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Classification of Male and Female Sweat Odor in the Morning Using Electronic Nose

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1st Irzal Ahmad Sabilla
Department of Informatics
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
E-mail: irzal.ahmad.s@gmail.com

2nd Rifki Aulia Irawan
Department of Informatics
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
E-mail: rifkiauliairawan@gmail.com

3rd Riyanarto Sarno
Department of Informatics
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
E-mail: riyanarto@if.its.ac.id

4th Asra Al Fauzi
Department of Neurosurgery,
Universitas Airlangga
Surabaya, Indonesia
asra.al@fk.unair.ac.id

5th Dedy Rahman Wijaya
School of Applied Science,
Telkom University
Bandung, Indonesia
dedyrw@tass.telkomuniversity.ac.id

6th Rudy Gunawan
Department of Neurosurgery,
Universitas Airlangga
Surabaya, Indonesia
rudygunawan10@gmail.com

***Abstract*—Biologically, there are two genders that are declared, which is male and female. Both genders have the same hormones but at different levels. The difference in the level of hormones causes both genders can be distinguished from several aspects, and one of them is from their sweat. In this study, we are using Electronic Nose (E-Nose) device for classify the gender between male and female based on their sweat odor and the time that is taken to get the sample is in the morning. E-Nose is a device that can identify various kinds of scents. The results obtained from this tool are signal waves that can be identified, compared, and processed. E-Nose has also been used in various fields. one of them is in the health sector. In this research the E-Nose consists of several sensors TGS, 822, 2612, 2620, 823, 826, 2603, 2600, 813, and SHT-15 connected to an Arduino. The data obtained were sampled and splitting 80% training dan 20% testing. Using regression with various methods, the highest accuracy is 80% using the Support Vector Machine (SVM) method.**

***Keywords*—Classification, Electronic Nose, Machine Learning**

I. Introduction

All normal humans sweat, sweat is produced by the sweat glands located in under the skin layer. The function of sweat is to control body temperature, when sweat is released, the skin will be moistened with sweat, and the temperature on the skin will decrease. Basically, the physical body of male and female has their own characteristics, not only physical, but hormones and characteristics as well. According to the World Health Organization (WHO), the adult age category is over 19 years of age [1]. Starting from this, the differences between the two genders begin to appear, the male tend to have more muscular body, and female's body tends to be more curvy [2].

One of the hormones that affects sweat is estrogen [3]. Estrogen has the role of regulating the human body through the bloodstream. From this body regulation will certainly affect the production of sweat. The estrogen hormone also plays a big role in the female reproductive system, so there are differences in male and female sweat. A study proves that female have a lower Sweat Secretion Rate (SSR) than male [4]. M. Harker et al studied that the difference between male and female based on their sweat with a sample of eccrine sweat [5]. Eccrine is a sweat gland that regulates body temperature as its main function. Though, there is no significant difference between metabolite composition and concentrations between male and female based on eccrine sweat. But, there is another gland that is responsible for body odor, it is the apocrine gland. The apocrine gland doesn't take direct responsibility in producing odors, sweat contains protein content that supports bacterial growth [6]. The bacterial growth is the factor that effects body odor.

Odor is a distinctive smell, especially an unpleasant one. It is identic with the sense of smell. Odor recognition in the human body is carried out using the olfactory system. For example, if a human want to recognize the scent of a cooking ingredient without looking into it, the human will sniff out the ingredients to recognize them based on their scent. As technology develop through many years, recently there is a device that act as an artificial nose, it is called Electronic Nose (E-Nose). It has an array of sensors that acts as a receptor [7]. The sensor array in the E-Nose device is usually built from several gas sensors, which each of the gas sensors have its own sensitivity to certain gases [7], [8]. In this research, we are using the E-Nose device that is using the Taguchi Gas Sensor (TGS), This sensor has demonstrated its ability in a paper studying difference of odor between humans [9]. The study also found that TGS 2602 and TGS 822 shows a high response to human body odor, lelono et al proposed that this sensor is also proven to differentiate the aroma of the Indonesian black tea, which is classified into three quality classes [10]. Based on the studies, we want to classify human gender based on their body odor.

In this study, we proposed to differentiate men's and female's sweat using E-Nose. We use sweat as the object to be compared, and for data collection only taken in the morning. As mentioned above, we are using the E-Nose device that is using TGS sensor 822, 2612, 2620, 832, 826, 2603, 2600, and 813. In this study, the steps taken are first to collect sample data that is needed, the smell of sweat is obtained from the armpit area. The smell of sweat is obtained by using a hose that is placed in the folds of the armpit, then the smell of sweat will be transmitted to the sensors mentioned above and each sensor will detect the scent to which each sensor is sensitive. After the data collected is sufficient, the next is the data processing process, where the data obtained from the E-Nose device will be classified using several machine learning methods and will be evaluated based on their accuracy, in this study using a Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Decision Tree (DT). Chapter 2 will discuss the materials and the method used in this research. Chapter 3 will discuss the results and discussion of data processing in this study. Chapter 4 will discuss the conclusions of this study.

II. MATERIAL AND METHODS

A. Materials

In this research, Experiments were carried out with certain limitations. The environment for the research includes training, testing and classification using machine learning that is carried out by utilizing the Spyder application. The hardware that is used in this research is a computer with the following specifications with CPU AMD Ryzen 5 3500 @ 3.6 GHz and RAM : 16 GB The device that is used to receive the data from the sample is the E-Nose (TGS-type) device. E-Nose is a device that has sensors that are sensitive to certain gases. The output of this device is data in the form of a gas density wave graph obtained from the sensors on this device. The data obtained is stored in a CSV file, which will be carried to the data processing stage. In general the E-Nose consists of several components, namely the headspace system, sample chamber, chamber, array sensor, voltage divider circuit, fan, power supply, control circuit, analog to digital converter (ADC) and output terminals. In this tool, it is using an Arduino as a microcontroller and it contains eight type of sensors, the list of sensors that is used and their specifications are as in Table I.

E-Nose can identify the components in a smell and analyse their compounds for information. E-nose has been used in many industries to differentiate a person with diabetes or not [11], classify between Arabica and Robusta Coffee [12], classifying the sweetness of pineapple aroma [13], detecting pork adulteration in beef for halal authentication [14]. E-nose can also attract considerable interest because it is cheaper, faster, more portable and easier than similar systems such as gas chromatography or mass spectroscopy [15]. The sensors contained in this device are as follows. In retrieving the signal obtained by this device, we use a software that has been made to obtain data from this device, for machine learning purpose, we use a Python program with several imports contained in the program, which is pandas, matplotlib, numpy, and pywt.

B. Data Sampling

The steps taken to retrieve data are as follows:

- Set up laptops and E-Nose devices;
- Connect the USB cable from the E-Nose device to the laptop.
- Turn on the E-Nose device, and run the device for 5 minutes, so that the sensors on the device are ready to use;
- Prepare a thin plasting hose of 2 pieces, and insert both ends of the hose in both holes in the E-Nose device;
- Clamp both ends of the hose that are not inserted on the device, making sure the hole is not covered by any objects such as skin or clothing;
- Wait for the data acquisition process for about 10 minutes and store the data obtained on the laptop;
- When you want to take samples from different people, make sure the hose is replaced so that there is no contamination.

When the hose is placed on the armpit as shown in Fig. 1, The E-Nose device pumps the odor of the armpit to the dissipated in the sensor chamber which contains variable TGS sensors and detects the gas according to each sensor type. After that, the sensor sends the signal data to the microcomputer to convert the signals from analog to digital, after that it will be sent to the computer for classification using machine learning [16]. The data obtained in this research is as many as 26 data, where there are 11 male data, and 15 data of female aged over 19 years. The time that is taken to get the sample is in the morning (05.00 AM – 11.59 AM).

C. Data Retrieval

Fig. 2 shows the methodology flow of this research. It explains that each sensor produces data from the microcontroller and is sent to the computer. The data that is pre-processed is in the form of CSV file, and in the pre-processing stage, some features is reduced to improve the accuracy of the classification. After the pre-processing stage, the data is splitting two parts, which is for the training and testing mechanism then the classification stage that uses machine learning. The result of the classification are evaluated using accuracy values. The data that is loaded contains several samples that is taken from the 60th to 180th-second, because in that period is the sampling phase of the overall record.

TABLE I. SENSORS IN THE E-NOSE DEVICE

Sensor	Cross-Sensitivity
TGS-822	Air, Methane, Carbon-monoxide, Iso-butane, n-Hexane, Benzene, Ethanol, Acetone
TGS-2612	Air, Ethanol, Methane, Iso-butane, Propane
TGS-2620	Air, Methane, CO, Iso-butane, Hydrogen, Ethanol
TGS-832	Air, R-12, R-134a, Ethanol, R-22
TGS-826	Air, Iso-butane, Hydrogen, Ammonia, Ethanol
TGS-2603	Air, H2S, Hydrogen, Trimethyl amine, Methyl mercaptan, Ethanol
TGS-2600	Air, Methane, CO, Iso-butane, Ethanol, Hydrogen
TGS-813	Air, CO, Methane, Ethanol, Propane, Iso-butane, Hydrogen
SHT-15	Air, Temperature, Humidity

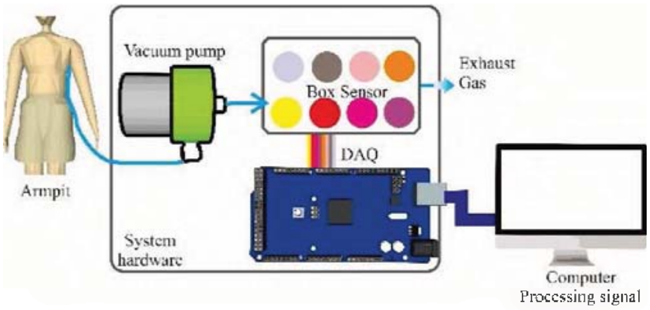

Fig. 1. Data Sampling Illustration

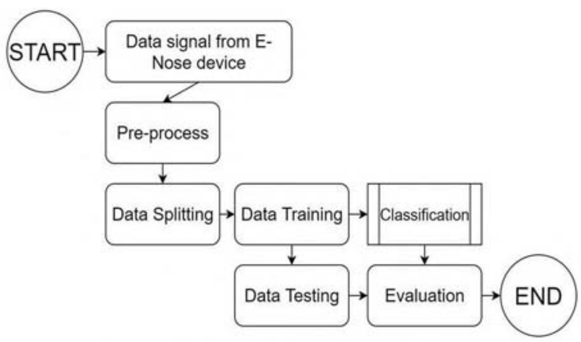

Fig. 2. Flow of Research Methodology

D. Preprocess

After the data retrieval process, the data needs to be normalized, to normalize the data, the values from each sensor are subtracted by its mean, then the data needs to be aggregated to get the mean, maximum, and minimum values of each sensor based on its file name. After the aggregation process, to determine the features that were influential and would be used based on the null hypothesis (H0), feature selection was carried out based on the Analysis of Variance (ANOVA). The null hypothesis states that the mean of the dependent variable is the same for all groups. To divide the aggregated data into two clusters, clustering model training uses them. The results that are generated are displayed on a scatter plot. It is necessary to perform oversampling on the data to adjust the number of the two classes, since the collected data has more data on the female class.

E. Classification

After the data goes through the pre-processing process, the data is ready to be used as a training data. Several models are used and it will be evaluated based on their accuracy in conducting the training. The model is also compared based on each algorithm's hyperparameter tuning. The search for the optimal parameter of each algorithm is carried out using the grid search method, it takes a set of values for each hyperparameter of the model that we want to tune, then it iterates over each possible parameter combination and fetches the best one based on the specified metrics. In this training stage, the data will go through the Principal Component Analysis (PCA) before entering the training stage. Below are the classification algorithms used in this research.

1) Support Vector Machine (SVM): Support Vector Machine (SVM) is a popular classification method because have a good accuracy. The SVM have two typical, linear and non-linear for classification [17]. SVM will find hyperplane by maximizing margin or distance between classes. This method is formally stated as in Definition 2.1 [18].

Definition 2.1. For example there is a training set k where k = $\{(\tau i\ ,\ vi)|i = 1, 2, \ldots , N\} \subset$ RM $X\ \{-1, +1\}$, where τi = (τi1, τi2, τi3, … , τim)T $\in$ RM.

Let w = (w1, w2, w3, … , wm)T $\in$ RM. The training sample set k is linearly separable if there exists hyperplane ϕ : wT$\tau + b = 0$ ($\tau \in R$M), $for\ \forall(\tau i\ ,\ vi) \in$k.

k is linearly separable when there are many hyperplanes satisfied to (1).

$$vi\ (w\mathrm{T}\tau + b) \geqslant 1\ where\ i = (1, 2, 3, \ldots N) \quad (1)$$

when separating hyperplane wT$\tau + b = 0$ do exist, then the hyperplane is The Optimal Separating Hyperplane. The margin is denoted as 2/$\|w\|$. The Optimal Separating Hyperplane is to minimize the value of $\|w\|$2/2 of the following constraint condition as shown in (2).

$$\begin{cases} \min s \frac{1}{2}\left||w|\right|^2 = \min s \frac{1}{2} w^T w \\ s.t.\ v_i(w^T \tau + b) \geq 1 \text{ where } i = (1, 2, 3, \ldots N) \end{cases} \quad (2)$$

It is used to solve the optimal of convex quadratic programming.

$$\begin{cases} \max \delta(\lambda) = \sum_{i,j=1}^{N} \lambda_i, \lambda_j\, v_i v_j (\tau_j{}^T\, \tau_i) \\ s.t.\ \sum_{i=1}^{N} v_i \lambda_i \geq 0, \lambda_i \text{ where } i = (1, 2, 3, \ldots N) \end{cases} \quad (3)$$

The optimal separating function obtained is described as

$$f(x) = sgn(w^{*T} \tau + \mathrm{b}^*) \quad (4)$$

Where $w^* = \sum_{i=1}^{N} v_i \lambda_i\, \tau_i$ and $b^* = v_j - w^{*T} \tau_j$ are the supporting vectors.

2) k- Nearest Neighbor (k-NN): k- Nearest Neighbor (k-NN) is a non-parametric method classification [19] it classifies data testing based on the distance function between data training to the nearest testing data which has the highest number [18]. In classification, the output of k- NN is a class membership where the objects are being assigned to the class based on its neighbors, it is shown in Definition 2.2. In Definition 2.3, it defines that the classification is based on distance every value, measure of k using distance metrics (Euclidean Distance) where k is a user-defined constant. To get better prediction, it is reccommended to set the value of k as an odd value [20]. Definition 2.2. Let x will be the class label of y, where y is the training data, and γ is the data test. The probability of data test γ belongs to the class x is the maximum as defined in k- NN(γ) $\overset{max}{\Longrightarrow}$P($x$, γ). β

Definition 2.3. The a and b is the two value and $(\overline{ab})$ is the length between the both value. The Euclidean distance d(a,b) is $\sqrt{\sum_{y=1}^{x} \left(a_y - b_y\right)^2}$, where a = (a1, a2, a3, ..., ax) and b = (b1, b2, b3, ..., bx).

3) Decision Tree (DT): Decision Tree (DT) is another machine learning technique that works with recursive partitioning of datasets to achieve a homogeneous classification of the target variables. To reduce the entropy of the target variable in the dataset, Decision Tree works at the moment of each separation [21]. In this research we used regression tree with Gini Index Classification for matric. Step to calculate Gini index for splitting tree. Calculate Gini for sub-node, using the above formula for success (p) and failure.

$$(\mathrm{q}) = (\ p^2 + q^2) \quad (5)$$

Calculate the Gini index for split using the weighted Gini score of each node of that split.

$$\text{Gini index} = 1 - \textstyle\sum_{i=1}^{c} (p_i)^2 \quad (6)$$

4) Evaluation

a) Accuracy: Based on Equation 1, the Accuracy (ACC) is calculated as the value of all correct predictions divided by the total value of the dataset. 1.0 is the best value of accuracy, whereas 0.0 is the worst value of accuracy. It can also be calculated by 1-ERR.

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} = \frac{TP+TN}{P+N} \quad (7)$$

ACC = Accuracy
TP = True Positive
TN = True Negative
FP = False Positive

FN = False Negative
P = Total Numbers of Positives
N = Total Numbers of Negatives

5) Specificity: Based on Equation 2, the Specificity (SP) is calculated as the value of True Negative (TN) predictions divided by the total value of negatives (N). Specificity is also called True Negative Rate (TNR). The best specifity is 1.0, whereas the worst is 0.0.

$$SP = \frac{TN}{TN+FP} = \frac{TN}{N} \quad (8)$$

SP = Specificity
TN = True Negative
FP = False Positive
N = Total Numbers of Negatives

a) Sensitivity: Based on Equation 3, the Sensitivity (SN) is calculated as the number of True Positive (TP) predictions divided by the total number of positives (P). Sensitivity is also called True Positive Rate (TPR). The best value of sensitivity is 1.0, whereas the worst is 0.0.

$$SN = \frac{TP}{TP+FN} = \frac{TP}{P} \quad (9)$$

SN = Sensitivity
TP = True Positive
FN = False Negative
P = Total Numbers of Positives

III. Result and Discussion

In this experiment, several methods were used, namely SVM, KNN, and decision tree. Table II contains the results and also its best value for each hyperparameters that we tuned in order to get maximum. Table III contains the results of the accuracy of each method used in this study, the highest accuracy value is obtained by using the SVM method, which is 80.08%. And the confusion matrix is shown in Fig. 2. The visualization of predictions in classification often uses a confusion matrix. This matrix stores true positive, true negative, false positive, and false negative information from a model's predictions. This matrix can help calculate the accuracy and analyse the result of a model. In Fig. 3, it shows the SVM Confusion matrix of the best parameters we have got, it can be seen that the LK row is written 6 and 5, 6 shows the number of data that was successfully predicted correctly, and 5 shows the number of data that failed to predict correctly.

TABLE II. Hyperparameter Tuning Value Of Svm,Knn,And Decision Tree

Model	Hyperparameter	Parameter	Best Parameter
SVM	C	100, 10, 1, 0.1	100
	Gamma	0.1, 1, 0.01, 0.5	0.5
KNN	N_Neighbors	2, 3, 4, 5, 6, 7, 8, 9, 10	2
	N_Jobs	1	1
	Weight	uniform, distance	Distance
Decision Tree	Criterion	Gini, Entropy	Entropy
	Max_depth	3, 5, 7	3

TABLE III. Obtained Accuracy From Each Model With Best Hyperparameters

Model	Accuracy
SVM	80.08%
KNN	76.92%
Decision Tree	69.23%

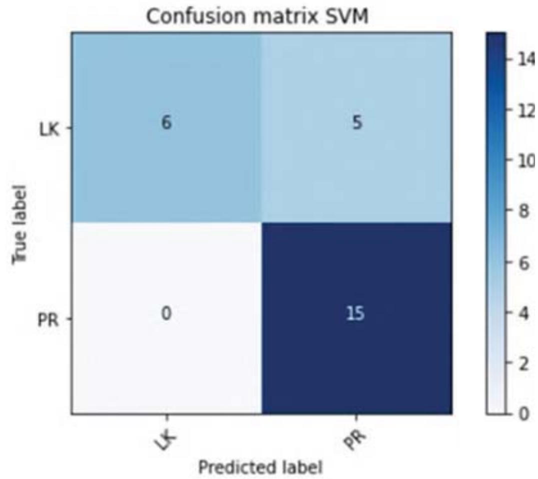

Fig. 3. Confusion Matrix of SVM

Whereas on row PR it is written 0 and 15, which shows that all test data have been classified correctly.

Conclusion

In this study, the E-Nose device succeeded in obtaining the highest accuracy in classifying the sweat odor of male and female using the data that is obtained only in the morning of 80.08%, where the method used was Support Vector Machine (SVM). Meanwhile, the accuracy from the other method that is used in this study such as KNN is 76.92% and the lowest accuracy being the Decision Tree is 69.23%. The confusion matrix shown in Fig. 2 shows that the two class (LK and PR) overlap in the second dimension. From that result, it can be hypothesized that the SVM result will be better than KNN. The hypothesis is based on how each model works. SVM transforms the dimension to separate the two class adequately. The confusion matrix above also shows that the SVM model has a slight bias towards the female (PR) class. It is because the model incorrectly predicts the male (LK) class as a female class. From the conclusion above, it is proved that this study can predict a human's gender using the odor of armpit sweat. The E-Nose device can be used to classify the sweat of male and female using the data that is obtained only in the morning with the accuracy of 80.08% with the combination of PCA and SVM, where PCA is used as pre-processing for dimensionality reduction and SVM as the machine learning method. For future research, the use of deep learning can be applied to potentially improve accuracy of this research.

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