Digital Zone
Jurnal Teknologi Informasi dan Komunikasi
Vol: 15 No 02 2024 E-ISSN: 2477-3255
Accepted by the Editor: 27-01-2024 | Revision: 06-08-2024 | Published: 30-11-2024

Digital Image Based DSS for Assessing Tomato Quality using AHP-TOPSIS Method

Wulandari[1], Dewi Fatmarani Surianto[2*], Jumadi M. Parenreng[3], Fhatiah Adiba[4]
[1,2,3,4]Program Studi Teknik Komputer, Fakultas Teknik Universitas Negeri Makassar
[1,2,3,4]Jalan Daeng Tata Raya Parang Tambung, Kec. Tamalate, Kota Makassar, Sulawesi Selatan
e-mail: [1]wlndry.nurdin@gmail.com, [2]dewifatmaranis@unm.ac.id*, [3]jparenreng@unm.ac.id, [4]adibafhatiah@unm.ac.id

Abstract

Tomatoes are a major export commodity in the country's plantation sector. This increases the urgency of efforts to increase tomato productivity, both in terms of quantity and quality. Evaluation of tomato quality currently relies on the degree of ripeness and skin texture. The conventional method currently used involves manual inspection, which can allow for misjudgment and economic loss. This research aims to use a digital image-based approach by utilizing a decision support system that combines the AHP and TOPSIS methods to assess tomato quality based on color and texture criteria. This research evaluates and ranks nine tomato images that have good quality, by giving higher priority to skin texture than skin color. Evaluation results from three tests showed that the system was able to determine the quality of tomatoes with an average kappa value of 0.78, which interpreted the results of good agreement between the system and expert judgments.

Keywords: *AHP, Decision Support Systems, Digital Image Processing, Tomato, TOPSIS.*

1. Introduction

Tomato with the Latin name Lycopersicon esculentum is a plantation commodity that has a variety of uses, ranging from cosmetics, food ingredients, and medicines [1], [2]. Therefore, tomato plantations have increased and made it a leading commodity in the country's exports. Indonesia is a producer of tomato fruit which managed to export as much as 103,669 kg with an export value of 224,973 USD in 2022, showing a decrease compared to the previous year [3]. Therefore, efforts are needed to increase tomato productivity, both in terms of quantity and quality, so that the export volume no longer decreases in the future.

Grouping the ripeness level of tomatoes is one method to evaluate their quality. In addition to examining skin color, tomato quality assessment can also be based on skin texture [4]. Currently, the conventional method used to assess tomato quality involves manual inspection. The main drawback of this conventional method is the length of time it takes, potentially leading to fatigue, which can result in errors in judgment [5]. Such errors can ultimately result in economic losses as low-quality tomatoes enter the market.

There are various factors or criteria that can be used as a reference to determine good quality is a challenge that needs to be faced [6]. However, with the development of current

https://doi.org/10.31849/digitalzone.v15i2. 19060

technology, it allows efficiency in data collection and analysis, especially by utilizing the development of existing information systems [7]. In overcoming these challenges, methods can be applied by utilizing the system to support decisions in solving problems efficiently and accurately by considering relevant criteria and data [8].

In previous research, a Decision Support System (DSS) has been designed to evaluate the quality of rice seeds by utilizing the Analytical Hierarchy Process (AHP) method which produces a ranking of alternatives in making decisions for selecting the quality of rice seeds based on the criteria of plant height and age, rice color and shape, moisture, 1000 seed mass, and rice grains [9]. Testing the system resulted in a good performance level reaching 75%. Another research, a similar system design was carried out for the selection of superior rice seeds with a different method, namely Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) based on the criteria of seed size, seed color, leaf weight and leaf height [10]. The results of the system feasibility test show that the user satisfaction level reaches the highest value of 96%. The next research, a similar system design was still carried out to select fruits worth selling with the Multi-Objective Optimization by Ratio Analysis (MOORA) method based on the criteria of fruit condition, fruit color, fruit texture, maturity level and fruit durability [11]. The results of this research developed a DSS to select marketable fruits, including kueni, watermelon, rambutan, snake fruit and pineapple.

In addition, there is also research to classify the maturity and quality of tomato fruit using Artificial Neural Networks based on the results of extracting color features from tomato images [12]. The classification test results using 40 test images, obtained an accuracy of 90%. Finally, there is the same research to classify the quality of tomatoes, based on the characteristics of color, texture and shape based on image processing [13]. The classification test results with 90 images as test data, obtained an accuracy percentage of 95.5%. Based on these studies, it can be stated that the combination of digital image processing techniques with decision support systems can potentially provide more useful information [14].

Quality assessment of tomatoes is an important aspect of the agricultural industry, especially in the context of export commodities. The degree of ripeness of tomatoes plays an important role in determining their quality, with attributes such as skin color and texture being key indicators. Traditional methods of tomato quality assessment rely on manual inspection, which is time-consuming and prone to human error, potentially leading to economic losses due to the entry of low-quality tomatoes into the market. Thus, developing an efficient and accurate method is needed to evaluate tomato quality to ensure the competitiveness of national export commodities.

Therefore, based on previous research and observations, this research aims to develop a digital image-based DSS with a combination of AHP and TOPSIS methods to assess tomato quality. The integration of AHP for determining criteria weights and TOPSIS method for ranking alternatives enables accurate and systematic evaluation. The evaluation criteria include a combination of features from the Red, Green, Blue (RGB) color space, as well as the Gray-Level Co-occurrence Matrix (GLCM) method to measure the maturity level and quality of tomatoes. The system was developed to automate the process of image feature extraction and analysis through a user interface, allowing users to upload images and get evaluation results quickly. From the combination of the method and the comprehensive automation of image feature extraction, the system is expected to contribute to digital agriculture and image processing, by presenting an innovative solution for better and more accurate tomato quality evaluation.

2. Research Methods

In this research framework, a series of stages are carried out to achieve the research objectives. Details of the proposed research stages can be found in Figure 1.

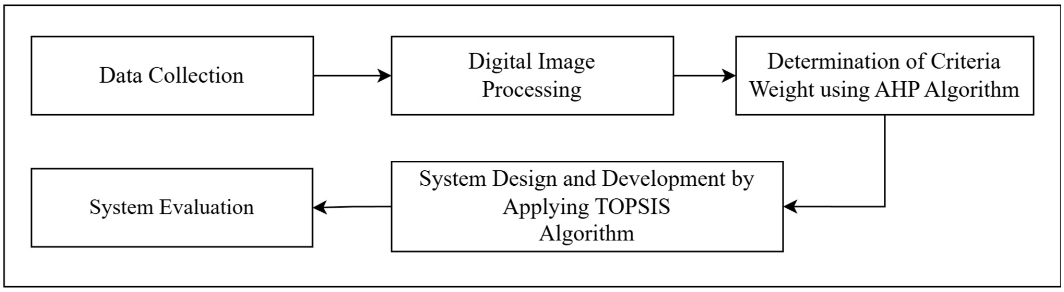


Figure 1: Flow of Research Stages

2.1. Data Collection

At this stage, the data collection of tomato fruit images involves images from good quality tomatoes to low quality tomatoes. The image capture process is carried out in a special box equipped with controlled lighting. The goal is that the captured image remains consistent and unchanged despite influences such as noise or changes in light intensity. The specifications and settings for camera image capture are shown in Table 1.

Table 1. Camera Specifications and Settings

Specifications	Description
Camera Type	Canon EOS 77D DSLR
ISO	800
Focal Length	55
Exposure Time	1/6 sec
F-Stop	f/5.6
Flash Mode	No Flash
Image Resolution	2976 × 1680 pixels
Image Dimensions	72 dpi

2.2. Digital Image Processing

After the tomato image data is collected, the next step is to process the image data. Digital image processing can be interpreted as a method that aims to improve the quality of images stored in the form of numerical data, so that they can be processed using a computer [15]. In this research, digital image processing was carried out using MATLAB software. The stages of image processing are in Figure 2.

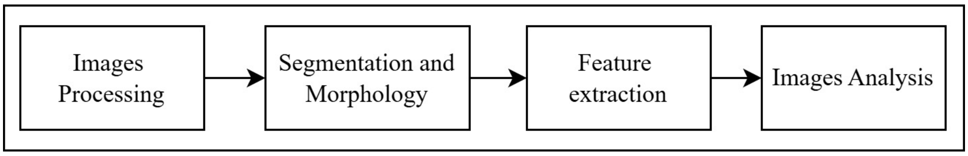


Figure 2: Flow of Image Processing Stages

The image processing process begins with the image preprocessing stage, where the image is converted into RGB color space. After the preprocessing stage, object segmentation and morphological operations are applied to the tomato image. Segmentation is performed with the Otsu method to separate objects from the background, followed by a series of morphological operations such as opening, closing, hole filling, and bwareaopen to obtain optimal segmentation results. After successfully segmenting the image, the next step is feature extraction. The extracted features include color features based on the RGB color space by calculating the average value of pixels in the image in each color channel, as well as texture features calculated using the GLCM method.

In assessing tomato quality, color and skin texture criteria play an important role. Color

https://doi.org/10.31849/digitalzone.v15i2. 19060

features are extracted from the RGB color space by examining the average value of pixel intensity in each RGB color channel to evaluate the color characteristics of tomatoes, where the dominance of red is often the main indicator of ripeness. In addition to the color criteria, the texture characteristics of tomato skin also affect the assessment. Therefore, GLCM is used to calculate a matrix that reflects texture patterns based on the spatial distribution of pixel intensities. The parameters used include contrast, energy, homogeneity and correlation values to provide information about the texture pattern of tomato skin.

From the results of feature extraction, data patterns are analyzed to identify features that describe good or bad tomato quality. This analysis process involves recognizing patterns that appear in the extracted feature data. This is done through graphical representation or presentation in the form of visualizations such as line charts that are used to summarize and summarize the basic characteristics of the feature data, thus enabling a better understanding of the patterns that appear in the data.

2.3. Determination of Criteria Weight using AHP Algorithm

The AHP method is a framework for decision support that breaks down complex problems with many criteria into a hierarchical structure. In this research, the AHP method was chosen because of its ability to determine the relative weight for each criteria and sub-criteria, thus clarifying the relationship between criteria and their impact on the final decision [16]. With AHP method, the relative weight for each criteria and sub-criteria in tomato quality assessment can be determined according to their relevance in assessing the overall quality of tomatoes. The steps in applying the AHP method to determine the weight value are as follows.

a. Determine the goals, criteria, and sub-criteria that are relevant to assessing the quality of tomatoes formed in the hierarchical structure.
b. Assessing criteria and sub-criteria is done to express the level of importance using a ratio scale of 1 to 9, which is represented using a pairwise comparison matrix.
c. Perform calculations to determine the local preference weight for each element. The determination of local preference weights is done by converting the pairwise comparison matrix into a normalized form. Normalization is done by dividing the cell value by the number of matrix column cells. The matrix normalization formula can be seen in equation (1).

$$P_{ij} = \frac{x_{ij}}{\sum x_i} \quad (1)$$

Description:
P_{ij} = Normalization result of i-th column, j-th row
x_{ij} = Value in the pairwise comparison matrix in the i-th column and j-th row
x_i = The value of the comparison matrix in the i-th column

After normalizing the pairwise comparison matrix value, the priority column value is calculated using the formula in equation (2).

$$\text{Priority Column Value} = \frac{\sum x_j}{\sum i} \quad (2)$$

Description:
Priority Column Value = Local preference weight
x_j = Normalization matrix value in the jth row
$\sum i$ = Number of rows

d. Determining logical consistency between elements and sub-criteria to ensure the priority order resulting from the pairwise comparison matrix remains logical. At this stage, a hierarchy consistency check is carried out, where if the Consistency Ratio (CR) value exceeds 10%, the matrix needs to be corrected, and if the CR value ≤ 10%, the results are considered valid [15].
e. Determine the global preference weight, which indicates the relative importance of each sub-criteria in assessing tomato quality. This weight is calculated from the local preference

weight with a CR value ≤ 10%, and is obtained by multiplying the local preference weight of the criteria by the local preference weight of the sub-criteria.

2.4. System Design and Development by Applying TOPSIS Algorithm.

System design is carried out to meet user needs by providing a clear and comprehensive description of the system design [17]. After the design, DSS development is carried out by utilizing MATLAB software. DSS provides a user interface and utilizes data that allows decision makers to integrate their thinking [18]. MATLAB software was chosen to develop a digital image-based decision support system because it not only provides efficient image processing tools and functions, but also allows the development of a Graphical User Interface (GUI) that facilitates use and interaction with the system. In the system development process, the TOPSIS algorithm is used to process user-submitted data. TOPSIS is a method in a multi-criteria-based decision support system that calculates the distance of each alternative to the positive or negative ideal solution [18]. The TOPSIS method is used to assess the quality of tomatoes because of its ability to arrange a clear ranking of alternatives based on their similarity to the ideal solution.

2.5. System Evaluation

After the system was built, the next step was to test the system 3 times, by randomly uploading various tomato images. The test results were then evaluated by comparing them with the human judgment of the image expert. One evaluation method that can be used to compare these two methods is Cohen's Kappa. Cohen's Kappa calculation is used in evaluation performance measurement to measure the level of agreement between two raters on categorical data, taking into account the probability of agreement due to chance [19]. Therefore, before evaluating with Kappa Cohen's, the results of ranking by DSS and manual assessment by experts (raters) will be converted into three categories, where rank 1-3 is a high quality category, rank 4-6 is a medium quality category, and rank 7-9 is a low quality category. The formula for calculating Cohen's Kappa is listed in equation (3), where P_o represents the proportion of observed agreement and P_e represents the proportion of agreement expected by chance [20].

$$\kappa = \frac{P_o - P_e}{1 - P_e} \qquad (3)$$

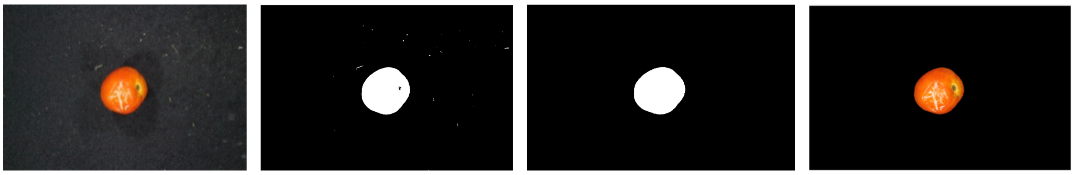
The interpretation of the assessment is based on the kappa value (κ) obtained, based on 5 semi-quantitative categories, namely poor ($\kappa < 0.2$), low ($0.21 < \kappa < 0.4$), moderate ($0.41 < \kappa < 0.6$), good ($0.61 < \kappa < 0.8$), and very good ($0.81 < \kappa \leq 1.0$).

3. Results and Discussion

In the data collection stage, 50 tomato images were generated, with 20 images used for the system knowledge base and 30 images for system evaluation. Some examples of tomato image results are shown in Figure 3.

Figure 3: Tomato Image Sample

The collected image data is then processed with the aim of extracting the features. Before the feature extraction process is carried out, the object segmentation and morphology process is carried out first to separate the object and background. This is done to ensure the accuracy of the feature extraction results obtained. The process of segmentation and morphology results as shown in Figure 4.



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

Figure 4: Result Image after (a) RGB Conversion,

(b) Segmentation, (c) Morphology and

(d) RGB Clean Segmentation

Figure 4(a) is the original RGB image, then the original image is segmented to produce an image like in Figure 4(b). The segmentation results shown in Figure 4(b) are still not perfect, because there is still a lot of noise in the background and there are holes in the object area. Therefore, morphology operation is required to produce a more optimized segmentation and morphology image, which is shown in Figure 4(c). The results of the segmentation and morphology are then applied to the original RGB image, resulting in the clean image shown in Figure 4(d). This clean image will have its features extracted. The results of the extraction of RGB color features and GLCM texture features are represented in graphical form in Figures 5-6, with the order of tomatoes from good quality to low quality.

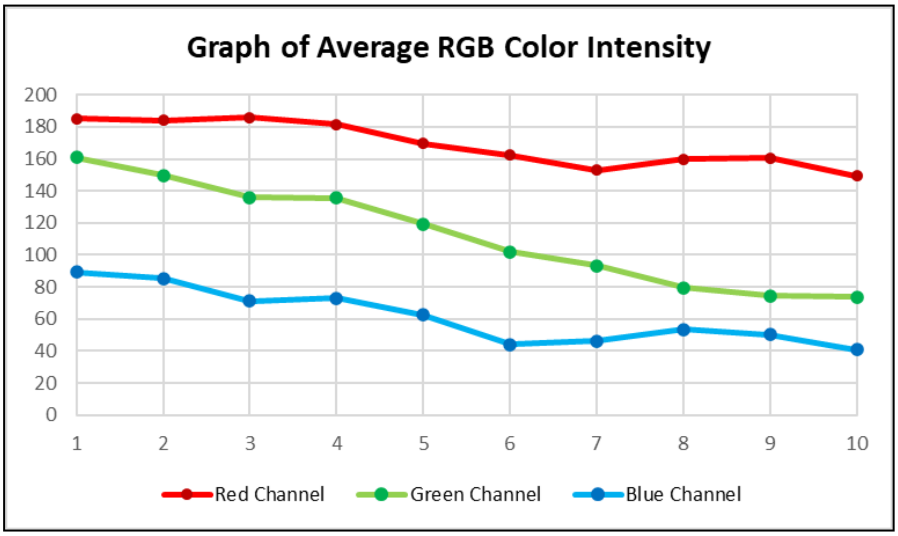
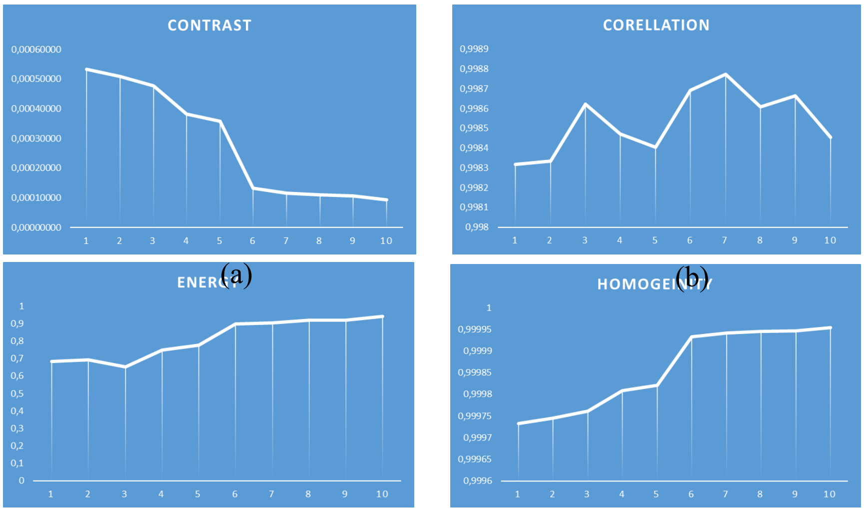


Figure 5. Graph of Average RGB Color Intensity

From Figure 5, it can be seen that the level of tomato ripeness can be determined by looking at the pattern formed on the graph. For the *red*, *green*, and *blue channels*, the high average value of pixel intensity indicates that the tomato fruit is not ripe, and the lower the average value of pixel intensity on the *channel*, the tomato image can potentially be identified as ripe. This is based on the fact that the higher the RGB color index value indicates that the extracted image is light in color and when the RGB color index value is smaller, it indicates that the extracted image is dark in color [21]. Based on this statement, tomatoes that are not yet ripe, have a green, yellow, or orange skin color will have a lighter color compared to the color of red or ripe tomatoes. To determine the redness, yellowness, and greenness of tomato fruit based on the RGB color space representation, *channel* R can be used for redness, *channel* R and G for yellowness, *channel* G for greenness, and *channel* R, G, and B for orange [22].



(a) (b)

(c) (d)

Figure 6. Average Graph of Texture Features (a) Contrast, (b) Correlation, (c) Energy and (d) Homogeneity

Based on Figure 6, it can be seen that the texture features generated from the GLCM method can provide information about the properties of the texture in the image, such as contrast, correlation, energy, and homogeneity. In Figure 6(a), it can be used to measure the difference in gray level in the image [23]. Meanwhile, correlation aims to assess the extent of the linear relationship of gray degree in a pixel [24]. In Figure 6(b) correlation can provide information about the extent to which colors or patterns tend to move together along the surface of the tomato fruit. Energy describes how uniform the distribution of pixel intensities is. The energy in Figure 6(c) focuses more on how evenly distributed the pixel intensities are, with high values indicating an even distribution or smoother texture. The homogeneity in Figure 6(d) can provide information on how uniform or to what extent the intensity varies on the fruit surface.

After analyzing the patterns from the feature extraction results, the next step is to perform calculations using the AHP algorithm to determine the weight value of each criteria. In the AHP algorithm, the first step is to create a hierarchy or mapping between criteria and sub-criteria used in assessing tomato quality. The following is a picture of the hierarchy that has been designed in this study.

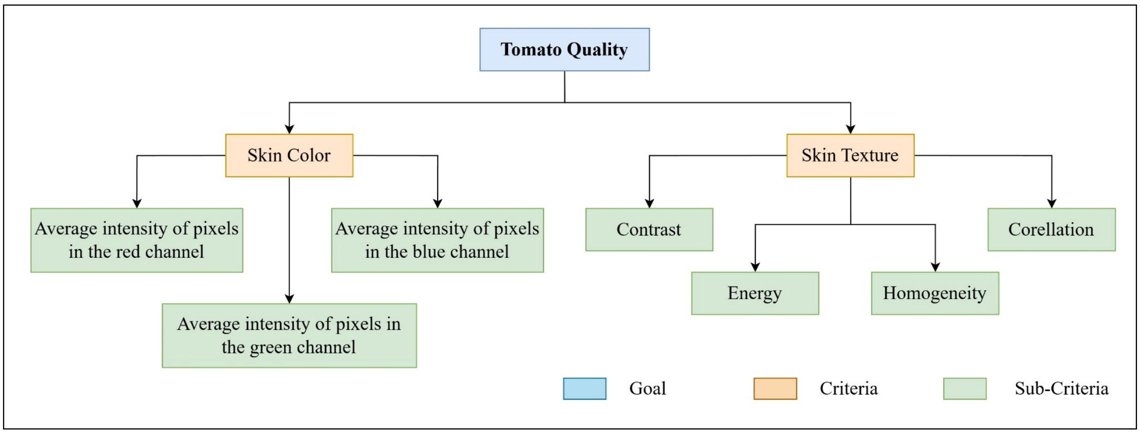


Figure 7: Hierarchy of Tomato Quality Determination

https://doi.org/10.31849/digitalzone.v15i2. 19060

Figure 7 shows that the goal of this decision support system is to assess the quality level of tomatoes. The criteria that will be the benchmark of tomato quality are in terms of color and texture of the skin. The two criteria each have sub-criteria related to the criteria themselves. The color criteria is taken from the RGB color space of the tomato image processing results, so the sub-criteria contained in the criteria are the average intensity of Red channel, Green channel, and Blue channel. Meanwhile, to determine the texture criteria of tomato skin, the GLCM method is used with four parameters that become sub-criteria supporting texture, namely contrast, correlation, energy, and homogeneity.

Next, the level of importance between criteria and sub-criteria is determined using a pairwise-comparison matrix. The following is a comparison matrix between color criteria and texture criteria.

***Table 2**. Results of Pairwise Comparison Matrix between Criteria*

Criteria	Color	Texture
Color	1	0,333333333
Texture	3	1
Total	4	1,333333333

From Table 2, it can be seen that the texture criteria is slightly more important than the color criteria. This determination is based on the assumption that if a tomato has a red color but has a poor skin texture, it can be decided that the tomato is of poor quality. Conversely, if the tomato has a poor color but has a good texture, then it can be decided that the tomato is not too bad. This is because for the ripeness or color of tomatoes, it is still possible to ripen after storage, while if the texture of tomatoes is not good, such as broken or cracked, then the tomatoes cannot be preserved. For the normalization results of the pairwise comparison matrix and the local preference weight values of each criteria, as in Table 3 below.

Table 3. Normalization Matrix between Criteria

Criteria	Color	Texture	Total	Local Preference Weight
Color	0,25	0,25	0,5	0,25
Texture	0,75	0,75	1,5	0,75
Total	1	1		

Table 4. Matrix Sum of Each Row and Calculation of Consistency Ratio Between Criteria

Criteria	Color	Texture	Total	Local Preference Weight	Multiplication Result
Color	0,25	0,25	0,5	0,25	2
Texture	0,75	0,75	1,5	0,75	2
Total					4
Number of Criteria					2
$\lambda\ maks$					2

From Table 4, it can be determined that the value of the random consistency index with two criteria is 0, and the consistency index is 0, resulting in a consistency ratio of 0, which is below the maximum limit of 10%. Therefore, the assessment of the level of importance made is acceptable. After that, calculations are carried out to determine the weight of local preferences for sub-criteria. The comparison matrix between sub-criteria is presented in Table 5-6.

***Table 5**. Results of Pairwise Comparison Matrix between Color Sub-Criteria*

Color Sub Criteria	Red	Green	Blue
Red	1	1	3
Green	1,00	1	3

Color Sub Criteria	Red	Green	Blue
Blue	0,33	0,333333333	1
Total	2,333333333	2,333333333	7

Based on Table 5, it can be seen that the value of the Red sub-criteria has the same level of importance as the Green value, and is slightly more important than blue. The Green sub-criteria is also slightly more important than Blue. From the pairwise comparison matrix between color sub-criteria in Table 8 above, the value of λ max = 3, random consistency index of three sub-criteria 0.58, and consistency index = 0, thus obtaining a consistency ratio of 0 which is below the maximum limit of 10%. Therefore, the local preference weight value of the color sub-criteria is obtained in Table 6.

Table 6. Weight of Local Preference for Color Sub-Criteria

Color Sub-Criteria	Local Preference Weight
Red	0,524675325
Green	0,333766234
Blue	0,141558442

Table 7. Pairwise Comparison Matrix between Texture Sub-Criteria

Texture Sub-Criteria	Contrast	Correlation	Energy	Homogeneity
Contrast	1	2	0,2	2
Correlation	0,50	1	0,333333333	1
Energy	5,00	3	1	3
Homogeneity	0,5	1	0,333333333	1
Total	7	7	1,866666667	7

Table 7 shows the matrix of importance between texture sub-criteria, where contrast has an importance level with a scale of 2 compared to correlation and homogeneity. Meanwhile, correlation has the same level of importance as homogeneity and energy has a level of importance with a scale of 3 compared to correlation and homogeneity. From the pairwise comparison matrix between texture sub-criteria in Table 14 above, the value of λ max = 4.187967739, random consistency index with four sub-criteria of 0.9 and consistency index = 0.062655913, so that the consistency ratio of 0.069617681 is obtained which is still below the maximum limit of 10%. Therefore, the local preference weight value of texture sub-criteria is obtained in Table 8 below.

Table 8. Normalization Matrix between Texture Sub-Criteria

Texture Sub-Criteria	Local Preference Weight
Contrast	0,205357143
Correlation	0,133928571
Energy	0,526785714
Homogeneity	0,133928571

From the calculation of the local preference weights, a global preference weight will be determined that describes the relative importance of each sub-criteria in assessing tomato quality. The global preference weights of the sub-criteria can be seen in Tables 9-10. The results of the calculation of global preference weights in Tables 9-10 will be used as weights in the process of determining tomato quality using the TOPSIS method, making it possible to make decisions based on predetermined criteria.

https://doi.org/10.31849/digitalzone.v15i2. 19060

Table 9. Global Preference Weight of Color Sub-Criteria

Color Sub-Criteria	Global Preference Weight
Red	0,107142857
Green	0,107142857
Blue	0,035714286

Table 10. Global Preference Weight of Texture Sub-Criteria

Texture Sub-Criteria	Global Preference Weight
Contrast	0,154017857
Correlation	0,100446429
Energy	0,395089286
Homogeneity	0,100446429

After obtaining the weight value for each criteria, system design and development are then carried out. Use case diagram is part of the system design that helps in identifying and modeling the main needs from the user's point of view. The Use Case diagram of the developed system is illustrated in Figure 8.

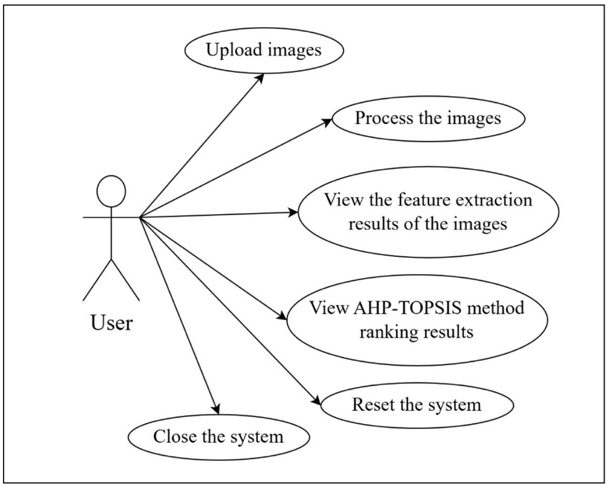


Figure 8. Use Case Diagram

From Figure 8, it can be seen that the developed system allows users to upload tomato images. After the tomato image is uploaded to the system, the user can process the images. After processing, the user can see the results of image feature extraction and ranking results based on the calculation of the AHP-TOPSIS hybrid method. In addition, the user can also reset the system, and finally the user can close the system.

Figure 9. System Development Results

After designing the use case diagram, the next step is to develop the system. The successfully built system can be seen in Figure 9. The developed system can extract features from the uploaded image, both color and texture features. The results of feature extraction between color and texture have different value ranges, where for color has a range of 0-255 and for texture has a range of 0-1. This will result in inaccuracies when performing calculations in the decision support system. Therefore, to process the feature extraction data, the TOPSIS method is used, where in this method, the calculation process is based on a normalized decision matrix, so that the difference in the value range of the two criteria will not affect the calculation results [25].

The attributes of each color criteria are determined based on the color intensity graph in Figure 5. For ripe tomatoes, Red channel is high and Green channel is low, while tomatoes that are not ripe or not red have a low Red channel and high Green channel. Blue Channel is also inversely proportional to Red channel. Therefore, Red channel is categorized as a benefit criteria, while Green and Blue channels are categorized as costs. The texture criteria are based on the graphs in Figure 6, where the contrast graph in Figure 6(a) drops, so it is categorized as a benefit. The correlation graph in Figure 6(b) is inconsistent, but tomatoes with poor texture have high correlation values, so they are categorized as costs. The energy and contrast graphs in Figure 6(c) and (d) show a consistent increase, so these criteria are also categorized as costs. The developed system was then tested as illustrated in Figures 10-12.

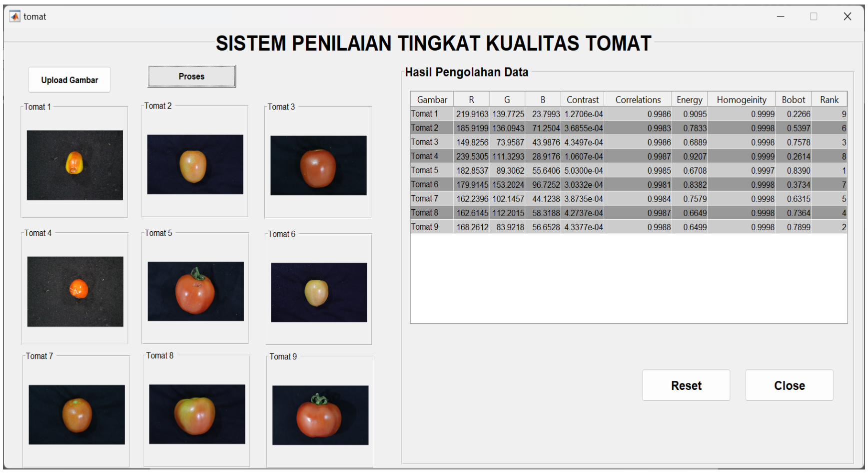


Figure 10: First System Test Results

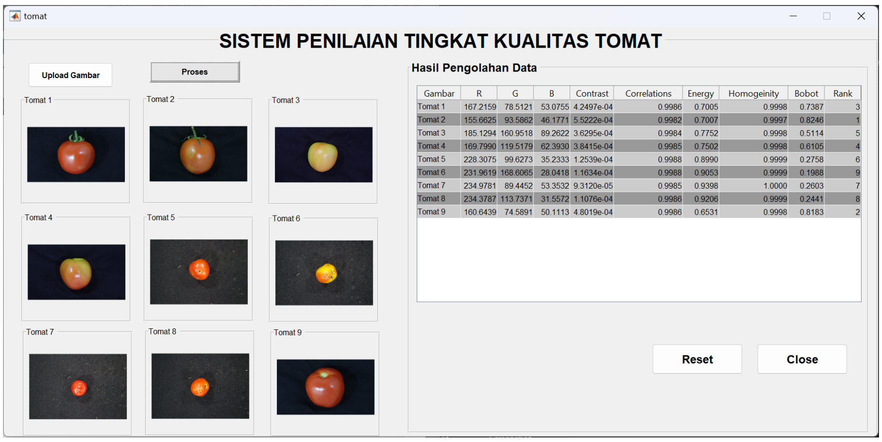


Figure 11: Second System Test Results

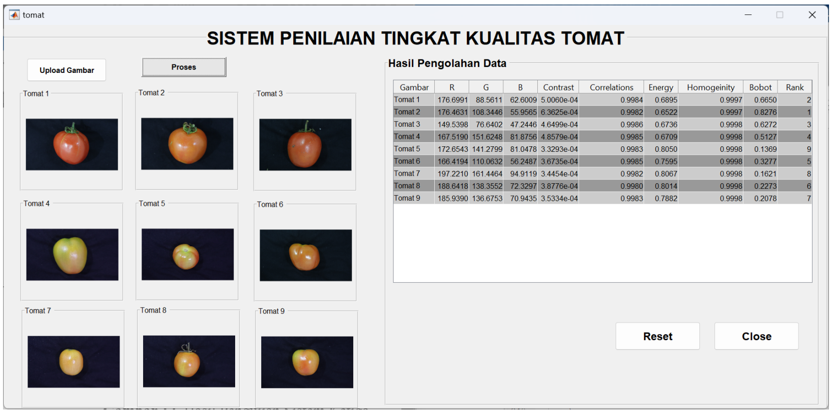


Figure 12: Third System Test Results

Based on the system test results in Figures 10-12, the comparison between the results of the system assessment and the assessment by the rater who is a lecturer who has a research focus and is an expert in the field of image processing is shown in Table 13.

Table 13. Comparison of DSS Assessment Results with Rater

Rank	1st System Test		2nd System Test		3rd System Test		Category
	DSS	Rater	DSS	Rater	DSS	Rater	
1	C-5	C-3	C-2	C-1	C-2	C-3	High Quality (H)
2	C-9	C-9	C-9	C-9	C-1	C-1	
3	C-3	C-5	C-1	C-2	C-3	C-2	
4	C-8	C-7	C-4	C-3	C-4	C-6	Medium Quality (M)
5	C-7	C-8	C-3	C-8	C-6	C-9	
6	C-2	C-2	C-5	C-5	C-8	C-8	
7	C-6	C-6	C-7	C-4	C-9	C-7	Low Quality (L)
8	C-4	C-4	C-8	C-7	C-7	C-5	
9	C-1	C-1	C-6	C-6	C-5	C-4	

After the comparison, the next step is to create a contingency matrix from the comparison in Table 13 so that Cohen's Kappa value can be calculated. This contingency matrix serves to summarize the evaluation results of the various categories assessed by the DSS and rater. The contingency matrix of the three DSS tests is presented in Table 14.

Table 14. Contigency Matrix between DSS and Rater Assessment Results

	System Test 1				System Test 2				System Test 3			
	H	M	L	Total	H	M	L	Total	H	M	L	Total
Rater: H	3	0	0	3	3	0	0	3	3	0	0	3
Rater: M	0	3	0	3	0	2	1	3	0	2	1	3
Rater: L	0	0	3	3	0	1	2	3	0	1	2	3
Total	3	3	3	9	3	3	3	9	3	3	3	9

After creating the contingency matrix from the comparisons in Table 13, the next step is to calculate Cohen's Kappa value to assess the level of agreement between the DSS and the rater. Based on the contingency matrix in Table 14, the kappa value of each test is calculated and listed in Table 15.

Table 15: Kappa value of DSS testing

System Testing	Observed agreement (P_o)	Expected agreement (P_e)	Kappa (κ)
1st System test	1,00	0,33	1,00

System Testing	Observed agreement ($\boxed{P_o}$)	Expected agreement ($\boxed{P_e}$)	Kappa (κ)
2nd System test	0,78	0,33	0,67
3rd System test	0,78	0,33	0,67
	Average		**0, 78**

Based on Table 15, the kappa value obtained of 0.78 indicates a good level of agreement between the assessment results from the dss and the rater. A kappa value in this range indicates that the DSS has achieved a good level of accuracy in evaluating tomato quality, almost equivalent to the manual assessment by the expert. In one of the previous literatures [9], the DSS developed was evaluated through user satisfaction with a satisfaction percentage of 75%, while in this study the DSS was evaluated using the Kappa Coefficient to test the proposed method with the results reaching 78%, which is in the interpretation of good agreement [20]. However, there are limitations and challenges in the development and application of this DSS. This can be seen in the results of the comparison of the DSS ranking with the rater in Table 13, where the ranking results are not much correct when the assessment results are not categorized. The DSS test results show a less than optimal ranking, with some ranking orders that do not match the rater's assessment.

4. Conclusion

Based on the experiments that have been carried out related to the Implementation of Digital Image-Based Decision Support System with Hybrid AHP-TOPSIS Method in Assessing Tomato Quality Level, seven criteria are used, three of which are the criteria for the intensity of the red channel pixels, the intensity of the green channel, and the intensity of the blue channel to assess the color of the tomato image. The other four criteria are used to assess the texture of tomatoes, namely contrast, correlation, energy, and homogeneity. The system evaluation results show that the DSS is quite capable of determining the quality of tomatoes with a kappa value of 0.78, which interprets a good agreement between the DSS assessment and the rater . In the test results there are some ranking results that are not in accordance with the expert, this is due to the determination of the level of importance between criteria and between sub-criteria that are still not optimal. In addition, the resulting image is still not too consistent, thus triggering errors in system assessment. It is hoped that future research can consider adding criteria, such as fruit size and shape, to more accurately assess the quality of tomatoes.

References

[1] M. Syahdan, H. A. Karim, dan I. Iinnaninengseh, “Peningkatan Produktivitas Tanaman Tomat (Lycopersicon Esculentum Mill.) dengan Pemberian Berbagai Jenis Pupuk Kompos dan Komposisi NPK,” *J. Agroterpadu*, vol. 1, no. 1, hlm. 29, Apr 2022, https://doi.org/10.35329/ja.v1i1.2818.

[2] A. P. Dewi Nazari, R. Rusdiansyah, A. P. Meklin Siregar, dan A. Rahmi, “Pertumbuhan dan Hasil Tanaman Tomat (Lycopersicum Esculentum Mill.) pada Pemberian Pupuk Zn dan Jarak Tanam yang Berbeda,” *ZIRAAAH Maj. Ilm. Pertan.*, vol. 45, no. 3, hlm. 241, Sep 2020, https://doi.org/10.31602/zmip.v45i3.3482.

[3] S. Rakhmawan, F. Nofrida, dan Suheri, *Statistik Perdagangan Luar Negeri Indonesia (Ekspor) 2022*, vol. 1. Jakarta: BPS RI, 2022.

[4] P. K. Ng’ang’a dan C. R. Vogl, “Quality perception of organically grown tomatoes (Lycopersicon esculentum Mill.) in Vienna, Austria,” *Int. J. Agric. Res. Innov. Technol.*, vol. 5, no. 2, hlm. 16–20, Jan 2016, https://doi.org/10.3329/ijarit.v5i2.26263.

[5] S. R. Rupanagudi, B. S. Ranjani, P. Nagaraj, dan V. G. Bhat, “A cost effective tomato maturity grading system using image processing for farmers,” dalam *2014 International*

Conference on Contemporary Computing and Informatics (IC3I), Mysore, India: IEEE, Nov 2014, hlm. 7–12. https://doi.org/10.1109/IC3I.2014.7019591.

[6] F. I.-R. P. Computer, "Implementasi Multi-Objective Optimization On The Basis Of Ratio Analysis (MOORA) Untuk Menentukan Kualitas Buah Mangga Terbaik," INA-Rxiv, preprint, Apr 2018. doi: 10.31227/osf.io/yqbse.

[7] Parlia Romadiana, Fitriyanti, dan Delpiah Wahyuningsih, "Penerapan Metode Fuzzy Multi Attribut Decision Making (FMADM) Dan Simple Additive Weighting (SAW) Untuk Penentuan Bujang Dayang Kota Pangkalpinang," *Techno Xplore J. Ilmu Komput. Dan Teknol. Inf.*, vol. 5, no. 2, hlm. 56–63, Nov 2020, https://doi.org/10.36805/technoxplore.v5i2.1150.

[8] E. L. Damanik dan R. M. Simanjorang, "Sistem Pendukung Keputusan Menentukan Pemutusan Hubungan Kerja Karyawan CV. Biring Ndu Cahaya Panglong Dengan Metode AHP," *J. Nas. Komputasi Dan Teknol. Inf. JNKTI*, vol. 4, no. 1, hlm. 7–13, Feb 2021, https://doi.org/10.32672/jnkti.v4i1.2659.

[9] M. Mulyadi, I. Ismail, dan Z. K. Simbolon, "Sistem Pendukung Keputusan Untuk Menentukan Kualitas Bibit Padi Menggunakan Metode Analytical Hierarchy Process," *Sisfo J. Ilm. Sist. Inf.*, vol. 4, no. 2, Okt 2020, https://doi.org/10.29103/sisfo.v4i2.7949.

[10] I. As'ad dan N. Kurniati, "Sistem Pendukung Keputusan Pemilihan Bibit Padi Unggul menggunakan Metode Topsis Technique for Order Preference by Similarity to Ideal Solution," vol. 3, no. 4, 2022.

[11] A. B. Nasution, D. Widyati, dan F. H. Ritonga, "Sistem Pendukung Keputusan Pemilihan Buah-Buahan Layak Jual Menggunakan Metode MOORA," *Sist. Pendukung Keputusan Dengan Apl.*, vol. 1, no. 2, hlm. 58–67, Sep 2022, https://doi.org/10.55537/spk.v1i2.116.

[12] N. I. Humaira B, M. Herman, N. Nurhikma, dan A. B. Kaswar, "Klasifikasi Tingkat Kualitas dan Kematangan Buah Tomat Berdasarkan Fitur Warna Menggunakan Jaringan Syaraf Tiruan," *J. Embed. Syst. Secur. Intell. Syst.*, vol. 2, no. 1, hlm. 18, Nov 2021, https://doi.org/10.26858/jessi.v2i1.20329.

[13] A. S. Agung, A. F. D. Sr, M. S. Hersyam, A. B. Kaswar, dan D. Andayani, "Classification of Tomato Quality Based on Color Features and Skin Characteristics Using Image Processing Based Artificial Neural Network," *J. Tek. Inform. JUTIF*, vol. 4, no. 5, hlm. 1021–1032, 2023, https://doi.org/10.52436/1.jutif.2023.4.5.780.

[14] L. Dinar, A. Suyantohadi, dan A. F. Fallah, "Estimation of Class Quality Analysis Based on Color and Shape Nutmeg (Myristica fragrans houtt) Using Image Processing Technology and Neural Networks," *J. Keteknikan Pertan.*, vol. 26, no. 1, hlm. 51–57, Apr 2012, https://doi.org/10.19028/jtep.26.1.51-57.

[15] P. A. R. Devi dan H. Rosyid, "Pemaparan Materi Dasar Pengolahan Citra Digital untuk Upgrade Wawasan Siswa di SMK Dharma Wanita Gresik," vol. 2, no. 4, 2022.

[16] I. M. Khusna dan N. Mariana, "Sistem Pendukung Keputusan Pemilihan Bibit Padi Berkualitas Dengan Metode AHP Dan Topsis," *J. Sisfokom Sist. Inf. Dan Komput.*, vol. 10, no. 2, hlm. 162–169, Jul 2021, https://doi.org/10.32736/sisfokom.v10i2.1145.

[17] N. P. L. Santiari dan I. G. S. Rahayuda, "Perancangan Sistem Informasi Aset Perusahaan Pada CV di Bidang Properti," *Best Account. Inf. Syst. Inf. Technol. Bus. Enterp. This Link OJS Us*, vol. 7, no. 1, hlm. 1–15, Jun 2022, https://doi.org/10.34010/aisthebest.v7i1.6127.

[18] R. W. Sari, A. P. Windarto, dan E. Irawan, "Penerapan Algoritma PROMETHEE Pada Seleksi Proposal Program Kreativitas Mahasiswa (PKM) pada STIKOM Tunas Bangsa Pematangsiantar," *Pros. Semin. Nas. Ris. Inf. Sci. SENARIS*, vol. 1, hlm. 641, Sep 2019, https://doi.org/10.30645/senaris.v1i0.70.

[19] K. R. Burgener, S. S. Lichtenberg, A. Lomax, D. J. Storm, D. P. Walsh, dan J. A. Pedersen, "Diagnostic testing of chronic wasting disease in white-tailed deer (Odocoileus virginianus) by RT-QuIC using multiple tissues," *PLOS ONE*, vol. 17, no. 11, hlm. e0274531, Nov 2022, https://doi.org/10.1371/journal.pone.0274531.

[20] W. Permatasari dan Y. Yerimadesi, "Analisis Validitas dan Praktikalitas dari Modul Minyak Bumi Berbasis Guided Discovery Learning," *Edukimia*, vol. 2, no. 1, hlm. 25–31, Feb 2020, https://doi.org/10.24036/ekj.v2.i1.a118.

[21] A. B. W. Putra, R. Rihartanto, dan A. M. Alhumaerah, "Penerapan K-Means Clustering Dalam Pengelompokan Lipstik Matte Lip Cream Berdasarkan Warna RGB," *JST J. Sains Terap.*, vol. 5, no. 1, Mar 2019, https://doi.org/10.32487/jst.v5i1.527.

[22] R. Vijaya, K. Prudvi, L. Ravi, dan M. Jogendra, "Grey level to RGB using YCbCr color space Technique," *Int. J. Comput. Appl.*, vol. 147, no. 7, hlm. 25–28, Agu 2016, https://doi.org/10.5120/ijca2016911180.

[23] R. A. Rizal *dkk.*, "Analisis Gray Level Co-Occurrence Matrix (Glcm) dalam Mengenali Citra Ekspresi Wajah," vol. 3, no. 2, 2019.

[24] A. Kurniasari, D. Erwanto, dan P. N. Rahayu, "Ekstraksi Fitur Tekstur dan Warna pada Kulit Katak Menggunakan GLCM dan Momen Warna," *J. ELTIKOM*, vol. 6, no. 1, hlm. 1–12, Jan 2022, https://doi.org/10.31961/eltikom.v6i1.287.

[25] A. Khorsandi dan L. Li, "A Multi-Analysis of Children and Adolescents' Video Gaming Addiction with the AHP and TOPSIS Methods," *Int. J. Environ. Res. Public. Health*, vol. 19, no. 15, hlm. 9680, Agu 2022,https://doi.org/10.3390/ijerph19159680.