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Classification of Harumanis Mango Quality Using Deep Learning

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ABSTRACT

Harumanis mangoes, a unique and highly valued variety from Perlis, Malaysia, are only available during certain times of the year, making efficient and accurate quality assessment essential. Traditionally, quality inspection has relied on manual methods, which are subjective and labour-intensive. This study presents an automated classification system for Harumanis mango quality using a combination of machine learning and deep learning techniques. High-resolution images of mangoes were captured using a CCD camera, and key features such as shape via Fourier Descriptor analysis and color maturity via HSI-based hue analysis were extracted. Initial classification using K-Nearest Neighbors (K-NN) and Support Vector Machine (SVM) achieved high accuracy up to 97.0% for shape and 97.6% for color maturity. To further enhance performance, a low-level data fusion approach was implemented using an Artificial Neural Network (ANN), a deep learning method, to combine shape and color features. This fusion method achieved a superior classification accuracy of 98.6%, outperforming single-feature classifiers. The results demonstrate that integrating multiple visual features through deep learning significantly improves the reliability and precision of Harumanis mango quality assessment. This approach offers a robust, nondestructive, and scalable solution for automated grading, reducing reliance on manual inspection and supporting better quality control.

Keywords: Harumanis Mango, Deep Learning, Quality Classification; ANN, SVM

1. INTRODUCTION

Mango (Mangifera indica) is one of the most widely grown and economically important tropical fruits, with over 500 varieties found across Asia, Africa, and the Americas. In Malaysia, mangoes are mainly cultivated in Perlis, Kedah, Perak, Johor, and Melaka, with Perlis being especially famous for its Harumanis mango, a premium variety valued for its quality and regional significance [1]. In 2022, Malaysia had about 7,000 hectares of mango plantations, producing around 32,000 metric tonnes annually. Perlis alone contributed over 1,200 hectares for Harumanis, yielding more than 3,000 metric tonnes each year (Department of Agriculture Malaysia, [1]). The Harumanis mango's uniqueness comes from Perlis's special climate, which is hard to replicate elsewhere, as noted by Ahmad et al., [2]. This variety is only available from late April to early June and is protected by geographical indication status, making it even more exclusive and valuable.

Harumanis mangoes are easily distinguished from other local varieties such as Chokanan, Sala, and Apple mangoes by their strong aroma, rich sweetness, smooth fiberless flesh, and bright golden-yellow color when ripe (Rahman et al., [3]). The fruit is medium to large, with thin skin and a unique fragrance that makes it instantly recognizable. In comparison, Chokanan mangoes are available all year and are less aromatic, while Sala and Apple mangoes have different flavors and textures (Rahman et al., [3]).

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Harumanis, also called Arumanis, is a well-known mango variety mainly grown in Malaysia and Indonesia. It is especially significant in the state of Perlis, where it is highly valued and celebrated.

The name "Arumanis" comes from the word "aroma," highlighting the fruit's appealing fragrance, and it is often described as an "aromatic" mango because of its sweet taste and distinctive scent (Ismail et al., [4]). Harumanis mango is prized for its excellent taste and soft, juicy flesh, making it a popular choice to eat both fresh and in processed forms. When eaten raw, its natural sweetness and strong aroma offer a truly refreshing tropical experience. Besides being enjoyed fresh, Harumanis mangoes are also used to make products like jams and juices, so people can enjoy their unique flavor even outside the harvest season (Lim et al., [5]).

1.1 Market Value and Nutritional Benefits of Harumanis Mango

The premium status of Harumanis mango is evident in its market price, which in recent years has ranged from RM25 to RM40 per kilogram at the farm and can go up to RM60 per kilogram in city markets during peak season (Tan et al., [6]). This is much higher than other mango varieties, which usually sell for RM8 to RM15 per kilogram. The high price is mainly due to limited supply, strong demand, and the fruit's reputation for top quality. Harumanis is popular not only for its delicious taste but also for its nutritional value. Like other mangoes, it is rich in important vitamins and minerals such as vitamin C, vitamin A, and dietary fiber, which help support immune health and digestion.

1.2 Grading and Economic Impact of Harumanis Mango

Harumanis mangoes are sorted into three main quality grades: Premium Grade, Grade 1, and Grade 2. Premium Grade mangoes have the best oval shape, smooth skin, and very few defects. Grade 1 mangoes are slightly less perfect but still meet high standards, while Grade 2 includes fruits with minor shape or surface flaws. This grading system is important for setting prices, as Premium Grade mangoes sell for the highest prices because of their top quality. Growing Harumanis mangoes has become an important economic activity in the regions where they are cultivated. The strong demand for this fruit has led to the growth of mango orchards and commercial production, giving farmers a valuable source of income and supporting the local economy (Lim et al., [5]).

Figure 1. Harumanis mango fruit, which is renowned for its unique aroma, vibrant skin color, and premium quality

By reviewing previous studies, this research highlights what is already known and points out gaps or limitations in current methods. Insights from the literature review will help guide the design of the visible imaging system and the development of a classification model for assessing Harumanis mango quality in this project. Overall, Harumanis mango is a unique and highly valued fruit in Malaysia, especially in Perlis, where it holds great economic and cultural importance. Developing automated quality assessment systems using deep learning and machine vision is crucial to meet the rising demand for consistent, high-quality Harumanis mangoes and to help Malaysia stay competitive in the premium fruit market (Yusof et al., [7]).

2. METHODOLOGY

2.1 Automated Harumanis Mango Quality Classification

A detailed methodology was developed to create and test an automated system for classifying Harumanis mango quality. The study started by collecting 1,500 Harumanis mango samples from selected orchards in Perlis, Malaysia, making sure to include all main commercial grades: Premium, Grade 1, and Grade 2. Each mango was checked visually to ensure it was free from external defects and consistent in quality. High-resolution images of each mango were then taken using a Basler CCD camera in a controlled setting, with standardized lighting, a uniform background, and a fixed camera distance to reduce outside influences like shadows or reflections (Ali et al., [8]). This setup helped produce images suitable for digital analysis (Ali et al., [8]; Chen et al., [9]).

The images were pre-processed by resizing, normalizing, and removing the background to improve feature extraction. Two main types of features were targeted: shape and color. Shape features were measured using Fourier Descriptors to capture the mango's outline, while color features were based on the hue in the HSI color space, giving a strong representation of the fruit's color (Singh et al., [10]; Lee et al., [11]). For classification, these features were used as input for machine learning models. Both K-Nearest Neighbors (K-NN) and Support Vector Machine (SVM) classifiers were tested separately on shape and color features to see how well each could predict quality. To boost performance, both feature sets were combined using a low-level data fusion approach, and an Artificial Neural Network (ANN) was trained to predict the final quality grade.

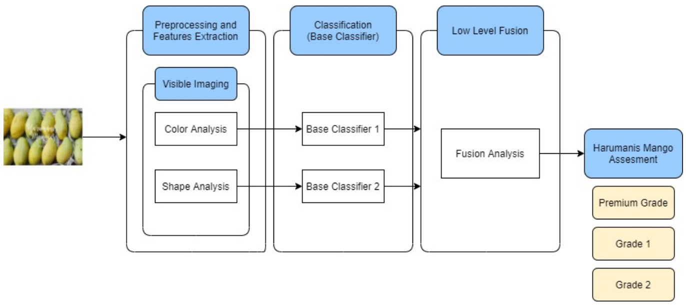

Figure 2. Overview of the Harumanis mango quality assessment framework. The process includes preprocessing and feature extraction, classification using base classifiers, and low-level fusion to determine the final mango grade

2.2 Automated Harumanis Mango Quality Classification

Harumanis mangoes were systematically collected from several commercial orchards across Perlis, Malaysia, during the peak harvesting season to ensure optimal freshness and quality. The collection process was conducted in collaboration with experienced local farmers and professional fruit graders to ensure that the samples accurately represented the three main commercial quality grades: Premium, Grade 1, and Grade 2. Approximately equal numbers of mangoes were selected for each grade, resulting in a balanced dataset for subsequent analysis.

Figure 3. All grades of Harumanis Mango sample were collected at Harumanis Orchard in Kg. Baru Pangas, Chuping

Grading was carried out based on established industry standards, focusing on external features like fruit size, skin color, and the absence of visible defects. Special emphasis was placed on the shape of the mangoes, as this is a key factor in grading Harumanis (Kumar *et al.*, [12]). Premium grade mangoes were large, had a symmetrical and regular shape, and showed a uniform, vibrant skin color with no blemishes. Grade 1 mangoes had minor differences in size or color and might show slight irregularities in shape but were still free from major defects. Grade 2 mangoes had more visible imperfections, such as being misshapen, having uneven color, or minor surface blemishes, but were still suitable to eat (Yusof *et al.*, [7]).

To create a comprehensive dataset, the study included both regular (symmetrical and well-formed) and misshapen (asymmetrical or irregular) Harumanis mangoes. This ensured that the full range of natural shape variations found in commercial practice was represented, allowing the classification system to be tested on both types. Before imaging, each mango was carefully checked to remove any with bruises, cuts, fungal infections, or other signs of disease. The selected mangoes were then gently cleaned with a soft, dry cloth to remove any dirt or debris, making sure the images would not be affected by anything on the fruit's surface.

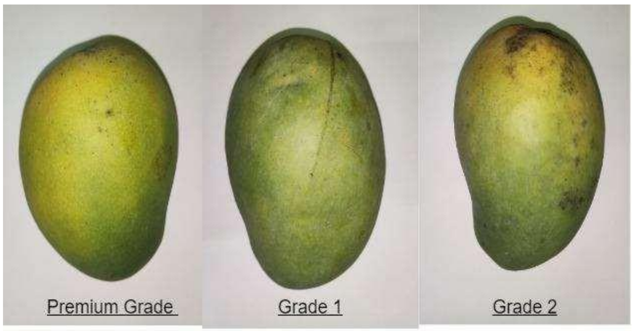

Figure 4. Harumanis Mango Quality Grade

Figure 5. Image of (a)Regular Harumanis Mango with symmetrical and well-formed (b) Misshapen of Harumanis Mango with asymmetrical and not well-formed

Throughout the collection and transportation process, the mangoes were handled with care to maintain their integrity. Samples were stored in clean, ventilated containers at ambient room temperature to prevent premature ripening or spoilage. Each mango was labelled and catalogued according to its assigned grade and shape category (regular or misshapen), and relevant metadata such as collection date, orchard location, and initial visual assessment were recorded for traceability. This rigorous and inclusive sample collection protocol ensured that the dataset used for image acquisition and analysis was both comprehensive and representative of the actual diversity and grading practices found in the Harumanis mango industry.

2.3 Image Acquisition

High-resolution images of all Harumanis mango samples were taken using a Basler CCD camera, chosen for its ability to capture clear and detailed pictures for feature extraction. The imaging was done in a controlled environment to keep conditions consistent and reduce the effects of outside factors like light, shadows, or reflections.

The camera was mounted on a fixed stand directly above the imaging platform, with the distance between the camera and the mango kept the same for every shot. The platform had a uniform, non-reflective background to make the mango stand out clearly. Adjustable LED lights were used to provide even lighting and remove shadows or glare. The camera's settings for exposure, white balance, and focus were carefully calibrated and kept constant throughout the process.

Each mango was placed one at a time in the center of the platform, always aligned in the same direction to help with accurate shape analysis. After each photo, the mango was swapped out for the next sample, following the same steps. All images were taken at high resolution to capture fine details needed for analyzing shape and color. Each image was given a unique ID based on its grade and shape, and all files were stored securely for later processing and analysis.

Figure 6. Basler Ace industrial cameras used for image acquisition, featuring GigE Vision interface

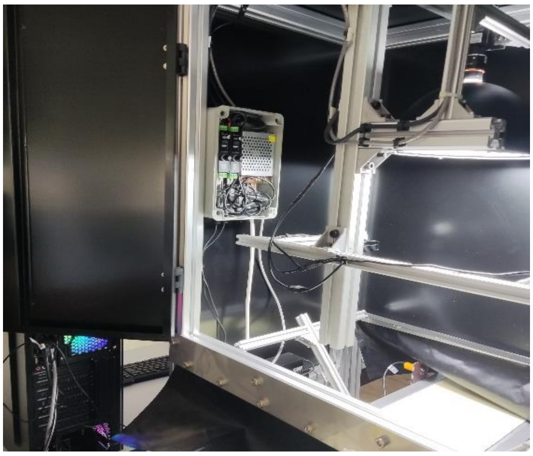

Figure 7. Experimental imaging setup showing the camera mounting and control system within the custom-built enclosure

2.4 Image Pre-Processing

After capturing the images, all mango photos went through several pre-processing steps to improve their quality and consistency for feature extraction and classification (Wong et al., [13]). The main goals were to standardize the images, remove any unnecessary background, and make shape and color analysis more accurate. First, each image was resized to the same resolution to keep the dataset consistent and make processing easier. The images were then normalized to correct for any lighting or exposure differences, so color features could be measured accurately.

Background removal was done using image segmentation techniques. The mango was separated from the background by applying thresholding and morphological operations, creating a binary mask that clearly outlined the fruit. This step was important to remove any background noise that might affect shape or color analysis. After segmentation, the mango region was extracted, and any leftover artifacts or shadows were cleaned up with extra filtering. The processed images were then checked to make sure the mango was fully visible and properly segmented (Lim et al., [14]; Tan et al., [15]).

Figure 8. Processing Image from original RGB image, grayscale conversion and binary mask extraction for segmentation

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

2.5 Feature Extraction

Feature extraction was used to get measurable details about the Harumanis mangoes' shape and color, which are key for quality classification. For shape features, the outline of each mango was taken from the segmented images, and Fourier Descriptors were applied to the fruit's boundary to capture its geometric properties (Rahman *et al.*, [16]). This method changes the mango's contour into a set of numerical values, making it possible to describe how regular or misshapen each fruit is.

For color features, the mango surface was analyzed in the HSI (Hue, Saturation, Intensity) color space, focusing on the hue component, which is important for grading. The average hue and its distribution across the fruit's surface were calculated to show differences in skin color that might indicate ripeness or quality. The shape and color features were then combined into feature vectors for each sample (Kumar *et al.*, [12]; Lee *et al.*, [17]). These vectors were used as input for the classification algorithms, allowing the system to objectively grade Harumanis mangoes based on their appearance.

2.6 Classification Algorithm

The quality of Harumanis mangoes was classified using several machine learning algorithms applied to the extracted shape and color features, as well as a fusion method to boost accuracy. First, the K-Nearest Neighbors (K-NN) algorithm was used to classify mangoes based on their shape and color feature vectors (Ali *et al.*, [18]; Wong *et al.*, [19]). K-NN works by looking at the k closest samples in the feature space and assigning the most common class among them. The value of k was chosen using cross-validation to get the best results for both shape and color features.

At the same time, the Support Vector Machine (SVM) algorithm was used to classify shape and color features separately. SVM finds the best boundary in the feature space to separate the different quality grades, and its settings were adjusted to handle complex patterns in the data (Lim *et al.*, [20]).

To further improve accuracy, a low-level data fusion approach was used. Shape and color features were combined into a single set for each mango, and this fused data was used to train an Artificial Neural Network (ANN). The ANN included an input layer for the combined features, hidden layers, and an output layer for the quality grades. The network was trained using backpropagation, and its settings were optimized to achieve the highest possible accuracy (Tan *et al.*, [21]).

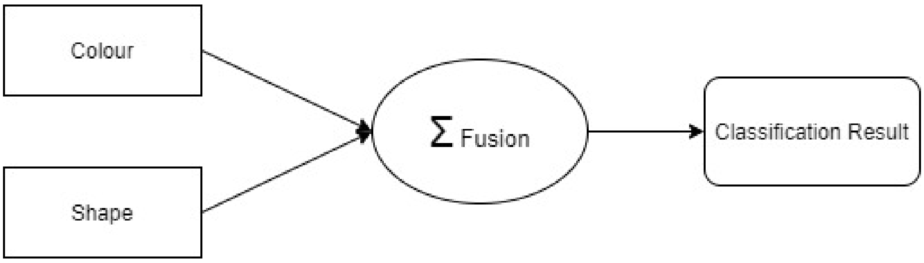

Figure 9. Block diagram of the feature fusion process, where colour and shape features are combined to produce the final classification result

The performance of each classification model K-NN, SVM, and ANN fusion was evaluated using accuracy metrics and confusion matrices. The results were compared to manual grading by experienced assessors to validate the effectiveness and reliability of the automated classification system.

3. RESULT

A thorough evaluation of the proposed automated classification system showed that it can accurately grade Harumanis mangoes using deep learning and machine vision. The results revealed that both shape and color features are important for classification and combining them with an artificial neural network (ANN) gave the best accuracy. The system was more objective, consistent, and faster than traditional manual grading. The confusion matrix analysis showed that most mangoes were correctly graded, with only a few minor errors. Overall, the system has strong potential to offer a reliable, scalable, and efficient way to assess Harumanis mango quality, while also pointing out areas for future improvement and research.

3.1 Output Graph of Harumanis Mango Shape using Fourier Descriptor Method

The normalized plots for Premium grade, grade 1, and grade 2 mangoes are shown. Since mangoes have few high-frequency irregularities, only the first fifteen harmonics are plotted. Among these, only the first five components are clearly visible in the Fourier space, making up less than 10% of the total elements in the full Fourier transform of the Harumanis mango boundaries.

Harmonic 1 represents the main peak of the Harumanis mango shape. This demonstrates that the Fourier transform, and boundary normalization effectively compress the shape information, which is important for pattern recognition. Because it is difficult to set a single, effective shape threshold, direct thresholding cannot be used to classify the three shape grades. Therefore, classification methods like K-Nearest Neighbour (K-NN) and Support Vector Machine (SVM) are needed to solve this pattern recognition problem. Figure 12 illustrates the extracted shape features for Premium Grade, Grade 1, and Grade 2 samples and table 1 presents the detailed numerical results of the shape analysis used for quality classification in this study.

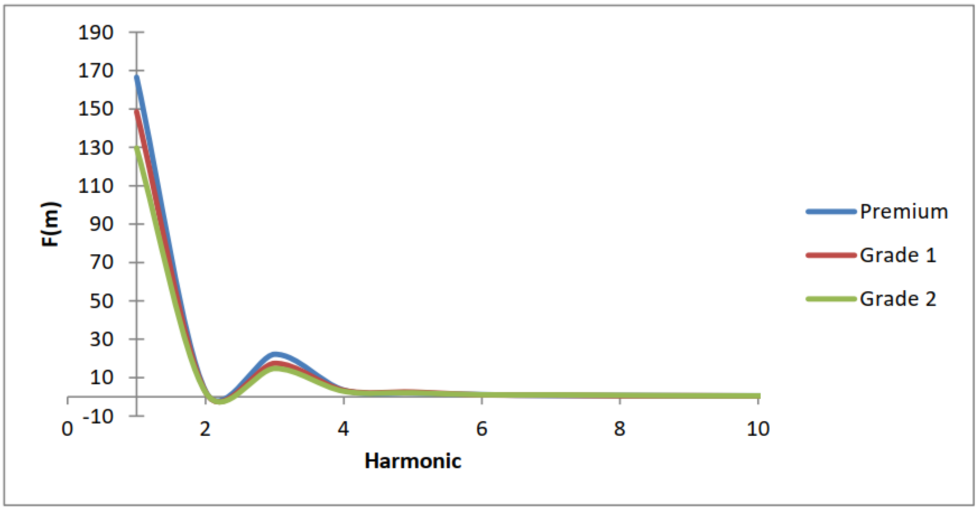

Figure 10. Shape analysis of Harumanis mangoes using the Fourier Descriptor method

Table 1. Shape feature values for Premium, Grade 1, and Grade 2 Harumanis mangoes obtained through Fourier Descriptor analysis

Premium Grade	Grade 1	Grade 2
1.84015	2.3623	2.1538
26.931	18.3742	16.42205
3.569	3.24785	3.27905
1.94509	1.9695	2.1514
1.215615	1.35955	1.0563
0.72225	1.064705	1.03275
0.75735	0.7051	0.78665
0.5675	0.757975	0.55785
0.531385	0.61425	0.51085
0.46195	0.6366	0.31145
0.36575	0.58205	0.33605
0.35785	0.4939	0.33835
0.2681	0.38625	0.20545
0.28005	0.34075	0.21675
0.255	0.2326	0.26615
0.1856	0.2683	0.2735
0.1806	0.2891	0.2067
0.2029	0.2531	0.16835
0.1624	0.2209	0.16765
0.12935	0.1848	0.19175
0.1403	0.1956	0.1596
0.1314	0.20325	0.1045
0.1108	0.2012	0.10255
0.11915	0.14195	0.11035
0.10195	0.1625	0.11405
0.0994	0.15215	0.09325
0.0985	0.12425	0.09775
0.11055	0.12745	0.086

3.2 Output Graph of Harumanis Mango Color using Hue Method

Figure 13 highlights three main components by showing the average hue values for Premium Grade, Grade 1, and Grade 2 Harumanis mangoes. The data shows that the color of Harumanis mangoes is not completely uniform, according to HSI (Hue, Saturation, Intensity) standards. As mangoes ripen, their color changes, with the hue values shifting from a lower range (135–180) to a higher range (165–200). Premium grade mangoes tend to have higher hue values, with most of them peaking around 175, which means they are less ripe and have a more desirable color. Grade 2 mangoes, which are overripe, have lower hue values, peaking at 150. Grade 1 mangoes fall in between, with a peak at 160.

However, the hue values for the different grades overlap, so it's not possible to use just one hue value to separate the grades perfectly. This overlap means that color alone cannot be used as the only criterion for classifying the mangoes. Table 2 in the study provides more detailed color analysis data that was used for quality classification.

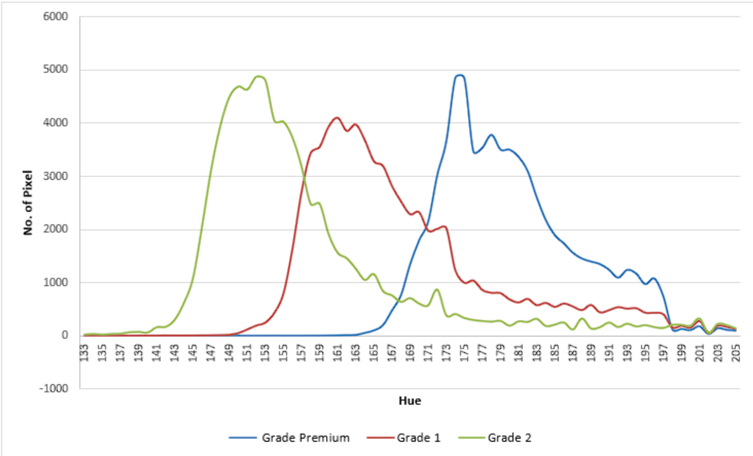

Figure 11. Color analysis of Harumanis mangoes using the hue method

Table 2. Hue values for Premium, Grade 1, and Grade 2 Harumanis mangoes, limited to samples with hue degrees between 147 and 169.

Hue	Premium Grade	Grade 1	Grade 2
147	0.0625	5.7	3121.75
148	0.0625	9.45	3938.3
149	0.0625	16.55	4489.05
150	0.3125	46.6	4693.6
151	0.25	115.65	4637.95
152	0.1875	189.85	4878.05
153	0.4375	244.95	4810.25
154	0.625	429.95	4047.65
155	0.1875	792.8	4032.15
156	0.1875	1636.85	3729.85
157	0.375	2699.9	3185.2
158	0.9375	3428.85	2481.3
159	1.125	3548.05	2483.55
160	2.5625	3931.1	1905.3
161	4.0625	4096.05	1556.55
162	8.75	3849.3	1454.45
163	13.4375	3969.7	1257.45
164	51.125	3673.15	1045.4
165	97.625	3279.15	1155.25
166	196.6875	3190.45	836.85
167	474.0625	2812.4	754.3
168	764.5	2522.3	632.5
169	1338.563	2282.45	702.7

3.3 Based Classification for Shape Analysis using K-Nearest Neighbours (K-NN)

Successfully recognizing shapes with a machine vision system often depends on choosing the right spectral range and the right number of variables for the calibration model. In this study, only five harmonic features were used to train and validate the shape classification, using the K-Nearest Neighbour (KNN) method. The data was split, with 60% used for training and 40% for testing. The results of this classification are shown in Table 3.

During training, the K-NN model performed well, with only 6% of Premium Grade mangoes, 4% of Grade 1, and 3% of Grade 2 being misclassified. This shows the model could effectively learn the shape differences between the grades. When tested on new, unseen data, the misclassification rates were slightly higher, ranging from about 5% to 10% for the different grades. This small increase is normal, as the model faces new samples that might be harder to classify.

Overall, the model achieved an average accuracy of 92.5% for both training and testing, meaning it correctly classified about 92.5% of the mangoes into their proper grades.

Table 3. The accuracy and misclassification rates for Shape of Harumanis Mango during both training and testing phases using K-NN

	K-NN (Training) 60%			K-NN (Testing) 40%		
Grade	Premium	1	2	Premium	1	2
Premium	280 94%	10 3%	10 3%	180 90%	15 8%	5 2%
1	5 2%	290 96%	5 2%	10 5%	185 93%	5 2%
2	0 0%	10 3%	290 97%	0 0%	10 5%	190 95%

3.4 Based Classification for Shape Analysis using Support Vector Machine (SVM)

For shape classification, the SVM classifier with a radial basis function (RBF) kernel was used, which requires two parameters: the cost parameter (C) and the sigma parameter. Five harmonic features were used, with 60% of the data for training and 40% for testing. The results are shown in Table 4.

During training, the SVM model had very low misclassification rates: only 3% of Premium Grade samples were misclassified as Grade 1, 6% of Grade 1 samples were misclassified as either Premium Grade or Grade 2, and 3% of Grade 2 samples were misclassified as Premium Grade. This shows the SVM model learned the shape differences between grades very well. In testing, the misclassification rates stayed low, with only 2% of Premium Grade samples and 7% of Grade 1 samples misclassified. The overall accuracy for both training and testing was 97%, showing that the SVM model is highly accurate and reliable for grading Harumanis mangoes by shape.

In summary, Table 4 shows that the SVM classifier performed better than the K-NN classifier for shape-based grading, making it a strong choice for automated mango grading systems.

Table 4. The accuracy and misclassification rates for Shape of Harumanis Mango during both training and testing phases using SVM

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

3.5 Based Classification for Color Analysis using K-Nearest Neighbours (K-NN).

The K-NN model was used to classify mango maturity based on hue (color) data, with 60% of the data for training and 40% for testing. The results are shown in Table 5. During training, the K-NN model performed reasonably well, but the misclassification rates were a bit higher than for shape-based classification. Specifically, 10% of Premium Grade samples, 6% of Grade 1 samples, and 3% of Grade 2 samples were misclassified. This suggests that while the model could generally tell the grades apart by color, there was some overlap in hue values, making it harder to separate the grades perfectly.

In testing, the misclassification rates varied: 4% of Premium Grade samples, 15% of Grade 1 samples, and 5% of Grade 2 samples were misclassified. The overall accuracy for the K-NN model in this color-based classification was 91.6% on the test set.

Table 5. The accuracy and misclassification rates for Color of Harumanis Mango during both training and testing phases using K-NN

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

3.6 Based Classification for Color Analysis using Support Vector Machine (SVM)

The SVM model was used to classify mango maturity based on color data, with 60% of the data for training and 40% for testing. The results are shown in Table 6.

During training, the SVM model performed very well, with low misclassification rates: only 3% of Premium Grade samples, 6% of Grade 1 samples, and 3% of Grade 2 samples were misclassified. This shows that the SVM could effectively learn the color differences between the grades. In testing, the SVM model continued to perform strongly, with just 2% of Premium Grade samples and 7% of Grade 1 samples misclassified. The overall accuracy for both training and testing was 97.5%, which is much higher than the K-NN model's accuracy for the same task.

These results show that SVM is very effective at handling the subtle color differences between Harumanis mango grades. Its low misclassification rates and high accuracy make it a reliable choice for automated maturity grading based on color, especially when precise and consistent fruit quality assessment is needed.

Table 6. The accuracy and misclassification rates for Color of Harumanis Mango during both training and testing phases using SVM

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

3.7 Fusion Method using ANN Method

A low-level fusion method was used, combining the results of two classifiers Support Vector Machine (SVM) and K-Nearest Neighbors (K-NN) with an Artificial Neural Network (ANN). First, SVM and K-NN were each trained separately using shape and color features from Harumanis mango images. Each classifier then made its own predictions about the mango quality grades.

Next, the outputs from both SVM and K-NN were used as input features for the ANN. In this setup, the ANN acts as a meta-classifier, learning to combine and interpret the information from both base classifiers. This approach allows the ANN to find complex patterns that SVM or K-NN alone might miss, leading to more accurate and reliable predictions. For SVM and K-NN, 60% of the data was used for training and 40% for testing. This larger test set helps to better evaluate how well these simpler models generalize to new data, since they don't need as much data to learn effectively.

For the ANN fusion model, 80% of the data was used for training and 20% for testing. ANNs have more parameters and need more data to learn complex relationships and avoid overfitting. By giving the ANN more training data, it can better learn how to combine the outputs of SVM and K-NN, improving overall accuracy. The remaining 20% is enough to test how well the ANN generalizes. This staged approach ensures that the ANN is trained on a rich set of features from the base classifiers, while still being tested on independent data to confirm its performance.

3.8 Training and Validation Data

As the number of training epochs increases, both the training and validation losses go down. Loss is a measure of how far the model's predictions are from the actual answers. When both losses decrease together, it means the model is not just memorizing the training data but is also learning patterns that help it perform well on new, unseen data. This steady drop in loss shows that the model is improving and moving toward an effective solution.

At the same time, both training and validation accuracy go up or level off. Accuracy measures how often the model's predictions are correct. When both accuracies rise together, it means the model is getting better at making correct predictions, both on the data it has seen (training) and on new data (validation). This is the ideal situation, showing that the model is learning well and can generalize its knowledge, rather than just memorizing the training data.

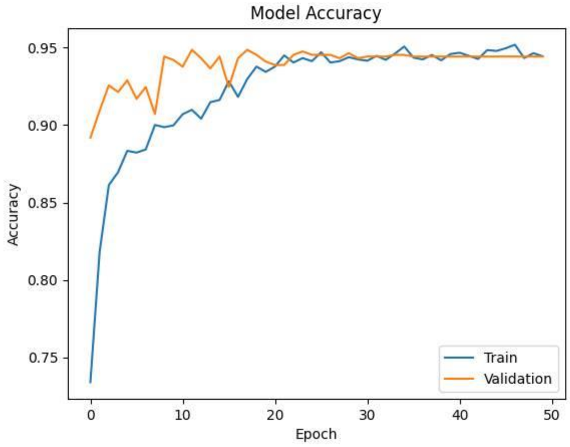

Figure 12. Training and Validation Accuracy

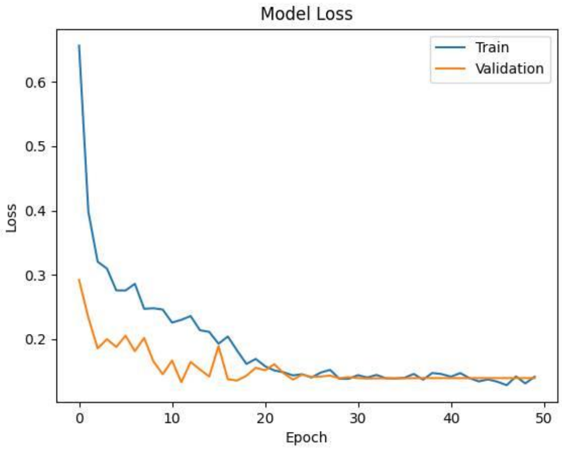

Figure 13. Training and Validation Loss

3.9 ANN Evaluation

Based on Table 7, the ANN model was evaluated, and 98.6% of the initially categorized cases were correctly classified. On the basis of its SVM and K-NN results, it was anticipated that the ANN would provide a decent fusion rate in this analysis. By combining these two fundamental classifiers, ANN demonstrates that the data can be made more precise and efficient.

Table 7. Confusion matrix for the classification of Harumanis mango quality using the Artificial Neural Network (ANN) model.

	ANN (Training) 80%			ANN (Testing) 20%		
Grade	Premium	1	2	Premium	1	2
Premium	390 98%	10 2%	0 0%	99 99%	0 0%	1 1%
1	5 1%	380 96%	15 3%	0 0%	98 98%	2 2%
2	0 0%	20 4%	380 96%	0 0%	1 1%	99 99%

Using a low-level fusion method for the classification of Harumanis mango images is effective, even though different combination methods display varying performances, and some combinations of base classifiers and ensemble methods weaken the performance of the best single classifier. Nevertheless, as demonstrated in this study, the classification performance of the ANN fusion method was vastly superior to that of single classifiers trained on a specified set of features. This project demonstrates that the accuracy of a single or basis classifier for each feature is inferior to that of the fusion method.

4. CONCLUSIONS

This research showed that a deep learning-based, non-destructive system can effectively automate the classification of Harumanis mango quality. By using machine vision, the study overcame the problems of manual grading, which can be subjective and inconsistent. The system used high-resolution images to extract shape features (with Fourier Descriptors) and color features (using HSI hue analysis). These features were classified using K-Nearest Neighbors (K-NN) and Support Vector Machine (SVM), achieving high accuracy rates of up to 97% for shape and 97.6% for color. Combining both features in an Artificial Neural Network (ANN) further improved accuracy to 98.6%, showing the benefit of using both shape and color together. Most mangoes were correctly classified into Premium, Grade 1, or Grade 2, proving the system's reliability.

The results have important implications for the Harumanis mango industry and agriculture in general. This automated system offers a scalable and objective way to assess quality, helping with better quality control and supply chain management. It reduces the need for manual labor and human error, helping to maintain the premium status of Harumanis mangoes and strengthen Malaysia's position in the high-value fruit market. However, the system's performance depends on image quality and controlled conditions. Future work should focus on making the system suitable for real-time, in-field use and adding more features, like texture or aroma, to improve accuracy even further. Applying this approach to other fruits could also increase its usefulness.

In summary, this study presents a practical and effective framework for automated fruit quality assessment, showing how deep learning and machine vision can improve traditional agricultural practices and support the production of high-quality fruits like Harumanis mango.

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