Determination of Tomato Fruit Stages Using Principal Component Analysis and Fuzzy Logic Algorithm

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***Abstract*— E-Nose Technology is an excellent non-destructive way to identify different gases and perform diverse working environments. It also provides accurate data and is less expensive. Philippine Statistic Authority data shows that the country's tomato production is still rising. The goal is to develop a portable e-nose device that uses fuzzy logic and principal component analysis to identify tomato ripeness. The researchers used MQ3, MQ4, MQ6, MQ7, and MQ135 sensors for the 60-day data acquisition of unripe tomatoes, where the researchers used principal component analysis. After applying the algorithm, MQ3 and MQ135 show low sensor responses. An Arduino Uno controlled the prototype and was connected to the Raspberry Pi 4 for its portability. The three essential sensors demonstrate a rise with each ripeness stage, while MQ6 and MQ7 show little differences in values. The result of the model's overall accuracy is 88%, while the weighted average precision for each classification is 88.7%, indicating that the method is reasonably accurate.**

***Index Terms*— E-nose, Fuzzy Logic Algorithm, Principal Component Analysis, MQ sensors, Raspberry Pi 4**

I. INTRODUCTION

Several researchers accomplished and developed the E-nose system in previous years. It is now widely utilized in various industries, including agriculture, manufacturing machines that generate gases, healthcare, and identifying gases to diagnose and treat ailments accurately. This system is a strong choice for determining the ripeness of fruits and a non-destructive method. Traditional methods have the disadvantage of requiring the fruits or vegetables to be tested for firmness by exerting force, which results in damage and spoilage. In assessing the ripeness of the fruits, other damaging approaches include measuring variables like pH, sugar level, and ethylene contents. Using our sense of touch, we can also determine the fruit's ripeness by testing its firmness. Nuclear magnetic resonance (NMR) and proton magnetic resonance (PMR), which measure the soluble solids, are non-destructive means of detecting fruit ripeness. Accommodating the acoustic impedances of the emitter and the fruit examined by the system using acoustic methods is a challenge[1]. A lack of information prevents vision systems from accurately evaluating how ripe a fruit is. E-nose is the most widely used non-destructive technology for determining the ripeness of fruits and vegetables, primarily due to its affordability[2]. By shrinking a large set to a smaller size that contains the majority of the information in the large group, Principal Component Analysis (PCA) is a technique for size reduction that researchers frequently use to reduce the dimensionality of large datasets. For a study to obtain acceptable accuracy from large data sets, it is necessary to reduce their size dimensionality while reducing information loss or conserving as much information as possible. It generates new uncorrelated variables that maximize variance[3].

Numerous sectors employ the electronic nose technique, and different algorithms in various combinations have demonstrated the high accuracy of the data for identifying and categorizing gases. The maturity of tomatoes can be assessed in a study using two typical engineering studies: one uses an E-nose system to collect the gases the tomatoes produce, and the other uses image processing. One researcher created an E-nose to classify the quality of chili sauce based on five metal oxide gas sensors and employed pattern recognition based on principal component analysis. Their results reveal a correct rate percentage of 97.8%.[4] Principal component analysis and KNN for increased classification were used by prior studies in a different survey of researchers in detecting harvested or commercially vegetables and fruits on spoilage problem in the refrigerator. The results showed excellent percentages for detecting spoilage.[5] Lastly, in another research to determine the ripeness of the tomatoes using different color models based on a neural network, they used 50 samples of test data and 20 samples of data. The sample training data consists of 10 unripe tomato pictures and ten images of ripe tomatoes, while the test sample consisted of 16 photos of ripe tomatoes and 36 unripe tomato images; their research shows the classification reached 96% with a true 48 and false 2 of the total 50 test data [6] There are six stages tomatoes ripening which are mature green, turning, breaker, light red, red ripe and pink.. When the tomato surface is green, it is in the mature green stage. At this stage, the flavor has not yet fully developed. The tomato's color goes from its mature green stage to another during the "Breaker Stage," During this stage, light pink or red color appears at the end of the fruit, indicating that the tomatoes are producing ethylene gas, which promotes ripening. The tomato's color changes from green to tannish-yellow, pink, or red at the turning stage when it is less firm than in the earlier phases. Pink Stage fruit has a pink or red tint covering more than 30% but less than 60% of its surface. More than 60% but less than 90% of the tomato's surface is in Light Red Stage's pinkish crimson or red color. Lastly, more than 90% of the tomato's character has reached the red-ripe stage, and the fruit is neither too hard nor too soft. [7][8]. In research that shows how to determine the level of spoilage, a multi-layered feedforward artificial neural network, especially a five-layered network, apply as a algorithm for process of the data: an input layer, three hidden layers, and an output layer, with propagation together, and using Stochastic Gradient Descent for the application of the training for the data gathered. Engineers use Python programming to create a neural network on the Raspberry Pi 4 Model B.[9] Air-tight sensor chambers are excellent for monitoring when dealing with gases that demand careful experimentation and observation. The researchers employed a section to monitor the gases emitted by fruit for this particular publication. When the ethylene sensor detects ethylene analog input to the gas sensor, it passes via the ADS115 ADC module, which converts the analog input into a digital signal and generates an output saved in a CSV file. Every fruit is watched for hours every day until they are overripe.[10]

Principal Component Analysis (PCA) and fuzzy logic algorithms are still unavailable in a portable E-nose device that can determine whether tomatoes are ripe. Researchers suggest good ventilation for the chamber during the ripening of E-nose fruit to provide excellent data from gas sensors.

The study's main objective is to determine the tomato fruit stages using Principal Component Analysis. Specific objectives of the study follows: (1) To use E-nose for the detection of gas for the tomato fruit stages (2) To implement the Fuzzy Logic Algorithm, the algorithm has the ability to develop accurate solutions from known knowledge and when the standard logic computer was not capable of managing data and expressing vague or subjective person thoughts for classifying tomato ripeness, (3) To implement confusion matrix for statistical treatment.

The study will assist tomato farm industries through the data obtained during the trial period and by evaluating the gas sensor response of the ripe, unripe, and overripe tomatoes.

Within 60 days, data will be gathered twice daily on the sample tomato starting at its mature green stage. Researchers used the principal component analysis to identify the most significant sensor contribution and ignore lower sensor responses. The test tomato is placed in a heated chamber between 28 and 32 degrees Celsius to lower the interior moisture content. The big datasets are reduced to smaller ones using principal component analysis, which retains most of their information. Researchers incorporated a DHT11 temperature sensor and five MQ sensors to detect the data. The gas sensors MQ3, MQ4, MQ6, MQ7, and MQ135, are used.

II. MATERIALS AND METHODS

A. Conceptual Framework

The researchers have developed an effective algorithm that can identify datasets after considering earlier bodies of work. This study aimed to categorize a tomato's stages using the gases that the fruit releases. The algorithm of choice pertinent to the topic was Principal Component Analysis (PCA). For the study to identify various approaches for determining a tomato's ripening stages, we have conducted further analysis of earlier works.[11] A few studies have used an E-Nose prototype to classify fruits and vegetables using machine learning methods.[12][13] These elements aid in formulating and establishing the theoretical body of knowledge that would be addressed by the real-time detection of tomato ripeness utilizing Principal Component Analysis (PCA) and fuzzy logic algorithm.

Researchers discovered that no gadget currently exists that uses PCA to determine whether a tomato is ripe. Having identified some problems that need to be addressed by researchers in this study, we must make solutions. This research aims to address various points to establish viable solutions for this problem to be solved in the most efficient way possible. Part of the solution would be collecting all available gas concentration data on all the sensors inside. By converting the dataset to digital from its analog state, the study would be able to identify the gases that stand out when a tomato's ripeness process happens. Upon finishing the task, the Principal Component Analysis (PCA) algorithm comes in. Applying the Fuzzy Logic Algorithm in classifying the stages of a tomato, researchers would get to produce a real-time device that could tell if a tomato is ripe, unripe, or overripe.

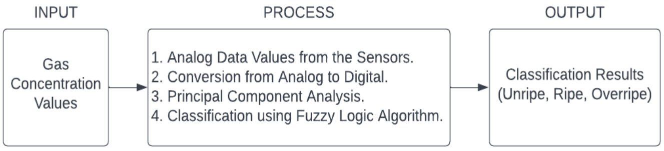

Fig. 1. Conceptual Framework

Figure 1 shows the intended conceptual framework of the research. There are five MQ gas sensors: MQ3, MQ4, MQ6, MQ7, and MQ135. The gathered data from the gas sensors will be the inputs to the Arduino UNO. After converting the values generated by the sensors from analog to digital, Principal Component Analysis (PCA) is the algorithm used to process the data set using the Raspberry Pi 4.[14] The final output display if the tomatoes' falls under the Unripe, Ripe, or Overripe classification using fuzzy logic algorithm. With the use of fuzzy logic tools such as the fuzzy logic designer, we could generate appropriate fuzzy values rules that would be essential in determining the accurate classification of the tomatoes subject to testing.

B. Hardware Development

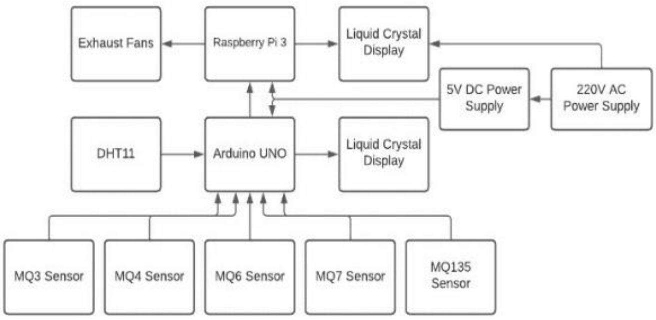

Fig. 2. Hardware Block Diagram

Figure 2 above illustrates the system's hardware block diagram. A 5V power supplies the Raspberry Pi 4 and the Arduino Uno. At the same time, the Liquid Crystal Display (LCD) is used to monitor and display the output classification of the tomatoes, and the 220V AC Power Supply powers it. The Arduino Uno is placed inside the container and used for gathering data from the gas sensors inside. DHT11 is the temperature and humidity sensor used to monitor the conditions inside the container and will be displayed using an LCD connected to the Arduino UNO. The Raspberry Pi 4 processes the collected data using the Principal Component Analysis (PCA) algorithm and powers the two exhaust fans. All processed data by the Raspberry Pi 4 and an LCD shows it.

C. System Development

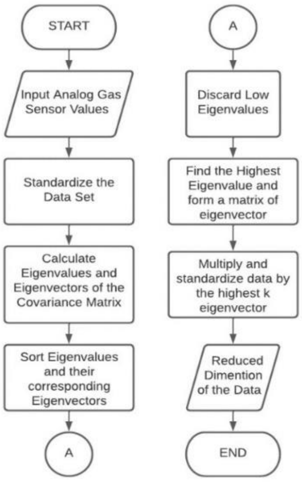

Fig. 3. PCA System Flowchart

Figure 3 shows the PCA system flowchart. It starts with the input of analog gas sensor values. Next is to standardize the data set. It would then calculate eigenvectors and eigenvalues of the covariance matrix to identify the principal components. Then finally, multiply the standardized data by the highest principal eigenvector. Discarding the low eigenvalues is for the reduction of the data but remains most of the information. We will use the highest eigenvalue because it has the most information. Fuzzy rules are created and will be based on the readings of the remaining MQ Sensors that the PCA will consider. The conditions are based on gathered data after conducting a 60-day experiment on the device.

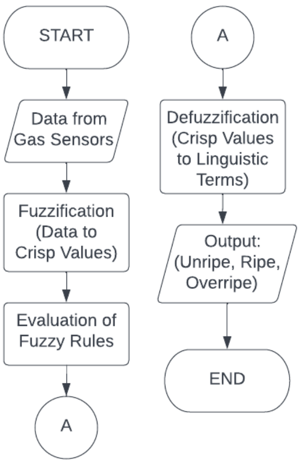

Fig. 4. Fuzzy Logic Algorithm System Flowchart

A fuzzy logic system converts sharp inputs into sharp outputs using the principle of fuzzy sets. An inference engine uses fuzzy rules in a fuzzy logic system. The engine produces outcomes that may also be fuzzy by taking inputs that may also be fuzzy. The starting step is finding the degree on which crisp inputs are belongs to the relevant sets.[14] The following step applies the input data to the antecedents of rules, once data input have fuzzified and their values membership been determined. A fuzzy operator is used to produce number that became an outcome of an eveluation of the conditions and when a given fuzzy rule contains numerous antecedents (AND or OR). A membership function that follows applies to this integer. To assess the conjunction of rule antecedents, use AND. Fuzzy logic systems typically implement this operation using the traditional fuzzy operation intersection. The same variable is frequently the subject of multiple fuzzy rules, and various outputs must be mixed. The results of all fuzzy rules are combined in an aggregate. Defuzzification is the final stage of a fuzzy logic system. Defuzzification is the polar opposite of fuzzification, which generates clear output for a fuzzy logic system from the combined production of fuzzy sets. [15].

TABLE I. MQ SENSOR VALUES FOR TOMATO CLASSIFICATION

SENSORS	LOW	MEDIUM	HIGH
MQ4	150 – 350	360 – 650	660 - 1000
MQ6	125 - 250	260 – 350	360 - 610
MQ7	125 – 250	260 – 450	460 – 610

Table I shows the MQ sensor range of values in low, medium, and high. These values are the inputs to determine the degree of each of the appropriate fuzzy sets and obtain their membership values. Low, Medium, and High numbers apply the antecedents of the fuzzy rules, and the three inputs create multiple precursors that an operator AND and OR to represent the result of the evaluation.

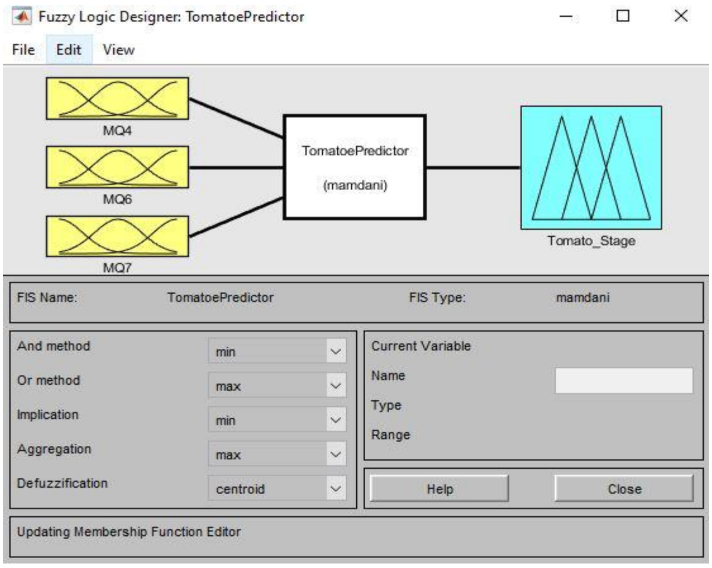

Fig. 5. Fuzzy Logic Designer

Figure 5 shows the fuzzy logic designer of the system and presents three input and one output variable. Input names are MQ4, MQ6, and MQ7, while with the output name Tomato_Stage, the designer displays the system information about its fuzzy inference system. Researchers used Mamdani

TABLE II. OUTPUT VALUES OF LINGUISTIC VARIABLES

Linguistic Term	Range
Unripe	MQ4 = LOW, MQ6 = LOW, MQ7 = MED
Ripe	MQ4 = MED, MQ6 = MED, MQ7 = LOW
Overripe	MQ4 = HIGH, MQ6 = HIGH, MQ7 = HIGH

Table II shows the system's three linguistic terms: Unripe, Ripe, and Overripe. Overripe shows that the three sensors are High, while Unripe and Ripe offer the opposite range in the three sensors.

Fig. 6.   Different Stages of Tomato

Fuzzy operators and sets are the verbs and subjects of the logic fuzzy technique; if-then techniqe used in formulating conditional statements that contains the algorthim of fuzzy logic. Before defining rules, it must specify input and output variables to the fuzzy inference system and its member functions. The fuzzy system rules are as follows:

Fuzzy Rules:

1. If MQ4 is LOW and MQ6 is LOW, and MQ7 is MEDIUM, then Tomato is Unripe
2. If MQ4 is Medium and MQ6 is MEDIUM, and MQ7 is LOW, then Tomato is Ripe
3. If MQ4 is High and MQ6 is HIGH, and MQ7 is HIGH, then Tomato is Overripe

Fig. 7.   Unripe Defuzzification Result

Figure 7 shows the unripe defuzzification result. If MQ4 and MQ6 s in low while MQ7 are in the medium range, the tomato stage result is Unripe.

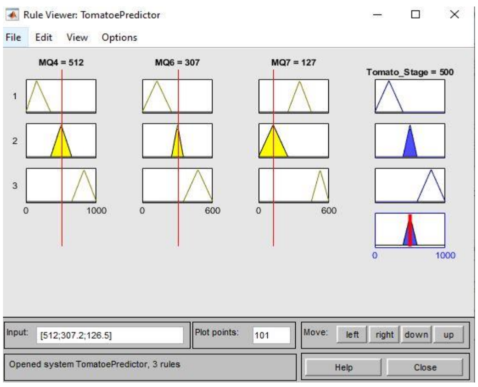

Fig. 8.   Ripe Defuzzification Result

Figure 8 presents the defuzzification result of ripe if MQ4 and MQ6 in medium-range while MQ7 is in low range the tomato stage output is Ripe.

Fig. 9.   Overripe Defuzzification Result

Figure 9 shows the defuzzification result of an overripe. If MQ4, MQ6, and MQ7 are in the high range, the tomato stage result is Overripe.

D. Experimental Setup

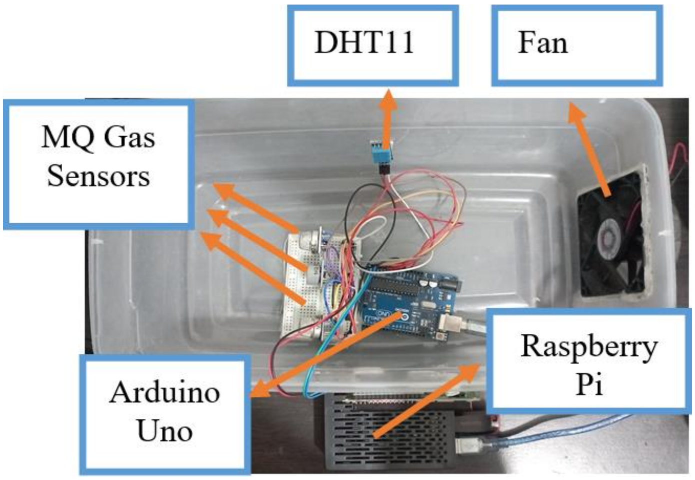

Fig. 10. Experimental Setup

Figure 10 shows the experimental setup of the system; the container is made from plastic material with one ventilation fan to prevent moisture inside. An Arduino Uno microcontroller powers the three MQ sensors, DHT11, and LCD components. At the same time, the Arduino and fan connect to the Raspberry pi that processes the principal component analysis algorithm in Matlab. MQ sensors need a 10-minute warm-up time for good accuracy, and place a tomato for 5 minutes each.

III. RESULT AND DISCUSSION

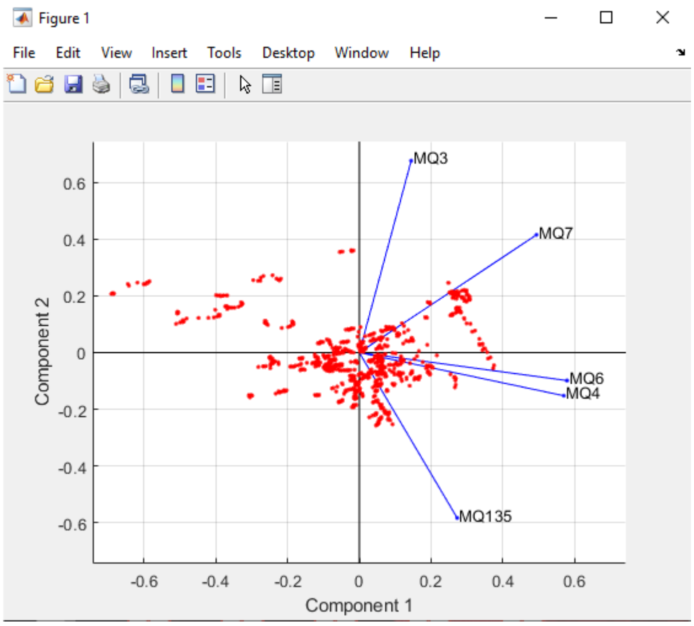

Fig. 11. 60-day Sensor Response for Unripe Tomato

Figure 11 shows the PCA results with two principal components of the 60 days of data gathered from unripe tomatoes. After performing PCA, MQ3 and MQ135 show that the two sensors have low sensor response while MQ7, MQ6, and MQ4 sensor gives high data contribution result; therefore, we remove the two insignificant and remain the three sensors.

We placed all the gathered data in the testing table. We utilized the table to identify if our system could adequately identify the classification of the tomato during the experiment. The predicted variety of the system is compared to the actual type of tomato to determine the system's accuracy in the investigation. The researchers used 15 tomatoes to test the system: six unripe, five ripe, and four overripe tomatoes.

TABLE III. TESTING TABLE

Sample #	Actual Classification	Predicted Classification	Remarks (TP or FN)
1	UNRIPE	UNRIPE	TP
2	UNRIPE	UNRIPE	TP
3	UNRIPE	UNRIPE	TP
4	UNRIPE	UNRIPE	TP
5	UNRIPE	UNRIPE	TP
6	UNRIPE	UNRIPE	TP
7	UNRIPE	UNRIPE	TP
8	UNRIPE	UNRIPE	TP
9	RIPE	OVERRIPE	FN
10	RIPE	RIPE	TP
11	RIPE	RIPE	TP
12	RIPE	RIPE	TP
13	RIPE	RIPE	TP
14	RIPE	RIPE	TP
15	OVERRIPE	RIPE	FN
16	OVERRIPE	OVERRIPE	TP
17	OVERRIPE	OVERRIPE	TP
18	OVERRIPE	OVERRIPE	TP

a. TP = True Positive

b. FN = False Negative

The confusion matrix can visualize the system's performance. All entries will denote the number of predictions made by the model in which it may classify it correctly or incorrectly. It will be labeled as follows: True Positive (TP) is when the chamber accurately predicted among the positive class as positive and False Negative (FN) is when the predicted positive type as Negative is mistaken.

TABLE III. CONFUSION MATRIX

		Predicted Data		
		Unripe (A)	***Ripe (B)***	***Overripe (C)***
Actual Data	Unripe (A)	7	0	0
	Ripe (B)	0	5	1
	Overripe (C)	0	1	4

There were two False Negative (FN) results when we conducted the tests. Researchers placed an overripe tomato, and the system detected a ripe one. The same goes for the other tomato that was ripe. The classifier saw it as an overripe tomato. The sixteen other tomatoes were correctly predicted by the system which indicates an accurate classifier.

$$Classifier\ Accuracy = \frac{Total\ TP}{Total\ Samples} \quad (1)$$

$$Classifier\ Accuracy = \frac{16}{18} = 0.88$$

The calculation in (1) shows the accuracy of the model. The fraction of samples is classified correctly by the system. The accuracy score indicates that the system classifier is relatively accurate.

$$Weighted\ Average\ Precision = \frac{7}{18} \times 1 + \frac{6}{18} \times 0.83 + \frac{5}{18} \times 0.8 = 0.887 \quad (2)$$

The weighted average precision equated to a high value which meant that classifying the stage of tomato was done by the system in a precise manner, garnering 0.887 or 88.7% average precision.

IV. CONCLUSION AND RECOMMENDATIONS

The above evaluation shows that we have met the general and specific objectives. After the study has the conducted, these are the following conclusions: (1) After experimenting with the unripe tomato until 60 days, we conclude that the unripe tomato in the market will never become red or ripe. Still, it will proceed to unripe wrinkled tomato. (2) The more extended the tomato is inside the chamber, the higher the output of sensors will produce. (3) Proper ventilation is required to prevent moisture inside the chamber. Moist can affect gas and gas sensor accuracy. (4) Tomatoes don't emit gas equally; size is a factor in increasing the gas it emits. Following the results of the statistical treatment, the researchers find the model reasonably accurate to the actual classifications of the tested tomatoes. Predicted classifications matched well enough to have a good accuracy and precision rating through all eighteen (18) samples of tomatoes to conclude the precision of the overall system developed. The researchers successfully developed an E-nose system for classifying different tomato stages using the Fuzzy Logic algorithm. The study reduced insignificant sensors using principal component analysis that runs on a Raspberry Pi 4 Model B. MATLAB Online software was used in processing the central component analysis algorithm because of the lack of storage.

The system has met all its intentions, specific and general. However, the study still has a lot of room for more improvements, especially if it incorporates diverse methods in processing data, hardware design, and classifying techniques. For future work, enhancement of prototype that places the sensors equally for the sensing of the gas of tomato. Also, applying more samples for better accuracy of the system, a premium gas sensor to improve the accuracy of the gas, determining the type of tomato used in the examples, and lastly having an automated data logging of the system are recommended.

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