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Automated Vision-Based Grading and Authenticity Verification of Harumanis Mangoes using Shape and Contour Analysis

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ABSTRACT

Harumanis mangoes are a premium agricultural product from Perlis, Malaysia, valued for their unique quality and export potential. Traditional grading methods rely on manual inspection, which is time-consuming, inconsistent, and susceptible to misclassification and fraud involving visually similar mango varieties. To overcome these limitations, an automated vision-based grading system was developed using NI myRIO and LabVIEW. The system captures top-down images in a controlled environment and processes them through a two-level shape analysis, including general shape and tail contour matching, to verify varietal authenticity. Surface defects such as black stains, brown stains, and bruises are detected using custom image processing pipelines, while weight estimation is performed using volume approximation with a correction model based on linear regression. The system achieved 100 percent identification accuracy for authenticity and demonstrated a strong correlation between estimated and actual weights, with an R-squared value of 0.9537 and an 80 percent reduction in mean absolute error. These results highlight the system's effectiveness in providing fast, consistent, and non-destructive grading for Harumanis mangoes in post-harvest applications.

1. Introduction

There are many tropical fruits cultivated in Asian countries, including durian, mango, rambutan, and mangosteen. These fruits are major sources of income for countries in Southeast Asia, such as Malaysia. The mango, scientifically known as Mangifera indica L. from the family Anacardiaceae, is one of the primary fruit crops in these countries, accounting for an average of 76% of global mango production [1]. Beyond its high nutritional value, mango is also utilized in the production of various products, including cosmetics and desserts [2]. As a result, it ranks as the second most traded tropical fruit globally.

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Among the different types of mangoes, Harumanis stands out as a variety unique to Malaysia [3]. The Harumanis mango is native to Perlis, the northernmost state in Malaysia, and is a well-known specialty fruit in the region. It possesses a distinct aroma and taste compared to other mango varieties [4]. The environmental conditions in Perlis, particularly its ambient temperature and soil characteristics, are highly suitable for cultivating Harumanis. This mango variety only bears fruit once a year during specific months, with the exact timing of the harvest varying based on environmental factors. These seasonal constraints contribute to the limited and inconsistent supply of Harumanis mangoes.

Traditionally, Harumanis mangoes are graded using weighing scales and classified based on visual inspection by human workers [5]. This manual method is labor-intensive and prone to inconsistency, especially when dealing with large harvests. Due to the fruit's sensitivity to physical damage, improper handling during sorting can result in post-harvest issues such as fruit rot and disease [6]. Beyond grading, the entire post-harvest handling process—including harvesting, sorting, packaging, and transportation—remains heavily reliant on manual labor. Due to the fruit's sensitivity to physical damage, improper handling at any of these stages can lead to significant post-harvest issues such as fruit rot and disease [7]. According to the Department of Statistics Malaysia, mango exports in 2022 amounted to 9,290 tonnes, a significant decline from 15,329 tonnes in 2018 [8]. This decrease is attributed to the combined effects of the COVID-19 pandemic and persistent manual labor issues. The pandemic not only disrupted local production but also reflected a global trend of declining agricultural activity.

Despite the reduction in output, global demand for mangoes continues to grow, driven by their widespread use in value-added products such as jams, beverages, and salads. This growing demand, paired with labor-related inefficiencies, reveals a critical flaw in the current post-harvest handling practices of mango plantations. Additionally, there have been recent incidents involving counterfeit Harumanis mangoes, where visually similar varieties are sold as genuine Harumanis [9]. These cases often stem from human error during the sorting process, where non-Harumanis mangoes are mistakenly packaged and sold as premium-grade fruit. Such post-harvest issues negatively impact both consumers and producers—consumers pay high prices for inauthentic products, while farmers struggle to scale production and maintain product integrity.

Smart agriculture technologies, particularly vision systems, have shown great promise in reducing dependence on manual labor in post-harvest operations. For Harumanis mangoes, the adoption of computer vision could enhance grading accuracy and efficiency. In general, computer vision systems rely on two main approaches: machine learning and deep learning, both of which offer potential solutions for automating the grading process [5]. Machine Learning vision-based system depends on the color, size, texture of the image to process the image for grading or classification purpose. For example, Ibrahim *et al.,* [10] designed a conveyor-based grading system using a CMOS camera to extract shape features with Fourier descriptors, followed by Stepwise Discriminant Analysis (SDA) for classification. Volume was estimated using the disk method, and weight prediction was performed via linear regression, achieving 92% accuracy in shape classification with strong correlations for both volume and mass estimation [10]. Similarly, Abu Bakar *et al.,* [11] proposed a grading system based on 2D shape descriptors and regression modeling, achieving 98.8% classification accuracy and a 0.98 correlation for weight estimation. Another study by Doan *et al.,* [1] utilized contour-based features to assess size and detect blemishes, with Random Forest achieving 91.32% accuracy in classifying Grade 1 mangoes.

Color-based grading has also proven effective. Mavi applied HSV color space features in conjunction with a Support Vector Machine (SVM), obtaining 91.88% accuracy in ripeness classification [12]. Abu Bakar *et al.,* [11] developed a ripeness indicator using internal and external color features throughout the mango's maturation stages. A fuzzy logic system evaluated the color channels, resulting in a classification accuracy of 92% [13]. Ahmad *et al.,* [14] in contrast, employed contour delineation and edge-template techniques to estimate maturity, where the mango was segmented via binarization to extract a final contour mask. This was used to compute a shape index with 87% accuracy, validated through human evaluation [14].

More advanced systems have integrated 360-degree imaging platforms, such as that developed by Chai *et al.,* [15] which utilized green-channel thresholding and ridge regression to estimate mango weight based on length, width, thickness, and area. The system recorded only 7.28% error in defect detection and 2.5% error in weight estimation [15]. Meanwhile, Khalid *et al.,* [16] introduced a system that combined pixel-based disease severity analysis with weight estimation using regression modeling. While the weight estimation achieved 72.25% accuracy, the disease classification was less reliable, as samples visually confirmed to be diseased were sometimes misclassified as healthy [16].

Texture-based classification has also been explored. One study used Local Binary Patterns (LBP) and Gabor wavelets to extract texture features, followed by classification with Random Forest and multi-class SVMs. This method achieved a high classification accuracy of 98.67% [17].

In recent years, deep learning approaches such as Convolutional Neural Networks (CNNs) have been applied to mango grading. These models are trained using large image datasets labeled by grade and can classify based on learned hierarchical features [5,6]. Unlike traditional methods, CNNs typically require more extensive training data, often in the range of 1,000 images per class, compared to the 100 images used in conventional machine learning methods. More recently, Vision Transformers have been utilized to classify mango ripeness. These models have demonstrated impressive performance, achieving an accuracy of 92.785% in ripeness classification [18].

While both machine learning and deep learning methods have shown high classification accuracy using individual features such as shape, color, and texture, there remains a lack of integrated systems that combine multiple features to improve robustness and reliability. This limitation is particularly problematic for high-value varieties like Harumanis, where subtle distinctions are critical. Furthermore, many existing systems rely on powerful desktop-class computing hardware, making them costly and impractical for deployment by small-scale or conventional farmers. To address these challenges, this study proposes a vision-based mango grading system designed for implementation on an FPGA-based embedded board. This approach enables real-time processing in a cost-effective, compact, and energy-efficient platform, thereby making advanced grading technology more accessible to local farmers.

This paper is organized as follows. Section II describes the methodology of the proposed system. Section III presents and discusses the experimental results. Section IV concludes the study and outlines future work directions.

2. Methodology

Our proposed method is to develop a vision system for mango type recognition and grade determination using the NI myRIO platform. The proposed system follows a typical computer vision pipeline, which consists of data acquisition, image preprocessing, image analysis, and final classification. As illustrated in Figure 1, the process begins by introducing the object—Harumanis mangoes—into the system. During the image acquisition stage, images of the mangoes are captured using a camera.

Next, the acquired images undergo enhancement and filtering in the image preprocessing stage. Unlike conventional training-based approaches, this system performs three parallel image processing tasks: shape analysis, texture defect detection, and weight estimation. These analyses are carried out concurrently to generate the necessary data for final classification. In the final grading classification stage, the results from all three components are combined to classify each Harumanis mango into the appropriate grade.

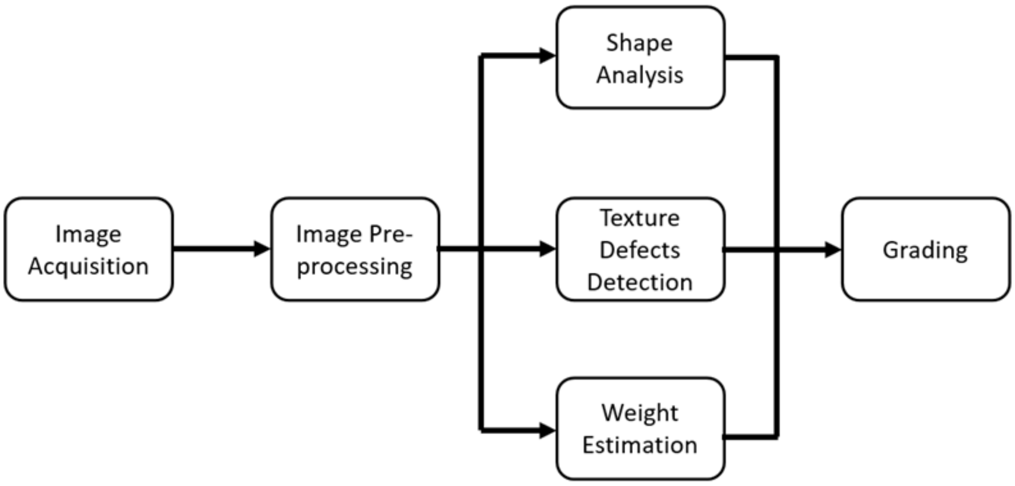

Fig. 1. System overview block diagram

The entire system is implemented on the NI myRIO-1900 controller. National Instruments myRIO is a versatile embedded platform equipped with a Xilinx Zynq system-on-a-chip (SoC), which integrates a dual-core ARM Cortex-A9 processor and an FPGA [19]. The device runs within the LabVIEW environment, offering a combination of hardware-level flexibility and user-friendly software control. NI myRIO was used across all stages of the system, including acquisition, processing, and classification [20]. Figure 2 shows the NI myRIO-1900 controller used in this setup.

Fig. 2. NI myRIO-1900 controller

2.1 Image Acquisition Setup

Image acquisition is the first step in the system where the mango image is being captured. The primary components of the system are webcam, square box, and LED strip lightning. The webcam is mounted on top of the box. The camera is positioned 35 cm from the bottom of the box, pointing downward. The mango is placed at the center of the box. To provide uniform illumination, LED strips are attached to the four walls of the box. The camera will capture top-down images at a resolution of 1280 x 720 resolution. Figure 3 shows the image acquisition setup which includes the internal looks and side looks.

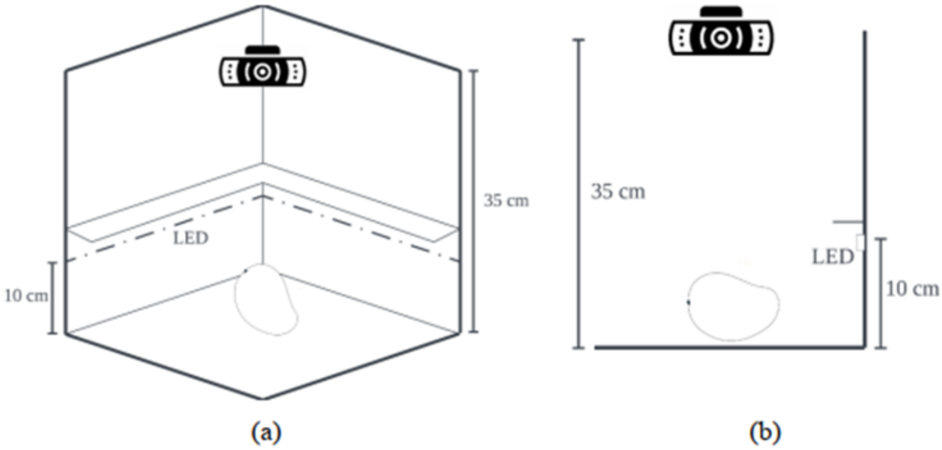

Fig. 3. Image acquisition setup (a) Internal view (b) Side View

The sample captured images are shown in Figure 4 below. As the sample from this setup is limited. We used image dataset sourced from Harumanis-Mango-294 Image Dataset. This approach allows for a diverse range of mango images to be used for training which helps to refine the analysis process and algorithms. Figure 5 shows the Harumanis dataset.

Fig. 4. Harumanis mango sample

Fig. 5. Harumanis-Mango-294 image dataset

2.2 Image Preprocessing

Image pre-processing is a crucial stage in the system. This stage involves several image enhancement operations, including grayscale conversion, binary thresholding using Otsu Method [21], and morphological filtering. These operations are designed to isolate the mango object and eliminate background noise, resulting in a clean binary image suitable for shape comparison. An example of the image transformation process is illustrated in Figure 6.

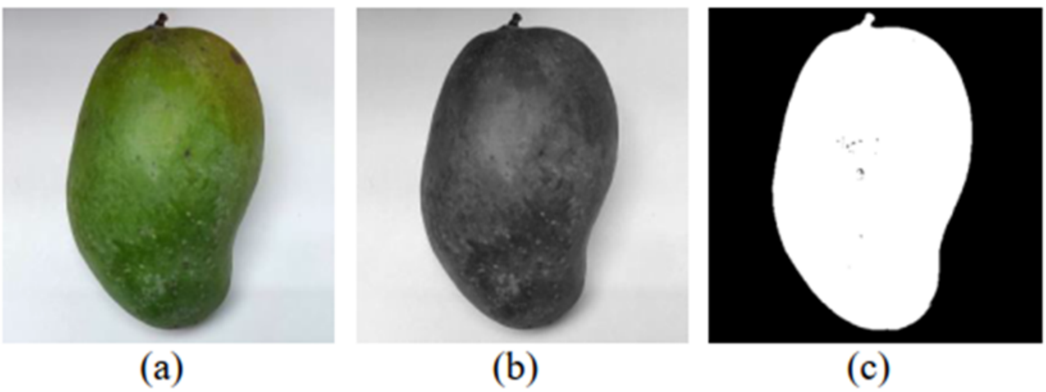

Fig. 6. Results of pre-processing (a) Original image (b) Grayscale (c) Binarize image

2.3 Shape and Contour Analysis

Shape analysis plays a key role in verifying the authenticity of Harumanis mangoes, as their unique geometry serves as a distinguishing characteristic. Shape Matching Function was used for this. A reference image of an ideal Harumanis mango is prepared and used in the Shape Matching function provided by LabVIEW's NI Vision Assistant. This binary template represents the standard morphology of a genuine Harumanis mango. Each input mango image is compared to this template, and a similarity score is calculated, where a score of 1000 denotes a perfect match. Lower scores indicate greater deviation from the reference. The reference image and its corresponding binarized templates—both full mango and tail section—are shown in Figure 6. Examples of matching results with different similarity scores are illustrated in Figure 7.

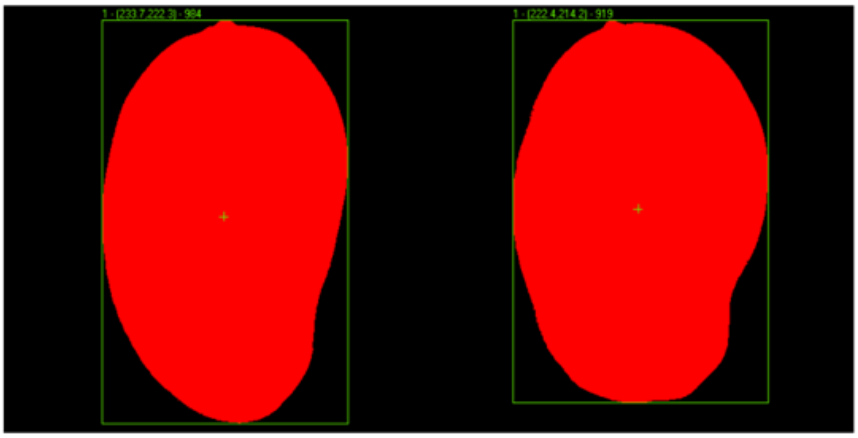

Fig. 7. Shape matching result of scores 984 and 919

To further improve classification accuracy, the system implements a second-level analysis based on tail contour matching. This is necessary because certain non-Harumanis mangoes may exhibit similar general outlines but lack the distinctive tail curvature characteristic of Harumanis. The tail region is cropped using a fixed region of interest (290 × 180 pixels) positioned at the bottom-right of the mango image. This section is matched against a tail-specific reference template to verify authenticity. Figure 8 shows the tail region mask used for this matching process.

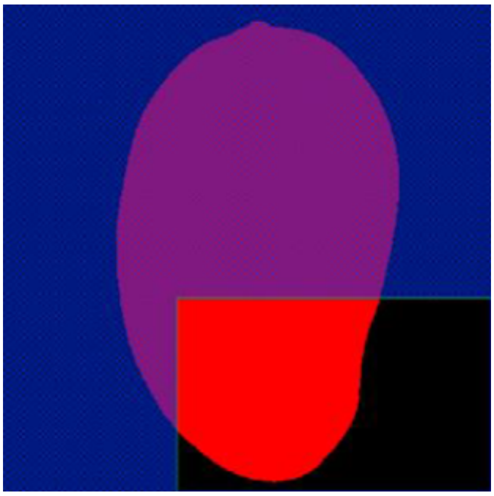

Fig. 6. Results of pre-processing (a) original image (b) grayscale (c) Binarize image

Threshold values for classification were empirically derived through testing on a dataset comprising 18 Harumanis mangoes and 10 samples from each of eight other mango varieties. The resulting shape similarity distributions, as shown in Figure 8 demonstrate that general shape matching alone is insufficient for distinguishing Harumanis from similar-looking varieties. Tail contour analysis provides additional discriminatory power.

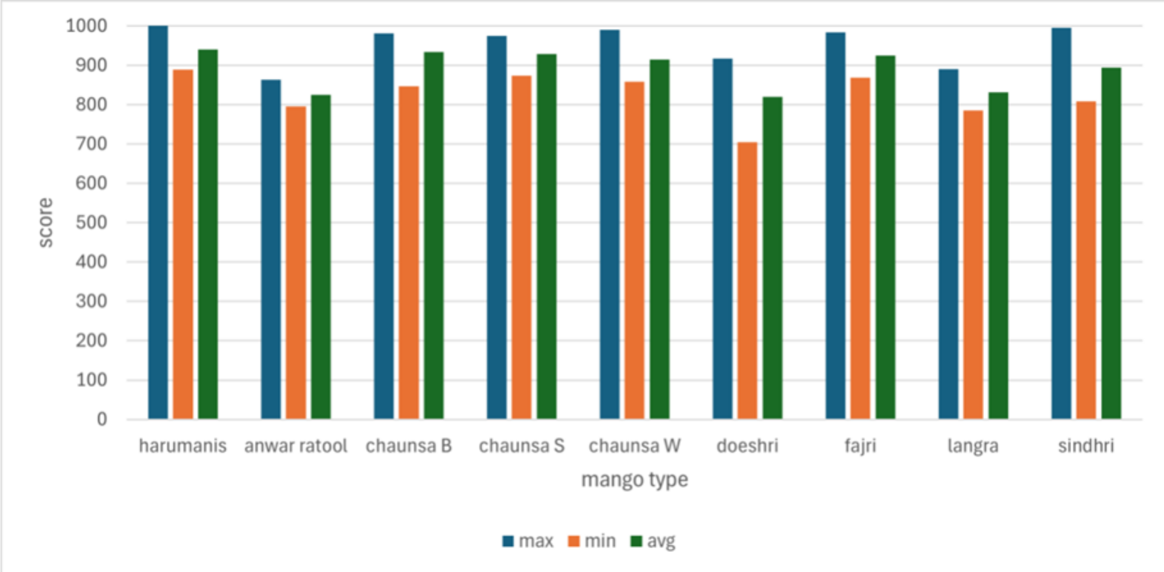

Fig. 6. Results of pre-processing (a) original image (b) grayscale (c) Binarize image

Based on this evaluation, the following score thresholds were adopted:

i. General shape matching score ≥ 866
ii. Tail contour matching score ≥ 928

This dual-level shape verification framework ensures robust identification of genuine Harumanis mangoes, reducing the risk of misclassification due to shape overlap with other varieties.

2.4 Texture Defect Detection

In addition to shape analysis, texture defect detection is employed to access the surface quality of Harumanis mangoes. The proposed system focuses on identifying three main types of visible defects whichh are the black stains, brown stains and bruises. These surface imperfections can affects the fruit grade and market value.

Two separate image processing scripts were developed for this task. One tailored for detecting black staind and the other for identifying brown stains and bruises. For black stain detection, the process begins wih extraction of green color plane from the pre-processed mango images. The green color plane was used to enhance the visibility of the dark region. A lookup table is applied to supress the brighter areas which allow black stain to become distinct. The result image is thersholded into binary format and used in the morphological operations of remove small objects and fill hole. Thisnoperations will refine the segmentation, which result the final output with only black stained regions. The black stain regions are quantified using particle analysis to determine their area coverage. Figure 7 shows the black stain region detection process.

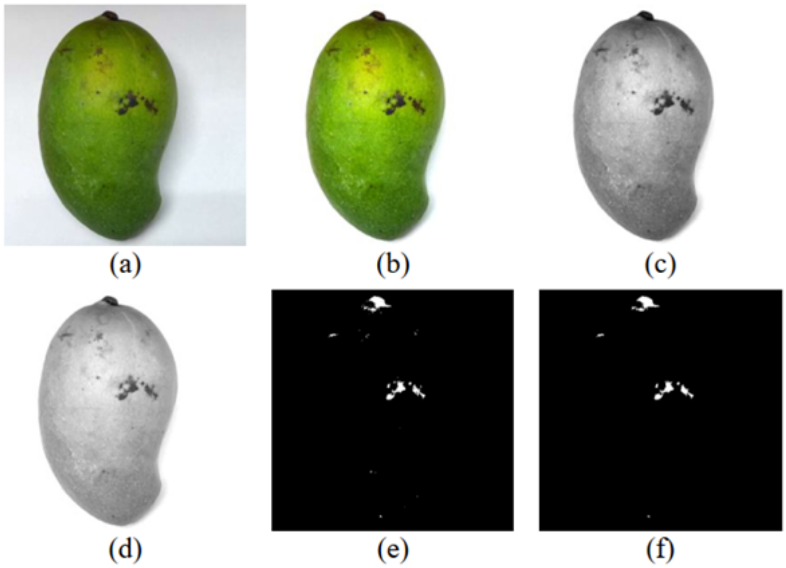

Fig. 7. Black statin processing (a) original image (b) pre-process image (c) Green plan extracted image (d) Lookup table (e) Thresholding (f) Morphological operations

For brown stains and bruises, the detection pipeline used a different color psace. Instead of grayscale and green channel analysis, Hue-Saturation-Lightness (HSL) color thresholding is applied directly to highlight brown and bruised regions. Following thresholding, the same morphological refinedment steps are conducted. The isolated regions are then anlayzed to calulate the total defect area. Figure 8 shows the brown stain and bruise detection process.

Fig. 8. Black statin processing (a) original image (b) pre-process image (c) Green plan extracted image (d) Lookup table (e) Thresholding (f) Morphological operations

The percentage of defect coverage is computed by comparing the defect area to the total segmented mango area. This ratio is used in the grading classification stage. The defect area is subtracted from the full mango mask, creating holes where defects exist. This facilitates the calculation of the defect coverage ration using the formula below (Eq. (1)):

$$Defect\ Coverage = 1 - \frac{Area\ if\ defect\ free\ mango}{Total\ mango\ area} \tag{1}$$

This metric provides a quantifiable and consistent assessment of surface quality, replacing subjective visual inspection. By accurately detecting and measuring surface defects, the system supports reliable quality classification aligned with commercial grading standards.

2.5 Weight Estimation

To complete the mango grading process, the proposed system incorporates a weight estimation module that approximates the mass of each Harumanis mango based on its shape dimensions. Unlike direct physical weighing, this non-destructive approach estimates weight using image-derived features, which supports automation and reduces reliance on manual handling.

The method begins by utilizing the binary shape generated during the earlier shape analysis stage. A bounding rectangle is fitted around the segmented mango object, and the width (W) and height (H) of this rectangle are extracted through particle analysis. These values are then used to approximate the mango's volume by modelling it as a vertical cylinder. The cylinder approximation formula is expressed as Eq. (2):

$$V = \pi(\frac{W}{2})^2 H \tag{2}$$

where V is the estimated volume of the mango in arbitrary units. An example of the bounding rectangle and its application for dimension extraction is shown in Figure 9.

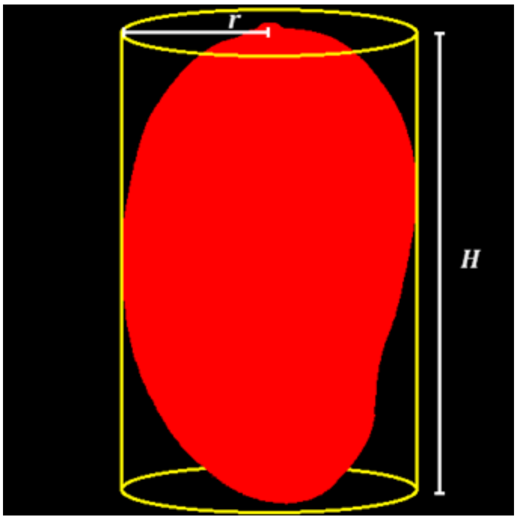

Fig. 9. Bounding rectangle of a Harumanis

Once the volume is estimated, the weight of the mango is calculated using a linear regression equation, derived from a correlation between estimated volume and actual weight is used for this purpose. The weight estimation is expressed as Eq. (4):

$$V = 2.256w - 157.7 \tag{3}$$

The equation is rearranged to solve the weight.

$$w = \frac{V + 157.7}{2.256} \tag{4}$$

After obtaining the initial weight estimate, a corrective linear equation is applied to fine-tune the results, ensuring higher accuracy. The formula is shown in Eq. (5).

$$w_{final} = 0.9112w - 56.867 \tag{5}$$

The high estimation accuracy and simplicity of the cylinder approximation approach make it suitable for real-time implementation within embedded systems. This estimation is used as one of the grading criteria, together with shape and texture defect results, in the final classification of mango quality.

2.6 Grading Mechanism

The final stage of the system integrates the outputs from shape analysis, texture defect detection, and weight estimation modules to classify Harumanis mangoes into predefined commercial grades. The grading criteria are based on the official standards set by the Perlis Department of Agriculture, which classify mangoes according to weight and the percentage of surface defect coverage.

The system uses a rule-based decision mechanism where the input mango must first meet the shape verification thresholds to be classified as a genuine Harumanis mango. Specifically, the mango must achieve a general shape matching score of at least 866 and a tail contour matching score of at least 928. Mangoes that fail to meet either threshold are rejected as non-Harumanis.

For those that pass the shape verification, the grading is determined by two parameters: estimated weight and texture defect coverage. Table 1 defines the thresholds used for classification:

Table 1
Grading requirements for Harumanis Perlis

Grade	Weight	Texture defect coverage
A	≥ 400g	< 5%
B	351g – 399g	< 10%
C	≤ 350g	< 15%
Rejected	N/A	> 15%

To calculate defect coverage, the defect area identified during the texture analysis is subtracted from the total mango area. The resulting ratio is used to evaluate the extent of surface damage, as shown in Figure 10. The calculation is performed using the Eq. (1).

Fig. 10. Subtracting defects from mango (a) Original image (b) Pre-processed image (c) Defects detected (d) Binarized mango with defects as holes

Only mangoes that satisfy both the weight and defect requirements for a given grade are assigned to that category. If the defect coverage exceeds 15%, the mango is rejected regardless of its weight.

This multi-criteria classification approach ensures that each mango is assessed holistically, accounting for authenticity, surface condition, and estimated mass. By embedding the grading logic into the system, the process eliminates subjective human judgment and enables consistent, real-time classification suitable for deployment in practical post-harvest environments.

3. Results and Discussion

To validate the effectiveness of the proposed vision-based grading system, a real-world test was conducted using a set of Harumanis mango samples. The system was evaluated under controlled indoor conditions using the image acquisition setup described in Section 2.1. A total of 8 mangoes were used in the test—5 were genuine Harumanis, and 3 were from other varieties. Figure 11 shows the captured Harumanis using the proposed image acquisition setup. Each mango was captured from two different orientations (flipped side), resulting in a total of 16 image samples.

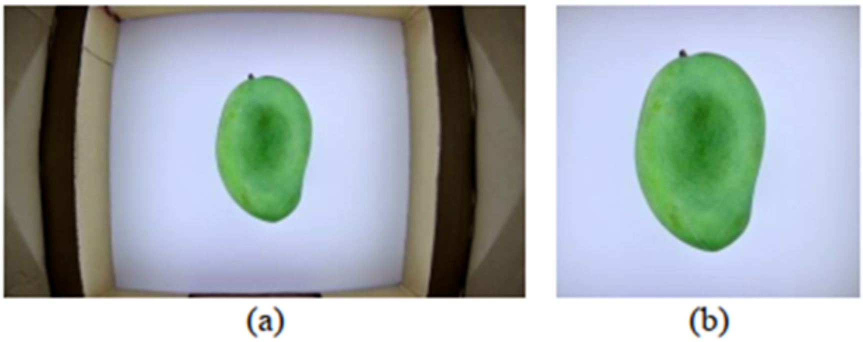

Fig. 11. Harumanis captured with proposed image acquisition setup (a) Raw image (b) Image cropped into ROI

3.1 Shape and Tail Recognition

The shape analysis module was used to classify each mango based on its general shape and tail contour. The initial threshold values—set at 866 for general shape and 928 for tail matching—were refined based on actual test results. Among the 10 genuine Harumanis samples (5 mangoes × 2 sides), the minimum observed shape score was 866.79, and the minimum tail contour score was 928.12. These values confirm the validity of the threshold settings used in the system.

Of the 6 samples representing non-Harumanis mangoes, 5 were correctly rejected by the system based on shape analysis. The one misclassified sample scored 996 in general shape and 962 in tail contour, which exceeded the rejection thresholds. However, upon visual inspection, the mango clearly differed in appearance from a genuine Harumanis as illustrated in Figure 12. This highlights a limitation of template-based shape matching, particularly in handling orientation and placement variability.

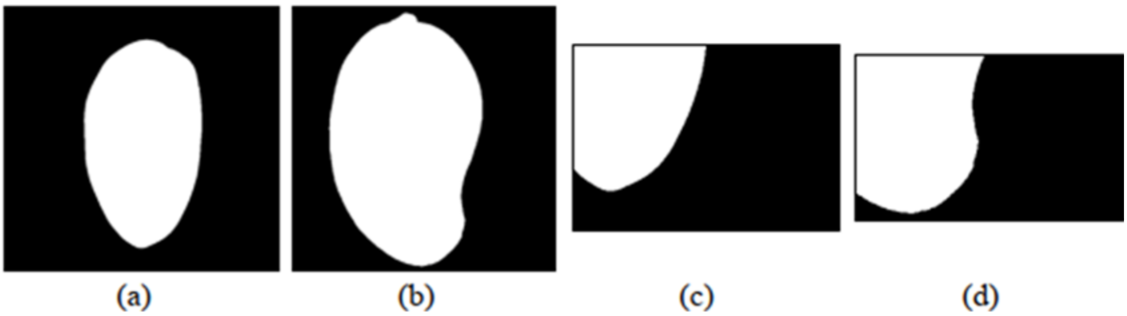

Fig. 12. Comparison between failed sample and template (a) General shape of failed sample (b) General shape template (c) Tail of failed sample (d) Tail template

Efforts to improve tail detection by enlarging the Region of Interest (ROI) showed that overly broad tail regions reduced specificity. For example, an oval object captured in the lower half of an image scored 968 despite not having the characteristic Harumanis tail structure. This is shown in Figure 13. These findings suggest that while shape matching is effective, its reliability is influenced by object positioning and template region precision.

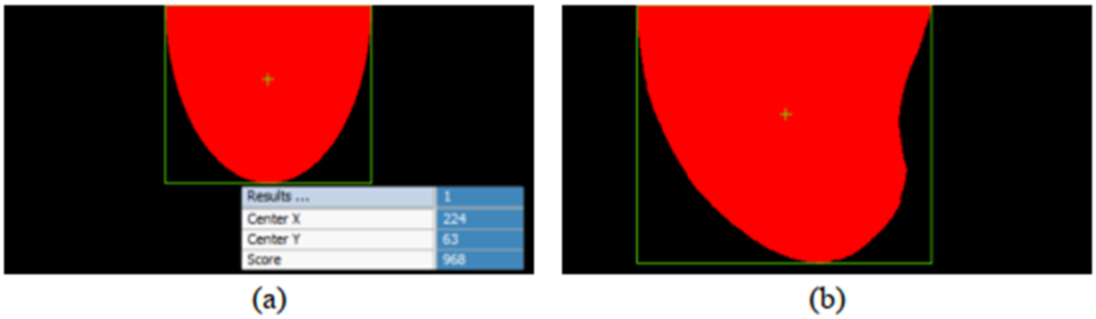

Fig. 13. Tail matching of an oval object scored 968. (a) Bottom half of oval object (b) Bottom half of template Harumanis Perlis

3.2 Texture Defect Detection Results

The texture analysis module performed consistently well across all 16 test samples. The system correctly identified mangoes with less than 5% surface defects as Grade A, and others with defect coverages in the 5%–15% range as Grade B or C, according to the standards. No false positives or negatives were observed in this component. The binary mask subtraction and particle analysis provided a robust method for calculating defect area coverage.

3.3 Weight Estimation Results

Weight estimation was evaluated by comparing the estimated weights via cylinder approximation and corrected regression with actual measured weights. The uncorrected regression model produced significant estimation errors. To address this, a corrective linear regression model was derived based on test data. This equation is shown in Eq.(5).

Application of this model led to a dramatic reduction in error. The Mean Absolute Error (MAE) dropped from 95.05g to 15.34g, reflecting an 83.86% improvement in estimation accuracy. Table 2 shows the metrics before and after weight estimation correction, while Table 3 shows MAE value before and after the correction.

Table 2
Metrics before and after weight estimation correction

Metric	Before correction	After correction
Linear relationship	$y = 9122x - 56.867$	$y = x - 0.0025$
Mean absolute error	95.046	15.34
R^2	95.37%	95.37%

Table 3
MAE value before and after the correction

Actual weight	Pre-correction	Error	Post correction	Error
203	312.35	109.35	228.06	25.06
203	318.86	115.86	234.00	31.00
304	362.72	58.72	274.01	29.99
304	370.13	66.13	280.77	23.23
340	422.03	82.03	328.11	11.89
340	423.02	83.02	329.01	10.99
468	481.67	124.06	483.21	15.21
468	487.48	108.14	468.69	0.69
383	592.06	98.67	382.51	0.49
383	576.14	104.48	387.81	4.81
MAE		95.046		15.46

The coefficient of determination remained high at $R^2 = 0.9537$, indicating strong correlation before and after correction. Figure 14 and 15 shows the correlation before and after the correction. The weight estimation remained stable across different viewing angles of the same fruit, demonstrating the system's consistency in practical scenarios.

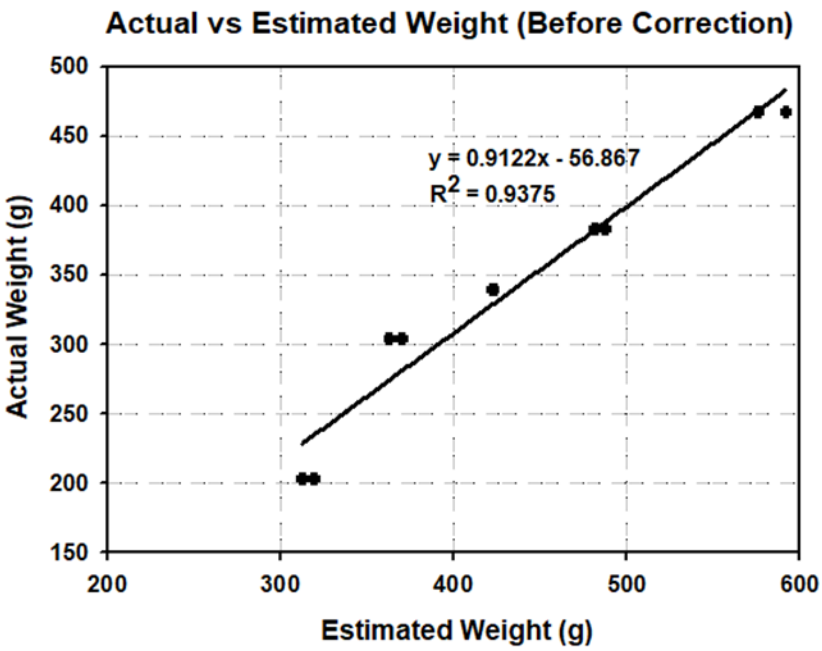

Fig. 14. Scatter plot for weight estimation before correction

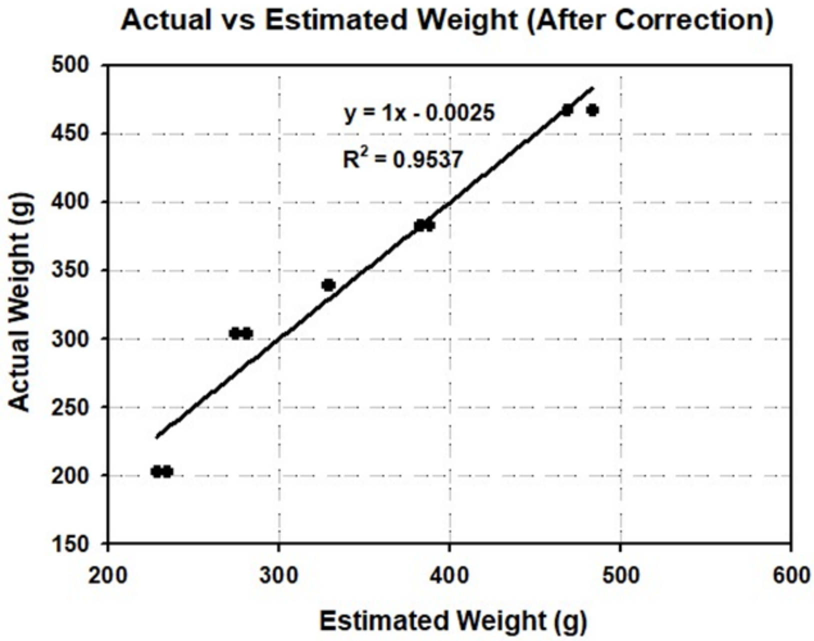

Fig. 15. Scatter plot of weight estimation after correction

3.4 Overall Classification Accuracy

Combining the results of shape, defect, and weight analysis, the system achieved an overall classification accuracy of 93.75%, correctly grading 15 out of 16 mango samples. The single misclassification stemmed from a false positive in shape recognition, indicating that further refinement of the tail contour algorithm or integration with learning-based shape classification could improve system reliability.

3.5 LabVIEW Front Display

To facilitate user interaction and system monitoring, a front panel interface was developed using LabVIEW. The interface provides real-time feedback throughout the grading process, from image acquisition to final classification. It displays the captured mango image, shape matching scores, weight estimation, and the calculated defect coverage percentage.

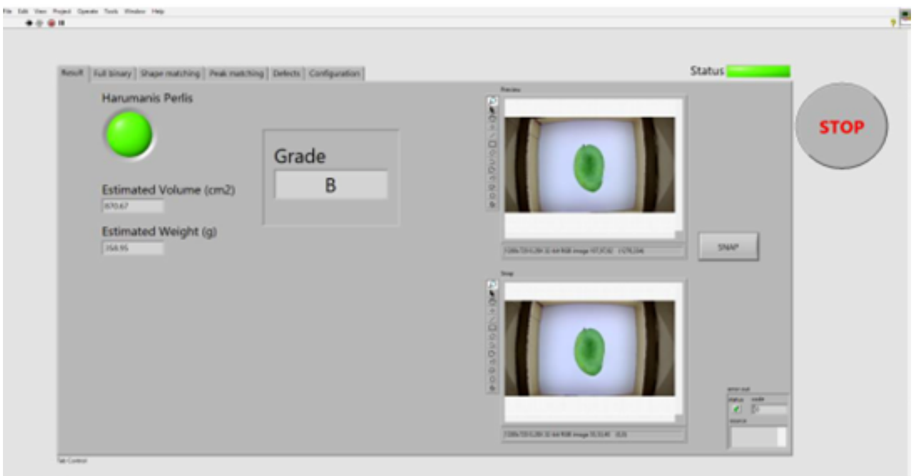

Fig. 16. LabVIEW front panel layout

The panel also includes visual indicators for each classification stage, showing whether the mango meets the predefined thresholds for shape, defect tolerance, and weight. Based on these combined criteria, the final grade—A, B, C, or Rejected—is displayed prominently on the interface, allowing for immediate decision-making by the operator.

This graphical interface enhances the usability of the system by offering intuitive, at-a-glance information while preserving the transparency of intermediate results. Figure 16 shows the front panel layout.

4. Conclusions

This study successfully developed and validated a vision-based system for the recognition and grading of Harumanis mangoes using the NI myRIO embedded platform. The system integrates three key modules—shape and contour analysis, texture defect detection, and weight estimation—into a unified framework for automated post-harvest mango classification.

The proposed shape analysis approach utilizes a dual-level matching mechanism based on both general fruit outline and tail contour, allowing for reliable identification of genuine Harumanis mangoes. Texture defects, including black stains, brown spots, and bruises, are accurately segmented using color plane extraction and morphological filtering techniques. Weight estimation is performed using a non-destructive volume approximation method, with a corrective regression model applied to significantly reduce error.

The system achieved a high classification accuracy of 93.75% across 16 mango samples, with a mean absolute error of 15.34g in weight estimation and an R^2 value of 0.9537, demonstrating strong correlation with ground truth values. Texture classification was consistently accurate across all test cases, and shape analysis proved effective, albeit with some limitations when encountering look-alike mango varieties.

This work demonstrates the feasibility of deploying intelligent grading systems on low-cost embedded platforms such as NI myRIO. The use of modular LabVIEW components further supports system scalability and hardware-software integration. While the current system relies on template matching and rule-based classification, future work can explore integrating learning-based models such as convolutional neural networks (CNNs) or Vision Transformers for more robust shape analysis and adaptive decision-making. Expansion of the training dataset and the inclusion of real-time conveyor-based testing would also strengthen the system's readiness for field deployment.

Ultimately, the proposed system offers a practical, accessible, and scalable solution for non-destructive mango grading, with significant potential for application in small- to medium-scale agricultural operations.

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