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Prediction of moisture and density in shrimp during hot air frying with artificial neural networks model

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ABSTRACT

In this research, artificial neural networks (ANN) was presented to predict changes in moisture and density of shrimp during hot air frying process (at three temperatures of 140, 160 and 180 degrees Celsius for 15 minutes). Neural networks in the form of multilayer perceptron (MLP) with sigmoid tangent transfer function in the hidden layer and linear transfer function in the output layer was designed to predict moisture (with two inputs: temperature and time) and density (with three inputs: temperature, time and moisture) in MATLAB software. Different backpropagation algorithms include Levenberg-Marquardt, Gradient descent, Gradient descent with adaptive learning rate, Adaptive learning rate backpropagation, Gradient descent with momentum, and Scaled conjugate gradient. The structure of the models was validated by calculating the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). Finally, the importance of the inputs in terms of the effect on the output variable for predicting moisture and density was investigated by designing the default hyperbolic tangent neural networks in SPSS software. The results showed that with the decrease in moisture and the development of pores in shrimp, the density of the product gradually decreased during hot air frying, and with the increase in the temperature of the process, a further decrease in density was observed. In the moisture model, the backpropagation algorithm of Gradient descent with momentum (R^2=0.989, RMSE=0.171, MAE=0.131) and in the density model, the Levenberg-Marquardt algorithm (R^2=0.974, RMSE=0.0096, MAE=0.0066) showed the minimum error in training. In the moisture neurocomputing, the importance of time and temperature variable was equal to 0.883 and 0.117, respectively. In the density neurocomputing, the importance of moisture, time and temperature variables were 0.588, 0.278 and 0.134, respectively. The Findings can be used in the design of artificial intelligence for controlling and creating automation in hot air fryers.

1- Introduction

In recent years, due to the risks associated with a high-fat diet, there has been a growing tendency among consumers to seek healthier and safer alternatives to fried foods. Additionally, reducing oil consumption in fried foods has become a necessity. In this regard, replacing traditional frying methods with systems that provide similar characteristics to fried foods while ensuring higher nutritional quality and greater accessibility has been under investigation. Therefore, hot air frying has been introduced as an alternative to deep frying. Hot air frying technology is available on the market [1], with some systems continuously evolving through constant aeration and direct contact with nonstick surfaces. However, all designs ensure uniform heat transfer between the air and the product being fried [2]. In this method, the product comes into direct contact with oil droplets dispersed in hot air, leading to dehydration and the gradual formation of a crust on the fried product [3]. Oil can be added before or during the process with a light coating on the food surface to enhance flavor, texture, and appearance [4]. Hot air fryers provide uniform heat transfer between the air and the frying product [2], resulting in consistent quality changes throughout the product [4]. Ultimately, hot air frying produces fried food with significantly lower oil content while maintaining moisture levels similar to deep fat frying [3]. In hot air frying, the product is heated evenly from all directions, and in most cases, there is no need to add oil [1]. Foods fried with hot air contain 80% less oil compared to deep fat frying [5], leading to 70% energy savings and a reduction in wastewater emissions from frying processes [6].

The American Heart Association recommends consuming various types of fish, shellfish, and shrimp at least twice a week [7]. Epidemiological studies have shown that in communities with a seafood-based diet, the incidence of heart attacks is significantly lower [8]. Shrimp meat has a high biological value due to its high digestibility (85%) compared to many other protein sources. The nutritional value of seafood for humans supports good health and optimal physiological function by providing all essential nutrients in sufficient amounts, thereby preventing nutrient deficiency-related diseases and chronic diet-associated disorders [9]. Shrimp is rich in high-quality protein, calcium, essential minerals, and various bioavailable compounds, while being low in calories and fat. Shrimp contains high-quality components such as proteins, fats, and amino acids, which serve as indicators of optimal physiological and biochemical conditions. Aquatic animal fats are excellent sources of essential fatty acids that cannot be synthesized by the human body and are necessary for growth, reproduction, and vitamin synthesis. Therefore, processing of shrimp and other seafood products should be carried out in a way that preserves their high nutritional value for consumers [10; 11; 12; 13].

One of the most important requirements for controlling a quality parameter is understanding its variations during the frying process, as any fluctuations in frying conditions can lead to undesirable quality changes [14]. Studying moisture changes and a biophysical indicator such as texture or density can be effective in controlling this modern process. Shrimp, being an irregularly shaped biological material, undergoes significant shrinkage during dehydration and frying. During dehydration, moisture escapes through the shrimp's pores, reducing the pore volume and apparent volume of the shrimp, thereby affecting the quality parameter of product density. The internal moisture gradient within the shrimp can also result in uneven shrinkage, leading to irregular deformation. Variations in moisture and density can influence the texture and dehydration behavior of the product during processing [15]. Understanding the textural properties of the product can also help predict its vulnerability during transportation [16]. Additionally, cooking shrimp can lead to a decrease in production yield, an important economic factor, due to changes in moisture content. During thermal processing, shrimp proteins undergo denaturation, which reduces their water-holding capacity, leading to lower production yield and dimensional changes in the product. Yield loss is a key criterion in implementing an appropriate cooking strategy for shrimp, and examining moisture and dimensional changes provides an informed approach to optimizing the cooking process. All these factors can be estimated using mathematical and intelligent models to assist industry professionals in optimizing shrimp thermal processing and improving quality. These models simplify the analysis of relationships between various influencing factors. For instance, "cooking charts" have been developed for large, medium, and small shrimp using mathematical models to achieve the target microbial level [17]. Overall, managing the quality characteristics of food products from the production stage to ensure control is a complex task [18]. Artificial Neural Networks (ANN) are a machine learning-based model designed similarly to the biological nervous system, including neurons, dendrites, and axons, and they can model complex nonlinear processes in the food industry. This method is an innovative approach to solving engineering problems and developing technology, offering advantages over mathematical modeling. ANN can be implemented in real-world engineering problems, significantly reducing time and costs [19].

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Researchers have studied the effect of hot air frying on the quality of seafood products such as sardine fish [20], fish cutlet [21], surimi lipids (fish products) [22], and fish [23]. Their findings indicate that hot air frying helps preserve the quality characteristics of seafood by reducing lipid degradation, leading to improved sensory evaluation from the consumer's perspective. A review of the literature reveals that no studies have yet been conducted on hot air frying for shrimp. Additionally, artificial neural network (ANN) modeling for predicting moisture content and density in hot air frying has not been explored. However, in a previous study, the physical quality parameters of frozen shrimp were analyzed using ANN and genetic algorithms [24]. The input variables in this study included freezing rate, thawing rate, storage time, and shrimp thickness, while the output variables consisted of color and texture. The results showed that the GANN model provided better predictions than multiple linear regression (MLR) and backpropagation (BP), with the lowest RMSE and the highest R^2.

The aim of this study was to utilize artificial neural network (ANN) to predict moisture content and density as two key quality indicators influencing the production yield of shrimp snacks. The first ANN model was designed to predict moisture content (one output variable) of shrimp, influenced by frying time and temperature in the hot air frying process (two input variables). The second ANN model was developed to predict density (one output variable), considering frying time, temperature, and moisture content (three input variables) based on experimental data. The significance of each input variable was also evaluated within the ANN structure. To ensure controlled conditions for analyzing the hot air frying process, the chemical composition and cross-sectional area of each shrimp were assumed to be uniform. Additionally, due to the minimal amount of oil added to the shrimp (0.01 g per sample), its oil absorption variation was considered negligible.

2-Materials and Methods

1-2- Shrimp Preparation

A sufficient quantity of fresh and uniform-sized whiteleg shrimp (*Litopenaeus vannamei*) was purchased from Gorgan shrimp farms in northern Iran (Bandar Torkaman Industrial Park, Shil Abzi Golestan Company). The shrimp were packaged in polyethylene bags and stored in a freezing chamber. Before sample preparation, the shrimp were thawed at room temperature for 10 minutes. After washing, they were cut into approximately cylindrical pieces with a diameter of 9 mm and a height of 15 mm. Prior to hot air frying, the initial weighing of the shrimp was conducted using a high-precision laboratory scale (*Sartorius GCA803S*) with an accuracy of 0.0001 g, and the weight was recorded.

2-2-Hot Air Frying Process

The hot air frying process was performed by spraying 0.01 g of oil onto the shrimp pieces and frying them at three different temperatures (140°C, 160°C, and 180°C) using a hot air fryer (*Geepas-Gaf2708*) for 15 minutes. The maximum hot air velocity in the fryer was 6.5 m/s, measured using a *hot wire anemometer (TES 1341)*. The samples were removed from the fryer at three-minute intervals. After the frying process, the shrimp pieces were placed on absorbent paper for approximately two minutes to remove excess surface oil. The final weight of the hot air-fried shrimp was recorded. The frying process was conducted in triplicate.

2-3-Moisture Content Measurement

The moisture content of the fried shrimp samples was measured according to the standard procedure for moisture determination in fatty samples. The drying process was conducted in a hot air oven at 103°C for 16 hours until a constant weight was achieved [25]. After drying, the sample-containing dish was cooled and weighed. The moisture content of the shrimp was calculated on a dry weight without oil basis using Equation (1). In this equation, M is the moisture content on a dry weight without oil basis (g/g, db), W_0 is the constant weight of the metal dish (g), W_1 is the weight of the dish with the sample before drying (g), W_2 is the weight of the dish with the sample after drying (g) and W_{oil} is the weight of the sprayed oil (0.01 g) [26].

$$M = \frac{W_1 - W_2}{W_2 - W_0 - W_{oil}}$$

2-4-Measurement of Volume and Density

The volume of the samples was determined using the solvent displacement technique with toluene by measuring the difference in solvent weight in a 150 mL flask in the presence and absence of the sample. After weighing, the fried samples were placed in the flask. The sample volume can be calculated using Equation (2). In this equation, *V* is the sample volume (cm³), V_f is the flask volume (cm³), M_s is the mass of the solvent (g) added to the flask, and ρ_s is the solvent density (0.866 g/cm³) [27, 28].

$$V = V_f - \frac{M_s}{\rho_s} \quad (2)$$

To estimate the density (ρ) of the samples, Equation (3) was used. The mass (*m*) was considered in grams, and the volume (*V*) in cubic centimeters. The density was calculated in *g/cm³* [29].

$$\rho = \frac{m}{V} \quad (3)$$

2-5-Artificial Neural Network Model Design

2-5-1 Network Structure

Figure (1) illustrates the structure of a multilayer perceptron (MLP) neural network. Similar to previous research [30], this model can be described as follows: In the input layer, the input data are assigned weights. In the hidden layer, these weighted data are summed according to Equation (4), and an activation function, based on the inputs, produces an output. In this equation, y_i is the dependent variable, x_i is the independent variable, w_{ij} is the weight of the connection between neuron *i* and neuron *j*, and b_j is the bias connection to neuron *j* [24]. The number of neurons in the hidden layer varies from 1 to 25 depending on the error in the output layer, while the number of layers' ranges from 1 to 3. All data were divided into three groups: training dataset, testing dataset, and validation dataset.

$$y_i = \sum_{i=1}^{n} f\left(w_{ij} x_i\right) + b_j \quad (4)$$

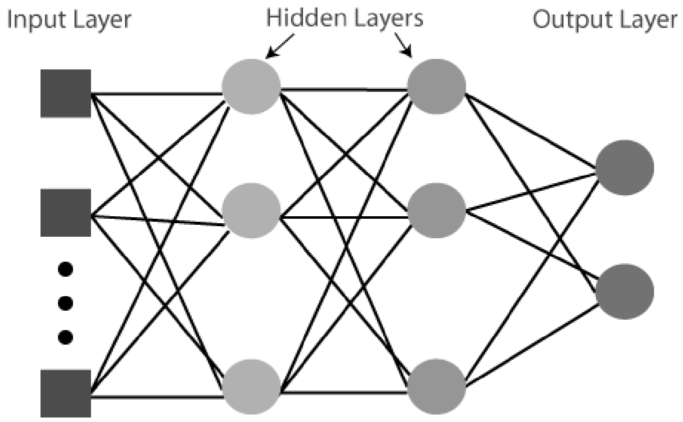

Figure 1- Schematic diagram on the structure of artificial neural networks as multilayer perceptron (MLP)

2-5-2-Network Design

Similar to the study by researchers [31], a multilayer perceptron (MLP) neural network was designed using the dedicated toolbox in MATLAB 2018a to accurately predict the studied variables (moisture and density). In this research, a three-layer backpropagation network was employed, with a tangent sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The backpropagation algorithms used in this study included Levenberg-Marquardt, Gradient descent, Gradient descent with adaptive learning rate, Gradient descent with momentum, Adaptive learning rate backpropagation, and Scaled conjugate gradient. For the neural network predicting moisture content, the input variables were temperature (°C) and time (seconds), while the output variable was moisture content (g/g dry matter). For the neural network predicting density, the input variables were temperature (°C), time (seconds), and moisture content (g/g dry matter), while the output variable was density (g/cm³). A total of 30 data points (67% of the dataset) were used for training, and 15 data points (33% of the dataset) were used for testing. The total dataset consisted of 45 independent and dependent data points.

2-5-3-Validation

The performance of the training and testing phases in the design of artificial neural networks was

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validated by considering the types of training algorithms used and the model structure. This validation was carried out by calculating the coefficient of determination (R^2) according to Equation (5), the root mean square error (RMSE) according to Equation (6), and the mean absolute error (MAE) according to Equation (7) [32].

$$RMSE = \sqrt{1/n \sum_{i=1}^{N} (O_i - P_i)^2} \tag{5}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| O_i - P_i \right| \tag{6}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n} (O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\left[\sum_{i=1}^{n} (O_i - \overline{O})^2 \right] \left[\sum_{i=1}^{n} (P_i - \overline{P})^2 \right]}} \right)^2 \tag{7}$$

In these relations, O_i represents the observed value of sample i, P_i is the estimated value for the same sample, n is the number of data points, $\overline{O}$ is the mean of the observed values, and $\overline{P}$ is the mean of the estimated values. The closer the values of RMSE and MAE are to zero, the better the prediction performance, indicating that the model has a high prediction capability.

2-5-4-Evaluation of Input Importance in Network Design

The importance of input variables in predicting moisture content and density was analyzed using a predefined hyperbolic tangent neural network in SPSS version 19. The neural network toolbox in SPSS generates multiple neural networks in the shortest possible time and suggests the optimal model, which can be used to assess the significance of input variables. In this phase, a total of 54 independent and dependent data points were used to make the network. The required number of data points for the training and testing phases was determined by the software. The validation of the training and testing phases was briefly assessed using the sum of squared errors (SSE) and relative error (RE), as reported by the software.

3-Results and Discussion

3-1 Moisture Changes in the Product During Hot Air Frying

Figure (2) illustrates the changes in shrimp moisture content during hot air frying, along with the standard deviation of experimental data, as a function of processing time. At the beginning of the frying process, the moisture reduction rate is high, and as the product loses moisture, the rate of change gradually stabilizes. As expected, water evaporation occurs more rapidly at higher frying temperatures, with the most intense moisture loss occurring during the first three minutes of the process. This is due to the sudden evaporation of surface-free water. During hot air frying, the partial vapor pressure difference between the product and the surrounding hot air drives water evaporation. This pressure difference is highest at the start of the process. These observations are consistent with the findings of many researchers [33–37]. Similar trends in moisture reduction during vacuum frying of shrimp have been reported, where higher temperatures resulted in greater moisture loss over time [37]. In another study on shrimp frying, researchers noted that the final moisture content of shrimp is influenced by frying medium conditions [38]. Additionally, researchers have stated that during frying, the rate of moisture loss increases until surface drying is complete and then gradually decreases [39]. Other studies have confirmed that the highest rate of moisture loss occurs during the initial stages of frying [26, 40].

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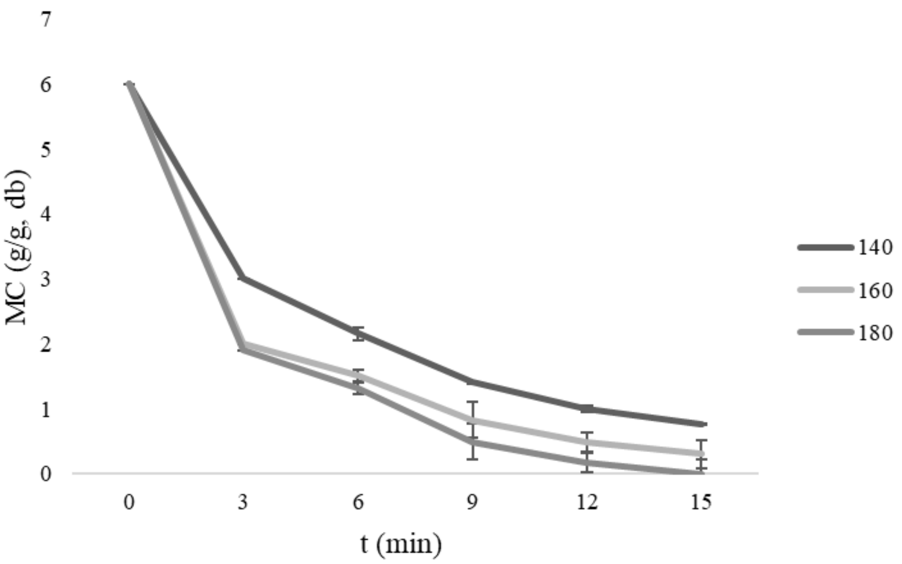

Figure 2- Changes in shrimp moisture content during hot air frying at different temperatures

3-2-Changes in Shrimp Density

Figure (3) illustrates the changes in shrimp density during hot air frying. As shown, shrimp density gradually decreased over time. An increase in frying temperature further reduced the shrimp density. At longer frying durations, the difference in density between different temperature conditions became more pronounced. Researchers have indicated that density is significantly influenced by processing variables and tends to decrease during frying due to water evaporation and the formation of pores. They have also reported that frying temperature has a negative impact on density; as temperature increases, mass transfer phenomena intensify, leading to a further reduction in density. Consequently, in conditions where mass transfer occurs more intensely, lower densities are observed. Moreover, in the initial stages of the frying process, when mass transfer phenomena are more intense, a greater reduction in density was noted [41]. It has also been established that water loss due to evaporation contributes to density reduction, with a steeper decline occurring in the early stages of frying [42].

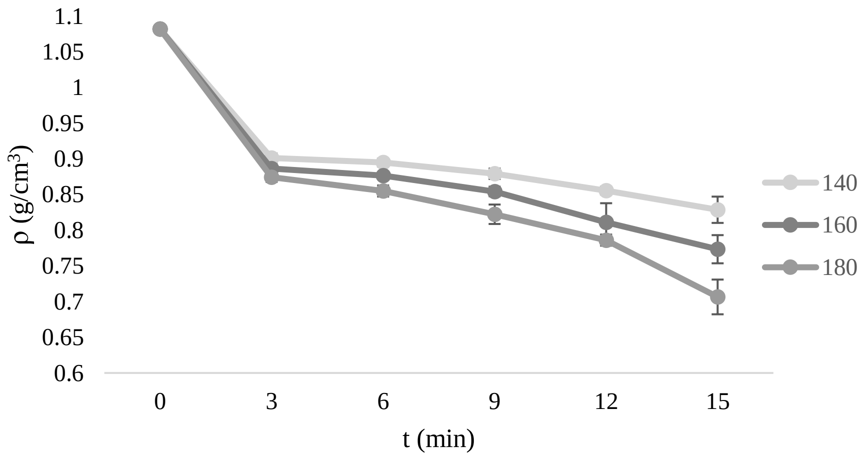

Figure 3- Changes in shrimp density during hot air frying

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3-3-Artificial Neural Networks Model in Moisture Content Prediction

Table (1) presents the results of moisture modeling using an artificial neural network for both the training and testing phases separately. As shown, the lowest error index values in the testing phase correspond to the gradient descent with momentum training algorithm. In this case, the model structure is 2-16-1, indicating two inputs in the first layer, 16 neurons in the hidden layer, and one output in the third layer. The values of R^2, RMSE, and MAE for this training algorithm in the testing phase are 0.989, 0.171 (g/g, db), and 0.131 (g/g, db), respectively. To validate the accuracy of the model and the selected structure (gradient descent with momentum), a scatter plot was used for the training phase (Figure 4-A) and the testing phase (Figure 4-B). In these plots, the actual moisture content is plotted against the predicted moisture content by the neural network. Additionally, the correction coefficient is considered by fitting a line on the experimental data corresponding to the model data.

Table 1- The results of the training and testing stages of the neural networks for moisture prediction

Training algorithm	Model structure	Training stage			Testing stage		
		R^2	RMSE (g/g, db)	MAE (g/g, db)	R^2	RMSE (g/g, db)	MAE (g/g, db)
Levenberg-Marquardt	1-2-2	0.9891	0.0877	0.0697	0.9720	0.1843	0.1454
Gradient descent	1-16-2	0.9892	0.0873	0.0682	0.9786	0.1714	0.1319
Gradient descent with adaptive learning rate	1-2-2	0.9854	0.1017	0.0842	0.9750	0.1758	0.1432
Gradient descent with momentum	1-16-2	0.9891	0.0878	0.0686	0.9787	0.1711	0.1317
Adaptive learning rate backpropagation	1-3-2	0.9904	0.0822	0.0583	0.9727	0.1830	0.1456
Scaled conjugate gradient	1-3-2	0.9909	0.0804	0.0574	0.9725	0.1836	0.1474

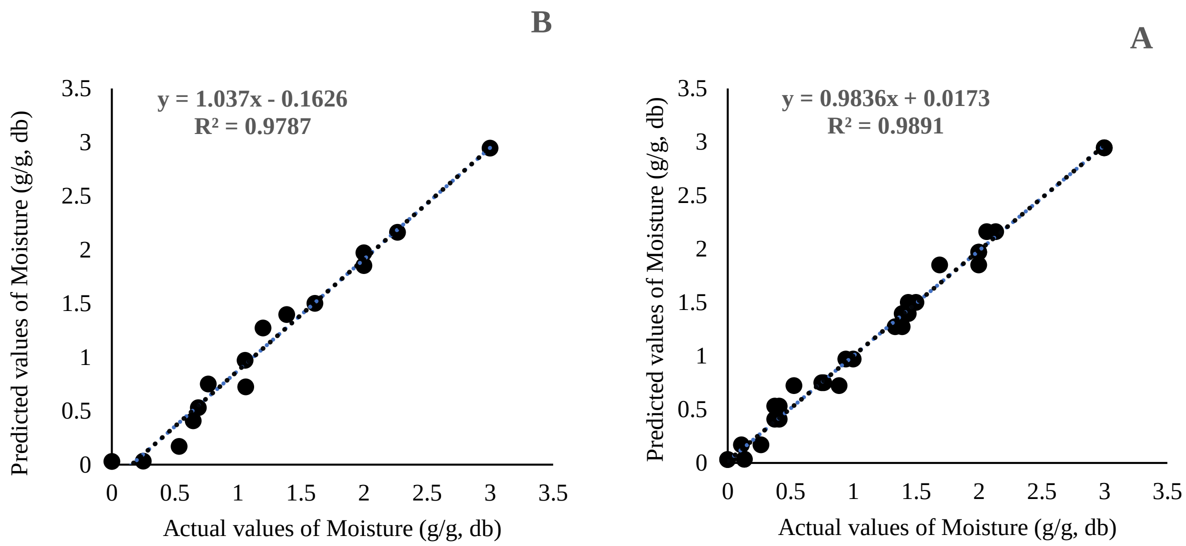

Figure 4- The actual values of moisture (g/g, db) versus the predicted values by the artificial neural networks in the training (A) and test (B) stages

3-4-Artificial Neural Network Model in Density Prediction

Table (2) presents the results of density modeling using an artificial neural network for both the

[DOI: 10.22034/FSCT.22.161.121]

training and testing phases separately. As shown, the lowest error index values in the testing phase correspond to the Levenberg-Marquardt training algorithm. In this case, the model structure is 3-1-1, indicating three inputs in the first layer, one neuron in the hidden layer, and one output in the third layer. The values of R^2, RMSE, and MAE for this training algorithm in the testing phase are 0.9740, 0.0096 (g/cm^3), and 0.0066 (g/cm^3), respectively. To validate the accuracy of the model and the selected structure (Levenberg-Marquardt), a scatter plot was used for the training phase (Figure 5-A) and the testing phase (Figure 5-B). In these plots, the actual density values are compared against the predicted density values by the neural network. Additionally, the correction coefficient is considered by fitting a line on the experimental data corresponding to the model data.

Table 2- The results of the training and testing stages of the neural networks for density prediction

Training algorithm	Model structure	Training stage			Testing stage		
		R^2	RMSE (g/cm^3)	MAE (g/cm^3)	R^2	RMSE (g/cm^3)	MAE (g/cm^3)
Levenberg-Marquardt	1-1-3	0.9356	0.0123	0.0089	0.9740	0.0096	0.0066
Gradient descent	1-20-3	0.9385	0.0121	0.0090	0.9692	0.0102	0.0071
Gradient descent with adaptive learning rate	1-1-3	0.9328	0.0126	0.0089	0.9647	0.0107	0.0067
Gradient descent with momentum	1-20-3	0.9385	0.0121	0.0090	0.9686	0.0102	0.0071
Adaptive learning rate backpropagation	1-1-3	0.9344	0.0124	0.0089	0.9685	0.0101	0.0066
Scaled conjugate gradient	1-1-3	0.9354	0.0124	0.0089	0.9728	0.0097	0.0066
Scaled conjugate gradient	**1-1-3**	**0.9354**	**0.0124**	**0.0089**	**0.9728**	**0.0097**	**0.0066**

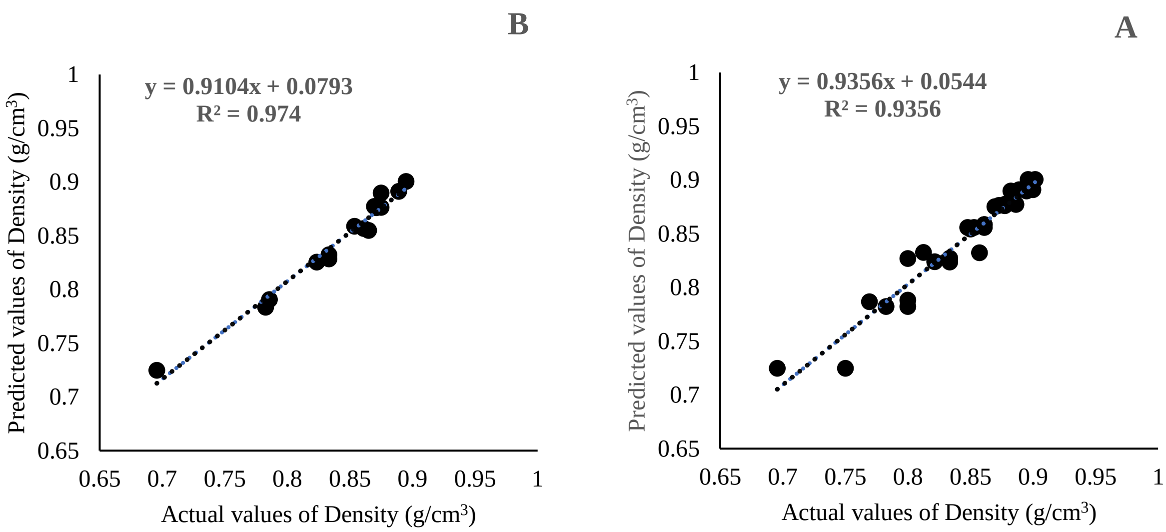

Figure 5- The actual values of density (g/cm^3) versus the predicted values by the artificial neural networks in the training (A) and test (B) stages

3-5-Importance of Input Variables in Moisture Prediction

Figure (6) illustrates the structure of the artificial neural network for moisture prediction in shrimp, with two variables in the input layer, one hidden layer using a hyperbolic tangent function, and one variable in the output layer. 72.2% of the data was used for the training phase, and 27.8% for the testing phase. In the formation of the neural network for

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moisture prediction, to examine the importance of the input variables, precise calculations were performed using the SPSS software. The sum of squared errors (SSE) and relative error (RE) for the training phase were estimated to be 0.18 and 0.009, respectively, while for the testing phase, they were 0.07 and 0.008, which were very satisfactory.

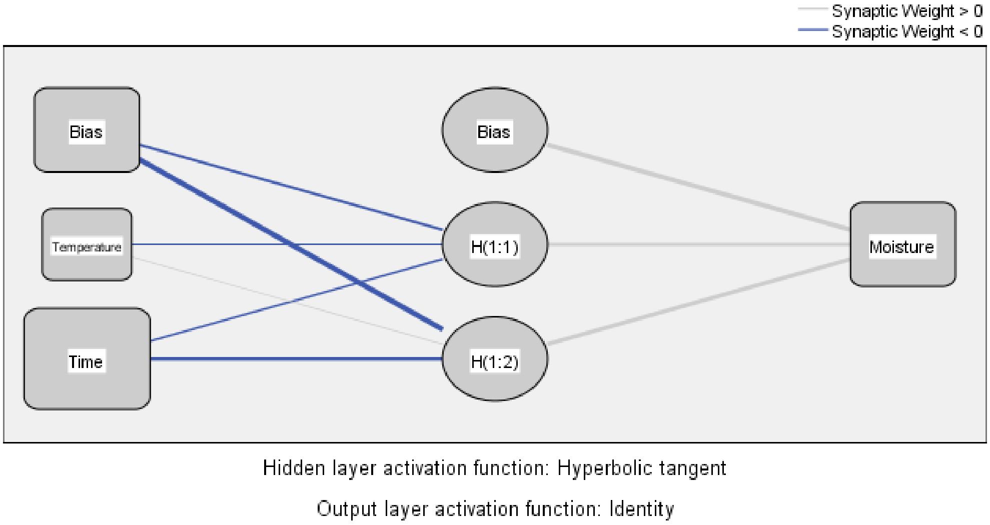

Figure 6- Artificial neural network for predicting moisture content of shrimp during hot air frying: input variables: temperature and time and output variable: moisture content.

Figure (7) illustrates the importance of independent variables in forming the neural network for predicting moisture. The importance of the temperature variable was 0.117, while the importance of the time variable was 0.883. The normalized importance, expressed as a percentage (assuming time has 100% importance in predicting moisture) was 13.2% for temperature. Similarly, researchers have identified frying time as a more significant factor in predicting moisture during deep frying compared to other input variables [43].

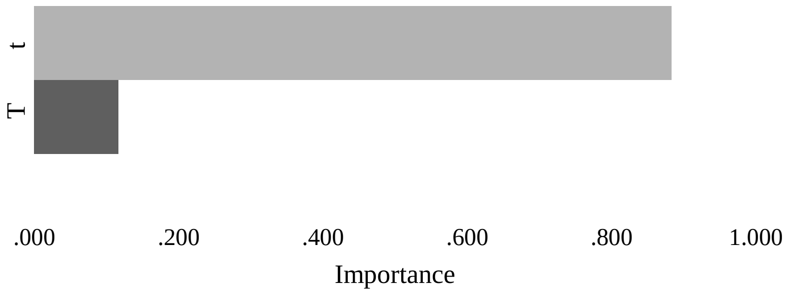

Figure 7- The importance of independent variables (Temperature "T" and time "t") in the formation of artificial neural network for moisture prediction

3-6-Importance of Network Inputs in Density Prediction

Figure (8) illustrates the structure of the artificial neural network for density prediction in shrimp, with three variables in the input layer, one hidden layer using a hyperbolic tangent function, and one variable in the output layer. 77.8% of the data was used for the training phase, and 22.2% for the testing phase.In the formation of the neural network for density prediction, to examine the importance of the input variables, precise calculations were performed using the SPSS software. The sum of squared errors (SSE) and relative error (RE) for the training phase were estimated to be 0.161 and 0.008, respectively, while for the testing phase, they were 0.14 and 0.037, which were very satisfactory.

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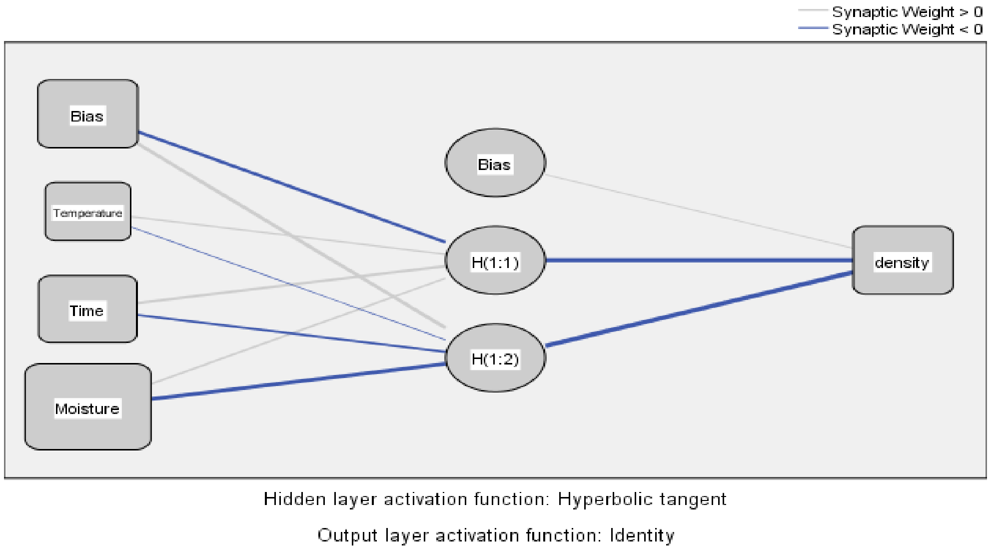

Figure 8- Artificial neural network for predicting density of shrimp during hot air frying: input variables: temperature, time and moisture and output variable: density.

Figure (9) illustrates the importance of independent variables in forming the neural network for predicting density. The importance values for moisture, time, and temperature were found to be 0.588, 0.278, and 0.134, respectively. The critical role of moisture in density prediction using artificial intelligence was clearly highlighted. The normalized importance, expressed as a percentage (assuming moisture has 100% importance in predicting density) was 47.3% and 22.8% for time and temperature, respectively. In line with these findings, researchers have emphasized the influence of moisture on density in determining optimal conditions for fried products. They observed that during frying, as temperature and time increase (or as the product remains exposed to frying conditions for a longer period), moisture evaporates, leading to the expansion of pores and product swelling. This results in an increase in specific volume and a reduction in density [43]. Other studies have also linked density variations during processing to the intensity of water evaporation and process duration. They reported that as evaporation intensifies or the process time extends, density decreases. Moreover, they noted that at high temperatures, a significant drop in moisture content leads to a more pronounced reduction in density, further underscoring the importance of moisture in density estimation [28]. Researchers have previously achieved promising results using similar models to predict quality attributes and process variables. The development of fuzzy systems for predicting the quality attributes and sensory characteristics of hot-air fried products, as well as the simulation of models for process automation, further highlights the significance of these findings for future research [45, 46].

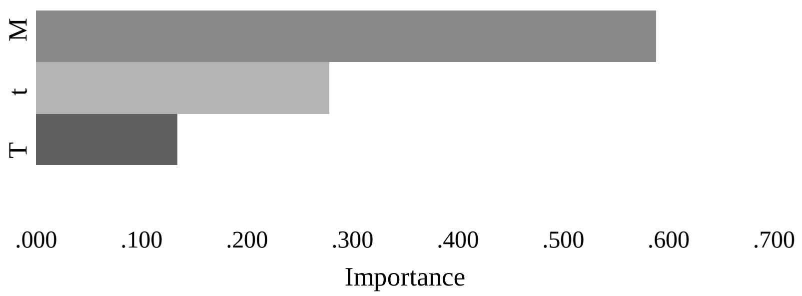

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Figure 9- The importance of independent variables (Temperature"T", time "t" and Moisture "M") in the formation of artificial neural network for density prediction

4-Conclusion

In this study, an artificial neural networks (ANN) model was developed to predict changes in moisture content and density of shrimp during hot air frying. At the beginning of the frying process, due to the partial vapor pressure difference between the product and the hot air, and the sudden release of surface-free water, intense evaporation was observed. As moisture content decreased and pores developed in the shrimp, the product density also gradually declined during hot air frying, with higher processing temperatures leading to a more significant density reduction. The ANN model effectively predicted these quality characteristics. Process time was found to be more influential than temperature in the predictive model for moisture content. In predicting density, moisture content had the highest importance, followed by time and temperature. Until now, the quantitative impact of various factors on moisture and density prediction had not been fully explored. The findings of this study can assist producers in estimating and analyzing shrimp yield loss. In the application of any novel food processing method, understanding key process parameters affecting product quality can help specialists improve process control. Future research should focus on intelligent modeling of the hot air frying process, aiming to design and develop automated industrial-scale equipment tailored to other quality attributes, such as color.

5-Reference

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مقاله علمی_پژوهشی

پیش‌بینی رطوبت و دانسیته در میگو طی سرخ‌کردن هوای داغ با مدل شبکه‌های عصبی مصنوعی

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چکیده

در این پژوهش، شبکه‌های عصبی مصنوعی (ANN) برای پیش‌بینی تغییرات رطوبت و دانسیته میگو طی فرآیند سرخ‌کردن هوای داغ (در سه دمای ۱٤۰، ۱٦۰ و ۱۸۰ درجه سانتی‌گراد به مدت ۱۵ دقیقه) ارائه گردید. شبکه‌های عصبی به صورت پرسپترون چند لایه (MLP) با تابع انتقال تانژانت سیگموئید در لایه پنهان و تابع انتقال خطی در لایه خروجی برای پیش‌بینی رطوبت (با دو ورودی: دما و زمان) و دانسیته (با سه ورودی: دما، زمان و رطوبت) در نرم افزار MATLAB طراحی شد. الگوریتم‌های مختلف پس‌انتشار شامل لونبرگ–مارکوارت، گرادیان نزولی، گرادیان نزولی با نرخ تطبیقی یادگیری، انتشار برگشتی با نرخ یادگیری متغییر، گرادیان نزولی با مومنتم وگرادیان مزدوج مقیاس‌شده بودند. ساختار مدل‌ها با محاسبه ضریب تبیین (R^2)، ریشه میانگین مربعات خطا (RMSE) و میانگین خطای مطلق (MAE) اعتبار سنجی شد. در نهایت، اهمیت ورودی‌ها از نظر تاثیر بر متغیر خروجی برای پیش‌بینی رطوبت و دانسیته با طراحی شبکه‌های عصبی پیش فرض تانژانت هایپربولیک در نرم افزار SPSS بررسی گردید. نتایج نشان داد که با کاهش رطوبت و توسعه منافذ در میگو، دانسیته محصول نیز طی سرخ‌کردن هوای داغ به تدریج کاهش یافت و با افزایش دمای فرآیند کاهش بیشتری در دانسیته مشاهده شد. در مدل رطوبت، الگوریتم پس انتشار گرادیان نزولی با مومنتم (R^2=0.989, RMSE=0.171, MAE=0.131) و در مدل دانسیته، الگوریتم لونبرگ–مارکوارت (R^2=0.974, RMSE=0.0096, MAE=0.0066) کمترین میزان خطا را در آموزش نشان دادند. در محاسبات عصبی رطوبت، اهمیت متغیر زمان و دما به ترتیب برابر با ۰/۸۸۳ و ۰/۱۱۷ بود. در محاسبات عصبی دانسیته نیز اهمیت متغیر رطوبت، زمان و دما به ترتیب برابر با ۰/۵۸۸، ۰/۲۷۸ و ۰/۱۳٤ بود. از یافته‌های این پژوهش در طراحی هوش مصنوعی برای کنترل و ایجاد اتوماسیون در سرخ‌کن‌های هوای داغ می‌توان استفاده کرد.