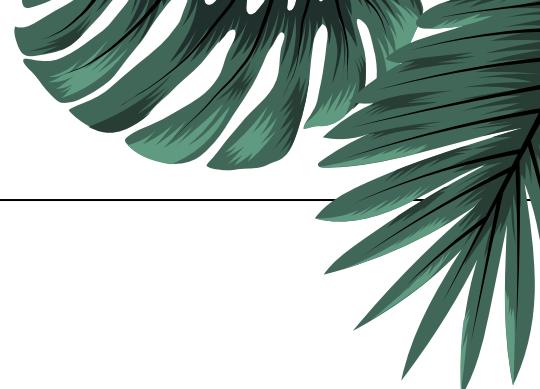


Cassava Disease Classification

By: Matthew Ocando & Daphne Hong

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About the Dataset

The dataset consists of **21,397 images** belonging to the following classes:

- Cassava Bacterial Blight (CBB)
- Cassava Brown Streak Disease (CBSD)
- Cassava Green Mottle (CGM)
- Cassava Mosaic Disease (CMD)
- Healthy



Cassava Brown Streak Disease (CBSD)

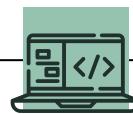
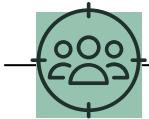


Cassava Mosaic Disease (CMD)



Cassava Green Mottle (CGM)

Defining the Problem – Cassava Plants



Key to Food Security

- Second-largest source of carbohydrates in Africa
- Can withstand harsh conditions

Impacts of Viral Diseases

- Can significantly impact yield
- Plants need to be treated quickly to limit spread

Current Solution

- Manual process, labor intensive & costly
- Constraints due to limited access to resources (e.g. mobile-quality cameras, low bandwidth etc.).

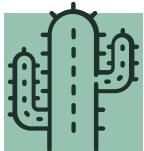
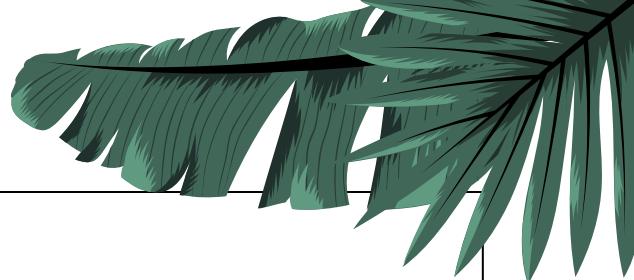
Problem Statement

Can the process of Cassava disease classification be made more efficient (e.g. faster, less labor intensive, and costly)?

02.

Data Preprocessing

Preprocessing



Checking for Missing Values

Data did not have 'N/A' that would require cleaning.



Data Augmentation

Rotation, zoom, horizontal/vertical shift, shear, & flip



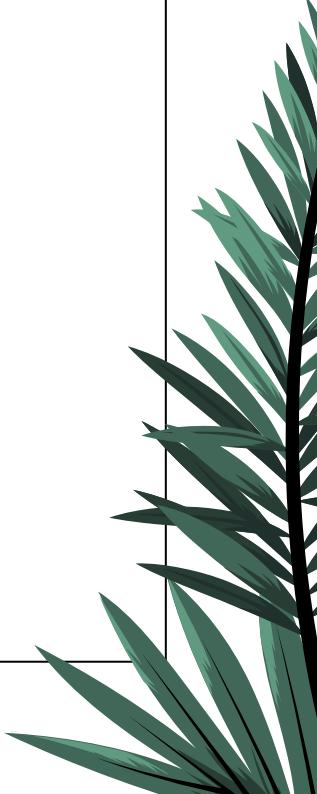
Normalizing the Data

Scale pixels to [0, 1] for efficiency during the training.



Train Test Split (80/20)

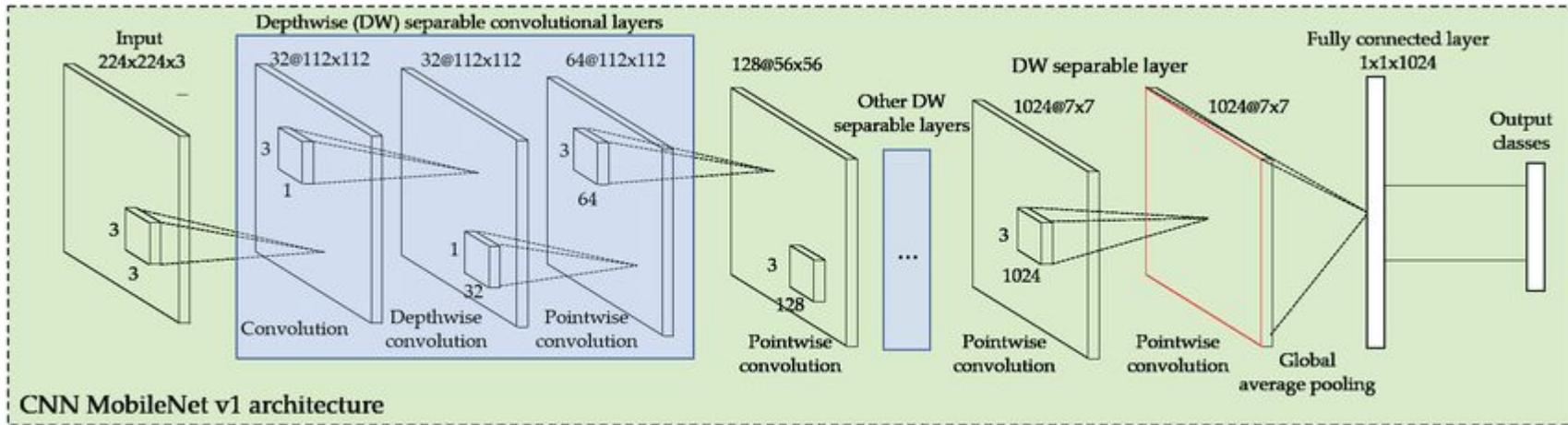
Creating training and testing set to estimate model robustness



03.

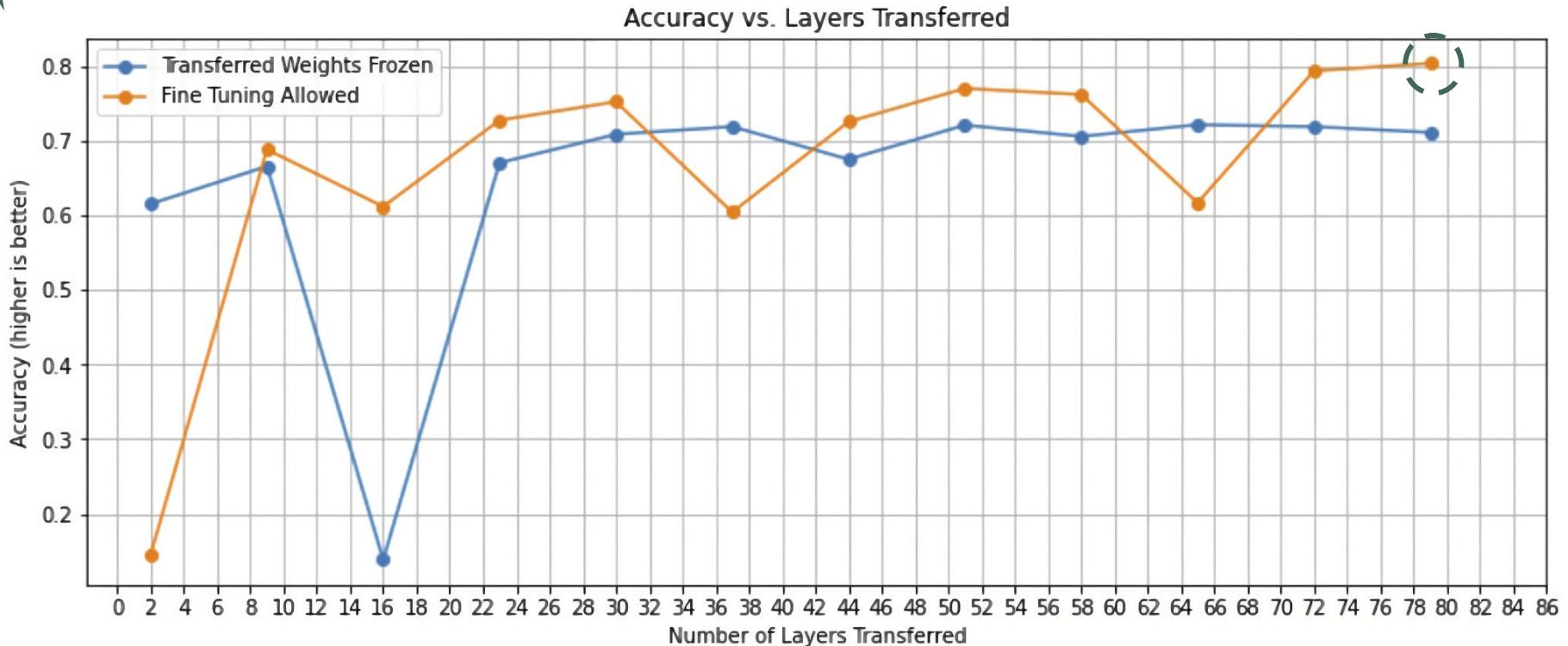
Transfer Learning

MobileNetV1 Architecture



- Pre-trained on ImageNet dataset
- Replaced output layer for 5 class classification problem
- Adjusted input layer to accommodate 128x128 dimension input images

Transfer Analysis



**At the end of
10 epochs...**

(base model)

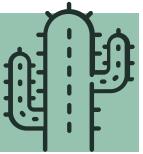
**Accuracy:
76.33%**

**Validation
Accuracy:
71.68%**

04. --- Model Compression



Compression Techniques



Pruning
(Magnitude + Iterative)

(10%, 30%, 50%, & 80%)

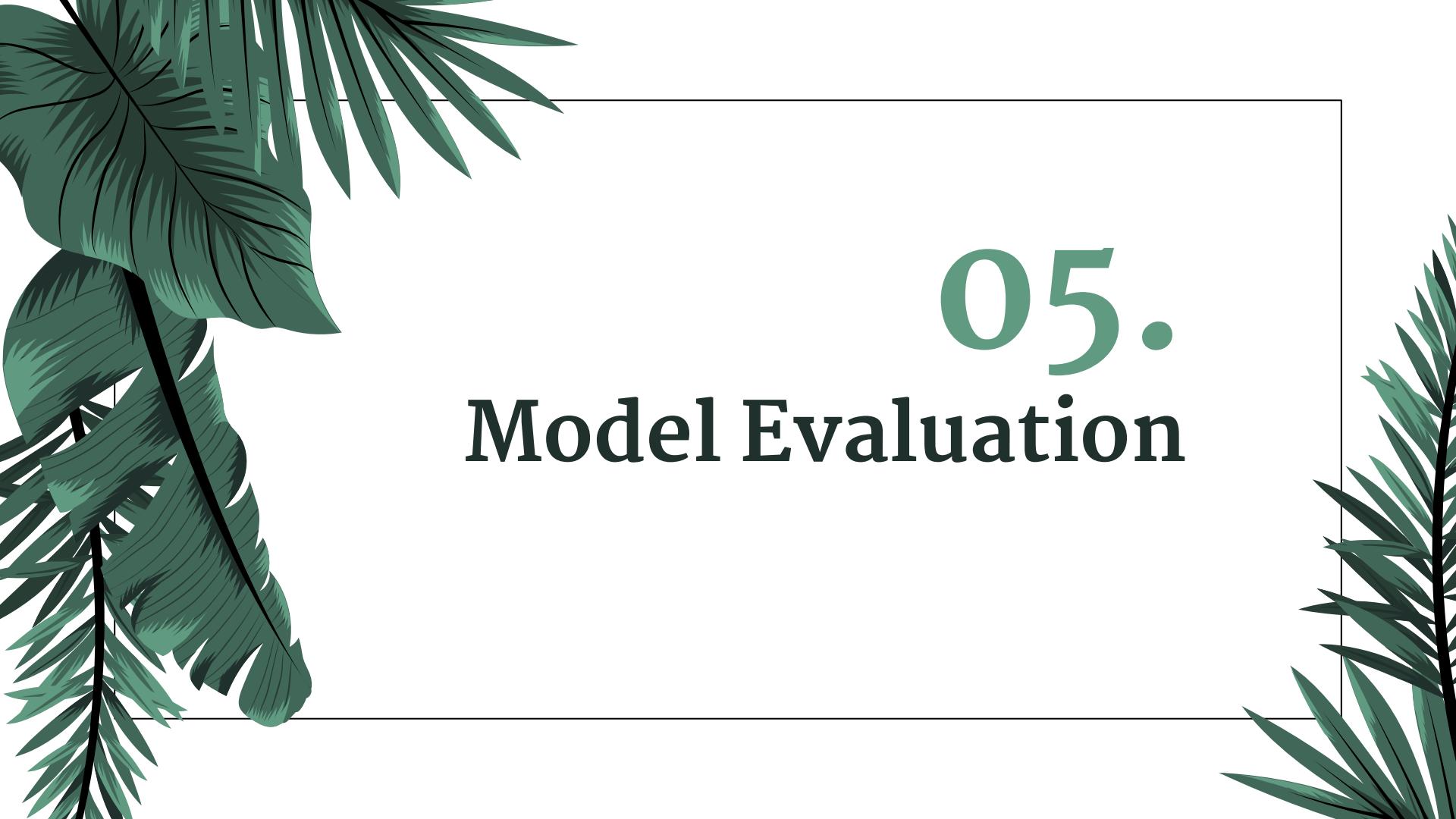


Quantization

(none, 8-bit, 16-bit)

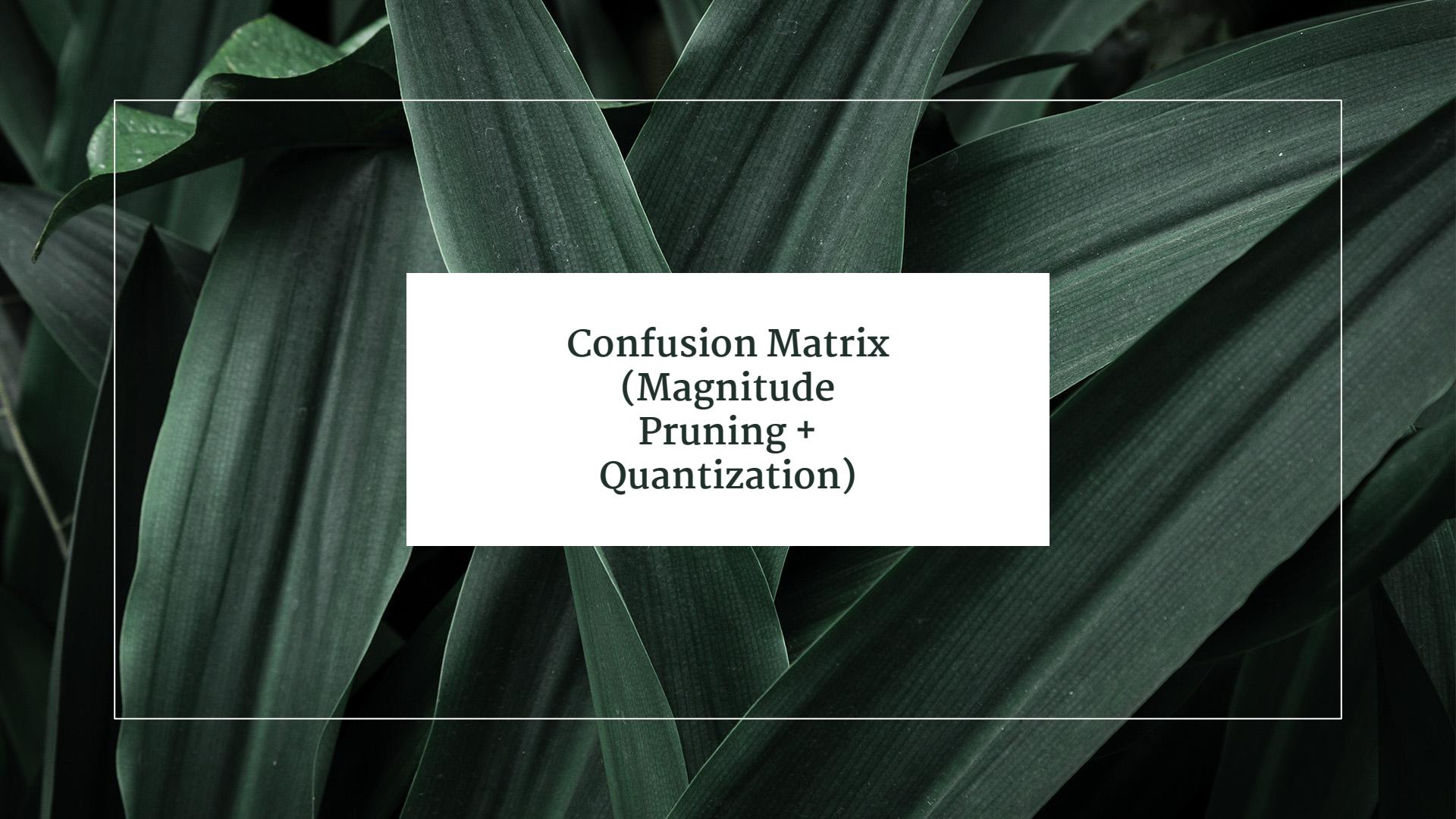
Effects of Pruning

Target Sparsity		Magnitude Pruning	Iterative Pruning
		Acc: 77.66% Val Acc: 71.45% Avg: 74.56%	Acc: 79.01% Val Acc: 68.49% Avg: 73.78%
		Acc: 79.21% Val Acc: 69.91% Avg: 74.56%	Acc: 77.73% Val Acc: 68.21% Avg: 72.97%
		Acc: 80.71% Val Acc: 66.29% Avg: 73.50%	Acc: 79.11% Val Acc: 71.77% Avg: 75.44%
		Acc: 77.89% Val Acc: 68.27% Avg: 73.08%	Acc: 80.04% Val Acc: 62.31% Avg: 71.18%



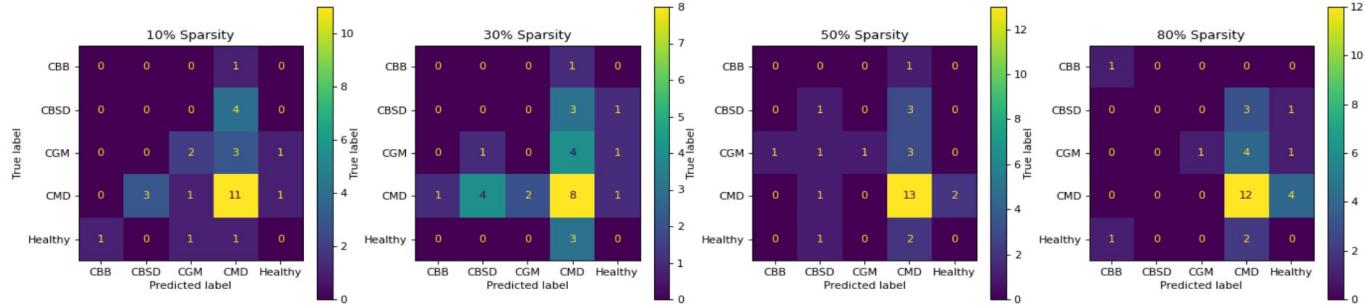
05.

Model Evaluation

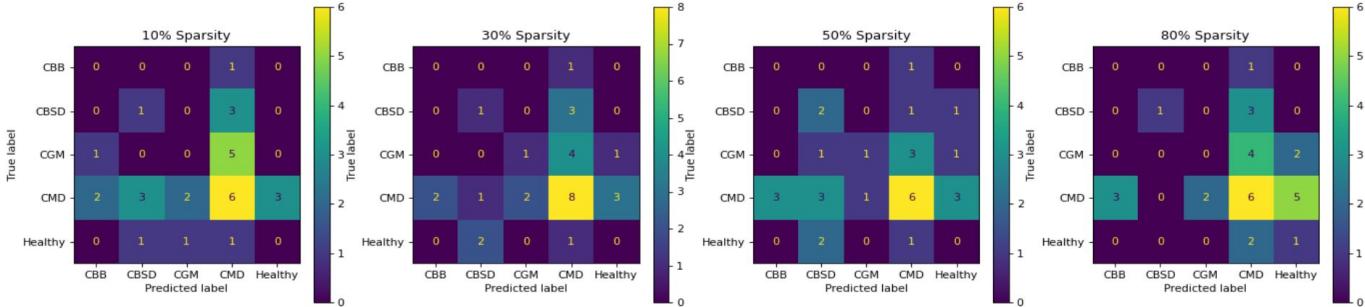


Confusion Matrix
(Magnitude
Pruning +
Quantization)

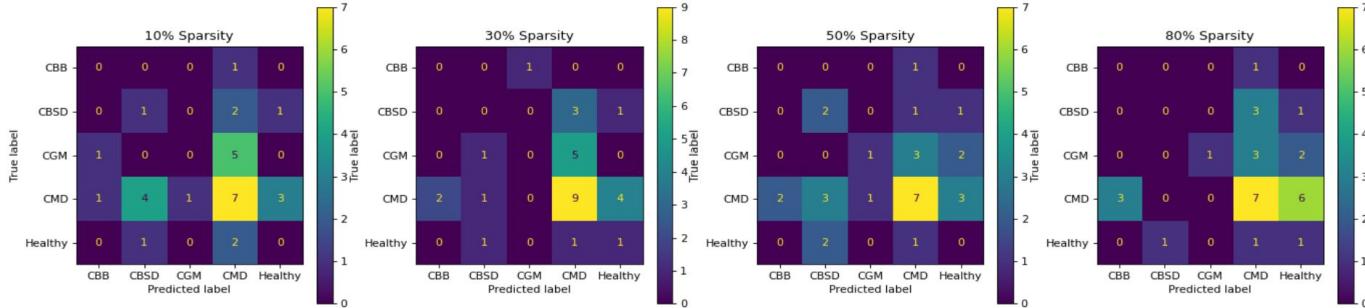
Magnitude Pruning - No Quantization



Magnitude Pruning - 8-Bit Quantization



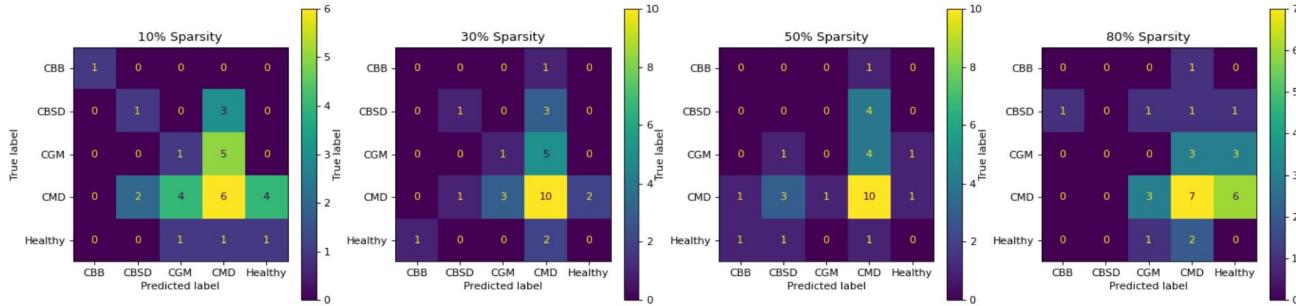
Magnitude Pruning - 16-Bit Quantization



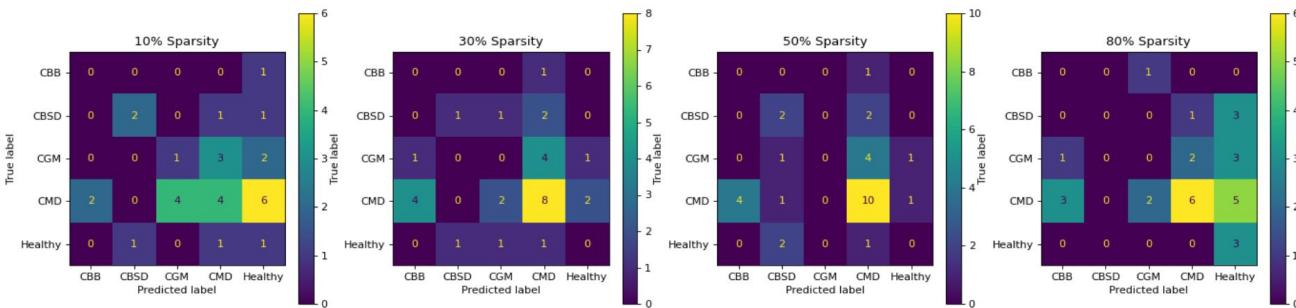


Confusion Matrix
(Iterative Pruning
+ Quantization)

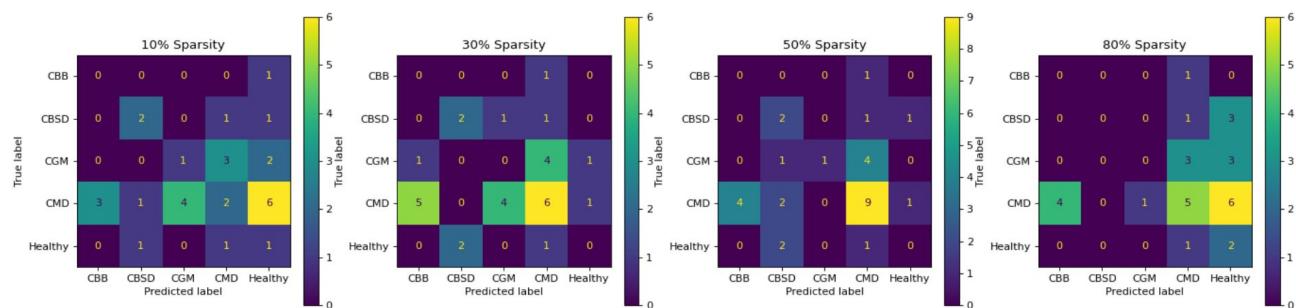
Iterative Pruning - No Quantization



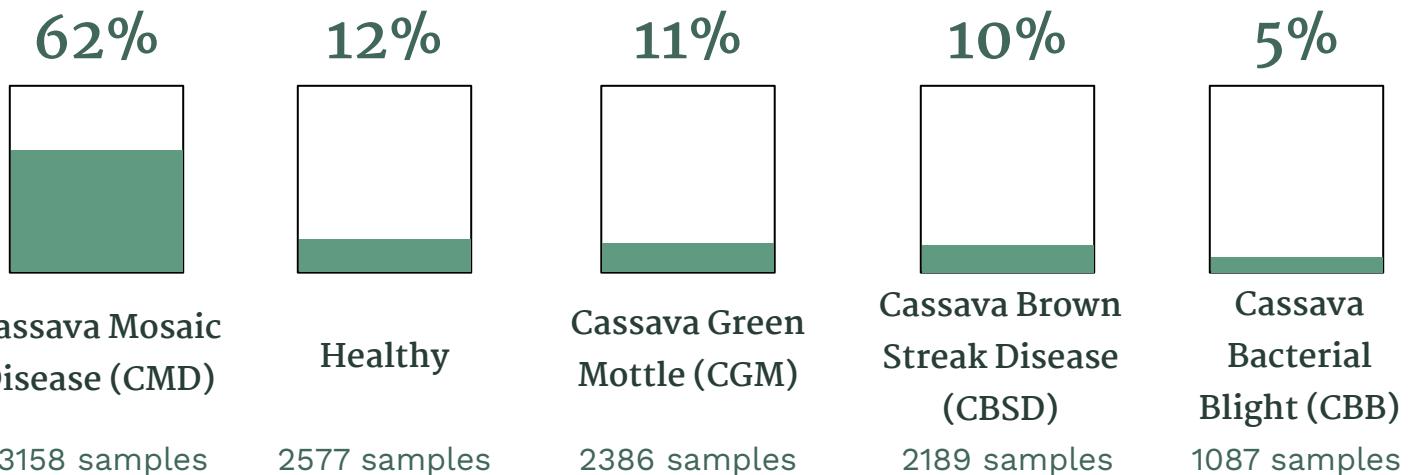
Iterative Pruning - 8-Bit Quantization



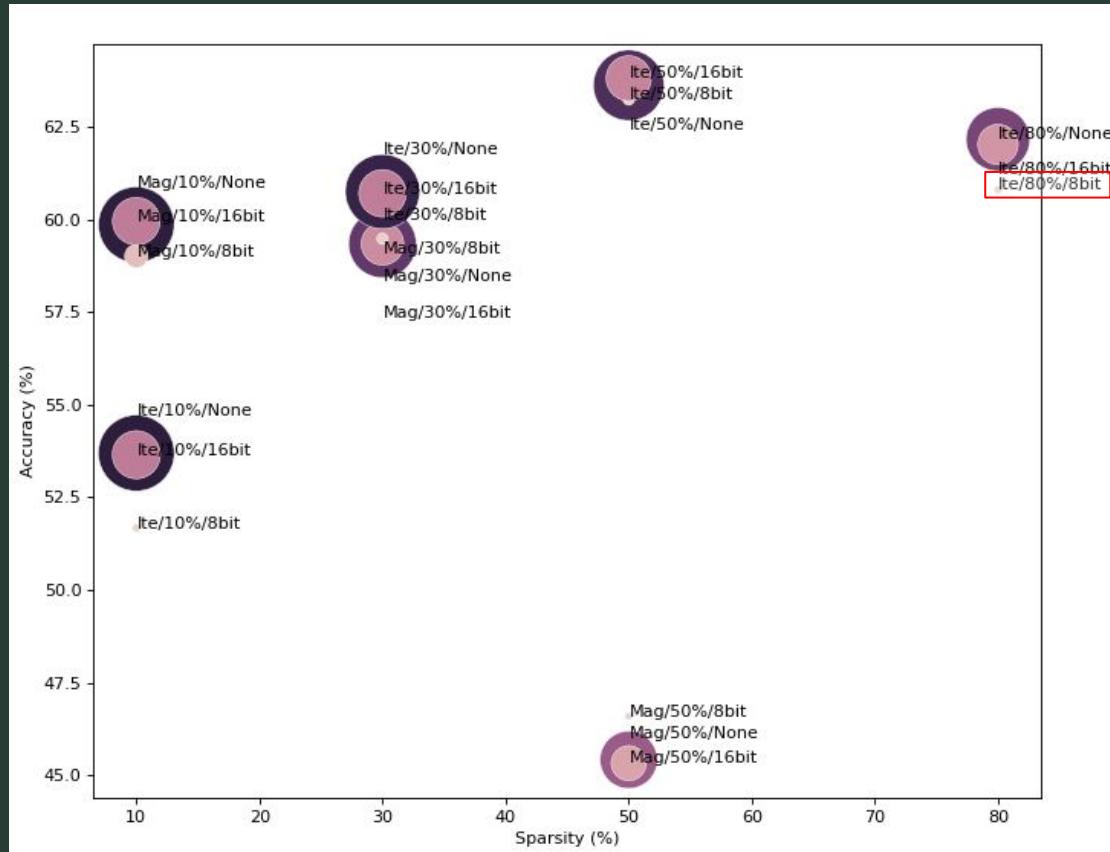
Iterative Pruning - 16-Bit Quantization



Distribution of Data Samples



Accuracy Trade-Off with Pruning & Model Size

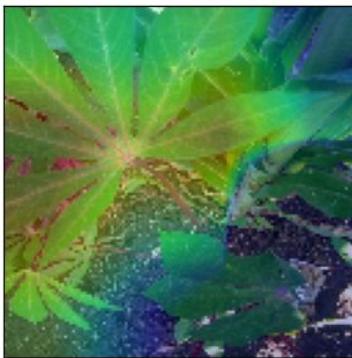


06.

Grad-CAM

(A visual interpretation technique to understand which aspects of the image the ML model is using to make its classification decision)

Grad-CAM – How It Works



A decorative border of various tropical leaves, including monstera and palm leaves, is positioned around the perimeter of the slide. The leaves are rendered in a dark green color with fine black veins.

Thank you for listening!

Questions?