

Plant Diseases Detection for Sustainable Agriculture

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Abstract--- Agriculture plays a crucial role in the economy of any country and agriculture, providing food, raw materials, and employment opportunities. However, plant diseases continue to be a significant threat to crop yield and food security. Early and reliable identification of such diseases is vital to mitigate their impact. Conventional identification methods are often dependent on expert analysis, which may be inaccessible in rural or remote regions and are prone to subjectivity and delays. To address these challenges, this work presents an automated system for detecting plant diseases using Convolutional Neural Networks (CNNs) based on the ResNet-34 model. ResNet-34 is selected due to its efficient handling of deep network training through residual learning, which enable better accuracy. The system is trained on the publicly available Plant Village dataset, comparing over 54303 leaf images categorized into 38 different plant disease classes. The approach includes preprocessing the images, applying transfer learning using ImageNet pretrained weights, and fine-tuning the model for better generalization. The result shows high performance on validation and testing datasets, showing the model works effectively in real-time plant disease detection. This solution is a practical and scalable tool aimed to helps the farmers with technological support, promoting healthy crops and sustainable agricultural practices and reduces the crops and financial losses due to disease in plants.

Keywords— CNN, ResNet-34, image-processing, Dataset, Plant diseases detection.

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I. INTRODUCTION

Agriculture is the backbone of our society and the agricultural products holds significant importance in the Indian economy and with the expansion of agricultural land in recent times, farming has become a major component in the country's economy. In India, around 75 to 85 percent of the population depend on agriculture for their living. However, crops and vegetables often suffer from significant losses due to plant diseases. These diseases not only reduce yield but can also indirectly affects the human health through the consumption of unhealthy byproducts from infected plants. The study of plant diseases involves analysing the visual traits and patterns on leaves. Detecting plant disease in early stage is essential for agriculture, as failure to do so can destroy the yield, quality, and safety of the agricultural product.

With the time, agriculture has also transformed a lot with the advancements in technology. The fast way to detect an early onset of Crop Diseases is crucial for farmers and optimizing agricultural production and our project mainly focuses on using machine learning algorithms to identify diseases in crops, this project may provides the valuable support to both farmers and researchers. Traditionally, farmers needs the expert knowledge to detect the plant diseases on early stages by inspecting crops to spot signs of disease—this method is time-consuming, less accurate, and prone to human error. [5].

With the rapid growth in artificial intelligence (AI), machine learning (ML), and computer vision, automated plant disease detection systems have emerged as promising alternatives of the traditional method of plant diseases detection. These systems can analyze leaf image to identify type of disease symptoms such as spots, discoloration, and texture changes with high accuracy as compared to traditional method with zero expert knowledge. Among various AI techniques, deep learning—particularly CNNs—has demonstrated exceptional performance in image classification tasks.

This project focuses on designing, training and implementing a CNN-based plant disease detection model using the ResNet-34 architecture for working of model in different layer. The main aim of this project is to provide a reliable, scalable, and user-friendly solution that can assist farmers in early stages of disease detection, to reducing crop losses and promoting sustainable agricultural practices and prevent the farmers from the financial losses.

II. LITERATURE REVIEW

There are various works done till now in this Topic a few of them has been given below. Plant diseases detection has become an essential area of research because it is important for protecting food supplies and reducing crop losses. By the use of computer vision, machine learning, and deep learning, it is easy to identifying and classifying plant diseases has become more accurate and efficient compared to traditional method. Khirade and Patil [1] proposed one of the most-early frameworks to detecting plant diseases using traditional image processing techniques. Their approach involved capturing images, segmenting them using K-means clustering unsupervised model to get then output and Otsu's thresholding, and then classifying the results with artificial neural networks (ANNs).

Singh et al. [2] develops a model that combines genetic-algorithms with image processing techniques to detect unhealthy regions on plant leaves. Their segmentation approach to detect the diseases area on the plant leaves and change in the colour in the plant leaves due to a particular type of diseases and effectively analysing the diseased area on the leaves and the colour patters. Amritraj and N Hans. [3] introduces a modern deep learning solution for plant diseases detection using the YOLOv5 architecture. The model was trained only on the eight different disease categories, their model provides a real-time detection and showing the practical implementation of deep learning in agriculture.

Bhosale and S. R. Zanwar. [4] They carried out a comprehensive study about various machine learning and deep learning approaches for classifying plant diseases across different crop types. The study underscored the effectiveness of Convolutional Neural Network (CNN) models like AlexNet, VGG, and ResNet, and stressed the importance of precision agriculture in enhancing crop surveillance and management.

Parmar and Rai [5] implemented many CNN-based models, including ResNet50 and customly-built networks, for giving the power to a web application for plant disease detection. Their models reached up to 95.58% accuracy and were designed with real- world use by farmer.

Nagababu et al. [6] they search for a hybrid approach combining Convolutional Neural Networks (CNNs), Gray-Level Co-occurrence Matrix (GLCM) features, and Support Vector Machines (SVMs) for identifying plant diseases. after that their findings indicated that CNN-based models achieved higher accuracy over the traditional techniques, although the study also had an acknowledged issues related to limited dataset variety and challenges in model generalization.

Harshavardhan and P. J. V. A. Krishna. [7] They utilized the ResNet-34 architecture and classify diseases in plant leaves and implemented it through a web-based application. Their platform achieved strong real-time performance and gives the users proper guidance for treatment based on diseases detected results.

V. Tiwari and A. K. Bairwa [8] They compared the different conventional machine learning algorithms techniques such as Random Forest and SVM with deep learning techniques like CNNs. Their report revealed that deep learning models generally deliver superior results when trained on extensive, well-annotated datasets, but they also emphasized difficulties related to accurate labelling and model deployment in field environments.

III. PROPOSED METHODOLOGY

1. Dataset: -

We search for dataset on different platform and then we find a dataset of the plant disease with 54303 images, is obtained from Kaggle. The plant diseases divided into 38 classes.

2. Preprocessing the image: -

The data collected is filtered and converted into standard pixel values, fixing of the dimension and used augmented using techniques like rotation, flipping and noise addition to improved model generalization.

3. Data exploration and Preprocessing :-

An exploration phase to gain insights into its structure and characteristics. Then we used Various techniques to preprocess all the images so that the model could effectively learn and extract features from the image data. CNNs usually work with fixed-size images to ensure consistency across the dataset, we resized all images to a uniform resolution of 256×256 pixels. After preparing the dataset, we normalized the pixel values by scaling them to a range between 0 and 1, dividing each pixel value by 255 [5].

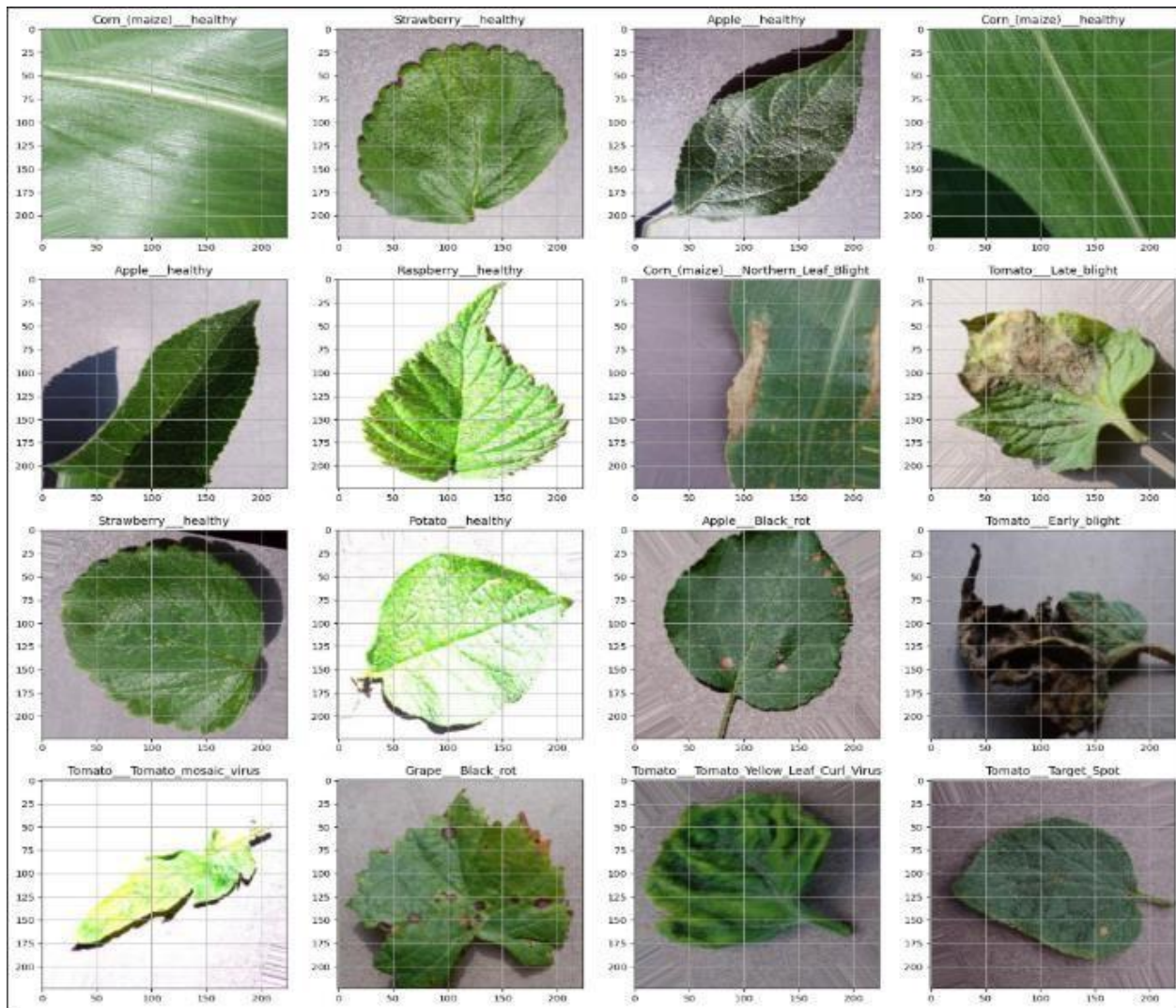


Figure 1:-Sample Image from the Dataset

4. Model Architecture: -

Firstly a CNN was developed using python then it is implemented on Google Colab platform. The model architecture had many layer and each layer have its own function in the architecture. It includes an input layer which is used to take the input from the user, multiple convolutional layers its used to build and learn patterns and pooling layers for feature extraction, followed by fully connected layers, and concludes with an output layer responsible for which show the output for a particular input as per user.

5. Training and Evaluation: -

For the training model or to increases the model's effectiveness, the dataset was divided into three subset and the subsets are:- training, validation, and testing subsets. During training process the dataset was passed through the model multiple times called as multiple epochs, CNN model was trained for 6 epochs using the Adam optimizer with backpropagation. For visualization we use matplotlib a python library used to represent the graph of accuracy and loss data during training and validation. And how the accuracy and loss changes with no. of epochs and also you can see the data obtain during the training process of our project .

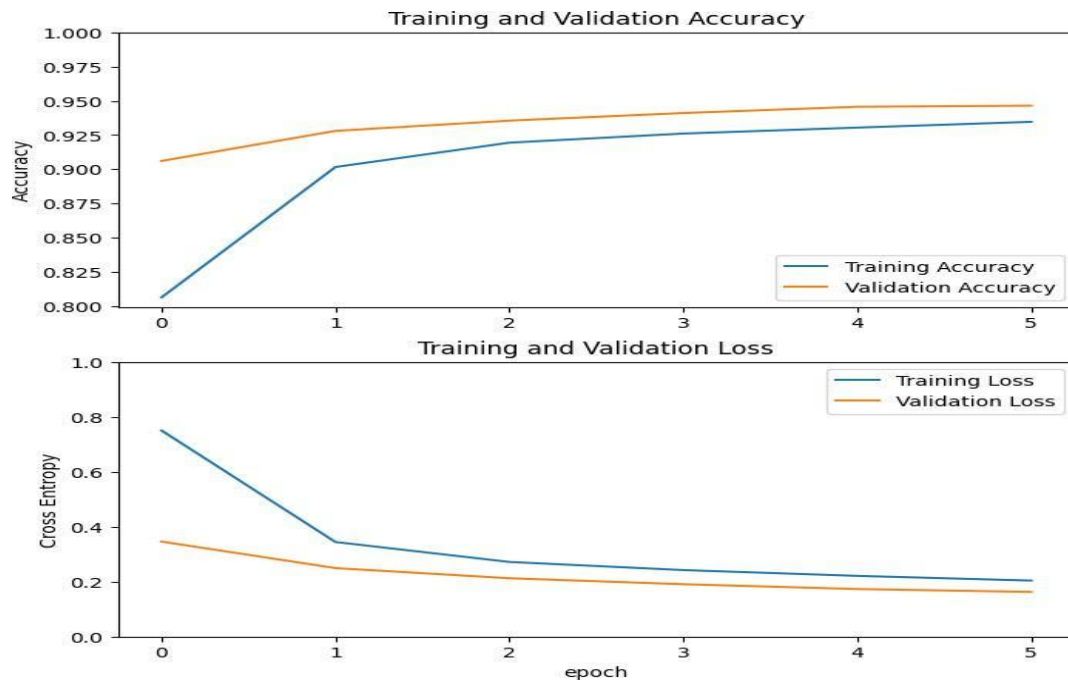


Figure 2:- Training and validation loss

This figure shows how the training and validation loss curves change when number of epochs increases. A significant decrease in both losses is observed from the first epochs, indicating that the model quickly learns the understanding the patterns in the training data. After the second epoch, we can notice the small change in the train and validation loss, which may be due to minor overfitting or variation within the validation set. However, the final epoch shows a continuously decreasing graph of train and validation loss shows in the fig-2, indicating the improvement in the model.

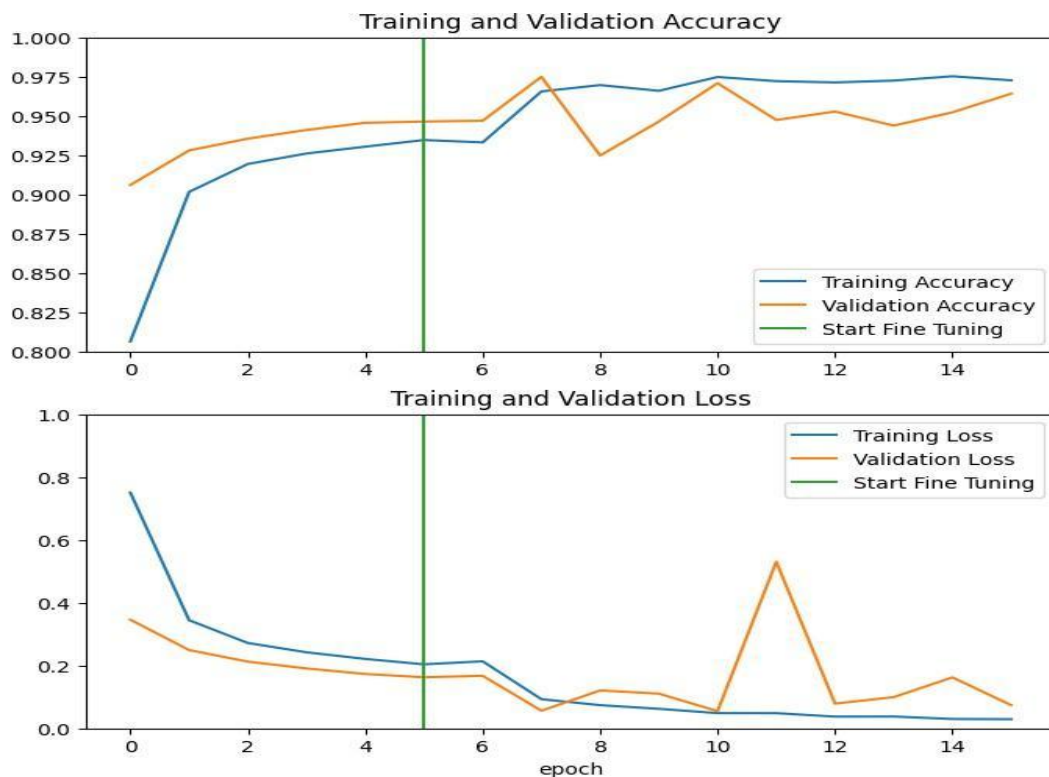


Figure 3:- Training and validation accuracy variation after fine tuning

This figure shows the progression of training and validation accuracy across ten epochs. The training accuracy increases regularly to 0.97, indicating consistent improvement in the model's learning. As similar we also observed improvement in the validation accuracy, which goes up to 0.96 by the sixteenth epoch during the training of this model. The close alignment between the two

curves suggests that the model generalizes well to unseen data, with no major signs of overfitting. Overall, the accuracy trends confirm stable and effective model convergence.

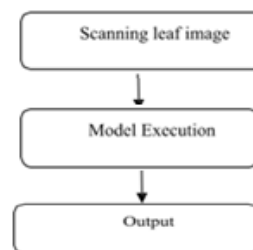
5. Deployment

The trained model was deployed with the system that whenever a valid image is scanned through the scanner, it is preprocessed and fed into the CNN model, the plant diseases successfully predicted and displayed over the screen

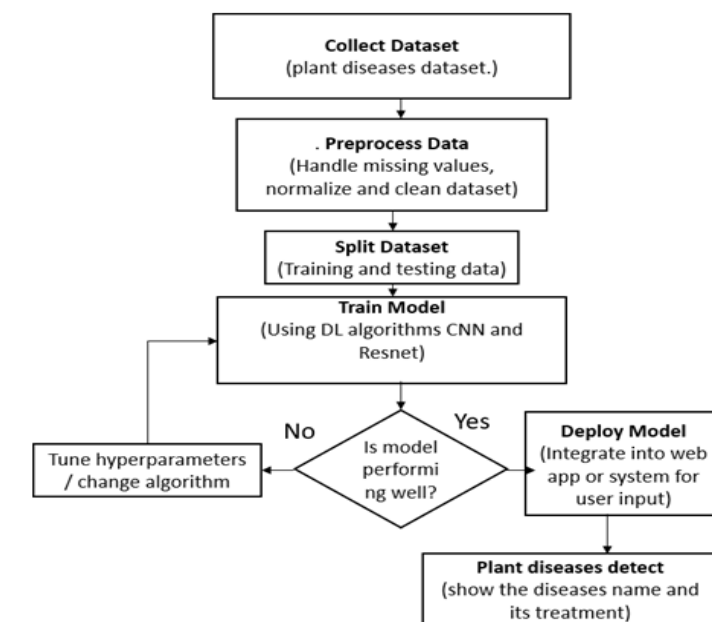
STEP BY STEP WORKING

The completed working has been describe in the three phase.

1. scanning leaf image
2. model execution
3. output



Workflow of the model



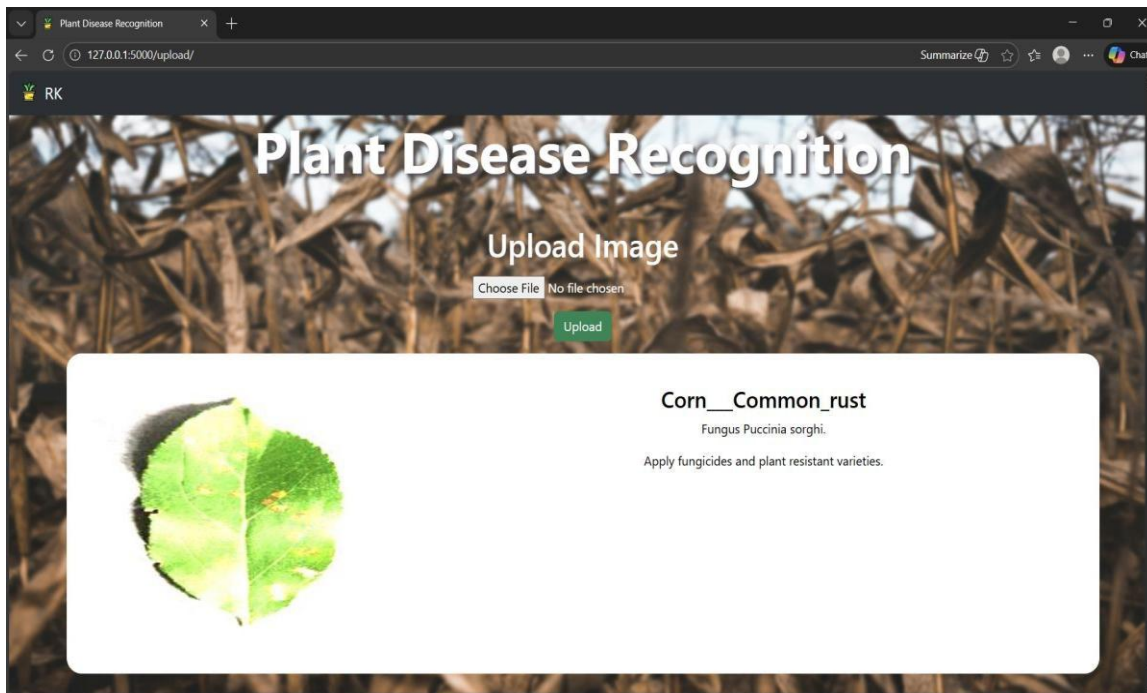
IV. IMPLEMENTATION DETAIL

The initial step is gathering a dataset of plant images, each labeled with the specific disease it shows. We used a Kaggle to find the dataset containing various plant leaf images categorized by their condition like healthy and type of different diseases, etc. These labelled samples help the model to learn patterns that link with the leaf to those type of diseases and the next step in data processing and training but before training, all images are resized to 256×256 pixels to maintain consistency and then normalized so that their pixel values fall between 0 and 1. The dataset is subsequently split into training and validation/testing sets in a 80:20 ratio. Now we designed a model particularly effective for tasks involving image analysis for that purpose we convolutional neural network. It includes convolutional layers to detect unique features of plant leaves, pooling layers to reduce complexity, and dense layers to interpret the data. A SoftMax output layer is used to classify the plant diseases mentioned in the dataset, which is divided into 38 classes. After that we trained the model using the prepared dataset. It learns by comparing its predictions with actual labels and adjusting its internal settings to reduce errors. This is done over several cycles (epochs) to improve accuracy. The Adam

optimizer and backpropagation are used during this process. After training, the model is evaluated on new, unseen data to assess its accuracy and ability to generalize. We use metrics such as accuracy, confidence, class index of the dataset and the treatment of that particular disease. After the model performs well, it is saved. This makes it reusable in real-time systems without the need for retraining. The saved model includes all the learned patterns and weights. So, after doing these things the model is ready to use and you can check the different plant leaf condition whether it is healthy or it is infected by some diseases.

V. OUTPUT

The output of this project provides a clear and informative result to the user. Upon analyzing the input leaf image, the system identifies whether the plant is healthy or showing signs of a particular disease. It displays the name of the detected disease along with a confidence score and the treatment of that particular disease, which helps the user to understand the plant diseases by seeing the output of the given input. We attach the output of our model after training and testing.



VI. RESULT

The proposed CNN model was trained on the plant disease dataset using Google Colab. During training, the model's performance steadily improved with each epoch. As illustrated in the figure below, the accuracy and loss curves demonstrate that the model maintained a healthy balance between training and validation accuracy, indicating it neither underfit nor overfit the data. Overall, the model reaches to an accuracy of about 96.42% on the validation set which you can notice in the figure given below.

The high accuracy of this model confirms that the model train perfectly and detects the plant leaf images in the dataset and working as well-structured CNN model and display the name of plant diseases and the treatment of that particular disease successfully.

*** Epoch 7/16	1537/1537	469s	229ms/step	- accuracy: 0.8891	- loss: 0.3985	- val_accuracy: 0.9469	- val_loss: 0.1673
Epoch 8/16	1537/1537	282s	164ms/step	- accuracy: 0.9608	- loss: 0.1067	- val_accuracy: 0.9749	- val_loss: 0.0561
Epoch 9/16	1537/1537	261s	163ms/step	- accuracy: 0.9695	- loss: 0.0758	- val_accuracy: 0.9247	- val_loss: 0.1206
Epoch 10/16	1537/1537	261s	162ms/step	- accuracy: 0.9645	- loss: 0.0675	- val_accuracy: 0.9464	- val_loss: 0.1105
Epoch 11/16	1537/1537	263s	163ms/step	- accuracy: 0.9710	- loss: 0.0591	- val_accuracy: 0.9708	- val_loss: 0.0548
Epoch 12/16	1537/1537	261s	162ms/step	- accuracy: 0.9744	- loss: 0.0476	- val_accuracy: 0.9474	- val_loss: 0.5304
Epoch 13/16	1537/1537	263s	163ms/step	- accuracy: 0.9700	- loss: 0.0372	- val_accuracy: 0.9528	- val_loss: 0.0788
Epoch 14/16	1537/1537	263s	164ms/step	- accuracy: 0.9718	- loss: 0.0376	- val_accuracy: 0.9438	- val_loss: 0.0993
Epoch 15/16	1537/1537	260s	162ms/step	- accuracy: 0.9743	- loss: 0.0299	- val_accuracy: 0.9523	- val_loss: 0.1623
Epoch 16/16	1537/1537	261s	162ms/step	- accuracy: 0.9751	- loss: 0.0308	- val_accuracy: 0.9642	- val_loss: 0.0736

CONCLUSION

From this project, we explored how AI (artificial intelligence), especially ml (machine learning) can help to tackle real world problems in agriculture and how we can use the ai/ml together to solve our problems. In this project we firstly trained a

Convolutional Neural Network (CNN) on a large collection of plant leaf images to recognize different plant diseases as soon as possible. we didn't build a physical device or use hardware like a Raspberry Pi, we just focus on developing a working model that could be used in real world later to solve the problems related to plant diseases and help farmers to detect diseases quickly, take action as soon as possible, and reduce crop loss. From this project we learnt how AI can be used in the field of agriculture to do farming smarter, more efficient, and more accessible for everyone—especially in rural areas that type of places where resources are limited. By the use of this model you can identify the plant diseases more quickly and accurately compared to traditional method and it does not require any expert knowledge to use that model.

Although the proposed system demonstrates strong performance on the Plants dataset, it is important that this dataset is collected under controlled laboratory conditions with uniform backgrounds and lighting. Real-world agricultural environments may introduce challenges such as varying illumination, complex backgrounds, and occlusions. Therefore, future work will focus on validating the model on real-field crop images and deploying the system on edge devices or mobile platforms to enable real-time disease detection for farmers.

VII. REFERENCES

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