Precision Agriculture Smart Rover

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***Abstract*—The Precision Agriculture Smart Rover is an AI-based system designed to detect plant leaf diseases and automatically spray pesticides when infection is identified. The system uses a Raspberry Pi 4 Model B as its central controller, which processes leaf images captured by a camera using a pre-trained Convolutional Neural Network (CNN) model to classify leaves as healthy or diseased. Based on the detection result, the Raspberry Pi activates a relay-controlled water pump to spray the pesticide solution through a nozzle only when a diseased leaf is detected, reducing unnecessary pesticide usage. An ultrasonic sensor detects obstacles, while a motor driver controls the rover's movement. Additionally, a web-based application displays the captured leaf image and detection result on a mobile phone for remote monitoring. The proposed system aims to reduce manual inspection, save time, and improve crop protection through AI-based disease detection and automated spraying. It provides an economical approach to precision agriculture with scope for future improvements in autonomous navigation and advanced disease classification.**

***Index Terms*—Precision Agriculture, Smart Rover, Plant Leaf Disease Detection, Artificial Intelligence (AI), Convolutional Neural Network (CNN), Raspberry Pi 4 Model B, Image Processing, Automated Pesticide Spraying, Targeted Spraying, Internet of Things (IoT), Smart Farming, Embedded Systems.**

I. INTRODUCTION

Agriculture is one of the fundamental sectors that contributes to human survival, food availability, and the economic progress of many countries. Despite its importance, crop production is frequently affected by plant diseases, which can damage leaves, weaken plant growth, lower agricultural output, and create additional expenses for farmers [1]. In conventional farming practices, identifying these diseases generally involves observing plants manually, a process that depends heavily on individual knowledge and regular field inspection [2]. Detecting infection at an early stage is important because delayed identification may allow diseases to spread and cause further damage to crops [3]. Therefore, adopting automated techniques for plant health assessment and timely pesticide application has become increasingly important in modern agriculture [4].

The development of Artificial Intelligence (AI), computer vision, and embedded computing has created new possibilities for automating agricultural activities [5]. Among the available deep learning techniques, Convolutional Neural Networks (CNNs) are widely used for examining plant images because they can learn important visual characteristics and distinguish between different image categories [6]. Compact computing platforms such as the Raspberry Pi also make it possible to perform image processing and hardware control within a small and affordable system [7]. Nevertheless, several existing plant disease detection solutions are primarily designed to identify and classify infections, with limited integration of pesticide control, mobile monitoring, and movable agricultural platforms [8]. Addressing these gaps requires a combined approach that connects disease recognition with an automated response mechanism [9].

Traditional plant disease monitoring methods often require farmers to inspect crops regularly and identify symptoms through visual observation. This process can be time-consuming, particularly when monitoring large agricultural fields. Human observation may also lead to incorrect identification due to similarities in disease symptoms. The use of image processing and deep learning techniques provides an alternative approach by enabling automated analysis of leaf

images and improving the consistency of disease classification [5], [6].

Recent developments in embedded systems have made it possible to implement artificial intelligence applications on compact and low-cost hardware platforms. The Raspberry Pi provides sufficient processing capabilities for running trained machine learning models and controlling external electronic devices. By integrating a camera with a Convolutional Neural Network (CNN), leaf images can be captured and classified without requiring continuous manual inspection. Combining this technology with automated spraying mechanisms can

This paper introduces a Precision Agriculture Smart Rover developed to combine intelligent leaf examination with controlled pesticide distribution. The proposed architecture uses a Raspberry Pi 4 Model B, a camera module, a CNN-based classification model, and an electronically operated spraying unit [10]. During operation, the camera obtains images of plant leaves and forwards them to the trained CNN model for analysis. The model examines the extracted image features and determines whether the leaf belongs to the healthy or diseased category. The resulting classification is used by the Raspberry Pi to manage a relay-controlled water pump. Whenever a diseased leaf is identified, the relay switches on the pump, allowing the pesticide solution to pass through the spray nozzle. If the classification indicates a healthy leaf, the pump is kept in the OFF state to avoid unnecessary spraying.[11][12]

In addition to disease identification and pesticide control, the proposed rover supports remote observation through a web-based mobile interface. The interface displays the classification outcome together with the corresponding captured leaf image, helping users understand the detection process [13]. An ultrasonic sensor is included to identify nearby obstacles, and the motor driver provides the required control signals for operating the rover's DC motors [14]. The integration of these components creates a system capable of combining image-based plant inspection, embedded decision-making, and automatic spraying. Furthermore, mobile-based result visualization makes it easier for users to access the detection information without directly interacting with the processing hardware [15].

The primary aim of this research is to design and implement an affordable agricultural rover that can recognize leaf diseases and control pesticide spraying according to the classification outcome [16]. The major contribution of this work lies in bringing together CNN-driven leaf analysis, Raspberry Pi-based control, an automatic pesticide delivery mechanism, and mobile application monitoring in one integrated platform [17]. By activating the spraying unit only when a diseased leaf is identified, the system is intended to minimize unnecessary pesticide usage, reduce the workload associated with manual inspection, and improve the efficiency of crop protection. Further development may include more advanced disease recognition models, voice-assisted operation, and autonomous rover navigation. These improvements could expand the system's capabilities and contribute to the wider adoption of intelligent technologies in precision agriculture [18].

II. LITERATURE SURVEY

The investigation described in [2] explores deep learning-based plant disease recognition through Convolutional Neural Networks (CNNs). The network is trained with labelled leaf photographs to learn distinguishing characteristics, including discolouration, irregular marks, damaged regions, and texture differences. After learning these patterns, the model can determine the health category of a given leaf image. This technique offers a faster alternative to conventional visual examination and supports automated disease classification. However, variations in illumination, image backgrounds, and plant varieties can influence classification performance. The research establishes the relevance of CNN architectures for developing automated agricultural disease recognition applications.

The research reported in [3] presents a portable disease identification arrangement developed around a Raspberry Pi computing board and a camera. Images collected through the camera are supplied to a trained machine learning model, which examines the visual characteristics of leaves to recognize possible infections. Processing the captured information directly on an embedded platform makes the arrangement compact and reduces the need for continuous connection to a desktop computer. This type of implementation is beneficial for field-based agricultural applications where affordability and portability are essential. However, extending the

system beyond disease identification by incorporating an automatic pesticide spraying facility can make it more useful for practical crop protection.

The approach introduced in [4] investigates the use of electronically controlled spraying equipment for improving pesticide application in agriculture. Control circuits are employed to operate the spraying unit based on specified operating conditions, allowing the delivery of chemicals to be managed more systematically. Such automation can reduce the physical effort required for repeated spraying activities and help control pesticide consumption. However, a spraying arrangement without an intelligent disease recognition facility may require human supervision or predefined instructions to determine when spraying is necessary. Combining visual disease assessment with electronic spray control can provide a more effective method of responding to plant infections.

The study presented in [5] highlights the importance of smartphone-based communication and remote supervision in modern agricultural applications. Mobile and web-based platforms can present collected information, display operating conditions, and provide users with convenient access to connected devices. These features make agricultural monitoring more accessible and reduce the need for users to remain physically close to the equipment throughout its operation. However, a monitoring interface by itself cannot examine plant diseases or independently manage pesticide distribution. Connecting mobile-based visualization with intelligent image classification and automatic hardware control can improve the overall functionality of smart farming solutions.

The work discussed in [6] focuses on the utilization of robotic vehicles for performing agricultural monitoring activities. Mobile platforms equipped with electronic sensors, cameras, and motor control circuits can move within agricultural environments and collect useful information about plant conditions. DC motors, together with suitable motor drivers, provide the required movement, whereas ultrasonic sensors can identify obstacles in the surrounding area. These technologies offer a foundation for developing mobile agricultural equipment with reduced human involvement. However, combining mobility with accurate disease recognition and an automatic spraying arrangement is important for developing a more comprehensive crop protection system.

Based on the concepts identified in the above studies, the proposed Precision Agriculture Smart Rover brings together intelligent leaf examination, embedded computing, controlled pesticide spraying, and mobile-based result visualization. A camera obtains plant leaf photographs, which are evaluated by a trained Convolutional Neural Network (CNN) to identify whether the leaf is healthy or diseased. A Raspberry Pi 4 Model B serves as the main processing and control unit, using the classification outcome to operate a relay-connected water pump and spray nozzle. The pump is switched on when disease symptoms are identified, whereas the spraying operation is disabled when a healthy leaf is recognized. Additionally, a web-based mobile interface presents the classification output along with the captured leaf photograph. The system is intended to simplify plant health inspection, limit avoidable pesticide application, and provide an affordable technological solution for precision agriculture.

III. METHODOLOGY

The proposed Precision Agriculture Smart Rover is developed using a Raspberry Pi 4 Model B, a camera module, and a CNN-based image classification model for detecting diseases in plant leaves. During operation, the camera obtains leaf images, which are analyzed by the trained model to determine whether the leaves are healthy or affected by disease. According to the prediction, the Raspberry Pi sends a control signal to a relay module that operates the water pump and pesticide spray nozzle. The system also includes a web-based monitoring platform through which users can view the detected leaf image and its corresponding classification result on a mobile phone. The overall functional architecture and interaction between the system components are presented in Fig. 1.

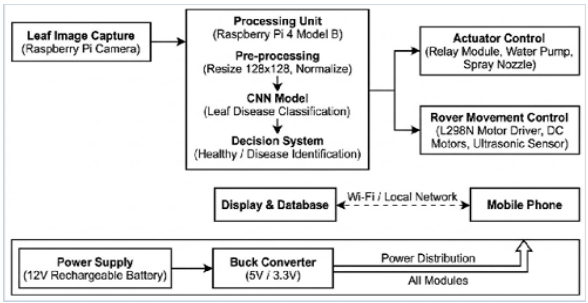


Fig.1. Block diagram of the proposed Precision Agriculture Smart Rover.

A. System Architecture

The system architecture is organized into five major sections: leaf image collection, intelligent disease identification, automatic pesticide delivery, rover motion control, and mobile-based supervision. A Raspberry Pi 4 Model B serves as the primary processing and control board, managing communication between the software and the connected electronic components.

Initially, the camera obtains photographs of plant leaves and sends the captured data to the Raspberry Pi for examination. The CNN-based trained model evaluates the images and determines whether the observed leaf is healthy or affected by disease. According to the prediction, the Raspberry Pi operates the relay module to control the water pump. When an infected leaf is identified, the pump is switched on to deliver the pesticide solution through the spray nozzle, whereas no spraying takes place for a healthy leaf. In addition, the web-based application presents the detection outcome together with the corresponding leaf photograph on a mobile phone, enabling users to monitor the system conveniently.

B. Image Acquisition and Data Processing

The camera module is used to obtain photographs of plant leaves from the surrounding environment under the existing illumination conditions. These images are then transferred to the disease recognition program operating on the Raspberry Pi or its associated processing platform. As an initial processing step, each captured image is adjusted to a resolution of 128 × 128 pixels so that its dimensions correspond to the input requirements of the CNN model developed during the training phase.

The CNN model examines the processed leaf image by identifying important visual characteristics, including differences in color, the presence of spots, and unusual patterns on the leaf surface. Using the features acquired during the training process, the model determines the condition of the input leaf and assigns it to either the healthy or diseased category. The predicted output is subsequently forwarded to the system's control unit, where the decision regarding pesticide spraying is made based on the identified leaf condition.

C. CNN-Based Plant Disease Detection

The plant disease identification unit is developed using a Convolutional Neural Network (CNN) that has been trained with a collection of labelled images representing both healthy and infected leaves. The network architecture includes convolutional operations to extract relevant image characteristics, pooling operations to reduce feature dimensions, and dense layers to generate the final classification output. During system execution, the image obtained from the camera is processed into the required input format and passed to the previously trained CNN model. The network examines the extracted features and generates a prediction indicating whether the input leaf is healthy or affected by disease. The reliability of this prediction is influenced by factors such as dataset size, image quality, sample variation, and correct image labelling. The model can recognize diseases across different plant varieties provided that suitable samples of those plants are included in its training dataset.

D. Automated Pesticide Spraying

The automatic pesticide distribution section is made up of a relay circuit, a water pump, a storage tank containing the pesticide mixture, and a connected spray nozzle. The Raspberry Pi acts as the control unit and operates the relay based on the disease classification generated by the CNN model. If the analysis identifies an infected leaf, a signal is sent to the relay to activate the pump, allowing the stored solution to pass through the nozzle and reach the targeted plant area.

In contrast, when the model identifies a healthy leaf, the relay is kept in the OFF condition, preventing the pump from supplying the solution. This automatic decision-making process helps minimize the application of pesticides when they are not needed. The operating time and spraying quantity can be configured based on the pump capacity and application requirements. Appropriate electrical isolation and switching arrangements are also necessary to ensure safe operation of the Raspberry Pi while controlling the pump.

E. Hardware Implementation

The developed prototype incorporates several hardware elements, including a Raspberry Pi 4 Model B, a camera unit, a relay board, a water pump, a spraying nozzle, a motor control driver, DC motors, an ultrasonic distance sensor, a rechargeable power source, and voltage-regulation circuits. The camera is

responsible for collecting plant leaf images, whereas the Raspberry Pi handles image analysis, disease identification, and coordination of the connected hardware components.

The relay module provides the switching operation required to activate or deactivate the pesticide spraying arrangement. Movement of the rover is achieved through DC motors operated by the motor driver circuit. An ultrasonic sensor is used to measure the distance from nearby objects and identify possible obstacles during movement. Electrical energy required by the different modules is supplied by a rechargeable battery, with suitable power-conversion circuits providing the necessary voltage levels. All these hardware components are connected to form a mobile agricultural platform capable of performing leaf disease detection and controlled pesticide spraying.

F. IoT Monitoring and User Interface

A browser-based monitoring platform is developed to make the disease identification output accessible through a smartphone or computer connected to the available network. The application presents the predicted leaf condition along with its associated image, enabling users to view the system's detection results remotely without requiring direct access to the Raspberry Pi hardware.

Depending on the operating mode, the user can provide a leaf photograph through the image upload option or obtain an image directly from the connected camera module. The submitted or captured image is forwarded to the trained CNN model for analysis, and the predicted category is displayed on the application interface. In future enhancements, a database can be incorporated to maintain records of previous inspections, including detection timestamps, classification outputs, and corresponding leaf photographs. This facility would help users access earlier results and track plant health observations over time.

G. Power Supply and Rover Movement

The rover operates using a rechargeable battery that provides electrical energy to the Raspberry Pi and other connected hardware through suitable voltage-conversion circuits. As the processing board, DC motors, and water pump have different power and current requirements, each component must receive an appropriate supply based on its electrical ratings to ensure safe and efficient functioning.

`A motor driver circuit is used to connect the Raspberry Pi control system with the DC motors and regulate the movement of the rover. This arrangement allows the mobile platform to travel across the agricultural field and position the camera and spraying unit near the plants for inspection. The ultrasonic sensor assists in recognizing nearby obstacles and provides information that can be used for movement control. More advanced autonomous navigation features can be incorporated in future development. Proper power distribution, voltage regulation, and electrical safety measures are essential to maintain consistent system performance.

H. Experimental Setup and Evaluation

The developed prototype is tested with a collection of leaf photographs covering both healthy and infected conditions to assess the performance of its individual modules. The evaluation includes camera-based image collection, preprocessing operations, CNN model predictions, relay switching, water pump control, and result visualization through the web application. Photographs of healthy leaves are provided to confirm that the spraying unit stays switched off, whereas images containing disease symptoms are used to verify whether the pump is activated based on the model's prediction.

Further evaluation is carried out to examine the quality of images captured by the camera, the switching response of the relay, the functioning of the water pump, and the presentation of detection results on a mobile device. The

rover's movement mechanism and obstacle identification capability are also examined using the motor driver and ultrasonic sensor. For proper performance assessment, experimental observations should document the dataset composition, classification accuracy, testing environment, processing time, pump activation period, and limitations identified during system operation.

IV. RESULTS

The developed Precision Agriculture Smart Rover employs a Convolutional Neural Network (CNN) running on a Raspberry Pi 4 Model B to examine plant leaf images and identify possible disease conditions. Based on the model's prediction, the Raspberry Pi

controls the relay module to operate the water pump and distribute pesticide through the connected spray nozzle when an infected leaf is detected. If the leaf is recognized as healthy, the spraying unit remains switched off. Additionally, a web-based monitoring application presents the predicted leaf condition along with its captured image, allowing users to access and observe the detection results conveniently.

A. Website

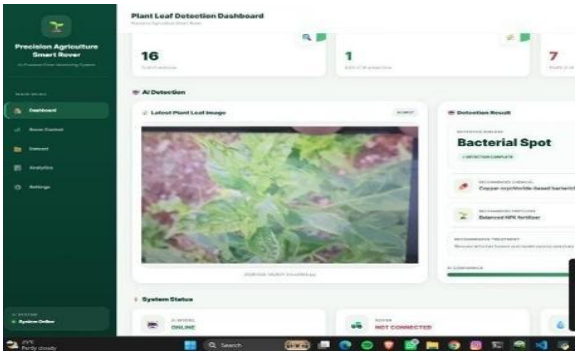


Fig. 2. Smart Rover website showing real time diseases in the leaf.

Real-time plant leaf disease identification (Fig. 2) is carried out using a camera interfaced with the Raspberry Pi4 Model B. The images captured by the camera are
supplied to a pre-trained Convolutional Neural Network (CNN) model, which classifies the leaves as either healthy or diseased. The model examines important visual characteristics, including spots, variations in leaf colour, and other visible signs of infection. The classification outcome, along with the captured leaf image, is presented on a mobile phone through a web-based application. If the system detects a diseased leaf, it automatically triggers the pesticide spraying unit to apply the pesticide through the connected nozzle.

B. Mobile Application

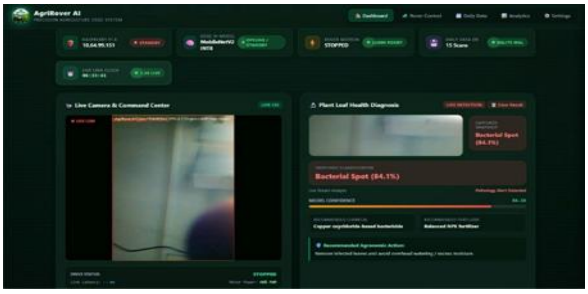


Fig. 3. Smart Rover control and live camera in mobile.

The web-based mobile application provides real-time information about plant leaf disease detection and can be accessed through a smartphone. It presents the image captured by the camera along with the CNN model's prediction, indicating whether the leaf is healthy or affected by disease. This allows users to observe and track the detection results easily using their mobile devices. If a diseased leaf is identified, the system automatically switches on the pesticide spraying mechanism. Thus, the application offers a convenient way to monitor plant health and supports effective disease management.

V. DISCUSSION

The Precision Agriculture Smart Rover combines Artificial Intelligence (AI), digital image processing, and embedded technology to enable automatic identification of plant leaf diseases. A camera is used to capture leaf images, which are then examined by a trained Convolutional Neural Network (CNN) model to determine whether the leaves are healthy or infected. By automating this process, the system minimizes the need for continuous human inspection and helps identify disease symptoms at an early stage. The Raspberry Pi 4 Model B functions as the main controller, processing the classification output and managing the pesticide application unit. If the CNN model identifies a diseased leaf, the Raspberry Pi sends a control signal to the relay, which switches on the water pump and allows the pesticide solution to pass through the spray nozzle. In the case of a healthy leaf, the pump remains switched off, preventing unnecessary pesticide usage.

A smartphone-compatible web application enables users to access the captured leaf images and their corresponding detection outcomes. Through this interface, the system can be monitored remotely without requiring direct interaction with the hardware components. Combining automated image analysis with controlled pesticide application can minimize manual effort and make plant health monitoring more convenient.

The rover is equipped with a movement arrangement that allows it to move, while an ultrasonic sensor helps identify obstacles in its path. However, the effectiveness of the system is influenced by factors such as camera image clarity, surrounding illumination, the quality and variety of training

images, and the prediction capability of the CNN model. Hence, evaluating the prototype under different operating and environmental conditions is necessary to assess its performance and reliability.

Overall, the proposed system offers an economical and practical solution for precision agriculture through the integration of automated leaf disease recognition and need-based pesticide spraying. Further development can focus on including a wider range of plant species and disease samples in the dataset, enhancing the model's prediction performance, and introducing autonomous navigation capabilities to improve the rover's operation.

VI. CONCLUSION

The Precision Agriculture Smart Rover introduces an intelligent system for identifying plant leaf diseases and carrying out automatic pesticide application. A camera captures images of plant leaves, which are analyzed by a Convolutional Neural Network (CNN) to determine their condition as healthy or diseased. The Raspberry Pi 4 Model B serves as the main processing unit and uses the classification output to operate the relay-controlled water pump and spray nozzle. When a diseased leaf is detected, the spraying unit is activated to distribute the pesticide solution. The captured images and their detection outcomes can also be accessed through a smartphone using a web-based interface.

The main objective of the proposed system is to minimize the effort involved in manual leaf inspection, prevent unnecessary pesticide application to healthy leaves, and make plant health monitoring more effective. The combination of AI-based image classification, embedded hardware, and automatic spraying provides a useful approach to precision agriculture. The system's effectiveness is influenced by the trained model's classification capability and the surrounding operating conditions. Further enhancements may include increasing the size and diversity of the training dataset, improving disease recognition performance, introducing autonomous rover navigation, and adding advanced monitoring functions.

VII. FUTURE SCOPE

The proposed Precision Agriculture Smart Rover offers several opportunities for future development. The CNN model can be further improved by using an expanded and more diverse dataset, enabling it to recognise a greater number of plant diseases with improved classification performance. Autonomous navigation can also be incorporated so that the rover can travel across agricultural fields and detect affected leaves with minimal human involvement. In addition, a dedicated smartphone application connected to a database could be developed to maintain records of detected diseases, captured leaf images, and pesticide spraying activities. The spraying unit may be upgraded with a controlled dispensing mechanism to regulate pesticide application and minimise chemical wastage. Cloud-based services and voice interaction can also be introduced to provide remote access, simplify system operation, and improve user convenience.

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