Comparative Modeling of Drying Kinetics for Potato Slices: AI-Based vs. Empirical and Semi-Empirical Approaches

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Abstract

Drying is a vital preservation method in the food industry, reducing moisture content while maintaining product quality and extending shelf life. This process involves complex heat and mass transfer mechanisms, necessitating accurate predictive models. This study compares various modeling approaches, including regression models, semi-empirical, and artificial intelligence (AI)-based methods, to simulate the drying process of potato slices. Experimental drying trials were run at 40°C, 50°C, and 60°C, both with and without phase change materials (PCM) and infrared radiation (IR). AI models (ANN, SVM, and RF) were trained and validated using experimental data. Their performance was evaluated against conventional and semi-empirical models using R^2, RMSE, MAE, and MBE. Results indicate that ANN achieved the highest predictive accuracy (R^2= 0.998, RMSE= 0.0656 g water g^{-1} dry matter), outperforming other models. SVM also demonstrated strong predictive capability, while RF performed slightly lower. Among semi-empirical models, the Midilli model provided the best fit but was less accurate than AI-based models. These findings highlight the superiority of AI-driven approaches, particularly ANN, in optimizing drying processes for the food industry.

Keywords: AI Modeling, Drying rate, Random forest, Semi-Empirical, SVM

Introduction

Drying is a widely used preservation technique used in the food and agricultural industries, aiming to reduce moisture content while preserving product quality and extending shelf life. The drying process is inherently complex, involving simultaneous heat and mass transfer, which makes mathematical modeling essential for optimizing drying conditions and improving energy efficiency. Over the years, researchers have developed various empirical, semi-empirical, and theoretical models to explain the drying kinetics of different products. Empirical models, such as the Page, Henderson-Pabis, and Newton models, are popular because of their simplicity and ability to fit experimental data (Lopes, Santos, Rodrigues, Pinho, & Viegas, 2023; Simpson, Ramírez, Nuñez, Jaques, & Almonacid, 2017). In a study on thin-layer drying models for rapeseed, the Page model demonstrated the best performance, with an R^2 value ranging from 0.9924 to 0.9966 and an RMSE between 0.0169 and 0.0296 (Lee, Lee, Kim, Kim, & Han, 2016). However, these models lack a strong physical foundation and are limited to specific experimental conditions. Semi-empirical models, including the Logarithmic and Wang-Singh models, attempt to bridge the gap between empirical and theoretical approaches by incorporating some physical principles while maintaining a simple mathematical form (Kutlu, İşcİ, & Demİrkol, 2015). Semi-empirical modeling of thin-layer drying has been extensively studied. Ertekin and Firat (2017) provided a comprehensive review of these approaches, while Chukwunonye, Nnaemeka, Chijioke, and Obiora (2016); Mahesh, Rengaraju, and Selvakumarasamy (2024); Kumar, Kumar, Hota, and Pandey (2025); and Benseddik, Azzi, and Allaf (2018) explored specific applications across diverse agricultural products. For example, in one study, a semi-empirical model based on Fick's second law was developed, achieving a coefficient of determination (R^2) between 0.991 and 0.999, with a mean absolute error (MAE) ranging from 0.008 to 0.032 (Kumar *et al.*, 2025). Similarly, in another study on the thin-layer drying of pumpkin slices, various semi-empirical models were tested, with the Midilli model showing the highest accuracy for predicting the moisture content of apple slices (Benseddik *et al.*, 2018). However, semi-empirical models are not universally applicable and require fitting to specific experimental conditions. Mathematical models derived from Fick's second law of diffusion provide a more fundamental understanding of the drying process, assuming moisture movement occurs through internal diffusion. These models are commonly applied to food materials with homogeneous structures. For more complex structures, researchers have extended these models using numerical techniques and computational fluid dynamics (CFD) simulations to enhance accuracy (Pham, Shrivastava, & Karim, 2021). In recent years, Machine Learning (ML) and artificial intelligence (AI) models, such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forest (RF), have gained attention for predicting drying kinetics with high accuracy (Kaveh, Abbaspour-Gilandeh, & Emadi, 2020; Zhang, Wang, & Zhu, 2019). These models can capture complex nonlinear relationships between drying parameters without relying on explicit physical assumptions. Despite their advantages, the application of AI models presents several challenges. These models generally require large, diverse datasets to minimize the risk of overfitting and to promote generalizability. Furthermore, models such as artificial neural networks (ANNs) are often considered "black boxes," as they provide limited transparency regarding their internal decision-making processes. Effective hyperparameter tuning and rigorous validation procedures are also critical to enhance model robustness and ensure reliable performance in real-world scenarios. In another study, the drying kinetics of solid wastes were modeled using both artificial neural networks (ANN) and semi-empirical models, with ANN demonstrating the most accurate simulation results (Perazzini, Freire, & Freire, 2013). Similarly, another study examined the thin-layer drying of tea leaves using various semi-empirical and AI-based models. The results showed that multilayer perceptron networks achieved the highest accuracy (Fathi, Roshanak, Rahimmalek, & Goli, 2016). This study aims to compare different mathematical models, including semi-empirical, regression, and AI-based methods, for simulating the drying kinetics of potato slices. The novelty of this research lies in the comparative analysis of AI-based methods (ANN, SVM, RF) and traditional models under varying drying conditions, demonstrating the superior predictive capability of AI in optimizing drying processes. By highlighting the strengths and limitations of each modeling approach, this study contributes to the growing body of knowledge on drying process optimization, with potential applications in food preservation, quality control, and energy-efficient drying technologies.

Materials and Methods

Sample preparation

Fresh potatoes (*Solanum tuberosum* L.) were procured daily from local markets to ensure consistent freshness and quality. The tubers were washed under running tap water, manually peeled, and sliced to a uniform thickness of 1.00± 0.05 mm using a precision slicer. Each experiment utilized approximately 60 g of fresh potato sample, with the initial mass measured using a high-precision balance (A&D GR-202, readability: 0.001 g). Initial moisture content (wet basis) was determined via oven-drying method by placing about 10 g of each sample in a forced convection oven (BMS55, Fan Azma Gostar, Iran) at 105 °C for 24 hours, following AOAC method 934.06 (AOAC International, 2000).

Solar dryer

The solar dryer used in this study was a custom-built hybrid system designed to provide controlled drying conditions for agricultural samples. It consisted of a compound parabolic collector (CPC), a temperature regulation unit, an equalizing chamber, a forced convection fan, a heating channel, a diffuser, and a drying chamber, as illustrated in Figure 1.

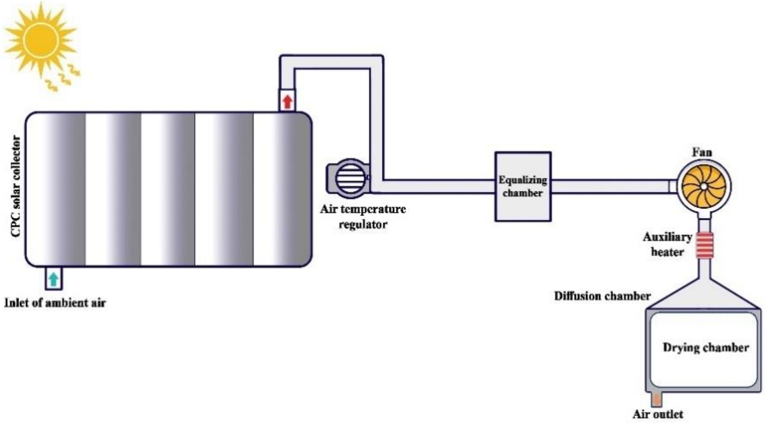

Fig.1. Schematic of the drying system

The CPC collector had an effective aperture area of 2.4 m^2 and a concentration ratio of 2.5. It was equipped with matte black-coated aluminum absorber tubes to enhance solar heat absorption. Polished stainless-steel reflectors, each 0.4 cm thick, were used to concentrate incident solar radiation onto the absorber tubes. The entire collector was installed at a 45-degree angle, matching the latitude (30° N) of the experimental site located at Shiraz University, to maximize solar gain throughout the day (Duffie, Beckman, & Blair, 2020). Solar energy served as the primary heat source, while a 1.5 kW auxiliary electric heater provided supplemental heating during periods of reduced solar radiation. The heater was activated when solar energy alone was insufficient to maintain the set drying temperature and was installed downstream of the air flow path to avoid interfering with solar collection.

Airflow was managed by a motorized damper controlled via a stepper motor (Ts310n247, torque: 6.5 kg·cm), which adjusted airflow based on target temperature input. Air circulated through the system using a centrifugal fan (Techtop, 0.4 kW, Italy), which delivered a consistent airflow of 2 meters per second, measured at the fan inlet using a Testo 435 anemometer with an accuracy of ±0.03 m s^{-1}.

An equalizing chamber, constructed from particle board and measuring 30 × 50 × 70 cm, was installed after the heating section to stabilize and distribute air evenly before entering the drying chamber. Inside the drying chamber, a mesh drying tray (25 × 25 cm, galvanized sheet metal) held the potato slices, and an IR lamp (250 W, Philips) was positioned 30 cm above the tray surface to provide additional thermal radiation during selected treatments.

Real-time mass loss during drying was tracked using a load cell (model L6D, Class C3, 3 kg capacity), installed beneath the drying tray. The load cell was connected to a data acquisition system that logged mass data at 30-second intervals, enabling accurate monitoring of drying progress. Drying continued until the samples reached a final moisture content of approximately 10% on a dry basis.

Phase change materials were used in select experiments to investigate their thermal storage effect. A total of 1500 g of paraffin wax (melting point approximately 56°C and latent heat of about 190 kJ kg^{-1}) was melted and divided into ten aluminum containers, each holding 150 g. These containers were placed uniformly at the base of the drying chamber beneath the drying tray to absorb and release thermal energy, helping to stabilize temperature fluctuations during the drying cycle.

Temperature control system

A temperature controller (XMT-803, China) automatically regulated the drying chamber's temperature. The system included an SSR relay (25DA, CRYDOM) and a PT100 sensor (±0.1°C accuracy). Ten temperature sensors were installed throughout the setup, while an SHT15 sensor (±0.05% RH, ±0.1°C accuracy) measured humidity changes before and after the drying chamber. Air velocity was set at 2 m s^{-1} at the fan inlet (182 cm^2 cross-sectional area) and monitored using a Testo 435 anemometer (±0.03 m s^{-1} accuracy).

Experimental design

The experiments were conducted to assess the combined effects of air temperature, infrared (IR), and phase change materials (PCM) integration on the drying behavior of potato slices. A factorial design with three variables was used, including three levels of air temperature (40°C, 50°C, and 60°C), two levels of IR radiation (with and without a 250-watt IR lamp), and two levels of PCM use (with and without PCM). This resulted in 12 distinct treatment combinations. Each treatment was replicated three times following a completely randomized design, resulting in 36 experimental runs in total. Drying continued until the samples reached a final moisture content of approximately 10% on a dry basis, as determined by the stabilization of mass readings. The resulting data were analyzed using analysis of variance (ANOVA) with a significance level of 0.05. When significant differences were detected, means were separated using Tukey's honest significant difference (HSD) test. All statistical analyses were performed using SPSS version 25.

Mathematical modeling

In this study, three categories of models were developed to simulate the drying kinetics of potato slices: (1) machine learning (ML) models, (2) regression models (linear and non-linear), and (3) empirical and semi-empirical models.

Machine learning (ML) methods

To model and predict the drying kinetics of potato slices, three supervised machine learning algorithms were employed: Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF). These models were selected for their proven ability to capture complex, nonlinear relationships between input variables and target outputs, especially in regression tasks related to food processing and drying kinetics.

In this study, the following input features were used for all ML models: drying temperature (°C), drying time (s), presence of infrared (IR) radiation (binary: 0= absent, 1= present), and presence of PCM (binary: 0= absent, 1= present). The target output variable for prediction was the moisture content of the potato slices, expressed on a dry basis.

Model assumptions

- The drying process was conceptualized as a functional mapping from a set of input features, namely drying temperature, time, presence of IR radiation, and presence of PCM, to the corresponding moisture content. Although moisture content naturally evolves in a continuous, time-dependent manner, each observation in the dataset was treated as an independent instance for the purposes of supervised learning. This approach enables the models to estimate moisture content at any given time point based solely on current experimental conditions, without incorporating sequential dependencies.
- Temporal dynamics were not explicitly modeled; instead, the machine learning models operated under the assumption that the moisture content at each time step could be predicted independently of previous values. This simplification facilitates the use of standard regression models and reduces computational complexity, while still achieving high predictive accuracy within the controlled experimental setup.
- External environmental factors, such as variations in ambient humidity or solar radiation, were considered negligible or

effectively controlled. This assumption is supported by the presence of an automated temperature control system and an auxiliary electric heater, which together maintained stable thermal conditions across all experiments.

ANN was chosen for its ability to model complex patterns through multiple hidden layers. The network architecture comprised three hidden layers with 64, 32, and 16 neurons, respectively. The hidden layers utilized the Rectified Linear Unit (ReLU) activation function, while the output layer employed a linear activation function. The model was trained with the Adam optimizer, employing a learning rate of 0.001 and a batch size of 32. The selected network architecture was determined based on practical constraints related to dataset size and model performance. Given the limited number of experimental samples, deeper architectures with more layers or neurons were avoided to reduce the risk of overfitting. Consequently, a relatively shallow configuration was adopted. The final architecture (64–32–16) was established through an iterative trial-and-error process, during which various configurations were evaluated and validated. This particular setup achieved an effective balance between model complexity and generalization capability, as evidenced by cross-validation performance.

SVM was selected for its robustness in high-dimensional spaces. It effectively captures nonlinear relationships through kernel functions. A radial basis function (RBF) kernel was employed, with hyperparameters including a regularization parameter (C) of 100, an epsilon value of 0.01 to define the regression margin, and a gamma value of 0.1.

RF was included as an ensemble learning method to enhance generalization and reduce variance. The model was trained using 100 decision trees, with a minimum of two samples per split to prevent overfitting.

Prior to model training, all input features, including temperature, drying time, infrared radiation, and the presence of PCM, were standardized to ensure optimal model performance. Standardization was performed using the transformation Equation (1) to center the data around zero with unit variance (Kelleher, 2019):

$$X_{scaled} = \frac{X-\mu}{\sigma} \tag{1}$$

where X represents the original feature value, μ denotes the mean, and σ represents the standard deviation of the feature.

To ensure robust model performance and generalization, the dataset was split into a training set (80%) and a test set (20%). Furthermore, ten-fold cross-validation was performed on the training set, where it was randomly partitioned into ten subsets. Each model was trained on nine subsets and verified on the remaining one, with this process repeated ten times. The final performance was averaged across all iterations, and the best hyperparameters were selected during this process. Model performance was subsequently tested on the test set to evaluate its generalization capability, reducing the risk of overfitting and providing a reliable accuracy estimate.

Model performance was assessed using multiple statistical metrics: the coefficient of determination (R^2) indicates how well the predicted values align with actual values; RMSE (g water g^{-1} dry matter) quantifies the average value of prediction errors; mean absolute error (MAE, g water g^{-1} dry matter) measures the total discrepancies between predicted and observed values; and mean bias error (MBE, g water g^{-1} dry matter) evaluates any systematic over- or underestimation. Lower RMSE and MAE values signify higher accuracy, while an R^2 value closer to one indicates a stronger model fit. The complete workflow of the ML models is summarized in Figure 2, which demonstrates the steps involved from gathering and preparing data to choosing a model and assessing its performance. By integrating these ML techniques, this study aimed to develop accurate and reliable predictive models for drying kinetics.

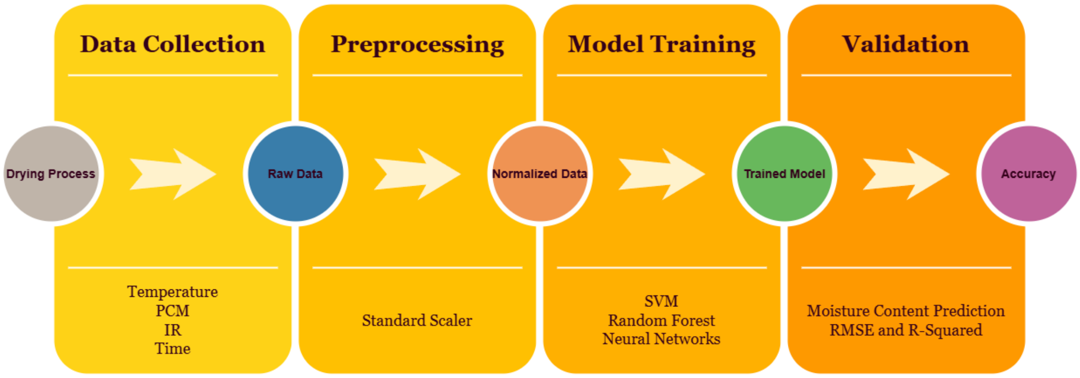

Fig. 2. The workflow of ML models for drying kinetics

Linear and non-Linear regression

Linear regression assumes a direct linear relationship between the dependent variable (moisture content) and the independent variables (time, temperature, PCM, and IR). In contrast, non-linear regression uses an exponential equation to model the relationship between moisture content and the independent variables, capturing more complex patterns in the data.

Empirical and semi-empirical models

Empirical models are based solely on experimental data fitting without requiring a strong physical foundation. These models are developed by analyzing experimental drying data and identifying the mathematical equations that best describe moisture loss. In this study, commonly used models, such as Newton, Page, Modified Page, Two-Term, Exponential Two-Term, Logarithmic, Midilli, and Approximation of Diffusion, were applied to represent the moisture ratio as a function of drying duration.

Results and Discussion

Drying rate

The drying rate of potato slices was calculated under different operating conditions (Figures 3 to 5).

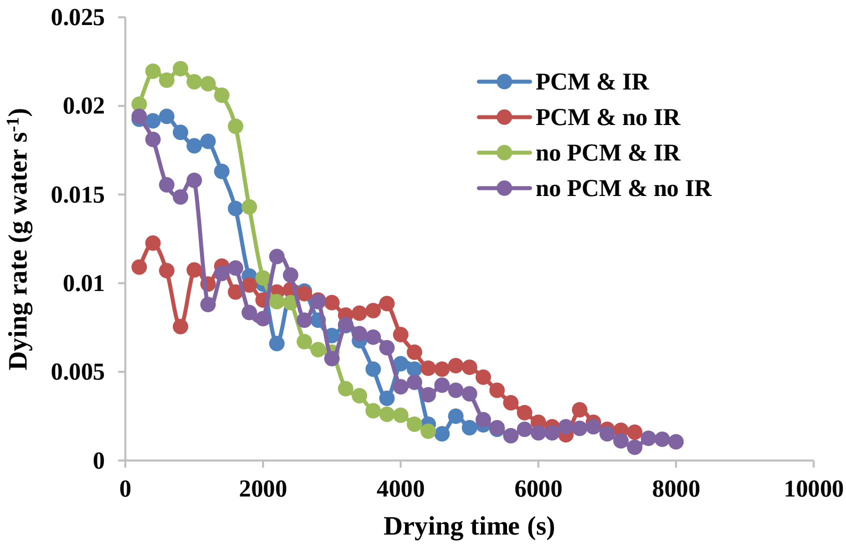

Fig. 3. Drying rate vs. time under different conditions at 40°C

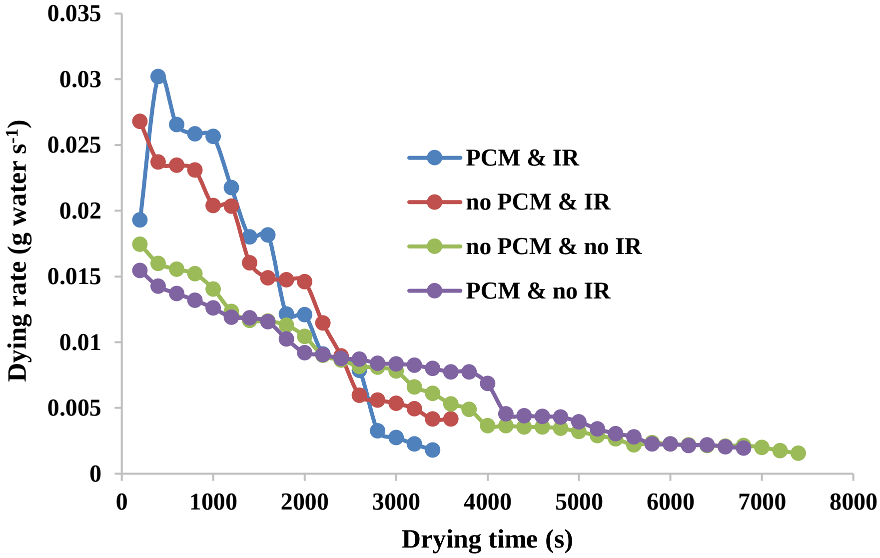

Fig. 4. Drying rate vs. time under different conditions at 50°C

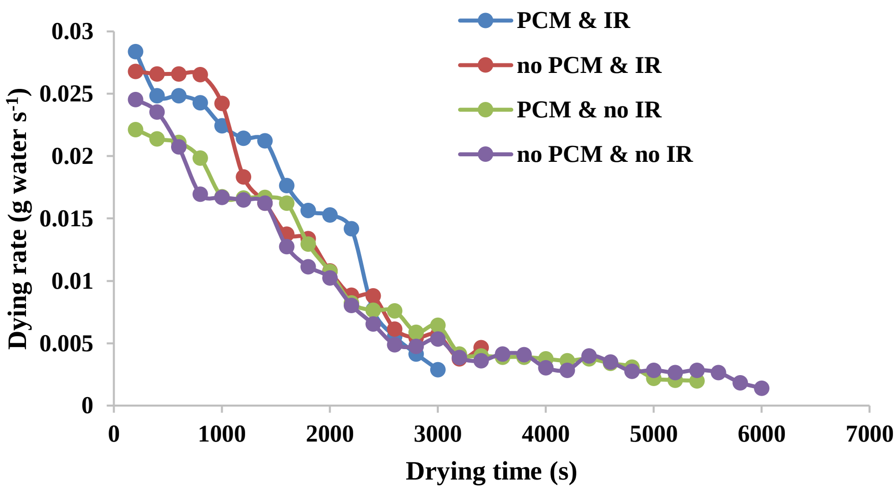

Fig. 5. Drying rate vs. time under different conditions at 60°C

The average slope of each drying curve is presented in Table (1), from which the following insights were derived:

1. **Effect of Temperature on Drying rate:** As temperature increases from 40°C to 60°C, the slope of the drying curves rises, indicating a higher drying rate. This trend is expected, as higher temperatures enhance moisture evaporation from the sample surface. Specifically, under no PCM & no IR conditions, the slope increases from 0.006249 at 40°C to 0.00817 at 60°C. Similarly, under PCM & IR conditions, the slope rises from 0.009217 at 40°C to 0.01671 at 60°C. These results confirm that increasing temperature significantly accelerates the drying process.
2. **Effect of PCM:** PCM serves as a thermal stabilizer, reducing temperature fluctuations and influencing the drying rate. In most cases: with PCM but without IR, the drying rate is slightly higher than without PCM. For example, at 60°C, the slope is 0.009267 with PCM compared to

0.00817 without PCM. Previous studies confirm the effectiveness of PCM in improving drying performance. Rakshamuthu *et al*. (2021) reported that PCM increased the drying rate of gooseberries in a solar dryer. Similarly, other researchers illustrated that PCM enhances dryer efficiency (Atia, Teggar, & Laouer, 2024; Poonia, Singh, & Jain, 2022; Madhankumar, Viswanathan, Wu, & Taipabu, 2023). With both PCM and IR combined, the drying rate is higher than when PCM is absent. At 60°C, the slope is 0.01671 with PCM & IR, compared to 0.014512 without PCM & IR. These findings suggest that PCM is more effective when combined with IR, leading to a more efficient drying process.

3. **Effect of IR radiation:** At all temperature settings, the addition of IR significantly increases the drying rate. For example, at 40°C without PCM, the slope increases from 0.006249 (without IR) to 0.011295 (with IR). Similarly, at 60°C without PCM, the slope rises from 0.00817 (without IR) to 0.014512 (with IR). This increase is attributed to the deeper penetration of infrared energy into the samples, accelerating moisture evaporation. However, a significant difference observed at 50°C can be attributed to the pronounced effect of infrared (IR) radiation at this temperature. At 40°C, although IR has a positive impact, the lower thermal potential of the drying air limits its effectiveness, and therefore, no sharp increase is observed in the IR curves. At 60°C, despite the high thermal potential of the air, the influence of IR appears to be limited, likely due to increased internal moisture diffusion resistance within the potato slices, which restricts further enhancement of the drying rate.
4. **Comparison of PCM and IR effects:** IR has a stronger impact on the drying rate compared to PCM, as seen in the larger differences in slope between IR and non-IR conditions. The combination of PCM and IR yields the highest drying rate. For example, at 60°C, the highest slope (0.01671) is observed under PCM & IR conditions.

For optimal drying performance, a combination of IR and PCM is recommended, as it maximizes the drying rate while maintaining thermal stability.

Table 1- Slopes of drying rate curves under different conditions

Experiment	Slope of curves
40C PCM & IR	0.009217
40C PCM & No IR	0.006651
40C No PCM & No IR	0.006249
40C No PCM & IR	0.011295
50C PCM & IR	0.014438
50C PCM & No IR	0.007337
50C No PCM & No IR	0.006689
50C No PCM & IR	0.013814
60C PCM & IR	0.01671
60C PCM & No IR	0.009267
60C No PCM & No IR	0.00817
60C No PCM & IR	0.014512

Mathematical modeling

After developing the ML, empirical, and semi-empirical models, validation was conducted, yielding the following results.

One-way analysis of variance for model performance

To statistically validate the differences in predictive performance among the developed models, an ANOVA was conducted using the RMSE values obtained under different drying conditions (temperature, presence of PCM, and IR application). The models compared included the ANN, SVM, RF, Non-linear Regression, and the best-performing Semi-Empirical model (Midilli). The tested null hypothesis was that there are no significant differences in mean RMSE across the different modeling approaches. The results of the ANOVA are presented in Table 2.

Table 2- One-way ANOVA results comparing model RMSE across drying conditions

Source of Variation	SS	Df	MS	F	p-value
Between groups	0.379	4	0.0948	12.51	0.0004
Within groups	0.076	10	0.0076		
Total	0.455	14			

The ANOVA results reveal a statistically significant difference in RMSE among the different modeling approaches ($F = 12.51$, $p < 0.001$). Post-hoc comparisons using Tukey's HSD test further indicated that the ANN model's performance (lowest RMSE) was significantly better than that of the semi-empirical and regression-based models. Although SVM and RF also performed well, only ANN showed statistically significant superiority in prediction accuracy across all tested conditions. These findings validate that the enhanced prediction accuracy of the ANN model is not merely a product of chance; instead, it signifies a statistically significant improvement in model performance.

Artificial neural network (ANN) model

The comparison between actual and predicted moisture content using the ANN model is shown in Figure 6. The performance metrics for the ANN model were evaluated for both training and test sets. For the training set, the R^2, RMSE, MAE, and SMBE were calculated as 0.999, 0.0583 g water g^{-1} dry matter, 0.0251 g water g^{-1} dry matter, and 0.005 g water g^{-1} dry matter, respectively. For the test set, the corresponding values were 0.998, 0.0656 g water g^{-1} dry matter, 0.03409 g water g^{-1} dry matter, and 0.0091 g water g^{-1} dry matter. These results demonstrate the ANN model's strong predictive accuracy and generalization capability. Since $|SMBE| \leq 0.1$, the model demonstrates excellent predictive accuracy. Additionally, Figure 7 presents the residuals versus fitted values, confirming the model's reliability. Several studies have reported similar high accuracy in moisture content prediction using ANN models. For instance, another research simulated the thin-layer drying of apple slices using convective and microwave drying methods, achieving R^2 values of 0.993 and 0.9991, respectively, underscoring the strong predictive capability of ANN models (Rasooli Sharabiani, Kaveh, Abdi, Szymanek, & Tanaś, 2021). Similarly, Sabzevari, Behroozi-Khazaei, and Darvishi (2021) employed an ANN architecture of 3-5-5-1 to model the drying of banana slices in a thin layer, successfully predicting moisture content. In another study, the impact of a novel vortex/swirling flow generator on fluidization streams in a fluidized bed dryer was investigated. ANN modeling was used to optimize the drying process for paddy, achieving an R^2 of 0.999 and an RMSE of 0.111, demonstrating the model's effectiveness (Chokphoemphun, Hongkong, & Chokphoemphun, 2024). Another study investigated the drying rate of *Citrus medica* under freeze-drying conditions, considering different slice thicknesses (3 mm, 5 mm, and 7 mm) and cabin pressures (0.008 mbar, 0.010 mbar, and 0.012 mbar). A feedforward multilayer perceptron ANN was employed to estimate the moisture content, mass loss ratio (MR), and rate of drying. The ANN model achieved an R^2 of 0.998 and an RMSE of 0.010574, demonstrating its high precision and reliability in characterizing the freeze-drying process (Topal, Şahin, & Vela, 2024). Additionally, another research analyzed the drying kinetics of potato cubes in a fluidized bed dryer using ANN modeling. Their findings provided important understanding into the effectiveness of ANN techniques for predicting the drying characteristics of potato products, further supporting the applicability of ANN in food drying processes (Azadbakht, Torshizi, Aghili, & Ziaratban, 2018).

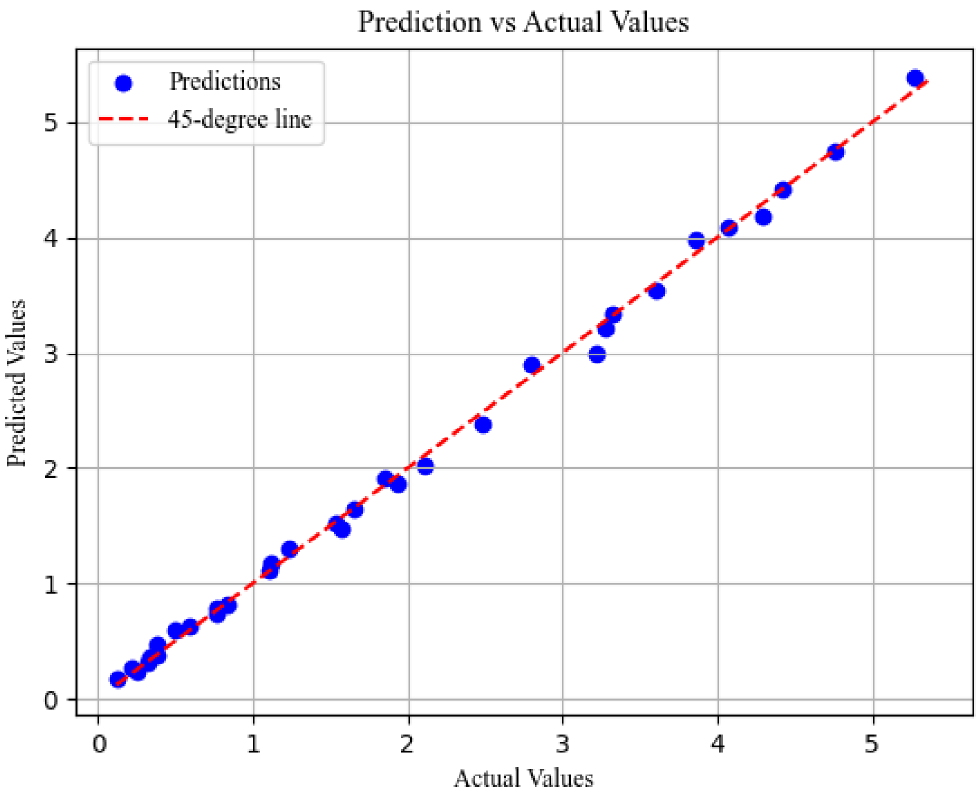

Fig. 6. Comparison of actual and predicted moisture content using the ANN model

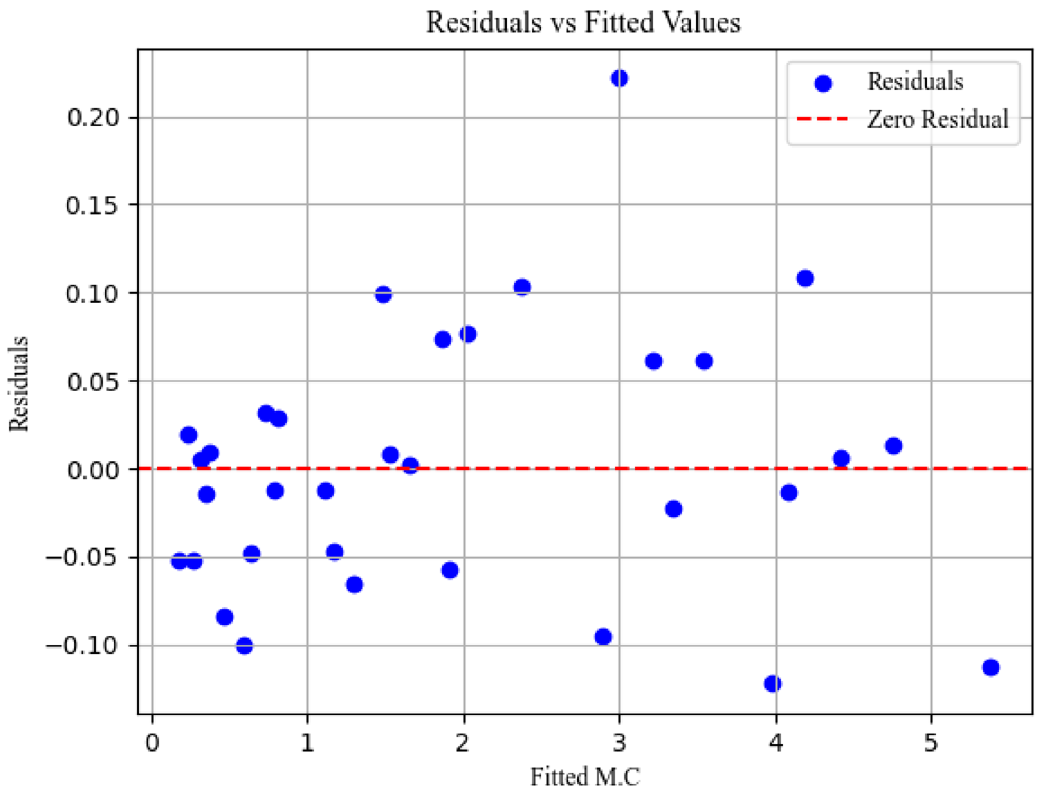

Fig. 7. Residuals of the ANN model versus fitted moisture content

Support vector machine (SVM) model

The relationship between actual and predicted moisture content is presented in Figure 8. The statistical evaluation of the SVM model on the training dataset yielded an R^2 of 0.998, RMSE of 0.0702 g water g^{-1} dry matter, MAE of 0.0512 g water g^{-1} dry matter, and SMBE of 0.008 g water g^{-1} dry matter. For the evaluation dataset, the corresponding values were 0.996, 0.0882 g water g^{-1} dry matter, 0.0603 g water g^{-1} dry matter, and SMBE of 0.010 g water g^{-1} dry matter, respectively. These results indicate strong predictive performance of the SVM model. Additionally, the residuals plotted against the predicted moisture contents, as shown in Figure (9), further confirm the model's reliability. To evaluate whether the difference in predictive performance between the ANN and SVM models was statistically significant, an independent two-sample t-test was conducted using RMSE values obtained under different drying conditions. The results showed that the ANN model (mean RMSE = 0.0656 0702 g water g^{-1} dry matter) performed significantly better than the SVM model (mean RMSE = 0.0882 0702 g water g^{-1} dry matter), with a t-value of –3.45 and a p-value of 0.0061 ($p < 0.01$). This confirms that the superior performance of the ANN model is not due to random variation, but is statistically significant. This trend has been observed in previous studies, where SVM performs well but generally does not surpass ANN in predictive capability. For instance, another research, investigated the prediction of moisture content in mushrooms during drying using ANN and SVM models. Their results showed that ANN achieved an R^2 of 0.998 and a relative RMSE (rRMSE) of 3.958%, in contrast the corresponding values for SVM were 0.973% and 15.749%, respectively (Karaağaç, Ergün, Ağbulut, Gürel, & Ceylan, 2021). These findings further support the superior accuracy of ANN over SVM in moisture content prediction. A similar study developed predictive models for the pyrolytic conversion of *Sargassum* sp. (Red Sea seaweed) using ANN and SVM. Their study demonstrated that ANN outperformed SVM, yielding higher accuracy and lower error rates, further validating the effectiveness of ML techniques in forecasting pyrolytic conversion processes (Saleem & Ali, 2017). Another research investigated ML modeling for the drying of mushroom slices, where ANN outperformed the SVM method, confirming its higher predictive accuracy in drying applications (Fartash Naeimi, Khoshtaghaza, Selvi, Ungureanu, & Abbasi, 2024).

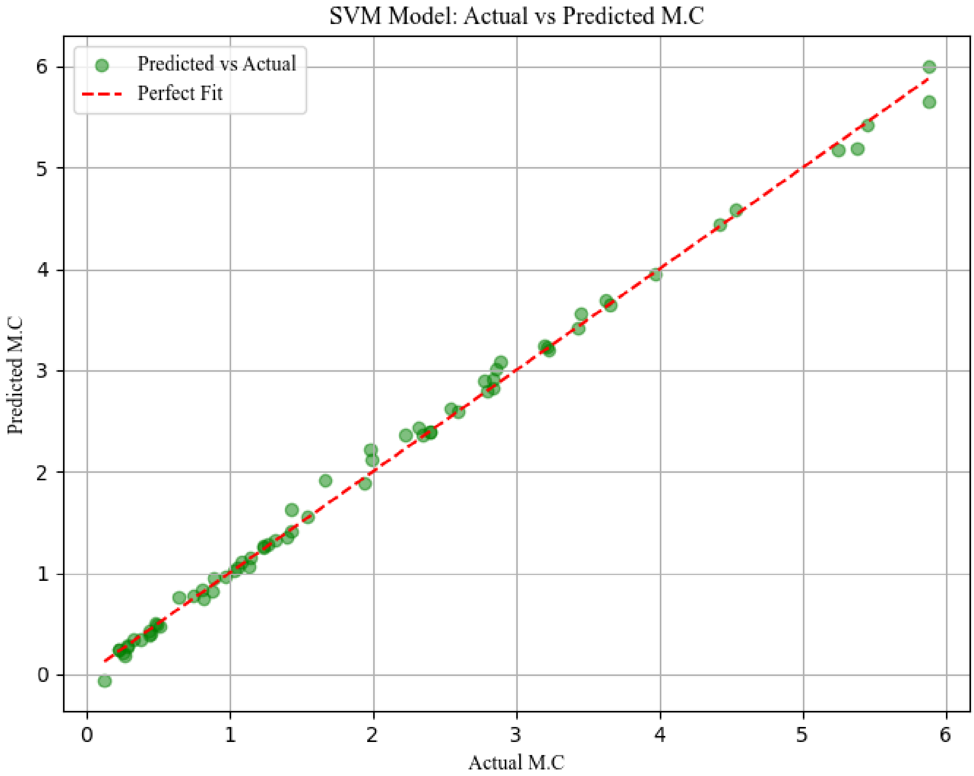

Fig. 8. Comparison of actual and predicted moisture content using the SVM model

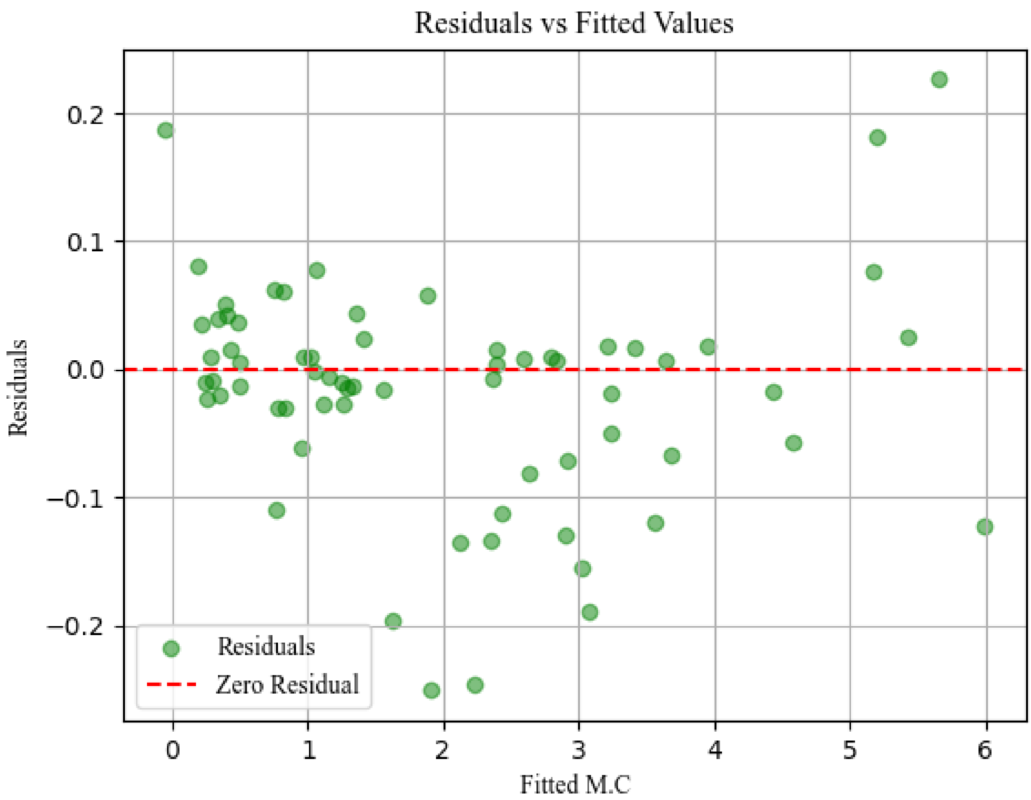

Fig. 9. Residuals of the SVM model versus predicted moisture content

Random forest (RF) model

The comparison of actual and predicted moisture content using the RF model is depicted in Figure 10, while Figure 11 presents the residuals of the RF model plotted against the predicted moisture content. Following the development of the RF model, the statistical metrics R^2, RMSE, MAE, and SMBE for the training dataset were calculated as 0.991, 0.153 g water g^{-1} dry matter, 0.1120 g water g^{-1} dry matter, and 0.0020 g water g^{-1} dry matter, respectively. For the evaluation dataset, the corresponding values were 0.9853, 0.1859 g water g^{-1} dry matter, 0.1397 g water g^{-1} dry matter, and 0.0030 g water g^{-1} dry matter, respectively. Thus, the RF algorithm can be considered a reliable model for predicting moisture content in potato slices during drying; however, its predictive accuracy is generally lower than that of ANNs and SVMs. Despite this, RF remains a valuable benchmark for assessing the performance of various machine learning models under consistent conditions. For applications where predictive accuracy is paramount, ANNs are particularly recommended due to their superior performance. Their architecture, characterized by hidden layers, enables them to capture complex, non-linear relationships in the data, making them especially well-suited for modeling drying processes. The thin-layer drying process of potato slices involves heat and mass transfer, which is strongly influenced by environmental conditions, temperature, and moisture. Compared to other methods, ANNs are better able to capture these dependencies. SVMs generally perform well in regression and classification tasks, especially with smaller datasets and optimized feature sets. Unlike RF, which relies on an ensemble of decision trees, SVM excels at finding optimal decision boundaries. As a result, when dealing with highly nonlinear data and minimal noise, SVM's performance can be comparable to that of ANN. However, RF tends to have lower accuracy in time-dependent predictions and continuous datasets, such as moisture variation over time. This is because RF is inherently more suited for classification tasks rather than regression problems. Additionally, RF may struggle to capture subtle moisture variations, leading to less accurate predictions with higher fluctuations. In summary, ANNs perform best when trained on large and diverse datasets, as they can optimize their weights and architecture to extract complex features. SVMs are more effective for small to medium-sized datasets, while RF may underperform when dealing with a high number of input variables or time-dependent data.

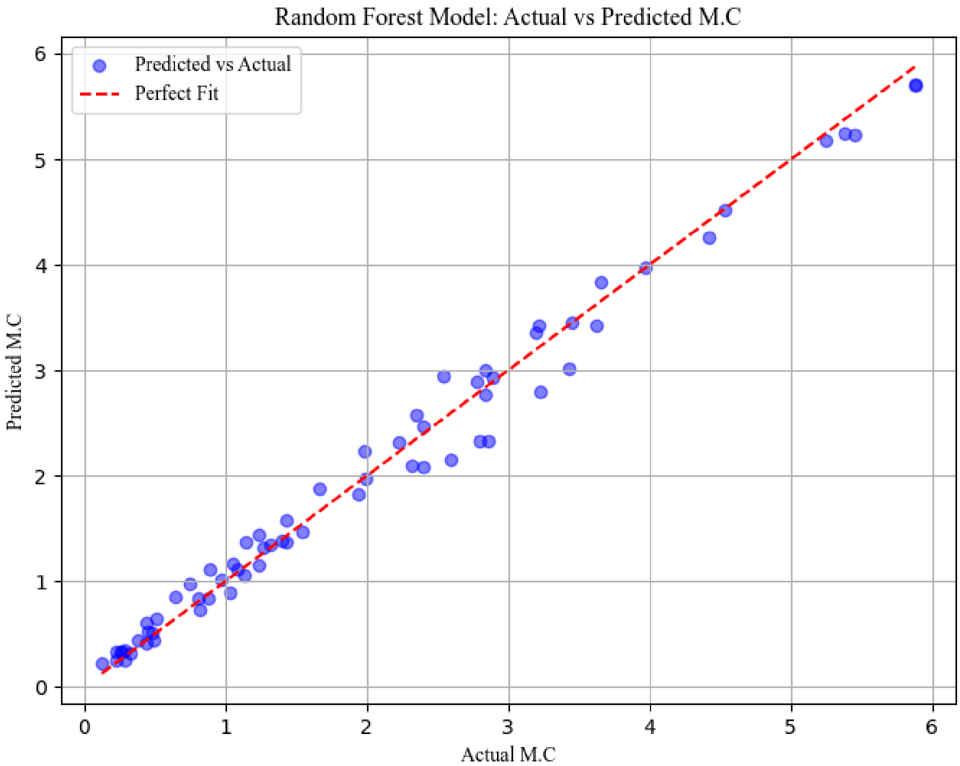

Fig. 10. Comparison of actual and predicted moisture content using the RF model

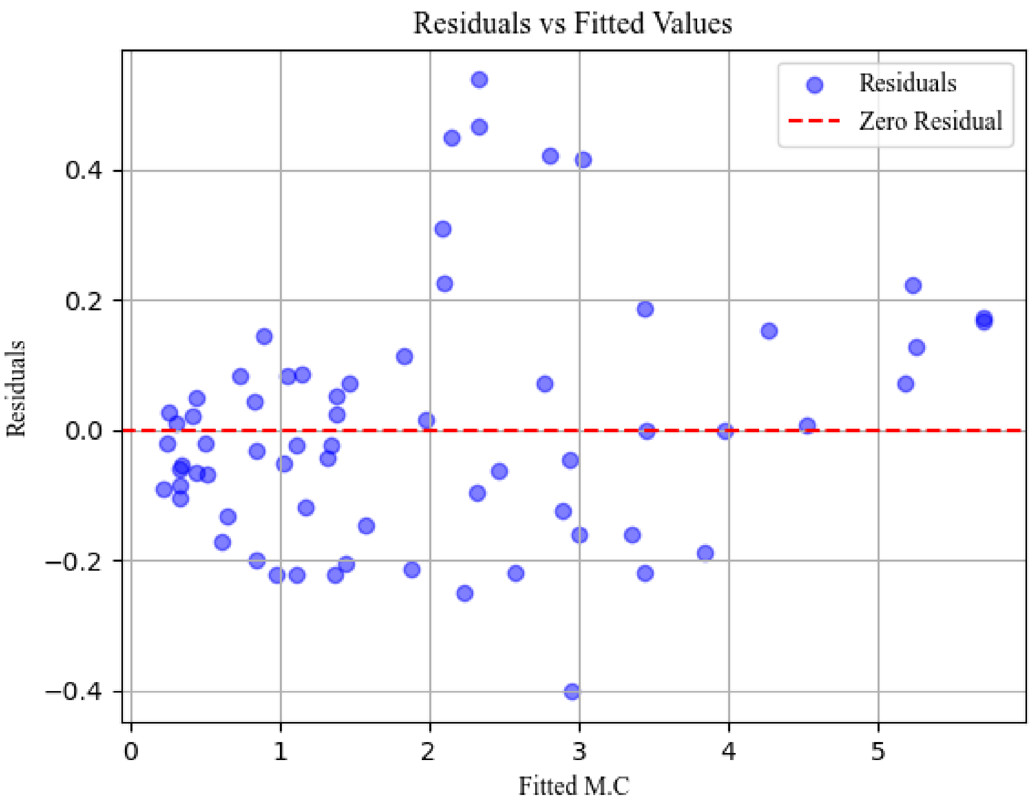

Fig. 11. Residuals of the RF model versus predicted moisture content

Regression models

Linear regression

We developed superposition mathematical models for different drying conditions: with PCM & with IR, with PCM & without IR, without PCM & with IR, and without PCM & without IR (Equations (2) to (5) in Table 3). These models predict the moisture content of potato slices as a linear function of temperature and time. As expected, the moisture content decreases as time and temperature increase, which is a typical result of the drying process. However, the models exhibit lower R^2 values and higher RMSE, MAE, and SMBE, indicating that they are less accurate compared to the AI models. Additionally, the predicted moisture content by the linear regression model versus the actual moisture content is shown in Figure 12.

Table 3- Performance of linear regression models for different drying conditions

Model	Equation	Eq. no	R^2	RMSE	MAE	MBE
PCM & IR	$M.C = -0.4929\ T - 1.5599\ Time + 1.8464$	(2)	0.7736	0.8877	0.6935	-0.3764
PCM & No IR	$M.C = -0.4212\ T - 1.5346\ Time + 1.9308$	(3)	0.94684	0.4019	0.3413	-0.1053
No PCM & IR	$M.C = -0.1588\ T - 1.6363\ Time + 1.9496$	(4)	0.9009	0.5021	0.4292	0.1419
No PCM & No IR	$M.C = -0.2810\ T - 1.2822\ Time + 1.6125$	(5)	0.7913	0.8964	0.6565	-0.4214

Note: RMSE, MAE, and MBE values are in g water g^{-1} dry matter

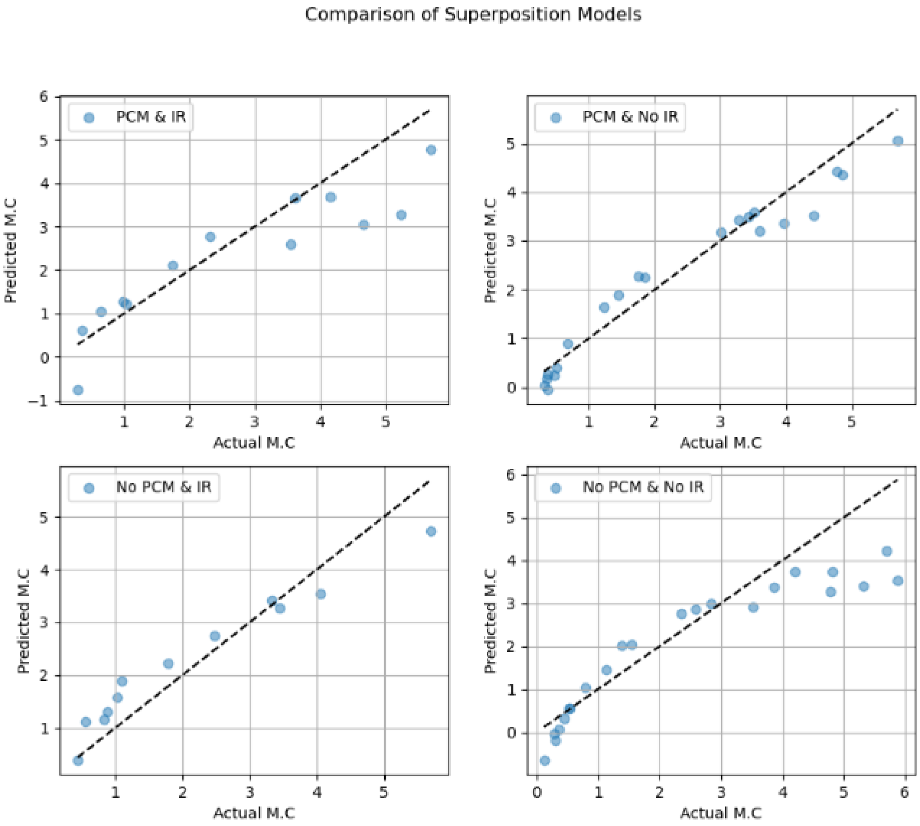

Fig. 12. Comparison of actual and predicted moisture content using the linear regression model

Non-linear regression

Among the different equations tested, the exponential model provides the best prediction of the moisture content during the drying process. Equation (6) is defined as:

$$M.C = 5.9893\exp(-0.0005\,Time) - 0.0111\log(T+1) + 0.1219\,PCM - 0.8198\,IR \quad (6)$$

where, Time is the drying time (in seconds), T is the drying temperature (°C), PCM and IR can either be 0 or 1, where 0 represents experiments without PCM or IR, and 1 represents experiments with PCM or IR.

The evaluation of the model shows that it has R^2, RMSE, MBE, and SMBE values of 0.93, 0.4058 g water g^{-1} dry matter, 0.3173 g water g^{-1} dry matter, and 0.0056 g water g^{-1} dry matter, respectively. These results display better proficiency than the linear regression models, but still fall short of the accuracy achieved by the AI models (ANN, SVM, and RF). This nonlinear model combines the empirical Henderson model with linear regression, leading to a better prediction than either model alone. However, since it does not utilize AI techniques for modeling, its accuracy is lower than that of the AI models. Given that the absolute value of SMBE is below 0.1, the model's accuracy is considered acceptable. The comparison between actual moisture content and the moisture content predicted by the non-linear regression model is presented in Figure 13.

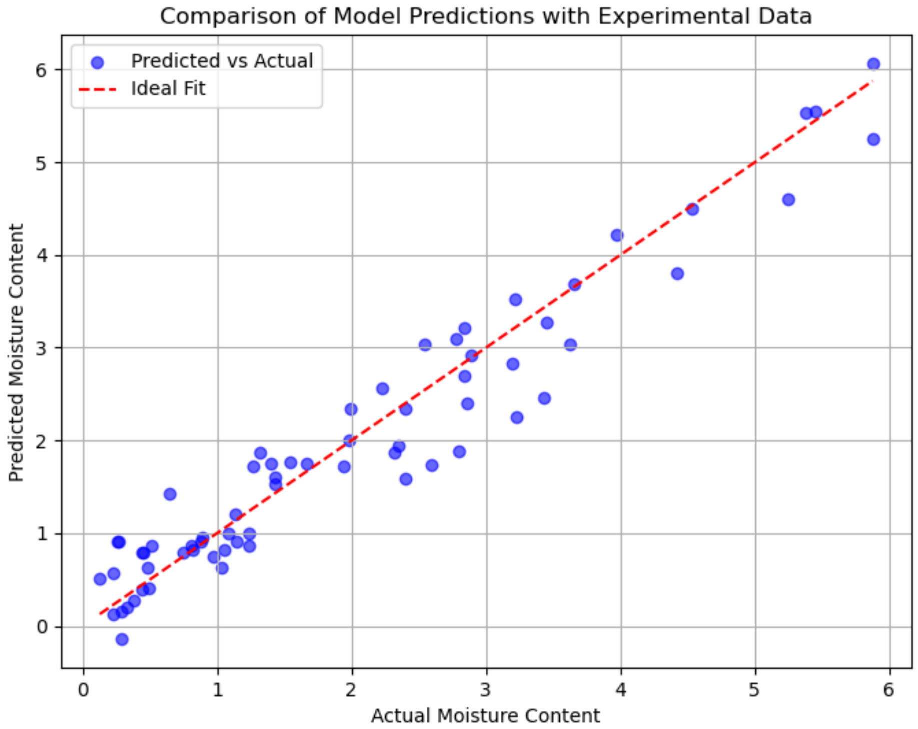

Fig. 13. Comparison of actual and predicted moisture content using the non-linear regression model

Semi-empirical models

The coefficients and statistical parameters of each model are provided in Table 4. Among them, the Midilli and the Approximation of Diffusion models exhibit the lowest errors. However, the evaluation of the results from the empirical and semi-empirical models shows that their accuracy is lower compared to the AI and nonlinear regression models. Another study was conducted to examine the modeling of drying kinetics using two different methods: semi-empirical and ANN models. The results showed that when total experimental data were involved, ANN outperformed the Midilli model (Karakaplan, Goz, Tosun, & Yuceer, 2019). ML models, particularly ANN, provide the most accurate predictions, significantly outperforming other models in terms of precision and error reduction. Nonlinear regression also proves superior to linear regression, as moisture content changes inherently exhibit nonlinearity. Among empirical models, the Midilli. model performs best, though with lower accuracy compared to ML models. While empirical models are useful for quick estimations, they lack the precision of ML approaches. For optimal predictions, ANN is recommended, but if computational efficiency is a concern, SVM serves as a viable alternative. Nonlinear regression offers better interpretability, and the Midilli model is suitable for fast empirical estimations.

Table 4- Coefficients of different semi-empirical models

Model	Coefficients	R^2	RMSE	MAE	MBE
Newton	k = 0.0005	0.8851	0.5283	0.4000	-0.0090
Page	k = 0.0009, n = 0.939	0.8863	0.5255	0.3972	-0.0045
Henderson and Pabis	a = 0.964, k = 0.0005	0.8868	0.5243	0.3994	-0.0198
Logarithmic	a = 0.945, k = 0.0006, c = 0.0325	0.8884	0.5209	0.3904	0.0000
Two-term	a = 0.9625, k_1 = 0.0006, b = 0.0133, k_2 = -0.0001	0.8885	0.5204	0.3904	0.0000

Midilli et al. (2002)	a = 0.955, k = 0.0003, n = 1.09, b = 0.0000	0.8892	0.5186	0.3915	-0.0017
Modified page	k = 0.0008, n = 0.7159	0.8851	0.5283	0.4000	-0.0090
Exponential	a = 0.4923, k = 0.0008	0.8871	0.5238	0.3932	0.0022
Approximation of diffusion	A = 0.9675, k = 0.0006, b = -0.0435	0.8879	0.5220	0.3898	0.0107

Conclusion

This study systematically compared different modeling approaches to predict the drying kinetics of potato slices under various drying conditions. The results demonstrated that AI models, particularly ANN, exhibited the highest accuracy in predicting moisture content over time, outperforming both empirical and semi-empirical models. While conventional models such as the Midilli and Approximation of Diffusion models provided reasonable fits, they lacked the precision and adaptability of AI-based approaches. Among AI techniques, ANN achieved the best performance, followed by SVM and RF, confirming the capability of ML in capturing complex, non-linear drying dynamics. Additionally, the study revealed that the drying rate increases significantly with temperature, IR radiation, and the presence of PCM. IR had a stronger effect on enhancing drying efficiency compared to PCM alone. The combination of PCM and IR yielded the highest drying rate, making it the most effective drying condition. Overall, the findings emphasize the superiority of AI models for drying process optimization. For industrial applications, ANN is the recommended model due to its ability to generalize drying kinetics accurately. Future research could focus on integrating hybrid AI models with computational fluid dynamics (CFD) for further optimization and exploring the impact of different drying conditions on food quality attributes.

Conflict of Interest

There is no conflict of Interest.

Authors Contribution

M. Moradi: Methodology, Project administration, Software, Supervision, Text Mining, Data pre and post processing, Validation, Writing, Review and editing services

R. Raeesi: Methodology, Software, Conceptualization, Data acquisition

A. Dehghani: Writing, Data pre and post processing, Statistical analysis, Visualization, Validation

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مدل‌سازی مقایسه‌ای سینتیک خشک‌کردن برش‌های سیب‌زمینی: روش‌های مبتنی بر هوش مصنوعی در مقایسه با روش‌های تجربی و نیمه‌تجربی

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چکیده

خشک‌کردن یکی از روش‌های حیاتی نگهداری در صنعت غذا است که با کاهش رطوبت، کیفیت محصول را حفظ کرده و ماندگاری آن را افزایش می‌دهد. این فرآیند شامل مکانیزم‌های پیچیده انتقال حرارت و جرم بوده و به مدل‌های پیش‌بینی دقیقی نیاز دارد. در این مطالعه، روش‌های مختلف مدل‌سازی شامل مدل‌های رگرسیون، مدل‌های نیمه‌تجربی، و روش‌های مبتنی بر هوش مصنوعی (AI) برای شبیه‌سازی فرآیند خشک‌کردن برش‌های سیب‌زمینی مورد مقایسه قرار گرفتند. آزمایش‌های خشک‌کردن در دماهای ۴۰، ۵۰ و ۶۰ درجه سانتی‌گراد، با و بدون استفاده از مواد تغییر فازدهنده (PCM) و تابش مادون قرمز (IR) انجام شد. مدل‌های هوش مصنوعی شامل شبکه عصبی مصنوعی (ANN)، ماشین بردار پشتیبان (SVM) و جنگل تصادفی (RF) با استفاده از داده‌های تجربی آموزش دیده و اعتبارسنجی شدند. عملکرد این مدل‌ها با مدل‌های سنتی و نیمه‌تجربی از نظر ضریب تعیین (R^2)، ریشه میانگین مربع خطا (RMSE)، میانگین قدرمطلق خطا (MAE) و خطای میانگین بایاس (MBE) مقایسه شد. نتایج نشان داد که شبکه عصبی مصنوعی (ANN) با دقت پیش‌بینی بسیار بالا (R^2= 0.998, RMSE= 0.0656) بهترین عملکرد را داشته و از سایر مدل‌ها دارای دقت بیشتری است. روش SVM نیز قابلیت پیش‌بینی مناسبی نشان داد، در حالی‌که RF عملکردی اندکی ضعیف‌تر داشت. در میان مدل‌های نیمه‌تجربی، مدل میدیلی (Midilli) بهترین برازش را داشت، اما نسبت به مدل‌های مبتنی بر هوش مصنوعی دقت کمتری نشان داد. این یافته‌ها برتری روش‌های مبتنی بر هوش مصنوعی، به‌ویژه ANN، را در بهینه‌سازی فرآیند خشک‌کردن در صنعت غذا برجسته می‌سازد.

واژه‌های کلیدی: جنگل تصادفی، مدل‌های نیمه‌تجربی، مدل‌سازی هوش مصنوعی، نرخ خشک‌کردن، SVM

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