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Classification of Flavored Filipino Vinegars Using Electronic Nose †

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Abstract: Condiments such as vinegar are made and fermented manually with the help of the human nose. We developed an electronic nose to classify pure Filipino vinegar varieties for automated vinegar classification. MQ sensors were used to determine the sensitivity of gas content of different vinegar flavors, namely, Sinamak, Pinakurat, and Iloko. Linear discriminant analysis was conducted for dimensionality reduction. A support vector machine (SVM) was employed to utilize the data gathered and accurately identify the varieties. 360 samples were included in the training dataset, while 108 samples were included in the testing datasets. The accuracy was 78.7%.

Keywords: food industry; electronic nose; mq sensors; linear discriminant analysis; support vector machine

1. Introduction

Vinegar is a common ingredient in different flavors from various origins. In the Philippines, Iloko from the Ilocos Region, Sinamak from Iloilo City, and Pinakurat, which originated in Iligan City, and other flavor varieties can be found. To classify these varieties, gas chromatography (GC), mass spectrometers (MS), or human senses are used. However, the acetic acid content of vinegar is dangerous and causes interferences [1–3].

An electronic nose is used to classify and recognize a variety of complex odors with an array of sensors [4]. The detection of the electronic nose comprises olfactory, evaluation, and signal accumulation [5]. Vinegar has long been regarded as a byproduct of fermented goods. People use vinegar as a condiment, a food preservative, and medicine. Vinegar is famous and widely used in Filipinos' everyday lives. In a tropical country, food quality worsens easily, and vinegar serves as a preservative for foods.

Vinegar classification has been conducted using a human nose. Different volatile compounds are detected by the e-Nose [6]. An existing method is used to detect different types of vinegar using headspace solid-phase microextraction (HS-SPME) in conjunction with GC. It resulted in an accuracy of 100% [1]. However, this method is not cost-efficient and requires chemical engineering knowledge. In classifying Chinese vinegar, an e-Nose using fuzzy foley-sammon transformation (FFST) showed 96.92% accuracy [2]. Neural networks such as deep convolutional neural networks (DCNNs) were also used [7]. The spoilage of tomato-based Filipino dishes at different temperatures was detected using various MQ sensors, too [8]. E-Noses are used in different areas of the food industry, such as discriminating coffee bean quality and aroma analysis and analyzing the ripeness

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of tomatoes and cantaloupes [9–12]. Improvements in the e-Nose enable more effective vinegar classification than before.

In the e_Nose, tin dioxide gas sensors (TGS) are used along with neural networks such as KNN, FNN, RNN, and DCNN. The Raspberry Pi microcomputer is often used due to its reliability and efficiency [13,14]. A support vector machine (SVM) is used to estimate the body mass index from 2D face images. The system yielded an accuracy of 91% [15]. Gas sensors mainly use TGS. E-Nose classification is accurate with the algorithms [7,16].

Based on the results, we developed an e-Nose for the classification of Filipino-flavored vinegar varieties using the linear discriminant analysis (LDA)–SVM algorithm. Using supervised learning, we collected three different classes of vinegar samples: Sinamak, Iloko, and Pinakurat. Linear discriminant analysis was used to reduce the dimensions of the extracted features. The developed e-Nose was evaluated for its performance using a confusion matrix. The developed e-Nose can be used in identifying other food ingredients and benefits local Filipino vinegar production.

2. Methodology

2.1. Conceptual Framework

Figure 1 shows the research framework of this study. MQ sensors were used for 60 samples. The gathered data were processed using the LDA–SVM algorithm to reduce the dimensions of features. The data were used to train the SVM algorithm. The system classified the vinegar samples, and the results were displayed on the LCD.

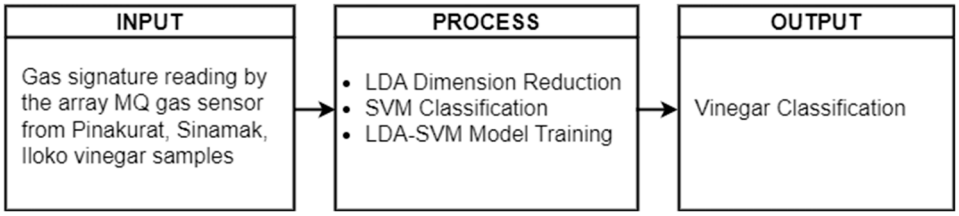


Figure 1. Input, process, and output of this study.

MQ gas sensors were used to classify Sinamak, Iloko, and Pinakurat vinegar. Five MQ gas sensors were used to collect training and test data: MQ2, MQ3, MQ4, MQ8, and MQ135 (Table 1).

Table 1. MQ sensors used in this study.

Sensors	Sensitivity	Gas Present in Vinegar
MQ2	Methane, Butane, LPG, Smoke Detection	Isobutanol, Methane Carboxylic Acid
MQ3	Alcohol, Ethanol, Smoke Detection	Ethyl Lactate, Ethyl Acetate
MQ4	Methane, CNG Gas Detection	Methane Carboxylic Acid
MQ8	Hydrogen Gas Detection	Acetic Acid
MQ135	CO, Ammonia, Benzene, Alcohol, Smoke Detection	Benzyl Alcohol, Ethyl Lactate, Ethyl Acetate

2.2. Hardware

Figure 2 represents the hardware component of the system. The MQ gas sensors were connected to an ADS1115 (Texas Instruments, Dallas, United States) a 16-bit analog-to-digital converter that was connected to the Raspberry Pi 4(Raspberry Pi Holdings PLC, London, UK) and an external power source. An SD card with a storage capacity of 64 GB

was used in the system. Raspberry Pi is a reliable microcomputer with acceptable accuracy and percentage error [17]. As an output device, an I2C 16 × 2 LCD was employed. The data collected by the MQ gas sensors were stored in the SD card. Previous studies showed the accuracy of the MOS sensor arrays of 75% for Pandan and 72% for Banaba [18]. A built-in 5 V exhaust fan was installed.

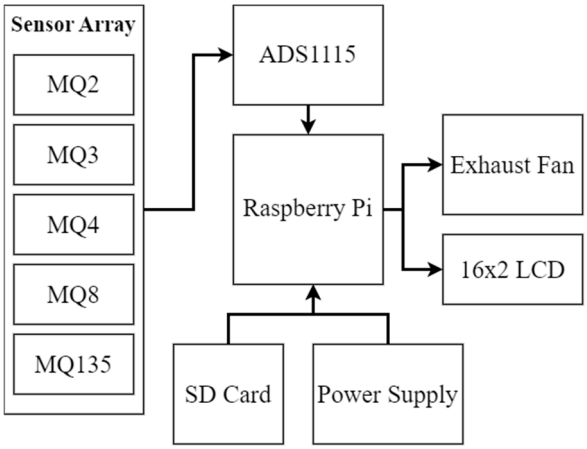


Figure 2. Hardware components of developed system.

2.3. Software Development

The e-Nose operated on the Raspberry Pi and sensors with software presented in Figure 3.

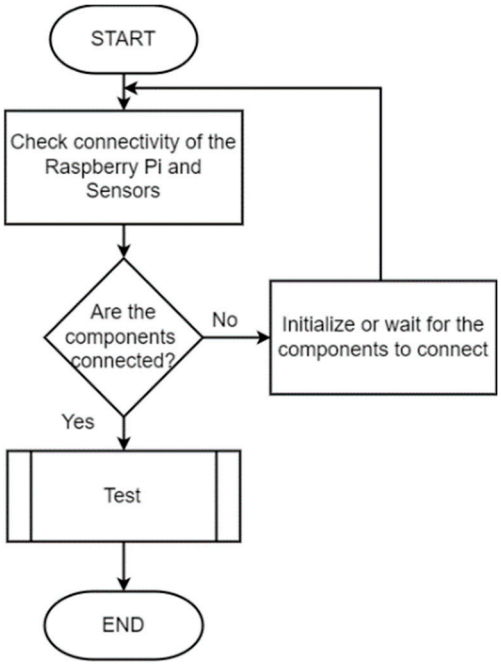


Figure 3. Software used in developed system.

Figure 4 shows the model training with data gathering. Samples were placed inside the gas chamber, and the data were collected and recorded in a .csv file format by the MQ sensors. The data was processed by LDA for feature dimension reduction. The reduced features were used for training. We used five features, and (1) was used to calculate the mean vector of each class denoted as μ, where N denotes the number of samples in class k,

ik represents the number of samples in class *k*, and x_i^k is a sample in class *k*. The equation of the step-by-step process of LDA to reduce features is (2).

$$\mu_k = \frac{1}{N_k}\sum_{i=1}^{N_k} x_i^k \tag{1}$$

$$\mu_k = \frac{1}{N}\sum_{k=1}^{K} N_k \mu_k \tag{2}$$

(3) was used to determine the scatter matrices for each class. The matrix was used to measure the scatterness of samples in each class. (4) was used to measure scatterness between the different class means. (5) was used to maximize the ratio of (3) and (4) by solving the generalized eigenvalue problem. In the equations, Λ represents the eigenvalues diagonal matrix, while *W* is the eigenvectors corresponding to the largest eigenvalues shown above. (6) was used to reduce the dimensionality while maintaining class separability.

$$S_w = \sum_{k=1}^{K}\sum_{i=k}^{N_k}\left(x_i^k - \mu_k\right)\left(x_i^k - \mu_k\right)^T \tag{3}$$

$$S_w = k = 1KNkuk - uuk - uT \tag{4}$$

$$S_W^{-1} S_B W = \Lambda W \tag{5}$$

$$Y = XW \tag{6}$$

We used the linear SVM algorithm to improve the system's accuracy. SVM was used to detect different classes of eczema, resulting in an accuracy of 83% [19]. SVM was also used to identify abnormal red blood cells, which yielded an accuracy of 83.3% [20]. SVM in this study was fed with the data that was dimensionally reduced by LDA. The trained LDA-SVM model classified the vinegar flavor after the LDA reduction (Figures 5 and 6).

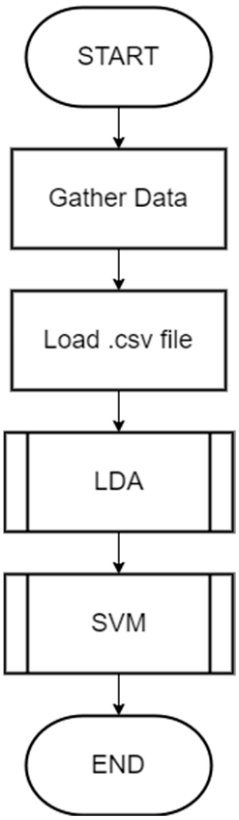


Figure 4. Model training flowchart.

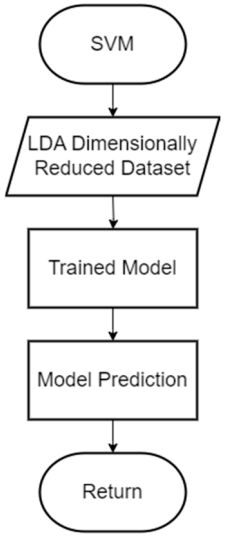


Figure 5. SVM training.

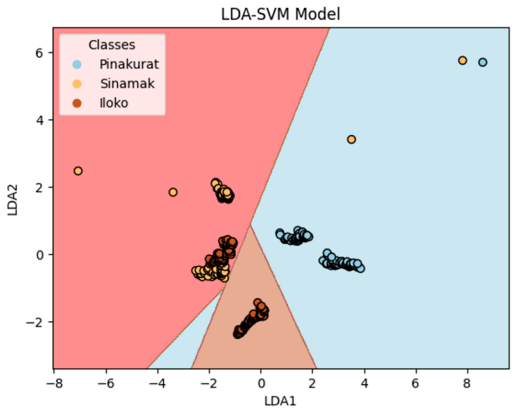


Figure 6. LDA–SVM model.

The LDA–SVM model classified Pinakurat, Iloko, and Sinamak vinegar (Figure 7).

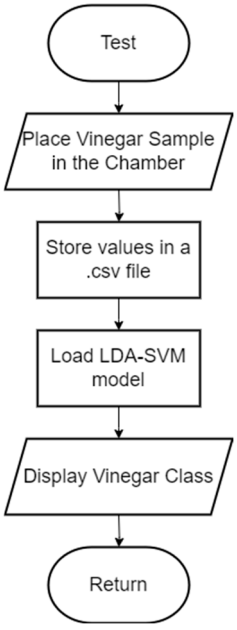


Figure 7. Model classification.

2.4. Experimental Setup

The experimental setup of the e-Nose is shown in Figure 8. The MQ gas sensor was attached to the chamber to ensure the gas contents of the sample were detected in the sealed chamber. The LCD displayed the classification result of vinegar. We used a real VNC viewer to monitor the behavior of the gas sensors and control the prototype. The classification of vinegar inside the chamber.

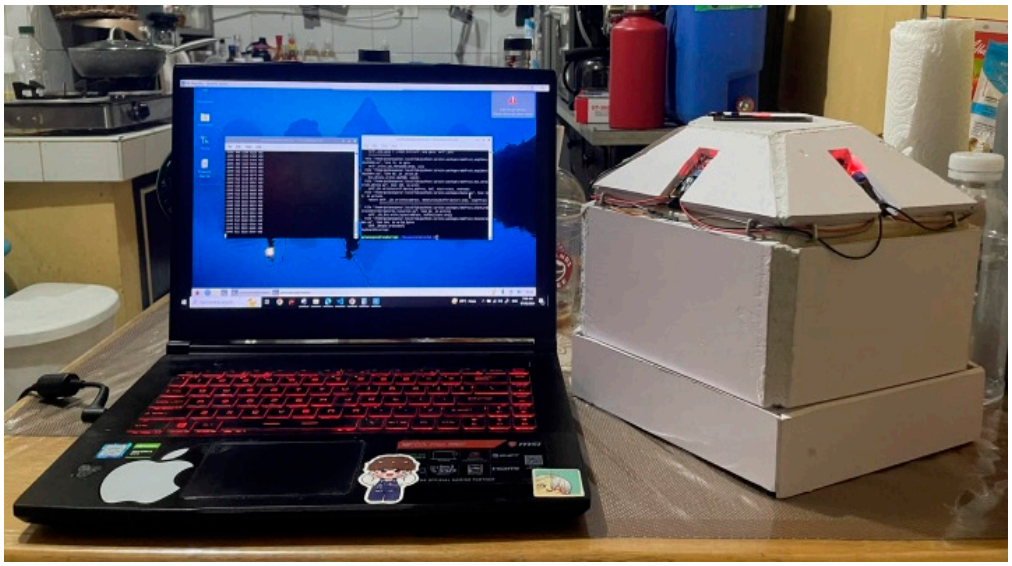


Figure 8. Experimental setup of e-Nose in this study.

3. Results and Discussion

3.1. Data

The collected data using the MQ sensors is presented in Table 2. Table 2 shows the features of vinegar flavors before LDA dimension reduction with five features.

Table 2. Sample Vinegar Data Before LDA Reduction.

Vinegar Flavor	MQ135	MQ8	MQ3	MQ4	MQ2
Pinakurat	881	5433	4748	5267	1425
Pinakurat	817	5449	4828	5395	1441
Iloko	1337	4534	3327	4227	1314
Pinakurat	881	5433	4748	5267	1425
Iloko	1353	4454	3151	4179	1346
Sinamak	127	1035	1603	1020	207
Sinamak	1934	5595	3629	5131	1771

Table 3 lists the dimension-reduced data. The remaining features were two and named LDA1 and LDA2.

Table 3. Sample Vinegar Data After LDA Reduction.

Vinegar Flavor	LDA1 Values	LDA2 Values
Pinakurat	−14.17041487	−0.570621815
Pinakurat	−16.22063184	0.46116660216968114
Iloko	5.371439689865838	−0.389170779
Iloko	6.710915978916585	1.2452827362266632
Sinamak	9.178909891882189	−1.125653828
Sinamak	9.129781152	0.37899708410468125

3.2. Statistical Analysis

The confusion matrix displays the overall count of accurate and inaccurate predictions made by the e-Nose employing the LDA–SVM model (Table 4). The table shows incorrect predictions regarding the Sinamak flavored vinegar. The testing data consisted of 108 samples which was 30% of the total samples. The Sinamak flavor had the most incorrect predictions, yielding 23 samples misclassified. The system's accuracy was calculated using (7). The accuracy was calculated as the sum of the true positives of the three classes divided by the sum of the true negatives. The model accurately classifies the flavored vinegar sample. The confusion matrix yielded 78.7% accuracy.

$$Accuracy = \sum_{\substack{i=1 \\ j=1}}^{3} \frac{A_{ii}}{A_{ij}} \quad (7)$$

Table 4. Confusion Matrix.

		Predicted			
		Sinamak	**Iloko**	**Pinakurat**	**Total**
Actual	**Sinamak**	13	0	23	
	Iloko	0	36	0	
	Pinakurat	0	0	36	
	Total				85

4. Conclusions and Recommendations

We classified flavored vinegar varieties using an e-Nose. The e-Nose distinguished Sinamak, Iloko, and Pinakurat Filipino vinegar. The LDA–SVM model showed an accuracy of 78.7%, demonstrating the effectiveness of the e-Nose. The Sinamak flavored vinegar showed the most incorrect classification. By using a nonlinear algorithm, higher accuracy can be obtained. More MQ sensors need to be used for better various gas detection. A smaller chamber at room temperature needs to be used to obtain better classification results. The dataset must be expanded to increase accuracy.

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