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Enhanced Plant Health Monitoring using Transfer Learning Models

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***Abstract*— Advancements in and Machine Learning and Deep learning have revolutionized the classification and detection of plant diseases, crucial for maintaining health of plant and productivity. Traditional approaches relying on physical observation are often unreliable and inefficient, leading to significant agricultural losses. This study focuses on utilizing image processing techniques to enhance efficiency and accuracy of detecting crop diseases, particularly in chili, banana, and citrus crops in Karnataka. Various viral diseases severely impact chili crops, necessitating advanced diagnostic techniques like Reverse Transcriptase PCR (RT-PCR). Similarly, banana and citrus crops face significant disease challenges that threaten their yield and quality. Our research utilizes transfer learning models to classify plant leaf diseases. By capturing plant leaf images and applying a series of pre-processing techniques, such as binarization and Gaussian filtering, we ensure high accuracy in disease detection. Pre-trained models, including various versions of MobileNet are utilized to classify disease stages based on leaf image analysis. Experimental evaluations demonstrate the superior performance of our proposed system, highlighting its potential in improving disease monitoring and management practices. This integration of advanced image processing, deep learning, and automated diagnostic systems offers a promising solution to enhance crop health and productivity, thereby safeguarding the economy and food security.**

Keywords*— *Image Processing, Crop Disease Detection, Transfer Learning Models, Deep Learning, Crop Health Monitoring, Agricultural Productivity Enhancement

I. Introduction

The classification and detection of plant diseases are crucial for maintaining crop health and productivity, which are essential for the global food supply and economy. Traditional methods of identifying plant diseases through physical observation can be unreliable and inefficient, leading to significant agricultural losses. Recent advancements in Machine Learning (ML) and Deep Learning (DL) and have created new opportunities to enhance the efficiency and accuracy of plant disease detection using image processing techniques [1].

Plant diseases significantly threaten agricultural productivity, especially in chili, a valuable vegetable vulnerable to fungi, bacteria, and viruses. Viral diseases from Potyvirus, Tobamovirus, Tospovirus, Begomovirus, and Cucumber mosaic virus (CMV) cause leaf mottling, stunting, and fruit deformation, leading to economic losses. Surveys in Karnataka's main chili-growing areas reveal widespread viral infections. Advanced diagnostic techniques like Reverse Transcriptase PCR (RT-PCR) are essential for accurate virus identification, aiding breeding and disease management. Despite the severe impact, research in Karnataka is limited, highlighting the need for more studies on virus specifics and transmission. Favorable climates for vectors and poor phytosanitary practices worsen the situation, reducing yield and marketability [2].

Chili is an essential spice and vegetable crop, enhances culinary flavor and is rich in minerals, vitamins, and pigments. However, anthracnose, caused by fungal pathogens like C. coccodes, C. capsica and C. acutatum severely affects chili cultivation, leading to significant economic losses. This disease impacts all plant parts, causing seedling blight, dieback, and fruit rot, with fruit rot notably reducing quality and marketability. Effective management requires disease-resistant varieties, timely fungicide application, and strict phytosanitary measures. Ongoing research is vital to understanding anthracnose and developing sustainable management strategies to protect this essential crop [3].

Banana (Musa spp.) is vital in tropical and subtropical regions for its nutritional and economic value but faces significant disease challenges affecting yield and quality. Effective detection and management are crucial for sustainable farming. Traditional visual inspections are time-consuming and require expertise. Advances in ML and image processing have improved detection efficiency and accuracy. These techniques involve capturing and processing banana leaf images, isolating affected areas, and using algorithms for disease classification. By adopting these innovations, researchers and farmers can better monitor and manage banana diseases, enhancing crop health and productivity [4].

Citrus crops face significant threats from diseases impacting yield and quality. Traditional visual inspections are time-consuming and require expertise [5].

In Karnataka, plant diseases significantly impact banana, chili and citrus crops, threatening yield and quality. Traditional visual inspections are time-consuming and require expertise. Technological advancements in image processing and machine learning offer promising solutions for early, accurate disease detection. These innovations enable timely intervention, improving crop health and productivity, and safeguarding the economy and food security. In Karnataka, traditional disease identification in chili, citrus and banana relies on visual inspections by experienced farmers or specialists. They look for signs like discoloration, spots, or wilting and may use manual techniques like leaf sampling and lab analysis for accuracy. These methods are labor-intensive, subjective, and require expertise, making large-scale surveillance challenging. In Karnataka, automated strategies using image processing and machine learning are emerging to address diseases in chili, citrus and banana crops. These methods analyze digital leaf images to identify symptoms efficiently, allowing timely intervention. Unlike manual inspections, they save time and reduce subjectivity, enhancing disease monitoring and crop productivity. Banana cultivation, vital to global economies, suffers from diseases and pests causing significant financial losses. Traditional manual inspections are labor-intensive and error-prone, while advanced methods like hyperspectral imaging are costly and complex. Automated solutions using artificial intelligence and image processing, particularly Convolutional Neural Networks (CNNs), enhance disease detection accuracy and efficiency, allowing early intervention and reducing costs [6].

Detecting plant leaf diseases in crops such as banana, chili, and citrus requires an advanced hardware system due to the limitations of traditional methods. By leveraging this advanced hardware, farmers can overcome the challenges of traditional methods, ensuring early detection and effective disease management.

In our system, we utilized 99 image sequences of plant leaf diseases as samples. To achieve consistent backgrounds, binarization technique is applied during pre-processing to eliminate background elements. This step significantly improves the precision of classification of disease. For feature classification and identification of different stages of leaf disease, pre-trained transfer learning models are used. During the testing phase, the system predicts the disease class by comparing the input image with trained samples based on a similarity score, enabling precise estimation of disease progression in plant leaves thus improving productivity.

II. LITERATURE REVIEW

In this section, we perform an efficient and complete search of several books, journals and databases related to the topic. Our survey provides a clear and coherent organization of the literature and a discussion of the similarities, differences, and relationships among the other state-of-art techniques that has motivated us to propose our system as well as evaluate its efficacy using standard evaluation metrics.

Sasikala Vallabhajosyula et. al. [7] introduces an innovative hierarchical residual vision transformer framework aimed at early detecting crop diseases, vital for safeguarding food security and agricultural productivity. By integrating Improved Vision Transformer and ResNet models, this novel approach efficiently extracts essential features while reducing computational complexity. Evaluation across diverse datasets, including Extended Plant Village Dataset, Local Crop and Plant Village demonstrates its superior performance compared to established models such as MobileNetV2, ResNet50 and InceptionV3. This study emphasizes the transformative potential of DL in precision agriculture, providing a more effective and efficient solution to address complex agricultural challenges.

Mitali V. Shewale and Rohin D. Daruwala [8] introduces an innovative method for swiftly and accurately identifying crop diseases using DL methods. Using specialized Convolutional Neural Network (CNN) architecture, it designed for leaf image analysis and trained extensively on a diverse dataset of diseased leaf and healthy leaf the model achieves exceptional accuracy in disease detection and classification, surpassing human visual capabilities. The study's significance lies in its crucial role in early disease detection, crucial for safeguarding crop yield and food security, with implications for real-time monitoring in automated agricultural systems. Future research directions include enhancing the model's adaptability across various plant species and environmental conditions, thereby enhancing its usability in agricultural settings.

Vaishnavi Monigari et.al. [9] introduces a DL model designed to foresee diseases of crop and mitigate significant agricultural productivity losses. Stressing the crucial importance of early disease detection to prevent yield loss, the authors propose a method that utilizes image processing techniques for disease identification. This study aims to enhance the accuracy of disease detection through leaf image analysis, through training CNN using a dataset comprising over 20,000 images from 15 categories of diseased and healthy plant leaves. Achieving an impressive 99.35% accuracy on a separate test set highlights the efficiency of this approach, making a significant contribution to precision agriculture. This research emphasizes how deep learning can effectively tackle intricate agricultural issues by enabling early detection of plant leaf diseases in an efficient manner.

Goel et.al. [10] introduced a deep learning model focused on early disease detection. Leveraging image processing techniques, they trained a dataset based on deep CNN containing over 20,000 images of both healthy and diseased plant leaves. Remarkably, the model attained an accuracy of 99.46% on an independent test set, highlighting its effectiveness. This research significantly contributes to precision agriculture, offering a powerful solution for timely disease identification and highlighting the transformative potential of deep learning in addressing complex agricultural challenges.

Nishaben Sodha et al., [11] explores the use of CNN for identifying plant diseases through image categorization. Focused on a multi-class classification problem using the Plant Leaf dataset with four distinct classes, the study evaluates three architectural models: ResNet50, InceptionV3, and ResNet152V2. Among these, ResNet152V2 appears as the most effective, boasting an impressive accuracy of 0.984 and a precision of 0.91 on the test set. This research underscores the prowess of deep learning in tackling image categorization challenges and highlights its potential significance in agricultural technology by streamlining disease detection processes.

Fan et al. [12] sheds light on the critical aspect of disease management in tomato (Solanum lycopersicum L.) farming.

The research utilizes pre-trained CNN such as Inception V3 and Inception ResNet V2, leveraging a dataset of 5225 images sourced from Plant Village and field recordings. It investigates the impact of varying dropout rates on model performance. Remarkably, the Inception V3 model achieved optimal accuracy of 99.32% and minimal loss of 0.03 with a 50% dropout rate, while the Inception ResNet V2 model achieved similar results with a 15% dropout rate. These findings highlight the potential of CNN models in swiftly and accurately diagnosing tomato diseases, suggesting broader applications in integrated plant disease management systems.

Liu et al. [13] introduces an innovative approach for early detection in tea plants for blister blight disease. By merging Internet of Things (IoT) technology with ML, the study aims to forecast blister blight occurrences more accurately. Utilizing IoT devices for real-time environmental monitoring in tea plantations, including factors like temperature, humidity, soil moisture, and light intensity, the research seeks to uncover correlations between environmental conditions and disease outbreaks. Through the development of a machine learning model trained on historical data analysis, the study achieves an impressive accuracy rate of around 99%. This integration of IoT-driven environmental monitoring and ML techniques empowers tea farmers with valuable insights, facilitating proactive disease management and resource optimization for improved crop productivity. The study underscores the potential of IoT-driven disease prediction models in advancing smart agriculture practices and promoting sustainable farming methods.

Harakannanavar et al. [14] tackle the urgent need for early plant disease detection to safeguard global food security and minimize agricultural losses. Focused on detecting diseases in tomato plants, the authors propose an innovative algorithm that combines CNN, K-Nearest Neighbor (K-NN) and Support Vector Machine (SVM) methods for precise disease identification. They pre-process the data by resizing collected leaf samples, enhancing their quality through histogram equalization, and extracting crucial features using techniques like K-means clustering, contour tracing and various descriptors such as Discrete Wavelet Transform and Grey Level Co-occurrence Matrix. Through classification with SVM, CNN, and K-NN, the algorithm achieves impressive accuracies: CNN (99.7%), K-NN (96.9%) and SVM (88.2%). These findings suggest the algorithm's potential in early symptom-based disease identification, offering farmers effective disease management strategies and promising improvements in crop yields.

Pal and Kumar [15] present an innovative method for detecting and categorizing plant leaf diseases by their severity, crucial for timely interventions to prevent further spread and bolster crop yield. The "AgriDet" framework merges traditional Inception-Visual Geometry Group Network (INC-VGGN) with Kohonen-based deep learning networks to recognize diseases and assess their severity levels. This classification empowers farmers to accurately discern healthy leaves from diseased ones, enabling tailored actions like targeted treatments or pruning. The framework demonstrates promising outcomes, achieving a 94.5% accuracy in disease detection and 93% in severity classification. By harnessing deep learning techniques, it furnishes actionable insights for precision agriculture. This research underscores the significance of early disease detection and severity assessment in smart agriculture, offering potential to improve crop health, minimize losses, and foster sustainable farming practices.

Ashwinkumar et al. [16] introduces a novel solution to India's significant annual crop losses of 35% due to plant diseases. They employ an optimal MobileNet-based convolutional neural network (OMNCNN) method for automated detection and classification of plant leaf diseases. The OMNCNN model integrates preprocessing, segmentation, feature extraction, and classification stages. It incorporates techniques such as bilateral filtering (BF) for image enhancement, Kapur's thresholding-based segmentation and optimization of MobileNet hyperparameters using Emperor Penguin Optimizer (EPO) algorithm. The classification employs an extreme learning machine (ELM)-based classifier. Through extensive simulations, the OMNCNN model demonstrates superior performance, achieving recall, F-score, precision, accuracy and kappa values of 0.985, 0.9892, 0.987, 0.985 and 0.985 respectively, surpassing recent state-of-the-art methods. This automated approach holds promise for early disease detection in agriculture, providing farmers with an effective tool to manage plant diseases, ultimately enhancing crop health and yield.

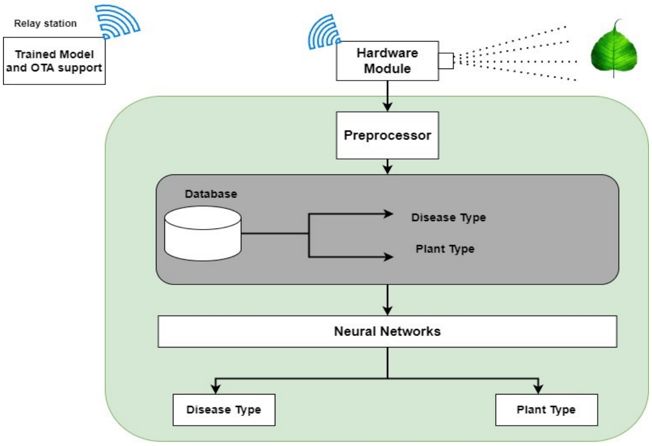


Fig. 1. Workflow and components of proposed plant leaf disease detection approach.

Embarking on research into plant leaf disease prediction using transfer learning holds immense promise for advancing agricultural technology and food security. Leveraging transfer learning allows us to utilize pre-trained models to identify diseases quickly and accurately in plant leaves, even with limited datasets. This approach not only accelerates the diagnostic process but also reduces the need for extensive, domain-specific data collection, making it more accessible and cost-effective. Ultimately, this research can contribute to healthier crops, increased yields, and more sustainable farming practices, addressing critical challenges in global food production and environmental conservation.

III. RESEARCH METHODS

We propose a research framework consisting of three key phases within a comprehensive system: Image Acquisition, Pre-processing, Feature Extraction and Transfer Learning Model. Each phase is crucial to general procedure, contributing to the accurate analysis of attained images. In the following segments, we provide a full outline of the method for every phase, emphasizing the particular steps involved and their importance in accomplishing consistent results. In this organized method, it aims to improve the efficiency of image analysis and deepen our understanding of the patterns and characteristics within the data.

A. *Image Acquisition:*

Plant leaf images are captured using a camera in RGB (Red, Green, and Blue) format. The RGB images are then processed through a color transformation structure and converted to a device-independent color space.

B. *Image pre-processing:*

To eliminate noise and other unwanted objects from the image, several pre-processing techniques are employed. These include image clipping, which involves cropping the leaf image to isolate the region of interest, and the application of smoothing filters to reduce noise. Additionally, image enhancement techniques are utilized to enhance contrast. These steps are crucial for improving the accuracy of maturity prediction and aiding in effective decision-making. Proper management of image size and background noise is essential for extracting meaningful features from plant leaf images, tailored to the specific domain.
Figure 1 depicts the workflow and key components of the proposed plant leaf disease detection approach.

The following sub-techniques are combined to effectively extract features from images:

- Image Resizing: During this stage, the input image is adjusted to a resolution of 200 by 200 pixels for better clarity and consistency. In our study, we address the issue of background noise in the RGB color model. Our approach involves several steps. Firstly, we convert the image to grayscale, creating an image convolution mask. This mask is then converted to binary format and utilized to apply a Gaussian-based technique for removing background noise from the image. Equations (1) and (2) present the mathematical description of this process.

$$\mathrm{I(J)_{gray}} = 0.299 \cdot \mathrm{I(J)_R} + 0.587 \cdot \mathrm{I(J)_G} + 0.114 \cdot \mathrm{I(J)_B} \quad (1)$$

In equation (1) $\mathrm{I(J)_{gray}}$ represents grayscale image, $\mathrm{I(J)_r}$ represents red channel of the RGB image, $\mathrm{I(J)_g}$ represents green channel of the RGB image, $\mathrm{I(J)_b}$ represents blue channel of the RGB image.

- Gray-scale conversion: Equation 2 is employed to convert color to grayscale image by averaging the RGB channel values. To transform a color image into grayscale, the mean calculation described in equation 2 is employed. The grayscale rendition of the leaf sample is depicted in Figure 2. Original and grayscale images of banana, citrus, and chili leaves are depicted in Figure 3.

$$Gray_i^p = \frac{(R_i + G_i + B_i)}{3} \quad (2)$$

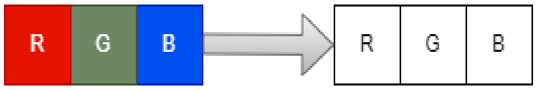


Fig. 2. RGB value of each pixel in grayscale conversion

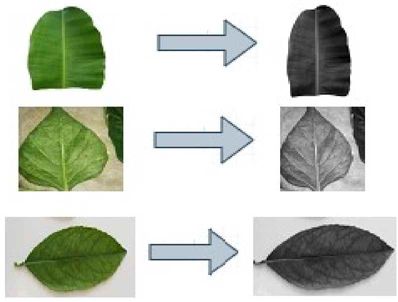


Fig. 3. Original and Gray scale images of Banana, Cirus and Chili leaves

- Gaussian filtering: A Gaussian filter is applied to pre-process plant leaf images, effectively reducing noise and smoothing the image. This enhances feature extraction by preserving essential details while eliminating irrelevant background information. This step improves the accuracy and reliability of subsequent disease classification stages. The Gaussian filter is used to smooth images, reducing noise and preserving edges. The Gaussian function is defined as:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (4)$$

C. *Feature extraction:*

It involves identifying key characteristics of plant leaf images, such as texture, color, and shape, to differentiate between healthy and diseased leaves. Advanced techniques, including pre-trained CNNs are used to automatically extract these features, enhancing the accuracy and efficiency of the disease classification process.

D. *Transfer Learning Models*

To enhance both accuracy and training efficiency, our system utilizes Transfer Learning (TL) alongside pre-trained models. In alignment with our maturity classification objectives, we have meticulously selected TL models: Mobile Net v1 96x96 0.25, MobileNetV1 96x96 0.2, MobileNetV1 96x96 0.1, MobileNetV2 96x96 0.35, MobileNetV2 96x96 0.1, MobileNetV2 96x96 0.05. These models have been extensively pre-trained on the expansive ImageNet dataset, which consists of vast number of images. The following sections provide a brief summary of each selected architecture. For a detailed comparison, refer to Table 1 which summarizes the implemented TL network.

TABLE I. OVERVIEW OF MOBILENETV1 AND MOBILENETV2 CONFIGURATIONS

Network Name	Depth	Size	Parameters
Mobile Net v1 96x96 0.25	88	17	1,063,466
MobileNetV1 96x96 0.2	88	17	850,773
MobileNetV1 96x96 0.1	88	17	425,387
MobileNetV2 96x96 0.35	53	17	1,964,496
MobileNetV2 96x96 0.1	53	17	561,789
MobileNetV2 96x96 0.05	53	17	280,895

Table 1 includes details such as sizes (in megabytes), network names, parameters and depths. This table is a valued reference, offering insights into performance metrics and unique attributes of every network. It assists in understanding distinct features of the network and their purposes in the proposed system.

The proposed methodology for plant disease identification system, as depicted in the diagram, combines hardware, preprocessing, neural networks, and a database for efficient disease diagnosis. The hardware module captures high-resolution images of plant leaves and transmits them to the preprocessor, which performs essential image processing tasks such as resizing, noise reduction, and feature extraction. The preprocessed data is then fed into neural networks, trained for image recognition and classification. These neural networks leverage a comprehensive database containing detailed information on various plant diseases and types, enhancing diagnostic accuracy. The system classifies the inputs into 'Disease Type' and 'Plant Type,' providing precise identification. Additionally, the system includes a relay station for deploying trained models and supports over-the-air (OTA) updates, ensuring the hardware module always uses the latest and most effective algorithms. This integration of advanced image processing, machine learning, and database management in real-time facilitates prompt and accurate plant disease detection, significantly contributing to precision agriculture. This technology enables farmers to make informed choices based on timely and accurate plant health data.

E. Algorithm

In the proposed algorithm, it details the process of classifying plant leaf stages by leveraging pre-trained classification models. It begins by capturing and resizing an image of the plant leaf to a consistent size. Next to distinguish the plant leaf from the background, adaptive thresholding is used. The algorithm then repeats through every pre-trained model, calculating weight derivatives related to plant leaf stages. This information aids in classifying the plant leaf image accurately into its respective stage. Through efficient processing, the algorithm ensures precise classification outcomes using the trained models.

ALGORITHM: PSEUDOCODE FOR THE PROPOSED SYSTEM

$Input$: $Plant\ leaf\ disease\ image\ captured\ using\ a\ camera,$
$f \leftarrow$ [Mobile Net v1 96x96 0.25, MobileNetV1 96x96 0.2, MobileNetV1 96x96 0.1, MobileNetV2 96x96 0.35, MobileNetV2 96x96 0.1, MobileNetV2 96x96 0.05]

$Output$: $Plant\ leaf\ disease\ type$

foreach model of pre-trained classification f, do
$for\ each\ training\ image\ sample, do$
Acquire the plant disease image in RGB format as $I(x_{org}, y_{org})$
Measure the Width and Height of the image as(W_{org}, H_{org})
Resize the image as $I_{(224\times224)} \leftarrow (W_{org}, H_{org})$
Determine the average intensity of the grayscale image $Gray_i^p \leftarrow \frac{(R_i+G_i+B_i)}{3}$
Feature extractor
for each image in a batch, **do**
$(W, H) \leftarrow (W_{org}, H_{org})$
$L_{stages} \leftarrow \{Anthracnose, Poedery\ Mildew, Root\ rot\}$

$$\partial(f_1) \leftarrow \left\{ \frac{\partial\left(Wts * \left[\frac{1}{1+e^{-f}}\right]\right)}{\partial(L_{stages})} \right\}$$

$$\partial(f_2) \leftarrow \left(\frac{1}{1+e^{-f_1}}\right)$$

end for

$$Map(I, L) \leftarrow \left\{\frac{\partial(I * f_2)}{\partial(f_2)}\right\}$$

end for
end for

IV. RESULTS

This segment offers an in-depth investigation and displays the findings from our experimental evaluation, which intended to assess the performance of our proposed system. We thoroughly inspect the findings from several tests, detailing their significance. These findings highlight the system's effectiveness and efficiency in achieving its objectives. The results discussed here serve as empirical validation, supporting the arguments and conclusions of this study.

TABLE II. MOBILENET VARIANTS FOR IMAGE RECOGNITION WITH DIFFERENT SCALES AND INPUT SIZES

Model Used for Research	Description
Mobile Net v1 96x96 0.25	MobileNet version 1 with input size 96x96 and scale 0.25
MobileNetV1 96x96 0.2	MobileNet version 1 with input size 96x96 and scale 0.2
MobileNetV1 96x96 0.1	MobileNet version 1 with input size 96x96 and scale 0.1
MobileNetV2 96x96 0.35	MobileNet version 2 with input size 96x96 and scale 0.35
MobileNetV2 96x96 0.1	MobileNet version 2 with input size 96x96 and scale 0.1
MobileNetV2 96x96 0.05	MobileNet version 2 with input size 96x96 and scale 0.05

Table 2 presents various MobileNet variants used for image recognition, each with different scales and input sizes. MobileNet v1 was employed with input dimensions of 96x96 and scales of 0.25, 0.2 and 0.1. MobileNet v2 was used with the same input size as 96x96 but at scales of 0.35, 0.1 and 0.05.

A. Experimental Setup

To carry out investigations and gather key findings, we applied a high-performance deep learning server with remarkable specifications: 2049 cores, clock speed of 1.79 TFLOPS and 128GB of Random Access Memory. This powerful infrastructure ensured the efficient and effective execution of our experiments. On the software side, we employed TensorFlow 2.1.3 as backend for our DL tasks, complemented by the Keras 2.1.2 API for model implementation and execution. This combination of advanced skills providing a robust groundwork for our experimental setup, which allows to obtain reliable and accurate results.

B. Dataset Description

Table 3 presents the dataset description consisting of 99 RGB images of Chili, Citrus, Banana, sourced from local fruit and vegetable store. By utilizing preprocessing techniques like binarization and Gaussian filtering, the dataset is analyzed with various MobileNet models, with MobileNetV2 (96x96 0.35) achieving the highest accuracy of 95%. The dataset and experimental setup were implemented using TensorFlow 2.1.3 and Keras 2.1.2 on a deep learning server.

TABLE III. DESCRIPTION OF DATASET

Feature	Description
Dataset Name	Plant Leaf Disease Detection Dataset
Number of Samples	99
Plant Types	Chili, Citrus, Banana
Image Format	RGB
Preprocessing Techniques	Binarization, Gaussian Filtering, Grayscale Conversion, Image Resizing
Transfer Learning Models Used	MobileNetV1 (96x96 0.25, 96x96 0.2, 96x96 0.1), MobileNetV2 (96x96 0.35, 96x96 0.1, 96x96 0.05)
Image Acquisition Source	Local fruit and vegetable stores, regional plant leaf disease specialists
Evaluation Metrics	TP, TN, FP, FN, Accuracy
Best Performing Model	MobileNetV2 96x96 0.35 with 95% accuracy
Experimental Setup	Deep learning server with 2049 cores, 1.79 TFLOPS clock speed, 128GB RAM
Software Used	TensorFlow 2.1.3, Keras 2.1.2

C. Analysis of Plant Leaf Disease and Dataset Compilation

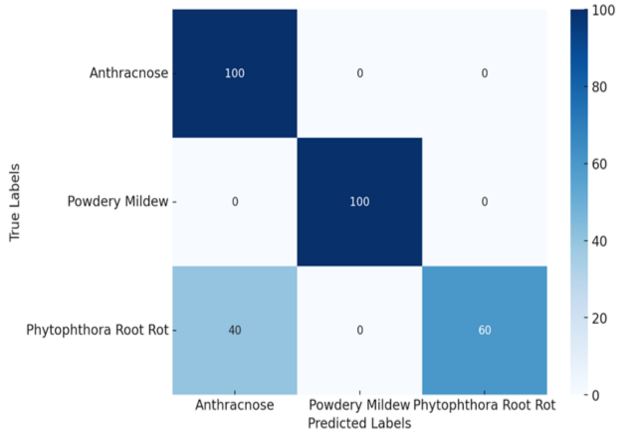
To evaluate the dataset, 99 carefully selected samples representing various plant types were analyzed. The samples were gained from local fruit and vegetable stores and we further enhanced the data from these specimens. Additionally, regional plant leaf disease specialists provided well-documented samples. Figure 4 depicts the illustration of leaf disease samples representing various plant types.

(i) Chili (ii) Citrus (iii) Banana

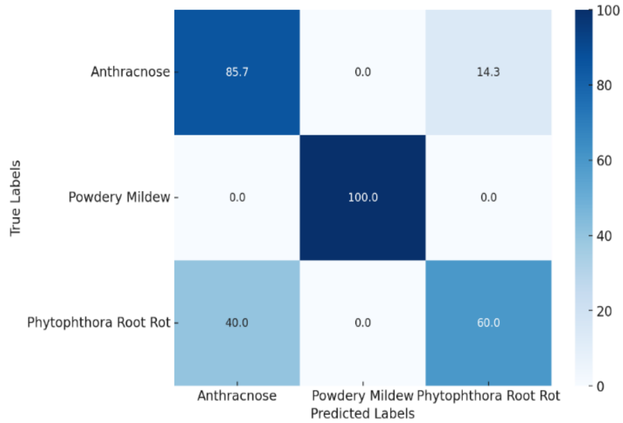
Fig. 4. Illustration of leaf disease samples from various plant types in Chili, Citrus and Banana

D. Experimental Inquiries

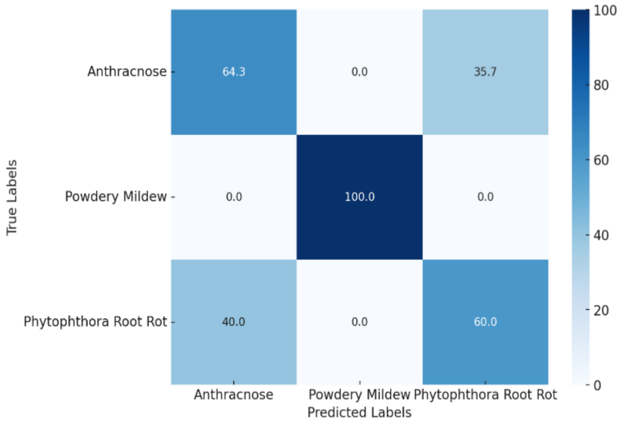
We calculated the efficiency of our method using different Transfer Learning approach. Our dataset comprised 99 samples which is evenly distributed across three different groups, allowing a thorough evaluation of the models' performance. To gain deeper insights into our results, we generated confusion matrix for individually chosen TL model. Figure 5 depicts the Confusion matrix illustrating the performance of selected TL Networks.



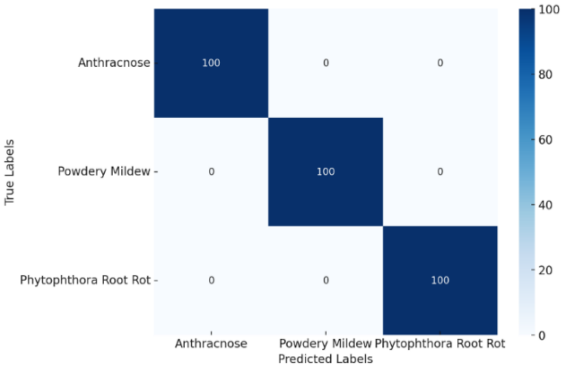
(i) MobileNetV196x96 0.25



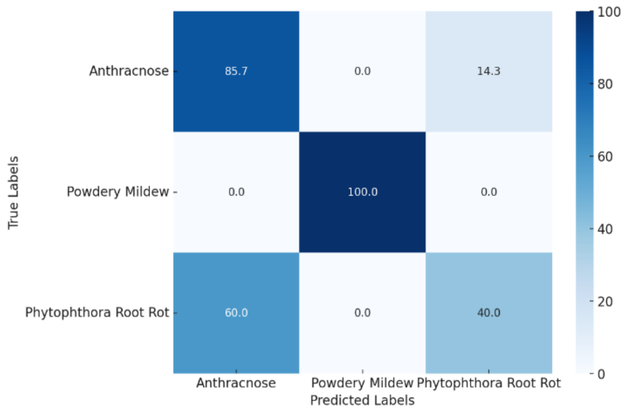
(ii) MobileNetV1 96x96 0.2



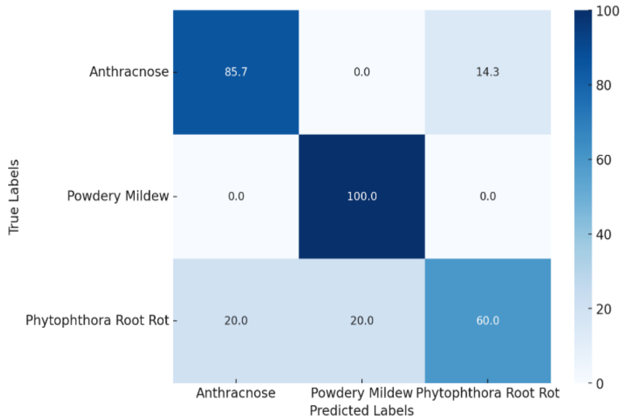
(iii) MobileNetV1 96x96 0.1



(iv) MobileNetV2 96x96 0.35



(v) MobileNetV2 96x96 0.1



(vi) MobileNetV2 96x96 0.05

Fig. 5. Confusion matrix demonstrates how the selected TL Networks perform, as outlined in Table 1

Table 3 provides an extensive statistical analysis of MobileNet networks, detailing key metrics such as True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN), and Accuracy (%). This detailed analysis provides valuable insights into the classification performance of various models, enabling a thorough assessment of accuracy, precision, recall, and other critical metrics necessary for understanding the classification outcomes.

TABLE III. DETAILED STATISTICAL EVALUATION OF MOBILE NET NETWORKS ACROSS VARIOUS CONFIGURATIONS

Metrics	**Network Name**					
	V1 96x96 0.25	**V196x96 0.2**	**V196x96 0.1**	**V296x96 0.35**	**V296x96 0.1**	**V296x96 0.05**
TP↑	45	37.5	30	47.5	35	37.5
TN↓	45	37.5	30	47.5	35	37.5
FP↑	5	12.5	20	2.5	15	12.5
FN↓	5	12.5	20	2.5	15	12.5
Accuracy (%) ↑	90	75	60	95	70	75

In Table 3 each network variant, identified by resolution and multiplier, shows distinct performance characteristics. For instance, V1 96x96 with a multiplier of 0.25 achieves 90% accuracy, while V2 96x96 with a multiplier of 0.35 achieves 95%. This detailed breakdown facilitates a nuanced understanding of how different model settings impact classification outcomes, crucial for optimizing mobile neural networks for specific tasks.

V. CONCLUSION

The study validated the effectiveness of using advanced image processing and DL techniques, especially transfer learning models, in classifying and detecting plant leaf diseases. By leveraging pre-trained MobileNet models, we achieved high accuracy rates in identifying disease stages in chili, banana, and citrus crops. Specifically, MobileNetV2 with a resolution of 96x96 and a scale of 0.35 demonstrated the highest accuracy at 95%, while MobileNetV1 with a resolution of 96x96 and a scale of 0.25 achieved 90% accuracy. The pre-processing techniques, including binarization and Gaussian filtering, significantly improved the accuracy of classification of diseases. The experimental results underscore the potential of these automated solutions to replace traditional, labor-intensive methods, offering a reliable and efficient approach to monitor and manage plant health. This technological advancement is crucial for enhancing agricultural productivity, safeguarding the economy, and ensuring food security.

Future research should aim to expand the dataset to include a broader variety of crops and disease conditions to improve the model's generalizability. Integrating real-time data collection systems with Internet of Things (IoT) devices can enhance the practicality of these models in field conditions, providing farmers with timely and actionable insights. Additionally, exploring the combination of multiple deep learning architectures and optimizing their parameters could further increase accuracy and efficiency. For example, experimenting with different versions of MobileNet or other architectures could reveal more effective models. Further studies should also investigate the economic impact of deploying these automated disease detection systems on a larger scale, aiming to make the technology accessible to small and medium-sized farms globally. Continued interdisciplinary collaboration will be essential to address the complex challenges in precision agriculture and ensure sustainable farming practices.

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