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Machine Learning in Gas and Air Quality Sensors: A Comprehensive Review

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Abstract Air pollution is now considered one of the greatest public health threats. Detecting pollution is unfortunately often too slow, too costly or not precise enough, but millions of people suffer every year due to bad air quality. This paper reviews the application of machine learning (ML) techniques in the enhancement of gas sensors and air quality monitoring systems. We describe which types of sensors are most frequently employed, what the key challenges they are facing are, and how these challenges are addressed with different ML methods. We also review real-world case studies, present comparisons of different ML approaches and discuss the future of this field. The paper is simple enough for anyone to understand the interplay between machine learning and sensors — and how that interaction makes a bigger difference when it comes to breathing in cleaner air.

Keywords: Machine Learning, depressive disorder, Machine Learning (ML), Natural Language Processing (NLP).

1. Introduction: Machine Learning in Gas and Air Quality Sensors

1.1 Overview

Air quality impacts all of us. Breathing polluted air can lead to severe health issues such as asthma, lung conditions, and cardiovascular diseases. As many as 7 million people die because of air pollution every year, the World Health Organisation (WHO) reports. This makes it the leading killer among all types of pollution-related deaths. To combat the issue, researchers and technicians have created sensors capable of sniffing out toxic gases in the air. Those sensors track things like carbon monoxide (CO), nitrogen dioxide (NO2), ozone (O3), particulate matter (PM2.5 and PM10), and a long list of other pollutants. But the problem with these sensors is that they are typically very inaccurate, and they drift with time (which means that their readings are slowly becoming wrong), and they can also be fooled by temperature, humidity, or other environmental factors. This is where machine learning comes in. Machine learning is a branch of artificial intelligence where computers are trained on data instead of receiving specific instructions. When we attach ML algorithms to sensor data, the system can learn to compensate for its own errors, detect patterns, and provide far more accurate readings. This review article summarises the current state of research on the application of ML in gas sensing and air quality monitoring [1] [113] [16] [110]. We cover: Types of gas detection sensors available on the market and in development, the challenges for these sensors

- The ways in which machine learning addresses these challenges
- Applications and case studies from the real world
- The prospective tracks of this research area, whether you're a student, a researcher, or simply someone interested in technology and clean air, this paper will provide you with a solid introduction to this exhilarating and vital field.

2. Background: Types of Gas Sensors

2.1 Definition and Classification of Gas Sensors

Before we get to machine learning, we need to know what kind of sensors actually detect gases. There are a few major types , and each has advantages and disadvantages [13] [14] [16].

2.1 Electrochemical Sensors: - They operate by interacting with a gas and generating a tiny electrical charge in an electrochemical sensor. The signal is stronger, more gas. These sensors are commonly employed for gases such as carbon monoxide, nitrogen dioxide, and ozone. They are inexpensive, compact, and simple to operate. Nevertheless, these are influenced by the temperature and humidity, and their accuracy decreases bit by bit over time (referred to as sensor drift) [11].

2.2 Metal Oxide Sensors (MOS): Certain metal oxides, e.g., tin oxide, zinc oxide, exhibit a change in electrical resistance upon exposure to particular gases and this property is exploited in metal oxide sensors. As the gas concentration varies, so does the resistance and the output of the sensor. They are extremely high-quality sensors and can detect minimal amounts of gas. The downside is that they have to be heated in order to work properly, which takes energy, and they can respond to a variety of different gases simultaneously, so it's difficult to tell exactly which one is present [17] [19].

2.3 Optical Sensors Optical sensors detect gases by using light. Since various gases absorb at different wavelengths of light, the sensor, by illuminating a sample with light and analysing the output, is able to know what gases are present. They are highly precise; however, they tend to be more costly in comparison to the electrochemical or metal oxide variety [21] [24].

2.4 Acoustic Sensors Acoustic sensors (piezoelectric sensors) are known to be the change in vibration frequency of a tiny crystal when gas molecules are adsorbed on the surface. They can be made very sensitive and very small, which means they can be made very sensitive and are very tiny. Graphene is not new, but at the same time, it is revolutionising technology. At the same time, they are also sensitive to changes in temperature and pressure [126] [131].

2.5 Photoionisation Detectors (PID) PIDs are a type of gas detection equipment that applies an ultraviolet light to ionise the gas molecules and quantify the consequent electric current. They are particularly sensitive to volatile organic compounds (VOCs) at very low concentrations. They are also used in industrial safety applications as per Figure 1 [33] [37] [40].

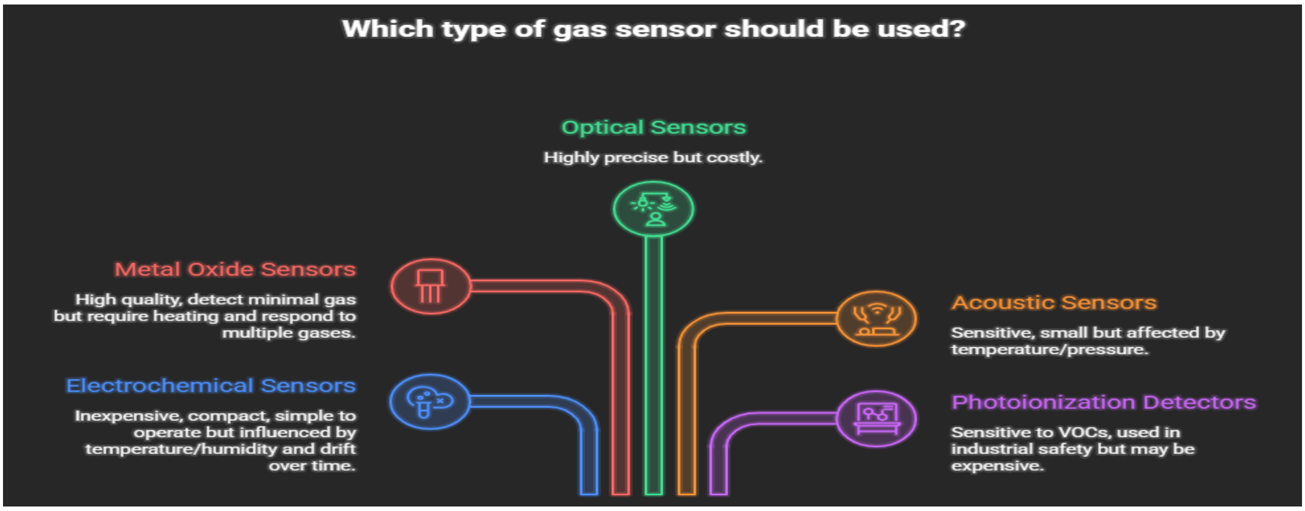

Fig.1. Types of Gas Sensors

3. Challenges in Gas Sensing

Although gas sensors have advanced significantly in the last few decades, there are still a number of critical issues prevailing. These are the challenges that give us insight into the importance of machine learning in this area [41] [142] [145].

3.1. Sensor: Drift Sensor drift means that a sensor's output slowly changes over time, even if the gas concentration being measured remains constant. This is due to the fact that the sensitive materials within the sensor slowly degrade or become contaminated. The effect of sensor drift is that the output of the sensor becomes increasingly unreliable. Conventionally, sensors must be frequently calibrated (induced with a known input, then checked the output), which is labour-intensive and costly. ML can learn to predict and compensate for drift by itself [149] [48] [157].

3.2. Environmental Noise Interference: - Temperature, humidity and atmospheric pressure are all known to influence the performance of gas sensors. A day next to a perfect sensor might be wrong on a hot, humid day. Machine learning models can be developed to adjust for such environmental considerations and provide corrected readings irrespective of the environment [159] [60] [67] [70].

3.3. Inaccuracy of cheap sensors: Low-cost sensors (the type that can be distributed in large numbers around a city) are generally far less accurate than high-end reference instruments. But the quality reference instruments are too costly to have one everywhere. ML can also be used to enhance the accuracy of low-cost sensors by performing comparisons of their readings with reference data in a training phase and then applying the corrections beyond it [73] [75] [77].

3.4.Missing Values and Data Gaps:- Sensors go down, get damaged, or go offline here and there in large sensor networks. This produces holes in the data. ML methods such as imputation (replacing missing values using nearby or past data) can fill in these holes, so the sensor network keeps working [81] [83] [88].

4. Machine Learning Methods Used in Gas Sensing

Numerous machine learning methods have been employed for gas sensing. Here, we outline the most significant in layperson's terms [85].

4.**1 Supervised Learning: Supervised learning is the most popular ML**

In supervised learning, we feed the algorithm with examples: we expose it to numerous sensor outputs with corresponding "right answers" (such as the actual gas concentration obtained by a reference instrument). The algorithm learns what sensor outputs are associated with which "right answers" and can then use this knowledge on new data. Popular algorithms of supervised learning in gas sensing are listed below:

- Linear Regression: A straightforward technique that identifies a linear correlation between sensor readings and gas levels. It's simple and quick to calculate, but it might not capture the relationship well if it is too complicated [87].
- Support Vector Machines (SVM): Another more powerful approach that determines the “best” mathematical border among the different groupings or numerical values. SVMs are also effective in high-dimensional spaces and can be tailored to specific applications by choosing an appropriate kernel function. They also function well with limited data and are noise-resistant!
- Random Forests: Another ensemble technique that trains multiple decision trees and then merges their outputs. Random forests are stable and accurate and can be used to model complex relationships between the variables [93].
- Neural Networks and Deep Learning: Connected to the human brain structure, neural networks are composed of layers of interconnected nodes that have the potential to learn extremely complex patterns. Deep learning (neural networks with multiple layers) has achieved state-of-the-art results across a wide range of gas-sensing applications [97].

4.2 Unsupervised Learning: Unsupervised learning is applied when we have data, but no labels (i.e. we do not have the right answers upfront). The algorithm attempts to identify the data's hidden structure and clusters without any human influence. • K-Means Clustering: Clusters sensor readings into clusters according to their similarity. That may allow us to separate different pollution events or different gas mix types.

• Principal Component Analysis (PCA): Identifies dominant patterns in the data and hence reduces the dimension. This is handy when you’re dealing with arrays of a lot of sensors that all make slightly different readings.

• **Auto encoders**: A kind of neural network that compresses data and then reconstructs it. **Auto encoders** may identify anomalous readings (outliers) that could potentially signal a gas leak or sensor failure [99].

4.3 Transfer Learning: -Learning allows for a model trained on a task or dataset to be used for, or adapted to, another related task. A model trained on data from one city, for example, can be transferred to a new city to be used without a full new training dataset in gas sensing. It is a time saver and cost-effective, especially when labelled data is limited [96] [97].

4.4 Recurrent Neural Networks (RNN) and LSTM: The air quality data is time sequence data, as the readings are obtained over time, and the previous readings could contribute to predicting the subsequent readings. Recurrent Neural Networks (RNNs) and a more sophisticated variant of RNN, Long Short-Term Memory networks (LSTMs), are specifically designed to handle time series data. They are able to remember past patterns and use them to enhance predictions. LSTMs have been extensively applied to predict air quality conditions hours or even days ahead [92].

4.5 Convolutional Neural Networks (CNN):-CNNs are well known in the area of image recognition, but may also be applied to sensor data. When sensor data follows a specific structure, CNNs effectively capture local features. They have been applied to electron noses (many sensor arrays) with excellent results on gas identification problems. 4.6 Gaussian Process Regression (GPR) GPR is a statistical ML method that not only predicts but also provides confidence in the predictions. This is very important in safety-critical systems, where not only what the gas concentration is, but also how sure we are about the reading, is needed [100][150].

4.6 Convolutional Neural Networks (CNN):-Federated learning is a recent ML paradigm in which a number of devices (e.g., air quality sensors placed in different locations) collaboratively train a shared model without disclosing their raw data to a central server. Every device trains locally, and the only thing shared is model updates. This is good for privacy and for reducing the volume of data that needs to be sent over a network [101] [135] [147].

5. Key Applications of Machine Learning in Gas Sensing

Include, but are not limited to, analysts in the breath, food and beverage, pharmaceutical, and chemical substances. Here are some of the most notable applications [111] [142].

5.1 Sensor Calibration and Drift Correction: Among the best-known use cases is using ML for sensor calibration and drift compensation. It has been demonstrated by scientists that they can enhance the accuracy of low-cost sensors considerably by training an ML model with data from those low-cost sensors and data from a reference instrument. For instance, a study in London applied random forests to calibrate for low-cost NO_2 sensors, and the error was reduced by more than 50 % compared to raw readings. A further study in Beijing employed LSTM, continuously accounting for sensor drift, demonstrating that the model could preserve its accuracy for months on end without manual recalibration [115] [157] [159].

5.2 Electronic Nose (E-Nose) Systems: An electronic nose typically consists of an array of several gas sensors of different types; the response of each gas to each sensor varies, and it is not possible to see one sensor's response to one gas [125]. The overall pattern of responses acts as a chemical fingerprint of the gas mixture. ML techniques are employed to interpret these fingerprints to determine what gases they contain. E-nose systems combined with ML have been applied to food quality control (spoilage detection), medical diagnosis (diseases from breath, etc.), environmental monitoring, and industrial safety (chemical leak detection) [119].

5.3 Air Quality Prediction: There is a strong incentive to forecast air quality in the future because it enables the authorities to predict health risk in advance and makes people aware prior to their outdoor activities. ML techniques (e.g., LSTM, DBN) and other deep learning-based methods outperformed the classical ones for air quality prediction. Models may be trained using historical air quality data, along with weather, traffic, and other information, to forecast pollution levels several hours or even days in advance of

[120][121].

5.4 Source Identification and Attribution Cars: Factories, cooking, burning, and plain old natural dust: A city's got all sorts of pollution sources. It is quite crucial to know the source of pollution to decide what kind of policies should be implemented. PCA and neural networks are other ML techniques that can analyse the chemical profile of the pollution and ascertain which and how many sources it had. And it is the source apportionment process [121][144].

5.5 Anomaly Detection: Anomaly detection is the task of identifying unexpected events in sensor data, such as a gas leak, faulty sensor, or unusual pollution incident. ML algorithms such as autoencoders and isolation forests learn from normalcy and subsequently raise an alarm when there is novelty. In industrial applications, gas leaks can be a major problem, so this is quite important [131][158][112].

5.6 Personal Exposure Monitoring: Wearable devices with sensors enable individuals to monitor the air they breathe while they walk or travel in a city. ML techniques can be applied to process this personal exposure information and provide health advice to individuals. For example, an ML model might recommend taking a different route to avoid a polluted block [113][119][118].

5.7 Indoor Air Quality Monitoring: Indoor air can be more polluted than outdoor air at times, because of the smoke of cooking and cleaning products, materials used in construction and more. ML models developed on indoor sensor data can detect hazardous gases such as CO, radon or VOCs and activate ventilation systems or raise alarms if detected levels become too high. Smart home solutions are progressively integrating ML-enabled air quality detectors to adjust indoor conditions [92] [83] [99].

6. Machine Learning Methods:

A Comparison of Application-dependent strengths and weaknesses of different ML algorithms. The strengths and weaknesses of various statistical pattern recognition and machine learning algorithms are different for different applications. The following table summarises a few of them:

Method Comparison

Characteristic	Accuracy	Data Needed	Speed	Interpretability	Best For
Linear Regression	Low-Med	Small	Very Fast	High	Simple calibration
SVM	Medium	Medium	Fast	Medium	Classification
Random Forest	High	Medium	Fast	Medium	Calibration, regression
LSTM / RNN	Very High	Large	Slow	Low	Forecasting, time series
CNN	Very High	Large	Medium	Low	E-nose, pattern recognition
GPR	High	Medium	Medium	High	Uncertainty estimation
Autoencoders	High	Medium-Large	Slow	Low	[No specific best use case]

Fig.2. Machine Learning Methods

From this comparison, it is evident that no method is strictly superior. The appropriate option depends on the particular application, the amount of data available, and the importance of model interpretability (i.e., understanding why the model makes specific decisions). For simple calibration problems where the data are sufficiently sparse, simple methods such as linear regression or SVMs are adequate. In applications such as multi-step forecasting or e-nose, where a considerable amount of data can be collected, DL techniques such as Long Short-Term Memory (LSTMs) and Convolution Neural Network (CNNs) can obtain the best performance. Gaussian Process Regression is also the preferred option when predictive uncertainty estimates are required [72] [75] [76].

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7. Datasets and Benchmarks Machine learning

Models require data to learn. Several known public datasets have played a significant role in pushing the boundaries of research.

7.1 UCI Gas Sensor Array Dataset: This benchmark consists of an array of 16 chemical sensors exposed to varying concentrations (in a wind tunnel) of two gases, ethanol and ethylene. The data include "snapshots" of sensor resistance. It is heavily used to benchmark ML algorithms for gas identification and regressive concentration analysis [121].

7.2Air Quality UCI Dataset: This dataset is based on a multisensor device, deployed in a site in the city of Barcelona, Spain, highly polluted by traffic. It contains measurements from metal oxide sensors and the corresponding measurements from reference instrumentation for CO, hydrocarbons, and ozone. It is also one of the most intensively analysed datasets for low-cost sensor calibration [129][139].

7.3 Beijing Multi-Site Air Quality Data: The dataset includes hour-wise air quality data (temperature, humidity, wind speed, etc.) from 12 monitoring sites in Beijing, China. It has found application in extensive research in air quality forecasting [154].

7.4 Open AQ and Purple: Air Data. Both are worldwide, near-real-time, open-access aggregators of air quality data from a myriad of low-cost sensors and reference instruments. This data is utilised by researchers to develop and test ML models for large-scale air quality monitoring [122].

8. Recent Advances and Trends

The pace of activity in ML for gas sensing is accelerating. Here are a few of the best recent additions.

8.1 Internet of Things (IoT): Integration Sensors are becoming Internet-enabled. Sensors are increasingly Internet-connected as part of the Internet of Things (IoT). This allows information from tens of thousands of sensors to be gathered in real time and analysed with ML models that are running in the cloud. The processed results can then be returned to the users as alerts or air quality reports on their mobile phones. Google, IBM and plenty of startups are building large IoT sensor networks for monitoring air quality [118].

8.2 Edge Computing Complex: ML models running in the cloud, however, need a good Internet connection and will cause lag. A newer phenomenon, "edge computing," is when the ML calculations take place on the sensor device (or close to the sensor device) rather than on the cloud. This makes the system quicker, and it can function even without an internet connection. Tiny ML (machine learning on very small microcontrollers) is a new and exciting field enabling this [159].

8.3 Graph Neural Networks for Spatial Prediction Due to the large number of sensors deployed in a city, it is also true that each sensor's readings are correlated with those of its nearby sensors. Graph Neural Networks (GNNs) are a class of ML that can explicitly capture such spatial relationships. Recent work demonstrated that GNNs can achieve superior performance over other methods in predicting air quality in locations where no sensors are available [121].

8.4 Self-Supervised and Few-Shot: Learning Condensation of training information (e.g., sensor readings matched with a ground truth measurement) is costly and slow. Self-supervised learning can learn useful representations from unlabelled data, and few-shot learning is able to build good models with only a limited number of labelled samples. These methods are extremely encouraging for the application of sensors in locations where training data is scarce [89].

8.5 Explainable AI (XAI):-There is an increasing worry about complex ML models being black boxes: they provide precise results, but no one knows why. Explainable AI (XAI) methods such as SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) give insights to the users, indicating which sensor readings and environment variables are the key players in a prediction model. This is crucial for developing confidence in an ML-based air quality system.

8.6 Hybrid Physical-ML Models:- - Instead of purely data-driven ML, investigators are now integrating physical knowledge (equations that describe how gases chemically behave) with ML architectures. This class of hybrid models tends to be more accurate and more robust with respect to scenarios different from the training data. They also need less training data than pure ML models [147].

9. Challenges and Limitations

Although machine learning has considerably enhanced gas sensing, some significant issues remain to be solved.

9.1 Data Quality and Quantity: The data for ML-based intrusion detection comes from the abnormal and normal records, which depend on the quantity and quality of data. The only limitation of using ML models is the quality of data that these models are trained on. We live in a world where few reference-grade air quality monitoring stations are established in many regions, let alone co-located low-cost sensors to collect labelled training data for training high-quality ML models. Enhancing the availability of superior reference data is a key challenge [112].

9.2 AI and the Integration of Neuromodulator Therapies: The data for ML-based intrusion detection comes from the abnormal and normal records, which depend on the quantity and quality of data. The only limitation of using ML models is the quality of data that these models are trained on. We live in a world where few reference-grade air quality monitoring stations are established in many regions, let alone co-located low-cost sensors to collect labelled training data for training high-quality ML models. Enhancing the availability of superior reference data is a key challenge [117].

9.3 Generalisation A model that works well in one city or climate may not work well in another. The air-quality trends, the instrumentation used, and local conditions can vary significantly from one location to another. Research is currently active in the development of models that generalise well across environments.

9.3 Sensor Ageing As sensors age, their properties shift, so an ML model trained on a new sensor might not perform as well on an older version of the same sensor. Methods for the progressive update of models for ageing sensors are the subject of our present research and were previously reported [107].

9.4 Computational Cost Deep learning models can be computationally expensive to train and run. With edge computing progressing, the challenge remains of executing sophisticated models on tiny, battery-powered sensor devices. Better ML algorithms for embedded systems are required [123].

9.5 No Benchmarking. There is no standard for evaluating and comparing ML models on gas sensing so far. Different research groups were using different datasets, different evaluation criteria, and different sensor configurations, so that the results were not comparable. The field might benefit from consensus benchmarks and testing regimens.

9.6 Privacy and Data Security Personal air monitors track where you go, and what you breathe there. This information may be sensitive for privacy reasons . With air quality monitoring becoming more prevalent, the concerns over data privacy and security should be handled with care [109].

10. Case Studies

To provide a more concrete representation of the concepts described in this review, three examples from real-world applications are presented here in which ML was effectively used for gas sensing.

Case Study 1: Low-Cost Sensor Net in London. A team from King's College London has established a pioneering low-cost electrochemical sensor monitoring network for NO2 and O3 monitoring throughout the city of London. They discovered that temperature and humidity had a substantial influence on the raw sensor data, rendering it unreliable. They reduced the error by 60% by training a random forest model using three months of colocated reference and sensor data. The calibrated sensors could, of course, then be deployed across the city, at a fraction of the cost of reference instruments, and provide a far more detailed spatial representation of urban air quality [120].

Case Study 2: Industrial Gas Leak Detection in China. Volatile organic compound leakage detection using a metal oxide sensor array was installed at a petrochemical plant in China. False alarms were frequent on those sensors, induced by ambient temperature variations and harmless background gases. The plant implemented an autoencoder-based anomaly detection approach, which is based on the sensor readings' usual patterns. The system alerted almost immediately on a true leak while eliminating more than 80% of false alarms compared to the previous threshold-based system [155].

Case Study 3: Breath Monitoring for Medical Diagnosis Scientists are exploring the application of e-nose technology coupled with ML to diagnose diseases in a non-invasive manner. In one research, an array of 32 sensors was used to analyse breath samples of patients with lung cancer and those without lung cancer. An SVM classifier trained on sensor data provides an accuracy of 85% for differentiating cancer patients from healthy controls. While not yet ready for clinical use, this result demonstrates the exciting potential of ML-powered e-nose systems for medical applications [139].

11. Future Directions

Considering the present knowledge in the field, we can highlight some relevant directions for the future.

► Larger, more diverse data sets: The creation of open-access data sets from a variety of environments and sensor types will enable more generalizable learning models.

► Standard benchmarks: There is a need for the community to coalesce around benchmark data sets and evaluation protocols to allow for a fair comparison of different models.

• Tiny ML for edge devices: To enable massive deployment, it will be crucial to design Jack-under 100kB Tiny ML models that run on tiny, low-power sensor nodes.

• Multi-sensor fusion: With multisensory data fusion (gas sensors and temperature, weather, traffic, satellite imagery) via advanced ML, the precision and completeness of air quality maps will be greatly enhanced.

• Longer-term field studies: Except for a couple of studies (which are short-term and minimal), most of the research to date is short-term studies. Needed: Long-term field studies (years, not months) to see how sensors and ML models hold up over time.

• Policy interface: Linking ML-based air quality monitoring with policy instruments (traffic management systems, industrial emission controls, public health warnings) is key to converting data into action [122].

• Global coverage: The very poorest & most polluted parts of the world have the least monitoring. Cheap sensors with ML correction could enable affordable monitoring in these neglected areas.

12. Conclusion:

This review demonstrates that gas sensing and air quality monitoring are now more than ever relying on machine learning.

The following are significant contributions of ML in this area:

• Increased reliability of inexpensive sensors by compensating for drift, cross-sensitivity, and environmental interference • Gas recognition and source attribution via sensor arrays (electronic noses)

• Accurate prediction of air quality several hours or days prior

• Real-time anomaly detection of gases, such as gas leaks

• Monitoring of air quality could be decentralised from costly reference stations to everywhere. From simple linear regression to more sophisticated deep learning networks, various types of ML methodologies have been effectively utilised in these tasks. The paradigm is shifting towards more connected, intelligent, and edge-enabled systems that can run in real-time with minimal human intervention [4]. Remaining challenges, such as data scarcity, generalisation, and computational resource limitations, are substantial, yet not overwhelming. With continued contributions from data scientists, sensor engineers, environmental scientists, and policy makers, ML-based gas sensing systems have a real chance to revolutionise the way we monitor and enhance air quality on a global scale. Clean air is a fundamental human right. Machine learning is by far our strongest weapon to make that right a reality for all [121].

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