Transactions of Tianjin University
https://doi.org/10.1007/s12209-024-00411-3

REVIEW

Potential of eNose Technology for Monitoring Biological CO_2 Conversion Processes

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Received: 28 May 2024 / Revised: 11 July 2024 / Accepted: 23 July 2024

Abstract

Electronic nose (eNose) is a modern bioelectronic sensor for monitoring biological processes that convert CO_2 into value-added products, such as products formed during photosynthesis and microbial fermentation. eNose technology uses an array of sensors to detect and quantify gases, including CO_2, in the air. This study briefly introduces the concept of eNose technology and potential applications thereof in monitoring CO_2 conversion processes. It also provides background information on biological CO_2 conversion processes. Furthermore, the working principles of eNose technology vis-à-vis gas detection are discussed along with its advantages and limitations versus traditional monitoring methods. This study also provides case studies that have used this technology for monitoring biological CO_2 conversion processes. eNose-predicted measurements were observed to be completely aligned with biological parameters for R^2 values of 0.864, 0.808, 0.802, and 0.948. We test eNose technology in a variety of biological settings, such as algae farms or bioreactors, to determine its effectiveness in monitoring CO_2 conversion processes. We also explore the potential benefits of employing this technology vis-à-vis monitoring biological CO_2 conversion processes, such as increased reaction efficiency and reduced costs versus traditional monitoring methods. Moreover, future directions and challenges of using this technology in CO_2 capture and conversion have been discussed. Overall, we believe this study would contribute to developing new and innovative methods for monitoring biological CO_2 conversion processes and mitigating climate change.

Keywords Electronic nose (eNose) · CO_2 conversion · Biological monitoring · Gas detection · Bioelectronic nose

Introduction

Gas analysis is crucial for understanding reaction kinetics, product yield, and process optimization. It is also pivotal in the identification of unwanted byproducts, impurities, or catalyst deactivation. It can be used to optimize reaction conditions such as temperature, pressure, flow rate, and catalyst loading [1]. Gas analysis can be conducted using various techniques such as mass spectrometry, gas chromatography, infrared spectroscopy, and electrochemical sensing. Each technique has its advantages and limitations in terms of sensitivity, selectivity, accuracy, and cost [2]. Carbon dioxide (CO_2) is a greenhouse gas that contributes to climate change. However, it can also be used as a feedstock for various chemical processes. Conversion of CO_2 into useful products such as fuels, chemicals, and materials is an active area of research. Biological and chemical CO_2 conversion are two different approaches to converting CO_2 into useful products. Chemical CO_2 conversion employs nonliving catalysts such

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as metals, metal oxides, and zeolites to convert CO_2 into fuels, chemicals, and other products [3].

Chemical CO_2 conversion offers several advantages, such as high reaction rates, product selectivity, and mild reaction conditions. However, it also suffers several challenges, such as high energy consumption, low CO_2 conversion efficiency, and environmental impact [4]. There are several biological methods to accomplish CO_2 conversion processes, such as biological uptake into algae for photosynthesis. This process employs photosynthetic microorganisms, such as algae and cyanobacteria, to capture CO_2 and convert it into biomass and other products such as chemicals, fuels, and feeds [5]. In catalytic conversion, enzymes or microorganisms are used as biocatalysts to convert CO_2 and other substrates (such as hydrogen, methane, or sugars) into fuels and chemicals such as methane, ethanol, acetate, and polyhydroxybutyrate [6]. In mineralization-based conversion, biological processes such as microbial carbonate precipitation or biomineralization are employed to convert CO_2 into inorganic carbonates such as calcium carbonate or magnesium carbonate [7].

Bioelectronic noses for specific odor detection processes are based on transgenic mice that express olfactory receptors as biosensors to detect and discriminate specific odors from CO_2 and other gases [8]. These conversion processes offer multiple advantages, including high selectivity, specificity, mild reaction conditions, high CO_2-fixation efficiency, low energy requirements, and use of solar energy and wastewater. The conversion efficiencies of these techniques can be increased by overcoming the challenges associated with product inhibition and low reaction rates, biocatalyst stability, biosafety, and scalability [9]. Electronic nose (eNose) technology is a sensor technology that can be used to detect and identify various gases and volatile organic compounds (VOCs) in the air. It works by detecting changes in electrical resistance when molecules bind to the surface of the sensor. eNose technology has potential applications in monitoring CO_2 conversion processes, as it can detect CO_2 and other gases produced during the process. This can help researchers optimize the process and ensure its efficiency [10].

eNose technology can also be employed to monitor air quality in industrial settings, detect hazardous chemicals, and diagnose medical conditions [11]. The eNose comprises a mechanism for detection, an array of gas sensors that are selectively overlapping, and a pattern recognition component. It detects hazardous or poisonous gas, which is not possible for human sniffers. It has provided external benefits to various commercial industries, as well as various scientific research fields such as agriculture, biomedical, cosmetics, environmental, food, and water [12]. Other than the above-mentioned applications, the eNose can be used to screen for infections at clinical points of care (Fig. 1) [13]. It operates on principles of human olfaction, and each sensor is sensitive to various molecules in specific manners. Commonly used sensors in eNose are based on metal–oxide–semiconductor field-effect transistors (i.e., MOSFET), conducting polymers, quartz crystal microbalance (QCM), piezoelectricity, and metal oxides [14].

This review is designed to investigate the use of eNose technology for monitoring biological processes that convert CO_2 into value-added products. This study identifies the potential applications of this technology, such as air quality monitoring, hazardous chemical detection, and medical diagnosis. Furthermore, it discusses the monitoring of gas emitted during biological CO_2 conversion processes and the advantages of eNose versus traditional gas analysis methods in biological CO_2 conversion.

Principles of eNose Technology

eNose technology is an analytical approach inspired by the human olfactory system. It comprises an array of sensors capable of detecting and recognizing complex mixtures of VOCs or gases, similar to the manner in which the human nose identifies various odors [15]. eNose technology relies on a combination of diverse sensors, data processing, and pattern recognition algorithms (Fig. 2) [16, 17] to analyze and identify complex gas mixtures, offering a rapid, noninvasive, and cost-effective solution for gas analysis in various research fields.

Sensor Array

eNose systems employ an array of chemical sensors, each with different specificities and sensitivities to various gas components. These sensors can be made of metal oxides, conducting polymers, QCMs, surface acoustic wave (SAW) sensors, or other materials [18]. Upon exposure to gas samples, the electrical properties (such as resistance, conductivity, or frequency) of these sensors change because of interactions with the gas molecules. Different sensors within the array uniquely respond to different gases [19]. The setup and working principles of the sensor array involve various aspects, as discussed in the following subsections.

Diversity of Sensors

eNose devices typically incorporate an array of diverse types of sensors, which may include metal oxide sensors (MOSs), conducting polymer sensors, QCM sensors, SAW sensors, or others [20]. Another important aim is to achieve varied sensitives, meaning each sensor within the array exhibits different sensitivities and responses to various gases or VOCs. These sensitivities are influenced by the sensor's material, surface properties, and interaction mechanisms with gas molecules.

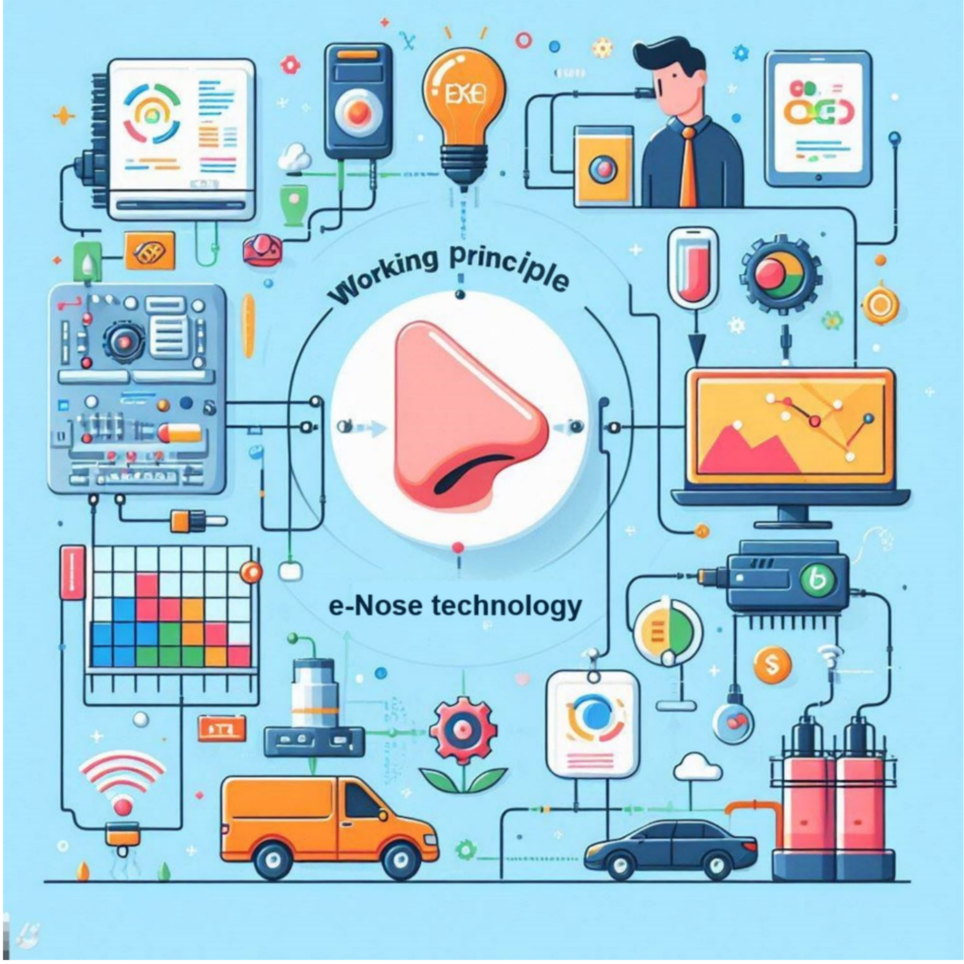

Fig. 1 Application of electric nose in various research fields

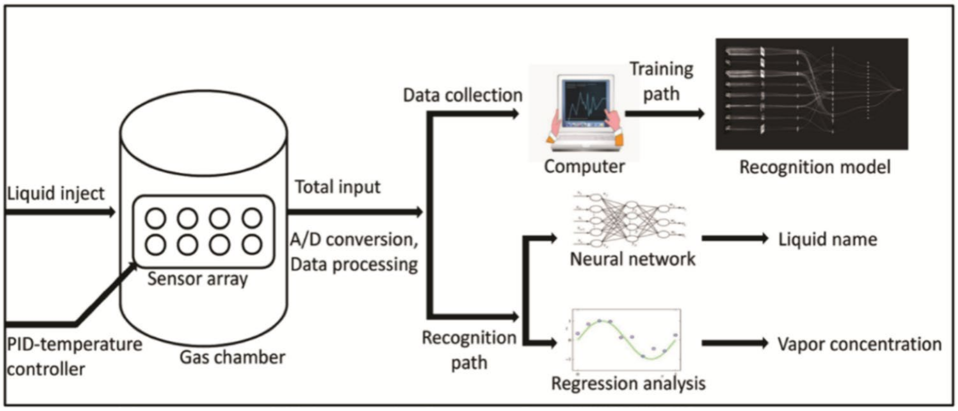

Fig. 2 Principles of eNose technology. Reproduced with permission from Ref.[17]. Copyright © 2020, MDPI

Sensor Responses

When exposed to gas samples, sensors respond via changes in their electrical properties [21]. For instance (1) MOSs experience alterations in resistance; (2) conducting polymer sensors exhibit changes in conductivity; and (3) QCM sensors may undergo shifts in resonance frequency because of gas adsorption or desorption.

Moreover, different gases or gas mixtures cause distinctive changes in sensor responses. This results in unique patterns of sensor outputs for each gas or VOC, hence forming a sensor-specific “fingerprint” for a detected gas mixture [22].

Data Processing

The eNose system collects data from the sensor array, following which it generates a multidimensional dataset based on the response pattern of each sensor to the gas mixture. Various features, such as peak heights, response times, or frequency shifts, are extracted from the raw sensor responses. These features represent the unique fingerprint of the gas mixture [23].

Pattern Recognition

Advanced statistical and machine learning algorithms are applied to process the extracted features. Common methods include principal component analysis (PCA), artificial neural networks (ANN), and support vector machines (SVMs) [24]. The eNose system identifies and distinguishes specific gas mixtures or classes by analyzing the patterns and correlations among sensor responses. It matches the collected data to predefined patterns already present in its database to recognize and classify the gases present in the sample [25].

Some key aspects must be considered. First is reproducibility, in which consistent and reproducible sensor responses are essential for reliable and accurate identification of gas mixtures. Second, sensors must be calibrated to maintain accuracy and reliability, ensuring that they consistently respond to specific gas components. Third, sensors in an eNose array might exhibit cross-sensitivity by responding to multiple gases. Hence, pattern recognition algorithms must account for this cross-sensitivity to accurately identify and differentiate gas mixtures [26]. The sensor array setup in eNose technology allows for simultaneous detection and analysis of multiple gases, offering a versatile and effective approach for gas analysis.

Working Principles

We now discuss the working principle of the sensors. First, the sensor array is exposed to a gas sample, allowing each sensor to interact with the volatile compounds present in the sample. Second, sensors interact with gas molecules and generate electrical signals corresponding to their responses. These signals are then collected and recorded. Third, the patterns of the signals collected, often represented as multidimensional data, are processed using pattern recognition algorithms. These algorithms are used to analyze the unique patterns in the sensor array's responses to different gases. Fourth, data analysis is conducted, in which statistical techniques, machine learning algorithms (such as PCA, ANNs, or SVMs), or pattern matching algorithms are employed to interpret the sensor array's response patterns and identify/classify the gases or gas mixtures present in the sample. eNose technology employs various types of sensors, each with distinct characteristics and specificities for detection [27].

The selection of sensor type depends on factors such as sensitivity, selectivity, response time, and application requirements. The following are some common sensor types used in eNose technology and their specificities:

(1) MOSs operate on the basis of change in resistance upon exposure to target gases [28]. Typically, they consist of metal oxide films such as tin dioxide (SnO_2), zinc oxide (ZnO), or tungsten oxide (WO_3). MOS sensors are sensitive to a wide range of gases and VOCs because of their high surface area and reactivity. They can detect reducing or oxidizing gases, affording them suitability for general gas-sensing applications.

(2) Conducting polymer sensors relies on changes in conductivity upon exposure to gases [29]. Conducting polymers such as polypyrrole or polyaniline are coated onto electrodes to detect gas-induced changes in conductivity. These sensors offer high sensitivity and selectivity toward specific gases because of their ability to undergo reversible chemical interactions. They can be customized to detect particular VOCs or gases on the basis of the polymer's functionalization [30].

(3) QCM sensors operate on the basis of change in resonance frequency of a quartz crystal when gas molecules adsorb onto its surface, altering its mass. These sensors exhibit high sensitivity and are commonly employed for the detection of volatile compounds and offer high mass sensitivity [31]. They are suitable for detection of trace amounts of analytes in gas mixtures.

(4) SAW sensors use piezoelectric materials to generate surface acoustic waves [32]. Gas adsorption changes the wave propagation in detection circuits, leading to frequency shifts. SAW sensors offer high sensitivity and are useful for the detection of changes in mass or viscosity caused by gas adsorption. They have applications in gas detection and environmental monitoring.

(5) Optical sensors use changes in light absorption, fluorescence, or refractive index upon exposure to gases [33]. They offer high selectivity and sensitivity for specific gases or analytes. Techniques such as colorimetric sensors, fluorescence-based sensors, or fiber optic sensors provide diverse detection capabilities.

(6) Carbon nanotube (CNT) sensors operate on the basis of changes in electrical conductivity when gas molecules interact with their nanotubes (Fig. 3) [11]. CNT sensors offer high sensitivity and less response times. They can be selective to specific gases by functionalizing the nanotube surface.

Each sensor type in eNose technology offers its advantages and specificities, allowing for a wide range of

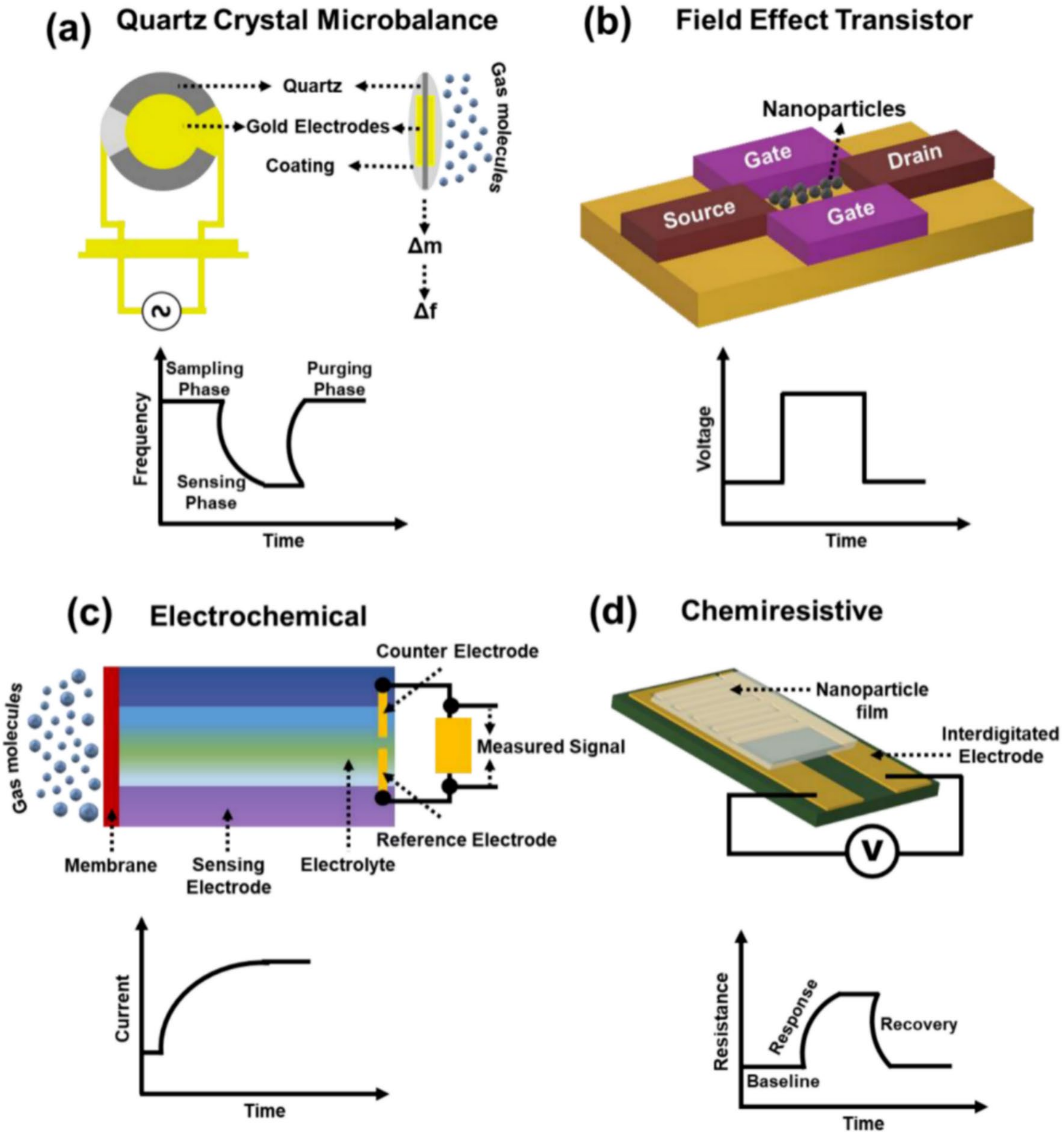

Fig. 3 Simplified schematic illustrations of different transduction mechanisms utilized in eNoses systems: **a** QCM, **b** FET, **c** electrochemical, **d** chemiresistive. Reproduced with permission from Ref. [11]. Copyright © 2021, MDPI

applications in gas sensing, environmental monitoring, food quality control, health care, and industrial process analysis. The selection of sensor type or combination depends on target gases, sensitivity requirements, and application contexts [34]. Data processing and analysis techniques in eNose systems are crucial in transforming raw sensor responses into meaningful information. Upon exposure to gas samples, the collected sensor data undergoes several key processing stages. Initially, signal conditioning techniques are applied to mitigate the noise and baseline variations, enhancing the quality of the data. Thereafter, feature extraction methods are employed to reduce the high-dimensional sensor data into lower-dimensional spaces via extraction of relevant features that encapsulate distinctive sensor response characteristics for different gases. These extracted features form the basis for subsequent analysis and could include peak heights, response times, or statistical parameters [35].

Using advanced statistical approaches and machine learning algorithms such as PCA, ANNs, and SVMs, the eNose system interprets the extracted features, recognizes patterns, and classifies or identifies the gases present in the sample. Training the system with known gas samples facilitates validation and testing, ensuring the accuracy and reliability of the model in the classification of unknown gas mixtures

[36]. The final output provides insights into gas identification or discrimination, often presented through visual aids such as clustering plots or classification scores, hence aiding in the interpretation of the results. These sophisticated data processing and analysis techniques empower eNose systems to efficiently characterize and classify gases, enabling applications in various fields. These techniques in eNose systems aim to convert raw sensor responses into actionable information, enabling the identification, classification, or/and quantification of gases or VOCs present in a sample. The selection of techniques depends on the application, the complexity of the gas mixture, and the desired level of specificity and accuracy in gas detection [37].

Application of eNose in Biological CO_2 Conversion

eNose technology is a pioneering tool in the field of biological CO_2 conversion, offering diverse applications that revolutionize monitoring, optimization, and control within this eco-friendly process(es). These systems enable real-time analysis of gas emissions, providing instantaneous feedback on the status and progress of CO_2 conversion. eNose devices facilitate process optimization by continuously monitoring the evolving gas profiles, allowing for fine-tuning of operating conditions to maximize conversion efficiency and product yields [38]. Furthermore, they are pivotal in ensuring product quality and consistency via the identification of variations in gas composition, thereby maintaining high standards and minimizing out of scope products. Other than process refinement, eNose technology considerably contributes to environmental monitoring, aiding in the reduction of harmful emissions and ensuring compliance with environmental regulations. In the fields of fermentation, microbial transformations, and biogas production involving CO_2, these systems offer insights into metabolic activity and gas evolution, optimizing growth conditions and increasing energy production from renewable sources. Their versatility extends across various industries, supporting sustainable practices in biofuels, food and beverage, pharmaceuticals, and others [39]. Ultimately, we believe that eNose applications in biological CO_2 conversion processes empower researchers and industries to achieve higher efficiency, sustainability, and environmental compliance in their transformative endeavors.

Real-time Monitoring of Gas Emissions During Biological CO_2 Conversion Processes

Real-time monitoring of gas emissions during biological CO_2 conversion processes via the use of eNose technology involves continuous and instantaneous analysis of the evolving gas profiles. This real-time monitoring capability is pivotal for assessing the progress, efficiency, and stability of CO_2 conversion processes. We now explain the manner in which eNose facilitates continuous gas analysis. eNose devices, equipped with arrays of sensors sensitive to various gases and VOCs, continuously sample the gas emissions generated during biological CO_2 conversion [40]. These sensors uniquely respond to different gases, capturing changes in gas composition in real time. As the sensors detect and analyze the emitted gases, the eNose system provides immediate feedback on the gas composition. This instantaneous response allows for swift detection of any deviations or changes in the gas profiles, enabling quick intervention or adjustment of process parameters if required. Moreover, eNose technology offers insights into the kinetics of the CO_2 conversion process by monitoring gas emissions in real time [41]. Changes in gas composition and their rates of evolution provide valuable information regarding the reaction progress and efficiency.

Real-time monitoring using eNose systems helps evaluate the stability of biological CO_2 conversion processes. Consistent and expected gas profiles indicate process stability, while deviations or irregularities in CO_2 conversion can indicate potential issues. Immediate analysis of gas emissions allows for the identification of optimal process conditions. Process adjustments can be made in response to real-time data to optimize factors such as temperature, pH, nutrient levels, or substrate concentrations for achieving increased conversion efficiency [42]. eNose devices log and store continuous data on gas emissions. Analysis of this data with time enables the identification of patterns, trends, or fluctuations in gas profiles, aiding in process trend analysis and long-term process optimization. Furthermore, real-time monitoring using eNose technology provides an early warning system by promptly detecting any irregularities or unexpected changes in gas composition. This proactive approach allows for the implementation of immediate corrective measures to maintain process integrity [43].

eNose Technology Case Studies

The eNose was able to detect changes in the VOCs produced by the microalgae, following which the growth conditions could be optimized. The variability of the effect of gases and VOCs released by the microbes on soil-dwelling organisms could be observed. For inoculation of *Pseudomonas fluorescens*, the soil was sterilized and treated with γ-irradiation. In addition to evaluating microbial growth, the above-mentioned study also quantified the activities of enzymes, including acid phosphatase, β-glucosidase, fluorescein diacetate hydrolase, and protease. A series of concurrent eNose surveys were conducted to monitor the presence of CO_2 gas and/or VOCs in the simulated soil environment. The samples analyzed represented the *olfactory fingerprint*, or odorant image, created by the eNose upon simultaneously detecting all or majority of the analytes. Using the eNose, the metabolic and growth stages of the inoculated bacteria could be effectively monitored throughout the incubation process. In addition, a direct relationship between the eNose's responses, the release of CO_2, and fluctuations in the population of *P. fluorescens* under different growth conditions was recorded. The subsequent objective fulfilled by the above-mentioned study was to determine whether eNose technology could accurately represent the axenic and gnotobiotic activity of the soil microbiome [44].

Another study showed that exhaled breath analysis using eNose can be employed to distinguish between lung cancer and chronic obstructive pulmonary disease (COPD). In addition, of the 37 patients with COPD who had received a clinical diagnosis of lung cancer within 2 years after inclusion in the study, the eNose had already correctly classified 33 as having lung cancer at baseline. With an accuracy of 87%, the eNose was able to discriminate patients with COPD who subsequently received a lung cancer diagnosis from those who did not [45]. Another study published in the European Respiratory Society's Open Research journal explored the potential of eNose technology in lung transplantation. The researchers observed that exhaled breath analysis using eNose technology holds promise as a point-of-care indicator of clinical status after lung transplantation (Fig. 4) [46].

Several studies have demonstrated the ability of eNose technology to differentiate with satisfactory accuracy between patients with asthma and healthy controls. A total of 322 patients with ILD and 48 healthy controls were included: sarcoidosis ($n = 141$), idiopathic pulmonary fibrosis (IPF) ($n = 85$), connective tissue disease-associated ILD ($n = 33$), chronic hypersensitivity pneumonitis ($n = 25$), idiopathic nonspecific interstitial pneumonia ($n = 10$), interstitial pneumonia with autoimmune features ($n = 11$), and other ILDs ($n = 17$). eNose sensors discriminated between patients with ILD and healthy controls, with an area under the curve (AUC) of 1.00 in the training and validation sets. Comparison of patients with IPF and those with other ILDs yielded an AUC of 0.91 (95% confidence interval (CI) 0.85–0.96) in the training set and an AUC of 0.87 (95% CI 0.77–0.96) in the validation set. The eNose reliably distinguished between individual diseases, with the AUC values ranging from 0.85 to 0.99 [47].

eNose offers several advantages over traditional analytical methods. It is noninvasive and can be used to analyze samples without requiring sample preparation or destruction. This technology provides real-time analysis of samples, which can be useful in monitoring biological systems. eNose is highly sensitive and can be used to detect trace amounts of VOCs in samples. It is relatively inexpensive compared with traditional analytical methods. eNose devices are portable and can be used in the field, which can be useful in remote

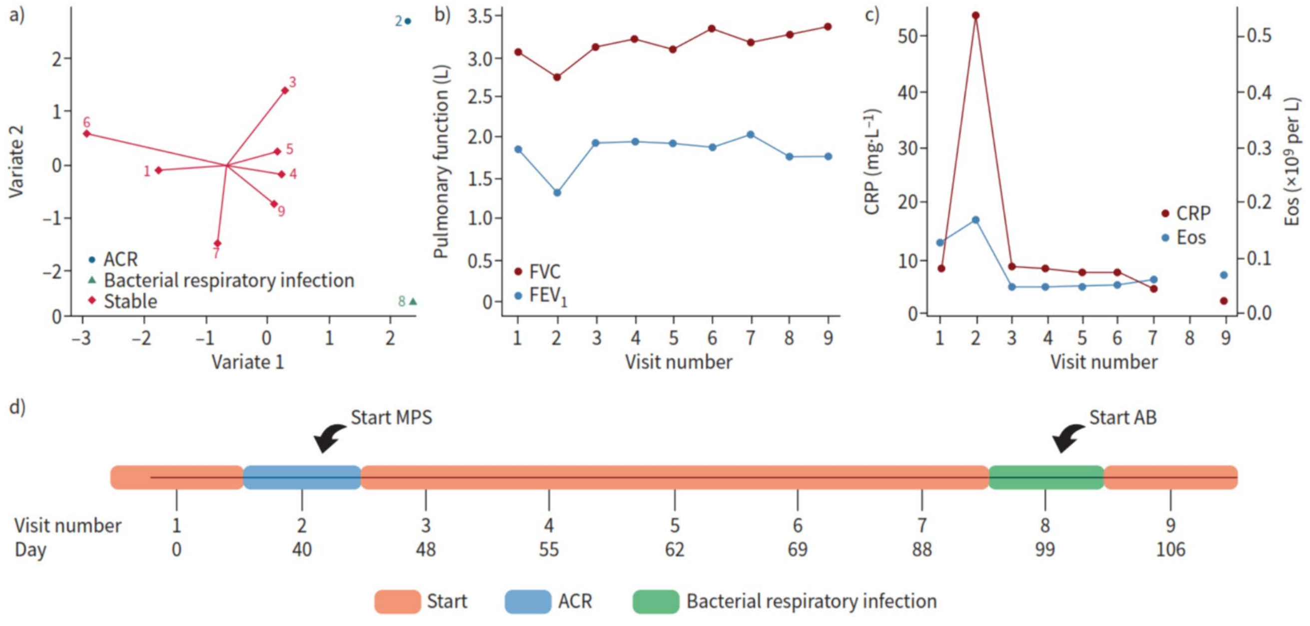

Fig. 4 Timeline of the case report of a lung transplant recipient. **a** Scatterplot of the partial least squares discriminant analysis (PLS-DA) results, using the first two latent variables obtained by the PLS-DA and the corresponding visit numbers. Each point is one measured sample. **b** The course of pulmonary function. **c** The course of the C-reactive protein (CRP) values and peripheral blood eosinophil counts (Eos). **d** Timeline of the patient's treatment. ACR: acute cellular rejection; FVC: forced vital capacity; FEV: forced expiratory volume in 1 s; MPS: methylprednisolone; AB: antibiotics. Reproduced with permission from Ref. [46], Copyright © 2021, ERJ

locations. Moreover, eNose technology can be used to analyze a wide range of samples, including biological, food, and environmental samples [48].

Advancements in eNose Technology

eNose technology has been rapidly advancing in recent years, thanks to the development of new materials, sensors, and algorithms. The advancements in this technology represent a revolution in gas-sensing capabilities, driven by various innovations across sensor development, data processing, and miniaturization. Novel sensor designs leveraging nanomaterials such as nanowires or nanoparticles have substantially heightened sensitivity, enabling the detection of trace amounts of gases. Functionalized sensor surfaces offer enhanced selectivity by targeting specific gas molecules, thereby expanding the range of detectable compounds [49]. Moreover, advancements in sensor array configurations have enabled multisensory integration, widened the range of detectable gases, and provided richer data sets for analysis. These advancements in sensor design have facilitated the creation of more accurate and versatile eNose systems. In tandem with sensor advancements, strides in data processing techniques have considerably augmented eNose capabilities. Advanced algorithms incorporating machine learning and pattern recognition methods have revolutionized the interpretation of complex sensor data. These algorithms allow for nuanced analyses, increasing the accuracy of gas identification and classification [50].

Sensitivity is a critical factor in defining the ability of innumerable analytical techniques to detect and quantify substances of interest, in particular, ammonia gas. Calorimetric methods exhibit a moderate-to-high range of sensitivities, depending on the technique and equipment used. The gas-sensitive tube technique exhibits a moderate level of sensitivity, which may vary depending on the specific tube and gas being detected. Although the sensitivity of the ion selective electrode (ISE) technique varies depending on the electrode and analyte being studied, it is generally high for specific ions. This means that the ISE technique can accurately detect and measure specific ions with a high level of sensitivity. Electrochemical techniques provide researchers with a wide range of sensitivity levels, ranging from moderate to high. The sensitivity level depends on the electrode and technique used in the experiment. Generally, titration methods exhibit moderate sensitivity, although this may vary depending on the technique and indicator used. Spectroscopic techniques, such as ultraviolet–visible, fluorescence, and atomic absorption spectroscopies, offer remarkable sensitivity. The accuracy of laboratory analysis and sampling depends on the analytical techniques employed. The sensitivity of an eNose can vary from moderate to high depending on the sensors and algorithms employed (Fig. 5) [51].

Real-time data processing capabilities have further enhanced eNose applications by enabling swift responses during gas-sensing operations, hence facilitating rapid decision-making and detection optimization. Furthermore, the miniaturization of eNose systems has been a transformative advancement, resulting in the development of portable, handheld devices suitable for diverse on-site applications [52]. Integration of these compact systems with wireless connectivity and Internet-of-Things (IoT) technologies has expanded their usability, enabling remote monitoring and

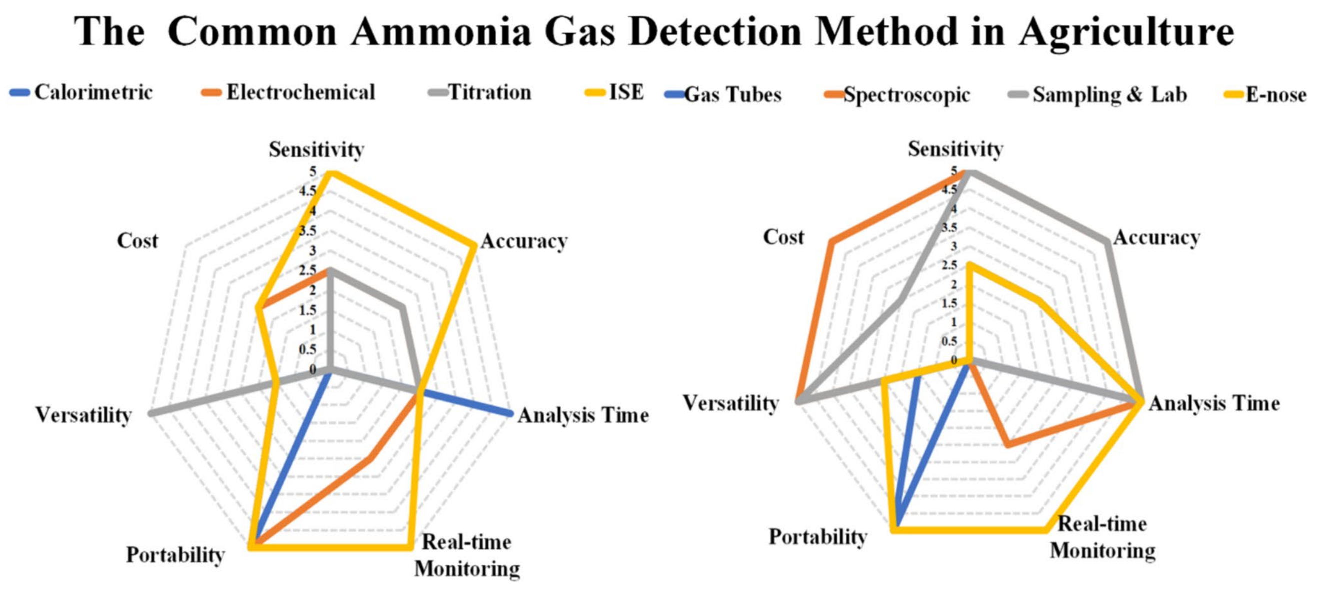

Fig. 5 The trend of eNose vs ammonia detection. Reproduced with permission from Ref. [51]. Copyright © 2020, MDPI

data transmission. This portability, in combination with enhanced sensor capabilities and advanced data processing, has widened the scope of eNose applications across industries, including environmental monitoring, health care, food quality control, and industrial processes. Researchers have been exploring new materials for eNose sensors, such as graphene, carbon nanotubes, metal–organic frameworks, and molecularly imprinted polymers [53]. These materials offer advantages such as high sensitivity, selectivity, stability, and biocompatibility. New types of sensors for eNose systems, such as electrochemical sensors, gas-sensitive tubes, ISEs, and biosensors, can detect a wide range of analytes with high accuracy and precision.

New machine learning algorithms such as ANNs, SVMs, random forests, and deep learning can enhance the performance and robustness of eNose systems by learning from data and adapting to changing conditions. Nanotechnology-based sensors have started a new era of heightened sensitivity and selectivity in eNose technology [54]. eNose systems have experienced a considerable boost in sensitivity via the incorporation of nanomaterials such as nanowires, nanoparticles, or nanotubes into sensor designs. These nanostructures offer high surface-to-volume ratios and unique surface properties, amplifying the interaction between gases and sensor surfaces. This enhanced interaction allows for the detection of even minute quantities of gases, enhancing the eNose's ability to identify and differentiate between various compounds [55]. Furthermore, the functionalization of these nanomaterials allows for customized interactions with specific gas molecules, hence increasing selectivity and enabling the detection of targeted compounds within complex gas mixtures. Thus, nanotechnology has revolutionized sensor capabilities, affording eNose systems with more sensitivity and discernment in the detection of gases and VOCs.

The integration of machine learning and artificial intelligence (AI) algorithms has been instrumental in advancing the capabilities of eNose technology vis-à-vis data interpretation and pattern recognition. These sophisticated algorithms can discern intricate patterns within complex sensor data, hence enabling precise gas identification and classification [56]. Machine learning models, including neural networks and pattern recognition models, are trained on extensive datasets, learning and adapting to unique sensor responses associated with different gases. This integration empowers eNose systems to interpret sensor data in real time, distinguishing subtle differences in gas signatures and swiftly identifying target compounds in diverse gas mixtures. The application of AI-driven algorithms has considerably increased the accuracy and speed of gas identification, thereby making eNose technology more robust and adaptable across various industries (Fig. 6) [57, 58].

The miniaturization of eNose systems has resulted in the development of compact, portable devices that can be easily employed in various settings, enabling on-site monitoring across diverse applications. These miniaturized eNose devices, when integrated with wireless connectivity and IoT technologies, offer remote monitoring capabilities, allowing for real-time data acquisition and analysis [59]. Their portability facilitates immediate deployment for on-site gas detection and analysis, providing rapid insights into environmental, industrial, or healthcare settings. This advancement has widened the scope of eNose applications, enabling efficient and convenient gas monitoring in field operations and industries requiring immediate and mobile gas-sensing solutions.

Challenges and Limitations

Several challenges and limitations persist in the field of eNose technology, hindering its widespread adoption and seamless functionality across various applications. A prominent challenge is sensor drift, which refers to the gradual change in sensor responses with time owing to environmental factors, aging, or usage. Sensor drift affects the accuracy and reliability of eNose systems, necessitating regular recalibration to maintain precision in gas detection. Moreover, ensuring reproducibility across different sensor batches or devices is challenging, as variations in manufacturing processes can result in differences in sensor performance, thereby affecting the consistency of results [60]. Calibration issues further complicate the standardization of eNose systems, raising the need for rigorous and standardized calibration protocols to achieve uniformity and reliability in gas sensing across various devices or laboratories.

Standardization of eNose systems for diverse biological systems or applications remains a considerable hurdle. Biological samples, with their inherent complexities and variations, pose challenges in the formation of standardized protocols for gas analysis. Different biological systems may emit varying gas profiles, requiring customized approaches for sensor calibration and data interpretation. This above-mentioned lack of uniformity impedes the development of universal standards for eNose applications in biological contexts, demanding customized calibration strategies for specific biological systems or samples. Overcoming this challenge necessitates comprehensive research efforts to establish standardized procedures adaptable across various biological matrices or environmental conditions [61].

Another critical challenge involves addressing the interferences and cross-sensitivity in the case of complex gas mixtures. eNose systems often encounter scenarios in which multiple gases coexist, resulting in interferences or cross-sensitivity among sensors. Distinguishing specific gases in complex mixtures becomes challenging, as sensor responses might be influenced by multiple compounds coexisting in the

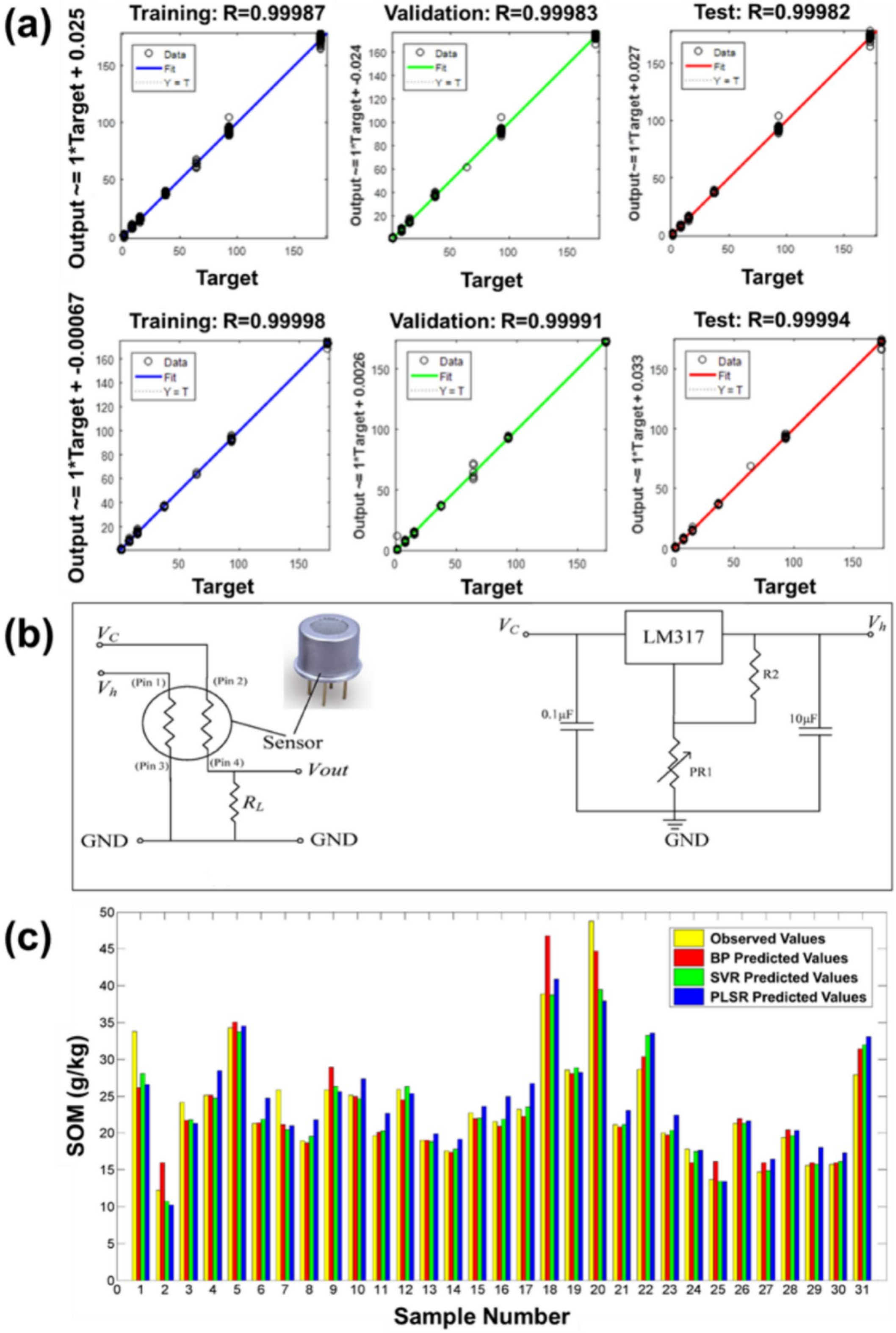

Fig. 6 **a** ANN analysis for predicted and measured data sets evaluating the pollution with petrol (up) and diesel (down). Reproduced with permission from Ref. [57]. Copyright © 2018, MDPI. **b** Circuit diagram; **c** comparison of analyzed data from different models. Reproduced with permission from Ref. [58]. Copyright © 2019, MDPI

techniques, sensor fusion methods, and the development of sensors with enhanced specificity to minimize cross-reactivity. In addition, advancements in machine learning algorithms that can discern complex patterns within sensor data are crucial for the accurate identification and discrimination of individual gases within intricate gas matrices [62].

In brief, challenges such as sensor drift, reproducibility, and calibration issues hinder the consistency and reliability of eNose systems. Standardization across diverse biological systems remains a complex task, requiring customized approaches for different applications. Addressing the issue of interferences and cross-sensitivity in complex gas mixtures necessitates advancements in sensor design, data processing techniques, and calibration strategies to increase sensor selectivity and accuracy in the discrimination of target gases within intricate gas compositions. We believe that efforts to mitigate these challenges will be instrumental in advancing the capabilities and applicability of eNose technology across various domains.

Future Perspectives

We opine that the future of eNose technology holds promising advancements for enhanced monitoring of biological CO_2 conversion processes. Nanotechnology and sensor design innovations may further increase eNose sensitivity and selectivity, enabling the detection of even lower concentrations of gases and volatile compounds involved in CO_2 conversion. Advanced sensor arrays and data processing algorithms may facilitate real-time, continuous monitoring of gas emissions, providing detailed insights into reaction kinetics and process dynamics. In addition, integration of intelligent sensor networks and IoT technologies could enable remote monitoring and control, optimizing biological CO_2 conversion efficiency and reducing environmental impact. These advancements are pivotal for achieving sustainable and efficient CO_2 conversion processes and fostering innovation in the fields of renewable energy and resource recovery.

Moreover, the integration of eNose with complementary analytical techniques has immense potential for comprehensive gas analysis in biological CO_2 conversion [63]. Coupling of eNose with chromatography or mass spectrometry techniques could provide in-depth chemical profiling, allowing for the identification and quantification of specific gases and intermediates involved in CO_2 conversion pathways. In addition, combining eNose with spectroscopic methods such as infrared or Raman spectroscopy could offer detailed, molecular-level information, enhancing the understanding of complex gas mixtures. The synergy between eNose and complementary analytical techniques could provide a holistic approach to gas analysis, offering valuable insights into reaction mechanisms and aiding in process optimization.

As eNose technology matures, regulatory aspects and industrial adoption in CO_2 conversion industries will be crucial in its widespread implementation. The establishment of standardized protocols and guidelines for eNose-based gas analysis in CO_2 conversion processes will be essential to ensure data accuracy, reliability, and comparability across different applications and industries [64]. Regulatory bodies and industry stakeholders must collaborate to develop standards for eNose technology, ensuring its validation, reliability, and adherence to industry-specific requirements. Moreover, fostering industrial adoption of eNose systems in CO_2 conversion industries will require demonstrating the technology's efficacy, cost-effectiveness, and regulatory compliance. Successful integration of eNose into industrial workflows could revolutionize CO_2 conversion processes, contributing to sustainable practices and the advancement of green technologies [60].

We believe that future perspectives of eNose technology in biological CO_2 conversion are characterized by advancements in sensor design, integration with complementary analytical techniques, regulatory standardization, and increased industrial adoption. These developments hold the potential to revolutionize gas monitoring and analysis, facilitating efficient and sustainable CO_2 conversion processes and paving the way for a more environmentally friendly and resource-efficient future.

Conclusions

The current state of eNose technology offers a transformative approach to monitoring biological CO_2 conversion processes. eNose systems, equipped with advanced sensor arrays and sophisticated data processing algorithms, enable real-time and continuous monitoring of gas emissions during CO_2 conversion. These systems exhibit heightened sensitivity and selectivity, capable of detecting and analyzing trace amounts of gases and volatile compounds involved in biological CO_2 conversion pathways. This technology allows for rapid detection and identification of gas profiles, offering valuable insights into reaction kinetics, process dynamics, and efficacy of CO_2 utilization strategies. eNose technology holds considerable potential in advancing the efficiency and sustainability of CO_2 utilization. By providing comprehensive insights into gas emissions and reaction intermediates, eNose systems aid in optimizing process conditions, enhancing conversion efficiencies, and minimizing resource wastage.

The precise monitoring capabilities of eNose contribute to CO_2 conversion process refinement, enabling the fine-tuning of parameters to maximize yields and product quality while reducing energy consumption and environmental impact. Moreover, eNose technology facilitates the identification of optimal conditions for CO_2 conversion, aiding in the development of sustainable practices and innovative approaches for the use of CO_2 as a valuable resource in various industries. Essentially, eNose technology has a prominent role to play vis-à-vis gas monitoring in biological CO_2 conversion processes, offering unparalleled capabilities for real-time analysis and optimization. Its potential to drive efficiency, sustainability, and innovation in CO_2 utilization highlights its importance as a transformative tool in the search for greener and more resource-efficient technologies.

Acknowledgements This work was supported by the National Key Technologies R & D Program of China during the 14th Five-Year Plan period (No. 2021YFD1700904), Henan Provincial Important Project (No. 221100320200), State Key Laboratory of Wheat and Maize Crap Science (No. SKL2023ZZ09), and the Henan Center for Outstanding Overseas Scientists (No. GZS2021007).

Declarations

Conflict of interest The authors declare that there is no conflict of interest.

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