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MOS gas sensor of meat freshness analysis on E-nose

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Abstract
The high demand of meat causes the seller mix the fresh and not-fresh meat. Electronic nose was used to detect the quality of the meat quickly and accurately. This research is proposed to test and analyze the sensitivity of MOS sensor in the electronic nose and simulate it using Matlab to identify meat classification using neural network. Test parameters based on Indonesian National Standard (SNI 3932-2008) requirement on the quality of carcass and meat. In this simulation, the number of neurons in the hidden layer was varied to find the most accurate identification. The sensitivity analysis of the MOS sensor was conducted by testing the meat sample aroma, calculate the sensitivity, identify the formation of input, hidden layer, outputs, and simulate the result of the varied formation. Then, found the number of the most optimal neurons. The result of the data training will be applied to the real instrument.

Keywords: *matlab, meat, metal oxide semiconductor, neural network, simulation*

1. Introduction

Meat is one of the most consumed meals by the people around the world. The high demand of meat is related to meat storage conditions after cutting that affects the quality of meat. Estimation of meat quality is usually based on the sense of smell or human vision that allows the occurrence of negligence [1]. The freshness level of meat is usually used to decide wether the meat is consumable or not [2]. The quality identification of fresh meat requires a number of laboratory tests according to SNI classification, namely; the number of bacteria, color, hardness, moisture content [3].

The high demand for meat causes the seller mix the fresh meat with the decayed ones (not-fresh meat). The purpose is a higher profit although that is illegal and it harms for the consumers [4]. Determining the safety of meat is conducted by quantifying volatile organic compound associated with the growth of microorganisms [5]. It is hard to know easily the quality of the meat on the market because the meat must be tested in the laboratory and also time consuming, for that reasons, the electronic nose coupled with different type of sensor arrays is used. An artificial intelligence program is needed to create that instrument needs to identify the classification of the meat on the market and neural network is one of common used programs [6].

The electronic nose is an instrument that have been developed in widely ranging to diagnose several object such as food industry and agriculture [7]. The electronic nose has been applied in several studies, such as to determine the quality of coffee under roasting [8], wine classification [9], detection of maturity of fruit [10], bread baking aroma [11], and evaluate the optimal harvest date of apples [12]. There are two types of electronic nose, those are direct and indirect. Indirect means such as quantiative analysis based on instrumental detection, while direct detection using sensory olfactomery and it is including molecular technologies, such as polymerase chain reaction (PCR), fluorencsence in-situ hybridization (FISH) and enzyme-linked immunosorbent assay (ELISA) [13-15].

Two main components of the electronic nose is a sensing system and a recognizing pattern system. Sensing system that coupled with a number of arrays or sequences from the

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different elements, such as chemical sensors, which is each element measure the different quality of the chemicals tested [16]. When gas samples are spread across the sensory arrays, then the odor molecules induces the physicochemical changes to the sensing materials. The circuit will be modulate the signal and the pattern can be used to classify the aroma [17].

A neural network is a network of a small group of processing paradigms which modeled human neural systems to non-linear statistics modeling data. A neural network has a set of interconnected parallel algorithms [18]. A neural network is an adaptive and capable system to solve problems based on the information through the network. A neural network is mostly used as a specific application, such as data classification or pattern recognition through learning process [19]. A neural network has already trained to recognize the gas then quickly identify the odor of gas because the recognition process actually involves only propagation process [20].

Matrix laboratory, usually called as Matlab, is a numerical computation and analysis designed in advance programming language using the characteristics and the form of a matrix. Matlab is a commercial product of Mathwork.Inc company which developed by using C++ language and assembler for the basic functions of Matlab. Generally, Matlab is used for mathematics and computation, algorithm development, modeling, simulation, and prototype creation, data analysis, exploration, visualization, and Graphic User Interface (GUI). Matlabhas some particular functions and various methods to solve any problems which categorized in the toolbox [21]. In this research, Matlab is used to simulate the result of varying formation of input, layer and output using graphic user interface (GUI).

Metal oxide semiconductor (MOS) widely used to make array for odor sensing, but many of them shows gas sensitivity under suitable condition [22, 23]. The basic principle of metal oxide semiconductor (MOS) sensor when the concentration of oxygen is 0% concentratio and the temperature of tin dioxide (SnO_2) material reaches 400^o C, the electrons will be across he green boundary. In clean air, donor electrons in tin dioxide (SnO_2) are atracted toward oxygen which is preventing electric current flow. If the sensor exposed by reducing gas, the surface density of absorbed oxygen decreased because the reaction of reducing gas. The electrons will be easy to flow in tin dioxide and its allowing current to flow freely through the sensor. The chemical reactions from the gas and the adsorbed oxygen on the surface of the tin oxide layer are varied, those depend on the reactivity of the sensing material and the temperature condition of the sensor. The gas concentration in the air can be detected by measuring the change of the resistance of the metal oxide semiconductor gas sensor [24].

Based on the problem above, this research proposed to identify level of meat freshness by using the MOS sensor types TGS2600, TGS2602, TGS2620, MQ135, TGS183. Then, neural network method will be used to indentify the result of MOS sensor, neural network method will be created on Matlab. The funcion of neural network method is to test the meat sample aroma to obtain the resistance ratio. The result of this research is the most optimal number of neurons for this detector systems.

2. Research Method

The method used is an indirect method. The aroma of the meat was taken by using injection tube then put it into the testing chamber. In the testing chamber, there are five gas sensors of metal oxide semiconductor type, which will verify the sample aroma exactly and simultaneously. The data read by the sensor will be acquired by the data acquisition. Each different sample will also result a different patterns. Those patterns will be learned by using a neural network with the determined target, that is the classification of meat freshness of each sensor

2.1. Data Collection

The steps of data collection and sample measurement is shown in Figure 1. The data collection is started by entering the sample into a vial bottle and end with normalization. The data used is the sensitivity of the average sensor output to the clean air and the gas sample in real-time. The sensitivity of the response sensor used equation as follows;

$$S = {}^{Ro}/_{Rg} \tag{1}$$

Where Ro is the sensor response to the clean air (reference) and Rg is the sensor response to the sample in ohm units. MOS type sensor sensing element is made of tin oxide material (SnO2) where Ro is the sensor response to clean air (reference) and Rg is the sensor response to the sample in ohm unit. In this case, the meat aroma is the reducer gas so that the resistance is always changed according to gas concentration.

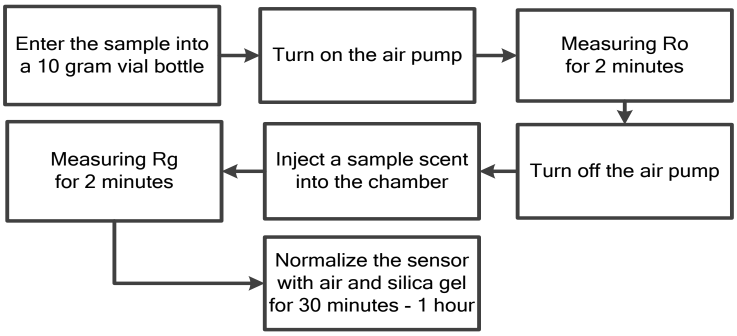


Figure 1. The step of data collection and sample measurement

2.2. Data Acquisition

Data acquisition is conducted as odor detection system. Hardware unit is designed for acquiring the response of sensors. The data acquisition design of the sample measurement is shown in Figure 2. The data acquisition used 5 types of MOS sensors, ie; TGS 2600, TGS 2602, TGS 2620, TGS 813 and MQ 135. The parameter used in the classification following SNI rule 3932:2008, such as; the number of bacteria, color, strictness and water content.

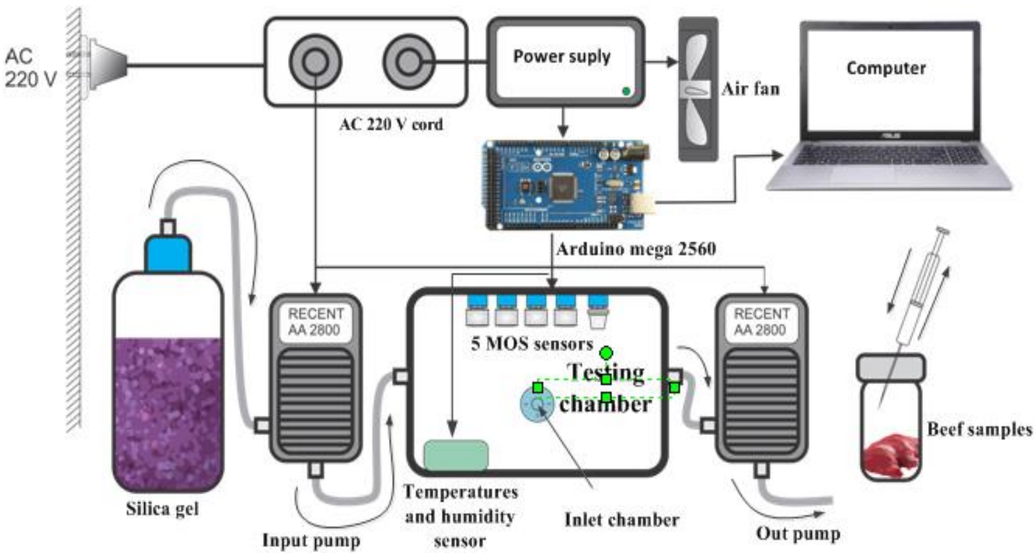


Figure 2. The data acquisition design of the sample measurement

2.3. Neural Network Structure Design

In this study, neural network structure designed by using the formation of 5-1-2 (5 input, 1 hidden layer, dan 2 output). The formation figure is shown in Figure 3. The input of this structure are TGS 2600, TGS 2602, TGS 2620, TGS 813 and MQ 135. The output of neural network structure design are consist of two outputs where it is indicate the meat freshness. Function of activation used in hidden layer is sigmoid biner and the output is linier.

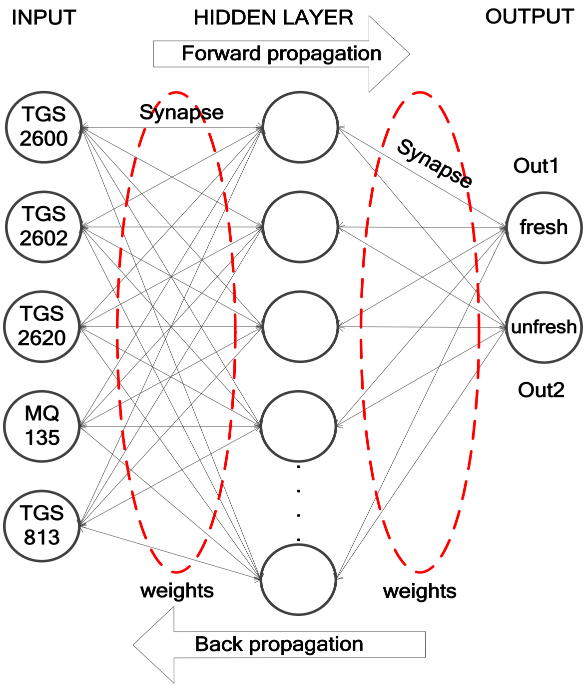


Figure 3. The multilayer perceptron structure of the designed neural network

The process of learning with backpropagation algorithm in the artificial neural network used equations (2) to (12) [25].

1) Steps in forwarding are:
   a) Normalize the input and desired output (within the range 0-1).
   b) Weighting value randomly to (-1) until (+1)
   c) initializing of bias value (1)
   d) Find the sum and sigmoid for *a Hidden layer* and *Output layer*

i) Hidden Layer, *Sum value:*

$$Z_j = \sum_{i=0}^{N} X_i . V_{ij} \tag{2}$$

with N = total synapse layer 2 (hidden layer), *Sigmoid value*:

$$Z_j' = \frac{1}{1 + e^{-Zj + bias}} \tag{3}$$

ii) Output Layer, *Sum value*:

$$Y_k = \sum_{i=0}^{M} Z_j' . W_{jk} \tag{4}$$

with M = total synapse layer 3, *Sigmoid value*:

$$Y_k' = \frac{1}{1 + e^{-Yk + bias}} \tag{5}$$

2) Steps in backward steps are:
a) Calculate the output error (∂_k). Output error=Output layer 3-desired output

$$Err_k(MSE) = \frac{1}{2}\left(d_k - Y_k^{'}\right)^2 \tag{6}$$

$$\partial_k = \frac{dErr_k}{dY_k^{'}} = d_k - Y_k' \tag{7}$$

b) Calculate the hidden error (∂_O)

$$\partial_O = \frac{dErr_k}{dZ_j} = \frac{dErr_k}{dY_k} \cdot \frac{dY_k}{dZ_j^{'}} \cdot \frac{dZ_j^{'}}{dZ_j}$$
$$Err_j = \frac{dErr_k}{dY_k} \cdot \frac{dY_k}{dZ_j^{'}} = \sum_{k=1}^{L} \partial_k \cdot W_{jk}$$
$$\partial_O = Err_j \cdot Z_j^{'} \cdot (1 - Z_j^{'}) \tag{8}$$

c) Updating weight for weight on Hidden-Output layer

$$\Delta W_{jk} = \eta \cdot \frac{dErr_k}{dW_{jk}} = \eta \cdot \frac{dErr_k}{dY_k} \cdot \frac{dY_k}{dW_{jk}} = \eta \cdot \partial_k \cdot Z_j^{'}$$
$$W_{jk} = W_{jk} + \Delta W_{jk} \tag{9}$$

d) Updating bias value on the output layer

$$\Delta bias_k = \eta \cdot \frac{dErr_k}{dbias_k} = \eta \cdot \frac{dErr_k}{dY_k^{'}} \cdot \frac{dY_k^{'}}{dbias_k} = \eta \cdot \partial_k \cdot 1$$
$$bias_k = bias_k + \Delta bias_k \tag{10}$$

e) Updating weight for weight on Input-Hidden layer

$$\Delta V_{ij} = \eta \cdot \frac{dErr_j}{dV_{ij}} = \eta \cdot \frac{dErr_j}{dZ_j'} \cdot \frac{daZ_j'}{dV_{ij}} = \eta \cdot \partial_O \cdot X_i$$
$$V_{ij} = V_{ij} + \Delta V_{ij} \tag{11}$$

f) Updating bias on the hidden layer

$$\Delta bias_j = \eta \cdot \frac{dErr_j}{dbias_j} = \eta \cdot \frac{dErr_j}{dZ_j'} \cdot \frac{dZ_j'}{dbias_j} = \eta \cdot \partial_O \cdot 1$$
$$bias_j = bias_j + \Delta bias_j \tag{12}$$

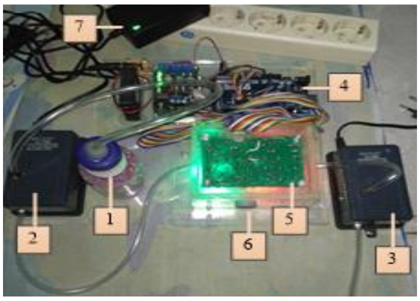
Where:
i,j,k : Respectively neuron number of input, hidden, and output layers
X_i : Input-i on input layer
$V_{i,j}$: Weight of input-hidden layer
Z_j : Summing result on neuron-j at hidden layer
Z_j` : Activation result on neuron-j ay hidden layer
$W_{j,k}$: Weight of hidden-output layer
Y_j : Summing result on neuron-j at output layer

Y_j` : Activation result on neuron-j ay output layer
η_0 : Initial learning rate
η : Learning rate iteration-n
k_0 : Constanta learning rate
∂_0 : Hidden error
∂_k : Output error
ΔW_{jk} : Updating change of weight on hidden-output layer
ΔV_{jk} : Updating change of weight on input-hidden layer
$\Delta bias_k$: Updating change of bias at output layer
$\Delta bias_k$: Updating change of bias at hidden layer

The training is done by giving variations on the number of neurons in the hidden layer, with the quantity 4, 8, and 16. Those variations is used to enlarge the dimension of recognition pattern. From those variations will be found the number of the most optimal neurons and the result of the data training will be applied in the real instrument.

3. Results and Discussion

The data acquisition system for sample measurement has been made as shown in Figure 4. The sample of meat used is 10 grams. On this acquisition data process, arduino is connected to COM11 then the the sampling calculation baseline will be analyzed. This process is conducted in food technology laboratory.



Description:
1 = silica gel for normalization of the sensor
2 = input pump to drain air into the chamber
3 = output pump to flow air out
4 = Arduino mega 2560
5 = chamber with sensor arrays MOS
6 = rubber inlet to inject aroma from the sample
7 = adaptor AC - DC

Figure 4. The data acquisition system for sample measurement

The parameters of this sample are tested in agriculture laboratory to find out the criteria of fresh and not-fresh meat as a reference training target. Based on Indonesian National Standard (SNI 3932-2008) requirement on the quality of carcass and meat, the meat is classified as fresh of the number of bacteria les then 0.46 x10^6 Cfu/g. The details result of the tested sample parameter is shown in Table 1.

Table 1. Freshness Classification of Meat from Laboratory Tests

No	Test Parameters	Test Equipment	Fresh	Not-fresh
1	number of bacteria	cup count method (TPC)	0,46x10^6 Cfu/g	1,18 x10^6 Cfu/g
2	color	color reader	L 28.5 a 0.2 b 7.1	L 39.6 a 3.5 b 11.9
3	strictness	penetrometer	140 gr	155 gr
4	water content	Digital weigher	10.03 gr	8.885 gr

Figure 5 shows that the data used for initial simulation is 22 data and each sensor has different sensitivity according to its characteristics. On the repetition 1-11 shows the sensor sensitivity was stable because the condition of meat samples is still good (under 4 hours) while on the repetition 12-22 showed the comparison sensitivity between the baseline and the sample aroma have bigger number because the condition of meat samples begin to decay (over 6 hours). GUI on Matlab is used to simulate the result of identification. The simulation is conducted after the ackquisition data saved as load data. Then the training can be run after the data input completely. The detail display and input of GUI of this study shows in Figure 6.

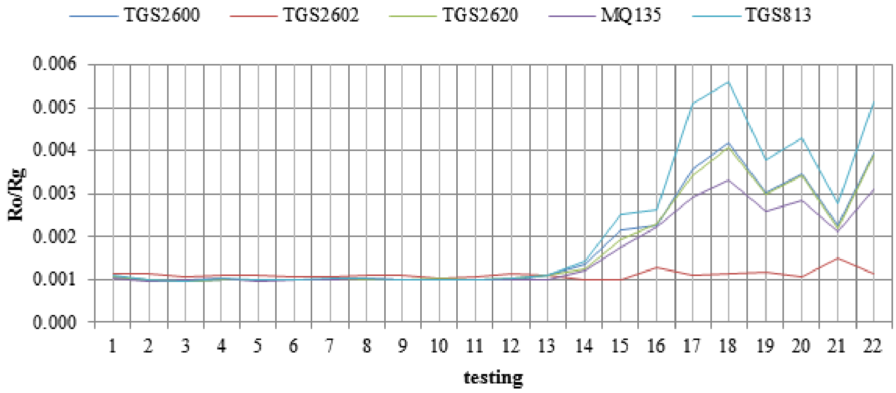


Figure 5. Sensitivity of MOS gas sensor

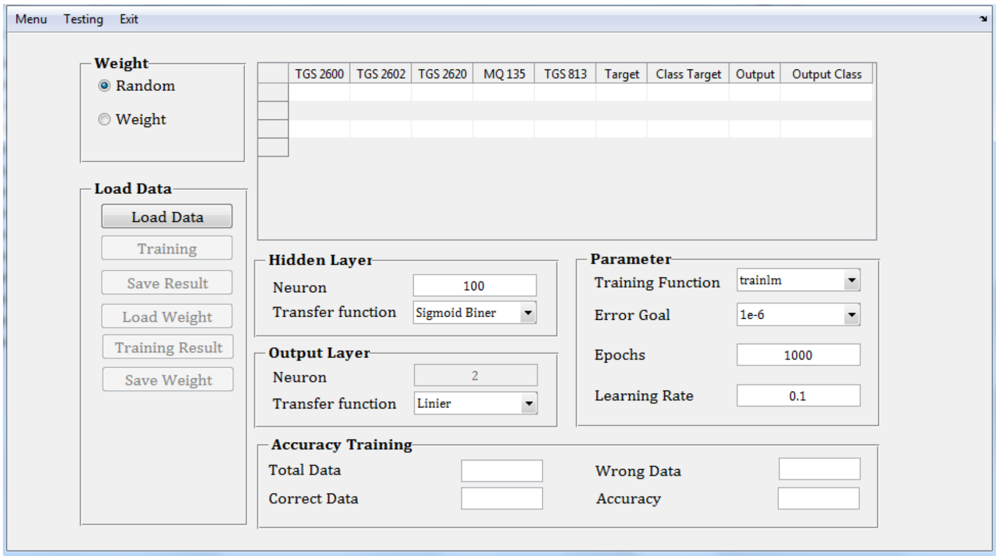


Figure 6. GUI simulations on Matlab

The results of the training process is shown in Figure 7 where the variation number of neurons in the hidden layer show that theaccuracy of this training is 100% where the wrong data is 0. Total data used are 22. The result of this training means that the recognizing a pattern of aromas from the fifth sensor sensitivity towards the conditions of the fresh and not-fresh meat up to 100%.

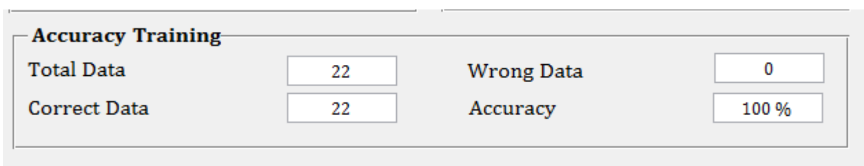


Figure 7. The result of three variations of neurons number training process

The next training test is conducted by using 10 sets of data to find the most optimal neuron number for each sensor. The source of data is located on arduino. The data is loaded and run the testing. The number of neurons variation used in this studi are 4, 8, and 16. The result of testing by using 4 neurons is shown in Table 2, 8 neurons is shown in Table 3, and 16 neurons is shown in Table 4.

Based on table, the results of testing with 4 neurons in the hidden layer with 10 times testing found that 7 meat on classification and 3 meat on not-fresh classification. But, this testing has 2 error identification with the percentage of success rate is 80%. The error identifitasion are in testing number 7 and 9.

The results of testing with 8 neurons in the hidden layer with 10 times testing found that 5 meat on fresh meat classification and 5 meat on not-fresh classification. There were no error identification on this testing process. The percentage of success rate is 100%. The detail result of this testing is shown in Table 3.

The results of testing with 16 neurons in the hidden layer with 10 times testing found that 6 meat on fresh meat classification and 4 meat on not-fresh classification. There were 1 error identification. The the percentage of success rate is 90%. The error identification result are is in testing number 8. The result of testing is shown in Table 4.

Table 2. The Result of Data Testing with 4 Neurons

No	TGS 2600	TGS 2602	TGS 2620	MQ 135	TGS 813	Output	Output Class
1	0.989	1.081	1	0.998	0.998	[1;0]	Fresh
2	0.998	1.103	1.003	1.006	1.014	[1;0]	Fresh
3	0.989	1.079	0.999	0.996	1	[1;0]	Fresh
4	1.015	1.058	1.023	1.006	1.004	[1;0]	Fresh
5	1.022	1.032	1.043	0.998	1.015	[1;0]	Fresh
6	1.702	0.982	1.564	1.427	1.771	[0;1]	Not Fresh
7	1.16	0.976	1.1	1.105	1.175	[1;0]	Fresh
8	3.939	1.138	3.894	3.109	5.144	[0;1]	Not Fresh
9	0.571	1.24	0.659	0.659	0.514	[1;0]	Fresh
10	1.913	1.246	1.871	1.743	2.106	[0;1]	Not Fresh

Table 3. The Result of Data Testing with 8 Neurons

No	TGS 2600	TGS 2602	TGS 2620	MQ 135	TGS 813	Output	Output Class
1	0.989	1.081	1	0.998	0.998	[1;0]	Fresh
2	0.998	1.103	1.003	1.006	1.014	[1;0]	Fresh
3	0.989	1.079	0.999	0.996	1	[1;0]	Fresh
4	1.015	1.058	1.023	1.006	1.004	[1;0]	Fresh
5	1.022	1.032	1.043	0.998	1.015	[1;0]	Fresh
6	1.702	0.982	1.564	1.427	1.771	[0;1]	Not Fresh
7	1.16	0.976	1.1	1.105	1.175	[0;1]	Not Fresh
8	3.939	1.138	3.894	3.109	5.144	[0;1]	Not Fresh
9	0.571	1.24	0.659	0.659	0.514	[0;1]	Not Fresh
10	1.913	1.246	1.871	1.743	2.106	[0;1]	Not Fresh

Table 4. The Result of Data Testing with 16 Neurons

No	TGS 2600	TGS 2602	TGS 2620	MQ 135	TGS 813	Output	Output Class
1	0.989	1.081	1	0.998	0.998	[1;0]	Fresh
2	0.998	1.103	1.003	1.006	1.014	[1;0]	Fresh
3	0.989	1.079	0.999	0.996	1	[1;0]	Fresh
4	1.015	1.058	1.023	1.006	1.004	[1;0]	Fresh
5	1.022	1.032	1.043	0.998	1.015	[1;0]	Fresh
6	1.702	0.982	1.564	1.427	1.771	[0;1]	Not Fresh
7	1.16	0.976	1.1	1.105	1.175	[1;0]	Fresh
8	3.939	1.138	3.894	3.109	5.144	[0;1]	Not Fresh
9	0.571	1.24	0.659	0.659	0.514	[0;1]	Not Fresh
10	1.913	1.246	1.871	1.743	2.106	[0;1]	Not Fresh

4. Conclusion

An analysis of five varied sensors exposed by reducing gas of meat sample aroma (both fresh meat and not-fresh meat) was conducted. The training process identified 5-1-2 formation pattern (5 inputs, 1 hidden layer, and 2 outputs in accordance with the target code) with the variation of neuron number in the hidden layer quantity 4, 8, 16 to found the most optimal weight and bias values for testing.

The training process has been conducted using vary number of neurons in the hidden layer of 4, 8, and 16 with 22 datasets of input that consisted of 11 data of fresh meat aroma and 11 data of not-fresh meat aroma. The result proves neural network method can detect the freshness of meat with a accuracy was 100%. It is found that the network is perfectly formed. Based on the simulation result, by using 4, 8 and 16 neurons in the hidden layer, the values percentage of successful detection were 80%, 100% and 90%. It can be concluded that the optimal number of neurons for this detection system is 8.

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