Portable E-nose For Enhanced Pizza Toppings Recognition Using MQ Gas Sensors

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In this paper, a portable electronic nose system was developed and evaluated for its performance in rating pizza toppings, as compared to subjective evaluation of quality. In this study, four pizza-topping types were prepared: P1: 100% minced beef with Edam cheese, P2: 50% minced beef and 50% minced Kadid (air-dried salted meat) with Edam cheese, P3: 100% minced Kadid with Edam cheese, and P4: 100% minced beef with parmesan cheese. Kadid was similar to plain meat with respect to perception and preference. The experiment was performed on 101 prepared pizza-topping samples. Our study objective was to differentiate between various pizza toppings using the developed portable E-nose. Additionally, we aimed to highlight the impact of lemon smell as an olfactory disturbance in this differentiation. For this purpose, several procedures for feature selection, machine learning techniques were evaluated. Firstly, a Principal Component Analysis (PCA) showed a modest grouping of pizza toppings except for P4 samples (based on parmesan cheese) which were more distinct from others. By applying One-way ANOVA feature selection before performing PCA, Cluster Analysis (CA) and Support Vector Machines (SVMs), a significant improvement was observed in the identification of the four pizza toppings. Finally, the results from CA reveal that the presence of an olfactory disturbance caused by lemon scent significantly alters the order in which toppings are identified by the portable E-nose, particularly affecting cheese recognition.

Keywords: E-nose; Gas sensors; Pizza; Umami; Data analysis; Machine learning; Feature selection; ANOVA; PCA; Cluster analysis; SVMs
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1. Introduction

Pizza is a popular dish enjoyed worldwide, known for its versatility in toppings and flavours. It is considered as a savoury dish consisting of several ingredients which include meats, vegetables and often various other ingredients [1]. Pizza quality inspection typically involves assessing various aspects of a pizza to ensure it meets certain standards [2]. Pizza toppings are a crucial parameter that affects its aroma and flavour; it can vary widely depending on personal preferences and regional traditions [3]. Sensory analysis is a systematic approach to evaluate and assess the sensory attributes of a food product like pizza. So, it could be used to study pizza differences and preferences. Sensory analysis is often conducted by trained panels or focus groups. It is therefore highly sensitive to human error due to its subjective and inconsistent nature [4]. Consequently, it seems preferable to perceive these differences and preferences, to set up and develop smart devices. With a view to assess the pizza quality, we can adopt the procedure followed for the fruit quality, which mainly uses some characteristics such as visual appearance, aroma and flavour in order to make a decision on the acceptance of the fruit [5]. As a traditional method, visual evaluation is generally applied. It is used to examine the pizza's appearance; to look at the colour of the crust, cheese and toppings. And finally to check for even distribution of toppings and whether the pizza has an appealing presentation [6]. For instance, Sun and Brosnan [1] have developed a computer vision device able to classify pizza base using its shape and size as features. The computer vision systems have also been used for the automatic classification [4]. However, the assessment of pizza topping using electronic nose (E-nose) to discriminate and identify topping content percentage is rarely mentioned.

According to J.W. Gardner and P.N. Bartlett definition [7], the electronic nose, often abbreviated as E-nose, could be defined as an instrument consists of an array of chemical sensors with partial specificity and an appropriate pattern recognition system that can detect and recognize odours or volatile compounds. This approach mimics the functioning of the olfactory sense of mammals, where many sensors function as the olfactory epithelium with a large number of different receptors. In this process, the olfactory cortex in the brain provides the learning operation. That is why the system was called "electronic nose". E-noses are well-suited for quick odour profiling and pattern recognition, while classical instruments excel in detailed chemical analysis and quantification of individual compound [8]. In principle, the sensor array used in the E-nose devices gives a fingerprint that characterizes all volatiles in the headspace of each sample [9]. E-nose devices are used in various applications, such as quality control in the food and beverage industry, environmental monitoring, and even for medical diagnoses. In recent years, these devices have been proposed and gradually applied to assess the food quality [10–13]. E-noses find various applications in food safety monitoring due to their ability to quickly and non-invasively assess the quality and safety of food products [14–19]. Some of the most common uses of E-noses in food safety monitoring include spoilage detection in which the E-noses can detect early signs of spoilage by identifying changes in the aroma profile of perishable foods, such as meats [19–21], fish and dairy products [22–24]. Quality control in which E-noses assess the freshness and quality of food items like fruits, vegetables and bakery products [25–28], and alcoholic beverages [29–32]. Shelf-life assessment in which E-noses can estimate the remaining shelf life of food products by monitoring changes in odour over time like cheese and other dairy products [33, 34], edible oils [35, 36] and tea [37, 38]. In the recent past, an electronic nose called Aeonose was used to differentiate between positive and negative people for COVID-19 based on VOCs [39].

The main objective of this study was to develop an efficient E-nose system dedicated to distinguishing between different pizza toppings, and to show how the accuracy of pizza toppings recognition can be improved through features selection, just before performing machine learning techniques. The data produced by the sensor array through the volatiles mixture of volatiles in the headspace of each sample can be interpreted using appropriate machine learning techniques, like Principal Component Analysis (PCA) for dimensionality reduction, Cluster Analysis (CA) for categorical data analysis or Support Vector Machines (SVMs) for classification and regression tasks. Using an E-nose system offers several advantages in various applications: (1) portable and non-destructive device, (2) cost-effective, (3) rapid screening, (4) continuous monitoring of food aroma; (5) minimum requirements for trained persons; (6) non-invasive; (7) safety; (8) early detection. To the best of our knowledge, this study represent the inaugural application of an E-nose with feature selection for a rapid pattern screening, leading to accurate classification of pizza samples based on their various topping.

2. Materials and methods

2.1. Sample preparation

In this work, we prepared four pizza-topping types for analysis:

- *P1*: Consisted of 100% minced beef combined with Edam cheese,
- *P2*: Containing 50% minced beef and 50% minced Kadid (air-dried salted meat), along with Edam cheese,
- *P3*: Consists of 100% minced Kadid in conjunction with Edam cheese,
- *P4*: Comprising 100% minced beef with parmesan cheese.

All Pizzas contain dough, red pepper and spices. Kadid is a sun-dried meat commonly found in Middle East and North Africa especially in Morocco and Tunis. Kadid is prepared from pieces of meat by adding salt, garlic and oil and drying the mixture in the sun for a period of 7 days [40]. Pizza was chosen for its richness in aromas and its diversity of ingredients that affect the taste and odour. The four types of pizza were prepared on the eve of the E-nose measurements. These samples were sliced into portions and cooked, just before the start of the measurements. We have taken great care to ensure maximum uniformity among samples. To study the influence of a disturbing odour, we redid the experiment with a new set, but this time we added the same amount of lemon to each sample.

2.2. E-Nose setup and measurement

After developing our first portable E-nose device in 2009 [41] and successfully using it to improve the classification of Moroccan virgin olive oil profiles [42, 43], and thus improve the recognition of fruit juice samples [44], we aimed in this work to develop a homemade system for Pizza aroma purpose.

As depicted in Fig. 1, the developed system comprises several components: a dynamic headspace sampling unit, a sensor block housing an array of gas sensors for detecting volatile compounds, an electronic control system, and data processing software facilitated by an Arduino Mega 2560. Arduino IDE (Integrated Development Environment) is an open-source software. It serves as a powerful tool for electronic development boards. The Arduino IDE is an essential environment for electronics programming and building interactive prototypes [45]. According to the specific needs of our study, we chose to use a board based on the AT mega 2560. It provides a large number of digital and analogue input/output pins, making it suitable for a wide range of applications. It includes various hardware peripherals such as timers, UART (serial communication), PWM (Pulse-Width Modulation), and more.

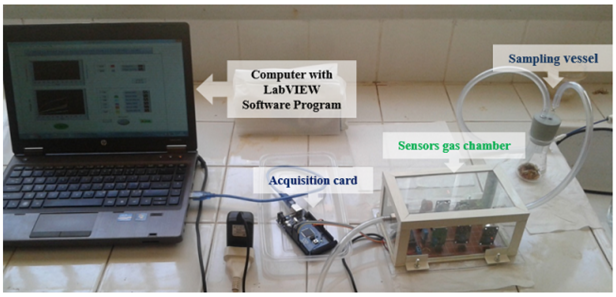


Fig. 1. Photo of the E-Nose system developed for this study.

The sensor block is represented by an array of six MOS (Metal Oxide Semiconductors), specifically MQ sensors from Henan Hanwei Electronics Co., Ltd. (Henan, China). The six sensors employed in our study are MQ-2, MQ-3, MQ-4, MQ-6, MQ-135, and MQ-138 with different sensing species. The MQ sensors principle operate by detecting changes in resistance when exposed to different gases. So the sensor's resistance decreases or increases depending on the concentration of the target gas in the headspace. This change in resistance is then converted into electrical signal, allowing the sensor to indicate the presence and level of specific gases.

To monitor the environmental conditions, we incorporated a digital humidity and temperature sensor (DTH11) into the sensor array. To facilitate the transfer of volatile compounds from the headspace sampling to the chamber housing the sensor array, we employed pure nitrogen as the carrier gas [46]. The sensor voltage variation was acquired then digitized with the help of a card based on the ATmega2560 microcontroller. We ensure communication between the sensors and Arduino Mega via a USB bus. By using a 10-bit high-resolution ADC, all analogue input signals were converted. The software that runs the E-nose system was developed with LabVIEW© (National Instruments Inc., Austin, Texas, USA). To conduct our measurements, we prepared samples from various types of pizza, ensuring that each piece weighed (8.7g ± 1mg). These samples were promptly placed in a refrigerator maintained at a constant temperature of (4 ± 1) °C. For each measurement, we retrieved a pizza sample from the refrigerator, heated it in an oven at (180 ± 2) °C for 5 min, and then transferred it into a 30 ml glass bottle for analysis. To capture the volatile compounds, we allowed the headspace (the space above the pizza sample) to interact with the sensor surfaces for 10 minutes. We achieved this by using nitrogen as the carrier gas, flowing at a rate of 100 mL.min-1. During this period, the sensor signals were meticulously recorded. The glass bottle used for analysis featured two holes in its lids—one for nitrogen inlet and the other for the outlet of volatile compounds from the headspace to the sensor array. To maintain consistency, we used new sealed bottles for each batch of pizza analysed. The output signals from the sensor array were acquired at 2-second intervals over a 10 min duration, allowing most sensors to reach a steady state.

2.3. Feature extraction and pre-processing

Feature extraction and pre-processing play crucial roles in E-nose applications for food classification. E-nose systems generate vast amounts of data from the sensors, which require careful handling to extract meaningful features and reduce noise. As software for pre-processing, features extraction and machine learning techniques, we used MATLAB 8.5.0 (MathWorks Inc., USA) and IBM SPSS Statistics version 20. The following subsections outline the essential steps in feature extraction and pre-processing for E-nose food classification applications.

2.3.1. Data Acquisition and Pre-processing

The first step involves collecting raw sensor data from the E-nose device. Each sensor generates a unique response pattern to different volatile compounds present in the pizza samples. The acquired signals typically represent changes in electrical resistance, conductivity, or other physical properties of the sensing elements. Before feature extraction, raw sensor data undergo pre-processing to enhance the quality of the signals and remove any artefacts or noise. Common pre-processing techniques include:

- Signal Filtering: Application of digital filters to remove high-frequency noise and baseline drift.
- Normalization: Scaling the sensor signals to a common range to eliminate differences in magnitude.
- Smoothing: Applying moving average or median filters to smooth out fluctuations in the signal.

2.3.2. *Feature extraction*

Feature extraction involves transforming the pre-processed sensor signals into a set of informative features that capture the relevant characteristics of the odour profiles. Feature extraction methods may include:

- Statistical Features: Calculating statistical metrics such as mean, standard deviation, skewness, and kurtosis of the sensor signals.
- Frequency Domain Analysis: Utilizing techniques like Fourier transform to extract frequency-domain features from the signals.
- Time-Frequency Analysis: Employing methods like wavelet transform to capture both temporal and frequency information simultaneously.
- Peak Detection: Consist of identifying the maximum amplitude (Peak Height) of sensor responses within specific time windows and/or quantifying the area (Peak Area) under the curve of peaks in sensor responses, providing information about the intensity and duration of odour signals.

2.4. Feature selection based One-way ANOVA

To enhance the accuracy of the classifiers in the defect prediction model, it is crucial to carefully select significant features [47, 48]. When large quantities of multivariate data are treated into a statistical analysis package, some features in the data will be found to be of greater value than others, which contain only noise. In the literature, there are several strategies of feature extraction and selection that have already been reported [49–52]. Essentially, the procedure consists of either a direct selection from the initially available features [53] or by computing new features called factors (e.g., by performing Factory Discriminant Analysis) and then selecting the significant features amongst them [54]. This method was successfully used to discriminate beers in one of our previous works [55].

In our approach, we identify relevant features by assessing one-way ANOVA and then eliminate features that lack significant variation in the raw data set. The F-statistic, calculated by comparing variance among group means to variance within groups, quantifies the ration of explained to unexplained variance. If the p-value (usually set at 0.05) is below a chosen significance level, we reject the null hypothesis, indicating significant differences among some group means. Next, we prioritize features with better discrimination ability, discarding noisy or unnecessary ones. This results in a set of features with a higher figure of merit for further analysis using machine learning methods. It is important to note that ANOVA assumes certain assumptions, such as normality of residuals and homogeneity of variances. If violated, adjustments or alternative methods may be necessary.

2.5. Data analysis

The data generated by the gas sensors will be subject to processing and analysis by different machine learning techniques such as Principle Component Analysis (PCA), Cluster Analysis (CA), and Support Vector Machines (SVMs).

PCA is a dimensionality reduction technique used in statistics and machine learning. Its main goal is to transform high dimensional data into lower dimensional form while retaining as much of the original variability as possible. PCA is frequently used in E-noses applications [56]. This technique consists of defining the subspace that best describes the distribution of data in the initial space [57, 58]. The principal components (PCs) are arranged in such a way that the first component explains the most significant variance, followed by the second component, which accounts for the highest remaining variance, and so forth. Cluster analysis (CA) was chosen to process and organize the data containing different types of pizza into groups. Clustering techniques are widely employed data mining tools that segment data into distinct groups [59, 60]. The final results of CA are presented and visualized as a dendrogram [61–63]. The stopping criteria in cluster analysis refer to the conditions that the clustering algorithm should terminate. The choice of stopping criteria depends on the specific clustering method used. Here are two common stopping criteria: The determination of a criterion of resemblance between individuals and the determination of similarity linkage between groups, a process called the aggregation criterion. In general, the data to be studied guides the user in choosing the distance, which could be of Euclidean type, Mahalanobis, Manhattan, etc. For the similarity linkage, many criteria have been proposed [59, 63], the four best known are:

- Single linkage clustering also known as nearest neighbour clustering, is a method employed in hierarchical clustering. In this approach, the distance between two clusters is determined by the shortest distance between any two points within the different clusters. Essentially, it connects clusters based on the closest pair of elements, gradually building a hierarchical structure.
- Complete linkage clustering also known as farthest neighbour clustering, is another method employed in hierarchical clustering. In this approach, the distance between two clusters is determined by the maximum distance between any two points within the different clusters. Essentially, it connects clusters based on the farthest pair of elements, gradually building a hierarchical structure.
- Ward's method, also known as Ward's minimum variance clustering. Initially, we start with n clusters where n represents the number of samples, so each cluster contains a single individual at the beginning. The process then, iteratively combines clusters to minimize the within-cluster variance. The method continues recursively, merging clusters step by step until we create a single unique cluster containing all individuals.
- Group average linkage (also known as average linkage or UPGMA - Unweighted Pair Group Method with Arithmetic Mean), is a hierarchical clustering method that was first published in 1955 [64]. In this approach, the distance between two clusters is determined by computing the average distance between all pairs of points in the two clusters. The result of group average linkage can be visualized as a dendrogram, it shows the sequence of cluster merges and the distance at which each merge occurs.

  Support Vector Machines (SVMs) are a set of supervised machine learning methods used for classification, regression, and outlier detection. Developed by Vapnik and his colleague [65]. SVMs strive to discover the optimal hyperplane that effectively separates distinct classes within a given feature space. This hyperplane maximizes the margin between data points of different classes, resulting in robust and accurate classification. It works well for both linearly separable and non-linearly separable datasets, by using a technique called the kernel trick, which transforms the input space into a higher-dimensional space [46, 66]. There are quite a few papers that solve the multi-classification problem by generalizing the original bi-class approach across different algorithms, such as One-vs.-one SVMs, One-vs.-rest SVMs or Mc-SVMs [67, 68].

2.6. Leave-one-out cross-validation

Leave-one-out cross-validation (LOOCV) is a technique commonly used in machine learning to evaluate the performance of a model, especially when the dataset is relatively small. In the context of a food classification application using an electronic nose (E-nose), LOOCV would involve the following strategy:

1. Data Preparation: Organize the dataset where each sample corresponds to the readings from the E-nose for a particular pizza type.
2. Leave-One-Out Splitting: For each sample in the dataset, one sample is set aside as the validation data, and the remaining samples are used for training the model.
3. Training Model: Train the classification model using the training samples, such as a machine learning algorithm tailored for the E-nose data.
4. Validation: Test the trained model using the left-out sample and evaluate its performance in predicting the correct pizza type.
5. Performance Aggregation: Once all iterations of LOOCV are completed, the performance metrics such as accuracy, precision, recall, and F1-score obtained from each iteration are aggregated to provide an overall assessment of the model's performance. This aggregated performance can then be used to determine the effectiveness of the E-nose-based classification system for the food classification application.

By utilizing LOOCV, the model's performance is evaluated on a diverse range of validation samples, ensuring robustness and reliability in assessing its ability to classify pizza samples based on their odour profiles captured by the E-nose.

2.7. Addressing Sensor Drift

Sensor drift refers to the gradual change in sensor response over time, leading to a deviation from its initial calibration. In the context of an electronic nose (E-nose), which relies on arrays of sensors to detect and discriminate between different odours, sensor drift can significantly affect its performance by altering the sensitivity or selectivity of individual sensors. This can result in reduced accuracy and reliability in odour detection and discrimination. To mitigate sensor drift and maintain the discrimination ability learned by the E-nose, several strategies can be implemented:

1. Regular Calibration: Periodic recalibration of the E-nose sensors can help correct for any drift that has occurred. By comparing sensor responses to known reference samples, adjustments can be made to ensure accurate odour detection.

2. Data Normalization: Normalizing sensor data by accounting for baseline shifts or variations in sensitivity can help compensate for drift. This involves adjusting sensor readings to a common reference point, improving the reliability of odour discrimination.

3. Sensor Redundancy: Including redundant sensors in the E-nose array can provide built-in backup and redundancy. If one sensor experiences drift, others can compensate, maintaining overall system performance.

4. Advanced Signal Processing Techniques: Utilizing advanced signal processing algorithms can help identify and correct for drift patterns in sensor data. Techniques such as principal component analysis (PCA) or machine learning methods can extract meaningful information from noisy sensor signals and improve discrimination ability.

5. Environmental Monitoring: Monitoring environmental conditions such as temperature, humidity, and air quality can help identify factors contributing to sensor drift. By controlling these variables or implementing corrective measures, drift can be minimized.

6. Sensor Maintenance and Replacement: Regular maintenance, cleaning, and, if necessary, replacement of sensors can help prevent or mitigate drift. Aging or damaged sensors may exhibit increased drift and reduced performance over time. By implementing these strategies, the E-nose can maintain its discrimination ability and continue to provide accurate and reliable odour detection, even in the presence of sensor drift.

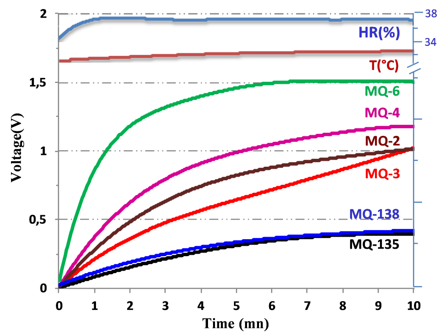
3. Results and discussion

3.1. E-Nose results on pizza aroma profiles

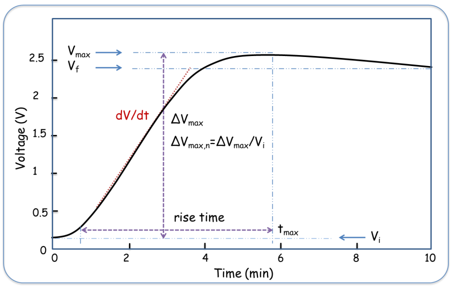
The MQ sensors array was initially exposed to all pizza samples successively, over the exposure time the resistance changes were acquired through voltage response. The voltage response V of an MQ sensor to a pizza sample, is calculated as follows:

$$V(t) = V_p(t) - V_N(t) \tag{1}$$

where V_N is the sensor's voltage in clean air (nitrogen) to establish a baseline and V_p is the sensor's voltage in the presence of the pizza sample.



(a) MQ sensors, temperature, and humidity (DTH11) sensor response to pizza 4(P4)



(b) Typical voltage transient with some features extracted.

Fig. 2. Voltage responses of MQ sensors array.

Fig. 2(a) illustrates the typical voltage signals (V(t)) generated by the sensor array when exposed to a sample of pizza 4 (P4). We note that the sensor signals tend to increase in value with longer exposure time of the pizza samples. Additionally, all curves from the different pizza samples exhibit similar behaviour. Furthermore, the sensors MQ-2, MQ-3, MQ-4 and MQ-6, have a good sensitivity to different types of pizza; however, MQ-135 and MQ-138 have low sensitivities (low values of voltage). On a different note, the relative humidity exhibited slight changes over time, yet it did not significantly impact the results, as demonstrated in prior studies [43, 66, 69].

3.2. Feature extraction

Our primary objective in this section is to extract meaningful information from MQ responses. Fig. 2(b) displays some features extracted from the MQ response curve, which we will utilize for our data analysis. Extract information from the response curve involves 16 features, such as:

- V_i : the initial (or baseline) voltage;
- $V_{0\text{-aver}}$ the average value of voltage response during the first 30 seconds of measurement;

- V_f : the final voltage;
- $V_{\text{s-aver}}$: the steady-state voltage measured as average voltages over the last minute;
- $V_{S-5\text{ min}}$: the voltage value at 5 min of a measurement;
- $V_{\max}$: the maximum value of the voltage;
- $\Delta V_{\max} = V_{\max} - V_i$: the maximum voltage change;
- $\Delta V_{\max,n} = (V_{\max} - V_i)/V_i$: the normalized maximum voltage change;
- A_V : the area under the voltage curve measured between the second and eighth minutes of a measurement. This area was estimated by the trapeze method;
- V_{d2-7} : the average rate of voltage change over the interval [2 min 7 min];
- V_{d2-8} : the average rate of voltage change over the interval [2 min 8 min];
- dV/dt : the dynamic slope of the maximum voltage change;
- $t_{\text{risel10-90}}$: the rise time of the voltage response, measured between 10 and 90% of the maximum voltage change;
- $t_{\text{rise20-80}}$: the rise time of the voltage response, measured between 20 and 80% of the maximum voltage change;
- $t_{\text{rises10-70:}}$ the rise time of the voltage response, measured between 30 and 70% of the maximum voltage change;
- $t_{\text{rise40-60:}}$ the rise time of the voltage response, measured between 40 and 60% of the maximum voltage change.

As the E-nose array includes six gas sensors, each measurement will be represented by: $6 \times 16 = 96$ features

3.3. PCA discrimination of pizza odours

Before applying PCA using the E-nose data elaborated without disturbing odours, an auto scale pre-processing approach was performed to the initial data. Fig. 3 shows the PCA plot performed on four pizza types gathered using entire database without disturbing odours. In this graph, we see that the variance explained by the first, the second and the third principal components reached 39.05%, 19.71% and 7.56% respectively. Based on this three-dimensional plot, we also note that the separation between all types of pizza was not easy to determine. In Fig. 3, PCA can differentiate perfectly pizza 4 (P_4) from pizzas 1 (P_1), 2 (P_2), and 3 (P_3) .P_4 and P_1 differ only by the type of cheese used. Parmesan used in P_4, was considered as a positive control contains umami flavour [70–72]. This differentiation between P_4 and P_1 is essentially based on the type of cheese: Parmesan representing umami [73] vs. Edam, that umami is a flavour is not an odour. These results show that the interplay of taste and aroma likely contributes to the overall perception of umami. This concept was proposed by Rolls [74] stating that umami can be considered as a rich flavour resulting from a combination of the taste of glutamate and a consonant savoury odour. In addition, this differentiation may also find its origin in the fact that the umami substances in P_4, enhances the intensity of aromas of its ingredients [73]. This reinforcement enhances the headspace (volatile compounds emitted by the pizza) and causes a net discrimination between P_4 and the other pizza types. In Fig. 3, we observed an overlapping region where clear differentiation between P_1, P_2, and P_3 was not evident. Therefore, we suggest a feature selection method aimed at removing any sensors or features that are redundant, and which may be causing this overlapping between pizza types. Several works followed this procedure to remove the non-informative features, and seems to produce good results [75, 76].

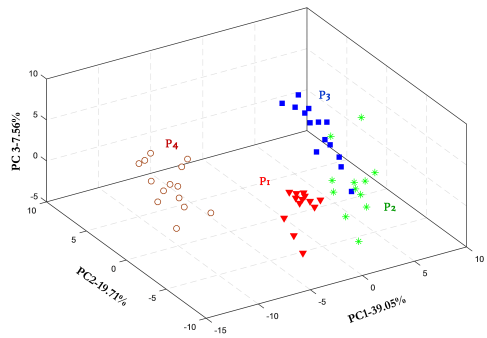


Fig. 3. 3-D PCA projection performed on four pizza topping types using the all E-nose data: P_1 for 100% minced beef with Edam cheese, P_2 for 50% minced beef and 50% minced Kadid with Edam cheese, P_3 for 100% minced Kadid with Edam cheese, and P_4 for 100% minced beef with parmesan cheese.

3.4. One-way ANOVA Feature selection results

To derive an optimal set of input features for machine learning techniques and enable accurate a posteriori classification of data into their priori classes, we perform feature selection [49, 50, 55]. For these reasons, a previous study was carried out to select the most significant features. Fig. 4 displays the selected ANOVA features with higher F-statistic values. The F-statistic threshold, which determines discrimination ability, was set to match the mean value of the inter–intra category variance ratio. In our specific case, this threshold is equal to Fm = 38.35. Therefore, all features with F value less than Fm, will be deleted from the initial database. Thus, the F- statistic threshold suggested that 61 features will be removed and only 35 features were in fact statistically informative to the outcome of the classification study.

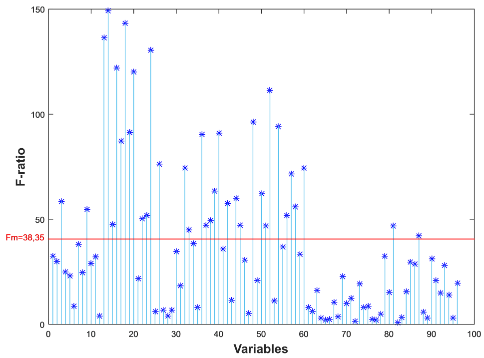


Fig. 4. The 35 ANOVA selected features with higher F-statistic, used in the final PCA, CA and SVMs models.

3.5. Radar plot representation

Radar plot representation is one of the most appropriate tools to present and describe concisely relationships between classes when it is associated with statistical analysis. So the radar plot method is recommended to anticipate the clusters classification [30, 46, 77]. Fig. 5 shows the radar plots used for visualizing whether pattern differences were developed among the different pizza types. To build up these plots, the values of MQ average rate of voltage change over the interval [2 min 7 min]: V_{d2-7} (variables which represent the higher F-statistic value), were normalized by the value corresponding to the maximum. Indeed, it can be seen in Fig. 5 that the differences existed especially between P_4 type and all the other types, while clear differences between all types were not as noticeable.

3.6. PCA based on One-way ANOVA feature selection data

Fig. 6 shows the PCA plot on One-way ANOVA selected features data. As noticeable in this plot, the three PC can express 92.19% of the information when using the selected features data and contribute potentially in separating the four pizza types. Hence, the graphic distinctly illustrates

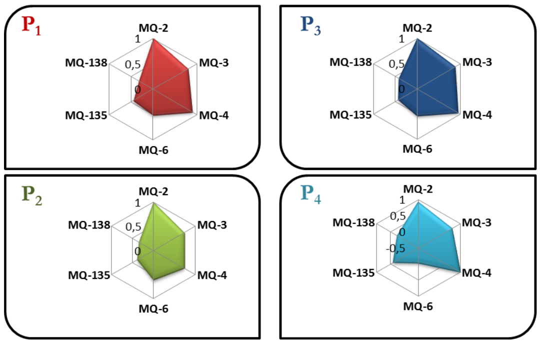


Fig. 5. Radar plots of the E-nose responses, expressed as the average rate of voltage change over the interval [2 min 7 min]: V_{d2-7}.P_1 for 100% minced beef with Edam cheese, P_2 for 50% minced beef and 50% minced Kadid with Edam cheese, P_3 for 100% minced Kadid with Edam cheese, and P_4 for 100% minced beef with parmesan cheese.

among all the four pizza types. Additional experimental details regarding PCA loadings can be found in the Supplementary Information (SI). By comparing Fig. 3 with Fig. 6, both before and after selecting the most discriminative features, we observe a significant improvement in the discrimination of pizza types. In fact, all pizza samples are now perfectly distinguished. Regarding the situation of Kadid about its ability to represent umami, no relationship was observed in Fig. 6 between P_4 and pizzas P_2 and P_3. This discrimination between the three pizzas could be due to a difference in concentration of their umami substances. In fact, umami is pleasant in a range of appropriate concentration [73, 78]. In addition, the Kadid, depending on the manner of its preparation, is salted [40]. Linscott and Lim [79] showed that salty and umami tastes could enhance the intensity of retronasally perceived identical odours of products, that helps to explain the discrimination between P_3 and P_4 which are based respectively on Kadid and umami.

3.7. K-means Cluster Analysis results

To explore the relationships between all pizza types and determine whether samples in different clusters (representing pizza types) exhibit similarity, we employed the K-means clustering method with Euclidean distance measurements. Specifically, we utilized the group average linkage technique. The results are presented in Fig. 7, which displays a dendrogram tree facilitating the identification of individual pizza samples. The best clustering between samples of the same types was obtained when K-means nearest group was applied as pre-treatment of the initial data. As we can see in Fig. 7, most of the clusters labelled with the same pizza

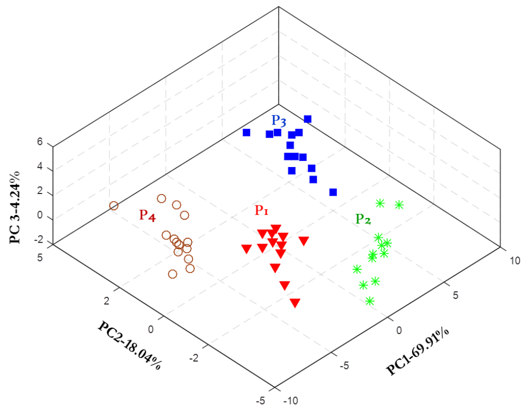


Fig. 6. 3-D PCA projection performed on four pizza topping types using One-way ANOVA selected features. P_1 for 100% minced beef with Edam cheese, P_2 for 50% minced beef and 50% minced Kadid with Edam cheese, P_3 for 100% minced Kadid with Edam cheese, and P_4 for 100% minced beef with parmesan cheese.

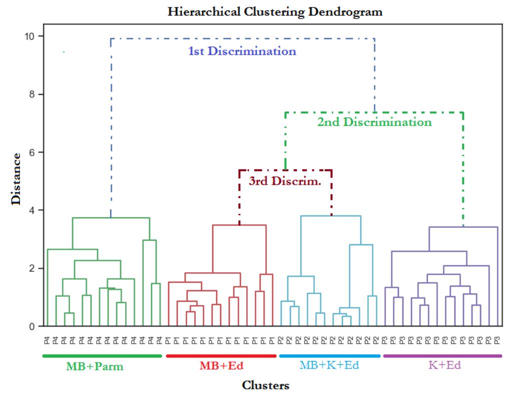


Fig. 7. K-means CA dendrogram performed on the One-way ANOVA feature selected data (MB: Minced beef meat, K: kadid, Ed: Edam cheese, Parm: Parmesan cheese).

types are grouped together. Therefore, it is worth noting that the four clusters corresponding to the four pizza toppings are perfectly grouped. Looking at this dendrogram, we can see the three clusters coming-off the three branches to the left of the Euclidean distance threshold of about 4.75, despite the fact that the K-means CA is considered as unsupervised method. As identified by Guggenmos, [80], the discrimination threshold can be lowered or raised in order to allow the selection of more or fewer groups or clusters. Furthermore, Fig. 7 shows that the first discrimination was based on the type of cheese used (cluster 1: P_4; cluster 2: P_1, P_2, and P_3), the second one was based on the presence or absence of minced beef meat (sub-cluster 1: P_1 and P_2; sub-cluster 2: P_3), whereas the last one was based on the presence or absence of kadid (sub-cluster 1: P_1; sub-cluster 2: P_2).

3.8. SVMs results

The one-vs.-rest SVMs neural networks with polynomial kernels (2^{nd} degree) have been applied as the identification and discrimination approach. The Leave-One-Out Cross-Validation (LOOCV) is an approach where, for each data point in our dataset, the model is trained on the rest of the data and tasted on that specific point. It helps us get a more reliable estimate of how well our model will perform on unseen data. If we only used one train-test split, we might get lucky or unlucky with the specific data points in that split. By repeating the process for all data points, we reduce the impact of luck and get a better sense of our model's true performance. LOOCV was applied to provide a robust evaluation of the SVM model's performance. Initially, we applied automatic scaling pre-treatment method to our dataset. Subsequently, we developed four binary classification models, each corresponding to a distinct type. In a one-vs-rest SVMs analysis for the four types of pizza toppings with respective sample sizes of 13, 12, 14, and 14, achieving a 100% result suggests that the SVMs method successfully classified each topping category without any misclassifications. This implies a robust and accurate model for distinguishing between the four pizza toppings.

3.9. Impact of lemon as disturbing odour on pizzas discrimination

About upsetting olfaction by a disturbing odour, we used 48 new pizza samples and added to each pizza sample a piece of lemon (1.94 g $\pm$ 1mg), then we started the E-nose characterization according to the same protocol as that described in section 2.2 for the 1st experiment. K-means cluster analysis results of the collected database, using the same ANOVA selected features that used in the first study, does not reveal the same discrimination as that obtained without disturbing odour (Fig. 7). Indeed, Fig. 8 shows that the first discrimination; in this second experiment, was based on the presence or absence of the minced beef meat (cluster 1: P_3; cluster 2: P_1, P_4 and P_2), the second discrimination was based on the presence or absence of kadid (sub-cluster 1: P_2; sub-cluster 2: P_1 and P_4), while the last one was based on the type of cheese (sub-cluster 1: P_4; sub-cluster 2: P_1). The olfactory disturbance caused by lemon smell significantly impacted E-nose's ability to identify pizza toppings, particularly when it came to distinguishing cheese. The results obtained above appear to align well with those reported by Belloute and Diouri [81]. The key findings from these experiments reveal that olfactory disturbance caused by the lemon smell significantly reduced the ability of blindfolded subjects to identify pizza toppings accurately. Specifically, the aroma of cheese, which was undetected, became masked by the olfactory disturbance. The results are also consistent with the findings of Paoulina et al. [82], who demonstrated that odour exposure influenced the ranking of savoury -tasting foods.

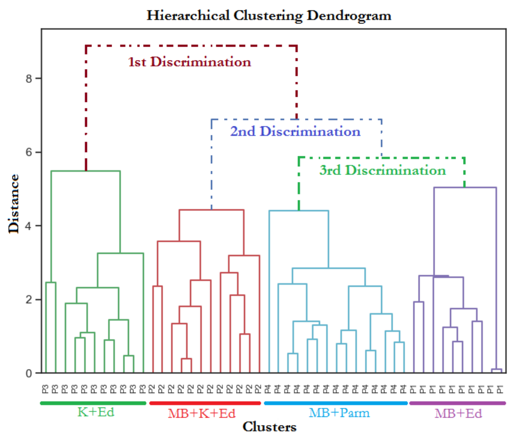


Fig. 8. K-means CA dendrogram performed on the selected data obtained with disturbing odour (MB: Minced beef meat, K: kadid, Ed: Edam cheese, Parm: Parmesan cheese).

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper

4. Conclusions

This study showcases the capability of a developed MQ E-nose as a fast and efficient technique specifically designed for rapid pattern recognition of pizza toppings. The experiment was carried out on 101 prepared pizza topping samples: 53 samples for the first experiment without olfactory disturbance and 48 samples for the second experiment with olfactory disturbance. For PCA performed on the first experiment using the raw data, no significant difference was found for the toppings of pizzas. However, the ANOVA feature selection coupled to machine learning techniques have given acceptable results regarding the pizza toppings discrimination. In addition, perfect identification of the four pizza toppings was obtained when performing ANOVA feature selection before applying PCA, CA and SVMs. Despite the similarities in the smell and taste of the four pizza topping types, the E-nose exhibited remarkable accuracy in distinguishing between the different pizza varieties. The results indicate also that the E-nose is effective and objective at identifying pizza toppings, which are subjectively gathered by the human nose. Interestingly, in the second experiment, CA results show that olfactory disturbance caused by a lemon smell significantly affected the E-nose's ability to identify toppings, especially cheese. This highlights the sensitivity of the E-nose to external odours and its potential impact on accurate topping detection. This study shows that the previously reported [81] in vivo smell detection differences have objective grounds.

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