ARTICLE IN PRESS

Available at www.sciencedirect.com

INFORMATION PROCESSING IN AGRICULTURE xxx (xxxx) xxx

journal homepage: www.keaipublishing.com/en/journals/information-processing-in-agriculture/

Fuzzy logic classification of mature tomatoes based on physical properties fusion

Seyed Mehdi Nassiri [a,*], *Amir Tahavoor* [a], *Abdolabbas Jafari* [a,b]

[a] Department of Biosystems Engineering, Shiraz University, Shiraz 71441, Iran
[b] Lincoln Agritech Ltd., Lincoln University, Lincoln 7616, New Zealand

ARTICLE INFO

Article history:
Received 10 March 2020
Received in revised form
1 September 2021
Accepted 12 September 2021
Available online xxxx

Keywords:
Fuzzy logic
Grading
Hardness
Tomato
Sorting

ABSTRACT

Grading of fruits and vegetables is an initial step after harvesting. It is also an essential operation before packaging. In the present study, different fuzzy algorithms for classification of mature tomato were applied and evaluated based on combinations of fruit color, size and hardness. Fuzzy membership functions of hardness were established by subjecting samples to Instron compression test as well as the rates of panelists. Each sample was also used for image processing to determine the color and size of fruit using Matlab image processing toolbox. Color and size fuzzy membership functions were established by published standard. The fuzzy If-Then rules were applied to classify the samples within five group outputs viz. "grade I", "grade II", "grade I-far market", "processing", and "storage". Eighty-one fuzzy rules were reduced to 25 rules by combining the compatible rules. Six fuzzy algorithms with different fuzzifiers (zmf, sigmf, gbellmf) and defuzzifiers (bisector, mom, and centroid) were applied, and the outputs were compared to the panelists' classifications in cross tables. According to the classification results, fuzzy algorithms grouped the fruits into correct classes with 90.9%, 92.3%, 88.7%, 87.4%, 92.4% and 93.3% accuracy for 6 models, respectively. The best result was observed with zmf and sigmf, and gbellmf as fuzzifier and mom as defuzzifier with 93.3% accuracy. Overly, the results revealed that the fusion of aforementioned tomato properties based on fuzzy membership functions could accurately classify the tomatoes in correct groups for different markets.

1. Introduction

Grading and sorting are the main processes after most fruits and vegetables harvesting. The importance of such processes, which are based on product size, shape and color, refers to consumer's preference. In most cases, sorting is a necessary stage prior to packaging. Value added fruits and vegetables by sorting, grading, packaging and labeling can be easily retailed in supermarkets, sold in wholesale markets and even exported to global markets.

Tomato is very sensitive food commodity for harvesting, transporting and processing [1]. It is a climacteric product which means ripening takes place after maturity even when detached from the plant. This agricultural product is very sensitive to external loads at the stage of ripening while storage. Therefore, sorting of mature, ripe and over-ripe tomatoes is essential for protecting soft fruits and provides desired period

* Corresponding author at: Department of Biosystems Engineering, Shiraz University, Shiraz 71441, Iran.
E-mail address: nasiri@shirazu.ac.ir (S.M. Nassiri).
Peer review under responsibility of China Agricultural University.
https://doi.org/10.1016/j.inpa.2021.09.001

of ripening for mature but unripe fruits. Recalling that production of tomato as one of the most five top crops in Iran [2], is wasted nearly 30 percent from harvest to consumption [3]. Therefore, it is important to prevent any losses by appropriate classification of harvested fruits. This is a recommended way for sustainable production of food source for global population [4]. It is also important for local food supply chain to provide tomatoes according to their consumer needs and tastes. Producers, processing industries and consumers can make proper decisions based on tomato ripening stages. In practice, tomatoes are classified by physical properties of the fruits that are extracted by different techniques.

Tomato can be classified with the aid of image processing based on apparent characteristics related to the maturity of the fruits [5]. Image processing based on physical properties of tomatoes (such as surface defects, color, shape and size) was also applied for sorting and grading according to the application purposes of the fruits [6-14]. It is reported that tomatoes were classified with minimum precision of 84% (for surface defects) [10] up to 100% (for size) [7], however single factor was applied for such grouping. Mechanical properties such as firmness was another approach for fruit grading/sorting [15-17]. There was a distinct trend for fruit firmness at different levels of ripeness (green mature, pink and red). Although firmness is a destructive technique, it showed that mechanical behavior of the fruit has capability for sorting criterion. All of the above characteristics (physical and mechanical) had the potential to classify ripe, unripe, and several desirable characteristics of tomatoes, though the classification has been based on Boolean algebra. This means that a clear boundary has been considered for the groups in the classification. If two successive classes have a transition zone (or overlap), Boolean algebra does not have the necessary capability for proper grouping.

In contrast, fuzzy logic creates new classification groups (shared area) with overlapped borders provided by membership functions [18-22]. Iraji et al. [20] offered a precise and efficient method by image processing and using fuzzy logic as well as neuro-fuzzy network (ANFIS) to produce nine group classifications. Using the seven features that were extracted from fruit pictures; they classified tomatoes in nine different groups. Fusion is another merit of fuzzy algorithm for combining different features that extracted from physical and mechanical properties of fruits.

Teoh et al. [23] achieved to 77.78% accuracy for sorting mangoes according to the three perpendicular dimensions of fruits by three triangle membership functions. For obtaining better system performance, they recommended an additional feature such as color for input membership functions. Moreover, additional inputs in fuzzy logic algorithm provide more information for multi-purpose fruit and vegetable sorting systems [24]. Alavi [18] simultaneously took into the account the length and freshness of date fruits in a fuzzy system, and graded the fruits in the right groups by 91% accuracy.

Considering all above, it was found that (1) no research study has taken into account the three colors of green, orange and red simultaneously as color indices for classification of tomato fruits, (2) different fuzzy membership function geometries and different justifications can be applied for establishing the functions, (3) there was no fusion of physical and mechanical properties for tomato sorting, and (4) fuzzy decisions are much closer to human perception than Boolean logic for food commodity classification. Therefore, the main objective of the present study was to combine three major factors of color, size and whole fruit hardness of tomato to classify the harvested fruits in appropriate groups by fuzzy logic.

2. Materials and methods

Two hundred and forty fresh tomatoes (Kia cultivar) were randomly selected from a greenhouse. Samples were manually harvested and transferred to the laboratory and then prepared for tests. Sixty eight fruits were used for making membership functions and the rest for model verification.

2.1. *Subjective and objective hardness tests*

Subjective hardness was determined by 7 panelist people according to the Likert ranking scale from 1 as the hardest to 5 as softest samples. Trained panelists were retrained to rank tomato hardness before experimental trials with an extra set of pre-selected samples [25]. The samples were kept and gently pressed with the hand palm and numbered (1–5) according to perceived hardness. These rates were then used for establishing fuzzy logic membership functions in three classes (hard, medium and soft) by plotting objective ranks vs. objective forces as described in Section 2.3. For this purpose, the same samples were subjected to a compression test by Instron (Santam, model-STM20, Iran) equipped with a 50 kgf load cell (Bongshin, Taiwan of China) (Fig. 1).

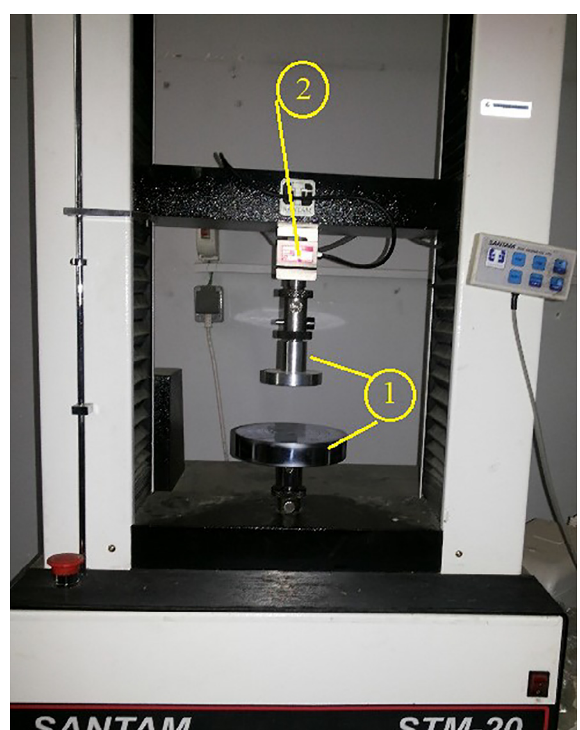


Fig. 1 – Instron machine for hardness measurement (STM-20). 1. Upper and lower compression probes; 2. Load cell.

Please cite this article as: S. M. Nassiri, A. Tahavoor and A. Jafari, Fuzzy logic classification of mature tomatoes based on physical properties fusion, Information Processing in Agriculture, https://doi.org/10.1016/j.inpa.2021.09.001

To simulate human perception related to the hardness of fruits, all samples compressed up to 3 N by 75 mm circular probe with the rate of 10 mm per second, and corresponding deformations were recorded [24]. Compression force was determined by pretests in such a manner that softer tomatoes were compressed without failure.

2.2. Color and size measurements

Image of the same samples were taken by 12 Megapixel Canon Powershot S3 camera (Japan) in a hemispherical image acquisition chamber (50 cm diameter). The camera was mounted on a stand at a height of 21 cm above the samples. The camera was set in macro and manual mode, the shutter speed and the aperture were adjusted to 1/80 s and f3.2, respectively, so that all images have the same setting. Four DC halogen lamps were located at the bottom of the chamber to provide an indirect illumination and eliminate the shadows (Fig. 2).

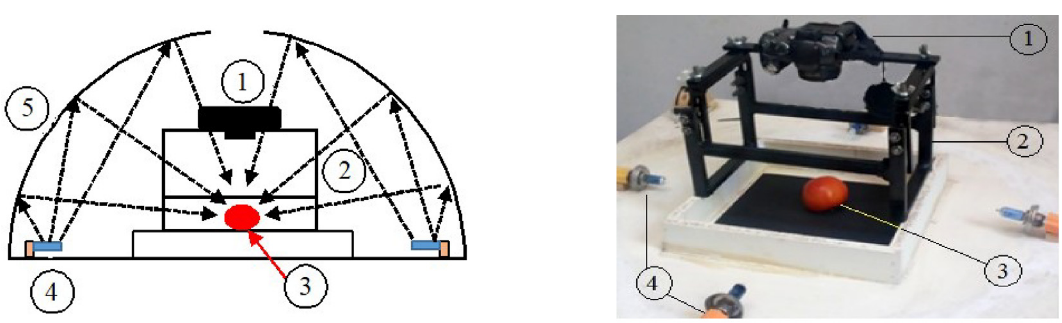
Images were then imported into Matlab software and image-processing toolbox was used for two purposes; firstly, for determining color components of the images, and secondly for determining fruit size as an objective measurement method. For the first, the initial RGB images were converted to HSV color space to determine the color components of the samples irrespective of the local intensities on the surface of the tomatoes. Top, bottom and lateral images of samples were used to compute the percentage of color pixels discussed in the Section 2.3. For the second, RGB images were converted into grayscale images and binarized (black and white) by considering appropriate thresholds derived from grayscale histograms. Some morphological operations like 'bwareaopen' and 'imfill functions' were performed to remove the noises. The resulting binary images were used to determine the size of fruits (Fig. 3). Mean of the tomato sizes from the top and lateral images were used for size determination.

2.3. Fuzzy system

Fuzzy systems are based on three major elements of fuzzifier (membership function), fuzzy interface, and defuzzifier rules (Fig. 4) [26].

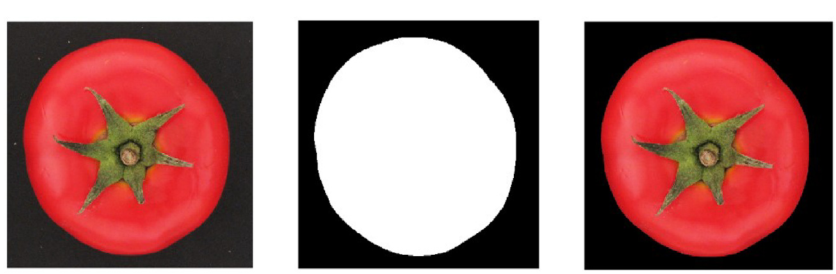
Trapezoidal, triangular, Gaussian and bell shape are most common and known membership functions (fuzzifiers). Therefore, based on categorical concepts of the algorithm, trapezoidal and bell shape membership functions were selected and used. By considering the results of subjective and objective tests, boarder of membership functions for hardness were determined as shown in Fig. 5.

Membership functions of fruits size and color were built by considering standard size and color classification for tomatoes [27]. According to the standard, tomatoes classified as small (5.50–5.79 cm), medium (5.72–6.43 cm), large (6.35–7.06 cm) and extra-large (more than 7 cm). Also, tomatoes classified as green (complete light to dark green), breaker (yellowness, pink or red less than 10% of surface), turning (yel-



(a) (b)

Fig. 2 – Image capturing test rig.



(a) (b) (c)

Fig. 3 – Implemented stages for tomato-background separation. Original image; (b) binary image; (c) color image imposed on binary image with logical "and"

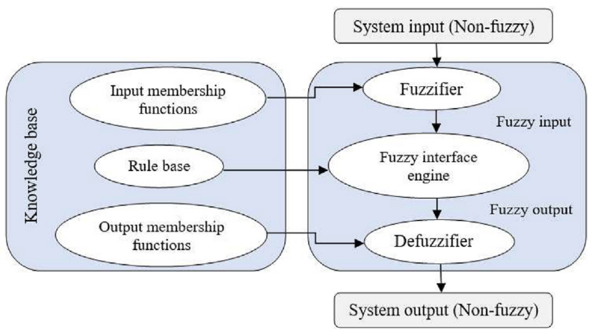


Fig. 4 – Fuzzy system block diagram [26].

lowness, pink or red more than 10% but less than 30%), pink (pink or red more than 30% but less than 60%), light red (pinkness or red more than 60% but less than 90%), and red (red more than 90%) according to the percentage of surface coverage by red color. Therefore, color components of all samples were extracted from color images and converted from RGB to HSV color space for distinct separation of color components of red, orange and green (Fig. 6). By such a manner, boundaries of membership function and overlap values were determined. The approximate percentage of covered surface by different color components was determined by the ratio of color pixels to all surface pixels.

The output membership functions created by experts in five different groups as “grade1”, “grade2”, “processing”, “far market”, and “storage” (Table 1). Grade1 and 2 are suitable for fresh use in near markets, processing refers to soft and ripe tomatoes for paste or juice production, far market refers to suitable fruits for fresh consume in markets distanced from a distribution center, and storage for unripe fruits that need to get to full red color. This classification can be different, region by region or country by country,

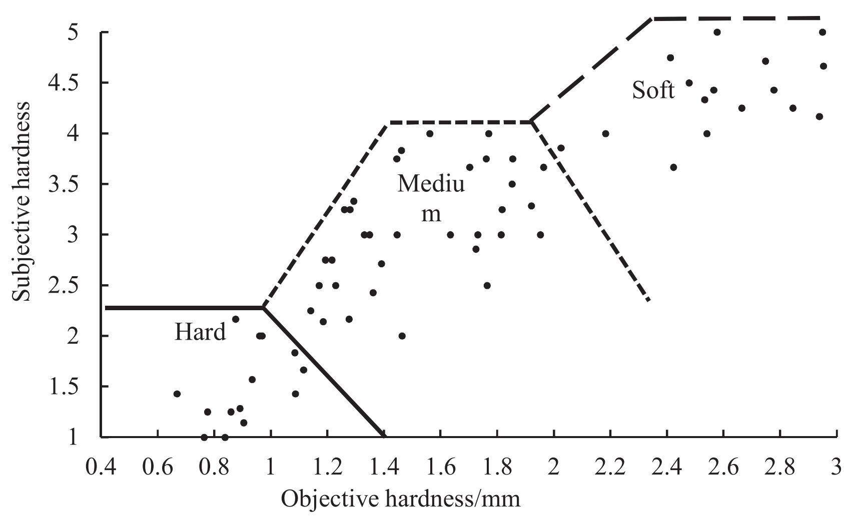


Fig. 5 – Determining boundaries of hardness membership function.

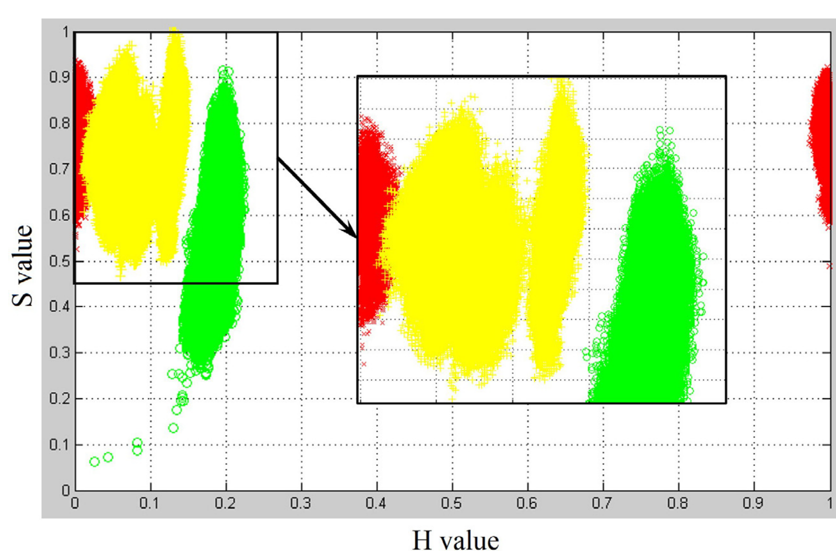


Fig. 6 – H vs. S component of a fruit surface color for separation of percentage of color pixels (green, orange and red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Please cite this article as: S. M. Nassiri, A. Tahavoor and A. Jafari, Fuzzy logic classification of mature tomatoes based on physical properties fusion, Information Processing in Agriculture, https://doi.org/10.1016/j.inpa.2021.09.001

Table 1 – If-then rules for converting fuzzy inputs to fuzzy outputs.

Color	Hardness	Hard			Medium			Soft		
	Size	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Red	Orange	Proc.	Grd. 1	Grd. 1	Proc.	Grd. 2	Grd. 2	Proc.	Proc.	Proc.
	Med. orange	Proc.	Grd. 1	Grd. 1	Proc.	Grd. 2	Grd. 2	Proc.	Proc.	Proc.
	Low orange	Proc.	Grd. 1	Grd. 1	Proc.	Grd. 2	Grd. 2	Proc.	Proc.	Proc.
Medium red	Orange	Proc.	Fr. Mt	Fr. Mt	Proc.	Grd. 2	Proc.	Proc.	Proc.	Proc.
	Med. orange	Proc.	Fr. Mt.	Fr. Mt.	Proc.	Proc.	Proc.	Proc.	Proc.	Proc.
	Low orange	Proc.	Fr. Mt	Fr. Mt	Proc.	Proc.	Proc.	Proc.	Proc.	Proc.
Low red	Orange	Stor.	Fr. Mt.	Fr. Mt.	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.
	Med. orange	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.
	Low orange	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.	Stor.

Proc., Grd. 1, Grd. 2, Stor. and Fr. Mt. refer to Processing, Grade 1, Grade 2, Storage and Far Market, respectively.

according to the consuming habits and interests and can be tuned locally.

Trapezoidal membership function was selected for outputs. Boundaries of functions were determined by the frequency of the classified fruits by trained panelist according to the rules in Table 1. Misclassification frequency was considered as percentage of fuzzy functions overlap and was computed by ratio of misclassification frequency to total frequency for each class. However, to ensure about acceptable dispersion among panelist classifications, kappa value was calculated for each class according to the multi-class grouping [28]. Kappa values for all five classes were more than 0.84 and it showed that panelists had an acceptable performance for classification [29]. No clear criterion for the percentage of overlaps were found in the literature, therefore the percentage of overlaps was considered 30% and the same for all functions according to the frequency of misclassifications.

Real input data for color, size and hardness converted to fuzzy input by membership functions, and then converted to fuzzy outputs by 81 linguistic If-Then fuzzy rules as given in Table 1. However, to make more appropriate and rational classification, 81 fuzzy rules were reduced to 25 rules by clustering the compatible ones as a final fuzzy rule system (Table 2) [30].

Combining all membership functions for size, color and hardness, fuzzy output of models then converted into real data ranged from zero to 500 by authors) by defuzzifiers (Mamdani case) that graphically illustrated in Fig. 7.

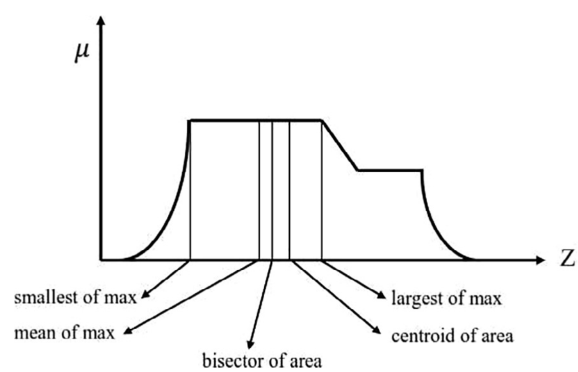


Fig. 7 – Graphical representation of different defuzzifiers.

Table 2 – Merging if-then fuzzy rules by considering compatible rules.

Fruit Color		Fruit hardness								
		Hard			Medium			Soft		
					Fruit size					
		Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Red	Orange									
	Med. Orange	Proc.	Grd. 1	Grd. 1	Proc.	Grd. 2	Grd. 2		Proc.	
	Low orange									
Medium red	Orange					Grd. 2			Proc.	
	Med. Orange	Proc.	Fr. Mt	Fr. Mt	Proc.	Proc.	Proc.Proc.			
	Low orange					Proc.				
Low red	Orange		Fr. Mt.	Fr. Mt.						
	Med. Orange	Stor.	Stor.	Stor.		Stor.			Stor.	
	Low orange		Stor.	Stor.						

Please cite this article as: S. M. Nassiri, A. Tahavoor and A. Jafari, Fuzzy logic classification of mature tomatoes based on physical properties fusion, Information Processing in Agriculture, https://doi.org/10.1016/j.inpa.2021.09.001

Table 3 – Six employed fuzzy models with different kinds of fuzzifier and defuzzifier functions.

Model	Fuzzifier (membership functions)			Output functions	Defuzzifier
	Left	Center	Right		
1	Trapezoid	Trapezoid	Trapezoid	Trapezoid	centroid
2	Trapezoid	Trapezoid	Trapezoid	Trapezoid	bisector
3	Trapezoid	Trapezoid	Trapezoid	Trapezoid	mom
4	zmf	gbellmf	sigmf	Trapezoid	centroid
5	zmf	gbellmf	sigmf	Trapezoid	bisector
6	zmf	gbellmf	sigmf	Trapezoid	mom

mom: min of max.

To find an appropriate fuzzy logic model in the present study, different kinds of membership functions and defuzzifiers were used and thereby six different models were created and compared as given in Table 3. Fuzzy toolbox in MATLAB 2014b was used to construct and run the trials.

2.4. *Model verification*

A new set of data (172 samples) were used to verify all fuzzy models outputs and select the best classification model. Therefore, the accuracy of classifications was calculated in contingency tables for all fuzzy models.

3. Results and discussion

3.1. *Results*

Final input membership functions were built according to the results of compression test and USDA standards values as shown in final form in Figs. 8–12. Fig. 8 is converted form Fig. 4 for hardness membership functions in which medium and soft sections of the curve were shifted vertically toward x-axis. Moreover, three trapezoidal parts of the curve were unitized to meet the appropriate value of membership function as y-axis. However, the boundaries were kept the same as obtained in Fig. 4. To draw out the proper values of sample color membership, two color values were considered simultaneously by applying Figs. 9 and 10. For instance, a sample with zero red and orange simultaneously, means the complete green sample. As discussed in the previous section, final output membership functions with trapezoidal shapes and 30% overlap were considered for fuzzy outputs and rated from zero to 500 (Fig. 12) [31].

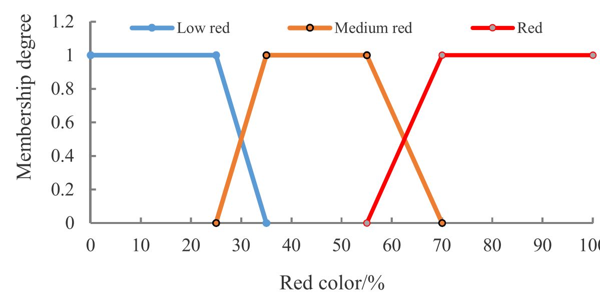


Fig. 9 – Input membership functions for tomato color (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

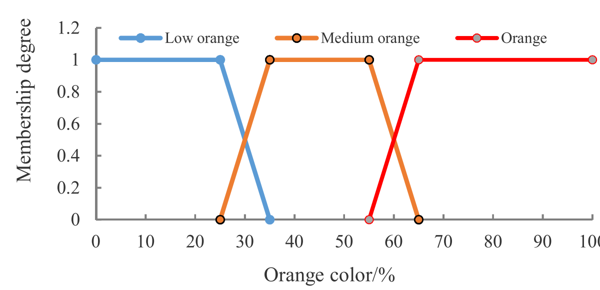


Fig. 10 – Input membership functions for tomato color (orange). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

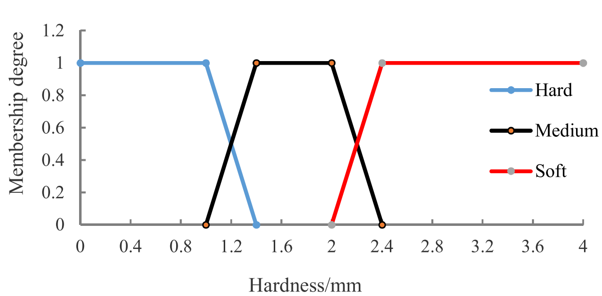


Fig. 8 – Input membership functions for tomato hardness.

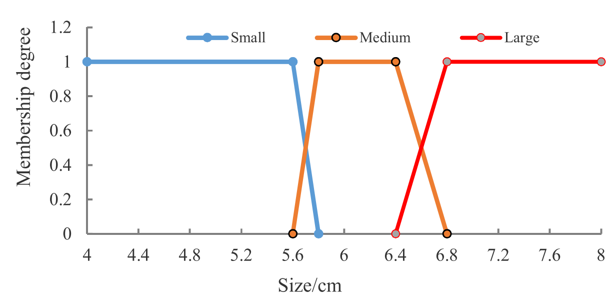


Fig. 11 – Input membership functions for tomato size.

Please cite this article as: S. M. Nassiri, A. Tahavoor and A. Jafari, Fuzzy logic classification of mature tomatoes based on physical properties fusion, Information Processing in Agriculture, https://doi.org/10.1016/j.inpa.2021.09.001

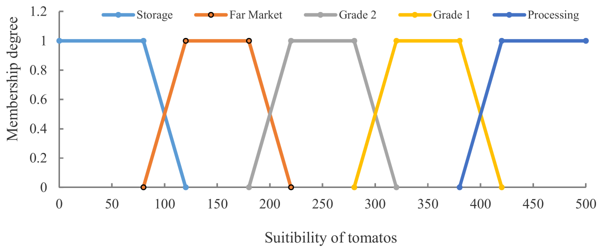


Fig. 12 – Boundaries of output membership functions (suitability for classifications).

Measured size, color and hardness of samples were subjected to six fuzzy models and the outputs were tabulated in cross tables. Table 4 shows a typical frequency of classified samples by fuzzy model 1. The experts classified the same samples. Having pairwise data (fuzzy and experts), accuracy and precision of models were computed as reported in Table 5. As it is clear, outputs of the sixth model (zmf, gbellmf and sigmf as fuzzifier, trapezoidal output function and mom as defuzzifier) were more accurate than others with 93.3% proper classification, followed by fifth and second models with 92.4% and 92.3% accuracy, respectively.

3.2. *Discussion*

Considering the results in Table 3, it is clear that classification accuracy of models 5 and 6 was affected by defuzzifier functions. In addition, the negligible difference between the accuracy of model 2 and 5 was due to the application of various membership functions. However, the trend was not the same for models 3 and 6 with the same defuzzifier and different fuzzifier function. It can be concluded that for such classification, different shape of fuzzifier, defuzzifiers should be evaluated, and appropriate match should be selected.

The lowest accuracy in all models took place for grade 1 and grade 2 as shown in Table 4 because of diversity in sensory evaluation. Some grade 1 samples classified in grade 2 class or vice versa. It might be due to two reasons, first, the same samples were subjected to two subjective and objective tests, and in other words, disturbed samples were used in second test. The other reason referred to dispersions in hardness values sensed by machine. The accuracy increased by increasing in hardness and decreasing in tomato redness. It means that the classification of mature but unripe tomatoes can be done more accurately. As reported by some researchers, it is noticeable that the rate of change in hardness and color components (or overall color) of tomatoes follow different trends. Hardness decays exponentially and faster than changes in color components [16,32-34]. The reason visually can be drawn from Fig. 4 (or Fig. 8) in which the boundarie of soft samples are wider than two other classes.

Nassiri et al. [35] reported higher classification accuracy for trapezoidal membership function of fruit hardness and mean of maximum (mom) defuzzifier. Sensitivity analysis showed that tomatoes classifications from grade 1 to grade 2 mostly affected by change in color and hardness, respectively. However, as recorded in Table 1, inaccuracy in classification for grade 1 and grade 2 might mostly be referred to difficulty in recognition of fruit hardness by a panelist. Pearson correlation coefficient of 0.89 between subjective and objective hardness approves a potential point for such misclassification (Fig. 5). They also reported that sensitivity of the models for reclassification of samples is not less than a three-day storage in ambient temperature. In other words, difference in percentage of proper classification is mostly because of fuzzifier

Table 4 – Cross table for determining accuracy of fuzzy model 1.

Subjective classification		Fuzzy algorithm output					Accuracy/%
		Grade1	Grade 2	Far market	Processing	Storage	
Grade 1	**44**	37	7	–	–	–	**84.1**
Grade 2	**50**	5	43	–	2	–	**86**
Far market	**27**	1	1	25	–	–	**92.6**
Processing	**32**	1	–	–	31	–	**96.9**
Storage	**19**	–	–	1	–	18	**94.7**

Table 5 – Accuracy (%) of all six fuzzy models.

Tomato classifications	Fuzzy model						Ave.	SD
	1	2	3	4	5	6		
Grade 1	84.1	77.3	61.4	84.1	84.1	79.5	**78.4**	**8.8**
Grade 2	86	88	86	80	88	90	**86.3**	**3.4**
Far market	92.6	96.3	96.3	92.6	96.3	100	**95.7**	**2.8**
Processing	96.9	100	100	90.6	93.8	96.9	**96.4**	**3.7**
Storage	94.7	100	100	89.5	100	100	**97.7**	**4.4**
Ave.	**90.9**	**92.3**	**88.7**	**87.4**	**92.4**	**93.3**		
SD	**5.6**	**9.7**	**16.3**	**5.2**	**6.4**	**8.7**		

Please cite this article as: S. M. Nassiri, A. Tahavoor and A. Jafari, Fuzzy logic classification of mature tomatoes based on physical properties fusion, Information Processing in Agriculture, https://doi.org/10.1016/j.inpa.2021.09.001

boundaries and defuzzifier algorithm. An attempt was made to find regular borders for hardness membership functions (Fig. 4), however boundaries overlapped as well as defuzzifier algorithm had significant effect on proper classification [36-38]. As reported by Villaseñor-Aguilar et al. [22], the overall accuracy might be increased by incorporating direct color features from RGB color space instead of using transformed data in other color spaces.

Nozari and Mazlomzadeh [39] employed 11 Gaussian membership functions for each of input extracted features of date fruits and reported 93.5% accuracy for classifications. In contrast, almost the same accuracy was gained with three membership functions in the present study. Moreover, another strength of the study was based on Mamdani fuzzy inference method in which a rating range was taken to the account for defuzzification [38]. Although, overlap in fuzzy membership functions is an important merit of fuzzy logic, especially when dealing with the subjective (human or environment) nature of outcomes [40], however as depicted by the results, the output drastically influenced by successive operations throughout fuzzification-defuzzification compiling [38]. The centroid method is reported to be the most prevalent and physically attractive of all the defuzzification methods [38], but as revealed in Tables 3 and 5, model 1 and model 4 did not work similarly with the same defuzzifier centroid method. On the other hand, model 6 with maximum accuracy of classification was not followed by model 3 with the same defuzzifiers (mean of max-mom). It may be concluded that all elements of Mamdani inference system (fuzzifier-fuzzy rules-defuzzifier) should be evaluated simultaneously according to the nature of the research data.

It was difficult to compare the output of the fuzzy logic based on fruit hardness due to lack of accessibility to close research works with the same idea, however there is some research on tomato classification based on fruit color, size and shape features [7,9,10,13-15,18,21]. Combination of three different features that have been employed here, have not been considered as classification criteria somewhere else (Table 6), however the present study has drawback of controlled image-capturing chamber.

Jahns et al. [41] reported that fuzzy image analysis attributes can be easily rearranged and optimized according to varying consumers' expectations. Therefore, combining more attributes mapped with consumers' preferences leads to multiple desirable outputs according to market needs. The results confirm feasibility of the proposed classification method and encourage the future continuation of the research in online tomato sorting.

4. Conclusion

In the present study, a combination of three physical and mechanical properties of tomato (color, size and hardness) were considered to classify the fruits by fuzzy algorithm. Hardness fuzzy membership functions were built based on local market demands. Fruits were categorized in five classes according to the fusion of three pre-introduced properties. A fuzzy model with zmf, gbellmf and sigmf as fuzzifier and mom defuzzifier classified tomatoes with an accuracy of 93.3%. Considering that, such fuzzy classification was in more agreement with customer's perception about ripe fruit and it outperforms the single feature classification, hence can be recommended for tomato sorting when the consumer preferences are different from place to place. Further research is needed to employ such algorithm on an online continuous test rig.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

Authors duly appreciate Shiraz University for funding the project.

REFERENCES

[1] Machado TA, Fernandes HC, Megguer CA, Santos NT, Santos FL. Quantitative and qualitative loss of tomato fruits during Mechanized harvest. Revista Brasileira de Engenharia Agrícola e Ambiental 2018;22(11):799–802.
[2] FAO. FAOstat: data; 2021. Accessed on http://www.fao.org/faostat/en/#data.
[3] Nemati H, Kaveh G, Vatandost S, Jalali T. Study on post-harvest loss of tomato for local retail market in Mashhad. Karafan J 2016;39:55–61 (in Persian).
[4] Berjan S, Capone R, Debs Ph, El Bilali H. Food Losses and Waste: A global overview with a focus on Near East and North Africa region. Int J Agric Manage Dev (IJAMAD) 2018;8(1):1–16.
[5] Polder G, van der Heijden GWAM, Young IT. Tomato sorting using independent component analysis on spectral images. Real-Time Imaging 2003;9(4):253–9.

Table 6 – Comparison between developed fuzzy algorithms for tomato sorting/grading considering different inputs.

Reference	Type of input				No of membership function (MF)				No of output MF	Accuracy or Error*
	Color	Size	Hardness	Shape	Color	Size	Hardness	Shape		
The present study	√	√	√	–	3	3	3	–	5	A 93.3%
[16]	√	–	–	–	3	–	–	–	3	–
[19]	√	–	–	–	3	–	–	–	2	E 536.99×10^{-6}
[21]	√	–	–	√	3	–	–	3	2 or more	–

* Sum of squared error.

[6] Arakeri MP, Lakshmana. Computer vision based fruit grading system for quality evaluation of tomato in agriculture industry. Procedia Comput Sci 2016;79:426–33.
[7] Behera SK, Mahapatra A, Kumar Rath A, Kumar SP. Classification and grading of tomatoes using image processing techniques. Int J Innov Technol Explor Eng (IJITEE) 2019;8(6S):545–50.
[8] Kaur S, Girdhar A, Gill J. Computer vision-based tomato grading and sorting. Link: https://ur.booksc.eu/book/69609980/97258a. 2018/2021.
[9] Lino ACL, Sanches J, Fabbro IMD. Image processing techniques for lemons and tomatoes classification. J Bragantia 2008;67(3):785–9.
[10] Omidi Arjenaki O, Ahmadi Moghaddam P, Moddares MA. Online tomato sorting based on shape, maturity, size, and surface defects using machine vision. Turk J Agric For 2013;37(1):62–8.
[11] Perin L, Peil RMN, Höhn D, Oliveira FKD. Cherry and Grape tomato fruits classification according different crop systems and defoliate levels. IDESIA J 2018;36(2):143–51.
[12] Semary NA, Tharwat A, Elhariri E, Hassanien AE. Fruit-Based Tomato Grading System Using Features Fusion and Support Vector Machine. In: Filev D. et al., editors. Intelligent Systems'2014. Advances in Intelligent Systems and Computing. Switzerland (Cham): Springer; 2015. p. 401–10.
[13] Wan P, Toudeshki A, Tan H, Ehsani R. A methodology for fresh tomato maturity detection using computer vision. Comput Electron Agric 2018;146:43–50.
[14] Wu J, Zhang B, Zhou J, Xiong Y, Gu B, Yang X. Automatic Recognition of Ripening Tomatoes by Combining Multi-Feature Fusion with a Bi-Layer Classification Strategy for Harvesting Robots. Sensors 2019;19(3):612–33.
[15] Gastelum-Barris A, Borquez-Lopez RA, Rico-Garcia ER, Toledano-Ayala M, Soto-Zarazua GM. Tomato quality evaluation with image processing: A review. Afr J Agric Res 2011;6(14):3333–9.
[16] Schouten RE, Huijben TPM, Tijskens LMM, Van Kooten O. Modeling quality attributes of truss tomatoes: Linking color and firmness Maturity. Postharvest Biol Technol 2007;45:298–306.
[17] Sirisomboon P, Tanaka M, Kojima T. Evaluation of tomato textural mechanical properties. J Food Eng 2012;111(4):618–24.
[18] Alavi N. Quality determination of Mozafati dates using Mamdani fuzzy inference system. J Saudi Soc Agric Sci 2013;12(2):137–42.
[19] Dorado LC, Aguila JIC, Caldo RB. Smart farm: automated classifying and grading system of tomatoes using fuzzy logic. LPU Laguna J Eng Comput Stud 2016;3(3):64–72.
[20] Iraji MS, Tosinia A. Classification Tomatoes on Machine Vision with Fuzzy the Mamdani inference, Adaptive Neuro Fuzzy Inference System Based (Anfis - Sugeno). Aust J Basic Appl Sci 2011;5:846–53.
[21] Hasan R, Monir SMG. Fruit maturity estimation based on Fuzzy Classification. In: Proc. of the 2017 IEEE international conference on signal and image processing applications. Malaysia; 2017. p. 12–4.
[22] Villaseñor-Aguilar MJ, Botello-Álvarez JEE, Pérez-Pinal FJ, Cano-Lara M, León-Galván MF, Bravo-Sánchez MG, Barranco-Gutierrez AI. Fuzzy Classification of the Maturity of the Tomato Using a Vision System. Link: https://www.hindawi.com/journals/js/2019/3175848. 2019/2021.
[23] Teoh YK, Abu Hasan S, Sauddin A. Automated mango fruit grading system using fuzzy logic. J Agric Sci 2014;6(1):41–7.
[24] George M. Multiple Fruit and Vegetable Sorting System Using Machine Vision. Link: https://www.longdom.org/open-access/multiple-fruit-and-vegetable-sorting-system-using-machine-vision-pdf. 2016/2021.
[25] Bourne M. Food Texture and Viscosity: Concept and Measurement. 2nd ed. USA: Academic Press; 2002.
[26] Mirabbasi R, Mazloumzadeh SM, Rahnama MB. Evaluation of irrigation water quality using fuzzy logic. Res J Environ Sci 2008;2(5):340–52.
[27] United States Standards for Grades of Fresh Tomatoes. Reprinted 1997.
[28] Davies M, Fleiss JL. Measuring agreement for multinomial data. Biometrics 1982;38(4):1047–51.
[29] Landis JR, Koch GG. The measurement of observer agreement for categorical data. Biometrics 1977;33:159–74.
[30] Bentley PJ. Evolving fuzzy detectives: an investigation into the evolution of fuzzy rules. In: Suzuki Y, Ovaska S, Furuhashi T, Roy R, Dote Y, editors. Soft Computing and its Engineering Applications. London: Springer; 2000. p. 89–106.
[31] Kavdir I, Guyer D. Apple grading using fuzzy logic. Turk J Agric For 2003;27:375–82.
[32] Lana MM, Tijskens LMM, Van Kooten O. Effects of storage temperature and storage of ripening on RGB color aspects of fresh cut tomato pericarp using video image analysis. J Food Eng 2006;77:871–9.
[33] Nassiri SM, Khajavi S, Ramezaniyan A. Image processing application to determine the color of tomato lycopene content in different temperature conditions. In: The first national conference on new technologies and post-harvest agricultural products. Iran, Mashhad: Agriculture and Natural Resources Research Center of Khorasan Razavi; 2014. p. 18–9 (in Persian).
[34] Van Dijk C, Boeriv C, Peter F, Stolle-smits T, Tijskens LMM. The firmness of stored tomatoes (cv.Tradiro): kinetic and near infrared models to describe firmness and moisture loss. J Food Eng 2006;77:575–84.
[35] Nassiri SM, Khajavi S, Jafari A. Sensitivity analysis of membership functions for tomato classification affected by storage temperature and duration. Iran Biosyst Eng J 2017;48:419–25 (in Persian).
[36] Bustince H, Femandez J, Mesiar R, Montero J, Orduna R. Overlap index, overlap functions and migrativity. Link: https://eprints.ucm.es/id/eprint/16893/1/Montero22.pdf. 2009/2021.
[37] Guillaume S, Charnomordic B. Fuzzy inference systems: an integrated modelling environment for collaboration between expert knowledge and data using Fispro. Expert Syst Appl 2012;39:8744–55.
[38] Wang C. A study of membership functions on Mamdani-type fuzzy inference system for industrial decision-making Doctor thesis. Pennsylvania: Lehigh University; 2015.
[39] Nozari V, Mazlomzadeh M. Date fruits grading based on some physical properties. J Agric Technol 2013;9(7):1703–13.
[40] Shang K, Hossen Z. Applying fuzzy logic to risk assessment and decision-making. Link: https://www.soa.org/globalassets/assets/Files/Research/Projects/research-2013-fuzzy-logic.pdf. 2013/2021.
[41] Jahns G, Møller Nielsen H, Paul W. Measuring image analysis attributes and modelling fuzzy consumer aspects for tomato quality grading. Comput Electron Agric 2001;31(1):17–29.

Please cite this article as: S. M. Nassiri, A. Tahavoor and A. Jafari, Fuzzy logic classification of mature tomatoes based on physical properties fusion, Information Processing in Agriculture, https://doi.org/10.1016/j.inpa.2021.09.001