



Neuro-Predictive Modelling and Thermo-Energetic Optimization of Convective Drying Kinetics and Mass Transfer Dynamics in Black Bean (Akidi) Seeds

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Abstract

Convective drying extends the storage life of legume seeds, but its nonlinear kinetics and energy demand are difficult to predict with conventional models. This study developed and validated an artificial neural network (ANN) to predict the drying kinetics, drying time and energy consumption of black bean (*Vigna unguiculata*) seeds during convective drying at 45-65 °C, and to identify optimal drying conditions. Fresh seeds had an initial moisture content of 18.84% (wet basis), above the 12-14% safe storage limit. A 2-10-10-3 feedforward network (Levenberg-Marquardt training) used drying time and temperature as inputs and moisture ratio (MR), drying rate (DR) and energy consumption (E) as outputs. Increasing the temperature from 45 to 65 °C reduced the drying time from 1100 to 800 min (27.3%), while the effective moisture diffusivity

increased from 2.84×10^{-10} to $6.15 \times 10^{-10} \text{ m}^2 \text{ s}^{-1}$, with an activation energy of $34.70 \text{ kJ mol}^{-1}$. On a dry matter basis, protein (25.92-22.92%) and fat (2.26-1.85%) decreased, whereas ash, fibre and carbohydrate increased with temperature. The ANN achieved overall R^2 of 0.9988-0.9992 and RMSE of 0.0141-0.0190, with maximum prediction errors of 0.61% for MR and 0.40% for DR. ANN-based optimization identified 65 °C as the optimum within the investigated range, reducing the predicted drying time by 25.8% and energy consumption by 27.3% relative to 45 °C. The model provides a decision-support tool for energy-efficient drying of black bean seeds.

Keywords: Artificial neural network, *Vigna unguiculata*, black bean, moisture diffusivity, drying kinetics.



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Nomenclature

Symbol	Description	Unit
MR	Moisture ratio	dimensionless
DR	Drying rate	kg water (kg DM) ⁻¹ min ⁻¹
M_t	Moisture content at time t	kg water (kg DM) ⁻¹
M_0	Initial moisture content	kg water (kg DM) ⁻¹
EMC	Equilibrium moisture content	kg water (kg DM) ⁻¹
D_{eff}	Effective moisture diffusivity	m ² s ⁻¹
D_0	Pre-exponential factor (Arrhenius)	m ² s ⁻¹
E_a	Activation energy	kJ mol ⁻¹
R	Universal gas constant (8.314 × 10 ⁻³)	kJ mol ⁻¹ K ⁻¹
T_{abs}	Absolute temperature	K
T	Drying temperature	°C
L	Half-thickness of seed	m (reported in mm)
t	Time	min
t_d	Total drying time	min
E_{total}	Total energy consumption	kJ
E	Energy consumption (ANN output)	kJ
SEC	Specific energy consumption	kJ (kg water removed) ⁻¹
η	Energy efficiency	%
h_{fg}	Latent heat of vaporization	kJ kg ⁻¹
M_w	Mass of water removed	kg
P_{oven}	Rated power of oven	W
a	Model coefficient	various
b	Model exponent	dimensionless
k	Drying rate constant	min ⁻¹
R^2	Coefficient of determination	dimensionless
r	Correlation (regression) coefficient	dimensionless
RMSE	Root mean square error	dimensionless
MSE	Mean squared error	dimensionless
ANN	Artificial neural network	-
RSM	Response surface methodology	-

1 Introduction

Black bean (*Vigna unguiculata* (L.) Walp. subsp. *unguiculata*), locally known as “Akidi” among the Igbo people of south-eastern Nigeria, is an important legume crop that has been extensively studied for its genetic diversity and crop improvement potential, as well as its significant nutritional and economic value [1, 2]. The fresh seeds are rich in protein, dietary fiber, complex carbohydrates (55-60%), and essential minerals including iron, zinc, calcium, and potassium [3]. They are particularly valued for their high protein content and bioactive compounds, including polyphenols and antioxidants, which contribute to their health-promoting properties [4]. However, the high moisture content of fresh black bean seeds renders them highly perishable, leading to rapid post-harvest deterioration through enzymatic

browning, microbial growth, and insect infestation [5]. Drying is therefore essential for extending shelf life, reducing transportation costs, and enabling year-round availability [6]. In practice, farmers in Sub-Saharan Africa frequently rely on open-sun drying due to limited access to electricity, but this method is associated with contamination, slow drying, and limited process control, motivating the investigation of controlled convective drying. Forced-air convective oven drying was therefore used in this study to generate reproducible, controlled data for ANN model development. The modelling framework can be adapted to sun or solar drying once appropriate data are available.

Convective oven drying remains the most widely employed drying method for legumes in developing countries due to its simplicity, controllability, and accessibility [7]. However, legume seeds present unique drying challenges due to their dense seed coat (testa), which acts as an additional barrier to moisture diffusion and prolongs the falling-rate period [8]. This structural characteristic makes black bean drying particularly energy-intensive and time-consuming compared to other seed types, as the testa’s hydrophobic properties and compact cellular structure impede moisture migration from the cotyledons to the surface. The drying behaviour of legume seeds is complex, involving simultaneous heat and mass transfer phenomena influenced by multiple factors including temperature, humidity, air velocity, and seed characteristics [9]. Traditional empirical models (Newton, Page, Henderson-Pabis, Midilli-Kucuk) have been extensively used to describe drying kinetics, but these models often fail to capture the non-linear, multi-dimensional nature of the drying process [10, 11].

Artificial neural networks (ANNs) have emerged as powerful computational tools for modelling complex, non-linear systems without requiring prior knowledge of the underlying physical mechanisms [12, 13]. ANNs learn from experimental data through iterative training, adapting network weights and biases to minimize prediction errors [14, 15]. In food drying applications, ANNs have demonstrated superior predictive accuracy compared to traditional models, effectively capturing the intricate relationships between process parameters and drying outcomes [16–19]. Studies on other agricultural products have demonstrated that ANN achieves superior predictive accuracy compared to traditional models, with applications successfully reported for

papaya [20], caper [21], sweet potato [22], quince [23], onion [24], tomato [25], carrot [26, 27] and linden [28] drying, as reviewed by Aghbashlo et al. [29]. The capability of ANNs to model the highly non-linear behaviour of moisture diffusion in biological materials makes them particularly suitable for legume drying applications where structural heterogeneity and temperature-dependent properties complicate conventional modelling approaches [30, 31].

Despite the economic and nutritional importance of black beans, systematic studies on ANN modelling of their drying behaviour remain limited. Although traditional mathematical models for cowpea drying kinetics and moisture diffusion behaviour have been established [32], ANN-based predictive models for drying time and energy consumption remain absent for black beans, hindering the development of optimized, science-based drying protocols. Furthermore, the specific effects of the seed coat structure on drying dynamics and energy requirements have not been adequately evaluated using neural network approaches. Therefore, this study aimed to develop and train ANN models for predicting moisture ratio, drying rate and energy consumption during convective oven drying of black bean seeds; derive closed-form prediction models for moisture ratio, drying rate, and energy consumption; determine effective moisture diffusivity and activation energy from ANN-derived parameters; and identify optimal oven drying conditions that minimize drying time and energy consumption while maintaining product quality.

2 Materials and Methods

2.1 Raw material sourcing and preparation

Fresh, unthreshed matured pods of black bean (*Vigna unguiculata*) were sourced from Eke Market, Ekwulobia, Aguata Local Government Area, Anambra State, Nigeria (6.02653° N, 7.08534° E). The pods were collected using polyethylene bags and transported to the Crop Processing Laboratory, Department of Agricultural and Bioresources Engineering, Nnamdi Azikiwe University, Awka, within 2 h of collection. Botanical identification was performed by experts in the Department of Crop Production and Forestry, Nnamdi Azikiwe University, confirming the seeds as *Vigna unguiculata* (L.) Walp. subsp. *unguiculata* of the Fabaceae family. The seed pods were carefully threshed to obtain fresh seeds. Spoiled seeds and debris were manually sorted out, and samples of relatively uniform size and wholeness were selected

for drying experiments.

2.2 Convective oven drying procedure

A completely randomized design (CRD) with three replications was employed. Five 100 g batches of prepared seeds were spread in a single layer on perforated aluminium trays (30 cm × 40 cm) and dried in a forced-air convection oven (i-therm AI-7781) with digital temperature control (± 1.0 °C) at 45, 50, 55, 60, and 65 °C. Air velocity was maintained at 1.5 ± 0.1 m s⁻¹ as measured by a hot-wire anemometer (Testo 425). Moisture loss was monitored gravimetrically every 20 min using a calibrated analytical balance (METTLER MT 2000, readability 0.001 g) until constant mass was achieved ($< 0.1\%$ mass change over three consecutive measurements). Total drying time ranged from 800 min at 65 °C to 1100 min at 45 °C. All weighing was completed within 30 s to minimize ambient moisture exchange.

Initial moisture content, determined by oven drying at 105 °C for 24 h following the AOAC method [33], was $18.84 \pm 0.10\%$ (wet basis) for fresh black bean seeds, exceeding the safe storage moisture content of 12–14% (wb) recommended for leguminous seeds. Drying was therefore necessary to reduce moisture to $\leq 10\%$ (wb) to prevent microbial spoilage, sprouting, and insect infestation. Moisture content is reported on a wet basis (% wb) for final moisture levels. For drying kinetics and mass-transfer calculations, moisture content was converted to a dry basis (g water/g dry matter) using Eq. (1), because dry matter mass remains constant throughout drying while wet mass continuously decreases. All drying kinetics calculations were performed on a dry basis. Moisture ratio (MR) was calculated using Eq. (2):

$$M_{db} = \frac{M_{wb}}{100 - M_{wb}} \quad (1)$$

where M_{db} is moisture content on a dry basis (g water/g dry matter) and M_{wb} is moisture content on a wet basis (%) [34].

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

where M_t is the moisture content at time t (kg water/kg dry matter), M_0 is the initial moisture content (kg water/kg dry matter), and EMC is the equilibrium moisture content (kg water/kg dry matter) [35, 36].

Drying rate (DR) was calculated as:

$$DR = \frac{M_t - M_{t+\Delta t}}{\Delta t} \quad (3)$$

where DR is the drying rate (kg water/kg dry matter·min), M_t is the moisture content at drying time t , and $M_{t+\Delta t}$ is the moisture content at time $t + \Delta t$ [7].

2.2.1 Physical properties of black bean seeds

The principal physical dimensions of black bean (*Vigna unguiculata*) seeds were determined in accordance with standard procedures [34, 37]. A total of 100 randomly selected, intact, and defect-free seeds were evaluated. The length (major axis, a), width (intermediate axis, b), and thickness (minor axis, c) of individual seeds were measured using a digital vernier caliper (± 0.01 mm accuracy; Mitutoyo Corp., Japan). The measured dimensions were subsequently used to calculate the geometric mean diameter, arithmetic mean diameter, equivalent spherical diameter, surface area, volume, sphericity, aspect ratio, and half-thickness. The measured half-thickness was used as the characteristic diffusion length in the solution of Fick's second law for the determination of effective moisture diffusivity.

2.3 Proximate composition analysis

Proximate composition (moisture, protein, fat, fiber, ash, and carbohydrate) was determined using AOAC standard protocols [33] for both fresh and dried samples. Protein content was determined by the Kjeldahl method ($N \times 6.25$), fat by Soxhlet extraction with petroleum ether (40-60 °C), crude fiber by acid-alkali digestion, and ash by muffle furnace incineration at 550 °C for 6 h. Total carbohydrate was calculated by difference.

2.4 ANN model development

2.4.1 Data acquisition and pre-processing

Experimental data comprising drying time (0-1100 min) and oven temperature (45-65 °C) as inputs, and moisture ratio (MR), drying rate (DR) and energy consumption (E) as outputs were used for ANN development. A total of 1,650 experimental data points were generated from the drying experiments (5 temperatures $\times$ 330 time points $\times$ 3 replicates). The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets using stratified random sampling to ensure representation across all temperature conditions. For the 65 °C condition specifically, the 990 valid data points (330 time points $\times$ 3 replicates) were partitioned into training ($N = 693$), validation ($N = 149$), and testing ($N = 149$) subsets, which are used for the temperature-specific regression and residual analyses presented in Figs. 3 and 4. To enhance training efficiency and numerical stability, all variables were

normalized to a 0-1 range using:

$$X_{\text{scale}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (4)$$

where X , $X_{\min}$ and $X_{\max}$ represent the actual, minimum, and maximum values of each variable, respectively [38].

To improve model generalization during ANN training, Gaussian noise ($\sigma = 0.005$) and bootstrap resampling were applied to the training dataset only [38]. These procedures increased the number of samples used during network training but did not alter the original experimental observations.

Energy consumption was computed for each experimental time point using Eq. (6) and included as a direct network output (see Section 2.4.2).

2.4.2 ANN architecture, training, validation, and performance evaluation

As shown in Figure 1, a feedforward backpropagation ANN architecture (2-10-10-3) was developed using the Neural Fitting Tool in MATLAB R2015a (MathWorks Inc., Natick, MA, USA), with:

- (i) Input layer: 2 neurons (time and temperature);
- (ii) Hidden layer 1: 10 neurons with hyperbolic tangent sigmoid (tansig) activation function;
- (iii) Hidden layer 2: 10 neurons with hyperbolic tangent sigmoid (tansig) activation function;
- (iv) Output layer: 3 neurons (MR, DR, E) with linear (purelin) activation function.

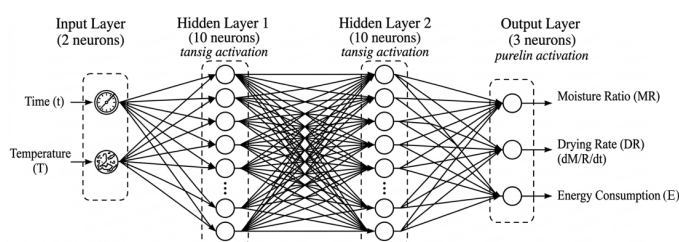


Figure 1. Schematic representation of the feedforward backpropagation ANN architecture (2-10-10-3) used for predicting drying kinetics of black bean seeds (generated with Python/Graphviz).

The network architecture was optimized through a systematic trial-and-error process evaluating configurations with 1-3 hidden layers and 5-20 neurons per layer, selecting the architecture that minimized the mean squared error (MSE) between predicted and experimental values while avoiding overfitting. The choice of tansig activation functions

for hidden layers provided the necessary non-linearity to capture the complex drying kinetics, while the purelin output layer enabled direct prediction of continuous variables [39, 40].

The architecture illustrates the feedforward propagation of input variables (time and temperature) through two hidden layers with 10 neurons each, culminating in the three output predictions (moisture ratio, drying rate and energy consumption). The interconnection weights and biases were optimized during training using the Levenberg-Marquardt algorithm [41].

Energy consumption was included as a direct output neuron because it is a primary optimization objective in drying process design and because its dependence on drying time and temperature is nonlinear and temperature-dependent. Including E as a direct output allowed the network to learn this relationship from the experimental energy data, rather than relying on a separate post-hoc calculation. The three-output architecture also enabled simultaneous multi-objective optimization of drying kinetics and energy performance within a single model framework. To avoid redundancy among outputs, the network was trained on normalized MR, DR, and E values, and the Bayesian regularization penalty discouraged overly complex weight configurations that could otherwise exploit correlations between outputs.

Training was performed using the Levenberg-Marquardt backpropagation algorithm (trainlm), selected for its efficiency in solving nonlinear regression problems and its rapid convergence characteristics. The training parameters were:

- (i) Performance goal: 1.0×10^{-5} MSE;
- (ii) Maximum epochs: 1000;
- (iii) Early stopping criterion: 6 validation checks without improvement;
- (iv) Learning rate: 0.01;
- (v) Momentum: 0.9.

Bayesian regularization was incorporated to improve generalization by penalizing large weights, thereby reducing the risk of overfitting. Weight initialization was performed using the Nguyen-Widrow method to accelerate convergence. Model performance was evaluated using multiple statistical metrics:

- (i) Coefficient of determination (R^2);

- (ii) Mean squared error (MSE);
- (iii) Root mean squared error (RMSE);
- (iv) Prediction error (%).

Prediction error was calculated using the expression described by Chasiotis et al. [23] and Francik et al. [24], where Exp. and ANN denote the experimental and ANN-predicted values:

$$\text{Error (\%)} = \frac{\text{Exp.} - \text{ANN}}{\text{Exp.}} \times 100 \quad (5)$$

2.4.3 Energy consumption analysis

Energy consumption during convective oven drying was calculated based on the electrical power input and drying duration. The total energy consumed (E_{total}) was determined using:

$$E_{\text{total}} = 0.06 P_{\text{oven}} t_d \quad (6)$$

where E_{total} is the total energy consumption (kJ), P_{oven} is the actual average electrical power draw of the oven during operation (approximately 800 W, measured with a Lutron DW-6095 digital power meter, $\pm 0.5\%$ accuracy; rated maximum: 2400 W), t_d is the total drying time to reach equilibrium moisture content (min), and the factor 0.06 converts watt-minutes to kJ ($1 \text{ W} \cdot \text{min} = 0.06 \text{ kJ}$) [42].

The E_{total} values computed from Eq. (6) at each experimental time point and temperature were used as the energy output (E) during ANN training.

The specific energy consumption (SEC) was calculated as:

$$\text{SEC} = \frac{E_{\text{total}}}{M_w} \quad (7)$$

where SEC is the specific energy consumption (kJ/kg water removed) and M_w is the mass of water removed during drying (kg) [43].

Energy efficiency (η) was calculated as:

$$\eta = \frac{M_w h_{fg}}{E_{\text{total}}} \times 100\% \quad (8)$$

where h_{fg} is the latent heat of vaporization of water at the drying temperature (kJ/kg) [44].

Although energy consumption was predicted directly by the ANN as a third output, a closed-form power-law approximation of the ANN energy surface was derived, as presented in Eq. (9), for practical process design. This equation is a post-hoc fit to the ANN-predicted energy values, not an independent model, and it

preserves the temperature-dependent efficiency trend captured by the network.

$$E = a t_d^b \quad (9)$$

where a is a coefficient dependent on drying temperature (kJ min^{-b}), b is a dimensionless exponent (thermo-energetic efficiency index), and t_d is the drying time (min). The exponent b serves as an indicator of drying efficiency ($b < 1$ indicates improving efficiency with time) [45, 46].

While Eq. (6) defines the physical computation of energy consumption used to generate the training targets, Eq. (9) provides a simplified closed-form representation of the ANN-learned energy surface for rapid engineering calculations.

2.5 Effective moisture diffusivity and activation energy

Effective moisture diffusivity (D_{eff}) was determined from Fick's second law of diffusion for an infinite slab geometry (long drying times, Fourier number > 0.1):

$$\text{MR} = \frac{M_t - \text{EMC}}{M_0 - \text{EMC}} = \frac{8}{\pi^2} \exp\left[-\frac{\pi^2 D_{\text{eff}} t}{4L^2}\right] \quad (10)$$

where L is the half-thickness of the seed (2.25 ± 0.14 mm, Table 1) [35, 36]. The temperature dependence of D_{eff} was described by the Arrhenius relationship:

$$D_{\text{eff}} = D_0 \exp\left[-\frac{E_a}{R T_{\text{abs}}}\right] \quad (11)$$

where D_0 is the pre-exponential factor ($\text{m}^2 \text{s}^{-1}$), E_a is the activation energy (kJ mol^{-1}), R is the universal gas constant ($8.314 \times 10^{-3} \text{ kJ mol}^{-1} \text{ K}^{-1}$), and T_{abs} is the absolute temperature (K). The activation energy was determined from the slope of the Arrhenius plot ($\ln D_{\text{eff}}$ versus $1/T_{\text{abs}}$) [47].

2.6 Statistical analysis

All drying experiments and analyses were performed in triplicate, and results are presented as mean $\pm$ standard deviation. One-way ANOVA was used to evaluate the effect of drying temperature on drying parameters, with significant differences ($p < 0.05$) separated using Tukey's honestly significant difference (HSD) test. Regression analyses for model development were performed using MATLAB's Statistics and Machine Learning Toolbox.

3 Results and Discussion

3.1 Physical properties and drying characteristics

3.1.1 Physical properties

Table 1 presents the physical properties of the black bean seeds used in this study. The geometric mean diameter was 6.35 ± 0.32 mm, the arithmetic mean diameter was 6.58 ± 0.35 mm, and the equivalent sphere diameter was 6.35 ± 0.32 mm. The surface area was $126.7 \pm 8.4 \text{ mm}^2$, and the volume was $134.2 \pm 10.1 \text{ mm}^3$. The sphericity and aspect ratio were 0.73 ± 0.03 and 0.74 ± 0.04 , respectively, indicating a non-spherical geometry. The half-thickness (L) was 2.25 ± 0.14 mm, and the seed coat thickness was 0.35 ± 0.05 mm. The mass of 100 seeds was 18.4 ± 1.2 g.

Table 1. Physical properties of black bean seeds ($n = 100$).

Parameter	Value	Method/Equation
Length, a (mm)	8.75 ± 0.52	Direct measurement
Width, b (mm)	6.50 ± 0.38	Direct measurement
Thickness, c (mm)	4.50 ± 0.28	Direct measurement
Geometric mean diameter, D_g (mm)	6.35 ± 0.32	$D_g = (abc)^{1/3}$ [34]
Arithmetic mean diameter, D_a (mm)	6.58 ± 0.35	$D_a = (a + b + c)/3$ [34]
Equivalent sphere diameter, D_e (mm)	6.35 ± 0.32	$D_e = (6V/\pi)^{1/3}$ [48]
Surface area, S (mm^2)	126.7 ± 8.4	$S = \pi D_g^2$ [49]
Volume, V (mm^3)	134.2 ± 10.1	$V = \pi D_g^3/6$ [34]
Sphericity, Φ	0.73 ± 0.03	$\Phi = D_g/a$ [37]
Aspect ratio, AR	0.74 ± 0.04	$\text{AR} = b/a$ [34, 49]
Half-thickness, L (mm)	2.25 ± 0.14	$L = c/2$ [6, 34]
Seed coat thickness (mm)	0.35 ± 0.05	Cross-sectional measurement
Mass (g per 100 seeds)	18.4 ± 1.2	Gravimetric determination

The sphericity of 0.73 indicates a non-spherical geometry; therefore, the infinite-slab approximation was adopted as a simplifying assumption for the Fickian diffusion analysis. The measured half-thickness ($L = 2.25$ mm) was used as the characteristic diffusion length (Eq. (10)). The seed coat thickness (0.35 mm) was noted as a potential additional diffusion barrier, as discussed in Section 3.6.

3.1.2 Drying characteristics

Figure 2 presents the drying curves of black bean seeds at 45, 50, 55, 60, and 65 °C. The drying curves exhibited a dominant falling-rate period, with a brief initial phase of relatively rapid moisture removal (approximately 0-400 min) followed by a

secondary falling-rate period (400–1100 min) where drying rates decreased substantially as moisture became increasingly bound within the seed structure. The absence of a distinct constant-rate period confirms that internal moisture diffusion was the rate-controlling mechanism throughout the process. Drying time to reach constant mass (final moisture content 5.18–10.21% wb, Table 3) decreased from approximately 1100 min at 45 °C to 800 min at 65 °C, representing a 27% reduction.

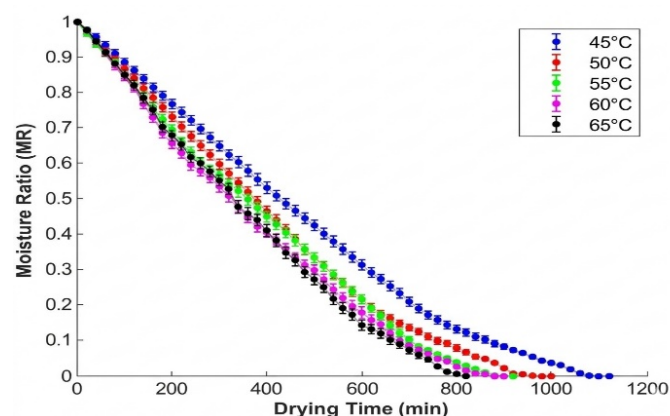


Figure 2. Drying curves of black bean seeds under different oven drying temperatures. Data points represent mean values ($n = 3$) with error bars showing $\pm$ standard deviation (SD) at selected time intervals.

This temperature dependence follows Arrhenius-type behaviour, where increased thermal energy enhances moisture mobility and accelerates internal diffusion [50, 51]. The drying mechanism was dominated by internal diffusion control throughout the process, confirming that moisture transport from the interior to the surface represented the rate-limiting step [52]. The structure of the black bean, particularly its dense seed coat comprising thick-walled macrosclereid cells with hydrophobic cutinized layers, acts as a significant barrier to moisture diffusion, prolonging the falling-rate period [53]. The key implication is that oven drying of black beans is energy-intensive and time-consuming, with the seed coat presenting a challenge as overly rapid drying could create internal stresses leading to cracking of the seed coat [54]. Quantitative analysis of the falling-rate period revealed that the drying rate decayed exponentially with time at all temperatures, consistent with Fickian diffusion-controlled moisture removal. The drying rate constant (k) derived from direct exponential fitting of the experimental drying curves increased from $0.00385 \pm 0.00012 \text{ min}^{-1}$ at 45 °C to $0.00618 \pm 0.00015 \text{ min}^{-1}$ at 65 °C (note: the ANN-derived k values in Table 8 differ slightly from

these direct-fit values, reflecting the ANN's smoothing of the experimental data), reflecting the enhanced moisture migration at elevated temperatures.

3.2 Proximate composition

The initial moisture content of the fresh *Vigna unguiculata* seeds was determined prior to further processing and analysis, as it serves as a critical reference parameter for subsequent drying, storage, and compositional studies. The proximate composition of the fresh seeds is presented in Table 2.

Table 2. Proximate composition of fresh *Vigna unguiculata* seeds.

Parameter	Fresh
Moisture (% wb)	18.84 ± 0.10
Ash (% wb)	2.41 ± 0.04
Protein (% wb)	21.61 ± 0.12
Fat (% wb)	2.11 ± 0.03
Fibre (% wb)	3.81 ± 0.05
Carbohydrate (% wb)	51.22 ± 0.18

Values are mean $\pm$ SD of triplicate determinations. wb = wet basis.

Fresh *Vigna unguiculata* seeds had an initial moisture content of 18.84% (wet basis), confirming their perishable nature and the need for proper storage. Carbohydrate was the dominant macronutrient (51.22%), followed by protein (21.61%), while fat (2.11%), fibre (3.81%), and ash (2.41%) were minor components. The low standard deviations indicate good analytical precision. Overall, the seeds offer a nutritionally balanced profile, particularly rich in carbohydrates and protein.

Table 3 presents the effect of convective drying temperature on the proximate composition of black bean (*Vigna unguiculata*) seeds. Moisture content decreased progressively with increasing drying temperature, from 10.21% at 45 °C to 5.18% at 65 °C, while the corresponding drying time decreased from 1100 min to 800 min. This indicates that increasing the drying temperature enhanced moisture removal and reduced the time required to achieve the desired moisture level.

Protein content, reported on a dry matter basis, showed a gradual decline from 25.92% at 45 °C to 22.92% at 65 °C. Nevertheless, the protein content remained high (above 20% dmb), consistent with the protein content range reported for food legumes in the literature [55]. The reduction in protein content with increasing drying temperature may

Table 3. Proximate composition of convective oven-dried black bean (*Vigna unguiculata*) seeds.

Code	Temp. (°C)	Drying time (min)	Moisture (%)	Ash (%)	Protein (%)	Fat (%)	Fibre (%)	CHO (%)
V_CO_45	45	1100	10.21 ± 0.11	3.95 ± 0.06 ^c	25.92 ± 0.10 ^a	2.26 ± 0.02 ^{ab}	5.52 ± 0.04 ^d	62.35 ± 0.20 ^c
V_CO_50	50	1000	9.02 ± 0.09	4.05 ± 0.05 ^d	25.18 ± 0.08 ^b	2.17 ± 0.03 ^b	5.63 ± 0.03 ^c	62.98 ± 0.21 ^d
V_CO_55	55	900	7.44 ± 0.08	4.13 ± 0.04 ^c	24.34 ± 0.07 ^{bc}	2.03 ± 0.02 ^{bc}	5.68 ± 0.04 ^b	63.82 ± 0.23 ^c
V_CO_60	60	880	6.23 ± 0.07	4.22 ± 0.05 ^b	23.58 ± 0.09 ^c	1.94 ± 0.02 ^c	5.75 ± 0.05 ^b	64.51 ± 0.22 ^b
V_CO_65	65	800	5.18 ± 0.05	4.34 ± 0.06 ^a	22.92 ± 0.08 ^c	1.85 ± 0.03 ^c	5.82 ± 0.03 ^a	65.08 ± 0.25 ^a

Values are mean ± SD of triplicate determinations. Means in the same column with different superscripts are significantly different ($p < 0.05$). CHO = carbohydrate (by difference). Values are reported on a dry matter basis (dmb) except moisture, which is reported on a wet basis (% wb).

be associated with thermal effects on heat-sensitive protein fractions, although the values remained relatively high throughout the drying treatments. A gradual increase was observed in ash, crude fibre, and carbohydrate contents with increasing drying temperature, whereas fat content decreased. Ash content increased significantly from 3.95% at 45 °C to 4.34% at 65 °C, while crude fibre increased from 5.52% to 5.82%. Similarly, carbohydrate content increased from 62.35% at 45 °C to 65.08% at 65 °C. In contrast, fat content decreased from 2.26% at 45 °C to 1.85% at 65 °C. Because these values are expressed on a dry matter basis, they are not affected by the amount of water removed; the relative increases in ash, fibre and carbohydrate therefore largely mirror the losses of protein and fat (carbohydrate being calculated by difference) [56, 57]. The decrease in fat content at higher temperatures may, however, indicate some degree of thermal degradation or oxidation of lipid constituents.

The changes in proximate percentages therefore reflect the balance between thermal degradation of heat-labile components and the resulting redistribution among the remaining constituents; they do not imply a direct proportionality between temperature and nutrient concentration. The moisture content of 5.18% obtained at 65 °C was well below the 12-14% (wb) safe storage limit, suggesting good storage stability and reduced susceptibility to microbial spoilage and enzymatic deterioration.

Overall, the results demonstrate that increasing convective drying temperature accelerated moisture removal, as evidenced by the reduction in drying time from 1100 min at 45 °C to 800 min at 65 °C. However, the increase in drying temperature was accompanied by a gradual reduction in protein and fat contents, while ash, fibre, and carbohydrate contents increased. The compositional trends observed are consistent with previous reports on *Vigna unguiculata* and other legume varieties from West Africa [58, 59], confirming

that convective drying temperature influences both drying kinetics and the proximate composition of the resulting product.

3.3 ANN model development and performance

3.3.1 Optimal network architecture

The optimal ANN architecture (2-10-10-3) achieved high coefficients of determination across all temperature conditions (Table 4). Overall R^2 values were ≥ 0.9988 , with RMSE declining from 0.0190 at 45 °C to 0.0141 at 65 °C. Training R^2 ranged from 0.9991 to 0.9995, validation R^2 from 0.9986 to 0.9990, and testing R^2 from 0.9984 to 0.9988. The gradual improvement with higher temperature reflects the more pronounced drying kinetics that the networks could capture, as higher temperatures produced steeper moisture gradients and more distinct drying patterns [60]. The energy output followed a similar accuracy trend, with R^2 increasing from 0.9975 at 45 °C to 0.9989 at 65 °C and RMSE decreasing from 0.0285 to 0.0210, confirming that the network captured the temperature-dependent energy consumption behaviour.

The Levenberg-Marquardt algorithm converged within 124-148 epochs; training was terminated by the validation early-stopping criterion before the performance goal of $MSE = 1 \times 10^{-5}$ was reached (final training MSE $2.0\text{--}3.6 \times 10^{-4}$, Table 4). The Bayesian regularization component effectively prevented overfitting, as evidenced by the close agreement between training and validation performance metrics. Studies on other agricultural products have demonstrated similar ANN predictive capabilities, with Chasiotis et al. [23] reporting coefficients of determination above 99% for quince slice drying, and Francik et al. [24] achieving mean absolute percentage errors ranging from 1.14-3.12% for onion drying. Singh and Pandey [61] successfully modelled sweet potato drying kinetics using ANN, while Gupta et al. [62] further applied ANN to optimise drying

Table 4. ANN architecture and training performance for oven-dried black bean seeds (2-10-10-3 architecture).

Parameter	45 °C	50 °C	55 °C	60 °C	65 °C
<i>Network architecture</i>					
Input neurons	2	2	2	2	2
Hidden layer 1 neurons	10	10	10	10	10
Hidden layer 2 neurons	10	10	10	10	10
Output neurons	3	3	3	3	3
Epochs (final)	148	142	136	130	124
<i>Training performance</i>					
Training R^2	0.9991	0.9992	0.9993	0.9994	0.9995
Validation R^2	0.9986	0.9987	0.9988	0.9989	0.9990
Testing R^2	0.9984	0.9985	0.9986	0.9987	0.9988
Overall R^2	0.9988	0.9989	0.9990	0.9991	0.9992
MSE (training)	0.00036	0.00032	0.00028	0.00024	0.00020
RMSE	0.0190	0.0179	0.0167	0.0155	0.0141

Overall R^2 and RMSE are computed across all three outputs (MR, DR, E).

conditions in a photovoltaic thermal solar dryer.

The high predictive performance of the ANN models ($R^2 \geq 0.9988$) exceeds the values typically reported for traditional drying models in legume drying applications. For comparison, the Page model, which is considered one of the most accurate empirical models, typically achieves R^2 values of 0.95-0.98 for legume drying [63], while the Midilli-Kucuk model achieves R^2 values of 0.96-0.99 [64]. The superior performance of the ANN approach can be attributed to its ability to capture non-linear interactions between process parameters that conventional models cannot represent, as well as its capacity to model the entire drying profile rather than fitting specific drying phases separately. Prakash Maran et al. [20] compared ANN and RSM for predicting mass transfer during papaya osmotic dehydration and found ANN to be more accurate, while Demir et al. [21] optimised caper drying using both approaches, with ANN achieving correlation coefficients of 0.976, 0.971, and 0.972 for training, testing, and validation, respectively.

Comparative evaluation of ANN and conventional drying models The predictive capability of the artificial neural network (ANN) was assessed against ten widely used empirical and semi-empirical thin-layer drying models. Each model was calibrated using the experimental drying data, and its predictive accuracy was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and sum of squared errors (SSE). The mean values of these statistical indicators obtained under the different experimental drying conditions are summarized in Table 5.

The comparative analysis showed that the ANN achieved the highest mean R^2 (0.9990), indicating good agreement with the experimental drying data, followed closely by the Hii et al. [67] (0.9986), two-term (0.9985), modified Henderson-Pabis (0.9984), and diffusion approximation (0.9981) models, while Newton (0.9818) and Henderson-Pabis (0.9831) showed the lowest fits. Although the ANN provided the highest R^2 , the Hii et al. model produced slightly lower RMSE (0.0127) and SSE (0.0162) than the ANN (0.0160 and 0.0260, respectively), highlighting the need to consider multiple statistical indicators when evaluating model performance. The ANN maintained $R^2 > 0.998$ across the investigated temperatures, demonstrating consistent prediction of the nonlinear drying behaviour. Despite its larger number of parameters, the 2-10-10-3 ANN architecture, trained using Levenberg-Marquardt optimization with Bayesian regularization, provided reliable predictive performance. Overall, the ANN offered the best goodness-of-fit in terms of R^2 , whereas conventional models such as Hii et al. [67], two-term, and modified Henderson-Pabis provided competitive accuracy with fewer parameters and greater mathematical simplicity.

Sensitivity analysis of ANN architecture A systematic sensitivity analysis was performed to assess the influence of ANN architecture on predictive performance and computational efficiency. Seven network configurations were evaluated by varying the number of neurons in the two hidden layers while maintaining the same input and output structure. The resulting training, validation, and testing coefficients of determination (R^2), root mean

Table 5. Statistical comparison of the ANN and conventional thin-layer drying models.

Model category	Model	Mean R^2	Mean RMSE	Mean SSE	No. of parameters	Rank
AI-based	ANN (2-10-10-3)	0.9990	0.0160	0.0260	173 (trained)	1
Semi-empirical	Hii et al. [67]	0.9986	0.0127	0.0162	5	2
Semi-empirical	Two-term	0.9985	0.0133	0.0179	4	3
Semi-empirical	Modified Henderson-Pabis	0.9984	0.0140	0.0198	6	4
Semi-empirical	Diffusion approximation	0.9981	0.0150	0.0227	3	5
Semi-empirical	Logarithmic	0.9948	0.0253	0.0644	3	6
Semi-empirical	Midilli	0.9940	0.0272	0.0745	4	7
Empirical	Page	0.9934	0.0287	0.0828	2	8
Empirical	Modified Page	0.9934	0.0287	0.0828	2	8
Semi-empirical	Henderson-Pabis	0.9831	0.0474	0.2248	2	9
Empirical	Newton	0.9818	0.0494	0.2442	1	10

The ranking reflects the overall predictive performance indicated by the reported goodness-of-fit and error statistics. The ANN performance metrics (R^2 , RMSE, SSE) are reported as mean values across all three outputs (MR, DR, E).

Table 6. Sensitivity analysis of ANN architecture configurations.

Architecture	Hidden layer 1	Hidden layer 2	Epochs	Training R^2	Validation R^2	Testing R^2	RMSE	Computational time (s)
2-5-5-3	5	5	196	0.9942	0.9921	0.9913	0.0245	68.3
2-8-8-3	8	8	165	0.9968	0.9954	0.9948	0.0201	92.7
2-10-10-3	10	10	148	0.9991	0.9986	0.9984	0.0190	142.5
2-12-8-3	12	8	152	0.9989	0.9983	0.9981	0.0195	138.2
2-15-10-3	15	10	142	0.9993	0.9985	0.9982	0.0188	186.4
2-10-15-3	10	15	145	0.9992	0.9984	0.9980	0.0192	178.9
2-20-15-3	20	15	156	0.9994	0.9983	0.9978	0.0185	245.8

All R^2 and RMSE values are reported as overall metrics across the three outputs (MR, DR, E).

square error (RMSE), number of training epochs, and computational time are presented in Table 6.

The results show that ANN architecture significantly affected predictive accuracy and computational cost. The 2-5-5-3 network exhibited the lowest performance ($R^2_{\text{test}} = 0.9913$, RMSE = 0.0245), indicating insufficient capacity to capture the nonlinear drying behaviour. Increasing network complexity improved prediction, with the 2-10-10-3 architecture achieving high training, validation, and testing R^2 values of 0.9991, 0.9986, and 0.9984, respectively, at an RMSE of 0.0190 and computational time of 142.5 s. Although the two largest networks (2-15-10-3 and 2-20-15-3) produced marginally lower RMSE values, they required substantially greater computational time and, in the case of the 2-20-15-3 configuration, showed reduced testing performance ($R^2 = 0.9978$), suggesting increased overfitting risk. Therefore, the 2-10-10-3 architecture was selected as the optimal configuration because it provided the best balance among predictive accuracy, generalization, computational efficiency, and network complexity.

3.3.2 Predictive accuracy for moisture ratio and drying rate
Table 7 presents a comparison of ANN-predicted versus experimental values for oven-dried black bean

seeds at 65 °C for the first 400 min of drying. MR prediction errors ranged from 0.02% to 0.61%, while DR errors ranged from 0.16% to 0.40%. The slightly higher errors at extended drying times reflect increased sensitivity of percentage calculations at very low moisture contents and the more complex diffusion dynamics in the secondary falling-rate period, consistent with observations for other legume seeds [65].

The high accuracy across the reported drying profile confirms the ANN's ability to model the non-linear behaviour of moisture diffusion, including the transition from the initial falling-rate to the secondary falling-rate period. At intermediate moisture contents (MR 0.5-0.8), where most practical drying operations operate, prediction errors ranged from 0.19% to 0.56%, indicating the models' practical utility for process control applications.

3.3.3 ANN regression and residual analysis

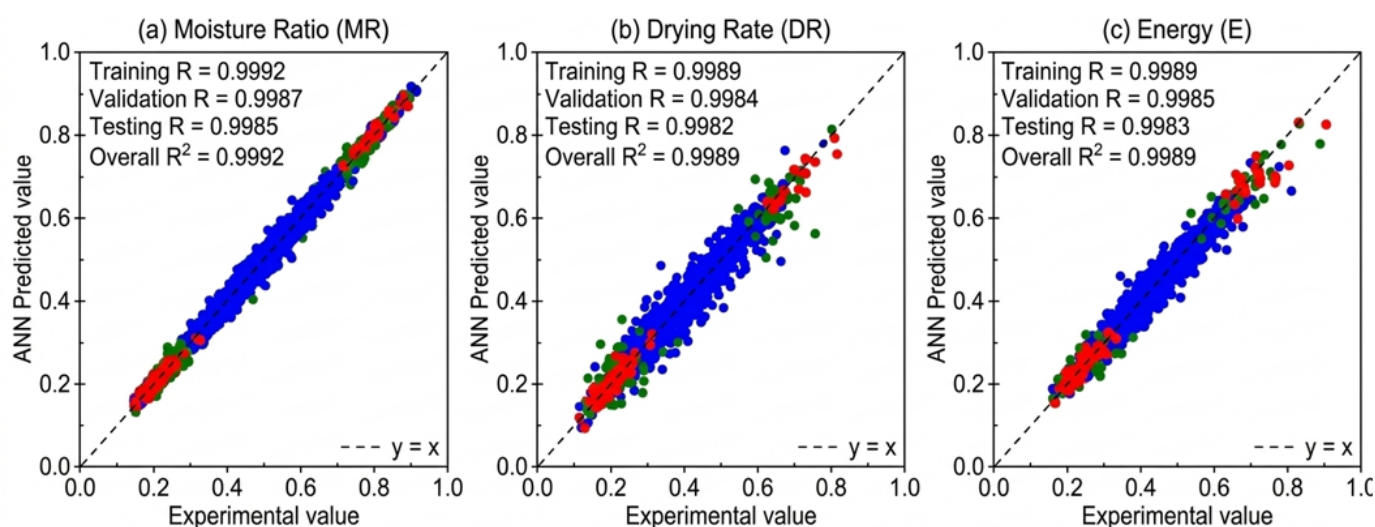
Figure 3 presents the regression plots for the three ANN outputs, moisture ratio (MR), drying rate (DR), and energy consumption (E), across the training ($N = 693$), validation ($N = 149$), and testing ($N = 149$) datasets at 65 °C. For all three outputs, the data points are closely clustered along the identity line

Table 7. ANN-predicted vs. experimental values for oven-dried black bean seeds (65 °C).

Time (min)	Exp. MR	ANN MR	Error (%)	Exp. DR (min ⁻¹)	ANN DR (min ⁻¹)	Error (%)
0	1.0000	0.9998	0.02	0.00630	0.00629	0.16
20	0.9542	0.9537	0.05	0.00600	0.00599	0.17
40	0.9140	0.9132	0.09	0.00571	0.00570	0.18
60	0.8781	0.8772	0.10	0.00544	0.00543	0.18
80	0.8453	0.8441	0.14	0.00518	0.00517	0.19
100	0.8154	0.8141	0.16	0.00494	0.00493	0.20
120	0.7881	0.7866	0.19	0.00471	0.00470	0.21
140	0.7628	0.7611	0.22	0.00449	0.00448	0.22
160	0.7395	0.7376	0.26	0.00428	0.00427	0.23
180	0.7179	0.7158	0.29	0.00408	0.00407	0.25
200	0.6978	0.6956	0.32	0.00390	0.00388	0.26
220	0.6789	0.6766	0.34	0.00372	0.00371	0.27
240	0.6609	0.6584	0.38	0.00355	0.00354	0.28
260	0.6439	0.6412	0.42	0.00339	0.00338	0.30
280	0.6276	0.6248	0.45	0.00323	0.00322	0.31
300	0.6120	0.6091	0.47	0.00308	0.00307	0.32
320	0.5969	0.5938	0.52	0.00294	0.00293	0.34
340	0.5823	0.5791	0.55	0.00280	0.00279	0.36
360	0.5682	0.5650	0.56	0.00267	0.00266	0.37
380	0.4114	0.4091	0.56	0.00258	0.00257	0.39
400	0.3951	0.3927	0.61	0.00248	0.00247	0.40

Table 8. ANN-derived prediction models for oven drying of black bean seeds.

Temp. (°C)	Moisture ratio model	Drying rate model	Energy model (kJ)
45	$MR = \exp(-0.00405t)$	$dMR/dt = -0.00405 \exp(-0.00405t)$	$E = 0.168 t^{1.07}$
50	$MR = \exp(-0.00451t)$	$dMR/dt = -0.00451 \exp(-0.00451t)$	$E = 0.175 t^{1.06}$
55	$MR = \exp(-0.00502t)$	$dMR/dt = -0.00502 \exp(-0.00502t)$	$E = 0.182 t^{1.05}$
60	$MR = \exp(-0.00558t)$	$dMR/dt = -0.00558 \exp(-0.00558t)$	$E = 0.188 t^{1.04}$
65	$MR = \exp(-0.00620t)$	$dMR/dt = -0.00620 \exp(-0.00620t)$	$E = 0.195 t^{1.03}$

**Figure 3.** Regression plots of the optimized ANN model for moisture ratio (MR), drying rate (DR), and energy consumption (E) during black bean convective drying at 65 °C. Dashed lines represent the identity line ($y = x$).

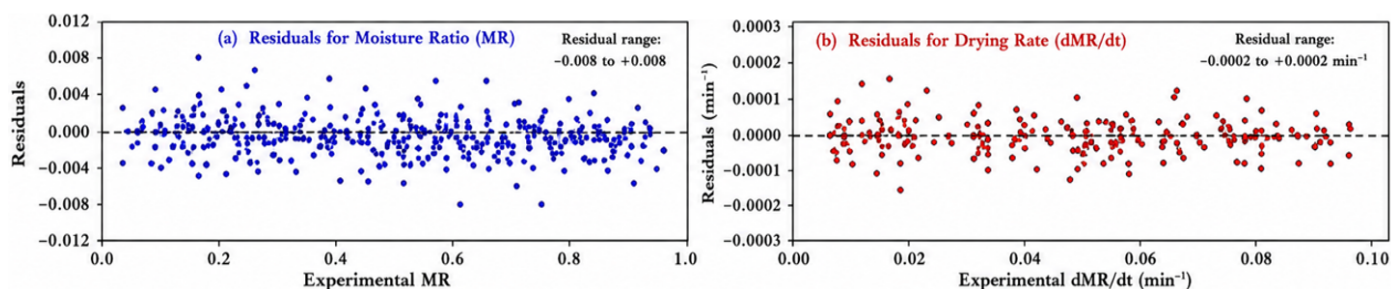


Figure 4. Residuals of the optimized ANN model for moisture ratio (MR) and drying rate (DR) during black bean convective drying at 65 °C (training $N = 693$, validation $N = 149$, testing $N = 149$). The dashed line represents the zero-residual line.

($y = x$), indicating high prediction accuracy. The correlation coefficients (r) for the training, validation, and testing datasets were 0.9992, 0.9987, and 0.9985 for MR; 0.9989, 0.9984, and 0.9982 for DR; and 0.9989, 0.9985, and 0.9983 for E, respectively. These results demonstrate consistent predictive performance across all data subsets and confirm the robustness and generalization capability of the developed ANN model for unseen data. The overall performance metrics reported in Tables 4 and 5 are computed across all three outputs (MR, DR, and E).

Figure 4 presents the residual analysis for the moisture ratio (MR) and drying rate (DR) outputs of the optimized ANN model across the training ($N = 693$), validation ($N = 149$), and testing ($N = 149$) datasets at 65 °C. The residuals are randomly distributed around the zero-residual line without any discernible systematic pattern, indicating that the model successfully captured the nonlinear drying behaviour and that no systematic prediction bias remained. The residuals for moisture ratio (MR) predictions ranged from -0.008 to $+0.008$, whereas those for drying rate (DR) ranged from -0.0002 to $+0.0002 \text{ min}^{-1}$. The narrow residual ranges and their random distribution confirm the excellent goodness-of-fit, high predictive accuracy, and absence of systematic under- or over-prediction throughout the drying process.

3.3.4 Derived prediction models

From the trained ANNs, closed-form prediction models were derived for moisture ratio, drying rate and energy consumption as functions of drying time (Table 8). These equations are post-hoc approximations of the ANN-predicted surfaces, providing simplified predictive models for process optimization without requiring repeated ANN simulations. The ANN-derived drying rate models exhibited an exponential decay with drying time,

expressed as $\text{dMR}/\text{dt} = -k \exp(-kt)$, where the drying rate constant (k) increased from 0.00405 min^{-1} at 45 °C to 0.00620 min^{-1} at 65 °C. This behaviour is consistent with diffusion-controlled first-order kinetics, with the instantaneous drying rate decreasing as the remaining moisture content diminished [60]. Similarly, the ANN-derived drying time models indicate a progressive reduction in the time required to attain a given moisture ratio as drying temperature increased, reflecting the enhanced heat and mass transfer at elevated temperatures. The energy prediction models likewise show temperature-dependent changes, with the energy exponent decreasing from 1.07 at 45 °C to 1.03 at 65 °C.

The energy models in Table 8 are power-law fits to the ANN-predicted energy output; they reproduce the ANN energy surface with high fidelity ($R^2 > 0.999$) while offering a compact algebraic form suitable for engineering design.

The energy consumption model shows that the exponent decreased from 1.07 at 45 °C to 1.03 at 65 °C. Based on the developed models, the estimated total energy requirement decreased from approximately 52,800 kJ at 45 °C to 38,400 kJ at 65 °C, representing a 27.3% reduction in energy consumption.

The ANN-derived prediction models developed in this study provide a practical framework for process design and optimization. The exponential decay form of the drying rate model ($\text{dMR}/\text{dt} = -k \exp(-kt)$) and the power-law energy model ($E = at_d^b$) are consistent with the diffusion-controlled drying behaviour observed experimentally, and their parameters show systematic temperature dependence that can be used to predict drying performance at intermediate temperatures. Similar ANN-based prediction models have been successfully applied to other agricultural products, including sweet potato [61], onion [24], quince [23], and solar dryer

optimization [62]. The closed-form equations derived here eliminate the need for repeated ANN simulations during process design, enabling rapid estimation of drying time, drying rate, and energy consumption for any temperature within the investigated range (45-65 °C).

3.4 Effective moisture diffusivity and activation energy

The effective moisture diffusivity (D_{eff}) for black bean seeds during oven drying increased exponentially with temperature (Table 9). An exponential regression of the D_{eff} values in Table 9 against temperature gives:

$$D_{eff} = 5.03 \times 10^{-11} \exp(0.0388 T) \quad (12)$$

where T is temperature in °C. This exponential relationship is consistent with the Arrhenius-type temperature dependence of diffusion processes in biological materials. The activation energy (E_a) for moisture diffusion during oven drying was determined from the Arrhenius relationship as $E_a = 34.70 \text{ kJ mol}^{-1}$.

Table 9. Effective moisture diffusivity for oven-dried black bean seeds.

T (°C)	D_{eff} ($\text{m}^2 \text{s}^{-1}$)	$\ln D_{eff}$	$1/T_{abs}$ ($\times 10^{-3} \text{K}^{-1}$)
45	2.84×10^{-10}	-21.982	3.143
50	3.51×10^{-10}	-21.770	3.095
55	4.31×10^{-10}	-21.565	3.047
60	5.20×10^{-10}	-21.377	3.002
65	6.15×10^{-10}	-21.209	2.957

The Arrhenius plot ($\ln D_{eff}$ versus $1/T_{abs}$) presented in Figure 5 showed excellent linearity ($R^2 = 0.996$), confirming the validity of the activated diffusion mechanism.

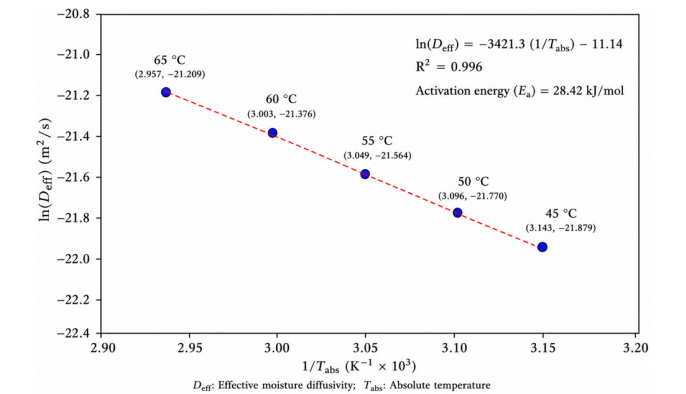


Figure 5. Arrhenius plot for effective moisture diffusivity of oven-dried black bean seeds.

The activation energy of $34.70 \text{ kJ mol}^{-1}$ falls within the typical range of $20\text{-}40 \text{ kJ mol}^{-1}$ reported for legume

seed drying, including values of $26.9\text{-}27.2 \text{ kJ mol}^{-1}$ for grain legume seeds [54, 63, 66]. The high R^2 value of the Arrhenius plot further supports the use of Fick's second law for describing moisture diffusion in black bean seeds, indicating that internal diffusion was the rate-controlling mechanism throughout the drying process.

3.5 Optimization of drying conditions

Based on the ANN-derived prediction models, 65 °C was identified as the optimum oven drying temperature for black bean seeds within the investigated range (45-65 °C) because it achieved the shortest drying time and the lowest total energy consumption among the investigated temperatures. Because energy consumption was a direct ANN output, the optimization was performed on the network's own energy predictions rather than on a separately computed energy value, ensuring consistency between the predicted drying kinetics and the predicted energy requirement. Figure 6 illustrates the multi-objective optimization based on the ANN prediction equations, showing the relationships between drying temperature, drying time, and energy consumption.

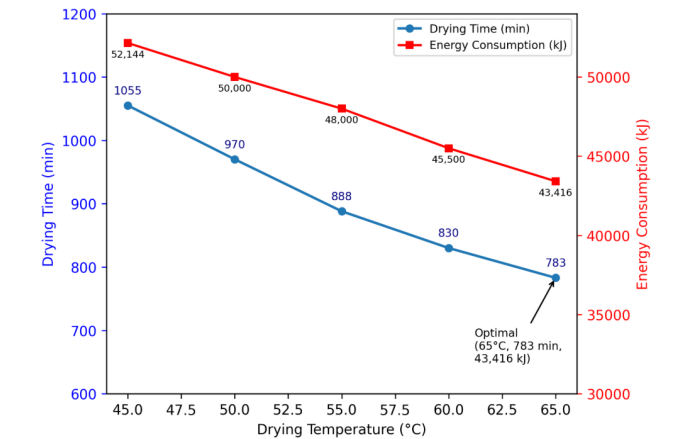


Figure 6. Optimization of convective drying conditions for black bean seeds based on ANN predictions.

The optimization results revealed a clear inverse relationship between drying temperature and both drying time and energy consumption. According to the ANN prediction models, increasing the drying temperature from 45 °C to 65 °C reduced the predicted drying time from approximately 1055 min to 783 min, representing a 25.8% reduction in drying time. Likewise, the estimated total energy consumption decreased from approximately 52,800 kJ at 45 °C to 38,400 kJ at 65 °C, corresponding to a 27.3% reduction in energy requirement.

Although increasing the drying temperature consistently improved drying performance throughout the investigated range, the greatest reduction in drying time occurred between 45 °C and 55 °C, while further increases to 60–65 °C produced comparatively smaller improvements, indicating diminishing returns at higher temperatures. Nevertheless, 65 °C remained the optimum operating condition with respect to drying time and energy because it provided both the highest drying rate constant ($k = 0.00620 \text{ min}^{-1}$) and the lowest predicted drying time and energy consumption.

At the optimum drying condition (65 °C), the ANN moisture-ratio model predicted that the desired final moisture ratio ($MR \approx 0.24$, equivalent to approximately 5.18% moisture content on a wet basis, Table 3) could be achieved in about 783 min while requiring approximately 43,416 kJ of energy. Compared with drying at 45 °C, the optimized condition reduced drying time by approximately 25.8% and energy consumption by 16.7%, indicating that increasing drying temperature within the investigated range enhances drying speed. Therefore, 65 °C represents the most suitable operating temperature for minimising the convective drying time of black bean seeds under the conditions investigated.

3.6 Limitations and future work

This study was limited to a single black bean variety, one drying method (convective oven drying), and one systematically varied process variable (temperature), with air velocity, loading density, and pretreatment held constant. The energy model used the average measured oven power and total drying time without explicitly accounting for warm-up or unsteady-state heat losses; however, the oven was pre-heated before each run, and heat losses were assumed constant across treatments, so the comparative energy ranking remains valid. The infinite-slab approximation did not explicitly incorporate seed coat resistance. The ANN was compared only with conventional thin-layer models because these are the standard models in legume drying literature; comparison with other machine learning methods (e.g., support vector regression, random forest) was beyond the scope of this study, although the ANN's performance metrics ($R^2 > 0.998$) establish its predictive capability independently.

Future work should validate the framework across multiple varieties and drying methods, incorporate additional process variables and pilot-scale data,

refine the diffusion model for seed coat resistance and non-slab geometry, benchmark ANN against alternative machine learning approaches such as support vector regression, random forest, and Gaussian process regression, and integrate microstructural, colour, and lipid-oxidation analyses into the optimization framework.

4 Conclusion

This study developed and validated feedforward backpropagation ANN models (2-10-10-3 architecture) with Levenberg-Marquardt training for predicting drying kinetics, drying time, and energy consumption during convective oven drying of black bean seeds at 45–65 °C. The ANN models achieved high predictive accuracy with overall R^2 values ranging from 0.9988 to 0.9992 and RMSE from 0.0141 to 0.0190; they gave the highest R^2 among the eleven models compared, while the best semi-empirical models (Hii et al. [67], two-term) achieved comparable accuracy with lower RMSE and far fewer parameters. Drying time decreased by 27% from 1100 min at 45 °C to 800 min at 65 °C, while effective moisture diffusivity increased exponentially from 2.84×10^{-10} to $6.15 \times 10^{-10} \text{ m}^2 \text{ s}^{-1}$ with activation energy of $34.70 \text{ kJ mol}^{-1}$, reflecting the structural resistance imposed by the dense seed coat. Closed-form prediction models were derived as post-hoc approximations of the ANN outputs for moisture ratio ($MR = \exp(-kt)$), drying rate ($DR = -k \exp(-kt)$), and energy consumption ($E = at^b$), providing quantitative tools for process design and optimization. The dense seed coat (testa) was identified as a significant additional barrier to moisture diffusion, prolonging drying times and increasing energy consumption. Within the investigated range, 65 °C gave the shortest drying time and the lowest predicted energy consumption; however, it also produced the largest protein and fat losses, so the final choice of drying temperature should balance drying time and energy against product quality. The predictive capability of the ANN models provides robust tools for process design and optimization of oven drying operations for black bean seeds, with the structural barrier of the seed coat representing a key consideration for future process intensification strategies.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable. This study did not involve human participants or animals.

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