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Comparative Machine Learning Modeling of Infrared Drying Kinetics in Cactus Fruit (*Opuntia ficus-indica*) Slices

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Abstract: This study aimed to comparatively evaluate machine learning (ML) models for predicting the infrared drying kinetics of cactus fruit (*Opuntia ficus-indica*) slices. Drying experiments were conducted at a constant temperature of 70 °C using slice thicknesses of 2, 5, and 8 mm. Approximately 200 experimental data points describing the temporal evolution of moisture ratio (MR) were obtained. In previous analyses, the Midilli–Küçük model was identified as the most suitable semi-empirical thin-layer model for this dataset. In the present study, the same experimental data were re-evaluated using nonlinear ML algorithms to further improve predictive accuracy. Support vector machines (SVM), artificial neural networks (ANN), random forest (RF), and linear regression (LR) were employed. Drying time and slice thickness were used as input variables, while moisture ratio was defined as the output variable. Model performance was assessed using a 10-fold cross-validation procedure. The results indicated that the SVM model achieved the highest prediction accuracy, with a coefficient of determination of $R^2 \approx 0.9998$ and a root mean square error of approximately 0.005, followed closely by the ANN model ($R^2 \approx 0.9990$). In contrast, the linear regression model failed to adequately capture the nonlinear characteristics of the drying process. Overall, the findings indicate that SVM and ANN provide accurate and effective alternatives to conventional empirical thin-layer models for predicting the infrared drying kinetics of cactus fruit slices.

Keywords: Artificial neural networks, infrared drying, machine learning, moisture ratio, Opuntia ficus-indica, support vector machines

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1. Introduction

The preservation of postharvest quality of agricultural products represents a fundamental engineering challenge in terms of ensuring global food security and minimizing economic losses (Ovando-Medina, 2023; Yu et al., 2025). Fruits and vegetables with high moisture content are particularly susceptible to microbial spoilage and enzymatic reactions; therefore, drying has emerged as one of the most widely applied unit operations for extending shelf life (Eroğlu, 2024; Khaledifard et al., 2025; Zartha Sossa et al., 2021). By reducing water activity to safe levels, drying effectively inhibits microbial growth while simultaneously providing significant advantages in storage and transportation through reductions in product volume and weight (Buzrul, 2022; Yang et al., 2024). However, conventional hot air drying methods, commonly used in the food industry, suffer from notable limitations, including low thermal efficiency, prolonged processing times, and undesirable quality degradation such as color loss, shrinkage, and nutrient deterioration (Yu et al., 2025; Zartha Sossa et al., 2021).

To overcome these limitations, infrared (IR) drying technology has emerged as a modern alternative based on the direct transfer of electromagnetic energy to the product (Sabbaghi et al., 2025; Zartha Sossa et al., 2021). During the IR drying process, radiant energy penetrates from the product surface into the inner layers, directly exciting water molecules and generating a volumetric heating. This phenomenon reduces heat transfer resistance, accelerates drying rate, and significantly shortens processing time. Particularly for foods dried in thin layers, IR technology offers high energy efficiency along with improved product quality (Anumudu et al., 2024; Sabbaghi et al., 2025).

Cactus pear (*Opuntia ficus-indica*) is a valuable agricultural product cultivated in arid and semi-arid regions, known for its high antioxidant capacity, rich vitamin content, and functional bioactive compounds that contribute to human health (Gouws et al., 2019; Moreno-Castillo et al., 2005). However, following harvest, the high moisture content of the fruit leads to rapid deterioration under ambient conditions, resulting in a sharp decline in market value (Rodriguez et al., 2019). Therefore, transforming cactus pear into shelf-stable and value-added products such as dried fruit, chips, or powders is of considerable industrial importance (Gouws et al., 2019; Rodriguez et al., 2019). Although infrared (IR) drying has been increasingly investigated for a wide range of fruits and vegetables, the available literature indicates that the studies specifically addressing the optimization of drying behavior of products with unique tissue structure and high sugar content, such as *Opuntia ficus-indica*, remain relatively limited (Ciriminna et al., 2019; Cruz-Rubio et al., 2020; Gouws et al., 2019; Touil et al., 2014). In this context, IR drying has been reported to offer potential advantages compared to conventional drying techniques, as it is associated with improved control of heat and mass transfer, which may contribute to reduced surface hardening effects and a more homogeneous moisture removal profile in sensitive agricultural products (Gouws et al., 2019; Touil et al., 2014).

Accurate modeling of drying kinetics is essential for the design, optimization, and process control of drying systems (Jibril et al., 2024; Kucuk et al., 2014; Martins et al., 2021). For this purpose, thin-layer drying models such as Page, Lewis, and Midilli–Küçük have been widely employed in the literature to describe time-dependent changes of moisture ratio (MR) (Kumar et al., 2012; Rashvand et al., 2024). Among these models, the Page and Midilli–Küçük equations are frequently preferred due to their ability to represent the drying behavior of many biological materials with high coefficients of determination and low error values (Doymaz, 2014; El-Mesery et al., 2024). Nevertheless, the empirical or semi-empirical nature of these models implies that their parameters lack direct physical meaning and are valid only under specific experimental conditions. When drying parameters vary, the generalization capability of such models diminishes, leading to reduced prediction accuracy (Buzrul, 2022).

In recent years, artificial intelligence and machine learning (ML)-based approaches have gained increasing attention in food engineering applications as a means of overcoming these limitations (Jibril et al., 2024; Li et al., 2023; Tepe, 2024). Algorithms such as artificial neural networks (ANN), support vector machines (SVM), and random forest (RF) are capable of modeling nonlinear and multivariate heat and mass transfer relationships with high accuracy (El-Mesery et al., 2025). ML-based models can learn implicit patterns within data without requiring prior assumptions about the underlying physical mechanisms, thereby demonstrating strong predictive performance in dynamic processes such as drying (Hazervazifeh et al., 2026; Zuo et al., 2025). Recent studies have reported that ANN- and SVM-based models achieve lower prediction errors and superior generalization ability compared to classical thin-layer models when estimating drying kinetics for various agricultural products (Martins et al., 2021). In particular, SVM has been shown to produce stable and reliable predictions even with relatively small datasets due to its structural risk minimization principle (Li et al., 2023).

A review of the existing literature indicates that most food drying studies focus either exclusively on classical thin-layer models or on the performance of individual machine learning algorithms (Kidane et al., 2025). Studies that directly compare the predictive performance of semi-empirical models and multiple machine learning approaches using the same experimental dataset remain limited. This gap is particularly evident in rapid and dynamic processes such as infrared drying, where critical parameters such as product thickness play a decisive role in moisture transfer behavior (El-Mesery et al., 2024). Evaluating the influence of such parameters through different computational intelligence methods represents an important research need in the current literature (Kidane et al., 2025).

The aim of this study is to reanalyze the infrared drying kinetics of cactus pear (*Opuntia ficus-indica*) slices, which were previously investigated using classical thin-layer drying models and reported in a full-paper international conference proceeding (Eroğlu & Çevik, 2025), by applying machine learning-based approaches, and to comparatively evaluate the predictive performance of artificial neural networks (ANN), support vector machines (SVM), random forest (RF), and linear regression (LR) models under a constant drying temperature of 70 °C and three different slice thicknesses (2, 5, and 8 mm) using a 10-fold cross-validation framework.

2. Materials And Methods

2.1. Raw Material and Sample Preparation

Cactus fruit (*Opuntia ficus-indica*) was used as the raw material in this study. Cactus fruits were obtained from a local market in Antalya, Türkiye. Fruits were selected from ripe but unspoiled specimens. After washing and cleaning to remove surface contaminants, the fruits were directly subjected to drying experiments with intact skins. The peel and seeds were not separated, and the samples were evaluated as whole slices to preserve their natural structure. The cactus fruit samples were sliced into three different thicknesses (2, 5, and 8 mm) using a stainless-steel knife. Slice thickness was measured and standardized using a digital caliper to ensure uniformity among samples.

2.2. Infrared Drying Experiments

Infrared (IR) drying experiments were carried out using a laboratory-scale infrared drying apparatus (Radwag MA 50R, Radwag Balances and Scales, Radom, Poland). All experiments were conducted at a constant drying temperature of 70 °C, which was selected as a fixed operating condition to ensure a consistent basis for evaluating the effect of slice thickness on drying behavior.

In addition to the standard configuration of the device, a perforated metal grid designed by the researchers was employed to facilitate moisture removal from both the upper and lower surfaces of the samples, which was expected to promote more homogeneous drying conditions. A schematic illustration of the infrared drying configuration, highlighting single-sided infrared heating and dual-sided moisture removal enabled by the perforated metal grid, is presented in Figure 1. The perforated grid was primarily introduced to facilitate vapor escape from both surfaces and potentially reduce mass transfer resistance, which is particularly important for thicker samples where restricting vapor removal to a single surface may lead to internal moisture retention and non-uniform drying.

At the beginning of each experiment, the initial mass of the samples was measured using a precision balance with an accuracy of ±0.001 g. Changes in sample mass during drying were recorded at varying time intervals (starting at 20 s during the initial rapid drying phase and gradually extending up to 6 min in the later stages) using the integrated weighing system of the device.

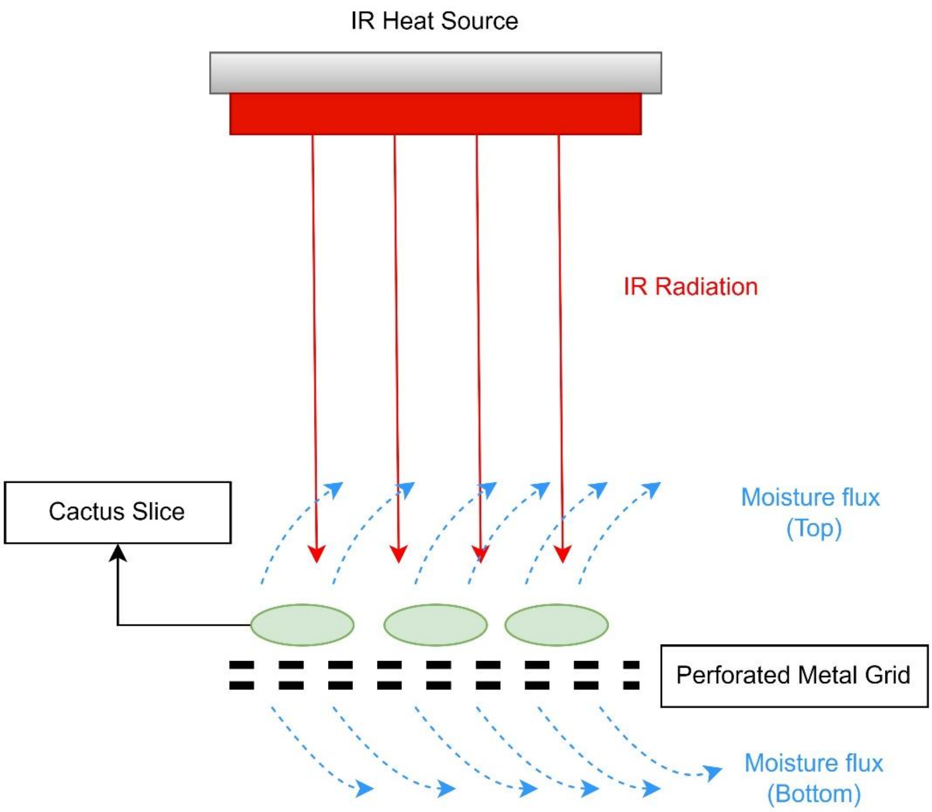

Figure 1. Schematic representation of the laboratory-scale infrared drying setup showing single-sided (top) infrared heating and dual-sided moisture removal from cactus fruit slices enabled by a perforated metal grid.

2.3. Moisture Ratio Calculation

The drying kinetics were evaluated using the dimensionless moisture ratio (MR) (El-Mesery et al., 2025), which was calculated according to the following equation (1):

$$MR = \frac{M_t - M_e}{M_0 - M_e} \tag{1}$$

where M_t represents the moisture content at time t, M_0 is the initial moisture content, and M_e denotes the equilibrium moisture content. Since the equilibrium moisture content was very small compared to the initial moisture content, it was neglected, and the moisture ratio was calculated using the simplified expression (Jibril et al., 2024):

$$MR = \frac{M_t}{M_0} \tag{2}$$

2.4. Dataset Structure and Input–Output Variables

The experimental dataset consisted of three variables for each observation: drying time (min), slice thickness (mm), and moisture ratio (MR). All data corresponding to the three slice thicknesses were combined into a single dataset for machine learning analysis.

For model development:

- Input variables: drying time (min) and slice thickness (mm)
- Output variable: moisture ratio (MR)

2.5. Machine Learning Models

To model the infrared drying kinetics of cactus fruit slices, several machine learning algorithms with different learning structures were employed and comparatively evaluated.

Artificial Neural Networks (ANN) were used due to their ability to approximate complex nonlinear relationships between input and output variables through interconnected layers of neurons. In drying applications, ANN models are particularly effective in capturing nonlinear heat and mass transfer behavior without requiring explicit physical assumptions (Khan et al., 2022).

Support Vector Machines (SVM) were employed for regression analysis owing to their strong generalization capability and robustness against overfitting, especially when working with relatively small datasets. By minimizing structural risk, SVM provides stable and accurate predictions for nonlinear drying processes (Hadjout-Krimat et al., 2023).

Random Forest (RF), an ensemble learning method based on multiple decision trees, was included to account for nonlinear interactions between variables through the aggregation of multiple weak learners. RF models are known for their resistance to noise and their ability to handle complex data structures (Sağlam & Çetin, 2022).

Linear Regression (LR) was used as a baseline model to represent linear relationships between variables and to highlight the limitations of linear approaches when modeling nonlinear drying kinetics (Khan et al., 2022).

2.6. Modeling Environment: Orange Data Mining

All machine learning analyses were conducted using Orange Data Mining, a visual programming-based data analysis software that enables reproducible machine learning workflows without the need for explicit coding. The experimental dataset was imported into the Orange environment, and all models were constructed using the same input–output structure.

Default hyperparameter settings provided by Orange Data Mining were used for all models to ensure a consistent and reproducible baseline comparison under identical modeling conditions.

The overall machine learning workflow implemented in Orange Data Mining, including experimental infrared drying data collection, dataset preprocessing, variable definition, model training, cross-validation, and performance evaluation, is schematically illustrated in Figure 2.

In addition to model training and cross-validation, Orange Data Mining was also used to generate parity plots, residual plots, and permutation-based feature importance scores for comparative model interpretation.

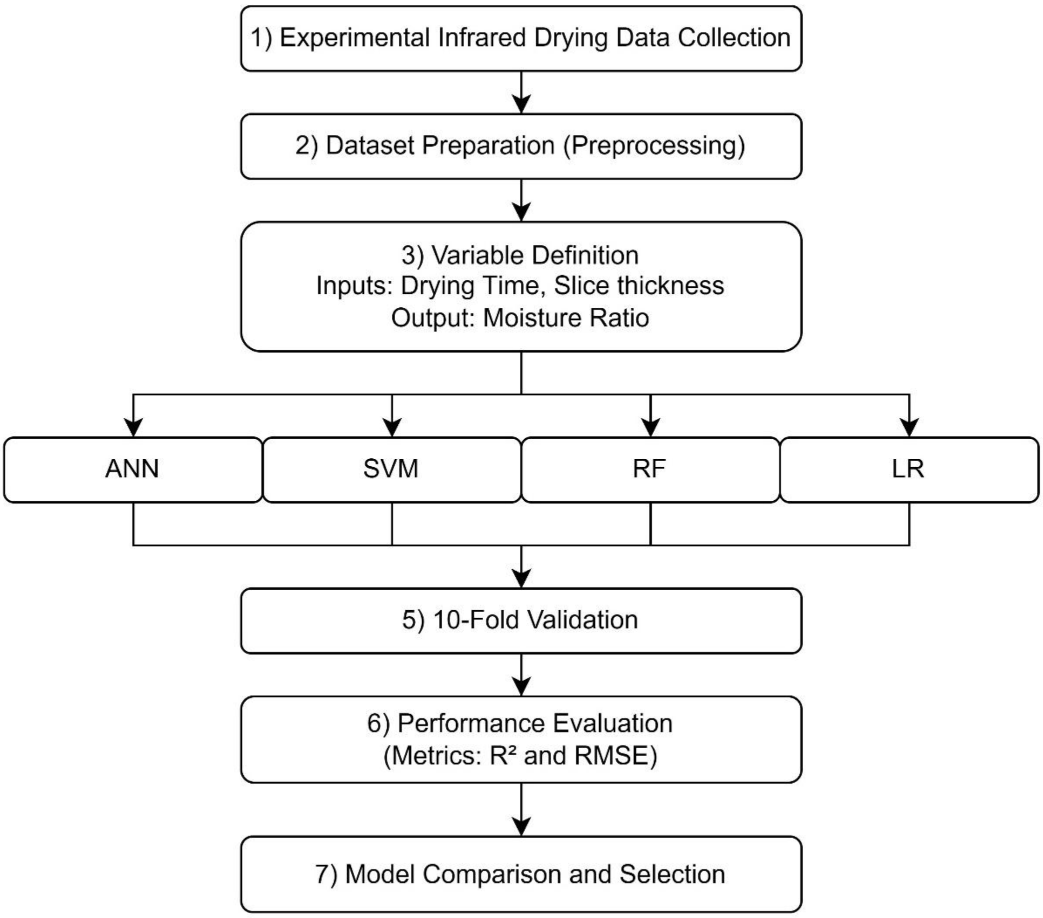

Figure 2. Workflow of the machine learning-based modeling approach implemented in Orange Data Mining for predicting the infrared drying kinetics of cactus pear slices.

2.7. Cross-Validation Procedure

Model performance was evaluated using 10-fold cross-validation (Sağlam & Çetin, 2022). In this procedure, the dataset was randomly divided into ten approximately equal subsets. In each iteration, nine subsets were used for model training, while the remaining subset was used for testing. This process was repeated until each subset had been used once as the test set (Khan et al., 2022).

All data corresponding to different slice thicknesses were evaluated together during the cross-validation process (Sağlam & Çetin, 2022).

2.8. Model Performance Evaluation

The predictive performance of the machine learning models was assessed using the coefficient of determination (R^2) and the root mean square error (RMSE), which are widely accepted statistical indicators for evaluating goodness-of-fit and prediction accuracy in drying kinetics and food process modeling studies (Sağlam & Çetin, 2022).

The coefficient of determination was calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(MR_{exp,i} - MR_{pred,i}\right)^2}{\sum_{i=1}^{N}\left(MR_{exp,i} - \overline{MR}_{exp}\right)^2} \tag{3}$$

where $MR_{exp,i}$ and $MR_{pred,i}$ represent the experimental and predicted moisture ratio values at the i-th data point, respectively, $\bar{MR}_{exp}$ denotes the mean of the experimental moisture ratio values, and N is the total number of observations (Hadjout-Krimat et al., 2023). The root mean square error (RMSE) was calculated using (Qadri et al., 2020):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(MR_{exp,i} - MR_{pred,i}\right)^2} \tag{4}$$

The combined use of R^2 and RMSE enabled a comprehensive evaluation of model performance by simultaneously capturing the overall explanatory power and the absolute prediction error of the machine learning models (Khan et al., 2022).

2.9. Graphical Analysis and Variable Importance

To further interpret model behavior, graphical analyses including parity plots, residual plots, and three-dimensional response surface visualizations were used. The relative contribution of input variables to moisture ratio prediction was evaluated for the SVM model using permutation-based feature importance analysis in Orange Data Mining. The resulting importance scores, expressed as the decrease in R^2 after permutation of each predictor, were normalized to percentage values for comparative interpretation. Final graphs and figure layouts were prepared using Microsoft Excel and MATLAB R2015a.

3. Results And Discussion

3.1. Overall Predictive Performance of Machine Learning Models

The overall predictive performance of the developed machine learning models for infrared drying kinetics of cactus pear slices was evaluated by comparing predicted and experimental moisture ratio (MR) values using statistical metrics and graphical analyses. The parity plots presented in Figure 3 illustrate the agreement between predicted and experimental MR values for the SVM, ANN, RF, and LR models.

As shown in Figure 3a and Figure 3b, both the Support Vector Machine (SVM) and Artificial Neural Network (ANN) models exhibited excellent agreement with the experimental data, with predictions tightly clustered around the 1:1 reference line. This strong correspondence indicates a high goodness-of-fit and confirms the capability of these models to capture the nonlinear drying behavior of cactus pear slices under infrared heating conditions. Similar trends have been reported in recent studies highlighting the effectiveness of ANN-based approaches in modeling complex drying kinetics of agricultural products such as potato slices (Tepe, 2024) and citrus fruits (Topal et al., 2024).

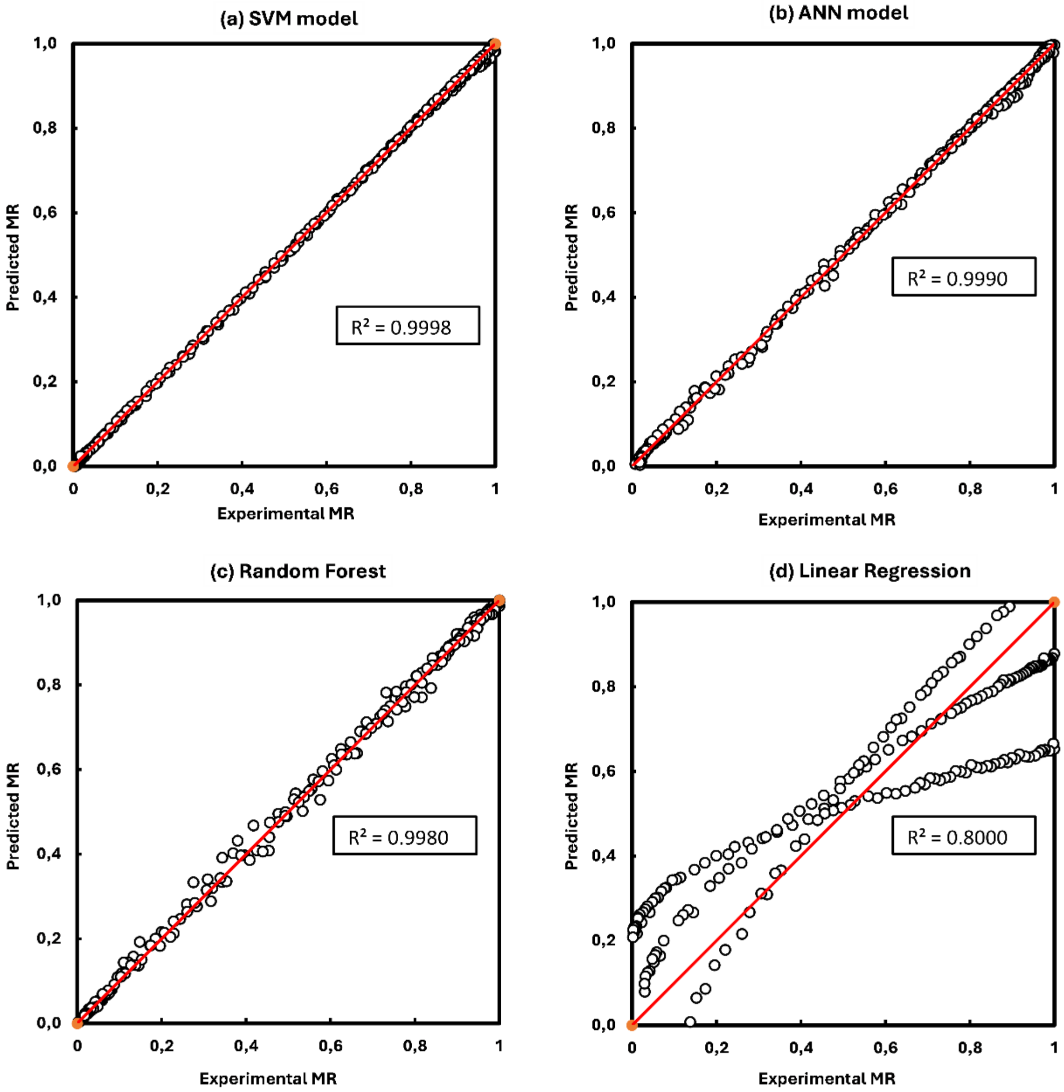

Figure 3. Comparison of predicted and experimental moisture ratio (MR) values obtained using (a) Support Vector Machine (SVM), (b) Artificial Neural Network (ANN), (c) Random Forest (RF), and (d) Linear Regression (LR) models for infrared drying of cactus pear slices. The dashed line represents the ideal 1:1 agreement between predicted and experimental values.

In contrast, the Random Forest (RF) model (Figure 3c) displayed a slightly wider dispersion around the 1:1 line, while the Linear Regression (LR) model (Figure 3d) showed pronounced deviations, particularly at low and high moisture ratio values. This behavior reflects the limited ability of linear models to represent nonlinear drying kinetics, a limitation frequently observed when modeling the dynamic moisture loss characteristics of biological materials (Sağlam & Çetin, 2022). The quantitative comparison of model performance is further supported by the RMSE values presented in Figure 4. Among all evaluated models, SVM achieved the lowest RMSE, followed closely by ANN, indicating superior prediction accuracy. The RF model yielded moderate error levels, whereas LR exhibited substantially higher RMSE values, confirming that linear modeling is inadequate for describing the complex heat and mass transfer phenomena governing infrared drying processes. These findings align with broader literature demonstrating that machine learning approaches (including SVM and ANN) provide significantly higher prediction accuracy compared to conventional semi-empirical models for various agricultural products (Çetin, 2022; Jibril et al., 2024).

The superior performance of the SVM model can be attributed to its structural risk minimization framework, which effectively balances model complexity and generalization capability, especially when experimental datasets are relatively small (Taheri et al., 2021). Likewise, the strong performance of the ANN model reflects its ability to approximate complex nonlinear relationships without requiring explicit assumptions regarding the underlying physical mechanisms. This feature provides a clear advantage over conventional thin-layer models, which often struggle to fully capture the rapid moisture removal behavior characteristic of infrared drying systems (Kilic, 2025; Sabbaghi et al., 2025). Overall, these results demonstrate that nonlinear machine learning approaches provide accurate and reliable alternatives to linear regression for modeling the infrared drying kinetics of cactus pear slices under the investigated conditions.

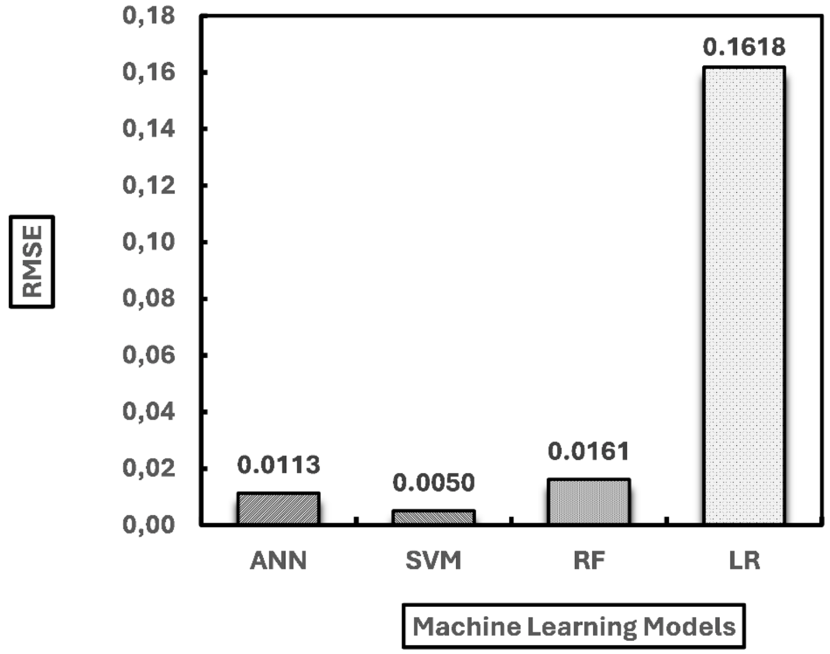

Figure 4. Root mean square error (RMSE) values of different machine learning models used to predict the infrared drying kinetics of cactus pear slices, highlighting the superior predictive accuracy of nonlinear models compared to linear regression.

3.2. Residual analysis and error distribution

Residual analysis was conducted to further assess the robustness and generalization capability of the developed machine learning models beyond conventional statistical performance indicators (e.g., RMSE, R^2, and χ^2), an approach strongly advocated in recent comprehensive evaluations of drying models (Buzrul, 2022; Kilic, 2025). The distribution, magnitude, and structure of residuals provide critical insight into whether a model adequately captures the underlying drying behavior without systematic bias.

An examination of the residual analyses presented in Figure 5 reveals clear structural differences among the predictive behaviors of the evaluated models. In the existing literature, Random Forest (RF) algorithms have frequently been reported to yield superior performance in drying kinetics prediction. For instance, Tran et al. (2025) demonstrated that RF was the most reliable model for capturing nonlinear drying behavior in Bitter gourd slices, while Sağlam and Çetin (2022) reported similar findings for apple slice drying. Likewise, Jibril et al. (2024) identified k-NN as the most accurate algorithm for modeling maize drying kinetics. In contrast to these general trends, the results obtained in the present study indicate that the Support Vector Machine (SVM) model exhibits the highest generalization capability for the investigated dataset. As illustrated by the residual distributions in Figure 5, the RF model showed a more localized clustering of residuals, whereas the SVM model exhibited a more homogeneous and randomly distributed residual pattern centered around zero. This behavior is consistent with the structural risk minimization principle emphasized by by Taheri et al. (2021).

These findings highlight that there is no universally optimal machine learning algorithm for modeling of drying kinetics. Instead, model performance is strongly dependent on dataset size, noise level, and the degree of nonlinearity inherent to the drying process. In this context, Support Vector Regression (SVR)-based approaches may provide more stable and reliable predictions than tree-based ensemble methods, such as RF or Gradient Boosting, particularly for moderate-sized experimental datasets. Consistent with the multi-criteria statistical validation framework proposed by Kilic (2025), the combination of low RMSE and high R^2 values obtained for the SVM model confirms its strong predictive capability not only for the training data but also for unseen observations.

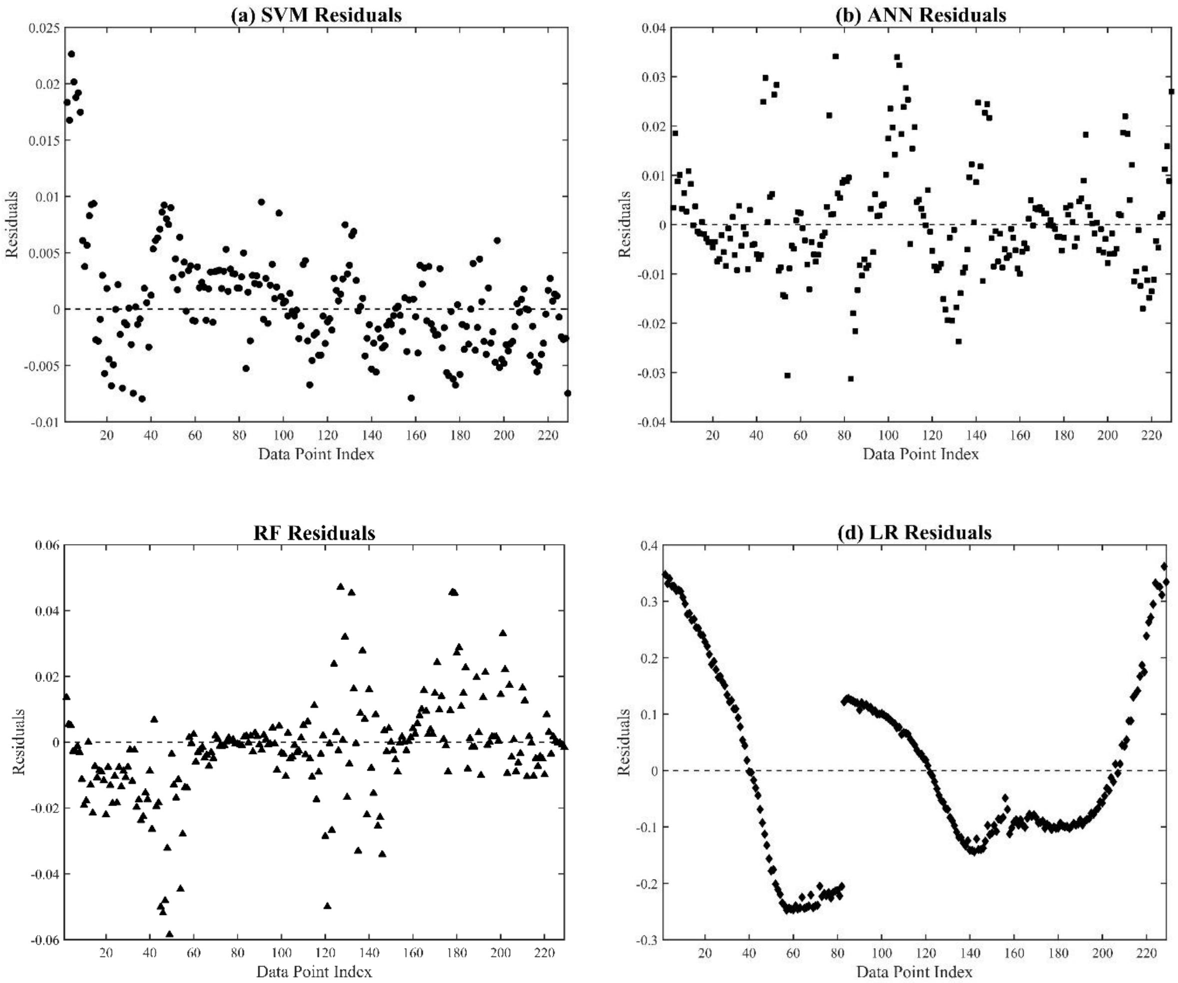

Figure 5. Residual distributions of machine learning models used for predicting the infrared drying kinetics of cactus pear slices: (a) Support Vector Machine (SVM), (b) Artificial Neural Network (ANN), (c) Random Forest (RF), and (d) Linear Regression (LR). The dashed horizontal line represents zero residuals, indicating perfect agreement between experimental and predicted moisture ratio values.

3.3. Effect of drying time and slice thickness on moisture ratio

The influence of drying time and slice thickness on the moisture ratio (MR) of cactus pear slices was further examined using the Support Vector Machine (SVM) model, which demonstrated the highest predictive accuracy among the evaluated approaches. Figure 6 presents the experimental and SVM-predicted MR profiles as a function of drying time for slice thicknesses of 2, 5, and 8 mm under infrared drying conditions.

As expected, the drying rate increased markedly with decreasing slice thickness. The 2 mm slices exhibited the most rapid moisture removal, reaching low MR values within a relatively short drying period, whereas the 8 mm slices required substantially longer drying times to achieve comparable moisture levels. This behavior reflects the increased internal mass transfer resistance associated with thicker samples, resulting from the longer diffusion path required for water migration from the core to the evaporating surface (El-Mesery et al., 2025). The phenomenon is governed by Fick's second law of diffusion, whereby an increase in sample thickness reduces effective moisture diffusivity and extends the falling-rate period typical of biological materials (Tepe, 2024; Zhang et al., 2024). The close agreement between experimental data and SVM predictions across all thickness levels indicates that the model successfully captured the observed drying behavior and reproduced the nonlinear trend of moisture removal with high accuracy. Such high fidelity in tracking the nonlinear moisture removal stage further supports the superiority of computational intelligence approaches over conventional semi-empirical equations in describing complex heat and mass transfer processes (Jibril et al., 2024; Srivastava & Sit, 2024).

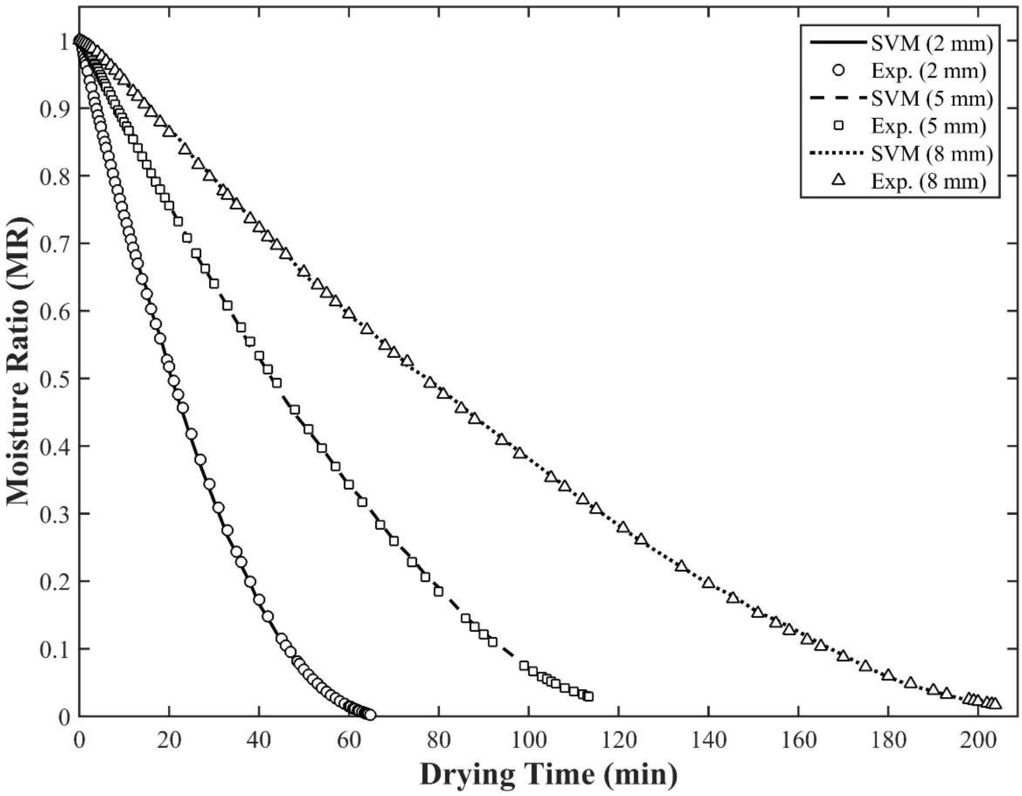

Figure 6. Experimental and Support Vector Machine (SVM)-predicted moisture ratio (MR) as a function of drying time for cactus pear slices with thicknesses of 2, 5, and 8 mm under infrared drying conditions.

The relative contributions of drying time and slice thickness to MR prediction were quantified by normalizing the permutation-based feature importance scores obtained from the SVM model, as illustrated in Figure 7. Drying time was identified as the dominant predictor, accounting for approximately 83.9% of the total relative importance, whereas slice thickness contributed 16.1%. Although slice thickness exhibited a lower relative importance than drying time, its contribution remained meaningful, particularly in shaping the drying trajectory and influencing the curvature of the moisture ratio profiles. This pattern suggests that drying time was the primary determinant of MR prediction, while slice thickness played a secondary but still relevant role. This interpretation is consistent with previous studies reporting that drying time is the main factor governing moisture ratio evolution, while slice thickness significantly affects drying kinetics by modifying drying rate and diffusion behavior (Çetin, 2022; Jiang et al., 2023).

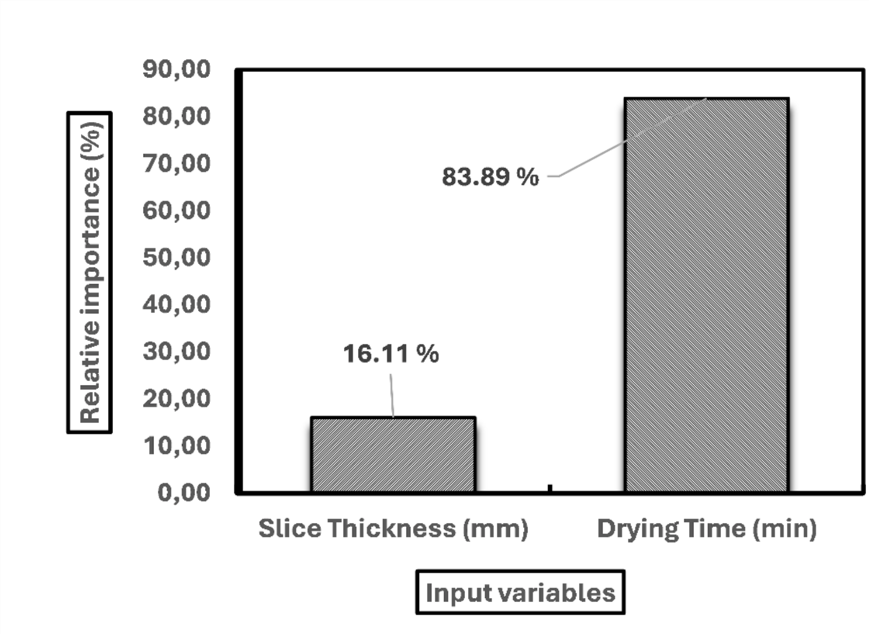

Figure 7. Relative importance (%) of input variables for predicting moisture ratio (MR) using the Support Vector Machine (SVM) model. The values were obtained by normalizing permutation feature importance scores based on the decrease in R^2.

The combined effects of drying time and slice thickness on moisture ratio are further illustrated by the three-dimensional response surface shown in Figure 8. The surface plot reveals a pronounced nonlinear decrease in MR with increasing drying time, with thicker slices maintaining higher MR values at equivalent drying durations. This interaction highlights the coupled influence of external energy input and internal diffusion resistance on infrared drying kinetics. The distinct curvature observed for thicker slices suggests a more diffusion-controlled regime, whereas thinner samples transition more rapidly through the surface-evaporation-controlled stage, as discussed in recent reviews on infrared heating and drying mechanisms (Ovando-Medina, 2023; Sabbaghi et al., 2025).

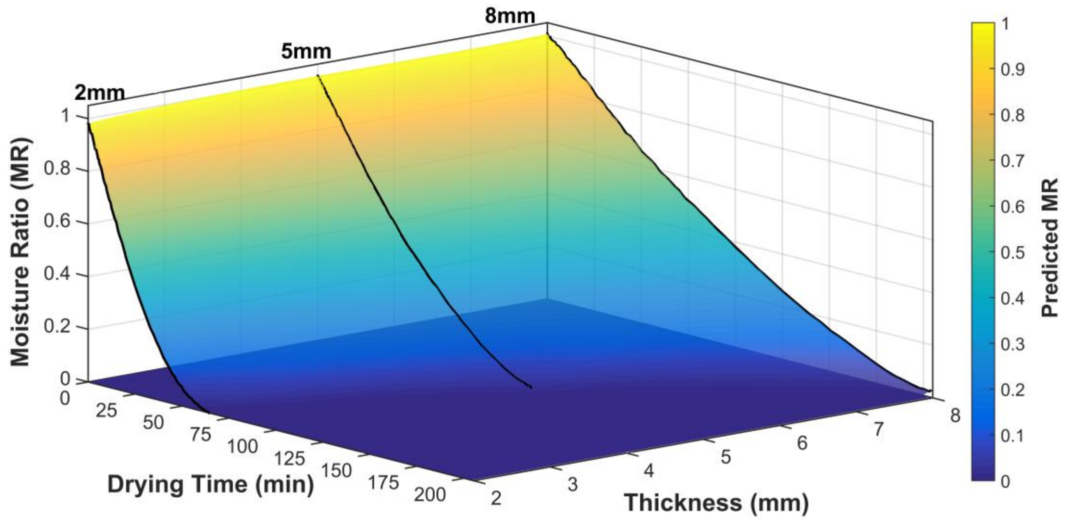

Figure 8. Three-dimensional response surface illustrating the combined effects of drying time and slice thickness on the predicted moisture ratio (MR) obtained from the Support Vector Machine (SVM) model.

Overall, the results indicate that although drying time primarily governs the instantaneous moisture ratio, slice thickness plays a decisive role in shaping the drying trajectory and total process duration. The ability of the SVM model to capture these coupled effects confirms its suitability for describing infrared drying behavior of cactus pear slices and provides a reliable basis for process optimization and scale-up considerations.

4. Conclusion

The main conclusions drawn from this study can be summarized as follows:

1. The infrared drying kinetics of cactus pear slices demonstrated pronounced nonlinear behavior, with drying time and slice thickness exerting a strong and interdependent influence on moisture ratio evolution.

2. Machine learning-based models exhibited substantially higher predictive accuracy than linear regression, highlighting the limitations of linear approaches in capturing the complex heat and mass transfer mechanisms involved in infrared drying.

3. Among the evaluated algorithms, the Support Vector Machine (SVM) model achieved the highest prediction performance, followed closely by the Artificial Neural Network (ANN), as evidenced by superior statistical indicators and residual distributions.

4. Overall, machine learning-based modeling provides a flexible and accurate framework for predicting infrared drying kinetics and may serve as a useful tool for future process optimization studies.

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Ethics Committee Approval

N/A

Ethics Statement

This article does not involve any studies with human participants or animals and therefore does not require ethics committee approval. The author also declares that AI-assisted tools (e.g., ChatGPT) were used only for English language editing, grammar correction, improvement of readability, and assistance in generating MATLAB codes for figure plotting. The experimental design, data analysis, model outputs, and scientific interpretations are entirely the original work and responsibility of the author.

Peer-review

Externally peer-reviewed.

Conflict of Interest

The authors have no conflicts of interest to declare.

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