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ENose design and structures from statistical analysis to application in robotic: a compressive review

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Abstract

Since 1982, the olfactory system of creatures has piqued the interest of academics who seek to create a comparable system. Despite its mysterious nature, the first stage has been successfully completed with the development of the ENose. Its extended applications have opened new doors for researchers, ranging from food quality testing to bomb detection and even, more recently, identifying those infected with the coronavirus. In this talk, we will review the structure and sensor behaviour of the ENose, as well as its applications, such as odour source localization and various applications in agriculture. The challenge of odour identification has prompted researchers to employ robots with sensors to investigate and locate odour sources. The present study aims to synthesize documented research and provide a fresh perspective on odour localization research efforts and tests conducted. The study highlights previous attempts to equip robots with sensors to explore the real indoor or outdoor environment. Initially, a review was conducted to investigate various aspects of the sector and the obstacles involved.

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1. Introduction

The electronic nose is a device used to investigate organic smell functions. The electronic nose is used to differentiate complicated volatiles by replicating the structure and principles of olfactory perception[1]. The olfactory system, sometimes known as the sense of smell, is the sensory system responsible for smelling (olfaction). Olfactory system is one of the unique abilities that has been linked to certain organs. Several hundred years ago, village doctors in rural China used the distinctively sweet scent of a patient's breath to diagnose diabetes. To establish the same diagnosis presently, doctors utilise a series of blood sample and laboratory analysis, but physicians may soon be sniffing their patients' breath again. This time, the physicians will have electronic noses that are small and inexpensive enough to fit in their pockets. An electronic nose is a device that attempts to mimic the anatomy and functions of the human nose[2]. The present study aims to compare and synthesize documented researcher work on ENose structure and odour localization with the real environment. The study provides an overview of research efforts and tests conducted to provide fresh perspectives on ENose and odour localization. The paper is organized as follows: Section 2 provides an overview of the history and aims of the ENose. Section 3 details the structure of the ENose, including both hardware and software components. Section 4 describes the various applications of ENose technology in different sectors. The paper concludes with Section 5.

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2. ENose History and aims

The history of ENose over the years has been shown in figure 1 starting from 1920 till the present time. As the figure shows£¬Zwaardemaker and Hogewind in 1920 [3], They proposed that scents might be recognized by detecting the electric charges formed on a thin water spray containing the odourant in solution, but they were unable to turn this into a practical apparatus. Hartmann and colleagues identified a polished metal wire microelectrode electrochemical sensor. A network of many senses was created to work concurrently by employing various combinations of metal electrodes, electrolytes, and applied possibilities. To detect scents, Moncrieff used a single thermistor (temperature-sensitive resistor) covered with a variety of materials, including poly (vinyl chloride), gelatine, and vegetable oil. He saw that the films he employed were non-specific, and he hypothesised that if he built an array of six thermistors with six different coatings, the resulting device would be able to differentiate between a huge number of distinct odours. Buck et al. 1965 [4], employed contact potential modulation to detect scents, whereas others employed conduction modulation. After then, it took nearly twenty years for the idea of an ENose to develop as a smart structure consists of an array of chemical sensing for odour detection. The term "ENose" came for the first time in the 1980s [5].

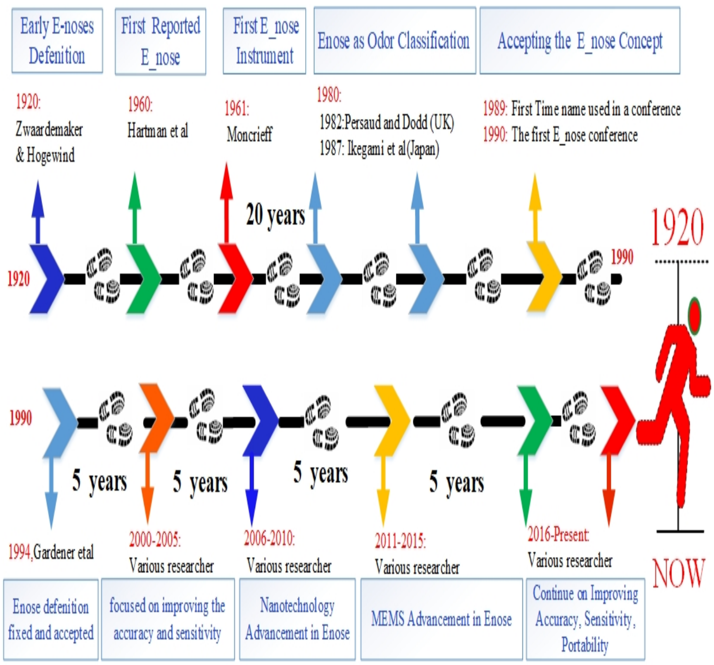

Figure 1. History of ENose.

Persaud and Dodd at Warwick University, UK, in 1982 [6], reported the earliest authentic reporting about an innovative device. The sensors employed in this experiment were essentially amperometric e11 electrochemical sensing devices. Hitachi Research Laboratory in Japan, Ikegam in 1987 [7]. By this point, advancements in electronics, sensors, and computers had combined to make an ENose a realistic prospect. In 1991, a segment of a NATO specialized training on chemosensory information processing was addressed to robotic olfactory system. A device that identifies simple or complicated "odours" by combining an array of electronic chemical sensors with partial specificity with a suitable sequence detection algorithm.

Gardner ultimately provided an acceptable definition of an ENose in 1994 [8]. A device consisting of an array of electronic chemical sensors with partial specificity and a suitable sequence recognizer capable of distinguishing simple or complex scents". The design of an ENose, on the other hand, shares many similarities with multi-sensor systems developed for the detection and measurement of individual components in a simple gas or vapour combination. The advancement of electronic nose technology, or ENose, can be traced back to the late 1980s and early 1990s, when researchers first began exploring the use of sensors for odour recognition and realization.

The first ENoses were developed in the late 1980s and early 1990s and were based on metal oxide sensors (MOS) or conductive polymer sensors. These early ENoses were limited in their ability to accurately detect and identify odours, and they often produced inconsistent results [9].

In the late 1990s and early 2000s, advances in sensor technology led to the development of more advanced ENoses, including those based on quartz crystal microbalance (QCM) sensors and surface acoustic wave (SAW) sensors. These ENoses were capable of detecting a wider range of odours and were more accurate than earlier ENoses.

In the late 2000s and early 2010s, the use of artificial neural networks (ANNs) in ENose applications became more widespread, as ANNs were able to effectively model the complex relationships between sensor outputs and odour properties. This led to the development of ENoses that were capable of accurately identifying odours, even in complex and challenging environments [10].During the years 2000-2005 period, researchers were focused on improving the accuracy and sensitivity of ENoses. They began incorporating more advanced sensors, such as metal oxide sensors, and developing better algorithms for analyzing the data collected by the sensors. The use of ENoses in the food and beverage industry also became more widespread, as they were used to detect contaminants and monitor product quality.

The record on 2006 to 2010 shows that the development of ENoses during this period was largely driven by advancements in nanotechnology. Researchers began using Nano sensors, which are smaller and more sensitive than traditional sensors, to improve the accuracy and sensitivity of ENoses even further. The healthcare industry also began to adopt ENoses, with applications such as disease diagnosis and monitoring becoming more common.

Research activity in the period of 2011 to 2015 indicated that, ENoses became more accessible and affordable, thanks in part to the development of microelectromechanical systems (MEMS) technology. MEMS allowed for the production of smaller and cheaper sensors, making ENoses more practical for a wider range of applications. The development of wireless communication technology also made integrating ENoses into larger systems, such as smart homes or industrial monitoring systems easier. as the final period 2016 to present shows the development of ENoses has continued to focus on improving their accuracy, sensitivity, and portability. Researchers are also exploring new applications for ENoses, such as air quality monitoring and security applications. One of the most promising areas of development is the use of machine learning and artificial intelligence to analyze the data collected by ENoses, which could allow for even more accurate and precise odor detection. With ongoing research and development, the future of ENoses looks bright, with potential applications in a wide range of industries [12].

Recent developments: In recent years, ENose technology has continued to evolve, with advancements in sensor technology and the development of new sensing materials, as well as the integration of ENoses with other technologies, such as cloud computing and Internet of Things (IoT) systems. This has led to the development of more advanced ENoses with improved accuracy, sensitivity, and reliability [11]. The ENose technology is modelled on the human nose since the two have several resemblances. Most animals and reptiles have a primary and secondary olfactory system [13]. The primary olfactory method recognizes airborne chemicals, whereas the secondary olfactory system recognises fluid-phase stimuli.Figure 2 demonstrated the biological nose and ENose comparison for sensing the volatile compounds.

The human nose is an amazing organ, with millions of various types of odour receptors. They allow an average person to identify 10000 distinct scents, that are generally a complex blend of vapours or volatile organic compounds, as chemists refer to them. Some are caused by chemical levels in the parts-per-trillion range in atmosphere [14]. By smelling, a properly functioning individual can identify the difference between new milk and poor milk, or go into a house and notice that a pie is baking. The use of the human sense of smell as an odourant instrument is limited for several purposes: it is highly subjective, easily fatigued, and difficult to understand. As a result, there is a significant demand for an instrument that can simulate the human sense

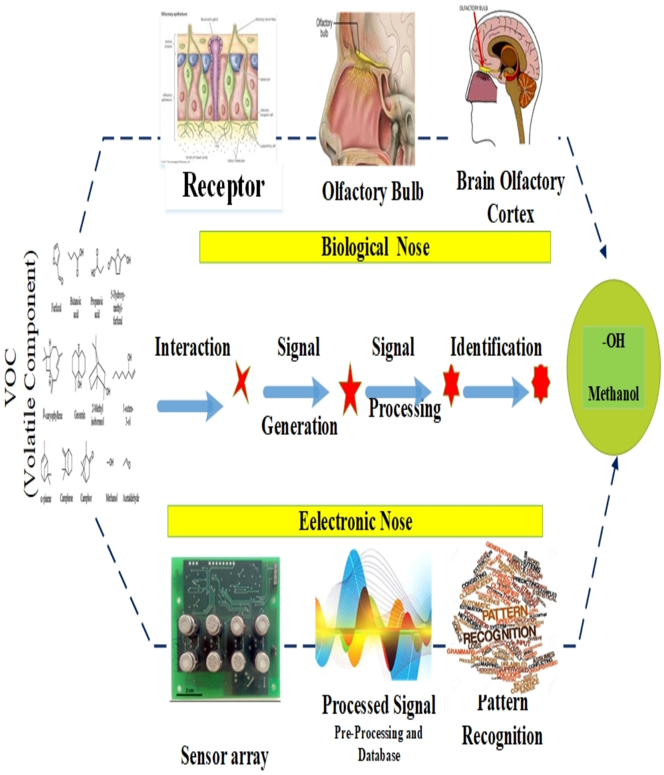

Figure 2. biological nose vs ENose.

of smell yet does not have such limitations in order to be employed in industrial applications. In this regard, ENoses might be employed in fields such as food, environmental industry, and medicine for a variety of activities such as pollution management and air-quality monitoring, industrial process control, sickness diagnosis, and safety considerations [15].The human nose and electronic nose (ENose) are both capable of detecting and identifying different odours, but they have some important differences.

Sensitivity: The human nose is highly sensitive and can detect a wide range of odour molecules, while ENoses typically use sensors that are not as sensitive as the human olfactory system. However, ENoses can often compensate for this by using multiple sensors in combination, which allows them to detect and identify a wider range of odours than would be possible with a single sensor [11].

Accuracy: The human nose is often more accurate in detecting and identifying odours, due to its highly developed olfactory system. However, ENoses can be trained to recognize specific odours with high accuracy, and they are often more consistent and reliable than the human nose [11].

Response time: The human nose can respond to an odour in a matter of seconds, while ENoses typically take a few seconds to a minute to respond. However, the response time of an ENose can be improved by using faster sensor technologies and more powerful computing systems [11].

Cost: The human nose is a naturally occurring biological system, while ENoses are typically composed of expensive sensors and electronics. However, the cost of ENoses has been decreasing over time, and they are becoming more accessible and affordable [11].The olfactory system of humans has been depicted in figure 3.

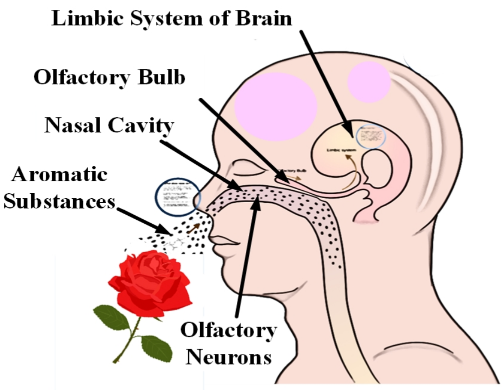

Figure 3. Olfactory System, or Sense of Smell System in humans.

Numerous meals' aromas and flavours are influenced by volatile organic molecules, which can serve as accurate indications of freshness and quality. However, a fresh-cut orange or a slice of Swiss cheese, for example, may contain hundreds of these compounds. The human nose has hundreds of distinct odour sensors, the response patterns of which are processed by the brain, which then searches its memory for matches to previously recorded response patterns. An electronic nose has much fewer sensors; commercial units typically contain between 10 and 50 sensing units.

3. ENose Structure

The structure of an electronic nose, or Enose, typically consists of several key components as indicated in figure 4.

•Sensing array: The sensing array is the core component of an ENose and consists of multiple sensors that are sensitive to different chemical compounds. The sensors can be made of various materials, including metal oxides, conductive polymers, quartz crystal microbalances, or surface acoustic waves. The sensor signals are collected and used to produce a unique signature for each odour [10].

•Sampling system: Sampling system: The sampling system is responsible for introducing the odour sample into the ENose. This can be done through various methods, including air flow, pumping, or diffusion. The sampling system must be carefully designed to ensure that the odour sample is evenly distributed across the sensing array [11].

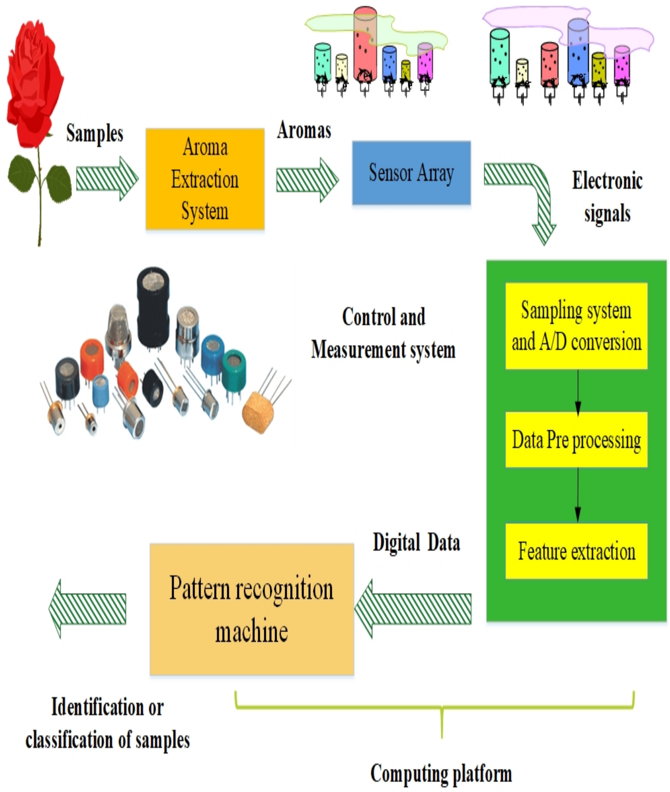

Figure 4. ENose Overview and structure parts and section.

•Data acquisition system: The data acquisition system is responsible for collecting and storing the sensor signals generated by the sensing array. This system typically includes amplifiers, analog-to-digital converters, and a computer for data storage and analysis [9].

•Pattern recognition system: The pattern recognition system is responsible for analyzing the sensor signals and identifying the odour. This can be done using various algorithms, including artificial neural networks, principal component analysis, linear discriminant analysis, or support vector machines. The pattern recognition system must be trained on a large and diverse set of odour samples in order to accurately identify odours [10].

An Electronic Nose (ENose) is a system, which can sense the different VOCs (Volatile Organic Compounds) just like a human nose. The ENose can sense these VOCs through different sensors. Organic polymers, metal oxides, quartz crystal microbalance, and even gas-chromatography (GC) or mass spectroscopy (MS) are examples of ENose detectors [16]. An ENose uses a simple structure. The structure of ENose is given in the figure 5. The structure consists of sampling systems, data pre-processing and feature extraction.

From fig.5 it can be seen how samples are identified and classified using the structure of ENose. The figure below shows the entire process of how sampling is done in ENose system.

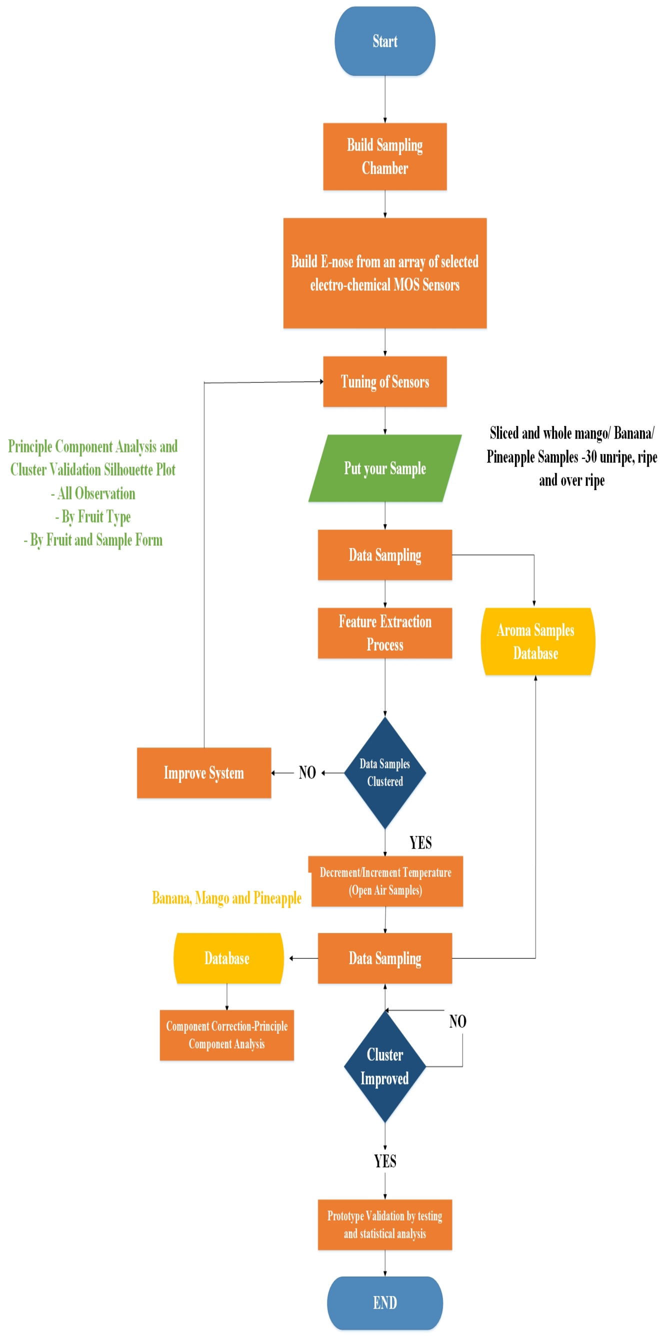

Figure 5. Flowchart of the ENose entire process of the sampeling method.

The figure 5 gives a clear idea and vision of ENose sampling process. As it shown the ENose sampling process involves a series of steps that enable the device to capture, analyze, and classify odours or flavors. Here is a clear idea and vision of the ENose sampling process:

•**Sampling:**The ENose sampling process starts with the collection of the sample that contains the odour or flavor. This can be achieved through different methods, such as headspace sampling or direct liquid injection. The collected sample is then transferred to the ENose for analysis.

•**Detection:** The ENose contains an array of sensors that can detect volatile organic compounds (VOCs) in the sample. Each sensor in the array is sensitive to specific VOCs, and together, they provide a unique fingerprint of the odour or flavor.

•**Analysis:** Once the ENose detects the VOCs in the sample, it sends the data to a computer or a microprocessor for analysis. The analysis involves the identification of the VOCs and their concentrations in the sample.

•**Classification:** The final step in the ENose sampling process is the classification of the odour or flavor. This is achieved through the comparison of the VOC fingerprint obtained from the sample with a pre-existing database of known VOC fingerprints. The ENose can then classify the sample as belonging to a particular odour or flavor.The vision of the ENose sampling process is to provide a fast, accurate, and non-invasive method of detecting and analyzing odours and flavors. The ENose can be used in a variety of applications, including food and beverage quality control, environmental monitoring, medical diagnosis, and homeland security. With further development, the ENose technology can potentially be used to diagnose diseases based on the analysis of breath or bodily fluids. Additionally, the ENose can be integrated with other technologies such as artificial intelligence and machine learning to improve the accuracy of odour or flavor classification. [17]

3.1. ENose Parts: sampling methods

There are different parts of the ENose. The first one to be discussed here is the sampling methods of an ENose. There are several methods for sampling in electronic nose (ENose) technology:

•**Direct injection:**Direct injection involves injecting the odour sample directly into the sensing array. This method is commonly used in laboratory settings but is not suitable for real-world applications due to the complexity and cost of the sampling system [10].

•**Diffusion:** Diffusion involves introducing the odour sample into the ENose through a porous membrane. The odour molecules diffuse through the membrane and are detected by the sensing array. This method is simple and inexpensive but may not produce accurate results if the diffusion rate is not uniform across the sensing array [10].

•**Air flow:** Air flow involves drawing air containing the odour sample into the ENose through a pump or fan. This method is widely used in real-world applications due to its simplicity and reliability. However, the air flow rate must be carefully controlled to ensure that the odour sample is evenly distributed across the sensing array [11]. In conclusion, the choice of a sampling system for an ENose application will depend on the specific requirements of the task, including the type of odourant to be detected, the desired level of accuracy and sensitivity, and cost considerations. [18]

Table 1. Advantages and Disadvantages of different ENose Sampling Methods

SAMPLING MODE	ADVANTAGE	DISADVANTAGE
Adsorption, Desorption	High accuracy, Air Chamber and tightness	Takes a long time, High. Collection material
STATIC Head Space, Desorption	Simple and Low cost. Suitable for volatile and semi-volatile odourants	Limited in accuracy and sensitivity. Not suitable for some odourants. Can be influenced by temperature and pressure.
Dynamic uniform extraction	Improved accuracy and sensitivity. Suitable for a wider range of odourants	Complex and costly. Can be influenced by temperature, pressure, and flow rate
Direct Sampling	Can be used for both volatile and semi-volatile odourants. High accuracy and sensitivity. Used for a wide range of odourants.	Takes a long time, High. Collection material
Air Contact Thermal desorption	Easy to operate No need for solvent and its automated	Accuracy is low Limited sample size, Limited compound range

•**Purge and trap:** Purge and trap involve drawing a known volume of air over the odour sample, trapping the odour molecules in a sorbent material, and then releasing the trapped odour into the ENose. This method is commonly used in industrial settings but is more complex and expensive than other sampling methods [11]. Table 1 shows the different sampling methods of ENose, along with its advantages and disadvantages.

3.2. ENose Parts: GAS SENSOR Type

Gas sensors are the second component of an ENose. A gas sensor is an instrument that can transform chemical compound concentrations into electric impulses and responds to the concentration of certain nanoparticles in liquids or gases [20].Table 2 shows the different types of sensors that can be used for gas detection along with their advantages and disadvantages.

Table 2. Characteristics of diverse types of gas sensors

SENSOR TYPES	ADVANTAGE	DISADVANTAGE
Optical	Good sensitivity, accuracy, reliability, and lengthy lifespan	Size reduction is challenging and costly
Surface acoustic wave	Good accuracy, quick reaction time, and integrated circuit integration	Complicated interfacing
Electrochemical	High Accuracy, low battery consumption, and superb clarity.	The maximum temperature is restricted, as is the life span.
Catalytic	Short size, Cheap and low operating cost.	Extremely susceptible to changes in the environment.
Semi-conductor (chemo resistive, chemo-resistive)	Cheap, quick reaction time, and a diverse spectrum of targeted gases	Sensitivity and selection are modest.

Chemicals detectors can also be based on the fundamentals of an electrical, thermal, mass, or optical sensor. The ENose gadget has the benefit of being low-cost and portable for in-person and virtual readings. The metal oxide semiconductor-based gas sensor is the most widely used. So they not only have a basic construction, a decent cost, a quick reaction time, and great accuracy, in addition to being user-friendly and long-lasting. Even though their activities are impacted by climate, moisture, and high energy consumption, they are widely employed in a variety of applications such as ENose for gas sensors, odour localization, plume monitoring, and so on. A table is shown to describe the characteristics of diverse types of gases. Table 2 gives the characteristics of different types of gas sensors along with their advantages and disadvantages. As Table 2 shows, gas sensors have different methods. Some of these methods are based on electrical variations with different materials, while some are based on other kinds of variations.

The electrical variation contains materials like metal oxide, polymer, carbon nanotubes and moisture-absorbing materials. The other methods which have different variations are optic, acoustic methods gas chromatograph and calorimetric methods. Sno2 is one kind of MOX Gas sensor which have a relativity high sensitivity and is used for various gas sensor responses. Gas sensors are mainly compared with respect to parameters like response time, reproducibility repeatability, energy consumption, sensitivity (PPM), selection, stability and production cost. but as the general problem all have some issues like; drift in output, long time responsibility, sensitivity, and environmental effect like humidity and temperature) [21].

The working temperature for this gas sensor is different which makes the limitation selecting these sensor type to solve this problem the array of sensors proposed. MOX gas sensors have several advantages, including:

•**Sensitivity:** MOX gas sensors are highly sensitive to low levels of gases in the air. They can detect a wide range of gases, including carbon monoxide, methane, and other volatile organic compounds.

•**Sensitivity:** Selectivity: MOX gas sensors can be designed to be highly selective for specific gases, making them useful for detecting gases in complex environments where multiple gases are present.

•**Low cost:** MOX gas sensors are relatively inexpensive compared to other types of gas sensors, making them a popular choice for many applications.

• **Fast response time:** MOX gas sensors can detect changes in gas concentrations quickly, typically within seconds, making them ideal for applications that require fast response times.

•**Robustness:** MOX gas sensors are highly robust and can operate in a wide range of temperatures and humidity¡¯s. They are also resistant to contaminants in the air, making them suitable for use in harsh environments.

•**Easy to use:** MOX gas sensors are easy to use and can be integrated into a variety of electronic devices, making them useful for a wide range of applications.

MOX (metal oxide) gas sensors are commonly used for detecting the presence of gases in the environment. While MOX sensors have many advantages, such as low cost, small size, and fast response times, there are also some disadvantages to consider. that can be listed as following:

•**Limited sensitivity:** MOX sensors have a limited sensitivity range, which means they may not be able to detect low concentrations of certain gases.

•**Cross-sensitivity:** MOX sensors can be sensitive to a wide range of gases, including those that are not being targeted. This can lead to false readings and inaccurate measurements.

•**Short lifespan:** MOX sensors tend to have a shorter lifespan compared to other types of gas sensors. The sensor's sensitivity can degrade over time, and it may need to be replaced periodically.

•**Temperature and humidity dependence:** MOX sensors can be affected by changes in temperature and humidity. High temperatures can cause the sensor's baseline resistance to increase, which can lead to inaccurate readings.

•**Calibration:** MOX sensors require regular calibration to ensure accurate readings. Calibration can be a time-consuming process and may require specialized equipment and expertise.

Overall, while MOX sensors have many advantages and are widely used in various applications, they do have some limitations that need to be considered when selecting a gas sensor for a particular application. The reactions of gas detectors vary depending on densities, temperatures, and humidity levels, and thus the goal of this research is to provide a more efficient model for TGS sensors and to investigate the influence of temperature, humidity, and gas density on the sensor's reactions.

The ENose can be made up an array of MQ and TGS chemo-sensors with varying degrees of sensitivities to various atmospheric chemicals, as it is shown in Table 3 along with their respective target gases.

An ENose's purpose is to detect odour samples and maybe determine its amount using a signal processing and pattern recognition system. Those two processes, nevertheless, can be further broken into the following [23]: pre-processing, feature extraction, prediction or classification, and decision-making. By exposing the samples to the sensors, a database of the predicted odour must be created.

3.3. ENose Parts: Pre-Processing and Post-Processing Techniques

Pre-processing methods attempt to adjust for sensing drifts, compress sensors' transient performance, and decrease variance from sample to sample. Baseline modification, response normalisation, and sensory transient compression are examples of common approaches. Pre-processing is an important step in the analysis of data generated by an electronic nose (ENose) as it can improve the accuracy and robustness of the pattern recognition system. Some common pre-processing techniques used in ENose systems include:

•**Normalization:** Normalization is a technique for scaling the sensor signals so that they have a similar range of values. This can improve the accuracy of the pattern recognition system by reducing the impact of variations in sensor sensitivity. Normalization can be done using techniques such as min-max normalization or z-score normalization [24].

•**Baseline correction:** Baseline correction is a technique for removing any offset or drifts in the sensor signals. This is important because it can improve the accuracy of the pattern recognition system by removing any systematic effects that are not related to the odour. Baseline correction can be done using techniques such as polynomial regression or moving average filtering [10].

Table 3. MQ and TGS Gas sensors variety as the most used gas sensor type for ENose[22]

Sensor	Target Gases
MQ2	Methane(0 to 100 PPM). Butane(0 to 5,000 PPM). Lpg(0 to 10,000 PPM) Smoke(0 to 1,000 PPM)
MQ3	Alcohol, Ethanol(25 to 500 PPM)
MQ4	Methane (0-100 PPM), Cng Gas(0 to 4000 PPM)
MQ5	Natural Gas (50-200 PPM), LPG(1,000 to 2,000 PPM
MQ7	Carbon Monoxide (10 to 500 PPM)
MQ9	Flammable Gases (100 to 1000 PPM)
MQ135	Benzene (10 to 1000PPM), Alcohol (10 to 300PPM), Smoke (10 to 300PPM)
MQ138	Benzene (10 to 1000PPM), Toluene (5 to 500PPM), Acetone (Up to 50PPM), Propane Form aldehyde Gas (Less Than 0.06 PPM)
TGS 821	Hydrogen Gas (50PPM)
TGS 822	Organic Solvent Vapors and Other Vocs (300 PPM)
TGS 825	Hydrogen Sulfide (5 PPM)
TGS 826	Ammonia (50 PPM) and Other Vocs
TGS 2600	Air Contaminants (Ethanol, Iso-Butane, Hydrogen) (1 to 30 PPM)
TGS2602	Vocs And Odourous Gases (1 to 30 PPM)
TGS 2610	Liquefied Petroleum (Lp) Gas and it's Component (500 to 10000PPM)
TGS 2620	Alcohol and Organic Solvent Vapours (50 to 5000PPM)

•**Denoising:** Denoising is a technique for removing any noise or unwanted signal fluctuations in the sensor signals. This can improve the accuracy of the pattern recognition system by reducing the impact of measurement noise or environmental noise. Denoising can be done using techniques such as wavelet denoising or Kalman filtering [10].

•**Feature extraction:** Feature extraction is a technique for reducing the dimensionality of the sensor signals and identifying the most important features of the pattern recognition system. This can improve the accuracy of the pattern recognition system by reducing the impact of irrelevant or redundant information. Feature extraction can be done using techniques such as principal component analysis or linear discriminant analysis [10]. The objective of feature extraction is twofold: firstly, to minimise the dimensionality of the measurement space, and secondly, to extract information important to pattern identification. PCA, ANN, LDA, and SVM algorithms are used for feature extraction. The objective of feature extraction is twofold: first, to minimise the dimensionality of the measurement space, and second, to obtain information important to pattern identification. It is often carried out using linear transformations such as principal component analysis (PCA) and linear discriminant analysis (LDA). Descriptions of popular statistical analytical techniques. Electronic nose (ENose) systems employ various feature extraction techniques to identify the unique signature of an odour from the sensor signals generated by the sensing array. Some of the commonly used feature extraction techniques are:

•**Principal Component Analysis (PCA):** PCA is a dimensionality reduction technique that seeks to identify the underlying structure in the data by projecting it onto a smaller number of orthogonal axes. This can help to reduce the complexity of the data and improve the performance of the pattern recognition system [9] [29–33].

•**Linear Discriminant Analysis (LDA):** LDA is a classification technique that seeks to project the data onto a lower-dimensional space that maximizes the separation between classes. The mathematical equation for Linear Discriminant Analysis (LDA) is:

$$w = (S_W)^{-1} \times (m_1 - m_2) \tag{1}$$

Where: **w** is the discriminant function or linear combination of features that separate the classes. S_w Is the within-class scatter matrix, which measures the variance within each class $\mathbf{m}_1$ and $\mathbf{m}_2$ are the mean vectors of the two classes. LDA aims to find the optimal discriminant function w that maximizes the between-class variance while minimizing the within-class variance. The solution to the equation is the optimal value for w. This can be useful in ENose applications where the goal is to distinguish between different odour classes [25, 26, 36, 37].

•**The Partial Lease Square Regression(PSLR):** PSLR integrates and generalizes the characteristics of PCA and multiple linear regressions. The purpose of which is to examine or predict a collection of dependent variables based on a set of independent variables or predictors. It is especially effective for forecasting a collection of dependent variables. [36, 37].

• **Artificial Neural Networks (ANNs):** ANNs are machine learning algorithms that are modelled after the structure and function of the human brain. They can be trained to recognize patterns in the sensor signals and identify odours. ANNs are commonly used as the pattern recognition system in ENose applications [11]. ANNs are machines teaching algorithms that are based on the organization and functions of the human mind. They can model complex relationships between inputs and outputs, and have been widely used in ENose applications. The mathematical equation for an ANN is a multi-layer feedforward network with the following form:

$$y = f(W_L) \times f(W_{L-1}) \ldots\ldots f(W_2) \times f(W_1 \times x + b_1 + b_2) \ldots\ldots) + b_L \tag{2}$$

Where x is the input, W_i are the weights, b_i are the biases, f is the activation function, and y is the output [13, 34, 35].

• **Support Vector Machines (SVMs):** SVMs are machine learning algorithms that seek to find the optimal boundary that separates the data into different classes. They are commonly used for classification tasks and have been applied to ENose applications to distinguish between different odour classes [26]. SVMs have supervised learning algorithms that can perform regression and categorization tasks. They are based on the idea of finding a hyperplane that maximizes the margin between classes. The mathematical equation for a linear SVM can be represented as:

$$y = W_x + b \tag{3}$$

Where x is the input, W is the weight vector, b is the bias, and y is the output. The goal is to find the optimal values of W and b that separate the classes [26, 37, 39].

•**Fourier Transform Infrared Spectroscopy (FTIR):** FTIR is a spectroscopic technique that measures the infrared spectrum of a sample. It can be used as a complementary technique to ENose systems to provide additional information about the chemical composition of the odour sample [25].

$$S(v) = \int_1 (i(t)) e^{[-2\pi i(vt)]} dt \tag{4}$$

where: S(v) represents the complex spectrum of the sample at frequency v, and I(t) represents the intensity of the sample as a function of time t. The $e^{([-2\pi \mathbf{i}(\mathbf{vt})])}$ represents the complex exponential function at frequency v and time t.

• **Deep learning methods,** specifically Artificial Neural Networks (ANNs), have been widely used in ENose applications due to their ability to model complex relationships between inputs and outputs. Two methods of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) [39].

•**Convolutional Neural Networks (CNNs):** CNNs are a type of ANN that are commonly used for image and signal processing tasks. They are designed to effectively handle spatial and temporal correlations in the data. The mathematical equation for a CNN is typically composed of multiple layers of convolution, activation, and pooling operations, which can be represented as follows:

$$y = f(\text{Conv}(x)) + b \tag{5}$$

where x is the input, Conv is the convolution operation, b is the bias, and f is the activation function [27].

•**Recurrent Neural Networks (RNNs):** RNNs are a type of ANN that are designed to handle sequences of data, such as time series or sequences of sensor readings. The mathematical equation for an RNN can be represented as:

$$h_t = f\,(W_h) \times h_{t-1} + (W_x) \times X_t + b) \tag{6}$$

where $\mathbf{h}_t$ is the hidden state at time t, $\mathbf{X}_t$ is the input at time t, $\mathbf{W}_h$ is the weight matrix for the hidden state, $\mathbf{W}_x$ is the weight matrix for the input, b is the bias, and f is the activation function [28].

The post-processing method includes all the deep neural and machine learning methods that are combined with ENose systems to produce an accurate tool for detection. The various work was done by different researchers, using different machine learning methods for ENose systems. The review of pervious research papers shows, To recognize the existence of one out of two gases, an ENose system was presented by Khalaf et al. 2008 [41]. The proposed system of the authors contains 8 sensors, 5 of which were gas sensors and the remaining 3 sensors were temperature sensors. The Support Vector Machine (SVM) was used to train the data model for this technique. While for the prediction of concentrations, least square regression was used to train the model. Experiments were conducted by the authors, and the result they obtained was quite good, as they found the regression method to be more effective for the recognition of tested VOCs (Volatile Organic Compounds). 20 gas samples for methanol, 24 samples for acetone and 16 gas samples for the mixture of both were experimented with, which gained an accuracy of 96.61% correctness.

In another study author Jean et al. 2017 [42], used machine learning algorithms for electronic nose (ENose) systems. The authors mainly focused on the previous studies on machine learning algorithms for ENose-based VOC (Volatile Organic Compound). Using various machine learning algorithms, from their work, it can be concluded that the neural network and the LMNN (Large Margin Nearest Neighbours) present good and quality output which is then followed by SVM (Support Vector Machine).

The detection of pollutant gases by using ML techniques was presented by Jambi Ratna Raja Kumar et al. 2019 [43]. By using the proposed method, some harmful gases to human beings like methanol, LPG and ammonia are detected. For this purpose, ENose systems were developed, especially in public areas to make sure the safety of every human being. The authors performed experiments and a MATLAB device was used for these experiments to get some good results. SVM, Na?ve Bayes, and ANN methods were used to check the sensitivity, specificity and accuracy. For SVM the sensitivity was 79.88%, specificity was 84.55% and accuracy was 83.54%. Similarly, for Na?ve Bayes, the calculations were 76.34%, 87.99% and 82.34%. And for ANN it was 84.55%, 89.45% and 86.77% respectively.

The ANN-based ENose systems have good numbers for sensitivity, specificity and accuracy. Based on 3D porous laser-induced grapheme (LIG) enhanced with palladium (Pd) and nano-particles has been developed by Jianxiong Zhang et al. 2019 [44]. The experiments were done with the fabrication of LIG and TLIG-GS. A novel gas sensing by applying Graphene Field-Effect Transistor (GFET) and Machine Learning (ML) to recognize the gas selection with some circumstances and by joining them with the unique characteristics of GFET and ENose properties were presented by Takeshi Hayasaka et al. 2020 [45].

Experiments were conducted by applying two GFETs for three different types of gases; one was Pristine GFET and the other was ALD-RuO2-GFET (Atomic Layer Deposition RuO2-Functionalized). The result they obtained for sensing by using the proposed methods of the authors were quite good. For the identification of volatile organic compounds (VOC) author Jianxiong et al. 2020 [44], discussed healthcare diagnosis, which will be done through a machine learning (ML) method known as Principle Component Analysis (PCA). The ML can assist PEIRA (plasma-enhanced infrared absorption), through diagnosis can be done easily. This method has the advantage of quick response, very high sensitivity and real-time monitoring.

A new type of sensor known as a multivariable sensor was presented by R.A. Potyrailo et al. 2020 [47]. For the detection of different gases, 3-D nanostructures were realized as sensors along with the capabilities it has. Experiments were conducted for non-condensable gases in the laboratory. For the detection of gases two different classes of detectors were used. One is single-output sensors and the other is traditional analytical instruments. Comparing the two detectors, the traditional analytical instruments cannot operate with power, size and cost. In another machine learning (ML) technique author Someya Goyal et al. 2020 [48], proposed a new technique which can combine with Arduino micro-controllers and control smoke detectors. The proposed method has the advantage of detecting cigarette smoke. This technique is applied in the areas where a sign of ¡°No Smoking¡± is present. The technology can turn the buzzer ¡°On¡± when it detects any cigarette smoke. The authors experimented with this functionality of the ENose by testing it with a cigarette and lighter. The authors further explained that the proposed technique is very important and quite successful when experimented with in public places. From their work, it can be concluded that ENose is very important in public places.

Using the Artificial Neural Network (ANN) regression module to see and predict the different levels of Volatile Organic Compounds (VOC) and smoke aroma intensities in wine samples were tested by Vasiliki Summerson et al. 2021 [49]. To access the wine samples, a cheap cost portable ENose was used by the authors. This lower-cost ENose combined with machine learning can make the vintner (Winemakers) a very low-budget tool for assessing the different levels of VOC and smoke aroma intensity in wines. The gas sensing methods, advantages, limitations and selectivity were discussed by Usman Yaqoob and Mohammad. Younis, 2021 [50]. The potential of machine learning (ML) used for gas sensor detection and identification were also discussed by the authors. The ML can process data and improve selectivity but at the same time, it also requires a huge amount of data which should be labelled accordingly for accurate training and testing of classifiers. From their review, it can be concluded that ML is very important and useful for the future generation of smart, selective and sensitive sensors. Because ML can solve critical problems which are related to any chemical gas sensors. The design and development of an ENose method that can detect and identify respiratory disorders by detecting VOC in throw-out breath were discussed by Abraham and Monikavasagom 2021 [51].

The proposed system was experimented with and applied in 27 Lung cancer patients, 22 chronic obstructive pulmonary diseases (COPD) patients, and 39 healthy people that include smokers and non-smokers as well. The classification was done by using SVM (Support Vector Machine) which was able to classify and gave an accuracy of 88.79%, a sensitivity of 89.58%, and a specificity of 88.23% for lung cancer. Similarly, for COPD the accuracy, sensitivity and specificity were 78.70%, 72.50%, and 82.35% respectively. From these results, it can be concluded that ENoses can be applied as diagnostic tools for patients. To study the recent progress and advancements of ML methods in ENose systems, author

Zhenyi Ye et al. 2021 [52], discussed the feature extraction, modelling, and sensor drift compensation of ENose technologies. But sometimes the VOCs (Volatile Organic Compounds) are very complex, and that makes it a challenging task for the machine learning methods. From the review of the authors, it can be concluded that a lot of work and achievements have been done for ENose systems by using ML methods, and with further and careful studies more achievements can be done for ENose systems by using ML. Using three different Deep Learning (DL) methods (Convnet, Resnet, and Multinose) and Support Vector Machine (SVM) method for the quick detection approach was presented by authors Gamboa et al. 2021 [53]. Five different ENose databases were experimented with. And from the result of the experiments, it can be concluded that the proposed method of the authors has the capacity, high skill and quick response time for ENose forecast. Furthermore, SVM has the best accuracy and best training time compared to the other DL methods. From this, it can also be concluded that SVM can be the best option to be used in the field of ENose systems.

For the identification of gas phase compounds faster, author Xiong et al. 2021 [54], reported a ML technology in addition to an ion mobility analyser. This method has a good ion mobility selection and good Volatile Organic Compound (VOC) recognition skills. Experiments were performed and three types of Multi-Switched Manipulation of Triboelectric Nano-Generator (SM-TENG) were used which had a friction area of 10, 24 and 49cm2.

The results obtained from the experiments were quite good and accurate. The ML method got a recognition and detection accuracy of 54.286%. The study of piezoelectric nanogenerators (PENGs) and triboelectric nanogenerators (TENGs) have influenced many researchers and so as author Zetian Yang et al. 2021 [55], who worked on PENGs and TENGs development. The authors discussed the structure and design of these technologies along with their advantages in applications. PENGs and TENGs are major discoveries in the field of self-powered flexible sensors.

Working on gas sensing with the development of machine learning and the internet of things (IOT) author Jianxiong Zhu et al. 2021 [56], presented a hydrogen (H2) sensor by the injection of reduced graphite oxide (rGO) and their applications. With machine learning ML-enabled PCA (Principle Component Analysis) technology and triboelectric textile as a power origin to IOT, the H2 concentration experiments and their applications performed good plasticity and can be folded up easily as well. The table below shows the different machine learning methods and technologies used for ENose. For the detection and prediction of VAP (Ventilator Associated Pneumonia), an ENose system was developed by Yu-Hsuan Liao et al. in 2022 [57]. The proposed method of the authors can detect metabolites of pneumonia at early stages as it was important because no other method can detect pneumonia at an early stage.

The ENose with 28 metal oxide gas sensors was developed in the proposed method, which can predict the existence of germs after the victim has been suctioned in the concentrated care area. For the experimentation, a total of 40 patients were tested. 20 of the patients were infected with Pseudomonas aeruginosa while the remaining was not infected. The results showed good accuracy for the detection. Support Vector Machine (SVM) and Artificial Neural Network (ANN) were used, as SVM gained an accuracy of 92.08%, while ANN gained an accuracy of 85.47%. From their work, it can be concluded that the proposed method is a cost-effective method for the detection of VAP at the early stage.

A one-dimensional convolutional neural network (1DCNN) and random forest regressor (RFR) which is as combined known as 1DCNN-RFR was proposed by Changquan Huang and Yu Gu 2022 [58]. This 1DCNN-RFR method is being used for the quantity recognition and detection of pork meat adulterated using ENose data. Experiments were conducted by the authors in two different parts. One was a training set where they used 147 samples of meat over 7 days. And the other was a test set where they used 63 samples for 3 days. The results they obtained from their experiments were quite good, and the authors suggested that the 1DCNN-RFR method has good potential for the quantity recognition and detection of pork meat adulterated. But one disadvantage of RFR is that its ability to extract is very poor.Table 4 shows some of common technologies comparison as the post-processing method.

3.4. ENose Parts: PPM and PPB calculation

Parts per million (PPM) is a unit of measurement that expresses the concentration of a substance in a sample. In electronic nose (ENose) applications, PPM is used to quantify the concentration of volatile organic compounds (VOCs) in an odour sample. Parts per million means 1 part of a solute that is present in a 106 parts of a solution. The PPM is used for a "Very Dilute" concentration of the preparation. That means PPM is used to measure a very small amount of something dissolved in something else. Another scale for measuring the gases is Parts per billion (PPB) which means 1 part of a solute that is present in a 109 parts of a solution. 5ppb means, 5g of solute is present in 109 g of solution.

•PPM calculation: To calculate PPM, you need to determine the volume or mass of the substance in

Table 4. Machine learning technologies comparison as the post-processing method in Enose. Support Vector Machine (SVM), Graphene Field-Effect Transistor (GFET), Machine Learning (ML), Artificial Neural Network (ANN), laser-induced graphene (LIG), palladium (Pd), piezoelectric nanogenerators (PENG) triboelectric nanogenerators (TENGs), one-dimensional convolutional neural network (1DCNN)

Method	Aims	Study Highlights	Ref
SVM	To recognize the existence of one gas among many, 20 gas samples for methanol, 24 samples for acetone and 16 gas samples for a mixture of both were experimented with, which gained an accuracy of 96.61% correctness.	High accuracy. Able to recognize one gas among many.	[41]
ML algorithms and SVM	Used machine learning algorithms for ENose based on VOC	Good accuracy for detection	[42]
SVM, and ANN	ML techniques used for pollutant detection. For SVM the sensitivity was 79.88%, and the accuracy was 83.54%. ANN sensitivity 84.55%, and accuracy 86.77% respectively.	The ANN-based ENose systems have good numbers for sensitivity and accuracy.	[43]
3D porous (LIG) enhanced with (Pd) and nano-particles	The experiments were done with the fabrication of LIG and TLIG-GS.	Good accuracy.	[44]
GFET and ML	A novel gas sensing by applying GFET and ML to recognize the gas selection.	Accurate and Successful Results.	[45]
ANN to predict the different levels of VOC	Lower-cost ENose combined with machine learning can make the vintner (Winemakers) a very low-budget tool for assessing the different levels of VOC and smoke	Low cost and accurate.	[49]
ML	The gas sensing methods, advantages, limitations and selectivity were discussed	Improved selectivity	[50]
SVM	The design and development of the ENose method can detect and identify respiratory disorders.	Good accuracy	[51]
Feature extraction, modelling, and sensor drift compensation	Recent progress and advancements in ML methods	Detect the complex VOC	[52]
Pattern Recognition Methods	Five different ENose databases were experimented with. Have the capacity, high skill and quick response time for ENose forecast.	Best accuracy and training time	[53]
ML in addition to the ion mobility analyser	Experiments were performed and three types of Multi-Switched Manipulation of Triboelectric Nano-Generator (SM-TENG) were used which had a friction area of 10, 24 and 49cm2.	Good ion mobility selection and good VOC recognition skills.	[54]
PENGs & TENGs	The structure and design of these technologies along with their advantages in applications were discussed	Good results for Flexible Sensors	[55]
PCA	Hydrogen (H2) sensors by the injection of reduced graphite oxide (rGO were presented.	Good plasticity and can be folded up easily.	[56]
SVM and ANN	For the detection and prediction of VAP (Ventilator Associated Pneumonia), an ENose system was developed	Cost-effective method for the detection of VAP at an early stage.	[57]
1DCNN-RFR	The 1DCNN-RFR method is being used for the quantity recognition and detection of pork meat adulterated using ENose data.	Good potential for quantity recognition.	[58]

question and the total volume or mass of the sample. The calculation is performed as follows:

$$PPM = \frac{\text{Mass of substance (g)}}{\text{Total mass of sample (g)}} \times 10^6 \tag{7}$$

Or:

$$\text{PPM} = \frac{\text{Volume of substance}}{\text{Total volume of sample}} \times 10^6 \tag{8}$$

Using the formula, we can calculate the PPM for any equation. It is important to note that the accuracy of PPM calculations in ENose applications is dependent on the accuracy of the sensors and the sampling system used.

• **PPB calculation:** The PPB is used for ¡°Extremely Dilute¡± concentration of the preparation. The calculation of the PPB is done by a simple formula that is,

$$ppb = \frac{\text{mass of solute in grams } (g)}{\text{mass of solution in grams } (g)} * 10^9 \tag{9}$$

Using this formula we can calculate the PPM for any equation These two scales can be converted to heave others as one PPM is equal to thousands of PPB. Calculating parts per million (PPM) or ppb of volatile organic compounds (VOCs) in an indoor arena using an electronic nose (ENose) typically involves the following steps:

• **Sample collection:** A sample of air is collected from the indoor arena using an appropriate sampling device, such as a pumped air sampler or a passive air sampler. The sample is then transported to the ENose for analysis. Analysis: The ENose analyses the sample by exposing the sensors to the odour molecules. The response of the sensors is recorded and processed using appropriate software to generate a data set.

•**Calibration:** The ENose data set is calibrated using reference compounds with known concentrations to obtain a calibration curve. This calibration curve is then used to convert the sensor response into quantitative measurements of the VOCs in the sample.

• **Data interpretation:** The resulting PPM values can be used to characterize the composition of the indoor air and to identify the sources of VOCs. It is important to note that the accuracy and reliability of the PPM calculation will depend on the performance of the ENose system, the accuracy of the calibration, and the quality of the sample collection and analysis. [17]

4. ENose Applications

ENose devices are appealing in a variety of sectors for a variety of reasons, including quick sample evaluation, qualitative and quantitative representation, and the utilisation of low-cost and small-size sensors suitable for manufacturing operations. A large variety of ENose technologies for sensor applications have been identified including as following: Food industry which in that ENoses can be used to monitor the quality of food products, such as detecting spoilage and off-flavours [59].

The Environmental monitoring that ENoses can be used to detect pollutants and toxic gases in the air. Medical diagnosis hired ENoses in the diagnosis of diseases such as lung cancer and diabetes. Security and defence with the ENoses usage to detect explosives and hazardous chemicals and Agriculture to monitor crop health and detect pests [11, 60].

The research contains a long list of ENose reviews that are organized and centre on mass spectroscopic analysis ENoses [61], biomedicine and universal healthcare application fields [62], forestry and agriculture applications [63], microbiological performance control of food products [64] and food industry [65], pharmacy software [66], working to develop chemical sensing devices [67], and so on. Below are a few of the uses for an electronic nose: Healthcare diagnosis and health management, environmental sensing, commercial food applications, explosives identification (NASA), development and research sectors, quality assurance labs, the process and production department, Identification of chemical odours Identification of pathogenic bacteria [68] There have previously been a number of studies that demonstrate the ENose to be possible surveillance equipment in fruit ripening for a range of fruits: however, they were confined to one fruit apiece as well as sampling methods are taken. ENose also has a significant influence on farming.

4.1. ODLS (ODOUR Localization System)

Electronic noses (ENoses) can be used with robots for odour localization systems. In such systems, the ENose is used to detect and identify odourants in the environment, while the robot is used to physically locate the source of the odour. Here's an example of how an ENose can be used with a robot for odour localization: Deployment in hazardous environments: ENoses can be integrated with robots to detect hazardous gases and fumes in hazardous environments, such as chemical spills or fires [69]. Search and rescue operations: ENoses can also be integrated with robots to locate people trapped in hazardous environments, such as building collapses or disaster sites, by detecting human odours. These examples show the potential for ENoses to be used with robots for odour localization systems, providing a useful tool for various applications in hazardous environments and search and rescue operations. The electronic nose (ENose) has significant potential for use in various robotic applications due to its ability to detect and identify odour and flavor compounds. Some of the key benefits of using ENoses in robotics include:

•**Sensitivity and specificity:** ENoses have the ability to detect a wide range of odour and flavor compounds with high sensitivity and specificity, making them useful for various applications such as food quality control, environmental monitoring, and medical diagnosis.

Real-time monitoring: ENoses can provide real-time monitoring of odour and flavor compounds, allowing for quick and accurate detection of changes in the environment.

•**Non-invasive:** ENoses are non-invasive, making them suitable for use in sensitive environments where traditional methods of odour detection, such as manual sniffing, may not be appropriate.

•**Integration with robots:** ENoses can be integrated with robots to provide real-time, remote sensing of odour and flavor compounds. This integration allows robots to detect and locate the source of odours in hazardous environments or search and rescue operations. Several platforms have been developed for odour source localization with robots, each with its unique features and capabilities.

A review of the available platforms and their performance in odour source localization with robots can provide insight into the current state of the field and guide future development. One example of a review of odour source localization platforms evaluated the performance of several ENose-based odour source localization systems. The study found that the use of ENoses in combination with robots showed promising results for real-time monitoring of odour sources, and that the performance of the systems was influenced by factors such as the type of ENose and the integration of the ENose with the robot. This review highlights the importance of considering the performance of the available platforms and the potential for ENoses to be used in odour source localization with robots, providing a useful tool for various applications in hazardous environments and search and rescue operations. [17]

Overall, the ENose has significant potential for use in various robotic applications due to its ability to detect and identify odour and flavor compounds with high sensitivity and specificity, and its ability to be integrated with robots for real-time, remote sensing. Most of the time the questions arise are that why animals aren¡¯t used for such detections as they have much more powerful senses than humans. Well, the simple answer to that is, it will take a very long time to train them for such instances. Also, there are some dangerous areas where they can¡¯t go or sense anything. If they work for longer periods, they can get fatigued. In some cases, animals can be used such as, birds used in mines to find gases like CO2, and CO. [21]

Dogs are used for rescuing and exploring in activities like bomb detection, drugs or people buried by avalanches. But nowadays with so much advancement in technology, even robots are used for such activities. It is because robots can be deployed quickly and maintained at a low cost. They can work for longer periods without getting fatigued. They can enter any dangerous 'area without any fear. Odour monitoring is an action that attempts to localise, discover, and occasionally examine the origin of an odour. In brief Odour tracking activities can be summarised in three modes; the first is Odour detection; which can detect an increase in the concentration. The second one is Source tracing; it follows the signal determined from the sensed gas distribution towards the source. And the last one in the Source declaration; determines the certainty that the source was found.

According to the survey, several researchers have created their sites. Several academics had employed the commercially accessible Koala and Kepera robots. The table below provides a summary of the work completed since 1996. The many approach and robotic stations, as well as the different environment sizes and types of the plumes, made comparing the researchers' efforts challenging [70]. Table 5 summarises the odour localization system which is proposed during the 1997 till 2013 due to the various reserch work in this period.as the tbale shown this activity began with the construction of an odour compass-direction detector, followed by basic algorithms to calculate the position of the odour. The variety and types of sensors utilised for the objective were varied. Recently, the implementations for systems built varied from basic alcoholic odour recognition to fuel leaks and bad odours from landfills. Initially, the habitats selected were contained, with diameters ranging from a few metres to tens of metres.

Later, the tests in hallways and wide open spaces are presented, and several techniques such as gradient-based, chemo taxis, anemotaxis, closest neighbour, and so on have been applied and their performance analysed. Robotic navigation is improved by algorithms that employ a wind vane or a wind sensor. The many strategies and robotic stations, as well as the variable size and type of the plume, make comparing the researcher's work challenging [71]. Experimentation has taken place on a variety of robotic setups. Some organisations have created their robots for the purpose. Animals normally require two types of information for hunting and localization tasks: odour presence and wind flow direction [72].

The 26XX sensors are among the most often used odour monitoring detectors. TGS800XX, MIC, ion detectors, Polymer, QCM sensor arrays, and prefabricated E nose are examples of other sensors. There is active research being conducted on several methodologies for odour localisation. There are two types of plume/odour localization algorithms: reactive plume

Table 5. ENose as the ODOUR Localization Activities in robotic 1997 till 2013

	Year	Application	Odour Type	Type of Sensor	Size of Area	Size of Area	Robot Name
1	1996-97	Odour Localization	Ethanol, hexanol	TGS 822, TGS800, TGS 813, and airflow sensor	40 x 70cm, 5.8m x 7.3m	Model male silkworm behaviour, gradient-based	made by researchers
2	2001-02	Odour Plume, source localization	Ethanol, methanol, iso propyl alcohol	Air flow and QCM, TGS sensors	47cm x 27cm x 27cm, 2.45x2.5, 5mx2m	Upwind, gradient-based, chemotaxis, neural network, Nearest Neighbor classifier	RAT, Koala, Super Scout II
3	2003-04	Chemical plume tracking,	Ammonia solution ethanol	Polypyrrole and TGS sensor	15.4mx5.1m 10.6mx .5m	Algorithm (E. code, Bombbyxmori, dung beetle)	RAT, Arthur, Koala
4	2005	Odour-source localization system	Ethanol	Cyranose sensor, TGS sensor, QCM, PIDs	LAB 5.9m 83.2m x2.7m , 2m x4.8m	OSM and HSM + visual, Upwind Tracking and Local Search	PIPI, TUAT, GaPTR11
5	2006-11	Odour source localization system, 3D, plume tracking	Ethanol, ions	TGS sensor, ion detector, mics 5521	24mx12cm, 12mx3m, 3mx3m	Casting, spiral surge, Bio-inspired Particle Plume (PP), particle	Koala, Robo Moth, Kaperall, Sniffer, ATRV-Jr
6	2012-13	leak localization system, odour localization	Methane, acetone, ethanol and 2-propanol gasoline	RMLD PID (sampling frequency 1Hz)	15m x 2.5m and landfill (18m x 11m), 6x3m	gas distribution mapping probabilistic plume mapping	ATRV-Jr

tracking and gas distribution mapping techniques [73, 74]. The odour technique used to find the responsive plume/odour monitoring region is made up of many methodologies taken from biological research as well as statistical (probabilistic) methods [75].

One of the most effective algorithms is connected to the Silk moth, the major reason being its behaviour for odour localization, which robots may mimic. To implement the odour localization system, many robot platforms were employed. Furthermore, the evaluation of systems reveals the employment of several platforms, as it can be shown in Fig 6.

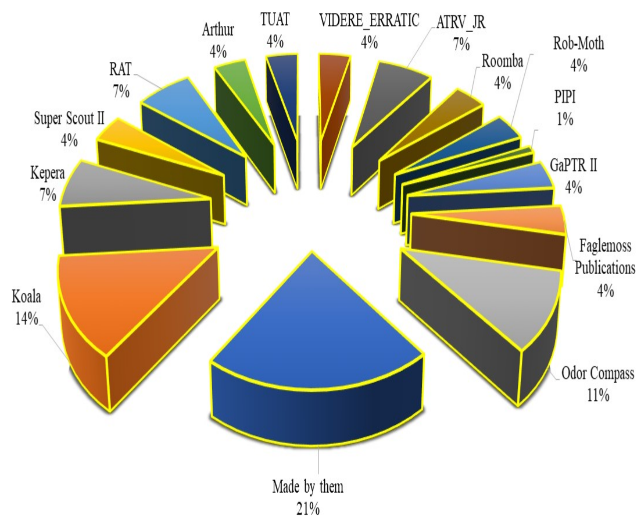

Figure 6. The Platforms rate used for ODOUR localization.

Figure 6 gives represent the robotic platform which is used the most for odour localization. All these robotic platforms are capable of localizing odour sources with high precision and accuracy. As it shown mostly researcher tried to make their own platform and koala plat form more hired for odour localization task.

The primary hurdles in this field are related to sensor restrictions and the complex behaviour of the odour plumes. Lower selection and sluggish sensor reaction, restricted sensing area (few centimetres) [76, 77], which decides algorithm efficiency and slows tracking [78, 79].

Because of this issue, some researchers have been obliged to utilise insects directly to guide the actual robot [80]. The second set of algorithmic gas transmission mapping approaches, on the other hand, worked separately on tracking the odour/plume for source location [81, 82]. Another element that influences the efficiency of the algorithm is the proportion of robots to field size, particularly for the gradient-based method with a single sensor. Furthermore, when employing several sensors, matching their responses may pose issues [83]. Because of the sluggish rate of molecular diffusion in compared to air velocity, the plume forms downwind from its origin [84].

Different types of robots can be used to integrate ENose and odour location technology, including ground robots, aerial drones, and underwater robots. Each type of robot has its unique advantages and disadvantages as shown in Table 6 when it comes to ENose and odour location tasks.

Table 6 shows the three different types of robots along with their advantages and disadvantages. Each of these robots has its strengths and limitations.

5. Conclusion

An electronic nose, or ENose, is a device that detects and identifies odours or volatile compounds. It is a sensory system that mimics the human olfactory system and can be used for a variety of applications, including food and beverage quality control, environmental

Table 6. Advantages and Disadvantages of different robots.

Robot Types	Advantages	Disadvantages
Ground robots	Good manoeuvrability and stability on the ground. Easy to deploy and use. Can reach confined spaces and difficult-to-reach locations	Limited mobility in rough terrain and obstacles. Potential damage to robot components in harsh environments
Aerial drones	Good mobility and flexibility for aerial navigation. Good for large-scale odour mapping. Can reach high and remote locations	Limited battery life and endurance. Challenges in windy conditions. Potential for air traffic interference and safety issues
Underwater robots	Good mobility and flexibility for underwater navigation. Good for monitoring and tracking underwater odours. Can reach remote and difficult-to-reach underwater locations.	Limited battery life and endurance Challenges with underwaternavigation and stability. Potential damage to robot components in harsh underwater environments.

monitoring, medical diagnostics, and safety and security.

The ENose typically consists of three main parts: a sample delivery system, a sensor array, and a pattern recognition system. The sample delivery system collects the odour molecules and delivers them to the sensor array, which consists of several types of sensors that respond differently to different types of odour molecules. The pattern recognition system then analyzes the response patterns of the sensors and identifies the odour based on its unique pattern.

The sensor array is the most critical component of the ENose. It can consist of different types of sensors, such as metal oxide sensors, conducting polymers, or surface acoustic wave sensors, each with its unique sensing mechanism. The sensors respond to different types of odour molecules, and their combined response creates a unique pattern that can be used to identify the odour.

Methods for data analysis and odour detection can include machine learning algorithms, such as artificial neural networks, and pattern recognition techniques. The choice of method will depend on the specific requirements of the odour location task, such as accuracy, speed, and cost The results of using ENose and odour location combination on different robots depend on various factors, including the type of robot, the odour source, and the environment.

However, in general, using ENose and odour location combinations on robots is effective in accurately detecting and locating specific odours, even in complex and dynamic environments. The ENose has several advantages over traditional chemical analysis methods, including its ability to detect multiple odours simultaneously and to detect low concentrations of odour molecules. It also has a fast response time, making it useful for real-time monitoring applications.

The future of electronic nose (ENose) technology is promising, with ongoing research and development leading to new advancements and applications. Some potential future directions for ENose technology include:

1. Improved accuracy and reliability: The development of new sensor materials, post-processing methods, and machine-learning algorithms will likely lead to more accurate and reliable ENose systems in the future. This will make ENoses more useful for a wider range of applications, such as food and beverage quality control, medical diagnosis, and environmental monitoring [85].

2. Integration with other technologies: In the future, ENoses may be integrated with other technologies, such as gas chromatography or mass spectrometry, to provide more detailed and accurate information about the composition of odour samples. This could lead to new applications in fields such as environmental monitoring, food safety, and medical diagnosis [86].

3. Miniaturization: Advances in microelectronics and nanotechnology may lead to the development of miniaturized ENoses in the future. This could make ENoses more portable, accessible, and cost-effective for a wider range of users and applications [87]. The table 7 shows the comparison of the use of ENose and odour location combination on different robot types and the results and methods used:

•**Mobile Robots:** Mobile robots are capable of moving around a given environment and can be equipped with ENose and odour location sensors to locate and identify specific odours.

•**Fixed-Wing Robots:** Fixed-wing robots, such as drones, can be equipped with ENose and odour location sensors to detect and locate odours in large open areas, such as fields and forests. Ground Robots: Ground robots can be equipped with ENoses and odour location sensors to navigate and locate specific odours in confined spaces, such as pipelines and buildings.

In conclusion, the ENose is a powerful tool for odour detection and identification. Its structure consists of a sample delivery system, a sensor array, and a pattern recognition system, which work together to mimic the human olfactory system. The ENose has numerous applications, including environmental monitoring, medical diagnostics, and safety and security. Its ability to detect multiple odours simultaneously and at low concentrations makes it a valuable tool in various industries. In summary, the future of ENose technology looks bright, with the potential for new advancements and expanded applications in a wide range of fields.

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