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RESEARCH ARTICLE

Smart Farm Rover: Autonomous Plant Disease Detection and Classification with Machine Learning

Arun Madakannu[1,*], **R. K. V. Giridhesh**[1] **and Sanjith Chandran**[1]

[1] Department of Electronics and Communication Engineering, Mepco Schlenk Engineering College, Sivakasi, Tamil Nadu 626005, India

Abstract

Agriculture plays a major role in India's growth. Timely prediction of diseases will minimize their impact and improve productivity in agriculture. This work focuses on designing a rover-based system for automated plant disease detection. The rover can be utilized to detect plants without human intervention. The COCO/SSD model is used for object detection. After detecting the plant, the motor is actuated to move the rover near it. The "Plant Village" dataset is used to train the model. It consists of various images of healthy and diseased plants. In this project, we have used tomato, potato, corn, and grape images to train the model for disease identification. We have used various deep learning algorithms such as VGG16, VGG19, and AlexNet. Among these, AlexNet achieved the highest testing accuracy of 95.72%. The AlexNet model is used to detect plant leaf diseases. Using Python, the model detects the plant leaf disease and notifies the user. Simple Mail Transfer Protocol (SMTP) is used to send the captured image and the predicted disease to the user. The ESP32-CAM and Raspberry Pi were used to perform plant detection and disease identification. Thus, identifying diseases with the help of a rover will increase productivity and benefit farmers.

Keywords: CNN, AlexNet, plant disease, rover, farming.

1 Introduction

Agriculture plays a major role in India's growth. Diseases in crops harm both production and quality. Visual identification of diseases across a large field is difficult and requires experts. One of the major reasons for failure in agriculture is inadequate surveillance by farmers. Agriculture also plays a vital role in the country's GDP and provides employment opportunities. A rover can be used as a substitute for field surveillance.

This paper presents the following contributions:

- The rover is designed to identify plants and actuate the motor to move toward them.
- Various deep learning models such as VGG16 and AlexNet are evaluated. The model with the highest accuracy is chosen for plant leaf disease identification.
- The final model, implemented on a Raspberry Pi,

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***Corresponding author:**
✉ Arun Madakannu
arunmadakannu@gmail.com

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predicts the plant leaf disease and notifies the user via email.

The introduction sets the stage by emphasizing the importance of early detection of plant diseases to reduce agricultural losses. It highlights the limitations of traditional methods and introduces CNNs as a potential solution. The paper outlines the goals of the work and describes its structure. The design of the authors' novel CNN for plant disease identification is explained, including training procedures, activation functions, layers, and any unique techniques used [1]. The study also addresses the difficulty of transmitting images over Low-Power Wide Area Networks (LP-WAN), which often suffer from low data rates and high energy consumption. The focus is on the Long Range (LoRa) protocol, which supports long-distance transmission but has limited data rates, raising concerns about its ability to transmit images [2]. A novel method combining the strengths of deep residual and dense networks is proposed to detect tomato leaf diseases using a modified residual dense network [3]. Another study highlights the need for automatic detection of maize leaf diseases, proposing enhanced deep learning versions of GoogLeNet and Cifar10 to improve accuracy and reduce network complexity [4].

The literature also outlines current and emerging challenges in agriculture and discusses the pros and cons of machine learning-based crop production prediction [5]. It points out difficulties in accurately localizing robotic vehicles in furrows, especially under conditions like satellite occlusion, which may affect the accuracy of real-time kinematic (RTK)-assisted GPS systems [6]. This approach is justified by the close link between environmental conditions and the life cycles of plant diseases. One project aims to predict disease onset before symptoms appear using environmental data gathered from IoT sensors in the field [7]. Other work aims to tackle climate change and transboundary plant pest and disease issues by leveraging advancements in IoT sensing technologies [8].

Overall, these studies demonstrate how integrating machine learning and image processing can help build reliable automated systems for plant disease identification, aiding crop management and improving yields [9]. One method uses deep learning to enhance features in leaf images for accurate disease detection, thereby offering a practical approach for automated maize disease identification [10]. Other works use dense CNNs [11] and modified LeNet-based CNNs [12] for maize leaf disease classification and tomato leaf disease classification [13].

The proposed system also provides the name of a local pesticide supplier along with information on total accuracy, timing, weather prediction, and plant disease details [14, 15]. This research further explores algorithms used for image segmentation and automated classification techniques for plant leaf disease detection. Plant leaf diseases are identified using deep learning techniques. Initially, support vector machines (SVMs) were used, but they did not achieve satisfactory accuracy. Hence, deep learning algorithms are employed. After detecting the disease, it is notified to the user.

The rover identifies plants and actuates the motor to navigate toward the crops. By using digital image processing techniques, support vector machines (SVMs), and other methods, plant leaf diseases can be identified and classified. The project is divided into three phases as described below:

- Phase 1 focuses on the rover hardware. The rover identifies the plant and actuates the motor to approach it.
- Phase 2 emphasizes image processing software to identify plant diseases.
- Phase 3 integrates the software with rover hardware and sends the disease information to the farmer.

The "Plant Village" dataset is obtained from Kaggle. It is a public dataset containing 54,305 images of healthy and diseased plant leaves collected under controlled conditions. It includes images of 17 basic diseases, 4 bacterial diseases, 2 caused by mold (oomycete), 2 viral diseases, and 1 caused by a mite. In this project, we focus on five crops, covering 25 disease classes. Early disease prediction can reduce negative impacts on agriculture. The rover can be used to automate this process, thereby enhancing agricultural productivity.

The paper is organized as follows: Section I covers the introduction and literature review. The proposed methodology and system architecture are discussed in the "Proposed Work" section. "System Design" details the hardware implementation. "Results and Discussion" presents the experimental setup, dataset format, and evaluation results.

2 Proposed Methodlogy

The creation of an automated plant disease detection system that combines deep learning algorithms, rover technology, and Internet of Things (IoT) connectivity is the proposed solution. The rover, equipped with sensors and cameras, uses the COCO dataset to identify plants. It then captures images of the plant leaves and sends them to a server for disease prediction. After evaluating several deep learning models such as CNN, VGG16, and VGG19, the best-performing model—AlexNet—is selected for disease prediction. Data preprocessing includes plant image augmentation, normalization, and scaling. The system design enables communication between the ESP32 camera on the rover and the server for transmitting images and receiving disease prediction results. Implementation involves testing the rover's ability to identify plants and capture images, as well as server-side evaluation of deep learning models. The discussion of findings highlights system performance and potential improvements. The objective of this proposed solution is to enable proactive disease control through early detection, thereby transforming agricultural practices.

2.1 Rover Design

The rover will detect the plant and actuate the motor accordingly. Real-time data is captured using the ESP32-CAM and compared with the COCO/SSD model. Based on the detected position of the plant, the motor is actuated. From Table 1, it is observed that if the plant is located in front of the ESP32-CAM, both motors begin rotating in the clockwise direction.

Table 1. Motor actuation logic.

Position	Motor-1	Motor-2
Right	Clockwise	Anti Clockwise
Left	Anti clockwise	Clockwise
Front	Clockwise	Clockwise

If the plant is located on the left side of the ESP32-CAM, motor 1 rotates in the anti-clockwise direction and motor 2 rotates in the clockwise direction. If the plant is located on the right side of the ESP32-CAM, motor 1 rotates clockwise and motor 2 rotates anti-clockwise. A 12-volt power supply is provided to the motor driver, which has four signal pins. The first two pins are used by motor 1, and the other two are used by motor 2.

The camera cannot detect the plant if the rover is too close to it. In such cases, the rover can be manually controlled by the user for motor actuation. The motor driver includes a built-in voltage regulator that steps down the voltage to 5 volts. This 5-volt output from the motor driver is used as input to the ESP32-CAM. Based on plant detection, the rover is actuated. The rover motor actuation logic is described in Table 1. Figure 1 shows the block diagram of the rover implementation.

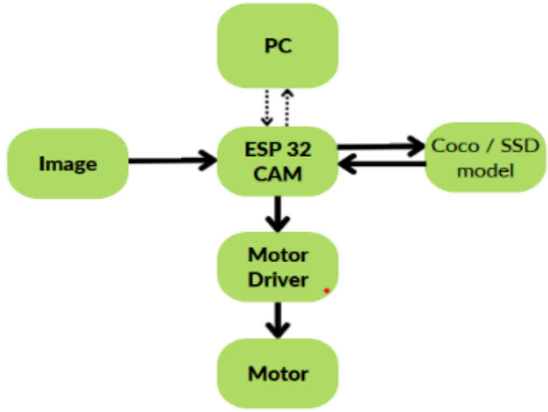

Figure 1. Block diagram of Rover implementation.

2.2 Disease Identification

Plant leaf diseases can be identified using deep learning models. The "Plant Village" dataset is obtained from Kaggle and is used to train the models. Various deep learning models such as VGG16, AlexNet, and others are employed to predict plant diseases. A custom CNN model consisting of three convolutional layers followed by three fully connected dense layers is also developed. The best-performing deep learning model is selected for disease prediction.

Raspberry Pi is used for hardware-based disease identification. This paper mainly focuses on five crops—apple, corn, grape, tomato, and potato—covering 25 classes of healthy and diseased plant samples. Raspberry Pi 3B+ is used for implementing the disease identification system. The output from the Raspberry Pi is sent to the user via email.

Table 2 shows the custom CNN model used for plant leaf disease detection. However, as shown in Section VI, the AlexNet model achieved the highest accuracy and is therefore used in the hardware for plant disease identification.

All the models which we considered are trained with the "Plant Village" dataset. We split the dataset into two namely test and train with a rough train-test of ratio is 80:20. The train consists of 25117 images in 25 classes. The test has 6280 images in 25 classes.

Table 2. Custom CNN architecture for plant disease identification.

Layer	Feature Map Size	Kernel Size
Input	1	-
Conv1	32	5 × 5
Maxpooling	32	3 × 3
Conv2	32	3 × 3
Maxpooling	32	2 × 2
Conv4	64	3 × 3
Maxpooling	64	2 × 2
FC1	-	-
FC2	-	-
FC3	-	-

2.3 Implementation in Raspberry Pi

The deep learning model with the highest accuracy is chosen. Raspberry Pi 3B+ is used to identify plant leaf diseases in hardware. Once the disease is identified, the result is sent to the user via email. SMTP (Simple Mail Transfer Protocol) is used to send the email notification. The image of the plant leaf, along with the identified disease, is sent to the user. The email contains both the captured leaf image and the predicted disease. Figure 2 illustrates the working principle of the Simple Mail Transfer Protocol.

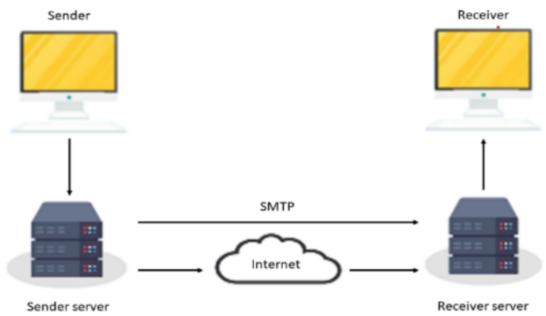

Figure 2. SMTP working principle.

The rover consists of an ESP32-CAM and a Raspberry Pi mounted on it. The ESP32-CAM is used to detect plants using the COCO/SSD model, which identifies objects in real time. The Raspberry Pi, running a deep learning model developed in Python, is used to identify plant leaf diseases. After disease identification, the user is notified with the predicted disease name and the captured plant leaf images via email.

To enable this notification feature, access for less secure apps must be allowed on the sender's email account. Figure 3 shows the complete working diagram of the rover. The rover consists of the ESP 32 CAM and the Raspberry pi mounted on the rover.

The ESP32-CAM is used to detect the plant and actuate the motor toward it. The Raspberry Pi is used to identify plant leaf diseases and notify the user via email. Both the Raspberry Pi and ESP32-CAM are mounted on the rover. The ESP32-CAM is dedicated to plant detection, while the Raspberry Pi is responsible for disease identification and user notification.

2.4 System Design

The ESP32-CAM is used to capture real-time images and compare them with the COCO/SSD model. Based on the detection, the motor is actuated to move the rover near the plant. The components used include the motor driver, motors, and ESP32-CAM. The motor serves as the actuator. The motor driver has four signal pins—two are used by motor 1 and the other two by motor 2. The power supply provides 12 volts as input to the motor driver. The motor driver has an inbuilt 5V regulator, and this 5-volt output is given as input to the ESP32-CAM.

The deep learning model with the highest accuracy is used for disease identification, and the user is notified via email. RealVNC Viewer is used to remotely access the Raspberry Pi 3B+ using its IP address. The trained model is deployed on the Raspberry Pi to identify plant leaf diseases. The identified disease, along with the captured image, is sent to the user via email.

3 Results and Discussion

The plant village dataset is used to train the model to identify the plant leaf disease. Figure 4 shows the various plant leaf samples.

The plant village dataset consists of 14 different crops which include 54,305 images of disease and healthy plant leaf. We have only used the dataset for apple, corn, grape, potato and tomato. The rover will detect the plant and actuates the motor based on the detected plant location. The constant 5 volts from the motor driver is given as the input to the ESP 32 CAM. Various deep learning algorithm such as VGG16, VGG19, AlexNet were developed and the model with high accuracy is chosen. The modified AlexNet architecture used in this work is shown in Figure 5.

Machine learning algorithm such as Support Vector Machine d minimum testing accuracy. Table 3 shows the testing accuracy of different models. The model with high training accuracy is chosen for implementation. As the AlexNet architecture has maximum testing accuracy this model is used to detect the plant leaf disease in the Raspberry pi hardware.

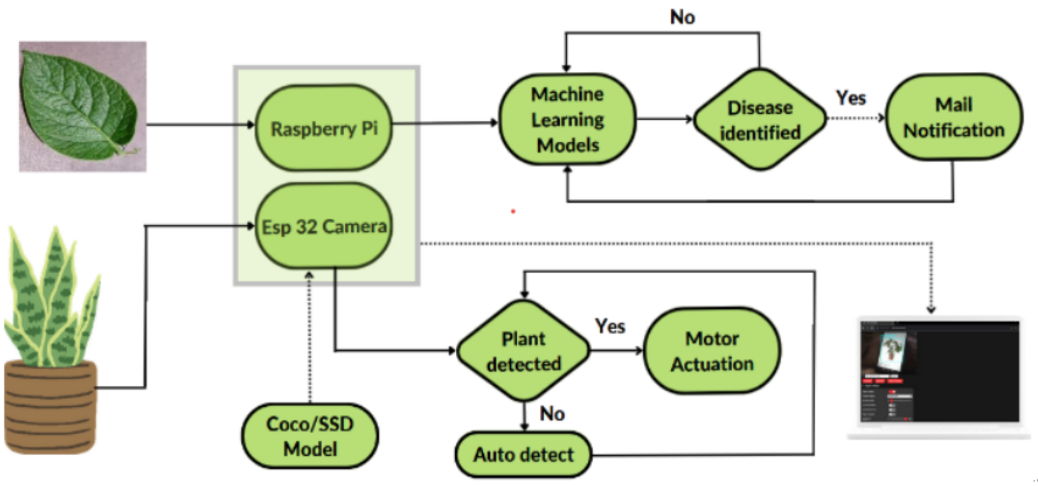

Figure 3. Flow chart of functioning of rover.

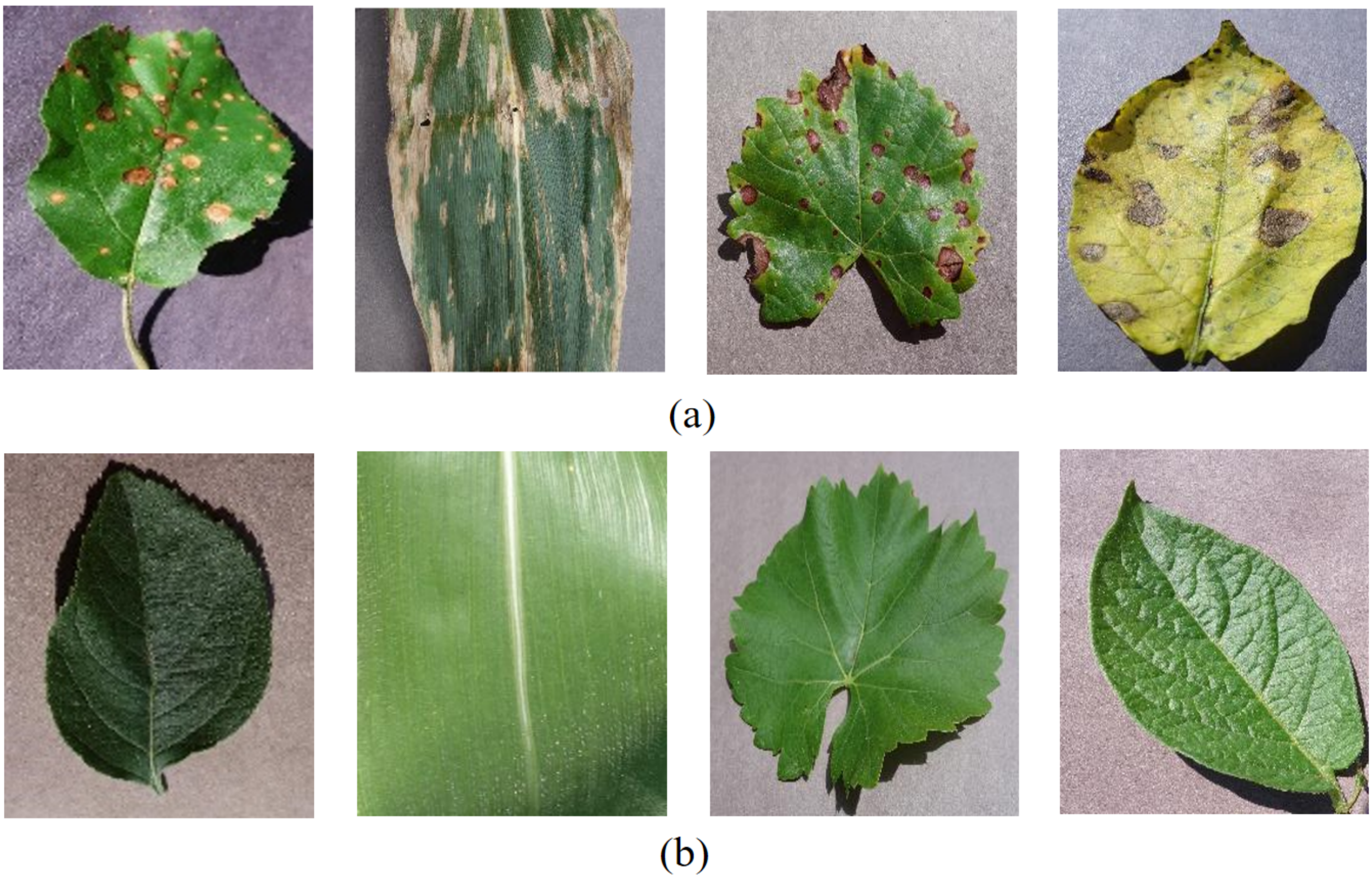

Figure 4. Sample leaves from PlantVillage dataset. (a) Disease Leaves. (b) Healthy Leaves.

Table 3. Performance measure of different CNN models.

Models	Accuracy (%)	Loss
CNN Model	95.17	0.1448
VGG16	98.15	0.0532
VGG19	97.69	0.0699
InceptionV3	97.03	0.0883
Alex Net	96.24	0.1131

Figure 9 shows the Raspberry Pi setup used for detecting plant leaf diseases. This setup includes a Pi camera and a Raspberry Pi 3B+. Initially, power is supplied using a power bank. The Pi camera captures the image of the plant leaf and, using the AlexNet model, identifies the disease.

The model is trained using a dataset containing five crops, comprising 25 classes of healthy and diseased plants. Figure 6 shows the ESP32-CAM interface and

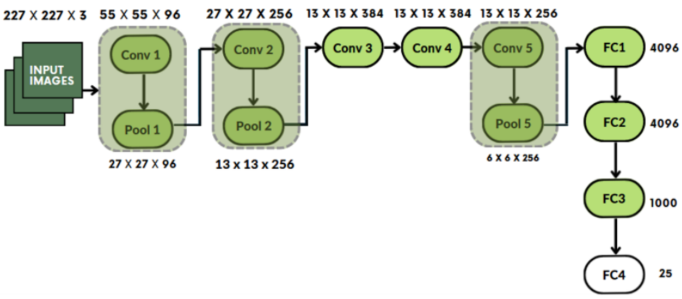

Figure 5. Modified AlexNet architecture.

its plant detection capability, which is used by the rover to move toward the detected plant.

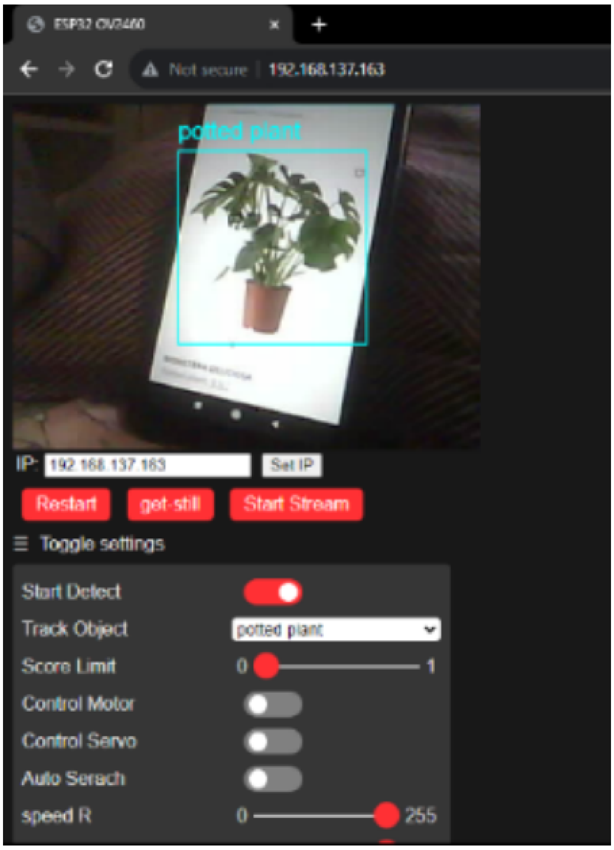

Figure 6. Plant detection output.

With the help of the interface, the rover can be controlled manually. However, the main objective of the rover is to identify plants without human intervention. Therefore, if the rover does not detect a plant, it performs an auto-search operation. The auto-search operation involves moving the rover in a clockwise direction.

The trained model was tested on unseen data to simulate real-world conditions. Since the AlexNet algorithm achieved the highest accuracy, it is used to identify plant leaf diseases. This step involves capturing images of plant leaves using the Raspberry Pi and rover setup, followed by running model inference to detect diseases. Figure 7 shows the disease prediction output generated by the AlexNet model.

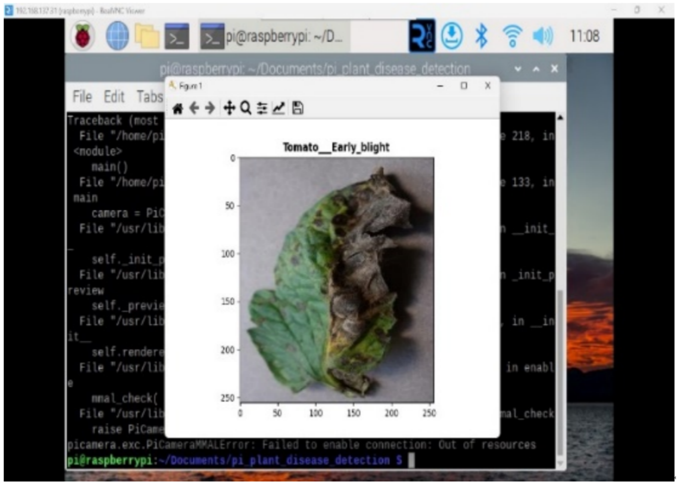

Figure 7. Disease detection output.

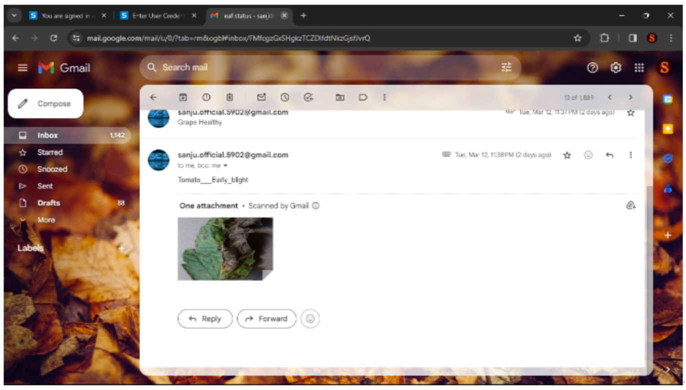

Figure 8. Mail Notification about plant disease detection.

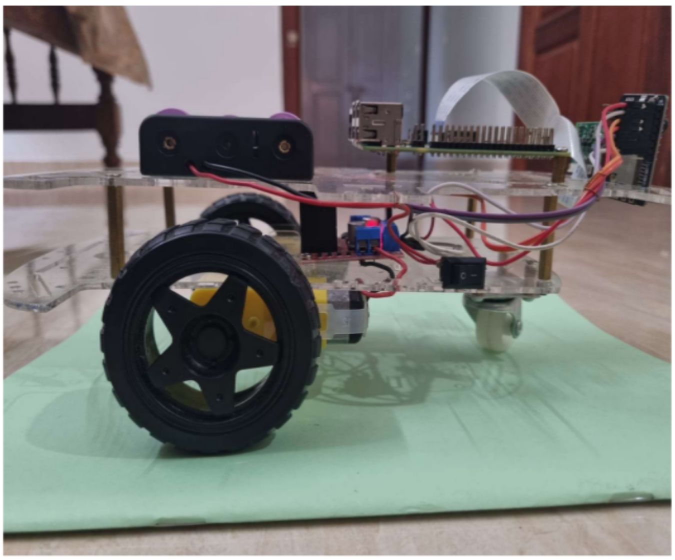

Figure 9. Designed Smart Rover.

Figure 8 shows the mail notification by Raspberry Pi sent to the farmer. This mail consists of predicted plant leaf diseases with the plant leaf image captured. Figure 9 shows the designed rover.

4 Conclusion and Furture Work

In conclusion, the modified AlexNet architecture has proven effective in predicting plant leaf diseases. The ESP32-CAM is used to detect the plant, after which the image of the leaf is captured and analyzed using the trained deep learning model. The identified disease is then sent to the user via email, providing timely alerts that can help maximize agricultural productivity. Our system demonstrated reliable performance in real-world agricultural conditions, accurately identifying common plant diseases such as powdery mildew, leaf spot, and blight. By combining the computing capabilities of the Raspberry Pi with the mobility of the rover, the system was able to capture leaf images from various locations within the field, improving coverage and detection effectiveness. The Raspberry Pi captures the images and executes the disease identification process through commands run in the terminal. In the future, the system can be enhanced by expanding the dataset with more plant images to improve model accuracy. Additionally, the current implementation using a three-wheel chassis can be upgraded to a tank chassis to achieve better mobility and terrain adaptability. Overall, the proposed system offers a practical and scalable solution for early plant disease detection, ultimately benefiting farmers through increased crop productivity.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Hassan, S. M., & Maji, A. K. (2022). Plant disease identification using a novel convolutional neural network. *IEEE Access*, *10*, 5390-5401. [CrossRef]

[2] Zinonos, Z., Gkelios, S., Khalifeh, A. F., Hadjimitsis, D. G., Boutalis, Y. S., & Chatzichristofis, S. A. (2022). Grape leaf diseases identification system using convolutional neural networks and LoRa technology. *IEEE Access*, *10*, 122-133. [CrossRef]

[3] Zhou, C., Zhou, S., Xing, J., & Song, J. (2021). Tomato leaf disease identification by restructured deep residual dense network. *IEEE Access*, *9*, 28822-28831. [CrossRef]

[4] Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2018). Identification of maize leaf diseases using improved deep convolutional neural networks. *IEEE Access*, *6*, 30370-30377. [CrossRef]

[5] Rashid, M., Bari, B. S., Yusup, Y., Kamaruddin, M. A., & Khan, N. (2021). A comprehensive review of crop yield prediction using machine learning approaches with special emphasis on palm oil yield prediction. *IEEE Access*, *9*, 63406-63439. [CrossRef]

[6] Levoir, S. J., Farley, P. A., Sun, T., & Xu, C. (2020). High-accuracy adaptive low-cost location sensing subsystems for autonomous rover in precision agriculture. *IEEE Open Journal of Industry Applications*, *1*, 74-94. [CrossRef]

[7] Liu, Z., Bashir, R. N., Iqbal, S., Shahid, M. M. A., Tausif, M., & Umer, Q. (2022). Internet of Things (IoT) and machine learning model of plant disease prediction–blister blight for tea plant. *IEEE Access*, *10*, 44934-44944. [CrossRef]

[8] Materne, N., & Inoue, M. (2018). IoT monitoring system for early detection of agricultural pests and diseases. *Proceedings of the 12th South East Asian Technical University Consortium (SEATUC)*. [CrossRef]

[9] Sharma, P., Hans, P., & Gupta, S. C. (2020). Classification of plant leaf diseases using machine learning and image preprocessing techniques. *2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, 480-484. [CrossRef]

[10] Lv, M., Zhou, G., He, M., Chen, A., Zhang, W., & Hu, Y. (2020). Maize leaf disease identification based on feature enhancement and DMS-Robust AlexNet. *IEEE Access*, *8*, 57952-57966. [CrossRef]

[11] Waheed, A., Goyal, M., Gupta, D., Khanna, A., Hassanien, A. E., & Pandey, H. M. (2020). An optimized dense convolutional neural network model for disease recognition and classification in corn leaf. *Computers and Electronics in Agriculture*, *175*, 105456. [CrossRef]

[12] Ahila Priyadharshini, R., Arivazhagan, S., Arun, M., & Mirnalini, A. (2019). Maize leaf disease classification using deep convolutional neural networks. *Neural Computing and Applications*, *31*(12), 8887-8895. [CrossRef]

[13] Priyadharshini, R. A., Arivazhagan, S., & Arun, M. (2023). A comparative study of traditional machine learning and deep learning approaches for plant leaf disease classification. *Applied Intelligence in*

Human-Computer Interaction, 47-65. [CrossRef]

[14] Pawar, S., Shedge, S., Panigrahi, N., Jyoti, A. P., Thorave, P., & Sayyad, S. (2022). Leaf disease detection of multiple plants using deep learning. *2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON)*, 241-245. [CrossRef]

[15] T. S. M., S. K. S., S. M. S., & Devi, P. R. (2021). Leaf disease detection using deep learning. *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 1797-1804. [CrossRef]

Arun MArun Madakannu received his PhD degree from Anna University in 2024 and the M.E degree in Embedded System Technologies from Anna University, Chennai in 2010. He is currently working in CloudThat Technologies in Bengaluru. Prior to this, he was working as Associate Professor in the Department of Electronics and Communication Engineering, Mepco Schlenk Engineering College, Sivakasi. He has published around 20 Technical papers in the International Journals/ Conferences. His research interests are focused on Machine Learning, Deep Learning and Generative AI. (Email: arunmadakannu@gmail.com)

R. K. V. Giridhesh has completed his B.E. in Electronics and Communication Engineering from Mepco Schlenk Engineering College in 2024 and is currently working as an RTL Design Engineer at SmartDV Technologies, Bengaluru. His interests include Digital Design, Verilog, and high-speed protocols. (Email: giridhesh2002@gmail.com)

Sanjith Chandran has completed his B.E. in Electronics and Communication Engineering from Mepco Schlenk Engineering College in 2024. His strong interests are in the area of VLSI and Embedded systems. (Email: sanjithchandran5902@gmail.com)