resizing: All images were resized to a fixed size suitable for input to the neural networks. For the YOLOv8 models, images were resized to 640×640 pixels while preserving the aspect ratio to avoid distortion.
- (4) Normalization: Pixel values were normalized to have zero mean and unit variance. This step allows faster convergence during training and ensures numerical stability.
- (5) Annotation Preparation: For the object recognition dataset, annotations in the form

of bounding boxes and class labels were prepared in YOLO format. Each annotation contains the class label and the normalized coordinates of the bounding box.

IV. Proposed Method

In this section, we present the proposed two-step framework for non-destructive detection of *Varroa destructor* infestation in bee colonies. The framework integrates advanced image processing models to efficiently perform object detection and classification tasks.

1. Overview of the Framework

The proposed framework is designed to accurately detect varroa mite infestation using comb-light images captured from inside the hives, thereby minimizing disturbance to the colonies. As shown in Figure 2, the framework consists of two main stages.

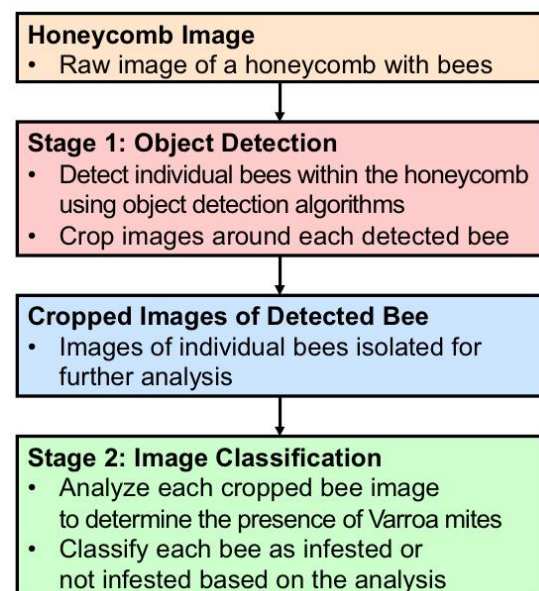


Fig. 2. Overview of the Proposed Two-Stage Framework for Non-Destructive Detection of *Varroa destructor* Infestations

In the first stage, the goal is to detect and localize individual bees within the hive images. The input comb light images are fed into the YOLOv8-n object detection model, which outputs bounding

boxes and class probabilities for each detected bee, distinguishing between workers and queens. Based on the bounding box coordinates, the images are cropped to obtain individual bee images.

In the second stage, the goal is to classify each detected bee as infested or uninfested with a *Varroa destructor*. The cropped bee images from the first stage are fed into the YOLOv8-clb image classification model, which predicts the infestation status. The infestation labels for each bee can then be aggregated to assess the overall health of the colony.

This two-stage approach allows for focused analysis on individual bees, improving the accuracy of infestation detection while maintaining high processing speeds suitable for real-time monitoring [20].

2. Detailed Description of Image Processing Models

The framework leverages the capabilities of the YOLOv8 architecture for both object detection and image classification tasks. Using models from the same family ensures compatibility and efficiency in the processing pipeline.

2.1 YOLOv8-n Object Detection Model

The YOLOv8-n model is a lightweight yet powerful object detection network derived from the YOLO family [21]. Its architecture consists of three key components: the backbone network, the neck, and the detection head.

The backbone network serves as a feature extractor that captures visual patterns from the input images. It uses CSP networks to improve gradient flow and reduce computational complexity. The neck, implemented using the path aggregation network (PANet), combines feature maps from different scales, facilitating multi-scale object detection. The detection head predicts bounding boxes, objectness scores, and class probabilities.

One of the notable features of YOLOv8-n is the adoption of an anchor-free detection approach. Eliminating the need for predefined anchor boxes simplifies model design and improves detection

performance, especially for small objects such as bees [22].

To train the YOLOv8-n model, we used a combination of loss functions, including localization loss (e.g., Intersection over Union [IoU] loss), objectness loss (e.g., binary cross-entropy), and classification loss (e.g., focal loss). The Adam optimizer with a learning rate scheduler allowed for efficient convergence. Hyperparameters such as batch size and learning rate were fine-tuned through cross-validation to optimize performance.

The YOLOv8-n model balances accuracy and speed, making it suitable for use on devices with limited computing resources. Its ability to perform real-time detection is critical for continuous monitoring applications [23].

2.2 YOLOv8-clb Image Classification Model

The YOLOv8-clb model is designed for image classification tasks and shares the backbone network architecture with YOLOv8-n. This consistency allows for seamless integration between the detection and classification stages. The model includes convolutional layers for hierarchical feature extraction, global pooling layers to aggregate feature maps into fixed-length representations, and fully connected layers to perform classification based on the extracted features.

Transfer learning was used to improve model performance and reduce training time. The model was initialized with weights pre-trained on large image datasets such as ImageNet. It was then fine-tuned on the varroa mite infestation dataset, allowing it to adapt to the specific characteristics of the task. For the classification task, cross-entropy loss was used for binary classification (infested vs. uninfested). The Adam optimizer was used with appropriate regularization techniques to avoid overfitting. Data augmentation techniques similar to those used in the object detection stage were applied to improve generalization.

Given the small size and subtle appearance of varroa mites on bees, high-resolution images and

careful preprocessing were essential. The model focuses on learning discriminative features that distinguish infested bees from healthy ones, such as the presence of mites on the bee's body. By using models from the same architecture family, the output of the YOLOv8-n detection model, cropped bee images, is directly compatible with the YOLOv8-cls classification model. This compatibility streamlines the processing pipeline and reduces overhead, increasing the overall efficiency of the framework.

V. Experiments

In this section, we evaluate the performance of the proposed two-stage framework through a series of experiments. The goal is to assess the accuracy and effectiveness of the YOLOv8 models in detecting bee objects and classifying varroa mite infestation. We also compare YOLOv8 with previous versions, namely YOLOv5 and YOLOv7, to understand how the advancements in YOLOv8 contribute to improved results.

1. Object Detection Stage

To accurately detect bee objects in hive images, we compared the predictive performance of three versions of the YOLO model: YOLOv5, YOLOv7, and YOLOv8. These models represent successive advancements in the YOLO series, each introducing improvements in architecture and performance.

1.1 Overview of YOLOv5, YOLOv7, and YOLOv8

YOLOv5 is an object detection model that builds on the YOLO family and introduces improvements in speed and accuracy over its predecessors. It includes a focus module and uses advanced data augmentation techniques such as mosaic and self-adversarial training to improve performance [24].

YOLOv7 further improves on YOLOv5 by introducing extended efficient layer aggregation networks (E-ELANs), which improve the ability to learn features without increasing computational cost. It also integrates model re-parameterization

techniques to optimize the architecture for both the training and inference phases [25].

YOLOv8, the latest in the series, introduces several significant enhancements:

- **Anchorless Recognition:** YOLOv8 takes an anchor-free approach, eliminating the need for predefined anchor boxes. This simplifies the model and reduces localization errors, especially when detecting small objects such as bees [26].
- **Improved Backbone and Neck:** Uses a new backbone mesh with improved feature extraction capabilities and an efficient neck component for better feature fusion [27].
- **Advanced Training Strategies:** YOLOv8 incorporates improved loss functions and optimization techniques, resulting in better convergence and accuracy [28].

1.2 Experimental Setup

- **Dataset:** The bee object detection dataset described in Section 3.1.1 was used for training and evaluation.
- **Evaluation Metrics:** Models were assessed using accuracy for each class (worker and queen bees), average precision (AP) for each class, and mAP at an IoU threshold of 0.5 (mAP@0.5).
- **Training Parameters:** Each model was trained under similar conditions to ensure a fair comparison. Hyperparameters such as learning rate, batch size, and number of epochs were optimized for each model through cross-validation.

1.3 Results and Analysis

The predictive performance of each model is summarized in Table 2.

Table 2. Performance Comparison of YOLO Models for Bee Object Detection

| Model | Accuracy (%) | | Average Precision (AP) | | mAP@0.5 |
|--------|--------------|-------|------------------------|-------|---------|
| | Worker | Queen | Worker | Queen | |
| YOLOv5 | 98 | 32 | 0.548 | 0.799 | 0.673 |
| YOLOv7 | 76 | 30 | 0.459 | 0.374 | 0.416 |
| YOLOv8 | 96 | 48 | 0.602 | 0.807 | 0.705 |

From the results in Table 2, we can see that:

- YOLOv5 achieved high accuracy in detecting worker bees (98%), but showed lower accuracy for queen bees (32%). Its mAP@0.5 was 0.673.
- YOLOv7 had lower accuracy for both worker bees (76%) and queen bees (30%) compared to YOLOv5 and YOLOv8, with a mAP@0.5 of 0.416.
- YOLOv8 outperformed the other models in most metrics, achieving accuracies of 96% for worker bees and 48% for queen bees and a mAP@0.5 of 0.705.

The improved performance of YOLOv8 is due to several factors:

- **Anchorless Detection:** YOLOv8's anchor-free approach simplifies the detection process and reduces errors associated with anchor box dimensions, improving performance when detecting small and irregularly shaped objects such as bees [29].
- **Improved Feature Extraction:** YOLOv8's improved backbone and neck architectures allow for better feature aggregation and fusion, resulting in more accurate object localization and classification [30].
- **Advanced Training Techniques:** YOLOv8 incorporates optimized loss functions and training strategies that improve convergence and generalization, contributing to higher accuracy.

While YOLOv5 demonstrated high accuracy for worker bees, it struggled with queen bee detection. This may be due to its reliance on anchor boxes, which can be less effective for objects of varying sizes and shapes. YOLOv7 did not perform as well in our specific application, possibly due to overfitting or inadequate adaptation to the characteristics of our dataset.

The lower accuracy in detecting queen bees across all models highlights a challenge in our dataset and task. Queen bees have distinct morphological features and are less represented in the dataset compared to worker bees. Expanding the dataset with more images of queen bees and

using data augmentation techniques focused on queen bee characteristics may improve detection accuracy in future work [31].

Accurate detection of worker bees is critical to our framework, as they make up the majority of the colony and are the primary subjects for infestation assessment. YOLOv8's high accuracy in detecting worker bees ensures the reliability of the subsequent classification stage.

2. Classification Stage

In the second stage, we evaluated the performance of the varroa mite infestation classification model using the cropped bee images obtained from the object detection stage.

2.1 Experimental Setup

- **Dataset:** The varroa mite infestation classification dataset described in Section II was used for training and evaluation.
- **Evaluation Metrics:** The performance of the model was evaluated using the accuracy for each class (infested and uninfested) and the overall average accuracy.
- **Training Parameters:** The YOLOv8-cls model was fine-tuned using transfer learning as described in Section 3.1.2. Hyperparameters were optimized to maximize classification accuracy.

2.2 Results and Analysis

The classification model shows significant variance in performance based on infestation status, as detailed in Table 3. The model is highly effective, with an accuracy of 99% for detecting infested bees while achieving an accuracy of 87% for identifying uninfested bees. This indicates the increased sensitivity of the model to the specific markers of infestation.

Table 3. Detailed Performance Metrics of the Classification Model

| Model | Accuracy (%) |
|------------|--------------|
| GoogLeNet | 89 |
| ResNet50 | 92 |
| YOLOv8-clc | 93 |

This difference in accuracy highlights the need for model refinement to improve reliability. The lower accuracy in detecting uninfested bees suggests that improvements are needed to ensure balanced performance across detection scenarios. These results direct future research toward improving model consistency and confirm the utility of convolutional neural networks in pest detection applications [32, 33].

The high accuracy in detecting infested bees indicates the effectiveness of the model in identifying the subtle visual cues associated with *Varroa destructor* infestations. The slightly lower accuracy for uninfested bees may be due to false positives, where uninfested bees are mistakenly classified as infested. This could be due to visual similarities or occlusions in the images.

To improve classification performance, especially for uninfested bees, future work could focus on:

- Improving Image Quality: Using higher resolution images or improving image preprocessing to better capture discriminative features.
- Expanding the Dataset: Enhancing the diversity of the dataset through generative model-based data augmentation to improve model generalization [31].
- Advanced Feature Extraction: Explore more sophisticated feature extraction methods or ensemble models to capture nuanced differences [34].
- Ensuring Data Quality: Detecting mode drop and collapse in generative models using techniques to maintain data diversity and quality, thereby improving overall model performance [35].

3. Discussion

The experimental results confirm the effectiveness of the proposed two-stage framework. The YOLOv8 models showed superior performance in both detection and classification tasks compared to previous versions.

The main findings are as follows:

- Advantages of YOLOv8: The architectural and methodological advances in YOLOv8 contribute significantly to its improved performance, making it well suited for our application.
- Effectiveness of the framework: The high accuracy achieved in both phases suggests that the framework can reliably detect *Varroa destructor* infestations non-destructively, providing a practical tool for beekeepers.

Despite the promising results, there are some limitations:

- Queen Bee Detection: The lower detection accuracy for queen bees indicates the need for more focused training in this class.
- Dataset Diversity: Expanding the dataset to include more variations in bee appearance, hive conditions, and environmental factors may improve model robustness.
- Real-World Deployment: Testing the framework in operational apiaries will provide insight into its practical utility and areas for improvement.

The experiments show that the proposed framework, leveraging the strengths of YOLOv8, achieves high accuracy in bee detection and varroa mite infestation classification. These results support the potential of the framework as a non-destructive, efficient solution for colony health monitoring.

VI. Conclusions

In this paper, we proposed a two-stage YOLOv8-based framework for non-destructive detection of *Varroa destructor* infestation in bee colonies, contributing to the advancement of

technology for smart beekeeping practices. The framework used comb-light images captured from inside the hives, minimizing disturbance to the bees and enabling efficient monitoring.

In the first stage, we used a pre-trained YOLOv8-n object detection model to identify and localize individual bees within the hive images. This model achieved a mAP@0.50 of 0.705, demonstrating its effectiveness in accurately detecting bee objects. By obtaining the bounding box coordinates, we were able to crop the images to focus on individual bees, providing high-quality input for the classification stage.

In the second stage, we used a pre-trained YOLOv8-cls image classification model to determine the infestation status of each bee. The model achieved an average accuracy of 93%, indicating a high degree of reliability in classifying bees as infested or uninfested with *Varroa destructor*. By aggregating the classification results of individual bees, the overall health of the colony can be assessed, allowing for timely intervention.

Traditional methods for detecting *Varroa destructor* infestations are often destructive and time-consuming, involving invasive inspections that can stress bees and disrupt hive activities. The proposed framework can provide a non-destructive and rapid alternative, allowing beekeepers to efficiently monitor infestation levels without causing additional harm to colonies.

For future research, we plan to explore more robust algorithms specifically tailored for detecting small objects such as varroa mites. This may involve integrating advanced image enhancement techniques or leveraging newer deep learning architectures to further improve detection and classification accuracy. By refining the proposed method, we aim to contribute to more effective and sustainable beekeeping practices, ultimately supporting the health and productivity of bee populations essential to global biodiversity and agriculture.

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