Engineering and Technology Journal e-ISSN: 2456-3358

Volume 10 Issue 08 August-2025, Page No.-6240-6248

DOI: 10.47191/etj/v10i08.17, I.F. – 8.482

A Multi-Sensor Classification Framework for Methane Leak Detection using Machine Learning Algorithms

Semiu Temidayo Fasasi[1], Oluwapelumi Joseph Adebowale[2], Zamathula Queen Sikhakhane Nwokediegwu[3]

[1]Colorado State University, USA

[2]Independent Researcher, USA

[3]Independent Researcher, Kansas, USA

ABSTRACT: Methane is a potent greenhouse gas and safety hazard, making its timely and accurate detection a critical objective in environmental monitoring and industrial safety. Traditional methane detection systems, often reliant on single-sensor architectures or manual inspections, suffer from limited coverage, high false alarm rates, and poor adaptability to dynamic conditions. This paper proposes a multi-sensor classification framework that integrates heterogeneous sensing technologies with machine learning algorithms to enhance leak detection reliability. The framework incorporates a hybrid sensor fusion strategy, robust feature extraction, and interpretable classification models such as support vector machines and ensemble methods. By addressing challenges related to sensor drift, environmental noise, and data redundancy, the system ensures scalable, fault-tolerant, and explainable detection. Theoretical considerations guide the design of a modular architecture capable of handling synchronized, normalized sensor data across diverse conditions. Practical implementation factors, including deployment constraints, fusion logic, and decision support mechanisms, are systematically analyzed. Evaluation protocols based on k-fold cross-validation and post hoc interpretability techniques ensure the framework meets the performance and transparency requirements of real-world applications. This work contributes a scalable, intelligent solution to methane leak detection and lays the groundwork for future advancements in adaptive learning, anomaly detection, and edge-based sensing systems.

KEYWORDS: Methane Leak Detection, Multi-Sensor Systems, Machine Learning Classification, Sensor Fusion, Environmental Monitoring, Explainable Artificial Intelligence (XAI)

1. INTRODUCTION

1.1 Background

Methane is a potent greenhouse gas with a global warming potential significantly higher than carbon dioxide over a 20-year time frame (Reay et al., 2010). Its uncontrolled release into the atmosphere from sources such as oil and gas infrastructure, landfills, and agricultural operations contributes to both climate change and air quality degradation (Molnár, 2018, Ogbowuokara et al., 2023). In addition to its environmental implications, methane poses serious safety hazards. Explosive concentrations of methane in confined spaces can lead to industrial accidents, making its early and accurate detection a public safety priority (Sobanaa et al., 2024, Un, 2023).

Traditional approaches to methane monitoring have relied heavily on manual inspections and fixed-point gas detectors, which are often limited in coverage and sensitivity (Alvarez et al., 2012). As industrial infrastructures grow more complex and geographically dispersed, these conventional methods have proven increasingly insufficient for detecting diffuse or intermittent emissions (Howarth, 2021, Le Fevre, 2017). Moreover, the latency between leak occurrence and detection increases the risk of prolonged exposure, operational inefficiencies, and environmental violations. Consequently, regulatory agencies and environmental organizations are intensifying their call for improved monitoring practices (Bogner et al., 2008).

Advancements in sensor technology and data processing capabilities have opened the door for intelligent, automated systems capable of continuous monitoring and rapid leak identification (Yussof and Ho, 2022). A multi-sensor system, where various sensor types operate in tandem, offers greater robustness, sensitivity, and fault tolerance (Chan et al., 2018, Farah and Shahrour, 2024). When paired with computational intelligence, such as pattern recognition and classification algorithms, these systems can deliver real-time assessments of leak presence and severity. The integration of machine learning with multi-sensor platforms represents a critical evolution in methane leak detection strategy, combining hardware resilience with adaptive decision-making capabilities (Chan et al., 2018, Bibi and Molloholli, 2024).

1.2 Problem Statement

Despite the technological progress in sensing systems, methane leak detection remains a complex and imperfect science. Traditional single-sensor setups are prone to failure in heterogeneous environments due to factors such as environmental noise, sensor drift, and varying emission concentrations. These limitations reduce detection reliability, particularly in large-scale or dynamic settings such as oil fields, storage facilities, and transport pipelines. Furthermore, many sensors operate optimally within narrow sensitivity ranges, which restricts their effectiveness in detecting both low-level leaks and high-concentration discharges with equal accuracy.

Manual inspections, often used to complement fixed sensors, are time-intensive, labor-intensive, and limited by human error. These methods are inherently reactive rather than proactive, identifying problems only after substantial methane accumulation has occurred. In regions where safety regulations are less stringent or enforcement is inconsistent, such systems contribute to delayed response times and increased environmental damage. Additionally, the cost of deploying dense networks of conventional sensors becomes prohibitively high when trying to achieve real-time, comprehensive monitoring over wide geographic areas.

Another critical challenge lies in the lack of integration between data acquisition and decision-making. Current detection systems typically produce raw or semi-processed data that require manual interpretation, leading to inefficiencies and delayed interventions. Without intelligent classification frameworks that can distinguish between true leak signatures and environmental or operational anomalies, false alarms remain frequent. This undermines user trust in automated systems and discourages widespread adoption. Addressing these constraints calls for a paradigm shift toward more intelligent, adaptive, and scalable detection architectures.

1.3 Research Objective

This paper proposes a novel framework for methane leak detection that combines data from multiple sensors with machine learning classification techniques. The aim is to develop a more resilient and accurate system that leverages the strengths of diverse sensor modalities, such as infrared, electrochemical, and semiconductor technologies, within a unified analytical model. The proposed framework does not rely on a single point of failure, thereby enhancing reliability under diverse environmental conditions. It also aims to capture complex gas signatures that would be missed by traditional methods, increasing both sensitivity and specificity.

A central contribution of this work is the integration of a machine learning–based classification pipeline that can automatically distinguish between true leak events and benign variations in sensor data. By learning from historical datasets and evolving operational patterns, the model adapts over time, improving its predictive accuracy. Unlike rule-based systems that depend on rigid thresholds, this approach can accommodate contextual variability and sensor drift. As a result, it is capable of making more nuanced decisions that align with real-world uncertainty and noise.

Beyond its technical merit, the proposed framework contributes conceptually to the fields of intelligent sensing and environmental monitoring. It demonstrates how synergistic integration of sensor diversity and algorithmic intelligence can overcome longstanding limitations in gas detection. The methodology outlined in this paper is intended to serve as a foundational blueprint for future development of scalable, intelligent methane monitoring systems, particularly in industrial and regulatory contexts where accuracy, reliability, and interpretability are essential. In doing so, it sets the stage for safer operations and more effective climate mitigation efforts.

2. LITERATURE REVIEW

2.1 Sensor Technologies for Methane Detection

Recent advances in gas sensing technologies have enabled the development of various instruments capable of detecting methane at different concentrations and across diverse operational environments. Among the most widely used are infrared (IR) sensors, which detect methane based on its absorption of specific wavelengths of IR radiation (Shuk et al., 2019, Aldhafeeri et al., 2020). These sensors are non-invasive, have fast response times, and offer selective sensitivity to hydrocarbons like methane. However, their performance can be affected by environmental factors such as humidity and temperature variations, which may lead to false readings or reduced accuracy in unregulated outdoor conditions (Akinsooto et al., 2025, Ogunnowo et al., 2025).

Catalytic bead sensors represent another established technology in methane detection. They operate by oxidizing methane gas on a heated catalyst, resulting in a measurable change in resistance. While catalytic sensors are cost-effective and simple to operate, they require oxygen to function and are vulnerable to poisoning by sulfur compounds or silicon-based vapors, limiting their reliability in contaminated or oxygen-deficient environments (Fu et al., 2023). Moreover, their sensitivity to a wide range of flammable gases can result in reduced specificity, making it difficult to distinguish methane from other hydrocarbons without complementary sensors (Okuh et al., 2025, Omisola et al., 2025).

A more sophisticated approach is tunable diode laser absorption spectroscopy (TDLAS), which offers high precision and selectivity by targeting the specific spectral lines of methane. TDLAS systems are especially useful for remote or point-based sensing in industrial applications. They provide real-time measurements with minimal interference from background gases (Okem et al., 2024, Okuh et al., 2024b). However, the high cost of deployment, calibration complexity, and maintenance requirements hinder their large-scale implementation in distributed sensing networks. These limitations underline the need for hybrid, multi-sensor platforms that combine the strengths of individual technologies while compensating for their weaknesses through data-level integration (Olanloye et al., 2024, Uddoh et al., 2024).

2.2 Machine Learning in Gas Leak Detection

The application of machine learning to gas sensing has expanded rapidly in the past decade, particularly in automating pattern recognition and anomaly detection. Supervised learning algorithms such as support vector machines, random forests, and artificial neural networks have been employed to classify gas concentrations, detect anomalies, and distinguish between gas types (Olajide et al., 2023b, Oluoha et al., 2023). These models are capable of learning complex, nonlinear relationships in sensor data, which are often difficult to capture with traditional statistical methods. Such approaches have shown promise in improving accuracy, especially when paired with high-resolution sensor data and robust feature engineering (Sagay-Omonogor et al., 2023, Adewoyin et al., 2024).

Sensor fusion is another area where machine learning has had a transformative impact. By integrating data from multiple sensors, fusion techniques enable the construction of higher-dimensional feature spaces, improving classification accuracy and fault tolerance (Asolo et al., 2024, Ayorinde et al., 2024). Early fusion approaches merge raw signals before classification, while late fusion aggregates decisions made by independent classifiers. Both strategies benefit from ensemble learning techniques that enhance robustness and generalizability. Despite these advances, challenges remain in developing fusion architectures that are both computationally efficient and adaptable to real-time conditions (Kufile et al., 2024, Ogeawuchi et al., 2024, Okuh et al., 2024a).

However, most existing studies focus on controlled environments with clean, pre-labeled datasets, limiting their applicability in noisy or dynamic real-world scenarios. Models trained on idealized data often fail to generalize when exposed to sensor drift, environmental interference, or partial sensor failure. Furthermore, the lack of transparency in many machine learning models creates trust and interpretability concerns, particularly in safety-critical applications. These issues underscore the need for frameworks that are not only accurate but also explainable, scalable, and resilient to operational variability (Knobelspies et al., 2016, Hodgkinson and Tatam, 2012).

2.3 Gaps and Opportunities

Despite the progress in both sensor development and machine learning, several research gaps persist that hinder the deployment of robust methane leak detection systems in real-world environments. One of the most critical limitations is the lack of effective sensor fusion logic that can dynamically adjust to heterogeneous data streams (Gbabo et al., 2023a, Ogunnowo et al., 2023). Many current approaches use static models that do not account for varying sensor quality or contextual factors such as weather, terrain, or industrial noise. This results in rigid systems that perform well under laboratory conditions but degrade quickly in operational settings (Okuh et al., 2023, Olajide et al., 2023a).

Another significant gap is the limited adaptability to sensor drift and aging. Over time, sensors experience shifts in baseline readings due to environmental exposure or material fatigue. Most machine learning models do not account for this phenomenon, leading to a gradual decline in accuracy (Adelusi et al., 2023b, Adelusi et al., 2023c). Incorporating online learning or adaptive calibration strategies into classification frameworks could enhance model longevity and reduce the need for frequent recalibration. Additionally, sensor redundancy and cross-validation strategies are underexplored in the context of real-time methane detection (Asata et al., 2023, Gbabo et al., 2023b).

Lastly, noise tolerance and model interpretability remain under-addressed in existing literature. Many deep learning models, though powerful, behave as black boxes and lack transparent mechanisms for users to understand decision-making processes (Fox et al., 2019). In safety-critical applications like gas leak detection, the inability to explain predictions can hinder trust and regulatory acceptance. This paper responds directly to these challenges by proposing a multi-sensor classification framework that integrates adaptable fusion techniques, drift-resilient machine learning, and interpretable decision outputs. By addressing these deficiencies, the proposed approach seeks to establish a foundation for the next generation of intelligent methane monitoring systems (Ogunnowo et al., 2022, Adelusi et al., 2023a).

3. METHODOLOGICAL FRAMEWORK

3.1 Multi-Sensor Data Architecture

A central component of the proposed framework is the multi-sensor data architecture, which integrates diverse sensor modalities into a unified stream of structured information. The architecture is designed to accommodate both continuous and event-triggered data inputs from different types of sensors such as optical, electrochemical, and resistive devices. Each sensor contributes a unique perspective on the presence and concentration of methane, and collectively they provide a more comprehensive and fault-tolerant measurement landscape. A local processing node or embedded edge unit collects the data, timestamping each signal to enable proper temporal alignment.

Data synchronization is essential for meaningful sensor fusion. Sensors often operate at different sampling frequencies and may be subjected to latency or jitter due to hardware limitations. The architecture applies temporal interpolation and buffer-based synchronization to align sensor outputs into a uniform time grid. Additionally, normalization techniques are employed to adjust for differing measurement scales and units across sensors. This typically involves min-max scaling or z-score normalization, ensuring that no individual sensor dominates the classification algorithm due to numerical magnitude alone.

To ensure robustness and resilience, redundancy handling is integrated into the data ingestion layer. This includes strategies for missing data imputation, sensor dropout detection, and consensus filtering. When sensor disagreement arises, majority voting or weighted averaging can be applied to determine likely values. These mechanisms make the architecture fault-tolerant, capable of continuing operation despite individual sensor anomalies. This architectural backbone ensures that the downstream machine learning components operate on clean, temporally aligned, and semantically rich data inputs, paving the way for more accurate and interpretable classification.

3.2 Machine Learning Classification Pipeline

The machine learning pipeline is designed to transform raw sensor data into actionable classifications, indicating whether a methane leak is present and potentially its severity. The pipeline begins with feature extraction, a process in which statistical, temporal, and frequency-domain characteristics are derived from raw sensor readings. Commonly used features include mean, variance, skewness, kurtosis, and slope of change within fixed time windows. In more complex implementations, time-frequency analysis such as Short-Time Fourier Transform or wavelet transforms may be employed to capture transient patterns associated with leak onset.

Following feature extraction, the data is passed to a set of candidate classification algorithms. Among the most effective are support vector machines (SVM), known for their performance in high-dimensional feature spaces and resistance to overfitting. Random forests, an ensemble learning method, provide robustness through bagging and feature sub-sampling, making them well-suited for heterogeneous sensor data. Gradient boosting methods such as XGBoost or LightGBM offer fine-grained control of model complexity and often achieve superior accuracy in structured data tasks. The choice of algorithm depends on the balance between model interpretability, computational efficiency, and detection performance.

Before entering the training phase, the dataset undergoes preprocessing and dimensionality reduction. Preprocessing includes outlier removal, signal smoothing, and label verification. Dimensionality reduction techniques like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) may be applied to reduce computational load and eliminate noise from irrelevant features. These steps are especially important in multi-sensor contexts, where feature proliferation can degrade model generalizability. The result is a streamlined and optimized feature set that feeds into the classifiers for training, validation, and real-time inference.

3.3 Model Training and Evaluation Protocol

Training the model involves a theoretically rigorous procedure designed to ensure statistical validity and robustness across various operating conditions. The process begins with dataset partitioning, typically using k-fold cross-validation, where the data is divided into k subsets or "folds." In each iteration, one fold is reserved for testing while the remaining k−1 folds are used for training. This approach allows the model to be evaluated across multiple data segments, mitigating the risks of overfitting and ensuring that performance metrics generalize beyond a single subset.

Performance evaluation employs standard classification metrics such as accuracy, precision, recall, and F1-score. These metrics provide insight into how well the model distinguishes between leak and non-leak conditions and how it balances false positives and false negatives. Additionally, the use of a confusion matrix allows for a granular understanding of each prediction class, offering a breakdown of true positives, false positives, true negatives, and false negatives. For probabilistic models, Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) scores can further quantify model discriminative ability.

To enhance trust and interpretability, the protocol includes post hoc model explanation techniques. Feature importance rankings are extracted to identify which sensor inputs most influence the model’s decisions. For more complex models like gradient boosting, tools such as SHAP (SHapley Additive exPlanations) can provide instance-level explanations, detailing how each feature contributed to a specific prediction. These explanations are essential for operational transparency, regulatory compliance, and iterative model refinement. Together, the training and evaluation protocol ensures that the classification framework is not only accurate but also robust, interpretable, and ready for deployment in industrial methane detection systems.

4. FRAMEWORK IMPLEMENTATION CONSIDERATIONS

4.1 Sensor Fusion Strategy

Sensor fusion is a critical component in multi-sensor methane detection systems, enhancing robustness by integrating information from multiple data sources. There are three primary fusion strategies: early fusion, late fusion, and hybrid fusion. Early fusion combines raw or preprocessed sensor data before classification (Zhang et al., 2024, Sahoo, 2024). This approach enables the model to learn joint feature representations and detect complex patterns that may be invisible in isolated data streams. However, early fusion can become computationally intensive and less scalable as the number of sensors and data dimensionality increase (Sun, 2024).

Late fusion, by contrast, involves performing independent classification on each sensor’s data stream, then aggregating the outputs, such as class probabilities or decisions, through methods like majority voting, weighted averaging, or rule-based logic. While this method is more modular and computationally efficient, it may miss synergistic patterns that span across multiple sensor modalities. It is also more vulnerable to decision-level inconsistencies when individual sensors deliver contradictory results, which can confuse downstream decision logic (Narkhede et al., 2021).

A hybrid fusion strategy offers the most robust solution in the context of methane detection. It combines the strengths of both early and late fusion by applying intermediate feature-level fusion. For example, certain sensors may share features at the early stage, while others are kept separate until a later aggregation point. This strategy allows for flexible architectural design, balancing computational efficiency with model accuracy. In volatile industrial environments where sensor noise, failure, or variability is common, a hybrid approach improves both adaptability and resilience, making it the preferred method for scalable, field-ready implementations (Yazdinejad et al., 2025).

4.2 Deployment Constraints and Environmental Variability

Real-world deployment of methane detection systems must contend with a variety of constraints that influence system performance, reliability, and maintainability. One of the foremost challenges is sensor placement (Toghyani et al., 2024). In industrial facilities such as gas processing plants or compressor stations, optimal sensor placement requires careful consideration of gas flow patterns, ventilation, and leak propagation pathways. Poor placement can result in blind spots or delayed detection, especially for small or slow-leaking emissions. Deploying sensors at varying heights, proximities, and orientations can help capture a more complete environmental picture (Li, 2024).

Ambient interference further complicates detection accuracy. Factors such as temperature fluctuations, humidity, dust, and the presence of other volatile compounds can alter sensor readings or degrade sensor longevity. For instance, high humidity may obscure optical sensor accuracy, while background hydrocarbons may trigger false positives in catalytic sensors (Khatib and Haick, 2022). Additionally, electromagnetic interference from nearby equipment may disrupt sensor communication or data integrity. These variables must be anticipated and mitigated through hardware shielding, signal filtering, and redundancy mechanisms in both sensor deployment and data acquisition protocols (Jalal et al., 2018, Spinelle et al., 2017).

Dynamic environments also present significant variability in terms of gas dispersion rates and background conditions. Industrial settings are rarely static, with machinery operation, human activity, and weather conditions introducing noise and unpredictability into sensor data. Over time, sensors themselves may experience drift or degradation, reducing their sensitivity or altering their calibration baselines. Adaptive mechanisms such as self-calibration routines, drift compensation algorithms, and periodic retraining of machine learning models can help ensure long-term reliability. Addressing these environmental and operational constraints is essential to translating the proposed detection framework into an effective, field-deployable solution (Yu et al., 2020).

4.3 Model Interpretability and Decision Support

In high-stakes applications such as methane leak detection, model interpretability is as crucial as predictive accuracy. Stakeholders, including safety engineers, regulatory bodies, and maintenance personnel, must understand not only that a leak has been detected, but also why the system reached that conclusion. Black-box models that lack transparency hinder user trust and complicate compliance with safety regulations. Therefore, integrating explainability mechanisms into the detection framework is essential to promote accountability and facilitate corrective action.

One powerful method for enhancing interpretability is the use of SHapley Additive exPlanations (SHAP). SHAP provides a local explanation for individual predictions by assigning each feature a contribution value toward the model’s output. In the context of methane detection, SHAP can highlight which sensors or derived features most influenced the classification decision, offering actionable insights. This is particularly valuable in fault diagnosis or post-event analysis, where understanding the origin of a prediction can guide field investigations and remediation strategies (Emmanuel, 2024, Wiggerthale and Reich, 2024).

Beyond SHAP, simpler tools such as feature importance rankings from tree-based models like random forests or gradient boosting can also aid interpretability at a global level. These rankings help prioritize sensor types or locations that consistently contribute to accurate detection, which can inform future system design and maintenance priorities. By embedding these interpretability tools into the decision-support layer of the framework, operators are equipped not only with predictive outputs but with contextualized, traceable justifications. This integration enhances operational trust, fosters user confidence, and ensures that the system serves as a reliable partner in safety-critical decision-making processes (Walker et al., 2023).

5. CONCLUSION

This paper presents a comprehensive multi-sensor classification framework designed to advance methane leak detection using machine learning techniques. By integrating heterogeneous sensor modalities and employing a layered classification pipeline, the framework enhances reliability across diverse environmental conditions. Unlike traditional systems that depend on a single sensor type or manual inspection routines, the proposed approach leverages data fusion and intelligent classification to deliver consistent, real-time detection capabilities. This design fundamentally improves system resilience and responsiveness in dynamic, safety-critical settings.

A key contribution lies in the framework's ability to reduce false positives and false negatives, a persistent challenge in conventional gas sensing. Through adaptive preprocessing, robust feature extraction, and well-calibrated classification models, the system distinguishes true leak events from ambient noise or non-critical fluctuations. This improves trust in automated alerts and minimizes operational disruptions caused by false alarms. Additionally, the use of interpretability tools such as feature importance rankings and SHAP values ensures that predictions are transparent and verifiable, further increasing stakeholder confidence in the system's decisions.

The framework also introduces scalability and adaptability that traditional approaches often lack. Its architecture supports modular sensor integration, redundancy handling, and drift compensation, which are critical for long-term deployments. The inclusion of fusion strategies, particularly hybrid fusion, enhances its capability to adapt to sensor failures and evolving site conditions without sacrificing accuracy. These design choices reflect a shift toward more intelligent, resilient systems that can self-adjust and maintain performance over time. Collectively, the proposed framework delivers a next-generation solution for methane detection that is robust, explainable, and field-deployable.

The proposed framework makes significant theoretical contributions to the fields of intelligent environmental monitoring and cyber-physical sensing systems. It demonstrates how integrating multiple sensor modalities with adaptive machine learning can produce a system that is greater than the sum of its parts. The methodological emphasis on fusion strategies and model explainability advances theoretical understanding of how classification systems can be made both accurate and interpretable. It provides a conceptual blueprint for future research exploring the intersection of environmental sensing, data fusion, and artificial intelligence.

In practical terms, the framework has substantial implications for industrial safety and regulatory compliance. As methane detection becomes increasingly scrutinized under climate policy frameworks, organizations are under pressure to deploy reliable and auditable monitoring solutions. The proposed system offers a means to meet these demands without excessive cost or operational complexity. It enables proactive leak detection, improves maintenance response time, and supports documentation required for environmental reporting and certification. Furthermore, its ability to function under variable operating conditions makes it suitable for deployment across a wide range of facilities, from oil and gas infrastructure to landfill sites and agricultural environments.

The framework also informs sensor selection and algorithm design, guiding practitioners on how to balance performance, cost, and complexity. It suggests that deploying a combination of high-precision and cost-effective sensors, integrated via a flexible fusion and classification architecture, can outperform single-sensor systems. From an algorithmic perspective, it promotes the use of ensemble classifiers and interpretable models over opaque, high-variance alternatives in safety-critical contexts. These insights equip engineers, researchers, and policymakers with the principles needed to design more effective methane monitoring systems in both new and retrofit scenarios.

Several avenues exist to extend and refine the proposed framework. One promising direction is the incorporation of adaptive learning models that evolve over time. Rather than requiring periodic manual retraining, future implementations could include online learning or semi-supervised approaches that update model parameters in response to new patterns in the data. This would allow the system to adjust to sensor drift, seasonal variation, or changes in operational conditions autonomously, increasing its longevity and reliability in long-term deployments.

Another area of interest is the exploration of unsupervised and semi-supervised anomaly detection techniques. While this paper focuses on supervised classification, many real-world leaks occur in contexts where labeled data are sparse or unavailable. Developing methods that can identify outliers or novel patterns without prior examples would improve early detection capabilities, particularly in under-monitored or novel environments. Clustering algorithms, autoencoders, and isolation forests could play a pivotal role in this domain, especially when combined with existing supervised pipelines in a hybrid decision system.

Finally, future research should examine the integration of the framework with edge computing paradigms. Deploying parts of the classification pipeline on local edge devices can reduce latency, preserve bandwidth, and enhance system autonomy in remote or infrastructure-limited areas. This is especially relevant for large-scale deployments across oil fields or rural environments, where cloud connectivity may be intermittent. Combining edge inference with centralized model updates and federated learning strategies could yield a scalable architecture that balances local responsiveness with global intelligence. These directions represent the next frontier in intelligent, distributed methane monitoring solutions.

REFERENCES

1. ADELUSI, B. S., UZOKA, A. C., HASSAN, Y. G. & OJIKA, F. U. 2023a. Blockchain-Integrated Software Bill of Materials (SBOM) for Real-Time Vulnerability Detection in Decentralized Package Repositories. *International Journal of Scientific Research in Civil Engineering,* 7**,** 102-116.
2. ADELUSI, B. S., UZOKA, A. C., HASSAN, Y. G. & OJIKA, F. U. 2023b. Predictive Analytics-Driven Decision Support System for Earned Value Management Using Ensemble Learning in Megaprojects. *International Journal of Scientific Research in Civil Engineering,* 7**,** 131-143.
3. ADELUSI, B. S., UZOKA, A. C., HASSAN, Y. G. & OJIKA, F. U. 2023c. Synthetic Data Generation for Workforce Analytics: A Review of GANs and Differential Privacy Techniques in Human Capital Forecasting.
4. ADEWOYIN, M. A., OGUNNOWO, E. O., FIEMOTONGHA, J. E., IGUNMA, T. O. & ADELEKE, A. K. 2024. Advances in AI-Based

Optimization for Multiphysics Fluid Dynamics in Product Design Engineering.

5. AKINSOOTO, O., OGUNNOWO, E. O. & EZEANOCHIE, C. C. 2025. The future of electric vehicles: Technological innovations and market trends. *Engineering and Technology Journal,* 10**,** 4392-4405.
6. ALDHAFEERI, T., TRAN, M.-K., VROLYK, R., POPE, M. & FOWLER, M. 2020. A review of methane gas detection sensors: Recent developments and future perspectives. *Inventions,* 5**,** 28.
7. ALVAREZ, R. A., PACALA, S. W., WINEBRAKE, J. J., CHAMEIDES, W. L. & HAMBURG, S. P. 2012. Greater focus needed on methane leakage from natural gas infrastructure. *Proceedings of the National Academy of Sciences,* 109**,** 6435-6440.
8. ASATA, M. N., NYANGOMA, D. & OKOLO, C. H. 2023. Reducing Passenger Complaints through Targeted Inflight Coaching: A Quantitative Assessment. *International Journal of Scientific Research in Civil Engineering,* 7**,** 144-162.
9. ASOLO, E., GIL-OZOUDEH, I. & EJIMUDA, C. 2024. AI-Powered decision support systems for sustainable agriculture using AI-Chatbot solution. *Journal of Digital Food, Energy & Water Systems,* 5.
10. AYORINDE, O. B., ETUKUDOH, E. A., NWOKEDIEGWU, Z. Q. S., IBEKWE, K. I., UMOH, A. A. & HAMDAN, A. 2024. Renewable energy projects in Africa: A review of climate finance strategies. *International Journal of Science and Research Archive,* 11**,** 923-932.
11. BIBI, A. & MOLLOHOLLI, M. 2024. Revolutionizing Medical Manufacturing with AI-Based Leak Detection Devices for Fluid Cassettes. *Research Gate*.
12. BOGNER, J., PIPATTI, R., HASHIMOTO, S., DIAZ, C., MARECKOVA, K., DIAZ, L., KJELDSEN, P., MONNI, S., FAAIJ, A. & GAO, Q. 2008. Mitigation of global greenhouse gas emissions from waste: conclusions and strategies from the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report. Working Group III (Mitigation). *Waste Management & Research,* 26**,** 11-32.
13. CHAN, T. K., CHIN, C. S. & ZHONG, X. 2018. Review of current technologies and proposed intelligent methodologies for water distributed network leakage detection. *Ieee Access,* 6**,** 78846-78867.
14. EMMANUEL, M. 2024. Machine learning models for hazard prediction using IoT inputs.
15. FARAH, E. & SHAHROUR, I. 2024. Water leak detection: a comprehensive review of methods, challenges, and future directions. *Water,* 16**,** 2975.
16. FOX, T. A., BARCHYN, T. E., RISK, D., RAVIKUMAR, A. P. & HUGENHOLTZ, C. H. 2019. A review of close-range and screening technologies for mitigating fugitive methane emissions in upstream oil and gas. *Environmental Research Letters,* 14**,** 053002.
17. FU, L., YOU, S., LI, G. & FAN, Z. 2023. Enhancing methane sensing with NDIR technology: Current trends and future prospects. *Reviews in Analytical Chemistry,* 42**,** 20230062.
18. GBABO, E. Y., OKENWA, O. K. & CHIMA, P. E. 2023a. Designing Value Realization Models for Stakeholder Benefits in Long-Term Energy Projects.
19. GBABO, E. Y., OKENWA, O. K. & CHIMA, P. E. 2023b. A Risk-Based Digital Governance Model for Ensuring Programme Assurance in Complex Infrastructure Delivery. *International Journal of Scientific Research in Civil Engineering,* 7**,** 67-81.
20. HODGKINSON, J. & TATAM, R. P. 2012. Optical gas sensing: a review. *Measurement science and technology,* 24**,** 012004.
21. HOWARTH, R. W. 2021. Methane and climate change. *Environmental Impacts from Development of Unconventional Oil and Gas Reserves; John, F., Stolz, W., Griffin, M., Bain, DJ, Eds*.
22. JALAL, A. H., ALAM, F., ROYCHOUDHURY, S., UMASANKAR, Y., PALA, N. & BHANSALI, S. 2018. Prospects and challenges of volatile organic compound sensors in human healthcare. *Acs Sensors,* 3**,** 1246-1263.
23. KHATIB, M. & HAICK, H. 2022. Sensors for volatile organic compounds. *ACS nano,* 16**,** 7080-7115.
24. KNOBELSPIES, S., BIERER, B., PEREZ, A. O., WÖLLENSTEIN, J., KNEER, J. & PALZER, S. 2016. Low-cost gas sensing system for the reliable and precise measurement of methane, carbon dioxide and hydrogen sulfide in natural gas and biomethane. *Sensors and Actuators B: Chemical,* 236**,** 885-892.
25. KUFILE, O. T., OTOKITI, B. O., ONIFADE, A. Y., OGUNWALE, B. & OKOLO, C. H. 2024. Designing Ethics-Governed AI Personalization Frameworks in Programmatic Advertising. *International Journal of Scientific Research in Civil Engineering,* 8**,** 115-133.
26. LE FEVRE, C. 2017. Methane Emissions: from blind spot to spotlight.
27. LI, Y. 2024. *Evaluation, Prediction, and Monitoring of Methane Emission from Oil and Gas*

Development. Massachusetts Institute of Technology.
28. MOLNÁR, A. 2018. Leaking away the future: the role of methane emission and natural gas supply chains in global warming. *Energy Policy Studies*.
29. NARKHEDE, P., WALAMBE, R., MANDAOKAR, S., CHANDEL, P., KOTECHA, K. & GHINEA, G. 2021. Gas detection and identification using multimodal artificial intelligence based sensor fusion. *Applied System Innovation,* 4**,** 3.
30. OGBOWUOKARA, O. S., LETON, T. G., UGBEBOR, J. N. & ORIKPETE, O. F. 2023. Developing climate governance strategies in Nigeria: An emphasis on methane emissions mitigation. *The Journal of Engineering and Exact Sciences,* 9**,** 17383-01e.
31. OGEAWUCHI, J. C., SHARMA, A., ADEKUNLE, B. I., ABAYOMI, A. A. & ONIFADE, O. 2024. Ethical Frameworks for AI Deployment in Financial Decision-Making: Balancing Profitability and Social Responsibility. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology,* 10**,** 905-917.
32. OGUNNOWO, E. O., ADEWOYIN, M. A., FIEMOTONGHA, J. E. & ODION, T. 2022. Advances in Predicting Microstructural Evolution in Superalloys Using Directed Energy Deposition Data.
33. OGUNNOWO, E. O., ADEWOYIN, M. A., FIEMOTONGHA, J. E. & ODION, T. 2023. A Conceptual Framework for Reliability-Centered Design of Mechanical Components Using FEA and DFMEA Integration.
34. OGUNNOWO, E. O., OGU, E., EGBUMOKEI, P. I., DIENAGHA, I. N. & DIGITEMIE, W. N. 2025. A pedagogical model for enhancing mechanical engineering education through experimental learning and laboratory techniques. *Journal of Materials Science Research and Reviews,* 8**,** 194-213.
35. OKEM, E. S., NWOKEDIEGWU, Z. Q. S., UMOH, A. A., BIU, P., OBAEDO, B. & SIBANDA, M. 2024. Civil engineering and disaster resilience: A review of innovations in building safe and sustainable communities. *International Journal of Science and Research Archive,* 11**,** 639-650.
36. OKUH, C. O., NWULU, E. O., OGU, E., EGBUMOKEI, P. I., DIENAGHA, I. N. & DIGITEMIE, W. N. 2023. Advancing a waste-to-energy model to reduce environmental impact and promote sustainability in energy operations. *Journal name needed]. Year*.
37. OKUH, C. O., NWULU, E. O., OGU, E., EGBUMOKEI, P. I., DIENAGHA, I. N. & DIGITEMIE, W. N. 2024a. Creating a Workforce Upskilling Model to Address Emerging Technologies in Energy and Oil and Gas Industries.
38. OKUH, C. O., NWULU, E. O., OGU, E., EGBUMOKEI, P. I., DIENAGHA, I. N. & DIGITEMIE, W. N. 2024b. A Strategic Model for Carbon Emission Reduction through Process Optimization in Energy Sector Operations.
39. OKUH, C. O., NWULU, E. O., OGU, E., EGBUMOKEI, P. I., DIENAGHA, I. N. & DIGITEMIE, W. N. 2025. Designing a reliability engineering framework to minimize downtime and enhance output in energy production.
40. OLAJIDE, J. O., OTOKITI, B. O., NWANI, S., OGUNMOKUN, A. S., ADEKUNLE, B. I. & FIEMOTONGHA, J. E. 2023a. Building a Working Capital Optimization Model for Vendor and Distributor Relationship Management. *International Journal of Scientific Research in Civil Engineering,* 7**,** 55-66.
41. OLAJIDE, J. O., OTOKITI, B. O., NWANI, S., OGUNMOKUN, A. S., ADEKUNLE, B. I. & FIEMOTONGHA, J. E. 2023b. Designing Cash Flow Governance Models for Public and Private Sector Treasury Operations. *International Journal of Scientific Research in Civil Engineering,* 7**,** 45-54.
42. OLANLOYE, O. O., ADENIYI, A. E., AWORINDE, O. H., OLAGUNJU, M., ADENIYI, J. K., ADELEKE, I. A. & NGOKA, M. U. Development of a stock prediction system using Deep Learning Model Approach. 2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG), 2024. IEEE, 1-7.
43. OLUOHA, O., ODESHINA, A., REIS, O., OKPEKE, F., ATTIPOE, V. & ORIENO, O. 2023. A Privacy-First Framework for Data Protection and Compliance Assurance in Digital Ecosystems. *Iconic Research and Engineering Journals,* 7**,** 620-646.
44. OMISOLA, J. O., ETUKUDOH, E. A., OKENWA, O. K. & TOKUNBO, G. I. 2025. Pore-Scale Modeling of CO_2-Brine-Rock Interactions in Carbonate Reservoirs: Numerical and experimental evaluation of geochemical and Geomechanical changes occurring during CO_2 injection in carbonate formations.
45. REAY, D., SMITH, P. & VAN AMSTEL, A. 2010. Methane sources and the global methane budget. *Methane and climate change.* Routledge.
46. SAGAY-OMONOGOR, I., BOLARINWA, T. & AKOMOLAFE, O. O. 2023. Overcoming

Challenges in Cancer Immunotherapy: Mechanisms and Clinical Solutions.

47. SAHOO, S. 2024. Sensor Fusion and Virtual Sensor Design for Enhanced Multi-Sensor Data Accuracy in Autonomous Systems. *International Journal on Smart & Sustainable Intelligent Computing,* 1**,** 21-39.
48. SHUK, P., MCGUIRE, C. & BROSHA, E. 2019. Methane gas sensing technologies in combustion: Comprehensive review. *Sensors & Transducers,* 229.
49. SOBANAA, M., PRATHIVIRAJ, R., SELVIN, J. & PRATHABAN, M. 2024. A comprehensive review on methane's dual role: effects in climate change and potential as a carbon–neutral energy source. *Environmental Science and Pollution Research,* 31**,** 10379-10394.
50. SPINELLE, L., GERBOLES, M., KOK, G., PERSIJN, S. & SAUERWALD, T. 2017. Review of portable and low-cost sensors for the ambient air monitoring of benzene and other volatile organic compounds. *Sensors,* 17**,** 1520.
51. SUN, M. 2024. Multi-sensor data fusion and management strategies for robust perception in autonomous vehicles. *Nuvern Applied Science Reviews,* 8**,** 59-68.
52. TOGHYANI, M., DADKHAHFAR, S. & ALISHAHI, A. 2024. Economic assessment and environmental challenges of methane storage and transportation. *Advances and Technology Development in Greenhouse Gases: Emission, Capture and Conversion.* Elsevier.
53. UDDOH, J., AJIGA, D., OKARE, B. P. & ADULOJU, T. D. 2024. Scalable AI-Powered Cyber Hygiene Models for Microenterprises and Small Businesses. *International Journal of Scientific Research in Civil Engineering,* 8**,** 177-188.
54. UN, C. 2023. A sustainable approach to the conversion of waste into energy: Landfill gas-to-fuel technology. *Sustainability,* 15**,** 14782.
55. WALKER, C. M., AGARWAL, V., LIN, L., HALL, A. C., HILL, R. A., MORTENSON, T. J. & LYBECK, N. J. 2023. Explainable artificial intelligence technology for predictive maintenance. Idaho National Laboratory (INL), Idaho Falls, ID (United States).
56. WIGGERTHALE, J. & REICH, C. 2024. Explainable machine learning in critical decision systems: ensuring safe application and correctness. *AI,* 5**,** 2864-2896.
57. YAZDINEJAD, A., WANG, H. & KONG, J. D. 2025. Advanced AI-Driven Methane Emission Detection, Quantification, and Localization in Canada: A Hybrid Multi-Source Fusion Framework. *Quantification, and Localization in Canada: A Hybrid Multi-Source Fusion Framework (April 10, 2025).*
58. YU, J., WANG, D., TIPPARAJU, V. V., TSOW, F. & XIAN, X. 2020. Mitigation of humidity interference in colorimetric sensing of gases. *ACS sensors,* 6**,** 303-320.
59. YUSSOF, N. A. M. & HO, H. W. 2022. Review of water leak detection methods in smart building applications. *Buildings,* 12**,** 1535.
60. ZHANG, Y., ZHANG, B., SHEN, C., LIU, H., HUANG, J., TIAN, K. & TANG, Z. 2024. Review of the field environmental sensing methods based on multi-sensor information fusion technology. *International Journal of Agricultural and Biological Engineering,* 17**,** 1-13.