



A U-Net-Based Segmentation Approach for Honeybee Pollen Detection Using Deep Learning

Derin Öğrenmeyi Kullanarak Bal Arısı Poleninin Tespiti için U-Net Tabanlı Segmentasyon Yaklaşımı

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Abstract

Pollen is the most important food source for maintaining both colony development and honey production in bee populations. Therefore, the presence of pollen in bee colonies is one of the biggest determinants of hive health. In this context, this study contributes to animal and agricultural sustainability by presenting a deep learning-based image analysis approach for the automatic detection of pollen carried by bees. The bee pollen recognition study was performed using the U-Net deep learning architecture applied to the Pollen Dataset. The U-Net model was selected due to its ability to preserve high-resolution spatial information between input images and corresponding segmentation maps, thereby improving detection accuracy. Experimental results show that the proposed model achieved a successful performance with an F1 score of 99.4%. In addition to technical performance, the study also highlights the potential applications of bee pollen detection in agriculture, particularly in supporting farmers, researchers, and policymakers with more informed decision-making processes. Overall, the findings indicate that advances in deep learning-based image analysis for pollen detection represent an important step towards promoting both environmental sustainability and agricultural resilience.

Keywords: Honeybee Pollen Detection, Deep Learning, Semantic Segmentation, Agricultural Sustainability

Öz

Polen, arı popülasyonlarında hem koloni gelişiminin hem de bal üretiminin sürdürülmesinde en önemli besin kaynağıdır. Bu nedenle arı kolonilerinde, polenin varlığı, kovan sağlığının en büyük belirleyicilerinden birisidir. Bu bağlamda, bu çalışma, arıların taşıdığı polenin otomatik tespiti için derin öğrenmeye dayalı bir görüntü analizi yaklaşımı sunarak hayvansal ve tarımsal sürdürülebilirliğe yeni bir katkı sağlamaktadır. Arı poleni tanıma çalışması, Polen Veri Kümesine uygulanan U-Net derin öğrenme mimarisi kullanılarak yapıldı. U-Net modeli, giriş görüntüleri ile ilgili segmentasyon haritaları arasındaki yüksek çözünürlüklü mekansal bilgileri koruyabilme ve böylece tespit doğruluğunu artırma becerisi nedeniyle seçilmiştir. Deneysel sonuçlar, önerilen modelin %99,4'lük bir F1 puanı ile başarılı bir performans elde ettiğini göstermektedir. Teknik performansın yanı sıra, çalışma ayrıca arı poleni tespitinin tarımda, özellikle çiftçileri, araştırmacıları ve politika yapıcıları daha bilinçli karar alma süreçleriyle ilgili desteklemedeki potansiyel uygulamaları da vurgular. Genel olarak bulgular, polen tespiti için derin öğrenme odaklı görüntü analizindeki ilerlemelerin hem çevresel sürdürülebilirliği hem de tarımsal dayanıklılığı teşvik etme yönünde önemli bir adım teşkil ettiğini göstermektedir.

Anahtar Kelimeler: Arı Polen Tespiti, Derin Öğrenme, Anlamsal Segmentasyon, Tarımsal Sürdürülebilirlik

1. Introduction

Pollen is one of the most important substances for plant pollination and the continuation of life. Although it is not yet widespread in Turkey, studies on pollination are quite common worldwide. Wind, rain, birds, and insects are important agents that facilitate pollination. The most important of these agents are honeybees, which contribute significantly to pollination by visiting thousands of flowers and trees. Numerous studies worldwide have shown that honeybees increase crop yields and market quality through their contribution to pollination [1]. Furthermore, honeybees do not use pollen solely for plant pollination. Pollen is also the most important source of protein for bees, and worker larvae and young bees feed on pollen during their early development. Therefore, the rearing of offspring in the bee colony, the efficiency of honey production, and hive health are closely related to the amount and diversity of pollen [2]. For this reason, beekeepers must regularly examine the amount of pollen in their hives. However, manual inspections of hives by

beekeepers involve smoking the bees, which stresses them and significantly affects honey yield.

Industry 4.0, along with IoT, artificial intelligence, sensors, and many other technologies, has begun to improve operations and increase efficiency in many sectors. Similarly, in the agriculture sector, many new studies are being conducted and products are being developed with Industry 4.0. In this context, similar technological developments are also taking place in the beekeeping sector. With IoT-equipped hives, it is now possible to track the pollen carried by honeybees and thus scale the pollen amount of the bee colony. This makes it possible to obtain information about the condition of beehives without smoking the bees, disturbing them, causing them stress, and reducing their productivity. This significantly increases bee welfare and honey yield. A literature review shows that such studies specific to the beekeeping sector are conducted using image-based analysis and deep learning approaches. As shown in Figure 1, honey yield per hive has been observed to decline worldwide. This situation demonstrates the need for innovative solutions in the history of

beekeeping. Beekeeping systems using IoT occupy a significant place among these solutions.

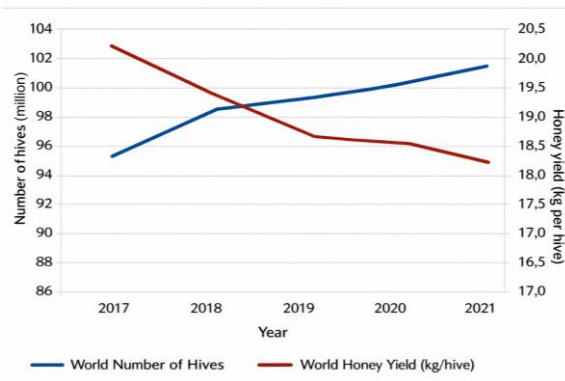


Figure 1. Global trends in the number of beehives and honey yield per hive between 2017 and 2021. The left y-axis represents the world number of hives, and the right y-axis represents the honey yield (kg/hive) [1].

In this study, a method is proposed to determine whether honeybees are carrying pollen. By integrating this system with IoT devices, information about hive health can be obtained. For this purpose, we performed image-based analysis using the open-source Pollen Dataset as the dataset. We used the U-Net architecture as the segmentation model. First, polygon-based labeled data was obtained, then the input images were resized, and the pollen-containing parts of the image were separated from the pollen-free parts by creating binary mask labels. The U-Net was trained with these mask images, and the model was evaluated to determine whether it could identify the pollen carried by honeybees.

Following the article, the literature review section identified pollen detection studies, followed by the methods section, and finally the results and discussion sections. The methods section discussed the dataset, working environment, and the model and metrics used. The results were presented in the results section. Our evaluations and future projections were discussed in the discussion section.

This study makes several original contributions to the literature.

- First, while the majority of existing studies on pollen detection focus on object detection or classification, this study introduces a semantic segmentation-based framework that enables pixel-level localization of pollen regions on honeybees.
- Second, the open-source Pollen Dataset was manually re-annotated using polygon-based labeling, and a dedicated binary mask dataset was generated for segmentation, which provides a new data representation for this problem.
- Third, the study demonstrates that the U-Net architecture can achieve very high segmentation performance on a relatively small dataset, highlighting its suitability for data-limited agricultural applications.
- Finally, the proposed approach offers a scalable and IoT-compatible structure that can be integrated into precision beekeeping systems for automated colony monitoring and decision support.

1.1. Literature survey

Literature studies show that computer vision and deep neural networks are applied in the fields of agriculture and animal husbandry. Furthermore, studies emphasize that pollen

detection has emerged as an important research topic. A study by [3] is a comprehensive review of 50 studies related to beehives, highlighting that only a limited number of studies directly performed pollen analysis. Most existing works have instead concentrated on bee traffic counting or varroa mite identification. As shown in Figure 2, the temporal distribution of studies and the methods employed reveal that advanced object recognition techniques have been underutilized in pollen-focused research.

Even within this limited body of work, several studies have introduced early frameworks for automated pollen monitoring. For instance, Narcia-Macias et al. developed a system aimed at evaluating pollen collection activity as an indicator of colony well-being. Their approach, integrated into the IntelliBeeHive platform, employed a YOLOv7-tiny model and achieved balanced results with a precision, recall and F1-score of 0.821 [3].

Similarly, Ngo et al. proposed an embedded imaging system designed to estimate pollen foraging efficiency. Their method incorporated a lightweight real-time YOLOv3-tiny network operating on continuous video streams and reported strong performance, obtaining an F1-score of 0.94, a precision of 0.91, and a recall of 0.99 [4].

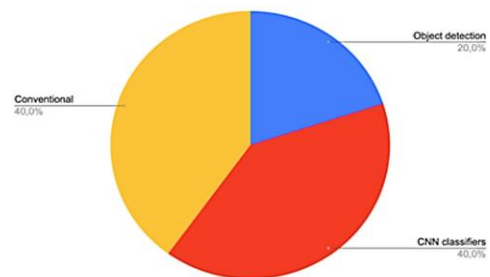


Figure 2. Techniques employed in pollen detection studies in the literature.

Other studies on pollen have examined various architectures. da Silva and colleagues compared different models using an open-source dataset. They obtained 1,290 labeled images from online videos as their dataset. They compared YOLOv7, YOLOX, CenterNet, Deformable DETR, Faster R-CNN, and Cascade R-CNN as models. YOLOv7 was found to perform best in terms of speed and accuracy, exceeding 77% AP75 [5].

Benahmed et al. used the YOLOv5 model to detect pollen on bees and combined the model with StrongSORT. They achieved 90% accuracy on over 1000 manually labeled images [6].

Le et al. used the open-source Pollen Dataset. They modeled a custom convolutional neural network. Their architecture outperformed the VGG16, VGG19, and ResNet50 models, achieving 98.95% precision, 98.99% recall, 98.96% F1 score, and 98.96% accuracy [7].

Yang et al. used VGG-16/Faster R-CNN to detect pollen from video images and reported a detection success rate of approximately 93% [8].

Rodriguez and colleagues proposed a Convolutional Neural Network (CNN)-based model. The model aims to track food-seeking behavior and identify pollen-loaded bees. The model achieved 96.4% accuracy on an open-source dataset. It outperformed classical classifiers such as KNN, Naive Bayes, SVM, VGG16, VGG19, and ResNet50 [9].

Yang, Collins, and Beckerleg proposed a system combining motion detection, color analysis, Kalman filtering, and Hough transform. The aim of the study was to investigate automatic

pollen sac counting. However, their methods achieved 76% accuracy [10].

Monteiro et al. conducted a study on pollen detection on bees. They used VGG, ResNet, Inception, Xception, DenseNet201, and DarkNet53 architectures as models. As a result, DarkNet53 and VGG16 achieved success rates of 99.1% and 98.6%, respectively, yielding more successful results than other models [11].

A review of the literature reveals that models within the scope of semantic segmentation have not been compared for pollen detection. A gap has been identified where the U-Net model could be used for pollen detection.

To fill this gap, this study used the U-Net architecture for detecting pollen on bees. U-Net is widely used in biomedical image segmentation. Compared to object detection and classification approaches, semantic segmentation provides pixel-level localization, enabling more precise identification of small and irregular pollen regions attached to the bee legs. Our work involves manually labeling an open-source dataset, then resizing it, separating pollen-covered regions from pollen-free regions using a binary mask, training the model on this created dataset, and finally evaluating its performance on a dedicated test subset.

2. Materials and Methods

2.1. Test Environmental Setup

The U-Net deep learning model for bee pollen detection was implemented using a MacBook Pro (2.3GHz Dual-Core Intel Core i5, Intel Iris Plus Graphics 640 (1536 MB), 8 GB 2133 MHz LPDDR3) and the following software libraries: Jupyter, OpenCV, Keras, and Tensorflow (Python). While model training was conducted on this platform, it is acknowledged that training duration could be substantially reduced with GPU-accelerated hardware.

2.2. Dataset

This study utilizes the open-source Pollen Dataset [9]. The dataset comprises 714 bee images at 180×300 resolution, with 368 pollen images and 346 non-pollen images. Before the training phase, the dataset was randomly divided into training and test sets with a ratio of 8:2. The training set consisted of 571 images (294 with pollen and 277 without pollen), while the remaining 143 images (74 with pollen and 69 without pollen) were reserved exclusively for testing. No test images were used during the training process. Figure 3 depicts example bee images with and without pollen from the Pollen Dataset.

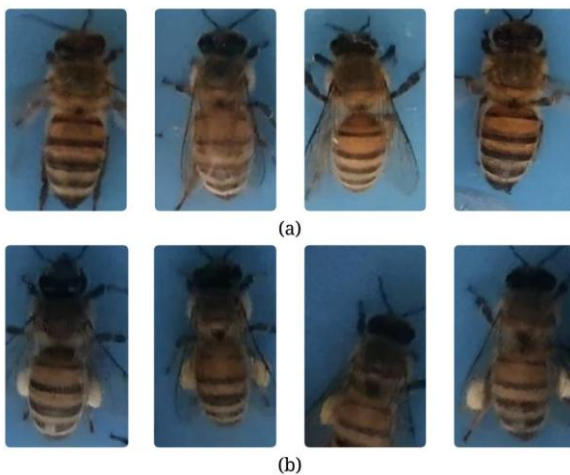


Figure 3. Representative images from the Pollen Dataset: (a) bees not carrying pollen, (b) bees carrying pollen.

2.3. Data preprocessing

The U-Net model generally performs best when the input images follow certain dimensional patterns, particularly square resolutions that scale in powers of two (e.g., 128×128, 256×256 or 512×512). Although this requirement is not absolute, architectures of this type tend to learn more effectively when the spatial dimensions remain consistent across the dataset. The images used in this study are 180×300 pixels. This difference in aspect ratio may reduce the success rate of stable feature extraction in some models. When there is such a difference in aspect ratio, the encoder-decoder structure may not be able to efficiently transfer what it has learned to the next part. This leads to a decrease in segmentation accuracy. U-Net commonly uses square shapes as input images. In this context, we resized the images to 256×256 pixels as a solution to this problem. We also converted the color RGB images to grayscale. We did this to simplify the learning process and reduce color-related variability. The pollen in the dataset was labeled using MakeSenseAI, an open-access labeling platform, and pollen was detected in 368 images. In this tool, pollen was drawn using polygons, and the resulting labels were exported and used in COCO-JSON format. Then, binary masks were created using the Python language to identify the pollen-containing parts in all these pollen-containing images. Finally, since the main objective of the study was to detect the presence of pollen, a single-class labeling strategy was adopted.

2.4. U-Net Architecture

U-Net is a convolutional neural network first introduced by Ronneberger, Fischer, and Brox in 2015. It was initially developed for segmentation tasks in biomedical imaging. Traditional CNN models focus on feature extraction. U-Net, however, preserves both contextual information and spatial details, enabling pixel-by-pixel segmentation. U-Net creates a symmetric structure because the encoder-decoder enables efficient feature learning and subsequent reconstruction. In this context, the model takes its name from this characteristic U-shaped arrangement [12]. Thanks to this design, U-Net delivers successful results even when training data is limited. Therefore, it has become a widely used segmentation model in medical and biological image analysis where high accuracy is required.

Figure 3 shows sample images from the Pollen Dataset showing bees without pollen (a) and with pollen (b).

U-Net uses the last pixel of the input image and assigns it to a pre-labeled class such as foreground or background. This is done using the following architecture:

- **Encoder:** Increases the number of encoder features and gradually reduces spatial resolution. It uses successive convolutions and downsampling operations. This captures semantic information and then identifies relevant structures in the image.
- **Skip Connections:** This layer is a fundamental feature of U-Net. It is used to connect the encoder layers to the decoder layers. These connections prevent the loss of spatial features during downsampling and transfer spatial features to the decoder stage. This increases accuracy during segmentation.
- **Decoder:** This part gradually restores the spatial dimensions of the feature maps using upsampling operations. At this stage, it uses the encoder outputs obtained from the skip connection and combines them with the upsampled features. This allows the model to create a segmentation map close to the original input layout.

Thanks to this architectural structure, U-Net is widely preferred in fields such as medical imaging and cellular analysis. By adjusting hyperparameters, it can work effectively even with small datasets.

2.5. Semantic Segmentation for Honeybee Pollen

In this study, semantic segmentation was used to detect pollen in honeybees. Figure 4 shows the general workflow. After resizing to 256x256, the RGB images were converted to grayscale. They were then fed into the network as input. The U-Net architecture was trained using Adam optimization. Binary cross-entropy was selected as the loss function. This choice was made due to the binary nature of the segmentation task. The accuracy metric was used as the model performance metric.

ReLU activation functions were applied to the hidden layers. Sigmoid activation was used for the final output layer. The reason for using sigmoid is to create probability maps representing pollen and non-pollen regions. The model was trained using processed images and mask labels. Training was performed for 150 epochs with a batch size of 4.

3. Results

Figure 5 shows the pollen regions detected by the U-Net model. The images in Figure 5(a) are original and show bees carrying pollen and bees not carrying pollen. The images in Figure 5(b) are prediction masks. They show the regions marked as pollen by the model. These areas indicated in the mask are aligned with the location of pollen in the original images, allowing the model to

accurately locate pollen at the pixel level. The clarity of this visual alignment supports the success rate achieved during the evaluation phase.

Figure 6 shows examples where the model produced incorrect or partially correct predictions. The original images in Figure 6(a) show cases where segmentation is difficult. The predicted masks in Figure 6(b) show two recurring types of errors. In the first example, the model assigns pollen labels to areas where pollen is not present. This is a false positive result. This situation was detected in cases where the contrast between the bee's body and the background was low. In the second example, the model successfully detected the actual pollen on the bee. However, it also marks an additional area as pollen. This secondary misclassification may be due to tissue patterns in the image that resemble real pollen. Similar misdetections were seen in the remaining examples in Figure 6.

To understand correct and incorrect predictions, a distributional analysis of the detected pollen areas was performed. As shown in Figure 7(a), the segmentation result produced a bimodal graph for the predicted regions. Subsequently, large area predictions (>50,000 pixels) were not considered correct because these values corresponded to the entire image. These were categorized as incorrect detections. Therefore, to obtain valid pollen detections in the system, a threshold value of 50,000 pixels was defined, and those below this threshold were accepted. Figure 7(b) shows the distribution of pollen detection areas accepted according to this thresholding rule.

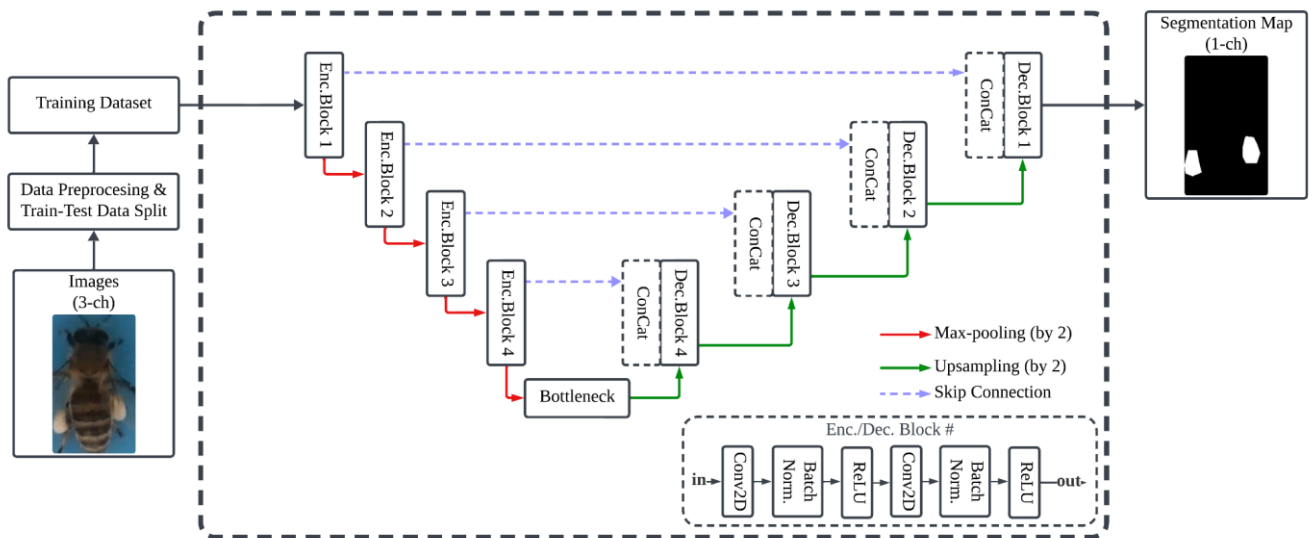


Figure 4. Overall workflow of the proposed methodology for honeybee pollen detection.

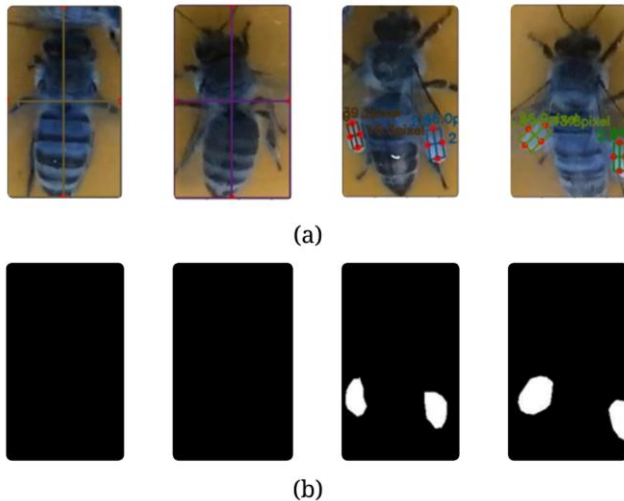


Figure 5. Representative examples of successful pollen detection: (a) original input images of bees with and without pollen; (b) corresponding predicted segmentation masks generated by the U-Net model, in which pollen regions are delineated.

Finally, the model was tested on 143 images. The U-Net architecture achieved 99.4% accuracy and a 99.4% F1 score. The model consistently performed well across the dataset.

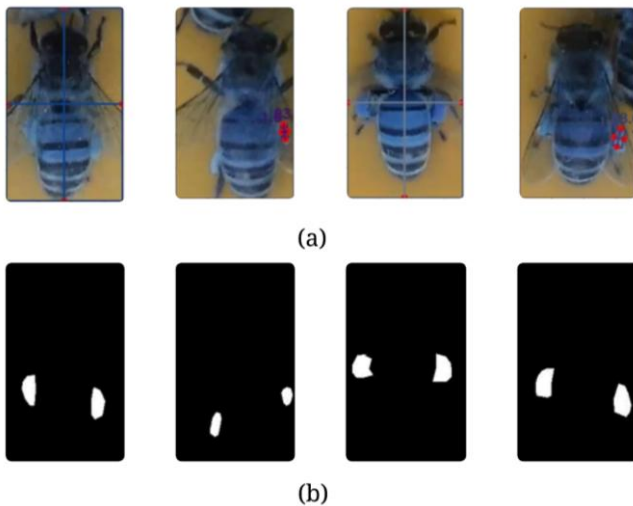


Figure 6. Representative examples of erroneous pollen detection by the U-Net model: (a) original input images illustrating cases of suboptimal performance; (b) corresponding predicted segmentation masks showing false positive and false negative predictions.

4. Discussion

According to experimental findings, the U-Net model achieved an F1 score of 99.4%, which is a highly successful performance on the Pollen Dataset compared to studies in the literature. When compared to the studies shown in Table 1, the segmentation accuracy achieved in this study is higher than that of [7] and [11]. These results demonstrate that U-Net is quite capable of capturing pollen regions.

Furthermore, the results closely match the performance levels described in [13] and [14]. This supports the suitability of deep learning-based segmentation methods for specific tasks in the agriculture and livestock sectors. Taken together, these results indicate that semantic segmentation can be a successful model for pollen detection in honeybee tracking systems.

The practical implementation of these results within the scope of Industry 4.0 points to new opportunities in agricultural technology, ecosystem monitoring, and beekeeping management. These areas, along with future research directions, are further outlined in the following sections.

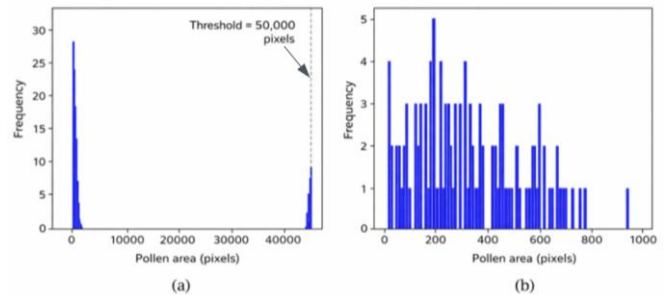


Figure 7. Analysis of pollen area values for optimal threshold selection: (a) Frequency distribution of pollen area measurements in all predicted regions (correct and incorrect); (b) Frequency distribution of pollen area measurements following the application of the refined threshold.

4.1. Impact Potential

Pollination is given particular importance abroad, and in this regard, organizations such as the North American Pollinator Protection, Coalition of the Willing on Pollinators, and the Muğla Province Beekeepers Association (MAYBİR) are conducting studies. Therefore, within the scope of these studies, pollen detection systems can contribute to increased yields in precision agriculture and plant pollination, and can help take pollination to more advanced levels. They can guide farmers in irrigation programs and fertilization plans. In the future, by identifying which plant species provide more pollen, farmers can prevent unnecessary expenses in their field management practices and take measures to increase crop productivity.

Table 1. Summary of the literature review and comparison with the proposed model.

Reference	Year	Models Used	Performance Metric (w/Model)	Success Rate (%)
[7]	2023	CNN (proposed), VGG16, VGG19, Resnet50	F1-Score (proposed CNN model)	98.96
[9]	2018	KNN, NB SVM, CNN, VGG16, VGG19, ResNet50	Accuracy (CNN)	96.40
[11]	2021	VGG16, VGG19, ResNet50, ResNet101, Inception V2, Inception V3, Xception, DenseNet201, DarkNet53	F1-Score (DarkNet53)	99.10
[14]	2023	ResNest, EfficientNet, NoisyStudent, VT 16x16, VT 8x8, BeeNet (proposed)	Accuracy (BeeNet)	99.18
[13]	2021	AlexNet, DenseNet201, GoogLeNet, ResNet101, ResNet18, VGG16, VGG19	F1-Score (GoogLeNet)	99.05
[15]	2020	DeepLabv3, AlexNet and ResNet, DeepLabV3	F1-Score (DeepLabv3)	95.00
Our Study	---	U-Net	F1-Score	99.40

From the perspective of beekeeping and bee colonies, pollen detection systems provide important clues about colony health. Determining the amount of pollen-laden bees entering the hive

provides important information about whether the colony is strong, whether it needs supplemental feeding, and whether the environment has sufficient flower sources for bee colonies. This contributes to honey yield and long-term colony sustainability in the beekeeping sector.

As a result, machine learning and deep learning-based pollen detection can facilitate monitoring colony nutrition status and offer new automation opportunities in bee behavior analysis. It can also indirectly contribute to pollination. Such automated approaches play an important role in scaling and monitoring colony health. Given increasing environmental pressures, accurate detection of pollen load on bees is becoming increasingly important for monitoring colony health at an early stage.

4.2. Future Potential

As advanced studies, early warning systems can be developed in pollen detection systems, followed by large-scale pollen mapping. Large-scale mapping initiatives can be presented as detailed visualizations of broad geographical areas within the scope of pollination. Such maps provide valuable inputs for environmental policy.

Early warning systems can be developed as early warning systems for agriculture and livestock farming. Thus, rapid changes in the pollen detection phase can be analyzed, and environmental plant diseases, pest activity, or ecosystem stress can be detected and measures taken. At the same time, sudden changes in the health of beehives can be detected and necessary measures taken.

When all these developments come together, pollen detection systems are of strategic importance both academically and in practical product applications. Pollen detection decision support systems, which can be produced by combining modern artificial intelligence techniques with sensor technologies, will benefit plants, bees, and humans alike. These innovations will support more informed decision-making processes and contribute to long-term ecological resilience.

Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval. The authors declare no potential conflict of interests.

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