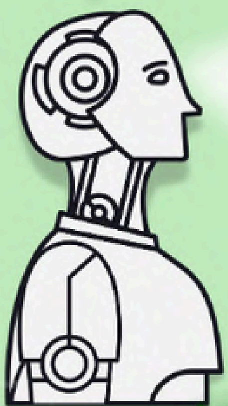


HERB-AI

PLANT DISEASE CNN CLASSIFIER

2211333 - Valentina Álvarez

2211848 - Diego García

2211861 - Erick Vargas

PLANT DISEASE CNN CLASSIFIER: HERB-AI

2211333 - Valentina Álvarez Valderrama
2211848 - Diego Garcia-Barajas
2211861- Erick Daniel Vargas

PROBLEMA

- Propagación rápida de plagas o infecciones de cultivos.
- Limitaciones de personal especializado.

OBJETIVO

Identificar y clasificar enfermedades que puedan afectar cultivos a través de la extracción de características que proporcionan las redes convolucionales, basado en las imágenes de hojas sanas y contaminadas.

DATASET

The classes are,

1.Apple_scab
2.Apple_black_rot
3.Apple_cedar_apple_rust
4.Apple_healthy
5.Background_without_leaves
6.Blueberry_healthy
7.Cherry_powdery_mildew
8.Cherry_healthy
9.Corn_gray_leaf_spot
10.Corn_common_rust
11.Corn_northern_leaf_blight
12.Corn_healthy
13.Grape_black_rot
14.Grape_black_measles
15.Grape_leaf_blight
16.Grape_healthy
17.Orange_haunglongbing
18.Peach_bacterial_spot
19.Peach_healthy
20.Pepper_bacterial_spot
21.Pepper_healthy
22.Potato_early_blight
23.Potato_healthy
24.Potato_late_blight
25.Raspberry_healthy
26.Soybean_healthy
27.Squash_powdery_mildew
28.Strawberry_healthy
29.Strawberry_leaf_scorch
30.Tomato_bacterial_spot
31.Tomato_early_blight
32.Tomato_healthy
33.Tomato_late_blight
34.Tomato_leaf_mold
35.Tomato_septoria_leaf_spot
36.Tomato_spider_mites_two-spotted_spider_mite
37.Tomato_target_spot
38.Tomato_mosaic_virus
39.Tomato_yellow_leaf_curl_virus

MÉTRICAS

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}}$$

$$\text{Accuracy} = \frac{\text{Correct predictions}}{\text{All predictions}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

$$WeightedAvgPrecision = \sum_{c \in \{Classes\}} Precision \cdot Wc$$

$$WeightedAvgRecall = \sum_{c \in \{Classes\}} Recall \cdot Wc$$

$$WeightedF1Score = 2 \cdot \left(\frac{WeightedAvgPrecision \cdot WeightedAvgRecall}{WeightedAvgPrecision + WeightedAvgRecall}\right)$$

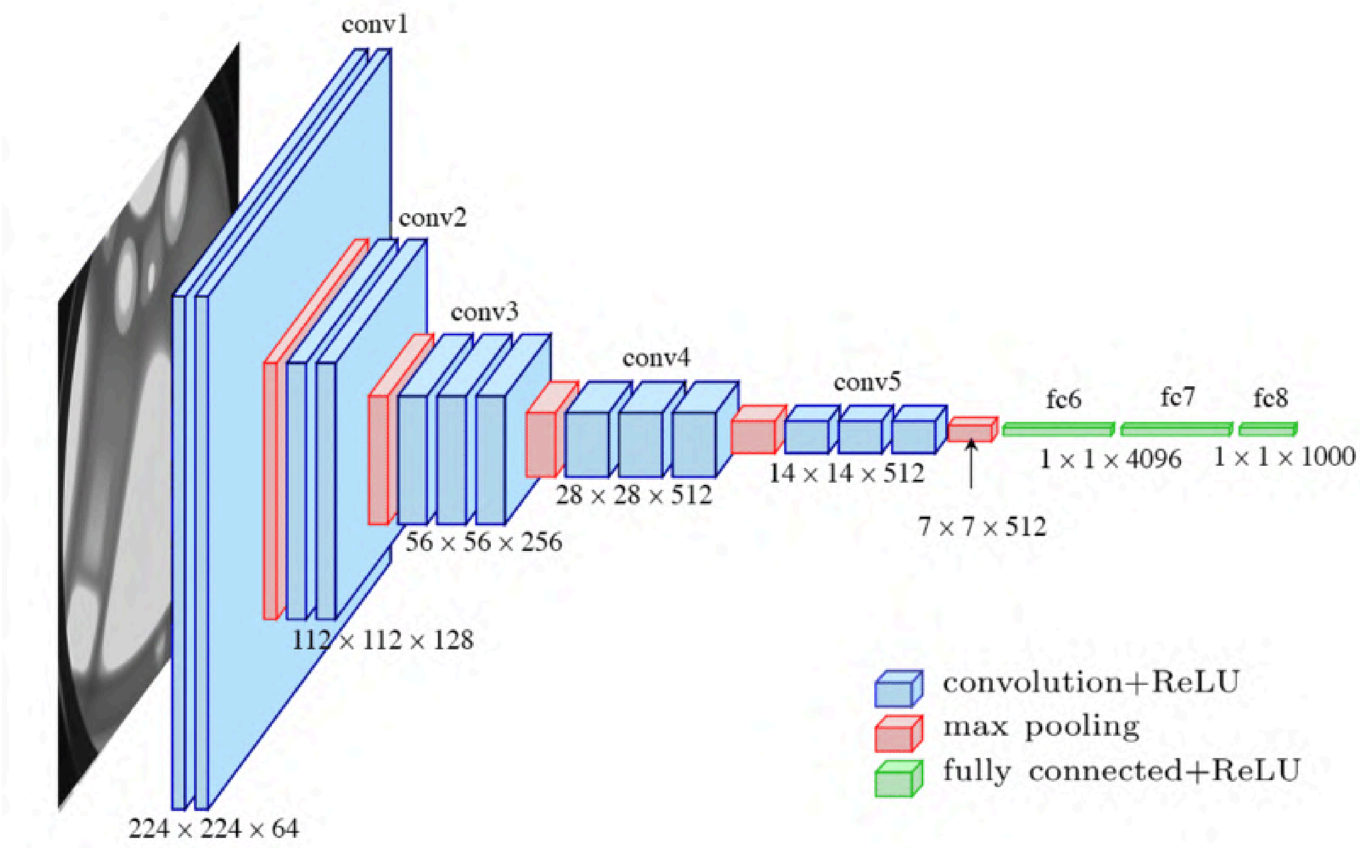
$$MacroAvgPrecision = \frac{\sum_{c \in \{Classes\}} Precision_c}{|\{Classes\}|}$$

$$MacroAvgRecall = \frac{\sum_{c \in \{Classes\}} Recall_c}{|\{Classes\}|}$$

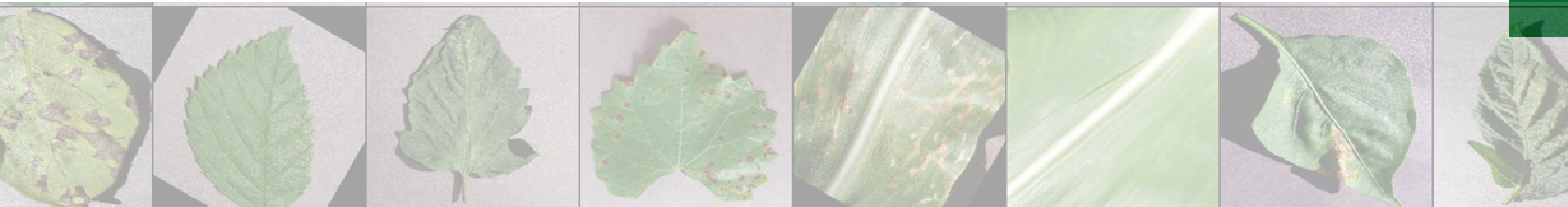
$$MacroF1Score = 2 \cdot \left(\frac{MacroAvgPrecision \cdot MacroAvgRecall}{MacroAvgPrecision + MacroAvgRecall}\right)$$

MODELOS DESARROLLADOS

VGGNET



Modelo 2: VGGNet. Tomado de https://medium.com/@siddheshb008/vgg-net-architecture-explained-71179310050f



✨ VGGNET ✨

📊 Arquitectura del Modelo

Input Shape:
`(128, 128, 3)`

⬇️

VGG16 Base (Preentrenado)

- Conv2D + MaxPool (Block 1) - 64 filters
- Conv2D + MaxPool (Block 2) - 128 filters
- Conv2D + MaxPool (Block 3) - 256 filters
- Conv2D + MaxPool (Block 4) - 512 filters
- Conv2D + MaxPool (Block 5) - 512 filters

Weights: ImageNet | Top layers: Excluidas

⬇️

🎯 Capas Personalizadas

- GlobalAveragePooling2D()
- Dropout(0.3)
- Dense(num_classes, softmax)

🚀 Proceso de Entrenamiento

1 Transfer Learning

VGG16 Base:
`Congelado (trainable=False)`

Optimizer:
`Adam(lr=0.0001)`

Loss:
`sparse_categorical_crossentrop`

Épocas:
`10`

2 Fine-tuning

Descongelado:
`Capas 4+ (trainable=True)`

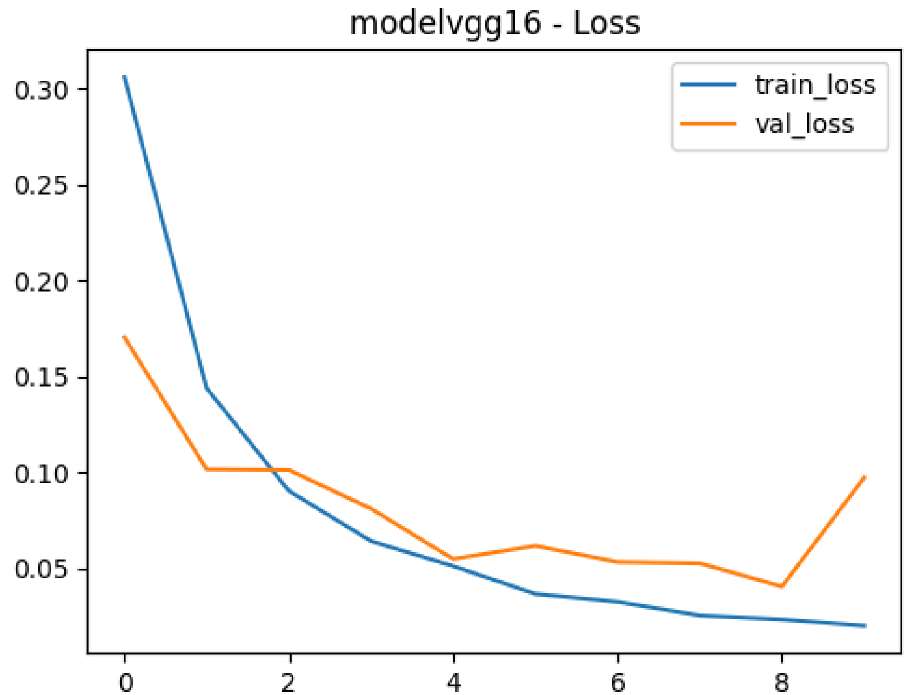
Congelado:
`Primeras 4 capas`

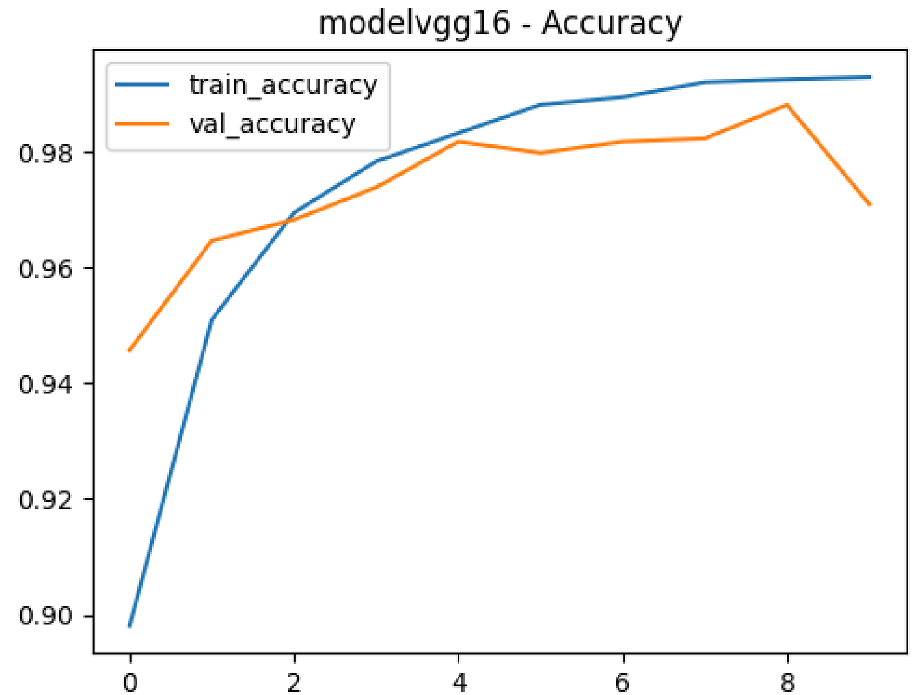
Optimizer:
`Adam(lr=1e-5)`

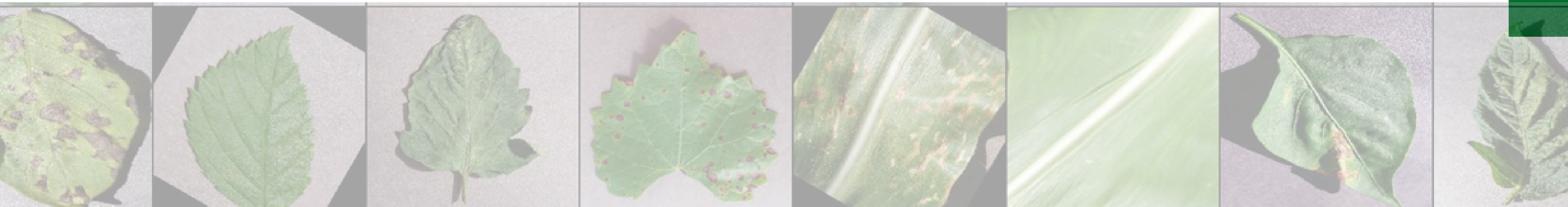
Learning Rate:
`Reducido para fine-tuning`

Capas Congeladas (No entrenable) | Capas Entrenables | VGG16 Preentrenado | Capas Personalizadas

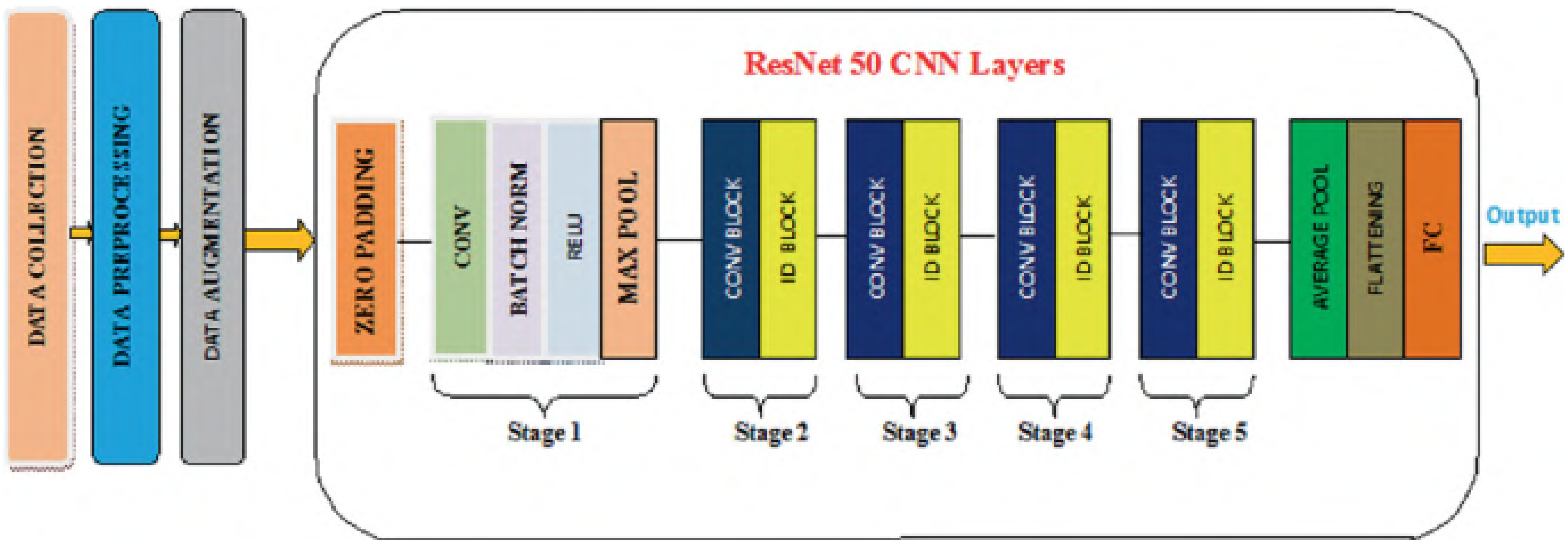
VGGNET


modelvgg16 - Loss
train_loss
val_loss
0.30
0.25
0.20
0.15
0.10
0.05
0
2
4
6
8


modelvgg16 - Accuracy
train_accuracy
val_accuracy
0.98
0.96
0.94
0.92
0.90
0
2
4
6
8

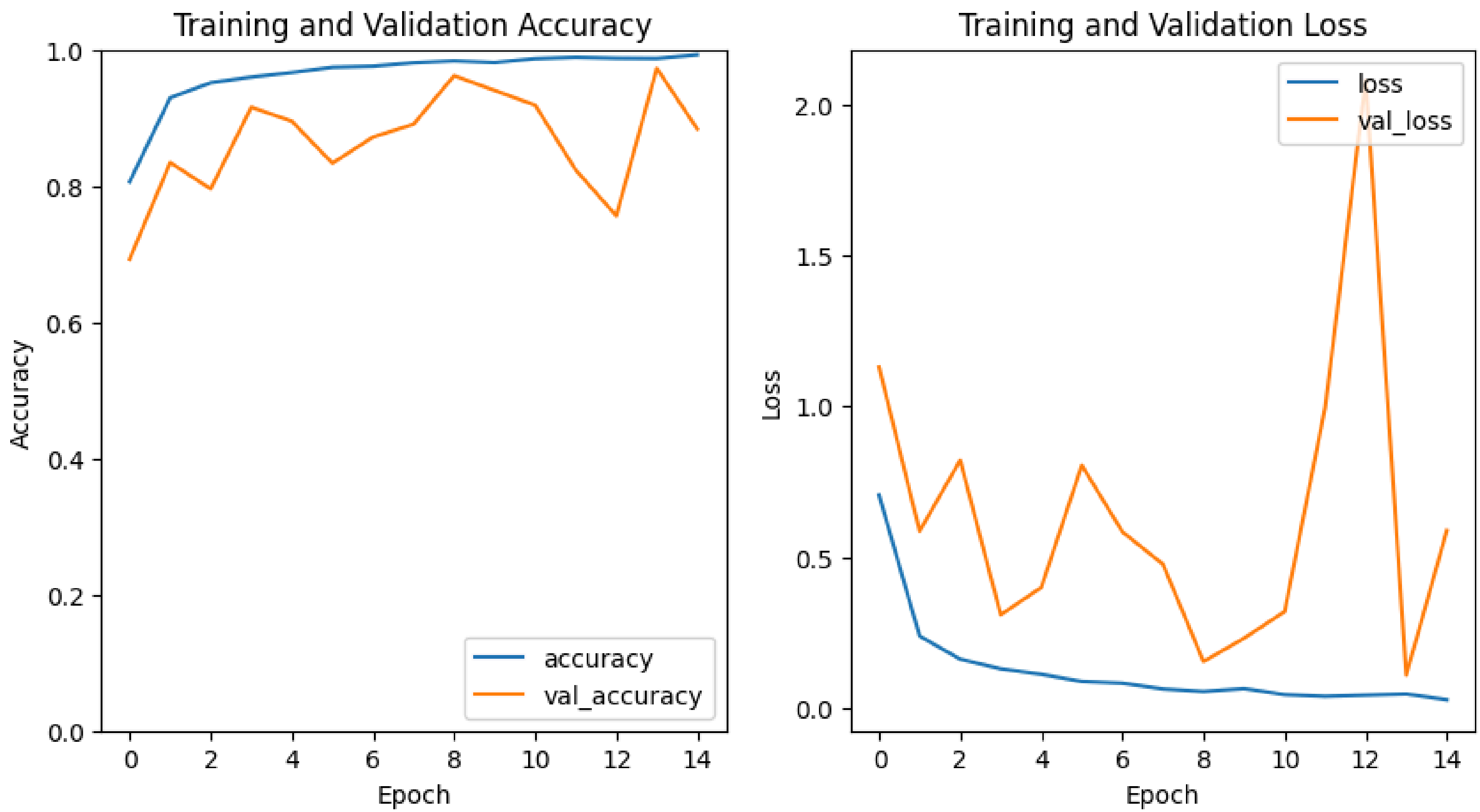


RESNET

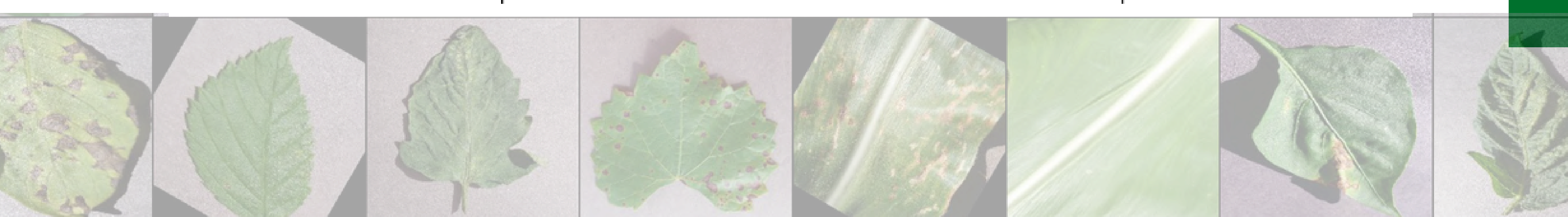


Modelo 1: ResNet. Tomado de https://www.kaggle.com/code/atharvaingle/plant-disease-classification-resnet-99-2#%F0%9F%8F%97%EF%B8%8F-Modelling-%F0%9F%8F%97%EF%B8%8F

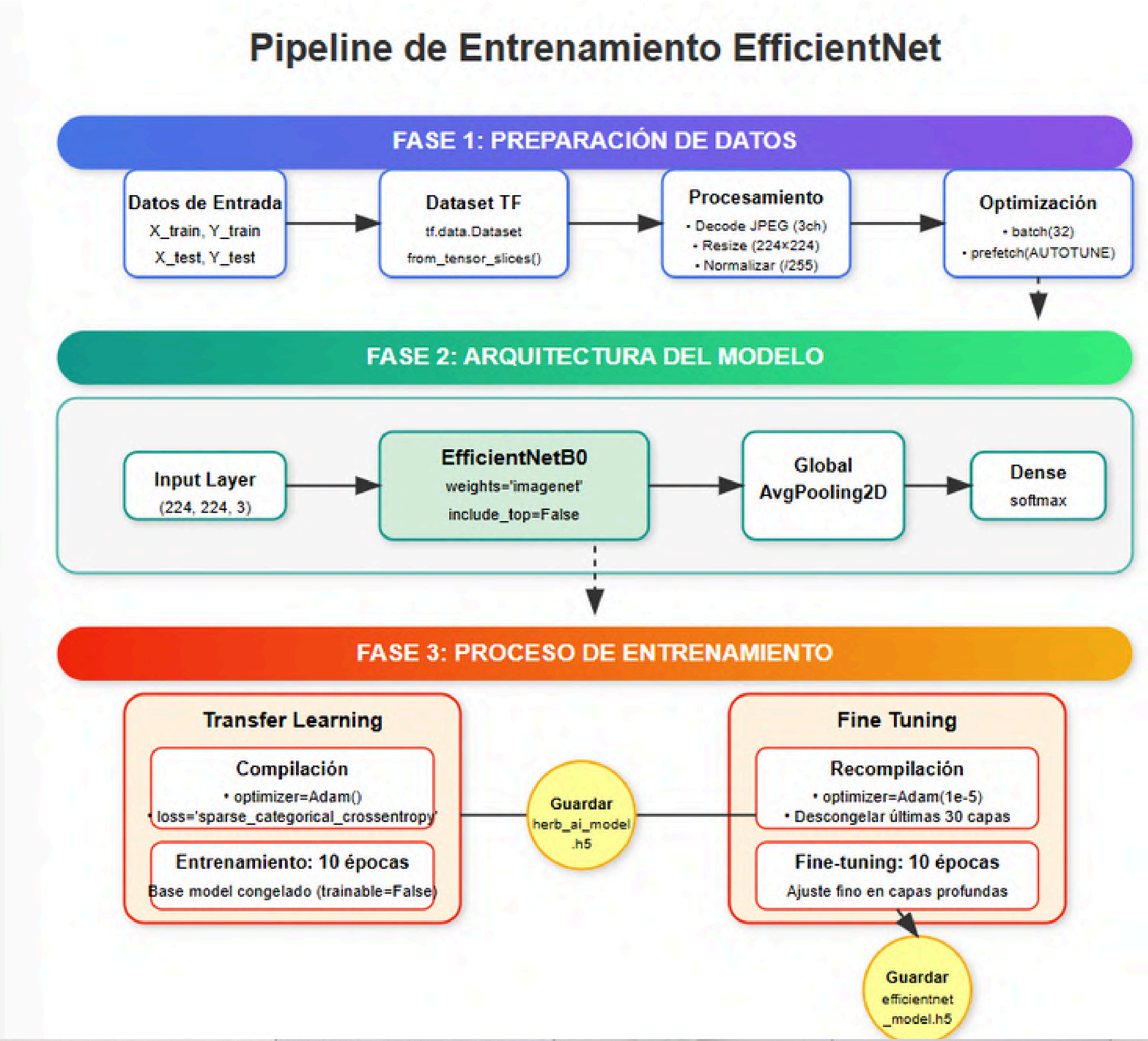
RESNET

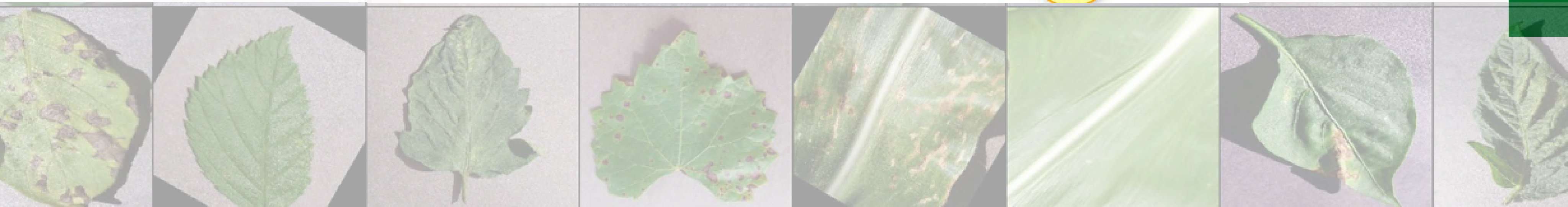


Training and Validation Accuracy
Accuracy
Epoch
accuracy
val_accuracy
0.0 0.2 0.4 0.6 0.8 1.0
0 2 4 6 8 10 12 14
Training and Validation Loss
Loss
Epoch
loss
val_loss
0.0 0.5 1.0 1.5 2.0
0 2 4 6 8 10 12 14



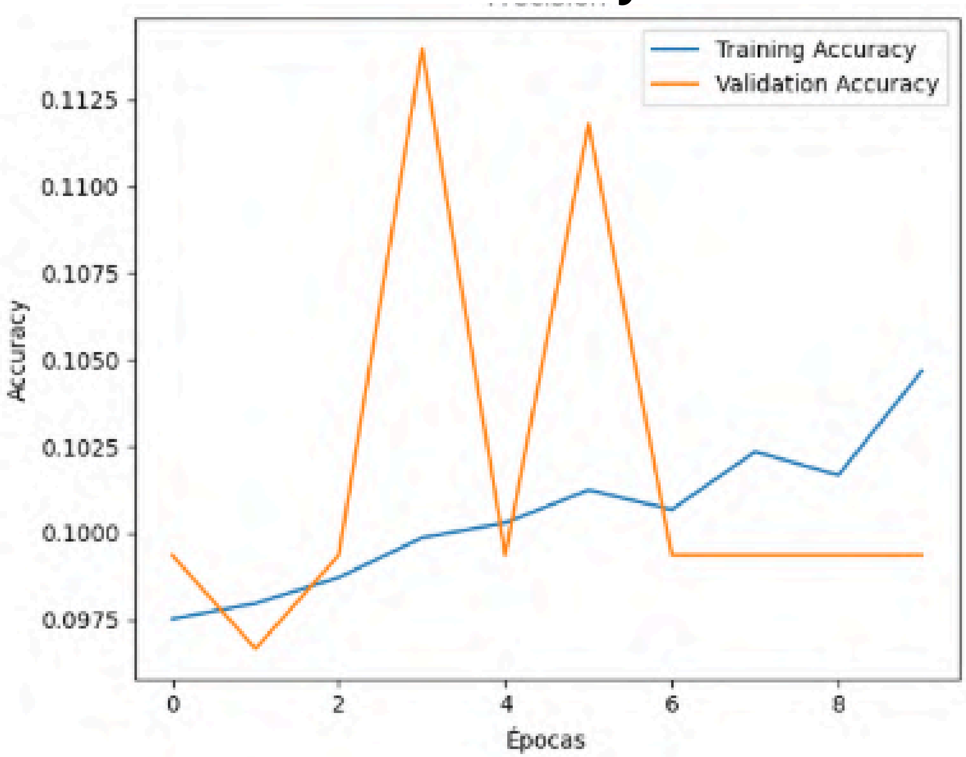
EFFICIENTNETB0



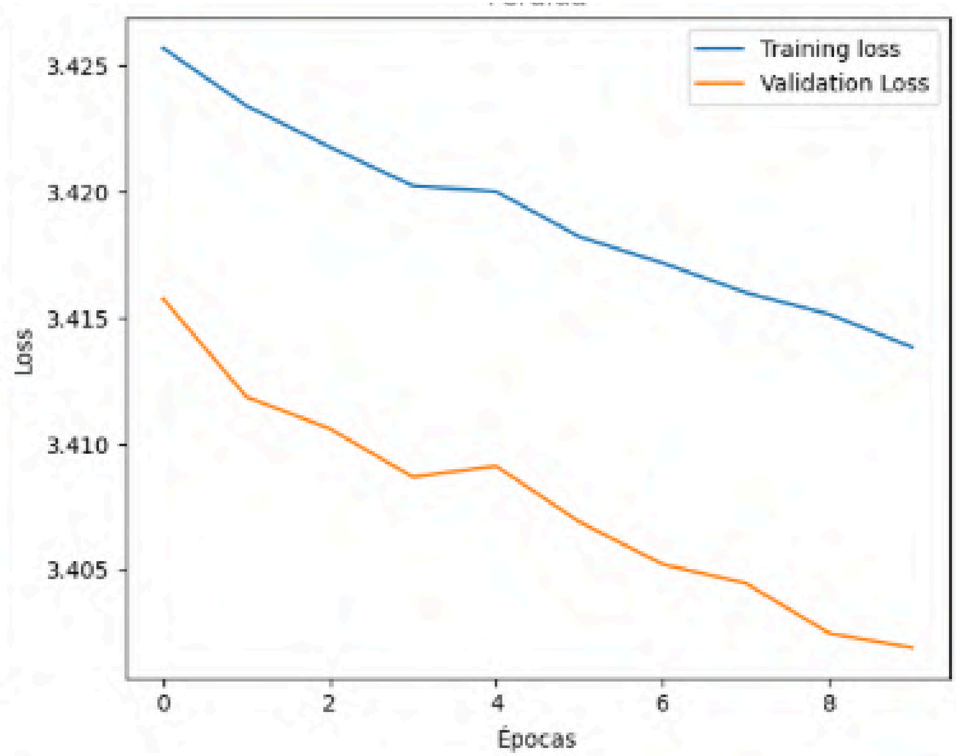


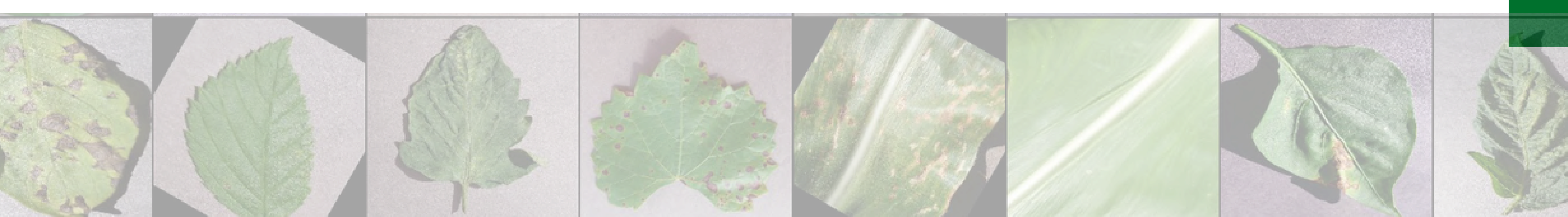
EFFICIENTNETB0

Accuracy

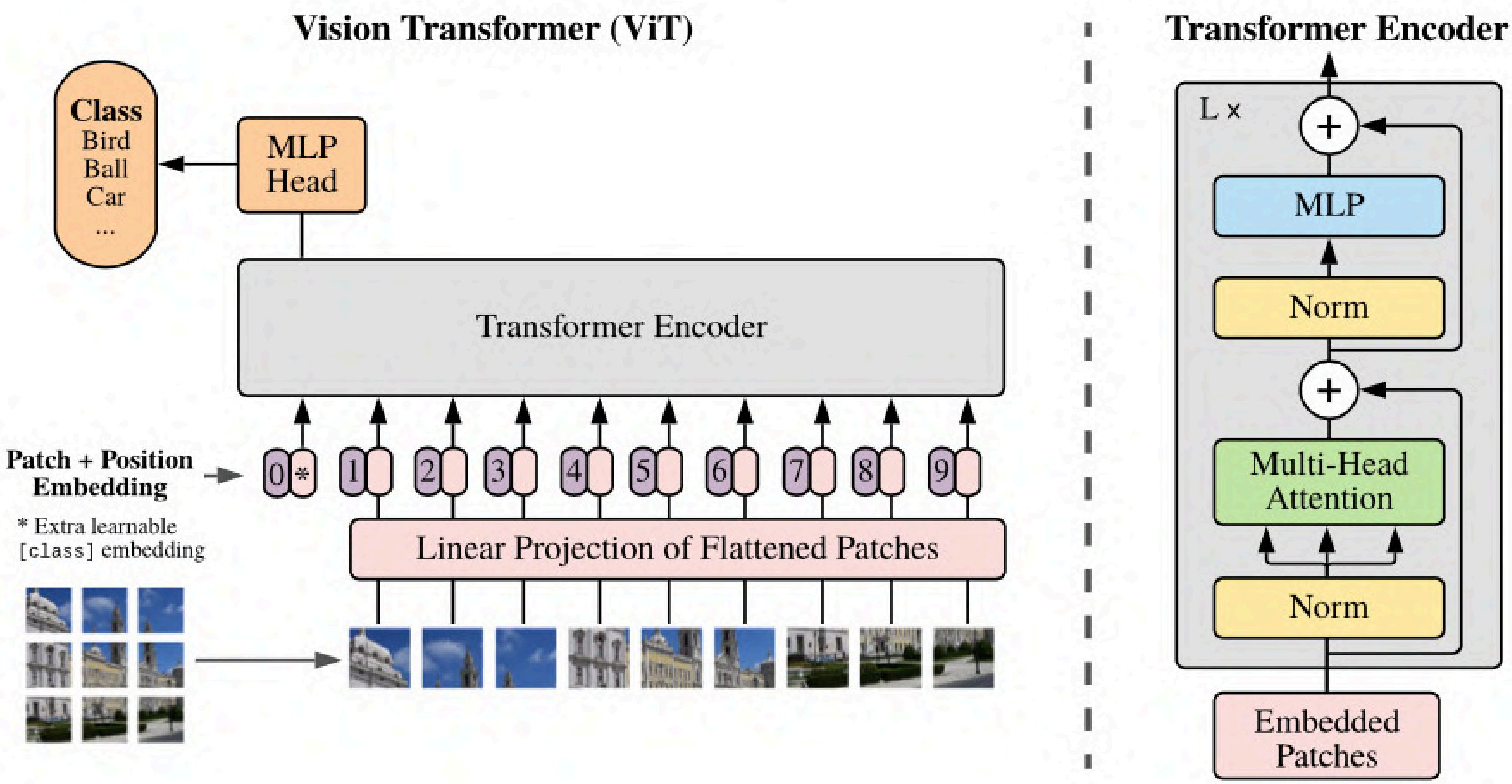


Loss

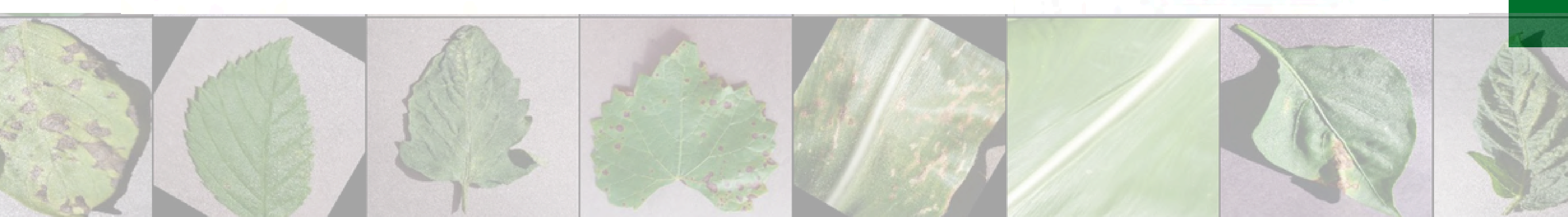




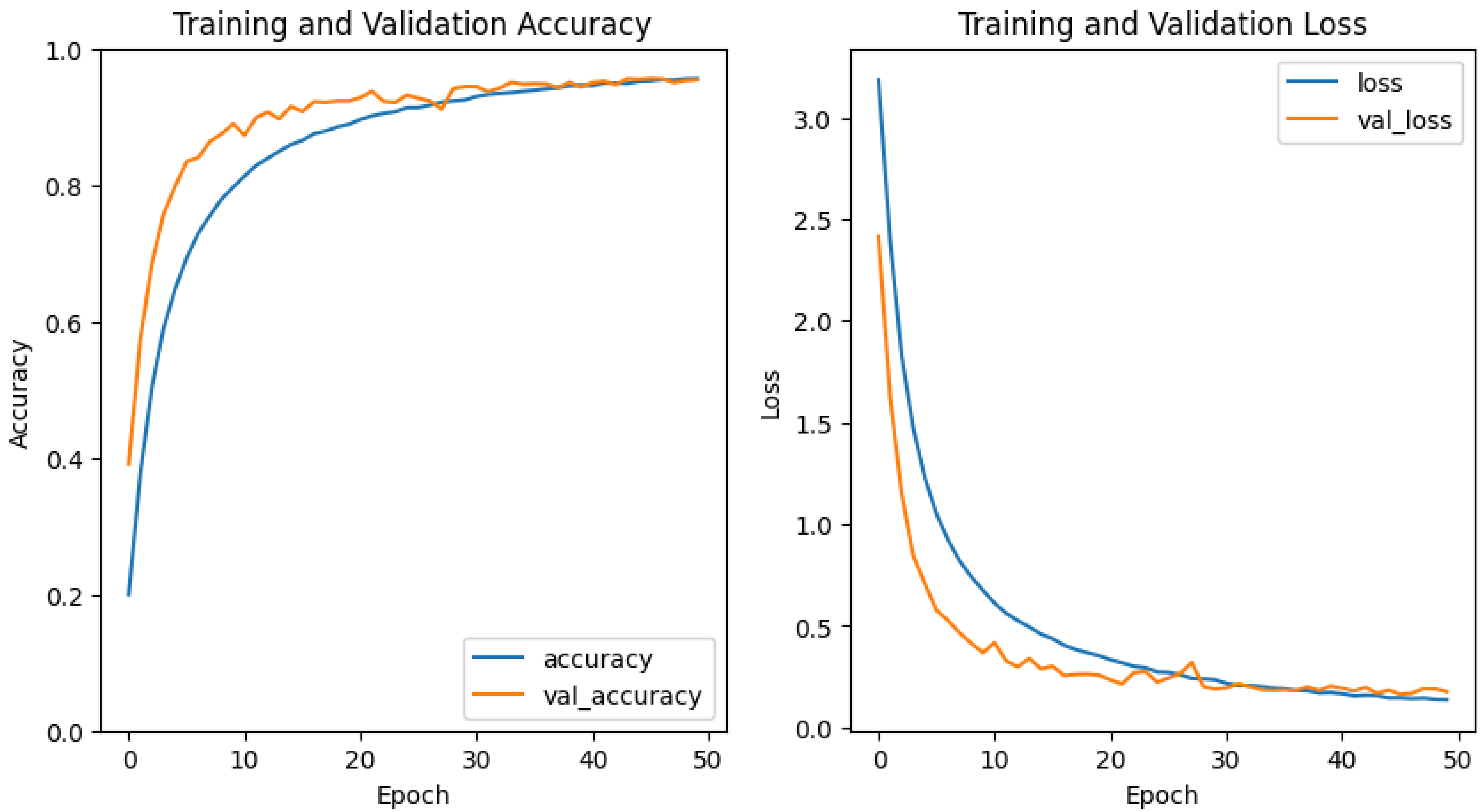
VIT

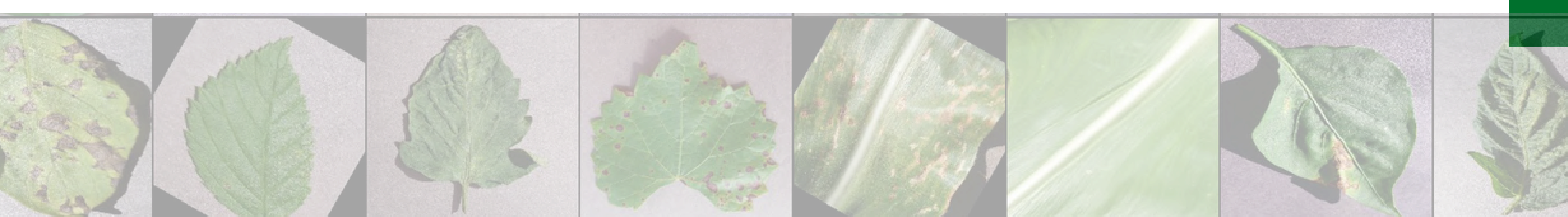


Vision Transformer (ViT)
Class
Bird
Ball
Car
...
MLP Head
Transformer Encoder
Patch + Position Embedding
* Extra learnable [class] embedding
0 *
1
2
3
4
5
6
7
8
9
Linear Projection of Flattened Patches
Transformer Encoder
L x
MLP
Norm
Multi-Head Attention
Norm
Embedded Patches



VIT


Training and Validation Accuracy
Accuracy
Epoch
accuracy
val_accuracy
0.0
0.2
0.4
0.6
0.8
1.0
0
10
20
30
40
50
Training and Validation Loss
Loss
Epoch
loss
val_loss
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0
10
20
30
40
50



RESULTADOS Y ANALISIS

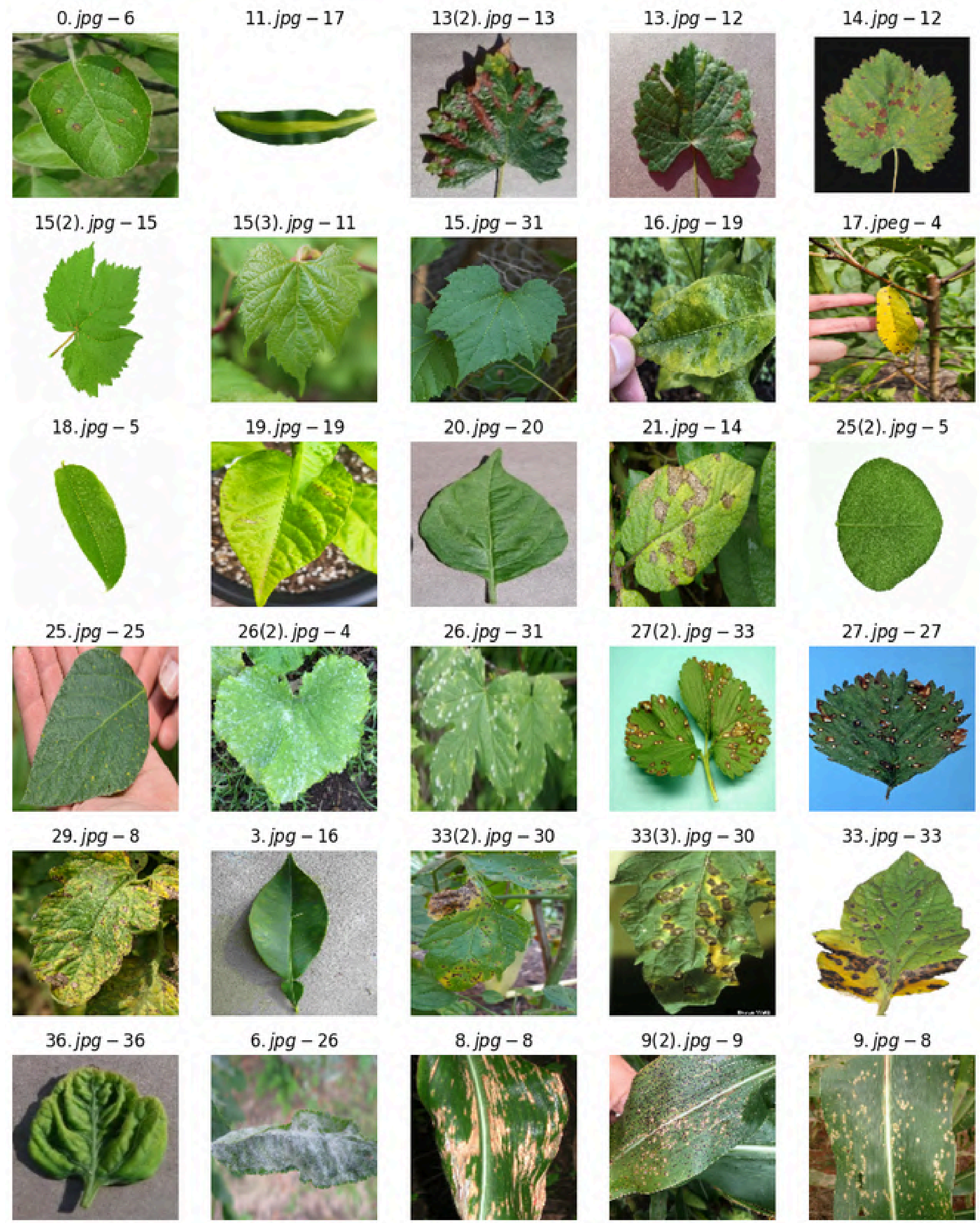
70-10-20

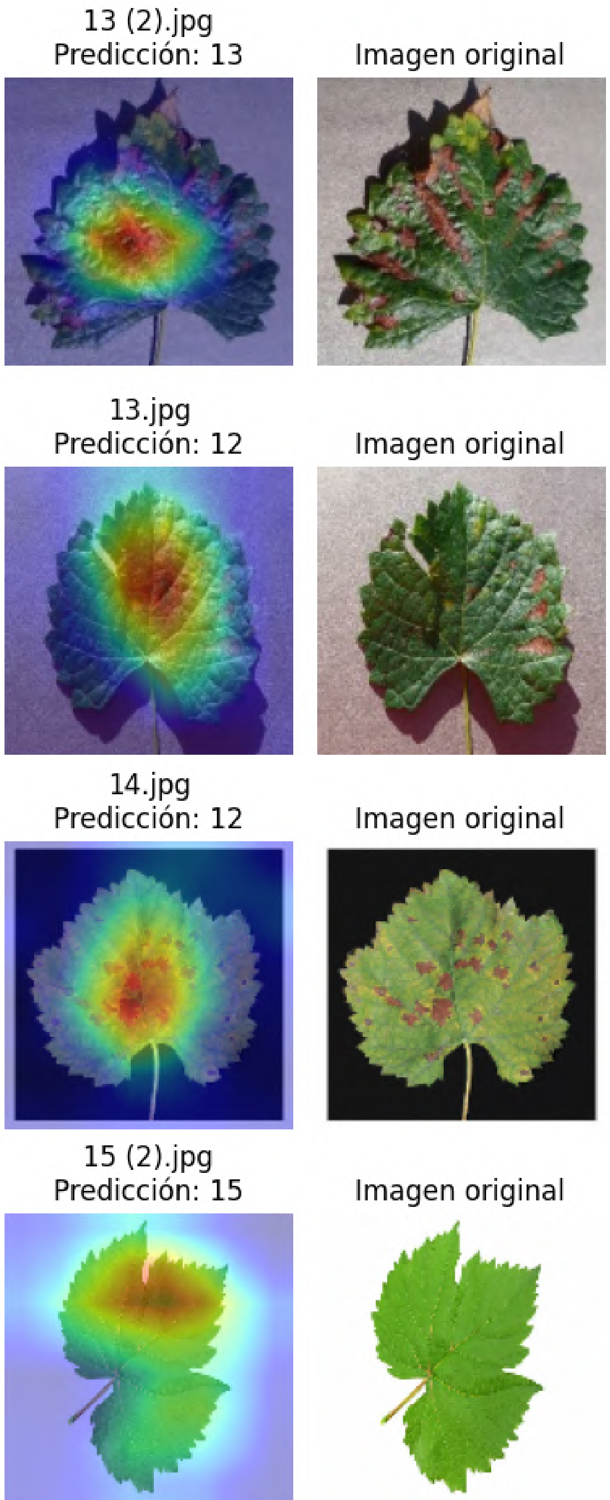
- Sklearn Accuracy: 0.9689
- Sklearn Macro Precision: 0.9669
- Sklearn Macro Recall: 0.9562
- Sklearn Macro F1-score: 0.9578

- Sklearn Weighted Precision: 0.9735
- Sklearn Weighted Recall: 0.9689
- Sklearn Weighted F1-score: 0.9683

Apple___Apple_scab	0
Apple___Black_rot	1
Apple___Cedar_apple_rust	2
Apple___healthy	3
Background_without_leaves	4
Blueberry___healthy	5
Cherry___Powdery_mildew	6
Cherry___healthy	7
Corn___Cercospora_leaf_spot Gray	8
Corn___Common_rust	9
Corn___Northern_Leaf_Blight	10
Corn___healthy	11
Grape___Black_rot	12
Grape___Esca_(Black_Measles)	13
Grape___Leaf_blight_(Isariopsis_Le	14
Grape___healthy	15
Orange___Haunglongbing_(Citrus_	16
Peach___Bacterial_spot	17
Peach___healthy	18
Pepper,_bell___Bacterial_spot	19
Pepper,_bell___healthy	20

Potato___Early_blight	21
Potato___Late_blight	22
Potato___healthy	23
Raspberry___healthy	24
Soybean___healthy	25
Squash___Powdery_m	26
Strawberry___Leaf_sc	27
Strawberry___healthy	28
Tomato___Bacterial_s	29
Tomato___Early_bligh	30
Tomato___Late_blight	31
Tomato___Leaf_Mold	32
Tomato___Septoria_le	33
Tomato___Spider_mit	34
Tomato___Target_Spo	35
Tomato___Tomato_Ye	36
Tomato___Tomato_m	37
Tomato___healthy	38





Análisis GRADCAM

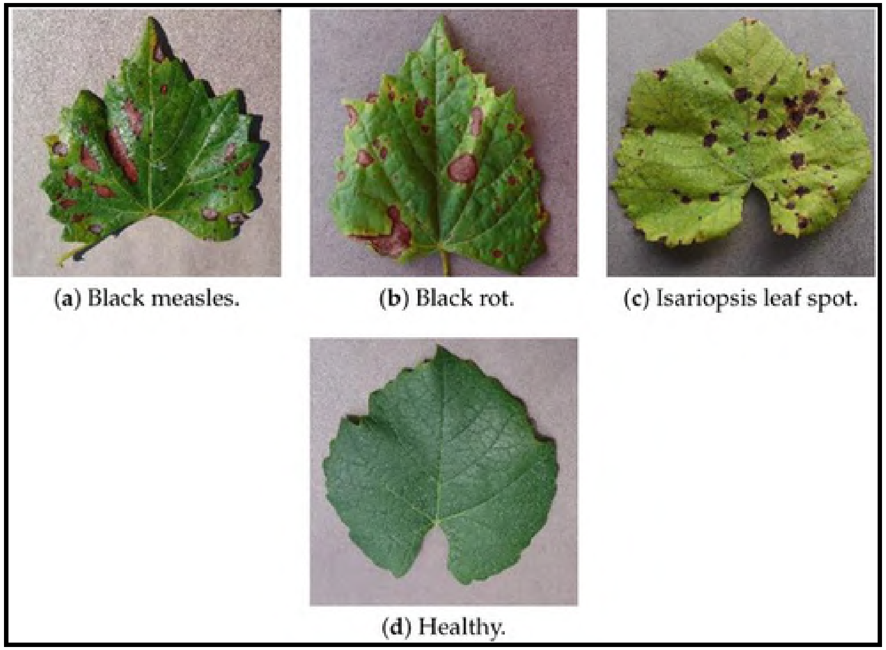
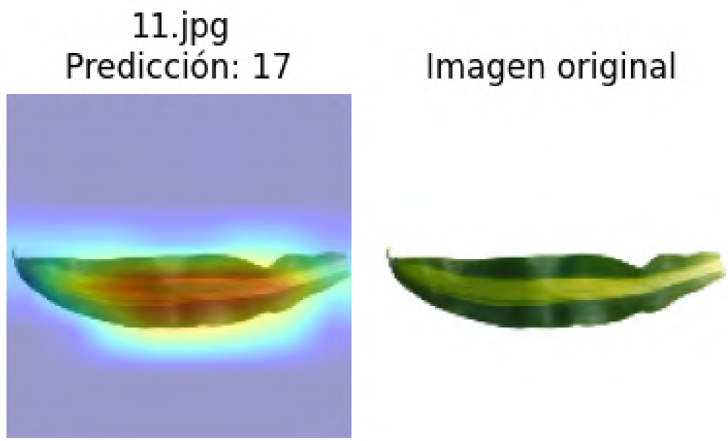
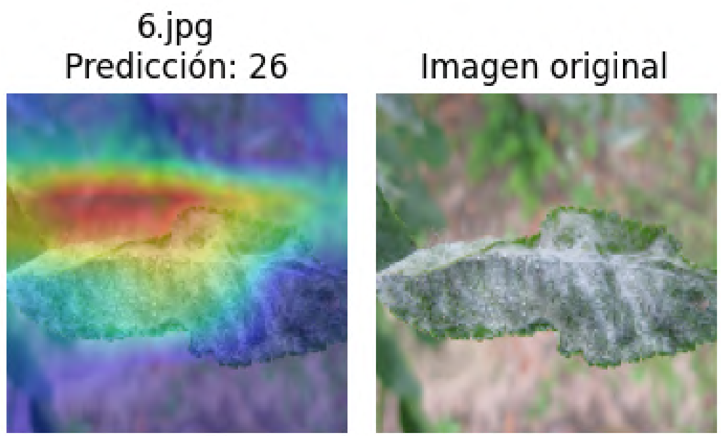


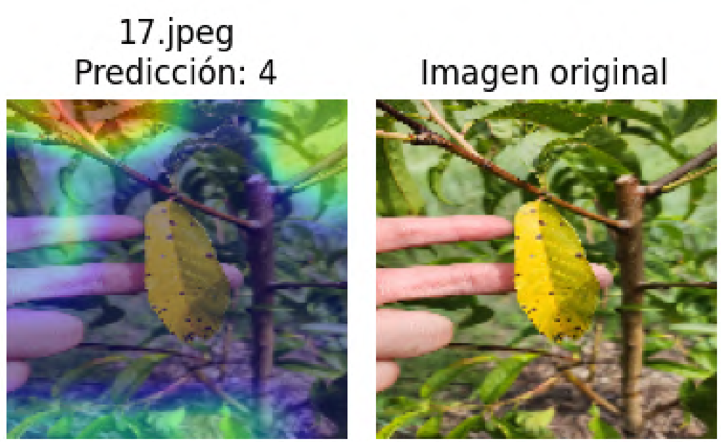
Figura 1: Enfermedades de la uva.
Tomado de *https://doi.org/10.3390/agriculture12101542*

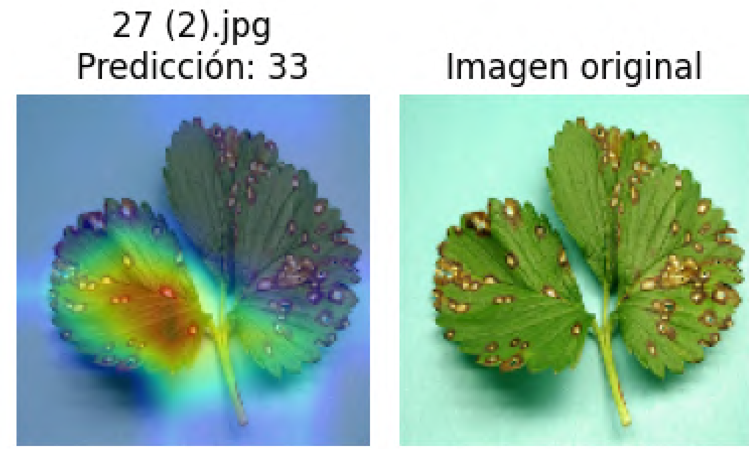
Grape___Black_rot	12	1180
Grape___Esca_(Black_Measles)	13	1383
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	14	1076
Grape___healthy	15	423

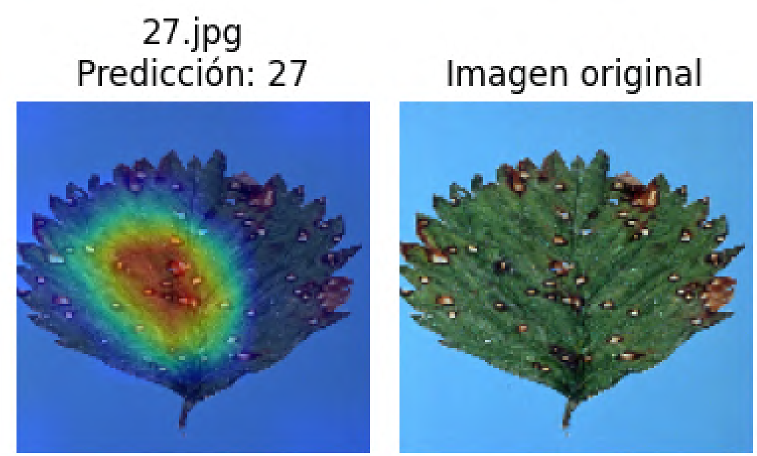
Análisis GRADCAM



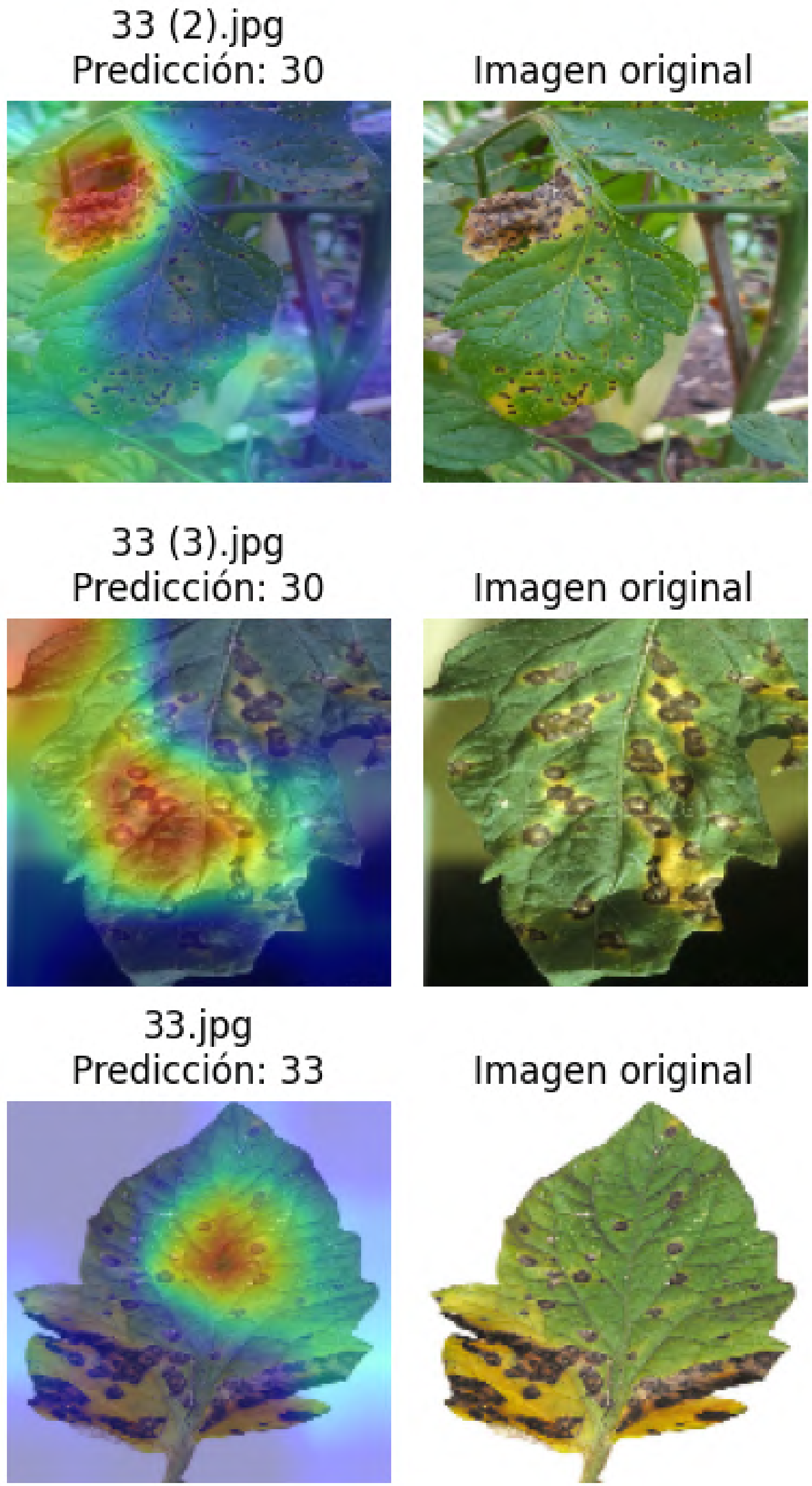


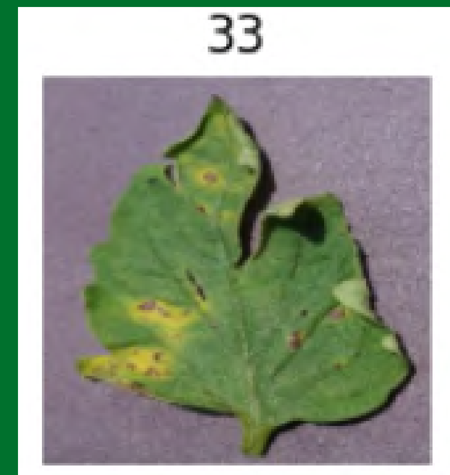






Análisis GRADCAM





Tomato___Early_blight	30
Tomato___Late_blight	31
Tomato___Leaf_Mold	32
Tomato___Septoria_leaf_spot	33

CONCLUSIONES

Conclusiones

- Reducir la cantidad de clases puede mejorar el rendimiento del modelo enfocándose en un solo tipo de cultivo.

- El análisis con Grad-Cam reveló problemas en la atención del modelo, presta atención a zonas irrelevantes como el fondo, lo que sugiere una necesidad de mejorar la calidad del dataset o aplicar técnicas de segmentación previa.

- El modelo mostro buen desempeño con el conjunto de validación y testeando, pero mal con imágenes externas extraídas de google, demostrando una escasa habilidad para generalizar en contextos reales.

TRABAJO FUTURO

Trabajo Futuro

- Combinar con un proceso previo de detección.
- Reentrenar con datasets menos sesgados (Fondo muy controlado).
- Tomar medidas para contrarrestar el desbalance de datos.


TURNO DE...
PREGUNTAS (fáciles)
COMENTARIOS (bonitos)
CRÍTICAS (constructivas)
APORTACIONES (monetarias)

¡GRACIAS!