

ANN MODELING OF THE EXTRUDED PRODUCTS PHYSICAL AND TECHNOLOGICAL PROPERTIES

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Abstract: This study used artificial neural network (ANN) modeling to predict and optimize the physical and technological properties of quinoa-enriched extruded products. A multilayer perceptron model was developed to estimate bulk density (BD), expansion index (EI), hardness (Har), number of fractures (NF), and crispiness work (Crw) as functions of screw speed (350–650 rpm) and quinoa addition (0–30%). The model demonstrated high predictive accuracy and successfully passed goodness-of-fit tests. Global sensitivity analysis revealed that screw speed was the dominant factor, while higher quinoa levels and screw speeds promoted expansion and reduced density and hardness. The ANN approach proved effective for modeling and optimization of extrusion conditions.

Keywords: artificial neural network, extrusion, quinoa, texture

Introduction

Artificial neural networks have been widely employed in food science research, with a great capability in approximating nonlinear functions and creating accurate predictions using input-output relationships (Ma et al., 2024). The application of ANN modeling in food extrusion has proven particularly valuable for reducing experimental runs, identifying optimal processing conditions, and understanding the relative importance of different factors that may influence the product quality (Khan et al., 2022; Szpicer et al., 2025).

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The incorporation of quinoa into extruded product formulations offers promising opportunities to develop value-added products with improved nutritional value and potential health benefits, making it an attractive option for the development of innovative functional foods and snacks (Muñoz-Pabon et al., 2022).

The physical and technological properties of extruded products, including bulk density, expansion index, hardness, number of fractures, and crispiness work, serve as critical quality indicators that determine consumer acceptance and product performance in various applications (Sahu et al., 2022; Nwadi, and Okonkwo, 2026).

This research focuses on developing ANN model to predict the selected physical and technological properties (BD, EI, Har, NF and Crw) of quinoa-enriched extruded products as functions of screw speed and quinoa addition levels. The model was validated using multiple statistical indicators and subjected to global sensitivity analysis to evaluate the relative importance of processing parameters on each quality attribute.

Materials and methods

Statistical analysis

The selected textural properties of the quinoa-based extruded products, as reliable indicators of extrusion performance, BD, EI, Har, NF, and Crw were retrieved from our previous research (Filipović et al., 2026). The artificial neural network modelling and sensitivity analysis of the experimental data, were performed using the StatSoft Statistica 10.0® software.

ANN modelling

The ANN model was created to predict and optimize the parameters: BD, EI, Har, NF and Crw, depending on the screw speed (300, 550 and 650) and the addition of quinoa (0, 10%, 20% and 30%).

A multilayer perceptron (MLP) architecture, consisting of input, hidden, and output layers, was employed to develop the ANN model. This structure is well suited for approximating nonlinear relationships, and normalized input and output data were used to enhance model performance and stability (Lončar et al., 2024). The artificial neural network model was trained using to the methodology previously explained by Pan et al., 2023. The weight coefficients and biases are

represented as matrices and vectors W_1 and B_1 , and W_2 and B_2 , respectively. The structure of the ANN model can be presented as:

$$Y = f_1(W_2 \cdot f_2(W_1 \cdot X + B_1) + B_2) \quad (1)$$

Y - the output matrix, f_1 and f_2 -the transfer functions of the hidden and output layers and X -the input matrix.

The weight coefficients W_1 and W_2 were iteratively adjusted during the training process to minimize the discrepancy between the experimental data and the ANN model predictions (Shi et al., 2023).

Global sensitivity analysis

Yoon's global sensitivity equation was used to evaluate the relative influence of the screw speed (300, 550 and 650) and the addition of quinoa (0, 10%, 20% and 30%) on BD, EI, Har, NF and Crw, in conjunction with the weight coefficients of ANN model (van Griensven et al., 2006):

$$RI_{ij}(\%) = \frac{\sum_{k=0}^n (w_{ik} \cdot w_{kj})}{\sum_{i=0}^m \left| \sum_{k=0}^n (w_{ik} \cdot w_{kj}) \right|} \cdot 100\% \quad (2)$$

w - weight coefficient, i - input variable, j - output variable, k - hidden neuron, n - number of hidden neurons, m - number of inputs.

Error analysis for the ANN model validation

The predictive performance of the ANN model was evaluated using several statistical indicators, including the coefficient of determination (r^2), reduced chi-square (χ^2), mean bias error (MBE), root mean square error (RMSE), mean percentage error (MPE), sum of squared errors (SSE), and absolute average relative deviation (AARD). These parameters, calculated according to the equations reported by Putarić et al 2022, assess the level of agreement between the predicted and experimental values and thereby determine the accuracy and reliability of the developed model.

$$\chi^2 = \frac{\sum_{i=1}^N (x_{\text{exp},i} - x_{\text{pre},i})^2}{N - n} \quad (3)$$

$$RMSE = \left[\frac{1}{N} \cdot \sum_{i=1}^N (x_{\text{pre},i} - x_{\text{exp},i})^2 \right]^{1/2} \quad (4)$$

$$MBE = \frac{1}{N} \cdot \sum_{i=1}^N (x_{pre,i} - x_{exp,i}) \quad (5)$$

$$MPE = \frac{100}{N} \cdot \sum_{i=1}^N \left(\frac{|x_{pre,i} - x_{exp,i}|}{x_{exp,i}} \right) \quad (6)$$

$$SSE = \sum_{i=1}^N (x_{pre,i} - x_{exp,i})^2 \quad (7)$$

$$AARD = \frac{1}{N} \cdot \sum_{i=1}^N \left| \frac{x_{exp,i} - x_{pre,i}}{x_{exp,i}} \right| \quad (8)$$

$x_{exp,i}$ - the experimental values and $x_{pre,i}$ - value obtained by the model, N- the number of observations and n -the number of – constants.

Results and discussion

For the observed responses (BD, EI, Har, NF and Crw) ANN model was conducted, Table 1. The weight coefficients and biases used for ANN model calculations for input parameters are given in Table 2, while the weight coefficients and biases used for ANN model calculations for output parameters are presented in Table 3.

Table 1. Summary of active networks

Net. name	Training perf.	Test perf.	Valid perf.	Train error	Test error	Valid. error	Train. Alg.	Error funct	Hidd. activa	Output activa
MLP 7-6-5	0.932	1.000	1.000	39.81	20.62	81.38	BFGS 3	SOS	Identity	Identity

Table 2. The matrice elements W_1 and B_1

Input	1	2	3	4	5	6
Screw speed(350)	0.394	-0.430	0.350	-0.467	-0.164	-0.127
Screw speed(500)	-0.130	0.113	-0.059	0.060	0.065	0.035
Screw speed(650)	-0.171	0.213	-0.081	0.368	0.062	0.156
Quinoa addition(0)	0.424	-0.327	0.230	-0.235	-0.109	-0.089
Quinoa addition(10)	0.094	-0.098	0.097	-0.117	0.008	-0.035
Quinoa addition(20)	-0.134	0.154	-0.103	0.227	-0.069	0.157
Quinoa addition(30)	-0.279	0.230	-0.188	0.169	0.039	0.112
Bias	0.089	-0.027	0.053	0.038	-0.059	0.031

Table 3. The matrice elements W_2 and B_2

Output	1	2	3	4	5	6	Bias
BD	0.263	-0.033	0.086	-0.309	-0.054	-0.196	0.201
EI	-0.181	-0.046	-0.005	0.278	0.058	0.178	0.747
Har	0.329	0.020	0.043	-0.194	-0.023	-0.225	0.249
NF	-0.188	-0.044	-0.001	0.355	0.023	0.234	0.486
Crw	0.260	0.004	-0.041	-0.205	-0.006	-0.251	0.196

Model validation

To evaluate the accuracy of the proposed ANN model, various performance metrics were calculated, including reduced chi-square (χ^2), root mean square error (RMSE), mean bias error (MBE), mean percentage error (MPE), total squared error (SSE), average absolute relative deviation (AARD), and coefficient of determination (r^2), Table 4.

Table 4. Tests for the created ANN model the "goodness of fit".

	χ^2	RMSE	MBE	MPE	SSE	AARD	r^2
BD	10.383	2.942	2.510	23.427	28.249	31.483	0.873
EI	0.129	0.328	-0.287	11.551	0.304	3.540	0.796
Har	75.014	7.906	4.221	13.287	536.384	80.378	0.849
NF	16.421	3.699	-0.134	12.658	163.997	40.372	0.901
Crw	2.552	1.458	0.499	23.472	22.529	13.428	0.701

The results indicate that ANN model successfully passed minor lack-of-fit tests, demonstrating their effectiveness in predicting the analyzed parameters.

Global Sensitivity Analysis

The impact of screw speed (350, 500 and 650rpm), and quinoa addition (0, 10, 20, and 30%), on BD, EI, Har, NF and Crw (Figure 1) was analyzed using Yoon's global sensitivity equation and the weight coefficients of developed ANN model.

The global sensitivity analysis demonstrated that screw speed and quinoa addition markedly influence the observed properties of the extruded products.

Screw speed showed the strongest overall effect. At 350 rpm, positive sensitivities were observed for BD (26.24%), Hardness (24.93%), and Crw (24.17%), while EI (-25.84%) and NF (-25.55%) were negatively affected, indicating the formation of denser and harder structures with limited expansion. On the other hand, 650 rpm showed a positive effect on EI (18.67%) and NF (19.24%) and a negative effect on BD (-16.65%), Hardness (-15.75%), and Crw (-17.48%), confirming that higher mechanical energy promotes expansion and reduces structural compactness. The intermediate speed (500 rpm) showed comparatively minor effects.

A similar trend was observed for quinoa addition. At 0%, BD (19.21%), Hardness (20.35%), and Crw (19.24%) were positively influenced, while EI (-18.10%) and NF (-17.33%) were negatively affected. Higher quinoa levels (20-30%) reversed this behavior, positively affecting EI (12.57-13.23%) and NF (13.01-13.48%) and negatively influencing BD (-11.78% to -13.97%), Hardness (-11.84% to -14.84%), and Crw (-12.98% to -14.28%). Overall, screw speed was the dominant factor, and both higher screw speeds and increased quinoa content favored expansion while reducing density and hardness. These results clearly demonstrate that optimization of expanded extruded products requires a balanced combination of higher screw speeds and moderate-to-high quinoa addition levels.

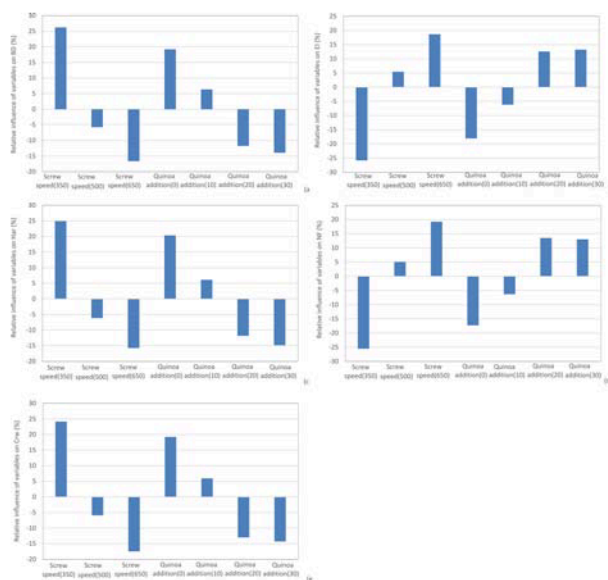


Figure 1. Relative importance of the screw speed and the addition of the quinoa on: a) BD, b) EI, c) Har, d) NF and e) Crw

Conclusion

The developed ANN model (MLP 7-6-5) proved to be an effective for predicting the observed physical and technological properties of quinoa-enriched extruded products. High coefficients of determination ($r^2=0.932$) and satisfactory error indicators confirmed the accuracy of the model. Global sensitivity analysis identified screw speed as the most influential processing parameter, while higher quinoa additions and increased screw speeds promoted expansion and reduced bulk density, hardness, and crispiness work. The obtained results demonstrate that ANN modeling can successfully describe complex nonlinear relationships in extrusion processes and serve as a reliable approach for quality improvement of functional extruded products.

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