Section A-Research paper

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INDENTIFICATION OF CHICKEN IN CHICKEN, BEEF AND LAMB EXPERIMENTS USING CONDUCTING POLYMER SENSOR SERIES AND KOHONEN ALGORITHM METHOD

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Abstract-- In a classifications of meat types circuit, the chicken, beef and lamb are based on the aroma of each type of meat. This principle is similar to the human nose and the principle is known as an electronic nose, using a Conductive Polymer sensor array consisting of 6 (six) pieces and using an Artificial Neural Network (NN) as pattern recognition and an ATMega16 microcontroller as data acquisition. Neural Network trained using Kohonen. In this paper, the chicken, beef and mutton were taken as test samples and placed in a closed container at room temperature. Tests were carried out 10 times to ensure the circuit could determine the type of chicken meat. The percentage of system success was 100%.

Keywords: conducting polymer sensor, kohonen algorithm, odor, artificial neural network

I. INTRODUCTION

The need for meat is urgently needed. Quality and fresh meat is needed. Mixed flesh can indicate an act that is not right. Therefore it is necessary to make techniques for determining the type of meat that can determine the type of chicken meat.

Conducting polymer is a type of conjugated polymer that exhibits changes in single and double bonds between carbon atoms in the main polymer chain to produce patterns of change voltage from exposure to several vapors of a specific odor in each of the desired results both fresh, less fresh and rotten, used eight sensors which are formed into a sensor array. Basically, the greater the number of sensor arrays, the better the voltage change pattern will be. This study used a type of polymer material, namely silicon DC-200, PEG-20M, 0V-101, 0V-17, DEGA, PEG-200, PEG-1540, and PEG-6000.

This sensor array is connected in series with a variable resistor to form a voltage divider circuit to produce a pattern of voltage changes resulting from changes in resistance.

The circuit for determining the type of meat uses an array of sensors that can detect a certain type of distinctive odor and
each sensor can detect that odor. This sensor mimics the working principle of the human olfactory system. This artificial olfactory system is known as an artificial olfactory system or electronic nose. Fig. 1 shows the relationship between human odor and the human nose.

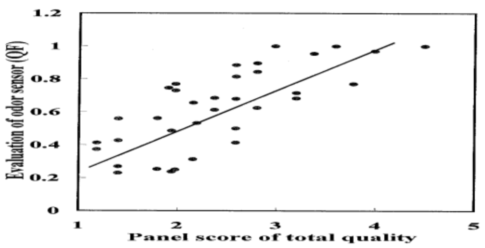


Fig. 1. Relationship between odor sensors (QF) and the human nose (panel score)

(Sindo, Sho et al, 2001)

Conducting polymer sensors are made from a mixture of polymer and carbon black powder. Polymers are materials with high resistance. The polymer functions as an insulator matrix and carbon black is used as a conductive matrix filler. When the mixture is exposed to chemical vapors, the chemical vapors will contact the polymer surface and diffuse into the polymer material mixture with carbon black. This will cause the surface area of the polymer to increase. The mixture of polymer with carbon black which is conductive causes the carbon black distribution area to become wider and the distance between the carbon black grains to increase, resulting in a change in the resistance of the polymer material mixture with carbon black. The change in resistance is proportional to the equation:

$$\Delta R = \frac{\rho.\Delta l}{A} \qquad (1)$$

Where is:

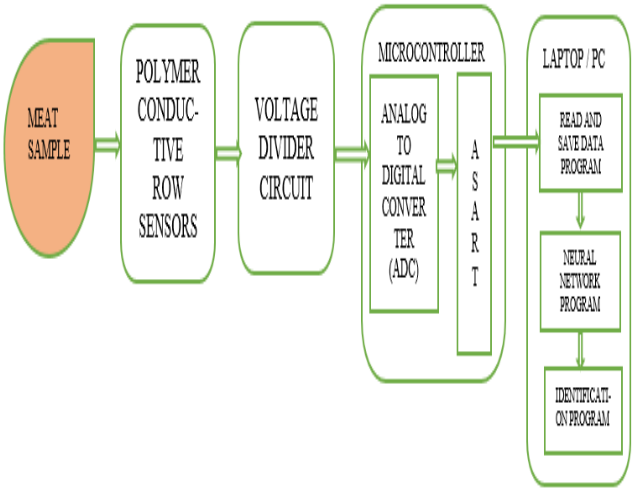
ΔR is the change in resistance
ρ is the value of the inhibition coefficient of the type of material
Δl adalah perubahan panjang bahan
A is the cross-sectional area of the material

The overall hardware system design can be described in the form of a block diagram as shown in Fig. 2 where the system consists of 5 sub-systems, namely:

1. Test samples in the form of chicken, beef and Lamb
2. Conducting Polymer Sensor Series as many 6 pieces
3. Voltage Divider Circuit
4. Minimum Microcontroller based on system ATMega16
5. Laptop/PC

II. METHODOLOGY

In general, the system consists of a series of sensors, a voltage divider circuit, an ATMega16 Microcontroller in which there is an ADC and serial communication, as well as an artificial neural network that runs on a computer/laptop. The block diagram of the system is shown in Fig. 2 and the overall research tool is shown in Fig. 6.



Fig, 2. Overall System Block Diagram.

Fig. 3 shows samples of meat for each type of meat placed in a closed container.

Fig. 3. Meat samples inside closed container

2.1. Conducting Polymer Sensor Array

The sensor array uses 6 (six) sensors made of different polymer materials and each sensor is made of polymer mixed with carbon black and then smeared on electrodes in the form of tracks on a piece of PCB.

The polymer materials used are silicon DEGA (used as Sensor 1), PEG-1540 (used as Sensor 2), PEG-6000 (used as Sensor 3), 0V-17 (used as Sensor 4), PEG-20M (used as Sensor 5) and 0V-101 (used as Sensor 6). Fig. 4 shows an illustration of the sensor array placement.

Fig. 4. Illustration of sensor array layout.

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2.2. Voltage Divider Circuit

The voltage divider circuit is shown in Fig. 5

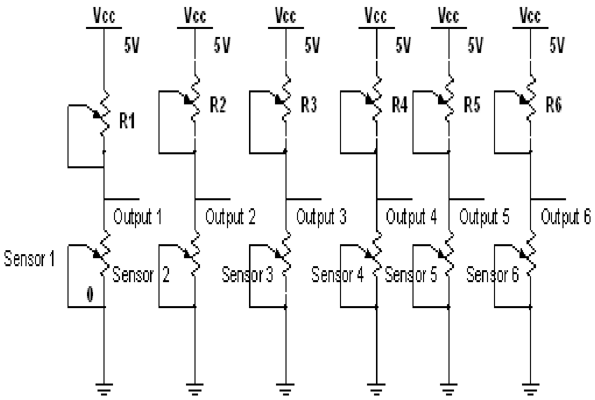

Fig. 5. Voltage Divider Circuit

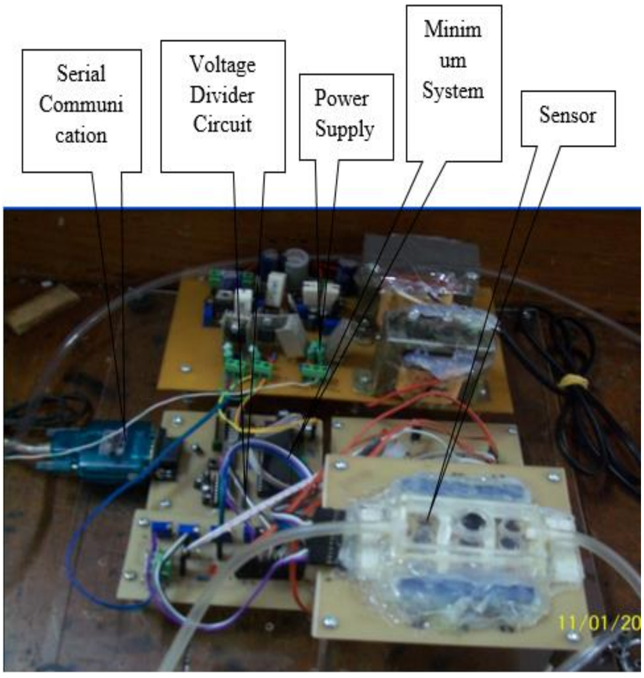

Fig. 6. Photo of Research Tools

2.3. Sensor Room Cleaning Process (Chamber)

The process of cleaning the sensor room (chamber) is carried out in the following way: Before the steam from the meat odor is entered into the sensor room, the sensor room is fed with Nitrogen (N_2) which is passed into the sensor room to clean the remaining steam from odors that previously entered the sensor room. N_2 is given before entering the sensor room with the aim of reducing humidity. This is done because some sensor elements are sensitive to humidity. The sensor chamber is cleaned with N_2 after being given steam from the odor until the sensor series voltage becomes the same or close to the reference voltage value when there is no steam in the sensor chamber.

The schematic of the air flow during the sensor room cleaning process is in Fig. 7

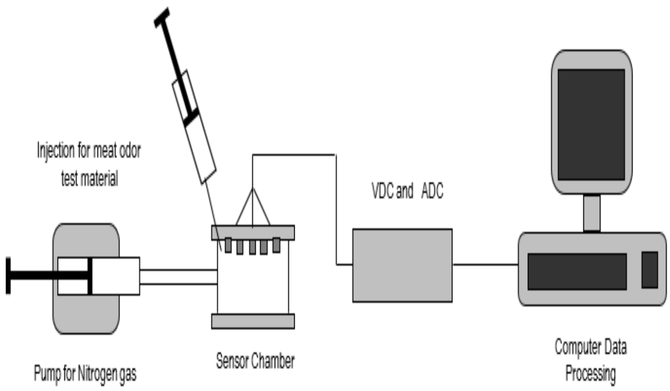

Fig. 7. Schematic of Air Flow during Sensor Room Cleaning Process

2.4. Sensor Array Voltage Change Response

The process of providing steam from the meat odor to the sensor room is carried out as follows: Steam from the meat odor is entered into the sensor room by injecting the meat odor taken from the meat container which is placed in a closed container into the sensor room. When the meat odor is injected into the sensor chamber, the sensor chamber is tightly closed. After taking the data for each condition, the sensor room is cleaned with N_2 according to Figure 7

The data retrieval process was carried out as follows: The experiment consisted of chicken samples, beef samples and lamb samples. These 3 meat samples were confirmed 1 day after being cut. It was first done by giving N_2 which was flowed into the sensor room to neutralize polymer sensors and gas particles that were still attached, then giving chicken meat odor steam and waiting for a response from the sensor until the condition was stable, after a while it was neutralized again with N_2 until the response back to its original state. Then proceed with giving steam from the smell of chicken, beef and lamb.

III.RESULTS AND DISCUSSION

3.1. Testing on Chicken

3.1.1. The Data Retrieval Process

Before testing the odor of chicken, the first N_2 was applied to neutralize the sensor series of steam particles that

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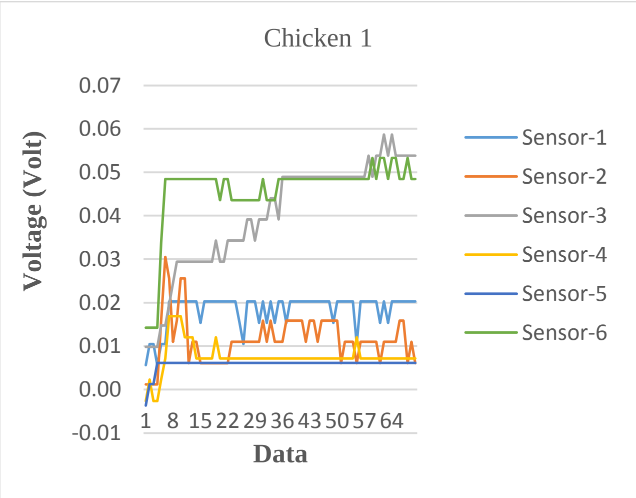
are still attached, then do the injection of steam from the odor of chicken and wait for the response from the sensor until the condition is stable, after a while then neutralized again with N_2 until response returns to its original state.

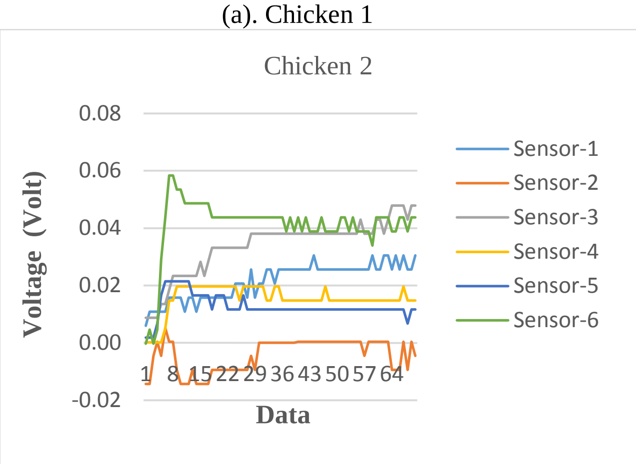
After N_2 was applied to neutralize the sensor series, the next step is the retrieval or exposure of steam for the odor of chicken. Exposure to the odor of chicken meat was carried out 2 times and the data was taken. The data taken as many as 70 data.

3.1.2. Sensor Series Voltage Change Response

During the process of exposure to a series of sensors with steam from the odor of chicken, responses were obtained as shown in Figures 8 (a) and 8 (b). From the voltage response graph, it can be seen that the change in voltage becomes relatively constant on average starting at the 21st second after giving steam, so that data retrieval for each steam is taken at the 21st second and above.



(a). Chicken 1



(b). Chicken 2

Fig. 8. Voltage Response of the 6 (six) Sensors

to Chicken Odor Steam

3.2. Testing on Beef

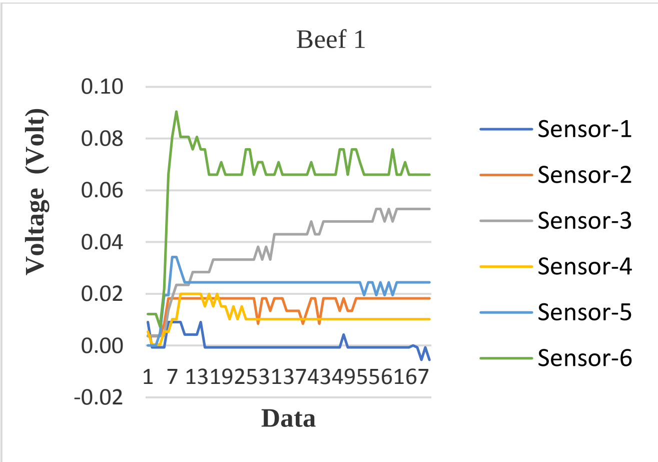
3.2.1. The Data Retrieval Process

Before testing the odor of beef, the first N_2 was applied to neutralize the sensor series of steam particles that are still attached, then injection of steam from the odor of beef and waiting for the response from the sensor until the condition is stable, after a while then neutralized again with N_2 until response returns to its original state.

After N_2 was applied to neutralize the sensor series, then the next step is the retrieval or exposure to steam for beef odor. Exposure to beef odor steam was carried out 2 times and the data was taken. The data taken as many as 70 data.

3.2.2.Sensor Series Voltage Change Response

During the process of exposure to a series of sensors with steam from the odor of beef, a response is obtained as shown in Figures 9 (a) and 9 (b). From the voltage response graph, it can be seen that the change in voltage becomes relatively constant on average starting at the 21st second after giving steam, so that data retrieval for each steam is taken at the 21st second and above.



(a). Beef 1

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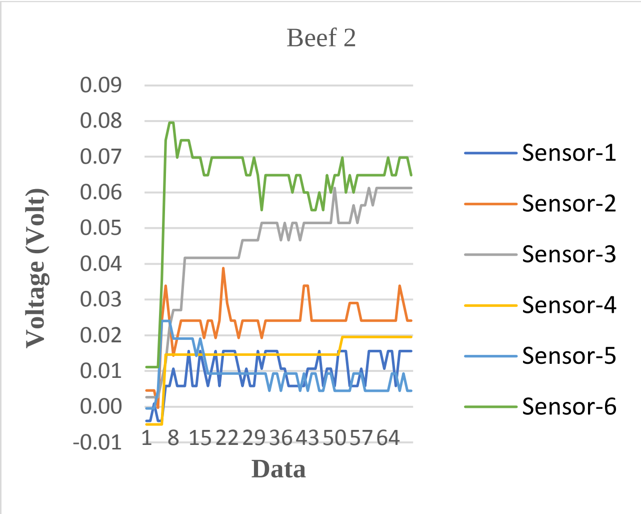


(b). Beef 2

Fig. 9. Voltage Response of 6 (six) Sensors to Beef Odor Steam

3.3. Testing on Lamb

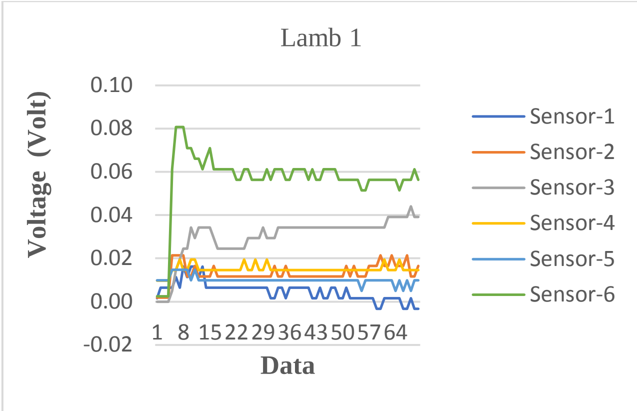
3.3.1. The Data Retrieval Process

Before testing the odor of lamb, The first N_2 was applied to neutralize the sensor series of steam particles that are still attached, then do the injection of steam from the odor of lamb and wait for the response from the sensor until the condition is stable, after a while then neutralized again with N_2 until response returns to its original state.

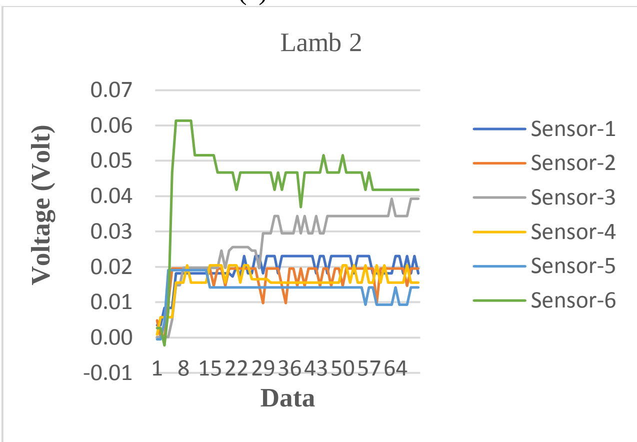
After N_2 was applied to neutralize the sensor series, the next step is the retrieval or exposure of steam for the odor of Lamb. Exposure to the odor of lamb was carried out 2 times and the data was taken. The data taken as many as 70 data.

3.3.2. Sensor Series Voltage Change Response

During the process of exposure to a series of sensors with steam from the odor of lamb, a response is obtained as shown in Figures 10 (a) and 10 (b). From the voltage response graph, it can be seen that the change in voltage becomes relatively constant on average starting at the 21^{st} second after giving steam, so that data retrieval for each steam is taken at the 21^{st} second and above.



(a). Lamb 1



(b). Lamb 2

Fig. 10. Voltage Response of the 6 (six) Sensors to Lamb Odor Steam

Based on the stability of the graph from Figures 4 until 6, the input data for the artificial neural net is taken at the 21^{st} second for chicken, beef and lamb with 10 data each and averaged. Table 1. shows the input data for the artificial neural net.

Table 1. Training Data for Artificial Neural Networks

Data	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Sensor 6	Noted
1	0,018768	0,009482	0,034262	0,007135	0,00611	0,044526	C 1
2	0,018231	-0,00894	0,034115	0,019208	0,01309	0,043696	C 2
3	-0,00064	0,017302	0,033725	0,01173	0,024438	0,068915	B 1
4	0,010703	0,025611	0,043695	0,014614	0,009336	0,068768	B 2
5	0,006452	0,011583	0,027371	0,015493	0,009873	0,058211	L 1
6	0,020137	0,018084	0,025611	0,017987	0,014223	0,046188	L 2

Noted: C 1 = Chickent 1 B 2 = Beef 2
C 2 = Chicken 2 L 1 = Lamb 1
B 1= Beef 1 L 2 = Lamb 2

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The pattern of changes in the voltage of the sensor series that has been normalized when exposed to steam from the meat odor is shown in Figures 8 until 10. Normalization is carried out according to the rules:

$$\frac{Xi}{\sum_{i=1}^{n} Xi} \quad \ldots. (1)$$

The average chicken meat data is shown in Table 2.

Table 2. Average Chicken Meat Data

Data	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Sensor 6
CM 1	0,018768	0,009482	0,034262	0,007135	0,00611	0,044526
CM 2	0,018231	-0,00894	0,034115	0,019208	0,01309	0,043696
Average	**0.0184995**	**0.000271**	**0.0341885**	**0.0131715**	**0.009600**	**0.044111**

The average chicken meat data in Table 2 produces a normalized pattern of changes in the sensor series voltage. The normalized pattern of sensor series voltage changes in chicken meat is shown in Fig. 11.

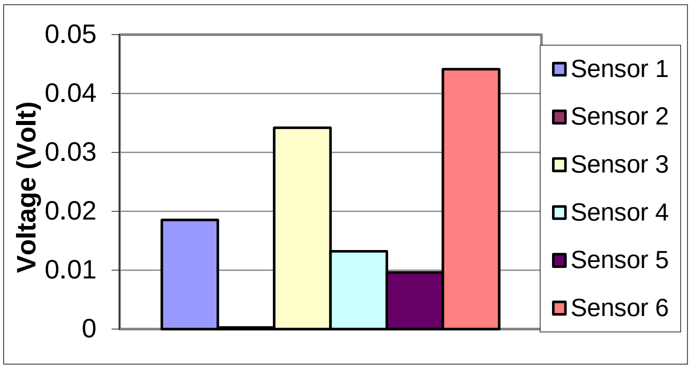

Fig. 11. Normalized Sensor Series Voltage Pattern against the Odor of Chicken

Fig. 11 is taken from the graph based on the average from Table 2. The pattern shown in Fig. 11 is a characteristic odor of chicken meat odor.

The average beef data is shown in Table 3.

Table 3. Average Beef Data

Data	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Sensor 6
Beef 1	-0.000640	0.017302	0.033725	0.011730	0.024438	0.068915
Beef 2	0.010703	0.025611	0.043695	0.014614	0.009336	0.068768
Average	**0.005034**	**0.021456**	**0.038710**	**0.013172**	**0.016887**	**0.068842**

The average beef data in Table 3 produces a normalized pattern of changes in the sensor series voltage. The normalized pattern of sensor series voltage changes in beef is shown in Fig. 12.

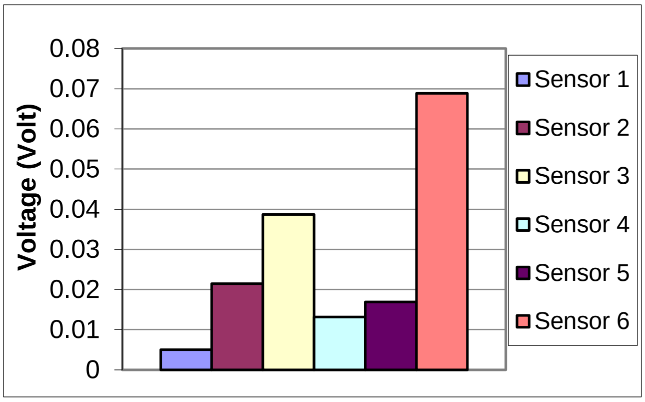

Fig. 12. Normalized Sensor Series Voltage Pattern against the Odor of Beef

Fig. 12 is a graph based on the average from Table 3. The pattern shown in Fig. 12 is a characteristic odor of beef odor.

The average lamb data is shown in Table 4.

Table 4. Average Lamb Data

Data	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Sensor 6
Lamb 1	0.006452	0.011583	0.027371	0.015493	0.009873	0.058211
Lamb 2	0.020137	0.018084	0.025611	0.017987	0.014223	0.046188
Average	**0.013294**	**0.014833**	**0.026491**	**0.016740**	**0.012048**	**0.052200**

The average lamb data in Table 4 produces a normalized pattern of changes in the sensor series voltage. The normalized pattern of sensor series voltage changes in Lamb is shown in Fig. 13.

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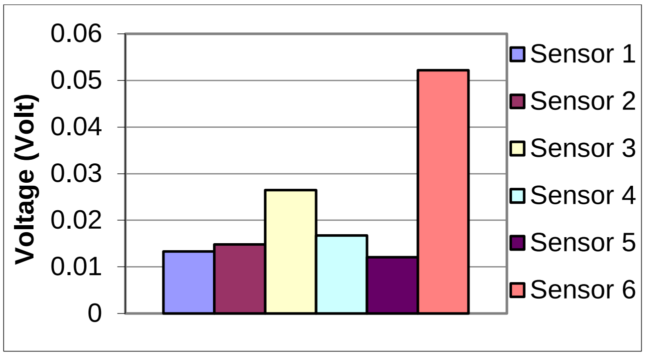

Fig. 13. Normalized Sensor Series Voltage Pattern against the Odor of Lamb

Fig. 13 is taken from the graph based on the average from Table 4. The pattern shown in Fig. 13 is a characteristic odor of lamb odor.

3.4. System Testing

After obtaining data from measuring the voltage difference to each sensor, the next step is to identify the vapor from the odor of chicken, beef, or lamb using the Kohonen algorithm. In this artificial neural net training, two layers are used consisting of six input nodes and three output neurons.

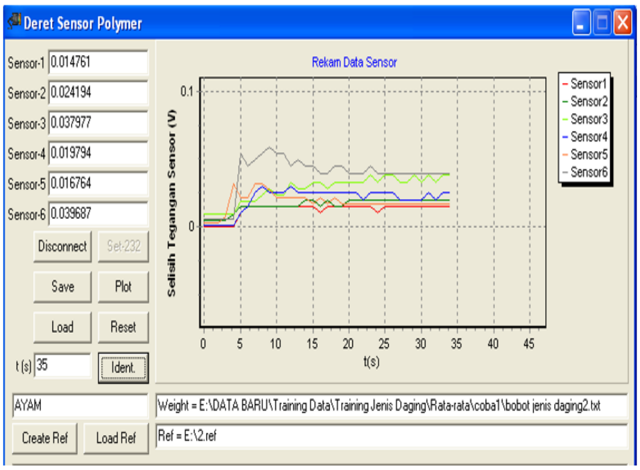

Fig. 14. Display of System Testing on Chicken

Fig. 14 shows the testing process on chicken after the training process on the Kohonen algorithm. It can be seen that the test was successful in detecting Chicken (written by "AYAM").

Then tested the chicken meat as much as 10 trials. The result is shown in Table 5

Table 5. Experimental Identification of Chicken Odor Types with Artificial Neural Network.

Experimental	Results
1	T
2	T
3	T
4	T
5	T
6	T
7	T
8	T
9	T
10	T

Description: T = True Test; F = False Test

So based on table 5, the steam identification test with artificial neural network on chicken was carried out 10 times with the results of 10 true tests and no false tests, so from this test the success rate in identifying chicken was ***100%***.

IV. CONCLUSSION

Classification system for determining the type of meat using a series of sensors consisting of 6 conducting polymers and an artificial neural network with a kohonen algorithm trained to recognize the sensor response pattern to vapors from the odor of chicken, beef and lamb. Testing and identification of vapor from odors has been carried out and successfully identified chicken in chicken, beef and lamb experiments are passed to the sensor. The overall success rate of identification is 100 %.

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