Vol. 11, No. 2 (2022) : 231 - 241 DOI : http://dx.doi.org/10.23960/jtep-l.v11i2.231-241

JURNAL TEKNIK PERTANIAN LAMPUNG

ISSN 2302-559X (print) / 2549-0818 (online)
Journal homepage : https://jurnal.fp.unila.ac.id/index.php/JTP

Non-Destructive Measurement of Rice Amylose Content Based on Image Processing and Artificial Neural Networks (ANN) Model

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Article History :

Received : 31 March 2022
Received in revised form : 25 May 2022
Accepted : 25 May 2022

Keywords :
Amylose,
Artificial neural networks,
Image processing,
Rice

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ABSTRACT

The purpose of this study was to develop a method of measuring the amylose content of rice using image processing techniques and an Artificial Neural Network (ANN) model. The rice samples came from six varieties, namely Way Apo Buru, Mapan P05, IR-64, Cibogo, Inpari IR Nutri Zinc, and Inpari 33. The amylose content was measured by laboratory tests and the color intensity was measured based on the RGB (Red, Green, Blue). The ANN model will correlate the RGB color intensity as input with the amylose content as the output. The ANN model used is backpropagation type with 3 input layer nodes and 2 hidden layers with 3-5-5-1 architecture. Variations in the training model used are 27 variations of the activation function. The amount of data used for model training of 30 data while for validation of 12 data. The best ANN model is determined from the high value of accuracy (100%-MAPE) and the value of coefficient of determination (R^2). The results showed the best network architecture on the activation function purelin-logsig-tansig. The R^2 value on the best training and validation results of 0.98 and 0.66 while the accuracy values for the best training and validation results of 98.15 and 66.82. The validation results show that the developed non-destructive method can be used to quickly and accurately measure the amylose value of rice based on RGB color value. The test results show that the non-destructive method developed cannot be used to measure the amylose content of rice quickly and accurately based on the RGB color intensity, so it needs further development.

1. INTRODUCTION

The components that make up agricultural products, especially food, are very important objects of study if we want to know well the benefits of these foodstuffs for human needs (Bantacut, 2010). The food material for the majority of people in Indonesia and in several other countries such as Thailand, Japan, China and so on is rice (Nuryani, 2013). The main content of rice is starch with a concentration of 80% and one of the constituent components of starch is amylose which is a carbohydrate polymer and is a straight chain glucose unit structure with 1,4-D-glucopyranoside bonds (Luna *et al*., 2015). Amylose content determines the physical appearance of rice in the form of color and texture so that rice is classified into rice with low amylose content (10-20%), medium (21-25%), and high (26-33%). Rice with high amylose content will make the rice expand, the texture is relatively separate ("pera"), not sticky, and becomes hard after cooling (Anugrahati *et al*., 2017).

There are at least three methods of measuring amylose content in rice, namely the I:KI binding method, colorimetry, and chromatography. The binding method I:KI is a method that uses a color indicator from the high and low bonding of starch molecules with iodine compounds. Iodine compound bonds with amylose content will produce a blue color while amylopectin content will produce a reddish purple color (Ardhiyanti *et al*., 2014). The colorimetric method also uses bonds with iodine compounds and the absorbance value of the sample is measured using a spectrophotometer at a wavelength of 620 nm (Fitriyah *et al*., 2020). The chromatographic method is a method that measures amylose through enzyme purification processes such as gel-filtration chromatography and ion-exchange chromatography (Nangin & Sutrisno, 2015). The three methods of amylose analysis are direct measurements that require contact with the object and can damage the object being analyzed. In addition, the three methods can be said to be complicated and require processing time in hours, and are not cheap. The drawbacks of this method can be avoided by indirect measurement.

The complexity of measuring amylose content has been the reason for using image processing techniques in observing research objects, especially in the agricultural sector (Brosnan & Sun, 2004; Kaur *et al*., 2014). Image processing technique is a method for converting an image into digital form and performing certain operations in order to obtain information on the image (Saranya *et al*., 2014). In image processing techniques, data is obtained only from object images so that this method is non-destructive, fast, and inexpensive (Chen *et al*., 2002).

In general, the amylose content is based on the color of the rice, so the more transparent the rice, the higher the amylose content (Widowati *et al*., 2020). This is based on the presence of rice genes that regulate aleurone in the womb (Aminah *et al*., 2019). The change in the color gradation of rice along with the change in amylose content is the basis for image processing-based measurements. This rice display will be captured and processed for the measurement of rice starch content (Hadipernata *et al*., 2020). The complexity of the gradation of rice objects becomes a separate problem when measuring. The complexity of this object will reduce the accuracy in prediction based on the extracted image features (Zhao *et al*., 2017).

The development of image processing techniques to overcome this problem is to combine it with an artificial neural network (ANN) model. In the application of image processing techniques, it is found that the relationship between independent variables and dependent variables is not linear and more complex so that the prediction results tend to be inaccurate if only using regression analysis (Goyal, 2013). The nonlinearity and complexity of the relationship can be overcome using an artificial neural network model so as to produce high accuracy in prediction (Lavalle *et al*., 2012; Seo, 2013).

Based on the previous description, non-destructive measurements will be carried out on the amylose content of rice. Image processing method was used to extract the color features of rice and an ANN model was developed to establish the relationship between rice color and amylose content. The results of this study are expected to be the basis for developing an information system for rice amylose levels and supporting decision making to determine the appropriate treatment for rice consumption.

2. MATERIALS AND METHODS

2.1. Rice Varieties Sample

The rice sample used is white rice, which is rice that has been removed from the husk and bran through two milling processes and then polished into white rice (Rachmat, 2012). The samples used consisted of six varieties of rice, namely Way Apo Buru, Mapan P05, IR-64, Cibogo, Inpari IR Nutri Zinc, and Inpari 33 with water content of 10.43%, 12.46%, 12.01%, 14.78%, 14.94%, and 11.54%, respectively. Seven samples of each variety were taken to test the amylose content and each sample was imaged three times. The total data of amylose content is 42 data with the number of images as many as 126 images.

2.2. Image Catcher Box

The initial stage in this research is to make a box for taking images with a size of 50 × 50 × 50 cm made of 2 cm thick Styrofoam. The inside of the box is lined with black manila paper for easy image segmentation. An 11 watt fluorescent lamp is used as a light source and mounted on the bottom of the research object. A 20 MP digital camera was mounted perpendicularly above the bulk rice sample which was placed evenly on a petri dish with a distance of 20 cm (Figure 1).

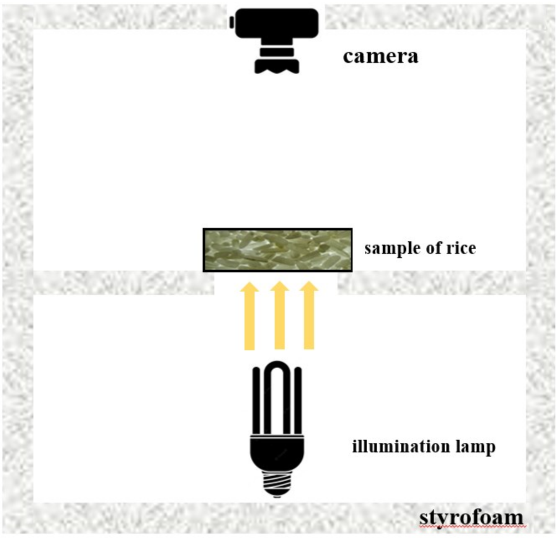
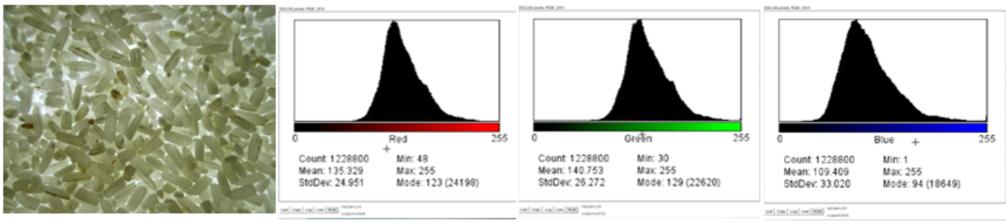


Figure 1. Schematic for capturing rice image

2.3. Rice Image Data Retrieval

The way image data retrieval works starts from capturing an image of rice using a camera and then storing it in the camera's memory. The RGB color features of the image will be extracted using ImageJ software as shown in Figure 2. The RGB color intensity of the rice will be recorded in the data table according to the label of the rice sample tested for its amylose content.



Rice image red intensity green intensity blue intensity

Figure 2. Measurement of color intensity value of rice

2.4. Amylose Content Analysis

Analysis of amylose content in rice requires tools including measuring flask, Kjeldahl flask, beaker glass, erlenmeyer, volume pipette, UV-Vis T60 spectrophotometer, analytical balance, and other laboratory equipment. While the materials used in this study included rice samples, potato amylose, CH_3COOH (acetic acid), NaOH, I_2, KI, 96% alcohol and aquades. The analysis is carried out in several stages, namely:

1. First, a standard amylose solution was prepared by weighing 100 mg of potato amylose and then adding 1 mL of 96% alcohol and 9 mL of 1 N NaOH. The solution was heated for 10 minutes, cooled for 1 hour, and diluted with distilled water to a volume of 100 mL.
2. Second, making a standard amylose calibration curve by preparing a standard amylose solution of 0.25; 0.5; 0.75; 1.0; 1.25; 1.5; 1.75; and 2.0 mL into a 100 mL volumetric flask. To this solution, 2 mL of 2% I_2 and 0.5 N acetic acid were added and the solution was diluted with distilled water to a volume of 100 mL to obtain a solution with a concentration of 2.5; 5.0; 7.5; 10.0; 12.5; 15.0; and 20.0 mg/L. The absorbance value of these solutions was then measured using a spectrophotometric method (UV-Vis T60 spectrophotometer). The standard curve is made based on the amylose concentration and absorbance values.
3. Third, the measurement of amylose content in rice using the spectrophotometric method. Rice of 100 mg was mashed and added with 1 mL of 96% alcohol and 9 mL of 1 N NaOH. The solution was heated at 100°C for 10 minutes, put into a 100 mL volumetric flask, and diluted with distilled water. Five (5) mL of the solution was put into a 100 mL volumetric flask and then 2 mL of 2% I_2 and 1 mL of 0.5 N acetic acid were added. The solution was diluted again with distilled water to 100 mL, shaken and allowed to stand for 20 minutes until the color turned bluish. Then the absorbance value of the solution was measured and included in the standard curve equation.

Amylose standard solution whose wavelength is known will be the basis for making linear regression formulas. The absorbance value of the rice sample will be converted to the linear regression formula as in Equation 1.

$$y = ax + b \tag{1}$$

where y is amylose concentration of rice sample, x is absorbance value of spectrophotometric measurement, a is coefficient value, and b is constant value.

2.5. Data Analysis

The data obtained from the observations were then analyzed using analysis of variance or ANOVA (Analysis of Variance) with a significance level of 95% and 99%. The ANOVA results which showed significantly different treatments were then continued with the DMRT (Duncan Multiple Range Test) test with a significance level of 95%. The data analyzed were RGB color intensity and rice amylose content in various varieties.

2.6. Development of ANN Model

The developed ANN model is backpropagation type ANN with supervised learning method. Network initiation begins with compiling training data and test data, determining training training (Leveberg-Marquardt), and setting a learning rate value of 0.1. The developed network has 4 layers which are divided into 3 nodes in the input layer, 5 nodes in the hidden layer 1, 5 nodes in the hidden layer 2, and 1 node in the output layer as shown in Figure 3. The network will be trained with a combination of logsig activation functions, tansig and purelin on each layer so that there will be 27 variations of the activation function. The combination of input layer variables (red-green, blue green, red-blue) and the number of nodes in the hidden layer is not a variation of ANN development in this study.

2.7. Model Testing

The final step in this research is model testing with the aim of testing the level of accuracy between the predicted value and the observed value. The test is carried out with indicators of accuracy and coefficient of determination (R^2). The accuracy test is a test to determine the magnitude of the estimation error of the model developed based on equations 2 and 3.

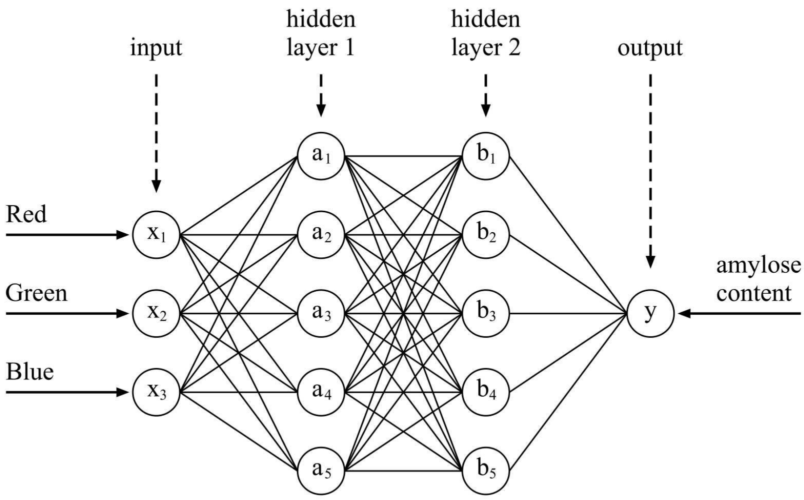


Figure 3. The form of ANN with 3-5-5-1 architecture

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{O_i - P_i}{O_i}\right] \times 100\% \quad (2)$$

$$Accuracy = 100\% - MAPE \quad (3)$$

where n is number of data, O_i is observation value of the i^{th}, and P_i is observation value of the i^{th}.

The coefficient of determination (R^2) is essentially used to measure how much the independent variable's ability to explain the dependent variable is. The largest coefficient of determination value is 1 and the smallest is 0. The prediction results of the model are considered very accurate if the plot formed between the observed and predicted values has an R^2 value of 0.9 to 1 (Haryanto *et al*., 2020).

3. RESULTS AND DISCUSSION

3.1. Rice amylose content

The Inpari IR Nutri Zinc variety had the lowest amylose content of 16.61±1.59%, while the highest was the Mapan P05 variety of 29.89±1.25%. The measurement of the RGB color intensity value shows the lowest red color intensity in the Inpari IR Nutri Zinc variety, the lowest green color intensity in the Inpari IR Nutri Zinc variety, and the lowest blue color intensity in the Way Apo Buru variety, while the highest red, green, and blue color intensities are found in the Mapan P05. This indicates that low amylose content is also followed by low color intensity and vice versa.

Analysis of variance (ANOVA) on research parameters showed that each rice variety has its own characteristics both in terms of color and amylose content. The F value which is greater than the calculated F shows significant results at the 99% level (Table 1). The results of the Duncan Multiple Range Test further test on each measurement parameter showed that the rice amylose (Table 2) and the RGB color intensity (Table 3) of each variety had their respective classifications based on the notation. There were varieties that were not significantly different from other varieties, but there were also varieties that were significantly different in both the average color intensity and amylose content.

Table 1. The results of the test of variance of the observation parameters

Parameter	F value	Significance level	
		95%	99%
Red color intensity	30,47	significant	significant
Green color intensity	28,07	significant	significant
Blue color intensity	54,19	significant	significant
Amylose content	36,93	significant	significant

Table 2. Amylose content of different rice

Rice variety	Mean	SD
Inpari IR Nutri Zinc	16,61a	1,59
Way Apo Buru	22b	4,6
Cibogo	24,04bc	0,58
IR-64	25,68c	0,48
Inpari 33	28,80d	0,96
Mapan P05	29,89d	1,25

Table 3. RGB color intensity for different rice

Rice variety	*Red*		*Green*		*Blue*	
	Mean	SD	Mean	SD	Mean	SD
Inpari IR Nutri Zinc	130a	4	131a	4	115b	2
Way Apo Buru	145b	8	146b	7	105a	6
Cibogo	134a	3	136b	4	118b	5
IR-64	141b	3	143b	3	120b	4
Inpari 33	142b	3	143b	3	129c	3
Mapan P05	157c	4	157c	4	138d	4

Table 4. Correlation coefficient of RGB color intensities

Color intensity	Correlation	Category
Red	0,63	Strong
Green	0,63	Strong
Blue	0,67	Strong

When classified based on the amylose content, the Inpari IR Nutri Zinc varieties are in the low category with a very fluffier texture, Way Apo Buru and Cibogo are in the medium category with a fluffier texture, while Mapan 05, IR-64, and Inpari 33 are included in the high category with a thick texture (Syamsiah & Masliah, 2019; Sari *et al*., 2020). The results of the correlation analysis in Table 4 show the correlation values of 0.63, 0.63, and 0.67 for the intensity of the red, green, and blue colors on the amylose content of rice. This shows a strong relationship between color intensity and amylose content because it is in the range of 0.60-0.799 (Sugiyono, 2007). The strong correlation indicates that the test results of the developed ANN model will be accurate.

The accuracy of the ANN model in its development is related to the selected feature extraction (Bodapati & Veeranjaneyulu, 2019), the amount of data used (Siregar & Wanto, 2017), as well as the ANN architecture developed (Rajbhandari *et al*., 2017). Table 5 is the result of developing the ANN model and provides an interpretation that a strong correlation analysis and accurate training results can provide accurate test results as well. The results of training and testing on the 3-5-5-1 architecture showed that the best activation function is revealed by the purelin-logsig-tansig activation function which gave an accuracy value of 98.15% for training and 66.82% for testing. The graph of the relationship between the best observations and predictions on the two ANN architectures can be seen in Figure 4.

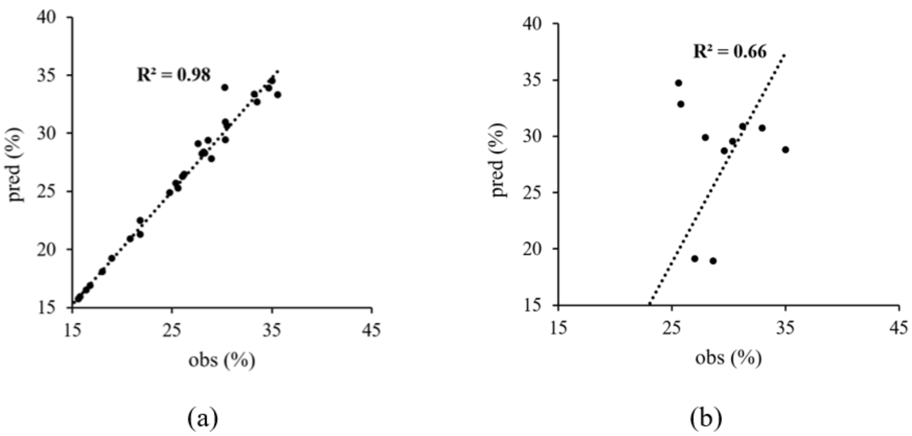


Figure 4. The best relation of observed and predicted values: (a) training, (b) testing

In Table 5 it can also be seen that the value of the coefficient of determination close to 1 only gives a small value of the coefficient of determination but this is inversely proportional to accuracy. High accuracy values in the model training process can also provide high accuracy values in model testing. The accuracy value from the results of the development of the ANN model shows a reasonable prediction interpretation (reasonable forecast) because the value is in the range of 60-80% (Lewis, 1982).

Table 5. Determination coefficient and accuracy during training and testing of different activation functions within ANN model with 3-5-5-1 architecture

No	Activation function	Training		Testing	
		***R*²**	**Accuracy**	***R*²**	**Accuracy**
1.	*logsig-logsig-logsig*	1,00	99,78	0,00	59,66
2.	*logsig-logsig-purelin*	1,00	99,79	0,06	64,12
3.	*logsig-logsig-tansig*	1,00	99,77	0,00	62,48
4.	*logsig-purelin-logsig*	0,96	96,93	0,45	83,42
5.	*logsig-purelin-purelin*	0,98	97,21	0,11	79,68
6.	*logsig-purelin-tansig*	0,96	96,93	0,50	81,34
7.	*logsig-tansig-logsig*	1,00	99,72	0,16	66,91
8.	*logsig-tansig-purelin*	1,00	99,78	0,28	83,65
9.	*logsig-tansig-tansig*	1,00	99,84	0,42	30,17
10.	*purelin-logsig-logsig*	0,83	93,67	0,27	83,56
11.	*purelin-logsig-purelin*	0,96	96,91	0,22	78,22
12.	***purelin-logsig-tansig***	**0,98**	**98,15**	**0,66**	**66,82**
13.	*purelin-purelin-logsig*	0,41	83,73	0,11	82,21
14.	*purelin-purelin-purelin*	0,40	83,72	0,10	82,22
15.	*purelin-purelin-tansig*	0,40	83,53	0,11	82,41
16.	*purelin-tansig-logsig*	0,95	96,58	0,23	76,08
17.	*purelin-tansig-purelin*	0,82	92,85	0,29	84,02
18.	*purelin-tansig-tansig*	0,94	96,45	0,18	81,11
19.	*tansig-logsig-logsig*	1,00	99,78	0,01	76,07
20.	*tansig-logsig-purelin*	1,00	99,88	0,09	73,25
21.	*tansig-logsig-tansig*	1,00	99,88	0,03	65,7
22.	*tansig-purelin-logsig*	0,87	93,68	0,29	83,69
23.	*tansig-purelin-purelin*	0,93	95,5	0,07	63,18
24.	*tansig-purelin-tansig*	0,91	95,47	0,44	87,81
25.	*tansig-tansig-logsig*	1,00	99,83	4×10^{-8}	63,28
26.	*tansig-tansig-purelin*	1,00	99,7	0,02	65,99
27.	*tansig-tansig-tansig*	1,00	99,71	0,56	64,68

Table 6. Comparison of research results related to the development of ANN models in predicting food ingredients

Food type	**Input variables**	**Output variables**	**Values of R^2 and accuracy**	**References**
Rice	RGB color intensi-ty	Amylose content	R^2 : 0.66 Accuracy : 66.82%	This work
Rice	Feature of rice grains and milling yield	Amylose content	R^2 : 0.84 RMSE : 0.88	(Sampaio *et al.*, 2021)
Corn	NIR absorbance data	Content of fat, carbohydrate, pro-tein, and water	CV (coeficient of variability) : 0.047–0.518	(Andrianyta & Budiastra, 2010)
Purple eggplant	CIELAB color	Eggplant quality (freshness and wiltyness)	Accuracy : 63,33%	(Astiningrum & Abdullah, 2020)
Carrot	Slice thickness, drying time	Water content	R^2 = 0.992 RMSE = 2,099	(Saputra *et al.*, 2020)

This research still requires further development efforts in developing a non-descriptive measurement method for rice amylose content even though it has reached a reasonable accuracy. Table 6 presents the results of research related to the content of food ingredients that can be used as a comparison in the development of the ANN model.

4. CONCLUSIONS AND RECOMMENDATION

Based on the research that has been done, the amylose content and color of rice in each variety showed significant differences in characteristics with a strong correlation category with values from 0.63 to 0.67. This can be seen from the results of the analysis of six rice varieties, namely Way Apo Buru, Mapan P05, Ir-64, Cibogo, Inpari IR Nutri Zinc, and Inpari 33. The artificial neural network model built on the 3-5-5-1 architecture shows high accuracy. high at the stage of training and testing the model. The best network architecture is obtained from the purelin-logsig-tansig activation function. The coefficient of determination (R^2) on the best training and testing results is 0.98 and 0.66 while the accuracy values for the best training and test results are 98.15 and 66.82. This accuracy value which is still relatively inaccurate requires further efforts to develop a non-destructive measurement method for rice amylose content.

ACKNOWLEDGEMENT

The author would like to thank the University of Jember which has provided financial support through the Research Grant for Dosen Pemula scheme from PNPB in 2020 so that this research can be carried out properly.

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