Recent advances in medical gas sensing with artificial intelligence–enabled technology

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Abstract
Recent advancements in artificial intelligence–enabled medical gas sensing have led to enhanced accuracy, safety, and efficiency in healthcare. Medical gases, including oxygen, nitrous oxide, and carbon dioxide, are essential for various treatments but pose health risks if improperly managed. This review highlights the integration of artificial intelligence in medical gas sensing, enhancing traditional sensors through advanced data processing, pattern recognition, and real-time monitoring capabilities. Artificial intelligence improves the ability to detect harmful gas levels, enabling immediate intervention to prevent adverse health effects. Moreover, developments in nanotechnology have resulted in advanced materials, such as metal oxides and carbon-based nanomaterials, which increase sensitivity and selectivity. These innovations, combined with artificial intelligence, support continuous patient monitoring and predictive diagnostics, paving the way for future breakthroughs in medical care.

Key Words: artificial intelligence; healthcare diagnostics; medical gas sensing; nanotechnology

Introduction
Medical gases are fundamental in healthcare, supporting a range of treatments from respiratory assistance to anesthesia and diagnostics. Oxygen (O_2) is crucial for patients needing supplemental O_2 due to low blood oxygen levels, while nitrous oxide (N_2O) is a common anesthetic and analgesic in both dental and surgical settings. Carbon dioxide (CO_2) is used in minimally invasive surgeries to expand body cavities, allowing better visualization, while helium mixed with O_2 can help alleviate airflow resistance in patients with obstructed breathing conditions. Medical air is administered to aid breathing without causing hypoxia, and nitrogen is often applied to power medical devices or; preserve biological samples through freezing. Despite their benefits, these gases pose significant health risks when misused or overexposed. Medical gases, when improperly used or overexposed, can lead to a range of serious health issues. Neurological disorders may arise from exposure to N_2O, which can cause neurological deficits and cognitive impairments with prolonged use.[1] Cardiovascular disorders are linked to air pollutants and particulate matter, which exacerbate ischemic heart disease and increase the risk of heart attacks.[2] Furthermore, certain gases can contribute to inflammation and cancer development, particularly when they introduce harmful substances like heavy metals into the body.[3] Gastrointestinal issues may also occur as a result of exposure to toxic gases, affecting digestion and organ function.[4] Additionally, medical gases have been implicated in nephrological disorders and complications during pregnancy, as toxic exposures can adversely affect kidney function and fetal development.[5] High O_2 levels can cause O_2 toxicity, leading to lung damage and oxidative stress, especially under hyperbaric conditions. Prolonged exposure to N_2O can lead to neurological damage and anemia, while excess CO_2 can result in respiratory acidosis and consciousness loss. Helium, although inert, can cause suffocation if inhaled in confined spaces without O_2, and nitrogen poses similar risks in closed environments by displacing O_2. The health risks associated with medical gas exposure underline the need for careful management and strict adherence to safety protocols in healthcare settings to ensure the well-being of both patients and medical professionals. Although specific global data on deaths solely from medical gas exposure is limited, general cases of toxic gas exposure (including gases like CO_2 is used in minimally invasive surgeries to expand body cavities, allowing better visualization) are significant. For example, unintentional carbon monoxide poisoning alone had a global mortality rate of approximately 0.366 per 100,000 in 2021.[6] Long-term air pollution exposure, including medical and industrial gases, is linked to millions of premature deaths worldwide due to respiratory and cardiovascular conditions.[7]

Accurate sensing of medical gases is critical in healthcare to prevent gas-related pathological conditions and ensure patient and staff safety. Monitoring systems detect and measure gas concentrations, preventing excessive exposure to gases which can lead to serious health complications. Advanced gas detection systems also reduce the risk of accidental leaks or accumulation of gases in confined areas, which could otherwise cause suffocation or explosive hazards. By enabling real-time data on gas levels, these sensors ensure that gases are administered within safe limits and help healthcare facilities maintain regulatory compliance and effective risk management protocols for patient care and environmental safety.[8] Medical gas sensors also play a critical

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role in monitoring specific biomarkers in the human body, particularly volatile organic compounds (VOCs) that can signal various diseases.[9] Traditionally, gas sensing relied on detecting concentration levels through chemical reactions or resistance changes. However, recent advancements have seen artificial intelligence (AI) integration in these sensors, enhancing their capabilities by introducing complex data processing and pattern recognition. AI enables sensors to discern complex gas patterns that would otherwise go undetected, making it a valuable asset in healthcare diagnostics AI significantly enhances sensor capabilities by improving data processing, enabling sophisticated pattern recognition, and facilitating real-time diagnostics. Through advanced algorithms, AI empowers sensors to analyze large volumes of data quickly and accurately, which allows for the detection of subtle changes that may indicate underlying issues.[10] This capability is crucial in various fields, particularly healthcare, where timely insights can lead to better patient outcomes. Moreover, the ability of AI to recognize patterns in sensor data can help identify anomalies and trends, thus enhancing predictive maintenance and operational efficiency.[11] Real-time diagnostics are further bolstered by AI, as it can process incoming data instantaneously, providing immediate feedback that aids in swift decision-making and intervention.[12] Despite the rapid advancements AI applications within the field of medical gas sensing, there remains a significant gap in comprehensive literature reviews that systematically address this intersection. Current studies primarily focus on the technical aspects of gas sensing and AI independently, rather than exploring their combined applications in healthcare settings. This lack of thorough review creates a barrier to understanding the full potential and challenges of integrating AI into medical gas monitoring systems. We aim to conduct a detailed literature study that synthesizes existing research, highlights successful implementations, and identifies areas needing further exploration. By filling this gap, we hope to provide valuable insights that can guide future research and enhance the development of AI-enabled medical gas sensors.

Data and Methods

We conducted an extensive review of the MEDLINE database via PubMed, focusing on English-language publications of any date. Our primary aim was to examine the behavior and interactions of key medical gases, including oxygen, nitric oxide, nitrous oxide, carbon dioxide, and xenon. We explored both conventional and advanced methodologies for measuring these gases and included research on AI and machine learning (ML)–enhanced methods for sensing biological and medical gases. Studies were rigorously screened to exclude duplicates and non-English texts, with preference given to the most current and detailed articles where overlaps occurred. For inclusion, studies needed to be original research or clinical trials, both randomized and non-randomized, as well as experimental studies, prospective observational and retrospective cohort studies, case-control studies, and review articles on medical gas sensing. Each qualifying study underwent detailed analysis, and supplementary references were consulted to ensure a thorough understanding of the topic.

Technological Innovations in Medical Gas Sensing Materials

Recent advancements in nanostructured materials and polymers have significantly enhanced medical gas sensing technologies, leading to improved sensitivity and selectivity. Researchers are increasingly utilizing nanomaterials such as nanowires, nanorods, and carbon-based structures due to their high surface area-to-volume ratio, which facilitates better gas adsorption and detection capabilities.[13] These materials often exhibit unique electrical, thermal, and optical properties that can be fine-tuned for specific gas-sensing applications. Moreover, the integration of conductive polymers with nanostructures is proving beneficial, as these composites can enhance the overall performance of gas sensors by improving response times and stability under varying environmental conditions.[14] Collectively, these developments pave the way for the creation of more efficient, miniaturized, and cost-effective gas-sensing devices that are essential for various applications, including environmental monitoring and healthcare.[15] Advances in nanotechnology have enabled the development of highly effective materials for gas sensing applications, particularly metal oxides and carbon-based nanomaterials.

Sensitivity and surface reactivity of metal oxides

Metal oxides, including tin oxide, zinc oxide, and titanium oxide, are widely used in gas sensors due to their high sensitivity. Their large surface-to-volume ratio enhances interactions with gas molecules, making it possible to detect low concentrations of gases. When a target gas interacts with the metal oxide surface, a change in conductivity occurs, which the sensor measures. This makes metal oxides highly responsive to toxic gases such as carbon monoxide, ammonia, and nitrogen dioxide, even at trace levels. Moreover, these materials can be tailored to respond selectively to specific gases by modifying their surface properties, doping with other metals, or using catalysts, thus improving detection accuracy for particular applications, such as environmental monitoring or health diagnostics.[16]

Carbon-based nanomaterials for volatile organic compound detection

Carbon-based nanomaterials, including carbon nanotubes and graphene, exhibit exceptional electrical and thermal properties, which are ideal for gas sensing. The molecular structure of carbon nanotubes and graphene provides an expansive surface area for gas adsorption, and their electrical conductivity changes upon gas molecule interaction. These nanomaterials can detect VOCs, which are biomarkers for diseases like asthma and other respiratory conditions, by identifying unique compounds in exhaled breath. Additionally, they are effective in detecting VOCs related to environmental pollution, offering a powerful tool for maintaining air quality.[17]

High selectivity through functionalization

Both metal oxides and carbon–based nanomaterials can be functionalized to improve selectivity, which is critical for distinguishing between similar gases. Functionalization involves attaching specific chemical groups or nanostructures to the sensor material, enhancing its selectivity for a particular target gas. This characteristic is crucial in medical diagnostics, where detecting specific VOCs in the breath can signal the presence of disease. Metal oxides can be selectively modified to respond to individual gases, while carbon-based nanomaterials can be tailored to enhance detection of VOCs linked to metabolic or infection-related biomarkers.[18]

Stability and longevity

Metal oxides and carbon nanomaterials exhibit excellent stability, which is beneficial for sensors requiring long-term use in harsh conditions. Metal oxides, are durable under various environmental conditions, allowing for continuous monitoring of toxic gases without significant degradation. Similarly, carbon-based nanomaterials resist oxidation and maintain performance over extended periods, which is advantageous for medical diagnostics and industrial applications.[19]

Potential in data analysis and predictive modeling

Sensors based on metal oxides and carbon nanomaterials contribute data that, when analyzed with predictive modeling, can indicate trends or predict hazardous events.[20] For instance, in healthcare, continuous monitoring of VOCs can provide data for predictive models to assess patient health status over time. In industrial settings, real-time data from sensors can predict toxic gas leaks, enhancing safety and preventative measures.[21]

Artificial Intelligence, Machine Learning, and Neural Networks for Medical Gas Sensing

AI encompasses a broad range of technologies aimed at enabling machines to perform tasks that requires human-like intelligence. Key areas in AI include natural language processing, computer vision, and decision-making, all of which depend on complex algorithms and large data sets. AI seeks to automate processes, make predictions, and perform cognitive tasks, with applications spanning healthcare, finance, manufacturing, and beyond. In recent years, advancements in AI have led to the development of systems that can analyze vast amounts of data, find patterns, and make informed decisions faster and often more accurately than humans can.[22] In an AI system, knowledge, algorithms, and goals are essential inputs that guide the agent's actions. Knowledge provides the agent with background information and rules, algorithms enable it to process inputs and make decisions, and goals define the desired outcomes. The agent interacts within an environment where it perceives observations, like data from sensors or external stimuli, to determine appropriate actions. Forward feedback occurs as the agent's actions influence the environment, while backward feedback provides information about the success of its actions, helping to adjust future decisions. In a block diagram (**Figure 1**), this flow can be visualized with nodes for input (knowledge, algorithm, goals), processing (decision-making of agent), and output (actions and feedback loop from the environment). **Table 1** outlines various applications of AI within the healthcare system.

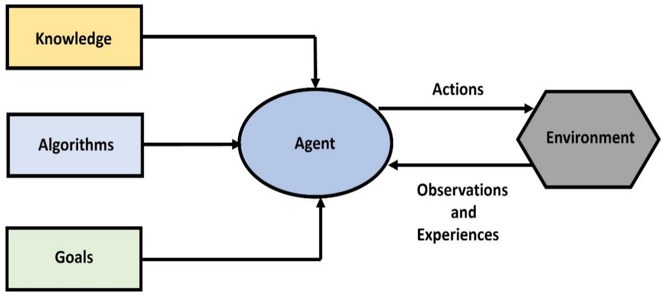

Figure 1 | Basic block diagram of an AI system
The flow diagram is visualized with nodes for input (knowledge, algorithm, goals), processing (decision-making of agent), and output (actions and feedback loop from the environment). AI: Artificial intelligence.

Table 1 | AI applications in healthcare

	Healthcare applications	Detailed description
1	Drug discovery	Speed up drug discovery and repurposing by using large-scale compound databases to screen chemicals and forecast their potential effects and interactions.
2	AI-assisted robotic surgery	Enable surgical robots to deliver real-time feedback to surgeons, enhancing precision and minimizing invasiveness in procedures.
3	Virtual nursing assistants	Track patients' health status, respond to their questions, send medication reminders, and notify medical staff when necessary.
4	Imaging analysis	Detect abnormalities, lower radiation exposure, and enhance image clarity across CT, MRI, and ultrasound imaging techniques.
5	Forecasting kidney disease	Assess the likelihood of chronic kidney disease or kidney failure using indicators like blood pressure, glucose levels, and demographic factors.
6	Connected medical devices	Gather and evaluate data from wearable devices, such as smartwatches, that monitor vital signs, physical activity, and various health metrics.
7	Preliminary diagnosis	Evaluate symptoms, medical history, and test results to determine a potential diagnosis or create a list of differential diagnoses for patients.
8	Prescription error recognition	Identify and prevent medication prescribing and dispensing errors, including potential drug interactions, allergies, and dosage miscalculations.
9	Researching and treating cancer	Examine genomic information, detect mutations, categorize tumors, suggest tailored therapies, and track patient responses in cancer care.

AI: Artificial intelligence; CT: computed tomography; MRI: magnetic resonance imaging.

ML is a subset of AI focused on developing algorithms that enable systems to learn from data and improve their performance over time without explicit programming. ML algorithms analyze data, detect patterns, and make predictions by adjusting parameters based on feedback from their performance. These algorithms are categorized into supervised, unsupervised, and reinforcement learning, each used for different types of tasks and data structures. ML is widely applied in areas such as recommendation systems, fraud detection, and medical diagnosis, helping systems adapt and evolve in response to new data.[22] **Figure 2** illustrates a structured process for data generation, processing, model training, evaluation, and system control, divided into three phases: data processing, training, and testing. Initially, the system generates raw data, which is then processed by extracting relevant features and targets, followed by data cleaning, and the application of feature importance techniques to enhance the data quality. In the training phase, models are developed to estimate specific targets, such as output power, coupling coefficient, and load resistance. These models are evaluated based on accuracy. In the testing phase, the system uses these trained models to process test data, identify the on and off regions, and decide whether the system should be turned on or off. If conditions are met, the system activates; otherwise, it shuts down, forming a feedback loop for continuous operation and decision-making.

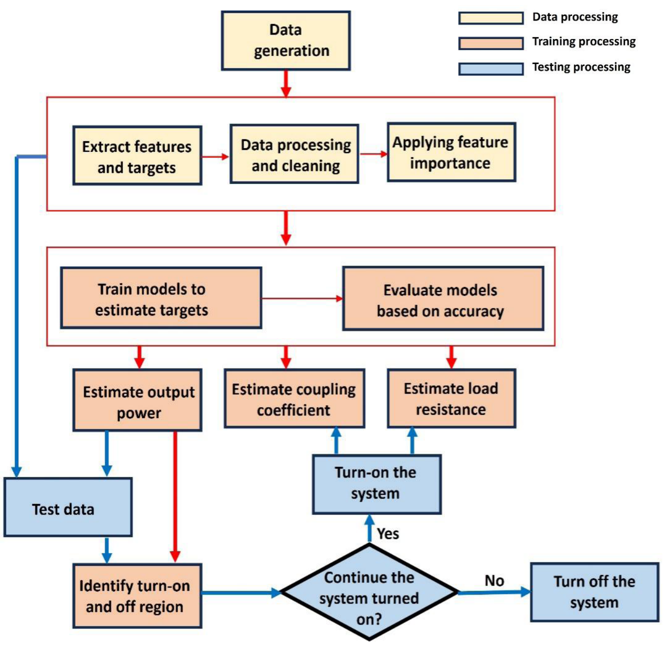

Figure 2 | Block diagram of the machine learning process.
It illustrates a structured process for data generation, processing, model training, evaluation, and system control, which is divided into three phases: data processing, training, and testing. A detailed description is mentioned in the previous paragraph.

Neural networks, inspired by the structure of the human brain, are a crucial aspect of deep learning within ML. They consist of layers of interconnected nodes (or "neurons") that process input data in ways that mimic how neurons process signals. Through multiple layers and adjustments based on training data, neural networks can recognize complex patterns and perform sophisticated tasks, such as image and speech recognition. By using backpropagation and gradient descent, neural networks fine-tune their internal parameters to reduce error rates, becoming more accurate over time. These networks have led to significant advances in fields like autonomous vehicles and medical imaging.[23] **Figure 3** illustrates a simple neural network, which consists of three main layers: the input layer, the hidden layer, and the output layer. The input layer receives multiple input signals (orange nodes), which are then processed through a set of weight-based functions in the hidden layer (blue nodes). The output layer (red node) combines the outputs of the hidden layer using another set of weights, known as linear weights, to produce a final output. This structure allows networks to approximate complex functions and patterns by leveraging localized responses in the hidden layer, making them suitable for tasks like function approximation, pattern recognition, and time-series prediction.

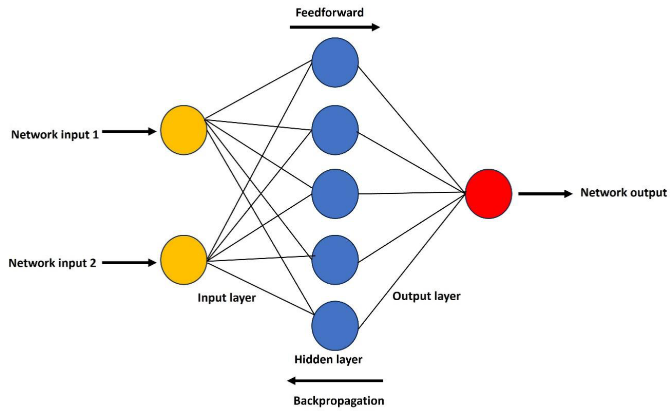

Figure 3 | Block diagram of artificial neural network.
It consists of three main layers: the input layer, the hidden layer, and the output layer. The input layer receives multiple input signals (orange nodes), which are then processed through a set of weight-based functions in the hidden layer (blue nodes). The output layer (red node) combines the outputs of the hidden layer using another set of weights, known as linear weights, to produce a final output.

In AI-enabled medical gas sensing, commonly used advanced ML algorithms techniques include convolutional neural networks (CNNs), recurrent neural networks, and support vector machines (SVMs).[24] CNNs excel at recognizing spatial patterns and gas distributions, while recurrent neural networks are well-suited for analyzing temporal data, enabling real-time monitoring of gas concentration changes.[24,25] SVMs are particularly effective for classification tasks, such as differentiating various gas types or diagnosing medical conditions based on sensor readings.[26] These advanced methods address the limitations of traditional approaches, which are often constrained by linear modeling, noise interference, and poor accuracy in dynamic or multi-gas settings. By leveraging capabilities such as noise reduction, complex pattern recognition, and predictive analysis, these algorithms enable more precise, adaptable, and efficient detection. For instance, ML models trained on extensive datasets can discern subtle gas concentration variations linked to specific health conditions.[27] This adaptability and accuracy provide a significant advantage in medical applications where sensitivity and reliability are critical. AI is also revolutionizing the field of medical gas sensing by enhancing signal transduction techniques and data interpretation capabilities. This development is leading to significant improvements in sensitivity, specificity, and real-time data processing. These advancements are critical in fields such as medical diagnostics, environmental monitoring, and biochemical sensing, where precise and timely detection of target molecules or biomarkers is essential.

Artificial intelligence–powered signal transduction

AI algorithms enable more efficient data processing from gas sensors, devices that convert biological responses into electrical signals. AI-based models, such as neural networks and ML algorithms, can interpret complex signal data patterns, improving detection systems' accuracy. For instance, AI can continuously monitor and analyze medical gas sensor data streams to detect minute changes in analyte concentrations, allowing for more rapid and sensitive detection of target substances, even in background noise.[28] This continuous real-time monitoring is especially beneficial in clinical diagnostics, where detecting early signs of disease can improve patient outcomes.

Enhancing sensitivity and specificity

Sensitivity and specificity are two critical metrics in medical gas sensing. Sensitivity refers to the ability of a sensor to correctly identify true positive cases, while specificity refers to the ability to accurately identify true negatives.[29] AI enhances these metrics by reducing errors in signal interpretation. For example, deep learning algorithms can distinguish between similar medical gas-converted biochemical signals, enhancing both sensitivity and specificity. This precision is especially valuable in fields like cancer detection, where high sensitivity and specificity are crucial to avoid false positives and negatives. By filtering and processing data with ML models, gas sensors can provide highly accurate and reliable results. The microscopic mechanism of advanced materials such as metal oxides and carbon-based nanomaterials in medical gas sensing lies in their specialized surface characteristics and ability to interact electronically with gas molecules.[30] Metal oxides such as ZnO and SnO_2 offer specific sites for gas adsorption and chemisorption.[31] These interactions result in measurable changes in electrical properties, such as resistance, facilitating gas detection. Similarly, carbon-based nanomaterials, including graphene and carbon nanotubes, exhibit exceptional conductivity, large surface areas, and tunable functionalization, which enhance their sensitivity and selectivity for specific gas molecules.[32] When integrated with AI, the sensor outputs of these materials are optimized through advanced ML techniques. AI algorithms, such as CNNs and SVMs, analyze intricate data patterns to identify gases more accurately. CNNs are adept at processing spatial variations in sensor signals, while SVMs excel at classifying sensor responses based on specific gas characteristics. This synergy enhances sensitivity, improves selectivity, and ensures greater resistance to environmental noise and interference, addressing the limitations of traditional gas sensing methods.

Real-time processing and decision-making

One of the most impactful contributions of AI in signal transduction is real-time data processing. AI algorithms can rapidly interpret large amounts of data from gas sensors, enabling immediate feedback and decision-making. This is achieved through techniques like real-time signal processing and predictive modeling, which allow gas sensors to provide continuous updates on analyte concentrations or the presence of specific biomarkers.[33] In healthcare, such real-time analysis can aid in critical monitoring scenarios, such as intensive care units or during surgeries where instant detection of abnormal biochemical changes is essential.

To ensure accurate and reliable AI-based real-time monitoring in medical scenarios, particularly under challenging conditions like high humidity or electromagnetic interference, the following approaches are essential[34]:

Durable sensor design: Developing sensors with materials and coatings that resist humidity and electromagnetic interference can enhance performance. Protective encapsulation and designs that reduce noise are effective solutions.

AI-powered noise reduction: Machine learning models can effectively filter out noise caused by environmental factors. These algorithms help differentiate genuine signals from disruptions created by electromagnetic interference or humidity fluctuations.

Dynamic calibration: Integrating real-time calibration systems allows the sensor to adjust its baseline automatically in response to environmental changes, ensuring consistent accuracy.

Secure data transmission: Utilizing reliable Internet of Things (IoT) protocols and blockchain technology ensures that data shared between sensors and medical systems remains secure and precise during transmission.

Robust testing: Conducting thorough testing under simulated harsh conditions before deployment ensures the system performs reliably in real-world environments.

These strategies together enhance the robustness, precision, and dependability of AI-based medical monitoring systems, even in demanding conditions.

Pattern recognition by artificial intelligence models

AI models rely on several characteristic parameters for identifying and distinguishing different types of medical gases such as O_2, N_2O, and CO_2. The primary parameters include:

Spectroscopic signatures: Gases exhibit unique absorption or emission spectra at specific wavelengths, allowing AI to distinguish them based on spectroscopic patterns.[35] For example, infrared absorption characteristics are commonly used for CO_2 detection, while ultraviolet-visible spectroscopy may aid in identifying O_2 and N_2O.

Concentration levels: AI systems analyze gas concentration patterns in the medical environment, measured in parts per million (ppm) or other units.[36,37] Thresholds for safe or expected concentrations serve as baselines for recognition.

Electrical properties: Changes in resistance, capacitance, or voltage across sensor materials can vary with different gas interactions, enabling pattern differentiation by AI models. For instance, interdigitated electrodes detect variances in gas-specific conductivity changes.[38,39]

Chemical reactivity: AI evaluates gas-specific reactions with sensor coatings or catalysts, producing distinct chemical byproducts or signals for identification.[40]

Environmental interactions: Factors like pressure, temperature, and humidity influence gas behavior. AI integrates these contextual data points to refine gas identification and minimize errors.[41]

These parameters are chosen based on their ability to provide clear, reproducible signals that differentiate gases effectively, while ensuring compatibility with the sensor's material and medical application context.

Self-Powered Gas Sensors for Continuous Monitoring

Self-powered gas sensors are innovative devices that generate their energy, eliminating the need for batteries or external power sources. These sensors typically harness energy from ambient sources such as kinetic, thermal, or electromagnetic energy, making them suitable for continuous, long-term monitoring applications. This capability is particularly beneficial in health care, where sensors can continuously monitor physiological conditions and environmental factors, providing doctors and biomedical engineers with precise, real-time data to optimize health management without frequent maintenance or power replacement. Additionally, advancements in wireless communication, such as 5G technology, can support these sensors by supplying power through wireless transmission, further enhancing their autonomy and reliability for remote or hard-to-reach locations.[42] The development of wearable, self-powered devices for medical gas sensing represents a significant advancement in continuous health monitoring. These devices use flexible gas sensors to detect biomarkers in breath or skin emissions, enabling real-time, non-invasive assessment of health conditions. Powered by energy harvested from the body or environment, such as body heat or motion, they eliminate the need for frequent battery replacements, increasing their practicality for long-term use. Continuous monitoring through these sensors allows for early detection of potential health issues, such as respiratory or metabolic disorders, by identifying abnormal levels of gases like O_2, CO_2, or VOCs.[8] This capability enhances disease management and preventive healthcare, helping individuals and healthcare providers monitor health dynamically and respond swiftly to changes in physiological states.[43] Innovative materials and energy-harvesting technologies are revolutionizing the way gas sensors operate by enabling them to function autonomously with minimal intervention. These advancements leverage ambient energy sources, such as solar, thermal, and vibrational energy, allowing gas sensors to generate power from their surroundings without needing external power sources or frequent maintenance.[44] By integrating such technologies, systems can achieve greater longevity and reliability, ultimately leading to smarter and more sustainable environments. AI and ML significantly enhance self-powered sensors by enabling continuous monitoring of various parameters without the need for external power or frequent maintenance. These technologies allow sensors to autonomously analyze data in real-time, improving accuracy and responsiveness. For instance, AI algorithms can process complex data streams from biosensors, facilitating rapid detection of changes in conditions, which is crucial in applications such as health monitoring and environmental sensing.[45] Furthermore, the integration of ML with energy harvesting technologies enhances the functionality of sensors, enabling multifunctional capabilities that support advanced applications in smart systems.

Development of a Real-Time Learning System for Medical Gas Sensing

The development of real-time learning systems for medical gas sensing is an innovative approach that combines advanced sensor technology with AI to enhance healthcare monitoring. These systems are designed to continuously track the concentration of gases used in medical environments, such as O_2 and N_2O, ensuring patient safety and optimal treatment conditions. By utilizing flexible gas sensors, researchers have made significant strides in improving the sensitivity and accuracy of these devices.[8] A recent study highlights the implementation of deep learning algorithms to facilitate real-time monitoring and leak detection in compressed medical gas systems.[46] These AI-driven systems analyze data streams from the gas sensors, allowing for immediate identification of anomalies and reducing the risk of hazardous situations.[46] Moreover, the integration of IoT technologies enhances the capabilities of these systems, enabling remote monitoring and automated responses to changing gas levels.[47] Additionally, research into AI-enhanced sensors focuses on improving the materials and structures of these devices to increase their efficiency and longevity.[12] By leveraging real-time learning, healthcare providers can ensure a safe and responsive environment, ultimately contributing to better patient outcomes. The block diagram represents a comprehensive system for data collection, processing, and analysis, leveraging IoT networks, AI, and ML to enable predictive maintenance and performance optimization. Starting with the System and Sensors component, data is gathered through an IoT network using industrial bus, wireless link, or fiber optics connections. This network (illustrated in **Figure 4**) integrates with various hardware interfaces, such as controllers, communicators, and screens on tablets or personal computers (labeled printed circuit board designed and human machine interface), allowing user interaction and monitoring. Data collected is sent to a Cloud server via 4G or 5G networks, where it is stored in the Data storage component. The data undergoes Signal conditioning processes—cleaning, synchronization, and segmentation—to prepare it for further analysis. Following conditioning, a Signal profile is created and processed through Feature extraction in time, frequency, and time-frequency domains. Extracted features are stored in the Feature library, which works in conjunction with a Model library and an Analytics engine. This analytics engine provides insights, including health assessments, performance optimizations, and predictive maintenance recommendations. Additionally, Web services connect the Analytics database to user devices over 4G/5G/Wi-Fi, allowing remote access and real-time updates via the internet protocol network, thus enabling continuous monitoring and decision-making.

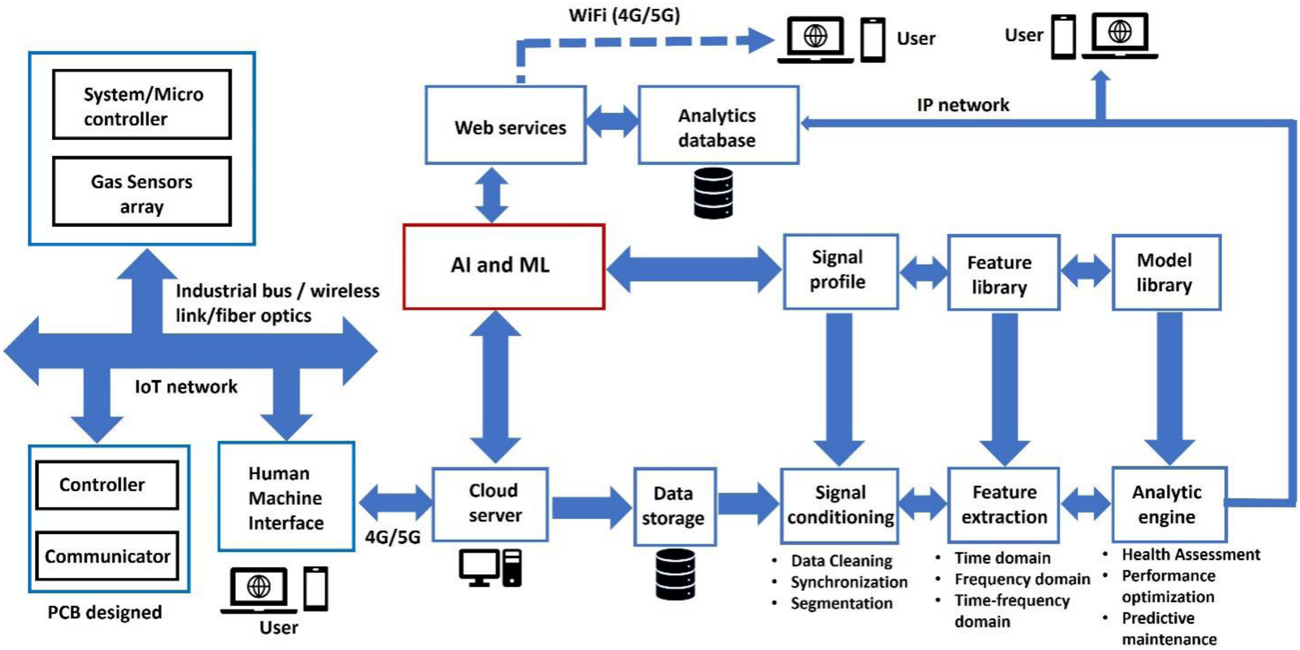

Figure 4 | Real-time machine learning system for medical gas sensing.
It integrates with various hardware interfaces, such as controllers, communicators, and screens on tablets or PCs, allowing user interaction and monitoring. A detailed description is mentioned in the previous paragraph. AI: Artificial intelligence; IoT: Internet of Things; IP: internet protocol; ML: machine learning; PC: personal computers; PCB: printed circuit board.

Case Studies: Artificial Intelligence–Enabled Gain Disease Detection

AI-enabled disease detection has made significant advancements, particularly in the use of breath analysis to identify respiratory diseases, early signs of cancer, and metabolic disorders. These technologies employ gas sensors that can detect specific gas biomarkers in exhaled breath, offering a non-invasive diagnostic method. For instance, breath analysis has been successfully used to diagnose conditions like asthma and chronic obstructive pulmonary disease by identifying VOCs associated with inflammation in the lungs. In the realm of cancer detection, AI-powered gas sensors are capable of distinguishing between healthy and malignant tissues by analyzing breath samples. Studies have demonstrated that these gas sensors can detect unique patterns of gases released by tumors, allowing for the early identification of diseases such as lung and colorectal cancer. By integrating ML algorithms, these systems enhance their diagnostic accuracy by learning from large datasets of breathomics, improving the identification of subtle biomarkers that indicate disease.[48] Moreover, AI systems can differentiate various metabolic disorders by analyzing changes in breath composition. For example, patients with diabetes often exhibit increased levels of acetone in their breath. AI models can monitor these fluctuations in real time, providing continuous health insights and enabling timely interventions.[49] This innovative approach not only facilitates earlier diagnosis but also promotes personalized medicine by tailoring treatment plans based on individual biomarker profiles. Overall, AI-enabled breath analysis systems represent a promising frontier in medical diagnostics, combining cutting-edge technology with practical healthcare applications to improve patient outcomes.

Several other pilot projects and clinical cases have explored the integration of AI with medical gas-sensing technology for continuous monitoring and predictive diagnosis. Key examples include:

Remote patient monitoring: AI-enhanced sensors integrated into the Internet of Medical Things systems have been used to continuously track patients' O_2 levels and respiratory gases, enabling early detection of hypoxia or hypercapnia. These systems utilize real-time AI algorithms to process data and alert healthcare providers when abnormalities occur, improving patient outcomes and reducing hospitalization rates.[50]

Predictive analytics for respiratory conditions: Pilot studies have leveraged AI models to analyze CO_2 and O_2 patterns in patients with chronic obstructive pulmonary disease or sleep apnea. These models predict exacerbations, allowing timely interventions.[51]

Achievements

Early intervention: Enhanced detection of respiratory distress before symptoms become severe, preventing complications.

Personalized care: Continuous monitoring tailor treatment plans to individual needs, improving healthcare outcomes.

Operational efficiency: AI integration reduces the burden on healthcare providers by automating data analysis and alerts.

Challenges

Data security: Safeguarding sensitive patient data in Internet of Medical Things networks remains a significant concern.

Environmental interference: Variability in temperature or humidity affects sensor accuracy.

Integration barriers: Ensuring seamless compatibility with existing healthcare systems requires substantial effort.

Future Directions and Emerging Trends

The future of telemedicine is poised for significant transformation through IoT technologies and advancements in AI. This synergy enhances remote patient monitoring, facilitates real-time data collection, and enables personalized healthcare solutions. IoT devices can continuously gather health metrics from patients, transmitting this information to healthcare providers who can use AI algorithms to analyze medical gas sensing patterns and detect anomalies. Emerging trends also indicate a shift towards greater personalization in healthcare, driven by AI methodologies. These systems can adapt treatments based on individual patient data, preferences, and responses, leading to more tailored healthcare experiences. Additionally, AI can enhance preventive healthcare applications by identifying risk factors by medical gas overdoses early through predictive analytics, potentially preventing the onset of chronic diseases. Material innovations are also critical, particularly in the development of more sophisticated gas sensors and wearable devices that improve data accuracy and reliability. This includes advancements in flexible electronics and biocompatible materials that allow for more comfortable and effective monitoring solutions. In conclusion, the integration of IoT with telemedicine, combined with innovative AI approaches and material technologies, holds the potential to revolutionize healthcare delivery, making it more efficient, personalized, and preventive.

Challenges and Limitations in Artificial Intelligence–Enhanced Medical Gas Sensing

The integration of AI in medical gas sensing technologies presents several challenges and limitations that impact their effectiveness and reliability. One significant issue is gas sensor accuracy, which can be compromised by factors such as calibration drift and environmental conditions. For instance, variations in temperature and humidity can lead to inconsistent sensor readings, making it difficult for AI models to deliver precise predictions.[12] Moreover, the robustness of AI models is critical for their application in gas sensing. Many AI algorithms operate effectively in controlled environments but struggle to generalize in real-world scenarios where data is noisy and varied. This "black-box" nature of AI can also lead to challenges in interpretability, making it hard to understand the model's decision-making process.[52] To address these issues, there is a pressing need for standardized data collection protocols. Consistent and reliable data gathering can enhance the quality of the datasets used for training AI models, ultimately leading to improved performance in medical gas sensing applications.[53] Additionally, minimizing sensor noise and interference—through better sensor design and signal processing techniques—is essential for achieving accurate and actionable insights in real-world applications.[54] In summary, while AI-enhanced gas sensing holds great promise, overcoming the limitations related to sensor accuracy, model robustness, and environmental influences is crucial for realizing its full potential.

Limitations

Incomplete integration of artificial intelligence and medical gas sensing

While AI applications have advanced, the integration of AI with medical gas sensing remains underexplored, with many studies focusing on either domain independently. This limits a comprehensive understanding of their combined potential and challenges.

Variability in environmental factors

Medical gas sensing technologies often struggle with consistency due to environmental factors such as temperature and humidity. These variables can distort sensor readings and affect AI model accuracy.

Data quality and availability

A lack of standardized protocols for collecting and managing data compromises the reliability of datasets used to train AI models, thereby reducing their generalizability and robustness.

Technical and interpretative challenges in artificial intelligence

Many AI models operate as "black boxes," where decision-making processes are not easily interpretable. This makes it difficult to validate the reliability of AI-enhanced medical gas sensing systems.

Scalability issues

While promising, these systems are not yet scalable for widespread clinical application due to high costs, limited compatibility with existing infrastructures, and regulatory hurdles.

Conclusions

The review underscores the transformative potential of integrating AI into medical gas sensing for enhanced accuracy, real-time monitoring, and improved healthcare outcomes. Advancements in sensor materials, such as nanostructures, combined with AI, present significant opportunities for detecting subtle gas patterns linked to health conditions. However, overcoming challenges like data quality, environmental variability, and interpretability is critical for future development. Addressing these limitations will pave the way for more reliable, scalable, and cost-effective solutions in healthcare diagnostics.

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