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Fuzzy Logic-Based Model for Predicting Quality of Fresh Tomatoes

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Abstract

The quality of tomatoes has become very important since their widespread use and diverse functions, both for fresh consumption and as raw materials for processed products. Conventional assessment of tomato freshness is still based on visual inspection and laboratory tests, which are inefficient. Meanwhile, the use of technology and artificial intelligence (AI), such as fuzzy logic, has been applied to evaluate food quality efficiently, accurately, and non-destructively. Thus, this study aims to design a fuzzy logic-based tomato freshness assessment system with quality-determining variables, which are hardness and color. The fuzzy logic-based tomato quality assessment system involves four main stages, namely fuzzification, rule base formulation, fuzzy inference, and defuzzification. Fuzzy rules are also developed to describe the logical relationship between variables in the form of "if-then". The application of the fuzzy method can improve the efficiency of tomato quality assessment activities by linking input variables (color and hardness) with outputs in the form of tomato quality levels. This system is similar to the human reasoning process, making it ideal for evaluating agricultural commodities. Therefore, the fuzzy model is an ideal method for determining the freshness quality of tomatoes, which requires a precision control system in diverse and uncertain conditions.

Keywords: Fuzzy logic, tomato, Predicting, Quality

INTRODUCTION

Tomatoes (*Solanum lycopersicum*) are one of the main horticultural commodities in many countries due to their high consumption and nutritional value. For example, their vitamin C, lycopene, and other antioxidant content (Nkolisa et al. 2019). Tomatoes can be consumed fresh or processed. However, tomatoes are perishable due to their high water content and rapid post-harvest respiration. The decline in tomato quality is evident in changes in color, texture, fruit firmness, and chemical content such as total soluble solids (°Brix), thus requiring a method of assessing freshness that is fast, accurate, and, if possible, non-destructive (Li et al. 2018).

Conventional food freshness assessment generally still relies on visual inspection and laboratory testing, which are time-consuming, costly, and often result in subjective interpretations (Salehi et al. 2020). With the development of artificial intelligence (AI) technology, intelligent computing approaches are increasingly being applied to improve the accuracy and efficiency of quality control in agricultural and horticultural products (Ali et al. 2021). One method that is rapidly developing is fuzzy logic.

Fuzzy logic is a computational method developed to handle uncertainty and linguistic data that cannot be expressed explicitly, such as in binary logic. In the context of assessing the quality of agricultural products, fuzzy logic allows the combination of several input variables, such as color, hardness, and moisture content, into a single output in the form of a freshness level with a certain membership level. In the context of assessing the quality of agricultural products, fuzzy logic allows the combination of several input variables such as color, hardness, and water content into a single output in the form of a freshness level with a certain membership level, for example, “fresh”, “somewhat fresh”, and “not fresh” (Li et al. 2018). This approach mimics the way humans make assessments by considering various interrelated factors. Thus, the evaluation results are more realistic and flexible than conventional classification systems. The application of fuzzy inference systems (FIS) can classify tomato quality with greater precision than conventional thresholding methods (Cano-Lara dan Rostro-Gonzalez 2024).

In Indonesia, fuzzy logic has also been applied in microcontroller-based post-harvest monitoring and agricultural environmental control systems. This shows the potential for applying fuzzy logic in tomato quality assessment systems (Anshory et al. 2025). Based on this background, this study aims to design a fuzzy logic-based tomato freshness assessment system. The expected result is a robust and practical fuzzy model that can be applied to determine the quality level of fresh tomatoes.

METHODS

This study began with a literature review to understand the principles and applications of fuzzy logic in assessing the quality of fresh agricultural products, particularly tomatoes. According to Nassiri et al. (2022), fuzzy logic based classification systems can effectively integrate physical parameters such as color, size, and hardness to determine fruit quality with an accuracy of up to 93.3%. This approach is superior to conventional visual assessment methods because it can handle uncertainty and linguistic variability in data. Other studies have also shown that color and hardness are key indicators reflecting the level of ripeness and freshness of tomatoes (Kaur et al., 2021; Silva et al., 2020). Based on these findings, this study simplifies the model by using only two main parameters color and hardness to design a practical yet representative fuzzy logic based prediction model for tomato quality.

Data analysis was carried out using two input variables (color and hardness) and one output variable (quality). The color variable ranged from 0 to 100 and was divided into three linguistic categories: Low Red, Medium Red, and Red. The hardness variable ranged from 0 to 4 with three linguistic terms: Mushy, Soft, and Medium. The output variable represented the overall tomato quality, categorized into three levels Bad, Moderate, and Good within a domain range of 0 to 10. The fuzzy inference system used in this study followed the Mamdani method, which consists of four main stages: fuzzification, rule base formulation, fuzzy inference, and defuzzification. Each numerical value was converted into a linguistic value using trapezoidal membership functions, allowing the system to process data that resemble human perception of product quality.

Color was selected as a primary input because it provides a reliable, quantifiable indication of tomato ripeness. Using digital image processing, the a* values obtained from each sample were assigned to the linguistic categories defined earlier in the Methods—low red, medium red, and red. This mapping allowed the system to capture gradual shifts in maturity and translate visual appearance into interpretable ripeness levels. The distribution of samples within these categories is shown in Figure 1, illustrating how color contributes to distinguishing between unripe, intermediate, and fully ripe tomatoes.

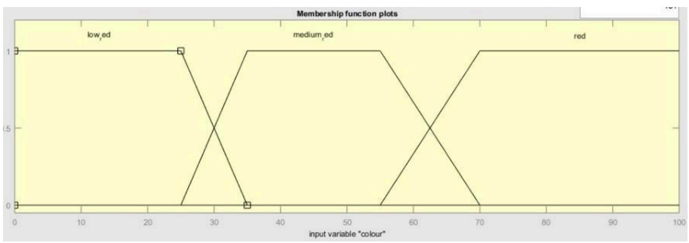


Figure 1. Input Variable Color

Hardness was incorporated as the second key input to represent textural changes during ripening. The measured firmness values were aligned with the linguistic groups mushy, soft, and medium, enabling the system to reflect the progressive transition in texture that occurs as tomatoes mature. Because the membership functions for hardness overlap, samples exhibiting intermediate softness could be represented more accurately, which supports the model's ability to handle natural variability. Figure 2 shows how the samples were distributed across these categories, demonstrating the role of hardness in differentiating quality levels and strengthening the inference results.

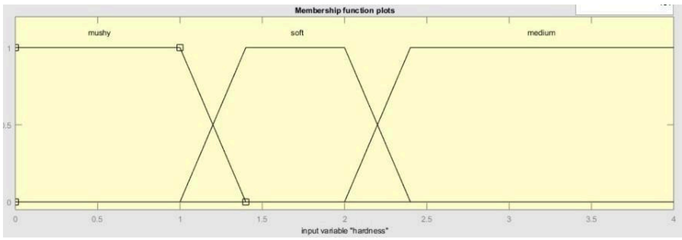


Figure 2. Input Variable Hardness

Fuzzy logic is commonly utilized for situations where the available data contain ambiguity, lack precision, or are affected by noise (Rindengan & Langi, 2019). In this research, a set of fuzzy rules was developed to model the relationships between variables using conditional "if–then" formulations. For instance, a tomato exhibiting Low Red coloration and Mushy texture is evaluated as having Bad quality; a combination of Medium Red color and Soft hardness corresponds to Moderate quality; and a tomato that is Red and Medium in hardness is identified as Good quality. The Mamdani inference approach was employed to compute the membership strength for each triggered rule, while the final assessment was derived through the Mean of Maximum (MOM) defuzzification technique, producing a single quality score ranging from 0 to 10. This procedure allows the system to approximate human-like reasoning in judging tomato freshness and ensures reliable, easy-to-interpret outputs for postharvest quality evaluation.

RESULTS AND DISCUSSION

Based on the established fuzzy logic model, this section outlines the performance of the system in estimating the quality of fresh tomatoes. The inputs of color and hardness were processed using the specified membership functions and rule structure, producing a single numerical quality outcome through the Mamdani inference procedure. The analysis explores how variations in the input values shape the final quality assessment and reviews the stability, logical alignment, and clarity of the model results. The evidence shows that the approach delivers consistent and well reasoned predictions, reinforcing its value as a supporting tool for evaluating tomato quality after harvest.

1. Variable Definition

The definition of variables is an important stage in the development of fuzzy logic systems because it determines the input and output parameters and their value ranges. In this study, two input variables were used, namely Color and Hardness, and one output variable, namely Quality. Each variable has a linguistic set and a value domain that allows numerical data to be translated into linguistic representations according to the perception of tomato quality. The Color variable consists of three linguistic sets, namely Low Red, Medium Red, and Red, with a value range of 0 to 100. A low value indicates a pale tomato, a medium value indicates a medium level of ripeness, and a high value indicates a deep red color as a sign of optimal ripeness. The Hardness variable has three categories, namely Mushy, Soft, and Medium, with a value range of 0 to 4, which describes the texture from soft to firm, which is considered ideal. Hardness is an important indicator because it is related to the freshness and shelf life of the fruit. The output variable Quality consists of Bad, Moderate, and Good with a value range of 0 to 10, describing the quality of tomatoes based on a combination of color and hardness.

Table 1. Definition of Input and Output Variables in the Fuzzy Model for Tomato Quality Prediction

Function	**Variable Name**	**Set**	**Universe of Discourse**	**Domain**
Input	Color	Low red		[0 0 25 35]
		Medium red	[0-100]	[25 35 55 70]
		Red		[55 70 100 100]
	Hardness	Medium		[0 0 1 1.4]
		Soft	[0-4]	[1 1.4 2 2.4]
		Mushy		[2 2.4 4 4]
Output	Quality	Bad		[0 2 4]
		Moderate	[0-10]	[3 5 7]
		Good		[6 8 10]

The Color variable consists of three linguistic sets, namely Low Red, Medium Red, and Red, with a value range of 0 to 100. A low value indicates a pale tomato, a medium value indicates a medium level of ripeness, and a high value indicates a deep red color as a sign of optimal ripeness. The Hardness variable has three categories, namely Mushy, Soft, and Medium, with a value range of 0 to 4, which describes the texture from soft to firm, which is considered ideal. Hardness is an important indicator because it is related to the freshness and shelf life of the fruit. The output variable Quality consists of Bad, Moderate, and Good with a value range of 0 to 10, describing the quality of tomatoes based on a combination of color and hardness. The relationship between variables is determined by three basic rules. First, if Color is Low Red and Hardness is Mushy, then Quality is Bad. Second, if Color is Medium Red and Hardness is Soft, then Quality is Moderate. Third, if Color is Red and Hardness is Medium, then Quality is Good. This rule indicates that quality improves with more mature color and stable hardness, while a combination of pale color and soft texture reduces quality. Thus, the fuzzy system can automatically and consistently assess tomato quality based on its physical parameters.

Figure 3. Fuzzy Logic Model

The fuzzy model developed in this study evaluates tomato quality by using color and hardness as the two main input variables. These numerical inputs were translated into linguistic categories—low red, medium red, and red for color, and mushy, soft, and medium for hardness—based on the membership functions defined in the Methods. This linguistic representation allows the system to interpret ripeness and texture in a more human-like manner and contributes to improved classification accuracy (Feng, 2018).

The quality output is generated through a set of "if–then" rules that link the two inputs to corresponding quality levels. The Mamdani inference method was applied because of its suitability for modeling human decision-making patterns (Sianipar & Handoko, 2020), with min–max operators used for logical operations, implication, and aggregation. This structure aligns with recent findings showing that integrating external physical characteristics improves the precision of tomato quality assessment (Cano-Lara & Rostro-Gonzalez, 2024).

Following the inference step, defuzzification using the Centroid method produces a single numerical score that represents the tomato's overall quality. This approach is consistent with previous applications of fuzzy logic in automated postharvest sorting, which report enhanced reliability and adaptability across variable product conditions (Harahap, 2022; Tanesan Wyot et al., 2016). Overall, incorporating color and hardness within a fuzzy inference framework helps address uncertainty in subjective quality evaluation and strengthens the consistency and efficiency of postharvest grading systems.

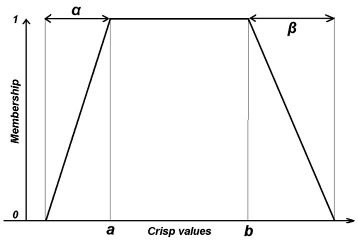
2.1 Membership Degree

The membership values derived from each input indicate how strongly a sample corresponds to the linguistic categories defined within the model. These values function as weighting components during the inference process, guiding how each input condition contributes to the final quality assessment. The reliability of the resulting output is closely linked to the appropriateness of the membership functions established during model construction, since these values play a central role in shaping the consistency of the system's decisions (Saputra, 2020).

Trapezoidal Curve Representation

The representation of a trapezoidal curve has a wider domain than the representation of a triangular curve, as follows:

$$\mu(x)=\begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a < x \le b \\ 1 & b < x \le c \\ \dfrac{d-x}{d-c} & c < x \le d \\ 0 & x > d \end{cases}$$



Based on the trapezoidal membership function, the membership set value μx(a,b,c) is obtained. The color intensity membership set model can be explained as follows:

$$\mu_{\text{medium red}}=\begin{cases} 0,\ x \le 25 \\ \dfrac{x-25}{35-25},\ 25 \le x \le 35 \\ 1,\ 35 \le x \le 55 \\ \dfrac{70-x}{70-55},\ 55 \le x \le 70 \\ 0,\ 70 \le x \end{cases}$$

$$\mu_{\text{low red}}=\begin{cases} 0,\ x \le 0 \\ \dfrac{x-0}{0-0},\ 0 \le x \le 0 \\ 1,\ 0 \le x \le 25 \\ \dfrac{35-x}{35-25},\ 25 \le x \le 35 \\ 0,\ 35 \le x \end{cases}$$

$$\mu_{\text{red}} = \begin{cases} 0, \; x \leq 55 \\ \frac{x-55}{70-55}, \; 55 \leq x \leq 75 \\ 1, \; 70 \leq x \leq 100 \\ \frac{35-x}{35-25}, \; 100 \leq x \leq 100 \\ 0, \; 100 \leq x \end{cases}$$

Based on the trapezoidal membership function, the membership set value µx(a,b,c) is obtained. The hardness level membership set model can be explained as follows:

$$\mu_{\text{mushy}} = \begin{cases} 0, \; x \leq 0 \\ \frac{x-0}{0-0}, \; 0 \leq x \leq 0 \\ 1, \; 0 \leq x \leq 1 \\ \frac{1.4-x}{1.4-1}, \; 1 \leq x \leq 1.4 \\ 0, \; 1.4 \leq x \end{cases}$$

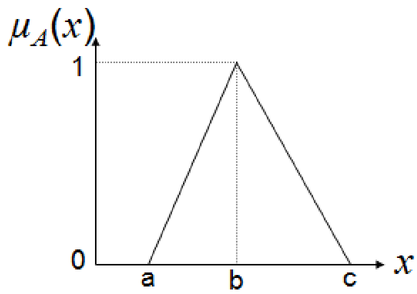
$$\mu_{\text{soft}} = \begin{cases} 0, \; x \leq 1 \\ \frac{x-1}{1-1.4}, \; 1 \leq x \leq 1.4 \\ 1, \; 1.4 \leq x \leq 2 \\ \frac{2.4-x}{2.4-2}, \; 2 \leq x \leq 2.4 \\ 0, \; 2.4 \leq x \end{cases}$$

$$\mu_{\text{medium}} = \begin{cases} 0, \; x \leq 2 \\ \frac{x-2}{2.4-2}, \; 2 \leq x \leq 2.4 \\ 1, \; 2.4 \leq x \leq 4 \\ \frac{4-x}{4-4}, \; 4 \leq x \leq 4 \\ 0, \; 4 \leq x \end{cases}$$

Triangular Curve Representation

The representation of a triangular curve is basically a combination of an upward linear curve and a downward linear curve, as follows:

$$\mu_A(x) = \begin{cases} 0 & \text{if } x \leq a \\ \dfrac{x-a}{b-a} & \text{if } a \leq x \leq b \\ \dfrac{c-x}{c-b} & \text{if } b \leq x \leq c \\ 0 & \text{if } x \geq c \end{cases}$$



Based on the triangular membership function, the membership set value μx(a,b,c) is obtained. The quality level membership set model can be explained as follows:

$$\mu_{\text{bad}} = \begin{cases} 0, \; x \leq 0 \\ \dfrac{x-0}{2-0}, \; 0 \leq x \leq 2 \\ \dfrac{4-x}{4-2}, \; 2 \leq x \leq 4 \\ 0, \; 4 \leq x \end{cases}$$

$$\mu_{\text{moderate}} = \begin{cases} 0, \; x \leq 3 \\ \dfrac{x-3}{5-3}, \; 3 \leq x \leq 5 \\ \dfrac{7-x}{7-5}, \; 5 \leq x \leq 7 \\ 0, \; 7 \leq x \end{cases}$$

$$\mu_{\text{good}} = \begin{cases} 0, \; x \leq 6 \\ \dfrac{x-6}{8-6}, \; 6 \leq x \leq 8 \\ \dfrac{10-x}{10-8}, \; 8 \leq x \leq 10 \\ 0, \; 10 \leq x \end{cases}$$

2. Fuzzy Rules

Fuzzy rules describe the logical connection between input and output variables within a fuzzy logic framework. Each rule expresses a conditional statement in the form of “if and then”, linking certain linguistic conditions of input variables to a qualitative outcome. In this case, two input variables are considered, colour and hardness, while the single output variable is quality. The colour variable represents the ripeness stage of the tomato with linguistic terms low red, medium red, and red. The hardness variable corresponds to the fruit’s firmness with linguistic levels mushy, soft, and medium. The output variable quality is described by bad, moderate, and good.

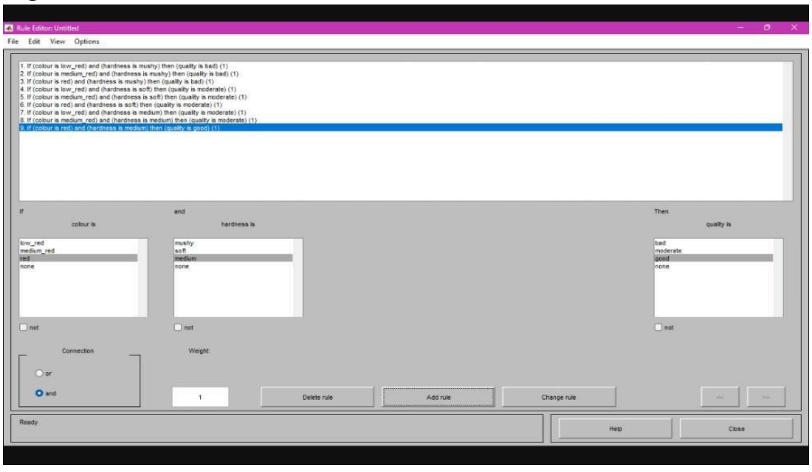


Fig 4. Fuzzy Rule Base Color and Hardness in Tomatoes

Figure 4 illustrates the fuzzy rule base developed to assess tomato quality. The system combines both colour and hardness conditions to determine the final quality score. Each combination provides a unique inference that represents different quality grades of the tomatoes. Generally, tomatoes that appear bright red and maintain a medium level of firmness are categorized as good quality. Conversely, tomatoes that are pale or overly soft are considered to have poor quality. The fuzzy logic system effectively captures human perception in evaluating fruit quality, while providing consistent, quantifiable results suitable for automation.

From the model's inference, a combination of red colour and medium firmness indicates the best-quality tomatoes. On the other hand, low redness and mushy texture correspond to lower quality levels. This demonstrates the usefulness of fuzzy systems in supporting automated grading or quality control processes for tomato products

3. Fuzzy Inference System

The Fuzzy Inference System (FIS) functions as the central mechanism within the fuzzy logic framework designed to estimate the quality of fresh tomatoes based on measurable indicators such as color and firmness. This system incorporates four primary stages fuzzification, fuzzy rule construction, inference, and defuzzification to convert quantitative input data into qualitative assessments that align with human perceptions of ripeness and texture (Feng, 2018).

In the constructed fuzzy model, the FIS employs two input variables, Color and Hardness, along with a single output variable, Quality. The relationship between these variables is defined through a set of fuzzy *if–then* rules, which encapsulate expert knowledge in tomato quality evaluation. For example, when the tomato color is categorized as *Low Red* and its hardness as *Mushy*, the resulting quality is considered *Bad*. Conversely, a *Medium Red* color combined with *Soft* texture corresponds to *Moderate* quality, while a *Red* color and *Medium* firmness indicate *Good* quality. These fuzzy rules represent the logical linkage between ripeness indicators and perceived overall quality (Tanesan Wyot et al., 2016).

The Mamdani-type Fuzzy Inference System is adopted due to its strong resemblance to human reasoning processes, making it highly suitable for evaluating agricultural commodities (Sianipar & Handoko, 2020). Within this approach, the inference process applies logical operators such as AND, OR, and implication—commonly executed through the *min* and *max* operators for rule aggregation. The *min* operator defines intersections (AND operation), while the *max* operator combines the outcomes of all activated rules. This logical mechanism produces smooth transitions among quality levels, accurately reflecting the gradual nature of tomato ripening.

Following inference, the defuzzification stage transforms the fuzzy output into a single crisp value representing tomato quality. The Centroid or *Center of Gravity* method is implemented due to its ability to yield consistent and representative outcomes, minimizing variability and improving prediction reliability. This method has been widely recognized in agricultural modeling for its robustness and ease of interpretation (Cano-Lara & Rostro-Gonzalez, 2024).

The integration of trapezoidal membership functions for both input and output variables enhances the model's capacity to handle uncertainty and continuous transitions between linguistic categories. This design enables accurate interpretation of variations in color intensity and texture softness, avoiding rigid or abrupt classifications. Consequently, the fuzzy inference approach contributes to greater consistency, reliability, and automation in postharvest quality control systems (Harahap, 2022).

Overall, the developed Fuzzy Inference System highlights the potential of fuzzy logic in translating subjective human evaluations such as ripeness and texture into objective numerical assessments. Through the Mamdani FIS framework, the system not only enhances classification precision but also supports adaptive and intelligent decision-making in food quality assessment. The synergy between expert-driven rules and mathematically structured inference positions fuzzy logic as a valuable tool for evaluating agricultural product quality under uncertain or variable conditions.

4. Defuzzification

Moment Calculation

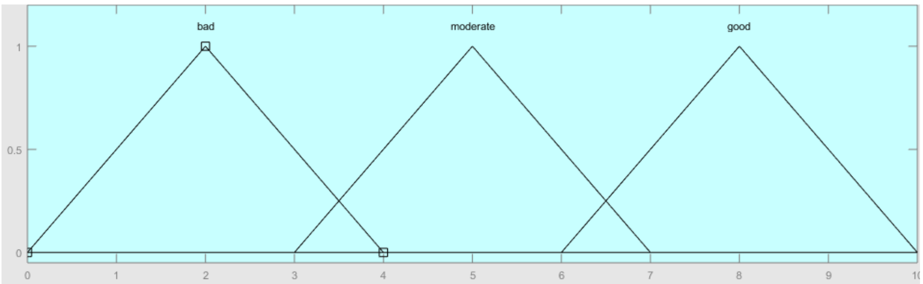


Fig 5 Output variable quality

$$z\_c\_bad= \frac{0+2+4}{3} =2$$

$$z\_c\_mod= \frac{3+5+7}{3} =5$$

$$z\_c\_good= \frac{6+8+10}{3} =8$$

$$A\_bad= \frac{4\times0,3}{2} =0,6$$

$$A\_mod= \frac{4\times0,6}{2} =1,2$$

$$A\_good= \frac{4\times0,2}{2} =0,4$$

$$M\_bad= 0,6\times2 =1,2$$

$$M\_mod= 1,2\times5 =6$$

$$M\_good= 0,4\times8 =3,2$$

Final Calculation

$$z^* = \frac{M_{bad} + M_{mod} + M_{good}}{A_{bad} + A_{mod} + A_{good}}$$

$$z^* = \frac{1.2 + 6.0 + 3.2}{0.6 + 1.2 + 0.4} = \frac{10.4}{2.2} = \mathbf{4.73}$$

The figure illustrates the defuzzification process in determining tomato quality based on color and hardness variables. Using the centroid (center of gravity) method, a final crisp value of 4.73 was obtained as the weighted average of the fuzzy membership degrees. The input variables—color and hardness—are represented by triangular membership functions that describe the linguistic terms such as pale–medium–red for color and hard–moderate–soft for hardness. Each fuzzy rule produces a certain activation level, resulting in three output membership functions for quality: bad, moderate, and good. The aggregated fuzzy output is then defuzzified to a single crisp value. This crisp output value (4.73) indicates that the overall tomato quality is categorized as “moderate”, meaning the sample tomatoes possess acceptable characteristics in both color intensity and firmness, aligning with medium ripeness and marketable quality levels.

Interpretation of Defuzzification

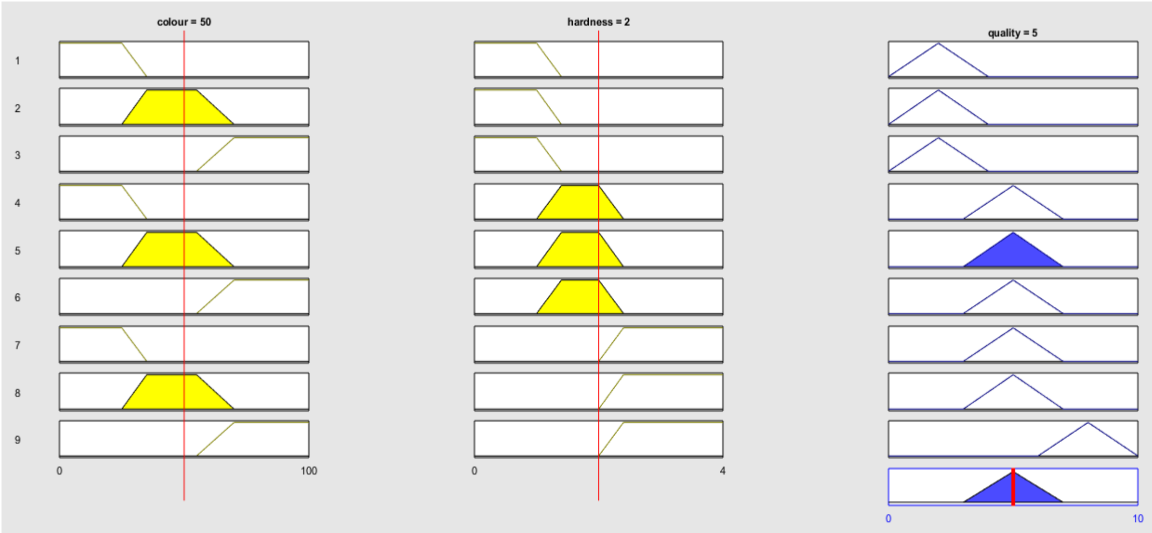


Fig 6 Matlab result calculation

Based on the figure, the calculation results using the MATLAB fuzzy inference system show that the input values of colour = 50 and hardness = 2 correspond to the fuzzy sets colour = moderate and hardness = moderate. According to the fuzzy rule base, these input conditions produce an output value of quality = 5, which belongs to the moderate category.

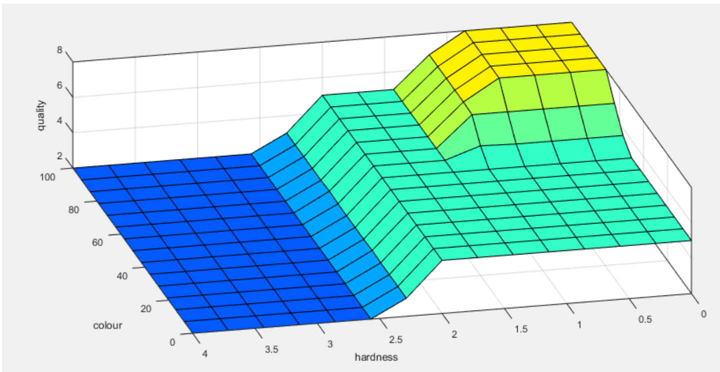


Fig 7 Matlab data surface result

CONCLUSION

The integration of fuzzy logic-based models in quality control systems can effectively predict the quality of fresh tomatoes without damaging the tomatoes themselves by using color (pink, medium red, red) and hardness (soft, medium, hard) as input parameters, as well as defining three logic rules. This system can then produce quality outputs categorized as bad, medium, and good. Tomatoes with low red color and soft texture are classified as bad quality because they represent fruits that are not fully ripe but have softened, resulting in low quality. Tomatoes with medium red color and soft texture are classified as medium quality because they represent tomatoes with a medium level of ripeness and a slightly soft texture, but are still acceptable in terms of quality. Meanwhile, tomatoes with red color and medium texture are classified as good quality tomatoes because the deep red color and firm texture are indicative of ideal conditions. has a high degree of similarity to human reasoning processes, making this system suitable for evaluating the quality of tomatoes and other agricultural commodities. Therefore, fuzzy models are an ideal method for determining the quality of agricultural products and other applications that require precision control systems in diverse and uncertain conditions.

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