

ISOEN 2026

THE 21ST INTERNATIONAL SYMPOSIUM
ON OLFACTION AND ELECTRONIC NOSE

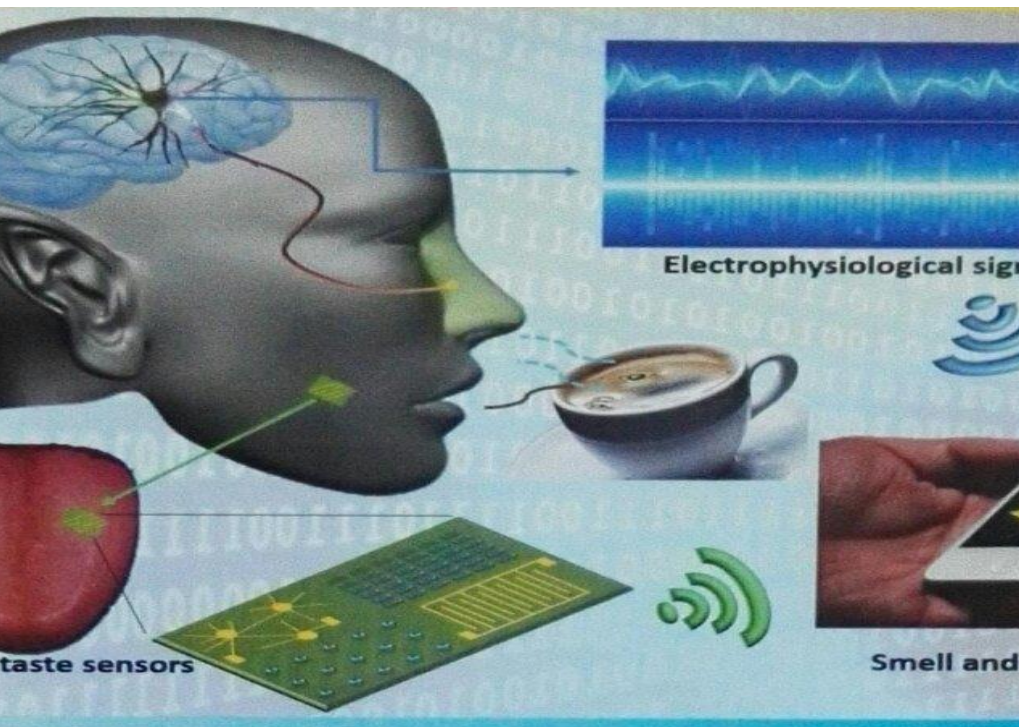
May 17-20, 2026 🌐 Chongqing, China

Bioinspired Electronic Nose for Odor Perception

Ping Wang

*Biosensor National Special Laboratory
Department of Biomedical Engineering
Zhejiang University, Hangzhou, China*

cnpwang@zju.edu.cn



Hangzhou City is Principle of Zhejiang Province in China



Map of China

Locations of provinces, autonomous regions and municipalities.



Zhejiang University

Hangzhou, Zhejiang, China, Close to Shanghai, largest city



Zhejiang University is currently one of the largest and best universities in China with a history of 129 years. It ranks top three together with Tsinghua University and Peking University in China, and is also one of the universities with the most comprehensive disciplines in China

Our Yuquan Campus of ZJU and College of BME & Instrument Science



This is the Yuquan Campus which is one of seven campuses of Zhejiang University that focus in Information Science



This is the building of our college of “Biomedical Engineering and Instrument Science” and our labs located here



The Contents of Talk

- 1. Electronic Nose**
- 2. Bioinspired Electronic Nose**
- 3. Applications of Bioinspired e-Nose for Odor Perception**



1st Part

Electronic Nose (e-Nose)



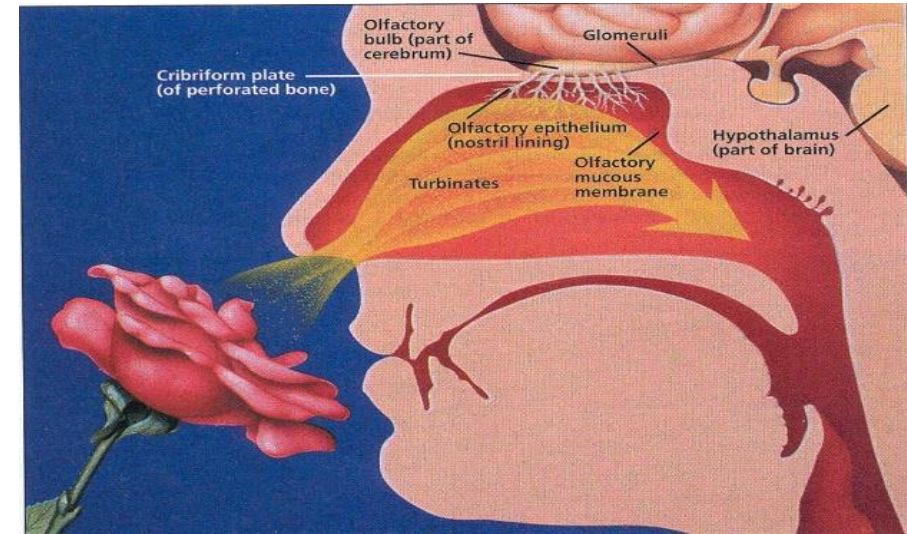
Electronic Nose (e-Nose)

The term "Electronic Nose" was presented in the 1980's.

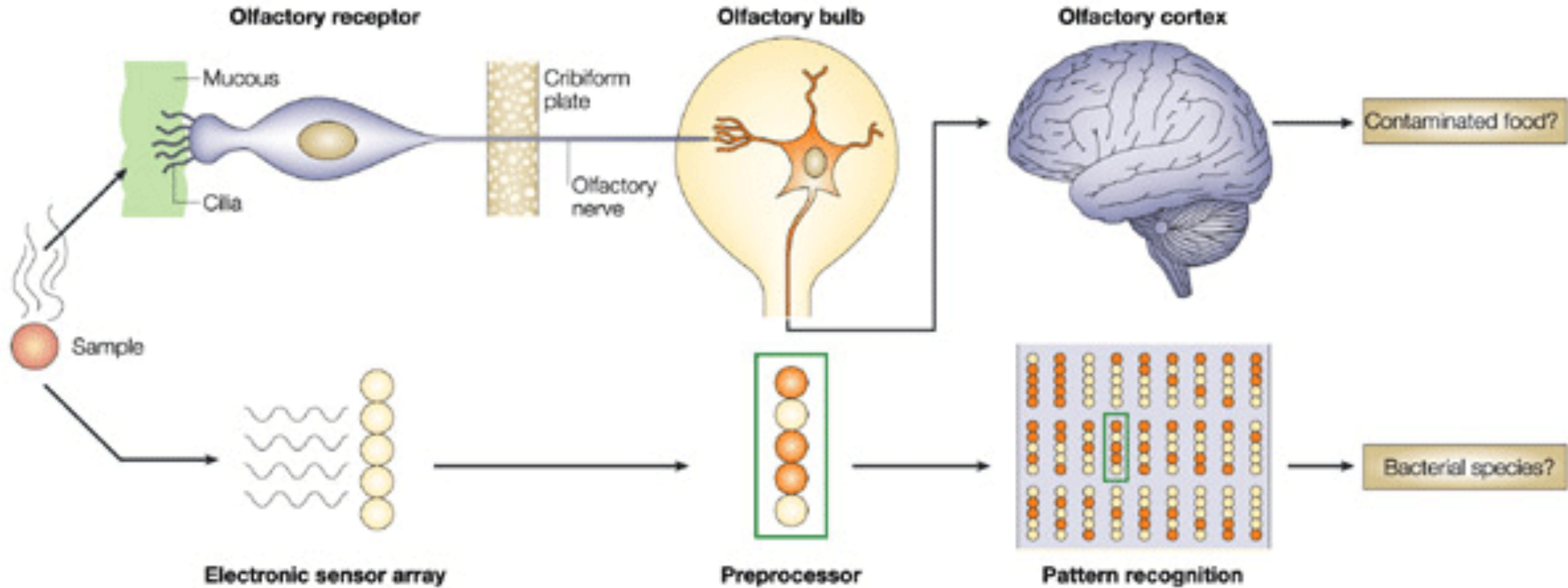
It became apparent that the animal and human olfactory systems operate on the same principle: A relatively small number of nonselective receptors can determine thousands of different odors.

"Electronic Nose" is a kind of electronic or optical analysis instrument and while it should be a kind of bionic instrument.

Prof. Gopel, Prof. Gardner, Prof. D'amico et al



e-Nose mimic human olfactory system



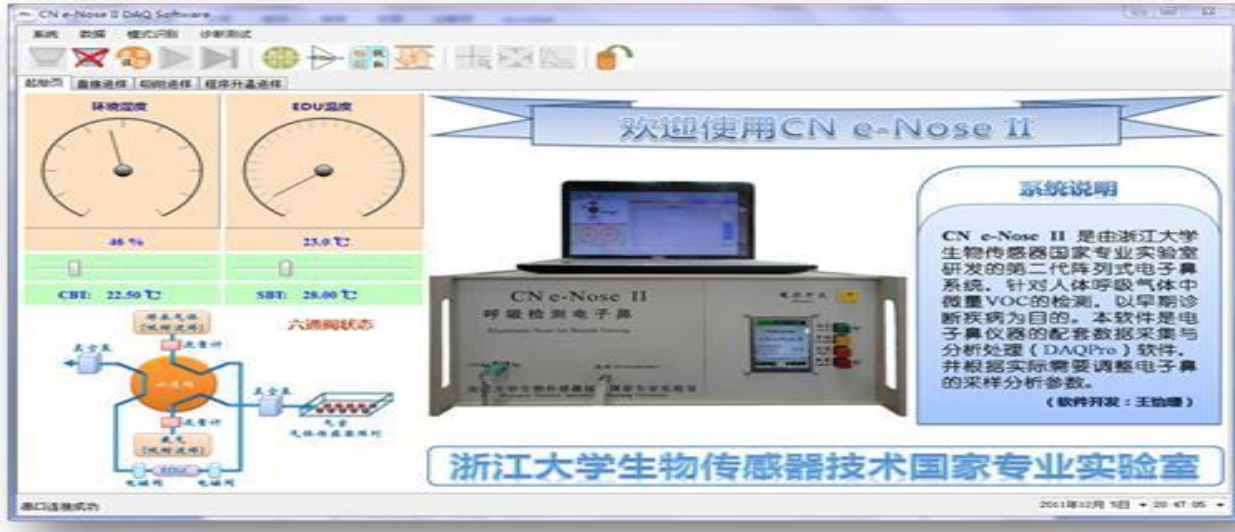
Comparing e-Nose with Human Nose



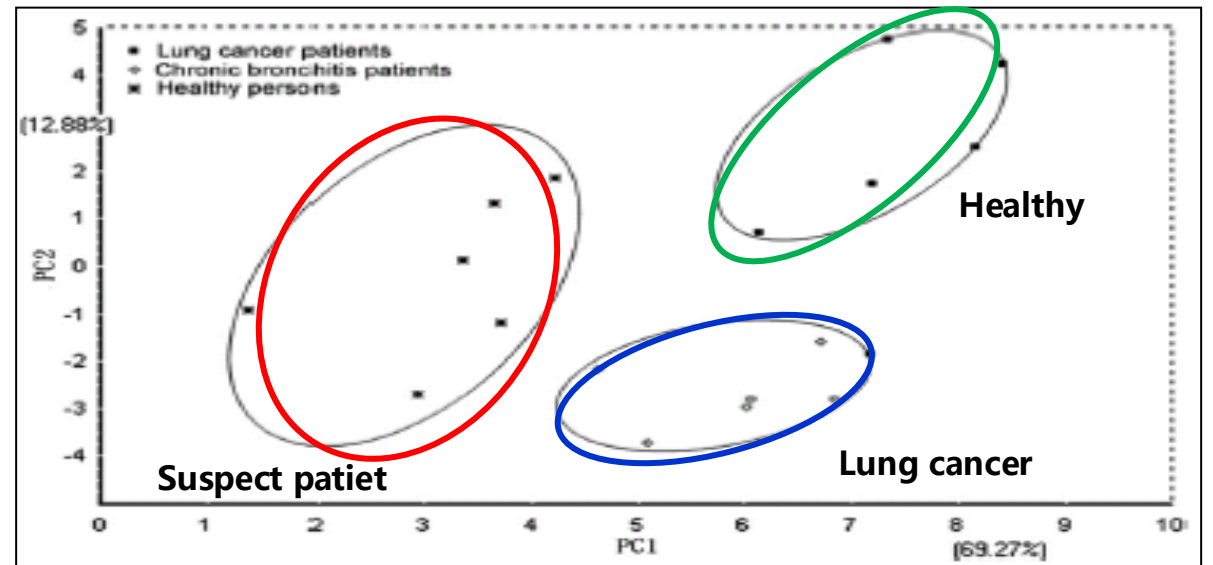
Table Comparing electronic nose with human nose ↵

| Bio-nose ↵ | Electronic nose ↵ |
|---|---|
| It uses the lungs to bring the odor to epithelium layer. ↵ | It employs a pump to smell the odor. ↵ |
| It has mucus, membrane and hair to act as filter. ↵ | It has an inlet sampling system that provides filtration. ↵ |
| The human nose contains the olfactory epithelium, which contains millions of sensing cells that interact with odorants in unique. ↵ | Electronic nose has a variety of sensors that interact differently with a group of odorous molecules. ↵ |
| The human receptors convert the chemical response to electronic nerve impulses whose unique patterns are propagated by neurons through a complex network before reaching the higher brain for interpretation. ↵ | Similarly, the chemical sensors in the electronic nose react with the sample and produce electrical signals. A computer reads the unique pattern of signals, and interprets them with some form of intelligent pattern classification algorithms. ↵ |

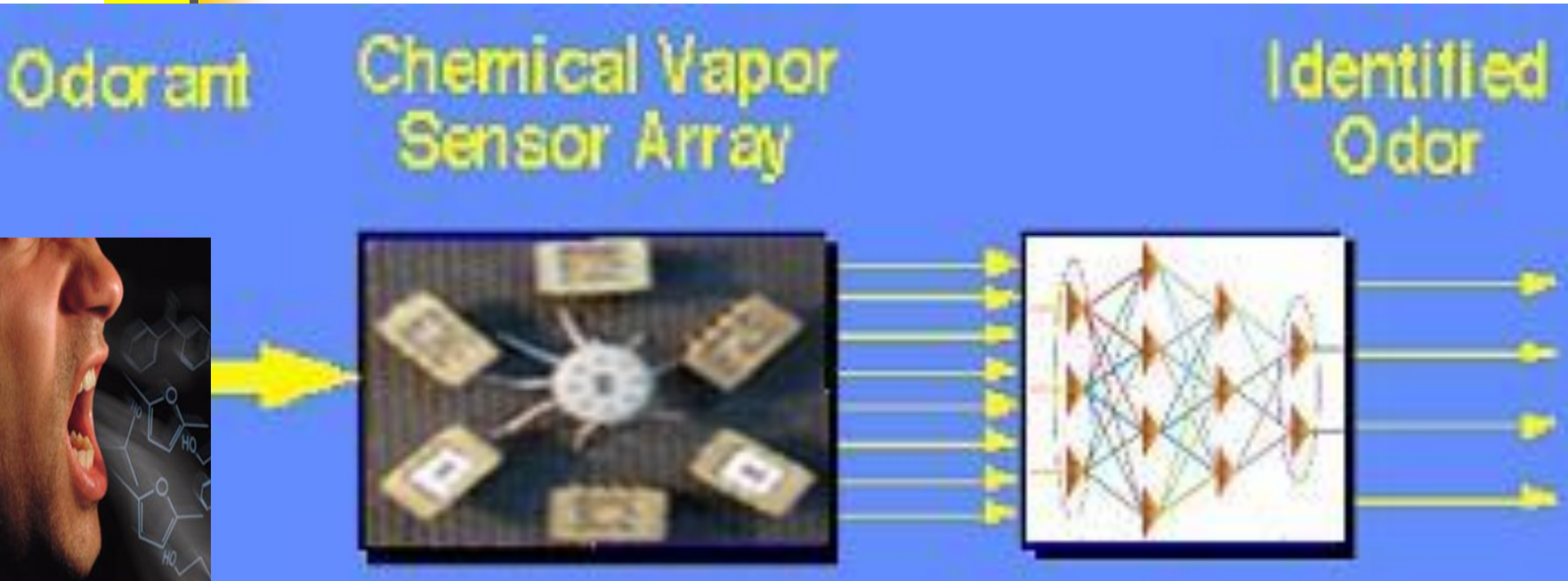
e-Nose for Health Monitoring



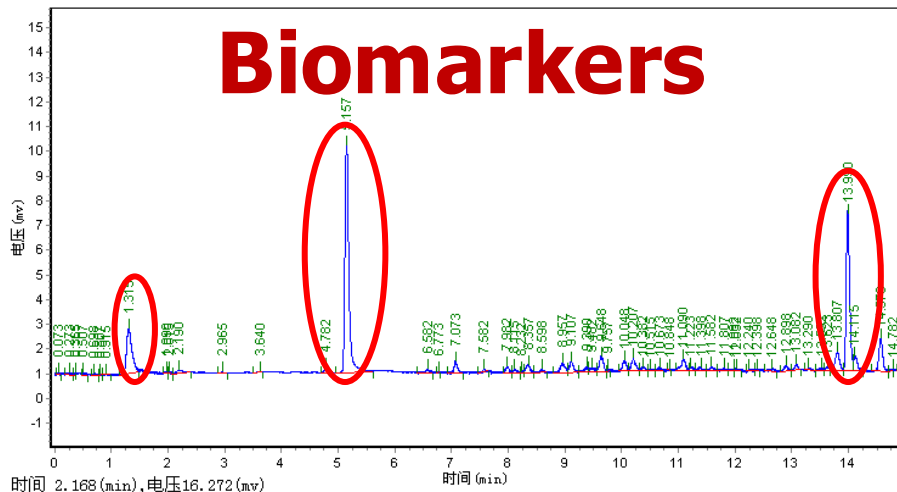
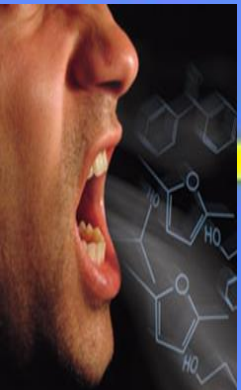
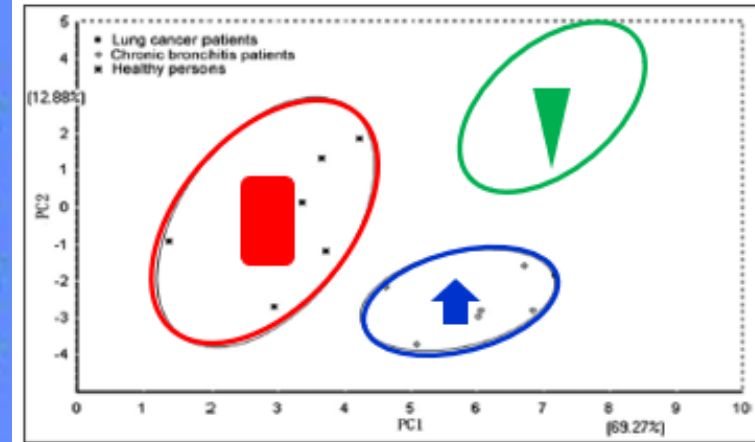
in home and communities service



e-Nose for Health Monitoring



Health/Patient



- Styrene (ethenylbenzene)
- Heptane, 2,2,4,6,6-pentamethyl
- Heptane, 2-methyl
- Decane
- Benzene, propyl-
- Undecane
- Cyclopentane, methyl-
- Cyclopropane, 1-methyl-2-pentyl-
- Methane, trichlorofluoro-
- Benzene
- Benzene, 1,2,4-trimethyl-

- 1,3-butadiene, 2-methyl- (isoprene)
- Octane, 3-methyl-
- 1-hexene
- Nonane, 3-methyl-
- 1-heptene
- Benzene, 1,4-dimethyl
- Heptane, 2,4-dimethyl
- Hexanal
- Cyclohexane
- Benzene, 1-methylethenyl-
- Hepatal

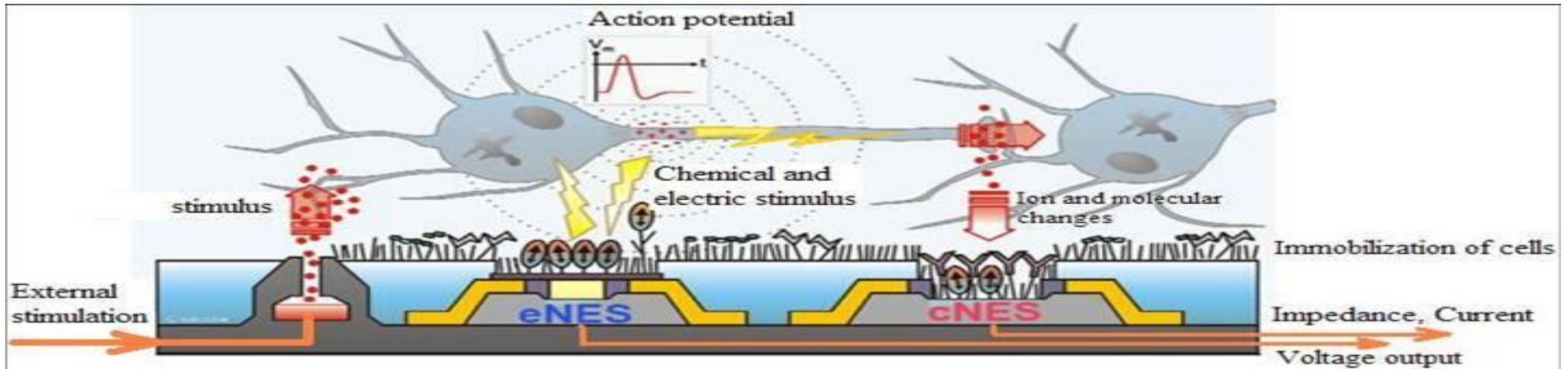
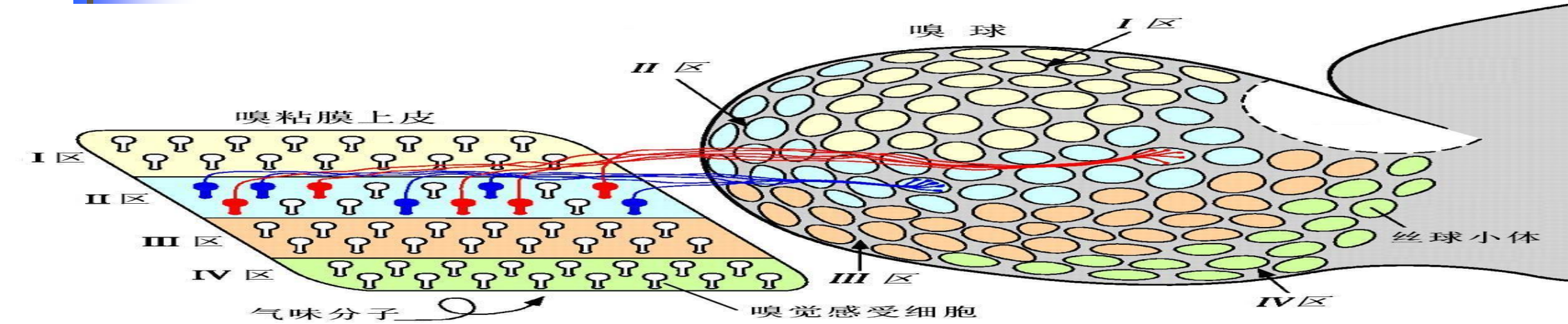


2nd Part

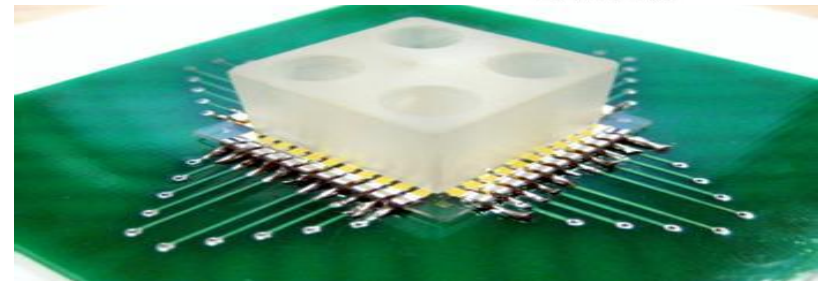
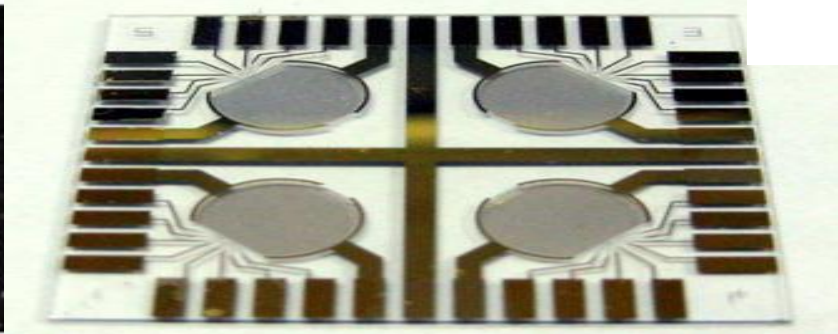
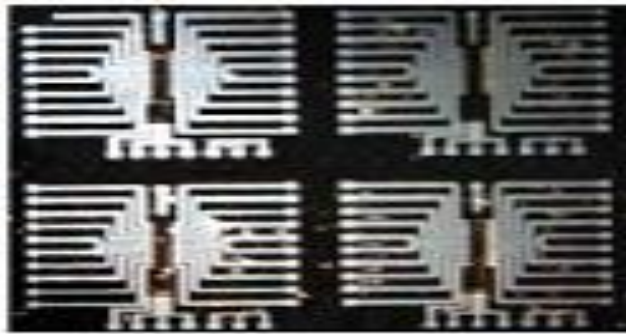
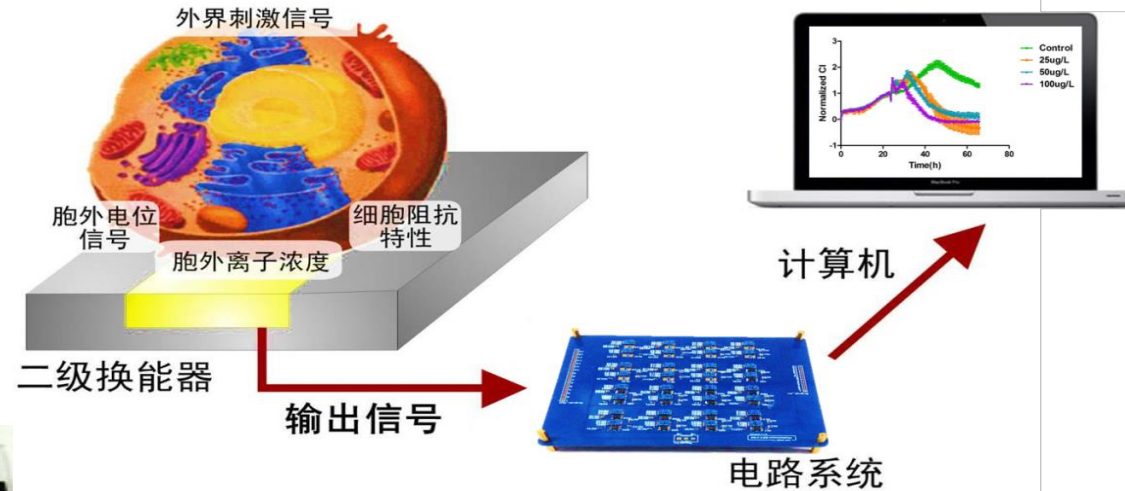
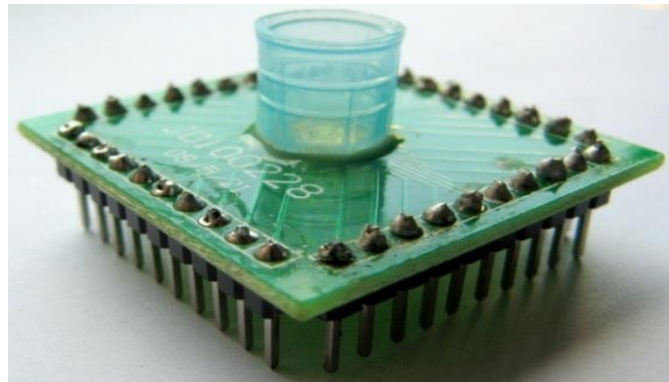
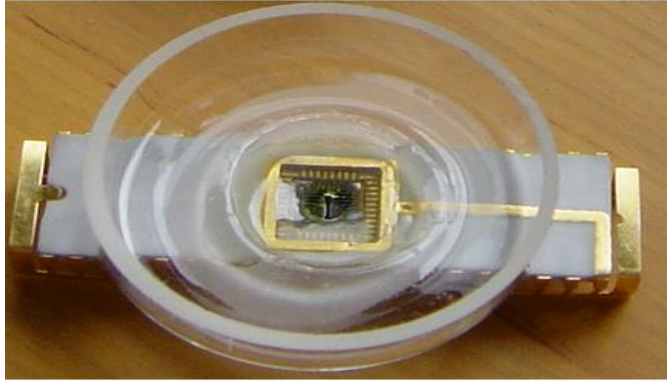
Bioe-Nose

In vitro and *in vivo*

In vitro Bioe-Nose uses Bioactive Elements and Biotechnologies

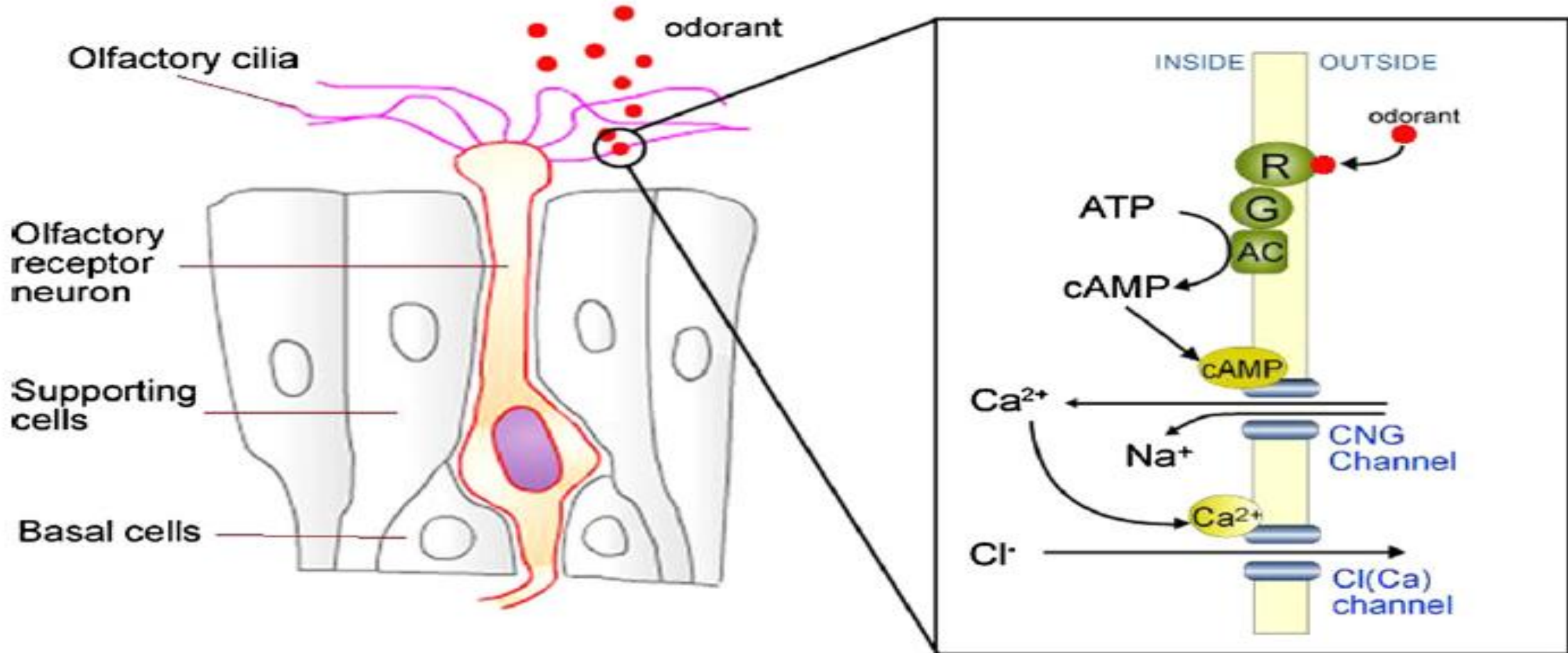


Bioinspired nose chips developed by us

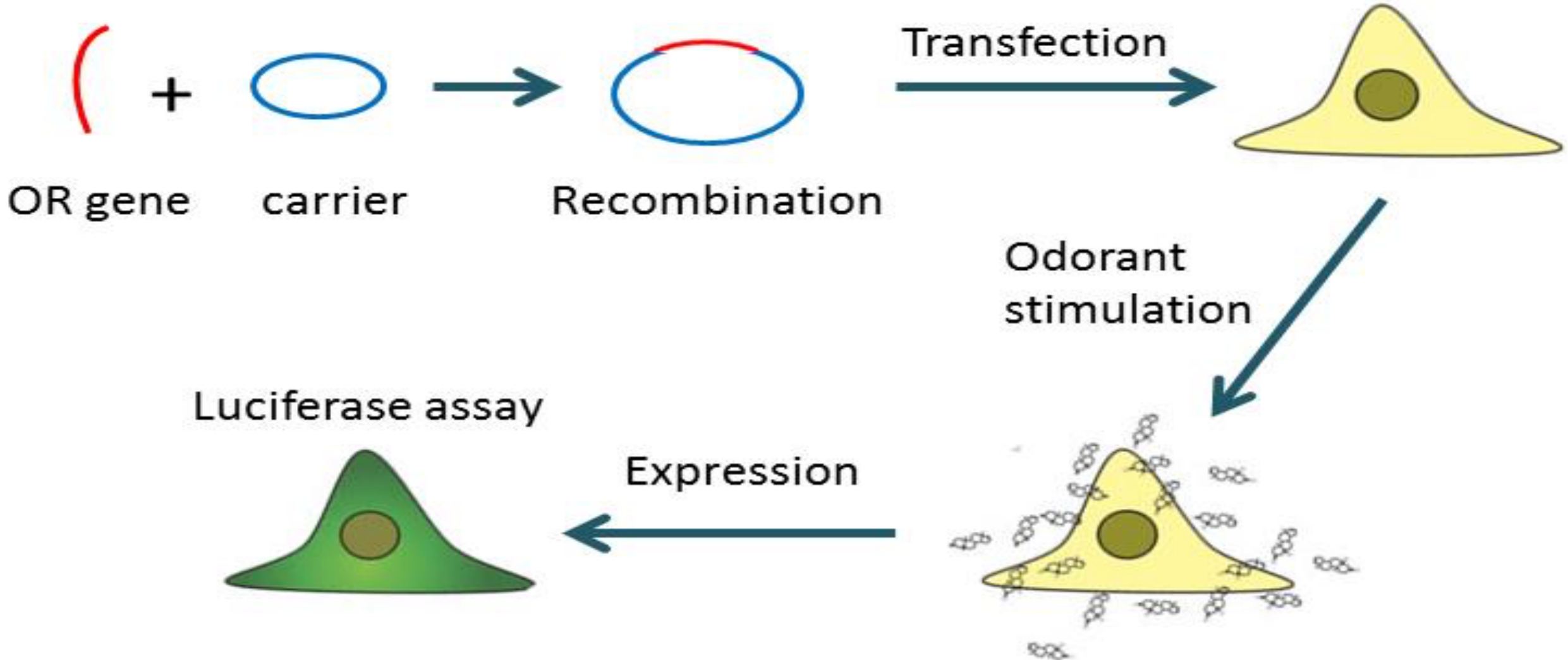


The development the device integrating FET array and culture olfactory cells on the device and detect the response under stimulants of odor or gases.

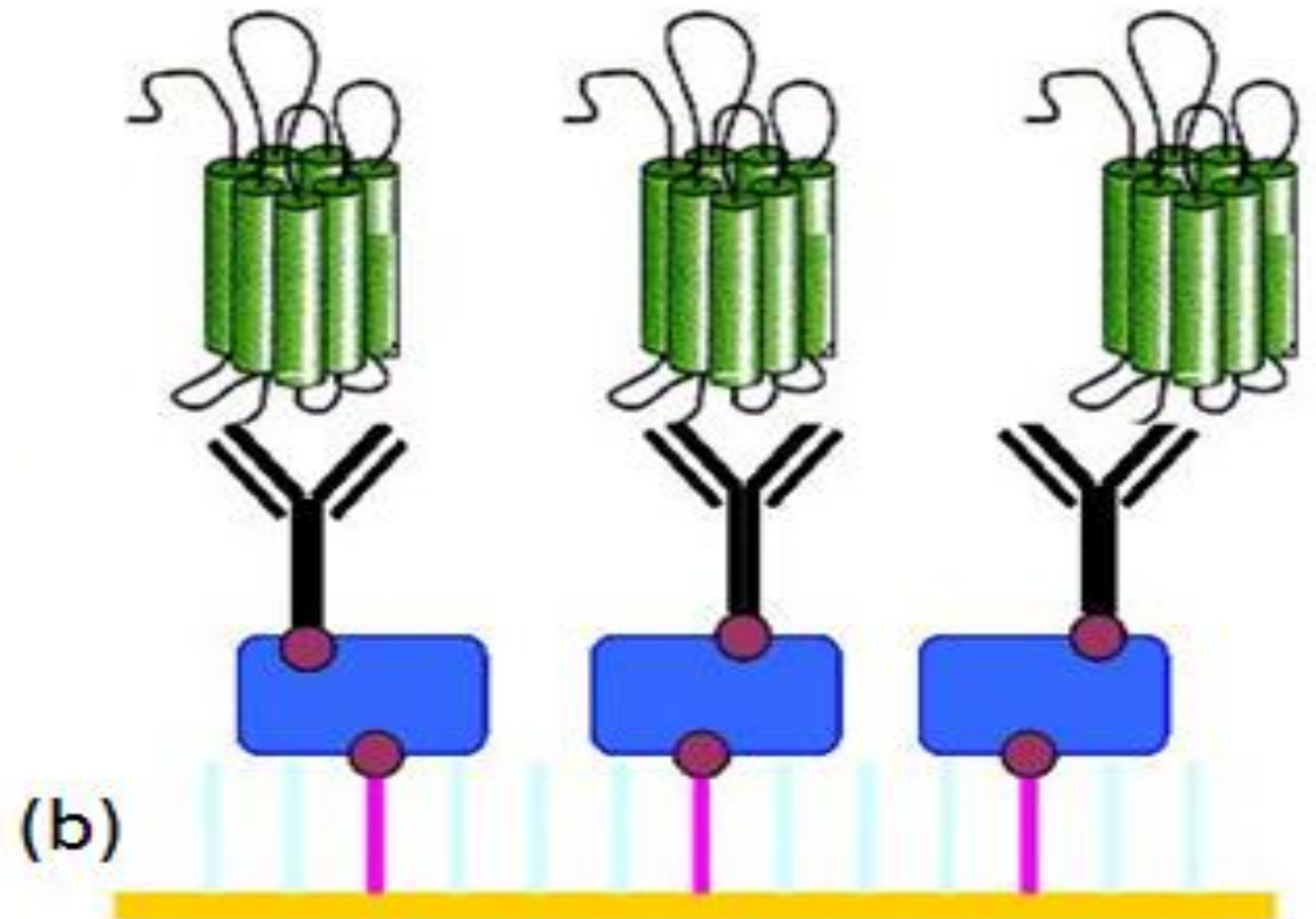
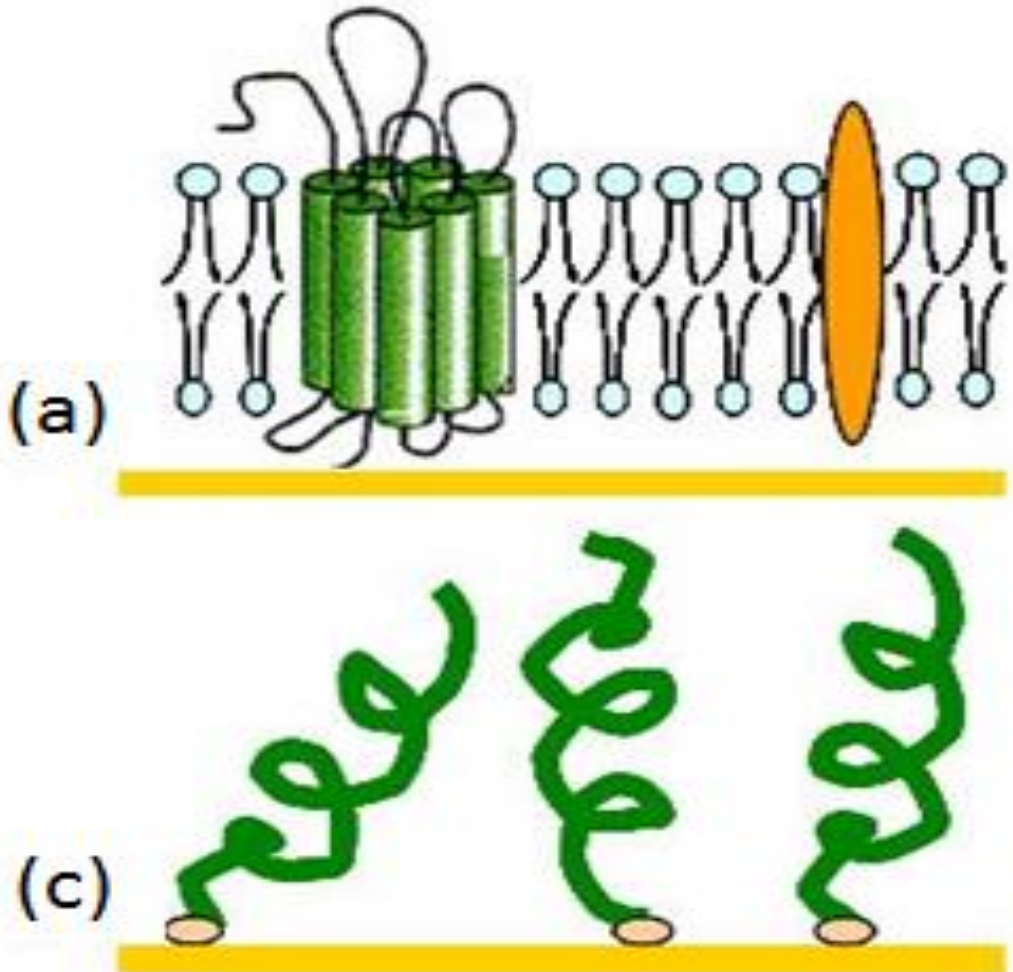
Olfactory receptor neuron and the ion channels in the cilia(纤毛)



The process of Cell-based Olfactory Receptor Synthesis and Expression



The immobilization methods for ORs coupling with transducers

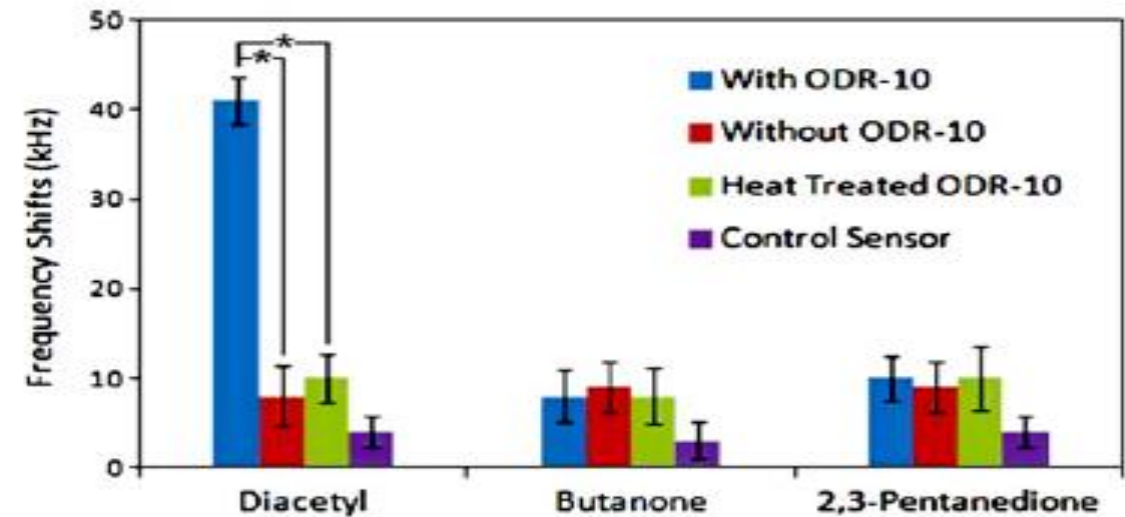
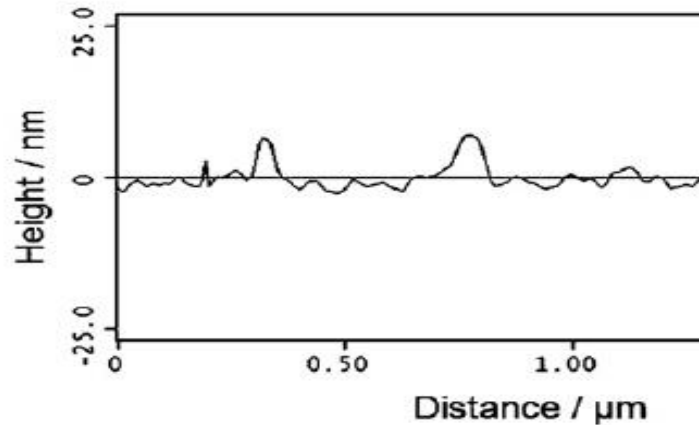
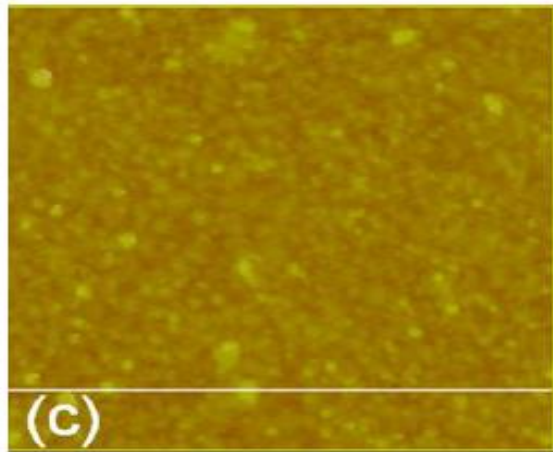
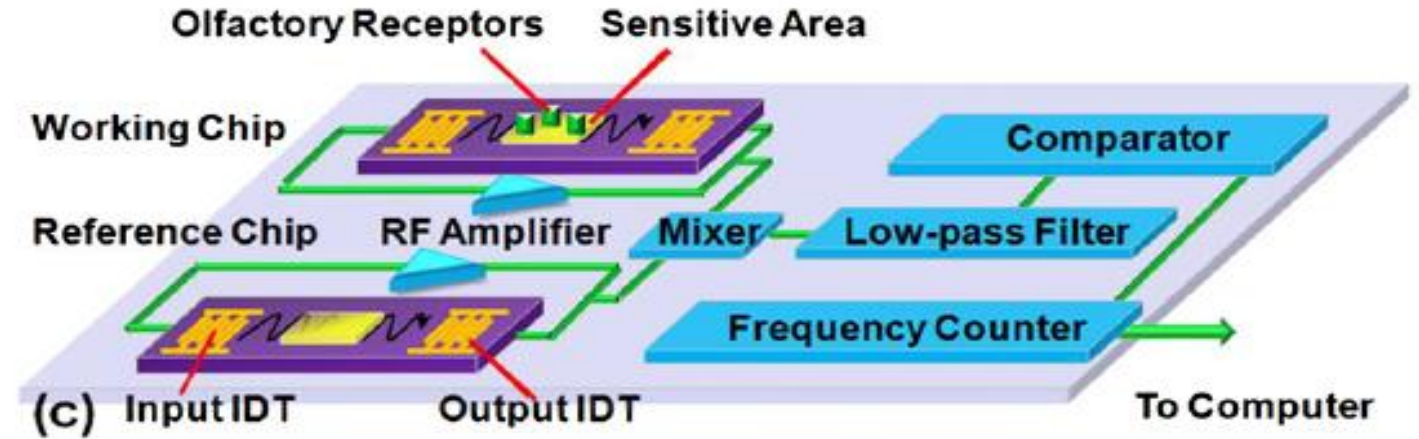


Receptor-based SAW sensors

surface acoustic wave (SAW)

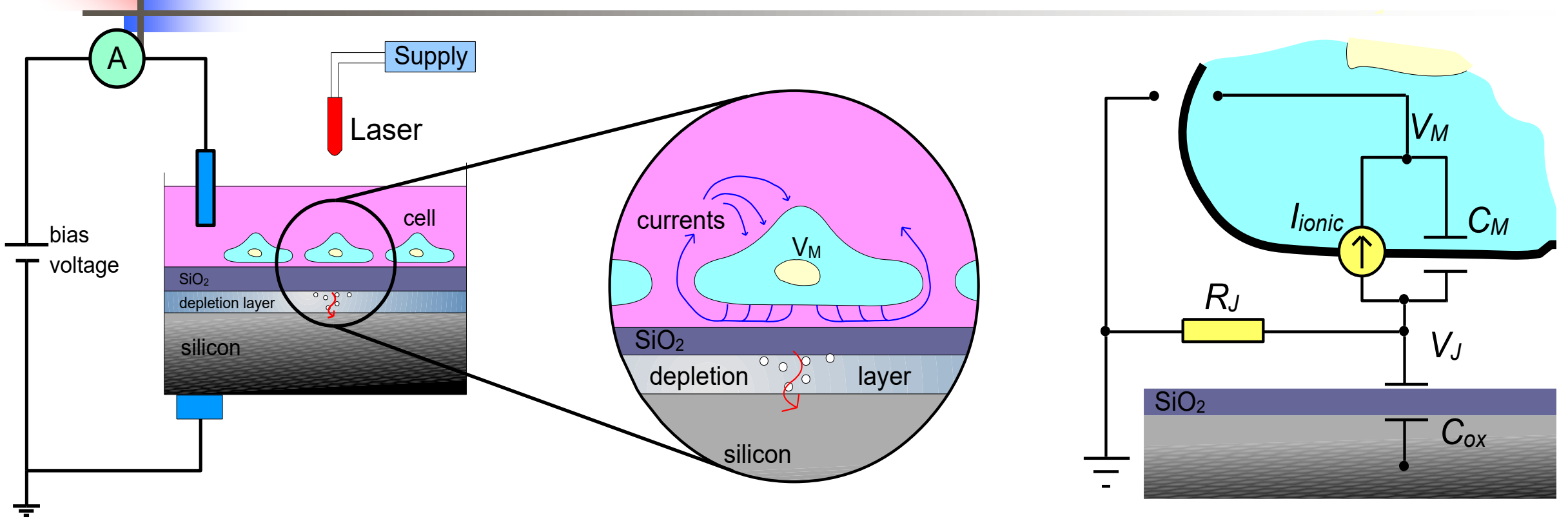
✓ Mass change

✓ Cell and receptor



AFM scans of the SAW chips with a sensitive surface immobilized with ODR-10 by SAMs.

LAPS for electrophysiological sensing for olfactory cells

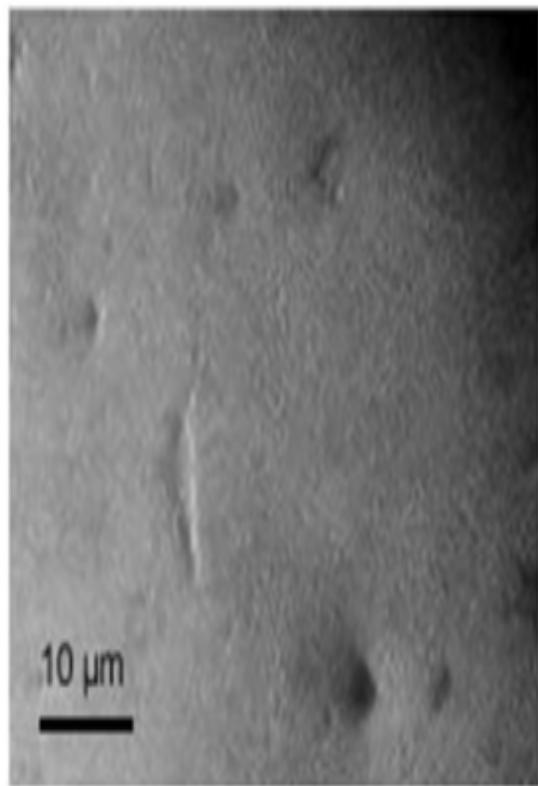


(a)

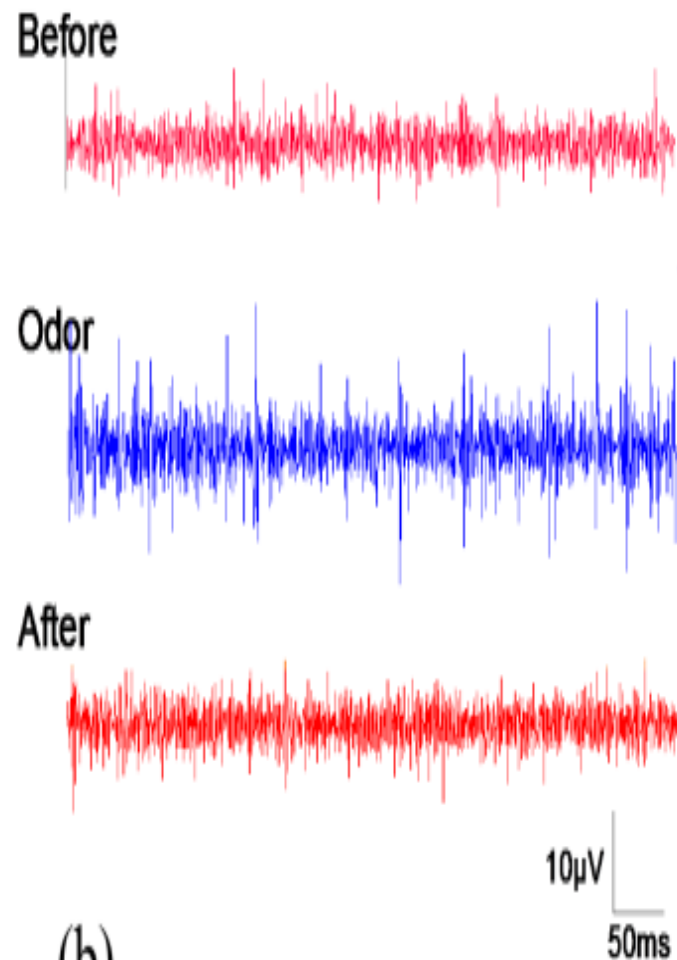
$$(b) \quad \frac{V_J}{R_J} = C_M \frac{d(V_M - V_J)}{dt} + I_{ionic} \quad (c)$$

Fig. 3.2. Principle of the olfactory-LAPS system. (a) The schematic of cell-based biosensor using LAPS. (b) Simplified cell-semiconductor interface. (c) Schematic circuit of the cell-

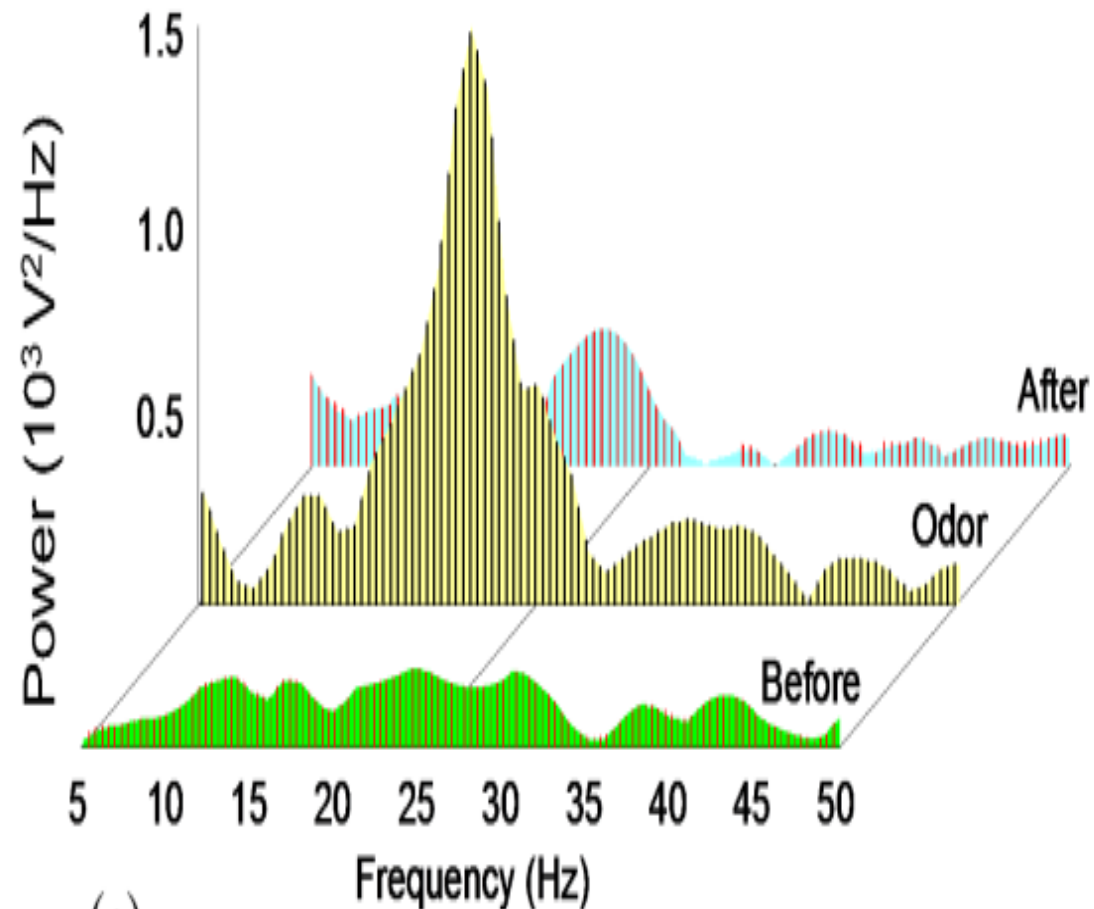
Odorant-elicited (激发) Extracellular Potential of the Olfactory Receptor Cells



(a)

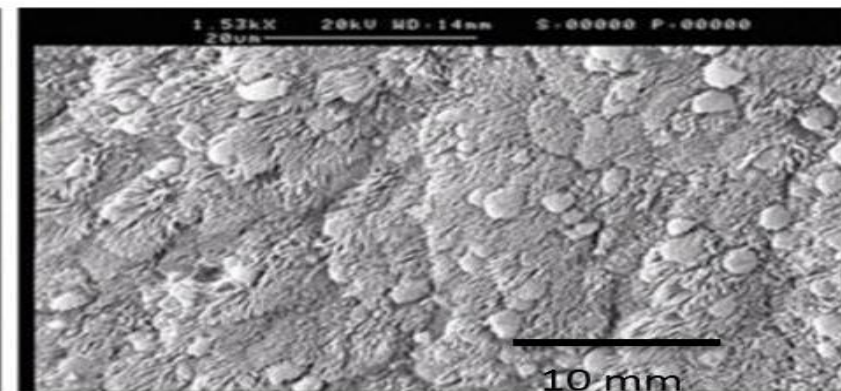
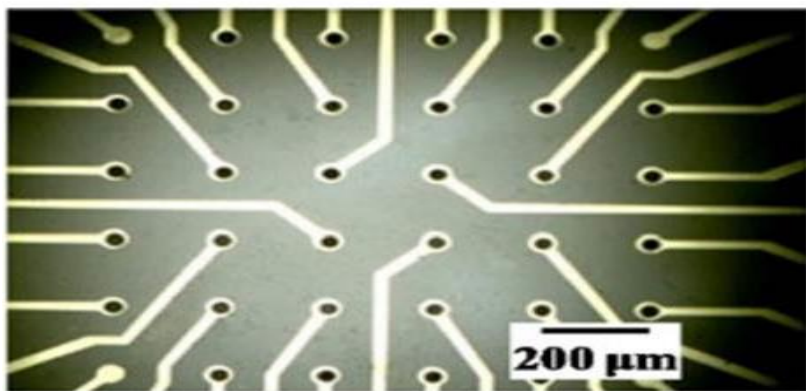
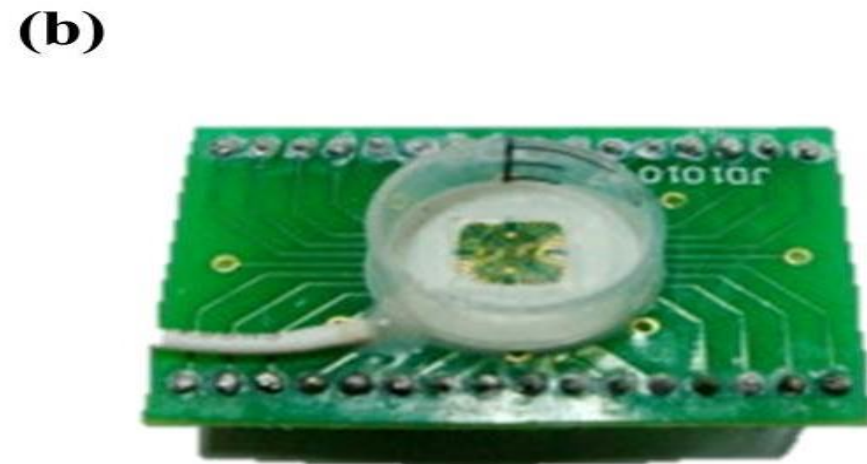
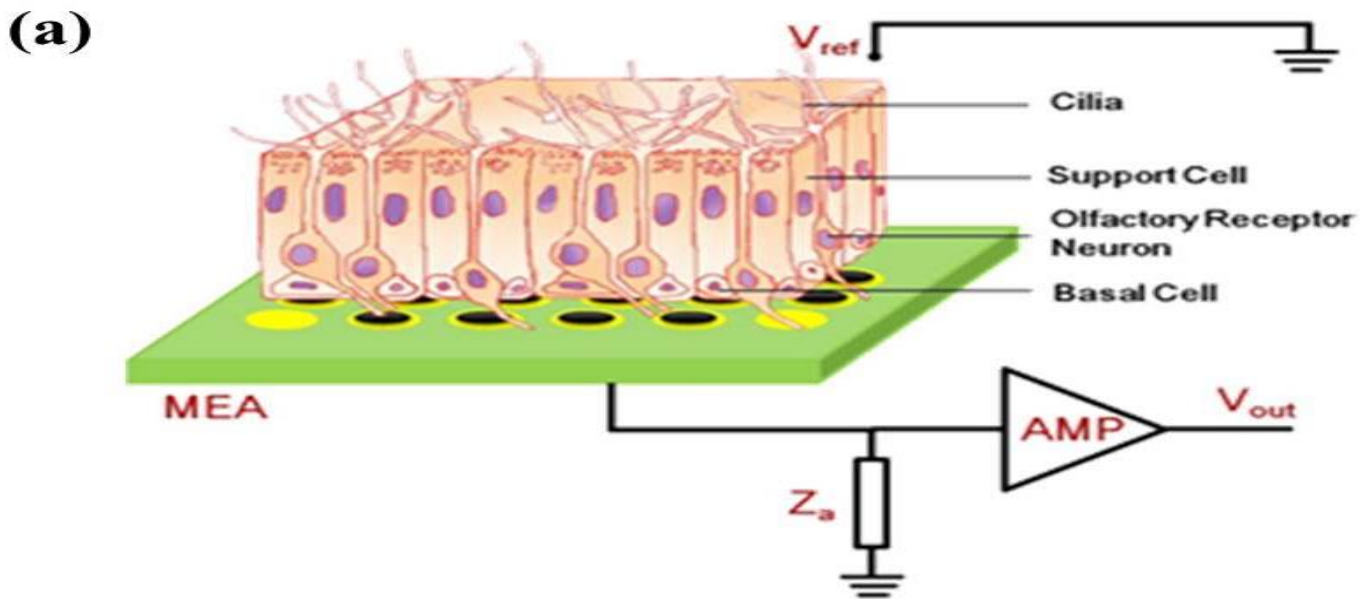


(b)



(c)

Design of the olfactory epithelium tissue-based Bioe-Nose



(c)

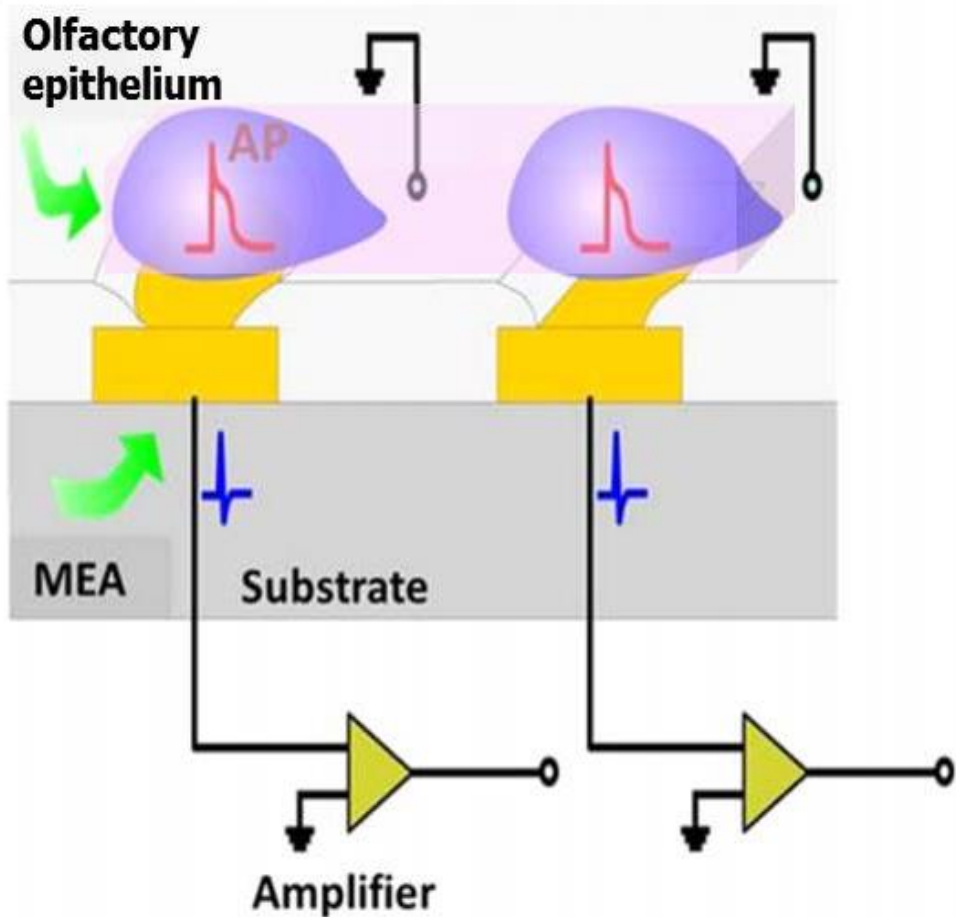
(d)

(e)

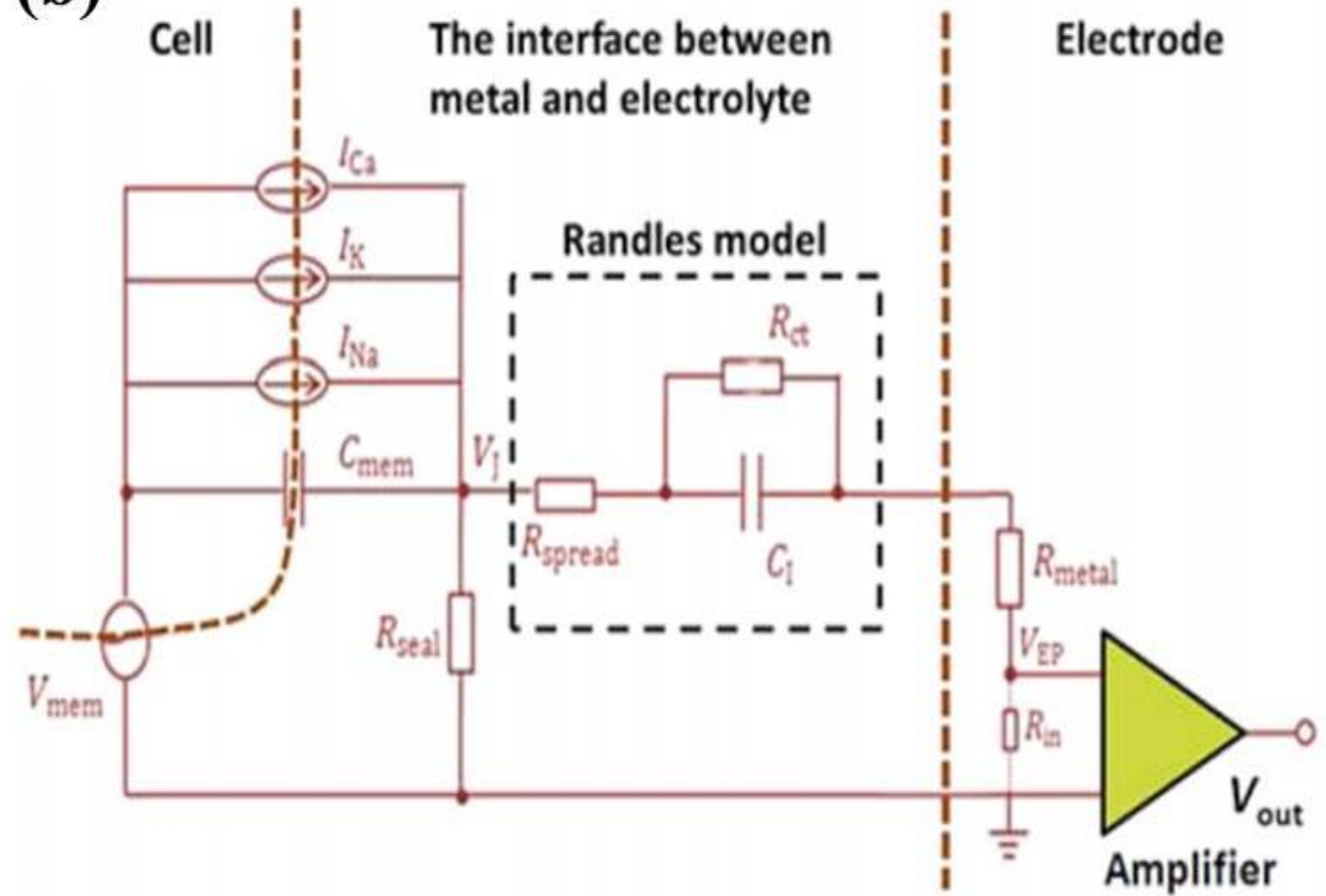
The working principles of olfactory epithelium-based MEA



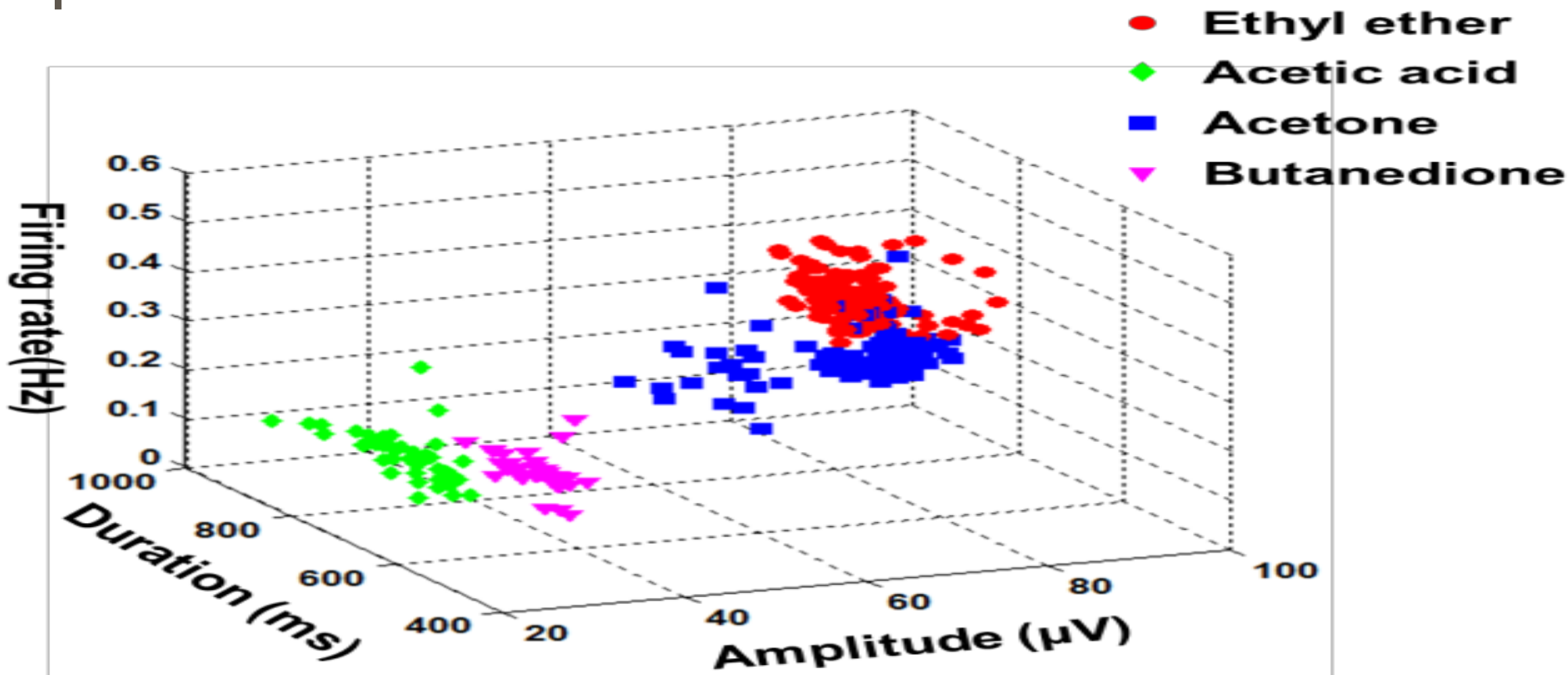
(a)



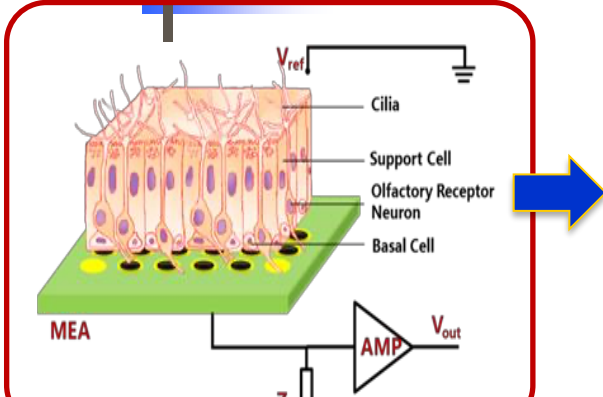
(b)



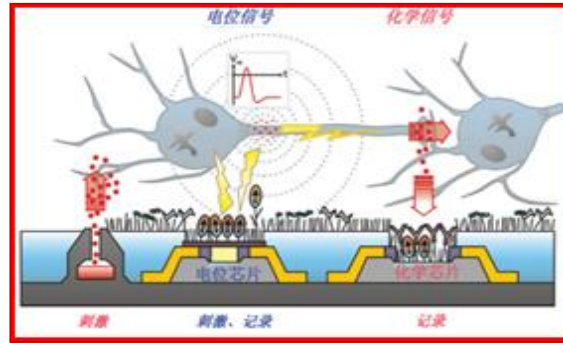
The Pattern Recognition Results Sensed by Olfactory Epithelium-based Bioe-Nose



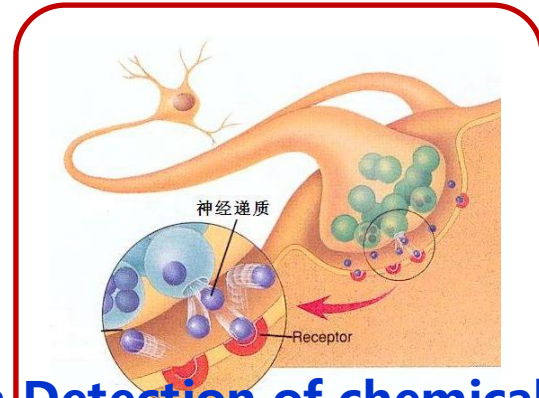
The Further Study on Bioe-Nose Need Combine *in vitro* with *in vivo*



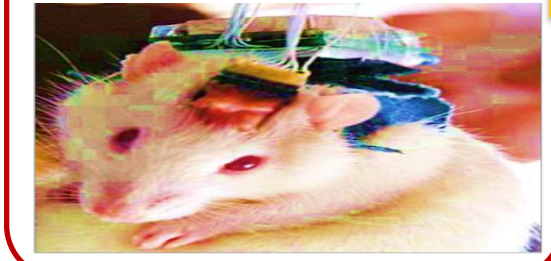
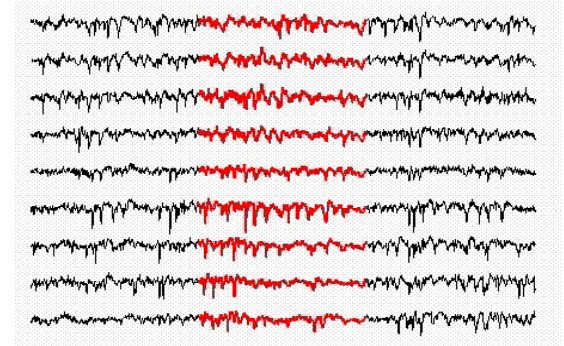
Cell/tissue sensors *in vitro*



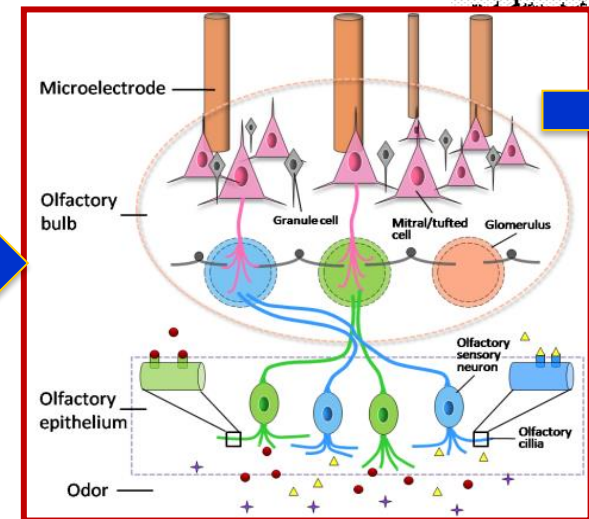
Neuron network *in vitro*



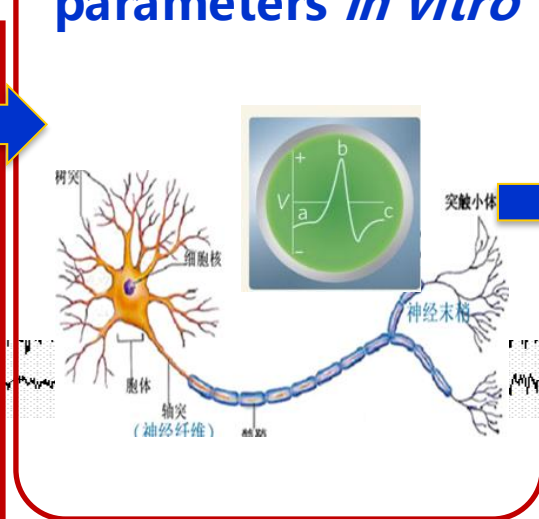
Detection of chemical parameters *in vitro*



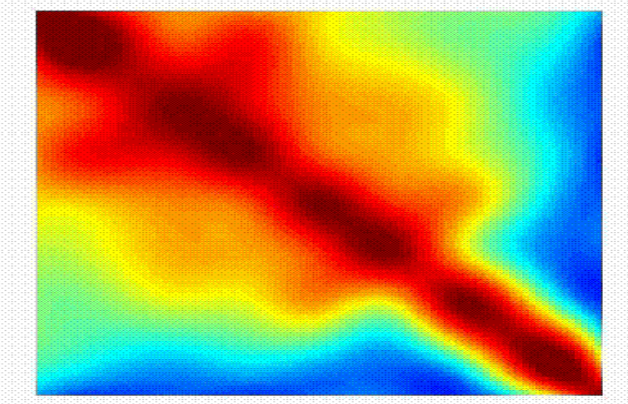
Cell/tissue sensors *in vivo*



Neuron network *in vivo*

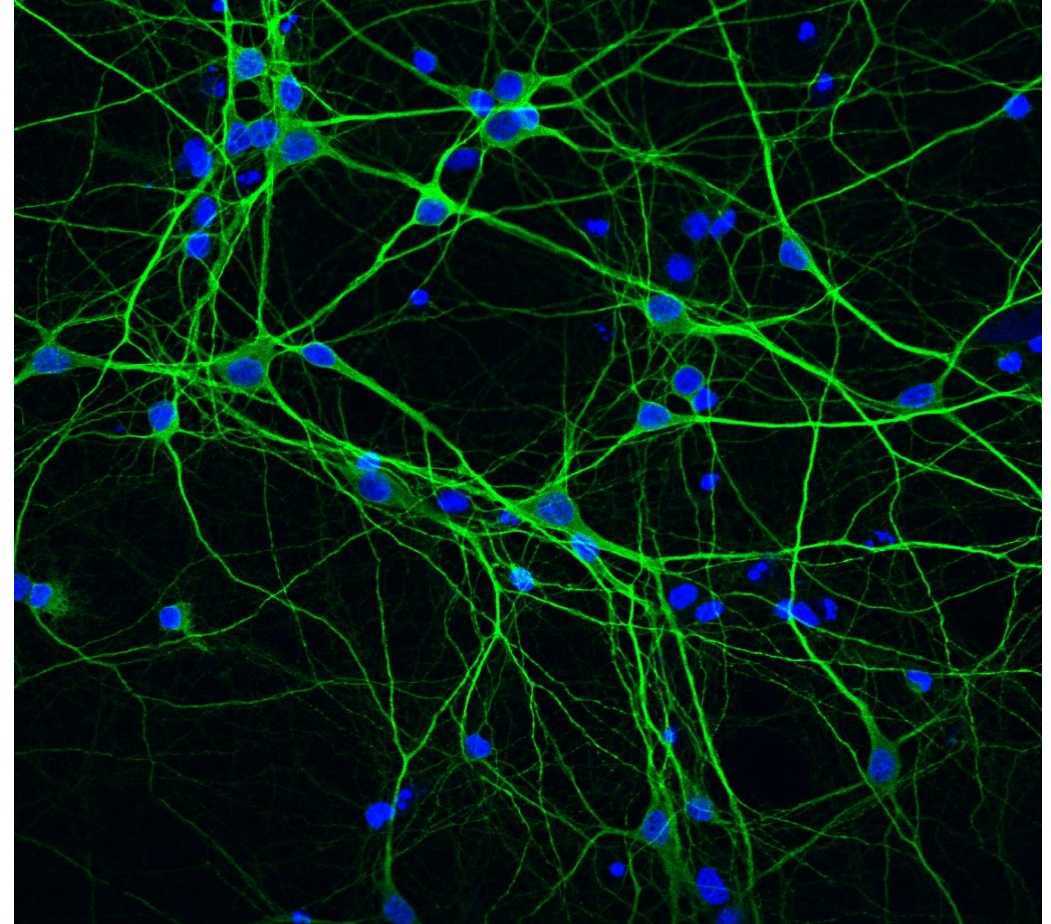
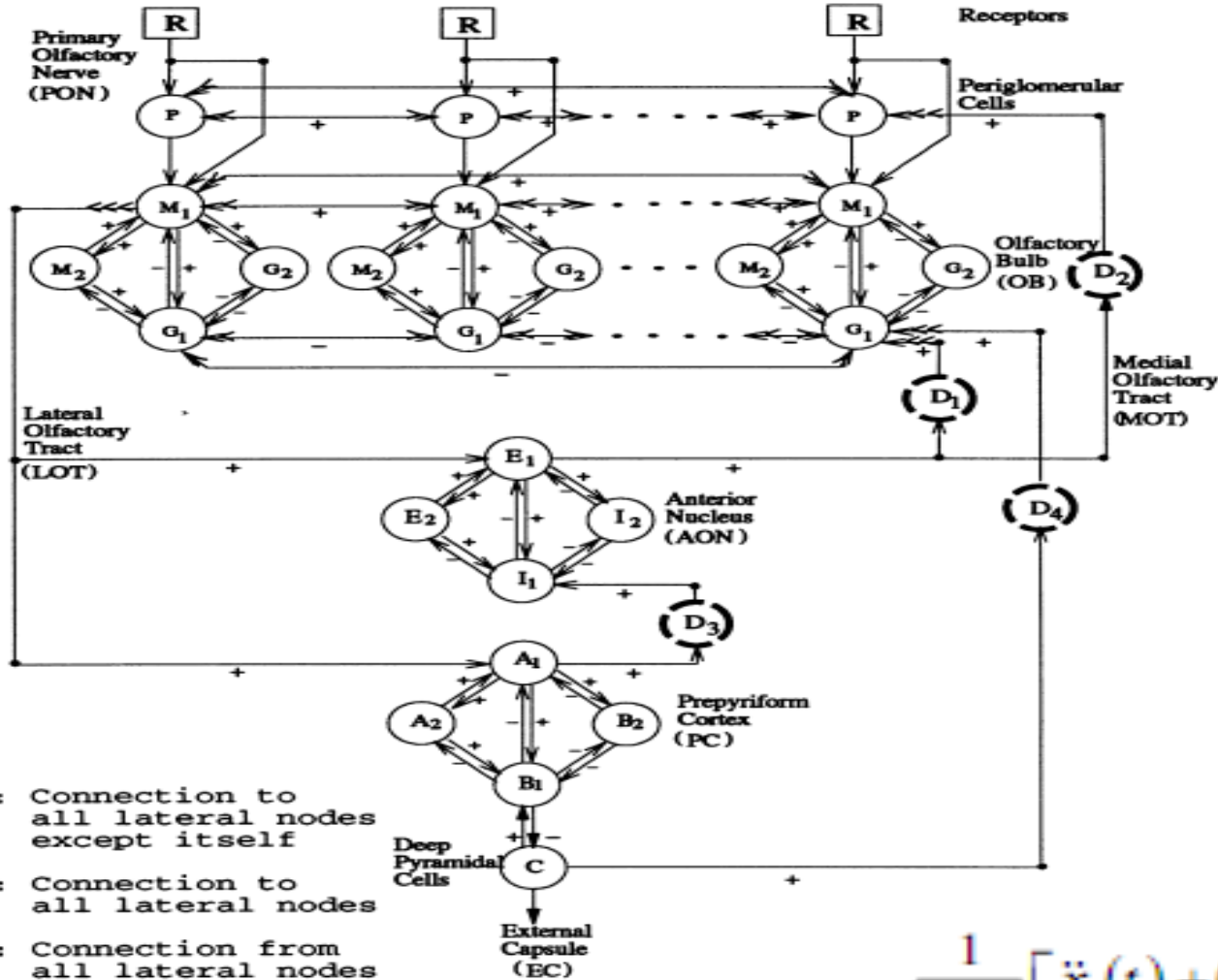


Detection of chemical parameters *in vivo*



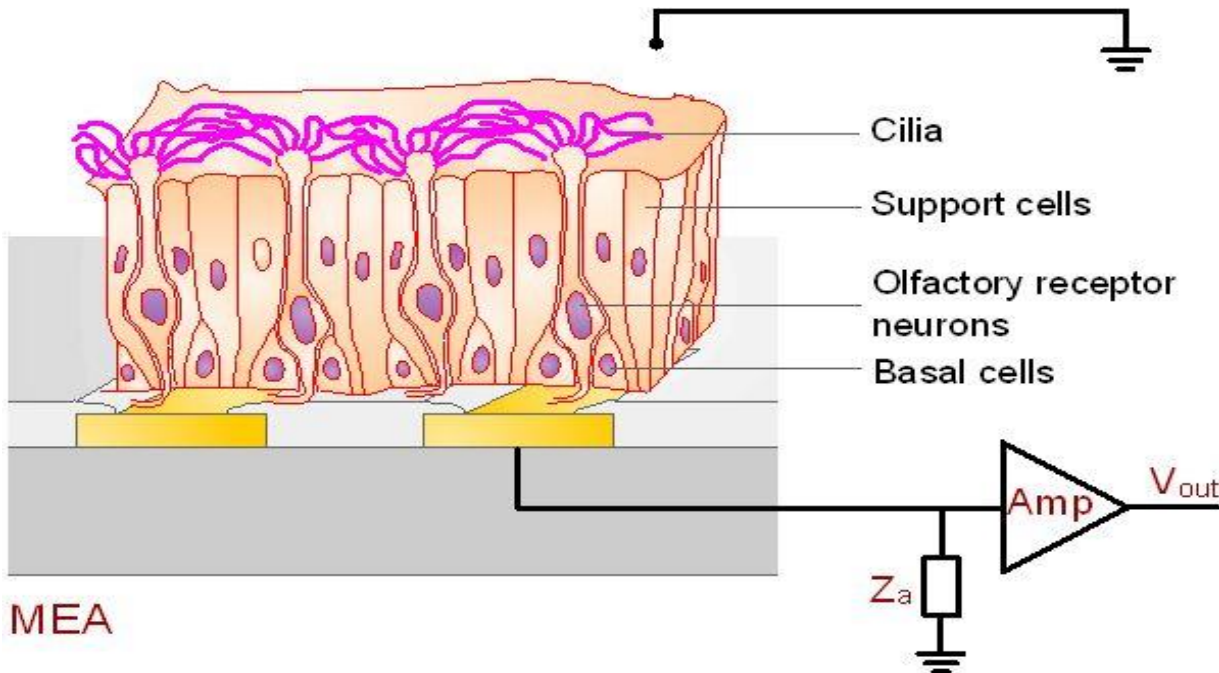
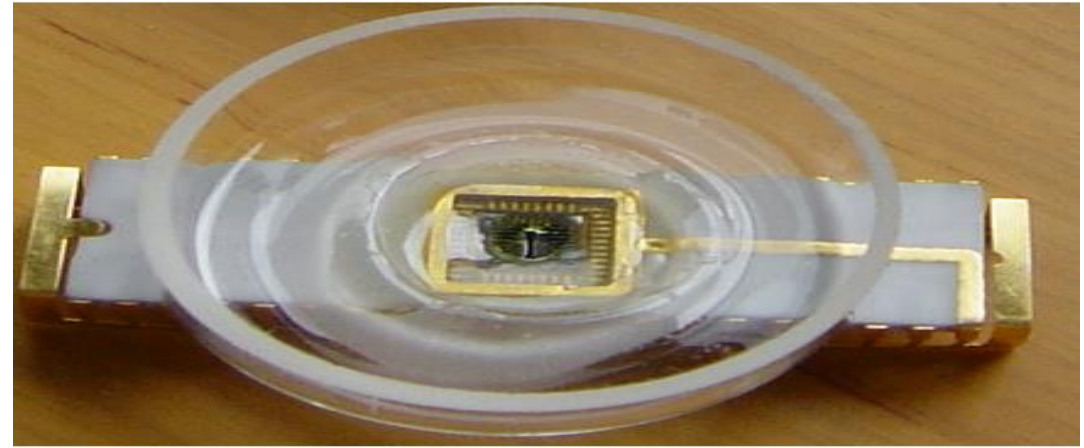
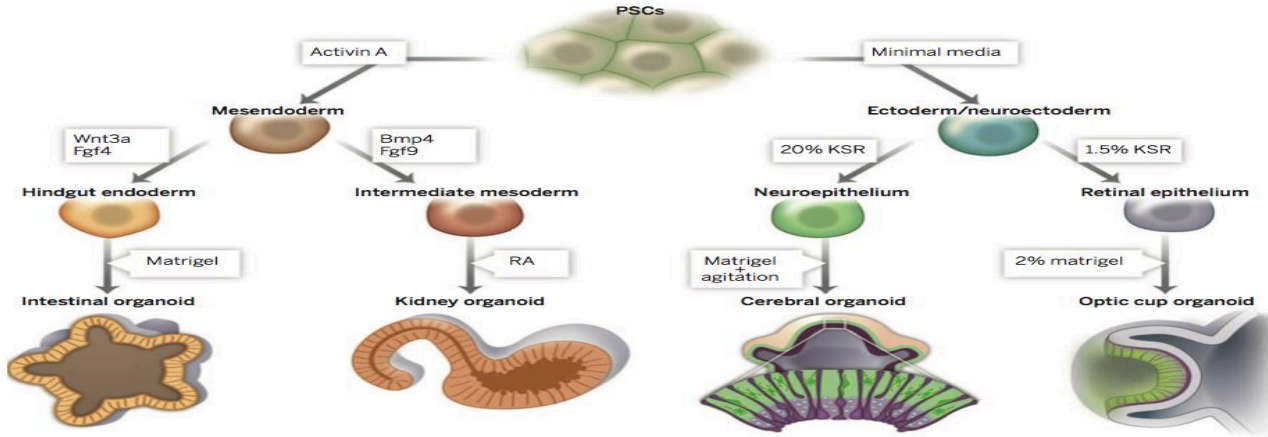
Synthesis and integrated analysis combined *in vitro* with *in vivo*

The Research on Olfactory Neural Network OE and OB *in vitro* and *Vivo*

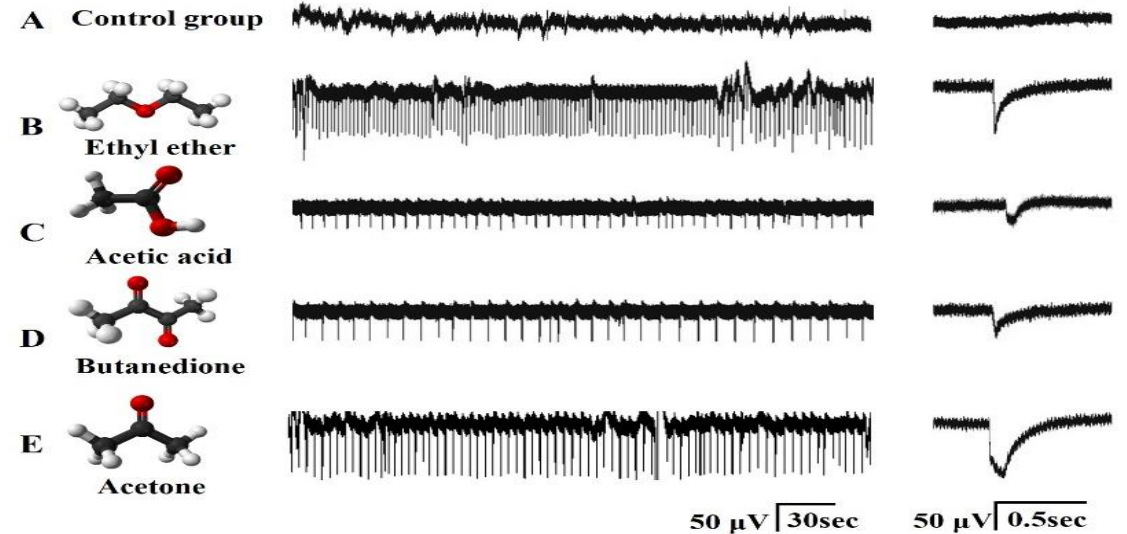


$$\frac{1}{a \cdot b} [\ddot{x}_i(t) + (a + b)\dot{x}_i(t) + a \cdot b \cdot x_i(t)] = \sum_{j=1}^N [W_{ij} \cdot y_j] + I_i(t)$$

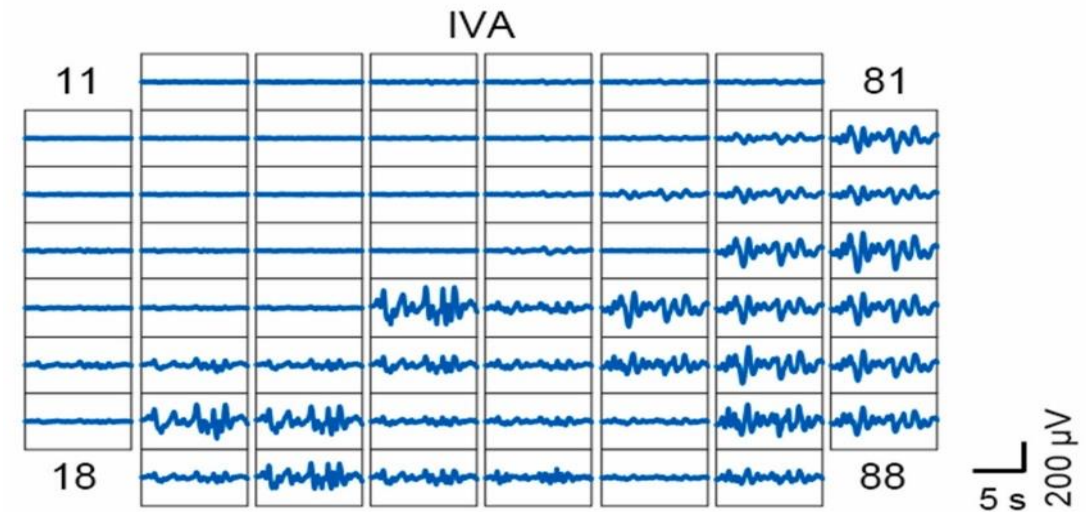
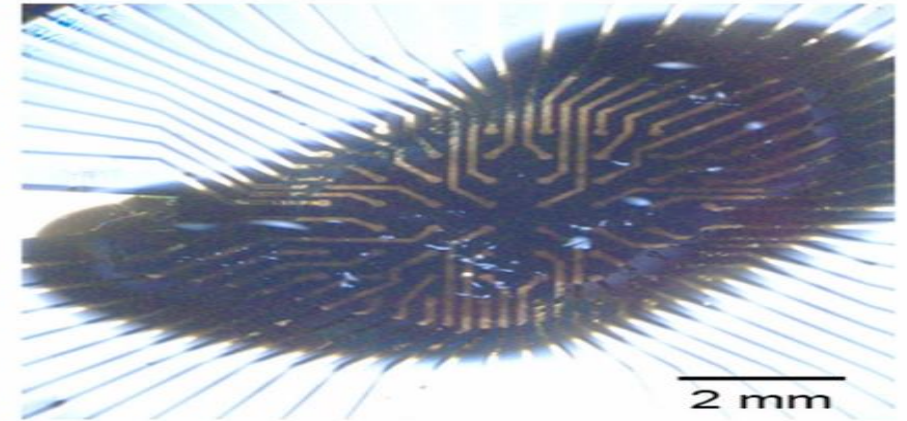
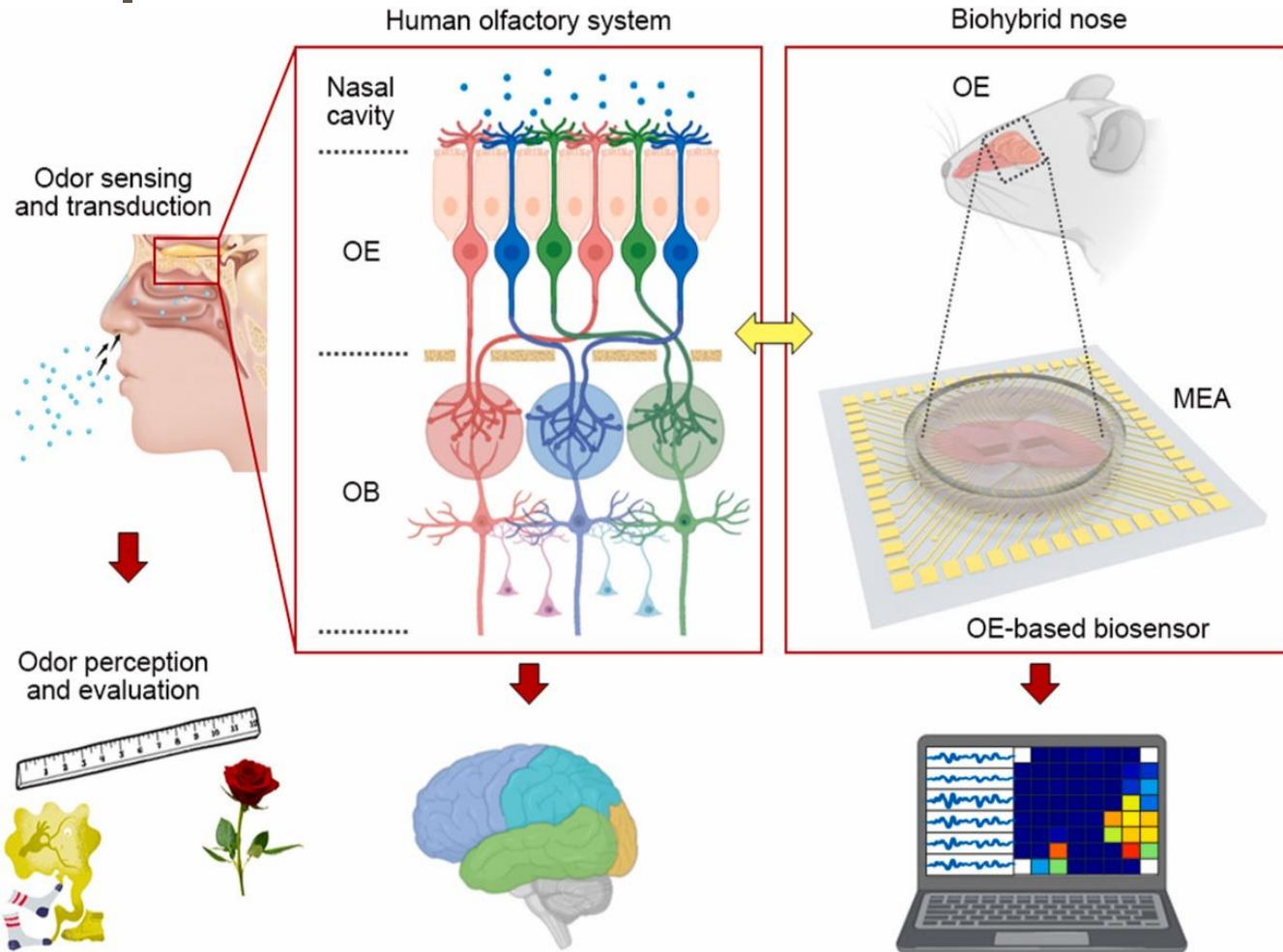
Bioe-Nose with living 3D cells and Organoids *in Vitro*



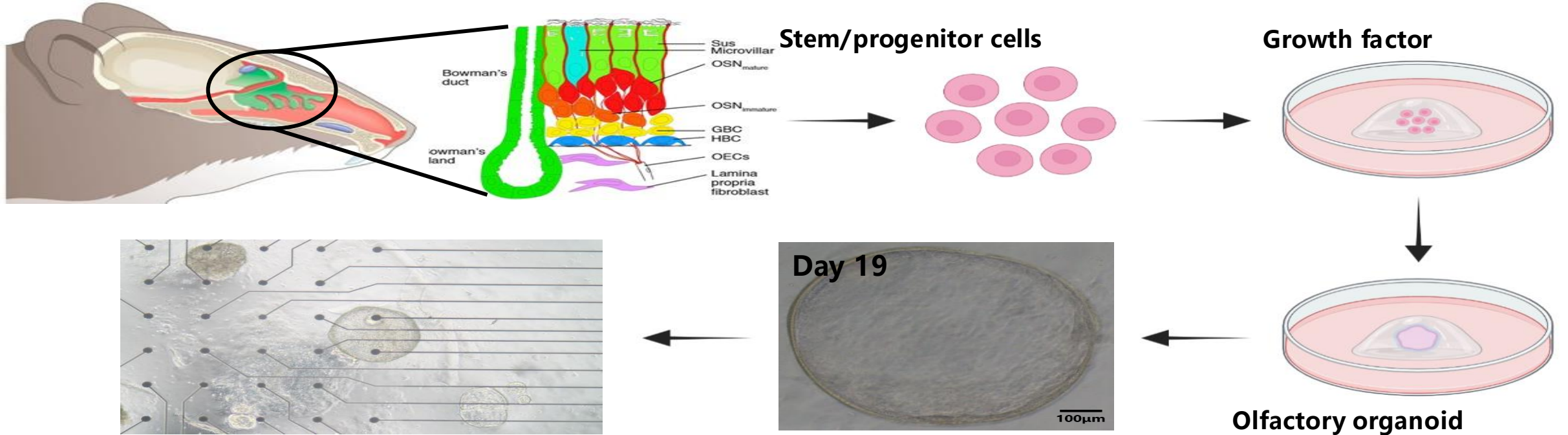
气味响应



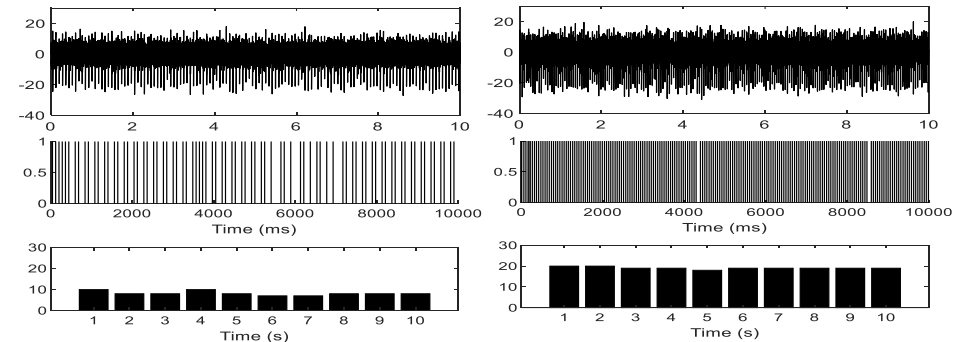
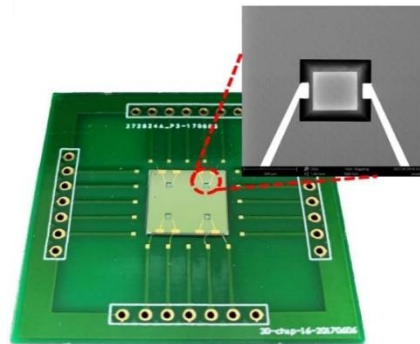
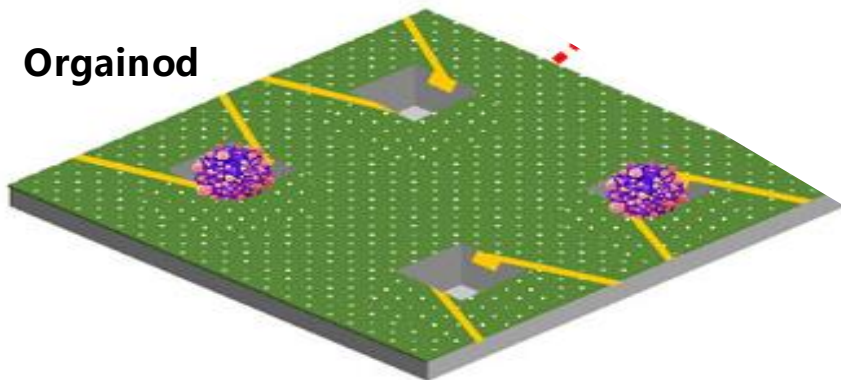
Oganoid-based Bioe-Nose *in Vitro*



Oganoid-based Bioe-Nose *in Vitro*

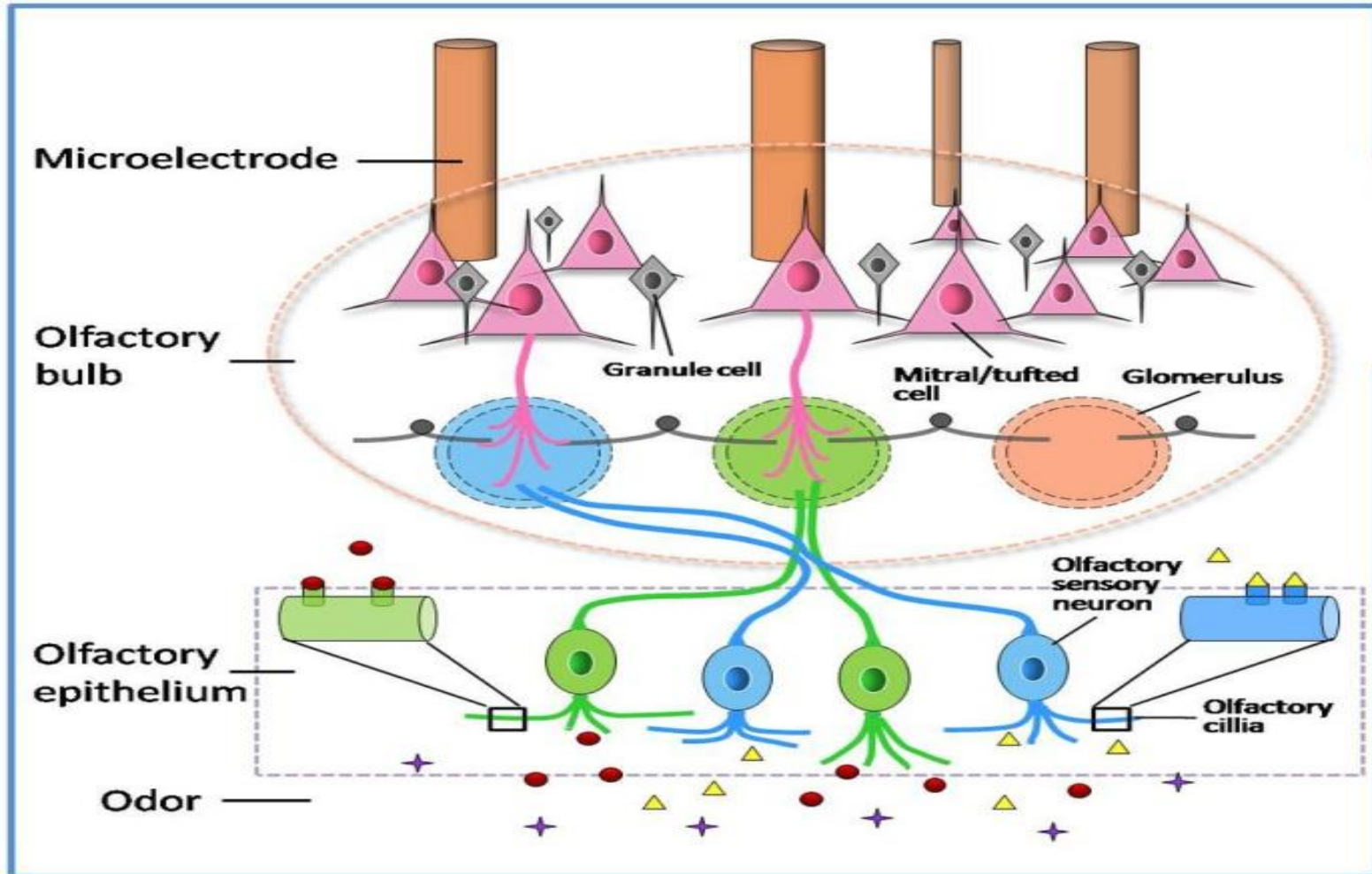


Orgainod

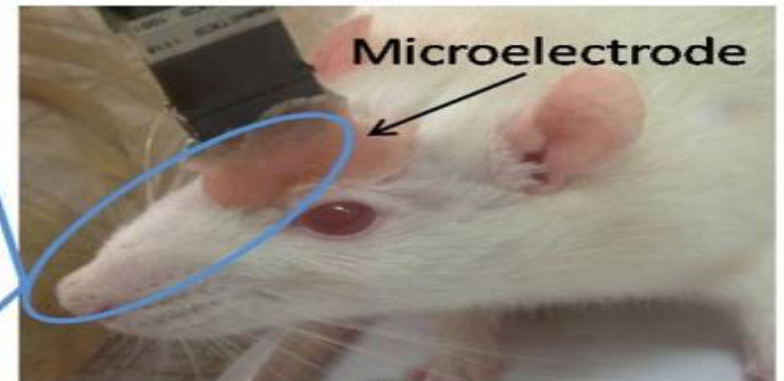


in the manuscript and see talk of Hao Wan

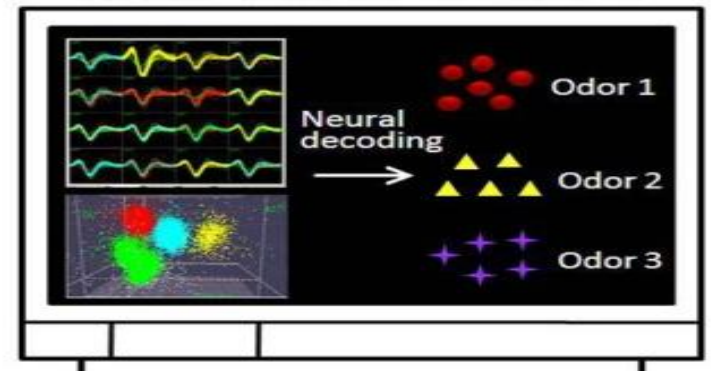
Bioe-Nose *in Vivo* Using BCI Techniques



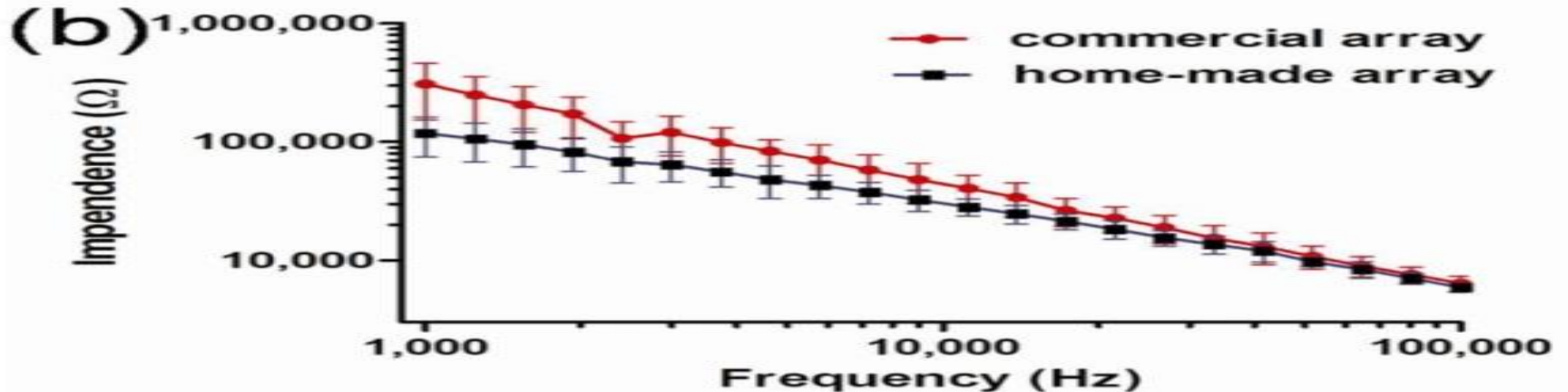
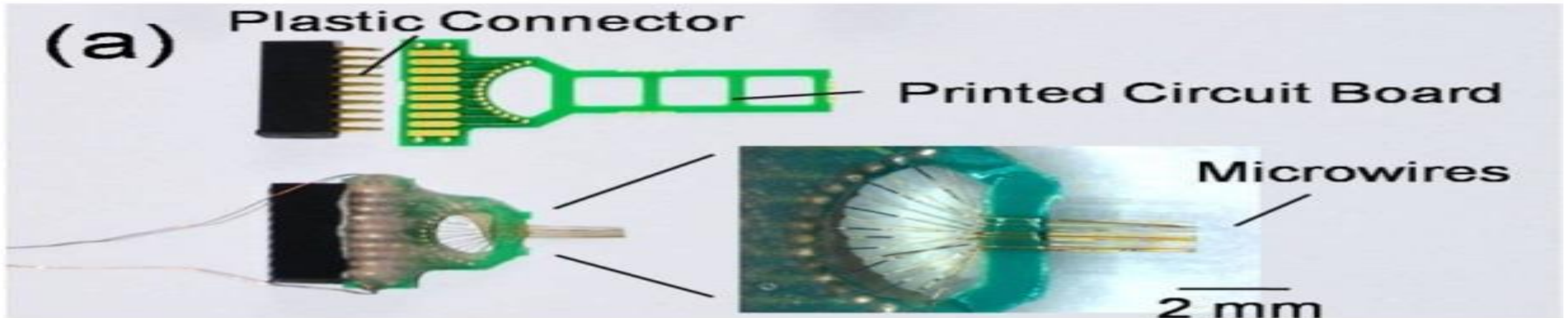
Sensor-odor interaction and Signal generation



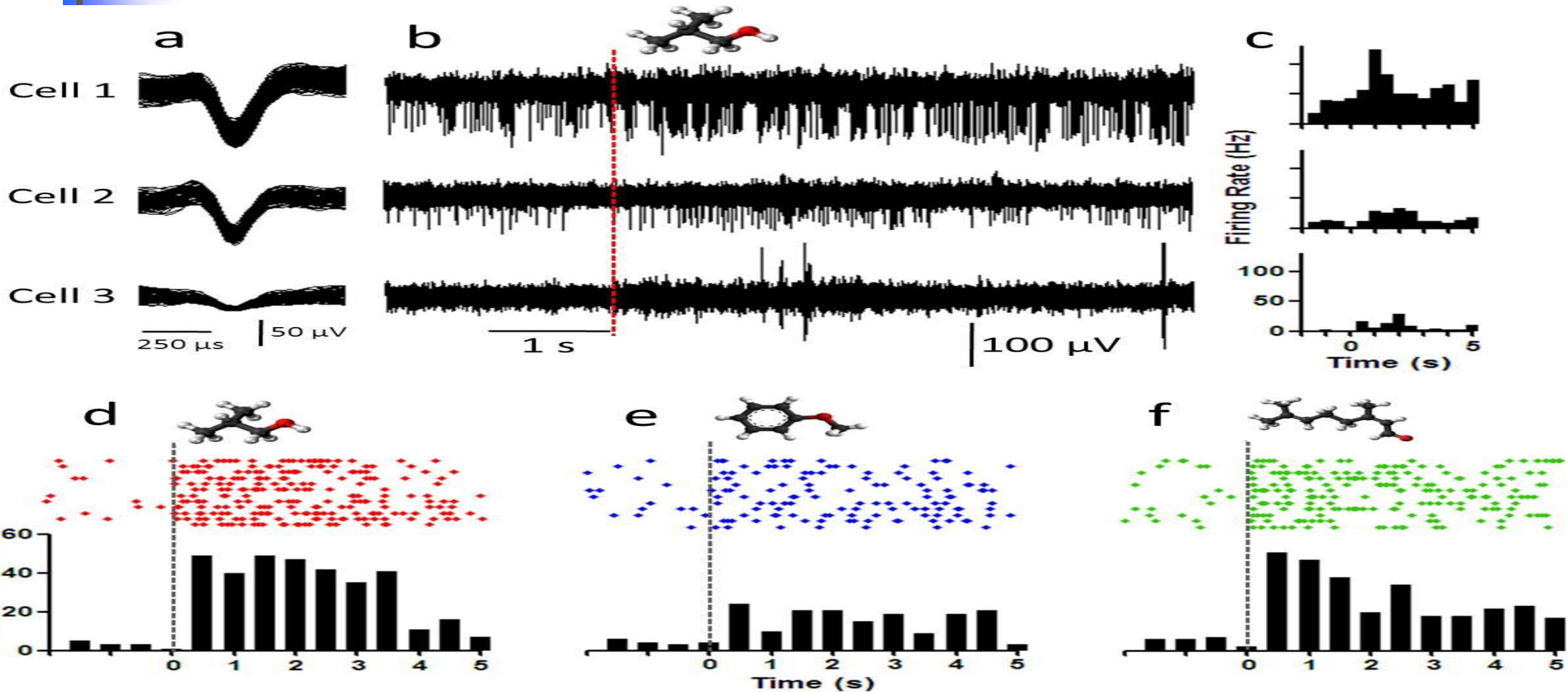
Pattern recognition and Odor discrimination



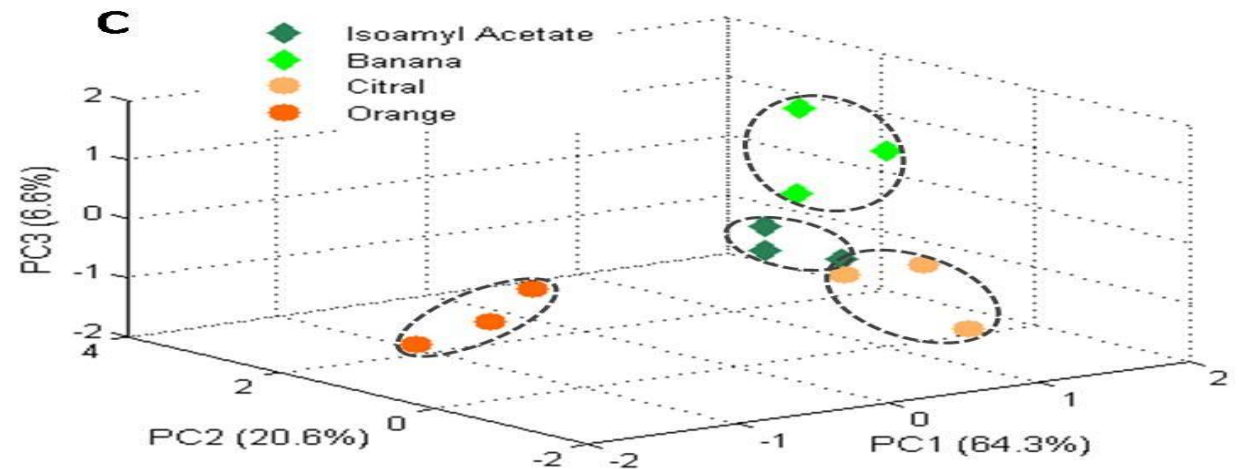
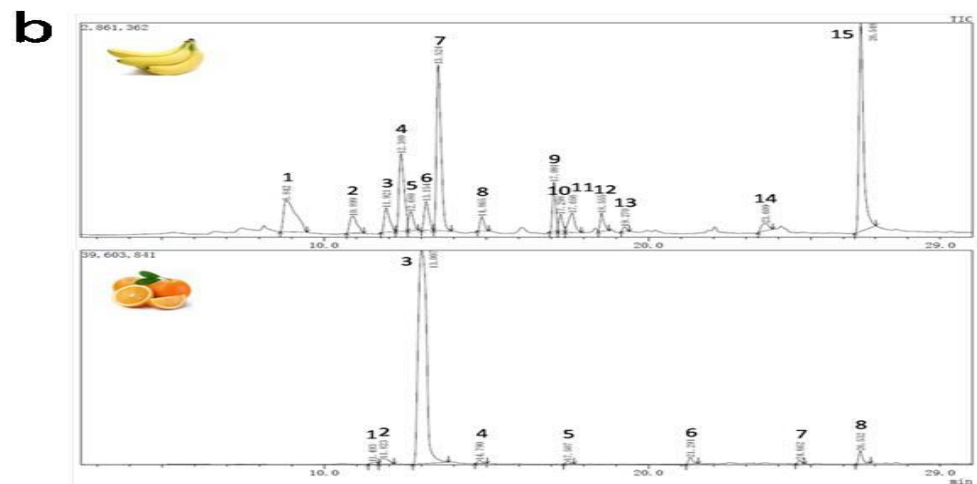
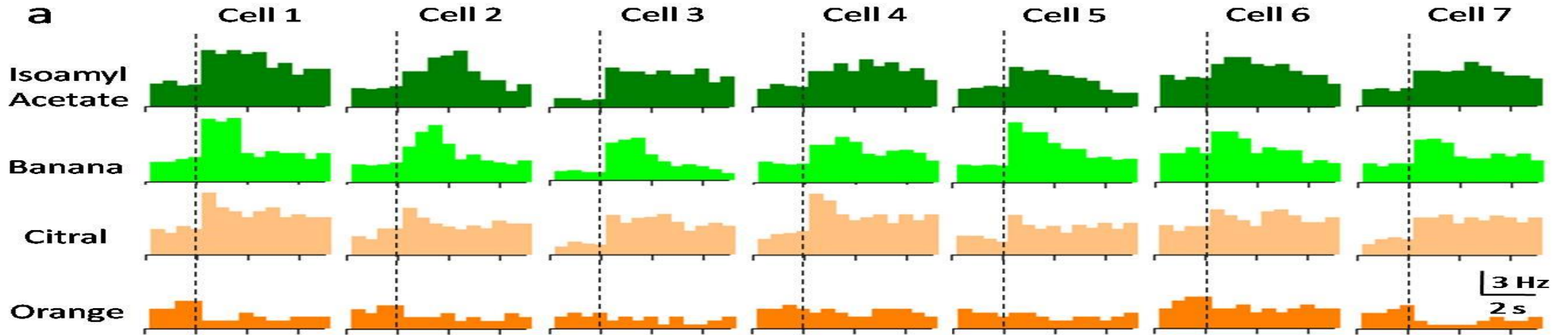
Mico/Nano Electrodes Arrays for Bioe-Nose *in Vivo*



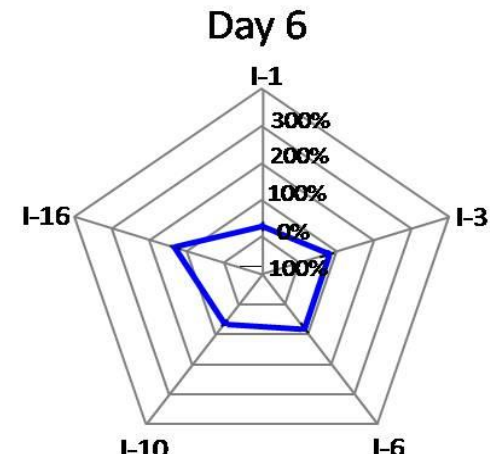
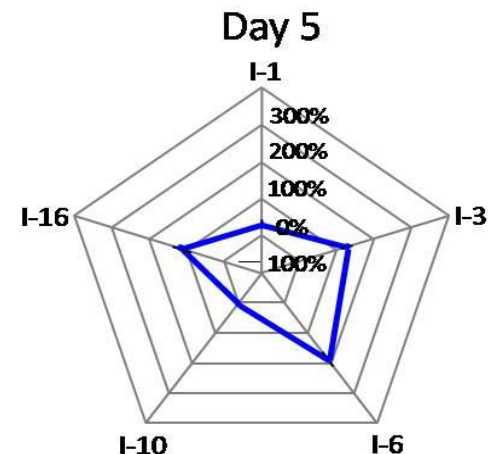
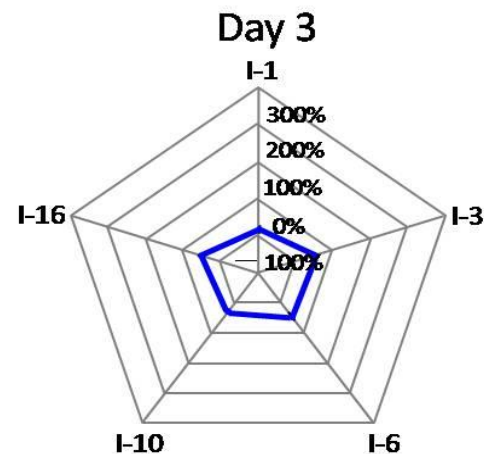
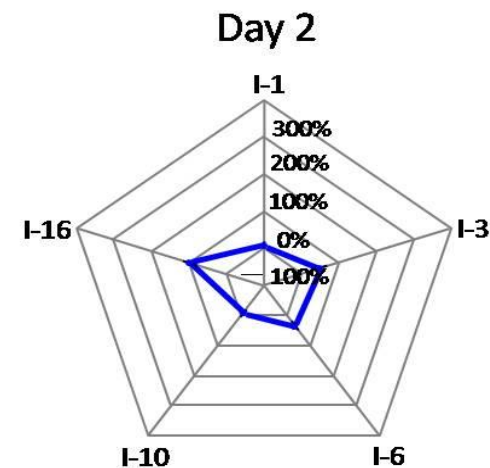
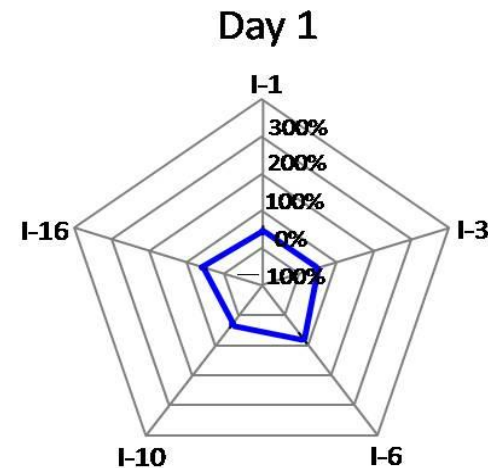
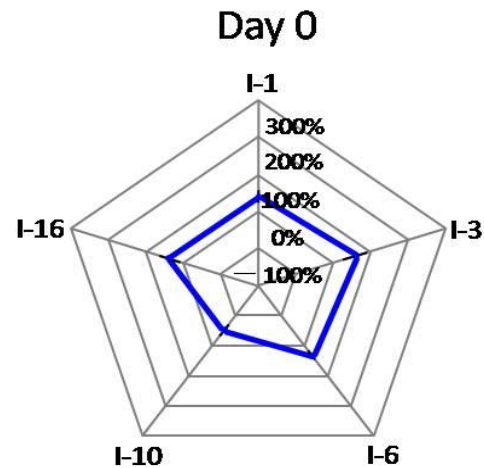
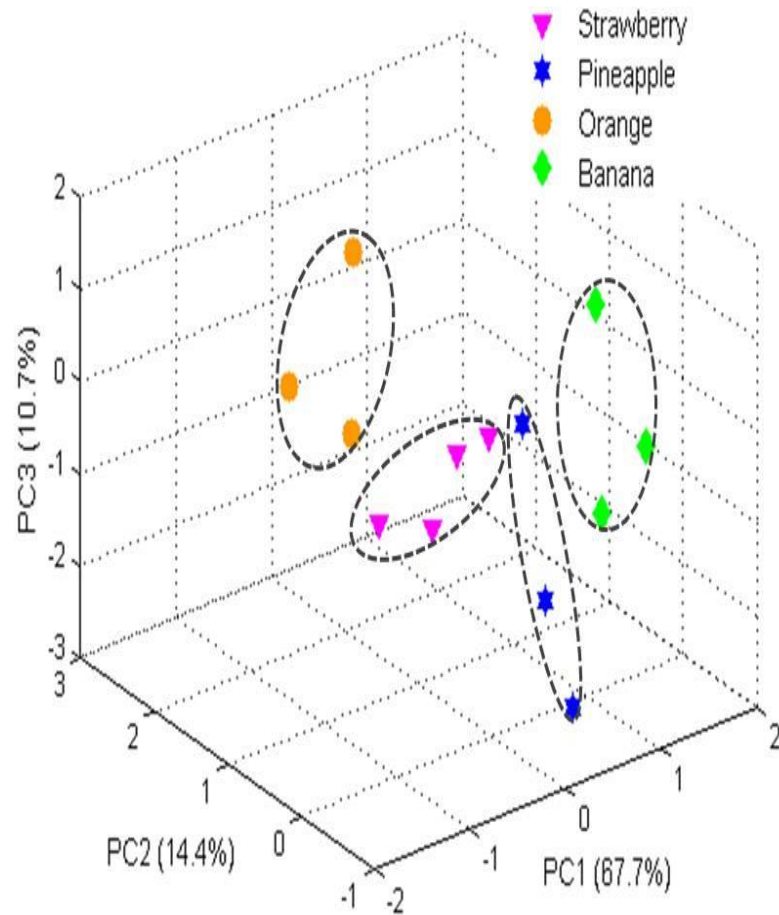
Odor detection and Signal Analysis of Bioe-Nose *in Vivo*



Odor detection and Signal Analysis of Bioe-Nose *in Vivo*



Odor Detection and Signal Analysis of Bioe-Nose *in Vivo*



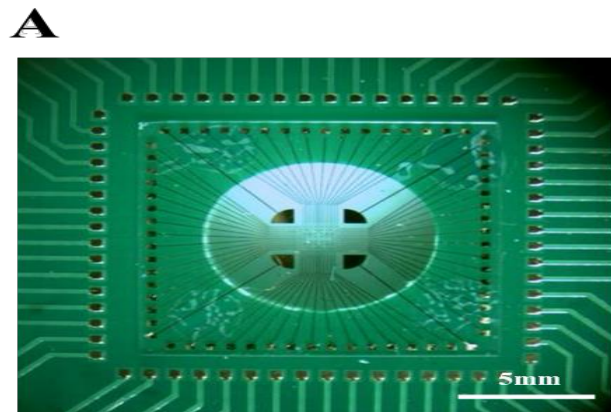
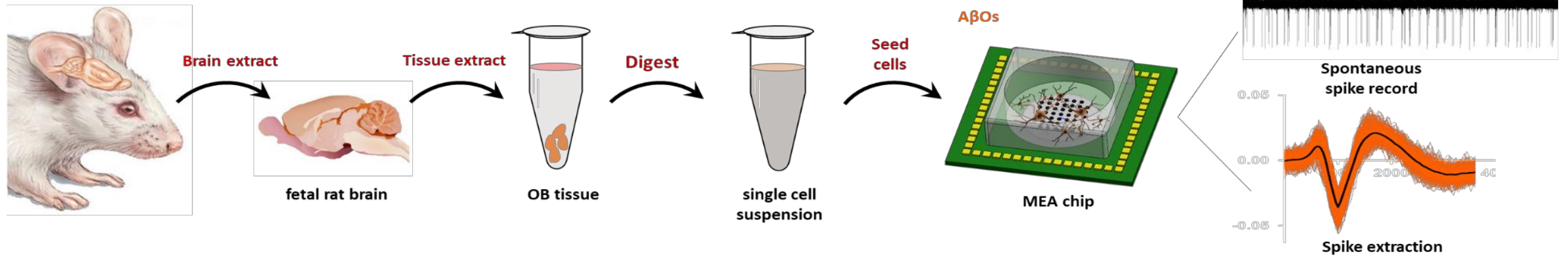


3nd Part

Applications of Bioe-Nose for Odor Perception

Bioe-Nose for AD disease Detection and Drug Screening in Therapy

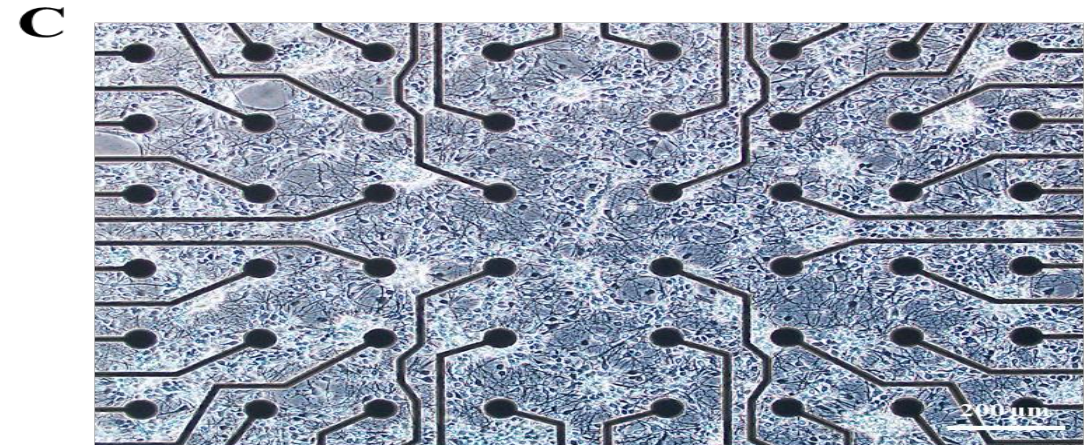
Olfactory Bulb Neuronal Network Chip-based Biosensor of Dysosmia Model in AD (Alzheimer's disease)



MEA Chip

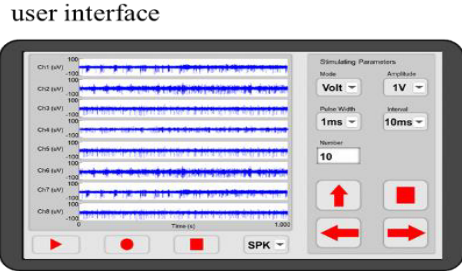


MEA System

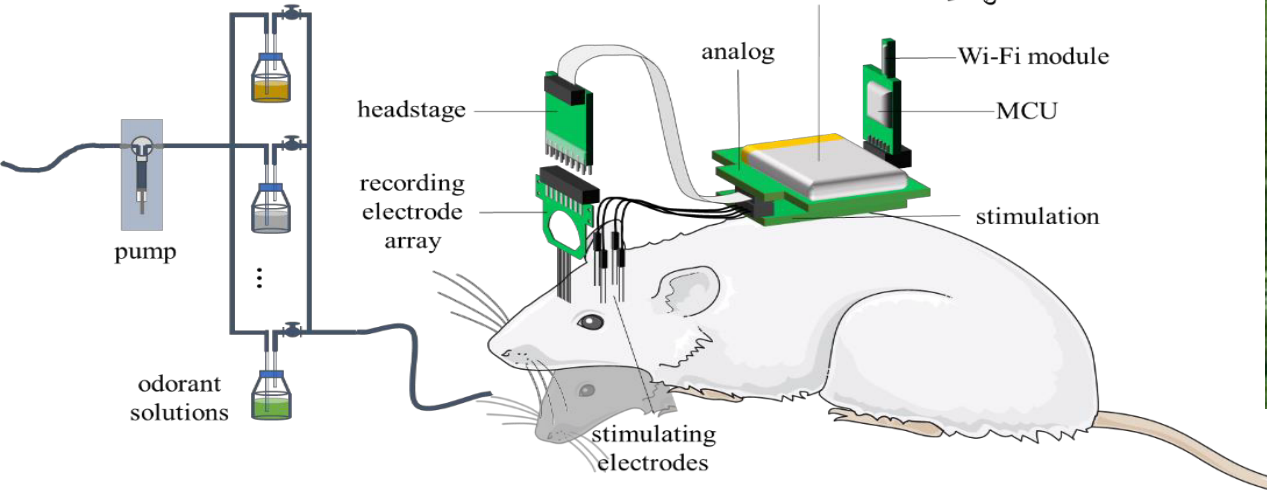
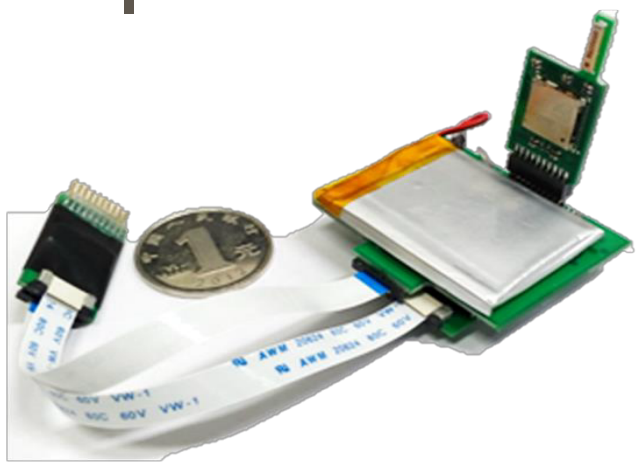


OB neuronal network on MEA

Animal Robot with Bioe-Nose *in vivo* for Hazardous Detection



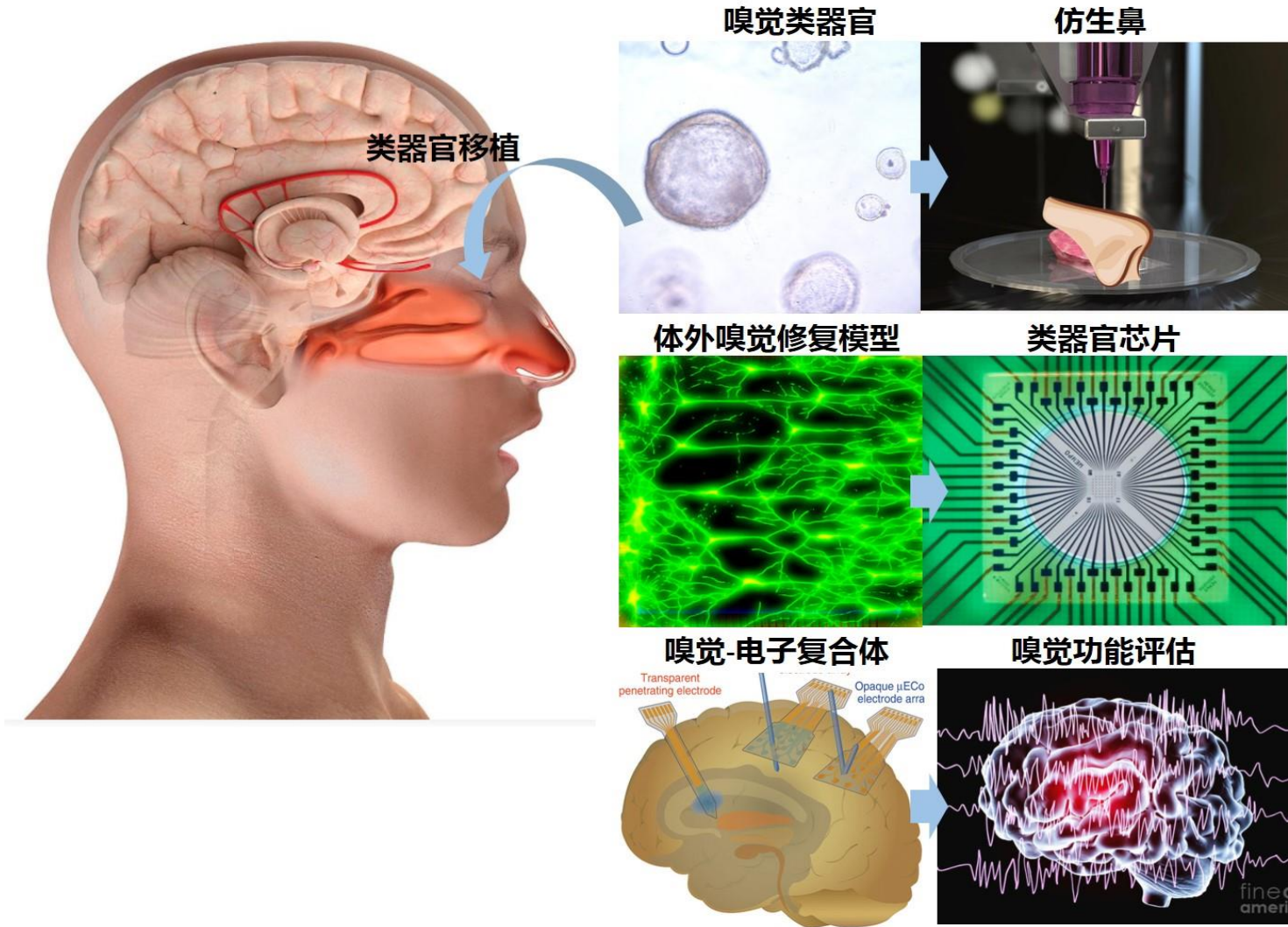
motion control instructions
electrophysiological data



Robots with Bioe-Nose for Food Quality Monitoring



Rehabilitation of Human Olfaction with Flexible Micro/Nano Bioe-Nose *in vivo*



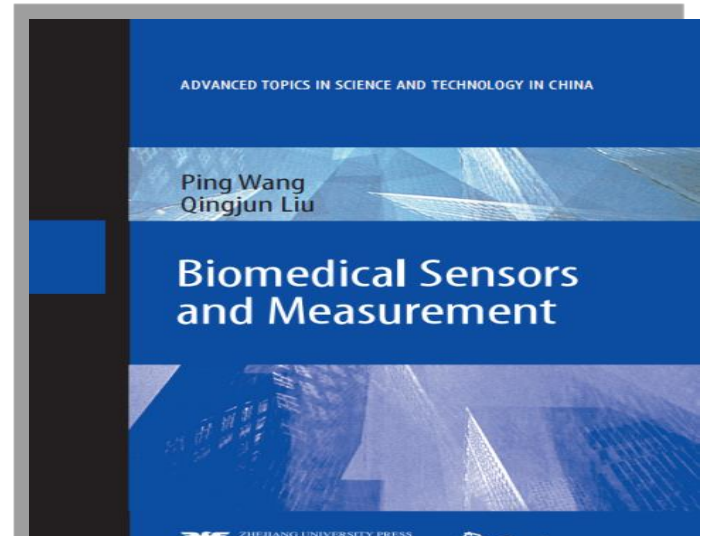
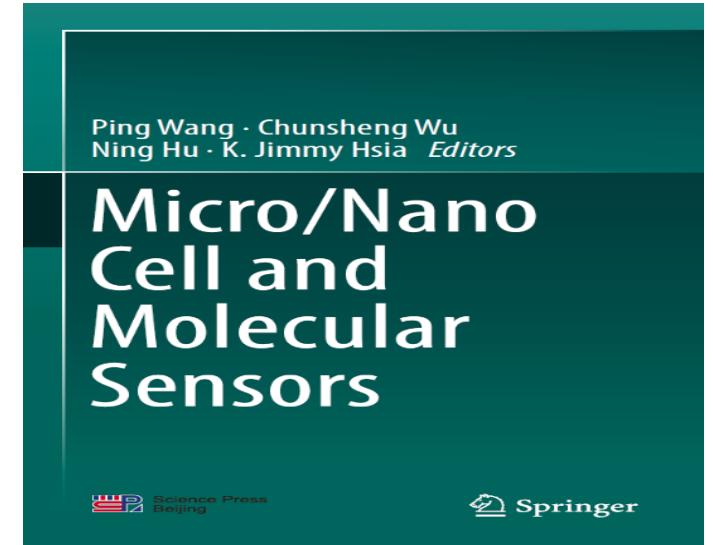
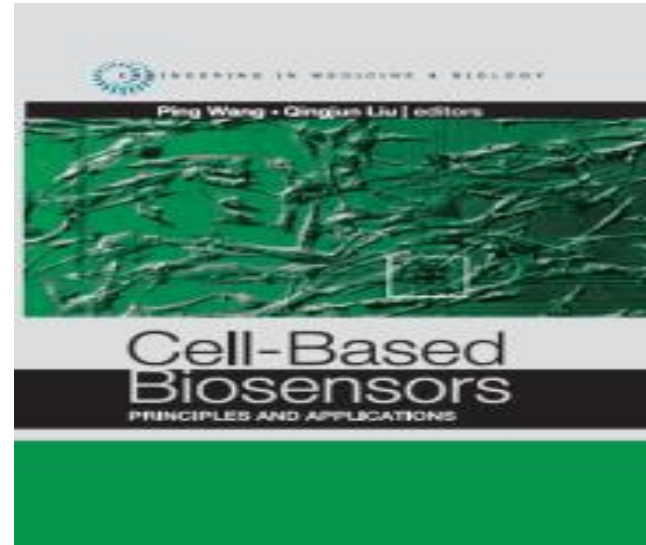
Olfactory regeneration and intelligent regulation

The complex is implanted in the nasal cavity

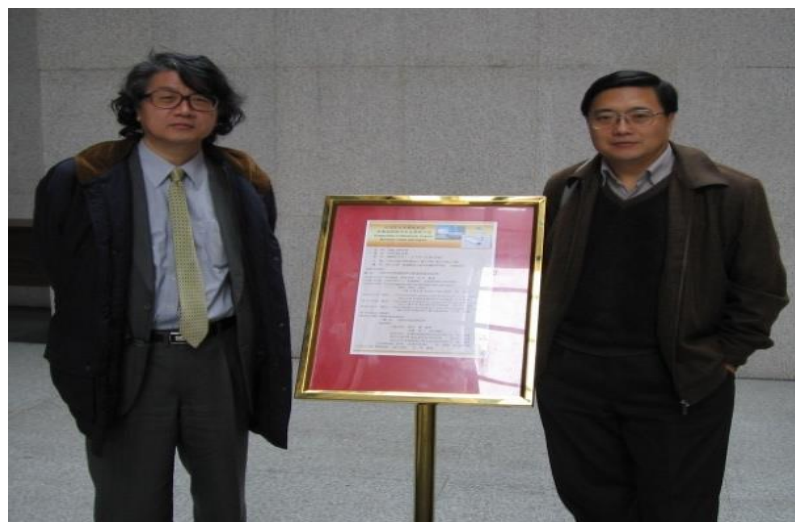
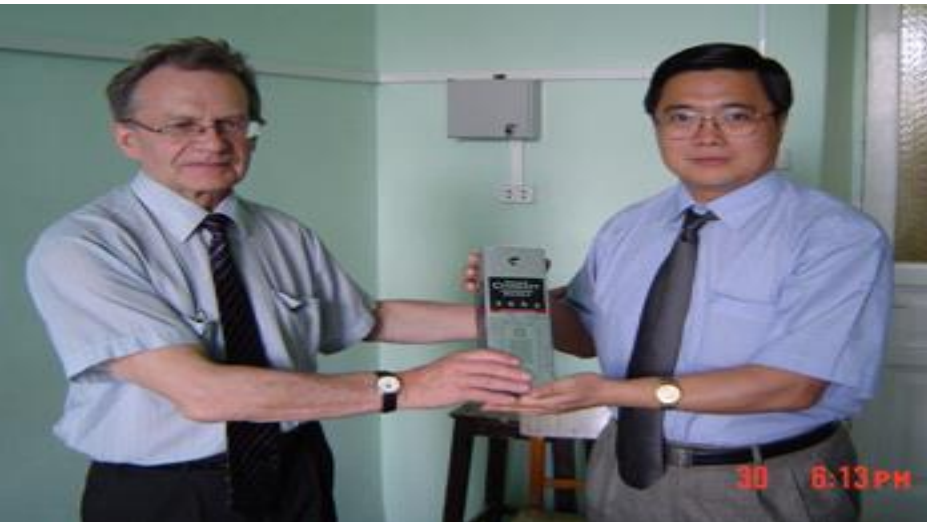
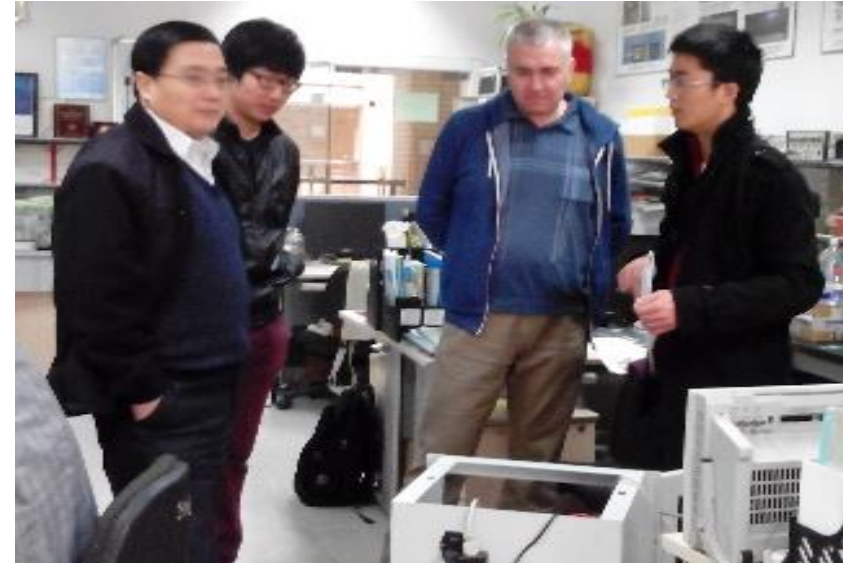
Flexible electrode and cell/organoid complex

Preparation of olfactory epithelial organoids

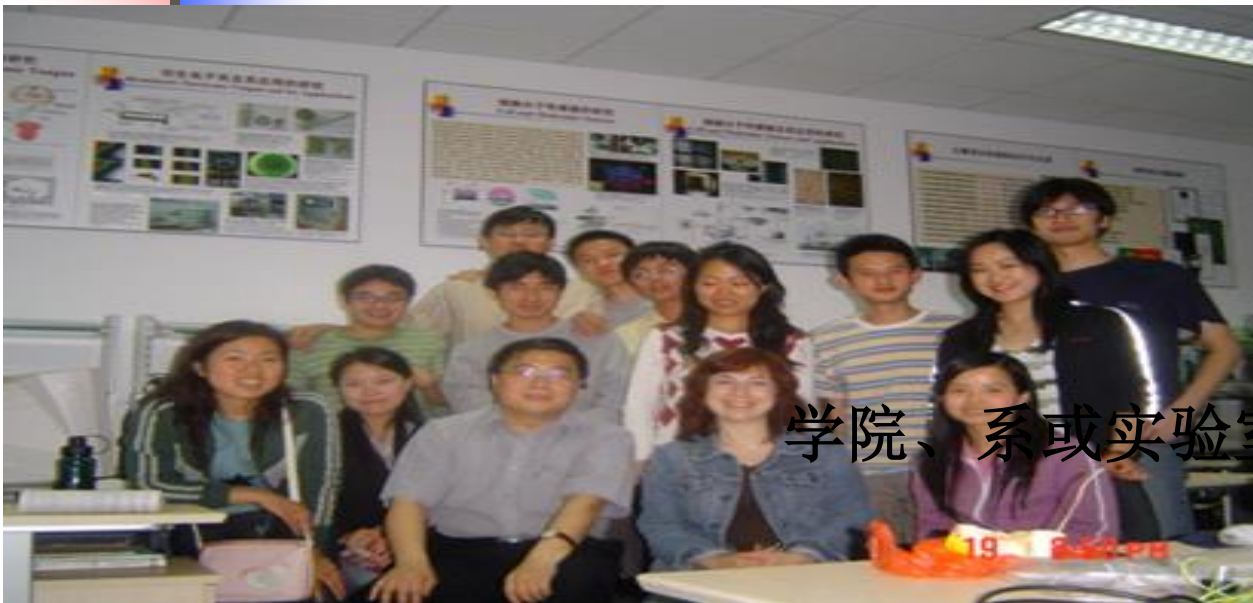
Our Some Published Books



International Exchanges and Cooperation



International Exchanges and Cooperation



学院、系或实验室等机构都可以





Thank you For your listening !



Ping Wang

***Biosensor National Special Laboratory
Department of Biomedical Engineering
Zhejiang University, Hangzhou ,China***

cnpwang@zju.edu.cn



Bioinspired Electronic Nose, Tongue & Recognition Algorithms

Hao Wan

**Key Laboratory for Biomedical Engineering of Ministry of Education, Biosensor National Special Laboratory,
Department of Biomedical Engineering, Zhejiang University, Hangzhou, China**

wh1816@zju.edu.cn





Outline

1. Dimensionality Reduction Methods

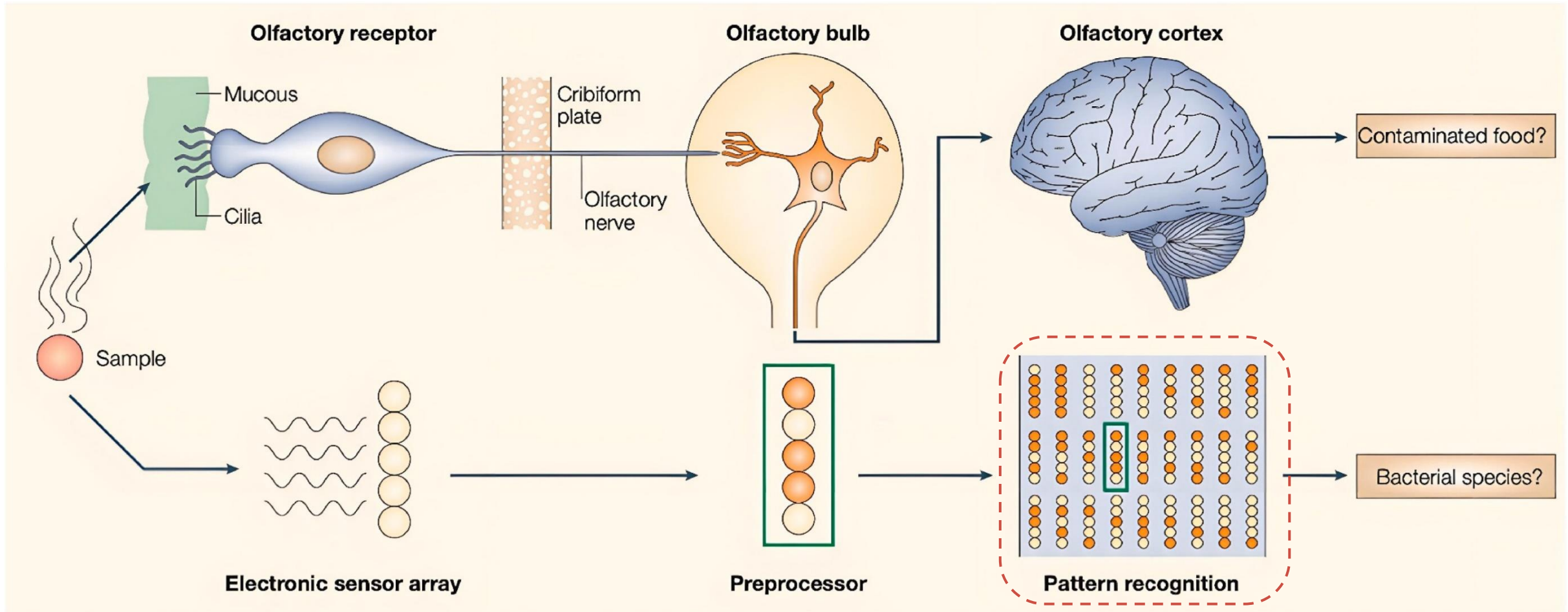
- PCA (Principal component analysis)
- LDA (Linear discriminant analysis)

2. Machine Learning & Neural Network Algorithms

- SVM (Support vector machine)
- ANN (Artificial neural network)
- CNN (Convolutional neural network)
- RNN/LSTM (Recurrent neural network)
- SNN (Spiking neural network)

3. Challenges and Future Perspectives





Pattern recognition algorithms are the key component in both electronic nose and electronic tongue, enabling accurate odor recognition across diverse data types.

Classification Metrics

| Metric | Equation | Description |
|-------------------------|---|---|
| Accuracy | $\frac{TP + TN}{TP + TN + FP + FN}$ | Ratio of correctly predicted samples to total predicted samples |
| Precision | $\frac{TP}{TP + FP}$ | Ratio of correctly predicted positive samples to the total number of positive samples predicted |
| Sensitivity (Recall) | $\frac{TP}{TP + FN}$ | Ratio of correctly predicted positive samples to the total number of true positive samples |
| Specificity | $\frac{TN}{TN + FP}$ | Ratio of correctly predicted negative samples to the total number of real negative samples |
| F1-Score | $2 * \frac{Precision * Recall}{Precision + Recall}$ | Harmonic mean of precision and recall |

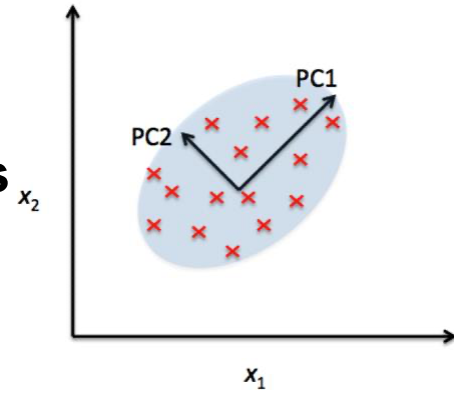


Regression Metrics

| Metric | Equation | Description |
|--------|--|--|
| MAE | $\text{MAE}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y})$ | Average of the absolute error |
| MSE | $\text{MSE}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y})^2$ | Average of the square error |
| RMSE | $\text{RMSE}(y, \hat{y}) = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y})^2}$ | Average of the square rooted error |
| MSLE | $\text{MSLE}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^n (\ln(1 + y_i) - \ln(1 + \hat{y}))^2$ | Average of the squared logarithmic error |
| MAPE | $\text{MAPE}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^n \frac{ y_i - \hat{y} }{\max(\epsilon, y_i)}$ | Ratio of absolute error and true value |
| R2 | $R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$ | Ratio of regression sum of squares to total sum of squares |

Principal Component Analysis (PCA)

PCA is an unsupervised linear dimensionality reduction method that transforms correlated high-dimensional data into a lower-dimensional space while preserving the most important variance.



- Transforms original variables into orthogonal principal components
- Principal components are derived from eigen decomposition of the covariance matrix

Characteristics

- ❑ First component captures the maximum variance
- ❑ Subsequent components capture decreasing variance
- ❑ All components are mutually orthogonal

Advantages:

- ❑ Reduces dimensionality
- ❑ Improves visualization and interpretability
- ❑ Preserves key information

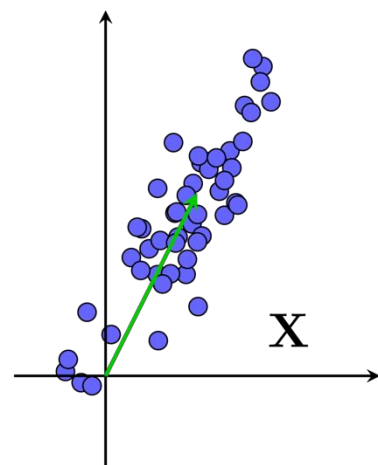


Principal Component Analysis (PCA)

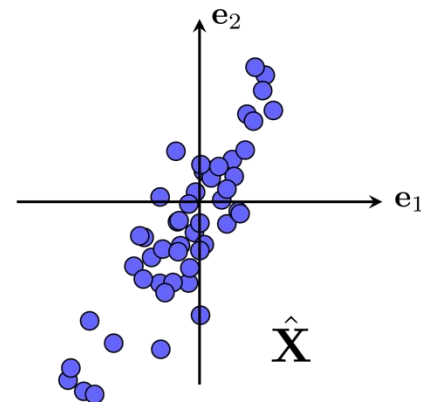
Steps in PCA

- Standardization
- Covariance matrix computation
- Eigenvalue and eigenvector computation
- Selection of principal components
- Projection of data onto principal component axes

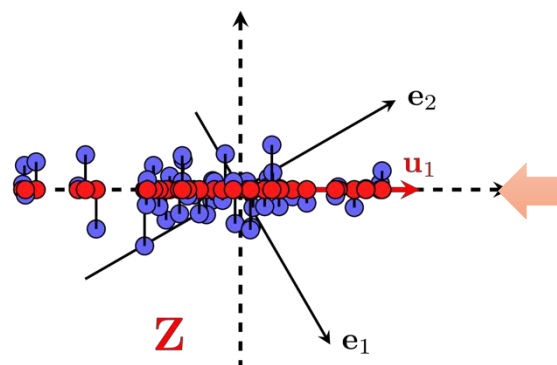
1. Find mean vector



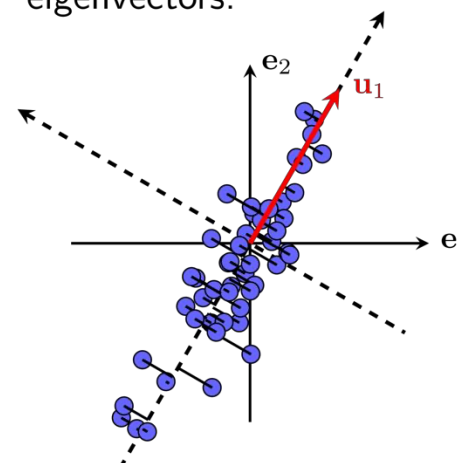
2. Subtract mean



7. Obtain projected points in low dimension.



6. Project data to selected eigenvectors.

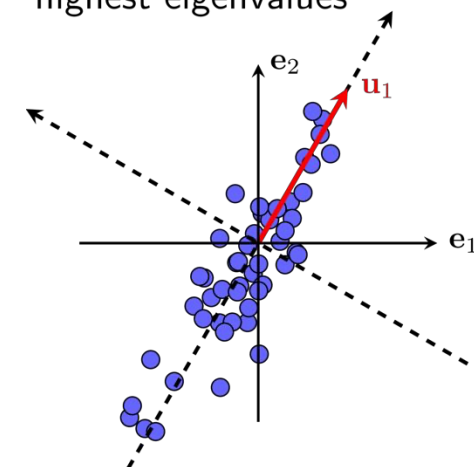


3. Compute covariance matrix:

$$S = \frac{1}{N} \hat{X} \hat{X}^T$$

4. Compute eigenvalues and eigenvectors of **S**:
 $(\lambda_1, \mathbf{u}_1), \dots, (\lambda_D, \mathbf{u}_D)$
 Remember the orthonormality of \mathbf{u}_i .

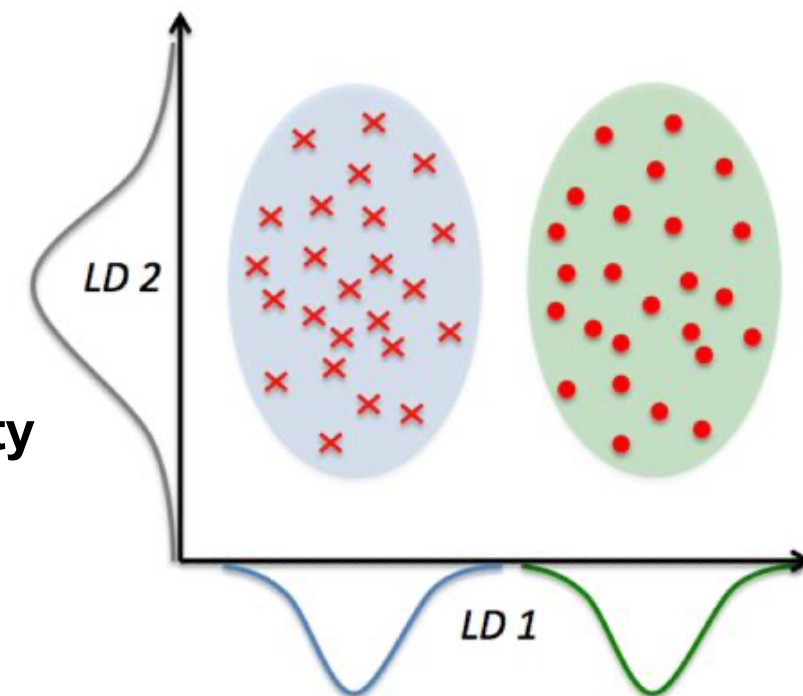
5. Pick K eigenvectors w. highest eigenvalues



Linear discriminant analysis (LDA)

LDA is a **supervised** dimensionality reduction method that projects data into a lower-dimensional space while maximizing class separability by minimizing intra-class distance and maximizing inter-class distance.

- Uses class label information (supervised learning)
- Maximizes between-class separability and minimizes within-class variance
- After training, classification can be performed using probability density functions in the projected space



PCA vs. LDA

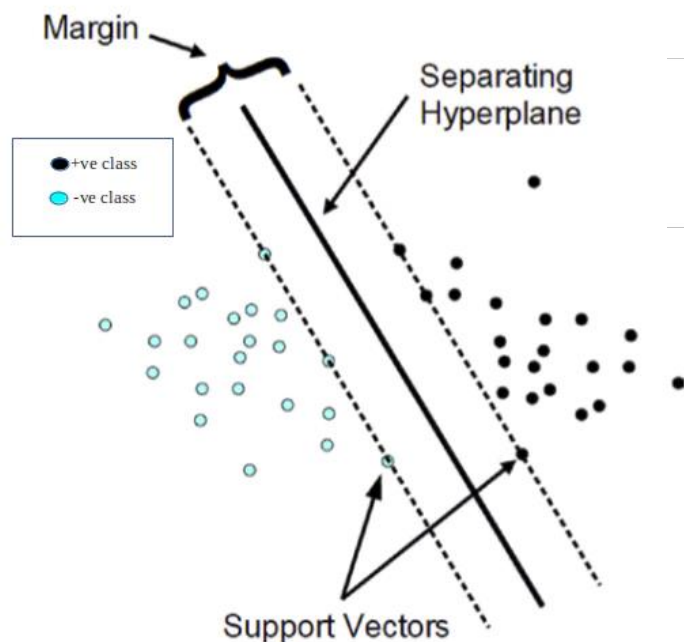
| Aspect | PCA | LDA |
|-------------------|------------------------------------|--|
| Learning type | Unsupervised | Supervised |
| Objective | Maximize variance | Maximize class separability |
| Uses labels | No | Yes |
| Optimization goal | Preserve global data structure | Improve class discrimination |
| Projection basis | Eigenvectors of covariance matrix | Eigenvectors of between/within-class scatter |
| Output features | Principal components | Discriminant components |
| Typical use | Feature compression, visualization | Classification tasks, feature compression, visualization |
| Limitation | Ignores class information | Sensitive to small sample size |



Support vector machine (SVM)

SVM is a **supervised** machine learning algorithm used for **classification and regression tasks**. It tries to find the best boundary known as hyperplane that separates different classes in the data.

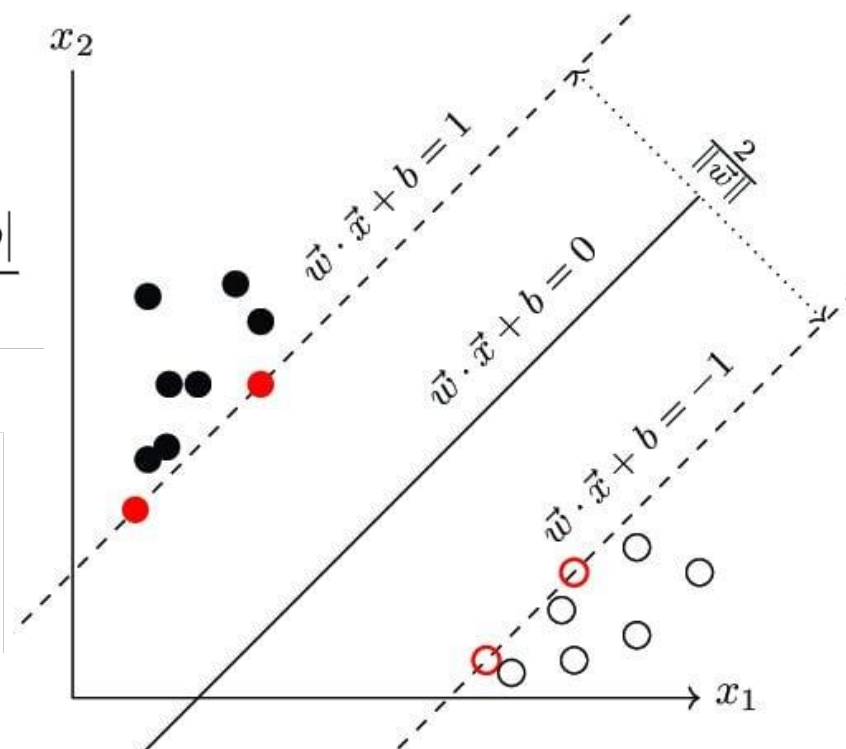
- **Core:** Find the best separating hyperplane/
Decision boundary



$$\begin{cases} w^T x + b \geq 1 & y = 1 \\ w^T x + b \leq -1 & y = -1 \end{cases}$$

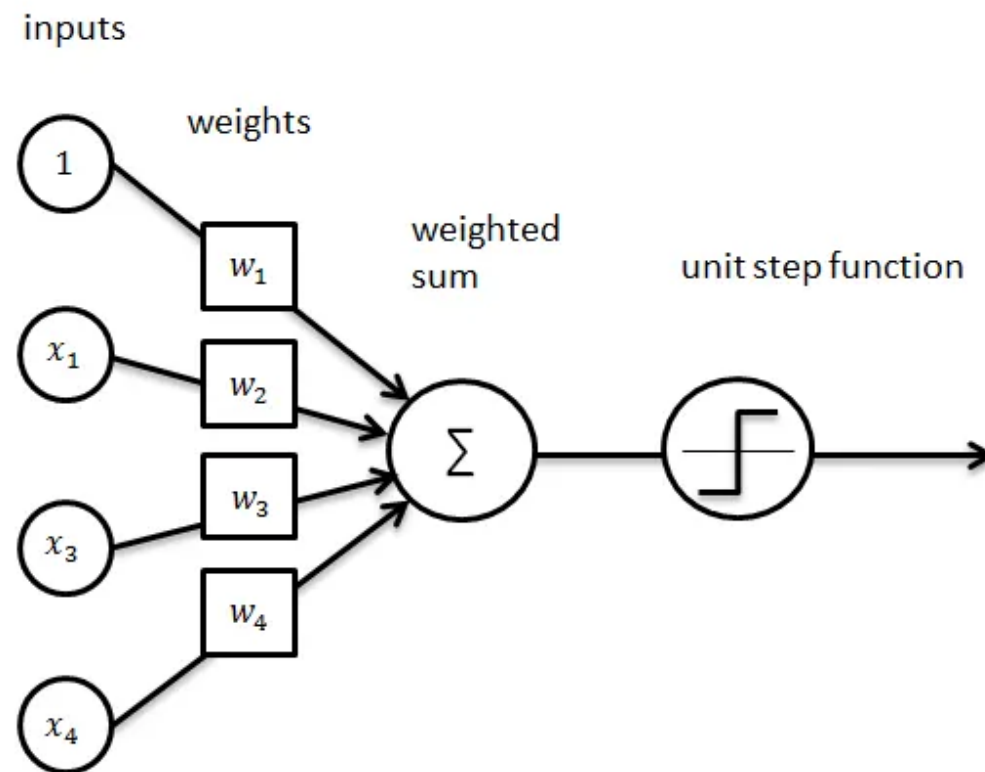
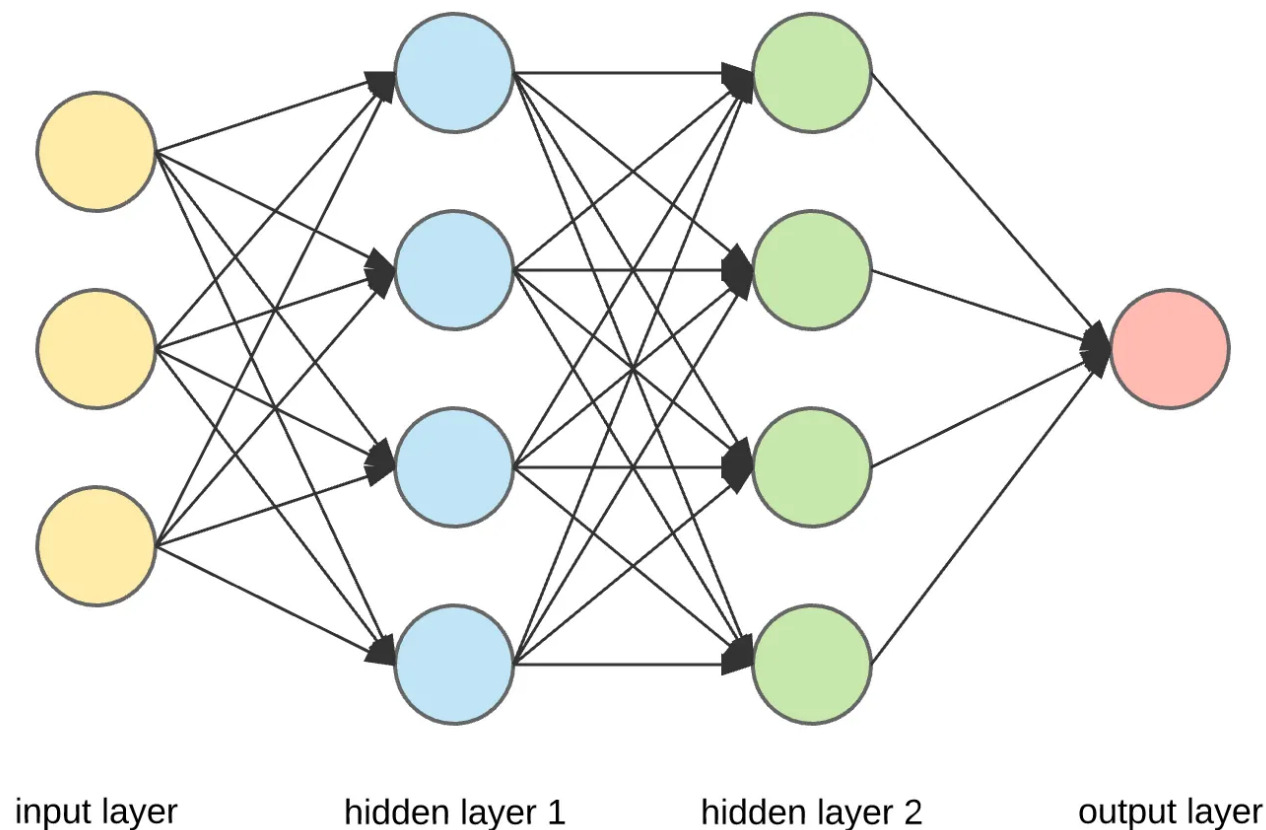
$$d = \frac{|w^T x + b|}{\|w\|}$$

$$\begin{aligned} \min f(w) &= \min \frac{1}{2} \|w\|^2 \\ \text{s.t. } g_i(w) &= 1 - y_i (w^T x_i + b) \leq 0 \end{aligned}$$



Artificial Neural Networks (ANNs)

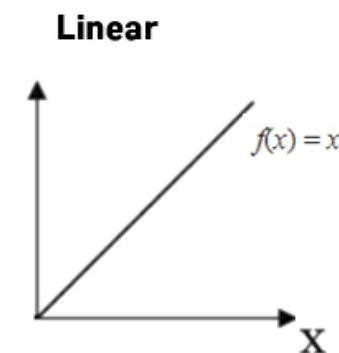
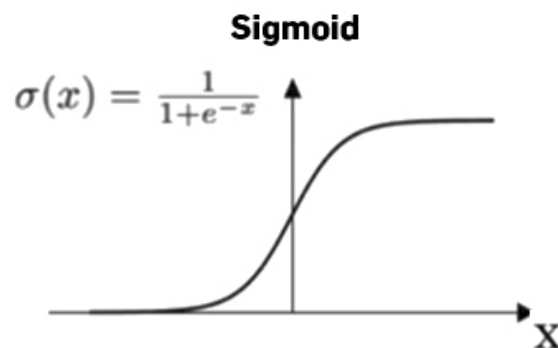
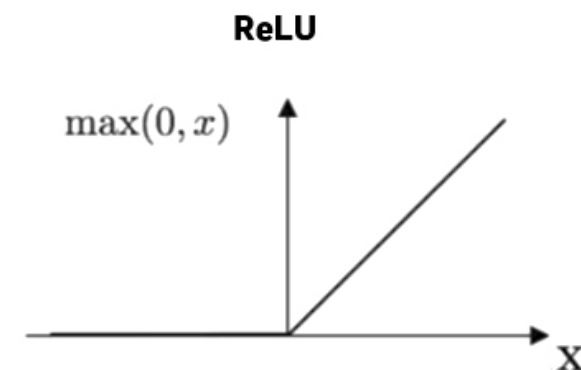
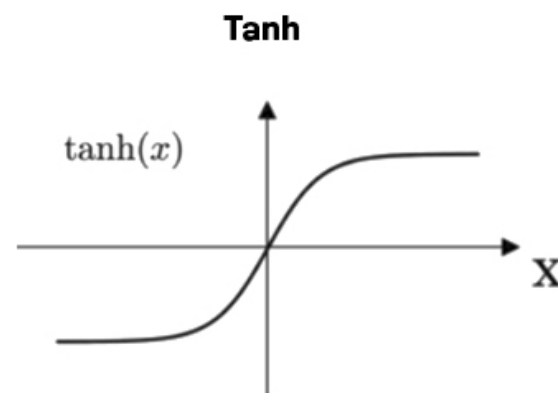
Artificial Neural Network (ANN) is a computational model inspired by the biological nervous system, capable of learning complex nonlinear relationships from data through interconnected artificial neurons.



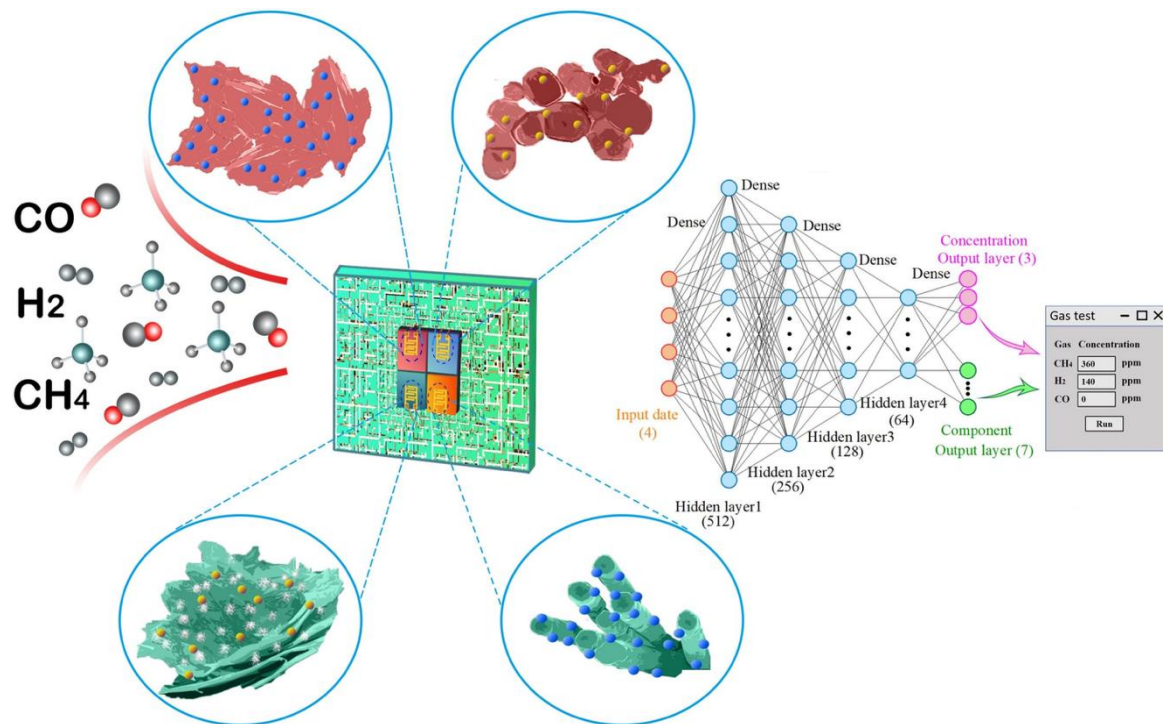
Activation functions

Activation functions introduce non-linearity into neural networks, enabling them to learn complex mappings between inputs and outputs.

- ✓ ReLU improves training efficiency by alleviating the vanishing gradient problem
- ✓ ReLU maintains stronger gradient flow, enabling effective training of deeper architectures.
- ✓ ReLU and its variants (e.g., Leaky ReLU) are commonly used in hidden layers for efficient learning.

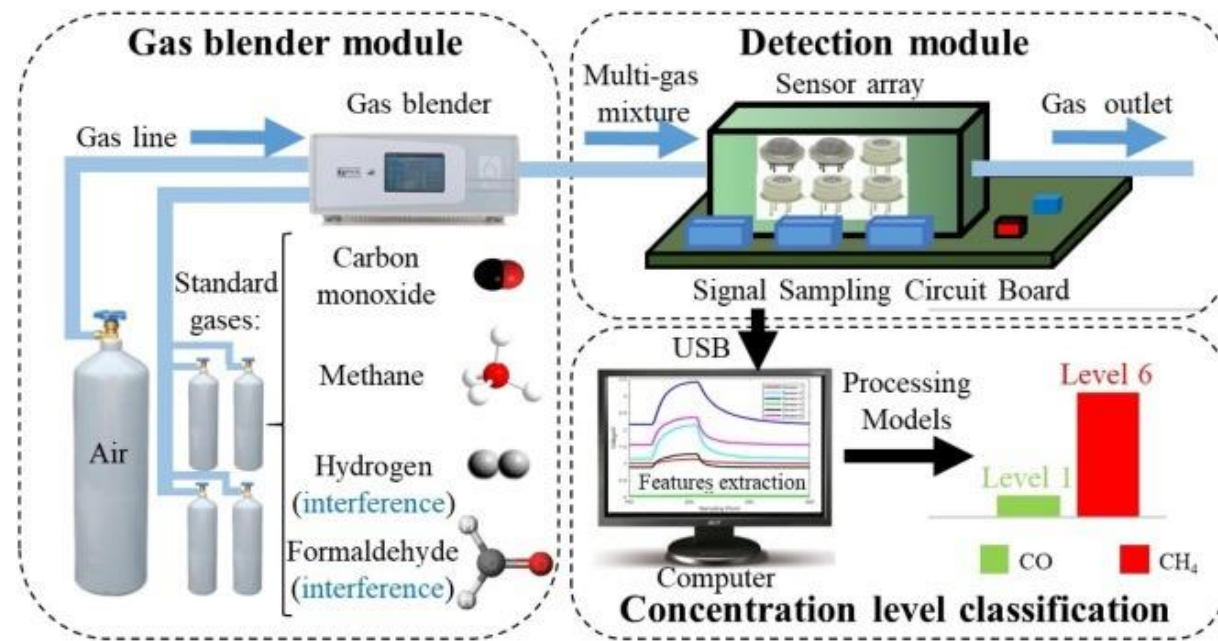


ANNs in Electronic Nose Applications



Artificial Neural Network for The Quantitative Recognition of Common Fuel Gases

Li W, Qi G, Ding H, et al. A metal oxide-based E-nose employing backpropagation artificial neural network for the quantitative recognition of common fuel gases[J]. Chemical Engineering Journal, 2025, 519: 165631.



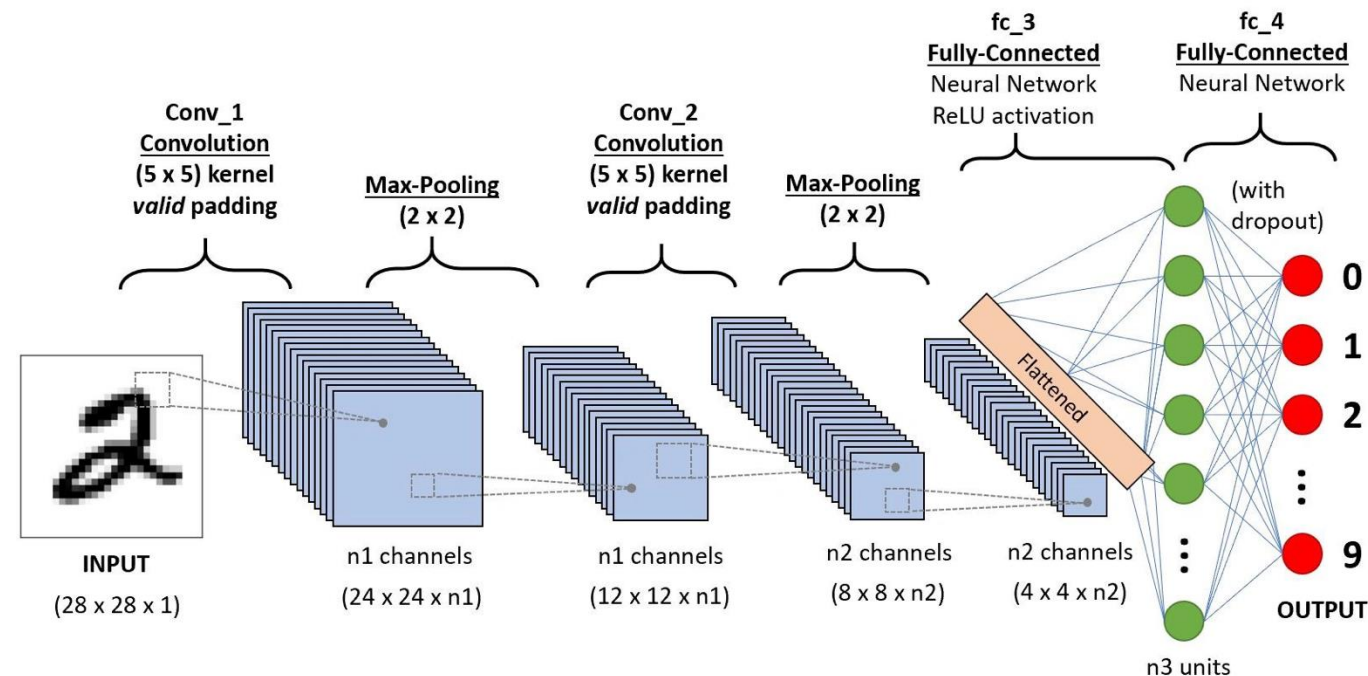
A miniaturized electronic nose with artificial neural network for anti-interference detection of mixed indoor hazardous gases

Zhang J, Xue Y, Sun Q, et al. A miniaturized electronic nose with artificial neural network for anti-interference detection of mixed indoor hazardous gases[J]. Sensors and Actuators B: Chemical, 2021, 326: 128822.

Convolutional Neural Networks (CNNs)

Convolutional Neural Network (CNN) is a deep learning architecture that automatically extracts local features through convolution operations and hierarchical representations.

- Automatic feature extraction
- Local receptive fields and shared weights
- Strong nonlinear representation capability
- Robust to noise and signal variation
- Efficient hierarchical feature learning

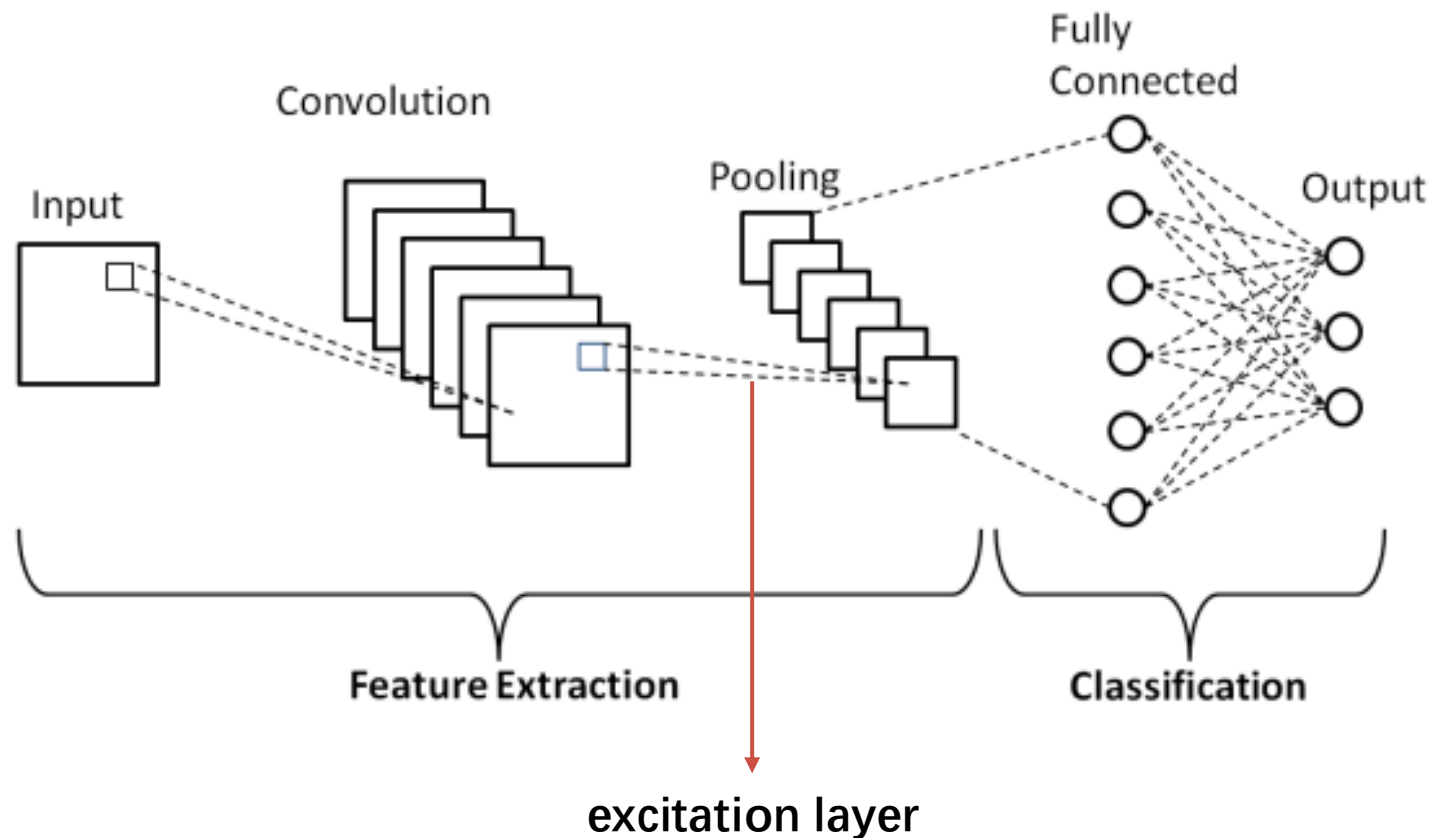


E-nose data as image-like inputs for CNNs.

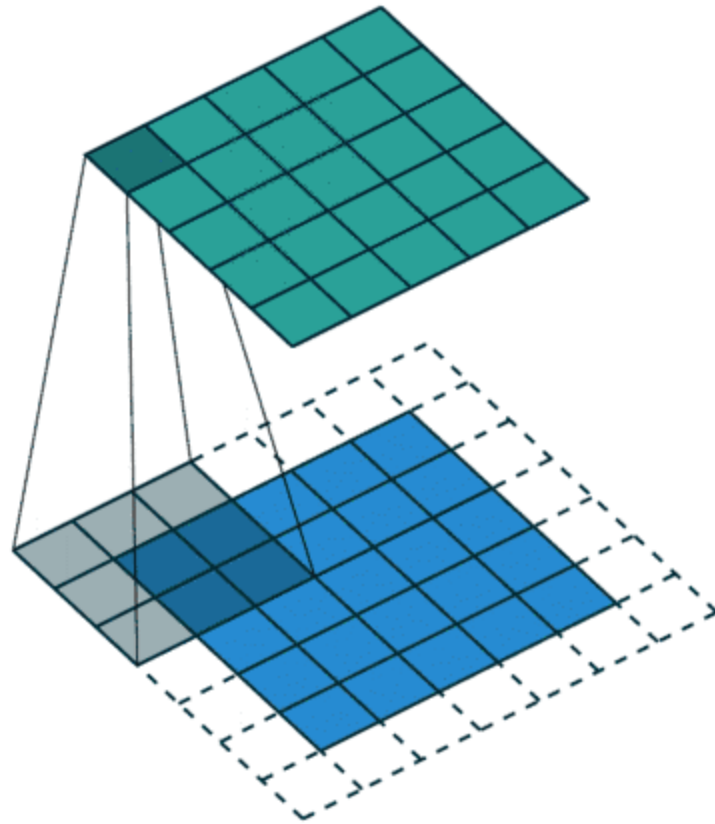
Convolutional Neural Networks (CNNs)

CNN consists of five main layers:

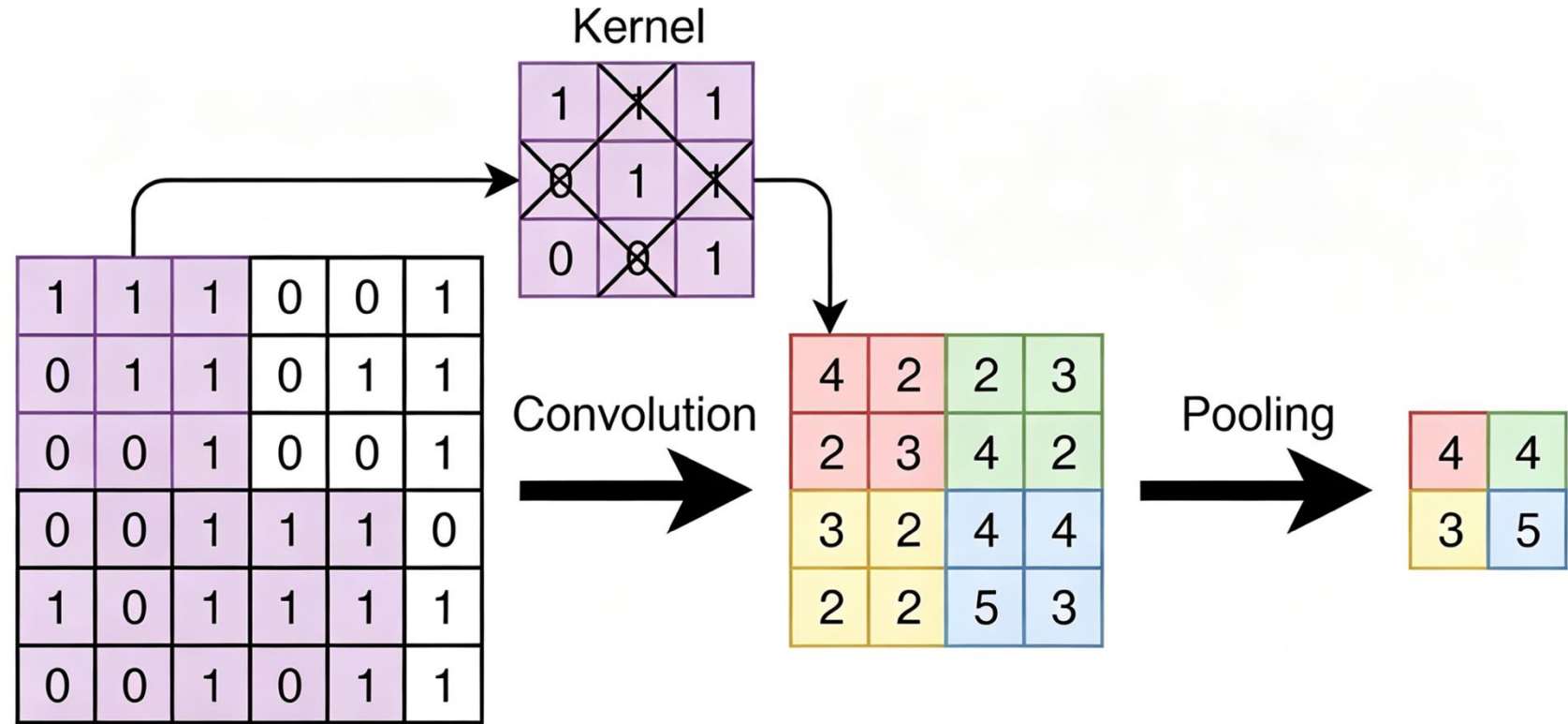
- data input
- convolution calculation
- activation function
- pooling layer
- fully connected



Convolutional Neural Networks (CNNs)



Convolution



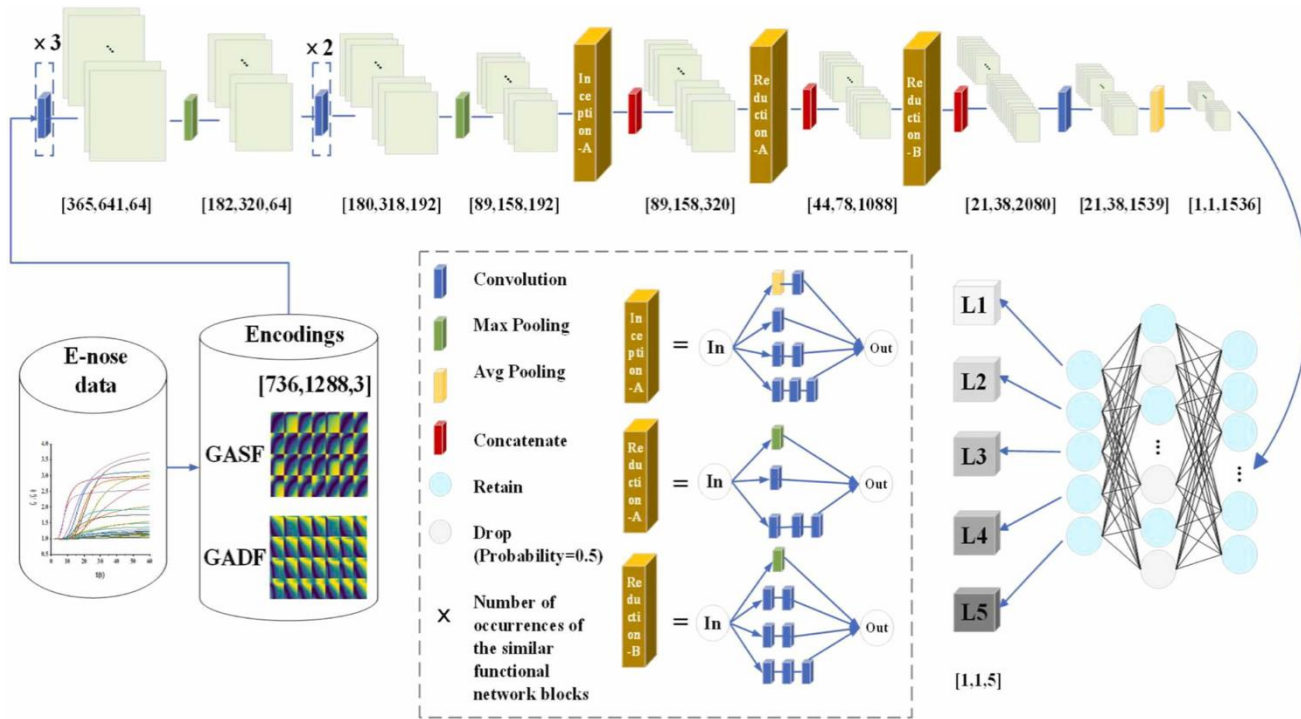
Convolve with a 3x3 kernel and stride 1

Max pool with a 2x2 filter and stride 2

Convolution And Pooling

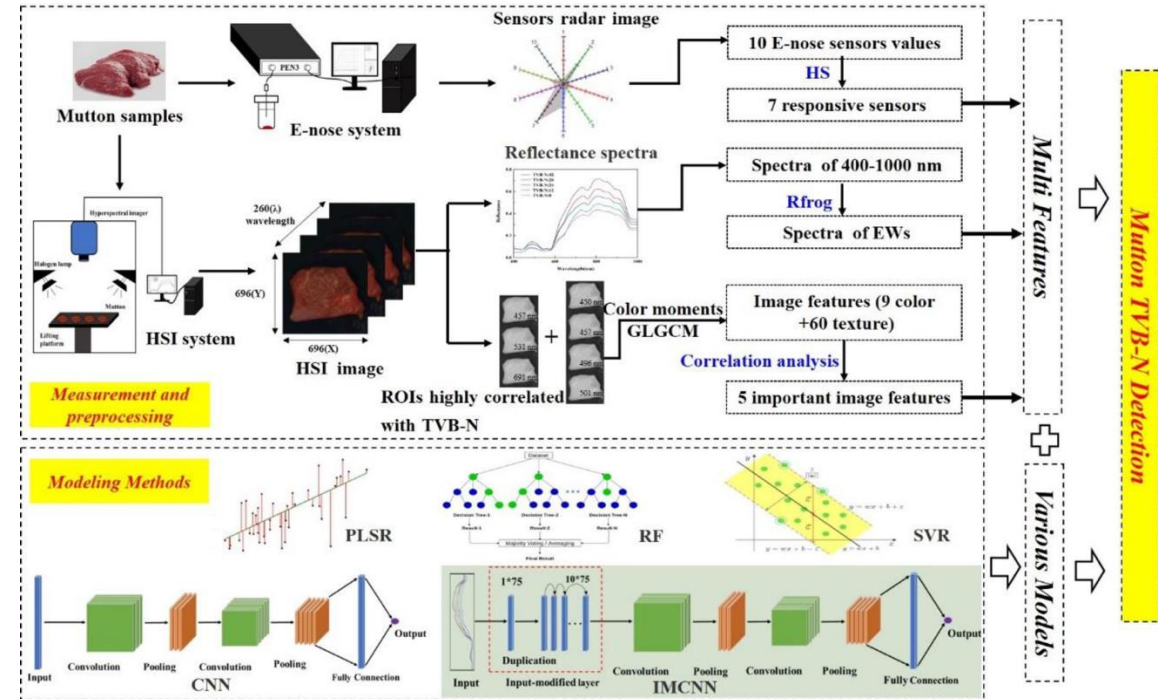


CNNs in Electronic Nose Applications



Gramian angular field-CNN Algorithm for Odor Intensity Classification

Xiong L, He M, Hu C, et al. Image presentation and effective classification of odor intensity levels using multi-channel electronic nose technology combined with GASF and CNN[J]. Sensors and Actuators B: Chemical, 2023, 395: 134492.

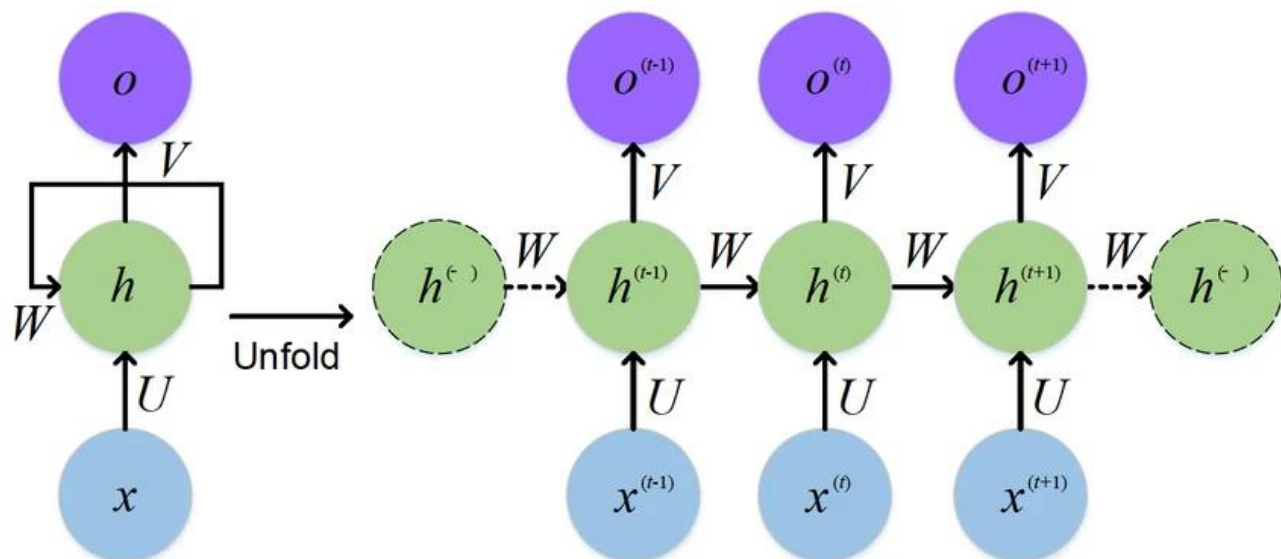


Fusion of electronic nose and hyperspectral imaging for mutton freshness detection using input-modified convolutional neural network

Liu C, Chu Z, Weng S, et al. Fusion of electronic nose and hyperspectral imaging for mutton freshness detection using input-modified convolutional neural network[J]. Food Chemistry, 2022, 385: 132651.

Recurrent Neural Networks (RNNs)

RNN is a neural network architecture designed for processing sequential and time-series data through recurrent connections and hidden memory states.



$$\mathbf{a}^{(t)} = \mathbf{b} + \mathbf{W}\mathbf{h}^{(t-1)} + \mathbf{U}\mathbf{x}^{(t)}$$

$$\mathbf{h}^{(t)} = \tanh(\mathbf{a}^{(t)})$$

$$\mathbf{o}^{(t)} = \mathbf{c} + \mathbf{V}\mathbf{h}^{(t)}$$

$$\hat{\mathbf{y}}^{(t)} = \text{softmax}(\mathbf{o}^{(t)})$$

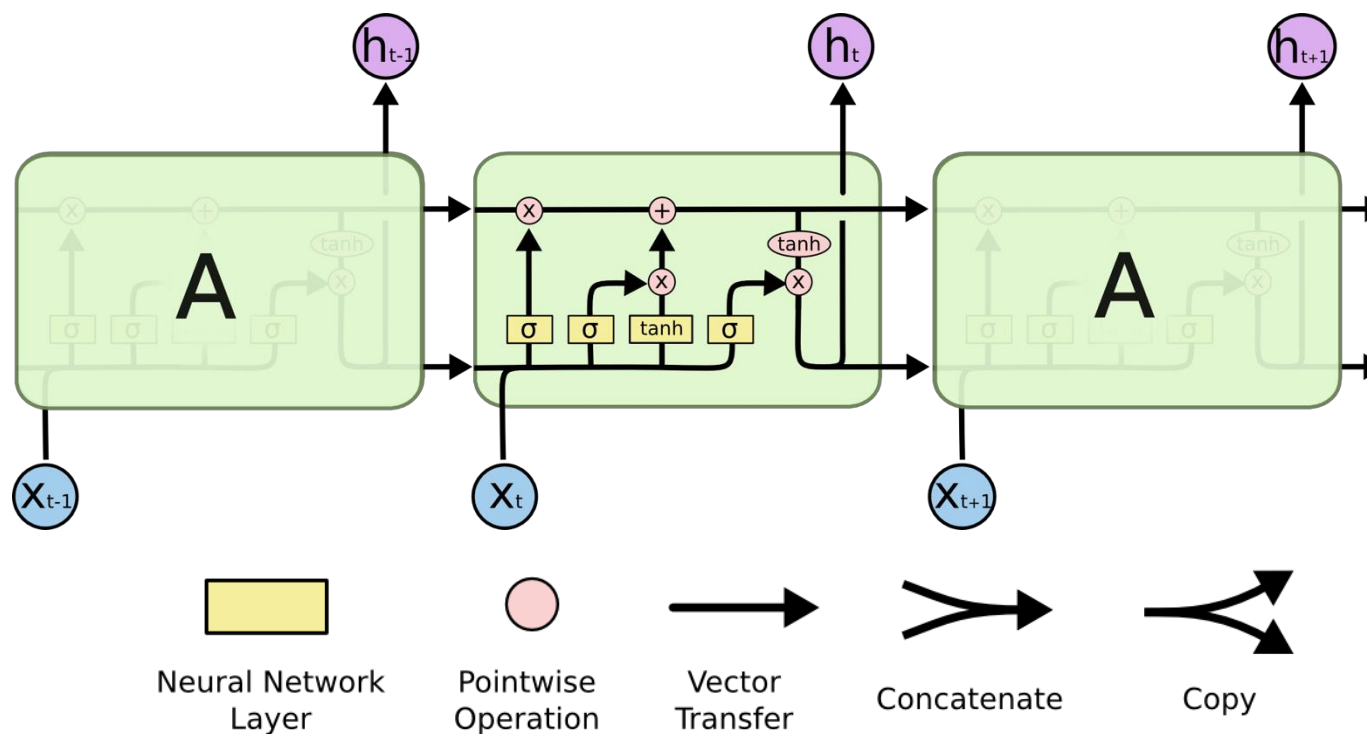
- ◆ Processes sequential/time-series data
- ◆ Hidden states retain historical information
- ◆ Suitable for variable-length input sequences
- ◆ Temporal dependencies modeled through recurrent connections

Limitations

- Difficult to learn long-term dependencies
- Gradient vanishing/exploding problem

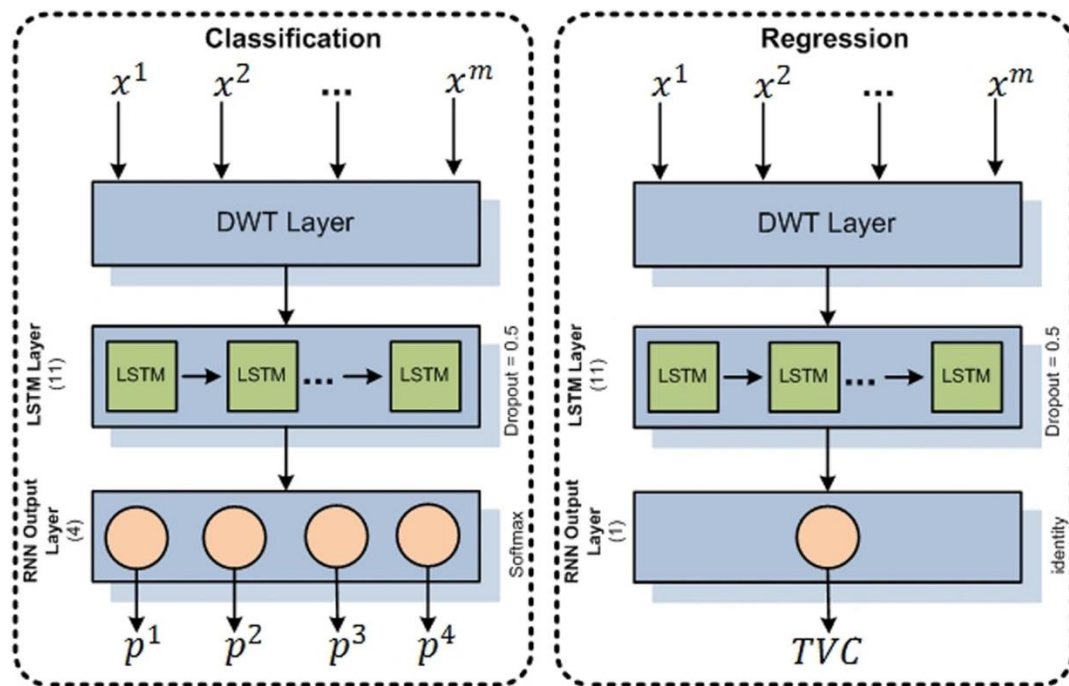
Long Short Term Memory network (LSTM)

LSTM is an improved RNN architecture that introduces memory cells and gating mechanisms to overcome long-term dependency problems.



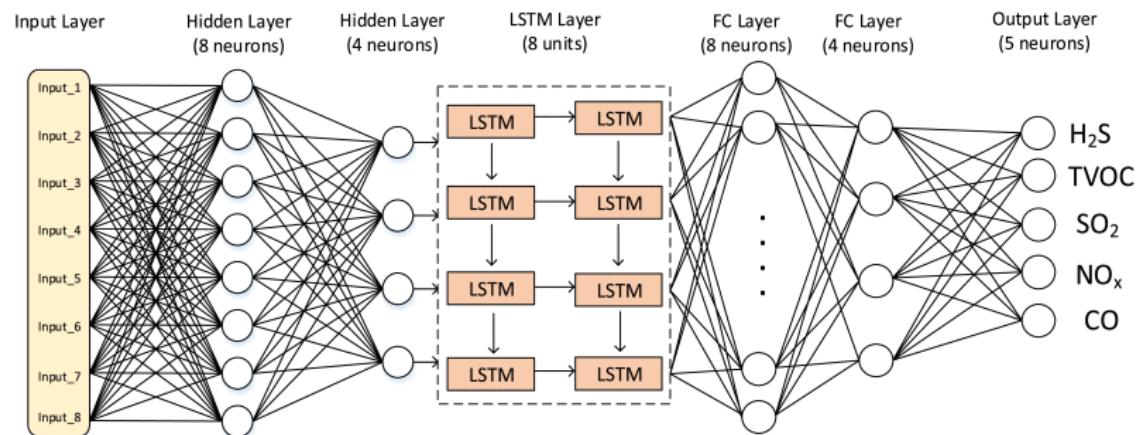
an LSTM contains four interacting layers

RNN/LSTM for E-Nose Applications



DWTLSTM for electronic nose signal processing in beef quality monitoring

Wijaya D R, Samo R, Zulaika E. DWTLSTM for electronic nose signal processing in beef quality monitoring[J]. Sensors and Actuators B: Chemical, 2021, 326: 128931.

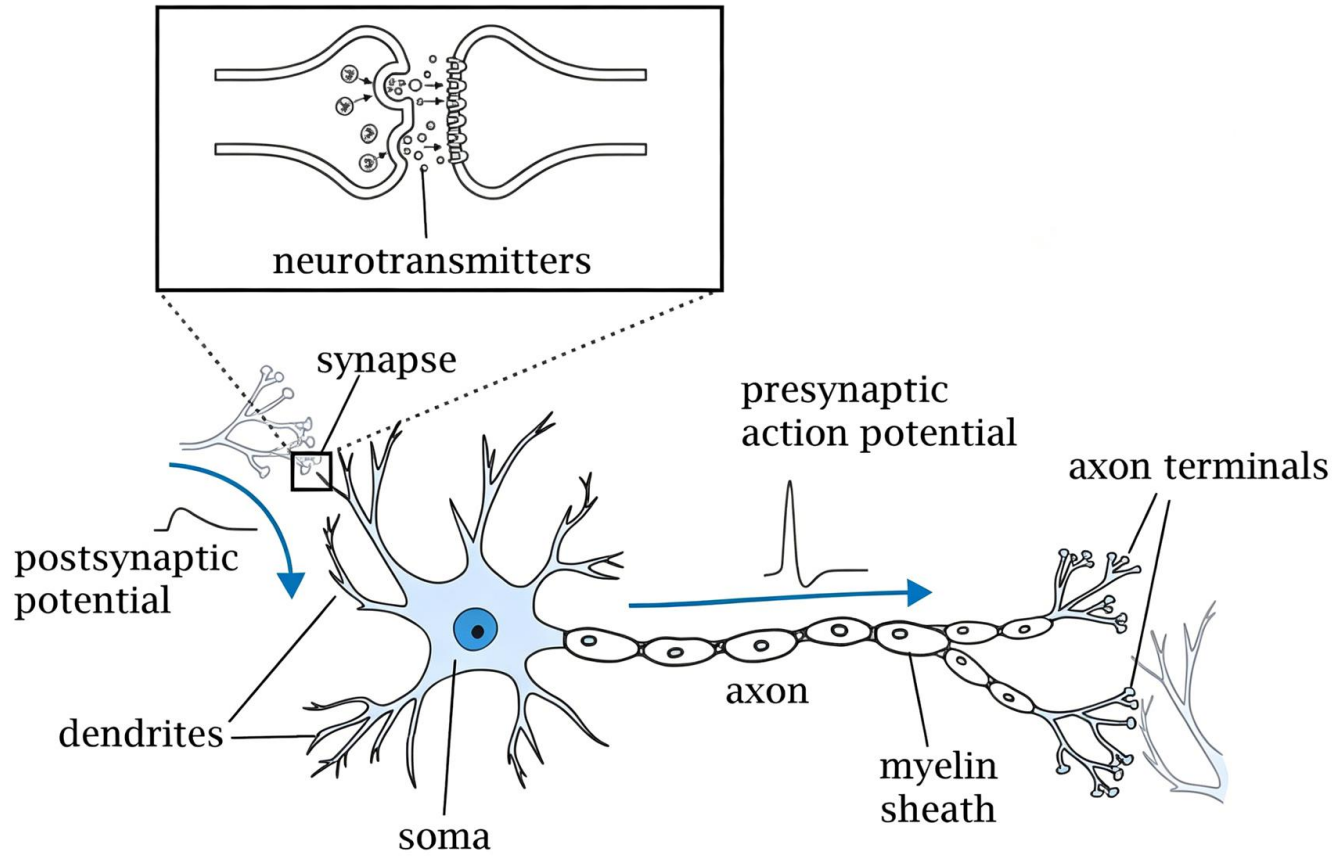


A Hybrid MLP-LSTM Model for Multi-Gas Concentration Prediction in IoT Systems

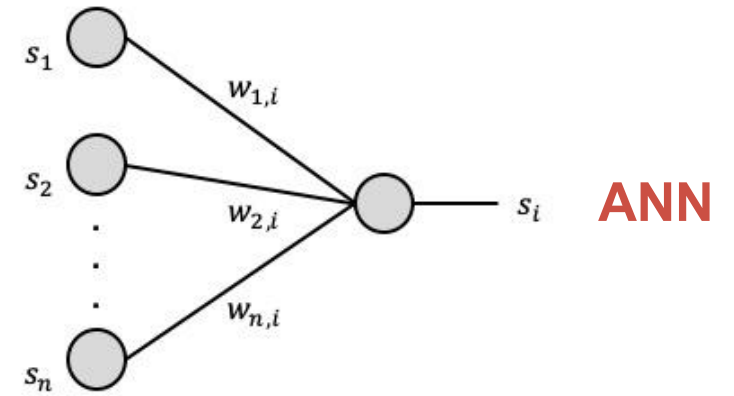
Ngo D T, Nguyen D H, Ng K Y, et al. Precision Concentration Estimation of Five Gases by Multiple IoT Gas Sensors and a New Hybrid MLP-LSTM Model[J]. IEEE Internet of Things Journal, 2025.



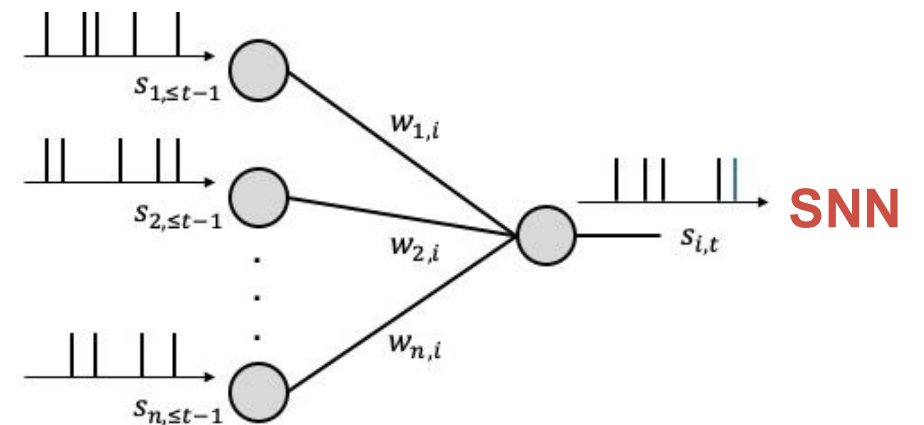
Spiking Neural Networks (SNNs)



biological neuron and synapse



ANN



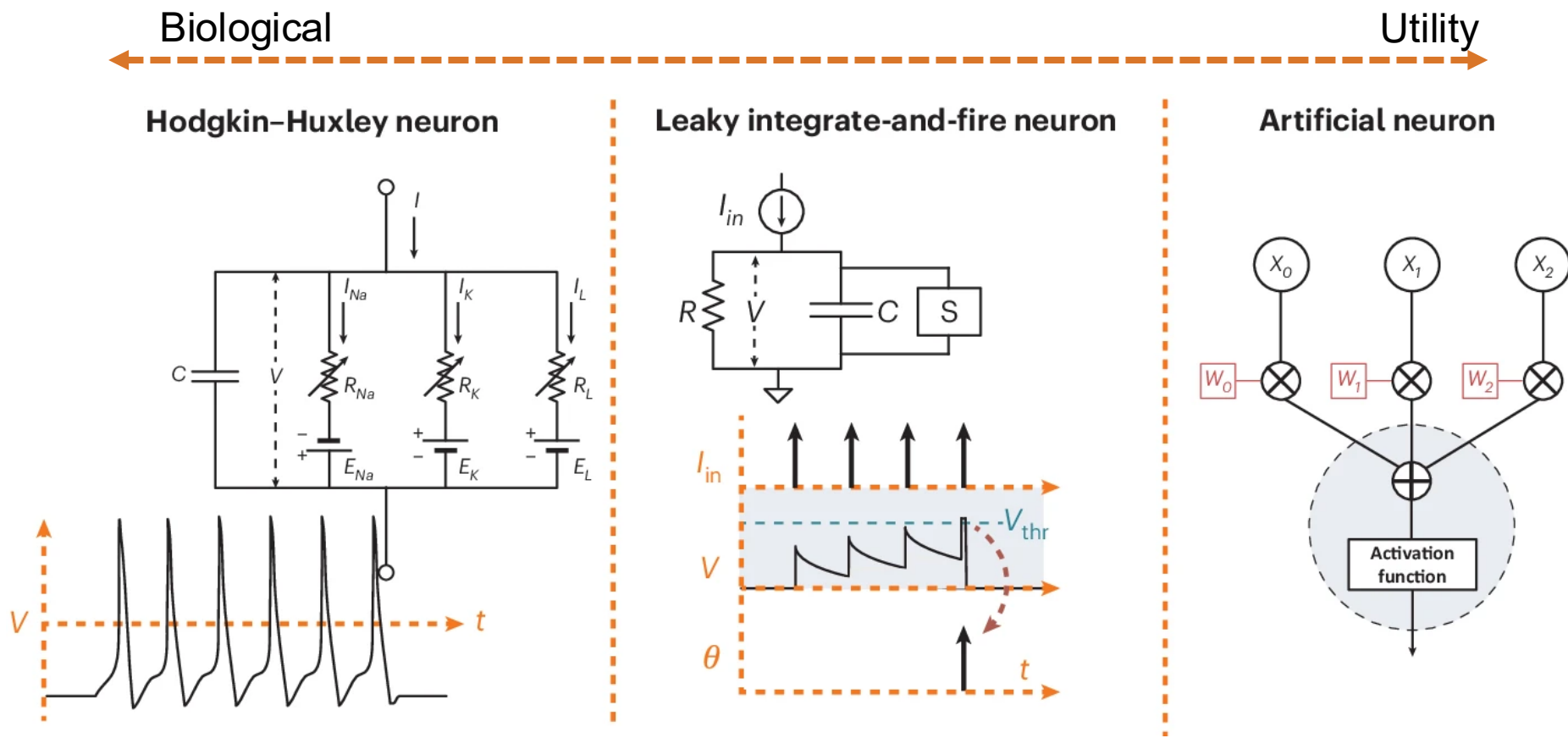
SNN



Spiking Neural Networks (SNNs)

Models of a spiking neuron

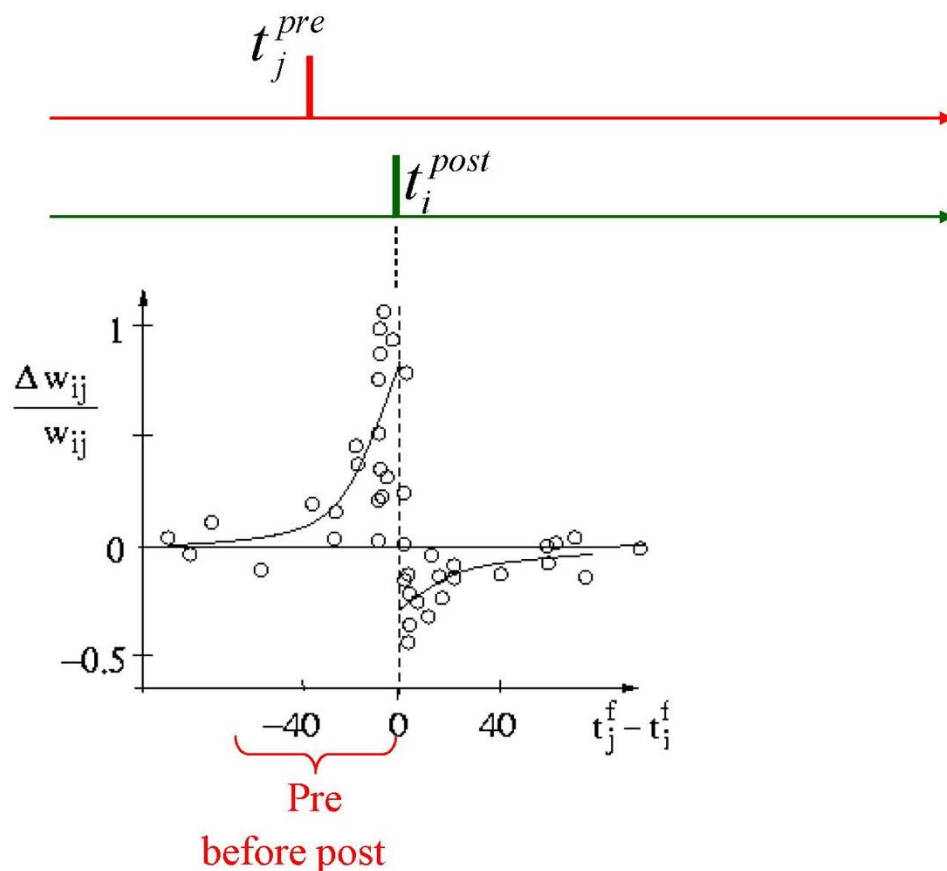
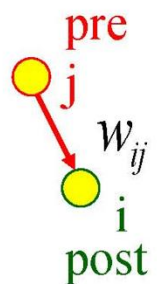
- Hodgkin-Huxley
- Spike response model
- Integrate-and-fire
- Leaky integrator
- Izhikevich model
-



Zhu R J, Gunasekaran S, Eshraghian J. Bridging the gap between artificial intelligence and natural intelligence[J]. Nature Computational Science, 2024, 4(8): 559-560.

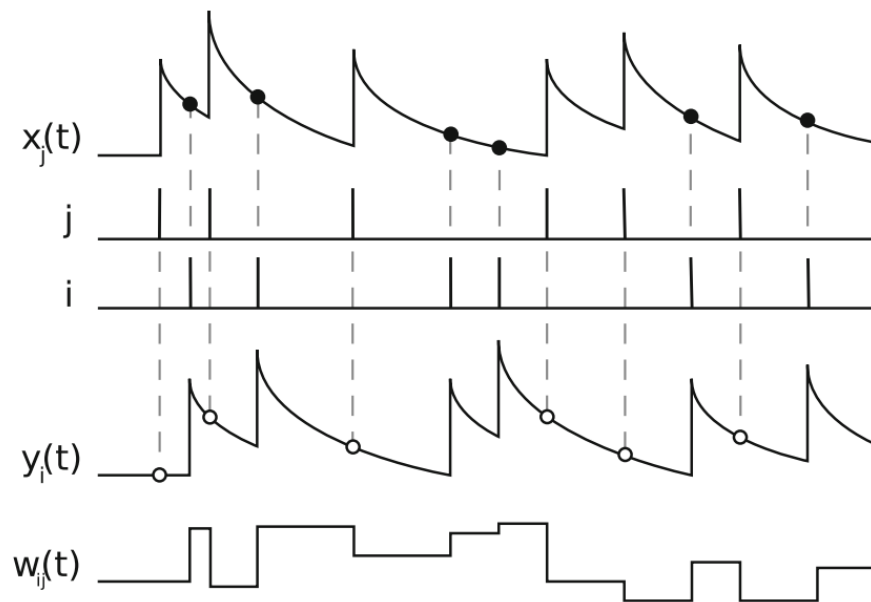


Biologically Inspired Learning Rule in SNNs



$$\Delta w = \sum_{f=1}^N \sum_{n=1}^M W(t_{post}^n - t_{pre}^f)$$

$$W(x) = \begin{cases} A_+ e^{-x/\tau_+} & \text{for } x > 0 \\ -A_- e^{x/\tau_-} & \text{for } x < 0 \end{cases}$$



Spike-Timing-Dependent Plasticity (STDP)

Applications of SNN in Electronic Noses

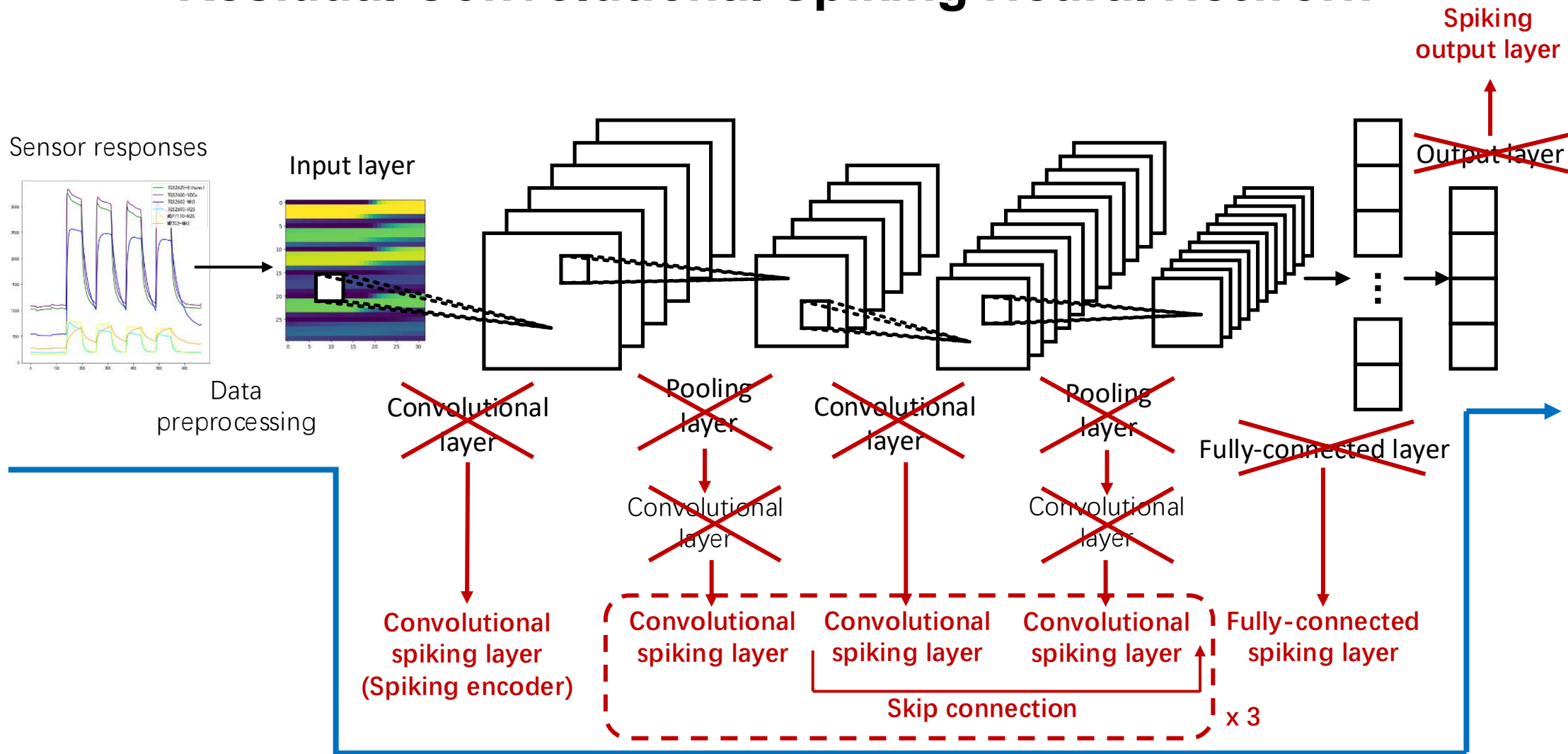
Convolutional-SNN for Spoiled Food Identification
 Xiong Y, Chen Y, Chen C, et al. An odor recognition algorithm of electronic noses based on convolutional spiking neural network for spoiled food identification[J]. Journal of the Electrochemical Society, 2021, 168(7): 0775-19.

Hybrid Plasticity FI-SNN for Gas Recognition
 Fu H, Fu P, Lu X, et al. A Brain-Inspired Hybrid Plasticity Feedforward-Inhibitory Spike Neural Network for Olfactory Perception[J]. IEEE Sensors Journal, 2025.

SNN-Based Odor Source Distance Estimation
 Xue Y, Mou S, Chen C, et al. Rapid distance estimation of odor sources by electronic nose with multi-sensor fusion based on spiking neural network[J]. Sensors and Actuators B: Chemical, 2025, 422: 136665.

BOSP Model for Gas Identification and Drift Suppression
 Yan J, Wu B, Liu T, et al. An SNN-based bionic olfactory signal processing network for odor recognition[J]. IEEE Sensors Journal, 2023, 23(12): 13186-13197.

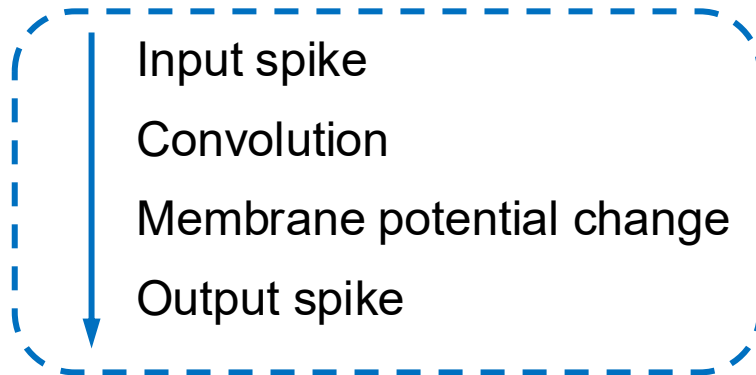
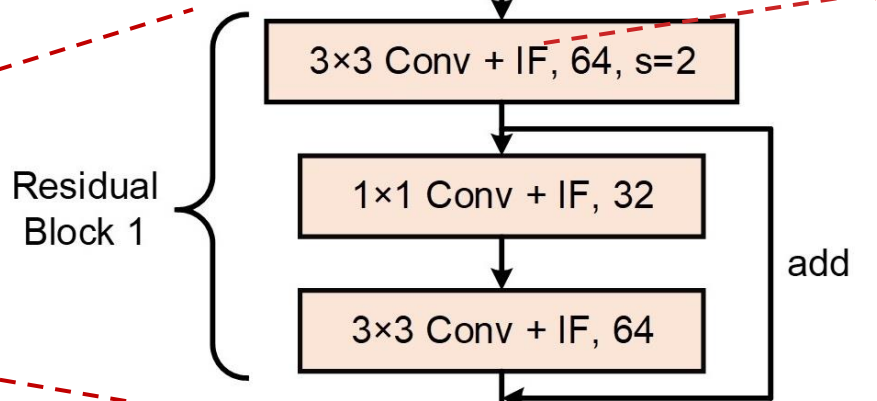
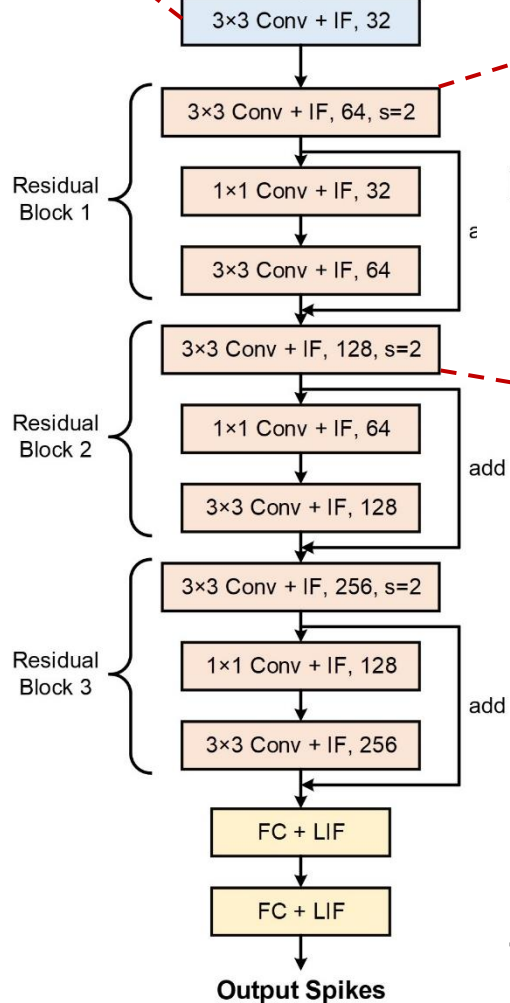
Residual Convolutional Spiking Neural Network



RCSNN-12

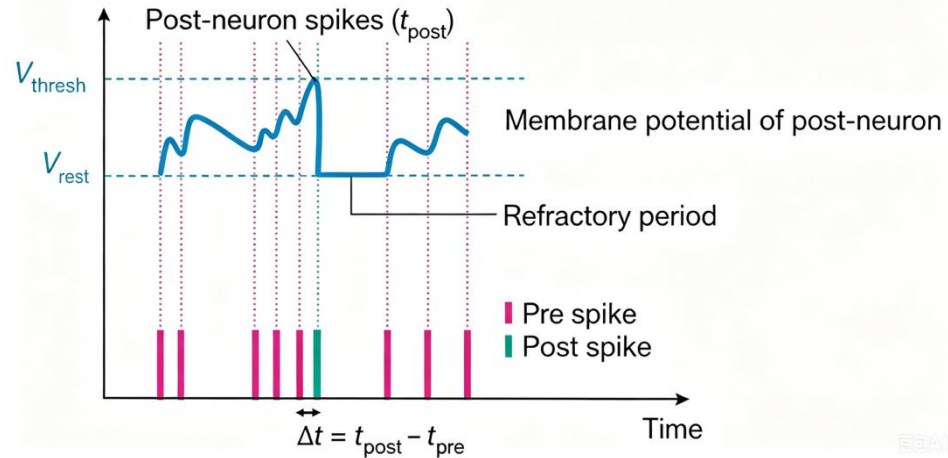
Spiking encoder

Preprocessd Data



Loss function: MSE
 Training method: surrogate gradient learning

LIF (Leaky-integrate-and-fire) model:



$$H(t) = f[V(t-1), X(t)]$$

$$S(t) = \varepsilon[H(t) - V_{threshold}]$$

$$V(t) = H(t) \cdot [1 - S(t)] + V_{reset} \cdot S(t)$$

IF (Integrate-and-fire) model:
 Similar to LIF, but will not leak

Spoiled food mixed odor dataset (Dataset-1)

| Number | Food sample category | | | | | Label |
|--------|----------------------|---------|---------|-----------|----------|------------------|
| 1 | Watermelon* | | | | | Fruit |
| 2 | Fresh grapes* | | | | | Fresh food (Air) |
| 3 | Chives* | | | | | Vegetable |
| 4 | Watermelon* | Grapes | Pear | Pineapple | | Fruit |
| 5 | Watermelon | Grapes* | Pear | Pineapple | | Fruit |
| 6 | Cowpeas | Chives* | Daikon | Celery | | Vegetable |
| 7 | Watermelon | Cowpeas | Chives* | Fish | Chicken | Vegetable |
| 8 | Watermelon | Cowpeas | Chives | Fish* | Chicken | Meat |
| 9 | Watermelon | Cowpeas | Chives | Fish | Chicken* | Meat |

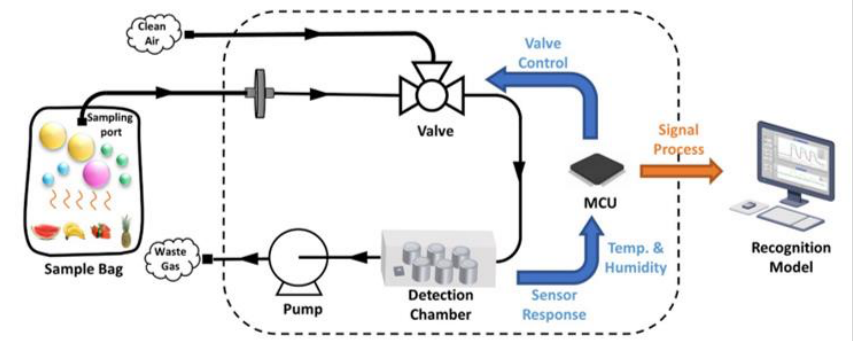
Rotten fruit odor dataset (Dataset-2)

| Number | Fruit sample category | Number | Fruit sample category |
|--------|-----------------------|--------|-----------------------|
| 1 | Fresh fruits (Air) | 6 | Grapes |
| 2 | Pineapple | 7 | Peach |
| 3 | Orange | 8 | Watermelon |
| 4 | Pear | 9 | Banana |
| 5 | Apple | | |

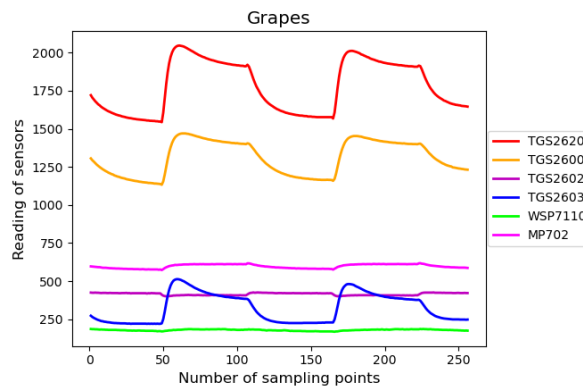


electronic nose

| Sensor Type | Target Gases |
|-------------|--|
| TGS2620 | Ethanol, hydrogen, isobutane, carbon monoxide, methane |
| TGS2600 | Hydrogen, ethanol, isobutane, carbon monoxide, methane |
| TGS2602 | Toluene, hydrogen sulfide, ethanol, ammonia |
| TGS2603 | Ethanol, trimethyl amine, methyl mercaptan, hydrogen |
| WSP7110 | Hydrogen sulfide, ethanol, ammonia, hydrogen |
| MP702 | Ammonia, ethanol, methane, carbon monoxide |



The output of the spiking encoder

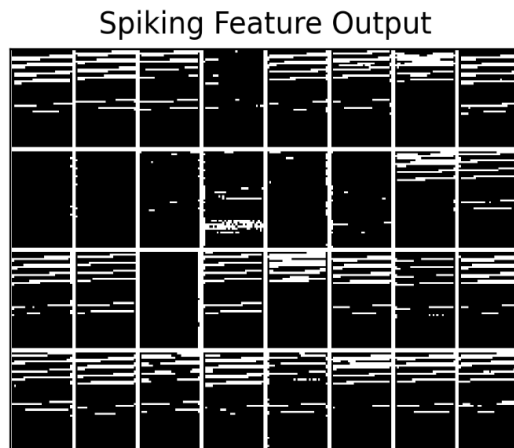


Sensor responses

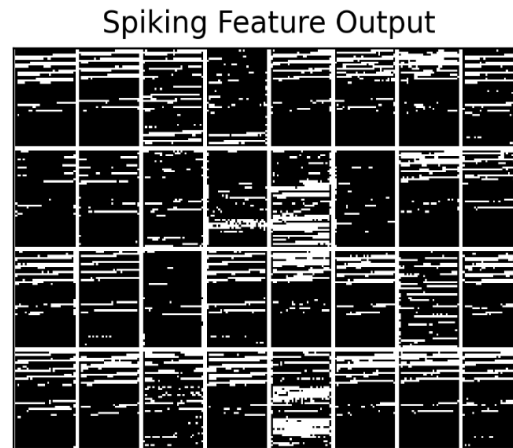
The first convolutional spiking layer (Spiking encoder)

Spiking feature output

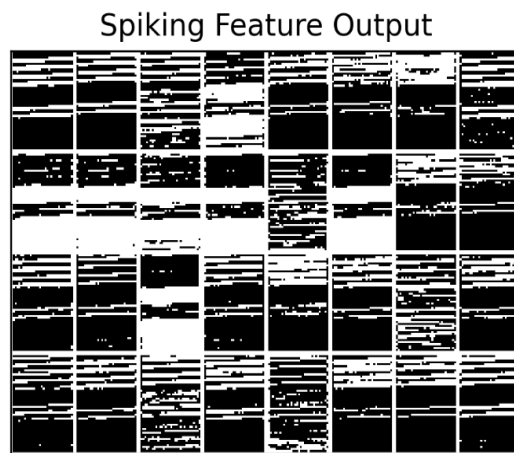
...



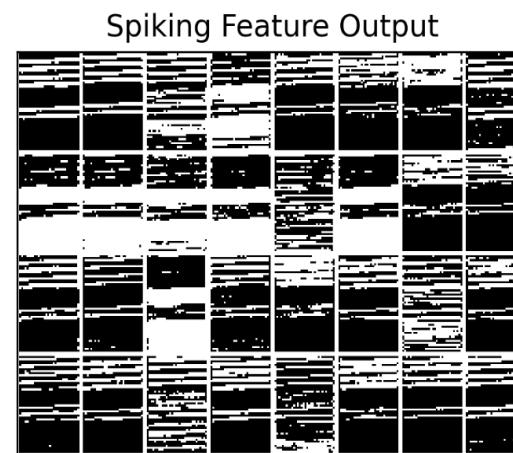
t = 1



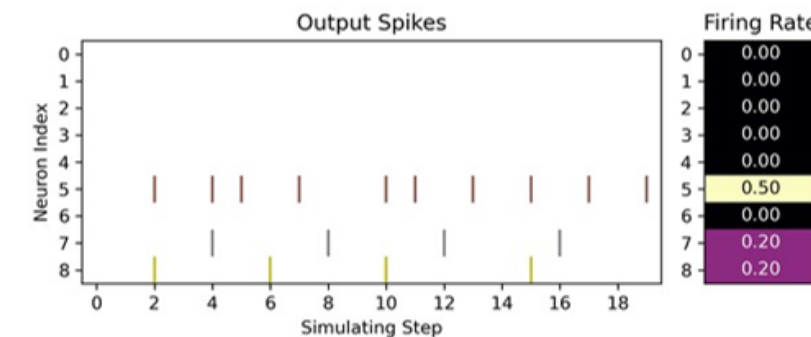
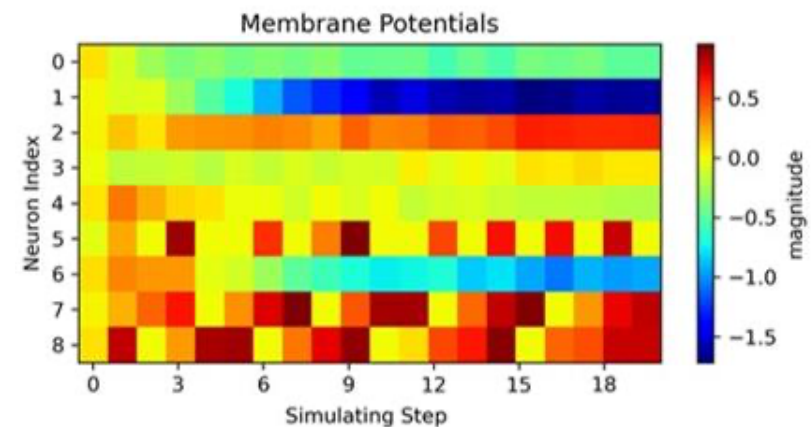
t = 9



t = 16

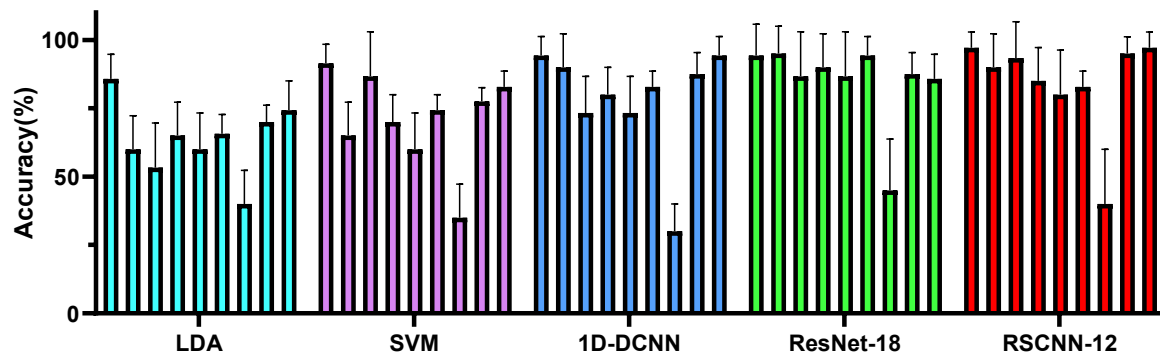


t = 20

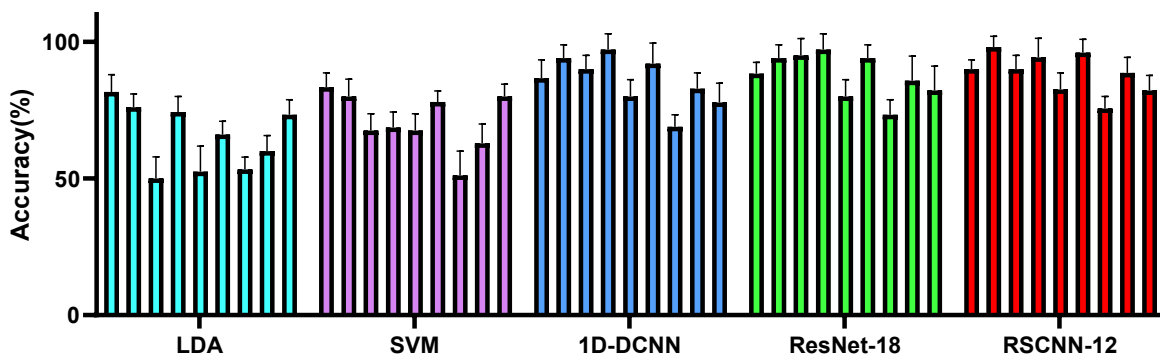


Test results of Dataset-1 & Dataset-2

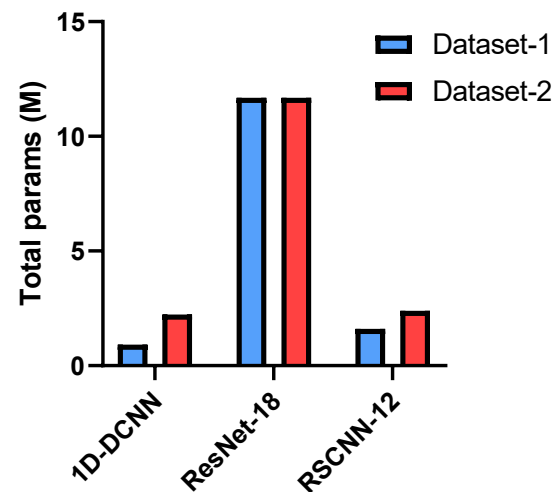
Dataset-1



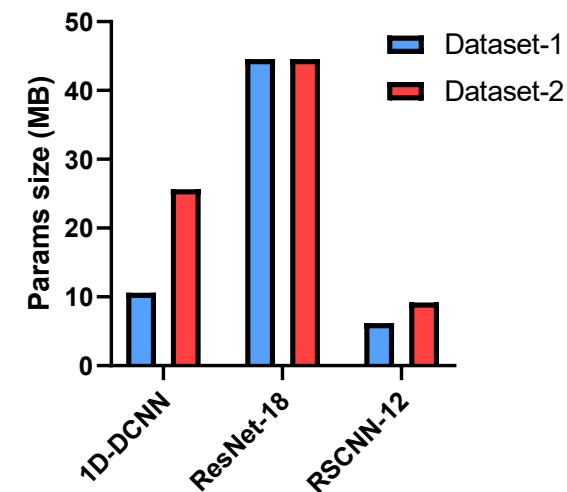
Dataset-2



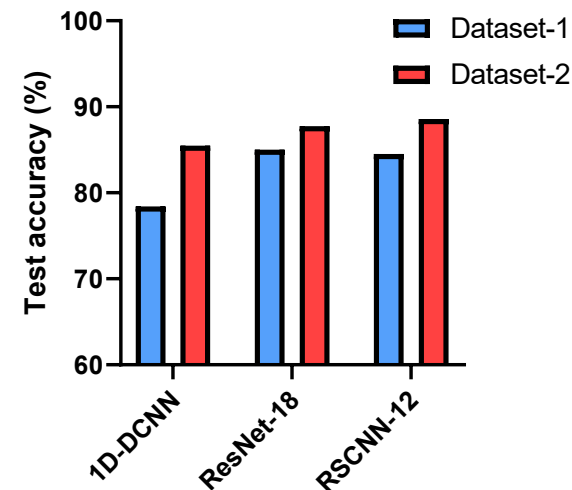
Total parameters



The size of parameters



Average test accuracy



| Model | Total params (M) | | Params size (MB) | | Test accuracy (%) | |
|-----------|------------------|-----------|------------------|-----------|-------------------|-----------|
| | Dataset-1 | Dataset-2 | Dataset-1 | Dataset-2 | Dataset-1 | Dataset-2 |
| 1D-DCNN | 0.92 | 2.23 | 10.62 | 25.65 | 78.40 | 85.48 |
| ResNet-18 | 11.68 | 11.68 | 44.57 | 44.57 | 85.01 | 87.75 |
| RCSNN-12 | 1.61 | 2.39 | 6.19 | 9.19 | 84.50 | 88.57 |



Challenges

1. Standardization & data efficiency:

- Lack of unified signal processing pipelines and limited labeled data hinder model generalization.

2. Robust adaptive recognition:

- Sensor drift, environmental variations, and unknown interferences require drift-robust and adaptive algorithms.

3. Lightweight intelligent models:

- Need hardware-friendly models (e.g., SNN, ANN variants) for compact IoT E-nose systems.





Prospects

1. IoT, Edge AI & Hardware-Friendly SNNs

- Low-power, portable, and real-time electronic nose systems for IoT applications

2. Advanced AI Algorithms

- Deep learning, transformers, reinforcement learning, transfer learning, online learning, and self-supervised learning for adaptive gas recognition

3. Adaptive Drift Compensation & Robust Recognition

- Drift suppression, environmental compensation, adaptive calibration, and self-learning algorithms for stable long-term sensing

4. Sense–Storage–Computing Integrated Chips

- Memristor-based neuromorphic olfactory systems combining sensing, memory, and computation



Thanks for your attention!

Hao Wan

**Key Laboratory for Biomedical Engineering of Ministry of Education, Biosensor National Special Laboratory,
Department of Biomedical Engineering, Zhejiang University, Hangzhou, China**

wh1816@zju.edu.cn



Bioinspired Electronic Tongue

Paper ID: Tutorial 1

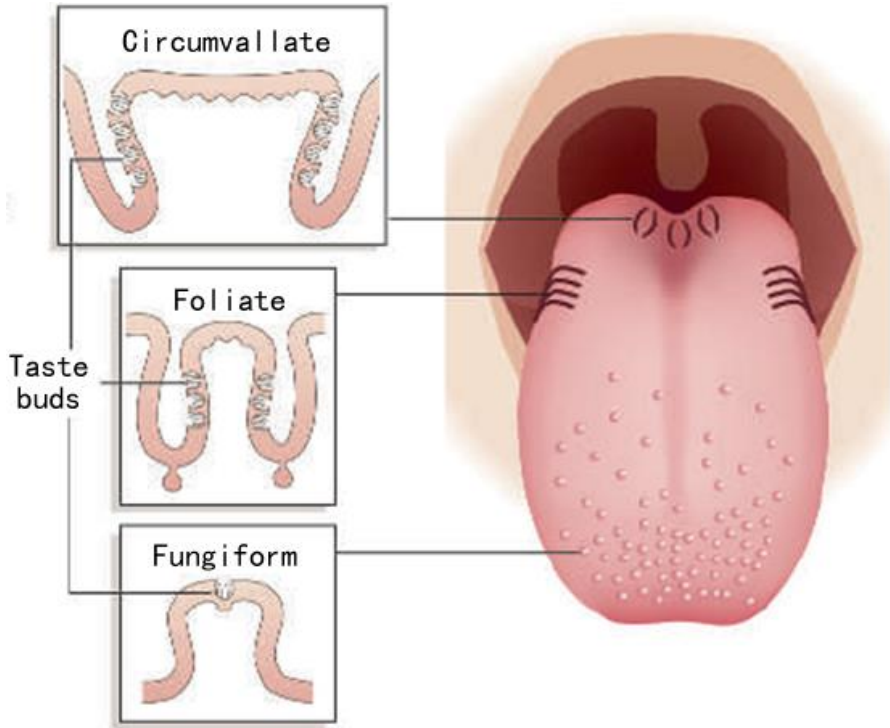
Chunsheng Wu

Xi'an Jiaotong University

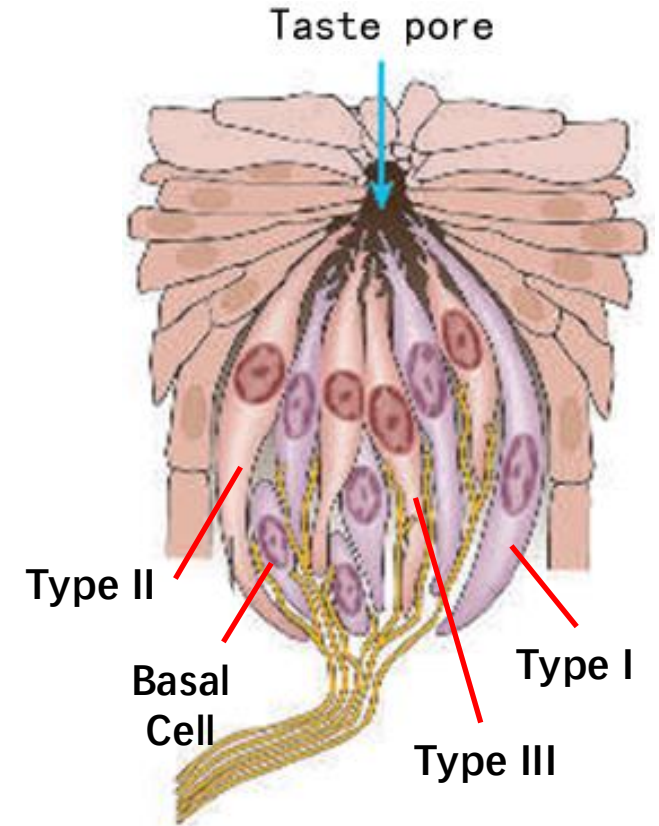
wuchunsheng@xjtu.edu.cn



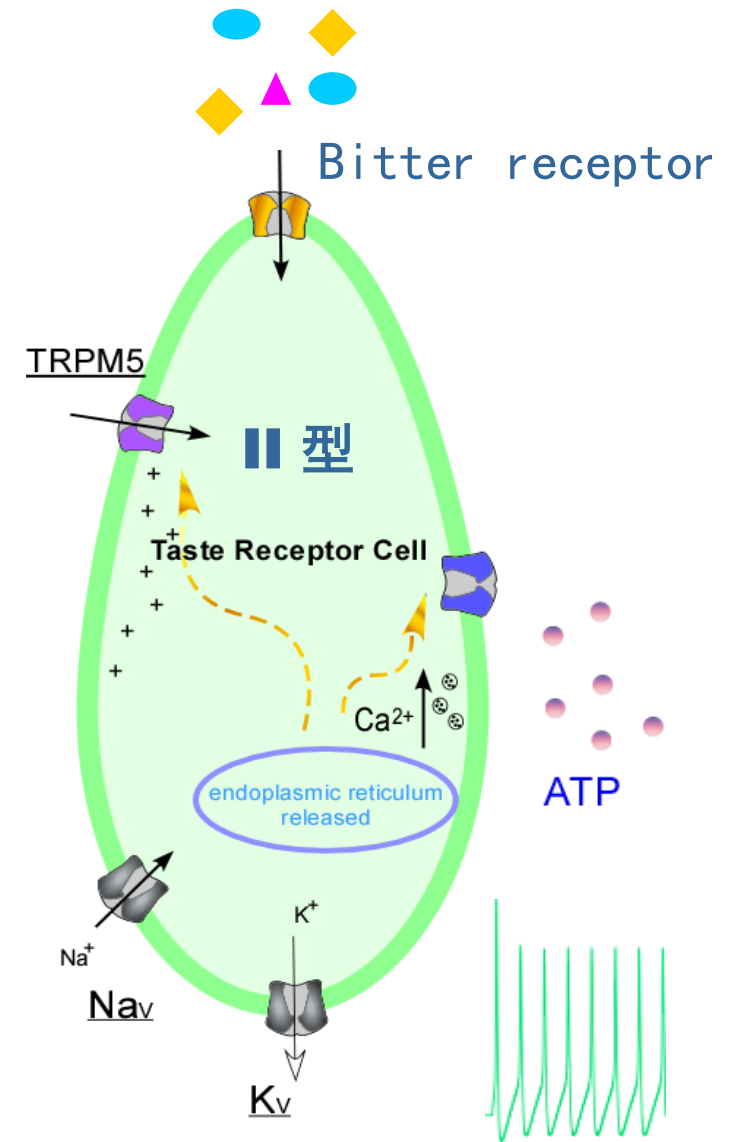
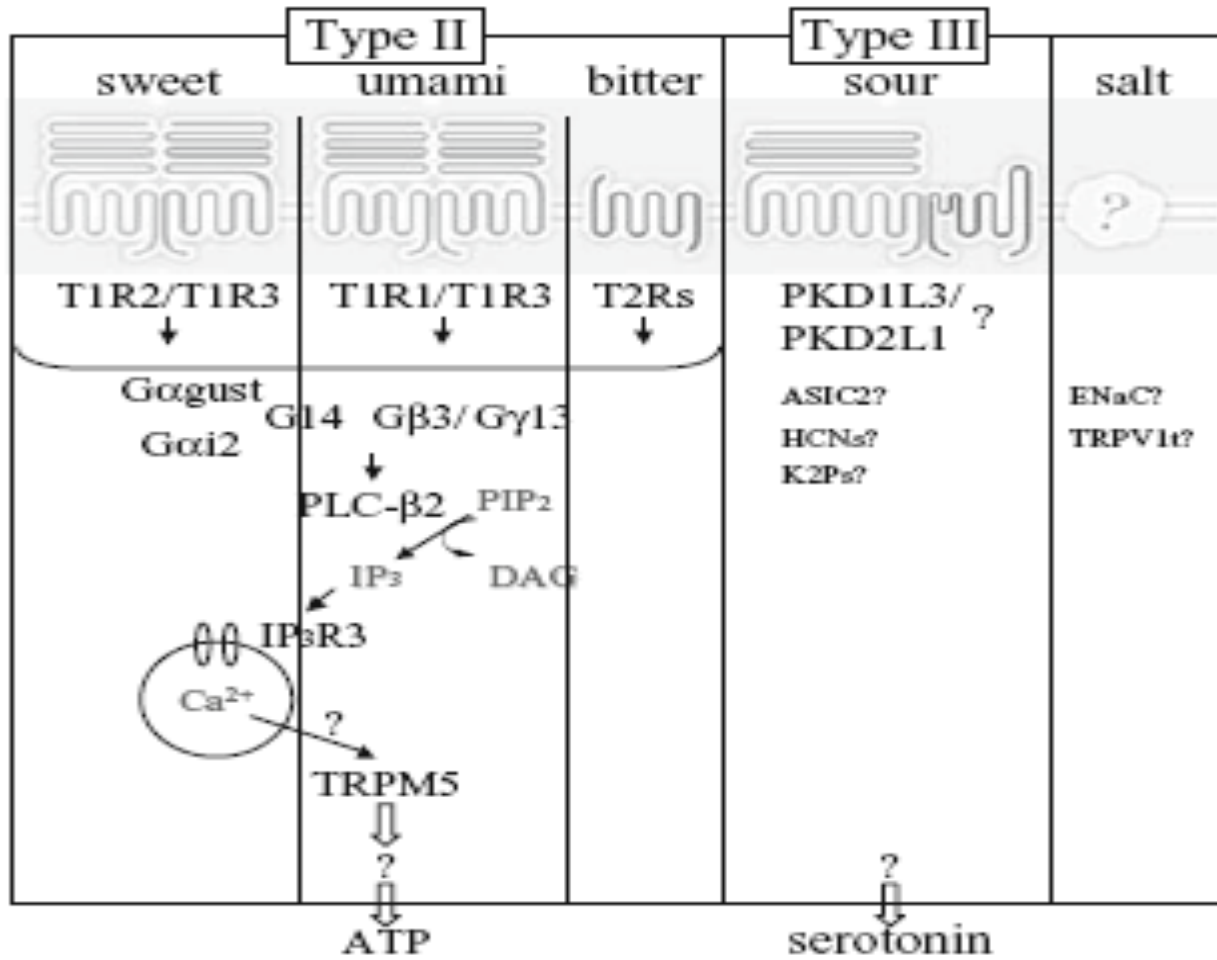
Biological Taste System



| | |
|--------|-----------|
| Sour | PKDL/ASIC |
| Sweet | T1R2+T1R3 |
| Bitter | T2Rs |
| Salty | ENaC |
| Umami | T1R1+T1R3 |

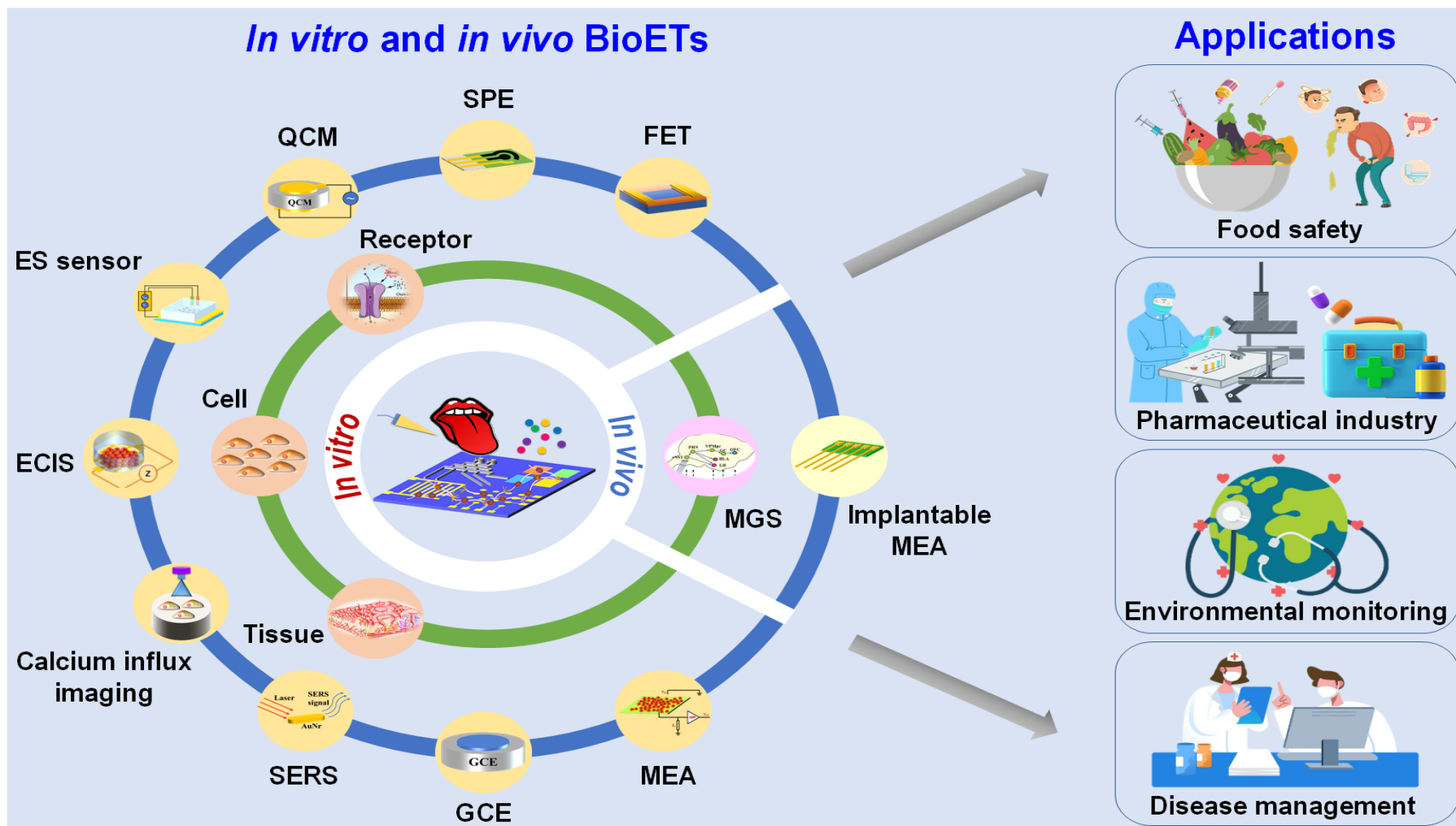


Biological Taste System



Ishimaru, 2009, *Odontology*

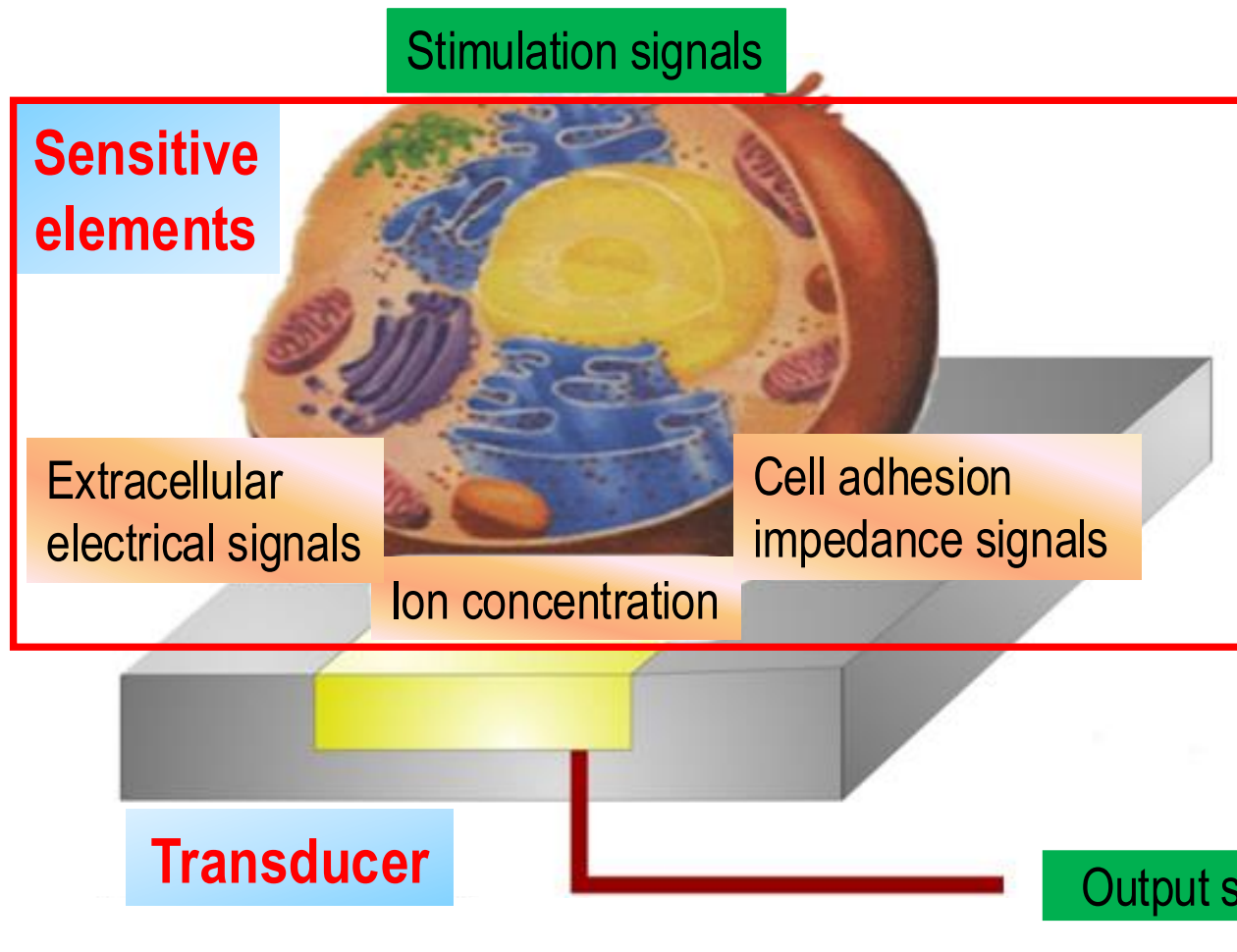
Bioinspired Electronic Tongue



- In 1990, e-Tongue was present (K. Hayashi, et al. Sensors and Actuators B 1990);
- e-Tongue is an array of chemical sensors, connected to a pattern-recognition system that responds to taste analyzes.

1. Biomimetic cell-based biosensors

Cell-based biosensors



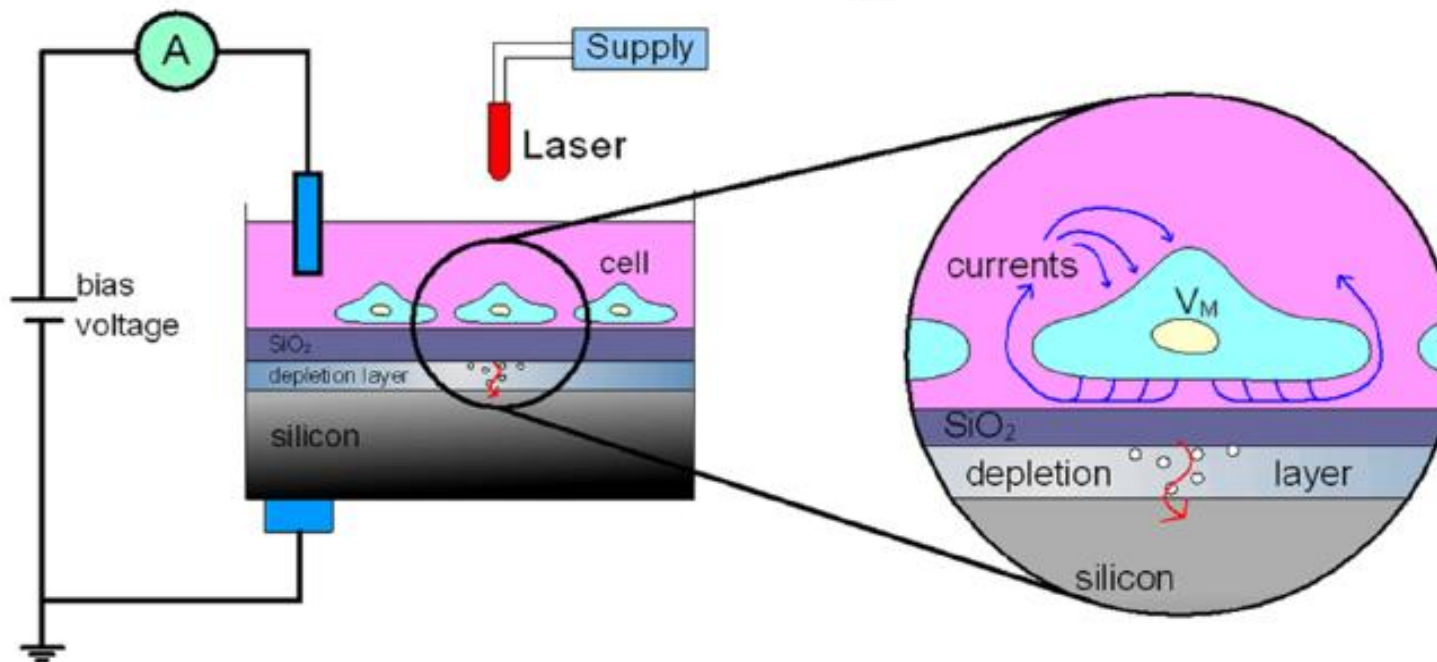
- Highly sensitive
- Long-term
- Non-invasive



Single-cell recording

1. Biomimetic cell-based biosensors

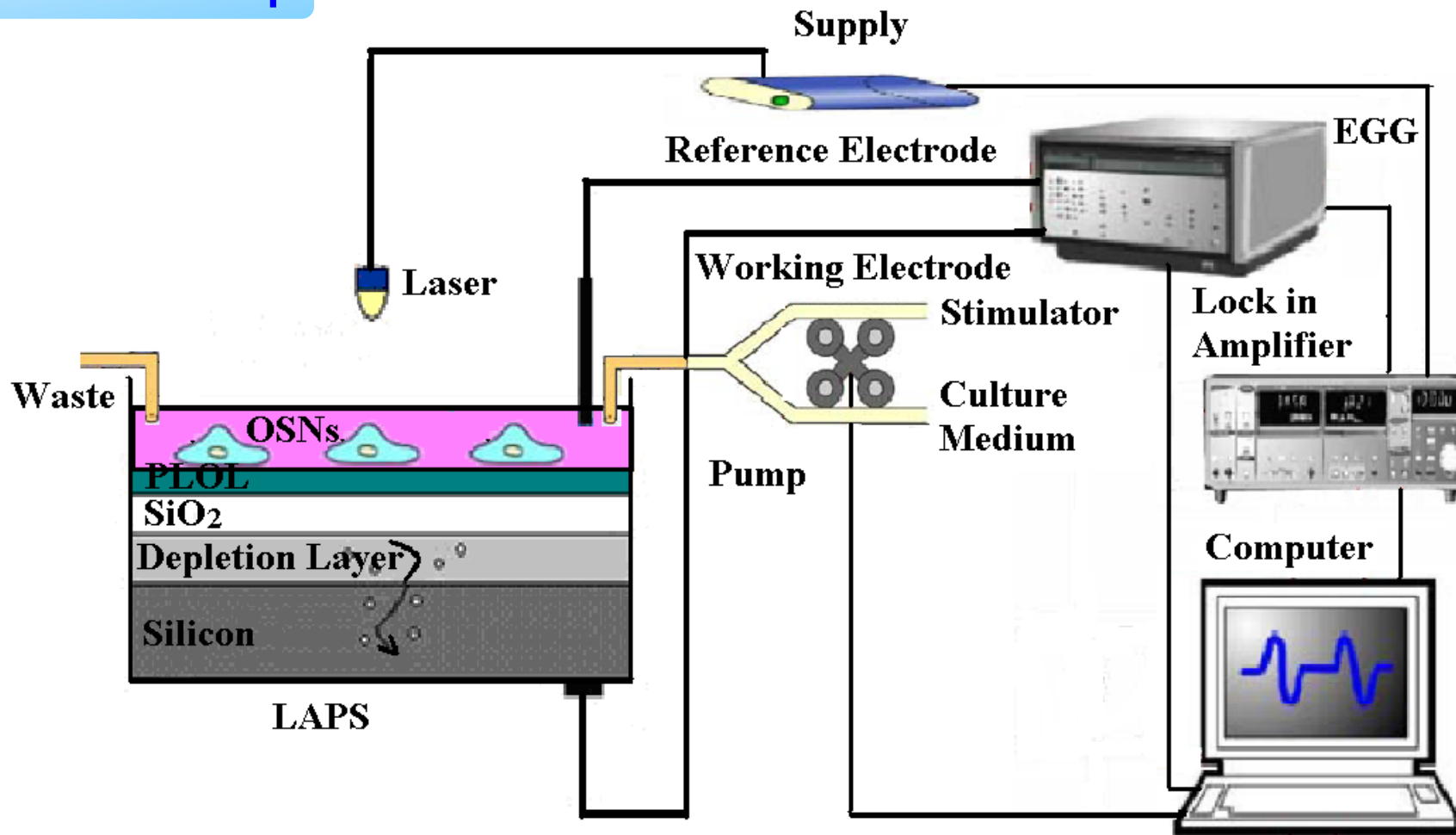
Light-addressable potentiometric sensor (LAPS)



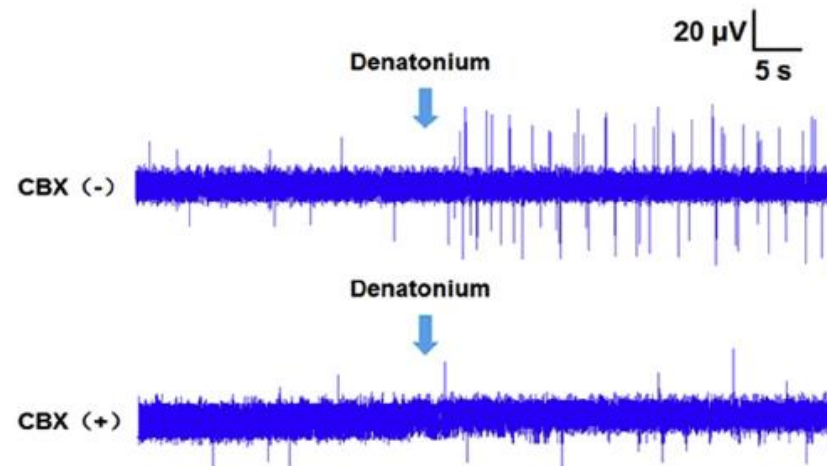
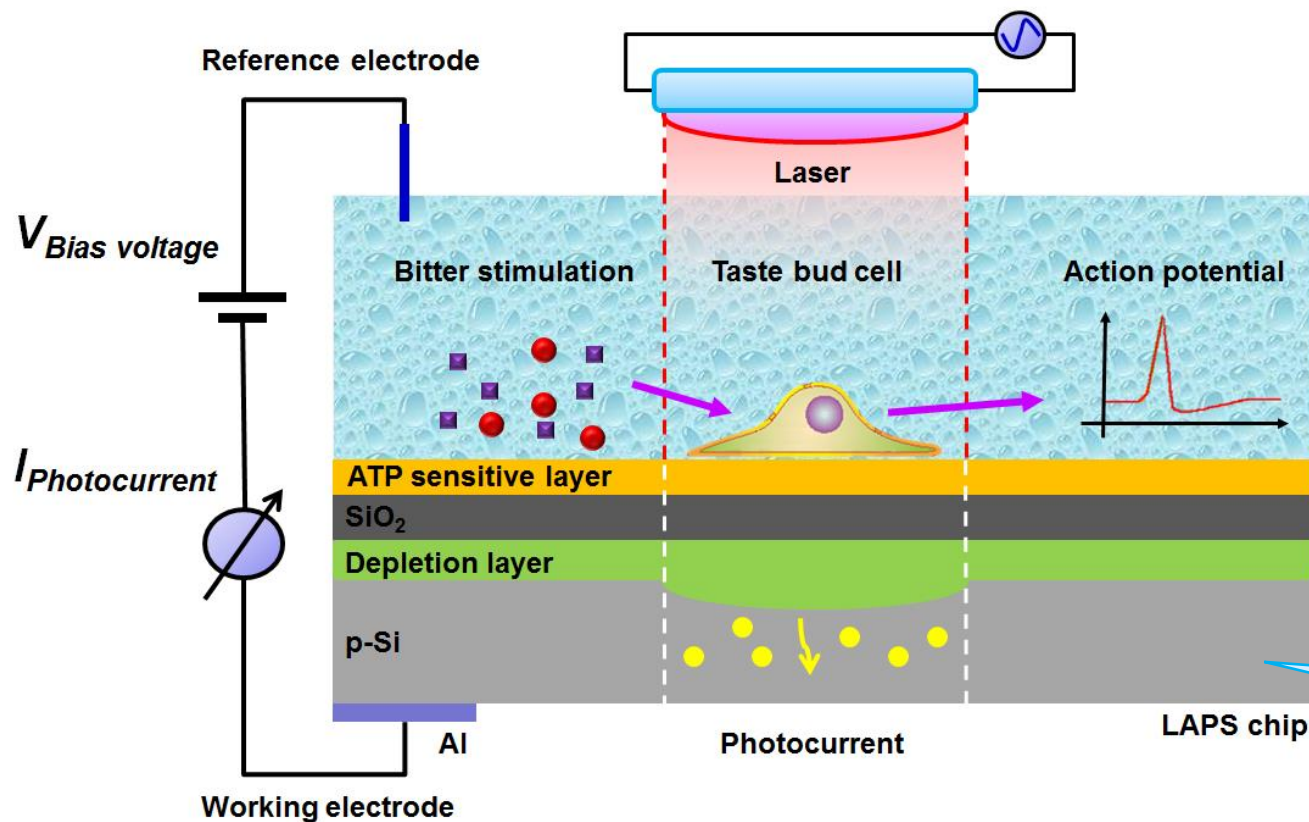
- Flat metal-free surface
- Light-addressability
- Extracellular recording
- Free of cell positioning
- Single-cell recording
- Long-term non-invasive measurement

1. Biomimetic cell-based biosensors

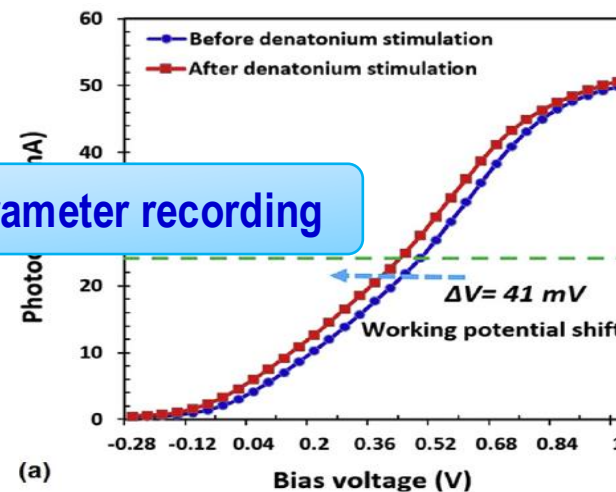
LAPS measurement setup



1. Biomimetic cell-based biosensors

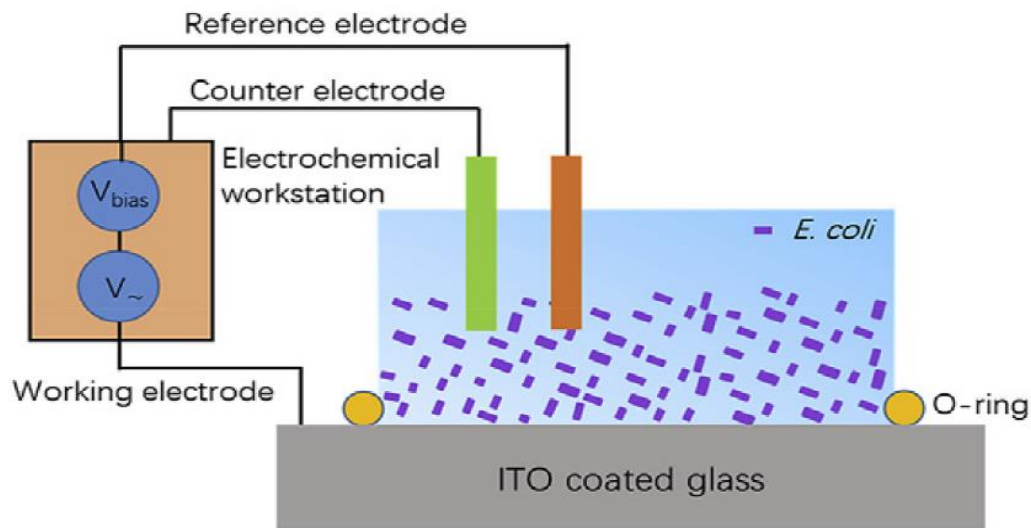


✓ Dual-parameter recording

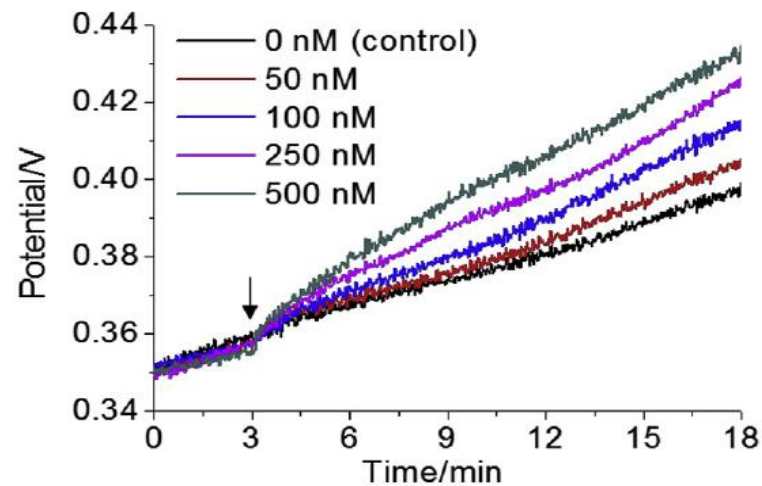
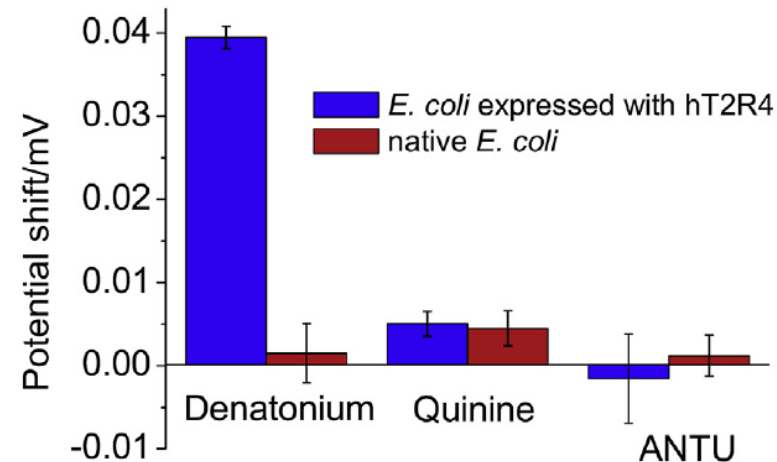
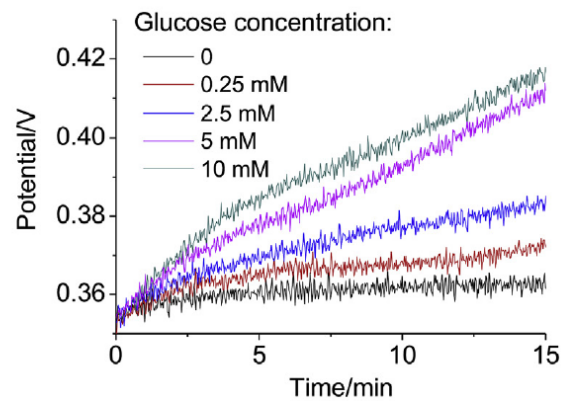
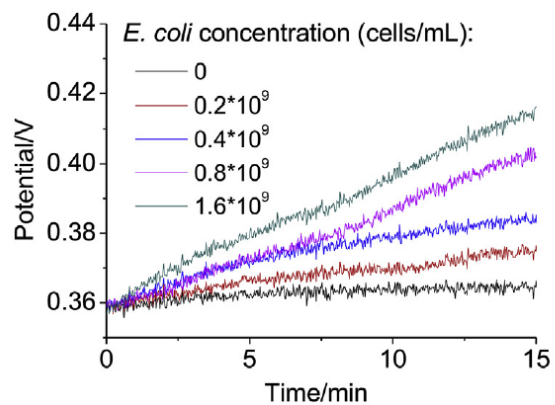


Extracellular recording of **membrane potential changes** and **ATP release** from single taste cell

1. Biomimetic cell-based biosensors

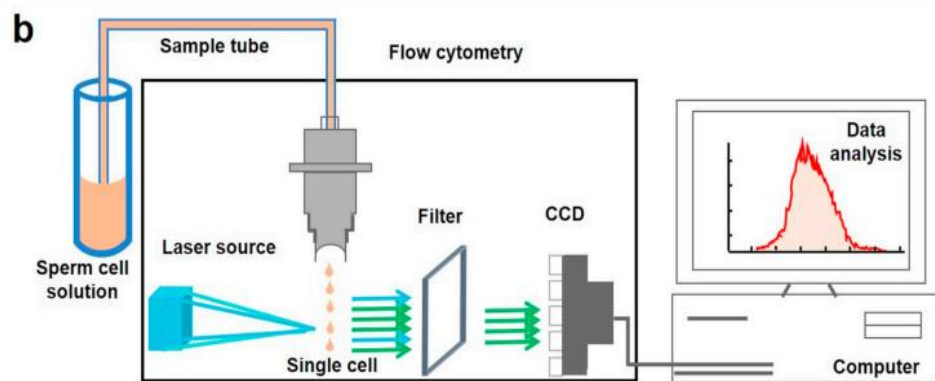
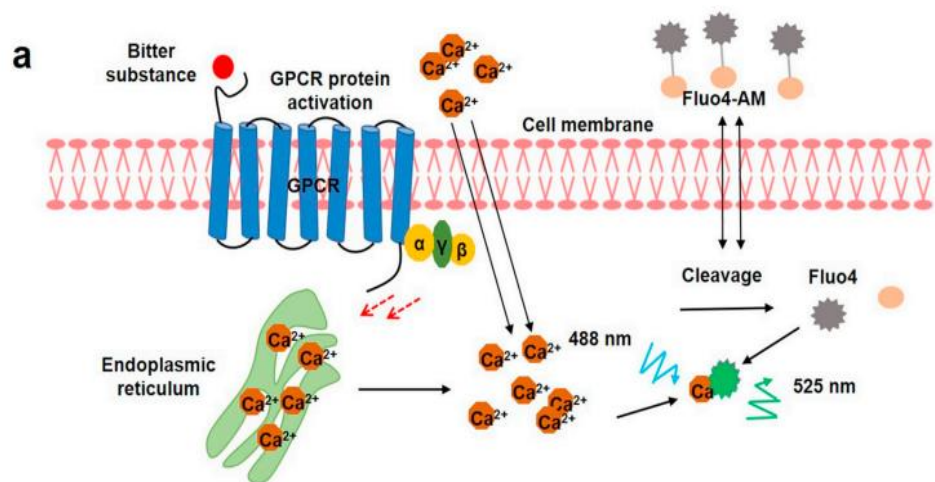


Bioengineered *E. coli* cells combined with ITO

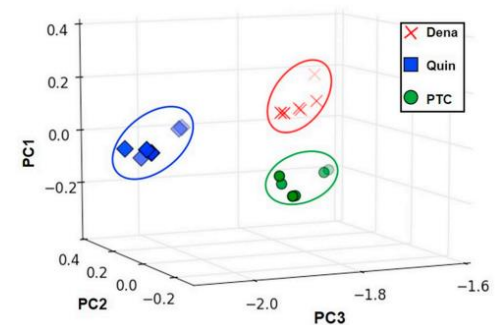
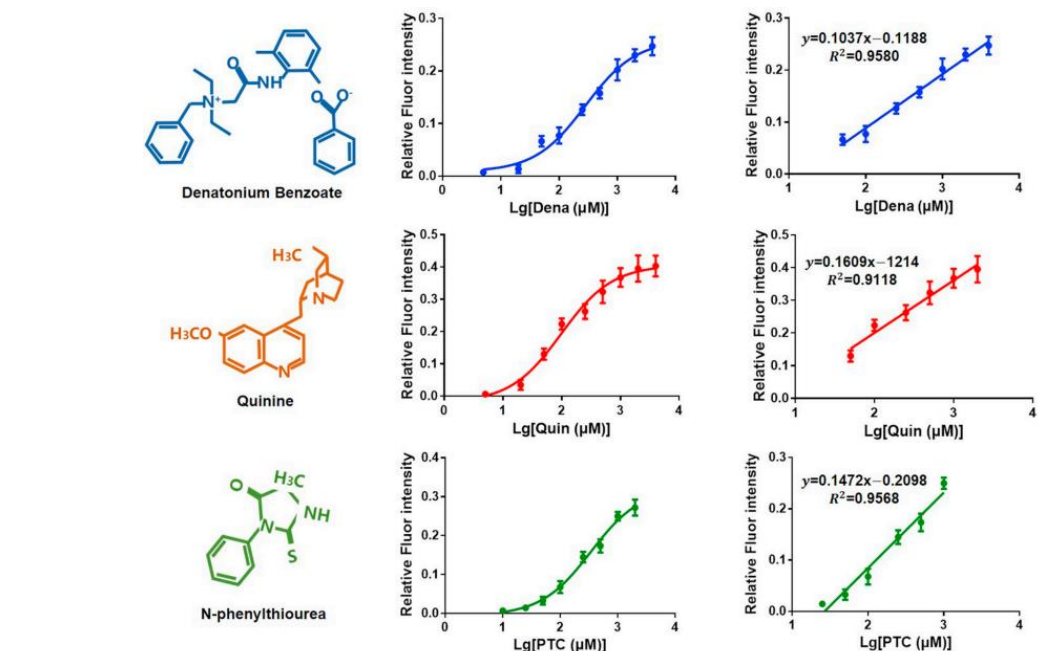
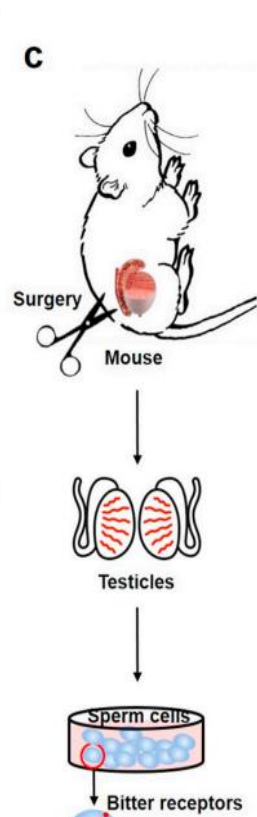


Specificity and sensitivity test

1. Biomimetic cell-based biosensors



Sperm cell-based biosensor for bitter detection

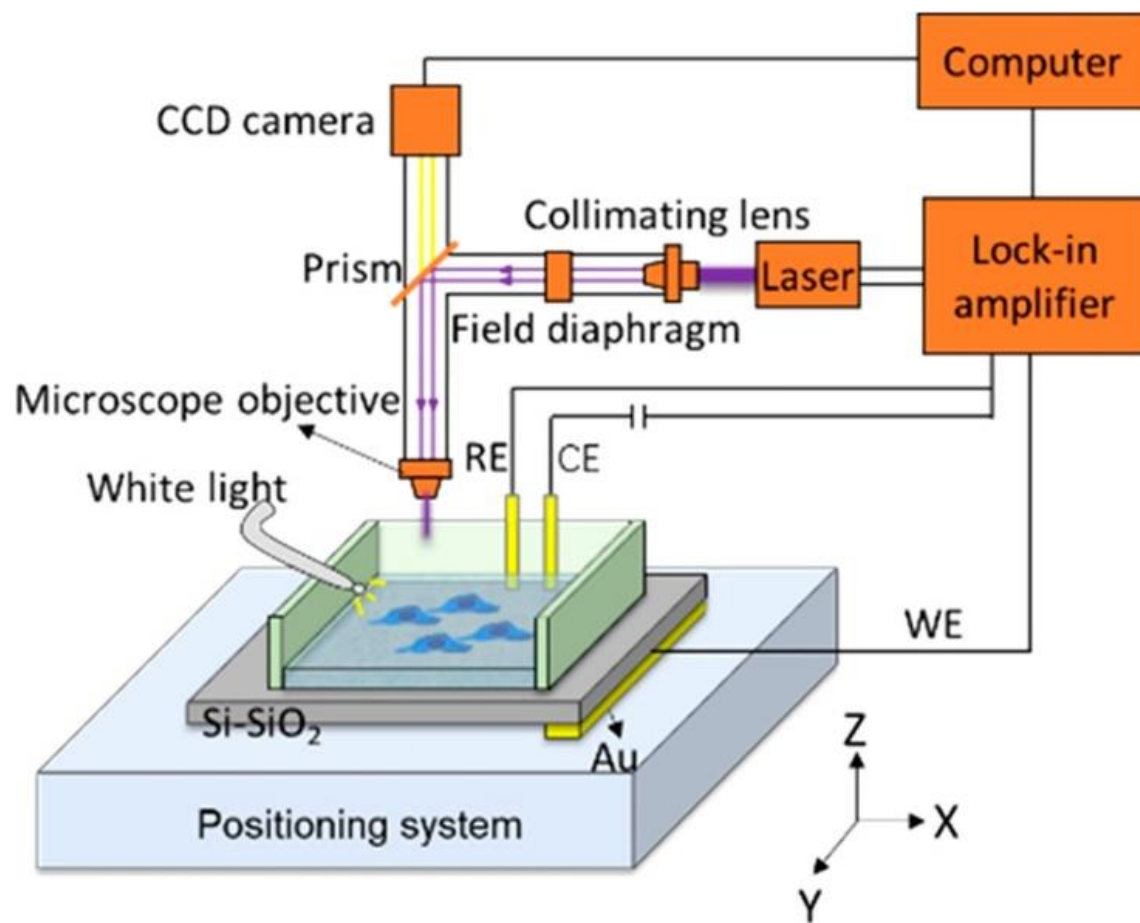


LOD for bitter sensing

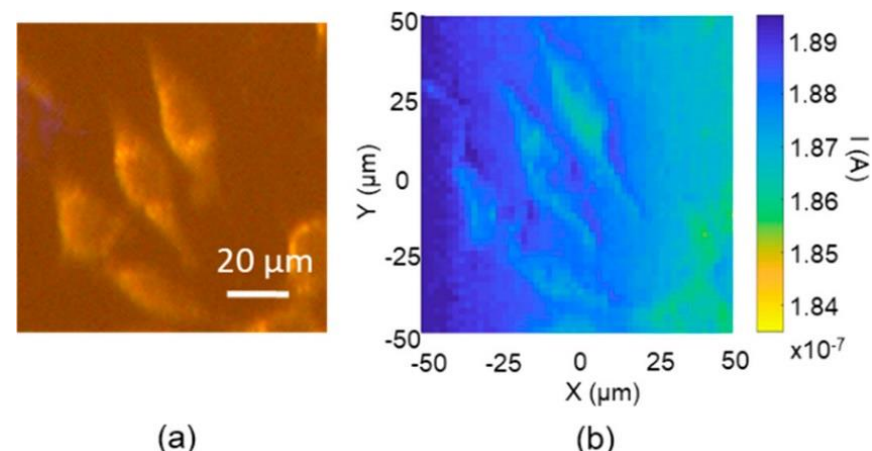
- Dena: 15.6 μM
- Quin: 5.7 μM
- PTC: 25.1 μM

1. Biomimetic cell-based biosensors

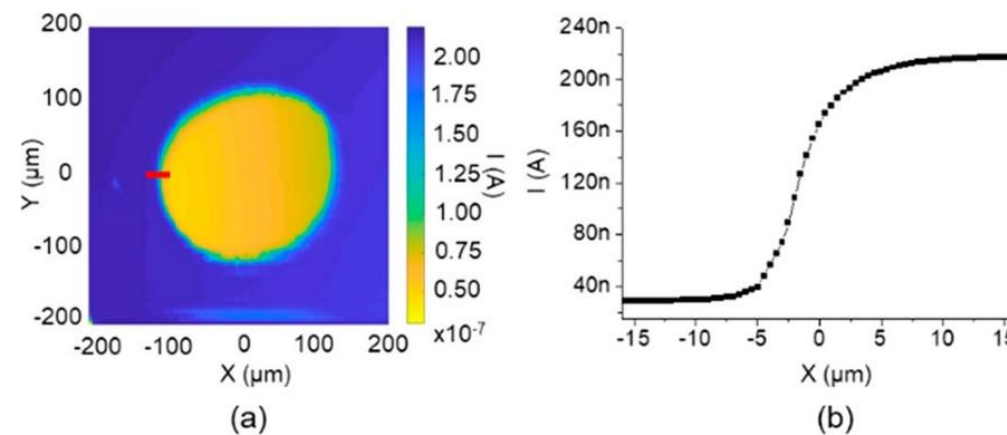
Single cell imaging



Scanning electrochemical photometric sensor (SEPS)



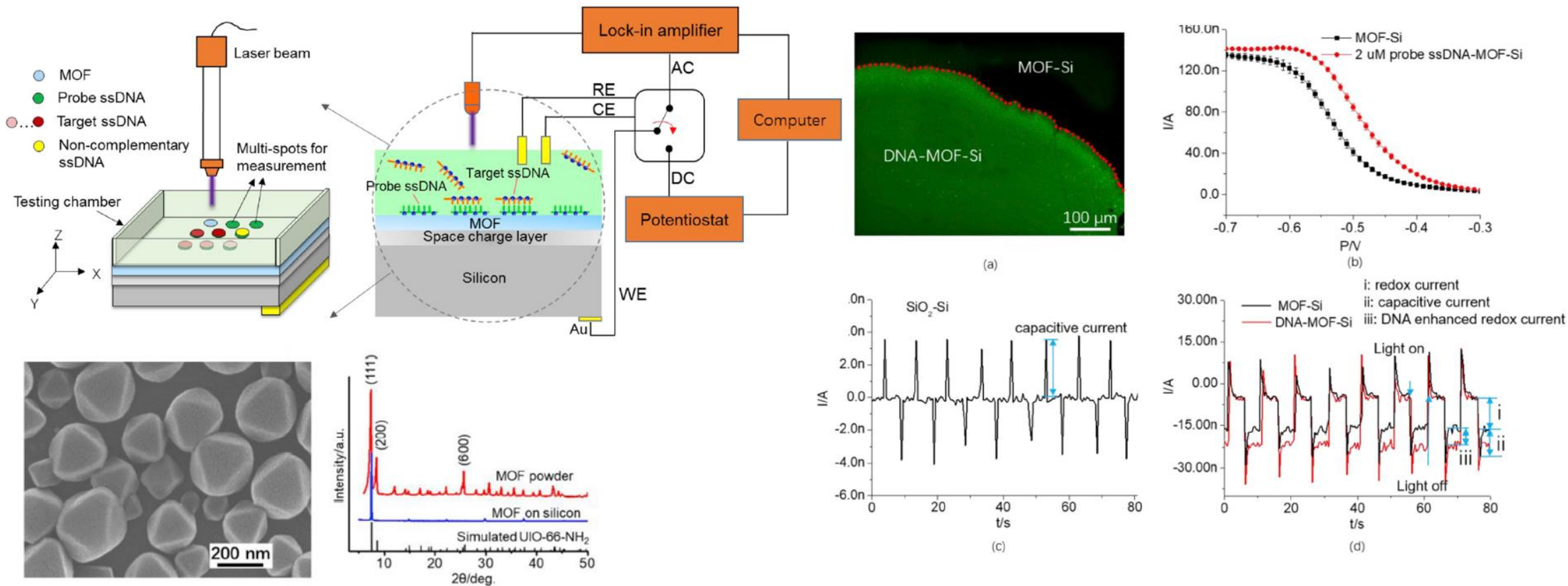
(a) Optical and (b) corresponding SEPS images of HeLa cells



SEPS image of a black ink dot coated on a bulk silicon surface

2. Biomimetic molecule-based biosensors

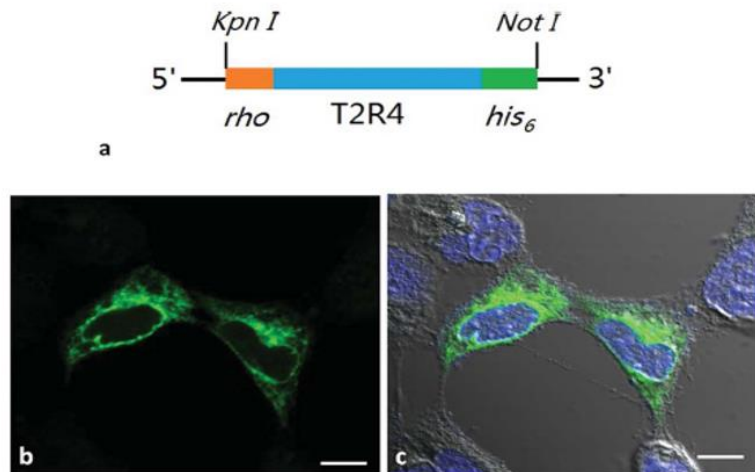
Modulated light-activated electrochemistry



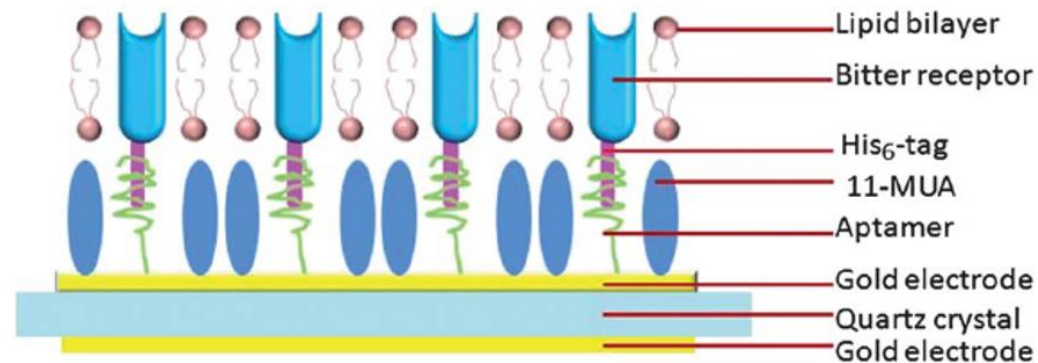
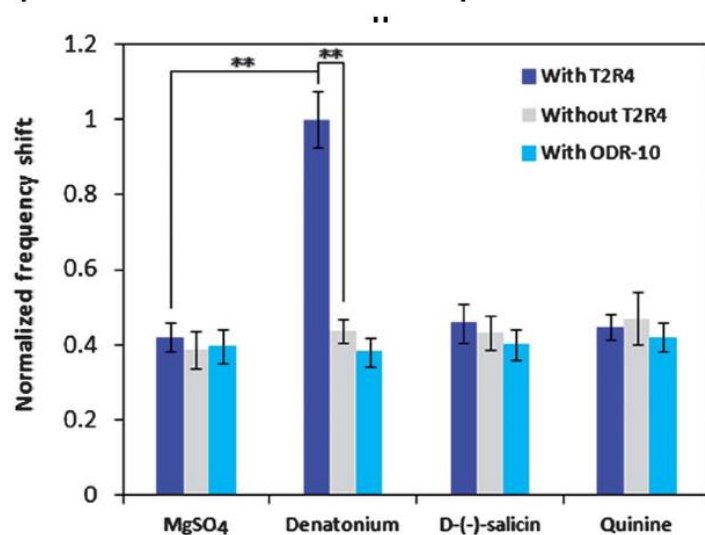
UIO-66-NH₂ nanoparticles grown on p-Si (100) surface

pH sensitivity: 47 mV/pH

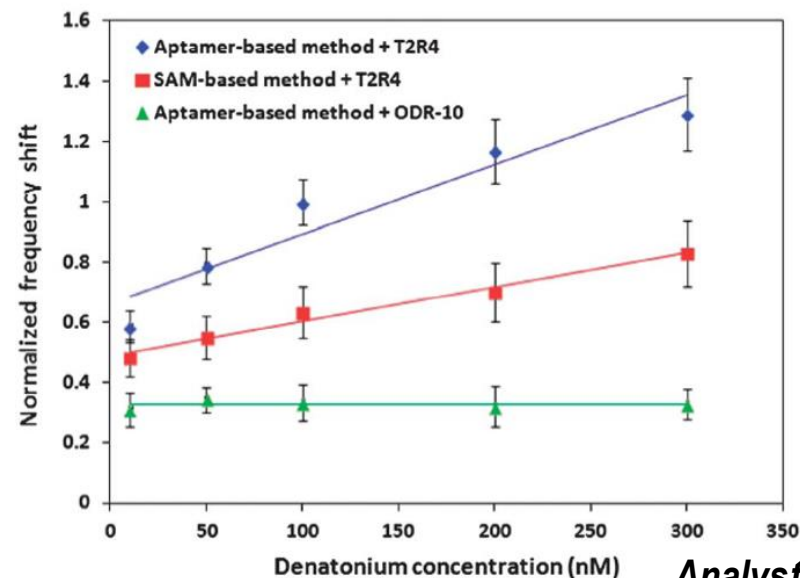
2. Biomimetic molecule-based biosensors



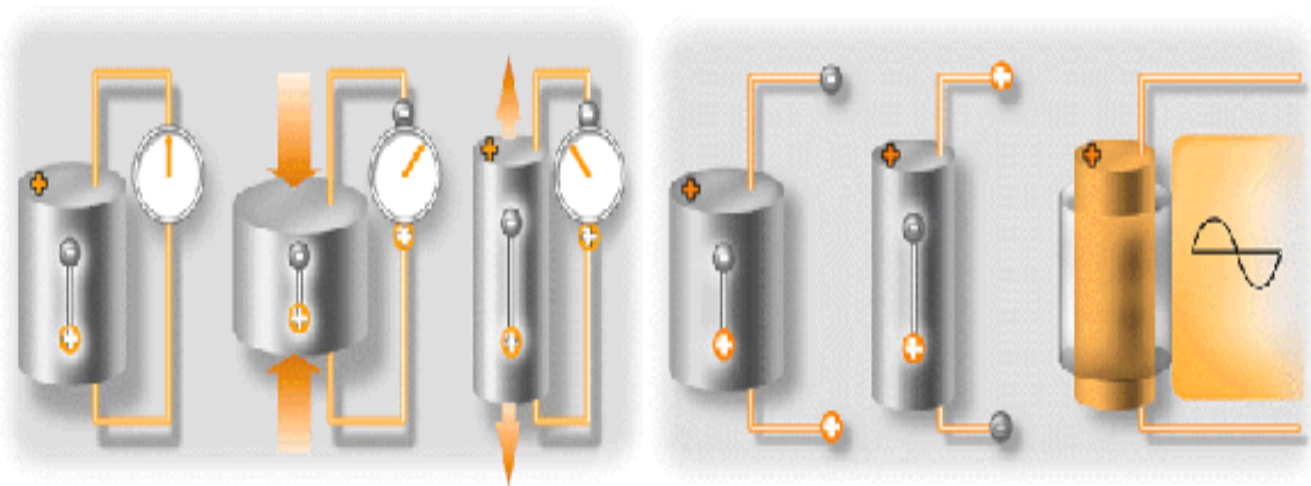
Expression of bitter receptor in HEK-293



Coupling of bitter receptor with transducer



2. Biomimetic molecule-based biosensors



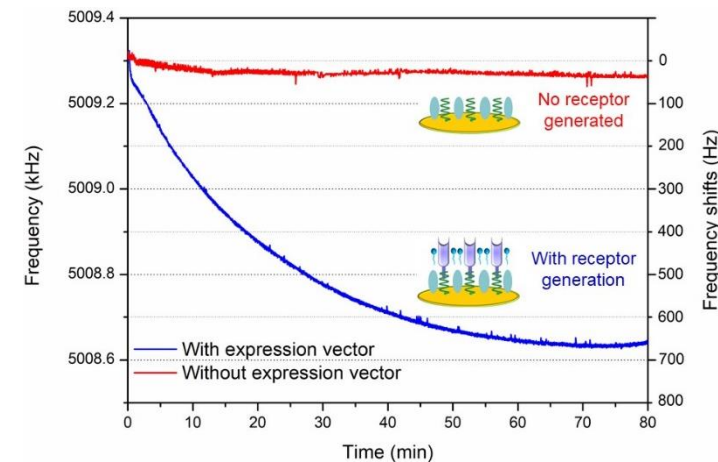
Quartz

Wire

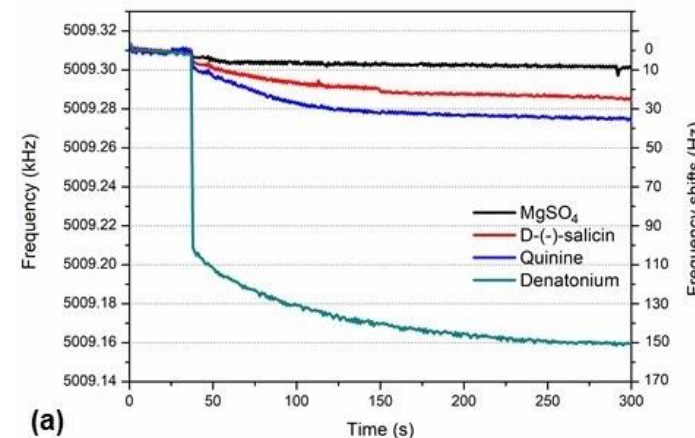
Mass-sensitive QCM device

$$\Delta F = C \times \frac{F^2 \Delta m}{A}$$

Linear range: 10 nM-0.1mM
Sensitivity: 4.96 kHz/mM
LOD: 5 nM

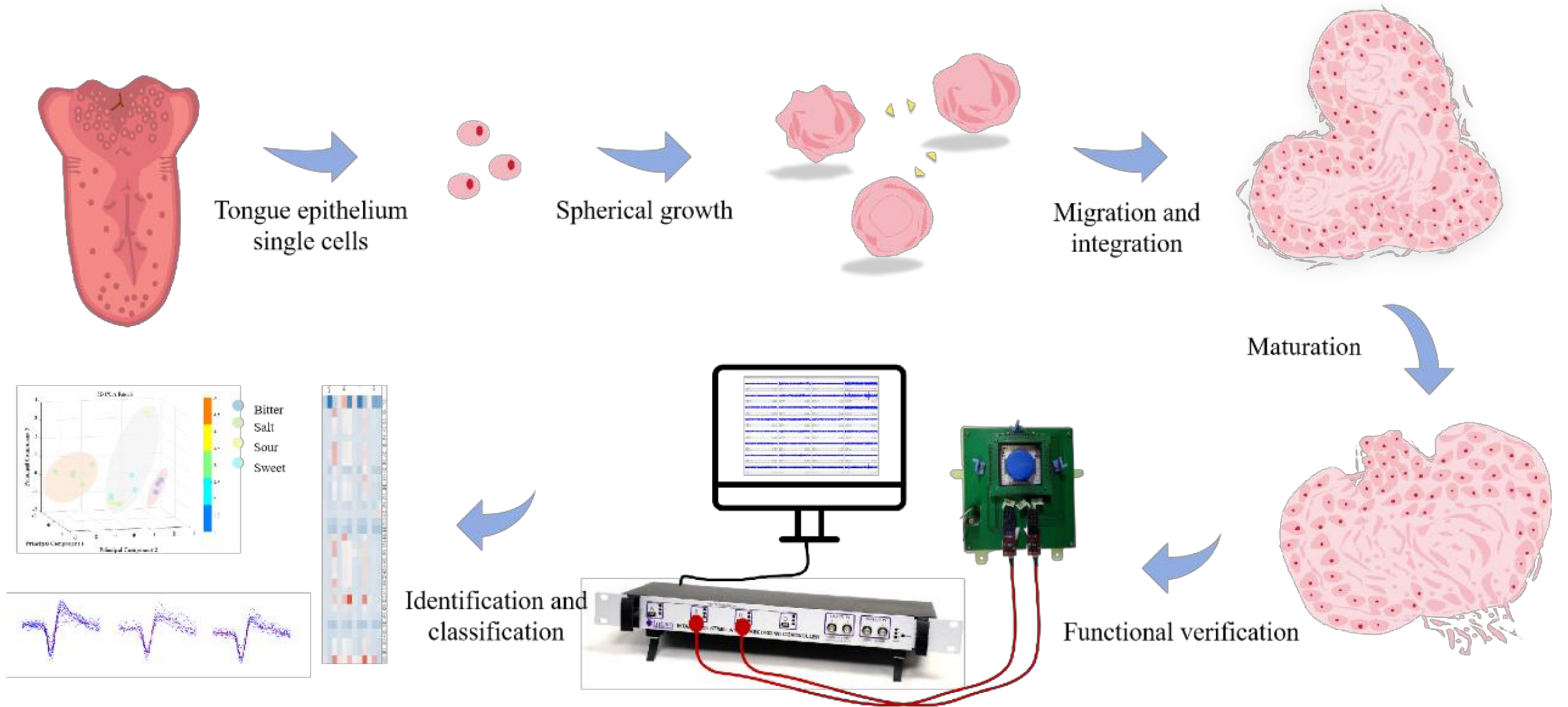


On-chip cell-free expression of taste receptor

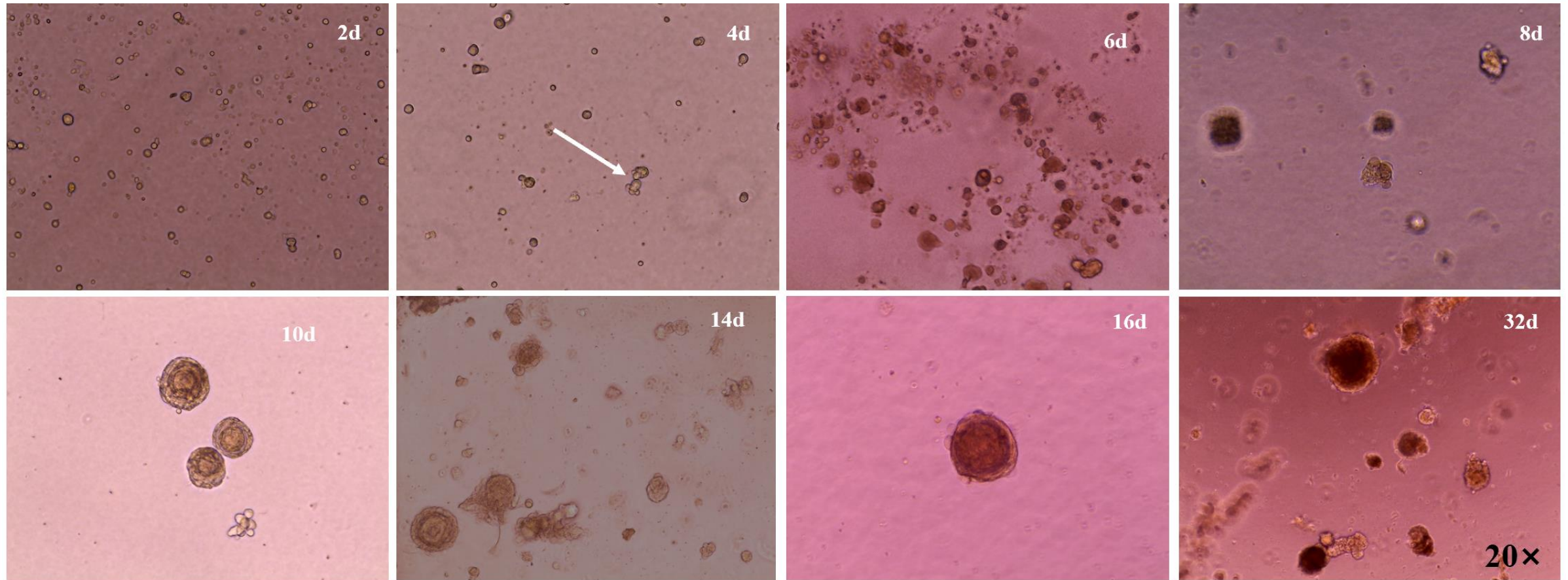


(a)

3. Biomimetic organoid-based biosensors

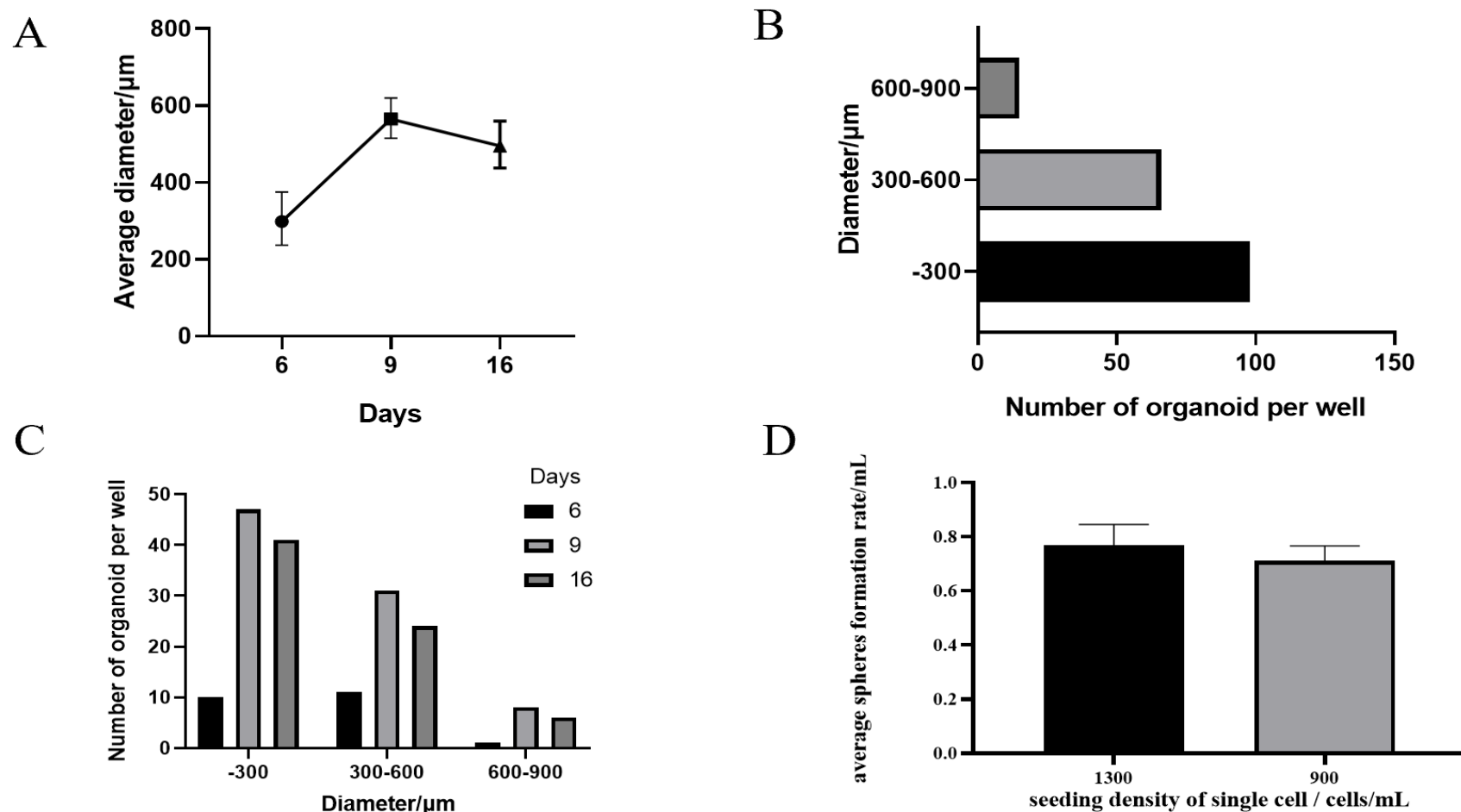


3. Biomimetic organoid-based biosensors



Taste bud organoids exhibit spherical structures and its diameter increases with culture time

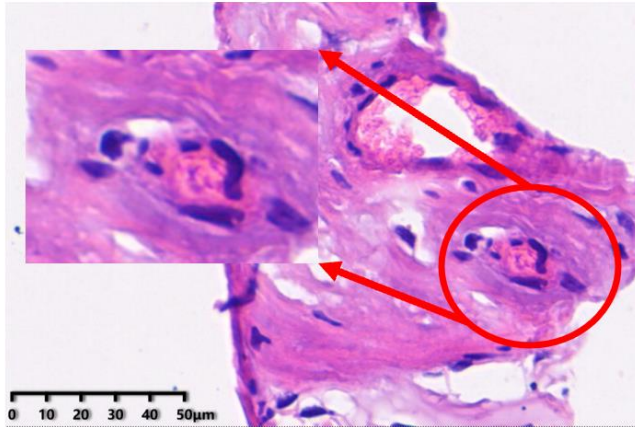
3. Biomimetic organoid-based biosensors



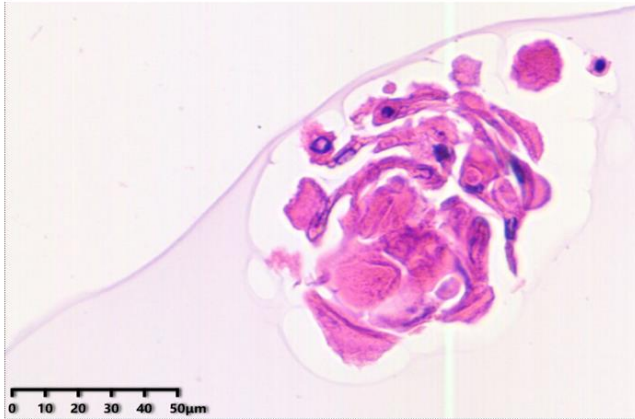
As the incubation time increased, the average diameter tended to increase overall, and was uniformly distributed at a low density of 30-50 cell spheres per well. The longer the days, the higher the number of large diameters throughout the culture period.

3. Biomimetic organoid-based biosensors

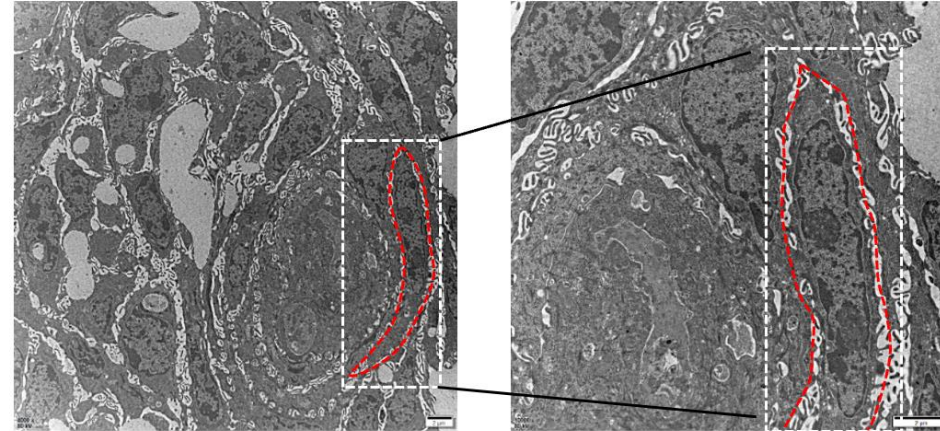
A



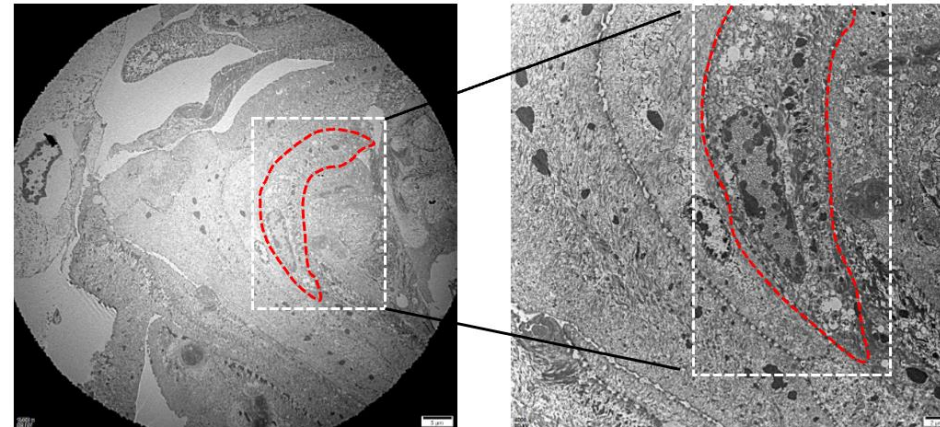
B



C

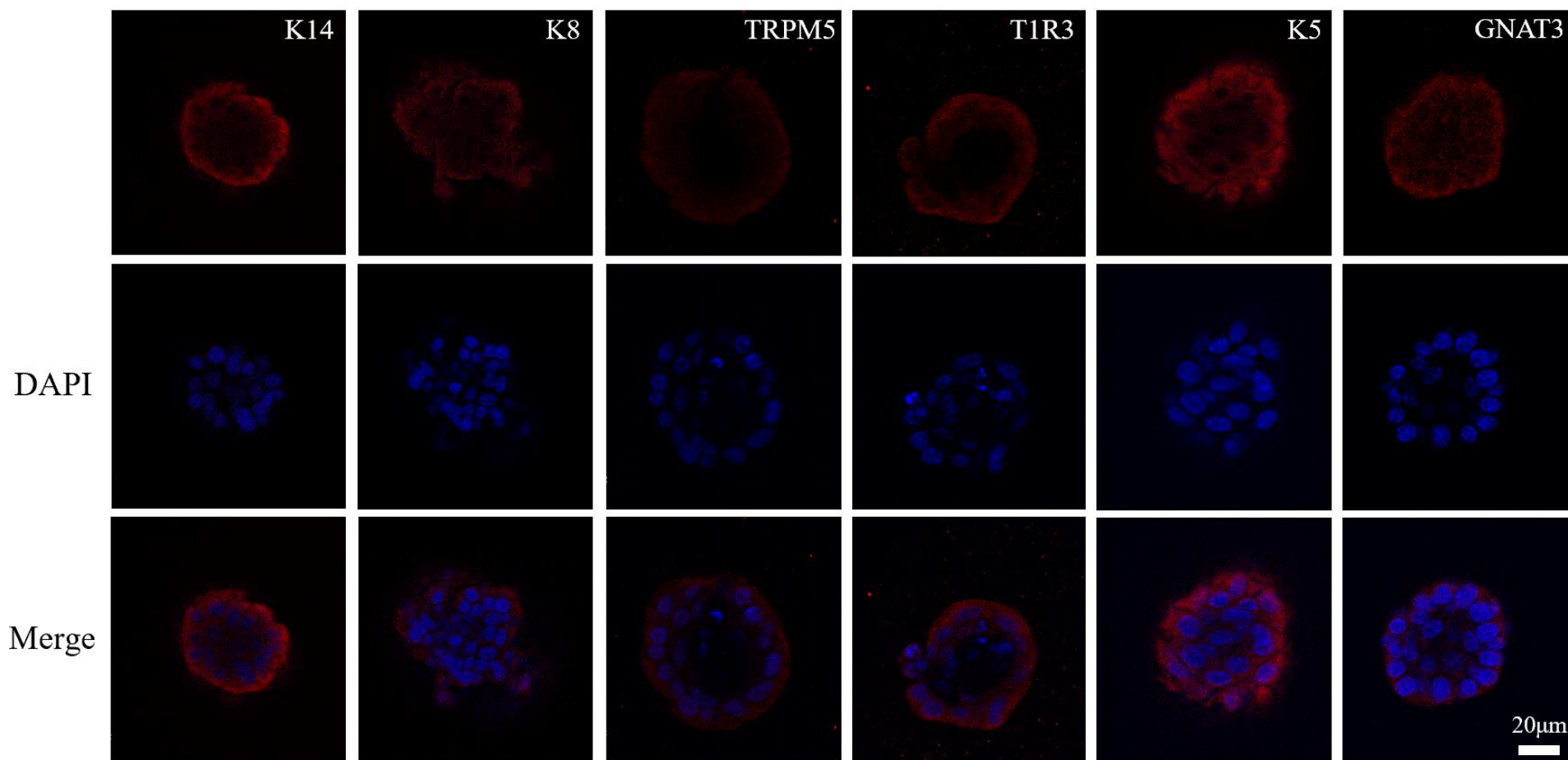


D



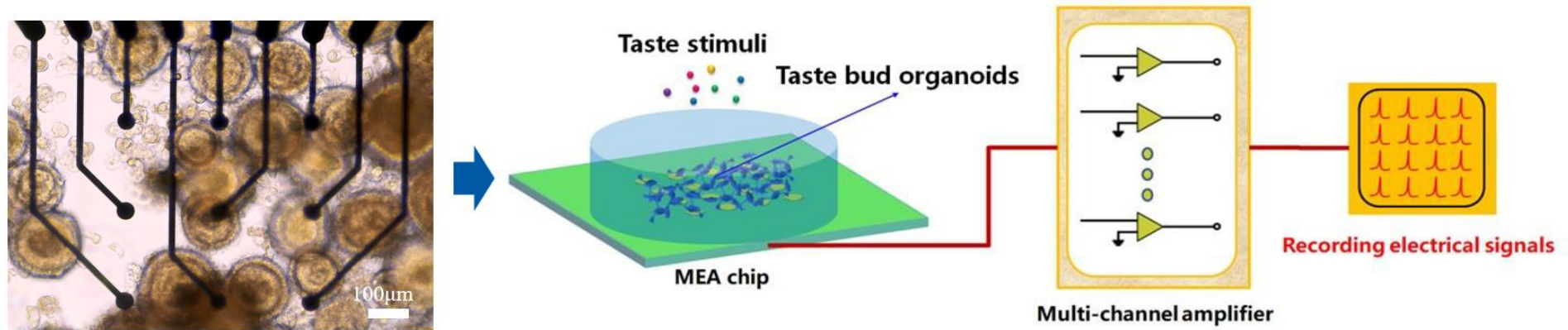
Onion-like structures resembling taste buds and mature, long stripes of taste cells allowed a preliminary determination that the cultures obtained were taste-like tissues

3. Biomimetic organoid-based biosensors

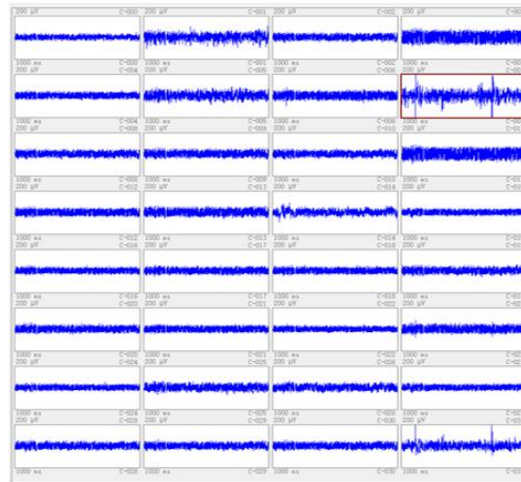


Mature taste cell markers are mainly expressed on border of organoid and proliferative cell markers are expressed inside organoids

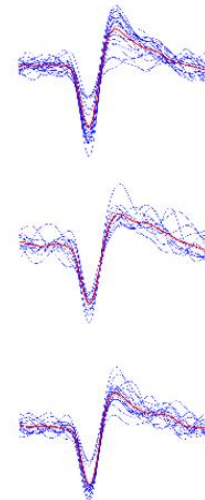
3. Biomimetic organoid-based biosensors



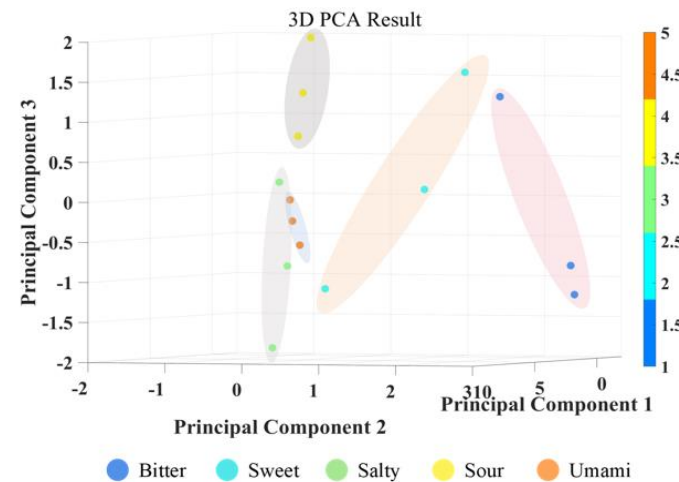
Raw signal recording



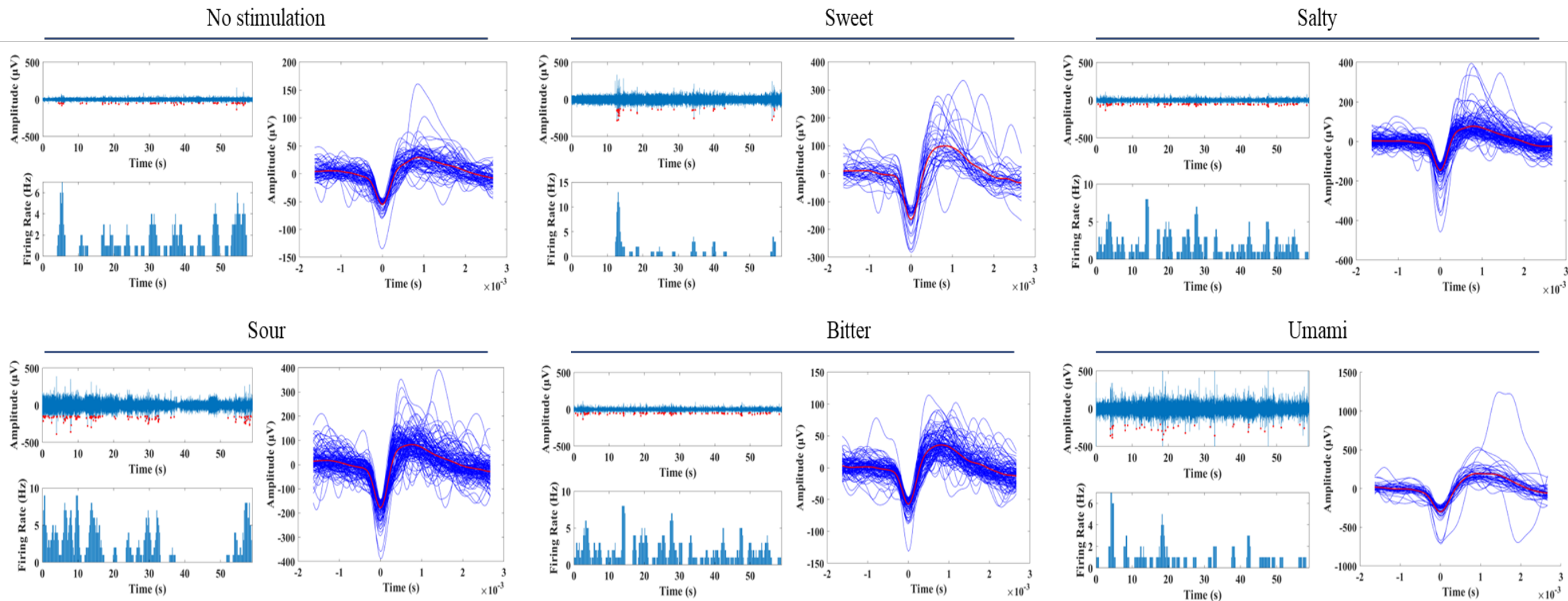
Spikes



PCA

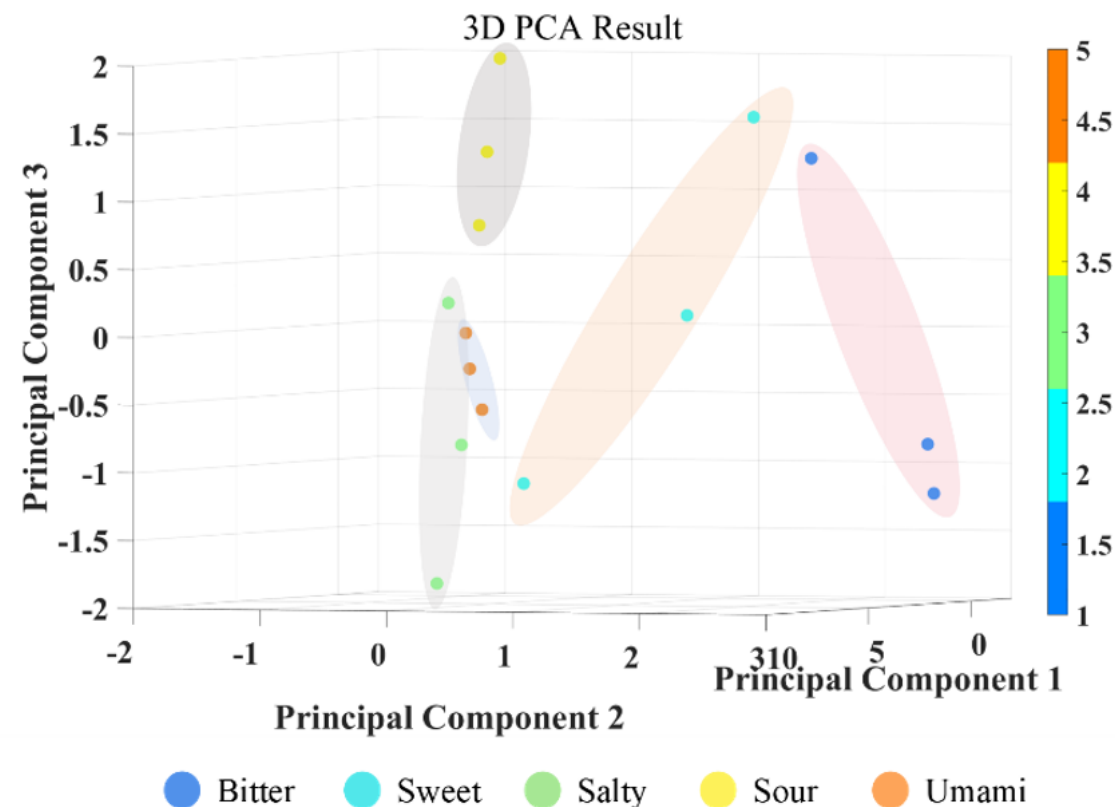
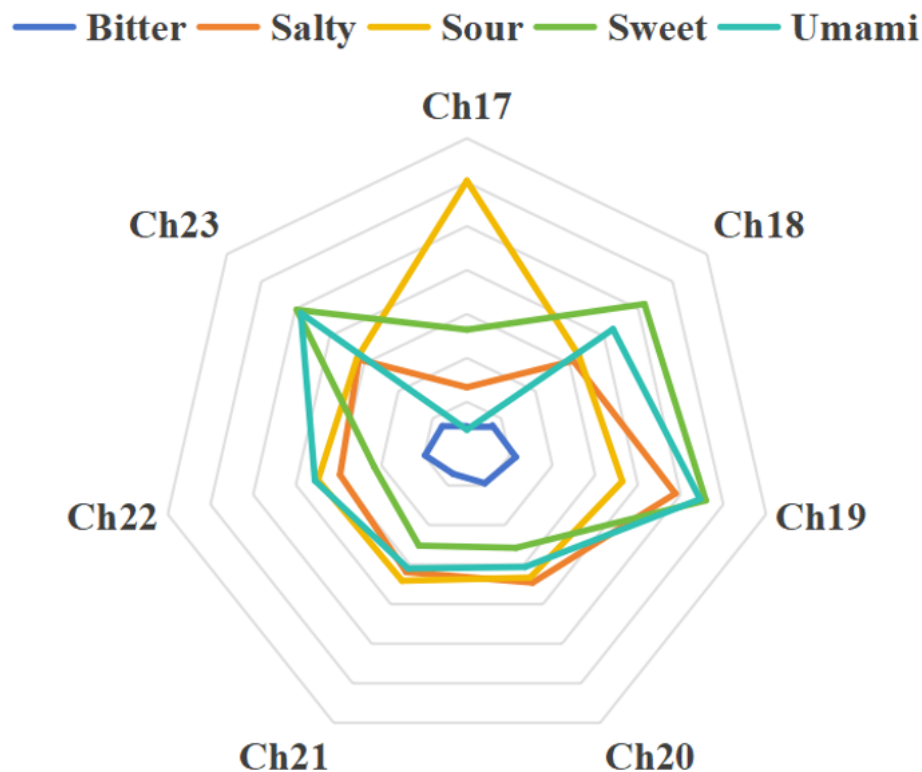


3. Biomimetic organoid-based biosensors



Significant peak potential issuance upon addition of taste stimuli, demonstrating that the MEA chip can detect the response of taste-like organs to taste stimuli

3. Biomimetic organoid-based biosensors



- Different tastes can stimulate specific electrical activity in taste bud organs through different channels.
- Principal component analysis has achieved the differentiation of multiple taste stimuli, with the first three principal components accounting for 93.02% of the total variance detected.

Thank you for your attention!

Institute of Medical Engineering (IME)

School of Basic Medical Sciences

Xi'an Jiaotong University

No. 76, Yanta West Road,

Xi'an, China, 710061

Tel&Fax: [+86 29 82657763](tel:+862982657763)

Email: wuchunsheng@xjtu.edu.cn

Website: <http://ime.xjtu.edu.cn/index.htm>

