2017 International Seminar on Sensor, Instrumentation, Measurement and Metrology (ISSIMM)
Surabaya, Indonesia, August 25th - 26th, 2017

Electronic Nose for Classifying Beef and Pork using Naïve Bayes

Dedy Rahman Wijaya[1]
School of Applied Science
Universitas Telkom
Bandung, Indonesia,
Department of Informatics
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
[1]dedyrw@tass.telkomuniversity.ac.id

Riyanarto Sarno[2], Aldhiaz Fathra Daiva[3]
Department of Informatics
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
[2]riyanarto@if.its.ac.id,
[3]fathra.aldhiaz13@mhs.if.its.ac.id

***Abstract*— Meat is one of the mainly consumed foods s by human. Hence, a certain degree of standards is required for it to be safely consumed. One of those standards includes the purity of the meat. There have been some cases of adulteration of pork in beef, possible to cause harm for the consumers. Therefore, in this research, we propose an easy to use and low-cost electronic nose system that is capable to determine whether the meat is a beef or pork. The electronic system was made using Arduino microcontroller and sensor array that consisted of eight Metal-Oxide Semiconductor gas sensors. For pattern classification, Naïve Bayes classifier preceded by min-max magnitude scaling was used to classify fresh beef and pork. The experimental result showed that the proposed system could distinguish beef and pork with 75% of classification accuracy based on k-fold cross validation.**

Keywords—Arduino, Electronic Eose, Machine Learning, Meat Classification, Naïve Bayes, Signal Processing

I. INTRODUCTION

Nowadays, meat is one of popular foodstuff in the world. It contains a good amount of important nutrients as it contains animal-based protein (ABP) which is digestible and more likely contains all the essential amino acids [1]. Furthermore, its consumption trend is growing, raising from 61 g per person per day to 80 g per person per day in 50 years' interval (1961-2011) [2]. Thus ensuring the quality and purity before consuming it is particularly important. For followers of some certain religious groups, they are obliged to know the source of meat they consumed. It is a prohibited for Muslim, Jewish, and Hindu to consume pork. [3]. While this is the case, some cases of adulterating meat scandal have occurred. Therefore, a method to identify whether the meat is adulterated or pure is a necessary. There are several ways to differentiate meat types that are checking physically (softness, odor, taste), visually (texture, color), chemically (compound), or biologically (microorganism). In this research, electronic nose (e-nose) is used to retrieve data regarding odor. E-nose is an instrument comprised of a number of metal oxide semiconductor sensors with each has its selectivity of measuring volatile compounds within the headspace of the sample. An electronic nose has shown to be a powerful tool in food quality assessment such as tea [4][5], odor related with beef spoilage [6], herbal drinks [7], tempeh [8], etc. Furthermore, it has some advantages of being low cost, flexible, reliable [9], and suitable for online monitoring and analysis [10]. It also has an advantage for rapid meat assessment against the sensory panel, total count of bacteria, TVB-N, and gas chromatography [13]. E-nose also has a potential to develop as real time monitoring system like the previous studies about the Electroencephalography (EEG) for fatigue-driver detection [11] and emotion detection system [12]. Thus, a research of developing an instrument of meat differentiation using machine learning utilized electronic nose is relevant. This research attempts to develop e-nose system in order to classify between meat and pork. The prototype of low-cost e-nose system is introduced for rapid halal verification

The remaining of this paper is organized as follows: Section II mentions previous related researches which are relevant to this study. Section III describes materials and methods used in the experiment. Section IV explains the results of the experiment. Finally, Section V is the conclusion.

II. RELATED WORKS

Several studies have shown the capability of e-nose to differentiate between different types of meat. Metal Oxide Semiconductor Sensors have been utilized for retrieving the data of meat odor. Principal component analysis (PCA) has been applied to differentiate between pure lard, pure chicken fat, beef fat, mutton fat, and adulterated samples of lard and chicken fat. Experiments were done at temperatures 50° to 200° C [14]. Another study distinguished minced mutton adulterated by pork with the ratio of pork weight at 0%, 20%, 40%, 60%, 80%, and 100%. Detection was done in the room temperature. Using Back Propagation Neural Network to detect a pork content is better than using Partial least square analysis (PLS), Multiple Linear Regression (MLR) [15]. A study done by Nurjuliana et al. used sheep, cow, chicken, and pork for meat samples and two porks, one chicken, and one beef sausages for sausage samples [16]. In addition, a low-cost e-nose system has been reported to distinguish animal fat (chicken, lamb, and lard) and vegetable oil (grape seed and sunflower) [17]. There are other studies related to machine learning that are also relevant for this research. One of them used Information Quality Ratio (IQR) in analyzing signals from seven gas sensors in order to find the most appropriate mother wavelets for classifying beef quality [18]. Feature selection technique has been used for sensor array optimization. Feature selection was done after denoising signal and avoiding data redundancy using wavelet transform method and Filter based Feature Selection Approach [19]. Another study aimed to classify twitter text based on personality using Naïve Bayes, k-Nearest Neighbor (k-NN) and Support Vector Machine (SVM). The experiment used "MyPersonality" Dataset with the original English version and translated iit into Indonesian version. The classification was done into six classes. Naive Bayes slightly outperformed the other methods [20].

III. Materials and Methods

A. Materials

In this experiment, the e-nose device was developed using an Arduino platform. Arduino Mega 2560 was used as a main board for eight Metal-Oxide Semiconductor (MOS) gas sensors along with temperature-humidity sensor. Several sensors used in this experiment also referred to our previous work about sensor array optimization for beef quality classification [19]. The Table I shows the list of sensors used in this experiment.

TABLE I. Sensors used for E-nose development

Sensor	Alias	Selectivity
MQ2	S1	LPG, i-butane, propane, methane, alcohol, Hydrogen, smoke
MQ4	S2	Methane (CH_4), Natural gas
MQ6	S3	LPG, iso-butane, propane
MQ9	S4	Methane, Propane, and CO
MQ135	S5	NH_3 (Ammonia), NO_x, alcohol, Benzene, smoke, CO_2
MQ136	S6	Hydrogen Sulfide (H_2S)
MQ137	S7	Ammonia (NH_3)
MQ138	S8	Toluene, Acetone, Ethanol, and Formaldehyde
DHT22	S9	Temperature-Humidity

According to the Table I, these components were assembled as shown in the **Error! Reference source not found.**. In this experiment, a one-ounce meat was prepared in a container. The container was inserted into a sample chamber and the data was recorded during 150 seconds in the room temperature to retrieve the ground truth data. Arduino sent the sensor response data to a computer using USB. The responses e-nose data were recorded in the CSV format. The sample chamber was flushed after the sampling procedure about three minutes. Ground truth data was required to obtain training data that also would be used as testing data. The total of collected data was 120 records that were divided into data

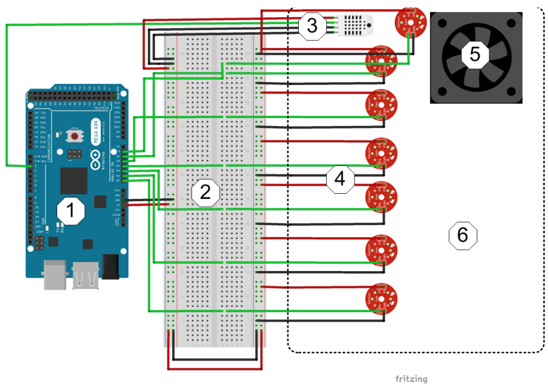


Fig. 1. The scheme of e-nose prototype. (1) Arduino microcontroller. (2) Project board. (3) Temperature-humidity sensor. (4) Gas sensors. (5) Flushing fan. (6) Sample chamber.

training and data testing using k-fold cross validation (k=10).

B. Methods

The MOS gas sensor used was an analog sensor, so the response of the gas sensor was the result of Analog to Digital Conversion (ADC) then the ADC values were averaged for each sampling. **Error! Reference source not found.** demonstrates a systemically process of e nose signal to classify beef and pork. Because the gas sensors were the resistive type, then the response values needed to be converted into sensor resistance values. The sensor resistance value (*Rs*) was computed by the following equation.

$$Rs = \frac{Vc - V_{RL}}{V_{RL}} * RL \tag{1}$$

where,

$$V_{RL} = \frac{ADC * Vc}{1023} \tag{2}$$

ADC, V_{RL}, *Vc*, *RL* were Analog to Digital value, current sensor voltage, standard sensor voltage (5 Volt), sensor load resistance measured by ohm meter, respectively. The each of sensor resistance values had a different magnitude. Hence,

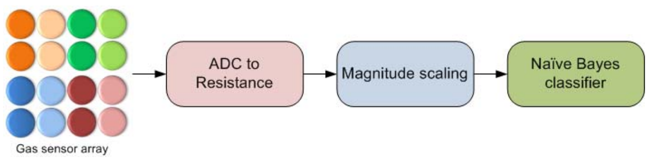


Fig. 2. The method of e-nose signal processing for classifying beef and pork

these values needed to equalize scale. The magnitude scaling helped to speed up the training process and performance improvement [21]. In this experiment, we used min-max normalization for magnitude scaling. Min-max normalization has been reported for better performance than decimal scaling, sigmoid, softmax, statistical column, and z-score [22]. Min-max magnitude scaling could be computed by the following equation.

$$Rs' = \frac{Rs - \min(Rs)}{\max(Rs) - \min(Rs)} \tag{3}$$

where *Rs, Rs', min(Rs), max(Rs)* were original value, scaled value, minimum value, and maximum value of *Rs* vector, respectively. Naïve Bayes classifier technique was used to distinguish between beef and pork based on e-nose signals. Naïve Bayes is the type of probabilistic classifier that based on a theorem of Bayes with naive assumptions between the feature predictors. It assumes that the predictors on the given class are independent of the other predictors (class conditional independence). It is simple and has been exhibited for high classification accuracy and speed for large dataset. It also has a comparable performance against a decision tree and selected neural network classifier [21]. Naïve Bayes can well performed with small number of training data to solve classification problem. we supposed to have the instance that represented by the tuple (*T*) of eight-dimensional attribute from the sensor responses as follows:

$$T = \langle s_1, s_2, \ldots, s_8 \rangle \tag{4}$$

s_1 to s_8 denoted the eight attributes correspond to the sensors. Each of the instances belonged to the beef class (C_{beef}) or pork class (C_{pork}). The Naïve Bayes classifier could predict that an instance (*T*) was a member of beef class, if it had bigger posterior probability than pork class had $(P(C_{beef} \mid T) > P(C_{pork} \mid T))$. The posterior probability could be expressed as follows:

$$P(C \mid T) = \frac{P(T \mid C)P(C)}{P(T)} \tag{5}$$

where $P(T \mid C), P(C)$ were likelihood and prior probability respectively. To construct a classifier from probability model, $P(T \mid C)P(C)$ needed to be maximized because $P(T)$ had a constant value. Thus, the Naïve Bayes classifier could be expressed as the function that set a class label $\hat{y} = C_i$ for *i* number of classes as follows:

$$\hat{y} = \underset{i \in \{1 \ldots I\}}{\arg\max} \left(P(C_i) \prod_{j=1}^{n} P(T_j \mid C_i) \right) \tag{6}$$

where *n* was the number of features/ predictors. In this study, the data analysis was performed using MATLAB 2015a.

C. Performance evaluation

The evaluation method was needed to measure the performance of the classification model built by machine learning methods. In this experiment, several evaluation metrics were used such as accuracy, precision, and recall. According to **Error! Reference source not found.**, they can be calculated by the equation.

TABLE II. CONFUSION MATRIX OF BEEF AND PORK CLASSIFICATION

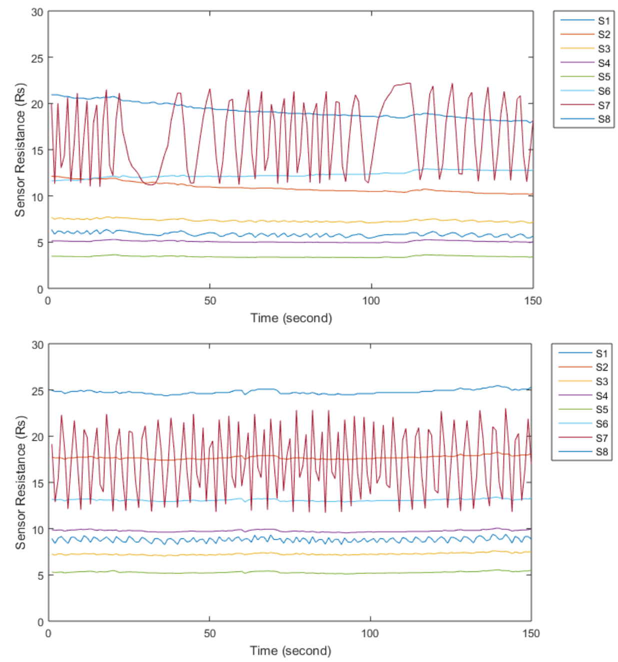
	Predicted: Beef	**Predicted: Pork**
Actual: Beef	TruePositive(TP)	FalseNegative(FN)
Actual: Pork	FalsePoisitve(FP)	TrueNegative(TN)

$$accuracy = \frac{\sum TP + \sum TN}{\sum total\_sample} \tag{7}$$

$$precision = \frac{\sum TP}{\sum predicted\_positive} \tag{8}$$

$$recall = \frac{\sum TP}{\sum label\_positive} \tag{9}$$

where, *TP, TN, total sample, predicted positive, label positive* were true positive, true negative, predicted condition positive, and condition positive based on the class label, respectively.



(a)

(b)

Fig. 3. The signal samples generated by sensor array. (a) beef (b) pork X-axis is time (second) and Y-axis is sensor resistance (*Rs*)

IV. RESULTS AND DISCUSSION

According to explanation above about material and method, we have performed the experimental procedure with the following results. **Error! Reference source not found.** shows the signal samples of beef and pork. Several sensors had different responses for beef and pork odor. For instance, sensor S7 (NH_3) had different responses for beef and pork. It generated different baseline and higher frequency for pork odor. The result also confirms why the pork smells like ammonia. The sensor S8 (acetone) also had a higher frequency for pork odor. Moreover, sensors S1, S2, S4, and S5 had a significant difference in their responses. Meanwhile, sensor S6 (H_2S) only had small difference response for beef and pork. It might be more significant if the meat began to rot. The explanation above means the majority of gas sensors used in this experiment is relevant to classify beef and pork. Furthermore, **Error! Reference source not found.** shows the confusion matrix to describe the performance of this proposed system.

TABLE III. CONFUSION MATRIX RESULT USING NAÏVE BAYES CLASSIFIER

	Predicted: Beef	Predicted: Pork	Class precision
Actual: Beef	44	16	73.33%
Actual: Pork	14	46	76.67%
Class recall	75.86%	74.19%	

The results of the classification present 75% of overall accuracy, precision, and recall based on k-fold cross validation. It means our proposed system can distinguish beef and pork samples with acceptable performance. The results show that application of e-nose technology coupled with proper pattern recognition methods can yield the low-cost and accurate system to distinguish beef and pork. Although this experiment is preliminary study, the results show that the system is interesting for further development the experiment about the various levels of adulteration between beef and meatMore advanced signal processing technique should be used to improve the system performance.

V. CONCLUSION

The e-nose system to classify fresh beef and fresh pork has been developed. Low-cost MOS gas sensors were used to build e-nose prototype. Furthermore, Naïve Bayes classifier that preceded by simple preprocessing successfully classified pure beef and pork with an acceptable performance. According to the experimental result, the proposed e-nose system could distinguish pure beef and pure pork without any additional heaters. This result shows that it is promising for future development to detect beef and pork mixture. The powerful multiclass classifier is needed to model the mixture meat. In addition, a more advanced e-nose signal processing method should be developed in the future. The further system development is useful for ensuring the quality and purity of meat that very important for Moslem, Jewish, and Hinduism to perform the religious rules.

ACKNOWLEDGMENT

We would like to thank Institut Teknologi Sepuluh Nopember and Universitas Telkom for supporting this research.

REFERENCES

[1] G. J. Hughes, K. S. Kress, E. S. Armbrecht, R. Mukherjea, and M. Mattfeldt-Beman, "Initial investigation of dietitian perception of plant-based protein quality," *Food Sci. Nutr.*, vol. 2, no. 4, pp. 371–379, Jul. 2014.

[2] P. Sans and P. Combris, "World meat consumption patterns : An overview of the last fi fty years (1961 – 2011)," vol. 109. pp. 106–111, 2015.

[3] J. R. Eliasi and J. T. Dwyer, "Kosher and Halal: Religious observances affecting dietary intakes," *J. Am. Diet. Assoc.*, vol. 102, no. 7, pp. 911–913, 2002.

[4] K. Triyana, A. Masthori, B. P. Supardi, M. Iqbal, and A. Bharata, "Prototype of Electronic Nose Based on Gas Sensors Array and Back Propagation Neural Network for Tea," *J. Math. Nat. Sci.*, vol. 17, no. 3, pp. 57–62, 2007.

[5] D. Lelono, K. Triyana, S. Hartati, and J. E. Istiyanto, "principal component analysis Classification of Indonesia Black Teas Based on Quality by Using Electronic Nose and Principal Component Analysis," *AIP Conf. Proc.*, vol. 1755, pp. 20003–1, 2016.

[6] D. R. Wijaya, R. Sarno, and E. Zulaika, "Gas Concentration Analysis of Resistive Gas Sensor Array," in *2016 IEEE International Symposium on Electronics and Smart Devices*, 2016, pp. 337–342.

[7] D. K. Agustika and K. Triyana, "Application of Principal Component Analysis and Discrete Wavelet Transform in Electronic Nose for Herbal Drinks Classification," *Adv. Sci. Technol. Soc.*, vol. 1755, pp. 1–7, 2016.

[8] S. N. Hidayat and K. Triyana, "Optimized back-propagation combined with radial basic neural network for improving performance of the electronic nose: Case study on the fermentation process of tempeh," *AIP Conf. Proc.*, vol. 1755, 2016.

[9] H. K. Patel, *The Electronic Nose : Artificial Olfaction Technology*. Ahmedabad: Springer, 2014.

[10] D. R. Wijaya and R. Sarno, "Mobile Electronic Nose Architecture for Beef Quality Detection Based on Internet of Things Technology," 2015, vol. 2, pp. 655–663.

[11] R. Sarno, B. T. Nugraha, and M. N. Munawar, "Real Time Fatigue-Driver Detection from Electroencephalography Using Emotiv EPOC+," *Int. Rev. Comput. Softw.*, vol. 11, no. 3, pp. 214–223, Mar. 2016.

[12] R. Sarno, M. N. Munawar, and B. T. Nugraha, "Real-Time Electroencephalography-Based Emotion Recognition System," *Int. Rev. Comput. Softw.*, vol. 11, no. 5, 2016.

[13] W. Wojnowski, T. Majchrzak, T. Dymerski, J. Gębicki, and J. Namieśnik, "Electronic noses: Powerful tools in meat quality assessment," *Meat Sci.*, vol. 131, no. February, pp. 119–131, 2017.

[14] M. Nurjuliana, Y. B. Che Man, and D. Mat Hashim, "Analysis of lard's aroma by an electronic nose for rapid Halal authentication," *JAOCS, J. Am. Oil Chem. Soc.*, vol. 88, no. 1, pp. 75–82, 2011.

[15] X. Tian, J. Wang, and S. Cui, "Analysis of pork adulteration in minced mutton using electronic nose of metal oxide sensors," *J. Food Eng.*, vol. 119, no. 4, pp. 744–749, 2013.

[16] M. Nurjuliana, Y. B. Che Man, D. Mat Hashim, and A. K. S. Mohamed, "Rapid identification of pork for halal authentication using the electronic nose and gas chromatography mass spectrometer with headspace analyzer," *Meat Sci.*, vol. 88, no. 4, pp. 638–644, 2011.

[17] K. Triyana, M. T. Subekti, P. Aji, S. N. Hidayat, A. Rohman, M. Taukhid Subekti, P. Aji, S. Nur Hidayat, and A. Rohman, "Development of Electronic Nose with Low-Cost Dynamic Headspace for Classifying Vegetable Oils and Animal Fats," *Appl. Mech. Mater.*, vol. 771, pp. 50–54, 2015.

[18] D. R. Wijaya, R. Sarno, and E. Zulaika, "Information Quality Ratio as a novel metric for mother wavelet selection," *Chemom. Intell. Lab. Syst.*, vol. 160, no. November 2016, pp. 59–71, 2016.

[19] D. R. Wijaya, R. Sarno, and E. Zulaika, "Sensor Array Optimization for Mobile Electronic Nose: Wavelet Transform and Filter Based Feature

Selection Approach," *Int. Rev. Comput. Softw.*, vol. 11, no. 8, pp. 659–671, 2016.

[20] B. Y. Pratama and R. Sarno, "Personality classification based on Twitter text using Naive Bayes, KNN and SVM," *Proc. 2015 Int. Conf. Data Softw. Eng. ICODSE 2015*, pp. 170–174, 2016.

[21] J. Han and M. Kamber, *Data Mining: Concepts and Techniques*, Second Edi. San Francisco: Morgan Kaufman Publishers, 2006.

[22] N. Chamidah, Wiharto, and U. Salamah, "Pengaruh Normalisasi Data pada Jaringan Syaraf Tiruan Backpropagasi Gradient Descent Adaptive Gain (BPGDAG) untuk Klasifikasi," *J. ITSMART*, vol. 1, no. 1, pp. 28–33, 2012.