

Colour Classification of Harumanis Mango Quality using Artificial Neural Network

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ABSTRACT

Harumanis mango, a premium variety originating from Perlis, Malaysia, are only produced during limited seasons, making reliable and efficient quality evaluation highly important. Conventional inspection methods are typically performed manually, which can be time-consuming and prone to subjective judgment. This study proposes an automated system for classifying Harumanis mango quality by using Artificial Neural Network (ANN). High-resolution mango images were acquired using a CCD camera, and important features, particularly colour maturity, were extracted through HSI-based hue analysis. Initial classification was conducted using K-Nearest Neighbours (K-NN) and Support Vector Machine (SVM), achieving accuracy levels of up to 97.6% for colour-based maturity assessment. To further improve classification performance, a low-level data fusion strategy was applied, which combines multiple colour-related features. This fusion-based model produced a higher accuracy of 98.6%, surpassing the performance of individual classifiers. The findings indicate that combining visual features with ANN techniques enhances the accuracy and consistency of Harumanis mango quality classification. The proposed method provides a reliable, non-destructive and scalable solution for automated grading, minimizing dependence on manual inspection while improving overall quality control processes.

Keywords: Harumanis Mango, Artificial Neural Network, Quality Classification, HSI Colour Analysis

1. INTRODUCTION

Mango (*Mangifera indica*) is among the most widely cultivated and economically significant tropical fruits, with more than 500 varieties distributed across Asia, Africa and the Americas. In Malaysia, mango cultivation is concentrated in states such as Perlis, Kedah, Perak, Johor and Melaka. Perlis particularly renowned for a premium variety of the Harumanis mango, highly valued for its quality and regional importance [1]. As of 2022, Malaysia had approximately 7,000 hectares of mango plantations, producing around 32,000 metric tonnes annually. Of this, Perlis contributed over 1,200 hectares dedicated to Harumanis cultivation, yielding more than 3,000 metric tonnes per year [1]. The distinctiveness of Harumanis mango is largely attributed to the unique climatic conditions of Perlis, which are difficult to replicate in other regions [2]. This variety is available only during a short harvesting period from late April to early June and is protected under geographical indication status, further enhancing its exclusivity and market value.

Harumanis mango can be easily distinguished from other local varieties such as Chokanan, Sala, and Apple mangoes due to their strong aroma, rich sweetness, smooth and fibreless texture, and

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bright golden-yellow colour when ripe [3]. The fruit is typically medium to large in size, with thin skin and a distinctive fragrance that makes it easily recognizable. In contrast, Chokanan mango are available throughout the year and are comparatively less aromatic, while Sala and Apple mangoes differ in both taste and texture [3]. Harumanis, also known as Arumanis, is a popular mango variety cultivated mainly in Malaysia and Indonesia, with particular significance in Perlis where it is highly regarded. The name “Arumanis” is derived from the word “aroma,” reflecting its characteristic fragrance, and it is often referred to as an aromatic mango due to its sweet flavour and unique scent [4]. This variety is highly prized for its superior taste and soft, juicy flesh, making it suitable for both fresh consumption and processed products. When consumed fresh, its natural sweetness and intense aroma provide a refreshing tropical experience. Additionally, Harumanis mango are commonly processed into products such as jams and juices, allowing their distinctive flavour to be enjoyed beyond the limited harvesting season [5].

1.1 Market Value of Harumanis Mango

The premium status of Harumanis mango is reflected in their market value, with prices in recent years ranging from RM25 to RM40 per kilogram at the farm level and reaching up to RM60 per kilogram in urban markets during peak season [5]. These prices are significantly higher compared to other mango varieties, which typically sell for RM8 to RM15 per kilogram. The elevated price is largely driven by limited production, high consumer demand, and the fruit’s strong reputation for superior quality. In addition to its desirable taste, Harumanis mango is also valued for its nutritional benefits. Similar to other mango varieties, it is a rich source of essential nutrients, including vitamin C, vitamin A and dietary fiber, which contribute to improved immune function and digestive health.

1.2 Grading System and Economic Impact of Harumanis Mango

Harumanis mango are categorized into three primary quality grades: Premium Grade, Grade 1, and Grade 2. Premium Grade mango exhibits an ideal oval shape, smooth skin and minimal defects. Grade 1 mango are slightly less uniform but still satisfy high-quality standards, while Grade 2 includes fruits with minor colour inconsistencies or surface imperfections [6][7]. This grading system plays a crucial role in price determination, as Premium Grade mango command the highest market value due to their superior quality.

The cultivation of Harumanis mango has become a significant economic activity in regions where they are grown. Increasing demand for this variety has encouraged the expansion of mango orchards and commercial-scale production, providing farmers with a valuable source of income and contributing to local economic development [5]. Figure 1 shows samples of Harumanis mango, which are also the ones used in this study.



Figure 1. Samples of Harumanis mango fruit

Through the review of previous studies, this research identifies existing knowledge while highlighting gaps and limitations in current approaches. The insights gained from the literature review serve as a foundation for designing the visible imaging system and developing an effective classification model for assessing the quality of Harumanis mango in this study.

Overall, Harumanis mango is a distinctive and highly valued fruit in Malaysia, particularly in Perlis, where it holds significant economic and cultural importance. The development of automated quality assessment systems based on artificial intelligence and machine vision is essential to meet the growing demand for consistent, high-quality produce, while also strengthening Malaysia's competitiveness in the premium fruit market [8].

2. MATERIAL AND METHODS

2.1 Harumanis Mango Quality Classification

A comprehensive methodology was designed to develop and evaluate an automated system for classifying the quality of Harumanis mango. The study began with the collection of 1,500 mango samples from selected orchards in Perlis, Malaysia, ensuring balanced representation across the three main commercial grades. The dataset comprised 500 samples each from the Premium, Grade 1 and Grade 2 categories. Each sample was visually inspected to confirm consistency and to ensure the absence of external defects. High-resolution images of the mango were then captured using a Basler CCD camera under controlled conditions, including standardized lighting, a uniform background and a fixed camera distance to minimize external factors such as shadows and reflections [6]. This controlled setup ensured the acquisition of high-quality images suitable for digital analysis [6][9].

Figure 2 shows an overview of the Harumanis mango quality assessment process for colour analysis. The captured images were subsequently pre-processed through resizing, normalization, and background removal to enhance feature extraction. Colour features were extracted based on hue values in the HSI colour space, providing a reliable representation of the fruit's colour characteristics [10][11]. These features were then used as inputs for classification models. K-Nearest Neighbours (K-NN) and Support Vector Machine (SVM) classifiers were applied independently to evaluate their effectiveness in predicting mango quality based on colour information. To further improve classification performance, a low-level data fusion strategy was implemented by combining the outputs of both classifiers, and an Artificial Neural Network (ANN) was trained to produce the final quality classification.

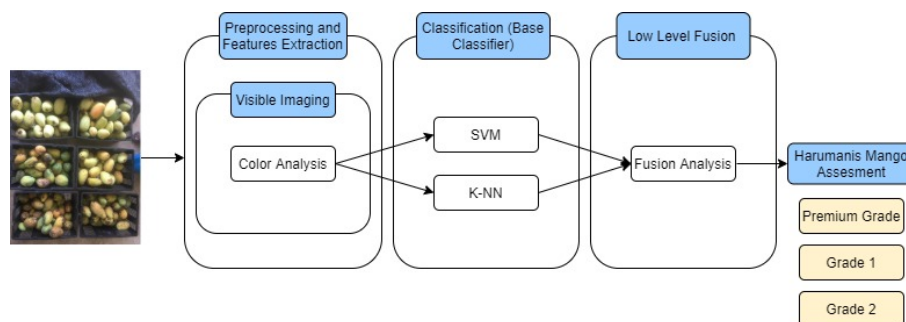


Figure 2. Overview of the Harumanis mango quality assessment framework

2.2 Model and Data Collection

The grading process follows established industry standards, focusing on external characteristics such as fruit size, skin colour and the absence of visible defects. Particular emphasis was placed on fruit hue colour, as it is a key criterion in Harumanis grading [12]. Premium grade mango was typically had vibrant skin colour and no visible blemishes. Grade 1 mango exhibits slight variations in hue colour and minor irregularities in shape but remained free from significant

defects. In contrast, Grade 2 mango shows more noticeable imperfections, including irregular uneven colour, or minor surface blemishes, although they remained suitable for consumption [8]. To ensure a comprehensive dataset as shown in Figure 3, both regular (symmetrical and well-formed) and irregular (asymmetrical or misshapen) shapes were included. This approach captured the natural variation present in commercial practice and allows classification system to be evaluated across a broader range of samples. Prior to image acquisition, each mango was carefully inspected to exclude samples with bruising, cuts, fungal infections or other signs of damages. These selected mangoes were gently cleaned using a soft, dry cloth to remove any surface dirt or debris, ensuring that image quality and feature extraction would not be affected by external contaminants.



Figure 3. Sample image of: (a) regular Harumanis mango with symmetrical and well-formed, and (b) misshapen Harumanis mango with asymmetrical and not well-formed

High-resolution images of all Harumanis mango samples were captured using a Basler CCD camera, selected for its ability to produce clear and detailed images suitable for feature extraction. The imaging process was conducted in a controlled environment to ensure consistent conditions and to minimize the effects of external factors such as lighting variations, shadows and reflections.

The camera was fixed on a stand above the imaging platform, with a constant distance maintained between the camera and each mango. A 16 mm lens was attached to the camera, optimized for a working distance of approximately 30 cm, with the manual focus set to this distance to ensure sharpness. The camera features a sensor size of 1/2.3", which is suitable for capturing detailed images necessary for both shape and colour analysis. A uniform, non-reflective background was used to clearly distinguish the fruit. Adjustable LED lighting provided even illumination, reducing shadows and glare. Camera settings, including exposure, white balance, and focus, were calibrated beforehand and kept constant throughout the image acquisition process, as shown in Figure 4.



Figure 4. Experimental imaging setup showing the camera mounting and control system within the custom-built enclosure

Each mango was placed individually at the center of the platform in a consistent orientation. After capturing each image, the mango was replaced with the next sample using the same procedure. All images were taken at high resolution to ensure sufficient detail for colour and feature analysis. Each image was labeled with a unique identifier based on its grade and stored securely for further processing and analysis.

2.3 Image Pre-processing

After image acquisition, all mango images underwent several pre-processing steps to improve quality and ensure consistency for feature extraction and classification [13]. The main objectives were to standardize the images, remove background noise and enhance the accuracy of colour analysis. First, all images were resized to a uniform resolution to maintain consistency across the dataset. Next, normalization was applied to reduce variations in lighting and exposure, allowing more reliable measurement of colour features. Figure 5 presents the workflow of the image pre-processing stage.

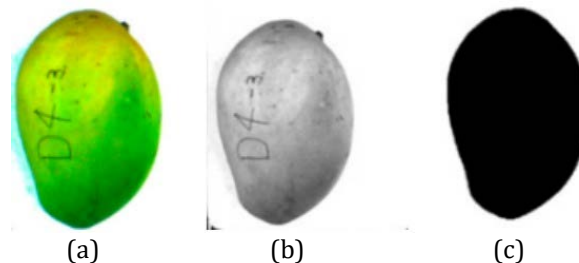


Figure 5. Pre-processing steps from: (a) original RGB image, (b) grayscale conversion and (c) binary mask extraction for segmentation

Background removal was performed using image segmentation techniques. Thresholding and morphological operations were applied to separate the mango from the background, producing a binary mask that clearly defined the fruit region. This step helped eliminate background interference that could affect analysis. The segmented mango region was then extracted, and any remaining noise or shadows were reduced through additional filtering. The processed images were reviewed to ensure that the mango were fully visible and accurately segmented [14][15].

Finally, the pre-processed images were stored in a structured database, with each image linked to its corresponding metadata, including quality grade and shape category. These clean and standardized images were then used as input for the subsequent feature extraction and classification stages.

2.4 Feature Extraction

Feature extraction was carried out to obtain measurable characteristics of Harumanis mango, focusing on colour for quality classification. This method converts the mango's outline into numerical values, allowing the system to describe whether the fruit is regular or misshapen.

For colour features, the mango surface was analysed using the HSI (Hue, Saturation, Intensity) colour space, with emphasis on the hue component, which is important for grading. The average hue value and its distribution across the fruit surface were calculated to capture variations in skin colour that may indicate ripeness or quality. The extracted shape and colour features were then combined into feature vectors for each sample [12][16][17]. These feature vectors were used as input for the classification models, enabling the system to objectively assess and classify Harumanis mango quality based on visual characteristics.

2.5 Classification Algorithm

The classification of Harumanis mango quality was performed using several machine learning algorithms applied to the extracted colour features, along with a fusion method to improve accuracy. First, the K-Nearest Neighbours (K-NN) algorithm was used to classify mango based on their feature vectors [18][19]. K-NN works by identifying the k nearest samples in the feature space and assigning the most frequent class among them. The value of k was selected through cross-validation to achieve optimal performance. In parallel, the Support Vector Machine (SVM) algorithm was applied to classify the colour features separately. SVM determines the optimal boundary that separates different quality grades in the feature space, and its parameters were tuned to better handle complex data patterns [20]. To further enhance classification performance, a low-level data fusion approach was implemented. Colour features for based classifier were combined into a single feature set for each mango, which was then used to train an Artificial Neural Network (ANN). The ANN consisted of an input layer for the combined features, one or more hidden layers, and an output layer representing the quality grades. The network was trained using the backpropagation algorithm, with parameters optimized to achieve the highest possible classification accuracy.

3. RESULTS AND DISCUSSION

3.1 Output Graph of Harumanis Mango Colour using Hue Method

Figure 6 illustrates the three primary categories by presenting the average hue values for Premium Grade, Grade 1 and Grade 2 Harumanis mango. The results indicate that the colour distribution of Harumanis mango is not entirely uniform based on the HSI (Hue, Saturation, Intensity) colour model. As the mango ripen, their colour gradually changes, reflected by a shift in hue values from a lower range (135–180) to a higher range (165–200). Premium grade mango generally exhibits higher hue values, with a peak around 175, indicating a less ripe state with more desirable colouration. In contrast, Grade 2 mango, which are considered overripe, show lower hue values, peaking at approximately 150. Grade 1 mango fall between these two categories, with a peak around 160.

Despite these trends, there is noticeable overlap in hue values among the different grades, making it difficult to distinguish them using a single hue threshold. This overlap suggests that colour alone is insufficient as a sole criterion for accurate classification.



Figure 6. Colour analysis of Harumanis mango using the hue method

3.2 Colour Analysis using K-Nearest Neighbours (K-NN)

The K-NN model was applied to classify mango maturity using hue (colour) features, with 60% of the dataset allocated for training and the remaining 40% for testing. The corresponding results are presented in Table 1. During the training phase, the K-NN model showed satisfactory performance; however, the misclassification rates were slightly higher compared to those observed in shape-based classification. In particular, misclassification occurred in 10% of Premium Grade samples, 6% of Grade 1 samples and 3% of Grade 2 samples. This indicates that although the model was generally capable of distinguishing between grades based on colour, the overlap in hue values posed challenges for precise separation.

During the testing phase, the misclassification rates showed some variation, with 4% of Premium Grade samples, 15% of Grade 1 samples and 5% of Grade 2 samples incorrectly classified. Overall, the K-NN model achieved an accuracy of 91.6% for colour-based classification on the test dataset.

Table 1 The accuracy and misclassification rates of Harumanis Mango using K-NN

Grade	K-NN (training) 60%			K-NN (testing) 40%		
	Premium	1	2	Premium	1	2
Premium	270	25	5	190	5	5
	90%	8%	2%	96%	2%	2%
1	10	280	10	20	170	10
	3%	94%	3%	10%	85%	5%
2	0	10	290	0	10	190
	0%	3%	97%	0%	5%	95%

3.3 Colour Analysis using Support Vector Machine (SVM)

The SVM model was also employed to classify mango maturity based on colour features, using 60% of the dataset for training and 40% for testing. The results are presented in Table 2. During the training phase, the SVM model demonstrated excellent performance, with low misclassification rates: 3% for Premium Grade samples, 6% for Grade 1 samples and 3% for Grade 2 samples. This indicates that the model was able to effectively learn and distinguish the colour characteristics associated with each grade. In the testing phase, the model maintained strong performance, with only 2% of Premium Grade samples and 7% of Grade 1 samples

misclassified. The overall accuracy achieved for both training and testing was 97.5%, which is significantly higher than the K-NN model for the same classification task.

Table 2 The accuracy and misclassification rates of Harumanis Mango using SVM

Grade	SVM (training) 60%			SVM (testing) 40%		
	Premium	1	2	Premium	1	2
Premium	290	10	0	195	5	0
	97%	3%	0%	98%	2%	0%
1	10	280	10	15	185	0
	3%	94%	3%	7%	93%	0%
2	10	0	290	0	0	200
	3%	0%	97%	0%	0%	100%

These findings highlight the effectiveness of SVM in capturing subtle variations in colour among different Harumanis mango grades. Its low misclassification rates and high accuracy demonstrate that it is a reliable approach for automated maturity classification based on colour, particularly in applications requiring consistent and precise quality evaluation.

3.4 Fusion Method using ANN

A low-level fusion approach was implemented by integrating the outputs of two classifiers, Support Vector Machine (SVM) and K-Nearest Neighbours (K-NN), using Artificial Neural Network (ANN). Initially, both SVM and K-NN were trained independently using colour features extracted from Harumanis mango images. Each model then generated its own predictions for the mango quality grades.

Subsequently, the prediction outputs from both SVM and K-NN were used as input features for the ANN. In this configuration, the ANN functions as a meta-classifier, learning how to combine and interpret the outputs of the two base classifiers. This enables the ANN to capture more complex patterns that may not be identified by SVM or K-NN individually, resulting in improved classification accuracy and robustness. For the SVM and K-NN models, 60% of the dataset was allocated for training and 40% for testing. This relatively larger test portion allows for a more thorough evaluation of their generalization performance, as these models typically require less data for effective learning.

In contrast, the ANN fusion model utilized 60% of the data for training and 40% for testing. Due to its higher number of parameters, the ANN requires more training data to effectively learn complex relationships and reduce the risk of overfitting. Providing a larger training set enables the ANN to better integrate the outputs from SVM and K-NN, thereby enhancing overall performance. The remaining 40% of data is sufficient to evaluate its generalization capability. This staged methodology ensures that the ANN is trained on informative features derived from the base classifiers while still being validated on unseen data to confirm its effectiveness.

3.5 ANN Evaluation

Based on Table 3, the ANN model was evaluated and achieved a classification accuracy of 98.6%, correctly identifying the majority of the initially categorized samples. Given the strong performance of both SVM and K-NN, it was expected that the ANN would yield an effective fusion outcome in this study. By integrating the outputs of these two base classifiers, the ANN demonstrates its ability to enhance the precision and overall efficiency of the classification process.

Table 3 Confusion matrix for the classification of Harumanis mango quality using the ANN model

Grade	ANN (training) 60%			ANN (testing) 40%		
	Premium	1	2	Premium	1	2
Premium	294	6	0	198	0	2
	98%	2%	0%	99%	0%	1%
1	3	288	9	0	196	4
	1%	96%	3%	0%	98%	2%
2	0	12	288	0	2	198
	0%	4%	96%	0%	1%	99%

The use of a low-level fusion approach for classifying Harumanis mango images has proven to be effective, although different combinations of classifiers and fusion techniques may yield varying levels of performance. In some cases, certain combinations of base classifiers and ensemble methods may even reduce the performance compared to the best individual classifier. However, as shown in this study, the ANN-based fusion method significantly outperformed the single classifiers trained on specific features. The findings indicate that relying on an individual classifier for each feature results in lower accuracy compared to the fusion approach, highlighting the advantage of integrating multiple classifiers to achieve better overall performance.

4. CONCLUSION

This study demonstrates that a non-destructive approach can effectively automate the classification of Harumanis mango quality. By utilizing machine vision techniques, the proposed system addresses the limitations of traditional manual grading, which is often subjective and inconsistent. High-resolution images were used to extract colour features through HSI hue analysis, which were then classified using K-Nearest Neighbours (KNN) and Support Vector Machine (SVM). These methods achieved high accuracy levels of up to 97.6%. The integration of features through an Artificial Neural Network (ANN) further enhanced performance, reaching an accuracy of 98.6% and highlighting the advantage of combining multiple feature representations. The 1% improvement represents a 41.7% reduction in error rate (from 2.4% to 1.4% error).

The most significant gain is in Grade 1 classification, which eliminates nearly 73% of errors in the most challenging category. Most mango samples were successfully categorized into Premium, Grade 1 and Grade 2, confirming the reliability of the system.

The dataset and classification of the mango samples were verified through manual inspection based on the predefined colour / hue classification criteria. The verification process was conducted with reference to the expertise and guidance of YA Harumanis and FAMA Perlis, under the supervision of the supervisor, as well as relevant past research related to this study. Each mango sample was reviewed to ensure that its assigned label corresponded to the appropriate quality category. This verification process was carried out before model training and testing to minimize misclassification and improve the reliability of the dataset.

The findings provide significant contributions to the Harumanis mango industry as well as the broader agricultural sector. The proposed automated system offers an objective and scalable solution for quality assessment, supporting improved quality control and more efficient supply chain management. By reducing dependence on manual inspection, it minimizes human error while helping to preserve the premium reputation of Harumanis mango and strengthen Malaysia's competitiveness in the high-value fruit market. Nevertheless, the system's effectiveness is influenced by image quality and controlled environmental conditions. Future research should focus on enabling real-time, on-field implementation and incorporating additional features, such as texture or aroma, to further enhance classification performance. Extending this approach to other types of fruits may also increase its applicability.

In conclusion, this research presents a practical and reliable framework for automated fruit quality evaluation, demonstrating how the integration of ANN and machine vision can modernize conventional agricultural practices and support the production of high-quality fruits such as Harumanis mango.

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