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ARAŞTIRMA MAKALESİ **RESEARCH ARTICLE**

The Prediction of Drying Performance of Banana Rings Dried By Osmo-solar Dehydration Method

Ozmo-solar Dehidrasyon Yöntemi İle Kurutulan Muz Halkalarının Kuruma Performansının Tahmini

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Abstract

Solar drying is known as the oldest and most common traditional food preservation method. However, if the product is indirectly contacted with the sun light, there is negative effect in the color and nutrient values of the product. Solar dryers have been developed to utilize the heat effect of the sun to solve these problems. It can be used in combination with osmotic dehydration to increase the efficiency of the solar drying process. Osmotic dehydration is applied as a pretreatment technique in the drying process. The pretreatments to be applied before drying have important effects on the quality and operating cost of the product to be dried. In addition, the osmotic dehydration pretreatment enables to shorten the drying time and increase the drying potential. In this study, bananas with high drying temperature and high moisture content were sliced into 3 mm rings, then osmotic dehydration pre-drying was applied, and then they were dried in a solar tray dryer. Sucrose and citric acid solution in 2.5%, 5%, 7.5% and 10% (w/v) concentrations were used for osmotic dehydration treatment. In addition, samples without osmotic dehydration were dried in a solar dryer to determine the effect of pretreatment. The input variables of the drying process are solution concentration (0%, 2.5%, 5%, 7.5% and 10%), type of solution (sucrose solution and citric acid solution), osmotic dehydration time (10, 30, 60 and 90 min) and sun drying time (60, 120, 180, 240 and 300 min). Output variables were chosen as moisture ratio and shrinkage rate. The results clearly showed that both the moisture ratio and the shrinkage ratio have increased due to increased solar dryer time, solution concentration and immerse time. Osmotic dehydration was found to be effective in dried banana rings in the solar tray dryer. Gradient Boosting Machine (GBM) was used to model the drying conditions and the model was successful. The correlation coefficient (R^2) values of the GBM model were respectively found as 0.94 and 0.83 for the moisture ratio and the shrinkage ratio.

Keywords: Drying, Osmotic dehydration, Solar tray dryer, Osmosolar dehydration, Gradient boosting machine

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Öz

Güneşte kurutma, en eski ve en yaygın geleneksel gıda koruma yöntemidir. Bununla beraber, eğer ürün doğrudan güneş ışınına maruz bırakılırsa ürün rengi ve besin değerine olumsuz etkisi olur. Bu sorunları çözmek için güneşin ısıtma etkisinden faydalanan güneş enerjili kurutucular geliştirilmiştir. Güneş enerjili kurutma işleminin verimini arttırmak için ozmotik dehidrasyon ile beraber kullanılabilir. Ozmotik dehidrasyon, kurutma işleminde ön işlem tekniği olarak uygulanmaktadır. Kurutulacak ürünün kalitesi ve işletme maliyeti üzerine kurutma öncesi uygulanacak ön işlemlerin önemli etkileri bulunmaktadır. Ayrıca ozmotik dehidrasyon ön işlemi kurutma süresini kısaltmayı ve kurutucu potansiyelini arttırmayı sağlar. Bu çalışmada, yüksek kurutma sıcaklığı ve yüksek nem içeriğine sahip olan muz 3 mm halka şeklinde dilimlendikten sonra ozmotik dehidrasyon ön kurutma işlemi uygulanmış daha sonra güneş enerjili raflı kurutucuda kurutulmuştur. Ozmotik dehidrasyon işlemi için %2.5, %5, %7.5 ve %10 (w/v) derişimlerinde sakkaroz ve sitrik asit çözeltileri kullanılmıştır. Ayrıca ön işlemin etkisini belirlemek için ozmotik dehidrasyon uygulanmamış örnekler de güneş enerjili kurutucu da kurutulmuştur. Kurutma işleminin giriş değişkenleri çözelti derişimi (%0, %2.5, %5, %7.5 ve %10), çözelti türü (sakkaroz çözeltisi ve sitrik asit çözeltisi), osmotik dehidrasyon süresi (10, 30, 60 ve 90 dk) ve güneşte kurutma süresi (60, 120, 180, 240 ve 300 dk) dir. Çıkış değişkenleri ise su kaybı ve büzülme oranı olarak seçilmiştir. Sonuçlar, hem nem kaybı hem de büzülme oranının güneş enerjili kurutucudaki kurutma süresi, çözelti derişimi ve çözeltide bekleme süresi ile arttığını göstermiştir. Gradyan Artırma Makine (GAM) yöntemi kurutma koşullarının modellemesinde kullanılmış ve model başarılı olmuştur. GAM modeli için korelasyon katsayısı (R^2) su kaybı ve büzülme oranı için sırasıyla 0.94 ve 0.83 olarak bulunmuştur.

Anahtar Kelimeler: Kurutma, Ozmotik dehidrasyon, Güneş enerjili raflı kurutucu, Ozmosolar dehidrasyon, Gradyan artırma makine

1. Introduction

It is a significant problem for the food sector to preserve fresh fruits and vegetables for a long time. There are various drying techniques for the food preservation. The drying techniques include hot air drying, vacuum drying, solar drying, microwave drying, and freeze-drying. The oldest and the most common traditional food preservation method known is the direct solar drying. However, it has several drawbacks like lengthy drying time, contamination issues, inability to process large quantities without impairing product quality, manual labor requirements, low energy efficiency, low final dried product quality due to prolonged exposure to high temperatures (Arslan et al., 2021). To solve these problems, many different dryers have been developed. However, the mechanical dryers are not that economical for energy costs. The quality of the foodstuffs such as cost, texture (crispiness, fluffiness and porousness), aroma, color, and taste in solar tray dryers are better than direct drying under the sunlight. In addition, drying time in the solar tray dryer is shorter than the direct solar drying and the drying potential substantially increases (Küçükatay et al., 2021; Aboud, 2013; Prakash and Kumar, 2013; Eren and Ertekin, 2007; İspir and Toğrul, 2009; Ochoa et al., 2006).

Pre-drying treatments such as scalding, blanch and osmotic dehydration were applied for drying efficiency (Şahin et al., 2012). Osmotic processes can be applied to improve the quality in the dried final products. It can be used in combination with osmotic dehydration to increase the efficiency of the solar drying process. It is the hybrid drying technique, also called osmo-solar drying, that removes a part of the moisture in food by the osmotic dehydration and then the rest of the moisture is removed by solar drying. The low-cost, crispy, fluffy, porous, and shelf-stable dried products can be obtained in shorter drying time by the osmo-solar drying. It decreases heat damage such as oxidation and the flavorings change as it takes place at temperatures lower than other drying methods. In addition, the dried products have porous structure whose rehydration capacity is high. Dried product quality and operating costs are significantly affected as the dryer potential is increased by the osmotic dehydration pre-treatment. Recently, the studies related to the implementation of the osmotic dehydration as drying pretreatment technique has become attractive (Lombard et al., 2008; Bórquez et al., 2010; Torringa et al., 2001).

Process parameters of the solar drying treatment should be modeled for the optimum production. For this reason, the local banana rings were dried by solar tray dryer in Mersin where there is the highest solar potential. More than half of the total vegetable and fruit production, especially the banana production, is cultivated in Mersin region.

Advances in machine learning regression algorithms methods are continuing and significant improvements have been observed in group learning algorithms, especially in terms of predictive accuracy. GBM is one of the powerful techniques from the machine learning techniques as it has shown significant success in a wide range of applications. No studies can be found on the food drying application by using GBM model. In this study, we employed GBM method to analyze and model the drying process to improve the prediction accuracy. The GBM was used to determine the optimum operating conditions of the banana drying by the osmo-solar dehydration for both the moisture ratio and the shrinkage ratio.

Osmo-solar drying process of banana is modeled upon the process conditions by GBM. Firstly, the model structure based on input and output data was developed by using GBM. GBM is proposed to be used to transform into a prediction algorithm for changes in the drying conditions. The effects of the parameters such as the immerse time, drying time, solution type and concentration of solution on the moisture ratio and the shrinkage ratio are predicted in this study. The prediction approach could determine the relation between the inputs and outputs. Osmotic dehydration experiments were carried out by using different kinds of the osmo-active solutions and different concentrations and solar drying experiments were performed using the natural convective solar tray dryer.

2. Materials and Methods

2.1. Experimental setup

Drying experiments were carried out with the natural convective (passive) solar tray dryer shown in *Figure 1*. The effect of drying conditions on osmo-solar dehydration drying process was determined by the GBM. Solar tray dryer consisted of solar collector and solar cabinet with stainless steel trays. There were 5 steel perforated trays in the solar cabinet. There was a door on the back of the dryer to allow these trays to be placed in the dryer.

The solar collector was used to supply the hot air to the cabinet. Solar collector consisted of black painted perforated plates placed on top of each other with 10 mm spacing to collect sunlight in the wooden case, and a glass panel that covers the top on the collector. The sun rays were collected at the collector surface, converted to heat, and transferred to the air in the solar cabinet by natural convection. The hot air firstly enters through the solar cabinet, then through the tray where the products are placed, the moist air is purged from the outlet vent, and that is how the drying process is completed.

Figure 1. Solar tray dryer

Most of domestic banana production (73%) is carried out in Mersin. The average moisture content of the samples used was found to be 88.2% on a wet basis. Bananas are considerably cultivated in Anamur (Subaşı et al. 2016; Akkova and Güven, 2018). The fresh organic Anamur banana was dried by using solar tray dryer in Mersin. Banana samples were peeled, and sliced to a ring shape of the thickness (3 mm) and then immersed in different solutions; then each sample was placed on the tray. Banana rings were firstly immersed in one of the osmo-active solutions such as sucrose and citric acid solution, and then dried in a solar dryer. Immerse time (10, 30, 60 and 90 min), the solution concentration (0, 2.5, 5, 7.5 and 10 %w/v) and solar drying time (60, 120, 180, 240 and 300 min) were chosen as independent variables. In addition, banana rings without pretreatment as control samples that were not immersed in any solutions were only dried in a solar dryer. The moisture ratio and the shrinkage ratio were determined at the end of the drying period. The measurements were replicated five times to obtain an average. The moisture ratio and the shrinkage ratio were calculated according to the following equations (1) and (2) (Pandya and Yadav, 2014; Askari et al., 2008).

$$\text{Moisture ratio} = \frac{M_0 - M_t}{M_o} \quad \text{(Eq.1)}$$

$$\text{Shrinkage Ratio} = \frac{D_0 - D_t}{D_0} \quad \text{(Eq.2)}$$

Where, M_0 and M_t are the sample mass (g), D_0 and D_t are the sample diameter (mm) at the beginning and at time t, respectively.

2.2. Gradient boosting machines (GBM)

Ensemble learning methods are techniques that provide more accurate results than a single model as they combine multiple models. Boosting method is one of the popular ensemble learning algorithms that has constructive iterative strategy (Hastie et al., 2009). The term boosting is used to describe a family of algorithms that weak models can convert into strong models. The method forms a model by training several relatively base models (also known as weak learners) and then combines them to form a more predictive model. Friedman introduced the GBM method by extending the boosting to the regression (Friedman, 2001; Natekin and Knoll, 2013). The fundamentals of GBM are based on the gradient-descent formulation of boosting method. Note that fitting criterion that estimates given x could in principle be used to estimate the negative gradient at line 4 of the following GBM algorithm using steepest-descent. The true functional dependence $f(x)$ and the form of the function estimate $\hat{f}(x_i)$= arg $\min_\rho \sum_{i=1}^{N} \Psi(y_i, \rho)$ estimate such that some specified loss function $\Psi(y, \rho)$ is minimized.

1. It is computed the negative gradient as the working response

$$z_i = -\frac{\partial}{\partial f(x_i)} \Psi(y_i, f(x_i)) \Big|_{f(x_i)=f(\widehat{x_i})}$$

2. It is fit a regression model g(x) for predicting z_i from the covariates x_i .
3. It is chosen a gradient descent step size as ρ= arg $\min_\rho \sum_{i=1}^{N} \Psi(y_i, \hat{f}(x_i) + \rho g(x_i))$.
4. It is updated the estimate of f(x) as $\hat{f}(x) \leftarrow \hat{f}(x) + \rho g$ (Friedman, 2001).

GBM involves combining an ensemble of weak learners as a weighted sum in order to reduce both the bias and the variance by adding new models to the ensemble sequentially. The main idea is to create new basic models that will show maximum correlation with the negative gradient of the loss function (Friedman, 2000). The loss functions can be applied to give a better intuition that would be resulted in consecutive error-fitting by the error function in the learning procedure. Due to fact that the response variables are continuous (y, R), specific loss functional $\Psi(y, f)$ commonly used for continuous response is shown in *Table 1* (Friedman, 2001).

Table 1. Specific loss functions for continuous response

Name	Equations	Explanation
The Laplace L1	$\Psi(y, f)_{L_1} = \|y - f\|$	The Laplace L1 loss function corresponds to the median of the conditional distribution
The Gaussian L2	$\Psi(y, f)_{L_2} = \frac{1}{2}(y - f)^2$	The Gaussian L2 loss function penalizes large deviations from the target outputs while neglecting small residuals. The GBM algorithm performs residual refitting.
The Huber	$\Psi(y, f)_{\text{Huber}, \delta} = \begin{cases} \frac{1}{2}(y-f)^2 & \|y-f\| \leq \delta \\ \delta(\|y-f\| - \delta/2) & \|y-f\| > \delta \end{cases}$	The maximum value of error is specified in the Huber loss function after Laplace L1 loss function is applied. The parameter δ specifies enhancing the effect of the loss function.
The Quantile	$\Psi(y, f)_{\alpha} = \begin{cases} (1-\alpha)\|y-f\| & y - f \leq 0 \\ \alpha\|y-f\| & y - f > 0 \end{cases}$	The quantile loss function predicts a conditional quantile of the response variable. The parameter α specifies the desired quantile of the conditional distribution.

In this study, the data set was obtained from experimental measurements which were identified with actual variables and estimated variables. Actual variables refer to the immerse time, the solution concentration, the solution type, and drying time as inputs of the model. Estimated variables refer to the corresponding labels of the response variable as the moisture ratio and the shrinkage ratio. The GBM model is developed using the scikit-learn library in the Phyton Programming language by tuning three key hyper parameters such as number of the base model, learning rate and loss function. The default values in the program were used for the rest hyper parameters. *Figure 2* shows schematic diagram of the GBM model.

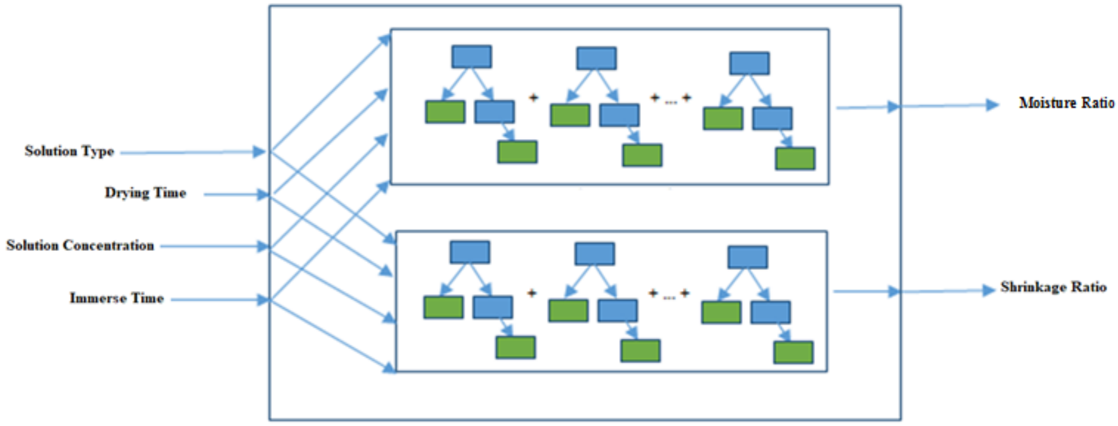

Figure 2. Schematic diagram of GBM model

Loss functions that have a significant effect on the properties of the GBM model are separately tested. The number of base models (M) refers to the number of decision trees in the ensemble. It is considered that enough trees are included to the model because of the complexity of the data. On the other hand, too many trees are avoided because of over-fitting problem. Therefore, the base model values are set between 10-500 by increasing 10. We set the learning rate, which is another parameter for the GBM Model, from 0 to 0.5 by increasing 0.1.

In machine learning regression applications, performance metrics are used to compare the trained model predictions with the measured (actual) data from the estimated (testing) data in order to evaluate performance of the regression model. Numerous performance metrics have been presented in the literature (Botchkarev, 2018). In this study, R-squared (R^2) and The Mean Absolute Percentage Error (MAPE) metrics were used as an indicator of predicted accuracy i.g measurement of error. R^2 accuracy metric is the coefficient of the determination. MAPE is one of the top most common metrics that represents the error as % of the measured value.

3. Results and Discussion

The performance of the GBM model is largely influenced by the parameters, including the number of trees, learning rate and tree complexity (variable interactions). Therefore, the GBM model needs to test the optimal combination of variables. To optimize the model, error rate tests were performed for all combinations and then the combination using hyper parameters that achieve a lower prediction error for the highest model performance was selected.

Figure 3 and *Figure 4* show the influence of different parameters (number of trees (M), learning rate (lr), and type of loss function on the value of MAPE as prediction errors respectively for the moisture ratio and the shrinkage ratio.

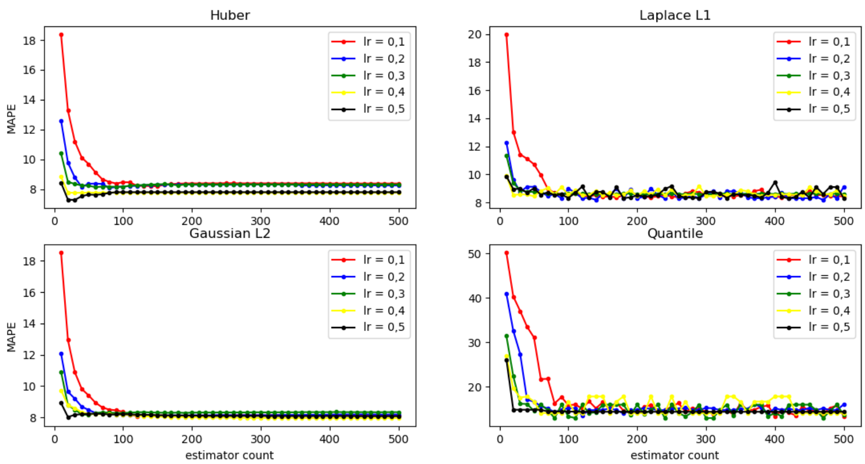

Figure 3. MAPE, M, lr and loss functions for the moisture ratio

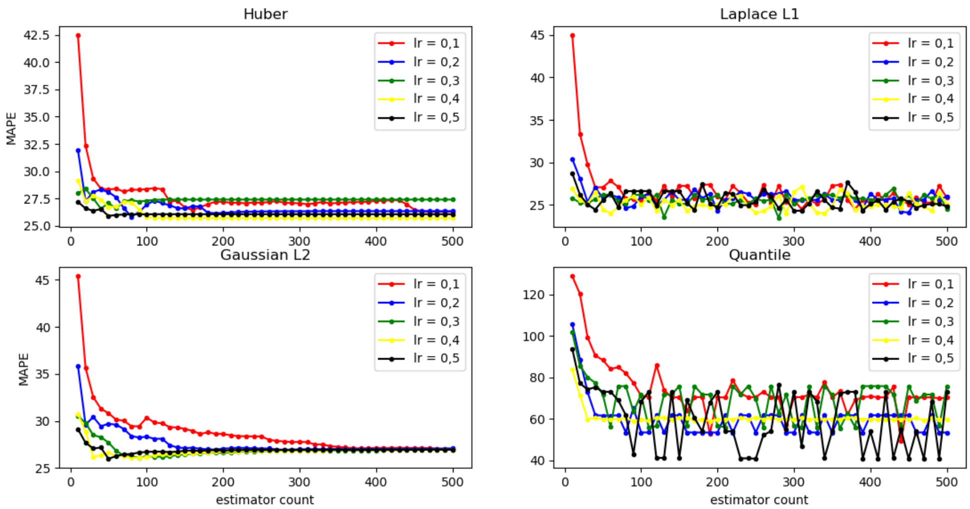

Figure 4. MAPE, M, lr and loss functions for the shrinkage ratio

As seen in *Figure 3* and *Figure 4*, MAPE values decreases until a certain value while M increases. Different slopes of lines indicate the effect of different learning rate on MAPE value. The minimum point reached by the learning rates shows the lowest error value. *Figure 3* shows that higher learning rates (lr=0.3, lr=0.4, lr=0.5) reach generally their lowest error value with smaller numbers of trees (M<100). Over-fitting problem that could lead to poor prediction performance could be seen in case of more increased M values (M>100). *Table 2* shows that the performance varies with the hyper parameters (M, lr, type of loss function).

Table 2. The results of the combination tested for the determination of hyper parameters

Response Variable	Loss Function	Number of Trees	Learning Rate	MAPE Value	R^2
Moisture ratio	Laplace L1	470	0,2	8,19	0.93
	Gaussian L2	370	0,4	7,96	0.93
	Huber	30	0,5	7,28	0.94
	Quantile	300	0,3	12,89	0.82
Shrinkage Ratio	Laplace L1	280	0,3	23,46	0.77
	Gaussian L2	50	0,5	25,99	0.83
	Huber	40	0,3	26,58	0.80
	Quantile	470	0,5	40,76	0.68

As seen in *Table 2*, for the moisture ratio, learning rate of 0.5 value reached its minimum error with number of trees of 30 for Huber loss function. For the shrinkage ratio, learning rate of 0.3 value reached minimum error with number of trees of 280 for Laplace 1 loss function. Furthermore, R^2 value of 0.94 showed the same optimal combination like MAPE for moisture ratio. But, it showed different combination variables such as Gaussian L2 loss function, number of trees of 50 and learning rate of 0.5 for the shrinkage ratio. It is clearly seen that the type of loss function also affected the selection of hyper parameters.

Consequently, different combinations of variables for the GBM model were tested and hyper parameters according to MAPE values for each response were selected. In this sense, the Huber loss function was considered for moisture ratio and the Laplace L1 loss function was considered for shrinkage ratio.

The graphs of training and testing with the hyper parameters are shown in *Figure 5* and *Figure 6* for the moisture ratio and the shrinkage ratio, respectively.

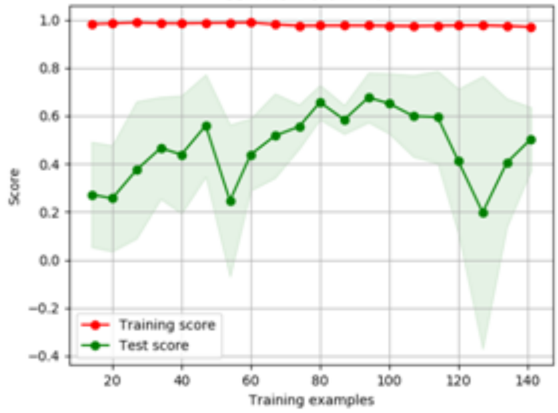

Figure 5. GBM training and testing results for the moisture ratio

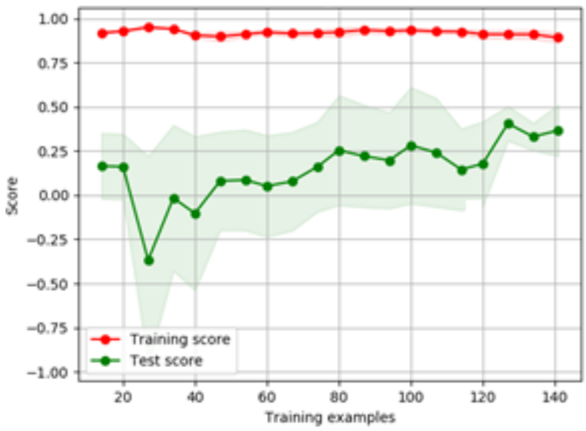

Figure 6. GBM training and testing results for the shrinkage ratio

Figure 7 shows the predicted results of the moisture ratio and the shrinkage ratio provided by the GBM model. The predicted value is suitable to the actual value.

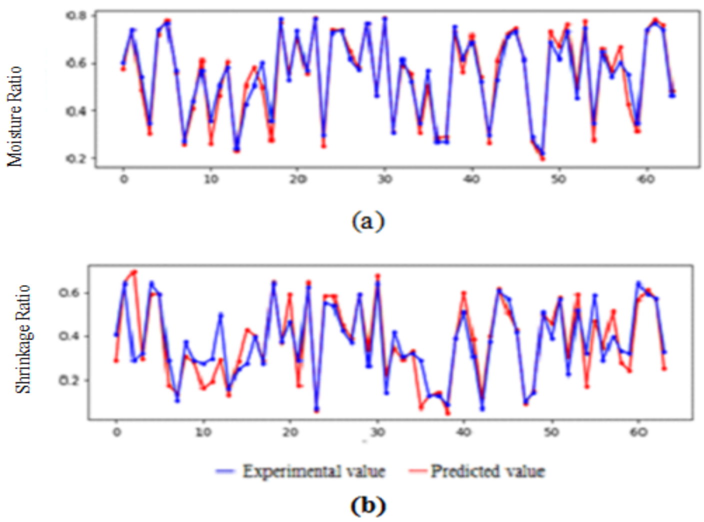

Figure 7 Comparison between experimental and predicted value
a) The moisture ratio b) The shrinkage ratio

Figure 7 shows that the inputs of the model had different influences on the moisture ratio and the shrinkage ratio as outputs. GBM method provided more accurate prediction for the moisture ratio than the shrinkage ratio.

A higher value of the correlation coefficient and the smaller values of MAPE and R^2 show better performance of the model. The results suggest better performances by the artificial neural network (ANN) as well as other two approaches *(Table 3)* (Yıldız et al., 2021).

Table 3. Performance indexes achieved using ANN and GBM

Moisture Ratio			**Shrinkage Ratio**	
Model	R^2	MAPE (%)	R^2	MAPE (%)
ANN	0.88	10.71	0.52	29.7
GBM	0.93	8.14	0.81	28.37

4. Conclusions

This study presents the drying conditions of osmo-solar drying methods of banana rings which were modeled and analyzed by the GBM. The influence of process parameters on the moisture ratio and the shrinkage ratio has been investigated. Estimation results showed that a good modeling design was made by using GBM. In addition, the results of error revealed that GBM was successfully performed. The effect of the hyper parameters such as number of the base model, learning rate and loss function on the value of MAPE and R^2 were determined. The loss function particularly affected the hyper parameters. Loss function was considered to Huber for moisture ratio and the loss function was considered to Laplace L1 for shrinkage ratio. The proposed GBM-based banana drying prediction method showed very good performance in terms of prediction accuracy with reached minimum error.

References

Aboud, A. (2013). Drying characteristic of banana rings undertaken the effect of passive shelf solar dryer and open sun drying. Pakistan Journal of Nutrition. 12 (3):250-254.

Akova S.B, Güven Ş (2018) Mersin meyveciliğinde muzun yeri ve önemi. Marmara Coğrafya, 37: 271-289.

Arslan, A., Soysal, Y., Keskin, M.(2021). Infrared drying kinetics and color qualities of organic and conventional sweet red peppers. Tekirdağ Ziraat Fakültesi Dergisi, 18(2):260-272.

Askari, G. R., Emam-Djomeh, Z., Mousavi, S. M. (2008). Investigation of the effects of microwave treatment on the optical properties of apple rings during drying, Drying Technology, 26: 1362–1368

Bórquez, R.M., Canales, E.R., Redon, J.P. (2010). Osmotic dehydration of raspberries with vacuum pretreatment followed by microwave-vacuum drying, Journal of Food Engineering, 99 (2):121-127.

Botchkarev, A. (2018). Performance Metrics (Error Measures) in Machine Learning Regression, Forecasting and Prognostics: Properties and Typology.

Eren, İ., Ertekin, F. K. (2007). Optimization of osmotic dehydration of potato using response surface methodology, Journal of Food Engineering 79: 344-352

Friedman, B.J., Hastie, T., Tibshirani, R. (2000). Special invited paper, 28:337-407.

Friedman, J., (2001). Greedy boosting approximation: gradient boosting machine. Ann. Stat. 29:1189–1232.

Hastie, T.J., Tibshirani, R., Friedman, J. (2009). The elements of statistical learning. New York: Springer

İspir, A., Toğrul, İ. T. (2009). Osmotic dehydration of apricot: kinetics and the effect of process parameters, Chemical Engineering Research and Design, 87(2):166-180

Küçükatay, O., Köse, E., Yıldız, Z. (2021). PLC kontrollü kurutucu konveyör tasarımı, Çukurova Üniversitesi Mühendislik Fakültesi Dergisi, 36(1): 249-260.

Lombard, G.E., Oliveira, J.C., Fito, P., Andrés, A. (2008). Osmotic dehydration of pineapple as a pre-treatment for further drying, Journal of Food Engineering, 85(2):277-284

Natekin, A., Knoll, A. (2013). Gradient boosting machines, A tutorial, 7.

Ochoa-Martínez, L. A., García-Quintero, M., Morales-Castro, J., Gallegos-Infante, J., Martínez-Sánchez, C.E., Herman-Lara, E. (2006). Effect of $CaCl_2$ and convective osmotic drying on texture and preference of banana. Journal of Food Quality. 29: 583–595

Pandya, R., Yadav, K.C. (2014). Study on effect of pretreatments and microwave drying on banana chips. IOSR Journal of Agriculture and Veterinary Science IOSR-JAVS, 7(7): 04-10

Prakash, O., Kumar, A. (2013). Historical review and recent trends in solar drying systems, International Journal of Green Energy, 10(7):690-738

Subaşı, O.S., Seçer, A., Yaşar, B., Emeksiz, F., Uysal, O. (2016). Production cost and profitability of banana in Turkey. Mediterranean Agricultural Sciences, 292: 73-78.

Şahin, F.H., Ülger, P., Aktaş, T., Orak. H.H. (2012). Farklı ön işlemlerin ve vakum kurutma yönteminin domatesin kuruma karakteristiklerive kalite kriterleri üzerine etkisi, Tekirdağ Ziraat Fakültesi Dergisi, 9(1):15-25.

Torringa, E., Esveld, E., Scheewe, I., Berg, R., Bartels, P. (2001). Osmotic dehydration as a pre-treatment before combined microwave-hot-air drying of mushrooms, Journal of Food Engineering, 49 (2-3): 185-191

Yıldız, Z, Gökayaz L., Köse, E., Mühürcü, A. (2021). Adaptive neural network based fuzzy inference system for the determination of performance in the solar tray dryer, Eurasian Journal of Food Science and Technology, 5(1):41-49.