Intelligent Compression And Fault Early Warning Of Time-Series Data For Key Equipment In Natural Gas Pipelines Based On An Edge-Cloud Collaborative Architecture

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Natural gas pipelines generate large volumes of acoustic time-series data, leading to challenges in bandwidth usage, storage requirements, and accurate fault detection. Traditional cloud-based anomaly detection methods are often inefficient due to limited compression capability, making them unsuitable for large-scale distributed monitoring environments. To address these issues, this study proposes an intelligent edge-cloud collaborative framework that integrates efficient data compression with early fault detection mechanisms. The system begins with data acquisition using the Natural Gas Pipeline Safety Monitoring Dataset. The preprocessing stage includes noise filtering, normalization, and statistical-frequency feature extraction to capture signal energy, frequency band characteristics, and correlation peaks. At the edge layer, compressed data is analyzed using a hybrid model combining Robust Random Cut Forest (RRCF) and Isolation Forest for real-time anomaly detection and fault alert generation. The cloud layer employs Long Short Term Memory (LSTM) networks for time-series prediction, missing data reconstruction, and long term fault forecasting. The proposed framework achieved a compression ratio of 5:1, reducing storage and transmission requirements while preserving critical acoustic information. For anomaly detection, the model achieved high accuracy and F1-score, demonstrating reliable fault identification. Prediction performance was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which measure forecasting error between predicted and actual pipeline conditions. Experimental results confirm strong performance, scalability, and suitability for industrial IoT applications.

Keywords: Edge-Cloud Collaborative Architecture, Natural Gas Pipeline Monitoring, Time Series Data Compression, Hybrid Anomaly Detection, Long Short-Term Memory, Fault Early Warning Systems

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1. Introduction

Natural gas pipelines generate continuous time-series data from sensors and valves, enabling energy transport [1]. IIoT supports monitoring but faces bandwidth and storage issues [2]. Edgecloud systems address these challenges through distributed processing [3] despite noise and data complexity. The proposed method improves fault detection and reliability. The edge devices in these architectures execute initial data processing tasks while they also transform information into compressed form which cloud systems use to perform advanced analysis and make automated decisions

The proposed DO-LSTM framework enhances forecasting performance by optimizing LSTM parameters automatically. Compared with conventional SARIMA and autoencoder-based approaches, it improves prediction accuracy and fault forecasting while maintaining computa-

tional efficiency. Acoustic monitoring enhances pipeline operational safety through early fault detection, while efficient time-series compression enables low-latency data transmission and reliable realtime monitoring. Edge-cloud framework uses buffering and timestamps to reduce jitter and interruptions, while edge processing ensures continuous operation during connectivity delays before cloud synchronization. The proposed method applies intelligent edge compression to reduce data while preserving fault features, enabling real-time anomaly detection, cloud-based forecasting, and missing data reconstruction.

Section 1 presents the background, problem statement, and scope. Subsequently, Section 2 covers literature review, gap, objectives, novelty, and contributions. Thereafter, Section 3 describes methodology with feature extraction, perception, edge, cloud layers, and Dandelion Optimizer. Next, Section 4 presents results, evaluation, and comparison. Finally, Section 5 concludes and outlines future work.

2. literature review

Previous works focused on edge-cloud pipeline monitoring and fault detection. Shi et al. [4] proposed ML-based edge-cloud anomaly detection but faced scalability and resource limitations. developed dynamic weight optimization for fault diagnosis with dataset and deployment constraints. Zhang et al. [5] introduced an edge-based multivariate anomaly detection framework for resource-limited devices. Although Zhang et al. [5] demonstrated the effectiveness of cloudsynchronized monitoring, reliance on continuous cloud communication may introduce latency and communication overhead in large-scale deployments.

The study aims to assess newly developed technologies used for pipeline integrity management and monitoring. The system has two main restrictions which include its inability to test in actual environments and its difficulties with executing large-scale operations and specific monitoring functions. proposed intelligent fiber-optic vibration signal recognition for pipeline monitoring but required large datasets and high computational resources. Zhao et al. [6] improved intrusion detection using spatio-temporal signals, though validation was limited. Dong et al. [7] integrated AI and IoT for pipeline safety but lacked real-world evaluation. Jing et al. [8], Mei et al. [9], Fahim et al [10], Lin et al. [11], and Gao et al. [12] contributed advanced monitoring methods, yet faced challenges in scalability, generalization, and deployment. However, these approaches mainly focus on detection accuracy Liu et al [13], Yang et al [14] and do not address data compression, edgecloud collaborative processing or distributed monitoring, which limits scalability Zuo et al [15] and efficient data transmission in large pipeline networks.

2.1. Objectives.

- Design edge-cloud framework enabling efficient compression of pipeline acoustic data.
- Develop hybrid anomaly detection using RRCF and Isolation Forest algorithms.
- Implement LSTM-based predictive modeling for fault forecasting and data reconstruction.
- Apply DO Optimizer for parameter tuning and reduced prediction error.
- Validate system scalability using Natural Gas Pipeline Safety Monitoring Dataset.

3. materials and methods

An edge-cloud framework integrates intelligent compression, hybrid RRCF-Isolation Forest detection, LSTM forecasting, and Dandelion Optimizer for efficient pipeline monitoring.

The Dandelion Optimizer is employed to automatically identify optimal parameter settings that improve the performance of the proposed framework. The optimization process alternates between exploration and exploitation phases to efficiently search the solution space and select parameter values that enhance anomaly detection accuracy and prediction performance while reducing computational complexity. The Dandelion Optimizer determines the optimal LSTM hyperparameter configuration by evaluating candidate solutions and selecting parameter combinations that minimize forecasting errors. Among the optimized parameters, learning rate, hidden layer size, and sequence length exhibited the strongest influence on MAE and RMSE reduction, thereby improving prediction accuracy.

An edge-cloud framework combines compression, hybrid anomaly detection, LSTM forecasting, and optimized low-latency fault monitoring.

The architectural workflow in Fig. 1 is designed to improve computational efficiency and reduce communication overhead in the edge-cloud environment. Acoustic signals are processed and compressed at the edge layer, while only essential information is transmitted to the cloud layer for advanced prediction and long-term monitoring. The edge-cloud architecture extracts acoustic features and performs edge-level intelligent compression to reduce data volume while preserving key fault information for efficient processing. A hybrid RRCF-Isolation Forest model handles anomaly detection at the edge, while LSTM-based prediction is carried out in the cloud, ensuring low latency and

improved accuracy validated through compression and detection metrics. The data exchange process among the smart perception, edge computing, and cloud computing layers is designed to efficient transmission and real-time fault monitoring.

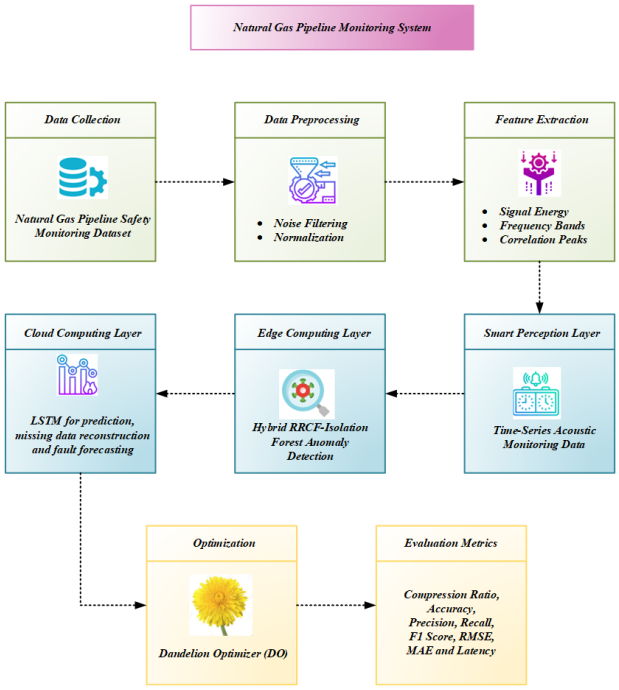

Fig. 1. Block Diagram of Proposed Method

Feature extraction converts acoustic signals into meaningful features, including energy, frequency bands, and correlation peaks for fault detection using Equation (1).

$$E = \sum(t = 1 \text{ to } N)x_t^2 \tag{1}$$

E represents total signal energy, X_t denotes acoustic amplitude, N indicates sample count, and FFT identifies dominant frequency components.

Statistical and frequency-domain features are extracted from acoustic signals to capture operational and fault-related characteristics. Fast Fourier Transform (FFT) is used to obtain dominant frequency components, while peak analysis and correlation analysis are employed to identify significant signal variations and temporal relationships that support anomaly detection and prediction. Normalization standardizes acoustic signals, removes scale variations, and improves machine learning model performance (Equation 2).

$$x_t' = \frac{x_t - \mu}{\sigma} \tag{2}$$

Where, x_t represents acoustic signal value at time t.x_t' denotes normalized signal value. μ indicates mean of signal dataset, while σ represents standard deviation of signal distribution. The autocorrelation and normalization operations are applied to enhance the quality and consistency of acoustic time-series data before feature extraction. Autocorrelation captures temporal signal patterns, while normalization ensures consistent data scaling for reliable analysis.

Signal energy is an important feature used to identify abnormal acoustic activity in pipelines. Leakage or mechanical faults typically produce energy fluctuations in acoustic signals FFT-based compression is adopted to reduce data volume by preserving dominant frequency components while removing redundant information. This enables efficient transmission without losing critical features required for anomaly detection and prediction. Autocorrelation analysis measures similarity between signals and delayed versions, identifying repeating acoustic patterns and detecting pipeline faults or leakage

Edge layer uses hybrid RRCF and Isolation Forest to detect anomalies in acoustic signals, improving accuracy, reducing latency, bandwidth, and enabling real-time fault detection.

The hybrid anomaly detection framework combines normalized anomaly scores from RRCF and Isolation Forest to generate a unified anomaly score for reliable fault identification. Observations with a combined score exceeding the experimentally validated threshold of 0.7 are classified as anomalies and forwarded for further analysis.

RRCF detects anomalies by measuring structural changes in random cut trees (Equation 3).

$$S(x) = \frac{1}{n}\sum_{i=1}^{n}\Delta_i(x) \tag{3}$$

S(x) is anomaly score; n is number of trees; Δ_i(x) measures displacement in tree i , indicating abnormal time-series behavior (Equation 4).

$$\Delta_i(x) = \text{depth}_i(x) - \text{depth}_i(\text{parent}(x)) \tag{4}$$

Δ_i(x) is displacement in tree i ; depth (x) is node depth; parent(x) is parent node. Isolation Forest uses path length for anomaly detection (Equation 5).

$$h(x) = \text{ path length of sample } x \tag{5}$$

h(x) represents the path length used to isolate a data point in an isolation tree. Shorter paths indicate anomalies, while longer paths represent normal observations, improving anomaly detection reliability, as expressed in Equation (6):

$$E(h(x)) = \frac{1}{T}\sum_{i=1}^{T} h_i(x) \tag{6}$$

E(h(x)) denotes the expected path length, $h_i(x)$ represents the path length in tree i , and T indicates the total number of trees. The anomaly score identifies normal behavior and abnormal pipeline conditions, including leakage and equipment faults, as expressed in Equation (7):

$$s(x,n) = 2^{-\frac{E(h(x))}{\sigma(n)}} \tag{7}$$

Where, $s(x,n)$ denotes anomaly score of samples x.$E(h(x))$ represents expected path length. $c(n)$ is the normalization factor, and n indicates total number of data samples.

The hybrid RRCF-Isolation Forest anomaly detection method for edge computing analysis is described in Algorithm 1 which detects abnormal acoustic signals used to monitor natural gas pipelines. The edge computing layer processes compressed acoustic signals locally to reduce latency, bandwidth consumption, and computational overhead. This enables rapid anomaly detection and efficient operation on resource-constrained edge devices while minimizing communication costs.

Algorithm 1: Hybrid RRCF-Isolation Forest Anomaly Detection at Edge Layer

Input:

Compressed acoustic time-series signal data $X = \{x_1, x_2, \ldots, x_n\}$

Output:

Anomaly score $s(x)$ and fault alert

1: Initialize RRCF forest with n trees

2: Initialize Isolation Forest with T trees

3: Input compressed acoustic signal data X

4: For each data point x in X do

// RRCF Anomaly Detection

Insert x into each random cut tree

Compute displacement score $\Delta_i(x)$

Calculate RRCF anomaly score

$$\mathrm{S}_{RRCF}(x) = \frac{1}{n}\sum_{i=1}^{n} \Delta_i(x)$$

// Isolation Forest Detection

Pass x through Isolation Forest trees

Compute path length $h_i(x)$

Calculate expected path length

$E(h(x)) = \frac{1}{T}\sum_{i=1}^{T} h_i(x)$

Compute Isolation Forest anomaly score

$s(x,n) = 2^{-\frac{E(h(x))}{\sigma(n)}}$

// Combined Anomaly Score

$\mathrm{S}_{\text{combined}}(x) = \mathrm{S}_{RRCF}(x) + \mathrm{S}_{IF}(x)/2$

If $\mathrm{S}_{\text{combined}}(x) >$ threshold then

Generate fault alert

End If

22: End For

23: Return anomaly scores and detected faults

Cloud-based LSTM predicts pipeline behavior, forecasts faults, reconstructs missing data, and supports maintenance. LSTM is selected for temporal prediction because of its ability to capture long-term dependencies in sequential acoustic monitoring data. Compared with conventional RNN-based approaches, LSTM effectively mitigates vanishing gradient issues and provides improved performance for missing data reconstruction, fault forecasting, and long-term trend analysis.

The forget gate filters irrelevant information, while the hidden state captures important temporal patterns at each time step, as expressed in Equation (8):

$$h_t = o_t \cdot \tanh(C_t) \tag{8}$$

h_t denotes the LSTM hidden state output, while o_t and C_t represent output gate activation and cell state, respectively.

Pressure disturbance pulses and acoustic sensor signals were synchronized using a common timestamp reference before multimodal analysis. This synchronization ensured temporal alignment between sensor channels and supported reliable feature fusion across the edge-cloud framework.

The intelligent data compression approach reduces redundant acoustic samples while preserving energy distribution and frequency characteristics, maintaining feature integrity for fault analysis while minimizing storage and transmission requirements. The hybrid anomaly detection model combines RRCF and Isolation Forest to capture both temporal irregularities. The computational burden of the edge computing layer was analyzed in terms of runtime latency, memory occupancy, and processor utilization to demonstrate its suitability for embedded IIoT gateway nodes.

The landing stage refines solutions through local search, while the fitness function minimizes prediction error for optimal parameter selection, as expressed in Equation (9):

$$\text{Fitness} = (1/\mathrm{N})\Sigma(\mathrm{i} = 1 \text{ to } \mathrm{N})\,(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2 \tag{9}$$

y_i and $\hat{y}_i$ denote actual, predicted values; N observations. Best solution updates whenever a candidate achieves lower prediction error during optimization. The LSTM used 80 and 40 units with a window size of 20, while the

Dandelion Optimizer employed 30 agents and 200 iter actions. Dandelion Optimization is employed to automatically identify suitable model parameters and reduce prediction error during training. The optimization process improves convergence behaviour and supports stable LSTM performance by balancing exploration and exploitation during parameter search.

The experimental setup ensures reproducibility through defined environment, data preparation, tools, and evaluation. The Natural Gas Pipeline Safety Monitoring Dataset provides acoustic timeseries signals for evaluating anomaly detection and prediction.

The Natural Gas Pipeline Safety Monitoring dataset was selected because it provides real-world acoustic monitoring signals representative of pipeline operational conditions and fault-related events. Additional dataset characteristics are provided to improve the reproducibility and understanding of the experimental setup. The dataset description includes information regarding sample volume, sensor deployment, and preprocessing thresholds used for acoustic signal preparation and analysis.

Preprocessing uses normalization and noise filtering to improve acoustic signal quality, consistency, and reliability before analysis. Wavelet denoising removes environmental noise and disturbances while preserving important acoustic features for reliable pipeline monitoring. Wavelet denoising effectively suppresses environmental disturbances while preserving leakage-induced acoustic features. This preprocessing step improves anomaly detection accuracy and monitoring reliability.

Experiments were conducted on a Windows 11 system with Intel i5-12400 CPU, 8 GB RAM, using Python 3.13.7 for implementation. Proper hyperparameter selection improves stability, convergence, and accuracy in Isolation Forest, RRCF, and LSTM models. Performance evaluation uses TP, TN, FP, and FN to assess anomaly detection accuracy, prediction error, compression efficiency, and overall Edge-Cloud system reliability.

4. Results and discussion

This section evaluates compression, anomaly detection, prediction, and resource efficiency, demonstrating accurate and reliable pipeline monitoring performance. The proposed framework was comprehensively evaluated using compression ratio, accuracy, recall, F1-score, MAE, RMSE, latency, and bandwidth usage metrics to validate compression, detection, prediction, and communication performance.

Table 1 demonstrates the comprehensive performance evaluation of the proposed framework across compression, detection, prediction, and communication metrics.

Table 1. Performance Evaluation of the Proposed Framework

Metric	Value
Compression Ratio	5 : 1
Data Reduction (%)	80
Accuracy	0.98
Precision	0.97
Recall	0.96
F1-Score	0.96
MAE	-
RMSE	-
Latency (ms)	-
Bandwidth Usage (Mbps)	-

Fig. 2 demonstrates efficient compression with a 5 : 1 ratio and 80% data reduction while preserving important acoustic information

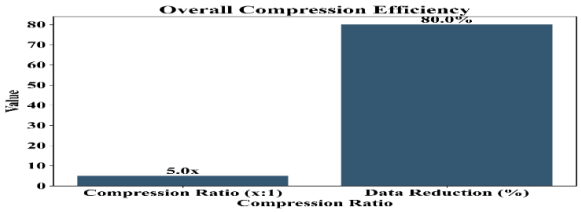

Fig. 2. Overall Compression Efficiency of Pipeline Monitoring Data

Fig. 3 shows the proposed hybrid model achieves the highest anomaly detection accuracy (96.50%)

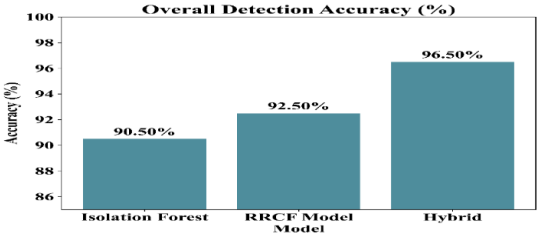

Fig. 3. Overall Detection Accuracy Comparison of Anomaly Detection Models

Fig. 4 compares Precision, Recall, and F1-score for Isolation Forest, RRCF, and hybrid models. The hybrid model achieves best performance, showing higher accuracy and reliable anomaly detection. The performance evaluation validates the proposed framework using compression, detection, prediction, and system-level metrics. The results demonstrate efficient data compression, reliable fault detection, accurate prediction, and low-overhead operation.

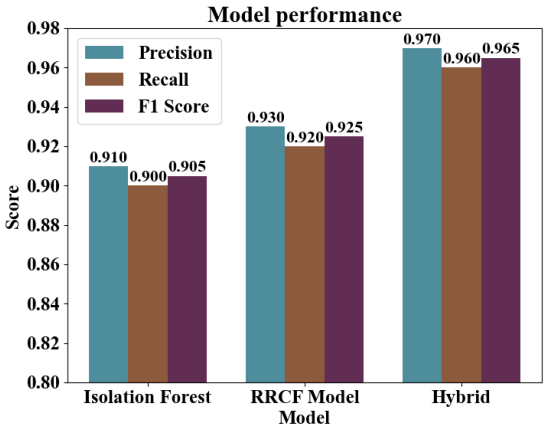

Fig. 4. Performance Comparison of Anomaly Detection Models

Fig. 5 compares Edge-cloud architecture minimizes bandwidth usage while ensuring efficient, reliable pipeline monitoring.

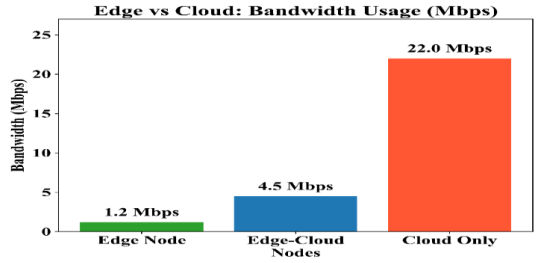

Fig. 5. Bandwidth Usage Comparison in Edge-Cloud Pipeline Monitoring

Fig. 6 compared Edge-cloud architecture achieves lowest latency, enhancing processing speed and system efficiency.

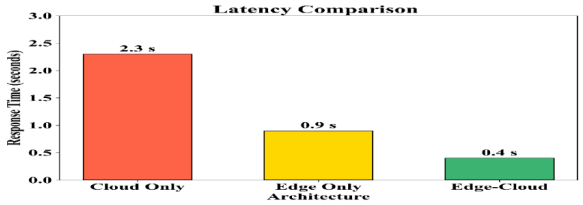

Fig. 6. Latency Efficiency Comparison Across Distributed Computing Architectures

Table 2 compares the proposed system outperforms existing models, achieving superior precision, recall, F1-score, and detection reliability. To provide a broader evaluation of the proposed hybrid RRCF-Isolation Forest model, additional comparisons were conducted against CNN, RNN, and One-Class SVM baselines. These approaches are widely used for industrial time-series anomaly detection and fault diagnosis.

The proposed hybrid model achieved the best overall performance with an F1-score of 96.5%, demonstrating the effectiveness of combining RRCF and Isolation Forest for anomaly detection. The hybrid approach benefits from the streaming-data sensitivity of RRCF and the efficient isolation mechanism of Isolation Forest, resulting in improved robustness and detection accuracy.

Table 4 compare the Edge-Cloud hybrid model achieves superior accuracy, lower latency, and enhanced overall system efficiency. Sensitivity analysis of sequence window length represents an important future research direction for evaluating temporal horizon effects on forecasting performance. The hybrid RRCF-Isolation Forest approach achieves a balanced precision-recall trade-off, reducing false alarms while effectively detecting anomalous events. This combination enhances overall anomaly detection reliability and supports robust fault identification.

Experimental results demonstrate improved compression, prediction, anomaly detection, and reduced resource consumption. Long-term monitoring environments may experience concept drift due to gradual changes in acoustic signal characteristics and operational conditions. Periodic model retraining and adaptive parameter updating can help maintain forecasting accuracy and anomaly detection performance under evolving pipeline conditions.

5. conclusion

The proposed edge-cloud framework achieves 96.5% accuracy through compression, hybrid anomaly detection, and LSTM prediction, with future multi-dataset validation. The proposed framework demonstrates promising performance on the selected dataset, broader validation using multiple industrial datasets and diverse operating conditions remains an important direction for future research. Such validation would provide further evidence regarding the generalizability of the LSTM-based prediction framework. Future deployment in large-scale industrial Internet of Things environments should consider communication bandwidth, computational resource availability, and real-time processing requirements. Evaluating the framework under practical deployment constraints will further support scalability and industrial adoption. The imbalance between normal operating conditions and rare leakage or equipment fault events, evaluation was interpreted using metrics that consider both positive and negative class performance. This strategy provides a more reliable assess-

Table 2. Performance Comparison of Intelligent Edge-Cloud Pipeline Fault Monitoring System

Models	Precision (%)	F1-score (%)	Recall (%)
GA-Att-LSTM Fault Detection	89.8%	84.2%	77.6%
RNN-AE Edge AI Model	94.3%	93.8%	93.5%
Proposed Intelligent Edge-Cloud Pipeline Fault Monitoring System	97.0%	96.5%	96.0%

Table 3. summarizes the comparative results

Model	Accuracy (%)	Precision (%)	Recall (%)	F1Score (%)
One-Class SVM	84.2	83.5	82.8	83.1
CNN	91.4	91	90.5	90.7
RNN	93	92.8	92.1	92.4
Isolation Forest	90.5	90	89.5	89.7
RRCF	92.5	92	91.6	91.8
Proposed Hybrid RRCF-IF	96.5	97	96	96.5

Table 4. Ablation Study Results of the Proposed Model

Architecture	Accuracy (%)	Latency (s)	Bandwidth (MB)
Edge-Cloud Hybrid (Proposed)	97.2	0.4	4.5
Edge Only	88.6	0.9	1.2
Cloud Only	91.3	2.3	22.0

ment of anomaly detection capability and reduces potential bias associated with class distribution imbalance.

The proposed framework was evaluated using the publicly available Natural Gas Pipeline Safety Monitoring Dataset and has not yet been validated on a live operational gas pipeline. Future work will focus on real-world field verification to assess the practical applicability and robustness of the framework under operational conditions.

Acknowledgement

Declaration

Data availability:

The dataset analyzed during current study is openly available in Mendeley Data repository at https://data.mendeley.com/datasets/km852pjxtw/1

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Author contributions

Meng Cai: Conceptualization, methodology, writing - original draft preparation.
Yi Ren: Data curation, software, validation.
Feng Liu: Supervision, review and editing.

Ethical approval

This study does not involve human participants or animals and therefore does not require ethical approval.

Consent to participate

Not applicable.

Consent to publication

All authors have read and approved the final manuscript and consent to its publication.

Competing interests

The authors declare that they have no competing interests.

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