smartHive: A Innovative Solution for Real-Time Varroa Mite Detection and Hive Monitoring

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Abstract

Bees are a cornerstone species of any ecosystem, responsible for the production of over 75% of global crops and maintaining biodiversity worldwide.[1] They contribute billions to the economy through pollination and the valuable products they produce.[2]

The Varroa mite (Varroa destructor) is the most serious pest of honey bees worldwide.[3][4] If undetected or left untreated, it is capable of decimating entire bee colonies and the ecosystem built on them.[5] Early and reliable detection is crucial to manage it's rapid spread.

In this report we present smartHive, an innovative beehive monitoring system designed to provide an automated method of detecting the presence of Varroa while also providing smart monitoring of essential hive metrics such as hive weight, internal temperature, and humidity.

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Introduction

Bees, while often overlooked, are one of the most essential insects on the planet in maintaining an ecological equilibrium. Their integral role extends far beyond their well-known role as pollinators as these insects are indispensable in supporting biodiversity and maintaining the overall health of ecosystems worldwide.[6]

Bees are crucial to Australia as they pollinate around 65% of our crops, including fruits, vegetables, and nuts, contributing billions to the economy annually. Without bees, the country's food production and biodiversity would suffer significantly. They are also extremely vital to Australia's ecosystem, supporting it by maintaining plant diversity and habitats.[7]

The potential death of out colonies would cause considerable ecological and economic disruption. However, bee populations worldwide, including in Australia, face numerous threats. Perhaps the most significant challenge in today is the Varroa mite (*Varroa destructor*).

Fig. 1 - Image of a Varroa mite - Source: USGS Bee Inventory and Monitoring Lab

Varroa mites are external parasites that attack both adult bees and their brood. They attach themselves to bees and feed on their haemolymph (similar to blood).[8] This not only weakens individual bees but also serves as a vector for various viruses and diseases, eventually killing the entire colony.

The impact of Varroa mites on bee populations can be devastating. Infested colonies often experience:

1. Reduced lifespan of adult bees
2. Deformed wings and bodies
3. Increased susceptibility to diseases
4. Complete collapse [5]

In Australia, the threat of Varroa mites was a extreme concern for many years, one which unfortunately came true only two years ago. The first detection of Varroa mite in New South Wales in June of 2022 raised significant concerns among Australian beekeepers and by September 2023, it was agreed that it was no longer possible to eradicate the parasite.[9] Just last month in August, Varroa mite was detected near the border of Victoria and New South Wales sparking concern among beekeepers throughout the country.[10]

Given the incredible importance of bees to the ecosystems in Australia as well as our agriculture, and the serious threat posed by Varroa mites, there is an urgent need for a effective monitoring and early detection system.

Method

After deciding to address the issue of Varroa mites, we began the design process to create our solution. The first step we took involved thoroughly researching existing detection methods to find specific issues that were lacking solutions. This initial research showed the absence of any commercial solutions for Varroa monitoring, particularly in real-time.

After extensive planning and consultations with experts we solidified how we would address the issues. Our focus was to create a system that would automate the detection process and simplify it to something can could become a everyday use in apiaries. Through our design process, we conceptualized smartHive, our monitoring system specifically designed to address the Varroa mite threat.

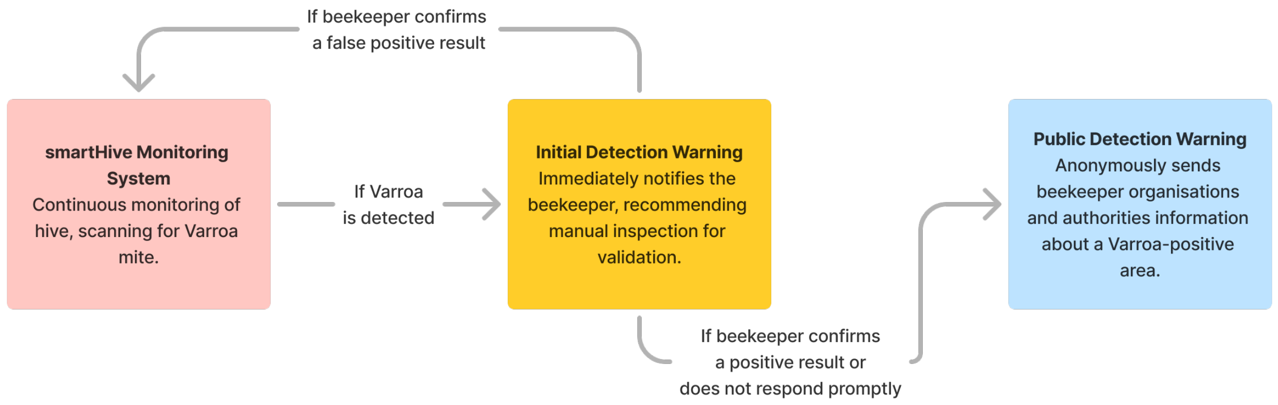

Fig. 2 - smartHive Varroa Detection Response Process Flow Diagram - Source: smartHive Project

We first decided on how the system should respond to a Varroa mite detection, resulting in the three-stage process shown in Figure 2. The smartHive monitoring system will continuously monitor the hive, scanning for any signs of Varroa mites. Upon detecting a potential Varroa mite carrying bee, the system will issue a initial detection warning - immediately notifying the beekeeper of the detection. Manual inspection will be advised to validate the detection and ensure accuracy. If it is either ignored, or confirmed, the system triggers a public detection warning, anonymously alerting the authorities about a Varroa-positive area, allowing for broader mitigation efforts. This process ensures both rapid response from the beekeeper, and the local authorities to help prevent the spread of Varroa mites.

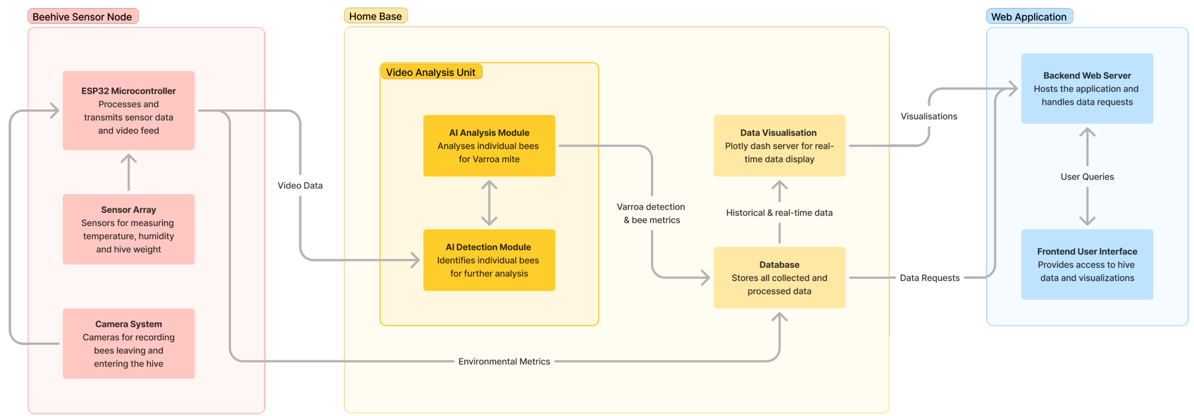

Fig. 3 - smartHive Monitoring System Process Flow Diagram - Source: smartHive Project

After an extensive design process, we completed our process flow chart. This flowchart outlines overall architecture of the smartHive system. Starting at the beehive with a sensor node, an ESP32 microcontroller processes and transmits data collected by the sensor array, which monitors hive temperature, humidity, and weight and the camera system. This data is sent to the home base, where the video analysis unit (our vision models) examines the bees for the presence of Varroa mite. All the collected metrics are stored in a database and fed into a data visualization tool powered by Plotly Dash to be relayed to the user interface for real-time display.

Gathering Data

With a design in mind, we shifted our focus to gathering the necessary data to train and test our system. We began by collecting extensive video footage of bees at our school apiary - capturing hours of video data of bees as they left and entered the hives to create a custom dataset for training.

To turn this raw footage into usable data, we began the meticulous process of hand-labelling over 400 images. This involved identifying and hand-labelling bounding boxes for the dozens of bees in every frame. Although it was a labour-intensive process, but it was crucial for creating a reference to train our bee detection models.

To be able to detect the presence of Varroa on bees, we also needed a dataset of labelled images containing bees with or without Varroa mite on them. As our beehive in based in Southern Victoria and is completely Varroa-free, we chose to use an open-source dataset from TensorFlow, designed for bee tracking and Varroa detection.

Training AI

Once our datasets was established, we began the critical step of training our AI models to detect Varroa mite. The first step in this process was selecting the most suitable architecture for our objectives. To detect bees, we chose the YOLOv10 architecture, the go-to choice for object detection model for its speed and accuracy in object detection tasks.[11]

Our YOLOv10 model was trained on our custom dataset with images downscaled to 640*640. We chose to keep all hyperparameters at their defaults, however, we chose to not utilize dropout during training, as it has been shown to often perform worse in newer architectures.[12] Our model was trained for 300 epochs on a T4 GPU on the free Jupyter Notebook service, Google Colaboratory.[13]

Alongside our bee detection model, we also developed an image classification model focused on identifying the presence of Varroa mite on bees. The architecture we chose to go with for this model was ResNet50v2, an improved version of the original ResNet architecture which has been extremely popular for it's extreme efficiency.[14][15] This model was also trained on a T4 GPU on Google Colab for 100 epochs, and utilized the open-source dataset from TensorFlow with ~7500 images at 300*150.[16]

Evaluation

After training our vision models, we needed to evaluate their performance to ensure they could detect Varroa mite effectively.

The main metric used to evaluate our object detection models was the mean Average Precision (mAP), a popular metric in measuring the accuracy of object detectors.[17] For our bee detection model, we were able to achieve a mean Average Precision at a 50% IoU threshold (mAP50) of 96%, showing our model's ability to precisely locate bees within a frame.

Similarly, our image classification model was able to achieve an accuracy level of approximately 98%. This high accuracy is crucial, as even a slight error in identifying Varroa mite can have significant consequences for our system.

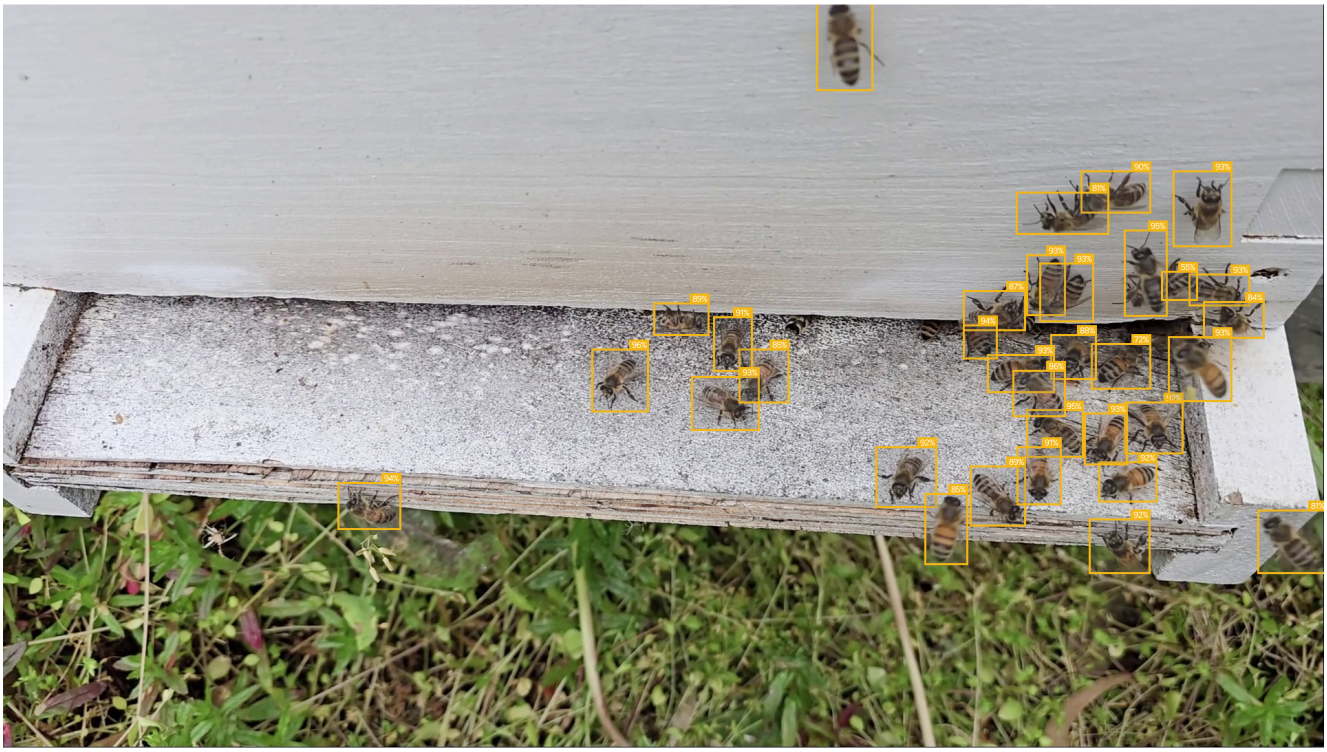

Fig. 4 - smartHive Bee Detection Demo - Source: smartHive Project

Challenges and Future Work

As we continue to progress with smartHive, we've identified crucial areas for improvement in future development. These challenges present opportunities to enhance the system's effectiveness and real-world applicability.

Real-world application of the Varroa mite detection model

Although our Varroa mite detection model can currently achieve 98% accuracy, we believe that this performance will not directly translate to real-world conditions. The controlled nature of the dataset creates the challenge of bridging the gap between theoretical performance and real-world efficacy. Factors such as varying lighting conditions or different camera positions would impact the model's accuracy in production.

To effectively address this problem, we will focus on collaborating with beekeepers to collect real-world images from active beehives in NSW in order to collate a custom dataset to help resolve this issue.

Real-World Testing with NSW Beekeepers

While controlled testing does provide many valuable insights, a system's real-world effectiveness can only be determined in real-world conditions. Deploying a testing model with beekeepers in NSW involves several challenges, such as finding willing testers within beekeeping associations, developing a user-friendly and functional prototype for testing, conducting regular check-ins to quickly address issues, and ensuring that proper support is available to testers who may run into issues with the system.

Conclusion

The smartHive system represents a significant step forward in addressing the critical threat posed by Varroa mites to bee populations in Australia and globally. By combining advanced AI technologies with real-time monitoring capabilities, smartHive offers a proactive approach to detecting and managing Varroa mite infestations.

However, the smartHive project is far from complete. Future work will focus on bridging the gap between laboratory performance and real-world application. Collaborations with NSW beekeepers for real-world testing and data collection will be crucial in refining the system's accuracy and usability under diverse conditions. With continued development and refinement, smartHive has the potential to become an incredibly powerful tool in the fight against the spread of Varroa.

References

[1] UNEP. (2019). *Why bees are essential to people and planet.* UNEP; UNEP. https://www.unep.org/news-and-stories/story/why-bees-are-essential-people-and-planet

[2] Wheen Bee Foundation. (2018). *Bees Matter – The Wheen Bee Foundation.* The Wheen Bee Foundation. https://www.wheenbeefoundation.org.au/about-bees-pollination/

[3] Department of Primary Industries. (2018). *Varroa Mite.* Www.dpi.nsw.gov.au. https://www.dpi.nsw.gov.au/biosecurity/seasonal-pests-and-diseases/spring/varroa-mite

[4] Allerton, M. (2024, September 18). Interview with Mike Allerton, ABA Biosecurity Officer [Online to smartHive team]. "The biggest biosecurity problem [in NSW] is Varroa. Absolutely."

[5] Gippsland Apiarist Association. (2022). *Varroa Mite – GAA.* Gippslandbees.org.au. https://www.gippslandbees.org.au/varroa-mite/-/3488/

[6] good living. (2017, September 1). *Why bees are so important to the environment*. Good Living. https://www.environment.sa.gov.au/goodliving/posts/2016/10/bees

[7] AB's Honey. (2022, July 5). *The Importance of Bees in Farming*. Australian Beekeepers Honey. https://abhoney.com.au/the-importance-of-bees

[8] Beeaware. (2022). *Varroa mites «Bee Aware*. Beeaware.org.au. https://beeaware.org.au/archive-pest/varroa-mites

[9] Outbreak. (2022). *Varroa mite (Varroa destructor) | Outbreak*. Outbreak.gov.au. https://www.outbreak.gov.au/current-outbreaks/varroa-mite

[10] Department of Jobs, P. and R. (2022, August 10). *Varroa mite – current situation - Agriculture*. Agriculture Victoria. https://agriculture.vic.gov.au/biosecurity/pest-insects-and-mites/priority-pest-insects-and-mites/varroa-mite-of-honey-bees/varroa-mite-current-situation

[11] Ultralytics. (2024). YOLOv10. Ultralytics.com. https://docs.ultralytics.com/models/yolov10

[12] Stack Exchange. (2018, September 19). Why should we use (or not) dropout on the input layer? Data Science Stack Exchange. https://datascience.stackexchange.com/questions/38507/why-should-we-use-or-not-dropout-on-the-input-layer

[13] Google. (n.d.). Colaboratory – Google. Research.google.com; Google. https://research.google.com/colaboratory/faq.html

[14] Sharma, V. (2021, November 23). ResNets: Why do they perform better than Classic ConvNets? (Conceptual Analysis). Medium. https://towardsdatascience.com/resnets-why-do-they-perform-better-than-classic-convnets-conceptual-analysis-6a9c82e06e53

[15] Sharma, V. (2021, November 23). ResNets: Why do they perform better than Classic ConvNets? (Conceptual Analysis). Medium. https://towardsdatascience.com/resnets-why-do-they-perform-better-than-classic-convnets-conceptual-analysis-6a9c82e06e53

[16] TensorFlow Datasets. (2019). bee_dataset. TensorFlow. https://www.tensorflow.org/datasets/catalog/bee_dataset

[17] Hui, J. (2019, April 3). mAP (mean Average Precision) for Object Detection. Medium. https://jonathan-hui.medium.com/map-mean-average-precision-for-object-detection-45c121a31173