Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 9, No. 5, October, 2025

Odor Profiling of Blood Shells Using TGS Gas Sensor and PCA-SVM Analysis

Suryani Dyah Astuti [1*], Nobuo Funabiki [2], Soegianto Soelistiono [1], Winarno [1], Deny Arifianto [3], Nadia Nur Ramadhani [1], Perwira Annissa Dyah Permatasari [1], Ahmad Khalil Yaqubi [1], Yunus Susilo [4], Ardiyansyah Syahrom [5]

[1] *Faculty of Science and Technology, Airlangga University, 60115, Surabaya, Indonesia.*

[2] *Department of Electrical and Communication Engineering, Okayama University, 60115, Okayama, Japan.*

[3] *Department of Engineering, Faculty of Vocational, Airlangga University, Surabaya, Indonesia.*

[4] *Faculty of Engineering, Universitas Dr Soetomo Surabaya, Surabaya, 60118, Indonesia.*

[5] *Medical Devices and Technology Centre, Universiti Teknologi Malaysia, 81310, Johor, Malaysia.*

Abstract

Blood cockles (*Andara granulosa*) are among the most popular animal protein sources due to their rich nutritional content and high economic value. The storage period and temperature are two critical factors that significantly influence the freshness of blood cockles. One key indicator of blood cockle quality is the odor they emit. An unpleasant or inappropriate odor can indicate contamination or a decline in quality, posing potential food safety risks. However, conventional methods of odor quality testing are often subjective, require specialized skills, and may not always be reliable. To address the limitations of human olfaction, advancements in gas sensor technology, specifically gas array sensors (also known as the electronic nose), have been developed. This research aims to profile the freshness of blood cockles by identifying their odor under different storage conditions using electronic nose technology. The study used fresh blood cockle meat, which was stored under varying temperature conditions: at room temperature, in a cooler, and in a freezer. The storage periods for the samples were 1, 2, 3, 4, and 5 days. The samples were placed in sealed bottles and tested using a gas array sensor. The data collected from this process were in the form of voltage readings, which were analyzed using machine learning techniques, specifically Principal Component Analysis (PCA). The data were then classified using a Support Vector Machine (SVM) model. The study results showed that the gas array sensor successfully classified the odor profiles, with PCA explaining 93.83% of the variance in the data. The SVM model achieved an accuracy of 89.66% for PCA-reduced data and 91.44% for non-PCA data.

Keywords:
Blood Cockles;
Electronic Nose;
PCA;
SVM;
Shelf Life;
Temperature.

Article History:

Received:	02	March	2025
Revised:	18	July	2025
Accepted:	28	August	2025
Published:	01	October	2025

1- Introduction

Shellfish are a popular source of animal protein enjoyed by people across all levels of society due to their delicious, savory taste and abundant nutritional content. Blood cockles (*Anadara granosa*) are a type of shellfish widely available in the market, valued for their nutritional and economic benefits. The nutritional content of blood cockles includes essential minerals such as calcium, phosphorus, iron, iodine, zinc (Zn), and selenium. They are also rich in vitamins like A, D, E, and K, and the B-complex vitamins (B1, B2, B6, and B12), with a protein content of up to 26 grams per 100 grams [1].

* **CONTACT**: suryanidyah@fst.unair.ac.id

DOI: http://dx.doi.org/10.28991/ESJ-2025-09-05-017

Previous studies have applied e-nose technology in food quality assessment, including meat freshness evaluation, spoilage detection, and bacterial contamination analysis [2]. However, research specifically focusing on blood cockles remains limited, particularly in developing robust pattern recognition models for classifying odor profiles under varying storage conditions. Several studies have demonstrated the effectiveness of PCA-SVM models in classifying odors in perishable foods, achieving high accuracy levels [3]. One study analyzing the effects of shelf life and temperature variations on chicken meat using a gas sensor array achieved a test accuracy of 98.70% [4]. Another study on seafood freshness assessment reported that PCA-SVM could successfully differentiate between fresh and spoiled samples with an accuracy exceeding 95% [5]. This study aims to bridge the gap by applying a PCA-SVM approach to classify blood cockle odor profiles based on gas sensor data, considering different storage times and temperature conditions. By utilizing six TGS sensors (TGS2600, TGS2602, TGS2611, TGS2612, TGS2620, and TGS826), this research provides a systematic method for blood cockle freshness evaluation, which could enhance food safety and quality control in seafood industries.

The quality of blood cockles is highly dependent on environmental factors such as habitat, water quality, and post-harvest handling methods. However, the freshness and quality of blood cockles sold in supermarkets are not always guaranteed. One critical indicator of blood cockle quality is the aroma they produce. An inappropriate aroma may signal contamination or decrease quality, potentially compromising food safety, as blood cockles are highly susceptible to spoilage. Moreover, storage time and temperature influence the product's quality [6].

Shellfish quality assessment methods still rely on sensory evaluations based on appearance, texture, smell, and colour. Traditionally, the human nose has been used to assess the freshness of shellfish by detecting their smell and physical inspection. However, human olfaction has limitations, particularly regarding standardization, as the evaluation is subjective and can vary from person to person [7]. Advancements in sensor technology have led to the development of the Electronic Nose (e-nose) system, which allows for the early detection of the quality and freshness of blood cockles. Research and development in e-nose applications have increased rapidly, offering solutions to various biomedical challenges and serving as an effective tool for distinguishing volatile substances [8].

The Electronic Nose (e-nose) is a device that mimics the function of the human nose and can detect and recognize odors through a sensor array [9]. It uses an array of gas sensors to substitute for olfactory receptors, which detect smells or aromas and generate specific patterns [10]. These devices employ susceptible sensors to detect volatile substances, and they utilize pattern recognition methods, providing a higher level of selectivity and reversibility in the system and making them applicable to a wide range of fields [11]. Numerous data analysis techniques have been developed to process the data generated by the e-nose. This review explores analytical aspects, from data normalization to pattern recognition and classification techniques [12]. In practice, the e-nose collects data from various volatile compounds, which interact with molecules and are analyzed through pattern recognition [13]. The e-nose offers several advantages: non-destructive, real-time, fast, versatile, safe, and cost-effective. The e-nose system comprises four main components: the gas sensor array, headspace system, data acquisition, and pattern recognition unit [14, 15].

The gas sensor commonly used in e-nose systems is the Metal Oxide Semiconductor (MOS) type, specifically the Taguchi Gas Sensor (TGS). The TGS sensor is designed to detect pollutant gases in the air, such as carbon monoxide, hydrocarbons, and nitrous oxide [16]. The TGS sensor comprises three parts: the sensing element, the sensor base, and the sensor cap. The sensing element is typically metal oxide, such as Figaro Engineering Inc. [17].

There are two processes in the headspace system: the sensing process and the purging process. In the data acquisition system, a microcontroller integrates the main components with a microcomputer [18]. For the pattern recognition process, various methods are employed, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Partial Least Squares (PLS), Multiple Linear Regression (MLR), and Cluster Analysis (CA). Artificial neural network (ANN) methods are also used, such as multilayer perceptron (MLP), fuzzy inference systems (FIS), self-organizing map (SOM), radial basis function (RBF), genetic algorithms (GAs), neuro-fuzzy systems (NFS), and adaptive resonance theory (ART) [19].

The sensors included TGS 2600, 2612, 2611, 2602, 2620, and 826, each providing different information [20]. The TGS 2600 sensor detects hydrogen and carbon monoxide, while the TGS 2602 can detect ammonia and hydrogen sulfide (H_2S). TGS 2611 is used to detect methane, TGS 2612 detects methane, propane, and butane, TGS 2620 is designed to sense volatile organic compounds (VOCs), and TGS 826 is used for ammonia detection [21]. The response patterns produced by these sensors are used to assess the quality of blood cockles infected with Vibrio sp. bacteria under varying storage times at room temperature.

The characteristics of voltage responses are studied to predict target groups that share similar properties. The Principal Component Analysis (PCA) method transforms the original variables, which are correlated with each other, into a smaller set of uncorrelated variables without losing significant information [22]. The data collected by the e-nose typically exists in high-dimensional space due to using a relatively large number of gas sensors, and several signal characteristics are extracted [23]. Each measurement is multivariate or observational. The primary goal of this method is to reduce the dimensions of interconnected variables, making it easier to interpret the data [24].

In this study, pattern recognition for blood cockle samples was carried out using the Support Vector Machine (SVM) method. SVM is a machine learning technique based on the principle of Structural Risk Minimization (SRM), which aims to find the optimal hyperplane that separates two classes within the input space. Its evaluation in various applications has established SVM as a state-of-the-art method in pattern recognition. The measurement data, extracted using PCA, serves as the input for the SVM process.

This paper begins by outlining the experimental setup and the techniques used to collect and analyze data. It then presents the results, focusing on the classification of odor patterns and the performance of the PCA-SVM model in evaluating the freshness of blood cockles. Following the results, the discussion compares these findings with previous research, highlighting their significance and any limitations. The paper concludes by summarizing the key discoveries and proposing directions for future research in this area. This research employed the PCA-SVM method with six types of TGS sensors: TGS2600, TGS2602, TGS2611, TGS2610, TGS2620, and TGS826. Odor cluster analysis using a gas sensor array to study the effects of shelf life and temperature variations on chicken meat, achieving a test accuracy of 98.70%. This study aims to analyze the data patterns from the gas sensor array in the Electronic Nose (E-Nose) and classify the odor profiles of blood cockles using the Principal Component Analysis (PCA) and Support Vector Machine (SVM) methods.

2- Material and Methods

2-1- Electronic Nose (E-nose) Technology

The E-nose simulates human olfactory perception using an array of gas sensors to detect volatile organic compounds (VOCs) released by the samples. In this case, the E-nose detects the gases emitted by the blood clams under various storage conditions. The sensors' responses to these VOCs are translated into data, providing a "smell" profile that can be analyzed to determine freshness.

2-2- Sensor Response and Calibration

The first step in data analysis involves calibrating the E-nose system. This ensures that the sensors respond accurately and reliably to known gas concentrations (H_2S gas in this case). Calibration is critical to the success of the E-nose method, as it establishes a baseline for sensor accuracy and precision. By evaluating the recovery rate and repeatability, the study ensures that the sensor data reflects the actual gas emissions from the clams without significant error.

2-3- Dimensionality Reduction (PCA)

The sensor data is processed using Principal Component Analysis (PCA), which is a statistical method that reduces the complexity of the data by identifying the main components or features that explain most of the variation in the data. PCA helps in visualizing and interpreting high-dimensional data, making it easier to identify trends or patterns in the odors emitted by the clams under different conditions.

2-4- Classification with Support Vector Machine (SVM)

After feature extraction through PCA, the data is classified using Support Vector Machine (SVM), a supervised machine learning algorithm. SVM helps in categorizing the blood clams into two groups: fresh and non-fresh, based on the extracted odor features. This classification approach allows the study to distinguish between the different stages of freshness, which is crucial for assessing food quality.

2-5- Applications and Practical Implications

This methodology has important applications in food quality monitoring, particularly in ensuring the freshness of seafood products. The combination of temperature and storage time variations simulates real-life conditions, making the research applicable to the food industry, where rapid, non-invasive freshness detection can lead to better inventory management, reduced waste, and improved consumer safety.

2-6- Sample Preparation

Blood clams purchased directly from fishermen were prepared in 1 kilogram. The shells were cleaned and opened to examine the shellfish's shape, colour, and texture. The clams were divided into three samples, each stored at different temperatures: 4°C, 12°C, and 25°C. Each sample was tested using an electronic nose, with data collected from 50 samples simultaneously.

2-7- Electronic Nose Set-up

In this research, the primary tool in the electronic nose gas array sensor system is located in the tube box. The E-nose tool will be combined with other components when data collection is carried out. Then, the PC is connected to the cable in the E-nose box. An illustration of the research tool setup can be seen in Figure 1.

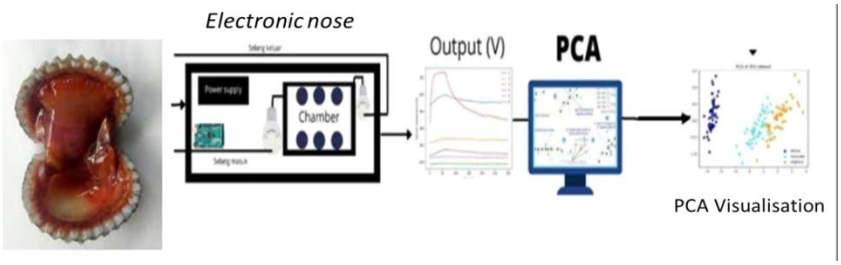


Figure 1. Set up of research tools

The total warm-up time is 20 minutes at a temperature of 50°C. Sample preparation takes 5 minutes, followed by 10 seconds for baseline measurement and 2 minutes for sensing. The purging stage lasts 250 seconds. These settings are configured using the PC's gas sensor array interface software. The samples used are fresh blood clams, with variations in temperature and storage time, and data are collected from 50 samples at each time interval. A plastic flexible tube connected to the sensor is attached to a glass beaker, each containing a sample. The beakers are covered with aluminium foil to prevent contamination from external air.

2-8- Data Testing and Analysis

The experimental procedure involved two stages: calibration measurements and biological sample analysis. Calibration was conducted using known H_2 S gas concentrations to evaluate sensor accuracy and precision. Accuracy was tested through recovery analysis (% recovery), ensuring results fell within a 10% tolerance, while precision was assessed using repeatability tests to calculate the relative standard deviation (RSD). For biological samples, fresh blood cockles were tested under time variations (1–5 days) and temperature variations (4°C, 12°C, and 25°C). Sensor responses, recorded as voltage data, were processed using Principal Component Analysis (PCA) for feature extraction and dimensionality reduction. Radar charts visualized the sensor data, and Support Vector Machine (SVM) classified the samples into fresh and non-fresh groups. This approach ensured accurate and reliable analysis of the samples.

3- Results

3-1- Sample Testing

The sensing process begins with a pre-heating stage to stabilize the gas sensor array, ensuring consistent performance in clean air conditions [25]. Each sensor requires a pre-heating duration of 900 seconds (15 minutes), during which it stabilizes to reach a consistent value. Figure 2 illustrates the pre-heating graph for each sensor. While this process ensures device stability, it is a preparatory step unrelated to the main experimental procedures. As such, details about the pre-heating process may be better suited for inclusion in the supporting materials.

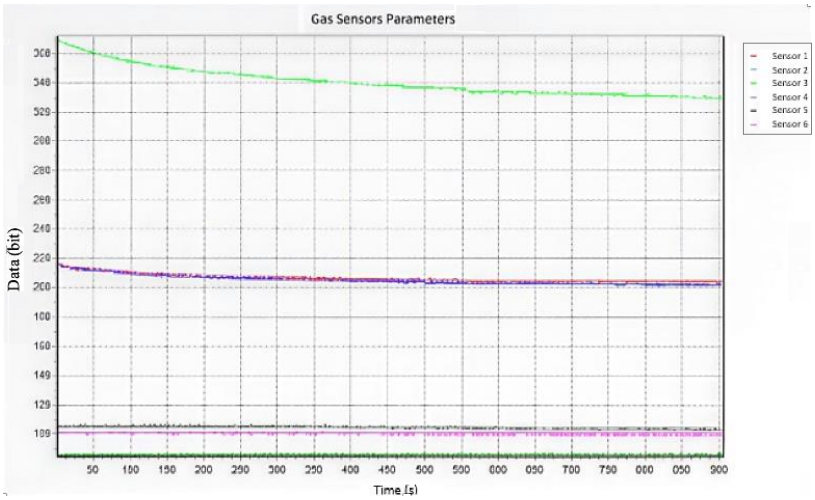


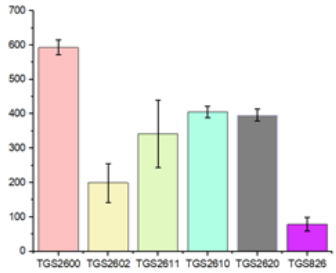
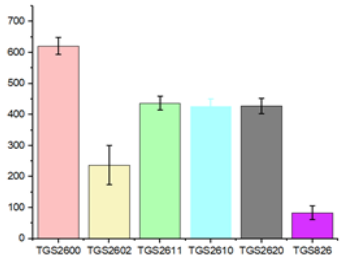
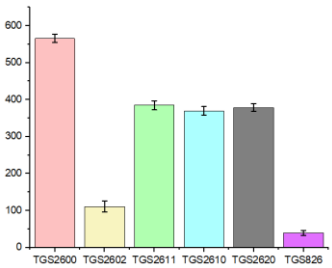
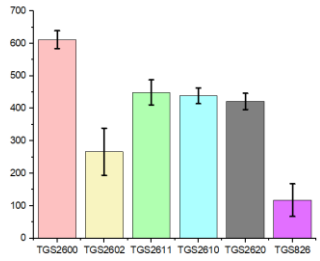
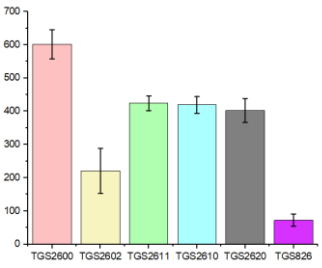
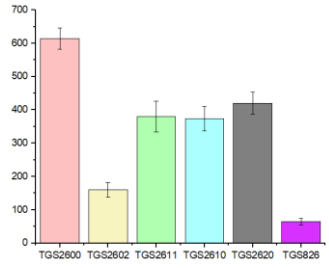
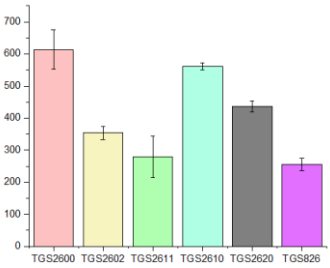
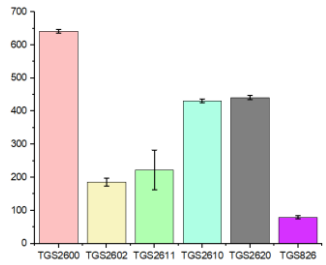
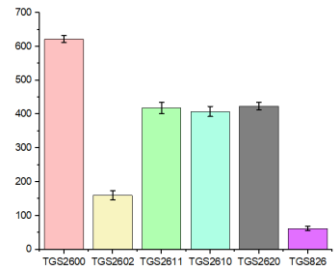
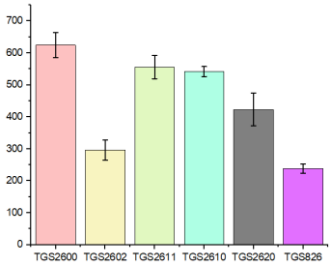
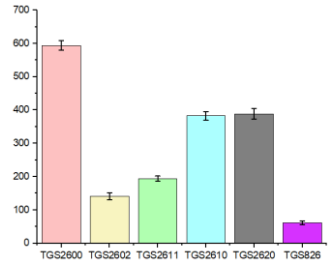
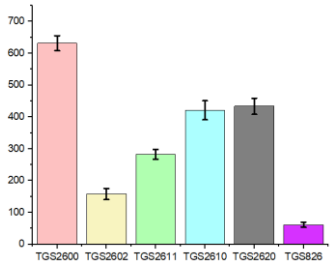
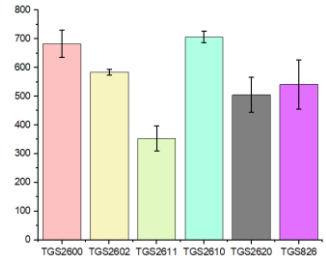
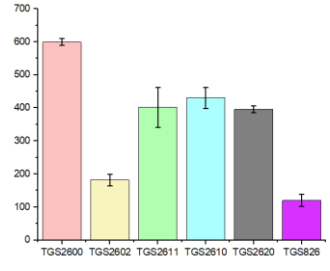
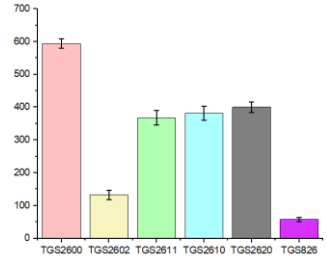
Figure 2. Image of Pre-Heating Sensor

3-2- Electronic Nose Sensor Response Test Results for Samples

In the sensing process using a gas array sensor, the odor produced by each blood cockle sample leads to different voltage responses based on temperature and storage time variations. The research involved testing samples at three different temperature settings: 25°C, 12°C, and 4°C, and five different storage times: 1 day, 2 days, 3 days, 4 days, and 5 days. For each variation, 50 data repetitions were collected over 6 minutes and 50 seconds. The results showed different gas array responses for each treatment. Specifically, the sensor response decreased as the storage temperature of the shellfish decreased.

Conversely, the sensor response increased with longer storage times. These results indicate that blood cockle samples can be differentiated based on the pattern of sensor responses resulting from each treatment. The response results of the gas array sensor for the 15 different treatments are presented in Table 1. At 25°C, the samples deteriorated the fastest, with the sensor response rising quickly over time. At 12°C and 4°C, spoilage occurred more slowly, with lower sensor responses observed throughout the study. The sensor effectively differentiated the freshness of samples based on their temperature and storage time. These findings demonstrate that the electronic nose (E-nose) is a useful tool for monitoring the freshness of blood cockles, with potential applications in food quality control and inventory management.

Table 1. Sensor response results

Shelf life	Sample		
	25ºC	12ºC	4ºC
1 Day			
2 Days			
3 Days			
4 Days			
5 Days			

3-3- TGS Gas Sensor Sensitivity Results

The array of gas sensors comprises several TGS, each calibrated for specific gas sensitivities. The response of each sensor is represented by voltage changes relative to its baseline in clean air, as recommended by the sensor manufacturer. In experiments with blood cockle samples, the TGS 826 gas sensor demonstrated the most significant response in distinguishing samples under different temperature variations. Similarly, the TGS 2610, 2602, and 2611 sensors distinguished samples. In contrast, the TGS 2600 and 2620 sensors were less effective, with the TGS 2620 failing to differentiate among samples. Figure 3 illustrates the relative responses of TGS 2600, 2602, 2611, 2620, 2610, and 826 sensors to the gases emitted by blood cockle samples under varying conditions.

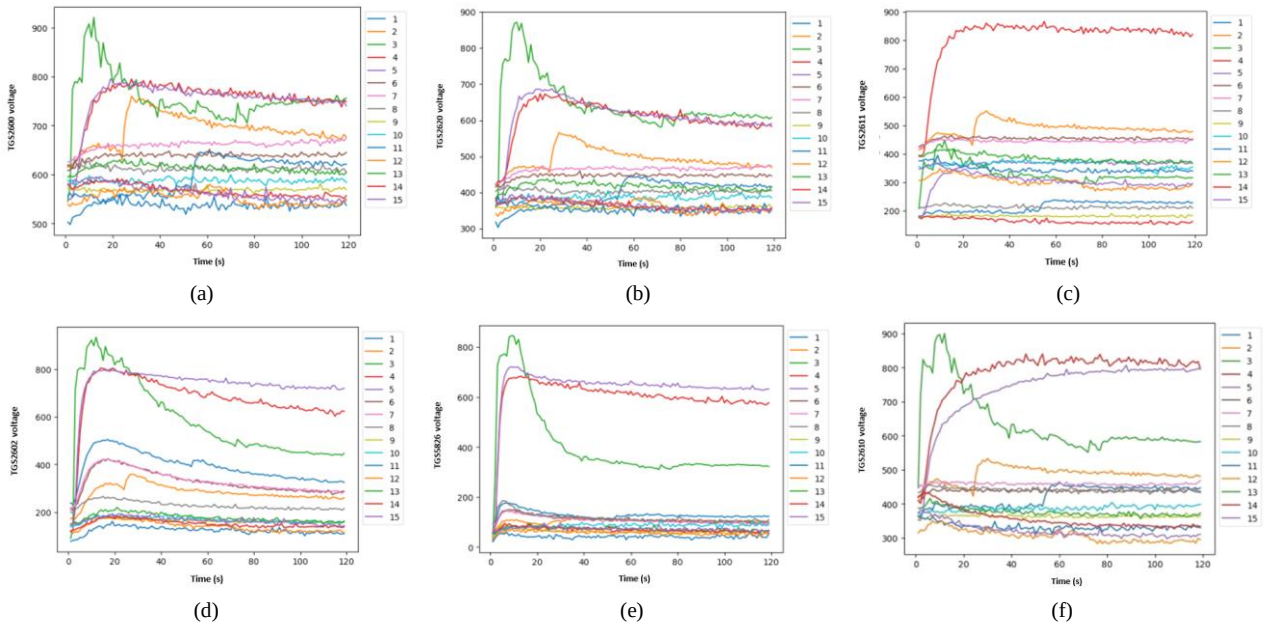


Figure 3. Sensitivity of gas sensors (a) TGS2600, (b) TGS2620, (c) TGS2611, (d) TGS2602, (e) TGS826, (f) TGS2610

The TGS 826 sensor showed the most significant and consistent response, making it the most reliable for distinguishing blood cockle samples at various temperatures. It is sensitive to the volatile organic compounds (VOCs) released during spoilage. The TGS 2610, 2602, and 2611 sensors also distinguished the samples, but their responses were less pronounced, indicating lower sensitivity to the specific VOCs emitted by the cockles. In contrast, the TGS 2600 and 2620 sensors were less effective, with the TGS 2620 failing to differentiate among the samples, suggesting it is less sensitive to the gases emitted by the blood cockles.

3-4- Sensor Validation Test Results

Hydrogen sulfide (H_2S) gas is a key indicator produced during the decomposition of shellfish, making it a critical target for sensor evaluation. The response of TGS 2602 and TGS 826 sensors to H_2S was tested using concentrations of 1 ppm, 2 ppm, 3 ppm, 4 ppm, and 5 ppm. Repeated measurements were conducted to assess accuracy, defined as a recovery value within 90%-110%. These results, presented in Table 2, validate the sensor's performance in detecting H_2S under controlled conditions. However, additional details about the setup and methodology for these measurements are absent in the materials and methods section. To address this gap, the experimental protocol for this test should be described in detail, including how these results supplement or verify the manufacturer's specifications.

Table 2. Table of H2S Accuracy Test Results

Concentration	Concentration based on voltage linearity		Recover percentage (%)	
	TGS2602	TGS826	TGS2602	TGS826
1 ppm	0.9598	1.0103	95.899%	101.037%
2 ppm	1.9859	2.0143	99.297%	100.716%
3 ppm	3.077	2.9978	102.594%	99.268%
4 ppm	4.051	3.966	101.263%	98.984%
5 ppm	4.927	5.037	98.534%	100.756%

Based on the information in Table 2, it can be concluded that both sensors, namely TGS 826 and TGS 2602, meet the accuracy requirements. This is because both sensors' H_2S gas measurements show values within the 10% tolerance range. The precision test is a method used to measure how closely test values align with one another under the same test conditions. This test calculates the consistency of repeated sensor responses on the same sensor. The consistency of the E-Nose sensor can be measured by calculating the Relative Standard Deviation (RSD) value, as shown in Table 3. The RSD value is categorized as precise if the percentage score is below 7.3% [26].

Table 3. Sensor Risibility Test Results

Sample	RSD (%)					
	TGS2600	TGS2602	TGS2611	TGS2610	TGS2620	TGS826
1	21.49391	56.572812	98.300377	16.535719	17.84932	19.919582
2	27.36339	72.454390	38.716066	24.27920	25.21537	50.298379
3	91.97353	207.47772	64.769054	109.4428	117.2083	94.743134
4	38.61822	131.95144	135.94605	115.4600	51.06010	148.3507
5	47.69463	102.65576	43.406487	89.822231	61.110429	85.521472
6	27.726641	63.021267	22.131452	24.619475	25.211652	22.568414
7	43.293655	67.799782	22.055367	24.949395	35.698255	18.004620
8	5.481459	12.100031	60.230344	5.734192	6.046907	5.168021
9	14.370807	10.051369	7.791535	13.437860	15.710256	5.715633
10	10.327871	17.472933	60.633506	31.310257	10.837928	18.605740
11	10.746895	14.407626	12.440592	11.685748	10.738392	6.798276
12	32.360238	22.197297	46.426063	36.778038	33.465603	10.128170
13	10.553367	13.427846	16.911356	14.858589	11.562119	6.246612
14	23.596897	17.481134	115.295351	29.677701	25.568805	7.718066
15	14.312413	13.754032	21.570101	20.729671	15.755786	6.617144

3-5- PCA

Principal Component Analysis (PCA) simplifies data by reducing its dimensionality while preserving essential variance, transforming original independent variables into new, uncorrelated variables [14]. The data analysis involves standardizing the data, constructing a covariance matrix, and calculating eigenvalues and eigenvectors. Eigenvalues indicate the variance captured by each Principal Component (PC). Table 4 presents the results of eigenvalue calculations.

Table 4. Eigen Value calculation results

Principal Components	Eigenvalues	% Variation
1	51007.2693	77.8187
2	10501.3151	16.0212
3	1989.4922	3.0352
4	1989.4922	2.1528
5	1411.1199	0.8746
6	573.3292	0.0971

From the results in Table 4, the eigenvalues and data variations representing the accuracy of the gas array sensor are obtained. The variation accuracy value in the cumulative sum graph in Figure 4. PC1 has an accuracy value of 77.8187%, PC2 of 16.0212%, PC3 of 3.0352%, PC4 of 2.1528%, PC5 of 0.8746%, and PC6 of 0.0971%. Therefore, data analysis using PCA utilizes PC1 and PC2, accounting for a cumulative variation value of 93.83%

of all data. In performing a good PCA, one criterion for determining the number of components is the percentage of variation. The number of PCs used in clustering should have a cumulative percentage of variance of at least 80% [27].

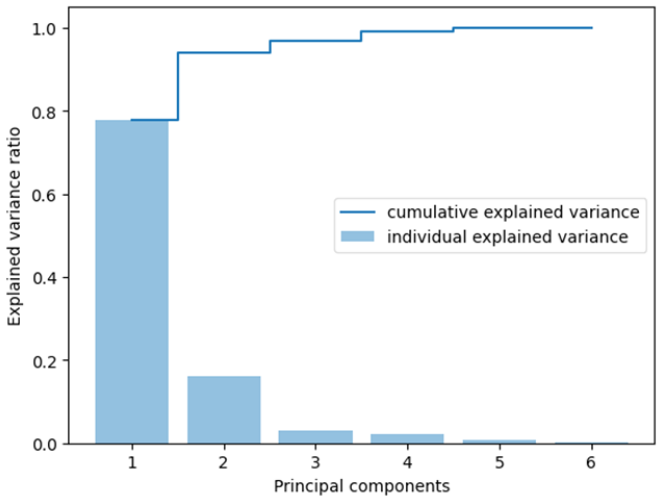


Figure 4. Graph of the sum of the principal component variation values

Figures 5-a and 5-b show the PCA score plot graph. The graph represents the location of the data cauterization. The graph shows 2 principal components originating from 6 TGS sensor variables, which are correlated with each other into 2 variables which are not correlated with each other.

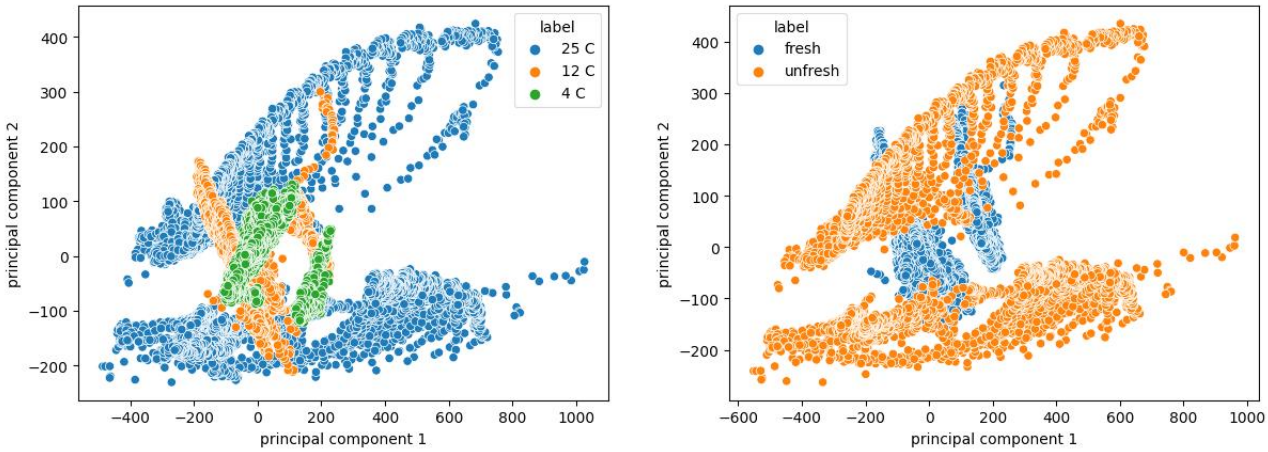


Figure 5. (a) PCA Score Plot graph based on temperature variations and (b) PCA score plot graph based on variations in blood cockle profiles (fresh and not fresh)

In Figure 5-a, the PCA score plot shows that temperature variations (4°C, 12°C, and 25°C) create distinct clusters, with two principal components effectively capturing the variation in gas emissions. Figure 5-b differentiates fresh and not fresh blood cockles, demonstrating that the sensor array can reliably classify spoilage levels. The separation of data points in both plots indicates that PCA successfully identifies patterns in the sensor data, correlating with temperature and freshness.

3-6- Support Vector Machine (SVM)

The study used a Support Vector Machine (SVM) with and without PCA to classify blood cockle samples as fresh or non-fresh. Using PCA (PC1 and PC2 as inputs) achieved 89.66% accuracy, while without PCA, accuracy improved to 91.44%. Results, shown in Figure 6, compare predicted and actual classifications. However, using training data to assess performance raises concerns about reliability. Independent testing or cross-validation is necessary for robust validation. With PCA (using PC1 and PC2 as inputs), the classification achieved 89.66% accuracy, while without PCA, accuracy improved to 91.44%. Using training data for performance assessment raises concerns about reliability, and independent testing or cross-validation is necessary for robust validation.

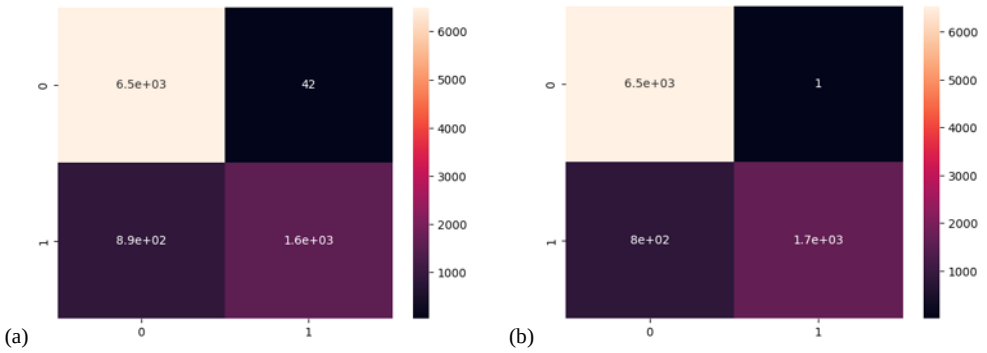


Figure 6. SVM confusion matrix (a) with PCA and (b) non-PCA

To determine the shelf life of blood cockles stored outside a cooler or freezer, a second machine-learning model was developed to predict the blood cockle profile for samples at 25°C (room temperature). This machine learning model, designed to predict the profile of blood cockles based on shelf life at 25°C, achieved an average accuracy of 94.26%. The details of the SVM prediction results are presented in Table 5.

Table 5. SVM Guess Results

Non-PCA Data				
Sample	Classification		Classification Results	Accuracy
	Fresh	Not Fresh		
First day	3367	833	Fresh	80.16%
Second day	58	3302	Not Fresh	98.27%
Third day	8	2992	Not Fresh	99.73%
Fourth day	5	2995	Not Fresh	99.83%
Fifth day	49	2951	Not Fresh	98.36%

4- Discussion

The electronic nose (E-nose) instrument consists of gas sensors and a pattern recognition system that detects objects based on their smell or aroma. The response generated by the E-nose is a voltage signal, which indicates the relationship between the odor concentration and the shellfish emissions. The higher the voltage produced, the higher the concentration of odor emitted by the shellfish.

In this research, the E-nose used comprises six sensors: TGS 2612, TGS 2600, TGS 2611, TGS 2602, TGS 2620, and TGS 826. Each sensor has a specific sensitivity to certain gases. TGS 2602 is highly sensitive to low concentrations of odorous gases such as ammonia and H2S. TGS 2611 is sensitive to methane gas, while TGS 2600 has high sensitivity to low concentrations of contaminant gases like hydrogen and carbon monoxide. The TGS 2612 gas sensor is susceptible to methane, propane, and butane gases. TGS 2620 is highly sensitive to organic solvent vapours, and TGS 826 is highly sensitive to ammonia gas. Some of the compounds in these gases are found in decaying blood cockles.

When the sensor interacts with volatile compounds emitted by the sample, each sensor responds with a different voltage, forming an exclusive pattern for each detected sample, thus enabling the detection of quality changes [28]. The mechanism of the gas sensor in responding to the gases emitted by the sample is illustrated in Figure 7.

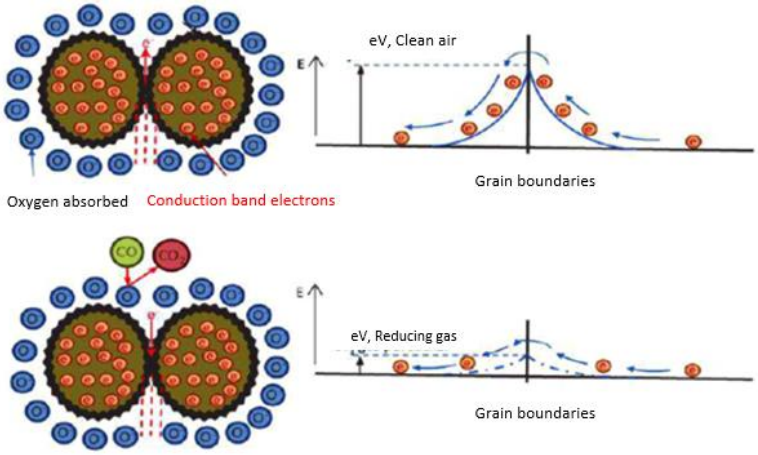


Figure 7. Gas Array Sensor System Mechanism [21]

The mechanism of the gas array sensor system to produce a voltage begins when the metal oxide crystal SnO_2 (Tin dioxide) is heated to a specific temperature in the air. Oxygen is absorbed on the surface of the crystal with a negative charge caused by the presence of an electron donor on the surface of the crystal. This electron donor is sent to the absorbed oxygen, resulting in a positively charged space layer. This creates a surface potential that inhibits the flow of electrons, producing electrical resistance [29].

The amount of oxygen adsorbed on the semiconductor surface in samples containing reducing gases decreases. This reduction lowers the height of the barrier wall. Decreased barrier wall height reduces the sensor's resistance to the reducing gas. Therefore, the higher the concentration of gas detected in free air, the lower the resistance value.

The voltage value is proportional to the current and resistance. However, the current plays a more dominant role in the sensor mechanism than the resistance. During the fresh air sensing process, O_2 particles bind to the sensor material, causing resistance to increase and the current value to decrease. On the other hand, when the sensed air sample contains pollutants, the O_2 in the previous air will attract the reducing gases (pollutants), causing the current and voltage to increase.

The sample testing mechanism can be seen in Figure 8. The first step that must be taken is to carry out a characteristic test. Characteristic tests involve response tests, accuracy tests, and precision tests. In the response test, H_2S material was used to test the sensor's response because H_2S is one of the compounds produced during the shellfish decomposition process. The test results show that the sensor can provide varying responses as the ppm H_2S concentration increases, indicating good response capability. In the accuracy test, H_2S is inhaled several times, and the tolerance of the measurement results is calculated within the range of 90%-110% of the previous response results. The results demonstrate that the tool can provide accurate results within this range [30].

Samples are tested using sensors that have undergone the preheating process. The process within the electronic nose system begins with detecting the sample's smell by the sensor array. The sensor responds to the gas emitted by the sample. It detects signals resulting from energy changes, such as converting smell to electrical energy in voltage. The sensor is made of metal oxide semiconductor material. Changes in the electrical properties of the metal oxide semiconductor are caused by interaction with gas molecules initiated by the absorption of oxygen in the semiconductor. The oxygen absorption process captures electrons from the conduction band [31].

Then, the data in the form of transactions is processed by a pattern recognition system. The sensing process starts from the aroma detected by the sensor array. Analog data is then converted into digital data by an analog-to-digital converter (ADC) to be stored on the computer for further analysis. Data from the ADC is processed so that the pattern recognition engine can analyze the signal more efficiently. The pattern recognition process classifies and predicts samples of unknown types. Figure 8 shows the sample testing mechanism.

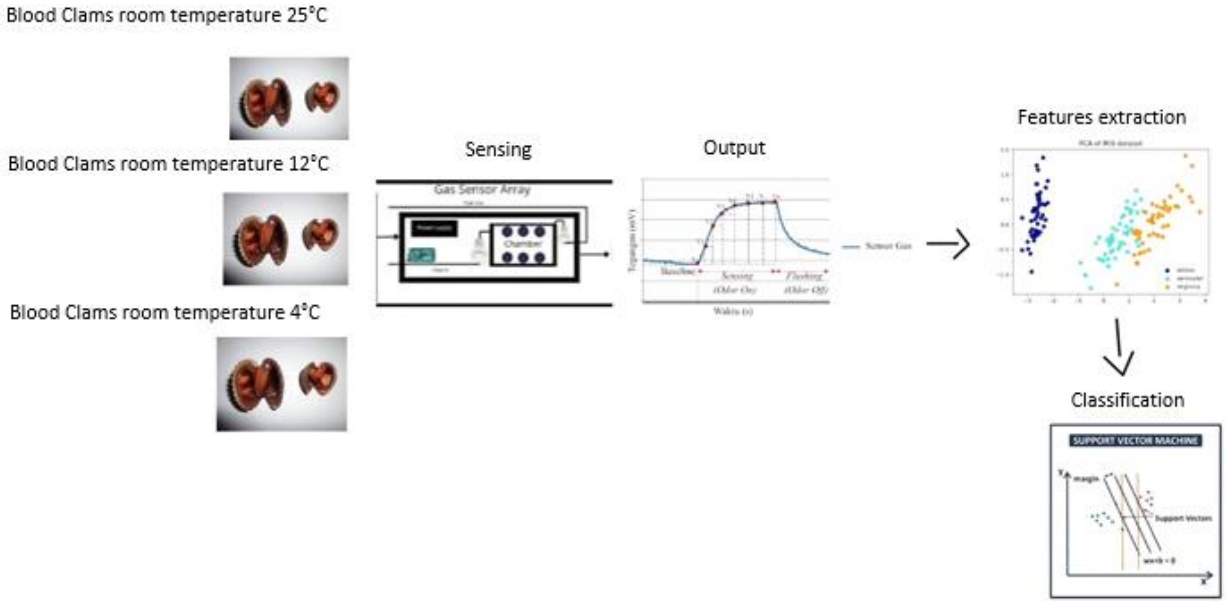


Figure 8. Sample testing mechanism

In this research, a method used to reduce features in the resulting data is Principal Component Analysis (PCA). PCA is a mathematical method that represents the variations within a dataset using several factors. Several main components, typically called principal components (PC), are linear data transformations to produce new variable spaces. As a result, PC1 contains more data variations than PC2, and so on [32]. The process of using PCA involves several stages. First,

data from a variety of samples is compiled. Then, a PCA pre-process is conducted by creating a covariance for each component based on the 6 TGS gas sensor variables. The following formula is used to create the covariance [33].

$$cov(x,y) = \sum_{i=1}^{n}(x_1 - \bar{x})(y_1 - \bar{y}) \quad (1)$$

The covariance matrix is used to find the eigenvalues. In the process of finding eigenvalues and determining eigenvectors, you can use the following formula:

$$|M - \lambda I| = 0 \quad (2)$$

$$Mv = \lambda v \quad (3)$$

where; M: covariance matrix, λ: eigenvalues, I: identity matrix and v: eigenvectors.

The aim of data analysis using PCA is to reduce the dimensions of correlated or related variables into fewer variables that are not linearly correlated to explain the variations that occur with as few main components as possible. The number of sensors in the electronic nose is represented by the number of variables in the PCA process. These variables are then reduced to two dimensions: the main component (PC1) and the second principal component (PC2). These two reduced components represent the percentage of significant variation values from the overall data variation. Visualizations in two-dimensional graphs are created to analyze and interpret the information qualitatively. The selection of PC1 and PC2 is based on the 2 eigenvectors with the highest eigenvalues, with a cumulative variation value of 93.81% of the total data. The two PCs will be used as new coordinate axes representing six sensor variations. The initial transformation involves converting the data into a 45000x6 matrix, which is then multiplied by the eigenvector with the highest eigenvalue, forming a 6x2 matrix, resulting in a 45000x2 matrix transformation [34].

The variations in the resulting data are expressed as each eigenvalue divided by the total eigenvalue. From the PCA calculations, the eigenvalues of each PC were obtained as follows: PC1, PC2, PC3, PC4, PC5, and PC6 were 51007.2693, 10501.3151, 1989.4922, 1411.1199, and 573.3292, respectively. The variation values of each PC, namely PC1, PC2, PC3, PC4, PC5, and PC6 were 77.8187%, 16.0212%, 3.0352%, 2.1528%, 0.8746%, and 0.0971%, respectively.

The classification process uses the Support Vector Machine (SVM) method. SVM is a machine learning method based on the principle of Structural Risk Minimization (SRM), aiming to find the best hyperplane that separates two classes in the input space. This research divides the classes into blood clams with fresh and non-fresh profiles. Data collected from the electronic nose, reduced by PCA, is used to build the machine learning database. The database is randomly divided into training subsets, representing approximately 80% of the total data, and testing subsets, representing approximately 20% of the total data. The test data is not used during the model development stage but is reserved exclusively for determining the model's performance [35].

In SVM, non-linear data classification uses a kernel trick, which can separate low-dimensional data and convert it into a higher-dimensional space [5]. The kernel function in SVM has several types, such as the linear kernel, polynomial kernel, and radial basis function (RBF). Each kernel function has its limitations when classifying high-dimensional data. The polynomial kernel and RBF are most suitable for classifying high-dimensional non-linear data [36]. There are several mathematical stages involved in the SVM algorithm. The first step is to determine the regression model function using a specific function:

$$-\frac{1}{2}w^2 + c\sum_{i=1}^{m}(\,\xi * \mathrm{i} + \,\xi\mathrm{i}\,) \quad (4)$$

$$s.t.\left\{\begin{pmatrix} y_i - w\xi(\mathrm{x}) - \mathrm{b} \le \varepsilon + \xi_i^* \\ w.\xi(\mathrm{x}) + \mathrm{b} - y_i \le \varepsilon + \xi_i \\ \xi_i^*\xi \ge 0\ (\mathrm{i} = 1,2,3,4..\mathrm{m}) \end{pmatrix}\right\} \quad (5)$$

where: w = Vector weight; c = Penalty factor; ξi = Relaxation component $\sum_{i=1}^{m} a_i^*(y_i - \varepsilon) - \sum_{i=1}^{m} a_i(y_i\varepsilon)$; ξ(x)= Linear transformation function; b = Offset; ε = Upper limit of error.

Then, in determining the model optimization, the equation is used:

$$max\ -\frac{1}{2}\sum_{i,j=1}^{m}(a_i^* - a_i)(a_i^* - a_i)k(X_i, X) + \sum_{i=1}^{m} a_i^*(y_i - \varepsilon) - \sum_{i=1}^{m} a_i(y_i\varepsilon) \quad (6)$$

$$\mathrm{s.t.}\left\{\begin{matrix} \sum_{i=1}^{m} a_i = \sum_{i=1}^{m} a_i^* \\ 0 \le a_i, a_i^* \le c(i = 1,2,3,4, \ldots m) \end{matrix}\right\} \quad (7)$$

To determine the regression of the SVM function, use the following equation:

$$\mathrm{f(x)}=\sum_{i=1}^{m}(a_i - a_i^*)\,k(X_i, X) + b \quad (8)$$

$$k(Xi, Xj) = \exp\left(-\frac{x_i - x_j^2}{2\delta^2}\right) = \exp(-\gamma Xi - Xj2), \gamma > 0 \quad (9)$$

Finding the optimal values for parameters (C) and (gamma) is crucial in determining the hyperplane. These two parameters are essential in governing how the data will be divided by the hyperplane. Therefore, searching for the values of (C) and (gamma) that provide optimal results is recommended.

After conducting the training and testing process on SVM, the accuracy results were 89.6% for data with PCA and 91.44% for non-PCA data. With these figures, SVM can be considered effective in classifying variations in blood cockle samples with fresh and non-fresh profiles. The accuracy value is obtained by calculating the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values derived from the confusion matrix. The accuracy of SVM classification on variations in blood cockle sample profiles can be seen in Table 6.

Table 6. SVM Classification Accuracy

PCA Data	**Fresh**	TP	FP
		6501	42
	Not Fresh	FN	TN
		894	1563
Non-PCA Data	**Fresh**	TP	FP
		6542	1
	Not Fresh	FN	TN
		796	1661

The accuracy value can be calculated using the equation:

$$\text{Accuracy} = \frac{(\text{True Positive (TP)} + \text{True Negative (TN)})}{(\text{True Positive(TP)} + \text{True Negative(TN)} + \text{False Positive(FP)} + \text{False Negative(FN)})} \quad (10)$$

Apart from accuracy, as a result of this research, the SVM model was also reviewed from other evaluations such as Precision, Recall, and F1-Score, as summarized in Table 7. The results show that the SVM model developed in this research has an accuracy of 89.66% for data using PCA and 91.44% for non-PCA data.

Table 7. Table of evaluation results

	Sample	**Precision**	**Recall**	**F1-Score**
PCA Data	Fresh	88%	99%	93%
	Not Fresh	97%	64%	77%
Non-PCA Data	Fresh	89%	100%	94%
	Not Fresh	100%	68%	81%

After creating an SVM machine-learning model to classify blood cockle profiles based on temperature and shelf life variations, a second machine-learning tool was developed to predict blood cockle profiles with variations in shelf life at room temperature or outside the cooler or freezer. Based on the results of the computational analysis, it can be observed that blood cockles began to be categorized as "Not Fresh" on the second to fifth day. The SVM machine learning model can predict the profile of blood cockles based on their shelf life with an average accuracy of 94.26%.

The TGS 826 gas sensor plays a dominant role in distinguishing samples with different temperature variations from the sensitivity tests conducted on the sensors. The TGS 2610, TGS 2602, and TGS 2611 gas sensors also provided significant differences in detecting blood cockle samples. However, the TGS 2620 and TGS 2600 gas sensors did not provide a good voltage response, with the TGS 2620 gas sensor being particularly ineffective at differentiating blood cockle samples. This is because the TGS 826, TGS 2610, TGS 2602, and TGS 2611 sensors have high sensitivity in detecting odorous gases such as ammonia, H2S, methane, propane, and butane [37]. These gases are associated with the decomposition process of fish and shellfish. NH3, H2S, and SO2 compounds are found in the final stages of fish and shellfish decomposition, indicating the presence of active spoilage microbes in shellfish [38].

Previous research on electronic noses (E-noses) used biofilm bacterial samples with six sensors: TGS 826, TGS 2600, TGS 2602, TGS 2611, TGS 2610, and TGS 2620 [28]. These sensors could detect biofilm bacteria in dental and oral

diseases, as indicated by high delta ADC values [4]. The PCA method to detect the quality of three types of freshwater fish with a gas sensor array (TGS 826, TGS 2600, TGS 2602, TGS 2611, TGS 2610, and TGS 2620), achieving cumulative variation values of 98.7% for pomfret, 98.8% for catfish, and 99.5% for tilapia [4]. A gas sensor array (MQ2, MQ3, MQ7, MQ8, MQ135, and MQ136) with the SVM method obtained an accuracy value of 98.61% [5]. Three types of marine biota were stored at room temperature with time variations of 2 hours for 30 hours, achieving 99% accuracy using the K-NN method [39].

The current research, which uses gas array sensors (TGS 2600, TGS 2602, TGS 2611, TGS 2610, TGS 2620, and TGS 826) with PCA and SVM analysis methods, successfully classifies blood cockles, resulting in a cumulative percentage of the two main components of 93.83% and an accuracy level of 88.66% using the SVM-PCA method and 91.44% for non-PCA [40].

The study considered environmental factors like humidity, air pressure, and potential contaminants. Control measures and baseline corrections were applied to minimize their impact on sensor readings. The storage conditions, including temperature and time, were carefully controlled during the study. These conditions were designed to mimic common storage practices for blood cockles, ensuring that the experiment accurately reflected real-world scenarios. By regulating these factors, the study aimed to produce reliable and consistent results relevant to typical cockle storage practices. The study involved sampling multiple individual cockles for each storage condition to ensure a representative analysis. By using a larger sample size, we aimed to improve the robustness of the data and account for any potential variability between individual cockles, enhancing the statistical significance of the results [41]. The results obtained from this research are good compared to previous studies. However, this research still has some limitations. Differences in storage conditions (temperature and storage time) can affect sensors' detection and classification results. Samples stored at room temperature with time variations proved more optimal for sensor detection. Additionally, the SVM-PCA method shows lower accuracy than the SVM method in previous research, likely due to the lower quality of data produced from the sensor, affecting PCA's ability to reduce data dimensions and retain critical information effectively [1].

5- Conclusion

The study demonstrated that the electronic nose utilizing the TGS 2600, TGS 2602, TGS 2611, TGS 2612, TGS 2620, and TGS 826 gas sensor array effectively detected odor variations in blood cockle profiles. Computational analysis using Principal Component Analysis (PCA) successfully reduced the six sensor variables into two principal components, explaining 93.83% of the cumulative variation. Principal Component 1 contributed 77.82%, and Principal Component 2 accounted for 16.02% of the variation, highlighting the ability of PCA to condense the sensor data while retaining critical information. The results showed that using SVM machine learning, the blood cockle profiles could be classified with 89.66% accuracy when PCA was applied and 91.44% accuracy when PCA was not used. These findings emphasize that PCA contributes to efficient classification, but the direct sensor data also offers strong performance. Further analysis with the SVM model indicated that the blood cockles could be classified as 'not fresh' from the second day onwards, achieving an impressive 94.26% accuracy. This finding suggests that the electronic nose, based on the gas sensor array, can reliably differentiate between fresh and non-fresh blood cockles based on odor profiles, making it a valuable tool for food freshness monitoring. Overall, the electronic nose system shows great promise for application in food quality control, particularly in detecting spoilage and ensuring product freshness.

6- Declarations

6-1- Author Contributions

Conceptualization, S.D.A. and N.F; methodology, N.F.; software, N.N.R.; validation, A.K.Y., N.F., and Y.S.; formal analysis, A.K.Y.; investigation, P.A.D.P.; resources, A.K.Y.; data curation, S.D.A.; writing—original draft preparation, A.S.; writing—review and editing, S.S.; visualization, S.D.A.; supervision, S.S.; project administration, P.A.D.P.; funding acquisition, S.D.A. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding and Acknowledgement

This research is supported by the Indonesian Endowment Fund for Education (LPDP) on behalf of the Indonesian Ministry of Higher Education, Science and Technology and managed under the EQUITY Program (Contract No. 4300/B3/DT.03.08/2025 and 297/UN3/HK.07.00/2025).

6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Grassi, S., Benedetti, S., Magnani, L., Pianezzola, A., & Buratti, S. (2022). Seafood freshness: e-nose data for classification purposes. Food Control, 138, 108994. doi:10.1016/j.foodcont.2022.108994.

[2] Munekata, P. E. S., Finardi, S., de Souza, C. K., Meinert, C., Pateiro, M., Hoffmann, T. G., Domínguez, R., Bertoli, S. L., Kumar, M., & Lorenzo, J. M. (2023). Applications of Electronic Nose, Electronic Eye and Electronic Tongue in Quality, Safety and Shelf Life of Meat and Meat Products: A Review. Sensors, 23(2), 672. doi:10.3390/s23020672.

[3] Wang, B., Liu, K., Wei, G., He, A., Kong, W., & Zhang, X. (2024). A Review of Advanced Sensor Technologies for Aquatic Products Freshness Assessment in Cold Chain Logistics. Biosensors, 14(10), 468. doi:10.3390/bios14100468.

[4] Nath, V. G., Bharath, S. P., Dsouza, A., & Subramanian, A. (2024). Machine Learning Algorithms for Smart Gas Sensor Arrays. Nanostructured Materials for Electronic Nose, 185–225. doi:10.1007/978-981-97-1390-5_8.

[5] Singh, R., Nickhil, C., R.Nisha, Upendar, K., Jithender, B., & Deka, S. C. (2025). A Comprehensive Review of Advanced Deep Learning Approaches for Food Freshness Detection. Food Engineering Reviews, 17(1), 127–160. doi:10.1007/s12393-024-09385-3.

[6] Gliszczyńska-Świgło, A., & Chmielewski, J. (2017). Electronic Nose as a Tool for Monitoring the Authenticity of Food. A Review. Food Analytical Methods, 10(6), 1800–1816. doi:10.1007/s12161-016-0739-4.

[7] Wilson, A. D., & Baietto, M. (2011). Advances in electronic-nose technologies developed for biomedical applications. Sensors, 11(1), 1105–1176. doi:10.3390/s110101105.

[8] Baietto, M., & Wilson, A. D. (2015). Electronic-nose applications for fruit identification, ripeness and quality grading. Sensors (Switzerland), 15(1), 899–931. doi:10.3390/s150100899.

[9] Astuti, S. D., Mukhammad, Y., Duli, S. A. J., Putra, A. P., Setiawatie, E. M., & Triyana, K. (2019). Gas sensor array system properties for detecting bacterial biofilms. Journal of Medical Signals and Sensors, 9(3), 158–164. doi:10.4103/jmss.JMSS_60_18.

[10] Astuti, S. D., Fanany Al Isyrofie, A. I., Nashichah, R., Kashif, M., Mujiwati, T., Susilo, Y., Winarno, & Syahrom, A. (2022). Gas Array Sensors based on Electronic Nose for Detection of Tuna (Euthynnus Affinis) Contaminated by Pseudomonas Aeruginosa. Journal of Medical Signals and Sensors, 12(4), 306–316. doi:10.4103/jmss.jmss_139_21.

[11] Xu, J., Liu, K., & Zhang, C. (2021). Electronic nose for volatile organic compounds analysis in rice aging. Trends in Food Science & Technology, 109, 83–93. doi:10.1016/j.tifs.2021.01.027.

[12] Scott, S. M., James, D., & Ali, Z. (2006). Data analysis for electronic nose systems. Microchimica Acta, 156(3–4), 183–207. doi:10.1007/s00604-006-0623-9.

[13] Park, S. Y., Kim, Y., Kim, T., Eom, T. H., Kim, S. Y., & Jang, H. W. (2019). Chemoresistive materials for electronic nose: Progress, perspectives, and challenges. InfoMat, 1(3), 289–316. doi:10.1002/inf2.12029.

[14] Astuti, S. D., Tamimi, M. H., Pradhana, A. A. S., Alamsyah, K. A., Purnobasuki, H., Khasanah, M., Susilo, Y., Triyana, K., Kashif, M., & Syahrom, A. (2021). Gas sensor array to classify the chicken meat with E. coli contaminant by using random forest and support vector machine. Biosensors and Bioelectronics: X, 9, 100083. doi:10.1016/j.biosx.2021.100083.

[15] Wang, M., & Chen, Y. (2024). Electronic nose and its application in the food industry: a review. European Food Research and Technology, 250(1), 21–67. doi:10.1007/s00217-023-04381-z.

[16] Astuti, S. D., Wicaksono, I. R., Soelistiono, S., Permatasari, P. A. D., Yaqubi, A. K., Susilo, Y., Putra, C. D., & Syahrom, A. (2024). Electronic nose coupled with artificial neural network for classifying of coffee roasting profile. Sensing and Bio-Sensing Research, 43, 100632. doi:10.1016/j.sbsr.2024.100632.

[17] Figaro Engineering Inc. (2015). TGS 2620 - for the detection of Solvent Vapors. Product Information. Figaro Engineering Inc, Osaka, Japan.

[18] Putra, C. D., Al Isyrofie, A. I. F., Astuti, S. D., Putri, B. D., Ummah, D. R., Khasanah, M., Permatasari, P. A. D., & Syahrom, A. (2023). Variational autoencoder analysis gas sensor array on the preservation process of contaminated mussel shells (Mytilus edulis). Sensing and Bio-Sensing Research, 40, 100564. doi:10.1016/j.sbsr.2023.100564.

[19] Tan, J., & Xu, J. (2020). Applications of electronic nose (e-nose) and electronic tongue (e-tongue) in food quality-related properties determination: A review. Artificial Intelligence in Agriculture, 4, 104–115. doi:10.1016/j.aiia.2020.06.003.

[20] Johnson, R. A., & Wichern, D. W. (2002). Applied Multivariate Statistical Analysis. Prentice Hall, New Jersey, United States.

[21] Pradhana, A. A. S., Astuti, S. D., Khasanah, M., & Ardianti, R. K. D. (2020). Detection of gas concentrations based on age on Staphylococcus aureus biofilms with gas array sensors. AIP Conference Proceedings, 2314. doi:10.1063/5.0034112.

[22] Saputra, B. E., Bintari, Y. R., & Risandiansyah, R. (2022). ccuracy and Precision Validation Test of Simple Staphylococcus Aureus and Escherichia Coli Staining Methods Using Methanolic Extract of Hibiscus sabdariffa Linn. Jurnal Bio Komplementer Medicine, 9(1). (In Indonesian).

[23] Everitt, B., & Rencher, A. C. (1996). Methods of Multivariate Analysis. The Statistician, 45(4), 535. doi:10.2307/2988560.

[24] Mohd Ali, M., Hashim, N., Abd Aziz, S., & Lasekan, O. (2020). Principles and recent advances in electronic nose for quality inspection of agricultural and food products. Trends in Food Science and Technology, 99, 1–10. doi:10.1016/j.tifs.2020.02.028.

[25] Hidayat, S. N. (2015). Application of a gas sensor array system to identify the aroma profile of tempeh during the fermentation process. PhD Thesis, Universitas Gadjah Mada, Yogyakarta, Indonesia. (In Indonesian).

[26] Aleixandre, M., Lozano, J., Gutiérrez, J., Sayago, I., Fernández, M. J., & Horrillo, M. C. (2008). Portable e-nose to classify different kinds of wine. Sensors and Actuators, B: Chemical, 131(1), 71–76. doi:10.1016/j.snb.2007.12.027.

[27] Tazi, I., Isnaini, N. L., Mutmainnah, M., & Ainur, A. (2019). Principal Component Analysis (PCA) Method for Classification of Beef and Pork Aroma Based on Electronic Nose. Indonesian Journal of Halal Research, 1(1), 5–8. doi:10.15575/ijhar.v1i1.4155.

[28] Papadopoulou, O. S., Tassou, C. C., Schiavo, L., Nychas, G.-J. E., & Panagou, E. Z. (2011). Rapid Assessment of Meat Quality by Means of an Electronic Nose and Support Vector Machines. Procedia Food Science, 1, 2003–2006. doi:10.1016/j.profoo.2011.09.295.

[29] Sujono, H. A., Rivai, M., & Amin, M. (2018). Asthma identification using gas sensors and Support Vector Machine. Telkomnika (Telecommunication Computing Electronics and Control), 16(4), 1468–1480. doi:10.12928/TELKOMNIKA.v16i4.8281.

[30] Ma, J., Fan, H., Zhang, W., Sui, J., Wang, C., Zhang, M., ... & Wang, S. (2020). High sensitivity and ultra-low detection limit of chlorine gas sensor based on In2O3 nanosheets by a simple template method. Sensors and Actuators B: Chemical, 305, 127456. doi:10.1016/j.snb.2019.127456.

[31] Ólafsdóttir, G. (2005). Volatile compounds as quality indicators in chilled fish: evaluation of microbial metabolites by an electronic nose. Ph.D. Thesis, University of Iceland, Reykjavik, Iceland.

[32] Isyrofie, A. I. F. Al, Afifudin, R., Susilo, Y., Kholimatussa'diyah, S., Winarno, & Astuti, S. D. (2023). Role of bacterial types and odor for early detection accuracy of bacteria with gas array. The 8Th International Conference and Workshop on Basic and Applied Science (Icowobas) 2021, 2554, 060003. doi:10.1063/5.0104211.

[33] Wijaya, D. R., Syarwan, N. F., Nugraha, M. A., Ananda, D., Fahrudin, T., & Handayani, R. (2023). Seafood Quality Detection Using Electronic Nose and Machine Learning Algorithms With Hyperparameter Optimization. IEEE Access, 11, 62484–62495. doi:10.1109/ACCESS.2023.3286980.

[34] Kaushal, S., Nayi, P., Rahadian, D., & Chen, H. H. (2022). Applications of Electronic Nose Coupled with Statistical and Intelligent Pattern Recognition Techniques for Monitoring Tea Quality: A Review. Agriculture (Switzerland), 12(9), 1359. doi:10.3390/agriculture12091359.

[35] Shi, H., Zhang, M., & Adhikari, B. (2018). Advances of electronic nose and its application in fresh foods: A review. Critical Reviews in Food Science and Nutrition, 58(16), 2700–2710. doi:10.1080/10408398.2017.1327419.

[36] Zhang, Z., Zheng, Z., He, X., Liu, K., Debliquy, M., Zhou, Y., & Zhang, C. (2024). Electronic nose based on metal oxide semiconductor sensors for medical diagnosis. Progress in Natural Science: Materials International, 34(1), 74–88. doi:10.1016/j.pnsc.2024.01.018.

[37] Jiang, Y., Wei, S., Ge, H., Zhang, Y., Wang, H., Wen, X., Guo, C., Wang, S., Chen, Z., & Li, P. (2025). Advances in the Identification Methods of Food-Medicine Homologous Herbal Materials. Foods, 14(4), 608. doi:10.3390/foods14040608.

[38] Gharibzahedi, S. M. T., Barba, F. J., Zhou, J., Wang, M., & Altintas, Z. (2022). Electronic Sensor Technologies in Monitoring Quality of Tea: A Review. Biosensors, 12(5), 356. doi:10.3390/bios12050356.

[39] Hardoyono, F., & Windhani, K. (2023). Combination of metal oxide semiconductor gas sensor array and solid- phase microextraction gas chromatography-mass spectrometry for odour classification of brewed coffee. Flavour and Fragrance Journal, 38(6), 451–463. doi:10.1002/ffj.3759.

[40] Peters, R., Veenstra, R., Heutinck, K., Baas, A., Munniks, S., & Knotter, J. (2023). Human scent characterization: A review. Forensic Science International, 349, 111743. doi:10.1016/j.forsciint.2023.111743.

[41] Pathak, A. K., Swargiary, K., Kongsawang, N., Jitpratak, P., Ajchareeyasoontorn, N., Udomkittivorakul, J., & Viphavakit, C. (2023). Recent Advances in Sensing Materials Targeting Clinical Volatile Organic Compound (VOC) Biomarkers: A Review. Biosensors, 13(1), 114. doi:10.3390/bios13010114.