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# Electronic Nose-Based Classification of Breath Odor in Fasting and Non-Fasting Individuals Using Principal Component Analysis

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**Abstract:** Breath odor contains volatile compounds that can reflect the body's metabolic condition, including those associated with fasting. This study aims to classify breath odor patterns in fasting and non-fasting individuals using an electronic nose (e-nose) combined with the Principal Component Analysis (PCA) method. The e-nose system was developed using an array of five MQ gas sensors (MQ-2, MQ-3, MQ-4, MQ-5, and MQ-6) to detect breath samples from 100 respondents, consisting of 50 fasting and 50 non-fasting individuals. The sensor responses were recorded and analyzed using PCA for dimensionality reduction and data pattern visualization. The results show that the first two principal components account for 81.2% of the total data variance, with contributions of 56.1% from PC1 and 25.1% from PC2. The PCA score plot demonstrates a relatively clear separation between the breath odor patterns of the fasting and non-fasting groups. These findings indicate that the developed e-nose system has potential as a rapid and non-invasive method for breath-based classification.

**Keywords:** E-Nose; Gas sensor; Pattern classification; PCA

## Introduction

Fasting is a physiological condition that induces changes in the body's metabolism due to the absence of food intake over a certain period. During this period, the body shifts from glucose utilization to the metabolism of energy reserves such as lipids, which may influence the composition of volatile compounds produced, including those present in exhaled breath (Muhammad, 2020). Volatile compounds in breath are known to be associated with physiological and metabolic conditions; therefore, changes in their composition have the potential to serve as indicators for distinguishing between fasting and non-fasting individuals (Cetó et al., 2013; Santos et al., 2022).

Various methods have been developed to analyze volatile compounds, one of which is the use of an electronic nose (e-nose), a sensory system that mimics the human olfactory mechanism by utilizing an array of gas sensors combined with pattern recognition techniques (Dang et al., 2014; Kim et al., 2022; Oh, 2024; Shingne, 2019). This system operates by capturing responses to volatile compounds, which are then processed into distinctive characteristic patterns (Xu et al., 2016). In practice, sensor response data are analyzed using chemometric methods such as Principal Component Analysis (PCA) for dimensionality reduction and pattern visualization (Chapman et al., 2020; Nurjuliana et al., 2011; Rosyad et al., 2016). The e-nose has been widely applied in various fields, including the food industry, environmental monitoring, and medical diagnostics (Hu et al., 2019; Peng et al., 2014; Qin et al., 2013).

Nevertheless, previous studies have mainly focused on odor classification in the context of diseases or product quality, such as the detection of diabetes mellitus, pulmonary tuberculosis, and food products (Tazi et al., 2019). Moreover, analytical methods such as PCA are typically limited to pattern visualization, with limited investigation of specific and dynamic

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physiological conditions, such as metabolic changes induced by fasting (Balcerczyk et al., 2020; Batushansky et al., 2019; Lépine et al., 2022). Therefore, the application of electronic noses for breath odor analysis in everyday physiological conditions remains limited.

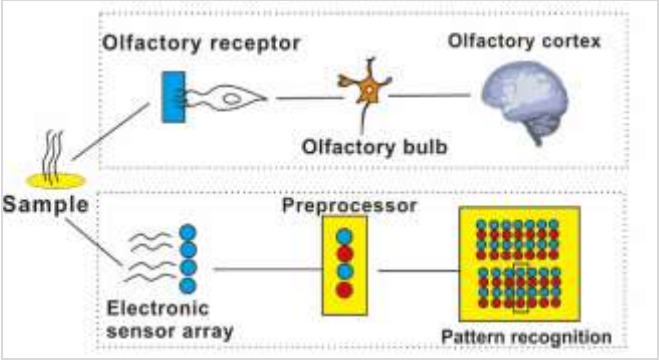



**Figure 1.** E-nose analogy

Based on this, the use of an electronic nose (e-nose) based on a gas sensor array combined with chemometric analysis such as Principal Component Analysis (PCA) represents a promising approach for the rapid and non-invasive identification and classification of breath odor patterns (Freddi et al., 2022; Rabehi et al., 2024). This approach enables the detection of differences in volatile compound patterns arising from variations in metabolic conditions, including those between fasting and non-fasting individuals.

However, studies on the utilization of an electronic nose (e-nose) to distinguish breath odor patterns between fasting and non-fasting conditions remain limited. Therefore, this study aims to classify breath odor patterns in individuals under fasting and non-fasting conditions using a gas sensor–based e-nose system combined with the Principal Component Analysis (PCA) method. This research is expected to contribute to the development of breath odor analysis as a non-invasive indicator of metabolic conditions.

## Method

The electronic nose was constructed using five MQ sensors, namely: MQ-2, MQ-3, MQ-4, MQ-5, and MQ-6, along with an Arduino UNO and a 5-volt power supply.

Breath odor samples were collected using a collection method with a balloon as the sampling medium. The total number of respondents in this study was 100 individuals, consisting of 50 fasting individuals and 50 non-fasting individuals. All respondents underwent a preliminary screening process to ensure their health condition, with the criterion of having no history of digestive disorders.

Prior to the sampling process, all respondents were instructed to brush their teeth using the same brand of toothpaste approximately 15 minutes before the measurement, in order to minimize the influence of external contamination on breath odor. Breath samples were collected by asking the respondents to exhale into a balloon, which served as the sampling container. Each respondent underwent a single sampling procedure. The collected samples were then introduced into the measurement chamber of the electronic nose system.

To maintain stability and avoid sensor memory effects, each measurement was preceded by a 15-minute flushing process using nitrogen gas. The sensor responses obtained from the e-nose system were recorded and stored in a data matrix of size 5 × 100, representing five gas sensors and 100 measurement samples. The first fifty data points correspond to samples from fasting individuals, while the remaining fifty data points were obtained from non-fasting individuals.

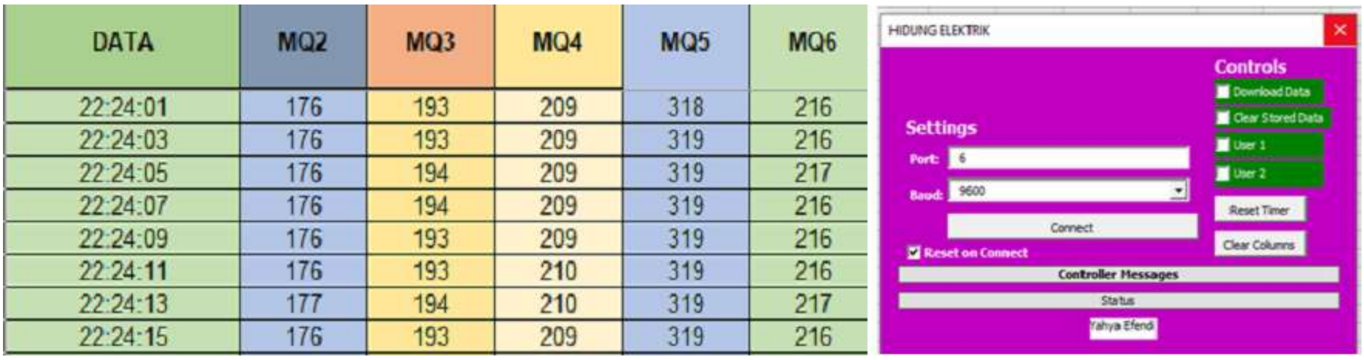
The obtained data were subsequently analyzed using a chemometric method, namely Principal Component Analysis (PCA). This method was employed to reduce the dimensionality of the data and to identify classification patterns based on variations in sensor responses. PCA produces eigenvalues and score plots, in which the first two principal components (PC1 and PC2) are selected based on the largest eigenvalues to represent the majority of the data variance, and are used for visualization and interpretation of classification patterns.


**Figure 2.** Research flowchart

## Result and Discussion

The developed e-nose system was utilized to detect breath odor patterns in fasting and non-fasting individuals. Prior to analysis, the system was evaluated to ensure the sensors' performance in consistently responding to volatile compounds. The data acquisition process consisted of two main stages, namely collection (sample acquisition) and purging (sensor cleaning), which aimed to maintain response stability and minimize sensor memory effects.

The response of each sensor to the breath odor samples is shown in Figure 3. Each MQ sensor exhibits a distinct response characteristic to the same sample, indicating varying sensitivities to volatile compounds. This variation produces complex multidimensional data, thus requiring advanced analytical methods to identify the underlying patterns.



| DATA | MQ2 | MQ3 | MQ4 | MQ5 | MQ6 |
|---|---|---|---|---|---|
| 22:24:01 | 176 | 193 | 209 | 318 | 216 |
| 22:24:03 | 176 | 193 | 209 | 319 | 216 |
| 22:24:05 | 176 | 194 | 209 | 319 | 217 |
| 22:24:07 | 176 | 194 | 209 | 319 | 216 |
| 22:24:09 | 176 | 193 | 209 | 319 | 216 |
| 22:24:11 | 176 | 193 | 210 | 319 | 216 |
| 22:24:13 | 177 | 194 | 210 | 319 | 217 |
| 22:24:15 | 176 | 193 | 209 | 319 | 216 |



**Figure 3.** E-nose response to odor

To address the complexity of multidimensional data, the Principal Component Analysis (PCA) method was employed as a technique for dimensionality reduction and feature extraction. Using five sensors, the original data reside in a five-dimensional space, making direct visualization difficult. PCA reduces this dimensionality into two principal components (PC1 and PC2), which are capable of representing most of the data variance.

The PCA results are presented in Table 1, which summarizes the eigenvalues, proportion of variance, and cumulative variance. The first two principal components have the largest eigenvalues, namely 2.8028 for PC1 and 1.2559 for PC2, contributing 56.1% and 25.1% of the variance, respectively. Cumulatively, these two components account for 81.2% of the total data variance, indicating that they are sufficiently representative for further analysis.

**Table 1.** Eigenvalue, Proportion and Cumulative

| Eigenvalue | Proportion | Cumulative |
|---|---|---|
| 2.8028 | 56.1% | 56.1% |
| 1.2559 | 25.1% | 81.2% |
| 0.4859 | 9.7% | 90.9% |
| 0.3134 | 6.3% | 97.2% |
| 0.1419 | 2.8% | 100.0% |

The scree plot shown in Figure 4 further reinforces these results, as the eigenvalues exhibit a significant decline after PC2. This indicates that components beyond PC1 and PC2 contribute relatively little to the overall data variance and can therefore be neglected in the analysis process.

The loading plot analysis in Figure 5 illustrates the contribution of each sensor to the formation of the principal components. The MQ2 and MQ4 sensors exhibit the most dominant contributions, as indicated by their longer vector lengths compared to the other sensors. This suggests that these two sensors have high sensitivity to the key volatile compounds that differentiate the breath odor of fasting and non-fasting individuals.

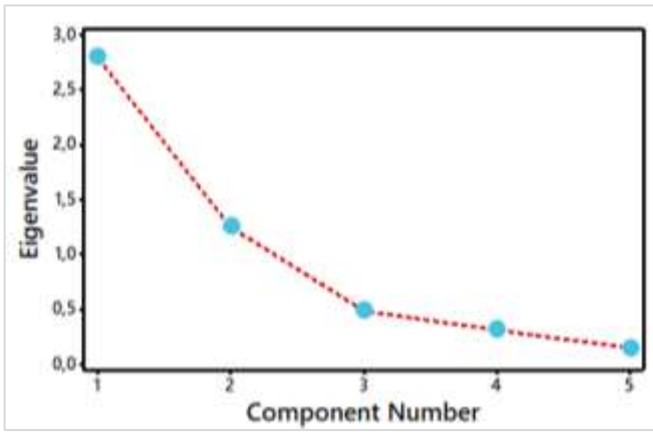




**Figure 4.** Scree plot

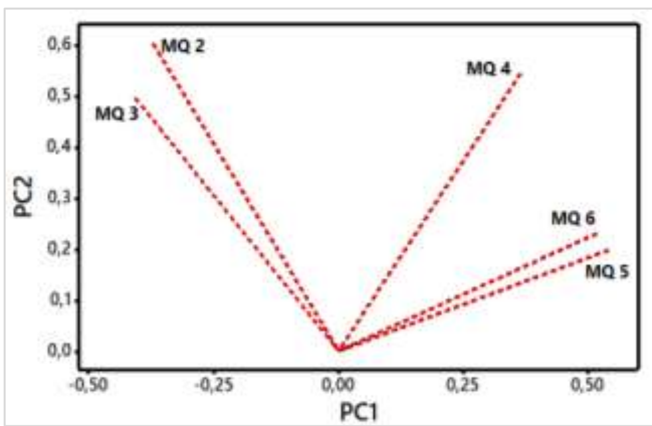




**Figure 5.** Loading plot of breath odor samples

In terms of characteristics, the MQ2 sensor is sensitive to various compounds such as hydrogen ($H_2$), volatile organic compounds (VOCs), alcohol, and other hydrocarbon gases, whereas the MQ4 sensor is more responsive to methane ($CH_4$) and natural gas. The dominance of these two sensors indicates that differences in the composition of volatile compounds associated with body metabolism play a significant role in the classification process.

The classification results using PCA are presented through the score plot in Figure 6. The plot illustrates the separation of two data groups, namely fasting and non-fasting individuals, based on the distribution of PC1 and PC2 values. This separation indicates that the e-nose system is capable of capturing differences in breath odor patterns associated with the body's metabolic condition.

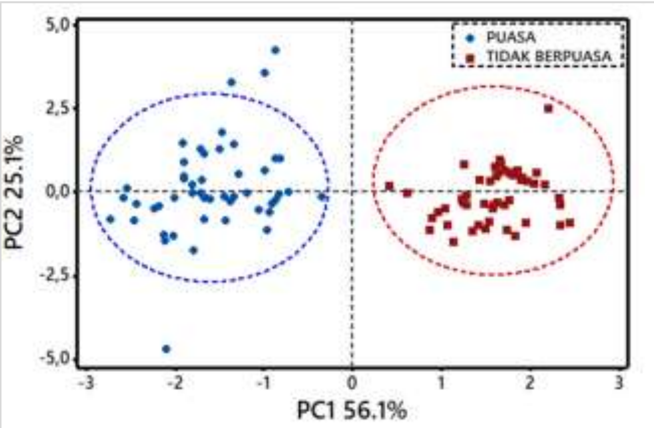



**Figure 6.** Score plot of classification of breath odor data of fasting and non-fasting people

Nevertheless, several data points were found outside their primary cluster (outliers), particularly in the fasting group. This is likely attributable to experimental factors, such as a suboptimal flushing process that may have left residual odors from previous samples. In addition, the use of balloons as the sampling medium may have contributed to aroma contamination, thereby influencing the classification results.

Overall, the results of this study indicate that the electronic nose (e-nose) approach combined with Principal Component Analysis (PCA) is capable of effectively identifying and classifying breath odor patterns. The separation observed in the score plot demonstrates distinct differences in the characteristics of volatile compounds between fasting and non-fasting individuals, which are associated with changes in the body's metabolism.

## Conclusion

This study successfully classified breath odor patterns between fasting and non-fasting individuals using an electronic nose (e-nose) system based on a gas sensor array combined with the Principal Component Analysis (PCA) method. The analysis results indicate that the first two principal components are able to represent most of the data variance, with contributions of 56.1% from PC1 and 25.1% from PC2, resulting in a total explained variance of 81.2%. The PCA score plot visualization demonstrates a clear separation pattern between the fasting and non-fasting groups, indicating that differences in metabolic conditions can be detected through the characteristics of volatile compounds in breath odor. Therefore, the developed e-nose system shows strong potential as a non-invasive and rapid method for classifying physiological conditions based on breath odor analysis. Future research may focus on developing advanced classification methods based on machine learning to further improve the accuracy and overall performance of the system.

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**Conflicts of Interest**
No conflict interest.

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