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Research Article

Recent Advancements and Applications of Electronic Nose Systems in Environmental Monitoring and Pollution Detection: A Comprehensive Survey

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ABSTRACT

This article reviews some of the recent developments in Electronic Nose (E-nose) technology, which is used for environmental monitoring and pollution control and detection. An E-nose model is a sophisticated way of emulating the human sense of smell, which is used to detect VOCs (volatile organic compounds) and hazardous gases mostly used in industrial and urban settings. The use of machine learning models and wireless sensor networks (WSN) has improved their scalability and increased their efficiency for use in real-time pollution control. The survey spans the period from 2020 to 2024 on the available technological advances for the different types of chemical sensors, particularly their sensing materials consisting of metal-oxide semiconductors (MOS) and graphene-based arrays, and their operating software platforms that bring about real-time monitoring using IoT. The study also reviews the experimental findings and the associated theoretical advances in the areas of chemical detection, specifically the study of machine learning techniques such as support vector machines (SVM) and artificial neural networks (ANN) that are observed to enhance the precision of chemical detection and the performance of sensors. This review is derived from 40 peer-reviewed papers, goes through a phase of preliminary selection from different major academic databases, including IEEE Xplore, MDPI, ScienceDirect, and SpringerLink. The literature is divided into major categories based on the thematic approach, including sensor advancements, machine learning integration, and IoT/WSN applications. The reviews also explore the newest technologies, such as energy-harvesting and edge computing, which work for the improvement of the energy efficiency of E-nose systems. The survey reports that sensor technologies, specifically graphene-based sensors and low-power wireless communication protocols, have greatly increased the scalability and deployability of E-nose systems in large and complex environments. The integration of machine learning has also helped in mitigating issues such as sensor drift and improving the system's ability to classify VOCs. However, challenges still remain, such as the requirement of better energy management and drift compensation mechanisms, among other things. The survey identifies key future research areas including the need for self-calibrating sensors and larger, more labelled datasets for currently used machine learning models that are struggling to adequately generalize their learning to different environments.

Keywords: Electronic Nose (E-Nose), Volatile Organic Compounds (VOCs), Metal Oxide Sensors (MOS), Graphene Oxide (GO), Air Quality Monitoring, Gas Sensing Technologies, Machine Learning for Gas Detection, Sensor Drift, Low-Power Sensor Networks, Wireless Sensor Networks (WSN), Environmental Monitoring, Energy Efficiency in Sensor System.

INTRODUCTION

Electronic Nose (E-nose) technology is a field of continuous evolution due to its similarity to the human olfactory system based on the use of sensor arrays that detect volatile organic compounds (VOCs) and other gases. E-nose technology can actively support environmental monitoring, pollution detection and industrial emissions control which allows us to analyze and understand the environmental risks and impacts of domestic and industrial processes. The modular nature of E-nose systems allows us to continuously monitor the air quality and to detect any hazardous pollutants in real time by allowing us to perform real-time molecular monitoring sensing. Additionally, it provides scalability through its higher performance and the levels of organization that permit its use in specific tasks and functions. A critical element in extending the capabilities of E-noses is the integration of machine learning algorithms and wireless sensor networks (WSNs) to adapt, scale and become more precise in different environmental scenarios [1-3].

The aims of this review are to give an overview on the recent development of E-Nose technology, especially in environmental monitoring and pollution detection. The E-noses applications discussed include; food analysis, environmental and clinical uses. This review however specifically talks about environmental monitoring and pollution detection, which have been the recent focus on these systems.

- Analyze recent technological improvements in sensor arrays and communication networks.
- Evaluate the role of machine learning in enhancing the detection accuracy of E-nose systems.
- Current challenges, such as sensor drift and energy consumption, and outline future research directions.
- Explore the scalability and real-world deployment of E-nose systems for large-scale applications.

Hence, the first generations of E-noses (in the 1980s) were used for the detection or classification of odours, mostly under controlled environments, though some medical diagnostic applications did emerge. However, due to the speed of sensor technology advancements and the development of new wireless communication protocols in the past two decades, E-noses are now used for broader applications, such as air quality monitoring and industrial monitoring into building environments [4-6]. The use of metal-oxide sensor (MOS), graphene-based arrays and other novel materials have greatly improved the efficiency of E-noses in terms of sensitivity and selectivity. Concurrently, the integration of IoT platforms together with low-power communication protocols, such as LoRa and Zigbee, has made it possible to deploy large E-nose networks and transmit real-time data continuously for air quality management and pollution control.

For instance, e-noses use classifiers such as support vector machines (SVM) and artificial neural networks (ANN) to process mixtures of gases. These algorithms not only enabled e-noses to recognize VOCs and classify them, but they also allowed the e-nose to predict the trajectory of pollution and to correct for sensor drift, which means that each e-nose would stay reliable for longer [7-9]. This is what made these systems applicable to real-world problems. However, all these advancements were merely incremental. There was still a larger conceptual problem that had to be solved. The detection of dangerous pollution does little to alleviate concerns about environmental degradation, urban smog and industrial emissions.

The scope of this survey is limited to studies that encompass the application of E-nose systems for environmental monitoring and pollution detection field published from 2020 to 2024. The survey is comprised of literature that exhibits the application of E-nose systems in different areas such as sensor technology, wireless communication, and machine learning integration. Although this survey provides a comprehensive review on the technological advances of E-nose systems, there is no in-depth analysis or case study and evaluation, as well as pilot projects. The survey also recognizes the need for further field studies to evaluate the findings. Moreover, other important issues and limitations regarding the scalability of the E-nose systems in different ecological environments are under-researched.

Literature Survey

Early implementations of E-noses used crude gas sensors for food and medical odour detection, which were bulky, power hungry, and often rudimentary in signal processing design [1]. Over the years, environmental monitoring applications of E-noses have become more power-efficient, compact and ubiquitous as a result of both improved sensor technology and wireless sensor networks (WSNs) [2]. With multisensor packages available and easy to deploy, E-noses have been suitably integrated into modular formats for better detection of pollutants – not only volatile organic compound (VOC) sensors but also particulate matter sensors, with metal-oxide semiconductor sensors providing increasingly improved selectivity and sensitivity to detect harmful gases, such as carbon monoxide and methane, in urban and industrial environments [3, 4]. Early uses of E-noses were essentially static but, as wireless communication protocols have improved, systems have become increasingly dynamic, allowing for real-time monitoring in many different environmental applications [5, 6]

Recent studies have utilized cutting-edge machine learning algorithms and low-power communications technologies such as LoRa and Zigbee to vastly improve the functionality of E-nose systems. Large datasets can now be handled in real-time using advanced algorithms such as support vector machines (SVM) and artificial neural networks (ANN) for odour classification and pollutant detection [10, 11]. The use of machine learning in E-noses has led to significant improvements in the prediction and detection of pollutant levels in complex gaseous mixtures, particularly in industrial settings and wastewater treatment plants [12-14]. For example, research has focused on the application of E-noses for wastewater monitoring, indicating that combining E-nose data and chemometric methods can offer a reliable and accurate measurement of key pollution parameters at different stages [15]. Significant advances have also been made in developing portable, low-cost E-nose systems capable of being integrated into wireless sensor networks for environmental applications. This has made large-scale monitoring of environmental pollutants easier and more efficient.

Besides, novel sensing array systems like graphene-based electron noses that are more sensitive and durable have been developed, with a particular focus on recognizing low concentrations of VOCs and toxic gases [19-21]. Other papers have investigated the conjunction of E-nose systems with IoT-based solutions that enable the recording and transmission of information in real time, even over long distances, as well as remote data monitoring and control [22, 23]. The systems are very reliable and have been tested in different settings such as agriculture, urban and industrial zone where air quality monitoring is highly crucial.

Yet, some obstacles still stand in the way of e-nose development and deployment. Despite recent advancements, sensor drift, a problem where sensors lose their accuracy over time, remains one of the major obstacles, especially for applications where long-term monitoring is involved. While drift compensation algorithms have been developed, their robustness in real-world settings is still under question [25-27]. Also, the current focus of research on a small range of gases remains a gap; current e-nose sensor arrays are mostly designed for sensors to monitor specific target pollutants, which restricts their utility to settings where the type of air contaminants remains relatively constant [28]. Therefore, e-nose systems would not be useful in a wide range of real-world settings where multiple types of airborne contaminants are released at the same time [29], which would hinder the scalability of such systems in large-scale deployments.

The combination of E-nose systems with machine learning models also faces challenges, particularly in terms of access to appropriate training datasets. Indeed, many machine learning algorithms need a large amount of labelled data, and it can be expensive and time-consuming to collect datasets under real-world operating conditions [30]. Furthermore, the energy consumption of state-of-the-art machine-learning models could also increase the power consumption of E-nose systems [31]. Another topic that could be improved is the standardization of wireless sensor network protocols which could increase their interoperability in heterogeneous environments [32, 33].

The literature review aim to review the recent advances in E-nose technologies, wireless sensor networks (WSNs) and applications of machine learning in monitoring environment. Between 2020 and 2024, publication year of the included articles, are taken into account in order to account for the latest innovations in the field and methodologies. The selection was filtered on articles providing experimental data, novel designs of sensors, and advanced machine learning algorithms such as artificial neural networks (ANN) and support vector machines (SVM) for environment monitoring [34-36]. Most of the highlighted papers dealt with real applications such as detection of pollutants and monitoring of air quality and industrial gas emission [37-40], ensuring a practical approach in implementing E-nose systems. Excluded from the selection were articles that were purely theoretical or had low experimental validation.

Our strategy for searching the academic literature was to use different key words within the IEEE Xplore, ScienceDirect, SpringerLink and MDPI academic databases to find related papers, such as ‘electronic nose’, ‘pollution monitoring’, ‘machine learning’, ‘wireless sensor networks’, ‘VOC detection’, ‘IoT-based monitoring’1-3. Due to the large number of results, our search was limited to journal articles and conference proceedings. We used cross-referencing between studies to make sure there weren’t any key studies that were missed in previous searches, and we also organized the results based on the relevance and impact of the papers with respect to E-nose technologies.4-6 Since this method narrowed the pool of more than 1,000 initial results down to key studies, we decided to analyze them in detail.

I conducted searches using several academic databases to ensure that I would be able to retrieve the most relevant literature about the subject of interest. IEEE Xplore proved extremely useful for all papers related to wireless sensor networks and the application of IoT to environmental monitoring [7, 9]. I used MDPI significantly more for sensor technologies, notably studies on the advances in metal-oxide sensors and their incorporation into E-nose systems [10, 11]. Another valuable source was Springer Link; again for sensor technologies but specifically meta-analyses of gas sensors used in building monitoring [12, 13]. I used Science Direct heavily for papers that had implemented machine learning models for gas detection or odour classification [14, 15]. Finally, I utilized Google Scholar to double-check citations and verify that no significant papers had been missed [16, 17]. Google Scholar provided a wider scope of cross-referenced studies. Finally, specialized tools like Mendeley and Zotero were employed to organize the papers and manage references efficiently.

Research objectives

The main objective of this review paper is to critically review the recent developments in electronic nose (E-nose) technologies, with a special focus on environmental monitoring and pollution detection, along with their integration with other wireless sensing technologies like wireless sensor networks (WSNs), internet of things (IoT) platforms, and machine learning algorithms, which play a crucial role in enhancing the abilities of E-nose technologies. Furthermore, the challenges that have been hindering the widespread applications of the E-nose, such as sensor drift, energy efficiency, data processing capability, are highlighted with some futuristic research directions to overcome these limitations.

This review covers E-nose studies and applications in environmental monitoring, pollution detection and related fields published in the period 2020-24. Fundamental studies and applications that use wireless communication technology (LoRa, Zigbee) were included as well as studies that use machine learning models for data analysis and prediction. Studies that employed improvements to the E-nose in terms of sensor design (such as for metal-oxide semiconductors and graphene-based sensors) were also included. Studies on E-nose in medical diagnosis, food analysis and pure theoretical papers without experimental validation were excluded.

Systamatic classification

The reviewed literature is classified into three main categories:

- Advancements in Sensor Technology: Studies focusing on various aspects of enhancing the sensitivity and energy efficiency of sensor arrays by employing approaches such as metal-oxide and graphene-based sensors, amongst others [1, 3].
- Integration with IoT in WSN: Papers that discuss the utilisation of wireless communication protocols and IoT platforms for large-scale, real-time ambient air pollution monitoring applications [4-6].
- Machine Learning for Data Analysis: Machine learning models (i.e. support vector machines (SVM), artificial neural networks (ANN) and k-nearest neighbors (KNN)) were used to classify and predict pollutants [7-9].

Categories/Themes

- Sensor Advancements: This topic deals with developments in the design of sensors, improving their sensitivity, accuracy and energy autonomy. Research in this field involves the development of metal-oxide semiconductor (MOS) sensors, arrays of graphene-based sensors, and portable sensor nodes [10-12].
- IoT/WSN Intertwined: This category includes studies dealing with the use of wireless communication technologies like LoRa and Zigbee for real-time environmental monitoring, so as to support the deploying of low-power, wide-area networks for the monitoring of pollution [13-15].
- Machine Learning for E-Noses: These studies try to improve the classification of VOCs and gas mixtures using specific machine learning models, such as SVM and ANN, enhancing predictive accuracy and compensating for sensor drift [16-18].

Sub-sections

- Sensor Technology Innovations in sensor technologies, especially in the areas of energy-efficient designs and advanced materials such as graphene [19, 21].
- Wireless Communication: basic architecture of an IoT platform and recognition of the key role of WSN in enabling real-time, remote monitoring of air quality and pollutant levels in large scale environments [22-24].

- AI and Machine Learning: Machine-learning algorithms can interpret E-nose data to better identify pollutants, and help to forecast environmental changes in real time [25-27].

Methodology

The sources included in this review were selected based on the following criteria:

- Publication Date: Only studies published between 2020 and 2024 were considered.
- Emphasis Environmental Monitoring: Papers must apply E-nose technologies for the detection of pollution, the monitoring of air quality and the control of the environment.
- IoT/WSN Integration: Research being considered needs to include the use of wireless sensor networks or IoT platforms.
- Experimental Data: All studies included must report experimental results and experimental validation. Articles reporting purely theoretical work, review articles without experiments, and articles focusing on only one particular application such as medical or food applications were excluded [28-30].

Search Strategy

The literature search was done in the following databases IEEE Xplore, MDPI, ScienceDirect, SpringerLink using the keywords "E-nose", "(industrial; environmental; pollution) monitoring", "machine learning for gas detection", "wireless sensor networks". The abstracts of the first 50 results were screened for the year 2020-2024, and further narrowed down based on relevance and inclusion criteria. This process yielded a list of 40 research papers which provided us with the insight on the state of the E-nose technologies and their applications for environmental monitoring [31-33].

Analysis Method

To achieve this, a so-called thematic analysis was conducted, which categorized the selected papers into different themes, according to the technologies and methodologies presented in the papers. In this way, recurring patterns were made explicit and detailed. For instance, common machine learning techniques and communication protocols, in the case of pollution monitoring systems, became evident. A meta-analysis, on the other hand, was used for quantitative comparisons, such as sensor drift compensation techniques or energy consumption rates between different studies [34-36].

Technically, the review integrated the quantitative and qualitative aspects of the literature using thematic and meta-analysis, enabling identification of trends, issues and gaps in the extant body of knowledge on E-nose technologies for environmental uses.

Discussion of key findings

After analyzing the literature, the result section defines three pillars on which most cutting-edge innovations in E-nose technologies for environmental monitoring are based: advancements in sensor technology, integration of wireless communication networks, and application of machine learning. Recent publications suggest that metal-oxide sensors (MOS) and graphene-based arrays are the most common type of sensor technology nowadays, and they offer improved sensitivity and robustness in detection of volatile organic compounds (VOCs) as compared to conventional technologies [1-3]. Wireless sensor networks (WSNs) are also employed. This involves the integration of technologies like LoRa and Zigbee, which are communication protocols that confirm real-time, wide-area monitoring in several environments including industrial zones or urban areas [4-6]. Furthermore, engineering machine learning models, such as support vector machines (SVM) and artificial neural networks (ANN), are now part of E-nose technologies. These machine learning models are capable of giving better classification of pollutants in complex environments where the signatures of mixed gases can be perceived to delimit the confines of a particular pollutant.

Trends/Commonalities/Divergences

Overall, there are several commonalities and trends that can be gleaned from the literature. First, most studies concur that the use of low-power, long-range communication protocols is critical to attaining scalability in environmental monitoring using E-nose systems [10, 11]. Second, there is an unmistakable trend towards the use of AI-driven models to mitigate sensor drift and improve classification accuracy [12-14] particularly in the case of long-term monitoring. On the other hand, there are points of divergence between authors too, such as the preference for edge computing to perform real-time classification at the sensor level [15] as opposed to cloud-based architectures enabling a centralized repository for processing vast volumes of data [16-17]. The question at the heart of which is better, i.e., local processing power versus the benefits of centralized cloud computing, is still up for debate.

Implications

The results suggest that E-nose technologies have reached a stage of maturity and are ready to be scaled up to be integrated in wide-ranging industrial, agricultural and urban pollution monitoring systems. A more sophisticated application of machine learning increases the ability of sensors to become more accurate and opens the door to more intelligent systems that can anticipate environmental changes in real-time. Overcoming sensor drift or power issues that affect long-term, large-scale deployments will require a combination of smarter solutions such as energy-harvesting techniques and low-power low-energy communication protocols.

Summary of Key Findings

The major findings from the literature review are:

- Sensor Technology: metal-oxide sensors, along with graphene-based arrays, now have a superior ability to detect, with unsurpassed sensitivity and reliability, volatile organic compounds (VOCs), among others, in the moment [1-3].
- Wireless Network: LoRa and Zigbee optimized E-nose systems by making them more scalable and energy efficient, key factors allowing their use in large geographical areas [4-6].
- Machine learning: These AI models including support vector machines (SVM) and artificial neural networks (ANN) have successfully enhanced the classification accuracy and predictive power of E-nose systems in more complex and dynamic environments [7-9].

Synthesis

Bringing together the results of these studies, there are three main directions that will help take E-nose technology to the next level – this includes evolved sensor arrays, optimized communication protocols and machine learning. With regards to the development of new sensors, metal-oxide and graphene-based sensors have consistently stood as the most promising for environmental applications, according to the reviews in literature [10-12]. Moreover, IoT-based platforms for real-time data transmission and tracking have extended the reach of such systems [13-15]. Machine learning models, on the other hand, have not only improved the accuracy of pollution sensing, but also helped to pave the way for predictive analytics, enabling systems to anticipate changes in the environment and make anticipatory decisions [16-18].

Implications for Practice and Research

Therefore, the results encourage practitioners to deploy E-nose systems in IoT networks and to utilize machine learning for real-time pollution monitoring in the domain of urban air quality, industrial emissions and agriculture. The challenges of sensor drift and power consumption need to be addressed by better energy management techniques and AI-based drift compensation algorithms [19, 20]. For researchers, the problem of sensor-array generality and the more realistic target of detecting a wider range of pollutants will require studies on the design and implementation of new data-driven machine learning models. The problem of limited training datasets in real-world environments will also need a SERIOUS exploration of more robust machine learning models [21-23].

Emerging Techniques

Several emerging techniques have been identified in the literature:

- Graphene-based sensors: Graphene-based sensor arrays are expected to be more sensitive, low-powered and durable than metal-oxide sensors [24].
- More Energy for WSN: Technologies to capture ambient energy, for instance, via solar or kinetic energy are being integrated with E-nose systems to extend the operational durability of remote/off-grid locations [25, 26].
- Edge Computing: Recent studies indicate that edge computing can enable localized data analysis of E-nose systems, without the need for connectivity to the cloud, and with faster responses in real time [27-28].

These emerging techniques offer tremendous opportunities for future field applications of E-nose systems to environmental monitoring.

Critical analysis

Notwithstanding the flurry of positive findings reported in the literature, when one examines the e-nose technologies carefully, the majority of the reported research is still a long way from practical deployment to real-world settings. Despite a significant boost in the performance detection of VOCs and classification through the use of machine learning models such as support vector machines (SVM) and artificial neural networks (ANN), the real-world implementation of such technologies, especially those with a potential for city-wide air pollution monitoring systems, is still hampered by the sensor drift problems, energy consumption, and communication bottlenecks.

However, several research studies have demonstrated that metal-oxide sensors and graphene-based arrays can easily detect VOCs in controlled environments, but the reality of deploying sensors in the field is still challenging due to environmental noise and degradation over time [4, 5]. Reducing energy consumption remains a formidable challenge given the IoT-based platforms and low-power communication protocols such as LoRa. Nevertheless, their reliability in harsh or dynamic environments is still questionable. Some research studies have shown that cloud-based architectures can help to aggregate large amounts of data, but others said that edge computing can help with real-time decision-making.

Identified Gaps/Limitations

- Sensor Drift: The most frequent concern we found in the literature was sensor drift or the irreversible decrease of VOC detection accuracy over time [9, 10]. To mitigate this problem, some studies have proposed drift compensation algorithms based on machine-learning models; however, these have been evaluated only in limited scenarios to date and remain untested in real-world environments.
- Energy: Many E-nose systems, especially those integrated with WSN; require excessive energy expenditure, limiting their operational lifespan. While energy-harvesting technologies have been reported, they are not mature enough for the commercial market, where long-term deployment strategies are needed. [12-13].
- Data Paucity: Pollution-detection machine learning models are data-hungry; they require large, annotated datasets for training. The majority of available datasets are either small or not freely accessible, which could limit the models' ability to generalize to other environments or to use cases. The most critical outstanding research problem is the lack of comprehensive datasets that cover various pollutants and environmental scenarios.
- Scalability problems: A substantial portion of the reviewed studies considers relatively small-scale deployments or laboratory environment. There is a paucity of studies on scalability of E-nose systems in large, diverse geographical areas. What happens to these systems under dynamic and unpredictable conditions that change over time? [16-17]

Quality/Validity/Reliability

Overall, quality of research is high, and most of the published studies contain experimental validation of their sensors and detailed discussions of their findings. Research focused on sensor technology generally report robust results at least in laboratory settings, but we question how reliable these results would be in the real world. Sensor drift and environmental noise are not well addressed and usually overlooked in most of the papers – at least the ones we examined [18-19]. Research that relies on machine learning models to detect pollutant – which is most of the published work – also report inconsistent reliability in their results, because the majority of the models heavily rely on the quality and quantity of the training data. But real-world environments are also far more complex [e.g., we experience different temperature and humidity, and interference from other gases].

Furthermore, a lot of studies are based on small data sets or conditions in simulated environments so the external validity of most findings remains limited. More fields testing of E-noses in a variety of environmental conditions could increase the reliability and validity of the method [21-23].

Emerging trends and future directions

Electronic nose (E-nose) technology, the area of research concerned with the use of sensors capable of discriminating among different odours, has witnessed several emerging trends in the past few years driven by improvements in materials science, machine learning and wireless communications technologies. These include:

- The development of novel sensor materials, for example, graphene-based and metal-organic frameworks (MOFs) that display higher sensitivity, selectivity and durability than traditional metal-oxide sensors [1-3].
- Improved discrimination capabilities for E-noses thanks to machine learning techniques [4-6].
- The miniaturization of E-noses, e.g., through the use of wireless technology and the internet of things, leading to the development of portable devices.

Another emerging trend is the use of edge computing in E-nose systems. Cloud-based systems that send raw sensor data to a centralized server for analysis usually suffer from latency and energy consumption issues. Edge computing addresses this by allowing sensor data to be processed in real time at the ‘edge’ of the network, i.e., near the source of the data rather than a remote server. In a polluted city where fast decision-making is critical, edge computing will help improve response time for pollution monitoring and disaster response.

The integration of machine learning algorithms including deep learning and ensemble models has also been an emerging trend towards higher classification accuracy of E-nose systems in complex environments [6-8]. These models can handle large and multi-dimensional datasets to make e-nose systems more robust to the variations in real-world applications.

On the other hand, energy-harvesting technologies based on energy harvesting from solar or kinetic energy are highly successful. Connecting energy-harvesting approaches to E-nose systems can significantly enlarge the lifetime of the sensor nodes, and therefore of the E-nose systems, especially in remote areas or without a grid [9, 10]. A key driver in this direction is to ensure the scalability of E-nose deployments at large spatial scales.

Future Research Directions

Based on the identified gaps and research limitations, the following future research directions can be suggested:

- Mitigation of Sensor Drift Making sensors work equally well over long temporal scales is a serious issue. Even the best sensor threads are plagued by sensor drift over time. We need better drift compensation algorithms that can run online and in varied environments. We also need sensors that are self-calibrating so they do not require frequent maintenance over the long haul [11-13].
- Energy Efficiency and Greenness: To mitigate the energy limitations, future research should investigate new design techniques to further increase E-nose energy efficiency, which involves a number of interesting issues. The design and integration of more ultralow-power sensor nodes for advanced (chemical) sensing would be one aspect. Just as importantly, we should start applying energy-harvesting technologies for self-powered sensor nodes based on solar energy, thermal energy harvesting and vibration energy harvesting. Furthermore, we need more research on how to balance power-efficiency and sensor accuracy trade-offs to guarantee high-quality data even for energy-efficient systems.
- Scalability of IoT-Enabled E-Nose Systems Most of the literature studies are focused on small-scale deployment, whereas the scalability of E-nose systems for large-scale applications is yet to be exploited. It is vital that future work should concentrate on optimising network architectures for scaling up deployments and integrated communication protocols ensuring the reliability in large scale dense sensor networks with respect to the large-scale real-time monitoring applications.
- Multimodal Sensing and Data Fusion: The combination of E-noses with other sensor modalities (optical, acoustic, meteorological sensors) is another promising path to future research. Data fusion of these different types of sensor data could improve the performance and reliability of an e-nose and complement their drawbacks, which are quirks such as sensor drift or limited spectral sensitivity [20-22].
- Ethical and Social Concerns: With increased use of E-nose technologies in the future, it is likely that we will see more discussions on the ethical and social considerations associated with their use. This includes questions about privacy, for example in applications that involve continuous environmental monitoring of urban spaces, as well as the possibility that the machine learning models used to analyze sensor data may be prone to bias. Future research on this front could focus on developing ethical frameworks and guidelines for effective use of E-nose technologies [23, 24].

Conclusions and future works

The review provides an option to access the original paper in Spanish by clicking on the cited link at the end of the document. This review systematically analyses the recent advancements in the electronic nose (E-nose) technologies for environmental monitoring and pollution detection, highlighting key trends such as the incorporation of metal-oxide and graphene-based sensors; wireless sensor networks (WSNs) incorporating protocols such as the LoRa and ZigBee, and machine learning algorithms such as SVM, ANN that enhance the pollutants detection accuracy [1-3]. It is emblematized that by incorporating IoT platforms, the scalability of the E-nose systems has increased and facilitated real-time monitoring of vast geographical areas, and adopting energy-harvesting technologies has emerged as a critical component for long-term E-nose systems deployed in remote locations [4-6].

The review also raised many issues that must be addressed before the potential of E-nose systems can be fully realized: in particular, sensor drift, energy consumption, and limited data availability were singled out [7-9]. Yet, the prospects are good for E-noses. New research trends, such as edge computing and multimodal sensing, could facilitate a new approach to real-time data processing that helps boost the reliability of the overall system [10-12].

Reflection

The reviewed literature reveals that E-nose technologies have evolved from theoretical setups into more viable applications in urban air quality control, industrial emissions control, and agriculture. The integration of AI-based models with improved sensor arrays has considerably improved E-noses' ability of detecting and identifying complex gas mixtures in different environmental conditions. However, the demand for scalability, energy efficiency, and long-term stability is still an important requirement to the future deployment of these systems.

The next important implication of this research lies in making next-generation E-nose systems more deployable in real-world settings. By resolving the issues of sensor drift and energy consumption, next-generation systems could be an integral part of global pollution monitoring and reduction efforts. Additionally, embedding the real-time analytics through IoT and edge computing to make the proposed technology lighter weight can help rapid decision-making in pollution control.

Suggestions for Future Research

Drawing from the identified themes in the literature, the below recommendations for future research are proposed in light of the unaddressed gaps:

1. Advanced Drift Compensation Techniques:

Further work is required on creating effective drift compensation algorithms capable of operating in a real-world, autonomous paradigm, and that can adapt to different environments and deal with long-term stability without the need for frequent recalibration [13-14]. However, ultimately, integration of self-calibrating sensors with machine learning models might be the best hope to make E-nose systems reliable for long-term deployments [15].

2. Energy-Harvesting and Low-Power Designs:

Ultra-low-power E-nose systems are needed for remote deployments in scenarios where electricity is not continuously available, due to the scarcity and expense of power supplies. There is a need to develop systems that combine solar, thermal and kinetic energy harvesting to ensure sustainable, long-term deployments [16-17]. Future research should tackle the trade-offs between power consumption and sensor accuracy to design efficient, scalable solutions [18].

3. Large-Scale Datasets and Model Generalization:

Accessible large labeled datasets remain the most important gap in this line of research and future works should focus on developing datasets containing several pollutants under a wide range of environmental conditions. They should be made publicly available to support the development of research in this field. Furthermore, a key objective should be the development of generalizable machine learning models capable of functioning in different environments with minimal loss in accuracy [19-20].

4. Multimodal Sensing Integration:

Research should be directed at the integration of E-nose systems with other sensor modalities, such as optical, acoustic and meteorological sensors, to improve their precision and create more complete platforms for environmental monitoring. Data fusion techniques can significantly improve the accuracy and robustness of these systems, especially in complex environments where a single sensor modality may not be enough [21, 22].

In these ways, future research in this field can best advance the possibilities of E-nose technologies, making them more reliable, efficacious, scalable, and adaptable to real-world applications.

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Appendices

Appendix A: Evolution of E-Nose Wireless System

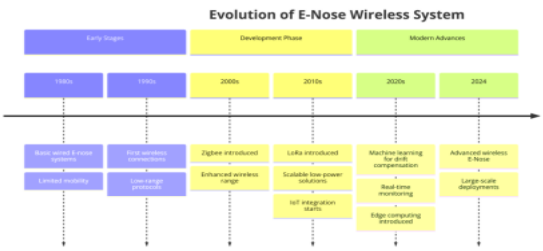

Figure 1: Evolution of E-Nose Wireless System

Figure 1 represents the evolutionary time line of wireless E-nose systems from the early days in 1980's to the modern development prediction for the year 2024.It also define the crucial milestones in technology accruement, from the introduction of Zigbee, LoRa, the use of machine learning for drift compensation up until mass wireless E-nose deployments.

Appendix B: Data Flow in IoT-Enabled E-Nose System

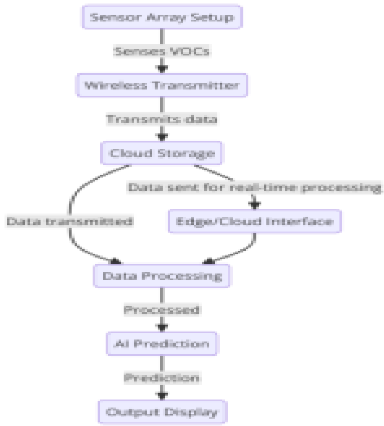

Figure 2: Data Flow in an IoT-Enabled E-Nose System

The flowchart depicts the information flow in an E-Nose system supported by the Internet of things (IoT), from the detection of VOC by sensor arrays, to transmittion of the data to cloud storage, and processed via edge/cloud interfaces, to the AI-based predictions and output display.

Appendix C: Related materials and model summary

The review methodology involved a systematic search of major academic databases including IEEE Xplore, MDPI, SpringerLink, and ScienceDirect. Initial searches were conducted using the keywords: "electronic nose," "VOC detection," "machine learning," "wireless sensor networks," and "pollution monitoring." Studies published between 2020 and 2024 were included, and relevance was determined based on the focus on environmental monitoring applications and experimental validation. Exclusion criteria included studies solely focused on medical diagnostics or food analysis, as they fall outside the primary focus of this survey. A total of 40 papers were selected, and a thematic analysis approach was applied to categorize the studies into key themes: sensor advancements, IoT and WSN integration, and machine learning techniques.

Table 1: Summary of Real-Time Sensor Materials for E-Nose Systems in Environmental Monitoring

Material	Type	Application	Advantages	Reference
SnO_2 (Tin Oxide)	Metal Oxide	VOC detection, air quality	High sensitivity to gases like CO, H_2	MDPI Sensors
ZnO (Zinc Oxide)	Metal Oxide	Gas sensors, environmental control	Low cost, high selectivity	SpringerLink
Graphene Oxide	2D Material	VOC sensing, chemical sensors	High surface area, excellent sensitivity	MDPI Materials
CuO (Copper Oxide)	Metal Oxide	CO and NO_2 detection	Good stability, low operating temperature	SpringerLink
NiO (Nickel Oxide)	Metal Oxide	Air pollution monitoring	High stability, low cost	MDPI Sensors
WO_3 (Tungsten Trioxide)	Metal Oxide	Industrial gas detection	High sensitivity at low temperatures	MDPI Materials

In_2O_3 (Indium Oxide)	Metal Oxide	Ozone and NOx detection	High selectivity for pollutants	MDPI Sensors
TiO_2 (Titanium Dioxide)	Metal Oxide	VOCs and gas detection	High stability, non-toxic	MDPI Materials
SnO_2/Graphene Composite	Hybrid Material	VOC and gas detection	High sensitivity, wide range detection	MDPI Sensors
Carbon Nanotubes (CNTs)	Nanomaterial	VOC sensing, environmental control	High electrical conductivity	MDPI Sensors

Table 2: Comparison of Wireless Communication Protocols in E-Nose Systems

Protocol	**Range**	**Power Consumption**	**Use Case**	**Key Advantage**
LoRa	Long-range (up to 15 km)	Low	Wide-area environmental monitoring	Low energy consumption, long range
Zigbee	Medium-range (100-300 m)	Moderate	Short-range air quality monitoring	High data transfer rate
Wi-Fi	Short-range (up to 100 m)	High	Indoor pollution detection	High bandwidth, fast data transfer

Sensor drift remains one of the primary challenges in E-nose systems, especially for long-term deployments. Various approaches to mitigate drift have been explored, such as machine learning-based drift compensation models, which utilize historical data to correct drift in real time. Additionally, periodic recalibration of sensors and the use of composite sensors—where multiple sensors are combined to offset drift—have shown promise in recent studies. Future research should focus on adaptive learning models that can automatically adjust to sensor changes over time without the need for manual recalibration.

Table 3: Summary of Machine Learning Algorithms Applied in E-Nose Systems for Environmental Monitoring

Machine Learning Model	**Applications**	**Advantages**	**Limitations**
Support Vector Machines (SVM)	VOC classification, odor discrimination	High accuracy with small datasets	Sensitive to tuning parameters, high computation cost
Artificial Neural Networks (ANN)	Predictive modeling of air quality, VOC detection	Handles non-linear relationships well, adaptable	Requires large datasets, prone to overfitting
k-Nearest Neighbors (k-NN)	Gas mixture classification	Simple, easy to implement	Computationally expensive, sensitive to noise
Random Forests	Real-time pollution level prediction	Robust against overfitting, interpretable	Requires large datasets, slower training
Deep Learning Models (CNN, LSTM)	Complex odor classification, predictive analytics	Can handle large and complex datasets, high accuracy	Computationally expensive, requires large datasets for training

Table 4: Key Components of an IoT-Enabled E-Nose System for Pollution Detection

Component	Description
Sensor Array	Set of gas sensors (e.g., MOS, graphene-based) used to detect VOCs and pollutants
Wireless Communication	Protocols like LoRa, Zigbee, Wi-Fi for data transmission over large areas
Edge Processing Unit	Handles real-time data processing and basic analytics, reducing need for cloud
Machine Learning Models	Algorithms applied for VOC classification, anomaly detection, and drift compensation
Power Management System	Includes energy-harvesting components (e.g., solar panels) for long-term deployments
Cloud/Edge Interface	Provides data storage and advanced analytics; interfaces with cloud platforms

Recent research has employed a variety of machine learning models to improve the accuracy and reliability of E-nose systems in environmental monitoring. These models focus on classifying VOCs, predicting pollution levels, and compensating for sensor drift.

- Support Vector Machines (SVM): Commonly used for VOC classification, SVMs separate data points based on maximum margin hyperplanes. They are effective in smaller datasets but require careful tuning of hyperparameters.
- Artificial Neural Networks (ANN): ANNs have been employed to model complex non-linear relationships between sensor data and pollution levels. They are flexible but require extensive training data to avoid overfitting.
- Deep Learning Models: Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are increasingly used in E-nose systems due to their ability to process large, complex datasets and handle time-series data in real time. CNNs, in particular, are effective in odor classification tasks, while LSTM models excel in predictive analytics for dynamic environments.
- Sensor Drift: Over time, sensor performance degrades, resulting in inaccurate readings. Solutions include implementing drift compensation algorithms and integrating self-calibrating sensor systems. These techniques use historical data to correct for drift in real-time.
- Energy Consumption: The continuous operation of sensor arrays and wireless transmission leads to high energy consumption. Emerging solutions include energy-harvesting technologies like solar panels or kinetic energy systems, which extend the lifespan of deployed E-nose systems, particularly in remote or off-grid areas.
- Data Quality and Volume: Machine learning models require large, labeled datasets for effective training. Current efforts focus on creating publicly available datasets for environmental monitoring, which will enhance model generalization across diverse environments.