Optimization Of Drying Kinetics, Physical Properties, And Predictive Modeling of Pumpkin (Cucurbita Maxima) Powder: A Comparative Analysis of Mathematical and Ann Approaches

Sinthiya R[1,3], Dr.ALovelin Jerald[2] ,Veerapandi Loganathan[4]

[1]Research Scholar, Department of Food Processing and Preservation Technology, School of Engineering, Avinashilingam Institute for Home Science and Higher Education for Women, Avinashilingam University, Coimbatore (India).
[2] Department of Food Processing and Preservation Technology, School of Engineering, Avinashilingam Institute for Home Science and Higher Education for Women, Avinashilingam University, Coimbatore (India).
[3]Department of Food Technology, Sri Shakthi Institute of Engineering and Technology, Coimbatore, Tamil Nadu, (India).
[4]Department of Food Technology, Nehru Institute of Technology, Kaliyapuram, Coimbatore, TamilNadu,(India).

***Corresponding Author**: Sinthiya R
*Research Scholar, Department of Food Processing and Preservation Technology, School of Engineering, Avinashilingam Institute for Home Science and Higher Education for Women, Avinashilingam University, Coimbatore (India). sinthiya1602@gmail.com.

Abstract
This study investigates the drying kinetics, physical properties, and predictive modelling of pumpkin (Cucurbita maxima) powder using both mathematical and artificial neural network (ANN) approaches. Pumpkin, a rich source of beta-carotene and antioxidants, holds significant potential as a functional food ingredient. The drying process was performed at three temperatures (65°C,70°C,75°C) using a tray dryer to examine its effects on moisture content, drying rates, and product quality. The results revealed that higher drying temperatures accelerated moisture reduction but also caused nutrient degradation and texture changes. Among the tested temperatures, 70°C provided the best balance between efficiency and quality, while 75°C achieved the fastest drying rate. Mathematical modelling using five drying models, including the Logarithmic and Diffusion models, demonstrated excellent correlation coefficients (R^2), indicating their efficacy in predicting drying kinetics. However, ANN models outperformed mathematical models, offering superior accuracy with higher R^2 values and lower errors across all parameters. The ANN approach highlighted its versatility and precision in modelling complex drying dynamics. Physical property assessments revealed significant changes in colour, density, hygroscopicity, solubility, and flowability. The study confirmed that drying temperature significantly affects these attributes, with higher temperatures improving solubility and flowability but increasing hygroscopicity and promoting colour changes due to browning reactions. This research emphasizes the importance of optimizing drying conditions and leveraging advanced modelling techniques like ANN for efficient production of high-quality pumpkin powder. These findings provide valuable insights for the food industry to enhance the application of pumpkin powder as a functional and nutritional ingredient.

Keywords: Pumpkin powder (PP), Drying kinetics, Artificial Neural Network (ANN), Mathematical modelling, Functional food ingredient, Physical properties.

Introduction

Pumpkin (Cucurbita moschata) is grown in large quantities both in the tropics and temperate climates, rich with beta-carotene a precursor of vitamin A and a strong antioxidant. These qualities thus make it an excellent candidate for enrichment. Pumpkin fruit is a good subject for the application as a functional ingredient in food industry because of its rich nutrition and low cultivation cost. The fruits are pickled after harvesting. On the other hand, the pulp pieces of pumpkins are stored for commercial purposes during winter season by the producers. Also, they prepare different dishes on it, like stuffed courgettes, fried marrow, and pumpkin with syrup and walnuts, which are the traditional flavors of the Turkish kitchen. It was specifically seen that the pumpkin producers in the villages wanted to consign the pieces of pumpkins freshly from one season to the next and also to export them to the regions where pumpkins do not grow in abundance. Because of this, aside from spending a lot more in this process according to the weight of the products, the products may get decomposed and could suffer internal or external damages in the exporting process. So, it is prudent to cut down on volume and weight to efficiently preserve the pulp pieces of the pumpkin so that they can be transferred and/or stashed without much hassle. Therefore, these negative effects should be minimized. The best way to accomplish this is by the drying of mammoth pumpkin by hot air.

Drying is one of the methods of conservation of agricultural products that is widely used and one of the most energy-intensive processes of the industry(Liu et al., 2020). It may also be carried out as a thin layer or deep

layer. The former has also been commonly used in drying agricultural products. Drying materials that are completely exposed to air flow through them is called thin-layer drying(Qu et al., 2020). One of the oldest methods for the preservation of food is drying, which consists in removing water from the product to provide microbiological safety (Reddy et al., 2017), and the most popular drying method includes convection. In this method the drying agent supplies heat to the material and removes moisture (in the form of water vapour) from the material at the same time. The method itself is low-cost, but it has the disadvantage of entailing a time-consuming process. During contact with oxygen that is present in the air, the product becomes exposed to high temperature for a long time, and such exposure reduces the content of some valuable components which readily undergo oxidation at elevated temperature. Another drawback of the convective method is the concomitant substantial shrinkage (Dhurve et al., 2021).
Because of its complexity, heat and mass transfer occur simultaneously in drying. Hence, optimizing the conditions for drying is important, and in this regard, mathematical modelling has proven to be an excellent tool (Azeez et al., 2019). In addition to this, modelling is used to predict the time taken during drying and the nature of general drying. Design and selection of dryers also require a thorough understanding of the drying behaviour. Several studies have been reported in the literature to predict or develop the most suitable mathematical model for drying kinetics. In general, to predict the drying behaviour of agricultural commodities different mathematical models, such as empirical, semiempirical, and theoretical, are used. Most empirical models validate exceptional fitting of data but overlook the basics of the drying processes in most drying experiments (Balasubramanian et al., 2011). Earlier, modelling of drying kinetics using mathematical models for fruits of pumpkin done through hot air drying (Inyang et al., 2018), oven drying (Sarkar et al., 2020), tray, heat pump dehumidifier (Karim & Hawlader, 2005) and microwave drying (Liu et al., 2021) has been cited. In addition, several studies have been conducted to examine the vacuum drying characteristics of carrot (H. Wang et al., 2020). The authors, however, could not find any reported literature on the study of drying behaviour for pumpkin that involves intelligent process modelling through ANN, mass transfer parameters estimation and calculations of drying energy. The purposes of this research were to study the effect of temperatures on the drying characteristics of pumpkin fruit as well as to search for the proper thin layer drying models by comparing mathematical modelling and Artificial Neural Network that describes its drying behaviour.

Materials and Methods

Pumpkin Powder Preparation

Pumpkins (Cucurbita maxima) were purchased from the market of Coimbatore, Tamil Nadu, India. The pumpkins were cut into 2 × 5-inch slices, from which seeds were manually removed and soaked in a 2% sodium metabisulphite solution for about 1-hour prior drying which will prevent enzymatic reaction and also helped in retaining the ascorbic acid and carotene content. The pulp was washed and kept in low-density polyethylene (LDPE) airtight bags at −10°C and were subjected to drying treatment within 24 h of storage. Dry matter estimation: Initial moisture content was estimated with the help of the hot-air oven method at 105°C for 24 h [28]. All readings were replicated thrice for accuracy. In most cases, drying was performed at multi-temperatures (65°C, 70°C, 75°C) to study the effect of temperature on drying rates. Samples are weighed periodically and moisture loss over time is monitored. Moisture content can be calculated for each time interval at either wet basis or dry basis.

Determination of moisture content, moisture ratio and drying rate

The moisture content of pumpkin was measured at different temperatures and methods for using Eqn. (1), and the observed data were plotted into a moisture ratio. Equation (2) is used to calculate the moisture ratio; this could be reduced by Equation (3) to be frequently relatively small, and its omission never results in significant deviations (Xu et al., 2022).

$$\text{Moisture content [\%]} = \frac{Initial\ weight - Final\ weight}{Initial\ weight} \times 100 \quad (1)$$

$$MR = \frac{M_t - M_e}{M_0 - M_e} \quad (2)$$

$$MR = \frac{M_t}{M_0} \quad (3)$$

where Mt is the moisture level at a particular point in time, Me represents the moisture content at the point of equilibrium, and Mi is the original moisture content.

Drying Kinetics of *Cucurbita maxima*

Studies on drying kinetics of Cucurbita maxima focus on dependence of drying kinetics of the material upon temperature, relative humidity, and air velocity. (Kalsi, Singh, Alam, & Bhatia, 2023) found that the higher the temperature, the higher is the rate of drying, but too much heat changes the texture and reduces the quality of pumpkin tissue. Several model authors have proposed drying laws for Cucurbita maxima, e.g., empirical models like the Page model, the Henderson-Pabis model, and the Lewis model, to predict drying and moisture loss with time (Loganathan et al., 2024). These models are useful for modelling drying curves, controlling processes, and to predict the final moisture content of the process.

Mathematical Modelling of Drying Processes

Mathematical modelling is considered one of the most important aspects in the prediction and study of the kinetic drying of agricultural products. The comparison between different models, such as the Newton, Page, and Modified Henderson-Pabis models, showed in table 1 (Ertekin Yaldiz, 2004). Mathematical models can predict the rate of moisture removal, and these rates help optimise the drying conditions. In Cucurbita maxima, fitting of the experimental data to such models may be utilised in optimising the best drying conditions, thereby enhancing quality control and lowering energy consumption (Xu et al., 2022).

The experimental moisture ratio data was fitted with five different thin layer semi-empirical models summarised in Table 1. Empirical constants a, b, c, k' and n were determined by regression analysis using the curve fitting tool of MATLAB v.2012 a (Math Works Inc., USA) using the values calculated from Eq. (1).

$$MR = \frac{M_t - M_e}{M_0 - M_e} \quad (1)$$

Where, Mt is the moisture content at time t (kg water/kg dry matter), Me is the equilibrium moisture content (kg water/kg dry matter), Mi is the initial moisture content (kg water/kg dry matter). The highest coefficient of determination (R2) and lowest sum of squared errors (SSE) and mean square error (MSE) values were used to select the most suitable equation which expresses the drying kinetics of moringa leaves.

Table 1: Different thin layer drying models

S.No	Model Name	Equation	References
1	Page	MR = $\exp(-kt^n)$	(Onwude et al., 2016)
2	Newton	MR = $\exp(-kt)$	(Onwude et al., 2016)
3	Logarithmic	MR = $a * \exp(-kt) + c$	(Onwude et al., 2016)
4	Henderson and pabis	MR = $a * \exp(-k\,t)$	(Onwude et al., 2016)
5	Diffusion	MR = $a * \exp(-bt)$	(Onwude et al., 2016)

Artificial neural network (ANN)

These are multi-parametric empirical models with parallel and nonlinear interconnectivity. The function of an ANN is somewhat like that of a human brain in terms of its adaptability to new information and efficient pattern recognition in fuzzy and imprecise data. ANN infrastructure: The ANN infrastructure consists of an input layer, one or more hidden layer(s) and an output layer in Figure 1. Each layer is comprised of a set of neurons or 'nodes'. These nodes have internal connections called 'weights' which decides which of the nodes to trigger based on the relative importance of a particular signal. The nodes perform data processing with the help of a mathematical transfer function (for example, TANSIGMOID, LOGSIGMOID, PURELIN etc.). ANN learns through iterations (epochs) without knowing the relationship beforehand between the variables under investigation. It tests each example, one at a time, using the inputs to obtain the solutions that it compares to a given pattern. According to the disparity in experimental and predicted values, ANN adjusts the network with the applications of alterations to the internal interconnects. This process of trial and error continues until the network predictions agree well with the target data within some reasonable degree of accuracy. The trained model is subjected to testing and validation and the predicted data is acquired through model simulations. In this work, a multi-layer 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 HLs was limited to 1 (Tarafdar et al., 2018).

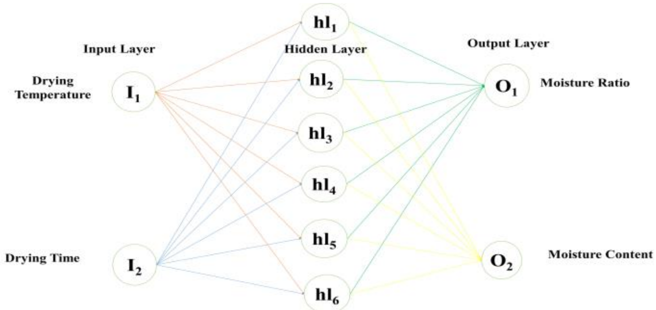

FIGURE 1: ANN model for drying.

Two different transfer functions for the HL were used (TANSIGMOID and LOGSIGMOID) and their relative performance was evaluated. PURELIN was applied as the transfer function in the output layer since sigmoidal transfer function applied in the output layer may degenerate the network (Dorofki et al., 2012). The training was done in MATLAB v.2012a using the Levenberg-Marquardt (LM) and Gradient Descent backpropagation with momentum and adaptive learning rate (GDX) as two different training functions. Even though LM is highly efficient in pattern recognition due to faster convergence of data, the performance of a training algorithm is sensitive to a learning rate; hence, GDX was run separately to identify any shortcomings, if present, while running by LM (Tarafdar et al., 2018a). Various combinations of HL, transfer function, and training algorithm were tried on the vacuum drying data. Model training was performed by 70% of the data. Testing and validation were performed on the remaining 30% of the data set, which was divided equally within both the former and the latter. Number of iterations and number of validation checks were restricted to 1000 to reduce processing time. Infrastructure ANN with the lowest MSE, the highest correlation coefficient (r), and the lowest complexity was chosen.

Impact of Drying on Nutritional and Physical Properties

Studies show that drying changes the colour and texture of *Cucurbita maxima* and its nutritional value; high temperatures can cause nutrient loss, especially in vitamin C and carotenoids, which are highly sensitive to heat (Chauhan et al., 2006). Low air-flow rates may help retain quality in colour and texture but will take longer to dry. Therefore, temperature and airflow must be controlled carefully in order to preserve the quality of dried Cucurbita maxima.

Water activity, water solubility index (WSI), and hygroscopicity (HG)

Water Activity (aw) of dried pumpkin powder was determined by using a water activity meter (Pawkit, Decagon Devices Inc., USA) at temperature 25.5 ± 1°C. Water solubility index (WSI) was measured following the methodology developed by (Luka et al., 2023) with slight changes. It includes the process of adding 0.2 g of grind powder with 10 mL of distilled water. The mixture was centrifuged at 3000 rpm for 10 min. The resulting supernatant was carefully transferred to a weighed petri dish and dried at 105°C. The Water Solubility Index (WSI) could be computed from Equation 2 (Ghnimi et al., 2016).

$$\text{Solubility Index } = \frac{Wt\ of\ the\ \text{supernatant}}{Wt\ of\ the\ initial\ sample}\ X\ 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where Ws is eight of the dried supernatant at 105°C, Wos is weight of the original sample.

Hygroscopicity (HG), the ability of a powder to absorb moisture from a high relative humidity environment, was measured for Stevia leaf powders following the procedure by (Zalpouri et al., 2023). In this experiment, 1 g of pumpkin powder was placed inside a desiccator, which was maintained at room temperature. After 7 days, the powders were weighed, and hygroscopicity was reported as HG (%) or grams of absorbed moisture per 100 g of dry solid. Hygroscopicity is calculated using the following equation 3:

$$\text{Hygroscopicity } = \frac{Increased\ Wt}{Initial\ Wt\ of\ the\ sample}\ X\ 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

where Δm represents the weight increase of the powder (g), and w denotes the initial weight of the powder (g).

Bulk density and tapped density

The dried pumpkin powder, prepared by various drying techniques was weighed for bulk and tapped density, following the procedure given by (Bakshi & Ananthanarayan, 2022). To calculate bulk density (Equation 4&5),

a known mass of material was poured freely under gravity's influence into a measuring cylinder. The pumpkin powder was suspended in a 100 mL measuring cylinder and tapped with the minimum movement until it attained its consistent volume, determining the tapped density.

Bulk Density = $\frac{Initial\ Wt\ of\ the\ sample}{Bulk\ Volume\ of\ the\ sample}$.. (4)

Tapped Density = $\frac{Initial\ Wt\ of\ the\ sample}{Tapped\ Volume\ of\ the\ sample}$.. (5)

Particle density and bulk porosity

The liquid displacement method, as described by (Padhi & Dwivedi, 2022) is used to determine the particle (true) density of dried Stevia leaf powder. The process involved the measurement of mass of the pumpkin powder, and then it was poured into a measuring cylinder filled with toluene. The volume of toluene displaced by the powder was measured, and the particle density is determined as per equation 6 below

Particle Density = $\frac{Initial\ Wt\ of\ the\ sample}{Volume\ of\ solvent\ Dispalced}$.. (6)

The porosity (equation 6) of the sample was computed using the difference between the bulk density and true density of the powder, according to (Camacho et al., 2022).

Porosity =*1* - $\frac{Bulk\ Density}{Tapped\ Density}$.. (7)

Flowability indexes

Angle of repose, cohesiveness and compressibility of pumpkin leaf powders were evaluated in terms of flowability indexes by method mentioned in (Camacho et al., 2022). Powders' cohesiveness was appraised using Hausner ratio, HR and compressibility was estimated by Carr index, CI. The value of CI and HR were calculated from the measurements of bulk and tapped density by applying equations 8 and 9, respectively. To determine the angle of repose, a fixed funnel was used to pour powder from a set height onto a level surface, and the pile would naturally take on the shape of a cone (Kalsi, Singh, Alam, & Sidhu, 2023).

$$\text{Hausner Ratio} = \frac{Tapped\ Density}{Bulk\ Density} \dots\dots\dots\dots\dots\dots\dots.(8)$$

$$\text{Carr's Index} = \frac{Tapped\ Density\ -\ Bulk\ Density}{Tapped\ Density} X100 \dots\dots\dots\dots\dots\dots\dots.(9)$$

Statistical analysis of ANN

To check the goodness of fit of the model, several statistical metrics were used such as Average Absolute Deviation (AAD), Mean Square Error (MSE), Mean Percentage of Error (MPE), Root Mean Square Error (RSME), Coefficient of Determination (R2), and Chi-square error (χ2). The calculations were done using equations (10-15). 'n' is the number of experiments, 'Xa' the experimental data, 'Xp' the predicted data, and 'Xm' mean experimental data. Each experiment was done three times, and the results were reported as mean standard deviation, according to the methodology described by (Hunter & Hunter, 1978).

$$AAD = \frac{\sum_{i=1}^{n}|X_p - X_a|}{n} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (10)$$

$$MSE = \frac{\sum_{i=1}^{n}(X_p - X_a)^2}{n} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (11)$$

$$MPE = \frac{100}{n}\sum_{i=1}^{n}\left|\left(\frac{X_p - X_a}{X_p}\right)\right| \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(12)$$

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}(X_p - X_a)^2}{n}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (13)$$

$$R^2 = \frac{\sum_{i=1}^{n}(X_p - X_a)^2}{\sum_{i=1}^{n}(X_p - X_m)^2} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(14)$$

$$\chi^2 = \sum_{i=1}^{n} \frac{(X_a - X_p)^2}{X_p} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (15)$$

Results and Discussion

Drying of pumpkin was started at an Initial Moisture Content (IMC) of 92 ± 1.0% on a wet basis in Tray Dryer (TD). The key observation reveals that the moisture content transfer was observable at the initial stage of drying. The drying moisture ratio curves and microstructures of pumpkin under three different drying temperatures are presented in Figure 2.

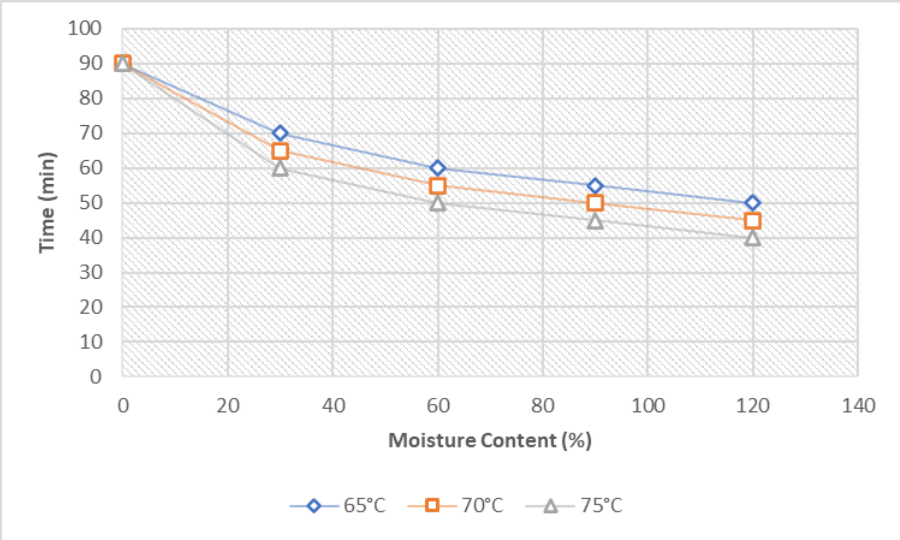

Figure 2: Moisture Content vs. Time

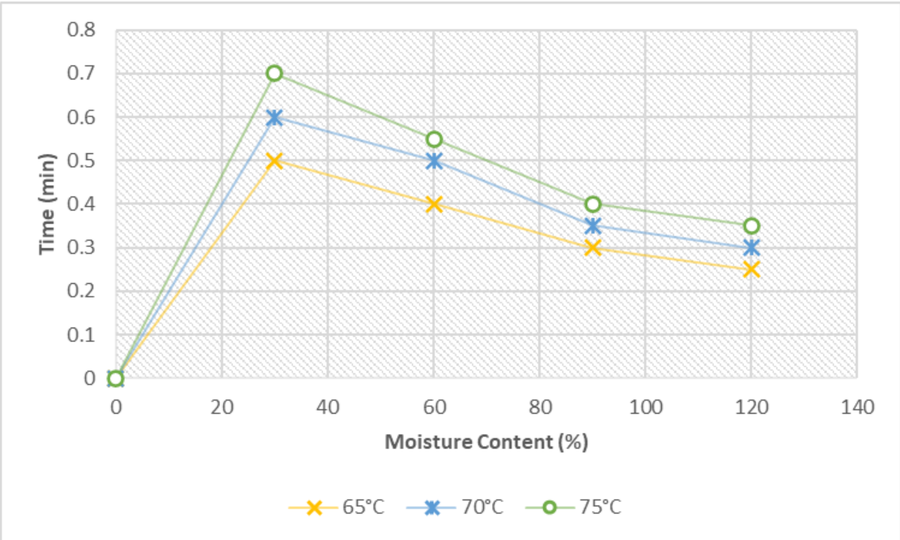

Figure 3: Drying Rate vs. Time

Moisture Content Reduction Over Time

At all temperatures, the moisture content decreases over time. This is the accepted pattern for drying processes. The approach to stabilization at higher temperatures therefore is inevitably gradual but results in generally faster reductions in moisture content at higher temperatures 70°C and 75°C compared to 65°C. After that the dramatic decline in the moisture content in the initial drying process for 75°C. This would support that higher temperature drying increases the moisture elimination rate apparently because water vaporizes better at higher temperatures.

Drying Rate

At all temperatures, the highest rates of drying occur at the beginning (0–30 minutes) in figure 3. For instance, at 75°C, the initial rate of drying is around 0.7%/min, which is significantly higher than at any lower temperature. This is probably due to the evaporation of free surface water that is lost more readily at the earlier stages of drying. Drying continues to decrease with time. This is observed at both temperatures but is further noticeable at 65°C. This slowing down has been recognized to result from the transition from free water removal to bound water, which requires energy and even more time to evaporate and subsequently decreases the drying rate naturally.

Effect of Temperature on Moisture Content and Drying Efficiency

Moisture content decreases continuously but at a slower rate at 65°C. After 120 minutes, the moisture content reduces to about 50% wet basis, which is relatively slower compared to the other temperatures. This lower rate of drying at 65°C can result in longer drying times, which is not efficient. Moderate temperature 70°C, drying rate is faster than 65°C. At 120 minutes, the moisture content is reportedly lowered to around 45%, and this shows a higher gain in drying efficiency over 65°C. The drying rate approaches equilibrium at roughly above 0.3%/min towards the end of the process as a balanced drying approach. Drying is apparently very efficient at 75°C, as the moisture content lowers to about 40% at 120 minutes. The highest initial drying rate is also at 0.7%/min, which means that the removal of moisture is faster. In this study, higher temperatures may result in loss of quality particularly on application when nutrients are degraded or texture changes will occur. Best Drying Conditions for the most efficient drying with least energy, 70°C appears to be correct. It is faster than 65°C without the risks of nutrient or texture degradation associated with higher temperatures, such as 75°C. In the event that fast drying is required and product quality can be managed, then 75°C is the fastest drying time(Rani & Tripathy, 2020).

Mathematical Modelling

The study systematically tested and compared the performances of several mathematical models, among them being Newton, Page, Logarithmic, Henderson and Pabis and Diffusion models, on different drying methods and temperature levels shown in table 2. Newton Model Provided adequate fit for TD method across the temperatures. Satisfactory correlation (R^2) and acceptable prediction accuracy (RMSE, SSE). The performance of TD Model has been diverse across the temperatures, optimal fit at 75°C. Moderate to good correlation with some variation in the accuracy of prediction. Page Model, Logarithmic Model, Diffusion Model has Strong fit, Henderson and Pabis Model shows Reasonable fit for TD method across temperatures with Excellent correlation and accurate predictions. Logarithmic Model shows consistently high R^2 values across temperatures. That means the model explains a very high percentage of the variance in the observed data.

Table 2: Mathematical values of different drying process of pumpkin

Mathematical model	Drying Method	Temp	K	a	b	n	R^2	RMSE	SSE	Adj R^2
Newton	TD	65	0.057				0.8136	0.1456	0.1495	0.7806
		70	0.091				0.8349	0.1611	0.1421	0.8031
		75	0.116				0.7943	0.1980	0.1358	0.7680
Page	TD	65	0.0103			3.047	0.9083	0.1046	0.0384	0.8831
		70	0.0120			3.5763	0.9103	0.09105	0.0091	0.8738
		75	0.0908			1.248	0.9403	0.1334	0.0201	0.9135
Logarithmic	TD	65	0.0043	1.488	2.12 × 10^10		0.9621	0.0495	0.0543	0.9338
		70	0.0072	1.546	3.06 × 10^12		0.9658	0.0555	0.0435	0.9267
		75	0.0097	1.705	5.76 × 10^9		0.9677	0.0705	0.0337	0.9159
Henderson and pabis	TD	65	0.004	1.5996			0.8508	0.0606	0.0579	0.8049
		70	1.4037	1.5411			0.8293	0.0641	0.0571	0.7805
		75	1.9865	1.7422			0.8473	0.0833	0.073	0.81
Diffusion	TD	65	3.514	0.3498			0.947	0.0511	0.0646	0.935
		70	3.4655	0.3532			0.948	0.0666	0.0847	0.9158
		75	3.8675	0.3484			0.9658	0.0912	0.0915	0.9147

All three models the Page, Diffusion, and Logarithmic-tend to work well from the standpoint of the R^2 values alone for the variability in the drying process data. Choice among these may be driven by criteria like simplicity, ease of interpretation, or specific requirements of the application. The best model can be a function of specific context and the objectives of your research or application (Calín-Sánchez et al., 2020; Kiremire et al., 2010). Based on R2 values alone, the Page, Diffusion, and Logarithmic models all reflect strong performance in explaining the variance within the drying process data. Mathematical modelling was used to fit the experimental data using five equations. The statistical results for all models are presented in Table 2. The data obtained which were analysed with various kinetic models, in an attempt to identify the greatest precise model for pumpkin. The best fit for pumpkin was observed to be from the Logarithmic and diffusion models which obtained high R^2 values. This result means that both Logarithmic and diffusion models well describe the drying kinetics of pumpkin under the experimental conditions applied, with a strong correlation between the predicted and actual data.

Performance of ANN

The training, validation, and testing cycles involving the ANN projections obtained substantially high coefficients of correlation (R), exhibiting outcomes in figure 4. Through the application of a different drying process, our findings indicate how efficiently an ANN algorithm estimates the kinetics of drying of pumpkin (Chen et al., 2020; Dash et al., 2020). The most effective ANN model displayed minimal RMSE (0.0042), Chi-square (0.00007), and a significant R^2 (0.9872). This analysis indicates the ANN model outperformed the mathematical models used in the study. The testing, training, and validation stages of the ANN projections exhibited significant improvements in the value of the correlation coefficients (R^2). The findings collectively emphasize the robust predictive capabilities of ANN models in the domain of drying kinetics (Kalsi, Singh, Alam, & Bhatia, 2023).

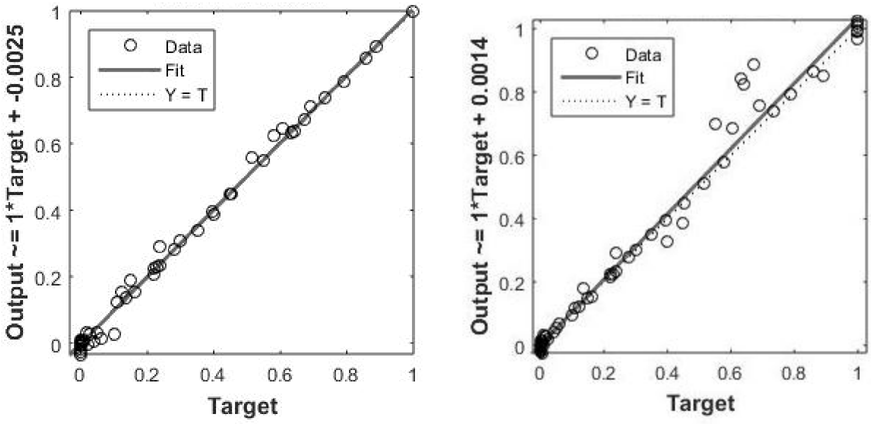

Figure 4: ANN modelling for Logarithmic and Diffusion Model

The moisture content of pumpkin was observed utilizing this design that showed up to possess a highly precise ANN (artificial neural network) all through the dryers. The success of the ANN approach highlights its capability to streamline the development of an effective prediction model for the drying process of pumpkin. This underscores the efficiency and versatility of artificial neural networks in capturing and modelling the complex dynamics of drying kinetics in different drying temperatures (Chasiotis et al., 2020; Yazdani et al., 2013).

Comparison between mathematical, ANN, modelling

Artificial Neural Network (ANN) approaches develop better projected results of the Moisture Percentage variable throughout the drying process of pumpkin, based on the results of an investigation of statistics amongst them. The ANN model's displayed MR possesses a greater R^2 coefficient than the ideal mathematical simulation, which could be displayed in Table 3 and Figure 4. In addition, when compared to mathematical and machine learning models, the machine learning model exhibits smaller values across all projected variables (chi-square and RMSE).

Table 3: Comparative analysis of mathematical modelling and ANN

Model	Drying Method	Mathematical Modelling	ANN
		R^2	R^2
Logarithmic	TD	0.9677	0.9872
Diffusion	TD	0.9658	0.9738

A number of studies showed identical findings proving ANN's better predicting capabilities over mathematical simulations. Compared to conventional (0.9677, 0.9658) modelling approaches, the method of ANN achieved the greatest R^2 value (0.9872, 0.9738) in this research. According to (Abbaspour-Gilandeh et al., 2020; Kaveh et al., 2018) an ANN model showed optimum outcomes with a coefficient of variation when it was used for estimating ratio of moisture content during the tray drying of almonds seeds. The R^2 values of 0.9872, 0.9738, were displayed for the best models developed employing conventional and neural networks approaches. These findings highlight the superior accuracy of ANN over mathematical models in reflecting the complex dynamics of the drying kinetics for pumpkin (Karaaslan et al., 2021; Mut et al., 2024).

Colour properties

Table 4 shows the colour characteristics for pumpkin dried at various temperatures. The convective drying significantly ($p < .05$) reduce the values of L*, b*, hue angle and chroma of pumpkin. The L*, a*, b*, hue angle and chroma ranged from 70.70 ± 0.64, 3.15 ± 0.56 and 31.26 ± 1.43 for 65°C, 59.32 ± 0.96, 6.53 ± 0.18, 35.35 ± 0.77 for 70°C and 59.02 ± 0.51, 11.73 ± 0.32, 37.33 ± 0.74 for 75°C respectively. The value of L* decreased with increasing temperature from 65 to 75°C. The decrease in the value of L* at higher drying temperatures may be associated with non-enzymatic browning and the formation of brown pigment [39]. The convective drying of pumpkin at the temperature of 65–75°C increased the value of a*,b*. (Kiremire et al., 2010) also reported similar decreasing trend of b* value from 9.54 to 8.12 followed by an increase to the value of 9.39 when Portulaca oleracea L. leaves were subjected to convective drying and temperature was increased from 40 to 80°C (Ozcan-Sinir et al., 2018). This devaluation of b* may be due to degradation of carotenoid pigments (Ponasenko et al., 2023).

Table 4: Color (L*, a*, b* values) of Pumpkin Powder (PP)

Temperature(°C)	***L (Lightness)****	***a (Redness)****
65	70.70 ± 0.64a	3.15 ± 0.56
70	59.32 ± 0.96	6.53 ± 0.18
75	59.02 ± 0.51	11.73 ± 0.32

Superscript letters indicate significant differences (p ≤ 0.05) within each column.

Water activity, water solubility index, and hygroscopicity

Water activity (aw) of dried sample was reported in Table 6. As the temperature of the drying air increased from 65 to 75°C, the aw value of the dried pumpkin decreased effectively from 0.64 to 0.30, which is a decline of 51.45%. Therefore, the water activity (aw) values of pumpkin powder obtained through convective drying were found to be below the safe storage level. The values of aw decreased with the rise in drying temperature due to increased water vapor migration with greater temperatures (Sultanova et al., 2024). Water solubility index (WSI) is an important physical property used to assess the ability of a powder to dissolve in water and release-soluble components, resulting in the formation of a homogeneous and stable solution. As demonstrated in Table 5, the WSI values of pumpkin powders varied from 40.10 ± 0.35 to 52.20 ± 0.30%. The increase in solubility with an increase in temperature probably results from simultaneous increases in porosity and uniformity of pores in the dried samples(Akter et al., 2022).

Table 5: Water activity, water solubility index, and hygroscopicity of Pumpkin Powder (PP)

Drying Temperature (°C)	**Water Activity (aw)**	**Water Solubility Index (WSI, %)**	**Hygroscopicity (HG, %)**
65	0.64	40.10 ± 0.35	5.24 ± 0.12
70	0.43	46.61± 0.24	6.31 ± 0.20
75	0.30	52.20 ± 0.30	7.98 ± 0.16

Hygroscopicity (HG) of hot air-dried pumpkin is presented in Table 6. The hygroscopicity of dried pumpkin powders was found to vary between 5.24 ± 0.12 and 7.98 ± 0.16%, based on the drying temperature used. In increasing order, the powders' hygroscopicity was 65°C < 70°C < 75°C. The increase in temperature results in an increase in hygroscopicity of dried pumpkin powder. Hygroscopicity of powders was found to decline with increase in temperature. (Karlović et al., 2023) reported that if the air temperature is increased from 70° to 90°C, the hygroscopicity of dried Agave rhodacantha Trel leaf powders increased.

Density (bulk, tapped, and particle) density, and bulk porosity

Table 6 shows the measurements of the dried pumpkin powder's bulk and tapped density. No significant ($p > .05$) change in bulk density of dried sample takes place when temperature was raised. It also shows that the bulk density of the sample is not varying with a change in temperature; Aprajeeta et al. also prove this (T. Wang et al., 2021). It is noted that the bulk and tapped density of dried pumpkin powder are within the range of 0.241–0.250 g/cm3 and 0.270–0.284 g/cm3, respectively. There was a declining trend for the values of both bulk (5.2 % decreases) and tapped (14.25% decrease) density as temperature of drying increased from 30 to 80°C. The reduction in density of the dried powder is due to the increased rate of evaporation of moisture at higher temperatures during drying.(T. Wang et al., 2021) The effect of the convective drying temperature was found significant ($p < 0.05$) on the particle density of the powder. With an increase in drying temperature, the particle density of the powder was also found to raise as can be seen in Table 6. The particle density ranges between 1.01 and 1.52 g/cm3. The porosity in porous media plays a leading role in changing the density due to variables like porosity and nature of shrinkage pattern. In present study, the increase in bulk density of pumpkin dried powder may be attributed to the densification of solid components like carbohydrates when water is evaporated.[57] This could be due the fact that porosity is inversely proportional to bulk density. Furthermore, the porosity of sample increases with the rise in the pores containing water being replaced by air (Sahoo et al., 2022). (Küçük et al., 2022)] reported that increasing the air temperature from 40 to 120°C during drying of blanched Carica papaya particle porosity of dried powders showed a variation between 0.536 and 0.621.

Table 6: Density (bulk, tapped, and particle) density, and bulk porosity of Pumpkin Powder (PP) Flowability indexes

Drying Temperature (°C)	Bulk Density (g/cm^3)	Tapped Density (g/cm^3)	Particle Density (g/cm^3)
65	~0.241	~0.270	~1.01
70	~0.245	~0.278	~1.19
75	~0.250	~0.284	~1.52

Table 7 displays the drying temperature effect on the Carr index, Hausner ratio, and angle of repose of the powder. It was observed that with the increased drying temperature, Carr index and Hausner ratio decreased. The compressibility of a material is classified as follows based on the Carr index (CI) values: very good when CI is less than 15%, good when CI is between 15% and 20%, fair when CI is between 20% and 35%, bad when CI is between 35% and 45%, and very bad when CI is greater than 45%, while a low cohesiveness is indicated when HR is less than 1.2, an intermediate cohesiveness falls within the range of 1.2 to 1.4, and a high cohesiveness is observed when HR exceeds 1.4. Powders with a repose angle up to 35º are classified as free-flowing. A repose angle between 35º and 45º is said to be roughly cohesive in nature. If the repose angle falls between 45º and 55º, the powder is termed cohesive, while a repose angle greater than 55º indicates a very cohesive nature. [61,62] In the present study, as the air temperature increased from 65 to 75°C, the values of CI, HR, and α varied between 6.20 to 12.75%, 1.354 to 1.671, and 24.27 to 31.43, respectively(Mut et al., 2024). Thus, CI, HR, and α values showed decrements with an increase in drying temperature. From experimental data, it is evident that powder of dried pumpkin possesses excellent flowability characteristics. The research also revealed that flow ability of the substance improves as the drying temperature increases.

Table 7: Density (bulk, tapped, and particle) density, and bulk porosity of Pumpkin Powder (PP)

Drying Temperature (°C)	Carr Index (CI, %)	Hausner Ratio (HR)	Angle of Repose (α, °)	Flowability Classification
65	12.75	1.671	31.43	Free-flowing
70	9.51	1.403	27.36	Free-flowing
75	6.20	1.354	24.27	Free-flowing

Conclusion

The study extensively investigated the drying kinetics, physical properties, and predictive modelling of pumpkin (Cucurbita maxima) powder using mathematical and artificial neural network (ANN) approaches. It highlighted the effectiveness of different drying temperatures on moisture reduction, drying rates, and the overall quality of the dried product. Among the tested drying methods, 70°C emerged as the optimal temperature for balancing efficiency and product quality, while 75°C offered the fastest drying rate at the cost of some nutrient and texture degradation. The comparative analysis of mathematical models revealed that the Logarithmic and Diffusion models provided the best fit for predicting drying kinetics, demonstrating strong correlation coefficients (R^2). However, ANN models outperformed traditional mathematical models in prediction accuracy and reliability, achieving higher R^2 values and lower errors across all parameters. This underscores the potential of ANN as a robust tool for modelling complex drying processes. The study also found significant effects of drying temperature on the physical properties of pumpkin powder, such as colour, density, water solubility, hygroscopicity, and flowability. Higher drying temperatures improved solubility and flowability but led to increased hygroscopicity and slight changes in colour due to non-enzymatic browning. Overall, the results highlight the importance of selecting appropriate drying conditions and predictive models for optimizing the drying process of pumpkin powder. This research contributes valuable perceptions for the food industry, supporting the efficient production of high-quality, nutrient-rich pumpkin powders for various applications.

REFERENCES

1. Abbaspour-Gilandeh, Y., Jahanbakhshi, A., & Kaveh, M. (2020). Prediction kinetic, energy and exergy of quince under hot air dryer using ANNs and ANFIS. Food Science & Nutrition, 8(1), 594–611.
2. Akter, F., Muhury, R., Sultana, A., & Deb, U. K. (2022). A comprehensive review of mathematical modelling for drying processes of fruits and vegetables. International Journal of Food Science, 2022(1), 6195257.
3. Azeez, L., Adebisi, S. A., Oyedeji, A. O., Adetoro, R. O., & Tijani, K. O. (2019). Bioactive compounds' contents, drying kinetics and mathematical modelling of tomato slices influenced by drying temperatures and time. Journal of the Saudi Society of Agricultural Sciences, 18(2), 120–126.
4. Bakshi, G., & Ananthanarayan, L. (2022). Characterization of lemon peel powder and its application as a source of pectin degrading enzyme in clarification of cloudy apple juice. Journal of Food Science and Technology, 59(7), 2535–2544.
5. Balasubramanian, S., Sharma, R., Gupta, R. K., & Patil, R. T. (2011). Validation of drying models and rehydration characteristics of betel (Piper betel L.) leaves. Journal of Food Science and Technology, 48, 685–691.
6. Calín-Sánchez, Á., Lipan, L., Cano-Lamadrid, M., Kharaghani, A., Masztalerz, K., Carbonell-Barrachina, Á. A., & Figiel, A. (2020). Comparison of traditional and novel drying techniques and its effect on quality of fruits, vegetables and aromatic herbs. Foods, 9(9), 1261.
7. Camacho, M. M., Silva-Espinoza, M. A., & Martínez-Navarrete, N. (2022). Flowability, rehydration behaviour and bioactive compounds of an orange powder product as affected by particle size. Food and Bioprocess Technology, 15(3), 683–692.
8. Chasiotis, V. K., Tzempelikos, D. A., Filios, A. E., & Moustris, K. P. (2020). Artificial neural network modelling of moisture content evolution for convective drying of cylindrical quince slices. Computers and Electronics in Agriculture, 172, 105074.
9. Chen, J., Wu, W., Cheng, R., Jin, Y., & Liu, Z. (2020). Optimization of hot air drying process of corn using genetic algorithm and response surface methodology. International Journal of Food Properties, 23(1), 753–764.
10. Dash, K. K., Chakraborty, S., & Singh, Y. R. (2020). Modeling of microwave vacuum drying kinetics of Bael (Aegle marmelos L.) pulp by using artificial neural network. Journal of the Institution of Engineers (India): Series A, 101, 343–351.
11. Dhurve, P., Tarafdar, A., & Arora, V. K. (2021). Vibro-fluidized bed drying of pumpkin seeds: Assessment of mathematical and artificial neural network models for drying kinetics. Journal of Food Quality, 2021(1), 7739732.
12. Ghnimi, T., Hassini, L., & Bagane, M. (2016). Experimental study of water desorption isotherms and thin-layer convective drying kinetics of bay laurel leaves. Heat and Mass Transfer, 52, 2649–2659.
13. Hunter, W. G., & Hunter, J. S. (1978). Statistics for experimenters. Interscience, New York, 453.
14. Inyang, U. E., Oboh, I. O., & Etuk, B. R. (2018). Kinetic models for drying techniques—food materials. Advances in Chemical Engineering and Science, 8(2), 27–48.
15. Kalsi, B. S., Singh, S., Alam, M. S., & Bhatia, S. (2023). Microwave Drying Modelling of Stevia rebaudiana Leaves Using Artificial Neural Network and Its Effect on Color and Biochemical Attributes. Journal of Food Quality, 2023.
16. Kalsi, B. S., Singh, S., Alam, M. S., & Sidhu, G. K. (2023). Comparison of ANN and ANFIS modelling for predicting drying kinetics of Stevia rebaudiana leaves in a hot-air dryer and characterization of dried powder. International Journal of Food Properties, 26(2), 3356–3375.
17. Karaaslan, S., Ekinci, K., & Kumbul, B. (2021). Drying characteristics and mathematical modeling of without pretreatment and pretreatment zucchini (Cucurbita Pepo L.) slices in a solar tunnel dryer. Avrupa Bilim ve Teknoloji Dergisi, 27, 575–582.
18. Karim, M. A., & Hawlader, M. N. A. (2005). Mathematical modelling and experimental investigation of tropical fruits drying. International Journal of Heat and Mass Transfer, 48(23–24), 4914–4925.
19. Karlović, S., Dujmić, F., Brnčić, S. R., Sabolović, M. B., Ninčević Grassino, A., Škegro, M., Šimić, M. A., & Brnčić, M. (2023). Mathematical modeling and optimization of ultrasonic pre-treatment for drying of pumpkin (Cucurbita moschata). Processes, 11(2), 469.
20. Kaveh, M., Sharabiani, V. R., Chayjan, R. A., Taghinezhad, E., Abbaspour-Gilandeh, Y., & Golpour, I. (2018). ANFIS and ANNs model for prediction of moisture diffusivity and specific energy consumption potato, garlic and cantaloupe drying under convective hot air dryer. Information Processing in Agriculture, 5(3), 372–387.

21. Kiremire, B. T., Musinguzi, E., Kikafunda, J. K., & Lukwago, F. B. (2010). Effects of vegetable drying techniques on nutrient content: a case study of south-western Uganda. African Journal of Food, Agriculture, Nutrition and Development, 10(5).
22. Küçük, H., Akbulut, U., & Midilli, A. (2022). Single-layer drying modeling of pumpkin (Cucurbita Maxima). Turkish Journal of Electromechanics and Energy, 7(3), 110–119.
23. Liu, Z.-L., Wei, Z.-Y., Vidyarthi, S. K., Pan, Z., Zielinska, M., Deng, L.-Z., Wang, Q.-H., Wei, Q., & Xiao, H.-W. (2020). Pulsed vacuum drying of kiwifruit slices and drying process optimization based on artificial neural network. Drying Technology, 39(3), 405–417.
24. Liu, Z.-L., Xie, L., Zielinska, M., Pan, Z., Wang, J., Deng, L.-Z., Wang, H., & Xiao, H.-W. (2021). Pulsed vacuum drying enhances drying of blueberry by altering micro-, ultrastructure and water status and distribution. Lwt, 142, 111013.
25. Loganathan, V., Vijayan, L., Balakrishnaraja, R., & Abdullah, S. (2024). Optimization of microwave-assisted extraction of Tamarindus indica seed oil: An in silico approach to development of potential hypolipidemic compound for reducing LDL cholesterol. Measurement: Food, 13, 100125.
26. Luka, B. S., Vihikwagh, Q. M., Ngabea, S. A., Mactony, M. J., Zakka, R., Yuguda, T. K., & Adnouni, M. (2023). Convective and microwave drying kinetics of white cabbage (Brassica oleracae var capitata L.): Mathematical modelling, thermodynamic properties, energy consumption and reconstitution kinetics. Journal of Agriculture and Food Research, 12, 100605.
27. Mut, I., Zalazar-García, D., Román, M. C., Baldán, Y., Fernandez, A., Fabani, M. P., Blasetti, A. P., Mazza, G., & Rodriguez, R. (2024). Transformation of Discarded Pumpkin into High-Value Powder: A Drying Process Model for Functional Food Ingredients. Agronomy, 14(7), 1424.
28. Onwude, D. I., Hashim, N., Janius, R. B., Nawi, N. M., & Abdan, K. (2016). Modelling the thin-layer drying of fruits and vegetables: A review. Comprehensive Reviews in Food Science and Food Safety, 15(3), 599–618.
29. Ozcan-Sinir, G., Ozkan-Karabacak, A., Tamer, C. E., & Copur, O. U. (2018). The effect of hot air, vacuum and microwave drying on drying characteristics, rehydration capacity, color, total phenolic content and antioxidant capacity of Kumquat (Citrus japonica). Food Science and Technology, 39, 475–484.
30. Padhi, S., & Dwivedi, M. (2022). Physico-chemical, structural, functional and powder flow properties of unripe green banana flour after the application of Refractance window drying. Future Foods, 5, 100101.
31. Ponasenko, A. S., Saparov, D. E., Sultonova, S. A., Samandarov, D. I., & Azimov, A. T. (2023). Theoretical study and mathematical calculations of the pumpkin drying process. IOP Conference Series: Earth and Environmental Science, 1231(1), 012040.
32. Qu, C., Wang, X., Wang, Z., Yu, S., & Wang, D. (2020). Effect of drying temperatures on the peanut quality during hot air drying. Journal of Oleo Science, 69(5), 403–412.
33. Rani, P., & Tripathy, P. P. (2020). Modelling of moisture migration during convective drying of pineapple slice considering non-isotropic shrinkage and variable transport properties. Journal of Food Science and Technology, 57, 3748–3761.
34. Reddy, R., Ravula, P., Arepally, D., Munagala, S., & Golla, S. (2017). Drying kinetics and modelling of mass transfer in thin layer convective drying of pineapple. Chemical Science International Journal, 19(3), 1–12.
35. Sahoo, M., Titikshya, S., Aradwad, P., Kumar, V., & Naik, S. N. (2022). Study of the drying behaviour and color kinetics of convective drying of yam (Dioscorea hispida) slices. Industrial Crops and Products, 176, 114258.
36. Sarkar, T., Salauddin, M., Hazra, S. K., & Chakraborty, R. (2020). Artificial neural network modelling approach of drying kinetics evolution for hot air oven, microwave, microwave convective and freeze dried pineapple. SN Applied Sciences, 2, 1–8.
37. Sultanova, S. A., Imanova, G. T., Safarov, J. E., Usenov, A. B., Ait-Kaddour, A., & Azimov, A. T. (2024). Mathematical modelling of pumpkin seed drying in a rotary thermosyphon dryer. Materials Research Innovations, 1–6.
38. Tarafdar, A., Shahi, N. C., Singh, A., & Sirohi, R. (2018). Artificial neural network modeling of water activity: a low energy approach to freeze drying. Food and Bioprocess Technology, 11, 164–171.
39. Wang, H., Liu, Z.-L., Vidyarthi, S. K., Wang, Q.-H., Gao, L., Li, B.-R., Wei, Q., Liu, Y.-H., & Xiao, H.-W. (2020). Effects of different drying methods on drying kinetics, physicochemical properties, microstructure, and energy consumption of potato (Solanum tuberosum L.) cubes. Drying Technology, 39(3), 418–431.
40. Wang, T., Yang, H., Zhu, G. C., Wang, Z. Z., Xie, Y. K., & Han, J. H. (2021). Effects of hot air, microwave and combined drying on nutritional properties and sensory quality of peanut. Acta Agric Nucl Sin, 35(9), 2102–2110.
41. Xu, W., Sun, H., Li, H., Li, Z., Zheng, S., Luo, D., Ning, Y., Wang, Y., & Shah, B. R. (2022). Preparation and characterization of tea oil powder with high water solubility using Pickering emulsion template and vacuum freeze-drying. LWT, 160, 113330.

42. Yazdani, M., Borghaee, A. M., Rafiee, S., Minaei, S., & Beheshti, B. (2013). Mathematical and neural networks modeling of thin-layer drying of peach (Prunus persica) slices and their comparison. European Journal of Experimental Biology, 3(3), 712–721.
43. Zalpouri, R., Singh, M., Kaur, P., Kaur, A., Gaikwad, K. K., & Singh, A. (2023). Drying Kinetics, Physicochemical and Thermal Analysis of Onion Puree Dried Using a Refractance Window Dryer. Processes, 11(3), 700.