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https://doi.org/10.5109/7395502

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 11, pp.87-92, 2025-10-30. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

A Vision-Based Approach for Mango Size Classification Using Fuzzy Logic

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Abstract: *Mango (Mangifera indica L.), the national fruit of the Philippines, ranks as the country's third most-produced fruit crop. Despite its economic importance, post-harvest processes such as size classification are still largely manual, resulting in inconsistent grading and inefficiencies. This study proposes a vision-based classification system combining image processing and fuzzy logic to provide a practical, low-cost alternative to traditional methods. Fruit images are captured under controlled lighting, processed to extract maximum length and width, and then classified using fuzzy logic based on the Philippine National Standards (PNS) for mango size. Experimental results yielded a classification accuracy of 90%, highlighting the effectiveness of the approach. The proposed system is simple, cost-efficient, and well-suited as a preliminary step toward the mechanization of mango grading in the Philippines. Furthermore, the method can be adapted for the classification of other crops with minimal modifications.*

Keywords: Mango Classification; Fuzzy Logic; Image Processing; Computer Vision; Post-harvest Operation

1. INTRODUCTION

Mango cultivation remains a key pillar of the Philippine agricultural economy, with the Carabao variety widely recognized for its exceptional sweetness and high export value. In the first half of 2023, national mango production was recorded at approximately 596.34 thousand metric tons, reflecting the crop's sustained importance. The Carabao mango accounted for 83.0% of this total, contributing 495.06 thousand metric tons. During the same period, mango cultivation spanned 184.03 thousand hectares, with Carabao mangoes occupying 144.11 thousand hectares [1]. In addition to its contributions to export revenue and agri-tourism, the mango industry provides critical support to rural livelihoods across the country. However, the sector continues to face persistent challenges in post-harvest operation, particularly in the sorting, grading, and quality assessment of mango fruits.

One key aspect of post-harvest quality control is fruit size classification, which directly impacts packaging, pricing, and marketability. Traditionally, this task is performed manually by trained laborers using visual estimation or weighing. While straightforward, manual grading is time-consuming, inconsistent, and susceptible to human error [2]. The lack of standardization can lead to product rejection, reduced consumer trust, and inefficiencies in the supply chain.

Recent technological advancements have enabled the use of computer vision and intelligent systems in agriculture and fisheries [3], [4], [5], [6], [7]. Image processing allows for non-destructive evaluation of fruit size and quality [8], [9], while fuzzy logic offers a robust framework for managing uncertainties inherent in agricultural product characteristics [10], [11]. Numerous studies have explored vision-based classification systems and fuzzy logic for fruits such as apples, bananas, tomatoes, and mangoes, employing features like color, texture, and shape [12], [13], [14], [15]. However, few systems align with national classification standards or are optimized for the practical realities of developing countries.

This study aims to bridge that gap by developing a simple yet effective mango size classification system using image processing and fuzzy logic. The system is tailored to classify mangoes into six categories: Too Small, Super Small, Small, Medium, Large, and Extra Large—based on the Philippine National Standards (PNS) [16]. The objectives are to (1) estimate mango size using geometric features extracted from images, and (2) evaluate the classification accuracy against weight-based ground truth values. The approach offers a scalable solution to improve quality assurance in mango grading and can be extended to other fruits with minimal adjustments.

2. MATERIALS AND METHODS

2.1 Training sample collection and ground truth labeling

A total of 200 green Carabao mangoes were randomly collected from various fruit stands across Guimaras Island, Philippines—a province internationally recognized for producing the world's sweetest Carabao mangoes. Each fruit was individually weighed using a calibrated triple beam balance to ensure precise measurement.

The mangoes were classified into size categories in accordance with the Philippine National Standards for Fresh Fruits – Mangoes (PNS/BAFPS 13:2004). Fruits with weights below the minimum threshold for the Super Small category were grouped into an additional class labeled "Too Small." The complete weight-based classification criteria are shown in Table 1.

The final distribution of samples across the size categories was as follows: 30 Too Small, 32 Super Small, 34 Small, 35 Medium, 39 Large, and 30 Extra Large.

Table 1. Size classification of 'Carabao' mangoes

Size	Weight (g)
Extra Large	>350
Large	300 – 349
Medium	250 – 299
Small	200 – 249
Super Small	160 – 199

2.2 Image acquisition system

To ensure the accurate extraction of geometric features, a controlled image acquisition setup was designed, as illustrated in Figure 1. An 8-megapixel webcam was mounted 40 cm above a white acrylic imaging platform and oriented vertically to consistently capture top-view images of centrally positioned mangoes, regardless of their natural orientation.

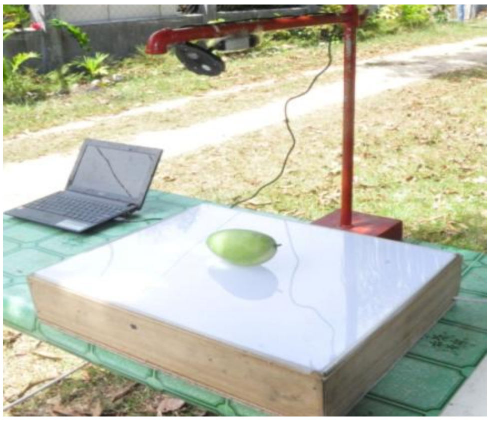

Fig. 1. Image acquisition set-up.

Images were captured at a resolution of 320 × 240 pixels in RGB bitmap format, balancing sufficient detail for dimensional analysis with low computational overhead for image processing. To ensure uniform illumination and minimize shadows and background noise, the setup employed six 20-watt fluorescent tubes arranged symmetrically around the imaging platform. A white acrylic sheet functioned as both the base and a light diffuser, providing consistent and homogeneous lighting conditions.

This imaging environment enabled consistent image quality and high-contrast segmentation between the mango and background that is an essential prerequisite for accurate preprocessing and feature extraction.

2.3 Image acquisition system

Image preprocessing and feature extraction were implemented using Visual C++. To support consistent segmentation, mango samples were photographed against a uniform white background.

The RGB images were first converted to grayscale, then binarized to segment the mango fruit from the background. To enhance boundary extraction and eliminate noise, morphological erosion was applied. The resulting clean, high-contrast binary image was used to extract two key geometric features: the maximum length (L_{max}) and maximum width (W_{max}) of the mango. The complete image processing workflow is summarized in Figure 2.

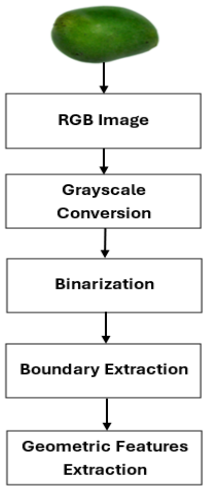

Fig. 2. Workflow for image processing.

2.3.1 Grayscale conversion and binarization

Each captured image, initially in RGB format, was converted to grayscale to reduce computational complexity while preserving essential shape and intensity features. Grayscale values range from black (0) to white (255).

Following this, image binarization was performed using a selected thresholding technique. Pixels with intensity values above the threshold were assigned a value of 1 (white/foreground), while those below were set to 0 (black/background). This conversion produced a binary image in which the mango was clearly segmented from the background.

2.3.2 Boundary extraction

After binarization, a morphological operation, particularly erosion, was applied to refine the fruit's boundary and suppress small-scale noise.

The erosion of a binary image A by a structuring element B is mathematically defined as:

$$A \ominus B = \text{Minimum}\,(A(x-i, y-j) \times B(i,j)) \tag{1}$$

This operation removes boundary pixels depending on the size and shape of B, reducing image noise while preserving the shape of the main object.

The precise boundary was extracted by subtracting the eroded image from the original binary image:

$$C = A - (A \ominus B) \tag{2}$$

This yielded a noise-free, two-pixel-thick boundary image suitable for accurate feature extraction.

2.3.3 Geometric features extraction

From the refined boundary image of each mango sample, two essential geometric features were extracted: maximum length (L_{max}) and maximum width (W_{max}).

Maximum Length (L_{max})

L_{max} was defined as the longest straight-line distance through the centroid that connects two opposing points on the mango's boundary. This was estimated by fitting a line of best fit using the Least Squares Method.

The centroid (X_c, Y_c) of the fruit was computed using:

$$X_c = \sum_{l=1}^{n} \frac{Xi}{n}, Y_c = \sum_{k=1}^{n} \frac{Yi}{n} \tag{3}$$

where n is the total number of boundary pixels, and (X_i, Y_i) are their coordinates.

Using these coordinates, the slope m_1 of the line of best fit was computed as:

$$m_1 = \frac{n\sum xy - \sum x \sum y}{n\sum x^2 - (\sum x)^2} \tag{4}$$

The y-intercept b of the line is calculated by:

$$b = \frac{\sum y}{n} - m_1 \frac{\sum x}{n} \tag{5}$$

The Euclidean length of this line, representing L_{max}, was then computed as:

$$L_{max} = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2} \tag{6}$$

Maximum Width (W_{max})

W_{max} is defined as the longest line segment that is perpendicular to the L_{max} and also passes through the centroid. The slope m_2 of the perpendicular line was determined using:

$$m_2 = \frac{-1}{m_1} \tag{7}$$

The length of this perpendicular line segment, W_{max}, was similarly calculated from the projected intersection points on the mango boundary.

A visual representation of these geometric features is shown in Figure 3, illustrating how L_{max} and W_{max} are derived from the mango's boundary.

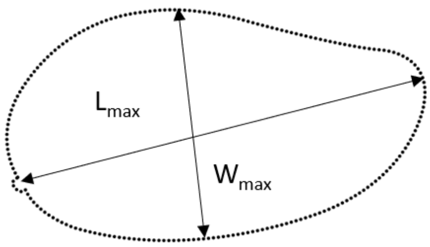

Fig. 3. Maximum length (L_{max}) and width (W_{max}) extracted from mango boundary.

2.4 Fuzzy logic classification model

The Fuzzy Logic System (FLS) in this study was designed to classify mangoes into six size categories: Too Small, Super Small, Small, Medium, Large, and Extra Large based on the L_{max} and W_{max} of the fruit. Classification followed the Philippine National Standards (PNS) for fresh mangoes.

The fuzzy logic process comprised the following key stages: fuzzification, inference, rule aggregation, and defuzzification [17], [18], as illustrated in Figure 4.

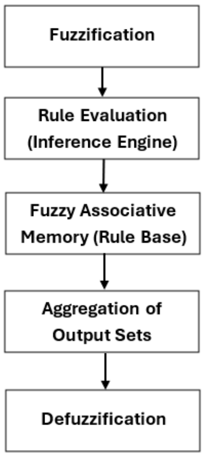

Fig. 4. Fuzzy logic process.

2.4.1 Fuzzification

Fuzzification involves converting crisp numerical inputs into fuzzy linguistic values using membership functions. In this study, both L_{max} and W_{max} were fuzzified into six linguistic terms: Too Small, Super Small, Small, Medium, Large, and Extra Large.

Trapezoidal membership functions were used for their simplicity and ability to handle overlapping input ranges effectively. Membership functions were constructed using the observed distribution of feature values derived from the 200 training samples. The shapes of these functions for L_{max} and W_{max} are illustrated in Figures 5 and 6, respectively.

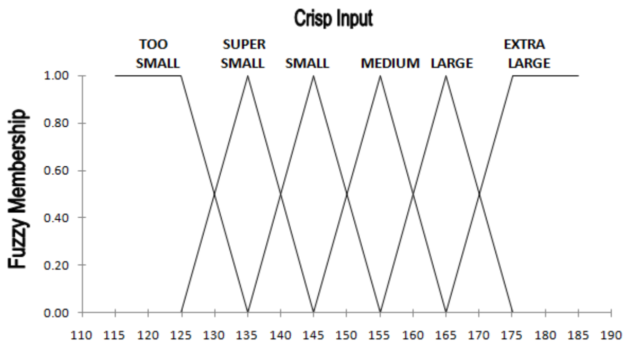

Fig. 5. Membership functions for L_{max} input.

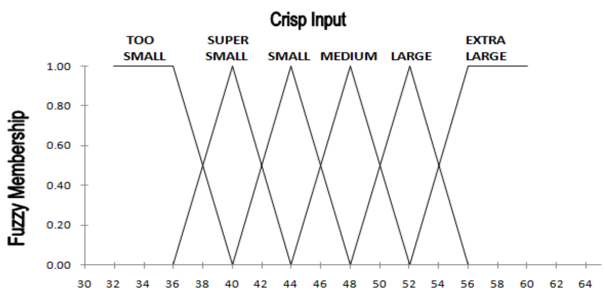

Fig. 6. Membership functions for W_{max} input.

2.4.2 Inference engine and rule base

The inference engine applies a set of fuzzy IF–THEN rules to determine how the input values relate to the output size category. A typical rule takes the form:

IF L_{max} is Medium AND W_{max} is Small, THEN Size is Small.

A total of 36 rules were developed based on the observed data on the training samples, forming the Fuzzy Associative Memory (FAM). These rules define how combinations of length and width correspond to specific mango size categories. The complete rule matrix is presented in Table 2.

Table 2. Fuzzy rules for 'Carabao' mango size classification

L_{max}/W_{max}	Too Small	Super Small	Small	Medium	Large	Extra Large
Too Small	Too Small	Too Small	Too Small	Small	Small	Medium
Super Small	Too Small	Super Small	Small	Small	Small	Medium
Small	Too Small	Super Small	Small	Small	Medium	Medium
Medium	Super Small	Small	Medium	Medium	Medium	Large
Large	Small	Medium	Medium	Large	Large	Extra Large
Extra Large	Medium	Medium	Medium	Large	Extra Large	Extra Large

2.4.3 Aggregation and defuzzification

After all applicable rules are fired, the output fuzzy sets are aggregated into a single fuzzy set using the maximum operator. To obtain a final crisp classification, defuzzification was performed using the centroid method, which calculates the center of gravity of the aggregated output fuzzy set. This method provided a balanced and representative value, especially in overlapping output regions [17].

3. RESULTS AND DISCUSSION

To evaluate the performance of the proposed vision-based approach for mango size classification system using fuzzy logic, a new set of 72 green Carabao mangoes was collected and used as test samples. Each fruit was individually weighed and categorized according to the Philippine National Standards (PNS) for fresh mangoes.

3.1 Classification performance

Table 3 presents the confusion matrix comparing the predictions of the proposed system with weight-based ground truth classifications. The diagonal entries represent correctly classified samples, while off-diagonal entries indicate misclassifications. The system achieved an overall accuracy of 90%, demonstrating its effectiveness in classifying mangoes into the correct size categories. The highest accuracy was observed for the Extra-Large category (100%), followed by Large (93%) and Super Small (92%). Lower accuracies in the Small (83%) and Medium (85%) categories are likely due to sample proximity to classification boundaries.

Accuracy assessment was performed by comparing the predicted size classifications with the ground truth labels based on actual mango weights. The overall accuracy was calculated as the ratio of correctly classified samples to the total number of test samples [19].

Table 3. Confusion matrix comparing fuzzy logic predictions vs. ground truth (weight-based)

Ground Truth ¥ Prediction	Too Small	Super Small	Small	Medium	Large	Extra Large	**Total Samples**	**Accuracy %**
Too Small	9	1	0	0	0	0	10	90
Super Small	1	11	0	0	0	0	12	92
Small	0	2	10	0	0	0	12	83
Medium	0	0	1	11	1	0	13	85
Large	0	0	0	1	14	0	15	93
Extra Large	0	0	0	0	0	10	10	100
Total	10	14	11	12	15	10	72	**90**

Table 4 provides a summary of classification performance for each size category. The results confirm that the proposed system performs best in the extreme categories (Extra Large and Large), and moderately well in the mid-range sizes (Small and Medium), likely due to greater overlap in their dimensional features.

Table 4. Summary of classification accuracy by size category

	No. of Samples	Correct Predictions	Accuracy (%)
Too Small	10	9	90
Super Small	12	11	92
Small	12	10	83
Medium	13	11	85
Large	15	14	93
Extra Large	10	10	100
Total	72	65	**90**

The classification performance was further evaluated using the standard metrics of precision, recall, and F1-score, defined as follows:

$$Precision = \frac{TP}{(TP + FP)} \quad (8)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (9)$$

$$F1 - score = \frac{2 \times (Precision \times Recall)}{(Precision + Recall)} \quad (10)$$

Table 5 shows the precision, recall, and F1-score for each mango size category. These metrics confirmed that the classifier not only achieved high accuracy but also maintained a good balance between false positives and false negatives. Performance was especially strong in the Extra Large and Large categories, while Small and Medium sizes showed slightly reduced recall, indicating occasional under-classification.

Table 5. Precision, recall, and F1-score by size category

Size Category	Precision	Recall	F1-Score
Too Small	0.90	0.90	0.90
Super Small	0.85	0.92	0.88
Small	0.91	0.83	0.87
Medium	0.92	0.85	0.88
Large	0.93	0.93	0.93
Extra Large	1.00	1.00	1.00

3.2 Error analysis and system limitations

Misclassification was primarily observed in mangoes whose actual weights feel close to the thresholds between adjacent categories. These borderline cases are inherently ambiguous, even in manual grading systems. Another source of error was the presence of irregularly shaped mangoes, which may distort the measured dimensions derived from top-view images. As the system currently relies solely on 2D geometric features, complex fruit shapes and orientation variability may affect classification accuracy.

4. CONCLUSION AND FUTURE WORKS

This study presented a vision-based system for mango size classification using image processing and fuzzy logic. The system employed a specially constructed imaging setup with uniform illumination to produce consistent image quality for extracting two key geometric features: maximum length (L_{max}) and maximum width (W_{max}). These features served as inputs to a fuzzy logic classifier that categorized mangoes into size grades in accordance with the Philippine National Standards (PNS).

The fuzzy logic model was trained on 200 mango samples and validated on 72 new samples. It achieved an overall classification accuracy of 90%, showing high agreement with weight-based ground truth supported by strong precision, recall, and F1-scores, particularly in the Extra Large and Large classes. These results confirm the model's reliability and its potential as a decision support tool for automated post-harvest grading.

The key contribution of this work lies in its combination of low-cost imaging, simple image processing, and interpretable fuzzy logic, offering a scalable, adaptable, and accessible solution for fruit grading in developing agricultural economies like the Philippines. Unlike black-box machine learning models, the fuzzy logic approach allows for transparent decision-making and easier rule customization.

To further enhance the system's applicability, three future directions are proposed. First, optimizing membership functions and expanding the fuzzy rule base could improve performance, particularly in borderline cases. Second, the system can be enhanced by incorporating additional input features such as fruit color, surface texture, or volume estimation, which may improve classification accuracy, especially for borderline cases and irregularly shaped mangoes. Third, integrating the software with mechanical sorting hardware would complete the transition to a fully automated mango grading system. These advancements will enhance throughput, accuracy, and practical deployment in commercial settings and pave the way for application to other crops.

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