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Using adaptive neuro-fuzzy inference system for classify date fruits

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Abstract The date fruit, which is produced mostly in the hot arid regions of Southern Asia and North Africa, in large quantities, is marketed all over the world as an important crop. Date grading is an important process for producers and affects the fruit quality evaluation and export market. In this research Adaptive Network Fuzzy Inference System (ANFIS) was applied as a decision making technique to classify the Mozafati dates based on geometric parameters. Three date parameters including the length, width and thickness were measured for 1000 date fruits. These dates were graded by both a human expert and ANFIS. Grading results obtained from fuzzy system showed 93% general conformity with the experimental results.

Keywords: Fuzzy logic, physical parameters, date fruit, date grading.

Introduction

Mozafati is the most valuable variety of the dates in Iran and contains 28% date production of this country which is the second world producer. (Anon, 2010). Automatic segregation of various date fruits cultivars required a deep knowledge of each cultivar physical characteristics. The aim of grading is to produce packed fruit which is uniform in size, shape, color, texture and moisture. For each variety the standards are different. Client's requirements can also determine the criteria during grading. For example varieties with a certain texture can be mechanically sorted for size using sorting machines (Zaid, 2002). Relatively few papers on date quality evaluation have appeared in the literature. Based on the evaluation criteria, they can be categorized into: dryness (Wulfsohn*et al*., 1993), firmness (Schmilovitch *et al*., 1995), moisture (Dull *et al*., 1991; Schmilovitch *et al*., 2003, 2006), and automatic date grading (Lee *et al*., 2008).

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AL-Janobi (1998) applied the line-scan based vision for inspecting fast moving on a grading conveyor belt date fruits, where it is capable of determining the color/quality of date fruits. AL-Janobi (2000) developed a color computer vision system consisting of a microcomputer with an image frame grabber and a charged-coupled device (CCD) color camera for sorting and grading Saudi dates based on color threshold technique. Many attempts have been made to make this process more efficient by automatic grading, but, owing to the complexity of the processes and the difficulty of imitating human senses, especially that of vision, no perfect solution has yet been found for date grading without human hands.

Self-learning techniques such as neural networks and fuzzy logic (Zadeh, 1965) seem to represent a good approach. Adaptive Network-based Fuzzy Inference System (ANFIS) can be used. It provides a mathematical framework that can convert a complicated set of variables into an automatic evaluation strategy (Mazloumzadeh *et al*., 2008, 2009).

ANFIS is a fuzzy based system that uses Artificial Neural Networks (ANNs) theory in order to determine the properties (fuzzy membership functions and fuzzy rules) of data samples. ANFIS combines fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule based Fuzzy Inference Systems (FIS) that approximates the way man processes information. ANFIS which is a specific approach in neuro-fuzzy developments has shown significant promise in modeling nonlinear functions. It learns features of the data set and adjusts the system characteristics according to a given error criterion. Fuzzy set theory has been applied to a wide range of problems in control, image processing, filter design, data clustering, pattern recognition, and event classification .

In recent years, more and more applications of fuzzy theory to agriculture have been reported: Chao *et al*. (1999) used a neuro-fuzzy based image classification system that utilizes color-imaging features of poultry viscera in the spectral and spatial domains was developed for this approach. Combining features of chicken liver and heart, a generalized neuro-fuzzy model was designed to classify poultry viscera into four classes. The classification accuracy was 86.3% for training and 82.5% for validation. Verma (1995) developed a fuzzy decision support system (DSS) to aid decisions related to quality sorting of tomatoes. Lameck *et al*. (2002) used application of fuzzy-neural network in classification of soils using ground penetrating radar imagery. Classifications of uniform plant, soil, and residue color images were conducted with fuzzy inference systems by Meyer (2004). Mazloumzadeh *et al*. (2008) used the Mamdani fuzzy inference system (MFIS) to evaluate and classify alternative date harvesting machines in the Iranian date harvest industry. The results obtained with MFIS showed an 86% agreement with those obtained by an expert. Grading and classification using fuzzy logic is always successful and may be better than conventional approaches, as shown by Simonton (1993), Chen and Roger (1994), Mirabbasi *et al*. (2008), Mazloumzadeh *et al*. (2008, 2009), Alavi *et al*. (2010) and Alavi (2012).

The main purpose of this study was to introduce a method of date quality grading using fuzzy logic and to compare the accuracies of the predicted results with grades directly suggested by a human expert.

Materials and methods

Fuzzy logic

Fuzzy logic provides a methodology to model uncertainty and the human way of thinking, reasoning and perception. In classical models variables have real number values, the relationships are defined in terms of mathematical functions, and the outputs are numerical values “crisp”. Models with fuzzy logic have variables which influence system behavior and relationships among the variables which describe the system. In fuzzy logic, the values of variables are expressed by linguistic terms such as “large, medium, and small”, the relationships are defined in terms of if-then rules, and the outputs are fuzzy subsets which can be made “crisp” using defuzzification techniques. The crisp values of system variables are fuzzified to express them in linguistic terms. Fuzzification is a method for determining the degree of membership that a value has to a particular fuzzy set. This is determined by evaluating the membership function of the fuzzy set for the value. A membership function is a mathematical function, which defines the degree of an element's membership in a fuzzy set. A fuzzy subset A is defined by a membership function, $\mu_A(t)$ where is the domain of the variable on which A is defined. The value of $\mu_A(t)$ for each t determines the degree to which each element in the domain belongs to A. Although both classical and fuzzy subsets are defined by membership functions, the degree to which an element belongs to a classical subset is limited to being either zero or one. On the other hand, in fuzzy logic the degree to which an element belongs to a subset may be any value in the interval [0, 1].

Adaptive Network-based Fuzzy Inference System (ANFIS)

ANFIS is an adaptive-network-based fuzzy inference system. ANFIS is used for developing TSK type of FIS. It can be trained by a Back-Propagation (BP) algorithm to model some collection of input/output data for the prediction of output according to the input. Functionally, it is equivalent to the combination of neural network and FIS.

ANFIS was first introduced by Jang (1993) which is suitable for TSK type of FIS proposed by Takagi and Sugeno (1985) and Sugeno and Kang (1988). In this paper, to state the general framework of ANFIS a system containing two inputs x and y and one output f are considered.

As mentioned above, for better explaining of the model we suppose there are two input variables x and y. We assume that each input has two membership functions A_1 and A_2 and B_1 and B_2, respectively. Then, a first-order TSK type of fuzzy if-then rule could be set up as:

$$\begin{aligned} &Rule\ i: IF\ \ x\ is\ A_i\ and\ \ y\ is\ B_i \\ &THEN\ \ f_i = p_i x + q_i y + r_i \quad \mathrm{i} = 1,2,\ldots,\mathrm{n} \end{aligned} \quad (1)$$

where f_i are the outputs within the fuzzy region specified by the fuzzy rule, n is the number of rules and p_i, q_i and r_i are the design parameters that are determined during the training process. The architecture of the ANFIS is shown in Fig. 1. The ANFIS consists of five layers including, the fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer.

In the first layer (fuzzy layer), x and y are the inputs of adaptive nodes A_i and B_i, respectively. A_i and B_i are the linguistic labels used in the fuzzy theory for describing the membership functions. The outputs of layer 1 are the fuzzy membership degree of the inputs which can be expressed as below:

$$O_i^1 = \mu_{A_i}(x),\ i = 1,2,\ldots,n \quad (2)$$

$$O_i^1 = \mu_{B_i}(y),\ i = 1,2,\ldots,n \quad (3)$$

where $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$ denote the membership functions degree.
Second layer is the product layer that consists of two fixed nodes labeled with Π. The output w_1 and w_2 are the weight functions of the next layer. The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y),\ i = 1,2,\ldots,n \quad (4)$$

Where O_i^2 is the output of layer 2.

The third layer is the normalized layer, whose nodes are also fixed and labeled with N. The outputs of this layer can be represented as:

$$O_i^3 = \overline{w_i} = w_i \Big/ \sum_{i=1}^{n} w_i \, , \; i = 1,2,\ldots,n \qquad (5)$$

Where O_i^3 is the output of Layer 3.

The fourth layer is the defuzzification layer. In this layer, the nodes are adaptive nodes. The relationship between the inputs and output of this layer can be expressed as below:

$$O_i^4 = \overline{w_i}(p_i x + q_i y + r_i) \; i = 1,2,\ldots,n \qquad (6)$$

Where O_i^4 is the output of Layer 4 and p_i, q_i and r_i are the constant parameters of the node.

The fifth layer is the output layer, whose node is labeled with S. This node performs the summation of all incoming signals, which represents the results of cleaning rates. The overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{n} \overline{w_i} f_i \; i = 1,2,\ldots,n \qquad (7)$$

Where O_i^5 is the output of layer 5 and the output of the system.

Development of a fuzzy system for evaluation of Mozafati dates

In this study, we have three sets of input data: Length, Width and Thickness. To determine the ANFIS input/output data, approximately 1000 Mozafati dates were selected from different location. A five terms rating system of Very good, Good, Medium, Bad and Very bad was established and applied to all 1000 dates. A numerical value was then assigned to each of the above mentioned terms: i.e. Very good=1, Good=2, Medium=3, bad=4 and Very bad=5.

TheANFIS model was implemented in Matlab software system. Matlab supports first-order ANFIS that has a single output and unitary weights for each rule (MathWorks, 2004).

In the ANFIS procedure, utilizing date grading a score between 1 and 5 to each date sample was assigned. The data set was divided into twosmaller sets namely: the training data set (700 samples) and the testing data set (300 samples). Purpose of the training process is tominimize the error between actual target and ANFIS output through training. This allows ANFIS tolearn features from the training data that it observes, and implementthem in the system rules. In the performance phase,a new data set (test data) that is not present in the training set, isintroduced to the learned system for evaluation. If the test error is adequatelysmall, it indicates that thesystem has a good generalized capability.

The training data set was used to train the ANFIS, whilethe testing data set was used to verify the accuracy and theeffectiveness of the trained ANFIS model for the computationof the date quality evaluation. Fuzzy system is implemented using the following FIS properties (Table 1):

Table 1. Specifications of the fuzzy inference system

Type	**Sugeno**
Decision method for fuzzy logic operators AND (intersection)	Product
Decision method for fuzzy logic operators OR (union)	Probabilistic or
Output combination method (Defuzzification)	Weighted average
Number of membership functions for input #1	9
Number of membership functions for input #2	9
Type of membership functions	Gaussian
Number of rules	9
Output function	Linear
Number of training epochs	100

The main structure of the proposed method is given by Fig. 1. Here, we use the inputs (correspond to x and y in the above section) and the output is considered to be the quality of date (correspond to f).

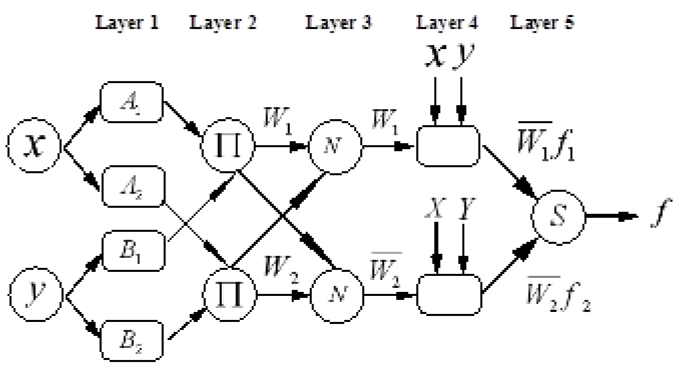

Fig. 1. ANFIS architecture.

The FIS parameters with minimum validation set error are selected as optimal. Using the training data set, Matlab simulator found the best performance by ANFIS in modeling the problem at hand with 9 fuzzy rules and

9 Gaussian membership functions for each input. Fig. 2 also shows the fuzzy rule architecture of the ANFIS model using Gaussian shaped membershipfunctions.

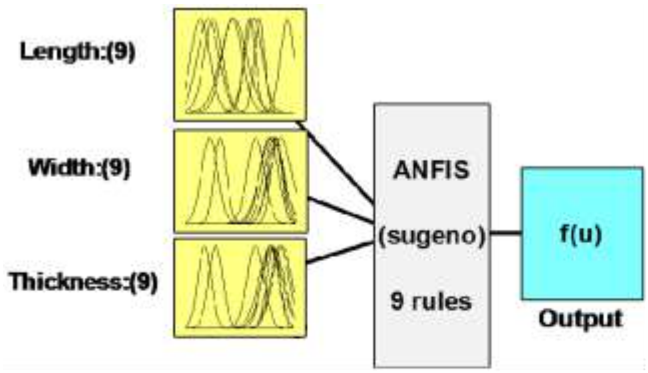

Fig. 2. The fuzzy rule architecture of the ANFIS using Gaussian membership function 3 inputs, 1 output and 9 rules

Results and discussion

In this study, the concentration Mozafati date values of Length, Width and Thickness are combined together by an ANFIS model to generate a new evaluation system that can be applied to evaluate Mozafati dates. We use the proposed method to learn the input-output relation according to learning data set. In the learning phase the ANFIS firstly makes the suitable membership functions for each input. In the sequel, the membership functions are tuned according to error correction training method by using BP algorithm. Also, the constant parameter of the linear output functions are adapt during to learning phase based on LMS algorithm. ANFIS model utilizes 300training data over the 100training periods.

ANFIStest results (predicted data) are compared with results obtained from expert (measured data) in Fig. 3. Horizontal access shows 300 testing data (30% of 1000 data) and vertical access shows date quality classes from Very good to Very bad. From thisfigure, one can see that the results obtained by ANFIS are in good agreement (93%) with theresults of the expert.

In a previous study (Alavi, 2012), Mamdani Fuzzy inference systems (MFIS) was used to evaluate date quality with an 91% accuracy. However, the ANFIS classifier presented in this study was found to be of higher accuracy than the MFIS model. In that system, in order to achieve the best results, optimal membership functions were selected through trial and error for that specific inputs; which was the main deficiency of that system. However, the proposed approach can be used in a general way for every data set.

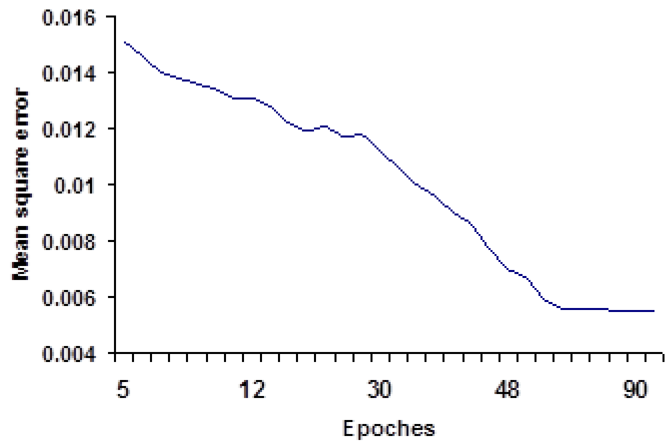

Fig. 3. The curve of network error convergence of ANFIS

In commonly used fuzzy inference systems, optimal membership functions are selected by trial and error. Furthermore, the rule structure is predetermined by an expert person for themodel. In practice, these models may not performsatisfactorily due to limited knowledge of the experts, and improper selection of membership parameters (Jang *et al*., 1997). In the proposed ANFIS based methodology, theparameters are tuned automatically during the learning stage, hencethe membership functions can properly represent the non-linear behavior of thesystem being studied with optimal performance.

In comparison with application of diagrams under the same conditions, the proposed methodology significantly decreases calculation time. For example, to evaluate 1000 date samples one can spend up to 2 hours, whereas, the proposed system decreases this time to only 2 minutes.

Membership functions to be used for agricultural applications should contain the non-linearity that exists between the input features and output categories. The nature of agricultural systems creates the need for modeling systems that are robust, noise tolerant, adaptable for multiple uses, and are extensible.

Lee *et al*. (2008) developed a machine vision system for automatic date grading using digital reflective near-infrared imaging. They could grade date samples with accuracy of 87%. Fuzzy logic in date grading has not been used yet as a grading technique in date industry, but many studies show it is a powerful technique for grading and classifying. For example Shahin and Tollner (1997) obtained 72% classification accuracy in classifying apples according to their water core features using fuzzy logic.

Kavdir and Guyer (2003) used fuzzy technique for apple grading. Grading results obtained from their system showed 89% general agreement with the results from the human expert. They combine trapezoidal or triangular membership functions with an exponential function, as in their study, improved classification accuracy of the system. In this research ANFIS was successfully applied to serve as a decision making technique in grading dates.

The application of soft computing techniques such as fuzzy logic to fruit classification will enhance the automation in this sector. In future studies, the performance of classification based on fuzzy logic should be compared with other mechanical and automated sorting techniques in addition to manual sorting.

Conclusion

A new application of ANFIS to evaluate and classify date quality was presented. In this study, the concentration values of Length, Width and Thickness are combined together through an ANFIS model to generate a new method that can be used instead of the expert. ANFIS models are powerful tools for building complex nonlinear relationships between inputs and outputs by learning from a data set.

The comparison between results of ANFIS and expert shows that the overall classification accuracy of the ANFIS model was 93%. It shows that the ANFIS model has much better predicting capability than the Mamdani Fuzzy Inference System (MFIS) of 91% accuracy that was created by an expert. Results indicate that ANFIS modeling is a promising alternative to the traditional approach and it significantly decreases calculation time in determining date quality.

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