Prediction of The Maturity Level of Pontianak Oranges (*Citrus Suhuniensis CV Pontianak*) Using Color and Texture Features of Digital Reflectance-Fluorescence Images and Partial Least Square (PLS) Model

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ABSTRACT
Pontianak sour orange (*Citrus suhuniensis* CV Pontianak) is one of the citrus varieties that is widely found among the Indonesian population. This fruit has a sweet taste with a hint of sourness. Often, there are mistakes in determining whether the fruit tends to be sweet or sour. The taste of the fruit is influenced by different composition contents within the fruit. This also applies to Pontianak sour orange, where the taste is determined by specific contents. The factors that influence the taste of this fruit are the total soluble solids (brix) and total acidity. During the ripening process of Pontianak sour orange, there is a rearrangement of compounds within the fruit. This process involves an increase in total soluble solids (brix), a decrease in total acidity, and a decrease in fruit hardness. During the ripening process of Pontianak sour orange, there are changes in the fruit's composition involving an increase in total soluble solids (brix), a decrease in total acidity, and a decrease in fruit hardness. The aim of this research is to develop a prediction model for the ripeness level of Pontianak sour orange based on digital reflectance and fluorescence image analysis using computer vision with color and texture features. The experimental laboratory method was conducted in two stages: destructive and non-destructive tests. Destructive testing was performed by measuring fruit firmness, total soluble solids (brix), and total acidity. Non-destructive testing was carried out by capturing fruit images using computer vision based on reflectance fluorescence. The classification modeling process used machine learning algorithms, including K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), Logistic Regression (LR), and Support Vector Machines (SVM). Partial Least Square Regression (PLSR) was used for predicting the ripeness level of the fruit, including fruit firmness, total soluble solids (brix), total acidity, and brix-acid ratio. The best model for classifying the ripeness level of the fruit was obtained using Support Vector Machine (SVM). In the prediction modeling of the physicochemical characteristics of Pontianak sour orange fruit, the results showed that for the all dataset with min-max scaling, the training accuracy was 0.97, and the testing accuracy was 0.97. In the regression model, the results showed that for the firmness parameter using the reflectance dataset, the training R^2 value was 0.82 and the testing R^2 value was 0.65. For the brix parameter using the fluorescence dataset, the training R^2 value was 0.55 and the testing R2 value was 0.56. For the acidity parameter using the all dataset, which was a combination of reflectance and fluorescence datasets, the training R^2 value was 0.83 and the testing R^2 value was 0.87. And for the brix-acid ratio parameter using the reflectance dataset, the training R^2 value was 0.72 and the testing R^2 value was 0.57.

Keywords: *Computer vision, Fluorescence, Partial Least Square Regression, Reflectance.*

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1. INTRODUCTION

Citrus plants are subtropical plants that are widely grown in Asia. Citrus plants are also cultivated in Indonesia, as Indonesia has a tropical climate that allows citrus plants to easily adapt throughout the archipelago. There are many citrus varieties in Indonesia, such as keprok, madu, bali, mandarin, and pontianak. Siam Pontianak orange, scientifically known as Citrus Suhuinensis CV Pontianak, is one of the popular sweet citrus varieties in Indonesia. As the name suggests, Pontianak orange is extensively cultivated in Pontianak, West Kalimantan. In 2004, the productivity of citrus farming was quite high, ranging from 17 to 25 tons per hectare [1]. Meanwhile, a siam Pontianak orange tree can produce 60-80 kg of fruit per year [2]. Based on this data, it is evident that citrus fruits are widely consumed by the Indonesian population. However, when purchasing oranges, consumers often struggle to determine the level of ripeness and rely on information provided by fruit sellers. The information provided sometimes does not align with the desired outcome because the selection of oranges is still done through traditional or manual methods, such as observing the color, shape, and firmness of the fruit [3]. Differences in chemical components are influenced by the fruit's age, ripeness level, and environmental factors during growth. Fruit harvested too early will have low Total Soluble Solids (TSS) content. Conversely, fruit harvested at the right time will have TSS content that meets the standard [4]. A common issue in the field is the misinformation provided by sellers to consumers, resulting in some consumers finding oranges that are less sweet or too acidic. This problem stems from the subjective and manual classification system based on the physical appearance of the fruit, including size, shape, and skin color. This problem can be addressed by implementing non-destructive measurement using computer vision to classify the quality of oranges. With this technology, consumers can be aided in determining the taste of oranges by building a prediction model without damaging the fruit through image processing [5]. The image processing involves the extraction of color and texture features. This study employed two testing methods: non-destructive and destructive, on siam Pontianak oranges obtained from Balijestro Indonesia. Non-destructive testing was conducted using computer vision with two different illuminations, namely reflectance and fluorescence. The development of a classification model for siam Pontianak orange ripeness was done through the extraction of image and texture features. The classification models used in this study were K-NN (K-Nearest Neighbor), SVM (Support Vector Machine), LDA (Linear Discriminant Analysis), and LR (Logistic Regression). The best model in terms of accuracy was selected from these models. Additionally, a PLSR (Partial Least Squares Regression) model was used for building a prediction model for citrus fruit ripeness.

2. MATERIALS AND METHODS

The samples of Siam Pontianak oranges used in this study were obtained from the Indonesian Citrus and Subtropical Fruit Research Institute (Balitjestro). The sampled oranges included level 1 (raw), 2 (semi-ripe), and 3 (ripe) fruits, with a total of 120 oranges. The collected samples were cleaned and labeled according to their ripeness levels. Two methods were employed to gather data: non-destructive data collection through capturing images of the oranges from top and bottom views, resulting in a total of 240 images. The images were captured using a DSLR camera (700 D model) in a mini studio equipped with two types of lighting: halogen lamps for reflectance images and UV lamps for fluorescence images. An illustration of the setup can be seen in **Figure 1** The LEDs have been turned on alternately either to acquire reflectance image (white LED) or fluorescence image (UV LED). Destructive data collection involved three types of measurements: sweetness and acidity levels measured using an ATAGO PAL-BX|ACID101 Brix Acidity meter, and fruit hardness measured using a penetrometer. The penetrometer was used by inserting the probe into three equatorial parts of the fruit. The results of all measurements were processed by a computer to enable the recognition of the oranges through feature extraction. Data analysis was performed using machine learning in Google Colaboratory using the Python 3.8 programming language with Numpy, OpenCV, scikit-learn, and Matplotlib libraries. Prior to inputting the data into the classification and regression models, image processing was conducted to extract color and texture features. The extraction of color features involved calculating the average values of each pixel in the samples. The color features used included RGB, Lab, and HSV, while texture features were extracted using the Gray Level Co-occurrence Matrix (GLCM), including Contrast, Homogeneity, Dissimilarity, Energy, and Correlation.

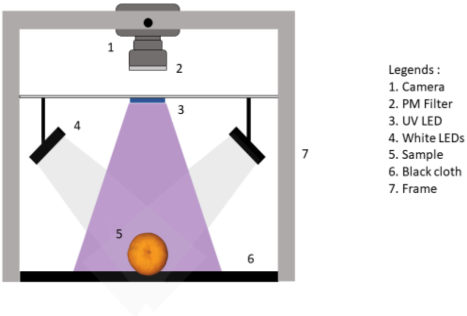

Figure 1 The reflectance and fluorescence dual imaging system

3. RESULTS AND DISCUSSION

3.1. Image Acquisition Results

The results of the non-destructive data collection were obtained using two types of lighting, resulting in two types of images: reflectance and fluorescence. The reflectance image can be seen in **Figure 2** while the fluorescence image is shown in **Figure 3** The image acquisition was performed for three different ripeness levels, classified based on color assessment using the human eye. The citrus fruit images were captured on the same day after harvest and up to the third day for each ripeness level. According to [6], most organs in citrus fruits accumulate a significant amount of flavonoids during their development, and these flavonoids can be visualized under UV light. The citrus peel has a high concentration of flavonoids as secondary metabolites [7].

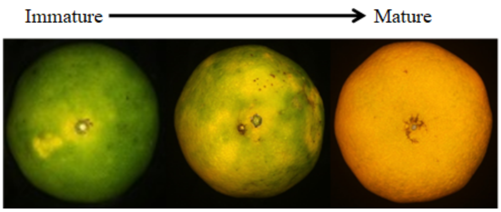

Figure 2 Citrus reflectance images with different maturity level

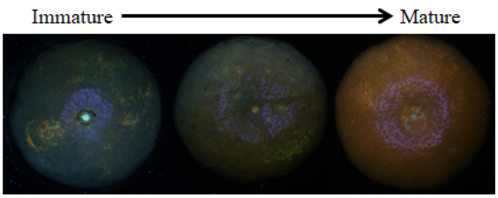

Figure 3 Citrus fluorescence images with different maturity level

As can be seen in **Figure 2 and 3**, that maturity level could be classified visually with reflectance image or fluorescence image. However, for internal maturity parameters such as Firmness, TSS, Acidity, and Brix/Acid ratio need to be investigated further, whether it can be classified using visual appearance in reflectance image only or fluorescence image may increase the classification accuracy. Additionally, there were some differences observed in the fluorescence images. As shown in **Figure 4**, there are prominent colors in the fluorescence image, but when compared to the reflectance image, no color differences can be detected. Damaged fruit skin exhibits strong green fluorescence, making UV light potentially useful for detecting surface defects on the fruit [6].

Figure 4 Image of Pontianak Siamese Citrus Fruit with High Fluorescence (Left: Normal image, Right: Fluorescence image)

The rupturing of oil glands allows the spreading of surface oil, which becomes visible under UV light. Hence, this can be an important parameter in determining optimal storage time [8]. Thus, fluorescence images can be used for detecting fruit damage and optimizing storage time in further research.

3.1. Image Acquisition Results

In **Figure 5**, the data parameters of orange ripeness based on ripeness categories can represent the characteristics and distribution of the data. The decrease in total fruit acidity occurs due to the ripening process, during which the acid content is utilized in the breakdown of starch into simple sugars, resulting in a decrease in total fruit acid as the orange ripens. Regarding the hardness measurement results, the average fruit hardness at ripeness level 1 (raw samples) was 3,14 kg/m^2, at ripeness level 2 (semi-ripe samples) was 2,32 kg/m^2, and at ripeness level 3 (ripe samples) was 1,44 kg/m^2. Thus, it can be observed from the results above that the hardness of siam Pontianak oranges decreases as the ripeness level increases. The decrease in fruit hardness occurs due to enzymatic activity that breaks down pectin compounds, leading to softening of the fruit. This enzymatic process is caused by pectinmethylesterase and polygalacturonase enzymes. The increase in TSS (Total Soluble Solids) values is caused by enzymatic processes that occur during fruit ripening, converting starch compounds into simple sugars such as glucose and fructose. The breakdown of compounds leads to the formation of a sweet taste in fruits with higher ripeness levels [9].

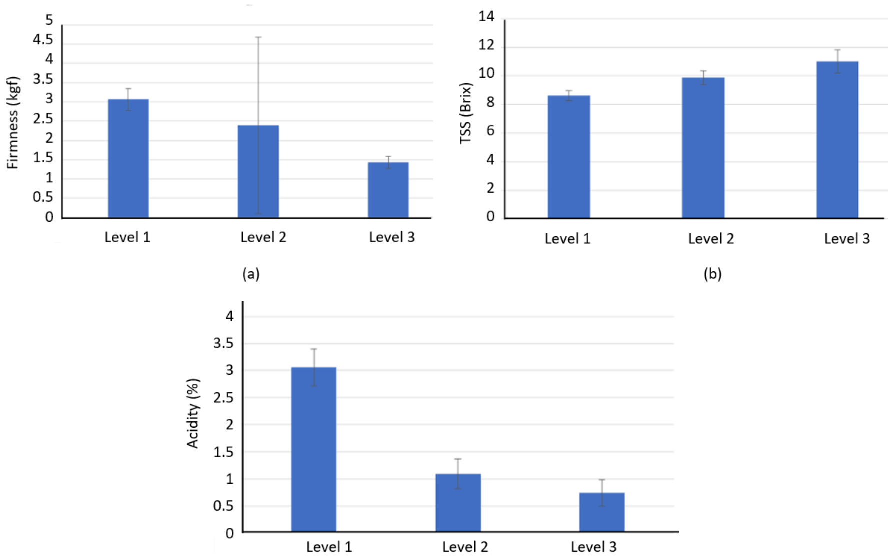

Figure 5 Destructive Measurements
(a. Average fruit hardness measurement, b. Average total dissolved solids (Brix) measurement, c. Average total acidity measurement)

The destructive and non-destructive data will be used to create datasets for training the classification and regression models. The color and texture feature extraction will serve as dependent variables, while the ripeness parameters will act as independent variables. The datasets will undergo classification to predict the ripeness parameter. The datasets will be inputted into KNN, SVM, LDA, and LR models. The training and testing results are shown in **Table 1.**

Table 1. Results of Training and Testing Process for Classification of Ripeness Parameters of Pontianak Siamese Orange Fruit Using Reflectance and Fluorescence Images

Data	Image Capture	Model	Scale	Training Accuracy (70 %)	Test Accuracy (30 %)
All (Reflectance + Fluorescence)	Top and Bottom View (AB)	KNN	None	0.95	0.91
			MinMax	0.95	0.92
		LDA	None	1.0	0.94
			MinMax	1.0	0.94
		LR	None	1.0	0.91
			MinMax	0.98	0.90
		SVM	None	0.95	0.89
			MinMax	0.98	0.91
	Top View (A)	KNN	None	0.91	0.89
			MinMax	0.91	0.90

Data	Image Capture	Model	Scale	Training Accuracy (70 %)	Test Accuracy (30 %)
		LDA	None	1.0	0.70
			MinMax	1.0	0.70
		LR	None	1.0	0.91
			MinMax	0.97	0.89
		SVM	None	0.83	0.71
			MinMax	0.97	0.97
	Bottom View (B)	KNN	None	1.0	0.88
			MinMax	1.0	0.88
		LDA	None	1.0	0.88
			MinMax	1.0	0.88
		LR	None	1.0	0.85
			MinMax	1.0	0.85
		SVM	None	1.0	0.88
			MinMax	1.0	0.88

Based on the classification model results, the training conducted by SVM exhibited an R2 value of 0.97. This value is considered high as the range of R2 values is from 0 to 1, where a value approaching 1 is considered good, while a value approaching 0 is considered less favorable. The training results indicate that the model learned well in predicting the ripeness parameters based on the orange images. In the testing phase, an R2 value of 0.97 was obtained. For the regression modeling using Partial Least Squares Regression (PLSR), the results are shown in **Table 2.**

Table 2. Results of Training and Testing Process for Regression of Ripeness Parameters of Pontianak Siamese Orange Fruit Using Reflectance and Fluorescence Images.

Data	Parameters	R^2 train	R^2 test
Firmness	Reflectance	0.82	0.65
	Fluorescence	0.81	0.50
	Combined	0.86	0.61
TSS	Reflectance	0.61	0.31
	Fluorescence	0.55	0.56
	Combined	0.67	0.35
Acidity	Reflectance	0.87	0.83
	Fluorescence	0.81	0.75
	Combined	0.83	0.87
Brix/Acid Ratio	Reflectance	0.72	0.57
	Fluorescence	0.69	0.51
	Combined	0.74	0.55

The regression model for the firmness parameter, using the reflectance dataset, resulted in a training R^2 value of 0.82 and a testing R^2 value of 0.65. For the brix parameter, using the fluorescence dataset, the training R^2 value was 0.55 and the testing R^2 value was 0.56. The acidity parameter, using the combined dataset of reflectance and fluorescence, had a training R^2 value of 0.83 and a testing R^2 value of 0.87. Lastly, the brix-acid ratio parameter, using the reflectance dataset, had a training R^2 value of 0.72 and a testing R^2 value of 0.57.

4. CONCLUSION

In the classification of fruit ripeness, the best model obtained was using Support Vector Machine (SVM). In the prediction modeling of physicochemical characteristics of siam Pontianak oranges, the results showed that using the all dataset with min-max scaling, the training accuracy was 0.97, and the testing accuracy was 0.97. Regarding the prediction models for the brix, acidity, firmness, and brix-acid ratio parameters, the training R^2 values were 0.55; 0.83; 0.82; and 0.72 respectively. The testing R^2 values were 0.56; 0.87; 0.65; and 0.57 respectively.

AUTHORS CONTRIBUTIONS

Dimas Firmanda Al Riza: Conceptualization, Methodology, Investigation, Formal Analysis, Writing - review & editing. **Salsabil Lazuardi Nugroho:** Investigation, Visualization, Writing - Original Draft. **Ahmad Avatar Tulsi:** Software, Data analysis, Writing - review & editing. **Mochamad Bagus Hermanto:** Resources, Writing - review & editing. **Yusuf Hendrawan:** Resources, Writing - review & editing. **Naoshi Kondo:** Resources, Writing - review & editing.

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