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Neuromarketing case study: recognition of sweet and sour taste in beverage products based on EEG signal features

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ABSTRACT

Consumers' acceptance of a food product hinges on its taste. Culinary practitioners typically conduct organoleptic tests to evaluate a food/beverage's taste. Organoleptic tests have a subjective nature, making a clear description difficult. In this study, we suggest implementing a brain signal-based electroencephalogram (EEG) taste assessment system to evaluate consumer responses to the tastes of a drink, specifically sour and sweet. The system distinguishes flavors based on EEG data. These classifiers, including recurrent neural network (RNN), long-short term memory (LSTM), and gated recurrent unit (GRU), are utilized for the classification process. Total 35 participants' EEG data were recorded for this study. Temporal (T3 and T4) and centro parietal (CP1 and CP2) channels are used for recording. EEG signal processing involves filtering, artefact elimination, and band decomposition into delta, theta, alpha, beta, and gamma frequencies. In the time domain of clean EEG data, mean absolute value, standard deviation, and variance are used for signal feature extraction. Several classifiers (RNN, LSTM, and GRU) will be fed with the signal feature values as input. An accuracy of 88.62% was achieved using LSTM in the classification. The RNN and GRU models achieved classification accuracies of 88.56% and 87.15% respectively.

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1. INTRODUCTION

In the food and beverage industry, consumer acceptance of a product is determined by the stimuli that arise through the five senses of sight, smell, taste and hearing [1]. However, the main factor that ultimately affects food acceptance is the taste stimulation caused by food [2]. The taste of a food product is one of the determinants of product acceptance by consumers. Thus, culinary entrepreneurs must optimize the taste of each food/drink they make. It is one of the main factors determining the success of a culinary business in the food/beverage sector. Hygienic food products claimed to provide health and practical benefits will still be difficult for consumers to accept if they are not liked or even disliked in terms of taste [3]. Tasting is a technique of recognizing the taste of food with the tongue [4]. Because the tongue is the sense of taste from the path of absorption of food ingredients into the human body, the sensation on the tongue is the taste closest to being used to represent food/drinks [5]. Currently, the taste assessment of food/drinks is usually carried out using organoleptic tests [6]. Organoleptic is a test of food ingredients based on a person's preferences and willingness to use a product [7]. The advantages of organoleptic tests are that they are easy and fast to perform, so the results of measurements and observations are also quickly obtained [8]. Meanwhile, the weakness of the organoleptic test is that the sensory properties cannot be described [9]. In addition, another weakness of the results of this organoleptic test is that the results are subjective or depend on the respondents being tested [10]. Subjectivity related to the results of food/beverage assessments can lead to debates for each tester because of their different perceptions of a product. Therefore, another assessment method is needed that can be used to overcome the weaknesses of food testing using organoleptic.

Using neuroscience to evaluate certain products can be an alternative or a breakthrough [11]. In the assessment of a product, the use of neuroscience to determine consumer behaviour/assessment of products sold on the market is neuromarketing [12]. Neuromarketing involves utilizing medical technology to inspect the consumer's brain response to marketing stimuli [13]. Research related to taste assessment using brain signals has begun to be carried out by researchers. Among them is Mouillot *et al*. [14], in their research, tried to distinguish gustatory evoked potentials (GEPs) from the sweet taste response of Sucrose, Aspartame, and Stevia. Taste response was measured using brain signals electroencephalogram (EEG). In validating the measurement results, a comparison instrument was used in the form of hedonic values from the visual analog scale (VAS). As many as 20 respondents measured their EEG signals at several points/channels, such as midline parietal (Pz), midline central (Cz), midline frontal (Fz), and frontopolar (Fp1 and Fp2). This study found that the P1 latency of GEP stimulated by sucrose tends to be shorter than the P1 latency of GEP stimulated by Aspartame and Stevia. In addition, no correlation was found between GEPs parameters and hedonic values based on the VAS. Based on an analysis of the results of the response to stimuli from Sucrose, Aspartame, and Stevia through EEG signals, it was also found that although the three stimuli had the same taste perception, the activation in the cerebral cortex tended to be different from one another.

In their research, Wu *et al*. [15] attempted to explore the parts of the brain that are responsive to the umami taste of monosodium glutamate (MSG) based on EEG signals. The doses of MSG used to stimulate participants included 0.05 gr/100 mL, 0.12 gr/100 mL, and 0.26 gr/100 mL. Based on the results of recording brain signals using EEG, it was found that the response to umami taste was found at a frequency of 2 Hz. Meanwhile, the brain locations responsive to umami stimuli are T4, F8, Fp2, Cz, and A2. In addition, the power spectral density (PSD) value of the right brain tends to be more sensitive to MSG stimuli. It proves that EEG signals have enormous potential for exploring the types of food/beverage tastes (especially for understanding related to the perception of umami taste). Atzingen *et al*. [16], in their research, also attempted to classify several types of sweeteners using the Convolutional Neural Network based on their sugar content. A total of 11 healthy participants recorded their EEG signals when stimulated with sucrose, sucralose, and aspartame. The recording was performed on the C3 and C4 channels of the human head. Signal pre-processing, such as filtering and artifact removal, is also performed to obtain a clean EEG signal. Signal feature extraction was performed to obtain the conditions' characteristics during the EEG recording and stimulation process. Based on the results of the EEG signal classification using CNN, an accuracy of 82.3% was obtained. It proves that the level of sweetness can be adequately distinguished using brain signals, and the CNN algorithm can be an alternative method for the classification process. Based on previous literature studies [14]-[16], we believe that brain signal-based taste recognition (EEG) still needs to be widely explored. Therefore, we intend to perform taste recognition (sweet and sour tastes) in beverage products using EEG signals. We will also classify the recorded EEG data using several classifiers such as recurrent neural network (RNN), long-short term memory (LSTM), and gated recurrent unit (GRU). The classification results are expected to be used as evidence that tastes can be distinguished optimally using brain signals.

2. METHOD

In this study, we carried out several stages, from recording of EEG data, pre-processing, feature extraction, taste classification based on EEG, and analysis of the results. For a more detailed explanation, we present it in each of the following sub-sections.

2.1. Electroencephalogram data recording

The EEG data recording was carried out using an OpenBCI/Ultracortex device. OpenBCI/Ultracortex is an open-source platform used for biosensing and neuroscience. This OpenBCI tool consists of an OpenBCI headset and an OpenBCI graphical user interface (GUI). The OpenBCI headset is attached to the head for the EEG data recording process, while the OpenBCI GUI displays the recording results [17]. This device has several electrodes, as many as 8 or 16 channels. However, this study only used four electrodes attached to the centro parietal (CP1 and CP2) and temporal (T3 and T4) areas. In addition, the electrode placement system using the OpenBCI device on the scalp has adopted the international 10-20 system [18].

A total of 35 participants recorded their EEG signals under taste-stimulated and neutral conditions. Neutral conditions are conditions when participants are given mineral water (tasteless) in their EEG data recording. Sweet taste stimulation was carried out by providing chocolate milk drinks to the participants, while sour taste stimulation was carried out by giving lemon-flavoured drinks. EEG data recording is carried out for 5 seconds in the taste stimulation process. Likewise, the EEG recording without stimulation is done for 5 seconds. In addition, after the completion of each data recording session, participants filled in the questionnaire. This questionnaire will be used for validation and the EEG data labelling process. For more details, Figure 1 shows the sequence of the EEG data recording process carried out in this study.

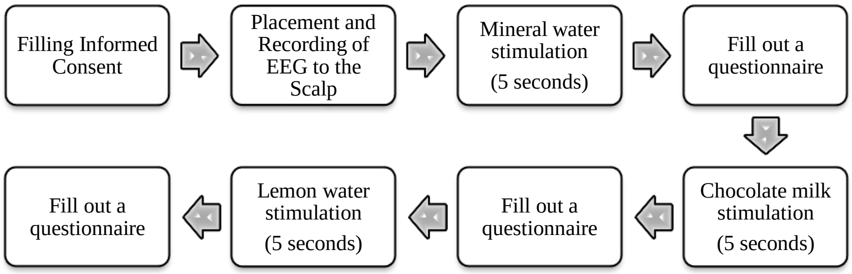


Figure 1. EEG data recording

2.2. Data pre-processing

Pre-processing is used to clean signals of artefacts. Filtering, artefact removal, and band decomposition constitute the stages of signal pre-processing [19]. Filtering occurs between 0.5 Hz and 45 Hz. Delta, theta, alpha, beta, and gamma brain waves lie within this frequency range [20]. The signal was filtered using a butterworth bandpass filter of order 4. The independent component analysis (ICA) method was employed for both filtering and artefact removal. With ICA, the EEG signal's artifact-free components will be isolated [21]. These artefacts stem from eye movements (electrooculogram), heart activity (electrocardiogram), and body muscles (electromyogram) [22]. Following ICA artifact removal, band decomposition ensues. This process aims to break down the EEG signal into several brain waves, such as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-25 Hz), and gamma (25-45 Hz) [23].

2.3. Feature extraction

The subband decomposed EEG signal undergoes feature extraction next. This step intends to isolate distinct features of the signaled in each subband [24]. EEG signals exhibit characteristics in the time, frequency, and time-frequency domains [25]. In this study, only time domain features are utilized. Signal features from each subband and each condition are divided into 100 data chunks. The taste of the drink will be determined from these data later. In this study, the distinct features highlighted are [26].

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{1}$$

Where: mean absolute value (MAV), $\sum_{i=1}^{N}|x_i|$=sum of absolute data values, and N=number of data.

$$S^2 = \frac{\sum(x_i-\bar{x})^2}{n-1} \tag{2}$$

Where: S^2=variance, x_i=the value of data, $\bar{x}$=the mean value, and n=number of data.

$$\sigma = \sqrt{\frac{\sum(x_i-\mu)^2}{N}} \tag{3}$$

Where: σ=standard deviation, N=the size of data, x_i=the value of data, and μ=the mean value.

2.4. Classification

Researchers compared the accuracy levels of various taste-classification algorithms. The algorithms employed comprise RNN, LSTM, and GRU. These algorithms are elaborately described.

2.4.1. Recurrent neural network

The operation of an RNN is identical to that of a regular neural network. The memory in the neurons is a different aspect of the architecture that sets it apart from standard neural networks [27]. RNNs have a memory that they can use to store historical data [28]. The RNN's decision-making mechanism considers the historical data in addition to the input data. As a result, this algorithm can reliably forecast or classify data and recognize data patterns. The RNN algorithm uses the feedback loop principle to anticipate the output layer by storing the result of one layer and giving it back as input. The neural network is explicitly given the first input values. The current information and the initial state are used to calculate the current state (if any).

2.4.2. Long-short term memory

LSTM has modified RNN. RNN cannot predict words based on previously stored data, so LSTM fills this gap [29]. As a result, the LSTM can remove information that is no longer applicable and remember a data set that has been retained for a long time [30]. The LSTM contains several crucial parts, more commonly referred to as "gates," that can integrate information and add to data collection. The LSTM system has four gates: an output gate, an input gate, an input modulation gate, and a forget gate. The four gates each have specific roles and responsibilities for gathering, organizing, and processing data. In addition to these four gates, LSTMs also include an internal cell state that serves as the repository for an information subset from the preceding unit [31].

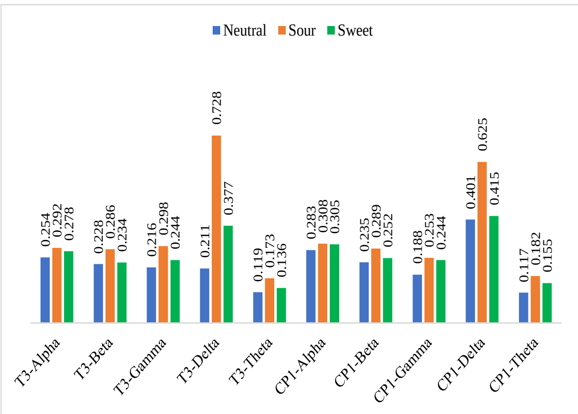
2.4.3. Gated recurrent unit

GRU is an artificial neural network architecture that belongs to the category of RNN, designed to overcome the vanishing gradient problem that often occurs when processing long sequence data [32]. GRU uses two gate mechanisms, namely "update gate" and "reset gate", to regulate the flow of information. The update gate determines how much information from the previous time should be kept, while the reset gate controls how much information from the past needs to be removed [33]. Compared to LSTM, GRU has a simpler structure, with fewer parameters, making it more computationally efficient and faster in training [34].

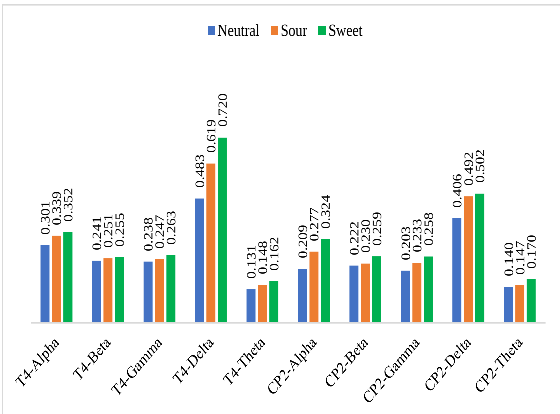
3. RESULTS AND DISCUSSION

There are three features of the EEG signal (in the time domain) extracted, including mean absolute value, variance, and standard deviation. These features are grouped by hemisphere (right-left) and sub-bands. The following is the result of the feature extraction of the EEG signal.

Based on the results of the mean absolute value feature extraction on the right and left hemispheres, the feature values for neutral tastes tend to be lower than those for sour and sweet flavours. It can be seen in all channels and subbands observed in this study. Related to sour taste, the value of the mean absolute value feature tends to be higher than the value of the sweet taste feature in the left hemisphere (Figure 2(a)). It can be seen on the T3 and CP1 channels for all subbands (alpha, beta, gamma, theta, and delta). In the right hemisphere (Figure 2(b)), the mean absolute value feature value of sweet taste tends to be higher than the sour taste feature value. These results can be seen on channel T4 and CP2 for all subbands.



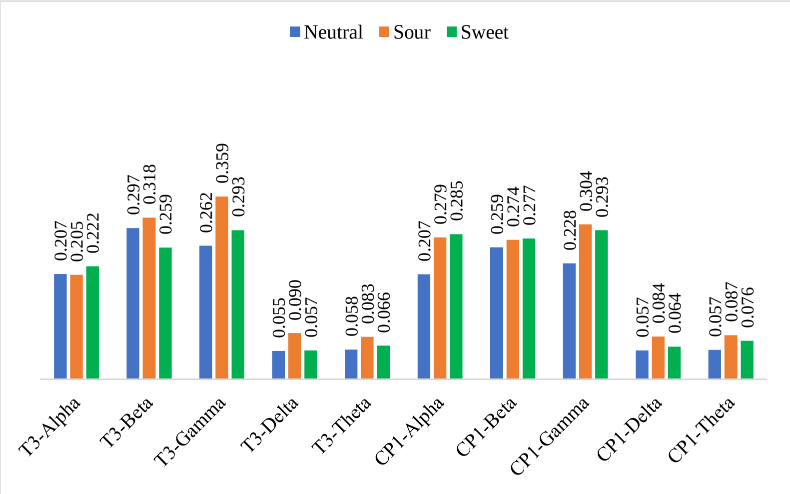
(a)



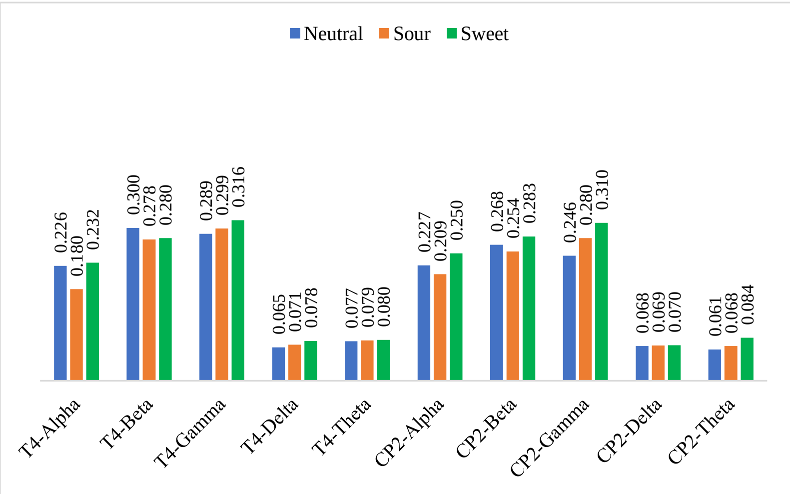
(b)

Figure 2. Features extraction; (a) mean absolute value of left-hemisphere and (b) mean absolute value of right-hemisphere

Unlike the case with the mean absolute value feature, which can be used to easily represent taste patterns (neutral, sour and sweet), the standard deviation feature value tends to change in each observation channel and sub-band. It proves that the observation of the standard deviation feature to distinguish sour and sweet tastes must be focused on more specific channels and sub-bands. For example, in the left hemisphere (T3 and CP1 channels) for the gamma, delta, and theta sub-bands, the feature value for sour taste tends to be higher than the feature value for sweet taste (Figure 3(a)). Whereas in the right-hemisphere (T4 and CP2 channels) for the gamma, delta, and theta sub-bands, the feature value for sour taste tends to be lower than the feature value for sweet taste (Figure 3(b)). However, the feature value for neutral taste remains the lowest.



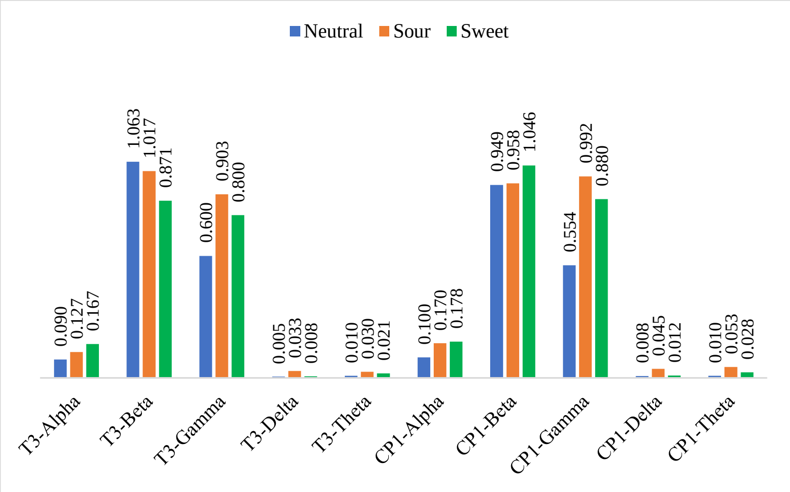
(a)



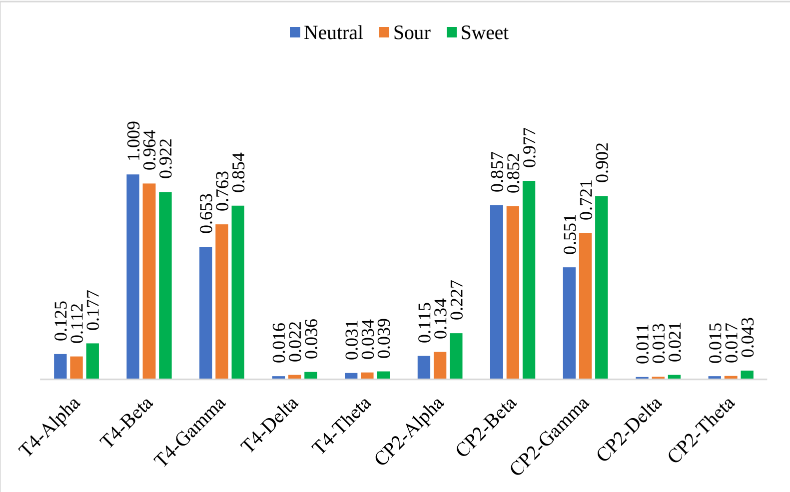
(b)

Figure 3. Features extraction; (a) standard deviation of left-hemisphere and (b) standard deviation of right-hemisphere

Similar to the standard deviation feature, observations of taste patterns (neutral, sour, and sweet) on the variance feature must also focus on more specific channels and sub-bands. For example, beta wave activity dominated at all locations, especially for neutral and sweet tastes, with a slight decrease in sour taste. Locations T3 and CP1 showed a predominance of beta activity for sour and sweet tastes (Figure 4(a)), while at T4 and CP2, beta activity was higher for neutral and sweet tastes (Figure 4(b)). Gamma waves also showed an important role, with higher activity for sweet tastes at locations T3 and T4, and higher activity for sour tastes at CP1 and CP2.



(a)



(b)

Figure 4. Features extraction; (a) variance of left-hemisphere and (b) variance of right-hemisphere

Alpha waves showed a relatively stable moderate activity pattern across all locations and tastes, with a slight increase for sweet tastes at location CP2. Delta and theta waves tended to be low across all taste conditions, although slight activity was recorded at certain locations, such as neutral taste at CP2. These results suggest that brain responses to different tastes can vary depending on the measurement location and specific wave frequencies. Sweet tastes tended to trigger higher activity at beta and gamma frequencies, especially at temporal locations (T3, T4), while sour tastes were more prominent at central-parietal locations (CP1, CP2). This reflects that taste has a specific influence on brain activity patterns, depending on the location and type of waves measured.

The results of feature extraction of the EEG signal are then used to classify taste that is sour and sweet. This study used several classifiers based on artificial neural networks, namely RNN, LSTM, and GRU. To classify the data, we use python programming with a data distribution of 75% for training and 25% for testing. Apart from that, we also vary the number of epochs from 400 to 2000. It aims to get the minimum epoch which can produce optimal accuracy in the training and testing process by each classifier. The following is the classification accuracy level based on three different classifiers.

Based on the classification results of 2 tastes (Table 1), the best accuracy value for the testing process is 88.62% using LSTM. This accuracy is also higher than when the classification process was carried out using the RNN (88.56%) and GRU (87.15%). The level of classification accuracy using LSTM is higher than other classifiers because LSTM can remember a collection of information that has been stored for a long time and delete data that is no longer relevant. It is the weakness of the RNN, which cannot predict words based on past information that has been stored for a long time. Meanwhile, for GRU (although it is also capable of remembering information over a long period), the architecture tends to be more straightforward than LSTM because data that is too old/ irrelevant to the latest data patterns will be automatically deleted. In addition, the LSTM also has an internal cell state which functions to store selected information from the previous unit.

Table 1. Classification accuracy of taste recognition (sour and sweet)

Parameter	Epochs	Algorithms		
		RNN	LSTM	GRU
Training	400	83.18	81.98	89.83
Testing		81.69	79.27	84.56
Training	800	90.55	89.93	96.67
Testing		86.48	85.69	86.14
Training	1200	93.27	93.40	98.46
Testing		87.32	87.89	**87.15**
Training	1600	94.29	95.64	99.04
Testing		88.28	88.39	85.97
Training	2000	94.78	96.26	99.34
Testing		**88.56**	**88.62**	85.58

Our findings in this study are that EEG recording can be used to study brain activity related to taste perception, including sweet, sour, and neutral tastes. These taste perceptions are generated by specific activation in the gustatory cortex area, located in the insular lobe and frontal operculum [35]. Sweet tastes are often associated with increased activity in the anterior insula and orbitofrontal cortex (OFC), which play a role in hedonic evaluation (pleasure) [36]. In contrast, sour tastes tend to activate more extensive areas in the insula and primary somatosensory cortex, because this sensation often involves a higher intensity or "surprise" component [37]. Neutral tastes, which have no emotional intensity or valence, usually produce more stable or less pronounced activity patterns than other tastes, with little activation spread across the gustatory area [38]. By analyzing EEG signals, such as the frequency or amplitude of certain waves, we can identify differences in brain responses to each type of taste, providing insight into how the brain processes sensory information from beverages.

Future research, the relationship of taste to memory and decision-making can be explored to further understand the complex interactions between the gustatory system and cognition. By integrating EEG with other imaging techniques, such as fMRI or MEG, multidimensional studies of taste can be conducted to provide a more complete picture of brain mechanisms.

4. CONCLUSION

Based on the experiments' results, it can be concluded that sour and sweet tastes can be adequately distinguished using the EEG signal features. The signal features include mean absolute value, standard deviation, and variance. In the extraction process, these features are grouped by channel (T3, T4, CP1 and CP2) and sub-band (alpha, beta, gamma, delta, and theta). We also found that the sour taste tends to be dominant (high feature value) in the left hemisphere, while the sweet taste predominates in the right hemisphere (high feature value). In addition, based on the results of the taste classification, the best accuracy value was obtained using the LSTM algorithm. However, the actual difference in the level of accuracy of the several classifiers used is insignificant. The optimal testing accuracy value using LSTM is 88.62%. Meanwhile, when the classification was carried out using RNN and GRU, the accuracy values were only slightly lower, namely 88.56% and 87.15%. It proves that this study's pattern of EEG signal feature values can be used to distinguish between sour and sweet tastes well. For further research, adding more signal features (in the time domain, frequency domain or even time-frequency domain) is necessary. In addition, signal feature selection is also needed to ensure that only the right features are used for further analysis so that not all features become input in the classifier. It is also necessary to determine the channel and sub-band to increase the accuracy of the classification process.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [YP] on request.

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