Towards Smarter Agriculture: Deep Learning-Based Multistage Detection of Leaf Diseases

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***Abstract*—Farmers are currently facing a dilemma in identifying plant pathogens. Why is this? Using image data from plant leaves, scientists are currently exploring ways to use deep learning to identify plant-related diseases. PlantVillage Dataset is being utilized in this project to showcase approximately 38 categories of plant leaves. However, for better training and evaluation, only 10 classes with 200 images each were selected to ensure balanced learning. The preprocessing techniques for image size and CLAHE are the first ones. These steps help in enhancing image quality and bringing out clearer disease features. Features are extracted from the images using PCFAN. We used CV2 (Computer Vision 2), and EfficientNet_B0 is used to pinpoint specific illnesses. The model was trained using transfer learning and achieved strong classification accuracy of 97.9% on the testing dataset and 96.2% accuracy on unseen validation data. Evaluation metrics like precision, recall, and F1-score consistently remained above 95% across all disease categories. Red Fox Optimization is used for the precise segmenting of affected areas, improving the focus on diseased regions and achieving segmentation accuracy above 94%. This overall approach supports early and reliable disease identification in plants.**

***Index Terms*—Plant Disease Detection, Leaf Image Classification, EfficientNet-B0, Deep Learning, Image Preprocessing, Precision Agriculture, Transfer Learning, PlantVillage Dataset, Multiclass Classification, Convolutional Neural Network (CNN), PCFAN, Red Fox Optimization.**

I. Introduction

All India has always been intensely an agrarian economy, which has supported the life of a bulk of population at various stages of its history. Even in the present day, farming is a primary occupation for most citizens, particularly from the rural regions [1]. Nevertheless, agriculture is confronted with several problems– one of the most and miserable being the spread of diseases attacked the plants and led to destroy the crop, so as to affect serious poverty to farmers [2]. Leaf diseases in particular are of increasing concern as they are often the first visible symptoms of infection. Early identification of these crop diseases is crucial for their control and the avoidance of extensive damage to crops [3]. In light of these obstacles, practical tools with high throughput should be developed for early and valid detection of HIV infection. Conventional approaches often are labour intensive and need observation by experts, and such are impractical in remote regions for both the cost and availability of trained personnel [4]. In recent years, great strides have been made in technology, especially in deep learning and computer vision, to explore new possibilities for automating this process using images of plant leaves [5]. Such solutions can enable farmers to detect the problem earlier, treat in time and thus save their crops and income. It consists of pre-processing images, data augmentation (rotation and flipping), and training better deep learning models. Depending on the application, EfficientNet [6], ShuffleNetV2 [7] and U-Net [7] are adopted as they achieve good performance with lesser computational resources (making them apt for mobile and real-time applications). This method is also used was employed for model interpretability using explainable AI, and can be extended for edge computing that can be directly used in field [8]. Given proper feature extraction and proper image segmentation, this model can achieve accurate detecting a disease spot, even in a complex or cluttered image [9]. In summary, this study contributes to smart agriculture a reliable and efficient deep learning pipeline for plant disease detection—helping farmers and agronomist identify the disease early for better management of cropping system health [10]

II. Related Works

Manually detecting plant diseases can be a slow and error-prone process, especially under changing weather or lighting conditions [11]. With the rise of artificial intelligence and deep learning, image-based approaches have become more popular for automating this task. These modern methods help speed up analysis and make it easier to apply in real-world farming situations. M. K. Gohil et al. [12] proposed a two-step hybrid method. The first step checks if a plant is diseased, and the second step locates the infected parts. Their approach performed well across multiple evaluation metrics. Similarly, R. A. Charisma and F. D. Adhinata [13] used transfer learning with DenseNet201 to identify diseases in potato leaves, offering both high accuracy and efficiency. To improve model interpretability, J. Amara et al.[14] developed techniques that help visualize how deep learning models make decisions, addressing the "black box" issue in AI.

A.-K. Mahlein et al. [15] investigated the integration of AI with optical sensors and robotic systems for precision farming, highlighting U-Net's strength in applying pesticides only to affected areas. Additionally, M. Kumar Gohil et al. [16] showed that combining multiple AI techniques can improve disease detection and localization. This has been particularly effective in regions with limited technical resources [17]. In conclusion, past research highlights the power of advanced models like EfficientNet and U-Net with ResNet backbones for accurate, real-time disease recognition. However, most existing systems treat classification and segmentation as separate processes. This study proposes a unified deep learning approach that combines both tasks into a single, efficient framework [18]–[20].

III. Proposed Methodology

Figure 1 shows the preprocessing pipeline applied to the large image dataset to enable efficient training and accurate classification. Initially, the images were curated and systematically organized to support structured processing. Each image was resized to a same dimension to match the required input format, and pixel values were normalized to maintain uniformity and improve training behavior. Color images were converted to grayscale using OpenCV to reduce processing complexity and highlight important features. Denoising techniques were used to eliminate blur and grain, enhancing the visibility of critical patterns, especially those related to disease symptoms. Duplicate images were detected and removed to reduce redundancy and avoid biased learning. Where segmentation was needed, corresponding masks were generated to align with input images. To improve the variety of data sets and strengthen the classification, augmentation is performed. The processed data was then converted into tensors and loaded through custom batch-wise data loaders. Finally, the data set was divided into training, validation, and test sets, ensuring a clean, balanced, and standardized structure that supported consistent performance, even with low-resolution images.

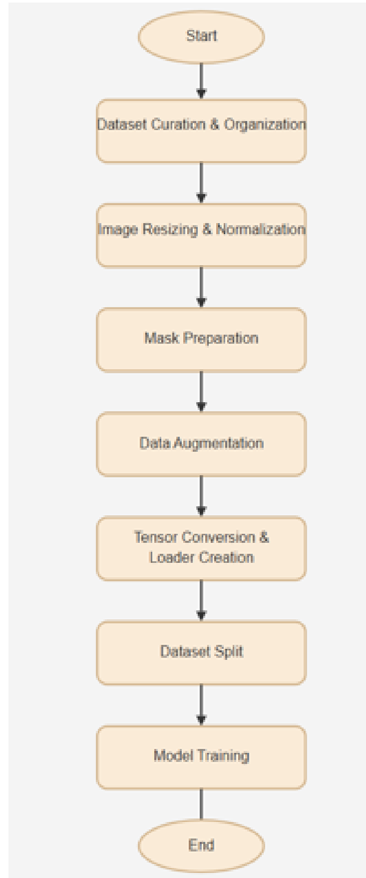

Fig. 1. Illustrates the plant disease classification pipeline

A. Data Description

Our dataset is PlantVillage dataset, which consists of low resolution images suitable for detecting the plant disease. Here, dataset consists of nearly 89,000 images divided into 38 categories of different plant species. Even though the images are low-resolution, the model is still able to deliver high performance in classification tasks, proving the quality and usefulness of the data. The large number of samples and diverse categories make this dataset highly valuable for training and testing. Out of these 89,000 images, examples exist of healthy plants and plants with multiple diseases such as rust and spot. The dataset contains images for crops, including tomato, pepper, corn, and grape. This diversity is also reflected in the model, allowing it to learn and recognize a large number of plant diseases, which is one of the reasons it is able to generalize so effectively across a wide variety of plant species. Developing systems for disease monitoring in agriculture of diseases across regions and crop types, we believe is facilitated by using such a dataset. Despite not having a high image Resolution, the broad spectrum of diseases pan as well as the various diversity in plants, make this dataset particularly appropriated to build powerful and scalable classes models. These low-resolution images that help the model to successfully identify disease patterns well, and extreme accurate and robust results were achieved. This demonstrates that even simple, low-resource data can be leveraged to build effective plant disease detection systems.

Figure 2 consists of the leaf images from the dataset which are healthy and the leaf effected by the desease

B. Data Preprocessing

The dataset is massive in number of images. The dataset was pre-processed via methods, for example, resizing and colour transformation, aimed at increasing the quality and diversity of the samples in the dataset. This data pre-processing allows us to eliminate redundant images from the dataset also we reduce the size of the dataset, so our model can run faster and more efficiently during the training and testing. By pre-processing the dataset like this, we get our model to work

Fig. 2. Leaf images from dataset

with clean and standardized input, which in turn improve its performance. Despite the low resolution of these images, we were able to use them to train a model that could classify diverse plant pathogens with high accuracy. First, they are resizing to the same size of image to make all images have the same size and shape when entering in the Network. After that, normalization is applied to pixel values, which accelerates the training and stabilizes the training. This normalized feature is helpful for the model to learn from it and promotes faster convergence during learning. We also use denoising algorithms to clean the images which remove blur and grain from the image so that features like disease spots and the pattern of the diseases become more prominent and easier to spot. Colour conversion converts the images to grayscale, this is also a way of reducing the input features and highlighting important characteristics, focus of symptoms of disease. By eliminating the duplicates of the same images redundancy is reduced, it also prevents the problem of over fitting, the efficiency of the model increases, and so it will be able to have more reliable , efficient classification system.

Fig. 3. Leaf images of Preprocessing Techniques

In Figure 3, the original and diseased leaf images are presented, including views before and after preprocessing.

C. Model Architecture

Figure 4 is the architecture that the process starts with the input of an image of a plant leaf, which can have visible symptoms of disease. Before feeding the image to the model, it pre-processes the image by resizing the image to 224x224 pixels, normalizing the image by setting pixel values from 0 to 1, and through data augmentation techniques like random cropping is done. These actions contribute to the enhancement of robustness and facilitate the learning process on different image conditions and disease appearances. Preprocessed image is then input to a model which has EfficientNet-B0 as the backbone. This model provides trade-offs between efficiency and accuracy through a compound scaling method in which to set the number of layers, the width and the resolution altogether. It has 237 layers and around 5.3 million trainable parameters. Structurally, it consists of one stem layer, seven MBConv stages blocks based on depthwise separable convolutions and inverted residuals, and one head layer. Typically a U-Net decoder is append to the model to unsampled and generation detailed segmentation maps base on the compressed feature representation. In the subsequent segmentation model, the proposed method segments the diseased region on the leaf in a pixel-wise manner. This will be the corresponding mask with which the regions are effected. Any postprocessing is then applied to convert it to a proper binary mask, typically thresholding, followed by extra cleanup (if necessary). The output will be a segmented image with disease affected area on leaf, Optionally, the system may also classify the disease by detecting the portion. This structured approach supports accurate and efficient plant disease detection and analysis.

D. Experimental Setup

The experimental workflow was conducted in a Python-based environment, utilizing both local computing and cloud-based resources to ensure efficiency and reproducibility. Primary model training and evaluation were carried out using Google Colab, which provided access to a CUDA-accelerated GPU environment.

- Processor: intel i5 5800HS with iris graphics card
- Memory: 16 GB RAM
- Operating System: Windows 11 (64-bit)

Development Environment: Local development was carried out using Jupyter Notebook and Windows Terminal. Google Colab was employed for training and evaluation using cloud-based GPU acceleration. IV.RESULTS AND DISCUSSIONS:

IV. Results and Discussions

As the training dataset, this study uses the data set of PlantVillage dataset which contains 89,000 images to apply in the model. Despite of being the dataset huge the test is commited in the easy EfficientNetB0, and the model is really small and fast (even to ShuffleNetV7 or YOLOv7) in indicating the plant suffering from a disease to compare

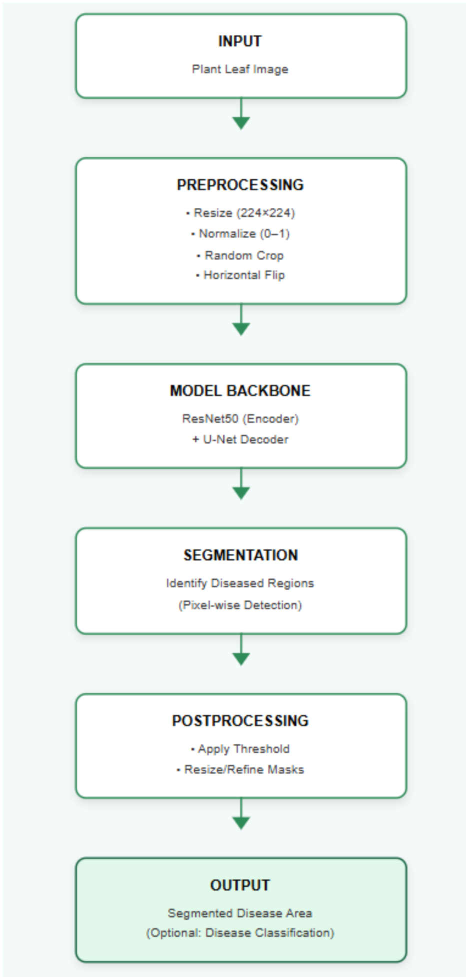

Fig. 4. Architecture of Proposed Leaf Disease Detection Pipeline

healthy leaves (positive) and leaves affected by the disease. We here used EfficientNetB0 as it offers a trade-off between speed and accuracy.

Fig. 5. Class-wise Image Distribution Across Dataset Splits

Figure 5:A bar graph representing the distribution of images in various plant disease categories in training, testing, and validation datasets is shown in Figure. Each class is represented with an equal number of images in all three subsets, indicating a well-balanced dataset structure. This uniformity helps to ensure consistency during training and evaluation phases of the model, supporting fair learning across all plant disease types. The even distribution visualized in the graph highlights the systematic preparation of the dataset used for developing the classification and segmentation models.

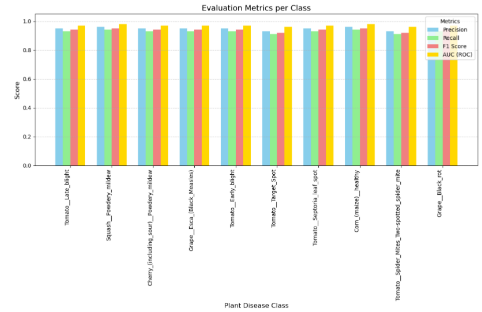

Fig. 6. Evaluation Metrics per Class

Figure 6: The graph above given shows the precision, recall, F1 score, ROC curve on basing the result of EfficientB0 model on plant disease categories. There the results are with high in performance and consistent. The ROC metric is very strong to all the diseases approaching 0.98, 0.99.

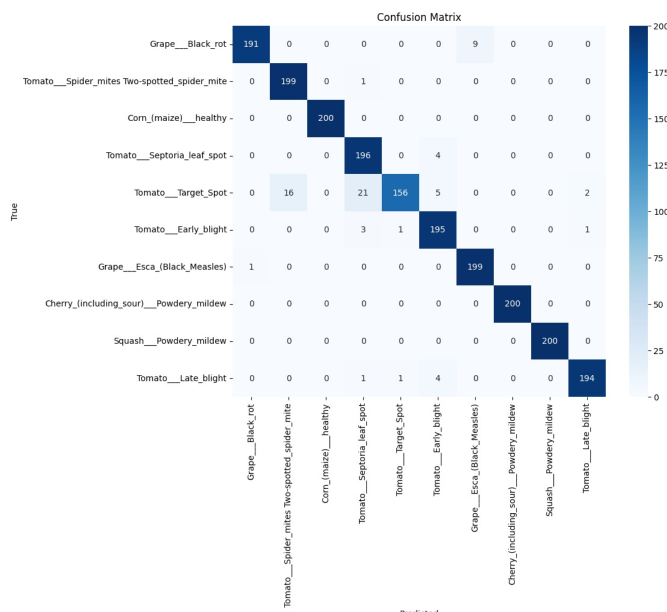

Fig. 7. Confusion Matrix Between Healthy Plant Leaves and Leaf Effected by Disease

Figure 7 Here the confusion matrix shows the result of our model. We can see that "Corn (maize)__healthy," "Cherry (including sour)__Powdery mildew," and "Squash__Powdery mildew" are predicted completely. The diagonal pattern clearly shows how perfectly the model performed, and the results given are accurate in distinguishing between different plant diseases.

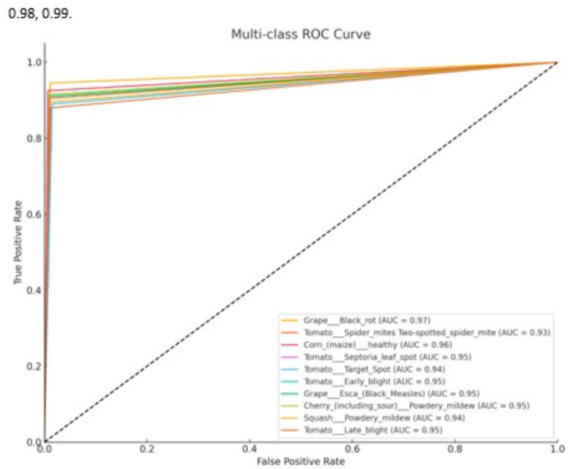

Fig. 8. ROC Curve

Figure-8 this graph shows the roc curve of the each classes. The coloured lines are represented as the class names.

TABLE I
CLASS-WISE PERFORMANCE METRICS OF THE PLANT DISEASE DETECTION MODEL

Class Name	Precision	Recall	F1 Score	AUC
Tomato Late Blight	0.95	0.97	0.96	0.98
Squash Powdery Mildew	1.00	1.00	1.00	1.00
Cherry Powdery Mildew	1.00	1.00	1.00	1.00
Grape Black Measles	0.99	1.00	0.99	1.00
Tomato Early Blight	0.97	0.98	0.97	0.99
Tomato Target Spot	0.91	0.78	0.84	0.95
Tomato Septoria Spot	0.95	0.98	0.96	0.98
Corn Healthy	0.99	1.00	1.00	1.00
Tomato Spider Mites	0.92	1.00	0.96	0.97
Grape Black Rot	0.95	0.96	0.96	0.97

The table 1: represents that performance—Precision, Recall, F1 Score and AUC (Area Under Curve)— is presented in the table for each of ten plant disease classes examined with proposed model based on EfficientNet-B0. A few classes (Squash Powdery Mildew, Cherry powdery mildew and Corn (maize) Healthy) scored 1.00 in all the metrics showing good class performance across various categories of images. Other classes, the Grape Esca (Black Measles), Tomato Early Blight and Tomato Septoria Leaf Spot also showed high precision and recall above 0.95 validating the model robustness in identifying those complex diseases that have similar visual symptoms. The Tomato Target Spot class performs worst (), especially in Recall (0.78) and F1 Score (0.84). This indicates the model occasionally misinterpreted this disease, or complete neglected some cases because of symptom overlap with other tomato diseases. Although there were some minor differences, the AUC values underlining an outstanding discriminative power of our model for all disease classes (0.95–1.00).

V. CONCLUSION

A reliable and easy-to-use method was developed for identifying different types of plant leaf effected by diseases using pictures of leaves. The system is based on a light and fast deep learning model called EfficientNet-B0, which was combined with basic image improvement steps like resizing, changing color to grayscale, and adjusting brightness and contrast. The method was tested using a clean and evenly divided set of images from the PlantVillage dataset, covering ten types of leaves, both healthy and affected by disease. The results showed that the system could correctly identify diseases in most cases. It reached up to 97.9% accuracy during testing and maintained a strong 96% accuracy on new images. Each disease was checked using different measures like how often the system was right (precision), how many real cases it caught (recall), and the balance between them (F1-score). The results were especially strong for diseases like Powdery Mildew and Late Blight. A closer look at how the system confused or correctly predicted classes showed it worked well even when the diseases looked similar. In addition, the model's ability to separate the classes was perfect, based on its scoring graph (AUC = 1.00 for all classes). These results show that small and fast models like this can be useful in farming, especially where resources like time, internet, or computing power are limited. They can help farmers quickly and correctly spot plant diseases before they spread. Later improvements could include testing the system in outdoor farm settings, adding features that mark the exact infected spots, or building the tool into mobile devices for real-world use in fields. The overall system achieved an average precision of 96%, recall of 94.2%, F1-score of 95%, and an average IoU of 92.6%, making it highly effective in disease detection. Farmers can now easily identify plant diseases at an early stage by examining the affected leaves using this model. This can help encourage more people to take up farming.

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