

# Fruit Quality Classification

[Group 2 - B2 DS]

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# 01. Introduction

1. Background & Content
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3. Scope



# Background & Content



## Why Fruit Freshness Classification Matters

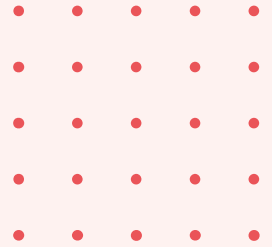
- Ensures consumer health
- Reduces post-harvest food waste
- Improves supply chain efficiency



## Problem

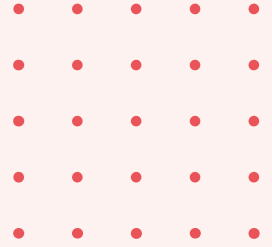
- Current manual inspection methods: slow and error-prone  
=> Automated, accurated, scaled classification system

# Project Objectives



- Build an automated system using image analysis
- Improve quality control processes
- Reduce post-harvest losses
- Support food safety efforts
- Contribute to smart agriculture and modern supply chain management

# Scope



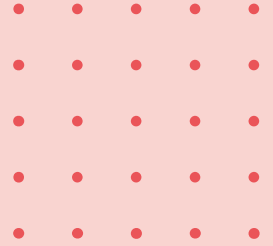
- Uses Convolutional Neural Network (CNN)
- Focus on 3 fruits: apples, bananas, oranges
- Simple classification: fresh or rotten
- Narrow scope => high accuracy
- Foundation for future expansion (more fruits, more detailed freshness levels)

# 02. Dataset

Data Description



# Data Preprocessing



## Image Collection

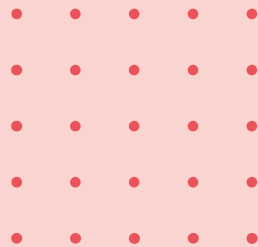
6 folders with 300 images per folder, ensuring a balanced representation across all classes

## Image Loading

Using OpenCV (cv2.imread)  
Failed to load => Skip and show a warning message



# Data Preprocessing



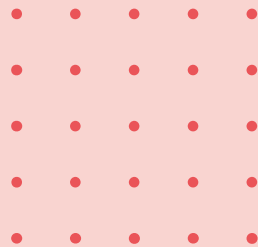
## Resizing

A uniform dimension 256 x 256 pixels to standardize input size, to ensure compatibility with CNN

## Normalization

Scale to the [0.0, 1.0] range

# Data Preprocessing



## Label Extraction

Based on the folder names,  
each label combine fruit type  
and freshness condition

## Data Storage

Storing in a NumPy array with  
the shape (1800, 256, 256, 3)

# Encode categorical into numeric form



## Label encoding

Encoding 'freshapples', 'freshbanana',  
'freshoranges', 'rottenapples',  
'rottenbanana', 'rottenoranges' to 0 to 5

## One Hot Encoding

'freshapples' to [1;0;0;0;0]  
'freshbanana' to [0;1;0;0;0]

...

# Shuffle & Split the dataset

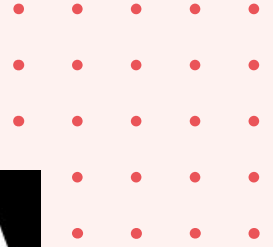
- Shuffle the ordered dataset into the unordered dataset
- Split the dataset into 3 subsets
  - + Initial Split: A training + validation set 90% and a testing set 10%
  - + Secondary Split: A training set 80% and a validation set 20%

# 03. Related Work

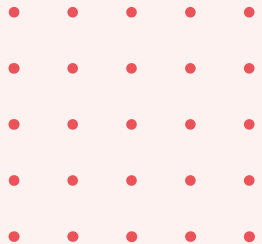
K-Means Clustering  
Algorithm



# K-Means Clustering Algorithm

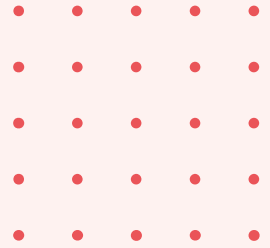


# 04. Algorithm & Model



Convolutional Neural  
Network  
(CNN)

## 4.1. Algorithm of CNN

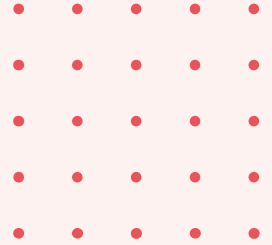


**Convolutional Neural Network (CNN):** specialized deep learning model

- Autonomous feature extraction
- Translation-invariant characteristics
- Identify patterns and features despite variations in position, orientation, scale, or translation

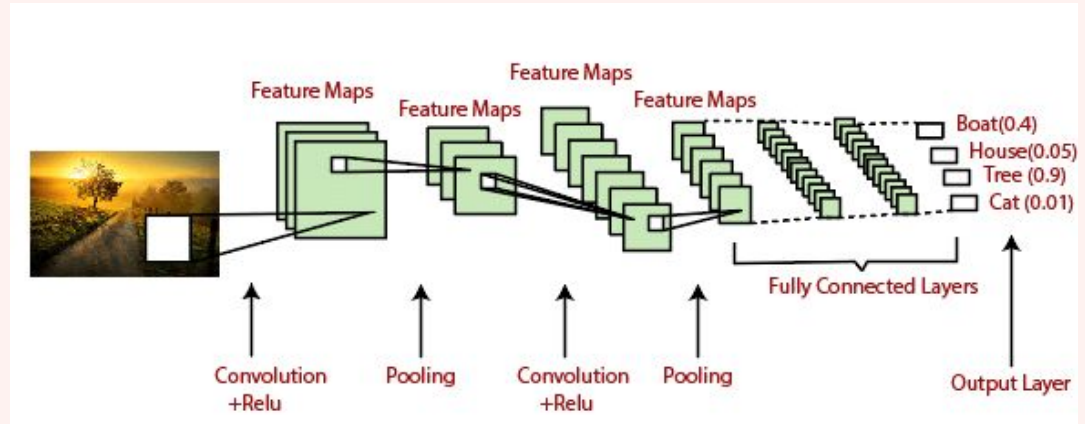


## 4.2. Components of CNN

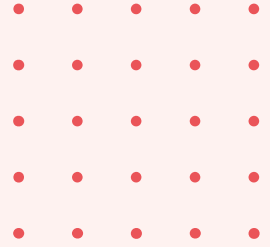


4 main components:

1. Convolutional layers
2. Activation function
3. Pooling layers
4. Fully-connected layers



## 4.3. Model's Architecture



**Contains:** 3 convolutional blocks & the fully connected layers

Layer Type	Hyper-parameter
Conv2D	32 filters of size 3x3, ReLU
MaxPooling2D	3x3 pool, stride (2,2)
Dropout	Rate = 0.3

[1st Convolution Block]

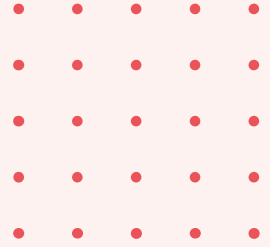
Layer Type	Hyper-parameter
Conv2D	64 filters of size 3x3, ReLU
MaxPooling2D	3x3 pool, stride (2,2)
Dropout	Rate = 0.3

[2nd Convolutional Block]

Layer Type	Hyper-parameter
Conv2D	128 filters of size 2x2, ReLU
MaxPooling2D	2x2 pool, stride (2,2)
Dropout	Rate = 0.3

[3rd Convolutional Block]

## 4.3. Model's Architecture



**Contains:** 3 convolutional blocks & the fully connected layers

Layer Type	Hyper-parameter
Flatten	
Dense	256 units, ReLU
Dropout	Rate = 0.3
Output Dense	6 units, softmax activation

[Fully connected layers]

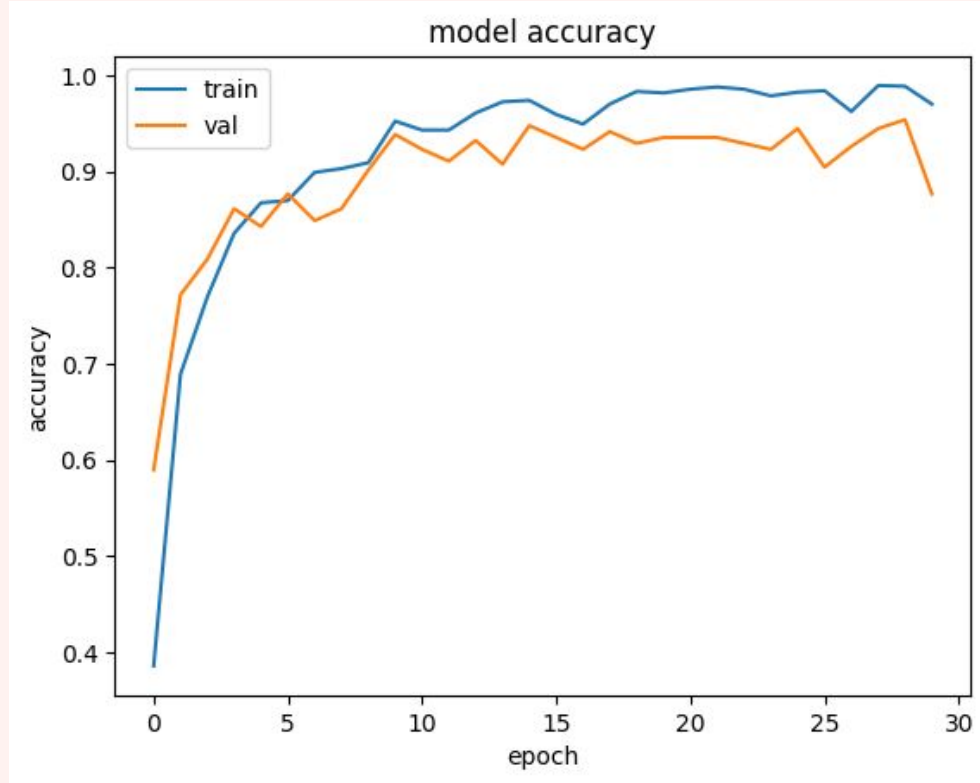
# 05. Result & Evaluation

Training vs Validation  
Performance

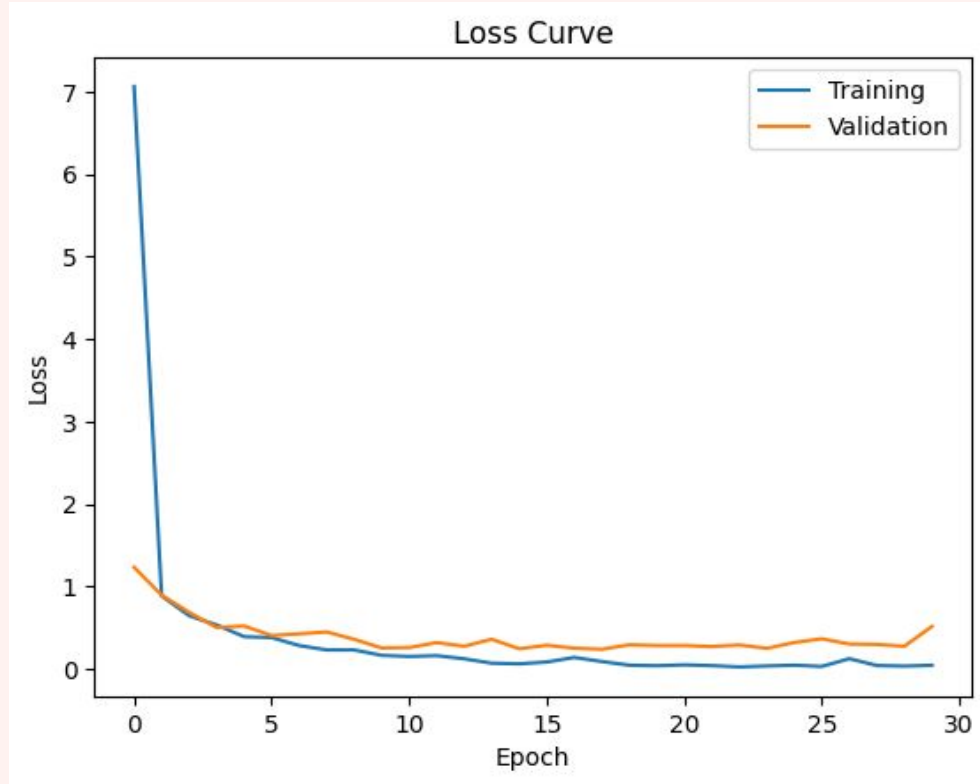
Confusion matrix

Classification metrics

## 5.1. Training vs Validation Performance



## 5.1. Training vs Validation Performance



## 5.2. Confusion Matrix

		Actual					
		Class 0	Class 1	Class 2	Class 3	Class 4	Class 5
Predicted	Class 0	30	0	0	2	0	0
	Class 1	0	32	0	0	1	0
	Class 2	0	1	36	0	0	2
	Class 3	3	0	0	22	1	0
	Class 4	0	1	0	0	18	0
	Class 5	1	1	3	1	0	25

Table 1: Confusion Matrix of the Fruit Quality Classification Model

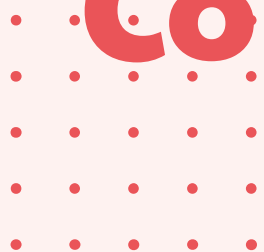
## 5.3. Classification Metrics

Class	Precision	Recall	F1-score	Support
0	0.88	0.94	0.91	32
1	0.91	0.97	0.94	33
2	0.92	0.92	0.92	39
3	0.88	0.85	0.86	26
4	0.90	0.95	0.92	19
5	0.93	0.81	0.86	31
Accuracy			0.91	180
Macro average	0.90	0.91	0.90	180
Weighted average	0.91	0.91	0.90	180

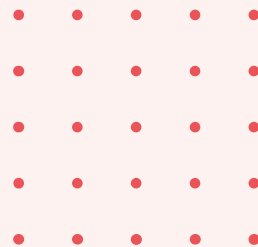
Table 2: Classification Report of the Fruit Quality Classification model



# 06. Discussion & Conclusion



## Discussion & Conclusion

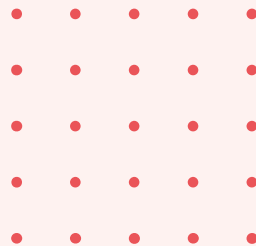


CNNs are potential in automating fruit quality classification tasks.

Misclassifications between fresh and rotten samples of the same fruit may due to subtle visual differences or inconsistent lighting conditions in the dataset.

The relatively small dataset size may restrict the model's robustness across broader conditions.

# Discussion & Conclusion



Future work:

- Increasing dataset diversity.
- Enhancing the model's ability to evaluate and classify.
- Optimizing for speed and performance.
- Deploying & testing the model in real-world environments.



# Thank you!