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Banana Ripeness Classification: A Comparative Approach with SVM, CNN, and KNN Integrating VGG16

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***Abstract*—This study presents a novel method for classifying the maturity of bananas by fusing handcrafted characteristics with deep learning based on VGG16. The accuracy of banana characterization is improved by combining data extracted by VGG16 with additional features as contrast, coarseness, directional features, ripeness factor, hue, and HSV values. By addressing the inherent difficulties in manual maturity assessment, this hybrid methodology provides the banana industry with a more precise and effective classification system. To evaluate the efficacy of the Support Vector Machine (SVM), k-Nearest Neighbours (KNN), and Convolutional Neural Network (CNN) models in classifying bananas using the combined feature set, the study uses a comparative analysis. The findings highlight the transformational potential of deep learning in agriculture, particularly in automating visual assessments for enhanced banana maturity determination, and have significant implications for customer happiness and supply chain efficiency. The findings show how machine learning may be applied in the real world to enhance agricultural practices and regulate fruit quality better.**

***Index Terms*— banana, SVM, CNN, KNN, fruit quality.**

I. Introduction

Bananas, one of the most widely consumed fruits in the world, are vital to both international trade and agriculture. Accurately assessing the maturity state of bananas is an important factor that affects all stages of the supply chain, from harvesting to consumer satisfaction.
Recent advances in technology, particularly in the fields of computer vision and machine learning, have made it possible to increase the productivity of banana production and consumption while also improving the accuracy of ripeness categorization. [10]
Conventional techniques for determining ripeness typically depend on the subjective opinions of individuals, which causes irregularities and inefficiencies in the supply chain. The requirement for automated systems that can precisely classify bananas into various maturity groups grows along with the demand for bananas. [2] Through ensuring that bananas are consumed at the optimal maturity stage, these devices improve food waste management and logistical processes. [1]
This study investigates the use of multiple feature categories in combination to determine the ripeness of bananas.

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The goal of the project is to develop a reliable model that can precisely identify the maturity stage of bananas by fusing cutting-edge deep learning techniques with conventional image-based features. [5, 8, 10] A more precise and sophisticated classification procedure is made possible by the integration of many data sets, including as high-level representations, texture features, and colour information, which provide a comprehensive view of banana qualities. [11]

A thorough dataset covering a range of ripeness classes—from Green and Midripen to Overripen and Yellowish Green—has been painstakingly assembled in order to verify the suggested methodology. This dataset captures the variation in banana ripeness assessment found in the real world and is used as a baseline for training and evaluating the algorithms.

While the agricultural sector navigates the difficulties of fulfilling the increasing global demand, this study offers insightful information about the integration of multi-modal indicators for improved banana maturity evaluation. The findings of this study have the power to drastically change how banana supply chains function, guaranteeing that fresh produce is distributed to customers worldwide on schedule.

II. Literature Review

Xiao, Bingjie, et al. studied fruit ripeness identification using the YOLOv8 model in their article published in August 2023 in Multimedia Tools and Applications.[15] Four datasets with pictures of apples and pears were evaluated as part of the study, and CenterNet and YOLOv8 were used for detection. While YOLOv8 showed precision between 94.7% and 99.5% with varied inference times from 2.8 to 17.3 ms, CenterNet's precision results ranged from 91.3% to 99.5% with an inference time of 10 ms. Notably, YOLOv8n outperformed CenterNet in 100 iterations. CenterNet had difficulties, including overfitting with higher pretraining weights and faltering at the same iteration count.

A novel strategy to identifying banana development stages was proposed by Mrs. S. Naga Sindhu et al. in the April 2023 issue of Dogo Rangsang Research Journal.[8] The R-CNN model was first pre-trained using the COCO dataset in the study, which also included segmentation and Mask R-CNN, two deep learning approaches. Compared to earlier research, the report demonstrated enhanced average weighted accuracy in successfully categorizing banana ripening stages. However, the study is deficient in providing precise quantitative indicators and results, and it makes few considerations about scalability and real-world application, which raises possible research questions.

The study by Nagnath Aherwadi, et al., published in December 2022 [1] in Electronics, looks into using deep learning algorithms to forecast fruit ripeness, quality, and life. It mainly focuses on banana and red banana. The study uses Convolutional Neural Networks (CNN) and AlexNet for model generation using both bespoke and Kaggle datasets. The focus on image-based classification rather than real-world quality assessment, the potential difficulties in generalizing to fruits with different ripening characteristics, and the limited investigation of practical applications beyond banana classification are some of the limitations, despite the high accuracy in banana classification.

Lukai Ma et al.'s August 2022 study, published in "Current Research in Food Science," [6] tackled the important problem of banana maturity prediction based on color and sweetness values at different stages of ripening. Six different maturity stages were identified, and two effective prediction algorithms were developed, by the researchers using a comprehensive methodology that included principal component analysis and cluster plots for classification, random forest, artificial neural network, and support vector machines for prediction. According to the investigation, different banana segments matured at different rates, which highlights the significance of taking specific banana segments into account when making accurate forecasts.Although the study made significant strides towards predicting banana maturity, it was not without flaws, such as insufficient information regarding data diversity and size. The foundation for future advancements in fruit quality prediction is laid by this work, which also provides valuable insights into the dynamics of banana ripening.

Swati Hira et al.'s research, which was published in July 2022 [4] of the "International Journal of Health Sciences," significantly advances the identification of fruit maturity through the use of image processing techniques. The study employed the "Fruit-360" dataset, which had 90,483 images of various fruits, such as avocado, banana, and apple, with a focus on 131 fruit classes. The dataset was used to build a test set of 22,688 photographs and a training set of 67,692 shots. Using the VGG-16 Convolutional Neural Network (CNN), the researchers obtained an astounding accuracy of 92.7% in their analysis. Interestingly, the study examined the suitability of the VGG16 model for pomegranates and peaches. Using data from a 2012 Logitech C920 webcam, the dataset indicated areas for future improvement and the need for better image quality. The researchers also acknowledged using manual methods to choose fruit groups, especially the laborious hand MATLAB classification procedure. Despite these drawbacks, the research contributes to fruit ripeness detection by providing insightful information about combining deep learning and image processing methods for precise and automated evaluations.

In a June 2022 [2] study that was published in the "International Journal of Agriculture, Forestry and Life Sciences," Ömer Faruk Bilgin et al. examine the qualities of 'Grand Naine' banana fruit at various stages of ripening in Kazanlı, Mersin, Turkey. The study uses spectrophotometry and HPLC for phenolic and sugar measurement, analyzing green, medium ripe, and overripe stages. The results show varied phenolic content and dominant sucrose levels rising during ripening. however limited to 'Grand Naine,' the research provides insight into the chemical ripening process; however, it acknowledges certain limitations, such as exclusive focus and limited discussion of external factors. This work provides a fundamental understanding of the ripening of 'Grand Naine' bananas, opening the door for further extensive research in various banana cultivars.

The study by Mr. K. Kranthi Kumar et al., which was published in May 2022 in the "EPRA International Journal of Research and Development (IJRD)," [7] focuses on the effective application of a Convolutional Neural Network (CNN) algorithm for fruit identification and ripening detection. This work applies the Multi-task Cascaded Convolutional Network (MTCNN) to training and testing using the "Fruit 360" dataset, which has almost 1000 photos per fruit. Notably, the MTCNN was able to identify fruits, including apples, oranges, and strawberries with 100% accuracy and 0% False Prediction Rate.

The algorithm uses color shifts to identify ripening. However, the study's scant treatment of model evaluation criteria points to a possible direction for future research to improve the thorough assessment of the suggested CNN algorithm's effectiveness.

The banana ripeness classification for 'Ambon Lumut,' 'Kepok,' and 'Raja' banana kinds is examined in a January 2022 study by Elizabeth Nurmiyati Tamatjita et al. in "Information Engineering Express".[12] The study obtained noteworthy classification accuracies: 93.33% for unripe, 80% for almost ripe, 66.67% for ripe, and 53.33% for overripe bananas using the HSV Colour Space features and Nearest Centroid Classifier. Overlapping results for the ripe and overripe groups and the effect of background removal on accuracy were among the challenges. The study recognizes potential image processing issues and emphasizes the significance of addressing particular banana kinds in ripeness classification. These results provide important new information for improving the accuracy of banana ripeness categorization algorithms.

The October 2021 paper by Widyawati Widyawati et al., published in "Teknika: Jurnal Sains dan Teknologi," describes the use of the YOLOv4 algorithm for real-time fruit ripeness detection. The study focuses on a 369-image dataset of bananas classified as ripe or unripe.[14] The study produced outstanding accuracy rates of 93.33% for ripe and 81.9% for unripe bananas, with an average of 87.6%, by training the YOLOv4 algorithm with 332 photos, which comprised 90% of the dataset over 6000 iterations. Notably, ripe bananas performed better in terms of detection. Additionally, the study showed that real-time processing performance averaged 5 frames per second, indicating possible gains with a multi-GPU design. These results highlight the potential of YOLOv4 for precise and effective classification and offer insightful information about real-time fruit ripeness detection.

III. MOTIVATION

Banana ripeness classification is crucial for efficient inventory management and reducing food wastage in agriculture. It enables timely harvesting decisions, optimizing
supply chain logistics, and contributing to sustainable practices.

A. Perception of the Problem

The challenge lies in accurately categorizing bananas into different ripeness stages using image analysis and machine learning techniques. This has significant implications for agricultural efficiency and food preservation.

B. Related Works

Previous studies in image processing and machine learning have demonstrated successful fruit quality assessment techniques, motivating our exploration in banana ripeness classification [12, 6].

IV. PROBLEM DOMAIN

The research spans image processing, machine learning, and agricultural technology, addressing challenges in automated fruit quality assessment. It involves methodologies from computer vision and statistical modeling to accurately categorize banana ripeness stages.

V. Problem Definition

The objective is to develop a robust methodology for classifying banana ripeness based on image features extracted from digital photographs. The classification model should accurately differentiate between unripe, mid-ripe, and overripe bananas using machine learning algorithms.

VI. Statement

This paper proposes a method for automated banana ripeness classification using integrated image processing techniques and machine learning algorithms.

VII. Innovative Content

Our approach innovates by combining traditional image processing methods with deep learning models, enhancing classification accuracy across diverse ripeness stages.

VIII. Problem Representation

The problem is formulated as a supervised learning task where image features such as color, texture, and shape are extracted. These features are then used to train classification models (SVM, CNN, KNN) to distinguish between different ripeness stages of bananas.

IX. Solution Methodologies

Various machine learning techniques including SVM, CNN, and KNN are explored for their effectiveness in banana ripeness classification. Each model is trained and evaluated using appropriate metrics to assess performance.

A. Dataset Composition

There are 273 photos of bananas in the dataset, categorized into four ripeness classes: unripe (green), yellowish green, mid-ripe, and overripe.

B. Data Preprocessing

Guided Filter in HSV Color Space → Morphological Filtering (Image Enhancement)

- RGB to HSV Image Conversion: To extract luminance information from color information, images are first transformed from RGB to HSV as shown in Fig. 1. This stage creates a more meaningful representation, which improves further processing [9, 12].
- Morphological Filtering: A guided filter is used in the HSV color space to improve image quality. By filling up pixel gaps and sharpening the image, morphological filtering enhances overall visual clarity.

Otsu's Technique (Binary Mask)

- Thresholding and Binary Mask Creation: Using Otsu's method, pixels with brightness above the threshold are set to black (0) and those with luminance below the threshold to white (1) to produce a binary mask as shown in Fig. 2. This mask separates the banana from the background [6].
- Background and Banana Area Calculation: By helping to differentiate between background and banana pixels, the binary mask makes it possible to calculate the total area of bananas and facilitates further analysis [3].

Figure 1. RGB to HSV Image Conversion

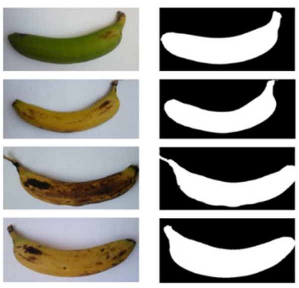

Figure 2. Binary mask using Otsu's Technique

Area of Brown Spots

- Brown Spot Detection: To distinguish brown patches on the banana peel with specific H, S, and V values, a color mask is applied.
- Calculation of Brown Spot Area: By calculating the overall area occupied by brown spots on the banana peel as demonstrated in Fig. 3, the color mask helps determine ripeness factors.

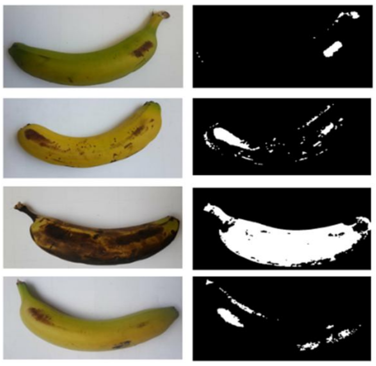

Figure 3. Calculation of Brown Spot Area

Data Preprocessing Results

- Ripeness Factor Calculation (RF): The ratio of the total area of brown spots to the total area of bananas gives the ripeness factor (RF) as shown in Equation 1.

$$RF = \frac{Total\ Area\ of\ Brown\ Spots}{Total\ area\ of\ bananas}$$

- Tamura Texture Features (F): The HSV ripeness mask extracts texture properties such as coarseness, directionality, and contrast. The feature vector including these properties supports a nuanced understanding of textural characteristics.

X. Experimental Work

Three different classification models—Support Vector Machine (SVM), Convolutional Neural Network (CNN), and k-Nearest Neighbors (KNN)—were utilized in the experimental phase to categorize banana ripeness stages.

A. Support Vector Machine (SVM)

The SVM model constructs a hyperplane to effectively separate banana images into various ripeness classes. Figure 4 illustrates the SVM architecture designed to maximize the margin between different ripeness classes [15].

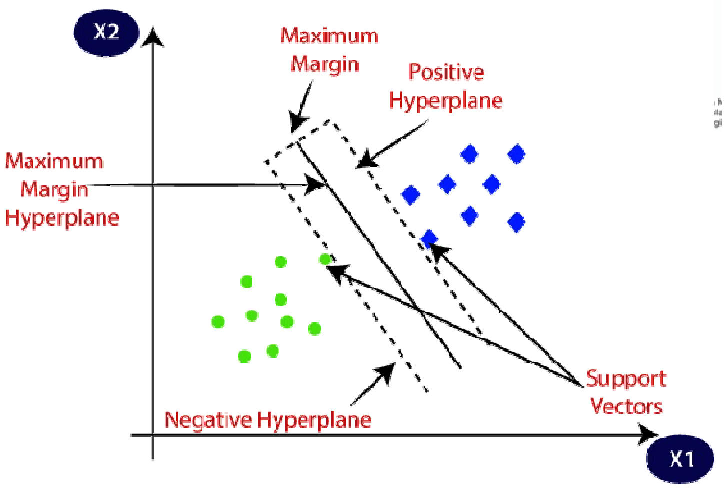

Figure 4. SVM Architecture

B. Convolutional Neural Network (CNN)

The CNN architecture automatically learns hierarchical representations from input banana images, aiding in accurate ripeness classification [13, 14]. Figure 5 outlines the CNN structure used to identify complex patterns in banana ripeness.

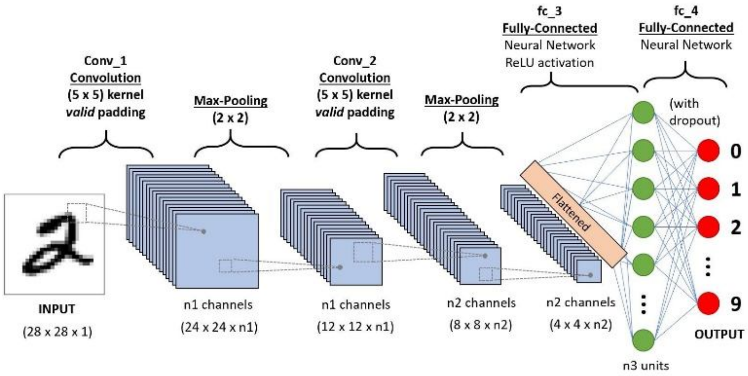

Figure 5. CNN Architecture

C. K-Nearest Neighbors (KNN)

The KNN model uses proximity to neighboring instances to classify banana ripeness, leveraging both traditional and deep learning features from the dataset. Figure 6 depicts the KNN approach for ripeness classification.

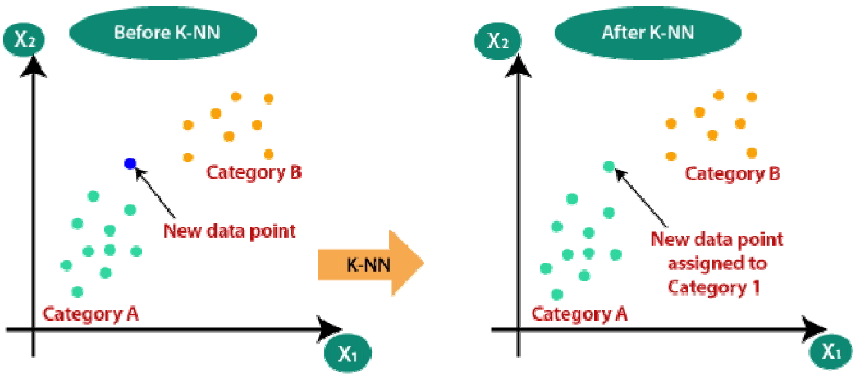

Figure 6. KNN Architecture

Each model was trained iteratively, optimizing hyperparameters for improved performance, and evaluated on metrics like accuracy and F1 score.

XI. Result and Analysis

A. Results and Sensitivity Analysis

In this paper, we investigated three machine-learning methods—K-Nearest Neighbours (KNN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM)—for determining the maturity of fruit. Here are the results of each method:

Using SVM

Fruit ripeness was classified by the SVM model with a 90.91% accuracy rate. Particularly in the ’Green’ class, it distinguished between ripeness stages with accuracy. Strong recall ratings indicated few misclassifications in the majority of the classes, and balanced F1-scores validated overall performance. The model performed well for Green (19 correctly classified) and Yellowish Green (10 correctly classified). However, there were some misclassifications for Midripen (1 from Overripen and 1 from Yellowish Green misclassified) and Yellowish Green (3 misclassified as Midripen) as shown in Figure 7.

Using CNN
The CNN model achieved an 89% accuracy in classifying fruit's ripeness, demonstrating strong precision and recall values across many ripeness stages. Specifically, the identification of 'Green' fruits demonstrated unusually high precision. The model performed well for Green (19 correctly classified) and Yellowish Green (11 correctly classified). However, there were some misclassifications for Midripen (1 from Overripen and 2 from Yellowish Green misclassified) and Yellowish Green (2 misclassified as Midripen) as shown in Figure 8.

Using KNN
The K-Nearest Neighbours (KNN) model successfully identified the level of ripenessin fruit with an accuracy of 81.82%. It performed well in categorizing 'Green' and 'Yellowish Green' fruits but showed more misclassifications compared to SVM and CNN, especially in 'Midripen' and 'Yellowish Green' categories as shown in Figure 9.

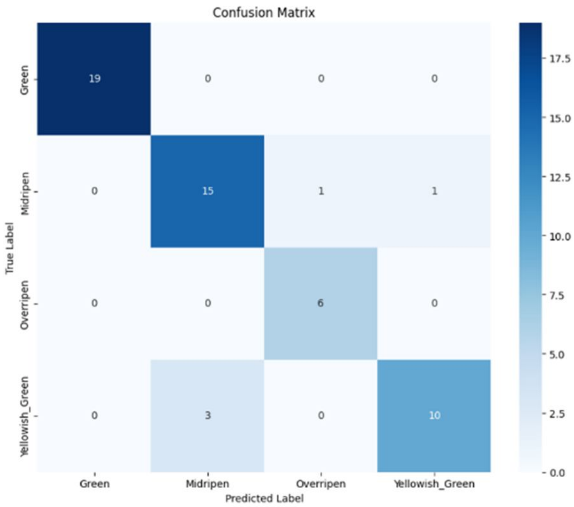

Figure 7. Confusion Matrix for SVM Architecture

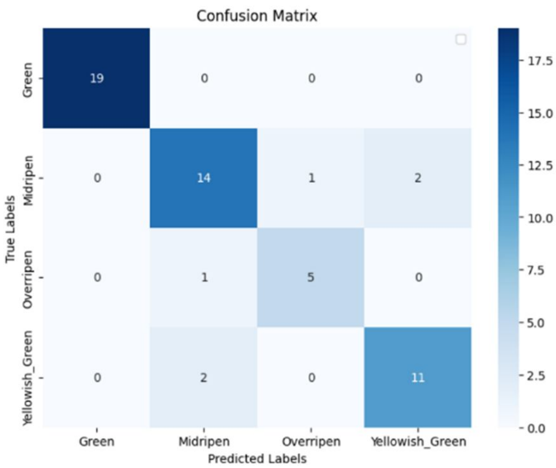

Figure 8. Confusion Matrix for CNN Architecture

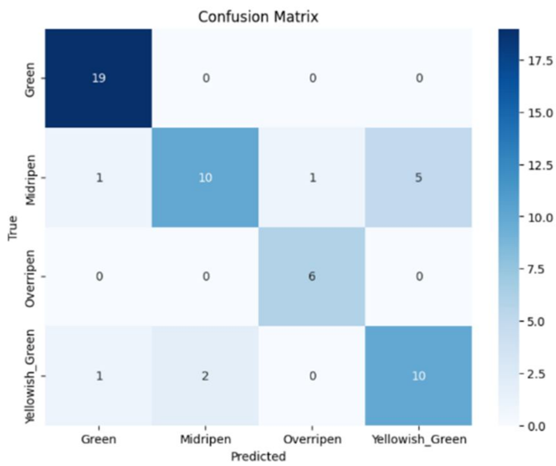

Figure 9. Confusion Matrix for KNN Architecture

B. Data Model

Each model's performance was evaluated using confusion matrices, which illustrate the classification accuracy and misclassifications across different fruit ripeness stages.

C. Comparison of Results

SVM proved to be the most effective of the three methods in identifying fruit ripeness, achieving the highest accuracy. CNN showed competitive performance, especially in precision for 'Green' fruits, while KNN demonstrated robustness in specific categories despite its lower overall accuracy.

D. Justification of the Results

The results demonstrate that SVM is suitable for accurate fruit ripeness classification, whereas CNN and KNN offer alternative approaches with their own strengths and weaknesses. The choice of method should consider specific application requirements and trade-offs between accuracy, precision, and computational efficiency.

XII. CONCLUSIONS AND FUTURE WORK

We looked at how well the Support Vector Machine (SVM), Convolutional Neural Network (CNN), and K-Nearest Neighbours (KNN) classified fruit ripeness in this study. SVM has the highest overall accuracy, closely followed by CNN and KNN, based on our findings. Nonetheless, the efficiency of every technique differed among various ripeness classes, emphasising how important it is to consider the particular characteristics of the dataset and algorithm.

We propose several lines of study for further research. First, researching ensemble methods that combine the benefits of multiple algorithms could improve classification's performance and robustness. More sophisticated feature extraction techniques or pre-trained deep learning models specifically created to categorise fruit ripeness could further enhance CNN's performance. Analysing how different data augmentation methods and hyperparameter adjustments affect model performance may lead to further developments. Finally, expanding the dataset to include a wider range of fruits and developmental phases would enable a more comprehensive analysis and generalisation of the proposed methodologies. Through continued research in these areas, we intend to improve state-of-the-art fruit ripeness categorization and contribute to applications in agricultural and food sector quality management.

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