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Intelligent Non-Invasive Sensing Method in Identifying Coconut (*Coco nucifera var. Ebunea*) Ripeness Using Computer Vision and Artificial Neural Network

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ABSTRACT

The use of coconut in the food industry is determined by the condition of its fruit ripeness level, which is very difficult to be conducted. The suitable non-invasive sensing method is the application of computer vision. The purpose of this study is to identify the coconut ripeness level based on several parameters of fruit volume, coconut flesh thickness, and coconut flesh weight by using Artificial Neural Network (ANN) modeling. The best ANN model resulted in 14 inputs consisting of color, texture, shape and size parameters. Color features include: Red, Green, Blue, Hue, Saturation, and Intensity. Textural features include: contrast, correlation, energy, homogeneity. The shape and size parameters include area, perimeter, eccentricity, and metric. The best ANN structure consisted of 14 inputs, one hidden layer with 100 nodes, and 3 outputs of coconut ripeness (indicated by coconut water volume, coconut flesh thickness and wet weight of coconut flesh). The best ANN model produced the smallest Mean Squared Error (MSE) training and MSE testing values of 0.002155 and 0.107265 with actual value correlations and predictions as measured by R-training and R-testing

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respectively of 1 and 0.90331. Thus, computer vision and ANN models can be utilized to predict the coconut ripeness level.

Keywords: Artificial neural network, coconut ripeness, computer vision, texture analysis

INTRODUCTION

Coconut is globally recognized as a very important fruit. Coconut (*Coco nucifera var. Ebunea*) farming becomes an important agricultural industry not only for all tropical countries, but it also offers a strong income potential for millions of small farmers worldwide (Nguyen et al., 2016). Coconut fruit has been broadly utilized both in food and non-food fields (Freire et al., 2017). Coconut flesh and ripe coconut water can be used as a source of protein and antioxidants (Rodsamran & Sothornvit, 2018). The economic value of coconut will increase with the presence of post-harvest handling and the application of appropriate technology (Rodrigues et al., 2018). To optimize the selling value and utilization of coconut, it is necessary to develop applications that can classify the level of ripeness according to consumer needs. The problem of fruit ripeness classification has proven to be a very complex matter which requires further development. The classification of fruit ripeness presents a significant challenge as the characteristics of fruit objects are difficult to distinguish and tend to have irregular patterns in one similar classification class (Hameed et al., 2018). Unfortunately, a non-invasive sensing application that can accurately predict the coconut ripeness level has not been invented. The coconut ripeness level will have a direct effect on some of the internal parameters of coconut such as the volume of coconut water, the thickness of coconut flesh, and the wet weight of coconut flesh (Terdwongworakul et al., 2009; Hahn, 2012). Therefore, the development of a non-invasive sensing with intelligent modeling systems to predict the internal conditions of coconut (such as the volume of coconut water, the thickness of coconut flesh, and the wet weight of coconut flesh) is very important to make. Yet, the ripeness classification of coconut does not have a standard, where researchers from various countries still apply different terminology (Ekanayake et al., 2010). In practice, not everyone can accurately determine coconut ripeness level. Only a few experts can determine whether the coconut is ripe or unripe. The conventional way to identify coconut ripeness is by shaking the fruit for analysis of the sound produced. The process still tends to be subjective in determining the level of ripeness, bearing different perceptions. Hence, it is necessary to develop an effective non-invasive sensing method in identifying coconut fruit ripeness, which has high accuracy, and without touching the observed object. One non-invasive sensing method that is proven reliable in characterizing biological objects is computer vision by using color, texture, and morphological parameters combined with intelligent modeling using artificial neural networks (ANN) (Hendrawan &

Murase, 2011a; Hendrawan & Murase, 2011b; Hendrawan & Murase 2011c; Hendrawan & Al Riza, 2016; Hameed et al., 2018).

The development of information technology enables fruit identification based on color characteristics, texture, and morphology with the help of digital cameras and computers. This computational method relies on indirect visual observation using a camera as non-invasive sensing (Peng et al., 2018). Computer vision has non-destructive, environmentally friendly, high accuracy, and simple tool as a good method for rapid evaluation of identification of fruit ripeness (Hussain et al., 2018). From the results of a review of several studies, computer vision using parameters of color, texture, size, and shape is found to be very effective in classifying the ripeness level of fruits and vegetables (Bhargava & Bansal, 2018). Wan et al. (2018) developed a computer vision system to predict the ripeness of fresh tomato, indicating an accuracy of 99.31%. Tu et al. (2018) had succeeded in developing computer vision to detect the ripeness level of passion fruit by using the red-green-blue depth images method. The results of predictions using computer vision had a high accuracy of 91.52%. Tan et al. (2018) had successfully developed computer vision to identify the ripeness level of blueberries by using color parameters, in which the accuracy level reached 96%. Mangoes ripeness prediction through system application with computer vision has also been successfully developed by Wendel et al. (2018).

The combination of computer vision methods with artificial intelligence algorithms has proven effective for increasing accuracy (Patricio & Rieder, 2018). ANN is a technique which has been successfully applied to obtain a connection between complex input and output. According to Akbar et al. (2018), ANN is strongly recommended to present complex and non-linear relationships among different parameters, because ANN is proven to be the best technique. Yossy et al. (2017) had successfully identified the ripeness of mangoes by using a combination of computer vision and ANN with an accuracy value of 94%. ANN has also been used successfully to detect the ripeness of strawberries (Habaragamuwa et al., 2018) and grapes (Zuniga et al., 2014). In the field of image analysis based pattern recognition in several studies prove that ANN works better than other classification methods (Bashir et al., 2009; Shi et al., 2009; Quintana et al., 2012; Ren, 2012; Rekha & Shahin, 2015; Sachdeva et al., 2016; Barkana et al., 2017; Chen et al., 2017). Malekmohamadi et al. (2011) evaluated the efficacy of support vector machine (SVM), Bayesian networks (BN), ANN, and adaptive neuro-fuzzy ineference system (ANFIS). The result showed that ANN provided the best results.

Referring to several previous studies as presented above, this study was conducted to identify the coconut ripeness level through a non-invasive sensing method by developing a combination of computer vision and ANN algorithm. Image parameters including color, texture, size, and morphology of extracted digital images were used to predict the coconut ripeness level which included the volume of coconut water, the thickness of coconut flesh, and the wet weight of coconut flesh. The resulting model will be useful for rapid evaluation of the coconut ripeness level with a simple, practical, and accurate tool.

MATERIAL AND METHODS

The material used in this study was *gading* coconut type obtained from Kalimas Village, Besuki District, Situbondo Regency, East Java, Indonesia. The coconut fruit samples used were 135 samples with three ripeness levels (young, half-ripe, and ripe) and with ripeness parameter values such as coconut water volume, coconut flesh thickness, and varying wet weight of coconut flesh. The process of taking coconut fruit images was conducted by using a Nikon Canon Powershot A2500 digital camera that was placed in a perpendicular position to the object (the coconut fruit). Image acquisition was carried out in a black box chamber with a white paper platform and the lighting system with 4 pieces of light (220 V / 6 W / 50 Hz) with the evenly distribution of light on the surface of the object. The image data processing tool was the Intel (R) Core (TM) i3 of 32 bit CPU computer 2.10 Ghz. The process of taking coconut fruit is illustrated in Figure 1. The image of the acquisition had been through the process of image processing to clear the noise and to separate the background from the object. Extraction of image features in this study was performed by using Visual Basic (VBA) software, developed by Hendrawan and Murase (2009).

This research was conducted in several stages, which were: (1) taking the image of coconut fruit; (2) extracting the image parameters including red-green-blue (RGB) color index, RGB conversion to hue-saturation-intensity (HSI), analysing texture, shape and size; (3) modeling the relationship of ripeness level based on fruit volume, flesh thickness, and wet weight of coconut flesh with image analysis; (4) structuring ANN and determining neural weights in ANN. Coconut image was recorded with a size of 1600 x 1200 pixels which was then carried out by binary to separate the background from the object. The resolution of the recorded image was a file with a .bmp extension with a new image size after image processing of 450 x 346 pixels. Cropping on the image aimed to make the image to be analyzed focused on the green bean coffe object. The coconut image was then analyzed by using MATLAB 2015a to obtain quantitative data with image parameters including RGB, HSI, area, perimeter, eccentricity, metric, contrast, correlation, energy, and homogeneity.

According to Florio et al. (2018), the area is represented by the number of pixels in an object area, while the perimeter is the number of pixels indicating the edge or part of an object. Wang et al. (2018) had used the perimeter and area to characterize agricultural products such as grain surface area. According to Francisco et al. (2013), eccentricity was a comparison parameter value between the distance of a minor ellipse foci and a major elliptical foci. An eccentricity object has a range of values between 0-1. Objects are elongated or close to a straight line value 1, while objects that are round or circular have

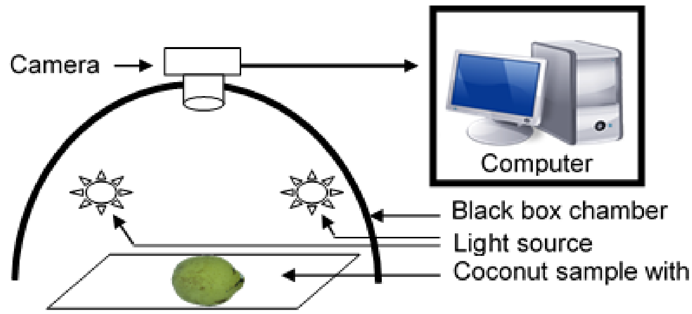


Figure 1. The design of image capturing process of coconut

value close to zero. Several studies have been conducted (Francisco et al., 2013; Sofu et al., 2016; Zhang et al., 2018) in relation with eccentricity in identifying and analyzing the fruits and food appearance properties by using the eccentricity parameter. The equation for eccentricity is as follows:

$$\mathrm{e} = \sqrt{1 - \frac{a^2}{b^2}} \quad [1]$$

Where e is eccentricity, a is the length of the axis major, and b is the length of the axis minor.

Metric is a quantity that shows the roundness of an object shape (Cassel et al., 2018). Metric values range from 0 to 1. The rounder the object, the more metric value approaches 1. Cohen et al. (2018) had successfully characterized biological objects with image analysis by using metric parameters. The metric value can be obtained by using the following equation (Li & Song, 2017):

$$metric = \frac{4\pi \times area}{perimeter^2} \quad [2]$$

Bhargava & Bansal (2018) in their research have shown the success of using texture parameters to detect various ripeness levels of fruits and vegetables. According to Haralick et al. (1973) and Hendrawan & Murase (2011a), some texture parameters can be defined as follows:

Energy is a gray level co-occurrence matrix (GLCM) feature that is used to measure the concentration of intensity pairs in the GLCM matrix.

$$\text{Energy} = \sum_{i}^{M} \sum_{j}^{N} p^2[i, j] \quad [3]$$

Contrast shows the size of the spread (moment of inertia) of the image matrix elements. If the contrast is far from the main diagonal, the contrast value is large. Visually, the contrast value is a measure of variation between the gray degrees of an image area.

Contrast = $\sum_{i}^{M} k^2 \left[\sum_{i} \sum_{j} p(i, j) \right]$ [4]

Correlation shows a measure of linear dependence on the degree of gray image to provide clues to the existence of linear structures in the image.

Correlation = $\dfrac{\sum_{i} \sum_{j} (ij).p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y}$ [5]

Homogeneity indicates the size of the proximity of each element in co-occurrence matrix.

Homogeneity = $\sum i, j \dfrac{p(i, j)}{1 + |i - j|}$ [6]

Where: *P(i,j)* is the *(i,j)th* element of a normalized co-occurrence matrix, and μ and σ are mean and standard deviation of the pixel element given by the following relationships:

$$P[i, j] = \frac{N(i, j)}{M} \quad [7]$$

$$\mu = \sum_{i}^{M} i \sum_{j}^{N} P[i, j] \quad [8]$$

$$\sigma = \sum_{i}^{M} (i - \mu)^2 \sum_{j}^{N} P[i, j] \quad [9]$$

Where: *N(i,j)* is the counted number in the image with pixel intensity of *i* followed by pixel intensity of *j* at one pixel displacement to the left, and *M* is the total number of pixels.

After the image parameters in the form of color, texture, shape and size were obtained, the data was then used as ANN input for the modeling process. The output of ANN model included the volume of coconut water, the thickness of coconut flesh, and the wet weight of coconut flesh. The learning model uses the back-propagation neural network (BPNN) method. BPNN has been tested as a learning method to predict fruit ripeness (Liu et al., 2010; Wan et al., 2018). Learning rates and momentum are arranged with a range of values [0, 1]. The data sharing used in ANN learning process included two groups such as training data and data testing with a ratio of 75.56%: 24.44% or the amount of training data as many as 102 data and testing data as many as 33 data. The data used as input and output parameters in BPNN learning is the treated data through the first normalization process by using equation 10 (Basheer & Hajmeer, 2000).

$$x_i = 2\left(\frac{z_i - z_i^{\min}}{z_i^{\max} - z_i^{\max}} \right) - 1 \quad [10]$$

Notes:
x_i = Normalization value
z_i = chosen value of each input
z_i^{min} = minimum value of the–i input data
z_i^{max} = maximum value of the–i input data

In determining the activation function, it depends on the expected output value of the ANN. One of the most useful functions is the sigmoid function (also known as the logistic function), defined as R and bounded between zero and one. Another commonly used function is the hyperbolic tangent, having a similiar shape to the sigmoid function. It is also a monotonic increase, ranging from -1 to +1 rather than 0 to 1 (Patterson, 1996).

RESULTS AND DISCUSSION

The parameters of coconut fruit ripeness carried out in this study applied the three parameters, such as: volume of coconut water (ml), thickness of coconut flesh (mm), and wet weight of coconut flesh (g). The results showed variations in coconut ripeness level starting from the young (with a range of coconut water volume value of > 200 ml; coconut flesh thickness of <5 mm; wet flesh weight of <50 g); half-ripe (with a range of coconut water volume valueof 100 ~ 200 ml; coconut flesh thickness of 5 ~ 15 mm; wet flesh weight of 50 ~ 200 g); mature (with a range of coconut water volume value of <100 ml; coconut flesh thickness of > 15 mm; wet flesh weight of > 200 g). Figure 2 shows a comparison among the image of young, half-ripe, and ripe coconut fruit. Visually, in terms of color, shape, and size, it is difficult to distinguish the classification of coconut from their ripeness level, especially to predict fruit ripeness parameters such as the volume of coconut water, thickness of coconut flesh, and wet weight of coconut flesh. However, some external appearances of coconut, although with limited information, can still be used as a tool to detect fruit ripeness. In general, the external appearance of young coconut has a more homogeneous texture compared to ripe coconut. The size of young coconut which is relatively smaller with a more rounded shape compared to ripe coconut can also be used as a prediction tool. The riper the coconut, the ripeness level is higher, indicated by the smaller volume of coconut water. Contrastingly, the thickness of coconut flesh and the wet weight of coconut flesh relatively increase. Some parameters of the external appearance of the coconut fruit can then be used as a feature subset that complements one another. This will provide information to accurately model the coconut ripeness level based on volume of coconut water, thickness of coconut flesh, and wet weight of coconut flesh. Therefore, the computer vision method (image analysis) approach is insufficient to predict the coconut ripeness level; therefore, supported by good modeling method such as ANN.

Table 1 shows the results of a linear model ($M=b_0+b_1X$) for shape and size parameter, texture parameters, and color parameters of coconut ripeness level. It is apparent that average shape and size parameter decrease along with the decreasing volume of coconut water, except the metric parameter which has a tendency to decrease marking a ripe coconut. The highest R^2 value of 0.1061 is obtained when using the eccentricity parameter. The average shape and size parameter increase along with the increase in coconut flesh thickness, except for eccentricity parameters which have the opposite pattern. The thicker the flesh of the coconut, the coconut fruit is relatively riper. The highest R^2 value of 0.3631 was obtained when using the area parameter. All shape and size parameters increase, along with the increasing wet weight of coconut flesh (the more wet weight of coconut flesh, the coconut fruit is more likely to ripe). The highest R^2 value of 0.529 was obtained when using the area parameter. Thus, it can be concluded that the average parameter of shape and size has a linear correlation with coconut ripeness level. However, linear equation models produced from various shape and size parameters are less likely optimal for identifying the coconut ripeness level.

Table 1 also shows a linear model of the relationship among texture parameters which include contrast, correlation, energy, and homogeneity towards coconut ripeness level. It shows a linear relationship among texture parameters to the volume of coconut water. From the linear curve, it is apparent that the average texture parameter except contrast texture has a linear upward relationship, where the more the volume of coconut water, the texture pattern tends to rise. Contrastingly, the more volume of coconut water, the contrast texture is lower. This is because the more the volume of coconut water, the ripeness level is higher

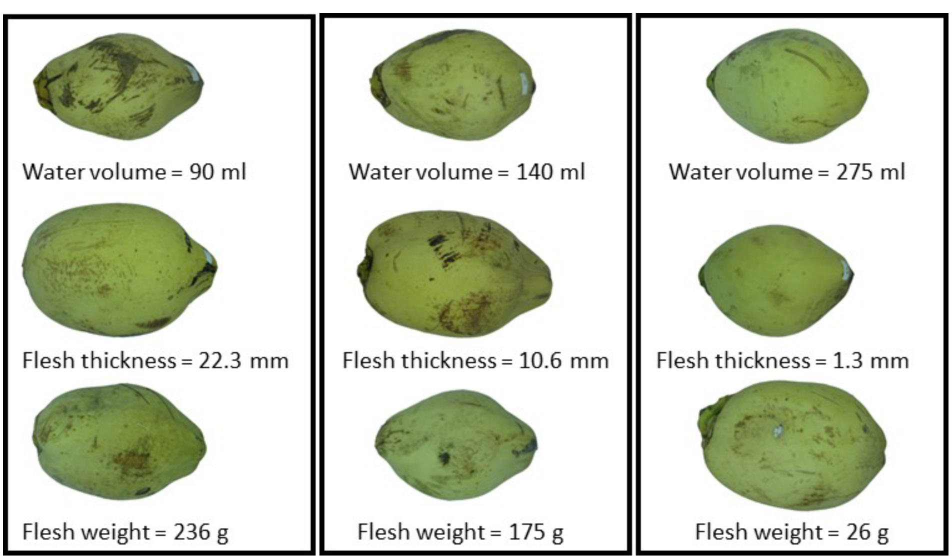


Figure 2. Coconut maturity stages: (a) fully mature, (b) mature, (c) young

and younger coconut has a tendency to have a uniform surface color. The highest R^2 value of 0.0715 was obtained when using homogeneity texture parameters. Table 1 shows the results of a linear model indicating the relationship of texture parameter to the thickness of coconut flesh. The results present that the thicker the coconut flesh, the averaged texture parameters will decrease, except for contrast texture parameter which has a linear upward curve pattern. This is because the riper the coconut fruit, the thickness of the coconut flesh will increase. While the riper the coconut fruit, the level of surface homogeneity will decrease, and the contrast value will increase. The highest R^2 value of 0.438 was obtained when using energy texture parameters. A linear model between texture parameter and wet weight of coconut flesh depicts that the heavier the wet weight of coconut flesh, the averaged texture parameters will decrease, except for contrast texture parameter which has an increasing linear curve pattern. This is because, the riper the coconut fruit, the wet weight of coconut flesh will increase. However, the riper the coconut fruit, the level of homogeneity, energy and the correlation on the surface of the fruit will decrease, and the contrast value will increase. The highest R^2 value of 0.6169 was obtained when using the texture energy parameter to model the coconut ripeness level which includes volume of coconut water, thickness of coconut flesh, and wet weight of coconut flesh using a linear model. Yet, the results are not optimal enough to accurately predict the ripeness level.

Table 1 also shows the relationship of the linear model of color index parameters, such as: mean-red, mean-green, mean-blue, mean-hue, mean-saturation, and mean-intensity to the coconut ripeness level based on the volume of coconut water, thickness of coconut flesh, and the wet weight of coconut flesh. It shows the correlation between color parameter and the volume of coconut water. Based on RGB color space, all RGB colors (mean-red, mean-green, and mean-blue) have a relationship of linear upward curves, where the more the volume of coconut water, the RGB value will also rise. It means that ripeness at the young coconut will occur faster as shown by the increasing index of the red, green and blue colors on the surface of the fruit. For HSI color space, mean-hue and mean saturity also have the similar pattern except for mean-intensity parameter that has a linear descending relationship, where the more the volume of coconut water, the intensity value is lower. This means the riper the ripeness of the coconut fruit, the intensity value will be higher. The highest R^2 value of 0.1466 was obtained when using the mean-blue color parameter. However, the linear model produced has not been able to optimally predict the volume of coconut water. The results show the identical pattern between the thickness of coconut flesh and the wet weight of coconut flesh. All RGB values had a pattern of downward liner models, where the thicker the coconut flesh and the heavier the wet weight of coconut flesh, the RGB value will be lower. This is in line with the previous results which showed that the riper the ripeness of the coconut fruit, the greenish value would be lower. Whereas, in the HSI color space, it is obvious that the mean-hue and mean-saturation values increase along

Table 1

The best model for predicting the ripeness level with some physical characteristics.

Dependent parameter	Independent parameter	The best model	Constant values of model		R^2
			b_0	b_1	
Shape and size parameters:					
Water volume	Area	Linear	0.4133	-0.0943	0.0189
Water volume	Eccentricity	Linear	0.5052	-0.2564	0.1061
Water volume	Metric	Linear	0.2495	0.1679	0.0306
Water volume	Perimeter	Linear	0.5023	-0.2231	0.0462
Flesh Thickness	Area	Linear	0.1331	0.4189	0.3631
Flesh Thickness	Eccentricity	Linear	0.3525	-0.0088	0.0001
Flesh Thickness	Metric	Linear	0.3011	0.0677	0.0048
Flesh Thickness	Perimeter	Linear	0.0031	0.5598	0.2833
Flesh Weight	Area	Linear	0.1950	0.8247	0.5290
Flesh Weight	Eccentricity	Linear	0.6081	0.0169	0.0002
Flesh Weight	Metric	Linear	0.5149	0.1489	0.0088
Flesh Weight	Perimeter	Linear	-0.0866	1.1436	0.4445
Texture parameters:					
Water volume	Contrast	Linear	0.4240	-0.1890	0.0625
Water volume	Correlation	Linear	0.1577	0.2599	0.0479
Water volume	Energy	Linear	0.3007	0.1153	0.0384
Water volume	Homogeneity	Linear	0.2230	0.2060	0.0715
Flesh Thickness	Contrast	Linear	0.2026	0.4650	0.3683
Flesh Thickness	Correlation	Linear	0.7701	-0.5295	0.1935
Flesh Thickness	Energy	Linear	0.5680	-0.3947	0.4380
Flesh Thickness	Homogeneity	Linear	0.6828	-0.4860	0.3880
Flesh Weight	Contrast	Linear	0.3457	0.8703	0.4852
Flesh Weight	Correlation	Linear	1.3313	-0.8950	0.2078
Flesh Weight	Energy	Linear	1.0438	-0.7640	0.6169
Flesh Weight	Homogeneity	Linear	1.2452	-0.9107	0.5121
Color parameters:					
Water volume	Mean red	Linear	0.2737	0.1680	0.0625
Water volume	Mean green	Linear	0.2718	0.1743	0.0610
Water volume	Mean blue	Linear	0.2281	0.2647	0.1466
Water volume	Mean hue	Linear	0.4130	-0.1216	0.0420
Water volume	Mean saturation	Linear	0.4625	-0.2093	0.0802

Table 1 *(Continued)*

Dependent parameter	Independent parameter	The best model	Constant values of model		R^2
			b_0	b_1	
Color parameters:					
Water volume	Mean intensity	Linear	0.2714	0.1762	0.0652
Flesh Thickness	Mean red	Linear	0.4320	-0.1551	0.0519
Flesh Thickness	Mean green	Linear	0.4398	-0.1722	0.0580
Flesh Thickness	Mean blue	Linear	0.4376	-0.1719	0.0604
Flesh Thickness	Mean hue	Linear	0.3200	0.0702	0.0136
Flesh Thickness	Mean saturation	Linear	0.2451	0.2200	0.0864
Flesh Thickness	Mean intensity	Linear	0.4369	-0.1681	0.0577
Flesh Weight	Mean red	Linear	0.7501	-0.2442	0.0484
Flesh Weight	Mean green	Linear	0.7602	-0.2672	0.0525
Flesh Weight	Mean blue	Linear	0.7514	-0.2562	0.0504
Flesh Weight	Mean hue	Linear	0.5757	0.1055	0.0116
Flesh Weight	Mean saturation	Linear	0.4675	0.3214	0.0693
Flesh Weight	Mean intensity	Linear	0.7539	-0.2573	0.0509

with the increasing thickness and wet weight of coconut flesh. However, mean-intensity values have a reverse curve pattern. The highest R^2 value for the correlation among color parameters with coconut flesh thickness and coconut wet weight is achieved by using mean-saturation parameters with values of 0.0864 and 0.0693, respectively. However, this linear model cannot be optimally used as a model in accurately measuring the thickness and wet weight of coconut flesh.

To get a more optimal and accurate model in identifying the coconut ripeness level based on three output parameters including coconut water volume, coconut flesh thickness, and coconut flesh wet weight, an intelligent modeling method such as ANN is needed. Figure 3 shows the ANN structure which includes as many as 14 results of extraction from coconut fruit images in the form of color index value, including: mean-red (R) as X_1, mean-green (G) as X_2, mean-blue (B) as X_3, mean-hue (H) as X_4, mean-saturation (S) as X_5, mean-intensity (I) as X_6, as well as parameters of size, shape, and texture ie area as X_7, perimeter as X_8, metric as X_9, eccentricity as X_{10}, contrast as X_{11}, correlation as X_{12}, energy as X_{13}, and homogeneity as X_{14}. Then the ANN structure also has one hidden layer consisting of 100 nodes. The output layer consists of 3 nodes in the form of coconut water volume as Y_1, thickness of coconut flesh as Y_2, and wet weight of coconut flesh as Y_3.

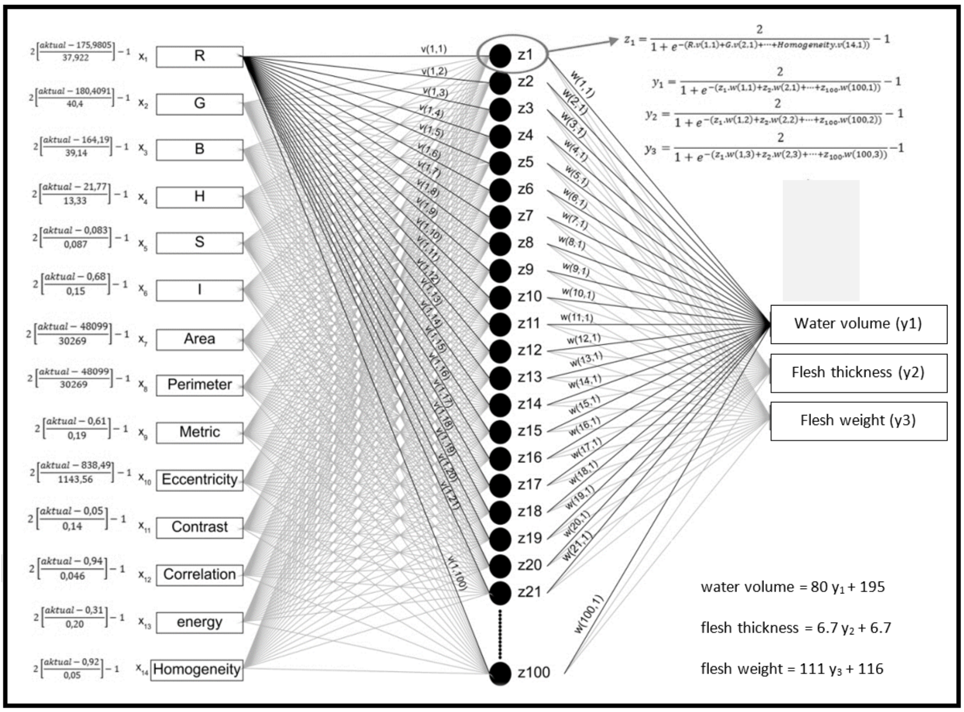


Figure 3. Structure of BPNN model for coconut ripeness prediction using image features

One of the most important processes is a sensitivity analysis of ANN model in identifying the best ANN model to be developed. Producing an expectedly good backpropagation training value requires the selection of good values from several parameters (the learning function, activation function, learning rate, momentum, and the number of nodes in the hidden layer). The value of these parameters may not be too high (large) or too low (small), therefore it must be optimized by selecting parameter values (Basheer and Hajmeer, 2000). Table 2 shows that the best results with the smallest Mean Squared Error (MSE) testing value of 0.107265 and R testing of 0.90331 are generated by a combination of 14 inputs (RGB, HSI, area, perimeter, eccentricity, metric, contrast, correlation, energy, and homogeneity) by using the learning functions (traincgb, tansig activation function, number of neurons in the hidden layer as many as 100 nodes, learning rate 0.2, momentum 0.9, and the number of iterations at 2000 times). The graph of the sensitivity analysis results is depicted in Figure 4.

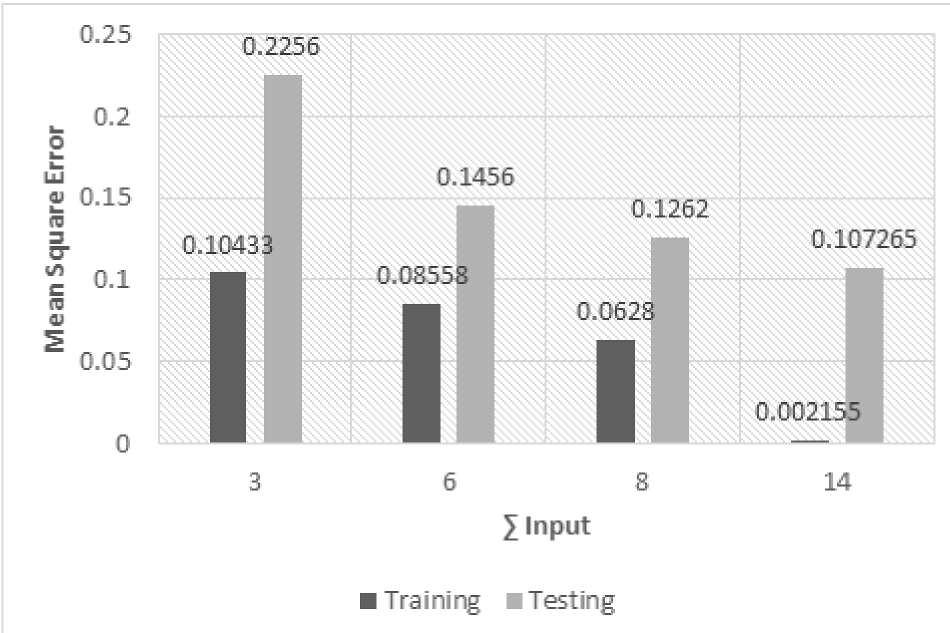


Figure 4. The results of the sensitivity analysis of training and testing with various input quantities

The learning algorithm applied to the prediction model of coconut ripeness level fruit is backpropagation with the supervised learning method; where there is a target value to be achieved by the developed ANN output. BPNN training is carried out in order to optimize the weight to obtain the best weights at the end of the training. During the training process, weights are iteratively arranged to minimize errors that occur. BPNN training uses the weight search method with minimum prediction errors. From the training data, a combination of input data produces a minimum MSE training value of 0.002155 by using a combination of all input data (14 inputs). Figure 5 shows the results of sensitivity analysis in ANN training process to predict the coconut ripeness level by using BPNN. The correlation coefficient value of ANN training data to identify the coconut fruit ripeness is quite good. The training process is carried out with 2000 iterations, but the results have been reached with a maximum of 1267 iterations. The number of nodes in the hidden layer is 100 and the training function is *traincgb*. The results of the training show the accuracy of the estimate reaches in number 1, where the number depicts the maximum value in determining the accuracy value (100% accuracy). This is confirmed by the distribution of data which shows the uniform regression line.

This ANN algorithm map will input data to the input layer towards the target at the output layer through neurons in the hidden layer. Hidden data layer is associated with the coconut weight which are then processed by using the activation function. Furthermore,

Table 2
Result of sensitivity analysis of the developed ANN model

Input	Learning function	Activation function	Learning rate (lr) & momentum (mc)	Nodes in hidden layer	Iteration	MSE Testing	R Testing
RGB - HSI - Texture - Shape and Size	Traincgb	tansig	lr = 0.2 mc = 0.9	20	2000	0.1570	0.8444
				40		0.1664	0.8676
				60		0.2988	0.8415
				80		0.1660	0.9177
				100		0.1073	0.9207
RGB	traincgb	tansig	lr = 0.2 mc = 0.9	20	2000	0.4971	0.5581
				40		0.2764	0.5567
				60		0.6499	0.8191
				80		0.3897	0.4916
				100		0.2478	0.5070
HSI	traingd	logsig	lr = 0.9 mc = 0.9	20	2000	0.3132	0.5118
				40		0.2256	0.5503
				60		0.4682	0.4669
				80		0.2684	0.6498
				100		0.2826	0.5012

Table 2 *(Continued)*

Input	Learning function	Activation function	Learning rate (lr) & momentum (mc)	Nodes in hidden layer	Iteration	MSE Testing	R Testing
RGB-HSI	traingdm	tansig	lr = 0.9 mc=0.9	20	2000	1.0719	0.6851
				40		0.4848	0.5473
				60		1.0858	0.4554
				80		0.1456	0.3360
				100		1.6429	0.4744
Texture-shape-size	trainlm	purelin	lr = 0.9 mc=0.9	20	2000	0.2217	0.6022
				40		0.1262	0.7334
				60		0.1574	0.8702
				80		0.2633	0.6385
				100		0.1641	0.6895

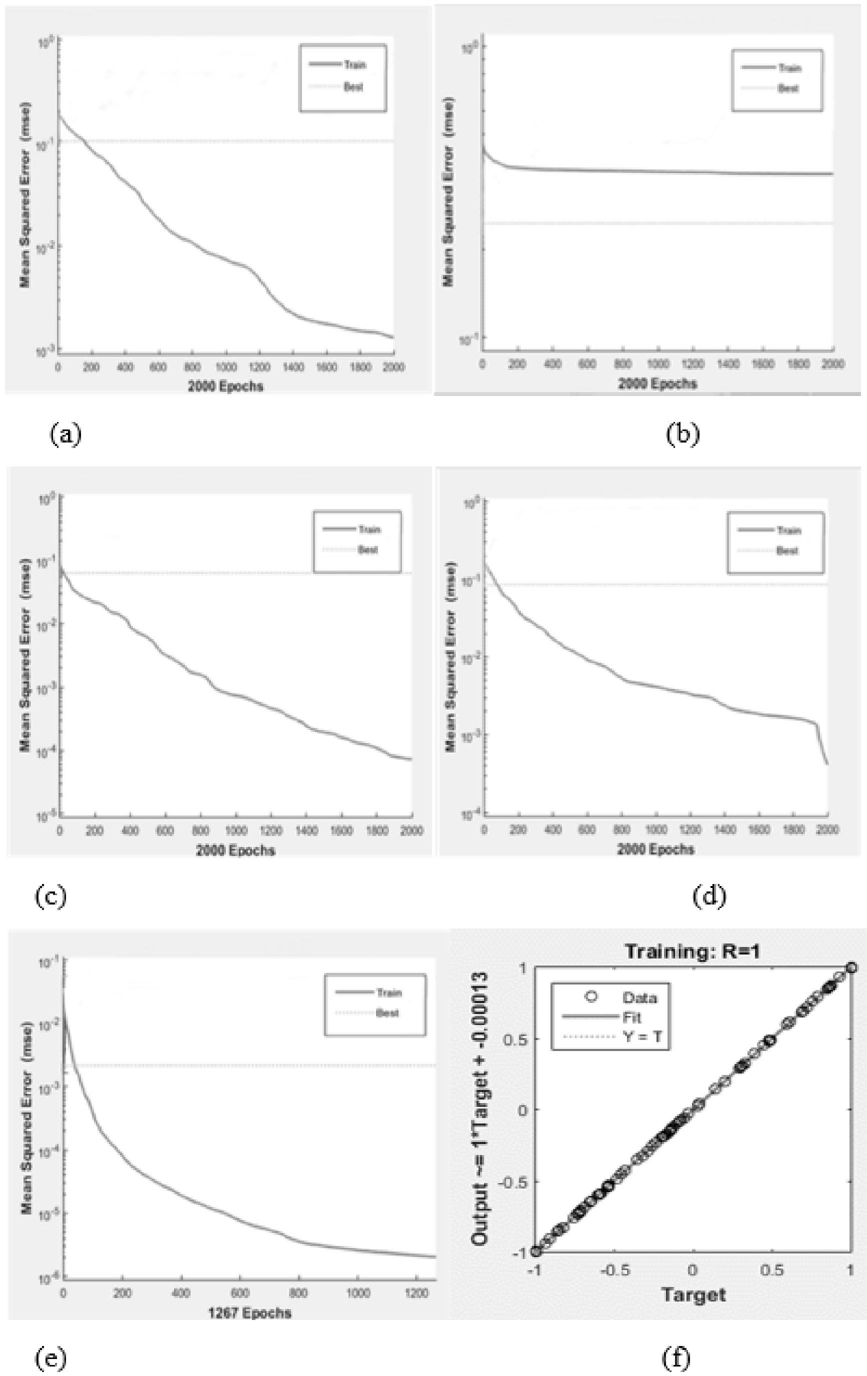
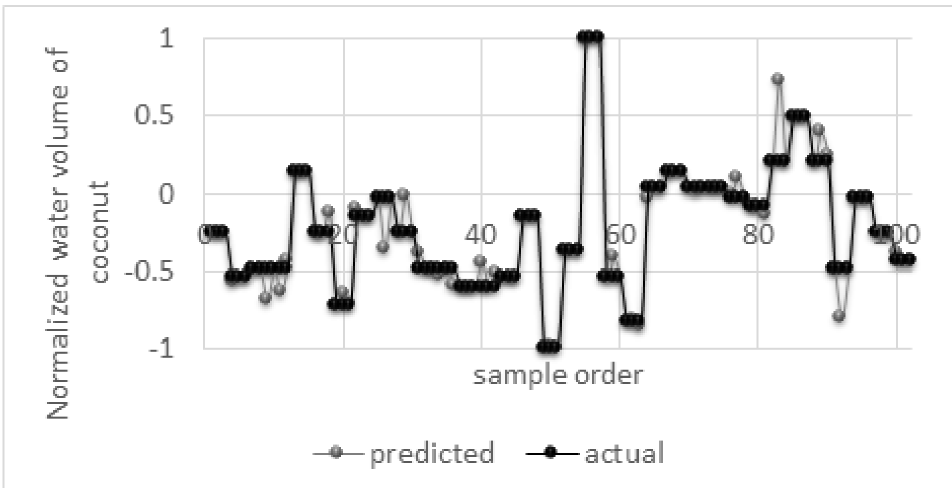
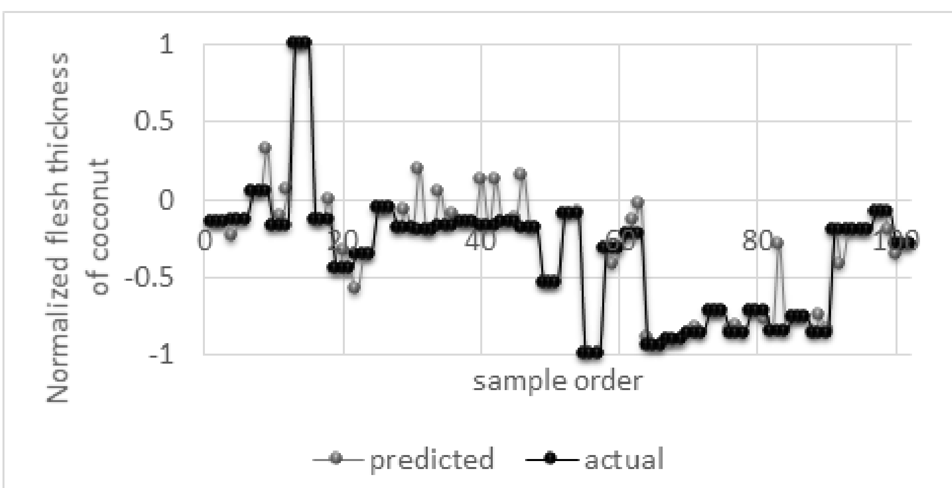


Figure 5. Sensitivity analysis in ANN training process with various types of input combinations and 100 nodes in the hidden layer: (a) RGB input; (b) HSI inputs; (c) texture inputs; (d) RGB-HSI input; (e) RGB-HSI input-texture-size forms; (f) regression of RGB-HSI-texture-shape input training data

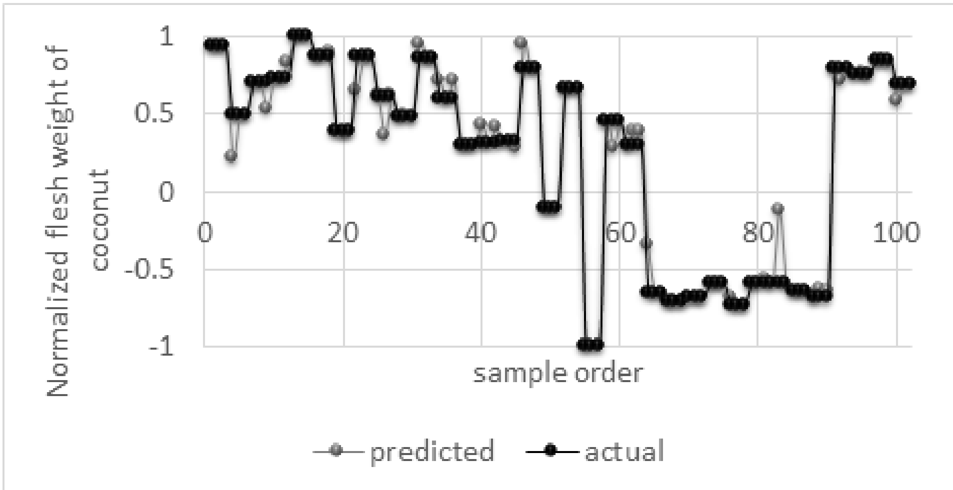
the processed data from the hidden layer is connected by hidden weights to the neurons in the output layer. The results obtained are then compared with the target data to obtain an error rate. The graph that shows a comparison between the prediction target and the actual target is illustrated in Figure 6 (a graph of the comparison of predictive and actual values of training data for the three outputs of coconut fruits produced by the ANN model). In Figure 6, it is noticeable that the spread is evenly distributed.



(a)



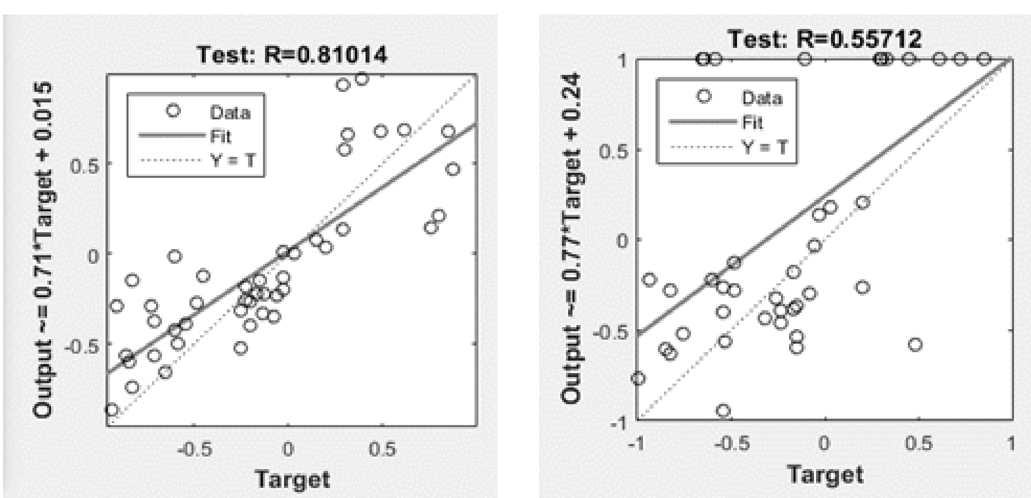
(b)



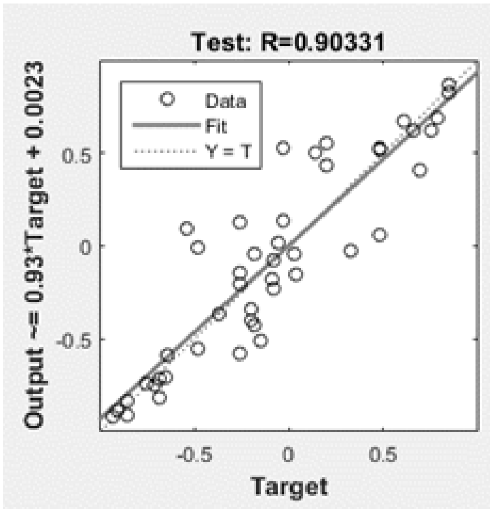
(c)

Figure 6. Comparison chart of predicted targets with actual targets of ANN training results; (a) volume of coconut water; (b) thickness flesh of fruit; (c) wet flesh weight

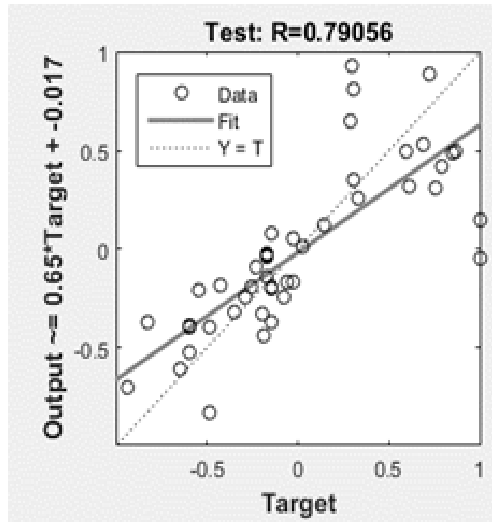
In the testing phase, the testing data is different from the trainin data. The data has indeed been separated from the start, which is 24.44% of the overall data. In the ANN model, there are three outputs (coconut water volume, coconut flesh thickness, and coconut flesh wet weight) with each MSE produced testing value at 0.11221; 0.285002; and 0.06552 with a total MSE of 0.107265. This value is the best ANN result with an R-testing value of 0.92071 as shown in Figure 7 (describing the results of the correlation coefficient value of ANN testing data to identify coconut ripeness level). The ANN model that has been developed with selected weights can optimally predict the coconut ripeness level.



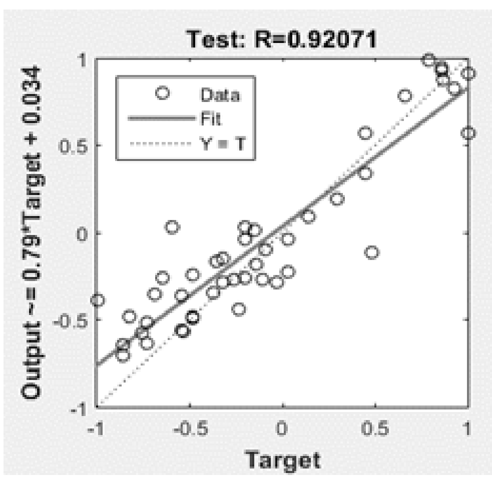
(a) (b)



(c)



(d)



(e)

Figure 7. Graph of sensitivity analysis of ANN testing data: (a) RGB input; (b) HSI inputs; (c) texture-shape inputs; (d) RGB-HSI input; (e) RGB-HSI-texture-shape input

CONCLUSIONS

The linear model, produced in this study for shape and size parameters that have the highest correlation with the volume of coconut water, is eccentricity with R^2 of 0.1061. In order to predict the best thickness and wet weight of coconut flesh, the researchers apply area parameters with R^2 of 0.3631 and 0.529, respectively. For the linear model with the best texture parameter to predict the volume of coconut fruit, is homogeneity with R^2 of 0.0715. Meanwhile, the best texture for measuring the thickness and wet weight of coconut flesh is the energy texture with R^2 of 0.438 and 0.6169, respectively. The best linear model for color parameter on coconut water volume is the mean-blue with R^2 of 0.1466. While the best color for measuring coconut thickness and wet weight is mean-saturation with R^2 of 0.0864 and 0.0693, respectively. The best results of the artificial neural network (ANN) model are found in 14 input structures (mean-red, mean-green, mean-blue, mean-hue, mean-saturation, mean-intensity, area, perimeter, eccentricity, metric, contrast, correlation, energy, and homogeneity), 1 hidden layer with 100 nodes in it, and 3 outputs (volume of coconut water, thickness of coconut flesh, and wet weight of coconut flesh). The ANN model produces the smallest Mean Squared Error (MSE) training and MSE testing values of 0.002155 and 0.107265 with R training and R testing of 1 and 0.90331, respectively. The model that has been produced is later applicable to accurately predict coconut ripeness level.

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