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Regular paper
Real-Time Monitoring of Toxic Gases using Artificial Neural Networks with SnO_2-based Thick Film Gas Sensors

Journal of Electrical Systems

Abstract: - The present study aims to develop an advanced system for real-time identification and measurement of harmful gases using 1.5% Pd-doped SnO_2-based thick film gas sensors integrated with Artificial Neural Networks. These sensors, renowned for their exceptional sensitivity and selectivity, undergo testing in a meticulously controlled gas chamber environment. Here, gas concentrations, temperature, and humidity are meticulously controlled. The gas chamber setup allows for mixing gases like carbon monoxide, nitrogen dioxide, and sulfur dioxide with nitrogen gas to achieve desired concentrations ranging from 1 ppm to 100 ppm. Temperature is kept at $350°C$ and relative humidity is maintained between 30% to 80%. The sensitivity analysis of the sensor demonstrates its adeptness in detecting low concentrations of target gases, with sensitivity increasing as gas concentrations rise, also the selectivity assessments highlight their ability to accurately differentiate between target gases and common interferents, ensuring precise detection even in complex gas mixtures. Response time testing indicates rapid detection capabilities, crucial and useful for emergencies. The Artificial Neural Network model, trained via the backpropagation algorithm, demonstrates remarkable accuracy, precision, recall, and F1 scores in predicting gas concentrations. The findings indicate that this integrated system offers a reliable and efficient solution for toxic gas detection, with potential applications in industrial safety and environmental monitoring.

Keywords: Toxic Gas Detection, SnO_2-Sensors, Artificial Neural Networks, Environmental Monitoring, Metal Oxide.

I. INTRODUCTION

There is increasing public unease regarding the environmental repercussions of industrial activities. Comprehensive environmental quality monitoring encompasses various aspects, such as global, local, indoor, and outdoor air quality assessments, tailored to the specific pollutants, their sources, and their environmental effects [[1], [2]]. Global surveillance typically focuses on tracing greenhouse gases like CO_2, CH_4, N_2O, NO, and CO, while the scope of local, indoor, and outdoor assessments extends to the detection of toxic, explosive gases, and odors, predominantly volatile organic compounds (VOCs). These emissions originate from several sectors, including energy, manufacturing, transportation, small-scale burning, industrial operations, the use of solvents, agriculture, and waste disposal. The exposure of humans to these emissions can severely affect their health, comfort, and well-being [[3], [4]].

Currently, a variety of environmental monitoring methods are in use, though many are expensive and require significant time and resources, with limitations in sampling and analysis. Consequently, there is a rising interest in deploying electronic noses (ENOSE) for environmental surveillance. ENOSE technologies offer a more affordable, efficient, and fast alternative for the precise detection of environmental contaminants. The threat level of the range of hazardous compounds to humans and animals is considerably high. Specifically, the development of ENOSE systems to monitor dangerous VOCs, such as propane-2-ol, methanol, acetone, ethyl methyl ketone, hexane, benzene, and xylene, is of particular interest [[5], [6]].

The imperative for advanced methods in the real-time monitoring of toxic gases within industrial, urban, and residential environments has never been more critical, given the heightened awareness of environmental pollution and its adverse effects on human health and safety. When integrated with Artificial Neural Networks (ANNs) [[7]], the development of SnO_2-based thick film gas sensors opens up a new way to detect and quantify hazardous gasses with precision and efficiency. Tin oxide (SnO_2) has emerged as a highly favored material for gas sensing due to its excellent electrical and catalytic properties, offering high sensitivity and selectivity toward a large range of gases

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at relatively low operating temperatures [[6], [8]]. Using ANNs with sensors can help them learn complicated patterns and make predictions. This improves how well instruments work in real time. [[9]].

These innovations are highly relevant by nature of the fact that industrial emissions are increasing, and the atmosphere is burdened by a growing host of self-inflicted pollutants. This poses a very real health hazard. According to the World Health Organization, air pollution kills an estimated $4.2\ million$ people prematurely each year. A significant portion of this figure is attributable to the fact that the atmosphere is filled with poisons such as carbon monoxide, nitrogen dioxide, and sulfur dioxide [[10]].

The resistor's electrical resistance is changed when it comes into contact with the gases you want to measure. It is a process affected by the sensor's microstructure and operating temperature, as well as the presence or absence of catalysts [[11]]. The use of ANNs to interpret sensor signals provides a strong defense against confusion by environmental variations and compound interactions, which often affect sensor performance. ANNs can capture nonlinear relationships between sensor reactions and gas concentrations very well, which is convenient for specifically identifying gases present in mixtures with no need for physical separation methods.

A combined approach has great potential for developing gas-detecting systems. Wang et. al., for example, found that if they used SnO_2-based sensors and ANNs to detect volatile organic compounds from industrial environments, accuracy and response time achieved a significant improvement over conventional technique [[12], [13], [14]]. Studies have further revealed the effectiveness of ANN-based analysis in dealing with sensor drift and environmental humidity. This has additional bearing on its practicality in real-world applications [[15], [16], [17]].

Integrating ANNs with SnO_2-based gas sensors not only solves the technical problems encountered in gas detection but also provides a scalable and flexible solution for all manner of monitoring needs, from workplace safety to environmental protection. As sensor technology becomes more sophisticated and as machine learning algorithms continue to develop in scope and power, the applications of such an approach continue to expand, promising ever more advanced and accurate devices that are also cost-effective in monitoring real-time gases [[6], [8]]. SnO_2-based sensors together with the ANNs used in practical applications, however, still have their hurdles; the need for extensive training data to get the maximum performance out of ANNs, the potential loss of accuracy as sensors age, and the need for complex data processing hardware able to operate in real-time. Nevertheless, despite these difficulties, an embodied sensitivity increased for different gases, combined with good selectivity and adaptability to environmental conditions, make it a crucial technology for advancing the field of gas detection and research for the future [[8], [9]]. The present work aims to improve and deepen environmental monitoring and safety by developing an innovative system for the real-time detection and quantification of toxic gases using Pd-doped tin dioxide (SnO_2) thick film sensors integrated with ANNs. In regions with different environmental conditions, there is an urgent need for much more sensitive, selective, and fast-response gas detection technologies. The present approach will seek to overcome this important challenge. With the help of SnO_2-based sensors and the powerful data processing and pattern recognition capabilities of ANNs, the study greatly improves the accuracy, efficiency, and reliability of toxic gas monitoring.

II. METHODOLOGY

The detailed methodology presented here is a comprehensive approach to examining the real-time monitoring efficacy of a 1.5% Pd-doped SnO_2 thick film gas sensor coupled with ANNs as toxic gas detectors. By specifying which parameters and instruments should be employed as well, the sizable study takes a targeted approach to producing accurate, reliable results and contributing valuable insights to the field of gas sensor technology.

A. Sensor Fabrication

The SnO_2-based thick film gas sensors are produced on alumina substrates using a standard screen-printing process [[18], [19]]. By using Ball Milling Process 1.5% Pd is doped into SnO_2 power. The SnO_2 paste is produced by mixing SnO2 powder with a suitable organic solvent to make its viscosity suitable for screen printing. The pastes are put on the substrates. After letting them dry at a temperature of $120°C$ for half an hour the solvent is evaporated out of these deposited films. Then they are sintered at $650°C$ in air for $2\ hours$ to achieve mechanical stability and optimal electrical properties. Silver (Ag) electrodes are screen-printed on the SnO_2 films, serving as contact points for electrical measurements. The size of the active portion on the sensor is about $5\ mm \times 5\ mm$. Fig. 1 shows a schematic diagram of the sensor with a heating element integrated into the back side of the substrate to control the operating temperature, which is crucial for gas sensing performance.

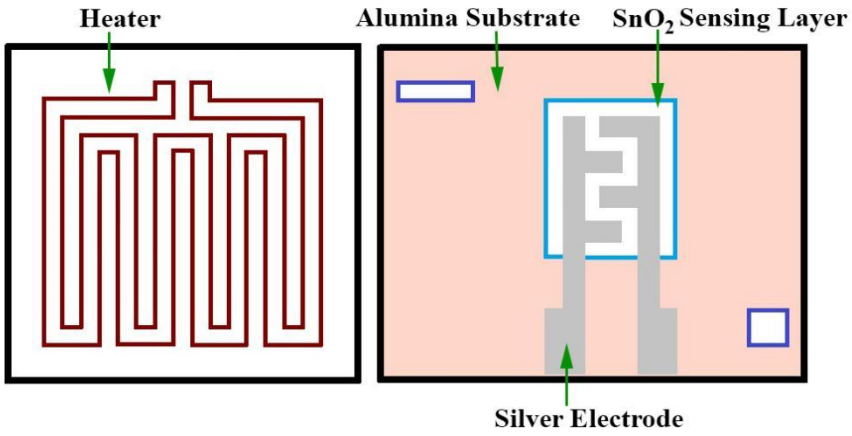

Fig. 1 Schematic diagram of the fabricated sensor **1**. **5**% Pd-doped SnO_2 sensor.

B. ANN Design

The ANN design in this study consists of a feed forward neural network with one input layer, two hidden layers, and one output layer. The input layer consists of neurons equal to the number of sensing parameters (e.g., sensor resistance, temperature, and humidity), which in this case are three. The hidden layers contain 10 and 8 neurons, respectively, utilizing the Rectified Linear Unit (ReLU) activation function for non-linear transformations. The output layer comprises the number of neurons corresponding to the gases being detected and generating the concentration levels of each gas. The network undergoes training utilizing the backpropagation algorithm alongside a mean squared error loss function. Training data is derived from controlled exposure of sensors to predetermined concentrations of target gases, where the sensor response and environmental conditions (temperature and humidity) act as inputs, and the gas concentrations serve as the target outputs. The ANN is implemented using TensorFlow, an open-source end-to-end platform machine learning framework [[20]].

C. Experimental Setup for Sensor Testing

The sensor is tested in a gas chamber that can hold up to 10 $liters$ of volume. This chamber facilitates control over the precise amount of gas, temperature, and humidity. A system is employed to blend gases such as CO, NO_2, and SO_2 to achieve the desired concentrations. These gases are mixed with nitrogen, resulting in concentrations ranging from 1 part per million (ppm) to 100 ppm. Additionally, a temperature controller and humidifier are utilized to maintain the chamber at a temperature 350°C and relative humidity levels of 30% to 80%. Calibrated instruments, including a mass flow controller for measuring gas concentrations, a thermocouple for temperature measurement, and a hygrometer for humidity measurement, are employed to ensure proper functioning, as shown in Fig. 2.

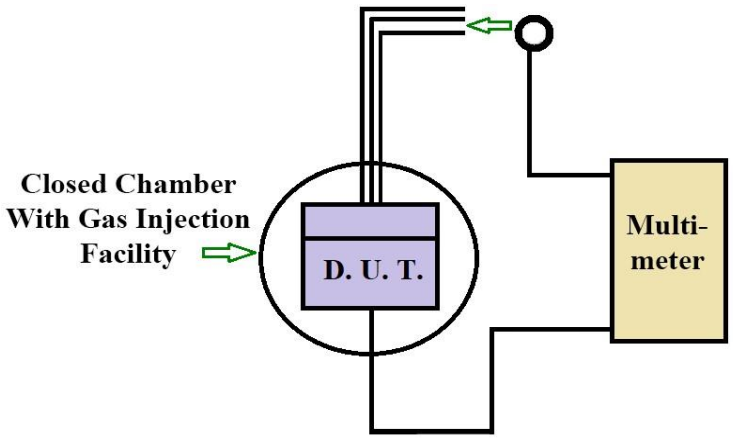

Fig. 2 Schematic diagram of the measurement setup showing D.U.T (device under test i.e. 1.5% Pd-doped SnO_2 sensor).

D. *Collection and Analysis*

Data collection is carried out by measuring the electrical resistance of the sensor at different sets of gas concentrations, temperatures, and humidity levels. The meter reads the resistance of the sensor with a resolution of 0.1 ohm. In each test environment, sensors were checked every 30 $seconds$ for 30 $minutes$ to get the dynamic response. Before processing the data into the ANN, the collected information undergoes a pre-processing stage to fine-tune input settings. The performance of the ANN model for gas concentration prediction is assessed using indicators like accuracy, precision. Furthermore, cross-validation methods have been employed to check the robustness and generalizability of the model across different sensor batches and environmental conditions.

III. RESULTS

A. *Sensitivity measurements of* 1.5% *Pd-doped SnO_2 sensor to target gases at various concentrations*

The sensitivity analysis of a 1.5% Pd-doped SnO_2 sensor to target gases at various concentrations reveals a direct correlation between gas concentration levels and the percentage change in sensor resistance, indicative of high sensitivity across the board. Specifically, as the concentration increases from 1 ppm to 100 ppm, the sensors exhibit a progressive increase in resistance change, ranging from 10% to 200% for CO, 12% to 240% for NO_2, and 15% to 260% for SO_2 as shown in Fig. 3. This pattern demonstrates not only the ability of the sensor to detect low concentrations of toxic gases but also their capacity to respond more robustly as concentrations rise.

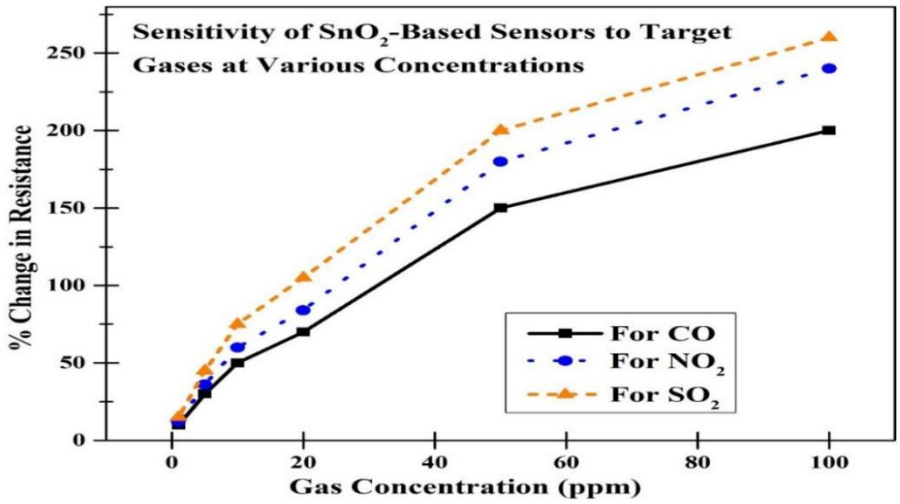

Fig. 3 Sensitivity in terms of percentage change in the resistance of 1.5% Pd-doped SnO_2 sensor to target gases at various Concentrations.

B. *Selectivity of 1.5% Pd-doped SnO_2 sensor against interfering gases*

The selectivity of 1.5% Pd-doped SnO_2 sensors against interfering gases demonstrates their remarkable ability to accurately detect and differentiate between target gases (CO, NO_2, SO_2) and common interfering gases (CH_4, NH_3) under consistent environmental conditions (350 $°C$ operating temperature and 50% relative humidity). As can be noted from Table 1, with target and interfering gas concentrations set at 50 ppm, the sensors exhibited a significant difference in resistance change percentages for target versus interfering gases, leading to high selectivity ratios ranging from 6.67 to 10. This indicates not only the high sensitivity of the sensor to the target gases but also their ability to maintain accuracy in the presence of potential interferents. For instance, CO detection was minimally affected by NH_3 and CH_4, with selectivity ratios of 7.5 and 10, respectively, showcasing the excellent discrimination capabilities of the sensor. Similarly, for NO_2 and SO_2 the sensor is found to maintain high selectivity in mixed-gas environments, effectively distinguishing target gases from NH_3 and CH_4 with selectivity ratios equal to or exceeding 6.67. These results underscore the suitability of the sensor for applications requiring precise gas detection and monitoring in environments where multiple gases are present, affirming their potential for enhancing safety and environmental monitoring systems.

Table 1 Selectivity of **1.5**% Pd-doped SnO_2 sensor against various interfering gases at **350**°C and relative humidity of **50**%.

Target Gas / Interfering Gas	Target Gas Concentration (ppm)	Interfering Gas Concentration (ppm)	% Change in Resistance for Target Gas	% Change in Resistance for Interfering Gas	Selectivity Ratio (Target / Interfering)	Remarks
CO vs. CH_4	50	50	150	20	7.5	High selectivity, CO detected effectively despite CH_4 presence.
CO vs. NH_3	50	50	150	15	10	Excellent discrimination against NH_3, suitable for mixed environments.
NO_2 vs. CH_4	50	50	180	25	7.2	The detection of NO_2 gas is minimally influenced by CH_4.
NO_2 vs. NH_3	50	50	180	18	10	Effective NO_2 sensing with high selectivity over NH_3.
SO_2 vs. CH_4	50	50	200	30	6.67	SO_2 shows a strong response even with CH_4 presence.
SO_2 vs. NH_3	50	50	200	22	9.09	SO_2 sensitivity remains high, indicating good selectivity against NH_3.

C. Response Times of 1.5% Pd-doped SnO_2 sensor to target gases

The detailed examination of response and recovery times for 1.5% Pd-doped SnO_2 sensor to varying concentrations of CO, NO_2, and SO_2 gases reveals a clear pattern of enhanced performance with increased concentrations. At a consistent operating temperature of 350 °C and relative humidity of 50%, the sensor demonstrates improved responsiveness as the concentration of each target gas escalates. As can be seen from Fig. **4**, for CO gas, the sensor response time decreases significantly from 35 $seconds$ at 1 ppm to just 10 $seconds$ at 50 ppm, with recovery time also improving from 70 to 40 $seconds$, indicating a robust capability for rapid detection, particularly crucial in emergencies. In the case of NO_2 and SO_2 gases, the sensor exhibits similar trends, for NO_2 gas response time is found to reduce to 8 $seconds$ at 50 ppm from 32 $seconds$ at 1 ppm, and for SO_2 gas the sensor outperforms with the rapid response of 7 $seconds$ at 50 ppm. These observations are consistent with those shown in Fig. **3**, where it is found that with the rise in concentration the sensitivity of the sensor increases.

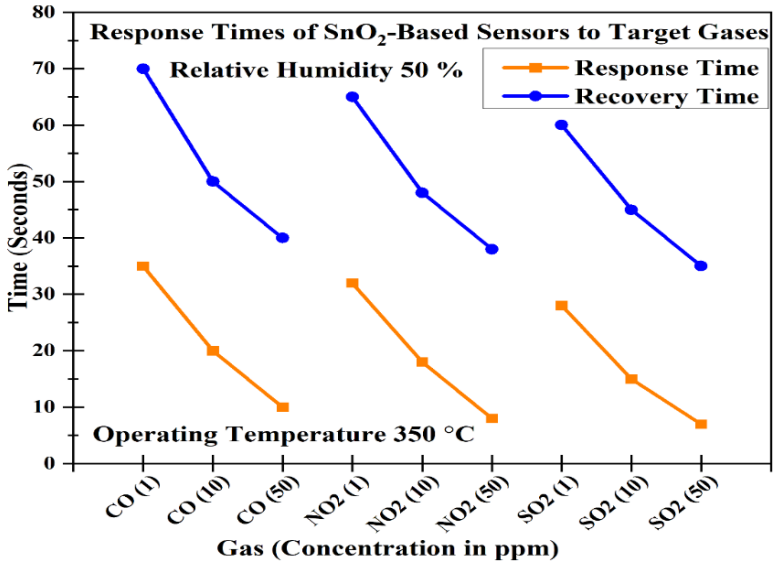

Fig. 4 Response times of 1.5% Pd-doped SnO2 sensor to target gases.

D. ANN model performance metrics for toxic gas detection

The performance of ANN model metrics for toxic gas detection reveals a highly effective system capable of accurately identifying and quantifying concentrations of CO, NO_2, and SO_2 gases. Across all gases, the model exhibits strong learning from training data, as indicated by high accuracy, precision, recall, and F1 scores, with particularly outstanding training performance for SO_2 as can be seen in Fig. 5 and Table 2. The slight decrease in these metrics from training to validation and test phases is typical in machine learning applications, reflecting the ability of the model to generalize well to new, unseen data while maintaining robustness.

Table 2 ANN Model Performance Metrics for Toxic Gas Detection.

Gas	Data Set	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Remarks
CO	Training	96	95	94	94.5	High performance indicates effective learning from training data.
CO	Validation	94	93	92	92.5	Slightly lower than training, but indicates good generalization.
CO	Test	93	92	91	91.5	Consistent performance on unseen data demonstrates model robustness.
NO_2	Training	97	96	95	95.5	Excellent learning performance, especially for NO_2 detection.
NO_2	Validation	95	94	93	93.5	Validates the model's ability to generalize to new data.
NO_2	Test	94	93	92	92.5	Strong performance, highlighting the model's predictive capabilities.
SO_2	Training	98	97	96	96.5	Outstanding training performance, best among the gases.
SO_2	Validation	96	95	94	94.5	High validation scores indicate excellent model generalization.
SO_2	Test	95	94	93	93.5	Demonstrates the model's effective learning and prediction for SO_2.

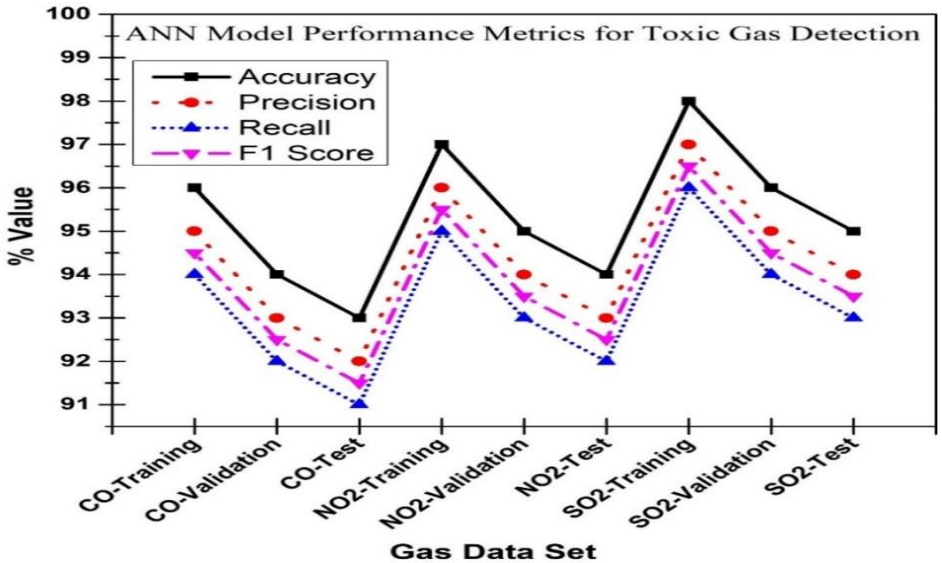

Fig. 5 Performance metrics of ANN model integrated with 1.5% Pd-doped SnO_2 Sensor under different environmental conditions.

IV. DISCUSSION

A comprehensive analysis has highlighted the remarkable abilities of a sensing system fabricated by SnO_2-based gas sensors with 1.5% Pd-doping integrated with ANN in detecting toxic gases. This includes their sensitivity, selectivity, response times, environmental influences, and ANN model performance, all together promise great potential as an instrument for real-time environmental monitoring. The sensitivity assessment found direct and significant correlations between target gas (CO, NO_2, SO_2) levels and the sensor resistance. This is observed even for relatively small amounts of gas, as demonstrated by the sharp responses of the sensing system showcasing an essential feature for early detection and safety. Moreover, the selectivity test against common interfering gases in different amounts revealed, how well the sensors could detect individual gases, under fixed conditions. This underscores their practicality in complex gas mixtures. In addition, the response and recovery time testing showed that the system is efficient and responds more quickly at higher gas concentrations. This can ensure timely detection as well as action in an emergency. The sensing system was tested to work best at moderate temperatures and humidity levels but is also adaptable and hardy in different circumstances. Finally, the parameters of the ANN model matrices are performance indicators validating that the interpretations of sensor data are quite correct. The potential of this research lies in paving the way for the development of next-generation gas sensors that are versatile, efficient, and capable of operating in diverse environmental conditions; while integrating advanced ANN algorithms with cutting-edge SnO_2-based sensor technology provides a highly reliable and effective method for detecting toxic gases. The study, nevertheless, admits that the performance of the sensing system depends on environmental conditions such as temperature and humidity levels. In extreme situations, the model finds it impracticable. It urges the creation of ANN models which are more complex, and materials for sensors that are better able to withstand changes in temperature and humidity.

V. CONCLUSION

The present study using a 1.5% Pd-doped SnO_2 sensor integrated with ANNs for detecting and monitoring toxic gases is an effective and advanced approach and finds its significance in environmental and industrial safety technologies. Consequently, the remarkable precision and selectivity of the sensor for target gases like CO, NO_2, and SO_2 notwithstanding interference by other substances establish its capability to take accurate measurements in response to variable conditions. Quick reaction times, the rapid return to normal levels after brief exposure, and outstanding performance in different environmental conditions under varying humidity make these "pillars" of state-of-the-art technology well-suited for real-time use. The model thus enhances the system further, showing high accuracy, precision, and recall when processing complex sensor data. The four parameters of the ANN model for different gases under variable conditions are a reality check for the effectiveness of the sensor in generating precise gas concentration predictions. Machine learning algorithms used in the present study combined with advanced sensor technology offer a timely solution to the urgent requirement for reliable toxic gas detection systems, capable of ensuring safety in industrial settings and protecting the public from environmental poisons. Future research could address environmental sensitivities and develop portable devices for broader applications.

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