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Procedia Computer Science 197 (2022) 677–684

Procedia Computer Science

www.elsevier.com/locate/procedia

Sixth Information Systems International Conference (ISICO 2021)

# Discrimination of durian ripeness level using gas sensors and neural network

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**Abstract**

In the agriculture industry, determining the ripeness level of fruits is a very important aspect. This is related to maintaining the quality of the production, and during the distribution process. Currently, human sensory tests are still commonly used to evaluate food products with inconsistent results. This study developed a system to discriminate the durian ripeness level using gas sensors and neural network based on the character of the fruit aroma. This system succeeded in distinguishing the ripeness of durian including unripe, ripe and overripe with performance evaluation values above 91%.



*Keywords:* Agriculture; durian ripeness level; food; gas sensors; neural network

## 1. Introduction

Fresh fruit is a source of essential nutrients needed for normal functioning of the body's systems, growth and health maintenance. Assessment of the ripeness level of fruits is very important in the agricultural and food industries. This correlates to maintain the quality of the product, both during the distribution process and when consumed by humans. In general, fruit ripening is associated with physiological and biochemical changes, such as softening of the pulp,

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1877-0509 
10.1016/j.procs.2021.12.188

increasing in size, accumulation of pigments, acidity, glucose content, and aroma [1]. Fig. 1 shows the changes in characteristics at the ripening stage of a tomato fruit.

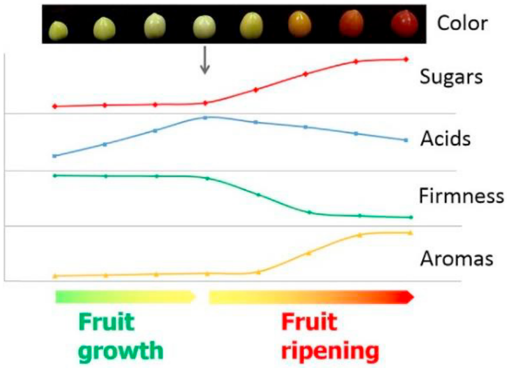


Fig. 1. Changes in characteristics during fruit ripening [1].

Determination of the level of fruit ripeness by human sensory tends to be inconsistent which can be influenced by factors of subjectivity, mood, and health. The presence of modern sensors and equipment is expected to solve this problem. Some methods are expensive or can damage the fruit structure. Evaluation of biochemical, physical, and physiological parameters is commonly used to determine the level of ripeness and quality of fruit. Assessment of the texture and physiological factors of the pulp can be carried out using the near infrared spectra method [2][3][4]. The portable equipment is readily available [5], but still has a high price for farmers in some developing countries. Computer vision technology is also frequently used to detect and identify ripeness of fruit [6][7]. However, direct illumination of the environment and color saturation can cause a lot of recognition errors. Non-destructive measurement of the level of fruit ripeness can also deploy the laser Doppler vibrometry technique [8]. This measurement of mechanical vibrations is less practical in its implementation, as well as difficulties in its calibration.

Many of the ripe fruits emit a pleasant aroma, while the unripe fruit tends not to smell or even bitter. Based on one of the characteristics of the fruit that is able to release volatile compounds, it can be identified the ripeness of the fruit through its aroma. This method is expected to be a tool that is cheap, easy to maintain, and does not damage the fruit structure. Quartz crystal microbalance gas sensor can be used to recognize the ripeness and freshness of the fruit [9]. However, the frequency measurement in this method is easily affected by the environment, as well as the crosstalk signals in line with the increasing number of sensors. The sensor response tends to drift after long periods of use. Gas chromatography technique is often involved in the analysis of volatile compounds produced by the fruit [10]. This technique is operated by skilled people, besides the identification process is time consuming, and expensive. Metal oxide semiconductor gas sensors can be used to detect volatile compounds produced by fruit [11], and meat [12]. This type of sensor requires a simple electrical circuit and has a robust response to changes in ambient temperature [13]. The electrochemical gas sensor can also be employed to assess the quality of fruit [14], and fish [15]. This type of sensor has high selectivity and sensitivity.

Durian (Durio zibethinus) is a fruit plant that is widely spread and grows well in Indonesia. There are dozens of types of durians that are cultivated on the islands of Java, Bali, Sumatra, Kalimantan, Sulawesi and Maluku. The fruit, which has been called "The King of Fruit", is also one of the leading tropical fruits as an export commodity for Southeast Asian countries. Durian is a type of climacteric fruits which are rich in nutrients that can contribute to human health [16]. The climacteric fruits tend to indicate that the process of fruit ripening is associated with an increase in cellular respiration accompanied by an increase in the concentration of ethylene produced at appropriate temperature conditions. Apart from being related to the fruit ripening process, the ethylene signal also reflects the degree of fruit dehiscence [17]. The nutritional composition of durian includes water, proteins, total lipids, ash, carbohydrates, dietary fibers, minerals, vitamins, and sugars [18]. While the content of volatile compounds in durian includes aldehydes (acetaldehyde, hexanal), sulphur compounds (diethyl disulphide, bis(ethylthio)methane, diethyl trisulphide), ester (ethyl acetate, methyl propanoate, ethyl propanoate, ethyl butanoate, propyl-2-methylbutanoate, propyl (2s)-2-

methylbutanoate, ethyl hexanoate, ethyl heptanoate), alcohols (ethanol), ketones (3-pentanone, 3-hydroxy-2-butanone), and acids (2-methyl butanoic acid, octanoic acid) [16].

In this study, a gas sensor array consisting of electrochemical and metal oxide semiconductor gas sensors were used to detect and measure the intensity of the aroma released by the durian. The sensor array will provide a specific pattern for each ripeness level. The neural network pattern recognition method was employed to recognize the ripeness level of the durian automatically after going through the learning phase.

## 2. Methods

The electronic part of the system for discrimination of durian ripeness levels consists of three gas sensors, an analog to digital converter (ADC) module, a neural network algorithm embedded in a microcontroller, and a display shown in Fig. 2. The sensors detect and measure the volatile compounds released by the durian which are converted to the appropriate voltage by the signal conditioning circuit. A voltage inverter circuit is employed to support split supply requirement for the signal conditioning circuit. The analog signal of each sensor is converted to a digital value by the 16-bit ADC module of ADS1115 which is then sent to the Arduino Uno microcontroller via the I2C serial communication protocol. Measurement of the sensor response is conducted every second. The sensor response patterns are then used as the neural network input to identify the durian ripeness level. The neural network learning phase is carried out on a computer where the resulting weight and bias values will be used in the testing phase by this network which is implemented into the microcontroller.

The gas sensors employed in this study are two amperometric-type electrochemical gas sensors (Winsen ME3-C2H4, and Alphasense H2S-B4), and a metal oxide semiconductor gas sensor (MQ-3). The ME3-C2H4 sensor is an ethylene ($C_2H_4$) gas sensor with a detection range of 0-200 ppm and a sensitivity of 0.04±0.012 μA/ppm. The Alphasense H2S-B4 sensor is a hydrogen sulfide ($H_2S$) gas sensor with a detection range of 0-100 ppm and a sensitivity of 1450 to 1900 nA/ppm. The MQ-3 sensor has a high sensitivity to ethanol ($C_2H_5OH$) with a detection range of 25-500 ppm. The basic circuit of electrochemical and metal oxide semiconductor gas sensors are shown in Fig. 3. U1A is a potentiostatic circuit that provides a constant voltage at the working (W) electrode with respect to the reference (R) electrode potential. The counter (C) electrode must produce an equivalent current when the working electrode oxidizes or reduces the gas. Meanwhile, U1B acts as a transimpedance amplifier which converts the current into voltage at the OUT pin. MQ-3 is a conductometric-type gas sensor where the gas absorbed on the surface of the tin dioxide ($SnO_2$) material will change its resistance at a temperature of around 350°C. This change in resistance $R_S$ together with the external resistance $R_L$ and the dc supply $V_C$ will provide a voltage divider circuit that produces an output voltage $V_{RL}$ that correlates with the gas concentration expressed as Eq. (1).

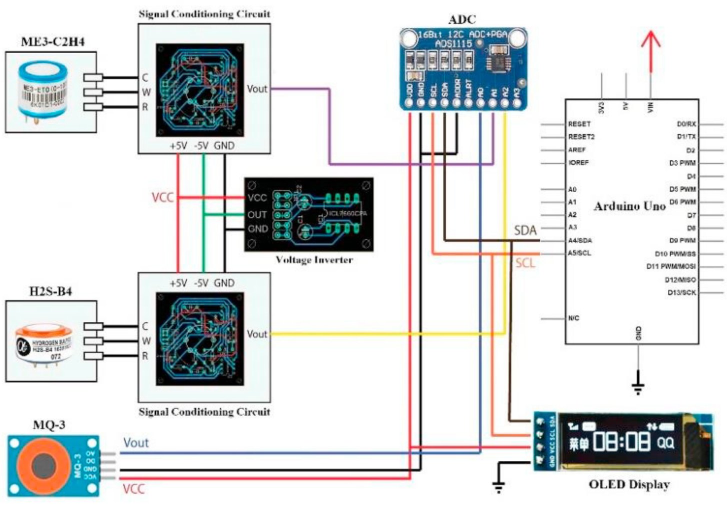


Fig. 2. Block diagram of the system for discrimination of durian ripeness levels.

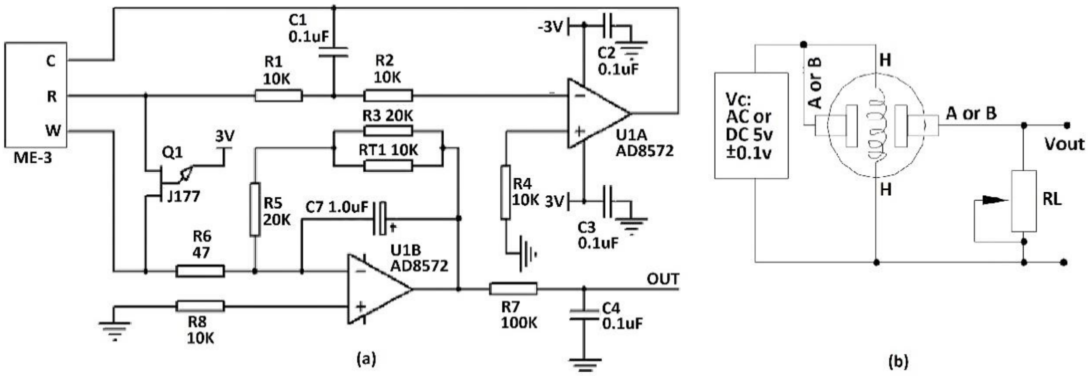


Fig. 3. The basic circuit of the gas sensors of: (a) electrochemical type [19]; (b) metal oxide semiconductor type [20].

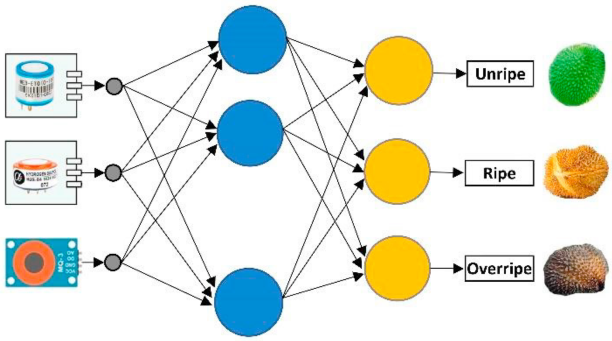


Fig. 4. The neural network architecture for discriminating durian ripeness levels.

$$R_S = \frac{V_C - V_{RL}}{V_{RL}} R_L \tag{1}$$

Neural Network is a computing system that is often used for pattern recognition purposes. The network will learn to perform tasks by considering examples without the need for special rules. This method can be used to correlate between input and output based on data patterns. The neural network used in this study consists of three layers as shown in Fig. 4. The input layer has three nodes which correspond to the number of gas sensors, while the output layer has three neurons which correlate with the durian ripeness levels. The hidden layer consists of 256 neurons with the activation function of the rectified linear unit (ReLU) to accelerate the learning process and optimize the success rate in the testing phase. This neural network algorithm is realized using the Python programming language with the TensorFlow library.

## 3. Results and Discussion

The sensor response measurements are carried out by exposing each sensor to the appropriate gas. The ME3-C2H4 gas sensor is injected with ethylene, where this gas is obtained from dissolving calcium carbide ($CaC_2$) into water with the reaction equation as given in Eq. (2).

$$CaC_2 + 2H_2O \rightarrow C_2H_2 + C_a(OH)_2 \tag{2}$$

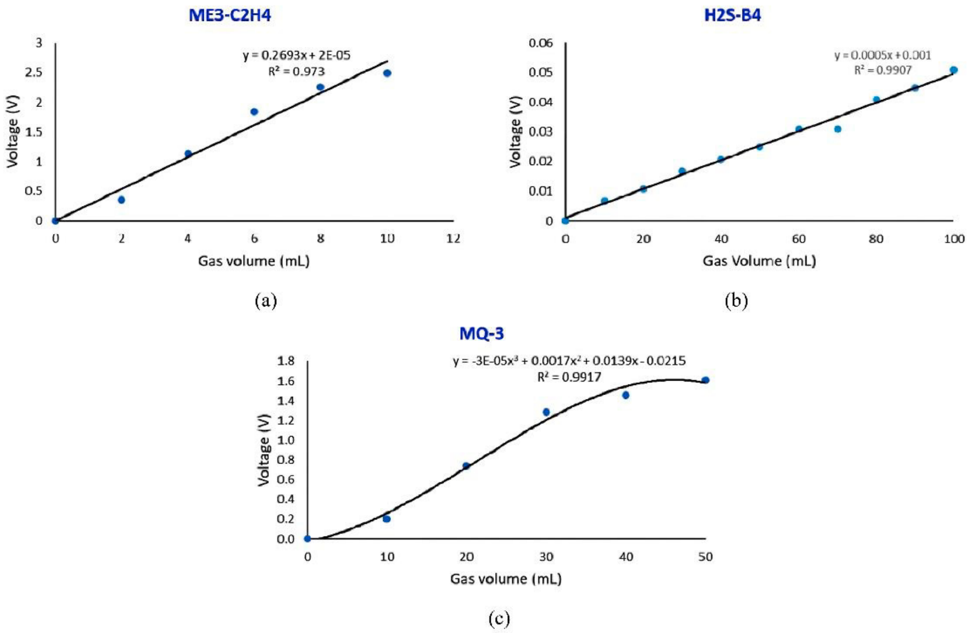


Fig. 5. The gas sensor response of: (a) ME3-C2H4; (b) H2S-B4; (c) MQ-3

The H2S-B4 gas sensor is exposed to hydrogen sulfide contained in the odor of livestock manure, which is produced when bacteria break down organic matter without oxygen. While the MQ-3 gas sensor is tested with ethanol. The measurement results of the sensor response after subtracting its baseline value are shown in Fig. 5. The electrochemical gas sensors show a linear response, whereas the metal oxide semiconductor sensor has a logarithmic response. This tends to align with the sensitivity characteristic curve shown on each its datasheet.

The learning data are obtained from nine durian samples consisting of three levels of ripeness. Fig. 6 shows the measurement of the volatile compounds released by the durian. The response of each sensor tends to increase and is recorded at 120 seconds for 20 seconds to represent the measured sample. The data are collected from 20 measurements for each sample which provide 180 datasets. The patterns of each level of durian ripeness are shown in Fig. 7(a). Each ripeness level tends to provide a unique sensor response pattern. The ethylene sensor response increases with increasing the ripeness level. Meanwhile, each hydrogen sulfide and ethanol sensor response has a high value at the ripe level.

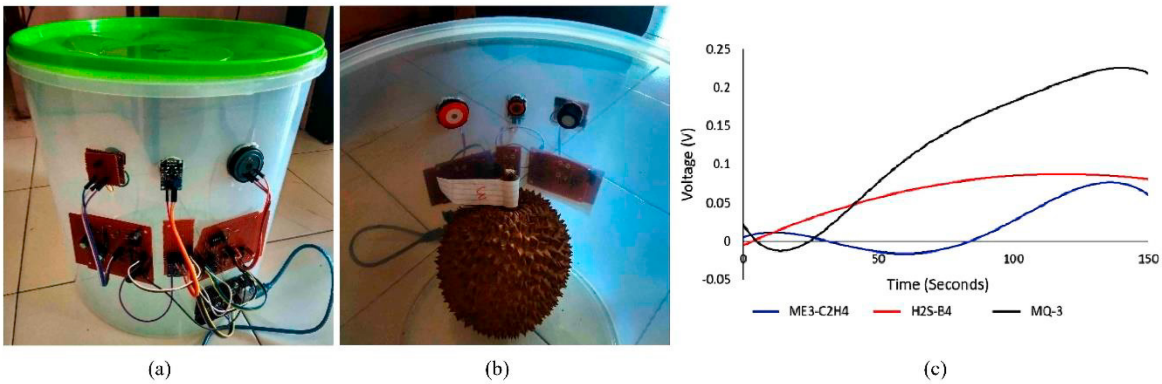


Fig. 6. (a) The equipment of the durian ripeness discrimination; (b) data collection; (c) sensor response.

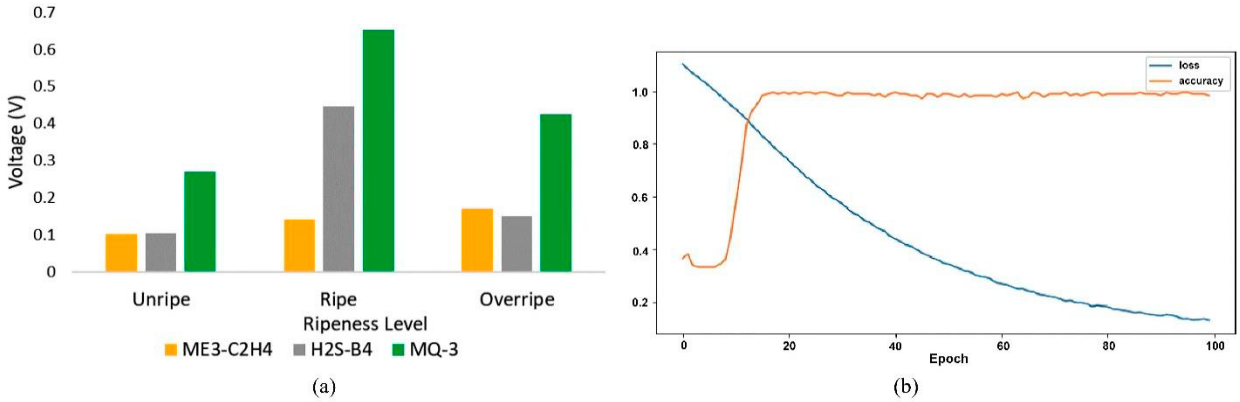


Fig. 7. (a) The sensor patterns on the ripeness level; (b) the neural network learning phase.

Table 1. The neural network testing phase.

| No | Test | Prediction | No | Test | Prediction | No | Test | Prediction | No | Test | Prediction |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Unripe | 93% Unripe | 16 | Unripe | 79%Unripe | 31 | Ripe | 79% Ripe | 46 | Overripe | 82%Overripe |
| 2 | Unripe | 91% Unripe | 17 | Unripe | 79%Unripe | 32 | Ripe | 56%Overripe | 47 | Overripe | 75%Overripe |
| 3 | Unripe | 87% Unripe | 18 | Unripe | 80%Unripe | 33 | Ripe | 56% Ripe | 48 | Overripe | 81%Overripe |
| 4 | Unripe | 84% Unripe | 19 | Unripe | 81%Unripe | 34 | Ripe | 51%Overripe | 49 | Overripe | 79%Overripe |
| 5 | Unripe | 82% Unripe | 20 | Unripe | 81%Unripe | 35 | Ripe | 57% Ripe | 50 | Overripe | 79%Overripe |
| 6 | Unripe | 80%Unripe | 21 | Ripe | 78% Ripe | 36 | Ripe | 81% Ripe | 51 | Overripe | 82%Overripe |
| 7 | Unripe | 79%Unripe | 22 | Ripe | 99% Ripe | 37 | Ripe | 59% Ripe | 52 | Overripe | 81%Overripe |
| 8 | Unripe | 79%Unripe | 23 | Ripe | 68%Overripe | 38 | Ripe | 57%Overripe | 53 | Overripe | 81%Overripe |
| 9 | Unripe | 80%Unripe | 24 | Ripe | 72% Ripe | 39 | Ripe | 56% Ripe | 54 | Overripe | 78%Overripe |
| 10 | Unripe | 80%Unripe | 25 | Ripe | 62% Ripe | 40 | Ripe | 52%Overripe | 55 | Overripe | 77%Overripe |
| 11 | Unripe | 79%Unripe | 26 | Ripe | 77% Ripe | 41 | Overripe | 79%Overripe | 56 | Overripe | 79%Overripe |
| 12 | Unripe | 79%Unripe | 27 | Ripe | 71% Ripe | 42 | Overripe | 77%Overripe | 57 | Overripe | 75%Overripe |
| 13 | Unripe | 78%Unripe | 28 | Ripe | 53% Ripe | 43 | Overripe | 89%Overripe | 58 | Overripe | 76%Overripe |
| 14 | Unripe | 79%Unripe | 29 | Ripe | 66% Ripe | 44 | Overripe | 71%Overripe | 59 | Overripe | 79%Overripe |
| 15 | Unripe | 79%Unripe | 30 | Ripe | 90% Ripe | 45 | Overripe | 79%Overripe | 60 | Overripe | 75%Overripe |

Neural network is employed as an algorithm for pattern recognition produced by the gas sensor array. The learning phase involves 120 datasets, and the rest is reserved for the testing phase. The loss and accuracy values for each epoch in the learning phase are shown in Fig. 7 (b). The loss function is a sum of errors made for each learning data set that describes how well the model is in each iteration. Whereas the accuracy metric is used to measure how accurately the model's predictions are compared to the actual data. After the iteration of 100 epochs, this network has a loss, and an accuracy of 0.1327, and 0.9833, respectively. This indicates that the neural network can recognize each level of durian ripeness. The values of the weights and biases of this network in the learning phase are used in the testing phase. The results of discrimination on durian ripeness levels by the neural network in the testing phase are shown in Table 1. This network perfectly predicts unripe and overripe levels. Several errors occurred while recognizing the ripe level. To evaluate the performance of this model, several parameters are calculated by using Eq. (3)-(6).

Table 2. The performance evaluation for the durian ripeness discrimination system.

| Ripeness | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Unripe | 1 | 1 | 1 | 1 |
| Ripe | 0.917 | 1 | 0.75 | 0.857 |
| Overripe | 0.917 | 0.8 | 1 | 0.889 |
| Macro-average | 0.945 | 0.933 | 0.917 | 0.915 |

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (3)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (4)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (5)$$

$$F1\ Score = \frac{2 \times precision \times recall}{(precision+recall)} \quad (6)$$

with true positive (*TP*), true negative (*TN*), false positive (*FP*), and false negative (*FN*) are the metrics of the confusion matrix. The performance evaluation for the durian ripeness discrimination system is shown in Table 2.

## 4. Conclusion

This study has developed a system to discriminate the ripeness level of durian based on its aroma. The gas sensor consists of ME3-C2H4, H2S-B4, and MQ-3 which detect and measure the volatile compounds released by the fruit. The sensor array of sensors can produce a specific pattern for each ripeness level. The neural network has been successfully trained and could discriminate the durian ripeness levels, namely unripe, ripe, and overripe with performance values of accuracy, precision, recall, and F1 Score of 94.5%, 93.3%, 91.7%, and 91.5%, respectively. This non-invasive method is expected to be implemented as a tool in diagnosing the quality of fruit or food at an affordable cost.


## Acknowledgements

We would like to thank Kementerian Riset dan Teknologi/Badan Riset dan Inovasi Nasional Republik Indonesia for financial aid support with Master Contract Number: 3/E1/KP.PTNBH/2021 and Researcher Contract Number: 812/PKS/ITS/2021.


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