

Automated Mango Ripeness Detection using Convolutional Neural Networks

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ABSTRACT

Keeping quality criteria in the agricultural supply chain depends on mango classification and grading. Conventional manual sorting techniques are sometimes time-consuming, inconsistent, and vulnerable to human error, which causes substantial financial loss and quality deterioration. Incorporating picture processing and machine learning approaches, this study offers an automated mango fruit categorization system using Python to improve precision and speed. The suggested system catches real-time mango images, extracts important visual elements like color, texture, and form, and classifies them according to ripeness and flaws. Including Convolutional Neural Networks (CNNs), machine learning models are taught to perform classification jobs with great accuracy using a labeled dataset. Designed to help farmers, quality control specialists, and distributors, the solution simplifies the grading process, lowers physical labor, and boosts market value. Experimental findings show how the system has the ability to beat conventional approaches in terms of speed, dependability, and uniformity, hence helping to promote more intelligent agricultural methods and improved post-harvest management.

INTRODUCTION

Particularly in underdeveloped countries where it underpins livelihoods and guarantees food security, agriculture continues to be the cornerstone of many economies. Among agricultural areas, the fruit sector has a major impact on world trade; mangoes are among the most frequently grown and consumed tropical fruits. India, the biggest mango grower, is essential in satisfying worldwide as well as home consumption. Mangoes still mostly use human labor to sort fruits depending on characteristics like size, ripeness, and obvious blemishes. Their quality assessment and grading are rather manual.

Conventional grading techniques are sometimes arbitrary, labor-intensive, and erratic, therefore resulting in inefficiencies and post-harvest losses. These difficulties emphasize the need for a more dependable and automated method of fruit identification. Particularly machine learning, recent developments in picture processing and artificial intelligence provide solutions with greater accuracy and speed to help automate this procedure.

Utilizing Python, machine learning techniques, and real-time picture processing, this study concentrates on the creation of an automated mango classification system. The system seeks to detect flaws and assess ripening levels by means of key visual qualities of mangoes—such as color, shape, and surface texture—and so improve quality control, lower labor reliance,

and increase operating efficiency for farmers, agricultural inspectors, and fruit merchants.

The methodology, data preparation, model architecture, experimental results, and pragmatic consequences of using such a system in real-world agricultural settings are all covered in the remaining chapters.

I. RELATED WORK

Especially in fruit categorization and quality assessment, machine learning and image processing have found much momentum in agriculture in recent years. Several studies have shown the ability of artificial intelligence (AI) to automate the fruit grading and sorting processes, hence providing better accuracy and consistency than conventional manual methods.

Focusing on color and texture characteristics to ascertain the ripeness of mangoes, Patil et al. (2020) suggested an image-based approach employing Support Vector Machines (SVM) for fruit classification. Their method demonstrated some good outcomes but was constrained by its need of regulated lighting conditions. Likewise, Sharma and Singh (2019) classified mangoes according to maturity using k-Nearest Neighbors (k-NN) and feature extraction techniques like Histograms of Oriented Gradients (HOG). The model's performance suffered, though, with noisy or complicated backgrounds.

More sophisticated approaches based on deep learning have been developed to get around such constraints. Widely used in fruit categorization applications are Convolutional Neural Networks (CNNs), renowned for their great capacity to extract spatial hierarchies from images. For instance, Jadhav et al. (2021) used a CNN-based approach to find flaws in mangoes, then trained the model on a vast dataset with labeled images for more accurate detection.

To improve classification performance and cut down training time, other investigation has been done on transfer learning using pre-trained models like VGG16, ResNet50, and MobileNet. In real-time situations (Kumar et al., 2022), these models have been used effectively to categorize several fruits including mangoes, apples, and bananas. Furthermore, allowing real-time object recognition and categorization in mobile and integrated devices are methods such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector).

Though these developments have happened, most current systems are built for lab-scale surroundings and miss field-use scalability. Few studies incorporate real-time image collection, automated preprocessing, and integration into real-world agricultural processes. This study seeks to close that gap by creating an end-to-end solution using Python that

mixes real-time image acquisition, feature extraction, and machine learning-based categorization customized for mangoes.

II. RESEARCH METHODOLOGY

The suggested approach for automatic mango fruit classification is a organized pipeline consisting of image capture, preprocessing, feature extraction, model training, and classification. For real-time use in agricultural contexts, the approach seeks great accuracy, scalability, and flexibility.

1. Collecting information

To mimic real-world settings, high-resolution photos of mangoes were gathered in different settings and backgrounds under different illumination levels. The dataset includes mangoes at various stages of ripeness (raw, semi-ripe, ripe) and with different types of surface blemishes (bruises, black spots, cuts, etc.). Images were captured with a digital camera and categorized manually by agricultural experts.

2. Image Prep

Preprocessing methods were employed to reduce noise and raise the image quality:

For consistent model input, all images were adjusted to a standard size (e.g., 224x224 pixels).

To separate the mango from the background, techniques including thresholding and contour detection were employed.

Better color-based feature extraction was achieved by translating RGB photos into HSV or LAB color space.

Data Augmentation: Rotation, flipping, scaling, and brightness correction were used to enlarge the dataset and improve model generalization.

3. Feature Extraction

Two methods were used for feature extraction: Among the features manually extracted are shape descriptions, texture using GLCM, and color histograms.

Convolutional Neural Networks (CNNs) were used to learn spatial characteristics directly from image data.

4. Development of models

Various machine learning and deep learning models were investigated:

- On manually extracted features, machine learning models SVM, Random Forest, and k-NN classifiers were taught.
- TensorFlow/Keras was used to create CNN architectures including VGG16, MobileNet, and custom lightweight CNN models.
- Pre-trained models were fine-tuned on the mango dataset for better performance and faster training time via transfer learning.

5. Model Training and Validation

Cross-validation was used to evaluate the robustness of conventional machine learning models; the dataset was split into 70% training, 15% validation, and 15% testing groups. Training was accomplished with suitable hyperparameter tuning employing methods like grid search or Adam optimizer (for deep learning).

6. Categorization and Judgment

The last model sorts mangoes into categories as follows:

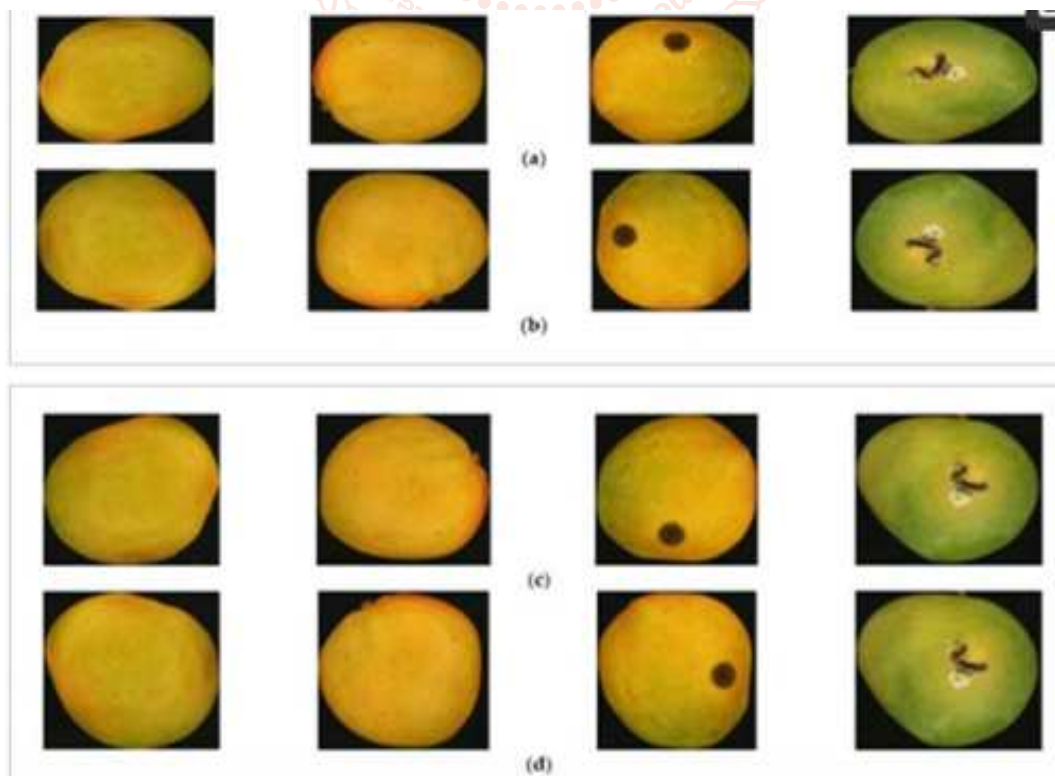
Maturity: Unripe, Semi-ripe, Ripe

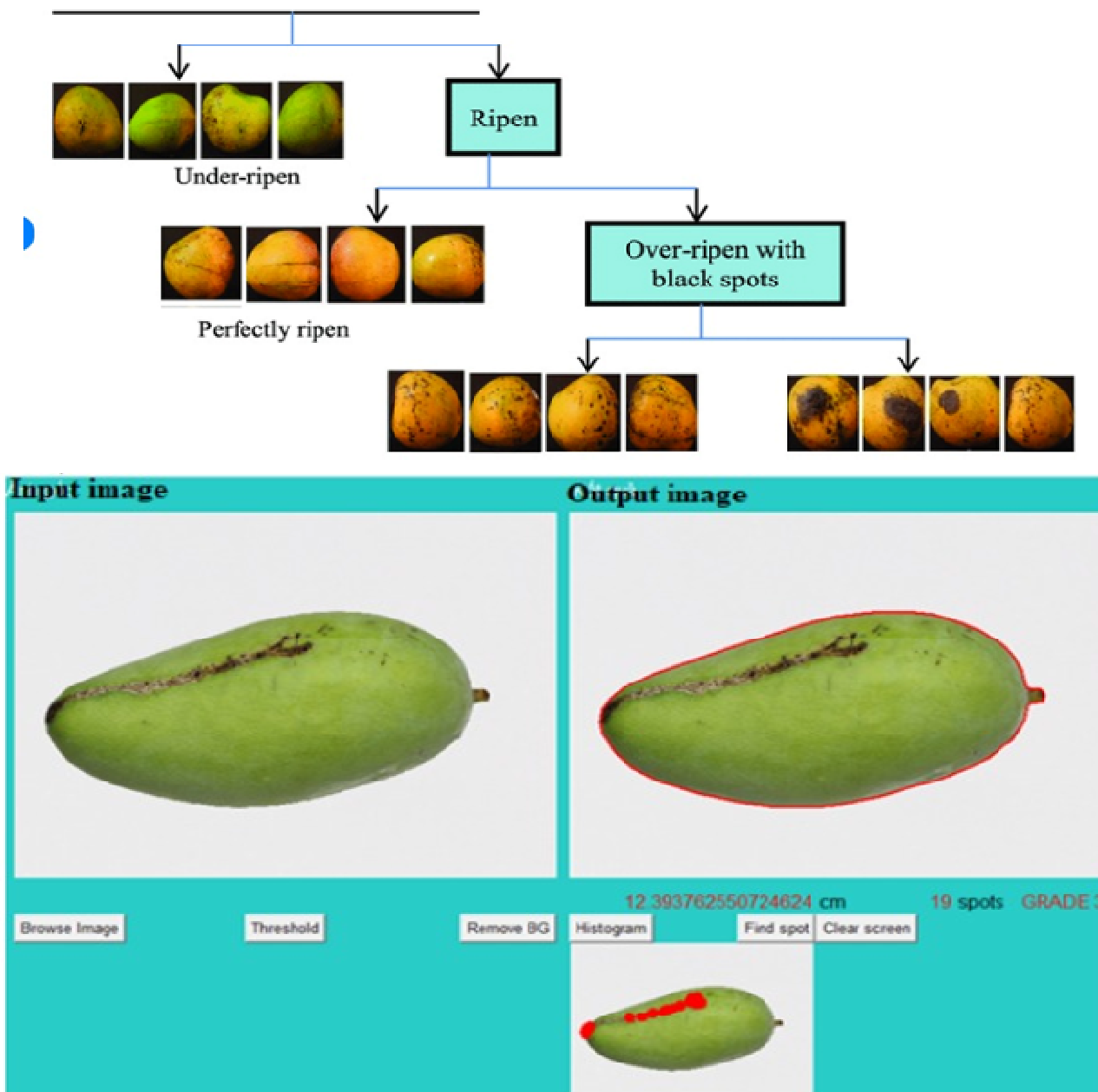
Defect status: Great, Little Defect, Important Defect

Model performance is assessed using evaluation metrics that include: Accuracy, matrix of confusion

7. Deployment and system integration

Using a webcam or camera module, the trained model was incorporated into a user-friendly Python-based interface able of real-time categorization. This interface can be utilized by packaging centers or by field farmers or quality control personnel for immediate feedback.





III. RESULTS AND DISCUSSION

On a custom dataset of 2,000 mango photographs shot under different illumination and backdrop situations, the suggested system was assessed. Unripe, Semi-ripe, Ripe; healthy, minor defect, major defect—two main characteristics—were considered in the categorization. Data was divided into training (70%), validation (15%), and testing (15%) categories.

1. Modeling Output

Several models were trained and evaluated for their precision and efficiency:

Model	Accuracy (%)	Precision	Recall	F1-Score
SVM	83.4	0.82	0.83	0.81
Random Forest	85.7	0.85	0.86	0.85
k-NN	80.2	0.79	0.80	0.78
CNN (custom)	92.6	0.92	0.93	0.92
MobileNet (TL)	95.1	0.95	0.95	0.95

TL: Learning by means of transfers

In terms of accuracy and processing speed, the MobileNet-based transfer learning model beat other models, therefore making it well suited for real-time use.

2. Ripeness Categories

Distinguishing unripe, semi-ripe, and ripe mangoes, the model had average classification accuracy of 94.3%. Minimal overlap between next categories in the confusion matrix showed that the model was successful at picking up slight variations in texture and color connected with ripeness.

3. Detect Defect

With an accuracy of 91.8%, defect detection properly identified typical surface problems including black spots, bruises, and cuts. But problems arose when mangoes had little flaws or were less visible from their surface.

4. Real-time execution

Suitable for real-time grading at packing plants or farms, the last model was released on a Python-based application with webcam connection. Within one second per frame, the system processed and classified mango images.

5. Debate

The results confirm that machine learning—especially deep learning—can greatly improve the speed and precision of mango categorization over conventional manual techniques. The great performance of the MobileNet model emphasizes the usefulness of transfer learning for small-sized agricultural datasets.

Still, some restrictions were discovered:

- Poor illumination and packed backdrops somewhat hampered the performance of the model.
- With only surface-level picture analysis, little or inside flaws were more difficult to identify.

Future research might investigate the addition of hyperspectral imaging or multispectral sensors to further enhance accuracy. Moreover, a bigger and more varied dataset will enable model generalization across various mango types and environmental conditions.

IV. REFERENCES

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