

Flora-Sense: Deep Learning Based Rose Plant Disease Detection and Cure Recommendation System

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Abstract—Rose plants are highly affected by several diseases that reduce plant quality and overall productivity. Conventional disease recognition in plants can be challenging because it depends heavily on regular field inspections and specialized agricultural knowledge. To address this issue, Flora-Sense was designed as a smart monitoring platform for rose plants that can recognize various diseases and provide appropriate treatment recommendations. The proposed framework analyzes rose leaf photographs to recognize diseases such as Powdery Mildew, Black Spot, Rose Rust, Downy Mildew, Rose Mosaic, and Gray Mold. Before model training, the collected leaf images undergo preprocessing operations including resizing and augmentation. The developed prediction model examines captured leaf images and determines the corresponding disease category. Based on the generated prediction, the system provides appropriate cure and prevention recommendations through an integrated platform. The proposed solution minimizes manual effort, improves disease prediction reliability, and supports efficient monitoring of rose plant health.

Keywords—Rose Plant Monitoring, Neural Network Model, AI-Based Agriculture, Intelligent Crop Analysis, Automated Plant Health System, Disease Prediction

I. INTRODUCTION

Agriculture has remained an essential part of human development and continues to contribute significantly to economic growth and food production. Among ornamental flowering plants, roses are widely cultivated because of their decorative value and commercial demand. However, rose plants are frequently affected by diseases such as Powdery Mildew, Black Spot, Rose Rust, Downy Mildew, Rose Mosaic, and Gray Mold, which negatively influence plant growth and flower quality. Traditional plant disease identification mainly depends on physical examination carried out by farmers and field specialists. On larger agricultural operations, early disease symptoms often go unnoticed, leading to substantial crop damage and considerable economic losses. Modern image-analysis

technologies have created new opportunities for developing automated crop monitoring systems. Neural-network-based models are capable of examining leaf images and identifying disease symptoms using visual characteristics such as texture, color variation, and leaf patterns. These capabilities make CNNs particularly well-suited for identifying plant diseases across varying environmental conditions. The feature-learning ability of neural network models enables effective recognition of disease symptoms under different environmental conditions. Flora-Sense is an intelligent disease analysis and recommendation system that examines images of rose leaves and determines the type of infection present, while also suggesting suitable preventive and corrective measures.



Fig. 1: Black spot and Downy mildew

The system employs a trained CNN model to classify various disease categories alongside healthy leaves, while providing suitable treatment recommendations that include both preventive measures and therapeutic options. Flora-Sense aims to provide farmers and gardeners with a precise, cost-effective, and user-friendly tool for early disease identification and management. By minimizing manual intervention requirements and enhancing diagnostic precision, the system promotes sustainable agricultural practices while reducing unnecessary pesticide applications. The developed platform supports efficient disease monitoring, minimizes manual effort, and assists growers in maintaining healthy rose cultivation practices.

II. LITERATURE SURVEY

Earlier research explored different computational approaches for recognizing crop diseases through digital image analysis and intelligent prediction models.

Ramcharan et al. [1] introduced a CNN-supported application for cassava leaf disease analysis using images collected from real agricultural environments. Their framework enabled faster disease recognition and supported field-level crop monitoring.

Rajendra et al. [2] developed a smart farming system using IoT sensors and cloud communication for monitoring agricultural conditions. Their work reduced manual supervision and improved environmental observation in farming applications.

Reddy et al. [3] utilized machine learning techniques to identify crop infections through image characteristics such as texture and color information. Their method improved the consistency of automated disease prediction.

Arivazhagan et al. [4] applied segmentation and texture evaluation methods to detect unhealthy regions in plant leaves. Their approach enhanced the identification of infected areas in crop images.

Ramesh et al. [5] enhanced neural-network performance for paddy disease recognition using evolutionary optimization strategies. Their approach improved classification efficiency and reduced prediction errors.

Waghmare et al. [6] created a machine-learning-based crop prediction system along with pesticide recommendation functionality. Their platform supported agricultural decision-making and preventive crop management.

Liakos et al. [7] examined different machine learning applications in agriculture, including crop supervision, disease recognition, and intelligent irrigation methods. Their review emphasized the importance of AI in modern farming systems.

A. S. Ahmad et al. [8] proposed an IoT-assisted greenhouse automation system for controlling environmental parameters and reducing disease spread. Their system improved greenhouse management through continuous monitoring.

Ferentinos et al. [9] implemented deep neural network models for crop disease classification under different environmental conditions. Their study demonstrated

reliable prediction capability across multiple plant categories.

Zhang et al. [10] presented a neural-network-oriented technique for identifying rose leaf diseases using images captured under natural lighting environments. Their work supported practical disease analysis for ornamental plants.

Kumar et al. [11] combined image segmentation methods with neural-network algorithms for recognizing rose leaf infections. Their framework improved disease differentiation and classification performance.

Sharma et al. [12] designed a hybrid learning framework integrating SVM and CNN methods for early rose disease prediction. Their model improved recognition accuracy on limited datasets.

Reddy et al. [13] investigated multiple predictive algorithms for analyzing health conditions in rose foliage. Their study evaluated multiple learning models and demonstrated the effectiveness of automated visual data evaluation for identifying plant infections in ornamental plants.

Srivastava et al. [14] presented a computational approach for recognizing rose leaf infections through digital image evaluation and intelligent learning models. Their system integrated CNN, SVM, and KNN models to enhance classification performance and support early disease diagnosis in rose plants.

Duman et al. [15] designed a smartphone-assisted application for identifying infections and pest-related symptoms in rose crops using deep convolutional neural networks. The proposed solution enabled rapid disease identification through an Android application suitable for practical agricultural use.

Guduru Ramakrishna Reddy et al. [16] analyzed leaf photographs to determine infection categories and generated management suggestions platform using InceptionV3 and MobileNetV2 architectures. Their system identified crop health conditions using photographs of leaves and provided suitable recommendations for disease management.

Liu et al. [17] developed an efficient disease recognition strategy that utilized transferable feature learning for rose plant analysis. Their method improved disease recognition under field while reducing processing overhead and resource consumption requirements for real-time deployment.

Ozkan et al. [18] introduced a crop-health recognition model that examined real-world leaf images through computational analysis methods on real-world agricultural images. The research evaluated conventional prediction algorithms alongside modern neural-network approaches and demonstrated improved classification performance under practical field conditions.

Based on this literature review, most current systems can only identify three to four plant diseases and do not provide comprehensive rose disease detection or treatment recommendation capabilities. While these systems deliver acceptable accuracy levels, the proposed CNN model successfully enhances prediction accuracy beyond existing methods. The proposed system addresses these shortcomings by detecting six distinct rose plant diseases and offering appropriate treatment recommendations for practical real-world use.

III. OBJECTIVE

The "Flora-Sense: Deep Learning Based Rose Plant Disease Detection and Cure Recommendation System" project aims to enhance rose farming efficiency and sustainability by automating disease identification and providing treatment guidance. Rose plants face significant threats from diseases like Powdery Mildew, Black Spot, Rose Rust, Downy Mildew, Rose Mosaic, and Gray Mold, all of which can severely impact plant health and crop yields. The suggested approach uses a Convolutional Neural Network (CNN) that leverages deep learning capabilities to analyze images of leaves and accurately identify diseases as they occur in real time. Built around a Raspberry Pi Zero 2W equipped with a camera module and control buttons, this system offers a portable, cost-effective, and easy-to-use approach. When the system identifies a disease, it delivers appropriate treatment and prevention recommendations via a web-based platform. Flora-Sense seeks to decrease reliance on manual plant monitoring, enable earlier disease identification, reduce agricultural losses, and encourage environmentally responsible farming methods through smart plant health monitoring.

IV. BLOCK DIAGRAM

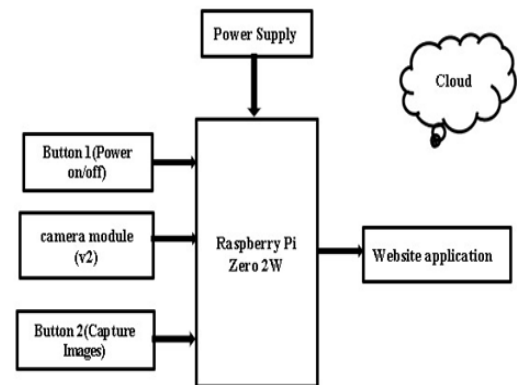


Fig. 2: Block diagram

V. PROPOSED SYSTEM

Hardware Components

1. Microcontroller (RaspberryPiZero2W):

Serves as the central control unit for the entire system. It analyzes leaf images through a deep learning model and coordinates communication across hardware components, software elements, cloud services, and the website interface.

1. Camera-Module(v2):

Takes detailed, high-quality photographs of plant leaves to identify potential diseases and transmits these images to the Raspberry Pi for processing and evaluation.

2. Website-Application:

Displays detected diseases, plant health status, and treatment suggestions through a user-friendly interface.

3. Cloud:

Stores images and analysis data securely for remote access, backup, and future reference.

VI. FLOW OF THE SYSTEM

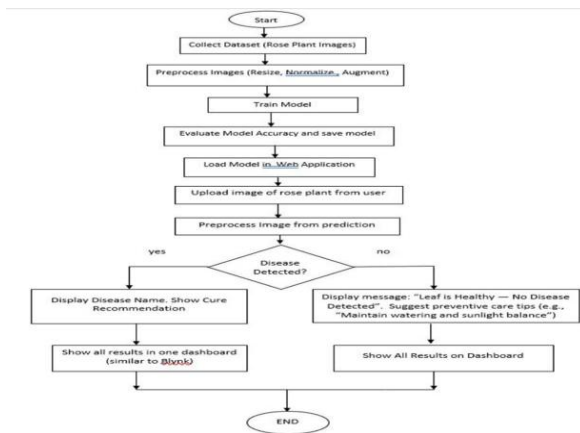


Fig 3: Flow Chart

VII. RESULTS AND DISCUSSION

The system we developed includes a Raspberry Pi Zero 2W, Camera Module V2, a CNN-based deep learning model, cloud connectivity, and a Streamlit web application that detects rose plant diseases in real time and suggests treatments. Images of rose leaves and flowers are captured by the Camera Module V2, then processed through image preprocessing methods and examined by our trained CNN model. The web application we created displays both prediction results and treatment recommendations. The figures that follow demonstrate the outcomes from different phases of system development and testing

1. As shown in figure 4, the image capturing process is initiated through the command prompt using a push button interface, where system messages such as "capturing image" and "image uploaded" are displayed after successful image acquisition.

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Stream configuration adjusted
[0:03:25.219397773] [1083] INFO Camera camera.cpp:1215 configu
[0:03:25.224147167] [1088] INFO RPI vc4.cpp:620 Sensor: /base/
nicam format: 2592x1944-pGAA/RAW
Still capture image received
✓ Captured: /home/saba___tamboli/images/img_1778128995.jpg
● Uploaded
  
```

Fig.4. Image capture using Raspberry Pi camera

rose plant leaf images captured using Raspberry Pi Zero 2W and Camera Module V2 are uploaded to the system for disease analysis and prediction.



Fig.5.Original Image

3. As shown in the figure 6 below, the captured images are preprocessed using resizing and normalization techniques to improve CNN model performance and prediction accuracy.



Fig.6.Preprocessed Image

4. Healthy leaf and healthy flower prediction are successfully identified by the developed CNN based system, as shown in the figures below 7 and 8.



Fig.7. Healthy Leaf Prediction Result

2. As shown in the figure 5 below, the original

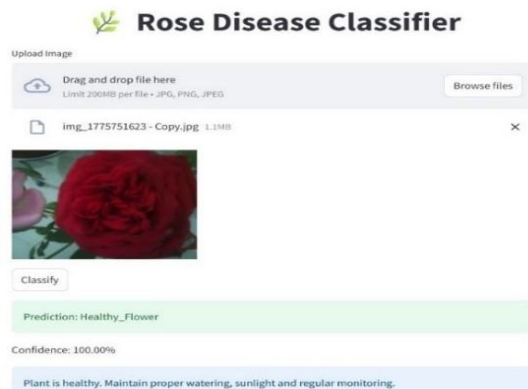


Fig.8. Healthy Flower Prediction Result

5. Similarly, the same process is carried out for diseased rose plant leaves and flowers which are successfully demonstrated.

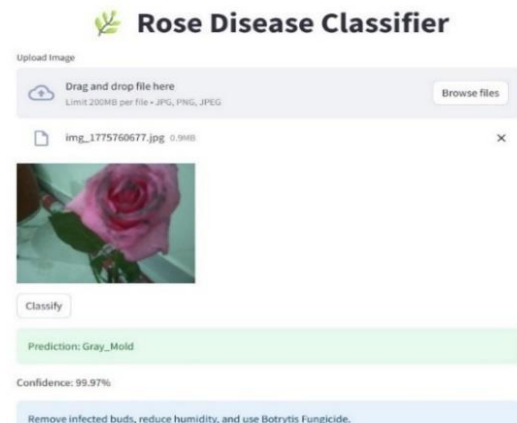


Fig.9. Gray Mold Prediction Result

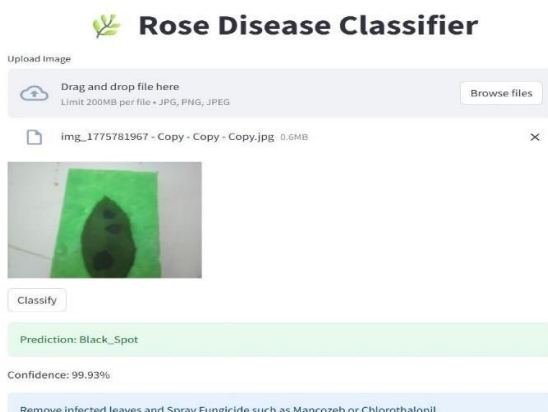


Fig.10 Black Spot Prediction Result

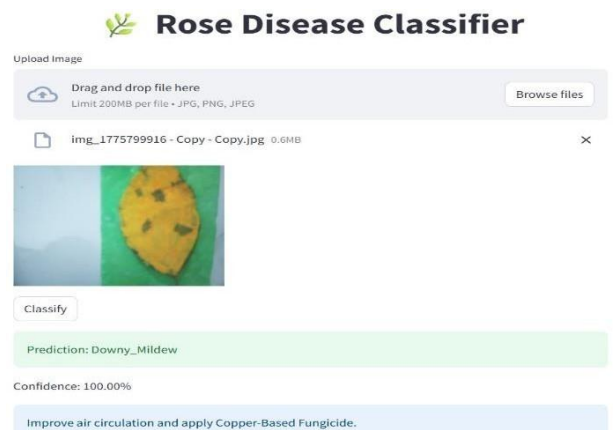


Fig.11. Downy Mildew Prediction Result

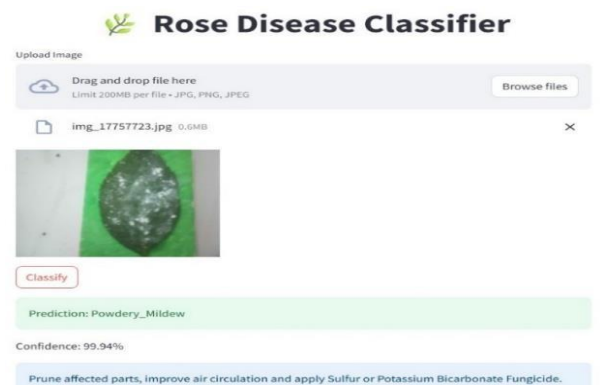


Fig.12. Powdery Mildew Prediction Result

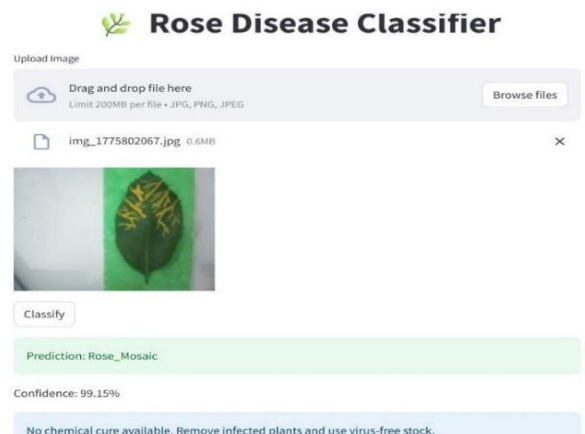


Fig.13. Rose Mosaic Prediction Result

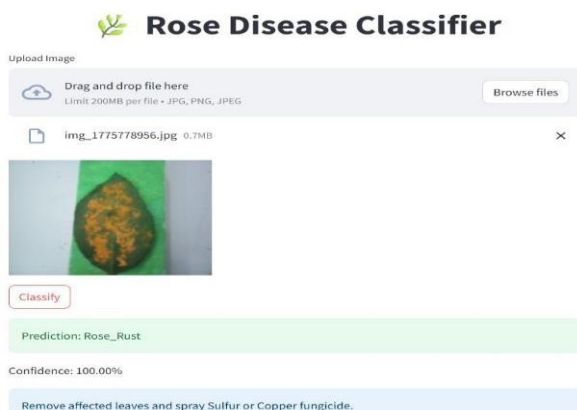


Fig.14. Rose Rust Prediction Result

6. Our CNN model reached acceptable accuracy and confidence levels when predicting both healthy and diseased rose plant images, as illustrated in the graph presented in figure 15.

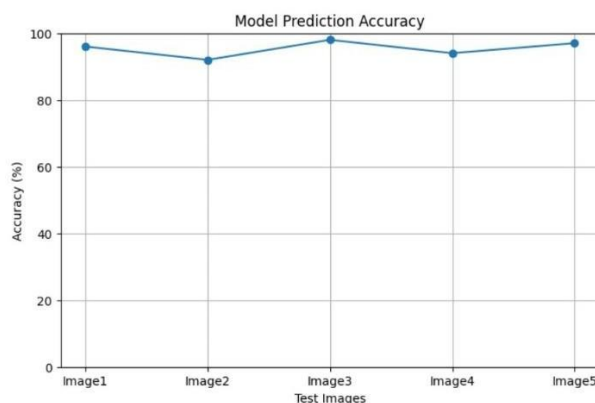


Fig.15. Model Prediction Accuracy Graph

Our completed system effectively detects rose plant diseases in real time by utilizing the Raspberry Pi Zero 2W, Camera Module V2, image preprocessing, and CNN-based deep learning methods. The system reliably recognizes healthy leaf and flower conditions while accurately predicting diseased leaves and flowers through our Streamlit web application, which incorporates cloud connectivity and treatment recommendation capabilities.

VIII.CONCLUSION

The presented system addressed the problem of slow and inaccurate manual detection of rose plant diseases, which often led to yield loss and delayed treatment. A CNN based model was implemented to classify diseases from leaf images and provide suitable cure recommendations. The proposed CNN model also achieved improved prediction accuracy compared to

existing systems. The system integrated Raspberry Pi, Camera Module V2, cloud connectivity, and a web application for real-time disease detection and monitoring. Multiple tests under different environmental conditions showed consistent accuracy and reliable performance. The presented system reduced human effort, enabled early disease identification, and improved plant health monitoring. The system we developed provides an effective, precise, and easy-to-use approach for identifying rose plant diseases in real time, tracking their progression, and managing crops in an environmentally sustainable way.

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