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Application of Generalized Regression Neural Network for drying of sliced bitter gourd in a halogen dryer

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Abstract

The influence of various drying characteristics in the experiment was explored in this study. The drying time and moisture content were used to evaluate the experimental outcomes. The drying of bitter gourd slices using a halogen dryer was done at varied thicknesses (3, 5, and 7 mm) and temperatures (60 °C, 65 °C and 70 °C). The results revealed that the drying time and equilibrium moisture content are considerably affected by the material drying thickness and drying temperature. Furthermore, the Generalized Regression Neural Network (GRNN) model is employed in this study to train and predict the moisture content of bitter gourd as an output parameter. The temperature, bitter gourd thickness, and drying time were considered as input parameters for the GRNN model. Three statistic measures as the R-square, the Root mean square error (RMSE) and the Mean relative percent error (P) were used to validate the accuracy of the trained GRNN model. In training with nine experimental condition datasets, the average score values of R-square, RMSE and P were obtained at 0.995197, 1.498966 and 0.091617, respectively. The test of trained GRNN has been conducted with good agreement between experimental data points and predicted points. The result revealed that GRNN was effective in predicting the moisture content of bitter gourd in a halogen dryer.

Keywords: ANN model; Drying temperature; Modeling; Moisture content; Prediction; Radiative drying.

Highlights

- The behavior of the sliced bitter gourd drying process is captured by employing Generalized Regression Neural Network model
- The predictable performance of Generalized Regression Neural Network is validated by using statistical measures

1 Introduction

Aside from freezing, drying is one of the oldest food preservation procedures and is essential to the operations of the food industry. It is critical to increase the fresh item shelf life while lowering packing costs and transportation weights. Therefore, drying is now widely used in a variety of fields which could be found in (Omari et al., 2018; Yan et al., 2019), particularly in the field of food preservation (Ahmed et al., 2013). Drying is a traditional technique for dealing with post-harvest agricultural products by removing moisture. During a drying process, heat and mass transfer from the inner to the outer surfaces of a drying material will occur simultaneously under the influence of external environmental factors such as temperature, humidity, velocity, time drying, as well as the properties and physical structure of the material. This is a thermodynamic and physical process interaction to lower moisture content to a minimum permissible limit that restricts microbial development and activity in agricultural products. The moisture content should be removed to the extent that the intended quality of the dried product can be maintained for a longer period of time. To accomplish this goal, the relationships between the components influencing the drying process must be modeled. However, it is clear that the drying process is greatly difficult due to impacted factors (Movagharnejad & Nikzad, 2007). Consequently, developing a mathematical equation that adequately describes the relationship between heat-mass transfer occurring inside the material and factors influencing the drying process is still difficult. As a result, dryness has increasingly developed during the last few decades.

A predictable model which is obtained by relating a set of input variables and response variables has become an essential strategy in the drying field. An accurate prediction of the drying model is possible resulting in optimized energy use and operating conditions, improved dried product, and thus efficient drying. Artificial Neural Networks (ANN) have been adopted for years in food processing to describe the drying behavior of various agricultural products due to their predictability. The strength of ANN is able to capture well patterns and nonlinear relationships in the experimental data provided, especially when mathematical information or any analytical solution for describing a relationship is nonexistent by Septien et al. (2020). Generally, the structure of an ANN consists of three layers such as the input layer, the hidden layer and the output layer. These layers have interconnected neurons or nodes. Each link connecting each neuron has an associated weight which is adjusted in the training phase to reduce the errors between the actual and the output values. Several studies based on ANNs have been conducted to identify nonlinear and complex drying systems and process behaviors. The ANN model (Backpropagation algorithm for feed-forward neural network) was employed to predict the dehydration characteristics of the pineapple slice in the entire drying process (Sarkar et al., 2020). This study observed the effects of hot air oven, microwave, microwave convection and freeze-drying on the dehydration behavior of sliced pineapple. Their result reported that the coefficient of correlation through the competent prediction of ANN models for dehydration kinetics of differently dried pineapple was highly accurate. The accuracy of multilayer perceptron ANN models for predicting the moisture content evolution was validated by using experimental data of quince slices in convective drying (Chasiotis et al., 2020). It was evident that MLP ANNs were robust enough to apply for various agricultural products. Similar works, ANNs have been also found by Bai et al. (2018), Azadbakht et al. (2018) and Di Scala et al. (2013), so on. Generally, the results of these studies indicated that the ANNs model selected was appropriate for modeling the drying process. Among ANN models, General Regression Neural Network (GRNN) which have also been widely used in different fields in past decades, is accepted as a model to evaluate the drying process in this study.

Bitter gourd is commonly found in tropical and subtropical areas such as Africa, Asia, and Australia. Because of its incredible nutritional value, bitter gourd is commonly recognized as an essential ingredient in Vietnam cuisine. It is also referred to as an herbal medicine with numerous therapeutic applications for people (Biswas et al., 2018). Accordingly, bitter gourd has received considerable attention in recent years (Yan et al., 2019; Yasmin et al., 2022; Jin et al., 2019; Bhattacharjee et al., 2016). Bitter gourd, on the other hand, has long been used as a traditional medicinal plant in Vietnam. Therefore, the nutritional benefits and numerous uses stated above are driving up demand for the dried bitter gourd product. In Vietnam, dried bitter gourd is commonly used to make herbal tea.

Numerous drying technologies are now being developed and used in the manufacturing business. In general, drying systems are divided into two categories: natural drying systems and artificial drying systems. Natural drying systems that use solar energy, geothermal energy, and wind energy offer the advantage of being less expensive. However, these still have significant disadvantages, such as the need for more initiative and the capacity to manage the drying process parameters. As a result, meeting the increasing demands for quality drying products in the industrial system would be difficult. Artificial drying technologies are highly developed such as convection drying, radiation drying (Chasiotis et al., 2020), radio wave drying (Ling et al., 2018), microwave drying (Omari et al., 2018), and so on. Among the drying systems described above, halogen drying technology has been developed by (Hebbar et al., 2004). Essentially, the findings of these published works demonstrated that drying technology utilizing halogen lamps is increasingly being used in the drying process due to its simplicity and efficiency in controlling the drying temperature, which is one of the most important factors in the drying process.

From a literature survey mentioned above, the drying process of sliced bitter gourd on a halogen dryer is adopted. Also, GRNN is developed as an approximating tool for predicting the drying process of bitter gourd slices on a halogen dryer such as the moisture content of the drying material through the parameters of thickness, temperature, and drying time.

2 Material and methods

2.1 Material

The fresh bitter gourds were purchased at a local market every morning. Moreover, the total quantity of gourds purchased is about 5 kg for all experiments. Whole bitter gourds were cleaned, and they were dried in a natural environment before conducting the experiment. The initial moisture content of the bitter gourd slices was dried in an oven at 105ºC until reaching constant mass (Jin et al., 2019). The experiment was carried out in a university laboratory, in Vietnam. On average, the initial moisture content of bitter gourd was determined about 92% - 95% (w.b.), and the results were quite similar to published researches of Biswas et al. (2018), Jin et al. (2019) and Yan et al. (2019).

2.2 Drying equipment

Drying was carried out in a halogen dryer that was self-made, as shown in Figure 1. The dryer's overall dimensions are 550 mm in length, 550 mm in width and 850 mm in height, including 2 rotary plates with 4 stainless steel trays. Each tray has various diameters of 4 mm holes. Each plate has 3 halogen lamps with a capacity of 100 W per bulb, so the maximum capacity of the halogen used in the drying model is 600 W. The maximum temperature in this halogen dryer chamber is 90 °C. The stainless-steel trays are placed on a rotating shaft, adjusted in rotation speed through the inverter device. The drying temperature was controlled by the SSR (Solid-state relay) device. When the temperature reaches the preset level, the SSR device regulates the halogen bulbs light intensity to lower the emitting temperature. In the drying model, there are 4 temperature sensors. One was at outside locations to receive temperature information environment. Each compartment has two temperature sensors that collect data on the drying temperature inside the chamber. The last one was placed at the outlet to measure the temperature information after the drying process. The moisture was removed from the chamber by two fans situated on the top of the oven.

Before each drying experiment, the halogen dryer was run for roughly 30 minutes without the samples until the necessary conditions were reached. When drying conditions were met, the drying process began. The bitter gourd samples were dried on dryer trays. During the experiment, temperature data is collected using the DDC-C46 device (Figure 1b) which is supplied by PNTECH Co., and it connects to the computer via the RS32 connection.

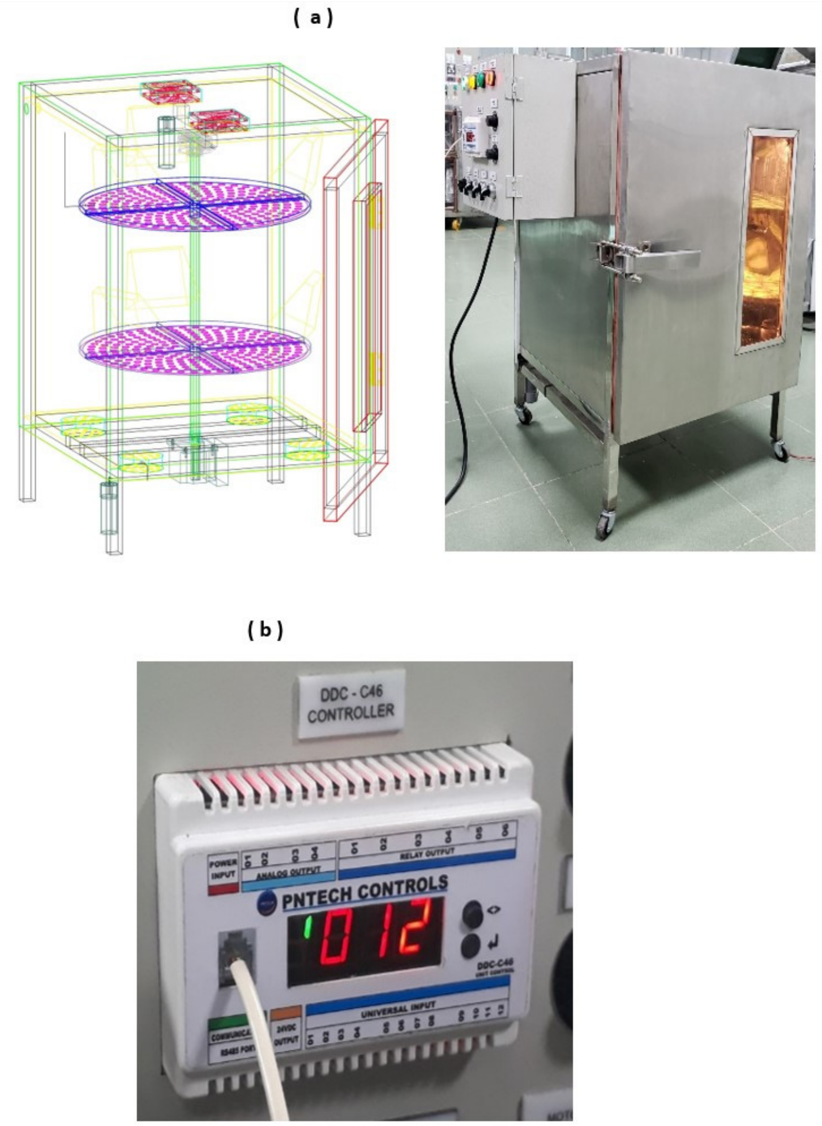

Figure 1. Halogen dryer– (a) The dryer; (b) DDC-C46 controller.

2.3 Determination of moisture content

During the drying process, the sample weight loss of the drying material was determined periodically every 30 minutes and calculated according to the following formula (Equation 1) in published articles by Jin et al. (2019) and Yasmin et al. (2022):

$$MC = \frac{m_c - m_k}{m_k} x100 \qquad (1)$$

where,

MC: moisture content wet basis of drying material at the time of determination, [%]

m_c: mass of drying material at time t, [g]

m_k: mass of drying material at the time of determination t + 1, [g]

2.4 GRNN modeling

GRNN is also a popular model for solving any complex, dynamic and non-linear problem from the data. The GRNN has totally four layers which are the input layer, two hidden layers (pattern layer, summation layer) and the output layer, as shown in Figure 2.

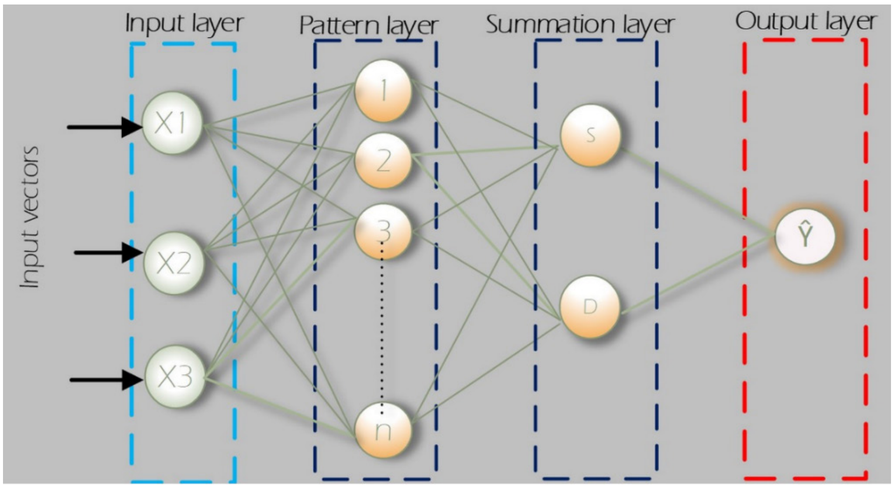

Figure 2. The basic structure of GRNN.

The input layer is connected to the pattern layer through the weights of the pattern layer. In this layer, each neuron presents a training pattern and its output. The pattern layer and summation layer are connected together. The summation layer has two different types: a single division unit and a summation unit. The summation and output layer together perform a normalization of the output set. In the training of networks, radial basis functions and linear activation functions are used in hidden and output layers. Each pattern layer unit is connected to the two neurons in the summation layer, S and D summation neurons. S summation neuron computes the sum of weighted responses of the pattern layer. On the other hand, D summation neuron is used to calculate unweighted outputs of pattern neurons. The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value $\widehat{Y\iota}$ to an unknown input vector x. The predicted value $\widehat{Y\iota}$ can be calculated in the Equations 2 and 3 as presented in Hannan et al. (2010).

$$\hat{y}_i = \frac{\sum_{i=1}^{n} y_i.\exp[-D(x,x_i)]}{\sum_{i=1}^{n}\exp[-D(x,x_i)]} \tag{2}$$

$$D(x,x_i) = \sum_{k=1}^{m}\left(\frac{x_i - x_{ik}}{\sigma}\right)^2 \tag{3}$$

y_i is the weight connection between the i_{th} neuron in the pattern layer and the S-summation neuron, n is the number of the training patterns, D is the Gaussian function, m is the number of elements of an input vector, x_k and x_{ik} are the j_{th} element of x and x_i, respectively, σ is the spread parameter, whose optimal value is determined experimentally.

For the evaluation of the GRNN model, a regression analysis was performed using statistical indicators such as Correlation coefficient (R-square) (Equation 4) and Root mean square error (RMSE) (Equation 5) which were obtained in Chasiotis et al. (2020), and Mean relative percent error (P) (Equation 6) which published in Movagharnejad & Nikzad (2007) as follows

(a) The R-square (R^2) is given by:

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 / \sum_{i=1}^{n}(y_i - \bar{y}_i)^2 \quad (4)$$

(b) Root mean square error (RSME):

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (5)$$

(c) Mean relative percent error (P)

$$P = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \quad (6)$$

where y_i is the measured value of the observed target in the experiment and $\hat{y}_i$ is the predicted value from observation of ith- target, n is the number of validation points. The accuracy assessment of a model is a compromise between these measured values. The larger the value of R-square and the smaller the value of RSME and P, the more accurate the model is.

3 Experimental setup

According to several published studies (Yan et al., 2019; Biswas et al., 2018), the drying temperature for bitter gourd ranges from 40 °C to 80 °C, depending on the thickness of the bitter gourd and the drying process. Hence, this study will investigate temperature drying and sample thickness as components influencing the drying process. Temperature values of 60 °C, 65 °C, and 70 °C were established. Also, bitter gourd slices with thicknesses of 3 mm, 5 mm, and 7 mm were chosen. The drying time was fixed at 9 h for all conditions of experiments. Each experiment was repeated three times, and an average value was computed for each.

4 Results and discussion

4.1 Results of experiment

The results of all experimental conditions were illustrated in Figure 3. There were three levels of temperature drying, i.e., 60 °C, 65 °C and 70 °C. Each drying temperature has three thicknesses of bitter gourd on trays.

Figure 3 depicts the effect of slice thickness on bitter gourd drying kinetics in a cabinet dryer. These curves clearly show that moisture loss was more remarkable at a thin slice. Almost half of the moisture was eliminated in 2 to 3 hours, and the remainder was reduced from 5 to 7 hours. This quick moisture loss occurred in the product's free water. The drying of bound water was seen to be slower.

Regarding the same temperature, Figure 3 indicates a shorter drying time for thin slices of bitter gourd and a longer drying time for thicker slices of bitter gourd. In the case of 60 °C, the 3 mm thickness of bitter gourd slices were only taken 6 hours to reach the equilibrium moisture content, while the drying time took 8 hours to reach the equilibrium moisture content for the 7 mm thickness of bitter gourd slices. Similar tendencies were illustrated for other experimental conditions. In particular, at 65 °C and the 3, 5 and 7 mm thicknesses were 6 h and 7 h, at 70 °C and the 3, 5 and 7 mm thicknesses were 3 h, 3 h and 7 h. The shortest drying time was with a drying condition of 70 °C (highest temperature) and 3mm-thick slices (thinnest thickness). Thinly sliced items dried faster because of the increased surface area exposed for a given volume of product.

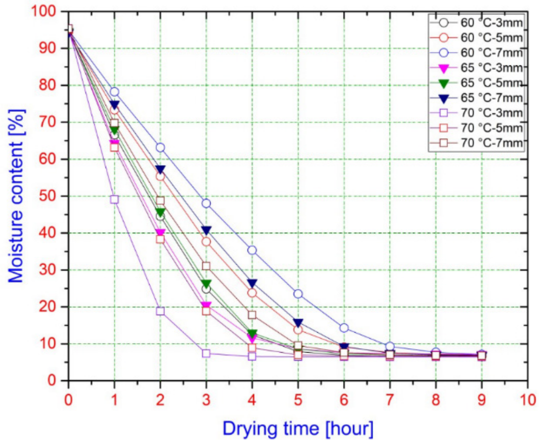

Figure 3. The moisture content of bitter gourd varied depending on the drying conditions.

Considering the same thickness, it is apparent from these curves that the rate of moisture removal was rapid at a high temperature. Figure 3 also indicates that increasing the drying temperature from 60 º C to 70 º C results in a considerable drop in bitter gourd moisture content. As the drying temperature rises, so does the entire drying time. For example, when the temperature was raised from 60 º C to 70 º C, the drying time of a 3 mm thick bitter gourd slice was lowered from 6 to 3 hours, i.e., at the time of obtaining balanced moisture content. A similar trend was seen for 5 mm and 7 mm thick-sliced bitter gourd at the same temperatures. This look is due to the stiff texture of bitter gourd, which takes a long time to dry. Higher temperatures increased the thermal energy in the samples, requiring them to dry faster.

Furthermore, the results in this study on the influence of drying temperature and the thickness of the drying material on the drying process were similar to those in the published articles (Yasmin et al., 2022; Sadin et al., 2014; Ocoró-zamora & Ayala-aponte, 2013).

4.2 Performance of models for predict drying moisture content

In this investigation, 270 data points were obtained from the nine conditions. One experiment condition was repeated three times. These experimental data were utilized to train and test a GRNN model for predicting the moisture content of bitter gourd during the drying process. The experimental results were divided into two groups at random. One set of data was utilized for training, while the other was used to test the model. Three independent variables, namely drying time, thickness, and temperature, as well as one dependent variable, namely moisture content, were used to train GRNN. When the test error (RMSE) and the mean relative percent error (P) are minimum and R-square is greatest, trained GRNN performs best. The Table 1 shows the results of nine conditions on training performance.

Table 1. The findings of the measurements of error in the drying time prediction results of the GRNN model.

No. dataset	Temperature	Thickness	R-square	RSME	P
1	60	3	0.999835	0.752876	0.051395
2	60	5	0.993648	1.878589	0.151456
3	60	7	0.999708	1.046925	0.067594
4	65	3	0.973659	2.614232	0.157713
5	65	5	0.995643	1.673283	0.171586
6	65	7	0.999594	1.064946	0.032563
7	70	3	0.999121	0.952297	0.04191
8	70	5	0.996503	1.460628	0.092816
9	70	7	0.999061	1.105271	0.057524
	Average-score values		0.995197	1.498966	0.091617

Consequently, the average R-square RMSE, and P values for training the GRNN model were 0.995197, 1.498966 and 0.091617, respectively. In comparison, the results of GRNN performance from the datasets of 2, 4 and 5 were lower than others. Overall, the results of the R-square value, the RMSE and the P value indicate that GRNN is highly accurate in approximating for the drying process.

For the test of the trained GRNN model, three experimental conditions such as the temperature of 70 °C and the thickness of 3, 5 and 7 mm were chosen. Figure 4 depicts the measured experimental moisture content bitter gourd values and the predicted moisture content bitter gourd values of the GRNN model. A flawless forecast is depicted in Figure 4 by a diagonal line inclined at 45 degrees from horizontal. It demonstrates that the bulk of data points along the training line are exceptionally close to this line, indicating accurate training prediction. In comparison, the prediction performance of the trained GRNN model at 70 °C and 5 mm thickness performed worse than in the other two cases.

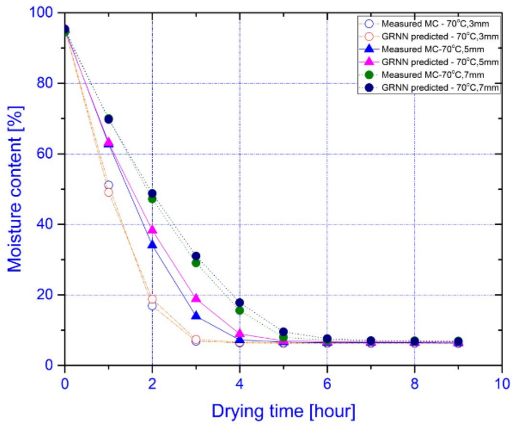

Figure 4. The prediction of GRNN for moisture content of bitter gourd on the three drying conditions.

5 Conclusion

This analysis assessed the drying characteristics of bitter gourd slices dried in a halogen dryer at various temperatures and material slice thicknesses. Drying time and ultimate moisture content were significantly affected by drying temperature and drying material slice thickness. During the drying process of almost all bitter gourd slices, decreasing rate phases were observed. According to the findings, the drying properties of bitter gourd in the drying process at a temperature range of 60 °C to 70 °C, the drying temperature, and material thickness all had a significant influence on moisture content and drying time. The shorter the drying time is, the higher the drying temperature or the thinner the thickness of the drying material is.

The Generalized Regression Neural Network (GRNN) model was also utilized to forecast the decrease in moisture content of bitter gourd slices during the halogen drying process. The drying behavior of bitter gourd in a halogen dryer, as well as the relationship between bitter gourd moisture content at drying temperatures of 70 º C and material thicknesses of 3 mm, 5 mm and 7 mm, were collected and forecasted using the GRNN model. The evaluation of GRNN model in the training stage of the nine-condition experiment was implemented. The results in average-score values of the evaluation model achieved an R-square value of 0.995197, an RSME value of 1.498966 and a P value of 0.091617. The validation of the predicable GRNN model was also performed. The outcome demonstrated that GRNN is an appropriate method for estimating the moisture content of bitter gourd in a halogen dryer. In addition, GRNN is also a promising model for optimizing the drying process to improve drying efficiency and save energy for industrial drying.

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