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Estimating Gas Concentration using Artificial Neural Network for Electronic Nose

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Abstract

E-nose is a sensor used to detect the existence of gas in the air. Some types of sensor has the ability to detect certain gas and also has different datasheet. Slope deflection is the method to determine the suitable sensor for the experiment. E-nose with MQ Family produces the ratio of existing air and base line air resistance, and it is usually equipped with a datasheet containing the consecration of detected gas in a certain value of the sensor to convert the output to the concentration of detected gas. The ratio is used to estimate the concentration of a gas. In this paper, Artificial neural network is used to estimate the concentration of a gas in the air based on the ratio. Providing the accurate calculation of the ratio is very important to increase the Electronic nose performance, and the result of this experiment showed that the Artificial neural network method achieves a good performance with smaller RMSE of 0.0433 compared with the existing methods.

Keywords: Artifical Neural Network, Sensor, Electronic Nose, Mangoes Ripeness

1. Introduction

Electronic Nose or E-Nose is a tool for simulating a human sense of smell [1].The human nose has a capability to smell a variety of gases, but E-nose is not only simulating a variety of gases but also identifying gas additives and detecting the harm ness of gases. There are plenty of free gas in the air, which provide smell and taste. E-nose has been applied in some fields, for example fisheries [2], medicine and pharmacy [3], health [4] which provide the appropriate result. E-nose has many sensors, that are: MQ 2, MQ 4, MQ 5, MQ 6, MQ 135, and more. Each sensor has different characteristics to identify the smell and taste of gas. Sensor MQ 2 is able to detect the existence of H2, Alcohol, LPG, and CH4 [5]. While Sensor MQ 3 has an ability to detect the existence of Alcohol, CH4, as well as CO [6]. Although

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MQ 2 and MQ 3 has the ability for detecting the existence of alcohol, they have different sensitivity level. Various kinds of gas that can be detected by certain sensor are tabulated in Table 1.

Table 1: Various kinds of gas that can be detected by a certain sensor

Sensor	Content
MQ 2	H2, LPG, CH4, CO, Alcohol, Smoke, Propane, Air
MQ 3	LPG, CH4, CO, Alcohol, Benzine, Hexane, Air
MQ 6	H2, LPG, CH4, CO, Alcohol, Air
MQ 7	H2, LPG, CH4, CO, Alcohol, Air
MQ 8	H2, LPG, CH4, CO, Alcohol, Air
MQ 135	Alcohol, NH4, CO2, Air
MQ 137	NH3, O2, C2H6O, Air
MQ 138	CH4, CO, Alkohol, Propane, Benzine, n-Hexane, Air

Each sensor has to graph datasheets provided by the manufacturer, which has X axis for mg/L value and Y axis for the ratio of Rs and Ro. In this development of E-nose system, the ratio value has the main role in determining the appropriate mg/L value based on the datasheets given. However, there is no further research for measuring the accuracy of the ratio value and mg/L. An electronic nose is a portable sensor with a relatively cheap price, connect with Arduino as a microcontroller, output of sensor readings will be easier.

The contribution to this research is to determine the measurement groundtruth from a datasheet, determine the suitable and stable sensor, comparison of the existing method, and propose a new method. The groundtruth can be determined using the image editor tool, Adobe Illustrator, for ease measurement of millimeter units. The ratio value movement in each sensor has tested. Calibration tools can be used to make sure the readability of the ratio value and mg/L value in the datasheets, or using manual measurement if necessary. The groundtruth are taken from 10 sensors E-Nose with 55 kinds of gas additives. Each gas additive has 35 nodes of Rs/Ro and mg/L value, so there are 1925 data that will be used. The more data, the higher the accuracy will be. Furthermore, mapping Rs/Ro and mg/L values using the Spyder tool so that can be visualized in the form as the graph. After the ratio value of Rs and Ro is obtained, compared with some curve fitting methods that have been done and the result of the proposed method gives the better results than those the other methods. This research uses curve fitting with Artificial Neural Network to convert into PPM or mg/L value where the reading result is very precise with the datasheet.

2. Literature Review

2.1. Curve Fitting

Curve fitting is the approaching method by making a calculation of arithmetics to approach between the output result from the signal (Rs/Ro) and each of datasheet sensor, and provide the similar result of gas concentration with the datasheet.

There are some of curve fitting methods, that are: exponential on Equation 1 and 2, normalization exponential, the power, and adjust the power. Each method has its own strenghtness and weakness, but those has the lowest error possibility. In the previous researches, the curve fitting accuracy of Rs/Ro using adjust power method [7] that can be found in Equation 4 and power method [8] in Equation 3. If using more data, Power method has less accuracy for estimating Rs/Ro. Adjust power method has almosts similar result with the datasheet, and better than power method. There are three other methods that are frequently used, but those Rs/Ro still have less accurate compared with power method and adjust power method.

Exponential Method Curve fitting

$$y = e^{ax+b} \tag{1}$$

Expand the equation will be

$$lny = ax + b \tag{2}$$

Power Curve Fitting Method

$$C = \gamma[\frac{Ro}{Rs}]^{\tau}, \gamma\tau\epsilon R^{+} \quad (3)$$

Adjust Power Method

$$C = 10^{\frac{\log \frac{\frac{Rs}{Ro}-\gamma}{\alpha}}{\beta}}, \alpha, \beta, \gamma \quad (4)$$

2.2. Mathematical Models Comparison

There are many methods for determining an error value, Residual Standard Error (RSE), R^2, Root Mean Squared Error (RMSE). The residual sum of squares (RSS) is the sum of the squares of residuals. A small RSS indicates a tight fit into the model to the data. The RMSE formulas square the error value and divided by the tested data, then giving the roots as a result [9]. Root mean squared error can be shown in Equation 5 or 6. Where y_i is the actual data, f_i is the prediction value, and n is the total data. The smaller the error value is the higher the accuracy.

$$RMSE = \sqrt{\frac{\sum_{i=1} = (y_i - f_i)^2}{n}} \quad (5)$$

This is for simplified equation

$$RMSE = \sqrt{\frac{1}{n} RSS} \quad (6)$$

3. The Proposed Method

3.1. Slope Deflection

Each sensor has different characteristics to detect gas content in the air. In order to avoid the use of sensors that can detect the same gas sensor, selection should be done. The right sensor is the one that is sensitive to the gas content by using Slope deflection method. To obtain a stable sensor when detecting the gas content, it can use the variant coefficient method. Slope deflection method is used to find the distance between the final value and the initial value of ratio, so that later can be calculated easily [10]. In addition to using the slope deflection method, coefficient of the variant for determining the stable sensor on the gas content to be tested. The equation of slope can be shown in Equation 7. y_2 is the end node from Y axis, and y_1 is the initial node from Y axis. x_2 is the end node from X axis, and x_1 is the initial node from X axis.

$$SLOPE = \frac{y_2 - y_1}{x_2 - x_1} \quad (7)$$

3.2. Artificial Neural Network

In order to find the accuracy of the ratio on the concentration of a gas according to the datasheet is very necessary. The smaller error value means that the ratio is more precise to the datasheet.

In this study, to predict the ratio values in gas concentration using the artificial neural network. Artifical Neural Network is known as a way of stimulating human brain work. This method consists of three layers, that are: an input layer, output layer, and hidden layer [11]. The data is processed from input layer in the output layer one by one, where the hidden layer placed between those two. However, only a few artifical neural network doesnt have a hidden layer, just input layer, and an output layer. Figure 1 is the visualization understanding of the artifical neural network.

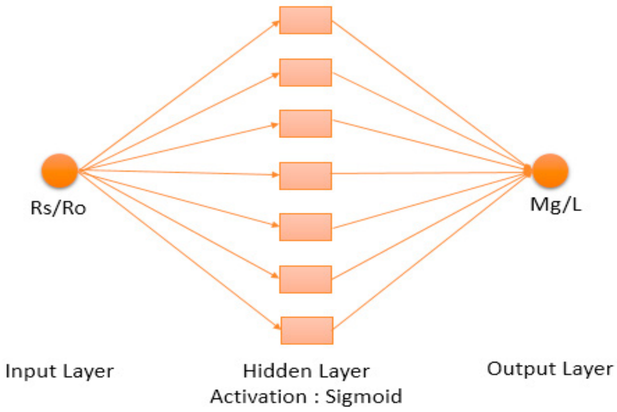

Fig. 1: Artifical Neural Network Principal

4. Result and Discussion

4.1. Finding The Right Sensors

This experiment use Arduino as a microcontroller. Based on the previous research, an alcohol content of mango fruit can be used to predict mango maturity level [12]. There are two ways of choosing the right sensor for detecting alcohol in mango, Slope Deflection for maintaining the sensitivity and Variant Coefficient for the stability of the sensor. The value of Slope deflection in the sensor MQ 2, MQ 3, MQ 138 can be seen in Table 2. The higher Slope value means that the sensor is more sensitive to the gas content, which is sensor MQ 3.

Table 2: The Result of Slope-Deflection

Sensor	Slope-Deflection
MQ 2	-0.003370
MQ 3	-0.1707685371
MQ 138	-0.000201371

The variant coefficient is used to find the stable point of the sensor and the value of the alcohol can be seen in Table 3. The smallest value from the comparison is sensor MQ 3. The less value of variant coefficient means that the sensor is more stable to calculate the concentration of alcohol before and after the presence of mango.

After selecting the sensor, it is placed on the Arduino microcontroller board that matched to the PIN input, then it started scanning the analog signal that converted to digital. The digital PIN will only recognize 0 as low value and 5 volts as a high value. In the Arduino Uno system, there is a calibration step of free air (RO AIR CLEAN FACTOR) right before the sensor is read, to provide a more accurate data response while detecting the gas concentration. Arduino scans the response data from the sensor periodically in real-time. The sensor uses the digital (ADC) value to get Resistance (Rs), can be found in Equation 8 and 9.

$$Rs = \frac{Vc - VRL}{VRL} xRL \tag{8}$$

$$VRL = \frac{ADC - Vc}{1023} \tag{9}$$

Vc is the voltage from microcontroller board. VRL is the voltage generated from the sensor in the tested area. RL is the resistance value from the sensor datasheet with kilo Ohm unit. The digital value is the result from the analog

Table 3: The Result Comparison of Variant Coeficient

Sensor	Data Testing	Variant Coeficient	Mean Variant Coefecient (Raw Mango, Ripe Mango)
MQ 2	Fresh Air	0.0204	
	Raw Mango	0.0563	0.1075
	Ripe Mango	0.1025	
MQ 3	Fresh Air	0.0208	
	Raw Mango	0.0261	0.0325
	Ripe Mango	0.0129	
MQ 7	Fresh Air	0.6496	
	Raw Mango	0.0706	0.0718
	Ripe Mango	0.0024	
MQ 8	Fresh Air	0.0034	
	Raw Mango	0.0599	0.1376
	Ripe Mango	0.1555	
MQ 138	Fresh Air	0.0230	
	Raw Mango	0.14001	0.1419
	Ripe Mango	0.0038	

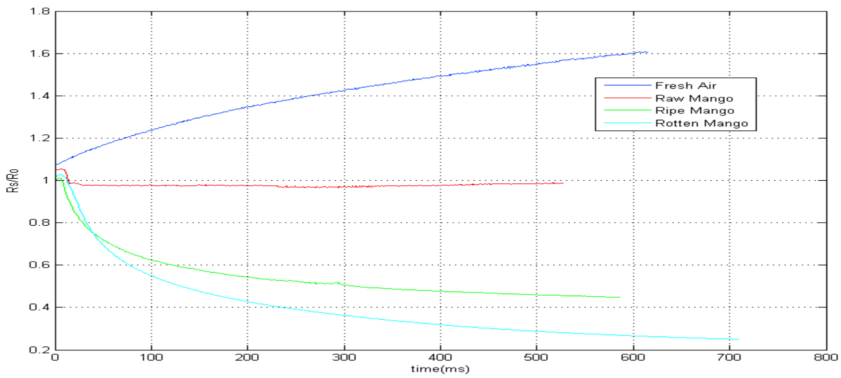

Fig. 2: Respon of Alcohol Gas Content on Sensor MQ 3

to digital conversion (ADC). In Arduino, The microcontroller has 10 bits resolution from 0 to 1023. The experiment used MQ 3 sensor to detect alcohol content of mango fruit. It can be seen in Figure 2 the differences in response and alcohol gas content in mango. It is the response of the sensor MQ 3 where the Rs/Ro value of the resulting mango for 400 seconds. Blue line is clean air. Red line is raw mango, green line is a ripe mango, and cyan line is rotten mango. Based on the test, the result shows that sensor MQ 3 has good accuracy for detecting the alcohol concentration of the mango. It also detects the difference between the raw fruit, ripe fruit, or rotten fruit concentration which shows in the graph.

4.2. Implementation of Artifical Neural Network

After obtaining Rs/Ro value, the data entered at the stage of value accuracy using the proposed method, that is Artifical neural network method. The first process in this method is the data entering the input layer is a neuron which is then passed to the hidden layer [13]. At this point, sigmoid will be active and search the best or smallest value for each data. Each data will be processed inside the hidden layer with 15 training times and nodes as much as 1 to 7, until it finds the value corresponding to the smallest error. The resulting output is the best value with a very small error.

Figure 3 is the comparison result of five methods based on the data from datasheet. The blue line is the data from the datasheet MQ 3. The green line is the Power method. The black line is the power adjust method. The magenta line

Table 4: Comparison of Error

Sensor	Gas Content	Exponential	Normalization Exponential	Exponential Orde 2	Power	Adjust Power	Proposed Method
MQ 2	CO	3,4202	0,3501	Nan	0,1359	0,1316	0,1096
	Smoke	4,0028	0,2120	0,0734	0,2577	0,0944	0,0356
MQ 3	Alcohol	2,1389	0,4736	0,125	0,1318	0,1157	0,0791
	Benzine	16,5369	0,4640	0,1538	0,2057	0,1727	0.1186
	Hexane	36.8787	0.1716	Nan	0.3363	0.1648	0.1038
	LPG	0.6244	0.1603	Nan	0.1966	0.1300	0.0769
MQ 136	CO	27.9280	1.2550	1.2316	3.7404	1.3291	0.4221
MQ 137	O2	2.0834	0.0006	0.0003	0.0004	0.0004	0.0001
	C2H6O	64.1439	9.9099	2.2172	2.5645	2.5180	0.8272
	NH3	18.5389	4.770	3.8990	5.5921	51.5669	1.6613
MQ 138	Benzene	3.9207	0.4019	0.0448	0.0511	0.0428	0.0240
	n-Hexane	842.084	390.285	71.1731	62.2718	60.9262	37.1647
	CH4	3.8889	0.3231	0.0589	0.1423	0.1251	0.0258
	CO	3.8912	0.2716	Nan	0.0795	0.0787	0.0329
	Alkohol	3.8661	0.3259	0.0602	0.1302	0.1054	0.0387
	Propane	815.440	279.161	80.4048	139.758	109.178	64.3945

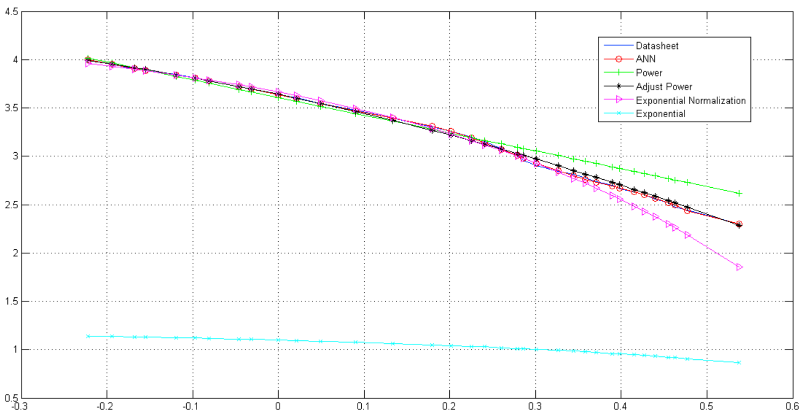

Fig. 3: Comparison to Five Curve Fitting Methods

is the exponential normalization method. The cyan line is the exponential method. And the red line is the Artifical Neural Network. A graph that has values close to the blue line is the red line. And also those methods have smaller RMSE rather than those the other methods. The result of comparison RMSE can be seen in Table 4. Mg/L value is correct compares with the data given from the MQ 3 sensor datasheet. This is proved by the small value of RMSE, that is 0.0433. Table 5 is the prediction of mg/L value using Artifical Neural Network methods very close to data from datasheet.

Experiments were performed on eight mangoes, three raw mangoes, two ripe mangoes, and three rotten mangoes. The data generated as much as 800 data values Rs/ Ro each mango. The experiment took 400 seconds in a closed place so the possibility of noise is very small. From the Figure 4, the blue line shows the Rs/Ro and mg/L data of the MQ 3 datasheet and the green line is the prediction of the Rs/Ro and mg/L values for raw mangoes. It also shows the prediction of the value of Rs/Ro and mg/L in ripe mango and rotten mango.

Figure 5 is plotting for ripe mangoes with red stripes. The results of the data have tested also match the MQ 3 datasheet. The Artifical Neural Network method also succeeds in predicting the value of Rs/Ro and mg/L in the rotten mango, and the results correspond to the MQ 3 datasheet. Prediction rotten mango can be seen in Figure 6. Figure

Table 5: The Result of Convertion to Mg/L

Class	n-Testing	Rs/Ro	Mg/L Neural Network	Mg/L Datasheet
Fresh Air	1	1.4062	0.2538	0.257
	2	1.0539	0.4646	0.47
	3	1.2303	0.3266	0.33
Raw Mango	1	0.9782	0.4833	0.43
	2	0.7261	0.6459	0.68
	3	0.9077	0.4971	0.43
	4	0.7770	0.5739	0.57
Ripe Mango	1	0.5466	1.0273	1.05
	2	0.6414	0.8131	0.8
Rotten Mango	1	0.3966	1.6919	1.7
	2	0.2853	2.6882	2.6
	3	0.4396	1.4283	1.5

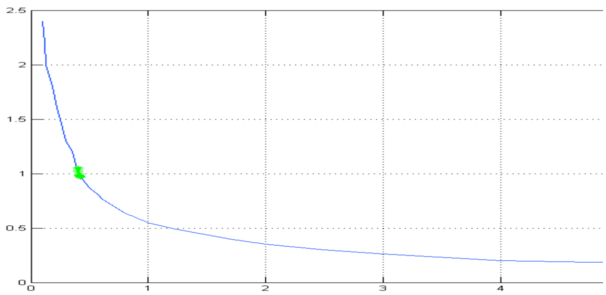

Fig. 4: mg/L value of Raw Mango

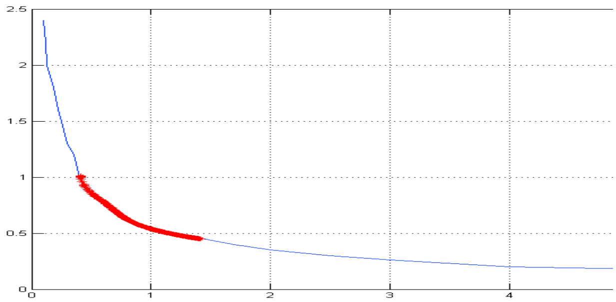

Fig. 5: mg/L value of Ripe Mango

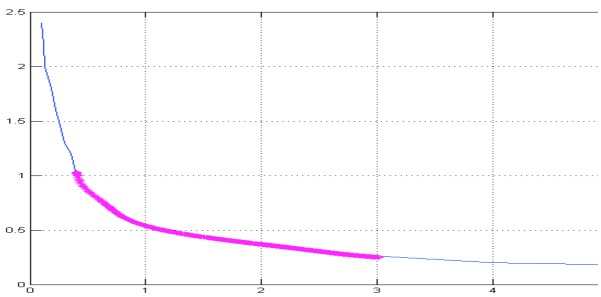

Fig. 6: mg/L value of Rotten Mango

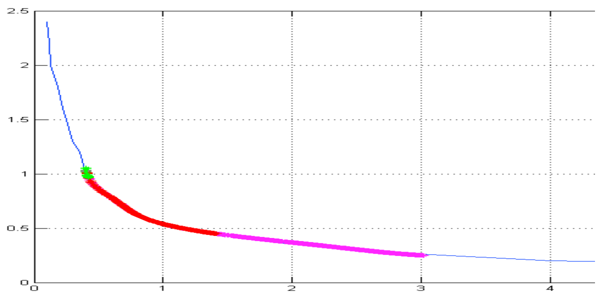

Fig. 7: mg/L value of Mango fruit maturity level

7 is the result of prediction mg/L value for raw, ripe, and rotten mango experiments made into one graph. It looks a different value of mg/L for mango maturity level.

5. Conclusion

After doing the research on several sensors in an electronic nose, each sensor has its own characteristics to calculate the gas concentration. Sensor MQ 3 is the right sensor to detect the alcohol gas content for mango fruit. The maturity level of mango can be predicted from the alcohol gas content. In addition, these sensors can identify raw mango, ripe mango, and rotten mango. There are some ways to determine the accuracy of ppm or mg/L using a curve fitting method, and the Artificial Neural Network method is suitable to be implemented in electronic nose sensors with the RMSE of 0.0433. These methods give a good result as the MQ 3 datasheet to estimate the value of mg/L in the alcohol concentration of mangoes.

Further research will be done classification of mango fruit maturity level of Rs/Ro value by SVM, k-NN method, decision tree, neural network, fuzzy and Extreme Machine Learning. And also a variety of fruits or another application E-Nose.

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