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Electronic Detection of Garlic Density in Various Kinds of Yogurts Using Statistical Features

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Abstract

Accurate detection of food components plays a critical role in developing modern culinary technologies and food safety practices. This study uses electronic nose technology to determine garlic concentration in garlic yogurts. An electronic nose system consisting of 11 different MQ brand gas sensors was used in the study. Five different yogurt types were prepared with three different garlic concentrations: plain, low, and high. A total of 225 odor records were taken from 15 yogurt samples, and various features were extracted from these data, which were analyzed using four different classification algorithms. The Extra Trees algorithm was the most successful method, with 89.14% classification accuracy, 89.80% sensitivity, and 94.57% specificity rates. The results of the study show that electronic nose technology can be used in many application areas, especially in smart kitchen devices analyzing food ingredients to provide information about freshness and composition, in the food industry to ensure standardization of product quality in production processes and to ensure that intense aromatic ingredients such as garlic are used in the right amount, and in the development of food products suitable for consumers' special diets or personal tastes.

Keywords: Garlic yogurt, Odor classification, Electronic nose, Extra trees algorithm

INTRODUCTION

In today's world, electronic systems can do many tasks, and odors can be detected electronically. Systems that do this job are called electronic nose (e-nose) systems. Although Alexander Graham Bell first proposed measuring odor in 1914 [1], Moncrieff conducted the first study to develop a device to detect odors in 1961 [2]. E-noses were invented by imitating the human odor detection system. A simulation of e-nose and human olfactory systems is given in Figure 1 [3].

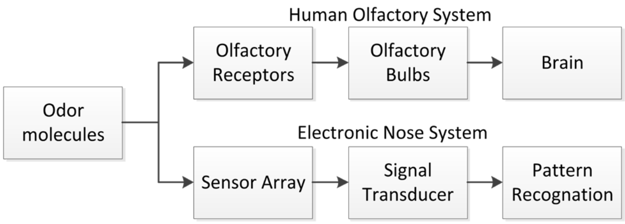

Figure 1. E-nose and human olfactory systems

Many studies have been carried out in food, health, and chemistry with e-nose, which has developed and increased in prevalence over the last 20-30 years.

Many studies have been conducted, from studies on perfume identification with e-noses in chemistry [4] to applications such as air quality monitoring, odor detection, and industrial emission control in environmental engineering [5].

Studies in the health field detect many diseases by using exhaled breath. Studies have been carried out on breathing diagnosis of many diseases using electronic noses, especially lung cancer [6], asthma [7], heart attack [8], diabetes 9], kidney diseases [10], and urinary tract infections [11].

Numerous studies have also been conducted in the field of food and beverages. There are many studies on detection by using an e-nose in food and beverages, such as tea [12], fruit juice [13] in quality determination studies; fish [14], cheese [15] in species identification studies; meat [16], milk [17] in spoilage studies; coffee [18], yogurt [19] in flavor determination studies; seafood [20], and chicken [21] can be given as examples in freshness determination studies.

There are studies in the literature using electronic noses on yogurt and garlic. Li Qiu et al. created a total of 12 different yogurt samples by taking three glasses from four different types of yogurt (plain and flavored). These samples contained 0.1%, 0.3% and 0.5% Rosa rugosa cv. Plena extract (RPE). The researchers classified these samples with a commercial electronic nose branded i-nose. They determined that flavored yogurts' smell differed from plain yogurt's [22]. In the other study, Kaur and his colleagues first examined the effect of yogurt on removing sulfur volatiles formed in the breath after garlic consumption and the role of yogurt components in this process [23]. They then examined the ability of yogurt and its components to deodorize raw and fried garlic volatiles, where they detected the volatile compounds formed after garlic consumption with an electronic nose and evaluated the effect of yogurt on these compounds [24]. In another application, Tamaki and his colleagues analyzed the odor components formed after consumption of raw and heated garlic in laboratory environments and living organisms (in vitro and in vivo) using e-nose. They found that raw and heated garlic had different olfactory characteristics in the breath and laboratory environment [25]. In such a study, using an electronic nose, Suarez and his colleagues investigated whether the source of the gases formed in the breath after garlic consumption was the mouth or the intestine. They also found that gases such as methanethiol and allyl mercaptan were found in high concentrations in the mouth, and allyl methyl sulfide was of intestinal origin [26]. In a study conducted on this subject, Makarechian et al. also evaluated the effects of different desiccation methods and pre-storage times on the aroma of garlic by using an electronic nose [27]. In a similar study, Liu et al. studied drying characteristics, quality changes, parameter optimization, and aroma analysis of garlic slices dried by microwave vacuum drying method with an electronic nose [28].

This study focuses on determining the amount of garlic in garlic yogurt, frequently used in kitchens, using electronic nose technology. Various studies have been conducted on yoghurt and garlic using electronic nose in the literature. In these studies, the classification of different aromas and components of yoghurt was examined. In addition, the effect of yoghurt consumption on volatile compounds of garlic was investigated. In addition, changes in the aroma of garlic depending on drying and processing methods were also evaluated. However, no study has directly determined the amount of garlic in yogurt via an electronic nose. In this context, this study provides an essential innovation for quantitatively analyzing garlic yogurts and the future use of such a device in innovative kitchen technologies. This method provides a practical solution, especially regarding the rapid and accurate detection of food components.

MATERIALS AND METHODS

This section explains the design of the electronic nose system, data collection processes, feature extraction methods and classification procedures in detail.

Building of the Used Electronic Nose System

The sensor block of the electronic nose built for the study was produced using the gas sensors listed in Table 1, together with their kits.

Table 1. Used Gas Sensors

No	Sensor Model	Sensed Gases	Sensitivity Range (ppm)
1	MQ-2	Methane, Butane, LPG, Smoke	300-10000
2	MQ-3	Alcohol, Ethanol, Smoke	10-1000
3	MQ-4	Methane, CNG Gas	200-10000
4	MQ-5	Natural Gas, LPG	200-10000
5	MQ-6	LPG, Butane Gas	200-10000
6	MQ-7	Carbon Monoxide	20-2000
7	MQ-8	Hydrogen Gas	100-10000
8	MQ-9	Carbon Monoxide, Flammable Gasses	10-10000
9	MQ-131	Ozone	10-1000
10	MQ-135	Air Quality (CO, Ammonia, Benzene, Alcohol, Smoke)	10-1000
11	MQ-137	Ammonia	10-100

MQ brand gas sensors were used with their own electronic kits. Gas sensors collected on a single card were placed in a storage container with a lid. The sensors' cables inside the box were brought out through a narrow airtight hole. The sensor kits were powered by a power supply, and the analog signal taken from the sensors was connected to the two Arduino Uno cards' analog inputs. Sensor output analog data was converted into digital data with Arduino cards and transmitted to the computer via the USB port. Sensor data were recorded using the software prepared in LabView. The e-nose system made for the study is given in Figure 2.

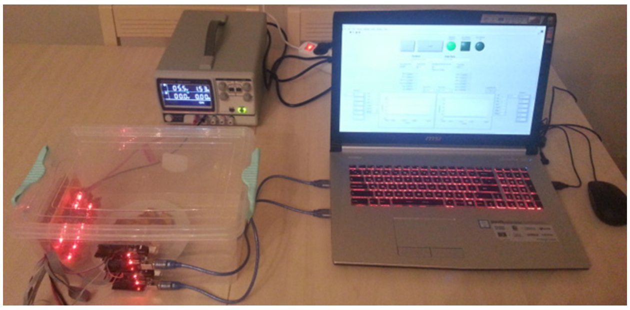

Figure 2. The electronic nose setup

Data Collection and Preprocessing Phase

In this study, five different types of yogurt were used. One hundred fifty grams of each of these yogurts were taken into a bowl. One bowl was left as plain yogurt. Two cloves of garlic were added to one of the other yogurt samples to make yogurt with less garlic. Five cloves of garlic were added to another sample to make yogurt with more garlic. These three different samples for a type of yogurt are shown in Figure 3.

Figure 3. Yogurt samples

The obtained yogurt samples were placed in the olfactory box of the electronic nose, and 15 odor records were taken from each one. The number of odor recordings taken is given in Table 2.

Table 2. Number of sniffing data

	Plain yogurt	Two cloves of garlic yogurt	Five cloves of garlic yogurt
Homemade yogurt	15	15	15
Light yogurt	15	15	15
Strained yogurt	15	15	15
Full-fat skimmed yogurt	15	15	15
Pan yogurt	15	15	15

All measurements were taken for 3 days, with freshly prepared samples, between 20:00-23:00, under 24-26 °C temperature and 50-70% humidity. The sniffing cycle begins by placing the yogurt sample in a ventilated e-nose odor box, closing the box lid, and launching the odor recording software. The e-nose sniffing cycle duration was 30 seconds, and 10 data were received from the sensors per second. Three hundred one data were recorded from a gas sensor in each round, and an 11x301 data matrix was obtained in one sniffing cycle. As seen in Table 2, 225 separate odor records were taken, resulting in a three-dimensional matrix with dimensions of 225x11x301.

In the preprocessing part, some gaps (missing values) were detected in the datasets obtained from the Arduino device during the data collection process. Missing values in the dataset were filled using neighboring non-zero values, ensuring the dataset's suitability for analysis. This method ensured that the missing data was estimated as accurately as possible and data integrity was maintained.

Feature Extraction Phase

The features of the received data were first extracted. Statistical values such as mean value, standard deviation, total, median, minimum, maximum, first quartile, and third quartile are used here, and their formulas are given in 1-8:

Here, x_{mean} is the mean value of a trial, x_{std} is the standard deviation value of a trial, x_{sum} is the total value of a trial, x_s is the last value of a trial, s is the value number of a trial, x_{median} is the value in the middle of a trial, x_{min} is the minimum value of a trial, x_{max} is the maximum value of a trial, x_{Q1} is the value in the 25% slice when a trial is sorted, that is, the 1st quarter (Q1) value, x_{Q3} is the value in the 75% slice when a trial is sorted, that is, the 3rd quarter (Q3) value.

$$x_{mean} = \sum_{x=1}^{s} \frac{x_1 + x_2 + \cdots + x_s}{s} \tag{1}$$

$$x_{std} = \sqrt{\frac{(x_1 - x_{mean})^2 + \cdots + (x_s - x_{mean})^2}{s-1}} \tag{2}$$

$$x_{sum} = x_1 + x_2 + \ldots + x_s \tag{3}$$

$$x_{median} = \begin{cases} x_{\frac{s+1}{2}} \\ \frac{1}{2}\left(x_{\frac{s}{2}} + x_{\frac{s}{2}+1}\right) \end{cases} \tag{4}$$

$$x_{min} = min(x_1, x_2, \ldots, x_s) \tag{5}$$

$$x_{max} = max(x_1, x_2, \ldots, x_s) \tag{6}$$

$$x_{Q1} = Percentile(x, 25) \tag{7}$$

$$x_{Q3} = Percentile(x, 75) \tag{8}$$

Classification Phase

In the classification process, not all features have the same meaning. In addition to critical features, unimportant features have also been produced. All these reduce the classification accuracy and add a burden to the calculation. Therefore, it is necessary to separate unimportant features and use essential features. In this study, feature selection was done using the Recursive Feature Elimination (RFE) method. Feature selection based on the Random Forest classifier was performed using the RFE method. The number of features to be selected was determined using the cross-validation method.

After selecting the features, the data were randomly selected as training, validation, and test data with a ratio of 60%-20%-20%, respectively. The classification was performed with four different classification algorithms.

Then, the test data were classified using these features by the most common classification algorithms: k-nearest Neighbor (kNN), Random Forest, Extra Trees, and Gradient-Boosting classification algorithms.

The kNN classification method is widely used and very useful in classification studies. In kNN classification, the distances between the data are calculated. Test data is classified according to its k nearest neighbors. The ideal k number was determined by the cross-validation method [29].

Random Forest is a standard classification method that makes decisions with multiple decision trees. Each tree is trained using randomly selected features for a random subset of the data. This method determines the final classification decision by a majority vote of the trees. Thus, thanks to the diversity of trees, the risk of overlearning decreases, and generalization ability increases [30].

The Extra Trees classification method is similar to Random Forest, except that it trains each tree on the entire dataset. Split points are chosen completely randomly. Because of this, trees are more diverse, and training times are generally faster. This method also prevents overlearning due to high randomness. The splitting criteria may be the Gini coefficient or entropy, but the splitting points are randomly chosen [31].

The Gradient Boosting method is one in which weak learners (usually decision trees) are trained sequentially by expanding additively and forming a strong ensemble. In each new tree, previous errors are tried to be corrected. The final classification is made by the weighted sum of all trees [32].

Figure 4 shows the flow chart of the classification process.

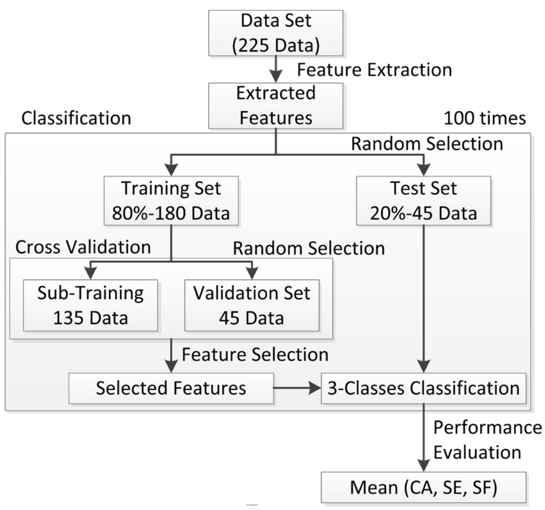

Figure 4. Classification Flow Diagram

The classification metrics were used to evaluate the performance of the classifiers.

$$CA = \frac{CCT}{TT} x100 \tag{9}$$

$$SE = \frac{TP}{TP+FN} x100 \tag{10}$$

Table 3. Selected Features

	MQ-										
	2	3	4	5	6	7	8	9	131	135	137
x_{mean}	F0	0.097	F16	F24	0.114	F40	F48	F56	F64	0.117	F80
x_{std}	F1	0.081	F17	0.123	F33	F41	F49	F57	F65	F73	F81
x_{sum}	F2	0.116	F18	F26	F34	F42	F50	F58	F66	F74	F82
x_{med}	0.123	F11	F19	F27	F35	F43	F51	F59	F67	F75	F83
x_{min}	F4	F12	F20	F28	F36	F44	F52	F60	F68	F76	F84
x_{max}	F5	0.073	F21	F29	F37	F45	F53	F61	F69	F77	F85
x_{Q1}	F6	0.060	F22	0.096	F38	F46	F54	F62	F70	F78	F86
x_{Q3}	F7	F15	F23	F31	F39	F47	F55	F63	F71	F79	F87
Total Effect (%)	0.123	0.427	-	0.219	0.114	-	-	-	-	0.117	-

$$SF = \frac{TN}{TN+FP} x100 \qquad (11)$$

CA: Classification Accuracy, SE: Sensitivity, SF: Specifity, CCT: Correctly Classified Trials, TT: Total Trials, TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative.

For the sake of the reliability of the classification process, the classification mentioned above was performed 100 times with the random selection of different training-test sets. The arithmetic average of 100 classification results was accepted as classification success.

RESULTS AND DISCUSSION

The study recorded the odor of 225 yogurt samples on a computer. They belong to 5 different yogurt types. One-third of the total 225 samples were plain yogurt, one-third had little garlic, and the other was yogurt with lots of garlic. All these samples were sniffed for 30 seconds, and sensor data were taken into the computer. Here, a matrix of values of 225x11x301 has been obtained, including 225 samples, 11 gas sensors, and 301 sensor output values.

Eight different features (x_{mean}, x_{std}, x_{sum}, x_{med}, x_{min}, x_{max}, x_{Q1}, x_{Q3}) were extracted from each sensor. These features were obtained from 11 sensors, reaching 11×8=88 features. The number of features to be selected was determined by testing with the cross-validation method, and the ten features that provided the best performance were selected. The RFE method was configured to select the ten most effective features among these 88 features. Feature extraction is one of the most fundamental components of the success of a classification study. Here, the more accurately the features the classifier uses are extracted, the higher the performance at the end of the classification [33]. The selected features and the selection percentages of these features are given in Table 3.

As seen in Table 3, the effective sensors are the MQ-2, MQ-3, MQ-5, MQ-6, and MQ-135 gas sensors. The total effect of each sensor on the result is expressed in the table. According to these results, the most effective gas sensors in detecting garlic concentrations of garlic yogurts with the e-nose used in the study were MQ-3, MQ-5, MQ-2, MQ-137, and MQ-6, respectively.

The test data were classified with four different classification algorithms using these features. The performances of the classification algorithms with CA, SE, and SF metrics calculated according to the average confusion matrix obtained as a result of classifications made with 100 different training-test data are given in Table 4 [34]. The number k in the kNN algorithm was determined by the cross-validation method, and the optimum value was selected as 3. For the Random Forest algorithm, the n_estimators parameter was used as 100, which is the default value of the scikit-learn library.

Table 4. Classification Results According to Classifiers

Classification Algorithm	CA (%)	SE (%)	SF (%)
Extra Trees	89.14	89.80	94.57
kNN-3	86.22	86.89	93.10
Random Forest	84.30	84.39	92.21
Gradient Boosting	82.00	82.00	91.00

For the test data of the Extra Trees Classification algorithm, which gives the highest CA accuracy in classifications, the average confusion matrix of 100 classifications in percentages is given in Table 5.

Table 5. Confusion Matrix for Extra Trees Classification (%)

		Predicted		
	Accuracy: 89.14% plain yogurt	yogurt with a little garlic	yogurt with lots of garlic	
Real	**plain yogurt**	96.0	4.0	0.0
	yogurt with a little garlic	6.7	82.7	10.7
	yogurt with lots of garlic	2.0	9.3	88.7

The pseudo-code of the study, generated only for the Extra Trees algorithm, is presented in Table 6.

Table 6. The Pseudo-Code of the Study

```
Input: Sensor data from 11 sensors
Output: Classification performance metrics (CA, SE, SF)
1. Load Data:
  a. Read sensor data from multiple Excel files.
  b. Ensure all files have the same shape.
2. Preprocess Data:
  a. Detect missing values (zeros) in the data.
  b. Replace missing values with neighboring non-zero values.
3. Feature Extraction:
  a. For each sensor, calculate 8 statistical features:
    - Mean, standard deviation, sum, median, minimum, maximum, Q1, Q3.
  b. Combine these features from all 11 sensors to form a feature set of 88 features.
4. Feature Selection with RFE:
  a. Use Recursive Feature Elimination (RFE) with Random Forest Classifier.
  b. Select the top 10 features based on importance scores.
5. Split Data:
  a. Divide the data into training (60%), validation (20%), and test (20%) sets.
6. Train and Test the Model:
  a. For 100 iterations:
    i. Randomly shuffle and split the data.
    ii. Train Extra Trees Classifier on the training set.
    iii. Predict labels for the test set.
    iv. Record accuracy (CA), sensitivity (SE), and specificity (SF) for each iteration.
7. Calculate Final Performance:
  a. Compute the average CA, SE, and SF across 100 iterations.
  b. Record the confusion matrix for the final model.
8. Return Results:
  a. Selected features from RFE.
  b. Average classification performance (CA, SE, SF).
```

Zeng et al. (2023) combined electronic nose technology with machine learning methods to determine the aroma types of plain yogurt [19]. In this study, garlic concentrations in yogurt were determined using an electronic nose. While both studies highlight the potential of electronic nose systems in food analytics, the current research focuses specifically on the quantitative analysis of garlic, an aromatic component.

Kaur and Barringer (2024) investigated the effect of yogurt on neutralizing the volatile sulfur compounds of raw garlic [23]. Another study by the same authors in 2023 analyzed how the volatile compounds of both raw and fried garlic were removed by yogurt and its components [24]. While these studies focused on the removal of garlic odor, the current study focuses on the determination and classification of the concentration of garlic in yogurt. Therefore, while previous studies evaluated the odor removal aspect of garlic, this study uses electronic nose technology to objectively measure the presence and amount of garlic.

Tamaki et al. (2008) analyzed the odor changes after garlic consumption with both electronic nose and gas chromatography [25]. However, this study focused on determining the concentration of garlic in different types of yogurt and offers a new application for the determination of food components.

The accuracy and performance of the MQ series gas sensors used in this study are based on the technical specifications of the manufacturer. Calibration and accuracy tests of the sensors are outside the scope of this study. However, the effectiveness of the sensors in detecting garlic concentration is indirectly supported by the high classification accuracy (89.14%) and sensitivity (89.80%) rates obtained with machine learning algorithms. In future studies, it is recommended to perform calibration studies using standard gases or reference samples in order to test the accuracy of the sensors in more detail. In addition, a more comprehensive evaluation of the sensor performance with additional experiments such as cross-sensitivity tests and repeatability analyses will increase the reliability of this technology in food analysis.

There are two limitations to the study. Among these, the first thing that stands out is the small number of samples. Since this is a research study, the number of samples has been kept small. Although there are different yogurts, it has been shown that the amount of garlic in garlic yogurt can be detected electronically. The number of samples will inevitably increase when the study needs to be integrated into any electronic system in the future. The second limitation is that the number of features is kept at eight. Classifiers may make this determination with higher accuracy by extracting various features.

CONCLUSION

In this study, an e-nose with eleven gas sensors was made. Fifteen different samples were obtained from five different types of yogurt, including plain, low garlic, and very garlic, and the odors of these samples were taken with the e-nose. Then, eight different features (x_{mean}, x_{std}, x_{sum}, x_{med}, x_{min}, x_{max}, x_{Q1}, x_{Q3}) were calculated for each sensor, and a total of 88 features were obtained. The most effective ten features were selected from these 88 features with the Recursive Feature Elimination (RFE) method. As a result of examining the selected features, it was determined that only the data of five gas sensors were significant in the study, and among these sensors, the MQ-3 gas sensor had the highest contribution. The significant sensors were identified as MQ-2, MQ-3, MQ-5, MQ-6 and MQ-135. These feature values were classified for 100 different training-test data selections with four different classification algorithms. The test data were classified using the most successful Extra Trees classification algorithm, which had 89.14% CA, 89.80% SE, and 94.57% SF performance, according to the average of 100 different classification results. As a result of the study, yogurts with different garlic densities were detected with high accuracy based on their odor profiles using the proposed method.

Acknowledgment

This research is not related to either human or animal use.

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