Parameters priority analysis for improving radio frequency heating uniformity in agricultural products drying based on machine learning

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Abstract

Drying is essential to reduce postharvest agricultural product losses to ensure food security. Traditional drying methods like hot air drying suffer from high energy consumption and low product quality. Radio frequency (RF) drying has emerged as a promising alternative to traditional methods due to its volumetric heating and deep penetration advantages. However, non-uniform heating of RF technology remains a critical challenge restricting further commercialization. Previous approaches (such as finite element software) in improving RF heating uniformity have limitations. Therefore, a parameter priority analysis method combining literature data and machine learning was proposed to improve RF heating uniformity in agricultural products drying. A total of 356 data points were extracted from 18 selected literature on RF drying via a systematic search (2014-2024) of databases, including Web of Science and Google Scholar, constructing a dataset after applying screening criteria. Twelve machine learning models were used for analysis, with superior models selected based on model performance. The gradient boosting models were selected for parameter priority analysis. Parameter priority analysis identified moisture content and material (agricultural products) thickness as key parameters (thickness dominated in fruits & vegetables, moisture content in nuts) influencing RF heating uniformity. Across heating methods (RF, Hot air-assisted RF, Vacuum-RF), moisture content remained the most influential, with electrode gap as the primary parameter for RF and Hot air-assisted RF, and moisture content dominating in Vacuum-RF. The developed parameter priority analysis method can be further expanded to improve RF heating uniformity in different application scenarios (such as thawing and pasteurization).

Keywords: Moisture content; Hierarchical modeling; Multiple scenarios; Feature importance; Optimization

1. Introduction

Globally, food security is a critical societal challenge amid population growth and climate change. Post-harvest loss of agricultural products is a key challenge threatening food supply stability (Zhang et al., 2022; Tang, Jing, & Jiao, 2024). Meanwhile, agricultural products processing faces increasing pressure to reduce environmental impact, as traditional energy-intensive operations drive greenhouse gas emissions and resource depletion (Zeng et al., 2022). In this context, drying is an indispensable post-harvest operation for agricultural products (Khan, Sablani, Joardder, & Karim, 2022). Drying plays a pivotal role in inhibiting microbial growth, extending shelf life, and preserving product quality (Ge, Chen, Liu, & Liu, 2024). However, traditional drying methods like hot air drying suffer from limitations of long drying time and high energy consumption (Panigrahi & Singh, 2025; Zhang et al.,2025). Moreover, non-uniform drying leads to over-drying in hot spots (causing nutrient degradation and other quality losses) and inadequate drying in cold spots, failing to effectively inhibit microbial growth and insect infestation (Hou, Johnson, & Wang, 2016). For some agricultural products like camellia oleifera fruits and maize, improper hot-air drying temperature causes shell hardening, unbalanced heat-moisture transfer, reducing processing efficiency and value (Ge, Chen, Liu, & Liu, 2024; Yang et al., 2025). Thus, developing efficient, low-energy, and uniform drying technologies is crucial for addressing global food security and sustainability challenges.

Radio frequency (RF) heating technology is a promising alternative to traditional drying methods due to its ability to heat volumetrically and penetrate deeply (Zhang et al., 2022; Luo et al., 2024). However, despite recent research, the unevenness of the RF heating process remains a challenge limiting its drying application (Chen, Wang, Li, & Wang, 2015; Chen et al., 2016; Zhang et al., 2017; Chen et al., 2021; Gao et al., 2025a; Liu et al., 2025). Selecting key influencing parameters is crucial (Huang, Marra, Subbiah, & Wang, 2018; Lei et al., 2024). These parameters exhibit complex relationships with heating uniformity (Tang, Jing, & Jiao, 2024). So far, methods like numerical analysis (e.g., finite element models) and empirical approaches have been used to optimize parameters affecting RF heating uniformity (Marra, Zhang, & Lyng, 2009; Hou, Johnson, & Wang, 2016; Huang, Marra, Subbiah, & Wang, 2018; Altemimi et al., 2019; Ling et al., 2020; Abea et al., 2023; Gao et al., 2023). However, finite element models often rely on boundary conditions, and material (agricultural products) properties (Chen, Wang, Li, & Wang, 2015; Chen et al., 2016; Huang, Marra, Subbiah, & Wang, 2018). Thus, new parameter analysis strategies are needed. Big data analysis, combined with machine learning (ML), provide new parameter analysis strategies (Siddique et al., 2025). In food processing, this combined approach has been employed in several studies (Hernández, 2009; Lu et al., 2020; Siddique et al., 2025). Existing literature data on RF heating uniformity and related parameters remained a gap in constructing a database for big data analysis. Meanwhile, ML combined with other tools (such as finite element simulation) has already been applied for optimizing processing parameters in the food processing field, which provides a reference (Khan, Sablani, Joardder, & Karim, 2022; Gao et al., 2025b).

Systematic literature data analysis methods such as meta-analysis have been employed in several food research studies to quantify variability and support process optimization (Rana et al., 2024; Karamcheti, Brightwell, Bremer, & Schofield, 2025). Compared with these methods, ML has been utilized in numerous food processing studies, demonstrating its feasibility (Davies et al., 2021; Karamcheti, Brightwell, Bremer, & Schofield, 2025). Thus, literature in RF drying was selected to construct a dataset, which was analyzed by ML. The objectives of this study were (1) to extract and construct a database of RF heating uniformity and related influencing parameters from literature, and identify parameter priority via ML; (2) to rank parameter priority in dataset segments for different agricultural products and RF heating methods; (3) to guide parameter adjustment based on priority for improving heating uniformity in RF drying applications using ML models.

2. Materials and methods

2.1 Literature data collection and screening

Based on the number of literature searches using selected keywords in Web of Science and Google Scholar, RF drying was selected for this study due to the largest number of research articles. Original literatures were identified by searching databases including Web of Science and Google Scholar, with a focus on RF drying. The search keywords encompassed 'radio frequency', 'radiofrequency', 'heating uniformity', and 'drying'. Furthermore, to address keyword synonymy in RF drying research, asterisks (*) were added to retrieve root-word variants (i.e., belonging to the same term). Keywords were searched in both full and abbreviated forms. The period ranged from 2014 to 2024 (both the years of submission and the years of publication). Those irrelevant search results (e.g., RF applications in medicine) that arose from database search issues were manually eliminated. The filtering function of electronic databases was utilized to exclude irrelevant document types (e.g., review literatures and meeting abstracts). After the above initial screening was completed, the following supplementary criteria were formulated for further screening. Further screening criteria were:

(1) The selected literature focused on the RF drying application;

(2) The literature clearly reported numerical results or visual charts of the heating uniformity index (with the calculation formula specified);

(3) At least three numeric quantifiable parameters (numeric quantifiable parameters include frequency (MHz), electrode gap (mm), power density (W/cm²), dielectric constant (ε'), loss factor (ε''), geometric parameters (cm), moisture content (%), heating time (s or min) related to heating uniformity were included.

After screening, 18 research articles were incorporated (Wang et al., 2014a; Wang et al., 2014b; Zhou et al., 2019; Gu, Zhen, & Jiang, 2020; Wang et al., 2020a; Wang et al., 2020b; Mao et al., 2021; Wang et al., 2021; Wang, Tang, & Zhao, 2021; Mahmood et al., 2022; Ai et al., 2023; Dag et al., 2023; Geng et al., 2024; Li et al., 2024; Luo et al., 2024; Wang et al., 2024; Zheng et al., 2024; Sun et al., 2025). As shown in Fig. 1, within the selected range, years of the literature and authors of the research were randomly distributed, not on a specific year or a particular research team, ensuring the timeliness and comprehensiveness of the data.

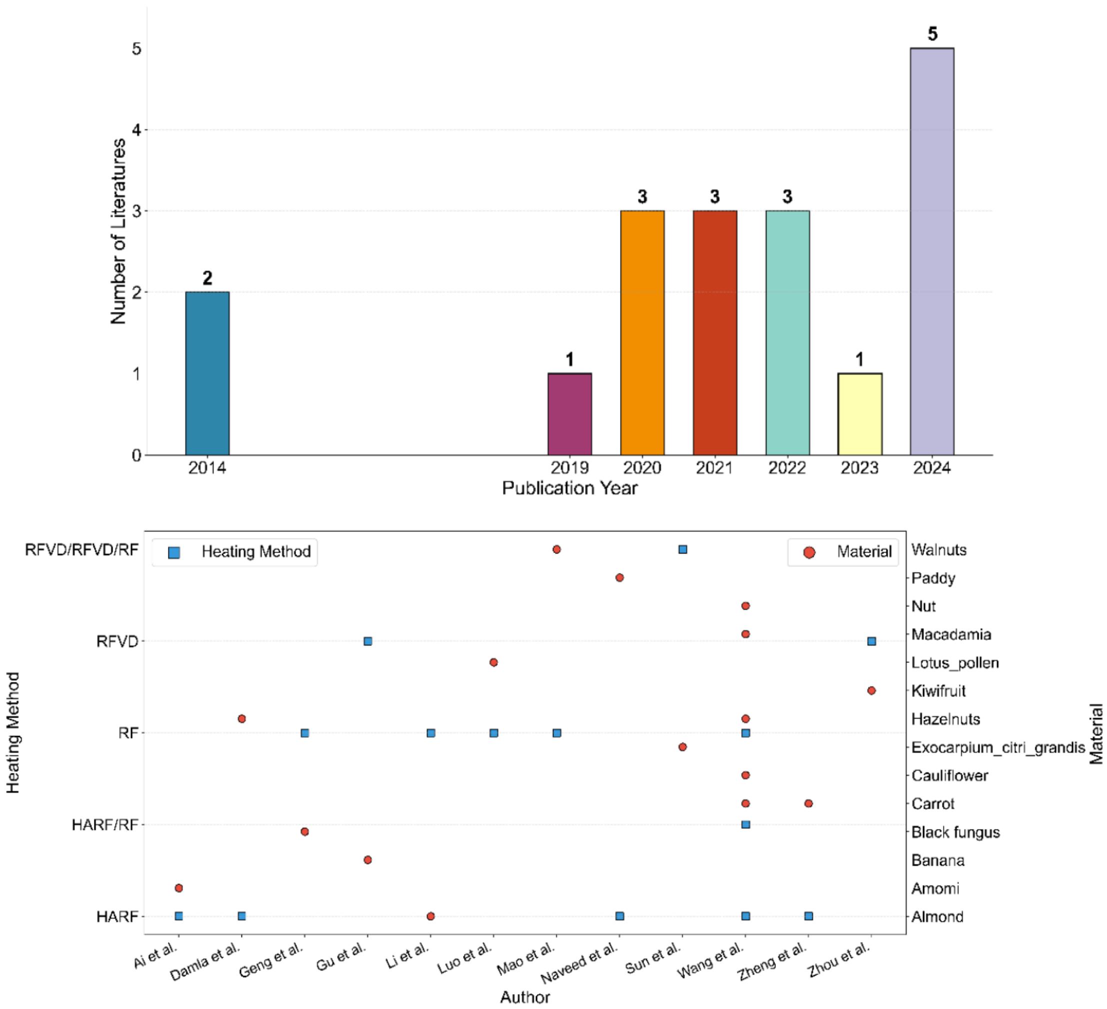

Fig.1. Literature statistics of radio frequency drying (2014-2024): The upper bar chart displays the numbers of selected RF drying literatures, while the lower scatter plot presents the heating methods (e.g., HARF, RF) and materials (e.g., nuts, fruits & vegetables) in different literature, clarifying literature sources for the multi-source parameter dataset.

2.2 Data screening and parameter selection

Through the visual charts in the literature, a total of 356 data points were extracted manually with the assistance of digitization tools (for points on linear graphs and unannotated bar charts, the corresponding data were extracted using Origin® 2022 (Origin Lab Corp., Northampton, USA)).

Microsoft® Excel 2019 (Microsoft Corporation, Redmond, WA, USA) was used to summarize the collected data. The dependent parameter extracted from the literature is the Heating Uniformity Index (λ), which is an indicator for evaluating the uniformity of temperature distribution during RF heating (Wang, Yue, Tang, & Chen, 2005). λ is uniformly defined as the ratio of the rise in standard deviation of sample temperature to the rise in average sample temperature during treatment. λ can be used to evaluate the heating uniformity of the treated samples (Wang, Yue, Tang, & Chen, 2005). A smaller λ indicates more uniform heating.

For numeric parameters, those affecting RF heating uniformity were selected based on prior literature, including material properties (the materials mentioned specifically refer to agricultural products in the selected literature), equipment settings, and container attributes. However, these parameters were not provided in all the literature. Therefore, for all the selected literature, the extraction and statistical analysis of these parameters were conducted. Only parameters with specific values, not missing in each literature, were selected to ensure the completeness of the data. The selected parameters: material thickness (mm), electrode gap (mm), moisture content (% w.b., wet basis), and container size (cm^3). The container size (cm^3) refers to the volume-related dimensions (length × width × height) of the container, tray, or other holding devices used for loading agricultural products s during the experimental determination of the heating uniformity index. The material thickness (mm) denotes the actual thickness in the literature experiments: for fruits and vegetables, it corresponds to the slice thickness after preprocessing (e.g., slicing); for nuts, it refers to the natural or adjusted thickness of the whole kernel or bulk layer; for grains, it indicates the bulk layer thickness of grains piled in the container during experiments (e.g., polished rice, wheat kernels stacked for RF drying or pest control). The moisture content (% w.b., wet basis) is the actual wet-basis moisture content of the agricultural products s measured in the original experiments. Specifically, it refers to the initial moisture content measured before the start of RF drying experiments, as dynamic moisture content (changing during drying) is not consistently reported in the selected literature and cannot be standardized for parameter priority analysis.

To address the critical error source of inter-study variability, along with agricultural products and heating method variations, three non-numeric parameters (material type, study variability, and heating method) were incorporated as independent parameters and subjected to one-hot encoding. One-hot encoding is a common technique in ML and data processing to convert categorical data into binary numerical features. One-hot encoding creates a separate binary column for each type, which is represented by a binary indicator parameter (Karamcheti, Brightwell, Bremer, & Schofield, 2025).

2.3 Dataset construction and preprocessing

The extracted parameter data encompass *λ*, four numeric parameters (material thickness (mm), electrode gap (mm), moisture content (% w.b., wet basis), and container size (cm^3)), and three non-numeric parameters (heating method, study variability, and material type) that quantify study variability. To eliminate the differences in parameter dimensions, standardization was carried out on the numeric parameters (material thickness, electrode gap, moisture content, container size). Feature standardization involved converting the feature values within the dataset to a specific range or distribution, ensuring that the data of different features possess the same scale. Z-score standardization was implemented on numerical features, with the mean of the numerical features set to zero and the standard deviation set to one. The data of different features were transformed to the same scale, eliminating the effects of dimensions and value ranges. The dataset was constructed using Microsoft Excel® 2019 (Version 16.52, Microsoft Corporation, Redmond, WA, USA), facilitating subsequent model processing.

2.4 Development of ML models for prioritizing RF drying parameters

2.4.1 Development and classification of ML models

Various ML models were employed based on the dataset to select the optimal model. In the RF drying dataset, nonlinear or linear relationships existed between parameters and RF drying uniformity. The computations were conducted on a Windows 10 (64-bit) system with hardware specifications: Intel i5-10200H CPU (4 cores, 8 threads), 16 GB DDR4 RAM, and NVIDIA GeForce GTX 2060. Python 3.12 (64-bit) (https://www.python.org/downloads/) and Scikit-learn 1.3.2 (Simple and Efficient Tools for Predictive Data Analysis) were used to construct 12 regression models. Models were classified into four main categories: linear models, support vector machines, tree-based and ensemble models, and gradient boosting models. Linear models included Linear Regression (ordinary linear regression), Lasso (L1-regularized linear regression), and Ridge (L2-regularized linear regression). Support vector machines included Support Vector Regression (SVR). Tree-based and ensemble models comprised Decision Tree, Random Forest (an ensemble of decision trees), AdaBoost (Adaptive Boosting), and Bagging (Bootstrap Aggregation regression). Gradient boosting models included LightGBM (Light Gradient Boosting Machine), XGBoost (eXtreme Gradient Boosting), Gradient Boosting (gradient-based regression), and CatBoost (Categorical Boosting).

2.4.2 ML model performance evaluation and selection

The model selection sub-module from the scikit-learn (sklearn) library was used to optimize the division of the training set and test set proportions. These proportions were determined through optimization for each specific dataset to maximize performance, and the random seed was fixed at 42 (a value aligned with domain conventions) to ensure the reproducibility of the results (Liu, Bober, & Kittler, 2023; Xie, Lin, Toh, & Zhou, 2025). The hyperparameters were optimized through grid search using the model selection submodule of the sklearn library. Targeted parameters included tree depth and learning rate.

Model performance was evaluated using the coefficient of determination (R^2) and the Normalized Mean Squared Error (*NMSE*), a normalized variant of the Mean Squared Error (*MSE*) that scales the error relative to the variance or range of the target values. The metrics sub-module of the Sklearn library in Python was used to evaluate model performance. R^2 is a dimensionless indicator that quantifies the ability to explain the data by comparing the model error with the benchmark error (Muthukumar, Gupta, & Saikia, 2024). R^2 was calculated using Eq. (1):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

Where y_i is the actual value, $\hat{y}_i$ is the predicted value, n is the number of samples, and $\bar{y}$ is the average value of the actual value.

Mean Squared Error (*MSE*) is the average value of the squared errors between the predicted value and the actual value, and it measures the average deviation between the predicted value and the actual value (Muthukumar et al., 2024). *MSE* was calculated using Eq. (2):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{2}$$

Where y_i is the true value of the i-th sample, $\hat{y}_i$ is the predicted value of the i-th sample, n is the total sample size.

NMSE is an indicator used to measure the difference between predicted values and actual values and is often used to evaluate the performance of models. It normalizes the *MSE* to enable the comparison of errors between datasets of different scales (Muthukumar et al., 2024). *NMSE* was calculated using Eq. (3):

$$NMSE = \frac{MSE}{Var(y)} = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)}{Var(y)} \tag{3}$$

Where y_i is the actual value, $\hat{y}_i$ is the predicted value, n is the number of samples, and $Var(y)$ is the variance of the dependent parameter.

2.4.3 Parameter priority analysis and visualization

To identify the parameter priority that affects the temperature uniformity in RF drying, ML models were used, providing a new parameter optimization strategy based on parameter priority. The numerical feature importance scores calculated by the ML models were used to quantify the priority of each parameter. Specific calculation methods:

Tree-based models obtain feature importance through the feature importance attribute within the model (Muthukumar et al., 2024). The attribute provides the contribution score of each feature to the prediction accuracy.

Random Forest: The Gini impurity reduction was calculated to quantify the parameter priority (e.g., electrode gap) on heating uniformity.

Gradient boosting models (LightGBM, XGBoost, CatBoost, Gradient Boosting): Information gain was used to evaluate parameters directly linked to heating uniformity, such as moisture content.

Linear Models (Lasso/Ridge): Regression coefficients were analyzed to quantify the priority of parameters on heating uniformity.

Support Vector Regression (SVR-Permutation Importance): Feature permutation tests were conducted to assess the priority of parameters.

The Matplotlib core visualization library, together with the Pandas library, was used to create static charts such as feature importance bar charts and comparison charts of actual values and predicted values. Visual processing enabled a clearer analysis of the order of feature importance.

2.5 Analysis of parameters priority affecting heating uniformity of RF drying and hierarchical modeling

The scikit-learn library was used for the calculation based on the principle of feature importance of the above models. The evaluation indicators for all the selected models were calculated after training, and then the type of model with the best performance was selected to conduct the parameter priority analysis. A certain type of model was chosen rather than a specific single model, because feature importance varied among different models. Even within the same type, feature importance may have slight fluctuations (Takefuji, 2025). To obtain stable and reliable feature importance, a comprehensive evaluation was conducted by combining the feature importance results of multiple models within a certain type of model.

Each test in the literature selected different heating methods and different agricultural products, which showed significant differences in dielectric constant and dielectric loss factors. Therefore, material type and heating method were chosen as the primary criteria for RF heating processes (targeting drying application). On the one hand, by refining the heating methods into RF, HARF (Hot air-assisted RF), and RFVD (Vacuum-RF), the resulting parameter priority guidelines can be more targeted to the unique operational characteristics of each heating method, offering precise guidance for parameter optimization in RF drying (Piedad, Larada, Pojas, & Ferrer, 2018). On the other hand, by delving into specific heating methods (RF, HARF, RFVD), the model can capture the unique parameter priority in the heating methods, distinguishing them from the overall parameter priority analysis. Therefore, through hierarchical modeling, the parameter sensitivity differences among different subsets (grouped by material type and heating method) were explored. In order to achieve the aforementioned exploration of parameter priority, the whole dataset needs to be divided. The dataset was grouped according to the following conditions: Material type: fruits and vegetables (such as bananas, carrots); nuts (such as macadamia nuts, walnuts); Heating method: RF, vacuum radio frequency drying (RFVD), and hot air-assisted radio frequency heating (HARF). All the data in the dataset were manually divided into sub-datasets for each scenario, and the same modeling method was adopted to establish models for each scenario. Each model was trained separately, and feature importance rankings across scenarios were derived. By comparing the differences in the ranking of feature importance, parameter priority analysis strategies for specific scenarios were provided. Furthermore, for the data distribution of the overall dataset and the classified dataset, plotting analysis was conducted using the Matplotlib and Pandas libraries of Python 3.12 to analyze the feature distributions before and after classification. The distribution of parameters in the dataset provided information on the data point count, value range, and proportion of each factor in the dataset for analyzing parameter priority in specific scenarios.

3. Results and discussion

3.1 Performance comparison of ML models in analyzing parameters influencing heating uniformity

The performance metrics for all evaluated ML models were summarized in Table 1. The linear models, including Lasso (R^2=0.4736, *NMSE*=0.5584), Ridge (R^2=0.4771, *NMSE*=0.5192), and Linear Regression (R^2=0.5323, *NMSE*=0.4644), exhibited lower R^2 and higher *NMSE* values among all models. These results indicated an insufficient capability of linear models to capture the complexities of the dataset, a limitation likely attributable to their deficiency in modeling complex nonlinear relationships, as noted in prior studies (Rahangdale & Raut., 2019; Gambella, Ghaddar, & Naoum-Sawaya, 2021; Ennaji, Verguetz, & El Allali, 2023). Tree-based models demonstrated an improvement over the linear models. For instance, Random Forest (R^2=0.5764, *NMSE*=0.4296) achieved an R^2 approximately 0.10 higher and an *NMSE* about 0.09 lower than the standard Linear Regression. This result underscored the ability of tree-based models to capture nonlinear patterns. However, their predictive performance can be susceptible to fluctuations in high-dimensional spaces with categorical parameters (Rahangdale & Raut., 2019; Gambella, Ghaddar, & Naoum-Sawaya, 2021; Ennaji, Verguetz, & El Allali, 2023). Gradient boosting models (Gradient Boosting: R^2= 0.5753, *NMSE*= 0.4217; LightGBM: R^2=0.5520, *NMSE*=0.4449; XGBoost: R^2=0.5805, *NMSE*=0.4166; CatBoost: R^2=0.6005, *NMSE*=0.3967) demonstrated better performance than linear models, tree-based models, and other models on overall datasets. Specifically, the R^2 values of the gradient boosting models were 0.12-0.13 higher than those of the linear models, while their NMSE values were 0.12-0.16 lower. These results further demonstrated the superiority of gradient boosting algorithms in predicting heating uniformity in RF drying. Gradient boosting models also exhibited strong fitting capabilities and robustness to complex nonlinear interactions in other related field studies (Rahangdale & Raut, 2019; Gambella, Ghaddar, & Naoum-Sawaya, 2021; Ennaji, Verguetz, & El Allali, 2023).

Table 1 Comparative analysis of model performance based on the overall dataset

Model	R^2	*NMSE*
Lasso	0.4736	0.5584
Ridge	0.4771	0.5192
Linear Regression	0.5323	0.4644
Decision Tree	0.5227	0.4740
Random Forest	0.5764	0.4296
Gradient Boosting	0.5753	0.4217
LightGBM	0.5520	0.4449
XGBoost	0.5805	0.4166
CatBoost	0.6005	0.3967
SVR	0.4505	0.5456
AdaBoost	0.4933	0.5032
Bagging	0.5668	0.4302

Notably, the overall R^2 values of all ML models (maximum 0.6005 for CatBoost) remained at a moderate level, which stemmed from challenges encountered by ML models when modeling heating uniformity in RF drying research. The dataset exhibited high heterogeneity, integrating samples across multiple material types (e.g., high-moisture fruits and vegetables, low-moisture nuts) and heating methods (RF alone, HARF, RFVD). This led to a scattered data distribution that hindered effective learning. This observation was consistent with findings from similar modeling studies, where data complexity was increased when categorical parameters (e.g., agricultural products category) introduced additional dimensionality (Islam, Sablani, & Mujumdar, 2003; Ispirova, Eftimov, & Seljak, 2020). Furthermore, the interactions between input parameters were highly nonlinear. Numerical parameters (moisture content, electrode gap) and categorical parameters (agricultural products category, heating method) formed a high-dimensional feature space, and even advanced gradient boosting models struggled to quantify the coupling effects fully (Khan, Sablani, Joardder, & Karim, 2022; Tarlak, 2023). Additionally, the data used in this study were collected from the literature, and factors related to these literature-derived data further impacted model performance. Specifically, variations in literature quality, data integrity, experimental equipment, and test conditions across studies introduced inconsistencies into the dataset (Chen et al., 2024). For example, differences in RF generator specifications, temperature measurement tools, or material pretreatment methods between experiments led to unavoidable variability in the collected data. Such inconsistencies made it harder for models to identify consistent relationships between parameters and heating uniformity, further constraining predictive accuracy. The present limitation arises from the obstacle of reconciling data-driven fitting with physical coupling scenarios (Chen et al., 2024). These factors collectively constituted the core challenges faced in the modeling process and identified clear directions for further improvements.

Regarding the RF system type, statistical analysis of the 18 selected literature showed that all adopted free-oscillating RF systems, with no data related to 50 Ohm matched RF systems or comparative studies on the two system types. Thus, the influence of system type differences on heating uniformity was not analyzed in this study. For the heating rate, systematic screening showed that heating rate data were not reported in most of the selected literature. Due to the lack of available and standardized data, the heating rate was not included in the parameter priority analysis. These omissions were mainly attributed to the limitations of existing RF drying literature data reporting, and future research could expand the literature scope or conduct targeted experiments to supplement relevant data.

Fig. 2 shows a comparison between the predicted heating uniformity values (blue points) and the actual heating uniformity values (red points) of the gradient boosting models, the linear models, and the tree models. The predicted values of gradient boosting models (e.g., XGBoost, CatBoost) were much closer to the actual values along the ideal fitting line (black line) compared to other models (e.g., Lasso, Random Forest). This result indicated that the gradient boosting models were superior in modeling the relationship between dependent parameters and the heating uniformity of RF drying, though the other models could also capture certain relationships. By comparing the dispersion of distances between predicted heating uniformity values and actual heating uniformity values of the four gradient boosting models, it was found that even for the same type of models, there were differences in their modeling capabilities. Furthermore, CatBoost (R^2=0.6005, *NMSE*=0.3967) outperformed XGBoost (R^2=0.5805, *NMSE*=0.4166), LightGBM (R^2=0.5520, *NMSE*=0.4449), and Gradient Boosting (R^2= 0.5753, *NMSE*= 0.4217) based on both R^2 and *NMSE* metrics. This might be due to non-numeric parameters (e.g., material type, heating method) increasing data dimensionality, thereby causing prediction performance fluctuations across datasets, also a common challenge in such modeling scenarios (Islam, Sablani, & Mujumdar, 2003; Ispirova, Eftimov, & Seljak, 2020; Khan, Sablani, Joardder, & Karim, 2022; Tarlak, 2023). Therefore, when conducting parameter priority analysis, it is necessary to combine multiple models rather than choosing a single model. Based on the above analysis, the gradient boosting models, which were superior to other algorithms (Linear, Random Forest, and others), were thus chosen for the subsequent parameter priority analysis on the RF drying dataset. Although ML conducts predictive analysis by capturing complex relationships in the data, it cannot directly determine whether the captured relationships conform to the theoretical knowledge of RF drying. Thus, subsequent analysis also incorporated the physical mechanisms and experimental data of RF drying.

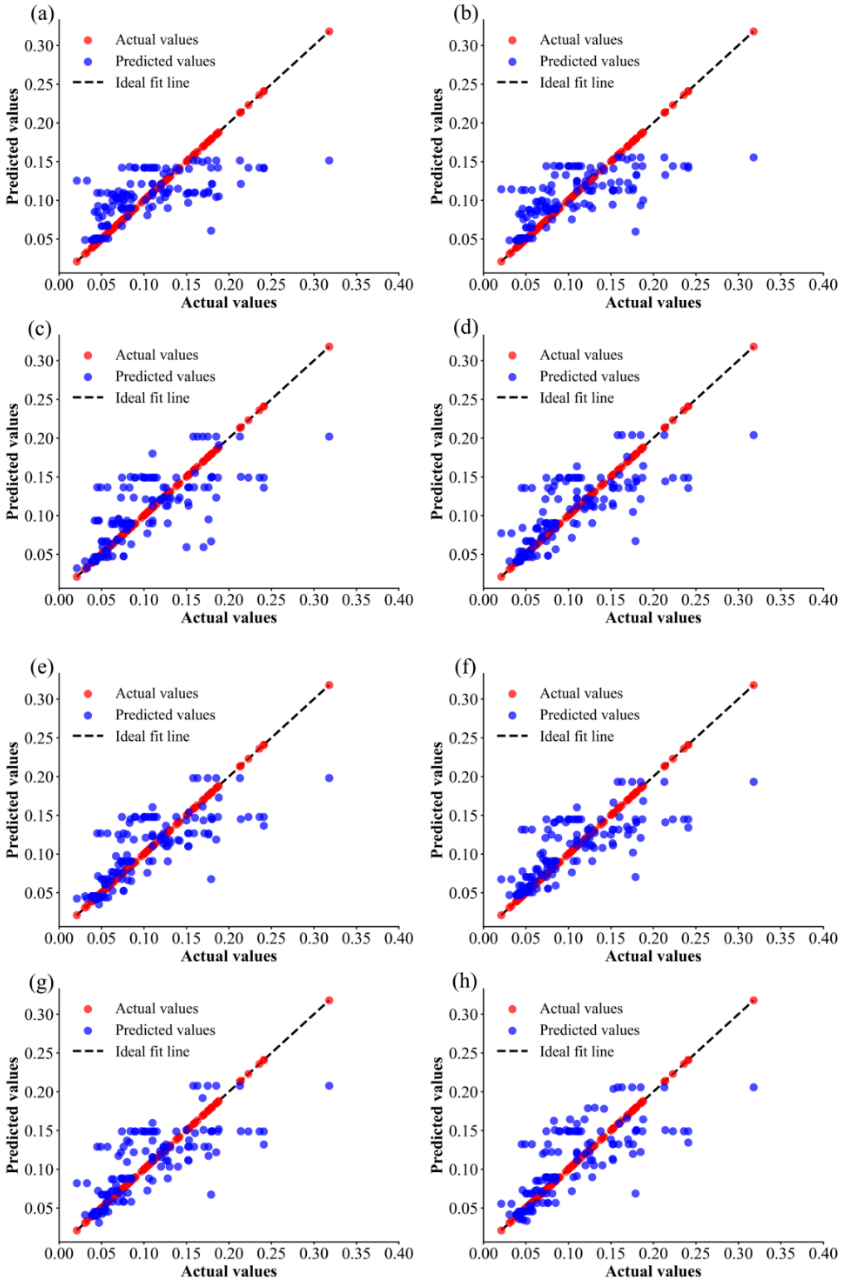

Fig. 2. Comparison of predicted and actual RF heating uniformity index (λ) among models. (a) Lasso model. (b) Ridge model. (c)Decision Tree model. (d) Random Forest model. (e) CatBoost model. (f) XGBoost model. (g) Gradient Boosting model. (h) LightGBM model. Each subfigure presents the relationship between predicted values (blue dots) and actual values (red dots), with the black dashed line as the ideal fit where the two align perfectly. Closer and less dispersed dots indicate better predictive performance for RF heating uniformity, while greater distance and dispersion correspond to poorer performance.

3.2 Global priority analysis of parameters affecting RF drying

Since the gradient boosting models performed best in the RF drying dataset, they were selected for the parameter priority analysis. As shown in Fig. 3, the results consistently identified moisture content as the parameter with the highest impact on heating uniformity, with high importance scores (e.g., 0.38 in CatBoost, 0.29 in Gradient Boosting). This result established moisture content as a critical parameter to prioritize in the RF drying process. This is primarily because moisture content directly impacts the dielectric constant and dielectric loss factor of agricultural products, two key properties that determine the efficiency of RF energy absorption (Guo, Tiwari, Tang, & Wang, 2008; Yang et al., 2014; Ling et al., 2015; Zhang, Zhou, Ling, & Wang, 2016; Zhu & Guo, 2017; Li et al., 2024a). For drying, uneven moisture distribution causes inconsistent RF energy absorption and uneven dehydration. Identifying moisture content as the top parameter priority provides clear practical guidance such as preconditioning initial moisture or targeted process adjustments. This result effectively improving drying consistency, reducing quality loss, and enhancing industrial production efficiency.

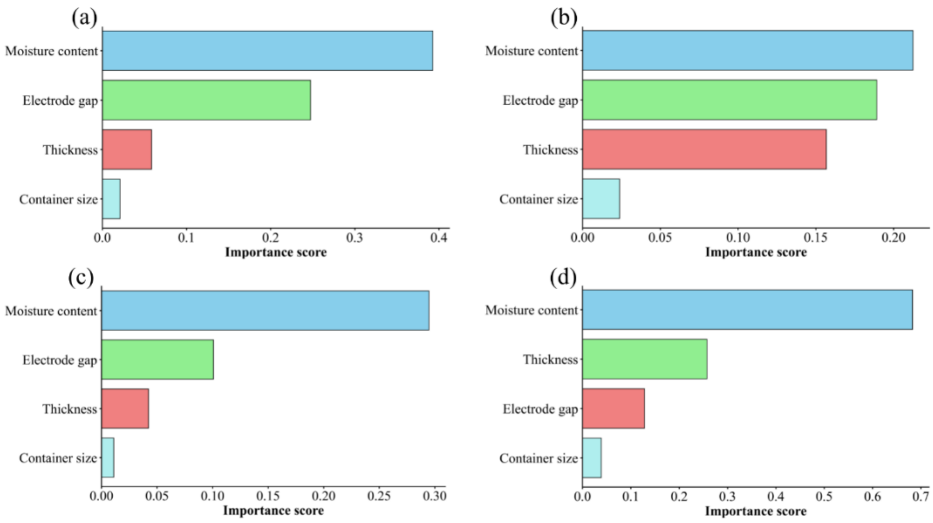

Fig. 3. Ranking of feature importance for parameters affecting RF heating uniformity (λ) in the whole dataset. (a) CatBoost model feature importance. (b) XGBoost model feature importance. (c) Gradient Boosting model feature importance. (d) LightGBM model feature importance. Each subfigure presents the sorted feature importance scores of different parameters (moisture content, electrode gap, thickness, container size) affecting RF heating uniformity (λ) for the corresponding model.

The analysis ranked electrode gap as the second most important parameter, with the second-highest scores (e.g., 0.24 in CatBoost, 0.19 in XGBoost). Electrode gap affects energy coupling efficiency by altering electric field distribution: a smaller gap can enhance the local electric field intensity, but excessively narrowing it may lead to edge effects and cause arc discharge (Huang, Marra, Subbiah, & Wang, 2018; Ling, Cheng, & Wang, 2020; Zhang, Zhang, Zhu, & Zhao, 2022; Zuo et al., 2023; Jin, Zhang, & Mujumdar, 2024a). For RF drying, optimizing electrode gap ensures uniform electric field, enabling a consistent moisture evaporation rate and avoiding some parts drying too quickly to cause nutrient degradation while others dry too slowly to result in prolonged processing time, which is crucial for industrial-scale continuous drying.

Although material thickness and container size have an impact on heating uniformity, their importance (material thickness scores around 0.10; container size scores <0.05) is relatively lower in our research results compared to moisture content and electrode gap (moisture content scores around 0.40; electrode gap scores around 0.25). For material thickness, it mainly regulates RF energy penetration—excessive thickness limits inner-layer energy, while overly thin thickness speeds up surface heat loss. Additionally, variations in material thickness (e.g., uneven thickness of samples or inconsistent bulk layers) can cause electric field distortion between electrodes, leading to abnormal enhancement or attenuation of local electric field intensity and further exacerbating uneven heating (Chen et al., 2024). The lower importance of material thickness stems from being overshadowed by the moisture content and electrode gap. The core role of the container size is reflected in changes to the material density and the boundary conditions of the electric field (Zhang, Huang, & Wang, 2017b; Zuo et al., 2023; Tasci, Liu, Erdogdu, & Ozturk, 2024). An overly large container may intensify electric field attenuation due to uneven agricultural products distribution, while an overly small container size limits processing capacity and increases heat loss at the walls (Zhang, Huang, & Wang, 2017b; Zuo et al., 2023; Tasci, Liu, Erdogdu, & Ozturk, 2024).

Overall, the parameter priority (moisture content > electrode gap > material thickness > container size) provided clear guidance for RF drying optimization. Prioritizing moisture content regulation and electrode gap adjustment directly improves heating uniformity and efficiency, while controlling material thickness and container size ensures batch consistency, all serving the ultimate goal of RF drying (fast, uniform, low-energy dehydration with quality retention).

3.3 Analysis of the priority of RF drying parameters in hierarchical modeling

Grains usually have low moisture content, high porosity, and low dielectric loss (Cui et al., 2020; Ling, Cheng, & Wang, 2020; Liu, Qu, Liu, & Wang, 2021; Zhang, Zhang, Zhu, & Zhao, 2022). Conversely, fruits and vegetables usually have high moisture content, compact structure, and high dielectric loss (Birla, Wang, Tang, & Hallman, 2004; Birla, Wang, Tang, & Tiwari, 2008; Lara, Takahashi, Nagaya, & Uemura, 2021; Tang, Jing, & Jiao, 2024). When RF heating is used alone, heating uniformity is largely affected by the dielectric properties of the agricultural products, specifically the dielectric constant (ε') and loss factor (ε'') that govern RF energy absorption (Yang et al., 2014; Zhu & Guo, 2017). Unlike combined methods (HARF or RFVD) that mitigate such discrepancies via auxiliary heat transfer, standalone RF heating lacks supplementary regulation, making local overheating more likely (Marra, Zhang, & Lyng, 2009). In the case of RFVD, the vacuum environment lowers heat loss caused by air flow (heat convection loss), thereby enhancing heating uniformity (Gu et al., 2020). HARF remedies the uneven heating in marginal zones (e.g., localized overheating or insufficient heating) of RF heating via hot air convection (Wang et al., 2020b; Wei, Xie, Zheng, Ren, & Yang, 2023). To reflect the priority of specific parameters in RF drying for different agricultural products and heating methods, the dataset was categorized by agricultural products and heating methods.

3.3.1 Dataset classification by material type

During the training of all materials, the model was primarily dominated by data points from high-moisture fruits and vegetables, which constitute a large sample size. Fig. 4 shows their distribution across various materials in the constructed dataset. However, due to the limitations of drying application scenarios, grains are primarily studied for RF pest control in the RF field, resulting in insufficient data points for grains (n<30). Thus, hierarchical modeling for the grain type could not be achieved (Fig. 4).

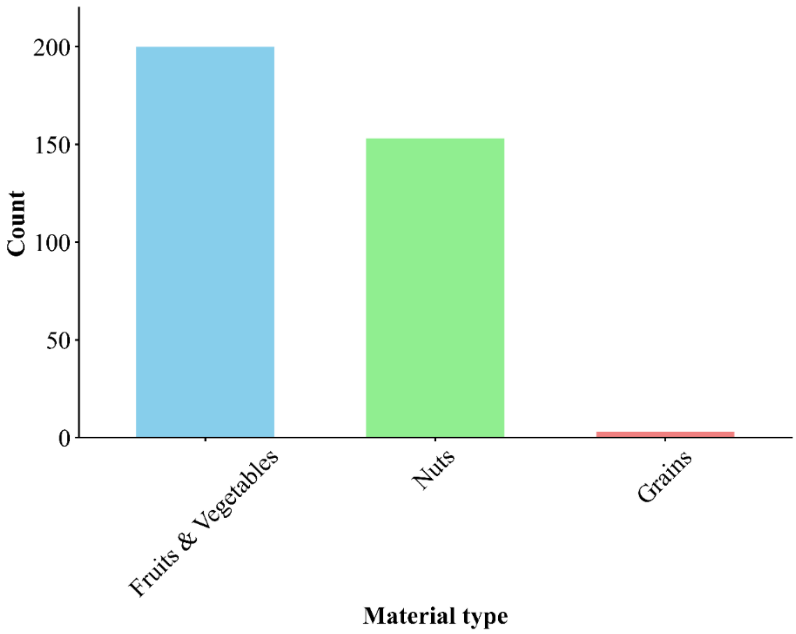

Fig. 4. Distribution of data points across different material type in the dataset. Count represents the number of data points; Material types include fruits & vegetables, grains and nuts. The distribution represents the quantity distribution of these data points in the constructed dataset.

Figs. 5-8 show the distribution of selected parameters (material thickness, moisture content, electrode gap, and container size) in the dataset. These distributions help explain the parameter effects on RF heating uniformity and minimize the impact of data distribution variations originating from different literature sources.

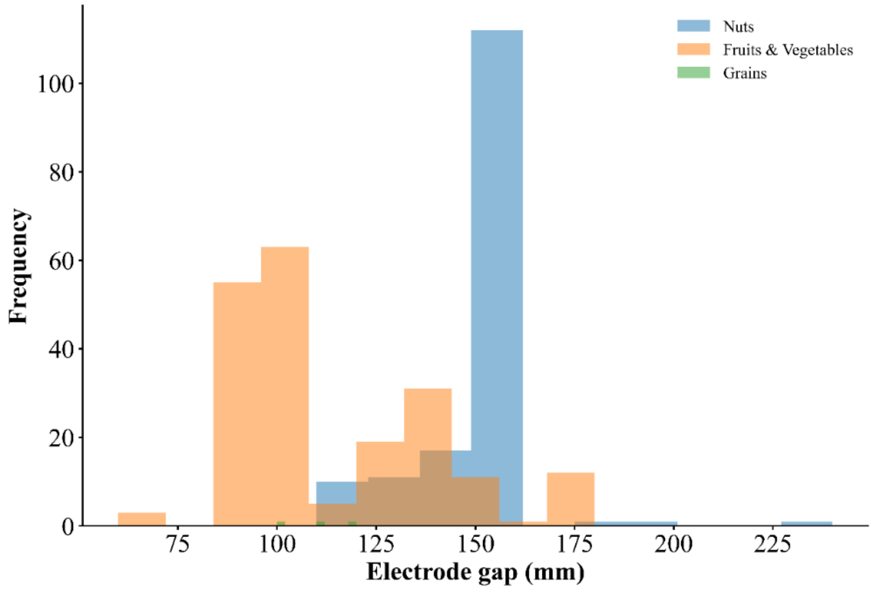

Fig. 5. Distribution of electrode gap across different material types in the dataset. Electrode gap refers to the specific numerical values set in the selected literature. The X-axis represents the electrode gap value (unit: mm), and the Y-axis represents the frequency (indicating the number of data points). This distribution reflects the quantity distribution characteristics of electrode gap values selected for different material types (fruits & vegetables, grains, nuts) in the collected literature experiments.

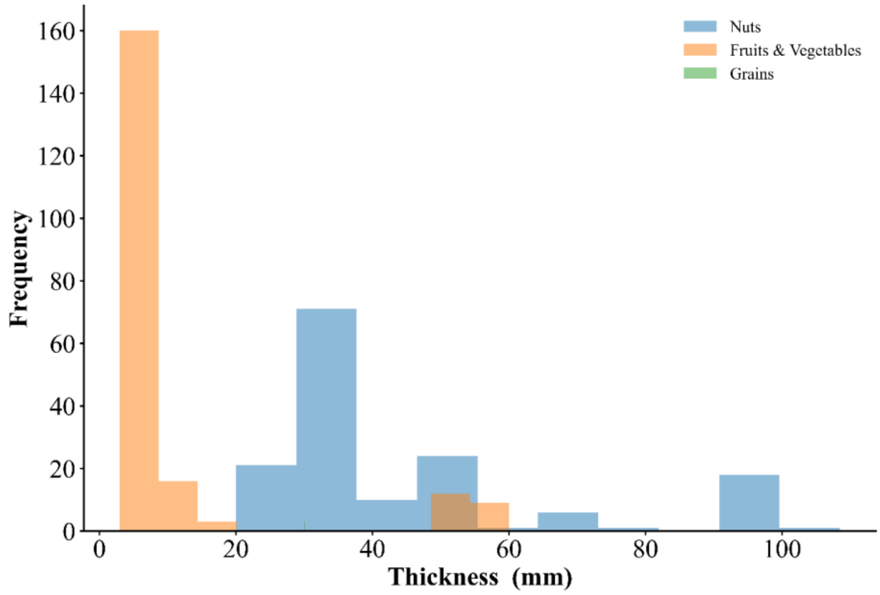

Fig. 6. Distribution of material thickness across different material types in the dataset. Material thickness refers to the actual thickness values of agricultural products used in the collected literature experiments. The X-axis represents the material thickness value (unit: mm), and the Y-axis represents the frequency (indicating the number of data points). This distribution reflects the quantity distribution characteristics of material thickness values for different material types (fruits & vegetables, grains, nuts) in the collected literature experiments.

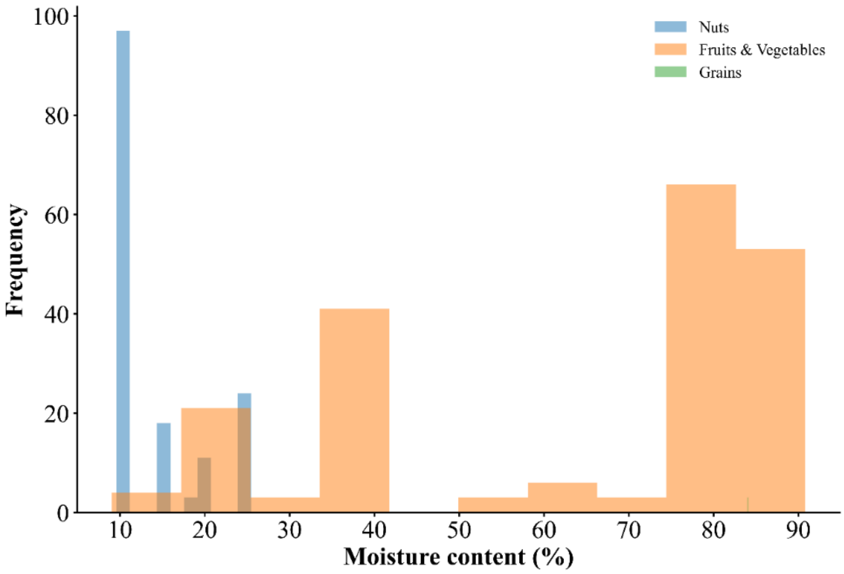

Fig. 7. Distribution of moisture content across different material types in the dataset. Moisture content refers to the initial moisture content parameter of agricultural products, expressed on a wet basis (% w.b.) as reported in the collected literature experiments. The X-axis represents the moisture content value (unit: % w.b.), and the Y-axis represents the frequency (indicating the number of data points). This distribution reflects the quantity distribution characteristics of moisture content values for different material types (fruits & vegetables, grains, nuts) in the collected literature experiments.

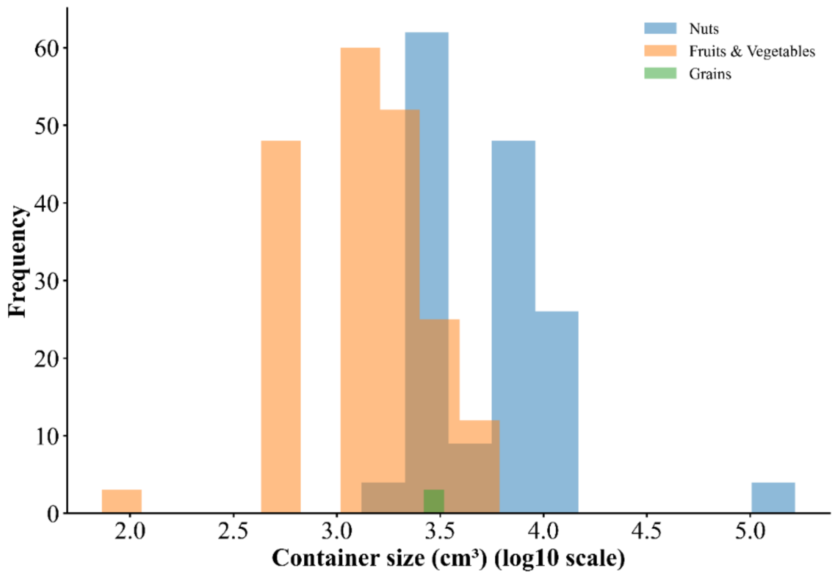

Fig. 8. Distribution of container size across different material types in the dataset. Container size refers to the volume parameter of containers/trays used for loading agricultural products in the collected literature experiments. The X-axis represents the container size value (unit: cm^3) with a log10 scale, and the Y-axis represents the frequency (indicating the number of data points). This distribution reflects the quantity distribution characteristics of container size values for different material types (fruits & vegetables, grains, nuts) in the collected literature experiments.

Tables 1S and 2S show the performance of the models for subsets divided by materials. The gradient boosting models performed better than other models on the subsets. For nuts, CatBoost achieved R^2=0.6102, *NMSE*=0.3813; For fruits and vegetables, LightGBM achieved R^2=0.6679, *NMSE*=0.3279. Therefore, the gradient boosting models were used as the tool for the subsequent parameter priority analysis.

Fig. 1S shows the feature importance ranking of the nut dataset. The difference in feature importance scores between the whole dataset and segmented subsets was due to the default non-normalized calculation mechanism of gradient boosting models (e.g., LightGBM, XGBoost), which use cumulative split gains (Kaneko, 2023; Lamens, & Bajorath, 2025). In smaller subsets, dominant features' split gains were amplified by concentrated data distribution, but their relative importance ranking remained consistent (Rengasamy et al., 2022; Kaneko, 2023; Lamens, & Bajorath, 2025; Takefuji, 2025). Since our analysis focused on ranking rather than absolute scores, this numerical variation did not affect the conclusion that core parameters (e.g., moisture content, material thickness) dominate in specific scenarios. The parameter ranking for this dataset changed compared to the overall dataset. The feature importance ranking for the nuts data (Fig. 1S) indicated that the moisture content is the key parameter affecting the nut material (e.g., 32 in CatBoost, 0.19 in XGBoost). Due to their low moisture content and high fat content, nut materials encounter problems of limited penetration depth during RF heating (Zhang, Zhou, Ling, & Wang, 2016; Li et al., 2024b). Therefore, in the heating process of nut samples, the primary focus should be on the pre-treatment to adjust the initial moisture content to a range conducive to better heating uniformity, given that moisture content varies naturally throughout drying and cannot be artificially controlled effectively. Moisture content varies naturally during drying and is hard to control in real time, making preconditioning even more essential. The electrode gap and material thickness also showed notable effects. For example, electrode gap scores around 18 in CatBoost, and material thickness scores around 400 in LightGBM. However, unlike fruits and vegetables, adjusting thickness for nut samples exhibits limited necessity as a key adjustment parameter in RF drying. Instead, optimizing the electrode gap proves more effective for enhancing heating uniformity in nut-specific RF processing (Wang et al., 2020a; Mao & Wang., 2023). Practically, preconditioning an initial moisture content (wet basis) of nuts before RF drying is suggested. Matching the dielectric property characteristics of low-moisture nuts, mitigates localized overheating. The preconditioning can be achieved via short-term air drying, which is low-cost and easy to integrate into existing production lines.

The feature importance ranking of fruits and vegetables obtained is shown in Fig. 2S. The results indicated that material thickness during RF heating was the key influencing parameter for the RF drying of fruits and vegetables (e.g., 50 in CatBoost, and 0.25 in XGBoost). This is mainly because these materials require special treatments such as slicing in actual experiments (Birla, Wang, Tang, & Hallman, 2004; Birla, Wang, Tang, & Tiwari, 2008; Lara, Takahashi, Nagaya, & Uemura, 2021; Tang, Jing, & Jiao, 2024), and the artificially selected material thickness may have shown an influence greater than the inherent moisture content characteristic of the material (Skara et al., 2023). Then, considering the secondary importance of moisture content described in Fig. 2S-moisture content scores 0.17 in LightGBM, 50 in CatBoost, it can be concluded that when drying fruits and vegetables by RF, the thickness of the agricultural products after slicing should be considered first, followed by the high moisture content of the agricultural products. Some studies in the field of RF also reported similar conclusions regarding moisture content and slice thickness (Bassey, Cheng, & Sun, 2021; Tang, Jing, & Jiao, 2024). On the one hand, existing RF experiments indicated that heating of agricultural products, especially fruits and vegetables, was influenced by material thickness (Tang, Jing, & Jiao, 2024). Sample thickness affects moisture migration during RF drying. Excessive thickness causes internal moisture accumulation, while overly thin samples accelerate surface moisture evaporation. Such uneven moisture distribution induces changes in dielectric properties, further exacerbating uneven heating. On the other hand, these differences were caused by the significant variations in the type of materials used in the research. These variations existed not only between large categories such as nuts, fruits, and vegetables but also included the differences in thickness selected for various subcategories of fruits and vegetables in the experiments (Jin, Zhang, & Mujumdar, 2024a; Jin, Zhang, Mujumdar, & Yu, 2024b; Tang, Jing, & Jiao, 2024). For industrial application, uniform slicing of fruits and vegetables to a suitable thickness range is recommended based on the feature importance analysis.

Hierarchical modeling split the dataset by material type, analyzed parameter priorities in these sub-data-sets, and combined them with the data distribution of RF heating process parameters (e.g., moisture content, material thickness, and electrode gap), thereby enabling precise determination of parameter priorities for each material-specific scenario. This enables precise parameter optimization for each material, directly guiding industrial drying process design to achieve efficient, high-quality dehydration.

3.3.2 Dataset classification by heating method

Although differences in heating methods were incorporated into the overall data model (targeting RF drying), independent modeling based on different heating methods can reveal the dominant parameters in this specific application scenario and reduce the impact of inter-study variations. Fig. 3S presents the data points of each subset partitioned by heating method; Figs. 4-7S illustrate the distribution of selected parameters for each subset; Fig. 8S shows the distribution of materials across subsets. The data distributions of these parameters, including variations in sample size and distribution balance across subsets, provided context for subsequent hierarchical modeling of parameter priorities based on heating methods. Data quantity and balance, such as small sample sizes (e.g., RFVD subset with n<100) and uneven distribution, directly affected modeling performance, requiring cautious interpretation.

The model performance results are shown in Tables 3S, 4S, and 5S. In the analysis of the segmented dataset, the gradient boosting models still performed better than the other selected models—for RF, LightGBM achieved R^2=0.8262, *NMSE*=0.1564; for HARF, LightGBM achieved R^2=0.7066, *NMSE*=0.2788, XGBoost achieved R^2=0.6903, *NMSE*=0.2942; for RFVD, CatBoost achieved R^2=0.8358, *NMSE*=0.1540, XGBoost achieved R^2=0.8378, *NMSE*=0.1524, which was similar to the situation in the previous global dataset. Therefore, the gradient boosting models were chosen for the subsequent analysis of parameter priority.

The parameter priority analysis results for the RF dataset are shown in Fig. 9S, which includes models such as CatBoost, XGBoost, Gradient Boosting, and LightGBM. The results indicated that when the RF heating alone was used for materials, the electrode gap was the primary influencing parameter (e.g., 0.25 in XGBoost, 170 in CatBoost), while material thickness was a secondary key parameter. Without assisted heating, the energy source is solely RF. Therefore, regardless of the material type, changes in electrode gap significantly affected the heating uniformity of RF drying, making it the main influencing parameter (Tiwari, Wang, Tang, & Birla, 2011; Huang, Zhu, & Wang, 2015; Wei et al., 2024). The electrode gap was followed by the moisture content and thickness. Some experiments in the RF field also demonstrated similar conclusions regarding different electrode gaps: for RF heating, the choice of electrode gap had a notable impact on the heating effect (Zeng et al., 2022; Skara et al., 2023). For industrial RF equipment, adjusting the electrode gap for bulk materials (e.g., grains) and sliced materials (e.g., carrots) optimizes may improve heating uniformity.

Fig. 10S shows the ranking of the priority of parameters based on the dataset corresponding to the HARF method, using gradient boosting models (CatBoost, XGBoost, LightGBM, Gradient Boosting). Electrode gap exhibited the highest feature importance score (e.g. 5 in CatBoost, 0.012 in XGBoost). This result indicated that the electrode gap was the primary factor to be considered in the HARF. From Fig. 10S, it could be concluded that while moisture content was the second most important influencing factor, the electrode gap remained the primary consideration for HARF. Because HARF relies on RF as the primary energy source for internal heating, the electrode gap directly regulates RF electric field distribution, while hot air only assists in surface moisture removal, weakening the regulatory role of moisture content (Wang et al., 2020; Mahmood et al., 2022; Elik et al., 2023; Wei et al., 2024). When HARF is used, in addition to RF as the energy source, hot air also provides an auxiliary heat source. The hot air, as an auxiliary heat source, mainly removes moisture from the surface of the agricultural products during drying but cannot effectively heat the interior (Wang et al., 2020; Mahmood et al., 2022; Elik et al., 2023; Wei et al., 2024). Thus, electrode gap and moisture content significantly affect heating uniformity and need to be prioritized. For industrial application, this means tuning electrode gap first and adjusting initial moisture content (e.g., pre-dry high-moisture fruits) to maximize drying efficiency and quality. The results showed that dividing the data into smaller datasets can capture the specific priority of parameters in various scenarios.

From the parameter priority results in Fig. 11S, it can be concluded that in the dataset for the RFVD method (with relatively few data points, $n<70$), using the RFVD method, moisture content exhibited higher importance than other parameters, with scores reaching 360 in the CatBoost model and 2.6 in the XGBoost model. RFVD is an innovative heating method in the field of RF drying (Skara et al., 2023; Zhang et al., 2025). The boiling point of water is reduced, and water evaporation is accelerated by virtue of operation in a vacuum environment (Ma et al., 2024). The high importance of moisture content aligns with the characteristics of RFVD, which leverages the lowered boiling point to promote water evaporation (Xie et al., 2020). Therefore, when using RFVD drying, moisture content should be prioritized. Regulating moisture content based on its natural initial level may lead to better heating uniformity in RFVD drying, which is similar to the conclusions of some studies (Zheng et al., 2024). For RFVD drying, agricultural products with relatively high initial moisture content (wet basis) should undergo pre-drying to an appropriate range, guiding industrial RFVD drying.

3.4 Scenario-specific priority of RF drying parameters

To summarize and more intuitively present the priorities of parameters affecting heating uniformity in scenario-specific contexts, Table 2 shows the parameter priorities for RF drying under different heating methods and material types. The table clearly highlights the priorities of critical parameters, such as moisture content, material thickness, and electrode gap, with results precisely tailored to distinct agricultural products types (e.g., fruits and nuts) and heating methods (RF, HARF, and RFVD). For fruits and vegetables (high moisture, compact structure), uneven thickness limits RF energy penetration, leading to localized overheating (Birla, Wang, Tang, & Tiwari, 2008; Tang, Jing, & Jiao, 2024). Industrial preprocessing can prioritize uniform slicing to optimize uniformity effectively. For nuts (low moisture, high fat), moisture content emerged as a critical regulatory factor. Preconditioning these nuts to optimal moisture content may effectively mitigate localized overheating, thereby preserving key quality attributes such as kernel color. For heating methods: only RF alone required precise adjustment of electrode gap to optimize heating uniformity, similar conclusions had also been drawn in the experiments investigating the effect of electrode gap on RF heating (Altin et al., 2025); HARF retained electrode gap as the primary parameter, as RF serves as the core volumetric heat source while hot air supplements surface drying (Wang et al., 2020b); RFVD prioritized moisture content, leveraging low boiling points caused by vacuum to optimize heating uniformity. These priorities could guide equipment and experimental design (e.g., intelligent sensors for real-time adjustment), directly addressing industrial RF drying pain points (uneven quality, high energy consumption, long cycles). Limitations include insufficient grain samples (n<30), scarce RFVD data (n<70), and a lack of time-dependent parameters (e.g., moisture migration).

Table 2 Summary of key parameter priorities in different RF drying scenarios

Scene	Type	Priority parameter	Material type	Heating method
Scenario 1	RF	electrode gap, moisture content	fruits & vegetables, nuts	/
	HARF	electrode gap, moisture content	fruits & vegetables, nuts, grains	/
	RFVD	moisture content	fruits & vegetables	/
Scenario 2	nuts	moisture content, electrode gap	/	RF, HARF
	fruits & vegetables	thickness, moisture content	/	RF, HARF, RFVD

Note:

Scenario 1 corresponds to modeling by dividing the dataset based on heating methods, and Scenario 2 corresponds to modeling by dividing the dataset based on material types. "/" indicates that the column does not require additional annotation, as the core information (heating method/material type) has been clarified in the "Type" column. Specifically: (1) When "/" appears in the "Heating method" column, it means the "Type" column has specified the heating method, and no additional information is needed; (2) When "/" appears in the "Material type" column, it means the "Type" column has specified the material type, and no additional information is needed.

4. Conclusion

Big data analysis integrated with machine learning methods using literature data was employed to optimize RF heating uniformity in agricultural products drying-addressing the challenges of non-uniform dehydration that restricts the commercialization of RF drying technology. The key findings indicated that moisture content and material thickness were the primary parameters influencing the heating uniformity of RF drying across various scenarios (different agricultural products and heating methods). A hierarchical modeling approach was used to identify distinct parameter priorities under different scenarios: when RF heating was used for the drying application alone, electrode gap was the primary parameter to prioritize; In the case of drying with combined heating methods (HARF and RFVD) for drying, moisture content was the critical influencing parameter. For fruits and vegetables, material thickness was the dominant factor, whereas moisture content was critical for nuts. Unlike traditional methods, this quantitative analysis of feature importance rankings provided targeted guidance for identifying the priority of RF drying parameters. The ML-based approach not only identified key parameters but also provided actionable operational guidelines for industrial applications, including uniform slicing of fruits and vegetables, preconditioning of nut moisture content, and electrode gap adjustment for different heating methods. These outcomes could advance the commercialization of RF drying technology, contributing to global food security by reducing post-harvest losses and supporting environmental sustainability through low-energy consumption.

Limitations of this study include dataset imbalance (particularly underrepresentation of grains and RFVD scenarios) and the lack of experimental validation for the developed ML models. Future work would involve embedding physical constraints via PINNs (e.g., Maxwell's equations) into ML frameworks, incorporating time-dependent parameters (e.g., moisture migration rate) and advanced algorithms (e.g., LSTM networks) to better capture transient drying behaviors, further refining the analysis of parameter priorities, and conducting experiments to validate the optimized parameters.

Declaration of generative AI and AI-assisted technologies in the writing process

No generative AI or AI-assisted technologies were used during the preparation of this work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

References

Abea, A., Gou, P., Guàrdia, M.D., Picouet, P., Kravets, M., Bañón, S., & Muñoz, I. (2023). Dielectric heating: A review of liquid foods processing applications. *Food Reviews International*, *39*(8), 5684-5702. https://doi.org/10.1080/87559129.2022.2092746.

Ai, Z.P., Zhu, G.F., Zheng, Z.A., Xiao, H.W., Mowafy, S., & Liu, Y.H. (2023). Successive Two-stage hot air-drying with humidity control combined radio frequency drying improving drying efficiency and nutritional quality of amomi fructus. *Food and Bioprocess Technology*, *16*(1), 149-166. https://doi.org/10.1007/s11947-022-02928-8.

Altemimi, A., Aziz, S.N., Al-Hilphy, A.R.S., Lakhssassi, N., Watson, D.G., & Ibrahim, S.A. (2019). Critical review of radio-frequency (RF) heating applications in food processing. *Food Quality and Safety*, *3*(2), 81-91. https://doi.org/10.1093/fqsafe/fyz002.

Altin, O., Farmanfarmaee, A., Topcam, H., Kong, F., Gogus, F., Marra, F., & Erdogdu, F. (2025). Effects of electrode configuration and orientation on electromagnetic field distribution and temperature evolution in radio frequency systems. *Innovative Food Science & Emerging Technologies*, *102*, 103970. https://doi.org/10.1016/j.ifset.2025.103970.

Bassey, E.J., Cheng, J.H., & Sun, D.W. (2021). Novel nonthermal and thermal pretreatments for enhancing drying performance and improving quality of fruits and vegetables. *Trends in Food Science & Technology*, *112*, 137-148. https://doi.org/10.1016/j.tifs.2021.03.045.

Birla, S.L., Wang, S., Tang, J., & Hallman, G. (2004). Improving heating uniformity of fresh fruit in radio frequency treatments for pest control. *Postharvest Biology and Technology*, *33*(2), 205-217. https://doi.org/10.1016/j.postharvbio.2004.02.010.

Birla, S.L., Wang, S., Tang, J., & Tiwari, G. (2008). Characterization of radio frequency heating of fresh fruits influenced by dielectric properties. *Journal of Food Engineering*, *89*(4), 390-398. https://doi.org/10.1016/j.jfoodeng.2008.05.021.

Chen, L., Wang, K., Li, W., & Wang, S.J. (2015). A strategy to simulate radio frequency heating under mixing conditions. *Computers and Electronics in Agriculture*, *118*, 100-110. https://doi.org/10.1016/j.compag.2015.08.025.

Chen, L., Huang, Z., Wang, K., Li, W., & Wang, S. (2016). Simulation and validation of radio frequency heating with conveyor movement. *Journal of Electromagnetic Waves and Applications*, *30*(4), 473-491. https://doi.org/10.1080/09205071.2015.1121841.

Chen, L., Subbiah, J., Jones, D., Zhao, Y.Y., & Jung, J. (2021). Development of effective drying strategy with a combination of radio frequency (RF) and convective hot-air drying for inshell hazelnuts and enhancement of nut quality. *Innovative Food Science & Emerging Technologies*, *67,* 102555. https://doi.org/10.1016/j.ifset.2020.102555.

Chen, A., Wan, F.X., Ma, G.J., Ma, J.M., Xu, Y.R., Zang, Z.P., Ying, X.Y., Jia, H.W., & Huang, X.P. (2024). Radio frequency vacuum drying study on the drying characteristics and quality of cistanche slices and analysis of heating uniformity. *Foods*, *13*(17), 2672. https://doi.org/10.3390/foods13172672.

Cui, M., Sun, W.W., Xia, L.Y., Wang, Z.M., Cao, Y., & Wu, Y. (2020). Effect of radio frequency heating on the mortality of Rhizopertha dominica (F.) and its impact on grain quality. *Journal of Stored Products Research*, *89,* 101695. https://doi.org/10.1016/j.jspr.2020.101695.

Davies, T., Louie, J.C.Y., Scapin, T., Pettigrew, S., Wu, J.H.Y., Marklund, M., & Coyle, D.H. (2021). An innovative machine learning approach to predict the dietary fiber content of packaged foods. *Nutrients*, *13(9),* 3195. https://doi.org/10.3390/nu13093195.

Dag, D., Farmanfarmaee, A., Kong, F.B., Jung, J., McGorrin, R.J., & Zhao, Y.Y. (2023). Feasibility of simultaneous drying and blanching inshell hazelnuts (Corylus avellana L.) using hot air-assisted radio frequency (HARF) heating. *Food and Bioprocess Technology*, *16(2)*, 404-419. https://doi.org/10.1007/s11947-022-02946-6.

Elik, A., Armagan, H.S., Gögüs, F., Oboturova, N., Nagdalian, A., Smaoui, S., & Shariati, M.A. (2023). Impact of radio frequency-assisted hot air drying on drying kinetics behaviors and quality features of orange peel. *Biomass Conversion and Biorefinery*, *13*(16), 15173-15183. https://doi.org/10.1007/s13399-023-04336-0.

Ennaji, O., Verguetz, L., & El Allali, A. (2023). Machine learning in nutrient management: A review. *Artificial Intelligence in Agriculture 9*, 1-11. https://doi.org/10.1016/j.aiia.2023.06.001.

Guo, W., Tiwari, G., Tang, J., & Wang, S. (2008). Frequency, moisture and temperature-dependent dielectric properties of chickpea flour. *Biosystems Engineering*, 101(2), 217-224. https://doi.org/10.1016/j.biosystemseng.2008.07.002.

Gambella, C., Ghaddar, B., & Naoum-Sawaya, J. (2021). Optimization problems for machine learning: A survey. European *Journal of Operational Research*, *290*(3), 807-828. https://doi.org/10.1016/j.ejor.2020.08.045.

Gao, J.L., Wu, M.T., Du, S.C., Zhang, H., Wang, S.J., & Ling, B. (2023). Recent advances in food processing by radio frequency heating techniques: A review of equipment aspects. *Journal of Food Engineering*, *357*, 111609. https://doi.org/10.1016/j.jfoodeng.2023.111609.

Gao, J., Liu, Y., Ao, J., Wang, S., Chen, J., & Chen, L. (2025a). An integrated mechanistic modeling and machine learning for radio frequency heating uniformity optimization of canola seeds. *Innovative Food Science & Emerging Technologies*, *106*, 104268. https://doi.org/10.1016/j.ifset.2025.104268.

Gao, J., Wang, S., Erdogdu, F., Marra, F., Sarghini, F., & Chen, L. (2025b). Machine learning-driven innovations in food processing: A systematic review of applications, challenges, and future developments. *Trends in Food Science & Technology*, *164,* 105204. https://doi.org/10.1016/j.tifs.2025.105204.

Geng, Z., Xie, Y.M., Ye, P.F., Sun, Y.N., Fu, H.F., Chen, X.W., Wang, Y.Q., & Wang, Y.Y. (2024). Effect of hot air-assisted radio frequency rotation heating system on improving heating uniformity of dried black fungus (Auricularia auricula). *Food and Bioproducts Processing*, *147*, 384-392. https://doi.org/10.1016/j.fbp.2024.07.022.

Ge, M., Chen, G., Liu, W., & Liu, C. (2024). Study of heat and mass transfer during drying process of maize grain pile based on computed tomography. *Biosystems Engineering*, 248, 82-96. https://doi.org/10.1016/j.biosystemseng.2024.10.003.

Gu, Y.X., Zhen, L.Y., & Jiang, H. (2020). Mathematical analysis of temperature distribution uniformity of banana dried by vacuum radio frequency treatment. *Drying Technology*, *38*(15), 2027-2038. https://doi.org/10.1080/07373937.2019.1611595.

Hernández, J.A. (2009). Optimum operating conditions for heat and mass transfer in foodstuffs drying by means of neural network inverse. *Food Control*, *20*(4), 435-438. https://doi.org/10.1016/j.foodcont.2008.07.005

Huang, Z., Zhu, H., & Wang, S. (2015). Finite element modeling and analysis of radio frequency heating rate in mung beans. *Transactions of the ASABE*, *58*(1), 149-160. https://doi.org/10.13031/trans.58.10660.

Huang, Z., Marra, F., Subbiah, J., & Wang, S. (2018). Computer simulation for improving radio frequency (RF) heating uniformity of food products: A review. *Critical Reviews in Food Science* *and Nutrition*, *58*(6), 1033-1057. https://doi.org/10.1080/10408398.2016.1253000.

Hou, L.X., Johnson, J.A., & Wang, S.J. (2016). Radio frequency heating for postharvest control of pests in agricultural products: A review. *Postharvest Biology and Technology*, *113*, 106-118. https://doi.org/10.1016/j.postharvbio.2015.11.011.

Islam, M.R., Sablani, S.S., & Mujumdar, A.S. (2003). An artificial neural network model for prediction of drying rates. *Drying Technology*, *21*(9), 1867-1884. https://doi.org/10.1081/drt-120025512.

Ispirova, G., Eftimov, T., & Seljak, B.K. (2020). P-NUT: predicting nutrient content from short text descriptions. *Mathematics*, *8*(10), 1811. https://doi.org/10.3390/math8101811.

Jin, W., Zhang, M., & Mujumdar, A.S. (2024a). A high-efficiency radio-frequency-assisted hot-air drying method for the production of restructured bitter melon and apple chips. *Foods*, *13*(2), 197. https://www.mdpi.com/2304-8158/13/2/197.

Jin, W., Zhang, M., Mujumdar, A.S., & Yu, D. (2024b). Influence of ultrasonic-assisted osmotic dehydration pretreatment on hot air-assisted radio frequency drying of bitter gourd. *Food Bioscience*, *59*, 103923. https://doi.org/https://doi.org/10.1016/j.fbio.2024.103923.

Kaneko, H. (2023). Interpretation of machine learning models for data sets with many features using feature importance. *Acs Omega*, *8*(25), 23218-23225. https://doi.org/10.1021/acsomega.3c03722.

Karamcheti, S.T., Brightwell, G., Bremer, P., & Schofield, M.R. (2025). Hierarchical bayesian linear mixed model to estimate variability in the thermal inactivation parameters for Listeria species. *Food Microbiology*, *128*, 104731. https://doi.org/10.1016/j.fm.2025.104731.

Khan, M.I.H., Sablani, S.S., Joardder, M.U.H., & Karim, M.A. (2022). Application of machine learning-based approach in food drying: opportunities and challenges. *Drying Technology*, *40*(6), 1051-1067. https://doi.org/10.1080/07373937.2020.1853152.

Lara, G., Takahashi, C., Nagaya, M., & Uemura, K. (2021). Application of radio frequency heating in water for extending the shelf- life of fresh-cut Japanese loquat fruit (Eriobotrya japonica). *Food Science and Technology Research*, *27*(6), 847-857. https://doi.org/10.3136/fstr.27.847.

Lamens, A., & Bajorath, J. (2025). Comparing explanations of molecular machine learning models generated with different methods for the calculation of shapley values. *Molecular Informatics*, *44*(3), e202500067. https://doi.org/10.1016/10.1002/minf.202500067.

Lei, D., Liu, Y., Xie, Y., Guo, J., Mowafy, S., Zhu, G., & Wei, L. (2024). Improving the energy efficiency of industrial radio frequency heat treatment by optimizing electrode sizes and reversal cycles. *Energy Conversion and Management*, *310,* 118498. https://doi.org/10.1016/j.enconman.2024.118498.

Ling, B., Guo, W.C., Hou, L.X., Li, R., & Wang, S.J. (2015). Dielectric properties of pistachio kernels as influenced by frequency, temperature, moisture and salt content. *Food and Bioprocess*, *Technology*, *8*(2), 420-430. https://doi.org/10.1007/s11947-014-1413-8.

Ling, B., Cheng, T., & Wang, S.J. (2020). Recent developments in applications of radio frequency heating for improving safety and quality of food grains and their products: A review. *Critical Reviews in Food Science and Nutrition*, *60*(15), 2622-2642. https://doi.org/10.1080/10408398.2019.1651690.

Liu, Q.Q., Qu, Y.T., Liu, J.X., & Wang, S.J. (2021). Effects of radio frequency heating on mortality of lesser grain borer, quality and storage stability of packaged milled rice. *LWT-Food Science and Technology*, *140*, 110813. https://doi.org/10.1016/j.lwt.2020.110813.

Liu, D., Bober, M., & Kittler, J. (2023). Constrained Structure Learning for Scene Graph Generation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *45*(10), 11588-11599. https://doi.org/10.1109/TPAMI.2023.3282889.

Li, M.G., Tian, Y.Q., Fan, L.M., Xu, J.J., Jiang, L.L., Li, R., & Wang, S.J. (2024a). Radio frequency drying on functional diversity of tiger nut flour: Effects on physicochemical, structural, and rheological properties. *International Journal of Biological Macromolecules*, *275,* 133717. https://doi.org/10.1016/j.ijbiomac.2024.133717.

Li, M.G., Tian, Y.Q., Jiang, L.L., Xu, J.J., Li, R., & Wang, S.J. (2024b). Developing effective radio frequency drying processes for tiger nuts: Dynamic analysis of moisture state, dielectric properties and quality. *Journal of Food Engineering*, *375*, 112058. https://doi.org/10.1016/j.jfoodeng.2024.112058.

Li, R., Gao, Y., Zheng, J.J., Li, M.G., Hao, Y.J., Jiang, L.L., Bai, S.Q., Zhou, D.T., Xu, J.J., Kou, X.X., & Wang, S.J. (2024). Developing a combined rotating and air-circulating system for improving radio frequency heating uniformity and controlling Aspergillus in almond kernels. *Innovative Food Science & Emerging Technologies*, *94,* 103696. https://doi.org/10.1016/j.ifset.2024.103696.

Liu, Y., Ma, J.C., Liu, Z.P., Wang, S.J., & Chen, L. (2025). An accurate approach to predict Salmonella Enteritidis PT 30 survival based on dynamic thermal resistance during hot air assisted radio frequency pasteurization of in-shell walnuts. *International Journal of Food Microbiology*, *437,* 111216. https://doi.org/10.1016/j.ijfoodmicro.2025.111216.

Lu, W.L., Chen, X.Q., Wang, L., Li, H.F., & Fu, Y.V. (2020). Combination of an artificial intelligence approach and laser tweezers raman spectroscopy for microbial identification. *Analytical Chemistry*, *92*(9), 6288-6296. https://doi.org/10.1021/acs.analchem.9b04946.

Luo, X., Zhou, D.T., Yang, G.J., Xu, J.J., Luo, Y., Li, R., & Wang, S.J. (2024). Development of radio frequency drying protocols for preserving the color and fragrance of lotus bee pollen. *Food Control*, *166,* 110696. https://doi.org/10.1016/j.foodcont.2024.110696.

Marra, F., Zhang, L., & Lyng, J.G. (2009). Radio frequency treatment of foods: Review of recent advances. *Journal of Food Engineering*, *91*(4), 497-508. https://doi.org/10.1016/j.jfoodeng.2008.10.015.

Mao, Y.X., Wang, P.H., Wu, Y., Hou, L.X., & Wang, S.J. (2021). Effects of various radio frequencies on combined drying and disinfestation treatments for in-shell walnuts. *LWT-Food Science and Technology*, *144,* 111246. https://doi.org/10.1016/j.lwt.2021.111246.

Mao, Y.X., & Wang, S.J. (2023). Recent developments in radio frequency drying for food and agricultural products using a multi-stage strategy: a review. *Critical Reviews in Food Science and Nutrition*, *63*(16), 2654-2671. https://doi.org/10.1080/10408398.2021.1978925.

Mahmood, N., Liu, Y.H., Munir, Z., Zhang, Y., & Niazi, B.M.K. (2022). Effects of hot air assisted radio frequency drying on heating uniformity, drying characteristics and quality of paddy. *LWT-Food Science and Technology*, *158,* 113131. https://doi.org/10.1016/j.lwt.2022.113131.

Ma, W.L., Zang, Z.P., Wu, B.W., Ma, G.J., Wan, F.X., Xu, Y.R., & Huang, X.P. (2024). Effect of radio frequency vacuum drying on drying characteristics and physicochemical quality of codonopsis pilosula slices. *Agriculture-Basel*, *14*(9), 1495. https://doi.org/10.3390/agriculture14091495.

Panigrahi, S. S., & Singh, C. B. (2025). Thermodynamic-based theoretical energy efficiency model for high-temperature grain drying. *Biosystems Engineering*, 258, 104248. https://doi.org/10.1016/j.biosystemseng.2025.104248.

Piedad, E.J., Larada, J.I., Pojas, G.J., & Ferrer, L.V.V. (2018). Postharvest classification of banana (Musa acuminata) using tier-based machine learning. *Postharvest Biology and Technology*, *145*, 93-100. https://doi.org/10.1016/j.postharvbio.2018.06.004.

Rahangdale, A., & Raut, S. (2019). Machine learning methods for ranking. *International Journal of*

Software Engineering and Knowledge Engineering, *29*(6), 729-761. https://doi.org/10.1142/s021819401930001x.

Rana, Y.S., Chen, L., Jiao, Y., Johnson, L.M., & Snyder, A.B. (2024). A meta-analysis of microbial thermal inactivation in low moisture foods. *Food Microbiology*, 121, 1014515. https://doi.org/10.1016/j.fm.2024.104515.

Rengasamy, D., Mase, J.M., Kumar, A., Rothwell, B., Torres, M.T., Alexander, M.R., Winkler, D.A., & Figueredo, G.P. (2022). Feature importance in machine learning models: A fuzzy information fusion approach. *Neurocomputing*, *511*, 163-174. https://doi.org/10.1016/j.neucom.2022.09.053.

Siddique, A., Gupta, A., Sawyer, J.T., Huang, T.S., & Morey, A. (2025). Big data analytics in food industry: a state-of-the-art literature review. *Npj Science of Food*, *9*(1), 36. https://doi.org/10.1038/s41538-025-00394-y.

Skara, T., Lovdal, T., Skipnes, D., Mehlomakulu, N.N., Mapengo, C.R., Baah, R.O., & Emmambux, M.N. (2023). Drying of vegetable and root crops by solar, infrared, microwave, and radio frequency as energy efficient methods: A review. *Food Reviews International*, *39*(9), 7197-7217. https://doi.org/10.1080/87559129.2022.2148688.

Sun, W.L., Liu, Y.H., Xiao, H.W., Lei, D.W., Mowafy, S., Ai, Z.P., & Peng, Z.K. (2025). Optimizing a successive two-stage drying process for exocarpium citri grandis: hot air drying with integrated temperature-humidity control followed by radio frequency drying. *Food and Bioprocess Technology*, *18*(5), 4461-4477. https://doi.org/10.1007/s11947-024-03729-x.

Tarlak, F. (2023). The use of predictive microbiology for the prediction of the shelf life of food products. *Foods*, 12(24), 4461. https://doi.org/10.3390/foods12244461.

Tasci, C., Liu, S.X., Erdogdu, F., & Ozturk, S. (2024). Improving radio frequency heating uniformity in peanuts: Effects of packaging geometry, electrode gap, particle size and interlayer displacement process. *Innovative Food Science & Emerging Technologies*, *95,* 103728. https://doi.org/10.1016/j.ifset.2024.103728.

Tang, Y.J., Jing, P., & Jiao, S.S. (2024). Application of radio frequency energy in processing of fruit and vegetable products. *Comprehensive Reviews in Food Science and Food Safety*, *23*(5), e13425. https://doi.org/10.1111/1541-4337.13425.

Takefuji, Y. (2025). Reevaluating feature importance in machine learning for food authentication: Addressing bias and enhancing methodological rigor. *Trends in Food Science & Technology*, *157, 104853*. https://doi.org/10.1016/j.tifs.2024.104853.

Tiwari, G., Wang, S., Tang, J., & Birla, S.L. (2011). Analysis of radio frequency (RF) power distribution in dry food materials. *Journal of Food Engineering*, *104*(4), 548-556. https://doi.org/10.1016/j.jfoodeng.2011.01.015.

Wang, S., Yue, J., Tang, J., & Chen, B. (2005). Mathematical modelling of heating uniformity for in-shell walnuts subjected to radio frequency treatments with intermittent stirrings. *Postharvest Biology and Technology*, *35(1)*, 97-107. https://doi.org/10.1016/j.postharvbio.2004.05.024.

Wang, Y.Y., Zhang, L., Gao, M.X., Tang, J., & Wang, S.J. (2014a). Evaluating radio frequency heating uniformity using polyurethane foams. *Journal of Food Engineering*, *136*, 28-33. https://doi.org/10.1016/j.jfoodeng.2014.03.018.

Wang, Y.Y., Zhang, L., Gao, M.X., Tang, J., & Wang, S.J. (2014b). Pilot-scale radio frequency drying of macadamia nuts: heating and drying uniformity. *Drying Technology*, *32*(9), 1052-1059. https://doi.org/10.1080/07373937.2014.881848.

Wang, Z., Lu, J., Tao, C., Zhou, J., & Tian, Q. (2021). Learning Channel-Wise Interactions for Binary

Convolutional Neural Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *43*(10), 3432-3445. https://doi.org/ 10.1109/TPAMI.2020.2988262.

Wang, W.J., Wang, W.J., Jung, J., Yang, R., Tang, J.M., & Zhao, Y.Y. (2020a). Investigation of hot-air assisted radio frequency (HARF) dielectric heating for improving drying efficiency and ensuring quality of dried hazelnuts (Corylus avellana L.). *Food and Bioproducts Processing*, *120*, 179-190. https://doi.org/10.1016/j.fbp.2020.01.006.

Wang, W.J., Wang, W.J., Wang, Y.Y., Yang, R., Tang, J.M., & Zhao, Y.Y. (2020b). Hot-air assisted continuous radio frequency heating for improving drying efficiency and retaining quality of inshell hazelnuts (Corylus avellana L. cv. Barcelona). *Journal of Food Engineering*, *279,* 109956. https://doi.org/10.1016/j.jfoodeng.2020.109956.

Wang, C.C., Kou, X.X., Zhou, X., Li, R., & Wang, S.J. (2021). Effects of layer arrangement on heating uniformity and product quality after hot air assisted radio frequency drying of carrot. *Innovative Food Science & Emerging Technologies*, 69, 102667. https://doi.org/10.1016/j.ifset.2021.102667.

Wang, W.J., Tang, J.M., & Zhao, Y.Y. (2021). Investigation of hot-air assisted continuous radio frequency drying for improving drying efficiency and reducing shell cracks of inshell hazelnuts: The relationship between cracking level and nut quality. *Food and Bioproducts Processing*, *125*, 46-56. https://doi.org/10.1016/j.fbp.2020.10.013.

Wei, S., Xie, W. J., Zheng, Z. H., Ren, L. Y., & Yang, D. Y. (2023). Numerical study on drying uniformity of bulk corn kernels during radio frequency-assisted hot air drying. *Biosystems Engineering*, 227, 117-129. https://doi.org/10.1016/j.biosystemseng.2023.01.020.

Wang, Z.X., Li, Q., Jiang, S.Y., Wang, X.M., Wang, S.J., & Hou, L.X. (2024). Improving radio frequency heating uniformity in cauliflower by changing density in different zones. *Food and Bioproducts*

Processing, *143*, 1-8. https://doi.org/10.1016/j.fbp.2023.10.004.

Wei, S., Tian, B.Q., Fan, H.P., Ren, G.Y., Yang, D.Y., & Ai, Z.L. (2024). Radiofrequency assisted hot air drying of corn kernels: Drying characteristics, uniformity, quality, and energy consumption. *Drying Technology*, *42*(12), 1846-1854. https://doi.org/10.1080/07373937.2024.2390110.

Xie, Y.C., Zhang, Y., Xie, Y.K., Li, X.Y., Liu, Y.H., & Gao, Z.J. (2020). Radio frequency treatment accelerates drying rates and improves vigor of corn seeds. *Food Chemistry*, *319* , 126597. https://doi.org/10.1016/j.foodchem.2020.126597.

Xie, X.Y., Lin, Z.J., Toh, K.C., & Zhou, P. (2025). LoCo: Low-Bit Communication Adaptor for Large-Scale Model Training. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *47*(6), 4285-4298. https://doi.org/10.1109/TPAMI.2025.3544764.

Yang, L., Liu, H.H., Cai, Y.C., Hayashi, K., & Li, K.F. (2014). Real-time moisture content measurement of wood under radio-frequency/vacuum (RF/V) drying. *Drying Technology*, *32*(14), 1675-1682. https://doi.org/10.1080/07373937.2014.917426.

Yang, P., Fu, H., Sun, P., Ren, L., Zheng, Z., Bu, Y., & Yang, D. (2025). Exploring the impact of drying temperature on Camellia oleifera fruit shelling through shrinkage strain, case hardening and microstructure. *Biosystems Engineering*, 260, 104325. https://doi.org/10.1016/j.biosystemseng.2025.104325.

Zhang, S., Zhou, L. Y., Ling, B., & Wang, S. J. (2016). Dielectric properties of peanut kernels associated with microwave and radio frequency drying. *Biosystems Engineering*, 145, 108-117. https://doi.org/10.1016/j.biosystemseng.2016.03.002.

Zhu, Z.Z., & Guo, W.C. (2017). Frequency, moisture content, and temperature dependent dielectric properties of potato starch related to drying with radio-frequency/microwave energy. Scientific

Reports, 7, 9311. https://doi.org/10.1038/s41598-017-09197-y.

Zhang, M., Chen, H.Z., Mujumdar, A.S., Tang, J.M., Miao, S., & Wang, Y.C. (2017). Recent developments in high-quality drying of vegetables, fruits, and aquatic products. *Critical Reviews in Food Science and Nutrition*, *57*(6), 1239-1255. https://doi.org/10.1080/10408398.2014.979280.

Zhang, S., Huang, Z., & Wang, S.J. (2017). Improvement of radio frequency (RF) heating uniformity for peanuts with a new strategy using computational modeling. *Innovative Food Science & Emerging Technologies*, *41*, 79-89. https://doi.org/10.1016/j.ifset.2017.02.009.

Zhou, X., Ramaswamy, H., Qu, Y.T., Xu, R.Z., & Wang, S.J. (2019). Combined radio frequency-vacuum and hot air drying of kiwifruits: Effect on drying uniformity, energy efficiency and product quality. *Innovative Food Science & Emerging Technologies*, *56* , 102182. https://doi.org/10.1016/j.ifset.2019.102182.

Zeng, S.Y., Li, M.G., Li, G.H., Lv, W.Q., Liao, X.J., & Wang, L.J. (2022). Innovative applications, limitations and prospects of energy-carrying infrared radiation, microwave and radio frequency in agricultural products processing. *Trends in Food Science & Technology*, *121*, 76-92. https://doi.org/10.1016/j.tifs.2022.01.032.

Zhang, Y., Pandiselvam, R., Zhu, H.K., Su, D.B., Wang, H., Ai, Z.P., Kothakota, A., Khaneghah, A.M., & Liu, Y.H. (2022). Impact of radio frequency treatment on textural properties of food products: An updated review. *Trends in Food Science & Technology*, *124*, 154-166. https://doi.org/10.1016/j.tifs.2022.04.014.

Zhang, Z.N., Zhang, B., Zhu, L., & Zhao, W. (2022). Microstructure, digestibility and physicochemical properties of rice grains after radio frequency Treatment. *Foods*, *11* , 1723. https://doi.org/10.3390/foods11121723.

Zheng, J.J., Jiang, L.L., Ye, X., Wang, X.J., Tian, Y.Q., Li, M.G., Li, R., & Wang, S.J. (2024). Developing a spouted bed for combined radio frequency-hot air treatments to improve the heating uniformity in high-moisture carrot cubes. *Journal of Food Engineering*, 375, 112077. https://doi.org/10.1016/j.jfoodeng.2024.112077.

Zhang, J.-S., Xiao, H.-M., Orsat, V., Raghavan, G.S.V., Torki, M., Wang, H., & Wang, H. (2025). Innovative green technology: Pulse cycle vacuum drying with carbon crystal heating poised to supplant conventional vacuum drying methods. *Renewable and Sustainable Energy Reviews*, *210*, 115200. https://doi.org/https://doi.org/10.1016/j.rser.2024.115200.

Zuo, Y., Li, Q.A., Zhang, Z.J., Yang, H.L., Wang, S.J., & Hou, L.X. (2023). Developing a square container with ideal dielectric constant for improving radio frequency heating uniformity in low-moisture agricultural products. *Journal of Food Engineering*, 343, 111386. https://doi.org/10.1016/j.jfoodeng.2022.111386.

Supplementary Information

Parameters priority analysis for improving radio frequency heating uniformity in agricultural products drying based on machine learning

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Table 1S Comparison of model performance for the nuts dataset

Model	R^2	$NMSE$
Random Forest	0.6122	0.3793
Gradient Boosting	0.6206	0.3711
SVR	0.4722	0.5163
LightGBM	0.6802	0.3129
XGBoost	0.6049	0.3865
CatBoost	0.6102	0.3813
Linear Regression	0.5362	0.4537
Decision Tree	0.5896	0.4014
Lasso	0.4709	0.5176
Ridge	0.5371	0.4529
AdaBoost	0.6118	0.3798
Bagging	0.5884	0.4027

Table 2S Comparison of model performance for the fruits & vegetables dataset

Model	R^2	$NMSE$
Random Forest	0.6588	0.3369
Gradient Boosting	0.6632	0.3326
SVR	0.5753	0.4194
LightGBM	0.6679	0.3279
XGBoost	0.6509	0.3447
CatBoost	0.6649	0.3309
Linear Regression	0.6227	0.3726
Decision Tree	0.6267	0.3686
Lasso	0.5647	0.4272
Ridge	0.6313	0.3614
AdaBoost	0.6147	0.3805
Bagging	0.6589	0.3359

Table 3S Comparison of model performance for the RF heating dataset

Model	R^2	$NMSE$
Random Forest	0.8220	0.1602
Gradient Boosting	0.8469	0.1219
SVR	0.8645	0.1378
LightGBM	0.8262	0.1564
XGBoost	0.7262	0.2452
CatBoost	0.8574	0.1308
Linear Regression	0.8371	0.1466
Decision Tree	0.8412	0.1429
Lasso	0.7582	0.2176
Ridge	0.8319	0.1513
AdaBoost	0.8111	0.1700
Bagging	0.8277	0.1551

Table 4S Comparison of model performance for HARF dataset

Model	R^2	$NMSE$
Random Forest	0.7494	0.2381
Gradient Boosting	0.6620	0.3211
SVR	0.5889	0.3906
LightGBM	0.7066	0.2788
XGBoost	0.6903	0.2942
CatBoost	0.6831	0.3011
Linear Regression	0.5648	0.4134
Decision Tree	0.6508	0.3317
Lasso	0.5775	0.4013
Ridge	0.5793	0.3996
AdaBoost	0.6456	0.3367
Bagging	0.7070	0.2784

Table 5S Comparison of model performance for RFVD dataset

Model	R^2	*NMSE*
Random Forest	0.8378	0.1520
Gradient Boosting	0.8377	0.1521
SVR	0.8185	0.1701
LightGBM	0.3042	0.6523
XGBoost	0.8378	0.1521
CatBoost	0.8358	0.1540
Linear Regression	0.7301	0.2530
Decision Tree	0.8378	0.1521
Lasso	0.7408	0.2430
Ridge	0.7409	0.2429
AdaBoost	0.8296	0.1598
Bagging	0.8268	0.1623

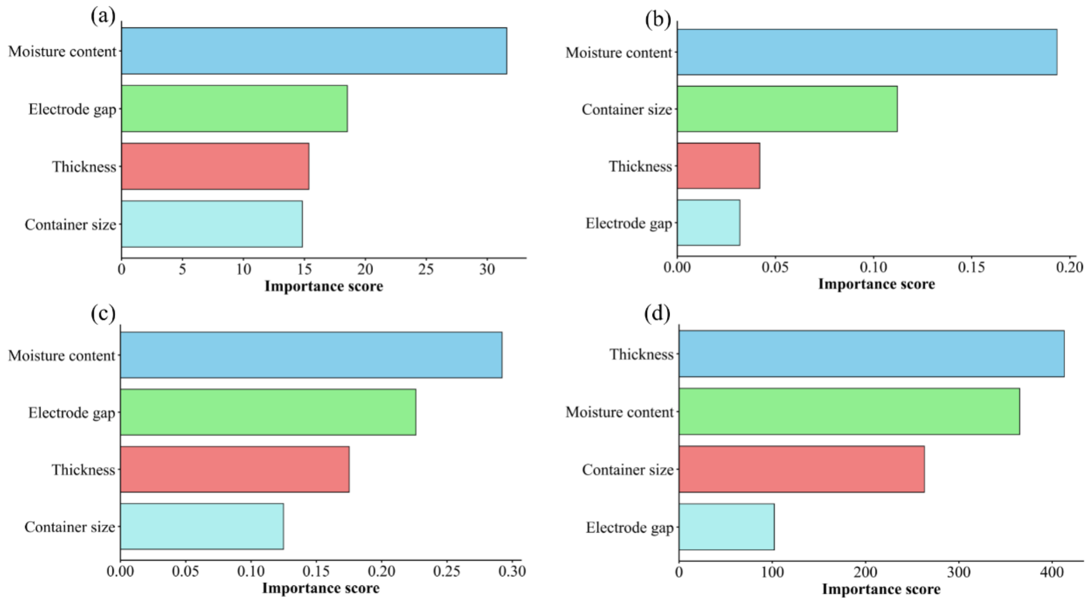

Fig. 1S. Feature importance of parameters affecting RF heating uniformity (λ) for nuts material. (a) CatBoost model feature importance. (b) XGBoost model feature importance. (c) Gradient Boosting model feature importance. (d) LightGBM model feature importance. Each subfigure presents the sorted feature importance scores of different parameters (moisture content, electrode gap, thickness, container size) affecting RF heating uniformity (λ) for the corresponding model.

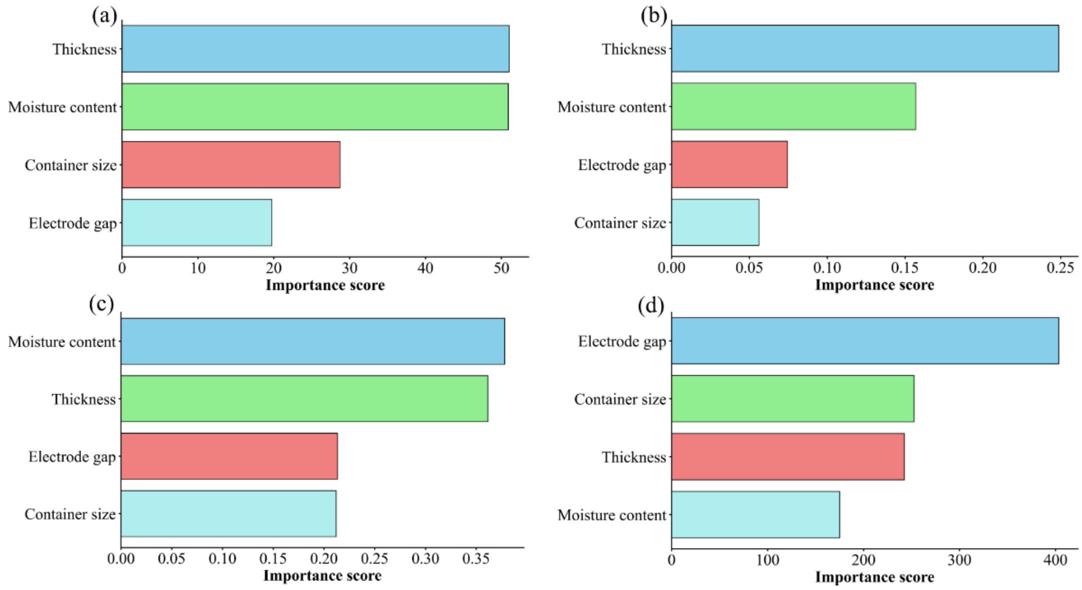

Fig. 2S. Feature importance of parameters affecting RF heating uniformity (λ) for fruits & vegetables material. (a) CatBoost model feature importance. (b) XGBoost model feature importance. (c) Gradient Boosting model feature importance. (d) LightGBM model feature importance. Each subfigure presents the sorted feature importance scores of different parameters (moisture content, electrode gap, thickness, container size) affecting RF heating uniformity (λ) for the corresponding model.

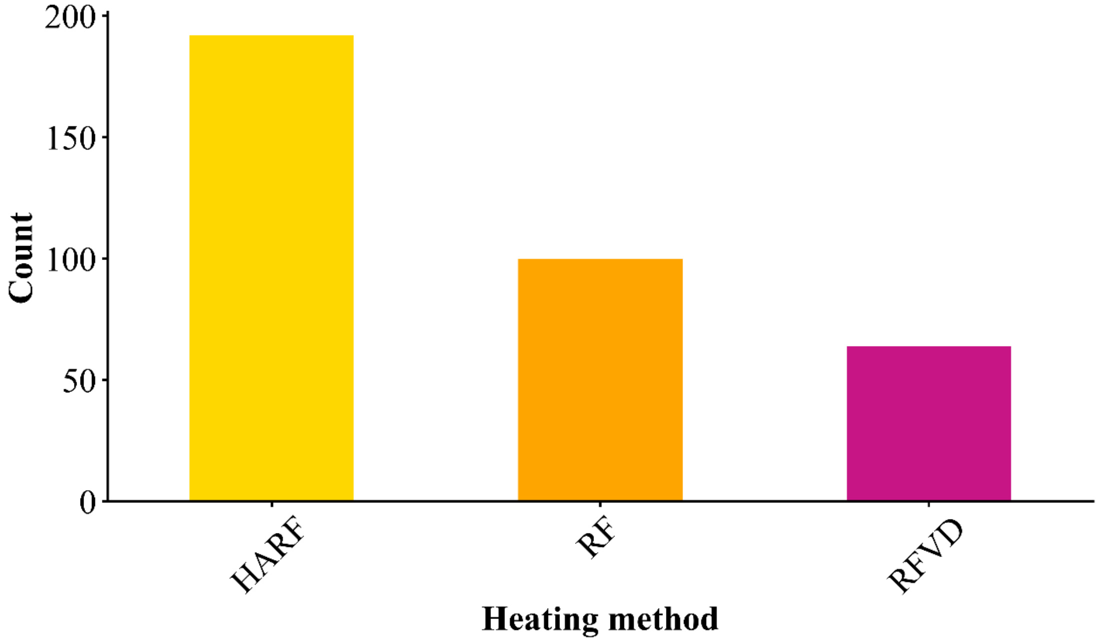

Fig. 3S. Distribution of data points across different heating methods in the whole dataset. The X-axis represents the heating methods, including radio frequency (RF), hot air-assisted RF (HARF), and vacuum-RF (RFVD). The Y-axis represents the frequency (indicating the number of data points). This figure reflects the quantity distribution of data points corresponding to each heating method in the constructed dataset.

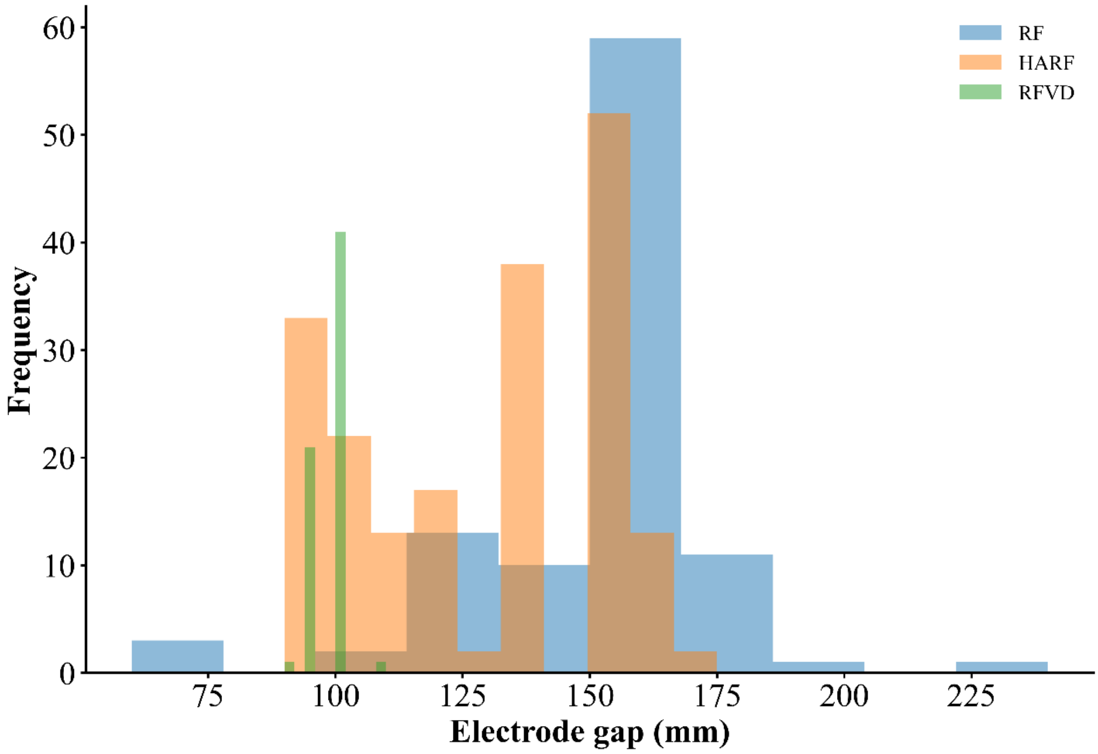

Fig. 4S. Distribution of electrode gap across different heating methods in the dataset. Electrode gap refers to specific numerical values set in the selected literature. The X-axis represents the electrode gap value (unit: mm), and the Y-axis represents the frequency (indicating the number of data points). This distribution reflects the quantity distribution characteristics of electrode gap values adopted for different heating methods (RF, HARF, RFVD) in the collected literature experiments.

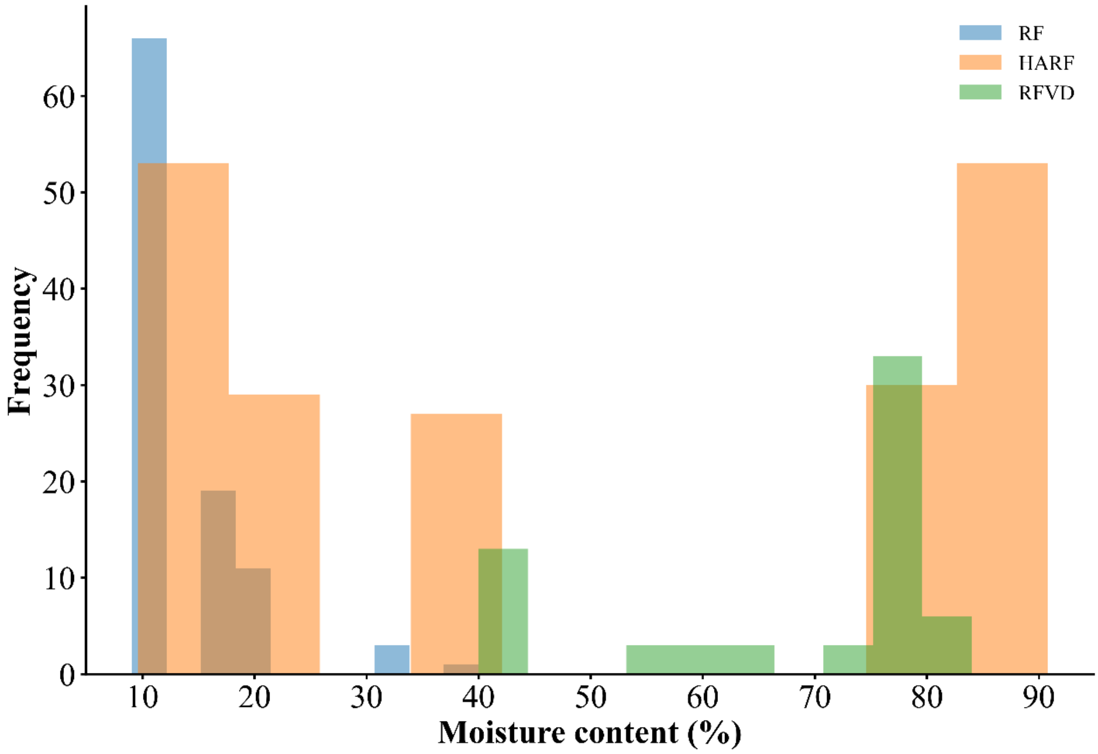

Fig. 5S. Distribution of moisture content across different heating methods in the dataset. Moisture content refers to the initial moisture content parameter of agricultural products, expressed on a wet basis (% w.b.) as reported in the selected literature experiments. The X-axis represents the moisture content value (unit: % w.b.), and the Y-axis represents the frequency (indicating the number of data points). This distribution reflects the quantity distribution characteristics of moisture content values for different heating methods (RF, HARF, RFVD) in the collected literature experiments.

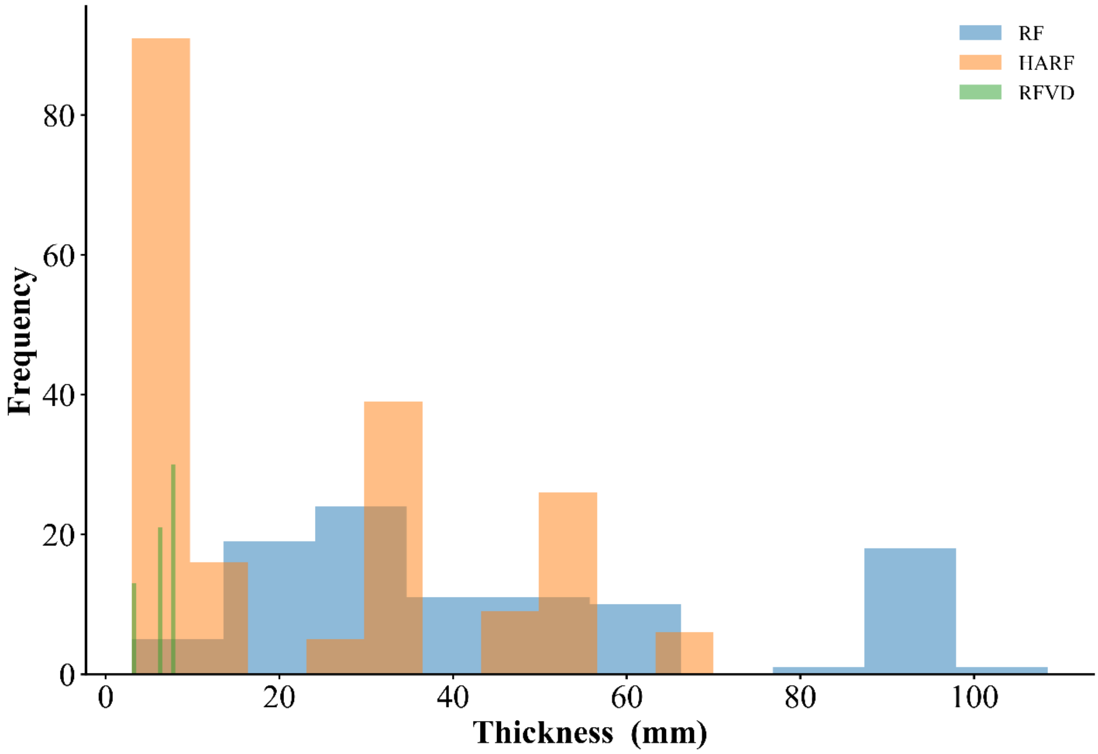

Fig. 6S. Distribution of material thickness across different heating methods in the dataset. Material thickness refers to the actual thickness parameter of agricultural products used in the selected literature experiments. The X-axis represents the material thickness value (unit: mm), and the Y-axis represents the frequency (indicating the number of data points). This distribution reflects the quantity distribution characteristics of material thickness values for different heating methods (RF, HARF, RFVD) in the collected literature experiments.

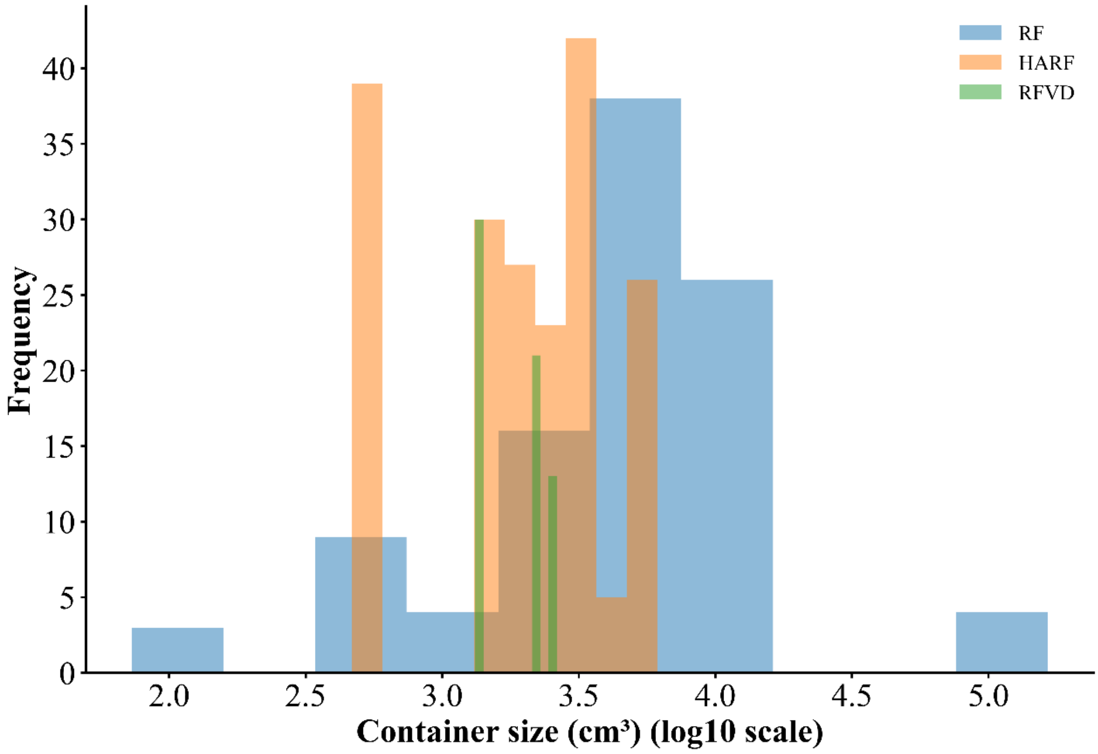

Fig. 7S. Distribution of container size across different heating methods in the dataset. Container size refers to the volume parameter of containers/trays used for loading agricultural products in the selected literature experiments. The X-axis represents the container size value (unit: cm^3) with a log10 scale, and the Y-axis represents the frequency (indicating the number of data points). This distribution reflects the quantity distribution characteristics of container size values for different heating methods (RF, HARF, RFVD) in the collected literature experiments.

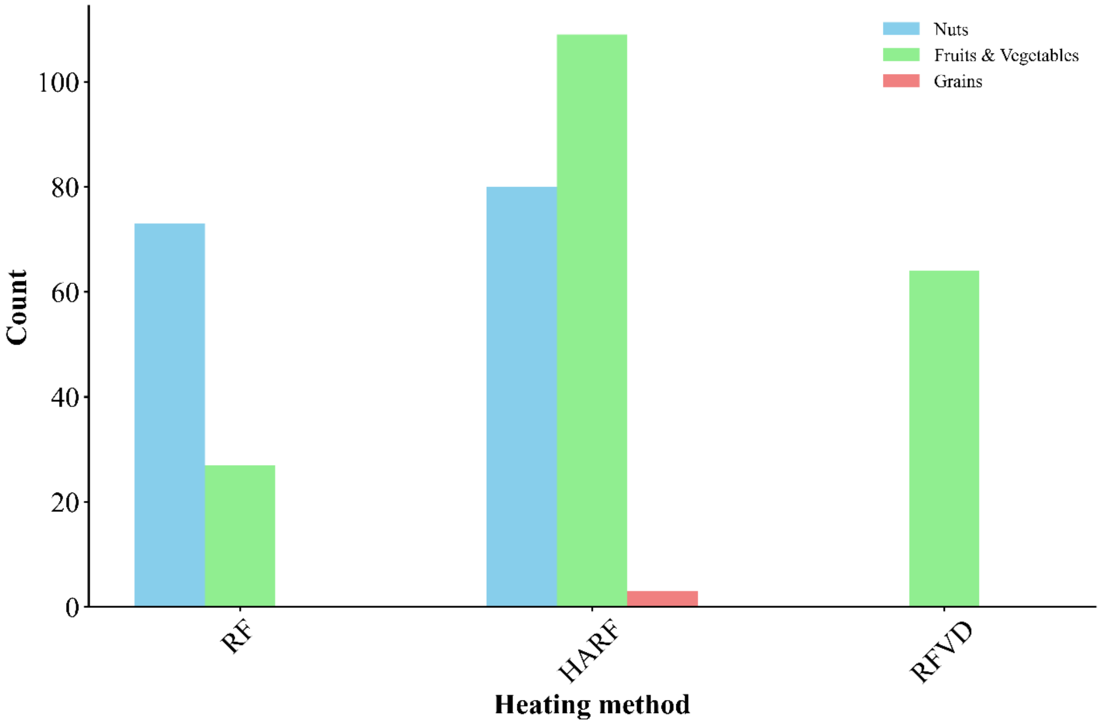

Fig. 8S. Distribution of agricultural product materials across different heating methods in the dataset. The X-axis represents the heating methods, including radio frequency (RF), hot air-assisted RF (HARF), and vacuum-RF (RFVD). The Y-axis represents the number of data points. This figure reflects the quantity distribution characteristics of different material types under each heating method in the collected literature experiments, providing data support for the subset division in subsequent parameter distribution analysis.

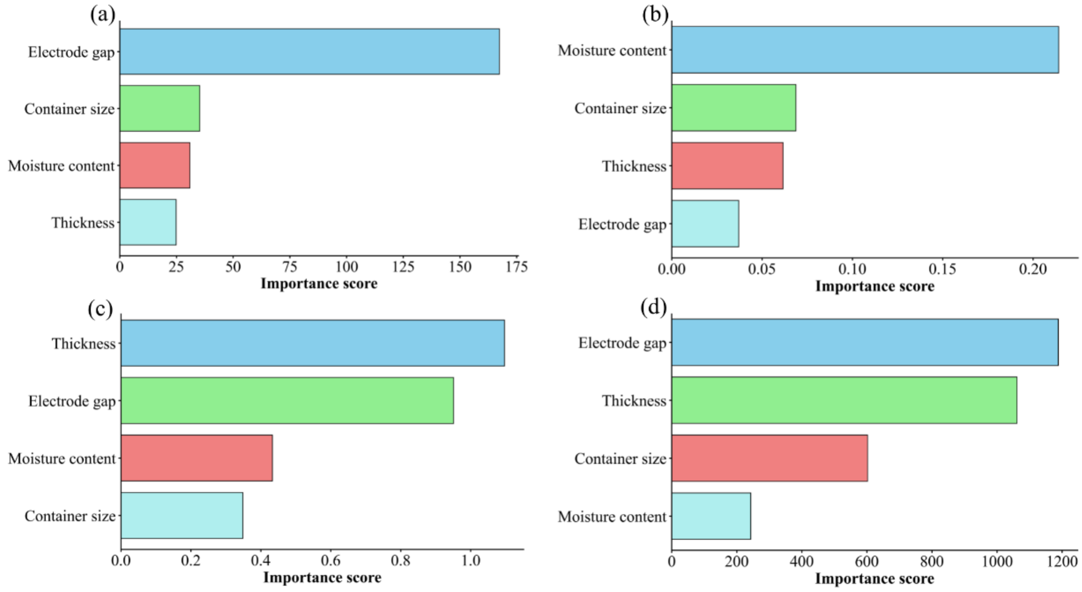

Fig. 9S. Feature importance of parameters affecting RF heating uniformity (λ) for RF method. (a) CatBoost model feature importance. (b) XGBoost model feature importance. (c) Gradient Boosting model feature importance. (d) LightGBM model feature importance. Each subfigure presents the sorted feature importance scores of different parameters (moisture content, electrode gap, thickness, container size) affecting RF heating uniformity (λ) for the corresponding model.

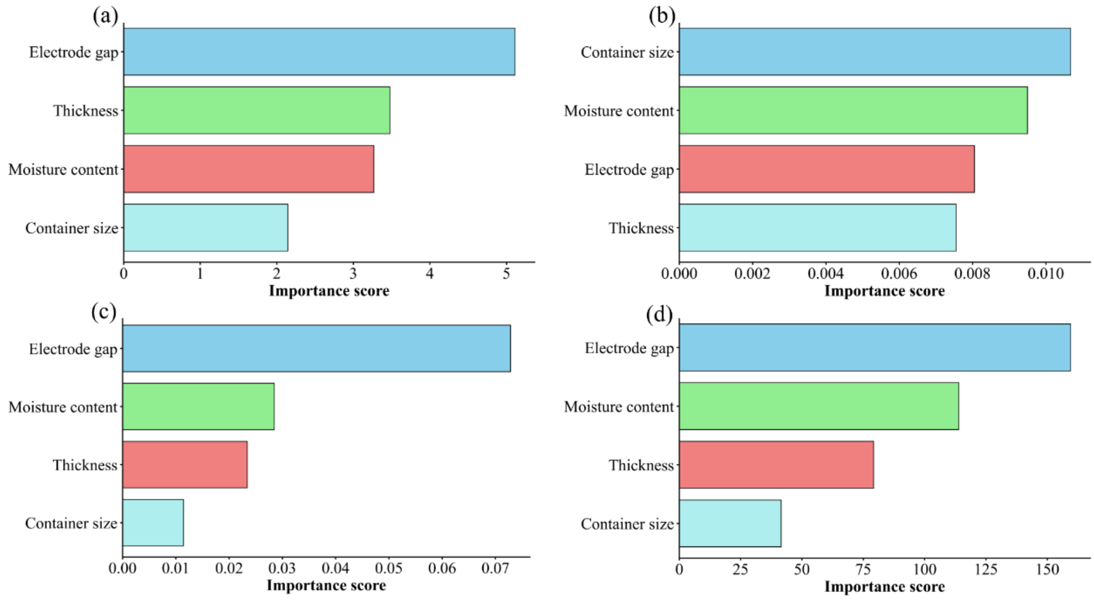

Fig. 10S. Feature importance of parameters affecting RF heating uniformity (λ) for HARF method. (a) CatBoost model feature importance. (b) XGBoost model feature importance. (c) Gradient Boosting model feature importance. (d) LightGBM model feature importance. Each subfigure presents the sorted feature importance scores of different parameters (moisture content, electrode gap, thickness, container size) affecting RF heating uniformity (λ) for the corresponding model.

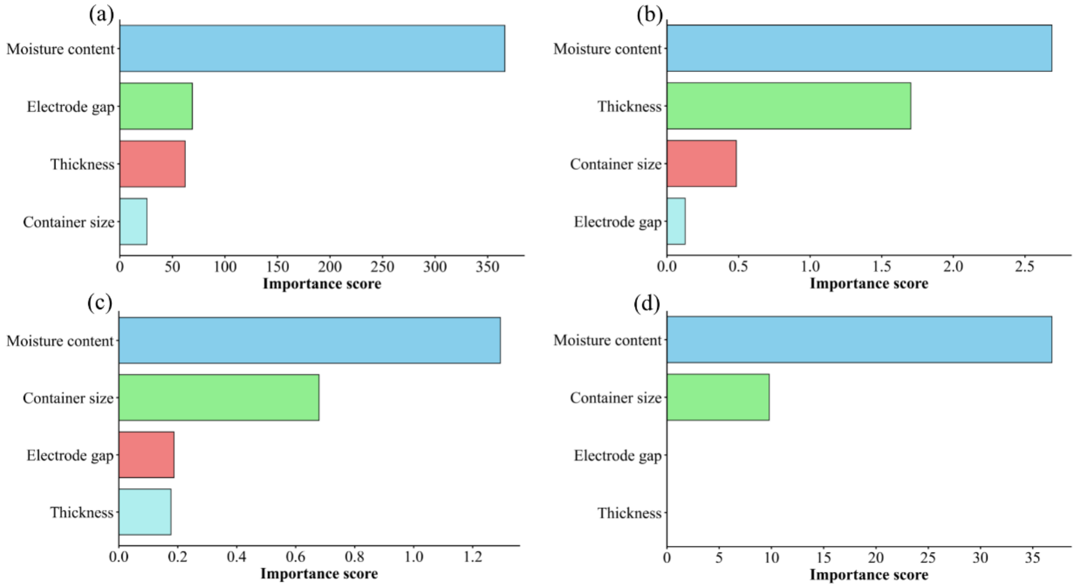

Fig. 11S. Feature importance of parameters affecting RF heating uniformity (λ) for RFVD method. (a) CatBoost model feature importance. (b) XGBoost model feature importance. (c) Gradient Boosting model feature importance. (d) LightGBM model feature importance. Each subfigure presents the sorted feature importance scores of different parameters (moisture content, electrode gap, thickness, container size) affecting RF heating uniformity (λ) for the corresponding model.