

## Recent development in electronic nose data processing for beef quality assessment

Riyanarto Sarno<sup>1\*</sup>, Dedy Rahman Wijaya<sup>2</sup>

<sup>1,2</sup>Informatics Department, Institut Teknologi Sepuluh Nopember,  
Raya ITS St., Sukolilo, Surabaya 60111, Indonesia

<sup>2</sup>School of Applied Science, Telkom University,  
Telekomunikasi St. Terusan Buah Batu, Bandung 40257, Indonesia

\*Corresponding author, email: riyanarto@if.its.ac.id

### Abstract

*Beef is kind of perishable food that easily to decay. Hence, a rapid system for beef quality assessment is needed to guarantee the quality of beef. In the last few years, electronic nose (e-nose) is developed for beef spoilage detection. In this paper, we discuss the challenges of e-nose application to beef quality assessment, especially in e-nose data processing. We also provide a summary of our previous studies that explains several methods to deal with gas sensor noise, sensor array optimization problem, beef quality classification, and prediction of the microbial population in beef sample. This paper might be useful for researchers and practitioners to understand the challenges and methods of e-nose data processing for beef quality assessment.*

**Keywords:** *beef quality assessment, data processing, electronic nose*

**Copyright © 2019 Universitas Ahmad Dahlan. All rights reserved.**

### 1. Introduction

Food is one of the basic needs for humans derived from animal and vegetable foods. Healthy and clean foods will reflect healthy body condition and resistance to disease. Conversely, unhealthy foods will reduce the physical condition so susceptible to various diseases. The main cause of unhealthy foods is the presence of congenital diseases. Foodborne diseases are a condition in which foods are contaminated by bacteria or other harmful substances that lead to a decrease in the quality of the food. In the USA, about 76 million food-borne illness cases occur each year. The economic losses that caused by diseases from the major pathogen are estimated at more than \$35 billion for medical costs and lost productivity annually [1]. European Food Safety Authority has been reported that more than 15% of the populations in Europe suffering from foodborne diseases. While in Indonesia, there are 1068 cases of food poisoning in 2016 [2].

Meat is one example of widely consumed foodstuff but it is also kind of perishable food. Food and Agriculture Organization (FAO) of the United Nations estimates that the beef has a high demand and still become one of the main sources of animal-based protein (ABP) in the world until 2050. The report shows that the total consumption will increase both of in developed countries and developing countries [3]. Another study also reported that the demand for ABP tends to rise from 23.1 kg/person/year to 42.20 kg/person/year during 1961-2011 [4]. These reports denote that the increasing trend of meat consumption in the world. Unfortunately, meat is highly perishable food due to improper handling and storage. When the animal is slaughtered, microorganisms find the way into the meat and lodge inside them then breed and damage the quality of meat. The exposure of ambient temperature and humidity make the deterioration of meat is faster.

Several methods were utilized for meat quality assessment encompasses sensory panel, total volatile basic nitrogen (TVB-N), total count of bacteria, and gas chromatography. However, most of them are complex, require special training, laborious, time-consuming, and high-cost [5]. In fact, the main standard of beef quality is the total count of bacteria. Nevertheless, this method takes a long time, especially for sample incubation period and preparation [5]. On the other hand, a real-time and fast assessment system is necessary for the meat industry to continuously monitor the quality of meat during distribution. For the end

consumer, a low cost and easy-to-use system is needed to avoid the risk of foodborne illness. In the last few years, several studies were performed to develop rapid meat safety system. Fourier Transform Infrared (FTIR) spectroscopy and electronic nose (e-nose) are utilized as an apparatus for meat quality detection. Several studies have been reported that FTIR spectroscopy is used to distinguish three sensory classes of beef (fresh, semi-fresh, and spoiled). They get favorable results (>90% of accuracy) [6–11]. On the other hand, several works have been reported that e-nose are utilized to differentiate fresh and spoiled beef with more than 96% of classification accuracy [12–16]. Moreover, e-nose were used to classify three classes of beef, i.e., fresh, semi-fresh, spoiled [17–20] and four classes of beef (“excellent”, “good”, “acceptable”, and “spoiled”) [21]. Actually, e-nose and FTIR spectroscopy have comparable performance for meat quality assessment. However, e-nose has several advantages than FTIR spectroscopy including low-cost and suitable for real-time and online analysis.

The rest of this paper is organized as follows: section 2 explains e-nose principles including basic components and this functionality. Section 3 discusses the prospects and the challenges related to e-nose development for beef quality monitoring and assessment. Section 4 explains the e-nose data processing to deal with these challenges including signal conditioning, feature extraction, and pattern recognition algorithms. Finally, section 5 is the conclusion.

## 2. Electronic Nose Principles

E-nose is a device that imitates the function of mammalian olfactory system. Hence, it also called as an artificial olfactory system. The main elements of e-nose are akin to the mammalian olfactory system. Basically, e-nose has three main components: gas sensor array, signal conditioning and feature extraction, and pattern recognition system as shown in Figure 1 [22].

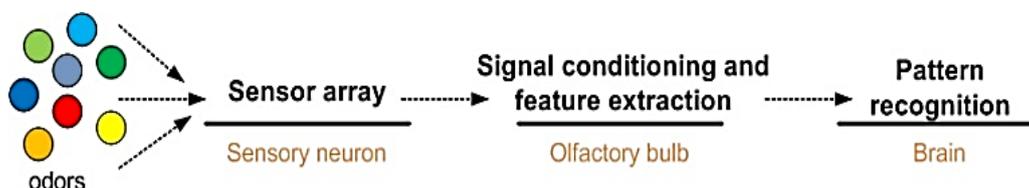


Figure 1. Basic functional components of e-nose

Gas sensor array consists of several gas sensors with various gas selectivity. Commonly, metal-oxide-semiconductor (MOS) gas sensor is used to tailor the gas sensor array because relatively cheap and fast-response. First, the gas sensor array detects odor molecules in the sample chamber and converts into multivariate data that represents the condition of the sample. Second, the signals produced by gas sensor array are conditioned and extracted to feed into the pattern recognition system. In a pattern recognition system, the extracted features are divided into data training and data testing. Data training is used to train the machine learning algorithm related to the pattern of these features. Afterward, data testing is used to test the performance of the trained machine learning model.

## 3. Electronic Nose System for Meat Safety: Prospects and Challenges

In the last few years, the studies of e-nose development for meat assessment system have been reported. In this section, prospects and challenges are described. Therefore, readers have an understanding of prospects and challenges of research in this field.

### 3.1. Prospects

Currently, e-nose system is used to substitute human olfactory function for specific tasks. Many e-nose devices are used for several applications in various areas such as food processing [21], [23], medical [24], and gas concentration analysis [25]. The flexibility to

implementation causes the growth of its utilization. In addition, low-cost implementation and fast detection make it suitable to use for Sensing as a Service (S<sup>2</sup>aaS) [26]. E-nose can be integrated with consumer electronics such as refrigerator and meat chiller to deliver the information about meat quality and meat shelf-life. Moreover, e-nose is also considered for development of smart packaging system. It can fulfil the requirement of the meat industry to continuously monitor the freshness, temperature, shelf life and microbiological status of food products from farm to plate to meet consumer satisfaction as well as minimizing food spoilage and wastage [27].

### 3.2. Challenges

On the other hand, there are some challenges for applications of e-nose correspond to e-nose data processing as follows:

a. Stabilizing ambient conditions

Changes in gases, humidity, and temperature affect the MOS gas sensors. Moreover, the changes in electrical voltage and current affect the captured sensor responses. Therefore, noises are included in the sensor responses. Efforts are implemented to stabilize the ambient conditions. However, the changes in gases and humidity still affect the MOS gas sensors.

b. The noise existence in e-nose signals

The source of noise can be caused by internal and external factors. For example, the signal of MOS gas sensor susceptible to contamination by internal noise such as thermo-noise and semiconductor noise [28]. Aforementioned, the external noise comes from the changes of relative humidity and temperature. In beef quality monitoring, the process of beef spoilage yields water vapor that changes the humidity level. Moreover, the existence of Sulphur and ethanol compounds that generated by protein decomposition lead to sensor poisoning [29]. Hence, it can be said that the type of sample also affects the stability of the sensor gas response.

c. Overlapping selectivity

The combination of several gas sensors that has the same selectivity causes overlapping selectivity. Actually, a gas sensor has the ability to detect more than one gas. The existence of overlapping selectivity in the sensor array causes not optimal sensor combination. The not optimal combination of gas sensor leads to performance degradation in the pattern recognition system, waste of electrical power, and enlarge the size of data [30].

d. The complex pattern caused by a variety of beef sample

The amount and composition of the volatiles emitted is not uniform for every beef cut and depends largely on the age, sex, breed, environmental conditions, feed, and the anatomy of the animal studied [31]. Hence, there is necessary to use various sample of beef cuts. Furthermore, these various amounts and compositions of the volatiles lead to the more complex pattern which causes difficulty to recognize in the pattern recognition system. For interested readers, an example of dataset is available in references [32, 33].

### 4. Electronic Nose Data Processing

In this section, correspond to the challenges that have been discussed before, e-nose data processing for beef quality assessment is explained encompasses signal conditioning, feature extraction, and pattern recognition algorithms for classification and regression tasks. Figure 2 shows the general taxonomy of e-nose data processing. In this paper, we do not discuss all of of these methods. However, we try to explain in more detail certain methods especially related to noise filtering and pattern recognition. For signal conditioning, several noise filtering methods have been reported including wavelet transform [34, 35], binomial smoothing [12, 13], and moving average [16]. The feature scaling is also needed for e-nose signal processing. The magnitude differences among gas sensors are the major reason to perform normalization [12, 13], [34]. Feature selection algorithms are also possible to be implemented for sensor array optimization problem. Not optimum combination of gas sensor is a common drawback of e-nose system. Several algorithms can be used encompasses filter, wrapper, and embedded. Filter algorithm is chosen because relatively fast, classifier independent, and simpler [36]. Commonly, raw e-nose signals should be extracted for further processing. Principal component analysis (PCA) is a common technique for feature extraction, notably for dimensional reduction [12–15], [17], [20], [37]. Another study used wavelet coefficient as input features [38, 39]. It has been reported for better performance than fractional change, relative,

difference, log, integral, derivative, and Fourier coefficient [38]. In addition, the formulation of gas concentration also can be used as input features for machine learning algorithms [25]. In the beef quality assessment, multiclass classification and regression tasks are two typical problems that must be handled. Pattern recognition methods can be utilized to differentiate sensory classes of beef. The prediction of microbial population is a more complex task because these continuous labels make it harder to predict. Several methods can be used for classification such as k-nearest neighbour [16], [34], support vector machine [14], [16, 17], [19], artificial neural network [15, 16], discriminant analysis [12, 13], and adaptive neuro-fuzzy inference system [20], [37] can be employed to predict the microbial population. The detail explanations are presented in the next section.

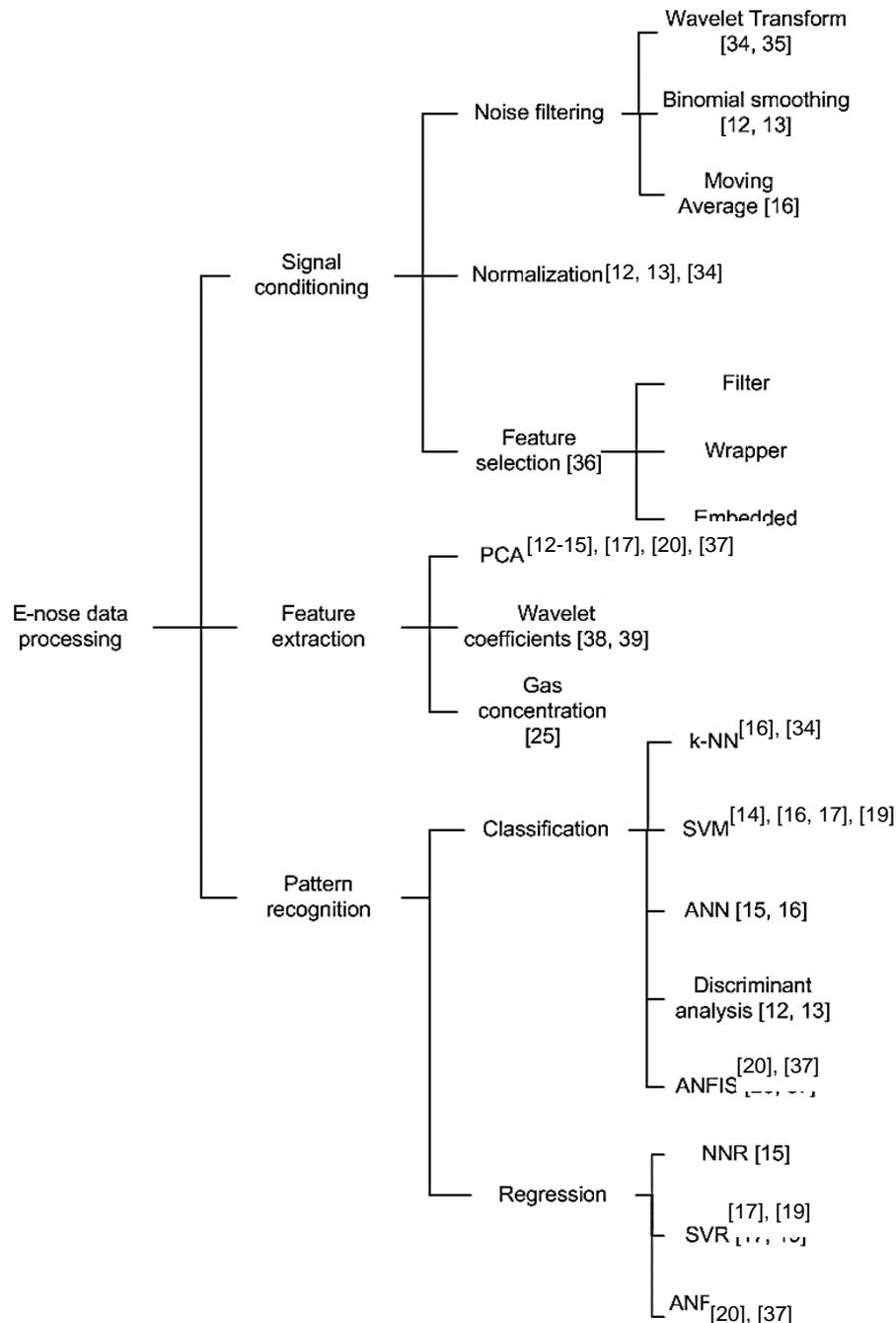


Figure 2. The taxonomy of e-nose data processing

#### 4.1. Signal Conditioning and Feature Extraction

Signal conditioning refers to eliminate redundant, unnecessary, and irrelevant data that generated by the gas sensor array. As explained before, the e-nose signal that contaminated by noise leads to the performance degradation of e-nose system. This noise contains irrelevant information regarding the test sample. To deal with this problem, the noise filtering method needs to be applied. Discrete wavelet transform (DWT) is a prominent method for non-stationary signal denoising. The DWT process of given signal  $a(t)$  can be mathematically expressed by

$$\text{dwt}(\varsigma, \tau) = \langle a(t), \psi_{\varsigma, \tau}(t) \rangle = \frac{1}{\sqrt{2\varsigma}} \int_{-\infty}^{\infty} a(t) \psi^* \left( \frac{t - \tau 2^{\varsigma}}{2\varsigma} \right) dt \quad (1)$$

where  $\varsigma$ ,  $\tau$ , and  $\psi$  denote scaling, translation parameter, and mother wavelet (MWT), respectively [40]. Moreover,  $\psi^*(.)$  implies complex conjugation of MWT. The proper signal reconstruction is needed to guarantee the process of noise filtering does not cause loss of essential information contained in the original signal. The proper wavelet decomposition level and the best-suited MWT are two important aspects for performing DWT. To determine the proper wavelet decomposition level, the frequency characteristic of each signal must be identified. The higher frequency needs lower level and vice versa. Then, the best-suited MWT is determined by comparing several MWT families including haar, daubechies, symlet, coiflet, and digital meyer. The information quality ratio can be used as a metric for MWT selection. This metric provides better sensitivity to detect the changes in signal structure than typical metrics e.g. mean squared error (MSE) and correlation coefficient. Moreover, it has better performance to keep essential information than these typical metrics. For interested readers, the process of signal reconstruction can be read in this paper [35]. The fine-tuned DWT also has been reported for successful implementation in our previous works [21], [24, 25], [41], [42].

Furthermore, sensor array optimization is needed to eliminate redundancy and unnecessary gas sensor. Feature selection can be used to determine the best features combination that related to the best gas sensor combination in the sensor array. Filter-based feature selection has been proposed to deal with sensor array optimization problem in the beef quality classification. The proposed method is successfully reduced the number of the gas sensor in the sensor array. For interested readers, the process of sensor array optimization can be read in this paper [30]. In the previous works, PCA is widely used for dimensional reduction and feature extraction [12–15], [17], [20], [37]. In addition, moving average [16] and wavelet coefficient [21] are also used for feature extraction.

#### 4.2. Pattern Recognition Algorithms

##### a. k-nearest neighbor

k-nearest neighbor (k-NN) is a simple machine learning algorithm that directly compares the testing and the training tuple to predict the class of a testing tuple. The closeness of them is measured by a particular distance metric such as Euclidean, city block, mahalanobis, and bhattacharyya distance. The commonly used distance metric is the Euclidean distance. The Euclidean distance between testing tuple ( $X_1$ ) and training tuple ( $X_2$ ) with n-dimensional attributes can be computed by (2).

$$\text{dist}(X_1, X_2) = \sqrt{\sum_i^n (X_{1i} - X_{2i})^2} \quad (2)$$

The k number of the closest tuple is selected to determine the label of the new tuple. The voting to assign the class label (class) is utilized:

$$\text{class} = \text{argmax}_{\text{class}_i} \left\{ \frac{k_{\text{class}_i}}{k} \right\}, i = 1, 2, \dots, m \quad (3)$$

while  $k_{\text{class}_i}$ ,  $k$ , and  $m$  are the number of neighbors which is labeled as class  $\text{class}_i$ , the total number of nearest neighbors, and the amount of possible class label. k-NN has been reported to classify two class of beef [16] and four classes of beef [21] with 96.2% and 85.50% of accuracy, respectively.

### b. Support Vector Machine

Basically, the support vector machine (SVM) uses linear optimal hyperplane to separate two classes. Nevertheless, in many e-nose applications, there is not safe to assume that data is linearly separable. Kernel trick can be used to process non-linear data including polynomial and radial basis function (RBF) [14], [16, 17], [19], [41]. Considering the training tuple  $X_i, i=1, \dots, l$  with  $n$ -dimensional attributes has the two possibilities of class labels ( $\text{class} \in \{-1, 1\}$ ). The primal optimization in the training process can be expressed as follows (4) [43]:

$$\begin{aligned} \min_{w, b, \xi} & \frac{1}{2} w^T w + C \sum_{i=1}^l \xi_i \\ (4) \quad & \text{subject to } \text{class}_i (w^T \phi(X_i) + b) \leq 1 - \xi_i, \xi_i \geq 0, i = 1, \dots, l \end{aligned}$$

$\phi(X_i)$  denotes a function that maps  $X_i$  into a higher-dimensional space.  $w$ ,  $C$ ,  $b$ ,  $\xi$  are slope/coefficients vector, regularization parameter, intercept/constant, and slack variable (variable to overcome noise and non-separable data inputs), respectively. Furthermore, the dual optimization problem is defined by:

$$\begin{aligned} \min_{\alpha} & \frac{1}{2} \alpha^T Q \alpha - e^T \alpha \\ (5) \quad & \text{subject to } \text{class}^T \alpha = 0, 0 \leq \alpha_i \leq C \end{aligned}$$

where  $e = [1, \dots, 1]^T$  is the all ones vector.  $Q$  is a positive semidefinite matrix ( $Q_{i,j} \equiv \text{class}_i \text{class}_j K(X_i, X_j)$ ,  $K(X_i, X_j) \equiv \phi(X_i)^T \phi(X_j)$ ) denotes the kernel function. Symbol  $\alpha$  means Lagrangian multiplier. Furthermore, the decision function is determined by the following sign function.

$$\text{class} = \text{sgn}(w^T \phi(X_j) + b) = \text{sgn}(\sum_{i=1}^l \text{class}_i \alpha_i K(X_i, X_j)) \quad (6)$$

when the  $w$  satisfies  $w = \sum_{i=1}^l \sum_{j=1}^l \text{class}_i \alpha_i \phi(X_i)$ . In the above condition,  $X_i$  and  $X_j$  denote the support vector and the testing tuple, respectively. Radial basis function (RBF) as the most common kernel function can be used. RBF kernel is given by (7):

$$K(X_i, X_j) = \exp(-\gamma \|X_i - X_j\|^2) \quad (7)$$

Gamma ( $\gamma$ ) implies how far the influence of a single training example reaches the hyperplane. It relates to the smoothness of boundary between classes. On the other hand,  $C$  parameter controls the trade-off between smooth decision boundary and classifying training points correctly. SVM got 98.81% and 89% of accuracy to classify two classes [14] and three classes of beef [17].

### c. Discriminant Analysis

The examples of the discriminant classifier are linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA). QDA is almost similar to LDA. The difference is QDA uses quadratic surfaces to separate data. In the previous studies, discriminant classifiers are used to differentiate fresh and spoiled beef samples. QDA was reported for better performance than LDA [12, 13]. The quadratic discriminant function is mathematically expressed by (8):

$$\delta(x)_{\text{class}_i} = -\frac{1}{2} \log |\Sigma_{\text{class}_i}| - \frac{1}{2} (x - \mu_{\text{class}_i})^T \Sigma_{\text{class}_i}^{-1} (x - \mu_{\text{class}_i}) + \log(\pi_{\text{class}_i}) \quad (8)$$

where  $\Sigma_{\text{class}_i}$ ,  $\mu_{\text{class}_i}$ ,  $\pi_{\text{class}_i}$  are covariance matrix, mean vector, and the prior probability of membership in  $i^{\text{th}}$  class. Unlike LDA, QDA has a different covariance matrix for each class. The QDA classifier involves plugging estimates for  $\Sigma_{\text{class}_i}$ ,  $\mu_{\text{class}_i}$ ,  $\pi_{\text{class}_i}$ , and assigning the  $x$  to the class with the highest output of  $\delta(x)_{\text{class}_i}$ . Thus, the class of  $x$  can be determined by (9):

$$\begin{aligned} \text{class} &= \text{argmax}_{\text{class}_i} \delta(x)_{\text{class}_i}, i = 1, 2, \dots, m \\ (9) \end{aligned}$$

while  $m$  is the total amount of possible class labels. QDA has been reported to classify fresh and spoiled beef with more than 96% of accuracy [12, 13].

#### d. Artificial Neural Network

Artificial neural network (ANN) contains three layers including input, hidden, and output layer. These layers are built from several neurons that convert the signals based on the connection weight, bias, and activation function. There are several activation functions which can be used such as radial basis function, sigmoid, and hyperbolic tangent. In the previous study, ANN was reported to distinguish fresh and spoiled beef sample. It contains 24 neurons in the hidden layer with sigmoid activation function [16]. The example of ANN architecture can be seen in Figure 3.

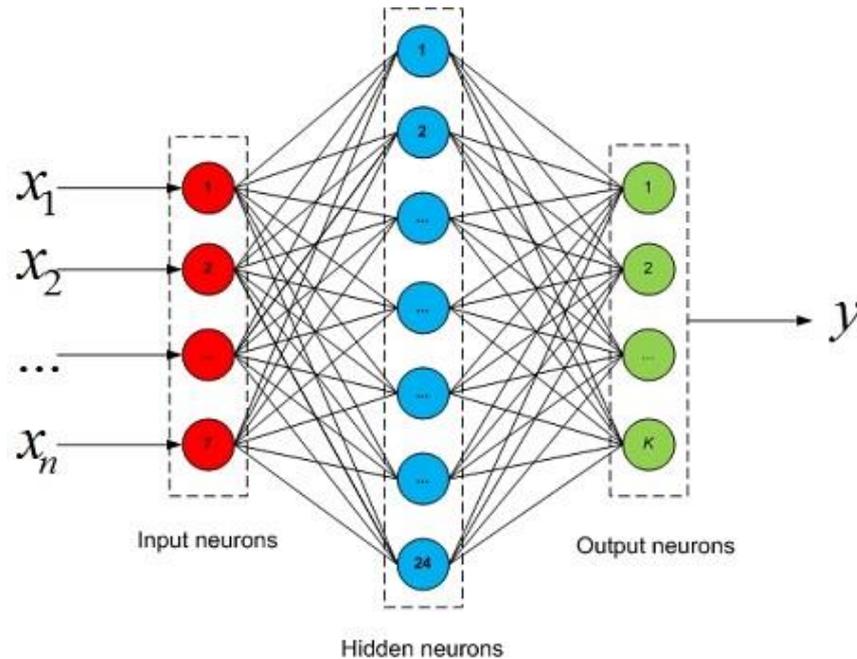


Figure 3. Neural network architecture

The sigmoid activation function is used in the hidden nodes. In the output layer, the softmax activation function is utilized to transform the input values from the hidden layer. Hence, every neuron in the hidden layer which receives the input vector  $\hat{X}$  from the previous layer is transformed to scalar output  $Y(f: \hat{X} \rightarrow Y)$  using an activation function as (10):

$$Y = F(y_{in}) = \text{activation}(y_{in}), y_{in} = \sum_{i=1}^n x_i w_i + b \quad (10)$$

where  $x_i$ ,  $w_i$ , and  $b$  denote the  $i$ th value of  $\hat{X}$ ,  $i$ th value of the weighted connection from the previous neuron, and bias, respectively. The sigmoid/logistic function is used on input and hidden neurons as the activation function. It can be computed by the (11)

$$F(y_{in}) = \frac{1}{1+e^{-y}} \quad (11)$$

for  $j$ th output neuron from total  $K$  output neurons, the softmax activation function is computed by (12):

$$F(y_{in}) = \frac{e_j^{y_{in}}}{\sum_{k=1}^K e_k^{y_{in}}} \quad (12)$$

in the previous study, ANN has been used to distinguish two classes of beef with 85% of accuracy [16].

e. Adaptive Neuro-Fuzzy Inference System

Adaptive neuro-fuzzy inference system (ANFIS) takes the advantages of fuzzy logic and artificial neural network. ANFIS can work by performing the learning ability of ANN to optimize the parameters of fuzzy inference system [44]. There are several advantages of ANFIS such as easy to implement, fast learning ability, and strong generalization ability [45, 46]. ANFIS was used to distinguish three classes of beef [18, 20]. The ANFIS architecture for simplified feature input ( $x_1$  and  $x_2$ ) is shown in Figure 4.

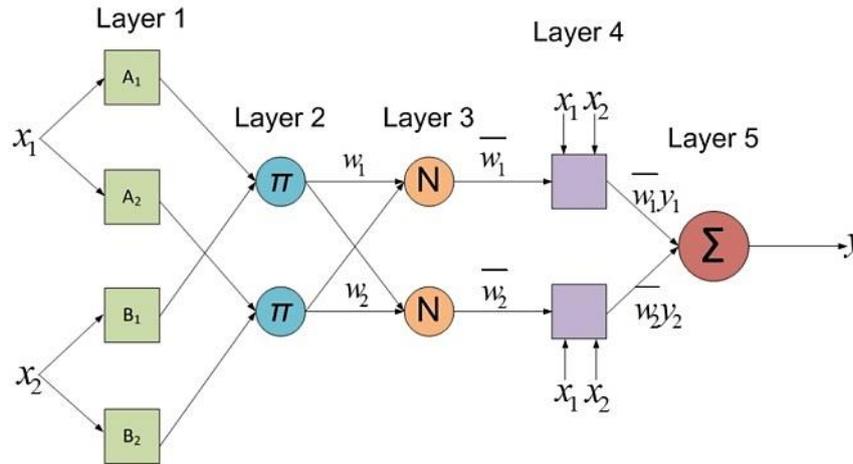


Figure 4. ANFIS architecture [45]

A square denotes an adaptive neuron and a circle shows a fixed neuron. The ANFIS architecture has five layers which explained below. Considering in this study, the first-order Sugeno model was used to construct the ANFIS. Suppose, two fuzzy rules considered as follows:

- Rule 1: IF  $x_1$  is  $A_1$  and  $x_2$  is  $B_1$  THEN  $y_1 = p_1x_1 + q_1x_2 + r_1$
- Rule 2: IF  $x_1$  is  $A_2$  and  $x_2$  is  $B_2$  THEN  $y_2 = p_2x_1 + q_2x_2 + r_2$

The first layer consists of adaptive neurons. They generate fuzzy membership grade from the given inputs. In this work, we used Gaussian membership function. It can be determined by (13):

$$O_i^1 = \mu(x) = \exp \left[ -\left( \frac{x-a_i}{b_i} \right)^2 \right] \tag{13}$$

where  $O_i^1$ ,  $\mu(x)$ ,  $a$ , and  $b$  denote the  $i$ th output in the first layer, membership function, and the parameters of the membership function, respectively. The second layer consists of fixed nodes. This layer uses AND operator to fuzzify the given inputs from the previous layer. The  $\pi$  symbol means multiplier between the two outputs of the membership function. The operation to compute the second layer output ( $O_i^2$ ) can be expressed by (14).

$$O_i^2 = w_i = \mu_{A_i}(x_1) * \mu_{B_i}(x_2), i = 1,2 \tag{14}$$

Moreover, the neurons in the third layer act as normalization role for the inputs from the second layer which marked by N symbol. The output from operation in the third layer ( $O_i^3$ ) is expressed as (15):

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2 \quad (15)$$

in the fourth layer, the neurons are adaptive. The output is the product of normalized firing strength from the previous layer ( $w_i$ ) and first-order Sugeno fuzzy model (first order polynomial function) as antecedents in Rule 1 and Rule 2. The output of the fourth layer ( $O_i^4$ ) can be computed by (16):

$$O_i^4 = \bar{w}_i y_i = w_i (p_i x_1 + q_i x_2 + r_i), i = 1, 2 \quad (16)$$

the fifth layer consists of a single neuron marked by  $\Sigma$ . It means that this layer performs the summation of all incoming inputs from the previous layer. The following equation expresses the output of this layer.

$$O_i^5 = \Sigma_i \bar{w}_i y_i \quad (17)$$

ANFIS was used to distinguish three classes of beef with up to 94% of accuracy [20], [37].

#### f. Neural Network Regression

Neural Network Regression (NNR) is utilized for the regression task to predict the microbial population. The prediction of microbial population is kind of regression problem because it yields continuous outputs as total viable count (TVC) value. The architecture of NNR is almost similar to Figure 4. The main difference is just one neuron in the hidden layer to produce the continuous output. The NNR architecture is shown in Figure 5.

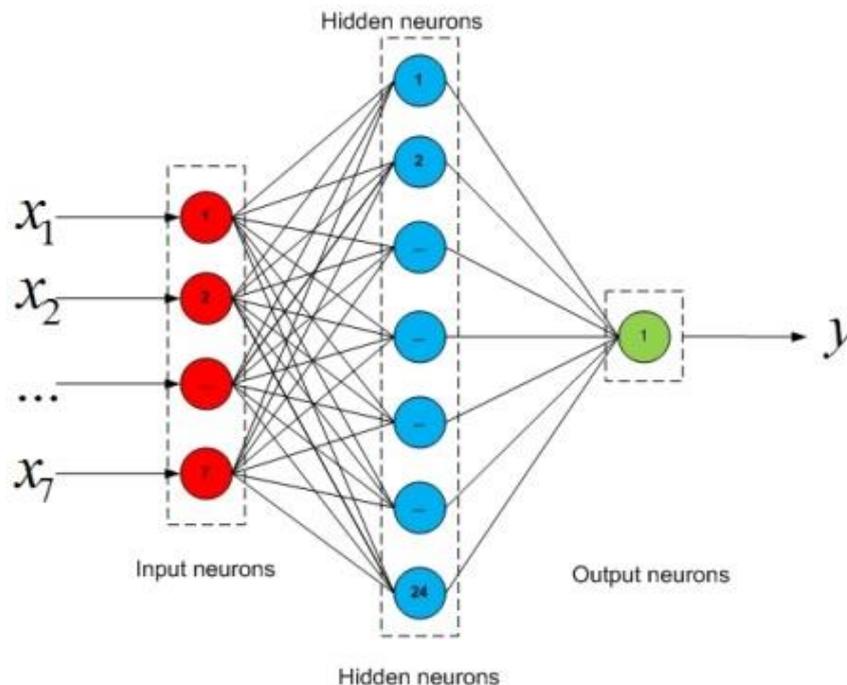


Figure 5. NNR architecture

in the input and hidden neurons, the sigmoid function is used for firing the output. Moreover, identity (linear) activation function is utilized in the output nodes.

#### g. Support Vector Regression

Support Vector Regression (SVR) has the same concept as SVM. However, an epsilon as the margin of tolerance is required to precisely predict the TVC value. Considering a set of data training,  $\{(X_1, Z_1), \dots, (X_1, Z_1)\}$  corresponds to the response of sensors where  $X_i, Z_i$  are

feature vector and target output, respectively. In  $\varepsilon$ -SVR, the primal optimization problem can be expressed as (18) [47]:

$$\begin{aligned} \min_{w, b, \xi, \xi^*} & \frac{1}{2} w^T w + C \sum_{i=1}^l \xi_i + C \sum_{i=1}^l \xi_i^* \\ \text{subject to} & w^T \phi(X_i) + b - Z_i \leq \varepsilon + \xi_i, Z_i - w^T \phi(X_i) - b \leq \varepsilon + \xi_i^*, \xi_i, \xi_i^* \geq 0, i = 1, \dots, l \end{aligned} \quad (18)$$

while  $w, C, \xi, \varepsilon, b$  denote slope matrix, regularization parameter, slack variable for soft margin, the margin of tolerance, and the intercept/bias, respectively. The symbol  $\phi(X_i)$  indicates mapping  $X_i$  into higher dimensional space. The dual problem optimization is given by (19):

$$\begin{aligned} \min_{\alpha, \alpha^*} & \frac{1}{2} (\alpha - \alpha^*)^T Q (\alpha - \alpha^*) + \varepsilon \sum_{i=1}^l (\alpha + \alpha^*) + \sum_{i=1}^l Z_i (\alpha - \alpha^*) \\ \text{subject to} & e^T (\alpha - \alpha^*) = 0, 0 \leq \alpha, \alpha^* \leq C, i = 1, \dots, l \end{aligned} \quad (19)$$

where  $\alpha$  and  $\alpha^*$  denotes Lagrangian multipliers.  $Q_{ij} = K(X_i, X_j) \equiv \phi(X_i)^T \phi(X_j)$  and  $e = [1, \dots, 1]^T$ . In linear SVR, the decision function is expressed by (20):

$$Y = \sum_{i=1}^l (\alpha_i - \alpha_i^*) \langle X_i, X \rangle + b. \quad (20)$$

In non-linear SVR, the kernel function e.g., RBF transforms the data input into a higher dimensional feature space to perform the linear separation. The decision function is computed by:

$$Y = \sum_{i=1}^l (\alpha_i - \alpha_i^*) \langle \phi(X_i), \phi(X) \rangle + b \quad (21)$$

$$Y = \sum_{i=1}^l (\alpha_i - \alpha_i^*) \langle K(X_i, X) \rangle + b. \quad (22)$$

the RBF kernel is used to deal with non-linear data that can be computed by (23):

$$K(X_i, X) = \exp(-\gamma \|X_i - X\|^2). \quad (23)$$

#### h. Adaptive Neuro-Fuzzy Inference System Regression

The utilization of ANFIS to solve regression as well as a classification task has the same mechanism. The end layer of ANFIS computes the summation of all previous inputs. Therefore, the explanation of ANFIS for regression is akin to ANFIS for the classification task.

## 5. Conclusion

In this paper, we have been discussed e-nose data processing for beef quality assessment. The background on the importance of developing e-nose for the meat quality assessment has been described. E-nose has several advantages such as rapid, easy to use, simple, and low-cost make it relevant for further development as an apparatus for meat quality assessment. However, several challenges must be faced related to e-nose data processing. Inconsistent, not precise, and irrelevant data are the main challenge in e-nose data processing. Several methods to tackle these issues are also discussed. This paper is a summary of our work over the last few years that describe our proposed methods to deal with these problems. In the future, e-nose is prospective to be developed as sensing as a service. Integration with consumer electronics such as refrigerator and meat chiller is useful for smart packaging system. It can fulfill the requirement of the meat industry to continuously monitor the freshness, temperature, shelf life and microbiological status of food products from farm to plate to meet consumer satisfaction as well as minimizing food spoilage and wastage. For future study, a robust deep learning method for time-series data analysis should be developed to overcome more complex pattern from various meat samples and sensor drift during the monitoring process.

## Acknowledgments

This work was supported by Institut Teknologi Sepuluh Nopember, Telkom University, and Ministry of Research, Technology and Higher Education Republic of Indonesia under the contract 128/SP2H/PTNBH/DRPM/2018 and 014/PNLT3/PPM/2018.

## References

- [1] Falasconi M, Concina I, Gobbi E, Sberveglieri V, Pulvirenti A, Sberveglieri G. Electronic Nose for Microbiological Quality Control of Food Products. 2012; 2012.
- [2] Makanan BPO. Graph of national poisoning case. , Jakarta (2016).
- [3] Alexandratos N, Bruinsma, J. WORLD AGRICULTURE TOWARDS 2030 / 2050 The 2012 Revision, Rome (2012).
- [4] Sans P, Combris P. World meat consumption patterns: An overview of the last fifty years (1961–2011), (2015).
- [5] Wojnowski W, Majchrzak T, Dymerski T, Gębicki J, Namieśnik J. Electronic noses: Powerful tools in meat quality assessment. *Meat Science*. 2017; 131(February): 119–131.
- [6] Kodogiannis VS, Petrounias I, Kontogianni E. *Identification of meat spoilage by FTIR spectroscopy and neural networks*. Proceedings of the International Joint Conference on Neural Networks. 2014; 1644–1651.
- [7] Papadopoulou O, Panagou EZ, Tassou CC, Nychas GJE. Contribution of Fourier transform infrared (FTIR) spectroscopy data on the quantitative determination of minced pork meat spoilage. *Food Research International*. 2011; 44(10): 3264–3271.
- [8] Kodogiannis VS, Alshejari A. An adaptive neuro-fuzzy identification model for the detection of meat spoilage. *Applied Soft Computing Journal*. 2014; 23: 483–497.
- [9] Zaragoza P, Fernández-Segovia I, Fuentes A, Vivancos JL, Ros-Lis JV, Barat JM, Martínez-Máñez R. Monitorization of Atlantic salmon (*Salmo salar*) spoilage using an optoelectronic nose. *Sensors and Actuators, B: Chemical*. 2014; 195: 478–485.
- [10] Kodogiannis VS, Petrounias I, Lygouras J. An intelligent based decision support system for the detection of meat spoilage. *Engineering Applications of Artificial Intelligence*. 2015; 323: 303–310.
- [11] Argyri AA, Panagou EZ, Tarantilis PA, Polysiou M, Nychas GJE. Rapid qualitative and quantitative detection of beef fillets spoilage based on Fourier transform infrared spectroscopy data and artificial neural networks. *Sensors and Actuators, B: Chemical*. 2010; 145(1): 146–154.
- [12] Balasubramanian S, Logue CM, Marchello, M. Spoilage Identification of Beef Using an Electronic Nose System. *Transactions of the ASAE*. 2004; 47(5): 1625–1633.
- [13] Panigrahi S, Balasubramanian S, Gu H, Logue CM, Marchello M. Design and development of a metal oxide based electronic nose for spoilage classification of beef. *Sensors and Actuators, B: Chemical*. 2006; 119(1): 2–14.
- [14] El Barbri, N Llobet, E El Bari, N Correig, X Bouchikhi B. Electronic Nose Based on Metal Oxide Semiconductor Sensors as an Alternative Technique for the Spoilage Classification of Red Meat. *Sensors*. 2008; 8(1): 142–156.
- [15] Balasubramanian S, Panigrahi S, Logue CM, Gu H, Marchello M. Neural networks-integrated metal oxide-based artificial olfactory system for meat spoilage identification. *Journal of Food Engineering*. 2009; 91(1): 91–98.
- [16] Najam ul Hasan, Ejaz N, Ejaz W, Kim HS. Meat and fish freshness inspection system based on odor sensing. *Sensors (Switzerland)*. 2012; 12(11): 15542–15557.
- [17] Papadopoulou OS, Panagou EZ, Mohareb FR, Nychas GJE. Sensory and microbiological quality assessment of beef fillets using a portable electronic nose in tandem with support vector machine analysis. *Food Research International*. 2013; 50(1): 241–249.
- [18] Kodogiannis VS, Alshejari. A. Neuro-Fuzzy based Identification of Meat Spoilage using an Electronic Nose. *2016 IEEE 8th International Conference on Intelligent Systems*. 2016; 710–717.
- [19] Mohareb F, Papadopoulou O, Panagou E, Nychas GJ, Bessant C. Ensemble-based support vector machine classifiers as an efficient tool for quality assessment of beef fillets from electronic nose data. *Analytical Methods*. 2016; 8(18): 3711–3721.
- [20] Kodogiannis VS. Application of an Electronic Nose Coupled with Fuzzy-Wavelet Network for the Detection of Meat Spoilage. *Food and Bioprocess Technology*. 2017;
- [21] Wijaya DR, Sarno R, Zulaika E, Sabila SI. *Development of mobile electronic nose for beef quality monitoring*. 4th Information Systems International Conference 2017, ISICO 2017, Procedia Computer Science. 2017; 124(November): 728–735.
- [22] Patel HK. *The Electronic Nose : Artificial Olfaction Technology*. Springer, Ahmedabad (2014).
- [23] Wijaya DR, Sarno R, Daiva AF. *Electronic Nose for Classifying Beef and Pork using Naive Bayes*. International Seminar on Sensor, Instrumentation, Measurement and Metrology (ISSIMM) Surabaya. 2017.
- [24] Hariyanto H, Sarno R, Wijaya D. Detection of Diabetes from Gas Analysis of Human Breath using E-Nose. 2017;
- [25] Wijaya DR, Sarno R, Zulaika E. *Gas Concentration Analysis of Resistive Gas Sensor Array*. 2016 IEEE International Symposium on Electronics and Smart Devices. 2016; 337–342.
- [26] Wijaya DR, Sarno R. Mobile Electronic Nose Architecture for Beef Quality Detection Based on Internet of Things Technology. 2015; 2. 655–663.

- [27] Ahmed I, Lin H, Zou L, Li Z, Brody AL, Mabood Qazi I, Lv L, Ramesh Pavase T, Ullah Khan, M Khan, S Sun, L Zhenxing Li C. An overview of smart packaging technologies for monitoring safety and quality of meat and meat products. *Packaging Technology and Science*. 2018; 31(7): 449–471.
- [28] Tian F, Yang SX, Dong K. Circuit and Noise Analysis of Odorant Gas Sensors in an E-Nose. *Sensors*. 2005; 5(1): 85–96.
- [29] Schaller E, Bosset JO, Escher F. Electronic Noses and Their Application to Food. *Lebensmittel-Wissenschaft und-Technologie*. 1998; 31(4): 305–316.
- [30] Wijaya DR, Sarno R, Zulaika E. Sensor Array Optimization for Mobile Electronic Nose: Wavelet Transform and Filter Based Feature Selection Approach. *International Review on Computers and Software*. 2016; 11(8): 659–671.
- [31] Preedy, V. *Electronic Noses and Tongues in Food Science*. Elsevier Inc., London (2016).
- [32] Wijaya DR, Sarno R, Zulaika E. Electronic nose dataset for beef quality monitoring under an uncontrolled environment, <https://data.mendeley.com/datasets/mwmhh766fc/2>.
- [33] Wijaya DR, Sarno R, Zulaika E. Electronic nose dataset for beef quality monitoring in uncontrolled ambient conditions. *Data in Brief*. 2018;
- [34] Wijaya DR, Sarno R, Zulaika E, Sabila SI. *Development of mobile electronic nose for beef quality monitoring*. *Procedia Computer Science*. 2017; 124211: S728–735.
- [35] Wijaya DR, Sarno R, Zulaika E. Information Quality Ratio as a novel metric for mother wavelet selection. *Chemometrics and Intelligent Laboratory Systems*. 2016; 160(November 2016): 59–71.
- [36] Wijaya DR, Sarno R, Zulaika E. Sensor array optimization for mobile electronic nose: Wavelet transform and filter based feature selection approach. *International Review on Computers and Software*. 2016; 11(8)
- [37] Kodogiannis VS, Alshejari A. A Fuzzy-Wavelet Neural Network Model for the Detection of Meat Spoilage using an Electronic Nose. *IEEE World Congress on Computational Intelligence (IEEE WCCI)*. 2016;
- [38] Distanto C, Leo M, Siciliano P, Persaud KC. On the study of feature extraction methods for an electronic nose. *Sensors and Actuators, B: Chemical*. 2002; 87(2): 274–288.
- [39] Distanto C, Persaud ML, KC Wavelet Transform for Electronic Nose Signal Analysis. Presented at the (2011).
- [40] Gao, R.X., Yan, R. *Wavelets: Theory and Applications for Manufacturing*. Springer, New York (2011).
- [41] Sarno R, Ridoean JA, Sunaryono D, Wijaya DR. Classification of Music Mood Using MPEG-7 Audio Features and SVM with Confidence Interval. *International Journal on Artificial Intelligence Tools*. 2018; 27(5).
- [42] Ridoean JA, Sarno R, Sunaryo D, Wijaya DR. *Music mood classification using audio power and audio harmonicity based on MPEG-7 audio features and Support Vector Machine*. *Proceeding-2017 3<sup>rd</sup> International Conference on Science in Information Technology: Theory and Application of IT for Education, Industry and Society in Big Data Era, ICSITech 2017*. 2018; 2018–January.
- [43] Chang CC, Lin C.J. LIBSVM: A Library for Support Vector Machines. *ACM Transactions on Intelligent Systems and Technology*. 2011; 2(3): 1–27.
- [44] Al-Hmouz A, Shen J, Al-Hmouz R, Yan J. Modeling and simulation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for mobile learning. *IEEE Transactions on Learning Technologies*. 2012; 5(3): 226–237.
- [45] Jang JSR, Sun CT. *Neuro-Fuzzy Modeling and Control*. *Proceedings of the IEEE*. 1995; 83.(3): 378–406.
- [46] Jang JSR, Sun CT, Mizutani E. *Neuro-Fuzzy And Soft Computing* Jang: a computational approach to learning and machine intelligence. Prentice-Hall (1997).
- [47] Vladimir N. Vapnik *Statistical Learning Theory*. Wiley (1998).