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HYBRID MODEL FOR PEST IDENTIFICATION AND TREATMENT RECOMMENDATION FOR RICE CROPS USING DEEP LEARNING METHODS

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ABSTRACT :

Rice is a globally significant crop that faces substantial yield and quality losses due to insect pest infestations. This research presents a pest detection and classification system specifically tailored for rice crops, employing a hybrid deep learning model that combines YOLOv5 for object detection and ResNet50 for classification, both utilizing pre-trained ImageNet weights. A dataset comprising 635 images of six common insect pest species was used for model training and evaluation. Data augmentation techniques were applied to enhance the system's robustness under varying image conditions. The hybrid model achieved an average classification accuracy of 96.12 percent, outperforming existing models. In addition to pest detection, the system provides specific recommendations for pest control, supporting more effective pest management strategies and contributing to improved productivity and sustainability in rice cultivation.

Keywords: Image processing, Deep learning methods, Pest identification, Pesticide recommendation.

INTRODUCTION :

Insect pests pose a significant challenge to rice cultivation, impacting both crop yields and quality. Given the global importance of rice as a staple food, effective pest management strategies play a crucial role in maintaining agricultural productivity. This research focuses on developing an accessible pest detection and management system that allows farmers to upload images of pests for identification. By analyzing these images, the system identifies the insect species and provides appropriate pest control recommendations, assisting farmers in managing infestations more efficiently.

Traditional pest identification methods often require expert knowledge, which may not be easily accessible in rural agricultural settings. This study addresses this limitation by offering a user-friendly platform that enables farmers to upload images and receive accurate pest identification. The system focuses on six major insect pests affecting rice crops: Brown Plant Hopper, Green Leafhopper, Rice Gall Midge, Rice Leaf Folder, Rice Stemborer, and Rice Sting Bug. By targeting these pests, the system provides a practical tool that simplifies pest management, reducing the need for expert intervention. By enabling farmers to upload pest images, the system identifies insects in the image and provides tailored recommendations for appropriate pesticides and treatments. This approach enhances pest management practices, minimizing crop losses and improving agricultural productivity. The system supports informed decision-making in pest control, promoting sustainable farming practices and contributing to better crop protection in rice-growing regions.

LITERATURE REVIEW

[1] M.A. Ebrahimi, M.H. Khoshtaghaza, S. Minaei, B. Jamshidi, "Vision-based pest detection based on SVM classification method, 2017" The study presents a mobile robot for real-time thrips monitoring in strawberry greenhouses. Controlled by LabVIEW and using a digital camera, it captures images for SVM-based detection. The MATLAB algorithm enhances contrast and uses color and shape features to improve accuracy, enabling automated pest identification and timely management.

[2] Xi Cheng, Youhua Zhang, Yiqiong Chen, Yunzhi Wu, Yi Yue, "Pest identification via deep residual learning in complex background, 2017" The paper proposes a pest identification system using deep residual learning with ResNet architectures, improving accuracy in complex farmland backgrounds. It integrates with agricultural technologies for real-time monitoring and suggests future improvements by combining object detection methods and adapting them for mobile platforms.

[3] Halimatu Sadiyah Abdullahi, Ray E. Sheriff, Fatima Mahieddine, "Convolution Neural Network in Precision Agriculture for Plant Image Recognition and Classification, 2017" The research presents a CNN-based system for accurate plant image classification and health monitoring, using an augmented dataset and VGG16 with SVM. Its real-time processing enhances plant care and agricultural practices.

[4] Gittaly Dhingra, Vinay Kumar, Hem Dutt Joshi, "Study of Digital Image Processing Techniques for Leaf Disease Detection and Classification, 2017" The study proposes digital image processing systems to automate plant disease detection, improving precision and efficiency. Future work includes adapting algorithms for outdoor conditions, developing mobile apps for real-time diagnostics, and expanding datasets for better accuracy.

[5] R. P. L. Durgabai, P. Bhargavi and S. Jyothi, "Pest Management Using Machine Learning Algorithms: A Review 2018" he paper reviews machine learning systems for pest management, covering image-based disease detection, predictive models for pest occurrence, IPM systems, crop yield prediction, real-time pest monitoring with wireless sensors, pest identification, geographic distribution prediction using climate data, and data mining for pattern extraction in agriculture.

[6] Zahid Iqbal, Muhammad Attique Khan, Muhammad Sharif, Jamal Hussain Shah, Muhammad Habib ur Rehman, Kashif Javed, "An automated detection and classification of citrus plant diseases using image processing techniques: A review, 2018" The paper reviews automated citrus disease detection methods, including image processing techniques and traditional machine learning algorithms. It highlights current strengths and limitations, emphasizing the role of deep learning in improving accuracy and setting a foundation for future research.

[7] Thenmozhi Kasinathan, Dakshayini Singaraju, Srinivasulu Reddy Uyyala, "Insect classification and detection in field crops using modern machine learning techniques, 2020" The system uses shape features for insect classification and CNNs for detailed recognition. The CNN model achieved up to 91.5 percentage accuracy.

[8] Everton Castelão Tetila, Bruno Brandoli Machado, "Detection and classification of soybean pests using deep learning with UAV images, 2020" The research compared five deep learning models for soybean pest classification, achieving up to 93.82 percent accuracy. These models, fine-tuned, outperformed traditional methods like SIFT, SURF, and SVM. The results highlight their effectiveness in pest management. CNN-based system for detecting and classifying plant leaf diseases in tomatoes, peppers, and potatoes, achieving 98.029\% accuracy. It uses over 20,000 images and a customized CNN for feature extraction and classification.

[9] Marwan Adnan Jasim, Jamal Mustafa AL-Tuwaijari, "Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques, 2020" This study proposes a CNN-based system for detecting and classifying plant leaf diseases in tomatoes, peppers, and potatoes, achieving 98.029\% accuracy. It uses over 20,000 images and a customized CNN for feature extraction and classification.

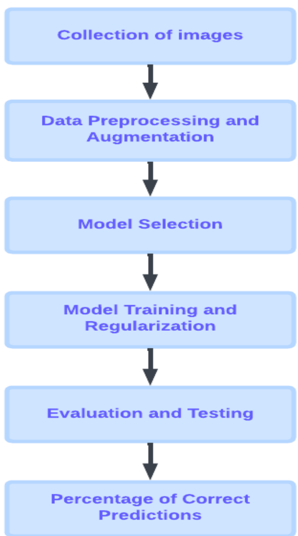
[10] Jun Liu and Xuewei Wang, "Plant diseases and pests detection based on deep learning: a review, 2021" The paper reviews deep learning, especially CNNs, for automated plant disease and pest detection, highlighting its advantages over traditional methods. It discusses detection approaches, datasets, challenges, and future research directions.

RESEARCH METHODOLOGY

This research follows a structured workflow, incorporating advanced methodologies and specialized strategies to address the complexities of pest detection in rice crops. The process begins with the systematic collection and curation of a dataset, focusing on six major rice pests. After data acquisition, the preprocessing phase ensures uniformity and enhances image quality through resizing, contrast enhancement, and normalization. These preprocessing steps are critical to preparing the dataset for efficient model training.

Data augmentation techniques such as random rotations, flips, and brightness adjustments are applied to improve model robustness across various environmental conditions. The workflow then proceeds to model selection, where YOLOv5 is utilized for object detection, while ResNet50 and EfficientNetB0 are considered for feature extraction and classification. Transfer learning with pre-trained ImageNet weights is implemented to accelerate model adaptation to the pest dataset. In the final phase, model performance is assessed using accuracy, precision, and recall metrics to determine the most suitable configuration for pest detection. This workflow ensures that the system is both accurate and reliable, capable of detecting and classifying pests under diverse conditions.

Fig. 1 Block diagram of overall Methodology



Data Collection and Preparation

This study focuses on six common insect pests that significantly damage rice crops, namely the Brown Plant Hopper, Green Leafhopper, Rice Gall Midge, Rice Leaf Folder, Rice Stemborer, and Rice Sting Bug. To effectively develop a pest detection system, a dataset comprising a total of 635 images was created, with up to 100 images allocated for each of the six pest classes. Table1 provides a detailed summary of the collection of images for these six pests.The collection process involved sourcing high-quality images that accurately represent each pest in various stages of their life cycle and under different environmental conditions. Careful labeling of these images was conducted to ensure the dataset's quality and relevance for training machine learning models. Each class, corresponding to one of the identified pests, was organized into separate folders to facilitate structured training processes. This organization not only aids in the efficient retrieval of images during model training but also enhances the model's learning process by providing clear, distinct examples for each category. By preparing the dataset in this manner, the study establishes a solid foundation for the model to effectively learn how to identify and classify each pest accurately. This systematic approach to dataset preparation is crucial for improving the model's performance in real-world applications, where accurate pest identification is vital for effective crop management and protection strategies.

Table1: Collection of Six pest images

Insect Names	**Insect images**	**Number of images**
Brown plant hopper		106 images
Green Leafhopper		103 images
Rice Gall Midge		107 images
Rice Leaf Folder		111 images
Rice stemborer		102 images
Rice sting bug		106 images

Data Preprocessing and Augmentation

Following dataset collection, the next crucial step was data preprocessing to enable effective model learning of distinguishing insect pest features. Initially, all images were resized to a uniform dimension for consistency. Contrast stretching enhanced image clarity, while auto-orientation techniques corrected misalignments. Pixel normalization scaled values between 0 and 1 to improve generalization. To mitigate overfitting, regularization techniques like dropout were implemented, and the learning rate was finely tuned. Various data augmentation techniques were applied to enhance model robustness against input variations, including horizontal flipping, random rotations, shearing transformations, and adjustments to color saturation and brightness. Additionally, random blurring and noise were introduced to simulate environmental disturbances. Collectively, these strategies aimed to create a robust training environment for accurately identifying and classifying targeted insect pests.

Model Selection

Object Detection

YOLOv5 for Object Detection: YOLOv5 was selected for object detection due to its ability to balance speed and accuracy, making it effective for rapid pest identification. It uses a single-stage neural network that predicts bounding boxes and class probabilities simultaneously, enabling the model to detect multiple pests in high-resolution images. *As shown in Fig. 2, the trained YOLOv5 model effectively handles the detection of six common pest images.* In this study, YOLOv5 was trained using the training set and is used to detect and localize pests by predicting bounding boxes around them. Its robustness in handling various pest sizes and positions within a single frame makes it well-suited for accurate pest detection in agricultural applications.

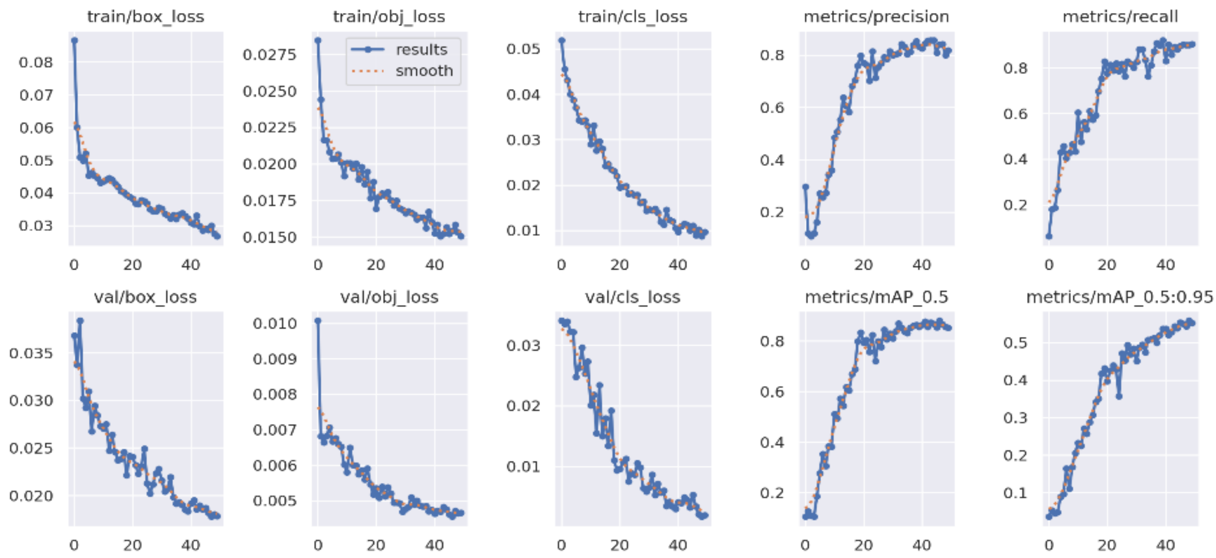


Fig. 2 Trained Yolov5 model for Six pest images

Feature Extraction and Recognition

ResNet50 for Feature Extraction and Classification: ResNet50 was chosen for feature extraction due to its strong performance in image classification tasks, especially for distinguishing subtle visual differences between similar objects. Fig. 3 provides a graphical representation of the ResNet50 Accuracy and Loss. In this research, ResNet50 is used to extract detailed features from pests detected by YOLOv5, aiming to improve classification accuracy. While it has been widely applied in agricultural tasks like plant disease detection, it has seen limited success in pest detection due to the challenges in identifying visually similar pests. By leveraging ResNet50, this study seeks to overcome these limitations and achieve higher accuracy in classifying closely related insect species.

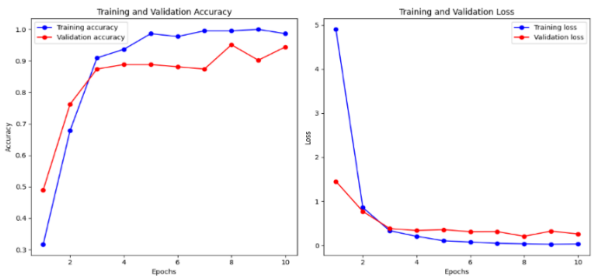


Fig. 3 Graphical Representation of ResNet50

EfficientNetB0 for Feature Extraction and Classification

EfficientNetB0 was chosen for its computational efficiency and accuracy in feature extraction. Its compound scaling method optimizes depth, width, and resolution simultaneously, allowing it to process large datasets of high-resolution pest images without heavy computational demands. *Fig. 4 illustrates the graphical representation of EfficientNetB0's Accuracy and Loss.* In this study, EfficientNetB0 is used to extract detailed features from pests detected by YOLOv5, improving classification accuracy. Unlike other models, EfficientNetB0 has not been widely explored for pest detection, making its use in this study a novel approach to classify insects with minimal visual differences efficiently.

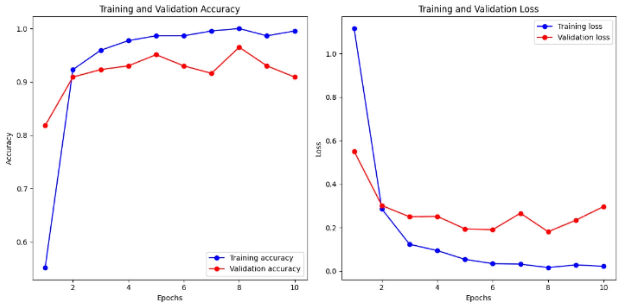


Fig. 4 Graphical Representation of EfficientNetB0

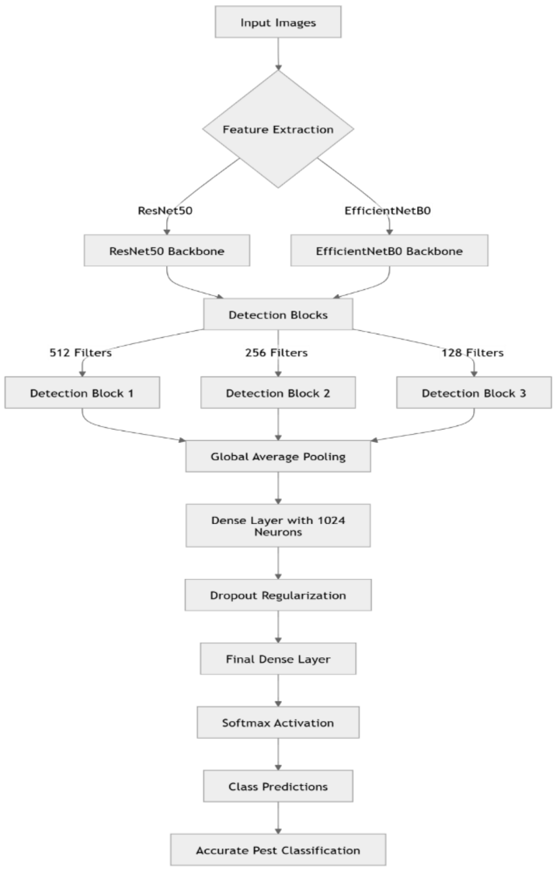
Hybrid Approach

The hybrid approach represents an innovative strategy to enhance the accuracy and efficiency of rice pest detection by leveraging the strengths of multiple models. This methodology capitalizes on the capabilities of YOLOv5 for real-time object detection and pairs it with advanced deep learning architectures for feature extraction and classification, specifically ResNet50 and EfficientNetB0.

Workflow of this hybrid approach

The diagram illustrates a hybrid model for pest detection and classification using deep learning. It starts with input images, which are processed through feature extraction by two architectures: ResNet50 and EfficientNetB0. The extracted features pass through several detection blocks with varying numbers of filters—512 in Detection Block 1, 256 in Detection Block 2, and 128 in Detection Block 3—to refine the features for enhanced classification. A global average pooling layer reduces the dimensionality of the feature maps, followed by a dense layer with 1024 neurons that learns complex feature combinations. Dropout regularization is applied to prevent overfitting, and a final dense layer with a softmax activation function generates probabilities for each class, ultimately facilitating accurate pest classification by leveraging the strengths of both ResNet50 and EfficientNetB0.

Fig. 5 Workflow of Pest Classification Utilizing YOLOv5 for Object Detection with ResNet50 and EfficientNetB0 for Feature Extraction



Implementation of Hybrid Approaches for Pest Detection and Classification

In this study, the hybrid approach was specifically implemented in two ways:

YOLOv5 + ResNet50: The combination of YOLOv5 and ResNet50 leverages the strengths of both models to enhance pest detection and classification accuracy. YOLOv5 serves as the initial framework for detecting and localizing pests within images by predicting bounding boxes. *As shown in Fig. 6, the graphical representation of the YOLOv5 + ResNet50 architecture outlines this combined approach.* Once pests are identified, ResNet50 takes over for feature extraction and classification. Its deep architecture and residual connections enable effective learning of subtle visual distinctions, crucial for distinguishing similar insect species with minor variations. This two-step process improves classification performance, ensuring not only accurate detection but also reliable identification of pests. *Fig. 7 further illustrates the confusion matrix of the YOLOv5 + ResNet50 model, highlighting its classification performance.* By addressing individual model limitations, this approach significantly enhances the effectiveness of pest management in agricultural settings.

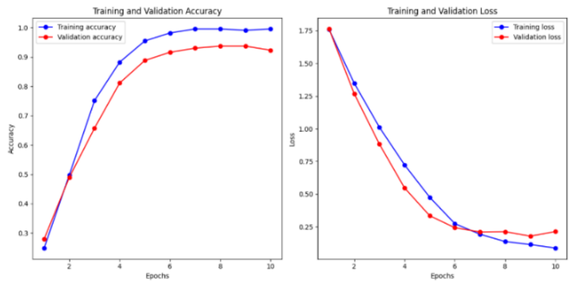


Fig. 6 Graphical Representation of Yolov5 + ResNet50

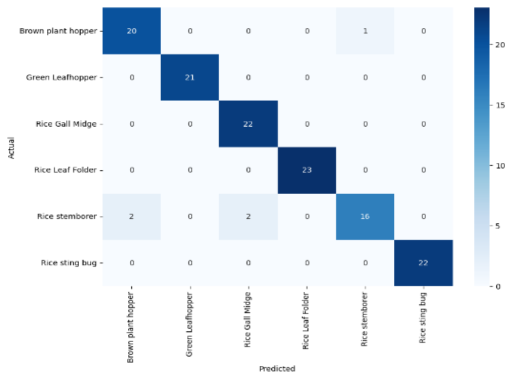


Fig. 7 Confusion matrix of Yolov5 + ResNet50

YOLOv5 + EfficientNetB0: The combination of YOLOv5 with EfficientNetB0 emphasizes computational efficiency while maintaining high classification accuracy in pest detection. YOLOv5 first detects and localizes pests in images using rapid bounding box predictions. *Fig. 8 illustrates the graphical representation of the YOLOv5 + EfficientNetB0 model used in this process.* EfficientNetB0 then extracts features and classifies the identified pests, leveraging its optimized architecture for effective scaling. This integration enables quicker processing times, making it suitable for real-time applications. *As shown in Fig. 9, the confusion matrix for the YOLOv5 + EfficientNetB0 model demonstrates its classification performance.* Overall, this approach streamlines pest identification, enhancing response times in agricultural pest management.

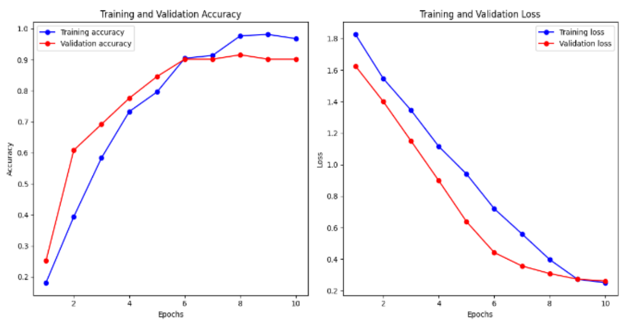


Fig. 8 Graphical Representation of Yolov5 + EfficientB0

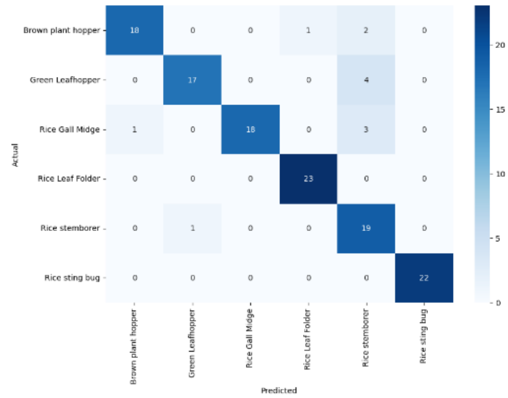


Fig. 9 Confusion matrix Yolov5 + EfficientB0

Evaluation metrics

In evaluating the performance of the hybrid models for pest detection and classification, two primary metrics were utilized: accuracy and confusion matrix. These metrics provide a comprehensive understanding of how well the models perform in identifying and classifying insect pests in rice crops.

Accuracy

Accuracy is a key performance indicator that measures the proportion of correctly identified instances (both true positives and true negatives) out of the total instances examined. In the context of the provided code, accuracy is computed after the model is trained and validated on the dataset. The formula used for calculating accuracy is:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Where:

- TP (True Positive): The number of correctly identified pests.
- TN (True Negative): The number of correctly identified non-pest instances.
- FP (False Positive): The number of non-pests incorrectly identified as pests.
- FN (False Negative): The number of pests incorrectly identified as non-pests.

Confusion Matrix

The confusion matrix provides a detailed breakdown of the model's classification results, allowing for a deeper analysis of its performance. It presents the true classifications versus the predicted classifications in a tabular format, typically represented as follows:

Table 2: Confusion matrix of pest classification

	Predicted Positive (Pest)	**Predicted Negative (Non-Pest)**
Actual Positive (Pest)	TP	FN
Actual Negative (Non-Pest)	FP	TN

The confusion matrix helps to visualize not only the accuracy of the model but also the types of errors it makes, such as:

- **False Positives (FP)**: The model incorrectly classifies a non-pest as a pest, which can lead to unnecessary pesticide use and increased costs.
- **False Negatives (FN)**: The model fails to identify a pest, potentially resulting in crop damage due to delayed response.
- **Precision**: Measures the accuracy of positive predictions:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

- **Recall**: Measures the ability to identify actual positives:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- **F1-Score**: The harmonic mean of precision and recall, providing a single score that balances both metrics:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

User Interface and Recommendation

Predictions and recommendations were created using the YOLOv5 + ResNet50 hybrid model, which achieved a high accuracy of 96.12%. This model effectively identified insect pests in rice crops, allowing the system to provide tailored pest control recommendations. *The user interface for this system was created using Gradio, enabling farmers to easily upload pest images and receive immediate predictions and recommendations which is, illustrated in Fig 10.* Once an insect class is predicted, the system suggests specific pesticides and Integrated Pest Management (IPM) techniques, which is particularly beneficial for farmers who may lack expertise in pest identification.

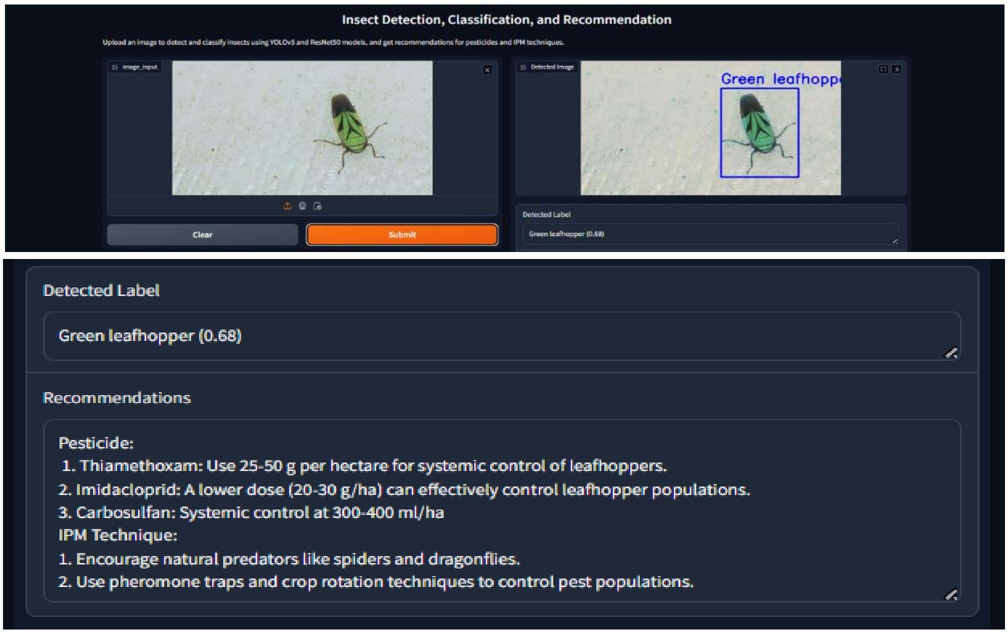


Fig. 10 User Interface using Gradio

RESULTS AND FINDINGS :

In this study, the performance of the models was evaluated based on their accuracy in pest detection and classification. The ResNet50 model achieved an impressive accuracy of ***94.63%***, demonstrating its ability to identify subtle visual distinctions among similar pests effectively. Meanwhile, the EfficientNetB0 model achieved a slightly lower accuracy of ***94.57%***, showcasing its efficiency in feature extraction and classification tasks.

However, the hybrid approach of combining YOLOv5 with ResNet50 significantly outperformed the individual models, attaining an accuracy of ***96.12%***. This enhancement in accuracy can be attributed to the strengths of YOLOv5 in real-time object detection, followed by the feature extraction of ResNet50. This two-step process allows for precise localization and classification of pests, making it particularly effective in agricultural applications.

On the other hand, the hybrid model of YOLOv5 with EfficientNetB0 yielded an accuracy of ***90.80%***. While this result is still commendable, it indicates that the combination was less effective than the YOLOv5 and ResNet50 pairing in accurately classifying the detected pests. The overall evaluation highlights the advantages of using a hybrid approach tailored to leverage the unique strengths of each model, ultimately leading to improved performance in pest management.

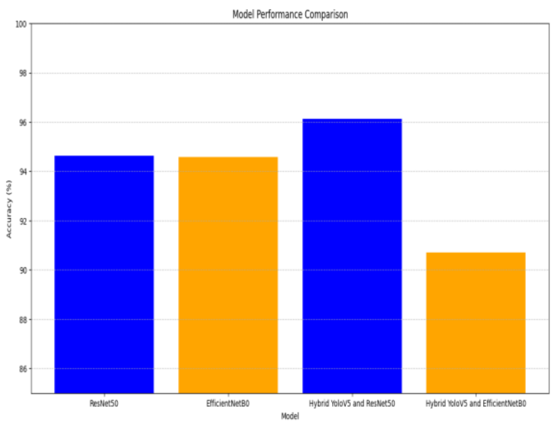


Fig. 11 Comparison Graph of Individual and Hybrid Models

CONCLUSION :

In conclusion, this research successfully advances the field of rice pest detection and management through the development of an innovative system that leverages deep learning techniques. By utilizing a structured dataset and robust preprocessing methods, the study evaluated the effectiveness of three models: EfficientNetB0, ResNet50, and a hybrid model combining YOLOv5 with ResNet50. The results demonstrated that the YOLOv5 + ResNet50 hybrid model achieved the highest accuracy of 96.12%, showcasing its superior capabilities in identifying and classifying pests across diverse and challenging image conditions. This model not only outperformed the others but also exhibited resilience against variations such as rotations and flips, establishing itself as a reliable tool for real-world applications.

Moreover, the system's capability to deliver precise pest identification and actionable insights represents a significant leap in pest management practices. By providing tailored recommendations for pest control, including specific pesticide suggestions and Integrated Pest Management (IPM) strategies, the system empowers farmers, especially in regions with limited agricultural expertise, to make informed decisions and take timely actions to safeguard their crops. This advancement not only enhances pest management efficiency but also contributes to more sustainable agricultural practices by reducing reliance on chemical treatments, ultimately promoting better outcomes for both farmers and the environment.

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