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Smart Plant Disease Prediction System Using Raspberrypi and Image Processing

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KEYWORDS

Raspberry pi, Camera module, Image Processing, CNN

ABSTRACT

This project presents a smart plant disease detection system that utilizes deep learning and embedded technology for real-time agricultural monitoring. The system captures leaf images using a camera module connected to a Raspberry Pi and processes them through image preprocessing techniques to ensure consistency and quality. A lightweight deep learning model is used to classify the leaf as healthy or diseased by analyzing features such as color, texture, and patterns. The model is optimized to provide accurate predictions with minimal computational requirements, making it suitable for practical field applications. An important feature of the system is the integration of an automated email notification module, which sends the detection results, including leaf type, disease status, confidence score, and captured image, directly to the user. This enables remote monitoring and timely decision-making. The proposed system is efficient, cost-effective, and suitable for modern smart farming solutions.

1. INTRODUCTION

Maintaining plant health is essential for improving agricultural productivity and reducing crop losses. Diseases affecting plant leaves can spread rapidly and negatively impact yield if not detected at an early stage. Traditional methods of disease identification rely on manual inspection, which is time-consuming and depends heavily on expert knowledge. In many rural areas, access to such expertise is limited, making automated solutions highly necessary.

With the growth of artificial intelligence, deep learning-based approaches have become highly effective for image classification tasks. In this project, a smart plant disease detection system is developed using a Convolutional Neural Network (CNN) approach. Specifically, the system utilizes the MobileNetV2 algorithm, which is known for its lightweight structure and high efficiency. This model is implemented using TensorFlow and optimized through transfer learning to improve accuracy while reducing training time.

The system is deployed on a **Raspberry Pi**, making it suitable for real-time and low-cost applications. A camera module is connected to the device to capture images of plant leaves. These images undergo preprocessing steps such as resizing and normalization using OpenCV and NumPy. These libraries help in improving image quality and preparing the data for model input.

After preprocessing, the image is passed to the trained MobileNetV2 model for classification. The model extracts important features such as color variations, texture patterns, and disease spots to determine whether the leaf is healthy or infected. The use of transfer learning allows the system to achieve high accuracy even with a limited dataset by leveraging pre-trained knowledge. An important feature of this system is the integration of an automated email notification module. Once the prediction is completed, the system generates an output that includes the leaf type, detected disease, and confidence score. This information, along with the captured image, is sent directly to the user's email. This functionality is implemented using Python-based email libraries, enabling real-time communication of results.

The inclusion of the email feature enhances the usability of the system by allowing remote monitoring. Users do not need to be physically present near the device to view results, making it highly beneficial for farmers and agricultural monitoring systems. For example, the system can detect a diseased leaf with high confidence and instantly notify the user, enabling quick preventive action.

In addition to the core functionality, the system is designed to be scalable and adaptable for different types of crops and environmental conditions. The modular architecture allows easy integration of new datasets and retraining of the model for improved performance. The use of optimized libraries ensures faster execution and reduced memory consumption on embedded hardware. Furthermore, the system can be extended by integrating IoT technologies, enabling data storage, remote access, and real-time analytics through cloud platforms.

Overall, the proposed system combines deep learning algorithms, efficient libraries, and embedded hardware to deliver a reliable solution for plant disease detection. The integration of real-time email alerts further improves its practicality, making it suitable for modern smart farming applications.

II. LITERATURE SURVEY

M. Saha *et al.* [1] discussed a technique for automatically identifying plant leaf diseases by utilizing machine learning techniques based on image features for early and accurate detection. The technique involved the use of digital image processing, machine learning, and computer vision. However, the technique heavily relies on handcrafted features and data sets.

A. S. Abade *et al.* [2] provided a comprehensive review on the recognition of plant diseases using Convolutional Neural Networks (CNNs). The author studied a large number of research works, which highlighted the effectiveness of deep learning in automatically extracting complex features from images of plant leaves. Despite the advantages, the author identified some challenges, such as diversity in the dataset and generalization in real-world scenarios.

M. Agarwal *et al.* [3] proposed a model for the detection and classification of tomato leaf diseases using a CNN model. Image preprocessing and feature extraction techniques were used to improve the accuracy of the classification. Despite the high accuracy of the proposed model, it consumes a lot of computational resources, which can be a challenge in generalizing the model.

A. Lakshmanarao *et al.* [4] has proposed a machine learning-based approach along with image processing techniques for the detection of plant diseases. This system is focused on feature extraction and classification using traditional machine learning techniques. However, the use of conventional techniques is limited.

A. Badage [5] proposed a system based on machine learning and image processing in Indian crop disease detection. The method employed segmentation and edge detection techniques in pattern recognition of the diseases. However, the method is restricted in the sense that it is based on traditional algorithms and is not adaptive to the data sets.

Q. Liang *et al.* [6] proposed a computer-assisted diagnosis system for plant disease detection and severity estimation using deep learning. The model has shown improvement in detecting disease severity but requires large data sets and computational power for its efficient implementation.

V. K. Vishnoi *et al.* [7] explored the detection of plant diseases through computational intelligence and image processing. The paper emphasized the need for feature extraction and classification; however, it also pointed out limitations in terms of accuracy.

H. Durmuş *et al.* [8] implemented deep learning techniques for the detection of diseases in tomato leaves. The study showed that the performance of the proposed technique was better than traditional techniques but was specific to certain crops and environments.

W. Malik *et al.* [9] propose an efficient technique for disease detection based on images using neural networks. Although the study focuses on medical images, the proposed technique proves that deep learning techniques perform better for classification problems.

From the literature survey, Various studies have been carried out in the field of plant disease detection using image processing, machine learning, and deep learning techniques. Early approaches mainly depended on handcrafted features and traditional algorithms, which required manual effort and often resulted in lower accuracy. With advancements in technology, deep learning methods, especially convolutional neural networks, have shown significant improvement by automatically extracting complex features from leaf images. Several models achieved high classification accuracy through preprocessing and feature extraction techniques. However, many of these approaches demand high computational resources and large datasets, limiting their use in real-time applications. Some methods are also restricted to specific crops and environments, reducing their general applicability. In addition, most existing systems do not provide user-friendly output or real-time notification. To address these limitations, the proposed system introduces an efficient lightweight model along with an automated email feature for instant result communication and improved usability.

III. PROPOSED METHODOLOGY

The overall workflow of the proposed plant disease detection system is illustrated in **Fig. 1**. The system is designed to provide real-time detection of plant diseases using image processing and deep learning techniques, along with an automated email notification feature to improve user interaction and accessibility.

The process begins with the image acquisition stage, where a camera module connected to the Raspberry Pi device captures images of plant leaves. These images act as the primary input for the system. Since raw images may vary in size, lighting conditions, and quality, a preprocessing step is applied to standardize the input data. This includes resizing the images to a fixed dimension and normalizing pixel values to a specific range. Image processing libraries are used to perform these tasks efficiently and ensure that the input is suitable for the model.

After preprocessing, the system performs feature extraction to identify important visual characteristics of the leaf. These features include color variations, texture patterns, and the presence of spots or irregularities that may indicate disease. The extracted features play a crucial role in improving the accuracy of the classification process. The processed image is then passed to a trained deep learning model for classification. The system uses a lightweight model that is optimized for embedded devices, allowing efficient execution on the Raspberry Pi platform. The model analyzes the input image and predicts whether the leaf is healthy or affected by a disease. If a disease is detected, the model also identifies the specific type of disease present in the leaf.

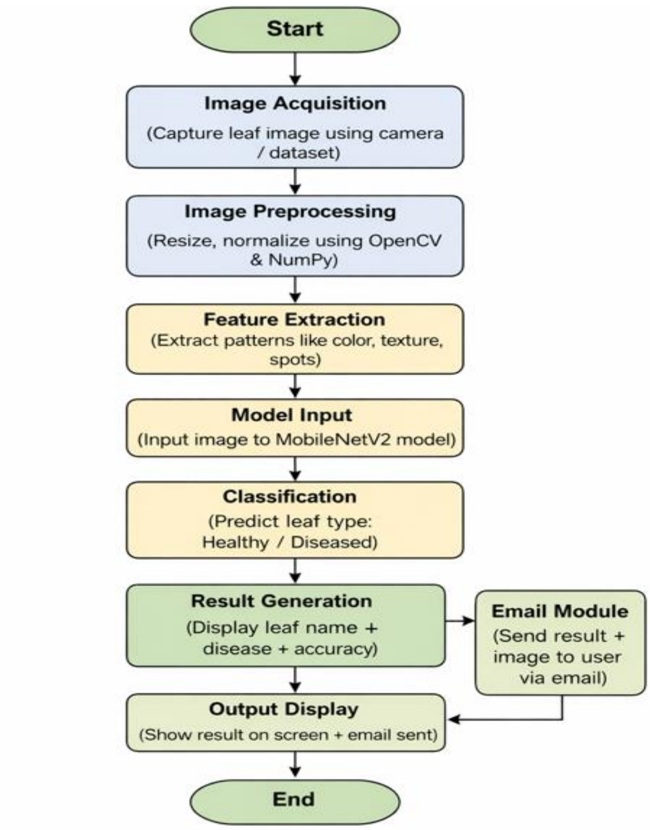

Fig.1: Flow chart of proposed system

Once the classification is completed, the system generates the output, which includes the leaf name, disease status, and confidence score indicating the reliability of the prediction. As shown in **Fig. 1**, an additional email notification module is integrated into the system to enhance its functionality. This module automatically sends the detected results along with the captured leaf image to the user's email address. This feature ensures that users receive real-time updates without needing to constantly monitor the system.

Finally, the output is displayed on the system interface, allowing the user to view the results directly. At the same time, the email notification provides remote access to the results, making the system more flexible and user-friendly. The integration of both on-screen display and email communication improves the overall usability of the system. In addition, the system is designed to be scalable and adaptable for different plant types and environmental conditions. The use of efficient algorithms and lightweight architecture ensures low computational cost and faster processing time. Overall, the proposed methodology provides an accurate, efficient, and practical solution for plant disease detection, making it suitable for modern smart agriculture applications.

IV. RESULTS AND DISCUSSIONS

The developed plant disease detection system was evaluated using sample images of bell pepper leaves under different conditions. The model demonstrated strong classification capability in distinguishing between healthy and diseased leaves, particularly for bacterial spot infection. The results obtained from the experimental setup are illustrated in Fig. 2 and Fig. 3.

Fig. 2 presents the output generated by the system through an automated email notification. The input leaf image was identified as pepper_bell, and the model classified it as affected by bacterial spot disease with a confidence score of 99.97%. This high confidence level indicates that the trained model has effectively learned the distinguishing features of bacterial spot, such as irregular dark lesions and yellowing of the leaf surface. The integration of an email-based alert system further enhances the practical applicability of the model, enabling real-time communication of results to users. This feature is particularly useful for farmers and agricultural practitioners who may not have direct access to the system interface at all times.

Fig.2: Output showing effected unhealthy leaf with bacterial spot sent through email

Fig. 3 shows the graphical user interface output of the detection system running on a Raspberry Pi platform. In this case, the input leaf image was classified as healthy with a confidence of 100.0%. The clear visualization of the leaf along with classification details demonstrates the system's ability to process images locally and provide instant feedback. The use of

Raspberry Pi highlights the system's feasibility as a low-cost and portable solution for field deployment. The interface also ensures user-friendly interaction, making it accessible even to non-technical users.

A comparison of the two results indicates that the model performs consistently across different input scenarios and output formats. Whether the result is delivered via email (Fig. 2) or displayed through a local interface (Fig. 3), the classification accuracy remains high. This consistency is crucial for building trust in automated disease detection systems. Moreover, the model's ability to correctly identify both diseased and healthy samples suggests that it is well-balanced and not biased toward a particular class.

However, certain challenges may still affect performance in real-world conditions. Variations in lighting, background noise, and image quality can influence prediction accuracy. For instance, blurred or low-resolution images may reduce the confidence level or lead to misclassification. Therefore, ensuring proper image capture conditions is essential for optimal performance. Additionally, expanding the dataset with more diverse samples could further improve the robustness of the model.

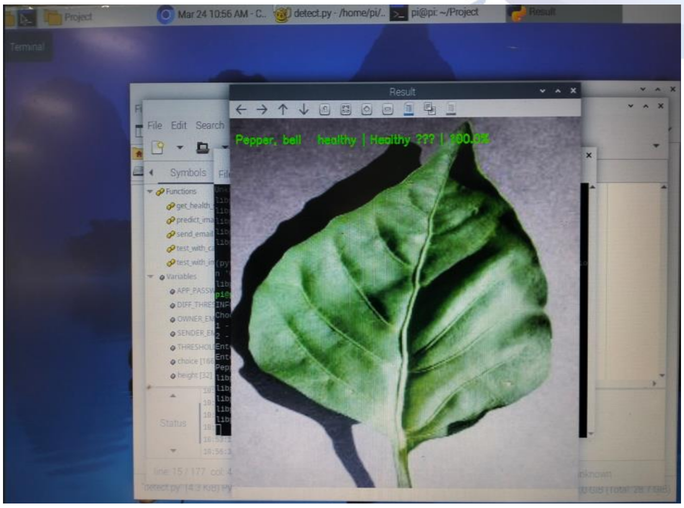

Fig.3: Output showing correct classification of a healthy pepper bell leaf with high confidence.

Overall, the results demonstrate that the proposed system is highly effective in detecting plant diseases with high accuracy and reliability. The combination of machine learning techniques, embedded system implementation, and real-time notification features makes it a comprehensive solution for smart agriculture applications. Future improvements can focus on extending the model to support multiple crops and diseases, as well as enhancing its adaptability to varying environmental conditions.

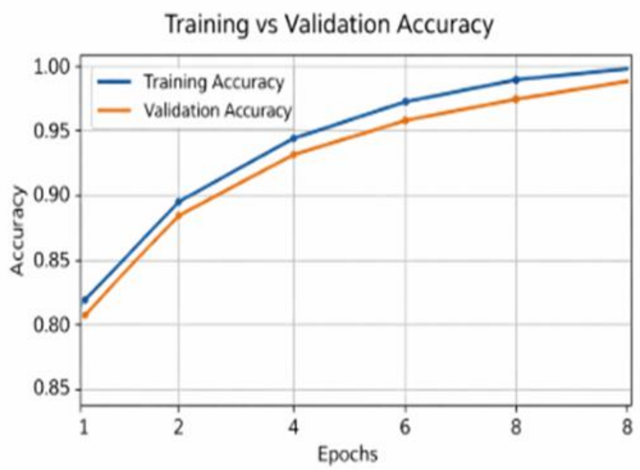

Fig.4:Training and validation accuracy of the proposed model over epochs

Fig.5:Training and Validation loss of the proposed model over epochs

The performance of the model in the course of training is further analyzed, as depicted in Fig. 4. It is observed that the accuracy of both the training and validation sets increases as the epochs increase. This shows that the model is learning effectively. The validation accuracy follows the training accuracy, showing that the model generalizes well and that there is minimal overfitting.

Additionally, the performance of the model in the course of learning, as depicted by the difference in the training and validation loss, is shown in Fig. 5. The fact that both the loss curves are decreasing shows that the model is learning and effectively minimizing the prediction errors. The validation loss follows a similar trend as the training loss. Moreover, the use of the MobileNetV2 model, as a result of transfer learning, helps in efficient feature extraction, and this results in a low computational complexity. The model, as a result of the conversion to TensorFlow Lite, runs efficiently on the Raspberry Pi device.

As a result, it can be concluded that the system works well, as shown by the results. The fact that the system can classify known images and unknown images accurately makes the system reliable.

V. CONCLUSIONS

The developed leaf disease detection system presents an effective and intelligent solution for early identification of plant diseases using advanced image processing and deep learning techniques. The system follows a structured workflow involving image acquisition, preprocessing, feature extraction, and classification using a Convolutional Neural Network, ensuring accurate and consistent results. The integration of TensorFlow Lite with Raspberry Pi enables real-time processing with minimal computational resources, making the system portable and suitable for field-level applications. A significant modification introduced in this project is the implementation of a mail-based output notification system, which automatically sends the detection results to the user's email. This feature includes details such as the identified disease and relevant insights, ensuring that farmers or users receive timely updates even without directly accessing the device. This enhancement improves accessibility, supports quick decision-making, and bridges the gap between technology and end users. The system reduces manual effort, increases reliability, and promotes efficient crop monitoring. Overall, the project demonstrates a practical, scalable, and user-friendly approach to smart agriculture by combining artificial intelligence with automated communication, thereby contributing to improved crop health management and productivity.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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