Vol. 13, No. 3 (2024): 739 - 749 http://dx.doi.org/10.23960/jtep-l.v13i3.739-749

JURNAL TEKNIK PERTANIAN LAMPUNG

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

Artificial Neural Network Model to Predict ^{O}Brix and pH of Banana Based on Color Parameters

Ferlando Jubelito Simanungkalit[1,✉], Hotman Manurung[1]

[1] Department of Agricultural Product Technology, Faculty of Agriculture, HKBP Nommensen University, North Sumatera, INDONESIA.

Article History:

Received : 29 February 2024
Revised : 19 April 2024
Accepted : 24 April 2024

Keywords:

Artificial neural networks,
Color,
Computer vision system,
CVS,
RGB.

Corresponding Author:
✉ ferlandosimanungkalit@uhn.ac.id
(Ferlando Jubelito Simanungkalit)

ABSTRACT

Artificial neural network (ANN) was used to predict internal quality parameters (°Brix and pH) of lady finger banana. This research consisted of three stages, namely: (1) capturing images of lady finger banana using a computer vision system; (2) measurement of °Brix and pH of the banana; (3) ANN architecture analysis using the Matlab R2019a application. The ANN architectural model consisted of 3 output models, namely: (1) °Brix values; (2) pH value; (3) °Brix and pH values. The ANN architecture analysis was carried out through two phases. Phase I consisted of 45 experimental units and phase II with 35 experimental units. The best ANN architecture to be used as a prediction model for °Brix and pH of golden banana fruit is ANN architecture model 3 with the number of neurons inside the hidden layer = 3; activation function in hidden layer = logsig; activation function inside the output layer = logsig; data transformation range 0 – 1; learning rate value = 0.01; learning algorithm = tradingda; with MSE (mean square error), MAE (mean absolute error) performance and R correlation coefficient from training results of 0.0954; 0.2619 and 0.6538; test results 0.0392; 0.1606 and 0.7000 and validation results 0.0289; 0.1474 and 0.7889.

1. INTRODUCTION

Bananas are a very popular fruit in the world and international trade (Jaiswal *et al*., 2014). Bananas are in fourth place in the world's food crops. Rich in potassium, vitamins C and B6, fiber, tryptophan and amino acids (Sheehy & Sharma, 2011). Optimal banana ripeness is needed to maintain quality and market price, followed by proper handling and packaging (Rajkumar *et al*., 2012). Lady finger banana (*Musa acuminate* Colla) is a variety of banana that has been widely processed into various food products, such as ripe banana chips (Nurhayati *et al*., 2014), banana pie (Ristiyana *et al*., 2022), jam (Herianto *et al*., 2015), and flour (Utomo *et al*., 2018). Akbar *et al*., (2017) also used lady finger banana (*Musa acuminate* Colla) as a research object to develop a multivariate analysis model application based on color parameters to predict Brix and pH in bananas.

Consumer preferences for fruit are determined by fruit quality which is influenced by physiological parameters such as color, starch, total soluble solids, sugar and dry matter. These parameters change during the ripening process, which causes changes in mechanical, chemical and physical properties (Jaiswal *et al*., 2012). The color of the banana peel will change during the ripening stage, followed with the development of the texture and taste of the fruit flesh which becomes softer. The color of banana peel will change from green to yellow and brown spots will appear at the ending of the shelf life which is the result of the synthesis of a number of pigments (Gomes *et al*., 2013). Monitoring the parameters that determine the quality of bananas while in the garden, the packing process and the shipping process is very necessary to produce bananas that are acceptable to consumers (Liew & Lau, 2012). Measuring the quality of bananas during the ripening period is important to keep the banana flesh in good condition, have good taste and peel color, and be able to prevent bruising (Soltani *et al*., 2011). The first stage of measuring fruit quality is evaluated based on color, luster and fruit size, the second is by measuring texture, acidity and total dissolved solids. All these parameters can provide notable information to consumers in making food fulfillment decisions. This quality measurement is mainly to maintain quality attributes in the fruit trade (Baiano *et al*., 2012).

Color is considered as the basic physical appearance of agricultural and food products. In fact, color has an important role in quality evaluation in research and food industry (Abdullah *et al*., 2004; Baiano *et al*., 2012). Color can be related to other quality parameters such as nutritional, sensory and visible or invisible damage, and can be used to help control these parameters (F. J. Francis, 1995; Pathare *et al*., 2013). Consumers' first assessment of food ingredients is based on their color, then other attributes such as taste and aroma. The color of food ingredients greatly influences the level of consumer acceptance, and therefore consumer decisions must be correct when buying food ingredients. Color is the first quality attribute assessed by consumers, and is the quality attribute of food ingredients that most influences the level of market approval. Objective measurements of the color of food ingredients are very necessary in the process of determining quality assurance and classification (Wu & Sun, 2013).

The use of color parameters to predict specific food quality indicators is still rarely explored and represents an opportunity for researchers (Sanaeifar *et al*., 2016). Texture and color are very important in determining the quality of bananas. Bananas undergo significant color and texture changes during the ripening process. Banana quality is determined by the parameters of peel color, taste and texture. The pH value is one of the key indicator of the banana quality because it determines the perception of sour and sweet bananas. In general, the more ripe a banana is, the more yellow the peel color will be or in some varieties the L, a and b (Lab) values will increase (Chen & Ramaswamy, 2002).

Currently fruit is sorted mechanically or manually based on internal quality attribute. To measure these attribute is destructive and involves manual work. Non-destructive mensuration of internal fruit quality attributes is becoming important for industry and consumers (Rajkumar *et al*., 2012). Traditional measurements use the fruit maturity index to evaluate changes in fruit peel color, softness, acidity, concentration of dissolved solids and volatile compounds (Baiano *et al*., 2012). Applications using sensors such as optical, chemical and tactile sensors correlate with human senses. Various techniques have been tried and reported to measure fruit quality parameters (Pathare *et al*., 2013).

The development of an instrument for measuring the internal quality of fruit non-destructively, which is effective and cheap, is needed to produce bananas that are high quality, acceptable to consumers, have a high selling value, and can be used as an instrument for sorting bananas to become quality raw materials for the food industry. Mathematical model that can be used as a prediction model for the internal quality of fruit is artificial neural network (ANN).

Masithoh *et al*., (2012) examined the ANN model to predict tomato quality based on RGB color parameters. Tomato quality parameters that can be predicted using the ANN model are brix, total carotene, citric acid and vitamin C. Al-Saif *et al*., (2022) used ANN to predict total dissolved solids, vitamin C, total sugar, reducing sugar and acidity from orange fruit. Huang *et al*., (2021) used ANN to predict soluble solids content, titratable acid content and fruit weight of loquat fruit using Ca, Mg, Fe, Mn, Cu, Zn, N, P and K content values from the soil and leaves of loquat trees. Abdel-Sattar *et al*., (2021) was developed an ANN model to predict total dissolved solids, total titratable acids, vitamin C, anthocyanin content and carotenoid content of peaches using data on skin color values, fruit weight, juice volume and percentage of roundness of fresh peaches. Harahap & Lubis, (2018) used the ANN model to predict oil palm fresh fruit bunches based on rainfall data and previous fresh fruit bunch yields.

2. MATERIALS AND METHODS

2.1. Materials

Lady finger banana, DM (demineralized) distilled water, distilled water, Merck buffer solution: pH 4 and pH 7.

2.2. Tools

Computer Vision System (Simanungkalit & Simanjuntak, 2020); hand refractometer Atago Master 53T; pH tester Hanna Instruments HI98107 pHep@; Pyrex beakers glass 100 ml, 250 ml and 500 ml; rinse bottle; filter cloth, mortar, personal computer (PC), Matlab R2019a and Microsoft Excel 2021 applications.

2.3. Methods

This research was carried out in two research stages. Phase I research was held at the Food Analysis Laboratory, Faculty of Agriculture, HKBP Nommensen University which consisted of: (1) taking digital images of banana fruit samples using a computer vision system from research results (Simanungkalit & Simanjuntak, 2020); (2) measuring the ºBrix of bananas using an Atago Master 53T hand refractometer; and (3) measuring the pH of bananas using the Hanna Instruments H198107 pHep@ pH tester. Phase II research was carried out using the Matlab R2019a application to analyze the most appropriate ANN architecture to be used as a prediction model for ºBrix and banana pH.

2.3.1. Phase I research methods

Fifteen (15) bunches of lady finger bananas that were of harvest age were harvested by the farmers in unripe condition and green in color. From all the lady finger bananas bunches, forty-three (43) lady finger bananas combs were obtained which were taken from the middle of the bunch. All the lady finger bananas combs were then stored for eight (8) days at room temperature (temperature ranges from 29-33ºC). Every day (from day 0 to day 7) one (1) sample of golden banana fruit was taken from the middle of the comb to be measured and analyzed in the laboratory, so that the total number of banana samples analyzed was 321 samples. With the following measurement method:

1. Taking digital photos/images of bananas using a Computer Vision System (CVS) resulting from research (Simanungkalit & Simanjuntak, 2020). Lady finger banana fruit samples that have been given a sample code are entered into the CVS image capture chamber, then photographed using a camera operated wirelessly with the Imaging Edge Desktop application as presented in Figure 1. Digital images of banana samples were transferred to a laptop and then measured for Red Green Blue (RGB) values using CVS image processing software;

Figure 1. From left to right: images of lady finger banana samples that had been taken with CVS from day 0 to day 7.

2. The golden banana fruit samples that have been photographed are then measured for total dissolved solids (ºBrix) using an Atago Master 53T hand refractometer. Before taking measurements, the Atago Master 53T hand refractometer is always calibrated using a drop of DM (demineralized) distilled water and it is ensured that the ºBrix measurement result is 0. The lady finger banana flesh is crushed using a mortar until it becomes lady finger banana pulp, then the lady finger banana pulp is filtered using a filter cloth, lady finger banana juice is then dripped onto the refractometer lens and then ºBrix measurements are taken (Akbar *et al*., 2017). Each sample of lady finger banana was measured 3 (three) times (triple). The measurement results are then recorded in the measurement results sheet;
3. The pulp of the lady finger banana fruit sample that has been completed is used for ºBrix measurements and then used to carry out pH measurements using the Hanna Instruments HI98107 pHep@ pH tester. Before taking measurements, the Hanna Instruments HI98107 pHep@ pH tester is always calibrated using Merck pH 4 and pH

7 buffer solution and ensure that the pH tester measurement results are in accordance with the buffer. 20 ml of DM distilled water (demineralized, pH = 7.0) was added to the gold banana pulp and then measurements were taken by dipping the pH tester into the gold banana pulp solution (Akbar *et al*., 2017). For each sample of lady finger banana fruit, measurements were taken 3 (three) times (triple). The measurement results are then recorded in the measurement results sheet;

2.3.2. Phase II research methods

Data of RGB, °Brix and pH measurements from 321 samples of lady finger banana fruit were then used to analyze the ANN architecture using the Matlab R2019a and Microsoft Excel 2021 applications. 70% was used for training (70% x 321 data = 225 data), for testing of 20% (20% x 321 data = 66 data) and for validation of 10% (10% x 321 data = 30 data). The ANN architectural model follows 3 ANN architectural models as in Figure 2, which was formulated from network parameters from research by Masithoh *et al*., (2012), Simanungkalit *et al*., (2013), and Simanungkalit & Naibaho, (2018). In total there are 85 ANN architectural analysis experimental units for each model with parameters as in Table 1 and Table 2. The ANN parameters in phase I research consist of number of neurons inside the hidden layer: 1, 3, 9, 27 and 81; activation functions inside the hidden layers: logsig, tansig and purelin; activation functions inside the output layer: logsig, tansig and purelin; and data transformation range: 0 – 1. The ANN parameters in phase II research consist of: training algorithms: traindx, traind, trainda, traindm, trainbfg, trainrp and trainlm; learning rate value: 0.0001; 0.001; 0.01; 0.1 and 1.

The ANN architecture consists of the number of neurons inside the input layer, number of hidden layers and the number of neurons inside the output layer. The determination of the ANN architecture is determined by the output performance of the model test results on target data/actual data (Coulibaly *et al*., 2001; Cynthia & Ismanto, 2017). Indicators commonly used in determining the best architecture are the cumulative average residual value (mean square error/MSE) and the coefficient of closeness between the model output and the actual data tested (R) (Harahap & Lubis, 2018). The best ANN prediction model of °Brix and pH of lady finger banana is determined based on the lowest

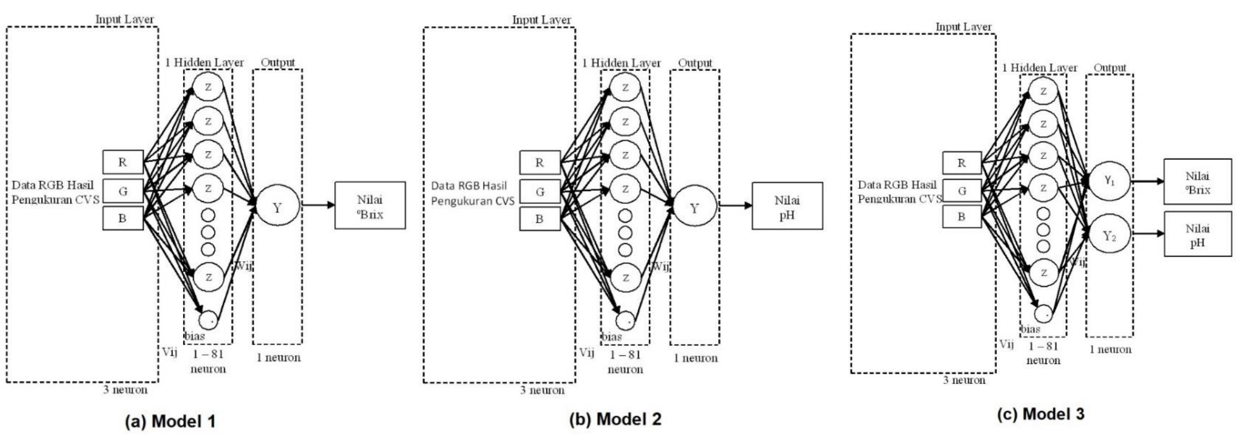

Figure 2. Architecture of the ANN model predicting °Brix and pH of lady finger banana.

Table 1. Number of ANN architectural parameters and number of phase I experimental units.

ANN Parameters	Neurons inside The Hidden Layer	Activation Function		Data Transformation Range	Total Experimental Units
		Hidden Layers	Output Layer		
Number of units	5	3	3	1	45

Table 2. Number of ANN architectural parameters and number of phase II experimental units.

ANN Parameters	Training Algorithm	Learning Rate Value	Total Experimental Units
Number of units	7	5	35

mean square error (MSE), mean absolute error (MAE) value and correlation coefficient (R) value closest to 1 from the results of training, testing and validation of the ANN architecture.

3. RESULTS AND DISCUSSION

Table 3 and 4 summarized the best model for each phase resulted from ANN after running the training and testing steps. The best models are based on the performance indicator values, namely MSE (least), MAE (least), and R (highest).

Table 3. Results of phase I analysis of the ANN models

Model	Hidden Layer	Code	Activation Function		Training Performance			Testing Performance		
			Hidden Layer	Output Layer	MSE	MAE	R	MSE	MAE	R
°Brix	3	Net16	Purelin	Logsig	0.0620	0.2027	0.5207	0.0336	0.1456	0.6468
pH	3	Net11	Logsig	Tansig	0.0243	0.1150	0.6735	0.0440	0.1659	0.7199
°Brix and pH	3	Net10	Logsig	Logsig	0.0954	0.2619	0.6538	0.0392	0.1606	0.7000

Table 4. Results of phase II analysis of the ANN models

Model	Code	Learning Rate Value	Training Algorithm	Training Performance			Testing Performance		
				MSE	MAE	R	MSE	MAE	R
°Brix	Net14	0.1	Traingda	0.0620	0.2027	0.5207	0.0336	0.1456	0.6468
pH	Net14	0.1	Traingda	0.0243	0.1150	0.6735	0.0440	0.1659	0.7199
°Brix and pH	Net13	0,01	Traingda	0.0954	0.2619	0.6538	0.0392	0.1606	0.7000

3.1. Architectural analysis of ANN model 1 (ºBrix prediction of model lady finger banana)

The ANN model 1 architecture analysis was carried out in 2 stages. Phase I consists of 45 experimental units with the analysis results presented as supplementary (Table S1). From the analysis results in phase I, an ANN architecture with the best experience performance from training and testing results was obtained, namely 16 experimental units with Net16 architectural code with the number of neurons inside the hidden layer = 3, activation function inside the hidden layer = purelin, activation function inside the output layer = tansig, performance of training results MSE (mean square error) = 0.0620; MAE (mean absolute error) = 0.2027 and correlation coefficient R = 0.5207 and test results performance MSE (mean square error) = 0.0336; MAE (mean absolute error) = 0.1456 and correlation coefficient R = 0.6468. The ºBrix values used as training and testing data are in the range of values: minimum = 4.97 and 5.27 as well as maximum = 23.93 and 23.17. The ANN Net16 architecture with the best experience performance from the training and testing results was then continued to be analyzed again in the ANN architecture analysis phase II which consisted of 35 experimental units. The results of the phase II ANN architecture analysis of the Net16 architecture are presented in Table S2. The results of the phase II architecture analysis produced an ANN architecture with the best experience performance from training and testing results, with the Net14 architecture code, namely learning rate = 0.1; learning algorithm = tradingda; performance of training results MSE (mean square error) = 0.0620; MAE (mean absolute error) = 0.2027 and correlation coefficient R = 0.5207 and test results performance MSE (mean square error) = 0.0336; MAE (mean absolute error) = 0.1456 and correlation coefficient R = 0.6468.

3.2. Architectural analysis of ANN model 2 (pH prediction model of lady finger banana)

The ANN model 2 architecture analysis was carried out in 2 stages. Phase I consists of 45 experimental units with the analysis results presented in Table S3. From the analysis results in phase I, an ANN architecture with the best experience performance from training and testing results was obtained, namely 11 experimental units with Net11 architecture code with the number of neurons inside the hidden layer = 3, activation function inside the hidden layer = logsig, activation function inside the output layer = tansig, performance of training results MSE (mean square error) = 0.0243; MAE (mean absolute error) = 0.1150 and correlation coefficient R = 0.6735 and test results performance MSE (mean square error) = 0.0440; MAE (mean absolute error) = 0.1659 and correlation coefficient R = 0.7199. The pH values used as training data are in the range of values: minimum = 4.47 and 4.47 as well as maximum = 5.97 and 5.80. The Net11 ANN architecture with the best experience performance from the training and testing results was then continued to be analyzed again in the phase II ANN architecture analysis which consisted of 35 experimental units. The results of the phase II ANN architecture analysis of the Net11 architecture are presented in Table S4. The results of the phase II architecture analysis produced an ANN architecture with the best experience performance from training and testing results, with the Net14 architecture code, namely learning rate = 0.1; learning algorithm = tradingda; performance of training results MSE (mean square error) = 0.0243; MAE (mean absolute error) = 0.1150 and correlation coefficient R = 0.6735 and test results performance MSE (mean square error) = 0.0440; MAE (mean absolute error) = 0.1659 and correlation coefficient R = 0.7199.

3.3. Architectural analysis of ANN model 3 (ºBrix and pH prediction of lady finger banana)

The ANN model 3 architectural analysis was carried out in 2 stages. Phase I consists of 45 experimental units with the analysis results presented in Table S5. From the analysis results in phase I, an ANN architecture with the best experience performance from training and testing results was obtained, namely 10 experimental units with Net10 architectural code with the number of neurons inside the hidden layer = 3, activation function inside the hidden layer = logsig, activation function inside the output layer = logsig, training results performance MSE (mean square error) = 0.0954; MAE (mean absolute error) = 0.2619 and correlation coefficient R = 0.6538 and test results performance MSE (mean square error) = 0.0392; MAE (mean absolute error) = 0.1606 and correlation coefficient R = 0.7000. The ºBrix and pH values used as training data are respectively in the range of values: minimum = 4.97 and 4.47 and maximum = 23.93 and 5.97. Meanwhile, the testing data is in a range of values: minimum = 5.27 and 4.47 and maximum = 23.17 and 5.80. The Net10 ANN architecture with the best experience performance from the training and testing results was then continued to be analyzed again in phase II of the ANN architecture analysis which consisted of 35 experimental units. The results of the phase II ANN architecture analysis of the Net11 architecture are presented in Table S6. The results of the phase II architecture analysis produced an ANN architecture with the best experience performance from training and testing results, with the Net13 architecture code, namely learning rate = 0.01; learning algorithm = tradingda; performance of training results MSE (mean square error) = 0.0954; MAE (mean absolute error) = 0.2619 and correlation coefficient R = 0.6538 and test results performance MSE (mean square error) = 0.0392; MAE (mean absolute error) = 0.1606 and correlation coefficient R = 0.7000.

The best ANN architecture analysis results are determined by paying attention to the R^2 correlation coefficient value which is closest to 1 (one) and the smallest mean square error (MSE) and mean absolute error (MAE) values. An R^2 value is commonly used to assess the result of a precise model, while MSE, MARE and MAE can be used to assess the accuracy of a model by residual analysis (Al-Saif *et al*., 2022).

The analysis outcome of Model 1, Model 2 and Model 3 show that the architecture with the best prediction performance from each model is the architecture consisting of 3 (three) neuron units in the hidden layer. This is in line with the statement of Kaveh & Chayjan, (2014) and Gholipoor & Nadali, (2019) that if neurons are insufficiently used, this avoids the network from learning. Overfitting can happen when there are too many hidden neurons, which hinders the ability to generalize the input/output relationship but enhances network learning and data memorization.

3.4. Validation of ANN model 1 architecture (ºBrix prediction model for lady finger banana)

The ANN model 1 architecture from the results of phase II ANN architecture analysis with the Net14 code which had the best predictive performance was then validated using data from ºBrix measurements of lady finger banana in the laboratory. The ºBrix values used as validation data are in the range of values: minimum = 18.57 and maximum = 22.03. The ºBrix prediction results for lady finger banana from Net14 were then compared with the data from lady finger banana ºBrix measurements in the laboratory. The validation results are presented in Table 5.

3.5. Validation of ANN model 2 architecture (pH prediction model for lady finger banana)

The validation results are presented in Table 6. The ANN model 2 architecture from the results of the phase II ANN architecture analysis with the Net14 code which had the best prediction performance was then validated using data

Table 5. Validation results of ANN model 1 architecture (output results predicting ºBrix values for lady finger banana).

No	Laboratory Measurement Results	ANN Prediction Results	ANN Architectural Error	Mean Square Error (MSE)	Mean Absolute Error (MAE)	Correlation Coefficient (R)
1	18.57	21.95	0.189	0.0356	0.1888	0.4036
2	20.80	22.85	0.114	0.0131	0.1145	
3	18.60	21.63	0.169	0.0286	0.1690	
4	20.03	22.04	0.112	0.0126	0.1121	
5	20.97	22.77	0.101	0.0101	0.1007	
6	22.03	22.62	0.033	0.0011	0.0327	
7	19.90	22.26	0.132	0.0174	0.1320	
8	20.97	22.92	0.109	0.0118	0.1088	
9	20.93	22.98	0.115	0.0131	0.1146	
10	21.53	23.00	0.082	0.0068	0.0824	
11	20.57	22.97	0.134	0.0179	0.1339	
12	20.83	22.95	0.118	0.0140	0.1184	
13	19.93	23.02	0.173	0.0298	0.1726	
14	21.43	23.07	0.092	0.0084	0.0919	
15	19.90	22.95	0.170	0.0290	0.1704	
16	19.43	22.78	0.187	0.0351	0.1873	
17	19.33	22.81	0.194	0.0378	0.1943	
18	21.10	22.86	0.098	0.0096	0.0981	
19	19.90	22.86	0.165	0.0273	0.1651	
20	21.07	22.81	0.097	0.0094	0.0971	
21	20.80	22.84	0.114	0.0130	0.1140	
22	19.23	22.87	0.203	0.0414	0.2034	
23	19.17	22.83	0.204	0.0417	0.2042	
24	20.40	22.85	0.137	0.0187	0.1366	
25	20.70	22.83	0.119	0.0142	0.1192	
26	18.90	22.86	0.221	0.0489	0.2212	
27	20.00	22.84	0.158	0.0251	0.1585	
28	18.60	22.88	0.239	0.0573	0.2393	
29	19.03	22.86	0.214	0.0458	0.2141	
30	19.67	22.82	0.176	0.0309	0.1758	
	Validation Results			**0.0235**	**0.1457**	**0.4036**

from measurements of the pH of lady finger banana in the laboratory. The pH values used as validation data are in the range of values: minimum = 4.5 and maximum = 5.77. The pH prediction results for lady finger banana from Net14 were then compared with the data from measurements of the pH of lady finger banana in the laboratory.

3.6. Validation of ANN model 3 architecture (ºBrix and pH prediction model for lady finger banana)

The ANN model 3 architecture from the results of the phase II ANN architecture analysis with the Net13 code which had the best experience performance was then validated using data from ºBrix and pH measurements of lady finger banana in the laboratory. The ºBrix and pH values used as validation data are in the range of values: minimum = 18.57 and 4.5 and maximum = 22.03 and 5.77. The prediction results of ºBrix and pH of lady finger banana from Net13 were then compared with data from measurements of ºBrix and pH of lady finger banana in the laboratory. The validation results are presented in Table 7. The validation results show that of the three predictive ANN architecture models analyzed, the ANN architecture model 3 with output results in the form of predicted ºBrix values and pH values for lady finger banana is the best model to be used as a prediction model for °Brix values and pH values for the lady finger banana. The MSE and MAE values from the validation results of the best model 3 ANN architecture are 0.0289 and 0.1474 with a correlation coefficient value of R = 0.7889. Sarwono (2006) stated R values of 0.75 – 0.99 indicates strong closeness. This means the model has strong closeness and is considered accurate for predicting results.

Table 6. Validation results of ANN model 2 architecture (output results predicting the pH of lady finger banana).

No	Laboratory Measurement Results	ANN Prediction Results	ANN Architectural Error	MSE	MAE	R
1	4.77	4.30	-0.353	0.125	0.353	0.5685
2	5.00	3.98	-0.770	0.593	0.770	
3	4.80	4.28	-0.390	0.152	0.390	
4	4.50	3.89	-0.457	0.209	0.457	
5	4.80	3.64	-0.872	0.760	0.872	
6	4.80	3.57	-0.922	0.851	0.922	
7	4.53	4.84	0.232	0.054	0.232	
8	5.10	3.58	-1.140	1.300	1.140	
9	5.17	3.58	-1.196	1.430	1.196	
10	5.10	3.56	-1.162	1.349	1.162	
11	5.13	3.74	-1.046	1.093	1.046	
12	5.37	3.90	-1.103	1.217	1.103	
13	5.37	3.57	-1.353	1.831	1.353	
14	5.33	3.54	-1.343	1.804	1.343	
15	5.40	3.68	-1.292	1.669	1.292	
16	5.40	5.50	0.079	0.006	0.079	
17	5.40	5.70	0.222	0.049	0.222	
18	5.33	5.67	0.255	0.065	0.255	
19	5.40	5.56	0.118	0.014	0.118	
20	5.67	5.46	-0.156	0.024	0.156	
21	5.63	4.72	-0.683	0.466	0.683	
22	5.57	5.52	-0.039	0.001	0.039	
23	5.60	5.64	0.031	0.001	0.031	
24	5.50	5.55	0.034	0.001	0.034	
25	5.63	5.54	-0.070	0.005	0.070	
26	5.47	4.72	-0.567	0.322	0.567	
27	5.47	5.58	0.086	0.007	0.086	
28	5.77	5.70	-0.049	0.002	0.049	
29	5.70	4.80	-0.677	0.458	0.677	
30	5.77	5.10	-0.502	0.252	0.502	
	Validation Results			**0.537**	**0.573**	**0.5685**

Table 7. Validation results of ANN model 3 architecture (output results predicting the ºBrix and pH of lady finger banana).

No	Measurement		ANN Prediction		ANN Architectural Error		MSE		MAE		(R)
	pH	Brix	pH	Brix	pH	Brix	pH	Brix	pH	Brix	
1	4.77	18.57	4.78	23.10	0.0071	0.2530	0.0001	0.0640	0.0071	0.2530	0.7889
2	5.00	20.80	4.97	23.16	-0.0241	0.1318	0.0006	0.0174	0.0241	0.1318	
3	4.80	18.60	4.82	22.93	0.0149	0.2421	0.0002	0.0586	0.0149	0.2421	
4	4.50	20.03	4.78	23.08	0.2137	0.1705	0.0457	0.0291	0.2137	0.1705	
5	4.80	20.97	4.83	23.16	0.0240	0.1221	0.0006	0.0149	0.0240	0.1221	
6	4.80	22.03	4.77	23.15	-0.0263	0.0624	0.0007	0.0039	0.0263	0.0624	
7	4.53	19.90	4.77	23.15	0.1791	0.1816	0.0321	0.0330	0.1791	0.1816	
8	5.10	20.97	4.95	23.16	-0.1140	0.1223	0.0130	0.0150	0.1140	0.1223	
9	5.17	20.93	5.06	23.16	-0.0817	0.1246	0.0067	0.0155	0.0817	0.1246	
10	5.10	21.53	5.15	23.16	0.0371	0.0911	0.0014	0.0083	0.0371	0.0911	
11	5.13	20.57	5.16	23.16	0.0258	0.1448	0.0007	0.0210	0.0258	0.1448	
12	5.37	20.83	5.20	23.16	-0.1315	0.1303	0.0173	0.0170	0.1315	0.1303	
13	5.37	19.93	5.18	23.16	-0.1442	0.1805	0.0208	0.0326	0.1442	0.1805	
14	5.33	21.43	5.34	23.16	0.0089	0.0968	0.0001	0.0094	0.0089	0.0968	
15	5.40	19.90	5.12	23.16	-0.2106	0.1822	0.0444	0.0332	0.2106	0.1822	
16	5.40	19.43	5.25	23.16	-0.1132	0.2084	0.0128	0.0435	0.1132	0.2084	
17	5.40	19.33	5.44	23.16	0.0290	0.2141	0.0008	0.0458	0.0290	0.2141	

Table 7. Validation (Continued).

No	Measurement		ANN Prediction		ANN Architectural Error		MSE		MAE		(R)
	pH	Brix	pH	Brix	pH	Brix	pH	Brix	pH	Brix	
18	5.33	21.10	5.39	23.16	0.0475	0.1152	0.0023	0.0133	0.0475	0.1152	
19	5.40	19.90	5.33	23.16	-0.0499	0.1822	0.0025	0.0332	0.0499	0.1822	
20	5.67	21.07	5.32	23.16	-0.2622	0.1168	0.0688	0.0136	0.2622	0.1168	
21	5.63	20.80	5.15	23.16	-0.3633	0.1319	0.1320	0.0174	0.3633	0.1319	
22	5.57	19.23	5.33	23.16	-0.1805	0.2197	0.0326	0.0483	0.1805	0.2197	
23	5.60	19.17	5.37	23.16	-0.1702	0.2230	0.0290	0.0497	0.1702	0.2230	
24	5.50	20.40	5.38	23.16	-0.0921	0.1543	0.0085	0.0238	0.0921	0.1543	
25	5.63	20.70	5.35	23.16	-0.2122	0.1375	0.0450	0.0189	0.2122	0.1375	
26	5.47	18.90	5.19	23.16	-0.2103	0.2380	0.0442	0.0567	0.2103	0.2380	
27	5.47	20.00	5.34	23.16	-0.0952	0.1767	0.0091	0.0312	0.0952	0.1767	
28	5.77	18.60	5.70	23.16	-0.0539	0.2548	0.0029	0.0649	0.0539	0.2548	
29	5.70	19.03	5.25	23.16	-0.3400	0.2308	0.1156	0.0533	0.3400	0.2308	
30	5.77	19.67	5.31	23.16	-0.3464	0.1949	0.1200	0.0380	0.3464	0.1949	
	Average						**0.0270**	**0.0308**	**0.1270**	**0.1678**	**0.7889**
	Validation Results						**0.0289**		**0.1474**		**0.7889**

ANN can learn complex relationships and simplify outcomes from pattern of input and output data. The main benefit of an ANN model is it ability to predict variety of non-linear functions, allowing to develop the most accurate prediction model without the need to determine the most suitable function beforehand. In conclusion, ANN is an effective method to use in simulating complex problems. An accurate of ANN architectural model and the appropriate learning algorithm can impact how well the ANN can solve problems (Baykal & Yildirim, 2013).

4. CONCLUSION

The artificial neural network model can be used as a prediction model for the ºBrix and pH values of lady finger banana based on the RGB (Red Green Blue) color parameters of the peel of lady finger banana. The artificial neural network model with the best predictive performance to be used as a prediction model for the ºBrix and pH values of lady finger banana based on the RGB (Red Green Blue) color parameters of the lady finger banana peel, was the ANN model 3 architecture with ANN output in the form of ºBrix and pH values of lady finger banana. The best model 3 ANN architecture consist of: number of neurons inside the hidden layer = 3 units; activation function inside hidden layer = logsig; activation function inside the output layer = logsig; learning rate value = 0,01; learning algorithm = traingda; with MSE (mean square error), MAE (mean absolute error) and coefficient of correlation (R) from training results 0.0954; 0.2619 and 0.6538; test results 0.0392; 0.1606 and 0.7000 and validation results 0.0289; 0.1474 and 0.7889.

ACKNOWLEDGMENTS

Thanks are expressed to the Directorate General for Strengthening Research and Development, Ministry of Research, Technology and Higher Education of the Republic of Indonesia for the Beginner Lecturer Research Grant 2023.

CONFLICT OF INTEREST

The author declared that there was no conflict of interest in completing this study.

REFERENCES

Abdel-Sattar, M., Aboukarima, A.M., & Alnahdi, B.M. (2021). Application of artificial neural network and support vector regression in predicting mass of ber fruits (*Ziziphus mauritiana* Lamk.) based on fruit axial dimensions. *PLoS ONE*, ***16***(1), e0245228. https://doi.org/10.1371/JOURNAL.PONE.0245228

Abdullah, M.Z., Guan, L.C., Lim, K.C., & Karim, A.A. (2004). The applications of computer vision system and tomographic radar imaging for assessing physical properties of food. *Journal of Food Engineering*, ***61***(1), 125–135. https://doi.org/10.1016/S0260-8774(03)00194-8

Akbar, Y.M., Masithoh, R.E., & Khuriyati, N. (2017). Aplikasi analisis multivariat berdasarkan warna untuk memprediksi Brix dan pH pada pisang. *Agritech, **37***(1), 108-114. https://doi.org/10.22146/agritech.17022

Al-Saif, A.M., Abdel-Sattar, M., Eshra, D.H., Sas-Paszt, L., & Mattar, M.A. (2022). Predicting the chemical attributes of fresh citrus fruits using artificial neural network and linear regression models. *Horticulturae 2022, **8***(11), 1016. https://doi.org/10.3390/HORTICULTURAE8111016

Baiano, A., Terracone, C., Peri, G., & Romaniello, R. (2012). Application of hyperspectral imaging for prediction of physico-chemical and sensory characteristics of table grapes. *Computers and Electronics in Agriculture*, ***87***(2012), 142–151. https://doi.org/10.1016/j.compag.2012.06.002

Baykal, H., & Yildirim, H.K. (2013). Application of artificial neural networks (ANNs) in wine technology. *Critical Reviews in Food Science and Nutritio*n, ***53***(5), 415–421. https://doi.org/10.1080/10408398.2010.540359

Chen, C.R., & Ramaswamy, H.S. (2002). Color and texture change kinetics in ripening bananas. *LWT - Food Science and Technology*, ***35***(5), 415–419. https://doi.org/https://doi.org/10.1006/fstl.2001.0875

Coulibaly, P., Anctil, F., Aravena, R., & Bobée, B. (2001). Artificial neural network modeling of water table depth fluctuations. *Water Resources Research*, ***37***(4), 885–896. https://doi.org/10.1029/2000WR900368

Cynthia, E.P., & Ismanto, E. (2017). Jaringan syaraf tiruan algoritma backpropagation dalam memprediksi ketersediaan komoditi pangan Provinsi Riau. *Seminar Nasional Teknologi Informasi Komunikasi dan Industri*, 271–282. https://ejournal.uin-suska.ac.id/index.php/SNTIKI/article/view/3306

Francis, F.J. (1995). Quality as influenced by color. *Food Quality and Preference*, ***6***(3), 149–155.

Gholipoor, M., & Nadali, F. (2019). Fruit yield prediction of pepper using artificial neural network. *Scientia Horticulturae, **250***, 249–253. https://doi.org/10.1016/J.SCIENTA.2019.02.040

Gomes, J.F.S., Vieira, R.R., & Leta, F.R. (2013). Colorimetric indicator for classification of bananas during ripening. *Scientia Horticulturae*, ***150***(2013), 201–205. https://doi.org/10.1016/j.scienta.2012.11.014

Harahap, I.Y., & Lubis, M.E.S. (2018). Penggunaan model jaringan saraf tiruan (artificial neuron network) untuk memprediksi hasil tandan buah segar (TBS) kelapa sawit berdasar curah hujan dan hasil TBS sebelumnya. *Jurnal Penelitian Kelapa Sawit*, ***26***(2), 59–70. https://doi.org/10.22302/IOPRI.JUR.JPKS.V26I2.42

Herianto, A., Hamzah, F., & Yusmarini. (2015). Studi pemanfaatan pisang mas (*Musa acuminata*) dan buah naga merah (*Hylocereus polyrhizus*) dalam pembuatan selai. *JOM FAPERTA, **2***(2).

Huang, X., Wang, H., Qu, S., Luo, W., & Gao, Z. (2021). Using artificial neural network in predicting the key fruit quality of loquat. *Food Science & Nutrition*, ***9***(3), 1780–1791. https://doi.org/10.1002/FSN3.2166

Jaiswal, P., Jha, S.N., & Bharadwaj, R. (2012). Non-destructive prediction of quality of intact banana using spectroscopy. *Scientia Horticulturae*, ***135***, 14–22. https://doi.org/10.1016/j.scienta.2011.11.021

Jaiswal, P., Jha, S.N., Kaur, P.P., Bhardwaj, R., Singh, A.K., & Wadhawan, V. (2014). Prediction of textural attributes using color values of banana (*Musa sapientum*) during ripening. *Journal of Food Science and Technology*, ***51***(6), 1179–1184. https://doi.org/10.1007/s13197-012-0614-2

Kaveh, M., & Chayjan, R.A. (2014). Prediction of some physical and drying properties of terebinth fruit (*Pistacia atlantica* L.) using Artificial Neural Networks. *Acta Scientiarum Polonorum. Technologia Alimentaria*, ***13***(1), 65–78. https://doi.org/10.17306/J.AFS.2014.1.6

Liew, & Lau, C.Y. (2012). Determination of quality parameters in Cavendish banana during ripening by NIR spectroscopy. *In International Food Research Journal, **19***(2), 751-758.

Masithoh, R.E., Rahardjo, B., Sutiarso, L., & Hardjoko, A. (2012). Model jaringan syaraf tiruan untuk memprediksi kualitas tomat berdasarkan parameter warna RGB. *Agritech*, ***32***(4), 411-417.

Nurhayati, Tamtarini, Jayus, Ruriani, E., & Hidayati, L.N. (2014). Sifat-sifat prebiotik ripe banana chip (RBC) *Musa sinensis*. *Jurnal Agroteknologi*, ***8***(1), 94–100.

Pathare, P.B., Opara, U.L., & Al-Said, F.A.J. (2013). Colour measurement and analysis in fresh and processed foods: A review. In *Food and Bioprocess Technology,* ***6***(1), 36–60. https://doi.org/10.1007/s11947-012-0867-9

Rajkumar, P., Wang, N., EImasry, G., Raghavan, G.S.V., & Gariepy, Y. (2012). Studies on banana fruit quality and maturity stages using hyperspectral imaging. *Journal of Food Engineering*, ***108***(1), 194–200. https://doi.org/10.1016/j.jfoodeng.2011.05.002

Ristiyana, S., Tanzil, A.I., Saputra, T.W., & Purnamasari, I. (2022). Pelatihan pembuatan pie pisang sebagai makanan khas di Desa Kandangtepus Kecamatan Senduro Kabupaten Lumajang. *Jurnal Pengabdian Magister Pendidikan IPA*, ***5***(1), 169–172.

Sanaeifar, A., Bakhshipour, A., & De La Guardia, M. (2016). Prediction of banana quality indices from color features using support vector regression. *Talanta*, ***148***(2016), 54–61. https://doi.org/10.1016/j.talanta.2015.10.073

Sheehy, T., & Sharma, S. (2011). The nutrition transition in the Republic of Ireland: Trends in energy and nutrient supply from 1961 to 2007 using Food and Agriculture Organization food balance sheets. *British Journal of Nutrition*, ***106***(7), 1078–1089. https://doi.org/10.1017/S0007114511001395

Simanungkalit, F.J., & Naibaho, B. (2018). Sistem pendukung keputusan monitoring dan peramalan harga beras Kabupaten Deli Serdang, Sumatera Utara. *Agritech,* ***38***(2), 208-216. https://doi.org/10.22146/agritech.16833

Simanungkalit, F.J., & Simanjuntak, R. (2020). Rancang bangun computer vision system (CVS) sebagai instrumen pengukuran warna buah. *Jurnal Agritech*, ***40***(1), 21–30. https://doi.org/10.22146/agritech.29102

Simanungkalit, F.J., Sutiarso, L., & Purwadi, D. (2013). Sistem pendukung keputusan berbasis jaringan syaraf tiruan untuk peramalan harga komoditas tanaman pangan. *Jurnal Agritech*, ***33***(1), 70–80.

Soltani, M., Alimardani, R., & Omid, M. (2011). Evaluating banana ripening status from measuring dielectric properties. *Journal of Food Engineering*, ***105***(4), 625–631. https://doi.org/10.1016/j.jfoodeng.2011.03.032

Utomo, B., Marsiti, C.I.R., & Damiati. (2018). Uji kualitas tepung pisang mas (*Musa Acuminata*). *Jurnal Bosaparis: Pendidikan Kesejahteraan Keluarga*, ***9***(3), 189–199. https://doi.org/10.23887/jjpkk.v9i3.22146

Wu, D., & Sun, D.W. (2013). Colour measurements by computer vision for food quality control - A review. *Trends in Food Science and Technology*, ***29***(1), 5–20. https://doi.org/10.1016/j.tifs.2012.08.004