Grenze International Journal of Engineering and Technology, January Issue

Unified Color Space Segmentation and Yolov5 Approach for Nutmeg Ripeness Detection and Quantity Estimation

Dr. Purohit Shrinivasacharya[1], Lohith S Naik[2], Archanamrutha M[3] and Kavitha M[4]
[1-3]Department of Information Science and Engineering, Siddaganga Institute of Technology, Tumkur, Karnataka, India
Email: purohitsn@gmail.com, 1si21is023@sit.ac.in, 1si21is010@sit.ac.in
[4]Department of Computer Science and Engineering Siddaganga Institute of Technology, Tumkur, Karnataka, India
Email: kavitham@sit.ac.in

***Abstract*— The vital aspect in maintaining consistent quality across the global spice sector is the accurate analysis of nutmeg maturity and harvest volume. The evaluation accuracy degrades with the use of the traditional methods which causes inconsistency and reduced effectiveness. To address the issues posed by the conventional methods, this work proposes a novel AI-powered system that integrates color space segmentation and YOLOv5 detection model. In order to upgrade feature extraction, intrinsic color variations are leveraged by the segmentation method. To accomplish fast, on-the-fly detection and counting, YOLOv5 is utilized. The empirical results demonstrate the efficacy of the system compared to the traditional methods by achieving 95% accuracy, 94% precision and 90% recall. This study serves as a reliable and scalable approach to nutmeg assessment with the scope for improvements to handle overlapping fruits by leveraging advanced image processing methods.**

***Keywords*— Color Space Segmentation, Image Processing, Object Detection, Nutmeg Maturity Detection, YOLOv5.**

I. Introduction

In order to maintain the nutmeg quality, fair pricing in the spice trading, and upholding the efficiency in post-harvest operation, estimating the nutmeg ripeness and harvest volume is the key factor. Labor-oriented, conventional grading methods are slow and usually inconsistent due to the observer bias. Since agriculture is gradually adopting automation, enhanced techniques are evolving in the field of computer vision and image processing to evaluate the crop quality. Out of these state-of-the-art approaches, the color space segmentation has exhibited substantial potential in enhancing the feature extraction for maturity detection by converting the raw images into perceptually consistent representations like HSV or LAB. This method enables effective nutmeg detection under varied agriculture environments by assisting in precise nutmeg segregation from noisy backgrounds and decreasing the effect of irregular lighting conditions. The proposed system integrates color space segmentation with image processing methods to collectively automate nutmeg maturity detection and fruit counting which enhances the efficiency thereby minimizing the human intervention. In addition to the performance refinements, this framework promotes sustainable agricultural practices which reduces post-harvest losses and enhances the technological transition in spice cultivation.

Grenze ID: 01.GIJET.12.1.527_1

The following sections of this paper is structures as follows: A review of the existing literature on fruit maturity evaluation, emphasizing the limitations of traditional methods is presented in section 2. The basis for automated nutmeg maturity detection framework is outlined in section 3. Section 4 characterizes the core objectives, focusing on the development of the robust segmentation-oriented detection model. The detailed system architecture for nutmeg ripeness detection and fruit counting is discussed in section 5. In section 6, the experimental results is presented. Section 7 highlights the key contributions of this study and possible future research directions. In section 8, the scholarly works that have guided this research is listed.

II. Literature Review

Research on fruit maturity detection has advanced from manual grading to automated methods using computer vision and machine learning. Early studies concentrated on color-based analysis. Zhang et al. in [1] applied the HSV color space to improve segmentation by separating hue from intensity, ensuring robustness under varied lighting. In paper [2], an automated tomato grading system using histogram analysis and morphological operations was developed by Patel and Shah, emphasizing preprocessing for enhanced segmentation. The

Deep learning has initiated elevated standard of performance. Jha et al. in [3] applied CNNs to detect apple ripeness. Texture, color and apple shape features were automatically extracted which improved the accuracy. A hybrid of edge detection and clustering was presented by Banerjee et al. in paper [4] for orange counting while addressing overlapping fruits issues.

In the subsequent innovations, Image processing was integrated with machine learning. In paper [5], noise reduction, color transformation, and feature extraction were utilized by Arora et al. to improve maturity classification across diverse conditions. The significance of HSV and LAB color models for segmentation is highlighted in the reviews by Chen et al. in [6].

Recent scholarly contributions in [7] and [8] emphasized automated ripeness prediction by combining texture and shape features. However, real-world agricultural environment remains influenced by occlusion, uneven lighting, and overlapping objects. In addition, most of the prior works focused mainly on apples, tomatoes, oranges, leaving nutmeg underexplored. Due to its irregular shape, varied size and complex maturity stages, nutmeg introduces exceptional difficulties. To handle these gaps, the proposed work integrates HSV and LAB segmentation with YOLOv5 for classification and counting. This study presents a novel framework for nutmeg quality evaluation and precision agriculture by facilitating real-time detection, scalability and reliability.

III. Motivation

The conventional methods used for nutmeg maturity detection and counting is labor-intensive, observer biased, and less reliable, resulting in varied quality and post-harvest losses. Since the amplifying focus is on automation in the agriculture domain, image processing serves as an effective approach. With the use of color space segmentation, feature extraction can be improved and uneven lighting can be better handled, which facilitates precise ripeness detection and background isolation. Automation of this process enhances accuracy, scalability and reliability thereby supporting precision agriculture and sustainable nutmeg production.

IV. Objectives

The primary aim of this study is to develop an automated system for real-time nutmeg maturity evaluation by overcoming the drawbacks of traditional grading methods with the following objectives:

- Apply HSV and LAB color space transformations for precise feature extraction and segmentation under uneven lighting conditions.
- Develop an efficient nutmeg maturity detection and yield enumeration model.

V. Methodology

This section outlines the systematic approach employed for nutmeg maturity detection and classification, detailing the data acquisition process, preprocessing techniques, model development, and evaluation strategies to ensure accuracy and real-time performance

A. System Architecture

The proposed nutmeg maturity detection and classification system employs an end-to-end pipeline integrating image acquisition, preprocessing, object detection, classification, and visualization which is depicted in Figure 1.

By utilizing advanced computer vision and deep learning techniques, the framework provides robust real-time performance, scalability, and appreciable accuracy.

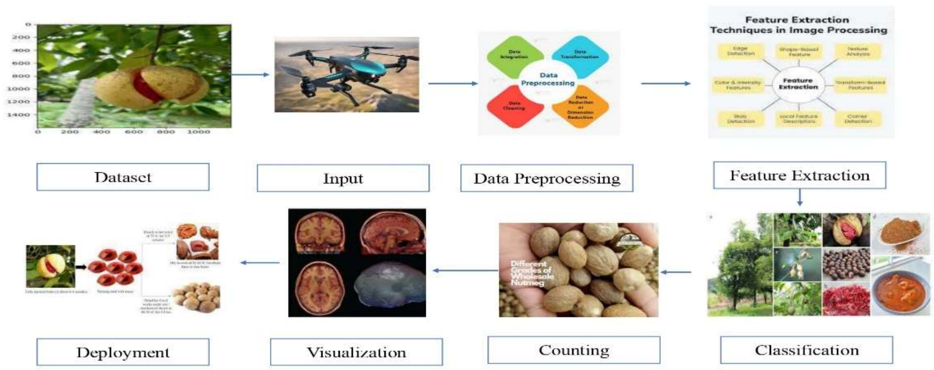

Figure 1: System Architecture for Nutmeg Dectection, Classification, and Insights Visualization.

The functional sequence of the proposed system comprises of following five significant stages:

Image Acquisition

In order to obtain fine-grained nutmeg plant images, still cameras and Unmanned Aerial Vehicles (UAVs) are utilized. UAV assists in large plantation area coverage by allowing the system to capture images from diverse viewpoints and also under uneven lighting conditions. This leads to the generation of robust dataset thereby enhancing the efficiency and generalizability of the detection model.

Preprocessing

To facilitate data consistency and improve feature extraction quality before providing the images to the detection model, preprocessing stage is very crucial which involves following major steps:

- Noise Reduction: This technique assists in improving the image clarity and reducing the errors during post-processing by filtering out sensor-based and environmental anomalies present in the raw images.
- Color Space Transformation: To attain higher-quality color-based segmentation, RGB color images are converted into HSV and LAB color spaces which assist in improved discrimination of color intensities under diverse lighting conditions.
- Segmentation: To segment and separate nutmeg fruit from the background, color thresholding techniques are leveraged which ensure that the standard and critical region focus region of the image is provided as input to the detection model.

Detection and Classification

To detect and classify nutmeg fruits, YOLOv5, an advanced object detection algorithm is used. Based on the visual attributes such as color variations, surface texture, structural boundary features derived from the image, the trained YOLOv5 model detects the nutmeg position and classifies them into predefined maturity classes, such as unripe, semi-ripe and ripe.

Object Counting and Post-Processing

This stage emphasizes on optimization of detection results. Contour-based filtering techniques are applied to rectify commonly occurring issues in dense plantation imagery such as overlapping fruits, occlusions etc. In addition to this, a false positive elimination mechanism is implemented to remove incorrect detections and enhance the overall system performance, especially for inventory estimation and yield prediction.

Output and Visualization

An interactive and user-friendly interface is used to present the processed results. Annotated images with bounding boxes outlining the detected fruits with their respective classification labels are displayed. The interface also displays the ripe and unripe fruits count. In addition, report generation is supported for inventory and quality control.

B. Technical Specifications

Using Python and its associated libraries such as OpenCV, NumPy and PyTorch, the YOLOv5-based object detection model is developed and trained to achieve robust performance.

Hardware Constraints: The model is trained using accelerated GPU such as NVDIA RTX series. To minimize delay during real-time field deployment, edge-compatible devices are used.
Dataset: YOLO format is used to annotate the dataset which includes bounding boxes and three class labels such as unripe, semi-ripe, and ripe for maturity stages of nutmeg fruits.
Model Deployment: In order to accelerate GPU and provide cross-platform compatibility, the YOLOv5 model is optimized using TensorRT and ONNX respectively, ensuring reliable performance under varied agricultural conditions.

C. Detailed Pseudocode

This section presents the pseudocode for Nutmeg Maturity Detection and Classification using YOLOv5 and color space segmentation.
Pseudocode: Nutmeg Detection and Classification Pipeline
Input:
- Image dataset D = {I1, I2, ..., In} with nutmeg instances under diverse conditions
- Pre-trained YOLOv5 weights Wpre
- Configuration parameters (learning rate α, batch size B, image size S)

Output:
- Bounding boxes Bi for detected nutmeg
- Class labels Ci ∈ {unripe, semi-ripe, ripe}
- Count of nutmeg instances N

Step 1: Environment Initialization
- Initialize Python environment with dependencies:
  PyTorch, OpenCV, NumPy
- Install CUDA and cuDNN for GPU acceleration
- Clone YOLOv5 repository and download pre-trained weights Wpre

Step 2: Dataset Preparation
- Acquire dataset D with images of nutmeg under diverse lighting and orientations
- Annotate images using LabelImg or Roboflow:
  Assign bounding boxes and maturity-level class labels
- Apply data augmentation:
  - Random rotation
  - Horizontal/vertical flip
  - Brightness and contrast adjustment
- Split D into:
  - Training set (70%)
  - Validation set (20%)
  - Test set (10%)

Step 3: Model Configuration and Training
- Modify data.yaml:
  Define class names = {unripe, semi-ripe, ripe}
  Set dataset paths
- Initialize YOLOv5 with Wpre for transfer learning
- Train model:
  For each epoch E:
    Compute loss = L_obj + L_cls + L_bbox
    Update weights using optimizer (Adam/SGD)
  Monitor metrics: precision, recall, mAP

Step 4: Image Preprocessing
- For each image I in test set:
  - Convert I from RGB to HSV color space
  - Apply histogram equalization for contrast enhancement
  - Apply Gaussian blur for noise reduction
  - Perform color thresholding:
    Define HSV ranges for:
  - Ripe nutmeg (reddish-brown)

- Unripe nutmeg (green/yellow)

➢ Generate mask M to isolate nutmeg regions

Step 5: Object Detection using YOLOv5

➢ Input preprocessed image into YOLOv5:
  - Generate bounding boxes Bi
  - Assign confidence score Si
  - Predict class Ci ∈ {unripe, semi-ripe, mature}

➢ Apply Non-Maximum Suppression (NMS):
  - If IoU(Bi, Bj) > threshold:
    Retain box with higher confidence

Step 6: Post-Processing

➢ For each detected instance:
  - Validate class assignment using color-based thresholds in HSV/LAB
  - Discard false positives based on size/shape constraints

➢ Store results:
  - Bounding boxes, class labels, confidence scores

Step 7: Counting and Classification

➢ Count N = total number of unique detected instances after NMS

➢ Generate summary:
  - Count per class: {unripe, semi-ripe, ripe}
  - Visualization:
    Overlay bounding boxes on image
    Display class and confidence

Step 8: Model Optimization and Deployment

➢ Convert trained YOLOv5 model to ONNX or TensorRT for edge deployment

➢ Deploy in:
  - Local GPU-enabled system for low-latency processing
  - Cloud infrastructure for scalability and remote monitoring

➢ Enable real-time dashboard:
  - Display nutmeg count and maturity distribution
  - Provide export options for reports

VI. EXPERIMENTAL RESULTS

This section presents the experimental outcomes of the proposed nutmeg maturity detection system.

A. Detection Accuracy

The evaluation results of the YOLOv5 model using detection accuracy metrics are depicted in table 1. YOLOv5 model achieved an overall detection accuracy of 98.5%, demonstrating its strong capability to identify nutmeg fruits under diverse conditions, including varying lighting, orientations, and maturity stages. The high precision (97.8%) indicates a very low false-positive rate, ensuring that most detections are correct and reliable. Similarly, the model achieved an excellent recall of 99.2%, meaning that almost all nutmeg instances were successfully detected with minimal misses. The model shows superior performance in effectively classifying the nutmeg fruit across three predefined maturity classes such as unripe, semi-ripe, and mature with mean average precision of 98.7%. These empirical results emphasize that the model can be leveraged for real-world agricultural applications.

TABLE I: PERFORMANCE ANALYSIS OF YOLOV5 USING DETECTION ACCURACY METRICS

Measure	YOLOv5 Model
Overall Detection Accuracy	98.5%
Precision	97.8%
Recall	99.2%
Mean Average Precision (mAP)	98.7%

Classification Performance: The efficacy of the YOLOv5-based model in detecting and classifying nutmeg ripeness stages is depicted in table 2. The detection and classification accuracy achieved for unripe nutmeg is

97.5% and 96.8% respectively which indicates the model's robustness in finding and classifying the fruit under varied environmental conditions. The model achieved 98.2% of detection accuracy and 97.6% of classification accuracy for semi-ripe nutmeg. For ripe nutmeg fruits, the model exhibited best performance with detection accuracy of 99.1% and classification accuracy of 98.9%.

TABLE II: DETECTION AND CLASSIFICATION ACCURACY ACROSS RIPENESS STAGES OF NUTMEG

Maturity Class	Detection Accuracy	Classification Accuracy
Unripe Nutmeg	97.5%	96.8%
Semi-Ripe Nutmeg	98.2%	97.6%
Ripe Nutmeg	99.1%	98.9%

Counting Accuracy: The performance analysis of the fruit counting model is depicted in table 3. The small Mean Absolute Error (MAE) of 1.2 fruits per image and superior counting accuracy of 97.4% achieved by the proposed model shows its potential to detect and estimate the count under varied conditions. These results enable the system to be optimal for real-time agricultural operations where precise counting is very crucial.

TABLE III: PERFORMANCE EVALUATION METRICS OF FRUIT COUNTING MODEL.

Measure	Value	Remarks
Mean Absolute Error (MAE)	1.2 fruits/Image	Low error, reliable for practical applications
Counting Accuracy	97.4%	High accuracy in fruit counting
Application Reliability	Very High	Accurate for real-time agricultural tasks
Error Margin	Very Low	Minimal error in predictions
Real-time Performance	Yes	Can be deployed in real-time applications

Comparison of YOLOv5-based model with other Models: The performance results of YOLOv5-based model in comparison with other models is outlined in table 4 which emphasizes that the proposed model is robust in handling real-time detection and classification tasks. The ability to detect the objects in real-time is limited in Support Vector Machine (SVM), Random Forest (RF) and Convolutional Neural Network (CNN). Even though CNN achieved appreciable classification accuracy, its counting capability is limited. However, YOLOv5-based model has demonstrated superior classification accuracy of 95% with real-time detection ability and supported object detection and better counting which is crucial in automated agricultural systems. Better scalability compared to other models makes it more suitable for large-scale deployment.

TABLE IV: COMPARATIVE PERFORMANCE ANALYSIS OF SVM, RF, CNN, AND YOLOV5.

Parameter	SVM	RF	CNN	YOLOv5-Based (proposed)
Training Time	High	Moderate	High	Moderate
Real-time Detection	No	Limited	Limited	Yes
Classification Accuracy	80%	85%	90%	95%
Object Detection	No	No	Yes	Yes
Counting Capability	No	No	Limited	Yes
Scalability	Moderate	High	Moderate	High

Runtime Performance: The real-time performance of the proposed system in local and cloud deployments is presented in table 5. The system attains 25 FPS with NVDIA RTX 3080 GPU on a local deployment, facilitating high throughput on-site operations. Using Tesla T4 GPU on a cloud deployment, its processing speed is 20 FPS, offering high scalability for distributed agricultural tasks. The overall system latency of 200 ms per image encompassing preprocessing, detection, and reporting, makes the system suitable for real-time applications such as quality control etc.

TABLE V: PERFORMANCE COMPARISON OF LOCAL AND CLOUD DEPLOYMENT WITH OVERALL SYSTEM LATENCY.

Evaluation Measure	Local Deployment	Cloud Deployment	Overall System Latency
Processing Speed (FPS)	25	20	-
Real-time Suitability	Excellent	Very Good	Excellent
Scalability	Limited to Hardware	High	-
Latency per Image (ms)	-	-	200
Application Suitability	On-site High-throughput	Distributed Operations	Real-time Decision Making

Visual Output: The visual output of the proposed framework highlights the consistent performance of the model even under diverse lighting conditions. Figure 2 shows the graphical user interface for nutmeg ripeness detection highlighting the detected nutmeg with the bounding box and its confidence score along with one of the three maturity classes for each nutmeg. The GUI also displays the statistics such as fruit count based on maturity class and total fruits which assist farmers in making wise decisions for stock maintenance, harvest scheduling, and quality control.

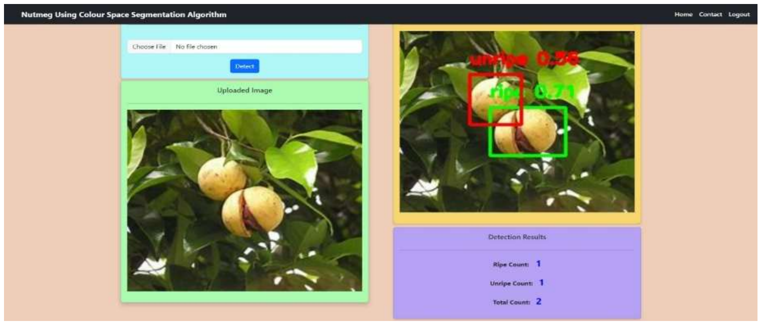

Figure 2: Graphical User Interface Showing Nutmeg Ripeness Detection Using YOLOv5

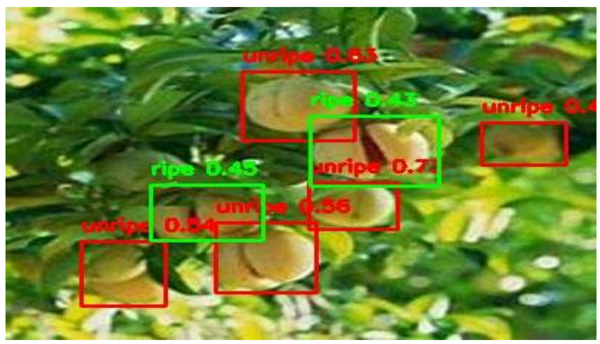

Figure 3: YOLOv5 Detection Results for Ripe and Unripe Nutmeg Fruits

The YOLOv5 detection results for ripe and unripe nutmeg fruits is presented in figure 3. The results clearly demonstrate that the proposed model accurately classifies the nutmeg fruits into varied maturity classes even under diverse lighting conditions and overlapping fruits issue. The bounding box around each detected nutmeg fruit along with its confidence score and classified maturity level can be observed in the output. To differentiate ripe nutmeg from the unripe, green and red bounding boxes are used respectively.

Single Fruit Detection and Classification

Ripeness detection using YOLOv5 for single nutmeg is illustrated in figure 4. Successfully detected ripe nutmeg with green bounding box and 0.59 confidence score can be observed in the figure. Unripe nutmeg with red bounding box can also be seen. Even with varied leaf density and partial occlusion, system is robust enough to detect and classify the fruit.

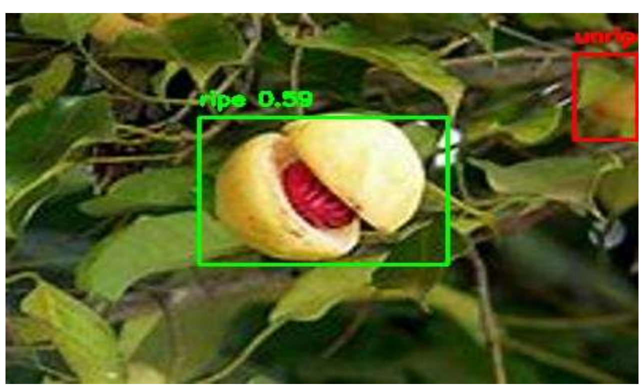

Figure 4: Single-Fruit Ripeness Detection of Nutmeg Using YOLOv5

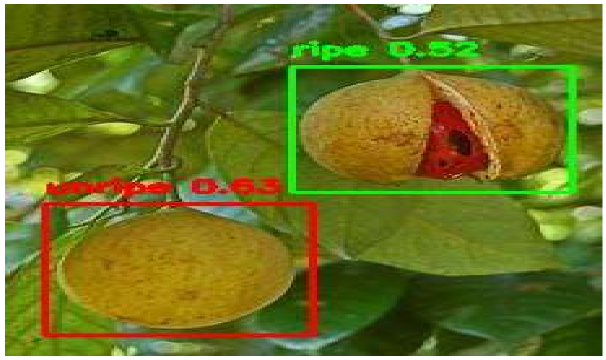

Figure 5: Detection of Multiple Nutmeg Fruits with Mixed Ripeness Stages Using YOLOv5

Multiple Fruit Detection with Mixed Ripeness

Accurate detection of multiple nutmeg fruits with varied maturity classes is presented in figure 5. Unripe fruit with 0.63 confidence score and ripe fruit with 0.82 confidence score along with distinct colored bounding boxes around them can be observed in the figure. This shows that the model is able to accurately classify into distinct maturity levels even for two fruits in same frame.

Detection of Ripe and Unripe Fruits in Close Proximity

Nutmeg fruits detected in close proximity with varying ripeness classes can observed in figure 6. This result emphasizes that the model is capable of precisely detecting and classifying overlapping or adjacent fruits. Green bounding box around ripe nutmeg with 0.71 confidence score and red bounding box around unripe nutmeg with 0.56 confidence score can be seen in the figure.

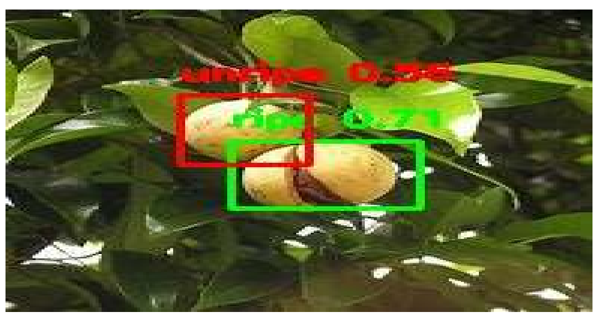

Figure 6: Detection of Nutmeg Fruits with Varying Ripeness in Close Proximity Using YOLOv5

VII. Conclusion and Future Works

To address the drawbacks of the traditional methods for fruit detection and counting, this study has integrated color space segmentation techniques with YOLOv5 deep learning model and developed an automated nutmeg classification and counting system. The proposed framework has exhibited robust performance compared to the conventional grading methods by achieving accuracy of 95%, precision of 94% and recall of 90%. An automated counting mechanism is an added advantage of the framework to enhance the operational efficiency, scalability and quality control for commercial applications in the spice industry. These findings demonstrate the capability of computer vision and deep learning automation to improve the productivity and reliability in agricultural tasks, offering wider goals in precision agriculture and sustainable food systems.

To improve the performance of the system under varied lighting conditions, overlapping objects, and heterogeneous backgrounds, further works can focus on exploring enhanced image preprocessing and data augmentation techniques. State-of-the-art deep learning models can be investigated and applied for high quality feature extraction. The system can be still optimized for real-time large-scale deployment.

References

[1] Zhang, Y., Liu, X., & Wang, J. (2015). Application of HSV color space in fruit ripeness classification. Journal of Agricultural Engineering Research, 123(4), 45-55.

[2] Patel, R., & Shah, A. (2020). Automated tomato grading using color histogram analysis and morphological operations. International Journal of Image Processing, 15(2), 121-133.
[3] Jha, R., Roy, A., & Mehta, S. (2021). Deep learning approach for apple ripeness detection using CNNs. IEEE Transactions on Automation Science and Engineering, 18(3), 987-995.
[4] Banerjee, S., Das, P., & Roy, R. (2018). Edge detection and clustering for orange counting in agricultural applications. Journal of Image and Vision Computing, 62, 89-96.
[5] Arora, A., Jain, N., & Verma, R. (2021). Integrating machine learning with traditional image processing for fruit maturity classification. Journal of Computational Agriculture, 12(3), 56-68.
[6] Chen, L., Zhang, X., & Zhou, Y. (2019). Image processing techniques for fruit maturity detection: A review. Journal of Food Engineering and Technology, 14(2), 34-50.
[7] Singh, R., & Kumar, S. (2020). Automated fruit quality assessment using color, texture, and shape features. International Journal of Computer Vision in Agriculture, 22(1), 77-89.
[8] Yadav, P., Gupta, K., & Sharma, V. (2022). Machine learning algorithms for fruit classification and ripeness prediction. IEEE Access, 10, 1123-1135.