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ORIGINAL ARTICLE

Intelligent Classification Of Stingless Bee Honey Using Enose

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ABSTRACT – Honey is an essential product produced by both honey bees and stingless bees. It is one of the most powerful natural products used for wound healing also known as natural sweetener that is widely available across the entire world. One of the problems required to sustain the bee honey by measuring and quantifying the quality. One of the methods to detect bee honey via odor signature. However, the difficulties in identifying the odour profile feature are common by using human or animal nose. The second challenge is to find efficient and accurate artificial intelligence methods to identify the odours. The objective of this research is to identify the stingless bee honey (SBH) using odour-profile feature. SBH is one of a bee species, yet different in size, it produces a honey that is clearer in colour as compared to natural honey bee. However, study on SBH grade is not yet extensively explored. Other than that, this research is done to measure the odour-profile by using E-nose which comprises of sensor array has been used to measure the samples of dataset from a few different types of SBH. Hence, this research aim is to classify stingless bee honey based on smell pattern recognition. The final step is the measured data were normalised and analysed using case-based reasoning (CBR) method. Interestingly, CBR classification had shown significant findings whereby it could achieved 100% rate of accuracy, specificity and sensitivity. In conclusion, classification of SBH odor-profile using CBR is feasible.

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INTRODUCTION

Food is a material that is primarily made up of protein, carbohydrates, fat, and other nutrients and is used in an organism's body to fuel growth and critical processes. Food digestion aids in the absorption and utilisation of nutrients by the body, which is necessary for nutrition. Plants are the primary food source, as they convert sunlight into food through photosynthesis. Other animals regularly use plant-eating animals as food sources [1]. In this study, we will look into honey, which is a type of food.

Honey has long been regarded as a gentle food and medicine by all generations, cultures, and civilisations, old and modern alike. Honey has been used to cure various ailments by topical application for at least 2700 years, although its antimicrobial and antibacterial properties were just recently recognised. Honey has been demonstrated to aid in the treatment of several ailments in humans. Honey has been shown in clinical tests to effectively remove the infection from severely infected cutaneous wounds and enhance tissue repair [2],. Indeed, honey's healing properties are related to its antibacterial activity, ability to keep wounds moist, and high viscosity, which helps to build a protective barrier against infection, and wound healing benefits from its immunomodulatory capabilities [3].

There are a few types of bees, which are honey bees and stingless bee honey. Honey bees and honey *Kelulut* or stingless bees are two forms of honey. In this research, we are going to study stingless bee honey. The stingless bee is a common species that may be found on practically every continent. Honey from bees has been utilised for a long time and in a variety of settings. This honey is distinguished by the fact that it is naturally stored in the pot (cerumen), which contributes to its medicinal effects, particularly in the healing of wounds [4]. Stingless bees are a species of honey-producing bee that is found in tropical areas. Due to limited output, their use for honey is being phased out. However, recent advancements in the production of stingless bee honey, notably in Southeast Asia, have reintroduced stingless bee goods to the market [5].

To differentiate all the bee honey made of stingless bees, an electronic nose is used. The electronic nose is a sensor that is designed to emulate human sensory abilities in detecting complex combinations of chemical substances, both biological and non-biological in origin. The electronic nose was created to replicate the human nose and detect unstable food components that can be used to check the quality of the food [6]. The electronic nose device, which was outfitted with 10 metal oxide semiconductor (MOS) sensors, was utilised to create a pattern of volatile chemicals in honey samples [7]. Electronic noses have brought numerous benefits to a wide range of commercial businesses, including agriculture, biomedical, cosmetics, environmental, culinary, manufacturing, military, pharmaceutical, regulatory, and many scientific research disciplines [8].

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The case-based reasoning (CBR) method is employed to achieve the best results. Case-based reasoning is a problem-solving method that entails locating and reusing solutions to similar, previously solved problems. The case base serves as a memory, and remembering is accomplished by retrieval based on similarity and reuse of the recovered answers. Newly solved problems can be saved in the case database, allowing the memory to expand as problems are solved [9]. CBR has numerous benefits over rule-based reasoning. CBR's knowledge representation scheme outperforms rule-based reasoning when it comes to recording and representing knowledge that is difficult to describe using explicit rules or is too case-specific [10]. The classification of accuracy, sensitivity, and specificity is determined by utilizing the CBR approach, which is based on the performance of data results in the template [11]. Before proceeding to the CBR method, some steps are needed to complete such as data measurement, data pre-processing, and feature extraction. Then to get the final result, intelligent classification and performance measure is needed to complete this project.

METHODOLOGY

Figure 1 depicts the whole flowchart for the analysis of stingless bee honey based on odour-profile utilising CBR. The procedure begins with the collection of raw data using e-nose technology. Following that, data pre-processing was performed utilising normalisation and mean calculation techniques. The features of each honey sample were then extracted to create the odour profile. Following that, the odour-profile was categorised using the CBR classification technique. Finally, the classification results will be analysed to identify the classification system's overall sensitivity, specificity, and accuracy for stingless bee samples.

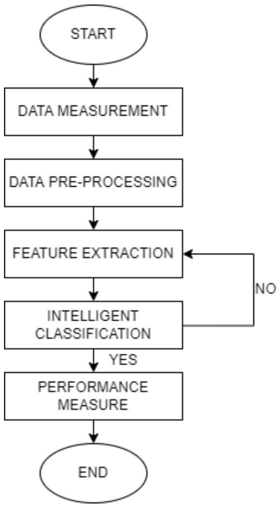

Figure 1. Overall Flowchart

Data Measurement

Honey odour data was collected using an electronic nose. This device is made up of a chemical sensor array, an odour chamber, an e-nose pump, and a microcontroller. The type of honey used for this study is from stingless bees, which is *kelulut*. Most Malaysian consumes this type of honey due to its advantages. *Kelulut* itself has a lot of benefits in treating disease. The honey samples which we used for this research consist of 11 samples in total. Each sample is taken from a lot of areas.

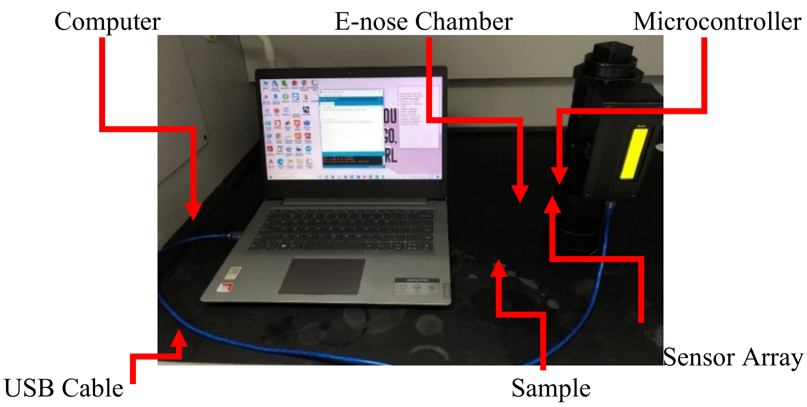

Figure 2: E-nose Experimental Setup

Figure 2 depicts the honey odour data measurement's experimental setup. A 100mL sample of each honey sample was obtained and placed in a sample dish to be analysed for odour data. For this electronic nose test, the standard sample volume is 100mL of honey, which is already appropriate for the sample dish size. Then, the scent is sucked into the e-nose chamber by a pump placed inside the upper half of the e-nose, and the sensor array measures the amount of honey scent that has gathered inside the chamber. Finally, the data was transferred to a computer using a USB cable.

Data collection took three minutes for each experimental session. 200 data measurements is obtained within three minutes, and the data was constant. For each sample, five times experiment was repeated. Table 1 will reflect the raw data that was collected.

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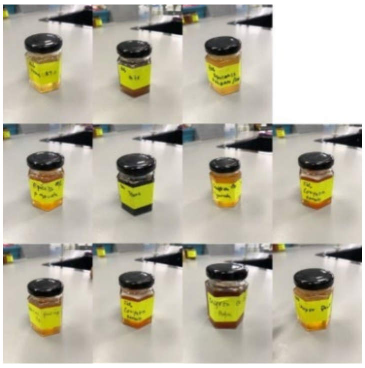

Figure 3. Sample of Stingless Bee Honey

Figure 3 depicts a sample of stingless bee honey. All samples are collected from different areas, which cause the different colours and odour produced by the bees. For this research, 11 samples of stingless bee honey are used.

Table 1. Data Measurement for honey odour-profile

Data Measurement	S1	S2	S3	S4
1	DM_{11}	DM_{12}	DM_{13}	DM_{14}
2	DM_{21}	DM_{22}	DM_{23}	DM_{24}
…	…	…	…	…
1000	DM_{10001}	DM_{10002}	DM_{10003}	DM_{10004}

For each sample in the table above, 1000 data measurements were obtained from 5 repeated experiments. Sensor 1 was indicated as S1, sensor 2 as S2, sensor 3 as S3, and sensor 4 as S4. As for data measurement of honey samples were represented as DM.

Data Pre-processing

The previously gathered raw data were normalised using equation (1). To obtain normalised values, divide each row of raw data measurement by the greatest value from its row. As a result, the value will be rescaled to a lower number in the range of zero to one (0-1). The normalised data's minimum and maximum values are 0 and 1, respectively. For odour-profile extraction, the normalised value is extremely useful. Then the values were displayed in Table 2.

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

R' = Normalized value
R = Data measurement
Rmax = The greatest value from each data measurement

Table 2. Normalised data for honey odour-profile

Normalized Data	S1	S2	S3	S4
1	ND_{11}	ND_{12}	ND_{13}	ND_{14}
2	ND_{21}	ND_{22}	ND_{23}	ND_{24}
…	…	…	…	…
1000	ND_{10001}	ND_{10002}	ND_{10003}	ND_{10004}

Table 2 depicts the normalised data table for the honey sample. 1000x4 data is used to normalise the data. Sensor 1 was indicated as S1, sensor 2 as S2, sensor 3 as S3, and sensor 4 as S4. As for data measurement of honey samples were represented as DM.

Feature Extraction

The features of each sample were retrieved from the normalised value. Using the clustering technique, the normalised value will be divided into groups. Each group will receive 10 cases based on the mean calculation of the normalised value. For the classification procedure, the cases of each category were recorded and saved in CBR memory as "stored cases".

Intelligent Classification

There are a few methods for classifying intelligence. The method that we used in this research is case-based reasoning. Case-based reasoning (CBR) is a cognitive science and artificial intelligence framework that models reasoning as predominantly memory-based. The “intelligent” reuse of information from previously solved problems (or cases) in CBR is based on the assumption that the more similar two problems are, the more similar their solutions would be. In case-based reasoning (CBR), there is a cycle in the case-based reasoning method which we called the CBR cycle. There are 4 components in the CBR cycle, which are retrieved, reused, revise and retain.

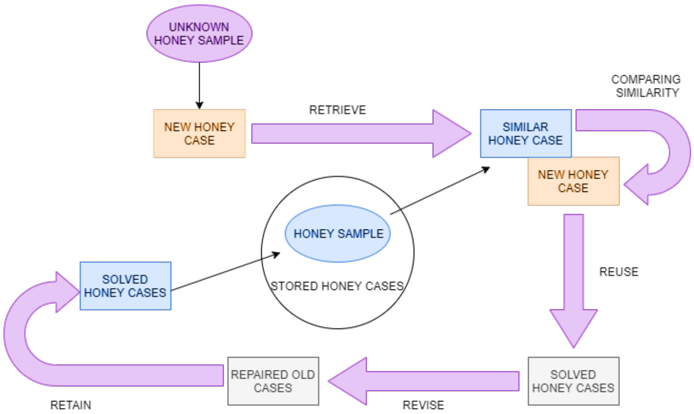

Figure 4. CBR cycle for honey odour-profile classification

As we can see in Figure 4, the cycle starts with the unknown honey which represented the test sample. The unknown honey sample's odour-profile then proceeded through a retrieval phase to retrieve the memory's stored cases. Because CBR learns from previous cases, it compared the unknown odour-profile honey sample to previously stored odour-profiles. If the unknown sample and the saved honey sample have a high similarity percentage, the algorithm will use the saved case information to make a decision or provide a solution. This classification technique is distinct from other classification techniques like ANN and K-NN because it does not require data training. One case out of 110 stored cases was taken for the determination of the similarity percentage between two cases in the CBR retrieval cycle. The remaining 109 cases will be left with the rest of the cases. The similarity percentage was calculated using Equation (2). If the percentage of similarity between two cases is the largest, it signifies that their distance is close and they belong to the same group.

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

T = Target case
S = Source case
n = The number of attributions for the honey sample
i = The single attribution for each case.
f = The similarity function formulation for the honey sample
w = The weight of each attribution.

Performance Measure

In the performance measure, the confusion matrix was used to evaluate the CBR Classification result. Then the sensitivity, specificity, and accuracy of the whole honey sample classification process were calculated using Equations (3) - (5).

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

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

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

The classification's sensitivity was computed by dividing the true positive value of the classification result by the total of the true positive (TP) and false negative (FN) values of the classification. The classification's specificity was determined by dividing the true negative (TN) by the total of false positive (FP) and true negative (TN). Then, the classification's accuracy was computed by dividing the total of true positive (TP) and true negative (TN) by the total case (P+N).

In this study, P, N, TP, TN, FP, and FN are used to get the final result of the CBR voting procedure. If these cases were anticipated as ‘A' in TP, then the actual result is also ‘A'. The same principle was used in TN, where the cases were expected to be ‘B,' and the actual result was also ‘B.' Different from FP, where the expected result for FP is ‘A.' But the actual result is ‘B,' and for FN is the same. The expected result was ‘B,' but the actual result was ‘A.'

The purpose of this study's accuracy measurement is to see how well the CBR performs with honey samples and how often the proper classification occurs. The number of "yes" predictions when the scenario is genuine "yes" is determined as a sensitivity measurement. The next step is to assess specificity by determining the total number of “No” predictions made when the case is truly “No.”

EXPERIMENTAL RESULT

Each sample was analyzed five times, which resulted in 200 data measurements for each experiment. Then the final data measurement will be 1000 data for a sample. As a result, for all samples, 11000 data measurements were taken as shown in table 3.

Table 3. Raw Data of Stingless Bee Honey

No. of Measurement	Sensor Reading			
	1	2	3	4
DM1	422	140	322	57
DM2	421	139	321	56
DM3	422	140	321	56
DM4	422	140	321	56
DM5	422	141	321	56
DM6	423	141	322	56
DM7	423	140	322	57
DM8	421	141	320	56
DM9	420	139	320	56
DM10	420	140	320	57
…	…	…	…	…
…	…	…	…	…
DM1100	356	141	301	89

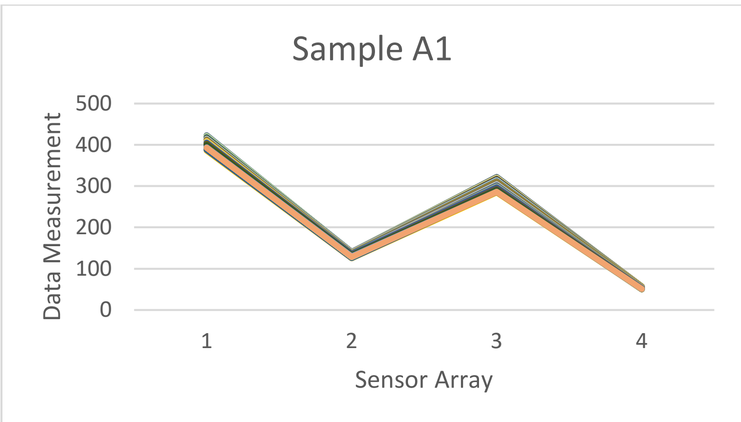

Figure 5. Graph of Data Measurement vs Sensor Array

Figure 5 depicts a graph of one honey sample in one experiment. The x-axis represents the sensor array, while the y-axis represents the raw data measurement in resistance value. The sensors utilized in the e-nose are labelled S1, S2, S3, and S4. Sensors S1 and S3 have the highest sensor reading for honey samples, whereas S2 and S4 have the lowest sensor reading for honey samples, respectively. Even though the patterns are nearly identical for each sample, they contain considerable variances between them that can be quantified and used in the classification process. A data pre-processing phase is required to make the pattern more noteworthy.

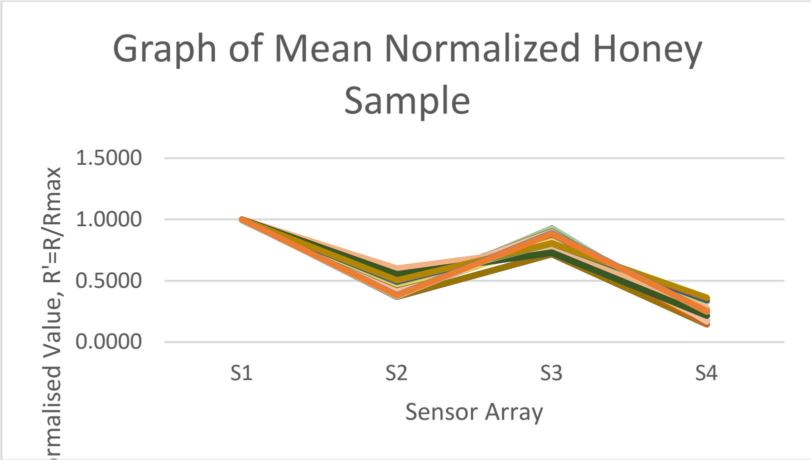

Figure 6. Graph of Mean Normalised Honey Sample

Figure 6 depicts a graph of the mean normalised for the honey sample. The X-axis depicts the sensor array, while the Y-axis depicts the normalised value. S1, S2, S3, and S4 are displayed in this graph, indicating the four sensors employed in the e-nose. Sensors S2, S3, and S4 demonstrate how the normalised value changes depending on the type of honey used. To put it another way, the degree of honey scent fluctuates when honey is sourced from different areas or different types of bees. Changes in the degree of honey odour were impacted by the type of honey.

Table 4. CBR Case for Honey Sample

SAMPLE	S1	S2	S3	S4	
A1	1.0000	0.3698	0.7186	0.1435	CASE 1
	1.0000	0.3695	0.7182	0.1435	CASE 2
	1.0000	0.3697	0.7182	0.1441	CASE 3
	1.0000	0.3690	0.7178	0.1436	CASE 4
	1.0000	0.3687	0.7173	0.1446	CASE 5
	1.0000	0.3694	0.7173	0.1441	CASE 6
	1.0000	0.3695	0.7163	0.1441	CASE 7
	1.0000	0.3689	0.7162	0.1446	CASE 8
	1.0000	0.3702	0.7168	0.1452	CASE 9
	1.0000	0.3715	0.7164	0.1453	CASE 10
A2	1.0000	0.4177	0.8462	0.1454	CASE 11
	1.0000	0.4173	0.8436	0.1457	CASE 12
	1.0000	0.4171	0.8409	0.1452	CASE 13
	1.0000	0.4178	0.8385	0.1457	CASE 14
	1.0000	0.4175	0.8355	0.1454	CASE 15
	1.0000	0.4182	0.8336	0.1455	CASE 16
	1.0000	0.4196	0.8305	0.1458	CASE 17
	1.0000	0.4191	0.8278	0.1464	CASE 18
	1.0000	0.4193	0.8261	0.1471	CASE 19
	1.0000	0.4180	0.8233	0.1468	CASE 20
A3	0.9933	0.3965	0.9273	0.1664	CASE 21
	0.9939	0.3936	0.9262	0.1656	CASE 22
	0.9942	0.3918	0.9265	0.1655	CASE 23
	0.9943	0.3923	0.9265	0.1662	CASE 24
	0.9945	0.3948	0.9262	0.1670	CASE 25
	0.9947	0.3957	0.9257	0.1669	CASE 26
	0.9953	0.3962	0.9243	0.1667	CASE 27
	0.9960	0.3959	0.9232	0.1667	CASE 28
	0.9964	0.3956	0.9234	0.1665	CASE 29
	0.9969	0.3958	0.9229	0.1667	CASE 30
A4	1.0000	0.3981	0.8331	0.1726	CASE 31
	1.0000	0.3998	0.8319	0.1727	CASE 32
	1.0000	0.4013	0.8309	0.1724	CASE 33
	1.0000	0.4019	0.8288	0.1727	CASE 34

	1.0000	0.4011	0.8271	0.1725	CASE 35
	1.0000	0.4016	0.8258	0.1727	CASE 36
	1.0000	0.4031	0.8253	0.1732	CASE 37
	1.0000	0.4034	0.8238	0.1734	CASE 38
	1.0000	0.4051	0.8234	0.1736	CASE 39
	1.0000	0.4075	0.8227	0.1742	CASE 40
A5	0.9961	0.4237	0.9072	0.1676	CASE 41
	0.9966	0.4251	0.9061	0.1681	CASE 42
	0.9973	0.4279	0.9055	0.1683	CASE 43
	0.9980	0.4314	0.9053	0.1686	CASE 44
	0.9986	0.4337	0.9044	0.1683	CASE 45
	0.9993	0.4341	0.9030	0.1680	CASE 46
	0.9999	0.4353	0.9018	0.1680	CASE 47
	1.0000	0.4368	0.9004	0.1683	CASE 48
	1.0000	0.4358	0.8981	0.1675	CASE 49
	1.0000	0.4361	0.8985	0.1677	CASE 50
A6	1.0000	0.4829	0.7875	0.2453	CASE 51
	1.0000	0.4834	0.7863	0.2467	CASE 52
	1.0000	0.4837	0.7854	0.2485	CASE 53
	1.0000	0.4830	0.7840	0.2468	CASE 54
	1.0000	0.4837	0.7834	0.2479	CASE 55
	1.0000	0.4850	0.7841	0.2479	CASE 56
	1.0000	0.4875	0.7836	0.2486	CASE 57
	1.0000	0.4876	0.7822	0.2492	CASE 58
	1.0000	0.4867	0.7817	0.2479	CASE 59
	1.0000	0.4904	0.7828	0.2509	CASE 60
A7	1.0000	0.4685	0.7774	0.2435	CASE 61
	1.0000	0.4670	0.7759	0.2426	CASE 62
	1.0000	0.4664	0.7752	0.2424	CASE 63
	1.0000	0.4674	0.7747	0.2434	CASE 64
	1.0000	0.4686	0.7735	0.2432	CASE 65
	1.0000	0.4720	0.7729	0.2444	CASE 66
	1.0000	0.4744	0.7713	0.2465	CASE 67
	1.0000	0.4744	0.7700	0.2468	CASE 68
	1.0000	0.4732	0.7683	0.2466	CASE 69
	1.0000	0.4713	0.7663	0.2458	CASE 70
A8	1.0000	0.5821	0.7708	0.2679	CASE 71
	1.0000	0.5836	0.7692	0.2675	CASE 72
	1.0000	0.5856	0.7693	0.2697	CASE 73
	1.0000	0.5873	0.7679	0.2688	CASE 74
	1.0000	0.5899	0.7670	0.2708	CASE 75
	1.0000	0.5920	0.7668	0.2719	CASE 76
	1.0000	0.5931	0.7660	0.2718	CASE 77
	1.0000	0.5950	0.7656	0.2705	CASE 78
	1.0000	0.6003	0.7666	0.2744	CASE 79
	1.0000	0.6009	0.7642	0.2750	CASE 80
A9	1.0000	0.5303	0.7372	0.2116	CASE 81
	1.0000	0.5372	0.7362	0.2126	CASE 82
	1.0000	0.5414	0.7340	0.2130	CASE 83
	1.0000	0.5448	0.7328	0.2133	CASE 84
	1.0000	0.5480	0.7315	0.2140	CASE 85
	1.0000	0.5497	0.7303	0.2143	CASE 86
	1.0000	0.5506	0.7294	0.2152	CASE 87
	1.0000	0.5519	0.7287	0.2159	CASE 88
	1.0000	0.5521	0.7279	0.2167	CASE 89
	1.0000	0.5538	0.7287	0.2173	CASE 90
A10	1.0000	0.4787	0.8084	0.3307	CASE 91
	1.0000	0.4821	0.8096	0.3352	CASE 92
	1.0000	0.4830	0.8081	0.3346	CASE 93

	1.0000	0.4774	0.8042	0.3263	CASE 94
	1.0000	0.4834	0.8040	0.3331	CASE 95
	1.0000	0.4841	0.8034	0.3327	CASE 96
	1.0000	0.4913	0.8042	0.3411	CASE 97
	1.0000	0.5001	0.8043	0.3535	CASE 98
	1.0000	0.5034	0.8045	0.3595	CASE 99
	1.0000	0.5044	0.8046	0.3632	CASE 100
A11	0.9956	0.3741	0.8913	0.2496	CASE 101
	0.9962	0.3762	0.8891	0.2499	CASE 102
	0.9967	0.3758	0.8878	0.2489	CASE 103
	0.9967	0.3760	0.8870	0.2494	CASE 104
	0.9967	0.3758	0.8864	0.2494	CASE 105
	0.9968	0.3737	0.8865	0.2476	CASE 106
	0.9978	0.3761	0.8868	0.2490	CASE 107
	0.9990	0.3785	0.8859	0.2495	CASE 108
	0.9999	0.3815	0.8850	0.2512	CASE 109
	1.0000	0.3813	0.8844	0.2499	CASE 110

Table 4 depicts the CBR case for honey samples. There are 110 cases in the table, with 10 cases for each sample. The first 10 cases (case 1 until case 10) represent honey sample A1. The second 10 cases (case 11 until case 20) represent honey sample A2. Then for the next 10 cases, (case 21 until case 30), (case 31 until case 40), (case 41 until case 50), (case 51 until case 60), (case 61 until case 70), (case 71 until case 80), (case 81 until case 90), (case 91 until case 100) and (case 101 until case 110) represent A3, A4, A5, A6, A7, A8, A9, A10, and A11 honey sample respectively. S1, S2, S3, and S4 are the sensors used in the e-nose. These cases will be referred to as "stored cases" and will be stored in the CBR memory for classification purposes.

For all circumstances, the maximum normalised value in this table is in the entire S1 column, which contains the value of '1', and the lowest normalised value is in the entire S4 column. Due to the prior raw data being separated with the highest value in each row, only column S1 contains the same value.

Previously, the entire column S1 was filled with raw honey data from sensor 1. Then, each row of the data measurement must be divided by the maximum value of S1, S2, S3, and S4 to produce normalised data.

From the data collected, the greatest value found in every row of data is from column S1. As a result, when the raw data collected was normalised, column S1 for each row of normalised data will always resulting a value of 1. The sensitivity of each sensor in the e-nose was built differently. The S1, which represents sensor 1, has high sensitivity compared to other sensors. The normalised data were then grouped into ten cases for each sample to obtain the odour features.

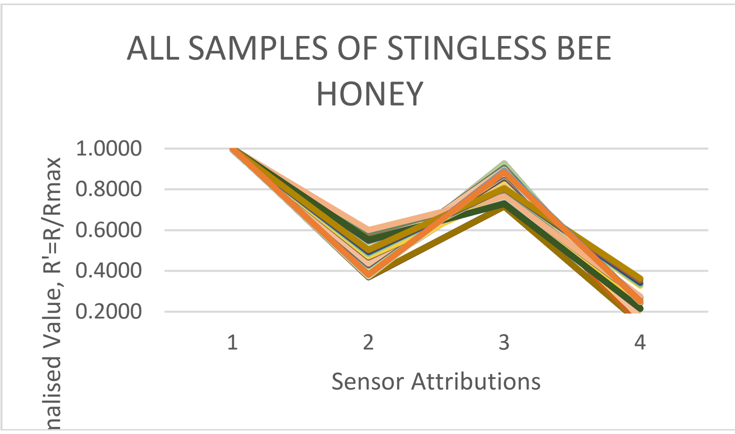

Figure 7. Graph of Clustering Data for All Samples

Figure 7 depicts the graph of clustering data for all samples. This graph is obtained from Table 4 which shows all the cases for all 11 samples.

Table 5. CBR Formulation for One Case of Honey Sample

Stored Case	Similarity Function	Normalised Similarity Function	Weighted Similatiry
1.0000	0.0000	0.0000	0.0000
0.3698	0.6302	0.7358	0.1839
0.7186	0.2814	0.3286	0.0821
0.1435	0.8565	1.0000	0.2500
	Max	Similarity	Sum
	0.8565	51.6084	0.5161

Table 5 depicts the CBR formulation for one case of the honey sample. The stored case is the stored case of the honey sample. The similarity function was calculated using Equation (6). The normalised similarity function was calculated by dividing the similarity function by the maximum similarity. The maximum similarity was gained from the highest value of the similarity function. Then the weighted similarity was calculated by multiplying the normalized weight and normalised similarity function. The sum of weighted similarity was calculated to get the similarity percentage.

$$Similarity\ function = abs(1 - abs)(current\ case - stored\ case) \quad (6)$$

Table 6. Weight Assignment

Attribution	Local Weight	Normalised Weight	Current Case
S1	1	0.25	
S2	1	0.25	
S3	1	0.25	
S4	1	0.25	

Table 6 depicts the weight assignment. The sensors in the e-nose are utilized to depict the attribution. The expert assigned a local weight value of 1 to each sensor. To conduct the odor-profile classification, the honey expert must first identify the local weight for each attribution, which can be heuristically changed to improve the classification result. So, the total attribution was calculated as 4. The normalised weight was calculated by dividing each of the local weight values by the total attribution. As for the current case, the value of the stored case will be put to calculate the similarity percentage between other cases.

Table 1. CBR Performance Evaluation

	RESULT										
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
TOTAL CASES	30	30	30	30	30	30	30	30	30	30	30
CONDITION POSITIVE (P)	30	30	30	30	30	30	30	30	30	30	30
CONDITION NEGATIVE (N)	0	0	0	0	0	0	0	0	0	0	0
TRUE POSITIVE (TP)	30	0	30	0	30	0	30	0	30	0	30
TRUE NEGATIVE (TN)	0	30	0	30	0	30	0	30	0	30	0
FALSE POSITIVE (FP)	0	0	0	0	0	0	0	0	0	0	0
FALSE NEGATIVE (FN)	0	0	0	0	0	0	0	0	0	0	0
SENSITIVITY = TP/(TP+FN)	1.00		1.00		1.00		1.00		1.00		1.00
SPECIFICITY = TN/(TN+FP)	1.00		1.00		1.00		1.00		1.00		1.00
ACCURACY = (TP+TN)/(P+N)	1.00		1.00		1.00		1.00		1.00		1.00
OVERALL SENSITIVITY	100.00										
OVERALL SPECIFICITY	100.00										
OVERALL ACCURACY	100.00										

Table 7 depicts the performance evaluation for honey odour-profile classification using the CBR method. Equations (3) - (5) were used to calculate the classification's sensitivity, specificity, and accuracy. As for the final result, 100 percent was gained for each overall sensitivity, overall specificity, and overall accuracy.

CONCLUSION

In the conclusion, this study indicates that 11 distinct stingless bee honey samples had varied odours. Variations in the chemical characteristics of the honey impacted the changes in the fragrance and odour-profile of the samples, resulting in variances in adulteration between samples. Even if the patterns and aromas of the stingless bee honey samples are identical, they may be classed. This is CBR's most important feature: the classifier approach manages to make classification even when the source instances kept in memory have a minimal number of dimensions. The categorization of a stingless bee honey sample olfactory profile using the case-based reasoning classification approach yielded a 100% classification rate.

Other than that, the odour-profile of the stingless bee honey is successfully measured by using an electric nose (E-nose). The electronic nose is a sensor that is designed to emulate human sensory abilities in detecting complex combinations of chemical substances, both biological and non-biological in origin. The electronic nose was created to replicate the human nose and detect unstable food components that can be used to check the quality of the food. So, to replace the actual nose of a human, this electric nose can be used to measure odours.

As a result, the objectives of this research are achieved by using an efficient method to classify the species of stingless bee honey (SBH).

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