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**ORIGINAL ARTICLE**

# Intelligent Classification of Cocoa Bean using E-nose

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**ABSTRACT** – Cocoa bean (Theobrama cacao) is an essential raw material in the manufacture of chocolate, and their classification is crucial for the synthesis of good chocolate flavour. Cocoa beans appear to be very similar to one another when visualised. Hence, an electronic device named the electronic nose (E-Nose) is used to classify the odor of cocoa beans to give the best cocoa bean quality. E-nose is a set of an array of chemical sensors used to sense the gas vapours produced by the cocoa bean and the raw data collected was kept in Microsoft Excel, and the classification took place in Octave. They then underwent normalisation technique to increase classification accuracy, and their features were extracted using mean calculation. The features were classified using CBR, and the similarity value is obtained. The results show that CBR's classification accuracy, specificity and sensitivity are all 100%.

## INTRODUCTION

The olfactory system is the sensory system used for smelling, which smelling is a vital sensation that allows species with odorant receptors to recognise food, threats and enemy [1]. The smell is one of the most significant ways for most living beings and humans to communicate with the world, as a smell can affect our sense of taste. The cocoa bean has been the world's most significant demand for its product which flavour and odor are the most significant characteristics and critical qualities of cocoa quality [2]. Odor is a mixture of tiny molecules with a very low concentration in inhaled air when it comes in contact with the human sensory system, which experiences the perception of odor [3]. Not all raw cocoa bean gives the smell of chocolate, and human sniffers cannot simply determine the odor of cocoa. Regardless of the significance of olfactory sense to humankind, the human nose only has 1,000,000 fragrance receptors compared to canines that have more than 100 million receptors that separate aromas, at any rate, multiple times [4]. The moderately poor affectability and separation capacities of the human sense have prompted the need for electronic instruments with sensors equipped to conduct rehashed segregations with a high probability of removing human fatigue [5].

Electronic nose (E-nose) is the most effective instrument for identifying good odor and bad odor to replicate a human's olfactory system [6]. E-nose is a set array of sensors that chemically interact with volatile organic compounds (VOCs) [7] that send signals to classify the odor. The sensors are unfixed to the gas molecules, and each sensor has a different sensing medium. The gas mixtures can be acknowledged from the characteristics of the response of the sensor. E-nose has been developed for qualitative classification and recognition of various kinds of environments and various foods [8]. It is easily operated, lower cost and time consuming method for odor classification of cocoa bean. It also detects the smell more accurately than the human sense of smell. It also determines the toxic or poisonous gas that human sniffers are impossible to sniff [9].

Artificial intelligence (AI) is applied in this research to classify the odor profile of cocoa beans to support human decision-making [10] and give the solution that can be mapped to the original case. AI aims to explain intelligence by creating computer programs that use symbolic inference or logic to provide intelligent behaviour [11]. It is not time-independent and requires every device to determine by having time in mind. Case-based reasoning or CBR is acknowledged that it offers a stored case to explain its reasoning by solving the problem by using the previous case that looks similar to the current case [12]. There are four stages of retrieving, reusing, revising, and retaining to classify the odor in the CBR system [13]. This system chooses a subset of cases from the database in retrieve point, closely related to the current case. For the next step, reuse fits the current problem from the cases chosen from the previous stage. The Revise stage is where the solution obtained is tested and checked that it has the right solution. For the final stage, retain will decide whether or not to integrate the newly solved case into the CBR database [14]. This intelligent classification can classify the odorant with a high accuracy rate compared to other intelligent classifications [15].

This paper shows the E-nose and CBR classifier to demonstrate an effective approach for cocoa bean classification. E-nose gathered data to establish the odor profile of cocoa beans, which was then classified using case-based reasoning.

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## METHODOLOGY

### Experiment Design

Figure 1 shows the flowchart on the process to get the classification of the cocoa bean. The data on the odor of raw cocoa bean was collected using e-nose. Then, the collected raw data will undergo pre-processing stage where the features will be derived using the normalisation method and arithmetic mean calculation to determine cocoa bean's odor profile. The data were then classified using a classifier of CBR. Lastly, the performance is measured to get the classification's sensitivity, specificity and accuracy percentages.
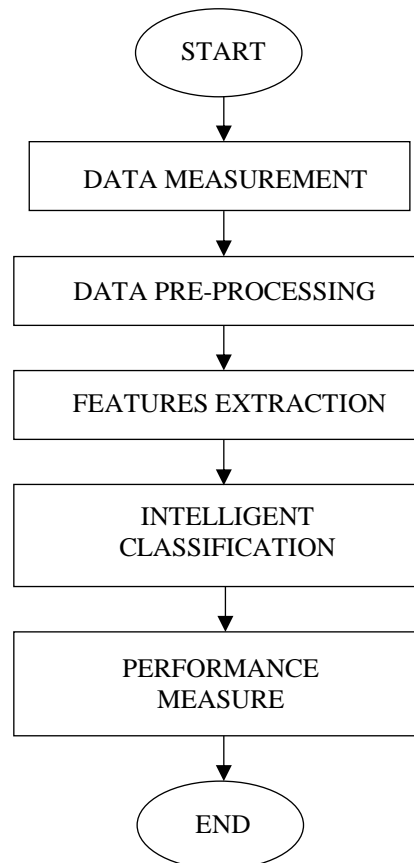


**Figure 1.** Flowchart for cocoa bean classification

### Data Measurement

Figure 2 depicts the flow of getting raw data of cocoa beans using E-nose. There are five types of the smell of cocoa bean: cocoa smell, musty smell, black pepper smell, smoke smell, and copra smell. The samples are weighted 30g each and placed into a dish plate. E-nose operated like an odor inhaler that inhales the odor extracted from a cocoa bean sample. Data collected was then trapped in the E-nose chamber, ready to transmit to the computer via a universal serial bus (USB) cable for data collection.
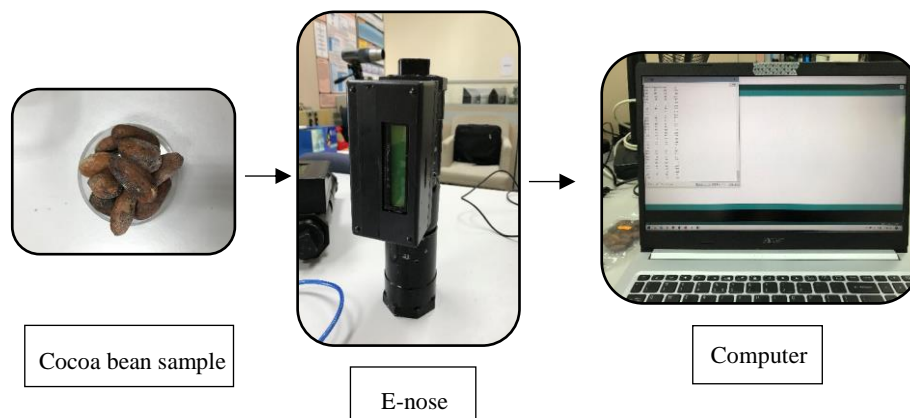


**Figure 2.** Flow of Collecting Odor of Cocoa Bean Sample

After 5 minutes in one experiment for every sample, the data measurement collected was 200. Then the experiment was repeated five times which gives the total result of 1000 data for every sample, and the data was tabulated on Table 1 in Microsoft Excel.

**Table 1** Table of raw data of cocoa bean

| Data measurement (DM) | Sensor Reading | | | |
|---|---|---|---|---|
| | Sensor 1 | Sensor 2 | Sensor 3 | Sensor 4 |
| $DM_1$ | $DM_{11}$ | $DM_{12}$ | $DM_{13}$ | $DM_{14}$ |
| $DM_2$ | $DM_{21}$ | $DM_{22}$ | $DM_{23}$ | $DM_{24}$ |
| . | . | . | . | . |
| . | . | . | . | . |
| $DM_{1000}$ | $DM_{1001}$ | $DM_{1002}$ | $DM_{1003}$ | $DM_{1004}$ |

## Data Pre-Processing

The DM of cocoa beans is normalised using the normalisation method in the pre-processing stage to eliminate any data anomalies that may influence the results using Equation 1. The maximum value separates each row in raw data calculation from its row to obtain a normalised value. This approach reduces data fluctuation and eliminates classification errors.

$$R' = \frac{R}{R_{max}} \qquad (1)$$

From Equation 1, $R'$ is the normalisation value, $R$ is the sensor's reading (ohm ($\Omega$)), and $R_{max}$ is the highest value of sensor reading. Hence, the normalisation method was used in which the data measurement was minimised from 1000 normalised data (5 experiments x 200 data samples) into 200 normalised data for every sample.

## Features Extraction

The amount of data was minimised in a dataset by generating new features from the original feature set. The mean normalised data were clustered from 200 mean normalised data times 5 for each type of cocoa beans sample to 10 cases. So in 1 case, there were 20 normalised data. After that, mean calculation is used for all experiments for every case, the mean normalised data for every cases were reduced from 20 dataset to 1 dataset. As a result, the data collected is ten times with four data measurements per sample.

## Intelligent Classification

CBR is then used to classify the derived features. This technique is a way of solving problems by referring to past cases and experiences that are applicable to the present situation. The CBR cycle of the cocoa bean has four phases, which are depicted in Figure 3.
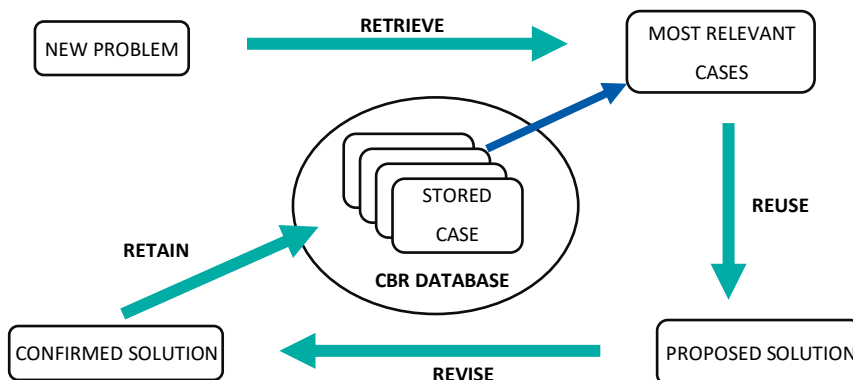


**Figure 3.** Case-Based Reasoning cycle process

In Retrieve point, this system chooses a subset of cases from the database closely related to the current case. For the next step, reuse fits the solution to the current problem from the cases chosen from the previous stage. The Revise stage is where the solution obtained is tested and checked that it has the right solution. Retain will decide whether or not to integrate the newly solved case into the CBR database for the final stage. The similarity value must be calculated before

CBR computation can be performed. In each scenario, the calculation was repeated. The formula represents in Equation (2)

$$Similarity\ (T,S) = \frac{\sum_{i=1}^{n} f(T_i, S_i) \times w_i}{\sum_{i=1}^{n} w_i}$$
(2)

From Equation (2), $T$ and $S$ denote as target and source cases, respectively. $n$ is denoted as the number of attributes in each case, $i$ denotes individual or single attributes from 1 to $n$, $f$ denotes the similarity function for attribute $i$ in cases $T$ and $S$, and $w$ denotes the value of attribute $i$ for weighing.

## Performance Measure

The final step in cocoa bean classification is to determine the performance measure, which was accomplished using the uncertainty matrix process. The Equations 3 to 5 were used to evaluate the sensitivity, precision, and accuracy of the cocoa bean samples classification.

$$sn = \frac{TP}{TP + FN}$$
(3)

$$sp = \frac{TN}{TN + FP}$$
(4)

$$acc = \frac{TP + TN}{P + N}$$
(5)

The notation of sn, sp and acc are the sensitivity, specificity and accuracy sequentially. TP is the true positive, which is number that correctly recognised class results, FP is the false positive which the results that eithere were correctly assigned to the class, TN is the number of correctly organised that do not belong to the class known as true negative and FP is false positive that were not recognised results. P and N are the positive and negative same as true and false results related corresponding. The confusion matrix is a table that describes the performance of a classification model. It contains information about the actual and predicted case. CBR voting table results were used to determine the number of true positives, false positives, true negatives, and false negatives.

## RESULTS AND DISCUSSION

Figure 4 shows the mean normalised value against sensor attribution of cocoa smell, musty smell, black pepper smell, smoke smell and copra smell of cocoa bean samples. The X-axis indicates sensor attribution, which is the amount of sensors installed in e-nose to recognise the volatile molecules of the cocoa bean, and Y-axis indicates the mean noramlized value of the sensor resistance after using normalisation technique mean calculation.
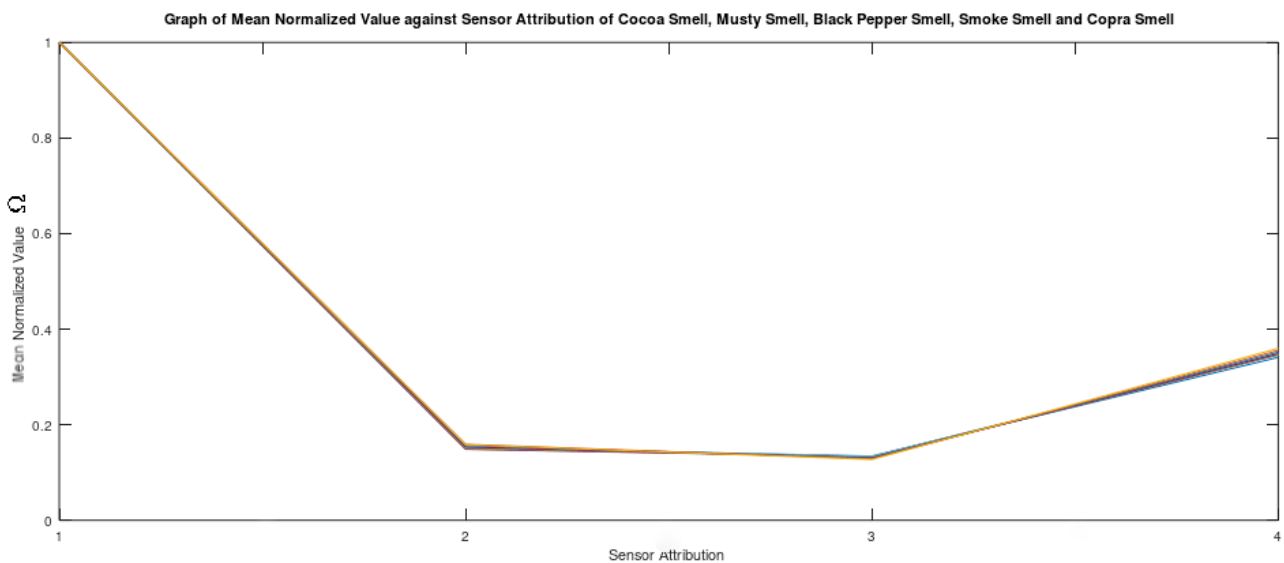


**Figure 4.** Graph of Mean Normalized Value against Sensor Attribution of Cocoa Smell, Musty Smell, Black Pepper Smell, Musty Smell and Copra Smell

In Figure 4, all samples were plotted in one graph to see the differences between each sample. Though the graphs plotted look similar, the characteristic of the smell is still different to each other. All the clustered normalised data were then tabulated in Table 2 on Microsoft Excel. The clustered data was assigned according to its sample and case. The table made up of 50 cases, with 10 cases for every sample. The first ten cases (from case 1 to case 10) represent a cocoa scent examination. The following ten cases (cases 11 through 20), (cases 21 through 30), (cases 31 through 40), and (cases 41 through 50) reflect musty, black pepper, smoke, and copra smell of cocoa bean samples, respectively. Sensors (S1, S2, S3, and S4) are located in the e-nose and are labelled 1, 2, 3, and 4 in Figure 4. To execute the classification procedure, these instances, also known as saved cases, will be stored in CBR memory.

**Table 2.** Data of Odor Profile of Cocoa bean sample

| SAMPLE | CASE ID | S1 | S2 | S3 | S4 |
|---|---|---|---|---|---|
| COCOA SMELL | CASE 1 | 1.0000 | 0.228049 | 0.157147 | 0.384785 |
| | CASE 2 | 1.0000 | 0.221301 | 0.150734 | 0.385856 |
| | CASE 3 | 1.0000 | 0.218008 | 0.149035 | 0.387133 |
| | CASE 4 | 1.0000 | 0.214192 | 0.144719 | 0.389100 |
| | CASE 5 | 1.0000 | 0.213344 | 0.141388 | 0.392772 |
| | CASE 6 | 1.0000 | 0.210119 | 0.140911 | 0.398511 |
| | CASE 7 | 1.0000 | 0.212586 | 0.141419 | 0.402968 |
| | CASE 8 | 1.0000 | 0.213860 | 0.138898 | 0.406596 |
| | CASE 9 | 1.0000 | 0.214027 | 0.137868 | 0.409534 |
| | CASE 10 | 1.0000 | 0.215952 | 0.137879 | 0.411046 |
| MUSTY SMELL | CASE 11 | 1.0000 | 0.170986 | 0.137891 | 0.349392 |
| | CASE 12 | 1.0000 | 0.172631 | 0.137650 | 0.351745 |
| | CASE 13 | 1.0000 | 0.173635 | 0.137129 | 0.352596 |
| | CASE 14 | 1.0000 | 0.173105 | 0.136103 | 0.356095 |
| | CASE 15 | 1.0000 | 0.174900 | 0.135591 | 0.357245 |
| | CASE 16 | 1.0000 | 0.176942 | 0.135075 | 0.357712 |
| | CASE 17 | 1.0000 | 0.179704 | 0.134827 | 0.363163 |
| | CASE 18 | 1.0000 | 0.178898 | 0.133366 | 0.366276 |
| | CASE 19 | 1.0000 | 0.178664 | 0.132044 | 0.366575 |
| | CASE 20 | 1.0000 | 0.179875 | 0.131473 | 0.369316 |
| BLACK PEPPER SMELL | CASE 21 | 1.0000 | 0.177648 | 0.154066 | 0.400234 |
| | CASE 22 | 1.0000 | 0.178130 | 0.152880 | 0.402738 |
| | CASE 23 | 1.0000 | 0.177103 | 0.151283 | 0.406872 |
| | CASE 24 | 1.0000 | 0.178930 | 0.150535 | 0.409902 |
| | CASE 25 | 1.0000 | 0.178527 | 0.148633 | 0.408920 |
| | CASE 26 | 1.0000 | 0.179319 | 0.147688 | 0.410664 |
| | CASE 27 | 1.0000 | 0.179839 | 0.148163 | 0.410733 |
| | CASE 28 | 1.0000 | 0.180081 | 0.147039 | 0.413421 |
| | CASE 29 | 1.0000 | 0.182264 | 0.146720 | 0.413965 |
| | CASE 30 | 1.0000 | 0.179893 | 0.147647 | 0.413783 |
| SMOKE SMELL | CASE 31 | 1.0000 | 0.203237 | 0.180994 | 0.435661 |
| | CASE 32 | 1.0000 | 0.202805 | 0.178592 | 0.438655 |
| | CASE 33 | 1.0000 | 0.204851 | 0.177611 | 0.442249 |
| | CASE 34 | 1.0000 | 0.203823 | 0.173792 | 0.446153 |
| | CASE 35 | 1.0000 | 0.203329 | 0.174673 | 0.445670 |
| | CASE 36 | 1.0000 | 0.204904 | 0.172032 | 0.448276 |
| | CASE 37 | 1.0000 | 0.203430 | 0.171720 | 0.448985 |

| | | | | | |
|---|---|---|---|---|---|
| | CASE 38 | 1.0000 | 0.206341 | 0.171483 | 0.451189 |
| | CASE 39 | 1.0000 | 0.204985 | 0.168265 | 0.455183 |
| | CASE 40 | 1.0000 | 0.203086 | 0.166430 | 0.455134 |
| COPRA SMELL | CASE 41 | 1.0000 | 0.151085 | 0.134554 | 0.340603 |
| | CASE 42 | 1.0000 | 0.150615 | 0.133087 | 0.345271 |
| | CASE 43 | 1.0000 | 0.149083 | 0.133688 | 0.348022 |
| | CASE 44 | 1.0000 | 0.148646 | 0.133164 | 0.346432 |
| | CASE 45 | 1.0000 | 0.151179 | 0.133083 | 0.346852 |
| | CASE 46 | 1.0000 | 0.153135 | 0.133425 | 0.347227 |
| | CASE 47 | 1.0000 | 0.153267 | 0.131165 | 0.348426 |
| | CASE 48 | 1.0000 | 0.156393 | 0.130159 | 0.351785 |
| | CASE 49 | 1.0000 | 0.158863 | 0.128616 | 0.355499 |
| | CASE 50 | 1.0000 | 0.158081 | 0.127293 | 0.359839 |

According to Table 2, the highest normalised value is 1.0000, which can be found in column S1, and the lowest normalised value is 0.127293 to 0.180994, which can be found in column S3. It is because on S1, the raw data was separated by the highest value in each row, and since then, every row of raw data has to be divided by the value of S1. The sensors in the e-nose have varying degrees of responsiveness.

## Intelligent Classification

Sensor attribution (S1 through S4) refers to the sensors that were used in E-nose. The sum of weights is called a normalised weight. The stored case of the cocoa bean application, also known as the previous case, is the source case, while the target case is the new case or case that needs to be checked. The similarity was calculated using Equation 2 and tabulated in Table 3 below shows the example similarity percentage.

**Table 3.** CBR Formulation Table

| SENSOR ATTRIBUTION | WEIGHT | NORMALIZED WEIGHT | SOURCE CASE | TARGET CASE | SIMILARITY FUNCTION | WEIGHTED SIMILARITY |
|---|---|---|---|---|---|---|
| S1 | 1 | 0.25 | 1.0000 | 1.0000 | 1.0000 | 0.25 |
| S2 | 1 | 0.25 | 0.228049 | 0.221301 | 0.993252 | 0.248313 |
| S3 | 1 | 0.25 | 0.157147 | 0.15074 | 0.993587 | 0.248397 |
| S4 | 1 | 0.25 | 0.384785 | 0.385856 | 0.998929 | 0.249732 |
| PERCENTAGE SIMILARITY BETWEEN 2 CASES (%) | | | | | | 99.64 |

## Performance Measure

The confusion matrix from CBR voting results is depicted in Table 4. This table can have a clearer picture of cocoa bean odour classification. There are actual and predicted results in this confusion matrix table. The actual case refers to the sample's actual situation, while the forecasting case is based on the formulation of CBR and voting outcomes. It showed that every sample consists of 30 cases that were predicted to be in their group. The data then is evaluated in performance evaluation to find its sensitivity, specificity and accuracy. Each category has 30 true positives, with a total of 150 true positives for all groups. The evaluation is tabulated in Table 5, where the sensitivity, specificity, and accuracy were calculated with a multiplication of 100%.

**Table 4.** Confusion Matrix Table

| TOTAL CASE = 150 | | PREDICTED RESULT | | | | |
|---|---|---|---|---|---|---|
| | | COCOA SMELL | MUSTY SMELL | BLACK PEPPER SMELL | SMOKE SMELL | COPRA SMELL |
| ACTUAL RESULT | COCOA SMELL | 30 | 0 | 0 | 0 | 0 |
| | MUSTY SMELL | 0 | 30 | 0 | 0 | 0 |
| | BLACK PEPPER SMELL | 0 | 0 | 30 | 0 | 0 |
| | SMOKE SMELL | 0 | 0 | 0 | 30 | 0 |
| | COPRA SMELL | 0 | 0 | 0 | 0 | 30 |

**Table 5.** CBR Performance Evaluation

| PERFORMANCE EVALUATION | COCOA SMELL | MUSTY SMELL | BLACK PEPPER SMELL | SMOKE SMELL | COPRA SMELL |
|---|---|---|---|---|---|
| TOTAL CASE | 30 | 30 | 30 | 30 | 30 |
| TRUE COCOA SMELL | 30 | 0 | 0 | 0 | 0 |
| FALSE COCOA SMELL | 0 | 0 | 0 | 0 | 0 |
| TRUE MUSTY SMELL | 0 | 30 | 0 | 0 | 0 |
| FALSE MUSTY SMELL | 0 | 0 | 0 | 0 | 0 |
| TRUE BLACK PEPPER SMELL | 0 | 0 | 30 | 0 | 0 |
| FALSE BLACK PEPPER SMELL | 0 | 0 | 0 | 0 | 0 |
| TRUE SMOKE SMELL | 0 | 0 | 0 | 30 | 0 |
| FALSE SMOKE SMELL | 0 | 0 | 0 | 0 | 0 |
| TRUE COPRA SMELL | 0 | 0 | 0 | 0 | 30 |
| FALSE COPRA SMELL | 0 | 0 | 0 | 0 | 0 |
| SENSITIVITY COCOA SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SENSITIVITY MUSTY SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SENSITIVITY BLACK PEPPER SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SENSITIVITY SMOKE SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SENSITIVITY COPRA SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SPECIFICITY COCOA SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SPECIFICITY MUSTY SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SPECIFICITY BLACK PEPPER SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SPECIFICITY MUSTY SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| SPECIFICITY COPRA SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| ACCURACY COCOA SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| ACCURACY MUSTY SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| ACCURACY BLACK PEPPER SMELL (%) | 100 | 100 | 100 | 100 | 100 |

| ACCURACY SMOKE SMELL (%) | 100 | 100 | 100 | 100 | 100 |
|---|---|---|---|---|---|
| ACCURACY COPRA SMELL (%) | 100 | 100 | 100 | 100 | 100 |
| OVERALL SENSITIVITY (%) | 100 | | | | |
| OVERALL SPECIFITY (%) | 100 | | | | |
| OVERALL ACCURACY (%) | 100 | | | | |

The sensitivity, specificity and accuracy of every sample gave results of 100% for each of the cocoa bean samples. The overall sensitivity, specificity and accuracy also showed the result of 100% for cocoa bean sample classification using the CBR classification technique.

## CONCLUSION

The results obtained from this research noted that cocoa bean samples, cocoa smell, musty smell, black pepper smell, smoke smell and copra smell have their odor profile. Changes in cocoa bean contents affected the changes in fragrance and odor-profile of the samples, resulting in variations in degradation levels between samples. Although the cocoa bean odor patterns plotted to seem identical, the cocoa bean sample classified 100% correctly to each smell. By applying CBR as intelligent classification, the distinct type of cocoa bean smell can be analysed with a rate of 100% in sensitivity, specificity and accuracy. It is suggested to conduct more experiments on other types of foods and things the humans can consume and threats that will harm the environment and living beings. Moreover, we will improvise how the data is determined after being collected by the E-nose to show the research's effectiveness and efficiency further.

## ACKNOWLEDGEMENT

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