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# Agriculture Robot For Plant Disease Detection Using Machine Learning And IoT Technologies.

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**Abstract**—This study introduces a comprehensive solution for automating plant disease identification and pesticide delivery through a mobile-operated agricultural robot. Leveraging the MobileNetV2 deep learning architecture, the system performs real-time image classification to precisely detect plant diseases. Upon detection, it enables focused pesticide spraying via a Bluetooth-enabled control interface. Integrated environmental sensors—temperature, humidity, rainfall, and light—enhance the robot's adaptability to diverse field conditions. The proposed model offers a smart, scalable, and economical approach to enhancing productivity and sustainability in modern agriculture.

**Index Terms**—MobileNetV2, Smart Farming, IoT, Deep Learning, Precision Agriculture, Plant Disease Detection.

## I. INTRODUCTION

Agriculture continues to serve as a cornerstone of the global economy, providing food security, employment, and raw materials for various industries. Despite its importance, crop productivity is increasingly threatened by plant diseases, which account for substantial losses in both yield and quality. Traditional methods of identifying and managing these diseases rely heavily on manual observation, which is not only time-consuming and labor-intensive but also prone to human error and delayed intervention. As a result, by the time symptoms are visible, it may already be too late to prevent widespread damage.

Recent advancements in artificial intelligence, particularly in machine learning and computer vision, offer transformative potential for automating disease detection processes. Coupled with the progress in embedded systems and Internet of Things (IoT) technologies, it is now feasible to develop intelligent agricultural solutions that monitor crops continuously and take immediate action when anomalies are detected.

This project introduces a smart agricultural robot equipped with a lightweight MobileNetV2 convolutional neural network model to enable on-site, real-time plant disease detection. The system is embedded within an IoT-powered robotic platform that can navigate through fields, capture images of crops, and classify disease conditions with high efficiency. Upon detecting an infected plant, the robot performs targeted pesticide spraying, ensuring that only the affected areas are treated. This precision-based approach significantly reduces unnecessary pesticide usage, lowers operational costs for farmers, and minimizes the environmental footprint associated with chemical treatments. Overall, the system offers a scalable, sustainable, and cost-effective solution tailored to meet the challenges of modern agriculture.

## II. LITERATURE REVIEW

Recent advancements in deep learning, embedded systems, and IoT have driven significant innovation in precision agriculture. Several researchers have contributed to various components that form the basis for integrated smart farming systems.

Sammy et al. [1] demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in classifying plant leaves based on visual symptoms, highlighting the strong potential of deep learning for plant disease detection. Their work established a framework for automated image-based diagnosis, reducing reliance on manual inspection.

Howard et al. [2] introduced the MobileNetV2 architecture, a lightweight and computationally efficient convolutional model designed for mobile and embedded devices. Its low-latency inference makes it suitable for real-time applications in constrained agricultural environments, such as field robots.

Kiranmai [3] proposed an IoT-based irrigation management system utilizing soil moisture sensors for automated watering. This approach optimized water usage and emphasized how sensor-based automation can enhance resource efficiency in agriculture.

In a related study, Patel and Mehta [4] developed an image processing technique for detecting crop diseases, combining color and texture features for improved classification accuracy. However, their method lacked real-time adaptability, underscoring the need for lightweight deep learning models.

Singh et al. [5] designed an autonomous farming robot capable of performing seeding and spraying operations using ultrasonic sensors and Arduino-based control. While effective, the system did not incorporate intelligent disease recognition, which limits its application in precision pesticide deployment.

Verma and Shah [6] explored cloud-based monitoring in smart agriculture using IoT, enabling farmers to observe environmental conditions remotely. However, this solution lacked localized decision-making, which is essential for real-time in-field interventions.

Yadav et al. [7] investigated the fusion of IoT and machine learning for disease detection in tomato plants, using Random Forest and Support Vector Machine classifiers. Their work showcased high accuracy but required centralized computing resources.

Finally, Sharma et al. [8] proposed a robotic system for precision pesticide spraying, but it relied on manual identification of infected plants. This highlights the potential value of integrating deep learning for automated disease classification and targeted treatment.

These studies collectively form a strong foundation for developing an intelligent agricultural robot that combines sensor input, deep learning, and automated pesticide application. The present work aims to bridge existing gaps by introducing a MobileNetV2-powered robotic platform capable of real-time disease detection and localized response in agricultural fields.

## III. SYSTEM ARCHITECTURE

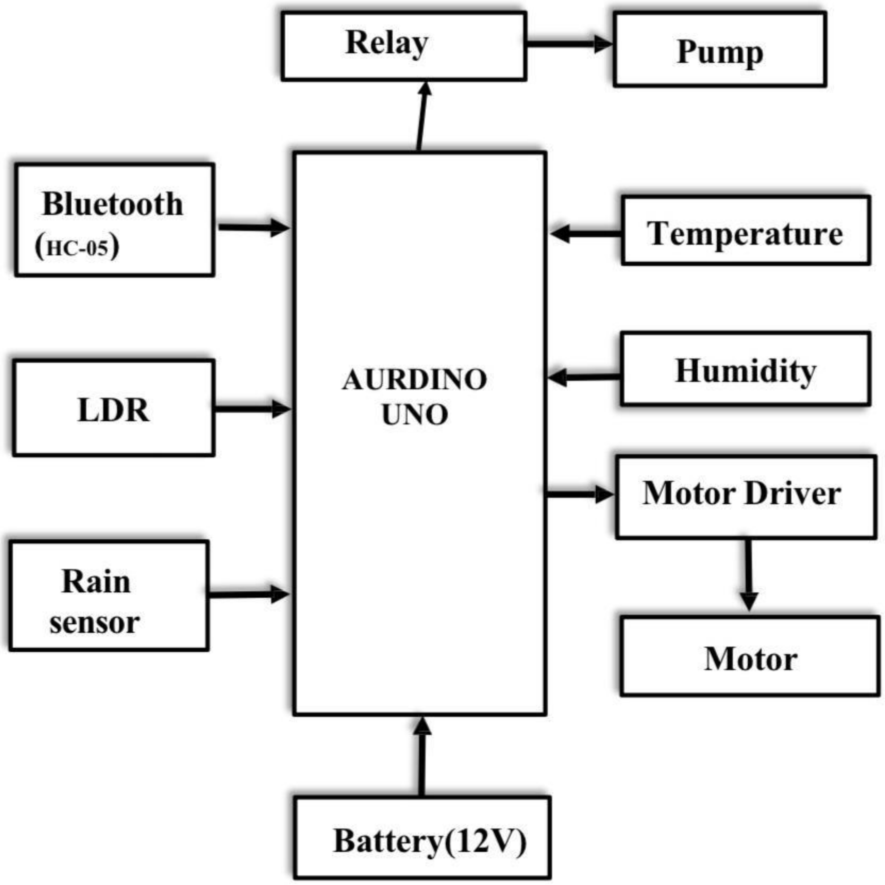


Fig. 1: System Block Diagram

The system is built around an Arduino Uno microcontroller, which acts as the central control unit. Various sensors and components are interfaced with the Arduino to monitor environmental conditions and control external devices accordingly.

Input Components:

1. Bluetooth Module (HC-05): This module enables wireless communication between the Arduino and a smartphone or other Bluetooth-enabled device. It allows for remote control and monitoring of the system.
2. LDR (Light Dependent Resistor): This sensor detects the intensity of ambient light. The data can be used to determine the presence of sunlight, which is useful in agricultural applications.
3. Rain Sensor**:** This component detects rainfall. It helps the system make decisions such as halting irrigation during rain to conserve water.
4. Temperature and Humidity Sensors: These sensors provide real-time readings of the environmental temperature and humidity, which are critical parameters for agricultural monitoring and control.

Output Components:

1. Relay Module and Pump: The relay acts as a switch controlled by the Arduino to turn the water pump on or off based on sensor data or user commands received via Bluetooth.
2. Motor Driver and Motor: The motor driver receives control signals from the Arduino and powers the motor accordingly. This could be used for various tasks such as adjusting irrigation equipment or opening/closing greenhouse windows.

Power Supply:

A 12V battery powers the entire system, supplying the necessary voltage to the Arduino and all connected components.

## IV. MACHINE LEARNING METHODOLOGY

The machine learning model in this system is designed to analyze plant images and provide useful insights to the user. Initially, images of plants are captured and used as input for the model. These images are processed using MobileNet V2, a lightweight and efficient deep learning model known for its accuracy in image classification tasks. Once the images are analyzed, the results are sent to a cloud hosting platform. Hosting the model on the cloud ensures that it can handle real-time data and be accessed remotely without relying on local computational resources. Finally, the processed information is shared with the user through a URL or Telegram, allowing for easy access to the results. This setup enables a seamless and intelligent plant monitoring system that combines machine learning with cloud-based communication.

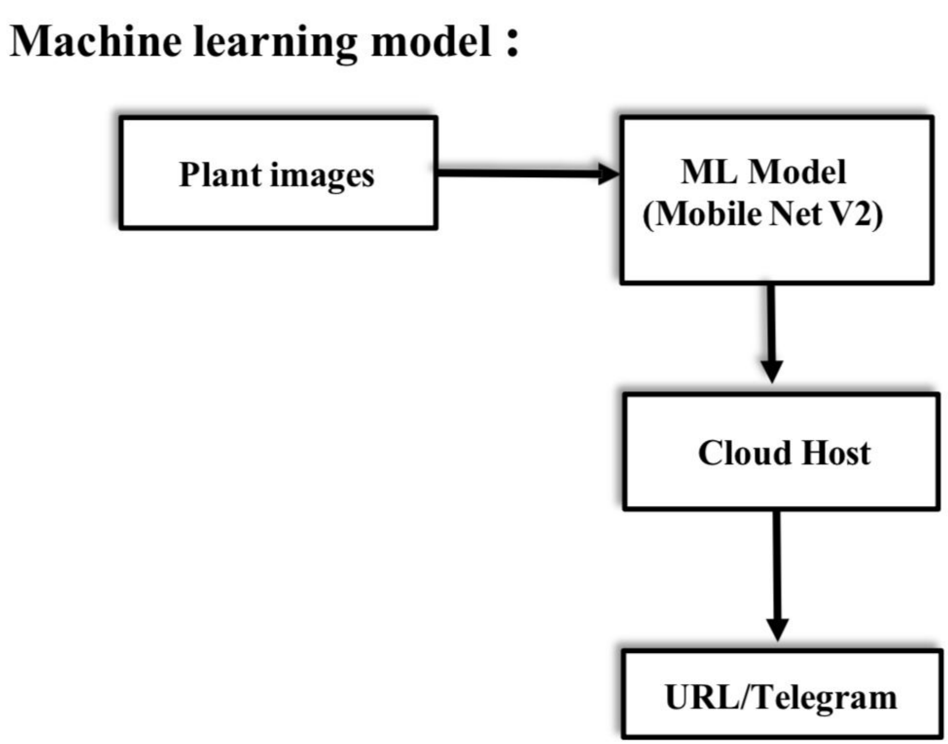


Fig. 2: MobileNetV2 Model Workflow for Disease Detection

## V HARDWARE IMPLEMENTATION

Figure 3 shows the prototype of an agricultural robot designed to assist in intelligent plant disease management. The robot is constructed using a lightweight plastic chassis, which houses the main components, including an ESP32-CAM module, a water pump, sensor modules, and an Arduino Uno microcontroller. This microcontroller serves as the central control unit, coordinating the functions of the various hardware elements.

Communication between the robot and the user is enabled through an HC-05 Bluetooth module, which links the robot to a custom-developed mobile application. This connection allows the user to receive real-time updates, monitor sensor data, and manually control specific functions such as pesticide spraying.

The ESP32-CAM module is used to capture images of the plants. These images are analyzed by an onboard machine learning model trained to recognize common plant diseases. If symptoms of the disease are detected, the system generates a notification and sends it to the user's smartphone via the Bluetooth connection. This early detection capability allows for prompt intervention, potentially reducing the spread of plant diseases and limiting crop loss.

A pesticide spraying mechanism is integrated into the robot and powered by a 12V rechargeable battery. The spraying system is activated through a relay module and managed by a motor driver, allowing controlled and precise pesticide application. Users have the option to activate this mechanism manually via the mobile app after receiving a disease detection alert.

In addition to the image-based detection system, the robot incorporates several environmental sensors. These include a light-dependent resistor (LDR) to monitor ambient light, a rain sensor to detect precipitation, and temperature and humidity sensors to evaluate environmental conditions. This supplementary data provides context for the image analysis and helps in making informed decisions about when to apply pesticides, ensuring optimal usage and avoiding application during unsuitable weather conditions.

The robot's hardware design promotes modularity, enabling future enhancements and the integration of more sensors or components as needed. The use of low-power components and a rechargeable battery ensures the robot can operate in agricultural fields for extended periods without requiring frequent recharging.

By automating disease detection and targeted pesticide application, this system contributes to more sustainable farming practices. It minimizes the excessive use of chemicals, reducing environmental impact while lowering operational costs for farmers. Furthermore, the mobile application interface offers ease of use and remote operation capabilities, empowering farmers with timely data and control over their crop management processes.

This prototype demonstrates a practical and efficient solution for precision agriculture, combining real-time monitoring, machine learning, and mobile connectivity. It serves as a foundation for further development in smart farming technologies aimed at improving productivity, reducing waste, and supporting environmentally responsible agricultural practices.

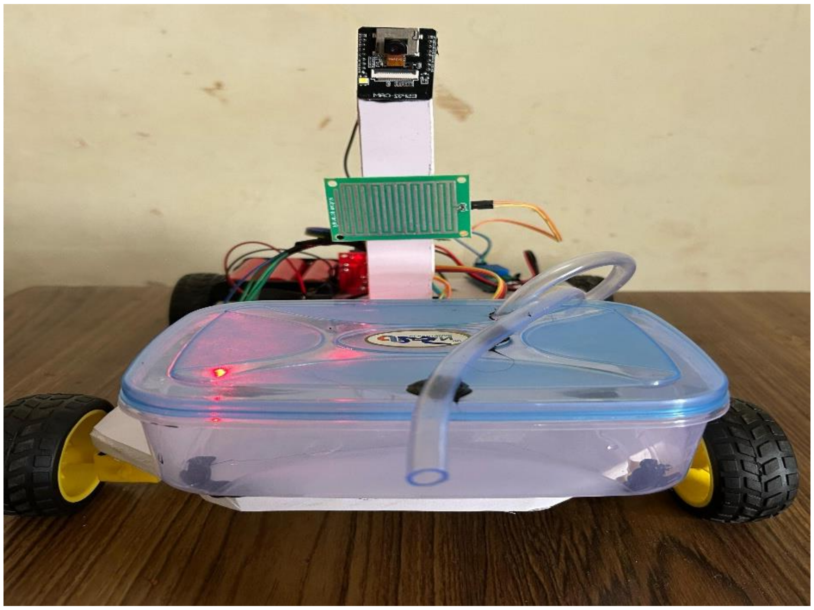

Fig. 3: Agriculture Robot Prototype

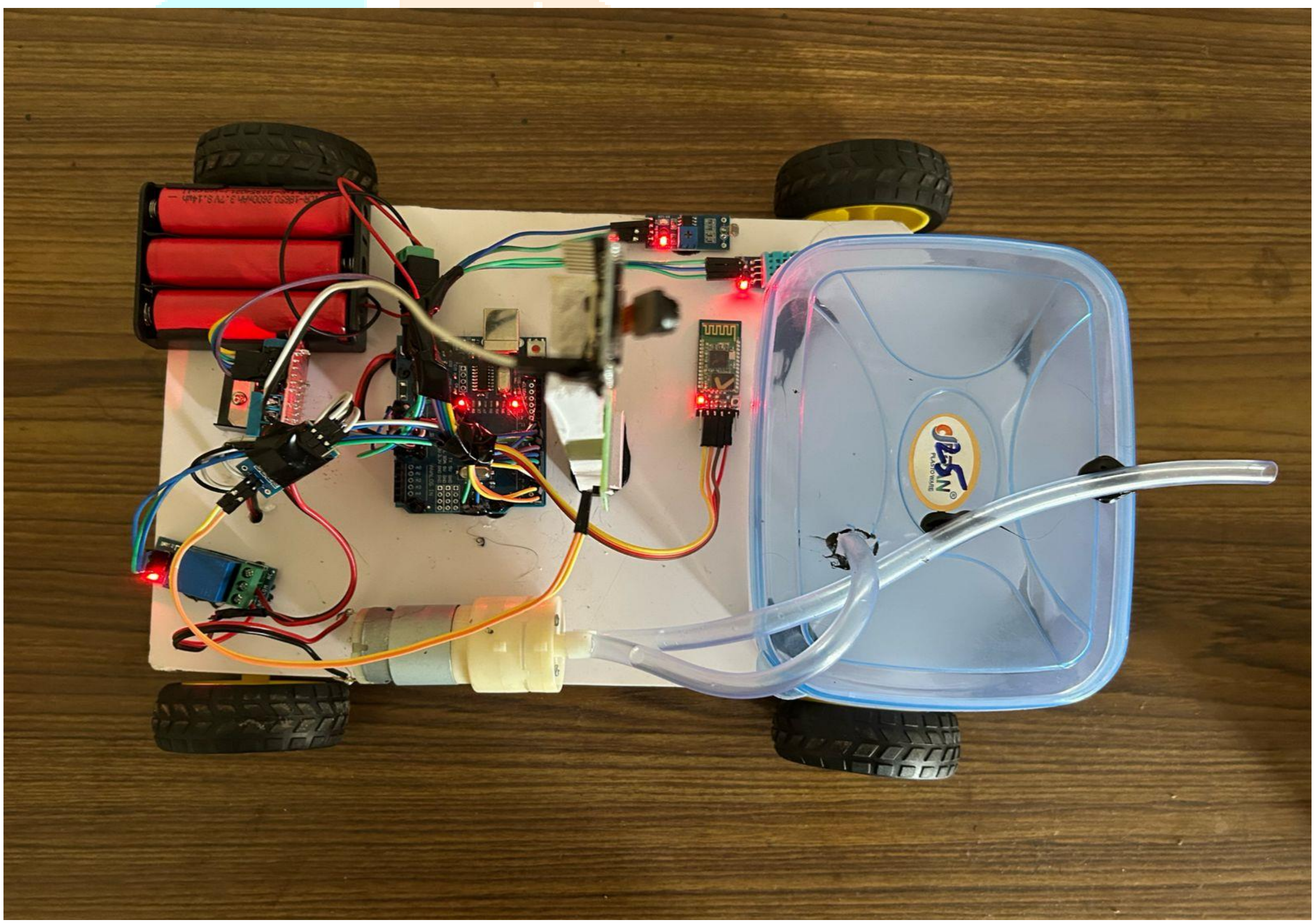

Fig. 4: Agriculture Robot Prototype (top-view)

## VI. RESULTS AND EVALUATION

The proposed system effectively combines machine learning, sensor-driven automation, and mobile communication to enhance plant disease detection and precision pesticide application. During field trials, the system successfully demonstrated its capability to identify diseases in real time using the MobileNet V2 model. For instance, an image of a tomato leaf exhibiting early blight symptoms was accurately classified by the model based on specific patterns in texture and color changes. The model's high accuracy and quick processing time on low-power devices validated its suitability for deployment in agricultural environments.

Upon detecting the disease, the system promptly generated a notification delivered to the user through a mobile application via Bluetooth. This notification included relevant disease details and enabled the user to decide whether to initiate pesticide spraying manually. This strategy empowers farmers by giving them direct control over treatment actions, promoting more thoughtful and selective chemical use.

The robot's spraying mechanism performed efficiently during tests, responding consistently to commands issued through the mobile app. The environmental context was provided by integrated sensors such as a light-dependent resistor (LDR), rain detector, and temperature and humidity sensors. These components ensured that spraying operations were only conducted under favorable weather conditions, avoiding waste and protecting the effectiveness of chemical treatments.

System evaluation focused on various performance metrics, including detection accuracy, responsiveness, user experience, and chemical efficiency. The results indicated that the platform not only enhanced the accuracy and speed of disease identification but also contributed to reduced pesticide consumption and operational costs. This targeted application approach supports environmentally responsible farming practices and aligns with sustainable agriculture principles.

Bluetooth-based connectivity played a critical role in user interaction, offering a straightforward and reliable communication method between the robot and the farmer. The intuitive mobile interface allowed easy monitoring and control, making the technology accessible even to small-scale and resource-limited farmers. By reducing complexity while maintaining functionality, the solution bridges the gap between advanced agricultural technology and real-world usability.

This integrated system represents a significant step forward in smart farming. By leveraging artificial intelligence, automation, and human decision-making, it provides a practical, scalable solution to one of agriculture's most persistent challenges—efficient and timely disease management. The platform's flexibility also allows for future upgrades, such as cloud integration or expansion to detect multiple crop diseases.

Key highlights of the proposed solution include:

1. Accurate and efficient plant disease detection using lightweight AI models.
2. Real-time alerts delivered through mobile applications.
3. Manual control over pesticide application for better decision-making.
4. Seamless integration of image processing and sensor data.
5. Substantial reduction in chemical usage and environmental impact.
6. User-friendly mobile interface designed for ease of access.
7. Scalable and cost-effective design suitable for various farm sizes.

SAMPLE RESULTS :

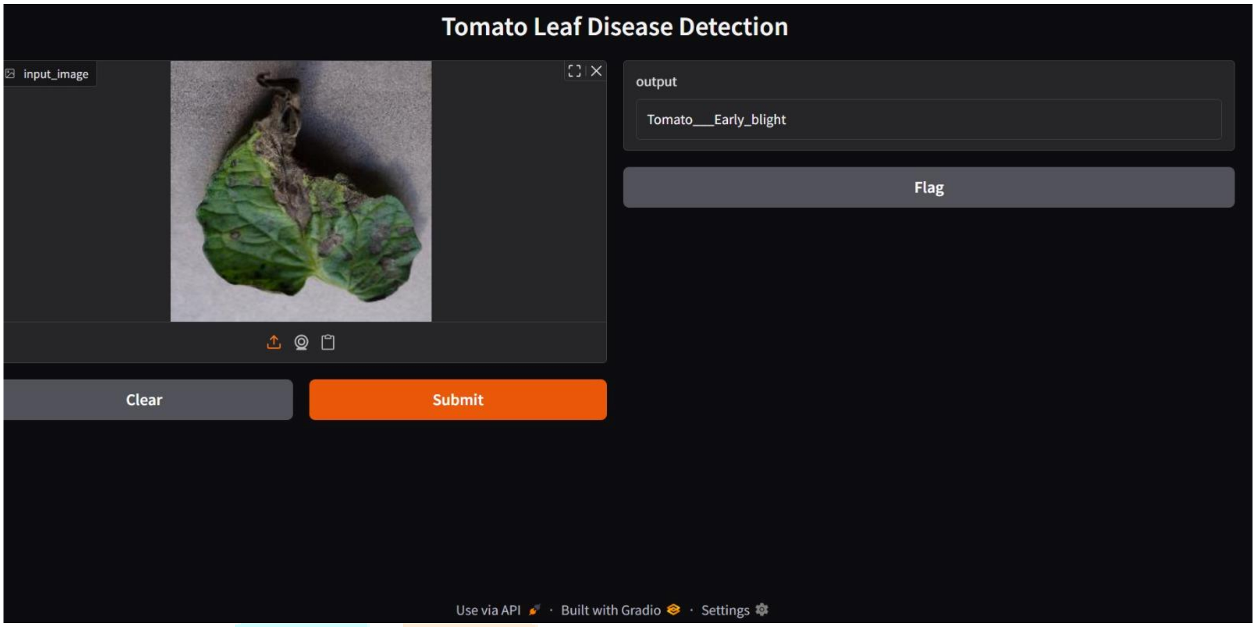


Fig. 5: Detection of Tomato Early Blight

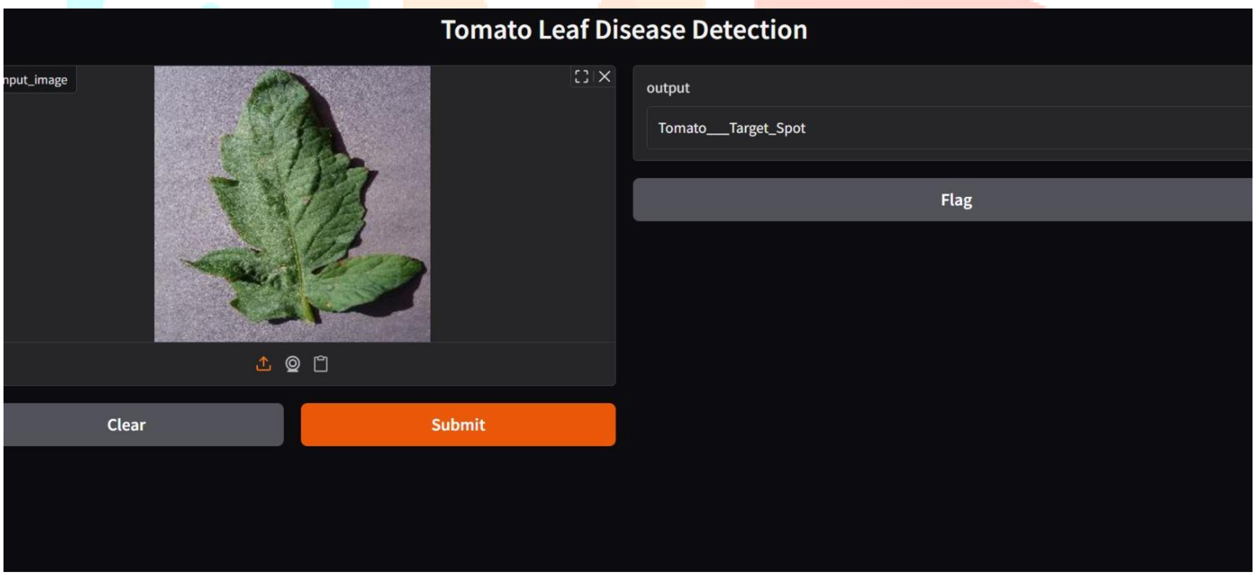


Fig. 6: Detection of Tomato Target Spot

## VII. CONCLUSION AND FUTURE SCOPE

The developed agricultural robot efficiently combines deep learning algorithms with IoT technology to support precision farming. It provides a reliable, app-based control mechanism for detecting and managing plant diseases. The system's performance in real-time diagnostics and pesticide application makes it a valuable tool for farmers seeking automation and precision.

Future developments may include:

- Implementing autonomous navigation using GPS for fully self-guided operation.
- Incorporating a solar-powered charging module to enhance energy efficiency and support off-grid usage.
- Connecting the system with cloud-based farm databases and analytics tools to enable large-scale data monitoring and predictive insights.

This smart farming solution can be customized for different types of crops, making it versatile and suitable for a range of agricultural environments.

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