

# Detecting aroma changes of local flavored green tea (*Camellia sinensis*) using electronic nose

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**Abstract.** Indonesia is currently the sixth largest tea producer in the world. However, consumption of the product in the country was considered low. Besides tea, the country also has various local flavor ingredients that are potential to be developed. The addition of local flavored ingredients such as ginger, lemon grass, and lime leaves on green tea products is gaining acceptance from consumers and producers. The aroma of local flavored green tea was suspected to changes during storage, while its sensory testing has some limitations. Therefore, the study aimed to detect aroma changes of local flavors added in green tea using electronic nose (e-nose), an instrument developed to mimic the function of the human nose. The test was performed on a four-gram sample. The data was collected with 120 seconds of sensing time and 60 seconds of blowing time. Principal Component Analysis (PCA) was used to find out the aroma changes of local flavored green tea during storage. We observed that electronic nose could detect aroma changes of ginger flavored green tea from day 0 to day 6 with variance percentage 99.6%. Variance proportion of aroma changes of lemon grass flavored green tea from day 0 to day 6 was 99.3%. Variance proportion of aroma changes of lime leaves flavored green tea from day 0 to day 6 was 99.4%.

## 1. Introduction

Tea has an important role in Indonesia's economic activity. The country is currently the sixth largest tea producer in the world [1]. However, despite having relatively high production level, local consumption of tea drinks is considered relatively low, only 0.2 kg/capita/year, compared to some countries, such as Ireland, UK, Pakistan, and India, respectively with a consumption rate of 3.5 kg/capita/year, 2.5 kg/capita/year, 1 kg/capita/year, 0.6 kg/capita/year [2]. Both condition, high in production level and low in local consumption, indicates the enormous economic potential that can be developed from the product.

Although Indonesia has a variety of local flavor sources, the potential has not been optimally utilized yet, including as local flavor that can be added to tea products. The addition of local flavor, besides increasing the consumption of tea, can also improve the utilization of local Indonesian flavor, so that more familiar not only to people in this country but also people around the world. Flavors that can be added to tea drinks can be sourced from various parts of the plant, i.e., leaves, fruit, seeds, stems or skin, or roots. Based on the criteria of consumer acceptance, availability, and processing yield, eight local flavors meet the criteria [3]. Three of these flavors, namely ginger, lemongrass and



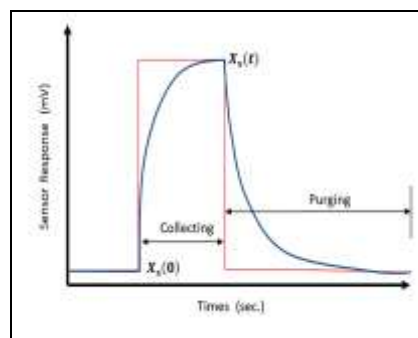
lime leaves were then used in this study. Green tea was used in this study because it contains more polyphenols than black tea or oolong tea due to differences in the processing of tea leaves [4].

The addition of local flavors to green tea products has highly accepted by tea consumers as well as sensory experts of tea producers. From several assessed aspects, the aroma of tea that has been added with local flavors, such as ginger, lemongrass, jasmine and lime leaves, becomes the most important aspect of consumer acceptance [5]. The flavor of tea can be divided into two categories: taste (non-volatile compounds) and aroma (volatile compounds) [6]. Aroma was an important indicator in determining the quality of a product [7]. The local aroma that added in green tea was suspected to change during storage. Meanwhile, according to [8], the sensory test has limitations because it is influenced by subjective factors that can cause errors. Therefore, this study was conducted to detect aroma changes of local flavors that added to tea products using electronic nose (e-nose).

## 2. Materials and Methods

A dry green Peko tea obtained from PT Pagilaran was used as green tea sample, while ginger, lemongrass and lime leaves were used as local flavor. The extraction was done using steam distillation method. About 1 kg of local flavor sample was extracted for 6 hours to obtain essential oil to be applied on dried tea leaf samples. The essential oil obtained was then sprayed on a dried tea leaves sample using a nebulizer (NE-C28 Omron, China). Nebulizer is a breathing apparatus with the working principle of breaking the liquid particles into smaller particles making it easier to evaporate. The tea and oil composition used was 0.5 ml of essential oil for 25 g of dried tea. Tea that has been added with local flavor was stored in room temperature inside an aluminum foil with the weight of each packing material 4 g.

The testing process was done by electronic nose which was developed by Laboratory of Material Physics and Instrumentation Universitas Gadjah Mada. This series of electronic nose was connected to a computer that already installed with Electronic nose G2 Delphi software. The result of the sensor output then transmitted serially to the data recording system on the computer. The analog data from the sensor will be converted into digital data by Analog to Digital Converter (ADC) to be saved to the computer and analyzed further.



**Figure 1.** Sensor response with maximum ( $X_s(t)$ ) and minimum response ( $X_s(0)$ ).

As shown in Figure 1, the typical of sensor response consists of baseline, collecting (sensing), and purging samples aroma. The type of signal manipulation is based on a fractional method. It means that the dimensionless sensor response ( $y_s(t)$ ) can be formulated as Eq. 1 [9]

$$Y_s(t) = (x_s(t) - x_s(0)) / x_s(0) \quad (1)$$

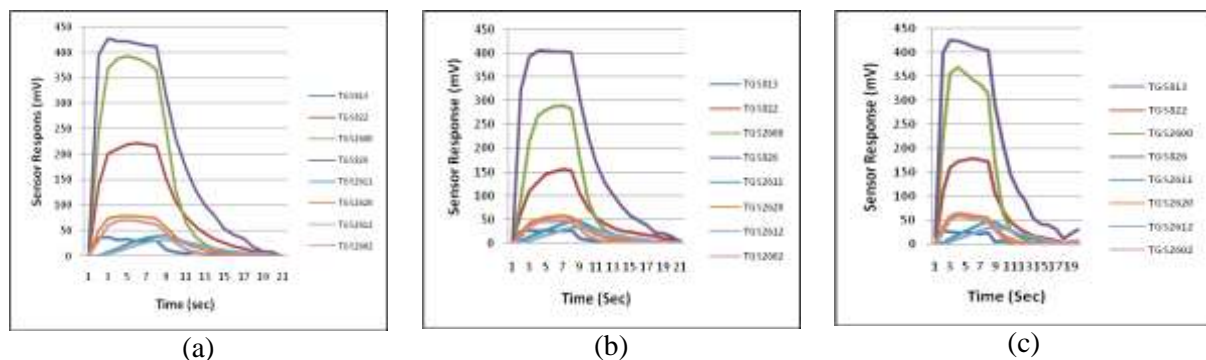
where ( $x_s(t)$ ) is the maximum of sensor response, while ( $x_s(0)$ ) is the baseline of sensor response.

The sensor response data then performed by signal preprocessing and feature extraction. Feature extraction aims to extract or retrieve the important values of a digital tracker signal. Taking the feature of a data was necessary to obtain main information from the data to be analyzed for the next process [10]. In this research, we used eight variables that represent the number of sensors in electronic nose, namely TGS813, TGS822, TGS2600, TGS826, TGS2611, TGS2620, TGS2612, and TGS2602. These eight variables will be reduced into two dimensions that consist the first principle component or  $PC_1$  and the second principle component or  $PC_2$ . These components can represent a significant percentage

the variance value of the total data variance and was used two dimensional data visualization graph for qualitative analysis and information interpretation [11]. To perform PCA analysis, in this research we used MINITAB 17.

### 3. Results and Discussion

Based on the observation of electronic nose sensor response, it can be seen that electronic nose produced different response signal characteristics in each type of tea sample with flavor of ginger, lemongrass and lime leaves.



**Figure 2.** Typical response of sensor array to flavored tea samples (a) ginger, (b) lemongrass, (c) lime leaves

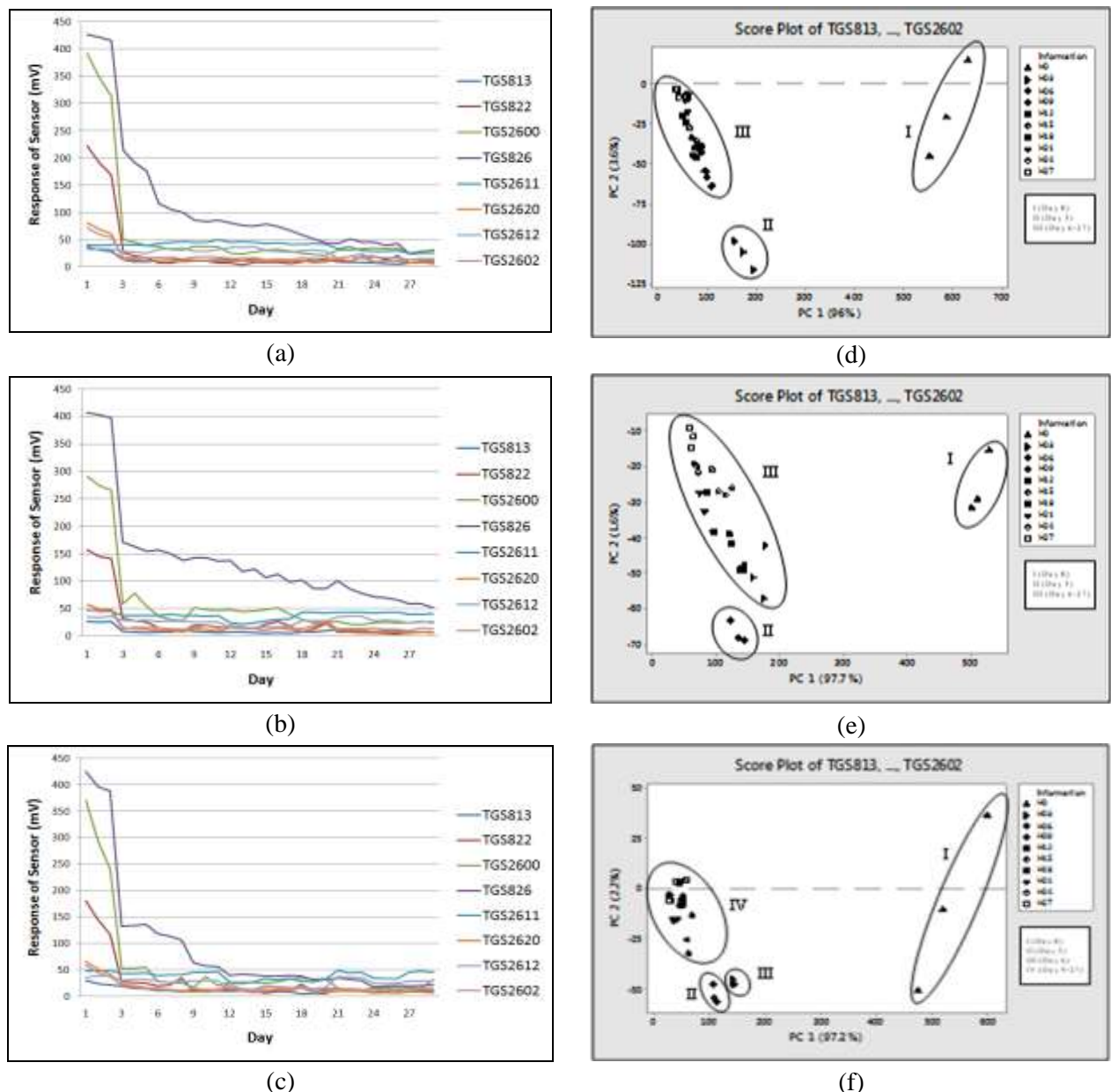
The aroma of the samples was converted into electrical signals (voltage) by the gas sensors. The electrical signals represent gas sensor response. The sensor response was a description of each of the gas sensor which response to the aroma samples with its characteristics [12]. This gas concentration from electrical signal was not for one type of gas, but for a group of gases. That was because the TGS gas sensor was non-selective gas sensor. The sensors in electronic nose are only capable of responding to classify different samples, not to test the content in the sample under test [13].

In general, the sensor response (Figure 2) for the three samples of flavored green tea (ginger, lemongrass, and lime leaves) have similarities, both speed, and amplitude response. But if we further analyze, TGS 826, TGS 2600 and TGS 822 sensors have large or strong amplitude compared to TGS 813, TGS 2611, TGS 2620, TGS 2612, and TGS 2602 sensors. Both TGS 826 and TGS 2600 sensors have the amplitude signal over 350 mV on ginger and lime leaves flavor, and then the signal amplitude beneath them are owned by TGS 822 sensors. The difference between the three samples of flavored green tea lies in TGS 826, TGS 2600, and TGS 822. While TGS 826 and TGS 2600 sensor gives strong respond in ginger (427 mV; 392 mV) and lime leaves (426 mV; 357 mV), but it gives a weak response in lemongrass (405 mV; 289 mV). Furthermore, TGS 822 sensors give strong respond in ginger (222 mV), but give a weak response in lemongrass (157 mV) and lime leaves (180 mV).

To make it easier to see the pattern of data generated from feature extraction, the data can be displayed in graphical form as shown in Figure 3 (a-c).

The pattern from the three graphs was almost the same that was a very drastic decline in the third day test on certain sensors. On average, there was three sensors that show a very high response on day 0 test. The decline data after third day was more invisible. In some sensors also seen flat pattern, did not show a significant decrease in response.

In the test of ginger flavored tea has a greater response value compared with the sensor response value for lemongrass and lime leaves flavored tea. This suggests that ginger flavored tea samples have a stronger aroma than the tea samples of lemongrass and lime leaves.



**Figure 3.** Feature extraction result of sensor response (a-c) and PCA score plot (d-f) of flavored tea samples, respectively from top to bottom, for ginger; lemongrass; and lime leaves. In score plot (d-e), the data were grouped into three, ie I (day 0); II (day 3); and III (day 6-27), whereas score plot (f), the data were grouped into four, ie I (day 0); II (day 3); III (day 6); and IV (day 9-27).

Figure 3 (a-c) displays the data in the form of graphic patterns from each sensor so that it can be compared the response of each sensor. However, the graph has not been able to analyze the aroma changes by combining the entire sensor response as input. Therefore, further data processing was done by Principal Component Analysis (PCA) that used eight electronic nose sensors as variables. PCA was an unsupervised pattern recognition methods used for multivariate analysis [14].

The analysis using PCA aims to reduce the dimensions of mutually correlated variables into linearly uncorrelated variables called the principle components to explain the maximum possible variance with the minimum number of major components [15].

To obtain PCA, in this research using software MINITAB 17. The number of dimensions in PCA processing can be determined by creating a score plot. Based on the score plot, only one dominant

factor and on the second factor and so on has a low eigenvalue or it can be said to be zero. Based on these results, the eight variables will be reduced to two dimensions consisting of the first principle component or  $PC_1$  and the second principle component or  $PC_2$ .

In general, the number of PCs that should be used as much as two or three PCs. Then the selected PC has a percentage of variance that indicates the PC's ability to describe the entire information of all previous initial variables [16].

The result of two-dimensional graphical visualization of PCA processor can be seen in Figure 3 (d-f). In the PCA processing of tea samples of ginger and lemongrass flavor, it can be seen that the collection of data points on days zero (group I) and third day (group II) can be completely separated from other points. As for testing day 6 to 27 cannot be separated perfectly and still overlap in one area (group III). It shows that electronic nose was able to distinguish the aroma of ginger tea and lemongrass tea sample on the day zero and the third day but not yet able to group the test results on day 6 to day 27 (group III). This was because on the day zero to the third day and on the third day until the sixth day clearly shows the decline in the aroma of the sample while on day 6 to day 27 (group III) there was a very small decline so it cannot be read clearly. The small response of sensors to fragrance on days 6 to day 27 was due to the volatile oil so it is likely that the test most of the added essential oil has released [17].

In the PCA processing results of lime leaves flavored tea samples can be seen that the collection of data points on days zero, third day, and sixth day (group I, II, and III) can be completely separated. As for the test day to 9 to 27 cannot be separated perfectly and still collected in one place (group IV). It shows that the electronic nose was able to distinguish lime leaves flavored tea samples on day zero, third day, and sixth day but not yet able to classify the test result on the 9<sup>th</sup> day until the 27<sup>th</sup> day (group IV). The result of the score plot for lime leaves flavored tea sample was different to the score plot of ginger flavored tea samples and lemongrass because in this score plot can already classify the test until the sixth day. It may because citrus essential oil has high rendement so it has a strong aroma on the sample [18].

PCA was employed to reduce the dimensionality and visualization of the datasets while retaining as much as possible of the variation present in the original dataset [19]. The eigenvalues are related to the variance (percentage variance) that can be explained by the main components [20]. On ginger flavored tea sample,  $PC_1$  explained 96% variation while  $PC_2$  explain 3.6% of the variation so that the accumulation of two principal components obtained 99.6% of variance data. For lemongrass flavored tea samples, the percentage value of variance for  $PC_1$  was 97.7% and for  $PC_2$  was 1.6% so that the cumulative variance percentage value of the two main components was 99.3% of variance data. The percentage value of lime leaves flavored tea for  $PC_1$  was 97.2% and for  $PC_2$  was 2.2% so that the cumulative variance percentage value of the two main components was 99.4% of variance data.

It means if the eight gas sensors are used as variables to classify three flavored tea samples, then the gas sensors are reduced to two variables. Hence, the two variables are able to explain respectively 99.6%, 97.7%, and 99.4% for ginger, lemongrass, and lime leaves flavored tea of the total variability of the eight variables. Based on [21] that studied about Japanese green tea flavor using electronic nose and used three principal component with the total variance percentage are 95.7%, it can be said that it has a good variance percentage. So, this reasearch has a good percentage of variation that can provide the enough information for the discrimination of the flavored tea samples. It means that electronic nose with eight sensors can only distinguish aroma ginger and lemongrass flavored tea until the sixth day, and for lime leaves flavored tea until the ninth day.

#### 4. Conclusion

Changes in flavored tea aroma, added with ginger and lemongrass flavor, until the sixth day, can be detected by electronic nose using eight sensors with percentage of variation of, respectively, 99.6% and 99.3%. Meanwhile in lime leaves flavor, until ninth day, can be detected with percentage of variation 99.4%.

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