Spoiled meat classification using semiconductor gas sensors, image processing and neural network

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Spoiled Meat Classification Using Semiconductor Gas Sensors, Image Processing and Neural Network

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***Abstract*—Spoiled meat level can be detected manually by using the senses of sight and smell. However, it can endanger the human body if the gas emitted by rotting meat exhaled directly because of the bacterial contamination. Furthermore, such classifications are inevitably somewhat subjective since everyone has different assessments of the spoiled meat. This research presents the use of semiconductor gas sensors to detect gas emitting from rotting meat as a substitute for human olfaction. In addition, a camera equipped with image processing using Grey Level Co-Occurrence Matrix is applied as a replacement for vision. The responses of gas sensor array and Grey Level Co-occurrence Matrix were processed by Neural Network to classify the spoiled meat level. The classification of Artificial Neural Networks has a high percentage of success up to 82%. This method can replace the role of human senses in meat classification automatically.**

***Keywords*—Grey Level Co-occurrence Matrix, Neural Network, Semiconductor Gas Sensor, Spoiled Meat Level**

I. Introduction

Meat is one of food sources which often consumed by society. However, rotten meats have been sold on the market nowadays as the cases emerged on the media [1]. A high-level of rotten meat can influence the health of consumers since it emits gases from the result of protein metabolism by bacteria Clostridium, Bacillus and Pseudomonas. The metabolism process will produce some gases such as ammonia (NH_3), hydrogen sulfide (H_2S), and Volatile Organic Compounds (VOC) [2]. Moreover, the bacteria in rotten meat also affect the color change and mucus-forming. It is as a result of bacteria Pseudomonas obtain the energy to grow in carbohydrate metabolism process [3]. The impact of rotten meat to a person's health triggers the need of a tool to classify the spoiled meat level.

Some studies on gas type detection have been conducted, such as electronic nose installed on a robot to search the gas source [4], [5]. In the research, Neural Network was used to identify gas types [6], [7]. Furthermore, there was a study on sensor tool for monitoring the harmful VOC compound [8]. A number of VOC compounds are released during food decaying process [9]. Additionally, some researches on gas classification can be presented by using feature extraction [10], [11]. Beef quality identification can be observed by using color analysis based on Indonesia National Standard (Standar Nasional Indonesia/SNI) [12]. A method to identify the spoilage of meat level can be conducted by using gas sensor array [13], [14].

In this study has classified the spoilage of meat level using semiconductor gas sensor as the sense of smell. In addition, an image processing using feature extraction is applied to observe the spoiled meat texture changes. Based on the bacterial metabolism of the spoiled meat, the semiconductor gas sensors are used to detect NH_3, H_2S and VOC gases. A camera is used to take the meat images to detect the texture. The result of semiconductor gas sensors and image processing are then processed by Neural Network to classify the spoilage of meat automatically after training phase.

II. Research Method

In this study, the spoiled meat level classification system consists of the gas type detection and image processing, shown in Fig. 1. The voltage of semiconductor gas sensor array was read by using microcontroller ATMega328 and sent it to the computer. Meanwhile, the image taken from camera was processed by using Grey Level Co-occurrence Matrix (GLCM) algorithm. The result of data processing from semiconductor gas sensor array and camera were used for Neural Network input. The meat spoilage level classification system block diagram can be seen in Fig. 2. In this study, light intensity measurement was carried out to present the best feature extraction in order to classify the spoiled meat level more effectively.

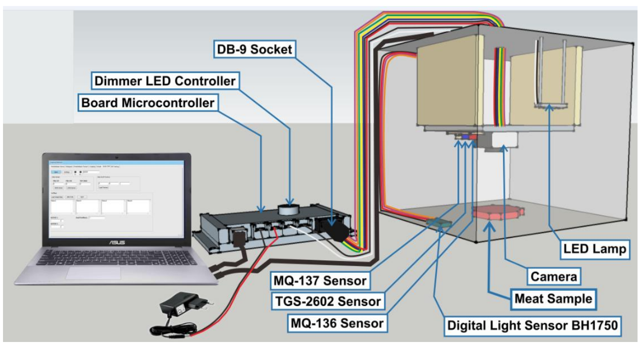

Fig. 1. The spoiled meat level classification system

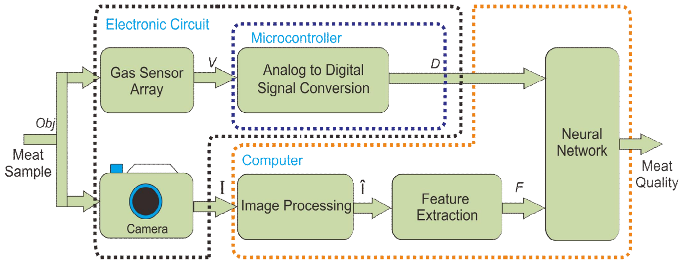

Fig. 2. The block diagram of spoiled meat level classification system

The light intensity measurement was performed by using digital light sensor BH1750. The 100 gram beef sample is put into a sealed box that is protected from outside light. The observation was conducted from 0 until 12 hours.

A. *Gas Sensor*

The gas sensor which used in this study are MQ-137 to detect NH3, MQ-136 to detect H_2S and TGS2602 to detect VOC. MQ-137 and MQ-136 sensors require voltage supply 5V ± 0.1V. The heater resistance in these two sensors are 31Ω ± 5%. The resistance value in gas sensor is 10KΩ. The sensor resistance will change in accordance with the concentration of the detected gas. The detection range of gas sensors can be seen in Table 1.

The result of gas sensor is a change of resistance value converted to analog voltage. The voltage of the gas sensor is converted by 10 bit analog-to-digital-converter (ADC) in microcontroller, then it is sent to the computer by using serial communication at a baud rate of 9600 bps.

B. *Image Processing*

The image sensor in this study is a webcam camera A4Tech with specifications automatic focus 10 cm to infinity with the resolution up to 16 Megapixel. The short-range focus and the best sharp image will make image processing stage easier to do. After taking the meat images by using the camera, the image would be sliced into size of 300x300 pixels. These meat images were taken every hour for a period of 12 hours. The next step was feature extraction using second order statistics of GLCM to detect the meat texture. Texture changes would be resulted in spoiled meat as an effect of mucus-forming caused by the spoilage bacteria. In feature extraction process using GLCM, there were RGB image conversion to Grayscale, matrix co-occurrence generation and second order statistical measurement. The features used in classification process consisted of Angular Second Moment (ASM), Inverse Different Moment (IDM), Contrast, Entropy and Correlation. The function of ASM feature is to detect the similar size of meat image, the IDM is to show the similarity of meat image in the same degree, Contrast is used to measure the gray levels of image pixels, Entropy demonstrates to measure the irregular grayscale, and Correlation is to measure gray level linear dependence between various grayscale values [15], [16]:

$$\mathrm{ASM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{ij}^{2} \tag{1}$$

TABLE I. THE DETECTION RANGE OF GAS SENSORS

Sensor Type	Detection Range
MQ-137	5-200 ppm NH_3
MQ-136	1-100 ppm H_2S
TGS2602	1-30 ppm VOC

where N is the number of gray levels in the image, i and j are the coordinate space, and P_{ij} is the normalized symmetrical GLCM.

$$\mathrm{IDM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \tag{2}$$

$$\mathrm{Contrast} = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N-1}\sum_{j=1}^{N-1} P_{ij} \right\}, |i-j| = n \tag{3}$$

$$\mathrm{Entropy} = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{ij} \log P_{ij} \tag{4}$$

$$\mathrm{Correlation} = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu_x)(j-\mu_y)}{\sqrt{\sigma_x \sigma_y}} \tag{5}$$

where μ_x is the average intensity of all pixels x, μ_y is average intensity of all pixels y, σ_x is variation of the intensity of all pixels x, and σ_y is variation of the intensity of all pixels y.

C. *Neural Network*

Neural Network in this study is back-propagation method used to classify the meat spoilage level. The Neural Network input is gas sensor values and GLCM features. The Neural Network consists of 2 hidden layers with 4 neurons in each layer. The Neural Network output has 2 neurons to determine 3 spoilage levels. The output of 00 is fresh, 01 is rotten, and 11 is putrid, as shown in Fig. 3. In the Neural Network, a training stage was performed in an error level of 0.001 with the learning rate of 0.5 and the momentum value of 0.6.

In back-propagation method, the training data is a set of input (p) and target (t), defined in (6). The next step is to calculate error between the actual and the desired output, defined in (7). There are two stages in back-propagation method, i.e. forward propagation and back-propagation. The forward propagation processes data from the input layer to the output layer. In this stage, the weight and bias initializations are conducted for every neuron. The first weight and bias are performed randomly, defined in (8). The summing value from the neuron input is converted by log-sigmoid transfer function to produce neuron output, defined in (9). The following stage is back-propagation which calculating local gradient, defined in (11) and updating weight, defined in (12) and bias, defined in (13), using derivatives of the log sigmoid transfer function, defined in (10). The calculation process in Neural Network

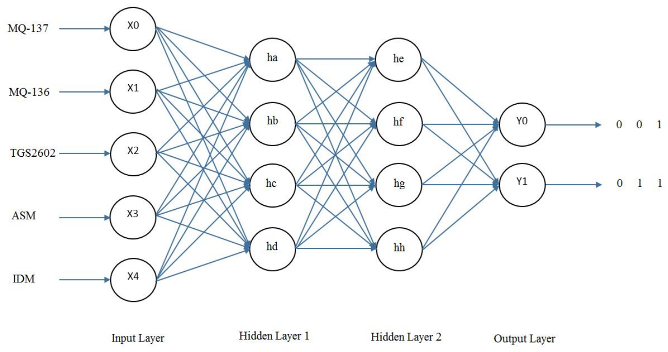

Fig. 3. The Neural Network Architecture for spoiled meat level classification

can be explained as the following:

$$\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\} \qquad (6)$$

where p is input and t is target vectors.

$$J = \frac{1}{2} \sum_{j=1}^{i} \left(t_j - \alpha_j\right)^2 \qquad (7)$$

where J is error, t_j is output target on neuron j, α_j is output on neuron j, i is the number of neuron, and j is number of neuron.

$$n_i = \sum_{j=1}^{k} w_{ij} p_j + b_i \qquad (8)$$

where n_i is neuron i, k is maximum number of neurons j, w_{ij} is weight from neuron i to j, P_j is input data normalized on neuron j, and b_i is bias in neuron i,.

$$\alpha = \frac{1}{1 + e^{-n_i}} \qquad (9)$$

where α is output of neuron.

$$\dot{f}(n) = f(n)[1 - f(n)] \qquad (10)$$

where $\dot{f}$ (n) is transfer function of derivative log sigmoid and f(n) is transfer function of log sigmoid.

$$\delta_j = \delta_{inj} * \dot{f}(n) \qquad (11)$$

where δ_j is gradient on neuron j and δ_{inj} is gradient on neuron ij.

$$w(n+1) = w(n) + \varphi * \delta(n) * y \qquad (12)$$

where w(n+1) is updated weight, w(n) is initial weight, y is output each layer node, φ is momentum value and $\delta_{(n)}$ is gradient neuron.

$$b(n+1) = b(n) + \varphi * \delta(n) * 1 \qquad (13)$$

where b(n+1) is updated bias and b(n) is initial bias.

III. Experiment Result

There are three stages used in this study, which are gas sensor data collection, meat image feature extraction, and the classifications using Neural Network. Fig. 4 shows the tool designed to classify the spoilage of meat. It consists of a box which contains meat, camera, three gas sensors, and light intensity sensor. The gas sensor and the light intensity sensor are connected to the microcontroller and then are sent to the computer, while the camera is directly connected to the computer.

A. Gas sensor examination

Fig. 5 shows the three gas sensor's responses every hour. In the initial response, the dominant sensor was MQ-137, but at higher levels of meat decay, MQ-136 yielded higher values because of the amount of H_2S released by meat [2].

B. Image Examination

The image examination was conducted by taking meat image size of 640x480 pixels which then sliced into the size of 300x300 pixels observed from 0 hours to 12 hours. The change in color and texture of the meat look increasingly black, and the texture looks rough as water shortages, as shown in Figure 6.

The next process is the extraction of a GLCM features. The ASM is decreasing every hour and approaching linear response, shown in Fig. 7. The IDM also shows the same result as the ASM, shown in Fig. 8. The Contrast is actually decreasing but there is an increased response in certain hours like at 1, 4, and 10 hours as shown in Fig. 9. The Entropy increases and decreases irregularly every hour as shown in Figure 10. The Correlation The overall value increases every hour but there is a decrease in certain hours as at 1, 4, and 6 hours, The Correlation increases every hour but there is a decrease in certain hours such as at 1, 4, and 6 hours as

Fig. 4. The equipment used in the experiments

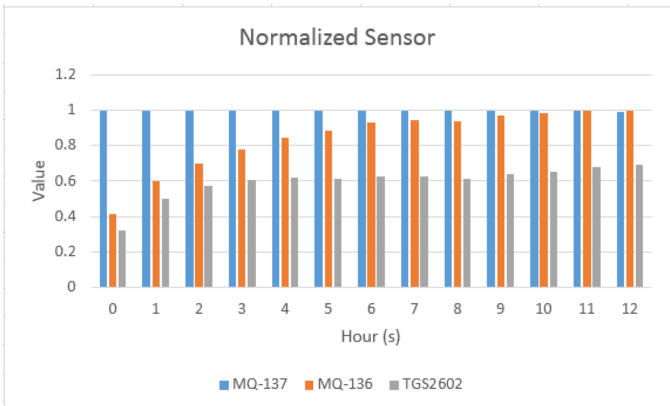

Fig. 5. The responses of the gas sensor array to the spoiled meat vapors.

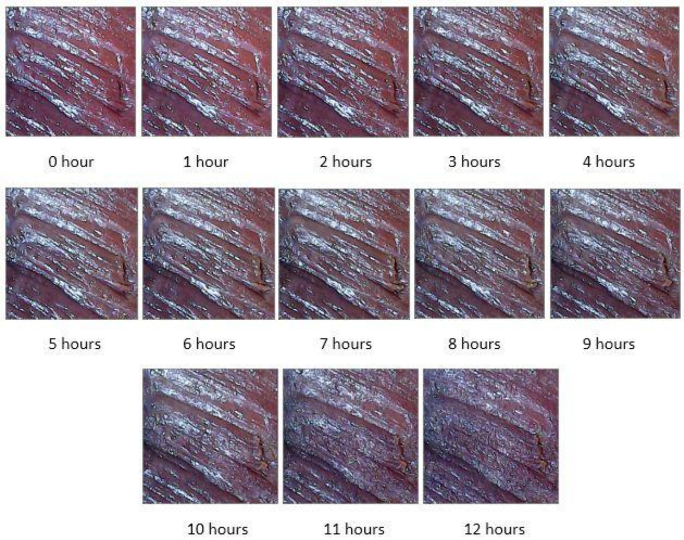

Fig. 6. The meat image size of 300x300 pixels

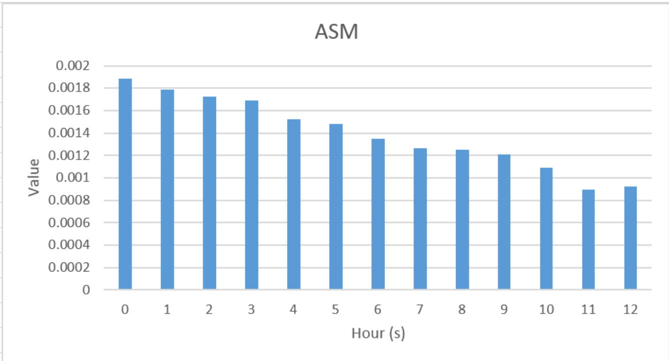

Fig. 7. The ASM value to the spoiled meat

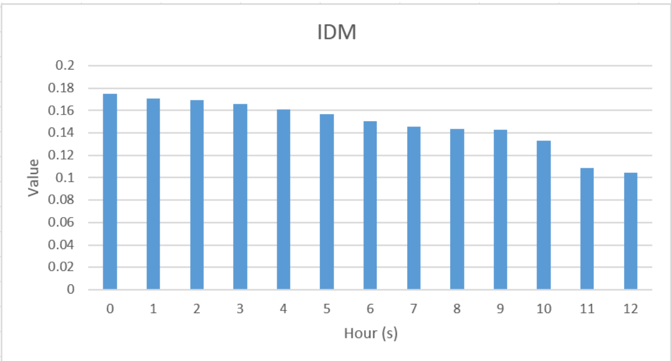

Fig. 8. The IDM value to the spoiled meat

shown in Figure 11.

Linear regression calculations were performed to determine the best intensity to represent the level of meat decay based on the response value. This examination has been performed on different conditions of brightness levels of 30, 60, 90, 120 and 150 lux, shown in Table 2. It shows that the best brightness level is 90-lux. In addition, linear regression calculations are also performed to select the best GLCM features based on the largest gradient and coefficient of determination, as shown in Figure 12. It is shows that the best GLCM features are ASM and IDM.

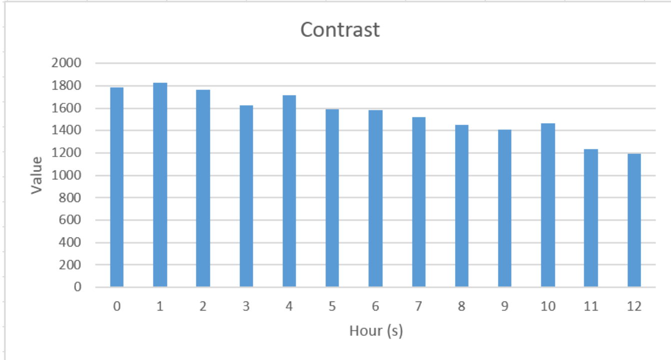

Fig. 9. The Contrast value to the spoiled meat

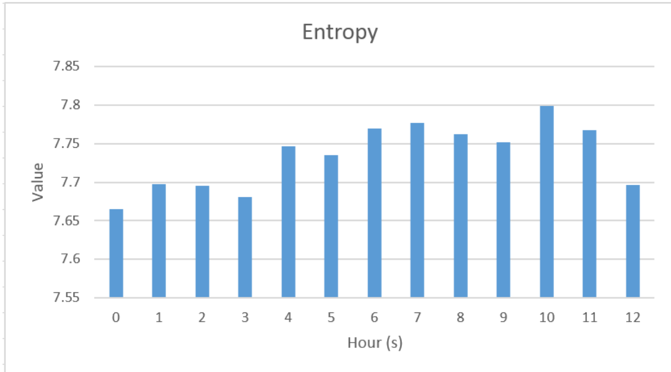

Fig. 10. The Entropy value to the spoiled meat

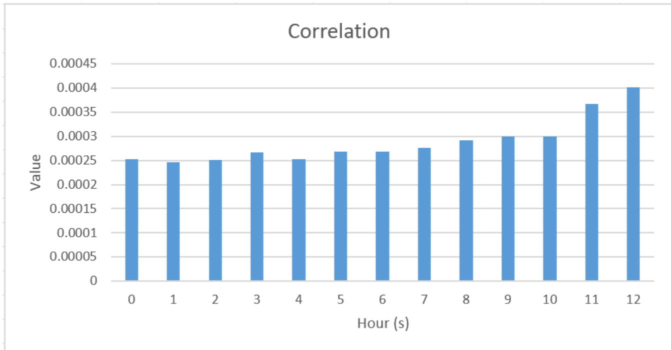

Fig. 11. The Correlation value to the spoiled meat

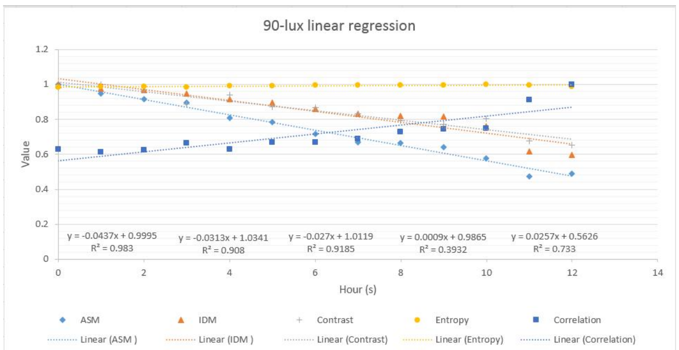

Fig. 12. Linear regression responses for the GLCM features

C. Neural Network Classification

At the training stage, the Artificial Neural Network can reach a level of error of 0.001 requiring 67.811 iterations, as shown in Figure 13. This training phase involved 24 samples of fresh, rotten, and putrid meats. Each sample consists of different meats. After the training phase, the examination stage was carried out using 28 other samples for three levels of meat rot. At the testing stage, Neural Network can recognize three classifications of decay with a success rate of up to 82%, shown in Table 3.

IV. CONCLUSION

In this study, the classification tool of meat spoilage has been designed to divide into three groups: fresh, rotten and putrid. The results show that the more rotten, the higher the response semiconductor gas sensor MQ-136 along with the increasing of H_2S gas. In addition, the best features of GLCM are ASM and IDM based on the highest gradient and coefficient of determination. The best light intensity that can be used for image processing is 90-lux. The Neural Network equipped with a semiconductor gas sensor array and GLCM image features can distinguish spoiled meat levels with success rate of up to 82%.

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TABLE II. DETERMINATION COEFFICIENT DATA IN DIFFERENT FEATURES AND LIGHT INTENSITIES

Light Intensities (lux)	ASM	IDM	Contrast	Entropy	Correlation	Rata-rata
30	0.8743	0.795	0.8475	0.1851	0.6846	0.6773
60	0.8794	0.8161	0.8799	0.1068	0.7039	0.67722
90	0.983	0.908	0.9185	0.3932	0.733	0.78714
120	0.7613	0.6547	0.5598	0.4373	0.5678	0.59618
150	0.9253	0.8686	0.6643	0.2185	0.5661	0.64856

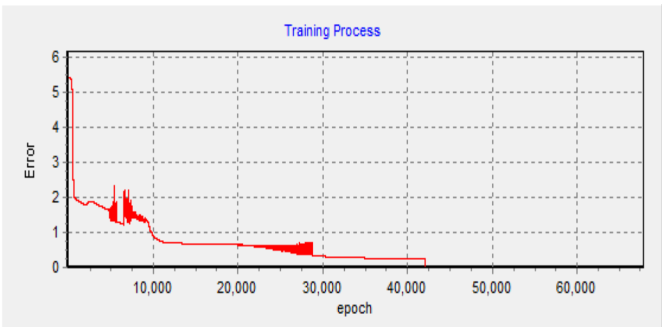

Fig. 13. The error value in Neural Network training stages

TABLE III. NEURAL NETWORK CLASSIFICATION RESULT

No	Meat data/samples	Classification result
1	Fresh	Fresh
2	Fresh	Fresh
3	Fresh	Fresh
4	Fresh	Rotten
5	Fresh	Fresh
6	Fresh	Rotten
7	Fresh	Fresh
8	Fresh	Rotten
9	Rotten	Rotten
10	Rotten	Putrid
11	Rotten	Fresh
12	Rotten	Rotten
13	Rotten	Rotten
14	Rotten	Rotten
15	Rotten	Rotten
16	Rotten	Rotten
17	Putrid	Putrid
18	Putrid	Putrid
19	Putrid	Putrid
20	Putrid	Putrid
21	Putrid	Putrid
22	Putrid	Putrid
23	Putrid	Putrid
24	Putrid	Putrid
25	Putrid	Putrid
26	Putrid	Putrid
27	Putrid	Putrid
28	Putrid	Putrid

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