Performance of Machine Learning Model to Predict Thermodynamical Properties of an Active Solar Dryer for Pistachio Nut Dehydration

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Abstract

Introduction: Pistachio is one of Iran's strategic products, playing a significant role in providing the country's foreign exchange resources. The quality of the dried product is of high importance. Therefore, solar drying is one of the new and suitable methods for drying this strategic product.

Materials and Methods: In this study, a solar dryer was used to dry fresh pistachios. Fresh samples were dried to a safe moisture content of approximately 5% (wet basis). During the drying process, the thermodynamic parameters of the solar collector (as the heat energy generator for the dryer) were measured, including solar radiation intensity and the temperature of the air exiting the collector. These parameters were then predicted using an intelligent artificial neural network system (multilayer perceptron network).

Results: The results of this research indicated that the single-layer neural network with 8 neurons in the hidden layer provided the best fit in predicting solar radiation intensity (R^2=0.988) and the temperature of the air exiting the collector (R^2=0.941).

Conclusion: Overall, the findings of this study showed that the artificial neural network has a high capability in predicting the thermodynamic characteristics of the solar dryer.

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1. Introduction

Pistachio (*Pistacia Vera* L.) is one of the main products of Iran, the United States, and Turkey. A significant portion of pistachios is consumed as a snack. However, pistachio kernels are used in the preparation of cakes, pastries, ice cream, and pistachio butter. Additionally, this product is a key ingredient in several traditional Iranian dishes such as Gaz, Baklava, and Qottab.

The complete processing line for this product includes peeling, washing, sorting, drying, grading, packaging, and storing the product. The most important stage in the post-harvest process of pistachios is drying the product. Due to the low thermal conductivity of agricultural products, heat transfer to the internal parts of these materials occurs very slowly. Therefore, drying them requires a significant amount of energy. Moreover, by selecting an appropriate drying method, it is possible to reduce drying time, which can lead to economic savings and help preserve the quality characteristics of the product.

Currently, two methods are used for drying pistachios: traditional methods (Open sun drying or shade, or a combination) and industrial methods. These methods have limitations such as long drying times, attacks by insects and birds, dust, and rain, high initial investment costs, excessive energy consumption (due to the use of fossil fuels), the accumulation of greenhouse gases in the atmosphere, resulting in global warming and environmental pollution [1]. Therefore, the use of a dryer that utilizes solar radiation energy for drying pistachios while reducing drying time and improving the quality of the dried pistachios seems essential and appropriate. In this regard, solar dryers have been recognized as a new solution and are increasingly growing in popularity. These types of dryers operate by passing heated air from the solar collector over the product and, compared to industrial dryers, have comparable energy efficiency. In areas with high sunlight hours during the pistachio harvest season, they can easily replace with traditional and industrial drying methods [2].

In scientific literature, extensive studies have been published on the use of intelligent systems (such as artificial neural networks) for predicting and optimizing drying kinetics parameters, quality characteristics of food products, and energy consumption during the drying process. These systems create complex nonlinear relationships between input and output variables and simultaneously examine multiple variables in a study to provide a robust decision-making and real-time monitoring system for process parameters online [3]. Today, the use of intelligent control systems in various industries (especially drying industries) holds a special place as a non-destructive tool. In designing an intelligent solar drying system and controlling the drying performance, it is necessary to establish nonlinear relationships between independent and dependent variables. Some of these studies on the smart drying process for various food products and agricultural products are presented in Table 1.

Table 1. Comparison of different models of artificial neural network (ANN) for prediction of drying characteristics of various products (nuts & other food and agriculture material).

Product	Type of model	Variables of AIT		Best arrangement*	Reference
		Inputs	Outputs		
Nuts					
Pistachio nut	FFBP	DAT, AV, DT & Product type	D_{eff} & SEC	[3-3-4-2]	[4]
Pistachio nut	MLP	DT & DAT	MR	[2-23-23-2]	[5]
Bittim Nuts (pistaciaterebinthus)	ELM	DT, DAT & AV	MC	[3-20-2]	[6]
Pistachio nut	FFBP	DAT, AV & DT	Nut weight	[3-15-1]	[7]
Pistachio nut	MLP	DAT, AV & DT	MC	[3-8-5-1]	[8]
Pistachio nut	RBFN	MC & DAT	Thermal Conductivity	[2-112-4-1]	[9]
Sesame seeds	MLP	DM & DT	MC	[2-6-3-1]	[10]
Other					
Papaya	ELM	MP, DAT, FT	DT	-	[11]
Mushroom	BELM	DT, DAT & AV	Color parameters	[3-25-3]	[12]
Mushroom	MLFNN	DT, DAT, AV& thickness	Exergy analysis parameters	–	[13]
Pomelo (Citrus maxima)	ANN	DM, T & DT	Mass, MR & MC	[3-10-3]	[14]
Pomelo (Citrus maxima)	ANN	DM, T & MR	DT	[3-10-1]	[14]
Broccoli florets	ELM	DT, BT, DAT & AV	MR	[4-50-1]	[15]
Potato, garlic and cantaloupe	FFBP	DT, DAT, AV & Product type	Effective moisture diffusivity	[3-8-7-1]	[16]
Potato, garlic and cantaloupe	FFBP	DT, DAT, AV & Product type	SEC	[3-5-5-1]	(16)
Potato, garlic and cantaloupe	FFBP	DT, DAT, AV & Product type	MR	[4-15-15-1]	[16]
Black cumin	ELM	DT, MP & DAT	MR	[3-93-1]	[17]

***[I−N_1−N_2−O]: I=input variables, N_1= the first hidden layer, N_2= the second hidden layer & O= Output variables.**

Abbreviation: AIT, Artificial intelligent technology; AV, Air velocity; BELM, ELM model integrated Bayesian methods; BT, Blanching time; CFBP, Cascade forward back propagation; DAT, Drying air temperature; DM, Drying method; DR, Drying rate; DT, Drying time; ELM, Extreme learning machine model; FFBP, Multilayer feed-forward back propagation; FT, Foam thickness; MLFNN, Multilayer feed-forward neural network; MLP, Multilayer perception; MP, Microwave power; MR, Moisture ratio; MC, Moisture content; RBFN, Radial basis function network; SEC, Specific energy consumption.

As previously mentioned, in traditional drying methods, controlling parameters during the drying process is not easily achievable, which is associated with variable product quality in each batch of drying. This situation is one of the most challenging problems of discontinuous systems. Therefore, using a solar dryer and employing machine learning techniques (MLT), such as artificial neural networks (ANN), for real-time monitoring of the quality parameters of the product and the control system of the dryer can minimize these issues and improve the quality of the food product.

Controlling thermodynamic indicators in solar drying systems is challenging due to the lack of control over weather conditions. If these thermodynamic indicators are not monitored and controlled in real-time, not only will the product not dry properly, but it may also lead to secondary contamination (such as mold growth) of the product. One useful solution in this area is the use of machine learning systems or MLS (such as artificial neural networks) to control these indicators and manage them with auxiliary systems (such as auxiliary heaters, solar batteries, humidifiers, etc.) as needed.

Therefore, the aim of this study is to predict the thermodynamic indicators of a solar dryer using artificial neural networks, and if positive responses are found, to explore the feasibility of its implementation.

2. Materials and Methods

2.1. Preparation of Raw Materials

Pistachios (*Pistacia Vera* L.) of the Kaleh Ghoochi variety were collected daily from one of the orchards in the village of Keyzur (located in the Sabzevar County, Razavi Khorasan Province). Before drying, the pistachio husk was removed, and to prevent the loss of surface moisture, the pistachios were stored in a sealed plastic container immediately after shelling, with the lid closed. The pistachios were then kept in the refrigerator at a temperature of 3°C until the start of the experiment.

2.2. Drying Process in the Solar Dryer

To dry the fresh pistachios, the solar dryer designed in this research was used. The dryer consisted of a porous plate collector, a drying unit, a centrifugal fan, a relative humidity control vent damper, connectors and pipes, an axillary electric heater, and an electronic control system. The body of the solar collector was made of white galvanized sheet metal. To prevent heat loss, the body of the solar collector was insulated with fiberglass. The body of the device was made of black iron sheet. Inside the drying chamber, two mesh trays measuring 0.88 m × 0.84 m × 0.04 m (length, width, and height, respectively) were installed. To prevent heat loss, the drying chamber was insulated with fiberglass. The airflow inside the dryer was provided by a centrifugal fan installed on the device. For measuring thermodynamic characteristics (temperature and relative humidity) of the dryer, a temperature and humidity module (2303AM) was used. To determine solar radiation intensity, was utilized a pyranometer installed at the meteorological station in this region (Theodor Friedrichs & Co, Typ 6006.0000, S/N 0408, Germany).

2.3. Modeling Using Artificial Neural Networks

For modeling the artificial neural network, SPSS software version 19 (2011) was used. The type of network designed was a multilayer perceptron (MLP), where the input layer consisted of two neurons (temperature and relative humidity of the ambient air) and the output layer consisted of two neurons (solar radiation intensity and the temperature of the air exiting the collector). Therefore, the artificial neural network model was designed based on 2 inputs and 2 outputs. The optimization of the structure of the artificial neural network was carried out by examining different network configurations and evaluating the correlation between the outputs of the neural network and the experimental data. To optimize the artificial neural network, various parameters such as the number of neurons in each hidden layer, the type of activation function in the hidden and output layers, the learning rate, and the momentum coefficient were evaluated. To find the best configuration, one hidden layer with 2 to 40 neurons in each hidden layer, learning rate of 0.4, a momentum coefficient of 0.9, and were used *sigmoid* logarithmic activation functions (Equation 1) in the hidden and output layers.

$$\log sig(z) = (1 + \exp(-z))^{-1} \qquad (0, +1) \qquad (1)$$

For modeling the neural network, the data was initially divided into two parts, with 70% of the data used for training and the remaining 30% for evaluating the network. To compare the performance of the neural network the following (Equations 2 & 3) statistical parameters was used.

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{N} (U_{p,i} - U_{e,i})^2}{\sum_{i=1}^{N} (\overline{U}_{p,i} - U_{p,i})^2} \right] \qquad (2)$$

$$MRE = \left(\frac{1}{N} \sum_{i=1}^{N} \frac{\left| U_{p,i} - U_{e,i} \right|}{U_{e,i}} \right) \times 100 \qquad (3)$$

In these equations, $U_{e,i}$ represents the experimental data at the i^{th} measurement, $U_{p,i}$ represents the data predicted by the artificial neural network at the i^{th} measurement, $\overline{U}_{p,i}$ is the mean of the data predicted by the artificial neural network at the i^{th} measurement, and N is the number of observations [18].

3. Results

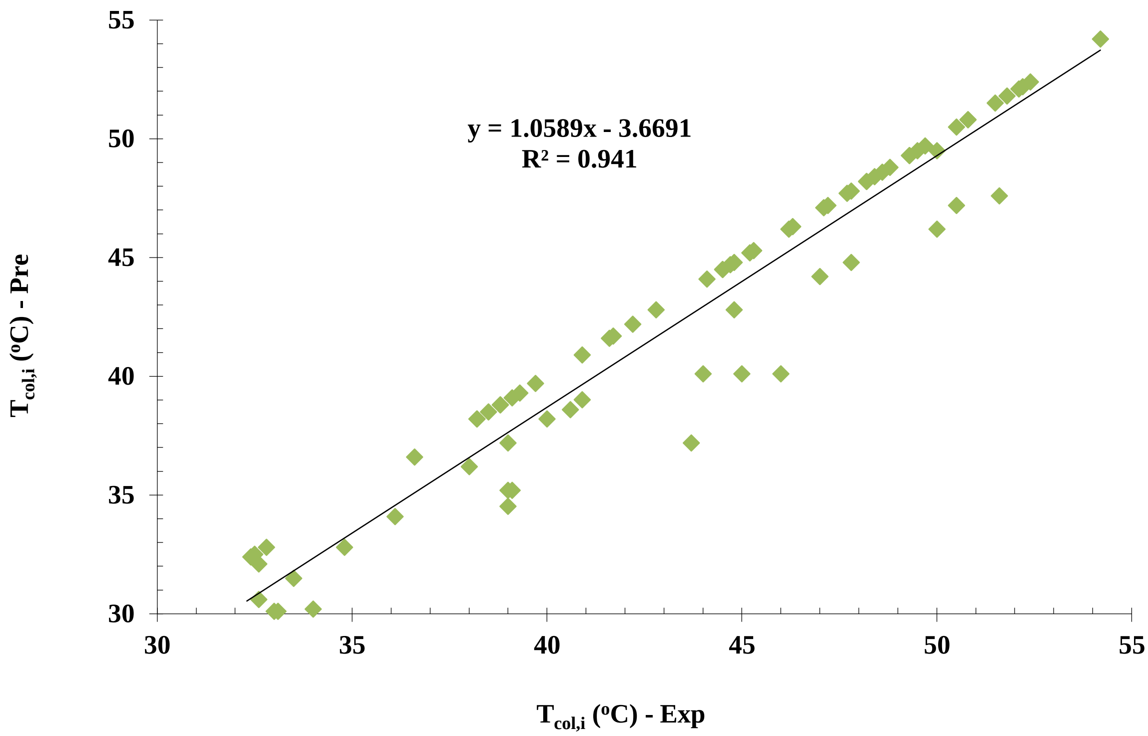
In this study, the parameters of solar radiation and the temperature of the air exiting the collector were predicted by the neural network. For this purpose, a perceptron neural network with one hidden layer, number of 2 to 40 neurons, 2 inputs (temperature and relative humidity of the ambient air), and 2 outputs (solar radiation and the temperature of the air exiting the collector) (Table 2) was used. The perceptron network was trained using the backpropagation learning algorithm along with momentum, where the momentum coefficient for all networks was set to 0.9 and the learning rate was set to 0.4. The results indicated that the neural network with 8 neurons in the hidden layer provided the best fit in predicting solar radiation and the temperature of the air exiting the collector. It is worth mentioning that these indices are among the most important indicators in the design of the device, as the quality of the dried product is highly dependent on the variations of these parameters.

Table 2. The results of the neural network in predicting the solar radiation (I) and the temperature of the air exiting the collector ($T_{o,col}$).

Network output	Statistical parameters	Number of neurons*								
		2	5	8	12	15	18	21	27	40
I	MRE**	0.6113	0.095	0.0635	0.497	0.7233	0.0448	0.0424	0.4867	0.4524
	R^2	0.530	0.868	0.988	0.551	0.336	0.862	0.755	0.558	0.655
$T_{o,col}$	MRE	0.2033	0.0606	0.0128	0.1319	0.4723	0.0497	0.0426	0.3657	0.1924
	R^2	0.806	0.940	0.941	0.878	0.531	0.927	0.881	0.829	0.828

*Hidden layer activation function and sigmoidal output were selected.
**Relative error of network training.

In Figure (1), a comparison of the experimental and predicted results for the best configuration of the artificial neural network (i.e., the 2-8-2 configuration) in predicting the thermodynamic indices of the solar dryer is depicted. As can be seen, the experimental and predicted data are scattered around the central line with high accuracy, indicating the high precision of the network in its predictions.



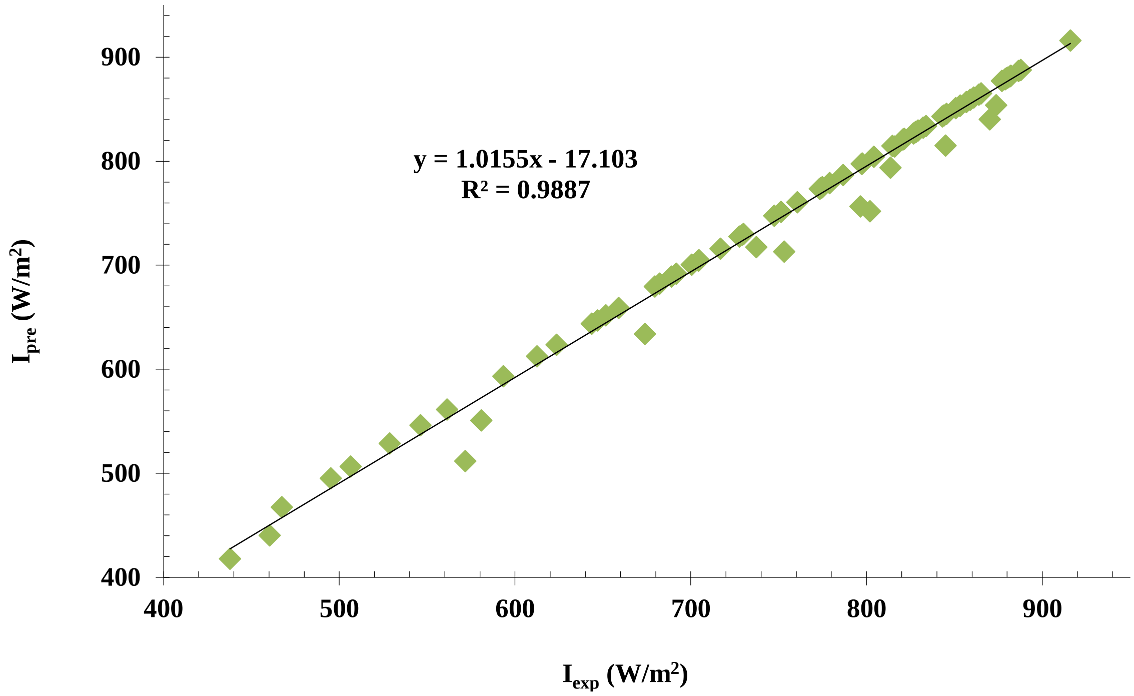


Fig. 1. Comparison of the experimental and predicted results of the thermodynamic indices of the solar dryer: a) temperature of the air exiting the collector and b) solar radiation.

4. Discussion

Drying agricultural products, as a method for preserving perishable goods, is an old and accepted technique that is still widely used around the world. Solar drying of agricultural products is a simpler method compared to other drying processes. Solar dryers are available in various sizes and designs and are used for drying different agricultural products. The thermal performance of solar air collectors depends on the material, shape, dimensions, and configuration. Additionally, the efficiency of the solar collector also depends on its type and model, as well as the amount of heat loss during operation. The drying efficiency can depend on the type of solar dryer, the amount of water evaporated during the drying period, the mass of the dried materials, the drying air temperature, the ambient air temperature, the latent heat of evaporation, solar energy on the heating surface (collector), and so on. Calculating this efficiency requires numerous processes and experimental studies. Generally, this method is time-consuming and complex. On the other hand, artificial neural network models represent a new approach to prediction. In previous studies, researchers have achieved high effectiveness from artificial neural network models in successfully describing the drying process. Additionally, studies have been conducted on the applications of artificial neural networks in predicting the thermal performance of solar collectors by several researchers [19]. An artificial neural network consists of a set of neurons with internal connections between them, capable of estimating output responses based on input information and data. Neural networks are typically organized and created in layers. The simplest and most common type of neural network used in many engineering sciences, including the present research, is the multilayer perceptron neural network with supervision, which utilizes the backpropagation method for training [5]. As previously mentioned, in this study, the parameters of solar radiation and the temperature of the air exiting the collector (the drying air temperature or input to the drying chamber) were predicted by the neural network. The results showed that the neural network with 8 neurons in the hidden layer provided the best fit in predicting solar radiation and the temperature of the air exiting the collector. Senkan and Ozdemir (2007) employed an artificial neural network model to predict the thermal efficiency of a solar collector. The input of the neural network included the inlet and outlet air temperatures of the collector, solar radiation, and the mass flow rate of air, while the thermal efficiency was considered as the output of the neural network [20]. Soozan and colleagues (2008) predicted the efficiency of a flat plate solar collector using an artificial neural network. The input layer of the network included the collector surface temperature, date, time, solar radiation, deviation angle, azimuth angle, and tilt angle. The efficiency of the flat plate solar collector was placed in the output layer. The advantages of neural network models compared to conventional evaluation methods include speed, simplicity, and the learning capacity of the neural network from samples [21]. Kasem and colleagues (2011) predicted the drying efficiency during the solar drying process of grape clusters in a box dryer using an artificial neural network. In this research, the modeling of the temperature of the solar dryer, wind speed, relative humidity of the ambient air, grape temperature, relative humidity of the solar dryer, and the moisture content of the grapes were examined in relation to the drying efficiency of the dried grape clusters using multiple linear regression analysis and artificial neural networks. The values of R^2, RMSE, and MAE for drying efficiency were determined to be 0.7068, 2.9227%, and 2.1748%, respectively, when using the ANN model in the testing phase. Furthermore, the neural network model demonstrated better predictions compared to the regression model for drying efficiency. This study is expected to be very beneficial for those who will be involved with solar drying systems in the future [19]. In a study by Tavakolipour and Mokhtarian (2012), the moisture ratio of pistachios was predicted using a perceptron artificial neural network. Their results showed that the best network was observed when using 7 neurons in the first and second hidden layers, with a coefficient of determination of 0.994 in this case [5]. These results confirm the findings of the present research. As a general rule, the ideal number of neurons in a neural network ranges from 2 to 20, and the efficiency of the model improves with an increase in the number of neurons in the hidden layers, an increase in the learning rate, and an increase in the momentum coefficient [22].

5. Conclusion

The analysis of thermodynamic data (solar radiation and the temperature of the air exiting the collector) using the perceptron artificial neural network showed that there was a desirable correlation between the experimental and predicted data (the coefficient of determination for solar radiation and the temperature of the air exiting the collector were obtained as 0.988 and 0.941, respectively). Overall, the neural network serves as a suitable alternative tool that establishes complex nonlinear relationships between input and output variables. By employing machine learning (such as neural networks) in solar drying systems, it becomes easier to monitor the thermodynamic characteristics of the dryer and, when necessary, to properly continue the drying process by providing the operational conditions for drying, which will result in the production of high-quality and uniform products.

Conflict of Interest

The authors of the present research declare that there is no conflict of interest.

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