Karadeniz Fen Bilimleri Dergisi, 13(4), 1738-1758, 2023. DOI: 10.31466/kfbd.1333223

KFBD

Karadeniz Fen Bilimleri Dergisi
The Black Sea Journal of Sciences
ISSN (Online): 2564-7377 https://dergipark.org.tr/tr/pub/kfbd

Araştırma Makalesi / Research Article

Enhancement of Convective Banana Drying: Effect of Ethanol Pretreatment on Drying Characteristics, Color Properties, Shrinkage Ratio and Comparison of Artificial Neural Network and Thin Layer Modeling

Tolga Kağan TEPE[1*]

Abstract

The effect of ethanol pretreatment on the drying characteristics, color properties, shrinkage ratio and comparison of thin layer and artificial neural network (ANN) were investigated in the current study. Ethanol pretreatment increased drying rate and reduced drying time. In addition to this, ethanol concentration and pretreatment time had positive contribution to drying rate. According to the statistical parameters, ANN modeling showed better performance in the prediction of moisture ratio of the banana samples in comparison to thin layer modeling. On the other hand, color properties were negatively affected by drying and ethanol pretreatments. L* and b* values decreased whereas a* values of the banana samples showed increment tendency. Also, total color difference (ΔE) was found to be higher than 5 value, indicating that non-trained observer notices the color change. Besides, it is obviously that ethanol pretreatment affected shrinkage ratio of the banana samples. Especially, diameter shrinkage ratio increased with the increment of ethanol concentration and pretreatment time.

Keywords: Drying, Ethanol, ANN Modeling, Color, Shrinkage Ratio, Banana

Muz Kurutmada Konvektif Kurutma Yönteminin İyileştirilmesi: Etil Alkol Ön İşleminin Kurutma, Renk Özellikleri ve Büzüşme Oranı Üzerine Etkisi ile Yapay Sinir Ağı ve İnce Tabaka Modellemesinin Karşılaştırılması

Öz

Bu araştırma, etanol ön işleminin kurutma ve renk özellikleri ile büzüşme oranı üzerindeki etkisini incelemeyi ve ince tabaka ile yapay sinir ağı (YSA) yöntemlerini karşılaştırmayı amaçlamaktadır. Etanol ön işleminin kuruma hızını artırdığı ve buna bağlı olarak kuruma süresini kısalttığı gözlenmiştir. Ayrıca, etanol konsantrasyonunun ve ön işlem süresinin kuruma hızına olumlu yönde katkısı bulunmaktadır. İstatistiksel parametreler ele alındığında, YSA modelleme yöntemi ince tabaka kurutma modellerine göre muz örneklerinin nem oranı tahmininde daha iyi performans göstermiştir. Bununla birlikte, renk özellikleri kurutma ve etanol ön işleminden olumsuz yönde etkilenmiştir. L* ve b* değerleri azalırken, muz örneklerinin a* değerleri artış eğilimi göstermiştir. Ayrıca, toplam renk farkı (ΔE) 5 değerinden yüksek bulunmuştur, bu da eğitilmemiş gözlemcinin renk değişikliğini fark edebileceğini göstermektedir. Ayrıca, etanol ön işleminin muz örneklerinin büzüşme oranını etkilediği gözlenmiştir. Özellikle örneklerin çapında meydana gelen büzüşme oranı, etanol konsantrasyonunun ve ön işlem süresinin artmasıyla birlikte artmıştır.

Anahtar Kelimeler: Kurutma, Etanol, YSA Modelleme, Renk, Büzüşme Oranı, Muz

[1]Giresun University, Vocational School of Şebinkarahisar, Food Technology Department, Giresun, Turkey, tolga.kagan.tepe@gmail.com

[1]https://orcid.org/0000-0003-0484-7295

[*]**Sorumlu Yazar/Corresponding Author**

Geliş/Received: 26.07.2023 **Kabul/Accepted:** 23.10.2023

1. Introduction

Banana, a valuable tropical and subtropical plant, has been cultivated worldwide for an extensive period. Among the major banana-producing countries, India holds the highest production, followed by China, Brazil, Ecuador, Indonesia, and the Philippines (Tunckal and Doymaz 2020). According to the data provided by TUİK (2022), Turkey produced 997,244 tons of bananas in 2022. Until the last decade, Turkey primarily produced *Musa Acuminata* var. "Dwarf Cavendish (DC)," making it the dominant banana variety in the country's production (TEPGE 2020). Banana is recognized for its high nutritional value, being rich in starch, sugar, vitamins A and C, dietary fibers, minerals, phenolic compounds, and antioxidant activity (Tunckal and Doymaz 2020; Macedo et al., 2020). Moreover, due to its disease risk-reducing properties, banana is considered a health-promoting food. Additionally, its appealing sensory attributes and affordability make it a highly favored fruit (Macedo et al., 2020).

Due to its high moisture content (70-80% wet basis), banana is highly susceptible to post-harvest losses (Dongbang and Nuantong 2020). The short shelf life after harvest results in a significant amount of banana waste (Macedo et al., 2020). Many plant-based foods undergo chemical reactions, microbiological activity, and physical alterations during the pre- or post-harvest period, necessitating high water content (Tepe and Tepe 2020). Drying has emerged as an alternative method to preserve fresh foods (Tepe and Tepe 2020, Batu and Kadakal 2021). Convective drying, the most used drying method, has been utilized to reduction moisture content, making lower water activity, providing longer shelf life, reducing microbial growth, preventing unfavorable chemical changes, by using heated air and provides reduction in weight and volume that results in lower packing, transportation and storage costs (Tunckal and Doymaz 2020; Tepe and Tepe 2020; Seyedabadi et al., 2017; Jarahizadeh and Dinani 2020; Huang et al., 2020). However, convective drying leads to adverse alterations in bioactive compounds and sensory attributes, such as color and flavor. Moreover, it requires high energy consumption due to its long drying time (Tepe, 2022; Gonzalez-Cavieres et al., 2021; Bozkır 2020). In most cases, fossil fuels or electricity are the primary energy sources used for drying (E.I.A 2018). Consequently, reducing environmental impacts and process costs are crucial challenges that need to be addressed (Rojas et al., 2020a). The drawbacks of the convective drying can be overcome by pretreatments suggested by Huang et al. (2020), Tepe (2022), Rojas et al. (2020b). In this context, the drying rate can be enhanced by several ways such as increasing permeability, enzyme deactivation, oxygen prevention (Srimagal et al., 2017; Qu et al., 2017; Bassey et al., 2020). Rojas et al. (2020a) emphasized that ethanol pretreatment is the promising method for eliminating the disadvantages of the convective drying. Besides, Llavata et al. (2020) noted that ethanol pretreatment effectively improves the drying of food products by causing structural changes and physical phenomena such as the Marangoni effect. This improvement is attributed to the underlying mechanism of ethanol pretreatment, which includes destruction or thinning of the cell wall, resulting in increased permeability and removal of intracellular air (Llavata et al., 2020; Rojas et al., 2020b). This pretreatment establishes a surface tension gradient between water and ethanol, triggering the Marangoni effect, which facilitates the movement of liquid from regions with low surface tension gradient to regions with higher tension, thereby aiding in water transportation (Rojas and Agusto 2018; Santos et al., 2021). Moreover, besides its positive impact on the drying process, ethanol is considered harmless, with no observed residuals (de Freitas et al., 2021).

According to Aghbashlo et al. (2015), the drying process is recognized as a complex, dynamic, and strongly interactive thermal operation, exhibiting high nonlinearity, and involving multiple variables. Hence, accurately predicting moisture content and quality parameters is crucial and indispensable for enhancing the overall efficiency of the drying process. (Bai et al., 2018). Mathematical modeling, particularly thin layer models, has been widely employed to achieve accurate predictions and comprehensive descriptions of the drying process. Such models facilitate the development of new drying equipment, optimization of dryers and drying parameters, and streamlined process control (Naderinezhad et al., 2016; Azimi-Nejadian and Hoseini, 2019). However, these mathematical models require a deep understanding of various factors, including experimental data estimation, process mechanisms, and intricate calculations. Addressing these challenges and attaining highly precise moisture content predictions during drying can be achieved through the application of black-box modeling techniques, such as artificial neural network (ANN) (Omari et al., 2018). Over the past years, artificial neural networks have found extensive application in modeling various processes within the field of food engineering (Guiné et al., 2015). ANN function similarly to the neural networks present in the human brain, comprising interconnected nerve cells (Bhagya Raj and Dash, 2022). Due to their learning capability and adaptability to nonlinear processes, ANN present numerous advantages over traditional modeling techniques. Consequently, ANN models have been successfully employed to predict moisture content and quality parameters during the drying process. (Bai et al., 2018).

The process of air-drying food materials is accompanied by significant physical and chemical changes, which exert a profound influence on the overall drying process (Senadeera, 2008). During the drying process of fruits and vegetables, shrinkage is a well-known physical phenomenon that significantly impacts the overall quality of dried food products (Senadeera et al., 2020). Shrinkage is a phenomenon commonly associated with the moisture content of a product and is typically expressed through a shrinkage ratio, which may be represented in volume, area, or thickness. The density of dried products is greatly influenced by this phenomenon, and its occurrence is directly correlated with the rate of water loss (Seeranguráyar et al., 2019). This negative phenomenon results in volume reduction, alterations in shape and porosity, an increase in hardness, and the occurrence of surface cracking (Senadeera et al., 2020; Brasiello et al., 2013). Furthermore, this phenomenon can lead to alterations in the texture, rehydration, and transport properties of the final dried products along changes in heat and mass transfer (Senadeera et al., 2020; Seerangurayar et al., 2019). Shrinkage is the phenomenon, that must be reduced, because of negative impression on consumers (Senadeera et al., 2020).

Recent years, banana production have significantly increased in Turkey. As previously mentioned, bananas are highly perishable fruits, making them susceptible to spoilage. Consequently, a significant amount of waste can occur due to this perishability. Additionally, there is limited study on the ethanol pretreatment prior to convective drying of banana, to the best of our knowledge. To contribute data for decreasing possible wastes resulted from banana, extending consumption type and obtaining lower drying time for saving energy consumption, this study focused on effect of ethanol pretreatment and time on drying characteristics, color properties, shrinkage ratio, and comparison of ANN and thin layer modeling to prediction of convective drying of banana.

2. Materials and Methods

2.1. Raw Material

In the current study, banana (*Musa Acuminata* var. Drawf Cavendish) samples were used as the experimental material. Firstly, the banana samples were hand-peeled and sliced to prepare for the drying experiment. Then, the banana slices were cut to a uniform thickness of 6±0.1 mm and a diameter of 3.03±0.1 cm. Subsequently, the initial moisture content of the banana samples was measured as 75.82±0.26% on a wet basis (WB).

2.2. Ethanol Pretreatment

Banana samples were immersed in solutions containing 50% and 100% ethanol for durations of 15 and 30 min, respectively. The immersion process was conducted using a ratio of 1:4 (w/v). Following the immersion period, the samples underwent filtration, and any excess solution on the surface was meticulously removed using filter paper. The ethanol absolute (Isolab) employed in the study had a high purity level, exceeding 99.9%. Specific codes of pretreated banana samples were assigned to the banana samples, such as 60 °C + 50 ET 15, 60 °C + 50 ET 30, 60 °C + 100 ET 15, and 60 °C + 100 ET 30.

2.3. Drying experiments

Both unpretreated and pretreated banana samples were dried under the exact same conditions. Initially, 100 g of banana sample was carefully weighed and then placed inside a drying oven (Nüve, FN 400). The convective drying process was performed at a constant temperature of 60 °C. To monitor the progress of drying, at regular intervals, the samples' weight was measured using a digital weight measure, ensuring a precision of 0.01 g. The drying experiments were continued until the moisture content of the samples reached 20% on a wet basis (WB), suggested by Macedo et al. (2020). To ensure accuracy and reproducibility, the drying experiments were conducted three times.

2.4. Calculation of Weight Changes After Ethanol Pretreatment

The study evaluated the weight reduction, water loss, and solid loss of banana samples pretreated with ethanol by employing equations suggested by Bozkır and Ergün (2020). These calculations, the initial weight and the final moisture content of the samples were measured. The weight reduction (WR), water loss (WL), and solid loss (SL) were calculated based on the following Equations (1, 2, 3) as provided below, respectively:

$$WR\,\% = \frac{w_i - w_f}{w_i} * 100 \tag{1}$$

$$WL\,\% = \frac{w_i * X_i - w_f * X_f}{w_i} * 100 \tag{2}$$

$$SL\,\% = \frac{\left[w_f * \left(1 - X_f\right) - w_i * (1 - X_i)\right]}{w_i} * 100 \tag{3}$$

Where w_i, w_f, X_i, and X_f refer to initial weight (g), final weight (g), initial fraction of water, final fraction water of the banana samples, respectively.

2.5. Drying Characteristics

Throughout the drying process, the moisture content variation was measured at specific intervals and determined using Equation (4), proposed by Tepe and Tepe (2020).

$$M_t = \frac{m - DM}{DM} \tag{4}$$

M_t is sample's moisture content at any time, expressed in g water g^{-1} DM. m represents the sample's weight in g. DM signifies the sample's DM content measured in g.

Equation (5) was used to calculate moisture ratio of banana samples.

$$\mathrm{MR} = \frac{\mathrm{M_t} - \mathrm{M_e}}{\mathrm{M_i} - \mathrm{M_e}} \quad (5)$$

The equilibrium moisture content (M_e) was regarded negligible in comparison to both the moisture content at any given time (M_t) and the initial moisture content (M_i). As a result, the moisture content values were expressed on a DM (Tepe and Tepe, 2020).

Equation (6) was used to compute drying rate (Tepe and Tepe 2020).

$$\mathrm{DR} = \frac{\mathrm{M_{t+\Delta t}} - \mathrm{M_t}}{\Delta \mathrm{t}} \quad (6)$$

The Δt indicates the time difference between two measurements, and M_t+Δt corresponds to the moisture content at the subsequent time point.

Fick's second law, suggested by Crank (1975) was used for infinite slab object with a constant of moisture diffusivity as Equation (7).

$$\mathrm{MR} = \frac{8}{\pi^2} \sum_{n=1}^{\infty} \frac{1}{(2n-1)^2} \exp\left(-(2n-1)\pi^2 \frac{\mathrm{D_{eff}} t}{4L^2}\right) \quad (7)$$

Equation (6) was used to calculate effective moisture diffusivity (D_{eff});

Where t is drying time and L is half-thickness of fresh sample.

When n=1 (long drying time), a simplified version of Equation (8) can be utilized (Tepe and Tepe 2020).

$$\ln(\mathrm{MR}) = \ln\left(\frac{8}{\pi^2}\right) - \left(\frac{\pi^2}{4L^2}\, \mathrm{D_{eff}} t\right) \quad (8)$$

When plotting the natural logarithm of MR against drying time (Equation 8), a straight line is obtained, and the slope of this line corresponds to the following Equation (9) (Tepe and Tepe 2020).

$$\mathrm{Slope} = \frac{\pi^2}{4L^2}\, \mathrm{D_{eff}} \quad (9)$$

2.6. Thin Layer Modeling of Drying of Banana

The values for root mean square error (RMSE), reduced chi-square (χ^2), and determination coefficient (R^2) were calculated using Equations (10), (11), and (12) respectively, as described below (Tepe 2022).

$$\mathrm{RMSE} = \left[\frac{1}{N} \sum_{i=0}^{N} (MR_{pre,i} - MR_{exp,i})^2\right]^{\frac{1}{2}} \quad (10)$$

$$\chi 2 = \frac{\sum_{i=0}^{N} (MR_{pre,i} - MR_{exp,i})^2}{N - n} \quad (11)$$

$$R^2 = \frac{\sum(MR_{pre} - \sum MR_{exp})^2}{\sum(MR_{pre,av} - \sum MR_{exp})^2} \quad (12)$$

Predicted moisture ratios (MR_{pre}) and experimental moisture ratios (MR_{exp}) were utilized to represent the data. N and n refer to the number of observation data points and constants of the thin layer drying models, respectively. Statistical parameter calculations and curve fitting were carried out using MATLAB software (R2015a, version 8.5) and its non-linear curve fitting toolbox with the trust-region algorithm. The model selection process was performed by seeking higher values of R^2 and lower values of χ^2 and RMSE to identify the most suitable model (Tepe and Tepe, 2020). The thin layer models utilized in the study are listed in Table 1.

Table 1. Thin layer models utilized in the study.

Model name	Model	References
Lewis	$exp(-kt)$	Tepe et al. (2022)
Henderson and Pabis	$aexp(-kt)$	Tepe et al. (2022)
Page	$exp(-kt^n)$	Tepe et al. (2022)
Parabolic	$a + bt + ct^2$	Tepe et al. (2022)
Wang and Sing	$1 + at + bt^2$	Tepe et al. (2022)
Midilli and Kucuk	$aexp(-kt^n) + bt$	Tunckal and Doymaz (2020)

2.7. Artificial Neural Network Modeling of Drying of Banana

The study utilized the Neural Net Fitting Toolbox, employing the Levenberg-Marquardt back-propagation algorithm, which is a widely recommended approach according to Omari et al. (2018). MATLAB software (R2015a, version 8.5) was employed for this purpose. In the current study, an artificial neural network (ANN) model was configured as inputs: drying time, pretreatment time and ethanol concentration and output: moisture ratio. The tansig function was chosen as the transfer function for the hidden layer, following the preference of Omari et al. (2018). The analysis of mean square error (MSE) and R^2 at different neuron numbers led to an ANN configuration with 4 neurons in the hidden layer. As addressed before, drying experiments were performed three times. Average moisture ratio of the banana slices during drying experiments were used. Sample numbers for experiments were given in Table 2. For training and validating the ANN model, the experimental data from the drying experiments were divided into three sets: 60% for training, 20% for validation, and 20% for testing. To prevent over-fitting, training was completed when termination conditions formed. Termination conditions were maximum 1000 epoch, 6 validation checks and 1e-07 performance gradient (Yıldız et al. 2015). To assess the performance of the ANN model, RMSE and R^2 values were calculated by comparing the data estimated by the model with the actual experimental data.

Table 2. Sample numbers for ANN modeling

Experiment	Training	Validation	Test
60 °C	13	5	5
60 °C + 50 ET 15	12	4	4
60 °C + 50 ET 30	11	4	4
60 °C + 100 ET 15	11	3	3
60 °C + 100 ET 30	11	3	3

2.8. Determination of Color Properties

Before and after the drying process, the color values of the banana samples were measured using 3NH NR10QC (China). To ensure accuracy, color measurements were taken at five different spots on each sample's surface. Between the color values of the fresh and dried product was determined by using the calculation of the total color differences (ΔE) (Equation 13). The ΔE value quantifies the magnitude of color change, with higher values indicating more significant color alterations during drying, as reported by Tepe (2022).

$$\Delta E = \sqrt{(L_0^* - L^*)^2 + (a_0^* - a^*)^2 + (b_0^* - b^*)^2} \qquad (13)$$

2.9. Shrinkage Ratio of Banana Samples

Dimensional changes during the drying process were assessed by measuring the diameter shrinkage (DS) and thickness shrinkage (TS) of the samples, following the method of Granella et al. (2022). DS represents the percentage reduction in diameter, and TS indicates the percentage reduction in thickness, comparing the dried sample dimensions to those of the fresh ones. Fifteen banana slices were used for each treatment to determine the extent of shrinkage.

2.10. Statistical Analysis

For the statistical analysis, SPSS software (ver. 22, SPSS Inc.) was utilized. To compare means at a significance level of $p<0.05$, one-way analysis of variance (ANOVA) and Duncan post-hoc test were employed. The standard deviation (SD) was also provided.

3. Findings and Discussion

3.1. The Drying Characteristics of The Banana Samples

Moisture ratio and drying rate of the banana samples were illustrated in Figure 1. Additionally, D_{eff} values and drying time were given in Table 3. It is obviously that ethanol pretreatment had crucial effect on the drying rate, drying time and D_{eff} values. Drying rate and D_{eff} values showed the increment as the ethanol concentration and pretreatment time increased. The highest drying rate and D_{eff} values were obtained from the samples coded 60 °C + 100 ET 30. Similarly, drying rate and D_{eff} values of the banana slices by pretreated ethanol solution were reported to be higher than the unpretreated banana slices by Granella et al. (2022). Additionally, it was notified by Granella et al. (2022) that longer pretreatment time provides higher drying rate and D_{eff} value. Likewise, findings in pineapple, melon, apple and apple fruits were noted by de Freitas et al. (2021), da Cunha et al. (2020), Tepe (2022) and Rojas et al. (2022b), respectively. Furthermore, Guedes et al. (2021) and Rojas et al. (2020) similarly emphasized that shorter drying time and higher drying rate can be obtained by longer pretreatment time. These all phenomena can be explained by the effect of ethanol pretreatment on the facilitating intracellular air removing, cell wall disruption or thinning and penetrating samples. Thus, water evaporation accelerates. On the other hand, Marangoni effect provides easier water transportation due to a surface tension gradient, that cause liquid movement from lower surface tension to higher surface tension (Guedes et al. 2021; Tepe and Kadakal, 2022; Tepe, 2022; da Cunha et al. 2020; Rojas et al. 2020; Santos et al. 2021). Moreover, longer pretreatment time with ethanol can have various effects. It can lead to increased air removal, thinner cell walls, and improved permeability. Furthermore, the stronger Marangoni effect is attributed to the higher ethanol concentration on the surface, influenced by a higher rate of immersion and prolonged pretreatment. As a result, these factors enhance moisture removal and improve drying efficiency throughout the drying process.

Table 3. Effective moisture diffusivity and drying time of the banana samples.

Experiment	D_{eff} ($m^2 s^{-1}$)	Drying Time (min)
60 °C	2.76×10^{-10}	570
60 °C + 50 ET 15	3.00×10^{-10}	480
60 °C + 50 ET 30	3.07×10^{-10}	450
60 °C + 100 ET 15	3.48×10^{-10}	360
60 °C + 100 ET 30	3.82×10^{-10}	300

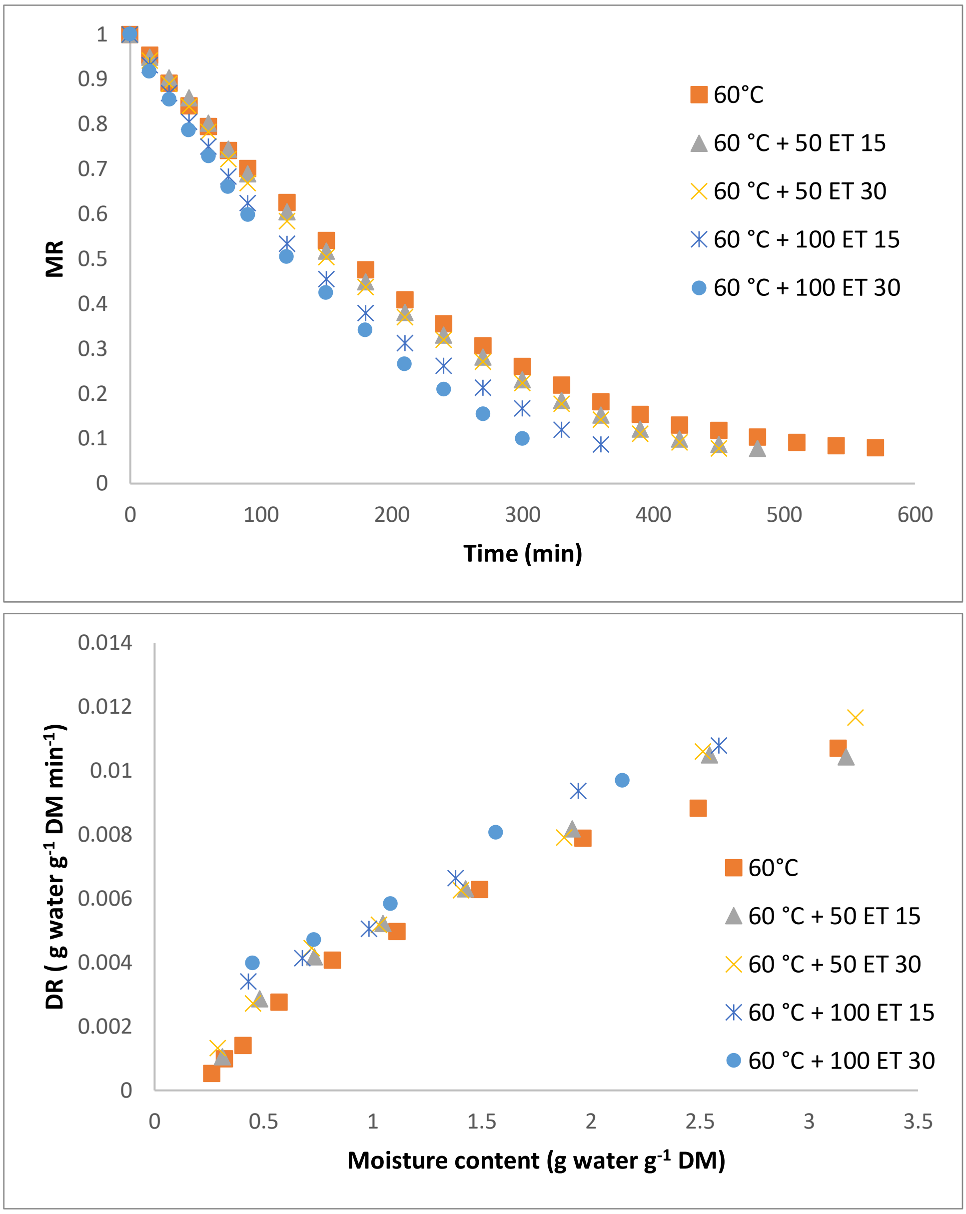

Figure 1. MR and DR of the banana samples during convective drying.

3.2 Thin Layer and ANN Modeling of The Drying of The Banana Samples

In the present study, two different approaches thin layer (traditional modeling) and ANN (novel black box modeling) to predict moisture ratio of the banana samples during convective drying were utilized. In Table 4, statistical parameters of used modeling type could be found. According to statistical parameters, all thin layer models showed good performance to describe the drying of the banana samples. Furthermore, Midilli and Kucuk model shows the highest R^2, the lowest chi-square and RMSE values among the other models for all drying experiments. La Fuente and Tadini (2018) notified that Midilli model gave the best fitting for untreated unripe banana samples. Macedo et al. (2020) reported that drying curve of the banana was suitably described by Midilli model. On the contrary, Dongbang and Nuantong (2020) noted the most appropriate model was Page model for banana samples dried at 60-65-70 °C. The variability of models can be attributed to several factors, including the variety of fruits, drying conditions, equipment used, initial moisture content, and the structure of the food matrix. On the contrary, the ANN modeling gave the better results than the thin layer modeling. According to Table 4, lower RMSE and higher R^2 values were obtained from the ANN modeling. Likewise, Yıldız et al. (2015) noted that the ANN modeling with the lowest MSE and the highest R^2 values had greater performance for the drying of the banana slices than the thin layer models. Similar phenomena (the lowest RMSE or MSE and the highest R^2 values of ANN in comparison to thin layer modeling) were reported by Şahin and Öztürk (2018) for fig, Murthy and Manohar (2014) for mango ginger, Rasooli Sharabiani et al. (2021) for apple and Chokphoemphun et al. (2023) for potato. Figure 2 and Figure 3 present the best validation performance and regression values of the ANN modeling, respectively. On the other hand, over-fitting must be checked during training ANN modeling. The fact that the validation and test error curves follow opposite trajectories during the training iterations is an undesirable situation. Such a situation implies that the desired level of success in training the artificial neural network has not been achieved (Kurtulmuş et al. 2020). Kurtulmuş et al. (2020) noted that similar trajectory of validation and test errors vectors indicates no over-fitting during training of ANN. As seen from Figure 2, validation and test error vectors showed similar behavior for all experiments. This indicates that no over-fitting occurred during ANN training in the current study.

Table 4. Model's statistical parameters of the drying of the banana samples.

Model	Experiment	Model Constants			χ^2	RMSE	R^2
Page	60 °C	k= 0.002403	n= 1.109		7.37×10^{-5}	0.008201	0.9992
	60 °C + 50 ET 15	k= 0.001760	n= 1.181		5.57×10^{-5}	0.007083	0.9995
	60 °C + 50 ET 30	k= 0.002261	n= 1.142		0.0001102	0.009929	0.9991
	60 °C + 100 ET 15	k= 0.002890	n= 1.126		0.0001472	0.011350	0.9987
	60 °C + 100 ET 30	k= 0.002879	n= 1.149		0.0002699	0.015210	0.9976
Henderson and Pabis	60 °C	k= 0.004528	a= 1.030		0.0002814	0.016030	0.9976
	60 °C + 50 ET 15	k= 0.004930	a= 1.048		0.0006373	0.023950	0.9948
	60 °C + 50 ET 30	k= 0.005037	a= 1.035		0.0005214	0.02160	0.9955
	60 °C + 100 ET 15	k= 0.005718	a= 1.029		0.0004978	0.020870	0.9956
	60 °C + 100 ET 30	k= 0.006285	a= 1.029		0.0008070	0.026300	0.9928
Wang and Singh	60 °C	a= -0.003486	b= 0.000003336		8.05×10^{-5}	0.008575	0.9993
	60 °C + 50 ET 15	a= -0.003692	b= 0.000003696		6.33×10^{-5}	0.007551	0.9995
	60 °C + 50 ET 30	a= -0.003839	b= 0.000004020		9.63×10^{-5}	0.009284	0.9992
	60 °C + 100 ET 15	a= -0.004448	b= 0.000005452		0.0001504	0.011470	0.9987
	60 °C + 100 ET 30	a= -0.004863	b= 0.000006369		0.0001134	0.009859	0.9990
Parabolic	60 °C	a= 0.9900	b= -0.003413	c= 0.000003228	6.45×10^{-5}	0.007487	0.9995
	60 °C + 50 ET 15	a= 1.0050	b= -0.003739	c= 0.000003779	6.36×10^{-5}	0.007352	0.9995
	60 °C + 50 ET 30	a= 0.9930	b= -0.003773	c= 0.000003897	9.59×10^{-5}	0.008987	0.9993
	60 °C + 100 ET 15	a= 0.9897	b= -0.004325	c= 0.000005165	0.0001441	0.010820	0.9989
	60 °C + 100 ET 30	a= 0.9818	b= -0.008502	c= 0.000019150	9.73×10^{-5}	0.008744	0.9993
Lewis	60 °C	k= 0.004369			0.0004182	0.020000	0.9960
	60 °C + 50 ET 15	k= 0.004657			0.0010103	0.030980	0.9907
	60 °C + 50 ET 30	k= 0.004823			0.0007130	0.025990	0.9932
	60 °C + 100 ET 15	k= 0.005504			0.0006170	0.024050	0.9938

	60 °C + 100 ET 30	k= 0.060420				0.0008827	0.028630	0.9907
Midilli and Kucuk	60 °C	k= 0.002053	a= 0.9920	n=1.139	b=0.00001527	7.22×10^{-5}	0.007723	0.9995
	60 °C + 50 ET 15	k= 0.001912	a= 0.9982	n=1.160	b=-0.00003662	5.39×10^{-5}	0.006566	0.9996
	60 °C + 50 ET 30	k= 0.003004	a= 1.0000	n=1.072	b=-0.0001181	4.30×10^{-5}	0.005824	0.9997
	60 °C + 100 ET 15	k= 0.004283	a= 1.0020	n=1.023	b=-0.0002275	3.41×10^{-5}	0.005054	0.9998
	60 °C + 100 ET 30	k= 0.004790	a= 0.9993	n=1.001	b=-0.0004440	4.02×10^{-5}	0.005356	0.9998
ANN	60 °C						**0.0031050**	**0.9999**
	60 °C + 50 ET 15						**0.0040847**	**0.9999**
	60 °C + 50 ET 30						**0.0029900**	**0.9999**
	60 °C + 100 ET 15						**0.0043536**	**0.9999**
	60 °C + 100 ET 30						**0,0052794**	**0,9999**

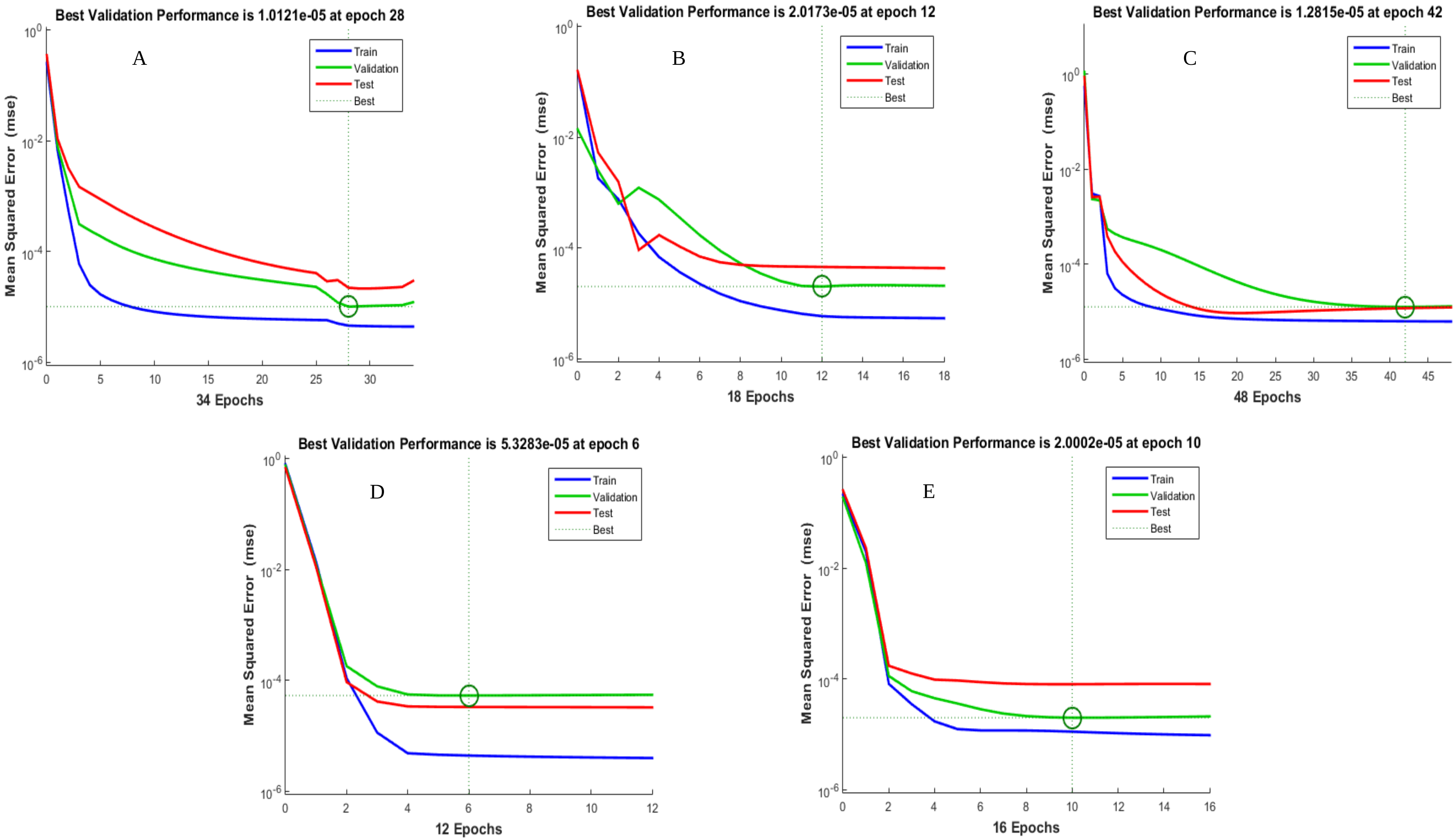

Figure 2. Best validation performance of ANN modeling of the banana samples (A: 60 °C; B: 60 °C + 50 ET 15; C: 60 °C + 50 ET 30; D: 60 °C + 100 ET 15; E: 60 °C + 100 ET 30).

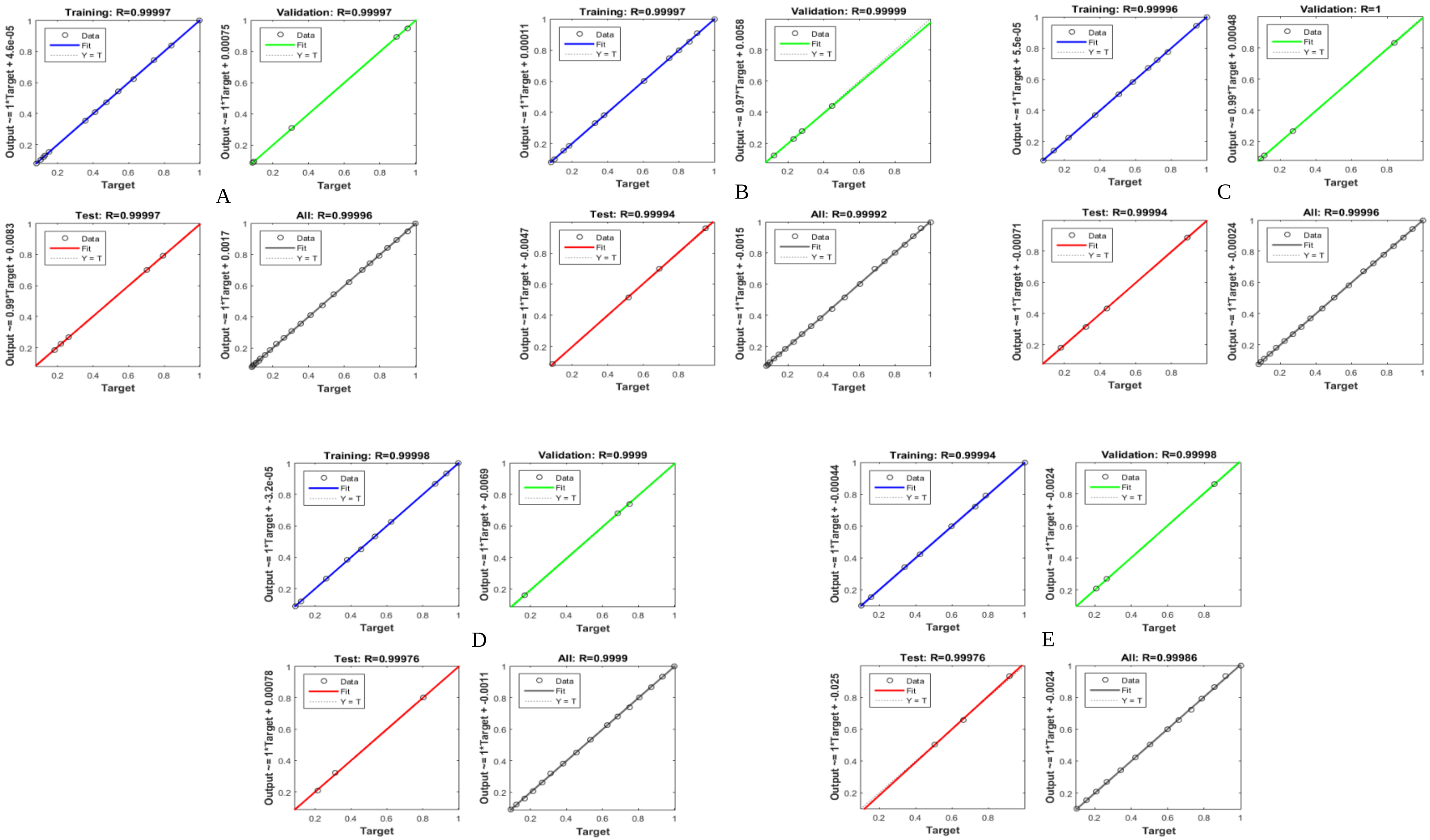

Figure 3. Regressions of ANN modeling of the banana samples (A: 60 °C; B: 60 °C + 50 ET 15; C: 60 °C + 50 ET 30; D: 60 °C + 100 ET 15; E: 60 °C + 100 ET 30).

3.3 Weight Changes of The Banana Samples During Ethanol Pretreatment

During pretreatments, weight changes in the samples can occur. In the current study, moisture content of the banana samples was found as 3.14 g water g^{-1} DM. However, moisture content of the banana samples changed after ethanol pretreatments. Therefore, weight loss, water loss and solid loss can come true depending on the moisture content chancing. After pretreatment moisture content of the samples coded 60 °C + 50 ET 15, 60 °C + 50 ET 30, 60 °C + 100 ET 15 and 60 °C + 100 ET 30 was determined as 3.16, 3.21, 2.59 and 2.15 g water g^{-1} DM. Moisture content (% on a WB), weight loss, water loss, and solid loss can be seen from Table 5. Lower weight loss, water loss and solid loss can be found in the banana samples pretreated with 50% ethanol. Higher ethanol concentration caused higher reduction in weight, water, and solid matter. This indicates that higher ethanol concentration higher disruption on the cell structure of the banana samples. Also, Tepe and Kadakal (2022) and Tepe (2022) explained this phenomenon with the thinner and more disrupted cell wall, resulting in more permeability.

Table 5. Moisture content and weight changes of the banana samples after ethanol pretreatment.

Experiment	Moisture Content (%)	WR (%)	WL (%)	SL (%)
60 °C + 50 ET 15	76.03	1.46	0.90	-0.56
60 °C + 50 ET 30	76.27	1.19	0.46	-0.73
60 °C + 100 ET 15	72.14	7.49	9.09	1.59
60 °C + 100 ET 30	68.23	12.30	15.98	3.68

3.4 Color Properties of The Banana Samples

Table 6 presents the color properties of the fresh and dried banana samples. It was determined that drying process and pretreatments had higher effect on color properties of the banana samples ($p<0.05$). As seen from the Table 6, L* values of the banana samples decreased in all cases. It indicated darker appearance on the surface of the banana samples. The highest L* value was observed at the unpretreated samples ($p<0.05$). Decrement in L* value could be explained with the enzymatic browning and probable pheophytin and pheophorbide, compounds derived from the chlorophylls (Tepe et al. 2022). Ethanol pretreatment had higher negative contribution to L* values of the samples. As previously addressed, ethanol pretreatment causes disruption of cell structure. Higher L* values decrement in ethanol pretreated samples may be related to more interaction between phenolic compounds and polyphenol oxidase under oxygen as a catalyst upon the disruption of the cells.

Additonally, a* values of the banana samples increased, whereas b* values decreased after drying process. In the literature, a* and b* values are related to masking effect of chlorophylls were reported (Tepe et al. 2022; Akar and Barutçu Mazı 2019). This means higher a* and b* value at lower chlorophyll presence. The increment of a* values could be explained with the degradation of chlorophylls by convective drying and extraction by ethanol solutions during pretreatment. Decrement of b* values may be also related to masking of carotenoids by darker surface due to lower L* value. On the other hand, total color difference (ΔE), indicating total color change in the sample, was found higher than 5, color chancing observed by non-trainer observers (Abbaspour-Gilandeh et al. 2021) in all cases. In the literature, some materials such as citric acid or EDTA inhibit polyphenol oxidase by chelating with copper (Soliva-Fortuny and Martin Belloso 2003; Adam et al. 2016). Adding of these materials to the ethanol solutions prepared for pretreatment could solve this issue.

Table 6. Color properties of the banana samples.

Experiment	L*	SD (±)	a*	SD (±)	b*	SD (±)	ΔE
Fresh	71.04[a]	0.69	7.83[a]	0.16	20.62[a]	1.07	0
60 °C	41.85[b]	0.96	10.10[b]	0.35	20.83[a]	0.91	29.28
60 °C + 50 ET 15	34.76[c]	0.82	10.51[b]	0.15	17.40[b]	0.60	36.52
60 °C + 50 ET 30	35.44[c]	2.42	10.48[b]	0.26	17.57[b]	1.33	35.83
60 °C + 100 ET 15	36.78[c]	1.82	10.12[b]	0.13	18.26[b]	1.14	34.42
60 °C + 100 ET 30	37.11[c]	1.42	10.43[b]	0.33	18.44[b]	1.11	34.10

*Different letters in the same column indicate significant differences with a confidence of 95%.

3.5 Shrinkage Ratio of The Banana Samples

As addressed above, shrinkage is a phenomenon, that occurs during convective drying due to water loss and directly affects quality of dried product. Diameter and thickness shrinkage ratio of the banana samples were presented in Table 7. Diameter shrinkage ratio of the banana samples increased with increment of ethanol concentration and pretreatment time ($p<0.05$). Besides, no remarkable difference between thickness shrinkage ratio of the samples was found ($p>0.05$). Considerable change in diameter shrinkage ratio of the banana samples could be explained with cell structure change by ethanol pretreatment. Granella et al. (2022) likely observed more reduction in thickness of the banana samples than diameter.

Table 7. Diameter and thickness shrinkage ratio of the banana samples

Experiment	Diameter Shrinkage (%)	SD (±)	Thickness Shrinkage (%)	SD (±)
60 °C	32.09^{b}	1.67	67.78^{a}	0.56
60 °C + 50 ET 15	33.18^{b}	2.25	67.77^{a}	1.09
60 °C + 50 ET 30	33.60^{ab}	3.07	67.23^{a}	0.57
60 °C + 100 ET 15	35.60^{ab}	2.57	66.31^{a}	2.28
60 °C + 100 ET 30	37.92^{a}	1.76	66.44^{a}	1.12

*Different letters in the same column indicate significant differences with a confidence of 95%.

4. Conclusions and Recommendations

In the present study, effect of ethanol pretreatment and time on drying characteristics, color properties, shrinkage ratio, and comparison of ANN and thin layer modeling to prediction of convective drying of banana were investigated. The results were briefly summarized below.

a. It is the fact that ethanol pretreatment is high potential pretreatment for increasing drying rate. In addition to this, ethanol concentration and pretreatment time had positive contribution to the drying rate and time of the banana samples.

b. When compared thin layer and ANN modeling, ANN modeling had greater performance to predict the moisture ratio of the banana samples.

c. Weight changes occurred after ethanol pretreatments. Higher weight reduction, water loss and solid loss was obtained from higher ethanol concentration and longer pretreatment time.

d. Color values of the banana samples were crucially affected by drying process and pretreatments. Higher decrement L* values was observed at ethanol pretreated banana samples. On the other hand, a* values increased whereas b* values decreased.

e. The impact of ethanol pretreatment on the shrinkage of the banana samples was evident. Particularly, the diameter shrinkage ratio of the banana samples increased with higher concentrations of ethanol and longer pretreatment times.

Immersing ethanol solution could be important pretreatment in the future. However, further studies are required to be done to reveal effect on bioactive compounds of the banana samples. On the other hand, ethanol pretreatment could be combined with other potential pretreatments such as ultrasound. Moreover, it is recommended that unfavorable effect of ethanol pretreatment on the color properties could be prevented by chelating agent such as citric acid or EDTA. Additionally, ANN modeling could be preferred instead of the thin layer modeling due to because of this study.

Authors' Contributions

TKT: Conceptualization; Investigation; Writing-original draft; Methodology; Visualization; Writing - review & editing.

Statement of Conflicts of Interest

The author has no conflict of interest.

Statement of Research and Publication Ethics

The author declares that this study complies with Research and Publication Ethics.

References

Adam, I. K., Adam, A. A., & Bello, B. A. (2016). Effect of polyphenol oxidase on browning of apple and garden egg. Dutse Journal of Pure and Applied Sciences, 2(2), 177-184.

Aghbashlo, M., Hosseinpour, S., & Mujumdar, A. S. (2015). Application of artificial neural networks (ANNs) in drying technology: a comprehensive review. Drying technology, 33(12), 1397-1462.

Azimi-Nejadian, H., & Hoseini, S. S. (2019). Study the effect of microwave power and slices thickness on drying characteristics of potato. Heat and Mass Transfer, 55, 2921-2930.

Bai, J. W., Xiao, H. W., Ma, H. L., & Zhou, C. S. (2018). Artificial neural network modeling of drying kinetics and color changes of ginkgo biloba seeds during microwave drying process. Journal of Food Quality, 2018, 1-8.

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.

Batu, H. S., & Kadakal, Ç. (2021). Drying characteristics and degradation kinetics in some parameters of goji berry (Lycium Barbarum L.) fruit during hot air drying. Italian Journal of Food Science, 33(1), 16-28.

Bhagya Raj, G. V. S., & Dash, K. K. (2022). Comprehensive study on applications of artificial neural network in food process modeling. Critical reviews in food science and nutrition, 62(10), 2756-2783.

Bozkir, H., & Ergün, A. R. (2020). Effect of sonication and osmotic dehydration applications on the hot air drying kinetics and quality of persimmon. Lwt, 131, 109704.

Bozkır, H., & Ergün, A. R. (2020). Effect of sonication and osmotic dehydration applications on the hot air drying kinetics and quality of persimmon. Lwt, 131, 109704.

Brasiello, A., Adiletta, G., Russo, P., Crescitelli, S., Albanese, D., & Di Matteo, M. (2013). Mathematical modeling of eggplant drying: Shrinkage effect. Journal of food engineering, 114(1), 99-105.

Chokphoemphun, S., Hongkong, S., & Chokphoemphun, S. (2023). Evaluation of drying behavior and characteristics of the potato slices in multi–stage convective cabinet dryer: application of artificial neural network. Information Processing in Agriculture.

de Freitas, L. D. C., Brandão, S. C. R., Fernandes da Silva, J. H., Sá da Rocha, O. R., & Azoubel, P. M. (2021). Effect of ethanol and ultrasound pretreatments on pineapple convective drying. Food Technology and Biotechnology, 59(2), 209-215.

Dongbang, W., & Nuantong, W. (2020). Investigation of Mathematical Modeling for Banana Slices Drying using Hot Air Technique. Naresuan University Journal: Science and Technology (NUJST), 28(3), 79-87.

Dongbang, W., & Nuantong, W. (2020). Investigation of Mathematical Modeling for Banana Slices Drying using Hot Air Technique. Naresuan University Journal: Science and Technology (NUJST), 28(3), 79-87.

E.I.A, 2018. Energy Information Administration: Today in Energy. Linda Doman, Washington DC.

González-Cavieres, L., Perez-Won, M., Tabilo-Munizaga, G., Jara-Quijada, E., Díaz-Álvarez, R., & Lemus-Mondaca, R. (2021). Advances in vacuum microwave drying (VMD) systems for food products. Trends in Food Science & Technology, 116, 626-638.

Granella, S. J., Bechlin, T. R., & Christ, D. (2022). Moisture diffusion by the fractional-time model in convective drying with ultrasound-ethanol pretreatment of banana slices. Innovative Food Science & Emerging Technologies, 76, 102933.

Guiné, R. P., Barroca, M. J., Gonçalves, F. J., Alves, M., Oliveira, S., & Mendes, M. (2015). Artificial neural network modelling of the antioxidant activity and phenolic compounds of bananas submitted to different drying treatments. Food Chemistry, 168, 454-459.

Huang, D., Men, K., Li, D., Wen, T., Gong, Z., Sunden, B., & Wu, Z. (2020). Application of ultrasound technology in the drying of food products. Ultrasonics sonochemistry, 63, 104950.

Jarahizadeh, H., & Dinani, S. T. (2019). Influence of applied time and power of ultrasonic pretreatment on convective drying of potato slices. Food science and biotechnology, 28(2), 365-376.

Kurtulmuş, F., Polat, A., & Nazmi, İ. Z. L. İ. (2020). Yapay Sinir Ağları Kullanarak Kayısının Farklı Kurutma Yöntemleriyle Kurutulmasında Kuruma Hızı Ve Nem İçeriği Parametrelerinin Modellenmesi. ÇOMÜ Ziraat Fakültesi Dergisi, 8(2), 261-269.

La Fuente, C. I., & Tadini, C. C. (2018). Ultrasound pre-treatment prior to unripe banana air-drying: effect of the ultrasonic volumetric power on the kinetic parameters. Journal of food science and technology, 55(12), 5098-5105.

Llavata, B., García-Pérez, J. V., Simal, S., & Cárcel, J. A. (2020). Innovative pre-treatments to enhance food drying: A current review. Current Opinion in Food Science, 35, 20-26.

Macedo, L. L., Vimercati, W. C., da Silva Araújo, C., Saraiva, S. H., & Teixeira, L. J. Q. (2020). Effect of drying air temperature on drying kinetics and physicochemical characteristics of dried banana. Journal of Food Process Engineering, 43(9), e13451.

Murthy, T. P. K., & Manohar, B. (2014). Hot air drying characteristics of mango ginger: Prediction of drying kinetics by mathematical modeling and artificial neural network. Journal of Food Science and Technology, 51, 3712-3721.

Naderinezhad, S., Etesami, N., Poormalek Najafabady, A., & Ghasemi Falavarjani, M. (2016). Mathematical modeling of drying of the potato slices in a forced convective dryer based on important parameters. Food Science & Nutrition, 4(1), 110-118.

Omari, A., Behroozi-Khazaei, N., & Sharifian, F. (2018). Drying kinetic and artificial neural network modeling of mushroom drying process in microwave-hot air dryer. Journal of Food Process Engineering, 41(7), e12849.

Omari, A., Behroozi-Khazaei, N., & Sharifian, F. (2018). Drying kinetic and artificial neural network modeling of mushroom drying process in microwave-hot air dryer. Journal of Food Process Engineering, 41(7), e12849.

Qu, J. H., Sun, D. W., Cheng, J. H., & Pu, H. (2017). Mapping moisture contents in grass carp (Ctenopharyngodon idella) slices under different freeze drying periods by Vis-NIR hyperspectral imaging. Lwt, 75, 529-536.

Rasooli Sharabiani, V., Kaveh, M., Abdi, R., Szymanek, M., & Tanaś, W. (2021). Estimation of moisture ratio for apple drying by convective and microwave methods using artificial neural network modeling. Scientific reports, 11(1), 1-12.

Rojas, M. L., & Augusto, P. E. (2018). Ethanol and ultrasound pre-treatments to improve infrared drying of the potato slices. Innovative food science & emerging technologies, 49, 65-75.

Rojas, M. L., Augusto, P. E. D., & Cárcel, J. A. (2020b). Ethanol pre-treatment to ultrasound-assisted convective drying of apple. Innovative Food Science & Emerging Technologies, 61, 102328.

Rojas, M. L., Silveira, I., & Augusto, P. E. D. (2020a). Ultrasound and ethanol pre-treatments to improve convective drying: Drying, rehydration and carotenoid content of pumpkin. Food and Bioproducts Processing, 119, 20-30.

Şahin, U., & Öztürk, H. K. (2018). Comparison between artificial neural network model and mathematical models for drying kinetics of osmotically dehydrated and fresh figs under open sun drying. Journal of Food Process Engineering, 41(5), e12804.

Santos, K. C., Guedes, J. S., Rojas, M. L., Carvalho, G. R., & Augusto, P. E. D. (2021). Enhancing carrot convective drying by combining ethanol and ultrasound as pre-treatments: Effect on product structure, quality, energy consumption, drying and rehydration kinetics. Ultrasonics Sonochemistry, 70, 105304.

Seerangurayar, T., Al-Ismaili, A. M., Jeewantha, L. J., & Al-Nabhani, A. (2019). Experimental investigation of shrinkage and microstructural properties of date fruits at three solar drying methods. Solar Energy, 180, 445-455.

Senadeera, W. (2008). The drying constant and its effect on the shrinkage constant of different-shaped food particulates. International Journal of Food Engineering, 4(8).

Senadeera, W., Adiletta, G., Önal, B., Di Matteo, M., & Russo, P. (2020). Influence of different hot air drying temperatures on drying kinetics, shrinkage, and colour of persimmon slices. Foods, 9(1), 101.

Seyedabadi, E., Khojastehpour, M., & Abbaspour-Fard, M. H. (2017). Convective drying simulation of banana slabs considering non-isotropic shrinkage using FEM with the Arbitrary Lagrangian–Eulerian method. International journal of food properties, 20(sup1), S36-S49.

Soliva-Fortuny, R. C., & Martín-Belloso, O. (2003). New advances in extending the shelf-life of fresh-cut fruits: a review. Trends in Food Science & Technology, 14(9), 341-353.

Srimagal, A., Mishra, S., & Pradhan, R. C. (2017). Effects of ethyl oleate and microwave blanching on drying kinetics of bitter gourd. Journal of food science and technology, 54(5), 1192-1198.

Tepe, F. B. (2022). Impact of pretreatments and hybrid microwave assisting on drying characteristics and bioactive properties of apple slices. Journal of Food Processing and Preservation, 46(10), e17067.

Tepe, F. B. (2022). Impact of pretreatments and hybrid microwave assisting on drying characteristics and bioactive properties of apple slices. Journal of Food Processing and Preservation, 46(10), e17067.

Tepe, T. K., & Tepe, B. (2020). The comparison of drying and rehydration characteristics of intermittent-microwave and hot-air dried-apple slices. Heat and Mass Transfer, 56(11), 3047-3057.

Tepe, T. K., & Tepe, B. (2020). The comparison of drying and rehydration characteristics of intermittent-microwave and hot-air dried-apple slices. Heat and Mass Transfer, 56(11), 3047-3057.

TEPGE, Republic of Turkey Ministry of Agriculture and Forestry Agricultural Economic and Policy Development Institute 2020, https://arastirma.tarimorman.gov.tr/tepge Accessed 27 April 2021

Tunckal, C., & Doymaz, İ. (2020). Performance analysis and mathematical modelling of banana slices in a heat pump drying system. Renewable Energy, 150, 918-923.

Turkish Statistical Institute. Production of fruits, beverage and spice crops. https://data.tuik.gov.tr/Kategori/GetKategori?p=tarim-111&dil=1. Accessed 22 July 2023

Yıldız, A. K., Polatcı, H., & Uçun, H. (2015). Farklı Kurutma Şartlarında Muz (Musa cavendishii) Meyvesinin Kurutulması ve Kurutma Kinetiğinin Yapay Sinir Ağları ile Modellenmesi. Tarım Makinaları Bilimi Dergisi, 11(2), 173-178.