Application of Artificial Neural Network Modelling on the Drying Kinetics of Yam Slices During Drying

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Abstract

The drying kinetics of yam slices is a critical process in food preservation, influencing both the quality and shelf life of the product. This study explores the application of Artificial Neural Network (ANN) modeling to predict the drying behavior of yam slices under various drying conditions. A series of experiments were conducted to obtain moisture loss at a varying thicknesses (5-12mm), temperatures (50-90°C) and air velocities(1.5-5.5m/s) at a time interval of for 0 - 220 minutes. To observe a good representation of situation diversity, experimental data were divided into learning and testing databases. The network's inputs (In) were air temperature (T)/80, air velocity (V)/5.5, slice thickness (d)/12, and time (t)/220; the output (Out) was moisture content (db). The collected data were then used to train and validate an ANN model, which was designed to capture the complex nonlinear relationships inherent in the drying process. The ANN architecture was optimized through a systematic approach, including the selection of appropriate input parameters (temperature, time, and air velocity) as well as the determination of hidden layers and neurons. The model's performance was evaluated using statistical metrics such as relative mean square error (MAE), standard deviation of MAE (STDA), percentage of relative mean square error (% MRE), standard deviation of % MRE (STDR), and R^2. From the findings all three drying kinetics achieved a minimum value of root mean square error (RMSE) in the range of 0.00052 to 0.00092. Results indicate that the ANN model effectively simulates the drying kinetics of yam slices. This research highlights the potential of ANN as a powerful tool for optimizing drying processes in the food industry. The findings contribute to the growing body of knowledge on the application of artificial intelligence in food technology, paving the way for future studies on other agricultural products.

Keywords: *Neural network, yam slices, modelling, drying, temperature, air velocities, time*

1. INTRODUCTION

The drying of agricultural products, such as yam slices, is a critical process in food preservation and quality maintenance. The kinetics of drying significantly influences the final product's texture, flavor, and nutritional value. Traditional methods for predicting drying kinetics often rely on empirical models, which may not adequately capture the complex interactions involved in the drying process. In recent years, artificial intelligence (AI) techniques, particularly neural networks, have emerged as powerful tools for modeling and predicting drying kinetics due to their ability to learn from data and capture non-linear relationships.

Neural networks, a subset of machine learning, consist of interconnected nodes (neurons) that process input data and can model complex functions. Their application in food science has gained traction, as they can effectively handle the variability and non-linearity inherent in drying processes Assidjo et al. (008;). For instance, studies have demonstrated that neural networks can predict moisture content and drying rates with high accuracy, outperforming traditional models (Akinmoladun et al., 2021).

The drying kinetics of yam slices, specifically, can be influenced by various factors, including temperature, air velocity, and slice thickness. By employing neural networks, researchers can integrate these variables into a predictive model that accounts for the intricate dynamics of moisture removal. A study by Akinmoladun et al., (2021).), for instance, used a feedforward neural network to forecast how yam slices would dry under various circumstances, and the results showed a strong connection between the predictions and the actual data.

Moreover, the use of neural networks in predicting drying kinetics not only enhances the accuracy of predictions but also facilitates the optimization of drying processes. By simulating various drying scenarios, stakeholders can make informed decisions regarding drying parameters to achieve desired product quality while minimizing energy consumption (Bai et al., 2023).

This study aimed to show the applicability and efficacy of neural networks in modeling and predicting moisture transfer during air drying of food items, as well as to anticipate the drying process of yam slices when a variety of independent variables are present. Experimental drying data of yam slices was used to validate the model.

2. MATERIALS AND METHODS

2.1 Principle of Artificial Neural Network

The basic components of neural networks function in parallel.Similar to nature, the connections between neurons have a significant impact on network function, and weight coefficient is assigned to each pair of neurons. In accordance with a particular architecture, the neuron is separated into layers and connected. The multiple layer perceptron (also known as the feed forward network) is the conventional network layout for function approximation. Both linear and nonlinear relationships between input and output vectors can be learned using the feed forward network, which usually has an output layer of linear transfer functions after one or more hidden layers of sigmoid neurons. Values outside of the -1 to +1 range can be produced by the network thanks to the linear output layer (Limin, 1994). For multi-layer networks, the weight matrices' superscript is determined by the number of layers. Two-layer networks make use of the proper nomenclature. Figure 1 depicts a simplified depiction of the selected network topology and behavior.

The multilayer neural network's theoretical architecture for predicting moisture content (MC, db)

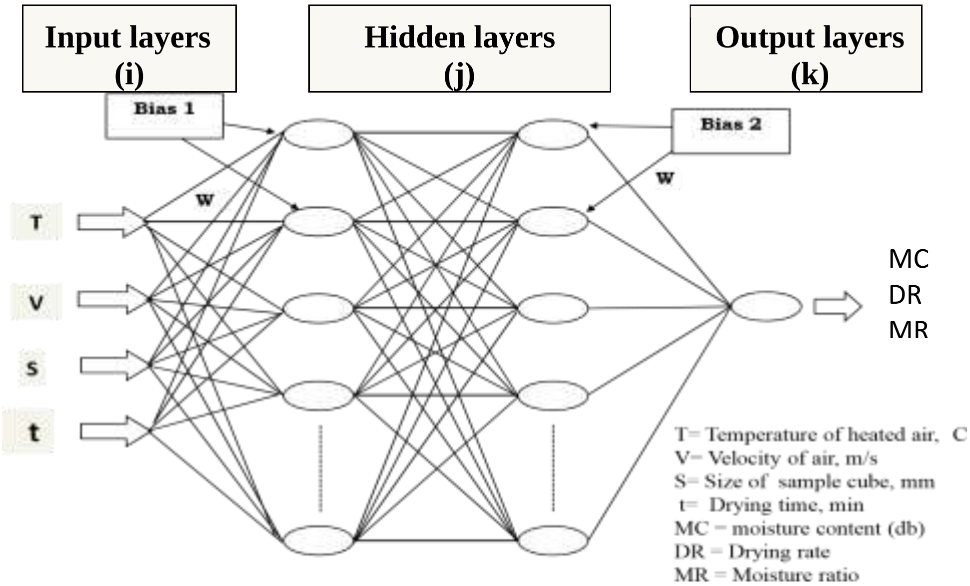


Fig.1. Artificial Neural Network Topological Structure, where k (number of inputs), ln (number of inputs), Out (output), W (weights), and b (biases).

In the process being studied, the quantity of variables that are input and output determines the number of neurons in the input and output layers. The input layer of this study comprises four variables: process air temperature (T), drying time (t)sample thickness (s), and air velocity (V). In contrast, the output layer has only one variable: moisture content (d.b.). It is challenging to determine the ideal number of neurons (ns) for the hidden layer since it depends on the task's complexity and nature, tt is usually established by trial and error. To create the neuron input n, the weighted inputs are mixed with the bias b of each neuron in the hidden layer. For the transfer function f, the argument is this sum, n.

$$n = Wi_{\{1,1\}}ln_1 + Wi_{\{1,2\}}ln_2 + \ldots\ldots\ldots\ldots + Wi_{\{1,k\}}\, ln_k + b \qquad \ldots(1)$$

Wi1 (weights) and b1 (biases) are two matrices that contain the hidden layer's coefficients. Following the computation of the weighted sum of the signals supplied by the hidden layer, the output layers arrange the resulting coefficients into matrices Wo3 and B3. The network output in matrix notation is provided by Equation (2).

$$Out = f'\{Wo_3 \text{ x } f\,(Wi_2 \text{ x}1n + b_2) + b_3\} \qquad \ldots(2)$$

Neurons in hidden layers can use any differentiable transfer function to produce output. A linear transfer function and a tangent sigmoid transfer function were used in this work to represent f and f', respectively. The network coefficients (weights and biases) equation is provided by equation (2).

2.2. Learning Algorithm

The application of artificial neural networks (ANNs) in modeling the drying process of yam slices involves a systematic learning algorithm procedure. This procedure typically includes data collection, preprocessing, model design, training, validation, and testing. Below is a detailed explanation of each step in the context of drying yam slices,

2.2.1. Data Collection

The first step involves collecting experimental data on the drying process of yam slices. This data typically includes variables such as Input Variables: Temperature, humidity, air velocity, slice thickness, and initial moisture content. Output Variables: Moisture content at various time intervals during the drying process.

Data collected through controlled experiments where yam slices are dried under the different conditions, and moisture content was measured at regular intervals. This is similarity with Afolabi & Adeyemi (2019). They investigated on modeling of drying kinetics of yam slices using artificial neural network.

2.2.2. Data Preprocessing

Drying yam slices with thicknesses of 5-12 with varying of 3mm at five distinct air temperatures ranging from 50-90°C with differences of 10°C and five air velocities velocities from 1.5 to 5.5m/s at discrepancies of 1m/s and at time interval of 0 - 220 minutes yielded experimental data. It produced approximately 1400 experimental data. To provide a good Experimental data were separated into databases for testing and learning to represent the diversity of situations. Slice thickness (d)/10, air temperature (T)/80, air velocity (V)/5.0, and time (t)/220 were the inputs (In) of the network, and moisture content (db) was the output (Out).

Once the data is collected, it needs to be preprocessed to ensure it is suitable for training the ANN. This step may include: Scaling the input and output data to a specific range (e.g., 0 to 1) to improve the convergence of the learning algorithm. Dividing the dataset into training, validation, and testing sets

2.2.3. Training the Model

The training process involves using the training dataset to adjust the weights of the network through a learning algorithm, typically backpropagation. The steps include:

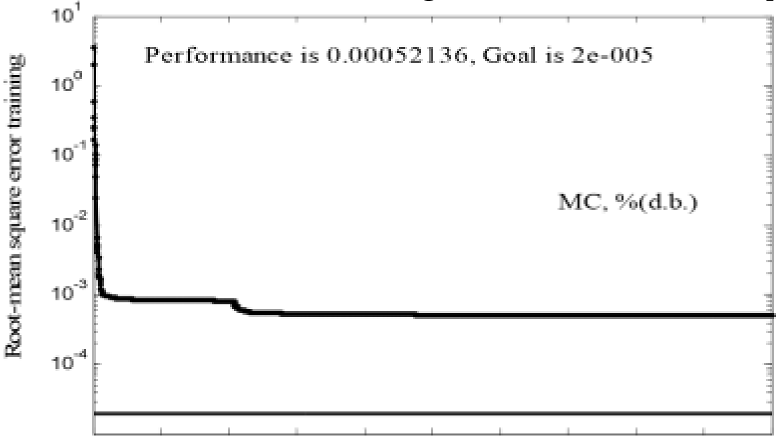
The network processes input data to produce predictions. The mean squared error, for example, is a loss function that is used to compute the difference between the expected and actual output. An optimization approach is used to change the weights after the loss has been transmitted back through the network.

2.2.4. Validation

During training, the model's performance is evaluated using the validation dataset. This helps in: Adjusting parameters such as learning rate, number of epochs, and batch size to improve model performance. Monitoring validation loss to ensure the model does not memorize the training data. this is in relation to Bishop (2006) investigation. After training and validation, the final model is tested using the testing dataset to evaluate its generalization performance. Metrics such as root mean square error (RMSE) and coefficient of determination (R^2) were commonly used to assess the model's accuracy Khashei & Bijari (2010).

3. RESULTS AND DISCUSSION

In the first attempt, ANN models were trained using a dataset that contained one output MC (dm/dt or MR) and four inputs (air temperature, air velocity, slice thickness, and time). The ANN model was set up differently. Trial-based adjustments were made to the learning rate, which establishes how much weight changes over a sequence of iterations to bring the predicted value within a reasonable range of the observed values, while keeping the hidden neurons constant at 8 in the first hidden layer and 4 in the second. Higher learning rates (η) were shown to produce poorly developed models in preliminary studies, which is in line with the conclusions of Rai and Chhaya & Rai (2008). Following these test runs, 0.05 was set as the learning rate and momentum. During training, simulations were conducted 2500 times at a progress rate of 50, and the neural network weights were set to the lowest practical forecasting error (Fig. 2).



0 250 500 750 1000 1250 1500 1750 2000 2250 2500

2500 Epochs

Figure 2 shows how the number of iterations (epochs) affects the root-mean-square error training.

A basic propagation network trained with the Levenberg-Marquardt algorithm was found to be quite good in generalizing and predicting the moisture content showing the final product after drying. All three drying kinetics achieved a RMSE (root mean square error) minimal value between 0.00052 and 0.00092. These findings were consistent with prior study (Chhaya and Rai, 2008). Figure 2 plots the RMSE values for the trial for moisture content against the number of iterations. The topology that produced the least amount of error in the fewest number of iterations when training the ANN was chosen.

3.1 Verification of ANN Models

The prediction performance of all three ANN models (MC, dm/dt, and MR) was confirmed using data from 20% of the instances that were excluded during the ANN models' original training. With a coefficient of determination of 0.9987, a standard deviation of 0.114, and a mean relative error of 8.258, Table 1 shows that the basic ANN model with two hidden neurons predicted MC.

Table 1 shows the ANN architecture with the minimum MRE for each combination when the treated sample is dried in hot air.

Architecture	MC (% db)	dm/dt (Drying rate)	MR
No. of hidden layer	2	2	2
No. of neuron first hidden layer	8	8	4
No. of neuron in second hidden layer	4	10	6
MAE	0.009	0.0160 17.300	0.0055
STD_A	8.200	0.0301 0.2370	9.4730
MRE	0.012	0.9940	0.0080
STD_R	0.120		0.1600
R^2	0.9982		0.9980

With a coefficient of determination of 0.9940, a standard deviation of relative error of 0.2370, and an average relative error of 17.300, the drying rate was predicted by the ANN model using two hidden neurons or dm/dt. The moisture ratio prediction (MR) had the subsequent coefficient of determination, MRE, and STDR: 0.9980, 0.1600, and 9.4730, respectively. Lertworasirikul and Tipsuwan (2008) used a single hidden layer with nine nodes and a logarithmic sigmoid transfer function to estimate the water activity and moisture content of semi-cracker cassava that was dried in a tray dryer using hot air. They found that the regression coefficient (R^2) and mean squared error were 0.9982 and 0.0010 respectively which closely match the findings of the present investigation. Eighty percent (80%) of each dataset was used for training, and the remaining twenty percent was used for testing. The information set was utilized to ascertain the ideal number of hidden layers and neurons per hidden layer during training in order to get the maximum prediction power. The artificial neural network's structure included neurons 2–10 and hidden layers 1 and 2. All combinations of neurons and hidden layers were learned. Calculations were made R2, the proportion of relative mean square error (% MRE), the standard deviation of % MRE (STDR), the number of hidden layers and neurons in each hidden layer, and the relative mean square error (MAE) and standard deviation of MAE (STDA). It was demonstrated that the drying procedure had an impact on the quantity of hidden layers and neurons in each hidden layer that generated the least level of error. The entire ANN structure is displayed in Table 3 for all data sets of blanched and treated samples as well as hot air-dried blanched samples. If there are sufficient neurons, a high The quantity of hidden layers is not necessary to reduce the error (Torrecilla et al., 2007). Two hidden layers were the most accurate forecast for most of the data set. The ANN designed for combined drying data is a little less accurate than one designed for individual circumstances.

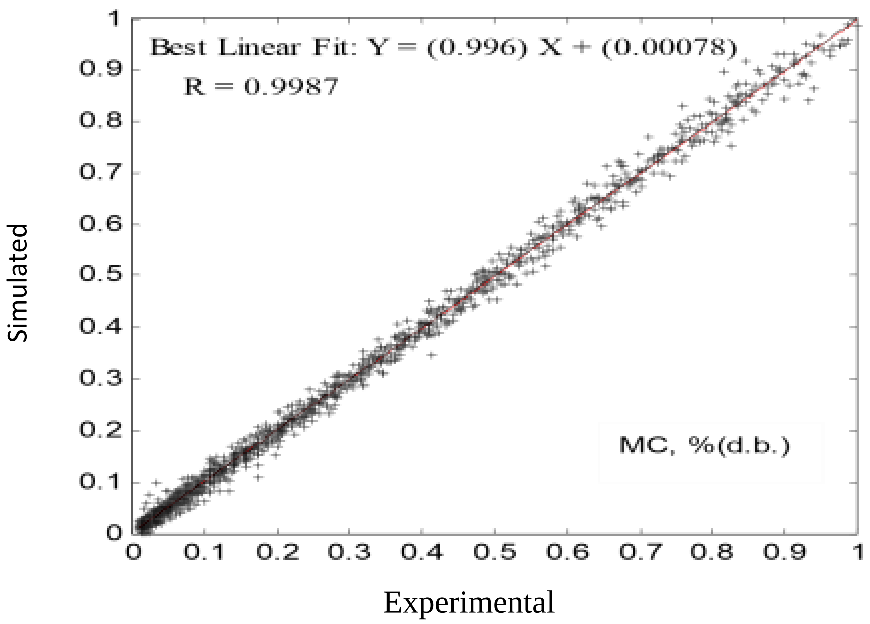


Figure 3 shows the correlation between the treated sample's experimental and anticipated results.

Figure 3 shows plots of experimentally measured moisture content, drying rate, and moisture ratio vs ANN-simulated values for all combined data. The correlation coefficients were all larger than 0.99. the R^2 values were while the R2 values for blanched samples were 0.9984, 0.9917, and 0.9987, respectively, the moisture content, drying rate, and moisture ratio had R2 values of 0.9987, 0.9930, and 0.9984. This proves that ANN is capable of precisely predicting the moisture ratio, drying rate, and moisture content. These results are similar to those of a previous study on cassava (Hernandez-Perez et al., 2004), where correlation coefficients more than 0.9998 were found between the observed and projected moisture content. The ANN's system equations for predicting moisture content, drying rate, and moisture ratio are shown in Table 3. The equation depicts each node's input, transfer function, as well as its respective weights and bias. The equations can be utilized in a computer program to forecast yam slices cube drying rate, moisture ratio, and moisture content (Islam et al. 2003). The moisture content, drying rate, and moisture ratio of blanched and treated samples had the lowest and greatest errors between actual and projected values, respectively, of 0.009-0.017, 0.0157-0.0330, and 0.0061-0.0212; for blanched samples, the corresponding errors were 0.009-0.017, 0.0181-0.0266, and 0.0082-0.0178. It is evident that the model correctly forecasted the drying kinetics seen in the experiment. This highlights how crucial it is to model food drying curves using artificial neural networks. Due to the fact that simulation is carried out using basic mathematical procedures, these models are not complicated and may therefore be utilized for online estimation in industrial air drying processes (Erenturk & Erenturk, 2007).

Table 2: ANN model for Moisture Content Prediction (dB, %)

Input variables:
X1 = Temperature, °C
X2 = Air velocity, m/s
X3 = Slice thickness, cm
X4 = Time, min
First hidden layer
H1 = tansig[(4.2554*X1+0.5461*X2+3.7369*X3+2.509*X4)-0.84272]
H2 = tansig[(3.8593*X1+0.8758*X2+2.5884*X3+0.9339*X4)-6.8799]
H3 = tansig[(-4.8827*X1+2.5006*X2-6.0765*X3-15.589*X4)-5.3058]
H4 = tansig[(0.2422*X1+0.5035*X2+0.7358*X3-1.0578*X4)-1.0176]
H5 = tansig[(-2.1996*X1+11.3534*X2+1.8041*X3+4.5596*X4)-3.9677]
H6 = tansig[(0.3429*X1-0.3593*X2-0.2657*X3-1.111*X4)-0.6475]
H7 = tansig[(-0.0215*X1+0.0277*X2+0.0179*X3+3.1194*X4)+5.1817]
H8 = tansig[(14.6736X1-31.4342*X2+14.8288*X3+12.956*X4)+12.0315]
Second hidden layer
G1= tansig[(0.1817*H1-0.8615*H2+0.0546*H3-0.4916*H4-0.0723*H5-0.9517*H6-10.1522*H7+0.0308*H8)+9.5811]
G2 = tansig[(21.5471*H1+8.1645*H2+2.8121*H3-19.1811*H4-2.225*H5-7.5634*H6+8.5984*H7-24.5878*H8)+14.8178]
G3 = tansig[(-0.9151*H1-0.020*H2+0.8406*H3-1.2553*H4-20.8199*H5-4.6587*H6+4.0193*H7+0.5970*H8)+15.8368]
G4 = tansig[(-0.1986*H1+0.8074*H2-0.0559*H3+0.4480*H4+0.0616*H5+1.0722*H6-21.7917*H7-0.0065*H8)+22.3392]
MC (output) = purelin[(1.5106*G1+0.0208*G2-0.0394*G3+1.7508*G4)-0.7470]

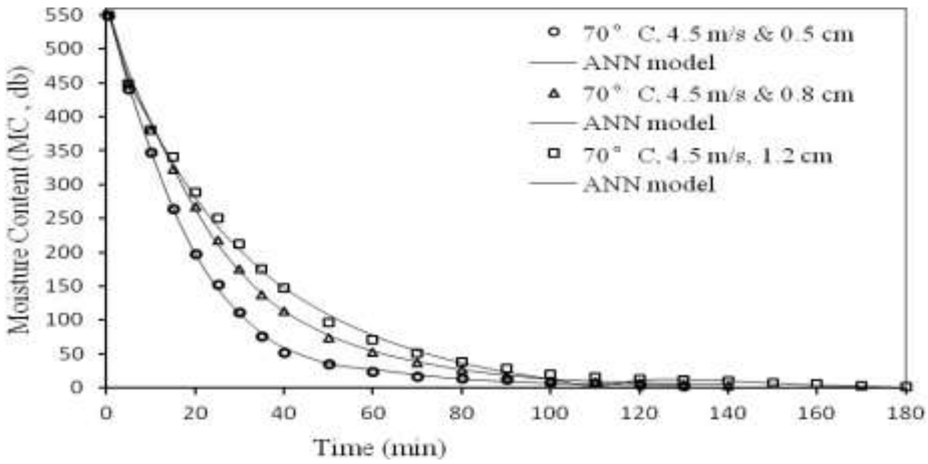


Figure 4: Simulations and experimental data on moisture ratio curves produced using the suggested model for yam slice drying kinetics.

Figure 4 shows how the models can forecast drying kinetics for a smaller validity range (e.g., 70^0C, 4.5 m/s & 0.5, 0.8, and 1.2 cm) at varying thicknesses, temperatures, and air velocities. Throughout the drying phase, the drying rate consistently dropped in each case (Diamante and Munro, 1993)

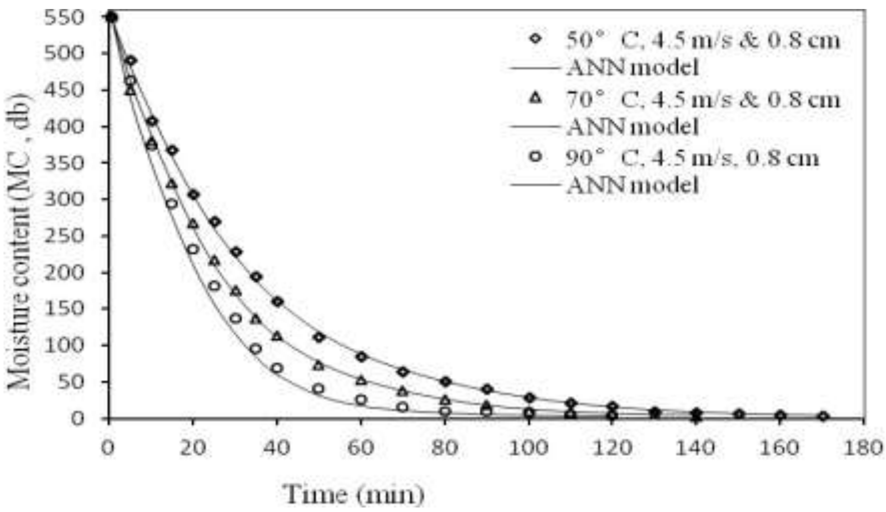


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Figure 5 shows the simulated curves and experimental data produced by the suggested model for the drying kinetics of yam slices.

The level of moisture Figure 5 displays some experimental data and simulated findings for moisture content that were gathered by the drying air temperature test database between 50 and 90^0C at a speed of 4.5 m/s and a size of 0.8 cm. The model's ability to predict the experimental drying kinetics is clearly successful. This highlights the significance of using artificial neural networks to model food drying curves. These models can be utilized for online estimate in industrial air drying processes since they are simple to use and simulation is achieved by basic arithmetic operations.

CONCLUSIONS

Using experimental data and numerical simulations under various operating conditions, the suitability of an ANN for modeling a hot air dryer was examined and demonstrated. According to the findings, the suggested ANN is effectively used to simulate a convective hot air drier for drying yam slices. The accuracy of the suggested neural network model in estimating the moisture content was greater than 0.05%. When the ANN was trained using a learning coefficient of 0.5 and 2500 iterations, it demonstrated an appropriate level of generalization and accuracy to predict the moisture content of the dried yam slices. Values greater than these did not considerably enhance the ANN's predictions. The suggested neural network model was shown to eliminate reliance on the mathematical model in addition to minimizing R^2. The experimental drying kinetics were thus successfully predicted by the neural network model. This demonstrates that since estimation is achieved by basic arithmetic processes, the significance of the artificial neural network model is not complicated. As a result, artificial neural networks can be effectively utilized for both online drying kinetics estimate and drying process control in industrial operations.

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