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IMAGE PROCESSING BASED PLANT FERTILIZER SPRAYING ROBOT

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Abstract: *The application of smart technologies in agriculture has transformed conventional farming practices, significantly increasing productivity and sustainability. In this research, we propose a novel method of agricultural automation through the development of an Autonomous Plant Spraying Robot. The system integrates Raspberry Pi and ESP32 microcontrollers along with servo motors to provide a flexible and robust solution for various agricultural operations. The Raspberry Pi functions as the central processing unit, offering substantial computational power and connectivity for real-time data processing and decision-making. The ESP32 microcontroller manages wireless communication and sensor integration, enabling remote monitoring and control of agricultural activities. Servo motors are employed for precise and efficient actuation, allowing the robot to carry out tasks such as spraying, irrigation, and harvesting with high accuracy and consistency. Key features of the project include modular design, scalability, and ease of customization. By leveraging open-source hardware and software platforms, the system remains adaptable and easily integrated with existing agricultural machinery and infrastructure. Furthermore, the use of servo motors enables the robot to navigate a variety of terrains and complex environments, broadening its applicability across diverse farming practices and landscapes. Through field testing and performance evaluation, we demonstrate the effectiveness of the robotic system in enhancing operational efficiency, reducing labor costs, and minimizing environmental impact. Future developments will focus on system optimization, integration of advanced sensing technologies, and real-world deployment to maximize its contribution to global food production.*

Keywords: *Smart Farming, automation, plant spraying robot, Raspberry Pi, image processing, machine learning.*

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1. Introduction

Agriculture continues to be the backbone of many economies, especially in developing nations, where a majority of people depend on farming for their livelihoods. A persistent

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challenge in this sector is the early detection and accurate diagnosis of plant diseases. If left untreated, such diseases can lead to major yield losses and threaten food security, with far-reaching economic consequences (Sibiya & Sumbwanyambe, 2023; Agarwal et al., n.d.). Traditional methods of identifying diseases rely on manual inspection by agricultural experts, a process that is slow, error-prone, and impractical for large-scale farming (Mahajan & Patil, 2024; Ahmad et al., 2020).

Recent advancements in artificial intelligence (AI) and computer vision have made it possible to automate plant disease detection with high precision. Convolutional Neural Networks (CNNs), in particular, have emerged as powerful tools capable of learning complex visual patterns in crop leaves (Hamuda, Glavin, & Jones, 2016). Li, Zhang, and Wang (2023) emphasized that CNN-based approaches consistently outperform traditional machine learning methods for agricultural diagnostics. Similarly, Kulkarni et al. (2022) demonstrated that integrating image processing with learning algorithms significantly enhances the recognition of disease symptoms. These findings are further reinforced by Chai et al. (2023), who successfully applied CNNs to diagnose tomato leaf blight, underscoring the value of computer vision in precision agriculture.

Additional studies provide evidence of CNN superiority over manual inspection. Singh et al. (2023) and Tiwari et al. (2022) confirmed that CNN-based frameworks improve both speed and consistency in disease recognition tasks. Kumar and Sharma (2021) further showed that hybrid deep learning models combining CNN and LSTM can improve stage-wise disease detection in crops. More recently, Wang et al. (2023) demonstrated the effectiveness of CNN-powered mobile applications in providing farmers with low-cost, accessible disease identification solutions, while Zhou et al. (2023) highlighted how transfer learning enhances cross-crop adaptability, making detection systems more scalable. Li, Zhang, and Wang (2021) also reviewed the state of CNN-based classification systems, supporting their reliability and robustness in real-world agricultural applications.

The growing body of research reflects a shift toward more generalizable and resource-efficient systems. Ngugi et al. (2024) surveyed deep learning applications in agriculture and noted how these methods have transformed disease diagnosis. Mustofa et al. (2023) emphasized the importance of CNN-based systems in detecting leaf pathologies under varying environmental conditions. Chougui et al. (2022) and Yilmaz et al. (2025) reviewed smart agriculture technologies and identified deep learning as the cornerstone of plant disease classification. Riyanto et al. (2025) outlined future research challenges, particularly in improving dataset diversity and model generalization for real-world deployment. Chen et al. (2024) explored edge-computing solutions to deploy deep learning models for real-time disease detection in low-resource environments. Becker et al. (2024) further demonstrated the integration of UAV-based aerial imaging with AI for mapping disease hotspots, highlighting the synergy of aerial and ground-level monitoring.

The integration of AI with agricultural robotics has opened new avenues for automation in farming operations. Agarwal et al. (n.d.) introduced a multifunctional AgriBot capable of real-time plant monitoring and treatment, illustrating the feasibility of mobile robotic platforms for disease detection. Ahmad et al. (2020) and Mohapatra & Mohapatra (2020) reviewed agricultural robots that reduce labor dependency and enhance operational efficiency. Pratihar et al. (2025) reported the development of autonomous pest-control robots for monitoring crops and administering pesticides. Fernandes et al. (2023) described swarm robotics in greenhouse monitoring, emphasizing scalability in controlled environments.

More recent explorations have combined reinforcement learning for navigation in complex agricultural environments (Li & Sun, 2022) and multimodal AI-IoT integration for plant health monitoring (Mohapatra & Panda, 2019). Additionally, Li, Zhang, and Wang (2023) highlighted the importance of real-time adaptability in CNN models for dynamic field conditions. Collectively, these studies demonstrate the shift toward intelligent, scalable, and field-ready agricultural systems, promising improvements in productivity, sustainability, and food security.

Building on these insights, the present study proposes a deep learning-based system for plant disease detection and classification. The objective is to design a robust and scalable framework that supports farmers in early disease identification, thereby improving crop yield and promoting sustainable agricultural practices.

2. Methodology

2.1. Prototype model

2.1.1. Hardware connection

In recent years, agricultural practices have undergone a significant transformation with the adoption of advanced technologies aimed at improving efficiency, productivity, and environmental sustainability. One such innovation is the development of autonomous robots for precision farming. The Sprinkling Robot exemplifies this advancement by integrating robotics with artificial intelligence to streamline crop management processes. This autonomous system is designed to monitor and maintain plant health by employing a Raspberry Pi, which is paired with a camera to capture real-time images of crops. These images are then processed using machine learning techniques to distinguish between healthy and diseased plants. By enabling timely and targeted interventions, this smart monitoring system minimizes the need for manual labor while contributing to improved crop yields and resource optimization.

The methodology for developing a smart agribot using image processing involves an integrated approach that combines computer vision, machine learning, and robotic control systems to automate essential agricultural tasks such as crop monitoring, disease identification, weed detection, and targeted spraying. The robot is equipped with a camera that captures real-time images of plants and leaves. These images are then analyzed using image processing algorithms to detect variations in leaf color, which are indicative of the plant's health status.

The captured data is processed by a Raspberry Pi, which serves as the central processing unit. It stores and analyzes the visual information to determine the appropriate response. For instance, if the system detects that the leaf color has turned yellowish or unusually dark—signs commonly associated with nutrient deficiency or disease—the robot initiates an automated response by spraying the required fertilizers or plant care solutions. Figure 1 represents the basic block diagram.

This automated detection and response mechanism significantly reduces the reliance on manual observation and intervention, enhancing precision in crop care and minimizing the risk of human error. Ultimately, the proposed system offers a cost-effective and intelligent solution to support sustainable farming practices and improve overall crop yield.

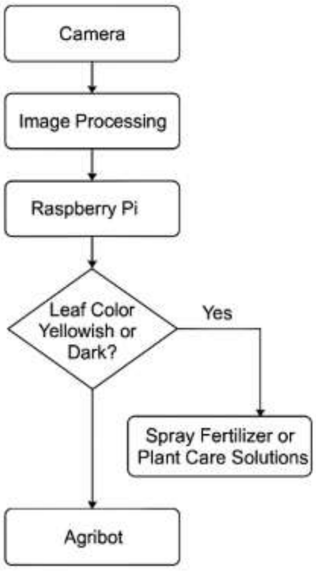

Figure 1. Block diagram of image processing-based smart spraying system

The heart of the system is a Raspberry Pi coupled with a webcam to capture real-time images of plants. These images are processed using computer vision algorithms to assess plant health parameters such as hydration levels, disease detection, and growth trends.

2.1.2. Actuator Control

For actuator control, the Raspberry Pi communicates with an ESP32 microcontroller via GPIO pins (pins 9 and 11 connected to ESP32 pins 15 and 16). The ESP32 acts as an intermediary, relaying commands to two motor drivers.

Motor driver 1 which Controls four servo motors to enable precise robotic movement and row navigation in the farm field. Motor driver 2 which Operates a water pump, facilitating automated irrigation based on plant health data.

This hierarchical design ensures low-latency coordination between the Raspberry Pi (decision-making), ESP32 (real-time control), and the actuators (motors and pump). By integrating machine vision with embedded automation, the system achieves autonomous operation, optimizing resource usage based on real-time plant diagnostics.

Figure 2. Automated plant inspection robot

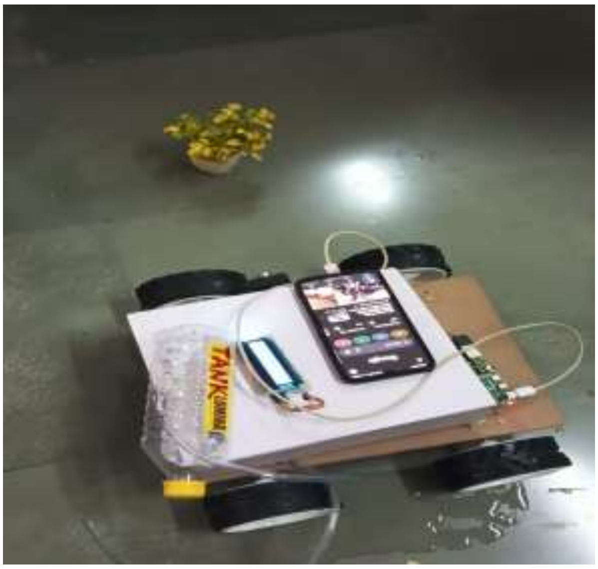

Figure 3. Prototype of automated plant inspection robot

Figure 2 and figure 3 represents the prototype model and it can automatically inspection the plant and spraying water as per the instruction given.

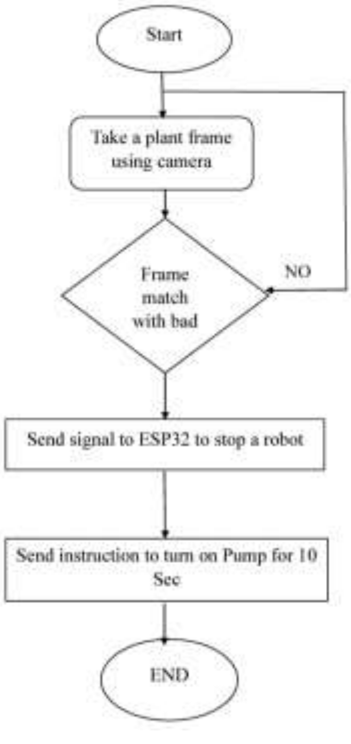

Figure 4. Flow chart smart farming system for defective plant management

Figure 4 is the flowchart which illustrates an automated system designed for detecting and addressing anomalies in plants. The process initiates with a camera capturing an image, or "frame," of a plant. This captured frame is then analyzed to determine if it exhibits characteristics indicative of a "bad" or problematic plant, such as signs of disease, pests, or improper growth. Should the analysis confirm a "bad" match, a signal is transmitted to an

ESP32 microcontroller, which in turn commands a robot to halt its movement. Following the robot's stop, an instruction is sent to activate a pump for a duration of ten seconds, presumably to administer a targeted treatment like a pesticide, nutrient solution, or water. If the plant frame is deemed healthy, the system cycles back to capture another frame, continuously monitoring plants in a repetitive loop. This entire sequence highlights an efficient, automated approach to plant health management, moving from detection to a specific, timed intervention. Table 1 is the observation during the experiment.

Table 1. Observation during the experiment

Plant	Observation
Plant Detection Accuracy	65%
Camera module resolution	640 x 480
Frame rate	30FPS
Delay in detection	1 sec
Scanning and data processing delay	2 sec
Maximum distance from plant to get better accuracy	3 feet
Image taken form garden plants based upon color	58 Images
Plant Detection Accuracy	65%

3. Outcomes of proposed model

The findings, as illustrated in Figure 7, show that the robot correctly identifies a healthy plant based on its green coloration. In contrast, Figure 6 demonstrates that upon detecting an unhealthy or "bad" plant—characterized by yellow leaves—the robot halts its movement, indicating successful implementation of the plant health assessment and response mechanism.

Subsequently, a pump is activated for ten seconds to dispense water onto the identified plant. Conversely, if a healthy plant is recognized, the robot simply confirms its status as a good plant, and the pump remains inactive. The field of smart agriculture robots is experiencing significant growth, with diverse applications emerging for farming, gardening, and nursery operations. These automated machines offer substantial advantages by lowering agricultural production costs, minimizing manual labor, and fostering more efficient and accelerated crop cultivation. Furthermore, smart agriculture robots can be effectively utilized for tasks such as fertilizer application and general plant maintenance in various garden settings.

Figure 5. Prototype model with small plant

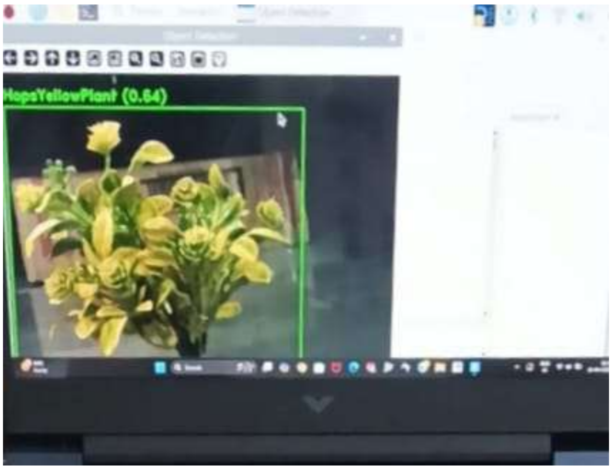

Figure 6. Image analysis with machine learning algorithm for unhealthy plant

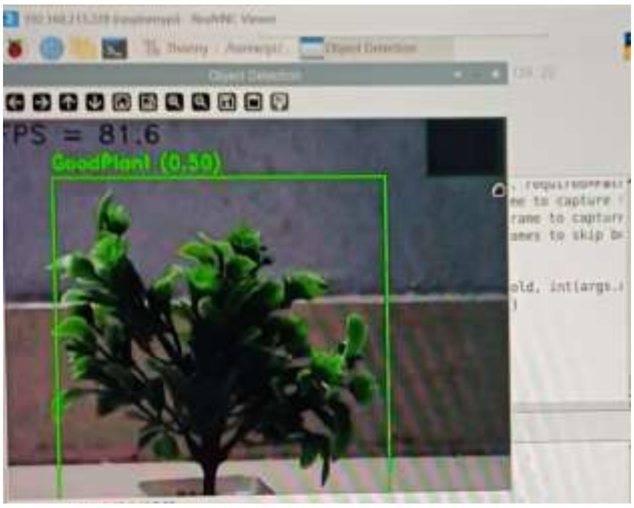

Figure 7. Image analysis with machine learning algorithm for healthy plant

4. Future scope

The automatic plant fertilizer robot, as conceptualized, holds significant future potential, particularly in advancing precision agriculture. By incorporating sophisticated image recognition and machine learning capabilities, such a robot can accurately assess plant health, pinpoint specific nutrient deficiencies, and apply fertilizers with remarkable precision, thereby minimizing waste. As sensor technology and artificial intelligence continue to evolve, these systems are poised to become increasingly autonomous, economically viable, and adaptable, broadening their accessibility to both large-scale agricultural operations and smaller farms. Furthermore, the integration of real-time data analytics, cloud connectivity, and the Internet of Things (IoT) will enable intelligent decision-making and remote oversight. This will ultimately contribute to enhanced crop yields, reduced environmental impact, and the widespread adoption of sustainable farming practices. This innovative technology directly supports global initiatives focused on sustainable agriculture and ensuring food security, marking it as a critical domain for future development.

5. Conclusion

The successful development and implementation of the autonomous intelligent farming robot underscore its potential to revolutionize modern agricultural practices. By combining computer vision, embedded systems, and automation into a cohesive and field-deployable platform, the study demonstrates a practical approach to precision agriculture. The integration of a Raspberry Pi for real-time plant health monitoring—based on leaf color analysis—alongside an ESP32 microcontroller for coordinated motor and irrigation control, showcases how diverse technologies can work together to optimize resource usage and reduce manual labor.

One of the key advantages of this system is its ability to perform continuous and automated crop surveillance, which enhances early disease detection and improves overall farm productivity. The use of motor drivers for autonomous movement and irrigation reduces the dependency on human intervention, offering a scalable solution particularly valuable in regions facing agricultural labor shortages. Furthermore, the modular design allows for easy integration of additional components such as environmental sensors, GPS modules, or machine learning models, thus providing a flexible foundation for future advancements.

However, the system also presents certain limitations. The current model's performance is influenced by external environmental factors such as lighting variability and uneven terrain, which may impact the accuracy of leaf color detection and robot navigation. Additionally, the reliance on a predefined set of visual cues for plant health assessment may limit its effectiveness across diverse crop types or under different growth conditions.

To address these limitations, future work should focus on enhancing the robustness of the vision system through improved image preprocessing and the incorporation of spectral or thermal imaging technologies. Incorporating machine learning algorithms trained on larger, more diverse datasets can also improve disease classification accuracy. Moreover, implementing adaptive path planning and obstacle avoidance using LiDAR or ultrasonic sensors can further enhance the robot's autonomy in complex farm environments.

In summary, this research marks a promising step toward the adoption of intelligent robotic systems in agriculture. With targeted improvements, such systems have the potential to support sustainable farming practices, increase crop yields, and reduce operational costs, contributing meaningfully to the future of smart agriculture.

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