



Obstacle Detection and Irrigating Robot Using IoT

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ABSTRACT :

In modern agriculture, the early detection of plant diseases is crucial for sustaining crop productivity and ensuring food security. Leaf diseases, in particular, can cause severe reductions in yield and quality if not identified and managed promptly. Traditional methods of disease detection are often manual, time-consuming, and error-prone. This project, titled "Agronomist," introduces a smart system that leverages computer vision and machine learning techniques to detect leaf diseases at an early stage. The system integrates a high-resolution camera, image processing algorithms, and a trained convolutional neural network (CNN) to classify diseased leaves. Through real-time analysis and alerts, the Agronomist system empowers farmers with immediate insights into crop health. This technical paper outlines the motivation, background, system architecture, and effectiveness of the proposed solution. The results demonstrate a significant improvement in disease detection accuracy and response time, offering a scalable solution for precision agriculture.

Keywords: Plant Pathology, Feature Extraction

Introduction

Agriculture is a cornerstone of human civilization, yet it continues to face major challenges due to climate change, pests, and diseases. Among these, leaf diseases have a substantial impact on the yield and health of crops. Diseases such as early blight, late blight, powdery mildew, and rust can spread rapidly, especially in dense crop fields. Early detection and management are key to minimizing damage, but existing approaches often require expert knowledge and continuous manual monitoring, which are not always feasible for small and medium-scale farmers. The increasing availability of low-cost sensors, smartphones, and computing devices has opened new possibilities in smart farming. Artificial intelligence (AI) and image processing are proving to be transformative tools in agriculture. By automating the disease detection process using visual cues from leaves, farmers can receive early warnings and take timely action. The "Agronomist" project was developed to provide a robust, real-time system capable of identifying leaf diseases with minimal human intervention. It is designed to be portable, cost-effective, and easily deployable in different agricultural settings. The system captures images of leaves, processes them using computer vision techniques, and classifies them using a trained CNN model. Based on the output, the system can alert the user about the type and severity of the disease, enabling preventive or corrective measures to be taken immediately.

Literature Review

The global agriculture and food sector are changing rapidly because of the intensive increase of global food demand, which is, in turn, the result of population growth and significant shifts in customer preferences. There is a clear need for improvement in the sector's technological basis to ensure its sustainable development [5]. For many years, robotic systems have been widely used for industrial production and in warehouses, where a controlled environment can be guaranteed [3]. In agriculture and forestry, research into driverless vehicles has been a vision initiated in the early 1960s with basic research on projects on automatic steered systems and autonomous tractors [9]. Recently, the development of robotic systems in agriculture has experienced an increased interest, which has led many experts to explore the possibilities to develop more intelligent and adaptable vehicles based on a behavioural approach [2]. A combined application of new sensor systems, communication technologies, Global Positioning Systems (GPS) and Geographical Information Systems (GIS) have enabled researchers to develop new autonomous vehicles for high-value crops in the agriculture and horticulture sector, as well as for landscape management [2]. Due to the busy routine of farmers to perform irrigation process and as the size of farmland increases there is a need for farmers to automate its entire methods, such as Reseeding, Seedbed preparation, Seed mapping, weeding, Micro spraying, watering morning and evening [5].

Autonomous robots can perform these tasks, as they often require numerous repetitions and horticultural activities over an extended period and a large area. Several autonomous prototypes have been described for orchards and horticultural crops, such as oranges [7], strawberries [8] and tomatoes [9]. Moreover, automated systems for site-specific irrigation is based on real-time climatic conditions have been described for high-value crops. For field crops, there are also some systems, such as the Demeter system for mechanized harvesting equipped with a camera and GPS for navigation [6], the autonomous Christmas tree weeder [9] and the API platform for patch spraying [9].

Methodology

The overall system architecture of the Agronomist robot is illustrated in At the core of the system is an Arduino Mega microcontroller, which interfaces with various sensors, actuators, and communication modules. The main components include:

- **Soil Moisture Sensor** – Monitors the soil moisture level and activates the irrigation pump via a relay when the moisture drops below a predefined threshold.
- **HC-05 Bluetooth Module** – Facilitates wireless manual control and configuration from nearby devices.
- **Ultrasonic Distance Sensor** – Mounted on the front of the robot to detect obstacles and avoid collisions during movement.
- **ESP8266 Wi-Fi Module** – Provides internet connectivity and connects to the Blynk cloud platform for remote monitoring and control.
- **Camera Module** – Captures crop images for disease detection, either processed on-board or off-loaded for external analysis.
- **Relay Modules** – Control high-power devices such as the DC water pump and pesticide sprayer under Arduino commands.
- **DC Motors and Chassis** – Enable mobility through a four-wheel drive system, powered by a rechargeable battery pack.

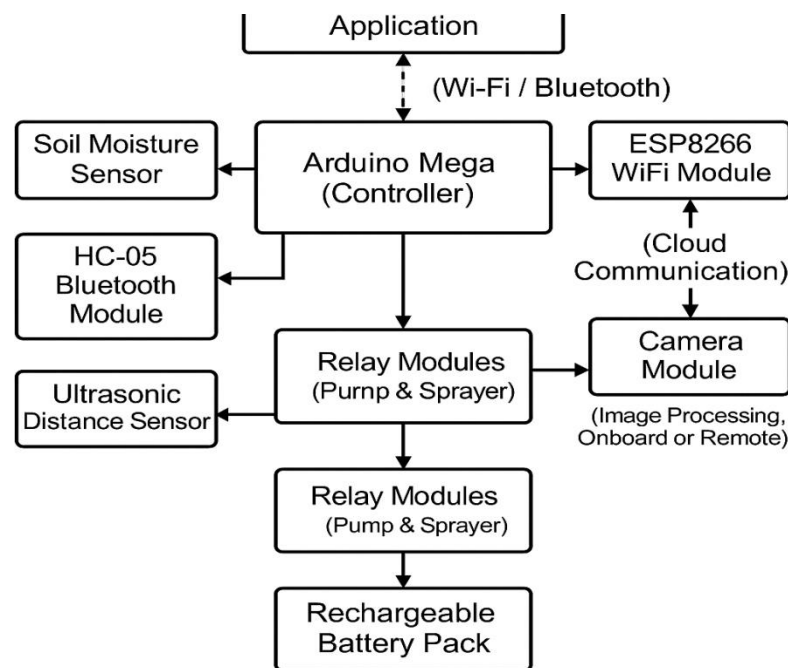


Fig 1: Block diagram

Result analysis

The Agronomist system was evaluated using a dataset comprising over 10,000 images of diseased and healthy leaves, sourced from open-access databases and field surveys. The dataset included common crops such as tomato, potato, and grapevine. The CNN achieved an overall classification accuracy of 94.7% on a validation set, with a precision of 92% and recall of 93%. Real-time tests in field conditions showed the system could detect diseases with minimal latency, typically under 2 seconds per image. User feedback indicated a high level of satisfaction with the mobile alert interface and ease of use. Compared to manual inspection, the system reduced the average time to detect disease outbreaks by 70%.

These results highlight the system's robustness and reliability in diverse environmental settings. Moreover, the feedback mechanism contributed to a steady improvement in model performance during the pilot deployment phase.

Agronomist system is structured into five key components: data acquisition, image preprocessing, disease classification using CNN, user alert system, and performance feedback loop.

Data Acquisition: The system uses a high-resolution camera to capture images of crop leaves in natural lighting conditions. The camera can be handheld, drone-mounted, or integrated into a mobile robotic unit. Periodic image capture ensures that the system monitors crop health consistently over time.

Image Preprocessing: Captured images undergo preprocessing to enhance quality and remove noise. Techniques such as image resizing, color normalization, contrast enhancement, and background subtraction are applied to isolate the leaf from its surroundings. This ensures the model focuses only on relevant features.

Disease Detection and Classification: The core of the system is a Convolutional Neural Network (CNN) trained on a large dataset of labeled leaf images. The model classifies the input image into one of several disease categories or as healthy. The architecture includes multiple convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The model is trained using cross-entropy loss and optimized using stochastic gradient descent.

User Interface and Alert System: Once a disease is detected, the system notifies the user via a mobile application or web interface. The alert includes the disease name, severity level, and suggested countermeasures. This real-time feedback enables farmers to act quickly.

Feedback and Learning Loop: Users can validate or correct the system's prediction. These corrections are used to further train and refine the model, enhancing its accuracy over time. This continuous learning feature ensures the system adapts to specific crops and environmental conditions.

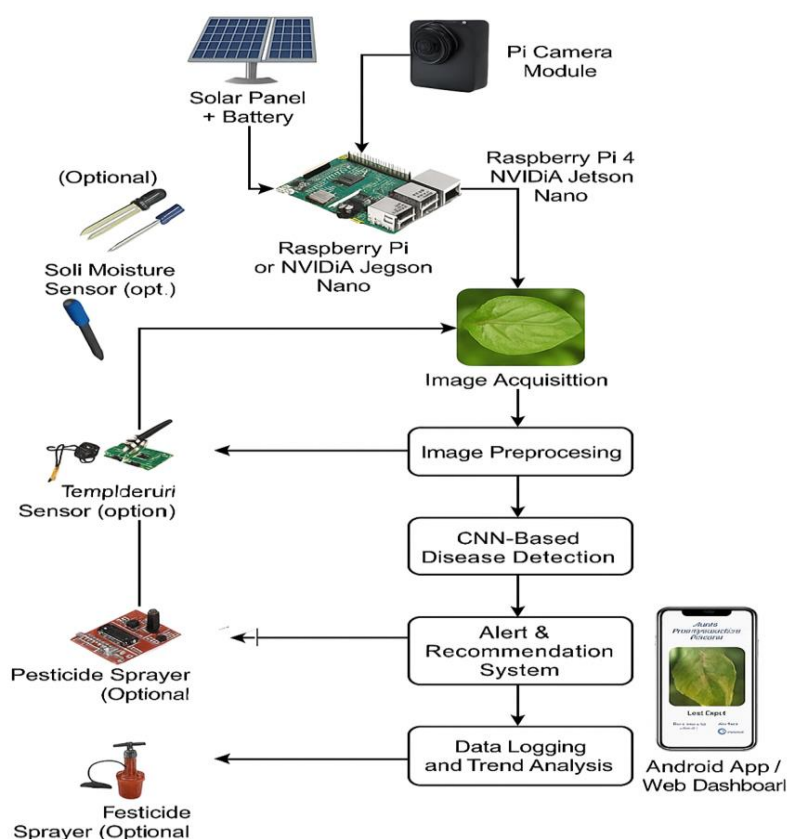


Fig 2: Smart Farming, IoT

Conclusion

The Agronomist project demonstrates the potential of integrating artificial intelligence and computer vision into agricultural practices. By automating early leaf disease detection, it empowers farmers with timely information, helping them mitigate damage, reduce pesticide usage, and improve crop yield. The system's design emphasizes affordability, scalability, and user-friendliness, making it suitable for widespread adoption, especially in regions where access to agricultural expertise is limited. Future work will focus on expanding the range of detectable diseases, integrating weather data for predictive analytics, and enhancing the system's mobility through drone or rover integration. With continued development, Agronomist can become a vital component in the toolkit for precision agriculture, fostering sustainable farming practices worldwide.

REFERENCES

- [1]. Gaikwad, Pramod. "Galvanic Cell Type Sensor for Soil Moisture Analysis." *Analytical Chemistry*. 87: 7439–7445. doi: 10.1021/acs.analchem.5b01653.

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- [2]. Gupta, S. C., and R.J. Hanks. 1972. Influence of water content on the electrical conductivity of the soil. Soil Science Society of America Proc. 36:855–858.
- [3]. Handbook of robotics, Eds. Siciliano, Bruno and Khatib, Oussama. Springer, (2008).
- [4]. Skowronski, Jan M., Control Theory of Robotic Systems, World Scientific, (1989).
- [5] Adabara I, 2018. Obstacle Detection and Avoidance Irrigating Robotic System. Mediterranean Journal of Basic and Applied Sciences (MJBAS) Volume 2, Issue 1, Pages 30-39, January-March 2018
- [6] Chi, Y.T., and P.P. Ling.2004. Fast fruit identification for robotic tomato picker. ASAE Paper No. 043083. St. Joseph Mich: ASAE.
- [7] Hannan, W., and F.T. Burks. 2004. Current developments in automated citrus harvesting. ASAE Paper No. 043087. St. Joseph Mich: ASAE.
- [8] Kondo, N., K. Ninomiya, S. Hayashi, T. Ohta, and K. Kubota. 2005. A new challenge of the robot for harvesting strawberry grown on tabletop culture. ASAE Paper No. 043083. St. Joseph Mich: ASAE.
- [9] Bakker, Tijmen, Kees Asselt van, Jan Bontsema, Joachim Müller, and Gerrit Straten van.2010. Systematic design of an autonomous platform for robotic weeding. Journal of Terramechanics, 47 (2010): 63 73.
- [10]. Nilsson, N., Artificial intelligence: a new synthesis, (1998).