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ANFIS-Aided Grading of Almonds by Using Sound Signals

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ABSTRACT

Due to the importance of products classification in agriculture, this study proposes a method for classifying four different grades of almond through sound signals by using ANFIS (Adaptive Neural Fuzzy Inference System). First, the required sound signals were captured via a microphone and the MATLAB Data Collection Toolbox by impacting the studied almonds against an "effect plate". Upon completion of data collection, classification, and statistical analysis based on 12 calculated statistical characteristics, the data related to the 5 superior characteristics were fed to the ANFIS graphic interface in the form of two Sugeno-type fuzzy models. The input vector in the first model (Model A) included the superior characteristics of entropy, range, and standard deviation. In the second model (Model B), the data related to skewness and kurtosis was considered. Respective efficiencies of these models were evaluated through statistical parameters. The general classification accuracy for models A and B were obtained as 90% and 82% respectively. The results indicated that the ANFIS system can effectively be used as an efficient tool for classification of almonds.

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INTRODUCTION

Grading of agricultural products is an important factor in their marketing. In the course of the multiple stages between harvest and consumption, the possibility exists that the separated grades of almond are mixed again. Moreover, due to the high costs of labor, subjective grading by workers, and importance of faster and more accurate grading, new methods for grading agricultural products are required. Also, high costs, non-uniform quality, and existence of different criteria for grading cause various problems [1]. Considering these problems, researchers have tried to introduce automatic methods for grading products. Due to the ascending trend of almond production at the global level, grading of almonds can play a major role in its export as well as in global trade. The annual global almond production is one million tons. With an annual production of more than 110 thousand tons, Iran is the third greatest producer of almonds in the world (after the United States and Spain) [4,2,6]. Almonds come in various grades. A system is required which can distinguish between different types of almond and simultaneously grade them, thus facilitating grading operations, increasing the speed of these operations, and omitting unnecessary transfer operations. The ANFIS system has high training, building, and classification capabilities. It also has the advantage of extracting fuzzy rules from the expert's numerical data or know-how for the purpose of creating a comparative rule. Moreover, through application of fuzzy "if …then" rules, the analyst can improve interpretation of the results and obtain a broader perspective with regard to the graders system structure as well as the decision-making process [10]. Neural networks and fuzzy techniques can provide an appropriate method for classification of agricultural products [8,1]. Today, various methods are used for grading these products. Pearson et al. [11] presented methods based on sound-analysis for separating ordinary pistachios from extra class (high quality) pistachios [5,11]. Fruit properties were distinguished based on mechanical, acoustic, optical, etc. methods (Zerbini, 2006). Moreover, a smart acoustic-based system for separation of various pistachio types was developed [9]. In a different study, sound propagation in association with ANFIS was used for grading walnuts with a classification accuracy of 100 percent. Using fuzzy logic and data mining for almond grading produced an accuracy of 84.16% [6]. In this study, aimed at for proposing a fussy inference system for grading almonds by using sound signals, ANFIS is implemented as a supporting system.

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METHODS AND MATERIALS

In this study, experiments were conducted on four almond grades, namely, Yalda, France, Shokofeh, and Shahrood 15, grown at Sanandaj Agricultural Research Institute (SARI) in Iran (Fig. 1) (Ebrahimi & Mollazade, 2010).

Fig. 1: The Studied Almond Grades.

As a first step, the four grades of almond were identified. Table 1 presents some of the physical characteristics of these varieties.

Table 1: Physical Characteristics of Four Grades of Almond.

Grade	Mass (gr)	Major diameter (mm)	Intermediate diameter (mm)	Minor diameter (mm)	Arithmetic mean diameter (mm)	Geometric mean diameter (mm)
Yalda	5.10	36.42	23.59	17.75	25.92	24.44
France	3.47	30.67	22.48	16.60	23.25	22.52
Shokofeh	2.07	29.99	20.44	12.52	20.99	19.72
Shahrood 15	1.49	28.16	15.87	11.43	18.48	17.16

Data Collection:

In this study, 105 almonds were collected from each grade for testing. Fig. 2 shows the algorithm used for the research. The test almonds were transferred from cold storage (12 degrees Celsius and 82% humidity) to room temperature. At the start of the test, room temperature was recorded as 20-23 degrees Centigrade [6]. The experimental acoustic apparatus (Fig. 3) included a chute with adjustable height and inclined at 35 degrees to the horizon. Upon sliding one by one down the chute, the almonds would impact against the effect plate located at the bottom. Two effect plates, one from stainless steel and the other from plywood, were installed under the microphone plate (Model Enping Huana DM-400, made in China).

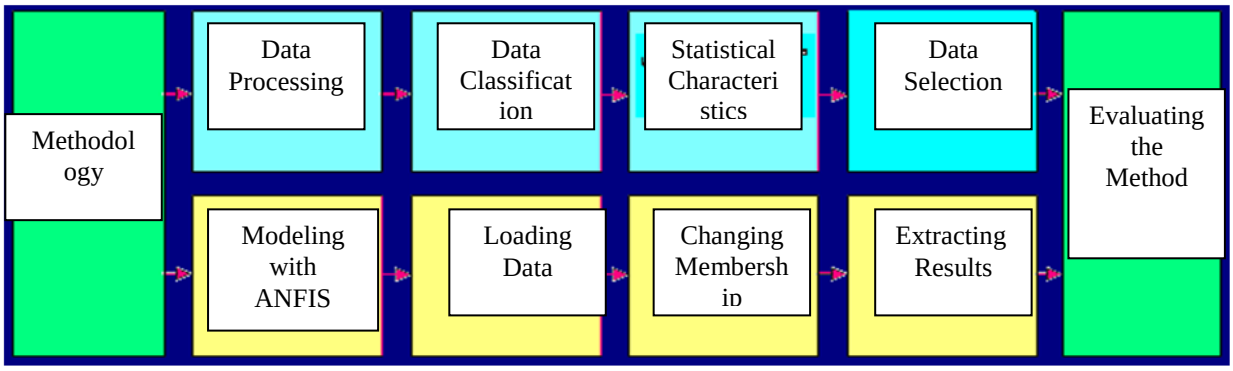

Fig. 2: Algorithm Showing the Research Procedure.

The sound signals resulting from the impacts were prepared at a digital sampling frequency of 44.1 kHz by using the apparatus shown in Fig. 3. Two effect plates (stainless steel and plywood) with two corresponding dropping heights of 14 and 24 cm were used at test conditions. However, only the data obtained for the stainless steel plate and its corresponding 14-cm dropping height were used for ANFIS modeling.

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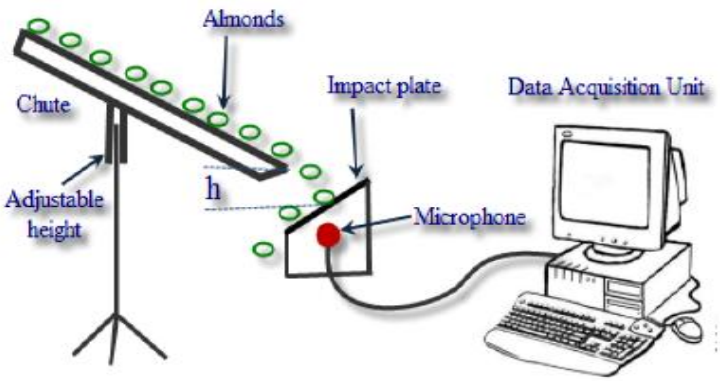

Fig. 3: Data Collection Tools.

The microphone output was sent to and recorded by a 2.53 MHz Pentium 4 computer running Windows 7 Operating System. The microphone output signal range varied between 0 and 7 volts. Data collection started once the microphone output had exceeded 0.1 V. The number of sample signal points obtained for each almond amounted to 500.

Data Classification:

The almonds were classified into four grades, namely, Yalde, France, Shokofeh, and Shahrood 15 (Table 2). A code was assigned to each grade, subsequently, and the data were classified into their respective grades.

Table 2: Data Classification.

Almond Grade	Yalda	France	Shokofeh	Shahrood 15
No. of Samples	105 x 500	105 x 500	105 x 500	105 x 500
Classification Code	0	1	2	3

Calculation of Statistical Characteristics:

Upon data classification and in order to reduce the number of data as well as select the appropriate for modeling, the computer software WEKA (Version 3.4.3) was implemented for data mining and calculating the important statistical characteristics [6]. The results are presented in Table 3.

Table 3: Calculated Statistical Characteristics.

Feature	Formula	Feature	Formula
Average	$\text{Aver} = \frac{\sum_{n-1}^{N} x(n)}{N}$	Root Mean Square (RMS)	$\text{RMS} = \sqrt{\frac{\sum_{n-1}^{N} x^2(n)}{N}}$
Standard deviation	$Stdv = \sqrt{\frac{n\sum_{n-1}^{N} x^2(n) - \sum_{n-1}^{N}(x(n))^2}{n(n-1)}}$	Crest factor	$\text{CF} = \frac{x_{max}}{RMS}$
Variance	$Var = (Stdv)^2$	Dispersion	$\text{Disp} = \sum_{n-1}^{N} \lvert x(n) - \text{Aver} \rvert$
Skewness	$Skew = \frac{n}{(n-1)(n-2)} \sum_{N-1}^{N} \frac{x(n) - aver}{Stdv}$	Entropy	$E = \sum_{n-1}^{N} x(n).\log_2(x(n))$
Kurtosis	$Kurt = \frac{\sum_{n-1}^{N}(x(n) - \mu)^4}{N \times (\sigma^2)^2}$	Range	$R = X_{max} - X_{min}$
Sum	$\text{Sum} = \sum_{n-1}^{N} x(n)$	Coefficient variation	$\text{Cv} = \frac{\text{Stdv}}{\text{Aver}}$

Data Selection:

Data collection is an important procedure in smart systems, and if appropriate characteristics are selected, classification results can be highly successful. In the present study, 12 characteristics were received for time domain sound signals, and subsequently, five characteristics termed “superior characteristics” were selected from among them. These are: entropy, standard deviation, skewness, range, and kurtosis. The data set for each

characteristic comprised 420 samples. Therefore, upon due reduction of the data number, a total of 1680 sound spectra was selected for modeling the four almond grades.

Modeling with ANFIS:

The Adapted Neural Fuzzy Inference System was used for modeling the data. For simplicity, we first describe a fuzzy system with two inputs, x and y, and a single output, z. For a Sugeno fuzzy model of the first degree, we consider a rule set comprising two "if…then" statements as follows:

$$\begin{cases} \text{Rule 1 if } X = A_1 \text{ and } y = B_1 \Rightarrow f_1 = p_1 x + q_1 y + r_1 \\ \text{Rule 2 if } X = A_2 \text{ and } y = B_2 \Rightarrow f_2 = p_2 x + q_2 y + r_2 \end{cases} \quad (1)$$

where A and B are the input membership functions and r, p, and q are the output functions. This fuzzy model is demonstrated in Fig. 4.

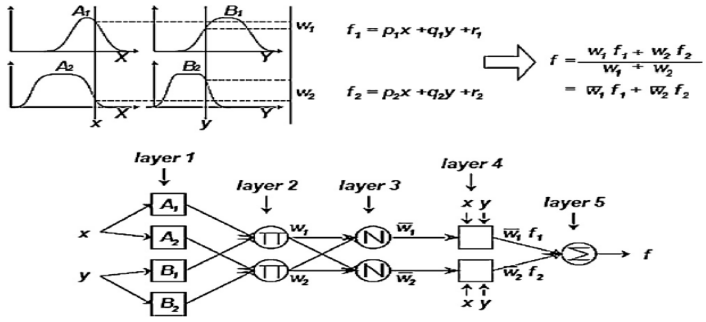

Fig. 4: A Sugeno Fuzzy Model with Two Inputs and Two Rules, and its ANFIS Structure.

In the following, each layer is separately described (Khalifa *et al*., 2012).

The First Layer, the Input Nodes: Each node in this layer represents a comparative node with an output defined as:

$$0_{1,i} = \mu_{A_i}(x) \qquad i = 1,2 \quad (2)$$

$$0_{1,i} = \mu_{B_{i-2}}(y) \qquad i = 3,4 \quad (3)$$

where x and y are the node inputs, and A_i and B_{i-2} are their corresponding fuzzy sets which can take any of the forms presented for the usual membership functions. The parameters of each node determine the shape of the fuzzy set membership function attributed to that node. For example, A_i represents a bell-shaped function.

$$\mu_{A,i} = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)\right]^{2b_i}} \quad (4)$$

where {ai , bi , ci } is the initial parameter set. The parameters in this set are actually the same as the nonlinear network parameters.

The Second Layer, the Rule Nodes: Each node in this layer calculates the activity degree for a law (rule). The nodes in this layer have a single function, i.e., they multiply the input signals from the previous layer, and deliver their product at the output:

$$0_{2,i} = w_i = \mu_{A_1}(x) \times \mu_{B_1}(y) \qquad i = 1,2 \quad (5)$$

The Third Layer, the Average Nodes: The nodes in this layer are shown as N and also perform a single operation. At this stage, the effectiveness of the laws (rules) is normalized:

$$0_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2} \qquad i = 1,2 \quad (6)$$

The Fourth Layer, the Resultant Nodes: The nodes in this layer are comparative and have the following function:

$$0_{4,i} = \overline{w_i}\ f_i = \overline{w_i}\ (p_i x + q_i y + r_i) \qquad i = 1,2 \quad (7)$$

The $\{p_i, q_i, r_i\}$ set comprises of the layer parameters called "resultant parameters" and are the same as the linear parameters in the network parameter set.

The Fifth Layer, the External Nodes: This layer has a single node which performs the single operation of calculating the total output from the input signals of the fourth layer:

$$O_{5,i} = Overall \quad out\,put \;= \sum_i \overline{w_i}\; f_i = \frac{\sum_i w_i\, f_i}{\sum_i w_i} \tag{8}$$

Therefore, we have networks the operations of which are identical to those of the Sugeno fuzzy model.

The algorithm presented upon classification included models A and B. In Model A, the superior characteristics of entropy, range, and standard deviation in a group were considered as input vectors for input to the ANFIS network, and in Model B, the network input comprised the set of data related to skewness and kurtosis.

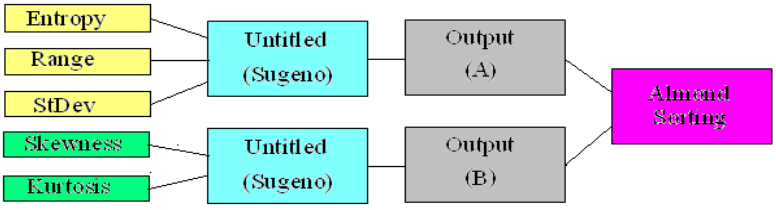

Fig. 5: The Model Designed for Grading Almonds.

Data Loading:

After designing the initial FIS, seventy percent of the data was allocated to training and the remaining thirty percent was used for testing the network. The data was loaded into the ANFIS network in the form of a data matrix. The total numbers of training data and test data in Model A were 882 and 378 respectively, whereas the corresponding numbers for Model B were obtained as 588 and 252. Table 4 shows the selected loading data quantities.

Table 4: ANFIS Input Data Characteristics.

	Input from Model B		Input from Model A		
	Entropy	Range	Standard Deviation	Skewness	Kurtosis
Number of Training Data	294	294	294	294	294
Test Data	126	126	126	126	126
Total	420	420	420	420	420

Determination of Membership Conditions:

For each model, an appropriate membership function was selected to minimize error. Gaussian and bell-shaped functions were chosen as input membership functions for models A and B respectively. For both models, linear membership models were considered as output.

Extraction of Modeling Results:

The desired results were obtained by loading the data into the ANFIS graphic interface, selecting the appropriate membership functions, and applying the training course to each model three times. For each model, the shape of fuzzy rules structure, rules control surfaces, number of fuzzy laws, and test results were obtained based on prediction (Figs. 6 and 7).

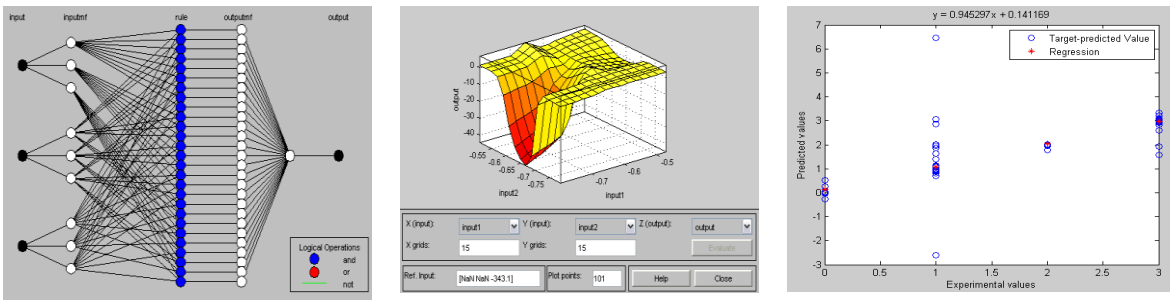

Fig. 6: *From Left to Right*: ANFIS Structure, Rules Control Surface, and Prediction Results for Model A.

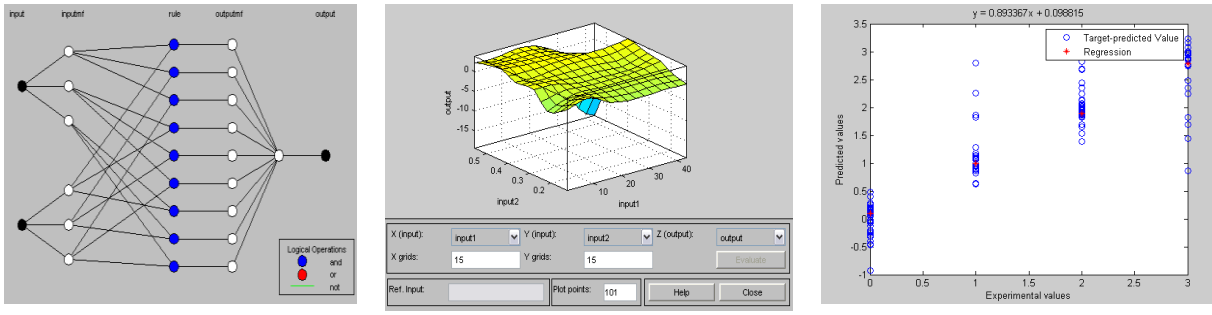

Fig. 7: *From Left to Right*: ANFIS Structure, Rules Control Surface, and Prediction Results for Model B.

The ANFIS results for each model included the following: mean squares error (MSE), sum of square errors (SSE), correlation coefficient (R), mean absolute error (MAE) and the predicted results.

Table 5: ANFIS Modeling Results.

Model- Result	r	SSE	MAE	MSE
Model A	0.842511	58.35951	0.202968	0.463171
Model B	0.916824	25.80557	0.275793	0.204806

RESULTS AND DISCUSSION

In this study, the following stages were completed: data collection, data classification, statistical characteristics calculation, data selection, and ANFIS modeling. Based on the results obtained from modeling the predicted results, a correlation degree of 0.84 for Model A and 0.92 for Model B was calculated. Therefore, as observed from Figs. 6 and 7, there is a high correlation between the experimental and the ANFIS predicted values. Also, 27 fuzzy rules were extracted for Model A, 9 fuzzy rules were extracted for Model B. For studying these rules and the membership functions in each model, and for determining the effects of input parameters on output parameters, we also obtained the shape of the output law control surface. In Figs. 8 and 9, the results of identifying each almond grade by the ANFIS prediction system in models A and B are shown. The statistical parameters sensitivity and general classification accuracy were employed to determine the ANFIS classification performance. In this sense, sensitivity is equal to the number of correctly identified grades divided by the total possible positive decisions. Also, general classification accuracy is equal to the number of correct decisions divided by the total possible decisions.

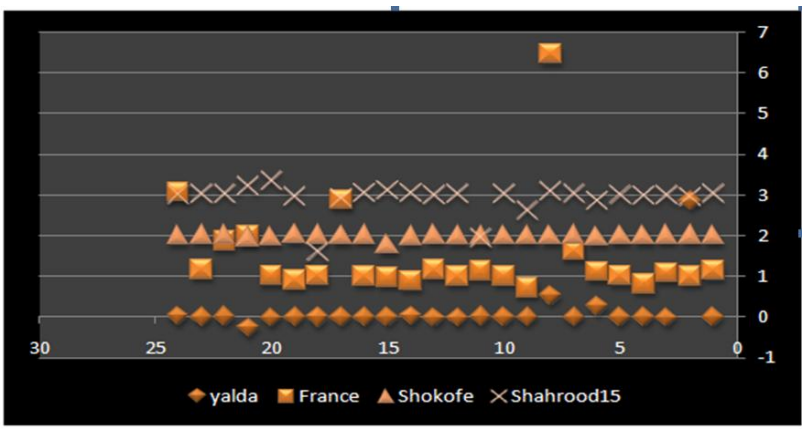

Fig. 8: Diagram showing ANFIS Almond Grade Identification in Model A.

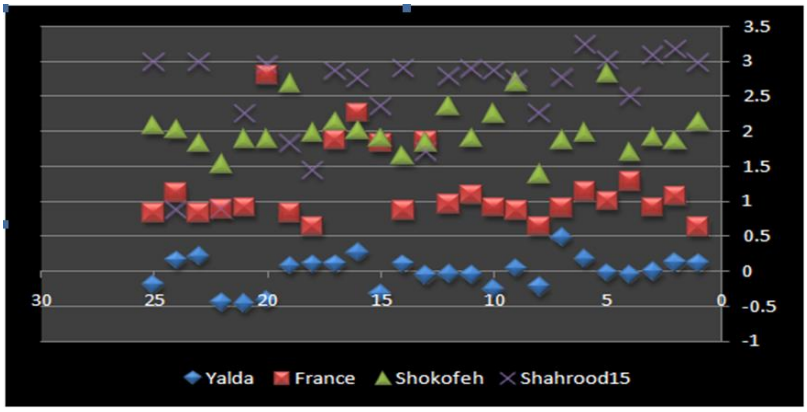

Fig. 9: Diagram showing ANFIS Almond Grade Identification in Model B.

Table 6: Perturbation Matrix obtained for the Models.

Model	Almond Grade	Yalda	France	Shokofeh	Shahrood 15
	Yalda	23	1	2	3
A	France	0	19	3	3
	Shokofeh	0	1	25	0
	Shahrood 15	0	1	1	23
	Yalda	25	0	0	0
B	France	0	20	4	1
	Shokofeh	0	1	21	3
	Shahrood 15	0	3	6	16

The experimental results fed as input to ANFIS were compared with the grading results obtained by the agricultural expert. For each almond grade, the perturbation matrix was determined to determine the prediction accuracy, and the corresponding results were favorable. For example, according to the diagram shown in Fig. 8 for Model A, of the 25 predictions for grade Yalda, one was identified as France and 2 were identified as Shahrood 15. Therefore, the classification sensitivity for Yalda is 92%. At the same time, in the diagram of Fig. 9 for Model B, all the 25 data for grade Yalda were correctly identified as Yalda, thus producing an accuracy of 100%. The related information for other grades of almond is presented in Table 7. Overall, the classification accuracy results indicated that the studied grades were different and could be distinguished from one another.

Table 7: Final Grading Results.

		Almond Grade			
Model	Statistical Parameter (%)	Yalda	France	Shokofeh	Shahrood 15
A	Sensitivity (%)	92	76	100	92
	Overall C lassification Sensitivity (%)	90			
	Sensitivity (%)	100	80	84	64
B	Overall C lassification Sensitivity (%)	82			

Conclusion:

In this study, sound signals in combination with the ANFIS analysis were used to classify almonds into four grades, namely, Yalda, France, Shkofeh, and Shahrood 15. The general classification sensitivity for models A and B were obtained as 90% and 82% respectively. Ultimately, a mean classification accuracy of 85% was obtained for both models. This result indicates that almond grading based on the sound signal method aided by ANFIS analysis is practical and yields satisfactory results. Therefore, it is recommended that further research be conducted into the possibility of applying ANFIS to develop and generalize the algorithm proposed in this article to include grading of other agricultural products.

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