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ORANGE PLANT LEAF DISEASE DETECTION AND CLASSIFICATION WITH IMAGE PROCESSING USING A DEEP CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT
The farming of citrus is a crucial component of Pakistan's fruit-based agricultural economy. But, the foliar diseases citrus canker, black spot, and greening have been posing a constant threat on citrus's productivity. An optimal solution is an early and accurate detection of these diseases to improve the productivity. Therefore, this paper proposes an automated citrus leaf disease detection and classification framework based on deep convolutional neural networks (DCNNs). The proposed solution has five stages: image acquisition (dataset), preprocessing, data augmentation, deep feature extraction and optimization, and disease classification. Firstly, the images are obtained from a public dataset downloaded from Kaggle. Secondly, preprocessing techniques are used to improve the image quality and shape, thirdly the data augmentation techniques are used to enhance the model generalization, fourthly pre-trained models DenseNet-121, MobileNet, and InceptionV3 with transfer learning technique to extract deep features, and finally Adam optimizer and categorical cross-entropy loss function are used to fine tune the pre-trained models for classifications. The proposed model is evaluated on accuracy, precision, recall, and F1-score metrics. All the models demonstrated robust performance while DenseNet-121 achieved the best performance. The evaluation results assured the robustness of the use of transfer learning-based DCNN in citrus leaf disease detection.

Keywords: Citrus, Inception V3, MobileNet, DenseNet, CNN

1. INTRODUCTION
Citrus plants are vulnerable to a variety of diseases that can significantly impact fruit quality and yield. A large amount of citrus fruit is wasted every year due to several citrus diseases including canker, greening, and blackspot. Therefore, early identification and detection of these diseases using modern technologies such as image processing, artificial intelligence, machine learning and deep learning has gained significant attention in precision agriculture (Khirade & Patil, 2015). Many methods have been developed for the early identification and accurate diagnosis of the leaf diseases from the images of infected leaves based on user-defined features (Geetharamani & Pandian, 2019). The most common statistical machine learning approaches for image classifications are Support Vector Machine, K-nearest neighbors, logistic regression, and decision tree (El Houby, 2018; Phate et al., 2019). Although these approaches have shown promising results but the recent advancements in deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown great potential in automating the detection and classification of plant diseases (Barman et al., 2020). It is therefore, the DCNN-based models do not rely on manual features rather they have the ability to extract and learn the features automatically from the provided image dataset.
Therefore, this study proposed a deep convolutional neural network (DCNN) to identity the citrus leaf disease. The proposed solution is a structured solution comprises of following steps:

- Image acquisition
- Preprocessing
- Data augmentation

- DCNN-based model for feature extraction
- Feature optimization
- Disease classification

In particular, firstly, citrus images dataset obtained from Kaggle, secondly, pre-process and transform these images to ensure a consistent shape, enabling the model to comprehend and learn from them. Thirdly the convolutional layer applies a convolution function to the data in order to extract features and learn complex patterns. Its primary purpose is featuring extraction. Before the training process, feature optimization is carried out. Transfer learning with a pre-trained CNN involves two crucial steps for feature optimization: freezing the pre-trained layers and fine-tuning the final layers. Popular pre-trained models such as DenseNet (Huang et al., 2017), Inception V3 (Szegedy et al., 2016), or MobileNet (Zamani et al., 2022b) which have been trained on extensive datasets like ImageNet (Deng et al., 2009) are selected. Following this, a pre-trained model is employed, adjusting its parameters, weights, and biases through a process known as model training. To minimize the difference between predictions and actual labels of the data, an optimization function called Adam is applied.

In conclusion, this research aims to contribute to the field of plant disease detection and classification by leveraging the potential of deep learning techniques, specifically deep CNN, for citrus plant leaf diseases. By automating the identification process, we strive to provide an accurate, efficient, and scalable solution that can assist farmers and agronomists in making informed decisions and safeguarding orange plant health and productivity.

The remaining paper is organized as, Section 2 provides a deep insight about the existing methods, Section 3 describes the dataset and methodology of the propose solution, Section provides the results and related discussion on the results, finally, Section 5 concludes the paper.

2. RELATED WORK

This section reviews traditional image processing techniques, classical machine learning approaches, CNN-based plant disease detection, and transfer learning in agricultural imaging.

A computer vision approach was used to identify orange leaf diseases and the grading of orange fruit using fuzzy logic. The algorithm used were support vector machine and k-means clustering. The identification of orange leaf disease by applying CNN with several procedures GLCM, fuzzy method, multi-SVM (Gómez-Sanchis et al., 2012) and the threshold value. Orange leaves and fruit disease were detected by CNN and deploying image dissection, grey-level co-occurrence matrix, and k-means clustering. The ultimate classification was accomplished by SVM using 13 features that were extracted from image.

A Machine learning based approach was applied using the regression technique for rust leaf disease identification. Gaussian process regression, v support vector regression, and partial least square regression was applied during the study. The orange lesions were identified using a nonlinear approach and a deep learning-based algorithm. The Exponential-Nonlinear activation unit was used to improve the ability of CNN for feature extraction. The residual network (RESNet) deep neural network was applied for the final classification (Agarwal & Tarar, 2021).

Oriented FAST, Scale-Invariant Feature Transformation (SIFT), Histogram of Oriented Gradients (HOG), and accelerated vigorous feature extraction strategies were employed in order to identify the illness in maize. Decision Tree (DT) and Random Forest (RF) were employed to assess each of these performances. The findings indicated that RGB is the best attribute that is more informative for classifying things and provides more accuracy than others. CNN and other machine learning techniques have found extensive use in agriculture. It has demonstrated outstanding results in a variety of application areas, including the calculation of production, automated illness detection, and infection prediction (Bao et al., 2021). The researchers used a novel approach based on CNN to construct a model for identifying 13 distinct plant diseases. The model was capable of differentiating between the background and the leaf image, and the experiment demonstrated an average improvement in accuracy of 96.3% (Doh et al., 2019).

An automated method based on a DCNN was utilized to detect guava leaf disease using an image dataset. The diseases that were being investigated were rust, leaf spot, and whiteflies. A guava leaf image dataset with four different classifications was created. The average accuracy improvement of the experiment was 98.74% (Kaur et al., 2020). A study used a machine learning method established on KNN algorithm to classify four citrus leaf diseases including Citrus Canker, Citrus Greening, Citrus Scab, and Citrus Variegated Chlorosis using hyperspectral imaging data (Parraga-Alava et al., 2019). The model achieved an overall classification accuracy of 93%. Another study used a deep learning technique established on CNN to develop an automated system to classify four types of citrus leaf diseases, Citrus Canker, Citrus Scab, Greasy Spot, and Melanose. The model achieved a high classification accuracy of 94% on a dataset of over 2,293 leaf images. These results demonstrate the potential of machine learning techniques for accurate and efficient citrus leaf disease identification, which could help farmers take timely action to prevent and manage plant diseases (Badillo et al., 2020). The authors employed pretrained models, including ResNet50, VGG16, ResNet150, Alexnet, and VGGNet, on a dataset obtained from Kaggle. The best accuracy improvement of 99.80% was achieved using ResNet50 on 38 different classes (Idress et al., 2024). In another study CNN to classify diseases caused by fungi in three fruits: Guava, Apple, and Custard Apple. The dataset used contained 14,181 real-time images with ten different classes, and included three versions of the dataset, i.e., white, black, and gray. The findings of the experiment demonstrated that color images were the most suitable for classification. AlexNet and Squeeze Net (Tian et al., 2020) were the algorithms employed in this work, with the highest accuracy obtained being 86.8%.

Based on the above literature it is evident that to cope citrus diseases are prolific research domain in the field of agriculture. The robust, timely and accurate detection of citrus diseases not only help farmer to increase its production but also play vital role in country’s economy in terms of foreign exchange. Hence, there is gap need to address utilizing more innovative and robust models for enhancing reliability, confidence of the farmer while handling citrus diseases. The upcoming section highlights the proposed methodology in detail.

3. PROPOSED METHODOLOGY

This section particularly covers the details of dataset description, preprocessing, augmentation, CNN architectures, and transfer learning strategy employed for this research.

3.1 Dataset

The dataset[1] for this study was retrieved from Kaggle which consists of RGB images of healthy, black spots, canker, and greening diseased leaves of oranges. To get the model as accurate as possible, a decent dataset is essential. Additionally, the dataset must be prepared so that our model can fully comprehend the data. The model will then be able to effectively use that dataset for learning. A random sample of infected and healthy leaves images from the datasets shown in **Figure 1**. The details of the images are provided in **Table 1**.

[1] https://www.kaggle.com/datasets/sourabh2001/citrus-leaves-dataset?resource=download

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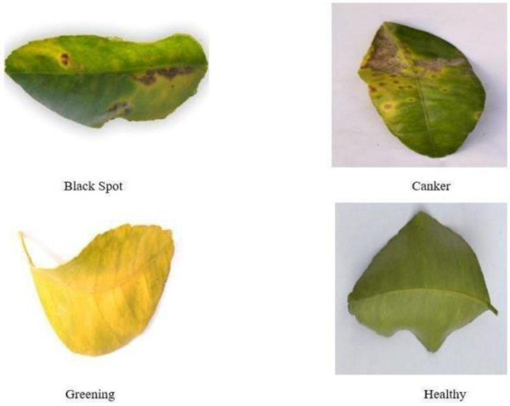

Figure 1: Data samples from each class of citrus leaf disease

Table 1: Dataset Details

Sr. No.	Image Description	Total Images
1	Leaves with Blackspot	171
2	Leaves with Canker	163
3	Leaves with Greening	204
4	Healthy leaves	116
5	Total Images	654

After obtaining the dataset the next step is to prepare the dataset for the model training and classification. The **Figure 2** shows complete methodology of the proposed solution.

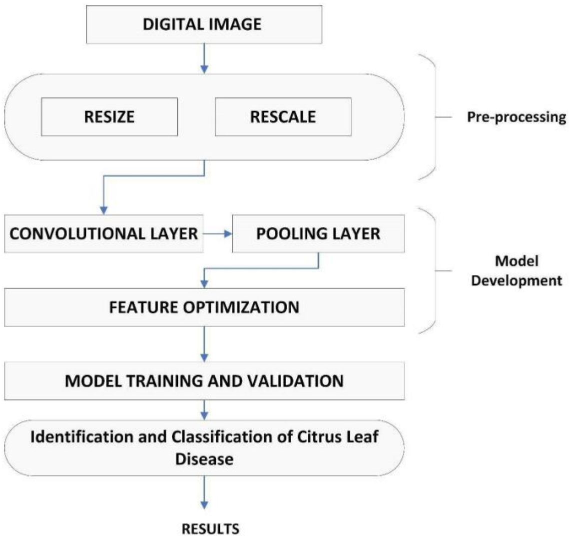

Figure 2: Methodology of the Proposed Solution

3.2 Pre-processing

This is a crucial step in developing a machine or deep learning pipeline. In this work the images are rescaled and resized before augmentation and training. The purpose of rescaling is to normalize the pixel values of the digital images of the dataset between a range of 0 to 1. Originally the images are of 1520×1417 (height and width). We have resized the image in 224×224.

3.3 Data Augmentation

A Deep Learning model that we train on a limited number of data samples has a propensity to over-fit. To expand the quantity of data samples, several picture augmentation parameters including zoom, shear, rotation, and others are routinely utilized. Images with these traits are created when these parameters are used to train a deep learning model. The total number of

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images were 654 and these were augmented to increase the size of dataset fed to the neural network as shown in **Table 1**. The augmentation was accomplished using python-based image data generator including rescale, shear range, horizontal flip, and zoom range. **Table 2** lists the detail of images after augmentation process.

Table 2: Data augmentation results

Sr. No.	Image Description	Total Images	Augmented Images
1	Leaves with Blackspot	171	50x171=8550
2	Leaves with Canker	163	50x163=3150
3	Leaves with Greening	204	50x204=10200
4	Healthy leaves	116	50x116=5800
5	Total Images	654	27700

3.4 Proposed Model

Figure 3 represents the stack of convolutional and pooling layers integrated to define the proposed model. As convolutional layer plays a vital role for CNN to extract features from citrus leaf image dataset, then most important features are selected from them using max pooling technique, four dense layer is added to combine features by convolutional and pooling layers for making predictions. At the end of these layers, a flatten layer is added to generate 1D array by reshaping 2D feature matrix. This layer helps for the classification of citrus leaf disease.

3.4.1 Convolutional Layer

This layer is the fundamental layer of any CNN model. The basic operation of this layer is to apply convolution operation that aims to extract all possible features from an image based on shape, texture, edges, and color. Convolutional layers in CNNs work by applying a series of filters to the input picture to extract information from it. The convolutional layer contains learnable variables, also known as kernels, which are responsible for extracting patterns from the input data. After convolution, a feature map is generated, which summarizes all the deep features in the input image.

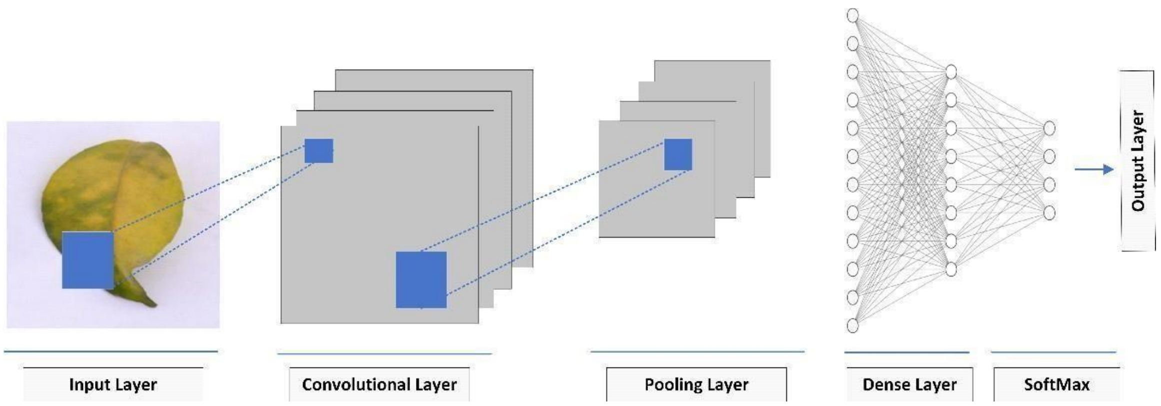

Figure 3: Layered architecture of proposed methodology

We used a CNN with the following architecture to identify orange diseases: First, a Convolutional layer with 32 filters of size 3 x 3 and a ReLU activation function was used in the initial block. Then, batch normalization was applied, and the Max Pooling layer with a size of (3,3) was selected along with a dropout layer that has a 25% dropout. To enhance the coherence of the convolutional neural network, batch normalization was applied after every layer.

The second block of the network consists of two convolutional layers with 64 filters of size 3 x 3 with batch normalization and ReLU activation function. Then, a dropout layer with a 25% dropout and a Max Pooling layer with a pool size of (2, 2) were added to the neural network.

The third block of the network utilized 128 filters with a size of 3 x 3. Two convolutional layers were used, each with batch normalization and a ReLU activation function. Following the pattern of the second block, a Max Pooling layer with a pool size of (2, 2) and a dropout layer with a 25% dropout were added.

3.5 Feature Optimization

One of the post-processing step is to remove the redundant features and preserve most salient features. To obtain this, a Non-Maximum Suppression (NMS) (Si et al., 2024) was applied to the proposed CNN feature maps. After removal of redundant features, we applied transfer learning using pre-trained models DenseNet-121, InceptionNet V3, and MobileNet to further optimize the features. The detail of the transfer learning is provided in the following section.

3.5.1 Transfer learning configuration

Table 3: Transfer learning configurations provides the configurational of the pre-trained models DenseNet-121, Inception Net V3 and Mobile Net with transfer learning. These models involve leveraging the powerful features of pre-trained models and fine-tuning it for a specific task using transfer learning. The customization involves adapting the model to the unique characteristics of orange leaf images, enabling accurate identification of diseases.

Table 3: Transfer learning configurations

Parameter	DenseNet-121	InceptionV3	MobileNet
Input Image Size	224 × 224 × 3	299 × 299 × 3	224 × 224 × 3
Pre-trained Dataset	ImageNet	ImageNet	ImageNet
Optimizer	Adam	Adam	Adam
Initial Learning Rate	1×10^{-3}	1×10^{-3}	1×10^{-3}
Fine-Tuning Learning Rate	1×10^{-4}	1×10^{-4}	1×10^{-4}
Loss Function	Categorical Cross-Entropy	Categorical Cross-Entropy	Categorical Cross-Entropy
Batch Size	32	32	32
Number of Epochs	15	20	25
Dropout Rate	0.5	0.5	0.5
Activation Function	ReLU	ReLU	ReLU
Output Activation	Softmax	Softmax	Softmax
Training Strategy	Transfer Learning + Fine-Tuning	Transfer Learning + Fine-Tuning	Transfer Learning + Fine-Tuning

Secondly, **Table 4** gives the detail of quantitative layer freezing and unfreezing technique to further enhance the model accuracy and results.

Table 4: Layer freezing details

Model	Total Layers	Frozen Layers (Approx.)	Unfrozen Layers (Approx.)	% Fine-Tuned (Approx.)
DenseNet-121	121	90	31	26%
MobileNet	28	20	8	29%
InceptionV3	311	250	61	20%

4. RESULTS AND DISCUSSIONS

The obtained results were discussed in this section. Along with the experimental setup for this work.

4.1 Experimental Setup

The model was implemented Python and its deep learning libraries and framework. The model was developed using Google colab an online computational resource equipped with

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GPU as well. In particular, we used Keras, TensorFlow, NumPy, CONV2D and other Python resources to develop and implement the proposed model.

4.2 Comparative Analysis of Models

Comparative analysis of DenseNet-121, MobileNet, and Inception V3 are discussed, highlighting DenseNet-121's superior performance and model limitations. The proposed model was trained, validated and tested on the plant disease dataset with 70%, 15% and 15% ratio respectively. The proposed solution is evaluated for accuracy, precision, recall, and F1-score metrics.

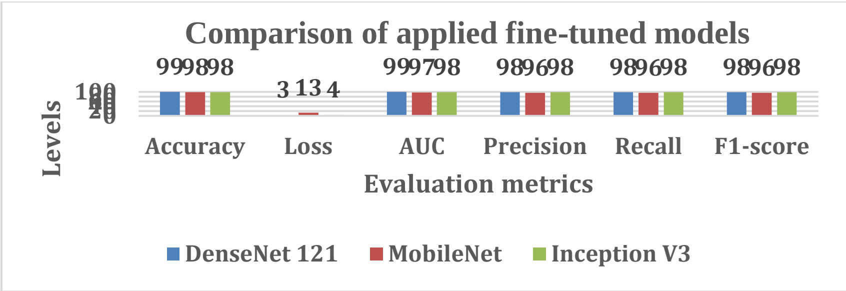

Figure 4: Comparison of applied fine-tuned models

Figure 4 provides detail comparison of evaluation metrics on the testing results of the proposed solution. All the models showed promising results and accuracy between 98 to 99%. The DenseNet-121 achieved best accuracy of 99% with minimum loss of 3%. While InceptionNet V3 achieved lowest performance in term of accuracy with loss of 14%. This is because InceptionNet V3 performs better in selected use cases only. Similar pattern can be seen on other metrics as well, where DenseNet-121 has outperformed all the counter parts.

4.3 Confusion Matrix

The confusion matrix is a table that is commonly used to evaluate the effectiveness of a machine learning or deep learning model, particularly one that employs supervised learning. In the confusion matrix, each row displays instances of each true class, while each column shows instances of each predicted class. It can also be displayed the other way around, with predicted classes in rows and actual classes in columns, we follow this convention in this section of our work. The term "confusion matrix" originates from its ability to quickly identify the various types of errors that exist in our classification processes. The confusion matrix of DenseNet-121, Mobile Net, and Inception V3 are presented in **Figure 5 –to- 07** respectively.

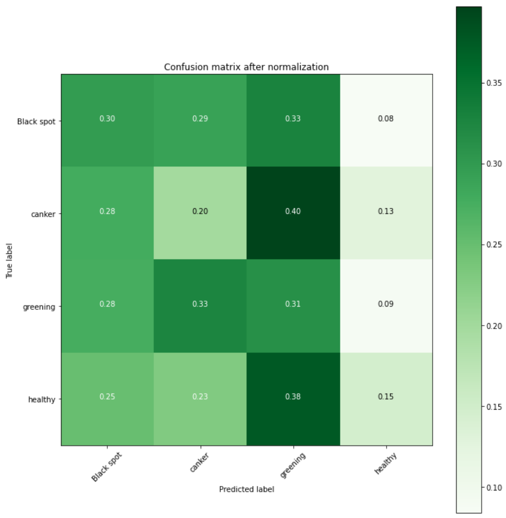

Figure 5: Confusion matrix of DenseNet-121

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The **Figure 5** demonstrates a confusion matrix of DensNet-121 showing the relationship between the actual and predicted classes of orange leaf disease categories with the values indicating the proportion of samples classified into each category. The higher values along the main diagonal reflect accurate classifications, while off diagonal entries represent misclassification patterns between disease classes. The variation highlights within the cell intensities reflects class-wise prediction performance. It reveals specific disease categories that are more prone to confusion. Generally, the confusion matrix delivers detailed insight of classification and classifier's weaknesses and strength beyond overall accuracy.

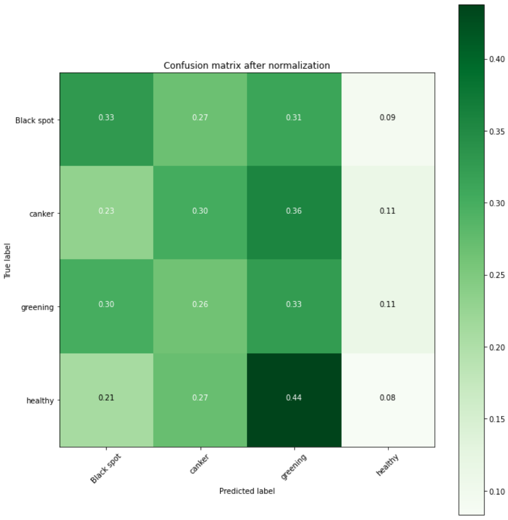

Figure 6: Confusion matrix of MobileNet model

The **Figure 6** illustrates a confusion matrix of MobileNet model depicting the relationship between predicted and actual classes for orange leaf disease classification. Particularly, few classes reveal stronger confusion with neighboring classes, describing the need for more discriminative feature engineering. In conclusion, this confusion matrix reflects a detailed class wise performance assessment by complementing aggregate evaluation metrics including F1-score and accuracy.

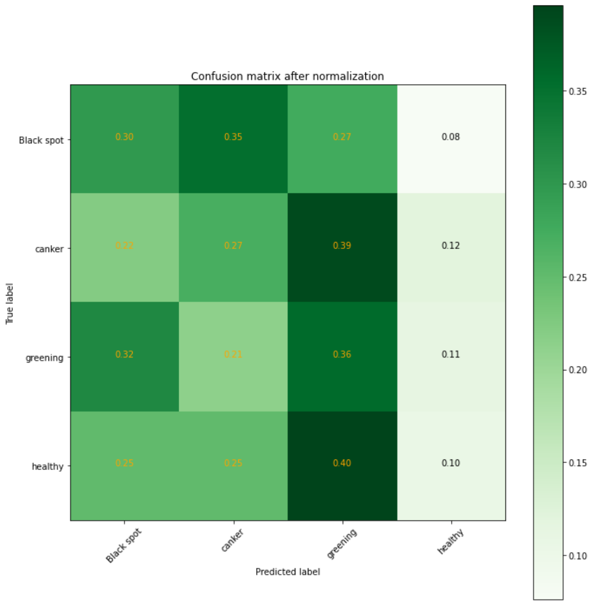

Figure 7: Inception V3 confusion matrix

The **Figure 7** depicts confusion matrix of Inception V3 model showing the connection between the predicted and actual classes in the orange leaf disease classification task. The variation in intensities across cells reveals that few classes are more consistently identified

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than others. Generally, this confusion matrix offers detailed understanding into the model's classification behavior beyond overall accuracy by supporting a more nuanced.

5. CONCLUSIONS AND FUTURE WORK

To enhance the production and quality of plants and their products, it is crucial to limit biotic variables that cause substantial crop yield losses. This can be achieved by utilizing successful computer vision and deep learning techniques, such as pattern recognition, categorization, and object extraction. A deep learning-based model has been developed to detect and recognize citrus leaf diseases. This research employed DenseNet-121, Mobile Net, and Inception V3 algorithms to identify citrus leaf diseases from a dataset of real-time images of citrus tree leaves acquired from Kaggle. The images underwent preprocessing and augmentation before training all three models, which included augmented images of healthy, canker, greening, and black spot leaves of the citrus tree. During accuracy testing, DenseNet-121 achieved the highest accuracy of 99%, and it is preferred over traditional methods due to its fast convergence rate, high training performance, and minimal preprocessing requirements for input images or features. Although the model can be optimized by increasing the number of images in the dataset and fine-tuning its parameters, determining the best parameters for a transfer learning model is an ongoing research issue.

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