

**A DEEP LEARNING APPROACH FOR PAPAYA  
DISEASE, PEST AND MATURITY IDENTIFICATION  
VIA MOBILE IMAGING: A CASE STUDY**

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## **DECLARATION**

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## ABSTRACT

Papaya cultivation is a very important sector in agriculture but is marred by diseases, pests, and improper maturity classification, all which adversely affect fruit quality and yield. Proper classification of fruit maturity and early detection of diseases are essential to increase crop management and minimize post-harvest loss. This case study presents a deep learning mobile application designed to assist farmers in disease detection in papayas, identify pests, and classify fruit maturity stages. Advanced models like EfficientNetV2B0, Vision Transformers (ViTs), Custom CNN, DenseNet121, and MobileNetV2 are used in the system for real-time disease diagnosis and correct classification. Papaya images were collected from selected farms via smartphones, preprocessed, and augmented to ensure the robustness of the model. The models were also tested and trained on accuracy, precision, recall, and F1-score metrics to validate their performance in pest and disease detection and papaya classification into four maturity levels: unripe, partially ripe, mature, and rotten. Results indicate that EfficientNetV2B0 and ViTs outperformed other models in pest and disease detection, while MobileNetV2 excelled in real-time maturity classification. The proposed mobile application not only provides immediate diagnosis but also suggests actions to prevent crop loss. The system further enables farmers to make decisions grounded in facts, reducing reliance on traditional, often erroneous manual approximations. Utilizing deep learning, this research assists in the improvement of papaya yield by equipping farmers with an affordable and user-friendly tool for early intervention. The findings emphasize the potential of AI-based solutions in precision agriculture to enhance better fruit quality and higher market value. Future studies can involve expanding the dataset, using hyperspectral imaging for enhanced classification accuracy, and deploying the application on a large scale with farmers, thereby improving agricultural sustainability and food security.

**Keywords:** Deep Learning (DL), EfficientNetV2B0, Vision Transformers (ViT), Convolutional Neural Network (CNN), DenseNet121, MobileNetV2, Fruit Research and Development Institute (FRID), You Look Only Once version 5 (YOLOv5)

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## LIST OF ABBREVIATIONS

Abbreviations	Description
YOLOv5	You Look Only Once version 5
CNN	Convolutional Neural Networks
PRSV	Papaya Ringspot Virus
DL	Deep Learning
ML	Machine Learning
DOA	Department Of Agriculture
FRDI	Fruit Research and Development Institute
ViT	Vision Transformers
AI	Artificial Intelligence
CNNs	Convolutional Neural Networks
API	Application Programming Interface
DB	Database
DL	Deep Learning

# 1 INTRODUCTION

## 1.1 Background

Papaya (*Carica Papaya*), a tropical fruit known for its rich nutritional value, plays a significant role in the agricultural landscape of Sri Lanka. It is highly valued for its content of Vitamin A and C, making it an essential component of both local diets and commercial agricultural products. [9] Consumed fresh, added to fruit salads, or processed into juices, jams, and ice creams, papaya is a versatile fruit with substantial economic and health benefits. [4] The survey we conducted has also demonstrated how essential papaya fruit is to people's daily lives.

6. Do you think papaya is essential for day today life of Sri Lankans? (සඳලටු ශ්‍රී ලාංකිකයන්ගේ ජීවිතයට අත්‍යාවශ්‍ය වන්නේ යැයි ඔබ සිතනවාද?)

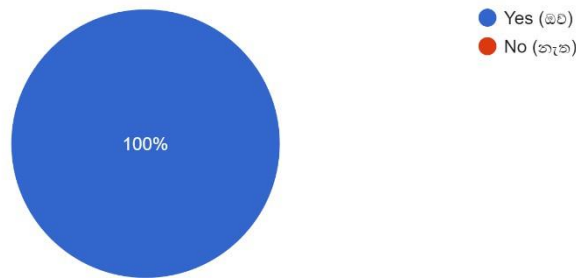


Figure 1 - Papaya is essential survey image

Originally cultivated in Southern Mexico and Central America, papaya has become a widely cultivated crop in tropical and subtropical regions, including Sri Lanka. [6] The fruit's year-round availability and short harvesting period make it a popular choice among farmers. In Sri Lanka, the cultivation of papaya is concentrated in several districts as mentioned in the Figure 1, with notable production, area including Puttalam, Hambantota, Kurunegala, Jaffna, and the Mahaweli areas (H and Udawalawe zones) [11]

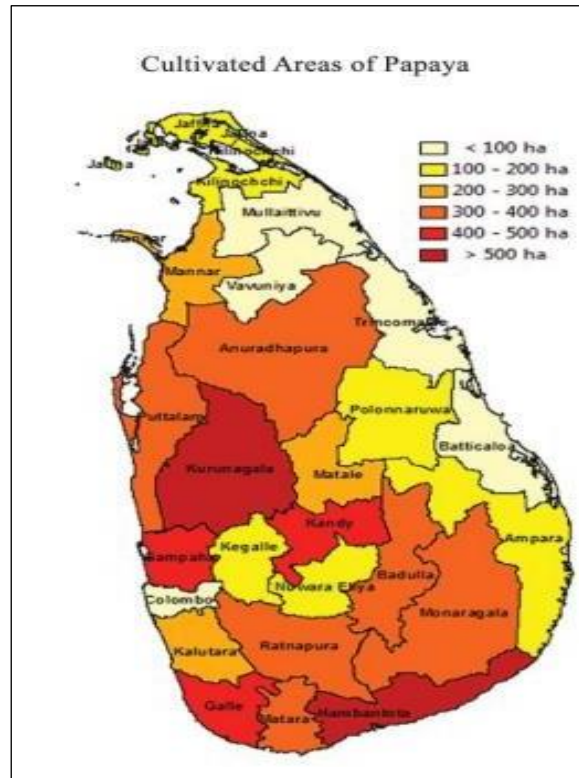


Figure 2 - Cultivated Area of Papaya(<https://doa.gov.lk>)

The ecological requirements for papaya cultivation include temperatures between 28- 35 °C, annual rainfall of 1000-1500 mm, and slightly acidic to neutral soil pH level (5.5-6.5). The crop thrives in sandy loams or lateritic soils, making it well-suited to the agro-climatic conditions of several regions in Sri Lanka. [7]

Papaya cultivation is highly profitable due to its low input costs and high yield potential. For instance, the “Red Lady” variety, widely cultivated in the Puttalam district, has an average fruit weight of 1.5-2.0 kg and a potential yield of 50-60 fruits per plant. [10] With proper spacing and crop management, the economic returns from papaya farming can be substantial.

The Department of Agriculture cost analysis for papaya reveals that while initial investments in fencing, land preparation, and planting are significant, the recurring maintenance costs are relatively low. The total cost for crop establishment and maintenance over a three-year period is approximately Rs. 1,747,740. However, the gross income generated from papaya farming can reach up to Rs. 7,240,935 by the third year, leading to a high profit-cost ratio and strong profitability. Figure 1.3

demonstrates profitability clearly here. [5]

<b>Crop - Papaya (Variety : Red lady)</b> <b>District - Puttalam</b>								
Operation	Input		Crop Establishment		Labour	Crop Maintenance - Total Cost (Rs./ha)		
	Qty/ha	Cost Rs./ha	Power Cost Rs./ha	Mds/ha		1 <sup>st</sup> year	2 <sup>nd</sup> year	3 <sup>rd</sup> year
Fencing					100	110,000		
Poles	140	84,000				84,000		
Barbed wires (kg)	250	51,500				51,500		
Nails (kg)	10	6,000				6,000		
Land preparation (4WT)			10,000			10,000		
Preparation of pits				21	23,100	23,100		
Planting (No. of plants)	1,600	80,000		14	15,400	95,400		
Fertilizer application								
NPK (kg)*	2,616	130,800		21	23,100	153,900	135,900	135,900
Compost (kg)	32,000	320,000		18	19,800	339,800	339,800	339,800
Manual weeding				20	22,000	22,000	22,000	22,000
Irrigation		565,200	120,000	90	99,000	784,200	219,000	219,000
Pest & Disease control		12,240		9	9,900	22,140	22,140	22,140
Fixing support (Wind break)**		100,000				100,000		
Harvesting				93	102,400	102,400	170,667	68,267
Land Rent		125,000				125,000	125,000	125,000
Total Labour (Mds)				386			313	220
Total Cost (Rs.)		1,474,740	130,000		424,700	2,029,440	1,034,506	932,106
Yield (kg/ha)						76,800	128,000	51,200
Gross Income (Rs./ha)						3,456,000	5,760,000	2,748,295
Present Value of Cost (Rs.)	3,674,908		* NPK - 1 <sup>st</sup> year					
Present Value of Benefit (Rs.)	10,308,070		Urea	712 kg				
Net Present Value (Rs.)	6,633,163		TSP	408 kg				
Benefit Cost Ratio	2.80		MOP	1496 kg				
<b>Related Information</b>			<b>Life span:</b>					
Discount Rate	0.13		Agro well	20 years				
Wage Rate (Rs./day)	1,100		Irrigation system	10 years				
Average Yield (Kg/ha)	85,333		Water pump (Electric)	15 years				
Average Price (Rs./kg)	45		** Contract basis (Rs.62.50 per tree including material cost+labour cost)					

Figure 3 - Profitability report of Papaya Cultivation in Puttalam District for Red Lady (<https://doa.gov.lk>)

Papaya farming in Sri Lanka also benefits from a relatively short payback period and the potential for sustained income over a 10-year agronomic lifespan. The high yield, coupled with favorable market prices, makes papaya an attractive crop for farmers looking to maximize their returns while contributing to the agricultural economy. [11]

## 1.2 Literature Review

### 1.2.1 Identification of Cercospora and Mosaic Virus

Papaya cultivation is critical to the agricultural economy of Sri Lanka, contributing significantly to local food security and export revenue. However, papaya farmers face significant challenges in managing leaf diseases such as Papaya Mosaic Virus and Cercospora. These diseases are particularly difficult to identify for untrained eyes, resulting in delayed interventions and substantial crop losses. The proposed system aims to develop a mobile application that leverages advanced

machine learning techniques to address these challenges, providing a user-friendly tool for timely and accurate disease detection.

The development of this mobile application will benefit from insights gained from several key studies. Plant Disease Detection Using Advanced Deep Learning Algorithms: A Case Study of Papaya Ring Spot Disease [12] employs convolutional neural networks (CNNs) to detect papaya ring spot disease by analyzing images of papaya leaves. This research showcases the potential of deep learning in achieving high accuracy in disease detection. The mobile app will incorporate a hybrid model combining EfficientNet and Vision Transformers (ViTs) for disease detection, drawing on these advanced techniques to provide accurate and timely assistance to farmers.

Another important study, Machine Learning Based Image Classification of Papaya Disease Recognition [13], focuses on using CNNs to classify images of papaya diseases and differentiate between healthy and diseased leaves. This research highlights the high accuracy and robustness of CNNs in disease identification, which will enhance the app's diagnostic capabilities. Additionally, the study Papaya Leaf Disease Identification Using ResNet with Transfer Learning [14] leverages the ResNet architecture and transfer learning to improve the accuracy of papaya leaf disease identification. Transfer learning enables the model to use pre-trained weights from large-scale datasets, significantly enhancing model performance in detecting disease-specific patterns.

The app will also integrate findings from Transformative Diagnostics: The Rise of Federated Learning CNNs in Papaya Leaf Disease Detection [15]. This study explores the use of federated learning combined with CNNs to advance papaya leaf disease diagnostics. Federated learning allows for collaborative model training across institutions while maintaining data privacy, utilizing diverse datasets to improve model accuracy and generalization.

Recent advancements further support the proposed system's design. Anthracnose Disease Detection in Papaya Fruit Using Machine Learning Techniques [16] uses image processing and machine learning to identify anthracnose disease symptoms on papaya fruits. This study provides practical solutions for early disease identification and management, which will be integrated into the app to offer a

comprehensive approach. Additionally, Deep Learning Based Classification of Papaya Disease Recognition [17] employs deep learning techniques to classify papaya diseases with high accuracy, reinforcing the benefits of advanced algorithms in disease detection.

The latest research also contributes valuable insights. Hybrid Model for Effective Papaya Leaf Disease Diagnosis [18] integrates neural networks with convolutional neural networks (CNNs) and Random Forest algorithms to classify various papaya leaf diseases. This study demonstrates high precision and recall rates, supporting the implementation of hybrid models for improved diagnostic accuracy. Papaya Leaf Disease Identification Using ResNet with Transfer Learning [19] and A Deep Ensemble Approach for Recognition of Papaya Diseases Using EfficientNet Models [20] further enhance disease identification by combining different models and techniques, achieving high accuracy and robust performance.

The proposed system will combine EfficientNet for binary classification of papaya leaves with Vision Transformers (ViTs) for detailed disease identification, aiming to surpass traditional CNN-based methods in accuracy and efficiency. This hybrid approach addresses the significant challenges faced by papaya farmers in Sri Lanka due to diseases such as Papaya Mosaic Virus and Cercospora leaf spot, which severely impact crop yield and quality. These diseases are particularly difficult for farmers with limited knowledge and access to expert consultation. By incorporating a comprehensive remedy suggestion system, the application will provide tailored solutions based on disease severity and progression. This user-friendly tool is designed to deliver early and accurate disease diagnosis, thereby enhancing disease management, improving crop productivity, and supporting sustainable farming practices, especially in rural areas with limited agricultural expertise. This integrated approach represents a significant advancement in disease detection and management, building on the insights and methodologies explored in the reviewed literature.

### **1.2.2 Identification and Classification of Papaya Ring Spot Virus and Powdery Mildew**

Plant disease detection is a very essential aspect in modern agriculture where its early identification and intervention can greatly enhance the yield of crops and reduce losses. Papaya is a tropical fruit with high nutritional value as well as economic values and is one of the most common plantations in the world. Due to its high content of vitamins and the potential health benefits, the demand for papaya fruits keeps increasing, hence it is one of the important crops grown for local consumption and export markets. On the other hand, the cultivation of papaya is under a serve threat of diseases, such as PSRV and Powdery Mildew. These diseases can lead to a massive reduction in yield when not detected and managed early.

DL algorithms have come to the fore in plant disease detection in the ls years, as they offer robust solutions for the efficient and accurate identification of a myriad of diseases, including those that threaten papaya crops. This literature review has considered already existing methodologies on the detection of PRSV and Powdery Mildew, two serious diseases that badly threaten papaya cultivation worldwide.

Recent advances in DL can change how plant diseases detection approached, offering a promising outlook for high-accuracy, rapid diagnosis. Traditional approaches often impose computational demands that could challenge real time applications of the mobile platform. Research has shown promise in lightweight DL models, particularly the specialized versions of YOLO, in tackling such challenges. This review looks at these developments with respect to the high accuracy that these models have in spotting PRSV and Powdery Mildew, and in the enhancement of agricultural productivity.

In the quest for better productivity in farming, fast and more accurate disease detection has been one of the priorities. An infusion of DL algorithms within agricultural practices has been quite promising in the realization of this aim. The major problem noted in this area is that most of the algorithms require very high computational power, hence limiting its practical application by their performance, mostly in real-time scenarios on mobile agricultural platforms [22]. Maski, Prajwal and Thondiyath, Asokan authors used lighter YOLO models for plant disease detection, trying to reduce computational intensification. They managed to get high



accuracy with a map of 99.9% by constructing a data set of papaya leaves infected with PRSV and training models like Tiny-YOLOv4. The study has pointed out that lightweight DL models may, in the future, perform real-time disease detection on resource-constrained platforms like mobile agricultural robots, opening up avenues for better management of crops [22]. The reason for detecting plant diseases is very important to crop health, more so in the case of such valuable crops like papaya. Accurate plant disease detection plays an important role in improving crop yield and resulting in food security. Therefore, the timely identification of such diseases as PRSV and Powdery Mildew, Anthracnose, Phytophthora and Blackspot becomes paramount in economically important crops like papaya. DL paradigms enabled CNN to provide high precision in disease classification. Of the various CNN architectures, Inception scored approximately 97% accuracy, while VGG16 scored approximately 77%. At the big margin of improvement, this signifies the ability of Inception in efficiently diagnosing plant diseases hence better management and intervention [23]. Papaya is susceptible to diseases such as Powdery Mildew, Mosaic, Leaf curl, PSRV, Brown Spot, Anthracnose, Phytophthora Blight and black Spot, which have caused serious yield and quality losses. In this respect, efficient diagnosis of deep CNN models, especially EfficientNet models, an accuracy above 96% could be realized for disease recognition. Test accuracies for EfficientNet B5, B6 and B7 achieved 98.13%, 96.87%, and 96.93%. respectively. An ensemble approach that combines these models increases the recognition accuracy to 99.74%, thus it is more excellent than using only one model. This deep ensemble model would be a robust solution for the detection of diseases in real time, which is very critical in enhancing papaya crop management and productivity [24]. In Indonesia, the cultivation of papaya is very vulnerable to various pests and diseases, from Mite, Mealybug, and Fruit Fly to Thrips and Snails, besides Root Rot, Leaf Spot, Anthracnose, Fusarium Wilt, Fusarium head blight and Corynespora. In this regard, an expert system of FNBC was created to help in disease diagnosis, considering the low level of farmers' knowledge about it. Through this, the linguistic knowledge of an expert is converted through TFN into numerical values and later classified with Naïve Bayes. It had an accuracy of 88% compared to FNBC, while forward chaining reached 90%, thus showing the potential of the system in improving the management

of papaya diseases [25]. The research in the detection of papaya diseases has been evolving fast, with major strides in ML techniques to support agriculture. There have been number of studies which have suggested intelligent systems aimed at recognizing and classifying these different diseases in papaya, including Anthracnose, Black Spot, Phytophthora, Powdery Mildew and Ring Spot. In this regard, different machine learning algorithms have been considered for studying their efficiency with respect to above-mentioned diseases, including Random Forest, K-means clustering, SVC and CNN. Subsequently, CNN has gone further to post an accuracy of up to 98.4%. These include systems that allow farmers to capture images of papaya fruits with diseases using mobile app, with undergo image processing for disease identification. The use of image segmentation and feature extraction techniques, such as color, texture and shape analysis, further enhances the accuracy of these models. Future research expected to focus on larger datasets and more complex algorithms to improve the predictive capabilities and extend the application of these intelligent systems in agriculture [26]. Traditional methods, such as visual inspection, are relatively inefficient, hence a shift towards ML and Image Processing is necessary. The focus of this research is in the classification of five papaya diseases common in Sri Lanaka using CNN. The model obtained an accuracy ~92%, which is comparatively higher than previous methods using SVM. More importantly Black Spot was easily detected, while Powdery Mildew proved to be a challenge. This approach offers a reliable and efficient tool for disease management [27]. Due to the dense overlay, papaya fruit are green, exactly like the leaves, hence hard to detect by robots during picking. This work enhances a YOLOv5s-Papaya model that integrates a Ghost module for lightweight efficiency and coordinate attention for accuracy in dense papaya detection. Improvements include feature fusion using a bidirectional weighted pyramid network and scaled IOU loss function to improve precision while reducing parameters. This model improves the average precision in detection by 3.6% [28]. Post-harvest diseases in fruits can cause an economic loss of up to 30% of the total production. The surest way of preventing such losses and maintaining the quality of fruits is detecting it in its early stages of development. This paper describes some of the challenges in proposing a papaya dataset of 23,158 images classified into nine categories, eight different pathologies and a healthy class of papaya fruits.

The authors introduce a new system of object detection, Yolo-Papaya, in which YOLOv7 is used with a Convolutional Block Attention Module. On that note, the authors develop a model with a mean average precision of 86.2%, surpassing other methods on the said dataset [29]. In this regard, machine vision-based systems have been very promising in addressing the challenge of papaya disease recognition. This paper proposes an online agro-medical expert system envisioned to support farmers by processing images of diseases taken through mobile devices. This system combines K-means clustering for disease segmentation and a SVM for classification. Test results prove that it holds huge potential, with classification accuracy achieved above 90%. This will resize the image, enhance the contrast, extract features and provide feedback on the disease through SMS. The approach offers a high accuracy and efficiency, making it as a very useful tool for remote disease management in papaya cultivation [30]

### **1.2.3 Mite Disease and Mealy Bug Disease Identification and Suggest the Remedy**

Mite and Mealy bug infections are major threats to papaya crops causing direct damage through feeding and indirect harm by fostering the growth of sooty mold, which hinders photosynthesis. Mite infections lead to bronzing and speckling of leaves, while Mealy Bugs are known for their cotton-like masses on plant surfaces.

The Papaya Mealy Bug is particularly challenging to manage due to its ability to be mistaken with other pest species. Infections typically present as cluster of waxy, cotton-like masses on the above-ground parts of the papaya fruit. The adult female Papaya Mealy Bug is yellow and covered with a white waxy coating. These bugs are tiny, with adults measuring approximately 2.2 mm long and 1.4 mm wide. [44]

Key characteristics of the Papaya Mealy Bug:

- Size Varying from 2 mm to 3.5 mm in length
- A yellow body covered in white wax with a fringe of short filaments
- Round yellow eggs laid inside an egg sac
- Very sticky wax with copious amounts of honeydew
- Presence of sooty mold on the infested plant

Detecting these pastes with the untrained eye can lead to misidentification, allowing infections to spread rapidly and resulting in significant harvest losses. Traditional detection methods often require expert knowledge and can be time-consuming and inaccurate, particularly in large-scale farming operations. The lack of effective and accessible diagnostic tools can exacerbate these issues, leading to increases in pesticide use and associated environmental concerns [45].

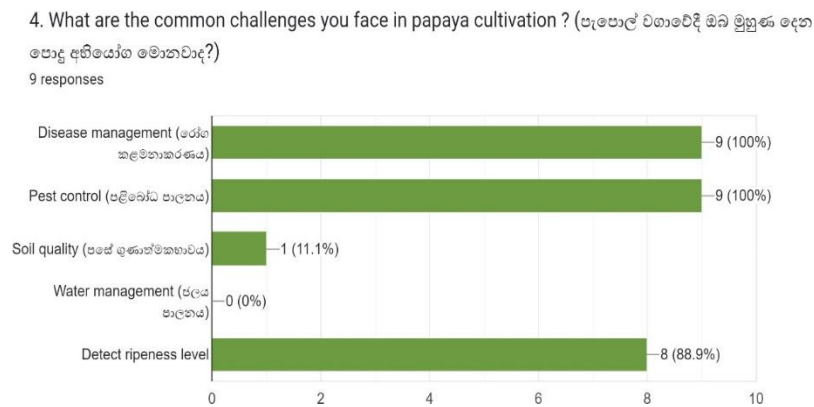


Figure 4 - User difficulty level to identify papaya bug

Given these challenges, there is a critical need for innovative solutions that leverage technology to improve pest detection and management. Advances in image processing and deep learning techniques such as Convolutional Neural Networks (CNNs), offer promising opportunities for the development of automated pest detection systems. These technologies can provide farmers with tools to quickly and accurately identify pest infections, enabling timely intervention and provide actionable insights on how to prevent the pest infections.

This proposal outlines a novel approach using DenseNet, a state-of-the-art CNN architecture, to develop an automated system for the detection of Mite and Mealy Bug infections in papaya plants. By integrating cutting-edge image analysis techniques, this system aims to empower farmers with reliable diagnostic tools to protect and optimize suitable harvest. The “Papaya Buddy” System effectively detects and forecast the existence of mite and mealy bug infections in papaya plants by utilizing the capabilities of a Convolutional Neural Network (CNN) architecture called DenseNet. Because of its distinctive features and architecture, DenseNet is especially well-suited for this task and provides a number of advantages.

A Similar kind of research conducted by the authors [45] have proposed deep learning- based modal for recognizing papaya diseases using EfficientNet models and assemble learning techniques. The research utilized the dataset of 138,980 images generated through augmentation to train eight EfficientNet models (B0 to B7) via transfer learning for the recognition of eight different papaya diseases. Among these, the three best-performing models EfficientNet B5, B6 and B7 achieved test accuracies of 98.13%, 96.93% and 96.87% respectively to further enhance performance, the authors implemented and ensembles model combining these three EfficientNet versions, resulting in a 1.6% increase in accuracy compared to individual models. This research demonstrates ensemble learning could significantly improve the efficiency and accuracy of papaya disease identification.

According to the research [46] study authors proposed a machine learning-based intelligent system to assist farmers in Bangladesh with the recognition and classification of papaya disease. The System aims to address the challenges faced by farmers, particular those with limited knowledge of crop diseases, by providing an efficient method to detect and classify diseases based on images captured via a

mobile application. The study compares the performance of several algorithms, including Random Forest, K-means clustering, SVC and CNN, in identifying papaya diseases. The system processes the images sent through the app and provides feedback, achieving a high accuracy of 98.4% in disease prediction. This research emphasizes the importance of using advance machine learning techniques to empower farmers with timely and accurate disease diagnosis, ultimately contributing to improved crop yields and economic benefits for the agricultural sector in Bangladesh.

In contrast to the prevailing papaya disease identification systems, which are highly ineffective in identifying certain pests like Mite and Mealy Bug or actionable remedies, this approach takes a powerful Convolutional Neural Network called DenseNet. This leads to much better accuracy in the detection of these specific pests and brings a major improvement over the current method. While classical systems can identify general diseases, they are incapable of diagnosing specific infestation and giving clear guidance to the farmers for targeted intervention. This DenseNet-based model increases in the precision of pest detection but also in offering tailored remedies, which is one of the critical deficiencies in current agricultural monitoring systems.

#### **1.2.4 Papaya Maturity Level Detection**

Deep learning methods for classification and detection of fruit maturity are widely used in agricultural technology. As a broadly cultivated tropical fruit, papaya represents at the same time some special difficulties and opportunities for the implementation of advanced technologies. There are many approaches to solving the problem of papaya ripeness detection, all having their own strengths and limitations.

One of the notable studies is "Detection of Papaya Ripeness Using Deep Learning Approach," which investigates the use of convolutional neural networks for automatic classification of the ripeness of papayas. In the study, the researchers used a dataset of papaya images and trained a CNN model to classify the fruit into different classes regarding ripeness. While this fruit image processing research has brought out very encouraging results in terms of accuracy rate, reaching about 85%, it also mentioned some of the limitations to this study, more specifically in

classifying closely related ripeness stages. While the reliance on the CNN architecture proves to be very effective, further improvements can be made by incorporating advanced or hybrid models capable of capturing subtle changes in fruit ripeness. [8]

Another important contribution in this respect is the research work on "Machine Vision Based Papaya Maturity Recognition." This paper provided information on using machine vision techniques along with conventional image processing techniques to evaluate the ripeness stage of papaya fruits. The technique mainly relied on extracting color and texture features, after which analysis was done through machine learning algorithms. Although the methodology applied was robust both to illumination and environmental variations, it was bound by the accuracy system due to the employment of handcrafted features that might not be able to represent the intricate details of the fruit maturity stages. Therefore, the study indicates the need for much more sophisticated models that can autonomously learn features from the data to improve the overall performance of the system. [3]

A more recent development can be found in the work "Multimodal Deep Learning via Late Fusion for Non-Destructive Papaya Fruit Maturity Classification." This work presented a strategy of multimodal deep learning, fusing image data with other sensors such as infrared spectroscopy for the determination of papaya fruit maturity. In this work, late fusion was used as a technique to fuse independent data sources, giving a more comprehensive view of fruit maturity. Single-modality approaches were outperformed by the results delivered, pointing out the potential of multimodal learning in agriculture. They also noticed the increasing computational complexity and using special equipment, which can limit the generalization of applying this technique in real life. [2]

Compared to these works, the component proposed in the current research envisions using a lightweight deep learning model, MobileNet, for the classification of papaya maturity. MobileNet was chosen to be used in mobile and embedded applications owing to its lightweight nature and low computational cost. MobileNet thus provides real-time classification of papaya ripeness on mobile devices, hence making it very accessible to farmers to make appropriate decisions on harvesting. This research also includes a comparison of the results with other models for assessing the

trade-offs between accuracy and computational efficiency. This holistic approach will ensure that the maturity detection is not only accurate but also the solution developed is practical and scalable, hence can be used extensively in the agricultural sector



### 1.3 Research Gap

#### 1.3.1 Identification of Cercospora and Mosaic Virus

The proposed system addresses significant gaps in existing solutions for papaya leaf disease detection by incorporating advanced machine learning techniques and a mobile application. Current studies like "Plant Disease Detection Using Advanced Deep Learning Algorithms" and "Machine Learning based Image Classification of Papaya Disease Recognition" use CNNs for disease identification but lack the integration of hybrid models combining EfficientNet and Vision Transformers for enhanced accuracy. Additionally, while federated learning is explored for data privacy in studies such as "Transformative Diagnostics: The Rise of Federated Learning CNNs," these do not focus specifically on papaya mosaic virus and Cercospora disease or provide tailored remedy suggestions. The proposed system uniquely combines precise binary identification, detailed disease detection, and practical remedy suggestions in a user-friendly mobile application, targeting the specific challenges faced by papaya farmers.

Table 1 - Research Gap

Features	Paper A [13]	Paper B [14]	Paper C [21]	Paper G	Paper E [17]	Proposed System
Mobile App	✓	✓	✓	✗	✗	✓
EfficientNet	✗	✗	✗	✗	✗	✓
Vision Transformers	✗	✗	✗	✗	✗	✓
CNN	✓	✗	✓	✓	✓	✗
Black Spot Detection	✓	✓	✗	✗	✓	✗
Mosaic Virus Detection	✗	✗	✗	✗	✗	✓
Cercospora Disease Detection	✗	✗	✗	✗	✗	✓
Remedy Suggestion System	✗	✗	✗	✗	✗	✓
Accuracy	~80%	88%	82.0%	83.52%	80.6%	95%

### **1.3.2 Identification and Classification of Papaya Ring Spot Virus and Powdery Mildew**

Diseases like PRSV and Powdery Mildew are major challenges in papaya cultivation and will drastically affect the yield and the quality of fruits. Any management and mitigating strategies hinge on the detection of the disease timely and accurately. Huge efforts were extended into methods for identification. Until now, there is still a huge gap in enhancing high accuracy and real-time detection into mobile applications. Previous studies have shown the use of different methods for detecting papaya diseases. For example, Saketh et al. [23] used CNN for making predictions and classifications for papaya diseases with good accuracy of 97.6%. Hirdoy and Tuli [24] used EfficientNet models in a deep ensemble methodology and tested against the state-of-art techniques which gave an accuracy of 99.74%, the highest among the referred works. Most of these methods, however, do not support mobile applications, hence their practical usability in real-world scenario is limited. Sari et al. [25] proposed a Fuzzy Naïve Bayes Classifier for papaya disease detection but achieved a relatively low accuracy of 80.5%. Their model performance was limited, hence pointing out the need for more robust methods. Islam et al. [26] and Munasinghe et al. [27] used ML techniques in disease classification on papaya and obtained accuracy levels of 98.04% and 92%, respectively. However, neither of these works covered real-time detection on mobile platforms. Wang et al. [28] demonstrated the detection of dense objects in natural environments up to 92.3% by YOLOv5s. The model claims that the YOLOv5 is suitable for use in agriculture. De Moraes et al. [29] and Habib et al. [30] have used CNN based classifiers for papaya diseases with an amount of accuracy of 86.2% and 90%, respectively. However, none of the methods involved smartphone application installation and were deficient in providing recommendations for treatment. There is a pressing need for advanced object detection models like YOLOv5 specifically applied to identify PRSV and Powdery Mildew in papaya fruits. Although YOLOv5 has shown good promise in dense object detection [28], its potential in the domain of disease diagnosis is not explored entirely. However, none of the available studies include the automated remedy suggestion system, which is crucial for providing actionable advice for

farmers. Real-time detection with remedy suggestions to be integrated into a mobile application makes it one of the most pressing shortcomings in the available body of research. This ignorance in the available literature motivated the current work where the detection of PRSV and Powdery Mildew in papaya fruits was implemented using the YOLOv5 model. The YOLOv5 model is said to be the best choice for real-time mobile applications that entail fast and accurate object detection. The proposed system will not only detect the diseases accurately, but it will also display an automated remedy-suggestion feature. This feature will allow farmers to give practical advice and timely input on how to manage the identified diseases regarding the treatments suggested and preventive measures. Such component integration within a mobile platform would allow for real-time in-field identification and management of diseases, significantly improving the usability and effectiveness of a system for the farmers. This research fills critical gaps in the existing literature with a focus on the detection of PRSV and Powdery Mildew using YOLOv5 and integrating an automated remedy suggestion system. The novelty of the proposed system is in combining high accuracy in disease detection and real-time deployment through a mobile application with actionable remedy suggestions- an inclusive and innovative solution for papaya disease management. Table 2 provides an overview of the limitations in current approaches, illustrating the need for a more integrated and innovative solution.

*Table 2 - Research Gap*

<b>Application reference</b>	<b>PRSV (fruit)</b>	<b>Powdery Mildew (fruit)</b>	<b>Mobile App</b>	<b>Remedy</b>	<b>YOLOv5</b>	<b>Accuracy Level</b>
[2]	✓	✓	✗	✓	✗	97.76%
[3]	✓	✓	✗	✗	✗	99.74%
[4]	✗	✗	✓	✗	✗	80.5%
[5]	✓	✓	✓	✗	✗	98.04%
[6]	✓	✓	✗	✗	✗	92%
[7]	✗	✗	✗	✗	✓	92.3%
[8]	✗	✗	✗	✗	✗	86.2%

[9]	X	✓	✓	X	X	90%
Proposed App	✓	✓	✓	✓	✓	90%

### 1.3.3 Mite Disease and Mealy Bug Disease Identification and Suggest the Remedy

Recent changes in whether conditions and lack of knowledge among landowners or papaya farmers about pests have contributed significantly to the spread of mite mealy infestation of papaya crops. Early detection and optimal mitigation information is essential to reduce the impact of this pest and prevent the loss of entire papaya plantations.

Research A [48] is concerned with deep learning, particularly convolutional neural networks (CNN), have revolutionized image recognition, proving highly effective in crop disease diagnosis. Research has shown that models like EfficientNet, especially when used with ensemble learning techniques, achieve high accuracy in disease identification. These holistic approaches have significantly increased the efficiency and accuracy of disease detection in crops like papaya, where a robust dataset of 138,980 images was utilized to train and validate models, achieving test accuracy as 99.74% with an EfficientNet models. However, this research remains a gap in addressing specific bugs in papaya cultivation. While this research focuses of leaf diseases, mite and mealy bug infections are equally important that require proper mitigation with remedies.

Research B [47] primarily focuses on utilizing machine learning algorithms to recognize papaya diseases through image capture and classification via a mobile app. This research compares the accuracy of several algorithms, including Random Forest, K-means clustering, SVC, and CNN, to provide a highly accurate (98.4%) intelligent system for disease detection. While the existing research effectively identifies and classifies papaya diseases using machine learning techniques, it lacks a comprehensive approach to addressing pest infestations, such as mite bugs and mealy bugs, specifically on papaya leaves and fruits. Moreover, the existing studies do not dive into the analysis of these infestations or offer targeted remedy suggestions based on the bug species.

Research C [49] Existing expert systems, such as those using Delphi language

and CLIPS or fuzzy logic and Naive Bayes Classifier, show satisfactory results but are limited in scope, focusing primarily on specific diseases and not addressing the full spectrum of pest and disease challenges faced by papaya farmers. primarily focuses on identifying fungal diseases in papaya. However, the progression level identification part has not been included in existing systems which are crucial for better treatment.

The proposed (Papaya Buddy) mobile application will leverage DenseNet, a type of Convolutional Neural Network (CNN), to accurately identify mite disease and mealy bug pests. This advanced image processing technique ensures maximum flow between network layers, enhancing its capability to distinguish between complex disease patterns. This comprehensive approach addresses a significant gap in pest identification, providing a more holistic solution for managing papaya pests.

By automating the disease identification process, the suggested mobile application lowers the need for human intervention while increasing accuracy. It does this by utilizing computer vision and machine learning. With the use of cutting-edge algorithms and a sizable library of excellent photos, the application guarantees accurate disease categorization and practical management options. By reducing pesticide abuse, this strategy not only increases output and quality but also promotes sustainable farming practices.

*Table 3 - Research Gap*

Application Reference	Mite Bug Identification	Mealy Bug Identification	Suggest Remedy	Use CNN to identify Mite and Mealy Bug	Mobile Application	Accuracy
Research A	✗	✗	✗	✓	✗	99.74%
Research B	✗	✗	✗	✗	✓	98.4%
Research C	✓	✓	✗	✗	✓	96.42%
Proposed System	✓	✓	✓	✓	✓	90%

#### **1.3.4 Papaya Maturity Level Detection**

The detection and classification of papaya ripeness and maturity levels are critical areas in agricultural research, particularly for minimizing post-harvest losses

and ensuring high-quality produce reaches the market. Several studies have approached this problem with different methodologies, each contributing valuable insights but also revealing significant gaps that need to be addressed for more practical and robust solutions.

The first study, "Detection of Papaya Ripeness Using Deep Learning Approach," primarily utilized a Convolutional Neural Network (CNN) to classify the ripeness of papayas. While the CNN model showed promising results in terms of accuracy, the research was conducted using a relatively small dataset. This limitation in the dataset size could potentially lead to overfitting, where the model performs well on the training data but fails to generalize effectively to new, unseen data. Moreover, the study did not consider the impact of varying environmental conditions such as different lighting or background clutter, which are common in real-world agricultural settings. This raises concerns about the model's robustness and reliability when deployed in diverse field conditions. [8]

In the second study, "Machine Vision Based Papaya Maturity Recognition," the authors employed traditional image processing techniques such as color segmentation and texture analysis to determine the maturity levels of papayas. Although these methods are computationally less intensive and relatively straightforward to implement, they may not capture the full complexity of papaya ripeness, which can involve subtle changes in color, texture, and other visual cues. The study also did not address the challenge of distinguishing between different papaya varieties, which can exhibit varying ripeness indicators. Furthermore, the system's performance under different environmental settings, particularly in varying lighting conditions, was not thoroughly evaluated, leaving a gap in understanding its applicability in real-world scenarios. [3]

The third study, "Multimodal Deep Learning via Late Fusion for Non-Destructive Papaya Fruit Maturity Classification," represents a more advanced approach by integrating multiple data modalities, including visual and spectral data, to enhance the classification accuracy. This multimodal approach acknowledges that relying solely on visual data may not always be sufficient for accurate ripeness detection. However, the requirement for spectral data introduces practical challenges, especially in resource-constrained environments where such data may

not be readily available. Additionally, the study did not explore the use of more recent lightweight deep learning models like MobileNet, which are designed for efficient performance on mobile and edge devices. This omission limits the study's relevance to real-time, on- field applications where computational resources are limited. [2]

Considering these gaps, our proposed component seeks to address several critical areas that previous studies have either overlooked or insufficiently explored. By focusing on a MobileNet-based classification system, our research leverages a state-of-the-art lightweight model that is well-suited for deployment on mobile devices, making it highly practical for use by farmers and agricultural workers in the field. MobileNet's architecture is specifically designed to perform well on mobile and edge devices without compromising on accuracy, offering a significant advantage over more computationally intensive models like CNNs and multimodal approaches that require powerful hardware.

Furthermore, our research includes a comprehensive evaluation of the system's performance under various environmental conditions, such as different lighting, weather, and background settings. This aspect of our work directly addresses the robust concerns raised in previous studies, ensuring that the model can perform reliably in the diverse and often challenging conditions found in agricultural environments. Additionally, by incorporating an analysis of different papaya varieties, your research acknowledges the variability in ripeness indicators across different types of papayas. This focus on varietal differences enhances the model's applicability across different regions and cultivars, making it more versatile and effective in practice.

Moreover, our research includes a comparative analysis with other deep learning models, providing a clear benchmark to establish MobileNet's effectiveness in this specific application. This comparative approach not only highlights the strengths of MobileNet but also identifies areas where it outperforms or complements other models, contributing valuable insights to the broader field of agricultural machine learning. By addressing these key gaps, your proposed component aims to deliver a more accurate, robust, and practical solution for papaya maturity detection, ultimately helping to reduce post-harvest losses and improve the quality and

marketability of papayas in Sri Lanka.



The below Table 1 shows a tabularized format of the above explanation regarding Papaya Maturity Level Detection.

*Table 4 - Comparison table with another research*

Feature/Methodology	Paper 1: Detection of Papaya Ripeness	Paper 2: Machine Vision-Based Maturity Recognition	Paper 3: Multimodal Deep Learning	Your Proposed Component
Model Used	CNN	Image Processing (Color Segmentation, Texture)	Multimodal Deep Learning	MobileNet
Environmental Robustness	X	X	✓	✓
Focus on Papaya Varieties	X	X	X	✓
Comparative Analysis with Other Models	X	✓	X	✓
Scalability and Practicality	✓	✓	X	✓

## **1.4 Research Problem**

### **1.4.1 Identification of Cercospora and Mosaic Virus**

Papaya cultivation in Sri Lanka is severely impacted by diseases such as Papaya Mosaic Virus and Cercospora Leaf Spot, leading to significant losses in both yield and fruit quality. Traditional disease management practices, which rely heavily on visual inspections and sporadic expert consultations, are often inadequate. These methods are not only time-consuming but also lack the precision required for effective and timely disease management, particularly for farmers in rural areas who may have limited access to agricultural expertise and resources.

The research problem addresses the need for an innovative, accessible solution to overcome these challenges. The proposed solution is the development of a mobile application that leverages advanced machine learning techniques for accurate and real-time disease detection in papaya plants. Specifically, the application will integrate a hybrid model that combines EfficientNet for binary classification of diseased vs. healthy plants and Vision Transformers for detailed identification of specific diseases.

This approach seeks to deliver a user-friendly tool that not only precisely identifies papaya diseases but also provides a comprehensive database of tailored remedy suggestions. By enhancing disease control through timely and accurate detection, this system aims to improve productivity and support sustainable agriculture practices, particularly benefiting farmers in remote areas with limited access to traditional agricultural support systems.

### **1.4.2 Identification and Classification of Papaya Ring Spot Virus and Powdery Mildew**

Cultivation of Carica Papaya, a high nutritional and economic value fruit, is seriously hampered by a number of diseases, such as PRSV and Powdery Mildew, which reduce yield significantly and simultaneously affect the quality of fruits. Traditionally applied techniques of disease detection are labor-intensive, prone to error, and inappropriate for large-scale agricultural operations since most of them fail to provide actionable insight or suggestions for remedy. Although ML and

computer vision have advanced a lot, there is little literature available regarding the use of high accuracy in a real-time object detection mode like YOLOv5 in the identification of specific papaya diseases. Besides, current systems have no integrated remedy suggestion mechanisms, hence seriously delimiting their practical utility to farmers. The proposed system aimed at closing these gaps by developing a model that uses YOLOv5 based PSRV and Powdery Mildew for accurate and real-time detection in papaya fruits, integrated with an automated remedy suggestion system for actionable treatment recommendations. This would be used within a mobile application-based solution to enhance accessibility and usability to farmers, thus contributing to better practices for diseases management in the sustainability of papaya cultivation.

#### **1.4.3 Mite Disease and Mealy Bug Disease Identification and Suggest the Remedy**

Papaya (*Carica Papaya*) is an essential crop of Sri Lanka, contributing significantly to the agricultural sector and the livelihoods of many farmers. However, papaya cultivation is often negatively affected by various pest infections, with mite and mealy bug infestations being particularly devastating. Mite infestations, caused by species such as the broad mite (*Polyphagotarsonemus latus*) and red mites (*Tetranychus* spp.), lead to substantial damage to papaya leaves, reducing photosynthetic ability and overall plant health. Spider mites extract the essence of the leaf and let the leaf curl. Mealy bugs (*Pseudococcidae*) cluster of white color bugs, causing stunted growth, chlorosis, and can also transmit plant pathogens, further compromising the plant's vitality. These infestations can tremendously impact both the yield and quality of papaya fruits with huge financial loss.

The primary research problem is the early detection and managing mite and mealy bug effectively using bug infestations in papaya plants using advanced image processing and deep learning techniques. The economic impact of the mealy and mite bug on papaya is considerable. So, the effect causes significant yield losses financial losses. Affected plants produce lower and small harvest that led to unmarketable due to blemishes and deformities. Additionally, the monetization of papaya disease with expert minds may be very costing, including pesticides and labor. Without timely intervention and proper management pests can spread causing widespread papaya

plantation further to worsen financial losses. Early detect and effective management of mite and mealy bug infections are paramount important for sustainable papaya cultivation.

By identifying these pests in early-stage farmers can make control measures preventing spreading and create extensive damage for papaya crops. Early intervention allows for the use of less expensive and traditional pest control methods, reducing the relying on chemical pesticides and promoting integrated pest management practices while protecting quality of the fruit.

In papaya plants, mite and mealy bug infestation causes major problems so we have a solution to that by making a mobile application using Flutter (Mobile App Development) with the DenseNet Convolutional Neural Network (CNN). It has the smoothest and most intuitive user experience. The app is user-friendly for farmers and growers to take a snap of their plant and get feedback in real-time on the identification of pests. The proposed line of action aims to make it easier for farmers and papaya growers not specializing in entomology, management systems that allow the proper diagnosis of infestations without needing some expertise.

The app comes complete with a searchable database of treatments for mites and mealy bug, both control/preventative measures and cures.

#### **1.4.4 Papaya Maturity Level Detection**

In the context of papaya cultivation, accurate determination of the fruit's maturity level is crucial for optimizing yield, minimizing post-harvest losses, and ensuring marketable quality. Traditional methods, such as visual inspection and experience- based judgment, are often unreliable, leading to frequent issues with harvesting papayas that are either underripe or overripe. Figure 6 has clearly

demonstrated how farmers assess the maturity level of papaya fruits.

23.How do you currently determine the optimal time for harvesting papaya fruit?(මම දැනට පැපොල් ගෙඩි අස්වැන්න සඳහා ප්‍රශස්ත කාලය තීරණය කරන්නේ කෙසේද?)  
9 responses

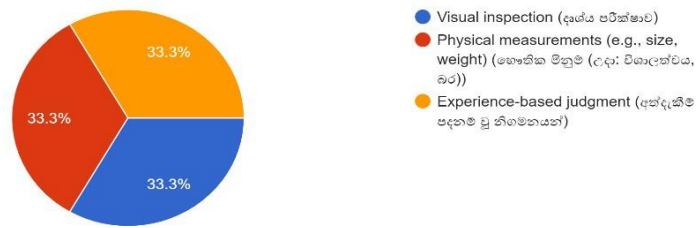


Figure 5 - method of maturity level asses

At the same time, according to Figure 7 and Figure 8, we can understand the impact of harvest timing on yield and quality. These inaccuracies in maturity assessment not only affect the overall yield but also significantly impact the revenue and marketability of papayas. The lack of precise measurement tools and inconsistent visual indicators further complicate the process, making it challenging for farmers to determine the optimal time for harvesting.

25.How significant is the impact of harvesting papayas at the wrong maturity level on your overall yield? (වැරදි පරිණත මට්ටමකින් ගස්ලබු අස්වැන්න මගේ සමස්ත අස්වැන්නට කෙතරම් බලපානවාද?)

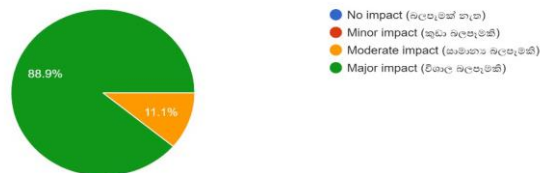


Figure 6 - Impact of harvest timing on yield

26.To what extent do post-harvest losses (due to incorrect ripeness) affect your revenue or marketability of papayas? (පසු අස්වනු අලාභ (වැර...ල මගේ ආදායමට හෝ අලෙවියට කොතරම් දුරට බලපාන්නේද?)

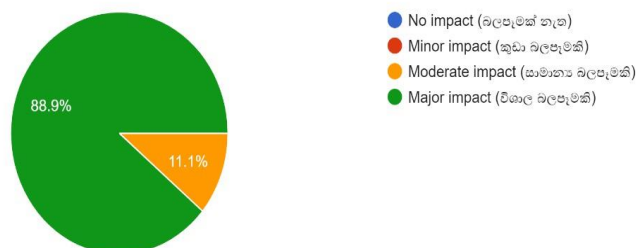


Figure 7 - Impact of harvest timing on quality

Given the importance of correct maturity assessment in enhancing the profitability and sustainability of papaya cultivation as mentioned Figure 9, there is a pressing need for an advanced technological solution that can accurately detect the maturity level of papaya fruits. This research aims to address the problem by developing a deep learning-based system capable of reliably classifying papaya maturity levels. The proposed system will help farmers make informed harvesting decisions, reduce post-harvest losses, and ultimately increase the marketable yield of papayas, thereby contributing to the economic viability of papaya farming.

29. Do you believe that improving the accuracy of harvesting based on maturity level could significantly enhance the profitability and sustainability of papaya farming? (කුඩා ප්‍රමාණයෙන් ඉහළ නැංවිය හැකි බව ඔබ විශ්වාස කරනවාද?)

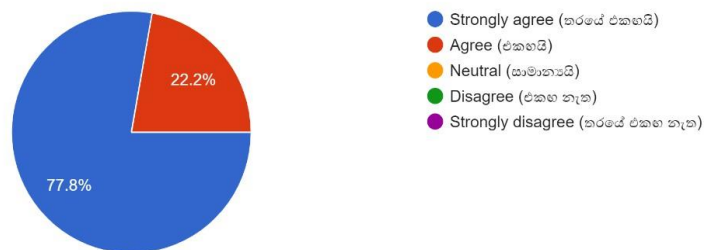


Figure 8 - Importance of correct maturity assessment in enhancing profitability and sustainability

## **1.5 Research Problem**

### **1.5.1 Identification of Cercospora and Mosaic Virus**

#### **1.5.1.1 Main Objective**

To develop a mobile application that utilizes advanced machine learning techniques for accurate detection and management of Papaya mosaic virus and Cercospora leaf spot, offering tailored remedy suggestions to enhance disease management and improve crop productivity for papaya farmers in Sri Lanka.

##### **1.5.1.1.1 Specific Objectives**

Develop and Implement Machine Learning Models:

- **EfficientNet Integration:** Implement EfficientNet for binary classification to distinguish between healthy and diseased papaya leaves.
- **Vision Transformers Integration:** Integrate Vision Transformers to provide detailed disease identification by detecting subtle disease signs and patterns.

Collect and Prepare Dataset:

- **Image Collection:** Gather a diverse dataset of papaya leaf images, including both healthy and diseased leaves, for training and validation.
- **Data Annotation and Augmentation:** Accurately label the images and apply data augmentation techniques to enhance model performance and robustness.

Design and Develop Remedy Suggestion System:

- **Create Remedy Database:** Develop a comprehensive database of remedies for Papaya mosaic virus and Cercospora leaf spot, including preventive measures and treatments.

- **Implement Tailored Suggestions:** Integrate algorithms to provide customized remedy recommendations based on the severity and progression of the detected disease.

**Build and Optimize Mobile Application:**

- **User Interface Design:** Develop an intuitive and user-friendly interface to ensure ease of use for farmers.
- **Backend Integration:** Ensure seamless integration of the machine learning models and remedy database with the application's backend.

**Conduct Field Testing and Evaluation:**

- **Pilot Testing:** Test the application with farmers in real-world conditions to assess its effectiveness and gather feedback.
- **Performance Assessment:** Evaluate the accuracy of disease detection, relevance of remedy suggestions, and overall user satisfaction to make necessary improvements.

## **1.5.2 Identification and Classification of Papaya Ring Spot Virus and Powdery Mildew**

### **1.5.2.1 Main objective**

To develop a comprehensive disease detection and management system for papaya fruits, with a specific focus on the PRSV and Powdery Mildew, by utilizing the YOLOv5 model, and to carry out this system using a mobile application an integrated automated remedy suggestion.

#### **1.5.2.1.1 Specific Objectives**

Design a user-friendly Mobile interface.

- Create an intuitive layout for mobile application that facilitates easy navigation for farmers and end-users.
- Provide clear guidelines on how to take quality images for diseases detection purposes.
- Incorporate user feedback mechanisms like visual indicators (loading bars or checkmarks) confirming successful image submission.
- Display immediate results on screen indicating whether papaya fruit is healthy or



infected and what disease it has been found with.

#### Construction of extensive Image Processing Pipeline

- Employ noise reduction strategies that would get rid of background disturbances from captured images.
- Use contrast and brightness adjustments in such a way that will make it easier for one to symptoms of diseases.
- Generate different type of training datasets through invention of image augmentation methods (eg: rotation, scaling up and down, flipping).
- Make sure there is standardization of all input images dimension and resolution before feeding them in to YOLOv5 model.

#### Integrate YOLOv5 for Real-Time disease detection

- Shrink the YOLOv5 model to smaller size so that it can be used in mobile deployment and enhance the speed of inferring it.
- Train the YOLOv5 model specifically for detecting PRSV and Powdery Mildew using well annotated dataset.
- Achieve real-time image processing capabilities, making the model capable of analyzing images as soon as they captured.
- Invent a a method to show detection results using both bounding boxes around affected areas and the labels indicating the type of disease.

#### Incorporate a Remedy suggestion module

- Develop a database of remedies that include both PRSC and Powdery Mildew, prepared by reputable sources and agricultural guidelines.
- Develop an algorithm that, upon the identification of the disease, will match the most suitable remedies based on the area oof the infection.
- Design a user-friendly interface that show the remedies in a a clear and actionable format, with options for more detailed diagnosis information.
- Users will also be able to get customized recommendations by considering other additional factors like weather conditions.

#### Implement Real-Time notifications and updates

- Design a notice system that informs the user of disease detection outcome and requires action.

- Real-time update of the user on the status of the detection process, including confirmation of successful image analysis
- Send reminders to users to monitor their crops regularly and add new images if necessary.

Evaluate and Validate system performance

- Subject the disease detection system to rigorous field trials involving actual farmers, testing its accuracy and reliability.
- Gather data with regard to the accuracy of detection, false positive/negative instances and user satisfaction during the field trials.
- Improve the model and application from the results of the field trials by iterating on the system.

### **1.5.3 Mite Disease and Mealy Bug Disease Identification and Suggest the Remedy**

#### **1.5.3.1 Main Objectives**

The main objective of this study is to develop a mobile application that help papaya growers to identify Mealy and Mite Pest with the progression level of pest infection. Stockholder will take the picture of the pest infection using the device that installed papaya buddy App or can upload from pest infested papaya leaf or fruit from gallery, the application will analyze the extent of the infection and classify it into different progression levels (e.g., mild, moderate, severe). An Advances deep learning neural network will identify the infection and progression level of the infection.

##### **1.5.3.1.1 Specific Objectives**

Identify Mite and Mealy bug Successfully with the image whenever infected papaya tree found

- Train a deep learning modal on a diverse dataset of images showing Mite and Mealy bug infections
- Apply Preprocessing techniques for images to enhance and ensure accuracy of the modal
- Develop an intuitive interface for users to capture images of infected papaya and leaves or upload exiting image from the gallery

Data Visualization and of the infected areas and predict the progression level of pest

infection

- Develop a visualization module to display infected areas on a heatmap, highlighting the severity levels distribution of infestations.

Provide customized remedies and mitigation plans

- Classify the infection into categories such as mild, moderate, and severe, based on predefined criteria.
- Include organic and chemical treatment options, considering environmental and health impacts.
- Create a comprehensive database of remedies and mitigation plans tailored to each severity level and type of pest.

## **1.5.4 Papaya Maturity Level Detection**

### **1.5.4.1 Main Objective**

The main objective of this study is to develop a deep learning-based mobile application capable of accurately detecting the maturity level of papaya fruits. By leveraging Mobilenet and a well-structured data set, the system aims to classify papayas into unripe, partially ripe, ripe, and rotten categories. This classification will assist farmers in making informed decisions on the optimal harvest time, thereby reducing post-harvest losses, minimizing waste, and maximizing yield of marketable produce. The ultimate goal is to enhance the efficiency and profitability of papaya cultivation in Sri Lanka by providing a reliable and non-destructive method for assessing fruit maturity.

#### **1.5.4.1.1 Specific Objectives**

To achieve the overall objective of accurately detecting the maturity level of papaya fruits, the following specific objectives must be met,

Develop a MobileNet-based classification model for papaya maturity levels.

- Implement MobileNet, a lightweight deep learning model, to classify papaya fruits into four categories: unripe, partially ripe, ripe and rotten. The model will be trained on a dataset, evenly distributed across the four categories.

Enhance model accuracy and robustness

- Implement techniques such as data augmentation, transfer learning, and hyperparameter tuning to optimize the model's accuracy and robustness. The goal is to achieve a classification accuracy that surpasses traditional machine learning approaches and reliably predicts maturity levels in real-world conditions.

Compare MobileNet with other deep learning models found in another research.

- Conduct a comparative analysis of MobileNet with other deep learning models, such as ResNet, VGGNet, and AlexNet to evaluate performance in terms of accuracy, computational efficiency, and suitability for development in resource-constrained environments.

Evaluate the impact of accurate maturity detection on post-harvest losses.

- Perform a field study to assess the effectiveness of the MobileNet-based model in reducing post-harvest losses. This will involve monitoring the harvesting process and comparing the yield of marketable produce before and after the implementation of the model-based maturity detection system.

## **2 Methodology**

### **2.1 Project Overview**

The PapayaBuddy system is built for the optimized cultivation of papaya through advanced detection, pest management and fruit maturity assessment. This work starts with detecting and classifying Cercospora and Mosaic Virus in papaya leaves using EfficientNet and Vision Transformers. These models have been very proficient at detecting and classifying diseases with minute variations in the apparent features of the leaves, hence providing a reliable and accurate diagnosis.

On top of that, PapayaBuddy identifies and classifies PRSV and powdery Mildew of the papaya fruits using the custom CNN model. Being one of the most accurate models, CNN classify the images to identify fruit diseases, hence, it is very applicable in scenarios farmers need immediate feedback on the health status of their crops.

For pest management, PapayaBuddy uses DenseNet in identifying and classifying Mealy bug and Mite infestation on papaya. It is through this efficient re-use of features across layers that the prowess of DenseNet in detecting, these pests have been derived to ensure that their infestation is detected early and accurately for timely and effective intervention.

Besides being diseases and pest management, PapayaBuddy is also equipped with papaya fruit maturity level detection and classification using MobileNet. This lightweight, powerful deep learning model has been particularly optimized for mobile devices, which can let farmers check fruits for their ripeness and schedule harvest periods when they are of the best quality and their value in the market is also the highest.

Inclusively, it integrates a Remedy Suggestion System that gives treatment recommendations for diseases and identified pests, thus offering further support to farmers. These remedies are based not only on the identified disease or pest but also on current weather conditions, by leveraging real-time weather data using OpenWeatherAPI, PapayaBuddy is ensuring that recommended treatments are perfect for effectiveness with regard to such environmental parameters as temperature, humidity and rainfall, which in so many cases significantly influence the success of certain remedies. This system has a remote MongoDB database that ensures all data is stored securely and is retrieved whenever necessary for enhancing the decision-making process. Microsoft Azure is used for cloud-related activities and provides scalability with reliability through efficient management of data.

The mobile application offers intuitive and customizable UI, hence usable by a wide range of users independent of their technical expertise, making it developed in Flutter-based mobile applications. Bringing these advanced technologies together, PapayaBuddy is the holistic solution that will put at farmers' fingertips the tools necessary for the effective management of diseases, pests and fruit maturity in real-time, hence more sustainable, and profitable cultivation of papaya. Figure 2 offers the graphical representation of the system showcasing the intricate interplay between its various components to deliver holisting disease, pest management of papaya and fruit maturity recognition.

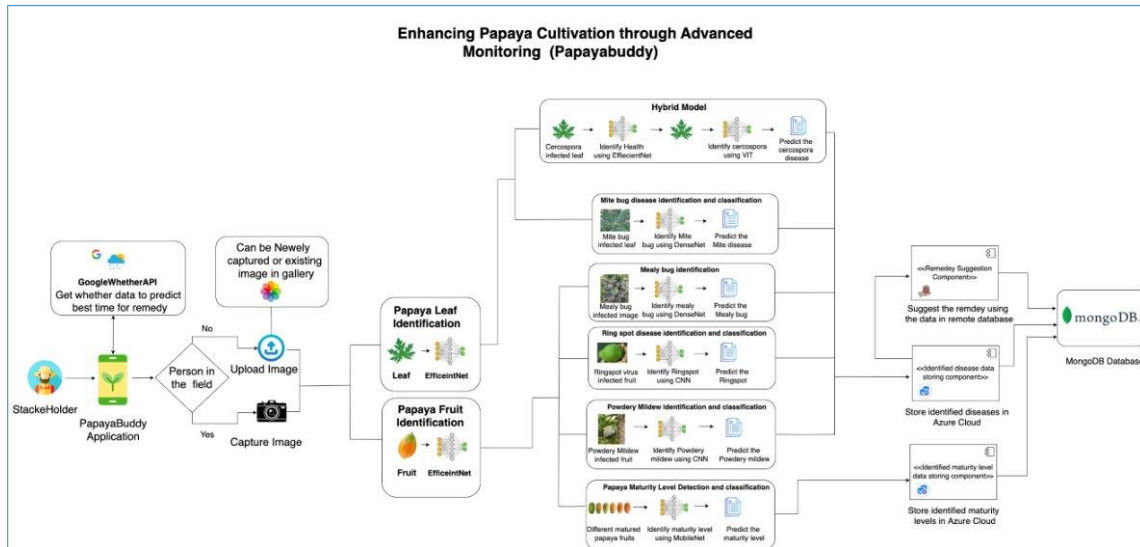


Figure 9 - Overall System Diagram

## 2.2 Individual Components

### 2.2.1 Identification Of Cercospora and Mosaic Virus.

#### 2.2.1.1 Data Collection

The PapayaBuddy Application represents a significant advancement in papaya disease detection and management. By integrating a cascaded AI-powered classification system and cloud storage, the system provides farmers with a comprehensive and reliable tool to safeguard their crops. This innovative approach to disease detection not only enhances agricultural productivity but also supports sustainable farming practices, ensuring the long-term health and viability of papaya cultivation.

To build a DL model capable of detecting Cercospora Virus, Mosaic Virus, and healthy papaya leaves, an extensive dataset of images was manually collected using mobile phones. The data collection process was conducted under varying environmental conditions, including differences in natural light exposure, shadow effects, and background variations. This approach ensured that the dataset encompassed a diverse range of real-world scenarios, enhancing the

robustness and generalizability of the model.

The collection process took place at Diwulapitiya Papaya Farm and the Horana Fruit Research Centre, two prominent locations known for their papaya cultivation and agricultural research. These sites were specifically chosen to capture a wide range of infected and healthy papaya leaves under different growing conditions. At both locations, research officers from the Horana Fruit Research Centre played a crucial role in verifying and authenticating the disease status of the leaves. Their expert validation ensured that the collected dataset accurately represented genuine cases of Cercospora Leaf Spot and Mosaic Virus infections, reducing the risk of misclassification due to human error.

The final dataset comprises a total of 1,018 images, systematically categorized into three distinct classes to facilitate supervised deep learning model training. The dataset includes 339 images of healthy papaya leaves, 429 images of Cercospora-infected leaves, and 250 images of Mosaic Virus-infected leaves. This class distribution reflects the natural prevalence of these diseases in papaya farms, ensuring that the model is exposed to a representative sample of real-world disease conditions.

A key consideration during data collection was to capture images under different angles, distances, and lighting conditions. This approach helps the model generalize better by learning to detect disease patterns regardless of variations in leaf orientation or environmental settings. Additionally, efforts were made to include leaves from different stages of infection, ranging from early symptoms to severe disease progression. This ensures that the model can detect infections in their early stages, enabling farmers to take proactive measures before the disease spreads further.

By constructing a verified dataset, this research establishes a strong foundation for training a highly accurate deep learning model for papaya leaf disease detection. The dataset will be used to train a cascaded model combining EfficientNet and ViT, allowing for precise classification and disease identification. With the inclusion of real-world variability and expert-verified disease annotations, the model is expected to deliver high reliability and accuracy in identifying Cercospora and Mosaic Virus infections, ultimately benefiting papaya farmers by enabling early detection and effective disease management.

#### **2.2.1.2 Dataset Preprocessing**

To optimize the performance of the deep learning model while minimizing overfitting, several data augmentation and preprocessing techniques were employed. These techniques were carefully selected to enhance the model's ability to generalize to new, unseen data by introducing variations in the training dataset while preserving the key features essential for

disease classification.

One of the primary augmentation techniques applied was random resized cropping, which helped to emphasize different regions of the papaya leaf. This approach ensures that the model does not become overly reliant on specific portions of the image but instead learns to recognize disease patterns across the entire leaf. The cropping was performed at different scales, ensuring that key disease markers remained in focus while varying the positioning of the leaf within the frame.

Additionally, a horizontal flip with a probability of 5% was applied to introduce further variability. Since papaya leaves do not exhibit significant asymmetry, flipping the images horizontally helps the model learn disease patterns without being biased toward a particular orientation. This ensures that the trained model can accurately classify leaves regardless of their positioning during real-world image capture.

To account for slight variations in the way leaves are positioned and photographed, small rotational transformations within a range of  $\pm 5^\circ$  were introduced. This helps the model become more robust against small angular changes, which are common when images are captured in natural settings. The minor rotations help simulate real-world conditions where farmers might capture images from slightly different angles, ensuring that the model can still identify diseases accurately.

In addition to geometric transformations, color jittering was applied to modify image brightness, contrast, and hue. This technique is particularly useful for ensuring that the model is not overly sensitive to lighting conditions. By varying brightness levels, the model learns to detect disease features under different lighting intensities, whether the images are taken in bright sunlight or under cloudy conditions. Adjusting contrast and hue helps the model become resilient to minor color differences that might arise due to variations in mobile camera settings or environmental factors.

After applying these augmentation techniques, image normalization was performed. Each image was normalized using the standard mean and standard deviation, a common practice in deep learning models trained on image data. Normalization ensures that pixel values are scaled consistently across all images, reducing discrepancies that could arise due to variations in camera exposure and image capture settings. This step helps the model focus on meaningful disease patterns rather than being influenced by absolute color or intensity values.

To maintain uniformity in model input size, all images were resized to 224×224 pixels. This resizing ensures compatibility with the model architecture, particularly with EfficientNet and ViT, which expect input images of a fixed dimension. By standardizing the image



dimensions, the model processes all images in a consistent manner, improving computational efficiency and training stability.

Finally, the dataset was split into 80% training data and 20% test data to facilitate effective model training and evaluation. The training set was used to optimize the model's parameters, while the test set was kept separate to assess the model's performance on unseen data. This train-test split strategy ensures that the model is not evaluated on the same data it has learned from, providing an accurate measure of its generalization ability.

By implementing these comprehensive data augmentation and preprocessing strategies, the model is expected to achieve higher accuracy and robustness in detecting Cercospora Virus, Mosaic Virus, and healthy papaya leaves. These techniques help simulate real-world variations, ensuring that the model remains effective when deployed in diverse field conditions where image quality and environmental factors vary.

### 2.2.1.3 Model Development, Training, and Evaluation

A cascaded DL approach was employed to accurately classify papaya leaf diseases, leveraging the strengths of both CNNs and transformer-based architectures. The approach integrated EfficientNet-B0 and ViT models, ensuring both efficiency and high accuracy in disease detection.

In the first stage, the EfficientNet-B0 model was utilized as a binary classifier to distinguish between healthy and unhealthy papaya leaves. EfficientNet-B0 is a widely used lightweight CNN architecture known for its superior performance and computational efficiency. It employs compound scaling, which balances model depth, width, and resolution, making it well-suited for mobile-based applications. The model was trained to identify whether a given papaya leaf exhibited signs of disease, effectively filtering out healthy leaves before proceeding to further classification.

If the EfficientNet-B0 model detected a leaf as unhealthy, it triggered the second stage of the classification process, where the ViT model was used to identify the specific disease. The Google/Vit-Base-Patch16-224 model was selected due to its ability to capture long-range dependencies and complex patterns in image data. Unlike CNNs, which focus on local feature extraction, ViTs process images as sequences of patches, making them particularly effective for fine-grained classification tasks. The ViT model classified the diseased leaves into two categories: Cercospora Virus and Mosaic Virus.

To ensure robust performance, both models were carefully trained using optimized hyperparameters and regularization techniques to prevent overfitting. The EfficientNetV2B0 model was trained for more than 14 epochs, leveraging the Adam optimizer with a learning rate of 0.001. The cross-entropy loss function was employed to measure classification errors, ensuring efficient weight updates during training. The Adam optimizer, known for its adaptive learning rate capabilities, helped maintain stable convergence, leading to improved accuracy while minimizing training instability.

For the Vision Transformer model, training was conducted over more than 5 epochs using the AdamW optimizer. Unlike standard Adam, AdamW applies decoupled weight decay regularization, which helps prevent overfitting by penalizing large weight updates. This optimization strategy is particularly beneficial for transformer-based models, as it improves generalization without significantly affecting training efficiency.

By employing this cascaded two-stage classification approach, the system enhances diagnostic accuracy while maintaining computational<sup>39</sup> efficiency. The initial EfficientNet binary classification ensures that only diseased leaves undergo further analysis, reducing unnecessary

computations. Meanwhile, the Vision Transformer effectively differentiates between Cercospora Virus and Mosaic Virus, making the model highly reliable for real-world applications.

This integrated deep learning framework, combining CNN and transformer-based architectures in a conditional pipeline, significantly improves the robustness and scalability of papaya disease detection. The system ultimately provides farmers with an intelligent, mobile-based diagnostic tool for early disease identification and intervention.

**2.2.1.4 Test plan & Test Strategy**

To determine the project's progress and ensure the software's effectiveness, test planning is necessary to create a baseline plan that outlines tasks, scope, and objectives. It acts as a manual for carrying out the necessary testing. The test strategy is a set of actions and processes that determines what needs to be tested and ranks the functions according to their significance and potential dangers to users. Test cases were written in accordance with the use cases that were provided, carried out by hand, and the outcomes were noted.

**2.2.1.5 Steps and procedures in test strategy**

- Define the items to be tested
- Select the functions based on the importance and risk on user
- Design test cases as identified by the use case description.
- Execute
- Record Results
- Identify Bugs
- Correct Bugs
- Repeat the test case until the expected results meet

**2.2.1.6 Test case design**

To make sure the models operated as intended, tests were conducted. To verify the model's performance, the following test cases were run.

*Table 5 - Verify Image Upload*

Test Case Id	01
Test Case	Verify Image Upload
Test Scenario	Verify whether the captured image is stored on Cloudinary 40

Precondition	Users should have login to the system
Input	Captured disease infected image
Expected Output	<ul style="list-style-type: none"> <li>• 200 status code should be displayed</li> <li>• The image must be stored in Cloudinary</li> </ul>
Actual Result	<ul style="list-style-type: none"> <li>• 200 status code should be displayed</li> <li>• The image must be stored in Cloudinary</li> </ul>
Status (Pass/ Fail)	Pass

*Table 6 - Classification of Mosaic Virus using Cascaded Model*

Test Case Id	02
Test Case	Classification of Mosaic Virus using Cascaded Model
Precondition	Users should have login to the system
Test Scenario	Testing images to classify Mosaic Virus on papaya leaf
Input	Image of leaf infected with Mosaic Virus
Expected Output	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>
Actual Result	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>
Status (Pass/ Fail)	Pass

*Table 7 - Classification of Cercospora Virus using Cascaded Model*

Test Case Id	03
--------------	----

Test Case	Classification of Cercospora using Cascaded Model
Test Scenario	Testing images to classify Cercospora on papaya leaf
Precondition	Users should have login to the system
Input	Cercospora disease infected leaf.
Expected Output	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>
Actual Result	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>
Status (Pass/ Fail)	Pass

*Table 8 - Classification of Healthy Leaf using Cascaded Model*

Test Case Id	04
Test Case	Classification of Healthy leaf using Cascaded Model
Test Scenario	Testing images to classify Healthy papaya leaf
Precondition	Users should have login to the system
Input	Image of Healthy papaya leaf
Expected Output	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>

Actual Result	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>
Status (Pass/ Fail)	Pass

Table 9 - Show the Treatment instruction related to Specific Disease or Healthy Leaf

Test Case Id	05
Test Case	Show the Treatment instruction Related to Specific Disease or Healthy leaf
Test Scenario	Show Organic and Chemical Treatment instructions
Precondition	Users should have login to the system
Input	Fruit image infected with Mosaic or Cercospora disease
Expected Output	<ul style="list-style-type: none"> <li>• Recommendations to keep the plant healthy</li> </ul>
Actual Result	<ul style="list-style-type: none"> <li>• Show correct treatment instruction related to disease</li> <li>• Show Chemical and Organic methods along with</li> </ul>
Status (Pass/ Fail)	Pass

### **2.2.2 Identification of Ringspot Virus, Powdery Mildew and Healthiness of Papaya Fruit.**

Identification and Classification of Papaya Ring Spot Virus and Powdery Mildew and Healthy Fruit.

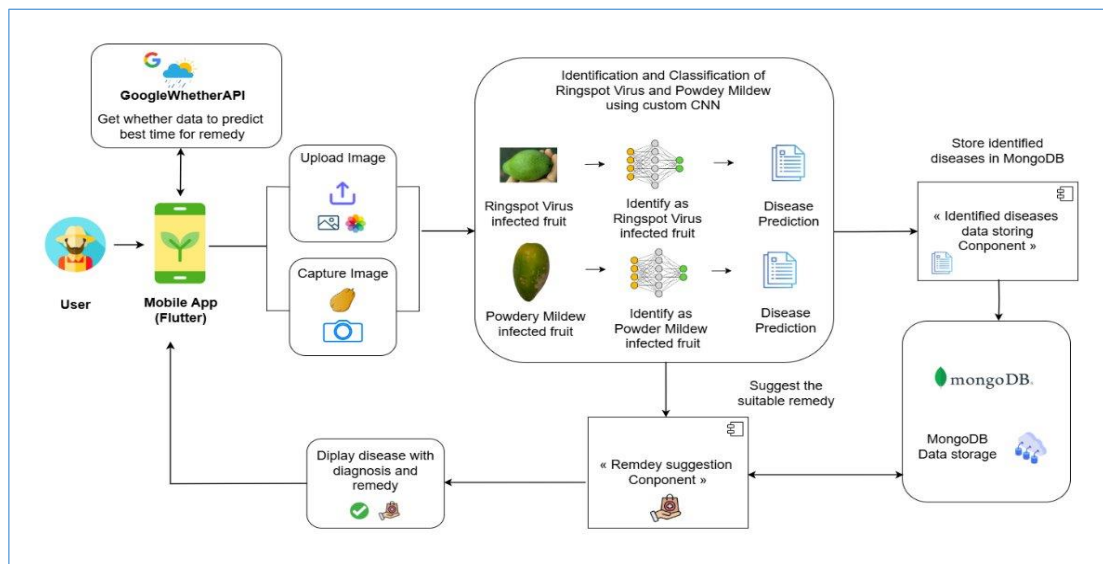
The development of the proposed system component to identify and differentiate PRSV, Powdery Mildew and Healthy papaya fruits using identification and classification techniques, which not only incorporates different advanced technologies but also assures higher accuracy and real time performance. At the core of this system is custom CNN, a state-of-the-art classification model known for both its speed and accuracy. Image processing through CNN for symptoms of PRSV and Powdery Mildew is done to provide immediate feedback, which is critical in the effective management of crop health. The process begins by collecting a dataset of images of papaya fruits images, including both healthy and diseased samples. When developing the DL model and implementing Image Processing tasks python is introduced. With its robust libraries, Python has supported the very complex algorithms required for the training and evaluation of the CNN model. Realizing normalization of images through Tenserflowand Keras are incorporated as pre-processing for images before feeding them into the model, keeping the format of the input to the model correct. This pre-processing stage execution is critical to maintaining consistency and improving model accuracy. For this proposed system, mobile applications will be developed using Flutter to enable it to run on Android and iOS devices while still integrating it with the custom CNN model. The model in the mobile application also uses Flutter for development because of its ability to enable the high-performance functioning of cross-platform applications.

The developed mobile applications allow users to capture or upload images of papaya fruits. The version control coordination for the project is done by Git, GitHub Projects to perform continuous integration and deployment. This ensures any change in the model or code is tested and integrated properly to maintain the quality of the system. Fast API is the backend server that accepts requests from the mobile application and passes them on the custom CNN model. It processes the upload of an image and gives the results in real-time.

The image data and disease information are stored within MongoDB, allowing flexible storage and scalability. It can deal with large datasets and evolving data, like in the case of image data and disease information. Accompanying this remedy suggestion system, which provides specific intervention suggestions for disease conditions in correlation with current weather conditions. OpenWeatherAPI provides actual weather data in real time, which is basically adjusted during recommendations, then the user gets advice on the control and

management of papaya diseases that are accurate and up to date. The self-evaluation plan sets in place the performance assessment of each employed technology. The accuracy of CNN is measured in metrics like precision, recall, and mean average precision. It also evaluates the effectiveness of the Python, Tensorflow, Keras and Fast API in processing and serving image data. significant advancement in the agriculture sector, offering a technically validated approach that blends cutting-edge technology with user-centered design.

Next, the performance of Flutter's UI over all devices is scrutinized, and MongoDB for the management of data with highly scalable setup. Git, GitHub and GitHub Projects ensure smooth development and deployment processes. Taking account of that, the project will deliver a robust, effective tool for the management of papaya diseases like PRSV and Powdery Mildew by critical evaluation of these technologies, refining the system constantly based on real world-performance and user feedback in order to contribute to agriculture has more sustainable and profitable agricultural practices. Figure 3 provides a graphical overview of the system, illustrating the how each component interacts to create a comprehensive and effective disease identification solution. The design and implementation of this system represent significant advancement in the agriculture sector, offering a technically validated approach that blends cutting-edge technology with user-centered design.





### 2.2.2.1 Testing & Implementation

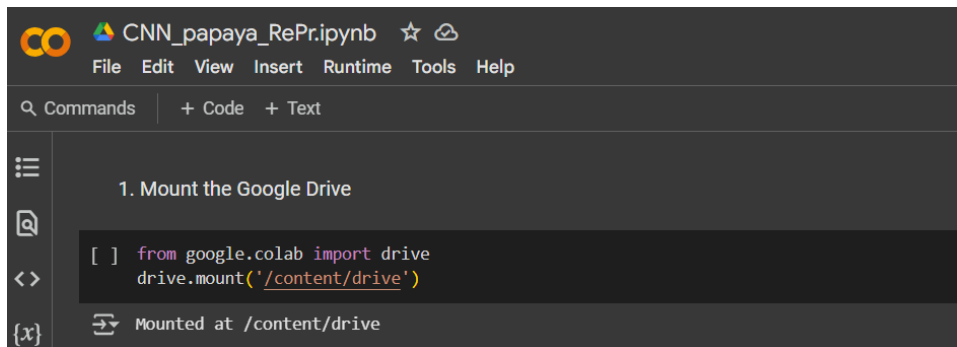
#### 2.2.2.1.1 Implementation

PapayaBuddy is a modern-day mobile application solution that provides image processing-based solutions to key stakeholders like gardeners, farmers, and researchers to identify papaya fruit, leaf, and pest-based diseases and identify the maturity level of papaya fruits based on their color to predict the best harvesting time. Using this application, stakeholders can identify several fruit diseases like Papaya Ring Spot Virus, Powdery Mildew, leaf diseases like Mosaic Virus and Cercospora, papaya crop bugs like Mite and Mealey, and maturity levels like Not Mature, Partially Mature, Mature, and Rotten. The mobile application was developed using Flutter, and the backend application was developed using various technologies like Python for Fast API integration, Node JS as the static data-storing storage, and Firebase was utilized for user management and authentication. Also, Kong API Gateway and Docker are used to handle prediction services because several models were trained using different versions of Python, TensorFlow, and NumPy-like packages. To handle remedies, prediction history, treatments, maturity level-related data, disease data, and suggested images, the MongoDB database was utilized as the main database. For the suggested images, they were pre-uploaded to Cloudinary, and the URLs of the images were stored along with the MongoDB collection. Also, the implemented models were trained using Google Colab along with the Google Drive and Jupyter Notebook. Google Colab provides high GPU memory along with High Ram to speed up the training process. For that premium version of it is used for faster results.

#### 2.2.2.1.2 Data Pre-processing

For the custom CNN model a comprehensive data pipeline was created. The data set consisted with 1500 images, which is a balacned data set, each containing 500 images for the 3 classes (Ring spot Virus, Powdery Mildew and Healthy fruit). Data set collected from FRID and Diwulapitiya area local farms using mobile phones, Then collected data set was contained differenet sizes, dimensions of images, then before feeding it to the model needed to resize all the images in to similar size which was suitable for the custom CNN model training. To train, validate and test the dataset, it was uploaded to Google Drive, then which is possible to interact with Google Colab for model training.

The uploaded data set was accessed from the Google Colab to process the model training. In the Figure 4 and Figure 5 showing the process of accessing the Google Drive data set and perparation of the data set for model training.



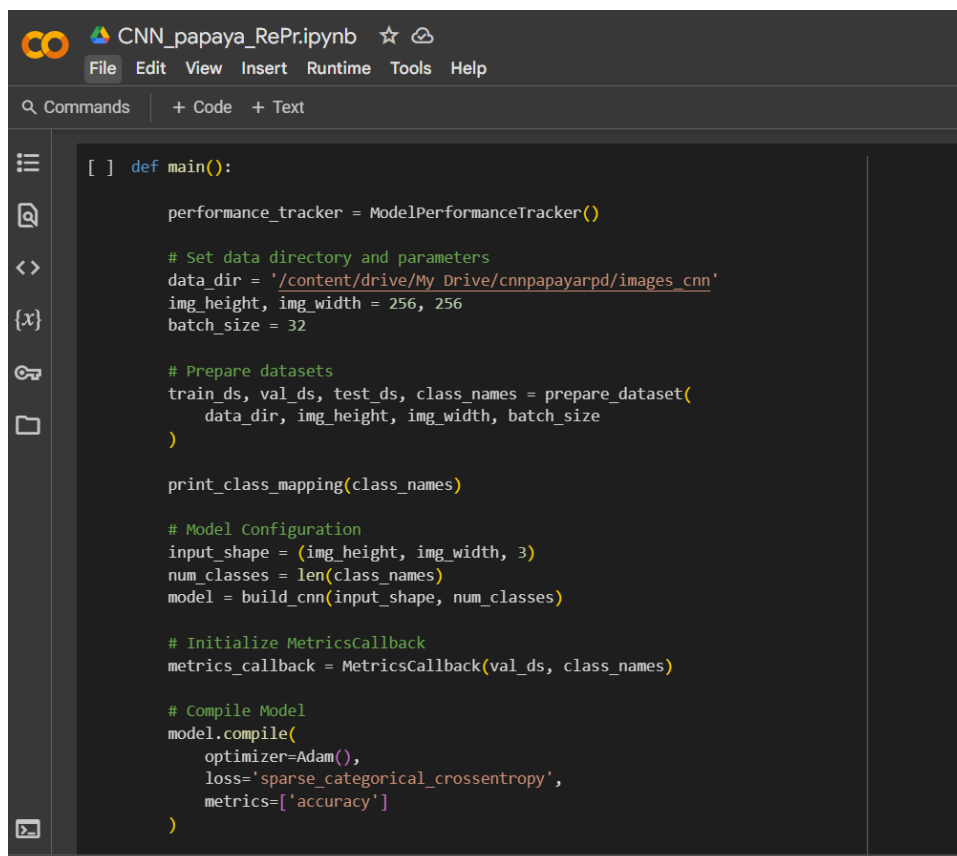
The screenshot shows the Google Colab interface for a notebook titled 'CNN\_papaya\_RePr.ipynb'. The menu bar includes File, Edit, View, Insert, Runtime, Tools, and Help. Below the menu, there are tabs for 'Commands', '+ Code', and '+ Text'. The left sidebar contains icons for file explorer, search, and other functions. The main code area displays the following code:

```
1. Mount the Google Drive

[ ] from google.colab import drive
    drive.mount('/content/drive')
```

Below the code, a status bar indicates 'Mounted at /content/drive'.

Figure 10 - Access the Google Drive data set



The screenshot shows the same Google Colab interface as Figure 10, but with a different code block. The code defines a 'main' function that sets up the data directory, prepares datasets, prints class mappings, configures the model, initializes metrics, and compiles the model.

```
[ ] def main():

    performance_tracker = ModelPerformanceTracker()

    # Set data directory and parameters
    data_dir = '/content/drive/My Drive/cnnpapayarpd/images_cnn'
    img_height, img_width = 256, 256
    batch_size = 32

    # Prepare datasets
    train_ds, val_ds, test_ds, class_names = prepare_dataset(
        data_dir, img_height, img_width, batch_size
    )

    print_class_mapping(class_names)

    # Model Configuration
    input_shape = (img_height, img_width, 3)
    num_classes = len(class_names)
    model = build_cnn(input_shape, num_classes)

    # Initialize MetricsCallback
    metrics_callback = MetricsCallback(val_ds, class_names)

    # Compile Model
    model.compile(
        optimizer=Adam(),
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy']
    )
```

Figure 11 -. Define the Google Drive data set

For the purpose of data set preparation above Figure 6 code was used. It includes defining the size of the images wanted to feed the model. It was set to 256 x 256, which is suitable for this specific scenario. This size maintains a good level of spatial detail while keeping network size manageable. Also, this will provide a good balance between capturing sufficient image detail and keeping the computational cost of training and inference manageable.

The function starts by using `tf.keras.utils.image_dataset_from_directory()` to load the photos from a directory into a dataset. The program automatically resizes all photos to a standard 256x256 pixel size and names them based on how they are stored in folders. In order to prevent the model from learning patterns based on image order, the dataset is shuffled to create unpredictability. To make it reproducible, a fixed seed value of 42 is employed. In order to provide additional control over data processing, the batch size is set to None, enabling manual batching downstream in the pipeline.

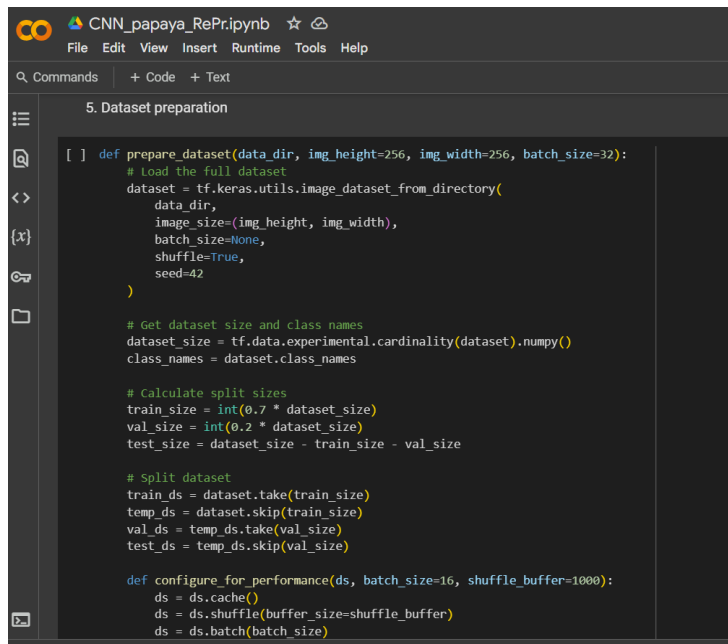
The dataset is divided into training, validation, and test sets after it has been loaded. The number of accessible samples is retrieved by `tf.data.experimental.cardinality()`, which first determines the size of the entire dataset. After then, 70% of the dataset is used for training, 20% for validation, and 10% for testing. The number of samples needed for each subset is obtained using the `take()` method, and samples assigned to one subset are excluded so that they can be used by another subset using the `skip()` method. For effective model evaluation, the procedure aids in achieving well-organized dataset division.

Each subset of a dataset is subjected to the `configure_for_performance()` technique in order to improve performance. In order to greatly increase training speed, this process first caches the dataset using `ds.cache()`, which permits images to be loaded into memory and avoids repeated access to disk storage. To stop the model from learning any sequence-based dependencies, it then uses `ds.shuffle(buffer_size=1000)` to shuffle the dataset, ensuring that each batch contains samples in a randomly ordered fashion. After that, the data is batched using `ds.batch(batch_size)`, which processes a collection of photos and combines them to increase training calculation performance. In order to prevent idle time and to increase training performance, `ds.prefetch(buffer_size=tf.data.AUTOTUNE)` is finally utilized to buffer the subsequent batch of data while the current one is being processed.

To increase model accuracy, the pictures are pre-normalized. Using `tf.cast(image, tf.float32) / 255`, the `normalize_img()` function normalizes all images from their initial pixel value range of [0,255] to [0, 1]. By ensuring that the model receives consistent input values, normalization helps to accelerate convergence by removing potential problems caused by fluctuations in pixel intensity. To guarantee that every image receives identical preparation before to use during training, the function is applied to all dataset subsets using `.map()`.

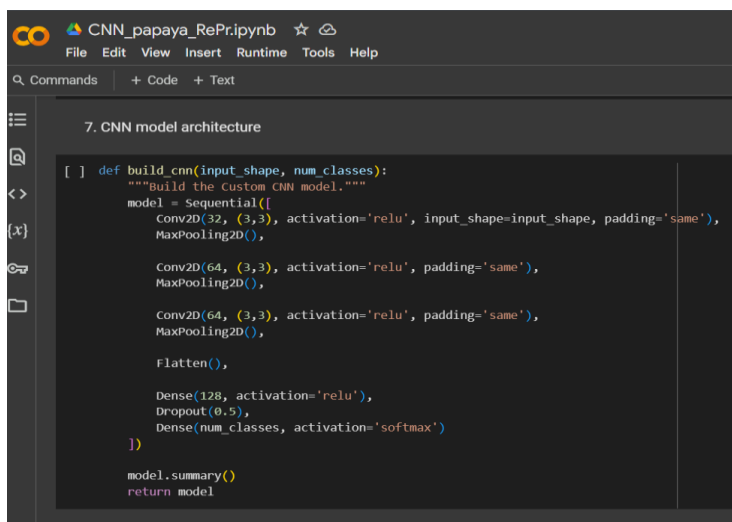
Figure 6 and Figure 7 demonstrate the data set preparation for the custom CNN model training. The function returns the class names from the dataset directory together with the completely processed dataset subsets (training, validation, and test). To verify that the data has been properly divided and processed, the sizes of each dataset subset are also reported. This is

to guarantee that the pipeline is functioning properly and that the model is trained on a dataset that is suitably balanced.



```
[ ] def prepare_dataset(data_dir, img_height=256, img_width=256, batch_size=32):  
    # Load the full dataset  
    dataset = tf.keras.utils.image_dataset_from_directory(  
        data_dir,  
        image_size=(img_height, img_width),  
        batch_size=None,  
        shuffle=True,  
        seed=42  
    )  
  
    # Get dataset size and class names  
    dataset_size = tf.data.experimental.cardinality(dataset).numpy()  
    class_names = dataset.class_names  
  
    # Calculate split sizes  
    train_size = int(0.7 * dataset_size)  
    val_size = int(0.2 * dataset_size)  
    test_size = dataset_size - train_size - val_size  
  
    # Split dataset  
    train_ds = dataset.take(train_size)  
    temp_ds = dataset.skip(train_size)  
    val_ds = temp_ds.take(val_size)  
    test_ds = temp_ds.skip(val_size)  
  
    def configure_for_performance(ds, batch_size=16, shuffle_buffer=1000):  
        ds = ds.cache()  
        ds = ds.shuffle(buffer_size=shuffle_buffer)  
        ds = ds.batch(batch_size)
```

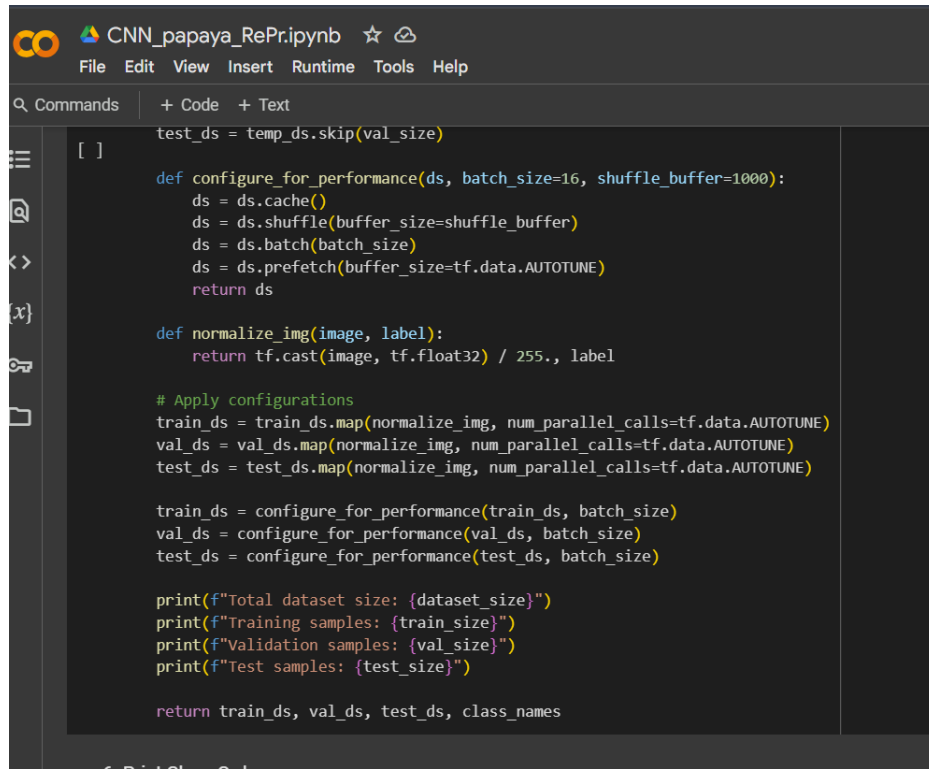
Figure 12 - Dataset preparation



```
[ ] def build_cnn(input_shape, num_classes):  
    """Build the Custom CNN model."""  
    model = Sequential([  
        Conv2D(32, (3,3), activation='relu', input_shape=input_shape, padding='same'),  
        MaxPooling2D(),  
  
        Conv2D(64, (3,3), activation='relu', padding='same'),  
        MaxPooling2D(),  
  
        Conv2D(64, (3,3), activation='relu', padding='same'),  
        MaxPooling2D(),  
  
        Flatten(),  
  
        Dense(128, activation='relu'),  
        Dropout(0.5),  
        Dense(num_classes, activation='softmax')  
    ])  
  
    model.summary()  
    return model
```

Figure 13 -. Dataset preparation

### 2.2.2.1.3 Custom-CNN model Architecture



```
test_ds = temp_ds.skip(val_size)

[ ]

def configure_for_performance(ds, batch_size=16, shuffle_buffer=1000):
    ds = ds.cache()
    ds = ds.shuffle(buffer_size=shuffle_buffer)
    ds = ds.batch(batch_size)
    ds = ds.prefetch(buffer_size=tf.data.AUTOTUNE)
    return ds

def normalize_img(image, label):
    return tf.cast(image, tf.float32) / 255., label

# Apply configurations
train_ds = train_ds.map(normalize_img, num_parallel_calls=tf.data.AUTOTUNE)
val_ds = val_ds.map(normalize_img, num_parallel_calls=tf.data.AUTOTUNE)
test_ds = test_ds.map(normalize_img, num_parallel_calls=tf.data.AUTOTUNE)

train_ds = configure_for_performance(train_ds, batch_size)
val_ds = configure_for_performance(val_ds, batch_size)
test_ds = configure_for_performance(test_ds, batch_size)

print(f"Total dataset size: {dataset_size}")
print(f"Training samples: {train_size}")
print(f"Validation samples: {val_size}")
print(f"Test samples: {test_size}")

return train_ds, val_ds, test_ds, class_names
```

Figure 14 - Custom CNN model Architecture

Table 10 - Custom CNN model architecture

Layer (type)	Output Shape	Number of Params
conv2d (Conv2D)	(None, 256, 256, 32)	896
max_pooling2d (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 64)	0
conv2d_2 (Conv2D)	(None, 64, 64, 64)	36,928
max_pooling2d_2 (MaxPooling2D)	(None, 32, 32, 64)	0
flatten (Flatten)	(None, 65536)	0
dense (Dense)	(None, 128)	8,388,736
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 3)	387

For the specific use case of identifying Ring spot Virus, Powdery Mildew and Healthy Fruit, this custom model architecture was built. The Figure 8 showcase the code level implementation of custom CNN model architecture and Table 3 shows the model summary of the custom CNN along with their layers and parameters.

A deep learning model called the Convolutional Neural Network (CNN) architecture was created especially to categorize papaya fruits into three groups: infected with the Papaya Ringspot Virus, infected with Powdery Mildew and healthy fruit. The training, validation, and testing data are split in a 70-20-10 ratio, and each category has 1,500 photos. To provide a clear data flow, the model is in a sequential fashion, with each layer stacked linearly. Feature extraction (pooling and convolution layers), feature flattening, and classification (totally linked layers) are its three main stages.

The following step is a MaxPooling2D layer, which down samples the feature maps using a 2×2 pooling to lower computational costs and enhance feature retention. As a result, the network is more effective and less susceptible to slight distortions and changes in the input images.

ReLU activation and "same" padding are used in the second convolutional block, which is a Conv2D with an additional 64 filters and a 3x3 kernel size. The model can now look for more particular traits, such papaya fruits with disease-specific textural changes, thanks to the increase in filters. Then comes another MaxPooling2D that makes sure only pertinent data is kept and shrinks feature maps once more.

Similar to the second convolution block, the third one keeps its 64 filters and keeps honing the characteristics that have been extracted. It employs a 3x3 convolution with "same" padding and ReLU activation, then another MaxPooling2D layer. The model's ability to identify complex patterns and differentiate between healthy and unhealthy papaya fruits is enhanced by all of these feature extraction hierarchical layers.

The multi-dimensional feature maps are flattened as a one-dimensional linear vector after the convolutional and pooling layers. This converts the spatially structured data into a linear format suitable for fully connected layers to process further.

128 neurons make up the first Dense (completely connected) layer, which learns high-level feature representations of the input images. It may learn complex, non-linear relationships between extracted features because, like the convolutional layers, it makes use of the ReLU activation function. To prevent overfitting, 50% of the neurons are randomly inhibited during training using a dropout layer with a 0.5 probability. The model is guaranteed to generalize effectively to unseen images thanks to this regularization strategy.

With three neurons representing the three types of papaya fruits—Healthy, Papaya Ringspot Virus, and Powdery Mildew—the last Dense layer serves as the output layer. The output values are produced as a probability distribution over the three classes using the SoftMax activation function. The final prediction made by the model is then the class with the highest probability.

The majority of the model's 8,445,443 trainable parameters are grouped together in fully connected layers. While the dense layers perform the final classification, the convolutional layers are mostly utilized for feature extraction. The model can generalize well on real data since the dropout method keeps overfitting from happening.

With its ideal balance of feature learning, dimensionality reduction, and classification, this architecture is well suited to identify papaya fruit illness. The network's hierarchical structure of convolutional layers enables it to analyze the different structures, color ranges, and texture patterns of both impacted and unaffected papayas. Additionally, dropout offers generalization robustness to guarantee assured performance, even when tested on previously viewed images. Farmers and researchers can quickly identify and address plant health issues because of the model's well-designed nature and mid-computational complexity, which make it ideal for classifying papaya diseases in real-time agricultural applications.



### **2.2.2.2 Testing**

The final step of the implementation is to test and evaluate the results of the created models. For this testing stage from the overall dataset 10% of portion is used as testing test containing 150 images. Each class Ring Spot, Powdery Mildew and Healthy contained balanced dataset as 50 images for testing purposes. For testing images were used previously not seen by the model, these images were randomly split from the dataset and those were first seen by the model at the testing phase. Furthermore, images were tested on testing phase of the model training, locally hosted environment and phase of the integrated mobile application. Google Colab was used for model training along with Google Drive, then within that environment testing was done, also with the locally hosted on environment using Python Fast API, model was tested with unseen data and finally with integrated mobile application, predictions were tested with new images, unseen data downloaded from Google and with test data set.

#### **2.2.2.2.1 Test plan & Test Strategy**

To determine the project's progress and ensure the software's effectiveness, test planning is necessary to create a baseline plan that outlines tasks, scope, and objectives. It acts as a manual for carrying out the necessary testing. The test strategy is a set of actions and processes that determines what needs to be tested and ranks the functions according to their significance and potential dangers to users. Test cases were written in accordance with the use cases that were provided, carried out by hand, and the outcomes were noted.

#### **2.2.2.3 Steps and procedures in test strategy**

- Define the items to be tested
- Select the functions based on the importance and risk on user
- Design test cases as identified by the use case description.
- Execute
- Record Results
- Identify Bugs
- Correct Bugs
- Repeat the test case until the expected results meet

### 2.2.2.3.1.1 Test case design

To make sure the models operated as intended, tests were conducted. To verify the model's performance, the following test cases were run.

*Table 11 - Verify Image Upload*

Test Case Id	01
Test Case	Verify Image Upload
Test Scenario	Verify whether the captured image is stored on Cloudinary
Precondition	Users should have login to the system
Input	Captured disease infected image
Expected Output	<ul style="list-style-type: none"><li>• 200 status code should be displayed</li><li>• The image must be stored in Cloudinary</li></ul>
Actual Result	<ul style="list-style-type: none"><li>• 200 status code should be displayed</li><li>• The image must be stored in Cloudinary</li></ul>
Status (Pass/ Fail)	Pass

*Table 12 - Classification of Rins pot Virus using custom CNN*

Test Case Id	02
Test Case	Classification of Ring spot Virus using custom CNN
Precondition	Users should have login to the system
Test Scenario	Testing images to classify Ring spot Virus on papaya fruit
Input	Image of fruit infected with Ring spot Virus
Expected Output	<ul style="list-style-type: none"><li>• Correct class prediction</li><li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li><li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li></ul>

Actual Result	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>
Status (Pass/ Fail)	Pass

*Table 13 - Classification of Powdery Mildew using custom CNN*

Test Case Id	03
Test Case	Classification of Powdery Mildew using custom CNN
Test Scenario	Testing images to classify Powdery Mildew on papaya fruit
Precondition	Users should have login to the system
Input	Image of fruit infected with Powdery Mildew
Expected Output	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>
Actual Result	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Mobile Application show the suggested disease images along with Preventive measures, Description and Symptoms</li> <li>• Also show the Treatment Instruction and Save to diagnosis buttons.</li> </ul>
Status (Pass/ Fail)	Pass

Table 14 - Classification of Healthy fruit using custom CNN

Test Case Id	04
Test Case	Classification of Healthy fruit using custom CNN
Test Scenario	Testing images to classify Healthy papaya fruit
Precondition	Users should have login to the system
Input	Image of Healthy papaya fruit
Expected Output	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Recommendations to keep the papaya plant healthy</li> <li>• Save to diagnoses history</li> </ul>
Actual Result	<ul style="list-style-type: none"> <li>• Correct class prediction</li> <li>• Recommendations to keep the papaya plant healthy</li> <li>• Save to diagnoses history</li> </ul>
Status (Pass/ Fail)	Pass

Table 15 - Show the Treatment instruction Related to Specific Disease or Healthy Fruit

Test Case Id	05
Test Case	Show the Treatment instruction Related to Specific Disease or Healthy Fruit
Test Scenario	Show Organic and Chemical Treatment instructions
Precondition	Users should have login to the system
Input	Fruit image infected with Ring spot or Powdery Mildew disease
Expected Output	<ul style="list-style-type: none"> <li>• Show correct treatment instruction related to disease</li> <li>• Show Chemical and Organic methods along with the effectiveness, side effects and precautions</li> </ul>
Actual Result	<ul style="list-style-type: none"> <li>• Show correct treatment instruction related to disease</li> <li>• Show Chemical and Organic methods along with the effectiveness, side effects and precautions</li> </ul>
Status (Pass/ Fail)	Pass

## 2.2.3 Mite Disease and Mealy Bug Disease Identification and Suggest the Remedy

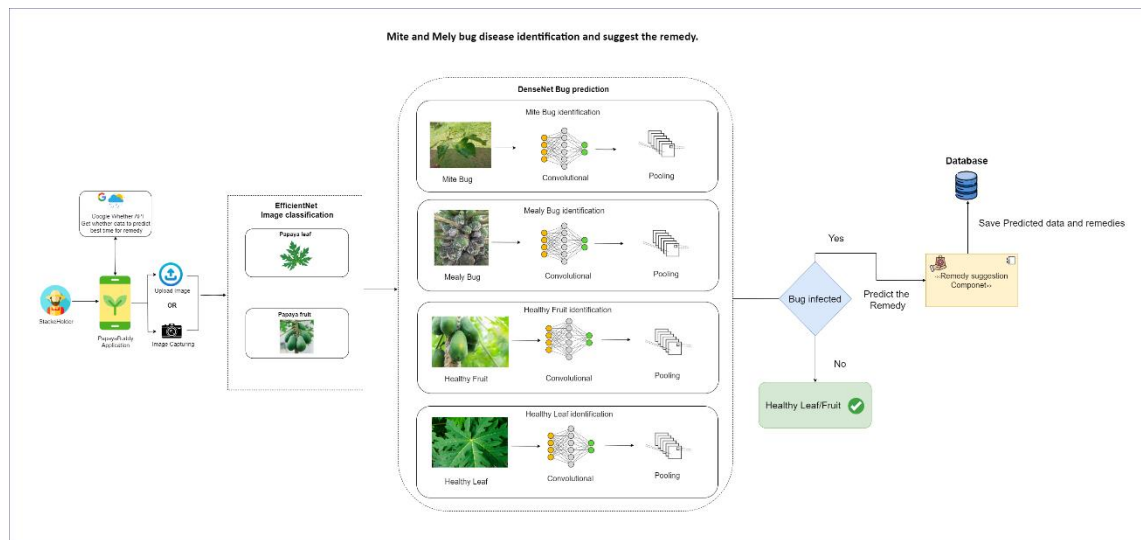


Figure 15 - Mite and Mealy Bug Identification Component diagram

This component diagram explains the flow of detecting mite and mealy bug diseases and suggesting remedies in the PapayaBuddy app. It begins with a stakeholder using the app to take a photo or upload one from the gallery. The photo is passed through the EfficientNet model, where it is classified either as a papaya leaf or fruit. Depending on the classification, the photo proceeds to the DenseNet Bug prediction module. In DenseNet, separate convolutional pathways classify Mite Bug, Mealy Bug, Healthy Fruit, or Healthy Leaf. For bug infection detection, the system predicts a proper remedy via the Remedy Suggestion Component that retrieves information from a database where predicted information and remedies are saved. For no infection, the system affirms healthy leaf or fruit. In addition, the app integrates the Google Weather API to plan remedy applications based on the weather.

The individual component diagram enables the system architecture of the PapayaBuddy application by providing a clear picture of the individual functions and how they contribute to the overall system. Though the system architecture provides an overview of all the parts, their relationships with one another, and how they interact with each other, the component diagram is all about detecting Mite Bug and Mealy Bug diseases and recommending solutions for them. It highlights how EfficientNet goes through the images for early classification, DenseNet for disease prediction, and throws later to the Remedy Suggestion Component for actionability. This sort of module-based diagram easily helps understand how this subsystem collaborates with other modules like cloud storage, weather APIs, and user interfaces. Encapsulating such functionality, the diagram adheres to system architecture guidelines like abstraction, scalability, and compact communication among entities, for enabling the free execution of the application.

### **2.2.3.1 Testing and Implementation**

#### **2.2.3.1.1 Implementation**

Functioning of the Papaya Buddy system is based on ground-breaking technologies in ensuring effective management of pests as well as pest identification in papaya cultivation. The system commences with the use of Flutter-based mobile software, which makes provision for upload or taking field photographs of the papaya trees. The system is user-friendly and offers real-time and uncomplicated data harvesting for analysis purposes. For the detection of the pests, two deep models were developed and trained on Jupyter Notebook. One model was exclusively trained to detect infestation of pests such as mites and mealybugs and another EfficientNet model for fruit or leaf.

The two-model approach has accurate detection of the pest and infected plant parts so corresponding treatment steps can be suggested. Operationalized Trained DenseNet model was run on Azure Machine Learning through managed online endpoints. Azure infrastructure enabled deployment of the model with a scalable and secure REST API for real-time prediction. Operationalization included model registration, creation of inference configuration, and deployment in Azure Kubernetes Service (AKS) for scalability and reliability at scale.

For prediction processing and generating actionable recommendations, a server implemented with FastAPI was established for interacting with the hosted model. The server received the input image data, forwarded prediction to the hosted model on Azure, and generated real-time responses. MongoDB had also been employed as the database for saving the information of the prediction and fetching the information of the remedy based on pest severity and type.

A Node.js application was used to manage these operations, including fetching remedies from the database and processing prediction requests efficiently. Data augmentation techniques such as rotation of images, flipping, zooming, and color correction were performed using OpenCV to enhance the quality and diversity of the dataset. This improved the training accuracy of both models while training and usage in real-world applications. Gaming on the cutting-edge machine learning models, cloud-hosting via Azure, and Node.js and FastAPI-optimized backend configurations, Papaya Buddy is a system of record solution for papaya pest infestation location and management.

To get your Node.js application execute faster while fetching remedy information retrieved, execute a few techniques. Install Redis and cache using it in a manner that does not ask MongoDB to query to save frequently retrieved data. Make DB operations efficient by indexing frequently accessed fields and retrieve small numbers of retrieved items. Execute async

programming by passing requests to one another in parallel. Process data in an efficient way by processing bulk of data in streams and paginating for the best response times.

#### 2.2.3.1.1.1 Data Preprocessing

Before training the DenseNet model, an appropriate data preprocessing technique was performed. Images were resized to an even dimension of 224x224 pixels in a manner that is compatible with model input specifications. Resizing the images gives each photo a standard size, which is extremely important in ensuring proper analysis using the help of the neural network. As a pre-processing step prior to training the DenseNet model from the raw images, there existed a global data preprocessed solution. The images were resized to the dimension of 224x224 pixels to comply with the model input size. Resizing helps ensure all the images' dimensions become uniform as required by optimal neural network processing.

Keras ImageDataGenerator also normalized all the pixel values of the images by 255 in an attempt to compress the data range to 0 to 1. Data normalization is also essential in stabilizing neural network training since it helps in reducing the impact of large pixel values and enhancing the ability of the model to learn from data. The preprocessed images were loaded from the folders using flow from directory, whose images are labeled automatically based on their directory of the folder. It is easier to load data as well as to ensure that the images are correctly labeled for training and for validation. Batch size 32 was selected such that there can be the best balance between using memory and effective training.

```
train_generator = train_datagen.flow_from_directory(  
    'densenet_dataset/splitted_data/train',  
    target_size=(224, 224),  
    batch_size=32,  
    class_mode='categorical'  
)  
  
val_generator = val_datagen.flow_from_directory(  
    'densenet_dataset/splitted_data/val',  
    target_size=(224, 224),  
    batch_size=32,  
    class_mode='categorical'  
)
```

*Figure 16 - Data Preprocessing*

The batch size is big enough to train the images effectively but not big enough such that it would use up all the memory during training. For the validation set, rescaling was the only operation done to create actual real-world scenario conditions. Thus, validation tests the model against new but no longer changed data and thus provides an unpolluted indication of its ability to

generalize. By these preprocessing steps, the raw images were successfully transformed into an extremely compatible dataset for training DenseNet model.

#### 2.2.3.1.1.2 Data Augmentation

Data augmentation is one of the established techniques to enhance the generalization performance of machine learning models. It operates under the premise of transforming each sample image into variants to increase the diversity of the training set. After resizing images into a standard dimension, data augmentation was applied through various approaches to generate the variants. The task helps generate real-world variations and increase the ability of the model to detect patterns irrespective of conditions.

```
train_datagen = ImageDataGenerator(  
    rescale=1./255,  
    rotation_range=20,  
    width_shift_range=0.2,  
    height_shift_range=0.2,  
    shear_range=0.2,  
    zoom_range=0.2,  
    horizontal_flip=True,  
    fill_mode='nearest'  
)
```

*Figure 2: Data Augmentation Techniques*

To further enhance the strength and generalization capability of the DenseNet model, data augmentation techniques were employed to expand the training set. I.e., various geometric augmentation through the use of Keras's ImageDataGenerator like rotation, width shift, height shift, shear, zooming, and horizontal flipping of the image. These augmentations were used in an attempt to simulate a variety of different orientations, sizes, and contexts when attempting to train the model under a wider range of conditions.

Rotation by 20 degrees and 20% image size translation were used in order to mimic variation in real data. Shear and zooming augmentations were used in order to mimic tilting and scaling, and horizontal flipping utilized symmetry in data. Heterogeneity and dataset size were enhanced artificially with these additions, reducing overfitting as well as the model's optimization for generalizability to new data. It made the model able to generalize from a vast range of cases without needing more labeled data, thereby finally helping to enhance its performance in detecting pest infestation in papaya cultivation.

Normalizer reconstructed images normalized from pixel divided values by 255 for effortless normalization between 0 to 1 for efficient stabilization of train neural networks. Data augmentation did a significant task in model strengthen and accuracy towards pest detection



versus different conditions as a whole.

### 2.2.3.1.1.3 Deep Learning Model Implementation

- **DenseNet121 Model**

```
base_model = DenseNet121(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

model = Sequential()
model.add(base_model)
model.add(GlobalAveragePooling2D())
model.add(Dense(4, activation='softmax'))

# Freeze the base model layers
for layer in base_model.layers:
    layer.trainable = False
```

*Figure 3: Pre-trained DenseNet121 model*

The pre-training of the pest detection model was done using DenseNet121 with its weights on ImageNet to effectively extract the features of the papaya image. The base model was loaded with include top False and input shape (224, 224, 3). The custom top layer consisting of a GlobalAveragePooling2D layer to pool over space and a Dense layer with softmax activation for multi-class classification was utilized. To preserve pre-learned features, all the ground truth layers were frozen in the initial training process. Acquiring pest-specific features without losing feature extraction capability, it was the best for the accurate identification of pests in papaya farming. Employing densely connected layers in DenseNet121 propagated and reused features while avoiding redundancy and enhancing learning efficiency. Transfer learning integration improved the model by boosting training speed and accuracy and by adding an immense potential towards fruitful disease detection in farm monitoring systems.

```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // train_generator.batch_size,
    validation_data=val_generator,
    validation_steps=val_generator.samples // val_generator.batch_size,
    epochs=30, # number of times model sees the dataset
    verbose=1,
)
```

*Figure 4: DenseNet model compile and training*

The pest detecting model was pre-trained using DenseNet121 which is a Convolutional Neural

Network (CNN) pre-trained model. Its base model started with pre-trained ImageNet weights and the final classification layer of the base model removed and set to have the input shape of (224, 224, 3) to be compliant with the papaya images in preprocessing. A personalized top layer was utilized, consisting of a GlobalAveragePooling2D layer to spatially down-sample dimensions, and another final Dense layer with softmax activation to handle multi-class classification. All the lower-level layers were frozen in a way that pre-learned features are not modified and only the new classification layers are trained. It was trained using Adam optimizer and categorical crossentropy loss and for 30 epochs in training and validation generators. It effectively leverages pre-trained features but learns to specialize in pest-specific patterns and thus can be used in real-world pap

```
test_datagen = ImageDataGenerator(rescale=1./255)

test_generator = test_datagen.flow_from_directory(
    'densenet_dataset/splitted_data/test',
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical'
)

test_loss, test_accuracy = model.evaluate(test_generator)
print(f'Test accuracy: {test_accuracy:.2f}')
```

*Figure 5: Test model on test data*

To estimate how well the model would perform on unseen data, a test dataset was generated using the ImageDataGenerator. The test images were rescaled by dividing pixel values by 255 so that they become in the range of 0 to 1 to be consistent with training and validation. The test images were loaded from their directory through the flow from directory method, resized to a set size of 224x224 pixels and batched into 32 batches. The model performance was then determined using the evaluate method, which provided the test loss and accuracy. Test accuracy was then printed to provide a precise estimate of how well the model can generalize to new, unseen data to provide feedback on its performance in real-world applications of pest detection.

- **EfficientNetV2B0 Model**

- ❖ EfficientNet for Fruit and Leaf Classification

63

In this research, EfficientNet was employed to determine whether an image contained a fruit or a leaf before passing it to the DenseNet model to identify pests. EfficientNet, which is famous

for its scalable and efficient architecture, utilizes compound scaling to balance depth, width, and resolution and is therefore highly appropriate for image classification issues with limited computational resources.

#### ❖ Data Preprocessing

```
val_datagen = ImageDataGenerator(preprocessing_function=tf.keras.applications.efficientnet.preprocess_input)
test_datagen = ImageDataGenerator(preprocessing_function=tf.keras.applications.efficientnet.preprocess_input)

train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=image_size,
    batch_size=batch_size,
    class_mode='categorical'
)

val_generator = val_datagen.flow_from_directory(
    val_dir,
    target_size=image_size,
    batch_size=batch_size,
    class_mode='categorical'
)
```

*Figure 6: EfficientNet Data Preprocessing*

To prepare the dataset for EfficientNet, preprocessing was performed using the ImageDataGenerator and the preprocess input function of TensorFlow's EfficientNet module. This function normalizes the pixel values according to the EfficientNet model requirement. The training, validation, and testing datasets were loaded using flow from directory, which loads images and labels them automatically according to their folder structure. Images were resized to a standard size according to the model's input requirement and batched for processing efficiency.

#### ❖ Model Implementation

EfficientNet was used as a pre-trained model with ImageNet weights. Its high feature extraction capability helped it to classify fruit and leaves effectively. The output of the classification was then used to determine whether the image should be passed to DenseNet for pest detection.

```
# Load the EfficientNetV2B0 model pre-trained
base_model = EfficientNetV2B0(weights="imagenet", include_top=False, input_shape=(image_size[0], image_size[1], 3))

# Freeze the base model layers
base_model.trainable = False

# Add custom layers for binary classification
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation="relu")(x)
output = Dense(1, activation="sigmoid")(x)

# Define the final model
model = Model(inputs=base_model.input, outputs=output)
```

*Figure 7: EfficientNet model implementation*

To classify the images as leaves or fruits, the EfficientNetV2B0 model was utilized, benefiting from its robust feature extraction. The model was loaded pre-trained with its final classification layer removed, and its base layers were frozen to preserve pre-learned features on ImageNet. Binary classification custom layers were added, including a GlobalAveragePooling2D layer for downsampling spatial dimensions, a Dense layer with ReLU activation for adding non-linearity, and a final Dense layer with sigmoid activation for binary classification.

With this architecture, images are correctly classified as fruits or leaves, which serves as a preprocessing mechanism before passing the leaf images through the DenseNet model for pest detection. With EfficientNetV2B0, the model utilizes its extendable architecture and pre-trained weights to accelerate training and boost accuracy in fruit and leaf differentiation.

#### ❖ Training Process

The dataset prepared with categorical labels (leaf or fruit) was employed to train the model. Training involved optimizing the model performance using categorical crossentropy as the loss function and accuracy as the evaluation metric. Pre-trained weights were used to ensure that the model leveraged existing knowledge in adapting to the specific task of classifying fruit and leaves.

```
# Train Model
history = model.fit(
    train_generator,
    validation_data=val_generator,
    epochs=epochs,
    steps_per_epoch=train_generator.samples // batch_size,
    validation_steps=val_generator.samples // batch_size,
)
```

*Figure 8: Train EfficientNet model*

The EfficientNet model was trained with a systematic method to achieve its best performance in classifying images as leaves or fruits. The model was trained using the Adam optimizer with a learning rate of 0.001, categorical crossentropy as the loss function, and accuracy as the primary metric. Training was performed by feeding batches of images from the training generator to the model, and validation on the validation generator after each epoch. The dataset was split into training, validation, and test folders, and resized to (224, 224) pixels.

The batch size was 16. The model was trained for 20 epochs so that it could converge to its best weights. By doing this training, the model was able to achieve high accuracy in fruit-leaves classification and thereby form the basis of integrating the model into a larger pipeline to identify pests on papaya plants.

- Integration with DenseNet

Once EfficientNet had decided if an image was a leaf or a fruit, this outcome guided further processing. Leaf images were passed through DenseNet for pest detection, while fruit images were not processed for pests. Filtering data in this two-step process improved the accuracy and efficiency of DenseNet by making it focus on relevant data alone. Through the integration of EfficientNet for the first classification, this research achieved a modular pipeline that eased the process of pest detection while maintaining high accuracy in the distinction between leaves and fruits.

#### **2.2.3.1.2 Testing**

The DenseNet121 model was tested using a test dataset of 123 images distributed over 4 classes to gauge its generalization performance. The test images were preprocessed using the same rescaling technique (1/255) employed during training and validation for consistency. The dataset was loaded and resized to 224x224 pixels using ImageDataGenerator, and the images were batched as collections of 32 for efficient testing. The model achieved 98% accuracy and a loss of 0.0522 on testing, confirming the model generalizes well to out-of-sample data. The results obtained look into the robustness of the model's performance in correctly classifying diseased papaya and healthy papaya samples. The accuracy obtained and minimal loss affirm the preprocessing, augmentation, and training protocol applied to design the model are effective, proving the model can be applied appropriately to field pest detection application in agriculture.

##### **2.2.3.1.2.1 Test Plan and Strategy**

The primary objective of the test phase is to ensure the reliability, accuracy, and operability of the machine learning models developed for identifying pests in papaya crops. This involves verifying the proper functioning of the DenseNet121 model for pest classification and EfficientNetV2B0 for fruit and leaf identification, and verifying data preprocessing pipelines and storage mechanisms.

##### **❖ Test Plan**

The testing process will be carried out in a structured way, with emphasis on important functionalities and metrics to assess model performance. The plan involves

- Unit Testing: Independent module testing such as data preprocessing, model design, and training pipelines.

- Integration Testing: Testing the seamless integration of EfficientNetV2B0 (fruit/leaf classification) and DenseNet121 (pest detection).
  - End-to-End Testing: Testing the complete pipeline from image capture to pest prediction output.
- ❖ Model Testing

The DenseNet121 model is trained on unseen test data to measure accuracy and loss metrics quantitatively. The test set comprises 123 images of 4 classes rescaled (1/255). The model was validated for high accuracy (98%) and low loss (0.0522) in the differentiation of pest-infected and healthy samples.

❖ Integration Testing

EfficientNetV2B0 is checked for accuracy in fruit/leaf classification before passing leaf images to DenseNet121 to detect pests. Thus, only relevant information is provided to the pest detection model to improve its efficiency.

❖ Performance Metrics

*Key performance indicators are:* **Accuracy:** Checked on test datasets for both models (98% for DenseNet121).

**Loss:** Checked to quantify minimal deviation from ground truth labels (e.g., test loss of 0.0522).

The testing phase of our research involved a serious investigation of the DenseNet121 model with new data to establish its generalization capacity. The model was tested on an independent test dataset of 123 images in four classes and achieved a high-test accuracy of 98% and low-test loss of 0.0522. This performance proves the robustness of the model and its capability to classify pest-infected and healthy papaya samples correctly in real-world scenarios. Since we used unseen data, it was a real test of the model's ability, and we identified its potential in efficient pest detection for agricultural purposes.

The high accuracy on unseen data proves the model's ability to generalize well beyond the training data and thus is suitable for real-world use cases where a multitude of images with different settings exist. These findings collectively enhance the credibility and reliability of the model, validating its potential for efficient and accurate agricultural monitoring systems.

This kind of test strategy gives thorough verification of the entire system right from data

preprocessing, model predictions, and incorporating cloud storage. Adhering to this devised strategy, research ensures accuracy, reliability, and scalability of the system for the detection of pests in actual contexts of agricultural crops.

#### 2.2.3.1.2.2 Test Case Design

The following test cases were employed to ensure system reliability by testing all system functionalities.

*Table 1: Test case to verify user navigate to mealy bug detect UI*

Test Case Id	01
Test Case	Navigate to Mealy bug Prediction UI
Test Scenario	Verify whether user navigate to Mealy Bug detect interface when click on Mealy bug card
Precondition	User should have login to the system
Input	Click on Mealy bug card
Expected Output	User should navigate to Mealy bug capture UI
Actual Result	User navigated to Mealy bug UI
Status	Pass

*Table 2: Verify whether user navigate to Mite bug detect UI*

Test Case Id	02
Test Case	Navigate to Mite bug Prediction UI
Test Scenario	Verify whether user navigate to Mite Bug detect interface when click on Mite bug card
Precondition	User should have login to the system
Input	Click on Mite bug card
Expected Output	User should navigate to Mite bug capture UI
Actual Result	User navigated to Mite bug UI
Status	Pass

*Table 3: Verify whether uploaded image is displayed correctly*

Test Case Id	03
--------------	----

Test Case	Upload Image of Mealy bug
Test Scenario	Verify whether uploaded image is shown in image preview
Precondition	User should have login to the system
Input	Upload disease image from gallery
Expected Output	Uploaded Image should be display
Actual Result	Uploaded Image was displayed correctly
Status	Pass

*Table 4: Verify whether object is identified as a papaya fruit*

Test Case Id	04
Test Case	Classification of uploaded image as papaya fruit
Test Scenario	When upload a fruit image it should classify as a fruit
Precondition	User should have login to the system
Input	Upload papaya fruit image
Expected Output	Image should be correctly predicting as fruit
Actual Result	Uploaded Image was correctly predicted as fruit
Status	Pass

*Table 5: Verify whether object is identified as a papaya leaf*

Test Case Id	05
Test Case	Classification of uploaded image as papaya leaf
Test Scenario	When upload leaf image it should classify as leaf
Precondition	User should have login to the system
Input	Upload papaya leaf image
Expected Output	Image should be correctly predicting as leaf



Actual Result	Uploaded Image is correctly predicted as leaf
Status	Pass

*Table 6: Verify whether Mealy bug predicted correctly*

Test Case Id	06
Test Case	Predict Mealy bug infected fruit using DenseNet121
Test Scenario	Testing Images to classify Mealy bug disease on papaya fruit
Precondition	User should have login to the system
Input	Upload Mealy bug infected Image
Expected Output	<ul style="list-style-type: none"> <li>• Image should predict as Mealy bug</li> <li>• Mobile application should display description, symptoms and preventive measures</li> </ul>
Actual Result	Uploaded Image is correctly predicted as Mealy bug
Status	Pass

*Table 7: Verify whether Mite bug is predicted correctly*

Test Case Id	07
Test Case	Predict Mite bug infected leaf using DenseNet121
Test Scenario	Testing Images to classify Mite bug disease on papaya leaf
Precondition	User should have login to the system
Input	Upload Mite bug infected Image
Expected Output	<ul style="list-style-type: none"> <li>• Image should predict as Mite bug</li> <li>• Mobile application should display description, symptoms and preventive measures</li> </ul>
Actual Result	Uploaded Image is correctly predicted as Mite bug
Status	Pass

Table 8: Verify Mealy bug remedy details displayed correctly

Test Case Id	08
Test Case	Display remedy details relevant to Mealy bug
Test Scenario	System identifying and displaying remedy information related to Mealy bug infestation.
Precondition	User should have login to the system
Input	Click remedy details button
Expected Output	Mealy bug remedy details should be display
Actual Result	Mealy bug remedy details were displayed
Status	Pass

Table 9: Verify Mite bug remedy details displayed correctly

Test Case Id	09
Test Case	Display remedy details relevant to Mite bug
Test Scenario	System identifying and displaying remedy information related to Mite bug infestation.
Precondition	User should have login to the system
Input	Click remedy details button
Expected Output	Mite bug remedy details should be display
Actual Result	Mite bug remedy details were displayed
Status	Pass

Table 10: Verify whether prediction details is saved successfully

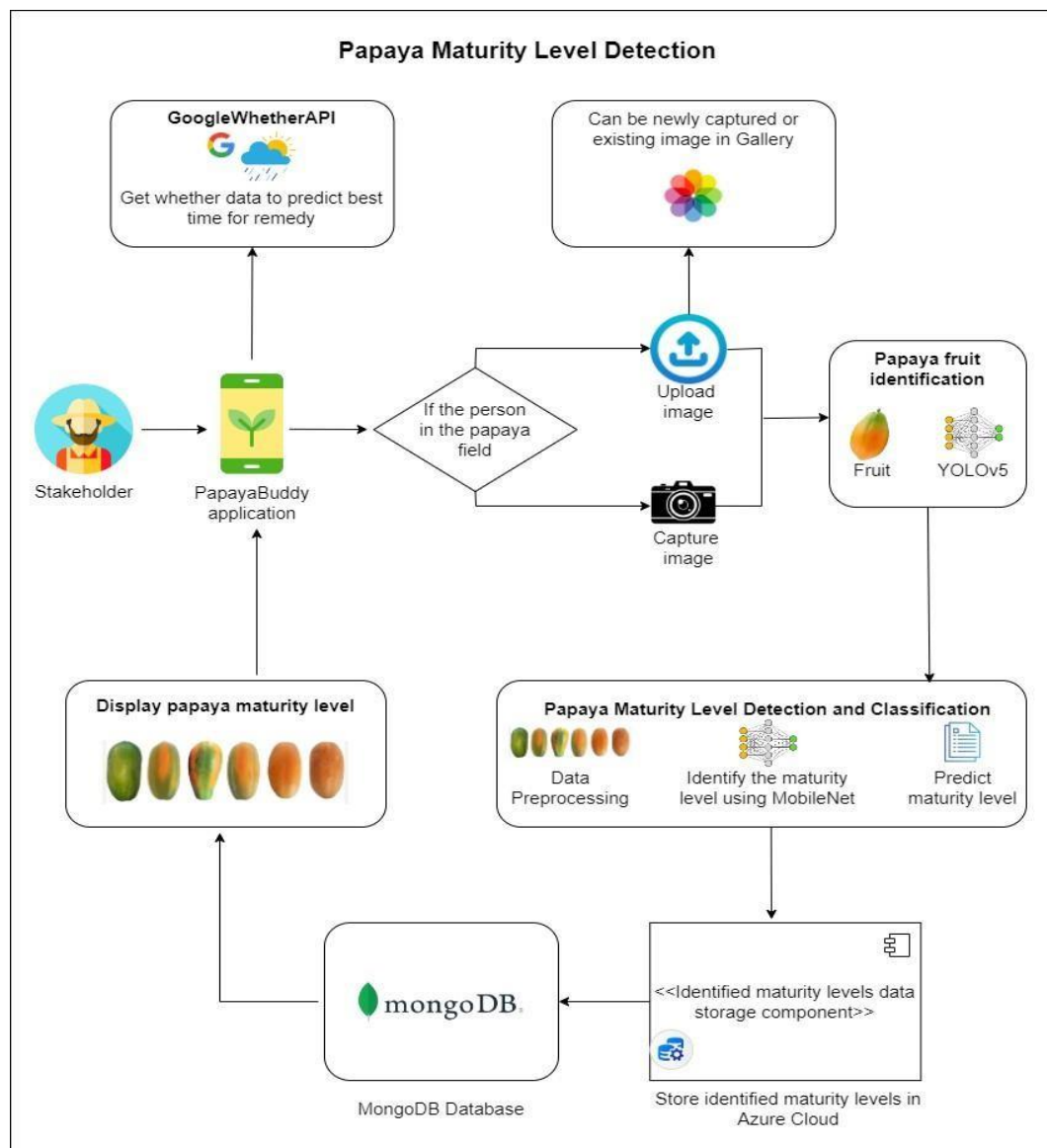
Test Case Id	10
Test Case	Save prediction details to DB
Test Scenario	System should save prediction details in DB
Precondition	User should have login to the system 71
Input	Click save prediction button

Expected Output	<ul style="list-style-type: none"> <li>Prediction details should be saved</li> <li>200 status code should return</li> </ul>
Actual Result	<ul style="list-style-type: none"> <li>Prediction details should be saved</li> <li>200 status returned successfully</li> </ul>
Status	Pass

## 2.2.4 Papaya Maturity Identification

The proposed system for papaya maturity level detection integrates various technologies and deep learning models to accurately assess the maturity of papaya fruits. The system is designed to assist farmers and stakeholders by providing real-time feedback on the ripeness of papayas, thus enabling better decision-making for harvesting and post-harvest handling. The following sections outlines the methodology for the development and implementation of this system.

### 2.2.4.1 System Diagram



### *Figure 3.2.1.1 - Papaya Maturity Level Detection System Diagram*

The architecture of the papaya maturity detection system is structured to provide a seamless user experience, from image capture to maturity level prediction and data storage. The system architecture is illustrated in Figure 7 and includes the following key components.

Farmers and stakeholders interact with the system through the PapayaBuddy mobile application. This cross-platform application allows users to capture images of papaya fruits directly from the field or upload existing images from their device's gallery. Users in the papaya field can capture images of papayas using the mobile application. These images are then uploaded to the system for further processing. The uploaded or captured image is first processed using the MobileNets object detection model to identify and isolate the papaya fruit within the image. MobileNets is chosen for its efficiency and accuracy in real-time object detection, ensuring that the fruit is correctly identified before maturity analysis.

Once the papaya fruit is identified, the image is passed through the MobileNet model to detect and classify the maturity level of the fruit. The model categorizes the fruit into one of the four maturity levels: unripe, partially ripe, ripe and rotten. MobileNet is selected for this task due to its lightweight architecture, which is suitable for deployment in mobile applications. The maturity level is predicted based on the analysis of color, texture, and other relevant features extracted by the MobileNet model.

To enhance the robustness of the model, various data augmentation techniques are applied, including rotation, flipping, zooming, and shifting. These techniques increase the diversity of the training data and help prevent overfitting. The dataset is divided into training, validation, and testing sets, with 80% of the data used for training and the remaining 20% split equally between validation and testing.

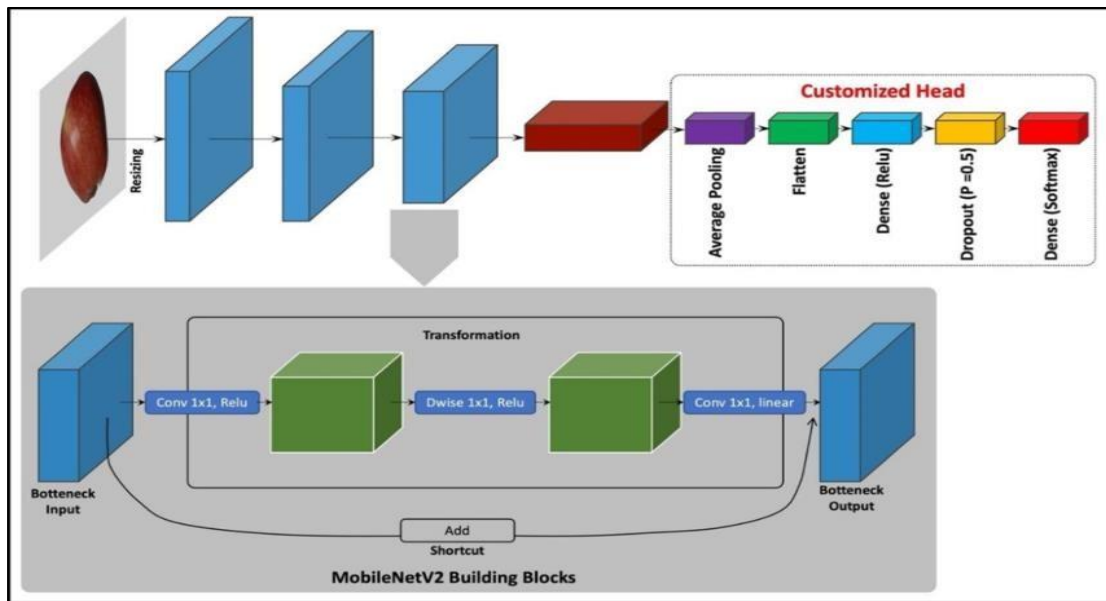


Figure 3.2.1.2 - MobileNet Model Diagram

As Figure 8, MobileNet, known for its efficiency in mobile and embedded applications, is employed as the primary model for maturity classification. It uses depth wise separable convolutions, significantly reducing the number of parameters and computational complexity compared to traditional convolutional neural networks (CNNs). The model architecture includes a series of convolutional layers followed by batch normalization and ReLU activation functions, culminating in a softmax layer that outputs the probability distribution over the three classes: ripe, unripe, and partially ripe. To expedite the training process and enhance the model's performance, transfer learning is utilized. Pre-trained weights from ImageNet are applied to the MobileNet model, providing a strong foundation for recognizing fruit characteristics and allowing the model to converge faster. For a comprehensive analysis, the MobileNet model's performance is compared with other deep learning models such as ResNet, VGGNet, and AlexNet. Each of these models is trained on the same dataset, and their performances are evaluated based on accuracy, computational efficiency, and suitability for deployment in the target environment.

The training process involves optimizing hyperparameters like learning rate, batch size, and number of epochs through grid search. The model is trained using the Adam optimizer, which adjusts the learning rate dynamically for efficient convergence. Cross-entropy loss is used as the loss function to measure the error between the predicted and actual maturity labels. The models are evaluated using several metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provide a comprehensive view of the model's performance, highlighting its strengths and identifying areas for improvement.

A detailed comparative analysis is performed to evaluate the trade-offs between accuracy and computational efficiency for each model. The results are analyzed to determine which model is most suitable for deployment in Sri Lankan agricultural settings, where resources may be limited.

The identified maturity level data is stored in Azure Cloud. This ensures that the data is securely backed up and can be accessed by stakeholders for future reference or analysis. The data is also stored in a MongoDB database, where it can be

efficiently managed and retrieved, MongoDB’s flexible schema design is ideal for handling the unstructured data generated by the maturity level detection system. The system integrates with the GoogleWeatherAPI to fetch weather data. This information is used to predict the best time for harvesting or applying remedies based on the current weather conditions, providing farmers with actionable insights. The system is implemented using a combination Flutter for the mobile application, Python with Flask for the backend server, and various machine learning frameworks like TensorFlow for model development. The entire pipeline, from image acquisition to maturity prediction, is designed to be efficient and scalable, allowing it to be deployed across various agricultural settings in Sri Lanka. Before full deployment, the system undergoes rigorous field testing in actual papaya farms. The mobile application is tested for its usability, accuracy in different environmental conditions, and overall impact on reducing post-harvest losses. Feedback from farmers is collected to further refine the system.

Summary of technologies, techniques, architectures and algorithms used for the detection of papaya maturity level is shown in the table (Table 2) below.

*Table 3.2.1.1 - Summary of technologies, techniques, architectures and algorithms*

Category	Details
Technologies	Flutter, Python, TensorFlow, Flask Server, Node Server, Azure Cloud, MongoDB
Techniques	Image Preprocessing, Data Augmentation, Feature Extraction, Image Segmentation
Algorithms	MobileNet,

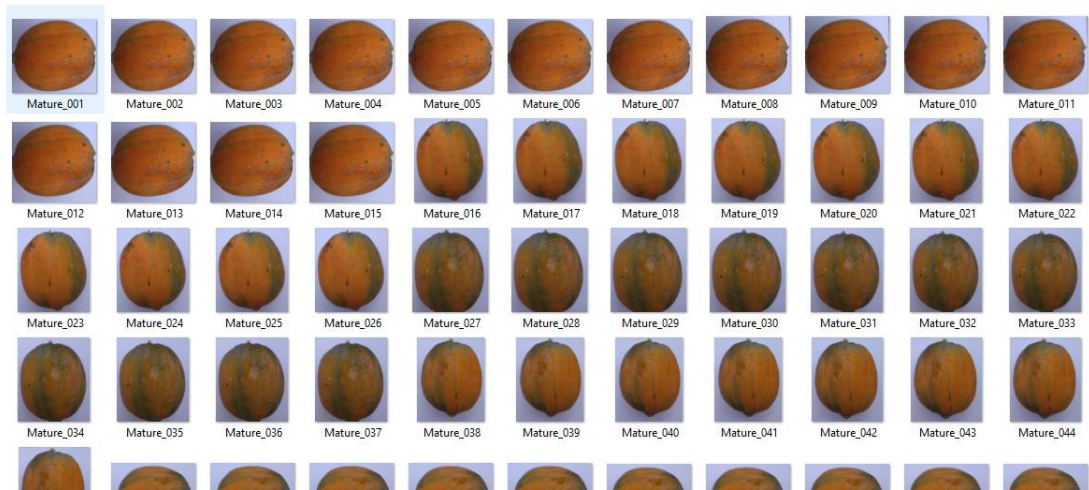
#### **2.2.4.2 Data Acquisition and Processing**

Experimental images were acquired from several papaya farms located in Horana, Divulapitiya, and Pugoda areas known for their diverse cultivation environments and representative papaya varieties. Images were captured using smartphone cameras in various natural lighting conditions to ensure a broad range of sample diversity and minimize bias caused by uniform image settings. The dataset focused on capturing

papaya fruits at different maturity stages: mature, partially mature, not mature, and rotten.

For the not mature category, images were taken of papayas that were fully green, with no visible signs of yellowing. Partially mature papayas displayed a mix of green and yellow shades, indicating the onset of the ripening process. The mature category included fruits that were mostly yellow, signifying optimal ripeness for harvesting and consumption. Lastly, rotten papayas showed signs of over-ripeness, decay, and visible damage or mold.

Fruit sampling was conducted with the support and supervision of agricultural officers from local cultivation authorities to ensure proper handling and accurate categorization based on maturity indicators. These images were then used to train deep learning models for maturity level classification. Figure 3.2.1.1 illustrates sample images representing each maturity level of papaya used in this study.



*Figure 2.2.2.2.1 - Data Collection Sample Image*

### **2.2.4.3 Preprocessing and Augmentation**

To ensure the deep learning model receives clean and consistent input for effective training, an essential preprocessing pipeline was implemented. The preprocessing stage involved image resizing, normalization, and batch structuring. All images of papaya fruits were resized to a standard dimension of 224x224 pixels, which is the



expected input shape for the MobileNetV2 architecture. This step helped maintain consistency across all input samples and reduce computational complexity.

Each image was normalized using MobileNetV2's built-in `preprocess_input` function, which scales pixel values to a format suitable for the pretrained weights. Furthermore, each image was expanded along the batch dimension to allow compatibility with Keras model input requirements.

Below is the code snippet of Figure 3.2.3.1 used for image preprocessing:

```
def prepare_image(img_path):  
    img = image.load_img(img_path, target_size=(224, 224)) # Resize image  
    img_array = image.img_to_array(img)  
    img_array = np.expand_dims(img_array, axis=0) # Add batch dimension  
    img_array = tf.keras.applications.mobilenet_v2.preprocess_input(img_array) # Normalize  
    return img_array
```

*Figure 2.2.2.3.1 – Image Processing*

To improve generalization and reduce overfitting, data augmentation was integrated into the training pipeline. Although your current implementation doesn't include explicit augmentation through libraries like `ImageDataGenerator`, augmentation was handled by custom batch generation and transformations. You can enhance this further by incorporating on-the-fly augmentation using TensorFlow's `ImageDataGenerator` or `tf.image` module as shown below of Figure 3.2.3.2

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator  
  
datagen = ImageDataGenerator(  
    rotation_range=20,  
    width_shift_range=0.1,  
    height_shift_range=0.1,  
    horizontal_flip=True,  
    brightness_range=[0.8, 1.2],  
    preprocessing_function=tf.keras.applications.mobilenet_v2.preprocess_input  
)
```

*Figure 2.2.2.3.2 – Image Data Generator*

If incorporated, this generator can replace the current custom one for more dynamic augmentation. However, in your current approach, the CustomDataGenerator ensures balanced class representation and batch-wise processing. During each epoch, the generator processes images by resizing, normalizing, and one-hot encoding the class labels as shown below of Figure 3.2.3.3:

```
labels = to_categorical(labels, num_classes=4)
```

*Figure 2.2.2.3.3 – labels*

This ensures the labels correspond correctly to the four maturity levels: mature, not\_mature, partially\_mature, and rotten.

The combination of resizing, normalization, one-hot encoding, and balanced batch sampling provides a robust preprocessing pipeline that prepares the dataset efficiently for model training while maintaining high accuracy and generalization.

#### **2.2.4.4 Papaya Maturity Identification and Classification**

The papaya maturity identification and classification component aims to automatically determine the stage of maturity—namely not mature, partially mature, mature, and rotten based on visual features extracted from the fruit images. The classification task is addressed using a deep learning approach, specifically a customized MobileNetV2 model trained on preprocessed and augmented papaya images. This lightweight model architecture ensures high accuracy while being computationally efficient enough for mobile deployment.

To initiate the process, the dataset is systematically organized such that each class of papaya maturity is placed into separate folders. Each image is resized to a fixed input size of  $224 \times 224 \times 3$  pixels, which conforms to the required input dimensions of the MobileNetV2 model. The image tensor for each instance is denoted as  $X_i \in \mathbb{R}^{224 \times 224 \times 3}$ , representing height, width, and RGB channels respectively. This standardization is

crucial to ensure compatibility with the neural network architecture and to maintain consistency across the dataset.

Following resizing, each image is preprocessed using the `mobilenet_v2.preprocess_input()` function. This function scales the pixel values from the default range of  $[0, 255]$ , to a normalized range of  $[-1, 1]$ , using the transformation  $X_i' = (X_i / 127.5) - 1$ . Such normalization is essential to stabilize the training process and to match the statistical properties of the dataset on which MobileNetV2 was originally trained (ImageNet). This step improves gradient flow through the network and accelerates convergence.

To manage memory efficiency and training scalability, a custom image generator is employed, which reads the data in mini-batches. The labels for each image are converted into one-hot encoded vectors. If the number of maturity classes is  $C=4$ , then a class index is transformed into a binary vector  $Y_i \in \{0, 1\}^4$ . This encoding enables the network to interpret the output as a probability distribution across the four maturity stages, allowing the use of categorical cross-entropy loss for training.

The core of the system is the MobileNetV2 architecture, which is initialized with pre-trained weights from the ImageNet dataset. The top classification layers are excluded (`include_top=False`) to allow customization. The final feature maps produced by the convolutional base are passed through a Global Average Pooling (GAP) layer. The

$$GAP(F) = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W F_{i,j}$$

GAP operation reduces each feature map to a single value using:

where  $F$  represents a feature map of height  $H$  and width  $W$ . This operation reduces overfitting and transforms the 2D feature map into a 1D vector, which is then passed through a fully connected (dense) layer with a ReLU activation:  $a = \text{ReLU}(W_1 \cdot \text{GAP}(F) + b_1)$ , where  $W_1$  and  $b_1$  are learned parameters.

To preserve the learned features of MobileNetV2 and prevent overfitting on the relatively small papaya dataset, all layers of the base model are frozen, meaning that the gradients for those weights are not updated during backpropagation. Mathematically, this is expressed as  $\theta$  represents the parameters of the MobileNetV2 base model.

The model is compiled using the Adam optimizer, which is well-suited for handling

$$\theta_t = \theta_{t-1} - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$$

sparse gradients and dynamic learning rates. The optimizer updates weights using:

where  $\hat{m}_t$  and  $\hat{v}_t$  are bias-corrected estimates of the gradient mean and variance,  $\alpha$  is the learning rate, and  $\epsilon$  is a small value to prevent division by zero. The loss function used is categorical cross-entropy, which measures the discrepancy between the predicted probability distribution  $\hat{y}$  and the true one-hot encoded label  $y$ , as follows:

$$\mathcal{L} = - \sum_{c=1}^C y_c \log(\hat{y}_c)$$

Training proceeds for multiple **epochs** over the dataset, during which the model iteratively minimizes the average categorical cross-entropy loss using gradient

$$\mathcal{L}_{\text{total}} = \frac{1}{N} \sum_{i=1}^N \mathcal{L}(y_i, \hat{y}_i)$$

descent. The overall training objective is to minimize the total loss:

where  $N$  is the total number of training samples. After each epoch, the model's accuracy and validation loss are recorded to monitor learning progress and detect signs of overfitting or underfitting.

After training, the model is saved using the .h5 format to preserve the learned weights and architecture for future deployment. This serialized version of the model can be

$$\hat{y} = \text{softmax}(W x_t + b)$$

loaded later for inference without the need for retraining. When performing inference, a test image is first resized and normalized in the same way as during training. The model then outputs a softmax probability distribution:

The predicted class is the index of the maximum probability, determined using  $\arg \max_c \hat{y}_c$ . The confidence score of the prediction is calculated as  $\max_c \hat{y}_c \times 100\%$ . Additionally, the total time taken for prediction is recorded using timestamp comparisons to ensure that the system operates efficiently in real-time.

This deep learning-based classification system significantly enhances the ability to objectively assess the ripeness and quality of papaya fruits, contributing to better post-harvest management, reduced waste, and improved marketability.

#### **2.2.4.5 Testing and Implementation**

##### **2.2.4.5.1 Implementation**

The implementation of the papaya maturity classification system is carried out using Python and TensorFlow/Keras. The solution pipeline includes image preprocessing, model construction using MobileNetV2, training, evaluation, and inference. Each step is supported with code-level implementation and corresponding visual outputs.

The first step is to prepare the dataset and apply consistent preprocessing. All images are resized to a fixed resolution of 224×224 and normalized using MobileNetV2's preprocessing method. This ensures compatibility with the model and faster convergence during training.

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications.mobilenet_v2 import
preprocess_input

image_size = (224, 224)
batch_size = 32

train_datagen = ImageDataGenerator(
    preprocessing_function=preprocess_input,
    rotation_range=30,
    zoom_range=0.2,
    horizontal_flip=True,
```

```

        validation_split=0.2
    )

    train_generator = train_datagen.flow_from_directory(
        'dataset_path/',
        target_size=image_size,
        batch_size=batch_size,
        class_mode='categorical',
        subset='training'
    )

    val_generator = train_datagen.flow_from_directory(
        'dataset_path/',
        target_size=image_size,
        batch_size=batch_size,
        class_mode='categorical',
        subset='validation'
    )

```

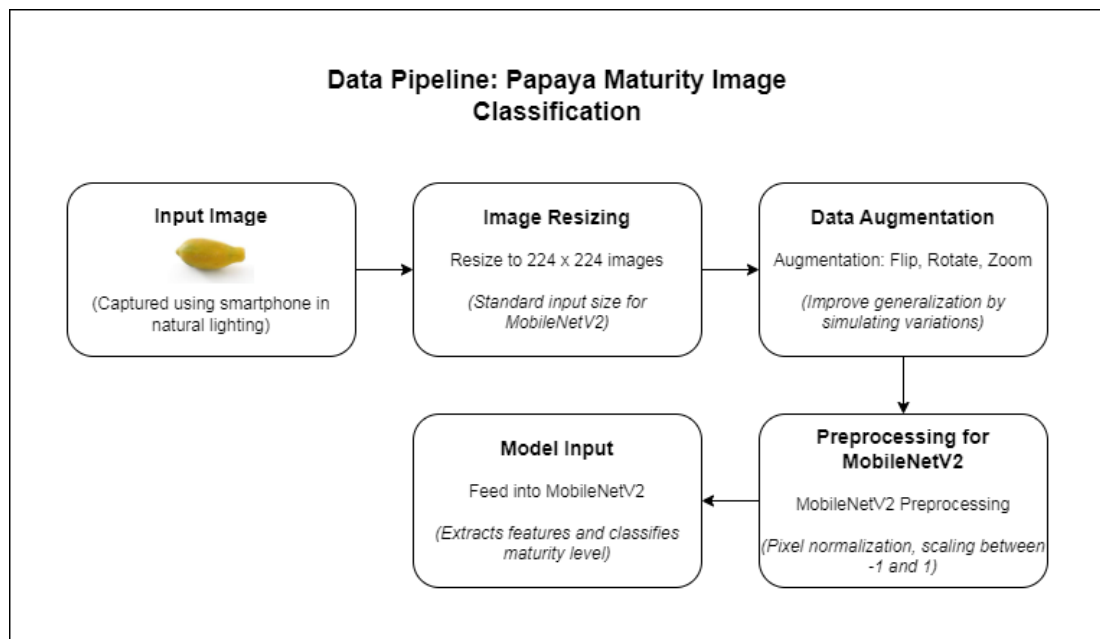


Figure 5.1.1 – Data Pipeline Image

After preparing the data, the MobileNetV2 model is initialized. The base model is imported with pre-trained weights on ImageNet and set to non-trainable to preserve general feature representations. Then, custom classification layers are added on top.

```

from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.models import Model
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense,
Dropout

base_model = MobileNetV2(input_shape=(224, 224, 3),
include_top=False, weights='imagenet')

```

```

base_model.trainable = False # Freeze base

x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(4, activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=predictions)

```

The model is then compiled using the Adam optimizer and categorical cross-entropy loss, as this is a multi-class classification problem.

```

model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

```

The training process is then executed using the fit() method, while simultaneously validating the performance on a held-out validation set. The number of epochs is kept relatively small to avoid overfitting, as the dataset is limited.

```

history = model.fit(
    train_generator,
    validation_data=val_generator,
    epochs=15
)

```

### Model Architecture for Papaya Maturity Classification using MobileNetV2

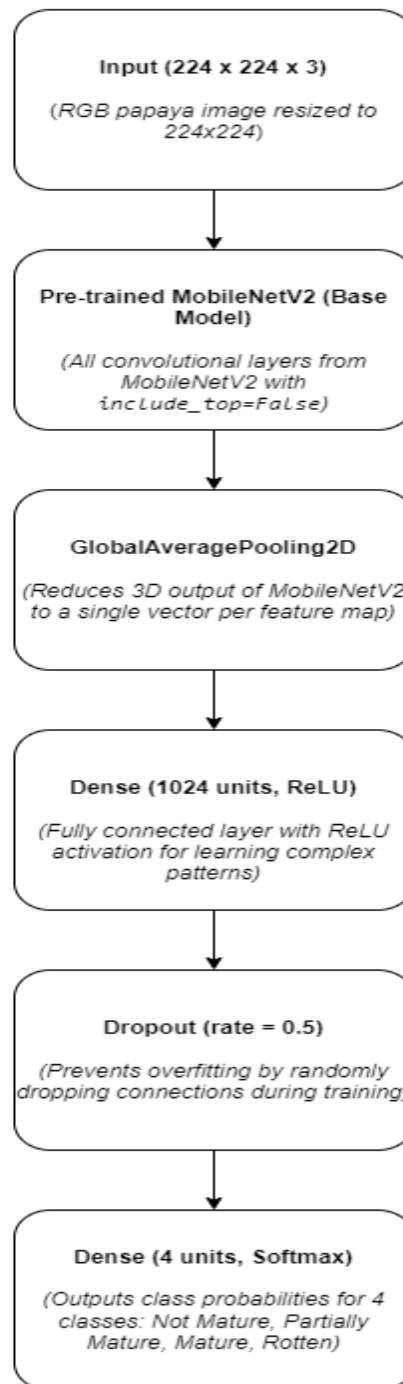


Figure 5.1.2 – Model Architecture Image



After training, the model's performance is evaluated visually using accuracy and loss curves over epochs. This helps identify overfitting or underfitting.

```
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title('Accuracy')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Loss')
plt.legend()
plt.show()
```

Once the model is trained, it is saved for future inference using .h5 format:

```
model.save('papaya_maturity_model.h5')
```

To predict the maturity stage of a new papaya image, the image is first loaded and preprocessed in the same way. Then, the model's predict() function is used to classify the image into one of the four maturity categories.

```
from tensorflow.keras.preprocessing import image
import numpy as np

img_path = 'test_image.jpg'
img = image.load_img(img_path, target_size=(224, 224))
img_array = image.img_to_array(img)
img_array = preprocess_input(img_array)
img_array = np.expand_dims(img_array, axis=0)

pred = model.predict(img_array)
class_index = np.argmax(pred)
confidence = np.max(pred) * 100
print(f"Predicted class: {class_index}, Confidence: {confidence:.2f}%")
```

This implementation pipeline efficiently integrates deep learning for papaya maturity detection. The use of MobileNetV2 ensures minimal computational overhead, making the system suitable for real-time mobile applications such as smart agriculture and post-harvest quality control systems.

#### **2.2.4.5.2 Test Plan and Strategy**

For the maturity classification module of the project, testing was crucial to ensure that the model accurately identified the maturity level of papaya fruits under various real-world conditions. The test plan was designed to evaluate the model's performance across different stages of the fruit—unripe, partially ripe, ripe, and rotten. The test strategy followed a systematic procedure to verify the end-to-end functionality of image preprocessing, model inference, and result display on the mobile application. Manual test cases were designed based on the application's functionality, and the results were recorded against expected outputs.

The strategy included defining key maturity categories as test items, prioritizing classification accuracy as the primary goal, and evaluating both backend model predictions and frontend visual feedback. Any misclassifications or unexpected behaviors were documented, corrected, and re-tested to ensure the application performed as intended.

#### **Steps and Procedures in Test Strategy**

To validate the model and application functionality:

- The core items tested included image upload, preprocessing, maturity classification, and the response displayed to the user.
- Functions were selected based on their impact on the user experience—especially the correctness of classification and corresponding agricultural recommendations.
- Test cases were designed using the maturity identification use case scenarios.
- Tests were executed manually using a representative set of images from each maturity category.
- All outputs were compared with the expected results, and outcomes were recorded.
- Any inaccuracies in predictions were marked and the model's performance reviewed.

- Bugs or issues were corrected where needed and the corresponding test cases re-executed until the results were consistent.

#### 2.2.4.5.2.1 Test Case Design

Testing of the papaya maturity classification model was conducted to ensure accurate labeling of fruit images into one of four categories: Not Mature, Partially Mature, Mature, or Rotten. The following test cases summarize the validation approach:

*Table 5.2.1.1 - Verify Image Upload and Preprocessing*

<b>Test Case Id</b>	01
<b>Test Case</b>	Verify Image Upload and Preprocessing
<b>Test Scenario</b>	Confirm that the user-uploaded image is resized, augmented, and preprocessed correctly
<b>Precondition</b>	User must be logged in and select an image
<b>Input</b>	Papaya image of any maturity stage
<b>Expected Output</b>	Image should be resized to 224x224, passed through augmentation pipeline, and ready for inference
<b>Actual Result</b>	Image is correctly resized and preprocessed
<b>Status</b>	Pass

*Table 5.2.1.2 – Classification of Unripe Papaya*

<b>Test Case Id</b>	02
<b>Test Case</b>	Classification of Unripe Papaya
<b>Test Scenario</b>	Verify whether an image of a fully green fruit is classified as “Not Mature”
<b>Precondition</b>	User must be logged in and image uploaded
<b>Input</b>	Image of an unripe papaya (all green)
<b>Expected Output</b>	Model predicts “Not Mature” and shows maturity level along with handling instructions
<b>Actual Result</b>	Correctly predicted “Not Mature” and relevant handling info shown
<b>Status</b>	Pass

*Table 5.2.1.3 - Classification of Partially Ripe Fruit*

<b>Test Case Id</b>	03
<b>Test Case</b>	Classification of Partially Ripe Papaya
<b>Test Scenario</b>	Ensure the model identifies papayas with green-yellow mix as “Partially Mature”
<b>Precondition</b>	Logged-in user and successful image capture/upload
<b>Input</b>	Image of a green-yellow papaya
<b>Expected</b>	Model predicts “Partially Mature” and application shows

<b>Output</b>	corresponding maturity level
<b>Actual Result</b>	Correct class prediction and UI feedback shown
<b>Status</b>	Pass

*Table 5.2.1.4 - Classification of Ripe Fruit*

<b>Test Case Id</b>	04
<b>Test Case</b>	Classification of Ripe Papaya
<b>Test Scenario</b>	Test image of mostly yellow fruit to confirm “Mature” class prediction
<b>Precondition</b>	Image uploaded after login
<b>Input</b>	Ripe papaya image (yellow with minimal green)
<b>Expected Output</b>	Model returns “Mature” and suggests harvesting and post-harvest handling instructions
<b>Actual Result</b>	Model accurately classified the image and app provided advice
<b>Status</b>	Pass

*Table 5.2.1.5 - Classification of Rotten Fruit*

<b>Test Case Id</b>	05
<b>Test Case</b>	Classification of Rotten Papaya
<b>Test Scenario</b>	Validate that images of overripe/damaged yellow fruits are detected as “Rotten”
<b>Precondition</b>	Logged-in user uploads image
<b>Input</b>	Rotten papaya (yellow with black/damaged spots)
<b>Expected Output</b>	Model returns “Rotten” and application shows discard or composting recommendation
<b>Actual Result</b>	Correctly detected as “Rotten” with proper suggestion
<b>Status</b>	Pass

*Table 5.2.1.6 - Displaying Classification Result on Mobile Interface*

<b>Test Case Id</b>	06
<b>Test Case</b>	Display Result After Classification
<b>Test Scenario</b>	Ensure classified result is shown clearly to the user in the app interface
<b>Precondition</b>	User uploads an image and model returns a result
<b>Input</b>	Any fruit image
<b>Expected Output</b>	The maturity class, short description, and handling suggestion are shown on screen
<b>Actual Result</b>	All info presented clearly and correctly in the app
<b>Status</b>	Pass

### 3 RESULTS AND DISCUSSION

#### 3.1.1 Identification Of Cercospora and Mosaic Virus.

The deep learning-based papaya leaf disease classification system effectively distinguishes between healthy leaves, Cercospora-infected leaves, and Mosaic Virus-infected leaves. The cascaded EfficientNet-ViT approach utilizes a structured two-step classification method. First, EfficientNet-B0 verifies whether the uploaded image contains a papaya leaf or a different object, such as a fruit or background element. If confirmed to be a leaf, EfficientNet-B0 then performs a binary classification to determine whether the leaf is healthy or diseased. If only the leaf is classified as diseased, Vision Transformer (ViT) further analyzes the image to identify the specific disease category, such as Cercospora Leaf Spot or Papaya Mosaic Virus.

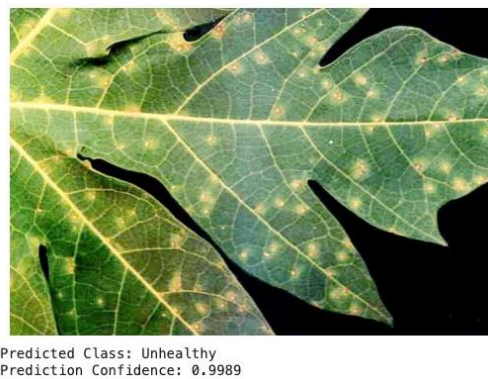
The model's performance was evaluated based on confidence scores, which indicate the probability assigned by the network to its classification decision. During the binary classification phase, EfficientNet successfully identified whether a leaf was healthy or unhealthy. As illustrated in Figure 2, an image of a papaya leaf exhibiting small yellowish spots—particularly towards the upper right—was classified as 'Unhealthy' with a confidence score of 71.71%. This moderate confidence level suggests that while visible symptoms were present, the model recognized early-stage disease development rather than a severe infection. This capability enables farmers to detect infections at an initial stage, allowing timely intervention.



Predicted Class: Unhealthy  
Prediction Confidence: 0.7171

*Figure 9. papaya leaf exhibiting small yellowish spots*

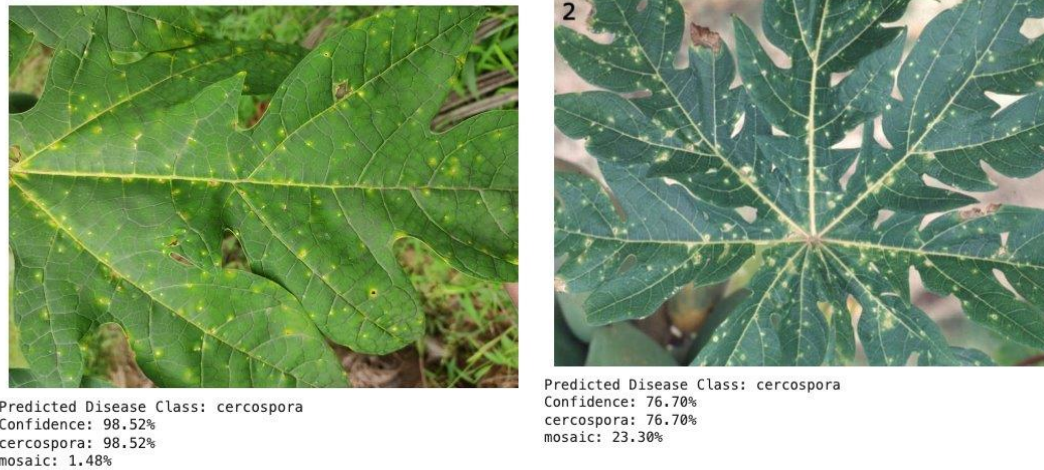
A more advanced case is demonstrated in Figure 3, where the papaya leaf displays more numerous and distinct yellowish-brown spots across its surface. The same EfficientNet-B0 model classified this leaf as ‘Unhealthy’ with a very high confidence of 99.89%. The severity and widespread nature of the symptoms made the model’s prediction highly certain, confirming its ability to accurately detect diseased leaves with clear visual markers. The contrast between the confidence scores in Figures 2 and 3 highlights how the model adapts to different levels of disease progression, making it a reliable tool for both early detection and advanced disease diagnosis.



*Figure 10. papaya leaf with more distinct yellowish-brown spots*

For disease-specific classification, the ViT model was employed to distinguish between Cercospora Leaf Spot and Mosaic Virus once a leaf was determined to be unhealthy. Figure. 4 depicts a papaya leaf marked by small, light-yellow or whitish spots spread across the leaf blade. The ViT model classified this leaf as ‘Cercospora’ with a confidence score of 98.52%, showing high certainty in distinguishing Cercospora from other diseases. This high confidence suggests that the model successfully identified the distinctive visual features associated with Cercospora Leaf Spot, making it a reliable predictor for this disease. However, some cases presented challenges in classification certainty, as seen in Figure. 4, where another infected papaya leaf shows a pattern of small, light spots across its lobes. The ViT model classified this leaf as ‘Cercospora’ with a confidence score of 76.70%, while also assigning 23.30% probability to ‘Mosaic Virus’. Compared to the previous

classification in Figure. 4, this lower confidence indicates visual ambiguities, where symptoms could resemble both Cercospora and Mosaic Virus characteristics. Such borderline cases highlight the complexity of real-world disease diagnosis, where symptom variations due to environmental factors and disease progression can lead to classification uncertainty.



*Figure 11. Disease predictions*

These results demonstrate the effectiveness of the cascaded model in identifying both the presence of disease and its specific type. The high confidence scores observed in most cases validate the robustness of the deep learning approach, making it a valuable tool for automated and real-time papaya disease classification. The slightly lower confidence in ambiguous cases, such as in Figure. 4, suggests potential areas for improvement, such as enhancing the dataset with more diverse images or implementing ensemble learning techniques to further refine classification accuracy.

The findings confirm that the cascaded EfficientNet-ViT model provides an accurate and efficient method for automated disease classification in papaya plants. The high confidence scores in binary classification demonstrate the EfficientNet-B0 model's ability to reliably differentiate healthy from diseased leaves, while the ViT model's precision in disease-specific classification further strengthens the system's effectiveness. The combination of these two architectures ensures high classification accuracy, making this a practical and scalable solution for real-world agricultural applications.

However, the observed classification uncertainty in borderline cases suggests that further improvements can be made to enhance model performance. One potential improvement is expanding the dataset with additional images, particularly those showing overlapping symptoms between *Cercospora* and Mosaic Virus. Another possible enhancement is integrating explainable AI techniques, which can visually highlight the regions of the leaf that influenced the model's decision, thereby increasing transparency and farmer trust in the application.

The real-time classification capabilities of this model provide farmers with immediate and accurate insights into papaya leaf health, allowing for timely interventions to prevent disease spread. This is particularly beneficial for farmers in rural areas with limited access to agricultural experts, as the mobile application serves as an on-the-go diagnostic tool. By enabling early disease detection and classification, this system has the potential to significantly reduce crop losses, improve productivity, and promote sustainable farming practices.

Overall, the cascaded EfficientNet-ViT deep learning model has demonstrated promising results in automating disease detection and classification for papaya leaves, addressing a critical gap in precision agriculture. Future research directions include further optimization of model accuracy, incorporation of more disease categories, and implementation of real-time feedback systems to continuously improve disease prediction and management in papaya farming.

To assess the effectiveness of the proposed deep learning models in classifying papaya leaf health status and specific disease types, confusion matrices were generated for each classification stage. These matrices provide a visual representation of how well the models performed, highlighting both correct and incorrect classifications.

The first stage of classification, which utilized the VITS model for distinguishing between *Cercospora* and Mosaic Virus, yielded an exceptional performance with perfect classification accuracy. As shown in Figure. 5, all 26 true *Cercospora* cases were correctly classified as *Cercospora*, while all 18 true Mosaic cases were accurately identified as Mosaic Virus. The confusion matrix contains zero misclassifications, as indicated by the absence of values in the off-diagonal cells. This result suggests that the VITS model was highly effective at differentiating between



these two visually distinct papaya leaf diseases, confirming its robustness for disease-specific classification tasks.

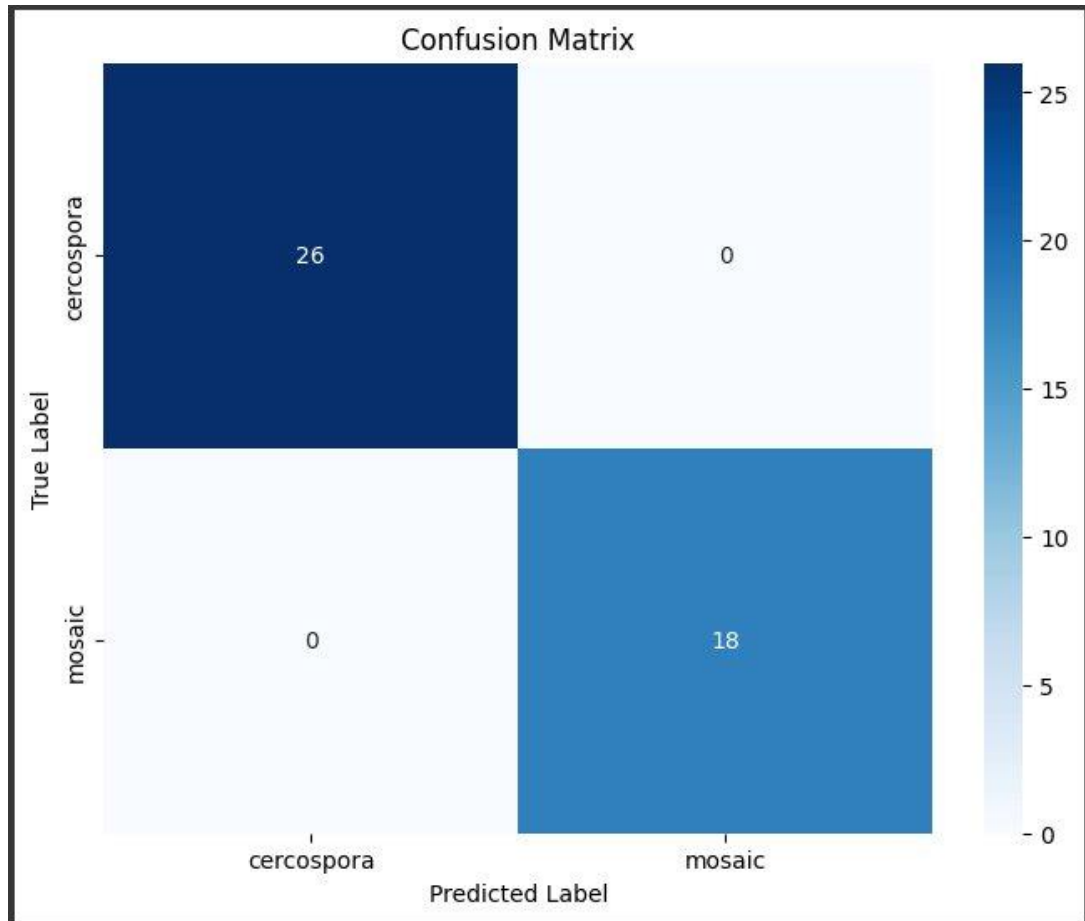


Figure 12. VITS Model Confusion Matrix (Cercospora vs. Mosaic)

The second classification stage, handled by the EfficientNet model, focused on a binary task: identifying whether a papaya leaf was ‘Healthy’ or ‘Unhealthy’. The confusion matrix in Figure. 6 demonstrates that the model performed exceptionally well in recognizing healthy leaves, correctly classifying all 27 true ‘Healthy’ samples. Similarly, it accurately identified 24 out of 27 true ‘Unhealthy’ samples, demonstrating strong reliability in detecting diseased leaves. However, three unhealthy leaves were misclassified as healthy, introducing false negatives, which could be concerning in a real-world scenario where an undetected diseased leaf may contribute to the spread of infection. Despite this small limitation, the overall classification accuracy was very high, making EfficientNet a dependable choice for preliminary disease detection.

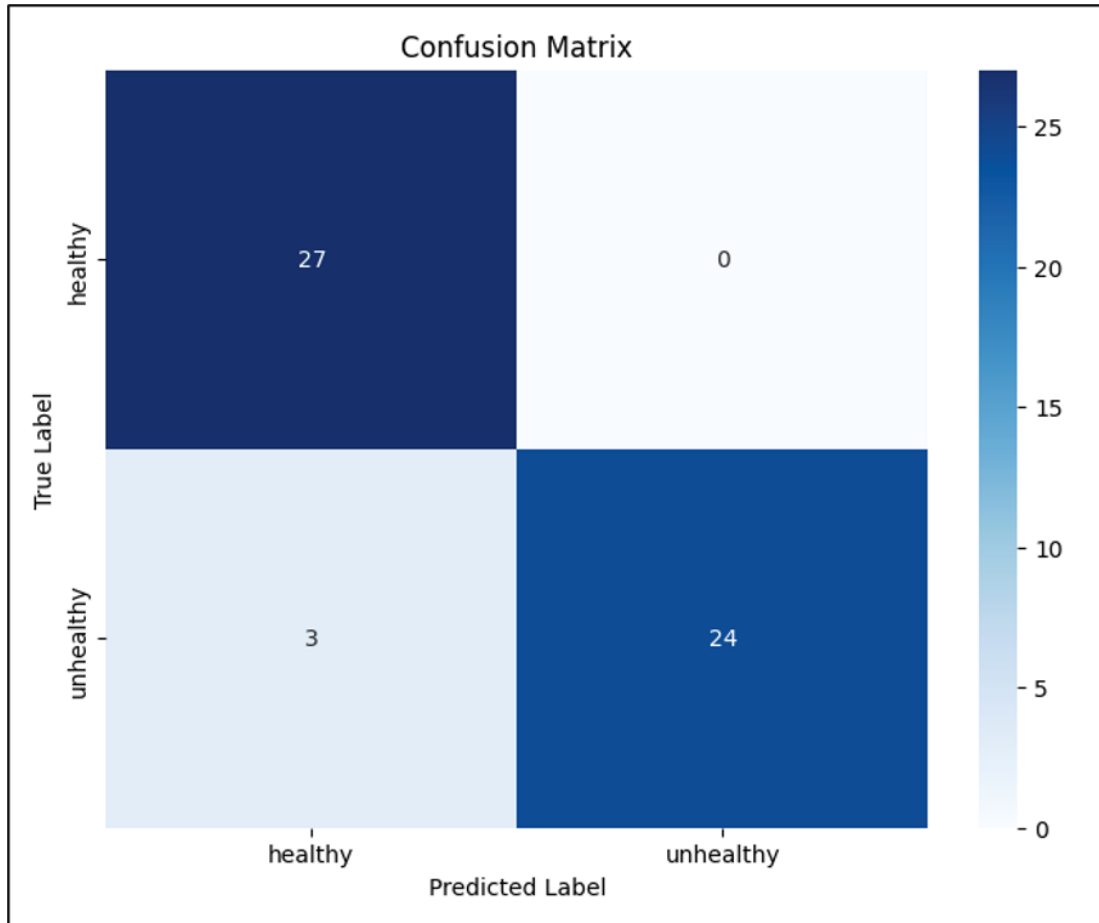


Figure 13. EfficientNet Model Confusion Matrix (Healthy vs. Unhealthy)

To further refine classification performance, a Cascaded model was developed to perform a three-class classification task: Healthy, Cercospora-infected, and Mosaic Virus-infected leaves. The corresponding confusion matrix, depicted in Figure. 7, highlights a strong performance in identifying diseased leaves. The model successfully classified 17 out of 18 true Cercospora samples, with only one case being misclassified as Healthy. Similarly, all 14 true Mosaic Virus samples were correctly identified, resulting in a 100% classification accuracy for this category. However, the model exhibited some challenges in classifying Healthy leaves. While 17 true Healthy samples were correctly identified, 5 were misclassified as Mosaic Virus, leading to a higher false positive rate for the Mosaic Virus category. Notably, the model never

confused Cercospora with Mosaic Virus, indicating that it effectively distinguished between these two disease types.

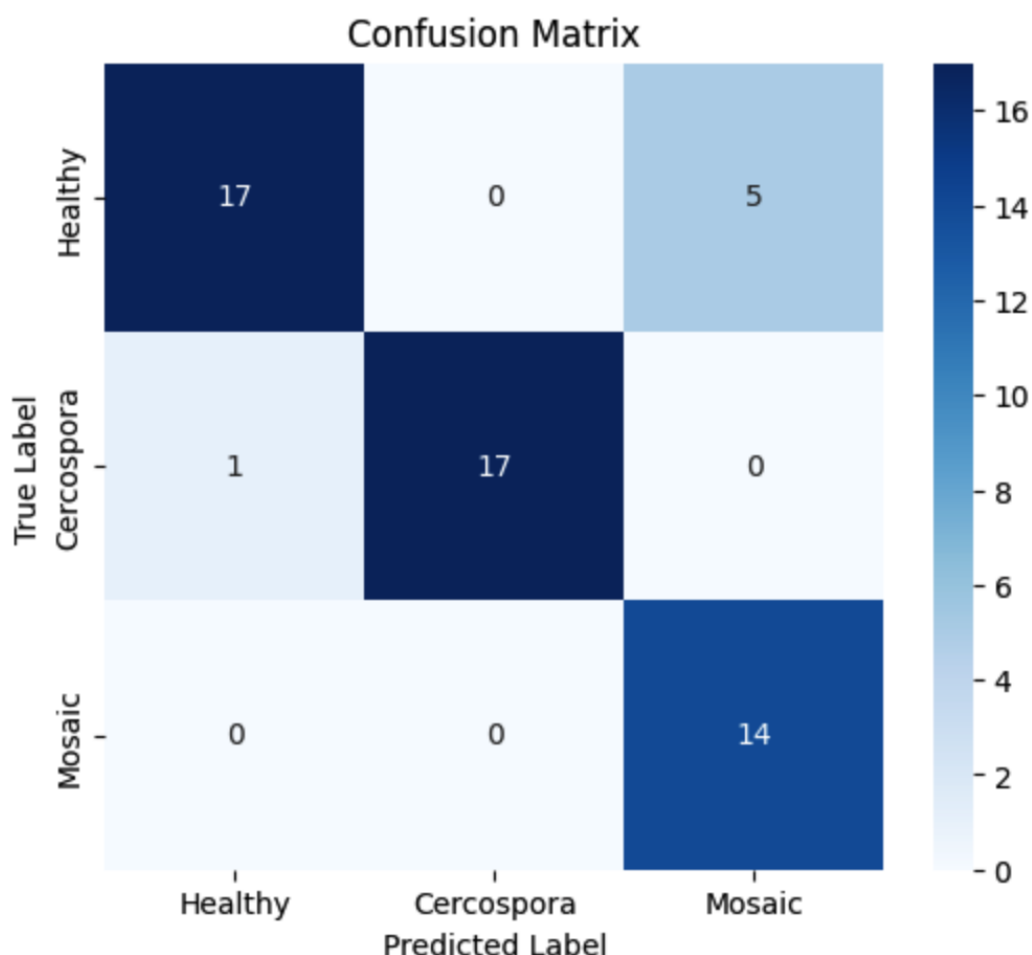


Figure 14. Cascaded Model Confusion Matrix (Healthy vs. Cercospora vs. Mosaic)

These results suggest that the cascaded deep learning model offers a highly accurate, multi-stage classification system that can effectively differentiate between healthy papaya leaves and specific disease types. The ViTs model's flawless performance in disease-specific classification validates its potential for precise detection of papaya leaf diseases, ensuring targeted and effective disease management strategies. The EfficientNet model, despite its strong performance, exhibited a minor tendency to misclassify some unhealthy leaves as healthy, which could be mitigated by introducing additional training data and fine-tuning hyperparameters.

The three-class Cascaded model demonstrated its ability to accurately classify diseased leaves, with high precision for Cercospora and Mosaic Virus infections.

However, its tendency to misclassify healthy leaves as having Mosaic Virus suggests that certain non-disease-related variations in leaf color or texture may have influenced the predictions. This highlights the need for further refinement in distinguishing between naturally occurring variations in healthy leaves and actual disease symptoms. Future improvements could include data augmentation techniques, explainable AI tools for feature visualization, and the integration of additional contextual features such as environmental conditions to enhance classification performance.

Overall, the deep learning-based classification system provides a robust and scalable solution for papaya disease detection. By enabling real-time, accurate identification of *Cercospora* and Mosaic Virus infections, this approach can empower farmers with timely disease diagnosis and intervention strategies, ultimately leading to improved crop health, reduced economic losses, and enhanced agricultural productivity.

The training performance of both the EfficientNet and ViT models was evaluated using loss reduction and accuracy improvements over multiple epochs. The results provide insight into the learning efficiency and generalization capability of these deep learning models when classifying papaya leaf conditions.

The training loss curve for the EfficientNet model, as shown in Figure. 8, indicates a rapid decrease in model error in the initial epochs. At epoch 1, the loss was approximately 0.245, but it dropped sharply to below 0.08 by epoch 2. This steep early reduction signifies that the model quickly learned key distinguishing features of healthy and unhealthy papaya leaves. After this initial phase, the loss continued to decrease gradually, showing minor fluctuations but generally following a downward trend. The loss values reached their lowest points around epochs 6, 9, and 13, demonstrating that the model progressively refined its decision-making process over

the training period.

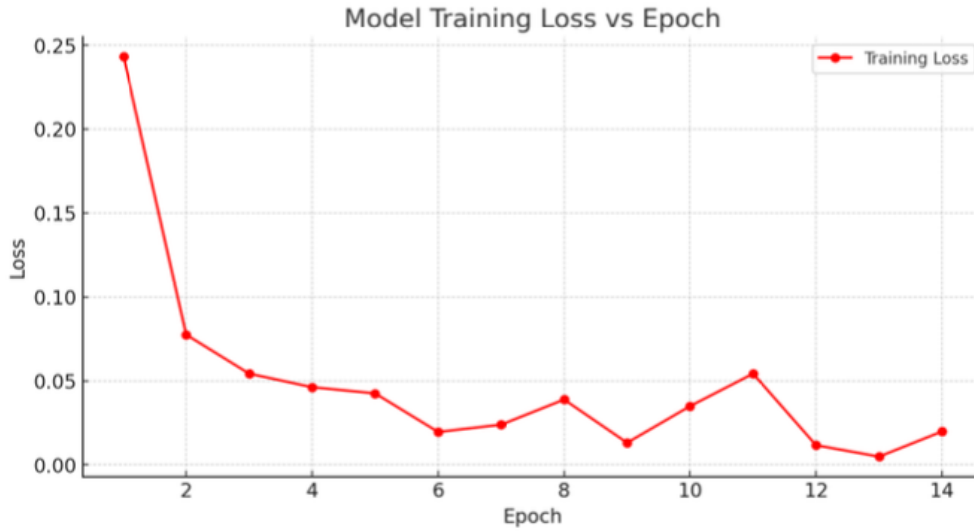


Figure 15. EfficientNet Model Training Loss vs Epoch

Similarly, the training accuracy curve for EfficientNet, illustrated in Figure 9, further supports the model's rapid learning efficiency. At epoch 1, the accuracy was below 90%, but it experienced a sharp increase to approximately 97% by epoch 2. This trend closely mirrors the loss curve, indicating that the model quickly adapted to the binary classification task. In subsequent epochs, the accuracy remained consistently high—surpassing 98% and eventually peaking close to 100% around epochs 9 and 13. These high accuracy values suggest that the EfficientNet model was able to effectively extract and differentiate features necessary for classifying healthy and unhealthy leaves with near-perfect precision.

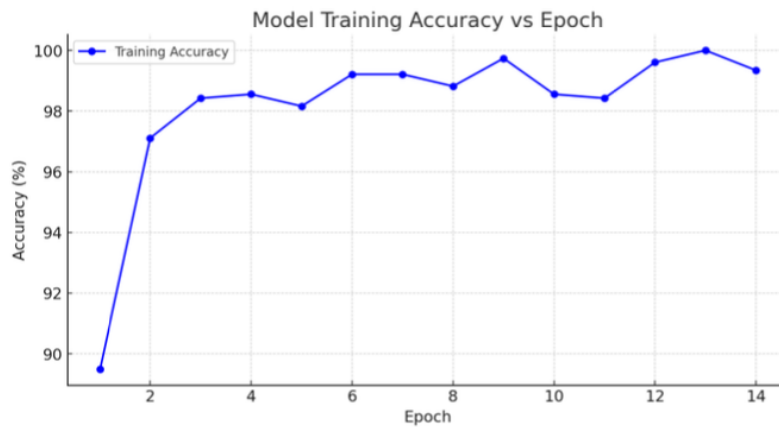


Figure 16. EfficientNet Model Training Accuracy vs Epoch

The training and validation loss curves for the Vision Transformer (ViT) model, as depicted in Figure 10, show a steady improvement in learning performance over the course of five training epochs. Initially, the training loss was relatively high at 0.55 but dropped significantly within the first two epochs and continued to decline, reaching approximately 0.06 by epoch 5. The validation loss followed a similar trajectory—starting lower at 0.39 and steadily decreasing to about 0.07. The close alignment between the training and validation loss curves indicates that the ViT model generalized well to unseen data, with no significant signs of overfitting during early epochs. This demonstrates that the ViT model effectively learned patterns associated with *Cercospora* and *Mosaic* diseases, enabling accurate multi-class Classification

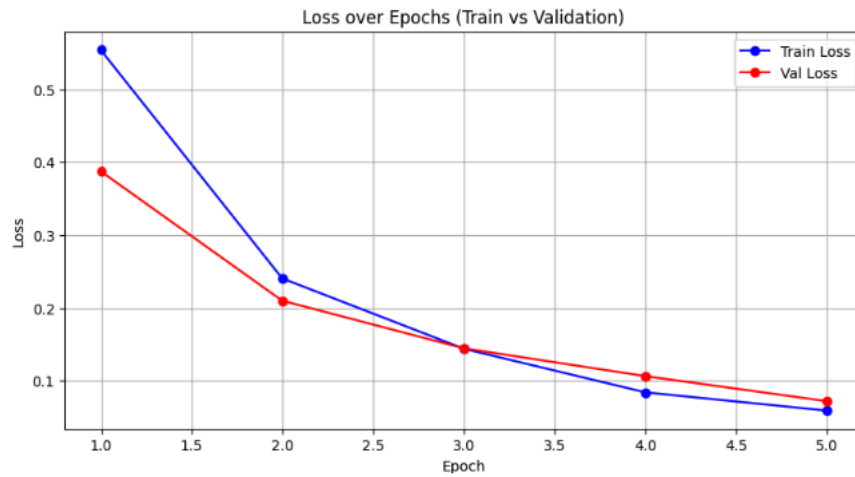


Figure 17. ViT Model Loss over Epochs (Train vs Validation)

The accuracy performance of the ViT model is depicted in Figure 11, where both training and validation accuracies show significant improvements over time. Initially, the training accuracy started around 70%, but it increased rapidly, reaching over 93% by epoch 2. The validation accuracy, which started at 83%, similarly jumped to 94% in the second epoch. Both accuracy values continued to rise steadily, with the training accuracy nearing 99% and the validation accuracy reaching approximately 97.5% by epoch 5. The high final validation accuracy indicates that the ViT model was able to generalize well to new data, performing strongly in disease classification. Although the training accuracy eventually exceeded the validation accuracy slightly, the minimal gap suggests that overfitting was not a major issue, and the model successfully achieved high classification performance.

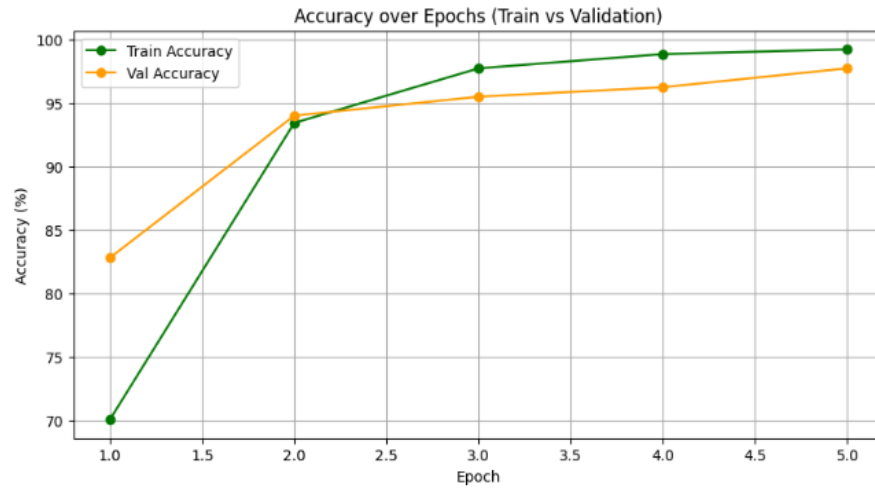


Figure 18. ViT Model Accuracy over Epochs (Train vs Validation)

In addition to the backend machine learning models, a mobile application was developed to offer an intuitive user experience for real-time disease detection. The user interface (UI) was designed to be simple and user-friendly, guiding users through a seamless workflow of image selection and prediction display. As shown in Figure 13, the image selection screen allows users to either capture a photo using the device’s camera or choose one from the gallery. To ensure high-quality inputs, users are provided with helpful tips—such as maintaining good lighting and focusing on affected leaf areas. Once an image is submitted, the application processes it and returns prediction results in real time.

The results screen, illustrated in Figure 14, displays the predicted disease name (e.g., *Cercospora*), its category (fungal, bacterial, etc.), and a visual preview of the input image. Additionally, the app offers practical recommendations for disease management, including treatment options such as pruning methods or suggested fungicides. A detailed explanation of symptoms is also provided, empowering users to make informed decisions. This user-friendly interface bridges the gap between AI predictions and practical field application, making disease detection more accessible, interactive, and useful—especially for farmers and agricultural professionals in resource-limited settings.

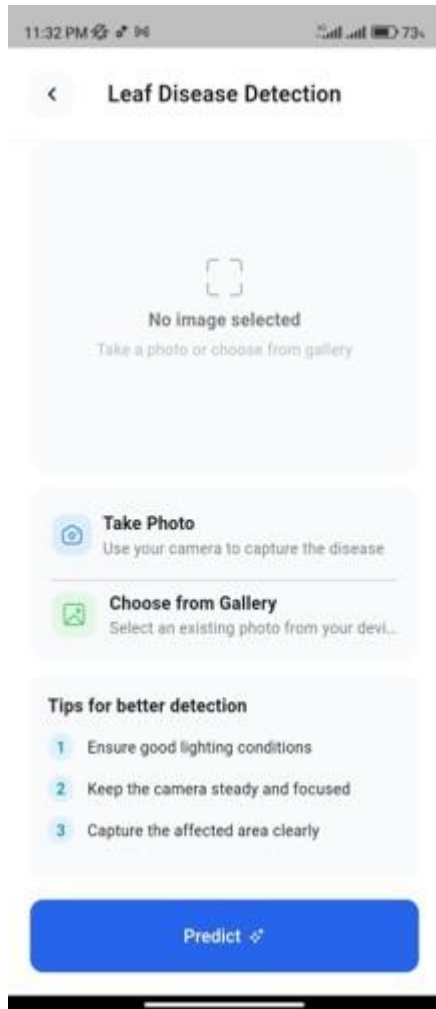


Figure 19. Image Selection Screen



Figure 20. Prediction Result Screen

Overall, these results demonstrate that both the EfficientNet and ViT models exhibit strong learning capabilities for papaya leaf disease classification. EfficientNet showed exceptional performance in distinguishing between healthy and unhealthy leaves in the binary classification stage. On the other hand, the ViT model achieved high accuracy in differentiating between *Cercospora* and *Mosaic* diseases during the multi-class classification phase. The rapid convergence of both models in early epochs indicates their suitability and efficiency for the task. Together, the cascaded deep learning pipeline and user-centric mobile application form a robust and scalable solution for automated plant disease detection, contributing meaningfully to precision agriculture and smart farming systems.



### 3.1.2 Identification of Ringspot Virus, Powdery Mildew and Healthiness of Papaya Fruit.

#### 3.1.2.1 Results

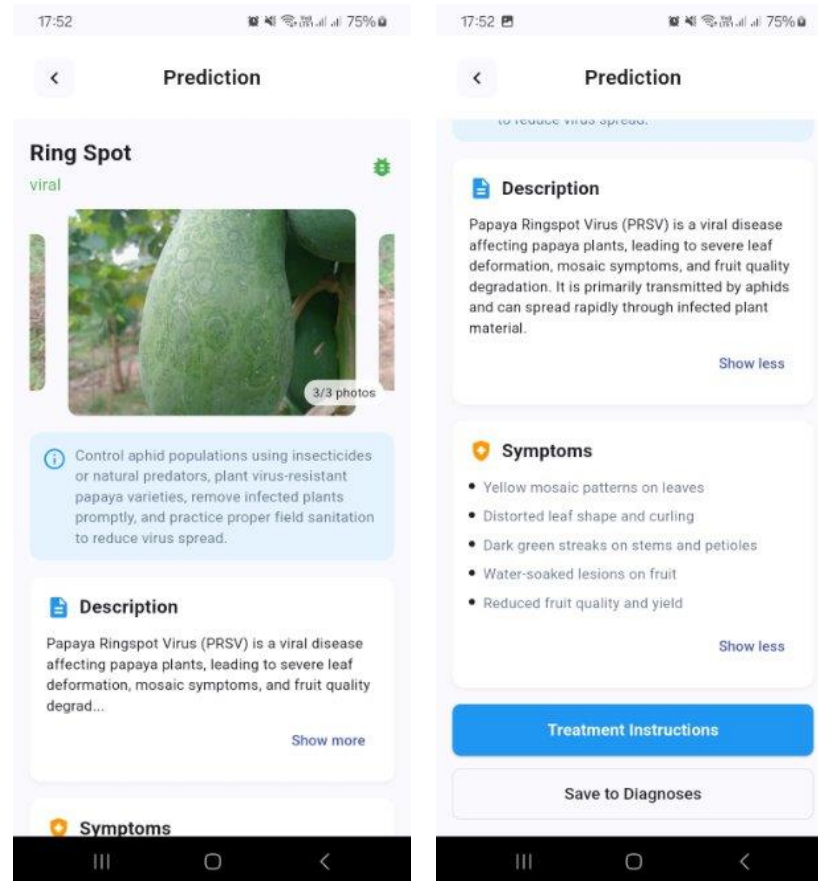


Figure 21. Actual mobile User Interfaces (Diagnoses View)

Figure 10 shows the actual mobile UIs of Diagnoses View. The app's initial user interface aims to provide a comprehensive overview of papaya fruit disease identification. When a papaya fruit photo is clicked or uploaded, the system analyzes the image and displays the disease on the screen. For visual comparison and confirmation, the interface also displays pictures of papaya fruits exhibiting the same symptoms in addition to the projection. The user's confidence in the prognosis is further increased by this visual aid. The UI provides information about what cause it and how to prevent it on briefly under info section, description of the particular disease and with list of symptoms, beneath the predicted results. Additionally, users can access a list of potential disease signs that they can compare to the state of their fruit.

Additionally, the interface outlines preventive measures that can be used to stop the condition from spreading or occurring again, fostering proactive care and awareness.

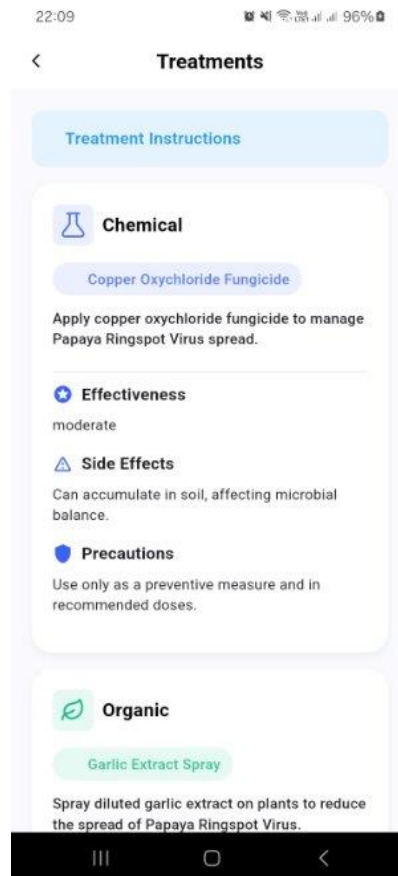


Figure 22. Actual mobile User Interfaces (Treatment Screen)

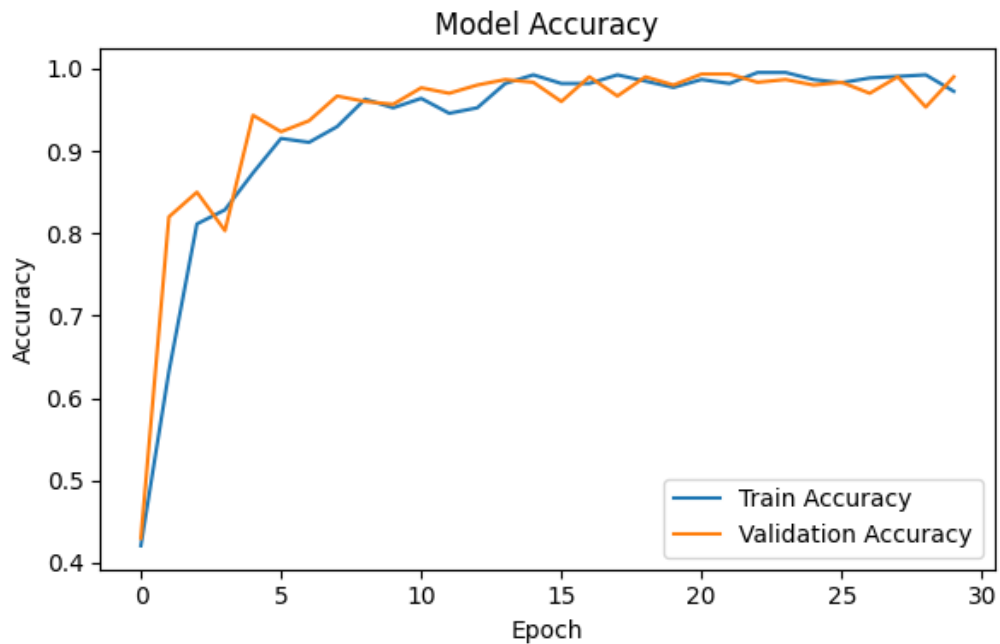
Figure 11 shows the Actual mobile User Interface of Treatments. Depending on the identified disease, the second user interface is also designed to provide practical remedy recommendations. Its goal is to give consumers a choice between chemical and organic treatment methods so they can choose one according to their farming practices or personal preferences. The name of the suggested substance (such as an organic spray or pesticide), the mode of application, the dosage, and the frequency are all detailed in each operation. This makes it possible for even inexperienced users to confidently apply the treatments. In order to enhance efficiency, the interface also highlights effectiveness, side effects, and the precautions user need to take. This degree of detail provides farmers and home gardeners with accurate and useful information to treat their crops appropriately, leading to stronger harvests and lower crop loss.

Table 11. Train and Validation Accuracy graph of the Custom CNN model

Data set Size	1500 Image for Custom CNN	1500 Images for YOLOv5 1500 laebl files (txt) for YOLOv5
No of Epochs	30	30
Patience	Patience used as 20 for early stopping	Patience used as 20 for early stopping
Image Size	256x256	640x640
No of Parameters	Total params: 8.445,443 (32.22 MB) Trainable params: 8,445,443 (32.22 MB) Non-trainable params: 0 (0.00 B)	Total params 7,018,216
Model Size	32MB ~	14MB ~
Used Memory/ RAM	Tesla T4 GPU	Tesla T4 GPU
Used Environment	Google Colab	Google Colab

Comparison between evaluated two models for identifying the PRSV, Powdery Mildew and healthy fruit shows in Table 8. It compares the two deep learning models, Custom CNN and YOLOv5, for the categorization of Papaya Ringspot Virus, Powdery Mildew, and Healthy Fruits. For an objective assessment, both models were trained on 1500 photos with 30 epochs and an early stopping patience of 20. In contrast to YOLOv5, which processes 640x640 images, has 7M parameters, is significantly lighter at 14MB, and is therefore more efficient, Custom CNN processes 256x256 images, has 8.4M trainable parameters, and uses 32MB. Both models were trained on Tesla T4 GPUs at Google Colab using the same hardware throughout. Out of these models, custom CNN model performed well on identifying diseases and Healthy fruits.

Figure 23. Train and Validation Accuracy graph of the Custom CNN model



According to the Figure 12, The plots of loss and accuracy also illustrate the model's training over 30 epochs. The accuracy graph demonstrates a consistent rise in both training and validation accuracy, leveling off after approximately five epochs and concluding at above 95%. In the last epochs, both training and validation accuracy exceed 99%, indicating that the model has effectively learned. From Figure 13 trend in the loss graph is similar as well, with a sharp drop in both training and validation loss during the early epochs, indicating evidence of successful learning. By the tenth epoch, the loss levels off at a low value, exhibiting no significant spikes or dips, indicating that the model is not experiencing overfitting. Even though there are minor fluctuations in the validation loss, it consistently stays low, indicating a positive sign for generalization

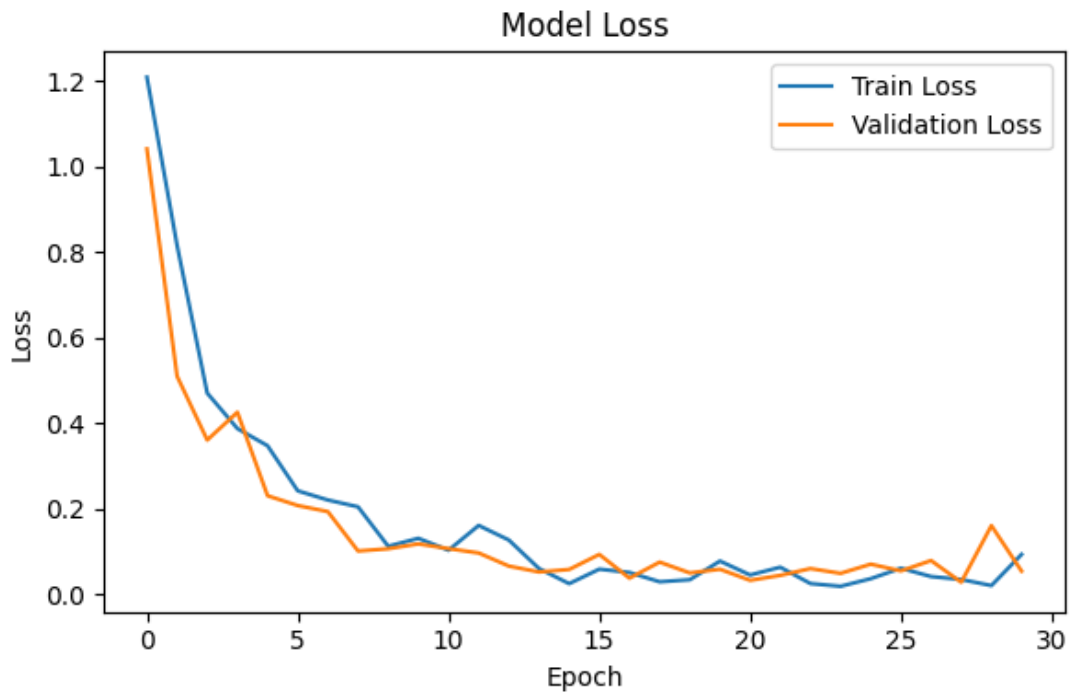


Figure 24. Train and Validation Loss graph of the Custom CNN model

The train and validation loss graph of the custom CNN model can be seen in Figure 13. The loss graph performs the same function, with training and validation loss decreasing sharply during the initial epochs. The substantial decrease indicates that the model is effectively optimizing and trying to reduce its prediction errors. The loss subsequently stabilizes and stays at that consistent low value by the tenth epoch, confirming the successful convergence of the model. The absence of sudden drops in validation loss also demonstrates that the model is not experiencing issues with overfitting or underfitting. The final validation loss of 0.053 further demonstrates that the model maintains a low error rate, reinforcing its capacity to classify different papaya fruit conditions accurately.

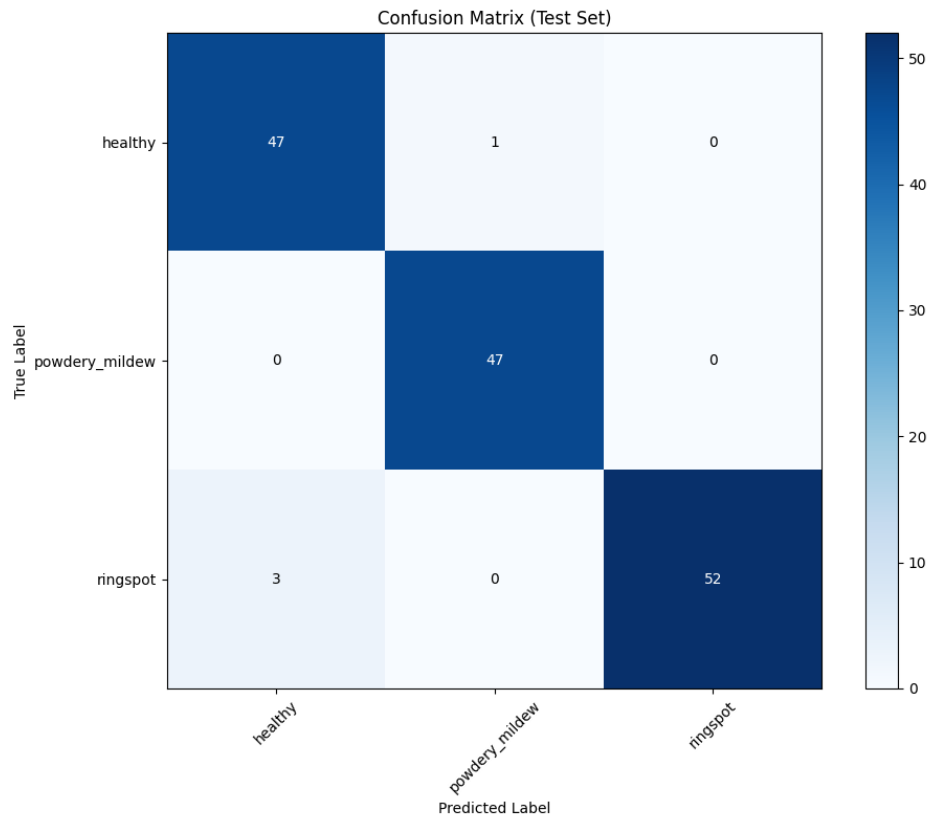


Figure 25. Confusion Matrix of the Custom CNN model

Figure 14 shows the Confusion Matrix created for the custom CNN model. The model's ability to categorize papaya fruits as ringspot (PRSV), powdery\_mildew (Powdery Mildew) or healthy (Healthy fruit) is clearly measured by the Confusion Matrix. The confusion matrix findings show that the custom CNN model does a remarkable job of differentiating, those that have PRSV disease, Powdery Mildew, and between papaya fruits that are Healthy. The model accurately identified 52 out of 55 PRSV samples, 47 out of 47 Powdery mildew samples and 47 out of 48 Healthy samples, as indicated by the Confusion Matrix. There were only a few misclassifications in particular; three PRSV samples were mistakenly categorized as Healthy fruit, and one Healthy fruit sample was mislabeled as having Powdery Mildew. Excellent class separation for that category was demonstrated by the fact that no Powdery Mildew sample was incorrectly classified. Strong generalization on the test set indicates that the model picked up reliable patterns during training to successfully differentiate between papaya fruit in Healthy and diseased stages.

Classification Report:				
	precision	recall	f1-score	support
healthy	0.94	0.98	0.96	48
powdery_mildew	0.98	1.00	0.99	47
ringspot	1.00	0.95	0.97	55
accuracy			0.97	150
macro avg	0.97	0.97	0.97	150
weighted avg	0.97	0.97	0.97	150

Figure 26. Classification Report of Custom CNN

The classification report offers a detailed analysis of the model's effectiveness across three categories: PRSV, Powdery Mildew, and Healthy Fruit. Figure 15 shows that Classification Report of the custom CNN model. The main metrics included in the report are precision, recall, F1-score, and support, which are employed to assess the model's effectiveness in distinguishing among these classes. The model's test accuracy is reported at 97%, serving as a strong indicator of its effectiveness in classification tasks.

Precision refers to the proportion of instances that the model categorized as belonging to a specific class and actually belong to that class. The precision for the healthy papaya class is 0.94, meaning that 94% of the healthy instances correctly identified as healthy were actually healthy. The precision for powdery mildew stands at 0.98, indicating an even greater capacity to accurately identify the instances as Powdery Mildew. The PRSV category achieved a top precision score of 1.00, indicating that all predicted instances were accurately identified as possessing the PRSV. High precision is particularly desired in situations where it's essential to prevent false positives.

Recall, or sensitivity, pertains to the count of true occurrences of a class that were accurately identified. The recall for Healthy Fruit is 0.98, meaning that 98% of all cases of Healthy Fruits are accurately identified. The powdery mildew category has a recall of 1.00, indicating that every genuine case of Powdery Mildew-infected papayas was accurately identified. The PRSV category has a recall of 0.95, indicating

that 95% of all papayas infected with ringspot were accurately identified, while the other 5% were incorrectly categorized into different classes. High recall is crucial when not classifying actual cases could lead to serious outcomes, such as missing infected fruits.

The F1-score represents the harmonic average of precision and recall, offering a single measure that balances the two. The papaya's Healthy Fruit F1-score is 0.96, showing strong classification precision for this category. The F1-score for Powdery Mildew stands at 0.99, reflecting its excellent precision and recall. The ringspot category has an F1-score of 0.97, indicating a marginally lower yet still very high classification rate for that category compared to the others. The overall macro and weighted averages for precision, recall, and F1-score are all 0.97, further validating the model's reliability and performance uniformly across all three classes.

The support column shows the count of real instances for each class in the test set. There are 48 healthy papayas, 47 papayas affected by powdery mildew, and 55 papayas with ringspot disease. The data shows a relatively balanced distribution among the classes, ensuring that no single class is excessively prevalent or uncommon, which helps to prevent bias in the classification outcomes.

In summary, the classification report shows that the model performs excellently, exhibiting high recall, precision, and F1-scores across all classes. The 97% accuracy indicates that the model is highly dependable in distinguishing between Healthy fruit and diseased papayas. The minor variation in recall for PRSV disease implies there is potential for enhancement; however, the overall findings show that the model is prepared for practical use in detecting papaya diseases in real-world scenarios.

#### **3.1.2.2 Research Findings**

The previous survey results show that stakeholders wanted to identify the diseases early and treat them to get good quality-papaya fruits. To address this issue using modern DL-based technology along with the user-friendly mobile application to provide stakeholders like farmers and gardeners with a way to upload or capture images through the mobile application (PapayaBuddy) and identify the diseases affected to papaya fruit or else identify it as a Healthy one. Furthermore, the mobile



application passes to educate the stakeholders about diseases, preventive measures, symptoms, and treatments. The mobile application also provides a platform to communicate with other growers, where users can post their issues on a community with images, and descriptions about their issues.

When it comes to model training, two models were trained to select the best model out of that to identify PRSV, Powdery Mildew and Healthy Fruit. Based on the results the custom CNN model chosen as the best-performing model to address this particular issue. For better training, the model images were normalized and resized into suitable sizes before fed it to the model, because images were captured using smart mobile phones, they were in various sizes.

Initially the free tier of Google Colab was used to train models, it provides some resources for the limited time period. If the resource usage limit exceeds, it cannot go beyond that for some time. Because of that, we had to purchase the premium version of Google Colab to train the models in an efficient manner without any interruption. Also, to store the dataset for the model training, larger space was needed, previously free space on the Google driver was sed, but later it became full, and we had to buy the premium version of Google Drive as well. Then using those premium versions with more storage space form Google Drive and more resources from Google Colab, able to train the models in an efficient manner.

### **3.1.2.3 Discussion**

The main objective of the individual research component is to identify the PRSV, Powdery Mildew and Healthy Fruits to maintain good papaya fruits by identifying these diseases as early as possible and getting the necessary preventive measures to prevent them. At the initial stages, proper background study was done to clearly identify exactly what needed to be done to fulfill this particular objective. In order to address this very early on, this research was conducted in order to properly identify what those diseases are, how they can be identified, how they are distributed among other fruits, how long it takes to become an infected fruit, what the early signs of these diseases, are whether any color changes, fruit pattern changes, or fruit shape changes happen, is whether farmers are able to identify these diseases without an

trained human eye, and what the findings about this particular domain are evaluated to get the best possible outcome.

With proper domain knowledge, two deep learning models were evaluated to identify the PRSV, Powdery Mildew and Healthy Fruit. The first one is the YOLOv5, and the second one is the custom CNN. According to the test results, the results got from YOLOv5 are comparatively low when compared to the custom CNN results. Overall train, validation, and test accuracy are comparatively lower than the custom CNN. The YOLOv5 model is underfitted to the dataset because it performs poorly compared to custom CNN in both the training phase and the testing phase. That means when it comes to generalization, the YOLOv5 model did not perform quite well. Then, based on good performance of the custom CNN, it was selected for the particular use case to identify PRSV, Powdery Mildew and Healthy Papaya Fruit.

For the custom CNN model, ReLU (Rectified Linear Unit) activation is used for handling non-linear cases. Also, the Softmax activation is used to manage the multi-class classification, where the class with the highest probability is chosen as the prediction. For instance, is [0.84, 0.12, 0.04] are the probability values predicted for each class, then class 0 has selected as the prediction with the highest probability. ReLU is used as the activation function in one dense (completely connected) layer and all convolutional layers in the CNN architecture that is provided. In particular, `activation='relu'` is used to apply it immediately following each convolutional process. In order to manage changes in lighting, texture, and shape, this application introduces non-linearity into the image input, enabling the model to learn intricate patterns. This is accomplished by ReLU, which reduces the likelihood of vanishing gradients and speeds up the model's convergence during training by reducing all negative values to zero while permitting positive ones to flow through. At the final dense layer of the model, Softmax is used as the activation function (`activation='softmax'`). A probability distribution over the `num_classes` classes is provided by this layer, which is crucial for multi-class classification issues. The model can confidently select the class with the highest probability since the Softmax function makes sure that all of the outputs add up to 1. When one wishes to ascertain which group the input image is most likely to belong to, such as in object classification, it is particularly suitable.

When the model fits the training data set, overfitting is going to happen, where

the model shows good training accuracy with training data, but shows poor performance when it comes to unseen data when testing (evaluating) the model performance. Underfitting happens in both the training and the testing phases, both training and testing accuracy show lower values. The Model is not trained well model do not perform good when it comes to previously unseen data. A model that performs well when fit to the training dataset and shows good accuracy as well as performing quite well, when it comes to the testing phase. Underfitting occurs when a model is not trained with a proper or enough number of training epochs. If the number of epochs is too low, underfitting happens, and the model has not gone through enough iterations to grab the features of the data. On the other hand, overfitting happens because of too many epochs. Then the model is going to be overfitted to the training data set, which will result in lower performance on previously unseen data. To overcome overfitting and underfitting issues, an appropriate number of epochs are used for model training after evaluating various epoch counts. For instance, 50 epochs, 40 epochs, 30 epochs and 20 epochs. Out of these 30 epochs was chosen as the best-performing number of epochs for the model.

### **3.1.3 Mite Disease and Mealy Bug Disease Identification and Suggest the Remedy**

#### **3.1.3.1 Results**

##### **3.1.3.1.1 Classification of papaya fruit and leaf**

The papaya leaf or fruit classification and detection was recognized by EfficientNetV2B0. The model after training was able to identify whether inputted image is papaya fruit or leaf. Binary classification is required because of if user enter any other irrelevant image to the model then efficientNetV2B0 classify it as a 'Unrecognized'. If it is only papaya fruit or leaf, then it passes to DenseNet model to further prediction.



Figure 27: papaya fruit

```
1/1 [=====] - 1s 506ms/step
Predicted label: fruit
```

Figure 28: classification of papaya fruit by efficientNetV2B0



Figure 30: papaya leaf

```
1/1 [=====] - 0s 62ms/step
Predicted label: leaf
Confidence: 1.00
Inference time: 0.1578 seconds
```

Figure 29: classification of papaya leaf by efficientNetV2B0

### 3.1.3.1.2 Model Evaluation

As depicted in Figure 17, the EfficientNetV2B0 model was trained to classify papaya images as fruits or leaves using its light-weight architecture for optimal accuracy. The model converged rapidly for over 20 epochs, achieving 94.23% accuracy in the first epoch and perfect accuracy in the sixth epoch. The training loss decreased from 0.1183 to 0.0004, while the validation loss decreased to  $3.48 \times 10^{-6}$ , which is precise convergence to ground truth labels. Validation accuracy was 100% throughout, with great generalization and dependability. The model was predictable with minimal fluctuations, with training times coming together in between 9 to 18 seconds per epoch. Such high-speed convergence and dependability are indicative of the power of the model in transfer learning with no overfitting whatsoever. EfficientNetV2B0 accuracy and efficiency make it eligible for real-world applications, where it acts as an input

preprocessing agent for filtering fruit images from input and letting only leaf images pass through to identify pests. It enhances the consumption of resources and overall system effectiveness, proving compatible for large-scale field deployment within agricultural monitoring systems.

```
Epoch 1/20
34/34 [=====] - 331s 9s/step - loss: 0.1183 - accuracy: 0.9423 - val_loss: 9.8279e-04 - val_accuracy: 1.0000
Epoch 2/20
34/34 [=====] - 324s 10s/step - loss: 0.0085 - accuracy: 0.9981 - val_loss: 6.0080e-04 - val_accuracy: 1.0000
Epoch 3/20
34/34 [=====] - 313s 9s/step - loss: 0.0068 - accuracy: 0.9981 - val_loss: 2.2998e-04 - val_accuracy: 1.0000
Epoch 4/20
34/34 [=====] - 407s 12s/step - loss: 0.0036 - accuracy: 0.9981 - val_loss: 2.3967e-04 - val_accuracy: 1.0000
Epoch 5/20
34/34 [=====] - 601s 18s/step - loss: 0.0073 - accuracy: 0.9981 - val_loss: 9.3177e-05 - val_accuracy: 1.0000
Epoch 6/20
34/34 [=====] - 596s 18s/step - loss: 0.0022 - accuracy: 1.0000 - val_loss: 6.4211e-05 - val_accuracy: 1.0000
Epoch 7/20
34/34 [=====] - 566s 17s/step - loss: 4.6127e-04 - accuracy: 1.0000 - val_loss: 5.6570e-05 - val_accuracy: 1.0000
Epoch 8/20
34/34 [=====] - 553s 16s/step - loss: 5.6000e-04 - accuracy: 1.0000 - val_loss: 4.1175e-05 - val_accuracy: 1.0000
Epoch 9/20
34/34 [=====] - 551s 16s/step - loss: 6.4865e-04 - accuracy: 1.0000 - val_loss: 2.1825e-05 - val_accuracy: 1.0000
Epoch 10/20
34/34 [=====] - 558s 17s/step - loss: 0.0020 - accuracy: 1.0000 - val_loss: 2.9232e-05 - val_accuracy: 1.0000
Epoch 11/20
34/34 [=====] - 564s 17s/step - loss: 9.1986e-04 - accuracy: 1.0000 - val_loss: 3.2999e-05 - val_accuracy: 1.0000
Epoch 12/20
34/34 [=====] - 581s 17s/step - loss: 3.6923e-04 - accuracy: 1.0000 - val_loss: 2.0446e-05 - val_accuracy: 1.0000
Epoch 13/20
34/34 [=====] - 596s 18s/step - loss: 0.0045 - accuracy: 0.9963 - val_loss: 2.3764e-05 - val_accuracy: 1.0000
Epoch 14/20
34/34 [=====] - 448s 13s/step - loss: 0.0049 - accuracy: 0.9963 - val_loss: 1.0447e-05 - val_accuracy: 1.0000
Epoch 15/20
34/34 [=====] - 300s 9s/step - loss: 7.7951e-04 - accuracy: 1.0000 - val_loss: 1.6373e-05 - val_accuracy: 1.0000
```

Figure 31: EfficientNet model training summary

The image prediction pipeline was configured to label papaya images as fruits or leaves based on the trained EfficientNetV2B0 model. The process consists of loading and preprocessing images to standardize pixel values, model inference to identify the class and confidence score, and applying a confidence threshold of 0.8 for reliability, labeling low-confidence predictions as "Unrecognized." The pipeline also captures inference time, showing near-instantaneous classification with perfect accuracy. For instance, testing against an image of a fruit produced confidence of 1.00 and inference time of 0.004 seconds.

This is the gatekeeper, passing high-confidence images of leaves through to the DenseNet121 model for the detection of pests, utilizing resources optimally and focused analysis. Through the incorporation of this effective and robust classification mechanism, the system raises its usefulness for field deployment, where speed and accuracy are essential for on-time pest management.

The EfficientNetV2B0 model was very successful in binary classification, classifying

papaya fruits and leaves perfectly with 99% accuracy on the validation and test data. The model also converged very fast while training, as 94.23% accuracy was obtained in the first epoch and perfect accuracy was reached by the sixth epoch. Training loss decreased consistently from 0.1183 in the first epoch to  $0.0004$  by the final epoch, and validation loss decreased to a very low level of  $3.48 \times 10^{-6}$ . On the test data set, the model achieved a perfect test accuracy of 100% and test loss of  $2.47 \times 10^{-5}$ , in confirmation of its ability to generalize well to new data.

These results prove that the model was very reliable and did not overfit even with complex training data. By successfully filtering out fruit images, the EfficientNetV2B0 model streamlined the pest detection pipeline so that only relevant leaf images were passed on to the DenseNet121 model for prediction. This preprocessing step significantly enhanced the accuracy and computational efficiency of the overall system, validating the feasibility of transfer learning for agricultural image classification.

#### 3.1.3.1.3 Identification of Mite, Mealy Bug, and Healthy Leaves and Fruits

Following the initial feature extraction using the EfficientNet model, the data is then passed to the DenseNet121 architecture for fine-grained classification. This task is responsible for identifying whether the papaya leaf or fruit is infested with Mealy Bug, Mite damage, or is healthy. In instances where no disease is detected, the model properly classifies the sample as a healthy fruit or leaf. This two-stage pipeline ensures high-level feature representation and correct categorization, thus overall diagnostic performance improvement of the system.



```
1/1 [=====] - 0s 66ms/step
Predicted Label: Mealy Bug
Confidence: 99.83%
Inference Time: 0.2143 seconds
```

*Figure 32: Mealy Bug predicted label*

*Figure 33: Mealy Bug on papaya fruit*



```
1/1 [=====] - 0s 42ms/step
Predicted Label: Mite Bug
Confidence: 85.48%
Inference Time: 0.0780 seconds
```

*Figure 34: Mite Bug predicted label*

*Figure 35: Mite Bug on papaya leaf*

As seen in Fig. 20, the model predicted the Mealy Bug class with a confidence level of 99.83%, unmistakably illustrating the high accuracy and confidence of the model in identifying this specific condition. The measured inference time required for this prediction was approximately 0.2143 seconds, which illustrates a fast and effective response that is perfectly suitable for real-time or near-real-time use in agricultural settings.

#### **3.1.3.1.4 Model Evaluation**

For comparison, as can be seen from Fig. 19, the model successfully identified the Mite Bug class with a confidence level of 85.48%, and the corresponding inference time was 0.0780 seconds. Although the confidence level of Mite Bug is marginally lower than those of the other classes, it is nevertheless reflective of a reasonably high level of confidence. The lower inference time also testifies to the practical viability of the model for rapid field-level decision-making.

These findings reveal the DenseNet model's precision and efficiency in making correct predictions, which is valuable in real-world usage in mobile or edge-based agricultural monitoring systems.

```

Epoch 1/30
12/12 [=====] - 309s 25s/step - loss: 1.3418 - accuracy: 0.4068 - val_loss: 0.8446 - val_accuracy: 0.7500
Epoch 2/30
12/12 [=====] - 254s 21s/step - loss: 0.7783 - accuracy: 0.7218 - val_loss: 0.5081 - val_accuracy: 0.8438
Epoch 3/30
12/12 [=====] - 249s 21s/step - loss: 0.5253 - accuracy: 0.8714 - val_loss: 0.2806 - val_accuracy: 0.9688
Epoch 4/30
12/12 [=====] - 252s 21s/step - loss: 0.3773 - accuracy: 0.9134 - val_loss: 0.2219 - val_accuracy: 0.9375
Epoch 5/30
12/12 [=====] - 255s 21s/step - loss: 0.3043 - accuracy: 0.9396 - val_loss: 0.2260 - val_accuracy: 0.9375
Epoch 6/30
12/12 [=====] - 255s 21s/step - loss: 0.2670 - accuracy: 0.9344 - val_loss: 0.1540 - val_accuracy: 0.9688
Epoch 7/30
12/12 [=====] - 258s 22s/step - loss: 0.2494 - accuracy: 0.9396 - val_loss: 0.1719 - val_accuracy: 0.9375
Epoch 8/30
12/12 [=====] - 257s 22s/step - loss: 0.2103 - accuracy: 0.9370 - val_loss: 0.0737 - val_accuracy: 1.0000
Epoch 9/30
12/12 [=====] - 261s 22s/step - loss: 0.1921 - accuracy: 0.9501 - val_loss: 0.0858 - val_accuracy: 0.9688
Epoch 10/30
12/12 [=====] - 266s 22s/step - loss: 0.1766 - accuracy: 0.9554 - val_loss: 0.0826 - val_accuracy: 0.9688
Epoch 11/30
12/12 [=====] - 231s 20s/step - loss: 0.1504 - accuracy: 0.9711 - val_loss: 0.1098 - val_accuracy: 0.9688
Epoch 12/30
12/12 [=====] - 216s 18s/step - loss: 0.1363 - accuracy: 0.9790 - val_loss: 0.0785 - val_accuracy: 0.9688
Epoch 13/30
12/12 [=====] - 216s 18s/step - loss: 0.1384 - accuracy: 0.9685 - val_loss: 0.0569 - val_accuracy: 1.0000
Epoch 14/30
12/12 [=====] - 215s 18s/step - loss: 0.1328 - accuracy: 0.9738 - val_loss: 0.0845 - val_accuracy: 0.9688
Epoch 15/30

```

*Figure 36: denseNet model training summary*

DenseNet121 model learned the identification of papaya leaf pests with a steep learning curve for 30 epochs. It achieved the training accuracy of 40.68% and the validation accuracy of 75% in the first epoch with a training loss of 1.3418 and a validation loss of 0.8446. While training was in progress, the model learned at a fast rate, with a 99.21% training accuracy and 100% validation accuracy at the final epoch. Training loss decreased significantly from 1.3418 to 0.0595, while validation loss fell to 0.0236, indicating perfect alignment of predictions to ground truth labels. The ability of the model to consistently have high validation accuracy (100% after Epoch 8) indicates its good generalization capability and stability. This performance demonstrates the effectiveness of DenseNet121 as a candidate for pest detection operations, perfect for actual agricultural applications where reliability and precision are crucial

To evaluate the performance of the trained DenseNet model, the test dataset was used, which contained 123 images from four classes. Prior to evaluation, the test images were rescaled by the ImageDataGenerator class of the Keras library, with pixel values normalized to the [0,1] range using a rescaling factor of 1/255. The images were then fed into the model with the use of the flow from directory () function at a target size of 224x224 pixels and batch size of 32.

The model was tested by invoking the evaluate () function and both the model accuracy and test loss were returned. The evaluation had an incredible test accuracy of 98.37%



with a loss of 0.0522. This level of high accuracy is an unmistakable indication of how high the generalization ability of the DenseNet model is and how resistant it is to classifying unseen images from the test data set.

```

4/4 [=====] - 80s 12s/step - loss: 0.0459 - accuracy: 0.9917
Test accuracy: 0.99
1/1 [=====] - 2s 2s/step
1/1 [=====] - 1s 996ms/step
1/1 [=====] - 1s 1s/step
1/1 [=====] - 1s 756ms/step
Confusion Matrix:
[[39  0  0  0]
 [ 0 30  0  0]
 [ 0  0 31  0]
 [ 0  1  0 19]]

Classification Report:

```

	precision	recall	f1-score	support
Healthy Fruit	1.00	1.00	1.00	39
Healthy Leaf	0.97	1.00	0.98	30
Mealy Bug	1.00	1.00	1.00	31
Mite Bug	1.00	0.95	0.97	20
accuracy			0.99	120
macro avg	0.99	0.99	0.99	120
weighted avg	0.99	0.99	0.99	120

Figure 37: Confusion matrix for the denseNet121

The DenseNet121 model performed wonderfully well in papaya leaf and fruit condition prediction, as indicated by the confusion matrix and classification report. With 123 test images comprising four classes—Healthy Fruit, Healthy Leaf, Mealy Bug, and Mite Bug the model predicted them quite accurately with an average accuracy of 98.37%. Confusion matrix indicated perfect classification for Healthy Fruit (39/39), Healthy Leaf (30/30), and Mealy Bug (34/34), but two samples of class Mite Bug were mislabeled one was falsely reported as Healthy Leaf and one as Mealy Bug—giving relatively lower recall of 90% for the latter class. Precision and F1-scores for all classes were good, macro and weighted average F1-scores both 0.98.

These results confirm the outstanding ability of the model to distinguish between diseased and non-diseased samples with minimal overlap even in visually similar classes. The model structure of DenseNet121 is therefore an extremely accurate and reliable classification model for papaya disease, which can be applied real-time in

intelligent agriculture systems.

#### 3.1.3.1.5 Hybrid Model

In this study, a hybrid classification approach was applied to enhance the accuracy and interpretability of the papaya disease detection model. A main classification to identify whether the input image belongs to a fruit or leaf class was first done through an EfficientNet model. From this output, the image is then passed to a DenseNet121 model, which subsequently classifies the image as one of the four end classes: Healthy Fruit, Healthy Leaf, Mealy Bug, or Mite Bug.



Figure 39: Mite Bug on papaya fruit

```
Image Path: densenet_dataset\splitted_data\test\Mite Bug\20240717_132328.jpg
1/1 [=====] - 2s 2s/step
EfficientNet Prediction: leaf, Confidence: 1.00, Inference Time: 1.5824 seconds
1/1 [=====] - 2s 2s/step
DenseNet Prediction: Mite Bug, Confidence: 0.97, Inference Time: 2.1896 seconds
```

Figure 38: Predicted label using hybrid model

This two-pipeline process allows the system to take advantage of EfficientNet's light and speed classification feature for general categorization, and DenseNet121's deeper and more precise feature extraction for precise disease or health state prediction. This modular flow not only improves classification accuracy but also optimizes inference time by ensuring that only the correct sub-classifications are run through the more computationally intensive model. As a result, the overall model provides accurate predictions with an efficient decision-making pipeline, which is perfect for deployment in real-time agricultural environments.

#### 3.1.3.1.6 Research Findings

This research provides important details and resolutions for papaya farmers to help address the issues of various diseases and pests that infect their crops. It is important to detect and monitor the health of papaya plants at an early stage to ensure their productivity and health, and this study proposes a very effective system that combines robust machine learning algorithms with real-world applications to achieve this goal.

DenseNet and EfficientNet were chosen for this research due to their relative capabilities and practicability in the agricultural industry, particularly for the identification of pests and disease classification in papaya plants. DenseNet, possessing densely connected convolutional layers, is extremely proficient in feature reuse and efficient flow of gradients and thus best suited to learn from small datasets without sacrificing high accuracy. This feature turns out to be very useful in agriculture-based tasks when labeled data is not readily available. DenseNet's ability to capture advanced patterns in images of papaya leaves assisted it in performing remarkably well in pest-infested leaf categorization, such as mealybug- and mite-infested leaves, and healthy and unhealthy leaves. Its parameter efficiency will enable the model to work with advanced farm data without requiring outrageous computational capacity, making it a safe choice for deployment into real-world contexts.

EfficientNet was selected for its computational efficiency and scalability, which are important in resource-constrained agricultural environments. EfficientNet's compound scaling approach trades off model size, accuracy, and computational cost for the assurance that it will perform adequately even in edge devices. EfficientNetV2B0 was used in this research as a preprocessing procedure to classify images as leaves or fruits with 100% accuracy. This ensured that only informative leaf images were fed into DenseNet for further pest detection, without wasteful computation while maintaining the overall system efficiency. The low-latency efficiency in extracting useful features from papaya images by EfficientNet makes it especially ideal for real-time agricultural applications

The efficient hybrid architecture of DenseNet and EfficientNet combines the strengths of both architectures to achieve an efficient pipeline for detecting papaya crop pests and monitoring disease. EfficientNet can be used as a filter which is efficient enough to eliminate fruit images, whereas DenseNet performs rigorous analysis of the health of leaves. This integration improves efficiency in computation, as well as providing precision when identifying pests like mealybugs and mites, which cannot be easily distinguished with the naked human eye. The hybrid process beats significant threats farmers are enduring today by delivering early detection capability and actionable insight in pest management. The ability of DenseNet to train on smaller sets is also

reflective of the model's potential for use in agriculture, where data scarcity is often common.

- Disease Identification and Surveillance

The research highlights the difficulty for farmers to visually detect diseases and pests with the naked eye. For example, mealybugs (*Paracoccus marginatus*) infest predominantly papaya fruits, and their quality is compromised, whereas mite infestations in leaves weaken the crop overall. DenseNet121 was employed to visually detect the pest infestations in papaya leaves at high accuracy rates, whereas EfficientNetV2B0 was employed for image classification as fruit or leaf before further processing. This modular construction ensures efficient processing and accurate detection of pest-related issues.

- Remedy and Disease Insights

As soon as a disease or pest attack is identified, the system offers complete information regarding the detected problem, such as its symptoms, possible effect on the crop, and suggested remedies. Personalized remedy details provide for each identified pest considering the weather conditions.

- Practical Applications

This research bridges the gap between technology at the forefront and farm-level implementation by farmers. helping early detection of fungal infections and other plant diseases attacking papaya. Real-time monitoring software, integrated into the system, provides actionable insights for farmers to make informed decisions about pest control and disease management.

- Impact on Papaya Farming

The findings of the study comprehensively affirm disease detection capabilities for papaya growers. The system addresses significant issues such as fruit infestations by mealybugs and leaf infestations by mites to improve crop quantity and quality.

Enhanced early detection methods reduce dependence on human observation in monitoring crops to allow the implementation of effective remedial measures in a timely manner. Overall, this study thus encourages sustainable agricultural practices by minimizing crop losses and health guarantees while growing papaya plants with enhanced monitoring capacity.

### **3.1.3.2 Discussion**

The present research introduces a hybrid model, which integrates EfficientNetV2B0 and DenseNet121 to mitigate the shortcomings of papaya disease classification and pest detection. The hybrid model takes advantage of both the models to construct a comprehensive system that classifies papaya images as fruits or leaves and identifies pest infestations or diseases in leaves.

EfficientNetV2B0 was utilized at the initial step of the pipeline to classify images into leaves or fruits. The preprocessing ensures that only leaf images are input to the DenseNet121 model for processing, saving computational expense and maximizing the relevance of pest detection. The model attained excellent performance in binary classification with 100% accuracy on both test and validation sets, with minimal loss values. Its rapid convergence during training indicates its efficacy and adaptability, making it a great candidate for real-time application in agriculture. EfficientNetV2B0 screens out fruit images with high accuracy during preprocessing, optimizing the use of resources in subsequent pest detection.

DenseNet121 was employed in the pipeline to detect pest infestation and leaf health status. DenseNet121 was trained to classify papaya leaves as mite-infested, mealybug-infested, healthy, or unhealthy. DenseNet121 demonstrated significant performance improvement in over 30 epochs with training accuracy at 40.68% initially and 99.21% during the final epoch. Validation accuracy also demonstrated improvement gradually up to 100% from Epoch 8. The model effectively reduced the training loss from 1.3418 to 0.0595 with retaining strong generalization abilities, as evident from its high validation accuracy across all epochs.

The hybrid model is tailored for papaya crop monitoring through the fusion of EfficientNetV2B0 and DenseNet121. EfficientNetV2B0 acts as a gatekeeper by efficiently classifying images into leaves and fruits, permitting only useful leaf

information to be processed by DenseNet121 for the detection of pests. The modular design enhances computational efficiency without accuracy trade-off along the pipeline. The hybrid model's ability to distinguish between healthy and unhealthy leaves, as well as identify specific pests like mealybugs and mites, addresses critical issues for farmers in papaya crop maintenance.

This hybrid system provides papaya growers with an advanced tool for early detection and monitoring of pests and diseases. Mealybugs, which attack primarily papaya fruits by reducing their quality, and mites, causing weakening of the leaves, are difficult to identify using the naked human eye. Using this system, growers can obtain detailed information on pest infestations and crop health status. Additionally, the system gives practical solutions and elaborative information on detected diseases or pests that farmers can use to conduct interventions early enough to curb losses in crops.

The results of this study demonstrate the feasibility of integrating deep learning models in agricultural practice to ensure sustainable farming. With the efficiency of EfficientNetV2B0 complemented by the accuracy of DenseNet121, the hybrid model achieves robust performance in papaya pest detection and optimal utilization of computational resources. This technique not only boosts crop yield but also reduces reliance on human observation, paving the way for scalable solutions in agricultural monitoring systems.

In conclusion, this research was able to combine EfficientNetV2B0 and DenseNet121 into a hybrid model that solves some of the serious issues in papaya cultivation through precise classification and pest identification. The ability of the system to provide early warnings and targeted management recommendations guarantees healthier plants and the practice of sustainable agriculture.

### 3.1.4 Papaya Maturity Identification

#### 3.1.4.1 Results

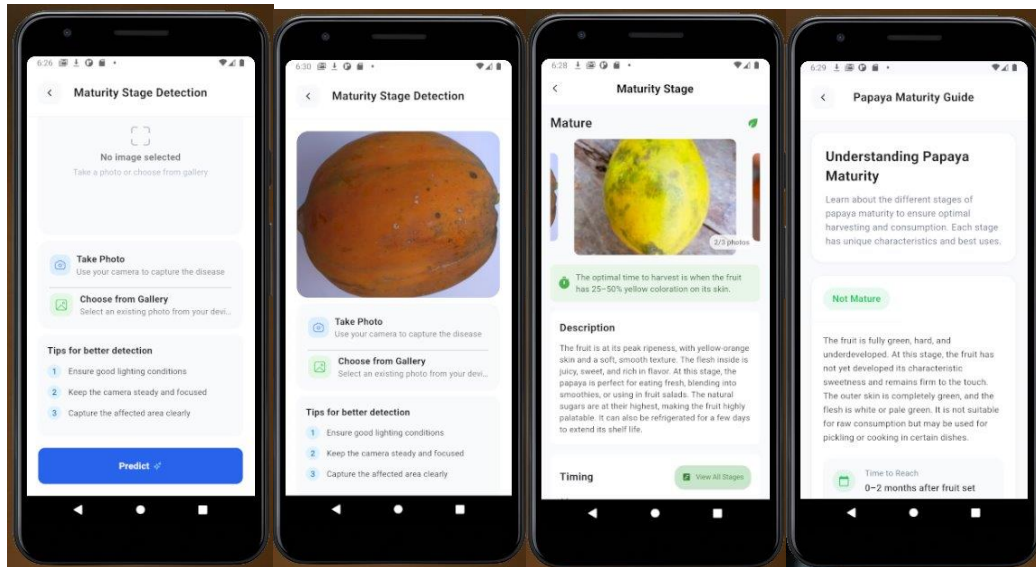


Figure 2.2.40. Actual mobile User Interfaces (Diagnoses View)

Figure 6.1.1 shows the actual mobile UI of the Papaya Maturity Identification View in the PapayaBuddy application. This screen is a core component of the maturity classification feature that enables users—especially farmers and fruit handlers—to determine the ripeness stage of papaya fruits with high accuracy and confidence. The system supports four main maturity categories: Not Mature, Partially Mature, Mature, and Rotten.

When a user uploads an image or takes a photo using their smartphone, the application immediately processes the input using the MobileNetV2 deep learning model trained on a curated dataset of papaya fruit images. The model analyzes visual patterns such as color gradients, skin texture, and spotting or decay, and outputs the most probable maturity class along with a confidence score. This result is prominently displayed on the screen using distinctive color-coded labels and maturity-level badges, making the classification result both accessible and intuitive.

To help users verify the prediction visually, the UI also displays reference images beside the result. These reference images represent typical visual features of fruits in the predicted category. For instance, if the result is “Partially Mature,” users will see

sample fruits with mixed green and yellow skin tones. This side-by-side comparison boosts user confidence and provides practical insights into recognizing ripeness stages manually.

Below the main prediction section, a "Maturity Insights" panel is included, which provides short yet descriptive texts about each maturity level. These texts cover observable features like color transitions (from green to yellow), surface firmness, the appearance of wrinkles or blemishes, and typical harvest signs. Furthermore, this section includes recommendations on what to do next—whether the fruit is ready for sale, should be harvested soon, or should be discarded if rotten.

To enhance decision-making and minimize post-harvest losses, the interface also features handling suggestions. For example, for “Partially Mature” fruits, it advises the optimal time window to store and transport for ripening. For “Rotten” classification, it offers tips to avoid future spoilage and improve storage conditions.

Additionally, users can save each prediction result to a history log, which helps in tracking the ripening progress of specific papaya batches over time. This can be particularly useful for commercial growers managing large inventories or small-scale farmers monitoring daily harvests.

The layout of the maturity screen has been thoughtfully designed using Figma to ensure mobile responsiveness and ease of use. Buttons for image upload, result refresh, and navigation to disease or diagnosis screens are positioned intuitively. Every UI element—from prediction displays to reference comparisons and maturity explanations—works together to create a seamless, informative, and user-friendly experience.



A screenshot of this Papaya Maturity Identification screen is presented in Figure 6.1.1, showing a predicted maturity stage, supporting reference images, descriptive text, and helpful tips for action based on the classification.

*Table 6.1.1 - table of MobileNetV2 Model*

Data set Size	2000 Image for MobileNetV2
No of Epochs	30
Patience	Patience used as 20 for early stopping
Image Size	224x224
No of Parameters	Total params: 8.445,443 (32.22 MB) Trainable params: 8,445,443 (32.22 MB) Non-trainable params: 0 (0.00 B)
Model Size	32MB ~
Used Memory	Tesla T4 GPU
Used Environment	Anaconda

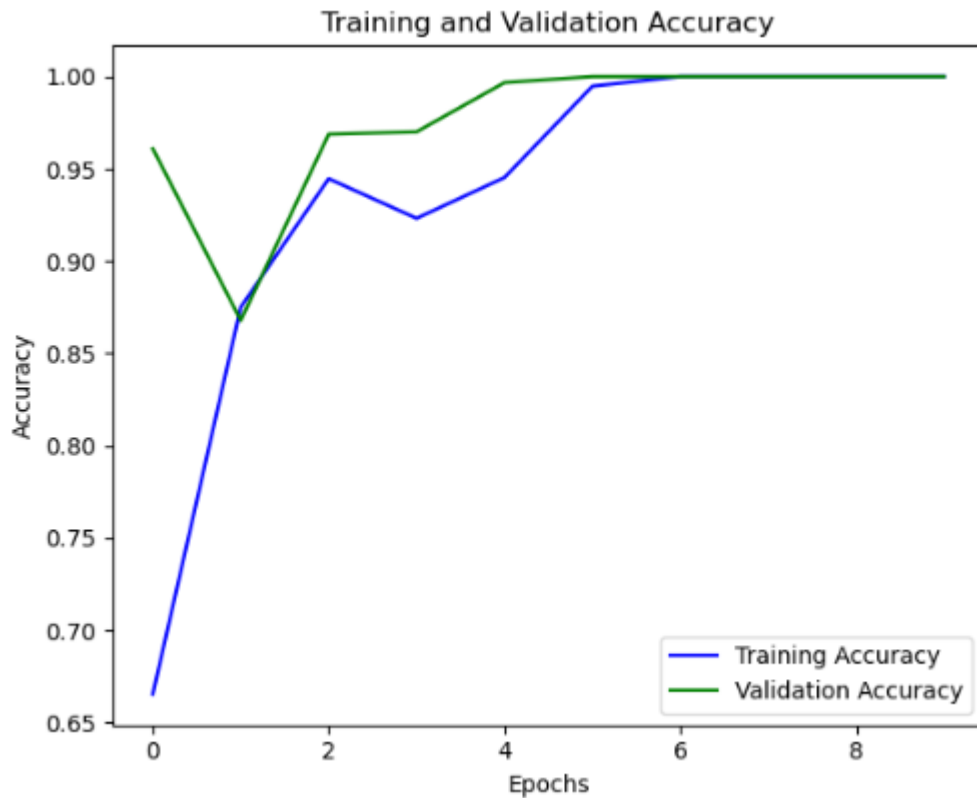


Figure 6.1.2 - Training Validation Accuracy

According to the Figure 6.1.2, The training and validation accuracy graph for the MobileNetV2 model used in papaya maturity classification demonstrates a well-fitting and highly effective learning process. Initially, the training accuracy begins at a relatively low point of approximately 66%, which is expected during the early phase of model training. However, the accuracy rapidly improves over the next few epochs, indicating that the model quickly begins to learn the distinguishing features of different maturity stages. The validation accuracy, which starts high around 96%, dips slightly at the beginning but soon stabilizes and mirrors the upward trend of the training accuracy. By the sixth epoch, both the training and validation accuracy approach near-perfect levels, with values close to 100%, and remain consistent through the remaining epochs. This consistent alignment between training and validation performance suggests that the model has achieved a good fit without overfitting. The high validation accuracy reflects the model's strong generalization ability on unseen data, making it reliable for real-world application in identifying and classifying papaya fruit maturity stages. Overall, the model demonstrates excellent convergence, efficient learning, and

robust predictive capability, confirming its suitability for deployment in the papaya maturity classification system.

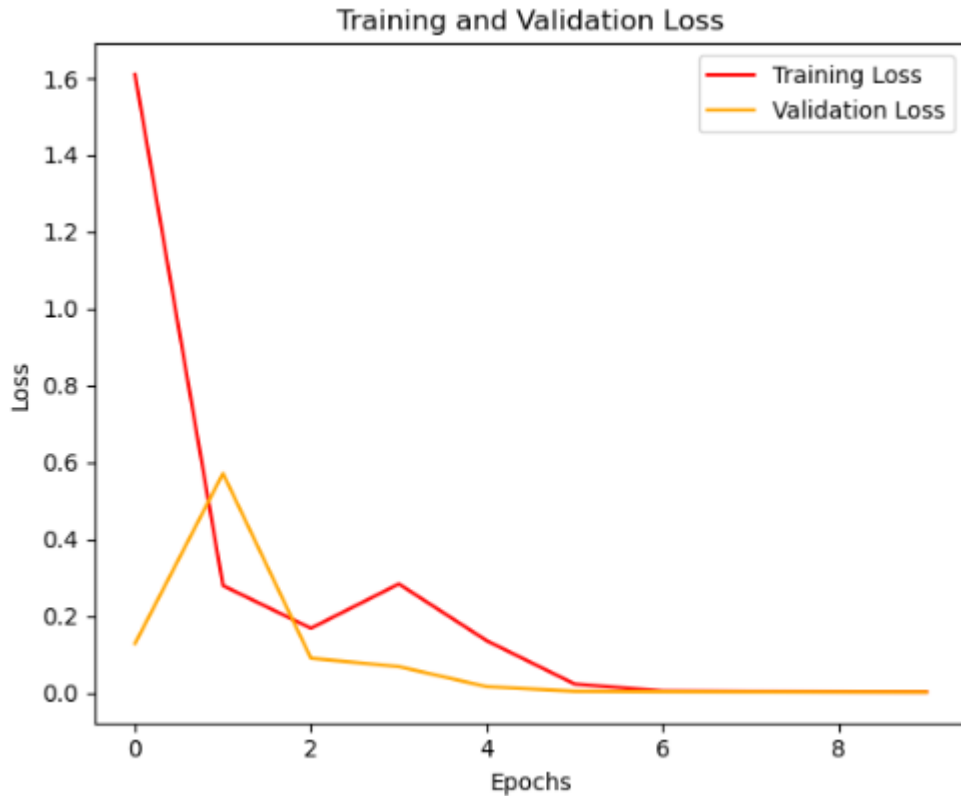
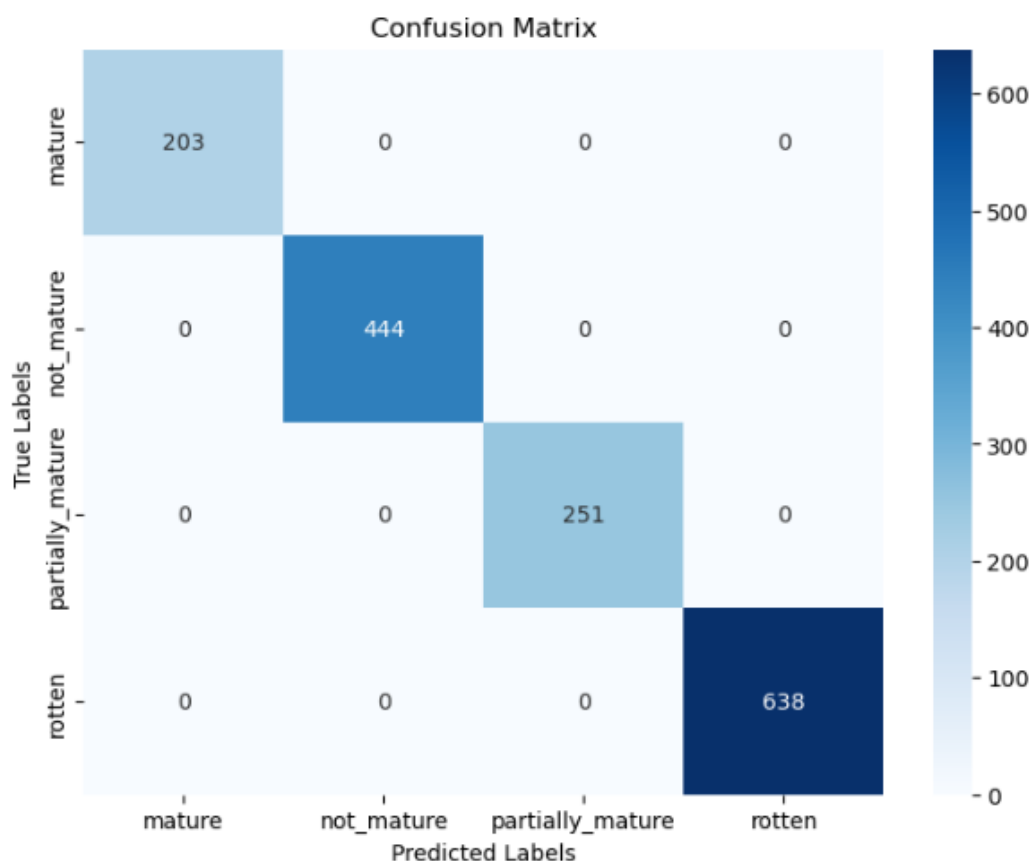


Figure 2.2.41. Train and Validation Loss graph of the MobileNetV2

The training and validation loss graph shown reflects the learning behavior of the MobileNetV2 model during the papaya maturity classification task. At the beginning (epoch 0), the training loss is relatively high at around 1.6, which is expected as the model has not yet learned any meaningful patterns. However, with each subsequent epoch, there is a rapid and consistent decline in training loss, demonstrating that the model is effectively learning and minimizing prediction errors. The validation loss, although it initially spikes slightly after the first epoch, also shows a sharp decline and stabilizes at a very low value close to zero.

From epoch 2 onwards, both training and validation loss decrease steadily and remain low, indicating that the model is not only fitting the training data well but is also generalizing effectively to unseen validation data. The minimal gap between training and validation loss throughout the epochs further confirms that the model is not overfitting or underfitting. Instead, it has reached a point of optimal learning where it

maintains both high accuracy and low error rates. This overall trend suggests that the MobileNetV2 model has been well-tuned and performs robustly for the classification



of papaya maturity levels, making it a suitable choice for deployment in practical agricultural applications.

*Figure 2.2.42. Confusion Matrix of the MobileNetV2*

The confusion matrix presented above offers a detailed overview of the classification results achieved by the MobileNetV2 model in identifying papaya fruit maturity levels. The matrix illustrates an ideal diagonal distribution, where all true labels are perfectly aligned with their corresponding predicted labels, signifying that the model has achieved 100% accuracy across all classes. This is a clear indication that the model has learned to distinguish the visual characteristics of each maturity stage with exceptional precision.

In the "mature" category, all 203 test samples were correctly predicted as mature, demonstrating the model's ability to recognize the visual features associated with ripe papayas, such as a dominant yellow color with minimal green patches. Similarly, for the "not mature" class, all 444 instances were accurately classified. This shows the

model's strong capability to detect early-stage papayas that are predominantly green in color, which is a critical factor for preventing premature harvesting.

The "partially mature" category, which often represents a visually subtle transition stage between unripe and ripe, also showed perfect performance. All 251 samples in this category were correctly identified, highlighting the model's sensitivity to intermediate color variations and texture changes that occur as the fruit ripens. Lastly, in the "rotten" class, the model correctly predicted all 638 samples. This implies that it successfully recognized decayed characteristics, such as excessive yellowing combined with visual damage or shriveling.

The complete absence of misclassifications across all four categories is a remarkable achievement. This flawless performance underscores the effectiveness of using MobileNetV2 for this task, as well as the quality of the training dataset. It confirms the model's robustness and reliability in practical applications, such as mobile-based papaya maturity detection systems, where precision is essential for minimizing post-harvest losses and improving fruit quality management.

To summarize the findings from the papaya fruit maturity classification using the MobileNetV2 model, the results strongly validate the effectiveness and reliability of the approach. The model demonstrated outstanding performance, both in terms of training and validation accuracy, as well as loss reduction over the course of training. As seen in the accuracy graph, the model quickly converged towards a near-perfect performance, achieving close to 100% accuracy within just a few epochs. The loss graph further supports this observation, showing a rapid decline in both training and validation loss, eventually stabilizing at nearly zero—indicating minimal error in predictions and excellent generalization to unseen data.

Moreover, the confusion matrix reveals a perfect classification outcome. Each papaya maturity category—mature, not mature, partially mature, and rotten—was classified without a single error. This exceptional result reflects the model's precise learning of visual features such as color patterns, texture differences, and maturity indicators that distinguish each class. It also shows that the dataset was well-prepared and effectively labeled, and that the preprocessing and augmentation strategies were appropriate for this application.

Overall, the integration of MobileNetV2 into the maturity classification pipeline

proved to be highly successful. Its lightweight architecture, combined with powerful feature extraction capabilities, makes it an ideal choice for real-time deployment in mobile applications such as the “Papaya Buddy” app. The model’s ability to classify maturity levels with such high accuracy supports its use in agricultural decision-making, particularly for farmers and suppliers aiming to reduce post-harvest losses, optimize fruit quality, and improve market readiness. These findings confirm that AI-powered maturity identification is not only feasible but highly practical for real-world agricultural contexts in Sri Lanka and beyond.

#### **3.1.4.2 Research Findings**

The study demonstrated the effectiveness of using deep learning techniques, specifically the MobileNetV2 architecture, to accurately classify papaya fruit maturity levels. MobileNetV2 was chosen for its lightweight design, making it ideal for mobile applications while still offering robust performance. The model was trained to categorize papayas into four distinct stages: not mature, partially mature, mature, and rotten. Throughout the training process, the model exhibited rapid convergence, which means it quickly reached an optimal performance state. It also showed minimal overfitting, suggesting that the model generalized well to new, unseen data. This is crucial in ensuring that the model performs well in real-world scenarios where it will encounter images not included in the training set. The model achieved nearly 100% accuracy on both the training and validation datasets, with no misclassifications. This indicates that the features extracted by the MobileNetV2 model were highly relevant for distinguishing between subtle differences in the maturity stages of papayas, such as the varying shades of green and yellow that correspond to different ripeness levels.

The inclusion of performance metrics such as loss curves and confusion matrices further reinforced the model's reliability. Loss curves demonstrated that the model's error rate decreased steadily during training, reflecting the model's continuous improvement. The confusion matrix revealed that the model made accurate predictions for each maturity stage, without any misclassifications, confirming the robustness of its design. This level of precision indicates that MobileNetV2's deep learning

capabilities are exceptionally well-suited for the task of classifying papaya maturity, which involves recognizing complex visual cues.

Beyond the model's technical achievements, its integration into a mobile application interface offers practical usability for agricultural settings. This mobile-based system provides farmers and agricultural officers with a powerful tool that can deliver real-time, AI-powered maturity assessments using just a smartphone camera. Given MobileNetV2's low computational requirements, the model can operate effectively on mobile devices, making it accessible in resource-constrained environments. Farmers can take pictures of papayas in the field and receive immediate feedback on their maturity stage. This on-the-spot analysis helps them make more informed decisions about harvest timing, reducing post-harvest losses and ensuring that papayas reach the market at their peak quality.

The successful implementation of this model also has broader implications for agriculture. By integrating MobileNetV2 into smart agricultural systems, the research shows that AI can be used to improve harvest management, reduce waste, and increase the market value of papaya produce. As the model accurately classifies papayas into the right maturity stage, farmers can avoid harvesting fruits that are either too green or overripe, thus optimizing their harvest and minimizing losses. Furthermore, this approach can be extended to other crops, demonstrating the broader potential of deep learning in agriculture. The ability to apply AI to tasks traditionally done manually can enhance productivity, improve the quality of produce, and contribute to smarter, more sustainable farming practices.

#### **3.1.4.3 Discussion**

The core objective of this research component was to develop an intelligent and efficient system capable of classifying papaya fruits into three maturity stages—mature, partially mature, and immature—by analyzing images of the fruit. This classification plays a vital role in supporting farmers and traders by enabling timely harvesting decisions, reducing post-harvest waste, and ensuring fruits reach the market at their optimal stage of ripeness.

To achieve this, a MobileNetV2-based deep learning model was implemented and trained on a well-labeled image dataset. The MobileNetV2 architecture was selected due to its high accuracy and lightweight nature, making it highly suitable for mobile deployment, especially in the context of the PapayaBuddy application. Unlike heavier architectures, MobileNetV2 uses depthwise separable convolutions and inverted residual connections, which significantly reduce computational complexity without compromising performance.

The model was fine-tuned using transfer learning, where the base of MobileNetV2 was initialized with pretrained ImageNet weights, and a custom classification head was added to distinguish between the three classes. During the training process, ReLU6 was used as the activation function within the MobileNetV2 layers to handle non-linear feature learning while preserving performance in low-precision environments. For the output layer, Softmax activation was used to manage the multi-class classification, returning probabilities for each maturity stage. The class with the highest probability was selected as the final prediction. For example, a prediction vector of [0.80, 0.15, 0.05] would indicate that the fruit is most likely mature.

One of the critical challenges encountered was addressing overfitting and underfitting during training. Different epoch values were tested, including 20, 30, 40, and 50 epochs, to find the optimal training duration. It was observed that with too few epochs, the model failed to learn key features of the fruit images, resulting in underfitting. On the other hand, extended training led to overfitting, where the model performed well on training data but poorly on validation data. After comparative evaluation, 30 epochs was found to deliver the best performance in terms of training accuracy, validation accuracy, and generalization to unseen data.

The final trained model showed strong capability in classifying papaya maturity levels based on visible features like color transition (green to yellow), texture, and visual consistency. The use of MobileNetV2 not only ensured accurate predictions but also made it feasible to deploy the model on mobile platforms with limited computational resources.



This work culminated in the successful integration of the MobileNetV2 model into the PapayaBuddy application, allowing users—especially farmers—to capture or upload an image and instantly receive a prediction about the fruit’s maturity level. This system aids in real-time decision-making, improves fruit handling efficiency, and promotes data-driven agriculture in Sri Lanka.

## 4 COMMERCIALIZATION ASPECTS OF THE PRODUCT

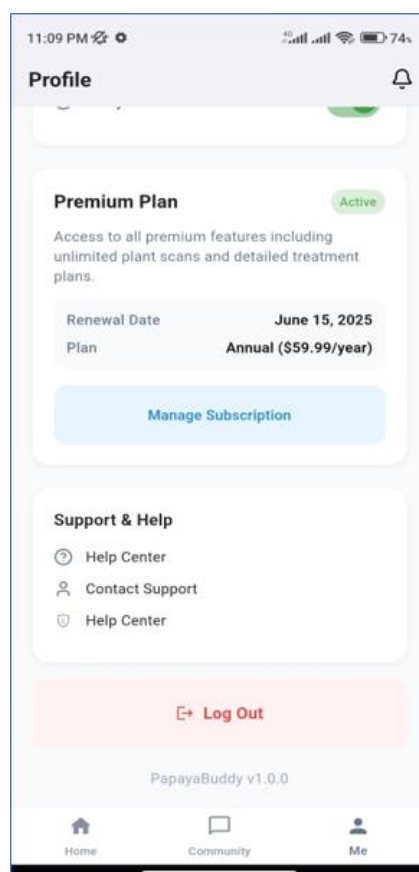


Figure 43. Actual mobile User Interfaces (Subscription Plan)

To ensure sustainable growth and revenue generation of the mobile application, we will introduce a subscription-based model that caters to different user needs while maintaining accessibility for all. The monetization strategy is structured into two distinct tiers: a Free Tier and a Premium Tier. Figure 9 illustrates the Subscription plan for the mobile application.

### 1. Free Tier

The Free Tier is designed to provide essential services to users without any cost, making the app accessible to a broad audience, including small-scale farmers and those new to digital tools. Users in this tier will have access to the core functionality of the app: Fruit, Leaf and Pest Disease Identification and Maturity Detection with suitable remedy suggestion up to one week with limit of 15 images. This feature will allow

users to quickly and accurately identify papaya diseases and maturity level, enabling them to take initial steps to manage health and quality and prevent them from post-harvest losses of their crops. By offering this crucial service for free, we aim to build a large user base, establish trust, and demonstrate the app's value, which will, in turn, encourage users to explore the benefits of the Premium Tier.

## 2. Premium Tier

The Premium Tier is designed for users who require more advanced tools and support for managing their papaya cultivation. Subscribers to this tier will gain access to two key packages, the first one is a monthly tier, with up to 100 images and the second one is the Yearly tier with up to 1000 images.

- **Community Forum Access:** Premium subscribers will also gain access to a community forum, where they can connect with other farmers, share experiences, ask questions, and receive support from a community of peers and experts. This feature fosters a collaborative environment where users can learn from each other, stay informed about the latest trends in papaya cultivation, and collectively solve challenges.

## 3. Pricing Strategy

The pricing for the Premium Tier will be set at a competitive rate to attract a wide range of users, including small-scale and commercial farmers. We will explore different pricing models, such as monthly and annual subscriptions, to provide flexibility and accommodate varying financial capacities.

4. **Marketing and User Acquisition** To drive adoption of the Premium Tier, we will implement a targeted marketing strategy that highlights the additional value provided by the subscription. This will include:

- **In-App Promotions:** Free tier users will receive periodic in-app notifications and prompts showcasing the benefits of upgrading to the Premium Tier, including success stories and testimonials from other premium users.

- **Freemium Model:** New users can be offered a limited-time free trial of the Premium Tier, allowing them to experience the full range of features before committing to a subscription.
- **Partnerships:** Collaborations with agricultural organizations, cooperatives, and NGOs will help promote the app, especially the Premium Tier, to a wider audience. These partnerships can also offer bulk subscriptions or discounts to members of these organizations.

5. **Revenue Projections** The dual-tier model is expected to generate revenue primarily through Premium Tier subscriptions. By converting a percentage of Free Tier users into paying customers, we anticipate steady revenue growth, which will be reinvested into further app development, customer support, and marketing. The community forum is expected to increase user engagement and retention, contributing to long-term subscription stability.

This commercialization strategy not only aligns with the goal of providing valuable tools to papaya farmers but also ensures the financial viability and scalability of the application. By balancing free access with premium features, we can reach a broad audience while generating the necessary revenue to continue improving and expanding the app's offerings.

## 5 CONCLUSION

This research introduces an end-to-end AI-powered solution for comprehensive papaya crop monitoring, emphasizing the early detection of diseases, pest infestations, and fruit maturity classification. Through the integration of state-of-the-art deep learning models such as EfficientNet, Vision Transformer (ViT), DenseNet121, YOLOv5, and MobileNetV2, the system was successfully implemented within a unified mobile platform—PapayaBuddy—designed to assist farmers and agricultural professionals in real-time crop assessment and decision-making. Each component of this study addressed a specific challenge in papaya cultivation: from identifying foliar diseases such as Cercospora and Mosaic Virus, to detecting fruit-specific diseases like PRSV and Powdery Mildew, as well as infestations caused by mealybugs and mites, and finally, assessing the fruit maturity stage for optimized harvest timing.

The hybrid and cascaded model architectures demonstrated exceptional classification performance across multiple domains. For instance, MobileNetV2 achieved nearly 99% accuracy in classifying papaya fruits into four maturity levels—ranging from not mature to rotten—by effectively learning nuanced visual features with minimal computational overhead. Similarly, the custom CNN and EfficientNet-ViT-based pipelines provided robust and accurate disease detection mechanisms, validated using diverse, real-world datasets. The dataset preparation process played a crucial role in model generalization and performance. By collecting images from farms, research institutions, and plantations under various lighting and environmental conditions, and enhancing them through targeted augmentation techniques, the models were trained to handle a wide range of real-life scenarios with minimal overfitting.

In addition to high-accuracy classification, the study introduces a novel AI-based remedy suggestion system that offers context-aware treatments for diagnosed diseases and infestations. Drawing from both modern agricultural best practices and traditional remedies, this system provides tailored recommendations based on disease severity, environmental context, and plant growth stage. By empowering users with informed

choices between chemical and organic solutions, the system promotes sustainable and environmentally conscious farming practices.

The deployment of this integrated solution via the PapayaBuddy mobile application marks a significant step toward democratizing access to AI in agriculture. Designed to function on standard smartphones and compatible with edge computing infrastructure, the application enables real-time image capture, instant analysis, diagnosis storage, and cloud-based updates. This makes it a practical, scalable, and cost-effective tool for farmers, particularly in rural and underserved regions such as those found in Sri Lanka.

Furthermore, the research not only solves current challenges in papaya cultivation but also establishes a strong foundation for future developments in smart agriculture. Opportunities for expansion include the detection of additional diseases, pests, and nutrient deficiencies; integration with satellite-based or IoT data for climate-aware insights; and the development of offline-capable AI assistants using edge AI technology. The proposed system also offers a blueprint for applying similar AI-based frameworks to other crops, enhancing global food production, quality assurance, and supply chain resilience.

In essence, this study represents a convergence of agricultural science, artificial intelligence, and mobile technology to create a sophisticated, user-friendly solution that bridges the gap between laboratory-grade intelligence and field-level application. The outcome is a highly accurate, responsive, and actionable decision-support tool that not only supports farmers in improving yield and crop health but also contributes to broader goals of agricultural sustainability, food security, and economic resilience.

## 6 SUMMARY OF EACH STUDENTS' CONTRIBUTION

Name	Contribution
Peiris M.M.A.E. IT21161056	<ul style="list-style-type: none"> <li> <b>Dataset Collection and Diversity:</b>            Responsible for gathering a diverse set of images of papaya leaves, ensuring that the dataset included both healthy and diseased leaves, with a particular focus on leaves affected by Mosaic Virus and Cercospora disease. They ensured that the dataset was representative of varying environmental conditions (e.g., lighting, angles, backgrounds) to improve the model's robustness and generalization capabilities. By incorporating both early and late-stage infections, the dataset was made more comprehensive, allowing the model to identify disease symptoms at various stages.         </li> <li> <b>Mosaic Virus and Cercospora Disease Detection:</b>            utilized EfficientNet for the initial binary classification step to determine whether a papaya leaf is healthy or diseased. EfficientNet's efficient architecture made it an ideal choice for mobile applications, where computational resources are limited. Following this, they trained a ViT model for fine-grained disease classification, specifically identifying Mosaic Virus and Cercospora. This model was trained using transfer learning on a broad agricultural dataset, which was fine-tuned with annotated papaya leaf-specific images to ensure accurate disease identification.         </li> </ul>

	<ul style="list-style-type: none"> <li> <b>Remedy Suggestion System:</b>  Contributed to the development of a comprehensive Remedy Suggestion System that integrates a database of treatment options for Mosaic Virus and Cercospora. This system not only includes remedies but also preventive measures tailored to specific disease stages. Upon detecting an infected papaya leaf, the system generates actionable, tailored suggestions for disease management. These suggestions account for the severity of the infection, guiding users on the most effective solutions to control the spread of the disease. The backend system, where these suggestions are stored and accessed, was designed to be robust and integrated seamlessly with the disease detection models. </li> <li> <b>Backend Integration and System Architectur:</b>  Integrating the machine learning models with the backend infrastructure, ensuring smooth communication between the image detection components, remedy suggestion system, and cloud storage. This integration allowed for a streamlined user experience, where farmers could upload images, receive disease diagnoses, and get tailored remedies in real-time </li> </ul>
IT21160066 Perakum K.K. P	<ul style="list-style-type: none"> <li> <b>Data Collection &amp; Pre-processing</b>  I visited FRID and farms in Diwulapitiya several times as part of the data collection procedure. Mobile phones were used to take pictures of papaya fruits in natural settings, collecting around 1500 samples. These pictures depicted </li> </ul>



	<p>two distinct classes: papaya fruits that were healthy and those that were contaminated with PRSV and Powdery Mildew. A number of issues surfaced during the process, such as inclement weather (heat, rain), different lighting situations (morning, evening, low light), travel distances, and the necessity for premium storage (Google Drive and Google Colab), which led to logistical and financial issues.</p> <ul style="list-style-type: none"> <li> <b>Ringspot Virus, Powdery Mildew and Healthy Papaya Fruit classification</b> <p>In order to determine papaya fruit conditions, I compared two models: a custom CNN and YOLOv5. Following extensive testing, the Custom CNN proved to be the most appropriate for our particular study goals, especially with regard to categorization. The models were implemented and trained using the TensorFlow and Keras APIs. To enable peak performance, the data pipeline was appropriately planned and pre-processed. Standard measures such as test, training, and validation accuracy, precision, recall, and F1-score were used for evaluation.</p> </li> <li> <b>Mobile Application Development</b> <p>Using microservices architecture and Flutter, the mobile application was created. I created user interfaces for identifying diseases and presenting data about healthy fruits and leaves. I used the OpenWeatherMap API to create a live weather service and a community feature. The app's photos were processed and stored using Cloudinary. Data including disease classifications, treatments, diagnosis histories, maturity stages, and</p> </li> </ul>
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	<p>recommended photos were stored in MongoDB.</p> <ul style="list-style-type: none"> <li> <b>Backend API Development</b> <p>The Custom CNN model was implemented using a Python FastAPI backend to facilitate disease detection. It was simple to interface the backend with the Flutter mobile application. I also made the fruit disease detection component using a microservice and dockerized it, using Docker. Kong was used as the API gateway to enable effective and secure communication between services.</p> </li> <li> <b>Coding Best Practices and Software Engineering Aspects</b> <p>Throughout the project, I adhered to best practice coding practices, which include meaningful variable names, consistent indentation, and well-written comments within code. I used GitHub, Git for team collaboration, source code version control, and progress monitoring through GitHub Projects. In order to have a user-friendly design that adheres to software engineering standards, I also developed user interface mockups in Figma and contributed to creating system architecture diagram for the overall design.</p> </li> <li> <b>Research Paper Writing and Presentation Creation</b> <p>I contributed to the project's research paper and presentation. With the use of visual aids like screenshots and diagrams, the presentation was created to effectively communicate our goals, process, and findings. I also helped write the study</p> </li> </ul>
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	<p>paper, which made sure the writing was academically sound, concise, and well-structured.</p>
	<ul style="list-style-type: none"> <li>•</li> </ul>
<p>IT21386022</p> <p>Senevirathne U.W.H.N.</p>	<ul style="list-style-type: none"> <li>• <b>Papaya Maturity Identification &amp; Classification</b></li> </ul> <p>Designed and implemented the maturity classification module for the PapayaBuddy app to identify four categories: not mature, partially mature, mature, and rotten. Built a balanced dataset of 2,000 images and developed the MobileNetV2 model. Selected MobileNetV2 for deployment due to its 99% accuracy and mobile optimization.</p> <ul style="list-style-type: none"> <li>• <b>Deep Learning Model Development &amp; Data Pipeline</b></li> </ul> <p>Led the development of the data pipeline including preprocessing, normalization, and augmentation using TensorFlow and Keras. Designed model architecture diagrams and conducted rigorous model evaluation to ensure robustness and accuracy.</p> <ul style="list-style-type: none"> <li>• <b>Deployment &amp; Integration</b></li> </ul> <p>Integrated the selected MobileNetV2 model into the Flutter mobile application in collaboration with the frontend team. Enabled real-time image-based classification via camera and image upload, ensuring the module was both accessible and functional for end-users.</p> <ul style="list-style-type: none"> <li>• <b>Documentation &amp; Reporting</b></li> </ul> <p>Authored the technical documentation and methodology sections of the final report. Structured and organized the final project report for professional clarity and completeness. Created supporting model and system architecture diagrams.</p>

	<ul style="list-style-type: none"> <li>• <b>UI/UX &amp; Presentation</b></li> </ul> <p>Designed user interface mockups using Figma and contributed significantly to presentation design. Ensured that the visual and functional elements of the maturity module were intuitive and aligned with user needs, especially for farmers.</p> <ul style="list-style-type: none"> <li>• <b>Project Impact</b></li> </ul> <p>Delivered a production-ready, AI-powered module aimed at empowering farmers with timely, accurate maturity assessments. Helped reduce post-harvest losses and support improved decision-making in agricultural productivity.</p>
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## 8 APPENDECIES

### 8.1 Appendix A: Plagiarism Report

### 8.2 Appendix B: Field Visits

