A Novel Mango Grading System Based on Image Processing and Machine Learning Methods

Thanh-Nghi Doan
Faculty of Information Technology,
An Giang University, An Giang, Vietnam
Vietnam National University, Ho Chi Minh City, Vietnam

Duc-Ngoc Le-Thi
Student of Faculty of Information Technology,
An Giang University, An Giang, Vietnam
Vietnam National University, Ho Chi Minh City, Vietnam

***Abstract*—Mangoes are a great commercial fruit and are widely cultivated in tropical areas. In smart agriculture, the automatic quality inspection and grading application is essential to post-harvest processing, due to the laborious nature and inconsistencies of traditional manual visual grading. This paper presents a low-cost, efficient, and effective mango grading system based on image processing and machine learning methods to generate higher quality fruit sorting, quality maintenance, production, and cut back labor concentration. A novel database of classified mangoes was collected and built in An Giang province. Methodologies and algorithms that utilize digital image processing, content-predicated analysis, and statistical analysis are implemented to determine the grade of local mango production. On our collected dataset, the proposed system achieved overall with an overall accuracy of 88% for all mango grades. The system shows compromised results for higher-quality fruit sorting, quality maintenance, and production while reducing labor concentration.**

***Keywords*—Smart agriculture; mango grading; image processing; machine learning methods**

I. Introduction

Mango production is a major industry worldwide, contributing significantly to the economy of many countries. Asia is the dominant continent in terms of mango production, making up approximately 76% of the global industry [18]. In many mango planting areas, the level of automation and efficiency of post-harvest processing is far from satisfactory in terms of accuracy and throughput: Although mango is a quick-rotten and short-lived fruit, its post-harvest processing is still carried out manually via visual inspection [14]. Mango farmers may face significant expenses if mangoes are not sorted promptly after harvest. When it comes to marketing mangoes, external quality features play a vital role in their grading. Size, shape, ripeness, and the presence of surface defects are commonly used standards for assessing mangoes [15]. To facilitate this grading process, computer vision techniques have emerged as the most widely employed approach in modern systems, particularly in quality inspection and grading. These techniques enable the creation of a machine vision system that not only mimics the human grading process but also significantly accelerates it. As a result, there is a growing demand for efficient and effective solutions that allow enterprises and farmers to leverage these new technologies. Over the past two decades, the field of agriculture has witnessed a shift from traditional human grading to automated grading for fruits. Many companies have adopted automated grading for various crops, including peaches and oranges [**?**]. Notably, a researcher has developed an image analysis-based system for grading apples. Their study involved training the system with numerous examples to enable it to become proficient in distinguishing fruit differences and creating a reliable reference dataset for the grading system [3]. To properly classify mangoes, it is important to be familiar with the mango grading standards. While color and size are significant criteria for fruit sorting, there is another crucial factor for sorting mangoes: the texture of their skin. Incorporating skin texture into the classification system can enhance the accuracy of sorting. Therefore, this study focuses on the processing and analysis of images to automate the grading and sorting process, which represents a crucial phase within the productive mango supply chain system.

II. Related Works

Grading and sorting fruits is a crucial stage in the agro-processing industry. Manual sorting of fruits is time-consuming, laborious, and prone to human error. Therefore, grading and sorting of fruits using image processing or computer vision techniques have gained significant attention in recent years. Various research studies have been conducted to develop automated systems for the grading and sorting of fruits. Regarding fruit grading and quality evaluation, the authors in [5] reviewed the basic process flow of fruit classification and grading. Feature extraction methods for color, size, shape, and texture are discussed with feature extraction algorithms used in computer vision and image processing such as Speeded Up Robust Features (SURF), Histogram of Oriented Gradient (HOG), and Local Binary Pattern (LBP). Additionally, this research briefly touches upon some popular machine learning algorithms like k-Nearest Neighbors (k-NN), Support vector machines (SVM), Artificial neural networks (ANN), and Convolutional neural networks (CNN). By presenting a theoretical foundation for the identification, classification, and grading of horticultural products, this study aims to facilitate the practical application of these methods in a real-world setting. The authors in [16] proposed an image processing algorithm combined with machine learning to detect and identify defects on the surface of mango skin. The algorithm consists of the main steps: extracting the area containing the mango fruit from the background and extracting the defective skin from the left region after improving the contrast of the left region from the input image. The researchers of [27] proposed a mobile visual-based system for food grading that involves three levels of image processing: low level for image acquisition and pre-processing, intermediate level for segmentation, representation, and description, and high level for recognition and interpretation. The study compared different classifiers, including SVM, k-NN, Random Forest, and Naive Bayes, and found that SVM performed the best with an accuracy of 98.5% using the extracted feature vector. The system successfully graded bananas based on ripeness and overcame the challenge of identifying and outputting small defects on the fruit. To evaluate the quality of apples and gauge their level of maturity, the authors in [1] employed algorithms that utilized digital fuzzy image processing, statistical analysis, and content analysis. Along with a variety of filtering techniques for processing images, MATLAB's color-based segmentation method has been adopted to improve precision in finding the RGB component of a good apple and a ripened apple. By converting the image to grayscale, the system generated a histogram graph to analyze the results. The data confirmed that this automatic grading system was beneficial in reducing processing time and decreasing errors in assessment. In another work, this research [13] reported an automatic adjustable algorithm for sorting and grading apples using linear SVM and Otsu's thresholding method [17] for color image segmentation. It automatically adjusts the classification hyperplane with minimal training and time required. Additionally, it is not affected by changes in lighting or fruit color, making it an efficient and reliable option. This approach can effectively segment and sort apples in a multi-channel color space and can be adapted for other imaging-based agricultural applications. In terms of processing time efficiency, the authors in [21] introduced a split and merge approach that exhibits advantages over both Otsu's method and graph-based segmentation. This approach utilizes both local and global characteristics of color intensities in an image to improve blemish detection. The method first subdivides the image into a set of disjoint and arbitrary regions using the k-means clustering algorithm, which groups together pixels with similar feature vectors. The regions are then merged iteratively, and a graph called Region Adjacent Graph (RAG) is built to represent neighborhood relations among the segmented regions. The merging process continues until the regions satisfy the homogeneous condition or until no further merging is possible. To achieve citrus diameter detection, the researchers of [2] employed Canny edge for edge detection and DP algorithm for contour extraction to find the two points with the largest distance in the contour to achieve citrus diameter detection, which achieves a good balance between false detection and missed detection, and has a good edge detection performance. Furthermore, the RGB color space is converted into HSV color space, and the parameters of the H component are extracted to obtain the citrus coloring rate, thus realizing the citrus appearance quality grading system. By comparing manual and systematic tests, the study's authors achieved a measurement accuracy of 99%. This level of accuracy is practical for real-world applications. The article [7] proposes a method for estimating the size, volume, and mass of a Laba banana using just a single camera mounted on top of the fruit. This addresses the need to avoid setting up multiple 3D or camera projections to calculate the volume of the object for weight grading. The proposed method involves capturing top-view images of the banana, converting them to grayscale, and applying a traditional Otsu thresholding scheme for the GREEN channel of the images. The height and width of the banana are estimated from the resulting segmented image, which is then used to calculate the banana's weight using the product of the estimated volume and the average density of bananas.

In addition to the aforementioned studies, a number of studies have been undertaken to investigate the grading of mangoes through the utilization of image processing or computer vision approaches. For example, in a comprehensive review [24], an overview of the computer vision-based mango grading system was presented, which has been widely adopted in research works. The study identified image acquisition, image pre-processing, segmentation, background removal, feature extraction, and classification as fundamental steps in the mango classification process. A detailed analysis of appearance-based mango grading was conducted, and a parameter-wise survey was recommended. The authors concluded that the accuracy of ripeness analysis is better when using HSV, HSI, and CIELab color models rather than RGB color models. Furthermore, geometrical features such as area, major axis, and minor axis provide better size-based classification, while thresholding techniques are successful in segmenting defects, and Fourier descriptors can be best used for shape classification. Many machine learning models were examined for classification; however, Support Vision Machine (SVM) and Fuzzy classifiers were found to perform better. By using the image-extracted parameters for grading, accurate, reliable, and consistent mango grading can be achieved. The authors in [19] defined seven Hue moments for shape analysis and improved efficiency by using Green's formula for calculating the Hue contour. This reduces computation time and resources needed for Hue moment calculation. For this reason that applying Green's formula to the Hue vector field of an image allowed calculation of the Hue moment using only the boundary, or contour, of the image. Binarized images were used to detect defective skin, where pure skin was black and damaged areas were white. The developed system achieved 83.33% accuracy, correctly sorting 10 out of 12 mangoes into their respective categories. Methodologies and algorithms that utilize digital fuzzy image processing, content-predicated analysis, and statistical analysis to determine the grade of local mango production have been implemented in [22] for the purpose of contributing for a design and development of an efficient algorithm for detecting and sorting the mango at more than 80% accuracy in grading compared to human expert sorting. By making use of the Fuzzy Inference Rule, which is capable of dealing with the inherent ambiguity and vagueness in images, it becomes possible to conduct more flexible and intuitive image analysis. Besides, this approach can enhance the accuracy of image segmentation and reduce noise. It has proven to be effective in several applications such as image enhancement, edge detection, and object recognition. Specifically, in this context, putting in the Fuzzy Inference Rule to compute the grade of mango based on three parameters - size, color, and skin - led to the improvement of the scheme based on digital image processing techniques by selecting the best threshold scheme that produced an accurate result of classification. The authors in [10] offered a novel evaluation of the internal quality of mango based on its external features and weight, using four machine learning models - Random Forest (RF), Linear discriminant analysis (LDA), Support vector machines (SVM), and K-nearest neighbors (k-NN). The models take inputs such as length, width, defect, and weight, and output the mango classifications into different grades. The captured images and load-cell signals are converted to structured data using data normalization methods and elimination of outliers (DNEO) and normalization and outliers are eliminated to improve the dataset. Morphological processing and different image processing algorithms including filtered noise, edge detection, and boundary trace are used to detect objects in binary images. The results show that this method is more effective than using external features or weight alone, and does not require expensive non-destructive measurements (NDT).

A growing body of research on image processing techniques for the quality grading of fruits highlights their potential, including for mangoes, as a non-destructive and automated alternative to traditional grading methods. Such techniques have the potential to improve the efficiency and accuracy of fruit grading. However, numerous techniques for sorting or evaluating mangoes have been studied both domestically and internationally, there is no universally effective approach due to the inconsistent standardization of mango grading. Because criteria used for grading mangoes may differ not only between regions and countries but also from the seller to seller. Consequently, it is worth noting that none of the discussed research on mango grading has explicitly focused on the local mangoes of An Giang province. And this shortage underscores the need for an intuitive grading system that meets the requirements of mango grading in this region. The aim of the image processing-based system for mango grading is to professionalize the grading process by utilizing computer vision techniques to enhance accuracy and efficiency. The main contributions of this paper include:

- Build a new comprehensive dataset of high-quality images of local mangoes in An Giang Province for training and evaluation of the system's machine-learning algorithms.
- Employ state-of-the-art image processing techniques to accurately and efficiently classify mangoes based on their size and blemishes, reducing human error and increasing the speed of the grading process.
- Create the groundwork for easy-to-use software that connects with the grading system, allowing users to upload images of mangoes and receive reliable and impartial grading results.
- Reduce the cost of manual grading by automating the grading process, thus reducing labor requirements, increasing throughput, and enhancing scalability.

III. Materials and Methods

A. Overview of the Proposed System

The proposed mango grading methodology consists of five essential steps. These steps involve image acquisition, followed by image augmentation to improve the dataset's diversity. Next, the state-of-the-art Otsu method [17] is utilized to isolate the mangoes and segment them from the background. Then, the contour analysis is performed to measure the mangoes' circumference accurately. In the final step, the effectiveness of our proposed method is evaluated on our mango dataset. By following these steps, our system utilizes several image-processing methods to effectively isolate and segment the mangoes, accurately compute their size, and detect blemishes using Canny edge detection and contour detection techniques. We leverage these techniques to identify an extensive range of blemishes, such as brown or black spots and insect scars. To evaluate the performance of our methodology, the Random Forest model is used to predict the mangoes' grades on the test set. We then calculate the $F_1 score$, along with accuracy, precision, and recall for each class, to evaluate the model's performance.

B. Data Collection and Preprocessing

Taiwanese mango is a popular mango variety due to its large, fleshy fruit, sweet flavor when the fruit is still green, origin in eastern India, and high-profit rates when exported to the Chinese market. Therefore, in this study, the Taiwan mango is used to acquire images and evaluate our proposed system. Our imaging system consisted of a Canon 1300D camera with a Canon 50mm f1.8 STM lens and a T660EX tripod to ensure stability. The camera was positioned 42 cm from the mango, with a TR120N1/40W.H bulb placed 63 cm above the mango to maintain consistent illumination. Multiple angles were captured for a comprehensive view of the mango. The mango is placed on a white background. Each fruit is captured at 5-6 different angles and the mango is rotated vertically along the stem. The complete experimental setup is illustrated in Fig. 1.

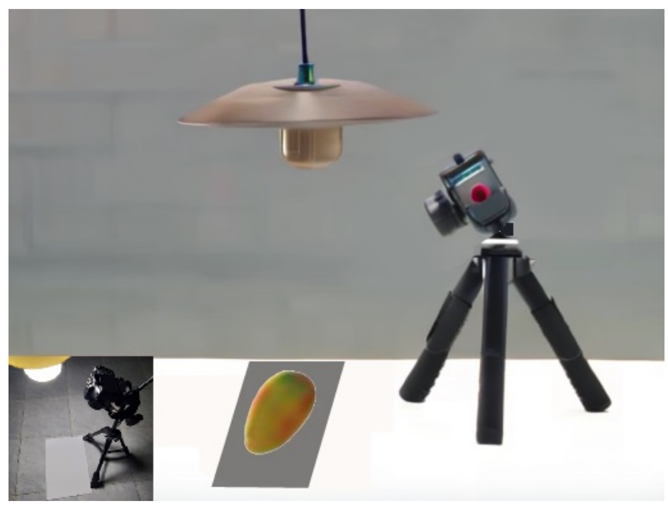

Fig. 1. Experimental setup for image collection.

Post-capture, each image is uniformly resized and their pixel values are normalized to adjust brightness and color. Additionally, the images are cropped to focus on the region of interest and remove any visible noise. However, having only 110 samples may not be sufficient for machine learning methodologies, as it can lead to overfitting. In order to improve the dataset, a multitude of data augmentation techniques was employed, including horizontal flipping, and rotation by 90 degrees both clockwise and counterclockwise, thereby augmenting the original dataset from 110 to 440 images. This augmentation process is visually depicted in Fig. 2. These augmentation techniques also help improve the generalizability of the model and avoid training overfitting, as well as the system will have more diverse instances to learn from the datasets [12], [23] (see Table I).

The images were categorized into three distinct groups based on the grading standards provided by local expert

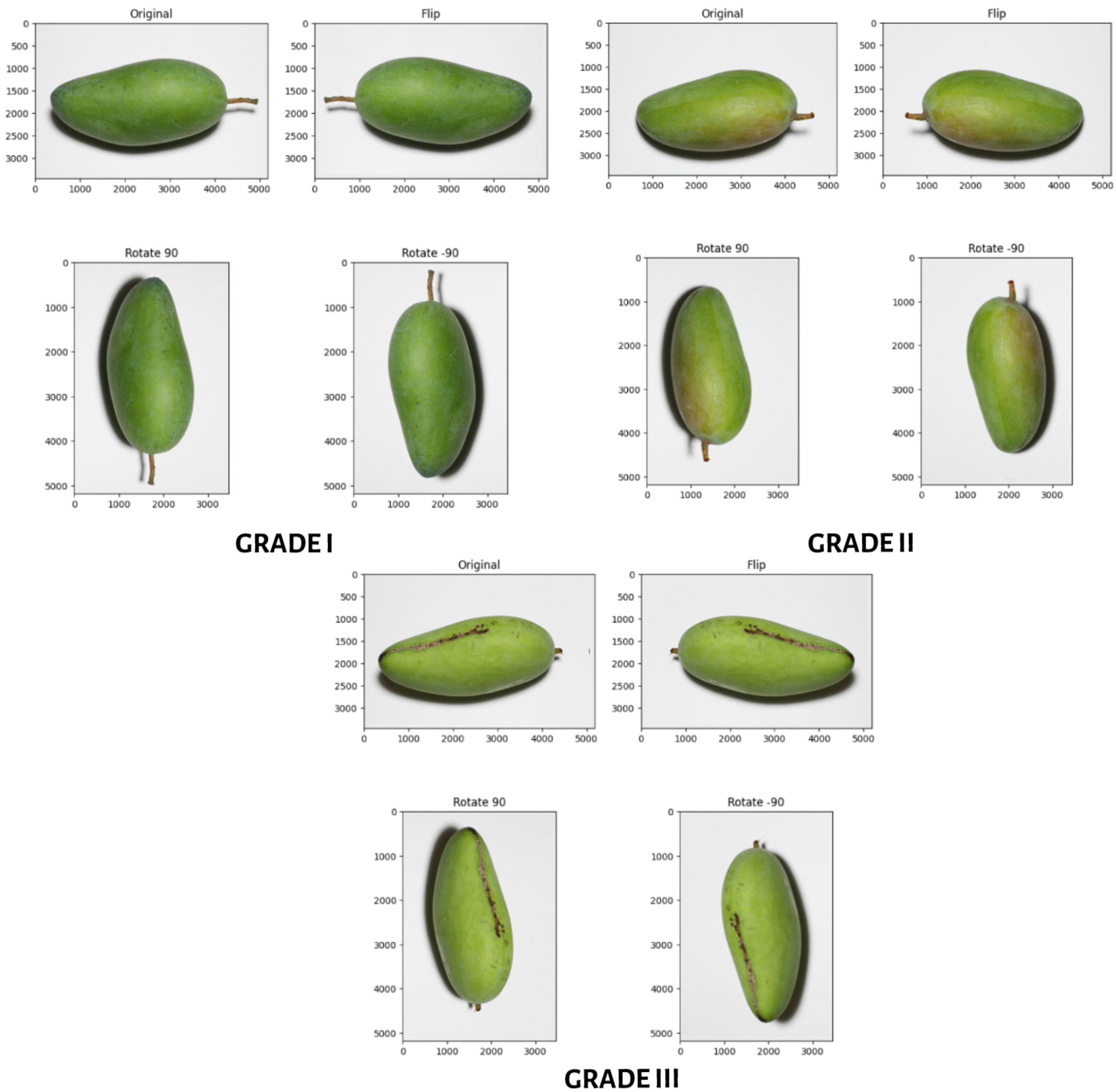

Fig. 2. Visual Representation of Data Augmentation Results.

TABLE I. THE TOTAL DATA SET AFTER DATA AUGMENTATION

Origin	Flipping	90° Rotation	−90° Rotation	Total
110	110	110	110	440

graders. These groups were Grade I, II, and III, and the details of these standards are shown in Table II. The dataset was then divided into a training set that contained 90% of the images. To evaluate the performance of image processing techniques on new and unseen data, 10% of the images were reserved for future evaluation. The training set was further randomly split into training and validation sets in an 80:20 proportion. This separation is crucial for ensuring that the techniques are robust and can generalize well to new data, beyond merely performing well on the training data. Some representative samples from our mango dataset are shown in Fig. 3. The first line exhibits images of a grade I mango, which is the best quality. Images in the second row are of Grade II mango, while the images in the third row are of Grade III mango, which is the lowest quality. An overview of the dataset structure is illustrated in Fig. 4.

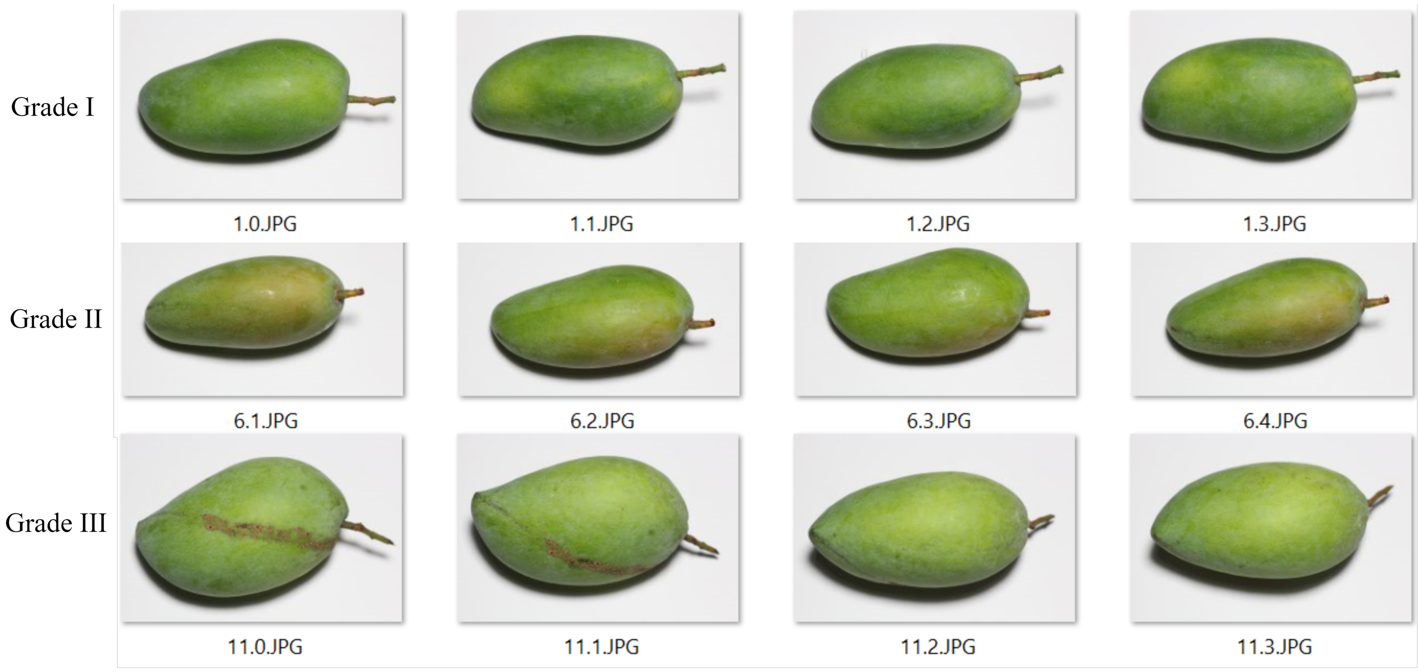

Fig. 3. Some representative samples from our mango dataset.

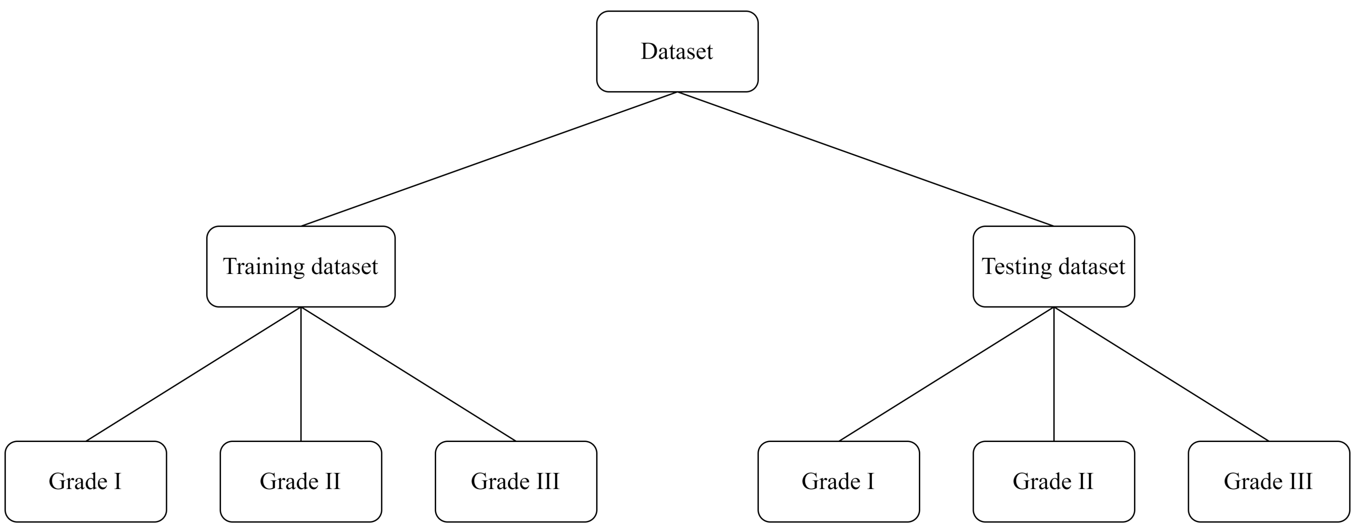

Fig. 4. Structure of mango dataset for image processing.

TABLE II. AN GIANG PROVINCE MANGO GRADING STANDARDS

Grade	Weight (g)	Blemishes	Description
I	> 620	Absent	Grade I mango has no dark spots, smooth, beautiful skin, is older, and weighs 620g or more.
II	500 - 620	Moderate	Grade II mango has few dark spots, flawless skin, and weighs 500-620gr.
III	< 500	Severe	Grade III mango is ripe, has dark spots, scars, and heavily soiled skin, and weighs 500g or less.

C. Image Segmentation using Otsu Method

The Otsu method is a popular technique characterized by its non-parametric and unsupervised nature of threshold selection [17]. It can determine the optimal threshold value used to segment an image into foreground and background regions. In the case of our study, this approach would be particularly useful when the background of the mango image has varying intensities and the lighting is uneven.

Given the input image be denoted as I with size $M \times N$. The gray levels of the image range from 0 to $L-1$, where L is the number of gray levels in the image. The histogram of the image is defined as (1):

$$H(k) = \frac{n_k}{N} \tag{1}$$

Where n_k is the number of pixels with gray level k and N is the total number of pixels in the image.

Let T be the threshold value, where $0 \leq T \leq L-1$, and let and be the weights of the background and foreground classes, respectively. The background class consists of pixels with a gray level less than or equal to, while the foreground class consists of pixels with a gray level greater than.

The mean intensity of the background class and foreground class is denoted as μ_0 and μ_1, respectively. The between-class variance σ_B^2 is calculated as (2):

$$\sigma_B^2 = \omega_0 \times \omega_1 \times (\mu_0 - \mu_1)^2 \tag{2}$$

The within-class variance σ_W^2 is also calculated for each possible threshold value T:

$$\sigma_W^2 = \omega_0 \times \sigma_0^2 + \omega_1 \times \sigma_1^2 \tag{3}$$

Here, σ_0^2 and σ_1^2 are the variances of the background and foreground classes, respectively. The total within-class variance is:

$$\sigma_T^2 = \sigma_W^2 + \sigma_B^2 \tag{4}$$

The optimal threshold value T^* is selected by maximizing the between-class variance σ_B^2:

$$T^* = argmax_{0 \leq T \leq L-1} \sigma_B^2(T) \tag{5}$$

By applying the Otsu method to our mango images, we obtain binary images where the mango is represented with white pixels, and the background is represented with black pixels, as demonstrated in Fig. 5.

D. Contour Analysis for Finding Mango Circumference

The contour area is a critical feature for size grading agricultural produce. Its measurement allows for the identification of size distribution, sorting, and grading of fruits and vegetables for the market. In fact, contour area calculation is a powerful tool in image processing applications for accurate size grading. In light of this, this study focuses on the use of the *findContours* function in the OpenCV library, a cross-platform, lightweight, and open-source computer vision library, which supports various machine languages [8], to detect mango contours in images, which is a fundamental step in contour area calculation. To ensure high-accuracy results, we have skillfully employed Otsu-based techniques in image preprocessing, helping us to effectively separate the mango fruits from their backgrounds. The result obtained from contour detection is shown in Fig. 6

However, selecting appropriate parameters using the *findContours* function is central to obtaining precise image segmentation, unsuitable parameter configuration could lead to potential errors, inevitably reducing the overall accuracy of the system. Thus, we conducted experiments to evaluate the effectiveness of different retrieval modes and approximation techniques. In terms of retrieval modes, four hierarchical retrieval modes were investigated, including RETR_EXTERNAL, RETR_LIST, RETR_CCOMP, and RETR_TREE. While RETR_EXTERNAL retrieves only the exterior or outermost contours of the objects in the images and ignores any nested contours inside them, RETR_LIST returns all of the contours as a flat list. RETR_CCOMP organizes all of the contours into a two-level hierarchy, where external contours come first, and boundaries of the holes reside on the second level. Finally, RETR_TREE reconstructs a complete hierarchy of nested contours. Each contour represents a node in a tree structure, and there exists a parent-child relationship between contours based on their nesting level. The RETR_EXTERNAL mode was found to be the optimal retrieval mode as it detected only the outer contours of the fruits.

In addition, our research has evaluated various approximation methods, including CHAIN_APPROX_NONE, CHAIN_APPROX_SIMPLE, and CHAIN_APPROX_TC89_L1. CHAIN_APPROX_NONE returns all the contours without removing any redundant points, making it the most precise representation of the contour. However, it is computationally expensive and less efficient due to the generation of a large number of points. CHAIN_APPROX_SIMPLE offers a balance between efficiency and accuracy; it only returns the endpoints of the contours, making it an ideal method for applications that require faster processing times. However, this method may lead to shape approximation errors and may not accurately represent curved contours. Conversely, CHAIN_APPROX_TC89_L1 provides a more precise representation of the original shape and is more accurate than CHAIN_APPROX_SIMPLE. However, it generates a large number of points and takes more time to process the contours. The outcomes of the experiments showed that CHAIN_APPROX_TC89_L1, a modified version of the Douglas-Peucker algorithm, produced the most desirable contour approximations.

In order to evaluate the efficacy of the contour detection technique, the circumferences of the fruits identified through this method were recorded and subsequently compared. The findings of this analysis have been reported in Table III.

TABLE III. CIRCUMFERENCE OF DETECTED MANGO FRUITS USING DIFFERENT COMBINATION OF RETRIEVAL MODE AND APPROXIMATION METHOD

Retrieval Mode	Approximation Method	Circumference (pixels)
RETR_EXTERNAL	CHAIN_APPROX_NONE	452
RETR_EXTERNAL	CHAIN_APPROX_TC89_L1	448
RETR_LIST	CHAIN_APPROX_NONE	1247
RETR_LIST	CHAIN_APPROX_SIMPLE	1298
RETR_LIST	CHAIN_APPROX_TC89_L1	1271
RETR_CCOMP	CHAIN_APPROX_NONE	1264
RETR_CCOMP	CHAIN_APPROX_SIMPLE	1279
RETR_CCOMP	CHAIN_APPROX_TC89_L1	1270
RETR_TREE	CHAIN_APPROX_NONE	1189
RETR_TREE	CHAIN_APPROX_SIMPLE	1227
RETR_TREEL	CHAIN_APPROX_TC89_L1	1219

The results indicate that using the RETR_EXTERNAL retrieval mode combined with the CHAIN_APPROX_TC89_L1 approximation method resulted in the most accurate detection of mango fruits, with a circumference of 448 pixels. Although the CHAIN_APPROX_NONE method produced the most precise representation of the contour, it required considerable computational resources and generated a high number of points, which could eventually affect the overall processing and detection speed.

Upon completion of the contour-detection step, the results

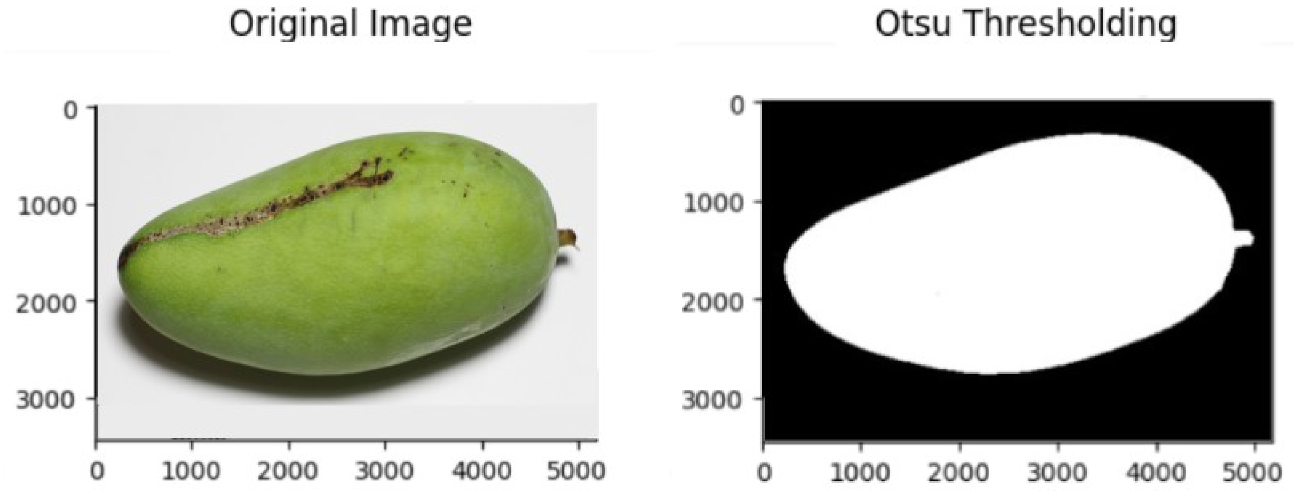

Fig. 5. Original and binary image of mango after Otsu thresholding for segmentation.

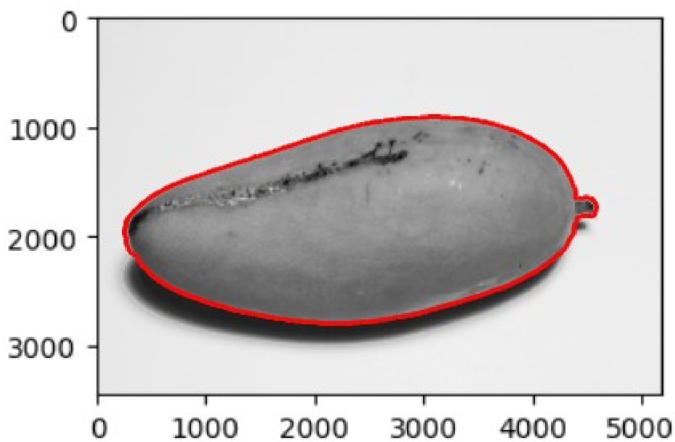

Fig. 6. Contour detected mango image.

were used for calculating the surface area by the *contourArea* function. The effectiveness of the contour area feature in mango size grading is evaluated by conducting several experiments. The results reveal that contour area is a highly effective feature in the mango size grading process, outperforming other commonly used features.

These exceptional results can be correlated with the capability of the contour area feature to capture the size and shape of the mango fruit accurately. Therefore, the implementation of contour area as a size grading feature is a robust and reliable approach that could be adopted in the industry to significantly enhance the grading process's accuracy and efficiency.

E. Blemish Detection

Blemish detection [9] is a crucial area of study in the context of mango grading, as it directly affects the overall quality and commercial value of the fruit. In recent years, there has been a considerable shift towards the use of image processing techniques for non-destructive and efficient evaluation of fruit quality [11]. One such technique that has shown promising results in blemish detection is the use of edge detection algorithms coupled with contour detection.

Canny edge detection [4] is a popular edge detection algorithm known for its noise immunity and high accuracy. Specifically, it detects the intensity changes that occur at the edges of the object and produces a thin line that outlines the object boundary. Canny edge detection is particularly useful in highlighting blemishes present on the mango's surface. Contour detection, on the other hand, identifies smooth curves that outline objects, making it ideal for identifying fruit blemishes.

By leveraging advanced techniques such as Canny edge detection and contour detection, we are able to achieve a multitude of advantages when evaluating fruit quality. These methods exhibit a remarkable level of accuracy, which means that even minor flaws and imperfections can be accurately identified. Furthermore, they are efficient and non-destructive, allowing for quick and smooth evaluations. Through their use, we can eliminate subjective judgments and human errors that are common with conventional inspection methods. That ultimately leads to more objective results, making the assessments of the fruit quality more dependable and reliable. Fig. 7 displays the outcome of utilizing the Canny edge detection technique.

Once the edge detection process is completed, the resulting output is used as input for the contour detection algorithm to accurately identify and extract the contours of the mango blemishes. The contour detection algorithm traces the edges detected by the Canny algorithm and links them to form closed contours, thus enabling the identification of the blemish areas.

Analyzing these contours, the algorithm is able to output the boundary coordinates of the blemish contours on the surface of the mango. In terms of visualization, the contour of the mango's blemishes is displayed in Fig. 8.

Additionally, Table IV illustrates the efficacy of the blemish detection algorithm through a set of representative samples. In order to accurately represent the entire dataset, the table includes various examples with both large and small blemishes, different values for each column, and a few instances of

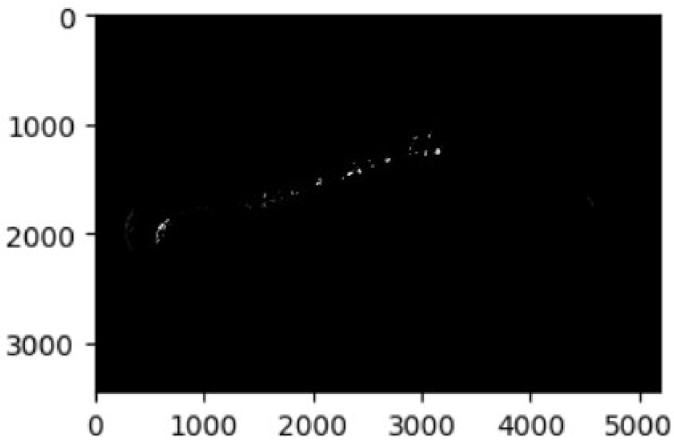

Fig. 7. Mango image obtained after canny edge detection.

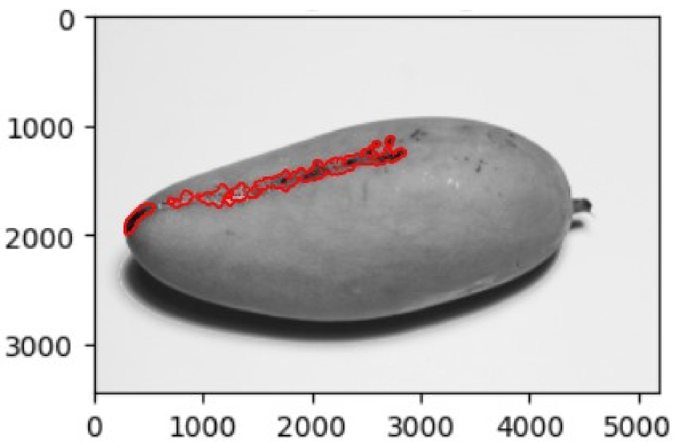

Fig. 8. Contour detection following the canny edge detection algorithm.

duplicate values. The selection of rows has been made with utmost care to ensure that the table is an accurate reflection of the data in its entirety.

TABLE IV. BLEMISH DETECTION ALGORITHM RESULTS

Area	Perimeter	X	Y	Width	Height
16.5	17.071067690849304	1323	1656	5	7
12.5	21.899494767189026	1042	1689	4	9
19.0	24.14213538169861	1431	1666	9	7
47.0	38.14213538169861	1230	1677	12	10
13.0	14.828427076339722	1261	1659	5	5
16.0	18.485281229019165	1080	1685	6	7
22.0	25.313708305358887	2376	2651	8	7
21.5	25.727921843528748	2796	2204	11	7
21.0	24.485281229019165	2268	2585	6	7
13.0	23.313708305358887	2998	1984	6	8
29.0	32.14213538169861	1262	2991	8	12
99.5	84.18376553058624	1324	1654	21	19
21.5	28.727921843528748	1278	1665	11	6
15.0	20.485281229019165	1241	2789	5	9
12.0	23.313708305358887	1233	1663	10	6

To summarize, the use of Canny edge detection and contour detection for identifying mango blemishes proves to be a promising non-destructive technique that enhances grading accuracy through reliable and effective edge detection. This approach also reduces inspection time and human errors, ultimately increasing grading efficiency.

F. Data Training with Random Forest Algorithm

The selection of an appropriate machine learning algorithm is critical for successful image processing. Decision Tree (DT) and Random Forest (RF) are commonly used due to their effectiveness in handling complex datasets and feature engineering. However, DT tends to overfit and require a large number of decision nodes, leading to slow and inaccurate predictions, while RF overcomes these limitations by using an ensemble of decision trees that randomly select feature and data subsets for training, resulting in higher accuracy [25].

The RF algorithm constructs a forest of decision trees by randomly selecting subsets of features and data samples from the training set [6]. The algorithm builds a decision tree on each selected subset, reduces variance, and improves accuracy by aggregating predictions of all decision trees. The RF comprises the following steps:

- Randomly select a subset of features and data samples from the training set.
- Build a decision tree on the selected subset.
- Repeat the above two steps multiple times to build a forest of decision trees.
- Predict the output by aggregating the predictions of all decision trees.

The RF algorithm uses a training dataset with N observations and M features to build T decision trees. For each tree t, a random subset of m features is selected, and a bootstrap sample of n observations is drawn. The algorithm builds a decision tree on this subset, and to obtain the final prediction for the i-th observation, the algorithm considers y_i as the true label of the i-th observation and $\hat{y}_{i,t}$ as the predicted label by the t-th decision tree. The final prediction is obtained by aggregating the predictions of all T decision trees in the forest using the formula:

$$\hat{y}_i = \text{aggregate}(\hat{y}_{i,1}, \hat{y}_{i,2}, ..., \hat{y}_{i,T}) \tag{6}$$

To optimize the performance of the RF algorithm for a specific task, fine-tuning its parameters is necessary. The following RF parameters were fine-tuned:

- *n_estimators*: the number of decision trees in the forest. Increasing the number of trees can improve accuracy but also increases computation time. A value of 100 was chosen as it provided good results without significantly increasing computation time.
- *max_depth*: the maximum depth of each decision tree. A higher depth can increase model complexity and lead to overfitting, where the model memorizes the training data instead of learning general patterns. To prevent overfitting while still providing good results, a *max_depth* of 10 was chosen.
- *min_samples_split*: the minimum number of samples required to split a node. This parameter helps to

balance bias and variance in the model, and a value of 5 was selected.

- *min_samples_leaf*: the minimum number of samples required to be at a leaf node. This parameter reduces the complexity of decision trees and prevents overfitting. A value of 2 was chosen.
- *max_features*: the maximum number of features considered when splitting a node. This parameter can help prevent overfitting by reducing the number of irrelevant features used in the model. The value of *sqrt* was chosen, meaning that the maximum number of features considered at each split is the square root of the total number of features.

By fine-tuning these parameters and validating the results on a separate validation subset, the model's complexity and accuracy were balanced, and overfitting was prevented, ensuring that the model would generalize well to new data.

IV. Results and Discussion

A. Experimental Setup

The experiment utilized Google Colab and the Python programming language to perform image processing techniques, while OpenCV was used to execute a variety of image processing operations such as Otsu thresholding, *findContour*, Canny edge detection, and contour detection for blemishes. The image dataset utilized in this study consisted of mango images with a uniform size of 640 pixels.

To assess the performance of the machine learning models, Scikit-learn (Sklearn) [20] was used to calculate various evaluation metrics such as accuracy, precision, recall, and F_1score. These metrics were computed for each grade of mangoes, including Grade I, Grade II, and Grade III, as well as for the overall performance of the models.

The experimental setup employed in the study ensured that the models were trained and evaluated using a standardized approach, thereby guaranteeing the validity and reliability of the results obtained.

B. Evaluation Metrics

Evaluation metrics play a crucial role in assessing the efficacy of image processing-based fruit grading methods. The selection of appropriate evaluation metrics is vital in determining the accuracy and reliability of the grading techniques employed. The F_1score is widely recognized as a key evaluation metric, as it offers a balanced measure of precision and recall, which are critical factors in fruit grading. The F_1score is a type of $Fscore$, commonly used in binary classification problems, which is calculated as the harmonic mean of $Precision$ and $Recall$ [26]. The F_1score is particularly useful when the dataset is imbalanced, a common scenario in fruit grading. The general formula (6) for the $Fscore$ is:

$$Fscore = \frac{(1+\beta^2)\cdot(Precision \cdot Recall)}{(\beta^2 \cdot Precision) + Recall} \tag{7}$$

Where β is a parameter that controls the relative weight of precision and recall. When β is set to 1, the formula reduces to the F_1score, which is often used as a default value.

In this study, the F_1score was selected as the primary metric and was calculated for each grade of mangoes by comparing the results of image processing techniques with the ground truth labels. Additionally, accuracy, precision, and recall were also computed to provide further insights into the performance of the image processing techniques. Accuracy measures the overall correctness of the predictions, while precision measures the proportion of true positives among all positive predictions, and recall measures the proportion of true positives that were correctly identified. To calculate accuracy, precision, and recall from the F1 score, the following formulas (8), (9), (10) were used:

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

Where TP is true positive, FP is false positive, TN is true negative, and FN is false negative. These formulas can be used to provide additional insights into the performance of image processing techniques for fruit grading, along with the F_1score.

The F_1score, along with other evaluation metrics, provides a quantitative measure of the effectiveness of image processing techniques for grading mangoes. The use of appropriate evaluation metrics ensures that the grading techniques employed are accurate and reliable, providing insights into the potential of these techniques for streamlining the grading process and improving the accuracy and consistency of grading mangoes.

C. Numerical Results and Discussion

To evaluate the effectiveness of our mango grading methodology, we chose the Random Forest model, which is ideal for handling small datasets and making predictions on a test set for evaluation purposes. By utilizing this model, we obtained comprehensive evaluation results for our image processing techniques based on parameters such as Accuracy, Precision, Recall, and F_1score. The clear and compelling evidence of our methodology's ability to accurately grade mangoes is reflected in the numerical presentation of our findings in Table V, as well as their virtual representation in Fig. 9. The combination of these two forms of data visualization serves to underscore the robustness and reliability of our approach.

As shown in Table V and Fig. 9, the image processing techniques used in the study achieved a high level of accuracy, with an overall accuracy of 88%. Table V shown that the highest accuracy was achieved for Grade I, with a accuracy of 91.32%, indicating that the technique performed well in identifying the highest-quality mangoes. Grade II had a slightly

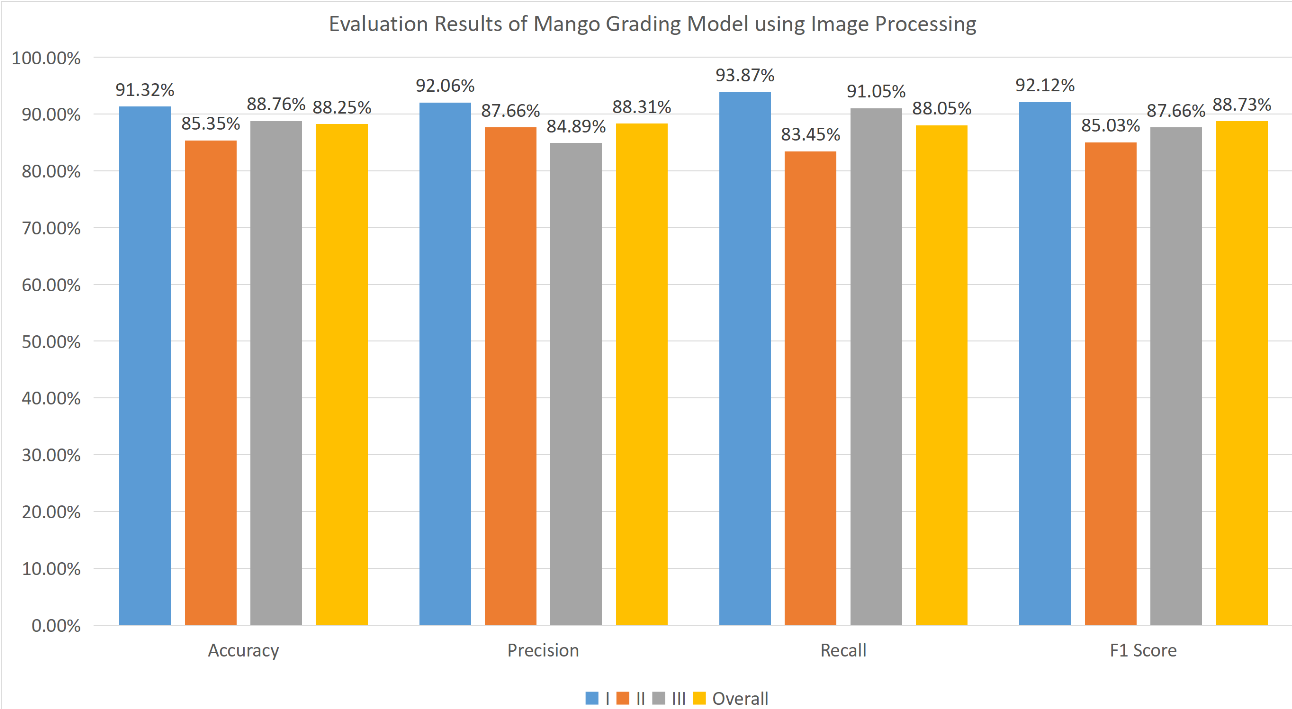

Fig. 9. Virtual evaluation results of mango grading model using image processing.

TABLE V. NUMERICAL EVALUATION RESULTS OF MANGO GRADING MODEL USING IMAGE PROCESSING

Grade	Accuracy	Precision	Recall	F1 Score
Grade I	91.32%	92.06%	93.87%	92.12%
Grade II	85.35%	87.66%	83.45%	85.03%
Grade III	88.76%	84.89%	91.05%	87.66%
Overall	88.25%	88.31%	88.05%	88.73%

lower accuracy of 85.35%, indicating that the technique was less successful in identifying the middle-quality mangoes. However, this accuracy score is still considered high and indicates that the technique is relatively robust. Grade III had an accuracy score of 88.76%, indicating that the technique performed well in identifying the lowest-quality mangoes.

The precision scores for the three mango grades were considerably elevated, with values between 84% and 92%. This signifies that the image processing technique accurately detected true positives, or the number of mangoes that were correctly identified for each grade while limiting the number of false positives, or the number of mangoes that were inaccurately identified. The highest precision score was observed for Grade I, indicating that the method was exceptionally precise in identifying the finest quality mangoes. Conversely, the lowest precision score was noted for Grade III, suggesting that the technique faced more difficulties in detecting the poorest quality mangoes.

Similarly, the recall scores for the three grades were also high, with values ranging from 83% to 93%. This implies that the technique was proficient in identifying all relevant occurrences, or the number of mangoes that were correctly identified for each grade while minimizing the number of false negatives, or the number of non-mangoes that were wrongly identified as mangoes. The highest recall score was obtained for Grade I, indicating that the technique accurately identified the highest-quality mangoes. On the other hand, the lowest recall score was obtained for Grade II, suggesting that the technique faced more challenges in identifying middle-quality mangoes.

Moreover, the F_1score for the three grades were also high, ranging from 85% to 92%. The F1 score is a measure of the harmonic mean of precision and recall, providing a balance between the two metrics. The highest F_1score was achieved for Grade I, indicating that the technique was highly successful in identifying the highest quality mangoes with a balance between precision and recall. Conversely, the lowest F_1score was observed for Grade II, implying that the technique experienced more difficulties in identifying middle-quality mangoes.

This study demonstrates the potential of image processing techniques to improve the precision and consistency of mango grading while streamlining the process. The implications of this study are noteworthy, as they imply that image processing techniques could be a reliable and effective means of grading mangoes. Furthermore, this study is in line with other research in the field, which also highlights the effectiveness of image-processing techniques for fruit grading. However, this study underscores the potential of utilizing a combination of techniques, such as Otsu thresholding, *findContour* of OpenCV, Canny edge detection, and contour detection for blemishes, to attain high levels of precision and consistency in grading mangoes. Therefore, this study provided valuable insights into the potential of image processing techniques for improving fruit grading's precision and consistency, and its implications could be instrumental in the fruit industry. The screenshot of the mango grading system is shown in Fig. 10.

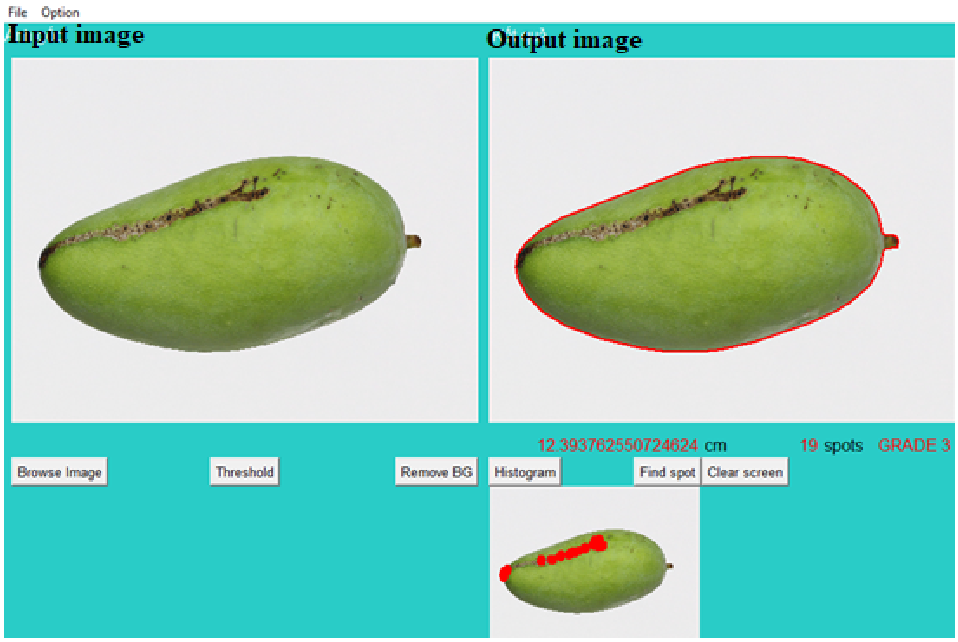

Fig. 10. The screenshot of the mango grading system.

V. Conclusions, Limitations, and Future Research

The proposed image processing system successfully has achieved the goal of automating the grading and sorting process of mangoes. By using the Otsu method for image segmentation and contour analysis for finding mango circumference, the system was able to accurately detect and classify mangoes based on their external quality features such as size, shape, and the presence of blemishes. The classification accuracy results showed that the proposed system is effective and efficient for grading mangoes, with an overall accuracy of 88%.

Despite the success of the proposed system, there are still some limitations and challenges that need to be addressed in future work. One of the limitations of the system is that it requires a controlled environment for image capturing, which can be challenging to achieve in real-world scenarios. Moreover, the system heavily relies on the quality of the input images, which can be affected by various factors such as lighting conditions and camera settings. Another challenge is the need for continuous updates and improvements to ensure the system's reliability and adaptability to new varieties of mangoes.

In future research, we aim to overcome the limitations and challenges outlined above and further enhance the accuracy and efficiency of the proposed system. To this end, research efforts should prioritize the development of more robust and precise image processing and analysis algorithms that can effectively handle variations in image quality, lighting, and camera calibration. Furthermore, we plan to explore various image segmentation and feature extraction techniques to augment the system's capacity to classify mangoes based on their quality features with greater accuracy. The use of advanced machine learning approaches, such as deep Convolutional neural networks, could also be explored to improve the grading and sorting process's accuracy and efficiency. Additionally, we intend to investigate the feasibility of integrating the proposed system with other mango supply chain components, such as harvesting and packaging, to create a fully automated system. Lastly, it is crucial to consider the proposed system's potential impact on the livelihoods of small-scale mango farmers and ensure that the technology remains accessible and affordable for them. Therefore, future research should strive to develop solutions that can benefit all stakeholders in the mango supply chain, from farmers to processors and consumers.

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