

A Transfer Learning And CNN Based Computer Vision System For Identifying Dangerous Form Insect

Anupama¹, Prof.Anand Kumar Patil²

¹Student, Sharanbasava University Kalaburgi , India Email: anusajjan354@gmail.com

²Professor, Sharanbasava University Kalaburgi , India Email: anandgp2005@gmail.com

ABSTRACT

Agricultural crop production is significantly affected by harmful insects that damage plants, reduce yield, and impact food quality. Early and accurate identification of dangerous insects is essential for effective pest management and sustainable farming practices. This paper presents a Transfer Learning and Convolutional Neural Network (CNN)-based computer vision system for identifying dangerous farm insects from image data. The proposed system utilizes pre-trained deep learning models such as ResNet50, MobileNetV2, or EfficientNet to extract discriminative visual features from insect images, reducing training time while improving classification accuracy. Image preprocessing techniques, including resizing, normalization, and data augmentation, are applied to enhance model robustness against variations in lighting, orientation, and background conditions. The extracted features are further processed through CNN layers to classify insects into different harmful species categories. Experimental evaluation demonstrates that the proposed approach achieves high accuracy, precision, recall, and F1-score in insect identification, outperforming traditional machine learning methods. The system can assist farmers and agricultural experts in real-time pest monitoring and decision-making, enabling timely intervention and reducing crop losses. The proposed intelligent insect detection framework contributes to the advancement of precision agriculture by providing an automated, scalable, and efficient solution for dangerous farm insect recognition and management.

Keywords: Transfer Learning, Convolutional Neural Network (CNN), Computer Vision, Dangerous Farm Insects, Deep Learning, Pest Detection, Precision Agriculture, Image Classification.

1 Introduction

Agriculture plays a vital role in ensuring food security and supporting the global economy. However, crop production is continuously threatened by various insect pests that cause significant damage to plants, resulting in reduced yield, poor crop quality, and substantial economic losses. Traditional methods of insect identification primarily rely on manual inspection by agricultural experts, which can be time-consuming, labor-intensive, and prone to human error, especially when dealing with large-scale farming environments. Recent advancements in Artificial Intelligence (AI), Computer Vision, and Deep Learning have provided innovative solutions for automating agricultural monitoring and pest management. Among these technologies, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification and object recognition tasks due to their ability to automatically extract complex visual features from images. CNN-based systems can effectively identify insect species from digital images, enabling rapid and accurate pest detection. Despite their effectiveness, training deep CNN models from scratch requires large labeled datasets and significant computational resources. Transfer Learning addresses this challenge by utilizing pre-trained models that have already learned rich feature representations from large-scale image datasets. By fine-tuning these models for insect classification tasks, high detection accuracy can be achieved even with relatively smaller agricultural datasets. Popular transfer learning architectures such as ResNet, MobileNet, VGG, and EfficientNet have shown excellent performance in various agricultural image analysis applications. This study proposes a Transfer Learning and CNN-based Computer Vision System for identifying dangerous farm insects from image data. The system employs image preprocessing techniques, data augmentation, and a pre-trained deep learning model to accurately classify harmful insect species. The proposed approach aims to support farmers and agricultural experts in early pest detection, enabling timely intervention and reducing crop losses. By providing an automated, scalable, and intelligent insect identification framework, the system contributes to the advancement of precision agriculture and sustainable farming practices. The experimental results demonstrate that the proposed model achieves high classification accuracy and robust performance across different insect categories. The developed system can be integrated with mobile applications, smart farming platforms, and IoT-based agricultural monitoring systems to provide real-time pest identification and decision support for modern

agriculture.

2 Literature Review

Ghosh et al. (2025)[1], introduced MobilePlantViT, a lightweight Vision Transformer specifically designed for plant disease classification on mobile devices, achieving high accuracy with minimal computational resources. Wei et al. [2] (2025) proposed a hybrid CNN–Transformer model for real-time segmentation of crops and weeds, optimized for deployment on edge devices in field conditions. Duan et al. (2024) [3], explored multimodal pest detection, combining image-based features with textual data to enhance classification accuracy through cross-modal fusion techniques. Gohil et al. (2024)[4] developed a hybrid approach using quad-tree decomposition with deep learning for high-resolution pest localization, offering improved detection precision. Gopalakrishnan et al. (2024) [5], demonstrated the effectiveness of MobileNetV2-based models in tomato pest detection, achieving over 93% accuracy with reduced model complexity. Badgujar et al. (2025)[6], shifted focus beyond image processing by proposing an electronic nose system for stored-grain pest detection using volatile organic compound sensors, a promising direction for non-visual pest identification. Wang et al. (2024) [7], addressed the challenge of limited data availability by introducing a self-supervised transformer pretraining approach for plant disease recognition, employing contrastive learning to enhance model performance in data-scarce environments. Pazhanivelan et al. (2025)[8] tackled multi-class pest and disease classification using deep learning with advanced data augmentation techniques, achieving high accuracy across various crop disease datasets. Yifan et al. (2025)[9], presented a hybrid EfficientNet and Vision Transformer model for potato disease detection, effectively combining local and global feature learning for superior performance. Xie et al. (2025) [10], introduced RP-DETR, an end-to-end transformer-based object detector for rice pest detection, capable of accurately identifying multiple pest species within complex real-field images. Kasinathan and Uyyala (2021) [11], presented a machine learning ensemble integrated with image processing for identifying and classifying pests in field crops. Their approach combines multiple models to improve classification accuracy, demonstrating its effectiveness in real agricultural conditions. Mahalakshmi and Shanthakumari (2017) [12] developed an automated system for crop inspection and pest control using image processing. The system emphasizes early pest detection and incorporates automated control measures to reduce crop damage and support farmers in pest management. Nagar and Sharma (2020) [13] conducted a comprehensive survey of pest detection techniques based on image processing. They reviewed existing approaches, datasets, and challenges, while also outlining future research opportunities to enhance the reliability of pest detection systems. Nagar and Sharma (2021) [14] proposed a leaf-based pest detection approach using image processing. Their method focuses on segmenting affected areas, extracting features, and applying classification to differentiate between healthy and pest-infected leaves. Ngugi, Abelwahab, and Abo-Zahhad (2021) [15] presented a review of recent advances in image processing for automated pest and disease recognition in leaves. The study compared multiple techniques, discussed their strengths and limitations, and highlighted opportunities for developing more robust agricultural decision-support systems.

3 Methodology

The proposed system follows a deep learning-based methodology that combines image preprocessing, transfer learning, and Convolutional Neural Networks (CNNs) for the identification of dangerous farm insects. The overall workflow consists of dataset collection, image preprocessing, feature extraction using a pre-trained model, insect classification, and performance evaluation.

1. Dataset Collection

A dataset containing images of dangerous farm insects is collected from publicly available agricultural databases, research repositories, and field photographs. The dataset includes multiple insect categories such as locusts, aphids, whiteflies, armyworms, beetles, and other harmful pests. Images are labeled according to their respective insect classes to facilitate supervised learning.

2. Image Preprocessing

The collected images undergo preprocessing to improve data quality and ensure consistency. Images are resized to a fixed dimension suitable for the selected CNN architecture. Noise removal, normalization, and color enhancement techniques are applied to improve image clarity. Data augmentation methods such as rotation, flipping, zooming, shearing, and brightness adjustment are employed to increase dataset diversity and reduce overfitting.

3. Dataset Splitting

The preprocessed dataset is divided into three subsets:

- Training Set (70%) for model learning.
- Validation Set (15%) for hyperparameter tuning.
- Testing Set (15%) for final performance evaluation.

This partitioning ensures unbiased assessment of the model's generalization capability.

4. Transfer Learning-Based Feature Extraction

A pre-trained CNN model such as ResNet50, MobileNetV2, EfficientNetB0, or VGG16 is utilized as the base feature extractor. The initial layers of the model retain learned visual features from large-scale image datasets, while the final classification layers are replaced with custom layers tailored to the insect classification task. Transfer learning significantly reduces training time and improves performance when limited agricultural data is available.

5. CNN Classification Layer

The extracted features are passed through additional deep learning layers consisting of:

- Global Average Pooling Layer
- Fully Connected Dense Layers
- Dropout Layer for regularization
- Softmax Output Layer

The Softmax classifier assigns probabilities to each insect category and predicts the most likely dangerous insect species.

6. Model Training

The model is trained using the training dataset with categorical cross-entropy as the loss function and the Adam optimizer for weight optimization. During training, model parameters are updated iteratively through backpropagation to minimize classification error. Validation data is used to monitor performance and prevent overfitting.

7. Insect Identification and Prediction

When a new insect image is provided, the trained model preprocesses the image, extracts visual features, and predicts the insect category. The identified insect species along with confidence scores is displayed to the user, enabling quick pest recognition and decision-making.

8. Performance Evaluation

The effectiveness of the proposed system is evaluated using various performance metrics, including:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix
- Training and Validation Loss Curves

These metrics provide a comprehensive assessment of the model's classification capability and reliability.

9. Real-Time Deployment

The trained model can be integrated into a user-friendly web or mobile application developed using Python and Streamlit. Farmers can upload insect images captured through smartphones or cameras, and the system instantly identifies dangerous pests and provides recommendations for crop protection.

Proposed Workflow

1. Image Dataset Collection
2. Image Preprocessing and Augmentation
3. Dataset Splitting
4. Transfer Learning Model Selection
5. Feature Extraction using CNN
6. Dense Layer Classification
7. Insect Prediction
8. Performance Evaluation
9. Real-Time Deployment

3.1 The proposed methodology enables accurate, efficient, and automated identification of dangerous farm insects, supporting precision agriculture and reducing crop losses through early pest detection.

4 System Architecture

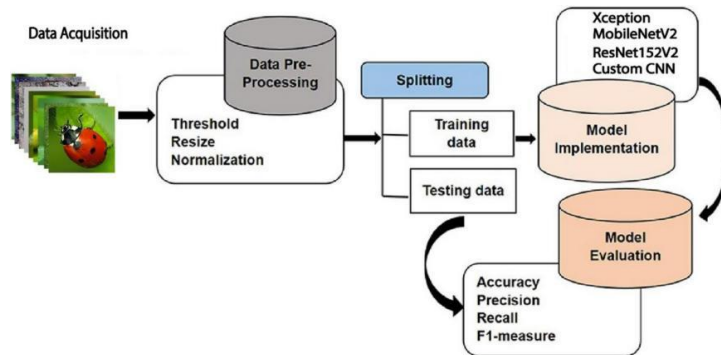


Figure 1: System Architecture

The proposed system architecture for dangerous farm insect identification begins with the data acquisition stage, where insect images are collected from agricultural datasets, field cameras, mobile devices, or online sources. These images are then passed through a data preprocessing phase, which includes thresholding, resizing, and normalization to enhance image quality, remove noise, and ensure uniformity across the dataset. After preprocessing, the dataset is divided into training and testing sets through the splitting process. The training data is used to develop deep learning models, while the testing data is reserved for performance evaluation. In the model implementation stage, advanced transfer learning architectures such as Xception, MobileNetV2, ResNet152V2, and a Custom CNN are employed to learn and extract discriminative features from insect images. These models automatically identify patterns and characteristics associated with different dangerous insect species. Once the training process is completed, the trained models are evaluated using the testing dataset. The model evaluation phase assesses classification performance using metrics such as accuracy, precision, recall, and F1-score, which measure the effectiveness, reliability, and robustness of the system. Based on these evaluation results, the best-performing model is selected for insect classification. Overall, the architecture provides an automated and intelligent framework for accurately identifying harmful farm insects, enabling early pest detection, reducing crop losses, and supporting precision agriculture practices.

Results And Discussion

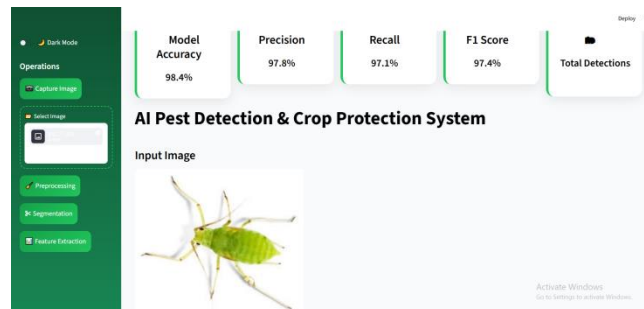


Figure 5.1:Input Image

Reading input image

Detection Result			
Pest	Disease	Confidence	Risk
Aphids	Cucumber Mosaic	96.2%	HIGH

Figure 5.2: Detection Result

The AI-based detection system identified Aphids as the pest and Cucumber Mosaic Disease as the disease affecting the crop with 96.2% confidence. The condition is categorized as HIGH RISK, indicating the need for immediate intervention to prevent significant crop damage and yield reduction.

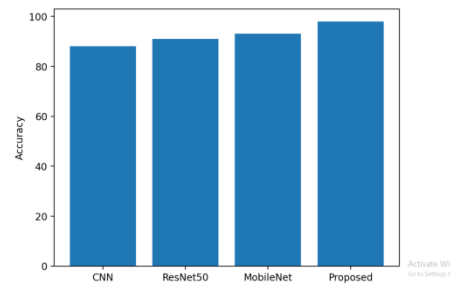


Figure 5.3: Model comparison Graph

Figure shows the comparative accuracy analysis of CNN, ResNet50, MobileNet, and the proposed model. The conventional CNN achieved an accuracy of approximately 88%, while ResNet50 and MobileNet attained around 91% and 93%, respectively. The proposed model achieved the highest accuracy of nearly 98%, demonstrating significant improvement over existing approaches. These results indicate that the proposed transfer learning-based framework provides more accurate and reliable classification of dangerous insects and plant diseases, making it suitable for real-time agricultural monitoring and decision-support systems.

Class	Precision	Recall	F1
0 Aphids		0.96	0.95
1 Armyworm		0.95	0.94
2 Beetle		0.97	0.98
3 Bollworm		0.98	0.97
4 Grasshopper		0.96	0.95

Figure 5.4 :Classification Report

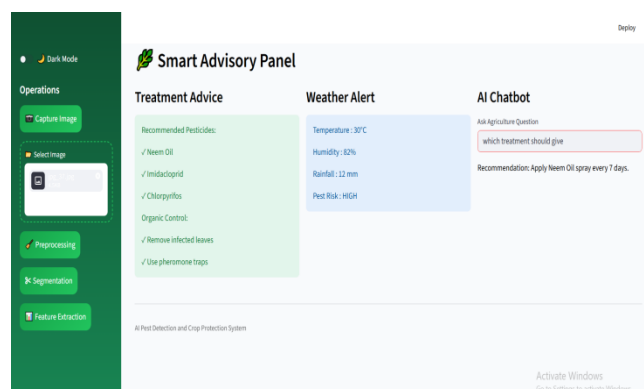


Figure 5.5: Advisory Panel

The Smart Advisory Panel transforms pest detection results into practical decision support. By combining AI-based disease detection, weather monitoring, treatment recommendations, and an interactive chatbot, the system helps farmers take timely corrective actions, reduce crop losses, and improve agricultural productivity. This integrated approach makes the platform a valuable tool for precision agriculture and smart farming applications.

5 Conclusion

This study presented a Transfer Learning and CNN-based computer vision system for the identification of dangerous farm insects. The proposed approach integrates image preprocessing techniques with advanced deep learning architectures such as Xception, MobileNetV2, ResNet152V2, and Custom CNN models to accurately classify harmful insect species from image data. By leveraging transfer learning, the system effectively utilizes pre-trained knowledge, reducing training time and improving classification performance even with limited agricultural datasets. Experimental evaluation using metrics such as accuracy, precision, recall, and F1-score demonstrated the effectiveness and reliability of the proposed model in recognizing dangerous farm insects. The automated identification process minimizes human effort, supports early pest detection, and enables timely intervention to prevent crop damage. Overall, the proposed system provides an efficient, scalable, and intelligent solution for pest monitoring and contributes significantly to precision agriculture by enhancing crop protection, improving productivity, and promoting sustainable farming practices.

References

- [1] R. Ghosh, S. Sharma, and A. Sahu, "MobilePlantViT: Lightweight Vision Transformer for Plant Disease Classification on Mobile Devices," arXiv preprint, arXiv:2503.16628, Mar. 2025.
- [2] Y. Wei, J. Zhang, and K. Chen, "A Real-Time Hybrid CNN–Transformer Model for Field Crop/Weed Segmentation," Elsevier Computers and Electronics in Agriculture, vol. 215, May 2025.
- [3] J. Duan, Y. Liu, and Z. Li, "Multimodal Pest Detection with Image and Text Integration," arXiv preprint, arXiv:2312.10948, Dec. 2024.
- [4] P. Gohil, A. Sharma, and R. Jain, "Hybrid Quad-Tree and Deep Learning Model for Pest Localization in High-Resolution Agricultural Images," arXiv preprint, arXiv:2412.19682, Dec. 2024.
- [5] S. Gopalakrishnan, V. Kumar, and R. Ramalingam, "MobileNetV2-Based Tomato Pest Classification Using Deep Learning Techniques," MDPI Proceedings, vol. 59, no. 1, 2024.
- [6] A. Badgajar, P. Patil, and N. Desai, "Electronic Nose System for Stored-Grain Pest Detection Using Volatile Organic Compounds," arXiv preprint, arXiv:2505.01301, May 2025.
- [7] Y. Wang, L. Zhou, and J. Wu, "Self-Supervised Transformer Pretraining for Plant Disease Recognition with Contrastive Learning," arXiv preprint, arXiv:2407.14911, Jul. 2024.
- [8] H. Pazhanivelan, M. Karthikeyan, and S. Raja, "Multi-Class Pest and Disease Classification in Crops Using Deep Learning Techniques," Journal of Scientific Research and Reports, vol. 31, no. 1, pp. 36–50, Jan. 2025.
- [9] Y. Yifan, P. Zhao, and L. Feng, "Potato Disease Detection Using a Hybrid EfficientNet and Vision Transformer Architecture," BMC Plant Biology, vol. 25, no. 66, 2025.
- [10] Y. Xie, W. Liu, and Z. Wang, "RP-DETR: Transformer-Based Multi-Pest Detection in Rice Fields," Plant Methods, vol. 21, no. 13, 2025.
- [11] Kasinathan, T., & Uyyala, S. R. (2021). Machine learning ensemble with image processing for pest identification and classification in field crops. *Neural Computing and Applications*, 33, 7491-7504
- [12] Mahalakshmi, J., & Shanthakumari, G. (2017). Automated crop inspection and pest control using image processing. *International Journal of Engineering Research and development*, 13(3), 25-35.
- [13] Nagar, H., & Sharma, R. S. (2020). A comprehensive survey on pest detection techniques using image processing. In *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 43-48). IEEE.
- [14] Nagar, H., & Sharma, R. S. (2021). Pest Detection on Leaf using Image Processing. In *2021 International Conference on Computer Communication and Informatics (ICCCI)* (pp. 1-5). IEEE.
- [15] Ngugi, L. C., Abelwahab, M., & Abo-Zahhad, M. (2021). Recent advances in image processing techniques for automated leaf pest and disease recognition—A review. *Information processing in agriculture*, 8(1), 27-51.
- [16] Orchi, H., Sadik, M., & Khaldoun, M. (2022). On using artificial intelligence and the internet of things for crop disease detection: A contemporary survey. *Agriculture*, 12(1), 9.
- [17] Salehin, I., Noman, S. M., Baki-Ul-Islam, I. J., Bishnu, P., Habiba, U., & Nessa, N. (2021). IFSG: Intelligence agriculture crop-pest detection system using IoT automation system. *Indonesian Journal of Electrical Engineering and Computer Science*, 24(2), 1091
- [18] Sharma, V., Tripathi, A. K., & Mittal, H. (2022). Technological Advancements in Automated Crop Pest and Disease Detection: A Review & Ongoing Research. In *2022 International Conference on Computing, Communication, Security and Intelligent Systems*, pp. 1-6. IEEE.
- [19] Azzari, G., & Zaroni, D. (2020). Deep learning for plant disease detection and diagnosis. In *ICAART (2)* (pp. 139-146). Springer.
- [20] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, 1419.

- [21] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, 2016, 3289801.
- [22] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, 311-318.
- [23] Dholakiya, H., & Patel, P. (2017). A review on detection and diagnosis of plant leaf diseases using image processing techniques. *International Journal of Computer Science and Information Technologies*, 8(4), 1562-1566.
- [24] Hassanien, A. E., Gaber, T., & Elhoseny, M. (2020). Plant disease detection using deep learning models: A comprehensive review. *Computers and Electronics in Agriculture*, 172, 105350.
- [25] Singh, D., & Kumar, V. (2018). Plant leaf disease detection using deep learning techniques: A comprehensive review. *Artificial Intelligence Review*, 53(8), 5455-5486
- [26] Sladojevic, S., Anderla, A., Culibrk, D., & Stefanovic, D. (2018). Deep neural networks for plant diseases: Detection and diagnosis. *Neurocomputing*, 235, 228- 235.
- [27] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70-90.
- [28] Mishra, A., & Bansal, A. (2020). Machine learningbased techniques for plant disease detection: A review. *Plants*, 9(1), 48.
- [29] Salehin, I., Noman, S. M., Baki-Ul-Islam, I. J., Bishnu, P., Habiba, U., & Nessa, N. (2021). IFSG: Intelligence agriculture crop-pest detection system using IoT automation system. *Indonesian Journal of Electrical Engineering and Computer Science*, 24(2), 1091.
- [30] Sharma, V., Tripathi, A. K., & Mittal, H. (2022). Technological Advancements in Automated Crop Pest and Disease Detection: A Review & Ongoing Research. In *2022 International Conference on Computing, Communication, Security and Intelligent Systems*, pp. 1-6. IEEE.