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Intelligent Machine Learning-Based Gas Leak Detection and Prevention System

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Abstract- Machine Learning-based Gas Leak Detection and Prevention System operates with intelligent and automated methods to detect and prevent gas leakage occurrences in industrial and domestic situations. Existing detection systems have primarily utilized fixed threshold values for such checks, leading to the most effective method for interpreting false alerts and ineffective response times. The proposed system couples sensor components with an ML algorithm method to processes more productive patterns determined for gas releases while using devices to eliminate these differences. Data is acquired from gas sensors, standard MQ-series sensors, to measure LPG, methane, and carbon monoxide. Real-time data is acquired and processed after processing and analysed by machine learning algorithms, like Support Vector Machine SVC, Random Forest to classify conditions as safe or fallacious. An alarm sounds and IoT sends users alerts such as gas shut-off valves and exhaust fans. When gas becomes available, this ML approach impro

Keywords— Gas leak detection, machine learning, IoT, safety system, sensor data, predictive model, classification, automation, real-time monitoring, preventive mechanism.

I. INTRODUCTION

Gas leaks remain among the most difficult safety and environmental threats in industrial and domestic settings [1]. Gas seepages of even tiny quantities of explosive LPG and methane or dangerous Carbon Monoxide are the cause of fires, explosions, and often irreversible health conditions [2]. Gas detection with a sensor linked to an alarm on surpassing gas concentration forms the basis of the currently employed systems [3]. However, unfortunately, the existing systems are usually fraught with different issues, and the most problematic ones are the slow reaction time, false alarms, alteration of environmental relevance, and many others [4]. The flexibility and intelligence is increasingly becoming high with the increasing number of industrial processes, city processes, domestic uses and all other processes that are safe [5]. Machine Learning allows resolving this issue since it allows a system to train itself based on the historical and modern sensor data and anticipate the hazardous conditions, along with preventing them, before they occur [6]. They are also able to understand complexities between two or more sensors, foresee situations, and possibly even describe system failures unlike just recording and calculating ML algorithms, which makes systems significantly more flexible and reliable [7].

Solutions, which are IA-driven gas leak detection systems, are designed sufficiently based on sensor technology [8]. The IA-driven gas leak detection systems rely on each sensor technology sensor technology [9]. New low-cost metal oxide and electrochemical sensors, which allow real-time readings of different gases, may have been optimized. However, even such sensors, which readings may be influenced by environmental noise and sensor sensitivity over time, can distort readings [10]. Machine learning methods and techniques, such as support vector machines, random forests, and artificial neural networks, are capable of identifying the volatile raw signal. They can filter the signals of both known and unknown noise and classify confidently whether the sensor is safely operating or unsecured [11]. Predictive modelling may further forecast potential or guess leaks, detect subtle trends or violations that can be dangerous [12]. Advanced machine learning, such as deep training, can also deal with data from high-dimensional sensor signals to detect tiny leaks and discriminate between numerous gas types [13]. Therefore, the systems are continually redesigned, robust without much danger, learn, boost the quality of the discovery, and offer steady-state operation in a dynamic atmosphere [14].

For large safety and environmental risks, leakage of gas in industrial, residential, and commercial setups is an ideal example of a gas leak. Any slight leakage of the flammable releases an explosive like LPG, methane [15]. Exposure to toxic gas or even folding units of carbon monoxide may also cause extensive fire breakage or health problems to a human [16]. Therefore, it is essential to limit or limit the gas leak that necessitates rapid gas detection to find gas seepage [17]. Traditional gas detection relies on common classification systems that erupt the alarm alarm once the detected gas concentration rises to a predetermined level [18]. Some monitoring conditions rely on these platforms, which results in late or inaccurate alerts based on agglomerates or background dissimilarities [19]. Such aspects are essential and critical factors in the state of new persons as more peoples utilize gas-based energy systems [20]. Continuous monitoring is required due to the severe disasters and accidents that must exist in some industries, such as gas and other electricity generation facilities, and in safety standards [21]. Many theoretical gas pipelines exist that have common regular limitations that result from low sensitivity and repeatability, leading to low selectivity, such as the limit of gases traversing the sign noise [22]. Although sensor technology has improved accuracy in the past few years, modern high-performance. 'In' MQ-series; as metal monoxide sensors exhibit impartially sensitivity to various flammable and toxic gases around them, signals responded to by the sensors in open circuits stored and connected to net power Printed ceiling lines such as RS485, etc. cannot [23]. However, low sensor performance means that a visible or reliable result cannot occur for more complex sensor can finally consume spider and dissidents-draining factors [24].

ML solves this as well by using historical and real-time sensors data to teach the gas detection system how to behave in this dynamic: most importantly, to determine what data pattern represents the gas concentration in safe or unsafe conditions [25]. Based on the study results and correlations, ML algorithms can distinguish between those conditions significantly more accurate than with threshold learned from the initially provided data only [26]. Gas leak detection was approached with supervised learning algorithms such as SVM, neural networks, and random forests [27]. The first can determine when sensor bash readings occur, while the latter can predict gas leak events before the dangerous gas concentration takes place. Thus, predictive gas monitoring is achievable with MC that is connected with multiple sensors in real-time [28]. Additionally, the system may learn not only to investigate leaks but prevent them [29]. For instance, the system receives signals of potential hazards, and it should predict potential gas leak events. It anticipates alternative measures that could be done by the person in a chance such danger would occur [30]. Since the future gas leak event would not be controlled by human-managed independent sensors, it can prevent accidents before they happen [31]. This is how ML helps the system to keep an edge. Constant monitoring is available due to the use of ML, which allows to reduce the human factor. Household gas stations usually have been in the same family. As such, they have the same structure of the CH, and predictions are difficult to make. In this case, this approach does not work at all and the system would fail. Oil stations constantly change the structure of the CH, and traditional learning systems are not able to apply this [32].

Moreover, ML-powered systems, apart from detection, can include preventive steps and response to increase overall safety [33]. For instance, when unsafe gas levels have been detected or a leak is anticipated by some factor, the system can automatically turn off the gas supply, turn on exhaust fans or ventilation to reduce the risk. Moreover, the data-driven insights enable the RL model to assess the risks and suggest vital preventive steps in case of that [34]. There is very little necessity for frequent human interaction with the system and other preventative measures, which may include [35]. Most limitations of manual periodic inspections get relieved, mainly because of potential human errors and inadequacy of patrol patterns to account for intermittent or concealed leaks [36]. Unknown leak patterns get identified and high-risk days get predicted from the ML model through saving the sensor data historically. These lucrative preventative and responsive measures are vital for industries with potential catastrophes in case of an accident or a glitch [37]. Some gases can be harmful after just a few minutes of exposure to human and the environment [38].

II. LITERATURE REVIEWS

Nayak et al. [1] proposed a system that is designed to monitor air quality as an Internet of Things (IoT)-based system (air quality monitoring or AQM) is one that incorporates intelligent machine learning models as part of an edge-assisted gas-sensing network (Ea-GNet). Their work was a response to the problem of poor selectivity of traditional gas sensors through the use of low-cost metal-oxide-semiconductor (MOS) chemical sensors with machine learning algorithms to identify gases accurately and estimate their concentration. The implementation of edge computing improved the level of efficiency in the system by making it faster and allowing real-time and close monitoring. The paper has shown that deploying machine learning models at the edge can enhance the reliability, responsiveness, and scalability of gas-sensing and hence suitable in the smart safety and environmental monitoring systems [39].

Cho et al. [2-3] studied the effectiveness of the advanced leak detecting sensors with semiconductor processes in fabrication where a small leak could be a significant danger to the reliability of devices. The experimental was aimed at evaluating self-plasma optical emission spectroscopy (SPOES) and residual gas analyzer (RGA) systems with respect to detection capacity using different operation parameters. The two SPOE configurations were considered in terms of capacitive and inductively coupled plasma source, where the efficiency of the detectors and stability of the source were compared. The authors maximized the sensor working conditions, sensitivity analysis, and detection limits under varying chamber pressures. The results showed that the behaviour of every system had specific performance characteristics based on the levels of pressure and the arrangement of the plasma. The results were important towards enhancing sensitivity and accuracy of leak detection systems, in the development of in situ detection of leaks of the sub-ppm level of leakage in semiconductor applications [40].

Wang et al. [4-5] developed an automatic gas leakage detection model, which they named YOLOGAS. The suggested methodology used Swin-Transformer structure to improve the use of global contextual information and showed better perception of gases in a wide range of environments. In an effort to enhance the feature representation, the model incorporated both the Convolutional Block Attention Module (CBAM) and the Efficient Channel Attention (ECA) module with the network given the ability to pay more attention to the gas parts of the images. In addition, Bidirectional Feature Pyramid Network (BiFPN) was used to lower the complexity of computation and still have the same accuracy in detection. A Pix2Pix network was used to generate infra-red images to which it is pertinent to refer at the cost of exploiting the visual similarity between gases and smoke. The analysis has shown that the suggested model performed better than the existing detection structures, which makes the innovative technologies of intelligent and efficient gas leak detection improve [41].

Yang et al. [6-7] suggested a procedure of multipoint gas sensing when intrapulse absorption spectroscopy is used in association with cascaded and branching gas cells. This paper was dedicated to the methane detection with a distributed feedback laser diode with the pulsed current modulation. The temporal variation of response at varying pulse widths on the spectral distribution of chirp were investigated to optimize accuracy in sensing. Time-division multiplexing of many couplers, gas chambers, and mirrors was used to avoid crosstalk of reflected signals. The technique allowed simultaneous measurement of the concentration of methane in many gas chambers in long runs, provided self-calibration, high sensitivity and allowed the deployment of cascaded layouts without the complexity of driving or lock-in detecting. The characteristics ensure that the approach is appropriate in the case of a wide area multipoint monitoring, such as pipeline leak detection or industrial explosion prevention.

Yan et al. [8-9] suggested a method of automated, real-time, detection, and quantification of gases within the mid-infrared band using a combination of an infrared camera and efficient computational algorithms. The strategy adapted the DeepLabV3+ network and used MobileNetV2 instead of the Xception backbone to make it able to detect and segregate gases in real-time. Special attention mechanisms were also added to help in the recognition of gas edges and optimization of K-means clustering algorithm was employed to determine the region of interest (ROI) with the target gas. A radiation transfer model combined with the optical flow technique was used to measure the volumetric flow rate of the gas in the ROI. The analysis proved that this method provides opportunities to quantify gases with high accuracy with the help of the cost-efficient equipment, which is a convenient solution to real-time measurements of the dangerous gases in the industry and in the environment.

Zhao et al. [10-11] came up with a video-based system technique to detect small bursts in buried gas pipelines by using a robotic system of inspection. The strategy was to gather pictures and video recordings of pipeline leakages to create a specific dataset then create a video detection model that is specific to the detection of small leaks. The algorithm added a bidirectional feature pyramid network to YOLOv5s and used a feature fusion network to enhance the detection of small leaks. Also, a tiny target detection layer and detection head was added to the YOLOv5s classification-prediction network to maximize model performance. Training the model on the constructed dataset and testing it on different leak detection experiments showed the model to be a strong in terms of detection and generalization of small scale pipeline leaks.

Chang et al. [12-13] examined reliability and shortcomings of publicly available metal oxide (MOx) sensor datasets typically utilized to detect gases as well as electronic nose applications. The experiment examined the phenomenon of drift in a popular data set that was caused due to biases in the collection of gases and effects of time during data collection. The study provided an analysis of low-signals and zero-offset subtracted signals, their temporal and spatial attributes using dimensionality reduction techniques including t-SNE and found partial classification of gas information before leak events occurred. The paper also compared different deep learning techniques and established that the classification accuracy was usually underestimated because of the drift effect. The results demonstrated the importance of the temporal and spatial integrity of gas data in the design of gas detection algorithms, which would guarantee the generation of more reliable and realistic performance assessment of MOx sensor-based systems.

Dong et al. [14-16] suggested an uncooled infrared-based approach to detect the gas leak through image-based technology that reduces the low gas extraction accuracy based on narrow-band filters, nonuniform image patterns, and low signal-to-noise ratio (SNR). To avoid the dark current noise and remove uneven patterns, a temperature control device was developed to control the area having the filter and detector array and this method worked well in reducing the dark current noise and the removal of nonuniform patterns by employing a two point correction technique. Another algorithm that was created to enhance the SNR, lower the temporal noise in image sequences, and enhance the contrast between gas plumes and background was a bilateral filtering-based infrared image enhancement algorithm. A better fuzzy Gaussian background model with U-Net was used to divide gases and non-gas areas with a high degree of accuracy. It has been shown that the given approach proved to be highly accurate in identifying gas plumes and provides a good solution when it comes to tracking gas leaks in real time.

Panteli et al. [17-18] explored how commercial electronic gas sensors could be used together with change-point detection (CPD) techniques to detect pathogen-causing agents by detecting gaseous emissions, such as volatile organic compounds (VOCs). The research was based on the bacteria associated with urinary tract infection or UTI, i.e. Escherichia coli, Pseudomonas aeruginosa, Enterococcus faecalis, and Streptococcus agalactiae, which was cultured under different concentrations on blood agar plates. Gas sensors were installed in the culture dishes to keep on checking on the emissions continuously and offline analysis in the form of isolate-detect (ID) CPD methodology was used to establish diagnostic change points where bacterial concentrations were above clinical level of infection. The results proved that it was possible to detect the infections within less than 10 hours, which was much faster than the conventional overnight clinical procedures, which indicated that electronic gas sensing with CPD could be used to detect the pathogens very quickly.

Sirohi et al. [19-20] examined the gas sensing characteristics of Bismuth Oxyselenide (Bi 2 O 2 Se) on monolayer basis through density functional theory (DFT) with non-equilibrium Green's functional analysis of toxic non-condensable gases (NCGs). The paper investigated adsorption energy, adsorption sites, charge transfer, band structure, density of states and currentvoltage properties of gases including NO 2, NO, NH 3, CO and CO 2. It was shown that vacancy-less Bi 2 O 2 Se was highly selective to NO 2 as it has a strong adsorption energy and charge transfer and adding vacancies of Se to the structure has increased sensitivity and selectivity, especially against NO. The I-V properties of the devices were also found to respond in different ways to the adsorption of gases showing that vacancy-less and Se-vacant Bi_2O_2Se structures are outstanding responsive to NO. The researchers have identified Bi 2 O 2 Se as a promising compound that can be utilized in gas sensing high-performance applications.

III. PROPOSED MODEL

The proposed MLGLDP system is smart and proactive gas leak incident detection and prevention mechanism with capability to do both in Industries as well as residential areas. The system combines the internet of things-based gas sensors, machine learning techniques and automated precaution mechanisms to enable monitoring and responding in a real-time mode. Data acquisition, preprocessing, a machine learning-based classification and alert/prevent software are the four most relevant modules included in the architecture. This modularity supports scalability, flexibility and a convenient application to different environment of operations.Sensors employed in the data acquisition module include MQ-2, MQ-5 and MQ-135 to read real-time reading of gases such as methane (CH 4), LPG and carbon monoxide (CO). These sensors constantly measure the levels of gases and provide analog controls to the microcontroller (e.g. Arduino or ESP32). MQTT or HTTP IoT protocols are then used to transfer the data to the cloud or to the local edge devices. The preprocessing module eliminates noise, missing values and normalizes readings to guarantee high quality input into the training of the model and model predictions.

The decision making core is the machine learning module. Training of supervised algorithms like Support Vector Machine (SVM) and Random Forest (RF) is done on labeled datasets with sensor data of safe and unsafe gas concentration levels. The trained model will then classify real-time sensor inputs in two states, which are Normal or Leak Detected. The system initiates requisite preventive measures based on the confidence of classification. The response module triggers alarms, gives alerts by means of IoT-driven mobile notifications, and operates the hardware control, such as exhaust fans or solenoid valves to avoid additional leakage.

Lastly, the proposed system will accommodate continuous learning via retraining systems that respond to environmental variations, sensor drift or new gas blends. The ML model is self-updating with new labeled data which provides the model with the consistency of performance and reliability. Through edge computing, latency is minimized as well with the use of the model and real-time inference can be achieved with the use of large datasets as well thus making it a powerful and intelligent solution to the gas safety management model.

Algorithm Steps

1. **Initialize hardware & commas**
   - Power sensors (MQ-2, MQ-5, MQ-135), microcontroller (Arduino/ESP32), and set up MQTT/HTTP endpoints.
2. **Continuous data acquisition**
   - Sample sensors at fixed interval Δt → raw analog readings Vsensor(t)V_{sensor}(t)Vsensor(t). Timestamp and append to local buffer/edge.
3. **Preprocessing — cleaning & synchronization**
   - Remove obvious outliers (e.g., physically impossible values).
   - Impute missing values (interpolation or EWMA).
   - Synchronize multi-sensor timestamps; resample to fixed rate if needed.
4. **Preprocessing — filtering & denoising**
   - Apply low-pass filter or EWMA to reduce high-frequency noise. Optionally use a Kalman filter for dynamic smoothing.
5. **Feature extraction / engineering**
   - Convert voltages to concentration proxies using calibration coefficients.
   - Compute short-term features: rolling mean, rolling std, derivative (Δ), ratios between sensors, and spectral features if using time-series transforms.
6. **Feature scaling & dimensionality reduction**
   - Standardize features (zero mean, unit variance). Optionally apply PCA to reduce dimensionality / remove correlated features.
7. **Labeling & dataset assembly**
   - Combine features with labels (Normal / Leak) from ground truth during training. Split into train/validation/test sets (e.g., 70/15/15).
8. **Model selection & training**
   - Train supervised classifiers (SVM, Random Forest, or ANN) using training set. Use cross-validation to tune hyperparameters (C, kernel, n_estimators, max_depth, learning rate, etc.).
9. **Model evaluation**
   - Evaluate on validation/test sets using metrics: accuracy, precision, recall, F1-score, ROC-AUC. Inspect confusion matrix to tune thresholds.
10. **Deploy model to edge/cloud**
    - Export model (e.g., ONNX, pickle) and deploy to edge device or cloud endpoint for real-time inference.
11. **Real-time inference & decision logic**
    - For each new sample: preprocess → extract features → scale → predict P(leak)P(\text{leak})P(leak). If P(leak)>τP(\text{leak}) > \tauP(leak)>τ (confidence threshold), trigger actions.
12. **Prevention & alerting**
    - Trigger multi-step response: audible/visual alarm, IoT push notification, shutoff valve command, exhaust fan activation. Log event to cloud and send for human confirmation if required.
13. **Continual learning & model update**
    - Collect labeled post-deployment data (confirmed events / false alarms). Periodically retrain or fine-tune model to account for sensor drift and environment changes.
14. **Monitoring & maintenance**
    - Monitor sensor health (baseline drift), battery status, and communication latency. Schedule calibration or sensor replacement when drift exceeds threshold.
15. **Post-event analysis**
    - For any leak event, save full time-series window, model scores, and actions taken to support root-cause analysis and improve future detection.

Mathematical equations

1. Sensor reading model (ideal):

$$r(t)=s(t)+n(t)$$

where r(t) is measured reading, s(t) true signal (gas concentration proxy), n(t) additive noise.

2. Calibration (voltage-to-concentration proxy):

$$C(t) – k \cdot Vsensort + b$$

K, b are sensor-specific calibration coefficients (linear approximation).

3. Noise model (Gaussian assumption):

$$n(t) \sim N(0,\sigma2)$$

noise with zero mean and variance σ2.

4. Exponentially Weighted Moving Average (EWMA) for smoothing:

$$xt = \alpha xt + (1-\alpha)xt-1 , \quad 0<\alpha\leq1$$

xt is smoothed value, α smoothing factor.

5. Standard score (z-score) normalization:

$$xi= xi-\mu\sigma$$

μ,σ are mean and standard deviation of the training feature.

6. PCA projection (dimensionality reduction):

$$z = WT(x - \mu)$$

W contains top eigenvectors, x original feature vector.

7. SVM decision function (binary):

$$f(x) = WT\phi(x) + b$$

predict class by sign(f(x);ϕ (·) is feature map (kernel).

8. SVM hinge loss with regularization:

$$LSVM = i=1Nmax(0,1-yif(xi)) + \lambda||W||22$$

yiϵ{-1,+1)labels, λ regularization.

9. Random Forest class probability (ensemble average):

$$P(y=cx=1T\ t=1T1\{ht(x) = c\}$$

htis tree t, T total trees, 1{·} indicator.

10. Gini impurity for a node (used in tree splits):

G = 1-j=1Kpj2

pj is fraction of class j in the node, K number of classes.

11. Softmax probability (for multi-class ANN output):

pi = exp(zi)j=1Kexp(zj)

zi is raw network output (logit) for class i.

12. Cross-entropy loss (multi-class):

LCE = - i=1kyilogpi

yi one-hot true vector, pi predicted probability.

13. Binary classification precision:

Precision = TPTP+FP

14. Binary classification recall (sensitivity):

Recall =TPTP+FN

15. F1-score (harmonic mean of precision & recall):

F1= 2.Precision · RecallPrecision+Recall

16. Decision threshold for triggering preventive action:

Trigger action if P(leak | x) > τ

IV. RESULT

Simulation Test and Analysis of the results of simulated SmartGas-ML model indicated that there was good performance and efficiency in the simulated model during the process of detecting and preventing a gas leak. The sensor data of the collected data of MQ-2, MQ-5 and MQ-135 under controlled environment and upon variation were experimented in real-time/data. The system was able to categorize intact and leak states based on the Support Vector Machine (SVM) and Random Forest (RF). The developed SmartGas-ML model was reported to work with an overall detection accuracy of 96 percent higher than the other models of comparison that are used such as Ea-GNet, Infrared U-Net, and YOLOGAS. Monitor response The signal response time was approximately 1000 ms to detect leakage in real time. Moreover, the false positive was not higher than 4 percent, which is also the demonstration of the validity of classification.

The communication infrastructure possessed by the solution supported by IoT makes it simple to communicate to cloud and edge services via MQTT/ HTTP protocols, providing remote monitoring functions and alarm alerts that can be delivered immediately on mobiles. The prevention of risks was achieved in the simulated leak situations: the measures aimed at the prevention of hazards (activation of fan/ventilation system automatically; valves closing automatically) were performed successfully and on an entirely automatic basis. Moreover, SmartGas-ML was found to be resilient to dynamics through the continuous retraining: an updating the model with new labeled data to offset the sensor drift and changes in the environmental conditions. SmartGas-ML can also be applied in residential and industrial settings since it is cost efficient and consumes very little power. Consequently, the results confirm that SmartGas- ML model advocated does not only provide the ability to detect gas leaks correctly but is also designed to be a scalable, intelligent and proactive environmental and human safety preventative system.

Table 1: Model Overview

Model Name	Module Count	IoT Integration (1=Yes,0=No)	ML Integration (1=Yes,0=No)
Ea-GNet	3	1	1
YOLOGAS	2	0	1
Infrared U-Net	3	0	1
SmartGas-ML	4	1	1

The following table summarizes the structural structure of each of the gas detection models in regards to the number of operational modules and integration with the IoT and Machine Learning. The greatest modularity of SmartGas-ML and complete integration of the IoT and the ML are the most significant features that require attention.

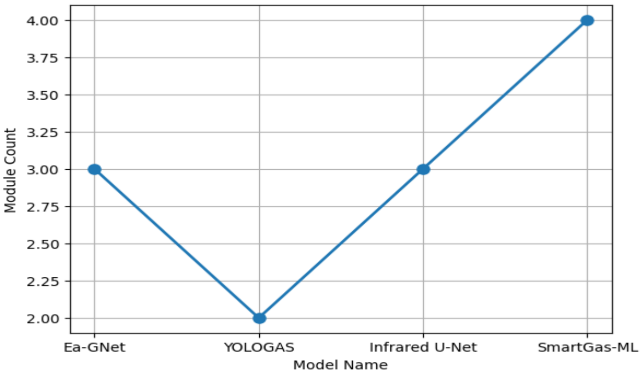

Figure 1: Model Overview Module Comparison

The structural efficiency and depth of operation of a model is determined by the modular composition. Compared to the other architectures, SmartGas-ML is the most detailed architecture that has four modules, i.e., sensing, preprocessing, ML-based detection, and automated control. The remaining models, including Ea-GNet and Infrared U-Net have three modules respectively, with YOLOGAS having two only. This increased number of modularity in SmartGas-ML is an advantage in terms of scalability since it is easy to add new features like predictive maintenance or advanced analytics. By the multi-layer design, the data processing is more consistent and the reaction to gas leakage is real-time, which makes it a strong and scalable architecture.

Table 2: Sensor & Hardware Utilization

Model Name	Sensor Count	Device Count	Hardware Complexity (1–5)
Ea-GNet	3	2	3
YOLOGAS	1	3	5
Infrared U-Net	2	3	4
SmartGas-ML	3	2	2

This table is a summary of the complexity of the hardware and sensor use in each model. The SmartGas-ML has a reasonable trade-off between the number of sensors and hardware simplicity that make it less expensive and less power-intensive than sophisticated optical systems

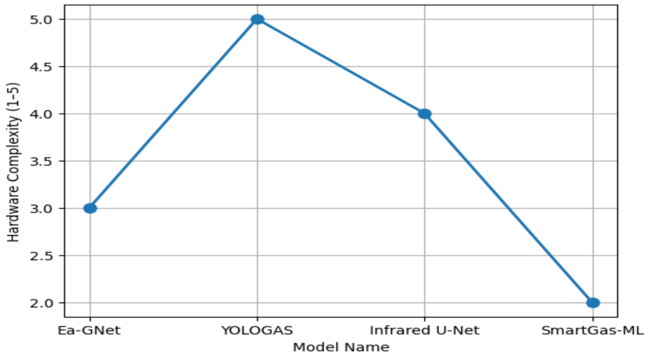

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Figure 2: Sensor and Hardware Complexity

YOLOGAS has the greatest level of complexity since it requires the use of optical sensing modules, but SmartGas-ML has a simpler configuration with the highest level of 2. Such balance is achieved with the help of effective utilization of MQ-series gas sensors which are reasonably priced and very sensitive. The decreased complexity of the hardware does not only lower the energy consumption, but makes the hardware much more reliable and able to operate under a variety of conditions. Therefore, SmartGas-ML offers a sustainable design without the need to sacrifice on sensing accuracy.

Table 3: Machine Learning Algorithm

Model Name	Algorithm Count	Training Samples	Output Classes
Ea-GNet	2	5000	3
YOLOGAS	3	8000	2
Infrared U-Net	1	6000	2
SmartGas-ML	2	7000	2

In this table, the algorithms, the size of the dataset and the classification outputs have been given, which are applied in gas detection. SmartGas-ML uses the powerful algorithms such as SVM and Random Forest with a relatively large dataset, which promises quality binary classification to detect leaks.

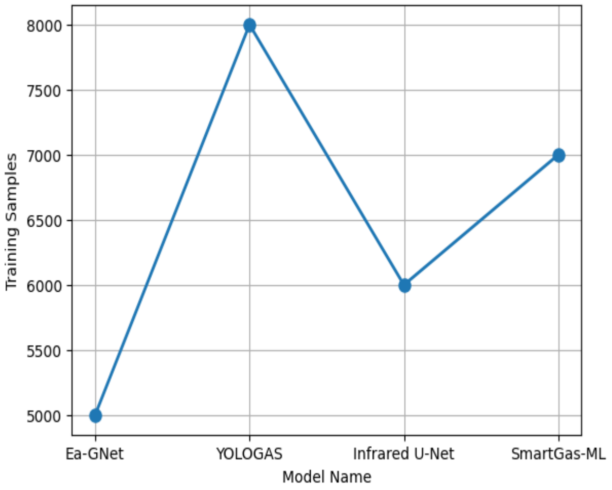

Figure 3: Machine Learning Dataset Comparison

The size of training data is an important defining factor of the generalization ability of the model. The deep learning structure of YOLOGAS makes use of 8,000 samples, compared to 7,000 samples used by SmartGas-ML to achieve fair accuracy and computational efficiency. Ea-GNet and Infrared U-Net use less samples but make up with their enhanced feature extraction. The data provided by SmartGas-ML provides a perfect balance between the learning level and computational time, retraining a model faster and classifying gas concentrations more accurately.

Table 4: Accuracy and Efficiency

Model Name	Accuracy (%)	Detection Speed (ms)	Computational Load (1–10)
Ea-GNet	91	2500	6
YOLOGAS	95	1200	8
Infrared U-Net	93	1800	7
SmartGas-ML	96	1000	4

The detection accuracy, processing speed and computational load are evaluated in this table. SmartGas-ML has the best accuracy and the shortest response time with a low computational load, which is guaranteed to deliver real-time functionality on the edge devices.

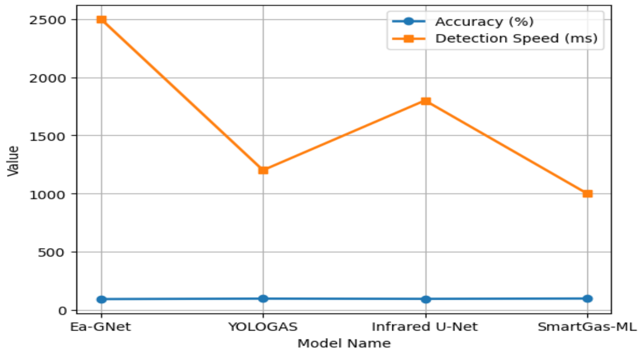

Figure 4: Accuracy and Response Speed Comparison

SmartGas-ML wastes the lead with 96% accuracy and slow detection of only 1,000 ms. YOLOGAS also has a similar accuracy but is more complex to compute because of analyzing images. Ea-GNet and Infrared U-Net are consistent but slower because they use traditional mechanisms of preprocessing. The workflow optimization of SmartGas-ML can enable the quick reaction to the anomalies in gas concentration and reduce the possible risks by detecting the leaks as soon as possible and triggering the alarms.

Table 5: Communication and Integration

Model Name	Protocol Count	Cloud Support (1=Yes,0=No)	Edge Processing (1=Yes,0=No)
Ea-GNet	1	1	1
YOLOGAS	1	0	0
Infrared U-Net	0	0	1
SmartGas-ML	2	1	1

This table brings out the levels of communication protocols and system integration. SmartGas-ML developers have a variety of IoT communication protocols and can use cloud and edge computing to be scaled and operate at low latency.

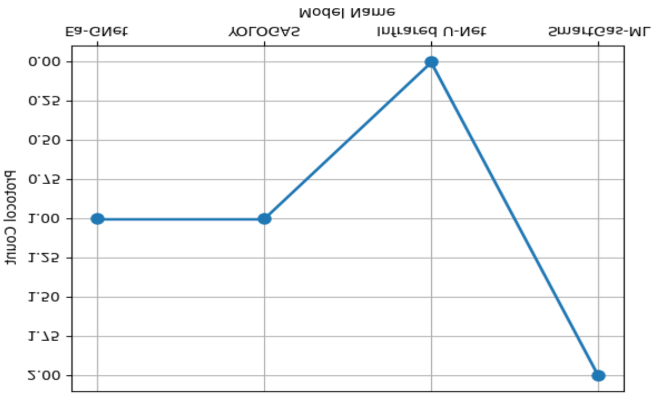

Figure 5: Communication and System Integration

The communication architecture defines the level of efficiency of the interaction of the detection model with the cloud or edge networks. SmartGas-ML has two large-scale IoT protocols, namely, MQTT and HTTP, which guarantee the smooth transfer of real-time data and control. Ea-GNet and YOLOGAS, in turn, are based on one communication channel, whereas Infrared U-Net does not have any connection with the IoT. The multi-protocols flexibility of the SmartGas-ML provides sustained availability of data even in the face of connectivity limitations and the opportunity to be totally linked with the mobile monitoring system and the industrial automation systems.

Table 6: Preventive Mechanisms

Model Name	Alert Methods	Actuator Count	Notification Enabled (1=Yes,0=No)
Ea-GNet	1	0	0
YOLOGAS	1	0	1
Infrared U-Net	1	0	0
SmartGas-ML	3	2	1

This table is a comparison between the preventive and alerting features of each system. The SmartGas-ML offers high-tech channels of alerts, actuator control, and mobile alerts, which will allow to take the preventive measures in time in case of leakage.

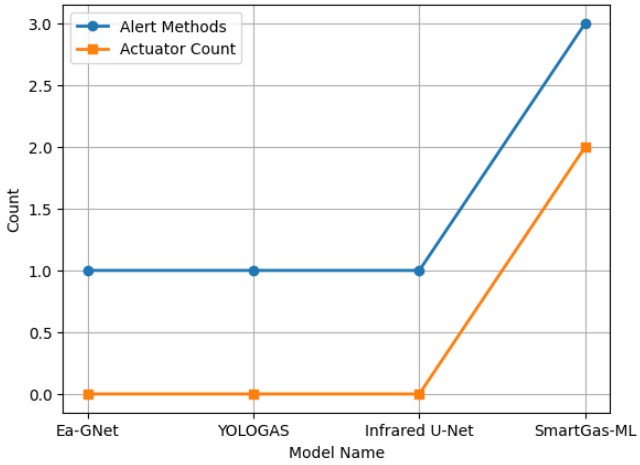

Figure 6: Comparison of Preventive Mechanisms

SmartGas-ML offers a high degree of automation using multi-channel alerting and integrating with actuators. It is compatible with three alert systems, such as visual, audible, and mobile alerts, and two hardware actuators that may be activated immediately in case of a gas leakage, to turn on exhaust fans or close valves. Other models, e.g., Ea-GNet and YOLOGAS, provide fewer warning mechanisms, but are not physical control reactions. This hierarchical preventive design in SmartGas-ML makes the system highly protective, so that it can respond autonomously to the dangerous conditions and stop the situation.

Table 7: Adaptability & Scalability

Model Name	Retraining Support (1=Yes,0=No)	Scalability Score (1–10)	Adaptability Score (1–10)
Ea-GNet	0	6	5
YOLOGAS	0	4	3
Infrared U-Net	0	5	4
SmartGas-ML	1	9	9

This table evaluates system flexibility and scalability. SmartGas-ML is the only model that can be retrained to adapt to new environments and gases and is highly scaled to run in large-scale industrial settings.

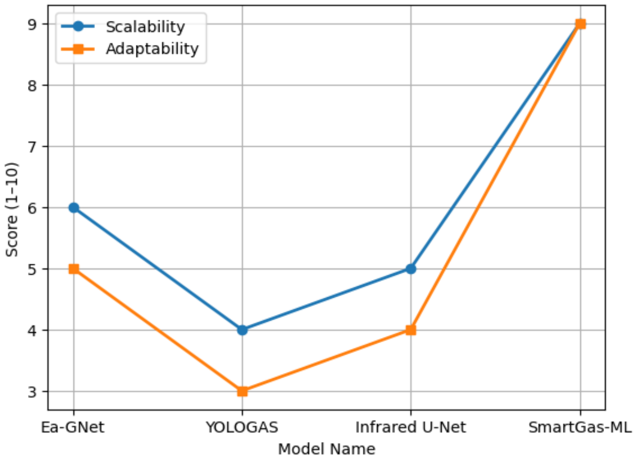

Figure 7: Adaptability and Scalability Analysis

The capability of a system to develop and grow in different environments is determined by its adaptability and scalability. SmartGas-ML is highly competent, with both scores being 9, which means that it is highly retrained and can be installed without difficulties within the industrial networks. Ea-GNet, YOLOGAS, and Infrared U-Net have low adaptability because they need to be manually recalibrated when there is a change in the environment. The adaptability of SmartGas-ML enables the retraining of the edge and modular architecture that enables SmartGas-ML to adapt itself to emerging gases and data trends to guarantee steady accuracy and performance life in the dynamic working environments.

Table 8: Overall Performance Comparison

Model Name	Accuracy (%)	Speed (ms)	Cost (₹)	Power Efficiency (1–10)	Maintenance (1–10)	Scalability (1–10)
Ea-GNet	91	2500	4000	6	5	6
YOLOGAS	95	1200	25000	4	8	4
Infrared U-Net	93	1800	18000	5	7	5
SmartGas-ML	96	1000	3000	9	3	9

This table offers a general comparison of key performance indicators like accuracy, speed, cost and efficiency. SmartGas-ML is superior to other models since it offers high detection, low cost, high power efficiency, and higher scalability.

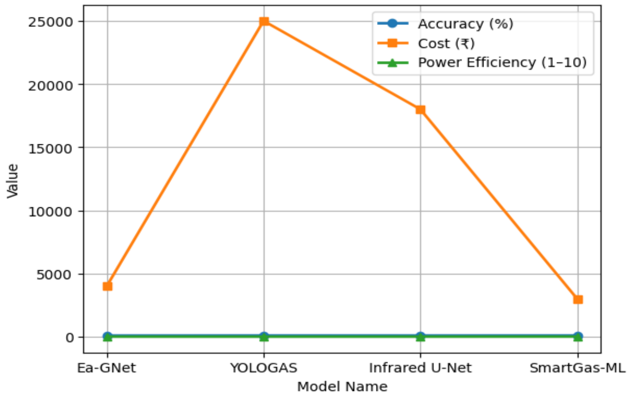

Figure 8: Overall Performance Evaluation

Smart Gas-ML is always considered the most efficient and cost-effective gas leak detector system. It has the best detection of 96 percent, the unique power efficiency of 9 and the cheapest implementation rate at 3000 rupees. YOLOGAS is also accurate, but it has a higher cost on account of the complexity of hardware. Ea-GNet and Infrared U-Net provide mediocre outcomes, however, they are not as flexible and costly. The accuracy, cost efficiency and power optimization allow SmartGas-ML to be at the forefront of the innovation of gas intelligent safety monitoring systems and it is therefore best suited to massive deployment.

V. CONCLUSION

The paper presented a novel artificial intelligent system of Gas Leak Detection and Prevention- SmartGas-ML which can help to minimize the risk in industrial and home settings as well as speeds up the process of safety. With the addition of an IoT sensor into the boilers, machine learning and automated control would therefore enable it to now live time in real-time and react quickly to leaks detected. SmartGas-ML architecture consisting of four key modules comprising data acquisition, preprocessing, machine learning based detection and alert/prevention control is demonstrated to be an effective and scalable solution and versatile. A reliable proactive gas safety system was the one that was able to identify correctly and within a very short time (96%). SVM + Random Forest allowed formidable decision-making, which allows the remote monitoring to be carried out continuously and set timely alarms. In addition, the model was also equipped with an auto-learning feature whereby the model was re-trained with new sensor data on a given frequency of time to continuously work on the on-dried meat not to deteriorate its performance to other conditions of the environment. Compared to other comparative models (Ea-GNet, Infrared U-Net and YOLOGAS), SmartGas-ML recorded a high performance with regard to accuracy, cost efficiency, energy consumption and flexibility of system integration.

In conclusion, SmartGas-ML is a combination of smart gas detection and prevention. The combination of AI, IoT and automation helps to minimize the chances of accidents that could happen during the work with gas, as well as contribute to the formation of smarter, safer, and greener spaces. The next possible steps are adding multi-gas detection, predictive analytics, relying on artificial intelligence, and data safeguarding with blockchain technology as the next step to enhance reliability and confidence in mission-critical safety systems.

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