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Article

Product differentiation of Sarawak premium rice using MOS gas sensors: comparison between transient and frequency response

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ABSTRACT

In Malaysia, rice, ranked as the third most crucial crop, faces challenges due to domestic consumption outpacing production, resulting in increased instances of rice adulteration. This underscores the imperative of maintaining integrity and quality standards across the entire supply chain. This study uses an electronic nose, comprising four metal oxide semiconductor (MOS) gas sensors, and employing temperature modulation, Principal Component Analysis (PCA) and supervised machine learning (classification models) to distinguish rice varieties such as Bario, Bajong, Borneo Fragrant, Biris, and Jasmine. The study evaluated 30 classifiers based on their classification and validation accuracy. Sensor data was first extracted from the transient response of sensors output voltage, yielding a 12-dimension dataset with response times of 30 s, 50 s, and 95 s. Classification models trained from this dataset achieved classification (training) accuracy of up to 100% and validation accuracy of up to 96%, where the best performing models are subspace discriminant and kernel naïve bayes classifiers. An attempt was also made to analyze the sensor data frequency response for rice classification. Comparison between the prediction results in the transient and frequency domains showed that transient response is better suited for the classification of rice.

1. Introduction

The increasing population and natural factors affecting rice production, coupled with the diverse range of rice varieties, have created opportunities for dishonest traders to profit by adulterating rice. Adulteration methods include blending lower-quality rice, adding similar-looking materials, and withholding clear information about the rice's origin and age. Even small amounts of undesirable substances can make it challenging to differentiate between genuine and fake rice. Such adulterated products pose serious health risks and can lead to harmful consequences. Recent reports have even surfaced about the use of plastic rice as an adulterant, underscoring the dangers of food adulteration [1-5]. This report suggests a swifter, cost-effective, and non-intrusive approach for geographically tracking the classification of Sarawak Premium Rice (Bajong, Bario, Biris, and Borneo Fragrant Rice) by the model, which is metal oxide semiconductor (MOS) Gas Sensors or electronic nose, which is more cost-effective, rapid, and non-invasive. To identify the most dependable classification models for this application, a variety of popular classifiers were trained and evaluated in this study. These included neural networks, naïve Bayes, linear regression, logistic regression, random forests, support vector machines (SVM) [6]. Classification accuracy was compared across these models to determine their efficacy for the task at hand. In a frequency domain representation, the emphasis is on illustrating the relationship between the signal's amplitude (or power) and frequency, as opposed to time. This approach proves especially beneficial for signals characterized by the superposition of multiple frequencies [7]. Transient and frequency response methods were devised to authenticate rice samples from Bario, Bajong, Borneo Fragrant, Biris, and Jasmine varieties. In the transient response approach, classification model training and prediction were iterated using sensor responses at various points in the sampling cycle. Conversely, in frequency response analysis, dip frequencies were recorded, and patterns were compared for identification. These methods facilitated the precise classification of rice varieties based on their distinct response characteristics.

2. Methodology

2.1 Preparation, storage, and sampling of rice

To create the training datasets utilized in this study to train the classification models, a total of 100 rice samples were meticulously prepared as follows:

- 20 samples of Bario
- 20 samples of Bajong
- 20 samples of Borneo Fragrant
- 20 samples of Biris
- 20 samples of Jasmine

To validate the trained classification models, a total of 25 rice samples were prepared as follows and predicted by the trained classification models:

- 5 samples of Bario
- 5 samples of Bajong
- 5 samples of Borneo Fragrant
- 5 samples of Biris
- 5 samples of Jasmine

Figure 1 illustrates the physical appearance of each type of rice samples used in this study. Each sample consisted of 8 grams of rice. These samples encompassed Sarawak Premium Rice varieties, including Bario, Bajong, Borneo Fragrant, Biris, and a standard rice type, Jasmine. The rice sample was stored in a zipper bag and labeled clearly with the name of the rice and the number of the rice.

This study utilized the MOS gas sensors module, sampling process, and feature extraction method practiced by Lee et al. in their studies [8-11]. Sensor response is defined as the change in sensor output voltage (voltage across an external load resistor) due to the change in resistance of the sensing material in the sensor. The change in sensor output voltage is calculated as a percentage change by comparing it with the sensor output voltage baseline, which was set to 1.0 V in this study.

For the construction of the MOS gas sensor array, four Figaro TGS series sensors were employed: TGS2600, TGS2602, TGS2620, and TGS2611. These selected MOS gas sensors possessed unique selectivity for target gases, as outlined in Table 1 [12-15].

The complete circuit configuration is shown in Figure 2. The microcontroller chosen for this purpose is the Arduino Uno, which facilitates the collection of sensory data during the sampling process and allows the data to be displayed on the Arduino software graphical user interface. Figure 3 illustrates the sample holder used to contain rice samples for headspace sampling.

Table 1. Sensor models used in this study

Sensor Model	Target Gases	Sensor Resistance
TGS2600	Air contaminants (hydrogen, ethanol, etc.)	10 to 90 kΩ in air
TGS2602	Air contaminants (VOCs, ammonia, H_2S, etc.)	10 to 100 kΩ in air
TGS2620	Alcohol, solvent vapours	0.68 to 6.8 kΩ in 5000 ppm methane
TGS2611	Methane, natural gas	1 to 5 kΩ in 300 ppm ethanol

Before sampling, the sensors' output voltages were calibrated to a baseline of 1.0 V by adjusting the resistance of the digital potentiometers (connected as external load resistors). During the sampling process, the sample holder containing rice sample was inserted into the sensing chamber. The sensing chamber was isolated from other pneumatic components using normally closed vacuum solenoid valves to prevent air or odor exchange. Upon completion of sampling, the solenoid valves were opened to introduce carrier gas. The air pump was then activated to purge volatile organic compounds (VOCs) from the sample and replace it with clean air at a flow rate of 2000 cm^3/min. This ensured the sensors returned to their baseline output voltage (1.0 V) in a chamber filled with clean air. Before initiating the rice sampling process, sensor warming was performed to enhance sensor stability. This involved placing a sample of 6 coffee beans into the sensing chamber and applying a heater voltage level of 5.0 V for 20 minutes. A cumulative quantity of 8 grams would be collected as sample data for Principal Component Analysis (PCA).

(a) (b) (c) (d) (e)

Figure 1. Sample of (a) Bajong, (b) Jasmine, (c) Borneo Fragrant, (d) Bario and (e) Biris

Temperature modulation of MOS gas sensors was employed by applying three heater voltages (4.6 V, 4.8 V, and 5.0 V) to produce three configurations of gas sensors sensitivity and selectivity. Data collection began at the 10th second, with the sensitivity level incrementing by 0.2 V every 30 seconds until reaching 5.0 V, then remaining constant for the subsequent 30 seconds. Following this, it decreased by 0.2 V every 30 seconds until reaching the threshold of 4.6 V. In the detailed sampling procedure shown in Figure 4, the total sampling time of 140 seconds (including a 10-second baseline period), a maximum purging duration of 20 seconds, and a maximum recovery phase of 200 seconds reveal that each sampling session required a maximum of approximately 360 seconds, equivalent to 6 minutes. This was notably faster compared to the 30-minute sampling cycle typically associated with the conventional GC-MS method.

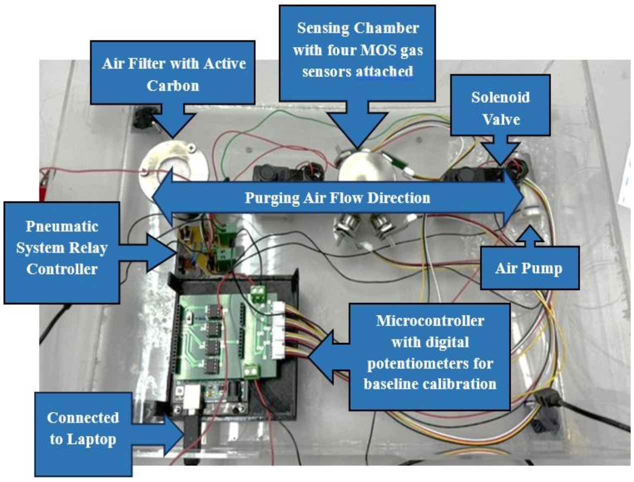


Figure 2. Complete circuit configuration of the MOS gas sensor array

Figure 3. Sample holder

2.2 Sample data analysis

A total of 100 training samples (20 samples per class) and 25 validation samples (5 samples per class) were collected for the principal component analysis (PCA), which was initially applied to the data matrix as a preprocessing step. Subsequently, the preprocessed data matrix was utilized for training 33 classification models from broad categories of the decision tree, discriminant analysis, logistic regression classifier, naïve Bayes classifier, SVM, k-nearest neighbor (KNN), ensemble classifier, and neural network. All 33 classification models underwent evaluation based on their classification accuracy on the training datasets and prediction accuracy on five test samples. The selected model with the highest accuracy was chosen, and if necessary, fine-tuning would be conducted.

2.3 Signal processing on the frequency domain

Figure 5 outlines the workflow for signal processing on the frequency domain. MATLAB was utilized for the signal processing method. In the program, the data obtained from the sensor response curve would undergo transformation into a frequency domain graph for signal processing. It was utilized to discern the signal behavior of each rice sample by identifying dips in the signal and recording their frequencies.

$$f = \frac{1}{T} \tag{1}$$

The sample rate was determined to be 1 Hz, as the overall sampling process takes approximately 130 seconds with a 1-second interval between each sample. This calculation was derived using the equation (1). This process was conducted for every variety of rice, and ultimately, the range of frequencies associated with the dips was compared to identify patterns. Dips are the main features extracted from a frequency domain graph. Dips in a frequency domain graph represent specific frequencies at which the signal's amplitude or power decreases significantly compared to neighboring frequencies. These dips often correspond to certain features or characteristics present in the signal. They serve as an important marker that can reveal valuable information about the underlying signals and help in interpreting and analyzing the data effectively. Based on the example in Figure 6, three dips are observed between 320.1 mHz and 386.3 mHz.

3. Results and discussion

3.1 Transient response

Table 2 shows the legend of the rice samples data on the principal components (PC) scatter plot generated using the processed data of the sensors' transient responses. Data was collected in two dimensions – a 4-dimensional dataset (from the response time of 80 s) and a 12-dimensional dataset (from the response times of 30, 50, and 95 seconds) – for comparison. Classification accuracy was assessed using a confusion matrix, employing a Cubic SVM model, as shown in Table 3. PC3 vs PC1 graph is shown in Table 3 solely for illustration purposes to demonstrate good interclass data separation that can even be observed by human eyes, which verifies the high accuracy in classification model training.

Table 2. Legend pf transient response scatter plot

Rice	Abbreviation	Color of data point on the scatter plot
Bario	BR	Yellow
Bajong	BJ	Orange
Borneo Fragrant	BH	Blue
Biris	BS	Purple
Jasmine	JS	Green

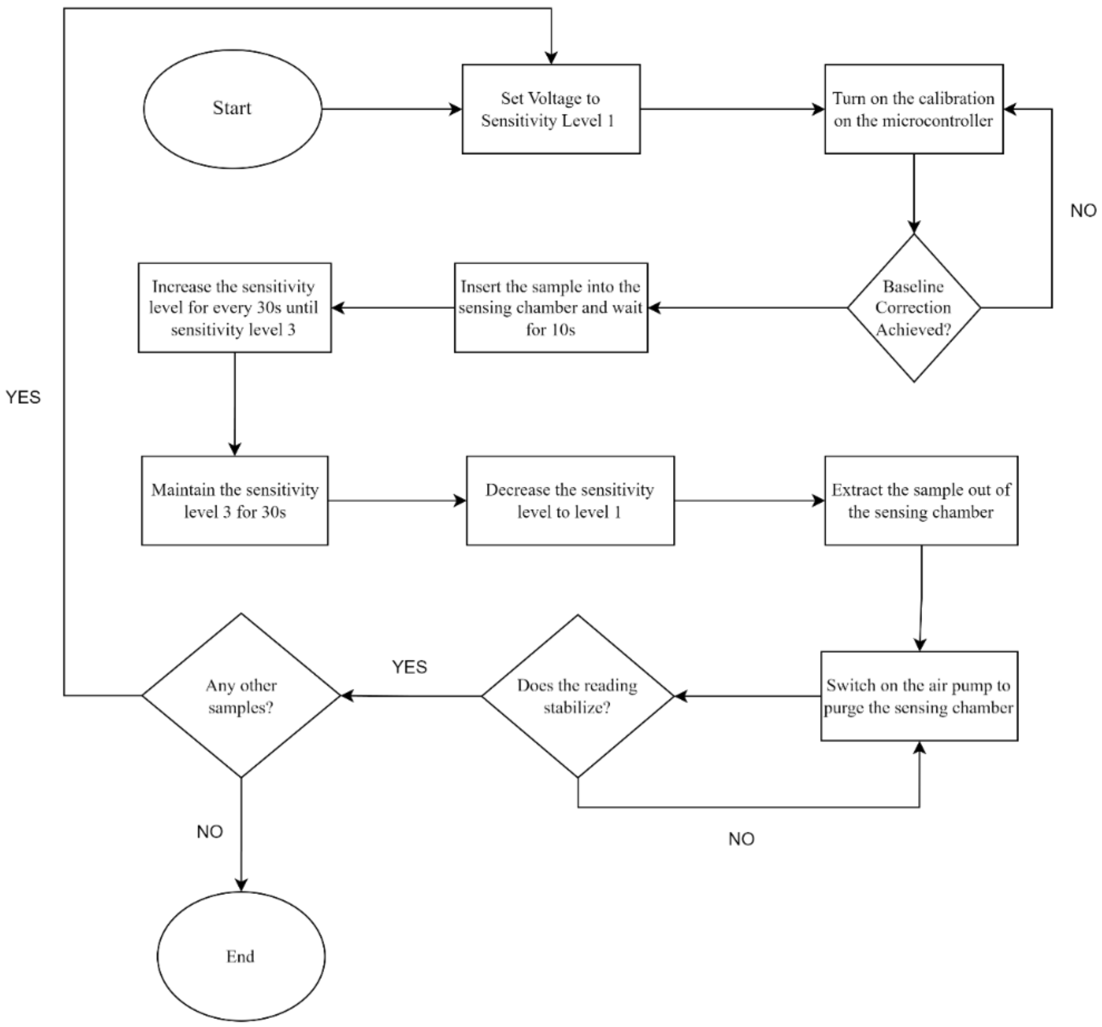


Figure 4. Sampling procedure

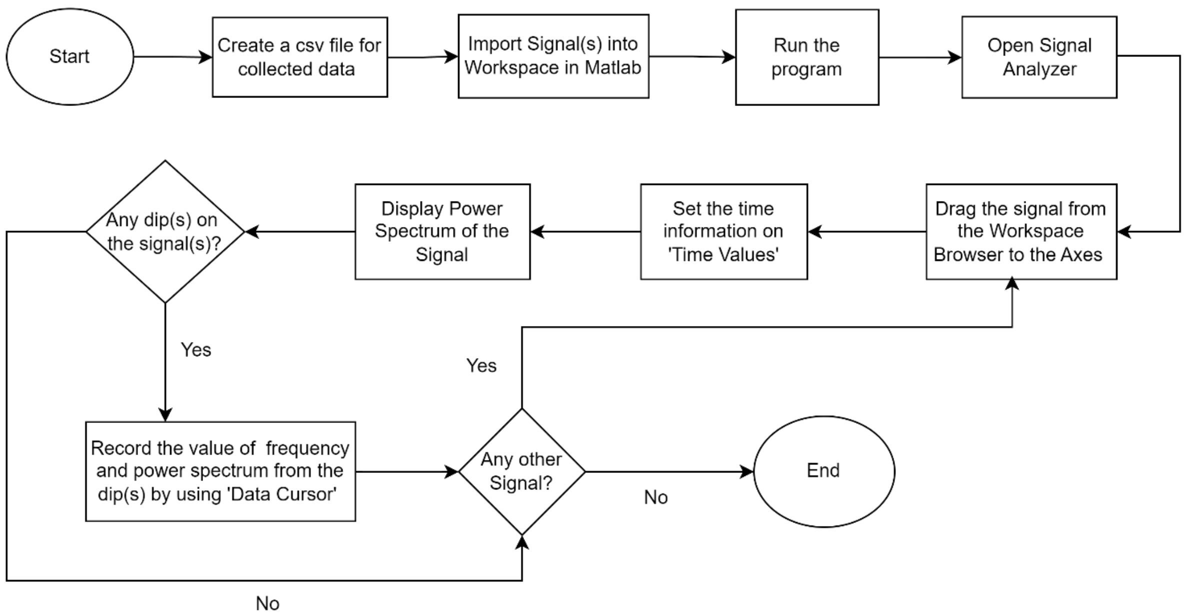


Figure 5. Procedures for frequency response signal processing

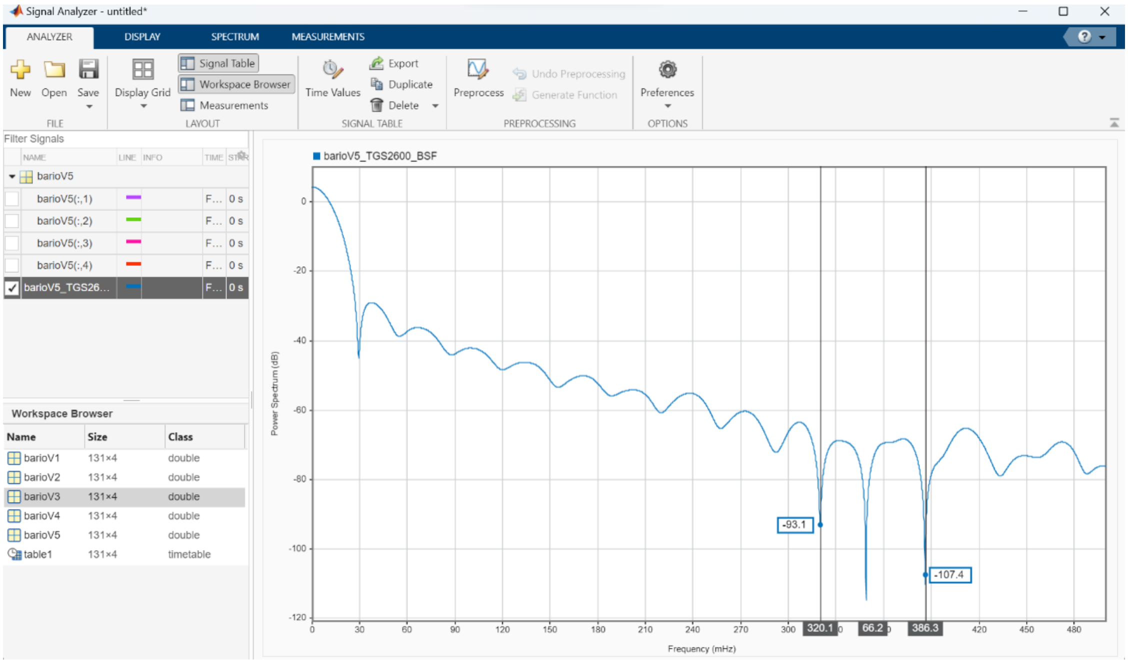
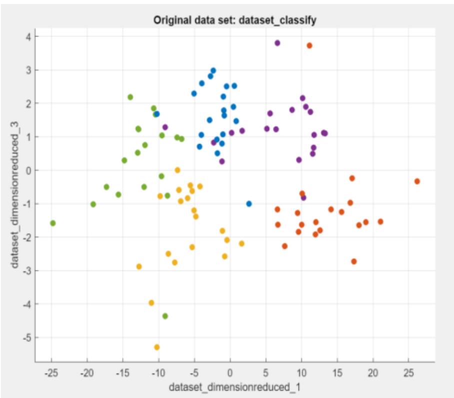
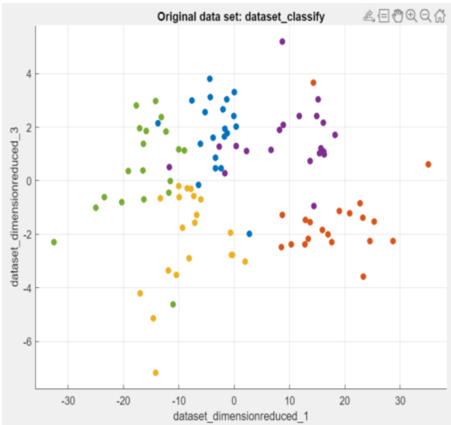


Figure 6. Example of dips: three dips are observed between 320.1 mHz and 386.3 mHz

Table 3. Classification model training accuracy: comparison between 4-dimensional and 12-dimensional dataset

Training Set: Dimension	Training Set: Time (s)	PCA Scatter Plot	Confusion Matrix
4	80		4 Dimension (80s) Model: Cubic SVM (99%)
12	30, 50, 95		12 Dimension (30s,50s,95s) Model: Cubic SVM (100%)

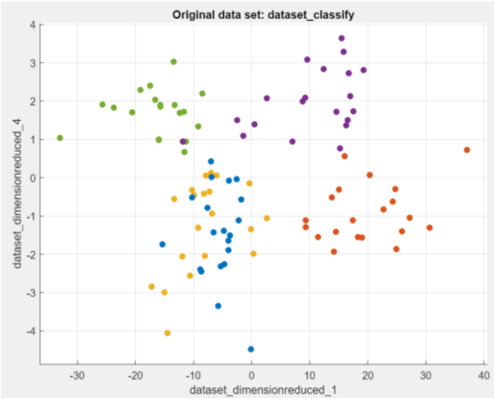
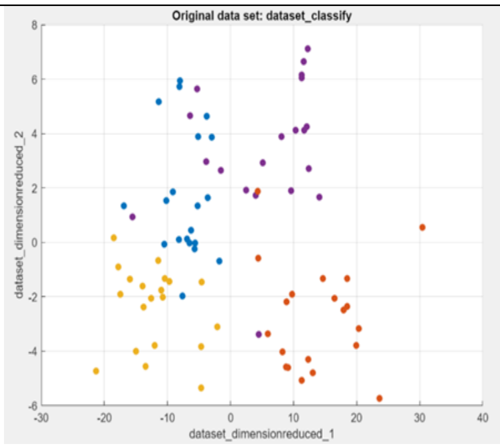
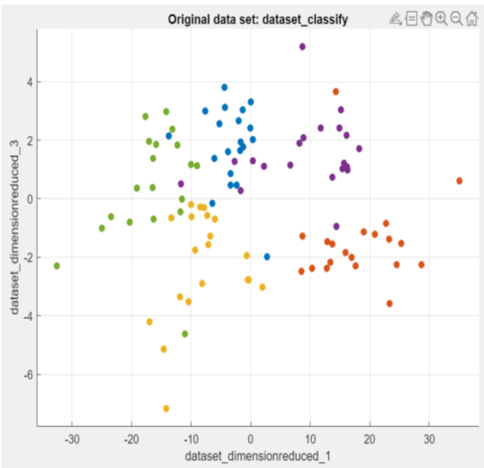
4 Dimension (80s)
Model: Cubic SVM (99%)

True Class \ Predicted Class	BR	BJ	BF	BS	JS
BR	20				
BJ		20			
BF			19	1	
BS				20	
JS					20

12 Dimension (30s,50s,95s)
Model: Cubic SVM (100%)

True Class \ Predicted Class	BR	BJ	BF	BS	JS
BR	20				
BJ		20			
BF			20		
BS				20	
JS					20

Table 4. Classification model training accuracy: comparison between different sets of response times

<table>
<tr><th colspan="2">Training Set</th><th rowspan="2">PCA Scatter Plot</th><th rowspan="2">Confusion Matrix</th></tr>
<tr><th>Dimension</th><th>Time (s)</th></tr>
<tr><td>12</td><td>30, 60, 95 (set 1)</td><td>
</td><td>
<table>
<tr><th colspan="7">12 Dimension (30,60, 95s)
Model: Coarse Tree (81%)</th></tr>
<tr><td rowspan="5">True Class</td><td>BR</td><td>11</td><td></td><td>9</td><td></td><td></td></tr>
<tr><td>BJ</td><td></td><td>19</td><td></td><td>1</td><td></td></tr>
<tr><td>BF</td><td>1</td><td></td><td>18</td><td></td><td>1</td></tr>
<tr><td>BS</td><td></td><td>1</td><td>3</td><td>15</td><td>1</td></tr>
<tr><td>JS</td><td>2</td><td></td><td></td><td></td><td>18</td></tr>
<tr><td></td><td></td><td>BR</td><td>BJ</td><td>BF</td><td>BS</td><td>JS</td></tr>
<tr><td colspan="7">Predicted Class</td></tr>
</table></td></tr>
<tr><td>12</td><td>30, 50, 90 (set 2)</td><td>
</td><td>
<table>
<tr><th colspan="7">12 Dimension (30,50, 90s)
Model: Coarse Tree (78%)</th></tr>
<tr><td rowspan="5">True Class</td><td>BR</td><td>19</td><td></td><td>1</td><td></td><td></td></tr>
<tr><td>BJ</td><td></td><td>20</td><td></td><td></td><td></td></tr>
<tr><td>BF</td><td>2</td><td></td><td>18</td><td></td><td></td></tr>
<tr><td>BS</td><td></td><td></td><td></td><td>20</td><td></td></tr>
<tr><td>JS</td><td>2</td><td></td><td>17</td><td></td><td>1</td></tr>
<tr><td></td><td></td><td>BR</td><td>BJ</td><td>BF</td><td>BS</td><td>JS</td></tr>
<tr><td colspan="7">Predicted Class</td></tr>
</table></td></tr>
<tr><td>12</td><td>30, 50, 95 (set 3)</td><td>
</td><td>
<table>
<tr><th colspan="7">12 Dimension (30s,50s,95s)
Model: Coarse Tree (84%)</th></tr>
<tr><td rowspan="5">True Class</td><td>BR</td><td>20</td><td></td><td></td><td></td><td></td></tr>
<tr><td>BJ</td><td></td><td>19</td><td></td><td>1</td><td></td></tr>
<tr><td>BF</td><td>1</td><td></td><td>18</td><td></td><td>1</td></tr>
<tr><td>BS</td><td></td><td>1</td><td>4</td><td>14</td><td>1</td></tr>
<tr><td>JS</td><td>7</td><td></td><td></td><td></td><td>13</td></tr>
<tr><td></td><td></td><td>BR</td><td>BJ</td><td>BF</td><td>BS</td><td>JS</td></tr>
<tr><td colspan="7">Predicted Class</td></tr>
</table></td></tr>
</table>

In the 4-dimensional dataset, the confusion matrix indicated a 99% accuracy rate, with one misclassification observed: a Borneo Fragrant rice sample incorrectly predicted as Biris rice. Conversely, the 12-dimensional confusion matrix demonstrated flawless 100% accuracy, with all rice samples correctly classified. Consequently, a 12-dimensional PCA scatter plot, considering the utilization of four MOS gas sensors, for comprehensive analysis.

Three 12-dimensional datasets were generated, each with different response times: Set 1 (30, 60, 95 seconds), Set 2 (30, 50, 90 seconds), and Set 3 (30, 50, 95 seconds). Utilizing a Coarse Three classification model, a confusion matrix was employed for comparison which shown in Table 4. While Set 3 allowed the classification of the rice samples with some errors, it was selected for further analysis.

Table 5 displays the best-performing classification models achieving a classification (training) accuracy of 100%. A comprehensive list of 14 classification models was provided for reference. During the classification models' validation stage, three distinct validation sets were selected as well as shown in Table 6, each corresponding to datasets generated at different response times: Set 1 (30, 60, 95 seconds with PC4 and PC1), Set 2 (30, 50, 90 seconds with PC1 and PC3), and Set 3 (30, 50, 95 seconds with PC3 and PC1). The Subspace Discriminant classification model was chosen for comparison. Set 3 stood out as the best-performing dataset, boasting an impressive accuracy of 96%, surpassing the others in accuracy among the compared sets.

Table 5. Classification models that achieved 100% classification (training) accuracy

Classification model	Classification accuracy of training data (% out of 100 training samples)
	Set 3 (30s, 50s, 95s)
Quadratic Discriminant	100
Quadratic SVM	100
Cubic SVM	100
Fine Gaussian SVM	100
Medium Gaussian SVM	100
Fine KNN	100
Weighted KNN	100
Bagged Trees	100
Narrow Neural Network	100
Medium Neural Network	100
Kernel Naïve Bayes	100
Subspace KNN	100
Wide Neural Network	100
Bilayer Neural Network	100

Table 7 showcases the top 6 classification models achieving the highest validation accuracy. Subspace Discriminant and Kernel Naïve Bayes both achieved 96% accuracy, while Coarse Gaussian SVM, Cosine KNN, Weighted KNN, and Bagged Trees attained an accuracy of 92%.

3.2 Frequency response

The exclusion method could be employed, which involves comparing frequency ranges and eliminating incorrect matches to identify the rice sample. Table 8 shows the comparison of the range of dips frequency across training and validation data for four sensors. It became apparent that identifying rice was challenging due to discrepancies in the frequency range between the training and validation sets. Some fell within the range, while others did not. Moreover, there were instances where the frequency ranges from a sensor for a specific rice sample overlapped with the range of another rice sample, suggesting that it did not exclusively pertain to one sample. Hence, it could be concluded that the rice sample cannot be identified solely through the comparison of the frequency range of dip occurrences.

Another comparison was conducted on the range of dips power spectrum in Table 9 to determine if rice could be correctly identified. However, the outcome mirrored that of the frequency range comparison, wherein the power spectrum range of a sensor for a rice sample did not closely match the validation set, and some overlaps occurred with other samples. Consequently, this comparison method was deemed inappropriate for rice classification analysis.

The signal processing method in the frequency domain may not be suitable for classification when dealing with a larger number of sample types, such as the five different types of rice in this case. With more types of samples, overlapped between frequency responses become more common, leading to difficulties in classification. Restricting the classification to fewer types, may yield more reliable results as it reduced the likelihood of overlaps and enhanced the distinctiveness of frequency responses for each type.

Table 7. Classification models with the highest validation accuracy

Classification model	Prediction accuracy of validation data (% out of 25 validation samples)
	Set 3 (30s, 50s, 95s)
Subspace Discriminant	96
Kernel Naïve Bayes	96
Coarse Gaussian SVM	92
Cosine KNN	92
Weighted KNN	92
Bagged Trees	92

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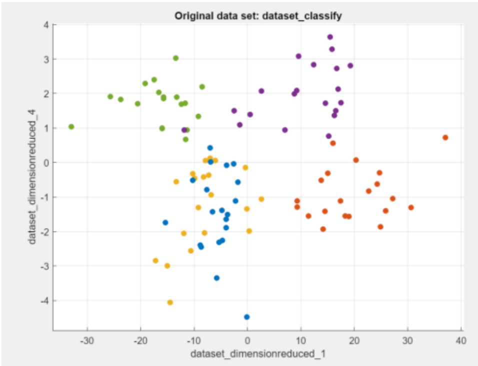
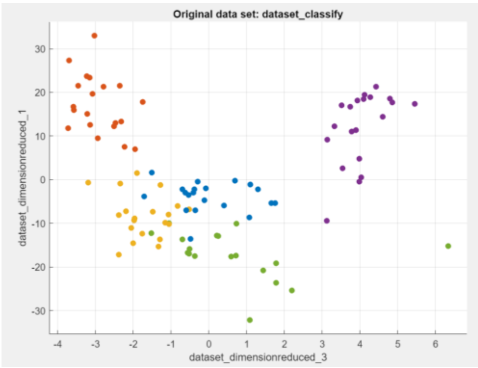
Table 6. Classification model validation accuracy: comparison between different sets of response times

<table>
<tr><th colspan="2">Validation</th><th rowspan="2">PCA Scatter Plot</th><th rowspan="2">Confusion Matrix</th></tr>
<tr><th>Dimension</th><th>Time (s)</th></tr>
<tr><td>12</td><td>30, 60, 95 (set 1)</td><td>
</td><td>
<table>
<tr><th colspan="7">12 Dimension (30,60,95s)
Model: Subspace Discriminant (80%)</th></tr>
<tr><td rowspan="5">True Class</td><td>BR</td><td>5</td><td></td><td></td><td></td><td></td></tr>
<tr><td>BJ</td><td></td><td>5</td><td></td><td></td><td></td></tr>
<tr><td>BF</td><td></td><td></td><td>0</td><td>5</td><td></td></tr>
<tr><td>BS</td><td></td><td></td><td></td><td>5</td><td></td></tr>
<tr><td>JS</td><td></td><td></td><td></td><td></td><td>5</td></tr>
<tr><td></td><td></td><td>BR</td><td>BJ</td><td>BF</td><td>BS</td><td>JS</td></tr>
<tr><td colspan="7">Predicted Class</td></tr>
</table></td></tr>
<tr><td>12</td><td>30, 50, 90 (set 2)</td><td>
</td><td>
<table>
<tr><th colspan="7">12 Dimension (30,50, 90s)
Model: Subspace Discriminant (68%)</th></tr>
<tr><td rowspan="5">True Class</td><td>BR</td><td>4</td><td></td><td></td><td></td><td>1</td></tr>
<tr><td>BJ</td><td></td><td>5</td><td></td><td></td><td></td></tr>
<tr><td>BF</td><td></td><td></td><td>5</td><td></td><td></td></tr>
<tr><td>BS</td><td></td><td></td><td>4</td><td>0</td><td>1</td></tr>
<tr><td>JS</td><td>2</td><td></td><td></td><td></td><td>3</td></tr>
<tr><td></td><td></td><td>BR</td><td>BJ</td><td>BF</td><td>BS</td><td>JS</td></tr>
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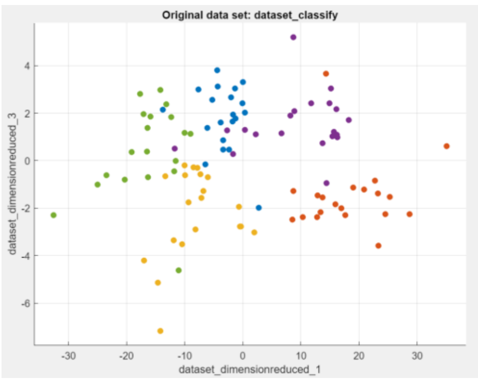
<tr><td>12</td><td>30, 50, 95 (set 3)</td><td>
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<tr><th colspan="7">12 Dimension (30s,50s,95s)
Model: Subspace Discriminant (96%)</th></tr>
<tr><td rowspan="5">True Class</td><td>BR</td><td>5</td><td></td><td></td><td></td><td></td></tr>
<tr><td>BJ</td><td></td><td>5</td><td></td><td></td><td></td></tr>
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<tr><td></td><td></td><td>BR</td><td>BJ</td><td>BF</td><td>BS</td><td>JS</td></tr>
<tr><td colspan="7">Predicted Class</td></tr>
</table></td></tr>
</table>

Table 8. Range of sensors dips frequency across training and validation data: comparison between five classes of samples

	Range of dips frequency (mHz)									
	Bario		Bajong		Borneo Fragrant		Biris		Jasmine	
Training(T)/ Validation (V)	T	V	T	V	T	V	T	V	T	V
TGS2600	411.1 - 483.4	320.1 - 422.2	358.7 - 460.1	354.3	329.2 - 402.9	352.1 - 417.5	346.0 - 487.3	370.8 - 480.1	319.5 - 469.1	370.6 - 445.9
TGS2602		419.4			380.8 - 450.9	383.5 - 417.8	327.8 - 484.6	370.3 - 440.9	473.7	321.2 - 469.6
TGS2620	346.0 - 377.5	316.2 - 477.4	448.1	369.7 - 418.9	311.2 - 469.9	384.2 - 483.4	317.3 - 419.6	314.5	380.2 - 465.2	406.2 - 429.9
TGS2611	352.1 - 385.5	352.6 - 424.4	351.0 - 469.1	460.3 - 483.4	355.9 - 482.7	358.1 - 485.6	421.6 - 485.6	317.3 - 486.5	456.4	426.5 - 490.1

Table 9. Range of sensors dips power spectrum across training and validation data: comparison between five classes of samples

	Range of dips power spectrum (dB)									
	Bario		Bajong		Borneo Fragrant		Biris		Jasmine	
Training(T)/ Validation (V)	T	V	T	V	T	V	T	V	T	V
TGS2600	(-97.1) - (-77.9)	(-110.2) - (-73.1)	(-100) - (-71.7)	-84.7	(-94.7) - (-67.5)	(-91.5) - (-81.1)	(-101.1) - (-76.6)	(-108.4) - (-79.8)	(-94.0) - (-69.1)	(-107.6) - (-82.3)
TGS2602		-81.3			(-86.5) - (-81.3)	(-87.7) - (-82.7)	(-99.9) - (-79.2)	(-95.4) - (-88.0)	-97.4	(-103.7) - (-82.7)
TGS2620	(-89.0) - (-83.9)	(-89.6) - (-76.9)	-74.4	(-91.5) - (-74.6)	(-84.6) - (-67.2)	(-87.2) - (-75.3)	(-103.2) - (-74.4)	-79.3	(-84.5) - (-75.4)	(-94.7) - (-85.7)
TGS2611	(-96.9) - (-89.4)	(-77.7) - (-76.2)	(-84.5) - (-77.4)	(-89.3) - (-84.1)	(-110.4) - (-72.7)	(-107.4) - (-78.9)	(-90.1) - (-87.7)	(-101.9) - (-84)	-98.5	(-96.4) - (-89.5)

4. Conclusion

The machine learning method achieves an optimal accuracy of 100% by analyzing the transient response within the training dataset. Furthermore, when this method is applied to the validation dataset, it also yields notably high accuracy levels, > 80%. The high accuracy suggests that the machine learning model effectively identifies most rice samples by recognizing their distinctive characteristics. On the contrary, the outcome of the signal processing on the frequency response did not meet expectations. It is found that this signal processing method is unable to interpret the behaviors exhibited by the rice samples. Therefore, the analysis of frequency dips did not effectively aid in identifying the rice samples as anticipated. In short, a machine learning method with transient response is recommended for the classification of rice samples.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work be original and not published elsewhere.

Data availability statement

The datasets analyzed during the current study are available and can be given upon reasonable request from the corresponding author.

Conflict of interest

The authors declare no potential conflict of interest.

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