Machine learning-enabled electronic noses and electronic tongues: A new paradigm for markers detection

Xiaoyao Wu [1], Yanlei Jing [1], Pengju Yin [1,2] *

1 School of Mathematics and Physics, Hebei University of Engineering, Handan 056038, China;

2 Natural Sciences and Science Education, National Institute of Education, Nanyang Technological University, Singapore, 637616, Singapore

* Correspondence: yinpengju@hebeu.edu.cn (P.Y.)

Abstract

With the rapid development of science and technology, artificial intelligence (AI) and machine learning (ML) have become the forefront of innovation. Electronic noses and tongues, which mimic human smell and taste perception, have great potential in fields such as environmental monitoring, food safety, medical diagnosis and quality control. However, the traditional electronic nose and tongue systems still face challenges due to the complexity of marker morphology and the limitations of sensors. Machine learning technology has also proven to be a valuable tool for improving traditional electronic nose and tongue technology. In this review, we introduce the principle and design of machine learning combined with electronic nose and tongue technology, analyze some recently published articles on machine learning-assisted electronic nose and tongue for marker detection, and review the practical application of machine learning technology in the field of electronic nose and tongue. It is believed that through continuous exploration and innovation, machine learning will promote the application of electronic nose and electronic tongue, realize intelligent monitoring and control, and provide help for human life and health.

Keywords: electronic nose and electronic tongue; Sensor; Machine learning; Marker detection

1. Introduction

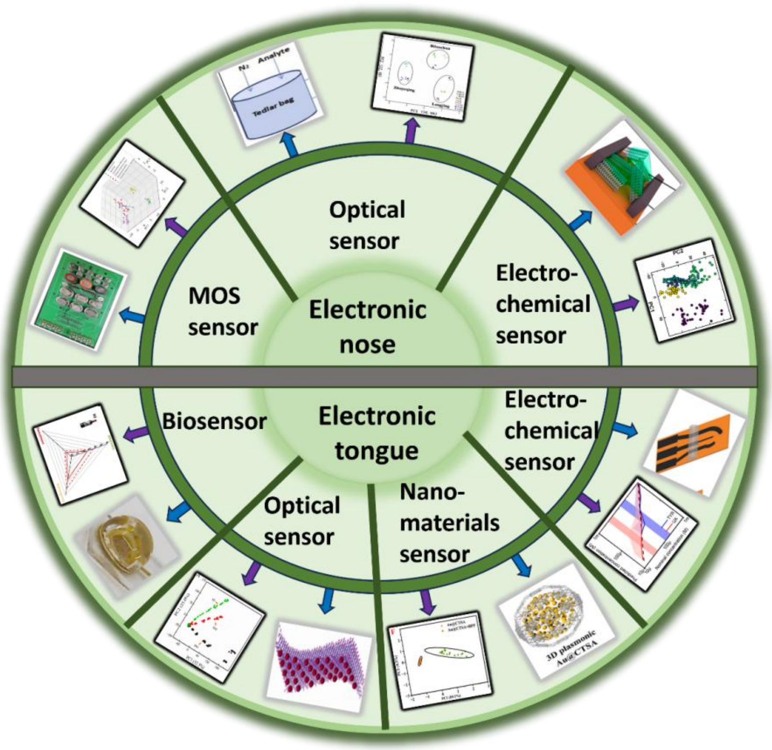
In the era of information technology, machine learning, as a core domain of artificial intelligence, has become a driving force for technological innovation and application development since its inception in the 1950s. Machine learning first gained recognition in the late 20th century and has since revolutionized fields such as finance, healthcare, image analysis, and natural language processing.[1] Its ability to handle large datasets and recognize complex patterns has paved the way for more intelligent systems and automation. The article aims to delve into the application of machine learning technology in electronic noses and tongues and explore how these advancements can enhance traditional sensing technologies.[2]

Electronic noses and tongues, as innovative tools that simulate human olfaction and gustation, have permeated various application domains, including food safety detection, environmental monitoring, medical diagnosis, and pharmaceutical quality control. Electronic noses typically consist of multiple types of sensors, such as electrochemical, metal oxide semiconductor (MOS), and optical sensors, which can sensitively detect volatile organic compounds (VOCs) and other gases. Electronic tongues, on the other hand, employ electrochemical, optical, biosensing, and emerging nanomaterial technologies to analyze the chemical composition of liquid samples. Although traditional electronic noses and tongues have demonstrated promising results in these applications, they often face challenges such as limited precision and sensitivity. The integration of machine learning technology offers a promising solution to overcome these limitations.

To overcome the limitations of traditional sensing, machine learning algorithms, particularly deep learning, have been introduced into electronic nose and tongue systems. These algorithms can process large amounts of complex sensor data, significantly improving system recognition accuracy and reliability. Compared to traditional data processing methods, machine learning-based electronic noses and tongues exhibit greater flexibility and adaptability, enabling them to better distinguish subtle chemical changes and provide more accurate analysis results in complex environments by empowering electronic noses and tongues with machine learning technology, their application potential has been greatly expanded, offering new solutions to traditional challenges.

The primary goal of this review is to extensively explore the key role of machine learning technology in electronic nose and tongue systems. First, we will introduce in detail the principle and process of machine learning-assisted electronic nose and electronic tongue for marker detection. Next, we will look at the application of machine learning techniques in different sensor arrays and some exciting examples.[3] Finally, we will consider the future trends of machine learning technology in electronic nose and tongue systems, as well as the challenges in medical detection, food detection, and other areas. Through this comprehensive review, we hope to provide readers with a thorough understanding of the current applications and future development directions of machine learning in electronic nose and tongue systems, offering valuable insights and inspiration for further research and application work in this field, and paving the way for new opportunities in sensor technology and analytical chemistry.

Scheme 1. Application diagram of electronic nose and electronic tongue combined with machine learning algorithm in marker detection



2. Machine learning in electronic nose and tongue

Machine learning, a subset of artificial intelligence, is dedicated to enhancing the performance of computer systems through learning and experience, without explicit programming. At its core, machine learning enables computer systems to discern patterns and principles from data, leveraging these insights to make informed predictions and decisions. In the era of information technology, the integration of machine learning has permeated various facets of our lives.

Electronic nose and tongue are important technologies to simulate human smell and taste. The basic principle is to use the sensor to convert the relevant signals of the substance to be measured into electronic signals to provide data input for subsequent analysis and processing. These sensors include optical, electrochemical, nanomaterial and biosensors, which can obtain Raman spectrum, fluorescence spectrum, frequency shift waveform, open circuit voltage response, conductivity change, current fluctuation and other information. The application of machine learning technology can realize the comprehensive analysis of information and extract key features from a large amount of data through feature extraction methods. These features are analyzed and processed by machine learning algorithms such as classification, regression, clustering and neural network, and the functions of sample classification and recognition and regression prediction are realized. It is worth noting that in the field of electronic nose and electronic tongue technology, the rapid development and application of machine learning has shown great potential in feature extraction, pattern recognition, classification and regression, injecting new impetus into the development of these two technologies.

Regarding feature extraction, sensor-generated data in electronic nose and tongue technology typically comprises extensive and intricate odor and taste information, often plagued by noise or redundancy. Direct utilization of such data may yield inaccurate analysis outcomes, impeding marker identification. Machine learning methodologies excel in extracting pivotal features from this data, facilitating a more nuanced characterization of olfactory and gustatory properties4. For instance, leveraging deep learning convolutional neural networks (CNNs), representative features can be extracted from sensor output signals, transforming complex electrical or optical data into analyzable formats. By mitigating noise and smoothing signals affected by external factors, key features can be discerned, enhancing the precision of marker detection.

In the realm of pattern recognition, machine learning's inherent capacity for efficient marker detection based on training data sets is leveraged. Electronic noses and tongues are frequently utilized to differentiate between various odors and tastes, with machine learning algorithms pivotal in training systems to recognize new samples. Algorithms like support vector machines (SVM) and deep learning models such as recurrent neural networks (RNN) have proven instrumental in accurately classifying complex olfactory and gustatory stimuli. Beyond traditional supervised learning, unsupervised methods like clustering algorithms automatically classify odors and tastes, enhancing comprehension of sample similarities and distinctions.

Regression models based on machine learning techniques play a key role in quantitative analysis of smells and tastes. By learning from known samples, these techniques can establish a mapping between sensory input and relevant parameters to provide accurate predictions for unknown samples. This ability is particularly valuable in areas such as medical diagnosis and food processing, where it can produce more accurate analytical results. For example, in the food industry, machine learning algorithms can be used to predict alcohol concentration in wine. By modeling the sensory features of a large number of known wine samples, the algorithm can learn the relationship between these features and alcohol concentration. The model can then be used to predict the alcohol concentration of new wine samples, providing an important basis for production and quality control.
Through the integration of machine learning, electronic nose and tongue technologies are evolving towards heightened intelligence, showcasing enhanced sensitivity, selectivity, non-destructiveness, and convenience. This convergence of technologies presents novel avenues for olfactory and gustatory perception and analysis. Notably, the significant strides made in applying machine learning to electronic nose and tongue technology have ushered in fresh perspectives and methodologies for odor and taste perception. As machine learning algorithms continue to advance, electronic nose and tongue technologies are poised to extend their applications across diverse domains, fostering innovation and progress in related industries.

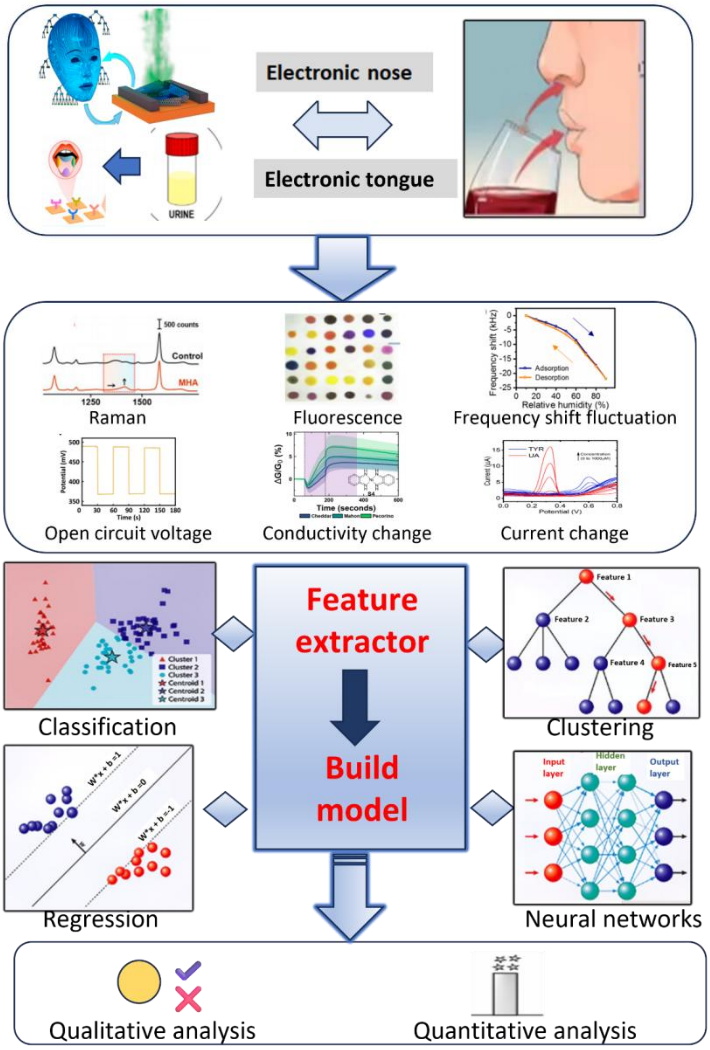


Figure 1. Workflow diagram of machine learning-assisted electronic nose and electronic tongue.

3. Machine learning-enabled electronic nose

The sense of smell plays a pivotal role in the recognition and detection of various odor markers. Extensive efforts have been dedicated to developing artificial olfactory systems that emulate the capabilities of biological systems. In recent years, propelled by the continuous advancements in machine learning technology, the electronic nose has emerged as an intelligent sensor mirroring human olfaction, garnering increasing attention. The integration of machine learning has ushered in novel prospects and avenues for electronic nose technology, enhancing its precision and reliability in discerning and categorizing gas compositions[5].

Electronic nose technology[6] encompasses three primary types based on distinct sensing principles: optical, electrochemical, and MOS . Typically, a judicious amalgamation of these sensing types is achieved, enabling the conversion of intricate electrochemical data into Raman spectroscopy or fluorescence spectra through optical sensing, thereby enhancing the interpretability and intuitiveness of the data. The optical electronic nose employs optical sensors to scrutinize the optical signals emanating from the sample, encompassing phenomena like light scattering, absorption, or emission, facilitating sample composition determination. In contrast, the electrochemical electronic nose employs electrochemical sensors to assess the electrochemical attributes of the sample, such as variations in parameters like current, voltage, or resistance, for sample composition identification. The MOS electronic nose, on the other hand, relies on a metal oxide semiconductor sensor to ascertain sample composition by gauging the alteration in resistance or capacitance between the sample and the sensor surface.

Moreover, the three distinct types of electronic noses delineated in this discourse exhibit varied advantages, drawbacks, and application scopes. For instance, the optical electronic nose is frequently employed in quality assessment and identification across domains like food, beverages, chemicals, and more. Leveraging machine learning algorithms, the optical electronic nose can assimilate and discern the characteristic spectra generated by diverse samples, thereby effectuating sample classification and quantitative analysis. In the realm of the electrochemical electronic nose, its applications span environmental monitoring, medical diagnostics, among others. Through the utilization of machine learning algorithms, the electrochemical electronic nose adeptly identifies noxious gases in the atmosphere, such as CO and CO_2, enabling real-time monitoring of their concentrations. The MOS electronic nose, commonly utilized in gas leak detection, patient respiratory monitoring, and related fields, can swiftly differentiate and identify various odors with the aid of machine learning, enhancing detection accuracy and efficiency.

3.1 Optical sensing method

An electronic nose is an apparatus designed to replicate the functionality of a biological olfactory system by utilizing optical sensors for the detection and analysis of airborne chemicals. The fundamental components of this electronic nose comprise a light source, an optical sensing material, and a signal detection apparatus.

The light source emits light at specific wavelengths, and when this light irradiates the environment containing the target gas molecules, interactions occur between the gas molecules and the optical sensing material, leading to alterations in the absorption, scattering, or emission characteristics of the light. The selection of optical sensing materials plays a pivotal role in determining the efficacy of the electronic nose, as different materials exhibit distinct responses to various gas molecules. The signal detection device is instrumental in capturing the modifications in the optical signal induced by the optical sensing material and converting it into a form amenable to further analysis.

Subsequently, these signals are inputted into a data processing unit, which leverages sophisticated machine learning techniques to decipher the signals and correlate them with the attributes of known gas molecules, thereby facilitating the identification and quantification of the gas composition. The integration of machine learning technology in the domain of optical sensing electronic nose, particularly in Raman sensing and fluorescence sensing, has demonstrated considerable promise. By amalgamating the heightened sensitivity of optical sensors with the robust data processing capabilities of machine learning algorithms, the performance and precision of electronic nose systems can be substantially enhanced.

3.1.1. Fluorescence sensing method

Fluorescence sensors[7, 8] use the properties of molecules that absorb and subsequently emit light to detect chemicals. Changes in fluorescence intensity and wavelength can be used as indicators of changes in the molecular environment, such as pH, temperature fluctuations, or the presence of specific chemicals. While fluorescence sensors offer advantages in terms of sensitivity and specificity, they encounter challenges when processing complex data. In the field of fluorescence sensing, the integration of machine learning techniques is essential to examine trends and patterns in fluorescence signals for the recognition of target molecules. Machine learning models skillfully process large amounts of fluorescence data, extract valuable features, and maintain high accuracy even in noisy or complex backgrounds[9].

Fluorescence sensing technology is used for sample detection and analysis in optical sensing electronic noses, highlighting the importance of machine learning in processing fluorescence spectral data. Through machine learning algorithm, feature extraction, pattern recognition and data analysis are carried out on complex fluorescence spectral data, and finally different samples are quickly identified. It is worth noting that algorithms such as neural networks can model and classify fluorescence spectral data, facilitating the identification and quantitative analysis of various compounds.

At present, with the continuous development and improvement of machine learning technology and fluorescent electronic nose technology, the integration of the two technologies has become an important way of marker detection. It is widely used in food[10], biology, environmental monitoring[11] and other fields. Tea, as a long and continuous drink, is deeply loved by people. At the same time, the quality of tea has become uneven, so the analysis of tea quality and type has become very important. In a recent study, researchers used a combination of an artificial electronic nose based on a colorimetric sensor array and machine

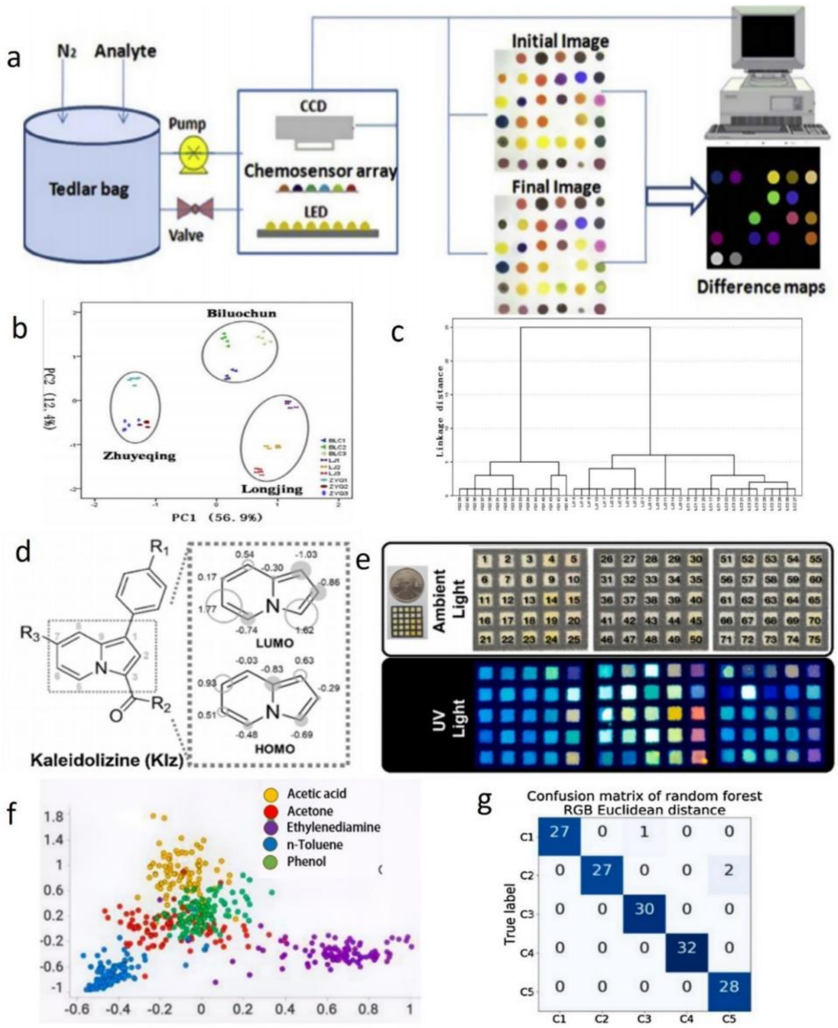


Figure 2. Machine learning assisted optical sensing-fluorescence sensor electronic nose for marker detection. (a) 6 × 6 Colorimetric sensor array and schematic diagram of detection system. (b) Scatter plot of PCA for Chinese green tea. (c) Hierarchical cluster analysis dendrogram for Chinese green tea. (d) Chemical structure of the Kaleidolizine (left) and schematic figure of the atomic coefficients of the HOMO and LUMO of indolizine core skeleton (right). (e) Photograph of fluorescent compound array made with 75 different KIz compound on wax-printed cellulose paper under irradiation with ambient light (up) and 365 nm UV light (down). (f) PCA analysis of data set acquired with pattern changes of fluorescent array, exposed with 5 different VOC (acetic acid (yellow), acetone (red), ethylenediamine (violet), phenol (green) and toluene (blue)). (g) Data description and summary of classification accuracy for each VOC type. c-e) Confusion matrices of 5-folds cross-validation Random Forest models

learning technology to classify and identify nine varieties of Chinese green tea from different places and grades through fluorescence sensing technology[12]. The basic principle and flow chart of green tea detection experiment are shown in **Figure 2a**. For all green tea odor analysis, all tea leaves are put into sealed bottles, gas is enriched at 22℃ for 10min, and then the gas is collected by syringe, and then transferred to Tedlar bag containing 3l ultra-pure nitrogen. Open the valve and pump to circulate the Chinese green tea gas in the system. When the gas enters the electronic nose sensor array printed with nano-porous porphyrins, dimeric metal porphyrins, metal phenol complexes and chemically reactive dyes on the hydrophobic film, the fluorescence sensor array will produce different colors according to the different Chinese green tea odors exposed to it. The reaction time is 5min. Then the fluorescence spectra of the original array and those after changing color will be collected. Finally, hierarchical cluster analysis (HCA) and principal component analysis (PCA), two machine learning algorithms, were used to analyze the fluorescence change patterns. The classification results of PCA machine learning algorithm are shown in **Figure 2b**. The score vectors obtained (i.e. PC1 and PC2) account for 69.3% of the total variance, and different types and qualities of tea can be well distinguished. In addition, the tea produced in the same place has an obvious clustering trend, reflecting the good sensitivity of the artificial electronic nose. The classification results of HCA machine learning algorithm are shown in **Figure 2c.** HCA analysis is a typical visualization analysis method for high-dimensional data. It calculates the similarity by measuring the Euclidean distance between the objects to be measured, so as to achieve the effect of priority clustering and stratification. The experimental results show that the artificial tongue and nose using colorimetric method can distinguish the origin and grade of green tea in China, which has important guiding significance for green tea industry.

Fluorescence sensing optical electronic nose also has a wide range of applications in VOCS (volatile organic gases). In a recent study, the researchers made the fluorescent sensing materials into Kaleidoscopic fluorescent arrays by special processing for VOCS research[13]. In this study, the researchers used a paper-based POC sensing array composed of kaleidoscopic fluorescent compounds for fluorescence signal sensing. The sensor array was designed with an indole structure (**Figure 2d**) as the fluorescence core skeleton, and 75 different KIz fluorescence derivative libraries were designed and synthesized. The fluorescence change patterns of KIz on the array were specific to the target chemicals adsorbed on cellulose paper. Under ambient light (top) and 365 nm ultraviolet light (bottom), fluorescent compounds made of 75 different KIz compounds on wax-printed cellulose paper were simultaneously present under a single UV excitation and produced different emission spectra (**Figure 2e**). Using the unique color-changing properties of the electronic nose, the researchers exposed 5 different VOCs in the sensor array 100 times, collected 500 sets of spectral data, used PCA (principal component analysis) method to classify the spectral data, the classification results showed a low accuracy, and then used the random forest method to analyze the spectral information again. More than 90% accuracy is achieved, and the resulting confusion matrix is shown in **Figure 2f**. The good experimental results obtained in the research make people have new methods and ideas for the study of VOCS.

The fusion of optical electronic nose based on fluorescence sensing with machine learning technology represents a cutting-edge approach to odor recognition and analysis. Combining highly sensitive fluorescence sensors with powerful data-processing machine learning algorithms offers advantages in terms of accuracy, real-time analysis, and adaptability, although cost and environmental constraints need to be considered. On the whole, the application prospect of the integrated technology is broad, and it has great potential and market value.

3.1.2. Raman sensing method

The integration of machine learning algorithms with Raman sensing technology has revolutionized scent marking detection, allowing rapid and accurate identification of target molecules from complex backgrounds. Raman sensing is a traditional method that relies on light scattering caused by molecular vibrations, providing complex molecular structural details through unique Raman spectroscopy. However, the complexity and time-intensive nature of Raman spectroscopy hinders real-time and online monitoring applications.

Introducing machine learning algorithms, such as support vector machines (SVM), principal component analysis (PCA), or deep learning networks, can automatically identify and resolve characteristic peaks in Raman spectra. By training the model to recognize the Raman spectrum of a specific gas molecule, the machine learning algorithm can quickly and accurately extract the information of the target molecule from the complex background to realize the identification and quantitative analysis of different odor components, thereby improving the detection speed and reducing human error.

With the advancement of machine learning technology, combining machine learning with optical sensing electronic nose has become an important method for marker detection. In 2019, William John Thrift et al. developed an odor compass using SERS sensing and machine learning, which proved effective in odor detection by identifying odor sources based on a few markers[14]. They used a two-dimensional self-assembly method, physical activation chemical self-assembly (2PAC), to create SERS surfaces, as shown in **Figure 3a**. **Figure 3b** illustrates the layout of the SERS sensor and analyte source. Benzenethiol (BZT) and 3-methoxybenzenethiol (MBZT) were chosen as analytes due to their similar SERS spectra and chemical affinity for gold nanoparticles. After obtaining Raman spectroscopy data, we pre-processed spectral data using noise reduction and smoothing algorithms before dividing it into training and validation sets (8:2 ratio). The NMF method reduced the spectral dimensions from 1011 wave numbers features to 3 NMF scores, enhancing model convergence for Raman data analysis, as depicted in **Figure 3e**. They successfully distinguished BZT and MBZT based on vibration spectrum characteristics using various machine learning methods. KNN (Convolutional Neural Network) and SVM (Support Vector Machine) classifiers achieved over 90% accuracy in odor analysis.

Additionally, they applied the SERS-based odor compass to locate bacteria, achieving an 82.95% classification accuracy on the test set using the support vector machine method, as shown in **Figure 3g**. These findings demonstrate the effectiveness of SERS-based scent compasses and the importance of integrating machine learning with electronic nose technology for precise marker detection.

Another good combination of optical electronic nose and machine learning is a SERS based electronic nose to distinguish and identify VOCS[15] in tea to achieve accurate classification of tea[16]. VOCs are gaseous compounds with distinct odors emitted from plant tissues[17, 18]. The device operates in a static headspace sampling environment to generate VOCs and detect quantitative differences based on collection time (**Figure 3h**). Transmission Electron Microscopy (TEM) images revealed the use of TAgNSs as the substrate for SERS detection (**Figure 3i**). TAgNSs offer a uniform polymer layer with strong adhesion and an absorption peak at 450nm, making them suitable for SERS substrate (**Figure 3j**). During experimentation, the electronic nose collected SERS spectra of black tea, Earl Grey, and rooibos teas overnight, capturing different VOCs present in each tea (**Figure 3k**). Pre-processing of the spectra revealed specific peaks corresponding to para-cymene, β-pinene, and acetylacetone. Principal Component Analysis (PCA) was employed to process and classify the overnight SERS spectral data.Remarkably, after averaging ten repetitions, the classification accuracy of overnight data approached 100% (**Figure 3l**). This demonstrates the electronic nose's proficiency in accurately identifying the aromas of different tea varieties by distinguishing their VOC profiles. Overall, this study showcases the capability of the developed electronic nose in VOC identification, paving the way for improved tea quality assessment and authentication.

While SERS and machine learn-based optical sensor technologies have advantages in sensitivity, selectivity, and multi-parameter analysis for marker detection, challenges such as data volume, processing complexity, and cost constraints remain. Overcoming these technical and cost-related barriers is essential to fully harness the potential of this combined technology in a variety of applications.

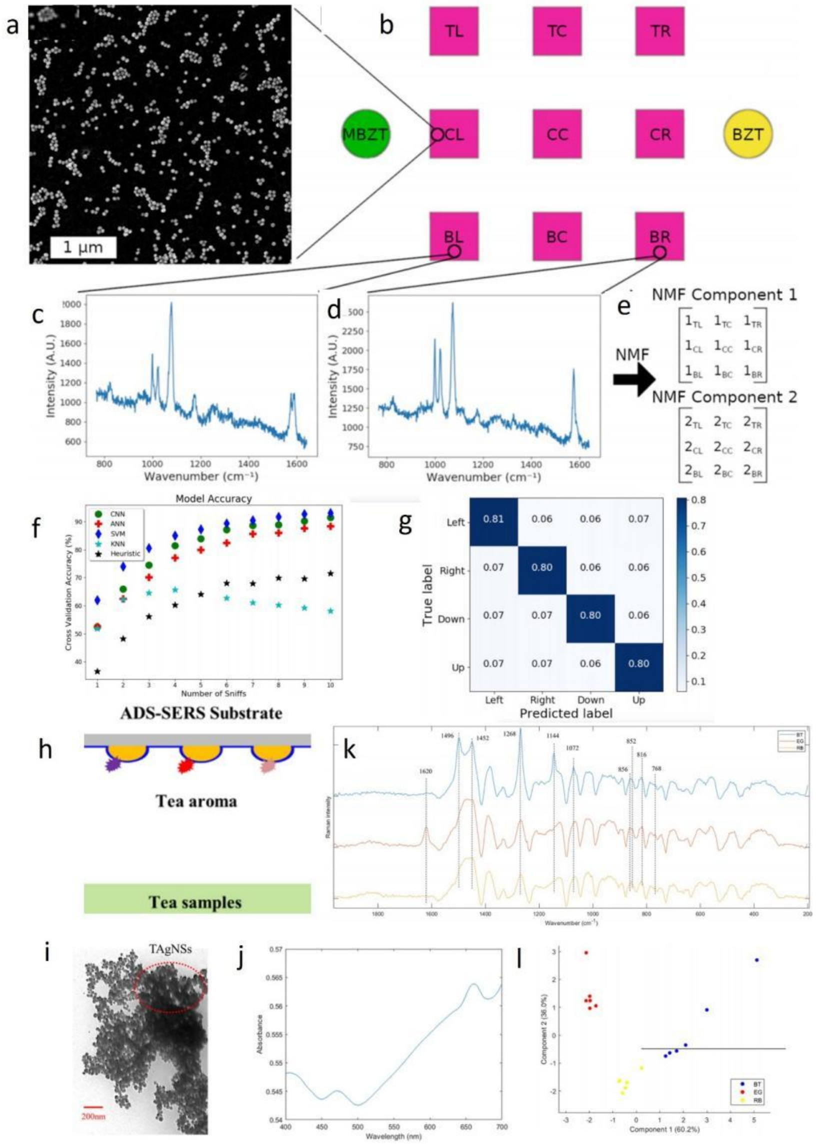


Figure 3. Machine learning-assisted optical sensing: Raman sensor electronic nose for marker detection. (a) SEM image of nanosphere assemblies that comprise the SERS sensors. (b) Schematic of SERS sensor arrays and example of multianalyte placement with respect to arrays. This schematic depicts the case where MBZT is exposed to the left of the sensor array and BZT is exposed the right of the sensor array. Representative SERS spectra of a BZT, MBZT mixture acquired from the SERS sensor in the (c) bottom left of the array and (d) bottom right of the array. SERS spectra are acquired with a 785 nm diode laser at 760 um and 0.3 s exposure time. (e) Schematic of the resulting input into the model that is constructed from NMF decomposition of the SERS spectra acquired across the sensor array (f) Cross-validation accuracy of the models used. (g) Normalized confusion matrix produced by a 1 sniff SVM model applied to the acetylacetone VOC test dataset. (h) SERS substrate device. (i) TEM image of TAgNSs. (j) UV−vis absorption spectrum of TAgNSs. (j) comparison of SERS spectra from three different tea aromas for overnight collection. (l) PCA plot based on SERS spectra of tea aromas for overnight collection.

3.2. Electrochemical sensing method

When it comes to modern substance detection technologies, electrochemical sensing electronic noses are a prominent solution. As a classical sensing approach, electrochemical sensing has been widely adopted and advanced in electronic nose applications. Electrochemical sensing utilizes electrochemical principles and techniques to detect and analyze chemical substances[19]. It measures signals such as current, voltage, or conductivity generated by chemical reactions to enable quantitative or qualitative analysis of the target substances. Common electrochemical sensors rely on different types of signals, including conductance, current, and voltage sensors. Conductance sensors primarily detect target substance concentrations by measuring changes in electrolyte conductivity. Current sensors use the current signals from electrochemical reactions for detection, while voltage sensors acquire signals based on the potential difference between the electrode and the substance being measured. These sensors can be combined with various electrochemical techniques, such as cyclic voltammetry, amperometry, and chronoamperometry, to detect and analyze diverse chemicals.

The electrochemical sensing materials widely used include metal oxides, carbon-based materials, and nanomaterials. The integration of electrochemical sensing and machine learning technologies has enabled electronic noses with advantages like high sensitivity, fast response, and ease of use, leading to their broad applications in real-time monitoring and rapid analysis.

The current sensing electronic nose generates the current signal by sensing the marker to be measured, and uses the machine learning algorithm to analyze and process the data, so as to realize the rapid and accurate detection of the marker. With the development of electrochemical sensing technology, machine learning-assisted current sensing has become a research trend. In a recent study, a multi-functional environmental sensor based on a single piezoelectric cantilever is proposed[20]. The basic principle is shown in **Figure 4a**. Using the properties of MoS_2 to produce unique properties when exposed to different environments, a thin film of MoS_2 is deposited on the surface of a 300×1000um^2 cantilever beam as the top electrode and sensing layer. By using the sensor to respond to the frequency shift (current) current signal under different humidity, different temperature and different CO_2 concentration, and then using the neural network algorithm to systematically process the output spectrum, it can realize the detection of a variety of signals, and the detection accuracy can reach more than 90%. Moreover, the author also proves through comparative experiments that the sensor can achieve high accuracy even in the environment of humidity interference. The results indicate that the proposed sensor has great potential in human-computer interaction and plant and human health monitoring.

Conductance sensing electronic nose is a conventional method for detecting gaseous substances. Conductivity sensing is a technique commonly used for electrochemical sensing electronic noses[21]. In conductivity sensing, the conductivity of the sensor changes as a result of the chemical reaction that occurs after the sensing layer comes into contact with the target substance. This change results in a change in electrical conductivity, which in turn produces a change in electrical conductivity (change in resistance) signal. By measuring and analyzing these signals, the detection and quantitative analysis of target substances can be realized. The electrochemical sensing electronic nose with conductance sensing has the advantages of fast response speed and high sensitivity. By combining with machine learning algorithms, the accuracy and reliability of detection can be further improved. In a recent study, researchers used a carbon nanotube-based sensor array（**Figure 4b**）to classify different types of cheese based on their odors[22]. The sensor array contained selectors that interacted with specific odor compounds found in cheeses, such as aldehydes, esters, alcohols, and sulfides.By exposing the sensor array to cheese odors and measuring conductivity changes **(Figure 4c**), the researchers successfully classified cheddar, Mahon, and pecorino cheeses using a KNN classification algorithm (**Figure 4d**). This study demonstrates the potential of combining electronic noses with machine learning for odor detection.

A voltage sensing electronic nose is an electronic device that uses voltage sensors to detect odors or volatile compounds. It often mimics how the human olfactory system works, detecting chemicals in the air to identify different odors or detect pollutants in the environment[23]. The working principle of the voltage sensing electronic nose usually includes the following steps: collection of gas samples, sensor collection of voltage signals, data processing, and pattern recognition. Voltage sensing electronic noses are widely used in many fields, including quality control in the food and beverage industry, disease detection in medical diagnosis, and air quality detection in environmental monitoring. They are often able to detect a wide range of different odors quickly and sensitively, and therefore have great potential in many applications[24, 25]. In a recent study, researchers developed an electronic nose for detecting hygiene-related odors by combining electrochemical gas sensors with machine learning algorithms[26]. Unlike traditional gas chromatography methods that can detect odors at concentrations of 50ppd, the electrochemical electronic nose created by the researchers has a detection limit of 1ppd. The electronic nose works by placing odorous gas in a sealed glass jar and passing it through the sensor pack via a transmission system（**Figure 4e**）. The sensor output is recorded by a data acquisition system at a specific frequency to track potential changes (**Figure 4f**). The researchers used the JMI method for feature extraction to evaluate the most informative feature subset and then applied the KNN algorithm for classification and identification of different odor sources, such as feces and urine (**Figure 4g**). The experiment yielded a 94.0% balance accuracy and 92.9% macro F1 score, showcasing the potential of combining potential sensing signals from electronic noses with machine learning algorithms for odor detection.

Electrochemical sensing technology has the advantages of high sensitivity, fast response speed and simple operation, so it has a wide application prospect in the field of real-time monitoring and rapid analysis. This electronic nose technology, which combines electrochemical sensing and machine learning, not only improves the sensitivity and accuracy of detection, but also opens up entirely new possibilities for medical diagnosis and biological research. In this section, we combine electrochemical sensing techniques with machine learning to explore electronic nose systems based on three different types of electrochemical sensing: conductance, current, and voltage. By analyzing and comparing the characteristics of these three sensing types, combined with machine learning technology for data processing and pattern recognition, we aim to improve the accuracy and sensitivity of the electronic nose system to detect complex mixtures, and provide new ideas and methods for realizing intelligent monitoring and control.

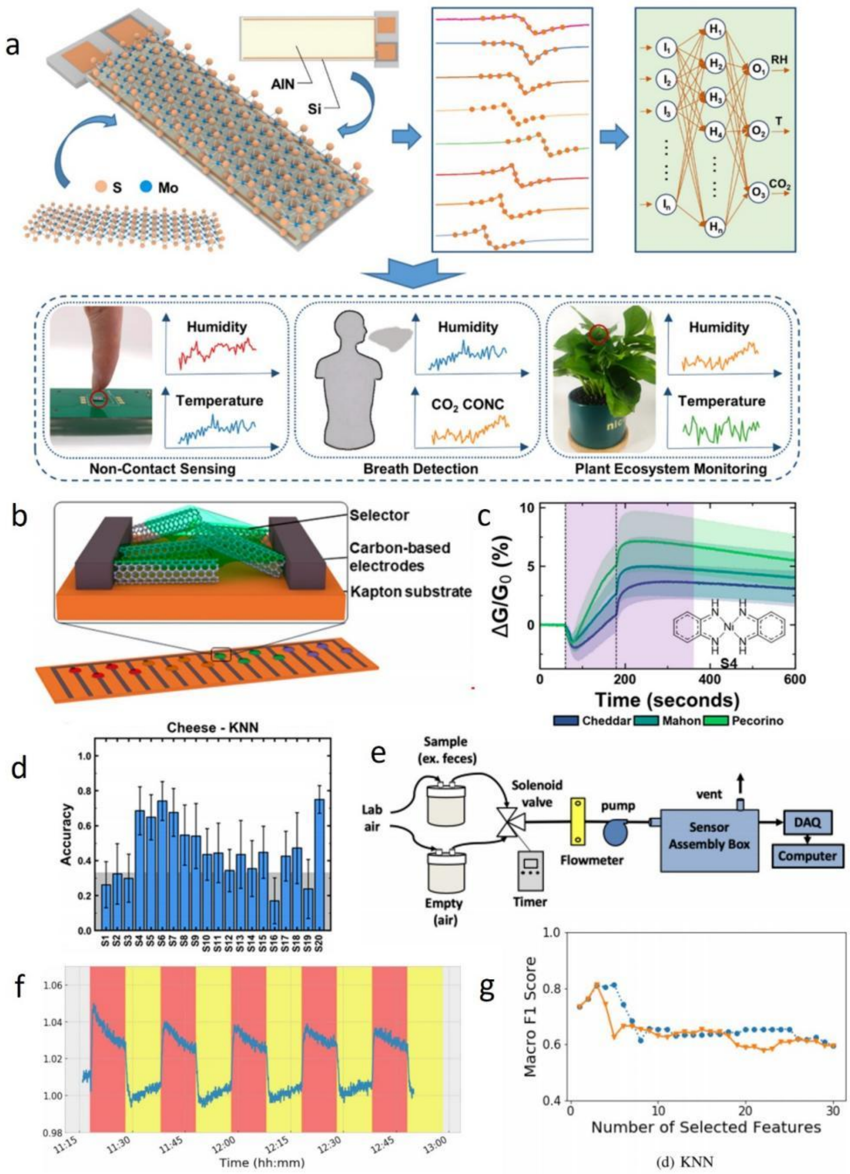


Figure 4. Machine learning assisted electrochemical sensing electronic nose for marker detection. (a) Schematic diagrams of the proposed multifunctional environmental sensor. (b) Schematic of sensing device with carbon-based electrodes deposited on a polyimide substrate. The active layer of SWCNTs and selectors is deposited between the electrodes. (c) Example of sensing response for one selector (S4) toward cheddar, Mahon, and pecorino. The response is represented as a change in conductance normalized to the conductance at the start of the exposure (ΔG/G0). (d) KNN models using single selectors for differentiating between cheddar, Mahon, and pecorino cheese. The shaded, gray area corresponds to random guessing (33% accuracy). (e) Components of the experimental setup. (f) Example of response of a gas sensor to multiple exposure over time to different odorant. Red band: period of odorant exposure. (g) Results for the classification of feces and urine odors: Classification performance using the JMI feature-selection methods and the classifiers KNN.

3.3. MOS sensing method

The MOS sensing electronic nose, a cutting-edge device in gas detection and chemical identification, seamlessly integrates MOS sensors with advanced machine learning technology. At its heart lie metal-oxide-semiconductor sensors, which meticulously detect environmental gas changes and translate them into electrical signals. These sensors operate on the principle that gas adsorption on a semiconductor surface triggers electrical resistance variations, enabling the discrimination and recognition of diverse odors or chemicals. MOS sensors have gained widespread acceptance in areas like food safety[27] and environmental monitoring[28] due to their swift response, high sensitivity, and cost-effectiveness.

Machine learning serves as a pivotal component in the MOS sensing electronic nose. It analyzes the sensor data and performs pattern recognition using sophisticated algorithms, ensuring precise identification and classification of various odors or chemical substances. This integration enhances the electronic nose's detection accuracy and reliability, allowing it to pinpoint the target substance with utmost precision. Furthermore, machine learning optimizes sensor performance and boosts its adaptability to complex odors, thereby expanding its practical application potential[29]. The application of machine learning technology has further augmented the benefits of the MOS sensing electronic nose, catapulting it to a more prominent role in the realm of gas detection and chemical recognition.

With the continuous progress of science and technology, the application of machine learning in the field of MOS sensors is also increasingly in-depth. In a recent study on wine properties, researchers used a bionic electronic nose combined with an array of MOS sensors and machine learning algorithms to detect the odors of different wines and differentiate between wines with different properties[30]. The electronic nose is mainly composed of a sensor array composed of six different MOS sensors (**Figure 5a**) and a single chip microcomputer based on the STM32F4 series. The work flow of the prototype electronic nose is divided into capture process and cleaning process (**Figure 5c**). When the grape odor is uniformly inhaled into the electronic nose, it is adsorbed by the MOS sensor, leading to an enhancement in electrical conductivity and stabilization at a constant level. During the cleaning process, the carbon adsorbent is uniformly sucked into the electronic nose by the flow control unit, and the analyte is removed from the sensor surface, which results in a decrease in conductivity, and eventually the signal stabilizes at another constant value (**Figure 5b**). Finally, BP neural network and support vector machine were used to analyze the wine properties, and the accuracy of wine region and variety identification was 94% and 92.5%, respectively, which achieved the best effect. The accuracy of identifying year and fermentation process was 67.3% and 60.5%, respectively, which also achieved good results. The results show that the bionic electronic

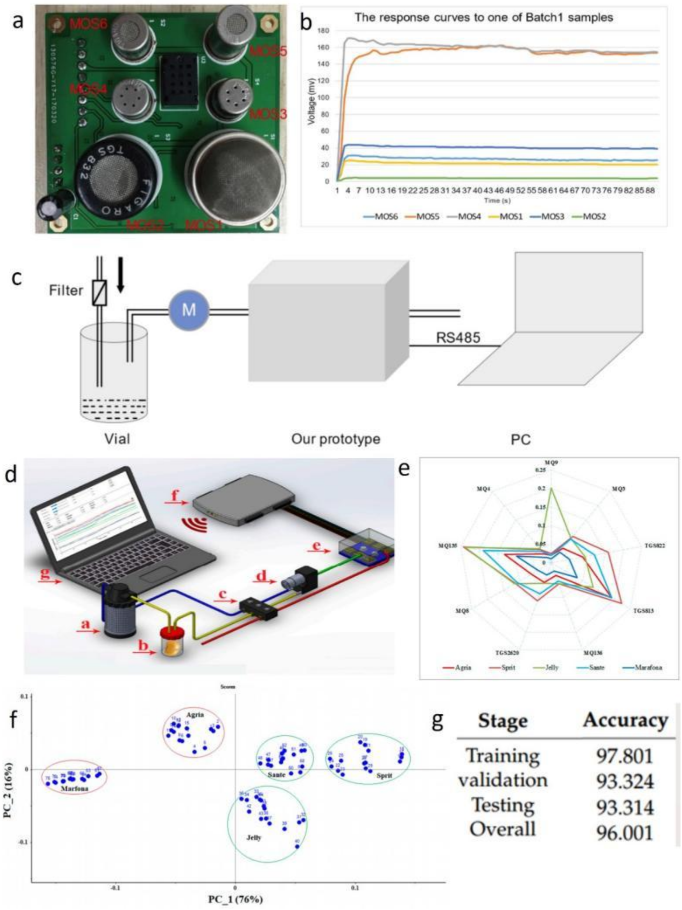


Figure 5. Machine learning assisted MOS sensing electronic nose for marker detection. (a) Printed circuit board (PCB) for data acquisition based on MOS sensor array. (b) Response curves to data from different batches. (c) Illustration of the sample detection. (d) 1. Schematic of an artificial olfactory (e-nose) system. (e) raw fingerprint chart (sensor intensities) of the VOCs potato cultivars. (f) Two-dimensional PCA plot to identify five different potato cultivars with data collected using an electronic nose. (g) Statistical results of the artificial neural network classification models.

nose developed in this paper is an alternative detection method to the traditional monitoring technology, and the device can be used to identify different wines. In addition, it also helps maintain business norms and safeguard the rights and interests of consumers.

Another study on MOS sensing electronic nose is a study on potato variety detection developed by Ali Khorramifar et al in 2021[31]. In this study, 9 kinds of sensors with the best response to VOCs were used to recognize potato odor. An electronic nose manufactured by the Department of Biosystems Engineering at Mohaghegh Ardabili University was used (**Figure 5d**). When the nose performs data acquisition, it first passes clean air through the sensor chamber to remove odors. After 100s potato gas is exposed to the sensor chamber, the sensor changes its output voltage due to exposure to potato odor, and its olfactory response is collected via a data acquisition card (**Figure 5e**). Finally, two-dimensional PCA algorithm (**Figure 5f**) and artificial neural network algorithm (**Figure 5e**) were used to analyze the voltage response of the sensor, and the classification of potato odor of species was realized with a high accuracy. Therefore, the results of this study can provide an effective basis for the rapid identification of potato varieties

In summary, the machine learning-assisted MOS sensor electronic nose shows strong potential and advantages in the field of gas detection and chemical recognition. It not only improves the accuracy and reliability of detection, but also expands the possibility of electronic nose in practical applications. With the continuous progress of technology and the expansion of application fields, it is believed that machine learning will play a more important role in the development of MOS sensing electronic nose.

4.Machine learning-enabled electronic tongue

In the wave of scientific and technological progress, machine learning has gradually become an enabler in many fields, including the application of electronic tongue technology for taste detection. The electronic tongue is an intelligent detection tool that simulates the human taste system, enabling rapid analysis of chemical components in liquid or solid samples by integrating sensor arrays and data processing algorithms.

The main sensing methods of electronic tongues can be categorized into optical sensing, electrochemical sensing, nanomaterial sensing, and biosensing. Optical sensing electronic tongues use optical technology to detect chemical substances, offering advantages like fast response and high sensitivity, but they tend to have poor stability in complex environments. Electrochemical sensing electronic tongues employ electrochemical methods, providing high selectivity and stability, yet with slower response speeds. Biosensing electronic tongues utilize biological components for detection, which more realistically simulates the human taste system, but requires stricter environmental conditions. Nanomaterial sensing electronic tongues leverage the characteristics of nanomaterials, exhibiting high sensitivity and fast response, although the stability of nanomaterials is a concern. Each sensing method has its unique application scenarios and advantages, and a combination of different sensing approaches can be integrated on the sensor to enhance the overall performance of the electronic tongue.

Machine learning plays a crucial role in electronic tongue technology. By analyzing the vast amounts of data collected by electronic tongue sensors, machine learning algorithms can identify and classify patterns of different chemicals, enabling more accurate marker detection. The introduction of machine learning enables the electronic tongue to better adapt to complex detection environments, improve the efficiency and accuracy of detection, and provide key support for marker identification. Leveraging machine learning to assist electronic tongue in marker detection can not only improve the accuracy of detection but also expand the application of electronic tongue in various fields. Therefore, machine learning is a crucial enabler for electronic tongue marker detection, bringing new opportunities and challenges for the development and application of electronic tongue technology.

Table I. Example of machine learning assisted electronic tongue.

Test substance	Sensor type	Data Analysis	characteristic	Purpose	Reference
Baijiu flavors	Optical (SERS) sensor; Nanomaterials sensor	PCA、SVM、PLS-R	PH-, PY-, MB- and AN- are used as four receptors	The identification of flavor and the content analysis of flavor molecules were realized by ML method	32
Multiple metal ions (Cr6[33]+, Fe3+, Fe2+, Hg2+)	Optical (Fluorescence) sensor; Nanomaterials sensor	SX model	Xylenol orange is used as a receptor	Identification and concentration analysis of various metal ions in the environment	33
Multiple proteins	Optical (Fluorescence) sensor; Nanomaterials sensor	LDA; PCA	Four kinds of fluorescent Au nanoparticles were used to construct sensing receptors	To realize the distinction of proteins in human urine, and effectively distinguish the serum of epilepsy patients and normal people	34
Wine flavor	Optical (Fluorescence) sensor; Nanomaterials sensor	CNN	Lanthanide Ion-Induced Forming MOF/HOF Composite were used to construct sensing receptors	Intelligent fluorescent tongue was used to distinguish various wine flavor compounds (Tannic acid, ionic ketone, etc)	35
Protein biomarker	Optical (SERS) sensor; Nanomaterials sensor	PCA, RF; ANN	Single-stranded DNA oligonucleotides encapsulated switches exhibit chirality changes, resulting in the formation of DNA-SWITCH sensor complexes.	The detection of protein biomarkers in uterine lavage fluid can realize the diagnosis of cervical cancer	36
Bisphenol compounds in water sample	Optical (SERS) sensor; Nanomaterials sensor	PCA; KNN	Three-dimensional plasma cellulose was utilized as the sensing material.	Realized the detection of traces bisphenol A (BPA), bisphenol S (BPS), and bisphenol F (BPF) in water sample,	37

4.1 Electrochemical sensing method

The electrochemical sensing electronic tongue represents a type of sensor rooted in electrochemical principles. Depending on the physical quantity being measured, electrochemical sensing technology can be categorized into three primary forms: potential, current, and conductance. Specifically, the potential sensor detects specific chemical substances by gauging changes in electrode potential, while the current sensor accomplishes detection by measuring alterations in the current flow on the electrode. Furthermore, the conductance sensor identifies target substances through assessing changes in the conductivity of the electrolyte solution. The electrochemical sensing electronic tongue has garnered widespread application in areas such as environmental monitoring, biomedicine[38], and food safety[39], among others. Its increasing popularity underscores its significance in marker detection. By integrating machine learning technology, electrochemical sensing has been further enhanced, evolving into a novel form of electronic tongue that has brought about significant advancements and innovations in the field of marker detection.

The working principle of current-type electronic tongue is based on the current signal generated by electrochemical REDOX reaction. This system typically employs a three-electrode configuration, comprising a working electrode, a reference electrode, and a counter electrode. When the target liquid is in contact with the working electrode, the REDOX reaction occurs, resulting in a corresponding current change[40]. The size of the current signal is proportional to the gas concentration, which provides a possibility for quantitative analysis. However, combining machine learning technology to realize qualitative and quantitative analysis of markers has become an important trend in its development. Recently, a study showed us a machine learning (ML) driven current-mode multimodal analysis device. The device uses molybdenum polysulfide (eMoSx) electrodeposited on laser-induced graphene (LIG) as a single sensing material[41]. It can simultaneously detect tyrosine (TYR) and uric acid (UA) in sweat and saliva, and its detection principle is shown in **Figure 6a.** The workflow is as follows: First, the multiplexer automatically selects the electrochemical module for testing through the developed script. These modules include cyclic voltammetry (CV), square wave voltammetry (SWV), differential pulse voltammetry (DPV) and large amplitude alternating current voltammetry (LAACV). The raw data is then processed to extract the component peaks, and the machine learning model is trained through an iterative process using a fitting constraint optimizer based on the data distribution. The optimized model is used to test unknown data to predict analytes and their concentrations **(Figure 6a**). When the machine learning algorithm was used for feature extraction and to predict the concentration of TYR and UA in saliva of healthy people, the results were shown in **Figure 6b**. The detection limits (LOD) of TYR and UA were increased to 60 μM and 60 μM, respectively, showing excellent prediction results. **Figure 6c** shows the linear machine learn-based current signal response of the sensor to analytes in artificial sweat. The detection limits of TYR and UA in sweat were 40 μM and 170 μM, respectively. The experimental results show that the combination of current tongue and machine learning method reduces LOD by two orders of magnitude, breaking through the limitation of traditional method in concentration prediction, and opening a new chapter for liquid concentration identification.

Voltage-type sensors measure voltage changes to accurately detect the presence and concentration of a target substance. The potential difference signal is closely related to the concentration, type and other characteristics of the substance, which is the key basis for qualitative or quantitative analysis. When machine learning technology is combined with voltage-based sensors, a large amount of voltage data is used to train the model so that it can accurately identify the voltage characteristics of different substances, so as to achieve accurate detection and quantitative analysis of the target substance. In addition, machine learning technology can also transform complex and difficult signals into intuitive and understandable graph signals, which greatly improves the efficiency and accuracy of signal processing. This new type of voltage-sensing electronic nose combined with machine learning technology is showing its great application value in more and more fields. Recently, a new bionic artificial electronic tongue system based on this combination of ideas has been reported[42]. By integrating multiple arrays of taste sensors, the system delicately simulates the structure of taste buds on the human tongue (shown in **Figure 6d**), and combines specific deep learning algorithms to simulate the complex functions of the taste system.

In the biological taste system, taste receptor cells in the taste buds undergo a series of biochemical reactions with the food, generating electrical signals that are ultimately interpreted by the brain into taste perceptions. The electronic tongue designed in this paper simulates the function of taste buds by integrating lipid membranes, which are very similar to taste receptor cells in taste buds, so that the electronic tongue system can efficiently detect and distinguish different taste characteristics, such as salty, sour, astringent and sweet, and then generate corresponding voltage signal changes (as shown in **Figure 6e**). By mimicking the physiological structure and function of the human tongue, the electronic tongue system successfully replicates the natural human ability to perceive taste. Specific deep learning algorithms process signals in the same way the brain does, allowing the system to achieve a complete simulation of the taste system. Even more remarkable, the artificial electronic tongue system achieved a classification accuracy of up to 95% in distinguishing between six different wines, even when more than a third of the data contained errors, reaching 90% accuracy (see **Figure 6f**). In addition, with deep learning technology, we were able to identify and recommend similar wines based on random data, providing valuable insights for personalized recommendations.

The conductive electronic tongue is a sensor array technology that uses electrochemical principles to simulate the human taste system to detect and identify components in complex liquid samples. The basic principle is to accurately detect and analyze the electrochemical response of the liquid sample through an array of different types of electrochemical sensors, thereby identifying the liquid or solid composition[43]. In liquid measurement, the main concern is the change of conductance. In solid measurement, the change of resistance is concerned. The advantages of conductive electronic tongues are significant, including the ability to detect a variety of liquid components, fast detection speed, short response times, and the potential for automation and intelligence. With the continuous integration of sensing technology and machine learning technology, electronic tongue has been able to better adapt to different environmental conditions, improve stability and versatility, and achieve more intelligent liquid analysis and judgment.

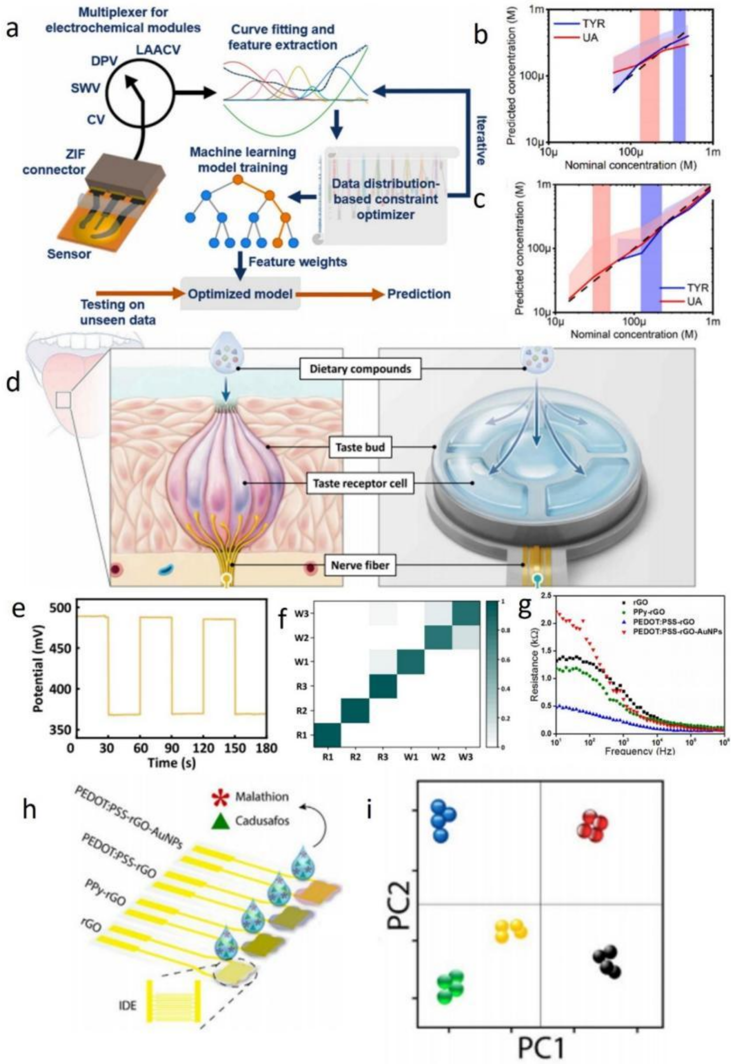


Figure 6. Machine learning assisted electrochemical sensing electronic tongue for marker detection. (a) Data collection, pre-processing, and machine learning analysis. Schematic flow chart depicting the electrochemical measurement modules, data flow, and data processing steps for training and testing the machine learning model. (b) Plot the results with two-step architectures, respectively, in mixture of TYR and UA. (c) Machine learning-based response to analytes in artificial sweat using eMoSx-LIG sensor with on-chip electrodes. (d) Conceptual comparison illustration of the biological taste system and biomimetic artificial E-tongue system, the perceptual pathway of taste. (e) Voltage response diagram of sensor array to astringency. (f) Confusion matrix for six types of wine. (g) Electrical resistance versus frequency data for each sensing unit in PBS buffer solution. (h) Schematic illustration of the impedimetric e-tongue system based on graphene hybrid nanocomposites for detection of trace levels of OPs pesticides. (i) PCA was the statistical technique used to treat the electrical resistance data collected by the e-tongue.

Recently, a report describes a novel electronic tongue design based on the principle of conductive electronic tongue, which uses graphene mixed nanocomposite materials and aided by machine learning algorithms to detect trace concentrations of organophosphorus pesticides[44]. The electronic tongue, which consists of four sensing units, was prepared by dripping a nanocomposite solution onto a gold cross electrode. These four sensing units (rGO, PPyrGO, PEDOT: PSS - rGO and PEDOT: PSS-RGO-AUNPS) produce corresponding resistance changes when the analytical sample is exposed to an organophosphorus pesticide. By processing these resistance data through principal component analysis (PCA), the electronic tongue enables precise classification of pesticide solutions at different nanomolar concentrations. In addition, the electronic tongue can effectively distinguish between real samples and samples prepared in buffer solutions, showing a correlation with the concentration and value of PC components. This example not only highlights the important role of machine learning in array-based sensing, but also provides a powerful paradigm for the integration of machine learning technology and electrochemical technology. The research of this new electronic tongue opens up a new way for the technological progress and application expansion in related fields.

These examples underscore the pivotal role of machine learning in electrochemical sensing electronic tongues for marker detection. By seamlessly integrating diverse electrochemical sensing techniques, including conductance, current, and voltage types, with sophisticated machine learning algorithms, the electronic tongue's detection capabilities and identification accuracy for trace target substances within complex samples undergo significant enhancement. Machine learning algorithms excel at extracting intricate patterns and features from vast sensor data sets, enabling the identification of subtle chemical signal differences. This pattern recognition prowess allows the electronic tongue to accurately discern the target substance, facilitating highly sensitive and selective detection, even in complex substrates.

In essence, the integration of machine learning technology has significantly broadened the application potential of electrochemical sensing-based electronic tongues in areas such as food safety, environmental monitoring, and medical diagnosis. This integration provides robust support for the rapid and accurate detection of chemical substances. The profound synergy between the electronic tongue and machine learning is poised to catalyze the continuous evolution and innovation of this novel sensing technology.

4.2 Optical sensing method

The optical sensing electronic tongue is an advanced electronic device that utilizes optical sensing technology to mimic the human taste system. Within optical sensing, fluorescence technology and Raman technology are two key sensing methods. Fluorescence technology detects specific characteristics of a sample by exciting it to emit fluorescence signals, whereas Raman technology leverages the frequency shift of scattered light after laser interaction with the sample to acquire sample information.

Optical sensing electronic tongues have found widespread application in various fields. In the food industry, they are frequently employed for quality control and detection of signature ingredients in foods, such as acidity, sweetness, and bitterness. Additionally, they are utilized in the realm of medicine and healthcare for drug quality control and disease diagnosis. As technology continues to advance, the application scope of optical sensing electronic tongues is also broadening.

In recent years, the rapid development of machine learning technology has given rise to a novel form of electronic tongue that integrates optical sensing technology. Machine learning algorithms excel at processing vast amounts of spectral data and extracting valuable insights from it. This integration has significantly advanced the electronic tongue's capabilities in marker detection, enabling more precise identification and quantification of target compounds. It has demonstrated immense application potential and promising prospects in fields such as medicine and environmental science. Below, we introduce this novel form of electronic tongue through the combination of machine learning technology with fluorescence sensing and Raman sensing technologies.

4.2.1. Fluorescence sensing method

The fluorescence sensing electronic tongue is an innovative multi-sensor array technology capable of detecting and identifying a diverse range of chemicals and biomarkers. Composed of multiple fluorescent sensors, each tailored to respond uniquely to specific substances, it creates a distinct fluorescent fingerprint. By integrating fluorescence sensor arrays with electronic signal processing technology, this technology mimics the taste sensation of the human tongue, facilitating rapid detection and analysis of various chemical substances.

The fluorescence sensing electronic tongue excels in its high sensitivity, selectivity, and swift response characteristics. It swiftly identifies and quantifies markers in complex samples, offering robust technical support in areas such as environmental monitoring, food safety, and medical diagnosis[45, 46]. With advancements in materials science and nanotechnology, the performance of this electronic tongue continuously improves, broadening its application scope.

Machine learning serves as a critical adjunct in the utilization of fluorescence sensing electronic tongues. Firstly, machine learning algorithms can process and analyze the vast data generated by the fluorescence sensor array, extracting valuable information to enhance detection accuracy and reliability. Secondly, it aids in optimizing the design and parameter settings of fluorescence sensor arrays, thus improving sensor performance. Additionally, machine learning can be employed to develop predictive models, enabling rapid prediction and classification of unknown samples.

In the recent study, the researchers successfully designed a new electronic tongue based on the principle of fluorescence sensing electronic tongue for qualitative and quantitative analysis of pyrethroid pesticides (pps)[47]. In this work, we constructed a sensor array consisting of three nanocomposite complexes, rhodamine B-CD@Au, rhodamine 6G-CD@Au, and coumarin 6-CD@Au, to distinguish between structurally similar PPs. The core principle of this sensor array is the use of CD@Au as a supramolecular indicator based on fluorescence resonance energy transfer (FRET). When three kinds of fluorescent dyes are assembled into CD on the surface of CD@Au, they will have the effect of fluorescence quenching. However, when pps gas is introduced, it replaces the original indicator (dye) due to its stronger binding capacity with CD, resulting in an increase in fluorescence intensity. In the experiment, three different fluorescent dyes were used to form three sensors to distinguish different pps. These sensors produce variations in fluorescence intensity depending on their affinity with the four different pps, enhancing the accuracy of the analysis results. Finally, a trained machine learning model is used to classify single or multi-component analytes. The results showed that deltamethrin, fenvalerate, cyfluthrin and fenpropathrin were identified successfully. At the same time, for these four pps multi-component mixed solutions, PCA (principal component analysis) can also achieve accurate classification.

In addition, Ranbir et al. have developed an innovative array of portable color sensors based on azo dyes to detect and distinguish pesticides and herbicides in food and soil samples[48].

Because of its unique photophysical properties, the azo sensor array can be combined with different metal ions to produce unique patterns for different pesticides and herbicides, forming fluorescence signals. This series consists of eight metal complexes that are used to distinguish nine different pesticide and herbicide analytes. In a 96-well plate, the color difference map of the sensor array is obtained by measuring the fluorescence response of each hole in the wavelength range from λ350 nm to λ650 nm. Finally, two machine learning methods, HCA and PCA, were used to analyze the color difference maps produced by different pesticides and herbicides according to the sensor. The tree diagram of the HCA shows the classification results of the analytes (repeated six times), and the minimum variance method is used to successfully classify the target analytes, such as pesticides and herbicides. PCA, on the other hand, presents the most important information in the data by calculating the principal components, and finds that the first three principal components account for 84% of the cumulative variance of the dataset. Both methods achieve 100% accurate classification of markers, showing excellent classification effect.

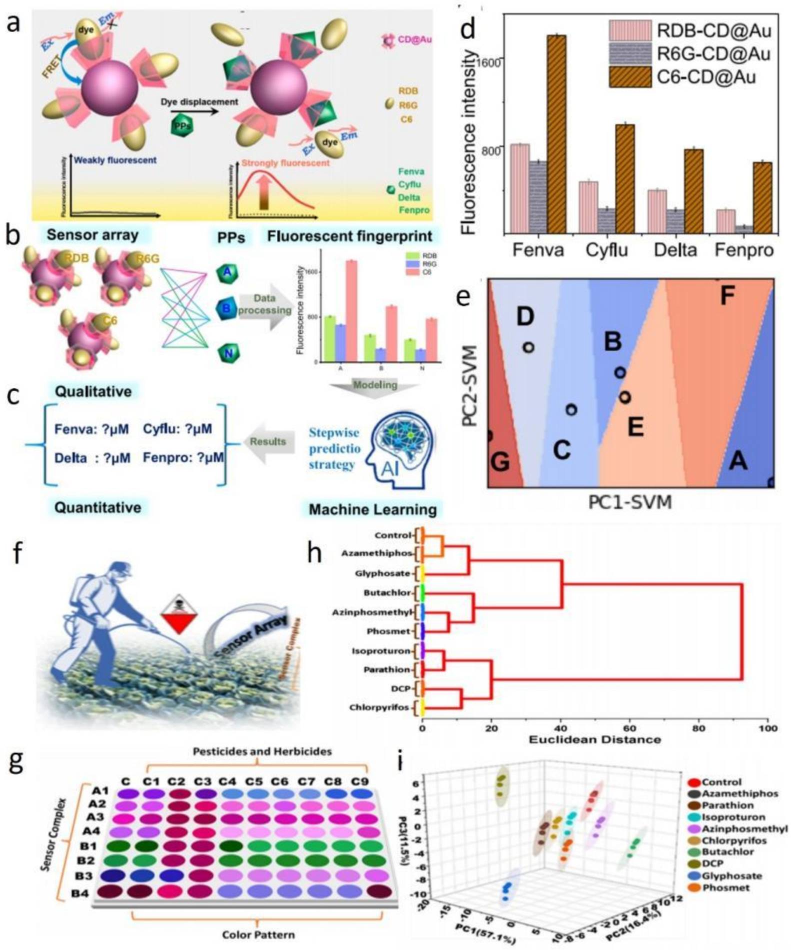


Figure 7. Machine learning assisted optical (Fluorescence) sensing electronic tongue for marker detection. (a) CD@Au based energy transfer detection of PPs. (b) The process by which fluorescent signals are generated. (c) Qualitative identification and quantitative prediction of 4 PPs by sensor array-ML algorithms. (d) Fluorescence sensor array with 4 PPs producing differential fluorescence signals. (e) Classification results obtained by the SVM dendrogram for 4 PPs. (f) Portable pesticide detection diagram. (g) Color difference map of the developed sensor array for the detection of pesticides and herbicides (0.1 mM both). (h) HCA circular dendrogram showing the classification of six trials of target analytes. (i) PCA score plot of the developed sensor array showing discrimination of various analytes with 84% of the variance explained by the first three principal components.

From these two studies, we can see that machine learning plays a key role in the detection of substances by fluorescent electronic tongues. Machine learning plays an irreplaceable role in fluorescence sensing electronic tongues. It can not only improve the detection ability of fluorescence sensing electronic tongue, but also expand its application field. With the continuous development and improvement of machine learning technology, it is believed that fluorescent sensing electronic tongues will play a more important role in the future, bringing more convenience and well-being to people's lives.

4.2.2. Raman sensing method

The SERS sensing electronic tongue is a cutting-edge detection tool that seamlessly integrates surface-enhanced Raman scattering (SERS) technology with sensor arrays. This integration holds immense potential in biomarker detection[49].

By leveraging the SERS effect, the electronic tongue significantly boosts the Raman scattering signal of the target substance, enabling ultra-sensitive detection of trace molecules. Meanwhile, the introduction of the sensor array enables the simultaneous detection of multiple markers, thus enhancing detection efficiency.

The SERS sensing electronic tongue excels in high sensitivity, specificity, and rapid response. The remarkable enhancement of the Raman scattering signal by the SERS effect allows for the effective detection of even extremely low-concentration markers. Furthermore, the array design empowers the electronic tongue to discern a diverse range of markers, opening up vast application possibilities. Nevertheless, challenges persist, such as the relatively high preparation cost and stringent environmental stability requirements.

With the rapid advancement of machine learning technology, it has become increasingly pivotal in the application of the SERS sensing electronic tongue. Firstly, machine learning algorithms aid in optimizing the design and parameter settings of SERS sensor arrays, thereby enhancing sensor performance. By analyzing vast experimental data, machine learning identifies the optimal array layout and excitation conditions, strengthening signal stability and intensity. Secondly, machine learning assists in processing and analyzing SERS sensing data, extracting valuable information. Since SERS signals are susceptible to various factors like excitation light wavelength and power, machine learning algorithms effectively filter out noise, extract crucial features, and boost detection accuracy and reliability.

In the recent study on SERS sensing electronic tongue, the researchers successfully designed a SERS taster[50] that could accurately analyze the flavor of wine by cleverly integrating SERS and machine learning technology. The taster enables multiple analysis of five wine flavor molecules at the microscale of one part per million with an amazing 100% accuracy. To achieve this, the researchers employed four different surface receptors, namely bare Ag, 4-mercaptopyridine (PY), 4-mercaptobenzoic acid (BA), and 2-naphthalenethiol (NT). These receptors have extensive chemical interactions with flavor molecules in wine, transmitting the unique information of the substance through SERS signals (**Figure 8a**). Five representative wine flavor molecules were selected for the study. These flavor molecules usually have a weak Raman scattering signal, so the researchers significantly amplified the signal strength by binding the receptors to the flavor molecules to generate a series of SERS graphs, which were connected in series into a "SERS superspectrum." The experimental results showed that the SERS taster showed excellent performance in distinguishing five wine flavor molecules. Through the combination of SERS superspectrum and principal component analysis (PCA), the researchers successfully classified the six flavor molecules clearly, and the data clusters of each flavor were well encapsulated in an ellipse with 95% confidence (**Figure 8b**). In addition, when SERS superspectrum is combined with support vector machine regression (SVM-R) machine learning algorithm, the accuracy of quantitative analysis is even more remarkable. In particular, when predicting the concentration of the flavor molecule MHA, the prediction coefficient was as high as 0.998(**Figure 8c**).

Another related study was conducted by Kunxia Ji et al., who combined purple phosphene (VP) modified by gold nanoparticles with convolutional neural networks[51] to achieve accurate detection and identification of polysulfonamides residues in the water environment (**Figure 8d**). In this study, gold nanoparticles modified with purple phosphene were prepared by in situ seed-mediated growth method as SERS substrates, and the sulfonamides in water samples were accurately identified and quantitatively analyzed by one-dimensional convolutional neural network. The results showed that the classification accuracy of this method reached 100% (**Figure 8e**), and the concentration prediction effect was also excellent (**Figure 8f**), providing a new and effective means for the detection of pollutants in water environment.

Machine learning is a pivotal and integral aspect of SERS sensing electronic tongues. It enables rapid and precise detection of multiple markers in complex samples. Furthermore, it assists in building predictive models for classifying and predicting unknown samples. With its exceptional performance, SERS sensing electronic tongue is advancing towards intelligence and integration, displaying immense potential in food safety, environmental monitoring, and medical diagnosis. The integration of machine learning is poised to fuel further innovations and breakthroughs in this technology.

4.3. Nanomaterials sensing method

Nanomaterial sensing technology[52] has emerged as a prominent research focus across various disciplines due to its unique advantages. Particularly, the nanomaterial sensing electronic tongue is gaining increasing attention as an innovative detection method. Leveraging the distinctive properties of nanomaterials, such as their high specific surface area and exceptional electrical conductivity[53], this electronic tongue facilitates rapid and precise analysis of liquid samples.

In marker detection applications, noble metal nanoparticles and carbon nanotubes[54, 55] are pivotal nanomaterials. Their remarkable physical and chemical attributes allow for specific interactions with biomolecules, ensuring highly sensitive detection capabilities. Nanomaterials can be categorized into two main types: physical and chemical. Physical nanomaterials, including nano-metals and nano-oxides, possess outstanding electrical, magnetic, and optical properties, making them ideal for constructing high-sensitivity sensors. On the other hand, chemical nanomaterials like nano-polymers and carbon-based nanomaterials identify and detect specific substances through targeted reactions or modifications. In the realm of electronic tongues, these materials enhance the capability to analyze complex samples effectively.

In the latest study, researchers successfully used a chemical nanomaterial called carbon dots[57] to construct a new differential sensing electronic tongue that can accurately distinguish eight different proteins. As a kind of luminescent nanomaterial, carbon dot has many advantages, such as good photostability, high quantum yield and good biocompatibility, and has become an important sensing material for protein research.

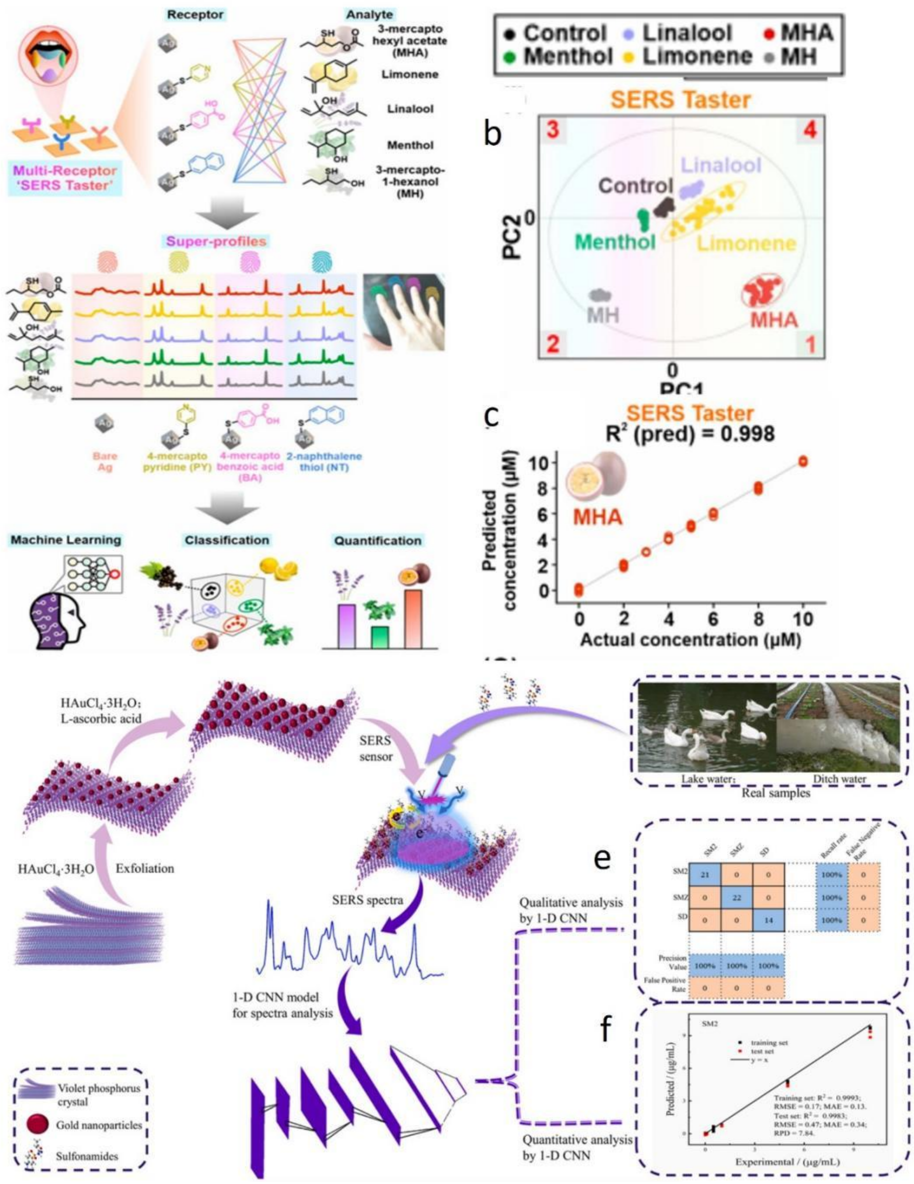


Figure 8. Machine learning assisted optical (Raman) sensing electronic tongue for marker detection. (a) Designing a multireceptor SERS taster to construct SERS superprofiles for machine-learning-driven identification and quantification of wine flavor molecules. (b) PCA score plot of the first two principal components showing the relative flavor data cluster separation using our SERS taster. (c) Calibration curves obtained using SVM-R for MHA using our SERS taster. (d) Raman spectra for discrimination and detection of multi-sulfonamides residues using AuNPs/VP substrates with the assistance of deep learning based on 1-D CNN. (e) SEM image of commercial violet phosphorus crystal. (f) confusion matrix for the result of 1-D CNN identification for multi-sulfonamides adulterated with different concentrations. (g) The relationship between actual values and predicted values of SM2 of the 1-D CNN model on the training set and test set.

The researchers prepared five carbon dots with different surface groups (**Figure 9b**) and, through non-covalent interactions with the analyte, constructed a sensing array to detect eight proteins in phosphate-buffered brine (**Figure 9a**). They collected fluorescence change data of eight proteins after contact with five carbon points (**Figure 9c**), and used linear discriminant analysis, a machine learning method, to successfully distinguish these eight proteins with 98% accuracy (**Figure 9d**). This fully demonstrates the advantages of carbon point nanomaterials in the field of biological detection, and the great potential of machine

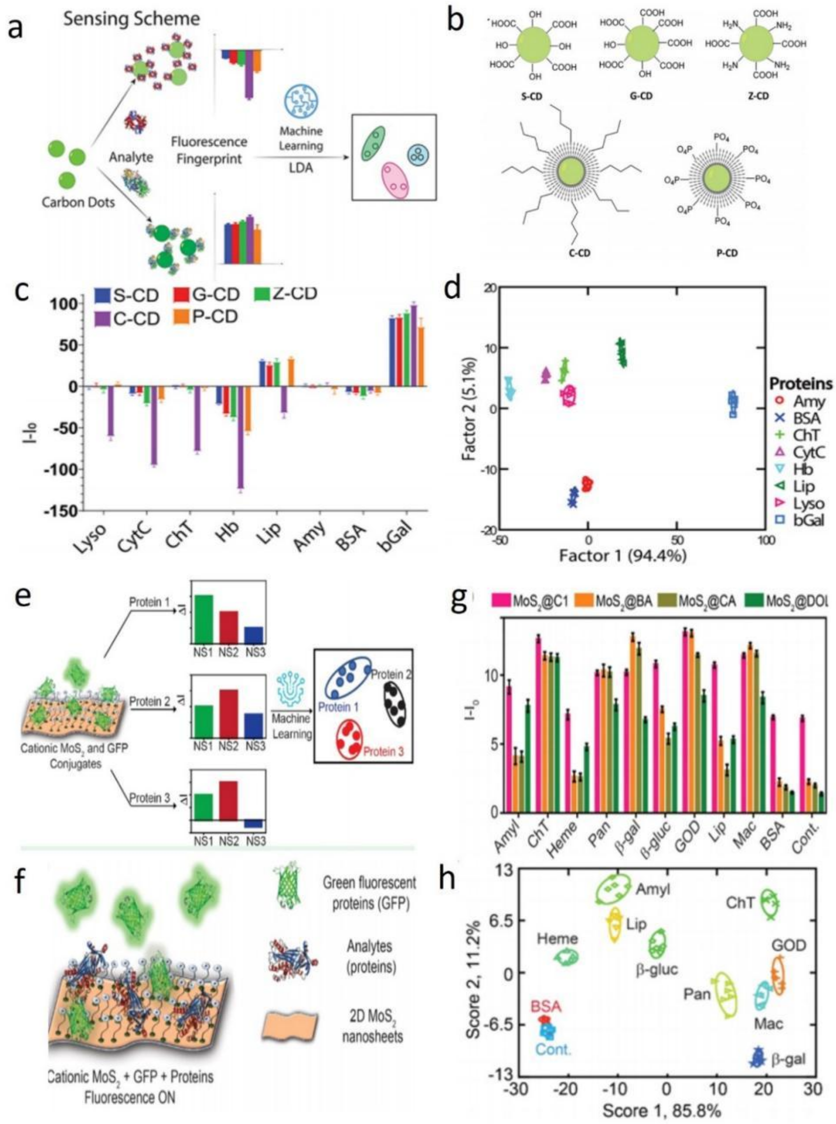


Figure 9. Machine learning assisted nanomaterials sensing electronic tongue for marker detection. (a) Sensing Event in CD Array-Based Sensing. (b) Schematic diagram of five types of CDs with varied surface functionality. (c) Change in fluorescence of the CD array in the presence of different proteins (100 nM in PBS). (d) LDA of the array response. (e) Schematic diagram of serum protein detection using sensor array. (f) displacement of GFP from the cationic MoS2 surface, followed by fluorescence regeneration upon analyte addition. (g) Fluorescence response pattern observed for different proteins against four cationic MoS2 and (h) their corresponding two-dimensional canonical score plots.

learning in analyzing sensing data.

Another study on nano-sensing electronic tongues in protein detection has also achieved remarkable results. The researchers developed a sensor array based on a two-dimensional platform using seven MoS2 nanosheets[58] with different functions as receptors and green fluorescent protein as signal sensors (**Figure 9f**). Through the interaction with the MoS2 nanosheet and the subsequent quenching of green fluorescent protein emission, the researchers successfully detected 15 different proteins at 50 nM using a machine learning algorithm (**Figure 9e**). After adding different types of serum proteins, the fluorescence change response of the sensor array was recorded in detail (**Figure 9g**). By classifying fluorescence changes using LDA analysis, the researchers successfully classified nine proteins with a 95% confidence interval (**Figure 9h**). These studies not only advance the development of nanosensing electronic tongue technology, but also provide a new and powerful tool for protein detection.

These examples demonstrate the profound impact of machine learning on the multi-analyte detection requirements. The pivotal role and fundamental contribution of machine learning algorithms in nanomaterial sensing electronic tongues are outlined. It can be affirmed that machine learning algorithms are essential to the advancement of nanomaterial sensing electronic tongue technology, enhancing its performance and efficiency while providing a more dependable and effective solution for detecting various analytes. With ongoing advancements and refinements in machine learning technology, the future of nanomaterials sensing electronic tongues holds promising potential for broader applications across diverse fields.

4.4. Biosensoring method

The biosensing electronic tongue is an advanced sensor system that combines biosensing technology with machine learning algorithms[59, 60]. It employs biological materials as sensitive elements to mimic the human taste system, enabling rapid and precise detection and analysis of complex tastes and odor components. This interdisciplinary technology integrates biology, chemistry, physics, and other disciplines to introduce novel analytical tools for the food industry, environmental monitoring, medical diagnosis[61], and beyond.

Choosing the right sensing material is crucial in biosensing electronic tongues. Enzyme sensors[62] exploit enzymatic catalysis[63, 64] to efficiently detect specific substrates, demonstrating high specificity and sensitivity. Antibody sensors leverage antigen-antibody reactions to accurately identify target molecules, offering excellent selectivity and stability[65, 66]. Cell and tissue sensors utilize the organism's functions for comprehensive analysis of complex samples. Each sensing material possesses unique characteristics and can be flexibly chosen based on specific detection requirements.

Biosensing electronic tongues have found widespread application across various fields. In food safety monitoring, they accurately detect additives and pollutants in food, safeguarding consumer health. In medical diagnosis, electronic tongues facilitate early disease detection, supporting precision treatment strategies. Additionally, in environmental monitoring, they assess water and air quality, providing a scientific foundation for environmental protection.

With the continuous development of machine learning technology, the combination of biosensing technology and machine learning has brought revolutionary progress to marker detection. By training and optimizing the machine learning model, the electronic tongue can achieve efficient and accurate analysis of complex samples, improving the sensitivity and accuracy of detection[67]. This new form of electronic tongue can not only identify a single marker, but also detect multiple markers simultaneously, providing strong support for early diagnosis and precise treatment of diseases.

In a recent study, researchers used machine learner-assisted nanoenzyme/bioenzyme duplex arrays to successfully detect multiple amyloid biomarkers by regulating enzyme activity[68]. Using the signal amplification effects of nanoenzyme and bioenzyme, they constructed fluorescent array sensors targeting a-β40 and a-β42 peptides. This sensing system converts weak signal differences into amplified fluorescence signals through the coupling of nano-enzymes and biological enzymes (**Figure 10c**), which improves the detection sensitivity. The study also analyzed the fluorescence pattern through machine learning, and realized the accurate distinction between a-β40 and a-β42, with an accuracy of more than 96% (**Figure 10b**), and even 100% (**Figure 10d**) under some algorithms. This technology is far more sensitive than traditional fluorescence sensors and provides A new method for the detection of ultra-low concentrations of Aβ peptide. Combined with the nanoenzyme/bioenzyme signal amplification strategy, this sensor array technology provides a powerful tool for simultaneous detection of low abundance biomolecules, especially for mass screening of diseases.

Another study identified eight organophosphorus pesticides through a cascade reaction system using an array of colorimetric sensors that bind nanomases to natural enzymes69. The combination of acetylcholinesterase and choline oxidase hydrolyzes acetylcholine to H_2O_2, while nanase catalyzes H_2O_2 to oxidize TMB to blue oxygen TMB (**Figure 10e**). Organophosphorus pesticides inhibit acetylcholinesterase activity, leading to color change. Combined with linear discriminant analysis, 8 organophosphorus pesticides were successfully identified in tap water (**Figure 10f**). This research provides a new method for the rapid and accurate detection of organophosphorus pesticides,which contributes to environmental protection and food safety.

Through two examples, it's evident that machine learning algorithms play a pivotal role in biosensing electronic tongues. By analyzing vast datasets and recognizing patterns, these algorithms enable the identification and classification of complex samples, thereby enhancing the accuracy and reliability of detection. Overall, as an emerging intelligent sensing technology, the development of biosensing electronic tongues not only advances the enhancement of traditional sensors but also offers novel solutions for intelligent detection in related fields. It is poised to play a significant role in the future.

5.Advantages and challenges of machine learning-assisted electronic noses and electronic tongues in markers discrimination

Electronic noses and electronic tongues, serving as artificial sensor systems[70, 71] that mimic human smell and taste, have showcased significant potential in marker recognition within various fields. Their attributes, including high sensitivity, good selectivity, rapid response, non-destructive testing capabilities, and portability, render them invaluable analytical tools. The incorporation of machine learning algorithms into these sensing technologies can bolster their performance and broaden their scope of applications.

From the standpoint of electronic nose technology, optical, electrochemical, and metal-oxide semiconductor (MOS) sensors emerge as three prevalent sensing methodologies. Optical sensing electronic noses boast high sensitivity and good selectivity, yet they are prone to interference from ambient light. On the other hand, electrochemical sensing electronic noses offer a swift response and cost-effectiveness but are susceptible to external disturbances. Meanwhile, MOS sensing electronic noses feature a simple structure and low cost, albeit exhibiting relatively poor selectivity. Integrating machine learning algorithms with these sensing technologies can effectively address their respective shortcomings, enhancing detection accuracy and reliability. This amalgamation holds immense promise across diverse domains such as environmental monitoring and food safety, among others.

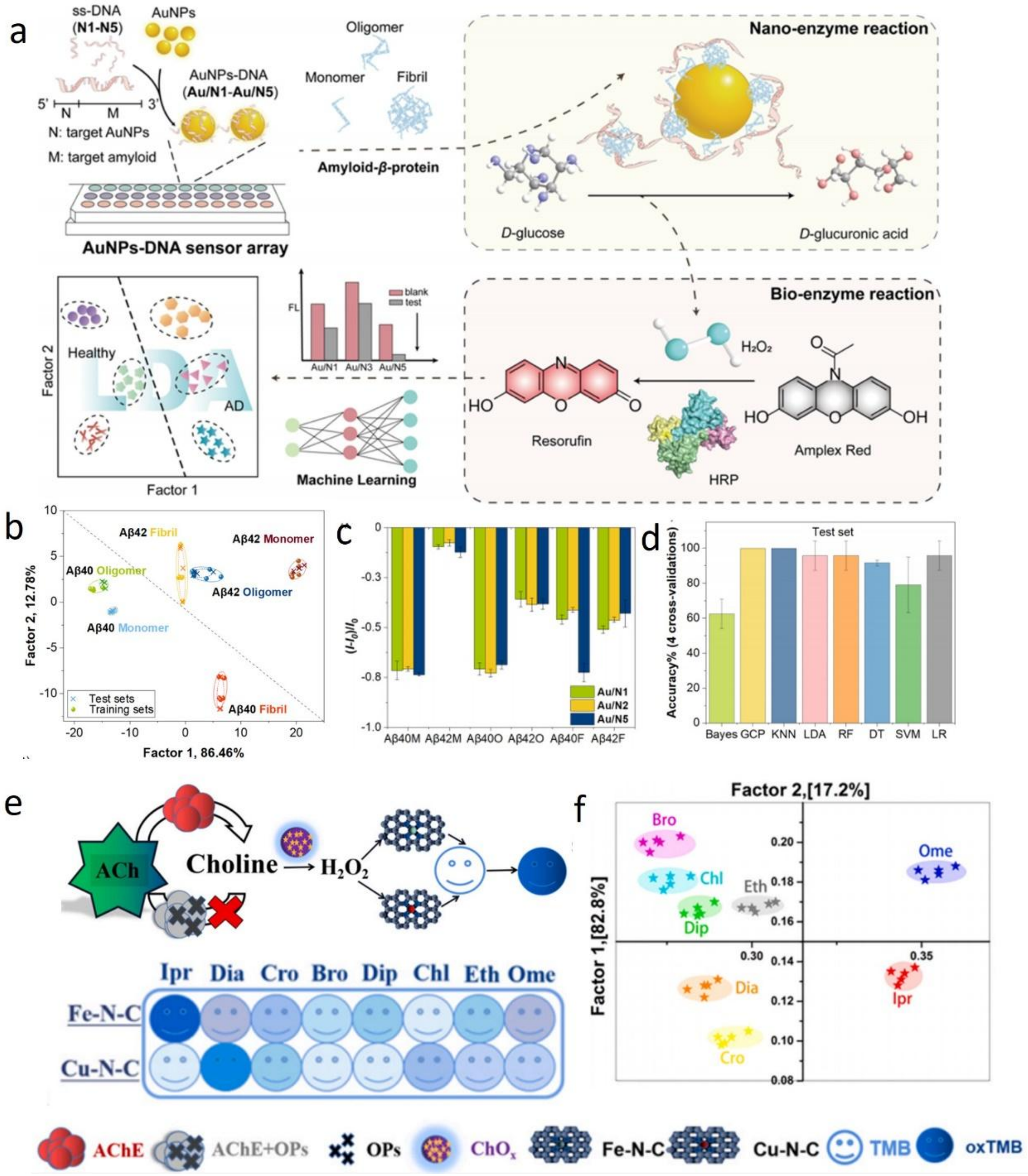


Figure 10. Machine learning assisted biosensing electronic tongue for marker detection. (a) . Dual enzyme-coupled signal amplification strategy to construct a fluorescent array sensor for detecting low concentrations of amyloid proteins. (b) LDA scatter plot of the sensor array response to Aβ aggregates at 200 nM. (c) Change in fluorescence response pattern obtained by treating A β protein (200 nM in tris buffer) with sensors. (d) Prediction scores of eight machine learning algorithms. (e) Schematic illustration of the discrimination principle of the sensor array based on nanozymes as sensor units. (f) The colorimetric response of sensor array to organophosphorus pesticides with a concentration of 1 ng mL-1 was obtained by using LDA method.

Similarly, in electronic tongue technology, four main sensing methods prevail: optical, electrochemical, nanomaterials, and biosensing. The optical electronic tongue excels in high sensitivity and good selectivity but comes with a larger volume. The electrochemical counterpart boasts a swift response and low cost but remains vulnerable to interference. Nanomaterial-based electronic tongues offer heightened detection sensitivity, albeit with a more intricate preparation process. Biosensing electronic tongues, mimicking human taste with high accuracy, may encounter stability issues. Integrating machine learning algorithms with these four sensing technologies can expedite the identification of complex flavor components, fostering diverse applications in food safety, medical diagnosis, and beyond.

Machine learning-assisted electronic noses and tongues hold substantial advantages in marker recognition, including high sensitivity, selectivity, rapid response, non-destructive testing, and portability. Nonetheless, practical applications face challenges such as enhancing anti-interference capabilities, cost reduction, and stability improvement. Continuous research and innovation are crucial to surmount these hurdles and further propel the development and deployment of these technologies.

6. Conclusions

This review systematically elucidates the pivotal role of machine learning in electronic noses and tongues. Initially, we delineate the operational principles of various electronic nose types (optical, electrochemical, MOS) and electronic tongue (optical, electrochemical, nanomaterials, biological), delving into machine learning's significant contribution to enhancing sensor performance. Machine learning facilitates automatic recognition, intelligent decision-making, and augments detection accuracy and reliability in electronic noses. As sensor technology and artificial intelligence advance, electronic noses and tongues are poised to assume greater prominence in food safety monitoring, medical diagnosis, environmental surveillance, and beyond.

Future research avenues encompass developing novel sensing materials and device structures to heighten sensitivity and selectivity, crafting more intelligent and efficient machine learning algorithms to bolster the electronic nose's analytical prowess, exploring multi-sensor fusion technology for comprehensive information collection and analysis, and prioritizing miniaturization, portability, and low power consumption of sensing systems to broaden application horizons.

In summary, machine learning-enabled electronic noses and tongues inject fresh momentum into the evolution of intelligent sensing technologies. We anticipate that with further research, electronic noses and tongues will exert a profound and expansive influence across various domains. Nonetheless, the realization of commercial applications for electronic noses and tongues necessitates addressing technical bottlenecks and cost constraints, which remain focal points for future investigations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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