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Development of an Optical Handheld Device and Decision Tree for Mango Ripeness Classification Based on Sweetness Quality

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Abstract

Reducing postharvest losses and ensuring the quality of mango production can be achieved through accurate, rapid assessment of mango ripeness. Fruit incision and pulp analysis using chemical substances are among the traditional methods that are correlated to invasive, damaging, and impractical for widespread use. Non-destructive testing using non-invasive sensing mechanisms offers a feasible alternative. However, these existing technologies often require complex analysis and extensive calibration, thereby limiting portability and accessibility. This study presents the development of an economical handheld optical device that integrates optical sensors with a decision-tree machine learning algorithm to classify mango ripeness based on sweetness quality. The system employs a 470 nm LED in conjunction with a BPW34 photodiode to measure the light reflectance of the mango. Using MATLAB, the corresponding output, a voltage signal, and the ground-truth data (ripe and unripe status) from the calibration study are used as the input and output of the decision tree classifier, respectively. The results yield an overall accuracy of 81.3%, whereas the benchmarking shows 100% correct ripeness status. The developed prototype provides a cost-effective, scalable, and user-friendly solution for precision agriculture, with recommendations for future enhancements in other internal quality aspects and large-scale benchmarking.

1. Introduction

The cultivation of mango (Mangifera indica L.) commenced approximately 4000 years ago in India and is among the most extensively consumed tropical fruits globally. Mangoes, part of the Anacardiaceae family, are valued for their unique fragrance, harmonious sweet-acidic taste, and substantial nutritional value [1], [2]. Asia dominates global mango production, accounting for over 80% of the world's supply, with total production reaching approximately 51 million tons in 2019. Over 22 million tons each year, India is the leading producer and exporter.

Mangoes are cultivated in over 85 countries, with the largest production occurring in India, China, Thailand, and Indonesia. Out of about 1,000 recognised mango varieties in India, approximately 30 are planted commercially, with only a select few produced on a large scale.

Fruit farming is essential for global food security and economic development, with mango agriculture increasingly impacted by climate change. High temperature with unpredictable weather may contribute to the reduction in mango maturation time by 12 to 16 days with 1.5°C temperature rise in areas such as Central Queensland. Assessment of fruit quality is vital in the case of environmental challenges. Such fruit qualities include internal characteristics such as sweetness, aroma, moisture, and nutrient composition, whereas external markers are characterized by ripeness, colour, and surface blemishes. Studies in [3],[4] explain that ripening is typically evaluated through physical characteristics such as hardness and form, biochemical indicators including sugar content and acidity, and physiological changes like skin colour.

Based on recent studies in Malaysia highlight production inefficiency and sustainability challenges associated with the cultivation of Harumanis mango in Perlis[5]. Mata Ayer and Chuping exhibited low technical efficiency due to insufficient utilization of inputs, including labour, fertilizer, and irrigation. They suggest that targeted training and efficient resource management could enhance yield and profitability, as observed in farmer Harumanis. Kamarudin et al. mentioned that the effect of nutrient concentration, particularly nitrogen and potassium, highlights the necessity for soil restoration to maintain productivity and fruit over time, and demonstrates that extending mango agriculture substantially influences soil, including pH and organic matter[6]. Maintaining long-term soil health to facilitate sustainable mango cultivation, climate-resilient practices, and efficient resource management is essential.

Impractical for large-scale commercial use and for traditional approaches to evaluating ripeness, such as destructive methods, including fruit slicing and chemical analysis, which are labour-intensive and time-consuming. Moreover, manual inspections reveal susceptibility to variability. Compared to traditional methods, Non-Destructive Testing (NDT) provides enhanced reliability and efficiency for commercial applications. NDT has emerged as a viable alternative, providing accurate, real-time quality assessment while preserving the fruit's integrity. Optical sensing, which utilises sensors to measure properties such as light reflectance and absorption. Several recent studies between 2020 and 2025 demonstrated the non-destructive testing technologies that can help improve the accuracy of fruit ripeness evaluation and quality [7], [8], [9], [10].

Various NDT methods such as visible and near-infrared (Vis-NIR) spectroscopy, hyperspectral, and multispectral imaging were used to assess mango maturity based on internal fruit characteristics and quality parameters, including sugar concentration, hardness, moisture content, pulp colour, sweetness, and firmness with Vis-NIR is said as superior compared to laser doppler vibrometer (LDV) [9], [11]. Varga et al conducted a thorough experimental study using diffuse reflectance hyperspectral imaging (HSI) to analyse light penetration in the tissues of fruits and vegetables at varying depths [12]. The findings indicate that light absorption is predominantly observed near the surface, particularly in the visible spectrum (400–700 nm), while scattering intensifies in deeper layers. This information is essential for improving the accuracy of non-destructive quality assessment systems [13].

A comprehensive review of light therapies, specifically UV-C and red/blue LEDs, for the management of postharvest quality was presented by [14]. The quantification of light absorption in tissue-simulating materials using optical techniques, including reflection and transmission, with a focus on LED and photodiode configurations. Additionally, near-infrared light penetrates deeply, necessitating the assessment of tissue structure and wavelength when analysing spectral data. The study indicates that specific absorption bands can trigger physiological responses that delay aging, improve antioxidant activity, and prolong shelf life.

Recent studies indicate that machine learning and deep learning can accurately evaluate fruit ripeness through multiple input modalities, such as image-based and spectral signals analysis. For example, the development of Fruit-HSNet and the implementation of artificial neural networks (ANNs) and random forests to leverage hyperspectral imaging for evaluating the ripeness of various fruits, such as avocado, mango, papaya, and strawberry, based on sugar content, firmness, and chlorophyll content [15]. Using hyperspectral reflectance input data yields a prediction accuracy of more than 90%. Besides that, the use of deep learning models, such as ResNet50 and InceptionV3, along with a convolutional neural network (CNN) utilising image-based analysis, facilitates ripeness prediction by evaluating the quality of various fruits, including avocado, kiwi, apple, and banana, from RGB photos [16]. Meanwhile, over 8,000 tagged photos were used to classify oil palm fruit into five maturity stages, achieving an accuracy of more than 85%, indicating the effectiveness of transfer learning and deep feature extraction in a ripeness detection system [17].

The aim of this work is to design and develop an optical device incorporating machine learning to evaluate the ripeness stage of mangoes based on their sweetness quality. The testing encompassed 150 mango samples at different stages of maturity, measuring the voltages of light passing through the mango. The contributions of this research include the development of an easy-to-use handheld optical device that quantifies mango optical reflectance as a voltage signal, the implementation of decision-tree classification based on voltage signal thresholds, and the evaluation of ripeness using both prototype and conventional techniques. The prototype is designed for real-time utilisation in agricultural fields, storage facilities, and retail settings; hence, it may help to improve decision-making in supply chain management [18],[19].

2. Methodology

This subsection outlines the methodology for developing a portable optical-sensing prototype with a decision-tree algorithm for classifying mango ripeness. There are six subheadings, starting with a brief introduction to system design and integration, hardware and software development, machine learning and performance metrics, and concluding with calibration, benchmarking, and testing.

2.1 System Design and Integration

Fig. 1 illustrates the overall systematic process, from the design of optical handheld devices to experimental validation and outcome reporting, for classifying mango ripeness. The process begins with the development of an optical sensing device and its corresponding analytical framework, utilising related software. Next, 150 mango samples at various ripeness stages were collected, and their corresponding voltages were measured. Meanwhile, the ripeness status was determined using the traditional method (slice and taste). These data were used in the decision tree algorithm to classify the mango condition. The result was based on the system's performance and accuracy in classifying mango ripeness.

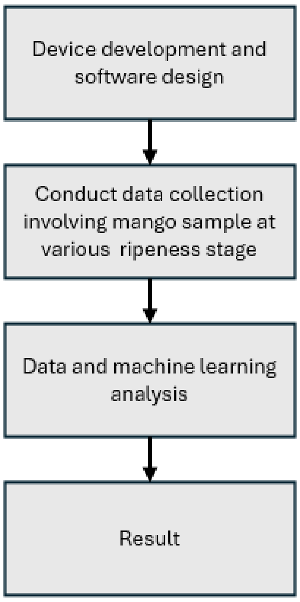

Fig. 1 *Overall process in the project*

2.2 Hardware Development

Fig. 2 shows the overall block diagram of a handheld optical device for evaluating mango ripeness, incorporating optical sensors and a decision-tree algorithm. Using a 470nm LED, its light penetrates the mango, and the reflected light is detected by a BPW34 photodetector. Then, the transimpedance amplifier converts the optical signal into a voltage. The Arduino Nano microcontroller processes the data and passes it to a decision tree algorithm to identify the mango's maturity stage as ripe or unripe. The OLED screen displays the ripeness status, along with its associated voltage value, providing users with instant feedback.

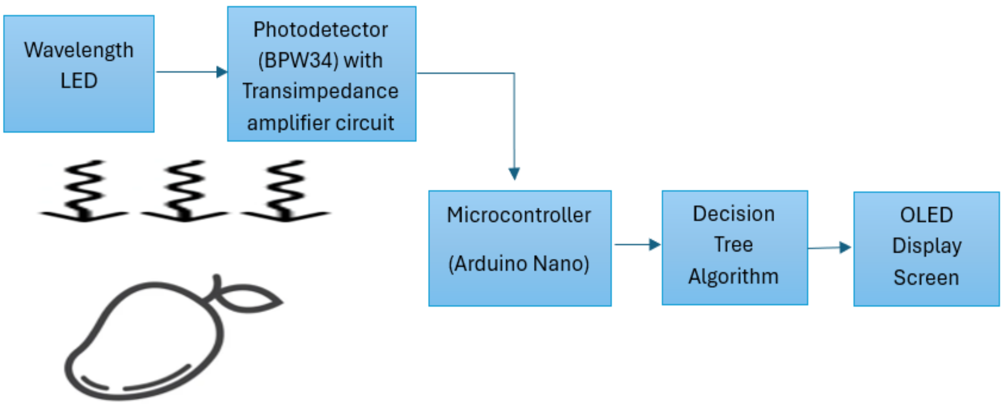

Fig. 2 *Block diagram of hardware development*

Additionally, Fig. 3(a) illustrates the circuit diagram of all components, including the LED and photodetector, whereas Fig. 3(b) shows the three-dimensional design of the prototype drawn in the Tinkercad program.

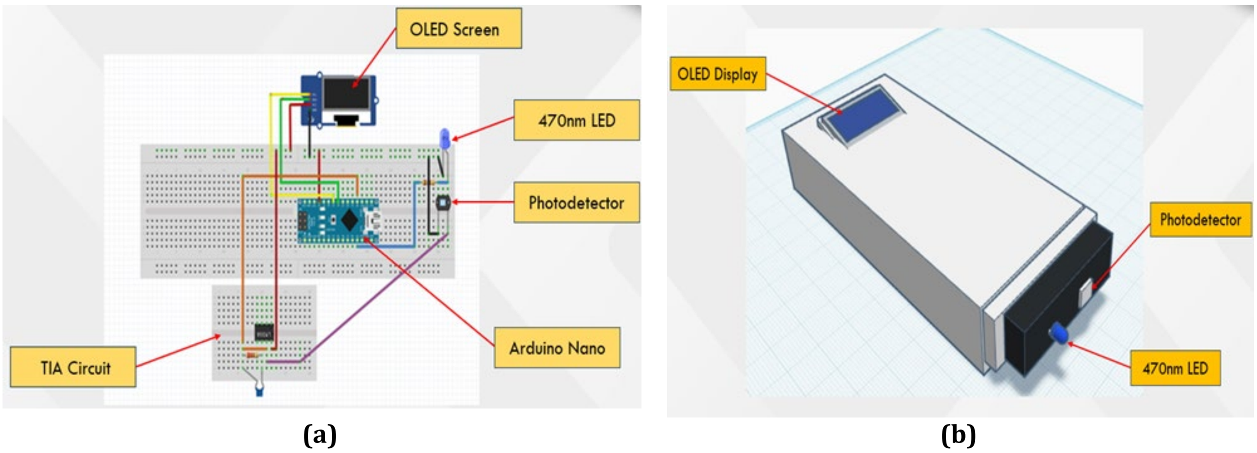

Fig. 3 *Hardware development: (a) Circuit connection; and (b) 3D design prototype*

2.3 Software Development

Fig. 4 illustrates the development process of a mango ripening monitoring system that employs light sensor data and a decision tree algorithm. The light reflected from the mango surfaces is collected by the photo detector. Then, the algorithm confirms whether the resulting voltage falls within an acceptable range. Next, the acquired data is used in the experimental calibration phase, which involves measuring and recording voltage levels and manually assessing ripeness (ripe or unripe). The calibration table that associates voltage levels with ripeness is then established for use in the decision tree for ripeness classification. The finalised algorithm is incorporated into the prototype hardware for real-time implementation. Finally, a benchmarking method is employed to compare the prototype's predictions with the actual ripeness status (via a post-cutting experiment), thereby validating the accuracy and consistency of the embedded model for ripeness classification.

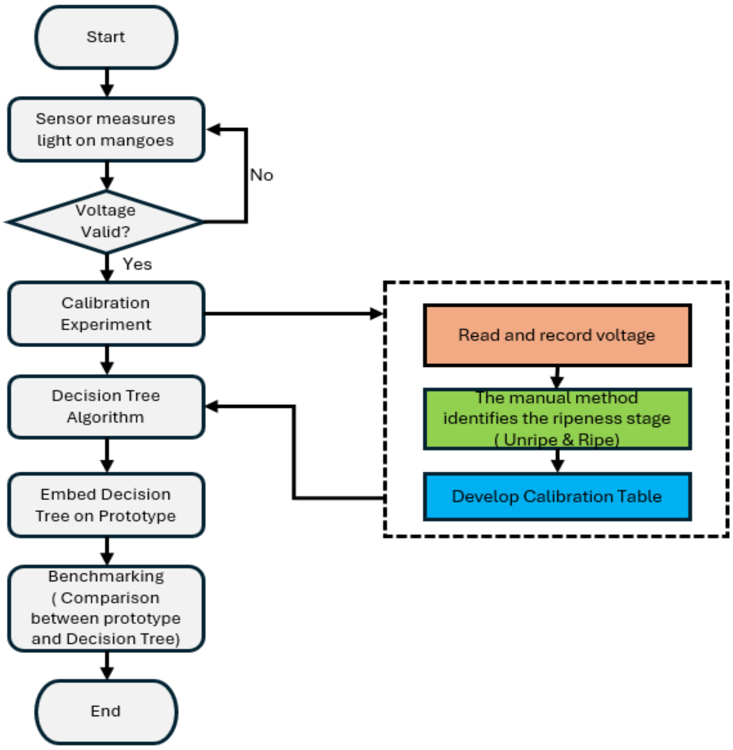

Fig. 4 *Software system development flowchart*

2.4 Machine Learning and Performance Metric

A decision tree serves as a mechanism for generating classifiers. Classification algorithms in data mining can process large volumes of data. This method can be used to assign categorical class labels to newly acquired data for classification. Classification techniques in decision trees include Iterative Dichotomies 3 (ID3), its successor ID3 (C4.5), Classification and Regression Tree (CART), and Conditional Inference Tree (CIT). This research selects a decision tree method because it is particularly effective for detecting mango maturity, given its simplicity, comprehensibility, and ability to transparently illustrate decision-making processes through a series of "if-then" rules. In contrast to intricate models such as neural networks or support vector machines, decision trees perform effectively with smaller datasets, manage noisy sensor data, and elucidate the non-linear correlations among light absorption and ripeness stage in mangoes. They are efficient, require minimal computational resources, and can be seamlessly integrated into more sophisticated techniques, such as Random Forests, if necessary, making them a pragmatic and dependable option for this project.

Classification accuracy is a performance metric that reflects the model's effectiveness at predicting instances from the training data. This study classified performance metrics into accuracy, precision, recall, F1-score, and ROC-AUC, as specified in equations (1) to (4). Table 1 presents the structure of the confusion matrix, where rows represent the actual classes and columns denote the predicted classes. The sample demonstrates two distinct ripeness phases. Additionally, TP represents True Positive, TN denotes True Negative, FP indicates False Positive, FN signifies False Negative, Ri refers to the rate of the i-th data, and If and II correspond to negative and positive data, respectively.

Table 1 *Confusion matrix structure*

True Class	Unripe	Ripe
Unripe	TN	FP
Ripe	FN	TP

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score = \frac{2TP}{2TP + FP + FN} \tag{4}$$

2.5 Calibration, Benchmarking and Testing

Table 2 presents the distribution of mango samples used in the calibration and decision tree study, comprising 150 mangoes, of which 80 were ripe and 70 unripe. The selection of the mango was based on the physical and colour appearance using the Federal Agricultural Marketing Authority (FAMA) grading index.

Table 2 *Compilation of sample data*

Amount of sample testing	Ripe	Unripe
150	80	70

Meanwhile, for benchmarking and testing the developed device, only 10 mango samples with varying ripeness were used, and this small sample set was sufficient to validate the prototype's functionality for small-scale testing. The benchmarking process began by labelling mango samples from M1 to M10. Each sample was then measured using the developed device, and the ripeness status (ripe or unripe) was recorded. To serve as ground truth data, the sample was then sliced to assess ripeness by taste. Both data sets (measured before and after cutting) were recorded in the table, and the accuracy was calculated. Figure 5 shows examples of ripe (M5) and unripe (M1) samples during the benchmarking process.

Fig. 5 *Traditional process of post-cutting sample to identify ripeness status for benchmarking purposes*

3. Result and Discussion

The result and discussion section presents and discusses four subsections: optical device prototype, experimental setup for calibration study, graphical plot of the decision tree based on the calibration study, and performance evaluation and benchmarking. The comparison of the proposed study and past studies can be found in the last subsection.

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3.1 Optical Device Prototype

Fig. 6 *Images of the developed prototype of a handheld optical device showing how it is used for detecting mango ripeness. Main components are labelled accordingly*

Fig. 6 depicts the developed handheld optical device prototype, showing the system's hardware components: a 470 nm LED light source for illumination, a BPW34 photodetector for capturing reflected light from the mango surface, and a probe containing the optical components. In addition, the device operates using a 5V USB supply, and the results are presented on a compact OLED screen.

3.2 Experimental Setup for Calibration Study

Fig. 7 shows the experimental setup for the calibration study. consisting of three primary steps: mango collection and labelling, reflectance measurements, and ground truth experiment. Figure 7(a) shows the collection and labelling of mango samples at various ripening stages, with each sample assigned to an identification code for easy tracking during the experiment. The measurement process using the developed device is shown in Figure 7(b). The optical sensor, a BPW34 photodiode, is positioned directly on the mango surface to collect reflected light data. The voltage signals are displayed in real time on the integrated OLED screen, and the measured value is recorded. Lastly, Figure 7(c) depicts the dissected mango to assess its sweetness as an indicator of ripeness, thereby providing ground-truth data to confirm device's classification accuracy. If the mango is sweet and the pulp is soft, it is considered ripe.

(a) (b) (c)

Fig. 7 *Experimental protocol during calibration study: (a) collection and labeling of mango samples based on FAMA grading index; (b) reflectance measurement on the mango sample; and (c) examination of mango pulp post-cutting for ground-truth data*

3.3 Graphical Plot of Decision Tree Based on Calibration Findings

Fig. 8 shows a decision tree model for classifying mangoes into two categories, ripe and unripe, based on a single input variable, x1, representing the voltage measured by the optical sensor. The classification procedure begins at the root node, where the initial judgement criterion is whether the voltage is less than 3.59855. First, mango samples are separated into two groups with lower and higher voltage measurements. The model applies voltage thresholds such as 3.5605, 3.57015, 3.59095, 3.6115, and others closely spaced around them. At each node, the system checks whether the measured voltage is below or above the specified threshold and directs the sample to the left or right branch accordingly.

As the tree descends, the range of voltages shrinks, allowing the model to build smaller, more specific sample groups. The close spacing of threshold values shows that even slight voltage changes affect ripeness classification. The optical sensor may be sensitive enough to detect subtle changes in the mango's internal or external features associated with ripeness. The classification continues until the sample reaches a terminal node, or leaf node, where it is declared “ripe” or “unripe”. The figure shows that the model uses rule-based classification to compare measured voltage values to learned thresholds, making the decision-making process clear, interpretable, and suitable for real-time implementation in the optical ripeness detection system.

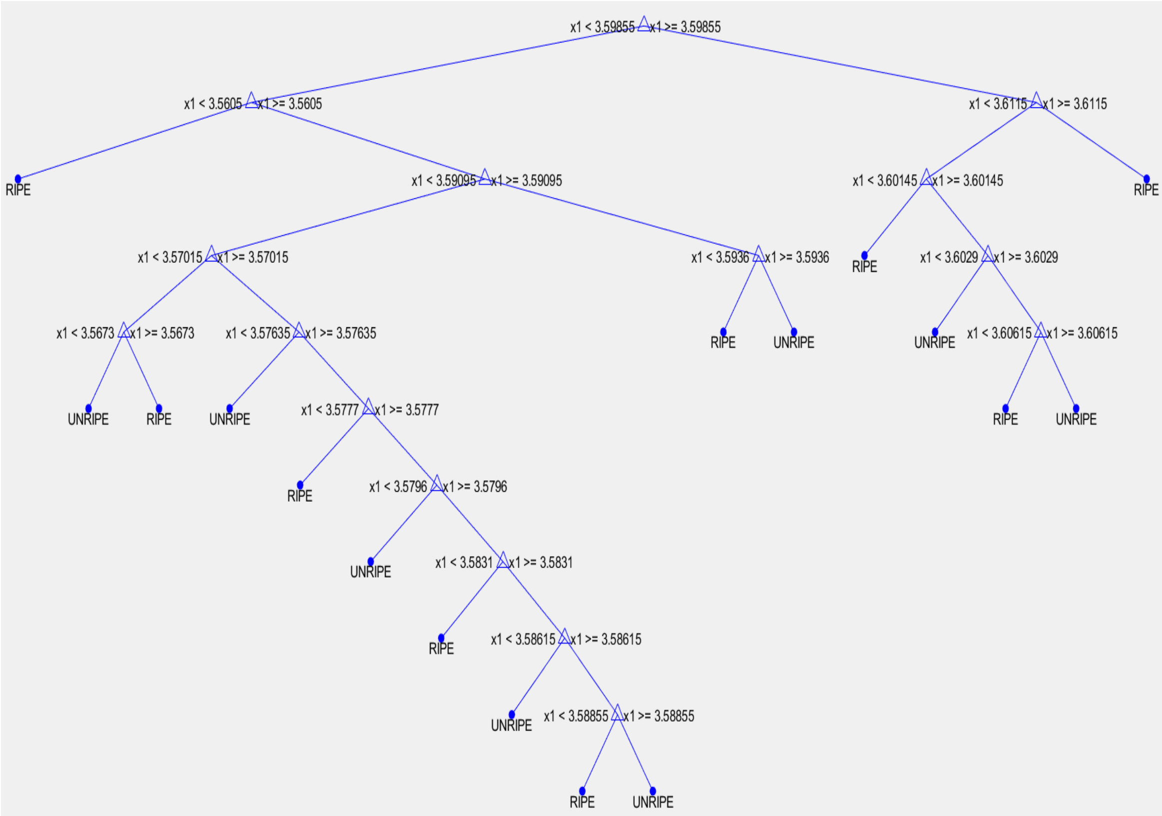

Fig. 8 *Mango ripeness classification model uses a decision tree based on feature x1. With terminal nodes indicating the final classification results, the tree displays hierarchical splitting thresholds that distinguish ripe from unripe samples*

3.4 Performance Evaluation and Benchmarking Findings

Table 3 shows that the confusion metric correctly identified 56 unripe and 66 ripe mangoes, while it misclassified 14 unripe mangoes as ripe and 14 ripe mangoes as unripe. Out of 150 samples, the model correctly predicted 128 and made 28 errors, resulting in an overall accuracy of 85.3%. This means the model is generally effective at distinguishing ripe from unripe mangoes, though it still makes some mistakes in both categories.

Table 3 *Confusion matrix structure*

True Class	Unripe	Ripe
Unripe	56	14
Ripe	14	66

Table 4 summarises the performance of the decision tree classifier across the two categories. For the unripe class, a precision of 80% indicates that 80% of the samples predicted as unripe are truly unripe. The recall of 80% indicates that the model correctly identified 3/4 of the actual unripe samples, with the remaining 20% misclassified as ripe. The F1-score of 80% reflects the balance between precision and recall, while the class-specific accuracy of 80% represents the model's effectiveness in distinguishing unripe fruit under a one-vs-rest evaluation. In the case of ripe fruit, precision is slightly lower at 82% due to some unripe samples being incorrectly labelled as ripe, whereas recall is higher at 82%, indicating strong sensitivity in detecting ripe fruit. The F1-score of 82% highlights a more favourable trade-off than for the unripe class, with a class accuracy of 80%. Overall, the model performs better at recognising ripe fruit, as evidenced by its higher recall and stronger F1-score, while its predictions for unripe fruit are more conservative, emphasising precision at the expense of recall. Meanwhile, overall accuracy for all classes is 81.3% and 81% for precision, F1-score and recall.

Table *4 Performance measurement of the decision tree*

True Class	Accuracy (%)	Precision (%)	F1-Score (%)	Recall (%)
Unripe	80	80	80	80
Ripe	82.5	82	82	80
Overall classes	81.3	81	81	81

Fig. 9 shows the ROC curve performance of the decision tree model in classifying ripe and unripe mangoes by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR). The curve rises steeply toward the top-left corner, indicating that the model is highly sensitive to atypical cases. The Area Under Curve (AUC) is 0.89, indicating very good discriminative ability, meaning there is an 89% chance that a randomly chosen ripe mango will be ranked higher than an unripe one. For example, at an FPR of about 0.05, the model achieves a TPR of 0.65, and at an FPR of 0.20. The TPR increases to 0.88, demonstrating the trade-off between minimising false positives and maximising true detection. Overall, the curve confirms that the model is highly effective at distinguishing between ripe and unripe mangoes, performing significantly better than random guessing.

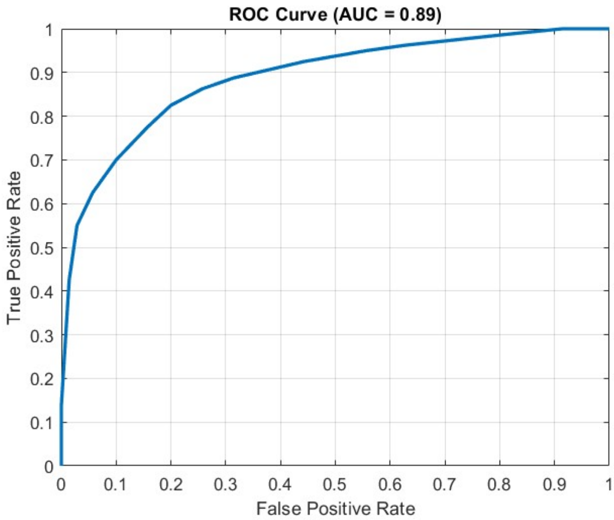

Fig. 9 *The ROC of the decision tree model shows a high AUC of 0.89, indicating good efficacy in discriminating between the ripe and unripe mango samples*

Table 5 presents the tabulated data for the developed system during the benchmarking and testing of 10 mango samples. Based on this table, the system's accuracy, compared to the post-cutting method, was 100%. For a small-scale validation, the developed prototype with a decision tree model accurately classifies mango ripeness status, compared with the previous study, which used a much more complex system. Table 6 summarises the comparison between our proposed study and previous research on mango ripeness prediction, based on the methods used and the study outcomes. Our proposed system uses machine learning with a decision tree and achieves 81.3% and 100% accuracy in detecting mango ripeness during calibration and benchmarking, respectively. One of the past studies used an optical fibre system with RGB LEDs, and a statistical method called multiple linear regression, which explained about 87.9% of the variation in mango maturity[20]. Another study used visNIR technology with partial least squares regression, explaining about 73% of the variation in ripeness [21]. Overall, different technologies can be used to detect mango ripeness, and our system produces results that are quite comparable to those in previous research. Meanwhile, Fig. 10 illustrates the real-time results from the benchmarking and testing experiment on 10 mango samples. The OLED screen displays the voltage reading and the mango sample's ripeness classification, with unripe (Fig. 10a) and ripe (Fig. 10b) statuses.

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Table 5 *Benchmarking and testing on 10 mango samples*

Sample ID	Developed prototype (Ripeness status)	Post-cutting (Ripeness status)
1	Unripe	Unripe
2	Unripe	Unripe
3	Unripe	Unripe
4	Ripe	Ripe
5	Ripe	Ripe
6	Ripe	Ripe
7	Ripe	Ripe
8	Ripe	Ripe
9	Ripe	Ripe
10	Ripe	Ripe

Table 6 *Comparison between our study and previous research on mango ripeness detection based on the method of classification and the study outcome*

Mango ripeness detection system	Method of classification/ prediction	Outcome of the study
Our proposed system	Machine learning: decision tree	81.3% of overall class accuracy during calibration and 100% of accuracy during small-scale benchmarking
Optical fibre system with RGB LEDs [20]	Statistical method: Multiple Linear Regression (MLR)	87.9% of the variation in the mango maturity index
visNIRS [21]	Statistical method: Partial Least Squares Regression (PLSR)	73% of ripeness variation

(a) **(b)**

Fig. 10 *The ripeness status display on OLED during benchmarking and testing showing: (a) Unripe status; and (b) Ripe status*

Limitations of The Study

Some notable limitations of this study are discussed in this subsection. A single wavelength was used to assess the ripeness of the mango by comparing the voltage reading with the traditional method (post-cutting taste examination); however, it is unable to assess other internal quality properties. Other than that, only the decision tree algorithm was used to classify ripeness status. Comparing it with other machine learning algorithms, such as Random Forests, can enhance the study's novelty. Additionally, external validation by testing models on different fruit types can help demonstrate that it is effective beyond the current mango samples.

4. Conclusion

In conclusion, based on the findings presented, all objectives set at the beginning were successfully achieved. An optical handheld device integrated with a decision tree was successfully developed for the classification of mango ripeness. A notable relationship between the measured voltage and ripeness category was established using the decision tree method. Overall, the proposed mango ripeness detection using a decision tree model performed well, achieving 81.3% accuracy during the calibration study and 100% during small-scale validation. The evaluation metrics, including accuracy, precision, recall, and F1-Score, were well-balanced, showing that the model performs well across both categories. Compared with previous studies, some approaches, such as optical fibre-based systems, reported slightly higher accuracy, while others, such as visNIR, showed slightly lower performance. Although the proposed system does not achieve the highest reported accuracy during the calibration study, it still provides reliable results, making it practical and effective for detection. This has been proven through benchmarking and real-time testing, with 100% accuracy during small-scale validation.

In the future, some improvements are recommended to make it more beneficial to the user and the agricultural community. Such improvements involve a combination of different wavelength LEDs, such as red, blue, and green LEDs, which are suggested to address other internal fruit qualities, including firmness, moisture content, and sugar concentration. Other than that, the prototype design can be improved to be more user-friendly and more aesthetically pleasing to hold. Regarding machine learning, we need to add more test samples to improve mango classification accuracy by strategically collaborating with the agricultural industry for large-scale benchmarking.

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Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this paper.

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Author Contribution

The authors confirm their contribution to the paper as follows: ***study conception and design:*** *Muhamad Amir Irfan Roslan, Nur Anida Jumadi;* ***data collection:*** *Muhamad Amir Irfan Roslan, Muhamad Nazri Nazrin;* ***analysis and interpretation of results:*** *Muhamad Amir Irfan Roslan;* ***draft manuscript preparation:*** *Muhamad Amir Irfan Roslan, Nur Anida Jumadi. All authors reviewed the results and approved the final version of the manuscript.*

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