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Apple Grading Using Fuzzy Logic

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Abstract: Classification is vital for the evaluation of agricultural produce. However, the high costs, subjectivity, tediousness and inconsistency associated with manual sorting have been forcing the post harvest industry to apply automation in sorting operations. Fuzzy logic (FL) was applied as a decision making support to grade apples in this study. Quality features such as the color, size and defects of apples were measured through different equipment. The same set of apples was graded by both a human expert and a FL system designed for this purpose. Grading results obtained from FL showed 89% general agreement with the results from the human expert, providing good flexibility in reflecting the expert's expectations and grading standards into the results. This application of apple grading can be fully automated by measuring the required features by means of high-tech sensors or machine vision and making the grading decision using FL.

Key Words: Fuzzy logic, fuzzy membership, apple classification, apple grading.

Bulanık Mantık Kullanarak Elma Sınıflama

Özet: Sınıflama tarımsal ürünlerin değerlendirilmesi için çok önemlidir. Ancak, el ile yapılan sınıflandırmadaki yüksek maliyet, taraflılık, tekdüzelik ve tutarsızlık hasat sonrası endüstriyi sınıflama operasyonlarında otomasyon uygulamasına gitmeye zorlamaktadır. Bu çalışmada, bulanık mantık elma sınıflamada karar verici destek olarak uygulanmıştır. Elmaların renk, boyut, ve bozukluklar gibi özellikleri farklı ekipmanlar aracılığı ile ölçülmüştür. Aynı elma toplulukları hem bir uzman hemde bu amaç için geliştirilen bir bulanık mantık sistemi tarafından sınıflandırılmışlardır. Bulanık mantık tarafından elde edilen sınıflama sonuçları uzman tarafından elde edilen sonuçlar ile % 89 oranında bir uyum göstermiş ve aynı zamanda da uzmanın beklentilerini ve sınıflama standartlarını sonuçlara yansıtmada iyi bir esneklik sağlamıştır. Buna göre, elma sınıflaması gerekli özelliklerin yüksek teknoloji sensörleri yada makina ile görüntüleme yolu ile ölçülerek ve sınıflama kararını da bulanık mantık aracılığı ile vererek tam olarak otomatikleştirilebilir.

Anahtar Sözcükler: Bulanık mantık, bulanık üyelik, elma sınıflama, elma derecelendirme.

Introduction

Agricultural produce is subject to quality inspection for optimum evaluation in the consumption cycle. Efforts to develop automated fruit classification systems have been increasing recently due to the drawbacks of manual grading such as subjectivity, tediousness, labor requirements, availability, cost and inconsistency.

However, applying automation in agriculture is not as simple as automating the industrial operations. There are 2 main differences. First, the agricultural environment is highly variable, in terms of weather, soil, etc. Second, biological materials, such as plants and commodities, display high variation due to their inherent morphological diversity (Blackmore and Steinhouse, 1993). Techniques used in industrial applications, such as template matching and fixed object modeling are unlikely to produce satisfactory results in the classification or control of input from agricultural products. Therefore, self-learning techniques such as neural networks and fuzzy logic (FL) seem to represent a good approach.

FL, which was first introduced by Zadeh (1965), is used to handle uncertainty, ambiguity and vagueness. It provides a means of translating qualitative and imprecise

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information into quantitative (linguistic) terms. FL is a non-parametric classification procedure, which can infer with nonlinear relations between input and output categories, maintaining flexibility in making decisions even on complex biological systems.

FL has a wide application in many industrial areas, such as subway trains, automobiles and washing machines. In recent years, more and more applications of fuzzy theory to agriculture have been reported: Simonton (1993) and Chen and Roger (1994) used FL in the classification of plant structures. They found good agreement between the results from fuzzy prediction and human experts.

FL was successfully used to determine field trafficability (Thangavadivelu and Colvin, 1991), to decide the transfer of dairy cows between feeding groups (Grinspan et al., 1994), to predict the yield for precision farming (Ambuel et al., 1994), to control the start-up and shut-down of food extrusion processes (Wang and Tan, 1996), to steer a sprayer automatically (Ki and Cho, 1996), to predict corn breakage (Zhang et al., 1990), to manage crop production (Kurata and Eguchi, 1990), to reduce grain losses from a combine (Newton, 1986) and to manage a food supply (Ben-Abdennour and Mohtar, 1996).

Shahin et al., (2000) compared FL and linear discriminant analysis in predicting peanut maturity. Reported prediction accuracies with the fuzzy model were 45%, 63%, and 73% when maturity was classified in 6, 5 and 3 classes, respectively. The respective accuracies from the classifier of linear discriminant analysis (LDA) using the same data were 42%, 56% and 70%. The fuzzy model improved maturity prediction compared to LDA.

Yang et al., (2000) applied a FL model to control site-specific herbicide application rates for a hypothetical crop field. The values of weed coverage and weed patch were inputs to a FL decision making system, which used the membership functions to control the herbicide application rate at each location. Simulations showed that the proposed FL strategy could potentially reduce herbicide application by 5 to 24%, and that an on/off strategy resulted in an even greater reduction of 15 to 64%.

The main purpose of this study was to investigate the applicability of FL to constructing and tuning fuzzy membership functions and to compare the accuracies of predictions of apple quality by a human expert and the proposed FL model. Grading of apples was performed in terms of characteristics such as color, external defects, shape, weight and size. Readings of these properties were obtained from different measurement apparatuses, assuming that the same measurements can be done using a sensor fusion system in which measurements of features are collected and controlled automatically. The following objectives were included in this study:

1. To design a FL technique to classify apples according to their external features developing effective fuzzy membership functions and fuzzy rules for input and output variables based on quality standards and expert expectations.

2. To compare the classification results from the FL approach and from sensory evaluation by a human expert.

3. To establish a multi-sensor measuring system for quality features in the long term.

Apple Defects Used in the Study

No defect formation practices by applying forces on apples were performed. Only defects occurring naturally or forcedly on apple surfaces during the growing season and handling operations were accounted for in terms of number and size, ignoring their age. Scars, bitter pit, leaf roller, russeting, punctures and bruises were among the defects encountered on the surfaces of Golden Delicious apples. In addition to these defects, a size defect (lopsidedness) was also measured by taking the ratio of maximum height of the apple to the minimum height.

Materials and Methods

Five quality features, color, defect, shape, weight and size, were measured. Color was measured using a CR-200 Minolta colorimeter in the domain of L, a and b, where L is the lightness factor and a and b are the chromaticity coordinates (Ozer et al., 1995). Sizes of surface defects (natural and bruises) on apples were determined using a special figure template, which consisted of a number of holes of different diameters. Size defects were determined measuring the maximum and minimum heights of apples using a Mitutoya electronic caliper (Mitutoya Corporation). Maximum circumference measurement was performed using a Cranton circumference measuring device (Cranton

Machinery Co.). Weight was measured using an electronic scale (Model no CT1200-S serial no: 3403, capacity 1200 ± 0.1 g). Programming for fuzzy membership functions, fuzzification and defuzzification was done in Matlab.

The number of apples used was determined based on the availability of apples with quality features of the 3 quality groups (bad, medium and good). A total of 181 Golden Delicious apples were graded first by a human expert and then by the proposed FL approach. The expert was trained on the external quality criteria for good, medium and bad apple groups defined by USDA standards (USDA, 1976). The USDA standards for apple quality explicitly define the quality criteria so that it is quite straightforward for an expert to follow up and apply them. Extremely large or small apples were already excluded by the handling personnel. Eighty of the apples were kept at room temperature for 4 days while another 80 were kept in a cooler (at about 3 °C) for the same period to create color variation on the surfaces of apples. In addition, 21 of the apples were harvested before the others and kept for 15 days at room temperature for the same purpose of creating a variation in the appearance of the apples to be tested.

The Hue angle ($\tan^{-1}(b/a)$), which was used to represent the color of apples, was shown to be the best representation of human recognition of color (Hung et al., 1993). To simplify the problem, defects were collected under a single numerical value, "Defect" (equation 1), after normalizing each defect component such as bruises, natural defects, russetting and size defects (lopsidedness).

$$\text{Defect} = 10 \times B + 5 \times ND + 3 \times R + 0.3 \times SD \qquad (1)$$

where B is the amount of bruising, ND is the amount of natural defects, such as scars and leaf roller, as total area (normalized), R is the total area of russeting defect (normalized) and SD is the normalized size defect. Similarly, circumference, blush (reddish spots on the cheek of an apple) percentage and weight were combined under "Size" (equation 2) using the same procedure as with "Defect."

$$\text{Size} = 5 \times C + 3 \times W + 5 \times BL \qquad (2)$$

where C is the circumference of the apple (normalized), W is weight (normalized) and BL is the normalized blush percentage. Coefficients used in equations 1 and 2 were subjectively selected, based on the expert's expectations and USDA standards (USDA, 1976).

Although it was measured at the beginning, firmness was excluded from the evaluation as it was difficult for the human expert to quantify it nondestructively. After the combinations of features given in equations 1 and 2, input variables were reduced to 3 defect, size and color.

Along with the measurements of features, the apples were graded by the human expert into 3 quality groups, bad, medium and good, depending on the expert's experience, expectations and USDA standards (USDA, 1976). FL techniques were applied to classify apples after measuring the quality features. The grading performance of FL proposed was determined by comparing the classification results from FL and the expert.

Application of Fuzzy Logic

Three main operations were applied in the FL decision making process: selection of fuzzy inputs and outputs, formation of fuzzy rules, and fuzzy inference. A trial and error approach was used to develop membership functions. Although triangular and trapezoidal functions were used in establishing membership functions for defects and color (Figures 1 and 2), an exponential function with the base of the irrational number e (equation 3) was used to simulate the inclination of the human expert in grading apples in terms of size (Figure 3).

$$\text{Size} = e^{X} \qquad (3)$$

where e is approximately 2.71828 and x is the value of size feature.

Fuzzy Rules

At this stage, human linguistic expressions were involved in fuzzy rules. The rules used in the evaluations of apple quality are given in Table 1. Two of the rules used to evaluate the quality of Golden Delicious apples are given below:

If the color is greenish, there is no defect, and it is a well formed large apple, then quality is very good (rule $Q_{1,1}$ in Table 1).

If the color is pure yellow (overripe), there are a lot of defects, and it is a badly formed (small) apple, then quality is very bad (rule $Q_{3,17}$ in Table 1).

A fuzzy set is defined by the expression below (Chen and Roger, 1994);

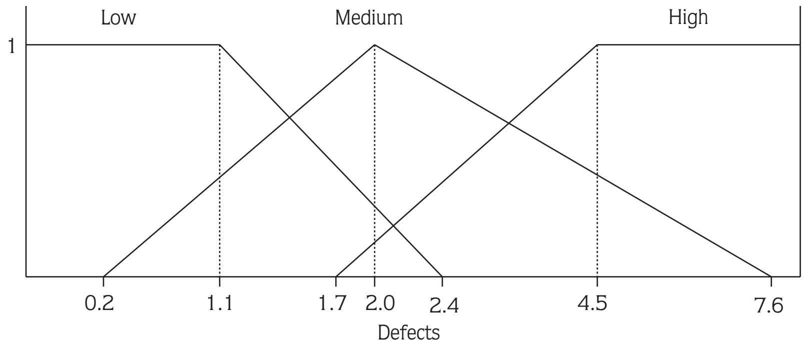

Figure 1. Membership functions for the defect feature.

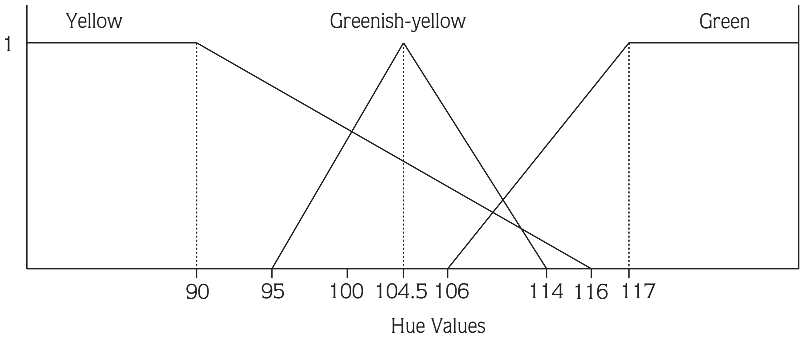

Figure 2. Membership functions for the color feature.

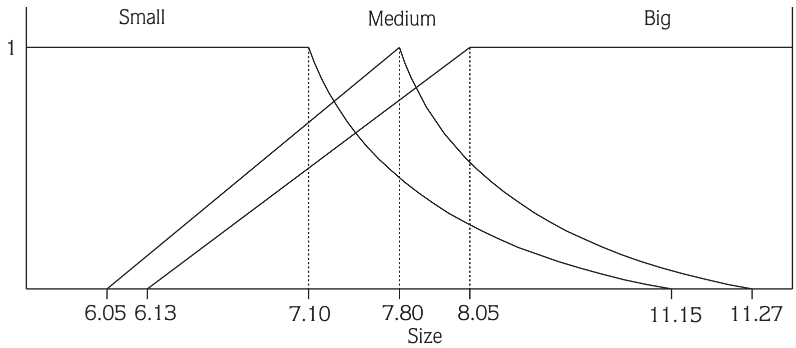

Figure 3. Membership functions for the size feature.

$$D = \{(x, \mu_D(x)) | x \in X\}$$

$$\mu_D(x): \rightarrow [0,1] \quad (4)$$

where X represents the universal set, D is a fuzzy subset in X and $\mu_D(x)$ is the membership function of fuzzy set D. Degree of membership for any set ranges from 0 to 1. A value of 1.0 represents a 100% membership while a value of 0 means 0% membership. If there are 3 sub-groups of size, then 3 memberships are required to express the size values in a fuzzy rule.

Three primary set operations in fuzzy logic are AND, OR, and the Complement, which are given as follows

$$\text{AND: } \mu_{C \cap D} = (\mu_C \wedge \mu_D) = \min(\mu_C, \mu_D) \quad (5)$$

Table 1. Fuzzy rule tabulation.

	C_1+S_1	C_1+S_2	C_1+S_3	C_2+S_1	C_2+S_2	C_2+S_3	C_3+S_1	C_3+S_2	C_3+S_3
D_1	$Q_{1,1}$	$Q_{1,2}$	$Q_{2,3}$	$Q_{1,3}$	$Q_{2,5}$	$Q_{3,8}$	$Q_{2,6}$	$Q_{2,7}$	$Q_{3,15}$
D_2	$Q_{2,1}$	$Q_{2,2}$	$Q_{3,3}$	$Q_{2,4}$	$Q_{3,6}$	$Q_{3,9}$	$Q_{3,11}$	$Q_{3,13}$	$Q_{3,16}$
D_3	$Q_{3,1}$	$Q_{3,2}$	$Q_{3,4}$	$Q_{3,5}$	$Q_{3,7}$	$Q_{3,10}$	$Q_{3,12}$	$Q_{3,14}$	$Q_{3,17}$

Where, C_1 is the greenish color quality (desired), C_2 is greenish-yellow color quality (medium), and C_3 is yellow color quality (bad); S_1, on the other hand, is well formed size (desired), S_2 is moderately formed size (medium), S_3 is badly formed size (bad). Finally, D_1 represents a low amount of defects (desired), while D_2 and D_3 represent moderate (medium) and high (bad) amounts of defects, respectively. For quality groups represented with "Q" in Table 1, the first subscript 1 stands for the best quality group, while 2 and 3 stand for the moderate and bad quality groups, respectively. The second subscript of Q shows the number of rules for the particular quality group, which ranges from 1 to 17 for the bad quality group.

$$\text{OR: } \mu_{C\cup D} = (\mu_C \vee \mu_D) = \max(\mu_C,\mu_D) \quad (6)$$

$$\text{Complement} = \bar{\mu}_C = 1 - \mu_D. \quad (7)$$

The minimum method given by equation 5 was used to combine the membership degrees from each rule established. The minimum method chooses the most certain output among all the membership degrees. An example of the fuzzy AND (the minimum method) used in IF THEN rules to form the Q_{11} quality group in Table 1 is given as follows;

$$Q_{11} = (C_1 \wedge S_1 \wedge D_1) = \min(C_1,S_1,D_1). \quad (8)$$

On the other hand, the fuzzy OR (the maximum method) rule was used in evaluating the results of the fuzzy rules given in Table 1; determination of the quality group that an apple would belong to, for instance, was done by calculating the most likely membership degree using equations 9 through 11. If,

$$\begin{aligned} k_1 &= (Q_{1,1},Q_{1,2},Q_{1,3}), \\ k_2 &= (Q_{2,1},Q_{2,2},Q_{2,3},Q_{2,4},Q_{2,5},Q_{2,6}), \\ k_3 &= (Q_{3,1},Q_{3,2},Q_{3,3},Q_{3,4},Q_{3,5},Q_{3,6},Q_{3,7},Q_{3,8},Q_{3,9},Q_{3,10}, \\ &\quad Q_{3,11},Q_{3,12},Q_{3,13},Q_{3,14},Q_{3,15},Q_{3,16},Q_{3,17}), \end{aligned} \quad (9)$$

where k is the quality output group that contains different class membership degrees and the output vector y given in equation 10 below determines the probabilities of belonging to a quality group for an input sample before defuzzification:

$$y = \lfloor \max(k_1)\ \max(k_2)\ \max(k_3) \rfloor \quad (10)$$

where, for example,

$$\begin{aligned} \max(k_1) &= (Q_{1,1} \vee Q_{1,2} \vee Q_{1,3}) \\ &= \max(Q_{1,1},Q_{1,2},Q_{1,3}), \end{aligned} \quad (11)$$

then, equation 11 produces the membership degree for the best class (Lee, 1990).

Determination of Membership Functions

It was stated by Shahin et al., (2000) that the lack of a systematic methodology for developing membership functions or fuzzy sets is a major limitation in designing a fuzzy system. Membership functions are in general developed by using intuition and qualitative assessment of the relations between the input variable(s) and output classes.

In the existence of more than one membership function that is actually in the nature of the FL approach, the challenge is to assign input data into one or more of the overlapping membership functions. These functions can be defined either by linguistic terms or numerical ranges, or both.

The membership function used in this study for defect quality in general is given in equation 4. The membership function for high amounts of defects, for instance, was formed as given below:

If the input vector x is given as x = [defects,size, color], then the membership function for the class of a high amount of defects (D_3) is

$$\begin{aligned} &\mu(D_3) = 0, \text{ when } x(1) < 1.75, \\ &\mu(D_3) = \frac{(x(1)-1.75)}{2.77}, \text{ when, } 1.75 \le x(1) < 4.52, \text{ or} \\ &\mu(D_3) = 1, \text{ when } x(1) \ge 4.52. \end{aligned} \quad (12)$$

For a medium amount of defects (D_2), the membership function is

$$\mu(D_2) = 0, \text{ when defect input } x(1) < 0.24 \text{ or } x(1) > 7.6,$$

$$\mu(D_2) = \frac{(x(1)-0.24)}{1.76}, \text{ when } 0.24 \leq x(1) < 2,$$

$$\mu(D_2) = \frac{(7.6-x(1))}{5.6}, \text{ when } 2 \leq x(1) \leq 7.6. \quad (13)$$

For a low amount of defects (D_1), the membership function is

$$\mu(D_1) = 0, \text{ when defect input } x(1) > 2.4,$$

$$\mu(D_1) = \frac{(2.4- x(1))}{1.3}, \text{ when } 1.1 < x(1) \leq 2.4 \text{ or}$$

$$\mu(D_1) = 1, \text{ when } x(1) \leq 1.1. \quad (14)$$

Calculations for the quality groups of color and size were performed using the same approach as defect. Three membership functions for the quality classes of defect, color and size are schematically shown in Figures 1, 2 and 3, respectively.

Defuzzification

The centroid method, which is also known as the center of mass, was used for defuzzification. After execution of the rules established and shown in the previous section, the output grades described below are obtained.

For low quality, degree of membership is calculated using equation 15.

$$sc = \frac{(y(3) \times (c + 1.5))}{2}, \quad (15)$$

where, $c = c_2 - c_1$, $c_1 = ((0.5 \times y(3)) + 0.75)$, and $c_2 = (2.25 - (0.5 \times y(3)))$;

y(3) is the low quality output from the output vector y (equation 10), c, c_1, and c_2 are shown in Figure 4 and sc is the area of the trapezoid formed. Membership degrees of sb and sa are calculated using the same approach in equation 15 for the medium and high quality classes.

In the defuzzification stage, the overall grade for a particular apple was found by taking the average of the weighted possible outputs using the weighted average method (Kartalopoulos, 1996). Equation 16 was used for this purpose

$$wa = \frac{sa \times (3.5) + sb \times (2.5) + sc \times (1.5)}{sa + sb + sc}, \quad (16)$$

where wa is the weighted average for the grade of a particular apple. From each of the 3 output categories, trapezoidal areas (sa, sb, and sc) were calculated for the apple being graded. Then, the weighted average of the 3 trapezoidal areas shown in Figure 4 was calculated to find the final grade for the particular apple.

Results and Discussion

In the results of the defuzzification process, grades for all the apples were calculated between 0 and 3.99. Grade (g) ranges for the output quality classes were chosen as follows: $2.3 \leq g \leq 4$ for the best class, $1.4 \leq g < 2.3$ for the moderate class and $0 \leq g < 1.4$ for the bad class. The resulting classification accuracies obtained from FL are given in Table 2 in comparison with the classification results from the expert.

FL predicted around 89% of apples correctly (Table 2). Misclassification errors observed were among

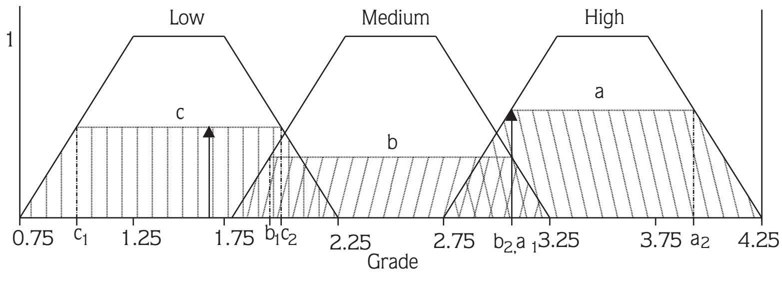

Figure 4. Membership functions for output quality groups and determination of a grade for an apple.

Table 2. Comparison of FL and expert in classification of apples.

		Fuzzy Logic Prediction				
	Class	1	2	3	Total Predicted	(%)
Human Expert	1	121	9	0	130	93.1
	2	6	33	2	41	80.5
	3	1	2	7	10	70.0
Total Observed		128	44	9	161*/181	
(%)		94.5	75.0	77.8		89.0

* Number of apples correctly classified by fuzzy logic

adjacent groups in general. This kind of error is usually acceptable.

Determination of membership functions in terms of shape and boundary has a clear effect on the result of classification performed by FL. This situation greatly depends on experience and knowledge. Finding the right shape and the boundaries for the membership function will increase the accuracy of the FL application. Statistics of the class populations, such as average, standard deviation and minimum-maximum values, could help the determination of membership functions. Therefore, parameters of FL, such as function shape, threshold, which is to determine the overlapping amount and condition among the membership functions, input and output levels, and function rules, must be tested to find the optimum classification result. These application criterions of FL that must be investigated are both disadvantageous as it takes time to apply all the alternatives, and powerful as it provides an opportunity to build a system compatible with the standards and expectations.

In previous studies, apples were classified with recognition accuracies of 86.1% and 85.9% using Fisher's linear classifier and Boltzman's perceptron network classifier, respectively, based on color features (Ben-Hannan et al., 1992). Shahin and Tollner (1997) obtained 72% classification accuracy in classifying apples according to their water core features using FL. The authors suggested that the low accuracy rate could be due to the variations in the visual properties of apples. This conclusion and the applications proposed in this study suggest that applying traditional triangular and trapezoidal membership functions may not represent the variations that quality classes of apples have been displaying. Therefore, combining trapezoidal or triangular membership functions with an exponential function, as in this study, may improve the classification accuracy.

Apples were classified based on their surface blemishes with a classification success of 96.6% using a multi-layer feed forward neural network classifier (Yang, 1993). Use of artificial neural networks provides a powerful tool for sorting operations. However, it is also associated with high computational cost and uncertainty about the working procedure of the classifier. FL, on the other hand, involves less computation and has clear implementation and working schemes.

Conclusion

FL was successfully applied to serve as a decision support technique in grading apples. Grading results obtained from FL showed a good general agreement with the results from the human expert, providing good flexibility in reflecting the expert's expectations and grading standards into the results. It was also seen that color, defects and size are 3 important criteria in apple classification. However, variables such as firmness, internal defects and some other sensory evaluations, in addition to the features mentioned earlier, could increase the efficiency of decisions made regarding apple quality. Particularly with recent studies focusing on non-destructive measurement of internal quality features of fruits, such as firmness (Lu et al., 2000), sugar content (Steinmetz et al., 1999) and internal defects, non destructive automated sorting of agricultural produce has been becoming more and more applicable. The application of soft computing techniques such as FL to fruit classification will enhance the automation in this sector.

In future studies, the performance of classification based on FL should be compared with other mechanical and automated sorting techniques in addition to manual sorting. Moreover, the shape of the membership functions may be predicted by applying cluster or statistical analysis techniques to the sub-samples of the data to be sorted. This could result in membership functions that closely represent the output classes and, therefore, improve the classification success of the FL classifier. Applying commonly used triangular or trapezoidal membership functions to the quality categories of agricultural produce may not work as it would for industrial operations. This may be due to the diversity and uniqueness of agricultural products. Membership functions to be used for agricultural applications should contain the non-linearity that exists between the input features and output categories.

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