Pollinators as Data Collectors: Estimating Floral Diversity with Bees and Computer Vision

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Abstract

This paper presents a bee-based environment monitoring system that uses pollen color analysis to estimate floral diversity. The study focuses on non-invasively assessing pollinator habitat quality using computer vision technology on honey bee hives. By strategically placing cameras at the beehive entrance, the system captures pollen color samples without disrupting the bees' natural foraging behavior. The collected pollen color data is analyzed using computer vision techniques, including pollen color classification and diversity assessment. The feasibility of the approach is evaluated through comparisons with laboratory analysis results and an appliance for capturing pollen color under ideal conditions. The study also includes the creation of a dataset for further research and advancements in the field of floral diversity estimation. The findings demonstrate the potential of using bees and computer vision technology for monitoring and understanding pollinator habitat quality.

1. Introduction

The decline in habitat quality has been identified as a main driver of the decline in insect abundance [20]. This raises significant concerns, particularly given the substantial reliance of the global agricultural industry on effective pollination services [12]. The suitability of the landscape for flower visiting insects seems to be determined by both quantity and quality of semi-natural habitat [13]. Therefore sufficient, continuous and diverse feed supply are key indicators of habitat quality.

Due to a lack of instruments, it is difficult to determine how well the living conditions for pollinators are in an area and whether measures taken to improve them were effective [22].

Western honeybee (*Apis mellifera*) colonies have been successfully employed as bio sensors. For instance, the COLOSS study [4] conducted a large-scale investigation on the spatial and temporal diversity of pollen collected by honeybee colonies. This study, known as the "Citizen Science Investigation on Pollen" (CSI-Pollen) [21], involved the collaboration of 750 beekeepers serving as citizen scientists. A remarkable total of approximately 18,000 pollen samples were collected and subjected to manual chromatic assessment.

This is largely enabled by the polylectic nature of bees [18] - a term referring to bees behavior of collecting pollen from only a single type of flower on each journey. Bee Hives act as biological samplers, bees flying from flower to flower, different bees collecting from various species within their geographic range. The different pollen grains varying in color and shape depending on their source plant [4]. By analyzing the pollen, we can assess the variety of plants in a given region, offering a snapshot of local plant biodiversity [2] [4].

Approaches like CSI-Pollen [4], Pollenyzer [2], Salazar-Gonzalez et. al. [17] or Thrasyvoulou et. al. [8] have been employed to assess pollen availability and diversity by utilizing invasive pollen traps that collect pollen from bees entering the hive, requiring the removal of pollen pellets from the bees' legs for subsequent analysis. However, these current methods, though valuable, suffer from the drawback of disrupting bees' natural foraging behavior [11] and massively reducing pollen available to the hive. To overcome this limitation, our study aims to explore the feasibility of the non-invasive pollen color extraction. By employing computer vision techniques and strategically placing cameras at the beehive entrance, we seek to retrieve the same information regarding pollen availability and diversity without disturbing the bees or compromising their pollen resources.

Computer Vision based monitoring system enabled determining bees activity [3] [14] and pollen ingress [19]. the possibility of assessing pollen collection was validated in different studies [10] [3].

The primary objective is to investigate the feasibility of non-invasively assessing pollinator habitat quality through the utilization of computer vision technology on honey bee hives, specifically focusing on the evaluation of pollen diversity.

2. Material and methods

Two different assumptions should be checked:

1. How good can Pollen color asses the environment

2. How good is pollen color assesment in the real world / at bees legs.

2.1. Methods for pollen evaluation

Firstly, we adopted a pollen color classification approach proposed by Conti et. al. [7] to establish a baseline for comparison with related work. The classification method involved determining the closest reference pollen color based on Euclidean distance in the LAB color spectrum. Secondly we propose a dynamic classification, by employing HDBSCAN. Subsequently, we calculated the Shannon index (H') to assess the diversity of the pollen samples based on the classification and laboratory results. Linear regression analysis was conducted, comparing the chromatic pollen analysis results with laboratory data, and evaluating the model using R-squared (R2) scores. The reported R2 were compared with those reported by Conti [7] and Borlinghaus [2], providing further insights into the performance of our proposed method.

2.1.1 Lab

The laboratory analysis of pollen color follows the DIN 10760-2002 [9] standard, commonly used to determine the botanical origin of honey. This method can also be applied to analyze pollen samples. A pollen sample is collected from a bee colony using pollen traps a specific time period. [8] To determine the relative pollen abundance, a representative sub-fraction of the sample is homogenized. The pollen is mechanically crushed and mixed with demineralized water. The resulting liquid preparation is examined under a light microscope. The identification of pollen species is performed using specialized literature and reference specimens by an expert.

Initially, an preliminary review is conducted at magnifications ranging from 400x to 1000x to identify the pollen species present. In a subsequent run, the quantities of pollen species in a random sub sample are determined. At least 500 pollen grains are counted in increments of 100. To ensure reliable results, the stability of percentage values is observed.

2.1.2 Pollen color capturing with camera dome

To collect pollen color samples, a dome-based setup was developed to ensure controlled and homogeneous data capture conditions. The dome was designed to meet several requirements, including shielding from ambient light, providing a sufficiently large specimen carrier, achieving homogeneous illumination of the pollen, and accommodating three different light sources for different recording modes. In this study only white light is used, while infrared and ultraviolet illumination have been recorded, too. The camera unit was also calibrated to match the characteristics of the specific light sources.

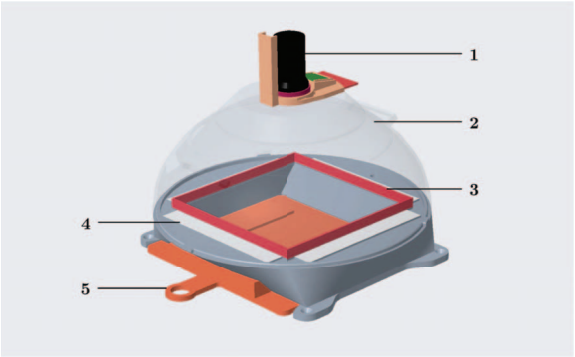


Figure 1: CAD model of the pollen camera dome (Camera Dome): The pollen camera consists of 1) camera unit including of Pi HQ camera (black), 2) dome, 3) lens hood, 4) illumination unit with four LED modules and 5) the sample carrier.

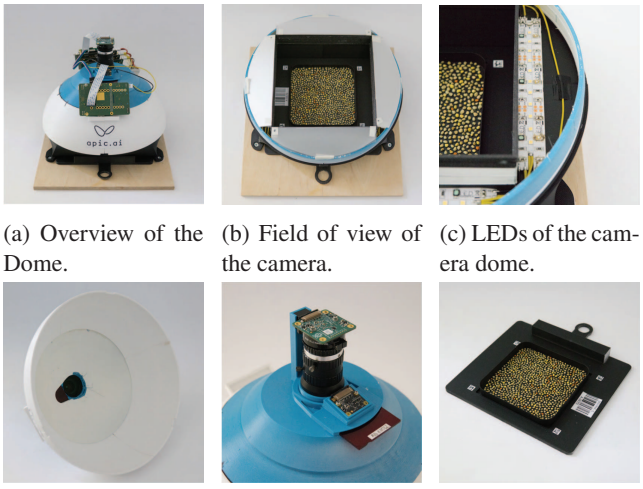
The dome setup (figure 1) utilized a Raspberry Pi High Quality Camera (HQ-Kamera) as the imaging device (fig 2e). Additionally, to minimize the impact of stray light in the lens, the LEDs were shielded up to the edge of the specimen aperture (figure 2b, 2c, 2d). The dome structure was 3D printed to provide stability and control over the imaging environment. The lighting within the dome followed the standard light D65 [1], providing white illumination (figure 2c).

During the data capture process, the bee pollen was placed in a Petri dish with a matte black lacquer coating (figure 3a, 2f). This coating served two purposes. Firstly, it enhanced the contrast between the pollen and the background, aiding in accurate color analysis. Secondly, it reduced the potential for reflections or glare that could affect the quality of the captured images.

After capturing the pollen color images using the dome setup, a series of processing steps were applied to determine a list of pollen colors. Each pollen should be represented by one color value.

First, a convolutional neural network with a U-Net as proposed by Rooeberger et al. [16] was trained to perform pixel-level segmentation of each individual pollen in the image. This segmentation step allowed for precise identification and isolation of the pollen within the image (figure 3b).

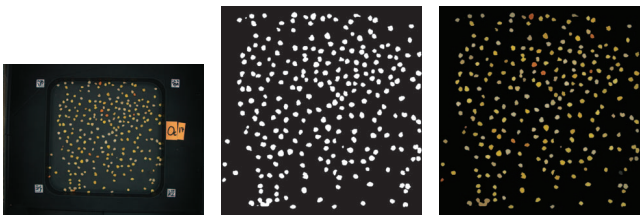
Following the pollen segmentation, the median color (median vector) of each segmented pollen region was calculated in the LAB color spectrum [6]. This measure provided a representative RGB and CIE-LAB color description for each pollen grain (figure 3c).



(a) Overview of the Dome. (b) Field of view of the camera. (c) LEDs of the camera dome.

(d) Inside of the dome. (e) Camera units and wavelength filter. (f) Pollen pellet sample tray.

Figure 2: Detailed dome images: Detail images of (a) Pollen camera with mounted Raspberry Pi's, (b) Open pollen camera, scrim deflection of LEDs and pollen sample on sample carrier, (c) Detail view of the Illumination unit, (d) interior view of dome, (e) detail view camera unit. HQ camera in center of image with large black lens, tilted next to it, the IR camera and long-pass filter, (f) sample carrier with Petri dish.



(a) Captured example image (Dome) (b) Segmentation Mask (Dome) (c) Picture with mean colors (Dome)

Figure 3: Example of the image processing of a sample collected in Stutensee, Germany (2022-07-14).

2.1.3 Pollen color capturing in the field (OnDevice)

In order to capture pollen color information in the field, we adapted a commercially available bee monitoring system from apic.ai [10, 3] to save the RGB color description of each pollen pellet that entered the hive on the leg of every bee. This approach, termed "OnDevice", allows the color assessment to occur directly on the monitoring device, without the need for remove the pollen from the legs of the bee for later assessment. For this study, we used the 2022 generation of apic.ai's hardware (figure 4), which is equipped with several components optimized for the accurate and consistent capturing of pollen color data. The hardware includes a dome through which the bees are walking through. This ensures even lighting conditions with standard light D65 LEDs [1] and reduces the influence of ambiant light (sun, shadows and weather). The device features a high-quality Pi HQ camera to capture detailed images of incoming bees, providing rich color information for the attached pollen. The system is solar-powered, making it a sustainable and low-maintenance option for continuous monitoring.

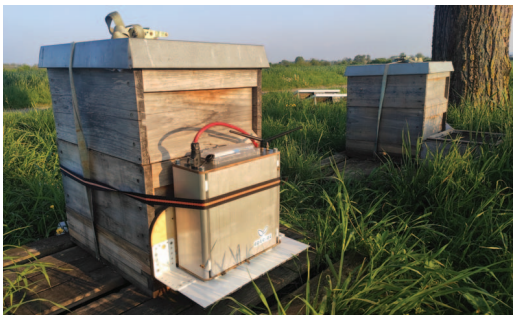


Figure 4: apic.ai Monitoring device attached to a hive at the Stutensee location. Bees are walking through the monitoring device into the hive. This hive has a bottom pollen trap and it is therefore not visible.

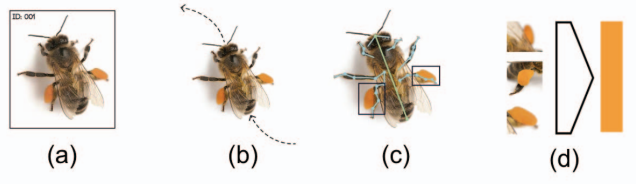


Figure 5: Representation of the the pipeline to capture pollen color information in the field. (a) Bees detection using U-Net. (b) Follow bees movement. (c) Pollen Detection on Bees using U-Net. (d) Extracting pollen color - Median Value.

In the field, the process of capturing pollen color involved the following steps (figure 5):

1. Bees detection using U-Net: A U-Net model was employed to detect and identify bees present in the field. This step aimed to localize the bees within the captured images (figure 6a).

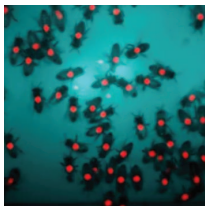
2. Follow bees movement: Once the bees were detected, a tracking algorithm was implemented to track the movement of each individual bee over time. This allowed for consistent monitoring and recording of their activities (figure 6b).

3. Pollen Detection on Bees using U-Net: Another U-Net model was utilized to detect and identify pollen present on the bodies of the tracked bees. This step facilitated the identification and extraction of pollen color information (figure 6c).

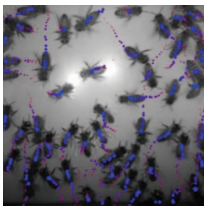
4. Extracting pollen color - Median Value: For each individual bees' pollen color was saved by computing the median pollen color from the detected pollen regions and afterwards the median for each image of the bee. This approach aimed to capture the representative color information for each individual bee (figure 7)

5. Dataset Creation for Comparison: To validate the accuracy of the pollen color capturing process, a dataset was created using pollen color data from a specific time interval. This dataset served as a basis for comparison with manual assessment techniques, allowing for an evaluation of the effectiveness of the proposed system in estimating floral diversity through pollen color analysis.

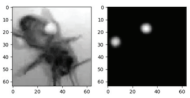
By implementing these steps, the OnDevice monitoring system enabled the capture and recording of pollen color information and its quantity in the field, facilitating the estimation of floral diversity through efficient and automated analysis methods.



(a) Segmentation of bees location probabilities (onDevice).



(b) Tracking of individual bees' (onDevice).



(c) Segmentation of bees' pollen (onDevice).

Figure 6: Process description of onDevice bees' detection, tracking and pollen segmentation.

(a) Example bee with dark blue pollen pallets.

(b) Example bee with bright yellow pollen pallets.

Figure 7: Example Bees showing one of the brightest and darkest pollen, while partialy covered by wings.

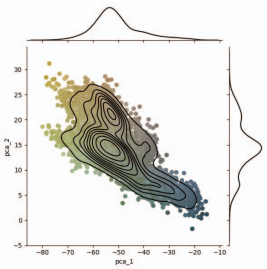
However, it is important to note that the visibility of pollen pellets is not always optimal. Several factors can affect the quality of the captured images, including occlusions by other bees, shadows cast by other bees, and the transparency of the bee's wings, which may partially obstruct the view of the pollen pellets and change the observed colors. These challenges necessitate careful consideration and additional post-processing to ensure accurate color representation and robust diversity estimation.

2.1.4 Chromatic color analysis

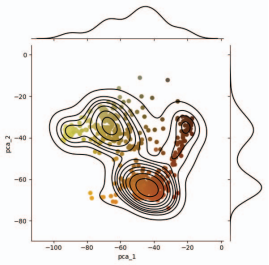
The chromatic properties of pollen color in the on-device system were analyzed using the LAB color space, which provides a perceptually uniform color model. Establishing a baseline for comparison initially involved utilizing delta E references based on the LAB color space, following the approach proposed by Conti et al. [7]. This method involved clustering pollen color samples based on their Euclidean distances in the LAB color spectrum, using 30 reference pollen colors.

A notable discrepancy was observed, however, as captured colors in the real world differed from the reference colors due to variations in lighting conditions and imaging devices (figure 9, 8). To address this issue, an exploration of an alternative clustering approach was made, leveraging the HDBSCAN algorithm [15], which does not rely on predefined reference colors. When HDBSCAN was applied to the full input dataset, it successfully identified clusters of similar pollen colors without the need for anchor colors. A color conversion matrix was then attempted to transform the captured RGB colors from the real world (onDevice) into the LAB color space for determining relevant anchor colors for the on-device system.

The intent of these efforts was to enhance the accuracy and reliability of the on-device pollen color analysis by accounting for variations in color appearance caused by real-world conditions.

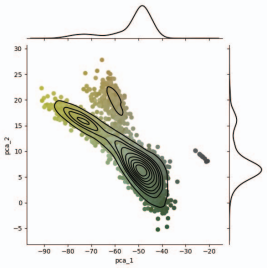


(a) PCA plot of ondevice colors in LAB color space of sample 2022810.

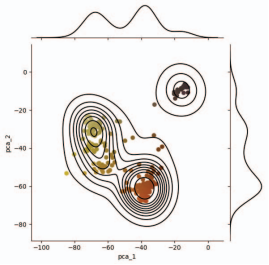


(b) PCA plot of dome colors in LAB color space of sample 2022810.

Figure 8: PCA plot of sample id: 2022810.



(a) PCA plot of ondevice colors in LAB color space of sample 2022789.



(b) PCA plot of dome colors in LAB color space of sample 2022789.

Figure 9: PCA plot of sample id: 2022789.

2.2. Dataset description

To investigate the pollen colors of foraging plants relevant to bees, we collected data through the use of pollen traps installed at various hive locations during different studies in 2022. The pollen traps, namely frontal and bottom pollen traps [5], were employed to collect pollen pouches, which were subsequently transferred to sample containers such as petri dishes or sample cups.

These pollen containers were then stored in a cool environment for further processing. In total, we generated a dataset comprising 24 pollen samples.

To ensure diversity in the dataset, the 24 samples are gathered from 4 distinct locations across Germany and 9 different bee hives. The sampling period spanned from 28th of July in 2022, to 6th of October in 2022. Each sample represented the captured pollen within a 24- to 48-hour time interval.

The dataset encompasses the following information:

1. RGB (red-green-blue) pollen color values (OnDevice): For every bee that entered the hive carrying pollen, we recorded a series of RGB color values representing the pollen color. These values were captured using our on-device system.

2. Ideal camera conditions of collected pollen (Dome): Alongside the RGB color values, we also obtained photographs of the collected pollen in a controlled setting. These images served as visual references for the appearance of the pollen samples.

3. Results of laboratory analysis: To determine the composition of the pollen samples, we conducted lab analysis. This analysis involved quantifying the share of pollen from different plant species present in each captured sample.

The collection of samples followed a specific order, beginning with non-invasive methods and concluding with laboratory analysis, which entailed the destruction of the pollen sample. A summary of the dataset is provided in Table 1.

Table 1: Dataset overview of location, hive and sample time

Location	Sample ID	Date	Hives ID
Stutensee	2022788	28-07-2022	2
Stutensee	2022789	28-07-2022	3
Stutensee	2022791	25-08-2022	2
Stutensee	2022792	25-08-2022	3
Stutensee	2022794	08-09-2022	3
Stutensee	2022796	29-09-2022	1
Stutensee	2022797	29-09-2022	2
Stutensee	2022798	29-09-2022	3
Stutensee	2022817	14-10-2022	1
Stutensee	2022819	14-10-2022	3
Stutensee	2022822	29-10-2022	3
Weingarten	2022799	21-07-2022	4,5
Weingarten	2022800	28-07-2022	4,5
Weingarten	2022801	11-08-2022	4,5
Weingarten	2022802	25-08-2022	4,5
Weingarten	2022803	08-09-2022	4,5
Weingarten	2022804	23-09-2022	4,5
Weingarten	2022816	06-10-2022	4,5
Düsseldorf	2022807	11-08-2022	6,7
Düsseldorf	2022806	24-08-2022	6,7
Düsseldorf	2022805	09-09-2022	6,7
Mayen	2022810	12-08-2022	8,9
Mayen	2022809	25-08-2022	8,9
Mayen	2022808	13-09-2022	8,9

The dataset presented here provides comprehensive information on the pollen colors of foraging plants collected by bees. It enables the exploration and analysis of the relationship between captured RGB color values of pollen pallets in field conditions, ideal-conditions as reference, and the composition of the pollen samples as determined by laboratory analysis.

3. Results

To evaluate the performance of our proposed methods for estimating floral diversity through pollen color analysis, we conducted a series of experiments to compare the number of pollen color classes with the number of unique plants in each samples of the lab report.

As this method has been used by Conti et. al. [7] and Borlinghaus et. al. [2] it helps to compare the results with related work (table 2).

Table 2: R-squared scores of the different clustering approaches, comparing the number of unique color clusters to the number of unique plants.

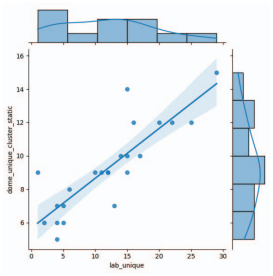
Approach	R-squared Score
Our Dome (static clusters)	**0.72**
Our OnDevice (HDBSCAN)	0.52
Borlinghaus et. al. [2] (static clusters)	0.45
Conti et al. [7] (static clusters)	0.44
Our OnDevice (static clusters)	0.26

As shown in the table 2, our study achieved r-squared scores that are comparable to or higher than those reported in related work. The clustering approach using reference colors on the dome-based setup and the HDBSCAN approach on both the dome-based setup and the on-device system outperformed the R-squared scores reported by Borlinghaus et. al. [2] and Conti et al. [7]. These results suggest that our proposed methods have the potential to improve the accuracy of estimating floral diversity through pollen color analysis using the standardized lighting and optics of our dome (figures 10a, 11a). While the OnDevice static clustering performed poorly (figure 10b), clustering approaches like HDBSCAN (figure 11b) provides a great opportunity to improve the estimation of floral diversity under real world circumstances including imperfect lighting, shadows and other shortfalls.

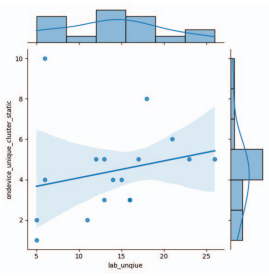
It is worth noting that R-squared scores alone do not provide a complete picture of the performance of the methods. Other factors such as the specific dataset, data collection process, and evaluation metrics should be taken into consideration when comparing our result with different studies.

4. Implications for application

The findings of our study have important implications for the application of bee-based environmental monitoring systems and the estimation of floral diversity using pollen color analysis. By employing computer vision technology on honey bee hives, we have demonstrated the feasibility of non-invasively assessing pollinator habitat quality.

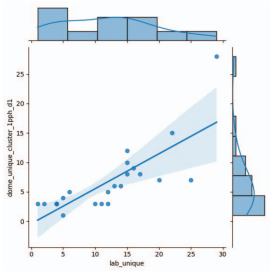


(a) Reference dome color clustering vs number unique plants r^2 0.704

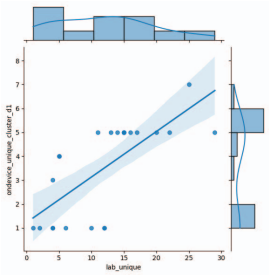


(b) Reference onDevice color clustering vs number unique plants r^2 0.259

Figure 10: Linear Regression of number unique color classes and number of unique plants in laboratory sample.



(a) HDBSCAN on Dome vs. number unique plants r^2 0.607



(b) HDBSCAN on onDevice vs. number unique plants r^2 0.515

Figure 11: Linear Regression of number unique HDBSCAN clusters and number of unique plants in laboratory sample.

The use of cameras placed at the beehive entrance allows for the collection of pollen color samples without disrupting the bees' natural foraging behavior. This non-invasive approach is crucial for continuously monitoring pollinator habitat quality and detect changes, as it ensures that the bees' foraging activities remain undisturbed.

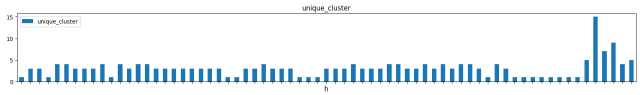


Figure 12: Amount of unique pollen colors measured by onDevice assessments of one hive at the Stutensee recorded from July till October.

The bar plot illustrated in Figure 12 provides some empirical evidence of a gap in food supply occurring towards the end of September and beginning of October, as indicated by a notable reduction in unique pollen colors.

These results are consistent with accounts provided by beekeepers, who have noted a similar drop in the availability of food sources during this period. The diversity loss in food sources as visually depicted in this study supports their claims.

The ability to accurately estimate floral diversity through pollen color analysis has significant practical applications. It enables the monitoring and understanding of pollinator habitat quality, which is crucial for the conservation and management of pollinator populations. By assessing pollen availability and diversity, we can gain insights into the health and productivity of pollinator habitats and identify potential gaps in food availability for pollinators. This information can inform land management decisions, conservation efforts, and the design of effective measures to improve pollinator habitat quality.

5. Discussion and Conclusion

The r-squared scores (table 2) show the improvements that can be made using dedicated color capture appliances. The effort of constructing a dome with accurate lighting resulted in better scores compared to related work [7], [2].

Furthermore, using a handcrafted set of pollen colors as anchors for the clustering performs greatly on good color measurements (Dome, borlinghaus et. al. [2], Conti et. al. [7]), while lacking behind on color measurements in a noisy environments (onDevice). Clustering methods like HDBSCAN offer the opportunity to better isolate relevant signals in pollen color measurements influenced by noise (onDevice) compared to handcrafted color anchors. Never the less the clustering of HDBSCAN on the onDevice data, provides only few classes, seen by the result of the regression: lab unique plants $= 2.511 + 2.707 *$ unique color clusters. Therefore it's discriminative ability is limited. Furthermore, there is still a lot of room for improving the color clustering methods, since HDBSCAN applied to Dome data performed worse that the static approach.

The analysis of pollen color directly in the field using the OnDevice system offers several advantages, including non-invasiveness, ease of deployment, and the ability to gather data in real time. However, it is important to acknowledge the limitations of the OnDevice system for accurate floral diversity assessment. Our findings indicate that the OnDevice system can differentiate between low floral diversity (1-4 clusters representing fewer than 14 plant species) and high floral diversity (greater than 5 clusters representing more than 14 plant species). Beyond this broad categorization, the accuracy of the OnDevice system for fine-grained discrimination among plant species becomes less reliable.

Factors such as variations in lighting conditions, occlusions, and shadows contribute to the challenges in accurately assessing pollen color directly in the field. Therefore, it is essential to interpret the results from the OnDevice system with caution and to use them in conjunction with controlled color capture methods, such as laboratory analysis or pollen color capturing with camera dome, to validate and corroborate the field assessment.

We acknowledge the current limitations of the OnDevice system and encourage the scientific community to contribute to further improvements. Developing more robust chromatic color analysis specifically target to the challenges of onDevice color data (occlusion, shadows, ...) could enhance the accuracy and reliability of field-based pollen color assessment. Advancements in this area will significantly contribute to the ongoing efforts to understand and protect pollinator habitat quality and floral diversity.

In summary, our study demonstrates the potential of using bees and computer vision technology for monitoring and understanding pollinator habitat quality. The non-invasive nature of our approach, combined with the accuracy of our proposed methods, opens up new possibilities for large-scale monitoring and research in the field of floral diversity estimation. By leveraging these advancements, we can better protect and conserve pollinators and their habitats, ultimately ensuring the sustainability of pollination services and the global agricultural industry.

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