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Application of Artificial Neural Networks for Predicting Cooking Dynamics in Industrial Sesame Seed Oil Extraction

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Abstract

Sesame seeds are a significant source of vegetable oil and were among the earliest grains used for oil extraction. In this study, aimed at designing an industrial-scale process for extracting oil from sesame seeds, we investigated three cooking temperatures (75 °C, 90 °C, and 105 °C) and three different moisture contents of the seeds leaving the cooking pot (4.5%, 5.5%, and 6.5%). The study focused on several responses: the oil content of the pressed cake, the quantity of extracted oil, the protein and moisture contents of the resulting meal, and the percentage of insoluble fine particles in the extracted oil. To predict these responses, an artificial neural network (ANN) model was employed. Among the various backpropagation feedforward networks with different topologies studied, the configuration with 2 input nodes, 5 hidden nodes in one layer, and 5 output nodes was selected based on its high correlation coefficient (R^2 = 0.997) and low mean squared error (MSE = 0.0002). The sigmoid hyperbolic tangent activation function was used, and the Levenberg-Marquardt learning algorithm with 1000 learning cycles was identified as the optimal neural model. The selected optimized models demonstrated high $R^2 \geq 0.97$ during the evaluation of their results.

Keywords

Sesame seeds, Oil extraction, Modeling, Cooking pot

Introduction

Sesame seeds are renowned for their abundant vegetable proteins and have been among the earliest oil seeds used for oil extraction [1]. The oil content of sesame seeds typically ranges from approximately 28% to 59% [2]. This valuable crop has been cultivated in Asia and certain regions of Africa, particularly in Sudan, Nigeria, and Ethiopia. Sesame oil is appreciated for its pleasant taste and aroma, making it a popular choice for cooking and as a salad oil. Additionally, it is utilized in the production of shortening, margarine, and certain medicinal preparations [3, 4]. Rich in polyunsaturated fatty acids and other beneficial components, sesame oil helps lower blood pressure and cholesterol levels in the human body [5]. Despite containing 85% unsaturated fatty acids, sesame seeds exhibit good stability against oxidative reactions [6, 7]. The fatty acid profile of sesame oil primarily consists of triglycerides, followed by diglycerides, free fatty acids, polar lipids, and, finally, monoglycerides. Additionally, sesame oil contains significant amounts of phytosterols, tocopherols, and lignans, including sesamin and sesamolin [8, 9].

The most common methods for extracting oil from sesame seeds are pressing and solvent methods, with the screw press method often employed on an industrial scale [10]. The residual product from the sesame seed oil extraction process, known as sesame meal, typically contains approximately 35.6% protein, 7.6% crude fiber, and 11.8% ash [2]. This byproduct is commonly used as animal feed and contains substantial amounts of phenols that could potentially be extracted [11].

Several significant studies have explored the use of supercritical carbon dioxide and ethanol for oil extraction [12, 13]. Research has also involved modeling and experimentally evaluating these extraction processes [14] and identifying and characterizing the phytosterols present in the extracted oil [15]. Additionally, efforts have been made to optimize oil extraction processes on an industrial scale [16].

Various parameters affect the qualitative and quantitative properties of extracted oil and the resulting meal from oil seeds. To optimize these outcomes, researchers have adjusted the temperature of the cooking chamber and the moisture content of the seeds exiting the cooker. Their aim is to determine the optimal conditions for extracting oil from sesame seeds [16]. For example, research on the effectiveness of temperature on the quality of extracted rapeseed oil found that higher temperatures increase oil acidity, suggesting that lower temperatures improve oil quality [17]. Similarly, increasing the temperature of the mixer during olive oil extraction also increases the oil's acidity [18]. In studies on sesame seed oil extraction using supercritical fluids, researchers identified optimal conditions for maximum extraction efficiency, suggesting that a pressure of 276 bar and a temperature of 70 °C yield the best results [19].

ANNs are currently powerful and reliable tools for predicting process parameters [20]. An artificial neuron consists of a primary processing unit with multiple inputs and one output, where inputs can come from other neurons or external sources. The output from one neuron can serve as input to multiple others, with input signals modified by specific weights [21].

Researchers have employed ANN modeling in various applications, such as predicting mass transfer in osmotic dehydration of African lemon peel [22], drying processes for carrots [23] and tomato slices [24], modeling wheat soaking [25], optimizing lycopene extraction from tomato waste and pulp [26], and modeling freezing and thawing times [27]. ANN has also been used to study freeze-drying behaviors in food products [28]. Additionally, neural networks and genetic algorithms have been used to predict parameters such as free fat content, lactose crystallization, and particle size mean in the production of spray-dried milk [29]. Mateo et al. [30] used neural networks to predict the accumulation of deoxynivalenol (vomitoxin) in barley grains contaminated with *Fusarium culmorum*, while other studies utilized neural networks and image processing methods to determine anthocyanin concentration in whole grape peels [31].

However, there appears to be a gap in research utilizing ANNs for sesame seed oil extraction. To address this, the current study aims to develop a simple, fast, precise, and efficient ANN model for sesame seed oil extraction on an industrial scale. In this study, various temperatures and moisture levels were applied to the sesame oil extraction process using ANNs to identify the optimal conditions for sesame oil extraction.

Material and Methods

Chemicals

Hexane (C_6H_{14}), sulfuric acid (H_2SO_4), a catalyst (a mixture of potassium sulfate (K_2SO_4) and copper sulfate ($CuSO_4$) in specific proportions), selenium dioxide (SeO_2), sodium hydroxide (NaOH), hydrochloric acid (HCl) (0.1 N), boric acid, and methyl red (2-(N,N-dimethyl-4-aminophenyl)) were supplied by Merck (Germany).

Apparatus

Centrifuge (Westfalia), flaker (Bühler), kjeldahl analyzer (Automatic Thermo, Japan), soxhlet extractor (Analyser 130, Tecator), digital balance (120-VF, England), oven (GEC avery), desiccator, and horizontal extractor (Desmet).

Sample preparation

Sesame seeds used in this study were sourced from Bushehr Province, Iran, and were subsequently transferred to the cotton and oil seeds company of Neyshabur, Khorasan, for oil extraction and meal production.

Oil extraction

After the samples arrived at the factory, the oil seeds were stored in silos arranged in a hive-like configuration. During the processing stage, waste materials such as thorns, broken and spoiled seeds, stones, and other foreign substances were removed through winnowing [32]. Following cleaning and sieving, the seeds were transferred to the cooking pot. At this stage, the temperature and humidity of the cooking pot were adjusted according to our design specifications. The seeds were processed at three different temperatures: 75 °C, 90 °C, and 105 °C. For each temperature, the output seeds had three different moisture contents: 4.5%, 5.5%, and 6.5%.

The processed seeds were then moved to a screw press machine for oil extraction. The pressed cake was transferred to the solvent extraction stage, where the remaining oil was extracted using C_6H_{14} as the solvent. After extraction, the solvent was separated from the oil-solvent mixture (micelle), and the meal was separated using a solvent separator system. The desmet horizontal extractor was employed for this extraction process.

Moisture content value determination

According to association of official analytical chemists [33] method, the moisture content of 2 g of sample was determined in plates which previously reached a fixed weight in the oven. Then, it was dried in the oven at the temperature of 105 ± 1 °C for 3 - 5 h. Afterward, the moisture content value has been computed regarding the $(1+x)^n = 1 + \frac{nx}{1!} + \frac{n(n-1)x^2}{2!} + ...$ [33, 34]:

$$Percentage\ of\ Moisture\ Content = \left(\frac{W_1 - W_2}{M}\right) \times 100 \quad (1)$$

Where: W_1 expresses initial weight of the empty plate plus sample before drying; W_2 represents the weight of the plate and the sample after drying; and M is the weight of sample.

Determination of oil content value

Oil content value was determined using Soxhlet system regarding method described previously by association of official analytical chemists [33].

Determining of protein quantity

The quantity of nitrogen in the meal was determined using an automatic Kjeldahl system, which includes three phases: digestion, distillation, and titration. The protein content was calculated using a conversion factor of 6.25 [35, 36].

Determination of insoluble fine partial content of the extracted oil

The extracted oil contains fine solid materials that need to be removed. This is achieved using sedimentation tanks, where the fine materials settle at the bottom of the tank in a solid form. The oil is then filtered [37, 38] to measure the insoluble fine particle content, 10 ml of oil was poured into centrifuge tubes and centrifuged at 4000 rpm for 10 min. The precipitated materials were then separated, weighed, and reported as a percentage of the total extracted oil [15].

Modeling using ANNs

To determine the optimal neural network for designing the oil extraction process from sesame seeds, MATLAB R2013a's neural network toolbox was used. The network was structured with two inputs: cooking temperature (X1) and moisture content of the seeds from the cooking pot (X2), arranged in a two-row matrix. The responses included the oil content in the pressed cake (Y1), the amount of extracted oil (Y2), protein content (Y3), moisture content of the meal (Y4), and the percentage of fine insoluble materials in the extracted oil (Y5) organized in a five-row matrix.

Various neural networks were designed using different activation and learning functions, with varying numbers of neurons in the hidden layer. The effectiveness of these networks was evaluated using two criteria: R^2 and MSE, computed with specific equations. Initially, a feedforward neural network with the highest efficacy was selected, and 1000 learning cycles were employed.

Neural networks were created with hidden layers containing between 1 and 10 neurons. Activation functions tested for connecting the input layer to the hidden layer included hyperbolic tangent sigmoid, logarithmic sigmoid, and linear. A linear activation function was consistently used to connect the hidden layer to the output layer. Additionally, two learning algorithms, Levenberg-Marquardt and resilient backpropagation (trainrp), were employed across different networks to assess their impact on network accuracy.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_{pi} - Y_{ei})^2}{\sum_{i=1}^{N}(Y_{pi} - \overline{Y})^2} \quad (2)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_{pi} - Y_{ei})^2 \quad (3)$$

Where: Y_{pi} represents the predicted moisture ratio by the network; Y_{ei} is the actual moisture ratio obtained from tests; $\overline{Y}$ denotes the mean of laboratory moisture ratios; and N stands for the total number of experiments.

Entering raw data into the network can slow down performance and reduce accuracy. Therefore, normalizing the input data is crucial for optimal results. Inadequate normalization may prevent the network from converging during training and achieving the desired outcomes. In this study, data normalization was performed using equation 4, which scales both inputs and outputs to a range between 0 and 1.

$$V_N = \frac{V_R - V_{\min}}{V_{\max} - V_{\min}} \quad (4)$$

Where: V_R is the initial raw data; V_{max} and V_{min} are the maximum and minimum values of preliminary tests; and V_N presents normalized data respectively.

Results and Discussion

Table 1, table 2, and table 3 compare the impact of varying the number of neurons on the accuracy of the backpropagation feedforward neural network. The transfer functions considered include the sigmoid hyperbolic tangent, sigmoid logarithmic, and linear functions, with a fixed learning cycle of 1000. Based on the MSE and R^2 values presented in table 1, table 2, and table 3 the feedforward neural network with a sigmoid hyperbolic tangent transfer function and the Levenberg-Marquardt learning algorithm-structured with a topology of 2-5-5 (2 neurons in the input layer, 5 neurons in the hidden layer, and 5 neurons in the output layer, as shown in figure 1)-was identi-

Table 1: Comparing how the number of neurons in the hidden layer, the choice of learning function, and the activation function (hyperbolic tangent sigmoid) affect the accuracy of predicting various properties of the sesame process in an industrial cooker.

Neurons number	Trainlm		Trainrp	
	R^2	MSE	R^2	MSE
2	0.946	0.0051	0.963	0.0021
3	0.937	0.0075	0.983	0.0032
4	0.991	0.0048	0.994	0.0024
5	0.997	0.0002	0.991	0.0041
6	0.983	0.0037	0.973	0.0015
7	0.962	0.0049	0.993	0.0013
8	0.933	0.0051	0.993	0.0011
9	0.946	0.0001	0.989	0.0011
10	0.992	0.0005	0.990	0.0016

Table 2: Comparing how varying the number of neurons in the hidden layer, different learning functions, and the sigmoid logarithm activation function impact the accuracy of predicting various properties of the sesame process in an industrial cooker.

Neurons number	Trainlm		Trainrp	
	R^2	MSE	R^2	MSE
2	0.976	0.0035	0.975	0.0066
3	0.996	0.005	0.993	0.001
4	0.991	0.001	0.926	0.0150
5	0.994	0.0015	0.943	0.0074
6	0.996	0.005	0.993	0.0012
7	0.972	0.0049	0.893	0.0013
8	0.953	0.0051	0.963	0.0016
9	0.965	0.0013	0.994	0.0011
10	0.994	0.0018	0.973	0.0104

Table 3: Comparing how the number of neurons in the hidden layer, the type of learning function, and the linear activation function affect the accuracy of predicting various properties of the sesame in an industrial process.

Neurons number	Trainlm		Trainrp	
	R^2	MSE	R^2	MSE
2	0.828	0.0571	0.763	0.0335
3	0.866	0.0121	0.821	0.0452
4	0.849	0.0771	0.825	0.0628
5	0.857	0.1042	0.993	0.001
6	0.996	0.004	0.729	0.0474
7	0.823	0.0169	0.793	0.0425
8	0.996	0.0051	0.993	0.0011
9	0.995	0.0021	0.989	0.0016
10	0.972	0.0073	0.844	0.0668

fied as the optimal network. This configuration achieved an R^2 value exceeding 0.997 and an MSE of 0.0002.

Furthermore, a higher R^2 between experimental data and predicted values (≥ 97.5%) confirms the suitability of the selected model for the responses (Figure 2). In 2007, a group of scientists modeled the drying of thin layers of sesame seeds using both mathematical models and ANNs [39]. The mathematical models studied included the screw model, Henderson and Pabis model, logarithmic model, and Weibull model. The results from these models were compared with those from the ANN model. The findings indicated that the ANN model was more precise and reliable than the other models examined. Compared to the mathematical models, the ANN demonstrated superior predictive capability for the desired parameters (data not presented). Table 1, table 2, and table 3 compare how the number of neurons in the hidden layer and the choice of learning algorithm affect the prediction accuracy of the backpropagation feedforward neural network and evaluate various transfer functions, including sigmoid hyperbolic tangent, sigmoid logarithmic, and linear, all with a consistent learning cycle of 1000 [40].

Based on the MSE and R^2 values presented in table 1, table 2, and table 3, the optimal neural network configuration was identified as a feedforward neural network using the

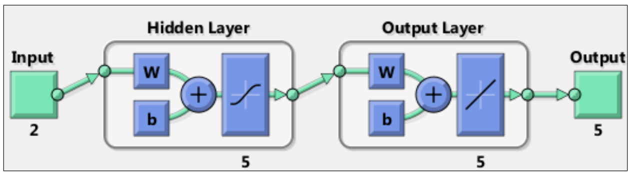

Figure 1: The structure of the selected optimized network: input layer consists of 2 neurons; hidden layer 1 comprises 5 neurons using a hyperbolic sigmoid tangent activation function; hidden layer 2 includes another 5 neurons employing a linear activation function; and output layer contains 5 neurons. 5 neurons in hidden layer with activation function of hyperbolic sigmoid tangent and 5 neurons in hidden layer with linear activation function.

sigmoid hyperbolic tangent transfer function and the Levenberg-Marquardt learning algorithm. This network, with a 2-5-5 topology (2 neurons in the input layer, 5 neurons in the hidden layer, and 5 neurons in the output layer, as shown in figure 1), demonstrated superior performance, achieving an R^2 value exceeding 0.997 and an MSE of 0.0002.

In this selected 2-5-5 neural network topology, the weight matrices are defined as follows: Matrix A represents the connections from the input layer (2 neurons) to the hidden layer (5 neurons), forming a 2 × 5 matrix. Matrix B represents the connections from the hidden layer (5 neurons) to the output layer (5 neurons), forming a 5 × 5 matrix. These matrices, A and B, determine the weights between their respective layers in the neural network.

$$A = \begin{pmatrix} 2.2265 & -1.7131 \\ 4.8947 & -0.71459 \\ -2.0058 & 0.73319 \\ 1.8633 & -0.2014 \\ 0.78885 & 1.823 \end{pmatrix}$$

$$B = \begin{pmatrix} 0.36262 & -0.11516 & -1.0058 & -0.5217 & -0.15092 \\ 0.44747 & 0.077901 & -2.1162 & -2.3009 & -1.0155 \\ 0.3206 & -0.67475 & -1.3611 & -2.1423 & 0.43214 \\ 0.3124 & -0.08988 & 1.0749 & 0.73538 & -0.36415 \\ 0.55584 & 0.15656 & -0.6154 & -0.4635 & 0.098345 \end{pmatrix}$$

Moreover, bias matrix for hidden layer (Matrix C) and output layer (Matrix D) is defined as Hessian matrix 5 × 1.

$$C = \begin{pmatrix} -2.0028 \\ -1.4386 \\ -1.5181 \\ 1.7473 \\ 2.8822 \end{pmatrix}$$

$$D = \begin{pmatrix} 0.26626 \\ -0.37873 \\ 0.32777 \\ 0.089548 \\ 0.028029 \end{pmatrix}$$

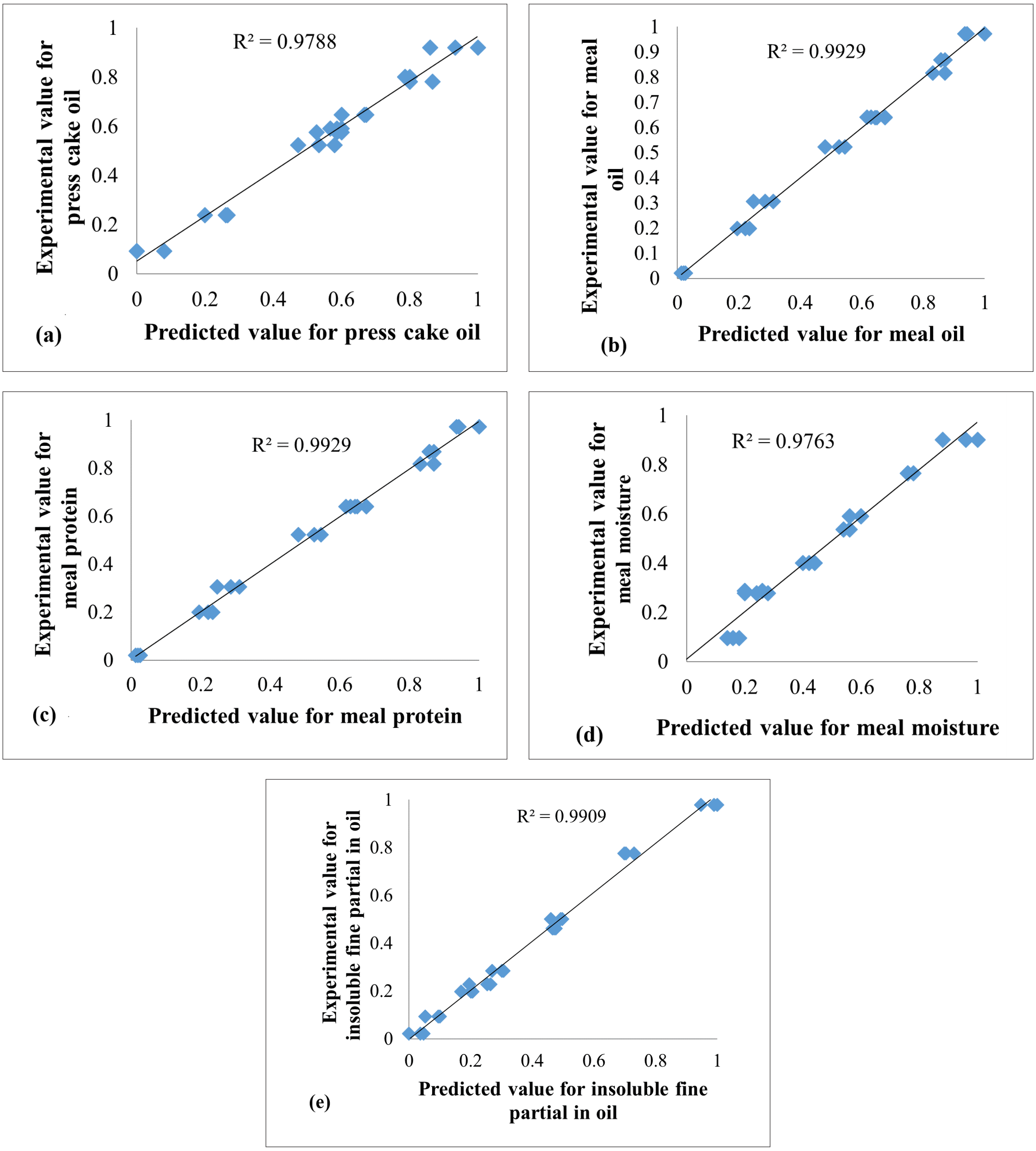

Figure 2: A simplified diagram illustrating the predicted changes by the neural network for the optimized topology (2-5-5) compared to the laboratory measurements for: **(a)** press cake oil, **(b)** meal oil, **(c)** meal protein, **(d)** meal moisture, and **(e)** insoluble fine particles in oil.

Conclusion

Given the complexity and numerous factors influencing the nutraceutical and pharmaceutical industries, this research highlights the neural network as a viable tool for optimizing sesame seed oil extraction. The identified network topology, utilizing a sigmoid hyperbolic tangent activation function with a 2:5:5 configuration (2 neurons in the input layer, 5 neurons in the hidden layer, and 5 neurons in the output layer), along with the weights and biases, establishes a foundation that can be integrated into neuro-fuzzy models.

By employing a straightforward mathematical equation, as defined in this study, and implementing it in user-friendly software like excel, it is possible to develop an accurate and accessible program for predicting key parameters in the sesame seed cooking process prior to oil extraction.

The high accuracy of the neural network model instills confidence in its predictions, making it a valuable tool for process optimization and control. This capability not only saves time and energy but also improves the quality of the final product.

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None.

Conflict of Interest

None.

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