Sensing and Bio-Sensing Research 37 (2022) 100508

Contents lists available at ScienceDirect

Sensing and Bio-Sensing Research

journal homepage: www.elsevier.com/locate/sbsr

Odor clustering using a gas sensor array system of chicken meat based on temperature variations and storage time

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A R T I C L E I N F O

Keywords:
Chicken meat
Electronic nose
Gas sensor array
Principal component analysis
Deep neural network

A B S T R A C T

Shelf life and temperature are two things that affect the freshness of meat. Generally, people identify the freshness of meat by looking at the texture, color, and even aroma of meat. These methods have less effective approaches to identify the freshness of meat. The limitations of the human sense of smell have led to the development of gas sensor array system technology. Research has been done on odor cluster analysis using gas sensor array with variations in shelf life and temperature in classifying the smell of chicken meat. The study used a sample of 20 g of chicken meat in a 150 ml bottle which was sensed using a gas sensor array system at a certain storage period and temperature. The shelf life used is a shelf life of 0 h, 6 h, 12 h, 18 h, and 24 h as well as variations in temperature 4 °C, 30 °C, 35 °C, 40 °C, 45 °C, 50 °C. The analysis is carried out using machine learning in the form of principal component analysis and deep neural network. In this study using the principal component analysis and deep neural network method, it can be seen that the gas sensor array is able to classify well. Meanwhile, the results of deep neural network model can be classified as fresh and unfresh chicken meat with a testing accuracy of 98.70%. The result showed that gas sensor array could classify chicken meat with high accuracy and the proposed method provides a significant improvement.

1. Introduction

Chicken meat, which is a part of poultry meat, is a good source of protein because of its low calorific value so it can be used to maintain body weight, people who are just in the healing stage, and people who are no longer actively working [1]. The relatively affordable price [2] as well as the ease of processing and digesting it into food make chicken meat a processed animal protein product for the majority of Indonesian people's consumption. Chicken that is specially developed as a source of meat is broiler chicken.

The process of rotting chicken meat is caused by several factors, including contaminants bacteria and enzymes. Bacteria can contaminate chicken meat during the process of cutting and washing that is not clean [3]. Enzymes found in fresh chicken meat are able to break down and break down several nutritional components (protein, fat) that cause meat spoilage [4]. In order to avoid spoilage, chicken carcasses need to be stored. The National Standardization Agency (BSN) stipulates that the storage of chicken meat carcasses can be carried out in fresh, chilled, and frozen forms (SNI 3924:2009). In addition, storage can also be done by varying the temperature, either through cooling or heating. The cooling process is able to inhibit enzyme activity and microbial growth so that spoilage can be avoided, while the heating process at high temperature chicken meat is able to sterilize food from microbial contamination. Purba's research [5] shows that heating during chicken meat processing can release volatile components in the form of different gases at each temperature. The high fat content causes chicken meat to tend lipid oxidation during the processing process. Lipid oxidation in meat occurs when meat spoilage resulting in an unpleasant odor [6]. Lipids together with proteins and carbohydrates play an unavoidable role in thermal interactions during food processing, especially with the

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https://doi.org/10.1016/j.sbsr.2022.100508
Received 29 April 2022; Received in revised form 8 July 2022; Accepted 12 July 2022
Available online 14 July 2022

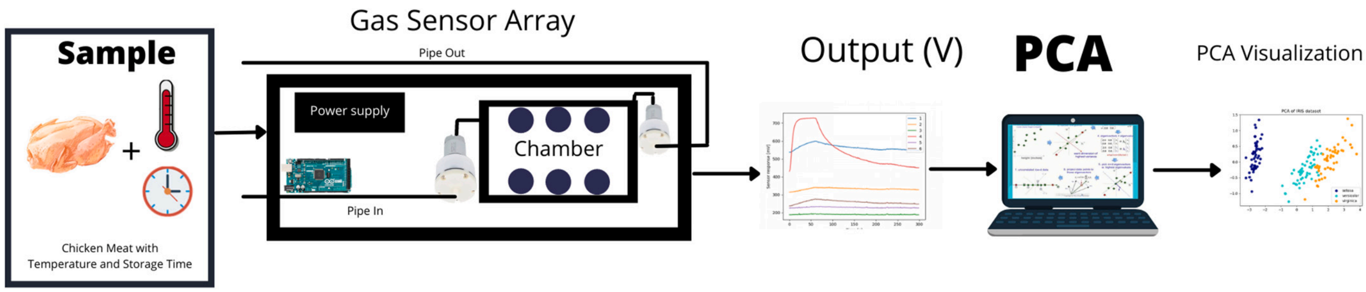

Fig. 1. Schematic diagram of experimental setup.

heating responsible for the appearance of volatile components [7].

The conventional method that are frequently used for meat damage and spoilage testing is the Eber test [8]. Eber test gives a qualitative result in the form of gas output on the tube wall, where the amino acid chain will be broken by strong HCl acid so that NH_4Cl (gas) will be formed. The Eber test is less efficient because it is not real time and requires additional HCl to break down amino acids. To overcome this problem, it is necessary to develop other instruments and methods should be used to generate faster data analysis, then it leads the researchers to develop a gas sensor array technology or electronic nose (*E*-nose) system. The use of gas sensor array has been used in the health as a means early detection of bacteria infection [9,10] and food industry as a means of monitoring food processing, bacteria contaminant [8], determining food shelf life, evaluating spoilage, and food quality control [11]. Publications related to the use of gas sensor array have received a positive response and are considered capable of being a renewal in determining the quality of food ingredients [12]. However, there have not been many further studies related to the effect of temperature variations on the odor emitted by chicken meat using a gas sensor array. Whereas in addition to the shelf life factor, temperature variations are also a factor that affects the smell of chicken meat [13].

Research by [14] proves that the gas sensor array is able to detect the NH4 compound which is an indicator when chicken meat undergoes decay. These compounds can be detected by a sensor array system that is lined up like a human olfactory nerve structure, so that it is able to produce different voltage patterns sensing for an odor or gas. Plotting the results of research by [15] with the method of principal component analysis also shows the ability of gas sensor array in classifying shelf life and temperature. Principal component analysis as a statistical method known as multivariate analysis is used because it can reduce the amount of measurement data information into one entity data that is easy to understand but still retains other data information. A study conducted by [16] proved that a low-cost gas sensor array system with the principal component analysis method was able to distinguish samples of pathogenic fungi Pythium intermedium and Phytophthora plurivora with an accuracy of 94%.

Generally, people identify the freshness of meat by looking at the texture, color, and even aroma of meat. These methods have less effective approaches to identify the freshness of meat. Based on previous research related to the application of electronic nose for quality detection of meat products [8,17], this study aims to classify the smell of chicken meat based on variations in temperature and shelf life using a gas sensor array system. The gas sensor array instrument used in this study has 4 MQ sensor consisting of sensors MQ7, MQ8, MQ135, MQ136 and using the principal component analysis and deep neural network to classify fresh and unfresh meat.

2. Material and methods

2.1. Chicken meat preparations

20 g of chicken meat purchased from the traditional market is mashed and then placed in a beaker glass. There are 6 temperature variations of 4 °C, 30 °C, 35 °C, 40 °C, 45 °C, and 50 °C. Each temperature variation was observed using an *E*-nose with an interval of 6 h. So, there are total 30 samples of chicken meat in this experiment.

Table 1
Point of sensory test.

Odor	Appearance	Texture	Value
Intensity Odor Odor Fresh Meat	**Intensity Color Carcass Cut**	**Elasticity**	
Odor very fresh, species specific	Color bright pink Texture is very strong,	very elastic	9
Fresh, species specific	Colorpink Pale	Strong texture, elastic	8
Neutral	Color ivory, brilliant	Texture is strong, slightlyelastic	7
Ammonia odor is starting to smell	Color ivory, dimming	Texture is loose, less elastic	5
Strong ammonia odor, sour odor	Color light beige	Texture loose	3
Foul odor, clear	Color brown, dull	Texture very loose	1
Odor Intensity Blood/Iron	**Appearance Flesh Fiber**	***Juicyness Odourless***	
Smells very fresh	fiber is not very visible	Squeeze does not come out water, clear	9
Fresh smell	fiber is not clearlyclearly	pressed Notpressed water comes out	8
Neutral	Fiber looks faint	Pressed slightly water comes out	7
Smell of blood starts to smell	Fiber starts to fade erlihat, white	Pressured water out of	5
blood smell a strong, rancid odor	fibers visible, white	Pressed very out of water	3
The smell of carrion, obviously	Fiber is very visible, very white	out of water	1
Intensity There was the smell of cooked	**Surface Pieces of Meat**	***firmness***	
smell of raw meat, specific, clear	Very dry	Solid, very compact	9
The smell was a bit raw	dried	Solid, compact	8
Neutral	humid	Dense, slightly compact	7
Odor slightly savory	A little wet	solid, less compact	5
smell savory powerful	wet, slimy	Flabby	3
The smell was strong, like cooked	wet, very slimy	Very soft	1

2.2. Gas sensor array (E-nose)

In this study, E-nose system contains of 4 sensors, MQ7, MQ8, MQ135, and MQ136. MQ7 can detect CO, H2, LPG, CH4, Alcohol, water with detection range 20–2000 ppm. MQ8 can detect H2, LPG, CH4, CO, Alcohol, water with a detection range of 60–1500 ppm. MQ135 can detect NH3, water, alcohol, NH4, toluene, acetone with detection range 10–300 ppm and benzene:10–1000 ppm. MQ136 can detect water, CO, NH4 and H2S with a detection range of 10–300 ppm and more for NH4. Sensor conducted with Arduino Mega and data acquisition using Jupyter Notebook from Anaconda. The set-up of this study can be seen in Fig. 1.

E-nose response output when viewed directly is difficult to distinguish between one sample and another. E-nose uses an array of gas sensors that are non-selective, and cross-sensitive, so to represent the results for easy analysis, multivariable pattern recognition methods such as principal component analysis are needed [18].

2.3. Sensory test

Sensory test is a test method using the human senses as the main tool for measuring product acceptance. Organoleptic testing has an important role in the application of quality [19]. Organoleptic testing can give an indication of spoilage, deterioration and other defects of the product. This test was conducted by 10 panelists consisting of 9 students from the Faculty of Veterinary Medicine, Universitas Airlangga and 1 lecturer from the Department of Veterinary Public Health, Faculty of Veterinary Medicine, Universitas Airlangga who are experts in the field of testing samples with sensory senses. Sensory test on chicken meat refers to Indonesian National Standard (SNI) as the testing standard. Fresh chicken meat has an average sensory test value of >7. There are 3 main parts that are discussed in sensory test, the appearance of the meat, the texture of the meat, and the smell of the meat. The overall table and sensory test scores for the panelists can be seen in Table 1.

3. Theory

3.1. Principal component analysis (PCA)

PCA is a mathematical tool that aims to represent the variation present in the dataset (i.e., responses used to characterize the samples) using a small number of factors [20]. Two- dimensional or three-dimensional projection of samples which having the axes (principal components, PC) as the factors usually constructed for visual analysis. Each PC is a linear combination of the original responses (that retain some correlation among) and PCs are orthogonal to each other. PCs iteratively calculated hold as much variation from original data set as possible, in a way that PC1 explains more the data variation than PC2, and PC2 explain more data variation than PC3 and so on [21]. There are several basic concepts in the PCA method:

- Standard Deviation: Standard deviation of a data set is a measure of how spread out the data values of the data are. For example, if we have two data sets [2 9 15 35] and [0 2 3 5], respectively, then the standard deviation of the first set will be greater than the second. This is indicated by the formulation of the standard deviation. The standard deviation value indicates that the values of the data in the set are spread far from the average value of the set. While the value of a small standard deviation indicates that the value of the data that is in a set gather around the average value of these collections [22]. *S* is the standard deviation value, *X* is a set of data, and $\overline{X}$ is the average value of *X*. The formulation of the standard deviation is shown below:

$$s = \sqrt{\frac{\sum_{i=1}^{n}\left(X-\overline{X}\right)^2}{n-1}} \tag{1}$$

- Variance: Variance is another way to measure the spread of the data in the set. In fact, the variance is the square of the standard deviation. Formula of variance shown below:

$$s^2 = \frac{\sum_{i=1}^{n}\left(X-\overline{X}\right)^2}{(n-1)} \tag{2}$$

- Covariance: Covariance is a measurement of how strong the relationship between two variables is. If both variables are at the expected values, then the covariance between these two variables will be positive. Otherwise, if one of the variables is above the expected value and the other variable is below the expected value, then the covariance between these two variables will be negative. Two variables are said to be independent if there is no relationship between the two variables. Covariance is always measured between two dimensions. If we have a three-dimensional data set (x, y, z), then we can calculate the covariance between the x and y dimensions, between the x and z dimensions, and between the dimensions y and z. Performing a calculation of the covariance between x and x, y and y, and z and z will return the variance of x, y, and z respectively. The general sample covariance equation is given by:

$$Cov\ (X, Y) = \frac{1}{n}\sum_{i=1}^{n}(X-\overline{X})(Y-\overline{Y}) \tag{3}$$

- Eigenvectors and Eigenvalues: If A is a square matrix with dimension (m x n) in C^n space, and x and b are vectors with dimension (n x 1), and there is a linear equation Ax = b then the transformation is carried out by matrix A on vector x to a new vector b. The eigenvector of the matrix A is a non-zero vector called v in the space C_n which is defined in the equation as shown below:

$$Av = \lambda v \tag{4}$$

The eigenvalue (λ) is a scalar commonly referred to as the eigenvalues of matrix A. Transformation very influenced by the magnitude of the eigenvalues owned by the eigenvectors. Therefore, reducing dimensions by removing eigenvectors with eigenvalues very small, will still retain important data information. The eigenvectors with the largest eigenvalues are called principal components (PC) [23]. The percentage of PC value can be calculated by equation as shown below:

$$PC\ (100\%) = \frac{Eigenvalues}{Variance\ Covariance} \times 100 \tag{5}$$

3.2. Deep neural network (DNN)

The concept of traditional artificial neural network (ANN) using models a fully connected layer which is a layer in which all activation neurons of the previous layer are connected with the neurons of the next layer [23,24]. Each connection has different weight and the weight is increased by bias in the next layer connection. The calculation of the weight and bias are 5 × 5 *weight* + 5 *bias*, 5 × 5 *weight* + 5 *bias*, and 5 × 1 *weight* + 1 *bias*. The total of 66 parameters will be regenerated to obtain the best result on the training process. Each layer has neuron and the activation function from the hidden layer and output layer will determine whether the neuron must be active or not. Some of the activation function that widely used are Sigmoid, Tanh, ReLu, and Softmax. The mathematical expression of Sigmoid function is as follows:

$$\frac{f(y)}{f(x)} = \frac{1}{1+e^{-x}}x\left(1-\frac{1}{1+e^{-z}}\right) \tag{6}$$

Where *x* is the weight dot bias. Sigmoid has ranged between 0 until 1 and Tanh −1 until 1 as shown:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{7}$$

Sigmoid and Tanh has many weakness that is perfected by ReLu. ReLu performed threshold from 0 until infinity as shown:

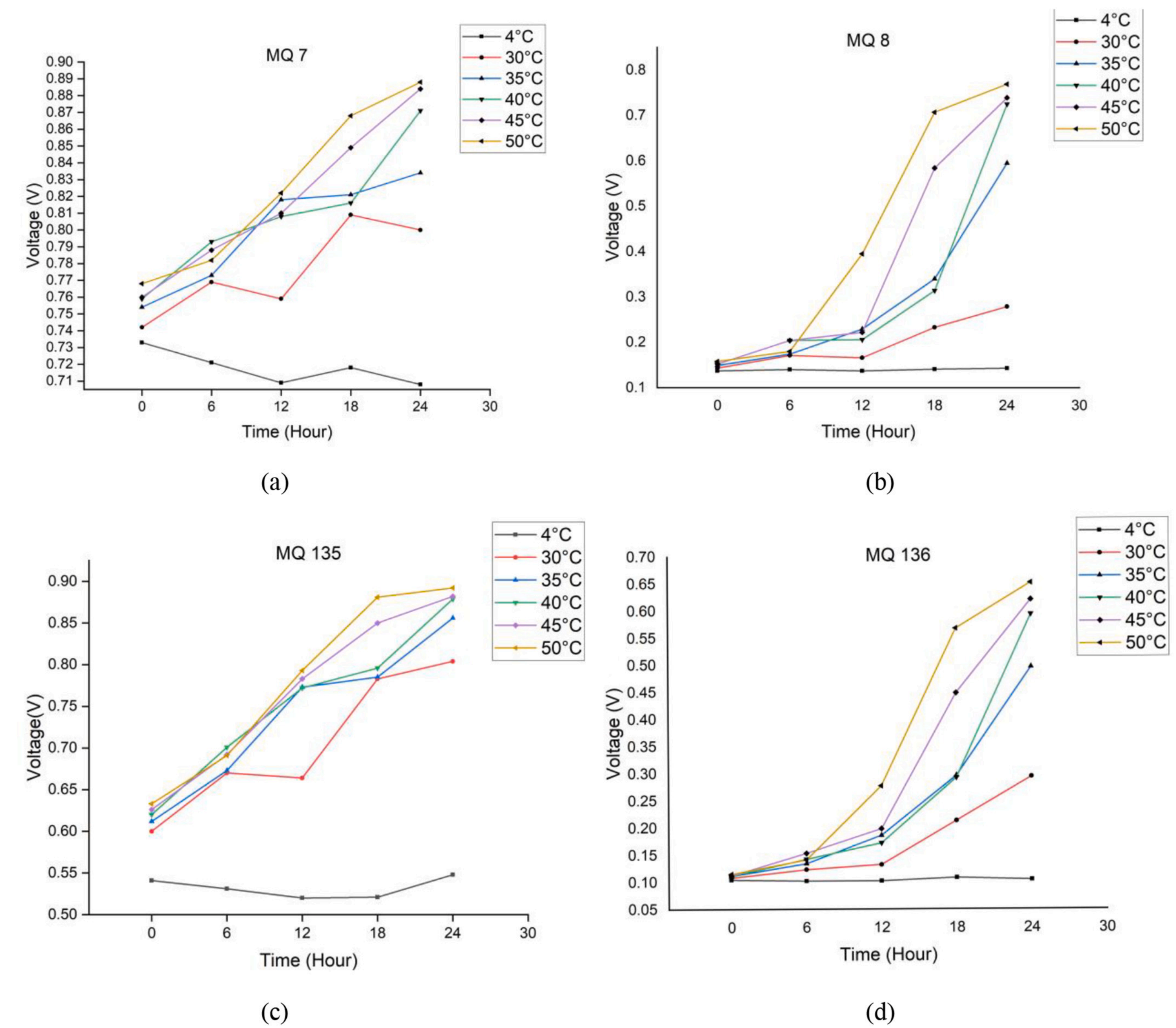

Fig. 2. (a) The result of MQ 7. (b) The result of MQ 8, (c) The result of MQ 135. And (d) The result of MQ 136.

$$\frac{f(y)}{f(x)} = \begin{bmatrix} 1\ x > 0 \\ 0\ x \le 0 \end{bmatrix} \tag{8}$$

Another activation function is Softmax as shown:

$$\sigma(z)_j = \frac{e_j^z}{\sum_{k=1}^{K} e_j^z} \tag{9}$$

Where σ is the probability of class member j as the input, z is the linear equation of the activation function, and K is the class predicted with j as part of that class. The linear equation of the activation function can be expressed as follows:

$$softmax = normalize(exp(wx + b)) \tag{10}$$

DNN have many differences with the traditional ANN. the more complexity on the feature, the more cost and time on the ANN. DNN has dropout, an algorithm to decide how many neurons are utilized, which is not present in ANN [25]. Moreover, in DNN, there is a parameter called loss function, which is a function to show the loss value of each possibility that will be generated by the DNN model. Thus, the loss function estimates the quality of each given weight, bias, and parameter. This function is executed when the learning model yields a high loss value. Thus, by utilizing this function errors are minimized. Loss function will compare the prediction of the output and the target with the formula that can be expressed as follows:

$$Loss\ Function = (Target - Prediction)^2 \tag{11}$$

DNN model ran some tests to compare the results of the available parameters. Some combination of Mother wavelet and decomposition level was made to find the best parameter. Highest accuracy indicated the best parameter, where the accuracy can be calculated by:

$$Acc_i = \frac{cc_i}{N_i} \times 100\% \tag{12}$$

Where Acc_i is the accuracy of the classifier, cc_i is the number of correctly classified sample, and N_i is the number of sample on i testing data. The average of Acc_i was calculated to get the final accuracy of the classifier.

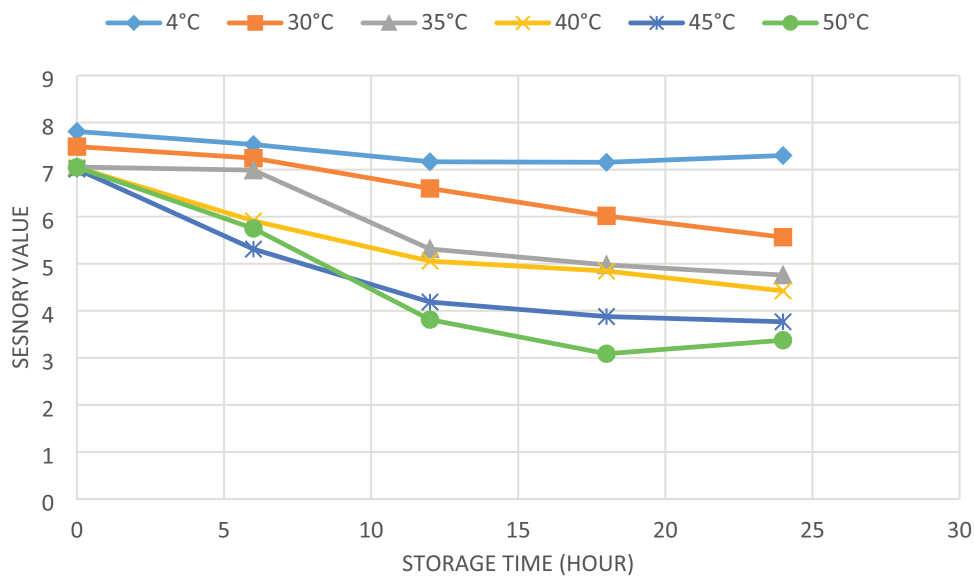

Fig. 3. The graph of sensory test.

4. Results and discussion

The *E*-nose sensor signal will experience a large change in amplitude when there is a sample with a strong aroma and a high concentration of compounds, compared to samples and compounds with a less pungent aroma concentrations and low of these compounds. *E*-nose system response test was conducted in order to know the value of the sensor during the sample testing time. The data generated each time the sample measurement shows 3 time structures, namely the stages of heating (pre-heating and baseline), smelling the sample (sensing), and cleaning (purging) [8]. The stage pre-heating of the sensor can also be called sample preparation before taking data. Sensor was left in the free air in the room for a certain time until a stable signal output response is obtained. This stability indicates that the sensor is ready for use and is in a ground state.

Sensing or smelling sensors on chicken meat samples was carried out during the storage period of 0 h (fresh), 6 h, 12 h, 18 h, and 24 h. Each variation of the shelf life has a temperature variation of 4 °C, 30 °C, 35 °C, 40 °C, 45 °C, 50 °C. The sensing time used is 120 s. This is done so that all the air contained in the 150 ml UC bottle can be sucked out entirely by the gas sensor array system. If the sensing time is set too long, the air density will mix so that the measurement is not optimal. The results of the gas sensor array response system at the sensing stage are then analyzed on a graph. The data still contains data where each signal increases and decreases. The stable value obtained is around 1500 data representing the characteristics of each sample during the time sensing, so that the data is cut to be used as a dataset. Purging or cleaning the chamber where the gases collect is the most important thing in a series of measurements with a gas sensor array system. The purging time is at least twice as much as the sensing time.

4.1. Gas sensor array responses to the sample

Response of each four MQ sensor in the *E*-nose system can be mapped for different patterns. The results of the E-nose system response based on temperature variations and shelf life can be seen in Fig. 2.

The sensors are also able to identify that the odor at 4 °C is always the same value because it is stored in the refrigerator. Ammonia (NH3 or NH4) is a gas that comes out due to the breakdown of protein in chicken meat when it will experience a decrease in freshness over time and heating. From the graph results, it can be seen that the production of NH3 increases with increasing shelf life and temperature. This is because the rot in chicken meat produces nitrogen compounds that are released when the protein network is damaged. Nitrogen has several forms, namely ammonia (NH3), nitrite, nitrate, ammonium, amine, and diatomic nitrogen [26]. Organic N comes from tissues of dead organisms, dirt/waste and feed residues which are transformed into ammonia through a decomposition/mineralization process by bacteria [4]. Ammonia comes from the direct release of the diffusion mechanism from organisms to the water. Then the urea is extracted and mineralized, and other organic materials such as feed residues, feces and the decomposition of colony bodies.

The addition of temperature also triggers the stretching of protein bonds in chicken meat. The bond is always stretched until finally at a hot temperature (above 150 °C) the protein will be denatured so that the protein is damaged [27]. Concentration of NH3 The highest obtained on the shelf life of 24 h for each sensor. From each of the shelf life of 24 h, the samples were heated at temperatures of 50 °C has a concentration of NH3 the highest compared with other temperature. At the cooling temperature, the chicken meat sample at 4 °C had value of NH3 concentration stable at all times. This is because the meat is stored at cold temperatures, its protein metabolism is inhibited so that it does not experience decay or breakdown. Chicken meat stored at cold temperatures is also able to maintain the structure of the meat, color, and smell so that the chicken carcass is still fresh and edible. Further analysis regarding this is described in sensory assays.

4.2. The result of sensory test

Test on chicken meat refers to SNI as the testing standard. Fresh chicken meat has an average organoleptic value of >7. There are 3 main parts that are discussed in organoleptic, namely the appearance of the meat, the texture of the meat, and the smell of the meat. There are three observation points in each section, the overall average of which can be seen in the Fig. 3.

As a result, meat at cooling temperature has the highest and most stable organoleptic value, so that its freshness quality can be maintained. In chicken meat that is at room temperature, its freshness is only in the range of 0 h and 6 h of shelf life. Even at the 6-h shelf life, meat heated at a temperature of 35–50 °C emits a strong odor, and the appearance of a lot of fiber so that the organoleptic value is reduced. During the storage period of 12–24 h, the whole meat had an organoleptic value of <7 so it was classified as not fresh, except for chicken which was stored at a cold temperature of 4 °C.

Table 2
Label from sensory test.

Storage Time (Hour)	Temperature					
	4 °C	30 °C	35 °C	40 °C	45 °C	50 °C
0	Fresh	Fresh	Fresh	Fresh	Fresh	Fresh
6	Fresh	Fresh	Unfresh	Unfresh	Unfresh	Unfresh
12	Fresh	Unfresh	Unfresh	Unfresh	Unfresh	Unfresh
18	Fresh	Unfresh	Unfresh	Unfresh	Unfresh	Unfresh
24	Fresh	Unfresh	Unfresh	Unfresh	Unfresh	Unfresh

Table 3
Percentages of variance in PCA

Component	% Variance	% Cumulative
PC1	0.75	0.75
PC2	0.18	0.93
PC3	0.068	0.998
PC4	0.002	1000

All points in the organoleptic test of this study have been visualized and captured in the form of photographs. The color and appearance of fresh chicken meat is seen from its brilliant carcass. When the meat begins to lose its freshness, the meat carcass begins to become dull, and smells like blood or iron. This odor is sometimes followed by bruising on the appearance of the meat caused by the rigor mortis process, which is the stage where processed meat products still have the quality and quality as when they were alive, but their body condition gradually becomes stiff [16].

The results of scoring on sensory test can be used as a reference to classify the smell of freshness of chicken meat based on shelf life and temperature [28]. The results of freshness based on sensory test for each shelf life and temperature can be seen in Table 2.

4.3. PCA clustering result

One problem of what often happens in machine learning is the “curse of dimensionality problem” where the machine has difficulty in handling a number of data inputs with very high dimensions. One of the most common ways to handle this process is to reduce the dimensions of the input data while preserving the information contained therein. One of the most frequently used methods is PCA, because PCA can reduce

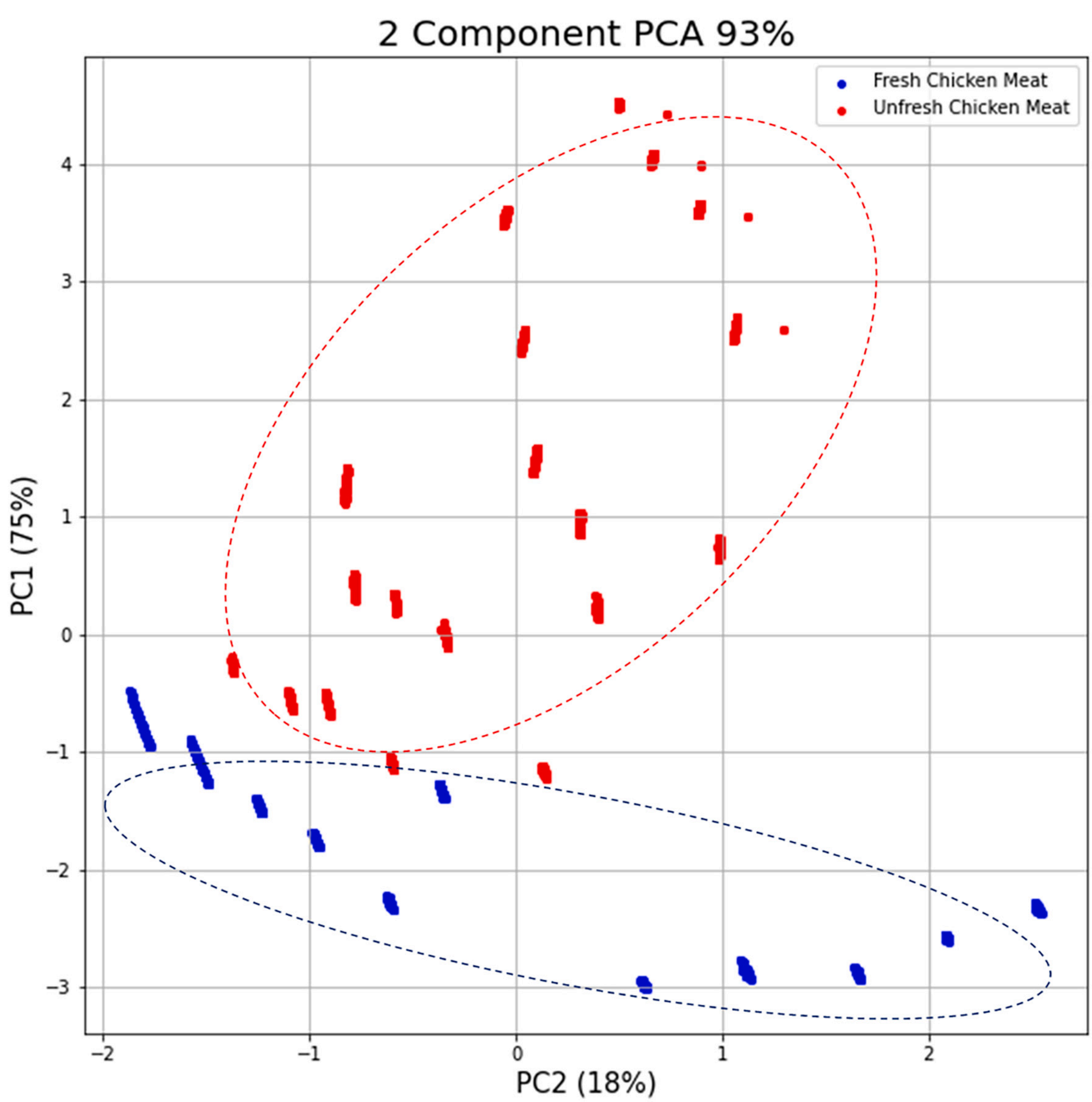

Fig. 4. Data visualization of PCA for fresh and unfresh chicken meat. Each color describe the cluster of two categories can be separated.

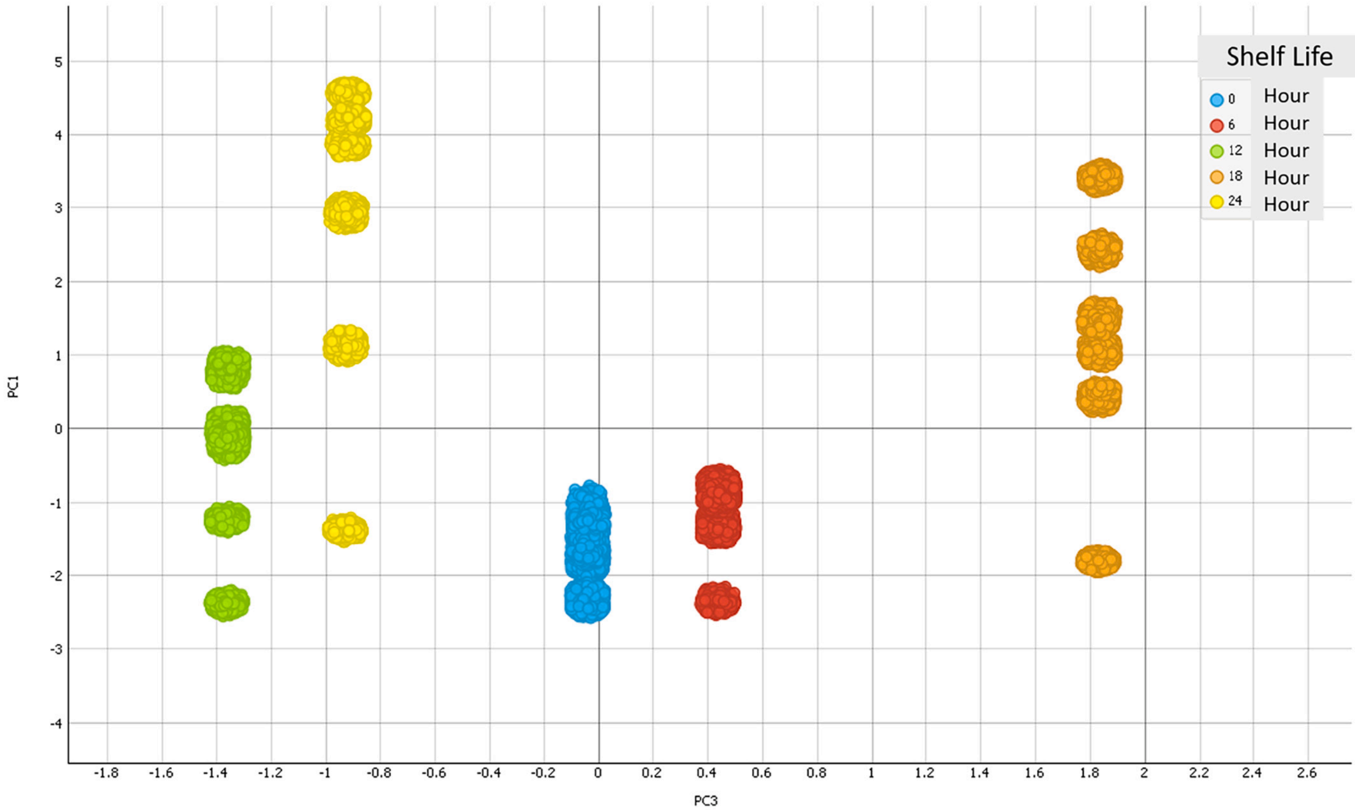

Fig. 5. PC1 and PC3 result based on variations in shelf life.

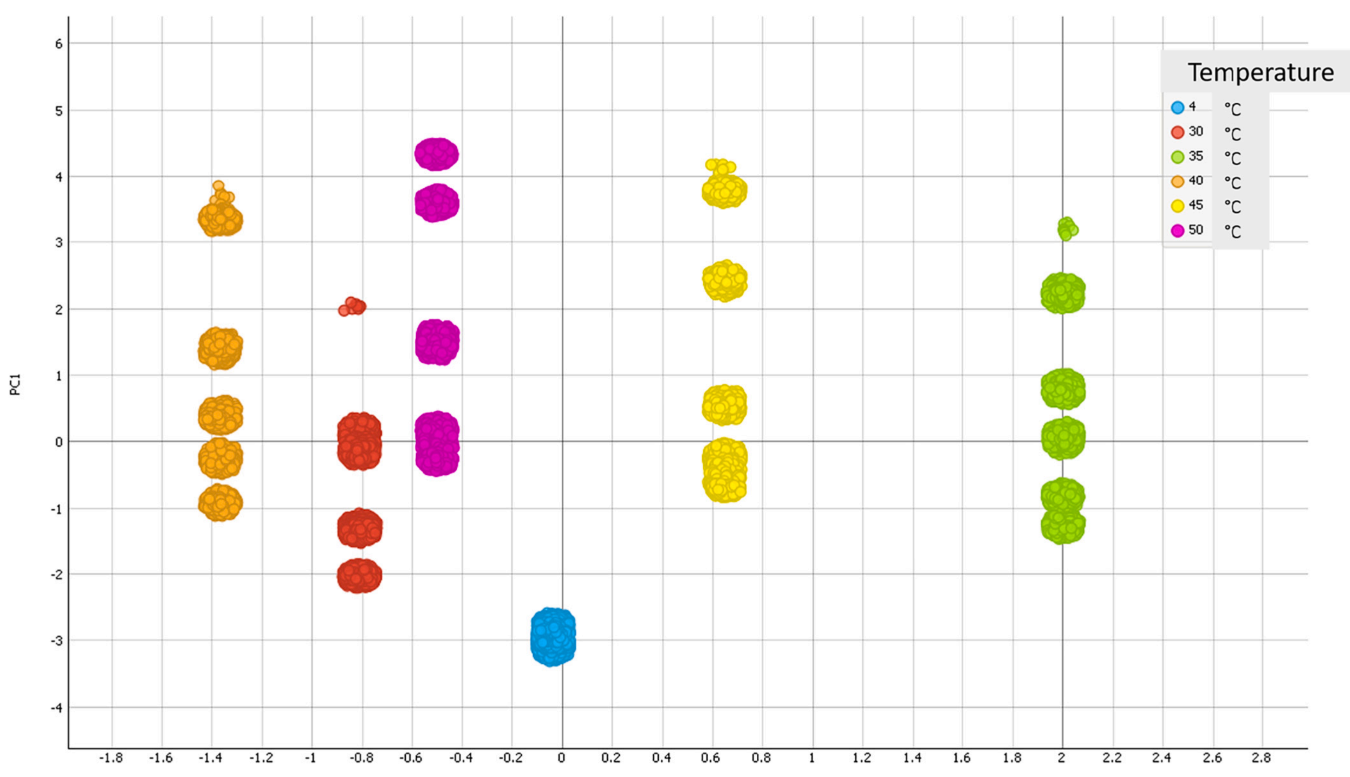

Fig. 6. PC1-PC4 Result based on Temperature Variations.

Table 4
Model summary of DNN.

Model: "Sequential"		
Layer (type)	Output Shape	Param #
dense (Dense)	(None, 500)	2500
dense_1 (Dense)	(None, 100)	50,100
dense_2 (Dense)	(None, 50)	5050
dense_3 (Dense)	(None, 2)	102

Total params: 57,572
Trainable params: 57,572
Non-trainable params: 0

dimensions to a minimum while maintaining the information contained in it. The use of PCA is used to classify samples based on variations in shelf life and temperature. The PCA method is done by looking for a covariance matrix to determine the correlation in each variable. The covariance matrix is then used to find the eigenvalue of each variable. Eigenvalue describes data information that is formed at the new coordinates (principal component) that is formed. The results of the calculation of each principal component (PC) value can be seen in Table 3 and the data visualization of PCA can be seen in Fig. 4.

Based on variations in shelf life, data can be visualized for each individual PC. PC 1 is used as the main component, followed by other components. The visualization results are selected based on the most discrete PC values. For PC1-PC2 and PC1-PC4 there are overlapping clusters and it is difficult to separate. So that the data visualization to classify odors based on shelf life, the results from PC1-PC 3 are used as shown in Fig. 5

From Fig. 5 can be classified the shelf life of the PC1 and PC 3 values, with a cumulative percentage of 95%. The classification results are:

If 0 > PC 1 > −3 and 0.2 > PC3 > −0.2 then, 0 h
If 0 > PC 1 > −3 and 0.6 > PC3 > 0.2 then, 6 h
If 1 > PC 1 > −3 and − 1.2 > PC3 > -1.6 then, 12 h
If 4 > PC 1 > −2 and 2 > PC3 > 1.6 then, 18 h
If 5 > PC 1 > −2 and − 0.6 > PC3 > -1 then, 24 h

Based on temperature variations, data can be visualized for each PC. PC 1 is used as the main component, followed by other components. The visualization results are selected based on the most discrete PC values. For PC1-PC2 and PC1-PC3 there are overlapping clusters and it is difficult to separate. So that the data visualization to classify odors based on temperature, the results from PC1-PC4 are used as shown in Fig. 6.

From Fig. 6, the temperature can be classified from the values of PC1 and PC4, with a cumulative percentage of 94.8%. The classification results are:

If − 2 > PC 1 > −4 and 0.2 > PC4 > -0.2 then, 4 °C.
If 2 > PC 1 > −3 and − 0.6 > PC4 > -1 then, 30 °C.
If 4 > PC 1 > −2 and 2.2 > PC4 > 1.8 then, 35 °C.
If 4 > PC 1 > −2 and − 1.2 > PC4 > -1.6 then, 40 °C.
If 5 > PC 1 > −1 and 0.8 > PC4 > 0.4 then, 45 °C.
If 5 > PC 1 > −1 dan − 0.4 > PC4 > -0.6 then, 50 °C.

4.4. Classification with DNN

After getting the PCA features, the data was divided into sections with 80% and 20% ratio. The 80% data was used as a training and 20% data was used for testing. After splitting the data, the next step was building the DNN model. In this work, sequential model was utilized with 2 hidden layers including input and output layer. The input dimension was set to four because we had four features. The hidden layers use ReLu activation function to reduce vanish gradient. In output layer the sigmoid activation function was used because we have only two classes. The model summary is shown in Table 4.

While compiling the model, the optimizer was set to "adam" and "binary cross-entropy" was set to find the loss. To evaluate the model, the performance metrics was calculated. The performance metrics was consisting of training & testing accuracy, precision, recall, f1-score and confusion matrix. All the parameters were calculated using testing dataset. Precision, recall and f1-score give better understanding of model if the data of both class is same.

Table 5
Training and testing accuracy for classification chicken meat.

	Training Data	Test Data
Accuracy (%)	98.85	98.70
Error	0.015	0.013

Table 6
Result of confusion matrix.

	Predicted: Negative	Predicted: Positive
Actual: Negative	931	24
Actual: Positive	0	854

Table 7
Classifier performance result.

	Fresh Meat	Unfresh Meat
Precision	100%	97.00%
Recall	97.00%	100%
F1-score	99.00%	99.00%

Training and testing accuracy were evaluated to verify if the model works correctly. Training and testing accuracy are shown in Table 5. The results show that the training data has an accuracy of 98.85% and an error of 0.015. The test data has an accuracy of 98.70% and an error of 0.013.

Confusion matrix were also evaluated to test the performance of a classification method. In this study, the confusion matrix stores classification information for fresh and unfresh chicken meat. Confusion matrix are shown in Table 6.

Therefore, the other subset of performance metrics can obtained, such as precision, recall, and f1-score, as summarized in Table 7. The result show that DNN model developed in the study has an accuracy of 98.70%.

4.5. Effect of storage time and temperature

The storage time greatly affects the condition of chicken meat, the longer the storage time, the risk of damage to the chicken. The surface of the meat, the taste and nutritional content of the meat will also be damaged. It can be seen if the meat has been damaged due to being stored for too long is the appearance of mucus on the surface of the meat, at hour 0 the meat looks very fresh, does not have a pungent smell, solid texture, not slimy, but as the duration of storage increases the intensity of the mucus increases. Issued is also higher. The peak of increasing mucus intensity occurred at the 24th hour. One of the causes of rot over time is due to autolysis. Autolysis is the process of breaking down proteins and fats by enzymes (proteases and lipases) present in chicken meat for a certain time [29]. These enzymes have actually been active since the chicken was alive, but at that time the results of their activity were used to produce energy and maintain the body. Autolysis begins with a decrease in pH. Initially, proteins are broken down into macromolecules, which causes increased dehydration and then further broken down into peptones, polypeptides, and finally into amino acids. Autolysis will change the structure of the meat so that the elasticity decreases.

In addition to mucus and decreased elasticity, the condition of damaged meat also triggers a pungent odor due to the reaction of compounds Ammonia which contain Nitrogen. Based on research [30] the ammonia content produced from time to time occurs because the protein content in meat is damaged. When the protein is ruined, the

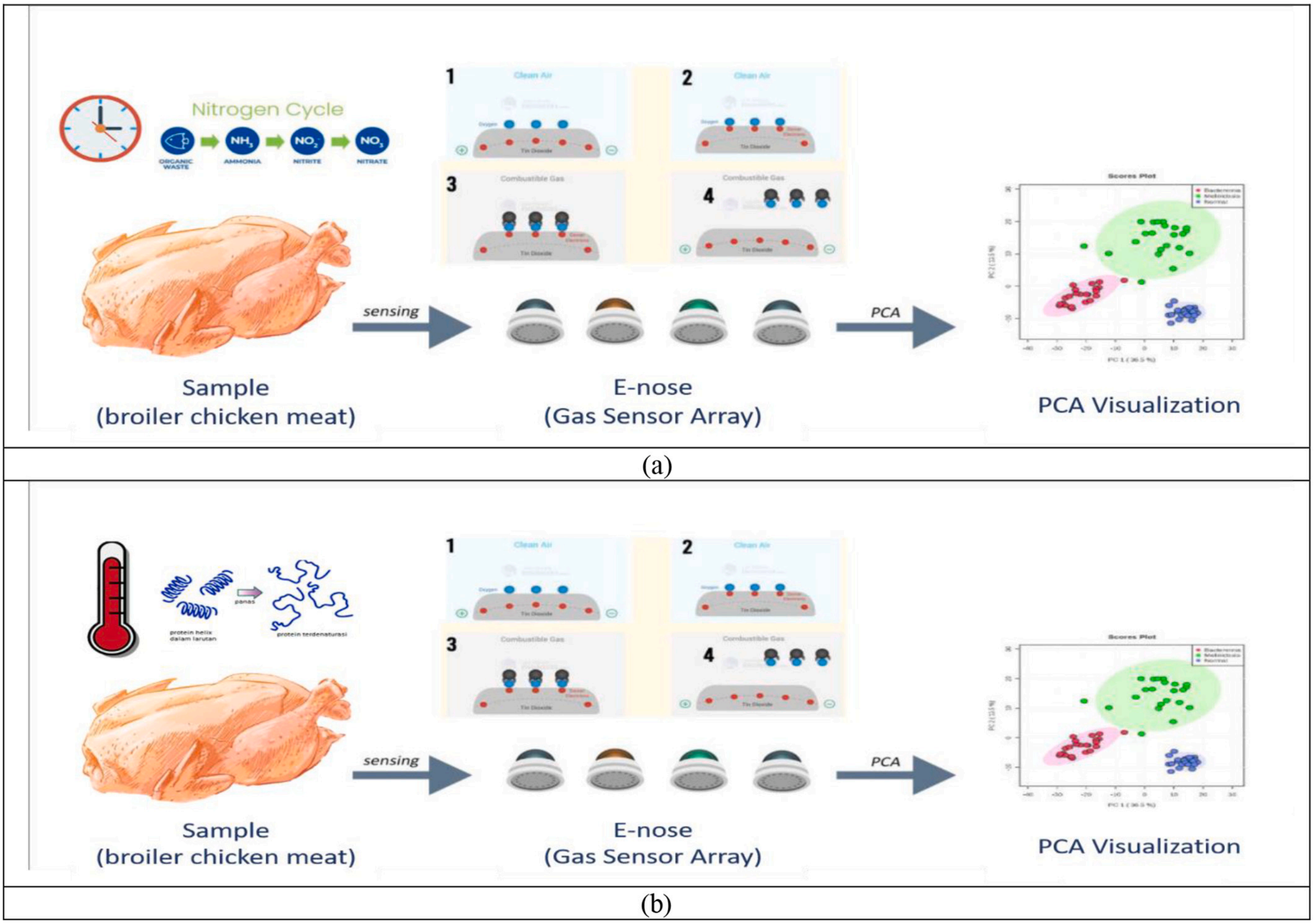

Fig. 7. (a) Research mechanism by storage time, (b) Research mechanism by temperature.

production of alcohol, ketones and hydrocarbons increases significantly so that a compound/enzymatic elemental reaction occurs which causes the production of Ammonia which produces a pungent odor.

Temperature also affects the condition of chicken meat, the hotter the temperature produced, the more pungent the smell of the meat, the stinging smell caused by the production of ammonia. Ammonia is produced when proteins react with heat, in chemistry the reaction of proteins with heat is described in the Mailard reaction. The Mailard reaction is a reaction between reducing sugars and amino components which increases in speed with increasing temperature and the depletion of water content in chicken meat [18].

It is known that the Maillard reaction plays an important role in the

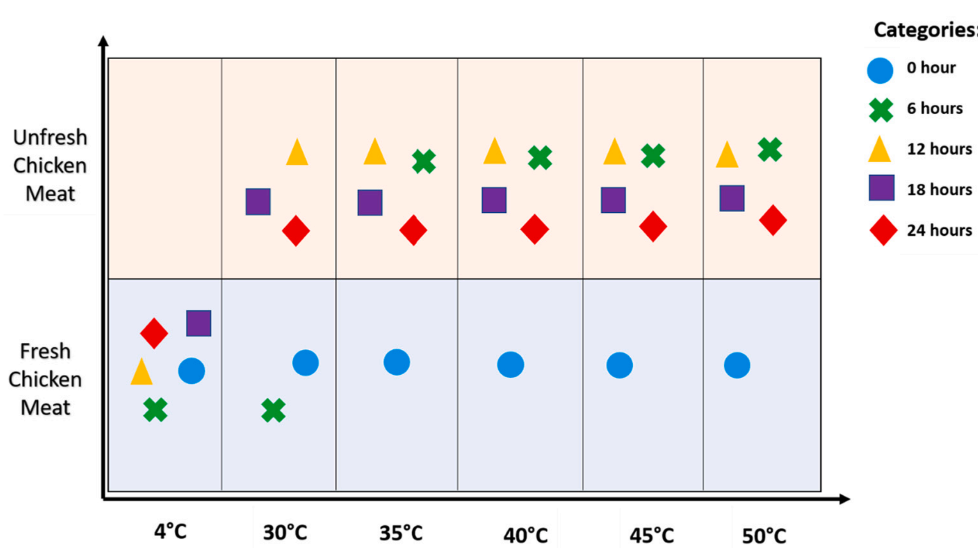

Fig. 8. Categories of fresh and unfresh chicken meat by the storage time and temperature.

formation of aroma, color, taste and texture changes in foods that are processed with heat and stored for a very long time. The understanding of the formation of the aroma became clearer after the development of the gas chromatography-mass spectrometer (CG-MS) analysis technique in the 1960s. Its use is prioritized to identify the volatile components of food stuffs. The study of the contribution of the Maillard reaction in heat treated foods continues and has contributed to the development of food chemistry. Maillard reaction in foodstuffs are very complex, this is due to the complexity of the components of these foodstuffs. The Maillard reaction occurs when there is a change in temperature. Changes in temperature will create a scent that can be smelled by the senses. Changes in temperature increase that occur gradually affect the creation of aroma, aroma is created due to the process of reducing water content, protein, and increasing the production process of ammonia. This triggers white gas to appear on the walls of the bottle so it can be seen that the meat is slowly spoiling due to increased temperature activity. Heating that occurs gradually causes damage to proteins in which there are amino acids, this event is called denaturation [31].

Denaturation is a process by which a protein undergoes a change in structure which in turn results in a change in function, which can lead to a total loss of biological function. When the protein solution is gradually heated to a critical temperature, the protein will run into a transition process from the original state to the denatured state. The temperature mechanism induces protein denaturation in a complex manner that causes instability of non-covalent interactions within the protein. Hydrogen bonds, electrostatic interactions and van der Waals forces are exothermic, so they destabilize at high temperatures and stabilize at low temperatures [32]. Research mechanism flow can be seen in Fig. 7 as the storage time and temperature being the influence factors in this study.

In this study using the PCA and DNN model, it can be seen that the gas sensor array is able to classify well, the meat with the treatment of storage time and temperature variations can be classified as fresh and unfresh meat with a testing accuracy of 98.70%. Fig. 8 shows the clustering result odor freshness of chicken meat based on storage period and temperature. If you want to get chicken meat with fresh meat quality, you can store the meat at a minimum temperature of 4 °C which is the refrigerator temperature. If you want to store meat at room temperature, which is around 30 °C, you can only store it 6 h after purchasing meat at the market. Moreover, if there is no cold medium to store, then fresh meat is best consumed immediately after purchase.

5. Conclusions

Sensors MQ7, MQ8, MQ135, MQ136 are able to detect the smell of chicken meat based on shelf life and temperature variations. The longer the storage time, the greater the voltage produced and the higher the temperature, the stronger the rotten meat smell. PCA and DNN model can be classified the freshness of the meat with a testing accuracy of 98.70%.

Limitations of this study just observing the voltage response generated by the gas sensor to the sample only. The results of the voltage reading produced by the sensor have not been compared with analytical methods such as Gas Chromatography Mass Spectrometry (GCMS) in determining the composition of gas compounds. Another limitation is we can put another gas, not only ammonia (NH4).

CRediT authorship contribution statement

Achmad Ilham Fanany Al Isyrofie: Conceptualization, Methodology, Resources, Data curation, Writing – original draft, Writing – review & editing. **Muhammad Kashif:** Conceptualization, Software, Validation, Formal analysis, Data curation. **Angger Krisna Aji:** Conceptualization, Software, Validation, Formal analysis, Visualization. **Nur Aidatuzzahro:** Conceptualization, Methodology, Validation, Investigation, Resources, Writing – original draft, Visualization. **Akif Rahmatillah:** Conceptualization, Methodology, Software, Validation, Investigation, Data curation. **Winarno:** Conceptualization, Software, Validation, Formal analysis, Writing – review & editing, Visualization. **Yunus Susilo:** Conceptualization, Methodology, Software, Investigation, Resources. **Ardiyansyah Syahrom:** Conceptualization, Validation, Supervision, Resources, Writing – review & editing. **Suryani Dyah Astuti:** Conceptualization, Methodology, Validation, Supervision, Investigation, Resources, Data curation, Writing – review & editing.

Declaration of Competing Interest

All authors stated that they have no recognized competing financial interests or personal connections that might have influenced the research presented in this publication.

Acknowledgement

We are very grateful to Directorate General Higher Education, Ministry of Research, Technology, and Higher Education for supporting this work.

Funding

This work was supported by Directorate General Higher Education, Ministry of Research, Technology, and Higher Education [grant number 367/E4/AK.04.ALKES/2021] and Matching Fund 2022.

Author statement

All authors participated in the manuscript preparation.

References

[1] S. Wulandari, L. Suryani, Salmonella detection on fried chickens sold at food stores and its sensitivity pattern on antibiotics, Mutiara Med. Ed. Khusus. 8 (2008) 101–106.
[2] N. Cohen, H. Ennaji, B. Bouchrif, M. Hassar, H. Karib, Comparative study of microbiological quality of raw poultry meat at various seasons and for different slaughtering processes in Casablanca (Morocco), J. Appl. Poult. Res. 16 (2007) 502–508, https://doi.org/10.3382/japr.2006-00061.
[3] S.D. Astuti, D. Arifianto, N.D.G. Drantantiyas, A.M.T. Nasution, Abdurachman, Efficacy of CNC-diode laser combine with chlorophylls to eliminate *staphylococcus aureus* biofilm, Proceeding - 2016 Int. Semin. Sensors, Instrumentation, Meas. Metrol. ISSIMM 2016, 2017, pp. 57–61, https://doi.org/10.1109/ISSIMM.2016.7803722.
[4] F. Fallah, Y. Ebrahimnezhad, N. Maheri-Sis, M. Ghasemi-Sadabadi, The effect of different levels of diet total volatile nitrogen on performance, carcass characteristics and meat total volatile nitrogen in broiler chickens, Arch. Anim. Breed. 59 (2016) 191–199, https://doi.org/10.5194/aab-59-191-2016.
[5] M. Purba, Poultry meat flavor by heating process and lipid oxidation, Wartazoa. 24 (2014) 109–118.
[6] D. Dave, A.E. Ghaly, Meat spoilage mechanisms and preservation techniques: a critical review, Am. J. Agric. Biol. Sci. 6 (2011) 486–510, https://doi.org/10.3844/ajabssp.2011.486.510.
[7] X. Chen, W. Fu, Y. Luo, C. Cui, I. Suppavorasatit, L. Liang, Protein deamidation to produce processable ingredients and engineered colloids for emerging food applications, Compr. Rev. Food Sci. Food Saf. 20 (2021) 3788–3817, https://doi.org/10.1111/1541-4337.12759.
[8] S.D. Astuti, M.H. Tamimi, A.A.S. Pradhana, K.A. Alamsyah, H. Purnobasuki, M. Khasanah, Y. Susilo, K. Triyana, M. Kashif, A. Syahrom, Gas sensor array to classify the chicken meat with E. coli contaminant by using random forest and support vector machine, Biosens. Bioelectron. X. 9 (2021), 100083, https://doi.org/10.1016/j.biosx.2021.100083.
[9] S.D. Astuti, Y. Mukhammad, S.A.J. Duli, A.P. Putra, E.M. Setiawatie, K. Triyana, Gas sensor array system properties for detecting bacterial biofilms, J. Med. Signals Sens. 9 (2019) 158.
[10] A.A.S. Pradhana, S.D. Astuti, M. Khasanah, R.K.D. Ardianti, Detection of gas concentrations based on age on Staphylococcus aureus biofilms with gas array sensors, in: AIP Conf. Proc., AIP Publishing LLC, 2020, p. 030012.
[11] A. Loutfi, S. Coradeschi, G.K. Mani, P. Shankar, J.B.B. Rayappan, Electronic noses for food quality: a review, J. Food Eng. 144 (2015) 103–111, https://doi.org/10.1016/j.jfoodeng.2014.07.019.
[12] J. Tan, J. Xu, Applications of electronic nose (e-nose) and electronic tongue (e-tongue) in food quality-related properties determination: a review, Artif. Intell. Agric. 4 (2020) 104–115, https://doi.org/10.1016/j.aiia.2020.06.003.
[13] V. Manuel, H. Bennetts, Fast Transient Classification with a Parallelized Temperature Modulated E-Nose, 2010, p. 83.

[14] K.P. Yashoda, N.M. Sachindra, P.Z. Sakhare, D. Narasimha Rao, Microbiological quality of broiler chicken carcasses processed hygienically in a small scale poultry processing unit, J. Food Qual. 24 (2001) 249–259, https://doi.org/10.1111/j.1745-4557.2001.tb00606.x.

[15] K. Timsorn, T. Thoopboochagorn, ScienceDirect evaluation of bacterial population on chicken meats using a briefcase electronic nose, Biosyst. Eng. 151 (2016) 116–125, https://doi.org/10.1016/j.biosystemseng.2016.09.005.

[16] P. Borowik, L. Adamowicz, R. Tarakowski, P. Wacławik, T. Oszako, S. Ślusarski, M. Tkaczyk, Application of a low-cost electronic nose for differentiation between pathogenic oomycetes pythium intermedium and phytophthora plurivora, Sensors (Switzerland). (2021) 1–16, https://doi.org/10.3390/s21041326.

[17] S.D. Astuti, A.I.F. Al Isyrofie, R. Nashichah, M. Kashif, T. Mujiwati, Y. Susilo, A. Syahrom Winarno, Gas array sensors based on electronic nose for detection of tuna (Euthynnus affinis) contaminated by Pseudomonas aeruginosa, J. Med. Signals Sens. 12 (2022) 158.

[18] S. Bedoui, H.C. Samet, A. Kachouri, Electronic nose system and principal component analysis technique for gases identification, Sensors, Circuits Instrum. Syst. (2018) 167–180, https://doi.org/10.1515/9783110448375-011.

[19] F.D. Mihafu, J.Y. Issa, M.W. Kamiyango, Implication of sensory evaluation and quality assessment in food product development: a review, Curr. Res. Nutr. Food Sci. 8 (2020) 690–702, https://doi.org/10.12944/CRNFSJ.8.3.03.

[20] R. Bro, A.K. Smilde, Principal component analysis, Anal. Methods 6 (2014) 2812–2831, https://doi.org/10.1039/c3ay41907j.

[21] L. Li, S. Liu, Y. Peng, Z. Sun, Overview of principal component analysis algorithm, Optik (Stuttg). 127 (2016) 3935–3944, https://doi.org/10.1016/j.ijleo.2016.01.033.

[22] M.A.A. Albadr, S. Tiun, M. Ayob, M. Mohammed, F.T. AL-Dhief, Mel-frequency cepstral coefficient features based on standard deviation and principal component analysis for language identification systems, Cogn. Comput. 13 (2021) 1136–1153, https://doi.org/10.1007/s12559-021-09914-w.

[23] H. Yu, Y. Wang, J. Wang, Identification of tea storage times by linear discrimination analysis and back-propagation neural network techniques based on the eigenvalues of principal components analysis of E-nose sensor signals, Sensors. 9 (2009) 8073–8082, https://doi.org/10.3390/s91008073.

[24] J. Wang, Y. Ma, L. Zhang, R.X. Gao, D. Wu, Deep learning for smart manufacturing: methods and applications, J. Manuf. Syst. 48 (2018) 144–156, https://doi.org/10.1016/j.jmsy.2018.01.003.

[25] S.H. Khan, M. Hayat, F. Porikli, Regularization of deep neural networks with spectral dropout, Neural Netw. 110 (2019) 82–90, https://doi.org/10.1016/j.neunet.2018.09.009.

[26] J.M.K.J.K. Premarathne, D.A. Satharasinghe, A.R.C. Gunasena, D.M. S. Munasinghe, P. Abeynayake, Establishment of a method to detect sulfonamide residues in chicken meat and eggs by high-performance liquid chromatography, Food Control 72 (2017) 276–282, https://doi.org/10.1016/j.foodcont.2015.12.012.

[27] Y.H.B. Kim, R.D. Warner, K. Rosenvold, Influence of high pre-rigor temperature and fast pH fall on muscle proteins and meat quality: a review, Anim. Prod. Sci. 54 (2014) 375–395, https://doi.org/10.1071/AN13329.

[28] S. Limbo, L. Torri, N. Sinelli, L. Franzetti, E. Casiraghi, Evaluation and predictive modeling of shelf life of minced beef stored in high-oxygen modified atmosphere packaging at different temperatures, Meat Sci. 84 (2010) 129–136.

[29] E.U. Ahiwe, M.E. Abdallh, E.P. Chang'a, A.A. Omede, M. Al-Qahtani, H. Gausi, H. Graham, P.A. Iji, Influence of dietary supplementation of autolyzed whole yeast and yeast cell wall products on broiler chickens, Asian-Australasian, J. Anim. Sci. 33 (2020) 579–587, https://doi.org/10.5713/ajas.19.0220.

[30] Y. Tatemichi, K. Kuroda, T. Nakahara, M. Ueda, Efficient ammonia production from food by-products by engineered Escherichia coli, AMB Express 10 (2020), https://doi.org/10.1186/s13568-020-01083-7.

[31] H.B. Wijayanti, A. Brodkorb, S.A. Hogan, E.G. Murphy, Thermal denaturation, aggregation, and methods of prevention, in: Whey Proteins, Academic Press, 2019, pp. 185–247.

[32] B. Wang, Y.P. Timilsena, E. Blanch, B. Adhikari, Lactoferrin: structure, function, denaturation and digestion, Crit. Rev. Food Sci. Nutr. 59 (2019) 580–596, https://doi.org/10.1080/10408398.2017.1381583.