AI-Assisted Hydrocarbon Leakage Detection and Incident Prevention in Saudi Arabia: Advancing Environmental Protection under Vision 2030

Abstract:

Hydrocarbon leakage remains an operational, environmental, and safety concern across upstream, midstream, and downstream systems, while Saudi Arabia pursues digital industrialization and stronger environmental performance under Vision 2030. This review critically examines how artificial intelligence can strengthen leakage detection and incident prevention by integrating pressure and flow analytics, acoustic emission, distributed optical-fiber sensing, infrared imaging, drones, corrosion prediction, transient simulation, and asset-health data. This integrative review compares sensing modalities, machine-learning architectures, validation practices, and deployment constraints rather than treating algorithmic accuracy as the sole measure of value. The evidence indicates that AI is most useful when it fuses complementary signals, accounts for changing operating regimes and connects detection outputs to maintenance and emergency decisions. Acoustic and pressure-based methods offer continuous internal surveillance but are sensitive to operational transients; optical, thermal, and aerial methods improve spatial awareness but depend on line of sight, atmospheric conditions, or inspection frequency. Predictive corrosion and failure models extend the system from leak recognition to prevention, although scarce labeled failures, class imbalance, and inconsistent reporting limit field generalizability. For Saudi conditions, a layered architecture combining edge sensing, hybrid physics-data models, explainable risk scoring, centralized governance, and human confirmation is more defensible than isolated black-box detection. The review proposes a Vision 2030-aligned implementation framework emphasizing environmental protection, resilience, data governance, workforce capability, and auditable performance. Research priorities include Saudi field datasets, climate-aware sensing, digital-twin validation, cross-asset transfer learning and incident-oriented evaluation metrics.

Keywords: artificial intelligence; hydrocarbon leakage; pipeline integrity; methane; machine learning; Saudi Arabia; Vision 2030; environmental protection

1.Introduction

Oil and gas infrastructure is designed around containment, yet leakage can emerge from corrosion, seal failure, construction defects, third-party damage, abnormal operations, fatigue, geotechnical movement, or equipment degradation. The consequences extend beyond product loss. A leak can escalate into fire or explosion, contaminate soil and groundwater, increase methane emissions, interrupt production, and impose reputational and regulatory costs. Reviews of pipeline leak detection consistently conclude that no single method is uniformly superior across leak size, fluid phase, burial condition, pressure regime, and environmental setting (Zaman et al., 2020; Lu et al., 2020; Behari et al., 2020). This matters in Saudi Arabia because hydrocarbon assets span extensive desert corridors, industrial clusters, gathering systems, processing facilities, terminals, and urban interfaces, creating heterogeneous detection problems rather than one standardized use case.

Artificial intelligence changes this problem in two related ways. First, it can classify complex patterns in high-frequency sensor data that are difficult to encode through fixed thresholds. Second, it can combine historically separate monitoring streams into a probabilistic assessment of abnormality, leak location, leak magnitude, and future failure risk. The uploaded structural reference similarly organizes AI in oil and gas around machine learning, IoT, monitoring, defect detection, predictive maintenance and emissions surveillance, providing a useful conceptual progression without supplying evidence for the present review. Recent scholarship shows that data-driven approaches are increasingly being coupled with acoustic emission, pressure transients, fiber-optic signals, infrared images, and integrity data (Banjara et al., 2020; Zuo et al., 2020; Muggleton et al., 2020).

However, high laboratory accuracy does not automatically translate into safer operations. Leakage is a low-frequency, high-consequence event, so training data are imbalanced and true field failures are scarce. Normal operating transitions can resemble leaks, while temperature, wind, vibration, sand, equipment state, and multiphase flow can shift data distributions. Machine-learning systems may therefore produce false alarms, miss unfamiliar leak signatures, or become unreliable when transferred between assets. Broader industrial maintenance research warns that model performance is often reported without sufficiently rigorous external validation or cost-sensitive evaluation (Leukel et al., 2021; Wen et al., 2022). A review focused only on algorithms would consequently understate the institutional and engineering conditions required for incident prevention.

The Saudi Vision 2030 context adds a strategic dimension. Environmental protection, resource efficiency, industrial digitization, and local capability development are mutually reinforcing when leakage monitoring is treated as an integrated integrity-management function rather than a stand-alone sensor project. Saudi-focused research has already linked machine learning with questions of energy use and environmental quality, demonstrating the relevance of digital methods to national sustainability objectives (Kahia et al., 2022). The central issue is therefore not whether AI can detect a leak signal, but how AI-assisted monitoring can be designed to produce reliable, timely, and auditable action across Saudi hydrocarbon operations.

2.Aim of the Study

This review aims to critically synthesize recent peer-reviewed evidence on AI-assisted hydrocarbon leakage detection and incident prevention and translate that evidence into a technically defensible implementation framework for Saudi Arabia. The review distinguishes detection, localization, quantification, and prevention as separate functions, examines how sensing and algorithms interact under real operating conditions, and evaluates how predictive integrity management can support environmental protection under Vision 2030. Rather than proposing that AI replace established engineering safeguards, the study assesses where AI can augment instrumentation, inspection, maintenance, and emergency decision-making, and where uncertainty still requires human verification or conventional protection layers.

3.Research Objectives

Five objectives guide the review. First, to compare the principal AI-enabled sensing and analytical pathways used for hydrocarbon leak detection, including pressure-flow analytics, acoustic emission, distributed optical-fiber sensing, infrared imaging and aerial or remote observation. Second, to evaluate the strengths and limitations of machine-learning, deep-learning, and hybrid physics-data approaches for leak detection, localization, and severity estimation. Third, to examine how corrosion prediction, failure forecasting and predictive maintenance can shift leakage management from reactive detection toward incident prevention. Fourth, to identify technical, data, governance, and human-factor requirements for reliable deployment in Saudi operational and environmental conditions. Fifth, to develop research and policy priorities that align leakage intelligence with environmental performance, industrial resilience and digital capability development under Vision 2030.

4.Research Questions

The review addresses five questions. What combinations of sensors and AI methods provide the most defensible coverage across hydrocarbon leakage scenarios? How do current studies balance sensitivity, false alarms, localization accuracy, computational demand, and field transferability? Which predictive integrity techniques can identify precursors such as corrosion or abnormal equipment behavior before containment is lost? What deployment constraints are especially relevant to Saudi pipelines, processing facilities, and remote assets? Finally, what research, managerial, and policy mechanisms are required to convert AI-generated alerts into verifiable incident-prevention outcomes rather than isolated technical demonstrations?

5.Review Methodology

We adopted a structured integrative review design because the topic spans process engineering, pipeline integrity, sensing, machine learning, maintenance, and environmental monitoring. The attached paper was used only as a structural and academic-writing reference; its claims and references were not treated as evidence for this manuscript. The evidence base for the substantive review was developed independently from peer-reviewed journal literature, with emphasis on work published from 2020 to 2025 and limited use of earlier publication dates where the final journal issue or DOI record fell near the review boundary.

Searches were conceptually organized around Scopus- and Web of Science-relevant journal domains and publisher databases, using combinations of terms such as “oil gas pipeline leak detection,” “hydrocarbon leakage machine learning,” “acoustic emission leak,” “distributed acoustic sensing pipeline,” “methane infrared deep learning,” “pipeline corrosion machine learning,” “predictive maintenance oil gas,” “drone pipeline artificial intelligence,” “transient leak detection,” and “Saudi environmental machine learning.” The search logic combined four concept groups: asset or fluid, failure mode, digital method, and outcome. We used reference chaining to identify complementary sensing and integrity studies. We checked bibliographic details and DOI strings for the final reference set against publisher pages, DOI-resolving records, or reliable scholarly metadata sources.

Inclusion criteria required peer-reviewed journal articles directly relevant to leakage detection, localization, methane or hydrocarbon observation, pipeline failure prediction, corrosion prediction, AI-enabled inspection, predictive maintenance, or the Saudi environmental-digital context. Studies had to provide sufficient methodological detail to support comparison. We excluded purely commercial reports, vendor claims, news items, non-peer-reviewed webpages, and sources with unverifiable bibliographic information. We considered water-pipeline studies only when they introduced transferable analytical methods, but the final evidence set prioritizes oil, gas, and industrial pipeline literature. No article-screening totals are reported because this review did not conduct a preregistered systematic review with a reproducible database export; inventing counts would create false precision.

Quality assessment focused on five dimensions: clarity of sensing configuration, transparency of data generation, appropriateness of validation, realism of operating conditions, and relevance of reported metrics to incident prevention. We applied particular caution to studies based solely on simulated leaks or balanced laboratory datasets because such designs can overstate field performance. We synthesized evidence thematically rather than meta-analytically because outcome definitions, leak sizes, sensor placements, sampling frequencies, and metrics were too heterogeneous for defensible statistical pooling. Table 1 therefore compares technology families qualitatively, while Figure 1 integrates the recurring evidence into a multilayer detection architecture. The synthesis also distinguishes detection accuracy from operational utility: an algorithm is valuable only if it identifies meaningful abnormality early enough, localizes it sufficiently, communicates uncertainty, and supports an appropriate response.

6.Thematic Literature Review and Critical Analysis

Conventional computational leak detection provides the baseline against which AI should be judged. Mass balance, negative-pressure-wave methods, pressure-point analysis, and real-time transient modeling exploit hydraulic changes caused by product loss. Their advantage is that they can operate continuously using process measurements already present in many control systems. Their weakness is ambiguity: pump starts, valve movements, demand changes, and multiphase behavior can create transients that resemble leakage. Sekhavati et al. (2022) show that computational methods differ in detection speed, localization capability, and operating assumptions, reinforcing the case for hybrid rather than universal solutions. AI can learn nonlinear relationships among pressure, flow, and temperature, but it should complement, not obscure, physical constraints. A model that predicts “leak” without consistency with mass conservation, wave propagation, or plausible location is difficult to trust in safety-critical service.

Acoustic emission is one of the strongest areas of recent data-driven research. Escaping fluid generates stress waves and broadband acoustic signatures that attached sensors can capture. Banjara et al. (2020) demonstrated that machine-learning classification can distinguish healthy and leaking pipe conditions from acoustic-emission features, while Rai et al. (2021) used event-level features and distributional testing to reduce dependence on conventional summary statistics. Ullah et al. (2023) later reported strong classification performance across leak conditions using time- and frequency-domain features. More recent deep-learning work uses transformed time-frequency representations and sequential architectures to learn features automatically (Siddique et al., 2024; Ullah et al., 2024). The attraction is sensitivity to small leaks and compatibility with continuous monitoring. The limitation is environmental noise and coupling: compressors, vehicles, structural vibration, soil conditions, and sensor attachment can change the signal pathway. Reported laboratory accuracy should therefore be interpreted as proof of analytical capability, not direct evidence of site-wide reliability.

Distributed optical-fiber sensing offers a different scaling advantage because a single fiber can monitor long distances. Zuo et al. (2020) demonstrated distributed acoustic sensing for pipeline leakage, while Muggleton et al. (2020) experimentally characterized gas-leak noise measured through optical fiber and highlighted the importance of background noise, gauge length, and installation conditions. For Saudi long-distance corridors, fiber sensing is attractive because it can provide spatially continuous awareness without dense point sensors. Yet optical-fiber analytics must distinguish leak signatures from excavation, traffic, wind-induced vibration, and routine operations. Machine learning can improve pattern recognition, but field labels are difficult to obtain. The practical research need is therefore for weakly supervised and anomaly-detection methods trained on abundant normal data and calibrated through controlled releases.

Optical gas imaging and infrared analytics are particularly relevant for methane and gaseous hydrocarbons. Meribout et al. (2020) identify infrared sensing as a major leak-detection pathway, while Wang et al. (2022) show how deep video models can move optical gas imaging from visual detection toward automated leak classification. Xiong et al. (2022) demonstrate deep-learning detection of underground micro-leakage through thermal imagery, illustrating that indirect surface-temperature effects can also be informative. These methods can inspect valves, flanges, tanks, and accessible pipeline sections without physical contact. Constraints include visibility, camera geometry, thermal contrast, wind, and atmospheric conditions. In hot, arid environments, background temperature and solar loading may reduce contrast at certain times of day, making local calibration essential. AI should be trained across seasonal and diurnal conditions rather than on a narrow thermal envelope.

Aerial and remote sensing extend coverage beyond fixed installations. Ravishankar et al. (2022) combine drones and AI for pipeline resilience assessment, showing how repeated image collection can identify physical deterioration that may precede failure. Ramachandran et al. (2024) use deep learning to map oil and gas infrastructure from satellite imagery, demonstrating the broader potential of automated geospatial asset intelligence. Although infrastructure mapping is not leak detection itself, accurate asset inventories are foundational for prioritizing inspections, reconciling emission observations with potential sources, and identifying unrecorded or changing surface features. Rutherford et al. (2021) further demonstrate the importance of reconciling measured methane emissions with inventories. For Saudi Arabia, drones and remote sensing could be especially useful over remote corridors, but operating procedures must account for aviation rules, data transfer, wind, dust, and battery performance.

Corrosion and integrity prediction connect detection to prevention. Soomro et al. (2022) review machine-learning approaches for integrity assessment of corroded pipelines and emphasize the importance of input parameters and data preparation. Ben Seghier et al. (2022) show that ensemble learning can predict internal corrosion rates with strong performance under the conditions they studied. Fang et al. (2023) similarly use machine-learning models trained on simulated corrosion scenarios for crude-oil and natural-gas pipelines, while Ismail et al. (2023) combine classification with probabilistic analysis and Xu et al. (2023) develop a hybrid approach for corrosion-rate prediction. These studies are important because a leak is often the terminal outcome of a degradation process. If AI can estimate corrosion growth, remaining margin, or inspection priority, interventions can occur before containment is lost.

Yet prevention models face a subtle validation problem. Corrosion datasets may combine simulations, laboratory measurements, and in-line inspection records that represent different physical realities. A model can fit corrosion rate accurately while still misranking actual failure risk if it incompletely represents wall thickness, defect interaction, stress, coating condition, cathodic protection, and operating history. Al-Sabaeei et al. (2023) similarly conclude that machine-learning failure prediction is promising but constrained by data reliability and heterogeneous validation. Accordingly, predictive integrity should be framed as risk support, not an autonomous declaration of fitness for service.

The broad oil-and-gas AI literature reinforces this socio-technical interpretation. Sircar et al. (2021) show that machine learning is being applied across upstream data-intensive tasks. Still, the diversity of applications also means that governance, data quality, and domain knowledge determine whether algorithms remain useful after deployment. Industrial maintenance reviews reach the same conclusion: failure prediction requires appropriate preprocessing, evaluation on unseen conditions, and integration with maintenance economics and decision processes (Leukel et al., 2021; Wen et al., 2022). For leakage prevention, the key transition is therefore from “model accuracy” to “decision reliability.” Figure 1 represents this transition as a layered architecture in which sensing, edge analytics, hybrid inference, risk interpretation, and response are linked but separately auditable.

Pathway	Primary signal	AI role	Key strength	Main limitation	Saudi relevance
Pressure/flow analytics	Hydraulic process variables	Anomaly classification; residual modeling	Continuous use of installed instrumentation	Transients can mimic leaks	Strong baseline for pipelines and process plants
Acoustic emission	Stress waves / vibration	Feature learning; event classification	Sensitive to small, rapid releases	Noise, coupling and sensor placement	Useful at valves, joints and critical segments
Distributed fiber sensing	Spatially distributed acoustic/strain response	Pattern recognition; localization	Long linear coverage from one sensing cable	Background vibration and installation effects	High value for remote pipeline corridors
Infrared / thermal imaging	Gas plume or thermal contrast	Detection; segmentation; size classification	Non-contact visual localization	Line of sight, wind and thermal background	Requires heat- and dust-aware calibration
Drone / satellite observation	Aerial imagery and plume/asset context	Object detection; change analysis	Rapid coverage of remote assets	Weather, flight constraints, revisit interval	Strong for remote inspection and asset intelligence
Integrity prediction	ILI, corrosion, maintenance	Failure probability;	Supports prevention before release	Sparse labels; simulation-to-field gap	Enables risk-based inspection and

	and operating history	corrosion-rate prediction			maintenance

Table 1. Comparative characteristics of AI-enabled hydrocarbon leakage monitoring pathways

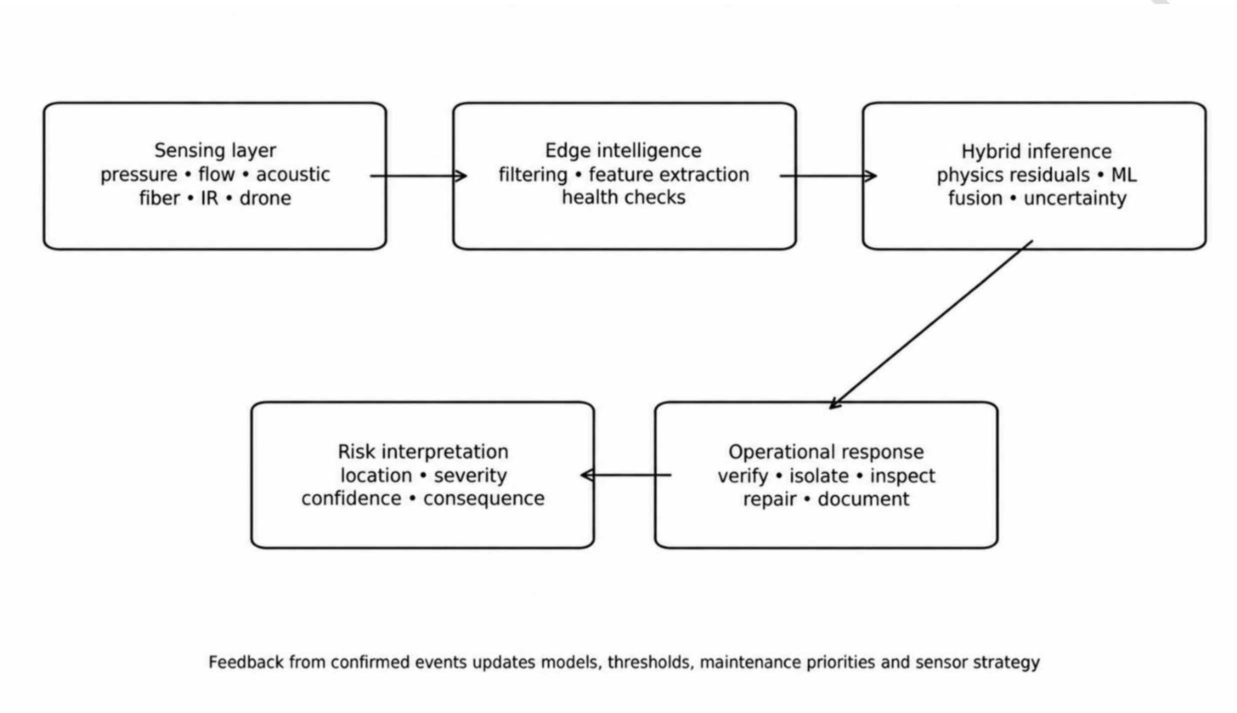


Figure 1. Layered architecture for AI-assisted hydrocarbon leakage detection and response.

The architecture separates sensing, edge processing, hybrid inference, risk interpretation, and operational response so that each stage can be validated and audited independently.

7.Discussion

The literature supports three main conclusions. First, sensor diversity is more important than algorithm novelty. Pressure-flow analytics observe internal process behavior; acoustic and fiber systems capture mechanical signatures; infrared cameras observe gas plumes or thermal effects; aerial imagery provides spatial context; and integrity models estimate precursor degradation. Each modality sees a different projection of the same risk. The most credible architecture therefore fuses modalities rather than attempting to perfect one channel. Table 1 shows why: technologies trade sensitivity, coverage, localization, cost, and environmental robustness. A fusion system can use agreement between independent signals to increase confidence and can downgrade alerts when evidence is inconsistent.

Second, hybrid physics-data models are better aligned with safety-critical deployment than unconstrained black boxes. Kim et al. (2024) demonstrate the value of combining dynamic pipeline modeling with machine learning under transient conditions. This direction matters because Saudi assets experience operational changes that can invalidate static thresholds. A hybrid model can generate expected pressure-flow behavior from physical equations, use machine learning to model residual patterns, and then compare the inferred event with feasible leak locations and magnitudes. Such architecture improves explainability because the operator can see whether the alert arises from hydraulic imbalance, acoustic evidence, thermal evidence, or a combination.

Third, treat leakage prevention as a closed-loop management problem. Detection is only the first stage. Operators must verify, localize, prioritize, and link alerts to isolation or maintenance procedures; record them for learning; and review them to improve the model. Figure 2 illustrates this closed loop. If AI is disconnected from work management, emergency response, and inspection planning, it may increase alarm volume without reducing incidents. Conversely, if risk scores are connected to consequence models and maintenance capacity, AI can help allocate inspections to assets where the expected environmental and safety benefit is highest.

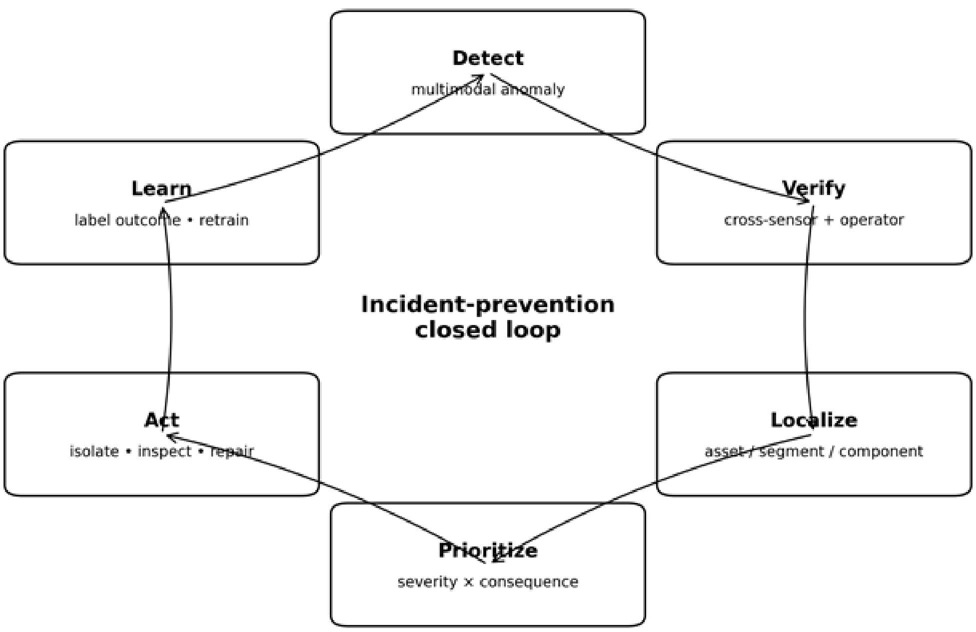
Saudi deployment introduces environmental and organizational considerations that the international literature underrepresents. High ambient temperatures can affect electronics and thermal contrast; dust can degrade optical systems; remote routes challenge communications and maintenance access; and large asset networks create heterogeneous equipment histories. These conditions argue for edge computing, sensor health monitoring, redundant communications, and periodic controlled-release or simulated validation. They also argue against importing a model trained on one foreign test rig and treating it as production-ready.

Vision 2030 alignment is strongest when leakage AI is linked to measurable environmental and industrial outcomes rather than described as digital transformation for its own sake. Kahia et al. (2022) demonstrate the broader importance of machine-learning analysis to Saudi environmental-quality questions. In hydrocarbon operations, relevant outcomes include shorter uncontrolled releases, faster localization, lower false-alarm burden, improved inspection targeting, reduced emergency shutdown exposure, and stronger methane accountability. These indicators can be audited over time and can support both operational excellence and environmental governance.

A final issue is uncertainty communication. Many machine-learning studies report a single accuracy figure, but operators need calibrated probabilities, confidence intervals, or decision categories. A 95% classification score may hide poor sensitivity to rare small leaks or performance collapse under new operating states. For safety use, evaluation should include time-to-detect, minimum detectable leak, localization error, false alarms per operating hour, missed-event rate, robustness to transients, data latency, and post-deployment drift. The objective is not to maximize a benchmark metric; it is to reduce expected harm while preserving operational continuity.

Operationally, this implies staging validation from historical replay to release testing and then monitored field deployment. Baselines should cover startup, shutdown, throughput changes, maintenance interventions, seasonal temperature ranges, and communication failures. Alert thresholds should be consequence-sensitive because a small release near people or sensitive habitat may deserve faster escalation than a comparable signal in a controlled area. Data quality indicators should travel with every prediction so operators can distinguish strong evidence from inference made under sensor degradation. Model drift should trigger review when residual distributions, calibration error, or false-alarm frequency change materially. Independent engineering checks should remain available because redundancy is a core safety principle, not evidence that artificial intelligence has failed. Over time, confirmed incidents, near misses, and false alarms should be converted into curated learning cases with traceable labels. This creates an institutional memory that improves both models and procedures. It also enables transparent comparison between sites because performance can be expressed through common operational metrics rather than vendor-specific accuracy claims. For Saudi organizations, the resulting learning system can support research workforce development and technology qualification while keeping environmental outcomes central. The same governance framework can extend from pipelines to valves, tanks, compressors, loading systems, and other hydrocarbon containment assets, provided each use case has defined hazard-sensing assumptions, response authority, and validation evidence. Ultimately, trustworthy automation should make abnormal conditions easier to recognize, explain, verify, and act upon without weakening established layers of protection. A further requirement is scenario-based assurance. Models should be challenged with slow seepage, sudden rupture, sensor dropout, simultaneous maintenance activity, and unusual product compositions because combinations expose brittle assumptions. Cybersecurity testing is also necessary when edge devices communicate with control networks since corrupted timestamps, spoofed measurements, or unavailable links can undermine accurate inference. Governance should define which outputs are advisory and which can initiate automated protective actions. Where automation is permitted, specify fail-safe behavior before deployment and rehearse it with operators. Environmental teams should participate in threshold design because ecological consequence is not identical to production consequence. Community proximity, groundwater vulnerability, and sensitive habitats can alter escalation priorities. Procurement contracts should preserve access to model documentation, performance logs, and retraining history so organizations are not locked into unverifiable black box services. Finally, cross-functional reviews should include process safety, integrity maintenance operations, data science, cybersecurity, and environmental specialists. Their combined perspective reduces the risk that technical optimization in one discipline creates hidden weakness in another and helps ensure that AI remains an accountable engineering aid rather than an isolated analytics product. Periodic external assurance can add a safeguard by independently checking sampling logic, alarm records, model changes, and unresolved events. This creates evidence that performance remains stable after software updates, sensor replacement, network reconfiguration, or changes in operating strategy.

Figure 2. Closed-loop incident-prevention cycle for operational use of AI alerts.



The value of an alert is realized only when detection is converted into verification, localization, prioritization, action, and structured learning.

8.Research Gaps and Future Research

The largest gap is the shortage of open, field-representative hydrocarbon leakage datasets. Many published studies rely on laboratory rigs, controlled releases, simulations, or curated class balances. Future Saudi research should establish governed datasets spanning pipelines, compressor stations, processing equipment, tank farms, and terminals, with metadata on operating state, weather, maintenance condition, and confirmed event outcome. Privacy and security constraints can be addressed through federated learning, secure data enclaves and shared feature standards rather than unrestricted raw-data exchange.

A second gap concerns domain shift. Models trained in one environment may fail when sensor placement, pipe diameter, product composition, soil coupling, or ambient conditions change. Researchers should explicitly evaluate transfer learning and domain adaptation across Saudi regions and asset types. Research should also examine climate-aware infrared and acoustic models that incorporate temperature, wind, and dust as contextual variables rather than treating them as noise.

Third, prevention research needs stronger integration between degradation models and leak-detection systems. Researchers often study corrosion prediction, vibration diagnostics, valve health, inspection history, and leak alarms separately. Digital twins could provide a common state representation, but they require continual calibration and uncertainty bounds. Future work should test whether hybrid digital twins can forecast risk earlier than conventional integrity rules without increasing false interventions.

Fourth, explainable and causal methods remain underdeveloped. Operators need to know which sensors, features, and physical inconsistencies drove an alert. Karimanzira (2023) shows the potential of attention-based anomaly detection, but interpretability must extend beyond visual attention weights to engineering explanations. Research should compare counterfactual explanations, Shapley-based feature attribution, physics residuals, and rule-constrained models in operator decision trials.

Finally, evaluation should become incident-oriented. Aljameel et al. (2024) synthesize leakage approaches but, like the broader field, reveal methodological diversity that complicates comparison. A Saudi test protocol could define common leak sizes, pressure regimes, detection-delay metrics, environmental conditions, and false-alarm reporting. Such a protocol would support procurement, research benchmarking and regulator-industry learning without prescribing a single technology.

9.Practical, Managerial and Policy Implications

For operators, the practical priority is a tiered architecture rather than wholesale replacement of existing protection systems. Table 2 proposes a deployment matrix. High-consequence assets should combine process analytics with at least one independent external or structural sensing channel. Edge devices should perform basic signal conditioning and anomaly screening, while centralized platforms should fuse evidence, retain audit trails, and coordinate risk scoring. Human confirmation should remain mandatory for ambiguous events and for actions with major production consequences unless an independent safety system already requires automatic shutdown.

Managers should govern leakage AI as a lifecycle asset. Model ownership, retraining triggers, sensor calibration, cybersecurity, change control, and incident feedback need assigned responsibilities. Procurement specifications should require field validation, not only benchmark accuracy, and should include performance under transient operations. Maintenance teams should receive alerts that translate into location, confidence, likely severity, and recommended verification steps rather than opaque model labels.

At policy level, environmental and digital objectives can be aligned through outcome-based reporting. Regulators and asset owners could encourage standardized metrics for detection delay, confirmed false alarms, inspection closure time and quantified release reduction. Shared testing facilities would help local universities, operators and technology firms validate sensors and models under high-temperature, dusty and long-distance conditions. Workforce policy is equally important: engineers need competence in both integrity fundamentals and data science so they recognize model limitations before making operational decisions.

The national opportunity is not merely to purchase AI systems but to build a Saudi capability for trustworthy industrial intelligence. Local datasets, validation protocols, cybersecurity practices, and engineering talent can reduce dependence on imported assumptions. This approach supports environmental protection while strengthening resilience and knowledge-based industrial development, which is more consistent with Vision 2030 than technology adoption measured only by the number of deployed sensors.

Layer	**Operational requirement**	**Performance evidence**	**Governance control**	**Vision 2030 contribution**
Field sensing	Redundant, maintainable sensor coverage	Detection delay; sensor uptime; minimum detectable event	Calibration and configuration control	Resource efficiency and environmental protection
AI analytics	Hybrid models with uncertainty reporting	False alarms/hour; missed-event rate; localization error	Versioning, retraining criteria and drift review	Digital industrial capability
Decision integration	Clear verification and escalation workflows	Time from alert to confirmed action	Human authority and audit trail	Operational resilience and safety
Data platform	Secure, time-synchronized multimodal records	Completeness; latency; label quality	Cybersecurity, access control and retention	Data-driven industrial ecosystem
Learning	Use incidents and	Post-event closure and	Independent review	Local knowledge,

system	near misses for improvement	model-improvement rate	and periodic revalidation	skills and innovation

Table 2. Vision 2030-aligned implementation and governance matrix

10.Limitations

This review has four limitations. First, it is an integrative review rather than a preregistered systematic review or meta-analysis, so it does not claim exhaustive coverage or report fabricated screening counts. Second, study heterogeneity prevents quantitative comparison across reported accuracy values because leak sizes, fluids, sensors, and validation designs differ substantially. Third, the literature contains more controlled experiments than long-duration field deployments, so conclusions about operational reliability remain cautious. Fourth, Saudi-specific peer-reviewed evidence on AI leakage detection is limited; consequently, the Saudi framework is an evidence-informed translation of international research combined with documented national environmental priorities, not a claim that every proposed architecture has already been validated locally.

11.Conclusion

AI-assisted hydrocarbon leakage management is best understood as an integrated safety and environmental capability rather than a single detection algorithm. The reviewed evidence shows meaningful advances in acoustic-emission classification, distributed optical-fiber sensing, infrared and thermal imaging, transient analytics, drone inspection, corrosion prediction and failure forecasting. These technologies can shorten detection time, improve localization and identify degradation before containment is lost, but their value depends on realistic validation, complementary sensing and disciplined decision integration.

For Saudi Arabia, a robust pathway is a layered architecture that combines existing process instrumentation with external sensing, edge analytics, hybrid physics-data inference, explainable risk scoring and closed-loop maintenance or emergency response. Such a design acknowledges the limitations of each modality and the operational realities of large, hot, dusty and geographically dispersed hydrocarbon assets. The strongest Vision 2030 contribution is not the use of AI itself; it is the measurable reduction of uncontrolled releases, environmental exposure and avoidable incidents while building domestic digital and engineering capability. Future progress therefore depends on Saudi field datasets, standardized incident-oriented metrics, climate-aware models, validated digital twins and governance systems that keep humans accountable for safety-critical decisions. AI can materially advance environmental protection when it is engineered as part of the integrity system, continuously tested against physical reality and judged by prevented harm rather than algorithmic novelty.

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