CNN-Based Multiclass Classification for Banana Ripeness Assessment: A Big Data Approach

*Estera Wisniewska*

*MSC Data Analytics*

*CCT College Dublin*

*Abstract*—

Keywords—

# Introduction

## Background

Bananas undergo a remarkable transformation in their nutritional composition and sugar levels as they ripen. This transformation is influenced by various factors, including the banana's inherent genetic makeup, external environmental conditions, and climatic factors. The ripening process of bananas has significant implications for their nutritional content.

As bananas ripen, their nutritional profile undergoes distinct changes. One of the most noticeable changes is the alteration in sugar levels. Unripe bananas are characterized by their high starch content, primarily in the form of resistant starch. As they ripen, this starch is gradually converted into simpler sugars, such as glucose, fructose, and sucrose. This transition from starch to sugars not only contributes to the banana's sweet taste but also makes these sugars more easily digestible and readily absorbed by the body.

Additionally, the nutritional content of ripe bananas differs from that of unripe ones. Ripe bananas tend to have a higher concentration of certain nutrients. For instance, the levels of antioxidants like vitamin C increase as the banana ripens. This means that a ripe banana may offer more antioxidant protection compared to an unripe one.

While human judgment remains a common method for assessing banana ripeness, there is an emerging technology that has the potential to revolutionize the way people select bananas at the supermarket.

In the future, the ability to employ a device for immediate, on-the-spot scanning of bananas, accompanied by the instantaneous provision of comprehensive data pertaining to their nutritional composition—encompassing precise measurements of assorted nutrients and sugar content—has the potential to bestow consumers with enhanced capabilities for making judicious choices in their selection of bananas, and possibly other food choices.

## Problem Statement

The absence of readily available and accurate methods for consumers to assess the nutritional content of fresh produce, such as bananas, during the purchasing process presents a significant challenge in making informed dietary choices. This research aims to address this challenge by developing a Convolutional Neural Network (CNN) model capable of classifying banana images into three distinct ripeness categories: green, yellow, and ripe. By harnessing the power of machine learning and image analysis, this project seeks to empower consumers with a tool that not only identifies the ripeness of bananas but also considers their evolving nutritional attributes, thereby enhancing their ability to make informed and health-conscious dietary decisions.

## Research objective

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Type | Sugar (g) | Protein (g) | Calories | Fiber(g) | Fat(g) |
| Green | 12 | 1.2 | 89 | 2 | 0.5 |
| Yellow | 12 | 1.1 | 100 | 2.6 | 0.3 |
| Ripen | 15 | 1 | 110 | 2.9 | 0 |

# Literature Review

## Cnn architecture for a big data

## Advanced Data Analysis

## Abbreviations and Acronyms

# Methodology

## Data collection

## Data Preparation

To initiate the CNN project, data loading and preprocessing are essential. The initial step employs the function load\_and\_preprocess\_image, which accomplishes several pivotal tasks. Firstly, it employs the OpenCV library (cv2) to read image files, a robust choice given its efficiency and wide acceptance in the computer vision community. Secondly, the function standardizes the images by resizing them to a fixed dimension of 960x540 pixels. This resizing operation ensures uniformity in the dimensions of all input images, which is indispensable for training a CNN model. Images of varying sizes can introduce complexities in terms of model architecture and hinder convergence during training.

Thirdly, the function scales the pixel values to fall within the range of 0 to 1. This scaling process transforms the pixel intensities from the original 8-bit integer representation to a floating-point representation between 0 and 1. This is a common practice in deep learning and offers several advantages. It prevents numerical instability during training, facilitates faster convergence, and enables the model to generalize better to new, unseen data.

The second part of data preparation was categorizing the dataset into distict classes and assigning appropriate labels. The code accomplishes this task by systematically navigating through the class folders (Green, Yellow, Ripe) and labeling images based on the folder names. The labels are assigned numerically, with 'Green' corresponding to 0, 'Yellow' to 1, and 'Ripe' to 2.

This labeling scheme is a product of careful consideration, aligning with best practices in supervised classification tasks. By assigning numerical labels, the model can effectively learn to associate image features with specific fruit categories. Moreover, this numerical representation simplifies the loss calculation and model evaluation processes, as many machine learning frameworks expect numerical labels.

## Creating CNN model

## Training the model and the Evaluation

# Results

## Research Findings

## Interpretation

## Limitations

## Suggestions for Future Reaserch

# Conclusion

##### References