Fruit 360 Classification

Presented by
Group 5

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II. Challenges

III. Methods

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Part I

Background

Introduction of Fruit 360 Project and Potential Usages of Fruit Classification in Various Industries

Fruit 360 Project

01. Foundation of the Project

- Development of Aritificial Intelligence and Machine Learning
- More sophiscated Algorithms and Architectures
- Easier Accessibility to Data (Images in this case)

02. Problems the Project Aims to Solve

- Growing Demand for Intelligent Systems
- Inefficiencies in Traditional Ways of Sorting

Applications of Fruit Classification System

Sorting Ripe Fruits

- Sorting ripe fruits from unripe ones
- E.g. categorize ripe bananas from green ones

Detection of Spoiled Fruits

- Identifying spoiled fruits
- E.g. Detect fungus presence on their skin

Fruit Disease Detection

- Spot signs of disease or pests
- Prevent spread of disease

Inventory Management

- Automatically classify different fruits in stock
- Optimize supply chain

Part II

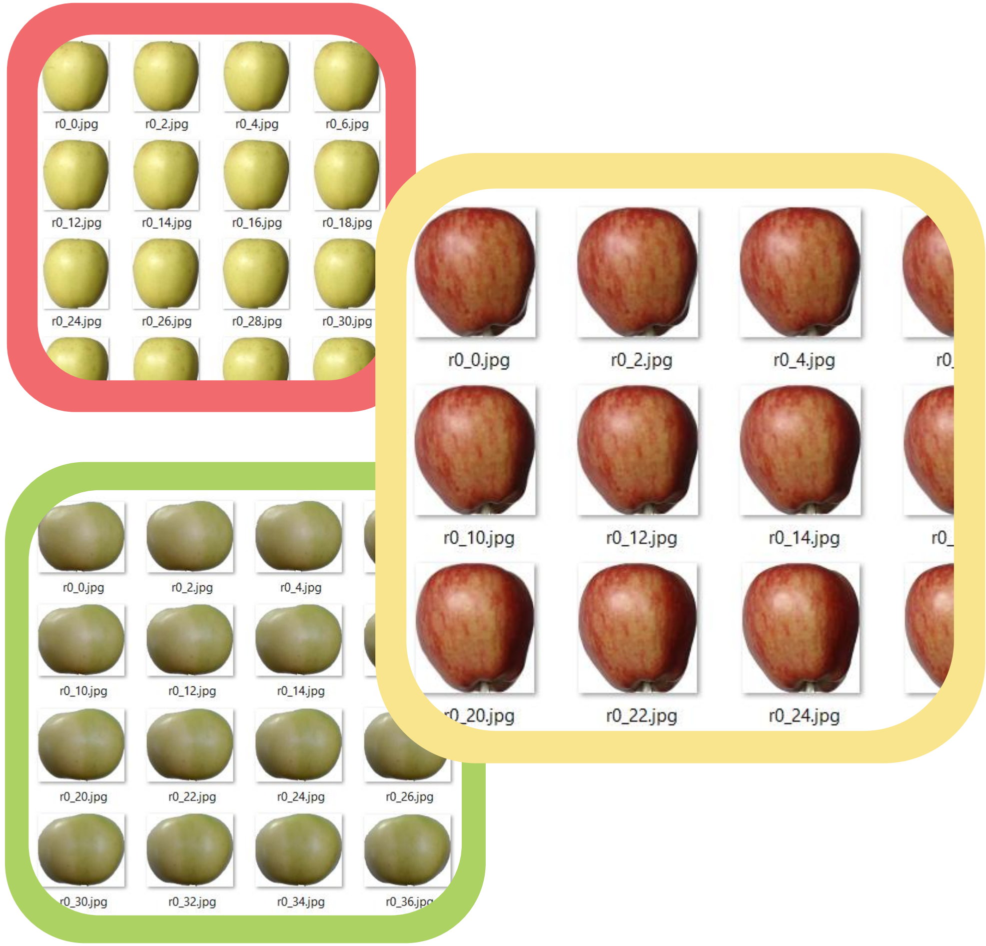
Challenges

The Challenges in Fruit Classification:

Challenge with the Fruit Itself and Challenges Brought by Datasets

Challenges - Dataset

Common in Image Classification



Small Images

- The size of all images are 100x100 pixels

Uneven Distribution

- The number of images in each class is not equal

Lack of Background

- Images have no background

Challenges - Fruit Features

Common in Image Classification

Differentiating between varieties with similar appearance:

- E.g. Apple braeburn vs Apple crimson snow
- medium-sized apples, slightly conical

Identifying fruits in different states:

- Different states: rotten, hit, scarred, fresh, or unfresh
- E.g. Golden apples in different state

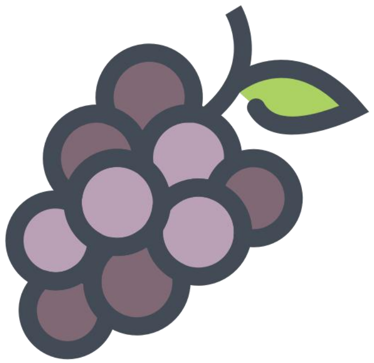
Part III

Methods

Data Augmentation Technique & Convolutional Neural Network Models

Methods - Data Augmentation

The Technique to Balanced The Dataset



What is Data Augmentation?

- A technique that generates new data from the original data with image transform

Geometric Transformations Applied:

- Rotation, Shift, Shear, Zoom, and Flipping

01.

Potential Problem

Bad performance on Validation dataset

02.

Cause

Training and Validation datasets have significantly different feature distributions.

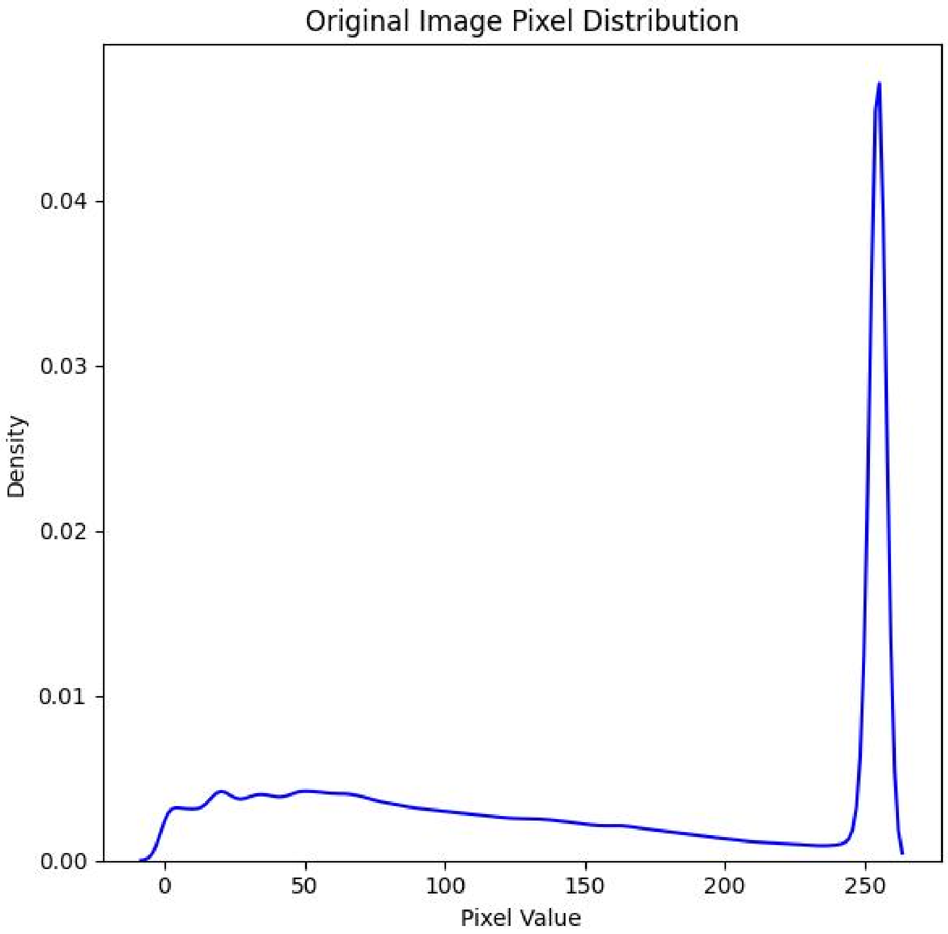
03.

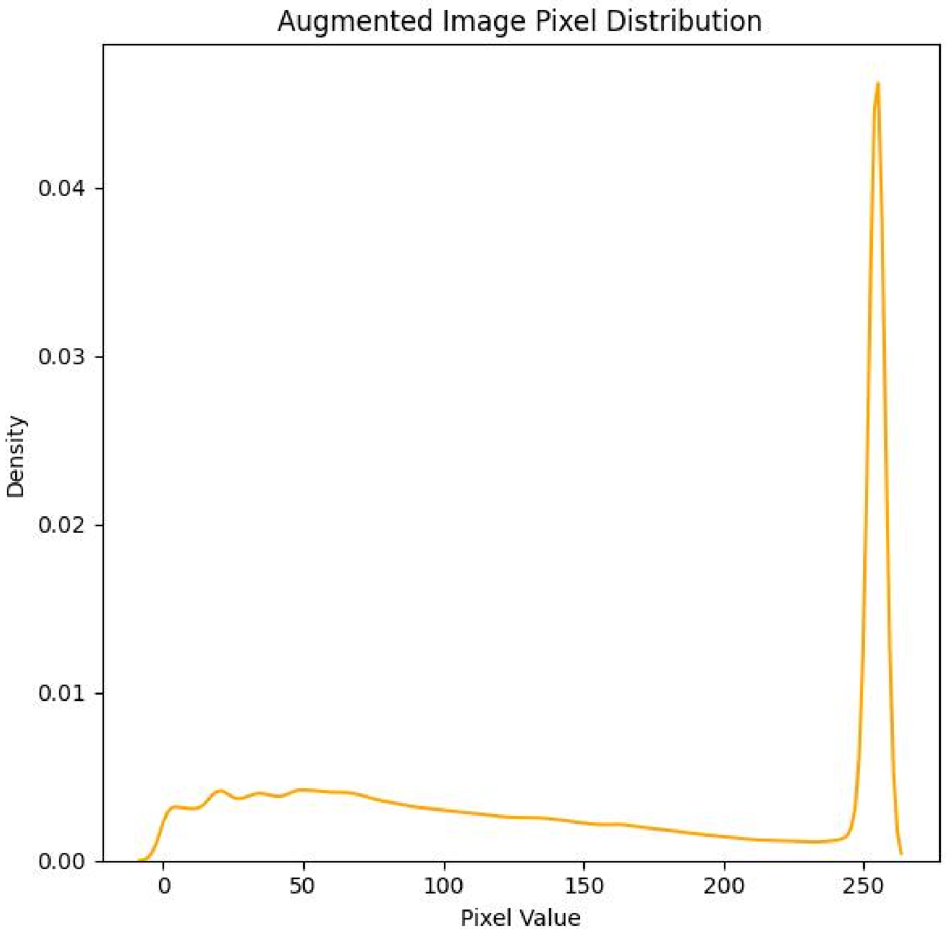
Improvement

Choose valid transformation types or values to create plausible variations of the image

Methods - Data Augmentation

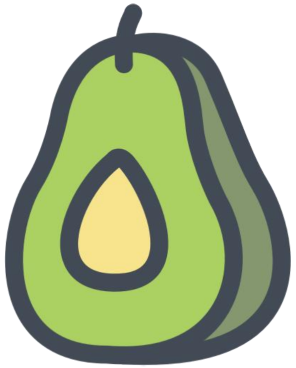
The Technique to Balanced The Dataset





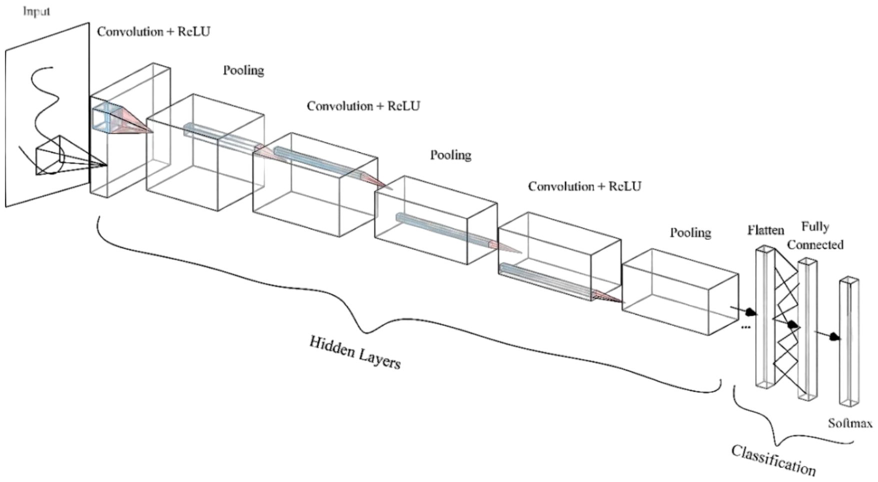
Methods - CNN Models (AlexNet)

The Architecture of the Model



Why are we choosing AlexNet?

- Easy implementation and high accuracy



01. Structure

- Input Layer
- Hidden layers
- Classification

02. Visualization of Prediction

03. Test Statistics

•Test accuracy: 0.9843192100524902

01. Structure

- Input Layer
- Hidden layers
    - Convolutional
    - Pooling
    - Convolutional
    - Pooling
    - Convolutional
    - Pooling
    - Convolutional
    - Pooling
- Classification
    - Dropout
    - Flatten
    - Fully Connected
    - Dropout
    - Fully Connected
    - Softmax

Model Summary:

```
model = tensorflow_based_model() # here we are calling the function of created model
model.compile(loss='categorical_crossentropy', optimizer='rmsprop', metrics=['accuracy'])
```

```
model.summary()
```

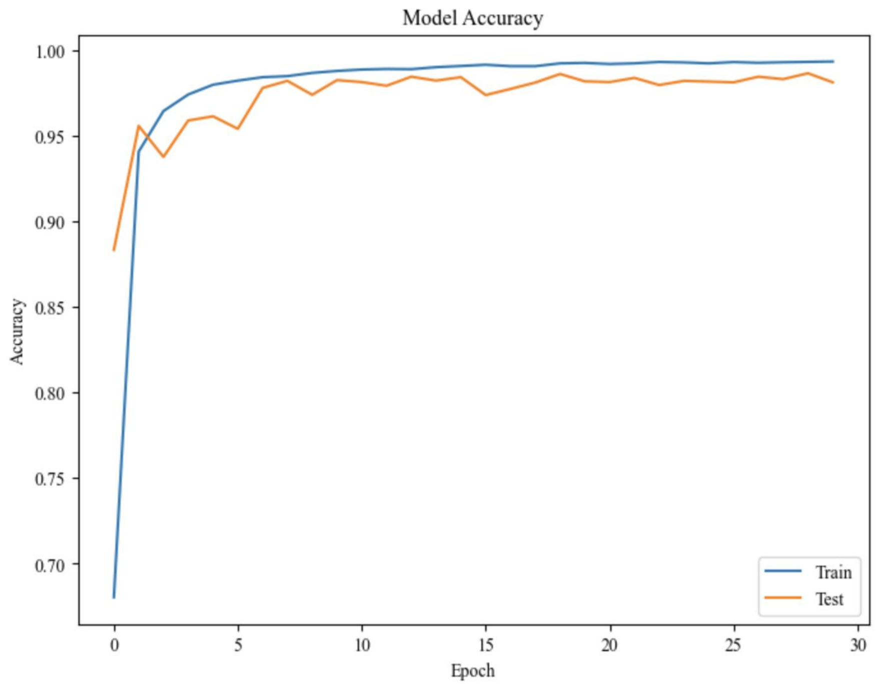
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 100, 100, 16)      208

 activation (Activation)     (None, 100, 100, 16)      0

 max_pooling2d (MaxPooling2  (None, 50, 50, 16)        0
 D)

 conv2d_1 (Conv2D)           (None, 50, 50, 32)        2080

 max_pooling2d_1 (MaxPoolin  (None, 25, 25, 32)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 25, 25, 64)        8256

 max_pooling2d_2 (MaxPoolin  (None, 12, 12, 64)        0
 g2D)

 conv2d_3 (Conv2D)           (None, 12, 12, 128)       32896

 max_pooling2d_3 (MaxPoolin  (None, 6, 6, 128)         0
 g2D)

 dropout (Dropout)           (None, 6, 6, 128)         0

 flatten (Flatten)           (None, 4608)              0

 dense (Dense)               (None, 150)               691350

 activation_1 (Activation)   (None, 150)               0

 dropout_1 (Dropout)         (None, 150)               0

 dense_1 (Dense)             (None, 131)               19781

=================================================================
Total params: 754571 (2.88 MB)
Trainable params: 754571 (2.88 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

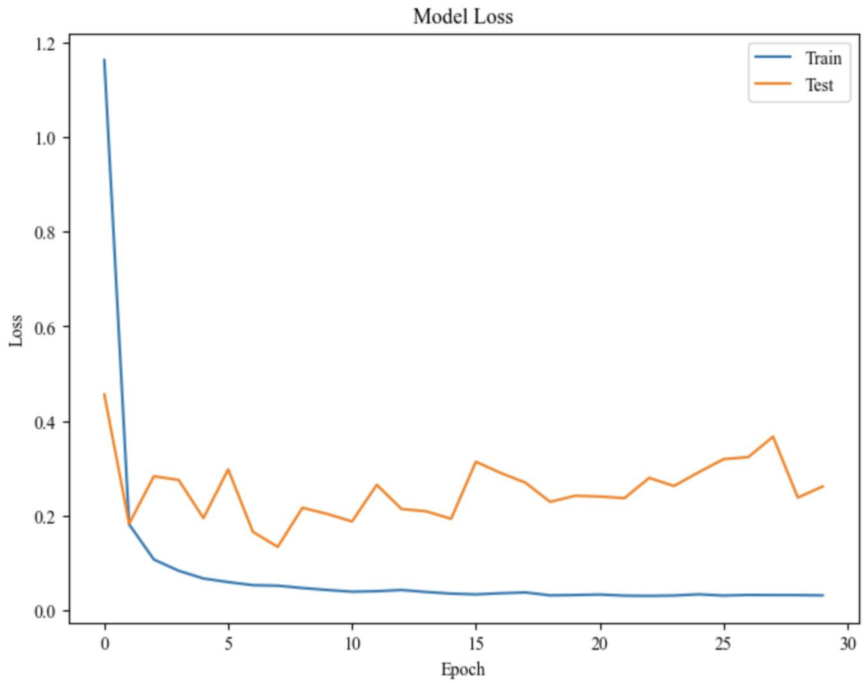
02.

Visualization of Prediction

03.

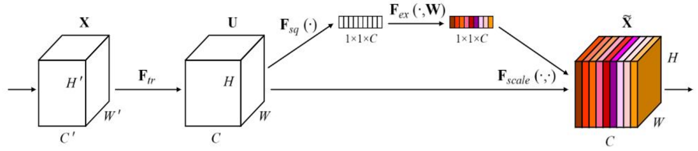
Test Statistics

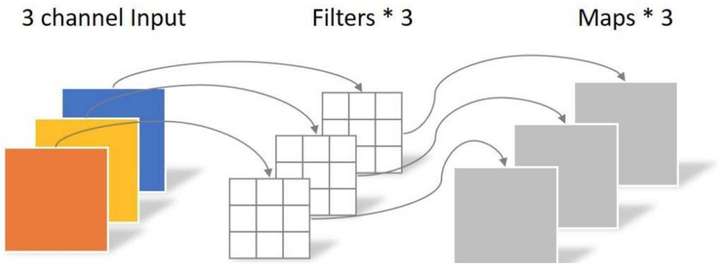




Methods - CNN Models (MobileNet)

The Architecture of the Model



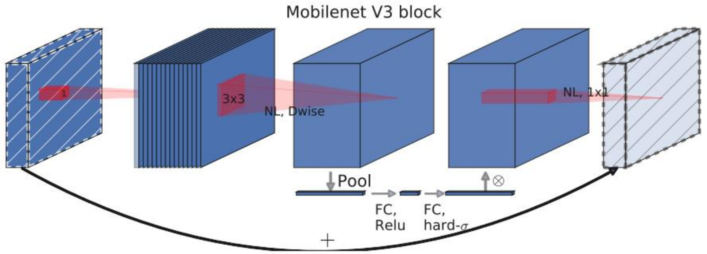


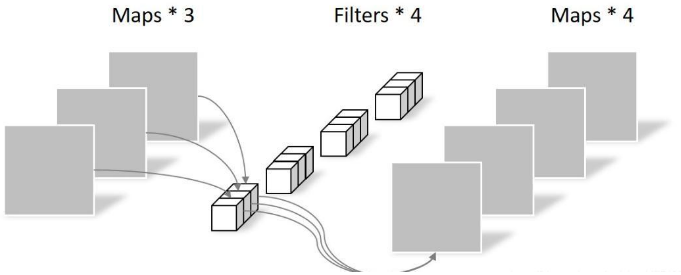
$$h - swish(x) = x(h - sigmoid(x))$$

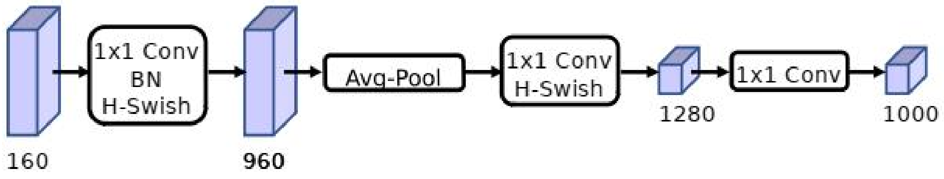
$$h - sigmoid(x) = \frac{ReLU6(x+3)}{6}$$

What is new?

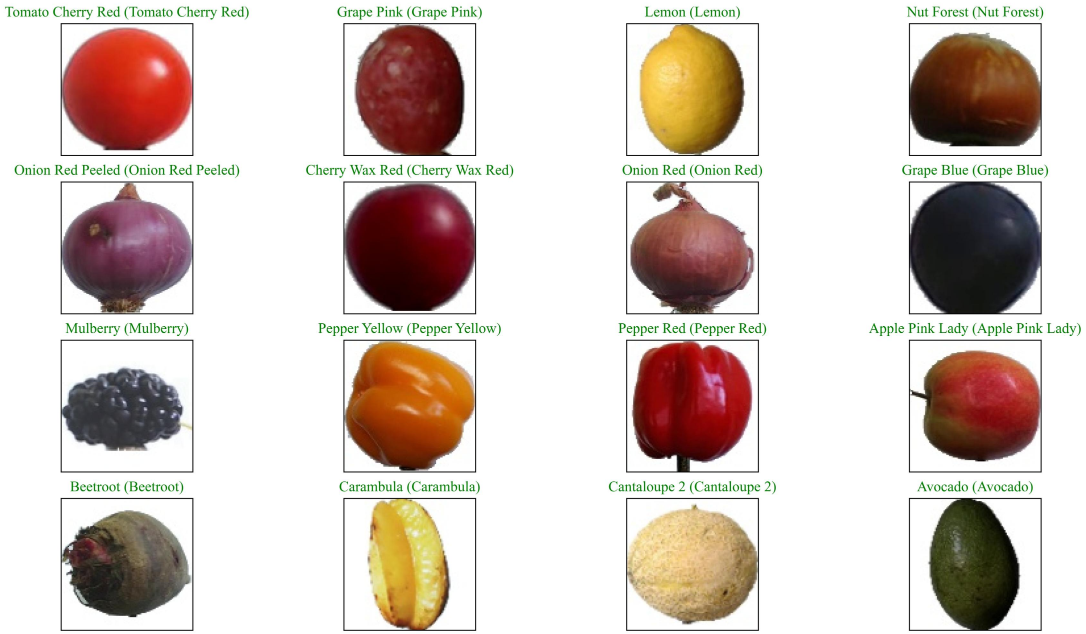
- squeeze-and-excitation block
- bneck structure contains
  - Depthwise Separable Convolution
  - Inverted residual block
  - squeeze-and-excitation net
- new last stage structure
- new activation function
  - sigmoid -> h-sigmoid
  - swish -> h-swish



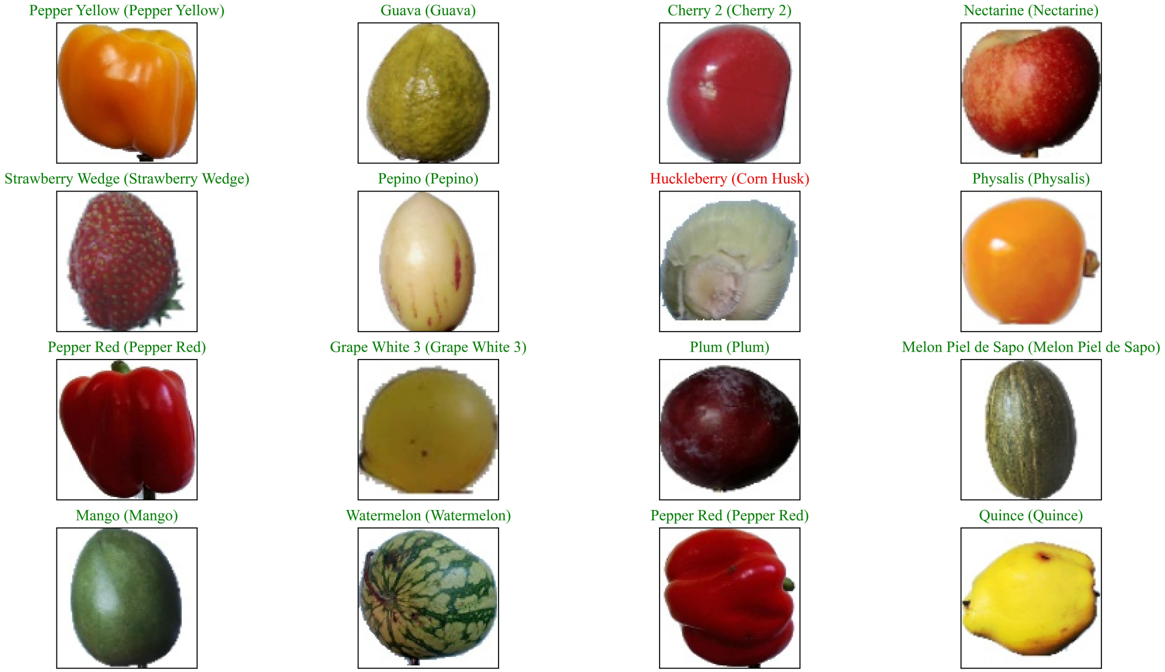




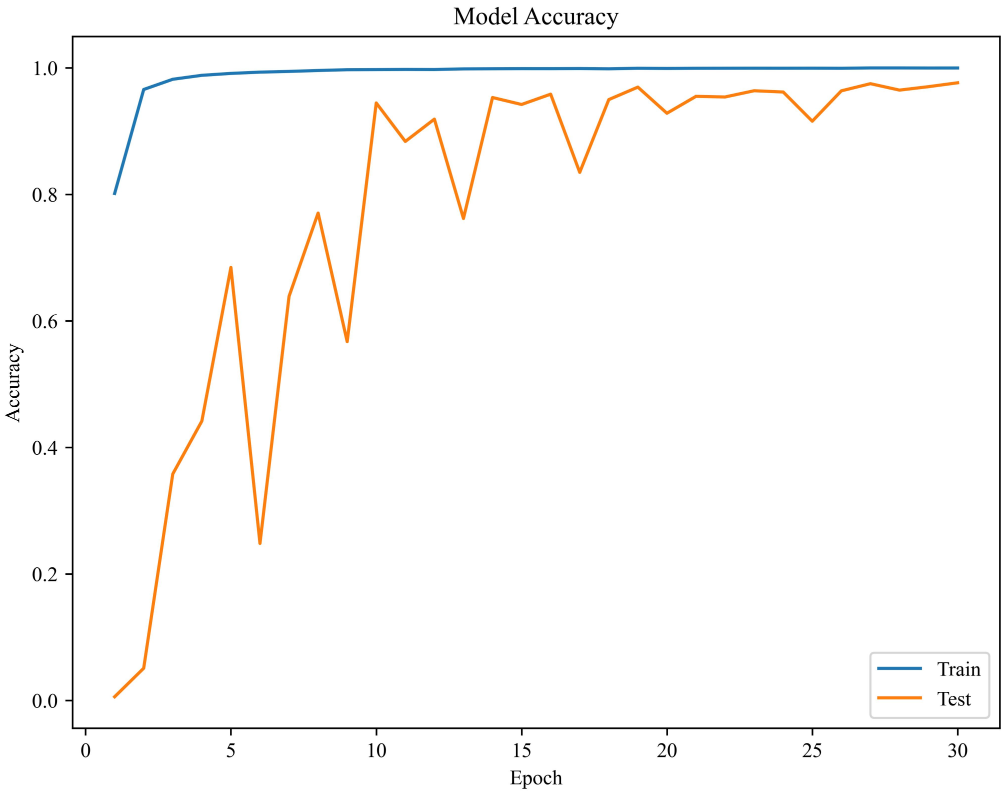
Prediction Result

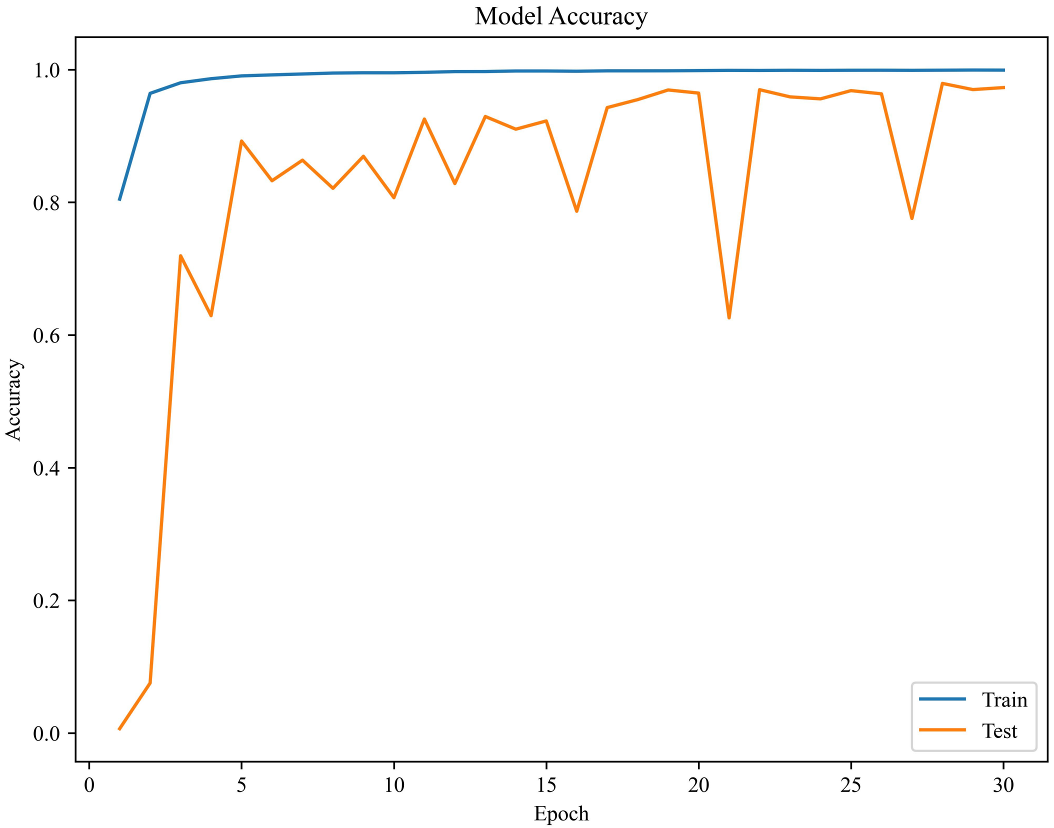


- MobileNet-large
- MobileNet-small



Test Statistics





- MobileNet-large
- MobileNet-small

Part IV

Conclusion

Result Analysis, Future Improvement, and Possible Future Study Topics

Reference

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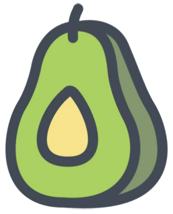

Thank You