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A Hybrid Monitoring Framework for Identifying Leaks in CCUS Pipelines Using Computer Vision and Sensor Fusion

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Introduction

The rapid global push toward decarbonization has positioned carbon capture, utilization, and storage (CCUS) as a critical pillar in achieving net-zero emissions targets. As industries such as power generation, cement, steel, and petrochemicals transition toward lower-carbon operations, large-scale deployment of CCUS infrastructure is accelerating worldwide. Central to this infrastructure are extensive pipeline networks responsible for transporting captured carbon dioxide (CO_2) from emission sources to utilization sites or long-term geological storage reservoirs. Transporting dense-phase or supercritical CO_2 presents unique operational and safety challenges. Unlike conventional hydrocarbon pipelines, CO_2 streams may contain impurities that influence corrosion behavior, phase transitions, and fracture propagation risks. Undetected leaks can lead to environmental damage, groundwater contamination, ecosystem disruption, and potential health hazards in confined areas. Moreover, because many CCUS pipelines traverse remote or environmentally sensitive regions, traditional inspection and monitoring methods such as periodic manual inspections or standalone pressure monitoring are often insufficient for early detection and rapid response.

Recent advances in artificial intelligence (AI), computer vision, satellite imaging, and Internet of Things (IoT) technologies offer transformative opportunities for pipeline monitoring. Computer vision systems, powered by deep learning algorithms, can detect subtle visual anomalies such as ground discoloration, vegetation stress, vapor plumes, or thermal irregularities indicative of leaks.

However, individual sensing modalities, when deployed in isolation, face inherent limitations. Visual systems may be affected by occlusion, weather variability, or terrain complexity. Satellite imagery may lack temporal resolution for immediate response. IoT sensors, while precise, may generate false positives due to normal operational fluctuations. These limitations highlight the importance of sensor fusion and integrated approach that combines multiple data sources to improve detection accuracy, reduce uncertainty, and enhance situational awareness.

This paper introduces a hybrid monitoring framework for CCUS pipeline leak detection that integrates computer vision, satellite imaging, and ground-based IoT sensing within a unified AI-driven architecture. The proposed system leverages continuous monitoring from fixed pole-mounted cameras (RGB, thermal, and infrared) alongside periodic wide-area satellite surveillance to achieve layered spatial coverage. In parallel, distributed IoT sensors provide real-time operational data, enabling event-driven triggers when anomalous pressure, acoustic, or flow patterns are detected. By correlating visual anomalies with sensor-derived indicators, the framework enhances both leak detection sensitivity and localization precision.

As CCUS networks expand to underpin global decarbonization strategies, ensuring pipeline integrity will be fundamental to public acceptance and long-term sustainability. Intelligent monitoring systems that combine AI-driven analytics with multimodal sensing offer a pathway toward proactive maintenance, early incident detection, and optimized asset management. By advancing a scalable and adaptive hybrid framework, this research contributes to strengthening the safety, reliability, and environmental performance of next-generation carbon transport infrastructure.

Literature Survey

Research on pipeline integrity monitoring and leak detection has advanced rapidly with the integration of digital sensing and artificial intelligence techniques. Traditional approaches have historically relied on Supervisory Control and Data Acquisition (SCADA) systems, which use pressure, flow, and temperature measurements to infer anomalies along a pipeline. While effective for detecting gross failures, SCADA-based methods often lack spatial resolution and can be insensitive to small or slow leaks, particularly in complex multiphase flows such as dense CO_2 streams encountered in CCUS networks (Alvarado et al., 2018).

To overcome these limitations, acoustic and fiber-optic sensing technologies have been explored. Distributed Acoustic Sensing (DAS) deployed along pipelines provides continuous vibration profiles that can reveal leak signatures, but distinguishing between leak-induced signals and environmental noise remains challenging (Li & Wang, 2020). Fiber Bragg Grating (FBG) sensors capture strain changes associated with pressure perturbations, yet installation costs and maintenance complexity can be prohibitive for long pipeline corridors.

Computer vision and imaging modalities have gained traction as complementary tools. Studies have demonstrated the use of thermal infrared and multispectral imaging to detect gas plumes and surface temperature changes associated with leaks (Zhang et al., 2021). Unmanned aerial vehicles (UAVs) equipped with RGB and thermal cameras enhance inspection frequency and accessibility of remote terrain, yet their operational range and weather dependency limit continuous observation.

Hybrid sensor fusion approaches that integrate multiple modalities are emerging to improve robustness. Recent works combine IoT sensor arrays, visual analytics, and machine learning models to correlate temporal and spatial data streams, achieving higher sensitivity and reduced false positives compared to single-source methods (Chen et al., 2023). These studies underscore the value of multimodal digital frameworks in enhancing CCUS pipeline monitoring reliability.

Methodology and Solution

The proposed hybrid monitoring framework integrates computer vision, satellite imaging, and IoT-based sensing within a unified AI-driven architecture to enable accurate leak detection, localization, and quantification in CCUS pipelines. The methodology is structured into four primary layers: sensing, data acquisition and communication, analytics and sensor fusion, and decision support.

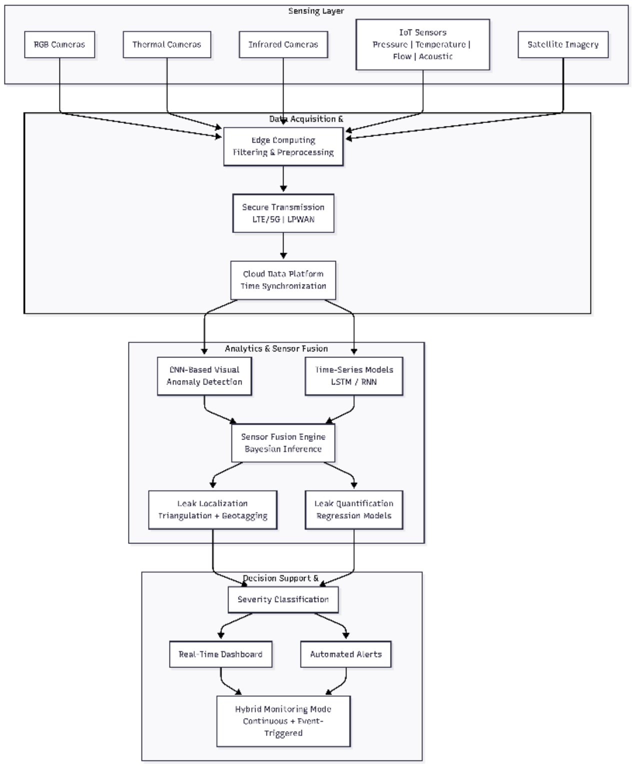

Figure 1: System Architecture

1. **Sensing Layer:** The sensing layer consists of heterogeneous monitoring components deployed along the pipeline corridor. Pole-mounted camera units equipped with RGB, thermal, and infrared sensors provide continuous visual coverage of high-risk segments such as joints, valves, and environmentally sensitive crossings. Thermal imaging enables detection of abnormal temperature gradients, while infrared cameras enhance the visibility of vapor plume under varying environmental conditions. In parallel, ground-based IoT sensor nodes are installed at predefined intervals to measure pressure, temperature, flow rate, and acoustic emissions. These sensors generate high-frequency time-series data reflecting operational states. Additionally, periodic satellite imagery provides wide-area surveillance, particularly for remote or inaccessible regions, supporting detection of vegetation stress, soil discoloration, or surface disturbances indicative of subsurface leaks.

2. **Data Acquisition and Communication Layer:** All sensing devices are connected through a secure edge-to-cloud communication framework. Edge computing modules preprocess raw data locally to reduce bandwidth consumption and latency. For example, image frames are filtered using lightweight anomaly detection models before transmission, and IoT signals undergo noise filtering and normalization at the edge. Data is transmitted via secure wireless protocols to a centralized cloud platform. Time synchronization mechanisms ensure accurate correlation between multimodal data streams. This layered communication architecture supports both continuous streaming from fixed cameras and event-driven transmission triggered by sensor anomalies.

3. **Analytics and Sensor Fusion Layer:** The core intelligence of the system resides in the analytics layer, where machine learning and deep learning models perform anomaly detection, correlation, and quantification. Convolutional Neural Networks (CNNs) are trained to detect visual indicators such as vapor plumes, discoloration, and thermal anomalies. Time-series models, including recurrent neural networks (RNNs) or LSTM architectures, analyze pressure and acoustic patterns to identify deviations from normal operating baselines. Sensor fusion is implemented using probabilistic data association and Bayesian inference techniques to combine evidence from visual and numerical data streams. When IoT sensors detect abnormal pressure drops or acoustic signatures, the system triggers targeted visual analysis for confirmation. Conversely, visually detected anomalies prompt verification against sensor readings to reduce false positives. Leak localization is achieved through triangulation of sensor nodes combined with geotagged imaging data. Regression models trained on simulated leak scenarios and historical datasets estimate leak magnitude and potential dispersion patterns.

4. **Decision Support and Operational Workflow:** The final layer consists of a real-time monitoring dashboard and automated alert system. Detected anomalies are classified according to severity levels, and alerts are issued to operators with geospatial coordinates and confidence scores. The system supports hybrid operation: continuous surveillance for baseline monitoring and event-triggered high-resolution analysis for rapid incident response. This modular and scalable architecture enables deployment across diverse terrains and pipeline scales. By integrating multimodal sensing with AI-driven analytics and

hybrid monitoring strategies, the proposed solution enhances detection sensitivity, reduces false alarms, and strengthens the operational integrity of CCUS pipeline networks.

Results

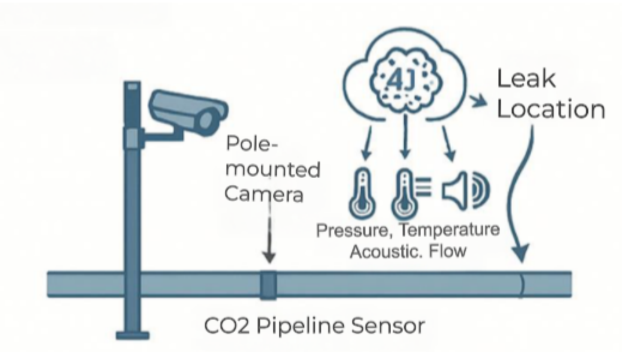

Figure 2: Multimodal Leak Detection and Localization Performance

Incident detection and localization are achieved by fusing visual data from ground-based cameras with CO_2 pipeline sensor data.

As illustrated in FIGURE 2, a pole-mounted camera continuously monitors the pipeline corridor while sensors supply pressure, temperature, acoustic, and flow rate measurements.

The Al system processes the combined data to identify leak events and obtain the leak locations.

The extent of leaks can be estimated by analyzing satellite imagery in conjunction with regression models.

FIGURE 3 demonstrates the quantification of a leak plume observed in a satellite image. A regression analysis, based on fluid simulations and historical data, estimates the magnitude of the CO_2 leakage.

The results confirm that combining visual and physical-sensor modalities substantially enhances detection reliability.

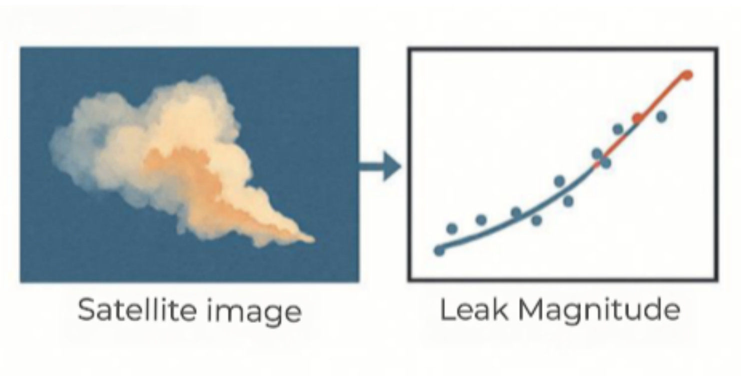

Figure 3: Leak Quantification Using Satellite Imagery and Regression Models

Conclusion

The proposed hybrid monitoring framework presents a scalable and intelligent solution for enhancing the safety and reliability of CCUS pipeline infrastructure. By integrating computer vision, satellite imaging, and IoT-based sensing within a unified AI-driven architecture, the system addresses key limitations of conventional single-modality leak detection methods. The fusion of multimodal data streams improves detection sensitivity, minimizes false positives, and enables accurate leak localization and quantification.

The hybrid operational model combining continuous surveillance with event-triggered analysis which ensures both broad coverage and rapid incident response. Edge computing capabilities reduce latency and bandwidth demands, while advanced machine learning algorithms enhance anomaly detection under varying environmental and operational conditions. This layered approach strengthens resilience in remote or hazardous terrains where manual inspections are costly and infrequent.

As CCUS deployment expands globally to support decarbonization strategies, ensuring pipeline integrity is critical for environmental protection, regulatory compliance, and public trust. The proposed digital framework contributes to proactive maintenance, real-time monitoring, and long-term infrastructure sustainability. Future work may focus on large-scale field validation, integration with digital twins, and adaptive learning models to further optimize system performance across diverse operational environments.

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