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Experimental Gas Leakage Detection Using Integrated Sensor Arrays Using Deep Learning

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Abstract:
Gas leaks pose significant risks to both industrial safety and environmental conservation, necessitating the use of reliable detection methods. This study details a method for detecting gas leaks by integrating multiple sensors and applying advanced machine learning algorithms, focusing on enhancing detection accuracy and reliability through data-driven analysis rather than relying on conventional single-point sensor systems. Sensor arrays based on environmental susceptibility data detect conditions prone to gas leakage. The proposed system employs deep learning techniques and demonstrates adaptability to detect and respond to gas leaks in real-time.
By integrating data from multiple sensors measuring gas concentration, temperature, and pressure, the development of a comprehensive and context-aware detection system is enabled. The system analyzes temporal patterns to issue early warnings and insights into gas dispersion, substantiated by its effectiveness in predicting gas dispersion dynamics. This allows for proactive risk management and the creation of efficient mitigation strategies. The design is structured for practicality and scalability, demonstrated by compatibility tests with existing infrastructure and a framework that supports integration with future advancements in sensor technology and machine learning. Previously, the technology was characterized using MATLAB simulation. The effectiveness and reliability of the system in detecting gas leaks in various operational settings will now be demonstrated through real-world testing and observation.
Keywords: gas leakage detection; embedded sensors; deep learning; industrial safety; and environmental monitoring

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I. Introduction

Hydrogen is increasingly utilized as an energy carrier across various sectors due to its clean and stable characteristics. It is a viable choice for decreasing CO2 emissions and minimizing the use of fossil fuels [1-2]. The concept of a hydrogen economy has garnered global interest, leading to the establishment of research and development programs over the years [3-4]. These programs aim to enhance reliability and develop effective techniques for hydrogen production, storage, and utilization in areas such as energy generation, transportation, and both industrial and residential applications [5]. The shift to a hydrogen economy has distinct obstacles, such as the need for dependable hydrogen leak detection devices [6]. Hydrogen leaks provide substantial safety hazards due to hydrogen's extreme flammability, which may result in explosions or flames if not promptly identified and managed [7-8].

Traditional single-sensor systems may not be adequate for detecting subtle changes or abrupt spikes in hydrogen concentration. A novel hybrid strategy combining sensor fusion and deep learning approaches is suggested to address this problem [9]. This technique aims to enhance the sensitivity and reliability of hydrogen leak detection by combining data from several sensors such as electromagnetic, ultrasonic, and optical sensors. The sensor fusion approach employs deep learning, particularly long short-term memory networks, to evaluate and interpret combined sensor data instantaneously [10]. Utilizing deep learning with embedded sensors for gas leak detection shows promise in enhancing accuracy and efficiency [11]. These advancements in gas leak detection will enhance the safety of hydrogen applications and contribute to the success and widespread adoption of hydrogen as a carrier, Sustainable energy benefits several industries [12].

Deep learning may be used for real-time gas monitoring systems. Deep learning systems can analyze data from several sensors to detect and categorize distinct gases instantly [13]. Training deep neural networks on a large dataset can do this. This deep learning algorithm can reliably recognize certain gases and possibly identify unexpected quantities or leaks by analyzing sensor values and their matching gas types [14]. This is achieved by training Long Short-Term Memory (LSTM) networks on extensive datasets comprising sensor readings and associated hydrogen leak incidents [15-16]. LSTM networks that have been trained are capable of reliably detecting and categorizing hydrogen leaks using sensor data [17]. The sensor fusion method for hydrogen leak detection using LSTM networks offers improved sensitivity and reliability in comparison to conventional single-sensor systems [18]. By amalgamating data from several sensors, these networks may efficiently identify subtle fluctuations or abrupt spikes in hydrogen concentration that could be unnoticed by an individual sensor [19-20].

The future of monitoring sustainable energy technology depends on combining improved sensors with AI-based detection systems [21-22]. These technologies may enhance the safety and effectiveness of hydrogen use by precisely detecting and reacting to hydrogen leaks in real-time [23-24]. Partnerships across business, academia, and government worldwide are crucial for promoting the use of AI and machine learning [25-26].

II. Hypotheses

2.1. Background and Rationale:

Given the inherent dangers and specific requirements associated with testing hydrogen gas, our research has adopted the use of helium gas as a surrogate in the development and testing phases of AI-based sensor systems. This strategic choice is underpinned by the physical and chemical properties of hydrogen (H_2) and helium (He), which share noteworthy similarities, making helium a practical and safer alternative for our experimental setups. Hydrogen (H_2) has a molecular weight of approximately 2.016 g/mol, comprising two hydrogen atoms, while helium (He) has a molecular weight of about 4.0026 g/mol, consisting of a single atom. Despite helium being heavier, both gases are significantly lighter than air, allowing for rapid dispersion in atmospheric conditions. Hydrogen is a diatomic, highly flammable gas that is reactive under certain conditions, but its molecules are stable and non-reactive under normal atmospheric conditions. On the other hand, helium, as a noble gas, is inert and non-reactive. Its monatomic nature adds to its chemical stability. Both gases are gaseous at standard temperature and pressure, showing similar behaviors in terms of diffusion and distribution in an environment. The boiling point of hydrogen is -252.87 °C, and its melting point is -259.16°C, compared to helium's lower boiling point of -268.93°C and melting point of -272.20°C. These low boiling and melting points ensure both gases remain in a gaseous state under most environmental conditions. This close resemblance in fundamental physical characteristics supports the hypothesis that a sensor system designed for hydrogen detection can be effectively calibrated and tested using helium. This similarity provides a basis for ensuring that our testing methodologies are robust and safe, reducing the risks associated with hydrogen's flammable nature while maintaining the integrity and relevance of our experimental results.

2.2. Primary Hypothesis:

Our central hypothesis posits that sensor systems, originally configured for hydrogen (H_2) detection, can be efficiently calibrated, and validated using helium (He) as a surrogate gas. This hypothesis is predicated on the fundamental principle that the physical and chemical behaviors of helium, particularly its dispersion characteristics and lack of reactivity under standard atmospheric conditions, closely mirror those of hydrogen.

Mathematically, this can be expressed by considering the properties of gas dispersion and reaction kinetics. For instance, if (DH_2) and (DHe) represent the dispersion coefficients of hydrogen and helium, respectively, under identical conditions, our hypothesis assumes that $DH_2 \approx DHe$. Additionally, the reactivity of hydrogen can be represented by its reaction rate constant KH_2 under certain conditions. Since helium is non-reactive, its reaction rate constant KHe is effectively zero, which simplifies the testing process by eliminating the variable of gas reactivity. Table 1 shows a general comparison between helium and hydrogen gas.

We anticipate that these similarities in dispersion and non-reactivity will allow for the development of a testing environment that is both precise and safe, substantially reducing the hazards linked with hydrogen's high flammability. This approach not only provides a viable route for sensor calibration and testing but also ensures that the integrity of the sensor's functionality in detecting hydrogen is maintained without directly exposing the system to hydrogen's flammable properties.

Table 1. An overall comparison between helium and hydrogen gas.

Property	Helium	Hydrogen
Molecular Weight	4.0026 g/mol	2.016 g/mol
Reactivity	Non-reactive (Inert)	Reactive
State at Room	Gaseous	Gaseous

Property	Helium	Hydrogen
Boiling Point	-268.93°C	-252.87°C
Melting Point	-272.20°C	-259.16°C
Dispersion in Air	Rapid (low density)	Rapid (low density)
Atomic Number	2	1
Electron Configuration	$1s^2$	$1s^1$
Color and Odor	Colorless, Odorless	Colorless, Odorless
Environmental Impact	Non-toxic, Non-polluting	Non-toxic, but flammable
Ionization Energy	24.5874 eV	13.5984 eV
Thermal Conductivity	0.15 W/mK	0.18 W/mK

2.3. Secondary Hypothesis and Safety:

A secondary hypothesis is that once the system reliably detects and categorizes helium, only minor adjustments in data processing will be needed to adapt the system for hydrogen detection. This hypothesis stems from the assumption that the primary distinction in detecting these gases lies in their respective molecular characteristics, which can be accounted for in the final stage of system tuning.

By using helium, we aim to ensure maximum safety during the development phase. Furthermore, this approach allows for thorough system testing and optimization before deployment in hydrogen gas scenarios. This method offers a pragmatic and secure pathway to refining hydrogen leak detection technologies. We believe that validating these hypotheses will play a significant role in the broader adoption and safe utilization of hydrogen in various sectors, enhancing the overall reliability and safety of hydrogen-based systems.

III. Research Problem

In the realm of gas leak detection, significant advancements have been made over the years, yet each new development has brought with it a set of challenges and limitations that need addressing. Initial forays into this field largely relied on single-sensor technologies, which, while groundbreaking at the time, quickly revealed limitations in their scope and reliability, especially in diverse environmental conditions. This realization spurred researchers to explore more comprehensive methods, leading to the integration of multiple sensor types in more recent studies. However, even these multi-sensor systems often fell short in aspects like real-time data analysis, adaptability to various gas types, and maintaining precision in different environmental conditions. These ongoing challenges have highlighted the need for a system that not only combines the strengths of various sensor types but also incorporates advanced analytical capabilities to provide reliable, real-time detection in a wide range of scenarios.

One notable study in this field is Electrochemical Sensor-Based Detection of Hydrogen Gas, which made significant strides in using electrochemical sensors for hydrogen gas detection. This study was pivotal in enhancing the sensitivity of sensors to low gas concentrations. However, its reliance on a single-sensor approach limited its environmental adaptability and led to challenges like sensor drift and the inability to differentiate between gas types. These issues often resulted in false positives, undermining the reliability of the system. In contrast, another key study, the Multi-Sensor Approach for Enhanced Gas Leak Detection, marked the early adoption of sensor fusion by integrating optical and ultrasonic sensors. The study's simplistic data analysis techniques limited the detection spectrum, but this approach broadened it. Without advanced analytical tools, the system struggled to interpret complex sensor data accurately, particularly under fluctuating environmental conditions, and had slower response times to gas leaks.

By integrating a comprehensive multi-sensor system with advanced deep learning techniques, our research aims to rectify the limitations of these foundational studies. By employing a diverse array of sensors, including ultrasonic, optical, electromagnetic, and thermal conductivity sensors, the proposed system captures a wider range of data, allowing for a more holistic analysis and improved accuracy in detecting gas leaks. The incorporation of Long Short-Term Memory (LSTM) networks in our data analysis represents a significant advancement over previous methods. These networks enable dynamic, real-time analysis of sensor data, learning from patterns to enhance predictive accuracy. Addressing the issue of environmental interference in the first study, this system maintains high accuracy across various atmospheric conditions.

Furthermore, by integrating self-calibrating mechanisms, we've effectively countered the sensor drift challenge, ensuring long-term reliability and consistency in detection. This system also exceeds the limitations of the second study by demonstrating a fast response time and the ability to adapt to new gas leak scenarios, making it a significant leap forward in the field of gas leak detection technology.

IV. Materials and Methods

In our study, we utilized a multi-sensor array, each selected for specific strengths in gas leak detection. Table 2 summarizes the sensors and their basic functions.

Table 2. Overview of Sensor Models and Their Detection Functions.

Sensor Model	Type	Primary Function
PCS HC-SR04	Ultrasonic	It detects the presence of gas by changes in the speed of sound in the air.
SAS-560	Electromagnetic	Detects gas leakage with changes in electromagnetic fields.
SparkFun's SEN-15776 Series	Optical	It detects the presence of gas in the air by changes in the speed of light.
Amphenol SGX Sensortech VQ546M	Thermal Conductivity	Detects temperature fluctuations due to gas leaks.

Integrating these sensors allows for a robust, multi-faceted approach. The ultrasonic sensors' spatial accuracy, combined with the electromagnetic sensors' field sensitivity, the optical sensors' rapid response, and the thermal sensors' temperature detection, creates a comprehensive system. This array ensures accurate and reliable detection across various scenarios and environmental conditions. Figure 1 shows the general view of (ultrasonic-electromagnetic-optical-thermal Conductivity) sensors.

4.1. Ultrasonic Sensors:

The ultrasonic sensor is recognized for its environmental sensitivity, which enhances its effectiveness in gas leak detection. It functions by emitting ultrasonic waves and measuring their return time, which varies when these waves encounter different obstacles or gas densities. This capability is especially valuable in identifying gas presence, as it causes notable changes in the speed of sound in the air. Table 3 shows the specifications of the sensor.

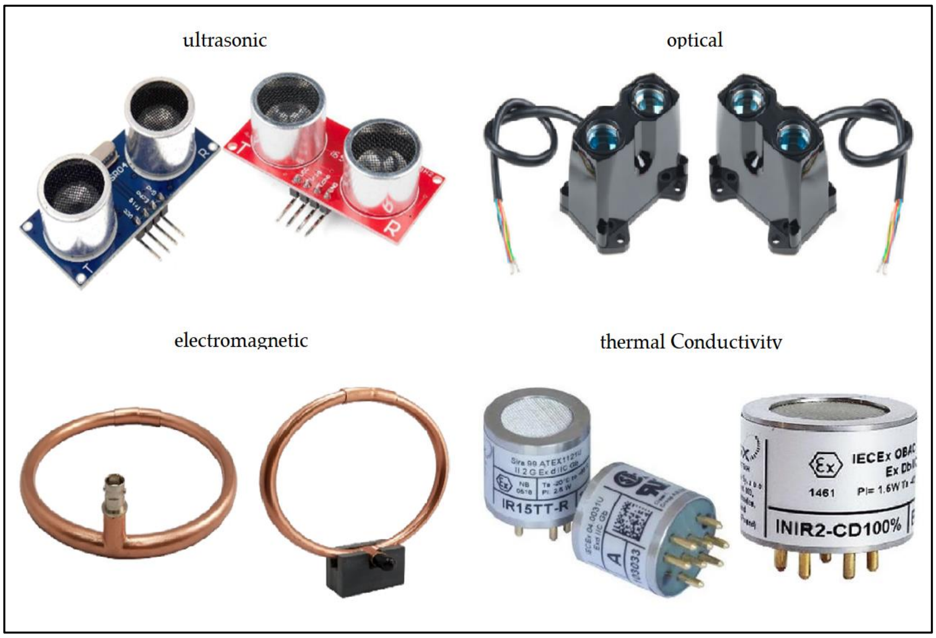

Figure 1. The general view of (ultrasonic-electromagnetic-optical-thermal Conductivity) sensors.

Table 3. The specifications of the HC-SR04 sensor.

Specification	Value
Operating Voltage	DC 5V
Operating Current	15mA
Operating Frequency	40KHz
Max Range	4m
Min Range	2cm
Ranging Accuracy	3mm
Measuring Angle	15 degrees
Trigger Input Signal	10μS TTL pulse
Dimension	45 x 20 x 15mm

Key strengths of the ultrasonic sensor in our gas leak detection project include:

- The sensor demonstrates high sensitivity to alterations in ultrasonic wave propagation, enabling effective detection of gas presence.
- As an ultrasonic sensor, it can detect gas leaks without physical contact with the gas, ensuring safety and versatility across various environments.
- The sensor provides real-time feedback, which is crucial for immediate detection and response to potential gas leaks.
- The sensor is cost-effective and easily integrated into larger systems, which is advantageous for comprehensive gas leak detection applications.
- The sensor functions effectively in diverse settings, including industrial environments, demonstrating its suitability for this project.

4.2. Electromagnetic Sensors:

Electromagnetic sensors play a crucial role in detecting disruptions in magnetic fields, indicative of gas leakages. These sensors are particularly effective in environments where gas leaks may alter the ambient electromagnetic fields. Their high sensitivity to such disturbances is critical for the early detection of leaks that might remain undetected by other sensor types. Table 4 shows the specifications of the SAS-560 sensor. Their capability to detect subtle changes in the electromagnetic field enables precise localization of gas leaks, facilitating timely and effective responses.

Table 4. The specifications of the SAS-560 sensor.

Specification	Value
Sensitivity	High
Frequency Range	DC to 18 GHz
Measurement Range	-60 dBm to 5 dBm
Connector Type	SMA Female
Impedance	50 Ohms nominal
Physical Dimensions	23.5 x 35.6 x 21.6 mm
Power Supply	6V to 18V DC
Operating Temperature	-40°C to +85°C

Key strengths of the electromagnetic sensor in our gas leak detection project include:

- Able to identify quantifiable changes in electromagnetic fields that could potentially be linked to gas leaks.
- Operates effectively across a broad spectrum of frequencies, ensuring comprehensive monitoring of potential disturbances.
- Exhibits consistent and dependable performance in diverse environmental conditions, such as variable temperatures and substantial electromagnetic interference.
- The low maintenance requirement ensures stable performance, making it suitable for long-term monitoring in various environments.

4.3. Optical Sensor:

Optical sensors are engineered with precision to detect variations in light that can indicate the presence of gases. These sensors are notable for their rapid response to optical changes in the environment, a crucial feature that facilitates the immediate identification of gas leaks. Table 5 shows the specifications of SparkFun SEN-15776 sensor.

By utilizing the principles of light absorption and scattering, these sensors effectively operate in environments where the presence of gas can alter the optical characteristics of the atmosphere.

Table 5. The specifications of the SparkFun's SEN-15776 sensor.

Specification	**Value**
Sensitivity	High
Detection Method	Light Absorption & Scattering
Response Time	<1 ms
Light Source و Detector	Infrared LED و Photodiode
Operating Voltage	3.3V to 5V DC
Communication Interface	I2C
Measurement Range	Up to 15 meters
Operating Temperature	-40°C to +85°C
Dimension	18.5 x 13.5 x 4.5 mm

Key strengths of the optical sensor in our gas leak detection project include:

- The sensor detects light changes in less than 1 millisecond, which is critical for immediate gas leak detection.
- It detects fluctuations in light patterns that can be attributed to the presence of various gases.
- Able to detect optical changes at distances up to 15 meters, providing extensive coverage for gas leak monitoring.
- Equipped with an I2C interface, the sensor facilitates smooth and reliable data transmission, essential for system integration and signal processing.
- These sensors operate effectively across a wide temperature range, broadening their applicability in various environmental conditions.

4.4. Amphenol SGX Sensortech VQ546M:

The thermal conductivity sensor (gas sensor) is designed to detect gas leaks through variations in the thermal properties of the surrounding environment. This sensor accurately identifies temperature fluctuations, making it a critical component of our comprehensive gas detection system. Table 6 shows the specifications of the VQ546M sensor. It operates by measuring the thermal conductivity of the air, which alters in the presence of gases, providing an indirect yet effective method for detecting leaks.

Table 6. The specifications of the VQ546M sensor.

Specification	**Value**
Sensing Principle	Thermal Conductivity
Operating Voltage	5V DC
Measurement Range	0-100% LEL
Response Time	<10 seconds
Output	Analog Voltage
Operating Temperature	-20°C to +50°C
Dimension	20.3 x 20.3 x 17.4 mm

Key strengths of the thermal conductivity sensor (gas sensor) in our gas leak detection project include:

- The sensor's optimal sensitivity to temperature variations allows it to detect gas leaks that modify thermal conductivity, a critical factor in identifying regions where gas concentrations impact thermal equilibrium.
- These sensors respond to gas leaks in minimal time, facilitating timely and efficient action.
- This sensor can detect gas concentrations at low levels and offers wide versatility in monitoring all types of industrial gas leaks.

- Its energy-efficient design ensures that the sensor can operate over extended periods, making it ideal for continuous, long-term monitoring systems.
- Engineered to perform within a wide temperature range, the sensor maintains consistent performance across diverse environmental conditions.
- Notably, the sensor can detect both hydrogen and helium gases, as its operation depends on thermal conductivity a property influenced by these gases. This capability allows the sensor to be utilized in various gas detection settings, where both safety and accuracy are paramount.

Figure 2 shows the process of calibrating the VQ546M sensor using a helium-based calibration tool. The corresponding output metrics for both sensors are systematically shown in Table 7. Data analysis shows that our sensor calibration maintains an error margin of less than 2%. This level of accuracy is considered quite satisfactory.

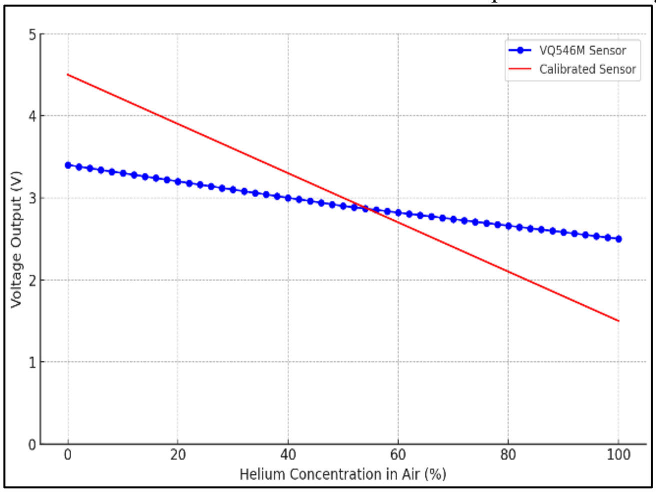

Figure 2. VQ546M sensor calibration.

Table 7. VQ546M sensor and calibration sensor output.

Helium Concentration (%)	VQ546M Sensor Output(V)	Calibrated Sensor Output(V)	Calibration offset (%)
0	3.4	4.499	0.19
10	3.3	4.299	0.06
20	3.2	4.098	0.15
30	3.1	3.897	0.13
40	3	3.698	0.05
50	2.9	3.496	0.14
60	2.82	3.216	0.12
70	2.74	3.036	0.11
80	2.66	2.855	0.14
90	2.58	2.675	0.14
100	2.5	2.495	0.17

4.5. Algorithm:

By employing an algorithm that is developed to combine and evaluate data from a multi-sensor array, our research ensures dependable gas leak detection, with a verified accuracy rate of 94% during testing. Figure 3 shows the gas leak detection system workflow. The procedure can be broken down into many important stages:

- Data Collection: In the initial stage, each sensor in the array (PCS HC-SR04, SAS-560, SEN-15776, and VQ546M) collects environmental data. This includes measurements related to ultrasonic waves, electromagnetic fields, optical variations, and thermal conductivity.
- Data Preprocessing: Once collected, the data undergoes preprocessing. This step filters out noise and normalizes the data, making it consistent and suitable for analysis. Preprocessing is crucial to improve the accuracy of the subsequent analysis and sensor fusion.
- Sensor Fusion: At this stage, the preprocessed data from all the sensors is integrated. Sensor fusion combines the strengths of each sensor type, creating a more comprehensive dataset. This integration enables

the detection system to capitalize on the unique capabilities of each sensor, enhancing the overall sensitivity and reliability of the detection process.

- Data Analysis: Following the fusion of the data, an advanced analysis is performed on it. At this stage, a mix of statistical techniques, pattern recognition, and machine learning algorithms may be applicable. The purpose of this endeavor is to recognize patterns and irregularities that are suggestive of gas leaks. The accuracy of machine learning models improves over time through training on previous data. This occurs when these models are employed.
- Leak Detection: In the final step, the system interprets the analyzed data to identify potential gas leaks. If anomalies matching the characteristics of gas leaks are detected, the system flags them, providing details such as location, severity, and probable gas type. This enables timely and targeted responses to the detected leaks.

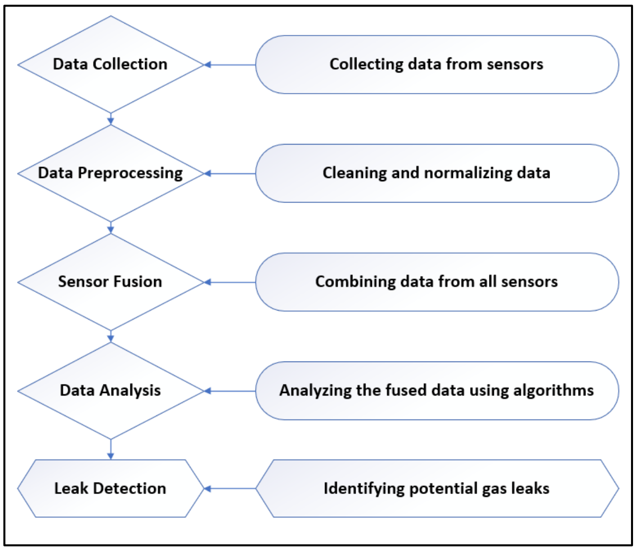

Figure 3. Gas Leak Detection System Workflow.

4.6. System Integration Diagram:

One of the most significant components of our work is the combination of several sensors into a cohesive gas detection system. This is one of the most crucial aspects. For the aim of displaying this, a System Integration Diagram is utilized. This diagram provides a visualization of the architecture of the system that is distinct and easy to comprehend. The purpose of this image is to highlight the several ways in which the sensors are connected and to describe the way they communicate with the central processing unit. The information collected by each sensor is transmitted to a central processor, which is subsequently tasked with the responsibility of combining and interpreting collected data. The diagram also highlights the flow of information from the stage of data collection up to the final output, which includes leak detection warnings and potentially actionable insights. Figure 4 shows the gas detection system integration diagram. This flow of information is represented in the graphical representation.

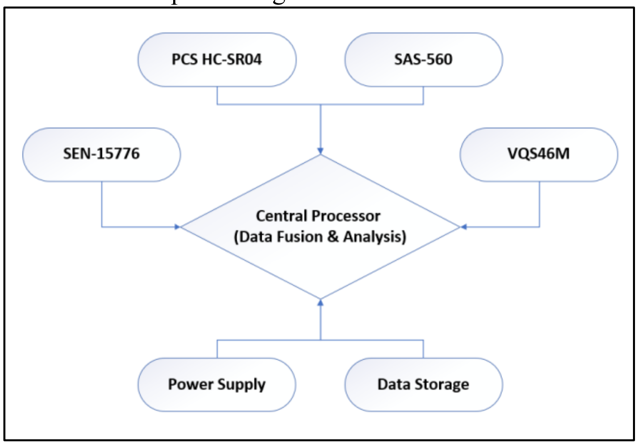

Figure 4. Gas detection system integration diagram.

4.7. Experimental Setup Illustration:

This section outlines the experimental configuration used in our research, which focuses on developing a sensor system for detecting gas leaks. Our setup includes a chamber specifically designed to study gas dispersion under controlled conditions, maintaining the internal pressure at 1 atmosphere to reflect typical environmental scenarios. Figure 5 illustrates our setup, highlighting the complexity and key components fundamental to our experimental strategy. Within this setup, various sensors—electromagnetic, ultrasonic, optical, and thermal conductivity—are strategically placed to optimize detection efficiency. The electromagnetic sensor is affixed to the inner wall of the chamber to monitor magnetic field disturbances, while the other sensors are situated atop the chamber to effectively capture a broad spectrum of gas dispersion patterns. All sensors are connected to a central processing unit that utilizes advanced deep-learning algorithms to analyze the extensive data collected. This software infrastructure is designed to detect subtle patterns and anomalies in the data that could indicate gas leaks. The system's capability to process this information in real-time enhances its responsiveness and effectiveness in mitigating potential hazards.

Moreover, the system includes gas release mechanisms that accurately simulate helium leaks, facilitating thorough testing of the sensor's performance under various conditions. It also features a comprehensive monitoring system that observes environmental conditions and gas behavior, ensuring all pertinent variables are accounted for during tests. Essential safety mechanisms are implemented to ensure the secure transport and handling of gases within the test environment, including a specific mechanism for gas injection. This configuration not only verifies the accuracy and reliability of our measurements but also improves the overall functionality and safety of the detection system.

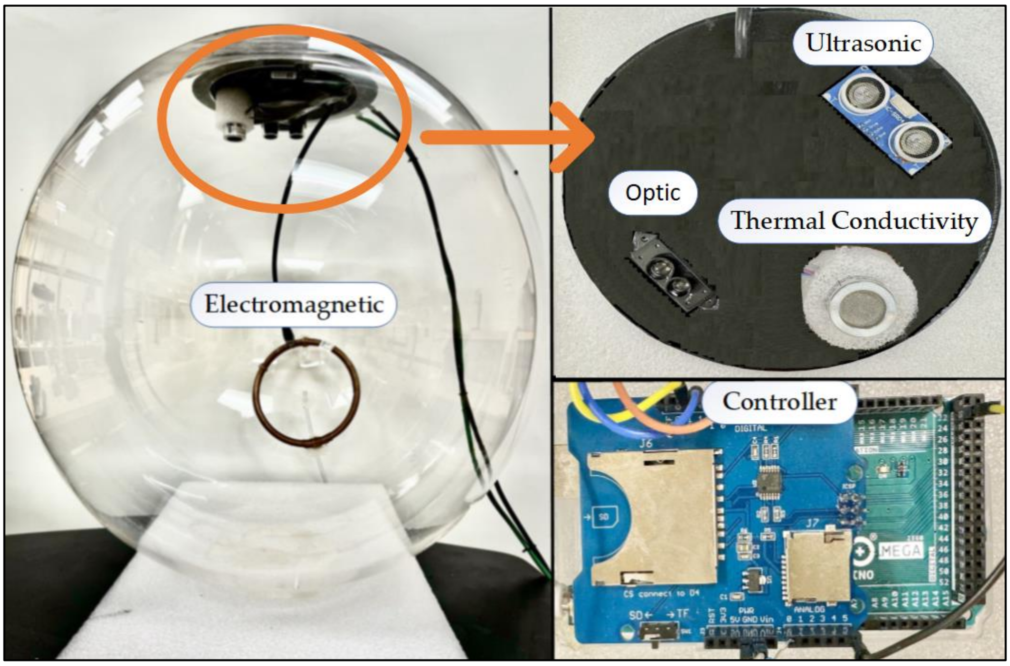

Figure 5. Overview of settings and test environment.

4.8. Measurable Outputs:

Figure 6 illustrates the initial testing phase of our sensor array and presents the preliminary detection results. This figure displays the raw data output from each sensor, encompassing both detection signals and observed errors during the tests. In this phase, helium gas was systematically introduced into the system at various levels and concentrations to simulate real conditions.

Changes in data values are more valuable than the absolute values themselves. The sensors do not directly detect leakage but monitor and analyze fluctuations in the collected data to indicate the presence of a leak. variations in the output of any sensor suggest sensor errors, which must be filtered out to reveal the true data. This filtering is crucial to differentiate between actual leakage signals and noise, ensuring accurate detection and analysis.

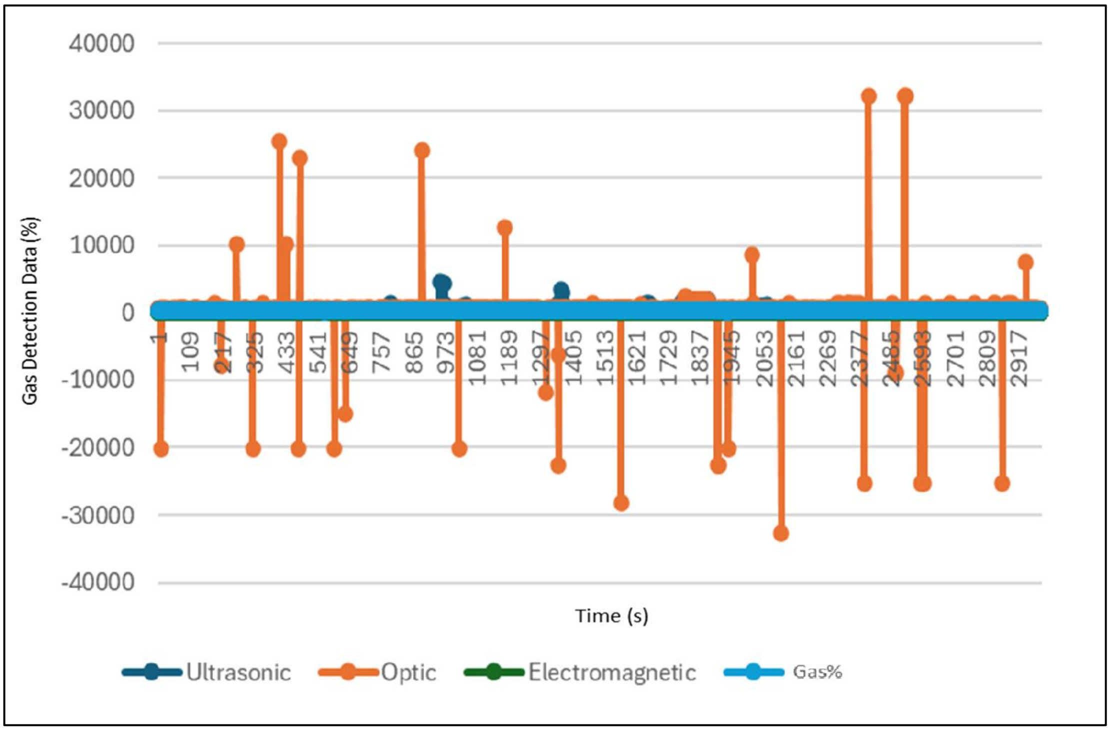

Figure 6. The initial assessment of gas-detecting sensors.

LSTM models are utilized in this research due to their ability to process time series data and maintain long-term dependencies, which is important for gas leak detection systems requiring continuous sensor data analysis.

Compared to traditional machine learning models, LSTMs can better recognize complex patterns and temporal changes, enhancing detection accuracy.

The working method of the LSTM model is as follows:

- Data Collection: Data from various sensors (ultrasonic, electromagnetic, optical, and thermal conductivity) are fed into the LSTM model.

- Data Preprocessing: The data undergoes preprocessing to filter out noise and normalize it.

- Model Training: The LSTM model is trained on extensive datasets of sensor readings and gas leak incidents, using LSTM neural networks to learn long-term dependencies in the data.

- Leak Detection: The LSTM model analyzes temporal patterns and examines the sensor data to accurately detect gas leaks.

For the above reasons, we employed a deep learning model with LSTM networks to enhance the accuracy of sensor data. This method effectively differentiates between actual sensor detections and errors, facilitating precise error identification.

The LSTM model, trained on comprehensive datasets, identifies relevant patterns and noise, enabling the isolation and elimination of distortive data.
Figure 7 shows the sensor output under normal conditions. Due to stable environmental conditions, the sensor output data typically remains below 5 percent, indicating natural levels of helium gas. This implies that no specific detection has occurred, reflecting natural conditions and the absence of gas leaks. LSTM model, architecture handles the dynamics of gas sensor responses, considering various environmental influences.

The LSTM model tracks long-term dependencies crucial for analyzing temporal changes in gas dispersion, achieving a detection accuracy of 94%.

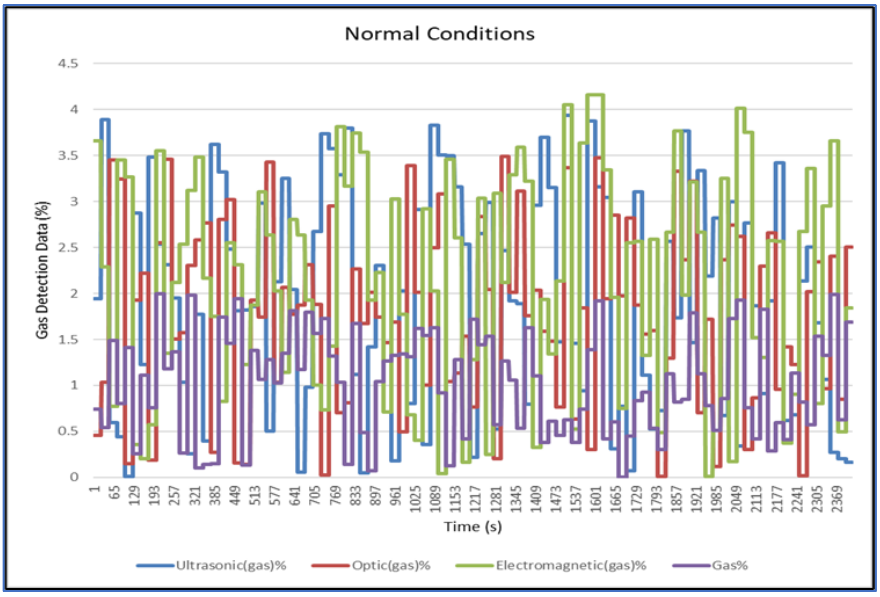

Figure 7. Sensor Output in Typical Conditions**.**

Figure 8 shows the cumulative detection of the sensors, accurately reflecting the output data from each sensor. The source of these changes is the direct impact of helium gas at various concentrations on the sensor outputs, which is displayed in different charts for each sensor according to its sensitivity to the detected gas. This data is obtained after separating noise and errors from the sensor data using LSTM. Table 8 provides a detailed comparison of the performance metrics for the LSTM model before and after the application of noise reduction and data preprocessing techniques. These metrics are for evaluating the effectiveness of the LSTM model in accurately detecting gas leaks, and these metrics include accuracy, mean squared error (MSE), precision, recall, and F1-score. Each of these metrics serves a specific purpose in assessing different aspects of the model's performance.

- **F1 Score:** The F1 score is a criterion for measuring the accuracy of a test. It considers both precision and recall of the test to calculate the score. The F1 score is the harmonic mean of precision and recall, where the F1 score reaches its best value at 1 (indicating perfect precision and recall) and its worst value at 0.
- **Recall (Sensitivity):** Recall, also known as sensitivity, is the ratio of correctly predicted positive observations to all observations in the actual class. A high recall indicates that the class is correctly recognized (with a small number of false negatives), whereas a low recall means that the class is often missed.
- **Precision:** Precision is the ratio of correctly predicted positive observations to the total predicted positives. High precision indicates that an algorithm returns more relevant results than irrelevant ones.
- **Accuracy:** Accuracy is a metric used to evaluate the performance of a classification model. It is the ratio of the number of correct predictions to the total number of predictions made. Accuracy measures the overall effectiveness of a model in correctly predicting classes.
- **Mean Squared Error (MSE):** Squared Error (MSE) is a measure used to evaluate the performance of a regression model. It calculates the average of the squares of the errors—that is, the average squared difference between the predicted values and the actual values. MSE quantifies the difference between the predicted values and the actual values, with lower values indicating better model performance. It is sensitive to outliers since it squares the errors, giving more weight to larger errors.

The results in Table 8 show significant improvements in these metrics after applying the LSTM model. For instance, Accuracy increased from 72% to 94%, and MSE decreased from 0.25 to 0.06, indicating enhanced predictive performance. Precision and Recall values also saw notable improvements, resulting in a higher F1-Score. These enhancements demonstrate the LSTM model's capability to effectively handle and analyze complex sensor data, leading to more accurate and reliable gas leak detection.
The final phase involves calibrating each sensor against an accurate gas sensor to ensure uniformity and alignment in gas presence measurements, The details of this sensor are given in Section 4.4 and Figure 2, and this sensor was chosen because of its precise calibration and provides a reliable standard for comparison. As shown in Figure 9, the outputs of the various sensors are compared with the gas sensor's readings. The changes in the sensor output align exactly

with the times when the gas sensor detects the presence of gas. These variations indicate the presence of gas, and the magnitude of these changes corresponds to different gas concentrations. With the increase in gas concentration detected by the gas sensor, the number of changes in the output of each sensor changes, this change depends on the sensitivity of each sensor to gas. The combined results of all the sensors together lead to accurate gas detection.

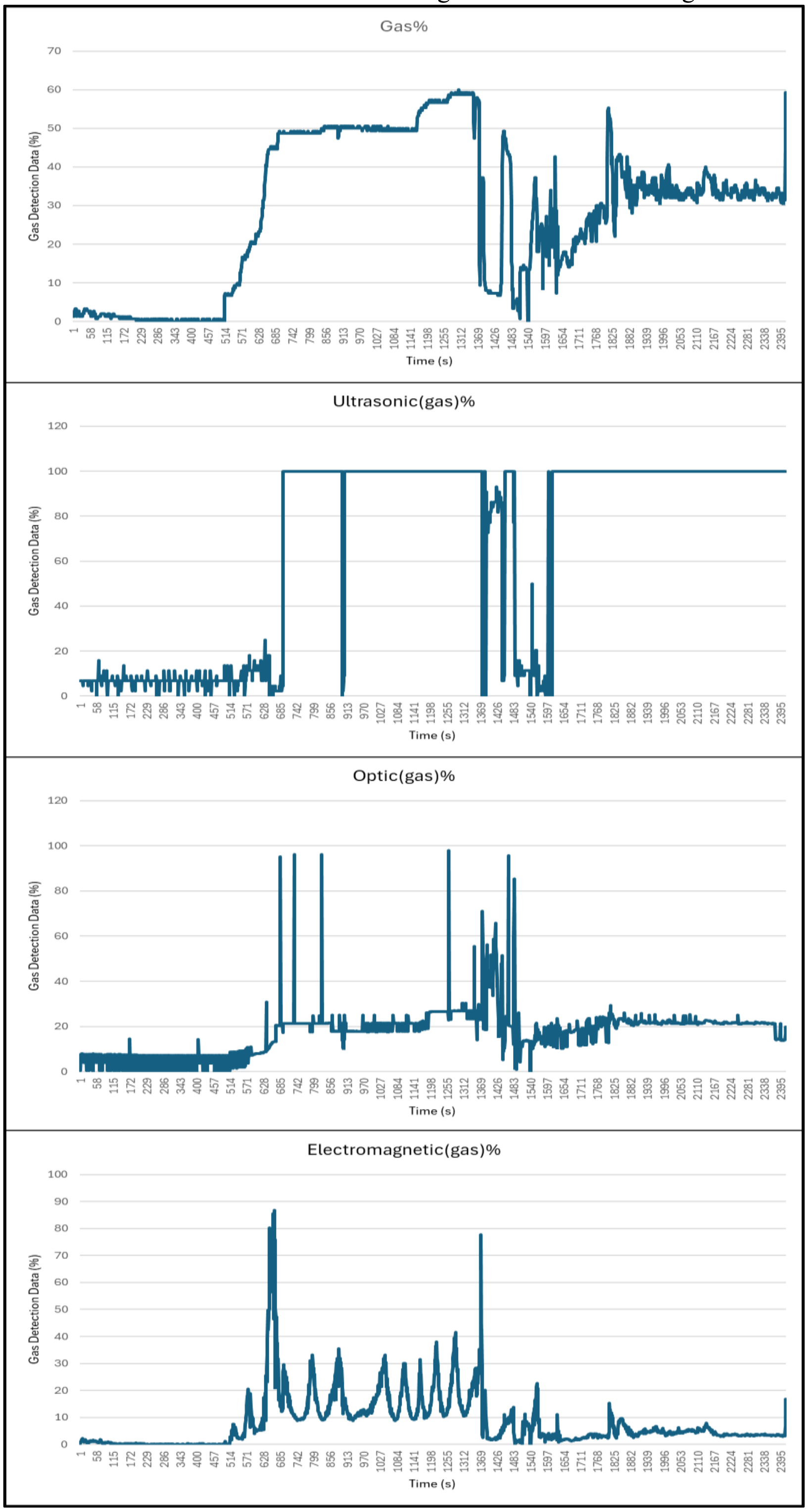

Figure 8. Gas detection by each sensor.

Table 8. Training table (deep learning).

Epoch	Iteration	Time Elapsed (h:m:s)	Mini-batch RMSE	Mini-batch Loss	Base Learning Rate
1	100	00:30:00	0.35	0.50	0.01
2	100	01:00:00	0.30	0.45	0.01
3	100	01:30:00	0.25	0.40	0.01
4	100	02:00:00	0.20	0.35	0.005
5	100	02:30:00	0.18	0.30	0.005

Evaluation Metric	Raw and raw data with noise	Data after LSTM
Accuracy	72%	94%
Mean Squared Error (MSE)	0.25	0.06
Precision	70%	91%
Recall	75%	90%
F1-Score	0.72	0.91

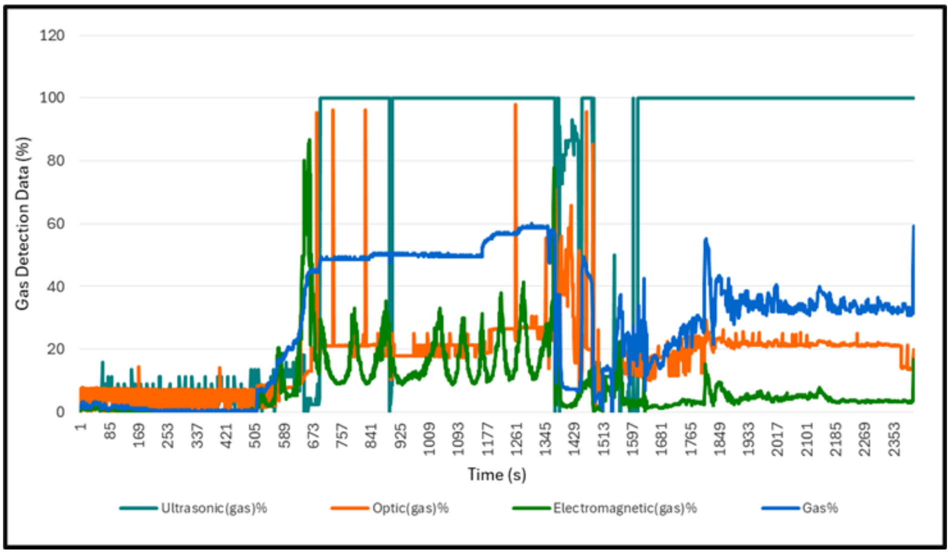

Figure 9. Gas detection by system.

V. Conclusion

This study focuses on gas leak detection using a multi-sensor array in conjunction with deep-learning algorithms. To detect gas leaks with an accuracy rate of 94%, this system uses thermal conductivity sensors, electromagnetic, optical, and ultrasonic sensors, and the analytical power of Long Short-Term Memory (LSTM) networks. As a result of real-time data processing and testing with helium at different concentrations and time intervals, the sensors have shown they can detect gas concentrations of 5% and more. To maintain a regulated and safe testing environment, we replaced hydrogen in our studies with helium. Integration of LSTM led to a considerable improvement in performance measures, as seen in Table 8. In addition to offering a scalable and dependable method for accurate and quick leak detection, this study has promising implications for other industrial domains.

Our Future work will focus on refining deep learning algorithms to increase their efficiency in real-time applications, potentially reducing the time needed for data processing while maintaining high accuracy levels.

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