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Investigation and Classification of Unpleasant Odor in Restroom Using Intelligent Signal Processing Technique

Muhamad Firdaus Ismail[1], Suhaimi Mohd Daud[2], Mujahid Mohamad[3], Muhammad Sharfi Najib[4]*

[1] *Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, Pekan Campus, 26600 Pekan, Pahang, MALAYSIA*

[2] *Centre for Advanced Industrial Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, Pekan Campus, 26600 Pekan, Pahang, MALAYSIA*

*Corresponding Author: suadri729@gmail.com, sharfi@umpsa.edu.my
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Abstract

Restrooms are essential facilities for urination and defecation, and maintaining hygiene and user comfort in these spaces is crucial. Despite similar structural designs, restrooms often exhibit varying odors, making odor detection and classification important for effective maintenance. The primary challenge is the effective detection and classification of various restroom odors to maintain hygiene and enhance user comfort. Traditional methods may not provide the accuracy or efficiency required for real-time applications. This study aims to develop a reliable method for differentiating between various restroom odors using an Electronic Nose (E-Nose) system integrated with Case-Based Reasoning (CBR) analysis. The proposed system employs the E-Anfun 1.0 model of the E-Nose to capture odor profiles. These profiles are then analyzed using a CBR framework to accurately differentiate and classify the odors. The system achieved a classification accuracy rate of 100%, demonstrating the effectiveness of integrating the E-Anfun 1.0 E-Nose with CBR for odor detection. The significant findings include the system's ability to accurately classify different odor profiles, which can be utilized to enhance restroom maintenance practices. In conclusion, this method offers a promising approach to improving the hygiene and comfort of public restrooms by providing accurate and efficient odor classification. The implementation of such a system can lead to better maintenance practices and an overall improvement in restroom hygiene standards.

1. Introduction

Restroom, also known as a toilet, refers to a room or booth used for urination and defecation [1] [2]. It is a facility provided by the authorities to the public. Public restrooms not only focus on the needs of consumers, but they also contribute to the comfort and hygiene of the restrooms in improving health and quality of life. Each restroom has a distinct odor because each person produces different volatile organic compounds [3]. To minimize the risk of open defecation and environmental pollution, we must focus on bathroom cleanliness, as each user prefers a fragrant and clean toilet [4]. Restricted access and low-quality toilets can lead to poor hand hygiene, resulting in illnesses such as gastroenteritis or uncomfortable conditions like threadworm [5].

On a global level, the World Health Organization (WHO) [6] is the health agency that considers a healthy environment for humanity. In Malaysia, the Department of Environment Malaysia (DOE) is responsible for ensuring that the environment is clean, safe, healthy, and productive [7]. Action by the authorities will be imposed on anyone who violates the Law of Malaysia Act 127, causing harm to the environment [8]. Under the principle of transparency, all relevant entities should establish clear standards for evaluating and assessing the quality of building air and its impact on public health and the environment [9].

Hygiene in public toilets is typically monitored through manual inspections. Data from many cities reveal that the manual inspection regime has systemic biases and enforcement is not uniform [10]. Yet, you cannot conduct odor research until you can assess their similarity and differences [11]. An electronic nose (e-nose) is an instrument composed of a series of partly sensitive electronic chemical sensors, an effective pattern recognition system, and is capable of detecting simple or complex odors [12]. The sample of air can be tracked using an electronic nose (e-nose) [13].

An intelligent classification method, called Case-Based Reasoning (CBR) methodology, was employed [14]. CBR is an approach to problem-solving that utilizes prior investigative cases and situations closely related to the present case. In the CBR method, previous case data and information are used as stored cases [15]. CBR offers effective classification solutions suitable for challenging domain environments and does not require a data splitting ratio for training and processing data, unlike other classification techniques [16].

This paper presents an investigation into unpleasant odour patterns in restrooms using an e-nose and classifies several cases of unpleasant odour profiles for restroom environments using a case-based reasoning classifier. The CBR classifier will undergo performance measurement for each of the samples to determine the classifier's performance.

2. Methodology

Fig. 1 shows the flowchart for the principal analysis of unpleasant odor restroom classification using CBR and odour profiles. The approach starts with collecting raw data using the E-Anfun 1.0 model and an E-nose device. This device features a sensor array with various sensors, including metal oxide sensors and electrochemical sensors, capable of detecting a range of volatile organic compounds (VOCs). Next, the pre-processing process, in which all raw data was calculated using normalization and the mean calculation technique, was performed. Then, the feature extraction step, where all the samples' unique features were extracted to establish the odour profile. Later, the CBR classification technique was used to classify the odour profiles. Last but not least, the overall sensitivity, specificity, and accuracy of the restroom sample's classification system will be determined by evaluating the classification result's results.

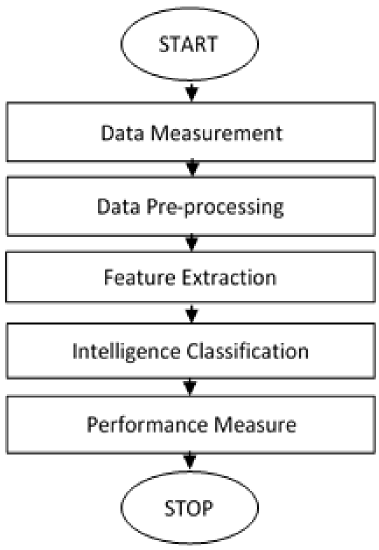


Fig. 1 *Flowchart for the principal analysis of unpleasant odor restroom classification*

2.1 Data Measurement

The E-nose data were collected from restroom samples taken at two different times, specifically from the women's toilet in the Chancellor Building at UMPSA Gambang. The samples were gathered during both the afternoon (around 1:00 PM) and evening (around 6:00 PM) periods. The E-nose detects odors by drawing air samples into its sensor chamber. VOCs in the air interact with the sensors, causing changes in electrical resistance. These changes are converted into electronic signals, generating unique odor profiles. Fig 2 illustrates the measurement of restroom odor data acquired through the E-nose.

Fig. 2 *The measurement of restroom odor data obtained via e-nose*

For each sample, five repeated experiments were performed, with each experiment involving 1000 measurements. A five-minute neutralization period was observed between experiments to ensure accurate results. The collected data were reported in Excel, totaling 5000 measurements per sample. Table 1 presents a sample from Experiment 1, conducted at the Chancellor Building at UMPSA Gambang, with similar data presented for Experiments 1 through 5. In total, 10,000 measurements were collected across two sampling points: the Afternoon Chancellor Building and the Evening Chancellor Building.

The use of five repetitions ensures reliable and consistent results by averaging out variations and minimizing random errors. Collecting 1000 measurements per experiment provides a detailed and representative dataset, enhancing the accuracy and reliability of the odor analysis.

Table 1 *Sample experiment 1 at chancellor building at UMPSA Gambang*

Data Measurement	S1	S2	S3	S4
1	DM11	DM12	DM13	DM14
2	DM21	DM22	DM23	DM24
3	DM31	DM32	DM33	DM34
4	DM41	DM42	DM43	DM44
-				
-				
-	....	...	...	...
1000	DM1001	DM1002	DM1003	DM1004

2.2 Data Pre-Processing

The raw data calculated was standardized to a range of 0 to 1. This standardization involved dividing each raw data point by the highest value in the dataset, a technique used to normalize data collected from several consecutive experiments. While the extraction of sample characteristics can be performed using raw data, normalization is a preferred method for rescaling measurements to a smaller range, thereby facilitating accurate analysis. The calculation of normalized data is based on Equation 1.

$$R' = R/Rmax \tag{1}$$

After that, use the mean calculation technique to obtain the average for each sample, normalizing 5000 data points to 1000 data points. The equation for calculating the mean is that every s1 in each experiment will be divided by 5; the same applies to sensors 2, 3, and 4. So, all data samples from 5 experiments are turned into 1 dataset divided by 5.

To further refine the dataset, box-plot statistical analysis was employed after normalization. The box-plot technique enabled the visualization of data distribution and the identification of potential outliers. By highlighting the spread and central tendency of the data, box plots facilitated the detection and treatment of anomalies that could skew the results. Addressing these outliers ensured that the data was of high quality, enhancing the accuracy and reliability of subsequent classification processes.

2.3 Feature Extraction

Based on the normalized value, the data were split into 10 cases for each sample from the standardized data, resulting in a total of 20 cases for all samples. Case data were then mapped into the visualized graphical analysis of each sample (odor-profile pattern). The mean of the normalized odor profile (5000 measurements) was established as a function. The odor-profile patterns were then registered for classification using CBR, as stored cases.

2.4 Intelligence Classification

CBR consists of four main cycles to be followed for classification, which involve collecting, reusing, updating, and maintaining information. Fig 3 illustrates the CBR cycles used for classifying restroom odors. The odor profile of an unknown odor sample was used in the retrieval process to restore the memory-contained cases. When CBR knows from previous cases, the system matches a new odor profile sample with an odor profile collected in previous cases. When the unknown sample exhibits a high degree of similarity to the stored restroom sample, the software may reuse the stored case information to inform its decision or response. This classification technique is somewhat different from other classification techniques (ANN, K-NN), since this technique does not involve training on data.

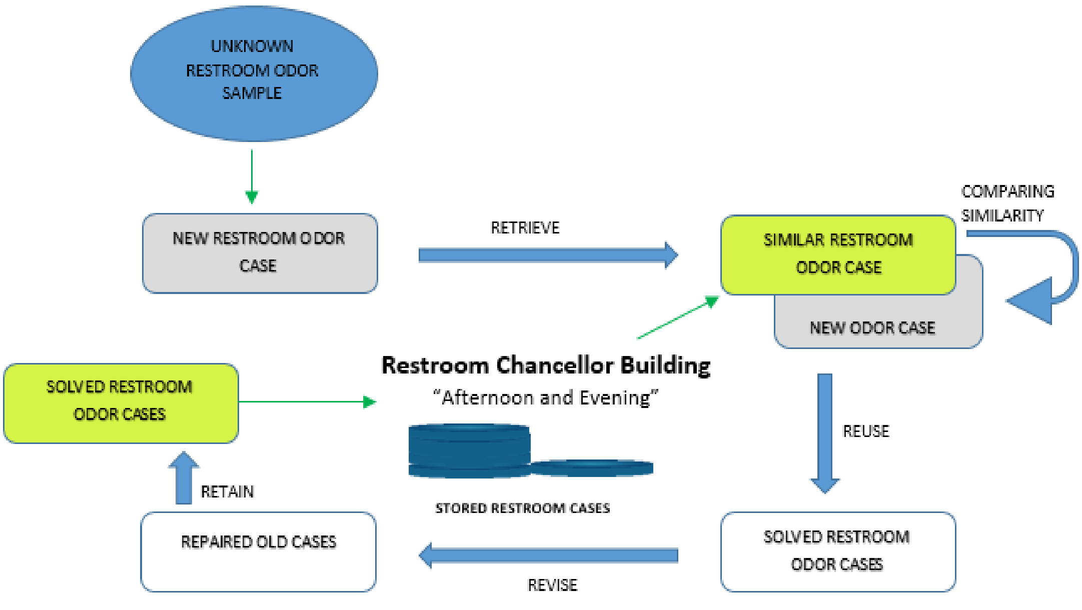


Fig. 3 *CBR cycle for classification of odor-profile restroom*

Each of the 20 cases deposited was chosen for measurement to calculate the percentage of similarities between 2 cases in the CBR retrieval process. The remaining 19 cases are then processed, leaving the remaining cases to be handled. Equation (2) was used to measure the proportion of parallels. When the proportion of differences in the two cases is the largest, this means that the difference between the two cases is minimal and falls into the same group.

$$Similarity\ (T,S) = \sum_{i=1}^{n} \frac{f(Ti,Si) \times Wi}{\sum_{i=1}^{n} Wi} \tag{2}$$

2.5 Performance Measurement

The CBR classifier for restroom odor will be further analyzed using a confusion matrix, which measures the system's sensitivity, specificity, and accuracy based on restroom samples, as outlined in Equations (3)to(5). To determine the prediction output and actual output, the three highest similarity values for each sample will be extracted, comparing the actual cases with the predicted ones. This approach will enhance the performance measurement of the CBR classifier.

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{FP} + \mathrm{FN}} \tag{4}$$

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{P} + \mathrm{N}} \tag{5}$$

Sensitivity is determined by dividing the true positive (TP) value by the sum of true positives and false negatives (FN) classifications. Specificity is calculated by dividing the true negative (TN) by the sum of false positives (FP) and true negatives. Accuracy is obtained by dividing the sum of true positive and true negative values by the total number of cases (P + N), where P is the total number of positive cases, and N is the total number of negative cases.

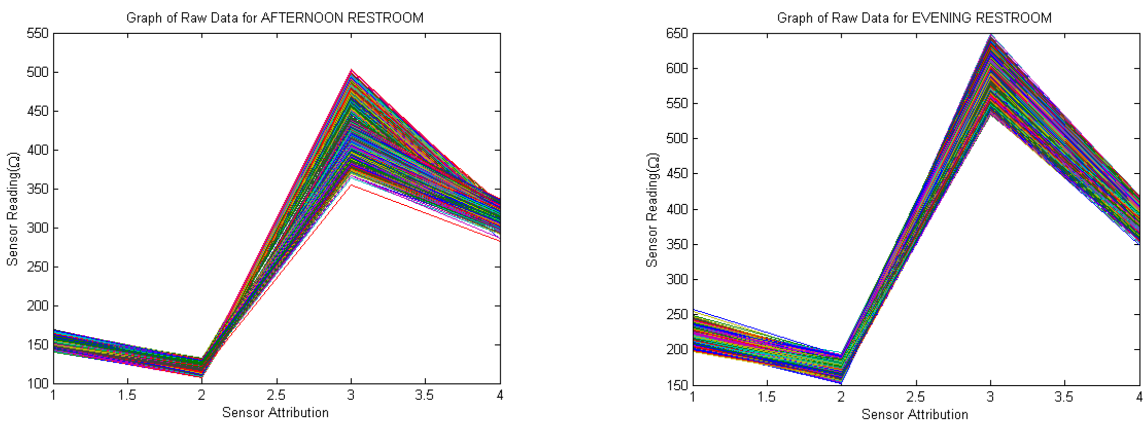
In this study, "Positive" refers to samples classified as having the odor of interest, while "Negative" refers to samples classified as not having the odor of interest. A "True Positive" (TP) occurs when a sample is classified as having the odor and actually does have the odor. Conversely, a "True Negative" (TN) occurs when a sample classified as not having the odor actually does not have the odor. A "False Positive" (FP) is when a sample classified as having the odor does not actually have the odor, and a "False Negative" (FN) is when a sample classified as not having the odor actually has the odor.

These classifications are based on predefined thresholds for sensor readings. If the sensor reading exceeds a certain threshold, the sample is classified as Positive; if it falls below the threshold, it is classified as Negative.

3. Results and Discussion

For each sample, five consecutive experiments were performed, yielding 1000 data measurements per experiment and 5000 data measurements per sample. Therefore, 10000 data measurements were compiled and tabulated for all samples.

Figures 4(a) and 4(b) display graphs of raw data against a sensor array for two separate restroom period odor samples. The Y-axis displays the resistance value of the raw data measurement, while the X-axis indicates the number of sensors. The sensors used by the e-nose are S1, S2, S3, and S4. In both afternoon and evening samples, Sensors S3 and S4 have the highest sensor readings for restroom samples, whereas S1 and S2 have the lowest sensor readings. Despite almost identical patterns, major variations can be measured for each sample, which are helpful for the classification process. The pre-processing phase of the data enhances the relevance of the pattern.



(a) (b)

Fig. 4 *Graph of raw data for chancellor building at UMPSA Gambang (a) Afternoon; (b) Evening*

10,000 previous data measurements were normalized by dividing each value in its own row by the highest value in each row of data measurements. The 10000 standardized data were then divided into two groups representing each sample, using the mean calculation technique to rescale the standardized data. Following that, 1,000 normalized values from each category were clustered into ten cases, from which the odor features would be extracted. Fig 5 shows the normalized value against the sensor array, where the y-axis represents the normalized resistance value, while the x-axis represents the sensor array.

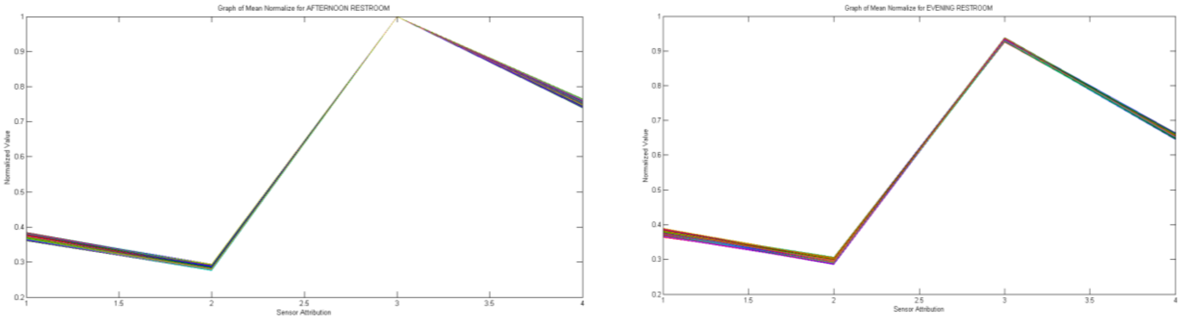
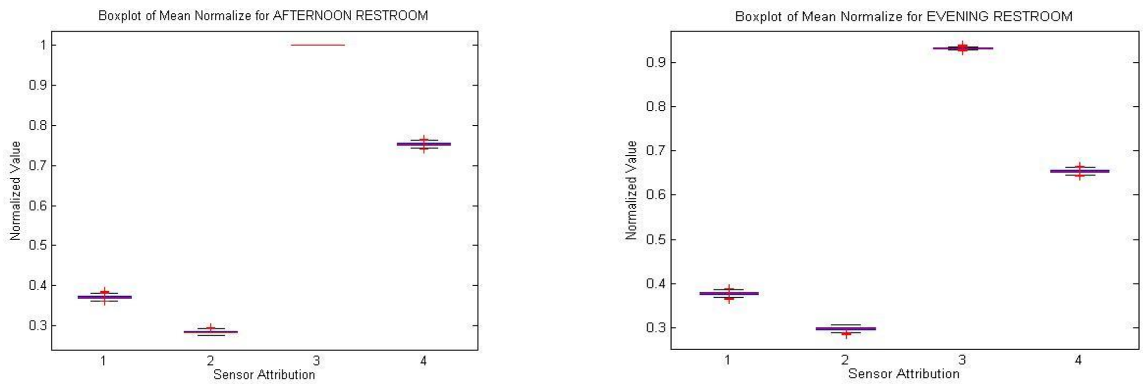


Fig. 5 *Graph of the mean normalized value against the sensor array*

Figures 6(a) and 6(b) display box-plot analysis of the mean normalized for both samples. In the afternoon restroom dataset, the box plots for each sensor (S1, S2, S3, and S4) show a clear distribution of normalized values. Sensor 1 and Sensor 4 exhibit a relatively higher median compared to Sensors 2 and 3. Specifically, the normalized value for Sensor 1 is centered around 0.4, while Sensor 4 shows values around 0.8. Sensor 2 has the lowest median value, around 0.3, and Sensor 3 shows a notable outlier with a value of 1, indicating an anomaly in the readings. The presence of this outlier suggests that further investigation may be necessary to understand the underlying cause, which could be due to sensor malfunction or an unusual odor event.

In the evening restroom dataset, the box plots show a similar trend to the afternoon readings but with some variations. Sensor 1 and Sensor 4 again display higher median values, approximately 0.4 and 0.8, respectively. Sensor 2 maintains the lowest median value around 0.3, and Sensor 3 has a median close to 0.9, with a slightly broader interquartile range compared to the afternoon dataset. The broader range for Sensor 3 indicates a greater variability in the sensor readings during the evening. The absence of significant outliers in the evening dataset suggests a more consistent odor profile during this time.



(a) **(b)**

Fig. 6 *Box-plot of mean normalized data sample (a) Afternoon; (b) Evening*

Table 2 presents the restroom sample CBR case library at the Chancellor Building of UMPSA Gambang, for both the afternoon and evening sessions, stored in the CBR memory. The table contains 20 cases, each representing ten cases. The highest normalized value in Table 2 is in column S3, which is entirely composed of '1'. Columns 3 from case 01 to case 10 have the same value for each case because the raw data were divided by the highest value in each row. The different values from each sensor are due to the varying sensitivities of each sensor, with Sensor 3 exhibiting the highest sensitivity to the odor of the restroom.

Table 3 displays the CBR voting results for restroom odor. The 20 CBR library cases consist of 2 restroom odor samples. K1 to K10 reflect samples from the afternoon at the Chancellor Building, while K11 to K20 represent samples from the evening. The value of K is equal to the number of Case IDs, using the voting colors red, green, and blue to signify the distance of similarity between each Case ID and its voting value. A red vote shows the interest closest to Case ID. A green vote indicates the second-highest value for Case ID, and a blue vote indicates the third-highest value for Case ID. The corresponding CBR vote is 100 percent for all Case IDs, meaning all voting values are found within the same voting group with all Case IDs.

Table 2 *CBR case library for restroom sample*

CASE ID	*S1*	*S2*	*S3*	*S4*
CASE_01	0.3798	0.2907	1	0.7562
CASE_02	0.3744	0.2875	1	0.7555
CASE_03	0.3703	0.2845	1	0.7539
CASE_04	0.3716	0.285	1	0.7528
CASE_05	0.3712	0.2838	1	0.7518
CASE_06	0.3704	0.283	1	0.7532
CASE_07	0.3687	0.2815	1	0.75
CASE_08	0.3683	0.2821	1	0.7504
CASE_09	0.3687	0.2817	1	0.7503
CASE_10	0.3667	0.2804	1	0.7506
CASE_11	0.3828	0.3017	0.9324	0.6546
CASE_12	0.3797	0.2996	0.9318	0.6533
CASE_13	0.38	0.2998	0.932	0.6539
CASE_14	0.3781	0.2988	0.9317	0.654
CASE_15	0.3764	0.2971	0.9311	0.6528
CASE_16	0.3761	0.2971	0.9314	0.653
CASE_17	0.3765	0.2971	0.9315	0.6532
CASE_18	0.3745	0.2959	0.9314	0.6536
CASE_19	0.3744	0.2951	0.9314	0.6539
CASE_20	0.3805	0.2997	0.9322	0.6553

Table 3 *CBR voting results for restroom odor*

		A-C BUILDING										E-C BUILDING									
		K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	K11	K12	K13	K14	K15	K16	K17	K18	K19	K20
A-C BUILDING	K1		99.7675	99.55	99.5675	99.5025	99.4975	99.3375	99.353	99.35	99.275	95.707	95.507	95.529	95.6551	95.77313	95.807	95.7861	95.9565	95.9045	95.6069
	K2	99.7675		99.7825	99.8	99.735	99.73	99.57	99.585	99.583	99.5075	96.029	95.813	95.849	95.7342	95.61122	95.6025	95.6383	95.5346	95.555	95.9277
	K3	99.55	99.7825		99.9275	99.9075	99.9425	99.7875	99.803	99.8	99.725	96.289	96.071	96.107	95.9912	95.86729	95.8585	95.8945	95.7898	95.8103	96.1861
	K4	99.5675	99.8	99.9275		99.935	99.91	99.77	99.785	99.783	99.7075	96.235	96.018	96.054	95.9386	95.81491	95.8061	95.8421	95.7376	95.7581	96.1331
	K5	99.5025	99.735	99.9075	99.935		99.925	99.835	99.85	99.848	99.7725	96.259	96.041	96.078	95.9621	95.83836	95.8296	95.8656	95.761	95.7815	96.1568
	K6	99.4975	99.73	99.9425	99.91	99.925		99.84	99.855	99.853	99.7775	96.261	96.043	96.08	95.9639	95.84004	95.8312	95.8673	95.7626	95.7831	96.1587
	K7	99.3375	99.57	99.7875	99.77	99.835	99.84		99.965	99.988	99.9075	96.427	96.208	96.245	96.1286	96.00423	95.9954	96.0315	95.9264	95.9469	96.3241
	K8	99.3525	99.585	99.8025	99.785	99.85	99.855	99.965		99.978	99.9125	96.461	96.242	96.279	96.1624	96.03791	96.029	96.0652	95.96	95.9805	96.3581
	K9	99.35	99.5825	99.8	99.7825	99.8475	99.8525	99.9875	99.978		99.91	96.425	96.206	96.243	96.1261	96.00171	95.9928	96.029	95.9239	95.9444	96.3216
	K10	99.275	99.5075	99.725	99.7075	99.7725	99.7775	99.9075	99.913	99.91		96.529	96.31	96.346	96.2295	96.10472	96.0958	96.1321	96.0265	96.0471	96.4257
E-C BUILDING	K11	95.707121	96.0291	96.2886	96.2353	96.2591	96.2611	96.4271	96.461	96.425	96.5291		99.882	99.895	99.8374	99.77721	99.7523	99.7598	99.6972	99.6523	99.89
	K12	95.507051	95.8128	96.0706	96.0177	96.0414	96.0432	96.2083	96.242	96.206	96.3095	99.882		99.987	99.93	99.87494	99.86	99.8575	99.7899	99.7699	99.9275
	K13	95.529106	95.8493	96.1072	96.0544	96.078	96.0799	96.2451	96.279	96.243	96.3464	99.895	99.987		99.9275	99.88239	99.8574	99.8649	99.7724	99.7275	99.955
	K14	95.655114	95.7342	95.9912	95.9386	95.9621	95.9639	96.1286	96.162	96.126	96.2295	99.837	99.93	99.927		99.92996	99.905	99.9125	99.85	99.815	99.9225
	K15	95.773129	95.6112	95.8673	95.8149	95.8384	95.84	96.0042	96.038	96.002	96.1047	99.777	99.875	99.882	99.93		99.98	99.9775	99.925	99.895	99.8523
	K16	95.806986	95.6025	95.8585	95.8061	95.8296	95.8312	95.9954	96.029	95.993	96.0958	99.752	99.86	99.857	99.905	99.98		99.9825	99.915	99.885	99.8274
	K17	95.786094	95.6383	95.8945	95.8421	95.8656	95.8673	96.0315	96.065	96.029	96.1321	99.76	99.857	99.865	99.9125	99.9775	99.9825		99.9175	99.8875	99.8349
	K18	95.956474	95.5346	95.7898	95.7376	95.761	95.7626	95.9264	95.96	95.924	96.0265	99.697	99.79	99.772	99.85	99.92498	99.915	99.9175		99.97	99.7723
	K19	95.90448	95.555	95.8103	95.7581	95.7815	95.7831	95.9469	95.98	95.944	96.0471	99.652	99.77	99.728	99.815	99.89497	99.885	99.8875	99.97		99.7573
	K20	95.606925	95.9277	96.1861	96.1331	96.1568	96.1587	96.3241	96.358	96.322	96.4257	99.89	99.927	99.955	99.9225	99.85234	99.8274	99.8349	99.7723	99.7573	

Table 4 displays the CBR performance assessment, which successfully demonstrated 100% accuracy, sensitivity, and specificity in classifying restroom sample odor profiles at the afternoon Chancellor Building and the evening Chancellor Building. The results of this study demonstrate the effectiveness of the Case-Based Reasoning (CBR) classifier in accurately identifying and classifying restroom odors, which is essential for the broader objective of classifying unpleasant odors. The performance metrics, including 100 percent accuracy, sensitivity, and specificity, indicate that the system can reliably distinguish between different odor profiles without any false classifications.

The successful classification of unpleasant odors using the CBR classifier provides a reliable method for enhancing restroom maintenance practices. By accurately identifying and addressing the sources of unpleasant odors, facilities can significantly improve hygiene and user comfort in public restrooms. This method offers a promising approach to maintaining hygiene and enhancing the overall user experience by providing accurate and efficient odor classification, thus improving public health and comfort.

Table 4 *Performance evaluation of CBR classification*

	Afternoon	Evening	Total
Positive	30	30	15
Negative	30	30	15
True Positive	30	30	15
True Negative	30	30	15
False Positive	0	0	0
False Negative	0	0	0
	Sensitivity (%)		100
	Specificity (%)		100
	Accuracy (%)		100

4. Conclusion

The study of restroom odor can be identified, even if the patterns and scents between each study are somewhat identical. This is the significant skill that CBR possesses, which is the classification method, since the source cases contained in the database contains minimal data measurements. Restroom sample odor-profile classification using case-based reasoning classification methodology has successfully achieved a 100 percent classification.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors are responsible for the study conception, research design, data collection, data analysis, result interpretation and manuscript drafting.

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