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SUNFLOWER OIL QUALITY EVALUATION: A MULTISENSORY APPROACH USING AN ELECTRONIC OLFACTION SYSTEM

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Abstract

The utilization of artificial neural networks (ANNs) for the precise classification of sunflower oil based on gas sensor responses is demonstrated in this study. Experimental data is collected through a cost-effective electronic nose featuring a gas sensor module. The trained ANN exhibits high precision in distinguishing different classes of sunflower oil.

Keywords: Sunflower oil classification, Electronic nose, Artificial neural networks (ANN), Food quality assessment, Multi-sensor system, Metal oxide sensors, Sensor data processing.

INTRODUCTION

Gas sensors play a pivotal role in various fields and applications within modern industrial society [1, 2]. Developing a selective sensor exclusively responsive to a single gas poses significant challenges. Consequently, the potential for broadening the applications of gas sensors largely hinges on signal processing advancements. Multi-sensor systems, particularly, offer a novel approach to measuring multi-component gas environments utilizing non-selective sensors.

The term "electronic nose" refers to an analytical device comprising non-selective gas sensors with cross-sensitivity, along with signal processing methods for the qualitative and quantitative evaluation of gases, vapors, aromas, and odors [3].

Research into the electronic nose's applications spans diverse domains of human activity. Leveraging its capabilities in gas detection and identification, it finds utility in numerous sectors such as food quality monitoring, medical diagnosis, hazardous gas detection, agriculture, environmental protection, explosive and drug detection, among others [4-6].

The assessment of food authenticity has gained paramount importance, particularly due to concerns regarding adulteration. Consequently, there is a growing demand for innovative tools to assess food quality both pre- and post-processing. The electronic nose emerges as a promising solution capable of simultaneous detection and discrimination of simple and complex odors. By harnessing the electronic nose, it becomes feasible to gauge adulteration levels in foods and ascertain concentrations of specific volatile compounds [7-9].

This study introduces a multi-sensor system for the recognition and classification of food products. The system comprises a sensor module incorporating three independent metal oxide gas sensor elements known for their low energy consumption. We utilize this multi-sensor system in the classification of sunflower oil employing an artificial neural network [10].

SENSOR MODULE

A sensor module for data acquisition has been created to oversee three primary categories of gases. This module possesses the ability to gauge the gas emissions associated with different types of foods, as depicted in Figure 1.

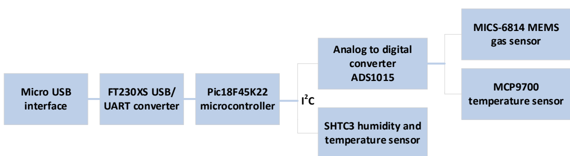

Fig. 1 *Block diagram of sensor module*

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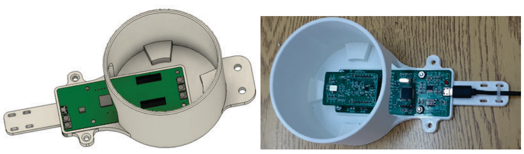
The sensor module incorporates the MICS-6814 gas sensor [10] to detect three specific gases: Carbon Monoxide (CO), Nitrogen Dioxide (NO2), and Ammonia (NH3). Employing a metal oxide sensor type, its resistive sensing elements alter their resistance in response to the gases being measured. Oxidizing gases, like ozone or nitrogen dioxide, prompt an increase in resistance within the sensing elements, whereas reducing gases, such as carbon monoxide or VOCs, induce a decrease in resistance. Encased within a specially crafted housing, as illustrated in Figure 2, the module ensures optimal functionality and protection.



a) 3d model *b) real system*

Fig. 2 *Sensor module*

A data acquisition virtual instrument has been created with LabVIEW to capture and store the data collected by the sensor onto a personal computer. The virtual instrument is depicted in Figure 3.

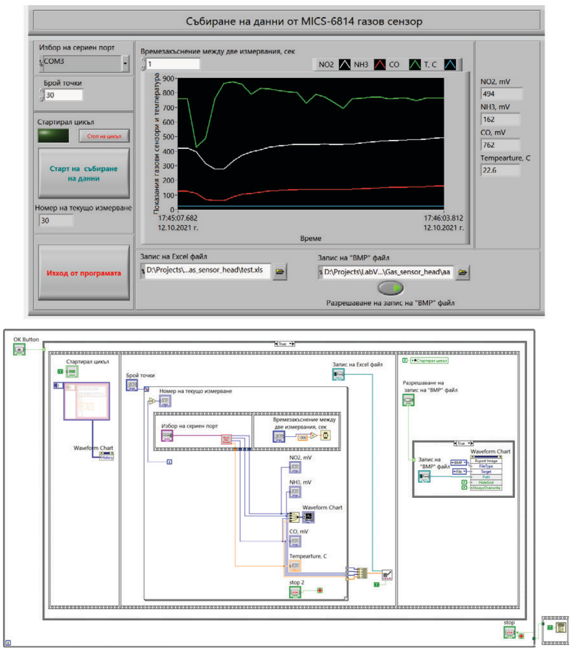


Fig. 3 *Virtual instrument for data acquisition*

The virtual instrument exhibits several key attributes, including a user-friendly interface, graphical depiction of acquired data, and the capacity to save data in an Excel file. Furthermore, users can plot data into BMP images and store them alongside the Excel file.

EXPERIMENTAL SETUP

For data acquisition from the gas sensor module, a glass vessel serves as the container for holding sunflower oil test samples. The sensor module is positioned atop the glass vessel, as depicted in Figure 4, and measurements are commenced.

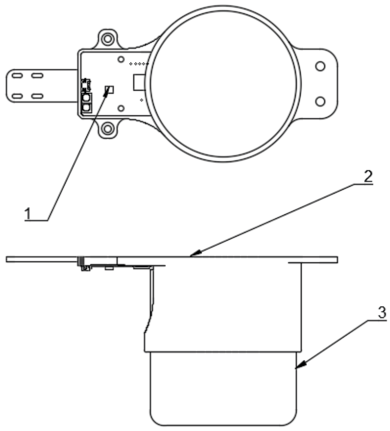


Fig. 4 *Drawing of experimental Electronic Olfaction System- 1) sensor module electronics, 2) plastic holder, 3) glass vessel with sunflower oil*

Throughout the measurements, the glass vessel can be positioned on a controlled heating plate, ensuring the maintenance of a temperature range between 40 and 50 ºC.

ACQUIRED DATA SETS

In the current study, diverse sunflower oil samples were employed, sourced from both the producer company and commercially available sources. Table 1 outlines the classifications of the utilized samples.

Table 1 *Classes of sunflower oil used in the research*

Class name	Class numbering	Description
D class	4	Degummed sunflower oil
E class	3	Extraction sunflower oil
F class	2	Filtered sunflower oil
P class	1	Product on market

Twenty test samples were extracted from each oil class and successively transferred into a glass container. Utilizing the sensor module, the properties of the oil in each sample were measured. Although the entire measurement process spans 5 minutes, only the data from the final 100 seconds is utilized to derive the average values of the sensor outputs in millivolts (mV). The sensor readings were preserved in separate files. Due to the necessity for the sensor module to establish and stabilize its readings, as illustrated in Fig. 5, a total of 150 measurement points were captured, with the last 50 points identified as stable values.

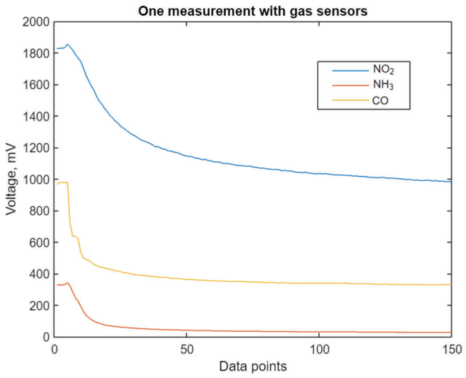


Fig.5 *One measurement with sensors transitioning to steady state*

To guarantee stable sensor readings and avoid excessively prolonged measurements, 150 values were determined as the optimal number to gather. From the 20 data files generated for each class, solely the last 50 points were extracted and consolidated to form a new file containing the summarized data for that class. Consequently, four training data files were generated for the four sunflower oil classes mentioned earlier. Figure 6 illustrates a graphical depiction of the data collected for class E sunflower oil.

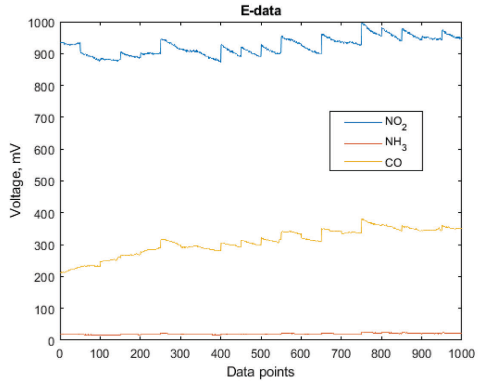


Fig. 6 *Last 50 acquired points of 20 measurements gathered together*

Figure 7 provides a visualization of the training data for all four classes. The graph illustrates that classes D, E, and P are closely clustered together, suggesting potential recognition inaccuracies due to their proximity.

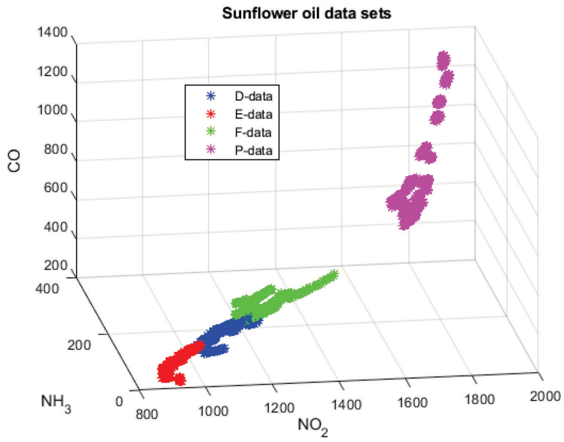


Fig.7 *Visualization of space places of different classes*

TRAINING OF NEURAL NETWORK

The Matlab environment was used to create an artificial neural network to be trained and recognize the different classes of oil. The neural network is created in the app tool – Deep Network Designer. The neural network has six layers, which are represented in Figure 8.

The first layer receives data from the three channels of the gas sensor module. The second layer consists of 30 neurons of the "fully connected" type, which findings enter the third layer representing a sigmoidal activation function. The fourth layer consists of 4 "fully connected" neurons entering a layer implementing a softmax function. The last sixth layer classifies the data received from the softmax layer to one of the four oil classes.

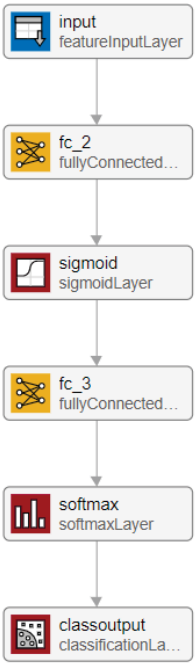


Fig.8 *Model of trained neural network*

Training the neural network involved employing a sample of 4000 vectors describing the four oil classes. Of this sample, 70% was allocated for training, while the remaining 15% each were assigned for validation and testing purposes. The network underwent training across 112 iterations, as depicted in Figure 9.

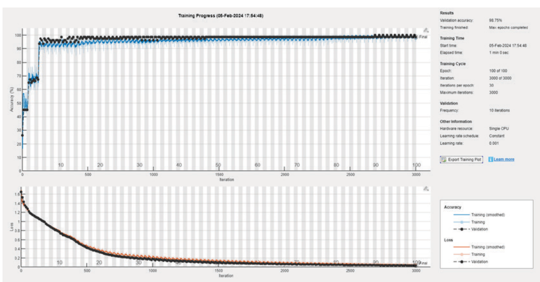


Fig.9 *The error graph of process of training*

Assessing Neural Network Performance

Upon completing training on a dataset, the effectiveness of a neural network can be assessed using a range of metrics to determine how accurately it predicts the desired outputs.

The selection of a suitable metric depends on the specific task and the criteria set by the application. While accuracy provides a measure of the ratio of correctly classified samples to the total number of samples, it may not be adequate in certain situations. For example, when one class significantly outweighs the others in prevalence, or when the consequences of false positive or false negative predictions vary. In such instances, precision and recall come into play. Precision evaluates the ratio of correctly predicted positive samples to all predicted positive samples, while recall evaluates the ratio of correctly predicted positive samples to all actual positive samples. The F1 score, a commonly used metric, combines precision and recall into a single value by calculating their harmonic mean. This score offers a balanced assessment of both metrics. All these metrics rely on the counts of true positives, true negatives, false positives, and false negatives, which can be summarized in a confusion matrix. This matrix introduces a tabular overview of correctly and incorrectly classified samples for each class, providing insights into the neural network's error patterns. Figure 10 illustrates the confusion matrix for the trained neural network.

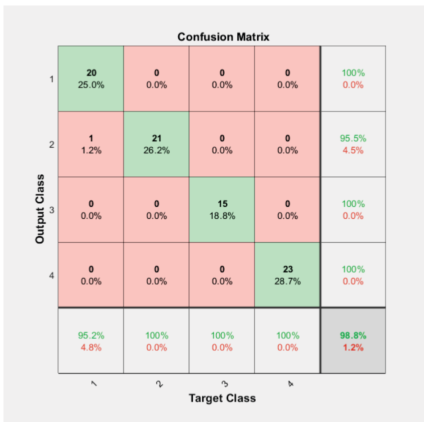


Fig.10 *Confusion matrix of trained ANN possibilities for classification*

The corresponding values for other metrics are detailed in Table 2.

***Table 2** Values of main metrics for ANN evaluation*

Metrics	Value
Accuracy	0.9938
Precision	0.9875
Recall	0.9875
F1Score	0.9875

TEST WITH SIMULATED DATA

For evaluating the performance of the trained neural network, simulated data with added random noise was utilized, as the experimental data closely resembled the training data for each oil class. The average readings of each sensor in the MICS-6814 for each oil class were used as the foundation for generating the simulated data.

To calculate the average sensor readings for each oil class, the following formula was used:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (1)$$

where N - the number of averaged values of x.

Table 3 introduces the average sensor reading values in mV for each of the different classes.

***Table 3** Average values*

Average values in mV	NO2	NH3	CO
D class	1061.58	34.642	423.78
E class	923.53	19.55	308.47
F class	1192.64	53.25	519.47
P class	1747.47	220.67	923.44

The added noise was generated using the standard deviations of the sensor readings for each type of oil. Formula (2) was utilized to calculate the standard deviation.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \qquad (2)$$

The findings for the standard deviations are presented in Table 4.

***Table 4** Standard deviations*

Standard deviations in mV	NO2	NH3	CO
D class	41.09	4.17	33.80
E class	28.21	2.29	41.38
F class	52.22	6.51	31.14
P class	63.17	45.50	172.08

Using the mean values and standard deviations of sensor readings, we generated 100 random readings for each oil class to simulate measurement data. These simulated data points showed standard deviations 20% larger than those observed in the actual measured data, as detailed in Table 4. The distribution of these simulated data points within the parameter space defined by the NO2, NH3, and CO sensors is depicted in Figure 11.

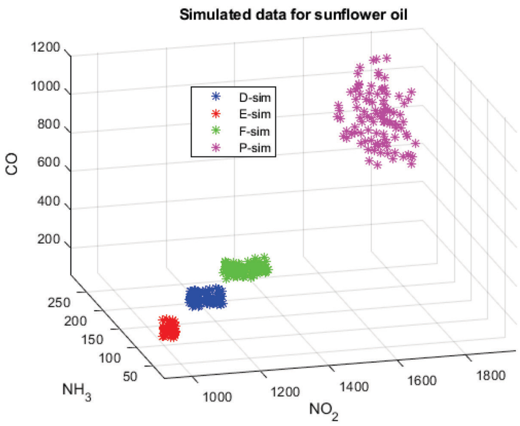


***Fig.11** Simulated classes for test*

Using the simulated data, the artificial neural network adeptly categorizes the input data into one of the four studied oil classes. Despite the simulated data's standard deviation being bigger than the real data used for training of the neural network, the simulated data is precisely identified and classified, as illustrated in Figure 12.

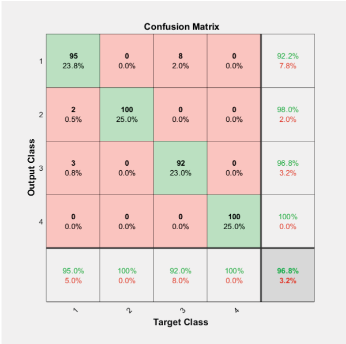


Fig.12 *Confusion matrix of simulated data classification*

From this evidence, it can be inferred that the trained neural network demonstrates proficiency in accurately classifying the specified classes of sunflower oil.

Table 5 *Values of main metrics*

Metrics	Value
Accuracy	0.9838
Precision	0.9675
Recall	0.9675
F1Score	0.9675

Future research will prioritize the collection of oil data from various manufacturers to explore whether data from different production stages across manufacturers are comparable or exhibit noticeable differences based on the manufacturer and process equipment employed.

CONCLUSIONS

The developed multi-sensor recognition and classification system, utilizing a sensor module with three independent metal oxide gas sensor elements, showcases low energy consumption. By utilizing experimental data from sunflower oil samples, an artificial neural network was successfully trained to classify different grades of sunflower oil with significant accuracy. Future endeavors will concentrate on amassing sunflower oil data from diverse producers to evaluate comparability across distinct production stages and potential variations based on the producer and processing equipment utilized.

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