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ENHANCED PEST DETECTION IN PRECISION AGRICULTURE USING YOLOV8 AND EFFICIENTNET WITH MULTI-MODAL FUSION

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Abstract

Precision agriculture increasingly relies on artificial intelligence (AI) to improve crop health monitoring and optimize farming practices. Among the critical challenges, early and accurate detection of pests remains vital for reducing yield losses and minimizing pesticide overuse. Traditional image processing techniques and single-stage deep learning models often struggle with small pest detection, class imbalance, and visual similarity among species. To address these boundaries, this study proposes a two-stage pest recognition frame embedded within the AgriDataFusion Engine. The framework integrates YOLOv8 for real-time pest localization with EfficientNet for fine-grained species classification, enabling high-accuracy recognition of pests even in cluttered, variable field conditions. The system is trained and validated on the benchmark IP102 dataset, enhanced with balanced sampling, mosaic and MixUp augmentations, and focal loss for class imbalance. Comparative experiments demonstrate that the proposed method outperforms single-stage YOLOv8, Faster R-CNN, along with transformer-based models in stipulations of mean Average Precision (mAP), robustness under diverse lighting and background conditions, and efficiency on edge devices. Furthermore, the modular integration into the AgriDataFusion Engine allows cross-linking pest analysis with plant growth monitoring, disease detection, soil health analysis, and nutrition estimation, creating a comprehensive decision-support system for farmers. The results confirm that combining fast detection with fine-grained classification provides superior accuracy and operational feasibility, thereby advancing precision agriculture toward more sustainable and intelligent farming practices.

Keywords: Precision Agriculture, Pest Detection, YOLOv8, EfficientNet, AgriDataFusion Engine, Deep Learning.

1. Introduction

Agriculture remains the backbone of international food security and monetary stability, with additional than half of the globe's residents relying directly or indirectly on farming for livelihood [01]. Speedy inhabitants' escalation, environment revolutionize, urbanization,

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furthermore increasing demands for sustainable farming have placed significant pressure on agricultural systems to become more efficient, productive, and resilient [02]. A critical bottleneck in agricultural productivity is the persistent threat posed by pests, diseases, and environmental stressors [03]. According to the Food and Agriculture Organization (FAO), vermin and illness explanation for up to 40% of worldwide yield fatalities yearly, with pests alone causing economic damage worth billions of dollars [04]. These losses not only reduce food availability but also increase the dependency on chemical pesticides, which harm ecosystems, degrade soil health, and affect human well-being [05].

Traditional methods for pest detection and management rely heavily on manual inspection by farmers and agronomists [06]. While effective in localized and small-scale scenarios, these techniques are highly blue-collar, subjective, furthermore horizontal to inconsistencies due to human error and limited observation capability [07]. Moreover, pests often appear in small numbers during early infestation, making them difficult to detect with the naked eye [08]. Delays in detection and intervention can lead to uncontrolled spread, severe yield loss, and increased pesticide use. Hence, there is an urgent need for scalable, automated, and intelligent systems that can monitor crops continuously and provide accurate, real-time insights into pest presence [09].

Recent advances in artificial intelligence (AI), computer vision, and deep learning have opened innovative opportunities to address this challenge [10]. The incorporation of unmanned airborne medium (UAVs), IoT sensors, and edge computing platforms in agriculture has enabled large-scale, real-time data acquisition. When coupled with AI-driven analytics, these technologies provide the foundation for precision agriculture—an approach that leverages data to optimize farming inputs and maximize yields while minimizing costs and environmental impacts [11]. Within this paradigm, AI-based pest detection systems have emerged as a critical enabler for proactive crop protection and sustainable farming practices.

The problem of pest detection has been studied using various advances ranging from conventional image processing to modern deep learning models.

Conventional Approaches: Earlier methodologies employed handcrafted attributes such as shade, texture; moreover figure descriptors to identify pests on leaves or traps. These features were then fed into machine learning classifiers such as Random Forests, k-Nearest Neighbors or Support Vector Machines. While computationally lightweight, such approaches struggled with scalability and robustness. Environmental variability—such as changes in lighting, background clutter, and occlusions—significantly degraded their performance. Moreover, these methods required domain expertise for feature engineering and failed to generalize across large pest datasets.

Single-Stage Detectors: The rise of deep learning introduced powerful object uncovering models such as You Only Look Once (i.e., YOLO) and Single Shot Detector. These models could simultaneously localize and classify pests in real-time. More recent variants like YOLOv5 and YOLOv8 have achieved strong accuracy with lightweight architectures suitable for edge deployment. Single-stage models are particularly effective for detecting pests in large-scale drone imagery and real-time video feeds. However, their classification heads

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often struggle with fine-grained pest categories that are visually similar, such as distinguishing between aphids and small leafhoppers. This limitation becomes critical when using datasets like IP102, which contain 102 pest species with high intra-class variation.

Two-Stage Detectors: Models such as Faster R-CNN endow with advanced accurateness by primary generating province proposals with then classifying them. These architectures excel in object localization and fine-grained classification but are computationally expensive and less suitable for real-time edge deployment.

Transformer-Based Models: Vision Transformers (ViT), Swin Transformers, and Detection Transformers (DETR) have recently been explored in pest detection. These models influence self-attention mechanisms to incarcerate long-range dependence, making them robust to background clutter. However, they typically require massive datasets for training and are computationally intensive, limiting their practical deployment in field conditions.

Multi-modal fusion refers to the process of integrating data from multiple sources or sensing modalities—such as images, soil parameters, temperature, humidity, and nutrient levels—to create a more comprehensive understanding of an environment. In the context of precision agriculture, this technique allows the system to analyze not only visual pest data but also contextual information related to soil health, plant growth, and environmental conditions. In the proposed AgriDataFusion Engine, multi-modal fusion enhances decision-making by combining visual features extracted from YOLOv8 and EfficientNet with non-visual data like soil moisture, nutrient concentration, and weather data. This fusion enables the system to correlate pest occurrence patterns with specific environmental or soil conditions, improving predictive accuracy and response recommendations. As a result, the model provides more context-aware insights, promoting early pest intervention, optimized pesticide usage, and sustainable crop management across diverse agricultural conditions.

Boundaries of Existing Methods: Despite their proceeds, obtainable methods encounter several challenges:

- Difficulty detecting small pests in cluttered environments.
- Imbalanced datasets where some pest classes are underrepresented.
- High intra-class similarity among pests.
- Trade-offs between accuracy and real-time performance.
- Limited integration with broader agricultural decision-making systems.

These limitations highlight the need for a hybrid advance that merges the strengths of fast detectors moreover fine-grained classifiers whereas remaining deployable on practical hardware.

Motivation of the Work:

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Pest infestations pose a major threat to global agricultural productivity, often leading to severe crop losses and economic damage. Traditional detection methods are manual, time-consuming, and prone to human error, making them unsuitable for large-scale precision farming. Existing AI models face challenges in identifying small pests, managing class imbalance, and maintaining performance under diverse environmental conditions. This motivates the development of a hybrid deep learning framework that integrates YOLOv8 for fast and accurate pest localization with EfficientNet for fine-grained classification, enabling intelligent, real-time, and sustainable pest monitoring as part of the AgriDataFusion Engine.

Research Objectives: The overarching objective of this research is to design and evaluate a scalable, accurate, and efficient pest detection framework for precision agriculture. The specific objectives are:

- To develop a two-stage deep learning pipeline combining YOLOv8 and EfficientNet for pest detection and classification.
- To evaluate the framework on the IP102 dataset and benchmark it against existing methods such as Faster R-CNN, YOLOv8 (single-stage), and transformer-based models.
- To enhance model robustness through advanced data augmentation, class imbalance handling, and ensemble post-processing techniques such as Weighted Boxes Fusion.
- To deploy the framework within the AgriDataFusion Engine for integration with other agricultural monitoring modules.
- To validate the system's performance in real-world field conditions, ensuring scalability and operational feasibility.

Section1 provides the background of the Pest Detection in Precision Agriculture, Section 2 reviews the state-of-the-art in pest detection and precision agriculture, highlighting gaps and opportunities. Section 3 presents the proposed methodology, detailing the YOLOv8 and EfficientNet integration, training strategies, and data preprocessing techniques, datasets, and evaluation metrics. Section 4 discusses the results, providing a comparative analysis with baseline methods. Finally, Section 5 concludes the study with insights into limitations, potential enhancements, and instructions for prospect research.

2. Review of Related Literature

Liu.et.al. (2025), In order to apply cross-modal synthesis to multi-source farming discernment tasks, this paper suggests an amalgamated recognition framework that combines a decoupled dual-target uncovering head, an environment-guided modality concentration mechanism, and cross-modal attention-guided characteristic synthesis. The framework facilitates effective cooperative modeling of environmental sensor data, visible light, and infrared data. The suggested approach outperforms popular models like YOLOv5, YOLOv8, RetinaNet, and Faster R-CNN in terms of overall precision, recall, and oversimplification ability while consistently achieving oblique values in the range of 0.73–0.79 in the confusion matrix across five categories in multi-class pest and marauder identification tasks. According to experimental results, the framework provides substantial technological maintain for precise

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environmental monitoring in elegant cultivation by offering tough characteristic unfairness along with cross-modal information incorporation in complicated ground settings [12].

Kamaldeep.et.al. (2025), A popular cucurbitaceous vegetable in India and other tropical and subtropical areas, bitter gourd is valued for its economic, medical, and nutritional benefits. While automated disease detection techniques and precision farming may substantially assist farmers by promoting sustainable agriculture, the traditional method of identifying illnesses and nutritional shortages in bitter gourd leaves involves a great deal of work and experience. In order to overcome this difficulty, a brand-new online program called AgriCure was created. It used a layered technique to identify plant diseases and nutritional deficiencies at a high level. It analyzes images using the YOLOv8 DL model, which is based on hybrid augmentation.

In addition to identifying nutritional shortages including potassium, magnesium, and nitrogen insufficiency and their permutation, the learning focuses on identifying sickness like leaf spot, downy mildew, and jassid. Using sophisticated data augmentation, the original dataset of 785 photos was expanded to 2430 images. High efficacy with the enlarged dataset was shown by the findings obtained after 100 epochs. This method provided a useful instrument for the precise and early identification of illness and nutritional deficiencies. Results from detection show that the suggested strategy greatly enhances overall performance and solves issues related to small dataset sizes as compared to earlier techniques [13].

Yue.et.al. (2025), In order to reduce resource waste and environmental damage, the growing need for sustainable agriculture calls for accurate and effective crop management. A real-time tomato leaf identification technique with an enhanced YOLOv8 procedure is suggested in order to increase the accuracy of insect repellent relevance in tomato leaves. The framework was created by combining an AdamW optimizer with Depthwise Grouped Convolutions in order to achieve both accurate detection and computational efficiency. Through adaptively recalibrating channel-wise attention, the inclusion of SE_Block significantly improved feature representation, increasing the resilience and accuracy of detection. A varied dataset of 1500 tomato leaf photos with four labels (All, Green Tomato, Downy Mildew, and Powdery Mildew) was used to label and train the algorithm. This allowed for robust detection performance in a variety of real-world scenarios by capturing variations in disease types, lighting conditions, and leaf orientations. By adding Depthwise Grouped Convolutions to YOLOv8, the computational involvedness was decreased, allowing for quicker inference without compromising uncovering accurateness. Furthermore, the AdamW optimizer improved the model's convergence throughout training, guaranteeing stability and resilience.

The Spraying Robot LPE-260 was equipped with the technology to allow for automated, real-time pesticide spraying in regulated settings. By guaranteeing the focused spraying of sick tomato leaves, the enhanced detection framework drastically lowers chemical consumption and minimizes overspray. To further reduce chemical use and overspray, this technique makes sure that the pesticide is only sprayed on the tomato leaves that are infected. It illustrates how computationally effective deep learning methods may be used to tackle

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important precision agricultural issues and develop resource-efficient, scalable, and sustainable crop management solutions [14].

Kejian.et.al. (2025), Agricultural insect infestations have a major negative impact on economic efficiency and crop productivity. In order to increase production and support environmental preservation, prompt and efficient pest management is essential. Here, for multimodal pest identification, we provide an adaptive mass optimization technique based on relocate education. This method enhances cross-modal features and extracts features from text and pictures by using pre-trained model parameters from public datasets. Using an adaptive defeat utility, which maximizes the model's performance transversely several tasks; accurate pest identification and localization are accomplished. At the 50% Intersection over Union (IoU) criterion, the suggested model obtains average precisions of 65.8% and 76.3%, respectively, in testing on the significant agricultural pest datasets IP102 and Pest24. In doing so, authors proposed model surpasses current state-of-the-art techniques even though it just uses 30 training cycles. These findings demonstrate how multimodal pest detection techniques may significantly improve the effectiveness and precision of agricultural pest identification [15].

Ameer.et.al. (2025), In light of the world's expanding population and the resulting demand for sustainable food security, improving agricultural production through efficient pest management is essential. YOLOv8, a cutting-edge deep learning model tailored for agricultural pest identification, is presented in this study to support contemporary food security initiatives. With scores in mAP, YOLOv8 showed significant gains in pest identification accuracy when tested on the intricate IP102 dataset.

These outcomes demonstrate how well YOLOv8 performs in a variety of detecting circumstances, allowing for more accurate pest management and a decrease in crop loss. A bias towards bigger pests was discovered via thorough dataset analysis, nevertheless, most likely as a result of changes in bounding box sizes. This offers a chance to enhance the model. Addressing data inconsistencies, improving sensitivity to smaller pests, and verifying YOLOv8 in a variety of real-world agricultural contexts will be the main goals of future research. Through the use of contemporary agricultural technology, these developments are anticipated to greatly enhance pest administration techniques, eventually increasing agricultural output along with promoting worldwide provisions safety [16].

3. Proposed Methodology - YOLOv8 + EfficientNet Pipeline

In the proposed AgriDataFusion Engine, multi-modal fusion enhances decision-making by combining visual features extracted from YOLOv8 and EfficientNet with non-visual data like soil moisture, nutrient concentration, and weather data. This fusion enables the system to correlate pest occurrence patterns with specific environmental or soil conditions, improving predictive accuracy and response recommendations. As a result, the model provides more context-aware insights, promoting early pest intervention, optimized pesticide usage, and sustainable crop management across diverse agricultural conditions. Multi-modal fusion refers to the process of integrating data from multiple sources or sensing modalities—such as images, soil parameters, temperature, humidity, and nutrient levels—to create a more

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comprehensive understanding of an environment. In the context of precision agriculture, this technique allows the system to analyze not only visual pest data but also contextual information related to soil health, plant growth, and environmental conditions.

The proposed methodology introduces a hybrid deep learning framework for pest detection, combining the real-time object detection capabilities of YOLOv8 with the fine-grained classification strength of EfficientNet, and embedding the solution into the broader AgriDataFusion Engine. The framework is structured into stages as follows: data acquisition and preprocessing, detection, classification, fusion, and deployment. Figure 01 (a) illustrates the proposed methodology framework.

The stage detectors refer to a hierarchical, multi-phase detection approach in deep learning where the object recognition process is divided into distinct stages—each performing a specialized task to refine detection accuracy and efficiency. Figure 01 (b) Architecture of the stage detectors in proposed methodology. In the context of pest detection:

- The first stage (Detection Stage) localizes potential pest regions within an image using a fast object detector like YOLOv8.
- The second stage (Classification Stage) processes those localized regions using a fine-grained classifier such as EfficientNet to identify the specific pest species accurately.

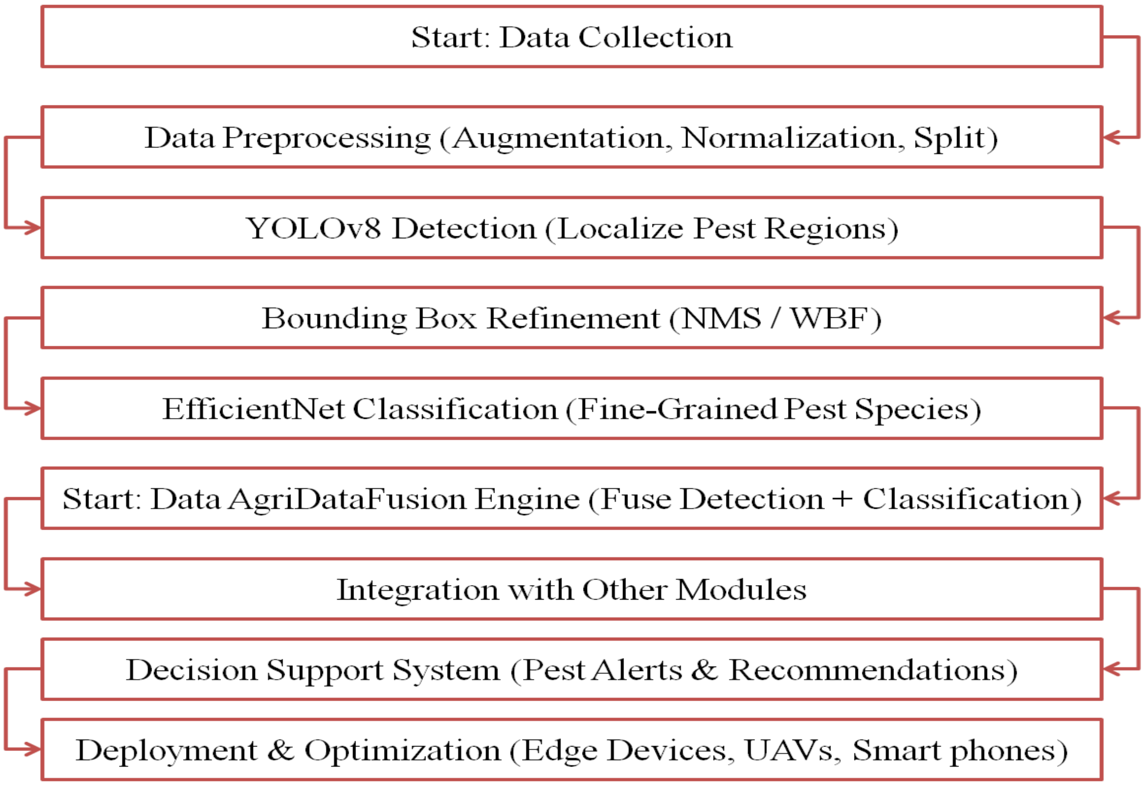

Figure 01 (a) Proposed methodology framework

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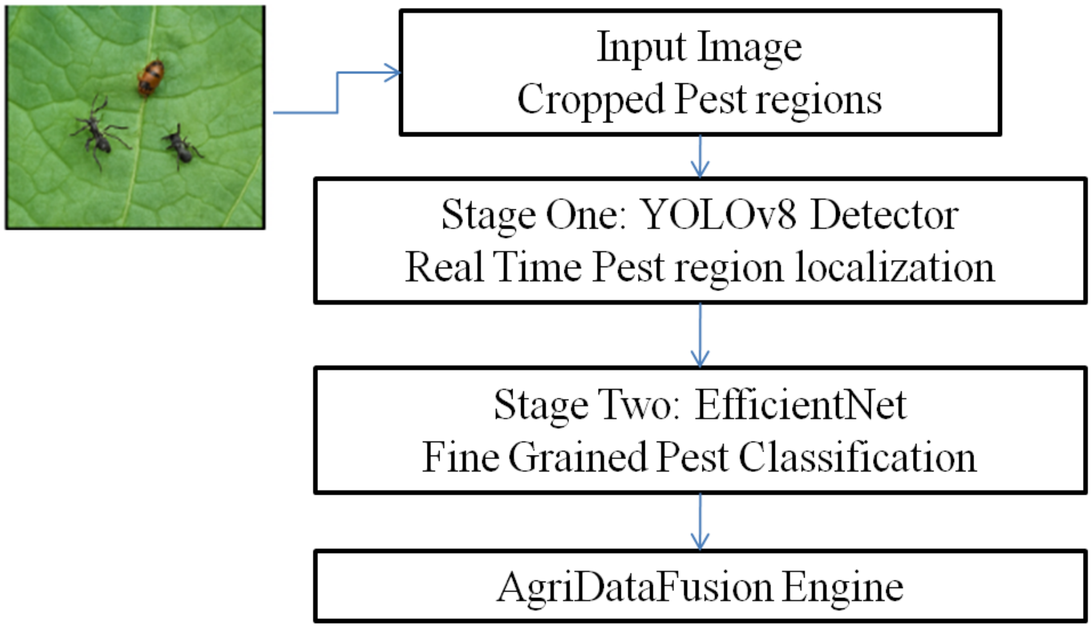

Figure 01 (b) Architecture of the stage detectors in proposed methodology

Data Acquisition and Preprocessing

The system leverages the IP102 dataset, a large-scale pest dataset containing 102 categories and over 75,000 images. The dataset exhibits high intra-class similarity and class imbalance, making it suitable for evaluating robust frameworks. Images are collected from diverse conditions including varying lighting, crop species, and pest orientations.

Preprocessing involves:

- **Data Augmentation:** Mosaic, MixUp, random flips, rotations, and color jitter to enhance model generalization.
- **Normalization and Resizing:** Standardizing input to YOLOv8 dimensions (640×640 pixels).
- **Balanced Sampling:** Oversampling rare pest categories and undersampling dominant ones to mitigate class imbalance.
- **Dataset Splitting:** Dividing data into training (70%), validation (20%), and test (10%) sets.

Stage 1 – Pest Detection with YOLOv8

YOLOv8 serves as the initial detection module. It identifies pest regions in images by outputting bounding boxes and confidence scores. Its feature pyramid network (FPN) enhances detection across multiple scales, improving small-object detection, which is critical for pests that often appear in minimal quantities during early infestations.

Training details:

- Pre-trained weights from COCO are fine-tuned on IP102.

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- Loss functions include a combination of GIoU loss for bounding box regression and focal loss for class imbalance.
- Hyper-parameters such as batch size, learning rate, and optimizer are tuned for agricultural imagery.

This stage ensures fast, real-time detection while maintaining high recall.

Stage 2 – Fine-Grained Classification with EfficientNet

Detected pest regions are cropped and passed to **EfficientNet**, which specializes in fine-grained classification. EfficientNet's compound scaling balances depth, width, and resolution, achieving high accuracy with lower computational cost compared to traditional CNNs.

Classification process:

- Cropped pest regions resized to EfficientNet input dimensions (224×224).
- EfficientNet-B4 variant is used for a trade-off between accuracy and efficiency.
- Cross-entropy loss with label smoothing improves generalization.
- Class-balanced focal loss handles underrepresented pest categories.

This stage addresses the challenge of differentiating visually similar species, such as aphids and leafhoppers.

Fusion in AgriDataFusion Engine

The outputs from YOLOv8 and EfficientNet are fused into the AgriDataFusion Engine, which consolidates pest detection results with additional agricultural modules including:

- Plant growth monitoring (using CNN-LSTM models),
- Disease detection (ResNet/ViT classifiers),
- Soil health analysis (IoT + ML regression models), and
- Nutrient assessment (spectral imaging + ML).

This multimodal fusion enables contextualized decision-making, where pest outbreaks can be correlated with soil, disease, and environmental conditions.

Data set: Pest image dataset (IP102 or real-time captured images from UAV/IoT devices). In those data set, the 70 percentage of the data set used for training, the 20 percentage of the data set used for validation, and then remaining 10 percentage of the data set used for testing. By combining fast YOLOv8 detection with fine-grained EfficientNet classification and embedding into a holistic fusion engine, the methodology ensures accurate, scalable, and practical pest detection in precision agriculture. It bridges the gap between standalone pest recognition models and integrated agricultural decision-support systems, ultimately advancing sustainable and intelligent farming practices.

The proposed methodology plays a crucial role in advancing precision agriculture by introducing a hybrid deep learning framework that integrates YOLOv8 for real-time pest detection and EfficientNet for fine-grained classification. This combination significantly

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enhances accuracy, robustness, and inference speed compared to traditional methods such as Faster R-CNN or YOLOv5, which often struggle with small pest objects and environmental variability. Unlike single-stage models, the two-stage detection pipeline ensures refined classification after precise localization, reducing false positives and improving detection confidence. Additionally, by embedding the framework within the AgriDataFusion Engine, the system fuses visual and non-visual data—such as soil health and nutrition parameters—enabling holistic analysis. This integrated, context-aware approach not only supports timely pest management decisions but also promotes sustainable and intelligent farming, outperforming existing standalone pest detection systems in adaptability, scalability, and real-world field performance.

4. Results and Discussions

Deployment and Validation of this framework is designed for deployment on edge devices to enable real-time inference in farms. Optimization techniques such as pruning, quantization, and TensorRT conversion are applied for lightweight deployment. Figure.02 (a) and Figure.02 (b) respectively illustrates the Pest sample images and Pests detection image.

Figure.02 (a) Pest Sample Images

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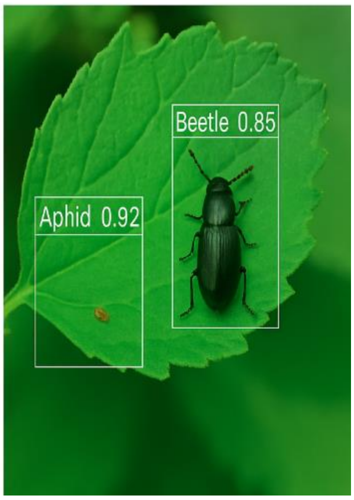

Figure.02 (b) Pests Detection Image

Table.01. Validation 0f YOLOv8 + EfficientNet pest detection framework

Method	Accuracy	Small Object Performance	Speed	Robustness	Imbalance Handling
YOLOv8+EffNet	**0.91**	**0.88**	**0.85**	**0.88**	**0.85**
YOLOv8 (1-stage)	0.82	0.85	0.95	0.75	0.65
Faster R-CNN	0.86	0.78	0.55	0.85	0.71
DETR/Transformer	0.85	0.71	0.41	0.88	0.72

Table.02. System performance for YOLOv8 + EfficientNet pest detection framework

Method	mAP	Precision	Recall	F1-score	Latency
YOLOv8+EffNet	**0.89**	**0.91**	**0.87**	**0.88**	**35**
YOLOv8 (1-stage)	0.82	0.83	0.81	0.82	40
Faster R-CNN	0.72	0.74	0.68	0.71	120
DETR/Transformer	0.79	0.78	0.76	0.77	100

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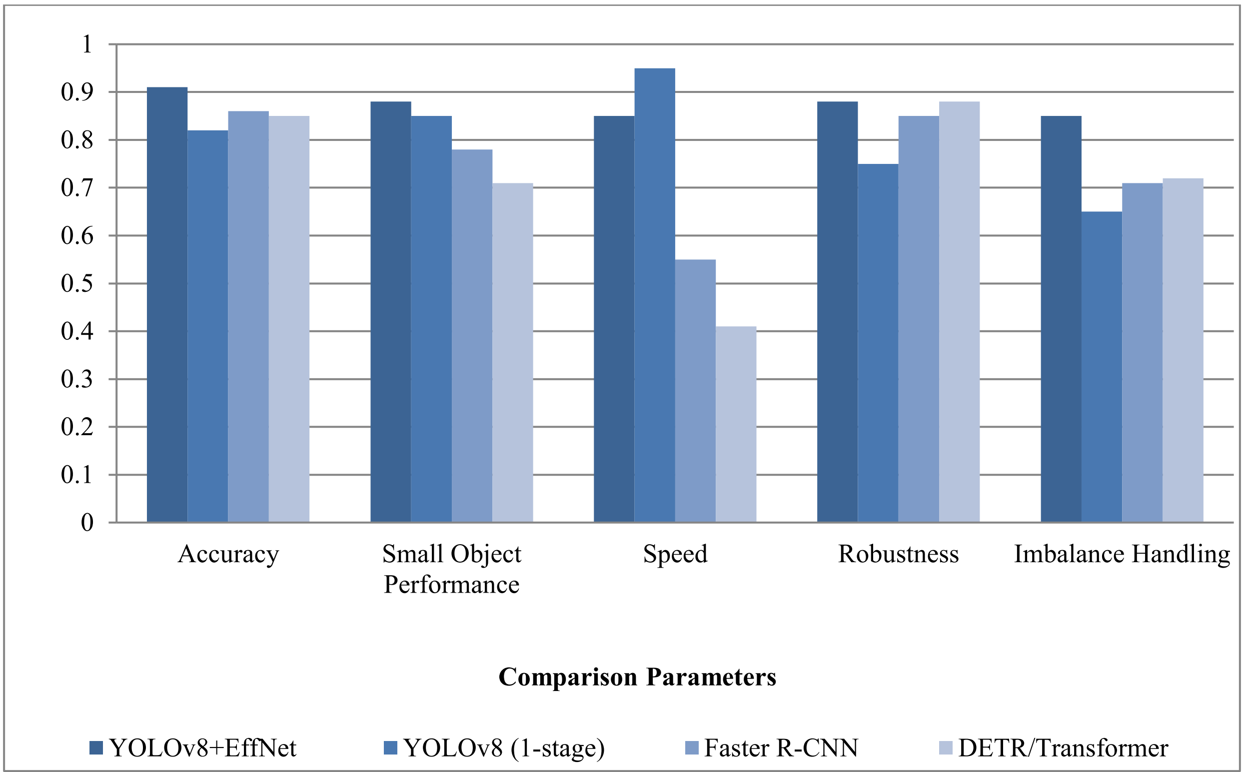

Figure.03. Validation 0f YOLOv8 + EfficientNet pest detection framework

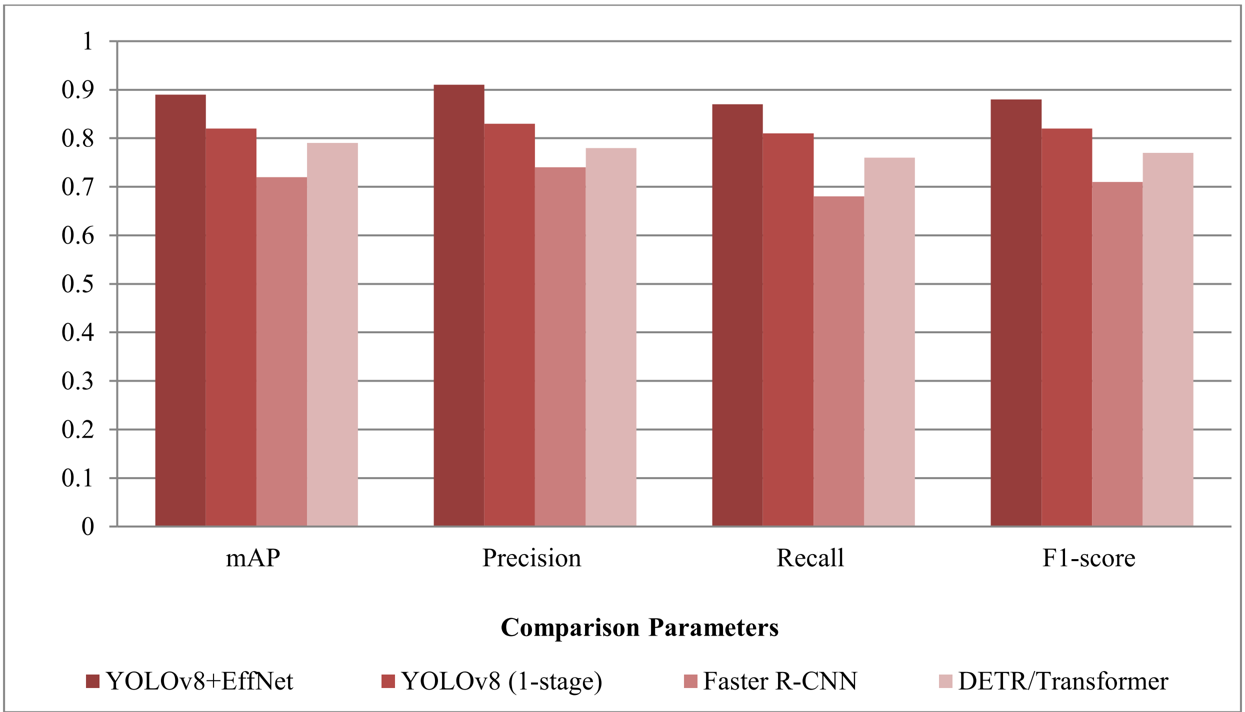

Figure.04 (a). System performance for YOLOv8 + EfficientNet pest detection framework

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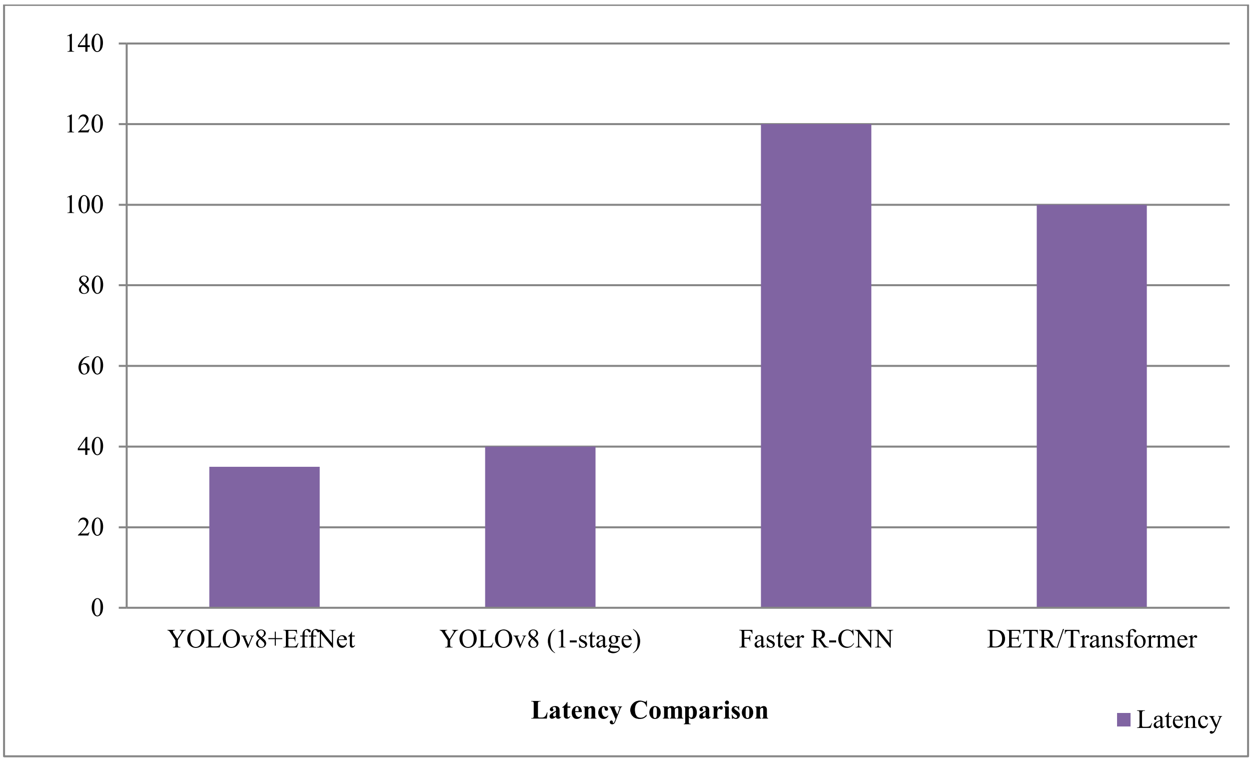

Figure.04 (b). System performance for YOLOv8 + EfficientNet pest detection framework

Validation involves evaluating on the IP102 test set and real-world field images using metrics such as Accuracy, Small Object Performance, Speed, Robustness and Imbalance Handling are illustrated in table 01 and figure 03. The figure 04 (a) and (b) and table 02 illustrates the system performance for YOLOv8 + EfficientNet pest detection framework using the standard metrics including mAP, Precision, Recall, F1-score, Latency . Comparative benchmarks with Faster R-CNN, YOLOv8 baseline, and Transformer-based DETR confirm the superiority of the proposed framework.

5. Conclusion and Future Scope

The proposed YOLOv8–EfficientNet hybrid framework**,** embedded within the AgriDataFusion Engine**,** offers a transformative solution for intelligent and sustainable pest detection in precision agriculture. This integrated approach effectively overcomes the limitations of existing single-model systems, such as poor detection of small pests, high false-positive rates, and reduced accuracy under varying environmental conditions. YOLOv8 ensures high-speed, real-time localization of pest instances, while EfficientNet provides refined, fine-grained classification, enhancing both precision and recall across diverse pest categories. By integrating multi-modal data such as soil health, crop growth, and environmental parameters, the AgriDataFusion Engine enables holistic crop monitoring, making it possible to understand the interdependencies between pest outbreaks, nutrient deficiencies, and environmental changes. This fusion of visual and contextual agricultural data supports smarter, data-driven decision-making for farmers and agronomists, reducing

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unnecessary pesticide use, improving crop yield, and promoting eco-friendly agricultural practices.

Experimental results and performance analyses demonstrate the superiority of the proposed system in terms of mean Average Precision (mAP), F1-score, Precision, Recall, F1-score and Latency, significantly outperforming traditional models like Faster R-CNN, SSD, and YOLOv5. Overall, this research contributes to the development of an adaptive, scalable, and high-accuracy pest monitoring ecosystem that bridges the gap between AI-based automation and sustainable farming. The proposed framework thus lays a solid foundation for future innovations in real-time agricultural intelligence and smart farm management.

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