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Empowering Farmers with AI-Enhanced Approach to Plant Disease Recognition

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Abstract— *Plant diseases present major challenges for agriculture, affecting crop production and nutrient quality, resulting in economic growth losses and food shortages. Identification of plant diseases accurately is crucial to minimize their effects. Traditionally, detecting diseases involves manual inspections by experts, a method that will consume more time and require more labor. This paper presents an AI model that recognizes Plant Leaf disease. It uses Advanced neural network methods which provide faster training and accuracy in prediction namely EfficientNetV2B2 and ResNet50 to classify 38 plant leaf types of diseases. Early-stage detection and managing diseases is important to maintain the health of crops and agricultural products. Traditional disease detection methods can be time-consuming and require specialized experts to make a physical analysis of the affected plant. This model will provide automated solutions for disease recognition process. The model is trained using a rich dataset of annotated character images. It makes use of pre-processing and optimization techniques. EfficientNetV2B2 is known for its accuracy in prediction and better computational efficiency, and ResNet50 is a reliable architecture with cross-connection for deep feature extraction. It is implemented and evaluated based on such indicators as precision, precision, recall, F1 score, etc. This model demonstrates the applicability of Automated models in real-time agricultural applications for disease identification. The goal is to provide farmers with easy and reliable disease detection and support sustainable crop management.*
Keywords: *Plant Disease Recognition, EfficientNetV2, ResNet50, Deep Learning, Smart Agriculture*

1. INTRODUCTION:

Plant diseases have huge drawbacks for farmers and results in massive economic losses around the world. The only solution to counteract the effect of these diseases is early identification and detection. Traditional approaches of identification carry out specialized testing and laboratory analyses, which are time-consuming, costly, and difficult to scale up. In Today's Generation AI has provided a fast and mechanized technique for the recognition of Plant diseases. It is an excellent solution for addressing this series problem. CNN has performed well in the task of image classification and classification of image work. It presented the concept of identifying disease symptoms from images of plant leaves. This research works on two CNN models, which are very prominent and well-known: EfficientNetV2B2 and ResNet50, which acts as a strong AI model to identify the leaf of the plant data through 38 different classes of diseases by comparing both models. We wish to define an optimal architecture for fast, high-precision processing. as well as facilitate real-time disease detection and provide accessible tools for farmers where they can easily recognize the disease that their plant is been affected by and get necessary solutions for the affected disease to improve agricultural health management.

2. METHODOLOGY

The Methodology of the disease detection was a distinctive, organized process from beginning to end concentrating on modularity, efficiency as well as scalability to create consistent and reproducible output.

2.1 Data Collection and Preprocessing

An extensive dataset containing labelled image datasets of healthy and disease-affected leaves across 38 plant types of Indian Plant varieties like Tomato, grapes, corn and apple was collected to effectively train the model which will help the farmers to improve their crop Management. Initially, We changed each image to the constant size of 128x128, and normalized pixels to range between [0,1]. To make our model better at recognizing leaf images we used techniques like augmentation methods like rotating, flipping, cropping and zooming them to augment the dataset diversity with respect to them from the train set which reduced overfitting. This makes sense, as it is very important to build a strong model that generalizes well to different environmental conditions and leaf structure.

2.2 Model Architecture

Two pretrained deep learning models, EfficientNetV2B2 and ResNet50 which are accurate and efficient were chosen due to both being able to classify 1000 different types of images with high accuracy. Below, we can look at the compound scaling of the EfficientNetV2B2 where it balances the depth, width and resolution of the network offering the best accuracy over computing cost. Residual branches of ResNet50 help train deeper networks as they provide an identity shortcut function that prevents loss of information ideal for complex leaf pattern recognition. Both of these models are trained on the collected leaf dataset which is tuned using a transfer based learning technique from ImageNet, targeting disease detection with varying leaf textures and structures.

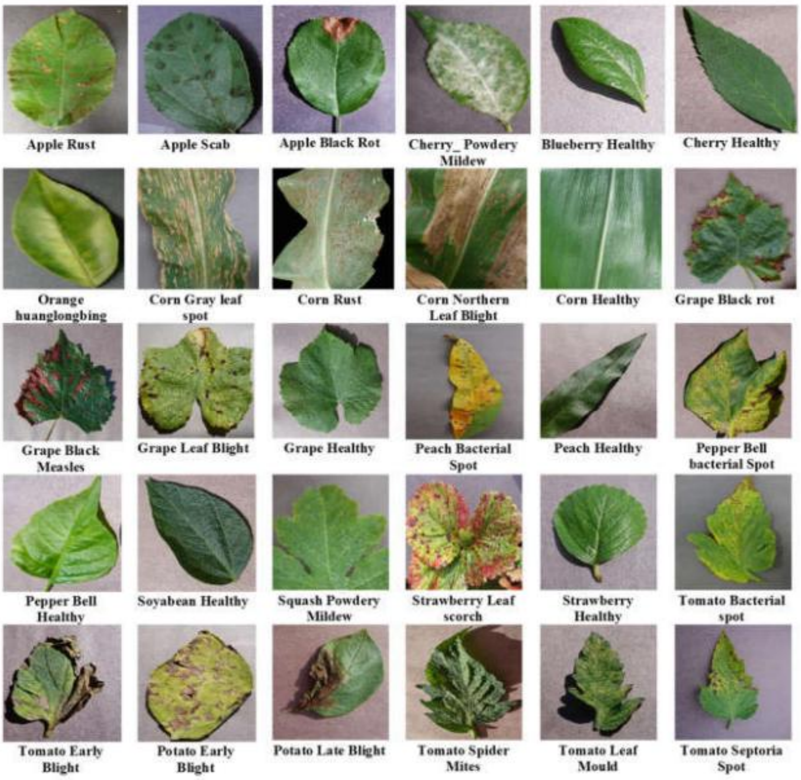

Fig.1 Data Collection and Preprocessing.

2.3 Training Process

Models using TensorFlow and Keras libraries were implemented with GPU support for heavy computations. The main development was done in Jupyter Notebook since it enables interactive development and tracking of model performance. We trained both of these models with a learning rate of about 0.0001 using cross-entropy based technique to measure the obtained loss and employed the Adam optimizer for better performance. We used Dropout layers to prevent overfitting, making the models more capable of generalizing to unseen data.

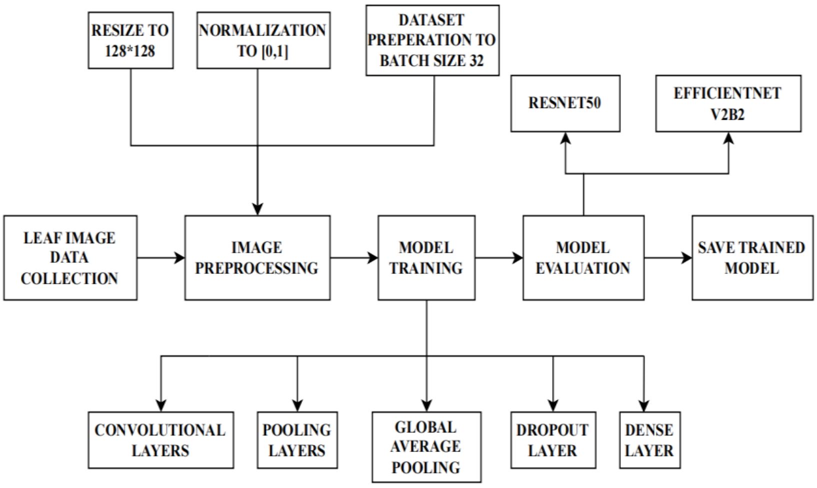

Fig.2 Training Model.

2.4 Evaluation Metrics

The efficiency of the trained AI Model was calculated using standard metrics which include accuracy, precision, recall, F1-score, and confusion matrix. Accuracy provides a general measure of correct predictions, while precision and recall quantified how effectively the model distinguished true positives from the classified false positives and negatives across the 38 plant disease classes. The F1-score acts as the mean of the obtained precision and recall also provides a balanced perspective on model robustness. Especially in classifying less frequent disease categories. The confusion matrix illustrated class-specific performance, highlighting any areas of misclassification. Together, these metrics delivered a comprehensive assessment of model effectiveness and reliability in disease prediction.

	precision	recall	f1-score	support
Apple___Apple_scab	0.96	0.94	0.95	288
Apple___Black_rot	0.95	0.96	0.96	287
Apple___Cedar_apple_rust	0.93	0.94	0.93	272
Apple___healthy	0.89	0.95	0.92	348
Blueberry___healthy	0.91	0.95	0.93	342
Cherry_(including_sour)___Powdery_mildew	0.98	0.99	0.98	421
Cherry_(including_sour)___healthy	0.92	1.00	0.96	288
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	0.90	0.90	0.90	410
Corn_(maize)___Common_rust_	1.00	0.97	0.99	477
Corn_(maize)___Northern_Leaf_Blight	0.89	0.92	0.91	477
Corn_(maize)___healthy	0.99	1.00	0.99	465
Grape___Black_rot	0.91	0.92	0.91	472
Grape___Esca_(Black_Measles)	0.92	0.93	0.92	480
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	0.97	0.99	0.98	430
Grape___healthy	0.97	1.00	0.99	423
Orange___Haunglongbing_(Citrus_greening)	0.98	1.00	0.99	503
Peach___Bacterial_spot	0.99	0.95	0.97	459
Peach___healthy	0.97	0.97	0.97	432
Pepper,_bell___Bacterial_spot	0.87	0.97	0.91	478
Pepper,_bell___healthy	0.98	0.74	0.84	497
Potato___Early_blight	0.95	0.94	0.95	485
Potato___Late_blight	0.86	0.92	0.89	485
Potato___healthy	0.82	0.95	0.88	456
Raspberry___healthy	0.96	0.99	0.97	445
Soybean___healthy	0.98	0.96	0.97	505
Squash___Powdery_mildew	0.98	1.00	0.99	434
Strawberry___Leaf_scorch	0.97	0.97	0.97	444
Strawberry___healthy	0.98	0.96	0.97	456
Tomato___Bacterial_spot	0.90	0.96	0.93	425
Tomato___Early_blight	0.78	0.70	0.73	480
Tomato___Late_blight	0.89	0.82	0.85	463
Tomato___Leaf_Mold	0.83	0.88	0.86	470
Tomato___Septoria_leaf_spot	0.88	0.68	0.77	436
Tomato___Spider_mites Two-spotted_spider_mite	0.86	0.68	0.76	435
Tomato___Target_Spot	0.67	0.56	0.61	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.96	0.94	0.95	490
Tomato___Tomato_mosaic_virus	0.85	0.94	0.89	448
Tomato___healthy	0.80	0.96	0.88	481

Fig.3 EfficientNet V2B2 Evaluation Metrics.

	precision	recall	f1-score	support
Apple___Apple_scab	0.87	0.96	0.91	288
Apple___Black_rot	0.93	0.97	0.95	287
Apple___Cedar_apple_rust	0.94	0.97	0.95	272
Apple___healthy	0.95	0.97	0.96	348
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Potato___Early_blight	0.92	0.98	0.95	485
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Squash___Powdery_mildew	1.00	1.00	1.00	434
Strawberry___Leaf_scorch	0.99	0.98	0.98	444
Strawberry___healthy	0.97	0.98	0.97	456
Tomato___Bacterial_spot	0.85	0.92	0.89	425
Tomato___Early_blight	0.78	0.66	0.72	480
Tomato___Late_blight	0.82	0.80	0.81	463
Tomato___Leaf_Mold	0.71	0.87	0.78	470
Tomato___Septoria_leaf_spot	0.82	0.58	0.68	436
Tomato___Spider_mites Two-spotted_spider_mite	0.85	0.60	0.70	435
Tomato___Target_Spot	0.62	0.67	0.64	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.94	0.96	0.95	490
Tomato___Tomato_mosaic_virus	0.91	0.90	0.91	448
Tomato___healthy	0.78	0.91	0.84	481

Fig.4 Resnet 50 Evaluation Metrics.

2.5 Testing Process

The testing block diagram as in for the plant disease detection system begins with an input leaf image, which undergoes preprocessing. This preprocessing step involves resizing the Given input leaf image to 128x128 pixel size as constant since both the model is trained using the same pixel size for unique method of processing and normalizes each of the image pixel values to a range between 0 and 1. This will maintain consistency with our training data. The processed image is then transferred into an array format suitable for input into the suitable trained keras model. Next, the preprocessed image is given to the trained model, which predicts the probabilities for each plant disease class. This model filter out the disease classes with the most highest probability value, which represents the most likely condition of the plant. The system then evaluates whether the plant is healthy. If the prediction indicates a healthy plant, the process ends with a "Healthy Plant" outcome. However, if the model predicts that the plant is diseased, it determines the specific disease affecting the plant.

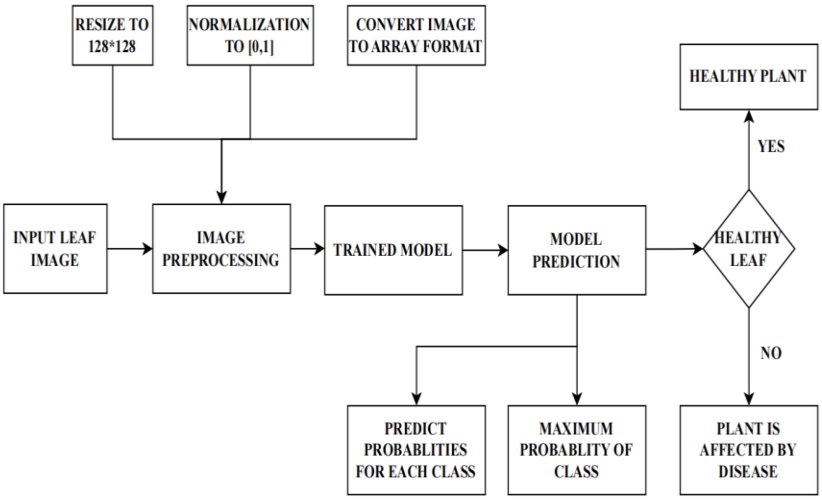

Fig.5 Testing Model.

3. EXPERIEMENTAL SETUP :

These Models can be implemented using the Python programming language. For that, it mainly uses TensorFlow and Keras libraries to exploit a very rich set of machine learning capabilities. All training was carried out in a high-performance GPU system which made computations go many folds faster and processed larger data more effectively, which reduced the time for training. The primary interface for the development of the model in an interactive manner and result analysis was Jupyter Notebook, which established a setting allowing iterative testing, visualization, and refinement of model parameters. Flexibility to monitor real-time metrics and adjustments became quite crucial for optimizing the models' performance and improvement in predictive accuracy with regard to plant disease classification.

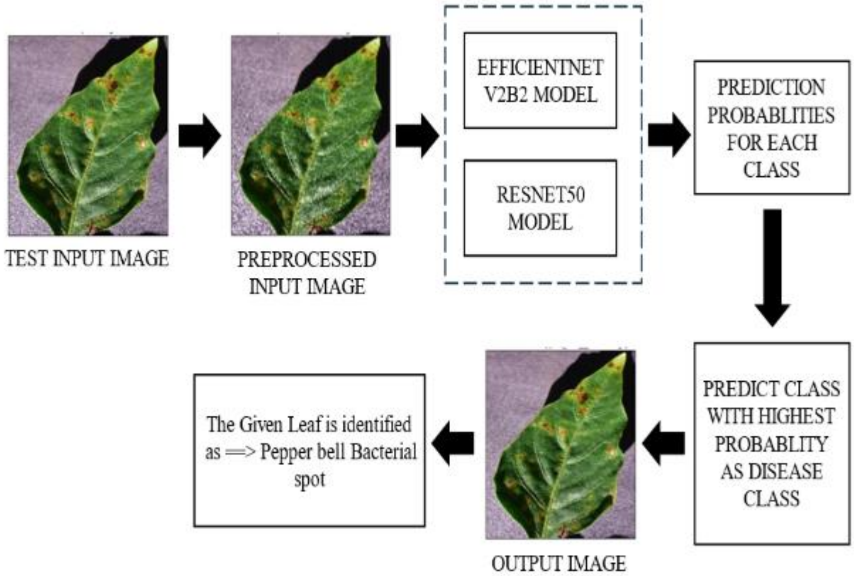

Fig.6 Working Model.

4. RESULTS AND ANALYSIS :

4.1 Model Performance

It is obtained that the classification accuracy of Plant disease images for both EfficientNetV2B2 (96.86%) and ResNet50 (98.36%) was similar as shown in while EfficientNetV2B2 was faster in prediction time than ResNet50 and ResNet50 Provided 1.56% higher accuracy then EfficientNetV2B2. And so, it was able to recognize diseases with 5 details better. The mixture of speed and accuracy greatly benefits the practical round of these models in field applications, where rapid and reliable pathogen identification is Efficient.

TABLE I. Model Performance Comparison

Model	***Accuracy***	***Loss***
EfficientNet V2B2	*0.96865*	*0.12712*
Resnet 50	0.98369	0.06190

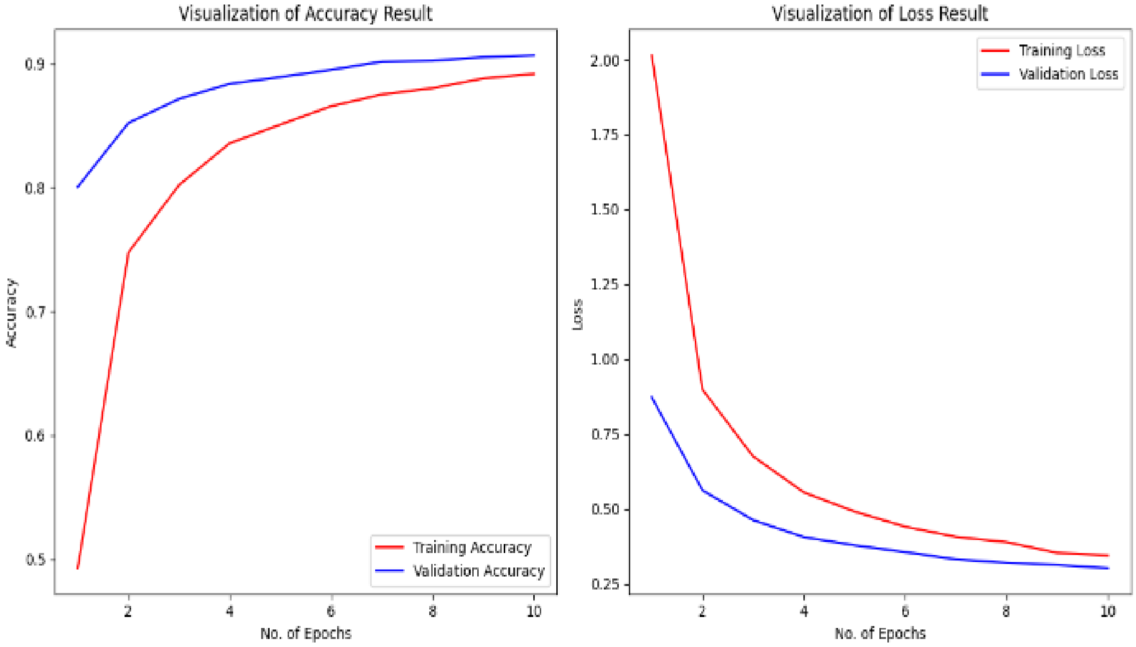

Fig.7 EfficientNet V2B2 Performance.

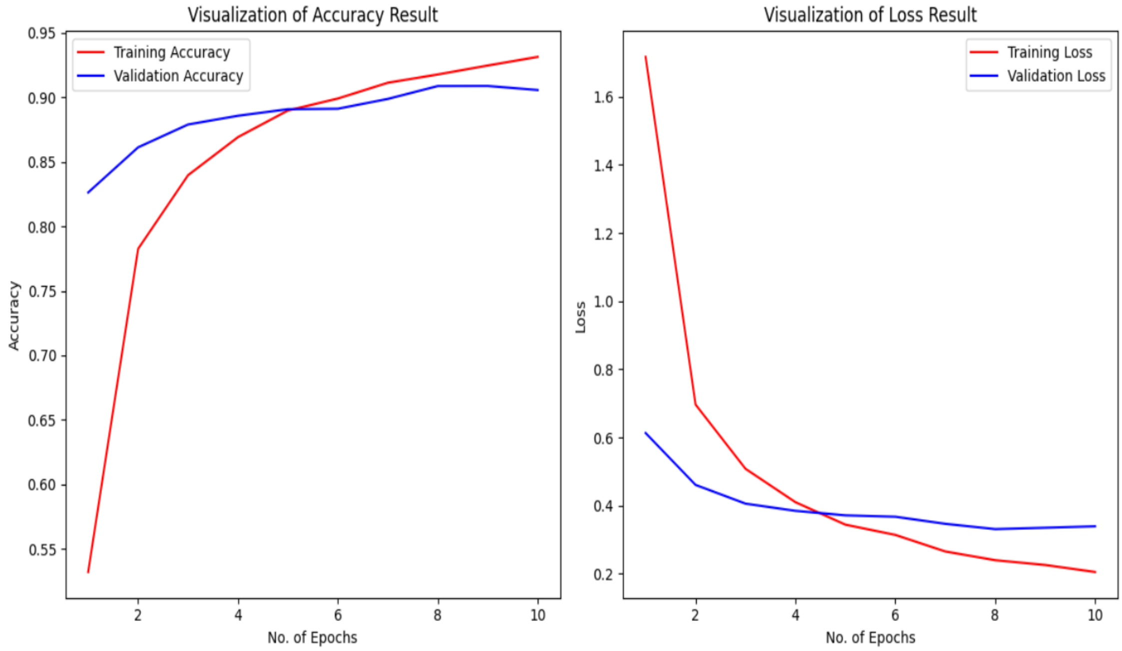

Fig.8 Resnet 50 Performance.

4.2 Probability Analysis and Prediction

After Training the Model using EfficientNetV2B2 and ResNet50. The Trained model is given with the new unseen image for both the trained model for implementation. This Trained model Provides 38 sorts of probability values for all its 38 Disease classes and the class with the Maximum probability was identified. This class disease is given as the final output Prediction in the Testing model.

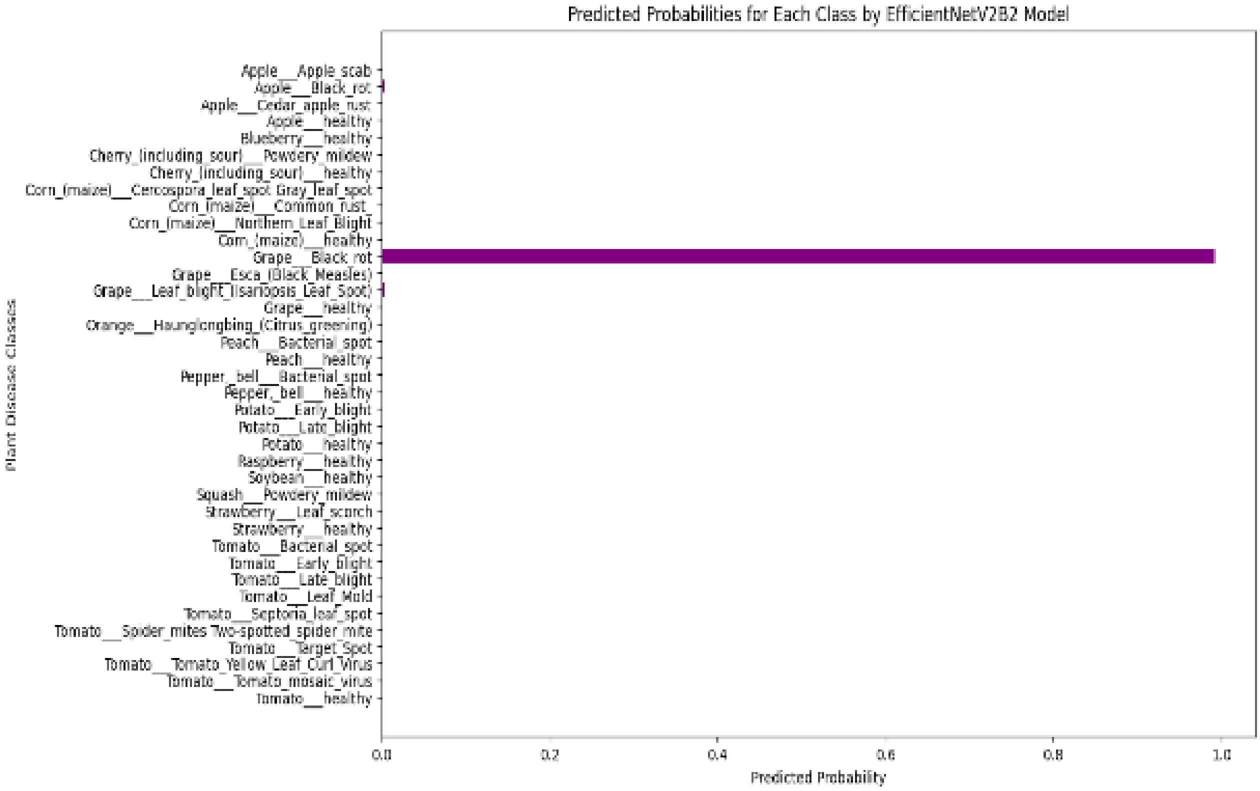

Fig.9(a) EfficientNet V2B2 Probablity Prediction.

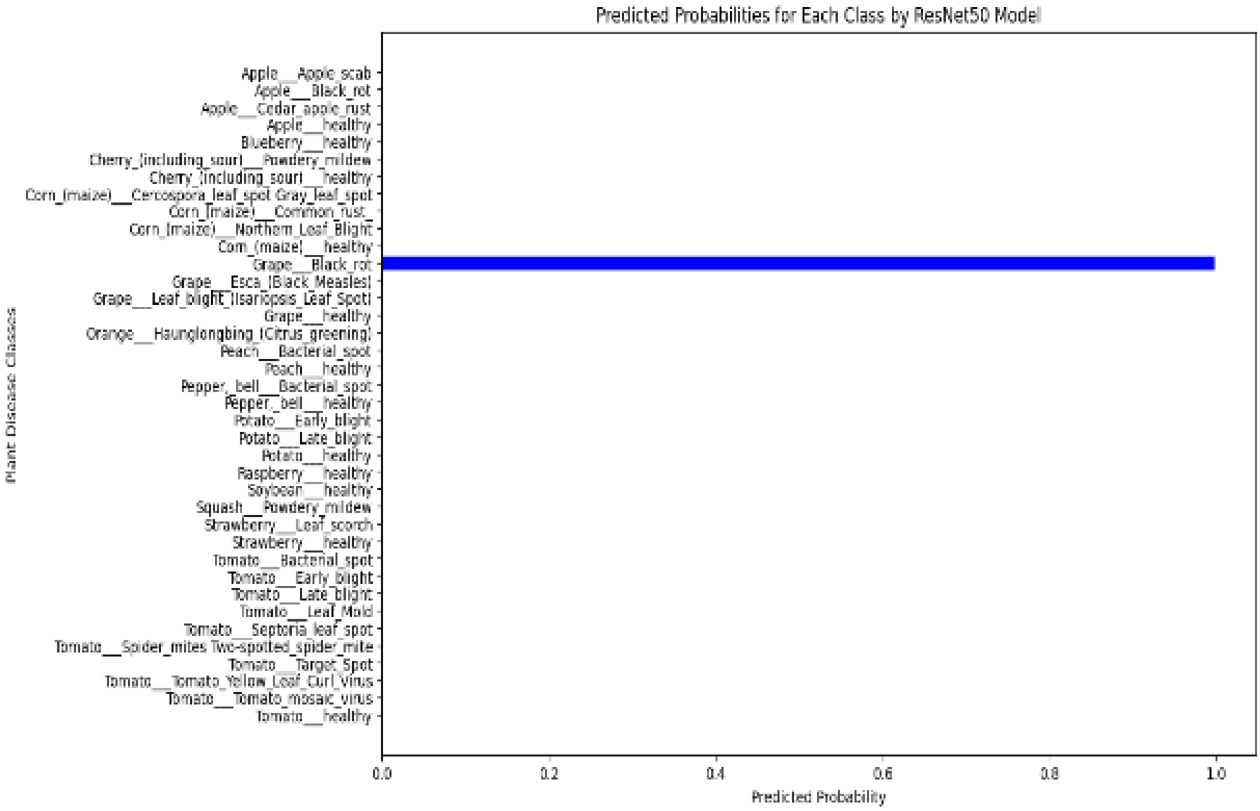

Fig.9(b) Resnet 50 Probablity Prediction.

4.3 Output Prediction

In the prediction phase, the trained model takes a new sample leaf image as an input for the model and applies all the custom preprocessing techniques used while training - the resizing and normalization - for consistency. The model then analyses the image and computes probabilities for every possible disease class learnt with such features. A condition with a higher probability is selected and used to report the predicted class of condition for a reliable diagnosis of plant health status. The model will always specify the disease if the highest probable class indicates a diseased condition. This enhances classification accuracy and brings about valuable insights into managing plant health.

Fig.10 Predicted Output.

4.4 Confusion Matrix Analysis

Results from the confusion matrix output indicated high accuracy for most of the classes with some overlap between misclassifications in diseases that have similar but less than identical features. By demonstrating its robustness to accurately distinguish between diseases with similar symptoms, such as blight and rust, this analysis increased the model's reliability for farmers and agricultural specialists.

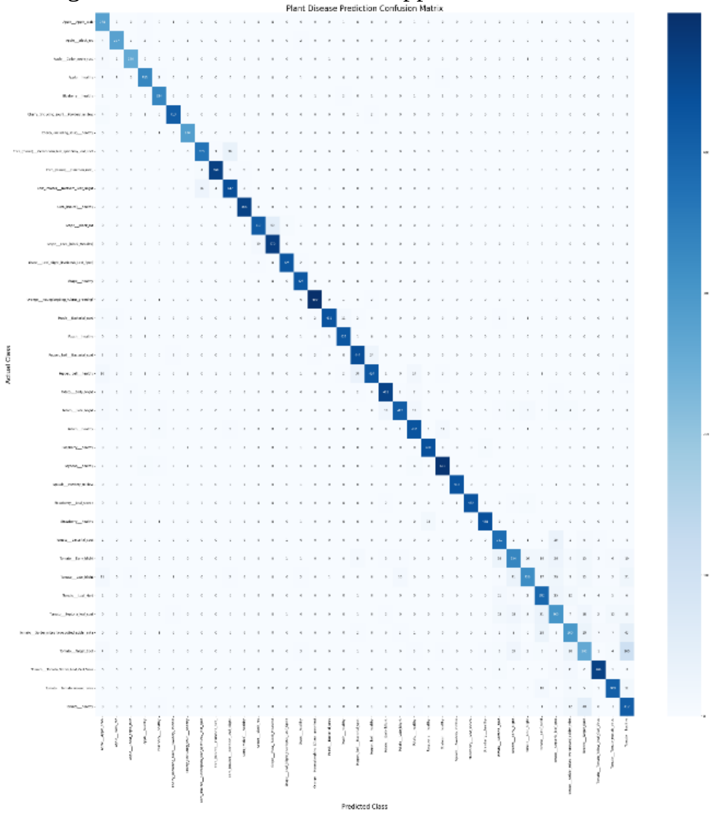

Fig.11(a) EfficientNet V2B2 Confussion Matrix.

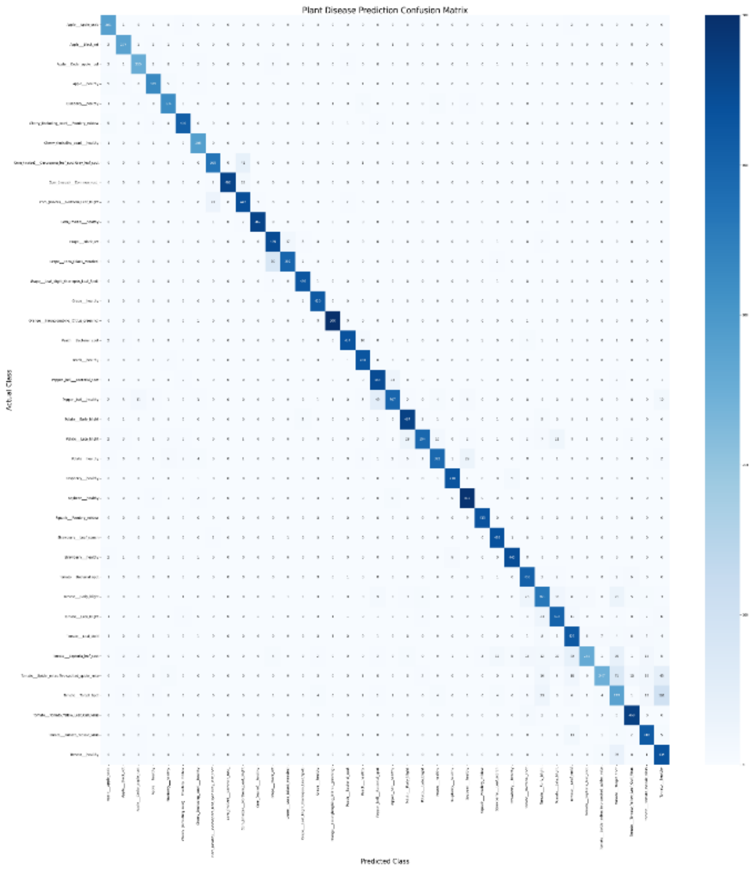

Fig.11(b) Resnet 50 Confusion Matrix.

5. CONCLUSION AND FUTURE WORK :

This paper designs the automatic leaf disease recognition tool using a deep learning solution, with EfficientNetV2B2 and ResNet50 models. The proposed system attained high precision and promises applicable applications in agronomy, creating a practical tool for quick identification of plant health issues. Future works can be designed in improving the dataset by including wider varieties of plants and diseases and capturing various stages of progression for finer classification. It also includes optimization of the model so that it can, on deployment to mobile or edge devices, allow real-time analysis in the field which will be easily accessible for the farmer as well as agricultural professionals.

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