

Real-time classification of Pasaman oranges using Mamdani fuzzy inference system and ESP32 microcontroller

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ABSTRACT

Manual classification of Pasaman oranges based on visual assessment of size and color often produces inconsistent results due to human subjectivity. This study develops an automatic classification system using a Mamdani fuzzy inference system (FIS) implemented on an ESP32 microcontroller. Fruit diameter is measured using a high-frequency sound wave ranging module (HC-SR04) ultrasonic sensor, while surface color is detected using a TAOS color sensor 3200 (TCS3200) color sensor. The obtained data are processed through fuzzification, inference, and defuzzification to classify oranges into three quality grades (A, B, and C). System performance evaluation shows strong agreement between the developed system and matrix laboratory (MATLAB) simulation, with a coefficient of determination (R^2) value of 0.9855, indicating reliable and consistent classification performance for automated agricultural grading applications.

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1. INTRODUCTION

Pasaman orange is one of Indonesia's leading citrus commodities, particularly from West Sumatra. This variety has many enthusiasts and therefore holds significant agribusiness potential [1]; however, its quality varies greatly, and classification technology has not been widely applied. Meeting market demands requires effective quality control to ensure consumer satisfaction and competitiveness against other citrus varieties [2]. Currently, classification is still performed manually, leading to low uniformity, inconsistency, and dependence on the operator's subjectivity. Similar challenges have also been observed in other fruits such as apples and mangoes, further highlighting the need for intelligent classification approaches [3].

Field observations revealed that manual grading is hampered by inconsistent standards and operator perception, which ultimately reduces market value and hinders competitiveness. Therefore, the development of an automated classification system is essential to improve reliability and efficiency [4]. Recent technological advances have made it possible to integrate sensor-based measurement and intelligent decision-making mechanisms into agricultural applications [5]. For instance, ultrasonic sensors enable real-time diameter detection, while color sensors provide accurate ripeness measurement [6], [7]. When combined with fuzzy logic, such systems have been proven effective for non-destructive fruit quality assessment [8], [9].

The Mamdani fuzzy inference system (FIS) is widely used due to its intuitive rule-based reasoning and effectiveness in processing sensor data [10]. Fuzzy logic was selected for its ability to handle uncertainty and emulate human reasoning in classification tasks [11]. By integrating diameter and color parameters, the Mamdani FIS enables adaptive and reliable classification despite variations in fruit characteristics [12], [13].

Its interpretability, minimal data requirements, and suitability for real-time implementation make it appropriate for agricultural grading systems [14], [15].

Despite these advances, few studies have focused on real-time, microcontroller-based fruit classification systems tailored to local commodities in Indonesia. Accordingly, this research aims to design and implement an automatic classification system for Pasaman oranges using Mamdani FIS and ESP32. The system is expected to improve accuracy, consistency, and efficiency in fruit grading, thereby supporting farmer productivity and contributing to the modernization of Indonesia's agricultural sector.

2. METHOD

This study employs an experimental approach aimed at designing and evaluating an automatic classification system for Pasaman oranges based on sensor-derived data. The method enables both system development and direct performance testing. The research was carried out in four main stages: variable observation, fuzzy logic system design, program performance testing, and evaluation. The classification system was developed on the ESP32 platform using the Arduino integrated development environment (IDE) software, with fuzzy rules coded using a custom function based on the Arduino-fuzzy library framework. The quality parameters of Pasaman oranges are determined by diameter and color index red, green, and blue (RGB), particularly the red component [16].

2.1. Variable observation

The study began with direct observation of classification practices among farmers in Nagari Ujung Gading, West Pasaman. Farmers typically classify oranges based on two criteria: fruit size (diameter) and skin color (green, slightly yellow, and fully yellow). Based on these practices, the oranges were grouped into three quality classes derived from a combination of size and color.

Color was quantified using the red (R) component value of the fruit skin, as the red spectrum strongly influences ripening color. The red component is a determinant factor in citrus maturity [17]. Prior to data collection, sensors were calibrated: the HC-SR04 ultrasonic sensor was validated against digital caliper measurements at multiple distances, while the TCS3200 sensor was calibrated under a constant light-emitting diode (LED) light source to minimize ambient lighting effects. Table 1 presents the pre-research measurements used as reference ranges.

Table 1. Pre-research measurements

Class	Diameter (cm)	Red ratio
A	4–6	0.3–0.46
B	5.3–7	0.43–0.57
C	6–7.8	0.54–0.6

2.2. Fuzzy logic system design

The Mamdani fuzzy logic method was employed to determine fruit classes based on diameter and color. This method is particularly suitable because it can process uncertain data, such as fruit color, which often lacks sharp boundaries. The system was implemented on the ESP32 microcontroller for real-time data processing. Previous studies have shown that color sensor technology contributes significantly to classification accuracy and reduces human error [18]. Moreover, fuzzy logic enables the handling of linguistic variables that are difficult to address using threshold-based methods [19].

The membership functions for both diameter and color were defined as trapezoidal functions derived from the observed ranges in Table 1, ensuring smooth transitions between overlapping categories. The rationale for using trapezoidal shapes is their ability to model gradual ripening boundaries and avoid abrupt thresholding.

The design process began with converting diameter and color data into fuzzy values (fuzzification). These inputs were then processed through a set of "if-then" rules coded in the ESP32 environment. For example, if the size is small and the color is green, then the fruit is classified as class C; if the size is large and the color is yellow, then it belongs to class A. After applying the rules, the results were combined and transformed into crisp outputs (defuzzification) using the centroid of area (COA) method to provide the final classification. Table 2 shows the fuzzy inference rules.

Table 2. If-then rules

No	If condition	Then
A1	Size is small and color is green	Class C
A2	Size is small and color is slightly yellow	Class C
A3	Size is small and color is yellow	Class C
A4	Size is medium and color is green	Class C
A5	Size is medium and color is slightly yellow	Class B
A6	Size is medium and color is yellow	Class B
A7	Size is large and color is green	Class B
A8	Size is large and color is slightly yellow	Class A
A9	Size is large and color is yellow	Class A

2.3. Program performance testing

The developed program was tested to evaluate classification performance and identify potential errors. The system outputs obtained from the ESP32 microcontroller were compared against the results generated by matrix laboratory (MATLAB) software. This comparison ensured that the classification process implemented in hardware corresponded with the established FIS in MATLAB. Sensor sampling was performed at a rate of 10 Hz to ensure stable readings. The ESP32 system was designed with an update cycle of 100 ms per classification, allowing near real-time performance suitable for on-field grading.

2.4. Evaluation

At the final stage, the classification results were re-evaluated to verify error rates during the grading process. The MATLAB-based FIS was used as a benchmark for comparison. The accuracy of the system depends significantly on the quantity and diversity of training data [20]. The performance criterion was based on the coefficient of determination (R^2). If $R^2 \leq 0.90$, system modifications were applied until the value exceeded $R^2 \geq 0.90$, ensuring reliable classification performance.

In addition to R^2 , confusion matrices were generated to analyze class-level accuracy for grades A, B, and C, providing a clearer evaluation of classification outcomes. While results indicated high accuracy, limitations remain in terms of sample size, variability of test fruits, and potential environmental effects (e.g., lighting or sensor noise). Nevertheless, the system demonstrates the potential of Mamdani FIS on ESP32 as a practical real-time solution for citrus classification in Indonesian agriculture.

3. RESULTS AND DISCUSSION

The decision-making system in this study was designed using Mamdani fuzzy logic, with diameter and color as decision variables. Mamdani fuzzy logic was selected because of its ability to handle uncertain and subjective data, making it suitable for classifying fruit quality where values often overlap. The fuzzy-based classification consists of three stages: fuzzification (converting data into fuzzy sets), fuzzy inference (decision-making using rules), and defuzzification (converting fuzzy results into crisp outputs).

3.1. Fuzzification

The first step involved defining fuzzy sets for each input and output variable. The classification tool employed three fuzzy variables: two inputs (size and color) and one output (quality). Input values obtained from the HC-SR04 and TCS3200 sensors were converted into fuzzy membership values. The trapezoidal membership function (Trapmf) was used because it effectively handles gradual value transitions within a defined range [21]. Table 3 presents the fuzzy universe.

Table 3. Fuzzy universe

Function	Variable	Universe of discourse
Input	Size	[0–10]
	Color	[0–1]
Output	Quality	[0–1]

3.1.1. Size variable (fruit diameter)

Fruit diameter was used as the primary parameter for classification. The membership functions for size were divided into three linguistic values: small, medium, and large. Figure 1 shows the membership function for the size variable.

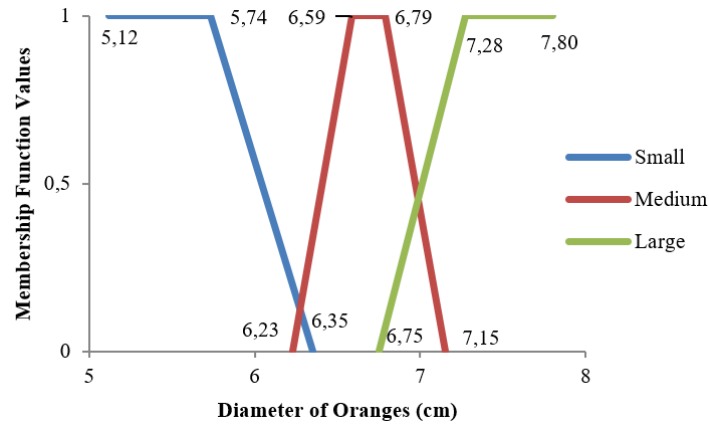


Figure 1. Membership function graph for size variable

Based on Figure 1, the ranges were: small (5.12–6.35 cm), medium (6.23–6.59 cm), and large (6.75–7.80 cm). Ambiguities occurred when a diameter overlapped two classes (e.g., 6.3 cm fits both small and medium). Fuzzy logic resolved such overlaps by assigning membership degrees to multiple categories. The membership functions were expressed as:

$$\mu_{Small}(x_{a1}) = \begin{cases} 1, & x \leq 5.735 \\ \frac{6.35-x}{6.35-5.735}, & 5.735 < x < 6.35 \\ 0, & x \geq 6.35 \end{cases}$$

$$\mu_{Medium}(x_{a2}) = \begin{cases} 0, & x \leq 6.230 \\ \frac{x-6.23}{6.59-6.23}, & 6.23 < x < 6.59 \\ 1, & 6.59 \leq x \leq 6.79 \\ \frac{7.15-x}{7.15-6.79}, & 6.79 < x < 7.15 \\ 0, & x \geq 7.15 \end{cases}$$

$$\mu_{Large}(x_{a3}) = \begin{cases} 0, & x \leq 6.75 \\ \frac{x-6.75}{7.15-6.75}, & 6.75 < x \leq 7.275 \\ 1, & x \geq 7.275 \end{cases}$$

The MATLAB simulation confirmed that the implemented membership functions matched the designed graph (Figure 2). The horizontal axis shows the measurement samples, whereas the vertical axis represents the detected distance values in centimeters obtained from ultrasonic sensors.

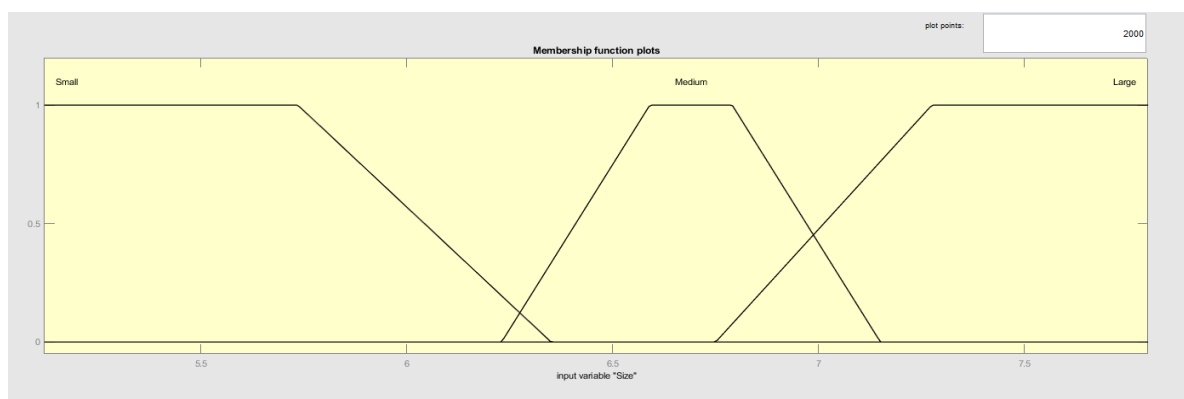


Figure 2. Size membership function in MATLAB

3.1.2. Color variable (red ratio)

The color variable was obtained from the red ratio of the TCS3200 sensor output. Three fuzzy sets were defined: green, slightly yellow, and yellow (Figure 3).

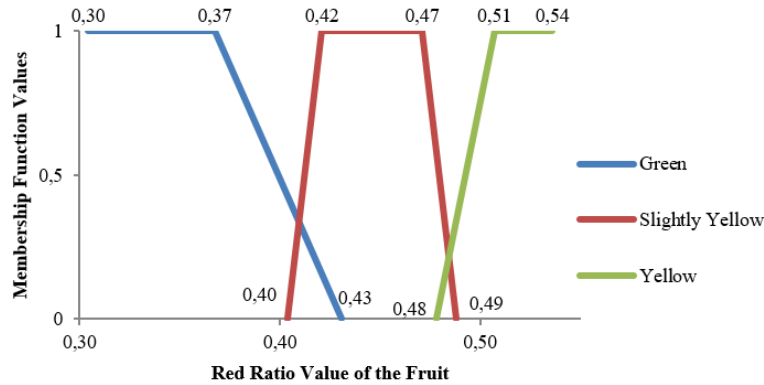


Figure 3. Membership function graph for color variable

The membership functions for color are defined as:

$$\mu_{Green}(xb1) = \begin{cases} 1, & x \leq 0.367 \\ \frac{0.431-x}{0.431-0.367}, & 0.367 < x < 0.431 \\ 0, & x \geq 0.431 \end{cases}$$

$$\mu_{SlightlyYellow}(xb2) = \begin{cases} 0, & x \leq 0.404 \\ \frac{x-0.404}{0.421-0.404}, & 0.404 < x < 0.421 \\ 1, & 0.421 \leq x \leq 0.471 \\ \frac{0.488-x}{0.488-0.471}, & 0.471 < x < 0.488 \\ 0, & x \geq 0.488 \end{cases}$$

$$\mu_{Yellow}(xb3) = \begin{cases} 0, & x \leq 0.478 \\ \frac{x-0.478}{0.507-0.478}, & 0.478 < x \leq 0.507 \\ 1, & x \geq 0.507 \end{cases}$$

The membership functions were defined similarly and verified in MATLAB (Figure 4). The ESP32 code implementation of these variables is shown in Figure 5. The horizontal axis represents the sensor reading index obtained during the measurement process, while the vertical axis indicates the corresponding RGB intensity values detected from the orange surface.

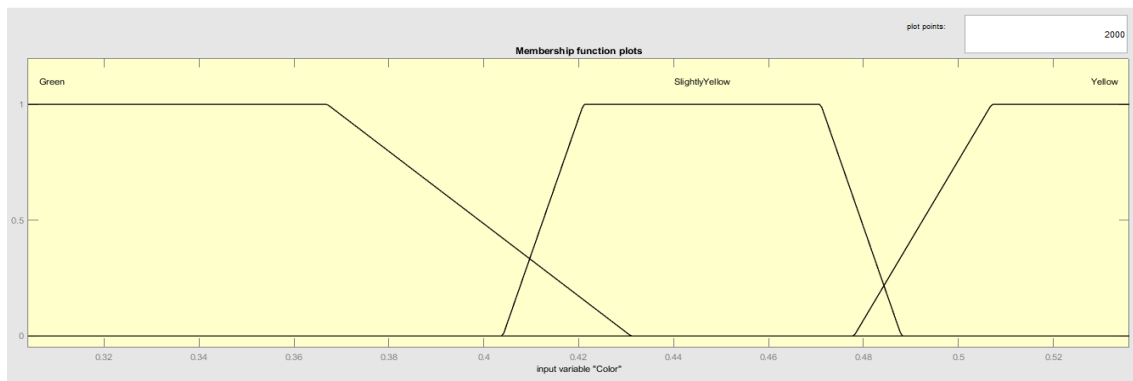


Figure 4. Color membership function in MATLAB

```

// Fuzzy Input 1: maxSize
FuzzyInput *maxSize = new FuzzyInput(1);
FuzzySet *small = new FuzzySet(0, 0, 5.735, 6.350);
FuzzySet *medium = new FuzzySet(6.23, 6.59, 6.79, 7.15);
FuzzySet *large = new FuzzySet(6.75, 7.275, 15, 15);
maxSize->addFuzzySet(small);
maxSize->addFuzzySet(medium);
maxSize->addFuzzySet(large);
fuzzy->addFuzzyInput(maxSize);
// Fuzzy Input 2: averageRedRatio
FuzzyInput *averageRedRatio = new FuzzyInput(2);
FuzzySet *green = new FuzzySet(0, 0, 0.367, 0.431);
FuzzySet *slightlyYellow = new FuzzySet(0.404, 0.421, 0.471, 0.488);
FuzzySet *yellow = new FuzzySet(0.478, 0.507, 1, 1);
averageRedRatio->addFuzzySet(green);
averageRedRatio->addFuzzySet(slightlyYellow);
averageRedRatio->addFuzzySet(yellow);
fuzzy->addFuzzyInput(averageRedRatio);
// Fuzzy Output: fruitQuality
FuzzyOutput *fruitQuality = new FuzzyOutput(1);
FuzzySet *C = new FuzzySet(0, 0, 0.2, 0.4);
FuzzySet *B = new FuzzySet(0.2, 0.4, 0.6, 0.8);
FuzzySet *A = new FuzzySet(0.6, 0.8, 1, 1);
fruitQuality->addFuzzySet(C);
fruitQuality->addFuzzySet(B);
fruitQuality->addFuzzySet(A);
fuzzy->addFuzzyOutput(fruitQuality);

```

Figure 5. ESP32 variable membership program

3.2. Rule

After fuzzification, the decision rules were implemented using Mamdani inference. The rules (Table 2 in Method) were programmed into the ESP32 (Figure 6) and MATLAB (Figure 7). The MATLAB rule viewer provided a visual validation of the inference process. Figure 8 shows the surface viewer illustrating how varying size and color inputs determine fruit quality.

```

// Define fuzzy rules
struct Rule {
    FuzzySet *size;
    FuzzySet *color;
    FuzzySet *result;
} rules[] = {
    {small, green, C}, {small, slightlyYellow, C}, {small, yellow, C},
    {medium, green, C}, {medium, slightlyYellow, B}, {medium, yellow, B},
    {large, green, B}, {large, slightlyYellow, A}, {large, yellow, A}
};
for (int i = 0; i < 9; i++) {
    FuzzyRuleAntecedent *ifCondition = new FuzzyRuleAntecedent();
    ifCondition->joinWithAND(rules[i].size, rules[i].color);
    FuzzyRuleConsequent *thenResult = new FuzzyRuleConsequent();
    thenResult->addOutput(rules[i].result);
    fuzzy->addFuzzyRule(new FuzzyRule(i + 1, ifCondition, thenResult));
}

```

Figure 6. ESP32 if-then rule program

```

1. If (Size is Small) and (Color is Green) then (Grade is Grade_C) (1)
2. If (Size is Small) and (Color is SlightlyYellow) then (Grade is Grade_C) (1)
3. If (Size is Small) and (Color is Yellow) then (Grade is Grade_C) (1)
4. If (Size is Medium) and (Color is Green) then (Grade is Grade_C) (1)
5. If (Size is Medium) and (Color is SlightlyYellow) then (Grade is Grade_B) (1)
6. If (Size is Medium) and (Color is Yellow) then (Grade is Grade_B) (1)
7. If (Size is Large) and (Color is Green) then (Grade is Grade_B) (1)
8. If (Size is Large) and (Color is SlightlyYellow) then (Grade is Grade_A) (1)
9. If (Size is Large) and (Color is Yellow) then (Grade is Grade_A) (1)

```

Figure 7. MATLAB if-then rule program

Figure 8 shows the 3D surface viewer in MATLAB, visualizing how the fuzzy rules respond to varying input values (red ratio and size) and produce output (fruit class). The surface illustrates a smooth transition: high red ratio and large size lead to high-quality fruit (Class A). This visualization helps verify the overall fuzzy system performance.

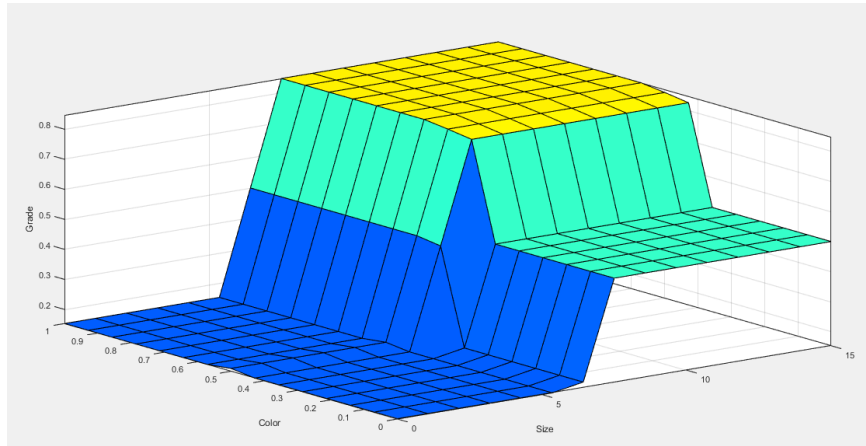


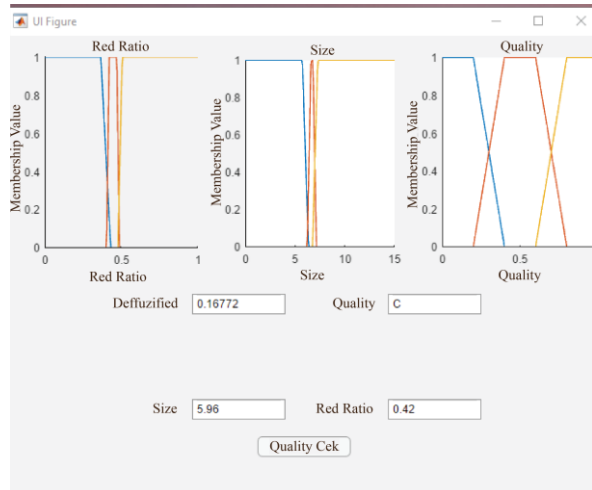
Figure 8. Surface viewer in MATLAB

3.3. Defuzzification testing

Defuzzification testing was conducted by comparing results from the orange grading machine and MATLAB. The same membership functions, variables, and rules were applied to both platforms to ensure consistency. Figure 9 illustrates this comparison: Figure 9(a) shows the classification results produced by the grading machine, while Figure 9(b) presents the corresponding results obtained from MATLAB. This side-by-side visualization highlights the similarity in outputs, confirming that the Mamdani fuzzy system implemented on the ESP32 microcontroller closely replicates the MATLAB benchmark.

Max size : 5.73,	Red Ratio : 0.32,	Defuzzified : 0.16,	Quality : C
Max size : 7.62,	Red Ratio : 0.32,	Defuzzified : 0.50,	Quality : B
Max size : 7.73,	Red Ratio : 0.50,	Defuzzified : 0.83,	Quality : A
Max size : 7.06,	Red Ratio : 0.45,	Defuzzified : 0.69,	Quality : A
Max size : 7.12,	Red Ratio : 0.33,	Defuzzified : 0.48,	Quality : B
Max size : 7.03,	Red Ratio : 0.59,	Defuzzified : 0.66,	Quality : A
Max size : 7.08,	Red Ratio : 0.40,	Defuzzified : 0.44,	Quality : B
Max size : 6.84,	Red Ratio : 0.51,	Defuzzified : 0.54,	Quality : B
Max size : 6.86,	Red Ratio : 0.64,	Defuzzified : 0.55,	Quality : B
Max size : 7.04,	Red Ratio : 0.46,	Defuzzified : 0.67,	Quality : A
Max size : 7.05,	Red Ratio : 0.32,	Defuzzified : 0.43,	Quality : B
Max size : 6.89,	Red Ratio : 0.33,	Defuzzified : 0.29,	Quality : C
Max size : 7.01,	Red Ratio : 0.42,	Defuzzified : 0.59,	Quality : B
Max size : 7.09,	Red Ratio : 0.45,	Defuzzified : 0.73,	Quality : A
Max size : 7.51,	Red Ratio : 0.40,	Defuzzified : 0.50,	Quality : B
Max size : 6.86,	Red Ratio : 0.64,	Defuzzified : 0.55,	Quality : B
Max size : 5.97,	Red Ratio : 0.35,	Defuzzified : 0.17,	Quality : C
Max size : 7.51,	Red Ratio : 0.32,	Defuzzified : 0.50,	Quality : B
Max size : 7.72,	Red Ratio : 0.49,	Defuzzified : 0.82,	Quality : A
Max size : 6.19,	Red Ratio : 0.34,	Defuzzified : 0.19,	Quality : C

(a)



(b)

Figure 9. Defuzzification results: (a) grading machine and (b) MATLAB software

This comparison ensures that the Mamdani fuzzy system implemented in hardware produces low reading errors. Figure 10 presents the correlation chart between the two outputs. The results showed a very strong correlation, with $R^2 = 0.9855$, and regression equation $y = 0.9784x + 0.0094$. An R^2 value this high indicates that the ESP32-based fuzzy system can replicate MATLAB's classification results with high reliability, making it feasible for real-time fruit sorting in agricultural contexts.

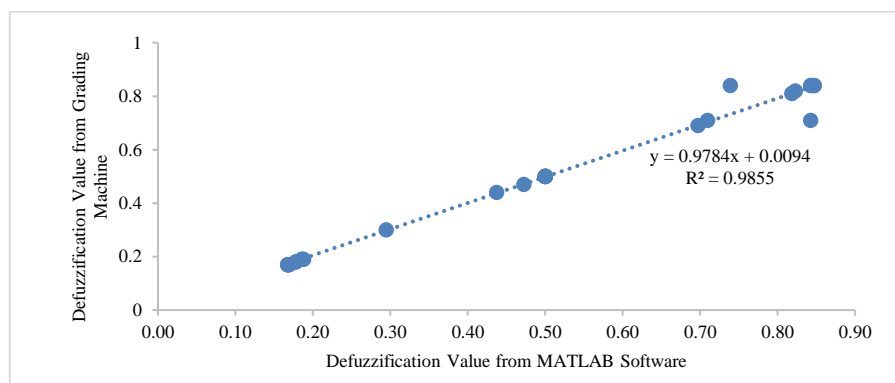


Figure 10. Defuzzification results comparison

These findings align with prior studies, where Mamdani-based fuzzy systems achieved error rates below 1% [22], classification accuracy up to 96% [23] and performance above 90% when sensors were combined with fuzzy inference [24]. Our system's performance ($R^2 = 0.9855$) is therefore consistent with these works, while also providing portability and potential scalability for other agricultural products [25]. Although confusion matrices were generated to evaluate classification outcomes, detailed performance metrics such as precision, recall, and F1-score were not quantitatively analyzed in this study. Future work should incorporate these metrics together with misclassification analysis to provide deeper insight into class-level performance and system robustness under varying environmental conditions.

However, some limitations remain. The system is currently limited to three quality grades (A, B, and C), and the TCS3200 color sensor may be sensitive to variations in ambient lighting, potentially affecting classification robustness. Future research should include class-level performance metrics (precision, recall, and F1-score) and misclassification analysis to identify sources of error and further improve real-world deployment.

4. CONCLUSION

This study successfully developed an automatic classification system for Pasaman oranges using the Mamdani FIS implemented on the ESP32 microcontroller. By integrating HC-SR04 for diameter measurement and TCS3200 for color detection, the system achieved high accuracy, with $R^2 = 0.9855$, demonstrating its reliability for real-time fruit grading.

The proposed system improves efficiency, consistency, and objectivity in orange classification, thereby supporting the digitization and modernization of agricultural practices in Indonesia. In practical terms, such a system could be adopted by farmer cooperatives or small-scale producers to enhance product uniformity and competitiveness in the market.

For future development, the framework can be expanded to classify multiple fruit types, integrated with internet of things (IoT) platforms for remote monitoring, or adapted into portable/mobile applications to increase accessibility. These enhancements would further strengthen its role in precision agriculture and broaden its applicability across diverse horticultural commodities. Future studies should also investigate computational efficiency and power consumption of the ESP32-based implementation to optimize long-term field deployment and energy utilization in agricultural environments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Ifmalinda		✓			✓		✓	✓		✓		✓	✓	
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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the articles.




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