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Maturity parameters characterization and classification of Lemon (*Citrus limon* (cv. California)) based on reflectance-fluorescence imaging and machine learning model

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Abstract Reflectance and fluorescence imaging were employed to assess maturity in California lemons (*Citrus limon* cv. California) based on skin color and texture, alongside internal quality indicators. Fluorescence imaging outperformed reflectance alone in predicting maturity levels, likely due to enhanced capture of biochemical and textural variations in lemon surface. Machine learning analysis using both support vector machines (SVM) and k-nearest neighbors (k-NN) revealed that SVM models trained on fluorescence images provided the most accurate classification. Specifically, fluorescence imaging data processed with SVM (without scaling) achieved 100% accuracy in training and 92% in testing, surpassing other model and feature configurations. These findings showed the utility of fluorescence imaging for potential, non-destructive lemon maturity classification, offering a promising framework for broader applications in citrus and other horticultural commodities.

Keywords: Non-destructive evaluation, Postharvest quality, Ripeness assessment, Skin color analysis, Texture features

Introduction

Indonesia is an agrarian country where the majority of the population works as farmers. According to the Central Statistics Agency of Indonesia (BPS), as of February 2022, approximately 9.74 million people were employed in the agricultural sector. Unsurprisingly, this sector significantly contributes to Indonesia's economy. Lemons are currently one of the most favored commodities among farmers. In addition, lemons serve multiple purposes, which is why they are often referred to as a versatile fruit and present a promising agribusiness prospect (Anwar *et al.,* 2019).

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Lemon (*Citrus limon*) offers natural antioxidant benefits as the fruit is rich in vitamin C, citric acid, essential oils, flavonoids, coumarin, polyphenols, and volatile oils in the peels, such as limonene (±70%), α-terpinene, α-pinene, β-pinene (Krisnawan *et al.*, 2017). In addition, consuming lemon's juice maintains and enhances immune system, balances body's pH, and promotes digestion (Miles *et al.*, 2021). To obtain high-quality lemon juice, harvesting must be timed optimally. As a non-climacteric fruit, lemon does not continue to ripen after being picked, so it should be harvested only when it reaches optimum ripeness (Mardia *et al.*, 2023). Because lemon quality is significantly influenced by maturity, determining the appropriate maturity level is essential.

Conventionally, measuring fruit ripeness is performed manually using visual perception to distinguish between ripe and unripe fruit based on color parameters, and tactile sensation to gauge the fruit's firmness. This method, however, is a subjective and inconsistent human judgment (Andri *et al.*, 2014). In addition, different methods are implementable in detecting fruit ripeness without causing fruit damages, including the use of spectroscopy and computer vision (Mukhtar *et al.*, 2021; Erha *et al.*, 2024). Additionally, fluorescence imaging has demonstrated promising results in evaluating maturity parameters of several other fruits, suggesting that it could also enhance the accuracy of maturity prediction for lemons (Nie *et al.*, 2021; Al Riza *et al.*, 2023). In term of developing prediction models, previous studies have utilized color features, shape features, and texture features using Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) to generate classification algorithm in machine learning. Correspondingly, machine learning model with the highest accuracy is expected to be developed by analyzing image features in RGB, HSV, and L*a*b*, as well as analyzing texture feature using Gray Level Co-occurrence Matrix (GLCM) method with SVM and k-NN algorithms (Al Riza *et al.*, 2024).

The primary objective of this study was to investigate the effectiveness of integrating reflectance and fluorescence imaging for non-destructive classification of lemon maturity levels. By extracting color and texture features and applying machine learning models (SVM and k-NN). The study aimed to establish a high-accuracy framework that enables rapid and reliable maturity assessment, thereby improving postharvest quality evaluation in citrus handling.

Materials and methods

Research location and time

The research was carried out in the Agricultural Power and Machinery Laboratory, Department of Biosystem Engineering, Universitas Brawijaya.

where both non-destructive and destructive tests were performed. Additionally, essential oil distillation was conducted in the Bioprocess Engineering Laboratory. The study took place from August 2022 to June 2023.

Equipment and materials

The experiment employed a mini studio, camera, LED lights, UV lights, color standard, power supply, LED pulse controller, laptop, Brix-acidity meter, penetrometer, lemon juicer, plastic cups, blender, food dehydrator, dark glass bottles, and a distillation setup. The materials included California lemons at three maturity levels (40 lemons per level) and distilled water. The lemons were obtained from an orchard in Batu City, Indonesia.

Research methodology

California lemons categorized into three maturity levels: unripe, half-ripe, and ripe. Maturity was determined based on color, diameter, and firmness. The method encompassed both laboratory experiments and image analysis, conducted in two stages: non-destructive and destructive. During the non-destructive stage, images were captured using a 50×50×60 cm mini studio equipped with a camera.

LED lights were used to acquire image reflectance, while UV lights to acquire image fluorescence. Each lemon sample generated two images, from the right and the left view. A total of 480 image data points were collected, consisting of 240 reflectance images and 240 fluorescence images. The process of collecting non-destructive data is illustrated in Figure 1.

Destructive measurements included fruit firmness measurement using AMTAST GY-4 penetrometer at three different test points; total soluble solids and titratable acidity in California lemons using ATAGO brix-acidity meter of PAL-BX|ACID F5 model with three repetitions; and essential oil obtained from lemon peels using simple distilled method. Workflow of the study is illustrated in Figure 2.

Data analysis

The data analysis was divided into different stages. In the first stage, a preprocessing process was conducted on the object image data from non-destructive test with thresholding to separate the object from the background using significant intensity values. Additionally, morphological operations were applied to the object images from the fluorescent light to remove noise (undesirable elements in the image) around the objects, as illustrated in Figure 3.

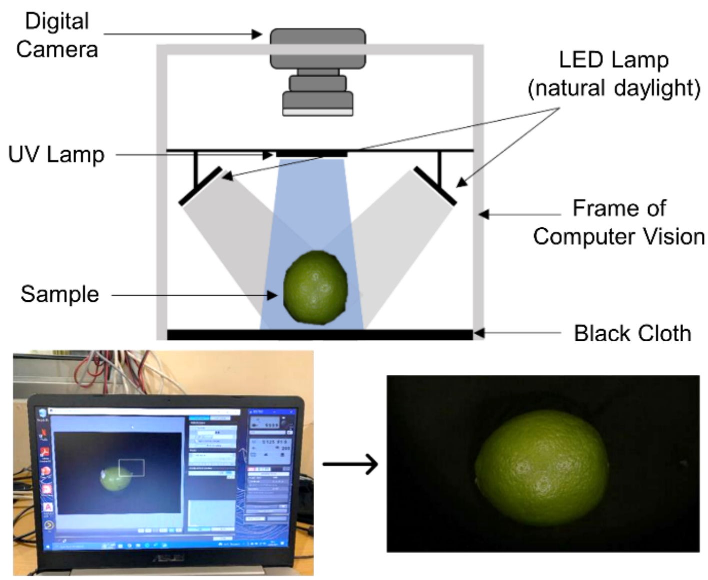


Figure 1. Illustration of object image acquisition

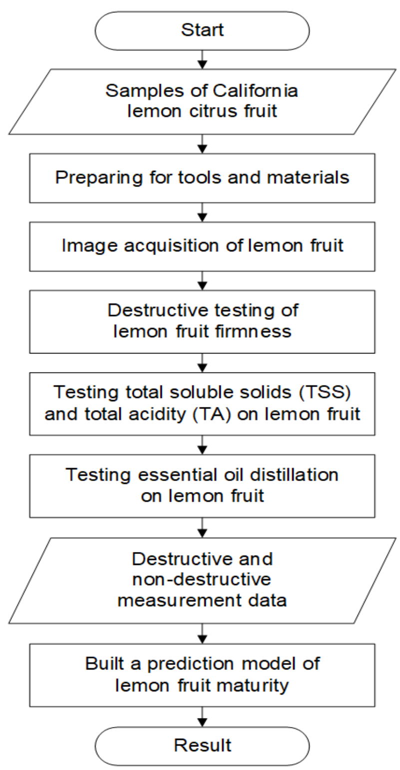


Figure 2. Diagram of the study workflow

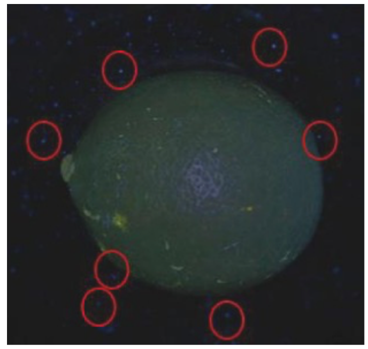


Figure 1. Results of fluorescence image

The next step involved color feature extraction using RGB, HSV, and L*a*b* as the parameters to subsequently calculate the average values. Color feature extractions were divided into three categories: reflectance image, fluorescence image, and a combination of both. Following this, during the texture feature extraction process, object images were initially converted to grayscale images. Afterwards, co-occurrence matrix was calculated with an orientation angle Ɵ of 0° and pixel distances of 1, 2, and 3. Afterwards, the selected texture feature information was calculated, including energy, correlation, and contrast. In the final step, the processed data from non-destructive and destructive test on California lemons were processed using machine learning through Phyton programming language. In this stage, the classification models involved SVM and K-NN. After that, comparing the SVM and K-NN models to determine the model with the highest accuracy level.

Results

Non-destructive measurement

The non-destructive measurement results obtained using reflection imaging is shown in Table 1. In the unripe maturity stage, the skin color was entirely green, while in the half-ripe stage, it appeared yellowish-green, and in the ripe stage, it was fully yellow. The transition from green to yellow is driven by the degradation of chlorophyll pigments, thereby converting the skin color from green to yellow as the fruit ripens. This change also signified the intensification of other pigments, particularly carotenoids. Prior to color and texture feature extraction, all data from the non-destructive measurements underwent preprocessing steps. The results of color feature extraction for both reflectance and fluorescence images are shown in Table 2.

Table 1. Results of non-destructive measurement

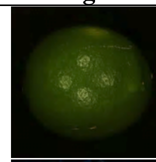
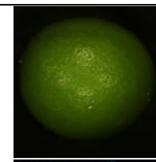
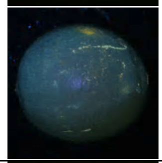
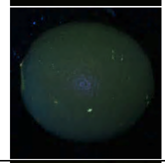
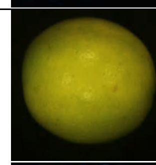
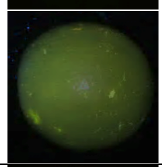
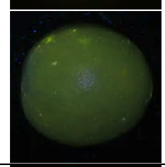
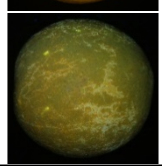
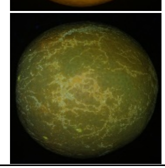
Level	Light	Right	Left
Unripe	LED		
	UV		
Half-ripe	LED		
	UV		
Ripe	LED		
	UV		

Table 2. Results of color feature extraction

Sample	R	G	B	L*	a*	b*	H	S	V
CA1 A (UV)	20.76	37.56	39.81	124.27	122.02	34.57	40.58	127.75	92.67
CA1 A	22.12	31.69	2.18	142.20	118.60	26.73	31.69	241.18	39.97
…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
CC40 B (UV)	74.34	81.89	33.92	154.55	117.05	84.25	82.04	151.00	35.36
CC40 B	153.42	112.00	5.91	183.03	136.29	127.00	153.42	245.52	21.27

Following color feature extraction, the texture feature extraction was performed using GLCM. The results of the texture feature extraction are presented in Table 3. The feature of label 0 represents features with a pixel distance of 1; feature of label 1 represented feature with a pixel distance of 3.

The collected data on energy features at pixel distances of 1, 2, and 3 had closely similar values, or between 0.89 to 0.99. On the other hand, the value of contract features constantly increased. This was due to the fact that the contrast feature was utilized to identify textures with different level of brightness and darkness of pixels in the image. A high contrast value indicated that the skin of the lemon acquired a high variation in pixel intensity in close proximity, or at pixel distances of 1, 2, and 3.

Table 3. Texture feature extraction

Sample	Energy 0	Corr 0	Contrast 0	Energy 1	Corr 1	Contrast 1	Energy 2	Corr 2	Contrast 2
CA1 A (UV)	0.96	0.97	3.93	0.96	0.96	4.30	0.96	0.95	5.46
CA1 A	0.96	0.98	1.29	0.96	0.97	1.43	0.96	0.96	1.90
…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
CC40 B (UV)	0.90	0.99	11.14	0.90	0.99	12.82	0.90	0.98	18.15
CC40 B	0.89	1.00	9.32	0.89	1.00	11.47	0.89	0.99	19.33

Destructive measurement

The results of the destructive measurements are shown in Table 4. According to these findings, there was no significant increase in TSS (Total Soluble Solids). Although the TSS values at the half-ripe stage were slightly higher than those of the unripe stage, they did not change further at the ripe stage.

Correlation matrix between non-destructive and destructive measurement

Correlation matrix analysis signified the correlation coefficients of a set of attributes. The correlation of each attribute is presented in the coefficient values of 1 to −1. In case the value approaches 1, the correlation between the two attributes was stronger. The results of the correlation matrix analysis are presented in Table 5.

Oil yield using distillation

Flesh and peels of the lemons were measured using TSS and TA which separated to be subsequently extracted using distillation method to obtain the essential oil. The total volume of essential oil obtained from the distillation test is presented in Table 6.

Table 4. Destructive measurement

Value	Unripe	Half-ripe	Ripe
	TSS (°Brix)		
Average	7.71	7.78	7.78
Minimum value	6.50	5.93	5.77
25% (Q1)	7.28	7.57	7.42
50% (Q2/Mean)	7.75	7.82	7.87
75% (Q3)	8.14	8.08	8.23
Maximum value	8.77	8.99	8.80
	TA (%)		
Average	5.43	5.64	5.43
Minimum value	4.06	4.53	4.16
25% (Q1)	5.02	5.35	4.96
50% (Q2/Mean)	5.43	5.62	5.35
75% (Q3)	5.86	5.98	6.08
Maximum value	7.37	6.68	6.67
	Fruit Firmness (kg/cm^2)		
Average	10.46	8.07	6.40
Minimum Value	7.12	5.72	2.99
25% (Q1)	9.14	7.40	5.39
50% (Q2/Mean)	10.44	5.53	6.39
75% (Q3)	11.99	8.64	7.14
Maximum Value	13.12	12.31	12.58

Table 5. Correlation matrix analysis

Features	R^2 value		
	TSS (°Brix)	TA (%)	Fruit Firmness (kg/cm^2)
	Color Feature		
R	0.06	0.01	−0.06
G	0.08	0.06	−0.62
B	0.07	0.05	0.04
L*	0.04	0.03	−0.59
a*	−0.01	−0.10	−0.32
b*	0.07	0.05	−0.63
H	0.06	0.02	−0.59
S	0	0	−0.28
V	0.02	0.03	0.51
	Texture Feature		
Energy0	0.06	−0.05	0.56
Corr0	−0.06	0.04	−0.48
Contrast0	0.07	0.05	−0.49
Energy1	0.06	−0.05	0.56
Corr1	−0.06	0.04	−0.47
Contrast1	0.07	0.05	−0.50
Energy2	0.06	−0.05	0.56
Corr2	−0.08	0.03	−0.46
Contrast2	0.07	0.05	−0.52

Table 6. Distillation test

Level	Wet Weight (g)	Dry Weight (g)	Total Oil Volume (mL)	Yield (%)
Unripe	1469	335	3.83	1.14
Half-Ripe	1908	429	5.69	1.31
Ripe	2278	477	5.38	1.12

Machine learning classification model

In the modeling process, the dataset was split into 80% for training and 20% for testing (Table 7). Classification was performed using both k-NN and SVM algorithms. The data were grouped into three subsets as combined reflectance and fluorescence (all data), reflectance-only, and fluorescence-only. Each subset was analyzed using both normalized and non-normalized data. Data normalization, which involves scaling values to a specific range, was conducted here via the min-max method.

Table 7. Results of machine learning model

Data	Model	Scaling	Training Accuracy	Testing Accuracy
All Data	KNN	MinMax	0.94	0.94
	KNN	None	0.94	0.92
	SVM (kernel: Linear)	MinMax	0.81	0.78
	SVM (kernel: Linear)	None	1.00	0.85
Reflectance	KNN	MinMax	0.96	0.96
	KNN	None	0.92	0.96
	SVM (kernel: Linear)	MinMax	0.96	0.96
	SVM (kernel: Linear)	None	1.00	0.87
Fluorescence	KNN	MinMax	0.92	0.84
	KNN	None	0.92	0.87
	SVM (kernel: Linear)	MinMax	0.92	0.90
	SVM (kernel: Linear)	None	1.00	0.92

Fruit firmness prediction

Besides the classification model, development of prediction model of each maturity parameter is tried to be developed. However, only model for firmness prediction that could obtain accuracy more than 0.6. Prediction model for fruit firmness measurement was conducted using Partial Least Square The overall data was divided into 80% of training data and 20% of data testing. The x-values or predictors consisted of color and texture feature extraction data, while y-values or predicted values consisted of fruit firmness measurement data. The results of the prediction model are presented in Table 8.

Table 8. Fruit firmness measurement prediction model

Data	R^2 Training	R^2 Testing
	random_state = 28	
All data	0.61	0.33
Reflectance	0.62	0.48
Fluorescence	0.46	0.60
	random_state = 58	
All data	0.68	0.18
Reflectance	0.68	0.18
Fluorescence	0.66	0.19
	random_state = 74	
All data	0.62	0.18
Reflectance	0.62	0.18
Fluorescence	0.62	0.18
	random_state = 81	
All data	0.57	0.60
Reflectance	0.59	0.52
Fluorescence	0.60	0.57
	random_state = 90	
All data	0.60	0.41
Reflectance	0.60	0.41
Fluorescence	0.60	0.41

As described in the table, the best model was attained using all data for random_state=81 with similar results: R^2 training 0.57 and R^2 testing 0.60. The results of the scatter plot are presented in Figure 4.

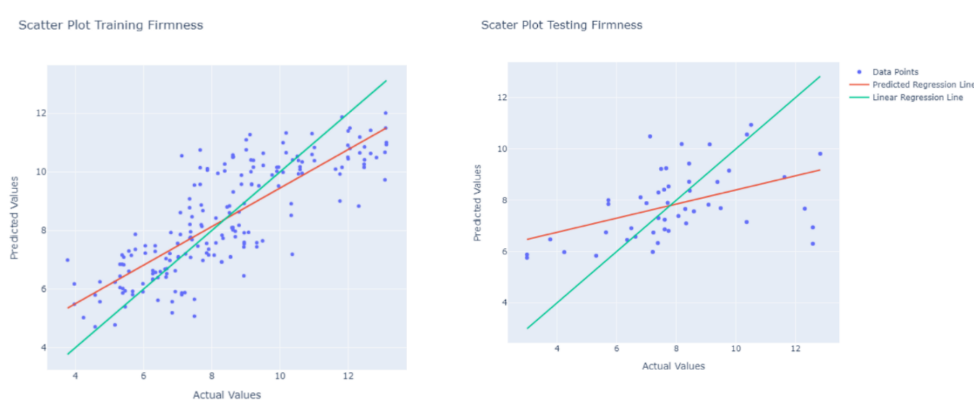


Figure 4. Scatter plot of fruit firmness measurement prediction firmness measurement prediction

Discussion

Non-Destructive measurement analysis

During UV light-based imaging (fluorescence mode), the lemon object images appeared blue and fades as the fruit ripened. Lemon peel is known to contain a flavonoid, a type of antioxidant belongs to phenol group. Phenolic compounds have conjugated bonds in the benzene ring, where electron transfer resonance occurs upon exposure to UV light (Suryadi *et al.*, 2021). Likewise, the previous study asserts that flavonoids are capable of absorbing UV light; in addition, UV radiation potentially minimizes the activity of ascorbate enzymes since ascorbic acid is a bioactive compound that is sensitive to light (Triastarani, 2021).

As presented in the table, as the fruit ripeness level increased, both the red color index (R) and the green color index (G) were higher. However, the blue color index (B) decreased as the lemon ripeness level increased. As mentioned earlier, one of the characteristics of lemon ripeness is the change in skin color from green to yellow. Nonetheless, RGB features generate different values. The previous study (Ifmalinda *et al.*, 2018) predicted the maturity level of Siam orange and discovers that the red color index increases as the fruit ripens, while the green and blue color index decreases. This aligns with the other study (Arifandie *et al.*, 2021) that the maturity of lemon is characterized by a change in color from green to yellow. This is a result of chloroplast transformation involved in photosynthesis, into chromoplasts. During the ripening process, the carotenoids accumulate simultaneously with chlorophyl degradation (Rahmawati and Putri, 2013). The L*a*b* feature increased as the maturity level increased. This is in line with the study (Rahmawati and Putri, 2013) that explained the values of L* (Lightness), a* (redness), and b* (yellowness) increase simultaneously with the increase of fruit ripeness. Degradation of chlorophyl pigments in the fruit's skin induced other pigments such as anthocyanin, xanthophyll, and carotenoids, resulting in a change in skin color from green to yellow-orange.

Destructive measurement analysis

The total soluble solids and total acidity in lemon juice increases as the fruit ripens, while the sugar level decreases. Lemon juice primarily consists of citric acid of approximately 60−75% of the TSS, while the total sugar level is approximately 1% of the lemon's weight (Ekaputri, 2018). According to previous study (Monago-Maraña *et al.,* 2021), total soluble solids represent the content of substances within a fruit. These substances include water soluble elements, such as sucrose, fructose, glucose, and pectin.

TA (Total Acidity) increased from the unripe stage to half-ripe stage, however decreased at the ripe stage. According to the previous study (Hassan *et al.*, 2015; Lado *et al.*, 2014, 2018), pH values and acidity percentage rises as the lemon fruit matures. In addition to the effect of sunlight towards skin color, fruits growing outside the canopy of the tree have less acidity, more total soluble solids, and faster fruit development rates compared to those growing under the tree canopy. To conclude, while TSS and TA provide information related to the chemical composition of the fruit, these elements should not be the sole criteria for determining the maturity level of lemons.

the average fruit firmness constantly decreased as the level of maturity increases. A study (Hassan *et al.*, 2015) stated that lemon's firmness gradually decreases as the fruit ripens. In line with another study (Jia *et al.*, 2023) where the report suggests ripe fruits soften as the cell wall composition changes. The fruit tissue breaks down as the carbohydrates are respired into simpler compounds, thus, softens the fruit.

Correlation analysis

As described in the Table 5, the correlation value between TSS measurement and the feature extraction of color and texture was nearly 0, in which the highest correlation was performed by color feature G of 0.08. In case the value in the correlation matrix approaches 0, the correlation between two variables presents weak linear correlation or is not correlated (Samrin and Irawan, 2019). Similarly, the correlation value between non-destructive measurements and TA was nearly 0, with the highest correlation on color feature G of 0.06. To conclude, the correlation between non-destructive measurements and TSS and TA measurements is non-linear.

As illustrated in the table, the fruit firmness measurement signified a positive linear correlation with the color feature V of 0.51. Additionally, there was a positive linear correlation between fruit firmness measurements and texture feature of Energy0, Energy1, and Energy2, with the same correlation value of 0.56. This indicates that fruit firmness affects the texture of lemon surface. Energy features are utilized to identify whether a texture in an image is rough or smooth.

Ripe lemons have a smoother surface as the skin cells change during ripening process. During this process, the fruit color and texture change and soften. Lemons have soft textures as the cells enlarge, and the gap between the cells increases (Albahry, 2011). As a result, the lemons' skin texture looks smoother and detectable by digital image processing.

Oil yield analysis of lemon with different maturity level

As described in the table, total volume of essential oil increased significantly from unripe level to half-ripe level, and subsequently decreased at the ripe level. Fully ripe lemons have greater oil glands with a greater gland volume, and increases as the fruits get more mature, particularly fruits with diameter of 50−90 mm, as characterized by the increase of essential oil yield as the fruits develop (Njili, 2020). On the contrary, the other study suggests that the highest essential oil yield in lemons is produced at the early fruit ripening stage and decreases afterward (Bourgou *et al.*, 2012). To conclude, the essential oil volume does not serve as a reliable reference for determining lemon maturity level.

The difference of essential oil volume in various lemons is attributed to the influence of extraction procedures and environmental conditions. Additionally, the extraction parameters greatly affect the yield of essential oil. Likewise, the supply of water during ripening process significantly affects the essential oil content (Bourgou *et al.*, 2012).

Classification and prediction modeling analysis

For classification model, SVM model performs better results with reflective and fluorescent lighting, compared to other models when normalization is not applied. In this particular case, the best machine learning model for fluorescent lighting data was performed by SVM model without scaling, with a training result of 1.00 and test accuracy of 0.92. This model was capable of classifying physicochemical parameters (fruit firmness, total dissolved solids, total titratable acidity) in California lemon's ripeness using reflective and fluorescent lighting.

On the other hand, non-destructive measurements and fruit firmness measurements signify positive linear correlation with the color feature V of 0.51. Furthermore, there is a positive linear correlation between fruit firmness measurements and texture features of Energy0, Energy1, and Energy2 with similar correlation value of 0.56. As presented in the Figure 4, scatter plot training, graph linear regression values and predicted values were close together. This indicates the existence of linear relationship between fruit firmness and the predicted values. As mentioned earlier, the value collected from R^2 training was 0.57. This suggests that variable X (fruit firmness value) could be explained by variable Y (predicted fruit firmness value) of 57%. While R^2 testing 0.60 value was 0.60, or the variable X could be explained by variable Y of 60%. Overall, these results emphasize the effectiveness of fluorescence imaging as a reliable, non-destructive method for classifying lemon maturity, and they suggest a potential framework for broader adoption in citrus and other horticultural produce.

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