

Analysis of Color Feature-Based Segmentation and Classification of Fruits Images Using Linear Discriminant Analysis Method

Andri Armaginda Siregar^{1*}, Susiana Khosasih², Mhd. Agung Irnanda³, Jalaluddin Nasution⁴, Rahmat Humala Putra Hasibuan⁵, Wahyu Saptha Negro⁶

^{1,2,3,4,5,6} Faculty of Engineering and Computer Science, Computer Science, Potensi Utama University, Medan City, Indonesia

Email: ^{1,*}andriarmagindasiregar@gmail.com, ²susianakhosasih21@gmail.com, ³agungirnanda16@gmail.com, ⁴jalaluddinnasution04@gmail.com, ⁵rahmathumala06@gmail.com, ⁶wahyusapthal1707@gmail.com

(*Email Corresponding Author: andriarmagindasiregar@gmail.com)

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Abstract

This study discusses the analysis of fruit image segmentation and classification based on color features, with bananas and strawberries as the research objects. This study addresses the problem of separating fruit objects from the background and automatically classifying fruit types using simple, efficient, and interpretable color features. The objectives of this study are to analyze the effectiveness of color-based segmentation and evaluate the performance of the Linear Discriminant Analysis (LDA) method in classifying fruit images and analyzing separability between classes. The proposed method includes image pre-processing, segmentation based on a combination of Lab* and HSV color spaces, color feature extraction in the form of average Hue and Saturation values, and classification using Linear Discriminant Analysis. The dataset used consists of images of bananas and strawberries, which are divided into training data and test data. The results show that color-based segmentation effectively separates fruit objects from the background and produces a clear feature distribution between classes. The classification process using LDA produces an accuracy rate of 100% on the test data, indicating that the color features used have high discriminatory power. Based on these results, it can be concluded that the combination of color-based segmentation and the LDA method is effective for fruit image classification and is capable of providing good class separability analysis with low computational complexity.

Keywords : Digital Image Processing, Color-Based Segmentation, Fruit Classification, Linear Discriminant Analysis, Color Features, Bananas, Strawberries.

1. INTRODUCTION

Recent advances in digital image processing have created significant opportunities in various fields, particularly in agriculture and the food industry. One of the crucial challenges faced is how to automatically identify and classify fruit with a high degree of accuracy. Accurate classification not only guarantees product quality, but also speeds up the supply chain from harvesting to distribution, thereby supporting industry efficiency and competitiveness.

Visual characteristics such as shape, texture, and color are the main determinants in distinguishing fruit types and ripeness levels. Among these three aspects, color features are often considered the most dominant because they represent visual characteristics that are easily recognizable by both systems and humans. Therefore, color-based analysis represents a relevant and effective strategy for fruit image segmentation and classification.

In this study, the objects studied were bananas and strawberries, two fruit commodities that have high economic value and a wide consumption rate. Bananas are known for their clear skin color changes throughout the ripening process, while strawberries have variations in red color that are indicators of quality and ripeness. These two fruits present both challenges and opportunities for image-based classification systems, as their visual differences can be exploited to improve grouping accuracy.

Color-based segmentation allows for more precise separation of fruit objects from the background, so that the extracted features truly reflect the intrinsic characteristics of the fruit. The next stage is classification, which serves to group images into specific categories. In this study, Linear Discriminant Analysis (LDA) was used as the classification method. LDA is known as a statistical technique that can maximize separability between classes by projecting data into a lower-dimensional space. This approach not only improves classification accuracy but also reduces computational complexity, making it an efficient solution for image-based systems.

Previous studies have shown that color features in digital images play an important role in the classification and quality assessment of objects, particularly in the agricultural and food domains. A number of studies have utilized Linear Discriminant Analysis (LDA) as a classification and dimension reduction method to distinguish the maturity level or type of objects based on color characteristics, such as mulberries [1], tomatoes [2], star fruit [3], bananas [4], red chili peppers [5], edelweiss flowers [6], and potato leaves [7]. The results of these studies prove that LDA is capable of providing fairly good to very high classification performance, especially when combined with relevant color features.

However, most existing studies focus on a single fruit type within a single experimental setting. Studies on mulberries [1], tomatoes [2], star fruit [3], custard apples [8], bell peppers [9], cabbage and carrots [10] evaluated the model on only one commodity, so the method's ability to distinguish between fruits with very different color

characteristics has not been adequately explored. Although multi-spectral imaging studies [11] and comprehensive surveys [12] cover various types of fruit, including bananas and strawberries, these approaches are general, complex, and do not specifically analyze the performance of LDA based on simple color features on specific object pairs.

Furthermore, some studies use algorithms other than LDA as the main classifier, such as SVM [13][14] KNN [15][1] MLP [16][12] Random Forest [17][7], or deep learning [16][8], which, although they produce high accuracy, sacrifice the interpretability and simplicity of the model. Even when LDA is used, its role is often limited to being a final classifier [5][7][18] or performance comparator [15][7], rather than a discriminative analysis tool for understanding the separability of color features between classes.

In terms of image segmentation, most studies treat segmentation as an initial technical stage without in-depth analysis of its impact on feature distribution and projection results in the discriminant space [1][2][5]. In fact, studies involving many classes or objects with high color variation show that segmentation quality greatly affects classification performance, as seen in the low accuracy of multi-class leaf classification using LDA [15][19][20].

Specialized research on bananas has indeed been conducted, both for banana classification using SVM [20] and for analyzing potato leaf quality and damage using LDA [7]. However, these studies did not use LDA as the primary method and did not explicitly relate the results to color feature separability analysis. On the other hand, research on strawberries has more often appeared in the context of multi-spectral imaging [11] or survey studies [12], rather than as the main object in lightweight and interpretive RGB/HSV/Lab*-based research.

Furthermore, most previous studies have focused solely on achieving accuracy, without discussing how color features are distributed in the discriminant space or the extent to which classes overlap [16][7][5]. In fact, understanding class separability is important to ensure that the model is not only numerically accurate, but also robust and explainable.

The purpose of this study is to analyze the effectiveness of color feature-based segmentation in separating images of bananas and strawberries, as well as to evaluate the performance of LDA in the classification process. The expected result is a tangible contribution to the development of a more efficient, accurate, and applicable fruit classification system, both on an industrial scale and as a stepping stone for further research.

Based on a synthesis of the 20 papers, it can be concluded that there are still research gaps related to the analysis of fruit image segmentation and classification based on color features that examine two different types of fruit simultaneously with contrasting color characteristics, using LDA not only as a classifier, but also as a feature separability analysis tool, analyzing the effect of color-based segmentation on feature distribution and class separation, emphasizing simplicity, efficiency, and model interpretability over complex deep learning-based approaches.

Therefore, this study proposes the analysis of banana and strawberry image segmentation and classification based on color features using the Linear Discriminant Analysis (LDA) method to fill this gap, with an emphasis on class separability analysis and visual interpretation of the discriminant projection results.

2. RESEARCH METHODOLOGY

2.1 Research Flow

This study applies a quantitative experimental approach with main stages that include image data acquisition, color-based preprocessing and segmentation, color feature extraction, classification model training using Linear Discriminant Analysis (LDA), and system performance testing and evaluation. The research flow is designed systematically to ensure consistency between the training and testing stages, as shown in Figure 1.

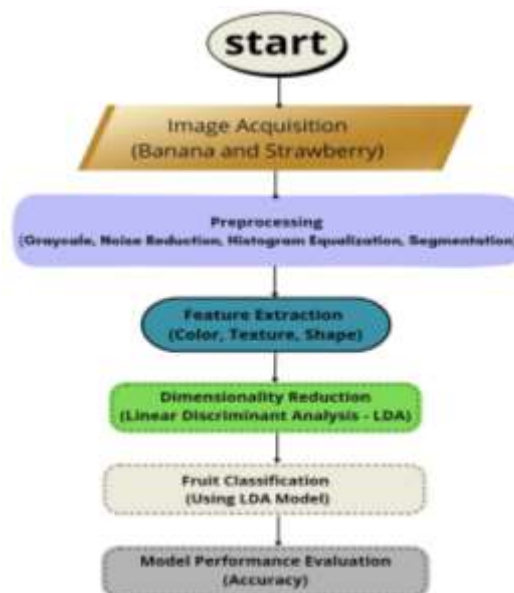


Figure 1. Flowchart of Research Flow

2.2 Acquisition and Image Dataset

The dataset used in this study consists of images of bananas and strawberries obtained from two sources, namely a public dataset and images taken directly using a digital camera. All images are stored in JPEG format with varying resolutions and lighting conditions, so that they are able to represent the variations in real environments commonly encountered in the process of capturing fruit images.



Figure 2. Training Data for Strawberry Images (Object A) and Banana Images (Object B)

The dataset is divided into two parts, namely training data and test data, as shown in Figure 1 and Figure 2. The training data is used to build and train a classification model based on Linear Discriminant Analysis (LDA), while the test data is used to evaluate the model's generalization ability on images not involved in the training process. The training data consists of 35 images, including 20 images of strawberries and 15 images of bananas. Meanwhile, the test data consists of 25 images, including 15 images of strawberries and 10 images of bananas.

Class labels were determined automatically based on image file names, so that each image could be consistently classified into either the banana or strawberry class. This approach ensured consistency in the labeling process and minimized annotation errors during the model training and testing stages.

2.3 Image Pre-processing

The image pre-processing stage aims to prepare images before segmentation and color feature extraction. At this stage, input images in RGB color space are converted to $L^*a^*b^*$ and HSV color spaces. Color space conversion is performed to separate color and luminance information and improve the system's ability to distinguish fruit objects from the background under varying lighting conditions.

In the $L^*a^*b^*$ color space, relevant color components are used to highlight the differences in color characteristics between objects and backgrounds. Meanwhile, conversion to the HSV color space is performed to represent colors in the form of Hue, Saturation, and Value, which are more stable against changes in light intensity. This pre-processing stage forms the basis for color-based segmentation and aims to improve object separation quality and feature extraction accuracy in the next stage.

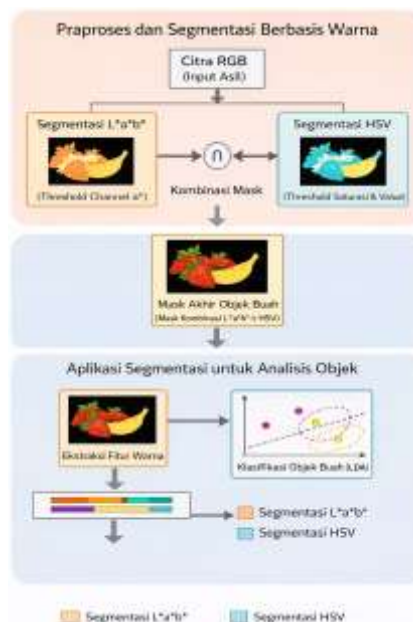
2.4 Color Feature-Based Segmentation

Image segmentation is performed to separate fruit objects from the background based on color characteristics. In this study, color feature-based segmentation is applied by utilizing a combination of $L^*a^*b^*$ and HSV color spaces to obtain more precise segmentation results.

In the $L^*a^*b^*$ color space, initial segmentation is performed by applying a threshold to the a^* channel, which represents the red-green color difference. This channel is chosen because it is able to highlight the dominant color characteristics of bananas and strawberries compared to the background. The initial segmentation results are then

refined using morphological operations to remove noise and fill in empty areas, thereby obtaining more complete object areas.

Next, additional segmentation is performed in the HSV color space by applying thresholds to the Saturation and Value components. This stage aims to filter out background areas that have low color saturation or light intensity that



does not represent fruit objects. The segmentation masks from both color spaces are then combined to produce a final mask that represents the fruit objects more accurately.

Figure 3. Conceptual Illustration of Pre-processing and Color-based Segmentation Stages

2.5 Color Feature Extraction

After the fruit object has been successfully separated from the background through the segmentation process, the next step is color feature extraction. In this study, color features are extracted only from pixels included in the object area based on the segmentation mask, so that the color information obtained truly represents the intrinsic characteristics of the fruit.

The color features used are the average Hue and Saturation values calculated from images in the HSV color space. Hue and Saturation features were selected based on their ability to represent the color type and saturation level of objects, as well as their relatively low computational complexity. The average value of each feature is used as a numerical representation of the image and is arranged in the form of a two-dimensional feature vector which is then used as input in the classification process.

2.6 Classification and Analysis of Linear Discriminant Analysis (LDA) Separability

Linear Discriminant Analysis (LDA) is a statistical method that aims to optimally separate data groups. It works by finding linear projections of data characteristics (features) that can increase the distance between different categories. In this study, LDA was used to group bananas and strawberries based on color estimates obtained from digital image analysis. The strategic function of LDA here is to simplify data complexity by reducing the dimensions of the many color and texture features.

The dataset used contains a collection of images of bananas and strawberries. The application of LDA is expected to classify and segment bananas and strawberries based on the color and shape of each fruit that has been collected.

The work stages begin with feature extraction from images of bananas and strawberries. The features extracted are mainly color components from the RGB and HSV models. In addition, all of the extracted numerical features then become input variables for the LDA model.

Mathematically, the working principle of LDA is to maximize the ratio between inter-class variation and intra-class variation. This is done by calculating the intra-class scatter matrix (S_W), which describes the diversity of data within a fruit category (for example, the variety of textures in all strawberry samples), and the inter-class scatter matrix (S_B) that measures the average difference in features between different fruit categories (e.g., the average color difference between bananas). The optimal combination of features produced by LDA will project the data into a new space where fruit categories based on color and shape can be more clearly separated. The mathematical formulation is given as follows[18]:

$$S_w = \sum_{i=1}^c S_i \quad (1)$$

$$S_B = \sum_{i=1}^c N_i(\mu_i - \mu)(\mu_i - \mu)^T \quad (2)$$

The working principle of Linear Discriminant Analysis (LDA) is to determine the best linear projection to separate classes. This projection is represented by the Eigenvector obtained from the following equation:

$$S_w^{-1} S_B W = \lambda W \quad (3)$$

The W matrix, which acts as the transformation matrix in LDA, contains the set of eigenvectors derived from the equation.

$$S_w^{-1} S_B \quad (4)$$

The next step after forming the W matrix is data transformation. The color feature data extracted from the banana and strawberry images is then transformed or mapped into a lower-dimensional feature space by applying:

$$Y = W^T X \quad (5)$$

Mathematically, Y (projected feature vector), X (initial feature vector), and W (eigen transformation matrix) are linked by a linear transformation equation. Through this projection, data is compressed into a space specifically designed to increase the distance between banana and strawberry classes based on visual indicators, thereby improving classification accuracy.

From an application perspective, LDA provides dual benefits by optimizing class separation while maintaining low computational complexity. In terms of efficiency, the dimensional reduction inherent in this method simplifies the model, significantly speeding up classification computation compared to the use of large numbers of raw features.

2.7 Evaluation Method

The classification system performance evaluation was conducted to assess the ability of the Linear Discriminant Analysis (LDA) model to accurately classify images of bananas and strawberries. The evaluation process was carried out using test data that was not involved in the model training stage, so that the evaluation results could represent the generalization ability of the system.

Classification performance was evaluated using an accuracy metric, which was calculated as the ratio of the number of correctly classified images to the total number of test images. Mathematically, accuracy is formulated as follows:

$$Accuracy = \frac{N_{correct}}{N_{total}} \times 100\% \quad (6)$$

where $N_{correct}$ indicates the number of correctly classified images, and N_{total} indicates the total number of test images.

In addition to calculating accuracy, an analysis of misclassified images is also performed by comparing the predicted labels and the original labels. This analysis aims to identify possible causes of classification errors, such as the influence of lighting conditions, segmentation quality, or similarities in color characteristics between classes. Thus, the evaluation focuses not only on the accuracy value, but also on understanding the factors that affect the performance of the classification system.

3. RESULTS AND DISCUSSION

3.1 Experimental Environment

All experiments in this study were conducted using a laptop with the following hardware and software specifications. The system used was an HP EliteBook 840 G6 with an Intel® Core™ i5-8365U processor with a base speed of 1.60 GHz, supported by 16 GB of RAM. These specifications were deemed adequate for running digital image processing, color feature extraction, and classification using the Linear Discriminant Analysis (LDA) method.

The operating system used is Microsoft Windows 11 Pro 64-bit (Build 22631), with DirectX version 12 support. All method implementations and testing were performed using MATLAB R2018A software equipped with the Image Processing Toolbox and Statistics and Machine Learning Toolbox. MATLAB was used for all stages of the experiment,

from image preprocessing, color-based segmentation, Hue and Saturation feature extraction, LDA model training and testing, to visualization of results through a graphical interface.

The use of this consistent experimental environment aims to ensure that the results obtained are stable, reproducible, and not affected by system configuration variations.

3.2 Image Segmentation Results

The image segmentation results show that the color-based approach is able to effectively separate fruit objects from the background. Initial segmentation using the L*a*b* color space on the a* channel successfully highlighted areas of objects that had significant red-green color differences from the background. However, in some images, the initial segmentation results still contained noise and detected background areas.

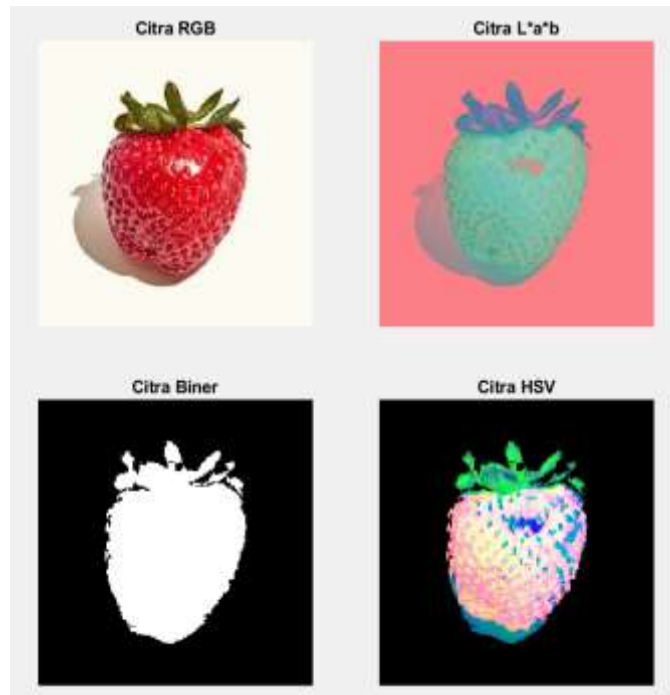


Figure 4. Fruit Image Segmentation Results Using a Combination of L*a*b* and HSV

Additional segmentation using the HSV color space, particularly in the Saturation and Value components, is able to filter background areas that have low color saturation and dark intensity. The combination of L*a*b* and HSV segmentation results produces a more precise final mask, with more complete object shapes and minimal noise. These results indicate that the simultaneous use of two color spaces is more effective than the use of a single color space.

3.3 Color Feature Distribution

The distribution of color features was analyzed based on the average Hue and Saturation values extracted from the segmented object areas. Visualization of feature distribution in two-dimensional space (Hue-Saturation) shows that banana and strawberry images tend to form two distinct groups.

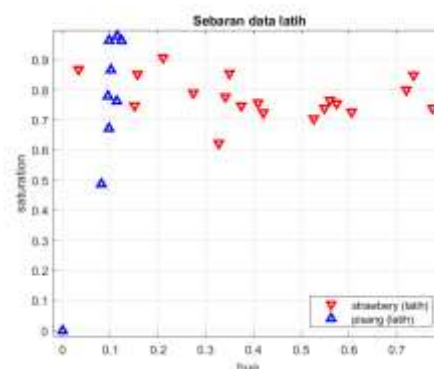


Figure 5. Distribution of Hue and Saturation Color Features in Training Data

The Saturation feature shows a significant difference between the two classes, with strawberries tending to have higher color saturation values than bananas. Meanwhile, the Hue value provides additional information about the differences in the dominant colors of each fruit. This distribution pattern supports the initial hypothesis that simple color features can effectively represent the visual characteristics of fruits.

3.4 LDA Classification Results

Based on the classification results using Linear Discriminant Analysis (LDA), the proposed system was able to classify images of bananas and strawberries in the test data with an accuracy rate of 100%. The LDA model trained using the training data produced a linear discriminant function that was effective in separating the two classes based on a combination of Hue and Saturation color features.

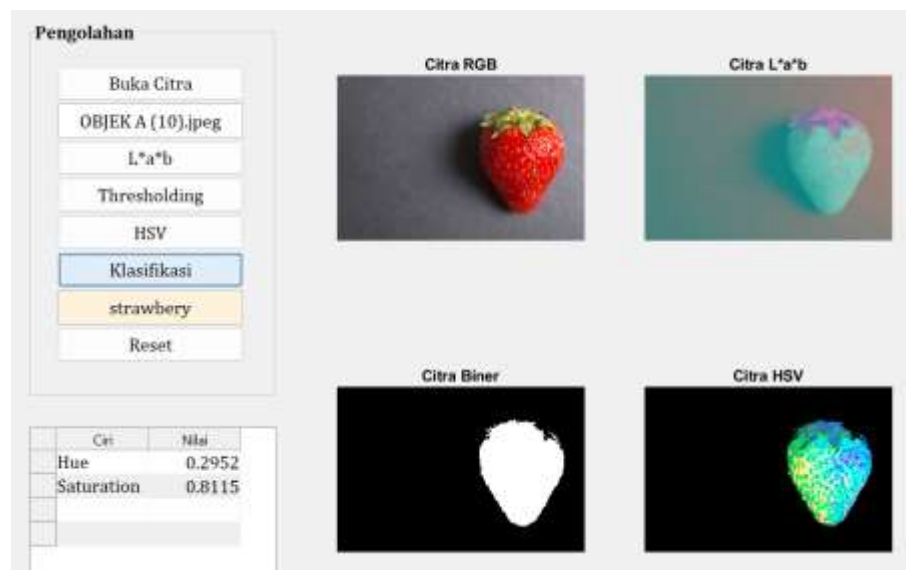


Figure 6. System Interface and Classification Results of Strawberry Images Using LDA

All test images were correctly classified according to their original labels, indicating strong class separability under the experimental conditions. These results show that the color features used have strong discriminatory power, and that the color-based segmentation applied is capable of producing consistent and relevant feature representations for the classification process.

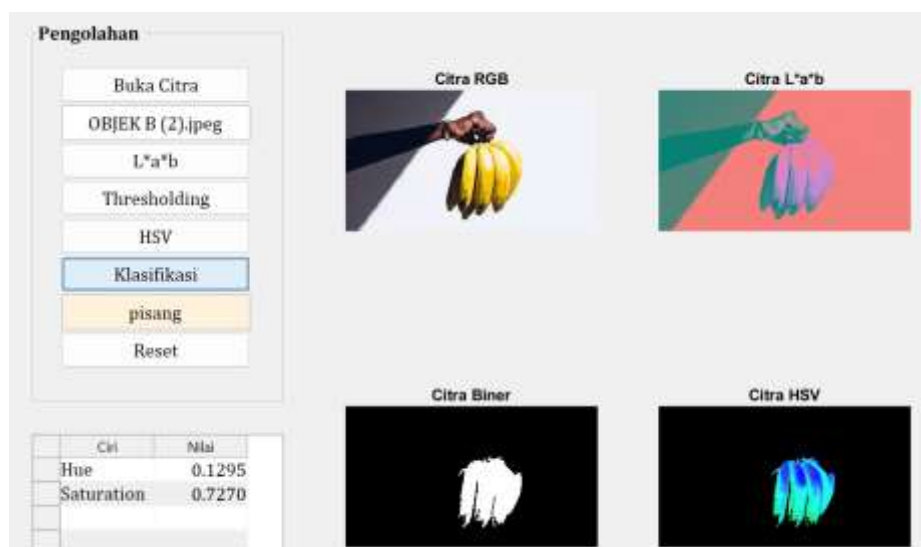


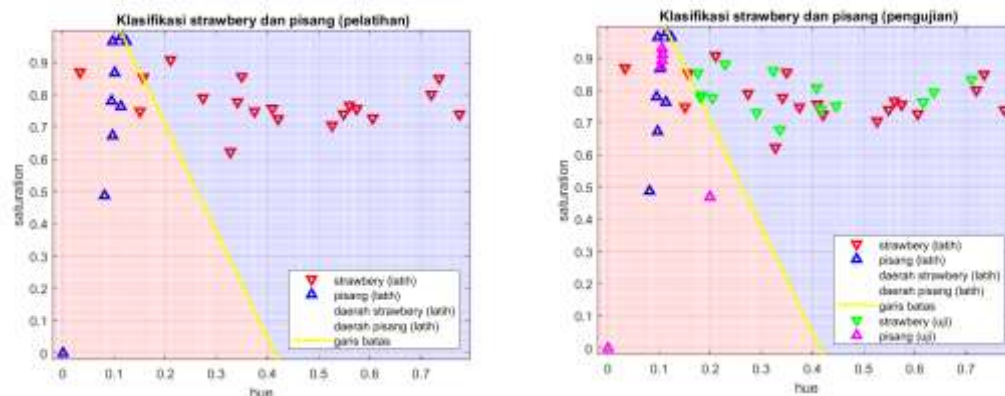
Figure 7. System Interface and Banana Image Classification Results Using LDA

Although Linear Discriminant Analysis is a relatively simple method, the results obtained show that LDA is capable of providing excellent classification performance in the case of fruit image classification based on color features. However, this accuracy was achieved in a test scenario with a limited amount of data, so testing on larger and

more diverse datasets is needed to further evaluate the model's generalization capabilities. Therefore, these results emphasize the validation of the method's effectiveness and feature separability analysis, rather than claims of large-scale generalization.

3.5 Class Separability Analysis

Class separability analysis was performed by observing the color feature distribution and decision boundary generated by LDA. The visualization shows that the two classes have a relatively small overlap, indicating that the color



features used have good discriminatory power.

Figure 8. Separability of Banana and Strawberry Classes Using LDA

The LDA decision boundary is able to linearly separate most of the training and test data. This finding reinforces the role of LDA not only as a classifier, but also as an analytical tool for understanding the relationships and separations between classes in feature space. Thus, these results support the research objective of evaluating the separability of color features between bananas and strawberries.

3.6 The Effect of Segmentation on Classification

Segmentation quality has been proven to have a direct influence on classification results. Imprecise segmentation causes the extracted color features to be mixed with background information, thereby potentially reducing classification accuracy. Conversely, good segmentation produces color features that are more representative of the characteristics of fruit objects.

The use of a combination of $L^*a^*b^*$ and HSV-based segmentation produces cleaner and more consistent object masks, which have a positive impact on feature distribution and class separation by LDA. This shows that the segmentation stage not only serves as a preliminary process, but is a key factor that determines the overall success of the classification system.

These findings confirm that color-based segmentation is not merely a preprocessing stage, but a determining factor that directly influences feature quality and the success of LDA-based classification.

4. CONCLUSION

This study presents a well-structured and interpretable approach to fruit image segmentation and classification using simple color features and Linear Discriminant Analysis (LDA). The methodological design is systematic, and the results demonstrate very strong performance, including perfect classification accuracy on the test data and clear class separability between bananas and strawberries. The emphasis on combining Lab^* and HSV color spaces for segmentation is appropriate and effectively justified, and the use of LDA not only as a classifier but also as a tool for separability analysis represents a clear strength of the work. However, the experimental evaluation is limited by the relatively small dataset, restricted lighting variations, and the use of only two fruit classes, which may affect the generalizability of the reported results. Future work would benefit from larger and more diverse datasets, inclusion of additional fruit types with overlapping color characteristics, and the integration of complementary features such as texture or shape, as well as comparative analysis with more advanced classification methods, to further validate the robustness and broader applicability of the proposed approach.

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