IoT-Based Autonomous Pesticide Sprinkling Rover Using Hybrid Computer Vision and Edge Computing

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Abstract*—Traditional methods of spraying pesticides often use too much chemical, which increases costs for farmers and harms the environment and people's health. This study introduces an IoT-powered autonomous rover designed for precise pesticide application in agriculture, offering a solution to these challenges. There are two controllers in the system. An ESP32-CAM module captures and handles real-time images, and an Arduino Uno manages movement and direction. A mixed computer vision approach combines Canny edge detection and HSV color space segmentation to find areas with crops and spot unhealthy leaves. Blob analysis helps tell the difference between signs of disease and natural aging in leaves, which makes it easier to judge how serious an infection is. Based on this evaluation, a customized micro-spraying method increases spraying efficiency and reduces unnecessary chemical exposure by applying pesticide only to the affected areas. The recommended technique successfully protects crops while allowing precise spraying with reduced pesticide usage, as shown by experiments done in controlled field settings. Decisions can be made instantly without the need for constant cloud connection when edge processing is integrated with IoT connectivity.

***Index Terms*—Precision agriculture, IoT, autonomous agricultural rover, computer vision, edge image processing, selective pesticide spraying, leaf disease detection.**

I. INTRODUCTION

To enhance agricultural productivity, chemical pesticides are commonly employed to shield crops from pests and diseases. Despite their ability to prevent significant yield losses, the uniform application of chemicals often results in high input costs, environmental pollution, and direct exposure hazards for farmers due to manual spraying. Much of the applied pesticide does not stick to a plant's surface but rather collects in the soil and water near the plant; this disturbs ecological balance and reduces application effectiveness. These restrictions emphasize the importance of using precise and effective methods to protect crops, which can reduce chemical usage while enhancing productivity.

Many technologies, including the Internet of Things (IoT), autonomous ground vehicles and vision-based agricultural monitoring, are now considered necessary for intelligent farm management in precision agriculture. Real-time field monitoring is made possible by IoT frameworks [1, 2], and robotic spraying systems can reduce manual labor and increase the efficiency of sprayer work [4, 5]. Images are employed in image-based disease detection methods to enable early diagnosis and targeted pesticide application, rather than disseminating treatments across the entire field. Despite being small, fragmented farms, current solutions may still require costly hardware, cloud computing, or separately implemented navigation and disease detection systems.

The paper proposes an inexpensive yet autonomous agricultural rover that can monitor crops in real time and apply specific pesticides to overcome these shortcomings. The system employs an Arduino Uno for navigation and motion control, with the ESP32-CAM module providing image acquisition and edge-level processing. The identification of infected regions is made possible by a lightweight vision pipeline that employs HSV color segmentation and Canny edge detection, with blob analysis being utilized to distinguish disease symptoms from natural leaf senescence. The proposed system combines sensors, decision-making, and action on a single platform to achieve precise spraying, reduce chemical waste, and be well-suited for precision agriculture in resource-limited farming settings.

The main contributions of these works are:

1) Creating an affordable self-driving rover that can accomplish navigation, on-road crop tracking, and selective spraying.

2) A way of diagnosing disease without the use of cloud technology in real time.

3) Despite the high detection accuracy and low response time, experimental evidence suggests that pesticide usage has significantly decreased.

II. LITERATURE SURVEY

The adoption of precision agriculture is a sustainable approach to reduce excessive reliance on agricultural products (agrochemicals) and enhance crop productivity [A]. The integration of robotics, the Internet of Things (IoT), artificial intelligence, and computer vision has resulted in automated crop monitoring and precise pesticide application. To reduce the risk of human exposure to toxic chemicals and to improve spraying efficiency, robots have been designed as a means of controlling pesticides. The use of motorized pumps and wireless control systems in semi-autonomous pest control schemes is aimed at improving operational safety by evenly dispersing pesticides.

By utilizing inexpensive sensors and network connectivity, pest monitoring systems can collect real-time field parameters through IoT technology. The use of continuous monitoring to determine crop health and pest activity across vast areas enables decision-making from the data. Though low input cost and remote monitoring are desirable, most platforms rely on cloud infrastructure rather than autonomous field mobility for real-time actuation.

Through the use of vision, autonomous agricultural vehicles can now utilize both navigation control and machine vision to spray crops in specific locations. These systems provide better crop coverage and spraying accuracy than conventional systems. However, they are mainly used in controlled settings like greenhouses and involve more expensive setup.

Computer vision and deep learning have made the detection of plant diseases more dependable. Preprocessing, feature extraction, and classification are used in multi-stage image processing to identify infected leaves earlier without waiting for the pesticide to be applied. However, many of these methods require very large amounts of computational resources and processing in the cloud, which adds to latency, and are therefore not suitable for low-cost farming environments.

Edge computing, which aims to overcome the limitations of cloud-based applications, has become a new standard in agricultural automation. Unlike traditional methods of signal conditioning, edge-based systems use data processing near the sensing unit to improve energy efficiency and reduce communication delays for real-time decision-making in remote farming areas. This method enables mobile agricultural robots to function with minimal network requirements and maintain reliability.

Integrated crop management systems with IoT, AI, and robotic platforms for automated monitoring and spraying have been the focus of recent research. In Table I, the current systems are compared against each other.

TABLE I *Comparison of Current Systems with the Proposed IoT-Enabled Autonomous Rover*

Parameter	IoT Mon.	Vision Spray	Cloud Det.	AI Spot	Proposed
Autonomous Navigation	✗	✓	✗	✓	✓
Real-Time Processing	Limited	✓	High latency	✓	✓
On-Board Processing	✗	✓	✗	Partial	✓
Targeted Spraying	✗	✓	✗	✓	✓
Chemical Optimization	Limited	Moderate	Indirect	High	High
System Cost	Moderate	High	Moderate	High	Low

However, the majority of current techniques rely on expensive hardware, high-power processors, or complex navigation systems, which limit their implementation in small and fragmented landholdings. Moreover, numerous systems handle either disease detection or automated spraying on their own and fail to offer a compact platform that integrates autonomous mobility with integrated on-board image processing and need-based pesticide application.

Therefore, an affordable autonomous agricultural rover that can integrate IoT connectivity, edge-based image processing, hybrid computer vision techniques, and selective micro-spraying into a single platform for real-time precision pesticide application is required.

This gap is addressed by the proposed system, which aims to make it affordable for small and marginal farmers.

III. RESEARCH GAP

The integration of sensing technologies, data analytics, robotics, and machine learning has made precision agriculture possible for crop monitoring, disease detection, and yield prediction, as well as automated input application with high spatial accuracy. Multispectral or hyperspectral sensors, drone-based imaging, IoT-enabled field monitoring, and cloud-connected decision platforms are commonly employed to enable data-driven farm management [1]–[3]. In large-scale farming environments [2], these technologies demonstrate significant potential for enhancing productivity, resource efficiency, and environmental impact reduction.

Small and marginal farmers are not able to adopt these solutions. High-resolution imaging devices, environmental sensor networks, and GPS-enabled machinery required for complete field coverage are among the costly sensing infrastructure challenges [5], [6]. Moreover, many systems today use cloud computing to process images and make decisions, but this leads to frequent operational costs, more energy used, and latency due to poor network reliability in outlying agricultural communities [6], [7]. Also, the implementation of machine learning and deep learning models on low-power embedded platforms is challenging due to high computational requirements in real-time field applications [8].

A significant research gap exists due to the inability of researchers to distinguish between disease detection and pesticide application. Numerous publications are focused on identifying crop stress and diseases through image analysis [3], [9], while others examine automated spraying mechanisms [10]. These components are usually created as separate modules rather than a unified closed-loop system. Therefore, there is a delay between detection and action, and the response is typically applied at the field level rather than at each individual plant level, which results in reduced efficiency of selective treatment and excessive chemical consumption [9], [10].

Small and marginal farmers are still unable to operate current precision agriculture systems due to high initial investment, ongoing maintenance expenses, the reliance on reliable internet connections, and system complexity. A precision agriculture platform that is cost-effective, integrated, and self-sufficient to handle sensing, decision-making, and actuation on low-power embedded hardware is necessary to overcome these challenges.

IV. PROPOSED FRAMEWORK

A structured Sense–Think–Act framework is employed in the proposed system to enable real-time crop monitoring and targeted pesticide usage. It combines visual sensing, lightweight image analysis, decision generation, and physical actuation into a continuous processing pipeline. The focus is on utilizing computationally efficient techniques to ensure reliable operation on low-power embedded hardware while maintaining plant-level detection accuracy under field conditions.

A. Operational Workflow

While in the field, a rover traverses the crop row while the vision module captures images at predetermined intervals. Every frame is transmitted to the processing unit for logical analysis. If infection is detected, the rover stops briefly for targeted spraying, then resumes navigation. The complete processing pipeline is: image acquisition → preprocessing → leaf segmentation → morphological feature extraction → disease detection → ripening–infection differentiation → decision generation → actuation control. Continuous monitoring and plant-specific intervention are made possible by this cyclic process.

B. Image Acquisition and Preprocessing

The use of an ESP32-CAM for image acquisition at a spatial resolution of 320×240 pixels allows for balancing processing speed, transmission latency, and diagnostic detail [11]. In order to improve feature reliability in different lighting and background conditions, the captured RGB image undergoes: (i) Gaussian filtering for noise suppression, (ii) contrast normalization for illumination consistency, and (iii) grayscale conversion for contour-based analysis. This stage ensures stable performance in real-field environments characterized by shadows, non-uniform lighting, and soil interference [12].

C. Leaf Segmentation Using Contour Detection

Region of interest extraction is done to separate the leaf from the background. Binary thresholding is applied to the grayscale image, followed by contour detection using border-following algorithms [11]. The contour with maximum area is chosen as the leaf region:

$$C_{lea}^{i} = max(Area(C_i))$$

This is a valid assumption since the target leaf occupies the major part of the captured frame [11]. The segmented region is then utilized for morphological and disease analysis, thus eliminating computational overhead and irrelevant background information [13].

D. Morphological Feature Extraction for Crop Identification

Lightweight geometric features are calculated from the segmented leaf to differentiate between monocot and dicot patterns without the requirement for sophisticated classifiers [13].

1) Aspect Ratio

$$AR = L / W$$

where L and W denote the lengths of the major and minor axes, respectively. AR > 3 → monocot leaf; AR ≤ 3 → dicot leaf.

2) Solidity

$$Solidity = A_{lea}^{i} / A^{conv_{e}^{x}}$$

Lower values of solidity indicate irregular or lobed leaf patterns [3]. The above features allow for the distinction of crop type based on computationally inexpensive operations [3].

E. Disease Detection Using Color and Structural Features

1) HSV Color Space Transformation

To make the system less dependent on variations in illumination, the segmented RGB image is converted to the HSV color space [3]:

$$I^{H}_{sv} = f(I^{BGB})$$

A hue-based mask is applied within the range 20° ≤ H ≤ 40°, which corresponds to yellow–brown lesion tones commonly associated with plant diseases [2].

2) Structural Damage Detection Using the Canny Operator

Color information alone can cause false positives because of natural pigmentation changes. Hence, the Canny edge detector is used to detect structural discontinuities due to pest damage, holes, or tissue degradation [11]. The combination of chromatic and structural information greatly enhances the reliability of detection [2].

F. Ripening–Infection Differentiation Using Blob Analysis

To prevent unnecessary pesticide application, the spatial distribution of infected regions is analyzed through blob detection. Let N^b represent the number of detected blobs [11]: a small number of large, uniform regions indicates natural ripening, while multiple small, scattered regions indicate infection. This strategy minimizes false actuation and supports responsible chemical usage [7].

G. Decision-Making Algorithm

The classification outcome is translated into control commands using a deterministic logic structure [7]: IF infection detected → stop rover, activate pump, spray for calculated duration, resume navigation; ELSE → continue navigation. This approach ensures fast execution and predictable real-time behavior [8].

H. Spray Duration Calculation

The spray duration is determined from the calibrated pump flow rate [6]:

$$T_s = V_{re}^{\varphi} / F_r$$

where T_s is the spray time, V_{re}^{φ} is the required pesticide volume, and F_r is the pump flow rate. This enables variable-rate and plant-specific pesticide application [6].

I. Real-Time Actuation and Navigation Control

Upon receiving the actuation command, the Arduino halts rover motion, the relay is triggered, the pump is activated for the computed duration, spraying is completed, and the rover resumes path tracking. Continuous feedback from IR sensors ensures accurate trajectory maintenance throughout operation [14].

J. Computational Efficiency

The proposed methodology intentionally excludes deep learning-based approaches to minimize computational complexity and enable reduced processing latency, low power consumption, and reliable real-time performance on embedded platforms [3], [9]. These characteristics improve economic feasibility and support practical deployment, particularly in small-scale agricultural environments where energy efficiency and cost constraints are critical [1], [15].

K. System Architecture

The system architecture of the proposed autonomous precision agriculture platform is illustrated in Fig. 2. It is layered and designed to ensure modularity and real-time performance, with efficient interaction of sensing, decision-making, and actuation components.

The user interface layer at the top enables remote system management, data processing, and supervisory control commands via mobile or web-based applications. The decision layer performs computational tasks including image processing, disease detection, and control logic execution. Through a cloud-based interface using TCP/IP, the computational modules and field hardware communicate bidirectionally. At the edge device layer, the Arduino Uno manages navigation control and actuators while the ESP32-CAM handles image acquisition and streaming. The physical layer includes DC pumps regulated by relay modules and IR sensors for line-following navigation.

V. RESULTS AND PERFORMANCE EVALUATION

The designed autonomous agricultural rover was tested in a controlled experimental setup to assess its capability to detect diseases and act accordingly, along with the effective use of pesticides. A total of 100 leaf samples, both healthy and diseased, were considered for the analysis. The experiment was performed on the basis of three primary parameters: classification accuracy, response time, and pesticide usage.

A. Classification Accuracy

The proposed image processing method resulted in a classification accuracy of 92% for infected and senescent leaves (Fig. 3). The feature-based detection technique performed well and remained consistent as the number of samples increased. The entire response time from image acquisition to spray activation was 1.5 seconds, even though the rover was traveling at a steady speed of roughly 0.2 m/s. This very short response time allows the rover to spray at the infected area precisely without missing the target region.

B. Pesticide Consumption

Fig. 4 compares the use of blanket spraying and selective spraying with their respective pesticide consumption. The implementation of targeted spraying resulted in a significant reduction in chemical usage. The proposed system conserved approximately 65% of pesticide, while avoiding more than 80% of unnecessary spraying by applying chemicals only when infection was detected.

C. Confusion Matrix Analysis

The confusion matrix in Fig. 5 summarises the classification outcome on the full 100-sample test set. The system correctly identified 46 of 50 infected leaves (true positives) and 46 of 50 healthy leaves (true negatives), yielding 4 false positives and 4 false negatives. The symmetric error distribution indicates that the model does not bias toward either class, which is desirable for balanced precision-agriculture deployment where both missed infections and unnecessary spraying carry significant costs.

TABLE II *Detailed Classification Metrics*

Class	Precision	Recall	F1-Score	Support
Infected	0.920	0.920	0.920	50
Healthy	0.920	0.919	0.919	50
Macro avg	0.920	0.920	0.920	100
Weighted avg	0.920	0.920	0.920	100

D. Precision, Recall and F1-Score

Both the Infected and Healthy classes achieve an F1-score of approximately 0.920, reflecting a well-balanced classifier. The near-unity precision-recall balance—0.920/0.920 for the Infected class and 0.920/0.919 for the Healthy class—demonstrates that the blob-based ripening-infection differentiator effectively suppresses false actuation caused by natural leaf senescence. The macro-averaged F1-score of 0.920 confirms that the lightweight feature pipeline achieves competitive performance despite intentionally excluding deep learning.

E. System Response Time Breakdown

The complete detection-to-actuation pipeline completes in 1,500 ms (1.5 s). Preprocessing and segmentation accounts for the largest share (420 ms), followed by disease-feature extraction (620 ms combined). Image acquisition contributes 180 ms, and actuation command transmission adds a final 220 ms. The decision logic itself takes only 60 ms owing to the deterministic IF-ELSE rule structure. This low overall latency ensures that even at 0.2 m/s rover speed, the system can halt and position the spray nozzle over the detected region before it passes out of range.

F. Pesticide Consumption Reduction

Fig. 7 compares pesticide consumption between the conventional blanket-spraying method (100% baseline) and the proposed selective micro-spray. The selective approach consumes only 35% of the chemical required for uniform coverage, representing a 65% reduction. Over 80% of plants that were healthy received no chemical treatment whatsoever. This result is consistent with the blob-analysis decision gate, which withholds actuation when spatial distribution indicates natural ripening rather than infection. At field scale, a 65% reduction in chemical usage directly translates to lower input costs and significantly reduced soil and water contamination.

G. Overall Performance Summary

Table III consolidates the measured performance indicators across all evaluation dimensions, confirming that the proposed system meets all design targets.

TABLE III *Summary of System Performance Metrics*

Parameter	Measured Value
Classification Accuracy	92.0 %
Precision (Infected / Healthy)	0.920 / 0.920
Recall (Infected / Healthy)	0.920 / 0.919
F1-Score (Infected / Healthy)	0.920 / 0.919
End-to-End Response Time	1,500 ms (1.5 s)
Pesticide Reduction	65 %
Unnecessary Spray Avoidance	> 80 %

VI. CONCLUSION

This work demonstrates the feasibility of a low-cost autonomous rover for precision pesticide application using a distributed IoT architecture [1], [8]. The integration of edge-based image acquisition, morphological feature analysis, and targeted spraying enables real-time crop monitoring and selective chemical application [7], [11]. The system achieved high classification accuracy with low latency while significantly reducing pesticide consumption. The use of affordable hardware components makes the solution suitable for small-scale farming and supports the adoption of sustainable agricultural practices [1]. Experimental evidence indicates that reliable decision-making can be achieved without the need for high-performance computing resources or continuous cloud connectivity [3], [9]. The modular design of the platform allows easy adaptation to different crop types and field layouts. In addition, the reduction in manual intervention improves operator safety and ensures consistent spraying performance [4], [5]. The proposed approach demonstrates that intelligent automation at the field level can bridge the gap between conventional farming and modern precision agriculture, particularly in resource-constrained environments [1], [15].

REFERENCES

[1] K. Sharma et al., “Integrating artificial intelligence and Internet of Things for precision agriculture: Recent advances and future challenges,” Smart Agricultural Technology, 2024.

[2] M. Majdalawieh et al., “Precision agriculture in the age of AI: A systematic review of disease detection techniques,” Smart Agricultural Technology, 2025.

[3] S. U. Khan et al., “A review on automated plant disease detection using machine learning and deep learning,” Journal of Agriculture and Food Research, 2025.

[4] M. González-de-Soto et al., “Autonomous systems for precise spraying: Evaluation of a robotised patch sprayer,” Biosystems Engineering, vol. 146, pp. 165–182, 2016.

[5] D. G. Koc et al., “AI-powered autonomous orchard spraying robot for precision agriculture,” Journal of Agricultural Engineering, 2025.

[6] H. Hejazipoor et al., “An intelligent spraying robot based on plant bulk volume for variable-rate application,” Computers and Electronics in Agriculture, 2021.

[7] Y. Bouhaja et al., “Mobile robot for leaf disease detection and precise spraying in real time,” Smart Agricultural Technology, 2025.

[8] F. M. Talaat et al., “IoT-integrated robotic system for automated plant disease detection and treatment,” Scientific Reports, 2026.

[9] Md. R. K. Shuvo et al., “An autonomous agricultural robot for plant disease detection using convolutional neural networks,” 2025.

[10] "Smart agriculture robot for plant disease detection and targeted pesticide spraying," International Journal of Scientific Research in Engineering and Technology, 2025.

[11] "Agni: A plant disease detection robot using image processing," International Journal of Engineering Research and Technology, 2023.

[12] A. S. Ibrahim et al., "AI-IoT based smart agriculture pivot for plant disease detection and treatment," Scientific Reports, 2025.

[13] R. Inamdar et al., "Precision pest and disease detection system using IoT and AI," 2023.

[14] Y. Du et al., "A low-cost autonomous robot for weed control with vision-based navigation," arXiv, 2021.

[15] A. Pretto et al., "Building an aerial–ground robotic system for precision farming," IEEE Robotics and Automation Letters, 2019.