

Review

Buzzing Through Data: Advancing Bee Species Identification with Machine Learning

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Supplementary Document

This Supplementary Document accompanies the paper "Through Data: Advancing Bee Species Identification with Machine Learning" and is designed to provide detailed insights into specific aspects of the study for enthusiastic readers seeking deeper understanding.

Figure S1 presents a focused view of only four of the nineteen tribes within the Apinae sub-family, highlighting some of the most significant groups within this classification. Among these, the Apini tribe is notable for encompassing the genus *Apis*, commonly known as the true honeybees. This tribe is renowned for its members' ability to produce honey and beeswax, both of which play crucial roles in commerce and agriculture due to their extensive use in food products and pollination services. Additionally, the Meloponine tribe, which consists of various stingless bee species, is distinctive for its members' lack of a stinging mechanism. These bees are celebrated not only for their production of honey, propolis, and beeswax but also for their cultural and medicinal value across diverse societies. The unique social structures and behaviors observed within the Apini and Meloponine tribes are of considerable interest for both ecological research and entomological studies, providing insights into the complex interactions within bee communities and their environments.

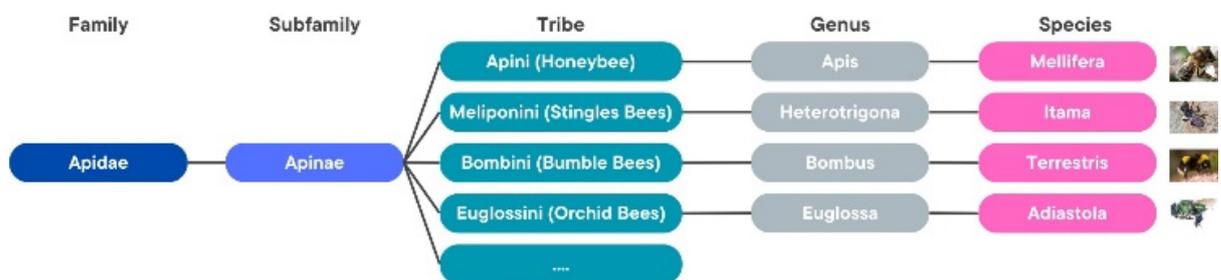


Figure S1. Four tribes among 19 tribes of the Apinae subfamily with an example species for each tribe.

The summaries of each study included in this systematic literature review are meticulously organized into tables based on the machine learning (ML) methods applied: Shallow Learning, Deep Learning, and a combination of both. These are respectively cataloged in Tables S1, S2, and S3. For clarity and ease of reference, each study has been assigned a unique publication number. This identifier is consistently used throughout the manuscript to enable quick referencing of the studies. The tables provide comprehensive details on each paper, including:

1. Publication No. - Unique identifier for each study.
2. Reference - Citation of the paper.
3. Citations - Number of times the paper has been cited.
4. Paper Title - Title of the study.
5. Publication Year - Year the study was published.
6. Data Type - Types of data used in the study (e.g., Images, Acoustic, Movement).
7. Species Focus - Focus of the identification (e.g., Stingless Bees (SB), Honeybees (HB), Other Bees, Other Species).
8. Species Count - Number of species analyzed.
9. ML Algorithms Used - Machine learning algorithms utilized in the study.
10. Study Location - Country or region where the study was conducted.
11. Includes Flying Insects - Indicates if flying insects are considered in the study.
12. Data Source - Origin of the dataset (e.g., Collected, Crowdsourced, Other Dataset).
13. Model Performance - Effectiveness of the developed model.
14. Notes - Additional remarks or important information.

These titles aim to provide clear, concise descriptions of each data point, ensuring easy navigation and comprehension of the table's contents.

Table S1. Summary of Publications Related to Shallow-Learning

| Publication No. | References | Cited by | Paper title | Year | Dataset (Images /Acoustic/ Movement) | Identification Focus (Stingless Bees(SB)/ Honeybees(HB)/ Other Bees/ Others) | Number of Species se | Utilized Machine Learning algorithms | Target Country | Is consider flying insect | Dataset (Collected/Crowd-Source/Other Dataset) | Performance | Remarks |
|-----------------|------------|----------|---|------|--------------------------------------|--|----------------------|--------------------------------------|----------------|---------------------------|--|-------------|---|
| 2 | [20] | 44 | Biodiversity informatics in action: identification and monitoring of Bee species using ABIS | 2001 | Images | Other Bee (Bombus bee) | 7 | SVM and KDA | N/A | No | Collected | Acc.=95 % | Mobilize the bee using ice for data collection. |

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|----|------|----|---|------|----------|---------------------------|----|--|--------|-----|-----------|-----------------------------------|--|
| 6 | [49] | 6 | Machine learning approach for automatic recognition of tomato-pollinating bees based on their buzzing-sounds | 2021 | Acoustic | SB, Other Bees and Others | 15 | LR, SVM, RF, DT, and an ensemble classifier | Brazil | Yes | Collected | Acc. =73.39% MacF1= 59.06% | Uses SongMeter SM2 to collect data |
| 7 | [51] | 7 | Identifying Bee Species by Means of the Foraging Pattern Using Machine Learning | 2018 | Movement | SB | 2 | MLP, SVM, RF | Brazil | Yes | Collected | Acc. = 87.41% | IR transponders stick to thoracic of the bee |
| 11 | [47] | 31 | Evaluating classification and feature selection techniques for honeybee subspecies identification using wing images | 2015 | Images | HB | 26 | LDA, KNN, Logistic, NB, DT, MLP and SVM | N/A | No | N/A | Acc.= 65.15% | |
| 13 | [12] | 23 | Automated classification of bees and hornet using acoustic analysis of their flight sounds | 2019 | Acoustic | HB, Other Bee and Other | 4 | SVM | Japan | Yes | Collected | Avg. Precision 0.89 | Record sound using AT9905, Audio-Tecnica) |
| 16 | [50] | 2 | Automated detection of the yellow-legged hornet (Vespa velutina) using an optical sensor with machine learning | 2023 | Movement | HB, Other Bee and Other | 7 | RF | Spain | Yes | Collected | Avg. Acc.= 80.1 ± 13.9% | |
| 19 | [46] | 24 | A reference process for automating bee species identification based on wing images and digital image processing | 2014 | Image | Other Bee (Orchid bee) | 5 | LDA, Logic Regression, SVM, KNN, Other Methods | N/A | No | Collected | Acc. 87.68% | |
| 20 | [44] | 4 | A fully automatic classification of bee species from wing images | 2021 | Images | HB, SB, Other Bee, Other | 48 | KNN | N/A | No | Collected | Acc. Species = 96% Genus = 99% | |

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|----|------|---|---|------|----------|------------------|---|----------------------|--------|-----|-----------|------------------------------------|
| 25 | [48] | 1 | Hierarchical classification of pollinating flying insects under changing environments | 2022 | Movement | HB, SB and Other | 7 | KNN, NB, RF, and SVM | Brazil | Yes | Collected | Avg. hierarchical F-measure= 94.08 |
|----|------|---|---|------|----------|------------------|---|----------------------|--------|-----|-----------|------------------------------------|

Table S2.Summary of Publications related to Deep-Learning

| Publication No. | Reference | Cited by | Paper title | Year | Dataset (Images /Acoustic/ Movement) | Identification Focus (Stringless Bees (SB)/ Honeybees (HB)/ Other Bees/ Others) | Number of Species se- | Utilised Machine Learning algorithms | Target Country | Is consider flying insect | Dataset (Collected/Crows-Source/Other Dataset) | Performance | Remarks |
|-----------------|-----------|----------|---|------|--------------------------------------|---|-----------------------|---|----------------|---------------------------|--|--|-----------------------------|
| 1 | [42] | 0 | DY-RetinaNet Based Identification of Common Species at Beehive Nest Gates | 2022 | Images | HB and Others | 3 | Improved RetinaNet(DY RetinaNet) | China | No | Collected | Avg. Acc. : 97.38% | Do Object Detection |
| 4 | [43] | 5 | Classification of Ecological Data by Deep Learning | 2020 | Images | Other Bee and Other | 29 | LeNet-5, AlexNet, ResNet50, Inception v3, Inception-ResNetV2, VGG-16 and VGG-19 | N/A | No | N/A | Acc. Of Butterfly:96.88%, Bee : 92.90% | |
| 5 | [13] | 7 | Image recognition using convolutional neural networks for classification of honeybee subspecies | 2022 | Images | HB | 7 | InceptionResNet V2, Inception-Net V3, MobileNet V2 and ResNet 50 | Italy | No | Other dataset | Avg. F1 Score: 0.99 | |
| 9 | [38] | 1 | A concatenated approach based on transfer learning and PCA for | 2021 | Images | HB and other | 4 | VGG, ResNet, XceptionNet, and EfficientNet | N/A | No | Other datasets | Acc. AUC: 0.9973 | Model based on transformer. |

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| | | | classifying bees and wasps | | | | | | | | | | | |
| 10 | [16] | 31 | Assessing the potential for deep learning and computer vision to identify bumble bee species from images | 2021 | Images | Other Bee (Bumble Bee) | 36 | ResNet, Wide ResNet, InceptionV3, and MnasNet | United States and Canada | No | Other datasets | Acc. : 91.7 % | BeeMachine web application utilized this model | |
| 15 | [40] | 33 | Image-based species identification of wild bees using convolutional neural networks | 2020 | Images | HB , Other Bee ,Other | 12 9 | B-CNN, MobileNet and Inception-ResNet | Germany, Brazil, United States and China. | No | Other Dataset | top-1 Acc. of 93.95% and a top-5 Acc. of 99.61% | | |
| 17 | [34] | 2 | A Deep Learning Approach to classify the Honeybee Species and health Identification Automatic acoustic recognition of pollinating bee species can be highly improved by Deep Learning models accompanied by pre-training and strong data augmentation | 2021 | Images | HB | 7 | Inception v3 | N/A | No | Other dataset | Acc. : 86% | | |
| 18 | [3] | 0 | Automatic acoustic recognition of pollinating bee species can be highly improved by Deep Learning models accompanied by pre-training and strong data augmentation | 2023 | Acoustic | HB and Other Bee | 16 | Pre-trained Audio Neural Networks(PANNs), and EfficientNet V2 | Chile | Yes | N/A | Macro F1-Score: 58.04 (± 2.47) | Zoom H4n Pro Handy Recorder is used to collect data | |
| 21 | [32] | 0 | Honey sources: Neural network approach to bee species classification | 2021 | Images | HB, Other Bee | 3 | Faster R-CNN with Resnet 101+FPN backbone | N/A | No | Collected | Acc. : 91% | Do Object Detection | |
| 23 | [37] | 0 | BeeNet: An End-To-End Deep Network For Bee Surveillance | 2023 | Images | HB | 11 | ResNest, EfficientNet, and NoisyStudent, Be eNet | N/A | No | Crowded sourced dataset and | Acc. : 92.45% | | |

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|----|------|---|---|------|--------|---------------------|---|------------------------------------|----------|----|-----------------------------|-----------------------------|--|
| 24 | [33] | 0 | Research on Mini-EfficientDet Identification Algorithm Based on Transfer Learning | 2022 | Images | Other Bee and other | 3 | EffientDet with one layer of BiFPN | N/A | No | Other dataset | Acc. of Chinese Bee: 98.66% | Do Object Detection |
| 26 | [36] | 1 | Image segmentation of meliponine bee using Mask-RCNN | 2020 | Images | SB | 1 | Faster R-CNN | Malaysia | No | Collected and Other dataset | Acc.:74% | Do Object Detection to differentiate SB and background |

Table S3. Summary of Studies related to combination of Shallow- and Deep-Learning

| Publication No. | References | Cited by | Paper title | Year | Dataset (Images /Acoustic/ Movement) | Identification Focus (Stringless Bees(SB)/ Honeybees(HB)/ Other Bees/ Others) | Number of Species se- | Considered Machine Learning algorithms | Target Country | Is consider flying insect | Dataset (Collected/Crows-Source/Other Dataset) | Performance | Remarks |
|-----------------|------------|----------|--|------|--------------------------------------|---|-----------------------|--|------------------|---------------------------|--|--------------------|--|
| 3 | [39] | 103 | A Vision-Based Counting and Recognition System for Flying Insects in Intelligent Agriculture | 2018 | Images | HB and Others | 6 | YOLO and SVM | N/A | No | Collected | Acc.: 90.18% | Do Object Detection |
| 8 | [35] | 5 | AI in apiculture: A novel framework for recognition of invasive insects under unconstrained flying conditions for smart beehives | 2023 | Images and Movement | HB and Others | 3 | DT,Ensemble, SVM, KNN, xception,googlenet and bagged trees | Pakistan | Yes | Collected | Acc.: 97.1% | Intel’s Real sense D435 depth camera use to capture data and calculate the 3D trajectories |
| 12 | [41] | 6 | Using the Software DeepWings© to Classify Honey Bees across | 2022 | Images | HB | 3 | DeepWing | Portugal, Spain, | No | Collected | M-line-ages: 71.4% | |

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| 22 | [52] | 7 | Image-Based Automated Species Identification: Can Virtual Data Augmentation Overcome Problems of Insufficient Sampling? | 2022 | Images | Other Bee , Other | 4 | VGG16 and SVM | N/A | No | Other Dataset | NET) is 0.943 SVM achieved 86.6% Accuracy of each class: Pleophylla: 80.07% Schizonycha: 85.16% Os-mia:85.90% Parides: 98.06% | Utilized Style-GAN to generate new data from the existing images and Generated heatmaps of specimen images to show contribution to decision making |
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