https://doi.org/10.17221/218/2025-RAE

Investigation of the drying kinetics of a residual nut mixture using mathematical models and artificial neural networks

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Citation: Duy T.H., Dang N.D.K., Han D.N.G., Vy P.T.T., Giau T.N., Hao H.V., Thuy N.M., Minh V.Q., Tai N.V. (2026): Investigation of the drying kinetics of a residual nut mixture using mathematical models and artificial neural networks. Res. Agr. Eng., 72: 121–131.

Abstract: The objective of this study was to evaluate the potential for the sustainable reuse and the value of the residual nut mixture (RNM) by-products (cashew nut, peanut, and soybean) after extraction. To investigate the drying kinetics, the RNM was dried at various temperatures (50 to 80 °C). The Balbay and Şahin model, which had a high coefficient of determination (R^2) of 99.62–99.96%, a low root mean square error of 0.007–0.021, and χ^2 of 0.001–0.005, was the one that best fit the experimental data out of the eight mathematical models that were used. Artificial neural networks showed higher and faster prediction capacity than the mathematical models. The effective moisture diffusion coefficient (D_{eff}) increased gradually with the temperature, with an activation energy (E_a) of 13.67 kJ·mol^{-1}. The RNM powder produced by the optimal drying process (60 °C for 3.75 h) has a bright colour, high polyphenol content (2.68 mg gallic acid equivalent (GAE)·g^{-1}) and antioxidant activity, low moisture content (4.9%) and relatively high nutritional value, especially protein (27.27%), lipid (40.19%), and fibre (4.2%). Under these conditions, not only is efficient drying and preservation achieved, but the quality of the by-product powder is also maintained.

Keywords: nuts by-products; drying temperatures; moisture diffusion; activation energy; statistical metrics

Vegan condensed milks are manufactured from a range of plants, and their quality is determined by the base ingredients, nutritional value, and how thoroughly they are blended to achieve the desired smoothness. Among the ingredients, soybeans are the most popular. The soybean is an important legume that provides all the essential amino acids for humans; it is consumed as a complete protein, although sulphur-containing amino acids such as cysteine and methionine are present in relatively low amounts. Soy isoflavones have antioxidant effects, and their role in preventing breast and prostate cancer has also been reported (Pejčić et al. 2023). Soybeans contain approximately 37–42% protein, the fat content of the seeds is approximately 19%, with relatively large amounts of unsaturated fatty acids (Kamshybayeva et al. 2017). Therefore, soybean consumption has been

Supported by the Can Tho University, Code: TSV2025-221.

https://doi.org/10.17221/218/2025-RAE

shown to offer numerous potential health benefits and reduce the risk of several chronic diseases. In addition, peanuts (*Arachis hypogaea* Linn) are a popular nut with a delicious flavour and high nutritional value. Peanuts and their products are beneficial to human health due to their nutritional value (lipid composition) and bioactive compounds, including phytosterols, phenolic compounds, stilbenes, lignans, and isoflavonoids. These bioactive substances shield the body from cancer, type 2 diabetes, and cardiovascular disease (Çiftçi and Suna 2022). Since peanuts are technically classified as legumes, their nutritional value, particularly their protein content, is comparable to that of soybeans and chickpeas. Additionally, peanuts contain both fat- and water-soluble micronutrients. Peanuts are low in cholesterol and abundant in fibre, vitamin E, and the B vitamins (thiamine, riboflavin, niacin, folate, and vitamin B6). Because they contain a wide range of macro- and micronutrients, peanuts have high nutritional value (Çiftçi and Suna 2022). However, peanuts contain 32 different proteins, 18 of which can cause allergies. These allergenic proteins can withstand chemical denaturation, high temperatures, and proteolytic enzymes (Toomer 2018). Cashew nuts are nutritious and tasty. It has been shown that cashew kernels reduce the risk of coronary heart disease and lower the low-density lipoprotein cholesterol levels. Cashew kernels include protein, fat and a variety of vitamins such as C, E, and D (Bes-Rastrollo et al. 2007). Cashew nuts include many unsaturated fatty acids, including oleic and linoleic acids, flavonoids, anthocyanins, tannins, dietary fibre, folate, and tocopherols (Cordaro et al. 2020). However, the extraction technique used to make vegan condensed milk from cashews, soybeans, and peanuts results in a huge amount of by-product residue high in protein, fibre, lipids, and beneficial compounds. Instead of being destroyed, this by-product can be properly repurposed to boost value while reducing the environmental impact. The majority of the by-products were formerly utilised as animal feed and fertiliser. However, this is also a possible source of by-products suitable for human consumption, with the quality depending on the type of nut.

Nut by-products contain a variety of health-promoting substances, including vitamins, minerals, phytochemicals/bioactives, fibre, lignin, protein, hydrolysed protein, peptides, polysaccharides, prebiotics, and oils, as well as antibacterial and antioxidant properties (Alasalvar et al. 2025). This is an opportunity to generate value-added food products while also reducing waste. When added to processed foods, the nutritional value improves, primarily by boosting the fibre and protein content (Zhao et al. 2025). Vong and Liu (2016) found that soybean by-products are often considered waste, with an estimated annual global production exceeding 4 million tonnes. High quantities of nutritious components, such as fibre (14.5–58.1%), protein (24.5–37.5%), and fat (9.3–22.3%), are still present in this by-product, along with trace amounts of ash and carbohydrates and bioactive substances including soyasaponins and isoflavones (Radočaj and Dimić 2013). In addition, peanut by-products can be well-utilised sources, as the high amino acid composition of peanut meal suggests they can serve as an ingredient for protein enhancement. Cashew nut meal has not been adequately processed despite its potential as a processed food ingredient with many benefits.

Drying is necessary to remove water from by-product compounds, thereby reducing deterioration while preserving their nutrient and phytochemical content, as many are oxidation-sensitive. One popular drying method is hot air drying. Since dried foods typically contain less than 25% water and have a water activity below 0.06, they can help minimise the production requirements, increase the storage capacity, and reduce the food weight and transportation costs. To simulate and verify the drying process, it is essential to use mathematical models and equations to predict its behaviour. Experimental errors are reduced by drying models, the drying process is improved, and energy consumption is reduced while profits are increased. Moreover, to forecast the drying behaviour, a variety of artificial intelligence models were used, including fuzzy networks, machine learning (ML), and artificial neural networks (ANNs). Compared to the mathematical models, these models showed improvements in the prediction, yielding quicker and more precise outcomes (Miraei Ashtiani and Martynenko 2024). The ANN method is a helpful statistical tool for non-parametric regression and is based on the biological neural system. One of the many benefits of using an ANN over conventional modelling approaches is its ability to include intricate data correlations. ANN enhances the adaptability, enhances the learning capabilities,

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and is a non-intrusive, online feature (Omari et al. 2018). To perform non-parametric regression, ANN serves as a useful statistical model inspired by the human brain (Selvi et al. 2022). Additionally, ANNs have been used in recent agricultural and food engineering research to predict several output parameters of drying processes (Jahedi Rad et al. 2018; Bannoud et al. 2024). As a result, engineers will benefit more from using ANNs when designing the drying apparatus. The use of soybean, peanut, and cashew nut wastes to produce a powder not only enhances the effectiveness of the by-products, but also extends their shelf life. Using nut residue helps reduce organic waste, limit greenhouse gas emissions, and promote ecological balance. At the same time, by-products can be turned into a variety of valuable items, such as nutritional supplements and fibre-rich dietary ingredients. This not only improves resource efficiency, but also promotes a circular economy, lowers costs, and provides a long-term source of added value for the nut milk processing business. The objective of this study was to find the best drying model (mathematical and ANN model) to describe the drying characteristics of RNM by developing a relationship between the experimental and predictive data, as well as to determine the best drying conditions based on the analysed physicochemical properties of the powder.

MATERIALS AND METHODS

Sample collection and preparation. Soybeans (*Glycine max*), peanuts (*Arachis hypogaea* L.), and cashew nuts (*Anacardium occidentale* L.) were purchased from local markets. The raw materials were cleaned of dirt through sieving, and damaged parts was removed. The peanuts and cashew nuts were roasted, dehusked, and ground separately with water at a ratio of 1 : 4 (w/v); while the soybeans were pre-soaked, dehusked, drained, and ground with water at a ratio of 1 : 3 (w/v). Filtrates from the three types of nuts were collected for research on the processing of vegan condensed milk products (the research was conducted simultaneously). The residue (Figure 1A) obtained from this process included soy, peanut, and cashew nut residues, which were combined at a ratio of 1 : 1 : 1 (w/w/w), commonly known as residual nut mixture (RNM), and used in this study.

Drying of the nut residue mixture. On a stainless-steel tray covered with wax paper, the RNM was spread out (sample thickness around 3 mm) (Figure 1B). Based on the results of early studies, the sample was dried in a convection oven (UN260, Memmert, Germany) at various temperatures (50–80 °C with 10-degree increments) until the moisture content reached equilibrium (< 6%). The drying kinetics of RNM were examined using sample weight measurements taken at 15-min intervals. A superfine powder grinding mill (QE-5000, Bigstar, Vietnam) was used and grind it into a fine powder. The powder was then sieved until the particles were around 100 μm in size. The sample was kept at 5 ± 1 °C in aluminum foil/polyethylene (Al/PA) packaging, and the RNM powder's physico-chemical properties were examined.

Drying kinetics. The drying kinetics of RNM were investigated using eight popular thin-layer drying models, as shown in Table 1.

(A) (B)

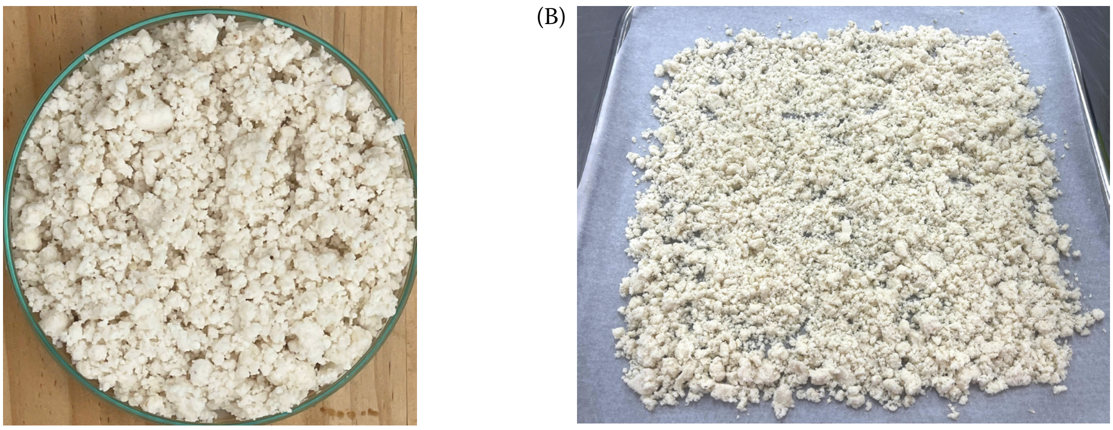

Figure 1. Residual nut mixture (RNM) (A) and RNM prepared for drying (B)

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Table 1. Thin-layer drying models were used for the residual nut mixture (RNM)

Model name	Model equation	References
Newton	$MR = \exp(-kt)$	Kucuk et al. (2014)
Logarithmic	$MR = a\exp(-kt) + c$	Akpinar and Bicer (2008)
Henderson and Pabis	$MR = a\exp(-kt)$	Rosa et al. (2015)
Wang and Singh	$MR = 1 + at + bt^2$	Şimşek et al. (2021)
Two-term exponential	$MR = a\exp(-kt) + (1 - a)\exp(-kat)$	Chavan et al. (2008)
Page	$MR = \exp(-kt^n)$	Akpinar and Bicer (2008)
Balbay and Şahin	$MR = (1 - a)\exp(-kt^n) + b$	Balbay and Şahin (2012)
Parabolic	$MR = a + bt + ct^2$	Sharma and Prasad (2004)

MR – moisture ratio

Moisture data at different temperatures were converted to a moisture ratio (MR) using Equation (1) (Toğrul and Pehlivan 2004).

$$\mathrm{MR} = \frac{M_t}{M_o} \quad (1)$$

where: M_o – the initial moisture content; M_t – the moisture content at time t.

Drying rate (DR). The drying rate was calculated according to Equation (2) (Toğrul and Pehlivan 2004).

$$\mathrm{DR} = \frac{M_{t+dt} - M_t}{dt} \quad (2)$$

where: M_{t+dt} – the moisture content (g water·g dry matter^{-1}) at time ($t + dt$).

By considering several factors, the optimal mathematical model for forecasting the drying kinetics of the by-product mixture was identified. The coefficient of determination (R^2) is a key consideration when selecting the best model. Additionally, the model's fit was evaluated using widely used statistical measures, including the chi-square (χ^2) and the root mean square error (RMSE). The formula for the above parameters is presented in Equations (3), (4), and (5) (Toğrul and Pehlivan 2004).

$$R^2 = \frac{\sum_{i=1}^{N}\left(\mathrm{MR}_i - \mathrm{MR}_{\mathrm{pre},i}\right) \times \sum_{i=1}^{N}\left(\mathrm{MR}_i - \mathrm{MR}_{\mathrm{exp},i}\right)}{\sqrt{\sum_{i=1}^{N}\left(\mathrm{MR}_i - \mathrm{MR}_{\mathrm{pre},i}\right)^2 \times \sum_{i=1}^{N}\left(\mathrm{MR}_i - \mathrm{MR}_{\mathrm{exp},i}\right)^2}} \quad (3)$$

$$\mathrm{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(\mathrm{MR}_{\mathrm{pre},i} - \mathrm{MR}_{\mathrm{exp},i}\right)^2\right]^{1/2} \quad (4)$$

$$\chi^2 = \frac{\sum_{i=1}^{N}\left(\mathrm{MR}_{\mathrm{exp},i} - \mathrm{MR}_{\mathrm{pre},i}\right)^2}{N - z} \quad (5)$$

where: $\mathrm{MR}_{\mathrm{exp},i}$ – the moisture ratio that was measured experimentally; N – the number of observations; z – a constant; $\mathrm{MR}_{\mathrm{pre},i}$ – the i^{th} projected moisture ratio.

Artificial neural network (ANN). The drying time and temperature matrix comprised the artificial neural network model's input layer, while the MR was in the output layer. To select the number of hidden-layer neurons, a trial-and-error approach was used, and ten neurons were selected to prevent overfitting (Liu et al. 2025; Thuy et al. 2025b). The matrix was divided into three parts: training (70%), testing (15%), and validation (15%). The data division was random, and the training algorithm used in this study was the Levenberg-Marquardt algorithm, with performance evaluated using regression coefficient (R) and mean square error (MSE) values. The study utilised MATLAB R2023a with the "nftool" function. The ANN model was evaluated against the experimental actual values for selecting the most suitable model.

Effective moisture diffusivity (D_{eff}) and activation energy (E_a). The D_{eff} for the RNM drying was estimated according to Fick's second law (Equation 6) (Zarein et al. 2015).

$$\mathrm{MR} = \frac{8}{\pi^2}\sum_{n=0}^{\infty}\frac{1}{(2n+1)^2}\exp\left(-(2n+1)\pi^2\frac{D_{eff}t}{4L^2}\right) \quad (6)$$

where: D_{eff} – the moisture diffusion coefficient (m^2·s^{-1}); t – the drying time (s); n – a positive integer; L – ½ the material thickness (m).

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Equation (7) is the result of linearising and further simplifying Equation (5) into a straight-line equation. Then, D_{eff} can be calculated according to Equation (8) (Zarein et al. 2015).

$$\ln(\mathrm{MR}) = \ln\left(\frac{8}{\pi^2}\right) - \left(\frac{\pi^2}{4L^2} D_{eff} t\right) \quad (7)$$

$$\mathrm{Slope} = \frac{\pi^2 D_{eff}}{4L^2} \quad (8)$$

The activation energy (E_a) can be calculated from the Arrhenius equation (Equation 9) (Sanjuán et al. 2003).

$$D_{eff} = D_0 \exp\left(\frac{-E_a}{RT}\right) \quad (9)$$

where: D_0 – the frequency factor of the effective diffusion coefficient ($m^2 \cdot s^{-1}$); E_a – the activation energy ($kJ \cdot mol^{-1}$); R – the universal gas constant (8.314 $J \cdot mol^{-1} \cdot K^{-1}$); and T – the absolute temperature (K).

Determination of the physico-chemical properties. The Folin-Ciocalteu assay was used to determine the total polyphenol content (TPC) (Fu et al. 2011). The reagent was evaluated for absorbance at 738 nm, and the reaction solution contained polyphenols extracted from the RNM powder. The acquired standard curve was then used to compute TPC as mg gallic acid equivalent per gram of sample (mg GAE$\cdot g^{-1}$). The scavenging activity of the stable 1,1-diphenyl-2-picrylhydrazyl (DPPH) free radical was used to gauge the product's antioxidant activity (Brand-Williams et al. 1995). A HunterLab ColorFlex colorimeter (ColorFlex L2, HunterLab, USA) was used to measure the colour values (L^*, a^*, b^*) and the browning index (BI) was calculated, and estimated by Equation (10) (Pathare et al. 2013). The Association of Official Analytical Chemists technique was used to determine the moisture, protein, fat, carbohydrate, ash, and fibre content (AOAC 2005).

$$\mathrm{BI} = \frac{100\left[\dfrac{a^* + 1.75L^*}{5.645L^* + (a^* - 0.3012b^*)} - 0.31\right]}{0.17} \quad (10)$$

Statistical analysis. Measurements were carried out in triplicate, and all the quantitative data were reported using the mean ± standard deviation (SD). Statgraphics Centurion XV.I software provides the data and model fit, the correlation coefficient, and RMSE, as well as parameter estimation (constants), as the output of the non-linear regression.

RESULTS AND DISCUSSION

Drying kinetics. The effect of the drying temperature on the MR and drying rate of the RNM is shown in Figure 2. The results showed that the MR of RNM decreased with an increasing drying temperature (Figure 2A); the drying time required to achieve the final powder moisture content (< 6%) was 4.5, 3.75, 3.25, and 3 h at 50, 60, 70, and 80 °C, respectively. It was observed that the drying temperature directly impacted the material's change in MR over time. The decrease in the sample's moisture content clearly demonstrates that moisture diffusion is crucial to the

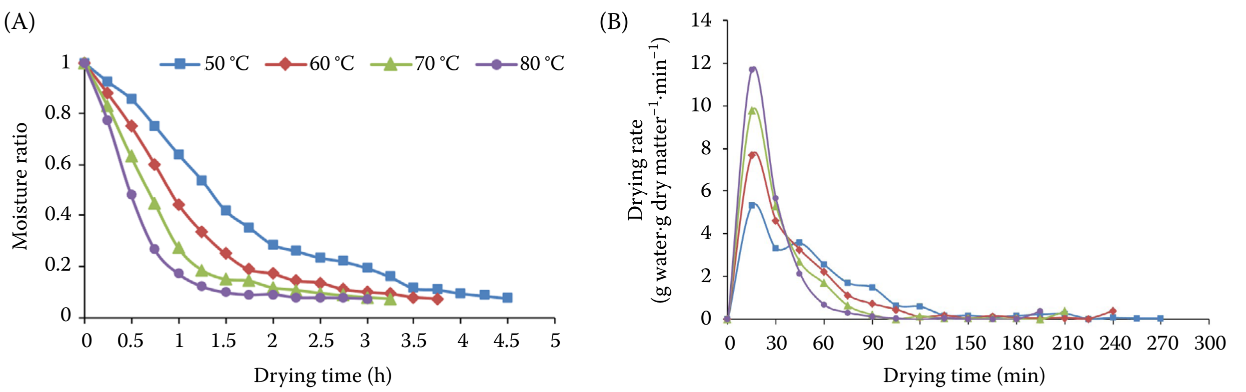

Figure 2. Drying curves of the residual nut mixture (RNM) at various temperatures: (A) changes in the moisture ratio and (B) drying rate with the drying time

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mass transfer mechanism within the material's structure. As the drying temperature increases, moisture loss from the drying material occurs more rapidly due to a larger temperature difference between the environment and the material, leading to shorter drying times at higher temperatures (Kaya et al. 2007). Figure 2B revealed that the drying rate typically increased significantly during the first 15 min of drying at various drying temperatures, then declined over longer drying periods. The drying rate increased as the drying air temperature rose. This demonstrates that as heat and mass transfer happen more quickly at higher temperatures, more water is lost.

As the temperature rises, the energy of water molecules also increases, making their escape easier and quicker. Le et al. (2025) found that the drying rate is usually higher at the early stage of drying, then gradually decreases with the drying time. In the later stages, the drying rate gradually decreases because the moisture transfer rate from the inside to the surface is lower than the evaporation rate at the material's surface. As a result, the drying rate drops dramatically at this stage, which is primarily controlled by the mass transfer within the material. According to certain drying kinetic investigations of peanut milk residue, cashew nut almonds, and okara, the drying air temperature is the primary factor influencing the MR and drying rate (Guimarães et al. 2018; Sanika et al. 2021; Almeida et al. 2025).

Mathematical modelling and ANN. The results presented in Table 2 show the statistical parameters of each model and its selection criteria (highest R^2, lowest RMSE, and χ^2 values), in which the residual moisture content of RNM dried at various temperatures was evaluated over time. All the models (Equation 11–42) showed high R^2 values, ranging from 93.27 to 99.96%, demonstrating their ability to describe the RNM drying process at different temperatures. The recorded RMSE values ranged from 0.007 to 0.082, and χ^2 values ranged from 0.0001 to 0.0080. In particular, among the eight mathematical models that were applied, the Balbay and Şahin model (Equation 35–38) showed a higher degree of fit at all the drying temperature levels than the remaining models through the highest R^2 value (0.9962–0.9996), the lowest values of RMSE (0.007–0.021) and χ^2 (0.0001–0.0005), meeting the acceptance criteria for a model to be considered as having high quality, when the χ^2 and RMSE values approach 0, the prediction fits better with the experimental data.

The ANN model (Figure 3) predicted the influence of the drying time and temperature on the MR value, employing a three-layer architecture: an input layer (drying temperature and time), a hidden layer with ten neurons, and an output layer (MR value). A hidden layer with ten neurons is commonly employed in predictive models for drying processes, such as lucuma foam-mat drying and field crab foam-mat drying (Thuy et al. 2025a, b). A model comprising ten neurons employs a validation technique to mitigate overfitting (Liu et al. 2025). The dataset is partitioned into three random segments: 70% for training, 15% for validation, and 15% for testing, which helps mitigate overfitting. The 2-10-1 model trained with the Levenberg-Marquardt procedure achieves optimal validation performance after ten epochs (Figure 3A). Moreover, as shown in Figure 3B, the total error for our model ranges from -0.04405 (leftmost bin) to 0.0527 (rightmost bin). The model exhibited R values of 0.9994, 0.9957, 0.9977, and 0.9988 for training, validation, testing, and overall performance, respectively (Figure 3C–F). The MSE values are 0.0001, 0.0004, and 0.0006 for the training, validation, and test datasets, respectively. The model demonstrates a near-perfect R value of 0.99 and an exceedingly low MSE, indicating its ability to forecast the influence of time and temperature on the MR accurately. This is corroborated by comparing the experimental value with the model-predicted value.

Comparing the selected model (Balbay and Şahin) and the ANN presented in Figure 4, it was observed that the ANN model (Figure 4B) exhibits superior predictive accuracy compared to the Balbay and Şahin model (Figure 4A). Furthermore, an ANN can process data at multiple temperatures using a single model concurrently. Simultaneously, each temperature utilised will become a model within the empirical model framework. Therefore, the ANN model also holds potential for industrial control systems. The ANN model would be selected for this investigation due to its higher predictive capabilities.

Effective moisture diffusivity and activation energy. Foodstuffs' intrinsic moisture migration properties, which include mechanisms such as liquid, molecular, vapour, and hydrodynamic diffusion, are reflected in their effective moisture

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Table 2. Model parameters and goodness of fit for the residual nut mixture (RNM) drying kinetics at different temperatures

Temp. (°C)	Model equation	Equation No.	R^2	RMSE	χ^2
Newton: MR = exp($-kt$)					
50	MR = exp($-0.5462t$)	(11)	0.9809	0.042	0.0019
60	MR = exp($-0.8069t$)	(12)	0.9839	0.039	0.0016
70	MR = exp($-1.0976t$)	(13)	0.9799	0.043	0.0020
80	MR = exp($-1.5003t$)	(14)	0.9741	0.049	0.0026
Logarithmic: MR = $a$exp($-kt$) + c					
50	MR = 1.1027exp($-0.5348t$) + 0.0415	(15)	0.9891	0.034	0.0014
60	MR = 1.0429exp($-0.8857t$) + 0.0154	(16)	0.9876	0.037	0.0017
70	MR = 1.0101exp($-1.2881t$) + 0.0417	(17)	0.9853	0.041	0.0021
80	MR = 0.9948exp($-1.8118t$) + 0.0510	(18)	0.9847	0.041	0.0022
Henderson and Pabis: MR = $a$exp($-kt$)					
50	MR = 1.0735exp($-0.5878t$)	(19)	0.9881	0.035	0.0013
60	MR = 1.0527exp($-0.8495t$)	(20)	0.9873	0.036	0.0015
70	MR = 1.0351exp($-1.1364t$)	(21)	0.9814	0.044	0.0022
80	MR = 1.0265exp($-1.5403t$)	(22)	0.9749	0.050	0.0030
Wang and Singh: MR = 1 + at + bt^2					
50	MR = 1 + $0.4352t$ + $0.0520t^2$	(23)	0.9896	0.032	0.0012
60	MR = 1 + $0.6254t$ + $0.1045t^2$	(24)	0.9875	0.036	0.0015
70	MR = 1 + $0.8025t$ + $0.1667t^2$	(25)	0.9704	0.055	0.0035
80	MR = 1 + $0.9697t$ + $0.2327t^2$	(26)	0.9327	0.082	0.0080
Two-term exponential: MR = $a$exp($-kt$) + (1 − a) exp($-kat$)					
50	MR = 0.9793exp($-0.5467t$) + (1 − 0.9793) exp($-0.5467\cdot0.9793t$)	(27)	0.9809	0.044	0.0021
60	MR = 1.0151exp($-0.8066t$) + (1 − 1.0151) exp($-0.8066\cdot1.0151t$)	(28)	0.9839	0.041	0.0019
70	MR = 0.6493exp($-1.2855t$) + (1 − 0.6493) exp($-1.2855\cdot0.6493t$)	(29)	0.9802	0.045	0.0024
80	MR = 0.5500exp($-1.9893t$) + (1 − 0.5500) exp($-1.9893\cdot0.5500t$)	(30)	0.9756	0.050	0.0029
Page: MR = exp($-kt^n$)					
50	MR = exp($-0.4717t^{1.2152}$)	(31)	0.9926	0.027	0.0008
60	MR = exp($-0.7697t^{1.1443}$)	(32)	0.9887	0.034	0.0013
70	MR = exp($-1.0959t^{1.0730}$)	(33)	0.9811	0.044	0.0023
80	MR = exp($-1.5228t^{1.0474}$)	(34)	0.9745	0.051	0.0030
Balbay and Şahin: MR = (1 − a) exp($-kt^n$) + b					
50	MR = (1 − 0.0734) exp($-0.5173t^{1.4035}$) + 0.0785	(35)	0.9962	0.021	0.0005
60	MR = (1 − 0.0903) exp($-0.9138t^{1.4700}$) + 0.0867	(36)	0.9986	0.013	0.0002
70	MR = (1 − 0.0916) exp($-1.4928t^{1.4903}$) + 0.0889	(37)	0.9980	0.016	0.0003
80	MR = (1 − 0.0791) exp($-2.3956t^{1.5171}$) + 0.0810	(38)	0.9996	0.007	0.0001
Parabolic: MR = a + bt + ct^2					
50	MR = 1.0308 − $0.4617t$ + $0.0568t^2$	(39)	0.9911	0.031	0.0011
60	MR = 1.0034 − $0.6288t$ + $0.1052t^2$	(40)	0.9875	0.037	0.0017
70	MR = 0.9677 − $0.7643t$ + $0.1573t^2$	(41)	0.9722	0.056	0.0040
80	MR = 0.9190 − $0.8663t$ + $0.2051t^2$	(42)	0.9442	0.079	0.0080

MR – moisture ratio; temp. – temperature; R^2 – correlation coefficient; χ^2 – chi-square; RMSE – root mean square error

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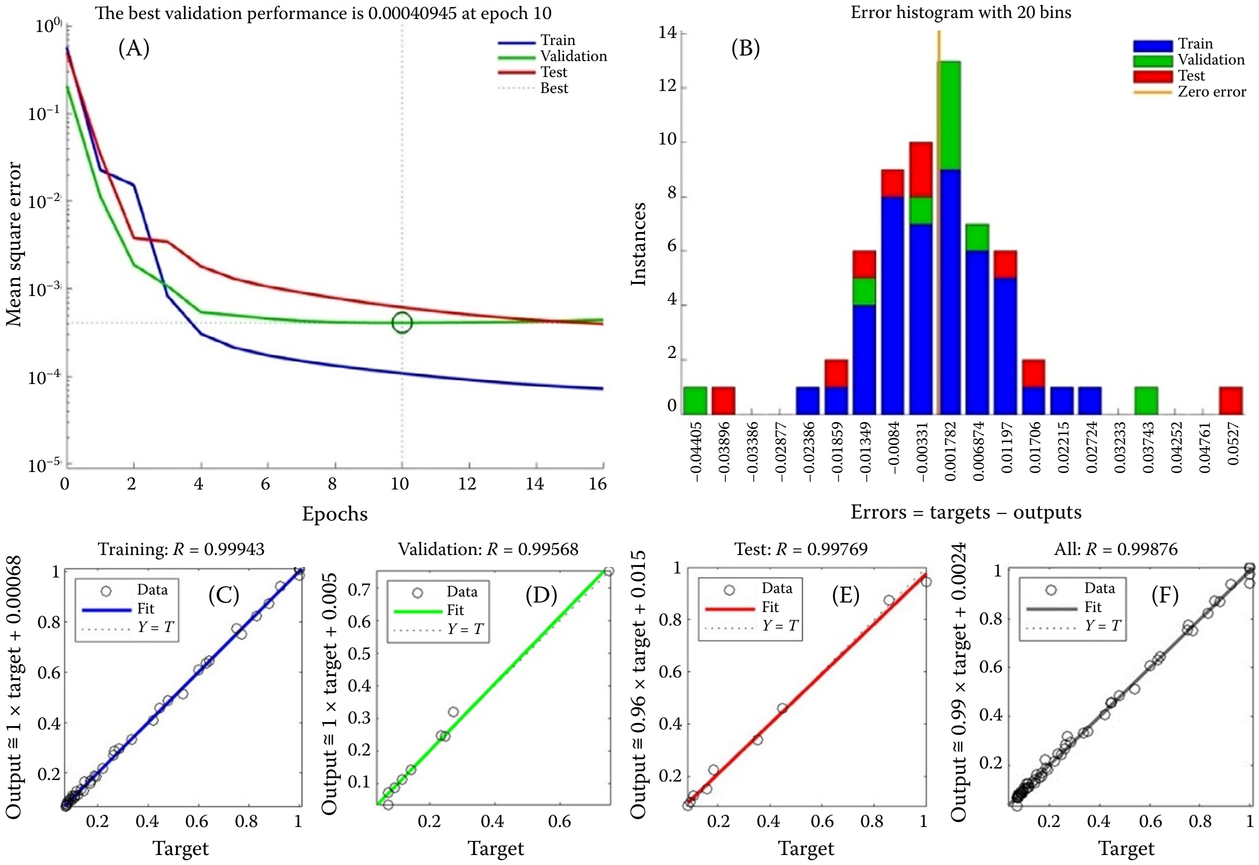

Figure 3. Artificial neural network (ANN) model performance: (A) validation performance, (B) error histogram, (C) training, (D) validation, (E) test and (F) all the dataset
R – coefficient of correlation; Y – Y axis; T – target

diffusivity (D_{eff}). Figure 5 displays the values of D_{eff} at various temperatures; they ranged from 6.13^{-10} to 9.50^{-10} m^2·s^{-1} as the temperature increased from 50 to 80 °C. For the entire dataset, the coefficient of determination (R^2) is 0.98, which is statistically significant. As the drying temperature rises, the D_{eff} values of RNM increase; more specifically, the sample's water molecule activity is enhanced by the higher temperature, thereby increasing the diffusion rate (Nadi and Tzempelikos 2018). For most dietary ingredients reported, the D_{eff} value ranges from 10^{-8} to 10^{-12} m^2·s^{-1} (Abbaspour-Gilandeh

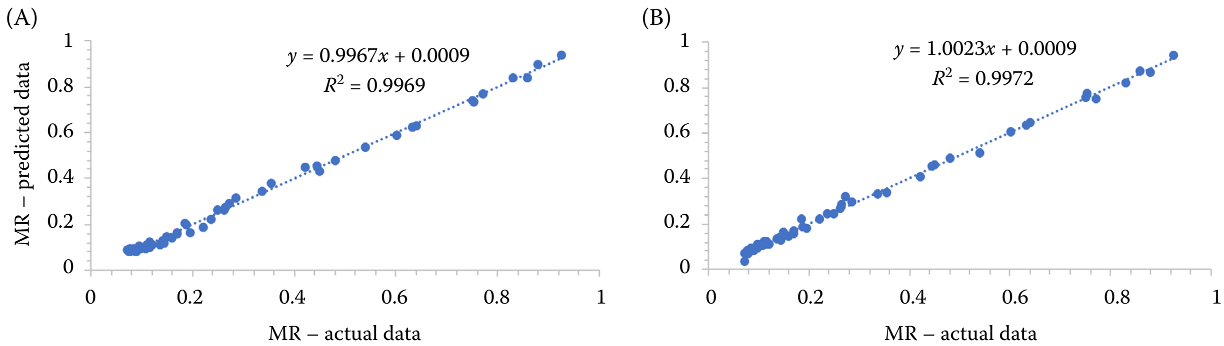

Figure 4. Regression analysis for comparing actual and predicted values from (A) selected (Balbay and Şahin model) and (B) artificial neural network (ANN) models

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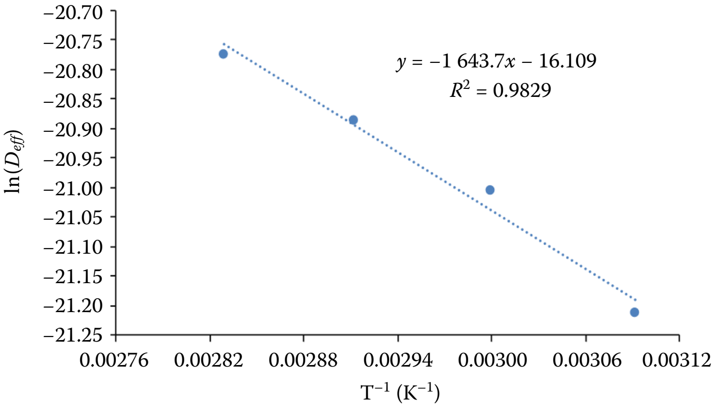

Figure 5. Relationship between the inverse of the effective moisture diffusivity (D_{eff}) and the temperature of residual nut mixture (RNM)

et al. 2020; Kasara et al. 2021). Based on the slope of ln(D_{eff}) against the reciprocal of temperatures [$T^{-1}(K)^{-1}$], the activation energy (E_a) was determined to be 13.67 kJ·mol^{-1}. The E_a value for drying RNM over the temperature range is within the usual range of 12–110 kJ·mol^{-1} for food items (Thuy et al. 2025a).

Physicochemical properties of the finished RNM powder. RNM dried at 60 °C yielded a powder with good flowability, a high TPC (2.68 ± 0.04 mg GAE·g^{-1}), and a vivid colour. The finished product's BI (243.55 ± 19.63) was just marginally higher than that of the initial undried sample (184.13 ± 7.82). The nutritional analysis revealed that, with a moisture level of 4.9%, the RNM powder included 40.19% lipids, 27.27% protein, 24.75% carbohydrate, 4.2% fibre, and 2.89% ash. A 67.35% DPPH radical-scavenging activity indicates a moderate to high level of antioxidant capacity, often observed in natural extracts, that have undergone processing to enhance their phenolic and polysaccharide content. This value means the sample successfully neutralises 67.35% of the free radicals in a standard DPPH assay. The lipid profile of peanuts is around 50% monounsaturated fatty acids, 33% fatty acids, and 14% saturated fatty acids. Additionally, cashew nuts contain 45% fat, including heart-healthy unsaturated fatty acids such as oleic and linoleic acids (Arya et al. 2016; Gonçalves et al. 2023). Soybean lipids are predominantly composed of unsaturated fatty acids (≈ 84%), mainly linoleic acid (53.46%) and oleic acid (22.09%), while saturated fatty acids such as palmitic (9.05%) and stearic acids (3.93%) are present in lower proportions (Mostofsky et al. 2001; Kokten et al. 2024). Besides, the protein content of the RNM powder is high because soybeans and peanuts are rich in protein. The highest biological value of any plant-based protein source is believed to be found in soybean protein. Exogenous amino acids, specifically phenylalanine, methionine, threonine, valine, isoleucine, leucine, tryptophan, and lysine, are present in amounts that are similar to those found in animal protein (Kudełka et al. 2021). All 20 amino acids are present in peanut protein, which is also the highest source of arginine (up to 12.5% of total proteins) (Arya et al. 2016). The carbohydrate content of RNM powder is moderate, but it is mainly high in fibre content. These nuts contain high fibre, especially insoluble fibre, which cannot be broken down in the small intestine, but can be fermented by bacteria in the large intestine; it helps regulate the blood sugar, lowers cholesterol, promotes regular bowel movements, and supports healthy digestion (Gonçalves et al. 2023). Nuts are also rich sources of minerals, such as magnesium, copper, and potassium, which are considered heart-healthy and reduce the risk of high blood pressure (Gonçalves et al. 2023). Plant/nut phenolics' ability to scavenge free radicals by giving them an electron or a hydrogen atom from an aromatic hydroxyl group is the primary cause of their possible health benefits. RNM powder has a comparatively strong DPPH free radical-scavenging capacity, which could enhance its free radical-scavenging capabilities for use in food processing. In addition, nuts' high antioxidant content slows the ageing process and reduces the risk of chronic illnesses such as diabetes, cancer, and cardiovascular disease.

CONCLUSION

From this study, the RNM was effectively utilised after drying. The kinetic model of Balbay and Şahin was chosen to describe this drying process, with the

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kinetic parameters determined and fully statistically analysed, indicating very high accuracy at all the drying temperatures ($R^2 \geq 0.9986$). Compared with mathematical models, ANNs showed higher predictive capacity and could forecast multiple outputs with a single model. The activation energy (E_a = 13.67 kJ·mol^{-1}) was determined at the average level, indicating that the material is susceptible to temperature variations during drying. Drying RNM at 60 °C for 3.75 h resulted in the optimal maintenance of the product's quality. Under these conditions, the RNM powder had a bright colour, maintained a high TPC, and low moisture content. The nutritional values and bioactive compounds remained at a reasonable level, making them a suitable alternative ingredient for food processing. With the new product developed from the reuse of grain by-products, RNM powder is expected to contribute to research on new food products from flour as an additional raw material. The reuse of nutritional grain waste not only increases resource value and production efficiency, but also contributes practically to sustainable development through waste reduction, ecosystem protection, and the promotion of a circular economy.

Acknowledgement

The authors thank the AGriCTU group at Can Tho University for their support with equipment and part of the funding.

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Received: December 4, 2025
Accepted: February 19, 2026
Published online: May 15, 2026