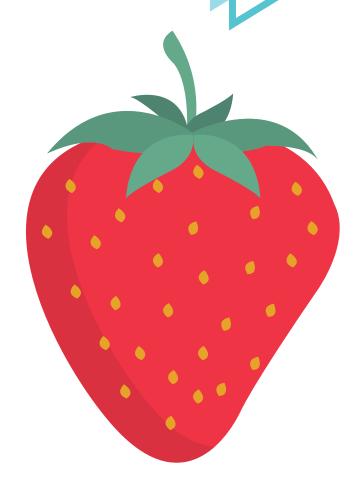


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- We want to build a model that can still tell it's a banana.
- So, our goal is to train a fruit classification model that doesn't just work in perfect lab conditions but also handles messy, real-world photos.







### **METHODS**



### METHOD 01

- Collected data from Fruits-360 l00 xl00 dataset
- Applied image preprocessing (resize, normalize, augment)
- Compared CNN performance with augmentation and no augmentation
- Compared optimizers (adam, RMSprop, SGD)
- Compared our CNN model and MobileNetV2 (transfer learning)
- Test ed on official test set → poor accuracy

### METHOD 02

- Collected data from Fruits-360 original-size dataset
- Applied image preprocessing (resize, normalization, augment)
- Built a new CNN and trained it with RMSprop optimizer
- Compared performance between our CNN model and MobileNetV2
- Tested MobileNetV2 on the original test set
- Fine-tuned MobileNetV2
  - Added a new classifier layer for the 8 real-world fruit categories (images collected by us)
- Trained the model using an 80/20 per-class split on our own real-world fruit images

## CHALLENGE 1

#### **MAIN CHALLENGE**

- Poor performance on the Fruits-360 l00 xl00 dataset
  - Model performed well on its training dataset but poorly on the test set
    - Close to 0 percent accuracy  $\rightarrow$  overfitting, failed to generalize to new data

#### **HOW WE SOLVED IT**

- Identified the root cause
  - The training dataset was very clean compared to real-world conditions
- Retrained on a new dataset
  - Trained on the original-size branch of the Fruits-360 dataset
  - Also trained on even messier, self-collected fruit images



## CHALLENGE 2

#### **MAIN CHALLENGE**

- Fruits-360 original size dataset includes 78 fruit classifications
  - We had limited time to take photos and collect 78 different fruits

#### **HOW WE SOLVED IT**

- Reduced the scope to 8 real-world different fruit classes
- Mapped detailed class names to broader categories
  - ∘ ex. Red cabbages and white cabbages → Cabbages
- Limitation: Reduced the number of fruit classes, small sample size → less reliable results, not fully representative of real world conditions





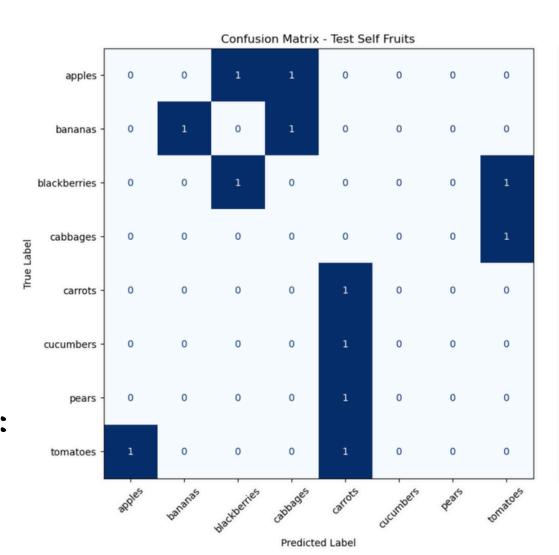
# TESTED ON OFFICIAL TEST DATA

## TESTED ON REAL-WORLD DATASET

Tested the same model (MobileNetV2) and fine-tuned) using our data.

- Total images tested: 12
- Correct predictions: 3
- Real-world testing accuracy:
  25.00%





Classificatio	n Penerti			
Ctassificatio	precision	recall	f1-score	support
apples	0.00	0.00	0.00	2
bananas	1.00	0.50	0.67	2
blackberries	0.50	0.50	0.50	2
cabbages	0.00	0.00	0.00	1
accuracy			0.25	12
macro avg	0.22	0.25	0.20	12
weighted avg	0.27	0.25	0.23	12

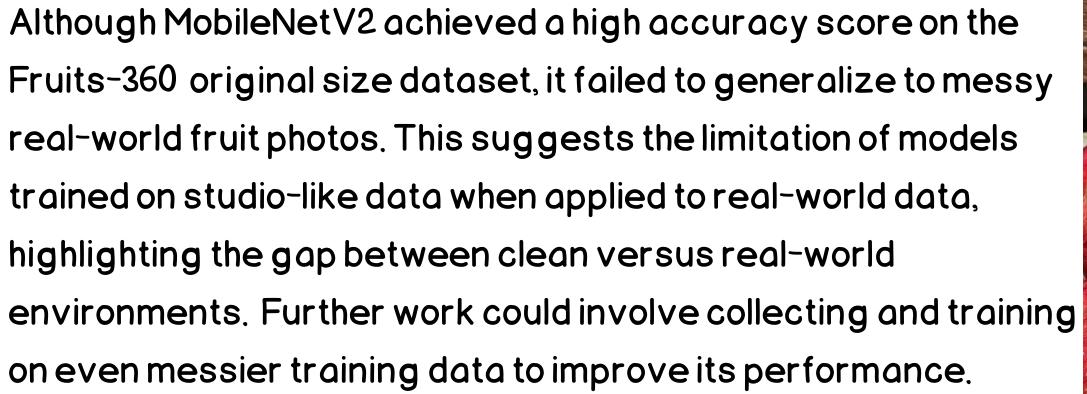
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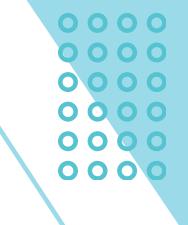
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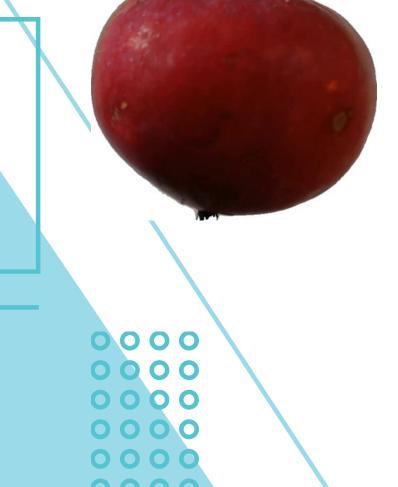






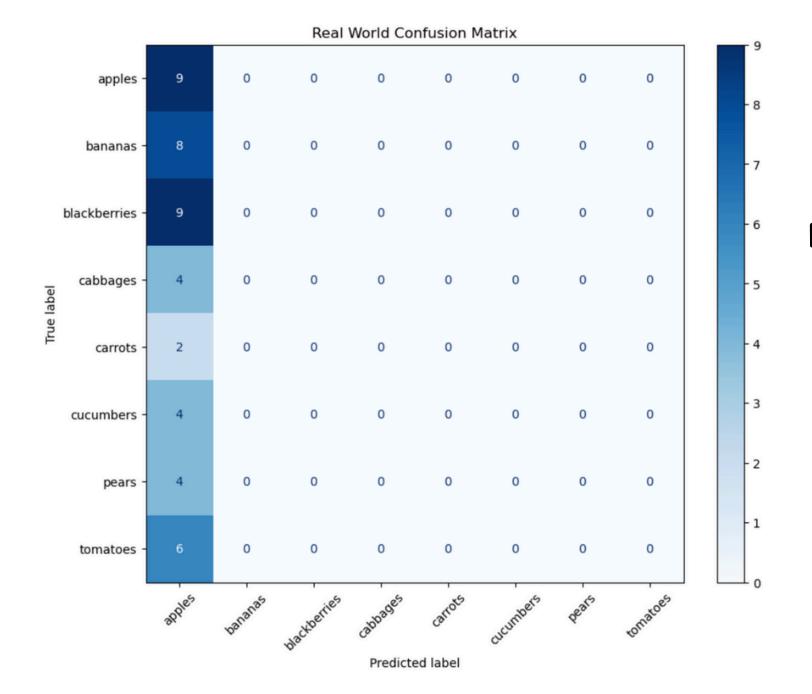






Classification Report:							
	precision	recall	f1-score	support			
apples	0.20	1.00	0.33	9			
bananas	0.00	0.00	0.00	8			
blackberries	0.00	0.00	0.00	9			
cabbages	0.00	0.00	0.00	4			
carrots	0.00	0.00	0.00	2			
cucumbers	0.00	0.00	0.00	4			
pears	0.00	0.00	0.00	4			
tomatoes	0.00	0.00	0.00	6			
accuracy			0.20	46			
macro avg	0.02	0.12	0.04	46			
weighted avg	0.04	0.20	0.06	46			

## **FUN FACT**



#### **BEFORE FINE TUNING:**

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Final Results:

Total images tested: 46

Correct predictions: 9

Real-world testing accuracy: 19.57%

The MobileNetV2 model before fine tuning predicted 'apple' for everything no matter what fruit was given.

The accuracy was achieved by always guessing "apple"



# THANK YOU

