PREDICTION OF BOESENBERGIA ROTUNDA (L.) DRYING USING HOT AIR AND ULTRASONIC VIBRATION VIA EXTREME GRADIENT BOOSTING

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การทำนายการอบแห้งของกระชายขาวด้วยลมร้อนและการสั่นสะเทือนความถี่สูงโดยใช้เทคนิคเอ็กซ์ตรีมเกรเดียนต์บูสติง

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ABSTRACT

This study used eXtreme Gradient Boosting (XGBoost) to predict the drying behavior of Boesenbergia rotunda (L.) under hot air and ultrasonic vibration. A dataset of 73 samples with temperature, time, and vibration as inputs was used. The model achieved high accuracy with R^2 = 0.99 and RMSE = 8.71 on test data. SHAP analysis revealed that ultrasonic vibration improved moisture reduction, especially during longer drying times. These results demonstrate the effectiveness of combining XGBoost and SHAP for understanding and optimizing complex drying processes in food and agricultural engineering.

บทคัดย่อ

งานวิจัยนี้ใช้เทคนิค XGBoost เพื่อพยากรณ์พฤติกรรมการอบแห้งของกระชายขาว (Boesenbergia rotunda (L.)) ด้วยลมร้อนร่วมกับคลื่นการสั่นสะเทือนความถี่สูง โดยใช้ชุดข้อมูลจำนวน 73 ตัวอย่างที่มีอุณหภูมิ เวลา และการสั่นสะเทือนเป็นตัวแปรนำเข้า โมเดลสามารถทำนายได้อย่างแม่นยำ โดยมีค่า R^2 เท่ากับ 0.99 และ RMSE เท่ากับ 8.71 จากข้อมูลทดสอบ การวิเคราะห์ด้วย SHAP แสดงให้เห็นว่าคลื่นเสียงช่วยลดความชื้นได้ดีขึ้นเมื่อใช้กับเวลาการอบแห้งที่นาน ผลลัพธ์นี้ชี้ให้เห็นถึงศักยภาพของการผสาน XGBoost กับ SHAP ในการเพิ่มประสิทธิภาพกระบวนการอบแห้งสำหรับงานด้านวิศวกรรมอาหารและเกษตร

INTRODUCTION

White fingerroot, also known as Chinese ginger, is an important medicinal herb primarily found in Southeast Asia (*Larsen, 1996; Taheri et al., 2022*). Its significance stems from both its culinary uses and its medicinal properties, making it highly valued in traditional medicine and modern pharmaceutical research. White fingerroot contains important nutrients, including vitamins, minerals, and antioxidants (*Trakoontivakorn et al., 2001; San et al., 2022*). Drying is an important step in processing herbs to enable them to be stored for a longer period and effectively retain their medicinal value (*Orphanides et al., 2016; Thamkaew et al., 2021*).

Ultrasonic vibration drying is an innovative drying technique that uses high-frequency sound waves to enhance the removal of moisture from various materials, including food, herbs, and industrial products (*Musielak et al., 2016*). This method leverages mechanical vibrations, typically at frequencies between 20 kHz-1 GHz, to break the bonds between water molecules and the material, allowing for faster and more efficient evaporation compared to conventional drying methods (*Yao, 2016; Cheeke, 2012*). In ultrasonic vibration drying, a transducer generates high-frequency sound waves that are transmitted into the material being dried. These waves cause rapid, microscopic vibrations in the material and the surrounding moisture. These vibrations break up water droplets and reduce the surface tension, enabling moisture to evaporate more easily. The process is highly efficient because the mechanical energy from the vibrations increases the rate of moisture transfer without requiring high heat (*Kahraman et al, 2021; García-Pérez et al., 2023; Thanompongchart et al., 2022*).

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The use of ultrasonic vibration for drying offers several significant advantages. Firstly, it enables faster drying times as the ultrasonic waves substantially accelerate the evaporation process. This method also consumes less energy because it operates at lower temperature compared to traditional drying techniques. Additionally, minimal temperature exposure is a key benefit, making it ideal for preserving sensitive materials such as herbs and food, which can otherwise lose essential nutrients, flavor, or texture due to excessive heat. Furthermore, ultrasonic vibrations promote uniform moisture evaporation, ensuring improved quality and consistency by preventing issues like over-drying or uneven results. Lastly, this drying method is environmentally friendly, as it is non-invasive and sustainable, relying neither on chemicals nor high temperatures, which makes it an eco-friendlier option (*Musielak et al., 2016; Gallego-Juarez et al., 1999).* However, ultrasonic vibration still poses a problem of high heat accumulation at the vibrator, resulting in a short lifespan. This technology is especially beneficial in industries where preserving the quality of sensitive materials is essential, such as food, herbs, and pharmaceuticals. Its ability to enhance moisture removal without high heat positions ultrasonic vibration drying as a modern, sustainable solution to traditional drying challenges (*Mujumdar, 2004; 2006*).

Machine learning (ML) can improve the industry by enabling more accurate predictions of drying behavior, thus optimizing efficiency, quality, and resource management. By analyzing large datasets generated during the drying process, ML models can uncover patterns and relationships between key variables like temperature, humidity, airflow, and material properties. These models, including regression models, neural networks, and support vector machines are trained to predict drying kinetics and outcomes (*Martynenko and Misra, 2020; Taur et al., 2019; Đaković et al., 2023*). ML models identify how these factors interact to influence the drying rate and moisture ratio (*Çetin, 2022*). Once trained, the model can accurately predict the behavior of agricultural products under given drying conditions (*Tagnamas et al., 2023*), offering insights into optimizing the process for better energy efficiency, faster drying, and improved product quality (*Soares et al., 2013*). Moreover, ML algorithms estimate product yields, optimal conditions, and variables or affect operational efficiency in others applications (*Katongtung et al., 2022; 2024a; 2024b; Kittichotsatsawat et al., 2023*).

The novelty of this work lies in the fact that an ML algorithm is applied to estimate the drying of white fingerroot with conventional hot air dryer combined with an ultrasonic vibration system. The objective of this study is to develop a predictive model for the drying behavior of *Boesenbergia rotunda* (L.) using hot air combined with ultrasonic vibration. The eXtreme Gradient Boosting (XGBoost) algorithm was employed to optimize and analyze the drying process with the goals of minimizing material waste, enhancing product consistency, and increasing overall processing efficiency. The findings emphasize the importance of dataset expansion in mitigating overfitting and improving the model's generalization capability, in line with prior studies (*Chamorro et al., 2026*). A larger and more diverse dataset enables the model to capture fundamental patterns more effectively, thereby increasing the accuracy and robustness of predictions in both experimental validation and practical applications.

MATERIALS AND METHODS

Experimental setup and procedure

The experimental dryer is a modified hot air oven integrated with an ultrasonic vibration system, as illustrated in Fig. 1(a). Positioned centrally beneath the product trays inside the dryer is an ultrasonic vibration unit operating at a frequency of 40 kHz, 60 W (Piezoelectric) with 1 unit set per tray. The dryer accommodates two tiers of product trays. To prolong the operational life and durability of the ultrasonic system, an air-cooling system is installed via ducts beneath the trays in Fig. 1(b). The system is programmed to operate in cycles of 1 min on and 5 min off.

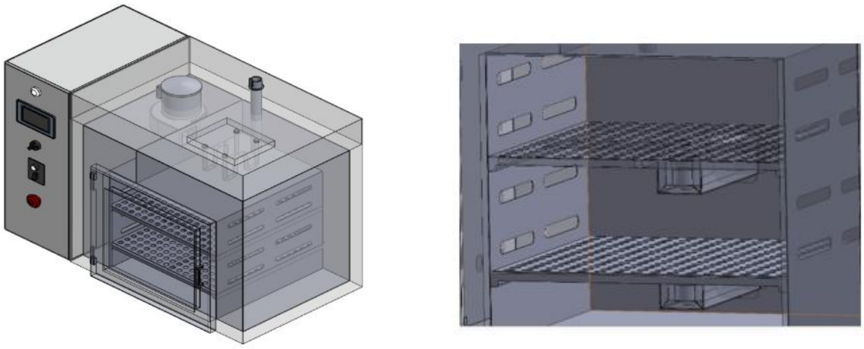

Fig. 1 – (a) Hot air dryer integrated with an ultrasonic vibration system and (b) installation of the ultrasonic vibration system underneath product trays

The dryer's heating system uses electric heaters and a fan to ensure uniform airflow and efficient moisture extraction through the top vent. White fingerroot (*Boesenbergia rotunda* (L.)) was prepared for drying by washing and cutting it longitudinally into pieces generally less than 1 cm thick and approximately 10 cm long. The pieces were arranged on mesh trays at 1.5 kg per tray, with a maximum spacing of 8 ± 1 cm. Two trays were used for each drying run. Each condition was tested in triplicate. Drying experiments were conducted at temperatures of 50 °C, 60 °C, and 70 °C using a combined method involving hot air and ultrasonic vibration. The dried white fingerroot was weighed every hour during the drying process. Afterward, samples were further dried in a hot air oven at 103 °C for 72 hours to determine dry matter content based on AOAC (1995) standards. The final moisture content was then calculated. According to *Rungsardthong, (2002),* the moisture content of dried white fingerroot suitable for storage should not exceed 7% on a wet basis.

Data analysis

In physics-based modeling, the drying process is analyzed through theoretical models derived from mathematical reasoning. This section establishes a boundary value problem by incorporating the governing equations of transport phenomena, along with relevant assumptions, initial conditions, and boundary conditions (*Akter et al., 2022*). The moisture content of the drying material decreases as it absorbs thermal energy, along with the sensible heat present in the surrounding air. During the drying process, the amount of thermal energy absorbed by the material corresponds to the latent heat required for the evaporation of its moisture (*Wengang et al., 2024*).

Determination of humidity on a wet basis is the ratio of the weight of water in a material to the material weight, calculated as:

$$M_w = \frac{(w-d)}{w} \times 100 \tag{1}$$

where:

M_w is moisture content wet basis (%), w is initial weight of the material (kg) and d is weight of dry material (kg). The initial moisture content of the white fingerroot was 93 ± 1.5% wb and the final value was lower than 7% wb.

The drying water evaporation rate is the amount of water that evaporates during the drying process per unit of time. It can be calculated by:

$$\dot{M}_w = \frac{M_w}{t} \tag{2}$$

where:

$\dot{M}_w$ is water evaporation rate ($kg_{(water)}$/h), M_w is evaporated water mass ($kg_{(water)}$) and t is time (h).

Machine learning model and evaluation

In this study, an ML model was developed to predict average moisture content using XGBoost, a widely used and highly efficient algorithm (*Katongtung et al., 2022; 2024a; 2024b*). XGBoost is a machine learning algorithm that builds multiple decision trees in an iterative fashion to solve both regression and classification problems. It is an implementation of gradient boosting that is optimized for performance and speed. Gradient boosting is a technique where weak learners, typically decision trees, are trained sequentially with each new tree attempting to correct the errors made by the previous ones. XGBoost has become widely used because of its ability to handle large datasets and its robustness across a variety of tasks, including structured/tabular data problems, where it often outperforms other models. It is also popular in many Kaggle competitions due to its competitive accuracy.

The high efficiency of XGBoost is derived from several key factors. One of the most important is regularization, as it incorporates both L1 (Lasso) and L2 (Ridge) techniques to prevent overfitting, allowing the model to generalize well on unseen data. XGBoost also benefits from parallel processing, enabling parallel tree construction, which reduces computational time and significantly improves training efficiency. Additionally, XGBoost is equipped with built-in mechanisms to handle missing data, a critical feature when working with real-world datasets. Its sparsity-aware learning optimizes performance when dealing with high-dimensional datasets that often contain many zero-valued features. Moreover, the algorithm includes automatic pruning of trees, helping to avoid unnecessary complexity, reduce model size, and enhance interpretability.

XGBoost is an ensemble learning method that implements gradient boosting using decision trees. The algorithm builds the model in an additive, stage-wise manner by iteratively fitting new trees to the residuals (errors) of previous predictions. The goal is to minimize a regularized objective function, which is composed of two main components (*Noh et al., 2024*):

(a) Loss function (L): This measures the difference between the predicted values and the actual values. For a given dataset with n examples, the loss is typically represented as:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) \tag{3}$$

where:

l is a differentiable loss function, y_i are the true values, and $\hat{y}_i$ are the predicted values.

(b) Regularization term (Ω): This term penalizes the complexity of the model to prevent overfitting. For decision trees, complexity might be measured in terms of the number of leaves and the magnitude of leaf weights. The regularization term for a tree model *f* can be written as:

$$\Omega(\boldsymbol{f}) = \boldsymbol{\gamma}\mathbf{T} + \frac{1}{2}\boldsymbol{\lambda}\sum_{j=1}^{T} \boldsymbol{w}_j^2 \tag{4}$$

where:

$\mathbf{T}$ is the number of leaves in the tree, w_j is the weight of the j leaf, γ is a parameter controlling the penalty for additional leaves, and λ is the L2 regularization term on leaf weights.

The combined objective function that XGBoost aims to minimize is:

$$obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \Omega(f_k) \tag{5}$$

where:

$\hat{y}_i^{(t)}$ is the prediction for the i^{th} instance at the t iteration, and f_k represents the k decision tree. At each iteration, the model updates its prediction by adding the output of a new tree f_t

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{6}$$

The new tree f_t is chosen by approximating the loss function using a second-order Taylor expansion and then optimizing the objective with respect to the structure and leaf weights of the tree. This results in an efficient, scalable algorithm that is capable of handling large datasets and complex models. XGBoost's effectiveness lies in its ability to balance model complexity with predictive accuracy through this rigorous mathematical framework, making it a popular choice for various machine learning tasks.

The dataset comprised 73 data points, with three input features (temperature, time and vibration), and one target output (average moisture), presenting a significant challenge in ML model development due to the limited number of data points and features. Despite these limitations, the model's performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE). Furthermore, the relationship between the input features and the target output was analyzed using Shapley values, providing a detailed explanation of the contribution of each variable to the model's predictions. Shapley values are used in machine learning to analyze the relationship between input features and the target output by quantifying each feature's contribution to the model's predictions. They provide a fair and consistent method to attribute the influence of each variable, offering detailed explanations of how each feature affects the prediction. Shapley values enable both local interpretability for individual predictions and global insights into overall model behavior. This approach ensures transparency in understanding the model's decision-making, helping to identify which variables drive outcomes and to what extent. The distribution of data used in this study is shown in Fig. 2. Shapley values originate from cooperative game theory and provide a fair distribution of a total payoff among players based on their individual contributions. Mathematically, consider a set *N* of players (or features) and a value function $v: 2^N \to \mathbb{R}$ that assigns a real number to every subset S$\subseteq N$.

The Shapley value $\emptyset_i$ for player ii is defined as:

$$\emptyset_i(v) = \sum_{S\subseteq N\setminus\{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}[v(S\cup\{i\}) - v(s)] \tag{7}$$

where:

N is the set of all players (or features), S is any subset of players not including ii, |S| is the number of players in S, |N| is the total number of players, $v(s)$ is the value (or payoff) of the subset S, and $v(S\cup\{i\}) - v(s)$ represents the marginal contribution of player ii to the subset S.

The fraction:

$$\frac{|S|!\,(|N|-|S|-1)!}{|N|!}$$

represents the probability of S occurring as the set of players preceding ii in a random ordering of N. In machine learning, Shapley values are used to attribute the contribution of each feature to the prediction made by a model, offering a robust and theoretically justified method for model interpretation.

The trained models were assessed using various performance metrics, such as the R^2 score and RMSE. These metrics were defined as follows: Eqs. (8)-(9) (*Katongtung et al., 2022; 2024a; 2024b*).

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y}_i)^2} \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}} \tag{9}$$

where:

y_i is represents the actual value, $\hat{y}_i$ is represents the predicted value, $\bar{y}_i$ is represents the mean value of the *i-th* data point, and *N* is the total number of data points.

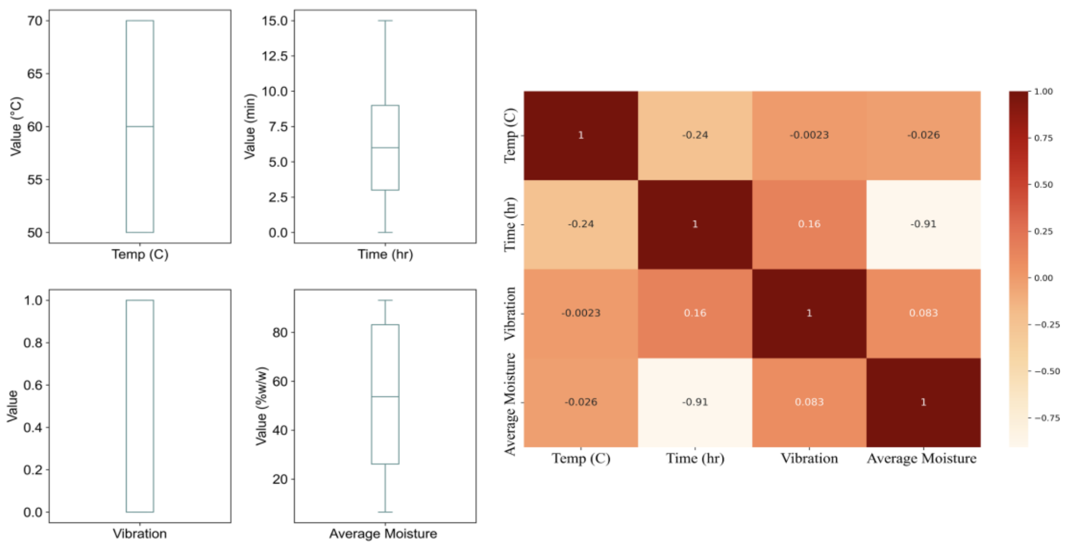

Fig. 2 – Box plot and heat map of the data set

In this study, cross-validation was not employed due to the limited size of the dataset, which comprised only 73 data points. Applying cross-validation under such conditions may lead to excessively fragmented training and validation subsets, potentially resulting in unstable performance estimates and diminished model generalizability. Therefore, a simple train–test split (75% training, 25% testing) was adopted to retain enough data for both model training and performance evaluation. To address potential overfitting, multiple regularization strategies were implemented during model development. These included early stopping, which halts training once performance on a validation set ceases to improve, as well as the tuning of regularization parameters such as lambda (L2 regularization), alpha (L1 regularization), and gamma (minimum loss reduction required to make a further partition). These techniques effectively constrained model complexity and contributed to enhanced generalization on unseen data. The incorporation of these regularization and validation strategies strengthens the reliability and transparency of the predictive modeling approach, particularly when working with limited datasets.

RESULTS AND DISCUSSION

Water evaporation rate

From the experiment, the water evaporation rate when using hot air drying combined with an ultrasonic vibration system is higher than conventional drying methods under all conditions. The maximum value was achieved at a drying temperature of 70°C, reaching 0.313±0.016 $kg_{(water)}$/h.

A 25% increase in performance was observed compared to the conventional hot air drying process. Additionally, a linear regression analysis was conducted based on experimental data, as illustrated in Fig. 3.

The results of this study showed that increasing ultrasonic vibration for drying significantly reduced drying time, which is consistent with previous research on pineapple drying (*Thanompongchart et al., 2022*). The dried white fingerroot exhibited superior quality in terms of its physical properties and active compound content, particularly when dried at a temperature of 60°C.

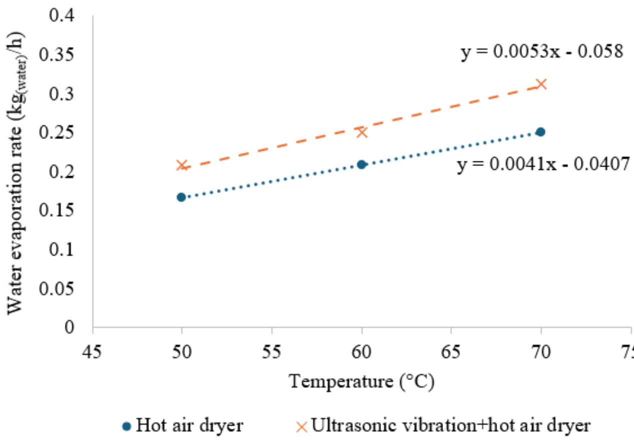

Fig. 3 – Water evaporation rate during drying of white fingerroot

ML model accuracy

In machine learning, a dataset is often split into two key sections: one for training and another for testing. The training portion is used to help the model recognize patterns and relationships in the data. As the model learns, it fine-tunes its internal parameters to improve its predictions or classifications. After training, the test set, which remains unseen by the model during training, is used to assess how well the model performs. This helps provide a fair evaluation of its ability to generalize to new data, offering insights into its overall accuracy and effectiveness. In this study, the dataset was divided into 75% training data and 25% test data to evaluate the performance of the ML model.

Fig. 4 presents the accuracy graph for the average moisture content prediction of the ML model, using both training and test data.

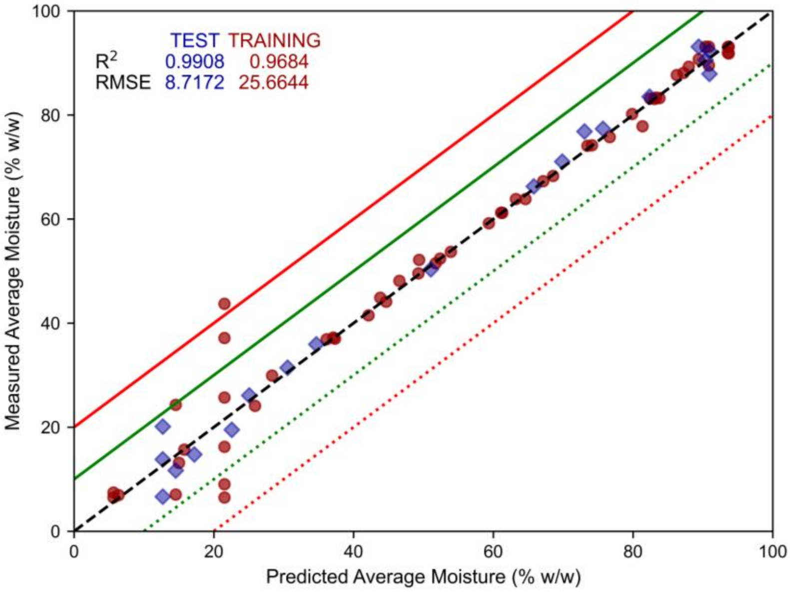

Fig. 4 – Distribution and accuracy of training and test data

The red line indicates the 20% error range, while the green line marks the 10% error range. The model demonstrated high prediction accuracy, with an R^2 value of 0.9908 and an RMSE of 8.7171. However, due to the relatively small dataset, the training data yielded an R^2 value of 0.9684 and an RMSE of 25.6644, which was a bit lower than the test prediction accuracy. This suggests that increasing the dataset size would reduce overfitting and enhance the reliability of the ML model.

In ML, overfitting occurs when a model learns not only the underlying patterns in the training data but also noise and random fluctuations that do not generalize to new, unseen data. As a result, the model performs well on the training dataset but fails to generalize, leading to poor performance on test or real-world data providing more examples for the machine learning model to learn from. When the dataset is small, the model is more likely to memorize specific details rather than learning general patterns, which leads to overfitting. With a larger dataset, the model is exposed to a wider variety of examples and variations, making it harder for the model to memorize individual points, encouraging it to generalize instead.

Increasing the size of a dataset offers several important advantages. Firstly, it helps reduce overfitting by providing more diversity in the data, allowing the model to distinguish between noise and true patterns. With a larger and more representative dataset, the model can capture generalizable trends instead of focusing on anomalies specific to the training set. Secondly, it improves generalization, meaning the model becomes better at making accurate predictions on unseen data. This ensures that the model performs well not just on the training data but also in real-world scenarios. Thirdly, increasing the dataset size enhances the reliability of the model, making it more robust and dependable by learning from a broader and more diverse set of examples. As a result, the model is less likely to make erroneous predictions, leading to more trustworthy and consistent outcomes. Lastly, a larger dataset helps reduce the variance in predictions, making the model less sensitive to small changes in the training data and resulting in more stable and reliable predictions.

Fig. 5 illustrates the use of Shapley values to explain the impact of individual variables on the model's predictions. The analysis reveals that drying time is the most significant factor, followed by vibration and temperature. The color of the SHAP summary plot further indicates whether the effect is positive or negative. In this study, it was found that longer drying times negatively affect average moisture content, whereas shorter drying times have a positive effect. Longer drying times can negatively affect the average moisture content of a material due to uneven moisture removal, with some areas drying too much while others retain moisture. This unevenness, combined with the potential for moisture reabsorption over time, increases the overall average moisture content. In contrast, shorter drying times promote more efficient and uniform moisture removal, reducing the chances of reabsorption and preventing over-drying in certain sections. Reduced drying time without raising temperature effectively minimizes color changes, decreases undesirable texture attributes (hardness, cohesiveness, gumminess, chewiness), and preserves bioactive compounds (*Yitayew and Fenta, 2021*).

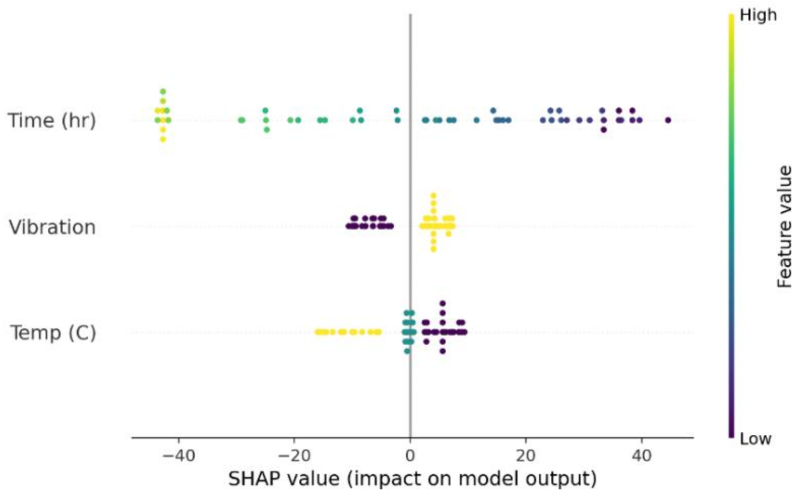

Fig. 5 – SHAP summary plot

Similarly, the vibration variable positively affects average moisture content during the drying process by enhancing moisture movement within the material, allowing water molecules to migrate more easily to the surface for evaporation. It improves airflow around the material, facilitating better interaction between the moist material and the drying medium, which helps carry away evaporated moisture more effectively. Additionally, vibration promotes uniform drying, ensuring no parts of the material dry excessively while others remain wet. It also reduces surface tension, making it easier for moisture to escape, and minimizes heat stress by distributing heat evenly. Together, these factors contribute to a more efficient and effective drying process, leading to a lower average moisture content (*Yang et al., 2024*).

The temperature variable influences average moisture content similarly to drying time, with higher temperatures negatively impacting moisture levels while lower temperatures have a positive effect. High temperatures can lead to rapid surface evaporation, causing the outer layers of a material to dry too quickly and potentially trapping moisture in the inner layers, a phenomenon known as "case hardening." This uneven drying not only increases average moisture content but can also degrade the quality of sensitive materials, such as food, by stripping away essential nutrients and flavors. In contrast, lower temperatures promote gradual and even moisture removal, reducing the likelihood of trapping moisture and preventing reabsorption from the environment. This controlled drying process helps maintain the quality of the material while effectively lowering average moisture content, leading to better overall results (*Mougang et al., 2024*).

Moreover, Fig. 6 showcases SHAP dependence plots, which help visualize how specific variables influence the average moisture content of a material. Fig. 6(a) focuses on the relationship between temperature and drying time. At a low temperature of 50°C, extending the drying time tends to have a positive effect on reducing average moisture content, meaning that longer drying periods at this temperature help remove more moisture. When the temperature is raised to a medium level of 60°C, the effect of drying time becomes minimal; in this range, increasing the drying time does not significantly change the average moisture content. Finally, at a high temperature of 70°C, shorter drying times become more beneficial for reducing average moisture content, suggesting that quick drying at this temperature effectively removes moisture without causing detrimental effects. Fig. 6(b) examines how vibration interacts with drying time. It shows that introducing vibration during the drying process has a more pronounced positive effect on average moisture content when the drying times are longer. This means that the benefits of using vibration in the drying process are more noticeable over extended periods, helping to enhance moisture removal compared to shorter drying times, where the effect is less significant.

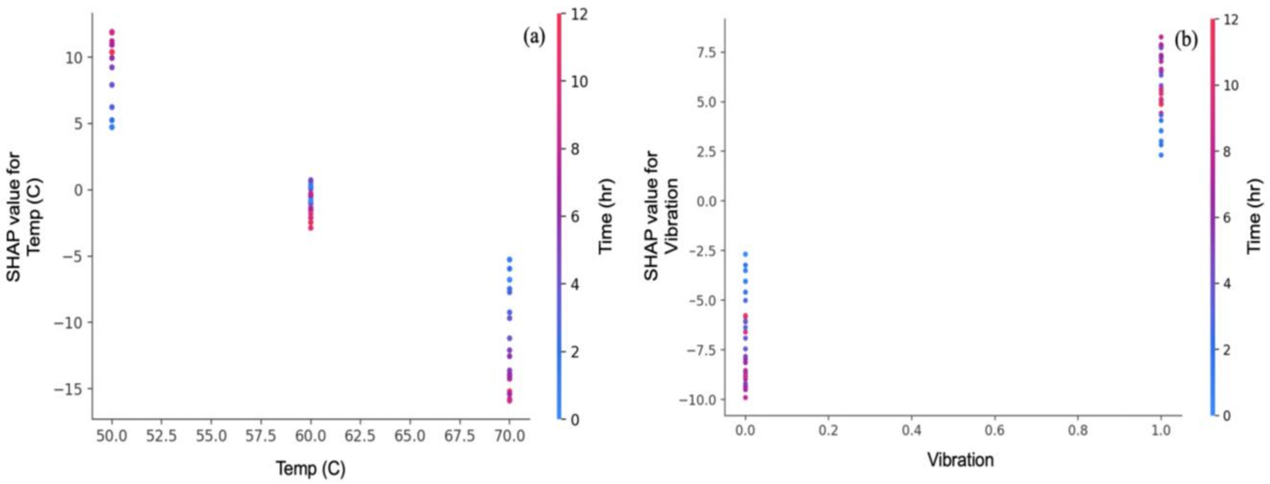

Fig. 6 – SHAP independence plot: (a) temperature and time; (b) vibration and time

Table 1 shows the prediction results from the ML model compared to experimental data at 50, 60, and 70°C, using combined hot air and ultrasonic vibration methods, based on a random selection of 10 runs. The results indicate that the ML model predictions closely align with the experimental values, with the smallest difference being 0.09 and the largest difference being 1.15. Overall, the predicted values demonstrate strong agreement with the experimental data, suggesting that the ML model is well-suited for predicting the average moisture content in the drying process. However, this ML approach may be effective under hot air drying combined with an ultrasonic vibration system. Further research may be required to develop and validate its applicability for other drying methods.

Table 1

ML average moisture content prediction results compared with experimental results

Run	ML (average moisture content)	Experimental (average moisture content)	Difference
1	79.87	80.19	0.32
2	5.62	6.48	0.86
3	63.22	63.85	0.63
4	90.36	90.59	0.23
5	12.67	13.82	1.15
6	43.80	44.89	1.09
7	73.47	74.09	0.62

Run	ML (average moisture content)	Experimental (average moisture content)	Difference
8	44.65	44.12	0.53
9	82.44	83.14	0.7
10	15.77	15.68	0.09

CONCLUSIONS

This study developed a predictive machine learning model based on the XGBoost algorithm to estimate the average moisture content during the drying of *Boesenbergia rotunda* (L.). The drying process employed a hybrid technique combining hot air and ultrasonic vibration. A dataset comprising 73 samples with three input features, temperature, drying time, and vibration amplitude was utilized. The dataset was divided into training and testing sets at a 75:25 ratio, yielding a high predictive performance with an R^2 of 0.9908 and RMSE of 8.7171 on the test set.

SHAP analysis was conducted to interpret model behavior, revealing that drying time was the most influential variable, followed by vibration amplitude and temperature. The findings indicate that shorter drying durations and moderate temperatures contribute to more uniform and efficient moisture removal, while ultrasonic vibration enhances internal moisture migration and airflow dynamics. Comparison between model predictions and experimental results at 50, 60, and 70 °C demonstrated strong agreement, confirming the model's robustness. However, the relatively small dataset may introduce limitations such as overfitting. Therefore, future work should focus on expanding the dataset to improve generalization capability and reliability. While the model has shown promising results under the hot air–ultrasound drying system, further investigations are recommended to assess its applicability across different drying techniques and material types.

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REFERENCES

[1] Akter F., Muhury R., Sultana A., Deb U.K. (2022). A comprehensive review of mathematical modeling for drying processes of fruits and vegetables. *International Journal of Food Science*, 2022, 6195257. https://doi.org/10.1155/2022/6195257

[2] AOAC. (1995). *Official Method of Analysis*, 16th ed., The Association of Official Analytical Chemists. Inc. Arlington, Verginia, USA

[3] Cheeke, JDM. (2012). *Fundamentals and Applications of Ultrasonic Waves*, 2nd ed. Boca Raton (USA): CRC Press.

[4] Chamorro M., Gallego F.A., Rojas J.C. (2026). Reducing overfitting in ResNet with Adaptive Lipschitz regularization. *Journal of Computational and Applied Mathematics*, 471. https://doi.org/10.1016/j.cam.2025.116747

[5] Çetin, N. (2022). Machine learning based estimation of drying characteristics of apple slices. *Current Trends in Natural Sciences*, 11(22), 44-52. https://doi.org/10.47068/ctns.2022.v11i22.006

[6] Đaković D., Kljajić M., Milivojević N., Doder Đ., Anđelković A.S. (2023). Review of energy-related machine learning applications in drying processes. *Energies*, 17(1). https://doi.org/10.3390/en17010224

[7] Gallego-Juarez J.A., Rodriguez-Corral G., Moraleda J.C.G, Yang T.S. (1999), A new high-intensity ultrasonic technology for food dehydration, *Drying Technology*, 17(3), 597–608. https://doi.org/10.1080/07373939908917555

[8] García-Pérez J.V., Carcel J.A., Mulet A., Riera E., Andrés R.R., Gallego-Juarez J. (2023). Ultrasonic drying for food preservation. In: *Power Ultrasonics*, 743-771, Woodhead Publishing

[9] Kahraman O., Malvandi A., Vargas L., Feng H. (2021). Drying characteristics and quality attributes of apple slices dried by a non-thermal ultrasonic contact drying method. *Ultrasonics Sonochemistry*, 73. https://doi.org/10.1016/j.ultsonch.2021.105510

[10] Katongtung T., Onsree T., Tippayawong N. (2022). Machine learning prediction of biocrude yields and higher heating values from hydrothermal liquefaction of wet biomass and wastes, *Bioresource Technology*, 344. https://doi.org/10.1016/j.biortech.2021.126278

[11] Katongtung T., Prasertpong P., Sukpancharoen S., Sinthupinyo S., Tippayawong N. (2024a). Predictive modeling for multifaceted hydrothermal carbonization of biomass. *Journal of Environmental Chemical Engineering*, 12(5). https://doi.org/10.1016/j.jece.2024.114071

[12] Katongtung T., Phromphithak S., Onsree T., Tippayawong N. (2024b). Machine learning approach for predicting hydrothermal liquefaction of lignocellulosic biomass, *BioEnergy Research.* https://doi.org/10.1007/s12155-024-10773-0

[13] Kittichotsatsawat Y., Boonprasope A., Rauch E., Tippayawong N., Tippayawong K.Y. (2023). Forecasting arabica coffee yields by auto regressive integrated moving average and machine learning approaches, *AIMS Agriculture and Food*, 8(4). https://doi.org/1052-1070. 10.3934/agrfood.202305 7

[14] Larsen K. (1996). A preliminary checklist of the Zingiberaceae of Thailand. *Thai Forest Bulletin (Botany)*, 24, 35-49.

[15] Martynenko A., Misra N.N. (2020). Machine learning in drying. *Drying Technology*, 38(5), 596-609. https://doi.org/10.1080/07373937.2019.1690502

[16] Mougang N.N., Tene S.T., Zokou R., et al. (2024). Influence of fermentation time, drying time and temperature on cocoa pods (Theobroma cacao L.) marketability. *Applied Food Research*, 4(2). https://doi.org/10.1016/j.afres.2024.100460

[17] Mujumdar A.S. (2004). Research and development in drying: Recent trends and future prospects. *Drying Technology*, 22(1), 1-26. https://doi.org/10.1081/DRT-120028201

[18] Mujumdar A.S. (2006). An overview of innovation in industrial drying: Status and R&D needs. *Transport Porous Media*, 66, 3-18. https://doi.org/10.1007/s11242-006-9018-y

[19] Musielak G., Mierzwa D,, Kroehnke J. (2016). Food drying enhancement by ultrasound-A review. *Trends in Food Science & Technology*, 56, 126-141. http://dx.doi.org/10.1016/j.tifs.2016.08.003

[20] Noh H., Lee S., Kim S., Mudawar I. (2024). Utilization of XGBoost algorithm to predict dryout incipience quality for saturated flow boiling in mini/micro-channels. *International Journal of Heat and Mass Transfer*, 231. https://doi.org/10.1016/j.ijheatmasstransfer.2024.125827

[21] Orphanides A., Goulas V., Gekas V. (2016). Drying technologies: Vehicle to high-quality herbs. *Food Engineering Reviews*, 8, 164-180. https://doi.org/10.1007/s12393-015-9128-9.

[22] Rungsardthong V., (2002). *Food Processing Technology*, 2nd ed. Bangkok, King Mongkut's University of Technology North Bangkok. (In Thai)

[23] San H.T, Khine H.E.E, Sritularak B., Prompetchara E., Chaotham C., Che C.T., Likhitwitayawuid K. (2022). Pinostrobin: An adipogenic suppressor from fingerroot (Boesenbergia rotunda) and its possible mechanisms. *Foods*, 11(19). https://doi.org/10.3390/foods11193024

[24] Soares J.D.R., Pasqual M., Lacerda W.S., Silva S.O., Donato S.L.R. (2013). Utilization of artificial neural networks in the prediction of the bunches' weight in banana plants. *Scientia Horticulturae*, 155, 24-29. http://dx.doi.org/10.1016/j.scienta.2013.01.026

[25] Tagnamas Z., Idlimam A., Lamharrar A. (2023). Predictive models of beetroot solar drying process through machine learning algorithms. *Renewable Energy*, 219. https://doi.org/10.1016/j.renene.2023.119522

[26] Taheri S., Teo C.H., Heslop-Harrison J.S., Schwarzacher T., Tan, Y.S., Wee, WY, Harikrishna, J.A. (2022). Genome assembly and analysis of the flavonoid and phenylpropanoid biosynthetic pathways in fingerroot ginger (Boesenbergia rotunda). *International Journal of Molecular Sciences*, 23 (13). https://doi.org/10.3390/foods11193024

[27] Taur K.H., Deng X.Y., Chou M.H., Chen J.W., Lee Y.H., Wang W.J. (2019). A study on machine learning approaches for predicting and analyzing the drying process in the textile industry. *The International Automatic Control Conference,* 13-16 November, IEEE. https://doi.org/10.1109/CACS47674.2019.9024364

[28] Thamkaew G., Sjöholm I., Galindo F.G. (2021). A review of drying methods for improving the quality of dried herbs. *Critical Reviews in Food Science and Nutrition*, 61(11), 1763-1786. https://doi.org/10.1080/10408398.2020.1765309.

[29] Thanompongchart P., Pintana P., Tippayawong N. (2022). Thermal performance enhancement in hot air and solar drying of pineapple slices with ultrasonic vibration. *Case Studies in Thermal Engineering*, 37. https://doi.org/10.1016/j.csite.2022.102296

[30] Trakoontivakorn G., Nakahara K., Shinmoto H., Takenaka M., Onishi-Kameyama M., Ono H., Tsushida T. (2001) Structural analysis of a novel antimutagenic compound, 4-hydroxypanduratin A, and the antimutagenic activity of flavonoids in a Thai spice, fingerroot (Boesenbergia pandurata Schult.) against

mutagenic heterocyclic amines. *Journal of Agricultural and Food Chemistry*, 49(6), 3046-3050. https://doi.org/10.1021/jf0100160

[31] Wengang H., Xiyu W., Jiajie M., Ping G., Lei W. (2024). Operation prediction of open sun drying based on mathematical-physical model, drying kinetics and machine learning. *Innovative Food Science and Emerging Technologies*, 97. https://doi.org/10.1016/j.ifset.2024.103836

[32] Yang X., Niu M., Wang S. (2024). Effects of vibration parameters on the drying kinetics of lignite in a vibrated fluidized bed. *Fuel,* 375. https://doi.org/10.1016/j.fuel.2024.132655

[33] Yao Y. (2016). Enhancement of mass transfer by ultrasound: Application to adsorbent regeneration and food drying/dehydration. *Ultrasonic Sonochemistry*, 31, 512-531. http://dx.doi.org/10.1016/j.ultsonch.2016.01.039

[34] Yitayew, T., Fenta, T. (2021). The effect of drying method on the texture, color, vitamin C and β-carotene content of dried mango slices (*Cv. Apple and Kent*). *Proceedings of 8th EAI International Conference part1*, 97-109. https://doi.org/10.1007/978-3-030-80621-7_7