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# Morphological feature extraction of microfauna using YOLOv8 and Efficient Net model

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***Abstract*—Agriculture plays a vital role in the economy and food production systems of many countries. Crop productivity and quality are significantly influenced by environmental and biological factors, among which insects play a crucial role. Insects are broadly classified into beneficial insects (pollinators) and harmful insects (pests). Pollinators such as bees and butterflies support plant reproduction through pollination, thereby enhancing crop yield, while pests cause severe damage to crops, leading to reduced productivity and economic losses. In recent years, the rapid increase in pest populations and the decline of beneficial pollinators have posed serious challenges to farmers. A major contributing factor to this issue is the improper identification of insects. Traditional methods of insect identification rely on manual observation and experience, which are often time-consuming and prone to errors. Misidentification can result in the excessive use of pesticides, negatively impacting the environment, soil health, and beneficial insect populations. With advancements in Artificial Intelligence (AI) and Deep Learning, automated systems for accurate insect classification have become feasible. These systems can analyze images and detect complex patterns that are difficult for humans to recognize. This project proposes a web-based application that utilizes deep learning models, specifically EfficientNet and YOLOv8, for the classification of insects into pests and pollinators. In addition to classification, the system provides detailed biological information, including binomial nomenclature, diet, habitat, and taxonomy of the identified insect. The proposed solution aims to assist farmers, researchers, and students by enabling accurate insect identification, reducing unnecessary pesticide usage, and promoting sustainable and environmentally friendly agricultural practices.**

***Index Terms*—Insect Classification, Agriculture, Deep Learning, Artificial Intelligence, EfficientNet, YOLOv8, Image Processing, Sustainable Farming.**

## I. INTRODUCTION

### 1.1 Background and Motivation

Agriculture plays a vital role in the economy and food production systems of many countries. The productivity and quality of crops are significantly influenced by various environmental and biological factors, among which insects play a crucial role. Insects are broadly categorized into beneficial insects (pollinators) and harmful insects (pests). Pollinators such as bees and butterflies contribute to the pollination process, which is essential for plant reproduction and crop yield, while pests cause severe damage to crops, leading to reduced agricultural productivity and economic loss [19]

In recent years, farmers have been facing increasing challenges due to the rapid growth of pest populations and the decline of beneficial pollinators. One of the major reasons for this problem is the improper identification of insects. Traditionally, farmers rely on manual observation and experience to identify insects, which is often time-consuming and prone to errors [4]. Misidentification can lead to excessive use of pesticides, which not only harms the environment but also destroys beneficial insects [12]

Fig 1.1 crop damaged by pest

1.2 Need for Intelligent Insect Identification

Accurate identification of insects is essential for effective pest management and sustainable agricultural practices. However, traditional methods are not always reliable due to the lack of expertise and the complexity involved in distinguishing between visually similar insect species [7]. This creates a need for efficient and reliable solutions that can assist in proper identification. With the advancement of Artificial Intelligence (AI) and Deep Learning, automated image-based classification systems have emerged as powerful tools in agriculture. These technologies are capable of analysing insect images, extracting meaningful features, and identifying patterns with high accuracy [9]. Deep learning models such as Convolutional Neural Networks (CNNs) and advanced architectures like Efficient Net have shown significant performance improvements in image classification tasks [15], [17]. Such systems reduce human effort, minimize errors, and support better decision-making. Various studies have demonstrated the effectiveness of deep learning-based pest detection systems, including lightweight models and real-time detection approaches [5], [6], [8]. The development of intelligent insect identification systems can help farmers, researchers, and students by providing quick and accurate results. It also contributes to reducing unnecessary pesticide usage, protecting beneficial insects, and promoting environmentally sustainable farming practices [2], [3]. Thus, integrating modern technology with agriculture is essential for improving productivity and maintaining ecological balance.

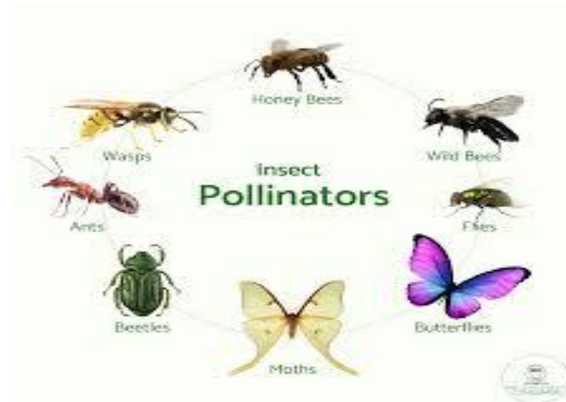


Fig 1.2. flow of pollinator

## II. METHODOLOGY

2.1 Overview

The proposed system follows a structured methodology for automated insect classification using deep learning techniques. The system processes input images through multiple stages, including preprocessing, object detection, feature extraction, and classification. The overall workflow is designed to ensure accurate identification of insects as pests or pollinators while also providing additional biological information [7], [12].

2.2 Data Acquisition

The system uses a dataset of insect images collected from publicly available sources and datasets [9]. The dataset consists of images belonging to two major categories: Pest insects• Pollinator insects These images include variations in lighting conditions, backgrounds, and orientations to improve model generalization [13].

2.3 Image Preprocessing

Before feeding images into the model, preprocessing is performed to improve data quality and consistency.

The following steps are applied:

- Resizing: Images are resized to a fixed dimension suitable for model input
- Normalization: Pixel values are scaled to a standard range
- Noise Reduction: Unwanted variations are minimized

- Data Augmentation (if applied): Rotation, flipping, and zooming to increase dataset diversity

This step ensures better feature extraction and improves model performance.

2.4 Object Detection using YOLOv8

The first stage of model processing involves detecting the insect within the input image using YOLOv8 (You Only Look Once version 8), a state-of-the-art object detection algorithm [5].

•YOLOv8 identifies the region of interest (ROI) containing to the insect

• It draws bounding boxes around detected objects

• Provides detection confidence scores

This step helps in isolating the insect from complex backgrounds, improving classification accuracy [14].

2.5 Information Retrieval

After classification, additional insect-related information is retrieved using an external knowledge source:

- Scientific name (binomial nomenclature)
- Taxonomy classification
- Diet and feeding habits
- Habitat details

This enhances the system by providing both classification and educational insights.

2.6 Frontend Interface

The frontend is developed using ReactJS and provides a user-friendly interface for interaction. The user can:

• Upload insect images

• View prediction results

• See confidence scores

• Access detailed biological information2This improves accessibility and usability for farmers, researchers, and students [21].

## III. PROPOSED WORK

3.1 Overview of the Proposed System

The proposed system presents an intelligent web-based solution for automated insect classification using deep learning techniques. The primary objective of the system is to accurately identify insects as either pests or pollinators from input images, thereby assisting agricultural stakeholders in making informed decisions [2], [10].

The system integrates advanced computer vision and deep learning models to process real-world insect images captured under varying environmental conditions [9]. By automating the identification process, the system reduces dependency on manual inspection, minimizes human error, and enhances efficiency in agricultural monitoring [4], [12].

3.2 System Architecture

The proposed system follows a client–server architecture consisting of a frontend, backend, and deep learning modules. The frontend is developed using ReactJS, which provides a user-friendly interface for image upload and result visualization, while the backend is implemented using FastAPI to manage data processing and communication between components [20], [21].

The system incorporates two main deep learning models:

•YOLOv8 for object detection [5]

• Efficient Net for image classification [15]

YOLOv8 detects the insect and extracts the region of interest from the input image, while Efficient Net performs feature extraction and classification. This combination improves both detection accuracy and computational efficiency [6], [8].

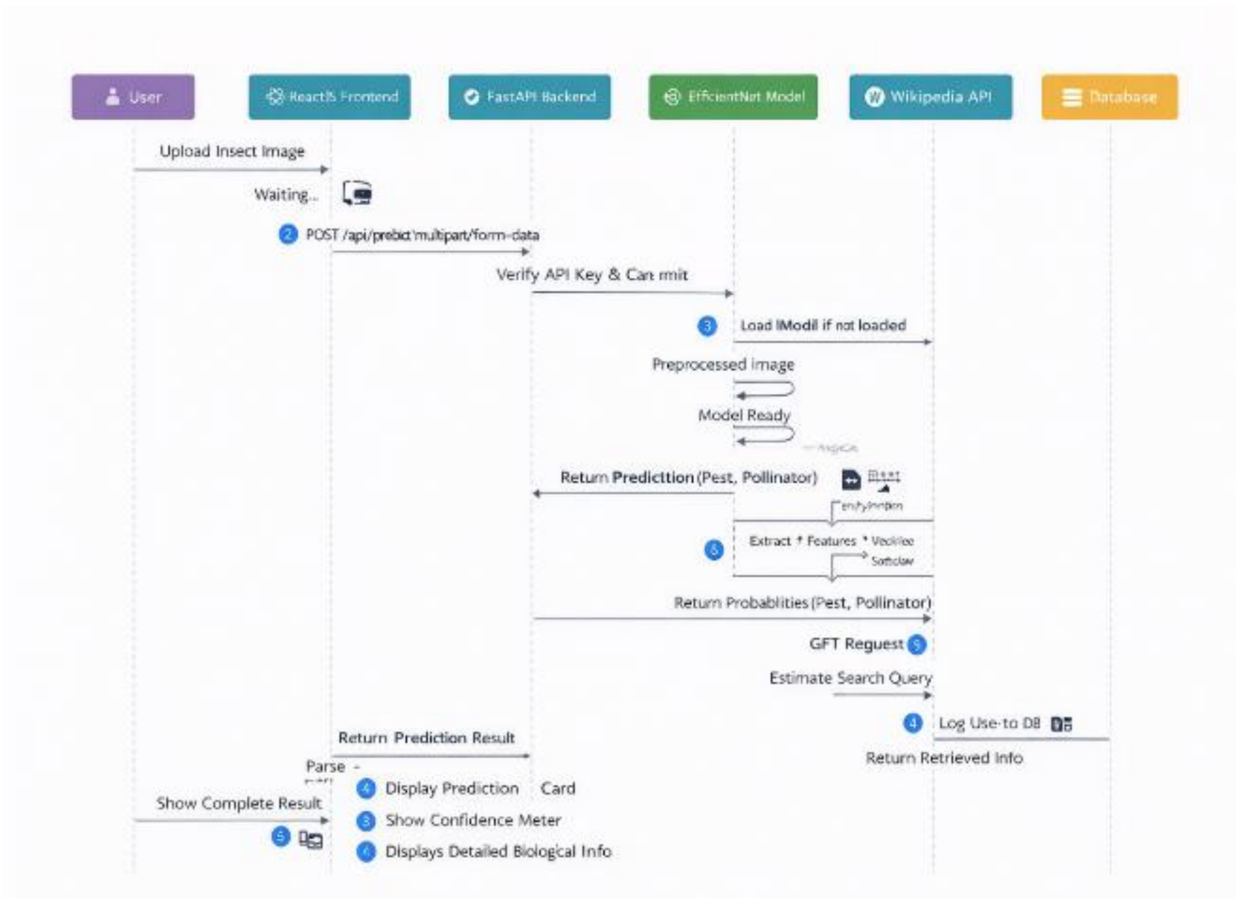


Fig 1.3 system architecture

## IV. RESULT AND DISCUSSION

The proposed system was evaluated using test images processed through the trained deep learning models.

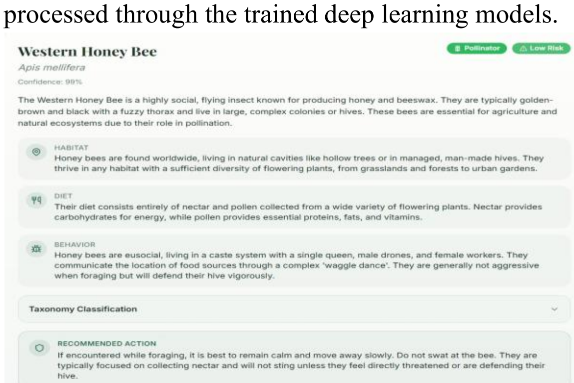


Fig 1.4 sample output of the proposed system

Fig. 1.4 shows a sample output obtained from the system, where the insect is correctly identified as a Western Honey Bee (Apis mellifera) and classified as a pollinator with a high confidence score of 99%. The system successfully provides not only classification results but also detailed biological information such as habitat, diet, behavior, taxonomy, and recommended actions. This demonstrates the practical applicability of the system in real-world agricultural scenarios.

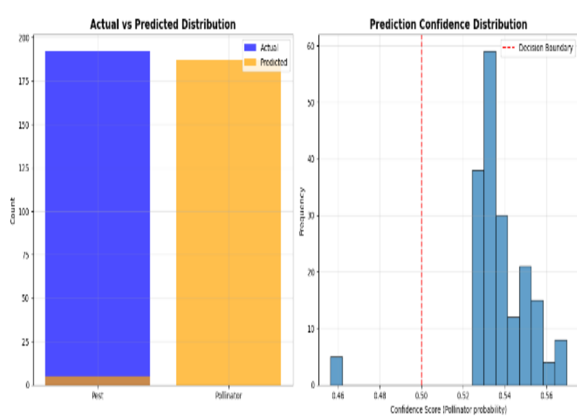


Fig 1.5 Training accuracy graph of the proposed model

## V. DISCUSSION

The results indicate that the proposed system achieves high classification accuracy due to the integration of advanced deep learning models. The high confidence score observed in Fig. 1.5 demonstrates that the model is capable of effectively distinguishing between pest and pollinator insects.
The accuracy graph in Fig. 1.5 shows a steady improvement in performance, confirming that the model successfully learns meaningful features from the dataset. The initial rapid increase in accuracy followed by stabilization is a typical characteristic of well-trained deep learning models.

Furthermore, the combination of detection and classification improves performance by focusing on the insect region and reducing background noise. Compared to traditional machine learning approaches, deep learning-based insect classification systems have shown improved accuracy, often exceeding 90% in real-world datasets.

The inclusion of additional biological information enhances the usability of the system, making it suitable for farmers, researchers, and students. However, the system may face limitations when dealing with low-quality images or visually similar insect species.

## VI. CONCLUSION

This paper presented a web-based intelligent insect classification system using advanced deep learning techniques for agricultural applications. The proposed system integrates YOLOv8 for object detection and Efficient Net for image classification to accurately identify insects as pests or pollinators. The system was designed to assist farmers, researchers, and students by providing reliable classification results along with detailed biological information such as binomial nomenclature, taxonomy, diet, and habitat. The experimental results demonstrate that the proposed approach achieves high accuracy and performs effectively under varying conditions. The inclusion of additional information and recommended actions enhances the usability of the system, making it more than just a classification tool. By reducing misidentification and minimizing unnecessary pesticide usage, the system contributes to sustainable and environmentally friendly agricultural practices. Overall, the proposed system highlights the potential of integrating artificial intelligence with agriculture to improve decision-making and crop management. Future enhancements can focus on expanding the dataset, improving model robustness, and developing mobile-based or real-time deployment solutions for practical field usage.

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