iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** X **Month of publication:** October 2026

DOI: https://doi.org/10.22214/ijraset.2026.85370

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue X Oct 2026- Available at www.ijraset.com

Plant Disease Detection and Automated Spraying Robot: A CNN and IoT-Based Approach for Precision Agriculture

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Abstract: ***Agriculture is a vital sector that directly influences food security and economic stability, yet crop productivity is significantly affected by plant diseases. Traditional disease detection methods rely on manual observation, which is time-consuming, subjective, and often inaccurate, especially over large agricultural fields. To overcome these limitations, this paper presents a Plant Disease Detection and Automated Spraying Robot that integrates image processing, deep learning, and robotic automation to enable precision agriculture. The system uses a smart camera to capture real-time images of plant leaves, which are analysed using a Convolutional Neural Network (CNN) trained to classify healthy and diseased leaves such as rust, powdery mildew, and viral infections.***

Based on the detection results, an ESP32-controlled mechanism automatically activates targeted pesticide spraying, ensuring accurate and timely treatment of infected plants. Obstacle detection and navigation are managed using ultrasonic sensors and motor drivers, enabling autonomous movement across the field. Cloud integration using Firebase allows real-time monitoring through a web dashboard that displays disease type and system status. Experimental results show an average detection confidence of 76-85% and a spray-activation accuracy of 100% when disease confidence exceeds the 60% threshold, with a total system response time of under 5 seconds. The proposed system reduces manual labour, minimizes pesticide wastage, limits farmer exposure to harmful chemicals, and improves crop yield.

Keywords: Plant Disease Detection; Convolutional Neural Network (CNN); Precision Agriculture; ESP32; Automated Spraying; IoT; Firebase; Image Processing.

I. INTRODUCTION

Agriculture has always been a fundamental part of human civilization, serving as the primary source of food and raw materials. The agricultural sector continues to face severe challenges such as climate change, pest infestation, soil degradation, and particularly plant diseases that drastically reduce crop yield and quality. Early detection and proper management of plant diseases are therefore crucial to ensure sustainable crop production and food security.

Traditional plant disease detection relies mainly on manual observation by farmers, who examine plants visually to identify symptoms such as discoloration, spots, or leaf curling. This process is time-consuming, subjective, and error-prone, especially when monitoring large cultivation areas. Hence, there is a growing need for automated, intelligent systems that can detect and classify plant diseases quickly, accurately, and efficiently.

This paper presents a Plant Disease Detection and Automated Spraying Robot that integrates real-time image capture with a Convolutional Neural Network (CNN) for disease detection. Based on the analysis, a microcontroller activates a spraying system to deliver pesticides precisely to infected plants, minimizing overuse of chemicals, improving timeliness and accuracy of treatment, reducing costs, and enhancing overall crop yield. The remainder of this paper is organized as follows: Section II reviews related work, Section III states the problem and objectives, Section IV describes the proposed methodology, Section V presents hardware and software components, Section VI discusses experimental results, and Section VII concludes the paper with future scope.

II. LITERATURE SURVEY

A review of existing approaches to automated plant disease detection and spraying was carried out to identify research gaps that motivate the proposed system. Table I summarizes five representative studies.

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A. Field Survey

A field survey was conducted in the Rattihalli agricultural region focusing on Tomato, Cotton, and Brinjal crops. Farmers reported reliance on the Plantix mobile application, which diagnoses disease from a leaf photograph with 75-90% accuracy for common diseases, but performs less reliably for early-stage symptoms or poorly lit images. The survey confirmed that an automated, field-deployable detection-and-spraying system would reduce cost, chemical wastage, and manual effort compared to existing manual and app-assisted practices.

TABLE I
SUMMARY OF LITERATURE SURVEY

Author(s) / Year	Technique Used	Key Result	Limitation
Santhosh et al. [1] (2023)	Image processing + ML classification, onboard spraying	Fully automated detection and spraying for tomato, potato, chili	No infection-severity analysis; limited scalability
Kamilaris & Prenafeta-Boldu [2] (2018)	Survey of CNN/RNN/transfer learning in agriculture	Deep learning outperforms classical image processing	Lacks real-world field deployment
Sladojevic et al. [3] (2016)	Deep CNN, solar-powered platform, SMS alerts	Classification accuracy up to 98%	No autonomous navigation or spraying
Priyanka et al. [4] (2022)	CNN-based image analysis, solar power, SMS alerts	Reliable large-field disease alerts	No autonomous navigation or automatic spraying
Ramesh & Gokul [5] (2019)	Lite-MDC CNN with depthwise separable convolutions	94.14% accuracy with 62% fewer parameters than VGG16	Dataset limited to pigeon pea; spraying not integrated

The reviewed works demonstrate strong progress in disease classification accuracy using CNNs, but most systems either lack autonomous field mobility, rely on SMS-based manual intervention, or do not integrate an end-to-end detection-to-spraying pipeline. This motivates the design of a fully autonomous robot that combines real-time detection with targeted, automatic pesticide spraying.

III. PROBLEM IDENTIFICATION AND OBJECTIVES

A. Problem Identification

1) Manual identification of plant diseases is time-consuming, subjective, and prone to human error.
2) Traditional approaches provide no real-time monitoring, causing delayed treatment of fast-spreading diseases.
3) Manual pesticide spraying is labour-intensive, non-uniform, and increases farmer exposure to harmful chemicals.
4) Absence of a targeted spraying mechanism wastes chemicals, water, and labour.
5) Conventional systems provide no data logging or analytics for preventive decision-making.

B. Objectives

1) To detect plant diseases using real-time image classification via a cloud-based CNN model.
2) To automatically activate a targeted pesticide-spraying mechanism upon disease detection.

IV. PROPOSED METHODOLOGY

Overall working principle of the proposed system is illustrated in the block diagram of Fig. 1. It shows the interaction between the power subsystem, main controller, sensors, camera, cloud model, and the spraying mechanism. The camera captures real-time images that are processed by a trained machine-learning model; based on the classification result, the ESP32 generates control signals to activate the spraying unit.

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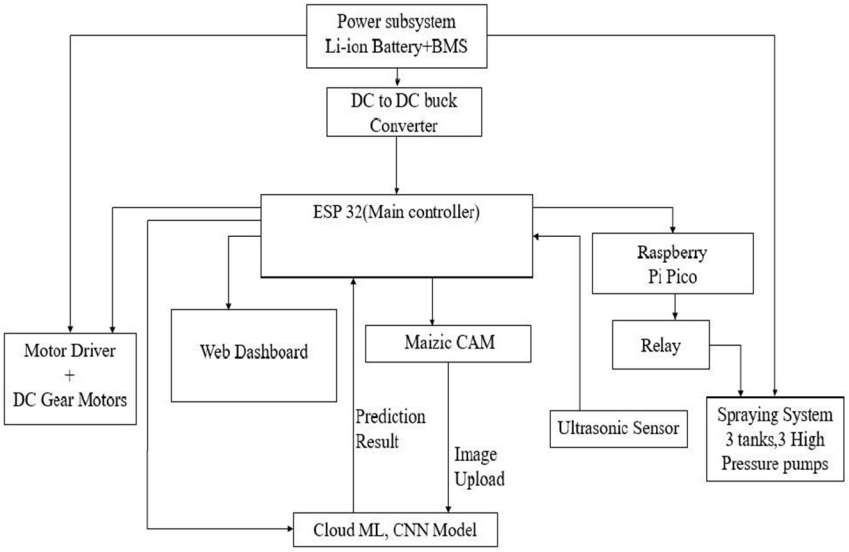


Fig. 1. Block diagram of the proposed system.

A. Data Collection and Preprocessing

Image data is obtained from two sources: the publicly available Plant Village dataset and real-time field captures using the Maizic smart camera, covering five major plant diseases along with healthy samples. All images are resized to 224×224 pixels and normalized. Noise reduction (Gaussian blur, median filtering) and conversion to grayscale/HSV colour spaces are used to extract diverse visual features. Data augmentation — horizontal/vertical flipping, rotation, zoom, and brightness/contrast adjustment — improves the model's ability to generalize to real-world field conditions.

B. CNN Model Development and Training

A custom Convolutional Neural Network is developed with multiple convolutional and pooling layers to extract low- to high-level features (texture, colour, leaf deformation), followed by fully connected layers for classification. ReLU activation is used in hidden layers and Softmax in the output layer. The model is implemented in TensorFlow/Keras. The dataset is split 80/10/10 for training, validation, and testing; the Adam optimizer and categorical cross-entropy loss are used, with dropout and early stopping to prevent overfitting. Hyperparameter tuning and transfer learning using pre-trained architectures such as ResNet50 and MobileNet are explored to further improve accuracy and reduce training time.

C. Cloud Integration

Firebase is used to host the trained model output and manage real-time communication. A RESTful API (Flask) handles communication between the ESP32 microcontroller and the cloud backend: the Maizic camera uploads an image, the model classifies the disease, and a JSON response containing the disease label and recommended pesticide is returned to the ESP32, which then triggers the corresponding spraying actuator.

D. System Flow

Fig. 2 shows the complete operational flow. After initialization, the robot continuously scans for obstacles using the ultrasonic sensor. If a plant is detected within 30 cm, the robot stops, captures an image, and uploads it to the cloud for classification. A healthy result resumes scanning; a diseased result (Rust, Powdery Mildew, or Leaf Virus) triggers the corresponding pesticide pump before the robot resumes its scanning route.

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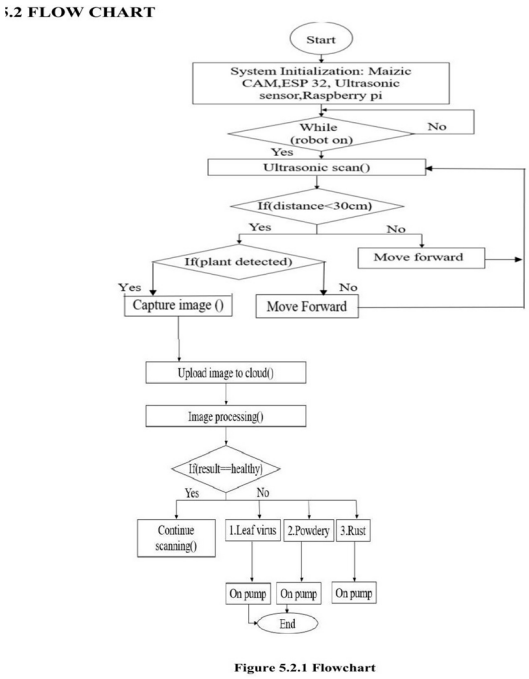


Fig. 2. Flowchart of system operation.

V. HARDWARE AND SOFTWARE DESCRIPTION

The system integrates the hardware components summarized in Table II. The ESP32 acts as the main controller, coordinating the Raspberry Pi Pico (sensor interfacing), the Maizic smart camera (image acquisition), the ultrasonic sensor (obstacle detection), and the motor driver and relay modules (locomotion and spraying actuation).

TABLE II
KEY HARDWARE COMPONENTS

Component	Key Specification	Function
ESP32	Dual-core 240 MHz, Wi-Fi + BLE, 34 GPIO	Main controller; cloud/dashboard link, actuation
Raspberry Pi Pico	RP2040 dual-core, 26 GPIO	Sensor interfacing, data acquisition
Maizic Camera	1080p PTZ, 4x zoom, IP66	Real-time leaf image capture
Ultrasonic Sensor	Range 2-400 cm, ±3 mm	Obstacle detection, navigation
Motor Driver (L298N)	6-12 V, 1-2 A/ch, PWM	Drives geared motors
Relay Module	5 V electromechanical	Switches pesticide pump
DC Geared Motor	3-12 V, multi-RPM	Wheel drive actuation

On the software side, Visual Studio Code is used as the development environment; OpenCV performs colour-space conversion, noise filtering, and feature extraction from leaf images; TensorFlow trains and deploys the CNN classification model; and Firebase provides real-time database storage and synchronization with the web dashboard.

VI. RESULTS AND DISCUSSION

The ultrasonic obstacle-detection logic and the relay-based spray-actuation logic were first validated through online simulation (Cirkit and Wokwi platforms) before hardware deployment, confirming reliable distance measurement (2-400 cm) and correct relay switching behaviour.

A. Detection Accuracy

The robot's ML-based classifier, combined with colour segmentation, was tested on healthy and diseased leaves under field conditions. Table III summarizes representative confidence scores obtained for each class.

TABLE III
DETECTION CONFIDENCE FOR DIFFERENT LEAF CONDITIONS

Condition	Detected Class	Conf. (%)
Healthy leaf	Healthy	98
Rust-infected leaf	Rust	72
Powdery-infected leaf	Powdery Mildew	65
Virus-infected leaf	Leaf Virus	62

Fig. 3 shows the live web dashboard during a Rust-detection event, displaying the bounding box around the region of interest, the disease label with confidence score, the spray status, and a time-stamped detection history log.

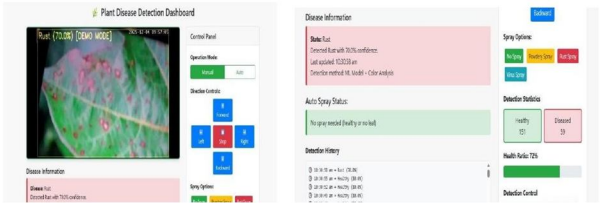


Fig. 3. Web dashboard output for rust-infected leaf detection.

B. Auto-Spraying Performance

The spraying actuator is triggered only when the detection confidence exceeds a 60% threshold, and the pesticide type is selected according to the detected disease, as summarized in Table IV. Spray-activation accuracy was measured at 100% whenever the confidence threshold was exceeded, confirming reliable coordination between the classification and actuation subsystems.

TABLE IV
DISEASE-SPECIFIC SPRAYING MECHANISM

Disease Detected	Pesticide Sprayed
Rust	Hexaconazole
Powdery Mildew	Carbendazim
Leaf Virus	Midacloprid
Healthy	No spray

C. Navigation and System Responsiveness

The robot supports both manual mode, controlled via virtual dashboard buttons with response latency under 200 ms, and autonomous mode, in which it navigates at a slow, steady pace while continuously scanning for disease. Overall system responsiveness was measured as: camera latency 100-250 ms, disease-detection time approximately 600 ms, and spray-activation delay approximately 800 ms, giving a total system response time of under 5 seconds. Average ML classification accuracy across tests ranged from 76% to 85%.

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These results confirm that the combination of CNN-based classification, colour-analysis verification, IoT dashboard monitoring, and autonomous robotic actuation provides a stable, precise, and field-deployable solution for real-time crop protection.

VII. CONCLUSION AND FUTURE SCOPE

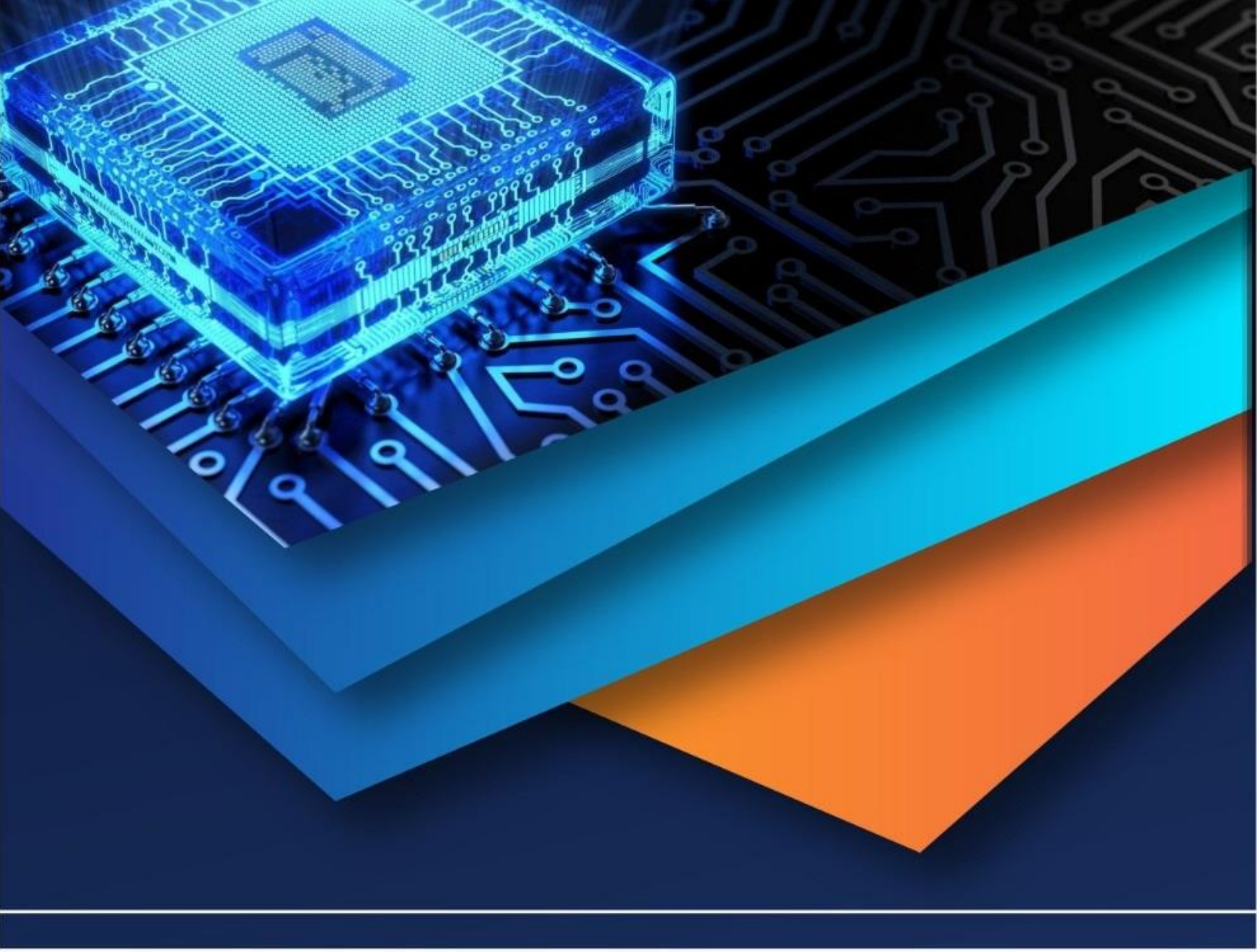
This paper presented a Plant Disease Detection and Automated Spraying Robot that integrates image processing, CNN-based deep learning, embedded control, and cloud communication to automate disease identification and targeted pesticide spraying. Experimental evaluation demonstrated reliable detection performance (76-85% average confidence), 100% spray-activation accuracy above threshold, and a total system response time below 5 seconds, while reducing manual labour, chemical wastage, and farmer exposure to harmful chemicals.

Future work will focus on fine-tuning pre-trained models with additional local crop imagery to improve accuracy, extending multi-crop and multi-disease support using the same hardware platform, incorporating GPS-based autonomous navigation, and enabling fully autonomous spray-decision-making based on confidence levels without manual oversight — advancing the system toward a complete, scalable smart-farming solution.

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