Paper presentation

Decoding human taste perception by reconstructing and mining temporal-spatial features of taste-related EEGs

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Taste is a key factor in consumer decisions and food quality evaluation.

“Taste isn't merely a flavor; it's the essence of experience”

Abstract

Traditional taste sensory evaluation, like **human panels** and **electronic tongues**, is prone to subjectivity and limited flexibility.

Decode objective taste perception by analyzing EEG signals corresponding to sour, sweet, **bitter**, and salty tastes.

TSRDA&TSCNN-CA provides an objective and effective method for the sensory evaluation of food taste.

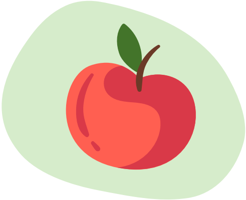
- Accuracy: 99.56%
- F1 score: 99.48%
- Kappa Value: 99.38%

TSRDA&TSCNN-CA

What!?

Temporal and **S**patial **R**econstruction **D**ata **A**ugmentation

Enhances the limited EEG dataset by reconstructing key features in both time and channel dimensions.

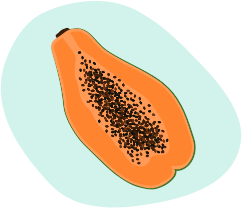


Temporal and **S**patial **CNN** with **C**hannel **A**ttention

A specialized CNN designed to extract both temporal and spatial patterns from the augmented EEG data for reliable taste classification.

TSRDA&TSCNN-CA

What!?

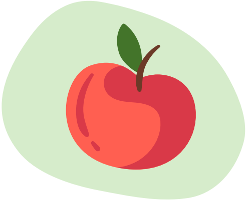


Experiments for **Data** collection

Collect taste related EEGs under controlled taste stimuli.

Temporal and **S**patial **R**econstruction **D**ata **A**ugmentation

Enhances the limited EEG dataset by reconstructing key features in both time and channel dimensions.



Temporal and **S**patial **CNN** with **C**hannel **A**ttention

A specialized CNN designed to extract both temporal and spatial patterns from the augmented EEG data for reliable taste classification.

Experimental Setup

Participants

nonsmoking subjects
ages 20–30

10 **males**

10 **females**

Pre-experiment
Instructions

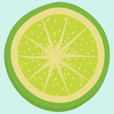
- Wash hair
- Brush teeth using unscented toothpaste
- No food for 2 hours before the experiment
- Water allowed

Why? To ensure **consistency** in physiological state and **minimize** interference.

Taste Stimuli

Sweet

Salty

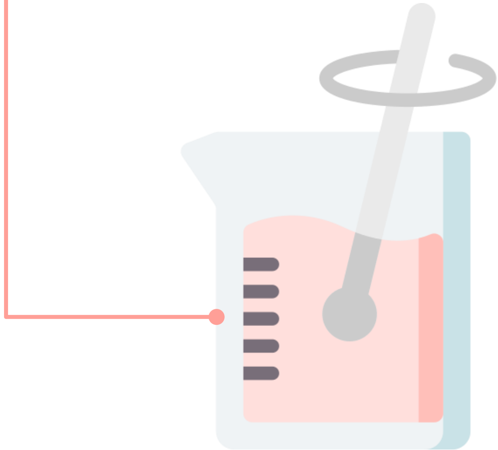


Sour

Bitter

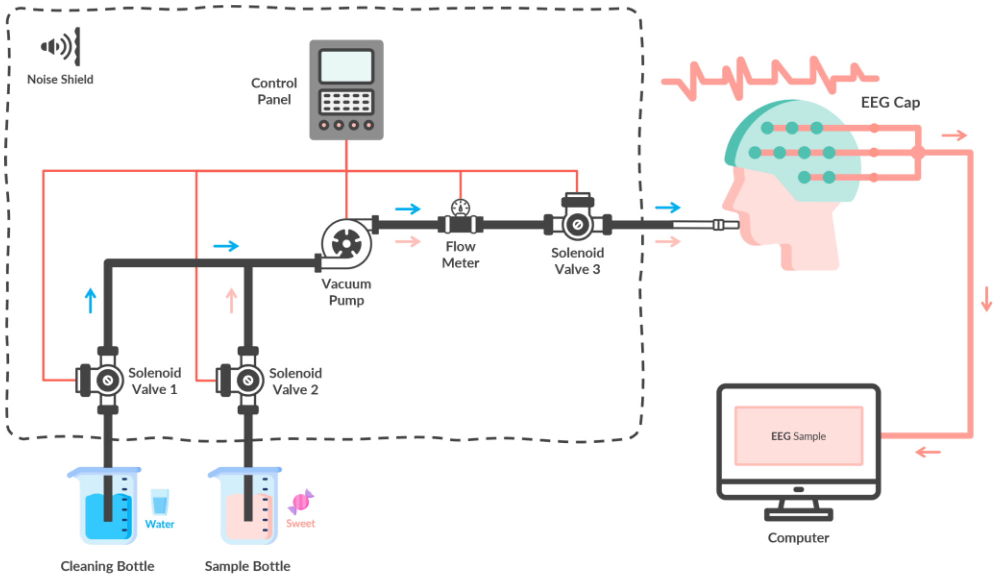
Record the **EEG responses** induced by each taste.

Solutions prepared according to previous studies.



This Ensures that each solution is **clearly** perceived **without discomfort.**

Taste-Evoker



Self-Developed

Low-Noise

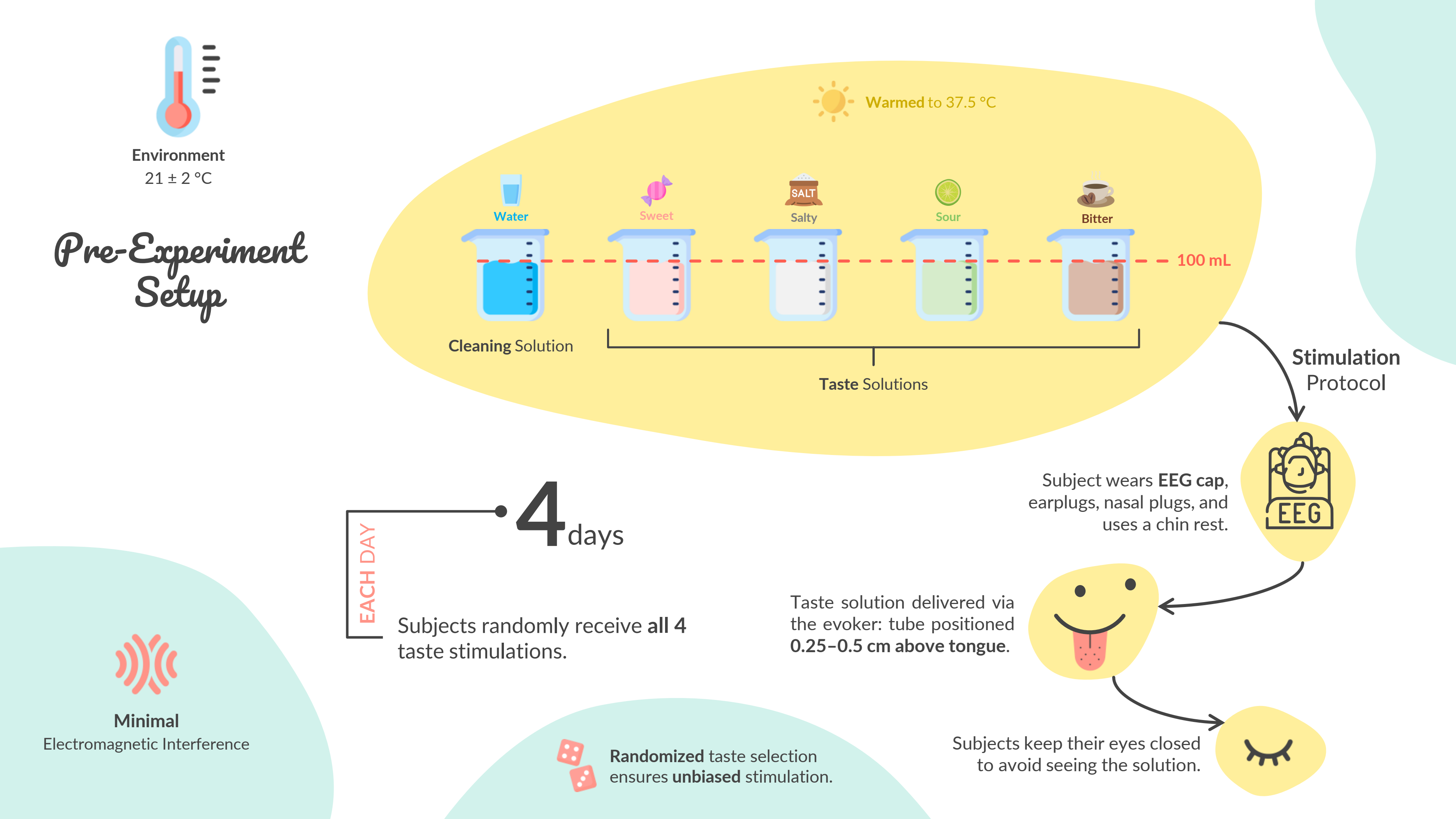
High-Precision and **High-Stability**

EEG Acquisition

NCERP-P EEG
Acquisition System

256 Hz
Sampling Frequency

21-channel EEG cap
Electrode Setup


Pre-Experiment Setup
Environment
21 ± 2 °C
Warmed to 37.5 °C
Water
Sweet
SALT
Salty
Sour
Bitter
100 mL
Cleaning Solution
Taste Solutions
Stimulation Protocol
Subject wears EEG cap, earplugs, nasal plugs, and uses a chin rest.
EEG
4 days
EACH DAY
Subjects randomly receive all 4 taste stimulations.
Taste solution delivered via the evoker: tube positioned 0.25–0.5 cm above tongue.
Subjects keep their eyes closed to avoid seeing the solution.
Minimal
Electromagnetic Interference
Randomized taste selection ensures unbiased stimulation.

Preprocessing

10s

Duration of each recorded segment during taste stimulation

→

Data Segmentation

Each segment divided into 5 samples (2s each)

→

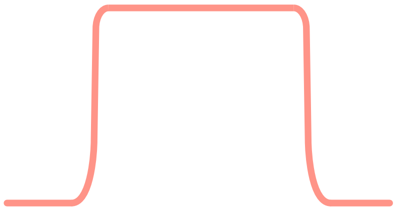
$$\underbrace{20}_{\text{Subjects}} \times \overbrace{4}^{\text{Days}} \times \underbrace{4}_{\text{Tastes}} \times \overbrace{5}^{\text{Segmentation}} = \underbrace{\mathbf{1600}\text{ EEG samples}}_{\text{TOTAL}}$$

MATLAB

Preprocessed by MATLAB and its built-in toolkit **EEGLAB**.

Filtering & **Downsampling**

0.5–50 **Hz**

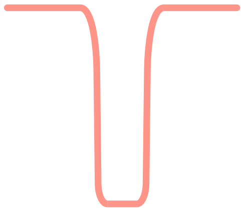


Bandpass Filtering

Removes low/high-frequency noise

→

49–51 **Hz**



Notch Filtering

Eliminates power line interference

→

From 256 **Hz**

↓

To 128 **Hz**

Downsample

To reduce sample size

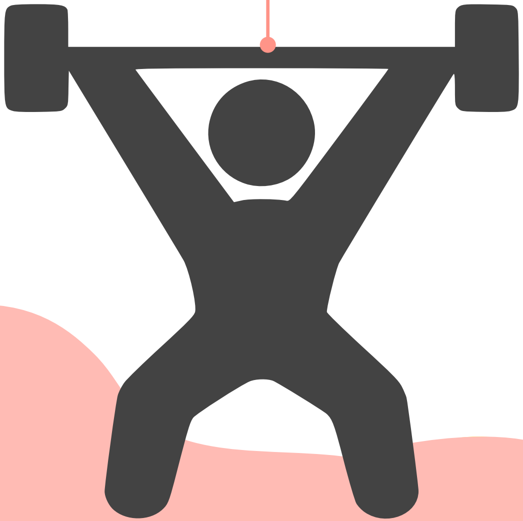
The **final** size of a taste-related **EEG sample** was $\underbrace{256}_{\text{W}} \times \underbrace{21}_{\text{H}}$

TSRDA

Temporal and **S**patial **R**econstruction
Data **A**ugmentation

CNNs require large amounts of data.

However, taste-related EEG datasets are generally **limited** due to **experimental complexities**.



Training Challenge

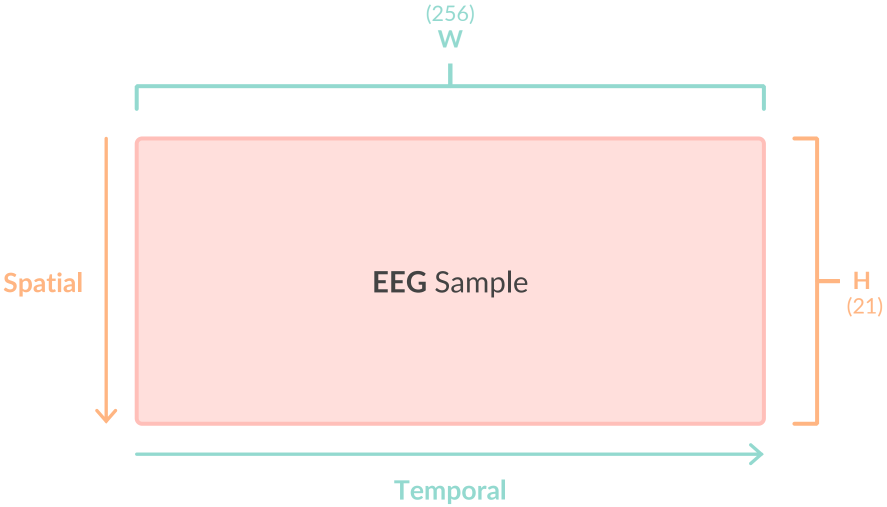
Solution

Data Augmentation

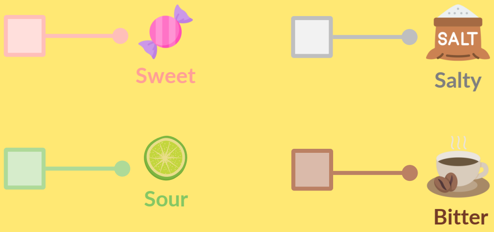
Increasing the diversity and volume of training data is critical to enhance model performance and avoid overfitting.

Enhances diversity in both **temporal** and **spatial** features.

Ingredients



Pre-Processed
Dataset



Recipe

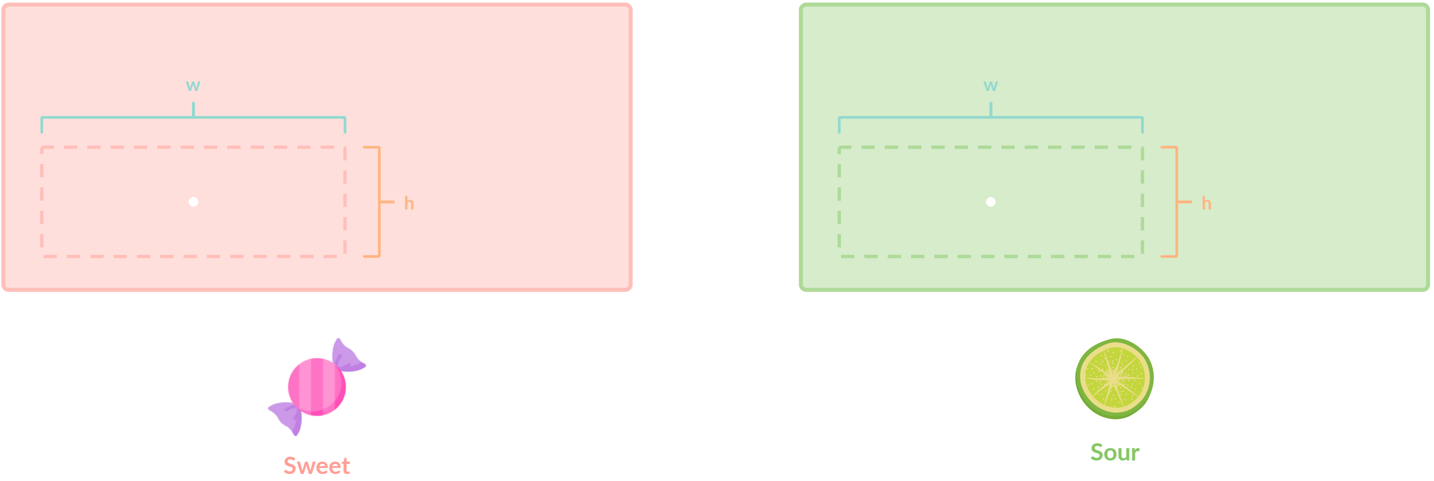
1. **Randomly** select two **EEG** samples from the Pre-Processed **Dataset**

Sweet

Sour

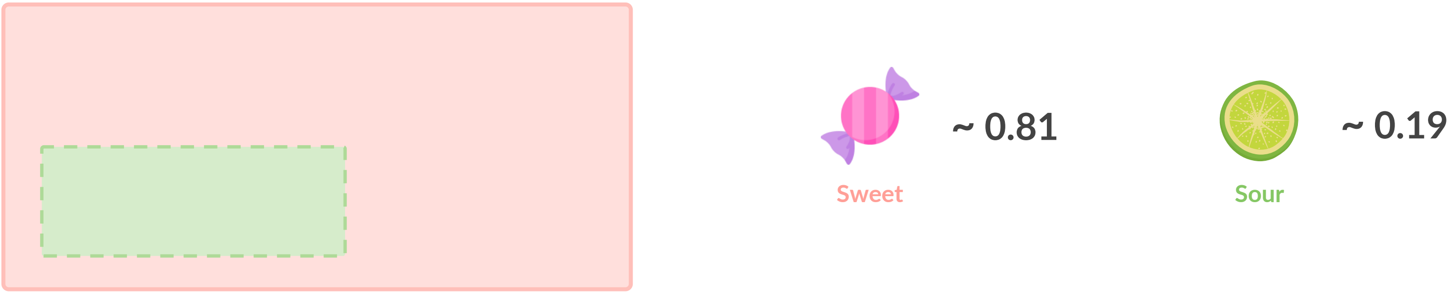
Recipe

2. From both samples, cut an **identically sized** data block of dimensions w × h from the **same location.**



Recipe

3. Insert the data block from the second sample into the first sample to create a **newly reconstructed sample**.



The new sample is assigned **two labels**, with each label's weight **proportional to the area** of the corresponding data block. During model training, these two labels are optimized according to their respective weights.

Recipe

Block Extraction Details

The **location** and **size** of the data blocks are not arbitrary

They are determined through **hyperparameter optimization** to maximize TSRDA's effectiveness.

The **centers** of the cutting blocks are:

- **Evenly** distributed along the **temporal** dimension;
- Mainly in the **lower half** of the EEG channels (**spatial**).

The dimensions w and h are **uniformly distributed** over their respective ranges, [0, W] and [0, H].

TSCNN-CA

Temporal and Spatial CNN with Channel Attention

Multi-View Channel Attention

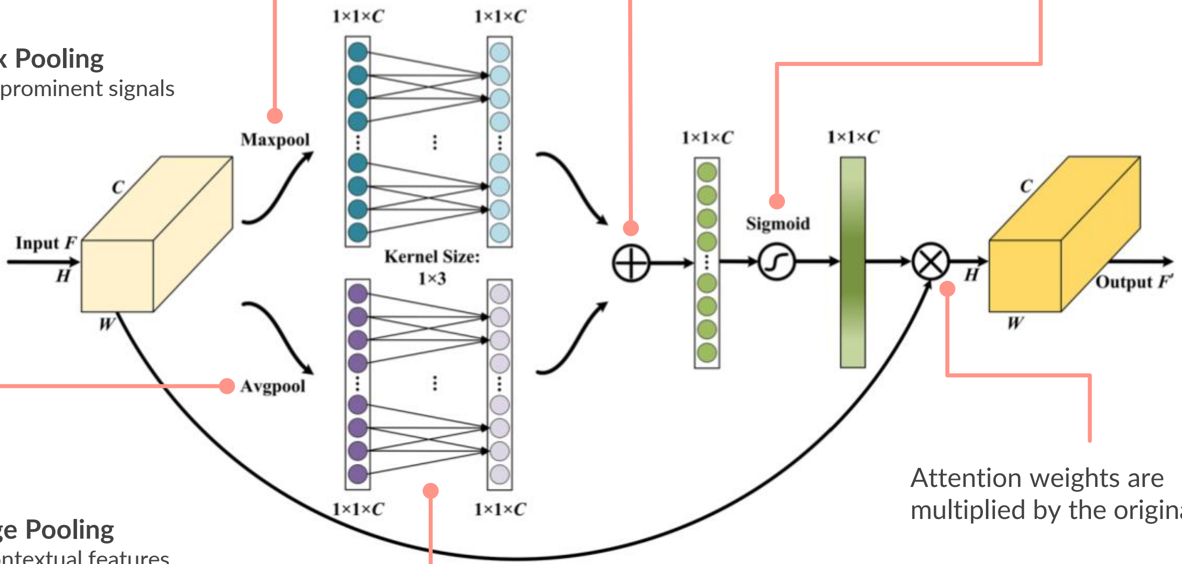
Objective

Empower the CNN to focus on **essential EEG features** while minimizing redundancy.

Information Fusion
Adds pooled outputs

Nonlinear Activation
Generates attention weights

Global Max Pooling
Highlights the most prominent signals



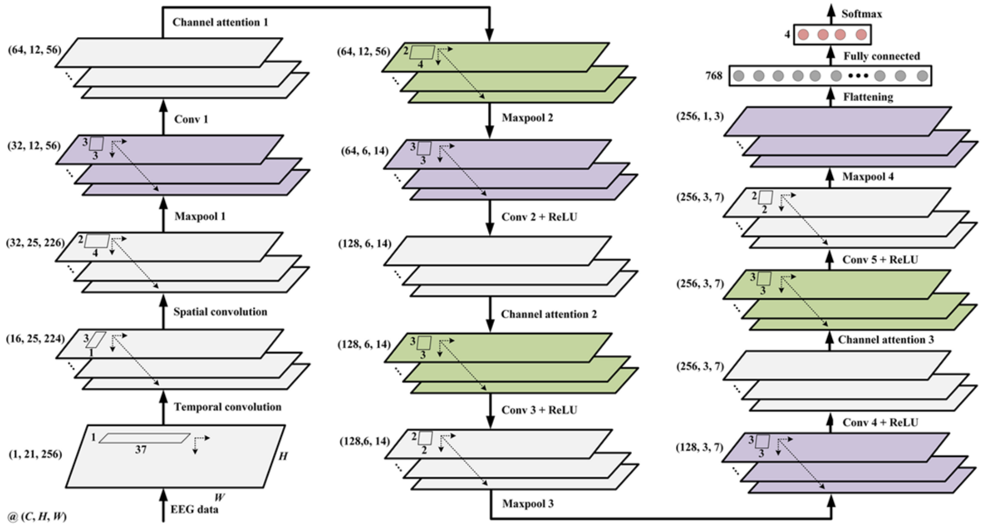
Global Average Pooling
Extracts the overall contextual features

One-Dimensional Convolution
Operates on the pooled features, promoting interaction across channels

Attention weights are multiplied by the original data

TSCNN-CA

Channel attention mechanism



CNNs

Have excelled in EEG classification by extracting rich, high-dimensional features.

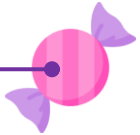
TSCNN-CA → Integrates both **temporal** and **spatial** convolutions to capture crucial patterns in taste-related EEG signals.

Results and discussion

Taste-related EEG topographic map

Brain response under different stimuli

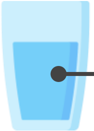
The average EEG topographic maps recorded under different taste stimuli reveal distinct patterns of brain electrical activity, indicating significant variation depending on the type of stimulus.



Sweet taste shows enhanced electrical activity in the parietal and temporal lobe regions

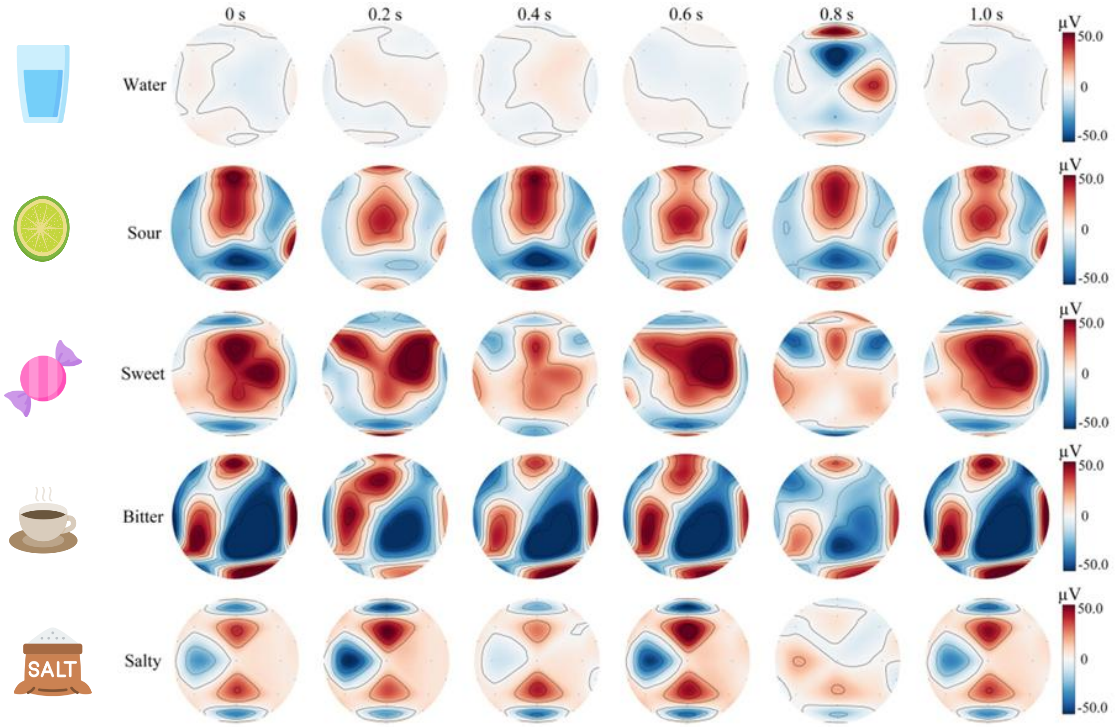
Bitter and sour taste shows pronounced electrical activity in the frontal, occipital and temporal lobes.

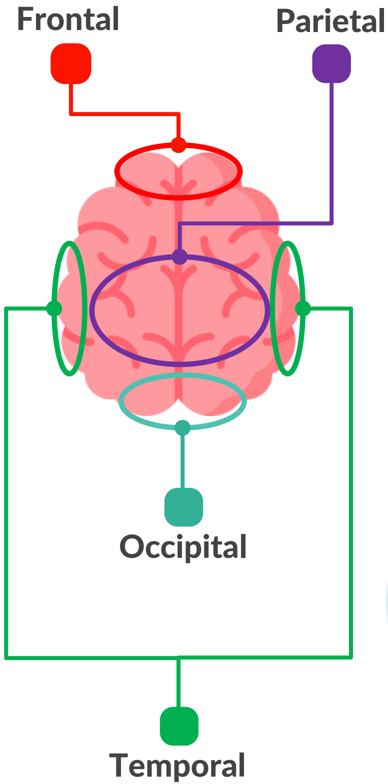
Salty taste primarily activated portions of the parietal and temporal lobe regions



Water triggers less brain activity than other tastes

EEG Topography Maps





Taste-related EEG experimental settings

Experimental test and evaluation metrics

Taste-related EEG four-classification experiments for subject independence and subject non-independence were performed.

Subject independence

Taste-related EEG samples of each subject were the test set, and the other subjects were the training set.

Subject non-independence

A total of 1600 taste-related EEG samples from 20 subjects were randomly divided into training and test sets at 3:1.

Model Hyperparameter

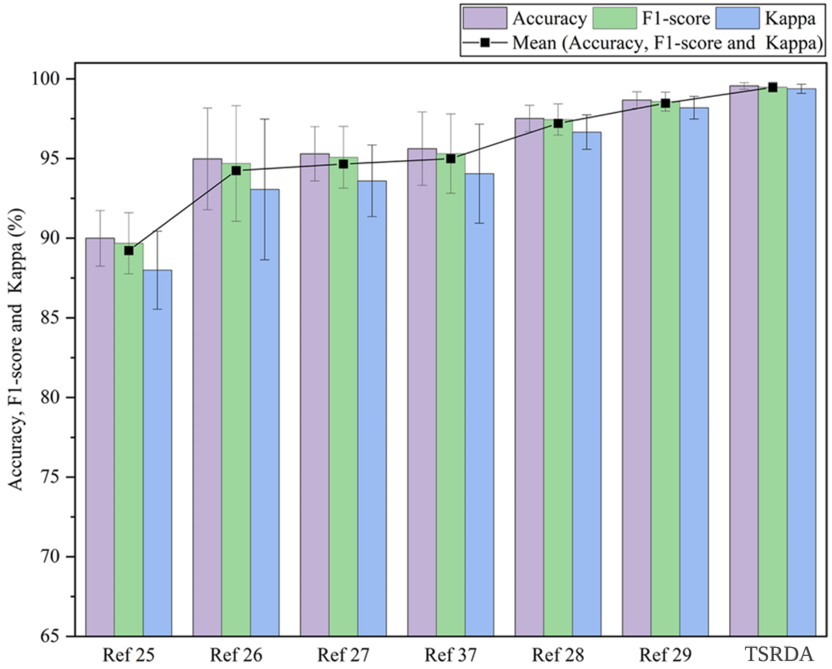
Expansion multiple of the TSRDA to the training set was 3. Training set batch size 64 and test set batch size 32. Optimizer used Adam, number of epochs 100, learning rate 0.0005 and weight decay was 0.001.

Effectiveness analysis of TSRDA

Evaluation index	Before augmentation	After augmentation
Accuracy ± std (%)	98.10 ± 2.03	99.56 ± 0.21
F1-Score ± std (%)	98.09 ± 2.04	99.48 ± 0.31
Kappa ± std (%)	97.39 ± 2.77	99.38 ± 0.29

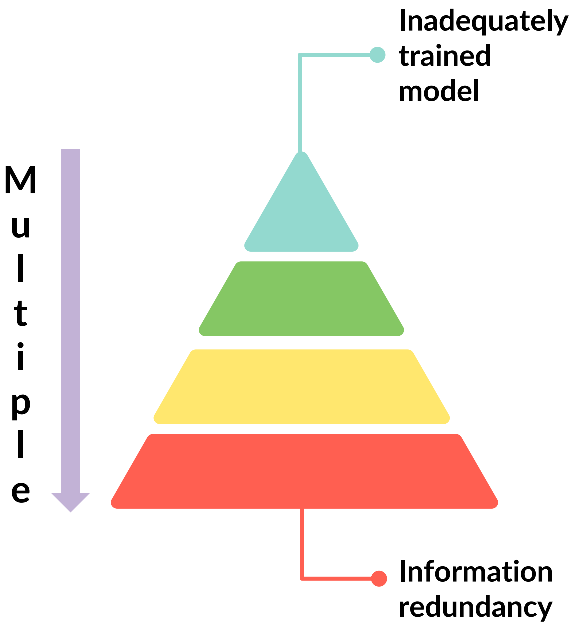
Comparison with state-of-art models

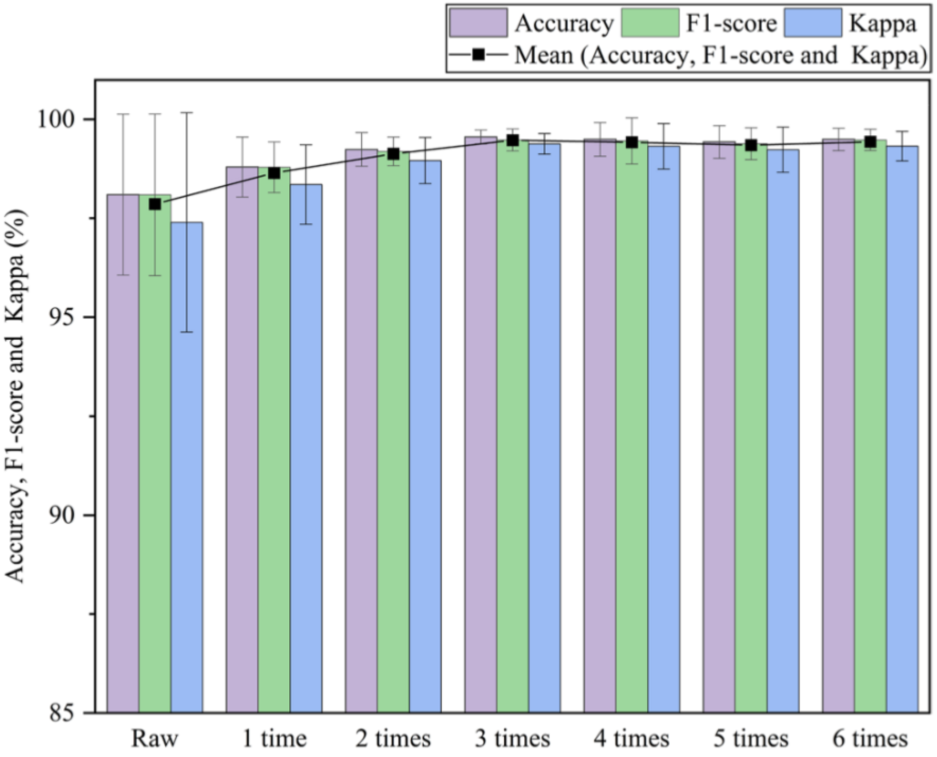
Reference	Augmentation method	Classification method
25	Add Gaussian noise	ResNet
26	Time division and reorganization	Shallow CNN
27	Brain area recombination	EEGNet
37	Sliding time windows segmentation	VGG-16
28	Sliding time windows segmentation	Deep CNN
29	CutCat	Deep CNN
This Paper	TSRDA	TSCNN-CA



Most techniques only focus on either **temporal or spatial dimensions**, not fully preserving the important **local features**.

TSRDA: Data augmentation multiple





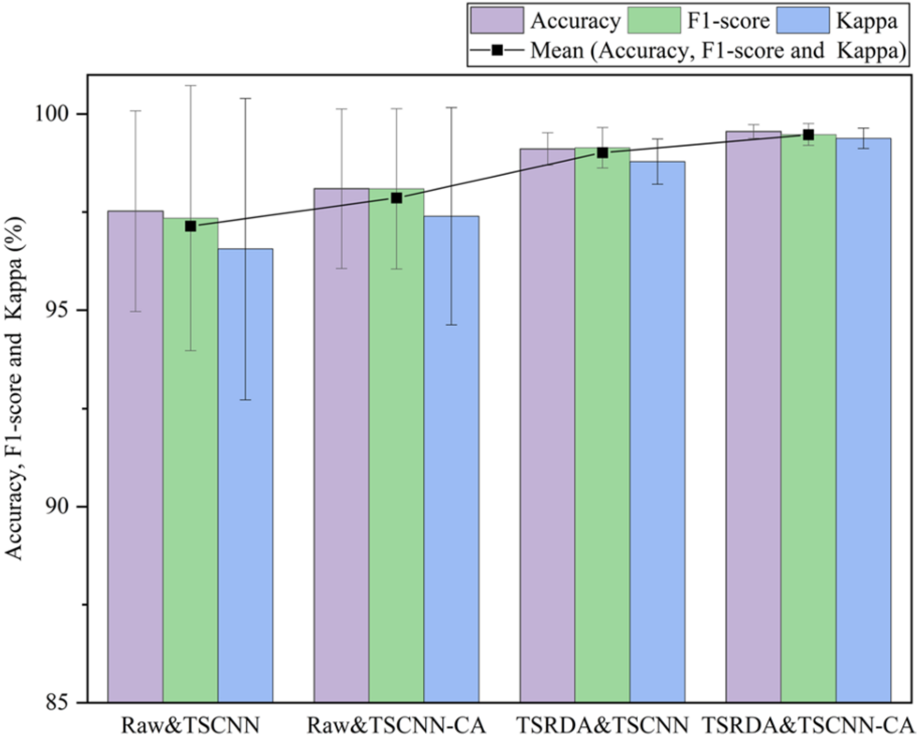
TSRDA and MVCA

TSCNN VS TSCNN-CA

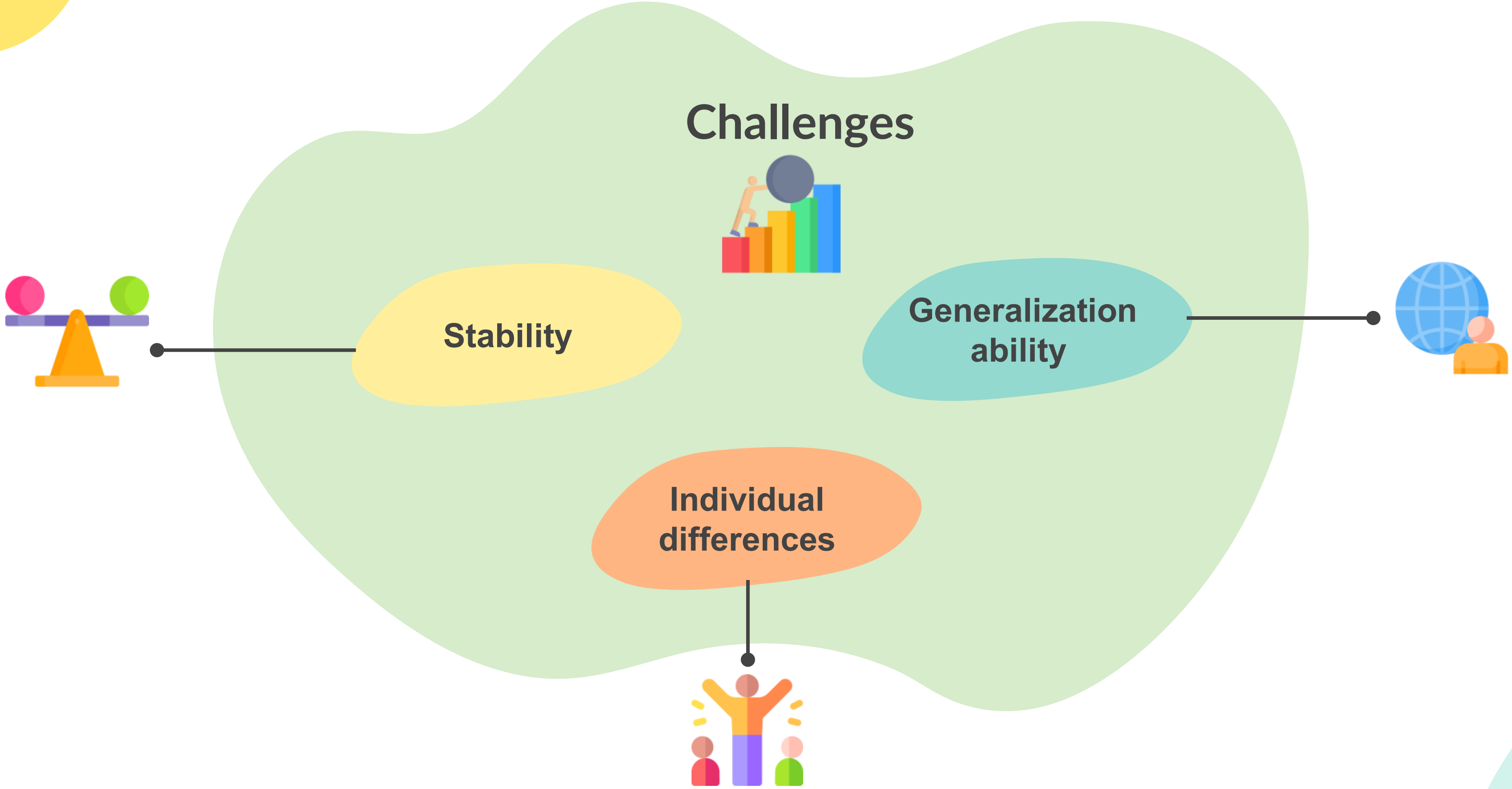
The introduction of MVCA method can better mine the important features of taste-related EEGs, avoiding redundant information.

Raw VS TSRDA

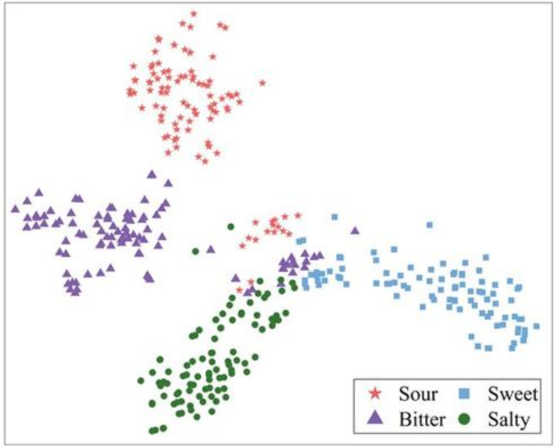
TSRDA effectively augmented the raw training set, improving the recognition accuracy and stability of taste-related EEGs.

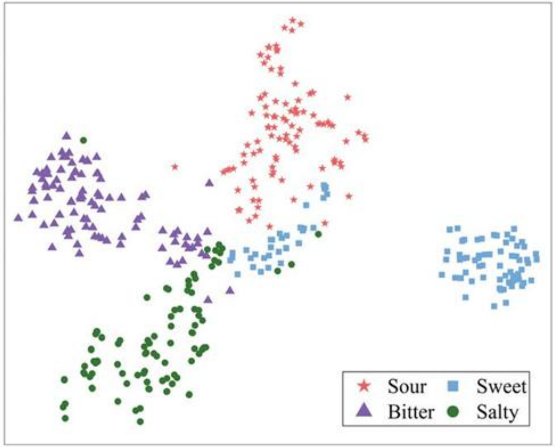


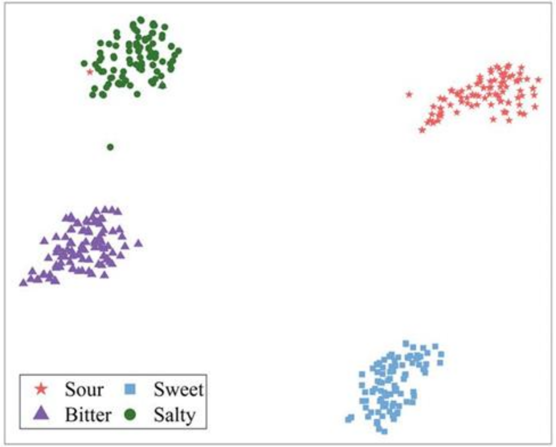
Subject-independent test



t-SNE Visualization of test set







Raw & TSCNN

Raw & TSCNN-CA

TSRDA & TSCNN-CA

Future directions and critical analysis

Limitations and future directions

Dataset scale & Universality

Increasing the subject pool is crucial for **broader applicability**. Cross-subject EEG recognition **remains a significant challenge.**

Data Acquisition Challenges

Taste-related EEG collection is costly and time-consuming, limiting dataset size. **TSRDA** offers a promising solution to **augment limited data**, though it may sometimes introduce **redundant information**.

Limitations and future directions

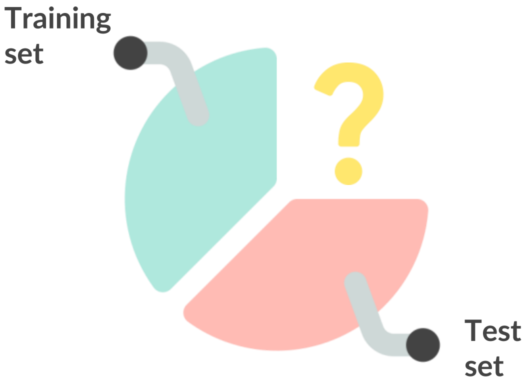
Enhancing Feature Extraction:

The **MVCA** module effectively mitigates **redundant information**, improving feature discrimination. Future work will explore applying these methods to **other EEG tasks**.

Automation & Optimization:

Currently, TSRDA relies on manual selection for reconstructing optimal temporal–spatial features. Integration of automatic methods (e.g., Grad-CAM) is planned to streamline reconstruction and boost effectiveness.

Is the experiment reliable?



Data split ambiguity:

The paper only discusses training and test sets, there is no explicit mention of a distinct validation set.

Hyperparameter Tuning Uncertainty:

It's unclear whether hyperparameter tuning was performed on a separate validation subset.

Without a dedicated validation set, it’s uncertain if the model’s tuning and performance measures were optimally evaluated.

This may affect the reported generalizability of the results.

Conclusions

Conclusions

Robust EEG Acquisition:

An experimental paradigm was established that effectively acquired taste-related EEGs induced by sour, sweet, bitter, and salty tastes.

Effective Data Augmentation (TSRDA)

An experimental paradigm was established that effectively acquired taste-related EEGs induced by sour, sweet, bitter, and salty tastes.

Superior Classification (TSCNN-CA with MVCA):

Combining TSRDA with the TSCNN-CA—enhanced by a multi-view channel attention (MVCA) module—ensures comprehensive model training and effectively mitigates redundant information for accurate taste decoding.

Overall Impact & Limitations

The combined approach outperforms state-of-the-art methods in decoding EEG signals for the four basic tastes. Although effective for basic tastes, the method does not yet accommodate mixed flavours—an area targeted for future research.

Thanks

for your attention