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# Title: Mobile Detection of Strawberry Plant Diseases Using MobileNetV3 and Kotlin

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# Introduction

- Strawberries are a key crop for Mexican agriculture and are in high demand internationally, placing Mexico among the top three exporters, with revenues of close to 400 million pesos in 2020, especially in Michoacán, Baja California, Jalisco, and Guanajuato **(Rocha et al., 2024).**

- However, pests and diseases such as powdery mildew and others threaten the quality and quantity of production and may even pose risks to human health **(Rehman et al., 2023).**

# Introduction

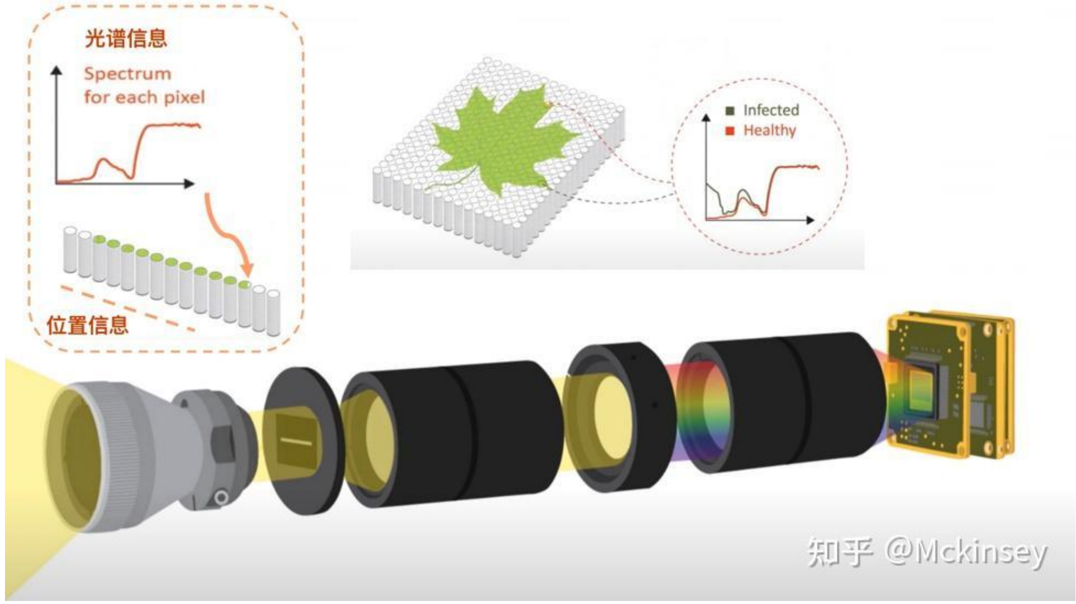
- Precision agriculture integrates robotics, remote sensing, data analysis, and image processing to optimize crop management **(Ngugi et al., 2021).**

- Image processing combined with machine learning enables fast, accurate, and affordable detection of pests and diseases by comparing affected and healthy plant areas **(Biswas et al., 2022).**

# Introduction

- Although hyperspectral methods provide high precision, their cost limits use; thus, mobile devices and visible spectrum imaging offer accessible alternatives for rural farmers **(Shin et al., 2021).**

- Lightweight CNN models like MobileNetV3 have shown efficiency for on-device disease detection in Android applications using TensorFlow Lite, supported by specific strawberry datasets for realistic training **(Liu et al., 2023).**



# Methodology

A dataset of strawberry images with the several diseases annotations obtained from the Kaggle was used, containing labeled images and allowing for segmentation/classification:

| Label | Class | Obtained | Augmented |
|---|---|---|---|
| 0 | Angular Leaf Scorch | 392 | 700 |
| 1 | Powdery Mildew | 470 | 700 |
| 2 | Blossom Blight | 179 | 700 |
| 3 | Healthy | 1000 | 700 |
| 4 | Leaf Scorch | 543 | 700 |

Method

**Data acquisition**

**Afzaal** * kaggle

Healthy

Leaf scorch

Blossom Blight

Angular Leaf scorch

Powdery Mildew

**Preprocessing**

Image scaling 224x224

Channel normalization

**Model used**

*MobileNetV3

**Evaluation**

Accuracy, Precision, Recall, F1-Score

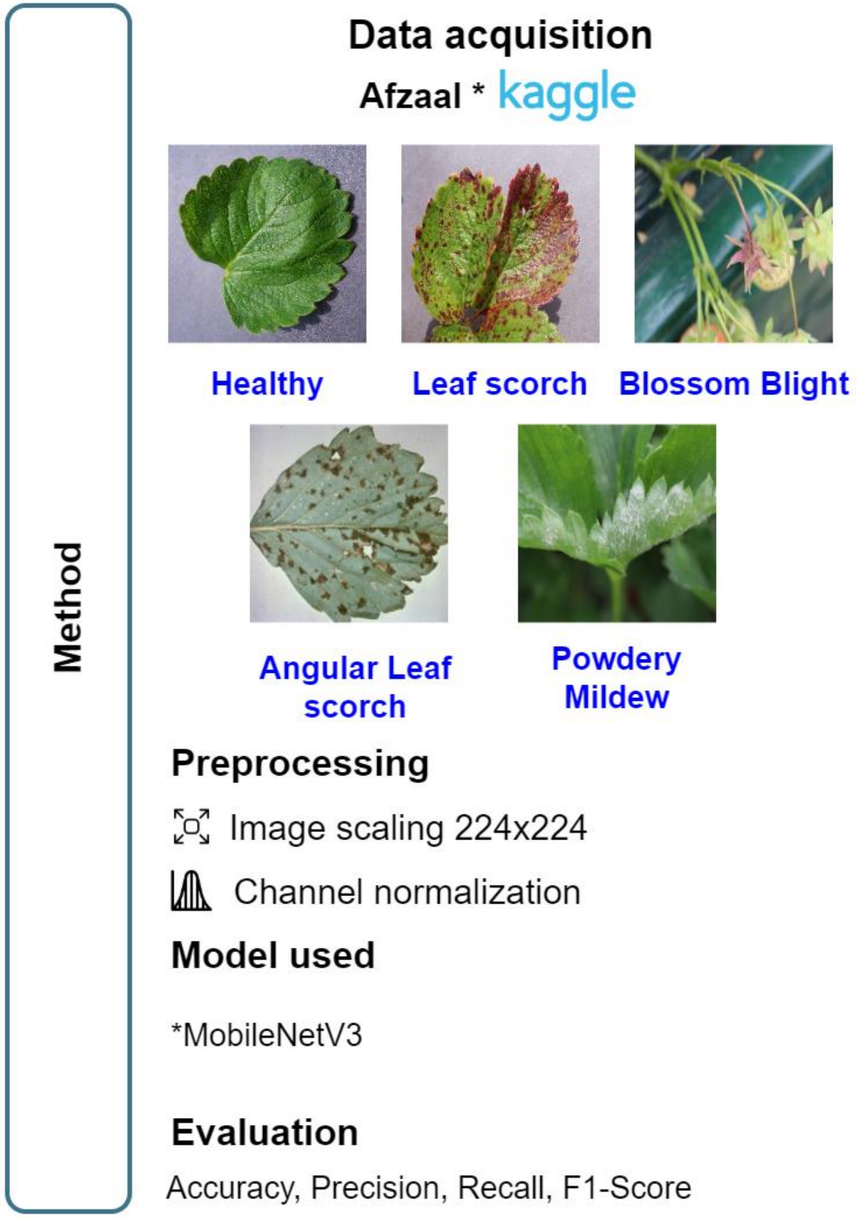
# Methodology

**Preprocessing**: The images were normalized to values in the range [0,1] using the next equation:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \qquad [1]$$

where $I$ represents the pixel matrix of the original image, and $I_{min}$, $I_{max}$ correspond to the minimum and maximum possible values (0 and 255 for RGB images). In order to strengthen the model in real field conditions—such as variations in lighting, orientation, and leaf scale—data augmentation techniques were applied with the following parameters:

| Technique | Parameter/Range |
|---|---|
| Random rotation | -25° < 0 < 25° |
| Horizontal reflection | p = 0.5 |
| Random zoom | 0.9 – 1.1 |
| Displacement | < 10% of image width/height |



# Methodology

The MobileNetV3 model was implemented in its Small and Large variants, previously trained with the ImageNet dataset. Based on this architecture, a transfer learning process was carried out with partial fine-tuning, freezing the last layers and adjusting the remaining layers of the bottleneck and the classifier.

The model performance was evaluated using the metrics:

| Performance Metric | Equation |
|---|---|
| Precision | $\frac{TP}{TP + FP}$ |
| Recall | $\frac{TP}{TP + FN}$ |
| Accuracy | $\frac{TP + TN}{TP + FN + TN + FP}$ |
| F1-score | $\frac{2.(precision.recall)}{precision + recall}$ |

Method

**Data acquisition**

Afzaal * kaggle


**Preprocessing**

Image scaling 224x224

Channel normalization

**Model used**

*MobileNetV3

**Evaluation**

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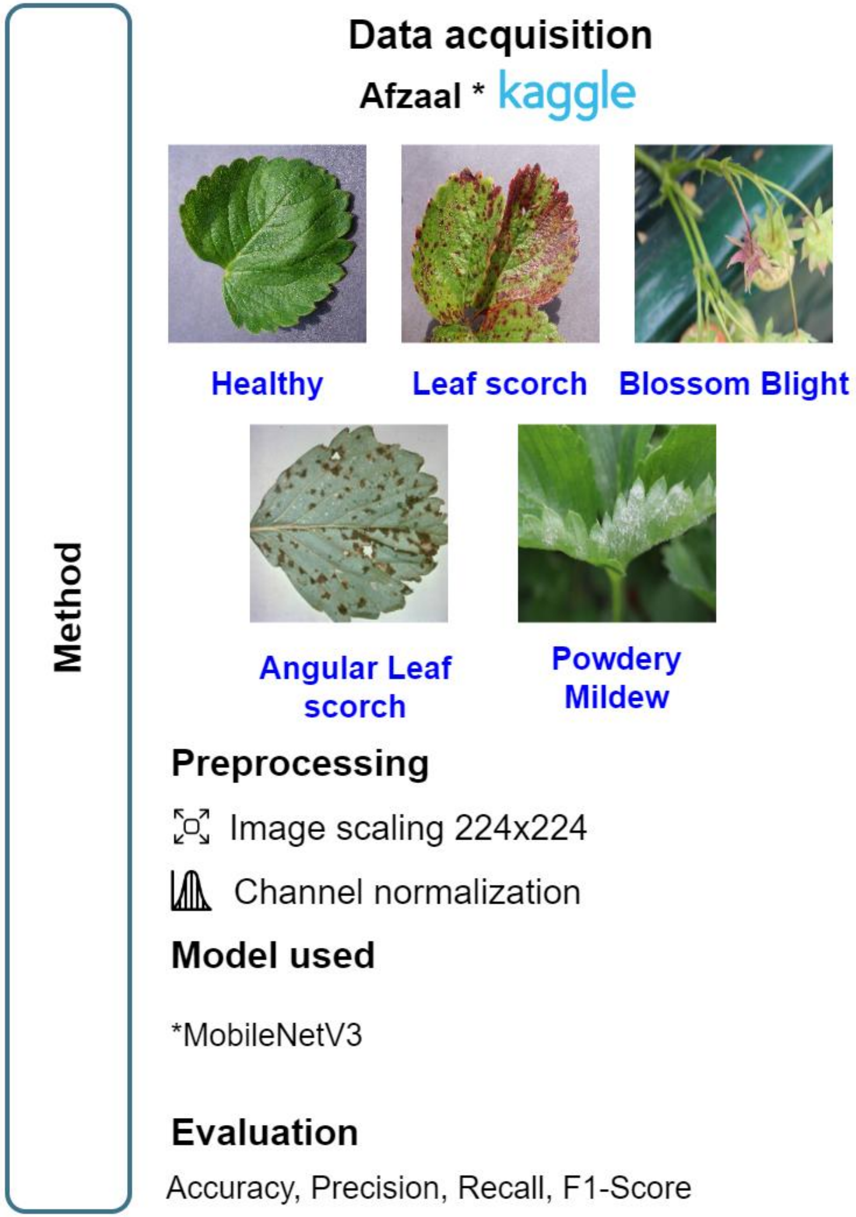
# Methodology

The model was lately exported to a TensorFlow Saved model and converted to .tflite and evaluated in device to measure latency, memory usage and power consumption.

The main components in the application architecture includes:

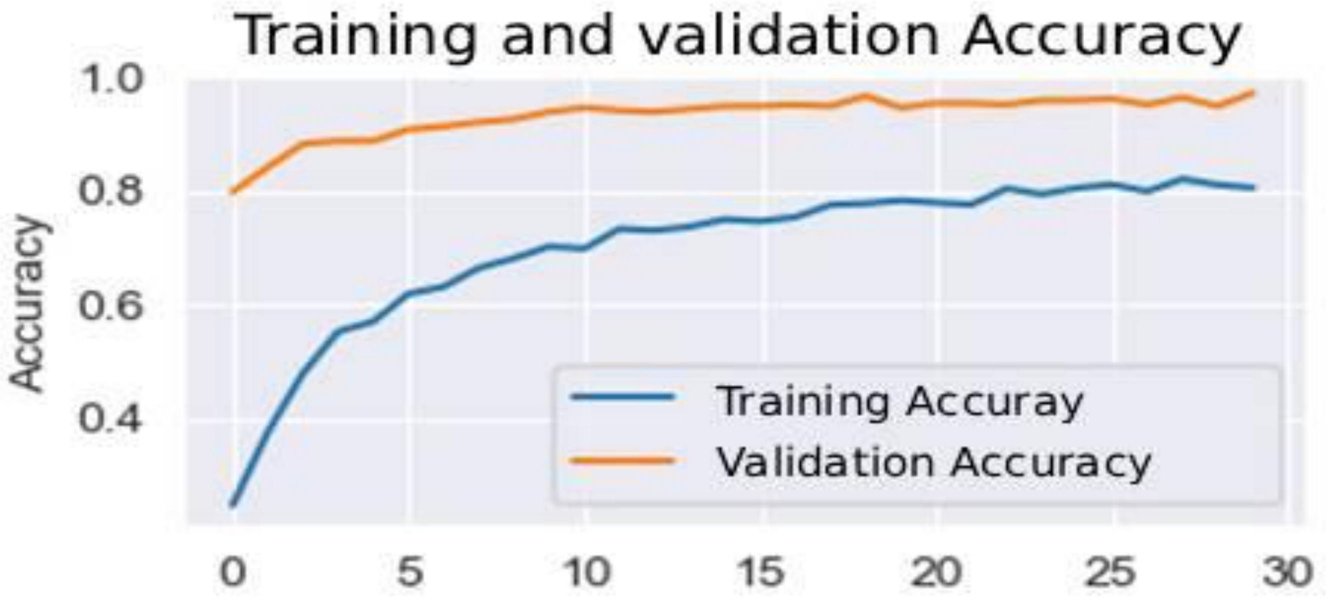
1. UI (Made with Kotlin and Jetpack Compose)
2. Camera Layer
3. Inference Module:
4. Storage: Room database

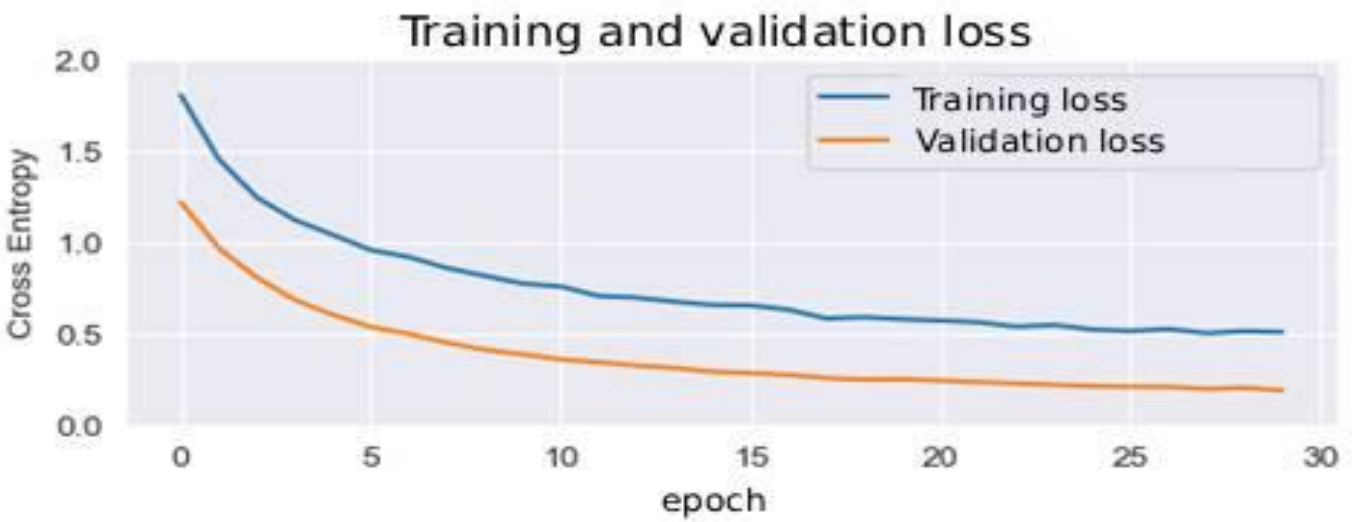


# Results

Preliminary results obtained with the MobileNetV3 architecture show significant performance in the classification of leaf diseases.

It is important to note that the quality and conditions of image capture have a significant impact on model performance, especially in classes that present mild symptoms or are under non-uniform lighting conditions.



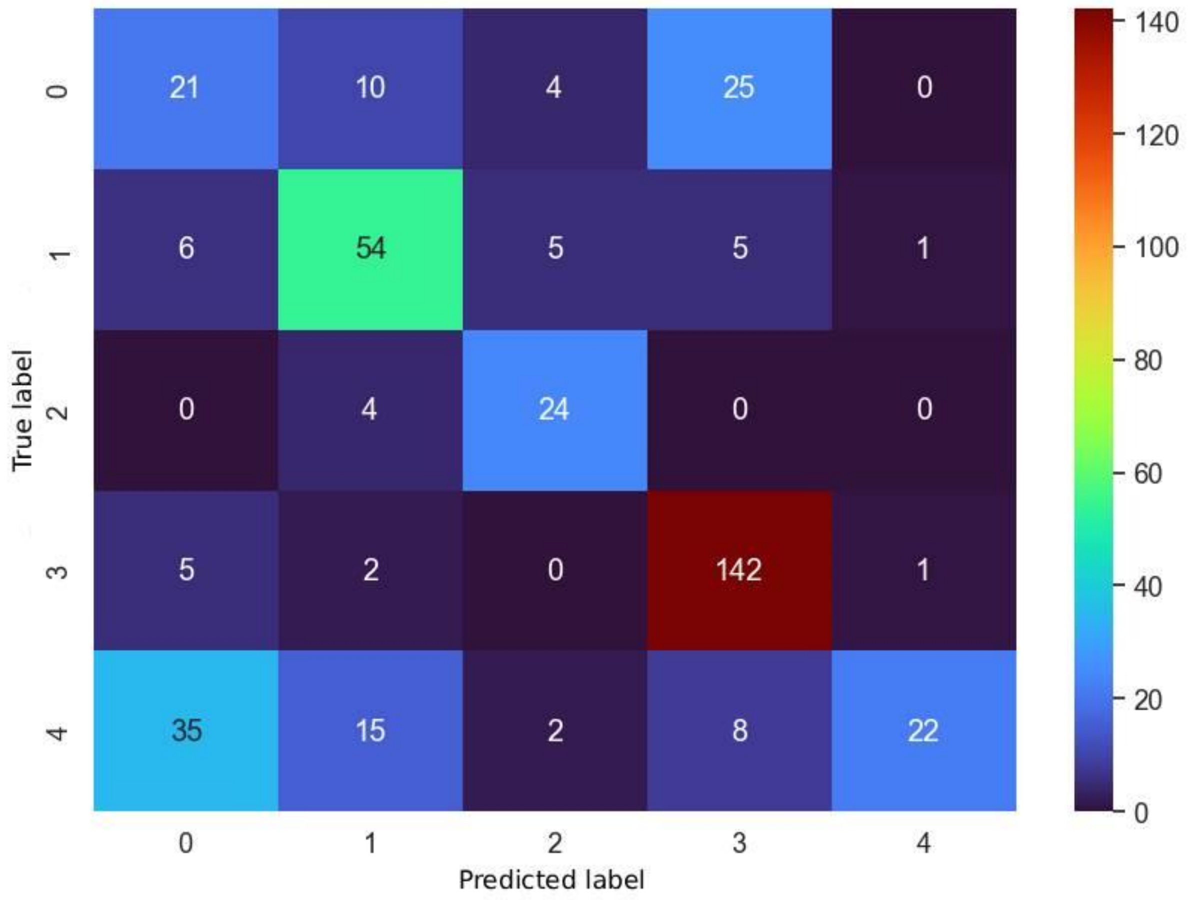



# Results

- During the training process, MobileNetV3 achieved an accuracy of 82% on the validation set.

- The model also obtained precision values of 91%, recall of 94%, and an F1 score of 86%, demonstrating an adequate balance between sensitivity and accuracy in predictions.

- The most frequent classification errors, highlighting greater confusion in the leaf scorch class, followed by angular leaf scorch were possibly due to its high visual similarity to other diseases and the model's limited ability to represent subtle features.



# Results

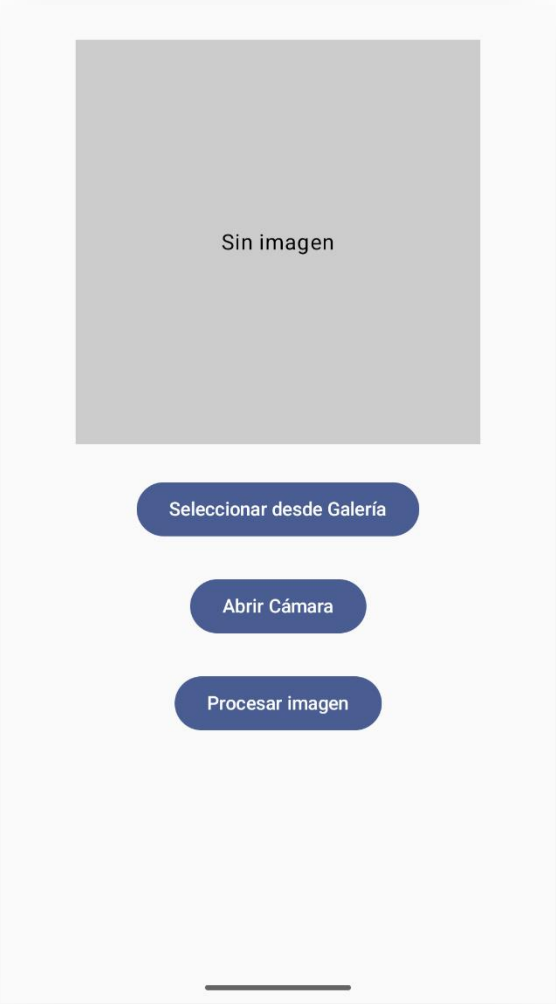
Results by class for MobileNetV3

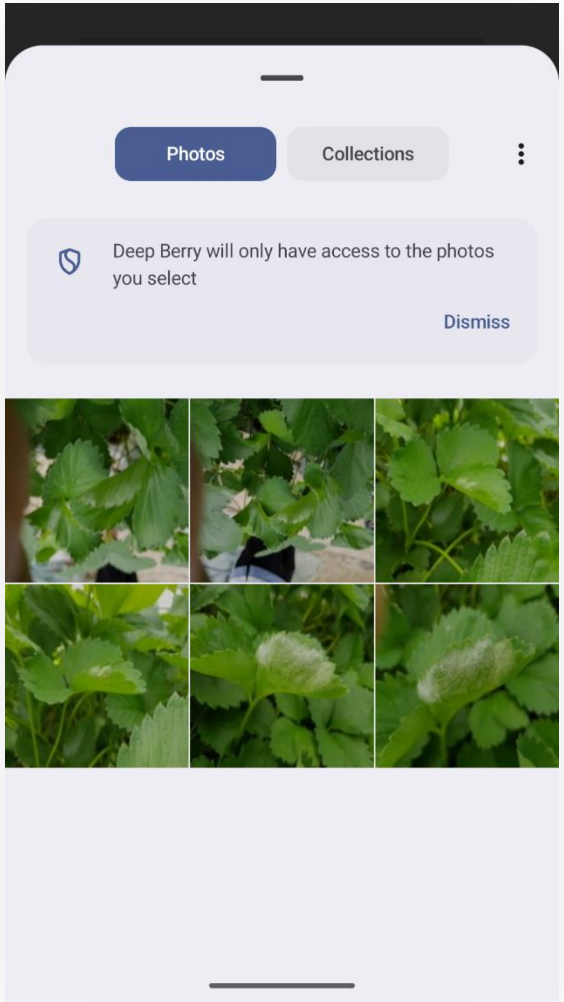
| Class | Precision | Recall | F1-Score |
| --- | --- | --- | --- |
| **Angular Leaf Scorch** | 90% | 93% | 85% |
| **Powdery Mildew** | 92% | 94% | 87% |
| **Blossom Blight** | 93% | 96% | 88% |
| **Healthy** | 89% | 86% | 86% |

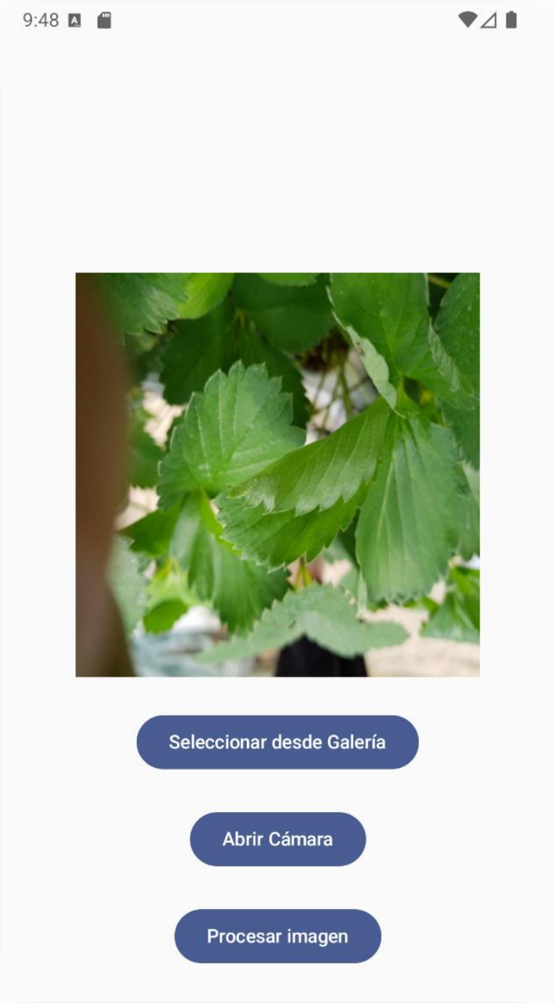
MobileNetV3 overall results

| Accuracy | Precision | Recall | F1-Score |
| --- | --- | --- | --- |
| **82%** | 91% | 94% | 86% |

# Results


Sin imagen
Seleccionar desde Galería
Abrir Cámara
Procesar imagen


Photos
Collections
Deep Berry will only have access to the photos you select
Dismiss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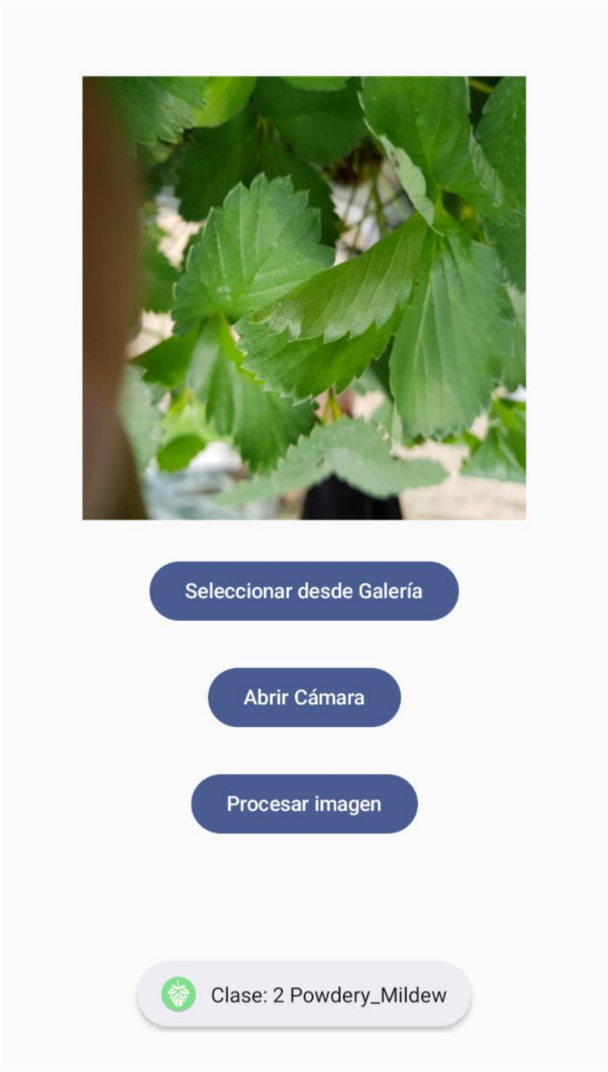
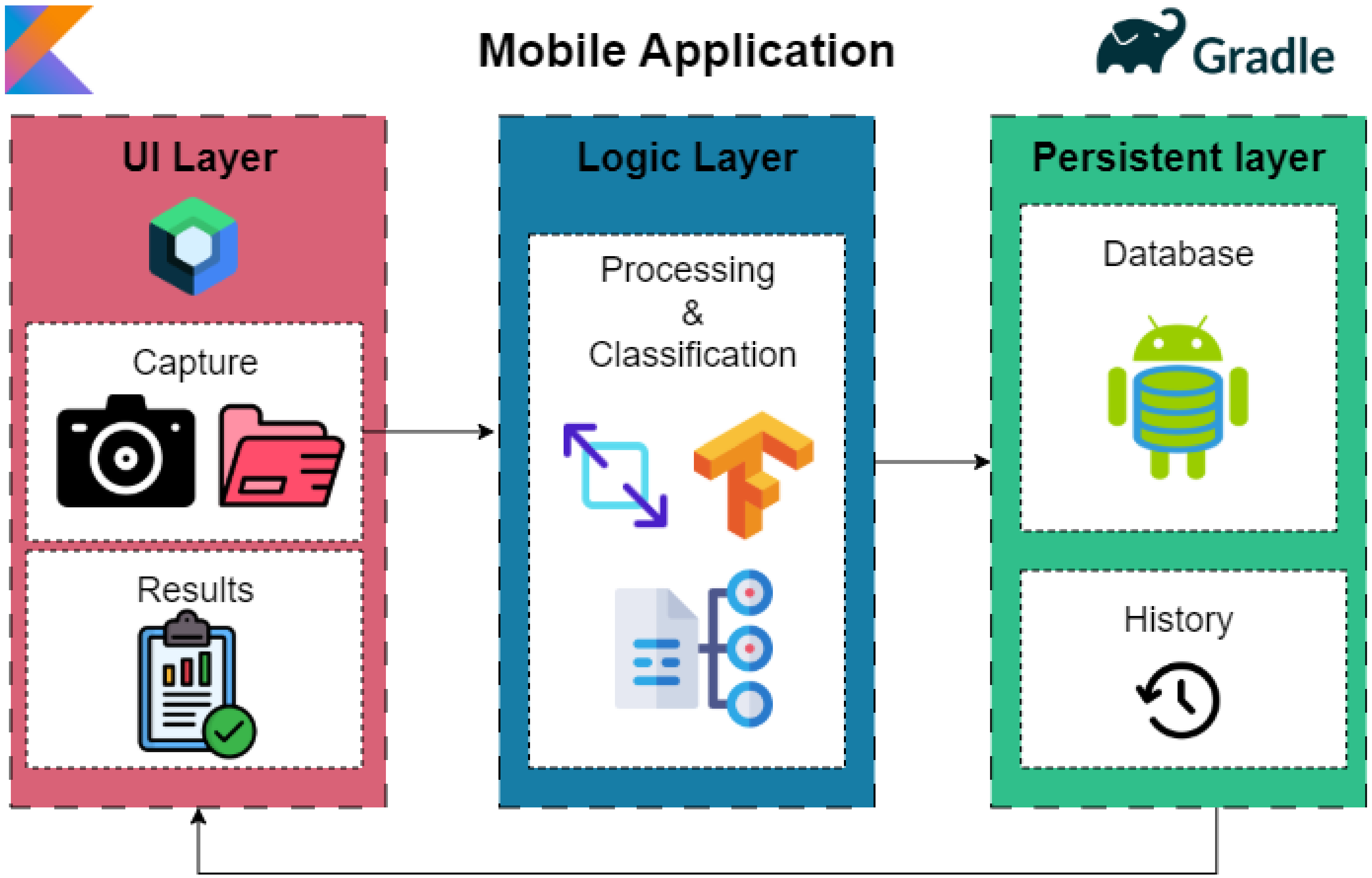
Seleccionar desde Galería
Abrir Cámara
Procesar imagen


Seleccionar desde Galería
Abrir Cámara
Procesar imagen
Clase: 2 Powdery_Mildew

# Conclusions

Developing an Android application in Kotlin that incorporates MobileNetV3 and TensorFlow Lite is a feasible and effective solution for early detection of diseases in strawberry plants. With a pipeline that includes fine-tuning and device testing, a practical support tool for producers can be achieved with adequate latencies for field use.



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