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ORIGINAL PAPER

Image-based South Asian bee species identification: a machine learning approach

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Abstract

Healthy ecosystems provide indispensable services like pollination, climate regulation, and soil formation. Pollination service provided by insects alone is valued at €153 billion. Bees are one of the major insect pollinators, making them economically important animals, yet their populations are threatened by anthropogenic pressures. Monitoring the distribution and diversity of wild bees becomes daunting as it involves extensive field surveys, sample collection, and traditional taxonomy. Logistic and ethical issues complicate this further. Machine learning (ML) on passively collected visual data can provide a non-invasive, large-scale solution to these problems. However, a significant challenge for ML application is the lack of geographically varying training data for different bee species, especially from species-rich tropical regions. In addition, these algorithms have predominantly been tested on image data collected under controlled conditions inside laboratories. ML models must be trained to perform on field-collected unrefined images of different bee species for rapid yet non-invasive diversity estimation. In this study, to challenge and bolster the existing deep learning networks, we collected 3250 field-captured images of major South Asian social bees (*A. dorsata, A. cerana, A. florea*, and *Tetragonula spp.*). We did not control these images for lighting and camera perspectives, which posed significant challenges to the models. We benchmarked this image dataset using standard convolution neural network (CNN) models, finding that MobileNet-V2 was the best model, achieving the highest accuracy of 98.4%.

Clinical trial number

Clinical trial number not applicable.

Implications for insect conservation

Our study provides a framework to rapidly quantify the economically important bee diversity, which will allow efficient conservation intervention across large spatial scales.

Keywords Machine learning · Bee diversity · Field data · Diversity estimation

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Introduction

Biodiversity, the variety of life forms within an ecosystem, is crucial in ecosystem functioning and resilience (Loreau et al. 2001). A healthy ecosystem provides free essential services, such as provisioning and regulating, which significantly impact a country's socio-economy (Costanza et al. 1998). Insect-mediated pollination, perhaps the most economically important service, valued at €153 billion (Gallai et al. 2009), contributes to 35% of the world's food production. Pollinators play a critical role in maintaining healthy genetic diversity in plants and also affect plant yield, including crop plants (Kasina et al. 2009; van der Sluijs et al.

2016). Bees, one of the most significant pollinators in the animal kingdom, are essential for sustaining ecological and economic stability (Indhu et al. 2022; Khalifa et al. 2021). In recent years, there has been a general decline in the numbers and diversity of both wild and domesticated pollinators worldwide (Potts et al. 2010). Ollerton (2015) indicated that globally, there had been a considerable drop in pollinator abundance and diversity in almost all geographic areas. Basu et al. (Basu, Bhattacharya, and Iannetta 2011a) suggested that declining pollinator-dependent crop productivity in India can be associated with pollination limitation, which can significantly impact the socio-economy of an agriculturally dependent country like India. Monitoring, maintaining and studying honey bee diversity and distribution is imperative to ensure food security and ecological balance (Indhu et al. 2022). Identifying and cataloguing species diversity is a laborious task. It requires time and trained research personnel/taxonomists, which comes with practical and logistic constraints (Colwell 2009). Passive recording methods like camera setups have multi-fold advantages over traditional field surveys. Firstly, passive information collection allows us to generate significant amounts of large-scale spatial and temporal data with minimal effort. Secondly, it can be deployed in areas where human intervention is undesirable, difficult or impossible. Further, it reduces human error and bias while performing traditional field work and taxonomy. Such passive monitoring methods have been demonstrated to be effective in other insects like agricultural pests and moths. (Jain et al. 2024; Kariyanna and Sowjanya 2024; Mendoza et al. 2023)

Advancements in ML, primarily deep learning and convolution neural networks (CNN) have caused a paradigm shift in fields such as traditional taxonomy and species identification (Gharaee et al. 2023a; Høye et al. 2021; Ruttner 1988; Sauer et al. 2024). One such important application of ML is in bee species and sub-species identification from visual data (C. De Nart D. 2022; M et al. 2021; Spiesman BJ 2024; Buschbacher et al. 2020; Nawrocka et al. 2017), where clean images under the microscope have been used for the identification of European bees. These studies focus on datasets curated under laboratory conditions, consisting of wing images of European bees photographed under a microscope in controlled lighting scenarios. They use wing venation patterns, an important classifier, to identify the bee species (Santoso, Juliandi, and Raffiudin 2018). These methods involve fine-scale morphological differences, so they cannot be applied to naturally collected large-scale data without invasive sampling (Kelley et al. 2021a; Kumar et al. 2010). Spiesman et al. (G. Spiesman B. J. 2021) and Kelly et al. (2021) have tested the effectiveness of CNNs on species identification using images of bumble bees and *Apis mellifera* collected across North America. This study shows that computer vision and deep learning can provide reliable classification based on visual data.

The literature survey shows a significant gap in machine learning datasets and approaches pertaining to tropical honeybees. Social bees in tropical countries have significantly higher diversity than in temperate regions (Roubik 2005). Owing to their distinct evolutionary lineage, tropical bees have significantly different morphological diversity (Borst 2015; Dar 2019), making existing ML models tested on the European bee dataset suboptimal for taxonomic purposes. In addition, passively collected large-scale field images tend to be noisy due to unreliable lighting, contrast, focus, motion blur, camera perspectives and the presence of other non-target species. As most of the prior studies tested the ML models on images collected in controlled artificial settings (high-resolution images using artificial light), it is important to test the models on noisy datasets, which can be collected in the field for rapid and non-invasive diversity estimation. The addition of noise can further challenge the existing models, making them more robust in biodiversity estimation.

Among the tropical countries, South Asian countries have extremely high human population densities and are fast developing. These countries face a serious threat to biodiversity due to anthropogenic pressures, including the economically relevant bee species. Most of these countries are also dependent on agriculture for their socio-economic sustainability. This scenario makes rapid estimation of bee diversity and population status essential for conservation interventions. Among the South Asian honeybees, four social native bee species that play an important role in crop production are *A.dorsata*, *A.cerana*, *A.florea*, and *Tetragonula spp.* (Meena et al. 2015; Bueno et al. 2023; Cervancia 2018; Nevard 2017). This native honeybee diversity has been known to exhibit density compensation to sustain pollination service during unpredictable rainfall conditions (Mukherjee et al. 2019). This diversity is even more critical as introduced exotic species like *Apis mellifera* and bumble bees do not thrive well in tropical conditions and are additionally susceptible to diseases like American Foul Brood, European Foul Brood and Chalk Brood, mites (*Varroa* spp. and *Tropilaelaps* spp.), and bird predation (Cervancia 2018). Despite their importance, scientific data on these pollinators is sparse and collected using widely varying invasive and labour-intensive methods (Cervancia 2018). Hence, in this study, we tested and benchmarked the existing ML models on a passively field-collected novel image dataset on major South Asian honey bees (South Asian Bee Dataset, SABD). We also compared the results of the existing models with a custom-written basic CNN model. Our dataset contained 3846 images collected from an agricultural field site in India under a natural setting using a solar-powered customized camera setup. The dataset included all four major South Asian bee species, viz. *A.dorsata*, *A.cerana*, *A.florea* and *Tetragonula spp.*

Materials and methods

Dataset

Data collection

Study Area and Study Species: - The data was collected from Anekal taluk (an administrative division of sub-district) of Bangalore Urban district in South India. Geographically, the region is located at 12.7105° N, 77.6911° E, flanked by the ever-growing Bangalore city on one side and large stretches of Bannerghatta National Park on the other. To conduct pollinator visitation observation in the study area, Chayote squash *Sechium edule*, a horticulturally dominant crop, was selected as the study species (Mukherjee et al. 2019).

Pollinator Visitation Observation: - A solar-powered automated camera setup was designed to capture the photograph of the potential pollinators. The set-up consisted of a DSLR camera (Canon EOS 400D) with a 70–300 Tamron lens mounted on a camera tripod. The camera setup (supplementary figure s_f_1.1) was attached to a solar-powered (polycrystalline 18 V 20 W 36-cell solar panel, 56 × 46 cm with aluminium casing) 18 V 5.0Ah battery (Bosch) which was operated using a custom-designed timer circuit. The timer circuit had three regulators, one controlling the gap between consecutive shots (set to 5 s), one controlling camera activity duration at one burst (set to 6 min with 6-minute gap), and one controlling overall active duration (set to 8 h). The circuit was connected to the power supply and to the camera shutter. At regular intervals, the circuit allowed power to pass on to the camera, which caused a shutter press (sensor exposure) and image capture. The images were collected at a continuous burst of six minutes with a gap of six minutes. During the six-minute photography burst, the camera captured a photograph every $6th$ second; hence, it captured 60 images in total during the six-minute period. The entire camera setup and the circuit were encased in a steel box. We conceptualized the camera setup based on Steen and Aase (2011) but developed it with the help of ReAP (Renewable Energy Applications and Products, Malleswaram, Bangalore, India). In our study setup, the camera focused on a particular group of flowers of *Chayote* sp. (approximately 25 flowers consisting of both male and female ones) for the entire day from morning to late afternoon. The camera setting was kept at ISO-400, aperture f/4.5– f/16, exposure 1/60–1/250 s, auto white balance, clicking JPEG images of 1936 × 1288 pixels in RGB colour format (24 bit). The raw data comprised 3,846 photographs collected over two days across two farmlands. For the first day, the camera was active between 0800 and 1600 h, collecting images across forty 6-minute sessions. On the second day, the camera was deployed to a different farmland (3 km from the first location) and was active between 0800 and 1400 h, collecting images across thirty 6-minute sessions. Both days were completely sunny and without any cloud cover or rain. These photographs were later processed and used to train the ML models.

Key features

The major features of our dataset are as follows:

(1) Irregular lightingangle and position:

Due to the above-mentioned data collection method, the images collected encompass a wide variety of lighting conditions and bee positions. The images range from well-lit to mere silhouettes of bees. The position and orientation of the bees also varied greatly, adding further complexity to the identification and classification task (Fig.1).

(2) Ants and wasps: Ants and other hymenopterans (like wasps), being morphologically similar and phylogenetically related to bees, served as a good “noise” in our dataset. Thus ensuring that the CNN models learnt to distinguish bees from other insects that visited the flowers targeted by the camera. Accordingly, these objects were marked separately using the label “notbee”.

(3) Partially visible and blurry bees: Due to the nature of data collection, there were numerous images where the bees are blurred to varying extents. The reason could be any of the two: motion blur and/or the bee lying outside the camera’s focal plane.

The images also contained partially visible bees, i.e., bees whose entire bodies were not visible in the image. The reason could be any of the two or both: (a) part of the bee lying outside the camera frame and (b) obstructions between the camera lens and the bee (like flower petals). To circumvent these issues, we manually cropped out and labelled individual bees.

Data processing

Images were annotated by hand using morphological cues and a visual key (Oldroyd 2006; Shoichi and Sakagami 1978). Makesense.ai (“Make Sense” 2024) was used to mark bees in the photographs using bounding boxes. We used six different labels to mark the boxes: bee, notbee, *dorsata, cerana, florea* and *tetragonula* (Fig. 2). The last four correspond to the species names of our dataset’s four

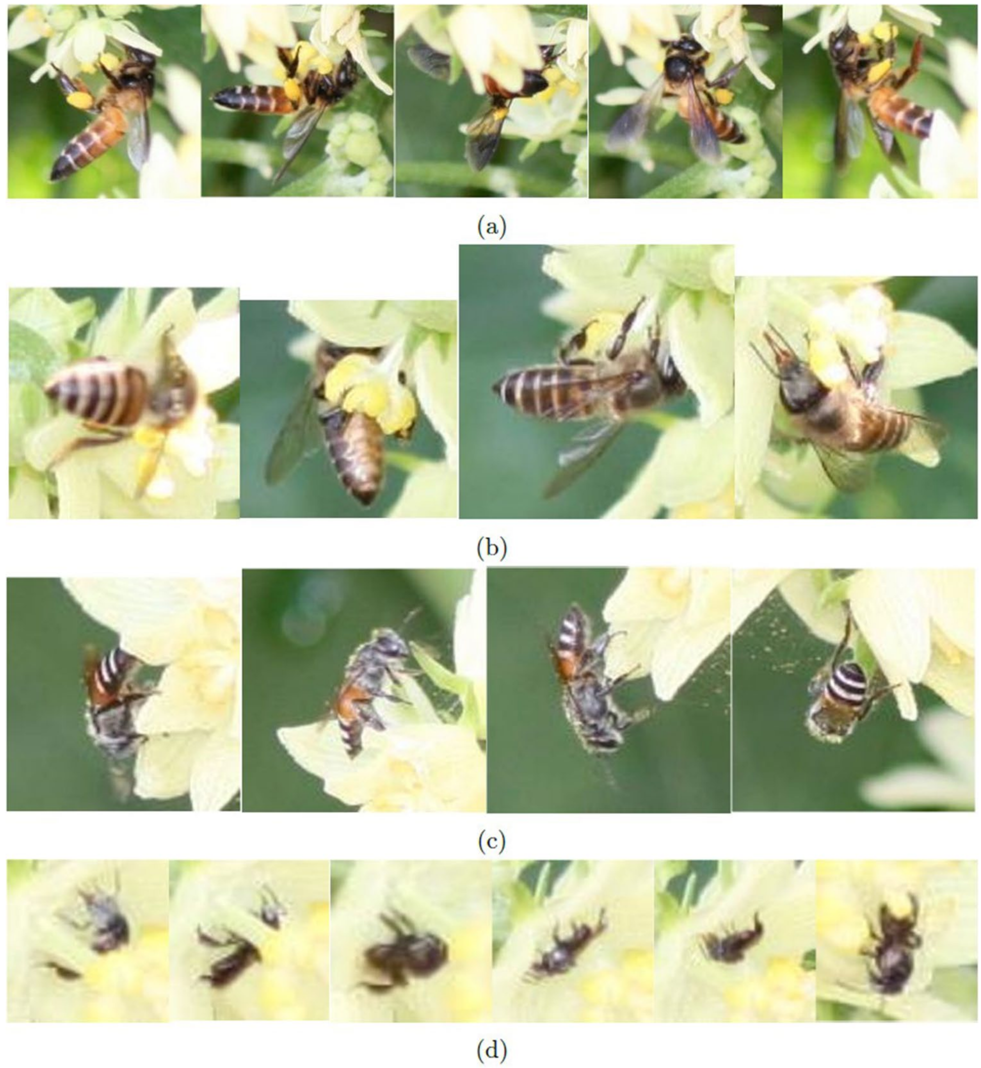


Fig. 1 (**a**) *A.dorsata*, (**b**) *A.cerana* (**c**) *A.florea* (**d**) *Tetragonula spp.* Examples of sequential images from our dataset (these images were cropped from sequential raw photographs shot 5 s apart). This shows the dynamic nature of bee position and orientation

different bee species. Objects that were identified to be not bees (e.g.:- ants, spiders, wasps, etc.) were marked as "notbee". Objects identified as bees whose species could not be identified were marked as "bee". Within each labelled directory, we created a sub-directory called "notclear". The images that could not be classified into a label without using contextual information (such as previous frame/following frame information, which allowed us to label an unclear image with its true label) available to us were deemed as unclear in the context of training data and hence segregated into a separate directory within each class. An image was considered unclear when the visual cues present in the image itself were insufficient to confidently label it into any of the classes (bee, notbee, *dorsata, cerana, florea* and *tetragonula*).

The annotations were exported, saved and compiled into a single csv file containing the file name, label, coordinates of the top left corner of the bounding box, height of the bounding box, and width. From this csv file, we cropped out the area containing the object of interest within the bounding boxes and saved them to a directory with respective label names. We then used the annotated data containing 3250 images to train the ML models. Based on the data processing, four distinct combinatorial datasets were generated (Table 1): -.

(1) wbnc (with class "bee", including not clear images):- Contained all the annotated images.

(2) wboc (with class "bee", only clear images):- Contained all the annotated images except those within the "not clear" sub-directory (i.e. wbnc - class (not clear)).

(3) wobnc (without class "bee", including not clear images):- Contained all the annotated images except the class "bee" (i.e. wbnc - class(bee)).

(4) woboc (without class "bee", only clear images):- Contained all the images in wobnc except for the images inside the "not clear" sub-directory (i.e. wbnc - class (bee) - class (not clear)).

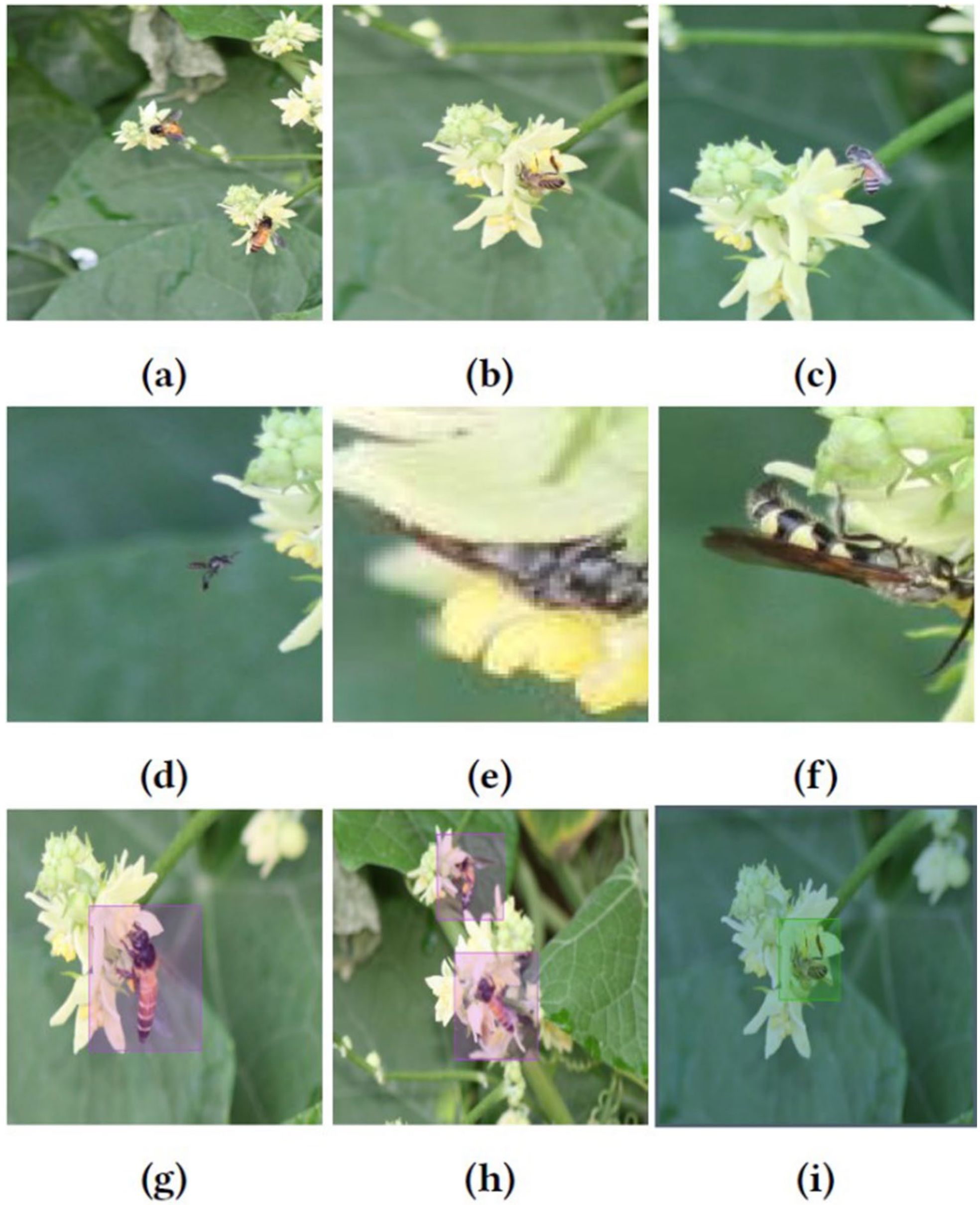


Fig. 2 From (**a**) to (**d**) *A.dorsata*, *A.cerana*, *A.florea*, *Tetragonula spp.* (**e**) object identified as "bee", (**f**) object identified as "notbee", which in this case is a wasp. Figures (**g**) to (**i**) show how bounding boxes are drawn around bees using makesense.ai

Table 1 Class distribution of our dataset

Class	wbnc	wboc	wobnc	woboc	Percentage wbnc	Percentage wboc	Percentage wobnc	Percentage woboc
Dorsata	111	98	111	98	3.4%	3.2%	4.1%	3.9%
Cerana	64	58	64	58	2.0%	1.9%	2.4%	2.3%
Florea	821	794	821	794	25.3%	26.2%	30.6%	31.6%
Tetragonula	1135	1051	1135	1051	34.9%	34.7%	42.3%	41.9%
Bee	569	516	0	0	17.5%	17.0%	0.0%	0.0%
Notbee	550	510	550	510	16.9%	16.8%	20.5%	20.3%
TOTAL	3250	3027	2681	2511	100.0%	100.0%	100.0%	100.0%

Models

To benchmark our dataset, we used Inception Net-V3 (Szegedy et al. 2016), MobileNet- V2 (Sandler et al. 2018), ResNet-50 (He et al. 2016), and VGG-16 (Simonyan and Zisserman 2014) based on their popularity in efficiently classifying image data. Besides, these models have been used successfully in other studies for bee species identification (B. J. et al. Spiesman 2021; Kelley et al. 2021b; Gharaee et al. 2023b; De Nart et al. 2022). The models were

Table 2 Comparison of inception Net-V3, MobileNet-V2, ResNet-50, and VGG16 architectures. PC - Parameter count in millions. D - Depth in the number of layers

Architecture	D	PC	Main Features
Basic CNN	12	27.3	Simple
Inception Net-V3	48	23.8	Factorized convolutions, Efficient grid size reduction, Asynchronous batch normalization
MobileNet-V2	53	3.4	Depth-wise separable convolutions, Inverted residuals and linear bottlenecks
ResNet-50	50	25.6	Residual learning, Identity shortcut connections
VGG16	16	138	Deep but simple architecture, Fixed kernel size (3 × 3) convolutions, Large fully connected layers

Table 3 Model training parameters

Parameter	Value
Batch Size	32
Number of Epoch	50
Learning Rate	0.0001
Optimizer	Adam
Loss Function	Cross Entropy Loss

implemented in Python framework using the torchvision package. We also ran a basic CNN model for comparison. The architecture of BasicCNN consists of five 3 × 3 convolutional layers with padding = 1, increasing channels from 3→32→64→128→256→512, each followed by ReLU and 2 × 2 max pooling, then a flattening step into a fully connected layer of 1024 units, and a final output layer matching the number of classes. The summary of the models is listed in Table 2.

Model training

We used models pre-trained on the ImageNet dataset (Deng et al. 2009). We trained the model again on the four variations of our dataset. This was required to ensure that the neural networks classify data points to the classes we define rather than those defined through pre-training. We resized the images in the datasets to 299 × 299 pixels and used a randomized split to generate training (80%) and testing (20%) sets. We did not opt for a session or timestamp-based spilt of the images because any session/timestamp-based split will be biased as there is a strong correlation between bee visitation and time of the day. Certain species are more frequent earlier in the day, whereas others are dominant later in the day. A split based on session or timestamp will bias the training or testing split with respect to species composition, lighting scenario, etc. The randomized split ensures that there are no session specific biases in either the training or the test sets. We used the same training set images to train all models, using the same parameters. The parameters used

Table 4 Model accuracy

Model	wbnc	wobnc	wboc	woboc
Inception Net-V3	0.874	0.963	0.878	0.978
MobileNet-V2	0.848	0.978	0.863	0.984
ResNet50	0.848	0.974	0.855	0.982
VGG16	0.772	0.966	0.847	0.956
Basic CNN	0.765	0.927	0.762	0.928

while training are given in Table 3. We ran all the codes on a Linux server equipped with Intel(R) Xeon(R) Gold 6138 CPU @ 2.00 GHz, 512 GB RAM, and 4 NVIDIA GeForce RTX 2080 Ti with 11GB VRAM each.

Model testing

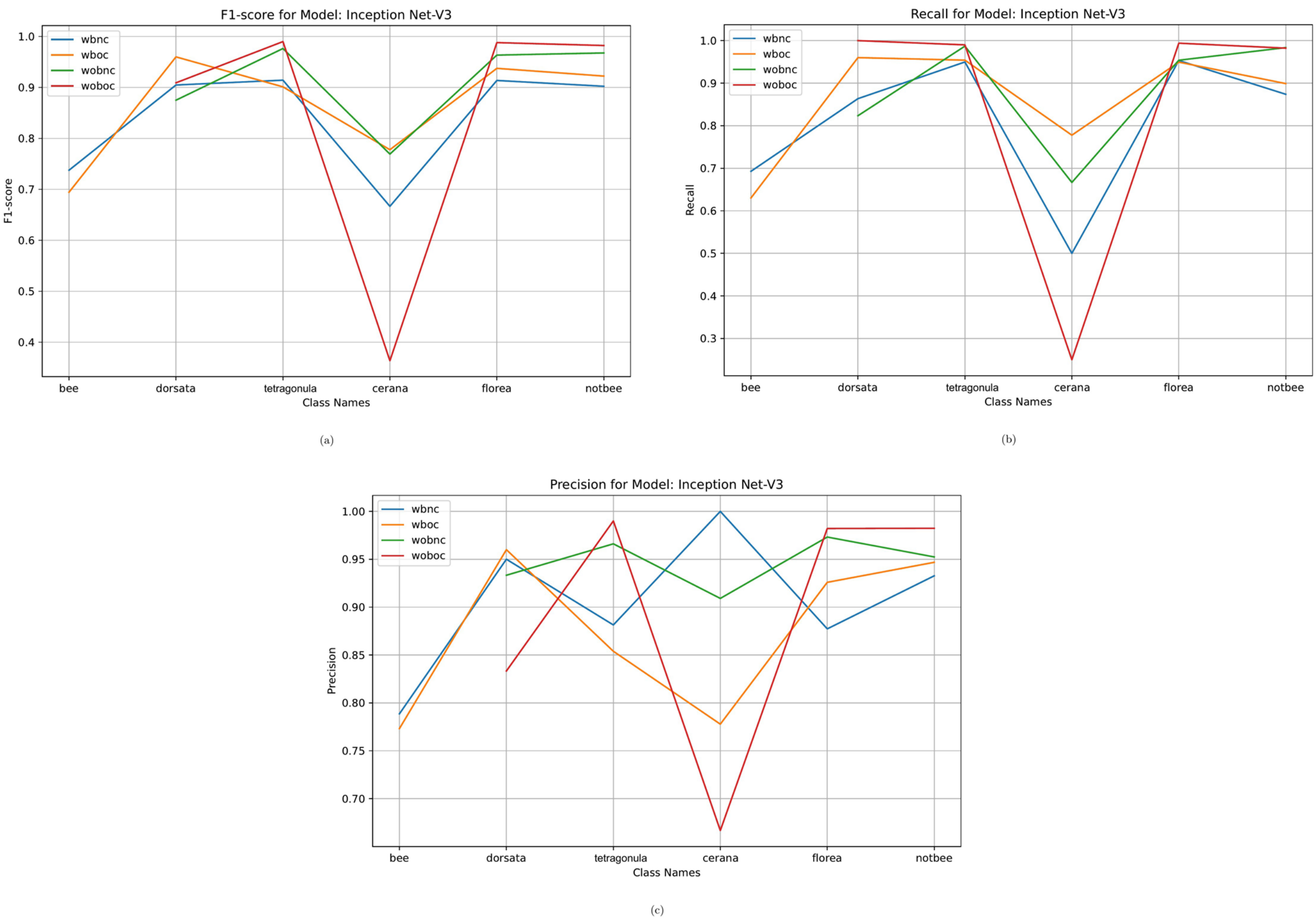
The classification reports and confusion matrices of each model were taken using sklearn.matrics module from the scikit-learn library.

Results

All established, pre-trained CNNs performed better than our basic CNN model on all dataset variations (Table 4). However, Inception Net-V3 had the highest average accuracy considering its performance across all the datasets (Fig. 3), and the MobileNet-V2 had the overall highest accuracy in the woboc dataset (Table 4).

All of the models, without exception, gave better accuracies on the woboc and wobnc datasets than on the wbnc and wboc datasets, i.e., in datasets where the class bee (not identifiable bee images) was not present (Table 4). There was a marginal increase in model accuracy when tested on wboc and woboc datasets compared to wbnc and wobnc datasets (Table 4). Except for VGG16, all other models recorded higher accuracy on the woboc dataset variant than what they recorded on wobnc (Table 4). These results validated our logical assumption that "not clear" images posed a significant challenge for the models (refer Fig. 4 for confusion matrix of MobileNet-V2's performance on woboc vs. wobnc datasets).

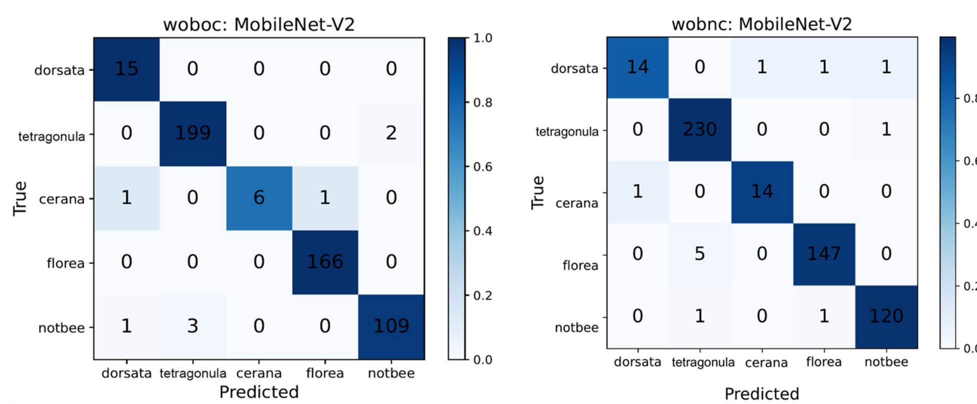
The classes "*cerana*" and "*dorsata*" were the two classes with a relatively low number of data points (Table 1). Of these, the classification metrics pertaining to the class "*cerana*" had significant fluctuations across dataset variants and models (supplementary figure s_f_3). Hence, the trends/values of the F1 score, recall and precision of the class "*cerana*" were less reliable. Class "*florea*" had marginally better F1-scores across dataset variants and models than the class "*tetragonula*" (supplementary figure s_f_3). Class "*dorsata*" had a lower F1-score than both "*tetragonula*" and



Performance metrics of Inception Net-V3

Fig. 3 F1, Recall and Precision scores of all classes across all dataset variants for the overall best model InceptionNet-V3

Fig. 4 Confusion matrices generated from the performance results of MobileNet-V2 on two dataset variations, wbnc and wobnc. The numbers inside the matrix represent the number of data points, and the colour of each cell is based on the normalised value of the cell indicated by the colour scale on the right



"*florea*" in the datasets where the class "bee" (not identifiable bee images) was not present (woboc and wobnc dataset variants, supplementary figure s_f_3.6).

In the datasets where the class "bee" was present (i.e. wboc and wbnc dataset variants), "*florea*" had a higher precision score than "*tetragonula*" across all models, suggesting better correct classification. This inequality was less pronounced in woboc and wobnc dataset variants. Barring VGG16, the other models showed noticeable trends in precision scores for class "*dorsata*", with class "*dorsata*" having (a) higher precision score than "*tetragonula*" in dataset variants with class "bee" (wbnc and wboc) (with the exception of Basic CNN) and (b) lesser precision score than "*tetragonula*" in wobnc and woboc dataset variants (supplementary figure s_f_3.12). This indicated that the correct classification of class *"tetragonula"* showed marked improvement when the class "bee" was removed from the dataset, while class "*dorsata"* was unperturbed by such changes.

Recall scores for both the classes "*florea*" and "*tetragonula*" were comparably high (>0.75) and showed relatively less variation across dataset variants and models. Recall scores of "*dorsata*" were lesser than that of "*tetragonula*" in the wobnc and wbnc dataset variants and similar to that of "*tetragonula*" in woboc and wboc dataset variants (with the exception of Basic CNN) (supplementary figure s_f_3.18).

Discussion

Leveraging image-based machine learning (ML) for bee identification is essential due to the extensive diversity of bee species and the limited number of taxonomy experts. This approach significantly enhances the efficiency of identification across complex environments and supports the development of mobile and web-based applications (B. J. et al. Spiesman 2021). These applications enable a wide range of users, from novice researchers to conservationists, to identify bee species using noisy field images. Consequently, image-based ML algorithms play a crucial role in quantifying bee biodiversity and promoting effective conservation interventions. This approach is particularly important for agriculture-dependent developing countries with high bee diversity (Basu, Bhattacharya, and Iannetta 2011b), which are experiencing rapid biodiversity loss due to anthropogenic pressures (Sodhi et al. 2009).

In this study, we introduce the South Asian Bee Dataset, which comprises field-collected images of the four primary social bees key to pollination service. Unlike conventional datasets curated primarily for taxonomy through ML, our dataset consists of field-collected images with uncontrolled conditions, thus challenging the existing ML models to become more resilient. Along with these challenges, we tested the model performance against non-targeted species (ants and wasps) that can occur in the natural environment while studying pollination service. We found that the model inception Net-V3 was the most robust model that performed consistently better than other models across most datasets with differing complexity levels.

The model performance declined significantly when we introduced the ambiguous class "bee" (low F1 score and recall value), where the correct bee species could not be identified. We found that the models were challenged by the presence of "not clear" images, signified by a decrease in model performance in the presence of unclear images in the dataset.

Despite all the challenges, given a sufficient sample size, all the models classified the different bee classes with considerable accuracy. Interestingly, the models showed significant accuracy in correctly classifying the non-bee visitors in our dataset, further highlighting their robustness. The accuracy across models and dataset variants was highest (98.4%) for Mobile Net-V2 without the classes "bee" and "not clear" (woboc dataset variant).

Conclusion

This dataset and our findings facilitate the training and testing of machine learning models designed explicitly for pollination visitation studies and honeybee biodiversity surveys in Southeast Asia. This represents an initial step towards the extensive application of machine learning in bee species classification and pollination studies using passively recorded data. These models, which exhibit robustness in handling noisy natural images, can be employed to classify and estimate not only bee diversity but also bee population status across vast and intricate landscapes without human intervention. This capability enables rapid assessment of bee biodiversity and facilitates swift conservation actions when necessary.

One of the limitations of the current study is the limited spatiotemporal sampling across two days and only two farmlands in one specific geographic location. To further enhance the robustness of such applications, more extensive sampling across multiple locations and longer timeframes is required to build a comprehensive database. It is also crucial to collect essential metadata, including timestamps and geographic locations of the photographs. Unlike traditional datasets, our dataset captures relevant ecological and contextual information such as temporal patterns and geographic data. These features allow for the analysis of temporal patterns in pollination visitation. Future directions for this research include further sampling, including algorithms for object detection from raw field images, tracking individual bees across images or video data, training machine learning models to quantify pollen load, a proxy for pollination potential of bees. This structured approach will ensure the dataset's applicability in broader ecological studies and conservation efforts, thereby significantly advancing the field of pollination research and bee biodiversity conservation.

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Author contributions RM and RD conceptualized and designed the study and the camera setup; RM acquired funding for the study setup, fieldwork, and conducted data collection; SCL, SrM and SM conceptualized the machine-learning (ML) algorithm; SCL and SrM processed the data, performed coding, analysis, data interpretation, and prepared the figures; SCL, SrM and RM wrote the manuscript; RM, RD and SM edited and gave critical comments on the entire manuscript; SMD facilitated fundraising and approved the initial study design. (RM – Ronita Mukherjee, RD – Rittik Deb, SCL – Srinivas C L, SrM – Sreerag M, SM – Subhankar Mishra, SMD – Soubadra M Devy)

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Data availability Dataset, code and supplementary material are available for public use at https://gitlab.niser.ac.in/smlab-research/sibd.

Declarations

Ethics approval This is an observational study. No ethical approval is required.

Financial & non-financial interests All authors certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Consent to participate This is not applicable since this study does not involve any human subjects.

Consent to publish This is not applicable since this study does not involve any human subjects.

Competing interests The authors declare no competing interests.

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