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CLASSIFICATION OF PAPAYA NUTRITION BASED ON MATURITY WITH DIGITAL IMAGE AND ARTIFICIAL NEURAL NETWORK

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Abstract— *Papaya is a tropical fruit with high nutritional content and significant health benefits. Nutritional components such as sugars, vitamin C, and fibre are strongly influenced by ripeness level. Identifying these nutrients usually requires laboratory tests that are time-consuming and rely on sophisticated equipment. Previous studies have focused on classifying ripeness levels, yet none have specifically addressed the classification of nutritional content. This study proposes a classification system for papaya nutrition based on ripeness using digital image processing and artificial neural networks (ANN). The method consists of six stages: image acquisition, preprocessing, segmentation, morphology, feature extraction, and classification with a trained ANN model. Experiments were conducted to evaluate feature combinations, including colour and texture features. The combination of LAB colour features and texture features-contrast, correlation, energy, and homogeneity-produced the best results. Testing on 75 images achieved an average precision of 97.22%, recall of 96.67%, F1-Score of 96.80%, and accuracy of 97.33%, with an average computation time of 0.02 seconds per image. These findings indicate that the proposed method provides fast and highly accurate classification of papaya's nutritional content, offering a practical alternative to laboratory testing. Nevertheless, the study is limited by the relatively small dataset and controlled acquisition environment. Future research should extend the dataset, incorporate deep learning approaches, and validate performance under real-world conditions to enhance robustness and generalization.*

Keywords: *Papaya Nutrition; Ripeness Level; Digital Image Processing; Classification; Artificial Neural Network.*

Intisari— *Pepaya merupakan buah tropis dengan kandungan nutrisi tinggi dan manfaat kesehatan yang beragam. Komponen nutrisi seperti gula, vitamin C, dan serat sangat dipengaruhi oleh tingkat kematangan. Identifikasi nutrisi biasanya memerlukan uji laboratorium yang memakan waktu serta membutuhkan peralatan canggih. Penelitian sebelumnya lebih banyak berfokus pada klasifikasi tingkat kematangan, namun belum secara khusus mengkaji klasifikasi kandungan nutrisi. Penelitian ini mengusulkan sistem klasifikasi kandungan nutrisi pepaya berdasarkan tingkat kematangan menggunakan pengolahan citra digital berbasis jaringan syaraf tiruan (JST). Metode yang digunakan terdiri dari enam tahap: akuisisi citra, praproses, segmentasi, morfologi, ekstraksi fitur, dan klasifikasi dengan model JST terlatih. Eksperimen dilakukan untuk mengevaluasi kombinasi fitur warna dan tekstur. Hasil terbaik diperoleh dari kombinasi fitur warna LAB dan fitur tekstur berupa contrast, correlation, energy, dan homogeneity. Pengujian pada 75 citra menghasilkan precision rata-rata 97,22%, recall 96,67%, F1-Score 96,80%, serta akurasi 97,33% dengan waktu komputasi rata-rata 0,02 detik per citra. Hasil ini menunjukkan bahwa metode yang diusulkan mampu mengklasifikasikan kandungan nutrisi pepaya secara cepat dan akurat, sehingga dapat menjadi alternatif praktis dibandingkan pengujian laboratorium. Meski demikian, penelitian ini masih terbatas pada jumlah dataset yang relatif kecil dan kondisi akuisisi terkontrol. Penelitian selanjutnya disarankan memperluas*

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dataset, menerapkan metode deep learning, serta menguji sistem pada kondisi nyata untuk meningkatkan ketahanan dan generalisasi.

***Kata Kunci**: Nutrisi Pepaya; Tingkat Kematangan; Pemrosesan Citra Digital; Klasifikasi; Jaringan Syaraf Tiruan.*

INTRODUCTION

Papaya fruit is known as one of the "king of fruits" in Indonesia because it is rich in benefits, nutrients, and vitamins that are very good for health[1]. This fruit is loved by many people, from all walks of life, both young and old, and is often a favourite fruit in various occasions[2]. Papaya grows widely in various tropical and subtropical regions in Indonesia, making it easy to find in the market because it is available throughout the year. Based on data from the Central Bureau of Statistics, Indonesia is one of the largest papaya producers in the world, with production reaching 1.2 million tonnes by 2023[3]. The high production of papaya makes the fruit not only plays an important role in fulfilling the nutritional needs of the community, but also as a superior economic commodity[4].

Papaya fruit is rich in nutrients, containing high levels of vitamins A and C[5], as well as various important minerals such as calcium, phosphorus, magnesium, and iron. In every 100 grams, papaya contains 3.65 mg of vitamin A and 78 mg of vitamin C[6]. Despite papaya's high nutritional content, many people are not fully aware of its nutritional content[7]. Human judgement of papaya's nutritional value is often inaccurate due to a lack of understanding of its nutritional composition and ripeness level[8]. Papaya fruits vary in nutrient content depending on the level of ripeness. Changes in the papaya skin, especially during the ripening process, can affect its nutritional content[9]. The nutritional composition of papaya undergoes substantial changes throughout the ripening process. Immature papaya contains the highest fiber levels—particularly in the skin—which gradually decreases as the fruit matures. Conversely, vitamin C content increases during the transition from unripe to fully ripe stages, reaching its peak in ripe papaya. Meanwhile, soluble sugars such as glucose and fructose also rise significantly as ripening progresses, resulting in a sweeter flavor profile in mature fruit[10]. These variations indicate the importance of selecting the ripeness level of papaya according to nutritional needs and consumption preferences. Therefore, the ability to identify the ripeness level of papaya based on its nutritional level is important to ensure consumers get the optimal nutritional content according to their needs.

In order to determine the nutritional content of papaya more accurately, time-consuming laboratory tests and sophisticated equipment are required[11]. Therefore, the utilisation of digital image processing can be used to determine the nutritional content of papaya through image analysis of the object under study[8]. This approach offers a more practical and efficient solution, which can help people choose papaya according to their nutritional needs. Thus, this research not only supports a healthy lifestyle, but also has the potential to increase the economic value of papaya as a superior commodity. In addition, this approach is expected to encourage the application of non-destructive technologies that are more accessible and more efficient than traditional laboratory testing methods.

In the study of fruit ripeness detection, various approaches have been developed to address the limitations of manual visual assessment, which is often inconsistent and inefficient. One relevant study was conducted by Wardani et al, who proposed an automatic papaya ripeness classification system using Support Vector Machine (SVM) combined with colour, texture, and shape features extracted from HSI and YCbCr colour spaces, GLCM texture descriptors, and integral projection. Their results showed that the highest accuracy achieved was 66% for the HSI feature set, while other feature combinations produced lower and more variable accuracy levels across ripeness classes. These findings indicate that although SVM can recognise maturity levels to a certain extent, the variability in feature separability and the computational complexity of multi-feature extraction present practical limitations for real-world implementation [12].

On the other hand, [2] applied the RGB method in a fruit ripeness detection system. Although this research introduced innovations in automatic detection, the results obtained only reached 50% accuracy. This shows that the RGB method still has limitations in its practical application. This research highlights the need for further development to improve the accuracy and effectiveness of the fruit ripeness detection system, but this research still has shortcomings in terms of accuracy consistency that can affect harvesting decisions, thus causing non-optimal results for farmers.

Several previous studies have employed Artificial Neural Networks (ANN) in fruit classification tasks by utilizing colour and texture features. For instance, [13] successfully applied ANN to classify banana ripeness using colour and texture features, achieving high accuracy despite challenges such as limited datasets and variations in lighting. Similarly, [14] demonstrated that ANN could effectively classify tropical fruits with an accuracy of around 95%, although the model performance was constrained by relatively small datasets and controlled image acquisition conditions. This evidence highlights the capability of ANN in modelling non-linear relationships among image features, while also pointing out the challenges of generalization. Motivated by these findings, the present study extends the use of ANN to focus on nutrient-based classification of papaya, combining LAB colour and texture features.

In addition to ANN-based approaches, other researchers have explored different algorithms and feature combinations for fruit classification. For example, [15] combined HSI colour features with the K-Nearest Neighbor (KNN) algorithm to classify fruit types and ripeness levels. The results showed improved accuracy but were still constrained by accumulated classification errors. This indicates the importance of combining diverse features to achieve more accurate and reliable identification of fruit ripeness, as classification errors can reduce product quality and selling value. Similarly, [16] developed a classification system for butter avocado ripeness using the KNN method based on skin colour. The system achieved 85.71% accuracy for unripe avocados, but only 66.66% for half-ripe ones, highlighting the challenges of maintaining high accuracy across all maturity stages. These individual studies align with broader findings in the literature. For instance, Xiao et al. reviewed numerous studies on fruit and vegetable classification and reported that traditional algorithms such as SVM and KNN generally achieve accuracies between 85% and 96%, while multi-feature fusion approaches can reach up to 97–99%. Such findings reinforce the importance of combining colour and texture features, which is consistent with the approach adopted in this study [17].

Then, research conducted by [15] aims to measure the effect of long storage of Bangkok papaya (*Carica Pepaya L.*) on vitamin C content as an immunostimulant during the Covid 19 pandemic. Using the UV-Vis spectrophotometric method, this study found that papaya stored for 3 days after harvest had the most optimal vitamin C content of 0.0699%, while after 6 days there was a decrease in vitamin C content of 15.45%. These results indicate that storage for 3 days provides the highest vitamin C content, which is important for maintaining the body's immune system. This study also showed a significant effect of storage time on vitamin C levels ($p < 0.05$).

In another study conducted by Laia, the perceptron artificial neural network method was applied to classify the ripeness level of mango fruit based on shape. This study used 40 mango images consisting of four categories: unripe, moderately ripe, ripe, and very ripe. The result of the test showed an accuracy rate of 50%, which indicates that there is still room for improvement in terms of ripeness recognition accuracy. This research shows that although the perceptron method is capable of classification, there are challenges in terms of accuracy, especially related to the amount of data and pattern complexity in fruit images[16]. recommends the use of higher resolution cameras as well as the incorporation of other classification methods to improve the accuracy of fruit ripeness recognition. This shows the importance of dataset quality and the use of better image processing techniques to achieve optimal results. However, this research still has challenges in terms of data validity that can affect accuracy, mainly due to the limited number and quality of datasets used. Research conducted by[18], which also focused on measuring nutrient content through a digital image processing approach. In this study, they developed a classification method for banana nutritional content based on colour and texture features using artificial neural networks (ANN) as the classification algorithm. The test results showed that this combination of LAB colour and texture features was able to achieve 98% accuracy, with high *precision*, *recall*, and *F1-Score* values.

Therefore, this research proposes the title Classification of Nutritional Content of Papaya Fruit based on Maturity Level. The proposed method consists of 6 stages, namely image acquisition, *preprocessing*, segmentation, morphological operations, feature extraction, and classification based on the trained model. By using this method, it is expected that the accuracy of the classification process can be improved, so that the prediction of the nutritional content of papaya fruit becomes more precise. In addition, this research aims that digital image processing technology can be utilised to select papaya fruit according to the desired nutritional needs.

Previous studies mainly focused on classifying fruit ripeness levels without directly linking them to nutritional content. While approaches such as SVM [12], RGB-based detection [2], or KNN [19] showed progress, their accuracy and consistency were still limited. Moreover, most of them emphasized visual maturity rather than nutritional identification. This

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study addresses that gap by introducing a classification system specifically designed to identify papaya's nutritional content (glucose, fructose, vitamin C, and fibre) based on ripeness, using digital image processing combined with Artificial Neural Networks (ANN).

Unlike most previous studies that focused mainly on fruit ripeness detection [2], [12], [15], [16], this study introduces a novel approach by directly classifying the nutritional content of papaya (glucose, fructose, vitamin C, and fibre) rather than maturity level alone. To the best of our knowledge, this is the first study that integrates LAB colour and GLCM-based texture features with an Artificial Neural Network (ANN) for nutrient classification.

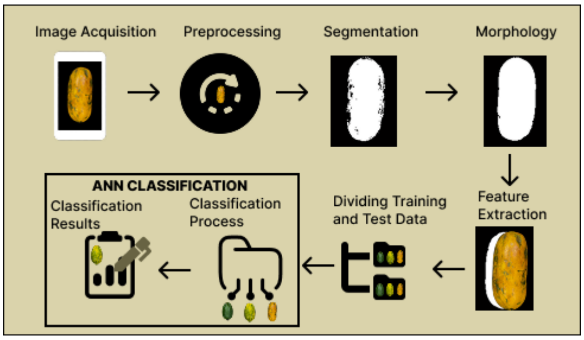
Previous studies using Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) achieved limited accuracy or high computation costs, while RGB-based approaches struggled with low performance. ANN provides flexibility in modelling non-linear feature interactions with efficient computation.

The contributions of this study are: (1) introducing nutrient-based papaya classification, (2) demonstrating the effectiveness of combining LAB and texture features, (3) applying ANN for accurate yet efficient computation suitable for real-time use, and (4) highlighting practical applications for non-destructive nutritional evaluation in agriculture.

Therefore, the main objectives of this research are threefold. First, to develop a digital image-based classification system capable of identifying papaya's nutritional content — including glucose, fructose, vitamin C, and fibre — according to its ripeness level. Second, to evaluate the performance of a six-stage processing pipeline consisting of image acquisition, preprocessing, segmentation, morphology, feature extraction, and classification using Artificial Neural Networks (ANN). Third, to validate the model's accuracy, precision, recall, and F1-Score compared to previous approaches, thereby addressing the existing research gap between visual maturity detection and nutrient-level classification.

MATERIALS AND METHODS

This research method consists of six sequential stages, namely image acquisition, *preprocessing*, segmentation, morphology, feature extraction, and classification using the trained model. The stages of the method can be clearly seen in Figure 1 where these stages are interrelated to ensure the success of the process of analysing and classifying the ripeness level of papaya fruit.



Source: (Research Results, 2024)
Figure 1. Stages of the proposed method

At this stage, the process of collecting papaya image datasets is carried out by capturing digital photographs of the fruit using image-acquisition devices such as smartphone or embedded cameras. Similar data-collection procedures were applied in recent studies, where fruit and vegetable images were obtained directly through camera-based acquisition to build training datasets for deep-learning models [6], [20]. This research resulted in a dataset of 315 acquired images, with each class having a minimum of 100 images. There are three classes in the dataset, which are based on the nutritional content, namely sugar content (Glucose and Fructose), vitamin C (Ascorbic Acid) and Fibre. The assessment of the nutritional content of papaya fruit is done visually by comparing the skin characteristics based on the ripeness level of the fruit, i.e. *Unripe*, *Half-ripe* and *Full-ripe*.

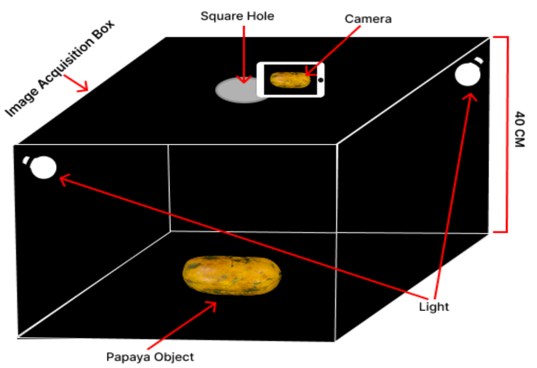
A. IMAGE ACQUISITION STAGE

Figure 2 shows the image capture process using an acquisition box equipped with lights in the four upper corners and a hole at the top to facilitate the camera to capture images of papaya fruit. A black cloth background is used, while a smartphone camera with settings according to Table 2 ensures stable image results and minimises noise and changes in light intensity. The stages of the proposed method in this study are presented in Figure 1, while the distribution of datasets by class (ripe, half-ripe, unripe) and data type (training data and test data) is shown in Table 1. The following is a presentation of the figure and table.

Table 1. Dataset Distribution Based on Class and Data Type

Class	Number of Datasets		Total
	Train	Test	
Mature	80	33	113
Half Ripe	80	20	100
Not Ripe	80	22	102
Total	240	75	315

Source: (Research Results, 2024)



Source: (Research Results, 2024)
Figure 2. Image Acquisition Process

Table 2. Smartphone Camera Settings and Specifications

Specifications	Description
Camera Resolution	12 MP
Image Size	3024 x 4032 Pixels
Zoom	2,16
Mode	No Flash
ISO	80
Exposure Value	-1,6
Camera Distance	40 cm
White Balancing	Auto
Focus Distance	1/100 sec

Source: (Research Results, 2024)

In table 2 above are the smartphone camera settings used, along with their specifications.

B. PREPROCESSING STAGE

The *preprocessing* stage is the first step in digital image processing which aims to prepare the data to be ready for further processing. First, the image is taken or read after going through the acquisition process. Next, the image is separated into three main colour channels, namely R, G, and B, to determine the most appropriate channel to use. In this study, channel G (*Green*) is chosen as the most suitable, and then the image is converted to *grayscale*. This step is important to simplify the image, so that objects in the image can be more easily recognised and analysed in the next segmentation stage[21]. After the G channel is selected, the contrast or brightness of the image is increased by applying a gamma value of 0.9 which is quite effective in increasing the brightness of the image.

C. SEGMENTATION STAGE

The segmentation stage is an essential image-processing step that aims to separate the main object from the background to simplify further analysis. This process commonly begins by converting the image into grayscale to reduce complexity, followed by applying a thresholding technique to differentiate the object from its surroundings. According to recent studies, segmentation may also involve basic boundary-refinement or region-based approaches, which help produce clearer object separation and support more accurate identification in subsequent analysis [22]. In this stage, image segmentation is performed by *thresholding* the *green channel* using an automatic intensity threshold determined by the *Otsu* method. This process separates the main object from the background based on the prominent green intensity of certain objects, such as ripe or unripe fruits. The result is a *binary* image where pixels with intensities above the threshold are considered objects, while those below it are considered background.

D. MORPHOLOGICAL STAGE

Morphological operation is a procedure that is often used in *binary* images, namely black and white, to change the structure of objects in the image. In morphological operations, some pixels in the *background* area will be merged into the object area, or vice versa[23]. Morphological operations are used in this study to remove *noise* in the segmented image, retain the main object, and remove small relevant areas. The process begins by constructing disc-shaped structural elements of different sizes (10, 15, and 50 pixels in radius) to be used in various morphological stages. The first step is *bwaareaopen* with a threshold of 30,000 pixels to remove small areas. Then dilation and erosion are performed successively using structural elements of 15 pixels to refine the contours of the object. *Imclose* (*radius/strell* of 10 and 50 pixels) and *imfill* operations are applied to close gaps and fill holes in the object, followed by an additional *bwareaopen* of 10,000 pixels to ensure only large objects remain. This series of processes results in a cleaner *binary* image ready for further analysis.

E. FEATURE EXTRACTION STAGE

Features are distinctive characteristics found in an object and can be used to distinguish one object from another. In digital image analysis, feature extraction is an important stage to recognise certain patterns or characteristics of the object under study[24]. The two main types of features used are colour features and texture features. Colour features include RGB, HSV, and LAB colour spaces, where the LAB component consists of L (brightness), A (green to red), and B (blue to yellow). The value range of L is 0-100, while A and B range from -128 to +127.

The texture features used in fruit image analysis, based on the Gray-Level Co-Occurrence Matrix (GLCM) method, include contrast, correlation, energy, and homogeneity. Contrast

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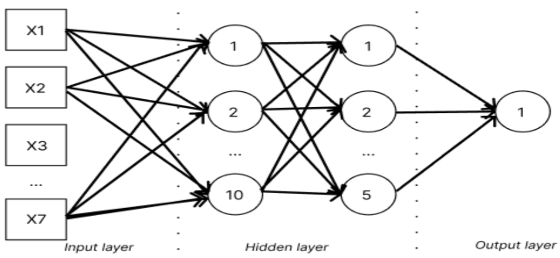
measures the intensity differences between pixels, while correlation reflects the relationship between neighbouring pixel values. Energy represents the uniformity of the texture, and homogeneity assesses texture smoothness by evaluating the closeness of pixel values to the diagonal of the matrix [25]. These features are commonly evaluated in combination—particularly with colour features—to assess classification performance using metrics such as accuracy, precision, recall, F1-score, and computational time. Recent studies show that integrating LAB colour features with GLCM-based texture descriptors yields optimal results in fruit ripeness classification, enabling more accurate and efficient identification of ripe fruit for agricultural and industrial purposes [26].

F. CLASSIFICATION STAGE

The initial stage in the classification of nutrient content based on the ripeness level of papaya fruit is to divide the image into two datasets, namely training data and test data, each consisting of three clusters: not ripe, half ripe, and ripe. The training data was used to build a classification model which was then tested on the test data[23]. The classification process was performed using an artificial neural network (ANN) algorithm, with a layered network architecture consisting of two hidden layers containing 10 and 5 neurons respectively, and a logsig activation function. The training uses the trainlm (Levenberg-Marquardt) algorithm to accelerate convergence, with a maximum of 1000 epochs and a target prediction error below 1e-6.

As shown in Figure 3, the JST has three main layers: input, two hidden layers, and output. The input layer contains seven main features, namely three colour features (L, A, B) and four texture features (contrast, correlation, energy, homogeneity). The output layer consists of one neuron that produces the maturity class. This structure allows the model to recognise complex patterns in the data and produce accurate classification of papaya ripeness.



Source: (Research Results, 2024)
Figure 3. Artificial Neural Network Architecture

RESULTS AND DISCUSSION

This study started by dividing 315 banana images into three ripeness classes: unripe, semi-ripe, and ripe, based on the main nutrients of sugar (glucose and fructose), vitamin C (ascorbic acid), and fibre. The dataset was then divided into training and test data, 80% (240 images) and 20% (60 images) respectively, with the addition of 15 additional test images (13 ripe, 2 not ripe) to maintain a balanced class distribution.

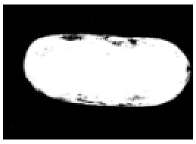
The difference in nutritional content based on the level of ripeness is visualised in Figure 4. Figure 4(a) shows a green high-fibre papaya, 4(b) shows a vitamin C-rich semi-ripe papaya with yellowish skin, and 4(c) shows a ripe papaya with a yellowish-orange colour, indicating high sugar content. To improve clarity in classification, the images are then processed through preprocessing stages such as brightness adjustment and conversion to grayscale.

Figure 5 shows the advanced processing results. Figure 5(a) shows the original image of papaya, 5(b) is the result of adding brightness to clarify the surface, and 5(c) shows the grayscale version which facilitates intensity and texture analysis. A segmentation process using the Otsu method is then applied to separate the object from the background more accurately.

4(a) 4(b) 4(c)

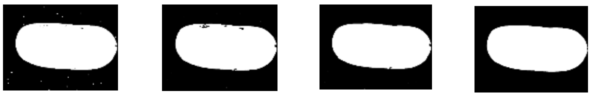
Source: (Research Results, 2024)
Figure 4. Image of the nutritional content of Papaya fruit: (a) high fibre, (b) high vitamin C, (c) high glucose and fluctose.

Source: (Research Results, 2024)
Figure 5. Image of Papaya: (a) Original image, (b) Original image + brightness, (c) grayscale image + brightness



Source: (Research Results, 2024)
Figure 6. Segmented image

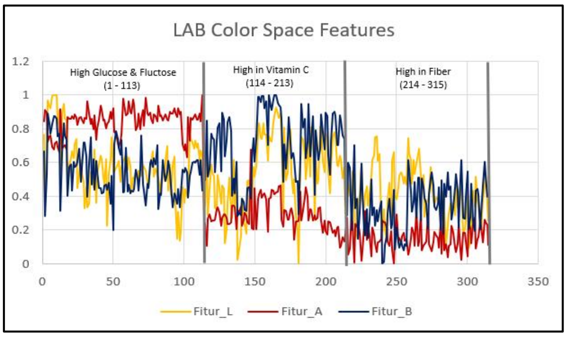
The segmentation results in Figure 6 using the Otsu method show that the main object is successfully separated from the background. This method works by determining the optimal threshold so that the oblong object shape can be isolated from the black background effectively. However, there is still noise in the form of black dots within the object area that should be clean, indicating that the Otsu method has not been able to completely remove the noise within the object area. Therefore, to obtain cleaner and more accurate segmentation results, further processing in the form of morphological operations is required.



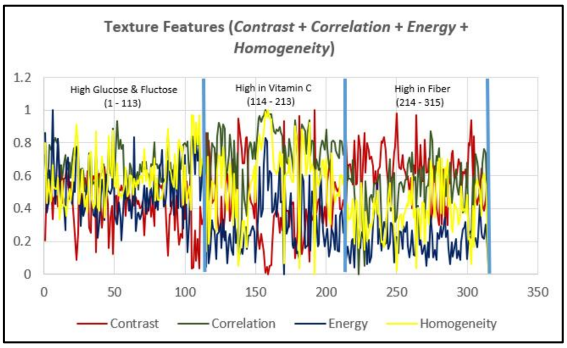
7(a) 7(b) 7(c) 7(d)

Source: (Research Results, 2024)
Figure 7. Morphological result image: (a) Dilation, (b) Erosion, (c) Closing, Hole Filling, 1st Bwareaopen, (d) Closing, Hole Filling, 2nd Bwareaopen

Figure 7 shows the results of several morphological stages applied in stages. In the initial stage, a dilation operation is performed to enlarge the object area and unify the parts that were previously disconnected due to the initial segmentation. Although dilation helps to unify the object, small noise is still found in the background. The next stage uses an erosion operation to smoothen the object boundaries and reduce noise, by scraping the outer edges of the object. However, this operation also slightly reduces the actual object area. To overcome this drawback, a combination of closing, hole filling, and bwareaopen operations are applied. The closing operation closes small gaps and joins separate parts of the object, while hole filling fills small holes in the object area. The bwareaopen operation is then used to remove any remaining small noise. This combination of steps is repeated to ensure that the segmentation result is clean, without side holes in the object, and free from background noise. With a cleaner final result that resembles the original shape of the object, this segmentation is able to improve the accuracy in separating the object from the background thoroughly.



Source: (Research Results, 2024)
Figure 8. Graph of LAB colour space feature values



Source: (Research Results, 2024)
Figure 9. Graph of texture feature values (Contrast, Correlation, Energy and Homogeneity)

The LAB colour feature extraction in Figure 8 successfully distinguishes the three ripeness stages of papaya: ripe, semi-ripe, and immature. The L (brightness), A (green-red) and B (blue-yellow) components show distinctive patterns at each stage. Ripe fruits (images 1-113) have high and stable L values and a predominance of red and yellow (A and B), reflecting high glucose and fructose content. Half-ripe (images 114-213) show LAB fluctuations due to colour transitions, with high vitamin C content. While unripe (images 214-315) is characterised by low L and B values and a predominance of green, indicating high fibre but not yet sweet.

In Figure 9, the texture features-Contrast, Correlation, Energy, and Homogeneity-also distinguish ripeness. Ripe fruits have a smooth texture with stable and high values, half-ripe show fluctuations, and immature have a rough texture with low and unstable values. Overall, the LAB colour and texture features were effective in classifying ripeness and indicating the nutrient content at each stage.

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Table 3. Testing Results

No	Feature Combination	Accuracy (%)		Missclassification Error (%)		Precision		Recall		F1 Score		Computation Time (s)	
		Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
1	RGB	98.33	97.33	1.67	2.67	98.33	97.22	98.33	96.67	98.33	96.80	0.15	0.02
2	HSV	97.08	77.33	2.92	22.67	97.32	76.83	97.08	77.58	97.11	75.79	0.18	0.02
3	LAB	97.92	94.67	2.08	5.33	97.92	93.89	97.92	94.65	97.92	94.18	0.16	0.02
4	Texture	80.00	81.33	20.00	18.67	80.85	82.60	80.00	80.05	80.26	80.64	0.16	0.02
5	RGB+Texture	99.17	94.67	0.83	5.33	99.17	94.87	99.17	93.33	99.17	93.52	0.17	0.02
6	LAB+Texture	98.75	97.33	1.25	2.67	98.80	97.22	98.75	96.67	98.75	96.80	0.14	0.02
7	HSV+Texture	98.75	90.67	1.25	9.33	98.80	89.65	98.75	90.96	98.75	90.03	0.14	0.02
	Average	95.71	90.48	4.29	9.52	95.88	90.33	95.71	89.99	95.75	89.68	0.16	0.02
	Highest	99.17	97.33	20.00	22.67	99.17	97.22	99.17	96.67	99.17	96.80	0.18	0.02
	Lowest	80.00	77.33	0.83	2.67	80.85	76.83	80.00	77.58	80.26	75.79	0.14	0.02

Source: (Research Results, 2024)

The main objective of Table 3 is to evaluate and determine the best combination of features in classifying the ripeness level of bananas. The evaluation is done using several important metrics such as accuracy, classification error, precision, recall, F1 Score, and computation time. Each combination of features is tested through the training and testing process to ensure that the results can be used as a reference in choosing the most effective and efficient combination of features in the classification process.

Based on the results in Table 3, the LAB+Texture feature combination proved to be the most superior. This combination achieved a testing accuracy of 98.75%, which is one of the highest values among all tested combinations. This high accuracy reflects the system's ability to correctly classify the maturity level, even when tested with data that resembles real conditions. In addition, the resulting classification error is also very low, at only 2.67%, indicating a very minimal level of prediction error.

In terms of precision and recall, the LAB+Texture combination also showed excellent performance, reaching 97.22% and 96,67%. respectively. High precision indicates the system's ability to identify the correct maturity class without many false positives, while high recall indicates the system's ability to capture all existing maturity categories. The balance between the two is reflected in the F1 Score value of 96.80%, which shows that the system is not only accurate, but also consistent in performing the classification. Efficiency is also an advantage of the LAB+Texture combination, with an average computation time of only 0.02 seconds per image. This shows that the system is not only accurate but also very fast, making it possible to apply this method in large-scale automated classification systems or real-time applications without compromising on performance. Although LAB+Texture is the best combination, there are several other feature combinations that also show competitive performance. The RGB+Texture combination, for example, achieved a test accuracy of 94.67% and a classification error of 5.33%. Although lower than LAB+Texture, this combination still provides quite high precision, recall, and F1 Score values and is worth considering as an alternative. Meanwhile, the HSV+Texture combination recorded an accuracy of 90.67% and an F1 Score of 90.03%, which performed quite well, but not as optimally as the previous two combinations.

Quantitatively, the proposed method achieved 97.33% accuracy, significantly outperforming previous papaya ripeness classification using SVM, which reported a maximum accuracy of only 66% across the tested feature combinations[12], avocado maturity detection using KNN (85.71%) [19], and RGB-based papaya detection (50%) [2]. It is also comparable to banana nutrient classification by Wulandari et al. [18] (98%), but with faster computation (0.02 s/image). This demonstrates that the proposed approach combines high accuracy with efficiency, making it competitive among existing methods.

The findings also hold practical significance. For the agricultural industry, this system can be embedded in automated grading and sorting processes. For farmers, the method can be integrated into smartphone-based applications, enabling rapid and low-cost assessment of papaya nutritional content. For consumers, it supports healthier choices by selecting fruits according to their nutritional value without laboratory testing.

Overall, the evaluation results show that the LAB+Texture combination is the most optimal choice for banana ripeness classification based on digital images, supporting high performance across all evaluation metrics and excellent computation time efficiency. Other combinations such as RGB+Texture and HSV+Texture can be used as backup options depending on the need and availability of features in real implementation.

Table 4. *Confusion Matrix of* Training Results

		Prediction		
		High Glucose & Fluctose	High Vitamin C	High fibre
Actual	High Glucose & Fluctose	80	0	0
	High Vitamin C	1	78	1
	High fibre	0	1	79

Source: (Research Results, 2024)

In Table 4, the *Confusion Matrix* results of the training process show that the training has run well, although there are some images that are classified into different classes. Some nutritional images based on the level of maturity were detected incorrectly or moved to another class. In particular, images of the ripe class (with high glucose and fructose content) were mostly classified correctly. However, in the semi-mature class (with high vitamin C content), there were 2 images that were misclassified to the mature and immature (high fibre) classes. Similarly, in the immature (high fibre) class, 1 image was misclassified to another class.

In Table 5, the *Confusion Matrix* results in the testing process show that the training has run well, although there are some images that are classified into different classes. Some nutritional images based on the maturity level are detected sala h or move to another class.

Table 5. *Confusion Matrix of* Testing Results

		Prediction		
		High Glucose & Fluctose	High Vitamin C	High Fibre
Actual	High Glucose &	33	0	0
	High Vitamin C	0	18	2
	High Fibre	0	0	22

Source: (Research Results, 2024)

Specifically, the images of the ripe class (with high glucose and fructose content) and the semi-ripe class (with high vitamin C content) were mostly correctly classified. However, in the immature class (high fibre), there were 2 images that were misclassified to other classes.

A closer examination of the misclassified images in the confusion matrices reveals that most classification errors occurred in the semi-ripe category, which represents papayas with high vitamin C content. These fruits display intermediate colour characteristics between green and yellow, causing overlapping LAB and texture feature values with the unripe and fully ripe classes. The semi-ripe surface also tends to have heterogeneous textures, which affect the consistency of contrast and homogeneity features used by the ANN model. This finding suggests that the transitional visual properties of semi-ripe papayas are the primary source of misclassification. To improve model performance, future studies could apply advanced illumination normalization, include more diverse training samples for semi-ripe fruits, or adopt deep learning architectures such as Convolutional Neural Networks (CNNs) that can better capture fine-grained texture variations.

Compared to previous methods, the proposed LAB+Texture feature combination with ANN achieved a testing accuracy of 97.33%, surpassing RGB-based ripeness detection by Widyasari et al. [2] (50% accuracy) and KNN-based classification by Saputra et al. [19] (85.71% at best). It also outperformed SVM-based models [12], which achieved limited accuracy (up to 66%) due to feature variability and sensitivity to illumination conditions. In contrast, the proposed approach attains both high accuracy and fast computation (0.02 s/image), making it more suitable for practical real-time fruit quality monitoring systems.Beyond technical performance, these findings have practical implications. The method can be applied in automated fruit grading lines, supporting farmers and distributors to classify papaya based on nutritional needs without laboratory tests. It also contributes theoretically by demonstrating the effectiveness of combining LAB and texture features in bridging the gap between visual maturity and nutritional estimation.

Figure 10 shows a 3D scatter plot to visualise the distribution of data based on three main features: the A and B colour components of the LAB colour space, and the Energy feature of the GLCM. This visualisation is effective in separating the three maturity classes based on colour and texture characteristics. Class 1 (ripe/high glucose & fructose) is shown in dark blue, with high A, B, and Energy values, indicating a predominance of red-yellow colour and uniform texture. Class 2 (half ripe/high vitamin C) is light green or bluish in colour, has a higher B value than A, and moderate

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

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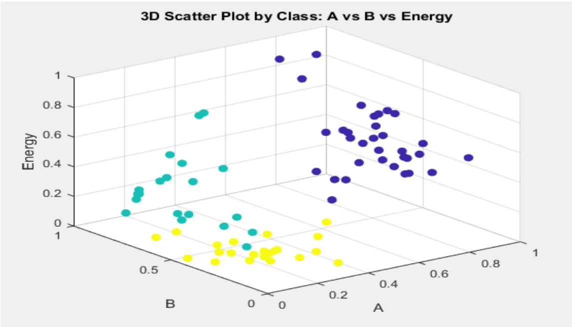
Energy-reflecting a yellowish colour and moderate texture. Grade 3 (immature/high fibre) is yellow in colour, has low Energy and wide colour variation, indicating a rough and non-uniform texture due to a more variable skin surface.



Source: (Research Results, 2024)
Figure 10. *3D scatter plot of* LAB (A+B) + Texture (*Energy*) feature combination

These results indicate that the combination of colour and texture features serves as a powerful parameter for maturity classification, producing a clear and distinct separation between classes. Such findings reinforce the potential of colour and texture-based identification systems in fruit image processing. However, despite these promising outcomes, the study still has several limitations. The dataset size was relatively small (315 images) and collected under controlled lighting and background conditions, which may limit generalization to real-world scenarios. In addition, the model remains sensitive to variations in illumination and background complexity. Moreover, the method has only been validated on papaya; extending its application to other fruit types would require retraining with larger and more diverse datasets.

CONCLUSION

The results demonstrated that the backpropagation Artificial Neural Network (ANN) was highly effective in classifying papaya fruit based on its nutritional content. By combining LAB colour features with texture features (contrast, correlation, energy, and homogeneity), the model achieved strong performance. Training with 240 images resulted in an accuracy of 98.75% and a computation time of 0.14 seconds per image, while testing with 75 images achieved an average precision of 97.22%, recall of 96.67%, F1-Score of 96.80%, and overall accuracy of 97.33% with a computation time of only 0.02 seconds per image. These results confirm that papaya nutrients such as glucose, fructose, vitamin C, and fibre can be classified accurately and efficiently.

Nevertheless, the study has several limitations. The dataset size was relatively small and collected under controlled conditions, which may not fully reflect field variability such as lighting changes or background complexity. Future work should focus on enlarging the dataset, testing robustness under uncontrolled environments, and comparing ANN with deep learning models such as Convolutional Neural Networks (CNNs). In addition, developing real-time mobile or IoT-based applications and extending the method to other tropical fruits would broaden its applicability and practical impact.

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