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Research Article

Sensor Array System Based on Electronic Nose to Detect Borax in Meatballs with Artificial Neural Network

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The categorization of odors utilizing gas sensor arrays with various meatball borax concentrations has been studied. The samples included meatballs with a borax content of 0.05%, 0.10%, 0.15%, 0.20%, and 0.25% (%mm) and meatballs without any borax. Six TGS gas sensors with a baseline of 10 seconds, a detecting period of 120 seconds, and a purging period of 250 seconds make up the gas sensor array used in this work. Artificial neural networks (ANNs) and principal component analysis (PCA), which are beneficial for feature extraction and classification, are used to handle the collected data based on machine learning approaches. Two models were produced by the data analysis: model 1, which only used the PCA approach, and model 2, which only used the ANN methodology. 90.33% is the total variance value of PC from model 1. In addition, the multilayer perceptron artificial neural network (ANN-MLP) technique for model 2 yielded accuracy values of 95%.

1. Introduction

One of the consequences of globalization is the rising prevalence of obesity. Globalization has the potential to influence people's eating habits, particularly their consumption of high-calorie fast food. This can be seen in the increased number of fast-food restaurants and street food vendors [1]. Bakso (meatball), also known as bebola, nemnuong, kofta, and polpette in other countries, is a popular street food in Indonesia [2].

Bakso (meatball) is made of ground meat that can be shaped to taste, but is typically spherical. It can be made with beef, chicken, pork, or fish. Meat is essential in meeting human nutritional needs because it is high in protein and contains a complete and balanced set of essential amino acids. Meat, on the other hand, can spoil quickly if contaminated with bacteria. This contamination not only causes economic losses for traders, particularly bakso (meatball) producers [3] but also leads to some vendors engaging in fraudulent practices by mixing in harmful chemical preservatives, such as borax, to extend shelf life and make bakso (meatball) appear more appealing to consumers. Borax ($Na_2B_4O_7.10H_2O$/sodium tetraborate decahydrate) is used to make fertilizers, industrial products [4], cleaning agents, and detergent raw materials [5], that using borax on tike samples can inhibit permeations and even cause death [6].

Electronic noses, such as gas sensor array systems, can detect bacterial contamination and the presence of hazardous substances such as borax in meat products, ensuring food safety and preventing health risks associated with contaminated food consumption [7].

The effects of eating foods containing borax include the development of brain, liver, fat, and renal diseases. High quantities of borax in food might result in fever, anuria, fainting, coma, or even death. Brakes may induce gastrointestinal tract inflammation, liver degeneration or decrease, brain swelling, and fluid buildup in organs and are carcinogenic for all cells and bodily tissues, including the kidneys. Within five to ten years, consuming borax-rich meals might cause liver cancer in susceptible individuals.

Borax is typically used in industrial fields such as raw materials for making glass, wood preservatives, wood antiseptics, soldering materials, antiseptic materials for cosmetics, making ceramics, making paper, making glass, controlling cockroaches, and as a cleaning agent used as raw materials in the production of detergents. But lice, mildew, and fungal development may also be avoided using borax in the textile sector. By combining it with sugar, borax may be used as an insecticide to kill ants, cockroaches, and flies. Borax, commonly known as boric acid, is used in the pharmaceutical industry as antiseptics for eye drops and topical medications for the mouth, eyewash, and additions to ointments, powders, and compress solutions [8].

Borax is first dissolved in water for this study, after which the amount of borax is measured using a variety of gas sensors as a voltage parameter. In addition, samples were prepared in six different permutations, including pure meatballs, meatballs mixed with borax. In addition, the model that had been in the sample container is linked to the gas sensor array, where the bau created by the sample is first pushed into the detecting chamber of the sensor array before being passed through the dryer. This is carried out to stop moisture from having an impact on the production.

Borax testing in food is usually done quantitatively with laboratory equipment, which can be time-consuming. This study was motivated by the lack of a nondestructive quantitative method for borax testing using gas sensor arrays [9]. Gas sensor arrays are an instrumentation tool that uses artificial intelligence concepts to function similarly to the human nose [10]. This refers to the human nose's various receptors that detect odors, whereas gas sensor arrays use sensors arranged within the device as receptors, employing a combination of gas detection and pattern analysis techniques to identify specific compounds or mixtures [11, 12]. E-nose technology has also been widely used in the medical field, including the detection of pulmonary diseases [13] and head or neck cancer [14].

Six different types of gas sensors, including the TGS 826, TGS 2600, TGS 2602, TGS 2611, TGS 2612, and TGS 2620, were employed in this investigation. The TGS's six gas sensor arrays can distinguish between meatball samples with varying amounts of borax. The response of the TGS gas sensor to the sample fragrance depicted in the PCA plot may be extracted into features and classified using the PCA approach. The data analysis process produced total PC1 and PC2 variances of 90.33 percent. The machine learning analysis technique multilayer perceptron artificial neural network (ANN-MLP), which employed six direct inputs from the data gathered in this work, was able to categorize the terization while categorizing the sensor response of pure meatball fragrance and meatball aroma, including borax. The accuracy of data analysis using the PCA technique and ANN-MLP has been tested in various data groups. The accuracy of data analysis using the PCA method is 90.33%, while the accuracy of data analysis using the ANN-MLP method is 95%.

TGS sensors were used in this study, with the gas sensor array designed using various TGS sensor types. In addition to TGS, the MQ (Mangan Qilail) gas sensor array belongs to the MOS (metal oxide semiconductor) sensor family, which can convert chemical quantities into electrical signals [15]. This technology was also used by [16] to classify chicken meat contaminated with *E. coli* bacteria and to evaluate the freshness of chicken meat at various temperatures and storage times [17]. In addition, gas sensor arrays have demonstrated the ability to detect bacterial growth and identify specific bacteria types in a variety of environments, including oral and dental diseases [18], identifying biofilm bacteria [19], and detecting gas concentrations based on age in *Staphylococcus aureus* biofilms [20], or a wavelet transform and the filter-based feature selection approach of the electronic nose signal [21].

This investigation used gas sensor arrays, an apparatus with an operating mechanism simulating a human nose, to conduct a quantitative borax test. This is about the human nose, which contains many receptors that are used to detect scents, but there is a sensor attached to it in the gas sensor array that serves as a receptor. The gas sensor array utilized in this work has the advantages of being reusable, simple to use, and reasonably priced.

The TGS sensor utilized in this work is one of several different TGS sensor types that comprise the array of gas sensors. The TGS 82 6 sensors detect ammonia gas; the TGS 2600 sensor detects hydrogen sulfide gas; the TGS 2602 sensor detects ethanol and other air contaminants; the TGS 261 1 sensor detects methane gas; the TGS 2612 sensor detects propane and butane; and alcohol and solvent vapors, as well as food vapors, are detected by the TGS 2620 sensor (Figaro, 201 : 8). The materials utilized in the gas sensor array itself provide odor stimuli. These stimuli eventually cause a reaction or output in the form of voltage. It may be inferred from tests of ginger essential oil's scent, where a peak voltage of 263 mV was attained in less than 60 seconds, that the output is influenced by the concentration of the sample's aroma.

Machine learning is used to process the output from gas extraction utilizing the gas sensor array. In this instance, just one algorithm, the artificial neural network-type multilayer perceptron (ANN-MLP) algorithm is employed for odor categorization. The multilayer perceptron can process multiple inputs with several layers and outputs, which may enable it to deliver results with a high degree of accuracy of 100 percent.

The example uses the meatball dough that you created. TGS 826, TGS 2600, TGS 2602, TGS 2611, TGS 2612, and TGS 2620 are the sensors that are used. The discussion and analysis in this experimental study pertain to the ammonia levels that each sample variation generated.

With this context in mind, the study's objective was to assess the reaction of a gas sensor array sensor using pure meatball samples with varying meatball compositions and levels of borax at 0.05%, 0.10%, 0.15%, 0.20%, and 0.25%. In addition, the project seeks to evaluate the performance of PCA in feature extraction and the ANN-MLP approach in data classification. The study's outcomes will determine the correctness of data management utilizing the PCA approach and the ANN-MLP method.

This study is anticipated to contribute to our understanding of how gas sensor arrays made up of several TGS gas sensors may detect changes in the amount of borax in meatballs and the temperature at which they are heated. This study is anticipated to serve as a benchmark for the development of TGS gas sensor combinations to get the best possible response when detecting borax in meatballs and for the development of the ANN-MLP algorithm in conjunction with PCA to classify the aroma of the TGS gas sensor response accurately.

TGS 826 detects ammonia gas, TGS 2600 detects hydrogen sulfide (H_2S) gas, TGS 2602 detects hydrogen, ethanol, and other air contaminants, TGS 2611 detects methane gas, TGS 2612 detects methane, propane, and butane, and TGS 2620 detects alcohol and solvent vapors, such as food vapors [22]. Machine learning is used to process the output of gas extraction using these gas sensor arrays. In this case, the artificial neural network multilayer perceptron (ANN-MLP) algorithm is used for odor classification. This sensor combination detects various gases and volatile organic compounds (VOCs) that may be present in food samples, which can aid in determining the presence of contaminants such as borax, which on recent study successfully detected germ in food substance [23]. Thus, in this study, data analysis combines both PCA and ANN methods [24], resulting in a robust and accurate classification of odors and potential contaminants in food samples.

2. Materials and Methods

This study's design treated the control group by affecting changes in the amount of borax in the meatballs. This research aims to establish the TGS sensor's capability to recognize fluctuations in meatballs' borax content, the effectiveness of PCA paired with ANN-MLP in calcifying sample scents and the degree of accuracy of PCA and ANN-MLP performance in categorizing sample odors. Instruments with gas sensor arrays are used to identify certain gas scents. Meatballs' natural incense and the organic chemical elements that comprise each meatball differ.

2.1. Sample Preparation. Several ingredients were required for the preparation of meatball samples, including chicken meat, tapioca flour, eggs, garlic, salt, pepper, and borax. The process was separated into two categories: meatballs with and without borax. Six varieties of meat balls were prepared, including pure meat balls and meat balls with 0.05%, 0.10%, 0.15%, 0.20%, and 0.25% borax concentration. At least 50 measurements were conducted for each sample of each variation of meatballs using a gas sensor array. Figure 1 illustrates the experimental set-up.

2.2. Sensor Response Test. The sensor response test was conducted by collecting data on borax solution samples with 0.05%, 0.10%, 0.15%, 0.20%, and 0.25% concentrations. Each variation of the borax sample used, including pure meat balls and meat balls mixed with borax at the aforementioned concentrations, was tested 50 times.

2.3. Collection of Data. The stage of data collection began with the aroma sensing of samples consisting of pure meatball dough and meatballs containing borax at concentrations of 0.05%, 0.10%, 0.15%, 0.20%, and 0.25%, heated to 53°C. Using PCA and ANN-MLP, the data gathered through sensing were categorized.

2.4. Data Validity Test. In this study, the input for the gas sensor array was the aroma detected from a sample heated to 53°C, and the output was obtained. The data validity was determined by plotting the sample's output versus its voltage.

2.5. Model Validity Test. The model validity test was conducted after receiving the results of the data validity test. Using the results of the data validity test, a model was developed. Using PCA or ANN-MLP analysis, the data were clustered and categorized to create the model. The model's accuracy level was then determined.

2.6. Data Analysis. Using a laptop/PC, the data obtained from testing samples with the gas sensor array were processed. The sample testing data, in the form of voltage values versus time, were saved in a CSV file format. The data were then processed using the subsequent procedures:

(1) Extraction of features which entails defining data based on the most pertinent and informative values to represent the overall sensor response characteristics. In this study, PCA was used to cluster the data [25].

(2) Utilizing a line plot graph to display the test data. This step is intended to display the data pattern acquired from the six TGS gas sensors. This data representation can illustrate the differences in sample data patterns.

(3) Using the ANN-MLP algorithm, process the meatball sample data based on the gas sensor array response. The objective of this method of data analysis is to reduce and obtain clusters of aroma variations

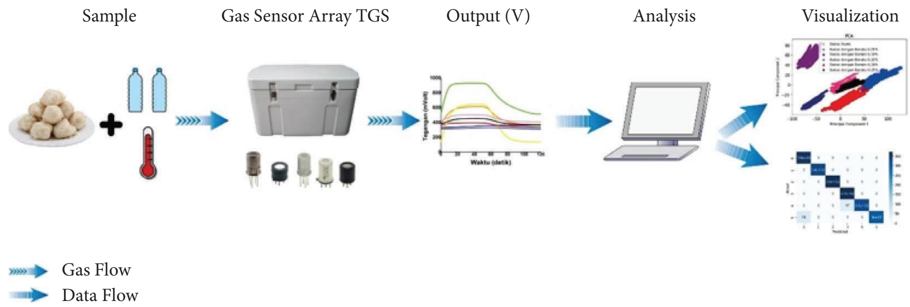

Figure 1: Schematic diagram of experimental apparatus.

that can be detected by the gas sensor array. Using the obtained grouping of data variations, the differences between pure chicken meatballs without borax and meatballs with added borax were accurately determined.

3. Results and Discussion

Sensor Response. Test results for borax solution ($\mathbf{Na_2B_4O_7.10H_2O}$). The sensor calibration test was conducted with borax samples, beginning with the dissolution of borax powder in water at concentrations of 0.05%, 0.10%, 0.15%, 0.20%, and 0.25%. The purpose of the borax solution sensor calibration test was to determine the sensor's sensitivity to the borax solution-produced gas. According to Sigma-Aldrich's material safety data sheet, borax is odorless. Figure 2 depicts the sensor response to the various concentrations of heated borax solution. Figure 2 demonstrates that the TGS sensor is able to detect the aroma of the borax solution, with TGS 2611 being more sensitive to the borax solution's aroma.

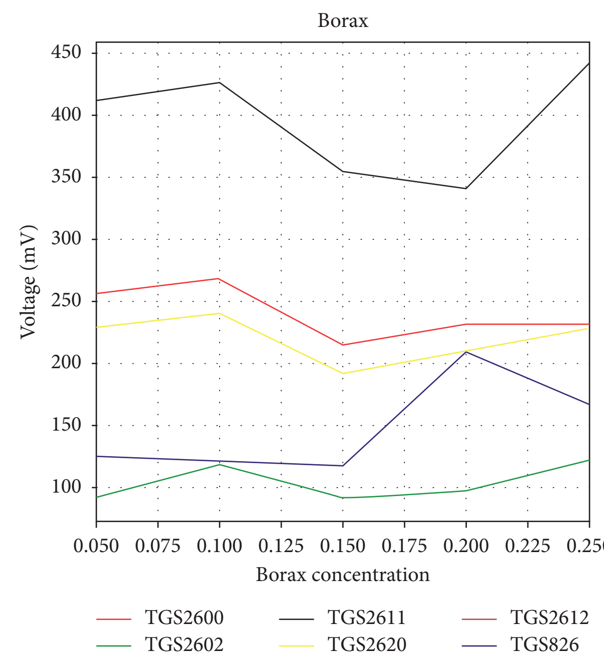

Figure 2: Sensor response graph to borax solution.

3.1. *Sensor Response Test Results for Bakso (Meatball) Sample.*

During data collection, 50 samples were collected for each variation, and each cycle lasted 6 minutes and 20 seconds. The collected data were displayed as a line plot graph to determine the voltage data range of each sensor's response based on the variation in borax concentration in the bakso (meatball) sample. The different voltage output values of the various samples resulted in distinct graph patterns between the concentration variations.

3.1.1. *Preheating Stage.*

Prior to data collection, the preheating stage (optimization of heating time) was performed to obtain a relatively stable output. During the preheating phase, the sensor was operated at a stable room temperature and with clean air to reach equilibrium. The process of preheating is depicted in Figure 3. Each sensor response has a specific voltage range and varies to reach a steady state, as depicted in Figure 3. The response of the sensor tends toward stability.

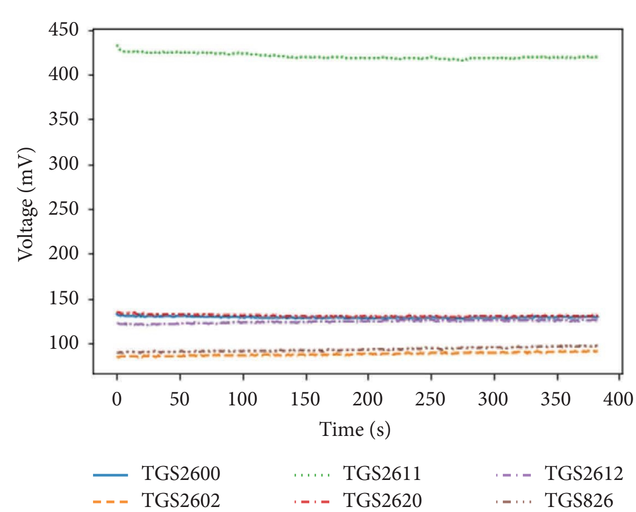

Figure 3: Preheating sensor TGS graph.

3.1.2. Baseline Stage. The baseline stage is the initial environment condition where the sensor begins collecting data based on the odor and temperature of the conditioned environment. This step is performed after the sensor has reached a steady state, and 10 seconds are required. This stage indicates the basic condition of the chamber environment, where a relatively stable sensor response is produced by the conditioned environment.

3.1.3. Sensing Stage. The sensing stage is the process of recognizing the sample's aroma under specific conditions, where the sample's temperature and chemical concentration affect the sensitivity of the sensor. During the required 120 seconds, all interconnected sensors must detect the aroma of the sample containing borax mixture concentrations of 0.05%, 0.10%, 0.15%, 0.20%, and 0.25%. The air concentration will overlap if the sensing time is too long, resulting in suboptimal measurements at this stage. Figure 4 combines the results of the sensor response test in the sensing process.

3.1.4. Purging Stage. The purging stage is the process of releasing the gas that has been collected in the chamber, which stores sample gases for sensor detection from the sensing stage. The purpose of purging is to remove the gases stored in the chamber so that the subsequent sample gas measurement is not contaminated and to return the conditions to a state close to equilibrium. This stage requires 250 seconds to evacuate the chamber's gases.

3.2. Sensor Validation Results. Reliable validation is required during the analysis process, which is one of the reasons for conducting a repeatability test. The purpose of the repeatability test is to determine the level of precision of a gas sensor array, where the gas sensor array used in this study is comprised of six different types of TGS gas sensors. This test was conducted by calculating the standard deviation (SD) as a percentage, and the results of the repeatability test for each TGS gas sensor are shown in Table 1.

Data with a repeatability test value of less than 20% is an effective validation parameter. However, as shown in Table 1, the repeatability test percentage in this study satisfies the requirements, as it is below 20%.

3.3. PCA Score Plots. PCA data analysis is an effort in data processing that reduces the dimension of data without sacrificing the information's intended meaning. Using PCA to analyze data involves multiple steps, including standardizing the data, locating the covariance matrix, and determining the eigenvalue and eigenvector values. The eigenvalue serves to explain the data information contained in the used principal component (PC). Table 2 displays the results of the eigenvalue calculation.

The value of the data variation derived from the eigenvalue calculation in this study represents the value of the gas sensor array with an accuracy of 64.99% for PC1 and 25.3% for PC2. Thus, data analysis with PCA using PC1 and PC2 accounts for 90.33 percent of the total variance.

The PCA score plot graph is utilized to determine data clustering and grouping. Figure 5 depicts a scatterplot with two PCs from six TGS sensor variables, where the score plot illustrates the clustering of data from six sample types. PCA does not require the assistance of other machine learning techniques to solve data clustering and classification in this study.

3.4. ANN Score Plot. In this study, a single model is employed based on the input data used for the analysis using the ANN-MLP technique. Table 3 displays the analysis of the ANN-MLP model.

Figure 6 depicts the structure of the ANN-MLP model with six input nodes. Based on the number of sensors, the input consists of 6 nodes, which send their data to the first hidden layer of 10 nodes, which then forwards it to the second hidden layer of 12 nodes, which produces 6 output nodes. Neurons in ANN are used as input or receiver of information from outside, where each neuron is connected by a connection link that has a weight value or weight. The weight between connections in a network architecture is given an initial value (learning value) and then ANN can be used as expected. SLN (single-layer network) is all input units in this network connected in all output units, even though they have different weight values.

3.4.1. Training Stage. In the training phase, 80% of the available data are utilized. Figure 7 depicts the accuracy and error rate obtained during training, as depicted in the training plot. The ANN score plot is a tool for visualizing the clustering and classification of data. In this study, the ANN-MLP analysis technique was applied to the input data. The input data conformed to the applied model, which in this instance employed a single model type based on the input data used.

3.4.2. Data Testing Stage. Following the training stage, the remaining 20% of the data were utilized for model validation. During the testing phase, the model generated the outcomes presented in Table 4. According to the purpose of this study, the number of outputs corresponds with the classification that has been formed. Class 0 refers to the sample without borax, class 1 to the sample containing 0.05% borax, class 2 to the sample containing 0.10% borax, class 3 to the sample containing 0.15% borax, class 4 to the sample containing 0.20% borax, and class 5 to the sample containing 0.25% borax.

Figure 8 exhibits, focusing on the training and testing results, the prediction results (x-axis) and the true value (y-axis) for each class of meatball samples analyzed using the ANN technique. The value 0 on the x- and y-axis represents the class of meatball samples with 0% borax variation. The value of 1 represents the class of meatball samples with 0.05% borax variation, 2 as the class of meatball samples with 0.10% borax variation, 3 as the class of meatball samples with

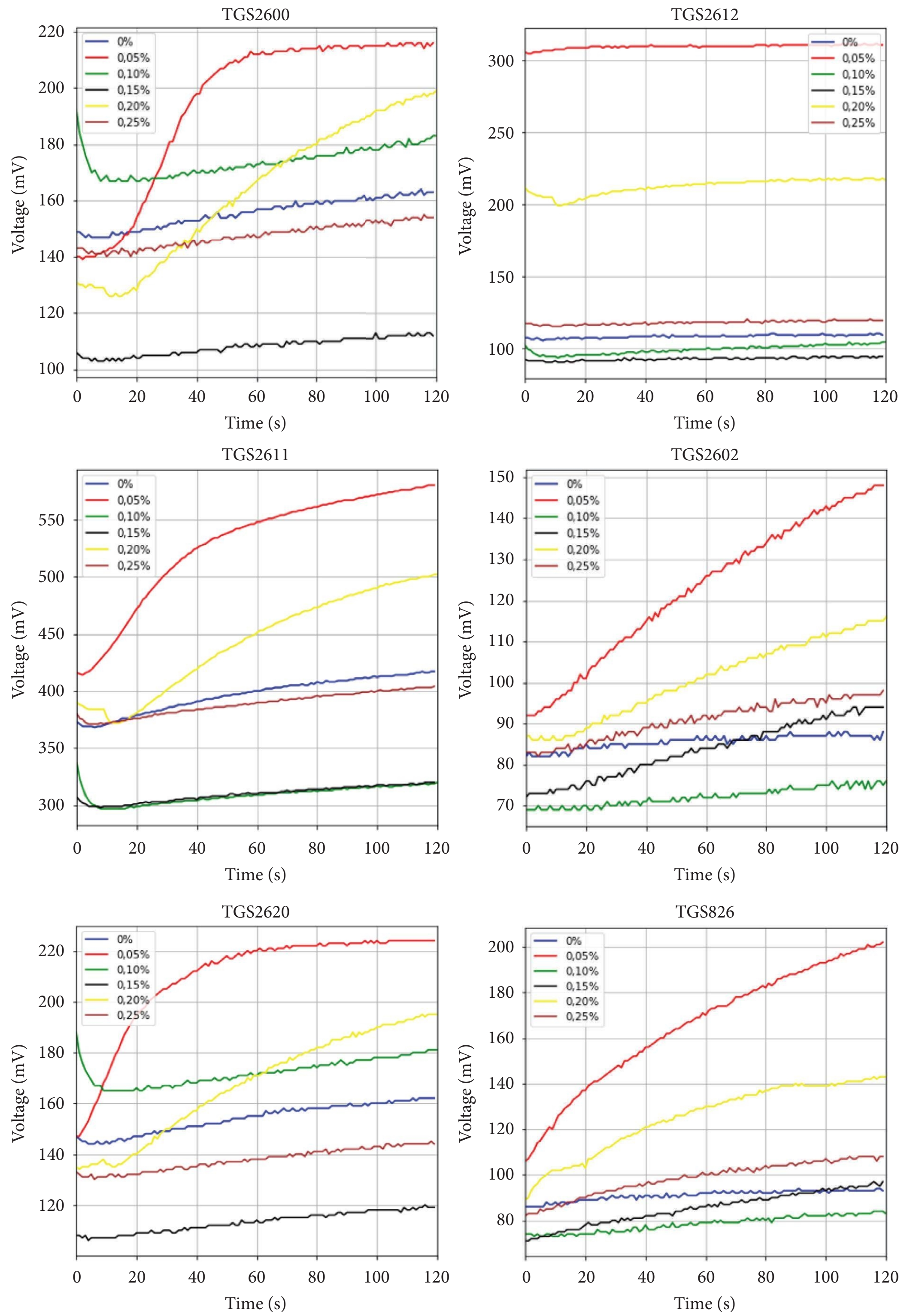

Figure 4: Sample sensing chart.

0.15% borax variation, 4 as the class of meatball samples with 0.20% borax variation, and 5 as the class of meatball samples with 0.25% borax variation.

The classification calculation is given in Table 4 for the precision rate, recall, average weight, and accuracy analyses based on the ANN-MLP method analysis. Precision is the prediction accuracy of the analysis model, whereas recall is the model's ability to extract information from the data. The *F*1 score is the weighted average comparison of precision and recall, and classification accuracy is the level of

Table 1: Gas sensors reality test result.

Sensor	Meatball sample without borax (0%)	Meatball sample with borax (0.05%)	Meatball sample with borax (0.10%)	Meatball sample with borax (0.15%)	Meatball sample with borax (0.20%)	Meatball sample with borax (0.25%)
	Standard deviation (%)					
TGS 2600	6.30	7.23	7.31	3.85	8.02	3.69
TGS 2602	2.57	6.33	4.08	8.64	5.91	4.17
TGS 2611	14.61	15.06	9.86	7.97	17.96	9.52
TGS 2620	7.14	6.89	7.55	5.91	7.93	3.06
TGS 2612	3.30	10.09	3.91	2.28	3.55	2.15
TGS 826	3.23	10.91	7.19	10.50	7.25	5.78

Table 2: Eigenvalue results.

	PC	Eigenvalue	% variations
Overall data	1	2569.09	64.98
	2	1002.32	25.35

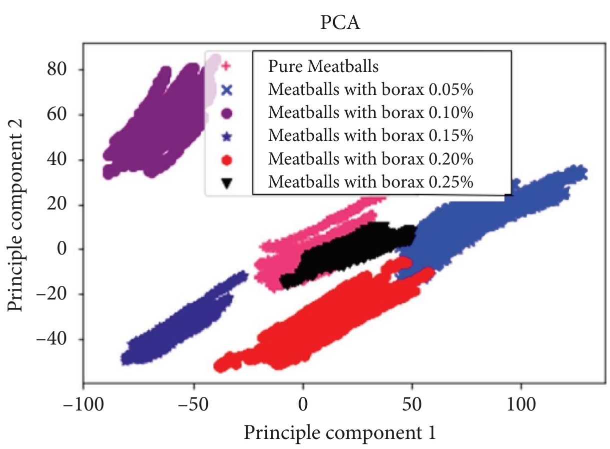

Figure 5: The graph score from PCA plot.

Table 3: The ANN-MLP model analysis.

Analysis model	Node input	Node output
(1) ANN	6	6

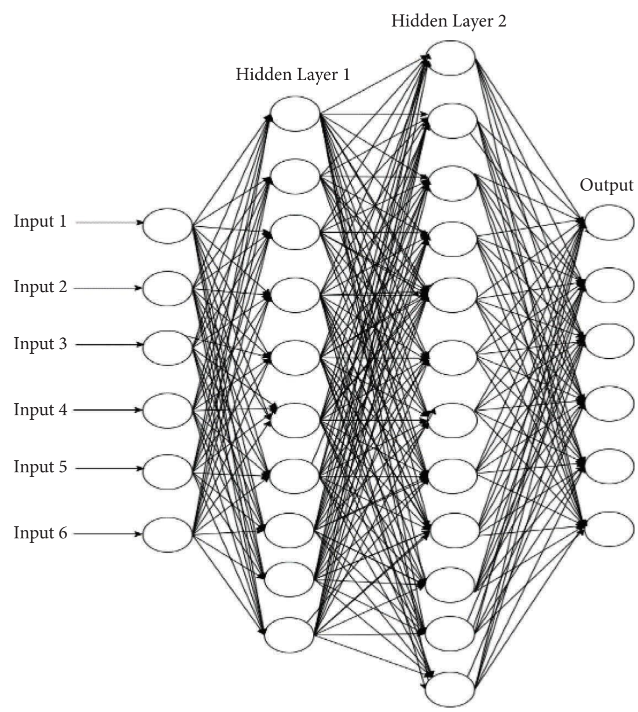

Figure 6: The model ANN-MLP with 6 node input.

classification accuracy of a model. Each precision, recall, and $F1$ score comprise a weighted average of the six mapped classes.

4. Discussion

A gas sensor array is an instrumentation device with a method comparable to the human nose for identifying specific types of odor. The gas sensor array instrumentation consists of a series of gas sensors that can detect specific gases, similar to how the human nose contains various receptors that detect odors. This investigation employs six types of TGS gas sensors: TGS 826, TGS 2600, TGS 2602, TGS 2611, TGS 2612, and TGS 2620.

The working principle of gas sensor array instrumentation begins with storing the sample in a 150 cc bottle. The sample used in this study is meatballs with various borax mixtures added to 5 ml of water and heated to 53°C. This study aims to accelerate protein denaturation by heating the sample. When protein undergoes denaturation, there is a significant increase in the production of alcohol, ketones, and hydrocarbons until it releases ammonia. The meatball sample produces ammonia when exposed to temperatures between 50°C and 90°C, accompanied by a decrease in its water and protein content [26].

When the heated sample emits an odor, the odor is passed through a dryer and then pumped into the sensing room, which is equipped with six sensors to prevent humidity interference. The selection of six TGS sensors is based on the reaction of the sample, namely, the temperature-induced denaturation of protein, where the ingredients of meatball samples containing protein and fat, when exposed to temperature, cause the breakdown of fat components into aldehydes, ketones, alcohols, acids, and hydrocarbons as the function of TGS 2611, TGS 2612, and TGS 2620 sensors and the breakdown of protein in the sample by protease resulting in the emergence of ammonia and hydrogen sulfide as the

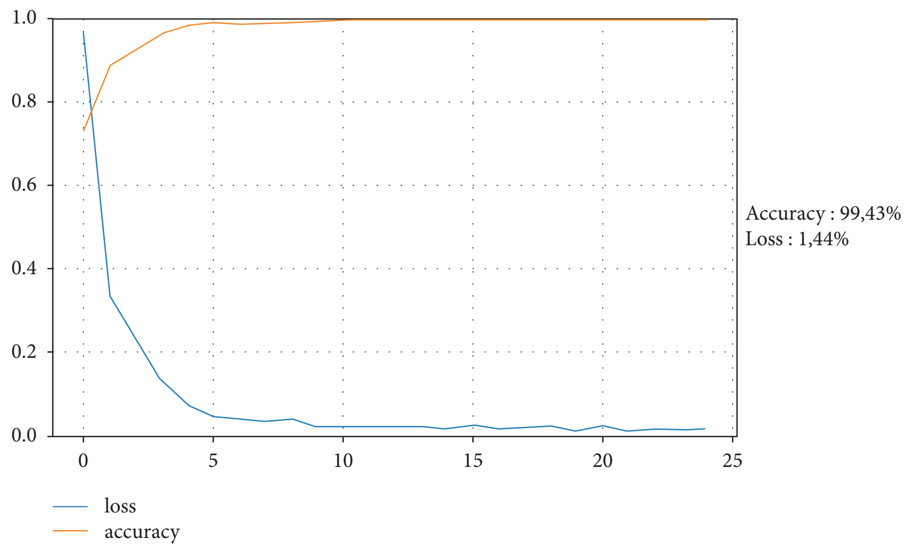

FIGURE 7: Plot showing training stage.

TABLE 4: The ANN model analysis test.

Remarks	Class 0	Class 1	Class 2	Class 3	Class 4	Class 5
Precision	0.87	1.00	1.00	0.89	1.00	1.00
Recall	1.00	1.00	1.00	1.00	0.87	0.85
*F*1 score	0.93	1.00	1.00	0.94	0.93	0.92
Support	359	338	365	370	374	356

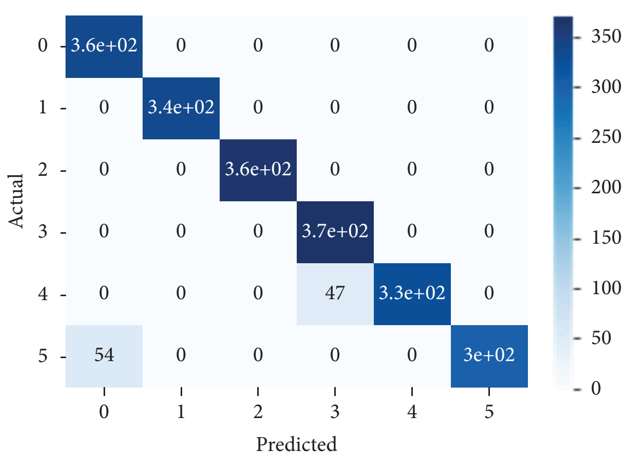

FIGURE 8: Confusion matrix ANN-MLP.

function of TGS 826 and TGS 2600 sensors. Hydrogen sulfide did not form in this study because oxygen was produced during the heating process and the sample was not in an anaerobic state.

When the sensor receives input in the form of analog signal, it produces a potential difference that adjusts the change in sensor resistance and can be measured in the form of output voltage in the form of digital signals. The .csv file contains the digital signal received by the gas sensor array instrumentation. Electron differences in each sensor result in potential differences, where the heated sample releases ammonia gas as a reducer, as depicted in Formula (1), and the negatively charged adsorbed oxygen density on the semiconductor sensor surface decreases, causing the barrier wall to also decrease.

$$NH_3 + O_2 \longrightarrow NO_2 + H_2O \quad (1)$$

When the barrier height decreases, the sensor resistance in samples containing reducer gas also decreases, and the greater the concentration of gas detected in free air, the lower the resistance value [27].

As a fundamental principle of physics, a low-resistance value results in a high output voltage. As shown in Formula (2), the principle of this sensor demonstrates that each sensor can detect a specific aroma based on the gas concentration, as each sample has a unique gas concentration. In this study, meatball samples with and without borax are distinguished by their aroma, whereas borax itself is odorless. Thus, the aroma which is the focus of this study is the aroma of the sample and the ammonia gas that is formed during the denaturation of protein; the ammonia gas content formed decreases as the concentration of borax used in the sample increases.

$$NH_3 + SnO_2 \longrightarrow \frac{1}{2}N_2 + SnO_2 + \frac{3}{2}H_2O \quad (2)$$

Protein solutions are gradually heated above the critical temperature, the proteins change from their native state to a denatured state [17, 28]. In this study, meatball samples containing varying concentrations of borax were utilized; the higher the borax concentration, the slower the protein denaturation process, resulting in a decrease in the amount of NH_3 produced by the meatball samples. According to Table 1, the line plot graph does not adhere to the principle of protein denaturation, which states that the higher the concentration, the less ammonia is produced, and vice versa.

To prepare the gas sensor array instrument, the sensors that will be used to collect data are preheated until they reach a steady state. Figure 4 depicts the preheating process, in which the output signal is relatively stable and the environment has been conditioned. After the instrument has been preheated, it can be used for data collection. The data collection procedure commences with the phases of baseline, sensing, and purging.

Prior to data collection, sensor testing was conducted using borax solutions with concentrations of 0.05 percent, 0.10 percent, 0.15 percent, 0.20 percent, and 0.25 percent. As depicted in Figure 2, the sensor testing results were plotted on a line graph. Based on the sensor response test, it was determined that the TGS 2611 gas sensor was more sensitive to the borax solution's odor.

During the baseline phase, environmental conditions were monitored for 10 seconds prior to data collection. During the sensing stage, which lasted 120 seconds, the sample's aroma came into contact with the sensor and the voltage difference between sensors was measured, as depicted in Figure 3. Different graphs were generated during the sensing stage due to the use of samples with different concentrations. After the sensing stage was completed, the purging stage was conducted for 250 seconds to remove any odor from the sample and return the chamber's environment to a stable state.

The data acquired through the data acquisition process were saved as a .csv file and then subjected to data analysis. Based on the training plot in Figure 7 and the test results in Figure 8 and Table 4, it was determined that the process of data recognition and information delivery using machine learning had a high level of accuracy, with an information acceptance accuracy rate of 99.43% for the ANN-MLP analysis technique. In addition, it was discovered that the ANN-MLP analysis model had a high-accuracy value for delivering information, but experienced overfitting with a 95% accuracy value.

The role of microbes and other hazardous substances in contaminating food [28] and causing infectious diseases is a problem in society. Detection of food quality through odors emitted or disease through the odor of infecting bacteria is one of the most promising early detection methods based on electronic nose because it can detect quickly and in real time. Although this method has the disadvantage that it cannot detect quantitatively with high accuracy like the gas spectroscopy method. Future research will try to correct this deficiency through sampling preparation methods at various concentrations and validation using different types of samples such as breath odor, saliva, or urine in cases of disease detection such as dental and oral diseases based on bacterial odor [29] and also diabetic [30].

5. Conclusions

In this study, a gas sensor array comprised of six different types of sensors (TGS 826, TGS 2600, TGS 2602, TGS 2611, TGS 2612, and TGS 2620) was utilized. All six TGS gas sensors were able to distinguish between meatball samples containing varying concentrations of borax. As indicated by the PCA plot, the PCA method was able to extract features and classify the responses of the TGS gas sensors to the sample aroma. Through data analysis, the cumulative variation of PC1 and PC2 was determined to be 90.33 percent. Using six direct inputs, the machine learning ANN-MLP analysis method was able to cluster and classify the sensor response of pure meatball aroma and meatball aroma containing borax. The grouping accuracy of the PCA and/or ANN-MLP data analysis methods was 90.33 percent and 95 percent, respectively.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Suryani Dyah Astuti and Fauziah conceptualized the study, developed methodology, contributed to validation, wrote, reviewed, and edited the article, performed supervision, and provided funding acquisition. Anak Agung Surya Pradhana and Riskia Agustina conceptualized the study, proposed the methodology, contributed to validation, and prepared the original draft. Perwira Annissa Dyah Permatasari and Cendra Devayana Putra wrote, reviewed, and edited the article, conceptualized the study, and contributed to validation. Harsasi Setyawati and Ahmad Khalil Yaqubi conceptualized the study, proposed the methodology, and contributed to validation. Winarno conceptualized the study and validated the original draft preparation.

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