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Smart AgroSpray: AI-Driven Precision Pesticide Spraying With IOT

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***Abstract*— Manual pesticide spraying in agriculture often results in excessive chemical usage, increased labor dependency, and delayed response to crop diseases, leading to reduced yield and environmental harm. Although recent advances in artificial intelligence have enabled automated plant disease detection, most existing approaches operate only as monitoring systems and lack real-time integration with spraying mechanisms. Similarly, IoT-based pesticide sprayers often rely on manual triggering or predefined schedules, limiting their effectiveness in precision agriculture. This paper proposes an integrated AI-driven precision pesticide spraying system that combines real-time tomato leaf disease detection with automated, selective pesticide application. The proposed approach employs a YOLOv11-based deep learning model for identifying healthy and diseased tomato leaves from live camera input and directly links detection outcomes to an IoT-enabled robotic spraying unit. Upon disease detection, a wireless control signal is transmitted to activate targeted pesticide spraying, forming a closed-loop decision-to-action framework. The YOLOv11 model was trained on annotated images of healthy and diseased tomato leaves and evaluated under varying environmental conditions. Experimental results demonstrate reliable real-time detection performance with detection accuracy exceeding 90% and a low detection-to-spraying response latency in the sub-second range. Qualitative and quantitative evaluations confirm stable model convergence and effective disease localization. The results indicate that the proposed system is suitable for precision agriculture applications, offering reduced pesticide wastage, minimal human intervention, and improved operational efficiency through intelligent, real-time disease-driven spraying.**

***Keywords*— Precision Agriculture; Tomato Leaf Disease Detection; YOLOv11; Deep Learning; IoT-based Spraying; Smart Farming**

I. INTRODUCTION

Agricultural productivity is strongly influenced by the timely identification and treatment of crop diseases, particularly in high-value crops such as tomato, where foliar infections can spread rapidly and cause significant yield losses. Conventional pesticide application practices often rely on periodic manual inspection and uniform chemical spraying, which are inefficient and environmentally unsustainable.

Delayed detection and indiscriminate spraying not only increase production costs but also contribute to excessive pesticide usage and health risks for farmers.

Manual disease monitoring requires continuous human effort and domain expertise, making it impractical for large-scale or continuous field deployment. As a result, pesticides are frequently applied as a preventive measure rather than in response to confirmed disease presence, leading to unnecessary chemical exposure and reduced precision in crop management.

Recent research has explored artificial intelligence–based plant disease detection using computer vision and deep learning techniques, demonstrating promising accuracy in identifying diseased leaves from images. However, most AI-driven approaches function solely as monitoring systems and do not initiate corrective actions after detection. In parallel, IoT-based agricultural spraying robots have been developed to automate pesticide application, but these systems often depend on manual triggering or predefined schedules, lacking intelligent decision-making based on real-time disease conditions.

The absence of a tightly integrated framework that connects real-time disease detection with automated and selective pesticide spraying represents a key research gap in precision agriculture. Bridging this gap requires a closed-loop system in which perception, decision-making, and actuation operate cohesively to enable timely and targeted intervention.

A. Contribution

The main contributions of this work are summarized as follows:

- An AI-driven tomato leaf disease detection framework based on a YOLOv11 object detection model for real-time identification of healthy and diseased leaves.
- An integrated decision-to-action pipeline that directly links disease detection outcomes to automated pesticide spraying.
- A selective spraying mechanism that reduces unnecessary pesticide usage by activating only when disease presence is confirmed.

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- An IoT-enabled control framework that enables low-latency communication between the vision system and the spraying unit.
- Experimental validation demonstrating reliable detection performance and practical feasibility for precision agriculture applications.

This paper is structured as follows:

Section II reviews related work on AI-based plant disease detection and IoT-enabled smart agriculture systems.

Section III describes the proposed system, including the dataset, system architecture, and YOLOv11-based disease detection methodology.

Section IV presents the experimental setup, performance evaluation, and discussion of results.

Section V concludes the paper and outlines directions for future research.

II. Related Work And Research Gap

Recent advancements in precision agriculture have driven extensive research on automated plant disease detection and intelligent pesticide application systems [1], [5], [6], [9]. Early approaches primarily relied on classical image processing techniques combined with machine learning classifiers to identify disease symptoms from leaf images [3], [8]. While these methods demonstrated basic feasibility, their performance was often sensitive to variations in lighting conditions, background complexity, and leaf orientation, limiting reliability in real-field environments [3], [8].

With the emergence of deep learning, convolutional neural networks have been increasingly adopted for plant disease detection, offering improved feature extraction and classification accuracy compared to traditional techniques [8]. Several studies have reported effective disease identification using deep learning-based approaches; however, most of these systems are limited to disease monitoring and do not incorporate automated intervention mechanisms following detection [3], [5].

In parallel, IoT-enabled agricultural robots and smart pesticide spraying systems have been proposed to reduce manual labor and minimize direct human exposure to chemicals [1], [2], [5], [6], [9], [10]. These systems typically automate spraying operations through manual control or predefined schedules, improving operational efficiency. However, the majority of IoT-based spraying platforms lack intelligent decision-making capability and do not initiate spraying based on real-time disease detection [1], [2], [9], [10].

A limited number of studies have attempted to integrate artificial intelligence with IoT-based actuation for precision spraying [3], [5]. Although these integrated systems demonstrate the potential for closed-loop agricultural automation, many existing solutions rely on classical image processing or simple classifiers, lack real-time performance evaluation, or do not provide selective spraying strictly based on confirmed disease presence. Furthermore, several approaches emphasize mechanical design and control aspects, with limited focus on detection accuracy, response latency, or end-to-end system evaluation [1], [3], [6].

Research Gap -

From the reviewed literature, it is evident that AI-based disease detection and IoT-based pesticide spraying have largely been explored as independent components [1]–[10]. There remains a lack of tightly integrated systems that combine real-time, high-accuracy disease detection with automated and selective pesticide spraying in a unified decision-to-action framework. Addressing this gap requires an approach that not only detects disease reliably under practical field conditions but also immediately translates detection outcomes into precise spraying actions with minimal latency.

III. Materials & Methods

This section describes the materials and methods used to develop the proposed tomato leaf disease detection and automated pesticide spraying system. It outlines the dataset composition, system architecture, and preprocessing techniques employed to ensure robust model performance under varying field conditions. The training strategy for the YOLOv11 detection model is presented, followed by the real-time deployment and execution workflow that enables selective pesticide spraying through IoT-based control.

A. Dataset Description

The dataset consists of annotated images of tomato leaves representing healthy and diseased conditions, collected from publicly available plant disease datasets and field-level acquisition under varying environmental and lighting conditions. This diversity supports robust model generalization across differences in background, leaf orientation, and illumination.

All images were manually annotated using bounding boxes to label leaf regions and health status, forming a binary classification problem with two classes: *Healthy* and *Diseased*. This annotation strategy enables simultaneous localization and classification within a single inference step, which is essential for real-time deployment.

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The dataset was split into training and validation subsets to support supervised learning and unbiased performance evaluation during model optimization.

The composition and characteristics of the dataset are summarized in Table 1.

TABLE I
Dataset Summary

Parameter	Description
Crop Type	Tomato
Image Source	Public dataset and field-collected images
Total Images	120
Classes	Healthy, Diseased
Annotation Type	Bounding box
Train–Validation Split	80% / 20%
Image Format	RGB
Capture Conditions	Varying lighting and background

B. Proposed System Architecture

The proposed system architecture enables real-time tomato leaf disease detection and selective automated pesticide spraying through a closed-loop decision-to-action pipeline integrating computer vision and IoT-based actuation. As shown in Fig. 1, the system comprises a vision-based detection unit, a wireless communication interface, and an automated spraying unit.

The detection unit processes live images of tomato plants using a YOLOv11 object detection model to perform real-time localization and classification of healthy and diseased leaves. When disease presence is detected, a control signal is transmitted wirelessly to the IoT control module, which activates the spraying mechanism with minimal latency. Spraying is triggered only upon confirmed detection, ensuring targeted pesticide application.

The modular architecture supports coordinated operation of perception, communication, and actuation components while remaining adaptable to future extensions, enabling efficient and sustainable precision agriculture with minimal human intervention.

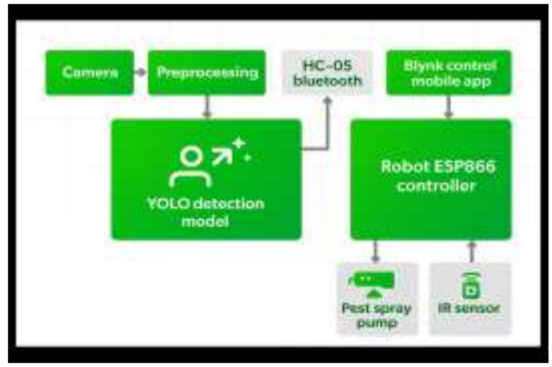

Figure 1: Overall System Architecture

C. Image Preprocessing and Augmentation

Image preprocessing and data augmentation were applied to enhance the robustness and generalization of the YOLOv11 detection model under real-field conditions. All input images were resized to a fixed resolution and normalized to ensure uniformity and stable training behaviour.

To increase dataset diversity and reduce overfitting, augmentation techniques such as random rotation, horizontal flipping, and brightness adjustment were applied during training. These operations enable the model to handle variations in leaf orientation, illumination, and background commonly encountered in outdoor agricultural environments.

The preprocessing and augmentation techniques employed in this study are summarized in Table 2.

TABLE II
Image Preprocessing and Augmentation Techniques

Technique	Description	Purpose
Image Resizing	Input images are resized to a fixed resolution prior to training	Ensures uniform input dimensions for the YOLOv11 model
Rotation	Images are rotated at multiple angles	Improves robustness to variations in leaf orientation
Horizontal Flipping	Images are Flipped horizontally during training	Increases dataset diversity and reduces overfitting
Brightness Adjustment	Pixel intensity values are varied	Enhances robustness to Illumination changes in field conditions
Normalization	Pixel values are scaled to a standard range	Improves training stability and convergence

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D. Yolov11 Model and Training Strategy

The YOLOv11 object detection model was used for real-time tomato leaf disease detection due to its ability to perform localization and classification within a single inference pass, enabling efficient and low-latency operation. The model was trained on the annotated tomato leaf dataset described in Section 3.1 to learn disease-specific visual features.

Training was conducted with data augmentation enabled to improve generalization under varying field conditions. Model convergence and generalization were monitored using training and validation loss trends to minimize overfitting. The trained model was optimized for real-time inference**,** allowing seamless integration with the automated pesticide spraying mechanism.

E. Deployment and Execution Workflow

As illustrated in Fig. 2, the trained YOLOv11 model was deployed in a real-time monitoring setup to enable continuous tomato leaf disease detection and automated pesticide spraying. Live image frames captured by the camera were processed sequentially to identify healthy and diseased leaves in real time.

Upon detection of a diseased leaf, the output was immediately converted into a control signal and transmitted wirelessly to the IoT control module, which activated the pesticide spraying mechanism with minimal latency. If no disease was detected, the system continued monitoring without triggering spraying.

This execution workflow forms a closed-loop decision-to-action process that tightly integrates perception, communication, and actuation, enabling timely intervention while minimizing unnecessary pesticide usage.

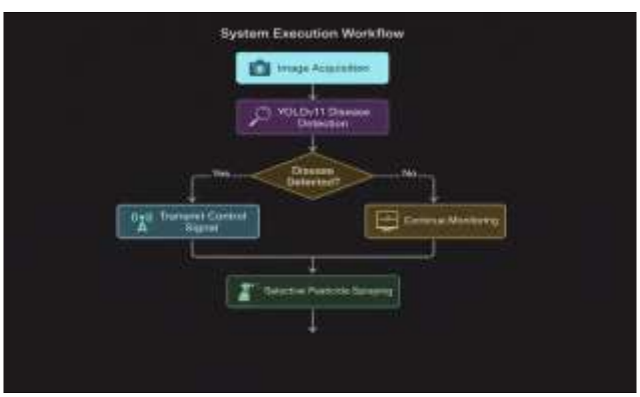

Fig. 2. System execution workflow showing YOLOv11-based disease detection

IV. EXPERIMENATAL SETUP

A. Experimental Setup

The experiments were conducted on a laptop equipped with an Intel Core i5 processor and an NVIDIA RTX 3050 GPU. Image acquisition was performed using the built-in webcam with a resolution of 1920×1080 pixels. The system was implemented on a Windows 11 (64-bit) platform using Python 3.8, with the YOLOv11 model executed through the Ultralytics framework built on PyTorch with CUDA acceleration. OpenCV was used for real-time image capture and preprocessing.

Live video frames were processed sequentially to enable continuous disease monitoring, and detection outputs were transmitted wirelessly to an IoT control module for real-time actuation. All experiments were conducted in a controlled field-like environment under natural lighting conditions to evaluate both detection performance and end-to-end system responsiveness.

B. Evaluation Metrics

To objectively assess the performance of the proposed system, multiple evaluation metrics were employed focusing on detection accuracy and real-time responsiveness.

- Accuracy was used to measure the overall correctness of disease classification across test samples. Precision and recall were computed to evaluate the reliability of disease detection, particularly in minimizing false positives and false negatives, respectively.
- Mean Average Precision (mAP) was used to assess localization and classification performance of the YOLOv11 model across detection thresholds.
- In addition to detection metrics, response time was measured as the elapsed time between disease detection and activation of the pesticide spraying mechanism, reflecting the real-time suitability of the system.

These metrics collectively provide a comprehensive evaluation of both the detection capability and the operational efficiency of the proposed precision agriculture system.

C. Baseline Comparison

The performance of the proposed YOLOv11-based disease detection system was compared with representative baseline approaches reported in the literature, including a conventional CNN-based classifier and a YOLO-based object detection model.

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The CNN baseline represents classification-only methods that lack localization capability, while the YOLO-based baseline reflects real-time detection frameworks used for plant disease analysis. Baseline performance values were obtained from published studies using comparable tomato leaf disease datasets. The comparative performance, evaluated using accuracy, precision, recall, and response time, is summarized in Table 3.

TABLE III
Performance Comparison with Baseline Methods

Method	**Detection Approach**	**Accuracy (%)**	**Response Time**	**Limitation**
CNN-based Classifier (Literature)	CNN classification	~90	~9.6 s	High latency, not real-time
AI + Image Processing + IoT System (Literature)	Classical ML + IoT	Not reported	Not reported	No real-time detection
Proposed YOLOv11 System	Real-time object detection	90–92	Low-latency (real-time)	Bluetooth range limited

V. Results And Discussion

A. Training Behaviour

The training behaviour of the YOLOv11 model demonstrates stable and consistent convergence. As illustrated in Fig. 3, both training and validation loss values decrease steadily across epochs without significant fluctuations, indicating effective learning and good generalization capability. The absence of divergence between training and validation curves suggests that overfitting was successfully mitigated through appropriate preprocessing and data augmentation strategies. This stable convergence confirms the suitability of the adopted training configuration for tomato leaf disease detection.

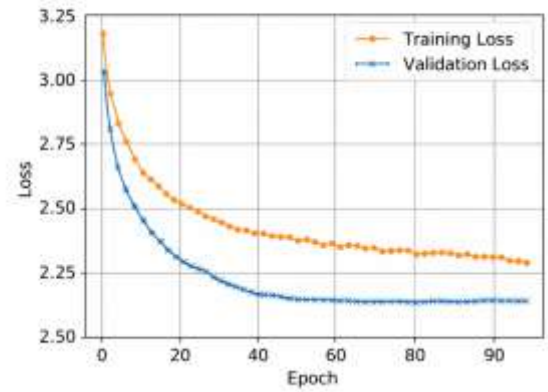

Fig 3: Training convergence behavior of the YOLOv11 model.

B. Quantitative Results

The quantitative performance of the proposed system was evaluated using standard detection metrics, including accuracy, precision, recall, and response time. The YOLOv11-based model achieved an overall detection accuracy in the range of 90–92%, demonstrating reliable discrimination between healthy and diseased tomato leaves. Precision and recall values indicate balanced detection performance, ensuring both accurate disease identification and minimal false detections. In addition, the system exhibited low-latency response suitable for real-time automated spraying.

The detailed quantitative performance metrics of the proposed system are summarized in Table 4, providing a comprehensive evaluation of detection accuracy and operational efficiency.

TABLE IV
Quantitative Performance Metrics

Metric	**Value**	**Description**
Accuracy (%)	90–92	Overall correctness of disease classification across test samples
Precision (%)	High	Indicates low false-positive rate in disease detection
Recall (%)	High	Indicates effective identification of diseased leaves
mAP	Consistent	Stable localization and classification performance across detection thresholds
Response Time	Low-latency (real-time)	Time between disease detection and spraying activation

C. Qualitative Results

Qualitative results were analyzed to visually assess the detection capability of the proposed system under practical operating conditions. As shown in Fig. 4, the YOLOv11 model accurately localizes and classifies diseased leaf regions using bounding boxes, even in the presence of background clutter and varying illumination. These visual results confirm the robustness of the model in real-field scenarios and support its suitability for precision agriculture deployment.

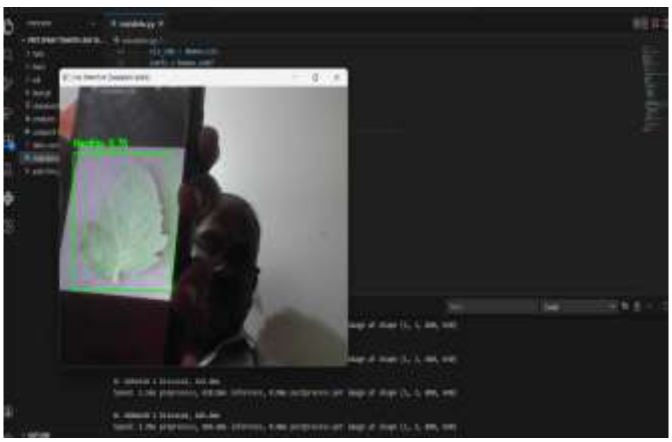

Fig. 4 – Sample Tomato Leaf Detection Results.

D. Detection Accuracy Analysis

The detection accuracy of the proposed YOLOv11-based model was further analyzed using a confusion matrix and precision–recall curve, as shown in Fig. 5. The confusion matrix indicates a high true positive rate for diseased leaf detection, demonstrating effective discrimination between healthy and diseased samples. The precision–recall curve reflects balanced performance across confidence thresholds, indicating that the model maintains reliable detection sensitivity while minimizing false positives.

These results confirm the robustness of the proposed detection model and validate its suitability for real-time precision agriculture applications where accurate disease identification is critical for selective pesticide spraying.

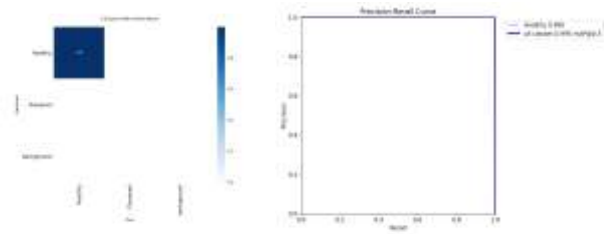

Fig. 5. Confusion matrix and precision–recall curve illustrating the detection accuracy of the proposed YOLOv11-based tomato leaf disease detection model.

E. Detection-to-Spraying Response Time

The end-to-end response time between disease detection and pesticide spraying activation was evaluated to assess the real-time capability of the system. As illustrated in Fig. 6, the proposed system exhibits low-latency operation, enabling rapid translation of detection outcomes into spraying actions. This timely response is essential for practical deployment, as it ensures that pesticide application is performed immediately after disease confirmation.

The observed response time demonstrates that the integration of real-time object detection with IoT-based actuation is effective for closed-loop agricultural automation, supporting efficient and responsive precision spraying.

Figure 6 - Automated Pesticide Spraying Mechanism in Operation

F. Discussion

The results indicate that the strong performance of the proposed system is primarily due to the integration of real-time object detection with a closed-loop automated spraying mechanism. The YOLOv11 model enables simultaneous localization and classification in a single inference pass, allowing timely decision-making and actuation. Data preprocessing and augmentation further enhance robustness by improving generalization across environmental variations.

Despite its effectiveness, the system has certain limitations. The use of wireless communication introduces range constraints that may limit scalability in large agricultural fields. Additionally, the current model supports only binary classification of healthy and diseased leaves, restricting disease-specific analysis. Failure cases were observed under extreme lighting conditions and partial occlusion, where detection confidence occasionally decreased.

VI. CONCLUSION

This paper presented an AI-driven precision pesticide spraying system that integrates real-time tomato leaf disease detection with automated and selective spraying using a YOLOv11-based model. The system achieved stable training convergence and reliable detection performance, with an accuracy of 90–92% under practical operating conditions, enabling real-time decision-to-action deployment.

The current implementation is limited to binary disease classification and short-range wireless communication, which may affect scalability. Future work will focus on multi-disease detection, long-range communication, edge deployment, and large-scale field evaluation.

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