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MEAT FRESHNESS IDENTIFICATION SYSTEM USING GAS SENSOR ARRAY AND COLOR SENSOR IN CONJUNCTION WITH NEURAL NETWORK PATTERN RECOGNITION

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ABSTRACT

Meat freshness level is an important factor to determine meat quality for consumption. In this research, a sensor system has been designed to identify the freshness level of meat in fast, precise and non-destructive manners. The system is implemented into a Raspberry Pi equipped by gas and color sensors as the freshness identifier tools to replace the human olfaction and vision in determining a fresh meat. Pattern recognition powered by a neural network is used to identify the meat's freshness. The neural network inputs are the odors sensed by the gas sensor array of MQ-136, MQ-137, TGS 2620 and Red, Green, Blue values sensed by TCS 3200 color sensor. Three levels of freshness have been tested, such as fresh meat, half-rotten meat, and rotten meat. The usage of the three gas sensors and one color sensor of the system is capable to acquire a distinct pattern for the three categories of freshness. The freshness identification of the meat has a high percentage of success up to 80%. The errors are caused by the small different of the pattern sensed by sensors for half-rotten meat and rotten meat; these two kinds of meat fortunately are not consumable. Thus, it may conclude that the system has 100% success degree to identify fresh meat and non-fresh meat. The implementation of the system is expected to replace the traditional measurement by the human senses (i.e. nose and eyes) to obtain equal measurement as different human examiner acquires different result, and to eliminate the impact of bacteria or virus from meats to examiner. It may also replace measurement system using chemical substances so the tested meat will be still consumable.

Keywords: *Color Sensor, Gas Sensor, Meat Freshness, Neural Network, Raspberry Pi.*

1. INTRODUCTION

Meat freshness level is one factor to determine the quality of meat. This freshness level is used to decide whether the meat is consumable or not [1]. Presently, traditional way to identify the quality and freshness level of a meat is still widely used. The mean is required a direct contact to a meat sample through human visual inspection and odor assessment by human nose. Moreover, meat freshness quality assessment by human sense such as in food industry is difficult to be quantified due to inconsistent, error prone, expensive and labor intensive measurement for routine quality application [2].

More modern technique is also used through the help of chemical method. Yet, this process requires a long time inspection, and it is relatively complex and destructive meaning that the meat sample will be broken or inconsumable due to the chemical substance during testing. Therefore, a system that is capable to identify meat freshness level in quick time, accurate and non-destructive is required [3].

With the help of meat characteristic decomposition, an electronic nose as an olfaction and color sensor as a vision can be occupied to identify meat freshness level. An electronic nose is an artificial olfaction model or device inspired by the human biological olfactory system which is able to detect, identify and classify an aroma of a sample [4]. An electronic nose, so-called e-nose, is an intelligent electronic device embedded in a processing unit such as DSP/FPGA and microprocessor/microcontroller which consists of a sensor array as an odor sensing and pattern recognition system in recognizing simple or complex odor [5]. Many studies and researches have been conducted related e-nose, for example e-nose system for quality monitoring system for coffee under roasting [6], wine identification and classification [7][8], detection of bread baking aroma [9], description of mango fruit maturity [10], and evaluation of the optimal harvest date of apple [11]. An electronic nose by applying gas chromatography with QCM sensor detector has been investigated [12]. The system was capable to discriminate the common organic solvents, not only for compounds of a particular class but also for compounds of different classes. Moreover, many studies and researches also conducted in applying e-nose for meat freshness identification and classification [1], [3], [13] and [14]; and e-nose system has been designed to monitor the freshness of the Moroccan Sardines with neural network pattern recognition and [15].

To replace the human vision, camera can be employed as a vision sensor to capture image containing RGB value. Appropriate mean is required, such that the used of high resolution camera and high computing of image processing in a computer with high Graphic Processing Unit (GPU). This results an expensive cost and longtime measurement due to the image processing. Therefore, a color sensor may be used instead of camera due to its inexpensive cost and faster processing compared with image processing.

In this research, Sensor system design to identify meat freshness level with electronic nose and color sensor is designed. The e-nose consists of three gas sensors to sense meat odor and a color sensor to obtain the RGB value of meat color as its color changes due to the change of its freshness. The combinations or patterns of outputs of gas sensor array and color sensor are processed in neural network to identify the freshness level of the meat. The implementation of this system is expected to replace the traditional measurement by the human senses, and to replace the measurement using chemical substances.

2. THEORITICAL BACKGROUND

2.1 Meat Freshness

Aroma, color, texture and taste can be used to determine the freshness level of meat. The taste quality of meat is influenced by volatile organic compound (VOC) content. Meat can be classified by an electronic nose acting like human nose. Aroma or smell from meat is formed by complex combination of VOC coming from a variety of chemical reaction in meat. Some researcher said that fresh meat has no smell at all [3][13].

Decomposition of meat can be caused by the activity of microorganisms in the meat or due to the release of intracellular and microbial extracellular enzymes in meat. The parameters of meat rot are, among others, the changes in color and aroma, texture, mucus formation, and gas formation.

Table 1. Freshness of meat based on TVB-N content

Meat Freshness Level	TVB-N Content
Fresh	< 15 mg / 100 g
Half rotten	15 – 30 mg / 100 g
Bacon	> 30 mg / 100 g

The current classification of freshness of meat is based on the total amount of volatile basic nitrogen (TVB-N) found in meat. TVB-N is the amount of nitrite material that is distilled from the vapor or gas from the meat under alkalization conditions. TVB-N contains all the nitrogen content that can form ammonia under these conditions. Based on the RRC Indonesian national standard GB2722-81, a correlation between the TVB-N values contained in the meat with the degree of freshness shown in Table 1. Fresh meat is defined as meat with TVB-N content smaller than 15 mg / 100 g of meat. Half fresh meat is worth between 15-30 mg / 100g of meat, and bacon is worth over 30 mg / 100 g of meat.

2.2 Electronic Nose

An electronic nose abbreviated as e-nose is an analytical instrument designed to act-like human nose. The analytical process is not only focused on identification or quantification of evaporated gas mixture but also more towards the quantitative description of the overall aroma profile includes the relationship between the components.

The two main components of an electronic nose are the sensing system and the pattern recognition system. Sensing systems may consist of arrays or series of different sensing elements (e.g. chemical sensors), in which each element measures the different properties of the chemicals tested. Any chemical or gaseous vapor exposed to an array or series of sensors will produce a characteristic or pattern characteristic of the gas.

By exposing an array of sensors to different types of gases, a database of patterns or characteristics of the gas can be constructed. The database of these patterns or traits can then be used to train pattern recognition systems. The purpose of this training process is to set the recognition system to generate a unique classification of each gas so that the identification process can be automatically implemented [16].

Artificial neural networks or often abbreviated as ANN have often been used to analyze complex data and can be used to perform pattern recognition.

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Therefore, the use of ANN along with e-nose can make pattern recognition of chemical gases. ANNs already trained for gas recognition purposes can quickly identify a gas in the odor. This is because the recognition process involves only an advanced propagation process that is essentially a multiplication operation and a sum in the matrix.

The working process of e-nose can be illustrated in Figure 1. The first part of the block diagram shows a sensor series/array which is the hardware of an e-nose. After the signal from the sensor array is obtained and stored in the computer, the first process of calculation will begin to extract the descriptive parameters of the sensor array response and prepare for the feature vector to continue to the next process of extraction [8]. The dimensionality reduction stage projects the initial vector feature toward the lower dimension to avoid problems associated with the data set that are spread over the higher dimensions. The feature vector on the low dimension that has been generated will be used to perform the process of classification or prediction. The classification process is the identification of an unknown gas sample using the data set that has been obtained through the training process. This process is done using artificial intelligent such as neural network as depicted in the last part of Figure 1.

2.3 Gas Sensor

Until now there have been several types of gas sensors that have been developed. Gas sensors are distinguished on the basis of their materials or forming materials such as metal oxide semiconductor (MOS), conducting polymer (CP), and piezoelectric sensors such as quartz crystal microbalances (QCM). MOS type sensor gas is one type of sensor that is most widely used to build electronic nose system. This is due to the high sensitivity and the relatively cheap price [17].

The working principle of the MOS type gas sensor can be summarized into two phases. The first stage is when the sensor is in clean air, the donor electrons inside SnO_2 will be attracted towards the oxygen absorbed on the surface of the sensing material to be prevent the flow of electric current. The second stage is when the sensor is in exposure to a detectable gas.

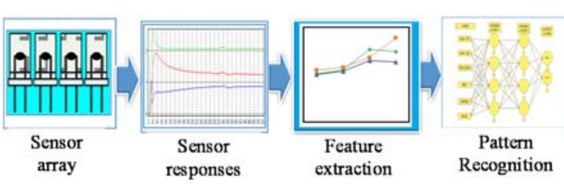
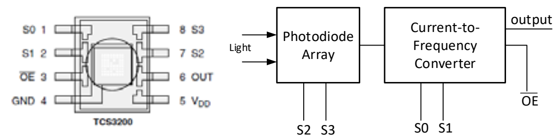


Figure 1: Block diagram of e-nose proses



(a) (b)

Figure 2: TCS3200 Color sensor (a) chip (b) block diagram.

This causes the surface density of the absorbed oxygen to decrease as the reaction to the gas. The electrons will then be released into the SnO_2 causing the electric current to flow freely to the sensor.

MOS type gas sensor widely used is the gas sensor type of MQ and TGS. The sensitive material of these gas sensors are SnO_2, which has a low conductivity level in clean air. When the sensor is exposed by the detected gas, the sensor's conductivity value will increase in proportion to the concentration of the gas in the air. Using simple electrical circuits, changes in sensor conductivity can serve as output signals related to the concentration of detectable gases in air [18][19].

2.4 Color Sensor

A color sensor is a sensor to detect RGB of a color of a subject. In this research, we employ TCS 3200 color sensor for the vision sense. The TCS 3200 color sensor is a programmable color light-to-frequency converter that combines silicon photodiodes and a current-to-frequency converter into a monolithic CMOS IC. Taken from TCS 3200 datasheet, the chip shape and diagram block of this sensor is shown in Figure 2(a) and 2(b) respectively, where the output of this sensor is a square wave with a 50% duty cycle whose frequency is directly proportional to the light intensity.

The output frequency scale of the sensor can be adjusted into three scaling options available through two input control pins. In the TCS 3200 sensor, the light to frequency converter reads an array of 8 x 8 photodiodes. Sixteen photodiodes have a green filter, 16 photodiodes have a blue filter, 16 photodiodes have red filters, and 16 other photodiodes without color filters.

The output frequency of this TCS 3200 generally ranges from 2 Hz to 500 KHz. Users can control the frequency values into three values of 100%, 20% and 2% through both programmable outputs of S0 and S1 pins summarized in Table 2. All photodiodes of the same color are connected in parallel. Pin S2 and S3 are used to select and to activate the photodiode groups which are red, green, blue, and clear as summarized in Table 3. TCS 3200 also has a

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Table 2. Correlation of S0 and S1 pins to frequency scaling

S0	S1	Output Frequency Scaling
L	L	Power down
L	H	2%
H	L	20%
H	H	100%

Table 3. Correlation of S2 and S3 pins to filter usage

S2	S3	Filter type
L	L	Red
L	H	Green
H	L	*Clear* (no filter)
H	H	Green

different sensitivity to red, green and blue. As a result, the RGB output value of white is not always worth 255.

2.5 Processing unit of Raspberry Pi and Arduino

Raspberry Pi is a single board computer (SBC) sized like a credit card that is developed in United Kingdom by the Raspberry Pi Foundation to promote teaching on the basic of computer science in schools. Raspberry Pi is designed like a SBC module so it can be referred to as a mini computer. In order to be accessed, Raspberry Pi should be connected to other required peripherals such as monitor screen (via HDMI) and input/output devices such as keyboard and mouse [20]. Raspberry Pi has its compatibility with electronic devices such as sensors, electronics components and programming languages that match for application in this research. This is because Raspberry Pi comes with a GPIO pin that we can also find on some types of microcontroller like ARM. In addition, it is also equipped with several communication protocols such as I2C and SPI. For data processing, the communication protocols can be used as communication with A/D converter chip or a microcontroller such as Arduino Uno.

Arduino Uno is a microcontroller based on ATmega328P. Arduino Uno has 14 digital input/output pins where 6 pins can be used as PWM outputs, then 6 analog input pins, a 16 MHz quartz crystal, has a USB port, a power jack, ICSP header and a reset button. Arduino has 10-bit A/D converter in default that will be used in this study. Like other microcontrollers, Arduino has its own programming application, Arduino Software (IDE) with C programming language. Furthermore, the programming language in Arduino is more user-friendly since the syntax in it has been simplified into a language that is easy to understand for whom not yet proficient in programming.

3. DESIGN IMPLEMENTATION

The system design can be categorized into two parts which are hardware and software designs. The hardware design covers the circuit implementation. The software design covers the program embedded in Raspberry pi and Arduino microcontroller. The software system consists of ADC reader program and color sensor on Arduino and neural network program using Lazarus on Raspberry Pi.

The block diagram of the overall system is illustrated in Figure 3. From the block diagram, it can be seen that the system identifies meat sample using electronic nose and color sensors placed in the sensor chamber. The electronic nose consists of an array of three different gas sensors: MQ-136, MQ-137 and TGS 2602. The three gas sensors are exposed to the odor emitted by the meat tested. The gas sensors then respond to the aroma of the meat by generating different voltage signals depending on the level of freshness of the tested meat. The voltage values of the three sensors in the electronic nose are read through 10-bit ADC of the Arduino microcontroller. While the color sensor will respond to the color of the meat by taking the RGB value of the meat color tested.

Signal data in the form voltages of three gas sensors and the RGB values of the color sensor will then be sent to Raspberry Pi via serial communication. The data received will be separated and classified by Lazarus software to become the inputs of the neural network. After the data are received, the data will be processed offline first before the online detection process done.

3.1 Hardware Design

The hardware system consists of electronic nose module, Arduino Uno microcontroller, Raspberry Pi, USB to TTL, color sensor, and sensor room/chamber construction. The chamber test has 10cm x 10cm x 10cm in size, as illustrated in Figure 4. The gas sensors are placed on the top of the

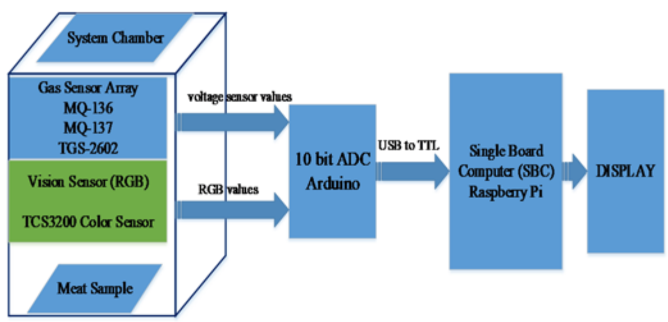

Figure 3: Block diagram of the system

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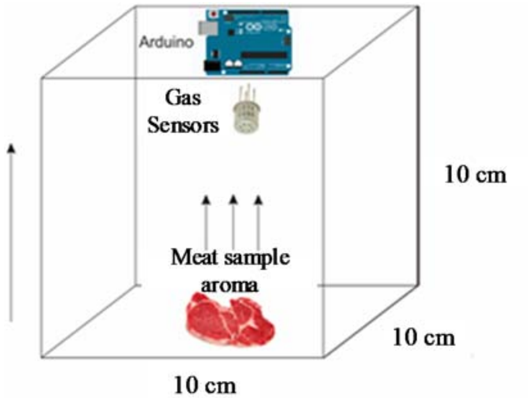

Figure 4: Design of Sensor Chamber

chamber and the meat sample is placed on the bottom side of the chamber.

Hardware design is begun with the electronic nose module in which three gas sensors are combined into a single PCB forming an array sensor. Then, the connection between the sensor array and microcontroller is set up. Accordingly, the hardware design includes the design of the chamber sensor. Figure 5 depicts the photograph of the array sensor of three gas sensors set up in a single PCB. The NH_3 and H_2S gasses are produced when a meat becomes rotten [1]. In order to measure the gas concentration when meat sample experiences decomposition, we can use gas sensors that are capable of measuring the concentration of these gases. This research is utilizing gas sensors of MQ-136 and MQ-137 that can detect H_2S and NH_3 respectively. For quality measurement purpose, we also add a TGS 2602 gas sensor because it has high sensitivity with low concentration odor such as ammonia and H_2S. It also has high sensitivity to VOC gas with low concentration like toluene from wood furnishing process.


Figure 5: Placement of Gas Sensors in the designed PCB

Table 4. Gas Sensor characteristics

Sensors	R_L (KΩ)	R_S (KΩ)	V_C
MQ-136	10 - 47	30 - 200	5V
MQ-137	10 - 100	900 - 4900	5V
TGS 2602	> 0.45	10 - 100	5V

Table 5. Gas response to clean air with chosen R_L

Sensors	R_L (KΩ)	Voltage for Clean air
MQ-136	22	2.30 V
MQ-137	10	1.95 V
TGS 2602	10	0.96 V

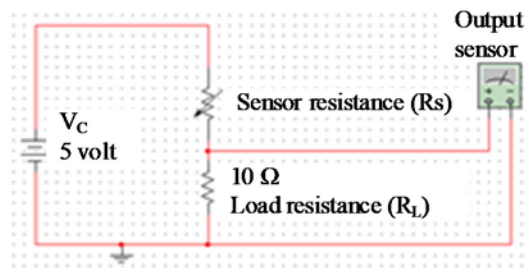

Figure 6: Resistance of gas sensor in voltage divider

As mentioned before, gas sensors have different resistance values when exposed to different types and concentrations of gases. The correlation between the value of the sensor resistance to the type and the gas concentration can be used to obtain information about the level of freshness of the meat. In theory, the fresh meat produces a different sensor response with meat that has begun to rot. By using the principle of basic voltage divider on each gas sensor, the freshness of the meat can be known as illustrated in Figure 6.

Table 4 lists the application characteristic of the gas sensors. The value of load resistance (R_L) is chosen to be fixed, while the sensor resistance value varies depending on the reaction to the gas type and concentration. We used R_L of 10 kΩ for MQ-137 and TGS 2602, and 22 kΩ for MQ-136. The sensor responses exposed to clean air are summarized in Table 5. Theoretically, the magnitude of the voltage value at the load resistance can be calculated as in equation (1) below,

$$V_L = \left(\frac{R_L}{R_S + R_L} \right) \times V_C \quad (1)$$

where V_L is the voltage at the load resistor that is connected to the A/D Converter, R_L is the load resistance, R_S is the resistance of the sensor and V_C is the input voltage sensor which is 5 volts.

TCS 3200 color sensor is used to retrieve data of the color characteristics of the meat under test. There

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are four color photodiode filters that are red, green, blue, and clear. The usages of these filter type are controlled by digital input "low" and "high" in the input pins of TCS3200 sensor chip which has been shown in Table 2. The output of this sensor is a square wave whose frequency will vary with the color detected by the photodiode. The frequency output can be scaled by the two input pins with digital input "low" and "high" as summarized in Table 3. In the design, to get the RGB value, the color sensor outputs are connected to the A/D converter pins of Arduino microcontroller. Therefore, it requires wiring connection between color sensors and Arduino. The wiring connection is illustrated in Figure 7.

3.2 Software Design

The software design includes programming of Arduino microcontroller, design of GUI and Neural Network in Raspberry. The GUI and NN designs are programmed using Lazarus software in Raspbian Operating System (OS), where the GUI display is an aid to run the process of identifying the freshness of meat. GUI view consists of two parts. The first part is the GUI view for the training process of the neural network as shown in Figure 8.

In the GUI view for the first part shows several clickable buttons to run the training process. The first step in the training process is to enter the value of the training gain, momentum update and

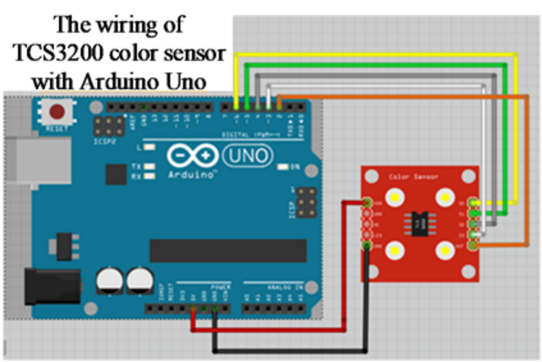

Figure 7: Wiring of TCS3200 Color sensor with Arduino

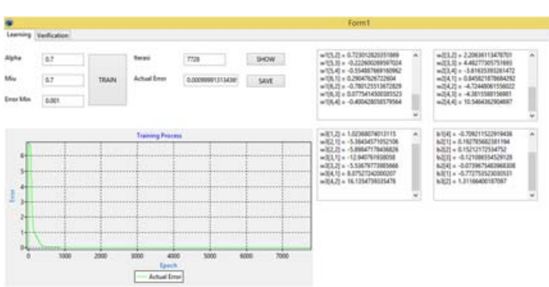

Figure 8: GUI interface in training process

Minimum Error on each box that has been provided. After the parameters of the training process is completed then the training process can be started by clicking TRAIN button on the GUI. The graphic shown in this view serves to display the current error value against the number of iterations that have been passed. After the training process is complete, then the last weight and bias can be displayed by clicking the SHOW button. The value of weight and bias of training results can also be stored in the form of text data that is ".txt" in the folder that has been determined by the user.

The second part of GUI display as shown in Figure 9 is an online user display interface of the process of reading data from gas sensors and color sensors and the process of identifying freshness of meat. To perform serial communication correctly, the first step is to fill the selection box from com port by choosing a path to use for serial communication. After filling the serial communication lines, the next step is to open the communication path that has been created by clicking the OPEN button. To close the serial communication path, click the CLOSE button. If the required serial communication parameters are in place, the serial data sent by Arduino will be received by the GUI immediately after the OPEN button is clicked. Information about the data from each sensor will be displayed in each box. The group box timer as shown in the GUI will start counting for 60 seconds when the START button is clicked. When the 60th second, the identification process will take place and the freshness of the sample meat will be shown by the GUI display. Figure 10 shows a serial data communication in Raspberry from Arduino.

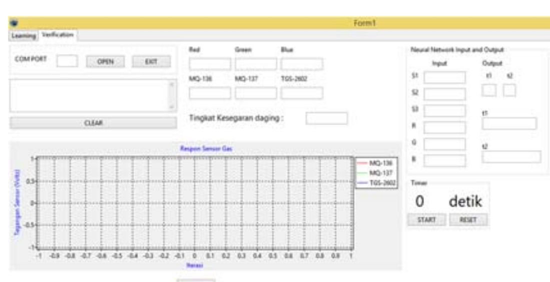

Figure 9: GUI interface in online identification

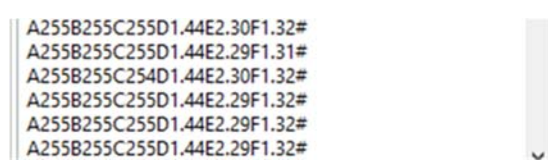

Figure 10: Serial data communication in Raspberry from Arduino

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The signal from the three gas sensors and the RGB values of the color sensor that has been processed by the A/D converter of Arduino microcontroller will be sent to Raspberry Pi in one data line via serial communication. Data delivery format that can separate and mark the process of data retrieval is required. Here, the marks A, B, C, D, E, and F are used to mark Red, Green, Blue, MQ-136, MQ-137, and TGS-2602 respectively. In example, data received on Raspberry Pi will have the format as shown in Figure 11. Later this data will be broken down by using a software program on the Lazarus in order to generate a single data for each information from three gas sensors and RGB of the color sensor.

The six data derived from data acquisition by Arduino and sent to Raspberry Pi via serial communication are used for identification process by neural network. The structure of the neural network can be seen in Figure 11. The neural network has 6 inputs derived from three gas sensors, and the RGB value. There are 3 layers composed of 2 hidden layer and 1 output layer. Both hidden layer consists of 4 neurons and the output layer consists of 2 neurons. The combination of two values of the neuron at the output layer will be the target of the neural network training. The fresh meat, half-rotten meat, and rotten meat are defined by the value of 00, 01, and 11, respectively.

The first step in designing a neural network program is the initialization of weight and bias. In the program line, the weight and bias values are determined randomly using a random number generator. The random syntax of the Lazarus program will generate a random number between 0 and 1. To get a random value between -1 and 1 then the random value is multiplied by 2 and then subtracted by 1. For forward propagation process is done by multiplying the inputs of the three gas sensors and the three color characteristics of the color sensor to each weight corresponding to the neuron. Then the bias will be added to each neuron.

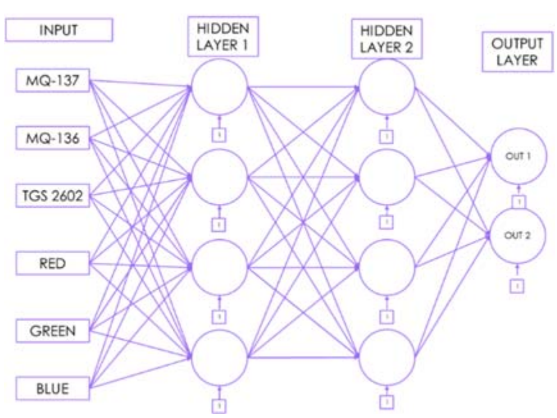

Figure 11: The design of neural network

Table 6 Samples of Meat Freshness Level

Meat Freshness Level	Definition of Freshness
Fresh	Meat in just-cut / from freezer
Half-Rotten	Meat in outside in room temperature for ±12 hours.
Rotten	Meat in outside in room temperature for more than 24 hours

4. MEASUREMENT TESTS AND RESULTS

The measurement test of the system is divided into three parts of tests which are gas sensor array test, color sensor test, and the entire system test including the identification result. The samples of meat tested are categorized into three parts which are fresh, half-rotten, and rotten as described in Table 6.

4.1 Testing on Gas Sensor Response

The experiments have been attempted to be consistent to obtain accurate data. Figure 12 shows the photograph of the system equipped with gas sensors in a chamber along with meat sample. The measurement data of gas sensors are taken in 60 seconds after the samples placed on the chamber.

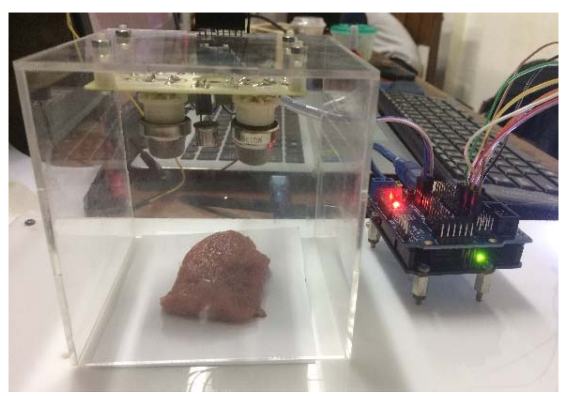
Figure 12: The photograph of gas sensor testing

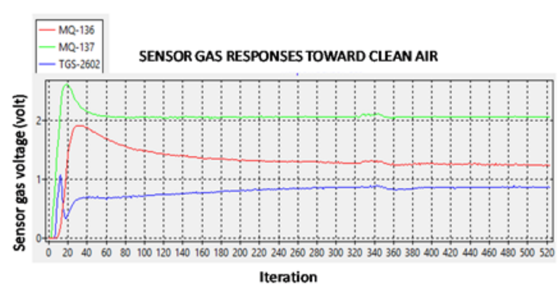

Figure 13: Testing of the gas sensors toward clean air

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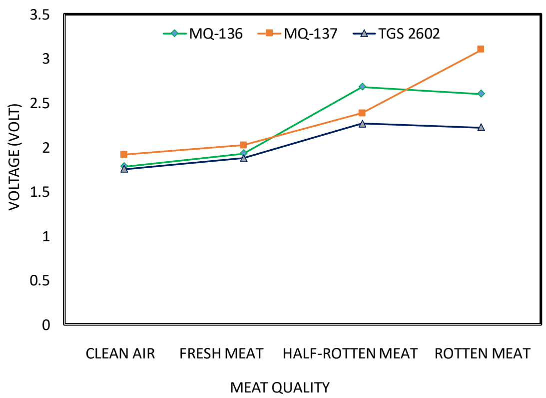

Figure 14: Response of gas sensors toward meat samples

The first testing of the gas sensor array is done in clean air condition. Figure 13 shows three sensor gas responses toward clean air flown into the chamber. The sensor response when the system is just turned on results a voltage value that rises sharply then after a while the signals experience voltage drops and then reach the steady state. The voltage value of the gas sensor in clean air can be used as a reference of the system created. Based on testing of gas sensor in clean air, this voltage value will change in a long time. To create a stable gas sensor response in clean air, a long warming of the gas sensor is required. This is necessary to increase the stability in reading the gas sensor signals.

Figure 14 shows the experiment result of gas sensors toward three kind of meat. The voltage values of these three gas sensors form a pattern that represents the state of a fresh meat. When compared with the value of gas sensor voltage in clean air, it can be seen that there is no significant difference. This is caused by the condition of fresh meat that does not emit a stinging smell. Further testing conducted with a sample of half-rotten meat. The condition of the meat in this state is to have an unpleasant odor but with a less concentrated aroma. When compared with the results of gas sensor testing on fresh meat samples, there is an increase in the voltage values on the three sensors. This indicates that the three sensors respond to the aroma produced by meat during the process of meat decay.

4.2 Testing on Color Sensor Response

Figure 15 shows the photograph of the system testing equipped with color sensors toward meat sample. The process of collecting color data from the meat is done by placing the color sensor closer to the surface of the meat to be tested so that the color of

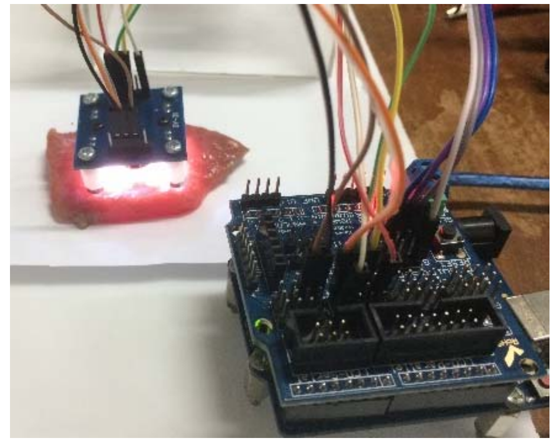

Figure 15: The photograph of color sensor testing samples

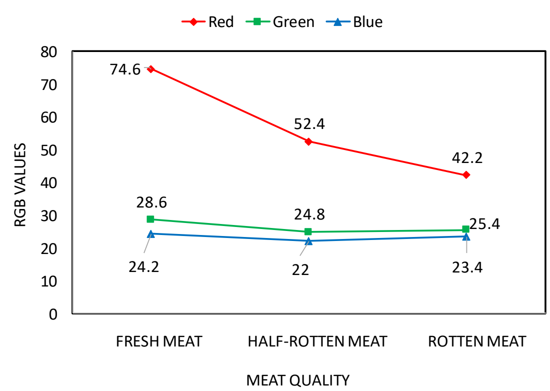

Figure 16: Response of color sensor toward meat samples

the meat surface will be captured by the photodiode of the color sensor. The color sensor response test toward meat samples are depicted in Figure 16. A pattern and relationship between the levels of freshness of meat to the color characteristics are shown. Fresh meat has the highest RGB value compared to two other meat samples. The RGB value obtained by this color sensor is displayed on the color selector application. The difference in redness of the meat color will be clearly seen. The red color will be darker if the meat is not fresh.

4.3 Testing for the Entire System

Here we will evaluate the entire identification system. Figure 17 shows the photograph of the entire system equipped with gas sensors, color sensors, and system processing unit. Based on the gas sensor test results, the sensor voltage values for each clean air condition are different. This impact in an uncertainty of the sensor voltage value in response to the tested meat sample. As shown in Figure 14, the voltage outputs of the MQ-136 and TGS 2602 sensors have almost the same value. Eventually, the voltage

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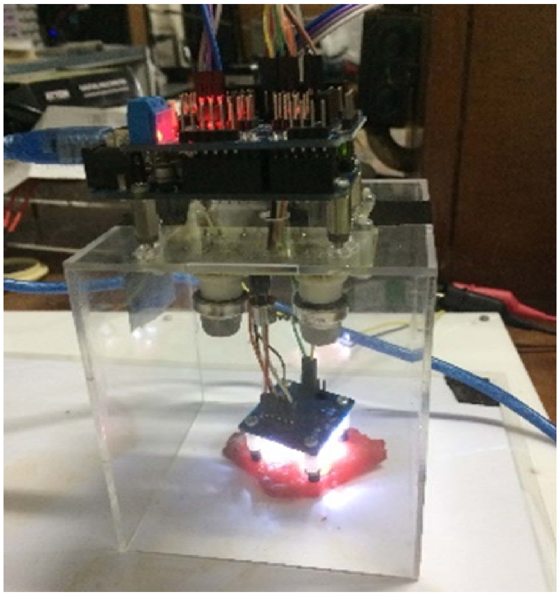

Figure 17: The photograph of the entire system

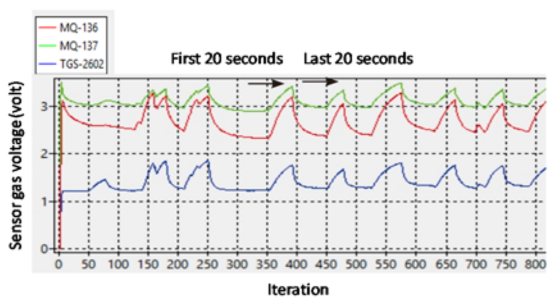

Figure 18: The baseline method of gas sensor response

outputs on the clean air conditions have different values. This will certainly lead to a pattern recognition error if this data is used as inputs for the neural network. Therefore, baseline method for data processing on gas sensors is used. The data retrieval process is 60 seconds counted after the meat tested entered the sensor room. To obtain the gas sensor voltage pattern for each meat sample with different freshness level, a baseline value of the gas sensor is used. Method to obtain the sensor gas values is to find the different of three sensor voltage outputs. The voltage outputs of three gas sensors from 1 second to 20 seconds will be recorded, summed and averaged. The calculation result is denoted as the bottom mean value V_{LOW}. The voltage values from 41 to 60 seconds are recorded and used to determine the mean value. The mean value is denoted as upper mean value V_{UP}. Then, the upper mean value will be subtracted by the bottom mean value resulting the difference of average voltage that is proportional to freshness level of the tested meat. The calculation process of the method is summarized in equation (2) to equation (3). Figure 18 shows the gas sensor responses after applying baseline method. It reveals the different responses from three gas sensors that is reliable to use as inputs to Neural Network for pattern recognition.

$$V_{LOW} = \frac{\sum_{t=1}^{t=20} V_{Sensor}}{20} \quad (2)$$

$$V_{UP} = \frac{\sum_{t=41}^{t=60} V_{Sensor}}{20} \quad (3)$$

$$V_S = V_{UP} - V_{LOW} \quad (4)$$

The test for three kinds of meat with 10 data of meats are summarized in Table 7 to Table 9. Figure 19 show the result of sensor gas array responses after applying the baseline method as in three equations of (2) to (4).

Testing of neural network software is done as the preparation to process all data obtained from the testing of color sensor and gas sensors. After the required data has been obtained, the first step is to do normalized data toward each data for the color and gas sensors respectively. The normalized process is done using the following formula,

$$Y_{norm} = \frac{Y}{Y_{max}} \quad (5)$$

Table 7 Output of sensors for Fresh Meat

Sensor Outputs in volt for Fresh Meat						
No	MQ 136	MQ 137	TGS 2602	Red	Green	Blue
1	0.0295	0.0665	0.0395	82	27	24
2	0.0450	0.0530	0.0560	74	22	18
3	0.0465	0.0530	0.0330	78	26	22
4	0.0530	0.0440	0.0725	80	26	22
5	0.0355	0.0195	0.0685	80	25	21
6	0.0575	0.0590	0.0755	83	26	22
7	0.0570	0.0580	0.0570	79	25	22
8	0.0635	0.0435	0.0505	74	30	26
9	0.044	0.0420	0.060	75	32	29
10	0.040	0.0555	0.074	81	32	28

Table 8 Output of sensors for Half-Rotten Meat

Sensor Outputs in volt for half-rotten meat						
No	MQ 136	MQ 137	TGS 2602	Red	Green	Blue
1	0.0260	0.0570	0.0920	55	27	24
2	0.0260	0.0520	0.0720	55	28	24
3	0.0620	0.1240	0.3020	55	29	25
4	0.0480	0.0255	0.2140	54	27	23
5	0.0445	0.0630	0.2780	55	29	25
6	0.0780	0.1880	0.2860	50	28	24
7	0.0535	0.1445	0.1855	54	28	24
8	0.0540	0.0980	0.2920	51	27	24
9	0.0820	0.1280	0.3920	48	25	21
10	0.0515	0.0805	0.2745	54	28	25

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Table 9 Output of sensors for Rotten Meat

Sensor Outputs in volt for half-rotten meat						
No	MQ 136	MQ 137	TGS 2602	Red	Green	Blue
1	0.0690	0.1285	0.1105	30	16	16
2	0.0445	0.1225	0.1020	29	16	15
3	0.0785	0.0915	0.0715	29	16	15
4	0.0800	0.1020	0.1320	30	16	15
5	0.0705	0.1575	0.1285	29	16	15
6	0.0980	0.1080	0.1100	31	17	16
7	0.0880	0.1160	0.2040	31	17	17
8	0.0920	0.0820	0.1480	25	14	13
9	0.0780	0.0430	0.1135	31	17	17
10	0.0715	0.0310	0.1445	27	15	14

in where Y_{norm} is normalized data, Y is the actual data and Y_{max} is the highest data for the same sensor in the same sample. After the normalization process, the data value will have range from 0 to 1.

There are 30 data inputs in which 10 couples of input/output for three meat conditions. These data become inputs for neural network. The system then has a training process. Figure 20 shows that the error value is reducing in training process as the number of iteration is increased. The training process is stopped when the actual error reaches the setting value of minimal error.

After the training process, the weight and bias values are obtained for online identification process. Table 10 reveals the testing result of 10 samples. From 10 times of experiments, it is obtained that 2

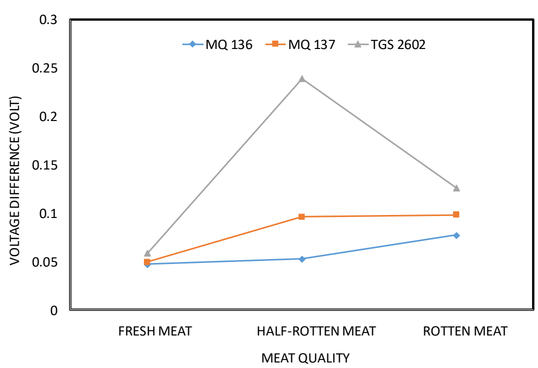

Figure 19: Voltage difference of gas sensor responses

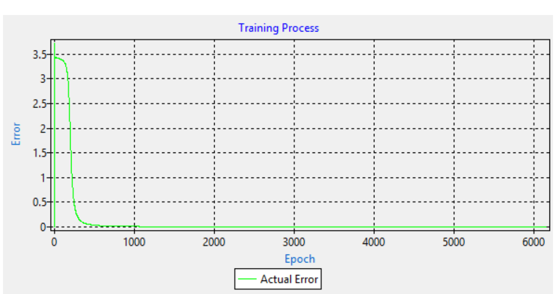

Figure 20: Training Process of neural network

Table 10 Online testing for 10 samples of meat

No	Target 1	Target 2	Testing Meats	Identification
1	0	0	Fresh	Fresh
2	0	0	Fresh	Fresh
3	0	1	Half-Rotten	Half-Rotten
4	1	1	Half-Rotten	Rotten
5	1	1	Rotten	Rotten
6	1	1	Rotten	Rotten
7	0	0	Fresh	Fresh
8	0	0	Fresh	Fresh
9	1	1	Rotten	Rotten
10	1	1	Half-Rotten	Rotten

samples experience wrong identification. Therefore, the percentage of success is 80%. However, the wrong identifications occur to the half-rotten meat and rotten meat, in which these kinds of meats are inconsumable.

5. DISCUSSION

The designed system is able to identify correctly between fresh meat and rotten meat. Half rotten meat is sometimes identified as rotten meat. This is due to their different small patterns. Besides, the identification error is caused by unequal environmental condition in which the meats undergo different decomposition. A baseline method for data processing on gas sensors has been adopted in order to have valid data for ANN input. Other methods may be employed work to obtain better performance. Pattern classification algorithms of Support Vector Machine [21] and k-nearest neighbor [22] may also be adopted and compared for future because they are better in sensitivity and specificity than ANN. Besides, high vision method will be adopted for future work using camera and good method of image processing. Another challenge is to measure the freshness level in ambient air, in which the air condition will affect in measurement.

6. CONCLUSIONS

Electronic nose system on a single board computer that has been developed showed its success in identifying the tested meats. A semiconductor gas sensor array of TGS2602, MQ137 and MQ138 as olfaction sensor and TCS3200 as RGB vision sensor can identify the odor and colors of different freshness of meat. Baseline method has been used to produce a clear output differences generated by gas sensors reacted to meat freshness level. The identification process with the neural network have been working very well, in which the electronic nose system is able to recognize the pattern of each freshness with success rate of 100% for fresh meat and non-fresh meat (i.e. half-

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rotten and rotten meat). The system may be expected to replace the traditional ways by human and chemical techniques.

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