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Classification of Dark Condiment Sauces Through Electronic Nose Using Support Vector Machine †

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Abstract

Condiment sauces such as soy sauce, fish sauce, oyster sauce, and Worcestershire sauce play a vital role in culinary practices and cultural identity, particularly in the Philippines. These sauces are distinguished by their unique volatile organic compound profiles, which define their aroma and flavor. With the growing demand for these condiment products, there is an increasing need for accurate and efficient methods to classify them, ensuring product authenticity and strengthening quality control. However, conventional approaches such as sensory evaluation and laboratory-based chemical analysis are often expensive, time-consuming, and subjective. To address this limitation, we used an electronic nose (e-nose) system integrated with a Support Vector Machine (SVM) classifier for the classification of dark condiment sauces. The system consists of an array of MQ-series gas sensors connected to an Arduino Mega 2560 for analog-to-digital conversion, with Raspberry Pi 5 serving as the primary processing unit. Sensor data undergo preprocessing steps, including standardization and dimensionality reduction through principal component analysis, before being classified using SVM. A total of 120 samples, consisting of 40 readings per condiment type, were used for training and testing, while 60 additional samples—15 per class—were reserved for validation. The e-nose system achieved a 95% classification performance, as evaluated using a confusion matrix and overall accuracy metrics. These results demonstrate the potential of the e-nose combined with SVM as a reliable tool for condiment classification. The system offers practical applications in quality control and product authentication. Future work may extend its capabilities toward spoilage detection, the integration of different gas sensors, and the classification of a wider variety of condiment sauces.

Keywords: electronic nose; support vector machine; volatile organic compounds; machine learning; condiments

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1. Introduction

Condiments such as soy sauce, fish sauce, oyster sauce, and Worcestershire sauce are widely consumed across diverse cuisines and are valued for their fermented flavors and distinct aromas. In the Philippines, the condiment market continues to expand rapidly, reflecting the increasing demand and significance of these products [1]. With this growth, the need for accurate identification and classification of condiment types has become increasingly important. Condiments are primarily distinguished based on their aroma, which is strongly influenced by volatile organic compounds (VOCs). These compounds are commonly analyzed using electronic nose (e-nose) technologies [2].

Traditional analytical methods, including gas chromatography (GC) and mass spectrometry (MS), have been extensively employed for condiment classification. However, these techniques are time-consuming, costly, and less practical for efficient and reliable classification. In contrast, electronic nose systems provide a promising alternative by detecting volatile gases through sensor arrays and integrating with machine-learning algorithms for classification [3,4].

Based on these considerations, we developed an electronic nose system (e-nose) to classify soy sauce, fish sauce, oyster sauce, and Worcestershire sauce, using a Support Vector Machine (SVM) classifier. SVMs are supervised learning algorithms widely applied to classification, regression, and outlier detection tasks [5]. They are recognized for their ability to model complex data with high accuracy and reduced risk of overfitting [6]. The classification process involves identifying an optimal hyperplane that maximizes the separation between classes without intersecting data points [7,8]. This hyperplane is determined primarily by support vectors, a subset of training data that defines the decision boundary [9]. Given these strengths, SVM is integrated into the proposed system to classify condiment sauces based on their VOC patterns.

In this study, we designed and implemented an e-nose system using MQ gas sensors to detect and analyze VOCs emitted by dark condiment sauces. We applied principal component analysis (PCA) for dimensionality reduction and trained an SVM classifier. The e-nose system performance was evaluated using a confusion matrix and overall accuracy.

The developed e-nose system provides a reliable solution for condiment classification. The system offers a user-friendly alternative to traditional laboratory methods, enabling efficient product identification and quality control, particularly for small-scale producers and communities with limited access to formal testing facilities. Additionally, it provides utility for individuals with sensory impairments by offering a non-human-dependent means of condiment classification. Ultimately, the e-nose system contributes to the development of accessible food-quality control tools, promotes inclusive technological innovation, and advances the application of AI in the Philippine food sector.

2. Literature Review

E-nose systems emulate the mammalian olfactory system by detecting VOCs through gas sensors and applying classification algorithms [10,11]. They have been increasingly utilized in food quality assessment, particularly for monitoring aroma profiles. E-noses have demonstrated effectiveness in diverse applications, including odor detection, raw material inspection, quality assurance, and process management [12].

Caya et al. integrated an e-nose with SVM to classify coffee beans, achieving at least 70% accuracy [13]. Anticuando et al. employed an MQ-based e-nose with deep learning to identify tomato ripeness stages, reaching 86% accuracy [14]. Balbin et al. measured avocado VOCs at different ripening stages using a Raspberry Pi-based e-nose, obtaining 82% accuracy [15]. Gabriel et al. applied an MQ3-based e-nose with fuzzy logic to detect cantaloupe ripeness, successfully distinguishing gas concentration ranges for unripe, ripe, and overripe samples [16]. Armada and Manlises classified oregano, spearmint, and peppermint using fuzzy logic, achieving an overall accuracy of 84.44%, with individual accuracies of 100%, 73.33%, and 80%, respectively [17].

Capoquian et al. differentiated animal- and plant-based edible oils using an e-nose with an Extreme Gradient-Boosted Decision Tree (XGBoost) model, achieving 95.83% accuracy [3]. Pableo et al. employed PCA–SVM to classify local fish-meat types with 98.66% accuracy [7]; Bautista et al. classified alcoholic beverages using an e-nose and SVM with 90% accuracy [18].

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In condiment-related studies, Palanas et al. developed an e-nose with MQ sensors and a linear discriminant analysis–SVM model to classify flavored Filipino vinegars, achieving 78.7% accuracy despite challenges with small datasets and linear modeling [19]. Nimsuk applied a neural-network-based e-nose to discriminate fish sauces, reaching 90.28% accuracy [20], while Lelono et al. classified chili sauce quality grades using PCA, reporting 97.8% accuracy [21]. Despite these advances, research specifically targeting dark condiment sauces remains limited. These sauces are visually similar and often share overlapping aroma profiles, underscoring the need for specialized classification systems.

3. Methodology

3.1. Conceptual Framework

Figure 1 illustrates the workflow of the e-nose system developed to classify soy sauce, fish sauce, oyster sauce, and Worcestershire sauce based on their emitted VOCs. The system input consists of gases released from condiment samples placed in a sealed chamber to ensure consistent collection. These emissions are detected by a gas-sensor array, which serves as the foundation of data acquisition. The process begins with the e-nose capturing analog signals generated by the detected gases. These signals are subsequently converted into digital form using an analog-to-digital converter, producing a dataset for further analysis. Preprocessing involves two steps: first, standardization is applied to normalize sensor responses; second, PCA is performed to reduce the dimensionality of the dataset. The preprocessed data are then input into an SVM classifier, a supervised learning algorithm well-suited for high-dimensional classification tasks. The SVM model is trained to recognize VOC patterns and accurately associate them with the corresponding condiment type. The final system output is the predicted classification of the sample, which is displayed on an LCD touchscreen interface, providing users with a clear and interpretable result based solely on the volatile compounds emitted.

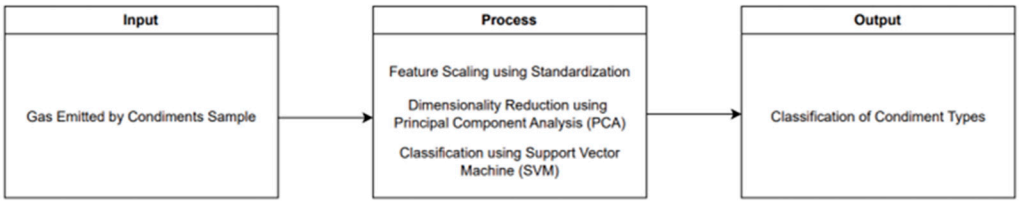


Figure 1. System workflow.

3.2. System Component

Figure 2 illustrates the interconnection of hardware components in the proposed e-nose system. The condiment samples are placed in a sealed container to allow the natural emission of VOCs, which are then introduced into a sensor chamber housing a gas-sensor array composed of MQ-series sensors, namely MQ2, MQ3, MQ135, MQ136, MQ137, and MQ138. Each sensor is sensitive to different groups of gases, and when used together, they show a characteristic VOC pattern that reflects the composition of each condiment type. The specific gas sensitivities of the sensors are listed in Table 1.

The gas sensors generate analog voltage signals proportional to the concentration levels of the detected gases. As the Raspberry Pi 5 (Pencoed, UK, Raspberry Pi) lacks native analog-input capability, the Arduino Mega 2560 (Turin, Italy, Arduino) is employed as an interface for the sensor array due to its ease of use and availability of multiple analog input pins. The Arduino performs analog-to-digital conversion and transmits the digitized data to the Raspberry Pi via serial communication. The firmware for analog-to-digital conversion was developed and uploaded using Arduino IDE version 2.3.6. As the primary computational unit, the Raspberry Pi 5 executes data preprocessing, dimensionality reduc-

tion through Principal Component Analysis (PCA), and condiment classification using a Support Vector Machine (SVM) model. A 5-inch LCD touchscreen display connected to the Raspberry Pi presents the classification results to the user. To ensure accurate and consistent sensing conditions, an exhaust fan is integrated into the sensor chamber to purge residual VOCs between measurements, thereby minimizing cross-sample contamination. Independent power supplies are used for the Arduino Mega 2560 and the Raspberry Pi 5 to maintain stable operation across all hardware components and prevent electrical interference.

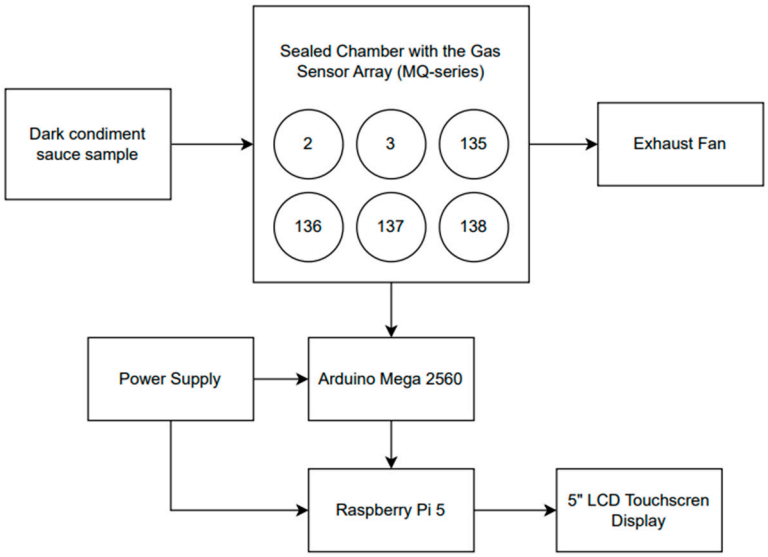


Figure 2. System components.

Table 1. MQ sensors used in this study.

MQ Sensor	VOCs
MQ2	Hydrocarbons, combustion gases
MQ3	Alcohols
MQ135	Amines, alcohols, aromatics
MQ136	Sulfur compounds
MQ137	Fermentation volatiles
MQ138	Ketones, aldehydes, aromatics

3.3. Software

Figure 3 illustrates the step-by-step procedure of the main software flow for the proposed electronic nose (e-nose) condiment classification system. The process begins with the capture of analog readings from the MQ gas sensors through the Arduino Mega 2560, which functions as the analog-to-digital converter. The digitized data are then transmitted to the Raspberry Pi 5 for preprocessing and analysis.

During preprocessing, feature scaling through standardization is applied to the collected dataset. Standardization ensures that each sensor feature has zero mean and unit variance, allowing all variables to contribute equally to the classification process regardless of their original scales. Without this step, features with larger numeric ranges may dominate, potentially introducing bias and degrading the performance of algorithms such as the SVM classifier. Standardization also enhances the effectiveness of PCA by enabling the model to capture genuine variance rather than scale-driven differences.

Following standardization, the dataset undergoes dimensionality reduction using PCA. PCA reduces the number of correlated input variables by extracting principal components

that capture the most significant variance in the dataset while minimizing information loss. This step improves classification efficiency and strengthens the SVM's ability to identify subtle VOC pattern differences among condiment types, particularly under high-dimensional input conditions. After dimensionality reduction, the preprocessed data were input to the classify_svm() function, which used a trained support vector machine (SVM) classifier model to classify condiment sauces. It was trained using Python 3.12.10 in Visual Studio Code version 1.113.0, utilizing the scikit-learn library for machine learning integration, along with NumPy and pandas for data processing. The model analyzes the preprocessed data and assigns each sample to its corresponding condiment class. The classification output is then returned to the main program and displayed on the LCD touchscreen interface, providing users with a clear and interpretable result of the identified condiment type. The graphical user interface (GUI) for the system was developed using Tkinter 8.6.

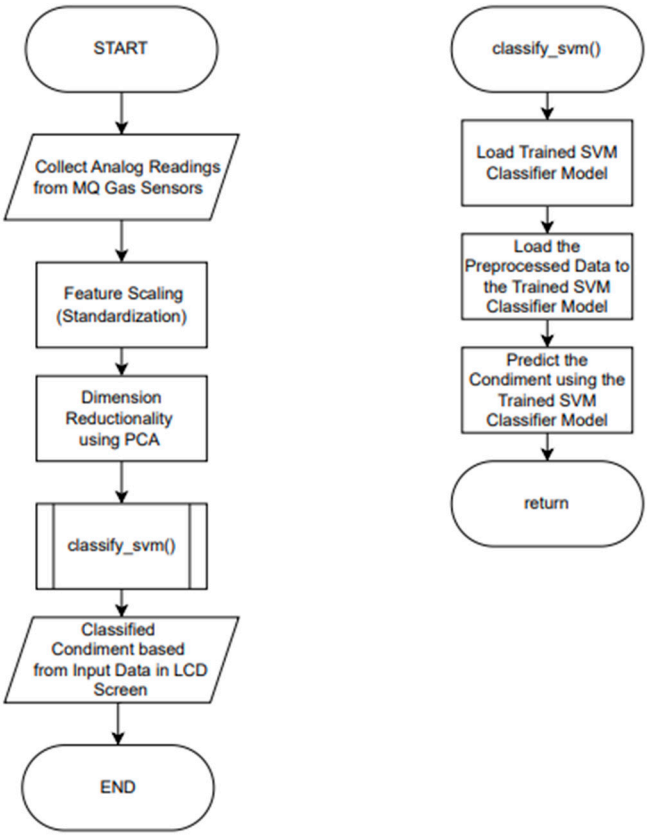


Figure 3. System software flowchart.

3.4. Experimental Setup

Figure 4 presents the experimental procedure for classifying condiment samples using the electronic nose system, designed to ensure accuracy and repeatability. Before the experiment, all MQ gas sensors underwent a one-time, one-hour burn-in calibration during which each sensor remained powered. This initial step stabilizes sensor performance and ensures consistency across subsequent measurements.

Each condiment sample was measured at 10 mL for uniformity and placed in a 15 mL medicine cup inside a sealed sensor chamber maintained at room temperature. Once positioned, the sample remains in the chamber for 10 min, allowing VOCs to interact with the gas sensors. Analog outputs from the MQ sensor array are acquired through the Arduino Mega 2560, which performs analog-to-digital conversion and transmits the digital readings to the Raspberry Pi 5. The Raspberry Pi 5 functions as the main computational

unit, executing preprocessing and analysis. These stages include standardization and dimensionality reduction using PCA, followed by classification with an SVM model to determine the corresponding condiment type. The classification output is displayed on a 5-inch LCD touchscreen connected to the Raspberry Pi 5.



Figure 4. Experiment and samples used in this study.

After each trial, the chamber was purged for 20 min using an exhaust fan to remove residual gases and restore neutral air conditions. This step minimizes cross-sample contamination and ensures sensor consistency between tests. All experiments are conducted in an isolated, room-temperature-controlled environment to maintain measurement accuracy and repeatability.

Figure 5 shows the condiment samples used in the study, which include soy sauce, fish sauce, oyster sauce, and Worcestershire sauce. Each sample was commercially sourced from local supermarkets to ensure consistency and represent commonly available consumer products. The brands selected were Kikkoman (soy sauce; Kikkoman Corporation, Chiba, Japan), Lorins Patis (fish sauce; Lorenzana Food Corporation, Sto. Tomas City, Philippines), Lee Kum Kee (oyster sauce; Lee Kum Kee (XinHui) Food Co., Ltd., Jiangmen City, Guangdong, China), and Lea & Perrins (Worcestershire sauce; Lea & Perrins, Worcester, UK). These brands were chosen based on their availability and popularity in the local market, ensuring that the system was trained using representative condiments commonly encountered by consumers.



Figure 5. Condiment sauces used in the experiment.

3.5. Data Collection

Table 2 summarizes the total quantities of VOC data collected from soy sauce, fish sauce, oyster sauce, and Worcestershire sauce. For each condiment type, 30 samples were prepared, yielding 120 samples in total. An additional 60 samples (15 per condiment type) were prepared specifically for validation, resulting in a complete dataset of 180 samples. Each sample was labeled according to its condiment type, and these labels were used during the training, testing, and validation stages of model development.

Table 2. Dataset for training and evaluation of the model.

Condiment	Number of Samples		
	Training	Testing	Validation
Soy sauce	21	9	15
Fish sauce	21	9	15
Oyster sauce	21	9	15
Worcestershire sauce	21	9	15
Total	84	36	60

From the 120 initial sample readings, the dataset was divided into a ratio of 70:30, with 70% allocated for training and 30% for testing. During data collection, the analog outputs generated by the MQ-series gas sensors (MQ2, MQ3, MQ135, MQ136, MQ137, and MQ138) were transmitted to the Arduino Mega 2560, which performed analog-to-digital conversion and forwarded the digitized readings to a desktop computer via serial communication. The Arduino Integrated Development Environment was used to program the Arduino Mega 2560, enabling sensor initialization, data acquisition, and continuous transmission of readings for subsequent processing and storage.

The desktop computer was used for storing the received data in CSV format and for model development, training, and testing. Once the classifier achieved satisfactory accuracy and stability, the finalized model was deployed to the Raspberry Pi 5 for system integration, providing a compact and efficient condiment classification system.

4. Results and Discussion

Figure 6 displays the classification output on the 5-inch LCD touchscreen of the e-nose system. The interface presents the predicted condiment class derived from processed sensor readings transmitted from the Arduino Mega 2560 to the Raspberry Pi 5. The output corresponds to one of the condiments included in this study, based on data collected during the ten-minute sampling process. Each validation sample is processed through the same workflow used during model training, which includes signal acquisition, standardization, PCA transformation, and classification using the trained SVM model. The system operates within the range of room temperature to ensure consistent VOC emission and stable sensor response throughout testing.

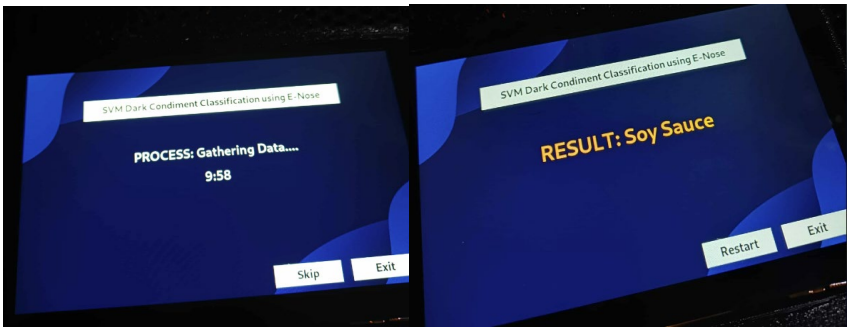


Figure 6. Output of the e-nose prototype.

Table 3 presents the confusion matrix generated from the SVM classifier output to evaluate classification performance across the four condiment types. A total of 60 validation samples were used, with 15 samples per class. The diagonal entries represent correctly classified samples, while off-diagonal entries denote misclassifications. The classifier correctly identified 15 soy sauce samples, 14 fish sauce samples, 13 oyster sauce samples,

and 15 Worcestershire sauce samples. Two oyster sauce samples were misclassified as fish sauce, and one fish sauce sample was misclassified as oyster sauce.

Table 3. Confusion matrix.

Predicted Labels	Actual Labels			
	Soy Sauce	**Fish Sauce**	**Oyster Sauce**	**Worcestershire Sauce**
Soy sauce	15	0	0	0
Fish sauce	0	14	1	0
Oyster sauce	0	2	13	0
Worcestershire sauce	0	0	0	15

Table 4 summarizes the classification results derived from the confusion matrix. Among the 60 validation samples, the SVM classifier correctly predicted 15 soy sauce samples, 14 fish sauce samples, 13 oyster sauce samples, and 15 Worcestershire sauce samples. These results are based on comparisons between predicted and actual condiment labels obtained during validation.

Table 4. Classification results.

Classification	Number of Samples	Number of Accurate Prediction
Soy sauce	15	15
Fish sauce	15	14
Oyster sauce	15	13
Worcestershire sauce	15	15
Accuracy	95%	

The overall classification accuracy was computed using Equation (1), which defines accuracy as the ratio of correctly predicted samples to the total number of predictions. In this equation, A_{nn} represents the sum of True Positives (TP), referring to samples correctly identified as their actual class, while A_{ij} accounts for the total number of predictions, including both True Positives (TP) and False Positives (FP). Applying this equation to the data in Table 4 yields an overall accuracy of 95%, indicating that the developed SVM classifier effectively distinguished between the four dark condiment types.

$$\text{Accuracy} = \frac{\sum_{n=1}^{4} A_{nn}}{\sum_{j=1}^{4} \sum_{i=1}^{4} A_{ij}} \quad (1)$$

5. Conclusions and Recommendations

The developed e-nose system, integrated with machine learning, accurately classified dark condiment sauces. The combination of the e-nose and SVM modeling achieved a classification accuracy of 95%, as validated through the confusion matrix and overall accuracy computation. These findings confirm that the system provides a reliable approach for condiment classification, demonstrating strong potential for applications in quality control and product authentication within the food industry. It is required to enhance system functionality by incorporating spoilage detection to assess product quality over time, integrating additional or alternative gas sensors to improve sensitivity and better differentiate overlapping VOC patterns, and expanding the classification scope to include a wider range of condiment sauces.

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