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Hazardous Gas Monitoring System Using AI and IoT Technology

P. Kalaivani[1], D. Pavithra[2], R. Bhuvaneswari[3], M. Nivetha[4], S. Pavithra[5]
[1]*Assistant Professor, Department of Electronics and Communication Engineering, Salem College of Engineering and Technology, Salem, Tamil Nadu, India – 636111.*
[2,3,4,5] *UG Students, Department of Electronics and Communication Engineering, Salem College of Engineering and Technology, Salem, Tamil Nadu, India–636111.*

***Abstract*—Over the past few years, the challenge has been the more extensive leakage of hazardous gases. Gas leakage can be easily predicted using the Internet of Things (IoT), but the accuracy of the prediction process is low. To address the problems associated with Convolutional Neural Networks (CNN), the early detection of gas leakage levels and hazardous gases offers more accurate performance. Furthermore, data preprocessing techniques aim to eliminate duplicate data, minimize unknown data, and maximize valuable data during preprocessing, which are crucial steps. Additionally, the Support Vector Machine (SVM) focuses on selected network connections within the processes, addressing each data type for a more accurate representation of performance. Moreover, the Decision Tree (DT) process involves selecting related features from the margin, which has a hierarchical tree structure, and analyzing the range levels in performance. Finally, the proposed method determines that early prevention in the gas leakage process is optimal for the weight rate, while long-term secure level testing is performed. Data transmission processes involve synchronous and asynchronous mechanisms, which measure the leak size, gas type, and surrounding conditions; these are evaluated for testing and validating the gas leakage prediction data. The process is more reliable, exhibiting a high level of performance, and the presented method maintains the standard scalability of the process. The proposed techniques reduce time complexity and low power consumption, with performance remaining within an accurate range of 92%.**

***Keywords*— Convolutional Neural Networks (CNN), Internet of Things (IoT), Decision Tree (DT), Support Vector Machine (SVM), Data Preprocessing Technique.**

I. INTRODUCTION

The gas monitoring for taxis is utilized in the Internet of Things (IoT); it measures water levels and various types of toxic gases to detect leaks early [1]. The presented method includes various sensors controlling the set points, and it classifies temperature, humidity, water level, and gas leakage levels in performance. The evaluated value is unknown for the gas, and it identifies mismatching data to predict the unpredictability of the values. Data collection predicts valuable information, and more clearly, the data in the techniques. It focuses on continuous monitoring, reduces signal noise frequency, and builds a strong network connection of each data performance [2]. The present method is addressed in the valuable point, to detect unintended space, and to require interpretable data. The sensor is used to detect or prevent gas leakage and water leakage, and other levels of the process. The hazardous gas is monitored and detected using the proposed method, a helmet-mounted system designed to detect toxic and dangerous gases during operations. The data transmission quickly responds to the situation to provide alerts to the workers and ensure a secure process. It identifies the water issue in different elements, such as the sewage and piping systems [3]. The Data Acquisition (DAQ) system measures the sensor signals, covering amplification, filtering, and process adjustment. Industrial automation and gas integration enable the security of automated performance. The various IoT methods handle critical situations, and multitasking is completed within specific times. The proposed techniques are suitable for any application, always maintaining the security of the overall performance time. Monitoring toxic gases poses significant challenges due to the limited measurement range in IoT applications. Current techniques, however, lack data transparency, and various environmental factors affect performance [4]. The different types of sensors for gas leakage detection are costly and hinder overall performance. These costs require more time and allow for a broader range of precision while automatically detecting increases in power consumption and frequent signal issues. Limitations concerning flammable gas ranges and a lack of selectivity in these techniques lead to increased e-waste, potential compatibility issues, data security risks, and a restricted dynamic range [5]. The presented methods are sometimes an issue of the systematic approach, and sudden environmental changes in the process slow down the level of predictive performance. The main contribution involves selecting related features from the margin with a hierarchical tree structure and analyzing the range of performance levels. Applying the collected value to selected network connections within the processes focuses on each data type for a more accurate representation of performance. It detects the object for point and size, calculates the one-sample error rate, classifies the data, and predicts the misclassification data for both processes.

II. LITERATURE SURVEY

According to the automated system, unknown gases are identified based on various sensors, each tailored for specific gas types, addressing issues despite its limited accuracy [6]. This method emphasizes detecting harmful pollution levels, while the variations highlight unique environmental characteristics of each site and the required safety precautions. However, the process lacks reliability, and communication relies on complicated techniques. The software and hardware system identifies harmful gases, though it lacks consistency in recognizing gas types. It primarily targets detecting more toxic gases generated during operation, but frequently indicates occurrences of the respective techniques [7]. The suggested approach incorporates the Internet of Things (IoT) to address the signaling challenge, facilitating the identification of unknown gases and mitigating unpredictable fluctuations in temperature and humidity during operation. However, this approach suffers from a lack of transparency and involves high computational expenses.

The optical fiber gas sensors measure temperature, humidity, and key factors ensuring safety in the coal mine tunnel process. Assurance of performance and data transmission is helpful for intelligent operation under the sewage and coal mine process, but it does not maintain standard performance stability [8]. The proposed method is an IoT aimed at reducing signal issues and focusing on stability, enhancing overall performance. However, the process is more energy-consuming, and more e-waste is generated from these techniques.

Conventional colorimetric gas sensors detect color changes and are easy to operate. They focus on specific analytes through chromogenic reactions. However, they have limited sensitivity, detection capabilities, and irreversible reactions [9]. The proposed method utilizes IoT gas sensor technology to enhance early detection of various types of gas and minimize irreversible reactions. Nevertheless, the process has limitations regarding flammable gas ranges and lacks selectivity in the techniques. Nanotechnology is developing gas sensors for small applications; its focus on the diligent monitoring and management of these gases is of profound importance, as are the Economic Impacts and Ethical and Social Concerns [10]. The proposed method utilizes a wireless sensor network for monitoring and multihop communications, with wired sensors installed in strategic locations. However, the process has a limited range and potential security vulnerabilities with the technology.

Liquefied petroleum gas (LPG) is a component used in wireless sensor networks (WSN), as well as in hardware and software for early warning gas leakage detection and monitoring applications. However, its range and connectivity are limited [11]. The proposed method operates in both single-hop and multihop modes, and the data acquired from various experiments are used to examine the system's robustness and data delivery reliability. However, the process encounters scalability challenges and a limited range with the techniques. Mechanization offers an energetic and ecological solution to the issue of organic waste treatment. It focuses on reducing gas pollution from fermentation by a factor, addressing the complexity of implementation, and enhancing flexibility [12]. The proposed method utilizes IoT to detect biogas and improve performance reliability. However, the process is sensitive to environmental factors and has a limited dynamic range. The real-time helmet-mounted system measures primary toxic gases and detects temperature and humidity, analyzing continuous monitoring of poisonous gases and alerting workers. However, the presented method has component limitations and systematic performance issues [13]. The proposed method is an IoT application for various sensors to detect more toxic gases in critical locations for early prevention. However, the process involves interoperability, complexity, and minimum required limit techniques.

The Sewage Wastewater Monitoring System (SSWMS) is intended to oversee wastewater and improve water quality. It analyzes water quality, pressure, and temperature while quantifying hydraulic dynamics to trace flow across the treatment facility, highlighting higher costs and potential delays [14]. The proposed method of industrial automation involves control systems for the sensors and monitoring performance, with automated systems responding to gas leaks for the proposed methods. However, this process relies on technology and presents reduced flexibility. The automatic monitoring system used for the early detection and prediction of gas levels analyzes water quality monitoring models using sensors. However, the presented method has low reliability and high time complexity [15]. The proposed method is a Data Acquisition (DAQ) system; real-time data is converted into digital data if called and measured in the physical parameters, and the collection of hardware and software. However, the process has potential compatibility issues and data security risks related to the techniques.

III. PROPOSED METHODOLOGY

The section identifies unknown information and minimizes the maximum data to normalize the process. Its initial data is correctly normalized for performance. Applying the value called selected network connections within the processes focuses on each data type for a more accurate representation of performance. The process involves choosing related features from the margin, which has a hierarchical tree structure, analyzing the level of the range in performance, calculating the one-sample error rate, classifying the data, and predicting the misclassification data for both processes.

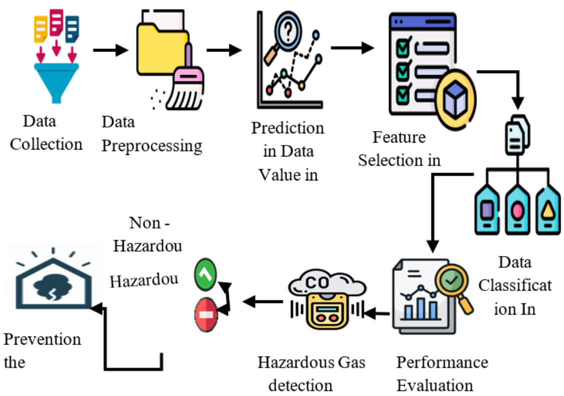
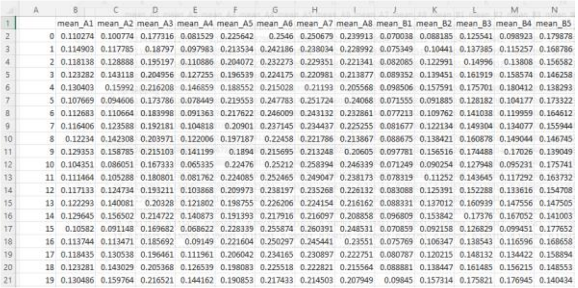


Fig. 1 Hazardous Gas Detection in CNN

Fig 1 is a hierarchical tree structure that analyzes the range level of performance. It calculates the one-sample error rate, classifies the data, and predicts the misclassification data for both processes.

A. Dataset Description

The section is a hazardous gas collected value selected from network connections within the processes that focus on each data type for a more accurate representation of performance. The process involves choosing related features from the margin, which has a hierarchical tree structure, and analyzing the range level of performance. It calculates the one-sample error rate, classifies the data, and predicts the misclassification data for both processes.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1		mean_A1	mean_A2	mean_A3	mean_A4	mean_A5	mean_A6	mean_A7	mean_A8	mean_B1	mean_B2	mean_B3	mean_B4	mean_B5
2	0	0.110274	0.100774	0.177316	0.081529	0.225642	0.2546	0.250679	0.239913	0.070038	0.088185	0.125541	0.098923	0.179878
3	1	0.114903	0.117785	0.18797	0.097983	0.213534	0.242186	0.238034	0.228992	0.075349	0.10441	0.137385	0.115257	0.168786
4	2	0.118138	0.128888	0.195197	0.110886	0.204072	0.232273	0.229351	0.221341	0.082085	0.122991	0.14996	0.13808	0.156582
5	3	0.123282	0.143118	0.204956	0.127255	0.196539	0.224175	0.220981	0.213877	0.089352	0.139451	0.161919	0.158574	0.146258
6	4	0.130403	0.15992	0.216208	0.146859	0.188552	0.215028	0.21193	0.205568	0.098506	0.157591	0.175701	0.180412	0.138293
7	5	0.107669	0.094606	0.173786	0.078449	0.219553	0.247783	0.251724	0.24068	0.071555	0.091885	0.128182	0.104177	0.173322
8	6	0.112683	0.110664	0.183998	0.091363	0.217622	0.246009	0.243132	0.232861	0.077213	0.109762	0.141038	0.119959	0.164612
9	7	0.116406	0.123588	0.192181	0.104818	0.20901	0.237145	0.234437	0.225255	0.081677	0.122134	0.149304	0.134077	0.155944
10	8	0.12234	0.142308	0.203971	0.122006	0.197187	0.22458	0.221786	0.213867	0.088675	0.138421	0.160878	0.149044	0.146745
11	9	0.129353	0.158785	0.215103	0.141199	0.1894	0.215695	0.213248	0.20605	0.097781	0.156516	0.174488	0.17026	0.139049
12	10	0.104351	0.086051	0.167333	0.065335	0.22476	0.25212	0.258394	0.246339	0.071249	0.090254	0.127948	0.095231	0.175741
13	11	0.111464	0.105288	0.180801	0.081762	0.224085	0.252465	0.249047	0.238173	0.078319	0.11252	0.143645	0.117292	0.163732
14	12	0.117133	0.124734	0.193211	0.103868	0.209973	0.238197	0.235268	0.226132	0.083088	0.125391	0.152288	0.133616	0.154708
15	13	0.122293	0.140081	0.20328	0.121802	0.198755	0.226206	0.224154	0.216162	0.088331	0.137012	0.160939	0.147556	0.147505
16	14	0.129645	0.156502	0.214722	0.140873	0.191393	0.217916	0.216097	0.208858	0.096809	0.153842	0.17376	0.167052	0.141003
17	15	0.10582	0.091148	0.169682	0.068622	0.228339	0.255874	0.260391	0.248531	0.070859	0.092158	0.126829	0.099451	0.177652
18	16	0.113744	0.113471	0.185692	0.09149	0.221604	0.250297	0.245441	0.23551	0.075769	0.106347	0.138543	0.116596	0.168658
19	17	0.118435	0.130538	0.196461	0.111961	0.206042	0.234165	0.230897	0.222751	0.080787	0.120215	0.148132	0.134422	0.158894
20	18	0.123281	0.143029	0.205368	0.126539	0.198083	0.225518	0.222821	0.215564	0.088881	0.138447	0.161485	0.156215	0.148553
21	19	0.130486	0.159764	0.216521	0.144162	0.190853	0.217433	0.214503	0.207949	0.09845	0.157314	0.175821	0.176945	0.140434

Fig. 2 Hazardous Gas Prediction Dataset

Fig 2 detects the object by point and size, calculates the one-sample error rate, classifies the data, and predicts the misclassification data for both processes. The collected value selects network connections within the processes, focusing on each data type for a more accurate representation of performance.

B. Data-preprocessing Technique (DPT)

The section collects data, identifies unknown information, and minimizes the maximum amount of data to normalize the process. Its initial data is correctly normalized for performance, making data reading more accurate in detecting missing data in the process.

Equation 1 is an identity that uncovers the unknown data, predicts the missing data, and provides an unpredictable process value. Let's assume the Z prediction data.

$$z_c^{pqs}(n) = \frac{z_c^{pqs}(n)}{\sqrt{\sum_{j=1}^{i} z_c^{pqs}(n)^2}} \qquad (1)$$

Equation 2 calculates the minimum and maximum data, with the minimum representing unnecessary space data while correctly maximizing the performance value. Let us assume the $\mu_e - min - \max\ range$.

$$\mu_e = \sqrt{\frac{1}{x_y}} \sum_{j=1}^{i} \left(z_c^{pqs}(n) - \sigma_n\right)^2 (\min - max) \qquad (2)$$

Equation 3 measures all kinds of data, which are normalized and called data for verification. It tests each individual's proposal on performance. Let us assume the $\mu_t - testing\ range$.

$$\mu_t = \sqrt{\frac{1}{x_y}} \sum_{j=1}^{i} \left(z_c^{pqs}(n) - \sigma_t\right)^2 \quad (3)$$

C. Support Vector Machine (SVM)

The section measures the prediction in each data type and detects the process rate. This allows us to test and analyze the data in comparison with the dataset. The application of the collected value selected network connections within the processes focuses on each type of data for a more accurate representation of performance.

Equation 4 is a collection of data that measures the equalizer of performance and calculates the correct process production. Let's assume the XY − total number of input variables.

$$XY = \frac{z_{correct}}{z_{total}} \quad (4)$$

Equation 5 measures the error type and calculates the data's misclassification to determine the average model prediction and the $pq - prediction\ of\ values$.

$$\frac{1}{pq} \sum_{i=0}^{p} \sum_{j=0}^{q} |x_{ij} - x_{pred,}ij| \quad (5)$$

Equation 6 is a calculation in the prediction for zero-valued targets and dataset compression between 0 and 1 measures each type of data process.

$$\frac{1}{pq_{non-zero}} \sum_{i=0}^{p} \sum_{j=0}^{q} \frac{|x_{ij} - x_{pred,}ij|}{x_{ij}} \quad (6)$$

Equation 7 predicts non-zero-valued targets, and the dataset compression between 0 and 1 measures each type of classification data processing.

$$\frac{1}{pq_{zero}} \sum_{i=0}^{p} \sum_{j=0}^{q} |x_{ij} - x_{pred,}ij| \quad (7)$$

D. Decision Tree in Feautre Selection Algorithm

The section analyzes decision-making, making the outcomes more predictable. It's based on machine learning for more accurate feature selection while calculating the gain ratio. The process involves selecting related features from the margin, which has a hierarchical tree structure, and analyzing the level of the range in performance.

Equation 8 is a problem-solving process, and various factors are involved in selecting the correct features and analyzing the range in performance.

$$\sum_{j=1}^{m} -s(p_i)\, log_2 s(p_i) \quad (8)$$

Equation 9 calculates the gain ratio and selected related features of the margin in the process, which has a hierarchical tree structure consisting of a root node, branches, internal nodes, and leaf nodes.

$$Gain(q) = T\left(\frac{q}{q+m}, \frac{m}{q+m}\right) - \sum_{j=1}^{m} \frac{q_{j+}m_i}{q+m} \times T \quad (9)$$

Equation 10 assesses the margin for detecting gas leakage within a specified performance range and determines the overall gas leakage level in the prediction process.

$$x = -\sum_{j=1}^{m} \frac{q_{j+}m_i}{q+m} log_2\left(\frac{q_{j+}m_i}{q+m}\right) \quad (10)$$

E. Convolutional Neural Network (CNN)

This section determines the natural language process and identifies the low-level performance features. It detects the object for point and size, calculates the one-sample error rate, classifies the data, and predicts the misclassification data for both processes.

As described in Equation 11, estimate a function by assuming a gas level check at the high level in the fully connected function. Let's take the z-threshold weight.

$$d = z_c \quad (11)$$

Calculate the error between the predicted and actual values, measured in the medium as shown in Equation 12. Let's assume M-Error, M_e −estimated value.

$$M_e = \frac{\left|\sum_{j=1}^{F-1} (y_j - \textcircled{o}_j)^2\right|}{F-1} \quad (12)$$

Calculate the one-sample error rate; low level is a measure, as shown in Equation 13M_x, where M_x is the error percentage.

$$M_x = \frac{\textcircled{o}_j - y_j}{y_j} \times 100\% \quad (13)$$

Estimate the normalization process as shown in equation 14. It measures the overall range of performance.

$$y_j = \alpha \frac{y_j - y_{min} + \beta}{y_{max} - y_{min} + \beta} \quad (14)$$

IV. RESULTS AND DISCUSSION

This section evaluates the precision, recall, accuracy, time response, and FN score across various parameters and approaches. Furthermore, the proposed method can use data transmissions for IoT technology, with 10051 data points in the attack dataset.

Table. 1 Simulation Parameter

Simulation	Parameter Name
Dataset Name	Hazardous Gas Detection Dataset
No of Dataset	17922
Training Dataset	10000
Testing Dataset	7922
Language	Python

As illustrated in Table 1, the simulation parameters were evaluated through 17922 data collected in the feature selection process. 10000 is a training dataset for the process, and 7922 is a testing dataset.

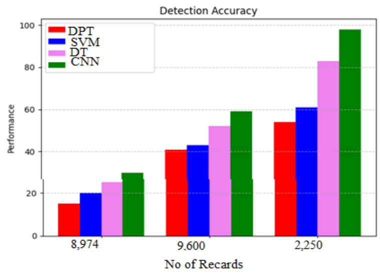


Fig. 3 Analysis of Accuracy

Fig 3 illustrates using accuracy analysis for secure health data exchange through IoT technology. This review assesses previous methods, including DPT, SVM, and DT, and contrasts them with the proposed CNN data method. The precision levels of the performance ratings for these methods are 85.6, 89.9, and 99.2, respectively, for the various performance levels in data protection.

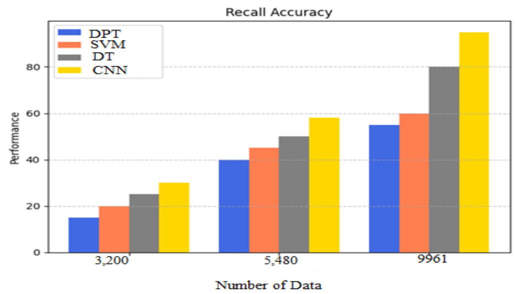


Fig. 4 Analysis of Recall

Fig 4 illustrates using recall analysis for secure health data exchange through IoT technology. This review assesses previous methods, including DPT, SVM, and DT, and contrasts them with the proposed CNN data method. The precision levels of the performance ratings for these methods are 85.6, 89.9, and 99.2, respectively, for the various performance levels in data protection.

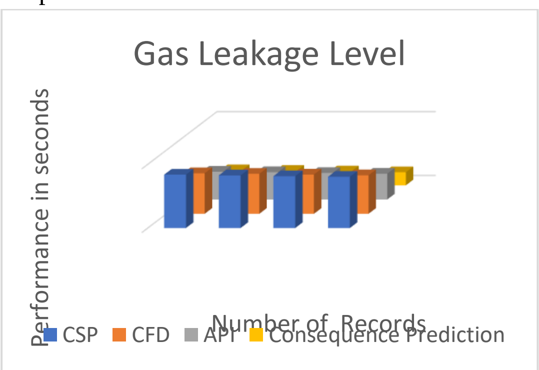


Fig. 5 Analysis of Gas Leakage Level

Fig 5 illustrates using time response analysis for secure health data exchange through IoT technology. This review assesses previous methods, including DPT, SVM, and DT, and contrasts them with the proposed CNN data method. The precision level of the performance ratings for these methods is 4.05, 3.67, 2.98, and 1.50, respectively, for the various performance levels in data protection.

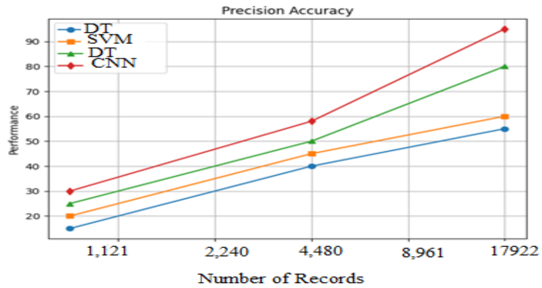


Fig. 6 Analysis of Recall

Fig 6 illustrates using performance analysis for secure health data exchange through IoT technology. This review assesses previous methods, including DPT, SVM, and DT, and contrasts them with the proposed CNN data method. The precision levels of the performance ratings for these methods are 85.6, 89.9, and 99.2, respectively, for the various performance levels in data protection.

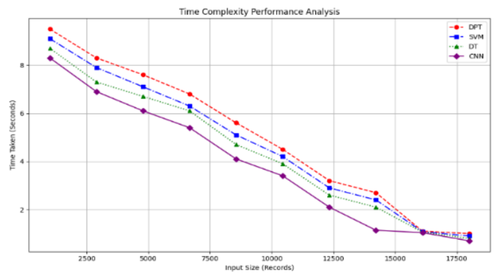


Fig. 7 Analysis of Time Complexity

Fig 7 illustrates using time complexity analysis for secure health data exchange through IoT technology. This review assesses previous methods, including DPT, SVM, and DT, and contrasts them with the proposed CNN data method. The precision level of the performance ratings for these methods is 4.05, 3.67, 2.98, and 1.50, respectively, for the various performance levels in data protection.

V. CONCLUSION

This study analyses the crucial role of IoT techniques in enhancing threat detection, prevention, and response in credit card fraud detection operations. Prediction analysts respond to hazardous gas detection and continuously maintain monitoring to improve performance. Performance measurement is enhanced using the F1 score, response time, recall, precision, and accuracy based on commonly used benchmark datasets for result comparison. The capacity to identify unknown data is improved by compressing vast information into practical archives and transforming the data. This process involves additional data classification and reduction. Each device utilizes local data to create a new local machine learning model through training. The temperature at which the liquid substance transitions to vapor at atmospheric pressure (in K) is an early indicator of the processes. The process is defined as any critical situation that is efficiently handled, completed within a specific time frame, performed with multi-tasking efficiency, and maintained for reliability; this process has achieved a 92% accuracy in fraud detection.

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