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# Enhancing Apiculture through Deep Learning: A Vision-based Honey Bee Classification

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***Abstract*—The work Honey Bee Classification aims to develop an advanced system for identifying and classifying various species of honey bees. Given the critical role honey bees play in pollination and maintaining biodiversity, accurate identification is essential for monitoring their populations and understanding the factors affecting their decline. Traditional methods of classification, which rely on morphological characteristics, are time-consuming and often prone to error due to the subtle differences between species. This project leverages the power of deep learning to provide a more efficient and accurate solution. The implementation of this deep learning-based approach not only enhances classification accuracy but also significantly reduces the time and effort required compared to traditional methods. The honey bee dataset used in the work has six classes of honey bee. The deep learning models DenseNet121, MobileNetv2 and ResNet50v2 used in the work were consistently trained over 10 epochs with 80:20 data split. DenseNet121 model achieved a high accuracy of 99.8%. The work successfully achieved its goal classifying honey bee using deep learning techniques. The results confirmed the efficacy data augmentation and advanced deep learning models in enhancing classification accuracy.**

***Index Terms*— crop, pollination, artificial intelligence, computer vision, deep learning, honey bee.**

## I. INTRODUCTION

In the bustling world agriculture, where crops provide sustenance and livelihoods, the role pollinators are paramount. Take, for instance, the vast fields almonds in California. Each spring, these orchards burst into a sea delicate blossoms, but their transformation into the coveted nuts depends heavily on the tireless work pollinators, primarily honey bees. These industrious insects' flit from flower to flower, transferring pollen and ensuring successful fertilization, thereby enabling the fruiting process. However, honey bee populations worldwide face numerous threats including habitat pesticides and diseases, making their conservation and management a critical concern for farmers and ecologists alike.

In India, four commercially important honey bee species are found: the little bee (Apis florae), rock bee (Apis dorsata), Indian bee (Apis cerana indica), and Italian bee (Apis mellifera) [1][2]. The first three are native, while Apis mellifera was introduced in the 19th century and is well-suited for domestication. Apis cerana indica has a limited flight range (1-2 km), making it less effective for pollination, whereas Apis mellifera and Apis dorsata can fly up to 5-6 km.

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However, Apis dorsata is difficult to domesticate. The Italian bee (Apis mellifera) is widely used for enhancing crop yields due to its ease of rearing and superior pollination efficiency, increasing yields by up to 25% compared to other pollination methods. Additionally, the recently discovered Apis karinjodian also plays a significant role in crop pollination [3].

Currently, stakeholders such as farmers, beekeepers, and ecologists rely on traditional methods for monitoring honey bee populations and hive health. This often involves manual inspections hives, visual assessments bee behavior, and occasional sampling for pests or diseases. However, these methods can be time-consuming, labor intensive, and prone to human error. Provide comprehensive insights into broader trends or subtle changes in honey bee populations over time. As such, there pressing need efficient accurate monitoring solutions that can aid stakeholders in making informed decisions regarding hive management, conservation efforts, and policy interventions.

To address these challenges, researchers and technologists have turned to innovative solutions, leveraging power artificial intelligence (AI) and deep learning (DL) to aid in honey bee classification efforts. Project involves development honey bee classifier - a sophisticated artificial intelligence system designed to analyze images and identify various aspects honey bee behavior, health, and population dynamics. The deep learning models DenseNet121, MobileNetv2 and ResNet50v2 are used in the work on the Honey Bee Dataset dataset. Six classes were considered in the proposed work are Buckfast, Carniolan, Frohheimstrasse, Indian, Southeast_dorsata and western_mellifera.

In summary, the study examines recent advancements in honey bee classification research, identifying deep learning techniques applicable for enhancing our methodology. We evaluate the usability and efficacy of these algorithms for classifying honey bees, alongside an assessment of relevant datasets concerning their size, quality, and usability. The paper is organized as follows: Section 1 offers a brief introduction to honey bee classification; Section 2 outlines the literature review; Section 3 discusses the materials and methodology; Section 4 analyzes the findings and their implications; and Section 5 provides concluding remarks.

## II. Related Works

Significant research has focused on reviewing challenges in apiculture along with honey bee classification, particularly using deep learning (DL) and image-based methods. Building on existing reviews in the field, the state-of-the-art work by various researchers is discussed below:

The paper [4] addresses a critical challenge in apiculture and ecosystem health: the rapid detection of Varroa destructor mite infestation in honeybee colonies. compared two classification methods based on AlexNet and ResNet as well as a semantic segmentation approach using DeepLabV3, with the latter achieved an accuracy of minimum 90.8% with an overall f-score of 0.95. Leveraging computer vision and deep learning, the authors present a significant contribution with both methodological and practical value.

The work [5] presented a significant and ambitious application of deep learning (DL) for comprehensive beehive health monitoring, directly addressing a critical need in apiculture and ecosystem preservation. They used robust methodology (transfer learning, feature fusion with SVM) trained and evaluated on a substantial dataset. The reported accuracy of up to 99.07% is impressive and strongly suggests the models' potential for integration into smart beekeeping systems for early warning and intervention.

This paper [6] addressed the critical challenge of detecting Varroa destructor mites on honey bees using image processing, specifically employing a key point analysis approach. It tackles a problem with significant economic and ecological implications, as mite infestation is a primary driver of colony collapse. his work lays a potentially useful foundation, particularly if the optimized pre-processing pipeline demonstrably enhances the performance of downstream deep learning-based mite detection systems, as suggested. Future work should focus on quantifying this downstream detection improvement and testing robustness across larger, more diverse datasets.

The paper [7] provided a timely and valuable systematic review of the rapidly evolving field of automated beehive monitoring via acoustics analysis, covering the decade from 2012 to 2021. It serves as both an excellent introduction and a crucial reference point for future studies aiming to advance bee acoustics for effective hive health assessment and conservation.

The paper [8] compared ML and DL to outline a highly relevant and methodologically promising study addressing a critical bottleneck in precision pollination ecology: the automated identification of efficient blueberry pollinators via their buzzing sounds. The popular DL models reached better performances at assigning bee buzzing sounds to their respective taxa than expected by chance.

In paper [9] authors demonstrated Convolutional Neural Networks (CNNs) applied to wing images are highly effective for automatically discriminating between European honey bee subspecies and a hybrid. Four CNN models (ResNet50, MobileNet V2, Inception Net V3, ResNet V2) were trained on a large dataset of 9,887 wing images representing 7 subspecies and one hybrid. CNN models achieved high accuracy (>92%) in classifying individual wings to their correct subspecies/hybrid.

The paper [10] presented a forward-looking, persuasive, and well-supported argument for the transformative potential of computer vision (CV) and AI in bee research and broader insect biodiversity monitoring. It effectively moves beyond technical specifics to articulate a grand vision for scalable ecological assessment.

Honey bee monitoring is one of the critical challenges specially in automated beehive monitoring. advance bee acoustics for effective hive health assessment and conservation is very much necessary now a days. It can be addressed through the application of Artificial Intelligence using deep learning. which in turn supports a critical need in apiculture and ecosystem preservation. State-of-art work done in this field using machine learning and deep learning need to be enhanced. So, the proposed work considers a diverse dataset and enhanced deep learning models to get good results.

## III. MATERIALS AND METHODOLOGY

Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), differs from classical machine learning by enabling computational models with multiple processing layers to learn hierarchical data representations. We selected three CNN classifiers recognized for their high performance in image-based tasks. This section describes the methodology and dataset employed.

### *A. Data set description*

The dataset used in the honey bee classification is honey bee dataset which comprises images from six distinct classes with total of 3919 images. All images are in colour and stored in PNG format, ensuring high-quality visual data for the classification task. The images have a size range between 100KB and 200KB, providing a harmonious blend of picture quality and storage efficiency. The source of this dataset was Kaggle, a well-known platform for data science and machine learning datasets. The six classes in the dataset represent various honey bee classes as shown in Table I along with their count.

TABLE I. HONEY BEE CLASSES

| Sl. No. | Honey Bee Class | Image Count |
|---|---|---|
| 1 | Buckfast Bee | 100 |
| 2 | Carniolan Bee | 300 |
| 3 | Indian Bee | 656 |
| 4 | Frohheimstrasse Bee | 1250 |
| 5 | Southeast Dorsata Bee | 200 |
| 6 | Western Mellifera Bee | 1413 |

Using PNG colour images from the well-structured, diverse Kaggle dataset gives the models access to detailed, high-quality visual information. This is essential for differentiating classes with subtle variations, enabling the project to achieve highly reliable and accurate honey bee classification. The outcome supports more effective and scalable apiculture environmental conservation. Figure 1 shows sample honey bee classes.


Figure 1. Sample Honey Bess classes.

## B. Methodology

The Figure 2. illustrates the comprehensive workflow for classifying honey bee. It starts with the collection is honey bee dataset, which includes images honey attire from different species. The dataset undergoes preprocessing steps resizing, normalization, and augmentation enhance quality variability the images. The dataset is divided training and testing subsets to facilitate model training and evaluation. The core the classification process involves a convolutional neural network comprises convolutional layers, pooling layers and fully connected layers. The CNN is trained subset to learn intricate patterns and features specific to each bee's species. Once the model is trained, it is evaluated using the testing subset to assess its accuracy and effectiveness in classifying the honey bee species. The evaluation phase includes calculating performance metrics such as accuracy, precision and recall. Each block represents a distinct module or process within the system, and lines connecting them depict the flow data and information throughout the classification pipeline. This diagram provides a high-level overview how the system processes input images, applies deep learning algorithms to classify them into honey bee.

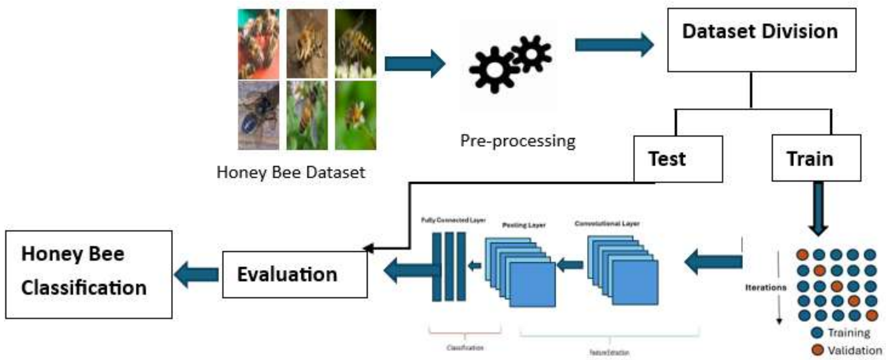


Figure 2. Methodology of Honey Bee Classification.

## C. Deep Learning Models

The three deep learning models used the honey bee classification are discussed in this subsection.

### *ResNet50v2*

ResNet50v2 is an advanced convolutional neural network that improves on its predecessor, ResNet50, by applying batch normalization before activation functions, enhancing stability and performance. With 50 layers, it combines convolutional, pooling, and fully connected layers to efficiently handle deep network training. Figure 3 shows architecture of ResNet50v2. Its residual connections address the vanishing gradient problem, enabling the model to learn from deeper architectures. ResNet50v2 excels in image classification, offers high accuracy, and is widely used in computer vision tasks and transfer learning due to its ability to process large-scale datasets effectively [11,12].

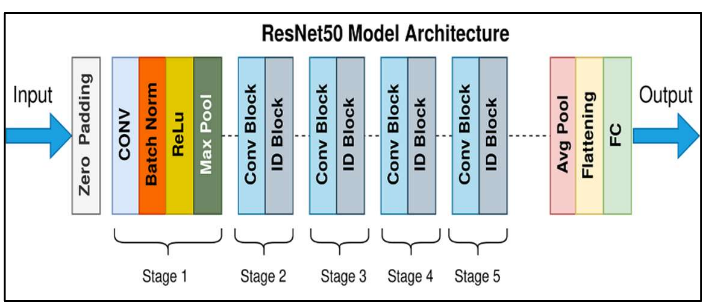


Figure 3. ResNet50v2 Model Architecture.

### *MobileNetv2*

MobileNetv2 is a type of convolutional neural network (CNN) designed for efficient computation Depth wise separable convolutions are used by MobileNetv2 to minimize computational effort and parameter count while preserving excellent accuracy. Figure 4 shows architecture of MobileNetv2. Because of its effective structure, the model is especially well-suited for mobile and embedded vision applications. MobileNetv2 uses a sequence of convolutional layers to process the input image and extract information for the purpose of classifying flowers. Each of the predetermined floral classes is given a probability in the final classification layer [13].

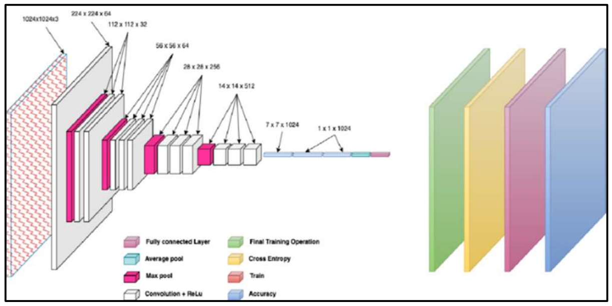


Figure 4. MobileNetv2 Model Architecture

*DenseNet121*

DenseNet121, or Densely Connected Convolutional Network, aims to improve gradient propagation and information flow across the network. With 121 layers, DenseNet121 is renowned for its unique connectivity structure, in which all layers before it receives inputs. Figure 5 shows architecture of DenseNet121Enhancing training performance and efficiency; this structure minimizes the vanishing gradient issue and encourages feature reuse. Across a range of image classification tasks, DenseNet121 has shown impressive performance, offering a mix between efficiency and accuracy. Because of its creative architecture, it is a good fit for applications that need deep learning models that are highly effective at using computational resources [12, 14].

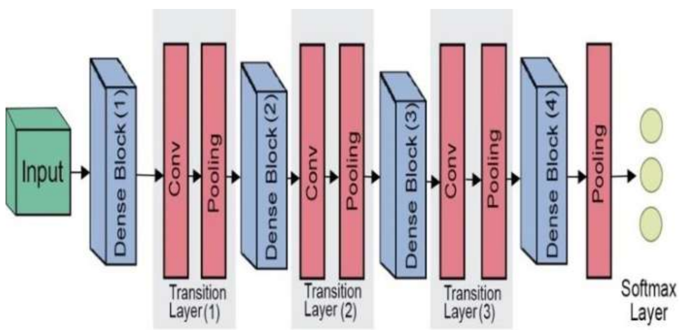


Figure 5. DenseNet121 Model Architecture

*D. Evaluation Metrics*

Training Deep Learning models like ResNet50V2, MobileNetV2 and DenseNet121 for image classification involves meticulous evaluation to verify their effectiveness in generalizing to unseen data. Various metrics are employed to assess model performance comprehensively.

- Accuracy evaluates the overall correctness of the model's predictions by measuring the proportion of correct predictions (both true positives and true negatives) out of the total number of predictions.
- Precision is crucial for evaluating performance in scenarios with imbalanced datasets. It represents the ratio of true positive predictions to the total number of positive predictions made by the model. High precision indicates that most of the positive predictions are correct.
- Recall, also important in imbalanced datasets, measures the ratio of true positive predictions to total number of actual positives in the data. It reflects the model’s ability to identify all relevant instances.
- F1-score combines precision and recall into a single metric by calculating their harmonic mean. This provides a balanced view of model performance, especially when both precision and recall are critical to the application.
- Confusion Matrix offers an in-depth view of classification results by displaying the counts of true positives, true negatives, false positives, and false negatives. This matrix helps in pinpointing specific types of errors the model makes, which can be essential for understanding and improving its performance.

Together, these evaluation metrics provide a comprehensive assessment of model effectiveness, allowing for the identification of strengths and weaknesses in various classification scenarios. They ensure that the models are not only accurate but also reliable and efficient in diverse applications.
Different assessment criteria, such as recall, accuracy and precision. To calculate this assessment, we need variables like true positive (TP), true negative (TN), false positive (FP) and false negative (FN) and they are defined as follows:
TP: Output given by the model is positive and is actually positive.
TN: Output given by the model is negative and is actually negative.
FP: Output given by the model is positive and is actually negative.
FN: Output given by the model is negative and is actually positive.
The accuracy was calculated using equation (1):

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (1)$$

The recall, precision and F1-score were calculated using equation (2), (3) and (4):

$$Recall = \frac{TP}{TP+F} \quad (2)$$

$$Precision = \frac{TP}{TP+F} \quad (3)$$

$$F1 - score = \frac{2*TP}{(2*TP)+FP+F} \quad (4)$$

IV. RESULTS AND DISCUSSION

This section discusses and compares the end results of honey bee classification achieved by three deep learning models: ResNet50v2, MobileNetv2, and DenseNet121. The evaluation uses a dataset of 3976 images, with 796 images (20%) reserved for validation. Model performance is primarily assessed by accuracy, with additional metrics (precision, recall, F1-score) calculated for each. The findings for each model are presented below:

*A. ResNet50V2*

ResNet50v2 is an improved version of the ResNet50V2 architecture, designed to enhance the training of deep neural networks by using residual learning. It consists of 50 layers, utilizing shortcut connections to bypass blocks of convolutional layers, which helps mitigate the vanishing gradient problem. ResNet50v2 is widely used in image recognition tasks and has significantly contributed to advancements in deep learning by enabling deeper network training. An accuracy of 99.7 % is obtained with ResNet50v2 on validation data. The confusion matrix is shown in the Figure 6.


Figure 6. Confusion Matrix for validation set of ResNet50V2 model.

*B. MobileNetv2*

MobileNetV2 is a lightweight convolutional neural network designed for efficient mobile and edge device applications. It introduces depth wise separable convolutions and linear bottleneck layers to reduce computational complexity and model size while maintaining high performance. With an 80-20 split between training and validation data, the model achieves an impressive accuracy of 99.2%. The Figure 7 displays a confusion matrix for a classification model predicting honey bee. The true labels are on the vertical axis and the predicted labels are on the horizontal axis. Correct predictions are indicated by the diagonal cells. For example, the model accurately identified 20 instances of Buckfast bee, 60 of Carniolan, 242 of Frohheimstrasse bee and so on.

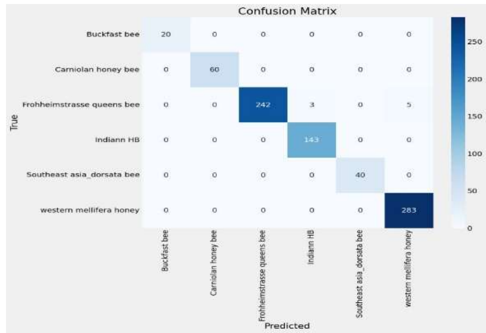


Figure 7. Confusion Matrix for validation set of MobileNetv2 model

*C. DenseNet121*

This architecture promotes feature reuse and gradient flow, significantly improving training efficiency and model performance. With 121 layers, DenseNet121 excels in extracting and propagating features throughout the network, reducing the risk of overfitting while enhancing accuracy in image classification tasks. Its dense connections help in leveraging all layers' learned features, making it highly effective for various computer vision applications. The Figure 8 shows the confusion matrix generated from the DenseNet121 model's validation dataset, assessing its performance across six distinct honey bees.

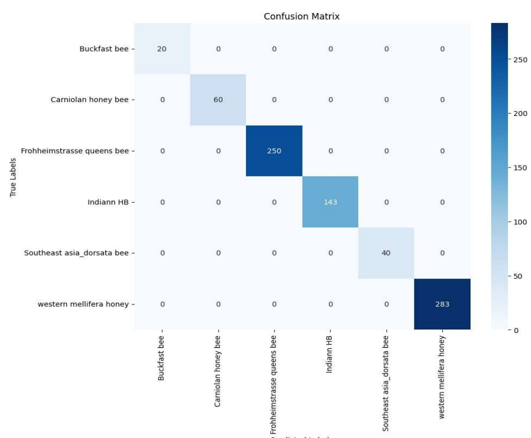


Figure 8. Confusion Matrix for validation set of DenseNet121 model

The Table II presents the accuracy of models trained using ResNet50V2, MobileNetV2 and DenseNet121. These metrics are assessed on a validation set after each training epoch to monitor overfitting by comparing performance on both training and validation datasets.

TABLE II. ACCURACY OF TESTED MODELS

| Models | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| MobileNetV2 | 99.2% | 0.99 | 0.97 | 0.98 |
| ResNet50V2 | 99.7% | 0.98 | 0.98 | 0.99 |
| DenseNet121 | 99.8% | 0.99 | 0.98 | 0.99 |

*D. User Interface*

The images in Figure 9 are the user interfaces of the project which shows the working of the project and its interaction with the users. UI provides upload and testing for classification uploaded files also displays the result.

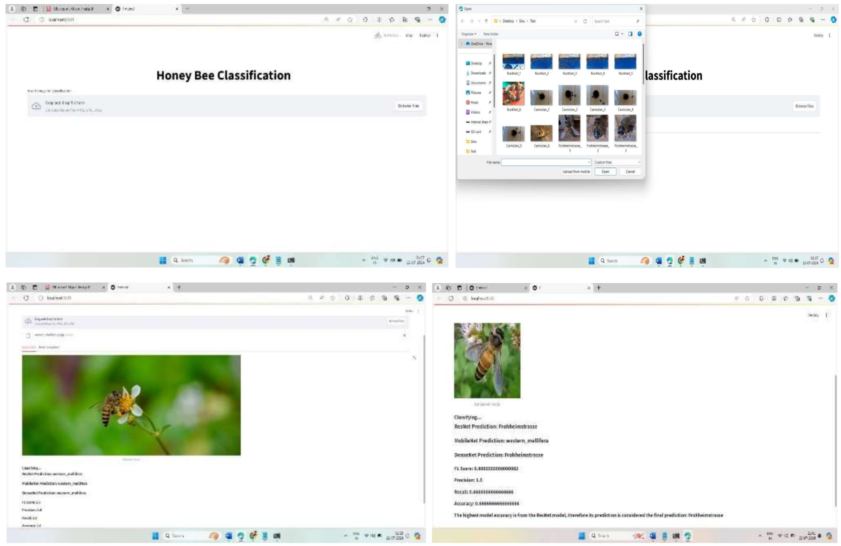


Figure 9. The User Interface page and Testing Images for classification

Figure 10 presents the ROC curves for all three models, plotting True Positive Rate (TPR) against False Positive Rate (FPR) across classification thresholds. The ideal curve bends sharply towards the top-left corner (high TPR, low FPR), indicating superior performance. The diagonal line represents random guessing, while the Area Under the Curve (AUC) quantifies overall discriminative power—higher AUC values (closer to 1) signify better accuracy. For the DenseNet121 model classifying honey bee species, analysing its ROC curve and AUC is crucial. This analysis reveals how effectively the model differentiates between species, guiding threshold optimization and model refinement to ensure reliable identification, which is key for cultural heritage preservation.

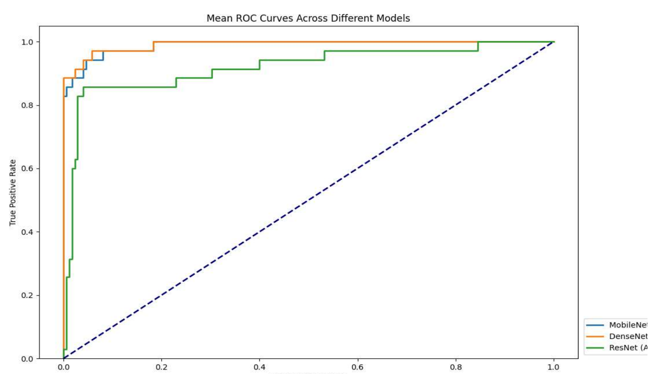


Figure 10. Mean ROC curve across different models

## V. CONCLUSIONS

This project successfully demonstrated the potential of deep learning for accurate honey bee classification in apiculture. Utilizing advanced models (ResNet50V2, MobileNetV2, DenseNet121) on a six-class honey bee dataset, significant accuracy was achieved in identifying bees. The dataset was split into various training-validation configurations, validating model robustness and generalization. Notably, the DenseNet121 model achieved 99.8% accuracy. The project successfully met its goal of classifying honey bees using deep learning techniques.

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