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Mathematical Model of Drying Edamame (*Glycine max* (L.) Merill) Using Food Dehydrator Technology Based on Multiple Linear Regression (MLR) and Artificial Neural Network (ANN)

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ABSTRACT

Edamame is included in perishable products or products that have a fairly short shelf life if post-harvest processing is not carried out. One of the post-harvest processing methods commonly used by the community is drying. The purpose of this study was to analyze the drying process of edamame related to the MLRL and ANN models. This study used a completely randomized design (CRD) with three variations of air velocity, namely 1 m/s, 3 m/s, and 5 m/s. Data collection was repeated three times every 30 minutes until 330 minutes. Multiple linear regression (MLR) model training and validation produce accuracy values of 88.03 and 82.23, and the value of R2 of 0.93 and 0.90. While the training and validation of the artificial neural network (ANN) model resulted in accuracy values of 88.34 and 82.15, and R2 values of 0.93 and 0.90.

1. INTRODUCTION

Soybean (*Glycine max* Mexx) is a food ingredient that has very high vegetable protein, is safe for consumption and the price is relatively more affordable when compared to animal protein sources. The protein content in soybeans is 35% and contains vitamins (vitamins A, E, K and several types of B vitamins) which are good for health. In Indonesia, soybeans are widely used as raw materials for processed products such as tofu, tempeh, soy milk, soy sauce and tauco. One type of soybean that has been cultivated in Indonesia is edamame soybean (*Glycine max* (L.) Merril) or better known as Japanese soybean (Akmalovna, 2022).

Edamame is included in perishable products or products that have a fairly short shelf life if post-harvest processing is not carried out. One of the post-harvest processing methods commonly used by the community is drying. Drying is the process of removing water from an agricultural material to the equilibrium moisture content with the surrounding air (An *et al.*, 2022). Drying has many purposes including maintaining the shelf life of a material and reducing the moisture content of the material to limit the growth of microbes that can damage the product. In addition, reduced water content can maintain quality characteristics such as taste and nutritional value (Wijaya & Hariono, 2020).

The protein content of edamame is more than 40% on averagei, ncluding all the essential amino acids that are not owned by other food crops. Edamame also contains high amounts of calcium, so it can strengthen teeth, bones and prevent osteoporosis. Phytoestrogens contained in edamame can also reduce the risk of heart disease, lower cholesterol and also reduce pain for post-menopausal women (Hariono *et al.*, 2018).

Edamame in Japanese is commonly referred to as a branched bean and *mao dou* in Chinese (hairy bean). This vegetable soybean originated in China more than 2000 years ago. Edamame is the same species as soybeans (*Glycine max* (L.) Merrill), but has larger seeds, a sweeter taste, smoother texture, and is easily digested by the body. These nutritious nuts taste good and are good for consumption. Edamame contains about 38% protein, and for example in 1.5 cups of edamame there are 11 grams of protein, while the average adult needs 46-63 grams per day. Edamame is also rich in calcium, vitamin A, and phytoestrogens (plant-produced estrogens) (Yudiastuti, 2021).

1.1. Drying Rate

In general drying can be interpreted as a reduction in the water content of a food product. Drying is the process of removing water from an agricultural material to a moisture content balance with the surrounding air or at a water content level where the quality of agricultural materials can be avoided from fungal attacks, insect activity and enzymes (Argo & Ubaidillah, 2020). The main purpose of drying is to evaporate the water content in the material so that the shelf life of the material becomes longer. Drying has a mechanism, namely the air in the drying process has a function as a heat provider to the material, so that evaporation of water will occur. Another function of the air is to transport water vapor to be released by the dried material. The speed of drying depends on the speed of the air, if the speed of the air is increased, the drying will be faster as well. When the final moisture content begins to reach equilibrium, it will make the drying time also increase or in other words faster. The factors that affect the drying process are (1) Physical and chemical properties of foodstuffs, (2) Arrangement of the composition of food ingredients, (3) Physical properties of the environment around the dryer, (4) The process of transferring from the heating medium to the material being dried is a two-step process during drying (Kamila *et al.*, 2019). Drying time determines how long the material is in contact with heat. Since most foodstuffs are heat sensitive, the maximum drying time should be used, i.e. the desired moisture content of the final product has been achieved with a short drying time. Drying with a high temperature and short time can reduce food spoilage more than a longer drying time and lower temperature. For example, if you are going to dry beans, drying with a rack dryer at 80 ^{o}C for 4 hours will produce dry beans that have better quality than drying for 2 days (Santos *et al.*, 2020).

Drying rate is the amount of time-based decrease in water content in food which is much influenced by the physical and chemical properties. It is very important to analyze the drying rate to determine the process of decreasing the water content that occurs from the beginning of the drying process until it reaches a constant water content. Importance drying rate is the basis for developing a rate prediction model drying. Predictive models can help interpret drying results without the need to do real experiments in the field (Díaz *et al*, 2018).

1.2. Artificial Neural Network (ANN)

Networking is an efficient way to map and provide solutions to complex problems. There are various types of networks that can be built but basically all networks consist of two components, namely a set of nodes and the relationship between these nodes (connections) (Wijaya *et al.*, 2020). One type of network sees these nodes as “artificial neurons”. This network is called an artificial neural network. An artificial neural network (ANN) is a computational model and artificial representation of a biological neural network (brain). This network attempts to simulate the learning process in a biological neural network (Ojediran *et al.*, 2020). The term artificial is used because this neural network is implemented using a computer program that is able to complete a number of calculation processes during the learning process. Artificial neural networks have been widely used in various fields such as engineering, medicine and finance (Cabaneros *et al*., 2019). Application ANN in agricultural engineering research are increasing in many areas including plant growth modeling (Aji *et al*., 2020), prediction rice amylose content (Saputra *et al*., 2022), prediction of biodiesel yield (Haryanto *et al*., 2020), and so on.

Biological neural networks consist of millions of nerve cells in charge of processing information. Nerve cells will receive signals/information through synapses located in the dendrites or nerve cell membranes (neurons). Received information that meets a certain threshold will activate neurons and send a response through the axon (Sun *et al*., 2019). Like biological neural networks, artificial neural networks also consist of several neurons called nodes and there are connections between these nodes (Adhitya *et al.*, 2017). These nodes will transform the information received through the outgoing connection to other neurons. In artificial neural networks, this relationship is known as weight. In other words, weights have the same function as dendrites or axons in biological neural networks. Information which is an input will be processed by a propagation function which will add up the values of all weights and will be compared with a certain threshold value through the activation function of each node. If the input passes the threshold, the node will be activated and will send output to all nodes associated with it (Chokphoemphun, 2018). In an artificial neural network, the nodes will be collected in layers called node layers. The information provided on the artificial neural network will be propagated layer to layer, starting from the input layer to the output layer through another layer known as the hidden layer (Cabaneros *et al*., 2019). The propagation process can be either backward or forward propagation and this process depends on the learning algorithm used on the network (Yudiastuti *et al*., 2021).

Several learning methods that are currently known include the hebb rule, perceptron, delta rule and backpropagation. Among the various learning methods, backpropagation is the most commonly used learning method (Guiné, 2019). This learning process is included in the supervised learning method. The learning process with backpropagation consists of two stages, namely the forward propagation stage and the backward propagation stage. In the forward propagation stage, the value or information that enters the input layer will be propagated through the network to the output layer. The resulting output value is compared with the expected output value so that the error value is obtained (Sarkar *et al.*, 2021). This error value is then used to correct the existing weights in the backward propagation stage. This process will continue to repeat until a certain condition becomes a condition for stopping the learning process (Kaveh *et al.*, 2018). This condition can be in the form of an error value or a certain number of iterations which if it has been achieved means the learning process has been completed (Liu *et al.*, 2020).

2. MATERIALS AND METHODS

The research was carried out during March-July 2022 at the Politeknik Negeri Jember, Indonesia. This study used a completely randomized design (CRD) with three variations of air velocity, namely 1 m/s, 3 m/s, and 5 m/s. Data collection was repeated three times every 30 min until 330 min.

2.1. Materials and Equipment

The equipment used in this research is a rack type food dehydrator, thermometer gun, digital scales, and thermocuples. The food dehydrator is designed to use iron as the main ingredient with a 1500 Watt electric heater as its heating power. The dimensions of this dryer are 70 cm x 80 cm x 80 cm for the rack and 100 cm for the height of the iron frame with a drying temperature of 40°C–60°C for 6–8 hours according to the object of the material being dried. The fan mounted on the dryer as a hot air blower measures 16 inches with a power of 18 Watts with adjustable speeds of 1, 3 and 5 m/s.

The material used is fresh edamame which has been ground as much as 2,400 grams for three repetitions of drying or 800 grams for each drying process. The fresh edamame as the research sample was obtained from the Tanjung market, Jember Regency with a moisture content of 73-78% material.

2.2. Determination of Moisture Content

This analysis begins by finding the total water content of the material first using the thermogravimetric method. This method is done by inserting a sample of 3 grams (milled edamame) into the oven for 24 hours at a temperature of 105°C with three replications. The water content of edamame is the moisture content of the wet basis which is calculated by Equation 1 :

$$M0 = \frac{W0-Wt}{W0}\ x\ 100\ \% \tag{1}$$

with M_0 = fresh edamame initial moisture content (%); W_0 = weight before oven (grams); and Wt = weight after oven (grams).

2.3. Material Drying

The parameter measured in this study was the weight of ground edamame (Wt) at each measurement time (30 minutes). Sample dried by forced convection by blowing hot air with a temperature of 70°C and the air rate in the drying chamber has three variations, namely 1, 3 and 5 m/sec from the data of the SATO brand anemometer, SK27V (0–40 m/s). Weighing of the material was carried out every half hour to determine the weight of the water lost and stops when the dry sample weight reaches a constant condition and does not decrease in weight or in this study up to 6 hours. Edamame drying was carried out nine times, namely three repetitions at three variations of air velocity in drying.

2.4. Statistic Analysis

Statistical analysis was carried out on the average value of the sum of the drying rate values for each measurement time (30 minutes) on three replications in each variation of the drying air rate. Statistical analysis used is a one-way test of variance with a level 99% significance and will proceed to Duncan Multiple Range Test (DMRT) if it is proven to be significantly different.

2.5. Development of Multiple Linear Regression (MLR) Model

The MLR model was made to obtain a linear equation between the drying time variable and the air rate in the drying chamber as the independent variable and moisture content as the dependent variable. The linear equation formed from the MLR model is as in Equation 2.

$$y = ax_1 + bx_2 + k \tag{2}$$

where y = water content value (%); x_1 = drying time (hours); x_2 = drying air speed (m/s); a = coefficient of x_1; b = coefficient of x_2; and k = equation constant.

2.6. Artificial Neural Network (ANN) Model Development

The ANN model was made to obtain a non-linear equation between the variable drying time and drying air rate as the independent variable and moisture content as the dependent variable. The ANN model developed as shown in Figure 1 is a backpropagation type ANN with a supervised training method.

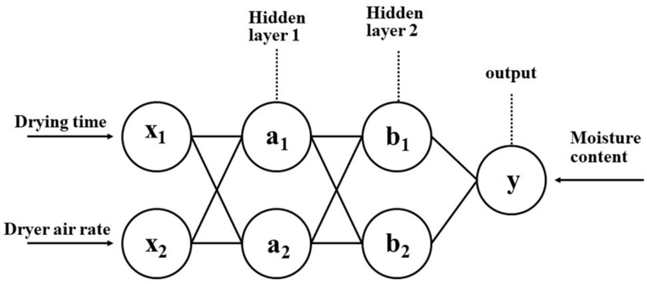

Figure 1. ANN architecture for drying rate prediction

The network architecture used is 2-2-2-1, which means 2 input nodes, 2 hidden layer 1 nodes, 2 hidden layer 2 nodes, and 1 output node. The type of network training used is trainlm (Levenberg Marquardt) with a network learning rate of 0.01 and an iteration of 1,000 times.Variation of activation function is a combination of activation function logsig and tansig in the ANN architecture. the activation functions that were trained and tested amounted to eight variations, namely logsig-logsig-logsig, logsig-tansig-logsig, tansig-tansig-logsig, tansig-logsig-logsig, tansig-logsig-tansig, tansig-tansig, logsig-tansig- tansig and logsig-logsig-tansig.

2.7. Model Validation

MLR model and the ANN model were tested for accuracy with the Mean Absolute Percentage Error (MAPE) value and the coefficient of determination (R^2). The MAPE test as in Equation 3 is a test to measure the performance of the model by measuring the magnitude of the estimation error percentage between the observed value and the predicted value. The lower the MAPE value, the more accurate the model.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{O_i - P_i}{O_i}\right] \times 100\% \tag{3}$$

$$Accuracy = 100\% - MAPE \tag{4}$$

3. RESULTS AND DISCUSSION

In Figure 2 it can be seen that the greater the air velocity in the drying chamber used in this study, the greater the decrease in water content. The water content used at the beginning of the test at each drying air rate (1, 3, and 5 m/s) and use temperature 70 ^{o}C was 74.12%. The rate of decrease in water content in the three drying air rates moves exponentially which shows a rapid decrease in the first two hours and then moves slowly until it reaches a constant moisture content.

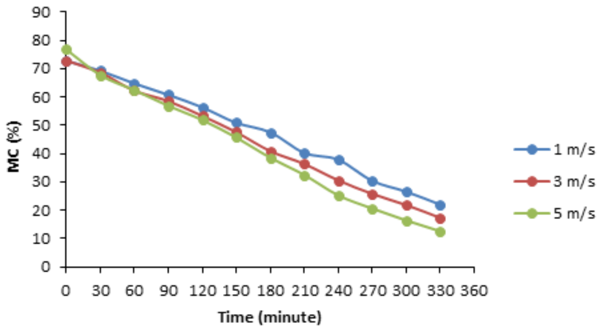

Figure 2. Drying rate on variations of drying air rate

The above data is continued to find the standard deviation of each treatment. In Figure 3, it can be seen that each treatment gave a different final result of water content. at drying air rates of 1, 3 and 5 m/s the final moisture content of the material was 22%, 17% and 13%, respectively.

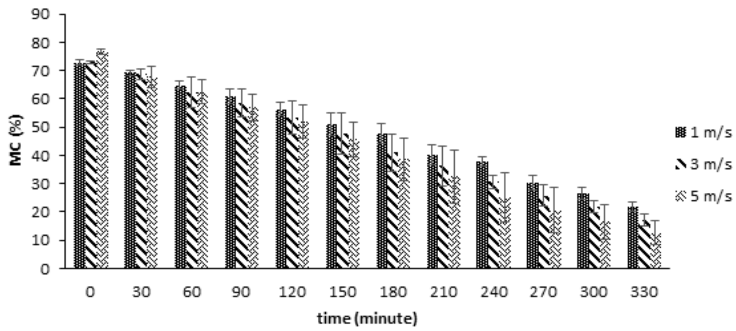

Figure 3. Interpretation of standard deviation values for all variations

3.1.Multiple Linear Regression Model (MLR)

Multiple Linear Regression Model (MLR) is a development of the Simple Linear Regression Model which only uses one input variable and not non-linear regression such as exponential regression or logarithmic regression. The amount of data for the development of the MLR model uses a proportion of 2:1, namely 2/3 data for training or 66 data and 1/3 data for testing or 33 data. The MLR model developed from the training data can be seen in Equation 5 and the graph of observations vs predictions from the training results can be seen in Figure 4.

$$y = -0,17x_1 - 1,48x_2 + 78,51 \tag{5}$$

where y = moisture content (%); x1 = drying time (minutes); x2 = air drying rate (m/s).

The P-values of x_1, x_2, and intercept of 1.3×10^{-56}, 4.3×10^{-42}, and 9.4×10^{-5} respectively that means significant because under the standard value of 0.05. The equation that have been build eligible to predict the moisture content from drying time and air drying rate from soybean drying.

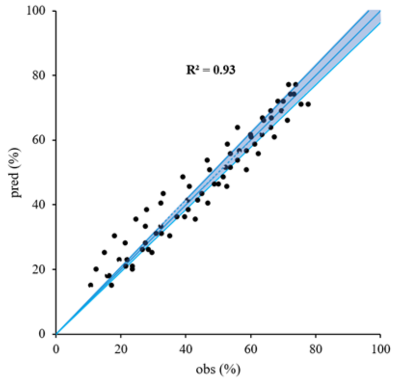

Figure 4. Observations vs. predictions on the results of the MLR model training (the shaded area is in the range of ±3.71% of the return)

The mathematical equation function of the MLR is used for validation so that the accuracy of the model can be known. The graph of observations vs predictions from the validation results can be seen in Figure 5.

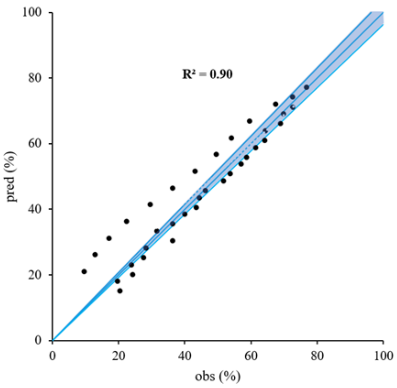

Figure 5. Graph of observations and predictions on the results of testing the MLR model (the shaded area is in the range of ±3.71% of the return)

3.2. Artificial Neural Network (ANN) Model

The Artificial Neural Network (ANN) model data was also developed with the same data as the model development data MLR. The developed ANN model is backpropagation type ANN with supervised training method. The network architecture used is 2 input nodes, 2 hidden layer 1 nodes, 2 hidden layer 2 nodes, and 1 output node. The results of the development of the ANN model can be seen in Table 1 which shows that the activation function purelin-purelin-purelin is the best activation function that produces the largest accuracy and R^2 value. Observation vs prediction graphs from training results and data validation results are shown in Figures 6 and 7.

Table 1. Comparison of the results of training and validation of the ANN model for various activation functions

Activation functions	Training		Test	
	Accuracy	R^2	Accuracy	R^2
logsig-logsig-logsig	89,95	0,95	77,85	0,86
logsig-logsig-purelin	90,00	0,95	77,72	0,86
logsig-logsig-tansig	89,99	0,95	77,75	0,86
logsig-tansig-logsig	89,96	0,95	77,74	0,86
logsig-purelin-logsig	89,66	0,95	77,78	0,86
tansig-logsig-logsig	89,98	0,95	77,83	0,86
purelin-logsig-logsig	89,67	0,95	77,77	0,86
tansig-tansig-tansig	89,87	0,95	78,01	0,86
tansig-tansig-purelin	89,98	0,95	77,88	0,86
tansig-tansig-logsig	89,67	0,95	77,78	0,86
tansig-purelin-tansig	89,83	0,95	77,66	0,86
tansig-logsig-tansig	88,56	0,94	81,76	0,90
purelin-tansig-tansig	89,06	0,94	81,38	0,90
logsig-tansig-tansig	47,26	-0,04	42,92	-0,33
purelin-purelin-purelin	**88,34**	**0,93**	**82,15**	**0,90**
purelin-purelin-tansig	86,89	0,91	79,02	0,85
purelin-purelin-logsig	88,71	0,93	81,13	0,88
purelin-tansig-purelin	89,98	0,95	77,79	0,86
purelin-logsig-purelin	89,98	0,95	77,79	0,86
tansig-purelin-purelin	89,98	0,95	77,79	0,86
logsig-purelin-purelin	89,98	0,95	77,79	0,86
tansig-purelin-logsig	89,67	0,95	77,78	0,86
tansig-logsig-purelin	90,01	0,95	77,69	0,86
logsig-purelin-tansig	89,83	0,95	77,66	0,86
purelin-tansig-logsig	88,93	0,94	81,43	0,90
purelin-logsig-tansig	89,83	0,95	77,66	0,86
logsig-tansig-purelin	89,99	0,95	77,72	0,86

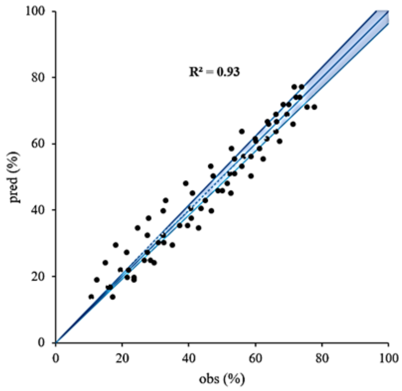

Figure 6. Graph of observations and predictions on the results of ANN model training (the shaded area is in the range of ±3.71% of the return)

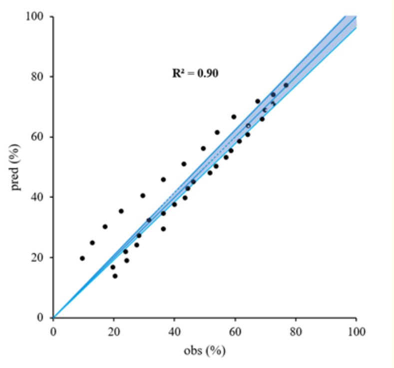

Figure 7. Graph of observations and predictions on the results of testing the ANN model (the shaded area is in the range of ±3.71% of the return)

The ANN model is transformed into a mathematical equation to simplify the manual analysis written in Equations 6 to 18. The equation is made based on the value of weight, bias, and type of activation function obtained from the results of the ANN simulation with the best architecture. The calculation begins by normalizing the input data x_1 (drying time) and x_2 (drying speed) to have a value of 0-1. The result of the final equation of this equation is the value of y which indicates the value of water content.

$$y_1 = \frac{x_1}{330} \quad (6)$$

$$y_2 = \frac{x_2}{5} \quad (7)$$

$$y_3 = 0{,}93y_1 + 0{,}22y_2 + 0{,}59 \quad (8)$$

$$y_4 = -0{,}57y_1 - 0{,}04y_2 + 0{,}59 \quad (9)$$

$$y_5 = y_3 \text{ (purelin)} \quad (10)$$

$$y_6 = y_4 \text{ (purelin)} \quad (11)$$

$$y_7 = 0{,}1y_5 + 0{,}82y_6 + 0{,}53 \quad (12)$$

$$y_8 = -0{,}85y_5 - 0{,}007y_6 + 0{,}75 \quad (13)$$

$$y_9 = y_7 \text{ (purelin)} \quad (14)$$

$$y_{10} = y_8 \text{ (purelin)} \quad (15)$$

$$y_{11} = 1{,}03y_9 + 0{,}44y_{10} - 0{,}29 \quad (16)$$

$$y_{12} = y_{11} \text{ (purelin)} \quad (17)$$

$$y = 78y_{11} \quad (18)$$

3.3. Model Comparison

The results of the development of the MLR Model and the ANN Model that have been validated are indicated by the accuracy value and the coefficient of determination (R^2).

The model is said to be the best if it produces the largest accuracy and R^2 value because it shows the accuracy of the prediction results. Table 2 which is a comparison table between the results of the Multiple Linear Regression Model (MLR) and the Artificial Neural Network (ANN) shows that the ANN model is more accurate for predicting drying rates.

Table 2. Comparison of training results and validation of prediction models

	Training	
Model	Accuracy	R^2
MLR	88.03	0.93
ANN	88.34	0.90
	Test	
Model	Accuracy	R^2
MLR	82.23	0.93
ANN	82.15	0.90

The accuracy of the ANN model in predicting the results has also been proven in several studies related to the drying rate of foodstuffs. The results of this study indicate that the coefficient of determination of the ANN model is above 0.9 or very accurate.

The graph of observations and predictions of the results of the training and testing of the MLR model and the ANN model shown has a shaded area in the range of ±3.71% return. This is based on the standard error of estimation in the acceptable range of 2.36-3.71% based on research of cassava (Sarnavi *et al.*, 2022). In graphs 4, 5, 6, and 7 it is found that the prediction results at the beginning have a higher error rate and have been shrinking lately.

4. CONCLUSIONS

Multiple linear regression (MLR) model training and validation produce accuracy values of 88.03 and 82.23, and the value of R^2 of 0.93 and 0.90. While the training and validation of the artificial neural network (ANN) model resulted in accuracy values of 88.34 and 82.15, and R^2 values of 0.93 and 0.90. These results showed that the MLR model is as good as the ANN model.

REFERENCES

Adhitya, R.Y., Ramadhan, M. A., Kautsar, S., Rinanto, N., Sarena, S.T., Munadhif, I., Syaiin, M., Soelistijono, R.T., & Soeprijanto, A. (2017). Comparison methods of fuzzy logic control and feed forward neural network in automatic operating temperature and humidity control system (oyster mushroom farm house) using microcontroller. *International Symposium on Electronics and Smart Devices* (*ISESD 2016*), 168–173. https://doi.org/10.1109/ISESD.2016.7886713

Aji, G.K., Hatou, K., & Morimoto, T. (2020). Modeling the dynamic response of plant growth to root zone temperature in hydroponic chili pepper plant using neural networks. *Agriculture*, ***10***, 234. https://doi.org/10.3390/agriculture10060234

Akmalovna, A.C. (2022). Characteristics and advantages of soybean benefits in every way. *Journal of Ethics and Diversity in International Communication*, ***1***(8), 67–69.

An, N-N., Sun, W-H., Li, B-Z., Wang, Y., Shang, N., Lv, W-Q., Li, D., & Wang, L-J. (2022). Effect of different drying techniques on drying kinetics, nutritional components, antioxidant capacity, physical properties and microstructure of edamame. *Food Chemistry* (*Part B*), ***373***, 131412. https://doi.org/10.1016/j.foodchem.2021.131412

Argo, B.D., & Ubaidillah, U. (2020). Thin-layer drying of cassava chips in multipurpose convective tray dryer: Energy and exergy analyses. *Journal of Mechanical Science and Technology*, ***34***(1), 435–442. https://doi.org/10.1007/s12206-019-1242-9

Cabaneros, S.M., Calautit, J.K., & Hughes, B.R. (2019). A review of artificial neural network models for ambient air pollution prediction. *Environmental Modelling and Software*, ***119***(June), 285–304. https://doi.org/10.1016/j.envsoft.2019.06.014

Chokphoemphun, S., & Chokphoemphun, S. (2018). Moisture content prediction of paddy drying in a fluidized-bed drier with a vortex flow generator using an artificial neural network. *Applied Thermal Engineering*, ***145***, 630–636. https://doi.org/10.1016/j.applthermaleng.2018.09.087

Díaz, A., Dini, C., Viña, S.Z., García, M.A. (2018). Technological properties of sour cassava starches: Effect of fermentation and drying processes. *LWT*, ***93***, 116–123. https://doi.org/10.1016/j.lwt.2018.03.029

Guiné, R.P.F. (2019). The use of artificial neural networks (ANN) in food process engineering. *ETP International Journal of Food Engineering*, ***5***(1), 15–21. https://doi.org/10.18178/ijfe.5.1.15-21

Hariono, B., Kurnianto, M.F., Bakri, A., Ardiansyah, M., & Wijaya, R. (2018). Improvement of sensory and chemistry quality of fried edamame by freezing. *IOP Conference Series*: *Earth and Environmental Science*, ***207***(1), 012048. https://doi.org/10.1088/1755-1315/207/1/012048

Haryanto, A., Saputra, T.W., Telaumbanua, M., & Gita, A.C. (2020). Application of artificial neural network to predict biodiesel yield from waste frying oil transesterification. *Indonesian Journal of Science & Technology*, ***5***(1), 62-74. https://doi.org/10.17509/ijost.v5i1/23099

Kamila, I., Karyadi, J.N.W., & Saputro, A.D. (2019). Drying characteristics of edamame (*Glycine max*. L. Merill) during freeze drying. *IOP Conference Series*: *Earth and Environmental Science*, ***355***, 012048. https://doi.org/10.1088/1755-1315/355/1/012048

Kaveh, M., Jahanbakhshi, A., Abbaspour-Gilandeh, Y., Taghinezhad, E., & Moghimi, M.B.F. (2018). The effect of ultrasound pre-treatment on quality, drying, and thermodynamic attributes of almond kernel under convective dryer using ANNs and ANFIS network. *Journal of Food Process Engineering*, ***41***(7), e12868. https://doi.org/10.1111/jfpe.12868

Liu, W., Zhang, M., Adhikari, B., & Chen, J. (2020). A novel strategy for improving drying efficiency and quality of cream mushroom soup based on microwave pre-gelatinization and infrared freeze-drying. *Innovative Food Science and Emerging Technologies*, ***66***, 102516. https://doi.org/10.1016/j.ifset.2020.102516

Ojediran, J.O., Okonkwo, C.E., Adeyi, A.J., Adeyi, O., Olaniran, A.F., George, N.E., Olayanju, A.T. (2020). Drying characteristics of yam slices (*Dioscorea rotundata*) in a convective hot air dryer: application of ANFIS in the prediction of drying kinetics. *Heliyon*, ***6***(3), e03555. https://doi.org/10.1016/j.heliyon.2020.e03555

Yudiastuti, S.O.N., & Wijaya, R. (2021). The chlorine reduction in edamame by water-ozonated minimally process. *Journal Research of Social Science, Economics, and Management*, ***01***(3), 269–276. https://doi.org/10.36418/jrssem.v1i3.26

Santos, P., Pitarch, J.L., Vicente, A., Prada, C., & García, A. (2020). Improving operation in an industrial MDF flash dryer through physics-based NMPC. *Control Engineering Practice*, ***94***, 104213. https://doi.org/10.1016/j.conengprac.2019.104213.

Saputra, T.W., Wijayanto, Y., Ristiyana, S., Purnamasari, I, & Muhlison, W. (2022). Non-destructive measurement of rice amylose content based on image processing and artificial neural networks (ANN) model. *Jurnal Teknik Pertanian Lampung*, ***11*** (2), 231–241. http://dx.doi.org/10.23960/jtep-l.v11i2.231-241

Sarkar, T., Salauddin, M., Hazra, S.K., Choudhury, T., & Chakraborty, R. (2021). Comparative approach of artificial neural network and thin layer modelling for drying kinetics and optimization of rehydration ratio for bael (*Aegle marmelos* (L) correa) powder production. *Economic Computation and Economic Cybernetics Studies and Research*, ***55***(1), 167–184. https://doi.org/10.24818/18423264/55.1.21.11

Sarnavi, H. J., Precoppe, M., García-Triñanes, P., Chapuis, A., Tran, T., Bradley, M. S., & Müller, J. (2022). Determining the heat of desorption for cassava products based on data measured by an automated gravimetric moisture sorption system. *Journal of the Science of Food and Agriculture*. https://doi.org/10.1002/jsfa.12153

Sun, Q., Zhang, M., & Mujumdar, A.S. (2019). Recent developments of artificial intelligence in drying of fresh food: A review. *Critical Reviews in Food Science and Nutrition*, ***59***(14), 2258–2275. https://doi.org/10.1080/10408398.2018. 1446900

Wijaya, R. Hariono, B., Saputra, T.W., Rukm, D.L. (2020). Development of plant monitoring systems based on multi-camera image processing techniques on hydroponic system. *IOP Conference Series*: *Earth and Environmental Science*, *411*, 012002. https://doi.org/10.1088/1755-1315/411/1/012002

Wijaya, R., & Hariono, B. (2020). The mathematical analysis of the drying of cassava grater by using pneumantic (flash) dryer with heat recirculation method. *Journal of Physics*: *Conference Series*, ***1569***, 042061. https://doi.org/10.1088/1742-6596/1569/4/042061

Yudiastuti, S.O.N., Wijaya, R., & Budiati, T. (2021). The effect of ozonation time and contact time of edamame washing on color changes using the continuous type ozone washing method. *IOP Conference Series*: *Earth and Environmental Science*, ***672***, 012066. https://doi.org/10.1088/1755-1315/672/1/012066