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Classification of Coffee Fruit Maturity Level based on Multispectral Image Using Naïve Bayes Method

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Abstract

The current research about the classification of coffee fruit ripeness based on multispectral images has been developed using the Convolutional Neural Network (CNN) method to extract patterns from high-dimensional multispectral images. The high complexity of CNN allows the model to capture complex features but requires more time and computational resources for model training and testing. Therefore, in this study, classification is performed using a more straightforward method such as Naïve Bayes because its complexity only depends on the number of features and samples. The method only considers each feature independently, so it has high speed and does not require a lot of computational resources. Naïve Bayes is applied to color and texture features extracted from multispectral images of coffee fruit. There are 300 features consisting of 60 color features and 240 texture features. Experiments were conducted based on the comparison of training and testing data and the use of each feature. The combination of color and texture features showed better performance than color or texture features alone, with the highest accuracy reaching 91.01%. In conclusion, using Naïve Bayes is still reasonably good in classifying the ripeness of coffee fruit based on multispectral images.

Keywords: *Coffee fruit maturity, Multispectral image, Naïve Bayes*

1. Introduction

Coffee (Coffea sp) is an agricultural commodity that plays a significant role in world economic growth. Coffee has become popular and favored because processed coffee drinks have a delicious taste and distinctive aroma from the best quality coffee. It is strongly influenced by the coffee fruit's maturity level at harvest time. Coffee picked when the coffee fruit is red or ripe will produce good quality coffee, while coffee picked when it is young will cause a reduction in the taste and aroma of coffee [1].

Researchers have made various efforts to develop a technology that can detect the maturity level of coffee fruit. One of the techniques used is the multispectral imaging technique, which is believed to be better than conventional imaging techniques, especially in checking the quality of agricultural commodities [2]. This technique can generate more data and capture spectral signs containing much information [3].

Multispectral images of coffee fruit are obtained using a special camera modified with specifications in the form of a wide electromagnetic spectrum, controlled illumination space, and narrow LED bandwidth [4], [5]. The camera produces 15 color channels, including violet, royal blue, blue, azure, cyan, green, lime, yellow, amber, red-orange, red, deep red, far red, and 2 Near Infrared (NIR). Meanwhile, an ordinary camera can only produce three color channels: red, green, and blue.

In research [4] utilizing the ability of the Convolutional Neural Network (CNN) method to extract patterns from high-dimensional multispectral images of coffee fruit. The high complexity of CNN allows the model to capture more complex features in multispectral images. However, it also requires more time and computational resources for training and testing the model. The complexity is depends on the model architecture, number of parameters, and the training complexity.

Therefore, this study conducted an experiment using a more straightforward method such as Naïve Bayes. This method was chosen because its complexity only depends on the number of features and samples. In addition, this method only considers each feature independently, so it has high speed and requires little computational resources.

2. Literature Review

This study conducted based on previous studies about classification of the maturity level of coffee fruit. Details of related studies can be seen in Fig. 1.

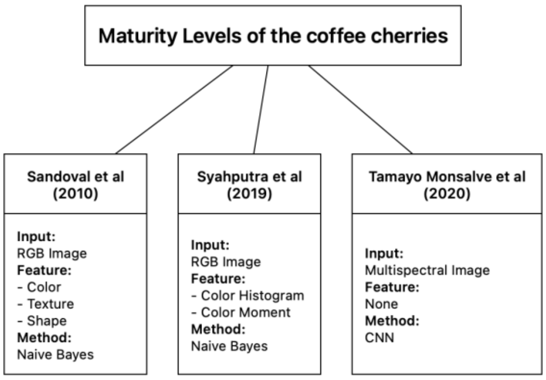

Fig. 1. Details of previous studies

Research by Tamayo Monsalve et al. [4] was conducted using multispectral images of coffee fruit where wavelengths were detected using instruments sensitive to particular wavelengths, including infrared and ultraviolet. Multispectral images allow the addition of information that the human eye cannot capture because multispectral images can capture larger wavelengths. In contrast, ordinary color imagery can only capture three wavelengths: red, green, and blue.

The three main components of a multispectral image camera are a wide electromagnetic spectrum, a controlled science space, and a narrow LED bandwidth. In Fig. 2, the camera is designed to produce 15 wavelengths with a wavelength range of 400-1000 nm.

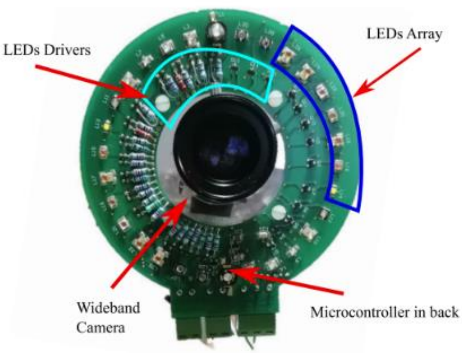

Fig. 2. Special multispectral image camera

The camera uses 30 LEDs with different power and a bandwidth of less than 20 nm. The illumination chamber controls glare, shadows, and light to prevent outside light from entering or reflecting from inside.

Sandoval et al. [6] conducted research using ordinary images; the classification method used was the Naïve Bayes method. Classifying coffee fruit maturity levels is based on color, texture, and shape features extracted from coffee fruit images. The three features are combined to produce a total of 208 features.

The features were then selected so that only nine final features were used for training. The feature selection process shows that the texture feature has a higher discrimination value. It proves that the classification of the maturity level of coffee fruit can not only be done based on color alone but can also utilize the texture of the coffee fruit. Data in color, texture, and shape features are continuous numerical data. So, to process it using Gaussian Naïve Bayes with an accuracy rate of 96.8%.

Research by Syahputra et al. [7] classifies the maturity level of coffee fruit based on color by utilizing color histograms and color moments. There are 19 features consisting of 10 color histogram features and nine color moment features. This study found that the use of color histogram features was better in characterizing the maturity level of coffee fruit than color moments.

Based on an in-depth study of the three previous studies, the method used in this study is obtained, as seen in Fig. 3.

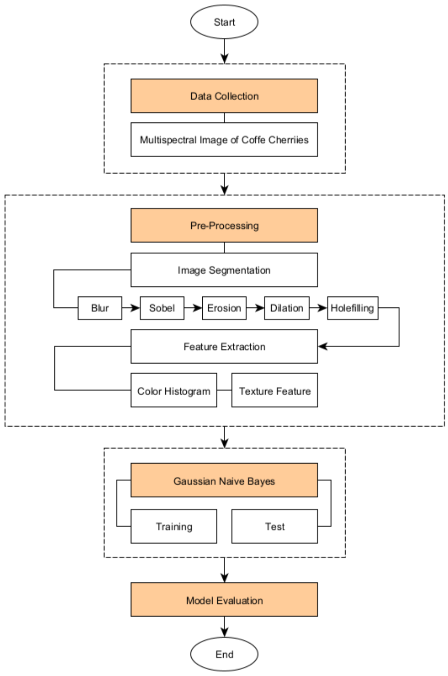

Fig. 3. The classification of coffee fruit maturity method

3. Methodology

3.1. Data Collection

Multispectral images of coffee fruit are obtained from the site https://doi.org/10.5281/zenodo.4914786 as numpy data. Multispectral images of coffee fruit totaled

640 images with a size of 224x224 pixels each. The multispectral image of coffee fruit has 15 color channels with different wavelengths, as shown in Table 1.

The maturity level of coffee fruit is grouped into five: immature, semimature, mature, overripe, and dry. The number for each maturity level can be seen in Table 2.

Table 1. Color channels in the multispectral image of coffee fruit

Wavelength	Color
410	Violet
450	Royal Blue
470	Blue
490	Azure
505	Cyan
530	Green
560	Lime
590	Yellow
600	Amber
620	Red Orange
630	Red
650	Deep Red
720	Far Red
840	NIR
950	NIR

Table 2. Number of pictures per ripening stage

Ripening Stage	Number of Image
Immature	130
Semimature	160
Mature	160
Overripe	112
Dry	78
Total	**640**

3.2. Image Pre-Processing

Multispectral image data goes through the segmentation process. It is needed to remove the unecessary background in the multispectral image of the coffee fruit. An extensive background can reduce the accuracy of the classification process of the maturity level of the coffee fruit.

The first phase is finding the mask of each image. The Gaussian blur method with 7x7 kernel is used to remove the detail of image. Sobel is applied to the previous result to find the edge of object. The Sobel done with the 3x3 x and y kernel. After that, morphological operations (erosion, dilation, and hole filling) applied to get the full filled object. The image is eroded using 5x5 kernel to remove small objects. Then The image is dilated using 3x3 kernel to emphasize the object. Furthermore, the hole filling operation applied to the dilated image. The result shown the several objects with white color.

The second phase is finding and cropping the coffe fruit object.

A well-segmented color channel is used to reference image cropping on other channels. The segmentation stages can be seen in Fig. 4.

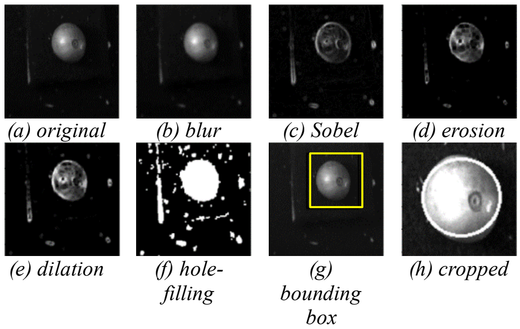

Fig. 4. Image segmentation process

3.3. Features Extraction

The multispectral image of coffee fruit that has been cropped according to the segmentation results on the best color channel, then feature extraction is carried out to find the values in a multispectral image that are unique characteristics of the image. Various features can be extracted, but the features used in this research include color and texture.

Color feature extraction uses a color histogram because it describes the distribution of colors in an image. Color histograms can be applied in various color spaces, one in multispectral images. This research utilizes the statistical values of the color histogram, including mean, variance, skewness, and kurtosis. The statistical significance can be calculated using the equation that has been presented in the equation below [8]:

$$Mean = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} P_{i,j} \tag{1}$$

$$Variance = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{i,j}-\mu)^2} \tag{2}$$

$$Skewness = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{i,j}-\mu)^3}{MN\sigma^3} \tag{3}$$

$$Kurtosis = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{i,j}-\mu)^4}{MN\sigma^4} - 3 \tag{4}$$

Texture feature extraction uses the Gray Level Co-Occurrence Matrix (GLCM) method. GLCM is a matrix representing the frequency of occurrence of two adjacent pixels at a certain intensity, distance, and angle. The GLCM matrix is processed based on four angular directions, namely 0°, 45°, 90°, and 135° with a minimum distance between pixels of 1 pixel [9]. Then, texture features, including contrast, energy, homogeneity, and correlation, can be extracted from the matrix. The equation for calculating texture features has been presented in the equation below:

$$Contrast = \sum_{i,j=0}^{levels-1} P_{i,j}(i-j)^2 \tag{5}$$

$$Energy = \sum_{i,j=0}^{levels-1} \sqrt{P_{i,j}^2} \quad (6)$$

$$Homogeneity = \sum_{i,j=0}^{levels-1} \frac{P_{i,j}}{1+(i-j)^2} \quad (7)$$

$$Correlation = \sum_{i,j=0}^{levels-1} P_{i,j}\left[\frac{(i-\mu_i)(i-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \quad (8)$$

Color feature extraction is done in each color channel, so color feature extraction produces 60 features. The extraction of texture features is done in each color channel with four angles, namely 0°, 45°, 90°, and 135°, so the extraction of texture features results in 240 features. If these features are combined, the total features amount to 300 features.

3.4. Gaussian Naïve Bayes

Naïve Bayes is an algorithm that applies simple probability calculations by summing frequencies and combinations of values in a data set [10]. However, the use of Naïve Bayes is adjusted to the nature of the data in the dataset. Color and texture features extracted from multispectral images of coffee fruit are continuous numerical data. So, that process is done using Gaussian Naïve Bayes [11]. Gaussian Naïve Bayes calculation is done with the following steps:

a. Calculate the average value of each feature based on the existing classes.
b. Calculating the standard deviation value of each feature based on the existing classes.
c. Calculating the prior probability by dividing the number of occurrences of a class by the total number of all classes.
d. Calculating the Gaussian value using the following equation:

$$P(X_i = x_i | Y = y_j) = \frac{1}{\sqrt{2\pi\sigma_{ij}}} e^{-\frac{(x_i-\mu_{ij})^2}{2\sigma^2 ij}} \quad (9)$$

e. Calculate the posterior probability value of each class by multiplying all the Gaussian values with the prior probability value.
f. The prediction result is obtained from the highest posterior probability value.

3.5. Model Evaluation

The classification process is based on the features used, namely color features, texture features, and a combination of color and texture features. The experiment was also conducted using K-Fold with the number of K is 10.

Through these experiments, we can find the performance of each experiment using Confusion Matrix. Confusion Matrix is a table that describes the performance of a particular algorithm. Each row in the table represents actual data, and each column represents predicted data [11]. The Confusion Matrix shown in Table 3. All of the parameters is averaging using macro average. Macro average is summing the parameters then divide by the parameter number. The parameters obtained from the Confusion Matrix table calculation include the following:

$$Precision = \frac{TP}{FP+TP} \quad (11)$$

$$Recall = \frac{TP}{FN+TP} \quad (12)$$

$$F1\,Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (13)$$

Table 3 Confusion Matrix

		Actual Values	
		Positive	Negative
Predicted Class	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

4. Result and Analysis

The multispectral image segmentation of coffee fruit was performed on 15 color channels. Experiments using blur, Sobel edge detection, erosion, dilation, and hole-filling methods performed sequentially show results as in the table below:

Table 4. Image segmentation experiment

Color	Number of failures
Violet	640
Royal Blue	627
Blue	573
Azure	571
Cyan	557
Green	493
Lime	354
Yellow	403
Amber	163
Red Orange	61
Red	97
Deep Red	276
Far Red	640
NIR	640
NIR	640

Images that fail to segment are images that are not segmented right on the coffee fruit object, or parts of the coffee fruit object are cut off. Based on the results presented in Table 4, the red-orange color channel has the least failure rate, which is 61 images. Therefore, the red-orange color channel is used as a reference for cropping other color channels.

Next, the multispectral image of coffee fruit is extracted to obtain the color and texture features described in the previous point. Extraction is done in each color channel, resulting in 60 color features and 240 texture features. If these features are combined, the total features amount to 300 features. The extraction results of each feature can be seen in Fig. 5 and Fig. 6.

Id	Violet_M	Violet_V	Violet_S	Violet_K	RoyalBlue_M	RoyalBlue_V	RoyalBlue_S	RoyalBlue_K	Blue_M	...
0	5.96	1.42	0.39	-0.24	8.02	4.06	0.34	-0.52	8.99	...
1	6.13	1.59	0.28	-0.40	8.21	4.70	0.28	-0.66	9.24	...
2	5.87	1.67	1.38	6.15	7.77	4.83	1.43	6.54	8.65	...
3	6.26	1.76	0.44	0.86	8.53	5.07	0.35	0.28	9.57	...
4	5.98	1.36	0.28	-0.36	7.97	3.85	0.27	-0.60	8.86	...
5	6.12	1.28	0.22	-0.33	8.31	3.66	0.18	-0.55	9.31	...
6	6.44	1.57	0.44	-0.28	8.16	3.86	0.46	-0.43	8.92	...
7	6.48	1.59	0.41	-0.32	8.25	4.07	0.45	-0.40	9.04	...
8	6.35	1.44	0.43	-0.22	8.03	3.66	0.49	-0.27	8.78	...
9	6.34	1.38	0.45	-0.07	8.08	3.47	0.42	-0.28	8.84	...

Fig. 5. Color feature extraction result

Id	Violet_Cor0	Violet_Cor45	Violet_Cor90	Violet_Cor135	Violet_Hom0	Violet_Hom45	Violet_Hom90	Violet_Hom135	Violet_Con0	...
0	0.60	0.56	0.58	0.58	0.66	0.64	0.65	0.64	1.13	...
1	0.65	0.60	0.61	0.62	0.66	0.64	0.65	0.64	1.11	...
2	0.60	0.54	0.54	0.51	0.67	0.65	0.66	0.65	1.32	...
3	0.62	0.59	0.59	0.59	0.64	0.63	0.63	0.63	1.33	...
4	0.60	0.58	0.57	0.55	0.66	0.65	0.65	0.64	1.07	...
5	0.56	0.54	0.55	0.52	0.65	0.65	0.65	0.64	1.13	...
6	0.62	0.61	0.62	0.59	0.65	0.64	0.65	0.64	1.17	...
7	0.62	0.61	0.61	0.59	0.64	0.64	0.64	0.63	1.21	...
8	0.58	0.57	0.57	0.53	0.64	0.64	0.64	0.63	1.18	...
9	0.57	0.56	0.57	0.54	0.65	0.64	0.65	0.63	1.17	...

Fig. 6. Texture feature extraction result

The dataset that has been obtained is classified using Naïve Bayes by considering the division of training data and testing data. The performance comparison of each classification experiment is presented in Table 5.

The precision of the three models does not have significant differences. The highest precision score obtained using the Color and Texture feature with the score is 91.65%. It means the model can predict each ripened levels precisely. The model also has the highest recall score with the score is 92.05%.

Table 5. Naive Bayes classification performance comparison

	Color	Texture	Color & Texture
Precision	91.11%	90.44%	91.65%
Recall	91.52%	90.79%	92.05%
Accuracy	89.98%	89.80%	91.01%
F1-Score	89.98%	90.65%	90.93%

The model with the Color and Texture feature had the highest accuracy and F1 score. The accuracy score is 91.01%, and the F1-Score is 90.93%. The model could predict the ripening stage accurately under any conditions.

As shown in Fig 7, the model had equal ability to predict each of the ripening stage. The highest number of missclassification is in the semimature ripening stage with 22 data. The lowest number of missclassification is in the dry ripening stage with only 1 data.

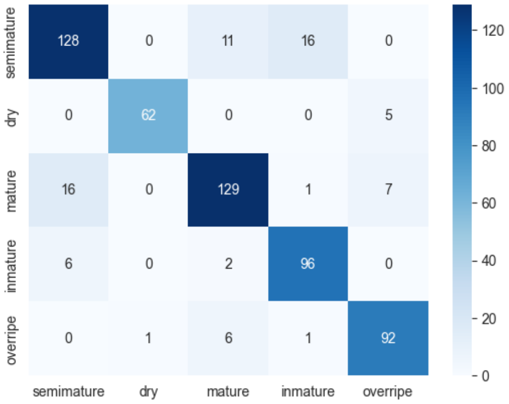

Fig. 7. Confusion matrix of Color & Texture Model

The performance of the combined feature is not significant. It only had 0.28% difference with the color feature model. As the complexity consideration, color feature model is recommended.

5. Conclusion

Based on the experiments, the classification of the maturity level of coffee fruit based on multispectral images using Naïve Bayes had an excellent performance. In contrast, it can not perform as well as the previous study. The previous study [4] had 98.47% of the F1-Score rate, and the best version of the experiments was 90.93% of the F1-Score rate. When the complexity is considered, the color feature model is recommended to be implemented in the system. Otherwise, CNN is considerable to use.

6. Limitations

The data used in this study using the data that has been published by [4]. The segmentation method proposed in this study limited to the condition in the dataset.

7. Future Work

Future studies should consider the dynamic background of the images. Thus the segmentation process can done dynamically without constrained to the background.

References

[1] Y. Abubakar, D. Hasni, and S. A. Wati, "Analisis Kualitas Buah Merah Kopi Arabika Gayo dan Korelasinya dengan Kualitas Biji Pada Ketinggian Berbeda," *Jurnal Tanaman Industri dan Penyegar*, vol. 9, no. 1, pp. 1–14, 2022, doi: 10.21082/jtidp.v9n1.2022.p1-14.

[2] J. Qin, K. Chao, M. S. Kim, R. Lu, and T. F. Burks, "Hyperspectral and Multispectral Imaging for Evaluating Food Safety and Quality," *J Food Eng*, vol. 118, no. 2, pp. 157–171, 2013, doi: 10.1016/j.jfoodeng.2013.04.001.

[3] D. Lorente, N. Aleixos, J. Gómez-Sanchis, S. Cubero, O. L. García-Navarrete, and J. Blasco, "Recent Advances and Applications of Hyperspectral Imaging for Fruit and Vegetable Quality Assessment," *Food and Bioprocess Technology*, vol. 5, no. 4. pp. 1121–1142, May 2012. doi: 10.1007/s11947-011-0725-1.

[4] M. A. Tamayo-Monsalve *et al.*, "Coffee Maturity Classification Using Convolutional Neural Networks and Transfer Learning," *IEEE Access*, vol. 10, pp. 42971–42982, 2022, doi: 10.1109/ACCESS.2022.3166515.

[5] M. A. T. Monsalve, G. Osorio, N. L. Montes, S. Lopez, S. Cubero, and J. Blasco, "Characterization of a Multispectral Imaging System Based on Narrow Bandwidth Power LEDs," *IEEE Trans Instrum Meas*, vol. 70, 2021, doi: 10.1109/TIM.2020.3010109.

[6] Z. Sandoval, F. Prieto, and J. Betancur, "Digital Image Processing for Classification of Coffee Cherries," in *2010 IEEE Electronics, Robotics and Automotive Mechanics Conference, CERMA 2010*, 2010, pp. 417–421. doi: 10.1109/CERMA.2010.54.

[7] H. Syahputra, F. Arnia, and K. Munadi, "Karakterisasi Kematangan Buah Kopi Berdasarkan Warna Kulit Kopi Menggunakan Histogram dan Momen Warna," *JURNAL NASIONAL TEKNIK ELEKTRO*, vol. 8, no. 1, p. 42, Mar. 2019, doi: 10.25077/jnte.v8n1.615.2019.

[8] O. D. Nurhayati, "Pengolahan Citra untuk Identifikasi Jenis Telur Ayam Lehorn dan Omega-3 Menggunakan K-Mean Clustering dan Principal Component Analysis," *Jurnal Sistem Informasi Bisnis*, vol. 10, no. 1, pp. 84–93, Jun. 2020, doi: 10.21456/vol10iss1pp84-93.

[9] R. Widodo *et al.*, "Pemanfaatan Ciri Gray Level Co-Occurrence Matrix (GLCM) Citra Buah Jeruk Keprok (Citrus reticulata Blanco) untuk Klasifikasi Mutu," *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, vol. 2, no. 11, pp. 5769–5776, 2018, [Online]. Available: http://j-ptiik.ub.ac.id

[10] A. Saleh, "Implementasi Metode Klasifikasi Naive Bayes dalam Memprediksi Besarnya Penggunaan Listrik Rumah Tangga," *Citec Journal*, vol. 2, no. 3, pp. 207–217, 2015.

[11] Q. Hasanah, H. Oktavianto, and Y. D. Rahayu, "Analisis Algoritma Gaussian Naive Bayes Terhadap Klasifikasi Data Pasien Penderita Gagal Jantung Gaussian Naive Bayes Algorithm Analysis Of Data Classification Of Heart Failure Patiens," *Jurnal Smart Teknologi*, vol. 3, no. 4, pp. 2774–1702, 2022, [Online]. Available: http://jurnal.unmuhjember.ac.id/index.php/JST