Original Article
Food Science and Technology

ISSN 0101-2061 (Print)
ISSN 1678-457X (Online)

https://doi.org/10.5327/fst.27623

Mathematical and artificial neural network modeling of hot air drying kinetics of instant "Cẩm" brown rice

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Abstract

Modeling moisture content variation under variable hot air dryers is challenging. In this study, mathematical models and artificial neural network (ANN) were investigated for modeling of instant "Cẩm" brown rice drying process. The experiments were done in four levels of hot air temperature (55, 60, 65, and 70 °C). The results demonstrated that among eight mathematical models, the diffusion approach could give the best prediction of moisture ratio during the drying process with the highest R-square and lowest mean square error. Besides, the ANN model with 10 hidden layers also could provide the best-fit model with the same criteria as the mathematical model. Compared with the ANN model, both can give a highly accurate prediction. However, the ANN model could be more beneficial in the up-scale process.

Keywords: brown rice; artificial neuron network; drying; modeling.

Practical Application: Using thin-layered mathematical model and artificial neural network (ANN) can predict the moisture content of instant brown rice during the drying process. In an industrial investigation, a robust ANN model for predicting the moisture content helps to better predict and control hot air dryers, which could help to easier to up-scale process.

1 INTRODUCTION

One of the most significant cereal crops and staple foods is rice (*Oryza sativa* L.). According to the degree of transformation, rice can also be divided into three types: paddy, brown rice, and white rice. Brown rice, also known as husked rice, cargo rice, or loonzain rice, is rice that has merely been husked, leaving the remaining rice germ and grain coat intact. According to the type and species of rice, brown rice might be red, purple, dark brown, or even light brown (Waewkum & Singthong, 2021). Recent research has been conducted to compare the nutritional value of whole brown rice grain and colored rice grain to white rice and to see whether there are any potential health benefits (Ngo et al., 2022). In general, brown rice has a higher nutrient content than white rice, including higher levels of protein, fat, vitamins, and minerals. Moreover, a higher amount of bioactive compounds has been found in entire grains of brown rice (Saleh et al., 2019). Vietnam is one of the major rice-producing countries. Besides, "Cẩm" brown rice is one of the local rice in the southern part of Vietnam, which contains high antioxidant compounds and nutrients (Le & Nguyen, 2019; Loan et al., 2022). It could also have the potential for producing instant rice to meet the needs of modern life. In general, instant rice could be produced by various methods. One of the simple methods is cooking and then drying to a certain moisture content (Loan et al., 2022). Drying is one of the key steps, which affected the reconstitution of instant rice. Therefore, controlling the drying process as well as the moisture content of cooked rice during drying is important. Generally, the principle of the drying process is based on the removal of water from the material using evaporation for a longer shelf life and minimizing packaging requirements. Due to the simultaneous heat, mass, and momentum transfer processes involved in drying, it is a complicated process. The complexity is heightened if drying conditions change at any point while the process is underway. Determining the impact of process factors, optimizing the drying process, integrating energy, and controlling the process all require appropriate models (Kumar et al., 2014). Throughout the past several decades, numerous research investigations have focused on the creation of mathematical and numerical models to characterize the drying processes (Hernandez-Perez et al., 2004; Thuy et al., 2020; Thuy et al., 2022a; Thuy et al., 2022b). Some of the assumptions used in mathematical models are easy to build (Kumar et al., 2014), whereas numerical models demand an in-depth understanding of the workings of the process, the estimation of several experimental parameters, and the use of sophisticated calculation techniques. The black-box modeling approach can be examined to get beyond these modeling challenges and effectively anticipate the moisture content with drying conditions. One black-box modeling approach that has advantages over other traditional modeling techniques is the artificial neural network (ANN) (Hernández, 2009).

A simple definition of nonlinear and complicated systems, quick computation, and adaptable performance are the key benefits of ANN (Bai et al., 2018). Moreover, Aghbashlo et al. (2015) provided an excellent evaluation of Farkas (2013)

Received 18 Apr., 2023
Accepted 10 May, 2023
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through a discussion of ANN's modeling capabilities for the drying process. The literature review demonstrated that the application and comparison between the thin-layered model and the ANN model of drying process of instant rice provided limited information. Therefore, in this study, the drying kinetic study of instant "Cẩm" brown rice was investigated, and robust static and dynamic ANN models for predicting the moisture content were developed and compared.

2 MATERIALS AND METHODS

2.1 Materials

"Cẩm" brown rice was harvested by the local farmer in Tien Giang Province (Vietnam), then de-husked by a local machine. The protein, lipid, carbohydrate, and moisture content of raw materials were 9.11, 3.09, 64.98, and 12.04%, respectively, from the previous study by Loan et al. (2022).

2.2 Drying experiment

The rice (200 g) was washed and then 400 mL of water was added as the good conditions for cooking (Loan et al., 2022). An electric cooker (KS-IH191V-GL, Sharp, Korea) was used in this study. The initial moisture content of cooked brown rice was 56.2% (on a wet basis). The sample was spread on the stainless steel tray with a thickness of 1 cm. The sample was dried at 55, 60, 65, and 70 °C until the attainment of equilibrium moisture content. The change in weight of the sample during the drying process was recorded (30-min interval) for calculating the moisture content at different time points. Three replicates were operated for each drying condition, and the average value of moisture content was used.

2.3 Mathematical modeling

The moisture ratio (MR) value was calculated as Equation 1 before fitting model.

$$\mathrm{MR} = \frac{M_t - M_e}{M_i - M_e} \qquad (1)$$

Where:

M_t: the moisture content at time t (% dry basis);

M_e: the equilibrium moisture content (% dry basis);

M_i: the initial moisture content (% dry basis).

Eight thin-layered semi-empirical models were selected to fit the actual MR data, as shown in Table 1. Regression analysis was conducted to find the drying constant (a, b, c, k, k_0, or n) of each model using the Stagraphics Centurion XV.I program. The highest coefficient of determination (R^2) and lowest sum of squared errors (SSE) and mean square error (MSE) values were used to select the most suitable equation that expresses the drying kinetics of instant brown rice.

2.4 Artificial neural network

A parallel and nonlinear interconnection characterizes ANNs, which are multi-parametric empirical models. When it comes to adapting to new information and effectively identifying patterns in ambiguous and imprecise data, an ANN's function is comparable to that of the human brain. An input layer, a hidden layer or layers, and an output layer make up the ANN infrastructure. A collection of neurons, or "nodes," make up each layer. According to the proportional relevance of a given signal, the internal connections between these nodes, known as "weights," determine which nodes to trigger. A mathematical transfer function controls the data processing in the nodes. Based on the difference between experimental and predicted results, ANN corrects the network by administering modifications to the internal connections. This process of trial and error continues till the network predictions are in good agreement with the target data and with a reasonable level of accuracy. The trained model is subjected to testing and validation, and the predicted data are acquired through model simulations.

In this study, a multi-layered feed-forward back propagation model was used. Drying time and temperature were provided to the model as input signals. Moisture ratio and moisture content were obtained as model outputs. For lower model complexity, the number of hidden layers (HLs) was confined to 1. Two different transfer functions (TANSIGMOID and LOGSIGMOID) were used for the HL, and their relative performance was analyzed. PURELIN was used as the transfer function for the output layer, as a sigmoidal transfer function in the output layer can degenerate the network (Dorofki et al., 2012). The model was trained in MATLAB v.2021a using Levenberg-Marquardt (LM) training functions. Model training was done using 70% of the data. Testing and validation were carried out using the remaining 30% of the data set divided equally between the former and latter. The number of iterations and validation checks was limited to 1,000 to decrease the processing time. An ANN infrastructure (Figure 1) with the lowest MSE, highest correlation coefficient (R^2), and lowest complexity was selected.

Table 1. Thin-layered models applied in mathematical modeling study of instant brown rice.

No.	Model name	Equation	Reference
1	Newton	$\mathrm{MR} = e^{-kt}$	(Lewis, 1921)
2	Henderson and Pabis	$\mathrm{MR} = a\,e^{-kt}$	(Henderson & Pabis, 1961)
3	Page	$\mathrm{MR} = e^{-kt^n}$	(Page, 1949)
4	Logarithmic model	$\mathrm{MR} = ae^{-kt} + c$	(Onwude et al., 2016)
5	Peleg model	$\mathrm{MR} = 1 - \frac{t}{a + bt}$	(Onwude et al., 2016)
6	Two-term	$\mathrm{MR} = ae^{-kt} + be^{-k_o t}$	(Onwude et al., 2016)
7	Diffusion approach	$\mathrm{MR} = ae^{-kt} + (1-a)e^{-kbt}$	(Kassem, 1998)
8	Wang and Smith	$\mathrm{MR} = 1 + at + bt^2$	(Wang & Singh, 1978)

2.5 Drying behavior

The effective diffusivity (D_{eff}) was calculated using the simplified form of Fick's diffusion equation (Equation 2) (Demiray & Tulek, 2017).

$$\ln(\mathrm{MR}) = \ln\left(\frac{8}{\pi^2}\right) - \left(\frac{\pi^2 t D_{\mathrm{eff}}}{4L^2}\right) \quad (2)$$

where:

D_{eff}: the effective moisture diffusivity (m^2/s);

t: the drying time (min);

L: the thickness (m).

The diffusivity values were obtained from the slope of the plot of ln(MR) versus time (t). The temperature dependence of moisture diffusivity was described by Arrhenius equation (Equation 3). Activation energy (E_a, kJ/mol) values were obtained from the plot of ln(D_{eff}) versus the reciprocal of absolute temperature (T, K).

$$D_{\mathrm{eff}} = D_o \exp\left(\frac{-E_a}{RT}\right) \quad (3)$$

Where:

D_o: the Arrhenius factor;

E_a: the activation energy (kJ/mol);

R: the universal gas constant (8.314 kJ/mol.K);

T: the drying temperature (K).

2.6 Mass transfer parameters

The determination of mass transfer properties, Biot number (B_i), and convective mass transfer coefficient (h_m) was done using Equations 4–6, as described by Dincer and Hussain (2002). Biot number is a dimensionless parameter that indicates the resistance to moisture diffusion within the product (Toğrul & Toğrul, 2007). B_i is affected by both product and drying medium properties and can be expressed as Equation 4.

$$Bi = \frac{24.848}{Di^{0.375}} \quad (4)$$

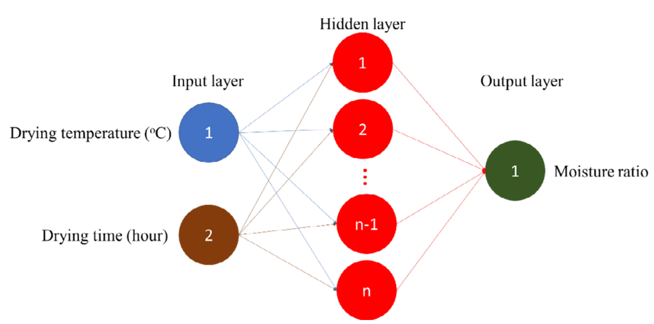

Figure 1. ANN structure and model in MATLAB application.

Dincer number (D_i) provides the relationship between flow velocity of the drying fluid and drying coefficient of the product (Akpinar & Dincer, 2005). D_i was calculated using Equation 5.

$$Di = \frac{v}{kL} \quad (5)$$

Furthermore, the convective mass transfer coefficient, h_m (m/s), was calculated using Equation 6.

$$Bi = \frac{h_m L}{D_{\mathrm{eff}}} \quad (6)$$

Where:

v: the drying air velocity (0.5 m/s);

L: the thickness of drying material;

k: drying constant determined from the semi-empirical model screened based on statistical indicators.

3 RESULTS AND DISCUSSION

3.1 Model fitting

3.1.1 Applying mathematical model

The change in moisture ratio during drying at different temperatures is shown in Figure 2. Initially, the moisture content of cooked dried rice was 56.6% (on a wet basis). During drying, the moisture content of cooked rice decreased, which led to a decrease in moisture ratio and time. It could be seen that the drying time decreased substantially from 5 to 2.5 h when the air temperature increased from 55 to 70 °C. The increased air temperature caused the drying procedure to transfer moisture faster, which is similar to the research on butterfly pea flowers (Thuy et al., 2021), purple sweet potatoes (Thuy et al., 2022a), and banana peel (Tai et al., 2021). These authors explained that higher temperatures could require greater supply of energy for the processing of water movement out of the food matrix.

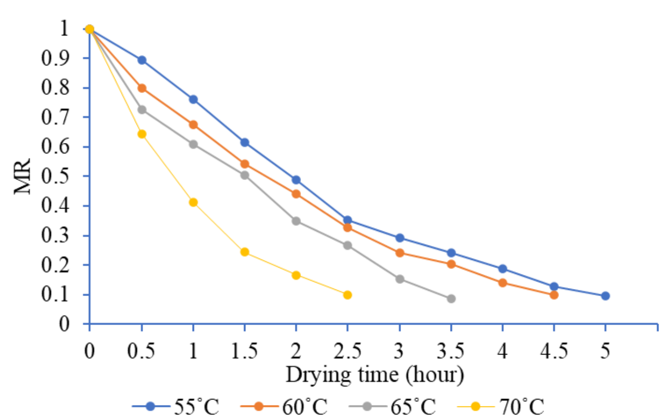

Figure 2. Moisture ratio versus drying time at different temperatures of cooked "Cẩm" brown rice.

The drying curve obtained from the actual experiment was found to be fitted with eight mathematical models (Table 1). Thin-layered modeling was successful to predict the moisture content and moisture ratio of dried samples. However, the fitted model depended on various parameters, including type of material, temperature, thickness of the sample, and time of the drying process. Generally, the criteria for selecting a fitness model are the highest R^2 and the lowest RMSE, chi-square, or MSE (Arabhosseini et al., 2009). In this current study, the model coefficient and the statistical results of eight models are presented in Table 2.

From Table 2, it could be seen that the R^2 and MSE values of eight models ranged from 96.68–99.95% and 0.0080–0.3050, respectively, which indicated that all of the models could well present the goodness of fit between actual and predicted data. Among the tested models, the diffusion approach model was the most suitable for expressing the moisture ratio at different temperatures with almost the lowest MSE and highest R-square. The diffusion approach was also used for describing the drying process of pomelo (Yildiz & İzli, 2019) and corn (Hacihafizoğlu et al., 2009). Another study on tarragon also showed that the diffusion approach model gave the best fit to predict drying behavior (Arabhosseini et al., 2009).

3.1.2 ANN model

The ANN model with two input parameters, time and temperature, was employed to make predictions regarding the moisture ratio. The statistical findings of training and validation are shown in Table 3. As can be seen in this table, the increasing number of hidden layers could lead the model to fit more with the actual data, which is presented by the increasing correlation coefficient (R^2) of the training and testing models. It was in line with the study by Selvi et al. (2022) who discovered that the networks were vulnerable to the number of neurons in the

Table 2. Model constant and statistical values of fitting model with actual MR data.

Model name	Model coefficient	R^2	MSE ($\times10^{-2}$)
55 °C			
Newton	k=0.3871	97.80	0.2202
Henderson and Pabis	a=1.0648; k=0.4146	98.53	0.1634
Page	k=0.2904; n=1.3014	99.74	0.0221
Logarithmic model	a=1.2618; k=0.2825; c=-0.2274	99.39	0.0767
Peleg model	a=3.02839; b=0.466859	99.07	0.1037
Two-term	a=0.5324; b=0.5324; k=0.4146; k_1=0.4146	98.53	0.2101
Diffusion approach	a=1.6417; k=0.2181; b=0.2757	99.23	0.0960
Wang and Smith	a=-0.3029; b=0.0242	99.44	0.0622
60 °C			
Newton	k=0.4446	99.31	0.0634
Henderson and Pabis	a=1.0177; k=0.4533	99.37	0.0651
Page	k=0.4005; n=1.1230	99.50	0.0345
Logarithmic model	a=1.1516; k=0.3392; c=-0.1563	99.85	0.0178
Peleg model	a=2.3669; b=0.5704	99.82	0.0190
Two-term	a=0.5088; b=0.5088; k=0.4533; k_1=0.4533	99.37	0.0867
Diffusion approach	a=-5.4831; k=0.2137; b=1.1267	99.84	0.0183
Wang and Smith	a=-0.356241; b=0.0351741	99.77	0.0229
65 °C			
Newton	k=0.542917	98.18	0.1745
Henderson and Pabis	a=1.0032; k=0.5448	98.18	0.2033
Page	k=0.5087; n=1.1000	96.88	0.2113
Logarithmic model	a=1.3005; k=0.3230; c=-0.3285	99.24	0.1019
Peleg model	a=2.0324; b=0.5234	99.23	0.0862
Two-term	a=0.5016; b=0.5016; k=0.5449; k_1=0.5449	98.18	0.3050
Diffusion approach	a=1.0020; k=0.4928; b=-2.2687	99.27	0.0976
Wang and Smith	a=-0.419351; b=0.0462833	98.80	0.1334
70 °C			
Newton	k=0.9030	99.93	0.0080
Henderson and Pabis	a=1.0044; k=0.9070	99.94	0.0095
Page	k=0.8960; n=1.0363	99.88	0.0080
Logarithmic model	a=1.0197; k=0.8715; c=-0.0178	99.95	0.0099
Peleg model	a=1.0103; b=0.6922	99.84	0.0232
Two-term	a=0.5022; b=0.5022; k=0.9071; k_1=0.9071	99.93	0.0190
Diffusion approach	a=1.6229; k=0.7723; b=0.7816	99.95	0.0094
Wang and Smith	a=-0.734815; b=0.152421	99.72	0.0405

Table 3. Results of the dynamic model using to predict the moisture ratio of instant "Cẩm" brown rice.

Number of hidden layer	Training		Test	
	R^2	MSE	R^2	MSE
1	0.9786	0.0036	0.9670	0.0022
2	0.9965	0.0008	0.9794	0.0026
3	0.9968	0.0004	0.9969	0.0016
4	0.9872	0.0022	0.9912	0.0043
5	0.9967	0.0005	0.9921	0.0015
6	0.9838	0.0036	0.9969	0.0018
7	0.997	6.0589×10^{-5}	0.9942	7.5183×10^{-4}
8	0.994	0.001	0.9658	0.0016
9	0.9998	3.6323×10^{-5}	0.995	3.4755×10^{-4}
10	1	0	0.9948	0.0010

deepest layers of their bodies. Therefore, fewer neurons led to underfitting, whereas an excessive number of neurons led to overfitting, causing an excessive amount of fitting. The training datasets were utilized to determine the optimal combination of neuronal and hidden layer counts for multi-layered modeling using neural networks and to find out which method had the most accurate predicting ability.

The ANN model with 10 hidden layers was elected to be the best structure for instant brown rice kinetic modeling with the highest R^2 and lowest MSE. This structure had 1.000, 0.99454, 0.999482, and 0.99743 of R for train, validation, test, and overall, respectively (Figure 3).

Recently, various studies used drying conditions and time as input data in ANN modeling and prediction of the moisture content like the static model in this study (Amini et al., 2021; Beigi & Torki, 2021; Chasiotis et al., 2020; Onu et al., 2022;

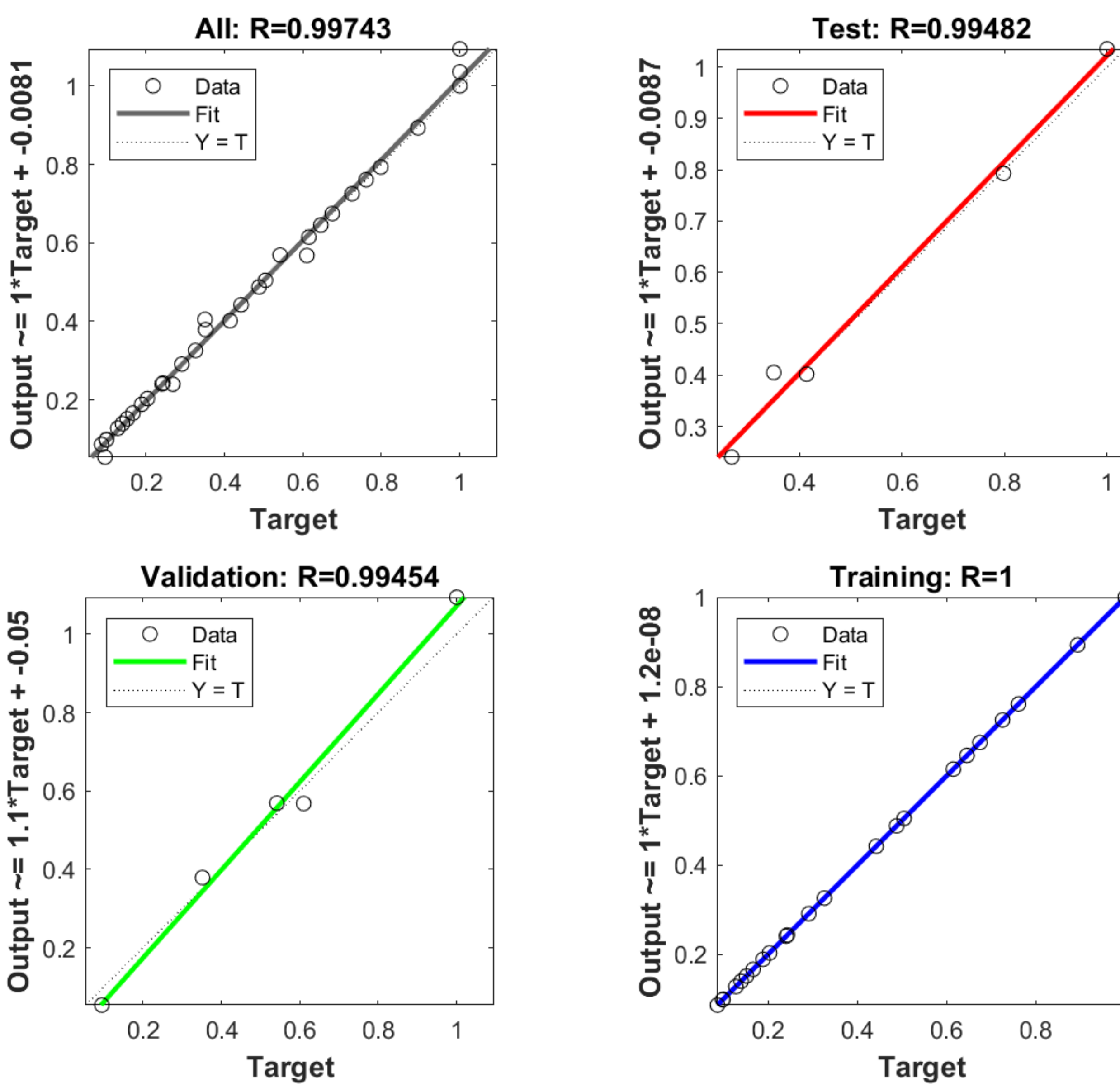

Figure 3. Regression ANN model of predicted and experimental data for instant "Cẩm" brown rice.

Salehi, 2020). The ANN model was trained using experimental data, through the “nntool” of MATLAB. Among the configurations tested, the most satisfactory performances during the training phase were achieved with the LM training algorithm (TRAINLM) (considering minimum error and less relationship complexity) using 10 neurons in the hidden layer, as previously discussed (Figure 4). Table 4 shows the weights and biases of the optimum network for instant brown rice.

3.1.3 ANN versus thin-layered mathematical model

Contrary to ANN, which provided a noticeably better fit to the experimental data, the chosen mathematical model (diffusion approach) showed lower R^2 and greater overall MSE than expected for the drying process at 70 °C (Table 5). Following the study by Jafari et al. (2016a), trained ANN had superior prediction abilities than the tested models regardless of the settings applied. Similar findings have been reported for the rapid applications of ANN with excellent accuracy in forecasting the drying kinetics of several goods, including green bell pepper (Jafari et al., 2016b), figs (Şahin & Öztürk, 2018), and button mushrooms (Tarafdar et al., 2018). The ANN model also had a nonlinear transfer function that made it better suited for nonlinear regression prediction, which led to higher R^2 and lower MSE values for the ANN model compared to the thin-layered model. When nonlinear and complicated interactions were applied to the system, ANN models performed better (Mavani et al., 2022). As a result, when compared to other evaluated models, the ANN technique produced a prediction of the MR with a higher degree of accuracy. It is intriguing to observe that the diffusion approach model was able to fiercely compete with the exceptional predicting powers of ANN, which may have been possible given the simpler drying of the data. Increasing the quantity and intensity of drying factors may cause semi-empirical models to go hysterical and necessitate the use of ANN. Therefore, the developed dynamic ANN model may be used in a predictive control system, which is able to estimate the forthcoming responses of the sample when certain process control parameters are given.

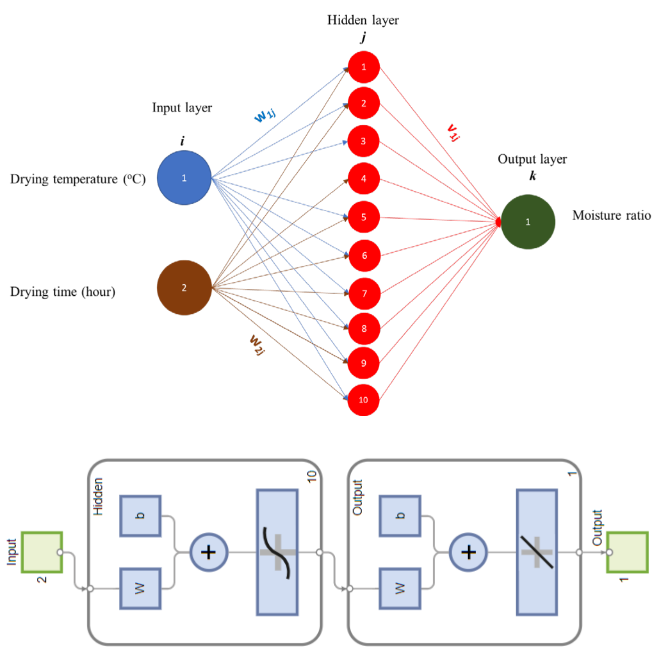

Figure 4. Optimum ANN model topology with 10 hidden layer neurons. The topology predicts moisture ratio when supplied with drying temperature and drying time as inputs.

Table 4. ANN topology weights and biases for moisture ratio prediction for instant “Cẩm” brown rice.

j	w_{1j}	w_{2j}	b_j	v_{j1}	b_k
1	-2.0126	4.4053	4.9560	0.3451	0.4393
2	-2.0718	-3.6199	2.7849	0.6754	-
3	4.9415	-0.6444	-2.5412	-0.1190	-
4	4.1807	-0.9282	-0.8880	-0.0460	-
5	-5.1298	-0.5503	1.2941	-0.1940	-
6	2.4264	3.9029	1.0102	-0.3936	-
7	2.7731	-1.5227	1.1325	-0.9497	-
8	-4.4029	1.4406	-2.1593	-0.4398	-
9	3.5736	-0.6772	4.1336	-1.0050	-
10	-2.0975	-3.8273	-4.9775	0.5622	-

3.1.4 Effective moisture diffusivity and activation energy

Food products’ effective moisture diffusivity illustrates their inherent moisture migration characteristics, which involve a variety of factors like liquid, molecular, vapor, and hydrodynamic diffusion (Roman et al., 2020). The estimated values of effective diffusivity (D_{eff}) are shown in Table 6 at various temperatures, from 4.81×10^{-11} to 9.35×10^{-11} (m^2/s). When drying temperatures increased, the D_{eff} value of instant brown rice also increased. This is explained by the increase in the product’s vapor pressure, which improved moisture transport at high temperatures (Shi et al., 2013). More specifically, the improved water molecule activity in the leaves will ultimately boost the heat produced by the rise in drying temperature, which will raise the diffusion rate (Nadi & Tzempelikos, 2018). The values of D_{eff} obtained from this study were within the reported range of moisture diffusivity for foodstuffs (10^{-11} to 10^{-9} m^2/s) (Zogzas et al., 1996).

The values of B_i and h_m are also listed in Table 6. The values of the B_i number, which ranged from 3.1655 to 5.1272, were found to increase as the temperature rose. A similar pattern was noted for vacuum-dried apples, which increased in temperature from 50 to 70 °C (Nadi & Tzempelikos, 2018). For instant brown rice at temperatures between 55 and 70 °C, the mass transfer

Table 5. Comparative evaluation of ANN and diffusion approach model for drying process of instant “Cẩm” brown rice.

Model	R^2	MSE
ANN	0.9973	0.0010
Diffusion approach	0.9923–0.9995	0.0094–0.0976

Table 6. Drying characteristics for instant “Cẩm” brown rice.

Drying temperature (°C)	k	D_{eff} (10^{-11} m^2/s)	B_i	h_m (10^{-9} m/s)
55	0.2181	4.81	3.1898	1.53
60	0.2137	5.13	3.1655	1.63
65	0.4298	6.70	4.1138	2.76
70	0.7732	9.35	5.1272	4.79

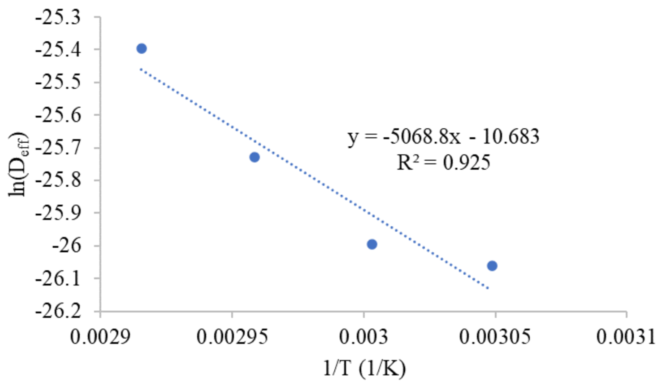

Figure 5. Arrhenius type relationship between effective moisture diffusivity and temperature.

coefficient (h_m) ranged from 1.53×10^{-9} to 4.79×10^{-9} m/s. This demonstrates that greater drying temperatures can achieve a higher rate of moisture transfer. Higher mass transfer rates come from drying at higher temperatures because it increases the sample's available heating energy and increases the activity of water molecules (Tarafdar et al., 2021).

A molecule's ability to start a chemical reaction is typically described as its activation energy. The plot of $\ln(D_{eff})$ versus $1/T$ was used to determine E_a for the instant brown rice, and the data were satisfactorily fitted by a linear equation (R^2=0.925, Figure 5). In drying kinetics, the influence of temperature on the effective moisture diffusivity is typically modeled using an Arrhenius type of equation. It was discovered that the E_a for instant brown rice was 42.14 kJ/mol.

4 CONCLUSION

One key step in the production of instant brown rice is the drying process after cooking. The cooked rice was dried at 55, 60, 65, and 70 °C. The results of experimental studies demonstrated that a temperature rise had a considerable impact on the pace of drying, which was later demonstrated by a rise in the mass transfer parameters. The diffusion approach model was the best at accurately predicting the drying kinetics of instant brown rice out of the eight selected models that were examined. When the diffusion approach model and ANN were compared, it became clear that the trained ANN's prediction power was greatly matched.

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