MONITORING OF VARROA INFESTATION RATE IN BEEHIVES: A SIMPLE AI APPROACH

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ABSTRACT

This paper addresses the monitoring of *Varroa destructor* infestation in Western honey bee colonies. We propose a simple approach using automatic image-based analysis of the fall-out on beehive bottom boards. In contrast to the existing high-tech methods, our solution does not require extensive and expensive hardware components, just a standard smartphone. The described method has the potential to replace the time-consuming, inaccurate, and most common practice where the infestation level is evaluated manually. The underlining machine learning method combines a thresholding algorithm with a shallow CNN—VarroaNet. It provides a reliable estimate of the infestation level with a mean infestation level accuracy of 96.0% and 93.8% in the autumn and winter, respectively. Furthermore, we introduce the developed end-to-end system and its deployment into the online beekeeper's diary—ProBee—that allows users to identify and track infestation levels on bee colonies.

Index Terms— Apiculture, Bee, Varroa, Mite, CNN, Machine Learning, Computer Vision

1. INTRODUCTION

Varroa destructor is an ectoparasitic honey bee mite that historically appeared on Eastern honey bee (*Apis cerana*), but spread to the Western honey bee (*Apis mellifera*) during the first half of the 20th century and its occurrence has become worldwide and now poses a major threat to apiculture. While the native host is resistant to Varroa infestations, Varroa populations in *A. mellifera* populations have grown uncontrollably; by enhancing a viral transmission (due to mite feeding) and weakening honey bee immunity, Varroa infestations pose a significant threat to honey bee health and have resulted in significant declines in *A. mellifera* populations globally [1, 2]. Varroa reproduction in *A. mellifera*, unlike *A. cerana*, occurs on worker brood, which is available in colonies for the whole year, allowing mite populations to grow dramatically. As a result, application of acaricidal pesticide is required for bee colonies to sustain their survival [3]. This action produces a substantial impact on colony dynamics and honey contamination. Thus, early and precise estimation of infestation level is crucial for the sustainability of apiculture.

Fig. 1. Varroa destructor mites on a beehive bottom-board photograph. Circles represents $2\times$ and $4\times$ zoom.

Varroa mite levels in colonies should be inspected regularly to ensure effective Varroa control and determine whether chemical intervention is necessary. Beekeepers typically monitor the mean abundance of mites—a number of mites per 100 bees—monthly to determine when the population of mites observed on adult worker bees has reached a threshold, with the goal of the mite populations below two mites per 100 bees. The monitoring techniques used are, for example, sugar rolls and alcohol washes, and sticky boards. Although these procedures are inexpensive, they are time-consuming, especially in apiaries with many colonies [1].

An accurate and inexpensive method for the Varroa mite infestation level monitoring is to manually count the Varroa individuals that fall on a solid board placed at the bottom of the hive (see Figure 1). Although this method has been used for years, it is tedious and time-demanding due to the small size of the individuals (1–2mm) and the fact that they are mixed with the various hive remnants (pollen, wax etc.).

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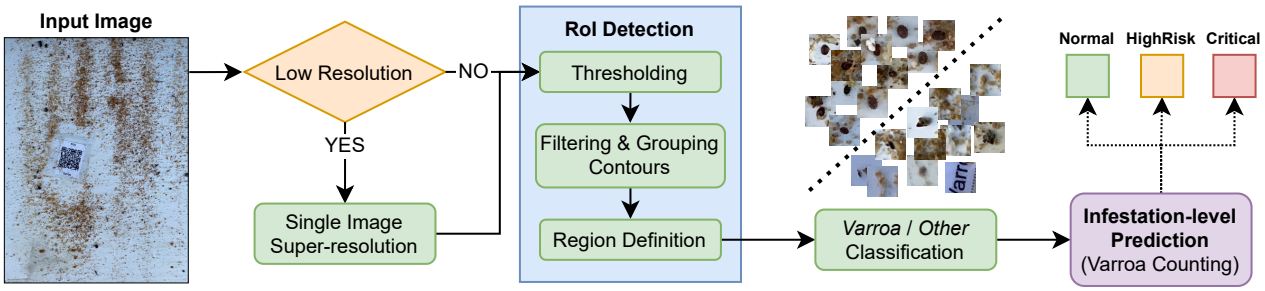


Fig. 2. Method overview. We check for low-resolution images, use ESCPN [4] super-resolution if needed, detect RoI via naive thresholding, perform binary classification (Varroa / Other), and indicate infestation level based on the number of Varroa.

The paper introduces the first system for an automated Varroa destructor mite detection on a fall-out board. It has the potential to replace the current counting approach done via the naked eye, which is both inaccurate and time-consuming. The proposed system is based on the standard computer vision approach and a shallow CNN while using a standard mobile phone with a camera without any additional investment and design changes in the hives.

2. RELATED WORK

Smart apiculture is a growing area with enormous potential to assist roughly 500 thousand beekeepers in managing around 100 million beehives globally. There have been several attempts to use computer vision methods in beekeeping with a focus on bee species identification and monitoring [5], honey bee counting [6], honey bee flight and movement analysis [7, 8, 9], and Varroa destructor detection [10, 11, 12, 13, 14]. The first method for Varroa mite detection was developed by Ramirez et al. [10], in a sandbox like environment, with a single Varroa destructor mite in an Africanized honey bee cell, using movement active area. Chazette et al. [11] introduced a system for possible destruction by laser while using CNN to identify Varroa on bees before they enter the beehive. Bee detection was done via an implicit shape model and classification by a custom CNN model. Bjerge et al. [12] developed a novel portable system to monitor the infestation level using a video monitoring unit with multi-spectral illumination and a camera placed at the entrance of the beehive. Shurisschuster et al. [13] used a two-stage approach with a beehive entrance camera for bee detection and further Varroa detection via a sliding window approach and AlexNet / ResNet or segmentation with DeepLabV3. Bilik et al. [13] utilized an object detection approach based on YOLOv5 [15] to identify the mites directly on honeybees.

Most methods of Varroa infestation level monitoring require special equipment to detect bees while they enter the hive or a camera system inside the hive; thus, the usability of the methods is limited. As beekeepers usually own dozens of hives, each with roughly 50 frames and tens of thousands of bees, it is unimaginable to operate such systems in real life.

3. METHODOLOGY

This section describes the new dataset for Varroa mite infestation monitoring and both building blocks of the proposed two-stage approach, i.e., (i) standard computer vision method for Regions of Interest (RoI) selection and (ii) shallow CNN for RoI classification. The method is illustrated in Figure 2.

3.1. Dataset

All images used for the dataset construction were collected for two years, captured on various devices, and include pre- and post-treatment cases. The final dataset comprises 400 photos of around 100 beehives, 200 with COCO-like instance segmentation annotations for Varroa detection evaluation and 200 with 3 types of infestation labels—Normal, High-Risk, and Critical—to allow unbiased end-to-end evaluation. As the critical number of mites per hive depends on the colony's size, the season, and the stage of treatment, the infestation categories are simplified via different Varroa count thresholds for winter and autumn seasons. Regions within the bottom-board with and without Varroa are displayed in Figure 3.

The COCO-like part of the dataset (200 photographs) was divided into two subsets (S1 & S2) to allow robustnes evaluation towards unwanted biases, i.e., type of camera devices, seasonality, number of positive samples, light conditions, background texture/colour, and compression algorithms.

- **S1**: Photographs taken mainly in the autumn months—highest Varroa activity—showing the bottom plates of the hive in the conditions before and after treatment.
- **S2**: Photographs from winter months—lowest Varroa activity—with a small number of Varroas.

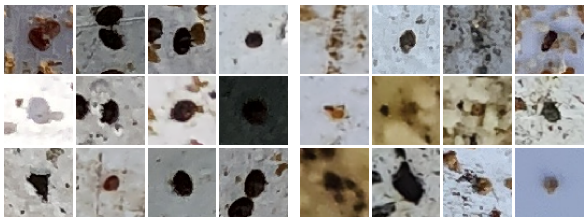


Fig. 3. Samples of objects on bottom board—hive remnants.

The development set was split into training and validation subsets (90/10), keeping the same class distribution. A description of the COCO-like dataset is in Table 1.

Dataset		Development set		Test set	
S1	S2	Photos	Varroas	Photos	Varroas
✓	×	100	7,213	18	992
×	✓	70	1,196	12	255
✓	✓	170	8,409	30	1,247

Table 1. Description of two datasets for Varroa Classification.

3.2. RoI Detection

Given the lack of annotated data for training conventional object detectors, e.g., YOLO, DETR and EfficientDet, we propose an alternative detection algorithm for the Region of Interest (RoI) selection based on standard computer vision techniques. Varroa mites are characterized by their dark colour; thus, a straightforward algorithm based on image thresholding allows the detection of potential RoIs with Varroa mites with a sensitivity close to 1. The proposed algorithm is visualized in Figure 4 and can be described as follows:

1. **Thresholding**: An image is converted to grey-scale and binarized via thresholding; 12 binary images are produced. Thresholds are equivalent to pixel intensity values on a scale $\langle 20, 140 \rangle$ with a step of 10.
2. **Contours filtering & grouping**: Each closed boundary region is filtered based on contour area in range $\langle 12^2, 60^2 \rangle$. Remaining contours with centers closer than 10 pixels are grouped across all the binary images.
3. **Region definition & extraction**: All RoIs are defined by location, calculated as a median value from all grouped contours. For every RoIs center, we cut the 60×60 area from the original image.

3.3. Classification

For the potential Varroa candidates classification, we propose two lightweight CNNs, VarroaNet-0.1 and VarroaNet-0.05, with 100k and 50k parameters, respectively. Both CNNs are composed of 3 convolutional, 3 pooling, and 3 linear layers.

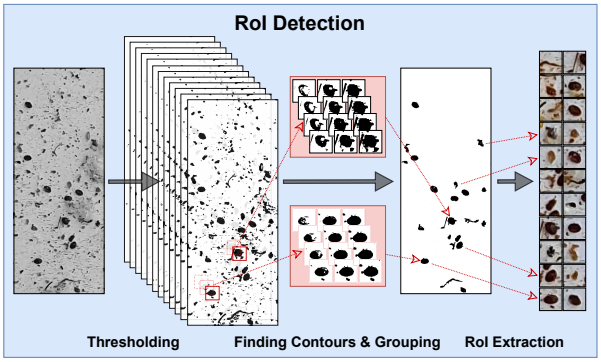


Fig. 4. RoI detection flowchart overview.

Training Strategy: All standard networks were fine-tuned from publicly available ImageNet-1k checkpoints using PyTorch and 21.11 Nvidia NGC Docker container. VarroaNets were initialized randomly. All architectures were optimized for 200 epochs by SGD with momentum set to 0.9 and a mini-batch size of 128. Start LR was set to 0.01 and decreased by the following rule—if validation loss is not reduced for 5 epochs, decrease LR by 5%.

Augmentations: Various augmentations from the Albumentation library [16] were used to increase the robustness to different visual conditions and devices. Namely, random jpeg compression, cutouts, blur, HSV shift, and brightest changes. Furthermore, image pixel values were re-scaled from $\langle 0, 255 \rangle$ to $\langle 0, 1 \rangle$ and normalized with a mean and standard deviation value of 0.5 in each channel in order to rescale values from $\langle 0, 1 \rangle$ to $\langle -1, 1 \rangle$ and achieve easier convergence.

Test-time: For CNN performance evaluation, the best performing checkpoints on the validation set in the case of Binary Cross-Entropy Loss were used.

3.4. Pre-processing

In order to increase the robustness against unseen data submitted to the ProBee platform, we preprocess the data to diminish the influence of possible low-resolution photographs. The size of Varroa on low-resolution photographs makes them unrecognizable if smaller than 12×12 pixels. Thus, all photos captured on devices with small sensors—usually $<$ 12MP—are artificially increased in resolution by the ESCPN [4] algorithm for the single image super-resolution to match the expected size of Varroa mite, i.e., area of $\langle 12^2, 60^2 \rangle$. The effect of the ESCPN is visualized in Figure 5. for two low-resolution Varroa samples on three different scales.

4. RESULTS

This section provides: (i) the performance comparison of proposed VarroaNet-0.1 and VarroaNet-0.05 with standard lightweight CNN architectures, (ii) the robustness analysis to data from different seasons for VarroaNet-0.1, and (iii) infestation-level confusion of the end-to-end system. The evaluation performance is measured via macro-averaged F1 score ($F1^m$), True Positive Rate (Sensitivity) and True Negative Rate (Specificity).

Fig. 5. Effect of ESCPN super-resolution algorithm.

RoI Classification. In order to provide a quantitative evaluation, the newly proposed VarroaNets are tested among different conventional lightweight CNN architectures, e.g., MobileNet-V3-S-0.75 [17], SE-MnasNet-0.75 [18] and FBNetV3 [19]. Even though achieved performance for both VarroaNet architectures shows insignificant performance differences (Refer to Table 2) in all measured metrics, compared to standard architectures, the model complexity for both VarroaNets is up to $100\times$ lower with an inference time of around 0.01s on a single CPU core—standard Xeon.

Furthermore, we studied the robustness of the method to seasonality, various devices and different bottom board colours. Interestingly, when tested on a different set than trained the drop in performance is significant, almost doubling the error rate in both cases. More preciselly, Specificity was reduced for S1→S2 by 11.6% and for S2→S1 by 5%. A closer examination of the performance on both datasets indicates that the winter months with a smaller number of bees—about $1/3$ of the regular population—are easier to classify. Primarily due to cleaner bottom boards caused by minimal activity. A more comprehensive comparison of the achieved scores is listed in Table 2 and Table 3.

Infestation-level Recognition. The critical number of mites per hive depends on the colony's size, the season, and the stage of treatment. During autumn, just in a week, thousands of dead mites might accumulate on the bottom board. On the other hand, after the treatment and in winter, the number of fallen mites should not exceed three mites per bee colony per month. Following the common practice, the evaluation is performed on subsets from the autumn and winter seasons separately and differently. For each season, a collection of 100 images is used. The measured mean infestation level confusion for autumn and winter are 4.0% and 6.2%, respectively. For a more comprehensive analysis and performance evaluation, refer to Figure 6.

Architecture	Sens.	Spec.	$F1^m$	Params
MobileNet-V3-S-0.75	98.3	89.3	91.6	1.0M
SE-MnasNet-0.75	**98.9**	88.5	93.0	1.6M
FBNetV3	98.8	89.9	**93.3**	6.6M
VarroaNet-0.1	98.1	90.4	91.2	0.1M
VarroaNet-0.05	98.4	**90.5**	92.1	**0.05M**

Table 2. Comparison with conventional lightweight CNN architectures. All networks share the training settings described in Section 3.3. Trained and tested on S1+S2 dataset.

Training		Sensitivity			Specificity		
S1	S2	S1	S2	S1+S2	S1	S2	S1+S2
✓	×	97.9	**99.6**	98.3	88.9	77.3	86.5
×	✓	93.9	98.6	95.0	86.8	**91.8**	87.8
✓	✓	**98.1**	97.7	**99.4**	**90.2**	91.0	**90.4**

Table 3. Robustness to different Seasons based on training data for VarroaNet-0.1.

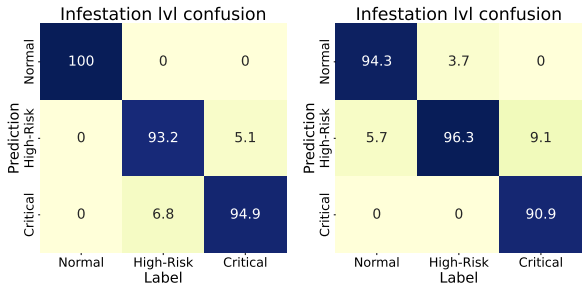
Qualitative evaluation. Most wrongly classified RoIs are those with irregular visual appearance, e.g., overlapping objects of the same color, extreme saturation and stacked Varroa mites, or RoIs not labelled as Varroa. We estimated, on a randomly sampled set of 200 RoIs, that 5–10% of wrong classifications of *Other* should be labelled as Varroa. Qualitative results as misclassified samples are shown in Figure 7.

5. CONCLUSION

The paper proposes a new automatic system for Varroa destructor infestation-level monitoring in Western honey bee hives. The design of the system, its performance validation and the deployment within the existing beekeeper application are described. Besides, the VarroaNets for Varroa mite recognition is introduced. With just 50 / 100k parameters, VarroaNets provide similar performance as standard CNNs with 10–100 times less complexity and inference time. The developed system achieved a mean infestation level accuracy of 96.0% and 93.8% in the autumn and winter, respectively.

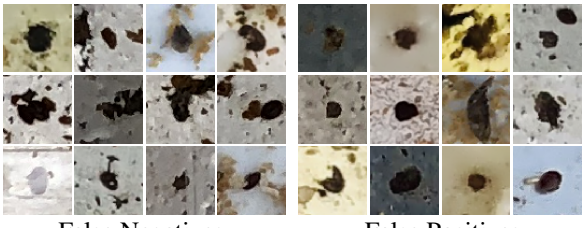
The major benefits of the proposed system including but not limited to: (i) inexpensive approach, free of additional costs, (ii) no special equipment is needed, just a smartphone, (iii) straightforward periodical measuring of Varroa infestation with required frequency, anytime and anywhere, (iv) providing valuable data about Varroa infestation levels across larger geographical areas reported by beekeepers.

The developed method is available through the REST API and publicly available through the free-to-use web application—ProBee. The data and code are available upon request for non-commercial usage.



Autumn Season Winter Season

Fig. 6. Normalized confusion matrices with infestation level confusion for Autumn and Winter Seasons.



False Negatives False Positives

Fig. 7. Samples of wrongly categorized regions of interest.

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