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Classification of Sweet and Sour Taste Using Electroencephalography (EEG)

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***Abstract*— For survival, humans require food and drink as a source of nutrition for the body. The taste of food and drink is crucial in the process of eating and drinking. Traditional taste evaluation can be performed through surveys, but this method is highly subjective. Therefore, Electroencephalography (EEG) is used as a more objective method to evaluate taste perception. EEG can record brain signals produced by food and drink taste stimuli. This study aims to investigate the perception of sour and sweet tastes involving 32 participants in the experiment. EEG signals were recorded at four channels, namely CP1, CP2, T3, and T4. Preprocessing and feature extraction stages were carried out using MATLAB, while EEG signal classification was performed using Python. The cleaned EEG signals were decomposed into Alpha, Beta, Gamma, Delta, and Theta sub-bands. Features such as Mean Absolute Value (MAV), Standard Deviation (STD), and Power Spectral Density (PSD) were extracted from EEG signals and computed to classify sour and sweet tastes. Four algorithms were used in the experiment, namely K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), Random Forest, and Gate Recurrent Unit (GRU). The best results were obtained using the GRU algorithm, which achieved an accuracy of 91.53% using the aforementioned three features. Meanwhile, for each feature, the best accuracy was achieved using the PSD feature and random forest algorithm, which reached an accuracy of 91.46%.**

Keywords—Taste perception, Sweet and Sour, Brain Signal, Electroencephalography, MAV,STD Power Spectral Density, K-NN, SVM, Random Forest, GRU algorithm.

I. INTRODUCTION

Taste buds are the gateway to balance energy and nutrition in humans. Therefore, they are extremely important in the criteria for selecting human food and for their health and survival[1]. Information conveyed through the gustatory system helps in identifying nutritious and edible food, allowing humans to avoid hazardous substances, and encouraging the selection of food based on nutritional content and personal preference [2]. The perception of taste in food and beverages is influenced by various subjective factors, such as hunger, appetite, health conditions, past experiences, individual preferences, and mood [3]-[4]. Human taste perception is difficult to understand and requires more objective research to gain better insights into the mechanisms involved. Broadly speaking, there are two ways to research human responses to food flavors, explicitly (questionnaires) and implicitly[5]. Explicit responses have some shortcomings, such as high subjectivity and evaluations made after tasting food/drinks (cannot be done directly)[6] .

Neuromarketing is a scientific discipline that focuses on non-invasive brain signal recording techniques to directly measure customers' brain responses to marketing stimuli (including food/beverage tastes), replacing traditional survey methods [7]. Research by Plassmann et al. (2015) discussed the advances and challenges in the field of neuromarketing and its potential for understanding consumer behavior. The authors stated that there is still much to be learned in the field of neuromarketing, including how the brain responds to taste stimuli, and future research should focus on this area[8]. One tool used in neuromarketing is electroencephalogram (EEG) for short.

Electroencephalography, often referred to as EEG, is a tool that records the electrical activity of the brain by attaching electrodes to the scalp. EEG has the advantage of being relatively cheap compared to other methods of neuromarketing. In addition, EEG is easy to operate and has good temporal resolution, making it widely possible to use in research related to brain responses to the flavor of food or drink [9].

The five basic tastes of food or beverage are sweet, sour, salty, umami, and bitter. Sweet and umami tastes determine the availability of nutrients in food [10], while salty taste determines the sodium content in food that functions to increase appetite and hunger. Meanwhile, sour and bitter tastes are considered unpleasant and function as indicators of toxicity and harmful substances in food [11]-[12]. Therefore, the gustatory system must make quick decisions about whether a substance is safe or hazardous to swallow[13]. The stimuli chosen in the study are sour and sweet tastes. The sweet and sour tastes are the most commonly found flavors in foods and beverages consumed by people worldwide [14]. Both are two tastes that have very different characteristics from each other, thus allowing for clear comparisons between the two in terms of brain activity that occurs. Sweet taste tends to be liked and sour taste tends to be avoided. There have been several previous studies that have shown that sour taste can affect brain activity in areas related to attention, emotion, and language[15]. While sweet taste has been associated with activity in areas related to reward and motivation[16]. Although the effects of both tastes require further research. By choosing sour and sweet tastes as stimuli, this study aims to explore the differences in brain activity that occur in response to both tastes.

Our hypothesis is that there are differences in human EEG signals as a response to these two tastes. To extract signal features, we will use the time-frequency domain and apply a classification algorithm. In the algorithm selection research, several studies have been conducted. First, in pneumonia detection research, two methods, CNN-XGBoost and CNN-LightGBM, obtained accuracy values of 97.60% and 97.45%, respectively [17]. Second, research on text classification using Naive Bayes, kNN, and deep learning algorithms showed that deep learning provided the highest accuracy of 86.01%, while Naive Bayes and kNN had accuracies of 75.27% and 80.10%, respectively [18]. Lastly, research on hypertension classification in teenagers using Fuzzy Decision Tree method showed that the developed model could produce 79 rules for respondents aged 12-17 and 60 rules for respondents aged 18-23, with the highest accuracy values of 87.18% and 87.50%, respectively [19].

In this study, we use machine learning algorithms: K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), Random Forest, and Deep Learning Algorithm: Gate Recurrent Unit (GRU) to classify EEG signals of sweet and sour tastes. The second part of this paper explains the research methodology, including participant selection, EEG signal recording, EEG signal processing, and classification. The third part discusses the research results, including EEG signal feature analysis (such as MAV, STD, and PSD), classification result analysis, and questionnaire result analysis. Additionally, there is a discussion section to explain the relationship between our research results and previous studies.

II. METHODOLOGY

A. Participant Selection

Thirty two healthy participants (17 female; 15 male) with average of age at (25.5 ± 5.5) years old participated in this experiment. Participants reported having no taste disturbances and no history of neurological or psychiatric disorders. Participants abstained from eating/drinking 1-2 hours prior to the measurement taking place. Each participant was given information regarding the goal of this study, and the possible effect when involving in this study They signed an informed consent form before the experiment began.

B. EEG Signal Recording

1) Tools

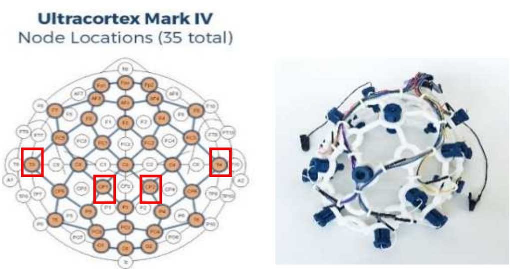

Fig 1. Ultracortex Mark IV headset[20]

The EEG signals were recorded using the Ultracortex Mark IV Headset. The device is capable of capturing EEG samples from 16-35 different channels from the user's scalp while wearing an EEG cap[21]. The OpenBCI Cyton Board was used for wireless communication between the hardware (Ultracortex Mark IV Headset) and the computer software. The board aims to record and monitor brain activity with a GUI-based application from OpenBCI. The EEG samples were taken at a rate of 256 Hz. Four dry electrodes were placed in the following head positions: CP1, CP2, T3 and T4 in the international 10-20 system. The ground electrode was placed at both earlobes of the participant. The four channels are located in the vicinity of the human brain's gustatory area The gustatory area is the region in the brain that is responsible for the perception of taste of food and beverages[22] .

2) Stimulus and Procedure

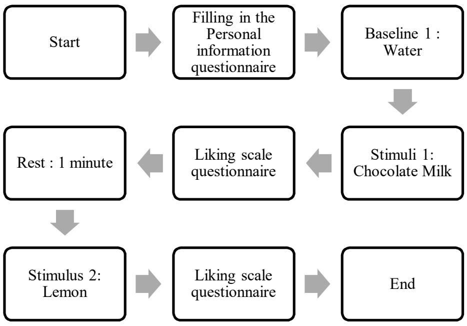

Fig 2. The Procedure of EEG Signal Recording

Each participant received two drinks with sweet and sour tastes. In this study, we will attempt to investigate the difference in EEG signal response to the sweet and sour tastes of the processed drinks. Instead of using natural ingredients for the taste stimuli as previously used [25]-[26], we used chocolate milk as the sweet taste and lemon juice as the sour taste. Sweet taste is a naturally preferred taste by humans . Chocolate milk contains high calories and is widely liked by people of all ages [25]. Sour taste represents a less preferred taste that typically elicits an avoidance response[11]-[12].

Subjects were instructed to close their eyes during the recording. Participants drank the solution for six seconds. The recording process took place during the six seconds of drinking the stimulus solution. There were two stimulus solutions, chocolate milk and lemon juice, and water as the baseline. After each recording of a stimulus, participants were asked to fill out a questionnaire. The questionnaire contained descriptions of the taste of the solution and a liking scale (score 0: did not like at all, and 10 means extremely liked) [26]. The order of the stimuli was water, chocolate

Fig 3. The EEG signal recording process during the insertion of sour taste stimuli

milk, and lemon juice. After drinking the chocolate milk, participants were asked to rinse their mouth with water. The purpose of recording EEG signals is to capture the brain's response to the sweet and sour taste stimuli of the processed drinks.

C. EEG Signal Proccessing

1) Preproccesing

The EEG signals obtained were processed using MATLAB (version 2022b). The raw data consisted of (fs x t) = (256 x 6) = 1536 data, which were collected for each channel, and there were 4 channels (T3, T4, CP1, CP2).The signals were filtered using bandpass (0.5-45 Hz), Automatic Artifact Removal (AAR), and Independent Component Analysis (ICA). Then, the signals were decomposed into five bands, namely Delta (0.5-4Hz), Theta (4-8Hz), Alpha (8-12Hz), Beta (12-25Hz), and Gamma (25-50Hz). Any remaining data after preprocessing was reduced to 1200 data points, which were then divided into 100 chunks. Feature extraction was performed on each chunk (12 data points). The results of this process yielded data with a size of 100 rows x 20 feature columns (4 channels x 5 frequency bands).

2) Feature Extraction

The feature extraction process used Mean Absolute Value (MAV), Standard Deviation (STD), and Power Spectral Density (PSD) features. The feature extraction was also performed using MATLAB.

a) Mean Absolute Value (MAV)

Mean Absolute Value (MAV) is the arithmetic mean of the absolute values of a set of data. MAV is calculated by summing all the absolute values of the data within a single chunk (12 data), and then dividing the sum by the number of data points (n=12) (Equation 1) [27].

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

b) Standard deviation (STD)

Standard deviation is a measure of the spread or dispersion of a set of data values around their mean. In this case, the mean value $\bar{x}$ is the average within one chunk, and n is the number of 12 data points. Standard deviation provides an insight into how far the individual values deviate from the mean value (Equation 2).[28].

$$STD = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}} \tag{2}$$

c) Power Spectral Density (PSD)

Then, PSD is a measure of the distribution of EEG signal energy in the frequency domain. PSD measures how much energy the signal is concentrated at a certain frequency (Equation 3) [29].

$$\text{PSD} = \frac{1}{P}\sum_{p=0}^{P-1}\hat{\text{I}}_{xx}^{(p)}(\omega) \tag{3}$$

Before entering the classification stage, there are three pre-processing steps to improve the accuracy of the classification. First, normalization, where the data scale is changed to a scale of 0 to 1 (refer to formula 4). Second, outlier data is removed using the IQR method (refer to formula 5). Data that falls outside the upper and lower limit is considered an outlier[30]. The third step is standardization (z-score), which aims to have a mean of 0 and a standard deviation of 1 (refer to formula 6).

a) Normalization

$$\text{x}_{\text{norm}} = \frac{\text{x} - \text{x}_{\text{min}}}{\text{x}_{\text{max}} - \text{x}_{\text{min}}} \tag{4}$$

b) Identifying Outliers: Inter-Quartile Range (IQR) Method

$$\begin{gathered} \text{IQR} = \text{Q}_3 - \text{Q}_1 \\ \text{Lower limit} = \text{Q}_1 - (1.5 \times \text{IQR}) \\ \text{Upper limit} = \text{Q}_3 - (1.5 \times \text{IQR}) \end{gathered} \tag{5}$$

c) Standardization

$$\text{X}_{\text{Stand}} = \frac{\text{x} - \overline{(\text{x})}}{\text{std}_{\text{dev}}(\text{x})} \tag{6}$$

3) Classification

Several studies have attempted to use classification algorithms on EEG data. K. Chandran et al. (2019) also investigated taste classification using EEG signals. Mean, median, standard deviation, kurtosis, root mean square value, and power spectral density were the features used to analyze EEG signals of sweet, salt, bitter, and sour tastes. The algorithm used was Artificial Neural Network (ANN) with an accuracy of 90% [31]. Then, Atzingen et al (2021) used a Convolutional Neural Network (CNN) algorithm to differentiate drinks with different sweeteners (natural vs. artificial), resulting in an accuracy of 82.3% [32]. In our study, we will use commonly used classification algorithms, K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), Random Forest [33], and the GRU algorithm [34].

a) K-Nearest Neighbors (KNN)

KNN stands for "K-Nearest Neighbors", a classification algorithm in data mining and machine learning. The algorithm works by measuring the distance between a new data point and known data points, then selecting the K nearest neighbors. The KNN algorithm will then determine the class of the new data point based on the majority class of the nearest neighbors. Although the KNN algorithm is simple and effective in making predictions, it takes a long execution time if the training data is large, and requires a lot of memory to store the data[27].

b) Support Vector Machine (SVM)

SVM stands for "Support Vector Machine", a supervised machine learning algorithm used for classification and regression analysis. The goal of the SVM algorithm is to find a boundary, known as a hyperplane, that separates the data into classes. The hyperplane is selected in such a way that it maximizes the margin, or the distance between the closest data points and the hyperplane. These closest data points are called support vectors and are the key elements of the algorithm. When the data cannot be separated into classes by a linear boundary, SVM can be used with a non-linear kernel to transform the data into a higher dimensional space where a linear boundary can be applied. SVM is often used in applications where there is a limited amount of data or the data has a high degree of complexity[27].

c) Random Forest

Random Forest works by constructing a large number of decision trees and combining their predictions to obtain a more accurate and stable final result, , such as information gain. The Random Forest algorithm randomly selects a subset of features to split the data at each node, instead of selecting the best feature, to decorrelate the trees and reduce overfitting. The final prediction is made by taking a majority vote or averaging the predictions of all the trees in the forest. Random Forest is a highly flexible and powerful algorithm that can handle a large number of features and missing data and is less prone to overfitting than single decision trees [33]

d) Gate Recurrent Unit (GRU)

GRU stands for "Gated Recurrent Unit". It is a type of recurrent neural network (RNN) architecture used for processing sequential data, such as time series or text. GRU is designed to solve the vanishing and exploding gradient problems that occur in traditional RNNs. It does this by controlling the flow of information through the use of "gates", which are elements within the network that regulate the flow of information into and out of the network's hidden state. The GRU architecture has two gates, the reset gate and the update gate, which work together to maintain a balance between preserving past information and incorporating new information into the hidden state. The hidden state is then used to make a prediction for the next time step in the sequence. GRU is a popular choice for tasks such as language modeling and speech recognition, as it is computationally efficient and capable of handling long sequences[34].

III. RESULT AND DISCUSSION

A. *Questionnaire results*

After tasting the stimuli (sweet and sour), participants described the taste and filled in a liking scale. From the taste description column, all participants described chocolate milk as sweet and lemon juice as sour. The average liking scores for sweet and sour tastes are presented in Table 1.

TABLE I QUESTIONNAIRE RESULTS

Participant	Liking scale (0 – 10)	
	Sweet (Chocolate milk)	Sour (Lemon Juice)
Man	9	4.8
Woman	9.35	4.94

B. *Fitur Extraction*

We extracted EEG signals by separating them based on brain wave bands and channels used, utilizing the features of MAV, PSD, and STD. The outcome of the feature extraction is shown in figure 2-6.

Figure 3 presents MAV features for all wave bands and channels used in this study. A notable difference is found in alpha and delta signals. For alpha signals, the MAV value for sweet stimuli is higher than that for sour stimuli, whereas for delta wave bands, sour stimuli have a higher MAV value than sweet stimuli. Theta, beta, and gamma wave bands show a pattern where channels CP1 and CP2 have higher values for sour stimuli, while channels T3 and T4 produce higher values for sweet stimuli.

Figure 5 presents PSD features. The PSD value pattern for sweet and sour stimuli is similar to the MAV feature. The most striking difference between sweet and sour stimuli is found in alpha and delta wave bands. For alpha wave bands, sweet solutions have higher PSD values than sour solutions in all channels. In contrast, in delta wave bands, sour stimuli

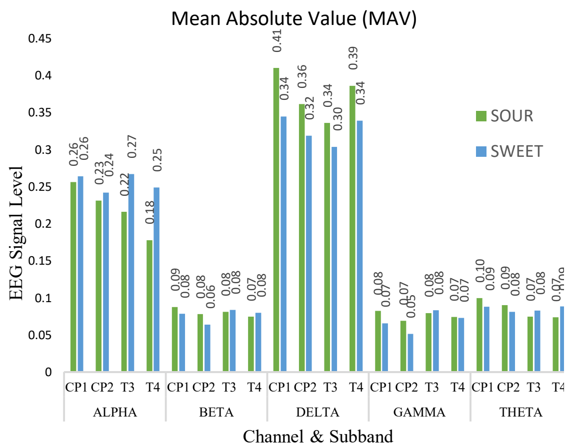

Fig 4. The Pattern of sweet and sour taste based on MAV feature

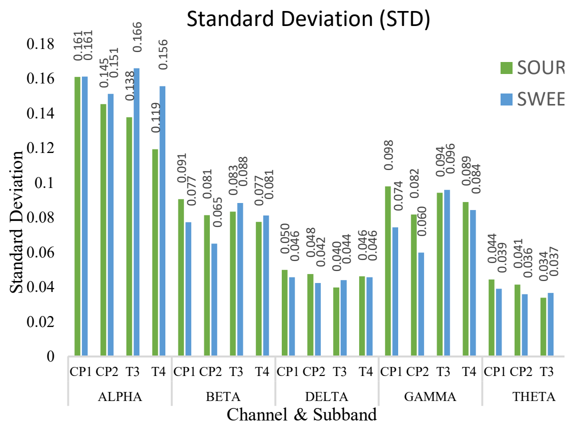

Fig 5. The Pattern of sweet and sour taste based on STD feature

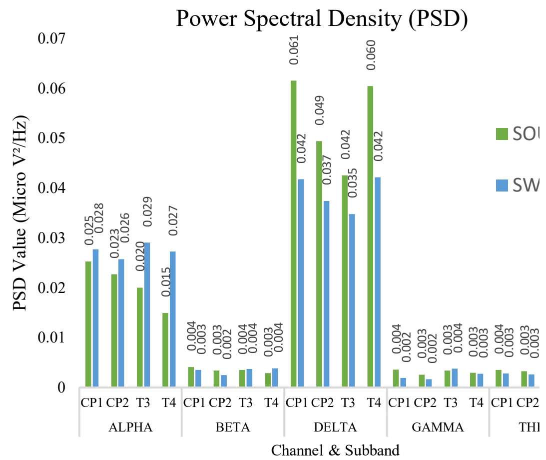

Fig 6. The Pattern of sweet and sour taste based on PSD feature

have higher PSD values than sweet stimuli. Beta, gamma, and theta wave bands show a similar pattern for channel pairs CP1 and CP2 versus T3 and T4. For channels CP1 and CP2, the PSD value of sour stimuli is higher than that of sweet stimuli. On the other hand, for channels T3 and T4, the PSD value of sweet stimuli is higher than that of sour stimuli.

Figure 4 presents STD features. In this feature, the difference between sweet and sour stimuli is particularly evident in beta and gamma wave bands, especially in channels CP1 and CP2, and in alpha wave bands, particularly in channels T3 and T4.

C. Classification

TABLE II CLASSIFICATION RESULTS

Classifier Algorithm	Train	Testing
KNN	87.16%	83.90%
SVM	86.70%	84.70%
Random Forest	100.00%	90.68%
GRU	97.21%	91.53%

In this classification stage, we employed four algorithms, namely K-NN, SVM, Random Forest, and GRU. The resulting accuracies are shown in Figure 6. The GRU

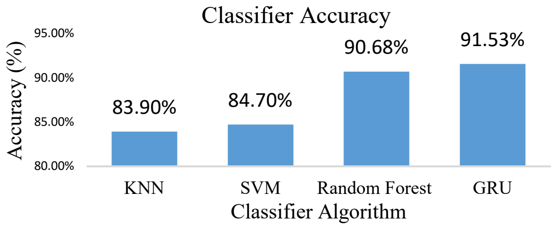

Fig 7. Classification of Sweet and Sour based on Classifier Algorithm

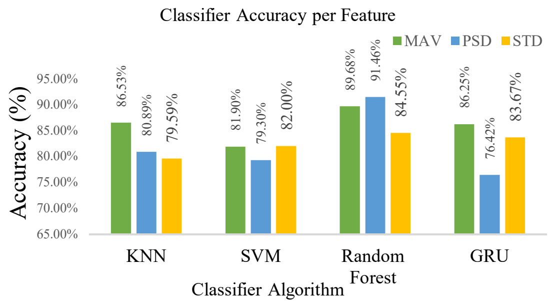

Fig 8. Classification of Sweet and Sour based on Classifier Algorithm per Feature

algorithm achieved the highest accuracy of 91.53%, followed by the random forest algorithm with 90.68%. The training and testing data accuracies are presented in Table 2. The SVM algorithm resulted in an accuracy of 84.7%, and the K-NN algorithm resulted in an accuracy of 83.9%.

Additionally, Figure 7 illustrates the comparison of accuracies for each feature (MAV, STD, and PSD). The highest accuracy was obtained by the PSD feature using the random forest algorithm, which was 91.46%. The second-highest accuracy was achieved by the MAV feature with the random forest algorithm, resulting in an accuracy of 89.68%.

D. Discussion

The aim of this study was to investigate brain responses to sweet and sour tastes and to distinguish between them. A total of 32 participants were given lemon juice and chocolate milk as sour and sweet stimuli, respectively. The solutions were then administered to the participants and their brain signals were recorded for six seconds while drinking the solutions. In this study, we used time domain and frequency domain features. Mean Absolute Value (MAV), Standard Deviation (STD), and Power Spectral Density (PSD) were extracted from the EEG signals. In the MAV and PSD features, the difference characteristics clearly appeared in alpha and delta waves and in all channels (CP1, CP2, T3, and T4). The MAV and PSD values for sweet taste were higher in all channels at alpha waves, whereas for sour taste, the MAV and PSD values were higher in delta waves. The results of this study are consistent with the findings of a previous study [23] that delta waves are used to encode taste information in the human brain. However, in beta, gamma, and theta waves, different patterns were observed between the channel pairs of CP1 and CP2 and T3 and T4. The MAV and PSD values for sour taste were higher than for sweet taste, especially in channels CP1 and CP2, while the MAV and PSD values for sweet taste were higher in channels T3 and T4. According to the feature extraction results, the four channels (CP1, CP2, T3, and T4) could be used to evaluate taste. This study also supports a research by [22] that found CP1 and CP2 channels are the closest to the location of insula, which is the primary gustatory area.

This study has utilized four types of algorithms to classify the differences in brain responses to sweet and sour tastes, namely K-NN, SVM, Random Forest, and GRU. Among the four algorithms, the GRU algorithm showed the best accuracy with a score of 91.53%, and when separated by features, PSD features with the Random Forest algorithm showed the best results with a score of 91.46%. Although only two basic tastes, sweet and sour, were used in this study, it has a positive impact on developing more objective methods for evaluating the taste of food and beverages in the future.

This study provides a deeper understanding of how the human brain responds to sweet and sour tastes at a neurophysiological level. The results of this research can pave the way for the development of technology that can help identify taste preferences and provide more satisfying food and beverage experiences for consumers. Furthermore, this study can also provide a basis for further research on how the taste of food and beverages can affect human health and nutrition, as well as help develop solutions to health problems related to sugar and acid consumption. Thus, this research has a significant positive impact on the development of science and technology in the fields of sensory and nutrition..

IV. CONCLUSION

In this study, it can be concluded that the method used in this research was successful in understanding the brain response to sweet and sour taste. Channels CP1, CP2, T3, and T4 in EEG device can be used as points in the cortical layer of the brain to the stimulation of food or drink taste. Alpha and delta waves are sensitive to sweet and sour taste, so they are suitable for the recognition of similar tastes in future research. The GRU algorithm provided the best accuracy compared to other algorithms in this study. The GRU algorithm provided an accuracy of 91.53% in classifying sour and sweet tastes in EEG signals. The method in this study can be used as a reference for future research, especially in evaluating similar tastes or other basic tastes.

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