Honey Sources: Neural Network Approach to BeeSpecies Classification

[1] RANJITA S D, [2] YASHODHA PUTTAPPA GANJI

[1]. Student, Department of MCA, BIET, Davangere

[2]. Assistant professor,Department of MCA ,BIET, Davangere

ABSTRACT

Bees are the main pollinators of the world and are dying at an alarming rate. Being able to classify them and study their habits is of paramount importance. Crowdsourced datasets are preferred methods for gathering data about the current state of bee populations in their natural environment. Such images, however, may be problematic to use due to large volume of images that place strain on the experts' capabilities of identifying the species. We propose a method to identify regions of interest in an image containing a bee and to correctly classify the species of the bee. In addition, the procedure works on large crowdsourced datasets (we worked with BeeSpotter) with minimal manual annotation and data augmentation. Our approach is capable of addressing two genus and related bee species and records 91% correct classification. A limitation of the Bee Spotter dataset is labeling just one bee per image which may contain two or more bees.We overcome this issue by classifying all bees even in cases of two genus. Finally, the proposed approach is compared with two other recent works which report similar accuracy, but are limited with stricter image preprocessing or photographic setup.

Keywords:bee species identification, image classification, regions of interest, object detection, faster r-cnn neural network.

1. INTRODUCTION

Bees play a key role in maintaining and regulating the health of flowering plants and agricultural settings [1]. In recent years there have been increasing concerns about the decline of bee populations around the world. The causes are either not fully understood or highly debated in the scientific community. Constant monitoring of bee population is needed to fully assess and prevent the loss of these key insects. One of the main steps while conducting this work is to create and maintain large databases of bee populations at the local, regional and international levels. This work focuses on one such database – BeeSpotter.

The BeeSpotter site is crowdsourcing photographs of bees in their natural habitat. The species in the photos are then annotated by one or two experts as well as an amateur. The photographs are taken by amateurs with a wide variety of cameras, light conditions, zoom, background, photographer skill and field of view. In addition, blurriness of the background or the whole image also contributes to the complexity of classifying the bees properly. Distinguishing between bee species can be very difficult, often requiring the use of specialized tools or microscopes. This often makesidentification while in the field impossible necessitating bringing the samples to the lab for analysis. Once everything has been sorted, all the relevant data needs to be tallied, organized, and input into a database. Small local surveys are already time consuming, but when scaled to regional and international levels the effort involved increases by an orderof magnitudes. Therefore, it is of great benefit to find ways to automate some of these processes, and what can't be automated should be made easier to handle for the researchers. One of many efforts currently being done to reduce burden on researchers is the creation of online submission databases. In these databases, everyday citizens can submit photographs with relevant information such as date, location, and time of day. These images are then identified by experts and added to the collective database.

One of the most successful automation tools is the machine learning method of neural networks. Previous attemptsutilizing convolutional neural networks have either focused on unrealistic lab generated images [2,3], or are limited to specific regions and species [4]. Focusing on the shape and anatomy of bee wings provides high accuracy when distinguishing between species [2,3]. However, this requires high quality close ups of the wing in order for the networkto recognize the unique patterns of each species. This limits its use in the field and relies on unrealistic perfect conditions when photographing the bee thus rendering large datasets like Bee Spotter unusable. Other applications utilize Bee Spotter but have many stipulations. Focusing only on the *Bombus* genus excludes identifying other groups of bees which limits agricultural use of the network, but identifies more species. Some works require the user to crop images tightly around the bee before submitting for identification. This complicates the submission, which diminishes th advantages a neural network provides to researchers. It also does not account for images with multiple bees [4].

This work proposes a method for the object identification followed by classification of the three most populous species in the BeeSpotter database - *Apis mellifera*, *Bombus griseocollis* and *Bombus impatiens*. Our approach successfully identifies a small object such as a bee and follows up by classifying it as one of three species. It does that working with crowdsourced photographs, regardless of deficiencies in the quality of the images and positioning of thebee(s). It also handles more than one bee per photo by identifying them and classifying even in cases of two different genus. The proposed approach and dataset are presented in Section 3, followed by results in Section 4. The work concludes in Section 5.

2. LITERATURE REVIEW

Honeybee subspecies classification is crucial for biodiversity conservation, ecological studies, and agricultural practices, and recent advancements in computer vision and machine learning have significantly enhanced the potential for automated identification. Traditional methods, which rely on morphological analysis and genetic testing, are accurate but time-consuming and require specialized knowledge. Nawrocka andKandemir (2018) have demonstrated the effectiveness of computer software for identifying honeybee subspecies and evolutionary lineages, marking a pivotal shift towards digital tools in this domain. The advent of deep learning, particularly convolutional neural networks (CNNs), has revolutionized image-based species identification. For instance, Buschbacher et al. (2020) utilized CNNs for identifying wild bee species, achieving high accuracy in handling complex visual patterns, while Spiesman et al. (2021) explored deep learning and computer vision for bumblebee speciesidentification, further validating these technologies' effectiveness in ecological studies. Key developments in deep learning, such as the introduction of Deep Residual Learning (ResNet) by He et al. (2015), addressed the vanishing gradient problem, allowing for the training of very deep networks and enhancing image recognition capabilities.In resource-constrained environments, lightweight models like MobileNetV3 (Howard et al., 2019) are essential, offering efficient performance on mobile and embedded devices without significant accuracy loss. Advanced object detection techniques, such as Faster R-CNN (Ren et al., 2017), have improved real-time detection tasks through the use of Region Proposal Networks, while instance segmentation methods, such as the improved Mask R-CNN model (Tian et al., 2020), can be adapted for identifying individual honeybees within images. Implementation frameworks like Detectron2 (Wu et al., 2019) provide a modular and scalable platform for these state-of-the-art models, facilitating their application in ecological informatics. The integration of these advanced techniques with traditional methods presents a transformative approach to honeybee subspecies classification, promising significant improvements in accuracy and efficiency. Future research should aim to enhance model robustness and generalizability across diverse environmental conditions, develop user-friendly applications for real-time identification, and incorporate multi-modal data to complement visual identification. These advancements underscore the potential for deep learning and computer vision to significantly contribute to ecological research and conservation efforts.

3. METHODOLOGY

The goal of our research has been to identify the various species of bees in a dataset such as BeeSpotter – it is a crowdsourced collection of photos of bees in their natural environment. That presents a variety of problems: the position and visibility of the bee and its scale compared to the background; the blurriness of the bee body and/or wings, both of which contribute significant information to a classifier; lighting conditions; presence of more than one bee, potentially from different genus. We started our work with traditional classification networks including Resnet [5], MobileNet V3 [6] as well as a few smaller custom networks. These networks performed well when similar images are presented to the network for classification but failed to generalize when the bee did not take up the majority of the image. After additional investigation, it became clear that the complex backgrounds of the flora are preventing the networks from focusing on the features of the bees and are instead making decisions based primarily from the background features. There is a need to locate the object first and then focus on identifying it.

3.1 Bee Detection Network

We use an object detection network to identify the bees in the image and evaluate whether the network is capable of classifying the bee species as well. Faster R- CNN [7] with a Resnet 101+FPN [8] backbone is our base network as it has a history of highly accuracy and performance with small objects though it does consume more resources than other object detection networks, e.g. YOLO. The loss function we utilize stems from [7]. We utilize the stochastic gradient descent optimizer supplemented with Detectron2's multistep parameter scheduler [9]. One of the reasons the Faster R-CNN is faster is because the CNN identifies regions of interest where then additional resources are put into classifying these regions. It also uses the same backbone convolutional network for region identification as well as theclassification process. One goal of the project is to reduce the number of manually annotated images needed to train the object detector. 300 randomly selected images per class are manually annotated with bounding boxes and transfer learning and patternmatching is used to annotate the rest of the training dataset. The bee detection network is trained to detect a single class "bee" that is the set of all hand annotated images.

We then iteratively train the network and utilize the resulting weights to augment the training dataset with additional annotations that are then used in future training iterations. The first pass is trained for 3000 iterations with a learning rate of 0.001 and is capable of machine labeling 4318 additional images with high confidence. The second pass is trained on both the hand annotated images and the machine labeled images for 10650 iterations with an initial learning rate of 0.005 and is capable of annotating an additional 8468 images with high confidence. Our proposed process isillustrated in Fig.1.

Identified regions in the images are considered valid with the following heuristic:

- If the network detects the object as a bee when thresholded above .99

- There is a single object detected in the image.

- Images that are already annotated with a bounding box are not updated.

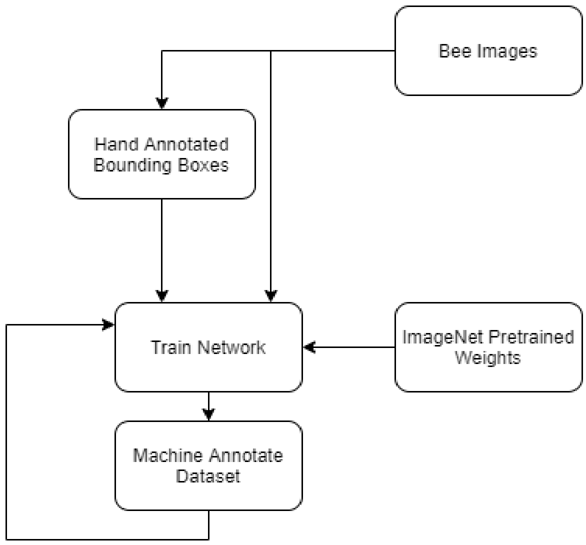

Figure 1. Proposed process for bee object location and
identification

The predominant majority of images contain only one bee per photo. The heuristic is developed with this assumption in mind by developing bounding boxes if the locator found one high confidence bee in the photograph. Bee Classification Network

To resolve the original image classification problem, we again select a standard Faster R-CNN with Resnet 101+FPN backbone as our base network. Slight modification to the standard design is adopted to use only a single class for the bounding box regression.

This design is selected as the true purpose of the network is to determine the species of the bee in the image. The location bounding box is only used to deselect the background and is not instrumental in the success of the final accuracy of the model.

The complete annotated dataset of the images that belongs to the three classes/species is randomly split into training, validation and testing sets. A random flip with a random crop is applied to augment the size of the dataset. All images are normalized to match the ImageNet standard.

Our final model is trained on a Nvidia Tesla V100 for 100000 iterations using pretrained weights trained on ImageNet. The batch size is 4 and the base learning rate 0.005. The learning rate is reduced with a gamma of 0.5 at 60000 and 80000 iterations, i.e. changes to 0.00025 at 60000, down to 0.0000125 at 80000. The average precision for each of the classes, class accuracy, total loss and validation loss are reviewed to prevent overfitting. Dataset, Preparation and Considerations Our dataset comprises images from the Bee Spotter website and consists of 15,347 crowd sourced images of bees that are annotated for species by an expert. The three most populous species in the dataset areselected for this study (Apis mellifera n=2867, Bombus griseocollis n=3047, and Bombus impatiens n=3494) to evaluate the feasibility of designing a system that is capable of determining the species of a bee given a mature, uncropped photo as input. The images consisted of bees in various lighting conditions, orientations, and crops. Some images are shown in Fig.2.

The proposed approach takes in a raw image, develops regions of interest, continues with

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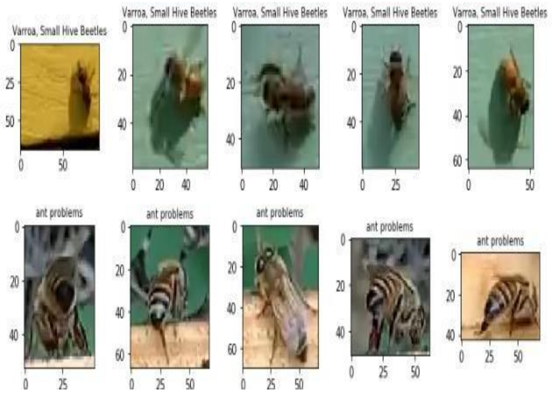
classification of these regions and presents the highest confidence region as the final species of the bee(s) inthe image. Empirically, results with confidence greater than 75% produced the most accurate classification. Fig.3 shows the result with all developedbounding boxes and the final determination of the bee detection and classification. All proposed regions of interest illustrated in Fig.3a are presented for classification purposes. Multiple regions of interest and classes are proposed for the image in Fig.3a. Fig.3b shows the identified bee species, which is determined by the box with the highest confidence.

Figure 2. Samples of images utilized inthis work.

4. RESULTS

The proposed method has recorded an average accuracy of 91%. This compares to other recent works with bees, but outperforms in terms of fewer required input restrictions. For example, we do not require a preliminary cropping of the image as a condition to neural network classification. The confusion matrices resulting from the testing of 832 images are shown in Fig.4. While the accuracy is at 91% overall, the network has very high accuracy (99.16%) in separating the genus into *Apis* and *Bombus* (Fig.4a). Since there are more samples of *Bombus* genus (twice the *Apis*), it is natural for the *Bombus* to be recognized at higher rate. The proposed framework exhibits slight doubts between the two *Bombus* species, but holds its own in the final classification (Fig.4b). We demonstrate a variety of correctly classified images in Fig.5. These results show the ability of the proposed method to correctly classify the species even with some deficiencies to the quality of the image. Consider the nature of the photos being taken by amateurs under various light conditions, potentially of a flying bee and variety of cameras with different levels of zoom.



(a) (b)

Figure 3: Sample raw image from the testdataset:

a) all proposed regions of interest

b) highest confidence region of interest representing thefinal classification of Bombus impatiens

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image. In other words,in the rare occasion of having an *Apis* and a *Bombus* bee in the picture, only one of these will be labeled in the dataset. Such images are treated as misclassification in the confusion matrix in Fig.4. However, Fig.6 illustrates the efficiency of our proposed method to identify and classify both bees correctly.

In all fairness, we have shown misclassified images, such as the one in Fig.7a, where two boxes overlap significantly and the correct genus, but incorrect species is assigned. Further, in Fig.7b, the bee is incorrectly classifiedas Bombus griseocollis when in fact it belongs to the Bombus impatiens class.

The work in [3] identifies multiple bee species based on wing characteristics alone. This approach requires a carefulsetup for the photographer to take a quality image of just the wing, which is difficult to replicate in the wild. The reported accuracy is 93.95%. Our work is based on raw images, which may or may not have the wings on display. While we work with much fewer species, the nature of the input images contributes to the vast differences in approach.

In [4] the reported accuracy for classifying 36 species within the *Bombus* genus is 91.71% (the best performing network used in the study). While the number is impressive, it must be noted that that the raw images must undergo anumber of preparatory steps before being presented to the neural network. These steps include image cropping, verification of the image quality regarding blurriness or obstructions and that the bee in the image belongs to the *Bombus* genus. Our method operates to similar accuracy, but recognizes the most three common Midwestern US Region bee species regardless of genus. We also demonstrate the ability of our model to recognize multiple bees per image when such are present.

Apis mellifera	*Bombus griseocollis*	*Bombus impatiens*
		
		
		

Figur 5. Correctly classified examples from the three bee species utilized in this work

Before concluding, we are illustrating another capability of the proposed model, which is unmatched by the other state-of- the-art bee classification methods. Fig.8 demonstrates the capability of our model to handle multiple bees in one photograph despite of the underwhelming light conditions. Both bees are correctly classified as Apis mellifera. As the first step in the proposed method is identifying regions of interest, the obvious missed opportunities are resultof lower identification confidence. Additionally, the network was not trained for recognizing multiple bees in one image due to the nature of the BeeSpotter dataset formation.

Figure 6. subspecies BeesIndentified

5. CONCLUSION

The proposed method is novel in its following features:

a) minimal number of hand-annotated images to training the region of interest locator network. tackling crowdsourced data with wide variety of image quality.

b) no requirement to manually crop the images prior to genus/species identification.

c) ability to correctly classify multiple bees per image. In our work we utilized the three most populous species in the BeeSpotter dataset, allowing for very minimal dataset augmentation as part of the training process. Early in the process we also encountered the significant dependency of bee species classification on the image background (color, type of flower, focus on surrounding flora).As the goal is to classify bees, we elected to focus on identification of regions containing bees and then classify the found apidae. The accuracy of our proposed method is close to a hundred percent when it comes to genus and hovers around 91% for the particular species. In comparison with other studies that focus on only one genus with similar accuracy, this work provides excellent results for two genus and multiple related species with minimal processing ofcrowdsourced images.

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