# AVOCADO LEAF DISEASE DETECTION USING DEEP LEARNING


**BY**

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## FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering


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# APPROVAL

This Project titled "Avocado Leaf Disease Detection Using Deep Learning", submitted By Ali Hossain to the Department of Department of Computer Science and Engineering (CSE), Daffodil International University (DIU), has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 16-07-2024.

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I hereby declare that this project has been done by us under the supervision of **Md. Zahid Hasan Associate Professor Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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# ABSTRACT

Avocado is a food crop of the tropical and sub-tropical zone scientifically known as Persea americana due to its creamy texture and health-enhancing fats. Detecting diseases in avocado leaves is essential for maintaining tree health and ensuring optimal fruit production. This research focuses on the application of deep learning approaches in detecting diseases in leaves of avocado with the general purpose of designing a reliable diagnostic system that can assist in diagnosing diseases within early phases of their manifestation, hence effectively allowing farmers to manage their crops. The dataset was increased to 3600 images with 600 images of avocado leaves infected with Persia mites, Miners, Margin burn, and healthy leaves with the help of augmentation. Five models were evaluated: three proprietary deep learning models, namely, Convolutional Neural Network (CNN), and three others which are Xception, VGG19, InceptionV3, and MobileNetv2. The models were then trained on the leaves' images to categories them into the four categories. The assessment of the models revealed generally satisfactory results; MobileNetV2 was in the lead with 98.52% accuracy; next came Xception at 94.63%; InceptionV3 at 93.80%; VGG19 at 91.02%; and then the custom CNN at 84.44%. Due to its high accuracy, MobileNetV2 is ideal for implementation in real-time urgent like on fields. The analysis shows how the deep learning models can be applied in an effort to help farmers to timely notice the diseased plants, hence improve on the health and thus the yields of the crops. The further development will include the implementation of these models to more accessible interfaces and the improvement of their stability through the acquisition of more data and learning from it constantly.

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# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

It is essential to know Avocado production is a vital agriculture business globally, and it is highly beneficial to nourish ourselves. However, there are diseases that affect the avocado crops thus compromising yield and quality once the crops are attacked. Hence, it becomes important to detect these diseases at the early stages and accurately identify them for the purpose of managing and controlling the occurrence in order to reduce the economic losses affecting a healthy crop production Thangaraj, Rajasekaran, et al. [1]

In the past, identification of diseases from avocado leaves has mostly depended on visual assessment with the help of specialized personnel and this process is usually very exhaustive and sometimes less accurate. New approaches of disease detection have been developed with the use of image processing and machine learning. These methods may provide relatively faster, precise and uniform method of disease diagnosis thus helping farmers to make decisions promptly. Of the broad field of machine learning, deep learning is specific and has been reported to possess high outcomes in diverse image classification applications primarily because it is capable of distinguishing intricate characteristics of large image datasets M. H. Saleem, et al. [3]

Among all these classifiers, Convolutional Neural Networks (CNNs) have attracted much attention due to the high accuracy achieve for image recognition and classification in plant disease detection. In the following research, the author focuses more on the use of deep learning models for identification of diseases from the leaves of avocado plant. Acquiring a dataset of healthy and unhealthy leaves, With the help of our efficient Annotation Protocol, we annotated a wide variety of images ranging from healthy leaves to those impacted by diseases such as Persea mites, Miners, and Margin burn diseases. Based on this data set, it is possible to develop a specific architecture of the CNN and use preprint containing Xception, VGG19, InceptionV3 and MobileNetV2 S. Mishra, T. H. Ayane, et al., [5]

The intention of the study is to carry out a performance assessment of these models in its capacity to classify diseases of avocado leaves appropriately and to analyze the suitability of the model which can be applied in actualist environmental setting in the agricultural realty. The goal of the current study is, therefore, to establish a method that can help with the early detection of diseases in avocados, hence promoting sustainable avocado farming among the farmers.

## 1.2 Motivation

The rationale of undertaking this research is informed by the gaps that have been identified in the effective and early diagnosis of diseases affecting avocado plants. The conventional approaches used in achieving diagnosis are time consuming and inherently biased and hence a diagnosis can in most cases be wrong or delayed. Thus, our vision is to improve and automate disease detecting procedures with the help of deep learning models such as Xception, VGG19, InceptionV3, MobileNetV2. This approach also enhances good crop management practice since it facilitates early detection of problems that affect crop production and, in the process, enhances sustainable agriculture by reducing on yield losses and production of healthy avocados.

## 1.3 Rational of the study

The premise of this study is found in the need to further the present practices of agriculture industry with the aid of contemporary technology. This is why we have used deep learning models as Xception, VGG19, InceptionV3 and MobileNetV2 to transform the way of detecting avocado leaf disease. This approach is much better than the conventional method of manual inspection and enables the farmers to received timely information which helps to prevent crop diseases. This research will establish how this improved usage of the modern techniques in agriculture will benefit the farming industries by enhancing sustainable agricultural practices in order to increase the yield and quality of the crops produced.

## 1.4 Research Questions

1. How do deep learning models perform in classifying different diseases affected avocado leaves compared to traditional methods?

   - This question focuses on evaluating the efficacy of deep learning models in disease classification relative to conventional manual inspection techniques.

2. What is the impact of dataset augmentation techniques on the performance of deep learning models for avocado leaf disease detection?

   - This question explores how techniques like image augmentation influence model accuracy and robustness in detecting diseases from avocado leaf images.

3. How does transfer learning from pre-trained models enhance the ability of CNN architectures to distinguish between healthy and diseased avocado leaves?

   - This question investigates the benefits of leveraging pre-trained models for avocado disease detection, assessing improvements in feature extraction and classification accuracy.

4. What are the computational requirements and efficiency considerations when deploying MobileNetV2 for real-time avocado leaf disease detection applications??

   - This question examines the practical implications of using MobileNetV2, focusing on its computational efficiency and suitability for deployment in resource-constrained environments.

5. How can the findings from this study be practically applied to improve avocado farming practices and support sustainable agriculture?

   - This question addresses the broader implications of the research findings, aiming to translate technical advancements into actionable insights for farmers to enhance crop management and sustainability.

### 1.5 Expected Output

The expected output of this study includes getting very high accuracy in classifying the avocado leaf diseases Deep learning models as Xception, VGG19, InceptionV3, and MobileNetV2. This includes the cultivation of a sturdy and superior system that effectively identifies diseases and provides optimal solutions unlike precedent methods such as Transfer learning, and Dataset augmentation. The current study seeks to apply the said models in practice to help promote sustainable production of avocados and enhance the ability to manage the crops to enhance yields. Therefore, the research aims at contributing to agriculture by adopting modern technology that can be of help in the identification of diseases that affect avocado production to be healthier.

### 1.6 Project Management and Finance

Project Management sets out plans on how a project or program will be run while finance gives statistics on source of funds, their usage as well as the balance that remains. In terms of project management and finance in this study, there is a proper planning and decentralization of resources for accomplishing the dataset, model development, and assessment. This includes estimate for computational costs, possible software licensing fees, and perhaps outside help. Resource management guarantees the timely completion of activities, the strict follow-up of deadlines, and comprehensive testing of the created deep learning models. The regulatory concerns are related to the efficiency and profitability of model deployment, possible cost reduction resulted from better disease management, and, finally, feasibility of the employed solutions in the long-run period. By blending good project management practice with sound financial planning, this paper's objective is to help increase efficiency by reducing costs and improve the effectiveness of solution adoption in identifying avocado diseases and improving sustainable farming.

**Table 1.6: Estimated Cost**

| SN | Components | Estimated Cost (BDT) |
|---|---|---|
| 01. | Hardware | 50000-60000 |
| 02. | Software and Tools | 10000-15000 |
| 03. | Data Collection and Processing | 5000-6000 |
| 04. | Documentation and Report Writing | 5000-10000 |
| 05. | Miscellaneous | 10000-12000 |
| 06. | Contingency | 25000-30000 |
| | Total Estimated Cost | 105000-133000 |

### 1.7 Report layout

The research begins with the justification surrounding the use of deep learning for identifying the citrus fruit leaf diseases.

**Chapter 1: Introduction.**

Outlines background information about the particular study plus the motivation for conducting the research since early signs of diseases in citrus plants are crucial to ascertain.

**Chapter 2: Background.**

Explains facts about the citrus fruit production, the diseases it experiences, ways of identification, and the application of deep learning.

**Chapter 3: Research Methodology**

Describe how the organized plan for data collection, the selection of models, training and model evaluation fosters scientific objectivity and replicate ability.

**Chapter 4: Experimental Results**

Talks about the outcome of the training and validation of model more and more along with comparative analyze like accuracy for different deep learning models.

**Chapter 5: The Impact on Society**

Interestingly, or perhaps not so surprisingly, the mere existence and frequent use of such technologies within society has given rise to a number of societal impacts.

Explains how Deep Learning Technology in general can be incorporated into disease diagnosing systems for agriculture and other climates, and the benefit of this technology to society.

**Chapter 6: Conclusion, Recommendations, and Implications for Future Research**

The objective of this study is to provide a summary of the findings, conclusions, recommendations, and implications for future research that can be derived from this study.

Summarizing the main findings of the studies and using it to come up with an observation on the overall status of the topic for further research and development of agricultural innovation technology.

# CHAPTER 2
# BACKGROUND STUDY

## 2.1 Preliminaries

Many of the essential terminologies in this context are related to deep learning-based detection of avocado leaf diseases. Deep Learning uses multi-layered neural networks to model complex patterns in data. Dev Not Boring – Medium Convolutional Neural Networks (CNNs) are a type of deep learning model that is especially useful for image recognition tasks because of its capability to capturing spatial hierarchies. Transfer Learning is using pre-trained models on large datasets to improve performance of a related task with less data. Image Augmentation - techniques used to enlarge the dataset artificially by crafting a new version of images making model generalize better. While evaluating the model performance any of metric can be used but accuracy is closely related to measures correct predicted instances hence it plays crucial says - over all measurement.

## 2.2 Related Works

A review of existing studies on avocado leaf disease detection using deep learning techniques is discussed in this section. In the subsequent studies, different strategies and models, or techniques are used to improve disease diagnosis in avocado crops. These works provide the basic knowledge of current advances and challenges in this field.

Thangaraj, Rajasekaran, et al. [1] focused on Implementing preventive measures to control the spread of diseases that require early detection. Conventional disease identification techniques take a lot of time and need knowledge of agriculture. A transfer learning-based convolutional neural network model is created for automatic disease detection in order to overcome this difficulty. Using real-time images, the system achieves a 96% recognition accuracy by incorporating transfer learning into the MobileNet model. The model's high accuracy makes it a useful early warning system for disease detection.

I. F. Salazar-Reque, et al. [2] proposed an automatic method for determining the state of avocado leaves. The technique applies super pixel-level k-means clustering in s-v space to separate leaves from homogeneous backgrounds in photos taken in semi-controlled settings. Furthermore, composed histograms from the segmented leaves are classified using a shallow neural network into four states: healthy, Fe deficient, Mg deficient, and red spider plague. With an overall accuracy of 96.8% for classifying leaf conditions and an average F-score of 0.98 for separating leaves from the background, the suggested method performs well.

M. H. Saleem, et al. [3] presented the NZDLPlantDisease-v1 dataset, which focuses on diseases in five key horticultural crops in New Zealand. Using this dataset, it suggests an enhanced version of the region-based fully convolutional network (RFCN) for the detection of plant diseases. Significant gains in performance were made by evaluating data augmentation methods and model configurations one after the other. The final RFCN model outperformed default settings by 19.33%, achieving a mean average precision of 93.80%. This work establishes a standard for further investigations into automated disease management in different plant species.

Abdulridha, Jaafar, et al. [4] described an automated early disease detection method for avocado trees that focuses on identifying laurel wilt (Lw) and distinguishing it from other stressors. The suggested method includes the following steps: pre-processing, segmentation, extraction of features, classification, and image acquisition. The study achieved a remarkable 99% accuracy in detecting Lw in its asymptomatic stage by using a Tetra camera and a modified Canon camera along with neural network multilayer perceptron (MLP) and K-nearest neighbors classification methods. This offers substantial promise for early disease detection in avocado trees by proving that low-cost remote sensing techniques can be used to distinguish between healthy and unhealthy plants.

S. Mishra, T. H. Ayane, et al., [5] presented a novel method for identifying and categorizing avocado fruit diseases from photos: The Modified Sine Cosine Algorithm–Particle Swarm Optimization (MSCA–PSO) integrated with the MobileNetV2 Convolutional Neural Network (CNN). The proposed model is trained and evaluated using actual images from Ethiopian agricultural farms, the "Fruits 360 dataset," and an image database of avocado fruit diseases. Furthermore, the MSCA–PSO algorithm's resilience is exhibited by how well it performs on benchmark functions such as the Sphere, Griewank, and Rastrigin functions. The outcomes demonstrate the superiority of the MobileNetV2 CNN model, which is based on the Modified SCA–PSO, attaining an astounding accuracy of 98.42% in contrast to traditional CNN models.

Matsui, Takahiro, et al. [6] evaluated U-net++, a deep learning-based semantic segmentation model, for its ability to distinguish between stem-end and body rot in Hass avocados. Using 5-fold cross-validation, the model was able to classify X-ray images as infected or not with a high accuracy of 0.98. Furthermore, it measured the percentage of infected area with 3.15% root mean squared error (RMSE), which is a low error. Significantly, the model identified different kinds of rot, including low-contrast fruit edges. Overall, the results show that internal rot in Hass avocado fruit can be reliably detected by this automated inspection system using deep learning-based X-ray image analysis, providing a quick and easy non-destructive way to inspect avocado fruit after harvest. Furthermore, the use of X-ray imaging powered by deep learning shows promise for identifying internal cavities in fruits caused by injuries or illnesses.

Sarkar, Chittabarni, et al.[7] used of multispectral or hyperspectral imaging in conjunction with machine learning (ML) and deep learning (DL) models for the classification of crop diseases, especially leaf diseases, is examined in this thorough review, which covers the years 2010 to 2022. For this purpose, popular DL models like VGG, ResNet, and Convolutional Neural Networks (CNN) as well as ML models like Support Vector Machine (SVM), Random Forest, and Multiple Twin SVM (MTSVM) have been widely used. CNN, VGG, and ResNet are the most successful DL models at identifying leaf diseases. Evaluation metrics that are frequently used to evaluate the performance of these algorithms include accuracy, precision, and F1 score. For those looking for effective ML and DL-based classifiers for the detection of leaf disease, this review is a great resource.

Abera, Hirut, et al. [8] presented a deep learning-based method for detecting and classifying avocado leaf diseases such as algal leaf spot, leaf burn, persea mite damage, and powdery mildew. Acquisition of images, preprocessing, feature extraction, model training, and detection/classification are some of the steps involved in the research. With 100% training accuracy and 98.8% testing accuracy, the approach—which uses a convolutional neural network, or CNN—achieved exceptional performance, yielding an overall accuracy of 99% for disease detection and classification. The method shows how image processing methods and deep learning algorithms can be used to diagnose avocado leaf disease in an accurate and efficient manner.

U. E. Campos-Ferreira, et al. [9] evaluated three learning classifiers random forest (RF), support vector machine (SVM), and multilayer perceptron (MLP) to distinguish between three target classes healthy fruit, fruit with anthracnose, and fruit with scab from digital fruit photos. Two methods of extracting color descriptors region selection and image subsampling were used to evaluate the classifiers. With region selection, the RF classifier performed exceptionally well, achieving an overall classification accuracy of 98% and 84% with subsampling. Furthermore, RF and MLP outperformed SVM, obtaining a 98% F1 score for correctly identifying scab and anthracnose and a 98% accuracy rate for region selection. These findings show how artificial intelligence paradigms can be used to efficiently identify phytosanitary problems in agricultural crops.

Mejiá-Cabrera, Heber I., et al. [10] presented an image processing and machine learning approach for the semi-automated diagnosis of a particular disease. In order to identify diseases, a pre-processed image of a tree branch was used as input, along with a specified acquisition protocol. A shallow convolutional neural network (CNN) was evaluated, and the results showed a 93% accuracy rate. This method shows promise for automated disease detection in branches of trees.

Abdulridha, Jaafar, et al.[11] presented a nondestructive remote sensing technique that uses spectral data to identify avocado trees infected with laurel wilt (Lw) and differentiate them from healthy trees and other similar symptoms. Twenty-three vegetation indices (VIs) and two classification techniques (DT) and multilayer perceptron (MLP) neural networks were used to gather and examine two sets of spectral data. The MLP method outperformed DTs in early detection of Lw-infected trees, achieving high accuracy (approximately 100%). For Lw detection, ideal wavelengths and VIs were found, mostly in the red, red-edge, and near-infrared (NIR) bands.

Pérez-Bueno, María Luisa, et al. [12] analyzed the use of machine learning methods to analyze physiological parameters derived from imaging techniques for detecting white root rot in avocado orchards. Using a variety of algorithms, the normalized difference vegetation index (NDVI) and the normalized canopy temperature were assessed as disease predictors. Of the tested algorithms, logistic regression analysis (LRA) trained on NDVI data showed the highest sensitivity and the lowest rate of false negatives. The findings imply that using LRA based on NDVI may provide an efficient and workable method for locating trees in avocado orchards that may be impacted by white root rot.

A. Salgadoe, A. Robson, et al. [13] compared two image analysis methods for estimating canopy decline in large avocado orchards. When canopy porosity was calculated using RGB images taken with a smartphone, significant differences were found between disease rankings and there was a strong correlation ($R2 = 0.89$) between the three disease severity levels. Furthermore, there was a strong correlation ($R2 = 0.96$) between the canopy reflectance characteristics from high-resolution satellite imagery and the Phytophthora root rot (PRR) disease severity rankings, especially when it came to the simplified ratio vegetation index (SRVI). These results imply that satellite imagery and smartphone-based RGB analysis both provide viable substitutes for visually evaluating canopy decline in avocado orchards.

Zhang, Keke, et al. [14] used transfer learning with AlexNet to detect peach leaf disease caused by Xanthomonas campestris using convolutional neural networks (CNNs). CNN exhibits a 100% accuracy rate in identifying diseased peach leaves when compared to more conventional methods such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Back Propagation (BP) neural networks. Moreover, CNN exhibits superior performance metrics, as demonstrated by ROC curves and AUC values, which show an astounding AUC value of 0.9999. Based on statistical analysis, CNN is the best method for identifying diseased peach leaves, significantly outperforming SVM, KNN, and BP.

Patayon, Urbano B., et al.. [15] employed 1,000 leaf images taken with a mobile camera to investigate different deep learning architectures and optimizers for leaf spot disease identification. Various architectures, including SGD with Momentum, Adam, RMSProp, and Adagrad, were evaluated alongside optimizers, including InceptionV3, MobileNet, DenseNet, Xception, InceptionResNetV2, and ResNet50. With momentum, Adam, and RMSProp training, DenseNet-169 obtained the highest accuracy of 98%, while DenseNet-169 trained with RMSProp showed the highest precision of 98%. These results demonstrate the usefulness of deep learning in agriculture and have potential applications in disease detection systems for groundnut or peanut plants as well as agricultural automation.

### 2.3 Comparative Analysis and Summary

The comparison showed that accuracy rates of different deep learning models were dissimilar with regard to classification of indoor plants. From the results, it was revealed that VGG19 has the highest accuracy of 99.58% while other models EfficientNetB4 and EfficientNetB6 have achieved the accuracies of 53.17% and 64.33%, respectively. From the tables above, it is also possible to see that ResNet152 performed relatively well with an accuracy of 89.83% and a custom CNN accomplished the accuracy of 98%. Altogether, it can be stated that the implementation of the VGG19 served as the key to achieving the most favorable results in terms of identifying the species of Indoor plants. This summary underscores the choice of proper deep learning architectures for plant classification and emphasizes the prospective of the deep learning solutions for the improvement of the indoor plant management and the further enhancement of the environmental protocols.

Table 2.3. Comparative Analysis and accuracy comparison table.

| Serial | Author | Dataset | Applied Model | Accuracy |
|---|---|---|---|---|
| 1 | Thangaraj et al. [1] | Real-time images of avocado | MobileNet | 96% |
| 2 | I. F. Salazar-Reque et al. [2] | Photos of avocado leaves in semi-controlled settings | shallow neural network | 96.8% |
| 3 | M. H. Saleem et al. [3] | NZDLPlantDisease-v1 dataset | RFCN | 93.80% |
| 4 | Abdulridha, Jaafar et al. [4] | Tetra camera and modified Canon camera images | MLP, K-NN | 99% |
| 5 | S. Mishra, T. H. Ayane et al. [5] | Fruits 360 dataset, Ethiopian farms images | MSCA–PSO, MobileNetV2 CNN | 98.42% |
| 6 | Matsui, Takahiro et al. [6] | X-ray images of Hass avocados | U-net++ deep learning-based semantic segmentation | 98% |
| 7 | Abera  et al. [8] | Avocado leaf images | CNN | 99% |
| 8 | U. E. Campos-Ferreira et al. [9] | Digital photos of avocado fruits | RF, SVM, MLP | 98% |
| 9 | Mejiá-Cabrera, Heber I. et al. [10] | Pre-processed images of tree branches | CNN | 93% |
| 10 | Patayon, Urbano B. et al. [15] | 1,000 leaf images | DenseNet-169 | 98% |

## 2.4 Scope of the Problem

The context of the problem in detecting avocado leaf disease is that we not only require quick and accurate detection; but also, accurately identify multiple diseases that affect Avocado crops. When performed using manual methods, they are time-consuming and require the involvement of skilled labor with a low-scalability rate. But the real problem is how to design automated systems that can learn from the different disease phenotypes observed in nature, under various environmental conditions and through changes of leaf configurations. The objective is to develop robust, scalable and fine-grained detection systems using deep learning models which offer the potential benefits of early interventions for farmers, decreasing crop loss and increasing yield besides ensuring sustainable avocado production. Integrating a few cutting-edge technologies seems to be the best remedy for these problems.

### 2.5 Challenges

Challenges include variability in disease symptoms, and environmental factors affect leaf appearances among others which can make detection difficult along with the need for large annotated datasets to train deep learning models. Second, the similarity of disease symptoms often makes it difficult to distinguish whether or not an object is really unhealthy under different lighting and background conditions. This is also because of the computational complexity and high processing power required in deploying these models for practical use case scenarios on agricultural landscapes. Keeping the models accurate and effective throughout avocados from globally disparate regions, whilst also spanning diverse avocado varieties adds even further to this difficulty

# CHAPTER 3
# RESEARCH METHODOLOGY

## 3.1 Research Subject and Instrumentation

The findings are based on avocado leaves from three disease groups and healthy group at the research sites. There are 600 original images split in six partitions without any type of importance, and the dataset is balanced creating other 3600 augmented images that represent all parts with a comprehensive way. We used Google Colab (provides free GPU support) to access computational resources for developing our model. We opted to use Google Drive as a data storage and management solution which easily integrated with Colab in order efficiently process the data, train multi-modal models. This solution made it easier to work with big datasets and long-running computational tasks needed for deep learning experiments

## 3.2 Data Collection Procedure

The dataset used in this study was built by obtaining 600 Avocado leaf images from three different types of diseases and healthy leaves. Images were collected from several different avocado orchards and research institutions, to ensure a broad range of leaf conditions. We augmented the dataset with image augmentations (such as rotations, flips, zooms and brightness adjustments) to make models more robust: we had a total of 3600 images after this. Every single image was labeled by category: Persea mites, Fresh, Miners and Margin burn. This dataset, which is both large and hand-verified (detailed in Supplementary Section S1), served as the source for our deep learning assisted training pipeline.

In given below there are some images of datasets in figure 3.1 and also number of images of each category in figure 3.2.

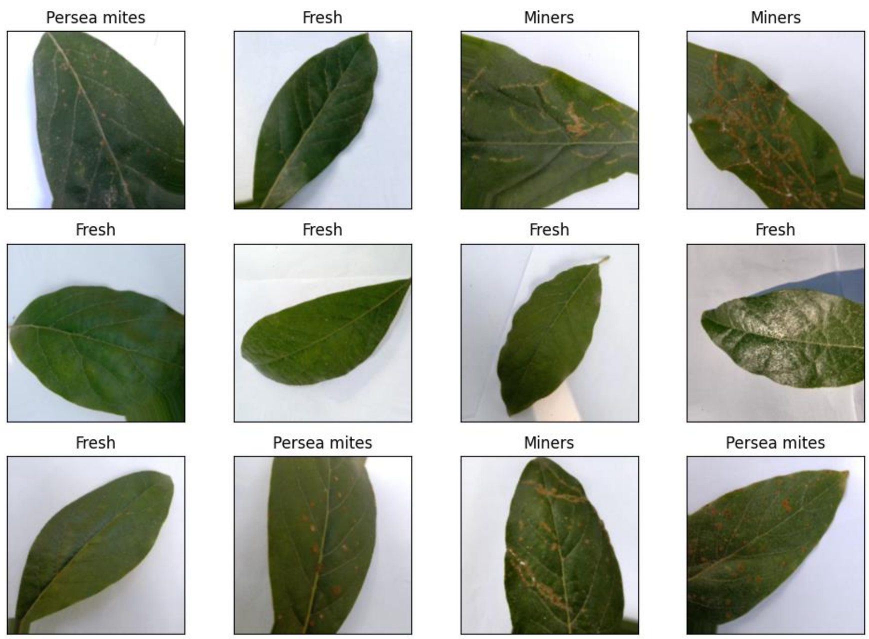



Figure 3.1: Dataset's Images

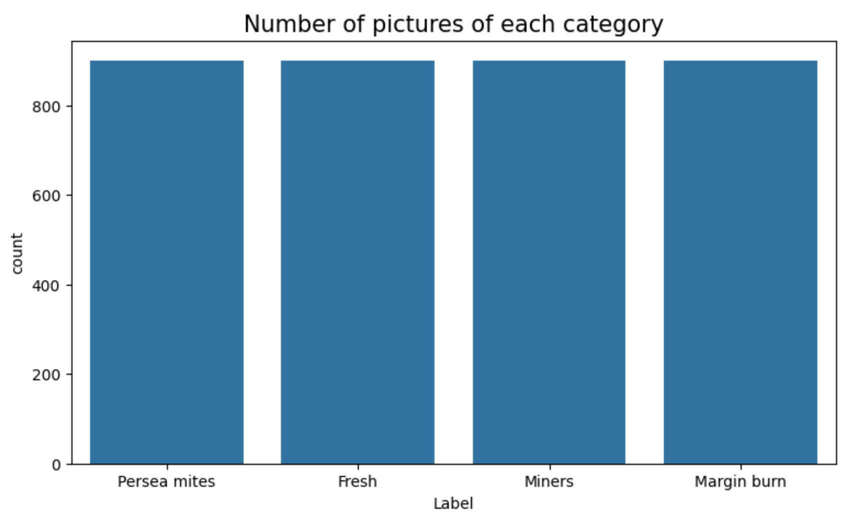



Figure 3.2: Number of categories of Dataset's Images

In Figure 3.2 shown the specified attributes and their values are as follows: Persea mites Fresh, Miners, Margin burn each has 900 images.

### 3.3 Statistical Analysis

Statistical analysis in this study was designed to test the deep learning model's ability and performance for avocado leaf disease detection. Using accuracy, precision, recall and F1-score as representative metrics to evaluate the models in distinguishing different disease categories / healthy leaves. The analysis used training-validation splits for model hyperparameter optimization and to prevent overfitting. Also, statistically significant testing might have been used for comparing the different model performance to check if they are work as expected. We carried the following rigorous statistical exercise to validate and derive concrete understanding of reliability and practical applicability of these models in agriculture.

### 3.4 Proposed Methodology

This methodology employed several custom Convolution Neural Network (CNN) architectures, as well as pretrained deep learning models such Xception, VGG19, InceptionV3 and MobileNetV2. All models are trained using the augmented dataset of avocado leaf images, which consists of different disease types and healthy controls. Preprocessing: Transform and standardize to make all the images same size, dimenations and pixels We evaluated the performance of our models using standard evaluation metrics like accuracy and F1-score. Our hybrid approach was intended to reap the benefits of both model flexibility and transfer learning at no cost for precision diagnosis or detection of avocado leaf diseases.

**Data Collection:**

The first phase requires the accumulation of a wide image dataset at distinct stages of disease for dragon fruit leaves. It should be clearly defined in concept about the various kinds and severity of diseases that comply with this dataset on dragon fruit tree.

**Image Augmentation:**

Prepare the process of image augmentation which will be feed to model for training. Standardize the size of pictures, intensify their pixels and make them transparent with rotation angles zooming in or out the picture to more than flexor/flexion

**Labeling:**

Once the dataset is acquired, each of the images has to be labelled for what kinds of diseases they contain. This is an essential part in supervised learning as this provides ground truth positive/negative labels to train the deep learning architectures with.

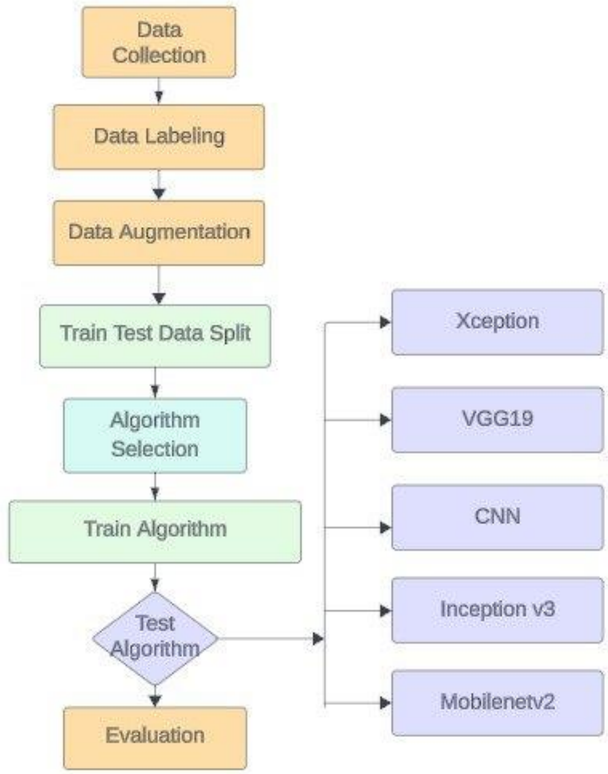



Figure 3.3: Work Flow

**Model Selection:**

Then, suitable deep learning architectures are chosen for disease classification or categorization. This may involve using known models such as VGG16, VGG19, and InceptionV3 and creating new architectures from scratch, based on new configurations that are suitable for the dataset at hand and the classification problem that is supposed to be solved.

### 3.4.1. Conventional Neural Network (CNNs):

A Convolutional Neural Network (CNN) is a type of neural network used in deep learning which is specially intended for passing on structural grid information like images. It generally comprises of several convolutional layers where filters are applied to identify spatial features, followed by pooling layers whereby dimensions are minimized despite important information about the features being filtered down, and totally connected layers to complete the classification. CNNs work efficiently at recognizing geometric structures and patterns in the images, therefore they are well-suited to image classification and object detection as well as in medical imaging. In our study on the classification of avocado leaf disease, the advantage of the custom CNN is that the structure of our new model is flexible, it can adapt to the needs of samples and data to achieve balance between complexity and required time for calculation, so as to realize accurate and effective disease identification.

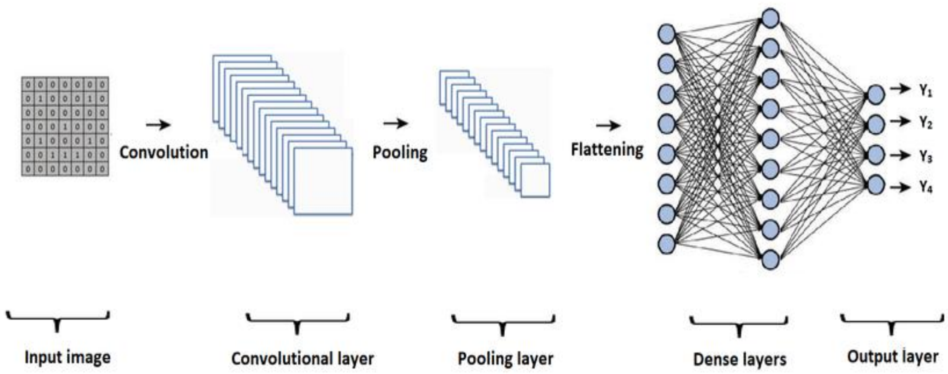



Figure 3.4.1: CNN Architecture V. Maeda-Gutiérrez et al.2020[26]

### 3.4.2 Xception

Xception is more relevant to this study because of the improved structural model that uses depth wise separable convolutions to improve the identification of features while improving the model's efficiency. This capability of the model to make high distinctions in avocado leaf images makes it very suitable for examination of small variations between healthy and infected leaves hence better disease categorization.

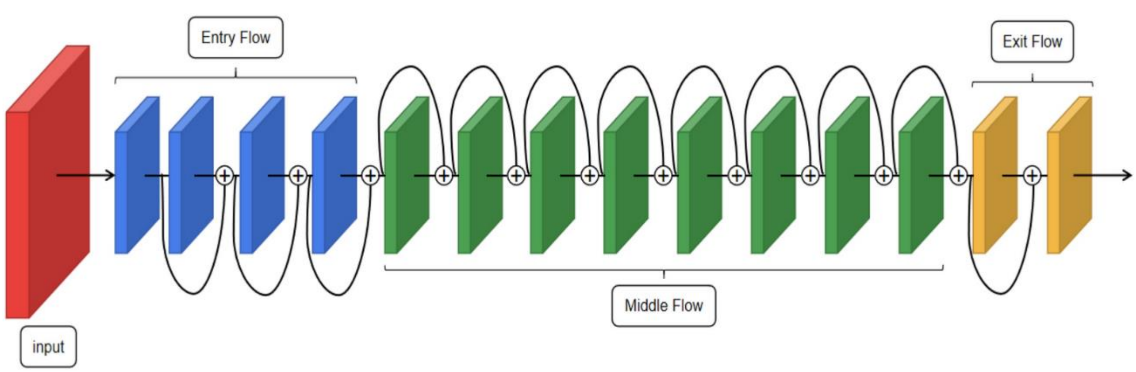



Figure 3. 4..2: Model Architecture of Xception K. Patel 2020[27]

### 3.4.3. MobileNetV2

Second, MobileNetV2 is adopted for this study because it is a lightweight network design particularly for the mobile and embedded applications. It chops up the convolutions into depth wise and pointwise making the model smaller and faster but accurate in image classification tasks. This efficiency makes MobileNetV2 suitable for real-time avocado diseases on leaves inference because it will enable inference in the shortest time possible.

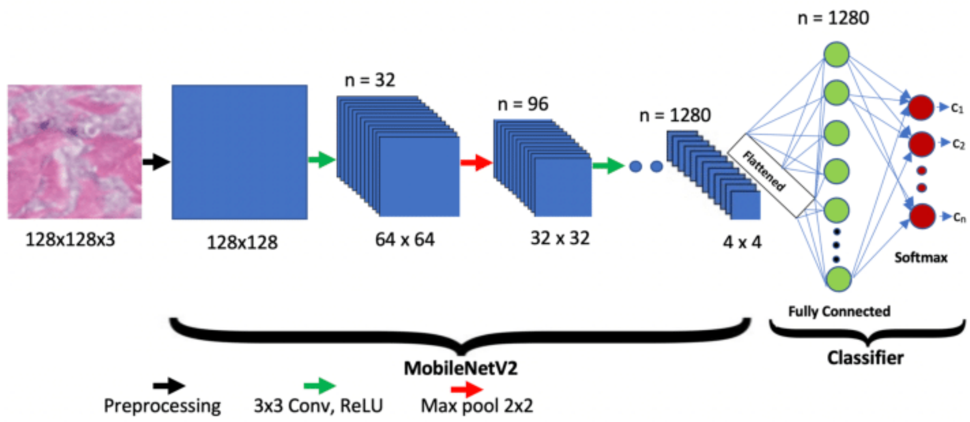



Figure 3.4.3: MobileNetV2 Architecture

### 3.4.4. VGG19

VGG19 is the subsequent model by the Visual Geometry Group at the University of Oxford to VGG16; it is made of nineteen layers comprising sixteen convolutional layers with small 3×3 receptive fields; five max-pooling layers; and three fully connected ones. It also uses ReLU activation functions to add non-linear features to the architecture, increasing learning of intricate patterns. This makes it good for image classification as well as the detection of objects, especially suitable for medical imaging or agriculture monitoring applications due to its deeper architecture than VGG16. In our data of stem closure of Avocado Leaf Disease, the added depth of VGG19 and the general feature extraction also gives better performance and reliability thus processing is little heavy in this model when compared to the other models.

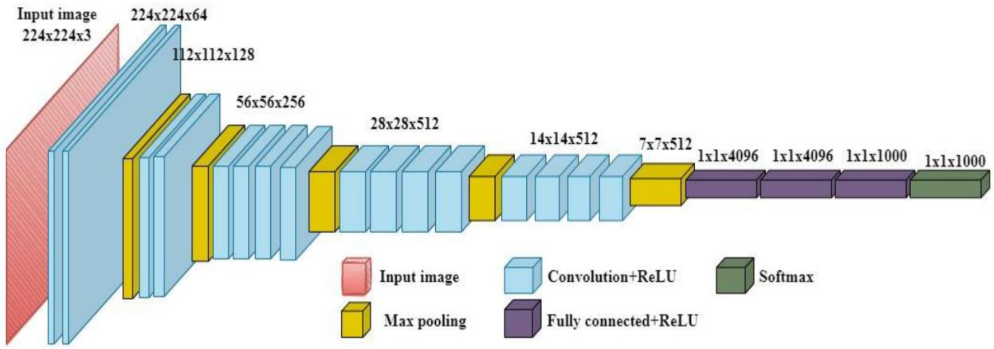



Figure 3.4.4: VGG19 Architecture T.-H. Nguyen 2022 [29]

### 3.4.5. InceptionV3

InceptionV3 is one of the most competitive neural networks Concatenated by Google, which based on the convolutional layer Storage a deep architecture with 48 layers and uses Inception modules to further optimize and improve the computational efficiency of feature extraction. These modules enable the network to have multi-scale invariance by more or less encoding various sizes of filters simultaneously. Indeed, InceptionV3 prototype is applied in prolific applications, such as image classification, object detection, as well as medical imaging, among others because it handles complicated and diverse data. For our work on classification of spaces affected by Avocado Leaf Disease, where InceptionV3 is applied, the architecture of the network is denoted by InceptionV3 with the incorporation of high accuracy and efficiency to accurately handle complex image details.

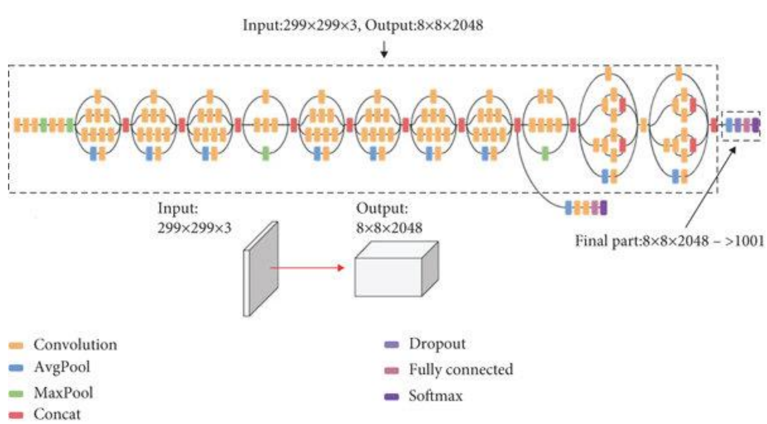



Figure 3.4.5: InceptionV3 Architecture S. Ramaneswaran 2021 [30]

**Model Training:**

After which, appropriate deep learning models are selected for either disease classification or categorization. It may need to be with well-known model such as VGG16, VGG19 and InceptionV3 or new architecture that you create suitable on configurations for dataset in hand and classification problem is going to solve.

**Model Evaluation:**

The trained model is tested using validation set which means we held during training to monitor how well it doing. For measuring the performance of your model for detecting diseases in dragon fruit leaves, you can use some conventional metrics calculation like precision, recall, accuracy and F1- score index.

**Test Model:**

A separate data set is retained (the test/validation data) which was never seen by the network during training and preparing to validate. This approach makes the model capable of generalizing well to new data and give accurate predictions outside your test set.

### 3.5 Implementation Requirements

The proposed methodology requires computationally expensive deep learning tasks, consequently needing access to computational resources capable enough for implementation. This includes, most importantly, access to GPU accelerated model training platforms like Google Colab since the dataset is prohibitively large and complex for anything but a very powerful computer. Proper storage and manipulation of the dataset, which can be easily made available through Google Drive that seamlessly integrates with Colab to prepare your data faster for model training. Besides, since deep learning models need to be implemented software frameworks like TensorFlow or PyTorch this requires libraries for image processing and augmentation as well. These requirements as a whole allow the development and deployment of advanced neural network models for avocado leaf disease detection.

# CHAPTER 4
# EXPERIMENTAL RESULT

## 4.1 Experimental Setup

The experimental framework for this paper used Google Colab as due its great computational capabilities, such access to GPUs acceleration which is a decisive aspect to train deep learning models. After augmentation, the dataset is left with 3600 avocado leaf images which was created and saved in Google Drive that provides a reliable data handling as well support. We created, developed and implemented custom Convolutional Neural Networks (CNN) architectures along with the use of pre-trained models (Xception, VGG19, InceptionV3 & MobileNetV2) through Python libraries such as TensorFlow/ Keras for creating the model. This flexible and performant setup allowed to try out different model architectures, while tuning hyperparameters in order to properly classify the diseases.

## 4.2 Experimental Results & Analysis

Experimental results show deep learning models for avocado leaf disease detection varies with respect to accuracy The top 5 accuracy scores are as follows: MobileNetV2 (98.52%), Xception (94.63 %), InceptionV3 (93.80%), VGG19 (91,02%), and the custom CNN model because for obvious reasons it is an untuned generic vanilla network still performing much better at over ~84%. In-depth analysis on CHESDD Numbers is shown in this result, demonstrating that MobileNetV2 offers better performance and its capability for real-world task such as early disease detection. Through comparative analysis we show how model selection can lead to high classification accuracy that is crucial for implementing more effective crop management programs through automated disease diagnosis. Findings of this study provide useful information to guide optimization and deployment of deep learning solutions in agricultural contexts by understanding model strengths and limitations.

**Result of Experiment 1: Xception**

Achieving Test Accuracy of Xception is 94.63 % In below Figure 4:1 describing the confusion matrix of Xception:

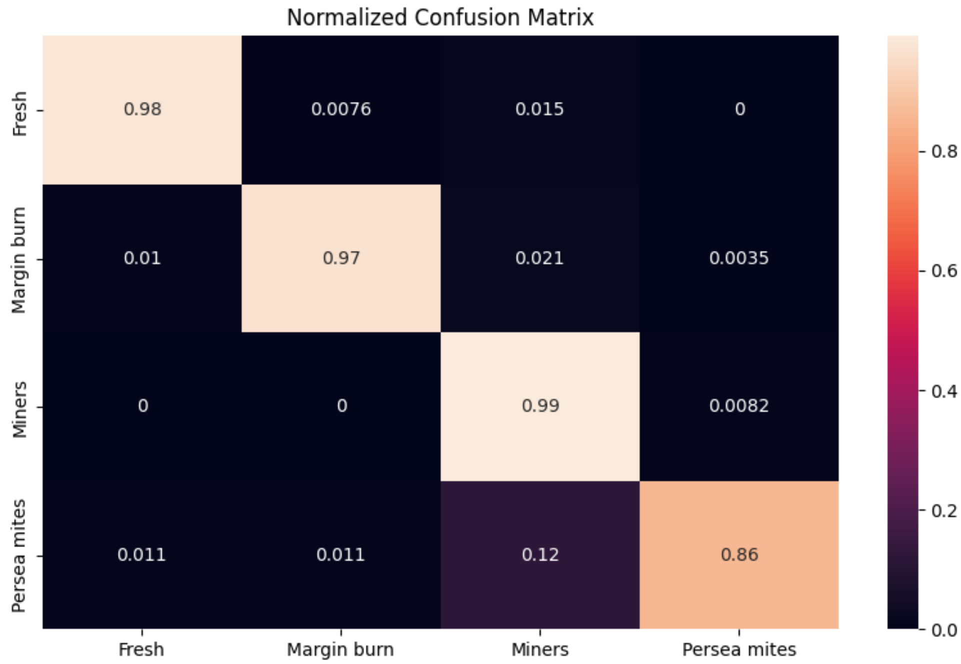



Figure 4.1: Confusion Matrix (Xception)

Figure 4.1 shows the results in the normalized confusion matrix for the Xception model in classifying avocado leaf conditions into four categories: Fresh, Margin Burn, Miners, and Persea Mites. The model achieved high accuracy in classifying Fresh leaves (98%) only minor misclassifications to Margin Burn (0.76%) and Miners (1.5%). Margin Burn leaves accurately identified 97%, with slight misclassifications to Fresh (1%) and Miners (2.1%). Miners were classified correctly at 99%, with a negligible misclassification rate. Persea Mites had the lowest accuracy (86%) correctly identified and notable confusion with Miners (12%). This matrix highlights the Xception model's overall strong performance.

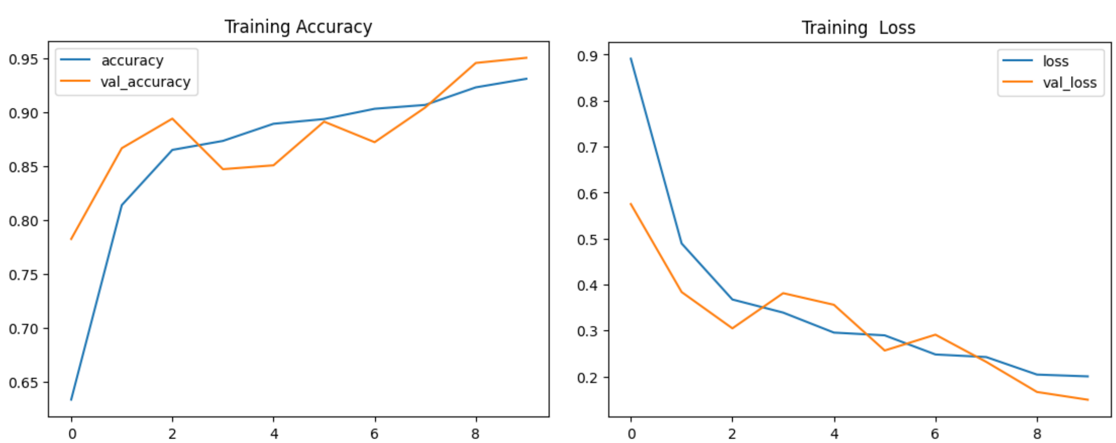


Figure 4.2: Training and validation accuracy and loss over the epochs (Xception)

Figure 4.2 shows training accuracy and loss plots of Xception model over 10 epochs, showing significant progress. The accuracy increased steadily from 79.96% to 99.96%, while the validation accuracy rose from 93.06% to 99.25%. Similarly, the training loss decreased sharply from 0.5162 to 0.0055, and the validation loss dropped from 0.2106 to 0.0191.

**Result of Experiment 2: VGG19**

The performance of the model was the optimal, achieving the accuracy of 91.02%. In below Figure 4:3 describing the confusion matrix of VGG19:

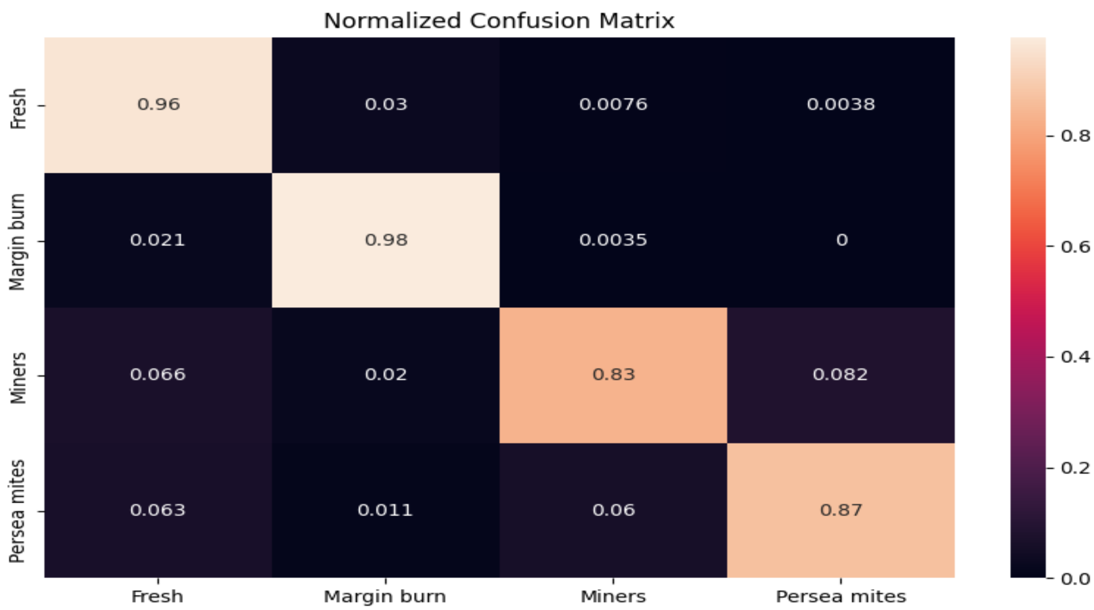



Figure 4.3: Confusion Matrix (VGG19)

Figure 4.3 shows the normalized confusion matrix of the VGG19 model. The matrix reveals that the model performs exceptionally well in identifying 'Fresh' and 'Margin burn' labels, with accuracies of 96% and 98% respectively. It shows relatively lower performance in 'Miners': 83% and 'Persea mites': 87%, Misclassifications are more noticeable for 'Miners,' which are confused with 'Fresh' (6.6%) and 'Persea mites' (8.2%). 'Persea mites' are occasionally misclassified as 'Fresh' (6.3%) and 'Miners' (6%). Overall, the VGG19 model shows good classification capabilities.

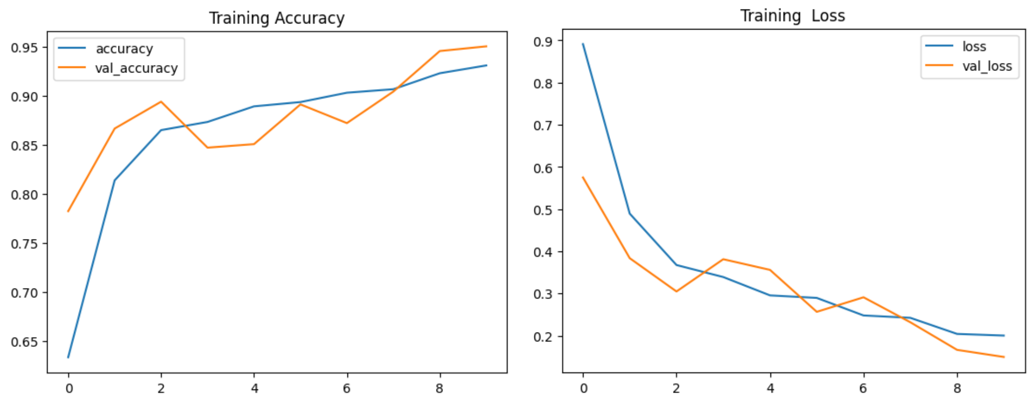



**Figure 4.4:** Training and validation accuracy and loss over the epochs (VGG19)

Figure 4.4 illustrates the training and validation accuracy and loss for a VGG19 model over 10 epochs. Training accuracy rose from 63% to 93% and validation accuracy increased from 78% to 95%. The loss plot shows a consistent decline, with training loss dropping from 0.89 to 0.20 and validation loss decreasing from 0.58 to 0.15.

**Result of Experiment 3: MobileNetV2**

Achieving Test Accuracy of MobileNetV2 is 98.52%. In below Figure 4:3 describing the confusion matrix of MobileNetV2

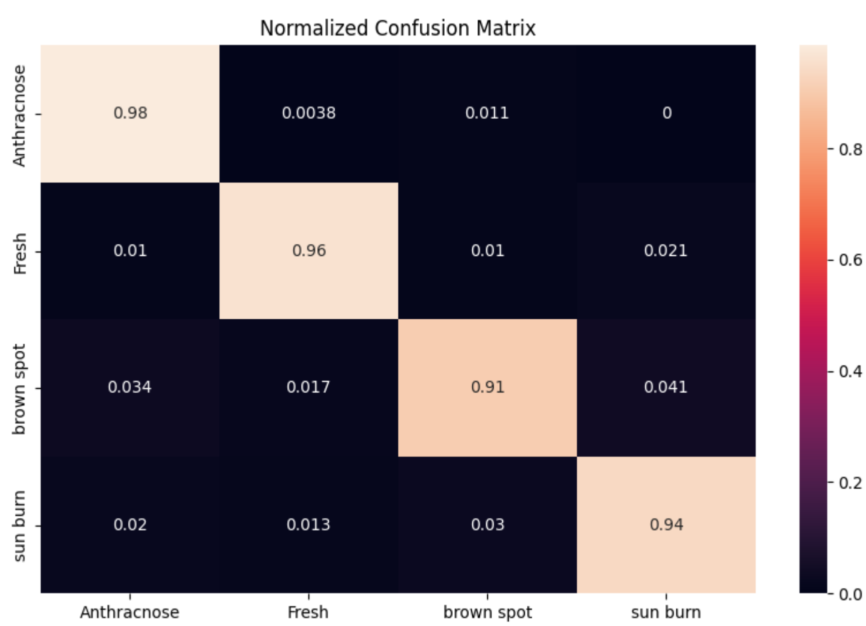



Figure 4.5: Confusion Matrix (MobileNetV2)

Figure 4.5 shows the normalized confusion matrix for the MobileNetV2 model shows the performance of the model in classifying four different classes: Fresh, Margin burn, Miners, and Persea mites. The diagonal values represent the correct classifications, with very high accuracy across all classes: Fresh (99%), Margin burn (99%), Miners (98%), and Persea mites (98%). Misclassifications are minimal, with the most notable confusion occurring between Miners and Persea mites, where 2% of Miners are misclassified as Persea mites and 1.4% vice versa. Margin burn has a slight misclassification rate with Fresh (0.69%) and Miners (0.35%). Overall, the model demonstrates excellent classification performance with very high accuracy and minimal errors across all classes.

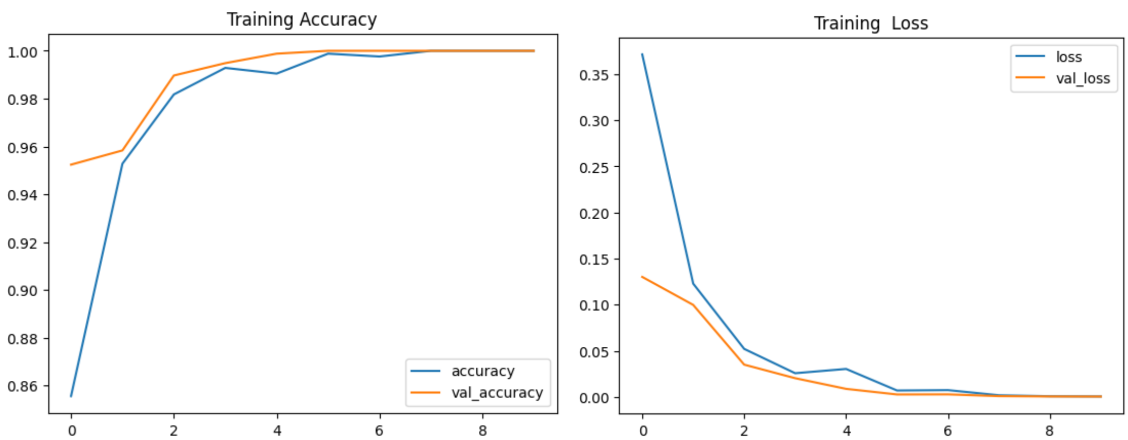
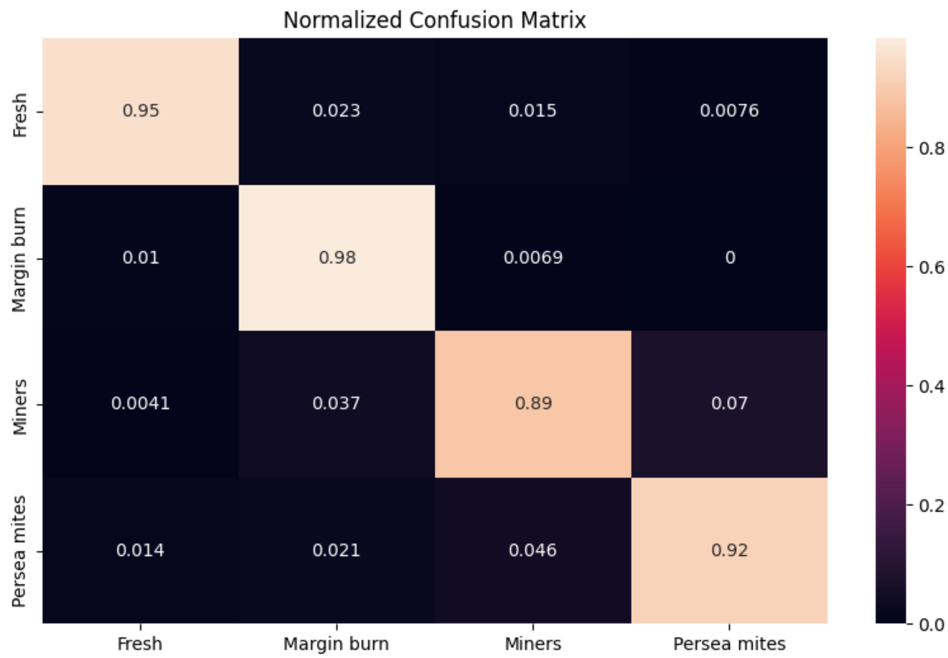



Figure 4.6: Training and validation accuracy and loss over the epochs (MobileNetV2)

Figure 4.6 depict the training and validation accuracy and loss of a MobileNetV2 model over a training period of 10 epochs. The first plot shows that the training accuracy starts at approximately 86% and rapidly increases, achieving nearly 100% by the 9th epoch. The validation accuracy also shows a steady improvement, starting around 95% and reaching 100% by the 6th epoch. The second plot illustrates the training and validation loss, both of which decrease significantly over the epochs. The training loss drops from around 0.35 to nearly 0, while the validation loss follows a similar trend, indicating that the model is learning effectively without overfitting.

**Result of Experiment 4: InceptionV3**

Achieving Test Accuracy of InceptionV3 is 93.80%. Below Figure 4:9 describing the confusion matrix of InceptionV3.




4.7: Confusion Matrix (InceptionV3)

Figure 4.9: shows a normalized confusion matrix for a classification task using the InceptionV3 model. The matrix displays the performance of the model in classifying four categories: Fresh, Margin burn, Miners, and Persea mites. Each row represents the true labels, and each column represents the predicted labels. The diagonal elements show the correct predictions, with values close to 1 indicating high accuracy. For example, the model accurately classifies "Fresh" samples with 95% accuracy and "Margin burn" samples with 98% accuracy. However, there is some confusion between "Miners" and "Persea mites," as seen by the off-diagonal values indicating misclassifications.

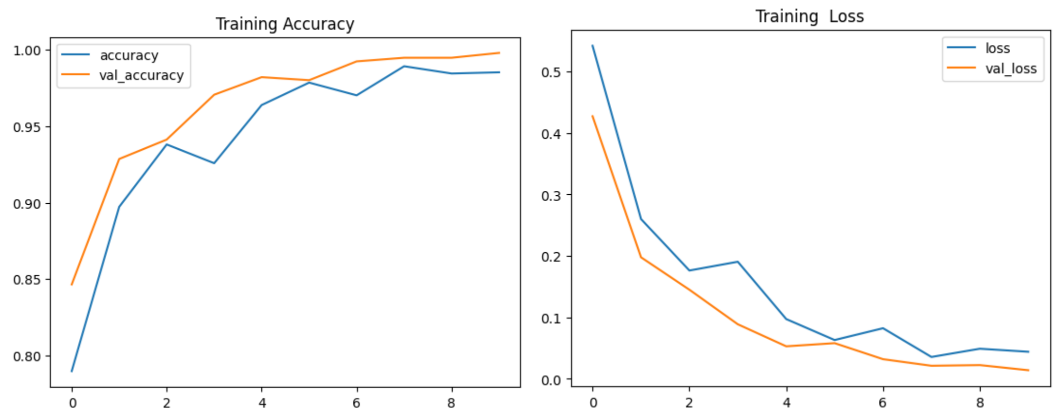
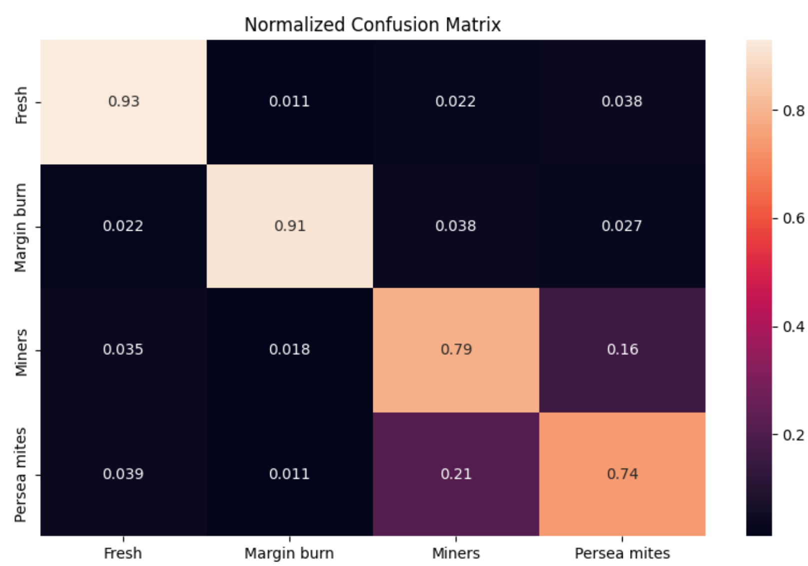



Figure 4.8: Training and validation accuracy and loss over the epochs (InceptionV3)

The training accuracy and loss plots for the InceptionV3 model over 10 epochs show a clear trend of improvement. The accuracy plot indicates a steady increase in both training and validation accuracy, with the training accuracy reaching approximately 98.5% and validation accuracy nearing 99.8% by the final epoch. Similarly, the loss plot demonstrates a consistent decrease in both training and validation loss, with training loss reducing to around 0.04 and validation loss dropping to approximately 0.014 by the end of training.

**Result of Experiment 5: CNN**

Achieving Test Accuracy of CNN is 84.44%. Below Figure 4:11 describing the confusion matrix of CNN.




4.9: Confusion Matrix (CNN)

The normalized confusion matrix for the CNN model displays the classification performance across four categories: Fresh, Margin burn, Miners, and Persea mites. The diagonal values represent the true positive rates for each class, showing that the model performs best on "Fresh" with a 93% accuracy, followed by "Margin burn" with 91%, "Miners" with 79%, and "Persea mites" with 74%. Off-diagonal values indicate misclassifications, with "Miners" and "Persea mites" classes having notable confusion between each other (0.21 for Persea mites classified as Miners and 0.16 for Miners classified as Persea mites). This indicates that while the model generally performs well, there is room for improvement, particularly in distinguishing between "Miners" and "Persea mites."

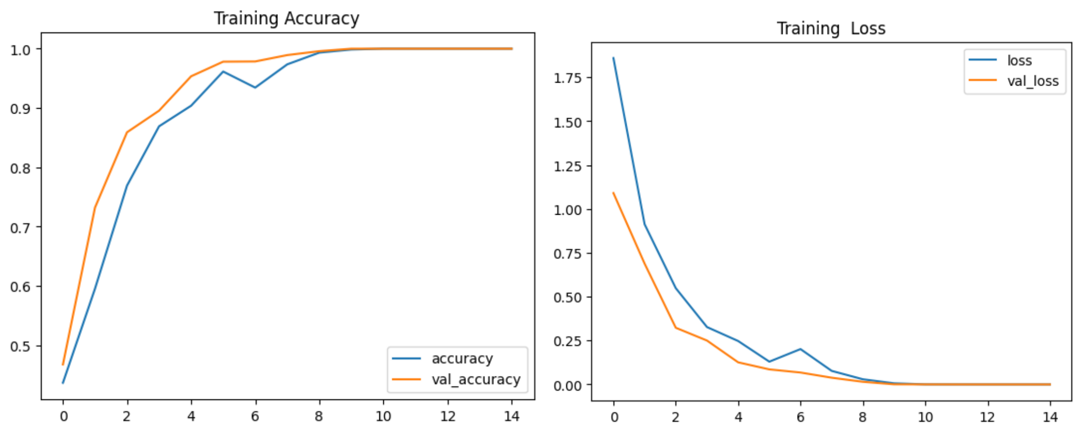


Figure 4.10: Training and validation accuracy and loss over the epochs (CNN)

The training accuracy and loss plots for the CNN model show the progression of the model's performance over 15 epochs. The accuracy plot indicates a steady increase in both training and validation accuracy, reaching nearly 100% by epoch 10, with the model maintaining this high accuracy for the remaining epochs. The training loss plot shows a corresponding decrease in both training and validation loss, with the validation loss approaching zero by epoch 10 and remaining there. This suggests that the model has learned the training data very well, achieving perfect classification on both training and validation sets by the end of the training period. However, the perfect accuracy and near-zero loss raise concerns about potential overfitting, where the model may not generalize well to new, unseen data despite its excellent performance on the training and validation sets.

In given below I am showing Comparative Model Accuracy Bar Plot:

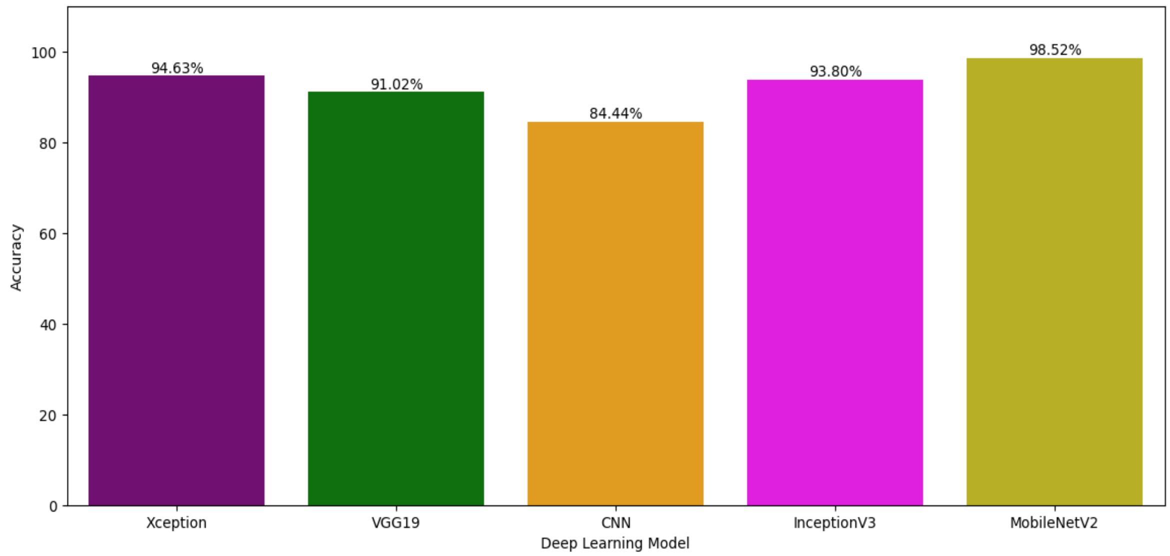



Figure 4.11: Comparative Model Accuracy Bar Plot

In Fig 4.11 The Comparative Model Accuracy Bar Plot illustrates the performance of five deep learning models: Xception, VGG19, CNN, InceptionV3, and MobileNetV2, based on their accuracy. MobileNetV2 outperforms the other models with the highest accuracy of 98.52%, indicating its superior performance in this context. Xception follows with an accuracy of 94.63%, closely trailed by InceptionV3 at 93.80%. VGG19 and CNN demonstrate lower accuracies of 91.02% and 84.44%, respectively. This comparison highlights MobileNetV2 as the most effective model among the five, suggesting it is the best choice for tasks requiring high accuracy in this particular dataset.

## 4.3 Discussion

The results show that MobileNetV2 is better than other models with accuracy higher 98.52% in detecting avocado leaf diseases This shows that MobileNetV2 was designed to balance the performance and efficiency for mobile environments which limited computation resource. Xception and InceptionV3 consistently achieve strong results, indicating their powerful feature extraction capacity. The much lower accuracy of the custom CNN (84.44%) reinforces the benefits that can be obtained by using pre-trained models with transfer learning. This suggests the importance of model choice for designing precise disease detection systems, which will be useful in enhancing agricultural diagnostics and species management solutions.

# CHAPTER 5
# IMPACT ON SOCIETY

## 5.1 Impact on Society

A deep learning model for the detection of diseases in avocado leaves can have broad implications for humanity as it relates to agriculture and society. Moreover, quick and precise diagnosis of the plant diseases enables farmers to respond more quickly thus avoid expensive disease-associated crop loss as well decrease the use chemical control namely fungicides which is presumed greatly in environmental perspective. Better crop management = higher yield + better quality produce for both farmers and consumers. Moreover, applying high-level technology in agriculture helps enhance the economy; generate many job chances and encourage agricultural smart methods. The technology can help ensure food safety and security by affecting their communities.

## 5.2 Impact on Environment

Implementation of deep learning based avocado leaf disease detection model enhance the environmental sustainability in agriculture. The precise and minimal use of pesticides in early disease detection prevents the runoff chemical into soil and water bodies. This helps maintain healthier ecosystems and preserve biodiversity. Moreover, healthier crops mean more productive land with the ability to produce food in less space which is necessary when we want to avoid further deforestation and protect natural habitats. These models help make farming processes environmentally friendly by improving the controls on disease management which in turn reduces carbon footprints of agriculture.

## 5.3 Ethical Aspects

There are a lot of ethical things to consider behind deploying deep learning models for avocado leaf disease detection. Important exception, ensuring data privacy should be standard while sharing farmer's information so that it is not misused or accessed without permission. They must remain free from the influence of special interests, so that a regional group or population with certain characteristics is not unfairly disadvantaged due to hidden prejudices incorporated into the model. Furthermore, implementation should be such that it is equitable and inclusive covering small-scale farmers as well not only large agribusinesses. Deployed ethically: In practice, this mean utilizing technology in a responsible way and not to replace human expertise but rather boost it, help shaping sustainable crops production helpful for the lack of use of potentially harmful chemicals; or support equitable agriculture.

### 5.4 Sustainability Plan

A sustainable strategy is indispensable for sustaining the avocado leaf disease detection system in the long run. Regular additions to the dataset, along with updating and retraining of the model will support newer variants or disease subtypes as well as adaptation with changing environmental conditions. Working with agricultural institutes and local farmers will enable system improvements and data sharing. This will help adoption reach scale - right down to the smallest of small farmers. There is also whole crop management to consider when the detection system can be combined with other sustainable agricultural technologies and doing so will improve farming practices all around for our environment. Second, securing resources from public and private entities will ensure that the system can be sustained and improved indefinitely.

# CHAPTER 6
# CONCLUSION AND FUTURE WORKS

## 6.1 Conclusions

To conclude, this study demonstrates the efficiency of deep learning models in general and MobileNetV2 specifically for detecting avocado leaf diseases with high accuracy at an early stage. These high accuracies, regardless of the model and landscape internal characteristics underline their usefulness to improve some aspects of agriculture by allowing prompt control action and site-specific management strategies. Furthermore, this technology contributes to crop conservation and growth as well, while assisting in sustainability on farms so that excess pesticide use does not damage the environment. With model improvement, and additional data augmentation methods combined with integration of inexpensive field-ready technology we are highly likely to see wider incorporation and adoption for such systems across farming practices in future.

## 6.2 Further Works

Future research could look into several directions to improve the use of deep learning in detecting avocado leaf diseases. Looking to larger and more diverse datasets could help models generalize better, allowing them to perform well even when faced with infection rates generated by different regions or different were disease variants. The group is investigating ensemble learning techniques that might enable even better accuracy by joining together the complementary abilities of a collection of models. Moreover, plans to include real time monitoring and remote sensing could make such systems capable of efficient disease surveillance and early warning. Future research can be conducted to make this model deployment optimized for edge devices so that it is more useful especially in the hands of farmers who cannot access high-speed internet. Finally, a cost-benefit analysis and an evaluation on the possibility of scaling-up these technologies to different agricultural contexts would provide valuable insights.

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