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PREDICTION OF THE DRYING KINETIC OF PERIWINKLE *(TURRITELLA COMMUNIS)* MEAT USING ARTIFICIAL NEURAL NETWORKS APPLYING THE OVEN-DRY METHOD

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ABSTRACT

The drying kinetics of periwinkle meat, a seafood delicacy, is crucial for optimizing preservation methods and ensuring product quality. This study explores the application of Artificial Neural Networks (ANN) to predict the drying kinetics of periwinkle meat under various drying conditions. A comprehensive dataset was generated through experimental drying processes, capturing variables such as temperature, thickness and drying time. The ANN model was developed using multi-layer feed-forward architecture, with input parameters (independable variables) including initial dying time, drying temperature, and thickness while the output (dependable variables) was the moisture content at different time intervals. The model was trained and validated using a portion of the dataset, achieving a high degree of accuracy in predicting moisture loss over time. Performance metrics, including RMSE and R-squared values, indicated that the ANN model effectively captured the nonlinear relationships inherent in the drying process. The average range of the Deff values was 3.12 × 10−12 m^2/s to 4.82 × 10−12 m^2/s. The highest R^2 value, 0.9996 was found in the ANN model, this demonstrated that ANN can serve as a powerful tool for modeling drying kinetics, offering insights that can enhance drying efficiency and product quality in the seafood industry. Ea had a value of 15.325 kJ/mol in oven drying method. This approach not only streamlines the drying process but also contributes to the development of more sustainable practices in food preservation. Future work will focus on refining the model and exploring its applicability to other seafood products.

Keywords: artificial neural network, periwinkle meat, thickness, temperature, drying time

1. INTRODUCTION

The periwinkle snail (Turritella communis), often referred to locally as "Isam" in Izon, is a sea food that is typically gathered (mostly by hand) along a sea estuary's tidal beach areas (Egbe, 2023). The production of several cuisines by residents of Nigeria's coastal regions and possibly elsewhere depends heavily on this meaty component. Locals consider periwinkle meat to be a good source of protein (Toyin 2015), and dried periwinkle flesh is well recognized to have higher nutritional value than fresh meat (Adebayo and Ogunjobe 2008). Fresh periwinkle meat degrades and decays quickly, so it needs to be preserved nearly instantly following the flesh is removed from the shell.

The drying process of food products, including periwinkle meat (Tympanotonus fuscatus), is a critical operation in food preservation and processing. Periwinkle, a mollusk commonly found in coastal regions, is a popular delicacy in various cuisines, particularly in West Africa. The drying of periwinkle meat not only extends its shelf life but also enhances its flavor and texture. However, the drying kinetics of periwinkle meat can be complex due to its unique biological and chemical properties, which can affect moisture removal rates during the drying process.

Understanding the drying kinetics of periwinkle meat is essential for optimizing drying processes, ensuring product quality, and minimizing energy consumption. Traditional methods of modeling drying kinetics often rely on empirical equations and assumptions that may not accurately capture the complexities of the drying process (Khan et al., 2018). As a result, there is a growing interest in employing advanced computational techniques, such as Artificial Neural Networks (ANNs), to predict drying kinetics more accurately.

The neural networks seen in machine learning models called artificial neural networks are inspired by the human brain. They have the ability to recognize intricate patterns in data, making them suitable for modeling nonlinear relationships in various fields, including food science (Zhang et al., 2019). ANNs have been successfully applied in predicting drying kinetics for different food items, including meats, fruits, and vegetables, demonstrating their potential to improve how accurate drying models are (Khan et al., 2020; Khoshtaghaza et al., 2019).

The application of ANNs to predict the drying kinetics of periwinkle meat is relatively novel. By utilizing experimental data on moisture content, temperature, and drying time, ANNs can be trained to model the drying behavior of periwinkle meat under various conditions. This approach can provide insights into optimal drying parameters, enhance product quality, and reduce energy costs associated with drying operations (Akinmoladun et al., 2021).

Despite the advancements in ANN applications in food processing, there is limited research specifically focused on the drying kinetics of periwinkle meat. This study aims to fill this gap by developing an ANN model to predict the drying kinetics of periwinkle meat, thereby contributing to the body of knowledge in food science and technology, this study will not only provide valuable insights into the drying behavior of periwinkle meat but also pave the way for further research in the application of machine learning techniques in food processing.

2. MATERIALS AND METHOD

2.1 Sample Preparation

The Ondewari market in the Southern Ijaw Local Government Area (SILGA) Bayelsa State, in the South-South part of Nigeria, was the source of a fifty-kilogram (50 kg) quantity of periwinkle snails (Plate 1 C, 45 kg worth). After being thoroughly group-washed with sanitized water, they were parboiled for approximately fifteen minutes. In a technique called tweaking, this was done to make it easier to separate the meat from each shell by weakening the link between the two. Each auger-shaped periwinkle snail had its tail section cut off with a cutlass by hand, and then tweaking was performed with sterile needles (Plat 1 B). Following immersion in a 5% NaCl solution, T100-g samples were placed in an oven set at 50, 60, and 70 degrees Celsius. Three duplicates of each experiment were conducted. A 0.01-mm precision digital scale was utilized to measure each sample's weight during the drying process in a WTC binder oven (Model WTCB 1718) with a maximum weight of 210g and power requirements of 8-14.5V, 50/60Hz, and 60V. Similar techniques were used on red palm weevil larvae by Zibokere and Egbe (2019), acute mud snails by Burubai and Bratua (2015), and catfish by Sankat and Mujaffar (2006).

1A: Group of single meaty part of the periwinkle snails. (Source: Egbe, 2023).

**1C: Full and adult auger-shaped periwinkle snails.
(Source: Egbe, 2023).**

1B: Auger-shaped periwinkle snails with the tail nipped to dislodge the meat. (Source: Egbe, 2023).

2.2. Kinetics of the Drying Processes

Moisture contents were measured on dry-basis using (Mohsenin, 1986). Using equation 1

$$M = \frac{w_i - w_f}{w_f} \quad \ldots \quad 1$$

2.3. Effective Moisture Diffusivity and Activation Energy

Comprehending the mechanism that transports moisture within the samples during their drying process was essential. During the Fick's diffusion process, the drying samples were subjected to a dimensional approach using an equation because its ease of representation of the mass transfer process. This method allowed for the calculation of the samples' effective moisture diffusivity. Equation (3-5) outlines Crank's (1975) solution to the diffusion problem stated by Fick.

$$\frac{dM}{dt} = De\left(\frac{d^2M}{dr^2}\right) \quad \ldots \quad 2$$

Equation 2 (Ndukwu and Karen, 2011)

$$MR = \frac{6}{\pi^2} e^{-nD_e t(\frac{\pi}{r})^2} \quad \ldots \quad 3$$

$$\ln(MR) = \ln\frac{6}{\pi^2} - nD_e\left(\frac{\pi}{r}\right)^2 t \quad \ldots \quad 4$$

$$D_e = \frac{Slope\ of\ plot\ [r^2]}{n\pi^2} \quad \ldots \quad 5$$

(Sahey and Singh, 2005)

2.4. Mathematical Thin-Layer Modeling

After the drying data was collected, it was fitted to five distinct statistical models. Table 1 lists the specific mathematical models that were employed, including logarithmic, Henderson, Page, and Newton and logarithms model. By using these models, prediction become more accurate and less assumptions are needed Khaled (2020).

Table 1. Mathematical thin-layer drying models.

Model No.	Model Name	Model Expression	Reference
A	Page model	$MR = \exp(-kt^n)$	Akoy,2014
B	Midilli et al. model	$MR = a \exp(-kt) + bt$	Zenoozian et al., 2008
C	Henderson and Pabis model	$MR = a \exp(-kt)$	Dash et al.,, 2013
D	Logarithmic model	$MR = a \exp(-kt) + c$	Antonio, et al., 2003
E	Newton model	$MR = \exp(-kt)$	Khaled,, 2020

2.5. Artificial Neural Network

Layers inside a neural network are arranged in interconnected configurations. A network with a single layer of feed-forward connections network having numerous feed-forward link layers, a recurrent network, and the three different types of ANN constructions that may be distinguished by their connection types, according to Haykin (1999). Among these constructions is a multi-story building. In agricultural and food systems modeling, layered feed-forward networks are commonly employed. A forward neural network comprises one or more hidden layers (h), a production layer (m), and an initial layer (n). This experiment was conducted using a multi-layer feed-forward network. Three input factors were used in this construction: thickness, temperature, and drying time. Training and test datasets were created by randomly splitting the data into 70% and 30%, respectively. As shown in Figure 2, the chosen hidden layer had a single-layer (Siger et al., 2021; Toker et al., 2004; Yıldırım, 2000). For the ANN model analysis, Weka 3.6, a program created in Hamilton, New Zealand, was used exclusively. Neural Fitting and Prediction, along with other related tasks, are generally performed by ANNs. Without the use of topic-specific neural network technologies, it might be feasible to forecast the future in this case.

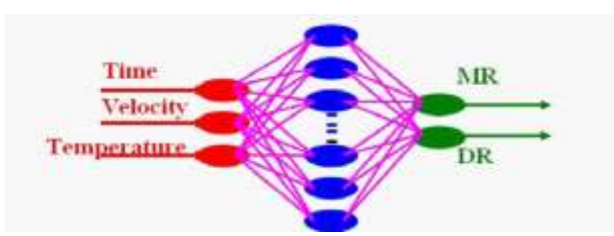

Figure 2. Artificial neural network applied in this research

2.6. Model Evaluation

Measurement findings showed the mean ± standard error. Using statistical criteria, the degree of fit between the models of computational intelligence (ANN) and mathematical thin-layer were evaluated. They included the RMSE and R^2. They were determined mathematically in line with the points suggested by Equations (6), (7), and (8).

$$R^2 = 1 - \left[\sum_{i=1}^{n}(MR_{pre,i} - MR_{exp,i})^2\right] \quad \ldots \quad 6$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(MR_{pre,i} - MR_{exp,i})^2}{n}} \quad \ldots \quad 7$$

$$\chi^2 = \frac{\sum_{i=1}^{n}(MR_{pre,i} - MR_{exp,i})^2}{n - k} \quad \ldots \quad 8$$

where what was actually observed based on the experimental data is denoted by Vexp, the projected value by Vpred, and the mean value by Vm. N (the total number of observations) was used to get the average of the actual observations. These were the R^2 and RMSE values: Reductions in both the R^2 and RMSE values were regarded as indicating better fitting quality.

3. RESULTS AND DISCUSSION

3.1. Behavior of the Drying Process

After the samples were applied at 50, 60, and 70 °C, Figure 3 shows the variations in the moisture ratio over time. The figure may reveal the moisture ratios of the samples utilized in the analysis. Increasing the drying period decreased the oven drying method approach's effectiveness. The oven drying method approach was utilized to attain the drying rates at the period when the rate was declining. As the drying process went on, it became clear from Figure 3 that the drying time consequently decreased. After 10 minutes of drying at 60 and 70 degrees Celsius, the moisture ratio values of 0.20 and 0.42 were achieved. The material was found to have a moisture ratio of 0.20 at 50 ◦C after 37 minutes of drying. In around 20 to 50 minutes, the material's moisture content decreased to 0.10 g [H2O] kg−1 [DM], depending on the drying temperature (Figure 3). The results also showed that a steeper slope resulted from raising the drying temperature, and the time required to dry the samples was reduced by almost 250%. The conclusion drawn from these results was that, as the air grew drier, the moisture in the periwinkle meat samples moved from the inner layer to the surface. The temperature rose to a point where water vapor leaked into the surrounding air environment from the dry material's surface, speeding up the drying process overall. Other research on the drying patterns of various materials have found similar results (Egbe, 2023; Egbe & Zibokere 2021, Ayadi, et al., 2014). As the drying temperature rose, the drying rate curves also grew steeper. The findings of several studies employing the oven drying method approach may be consistent with this observation (Sharma et al., 2021; Adak et al., 2017).

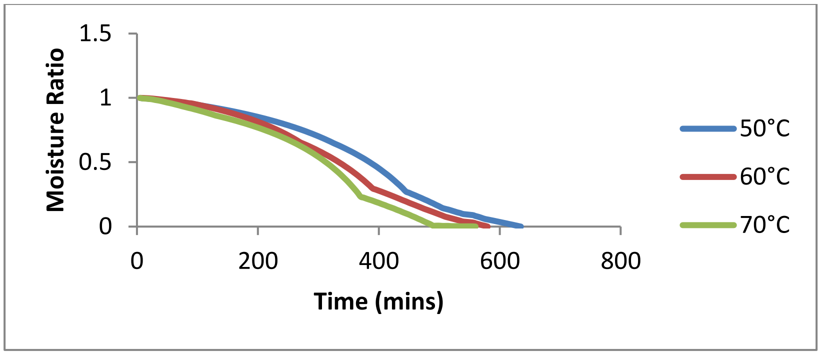

Figure 3: Drying curve at different temperature for Periwinkle Meaty (*Turritellacommunis)*

3.2. Effective Moisture Diffusivity (De) and Activation Energy

(De) is a measure of how quickly moisture moves through the material during the drying process. It has a significant impact on how quickly the moisture is extracted from the periwinkle meat. Within the research, (ANNs) was employed to model and predict De based on various drying conditions by analyzing the drying kinetics, the ANN helped identified optimal conditions for maximizing moisture removal while maintaining the quality of the periwinkle meat on the other hands, the Ea refers to the least amount of energy needed for the moisture diffusion process to occur. It is an important parameter in understanding the temperature dependence of the drying rate. In this study, the Ea was determined by analyzing the relationship between drying temperatures and the Ea. A higher Ea indicated that more energy is required to facilitate moisture movement, which can affect the efficiency of the drying process.

Table 2 displays the several possible values for the De. The De values ranged from $3.12 \times 10{-}12\ m^2/s$ to $4.82 \times 10{-}12\ m^2/s$ on average. Raising the drying temperature from 50 °C through 70 °C resulted in a considerable rise in De, as shown in Table 2. One possible explanation for this result could be that greater temperatures increased the activity of water molecules, which in turn increased the diffusivity of moisture. When used for food material drying, the De values obtained in this investigation were within the usual range of 10−6 to 10–12 m2/s. The Deff values were in line with those from other studies on the drying of apples (2.27–4.97 × 10−10 m2/s), persimmon slices (1.330–9.221 × 10−9 m2/s), pumpkins (1.19–4.27 × 10−9 m2/s), and strawberries (2.40–12.1 × 10−9 m2/s) (Khaled, 2020; Xiao, et al., 2010; Sacilik, & Elicin, 2016).

Table 2. Values of activation energy and effective moisture diffusivity in periwinkle samples that were dried in an oven

Drying Temperature (°C)	Deff (m2/s)	D_0 (m^2/s)	E_a (kJ/mol)
50	3.13×10^{-12}		
60	4.47×10^{-12}	1.846×10^{-9}	15.325
70	4.82×10^{-12}		

However, the Arrhenius diffusivity constant, often known as the "preexponential factor" equation (D0), was calculated by the researchers to be 1.846 × 10−9 m^2/s for periwinkle meat. The energy needed for activation in oven drying method was calculated by graphing ln(Deff) against 1/(T + 273.15). As illustrated in Figure 4, this, in contrast was a function of the gradient times the universal gas constant (R) and proportionate to the Ea. With the help of the oven drying method value, which is shown in Table 2, the energy needed for activation was determined. Ea had a value of 15.325 kJ/mol in oven drying method. This result fell between 15 and 40 kJ/mol, which is the range for a number of foods (Madan et al., 2014). When evaluating the activation energies of fruits and vegetables, over 90% of the values observed in earlier research fell between 14.42 and 43.26 kJ/mol; for instance, bamboo has an activation energy of 28.60 kJ/mol (Younis, 2018). The current investigation revealed a comparatively low activation energy for periwinkle flesh. The temperature sensitivity of diffusivity is indicated by the Ea value. This implies that the susceptibility of diffusivity to temperature decreases with decreasing Ea value; hence, a lower value denotes greater moisture diffusivity. Therefore, in the current investigation, the diffusion of moisture and subsequent evaporation from the periwinkle fleshy surface needed approximately 15.325 kJ/mol of energy.

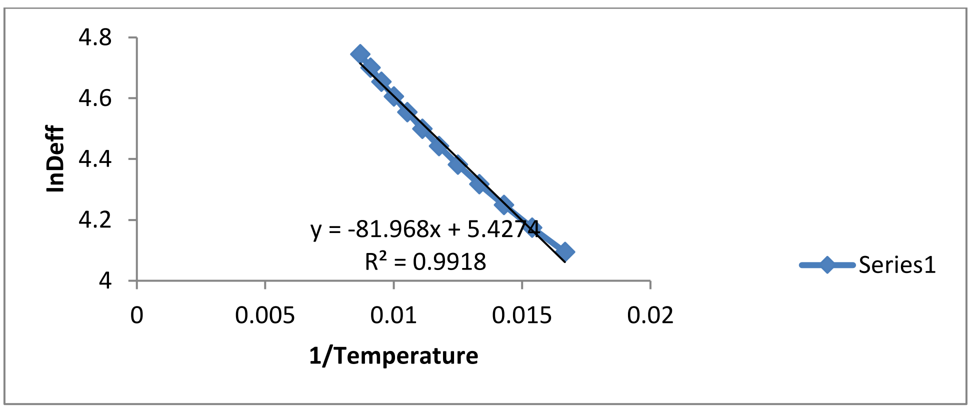

Figure 4. Relationship between temperature and effective moisture diffusivity.

3.3. Comparison of Different Mathematical Models of Thin Layers

To describe the samples drying dynamics during oven drying method, mathematical thin-layer techniques were applied. Table 3 shows several mathematical models that fit the data, taking into account the sample's experimental moisture content data, including model A, B, C, D, & F, the Page model fits the experimental data. adequately described the drying kinetics of periwinkle meaty, even though all five models were appropriately selected for the data. Under every oven drying method condition, the samples' RMSE values were less than 0.0200 and their R^2 values were greater than 0.9900. Table 3 was used to obtain the temperatures; the findings were similar to those obtained with the other four models. With the exception of Model, A, C, & E, which showed R^2 values of 0.9994 and 0.9935 at 70 ◦C, respectively, the model fit the experimental data the best, with the highest R^2 of >0.9991 and the lowest RMSE of <0.0150 at all three temperatures. All the models investigated were also deemed appropriate by Khaled et al.,

(2020) for forecasting the drying kinetics of persimmon slice samples. Younis (2018) found similar results when he discussed the drying qualities of garlic slices and evaluated the applicability of these models as well as any other pertinent models.

Table 3. Mathematical drying model evaluation for periwinkle meaty samples subject to oven drying method.

Oven Drying Temperatures (°C)	Model Constants & Coefficients	Models	R^2	RMSE
	k = 0.0462, n = 1.0341	A	0.9995	0.0093
	k = 0.0412, n = 1.0391, a =0.9999, b= 0.0001	B	0.9999	0.002
	a = 1.0102, k = 0.0341		0.9991	0.0097
	a = 1.0062, k = 0.0541, c = 0.0060	D	0.9991	0.0099
50	k = 0.0631	E	0.9989	0.0108
	k = 0.00921, n = 0.9910	A	0.9935	0.0293
	k = 0.0721, n = 1.1391, a =0.9990, b= 0.0009	B	0.9994	0.0102
	a = 1.0002, k = 0.0941	C	0.9994	0.0297
	a = 0.9962, k = 0.1041, c = 0.0260	D	0.9961	0.0199
60	k = 0.0631	E	0.9939	0.0208
	k = 0.02921, n = 0.7910	A	0.9935	0.0296
	k = 0.1721, n = 1.1341, a =0.9914, b= 0.0092	B	0.9984	0.0142
70	a = 0.9952, k = 0.1941	C	0.9994	0.029

3.4. Results of Artificial Neural Network

The ANN model used temperature to estimate the moisture ratio, time, and different levels of sample thickness. The training and validation statistics data are shown in Table 4. To determine which method had the most predictive potential, the ideal number of neurons and hidden layers for neural network-based multi-layer modeling was found using the training datasets. By comparing the outcomes of the test set (0.9986 and 0.9974) with the training set (0.9769 and 0.9743), The best data was obtained using the oven drying method design that had two hidden layers of 12 and 18 neurons (6 and 6 neurons; 9 and 9 neurons). As an illustration, Table 4 shows that there are three hidden layers with nine, eighteen, and twenty-seven neurons, two hidden layers with six neurons, and one hidden layer with three, six, and nine neurons. The number of neurons in the deepest body layers of the networks was also discovered to have an impact on them. Thus, fewer neurons resulted in underfitting, while too many neurons caused overfitting, which resulted in too much fitting. Evidence was presented by Khaled et al., (2020) investigated that an artificial neural network (ANN) with two hidden layers and twelve neurons correctly predicted the variations during the various phases of hot-air drying (HAD) and vacuum drying (VD) at varying drying temperatures of 50°C, 60°C, and 70°C for samples with thicknesses of 5 mm to 8 mm. When it comes to microwave-vacuum drying, it has also been demonstrated that ANN models with two hidden layers can accurately predict how various fruits and vegetables, like pepper, apple slices, and mushrooms, will dry (Ghaderi, et al., 2014; Nadian, et al., 2012).

Table 4. Results of statistical analysis of periwinkle sample drying kinetics for the ANN model

No. of Hidden Layers	No. of Neurons	Training		Test	
		***R*2**	**RMSE**	***R*2**	**RMSE**
1	3	0.9720	0.0744	0.9988	0.0151
1	6	0.9670	0.0756	0.9953	0.0193
1	9	0.9817	0.0676	0.9876	0.0301
2	3, 3	0.9659	0.0736	0.9984	0.0132
2	6, 6	0.9869	0.0656	0.9996	0.0211
2	9, 9	0.9853	0.0678	0.9984	0.0326
3	3, 3, 3	0.9534	0.0795	0.9972	0.0214
3	6, 6, 6	0.9722	0.0716	0.9981	0.0162
3	9, 9, 9	0.9742	0.0687	0.9971	0.0411

3.5. A Comparative Analysis of Artificial Neuron Networks and Mathematical Thin-Layer Models

The best outcomes for the prediction of the moisture ratios utilizing the top two mathematical thin-layer models (Page and Midilli) and the computational intelligence (ANN) model are summarized in Table 5. Twelve neurons and two hidden layers are used, the best results from using the ANN for oven drying method were an R^2 of 0.9996 and an RMSE of 0.0211. On the other hand, the oven drying method's mathematical thin-layer models at 50°C and 70°C showed that the RMSE ranged from 0.0093 to 0.0020 and the R2 ranged from 0.9995 to 0.9999. With values >0.9900 and <0.0100, respectively. Comparing the moisture ratio prediction using the models (A,B&D), the ANN-developed model produced the highest R^2 result and the lowest RMSE (Table 5). The results showed that the ANN provided the best results, which was in line with findings from earlier research that supported the use of an ANN as a data prediction strategy to improve its performance (Khaled et al., 2020; Benzie & Strain, 1996). Findings from the study demonstrated that the computer model may be used to real-world issues concerning the drying of periwinkle meat samples under various circumstances that are based on ANN. Thus, management of the drying procedure and the materials used as inputs might optimize profit, product quality, and energy efficiency. Using the ANN method to drying led to an improvement in drying performance overall.

Table 5. Statistical results of drying kinetics of periwinkle samples for computational intelligence and mathematical models using oven drying method.

Model		*R2*	RMSE
Computational intelligence	ANN	0.9996	0.021
Mathematical model	Logarithmic	0.9998	0.0055
	Page	0.9995	0.009
	Midilli	0.9999	0.0025

4. CONCLUSIONS

In conclusion, the application of artificial neural networks (ANN) for predicting the drying kinetics of periwinkle meat (*Turritella communis*) using the oven dry method demonstrated a promising approach to enhance the understanding and optimization of drying processes. The ANN model effectively captures the complex relationships between drying parameters and moisture content, providing accurate predictions that can aid in improving drying efficiency and product quality. This study highlights the potential of integrating advanced computational techniques in food processing, paving the way for more efficient and sustainable methods in the seafood industry. The results showed that in periwinkle samples significantly affected the activation energy, water diffusivity, and moisture evaporation rate. The samples' moisture diffusivity and drying kinetics were impacted by increases in drying temperature and sample thickness. Between 3.12 × 10−12 m^2/s and 4.82 × 10−12 m^2/s, the effective moisture diffusivity varied, with an average of 4.82 × 10−12 m2/s. For each molecule, the activation energy was 15,325 kilojoules. Both the logarithmic and Midilli models provided a satisfactory description of the drying kinetics of periwinkle ($R^2 > 0.9999$). The highest R^2 value, 0.9996, was found in the ANN model. The results demonstrated that the ANN was more accurate than mathematical thin-layer models. The theoretical models were limited to certain experimental conditions, whereas the ANN model could describe a wider range of experimental data. Therefore, the ANN may be considered a good substitute modeling method to comprehend the samples' drying behavior. Additionally, online monitoring, managerial activities, and industrial drying processes could all benefit from the successful application of ANNs. However, more research is needed to ascertain whether ANNs can effectively predict how drying will alter the nutritional composition of fruits and vegetables.

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