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Image-Based Condition Recognition for Refined Oil Pipelines Using WGAN-Augmented Enhanced CNN

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Abstract: Accurate identification of operating conditions in refined oil pipelines is vital for maintaining transportation safety and preventing anomalies amid escalating energy demands. However, frequent field operations induce variations in pipeline conditions, and existing methods struggle with non-uniform sample dimensions across these conditions, complicating precise recognition due to overlooking latent heterogeneities and often suffering from suboptimal performance caused by imbalanced datasets, particularly the scarcity of anomalous samples. This paper introduces an innovative data-driven framework for pipeline condition recognition by transforming tabular operational data into standardized image representations, mapping condition information directly to pixel points to enable uniform input for deep learning models. To address the real-world challenge of limited anomalous samples, practical scenarios are simulated using a Conditional Wasserstein Generative Adversarial Network (CWGAN) for targeted image-based data augmentation, generating balanced datasets while validating synthetic samples against originals through metrics such as KL divergence to ensure distributional similarity and feasibility. After in-depth analysis of the augmented data's impact on model robustness, an enhanced Convolutional Neural Network (CNN) incorporating parallel convolution kernels and self-attention mechanisms is developed to extract multi-scale features and output condition probabilities. Eventually, several simulated cases mimicking real-world operational imbalances with scarce anomalous samples are used for model verification and performance comparisons. Combined with CWGAN augmentation, the effects of different CNN architectures on identification metrics are tested. The results demonstrate that the proposed framework achieves more accurate recognition than other methods, with a 98% overall accuracy, a 25% improvement in F1-score, and increases in precision and recall to over 0.95. It is suggested that the proposed framework excels in handling imbalanced and heterogeneous data while capturing complex operational patterns and nonlinear dependencies, providing technical support for the efficient management of refined oil pipelines.

Keywords: Refined Oil, Pipeline Condition Identification, Image transformation, CWGAN augmentation, Enhanced CNN.

1. Introduction

Refined oil pipelines are a key component of large-scale energy transportation systems, and their safe and stable operation is fundamental to energy supply security. In practice, frequent operational activities such as pump regulation, valve switching, and scheduling adjustments lead to continuous variations in operating conditions. Timely and accurate identification of these conditions, particularly abnormal states, is therefore critical for risk prevention and intelligent pipeline management (Du et al. 2024).
The increasing deployment of digital monitoring systems has enabled data-driven approaches for pipeline condition identification. However, practical application remains challenging due to the strong nonlinearity, complex temporal–spatial coupling, and pronounced heterogeneity of pipeline operating data. In addition, real-world datasets are typically highly imbalanced, as abnormal conditions occur far less frequently than normal operations, resulting in insufficient representation of anomalous patterns and degraded recognition performance.
To overcome these challenges, this study proposes a data-driven framework for refined oil pipeline condition identification. A standardized representation strategy is first introduced to transform heterogeneous tabular operational data into image-based formats, allowing different operating conditions to be mapped into uniform inputs for deep learning models. To address data imbalance, a Conditional Wasserstein Generative Adversarial Network (CWGAN) is employed to generate condition-specific synthetic samples while preserving the underlying data distribution. Based on the generated representations, an enhanced convolutional neural network is developed to extract discriminative features and accurately identify complex operating conditions. The proposed framework provides a robust and scalable solution for intelligent condition identification in refined oil pipeline systems.

2. Literature review

Given the complex operational environment and safety-critical nature of refined oil pipelines, accurate identification of pipeline operating conditions is essential for ensuring secure transportation and preventing potential anomalies. Existing pipeline condition identification methods can generally be classified into three categories: physics-based methods, traditional machine learning methods, and deep hybrid learning methods.
Physics-based methods for pipeline condition identification are mainly developed from hydraulic principles and empirical formulations, inferring operating states through analytical models of pressure, flow rate, and related variables. Despite their clear physical interpretability, physics-based methods are typically built on fixed assumptions and boundary conditions, which limits their ability to capture rapidly changing pipeline operations and results in high computational cost and reduced accuracy when applied to large-scale, multi-condition scenarios.
Simple machine learning methods have been widely applied to pipeline condition identification due to their ability to automatically learn patterns from operational data without requiring detailed physical modelling. Alzannan et al. (Alzannan 2022) proposed machine learning-based anomaly detection models for oil and gas pipeline leakage, evaluating several machine learning algorithms. Lang et al. (Lang et al. 2021) proposed an improved least squares twin support vector machine, optimized by particle swarm optimization, for pipeline weld and defect recognition from Magnetic Flux Leakage (MFL) signals. Nevertheless, simple machine learning methods often struggle with high-dimensional, nonlinear, and heterogeneous pipeline data, limiting their ability to accurately identify multiple operating conditions simultaneously.

Deep hybrid learning methods have been developed to overcome the limitations of both physics-based and simple machine learning approaches by leveraging advanced representation learning techniques, enabling more accurate recognition of non-linear, high-dimensional, and rapidly varying pipeline operating conditions. Wang et al. (Wang et al. 2022) proposed an intelligent monitoring framework for multi-product pipelines that fuses temporal and spatial features to distinguish steady, unsteady, and abnormal conditions. Zheng et al. (Zheng et al. 2021) proposed a semi-supervised method for multi-product pipeline condition recognition, pre-training a multi-layer neural network with stacked autoencoder on unlabelled Supervisory Control and Data Acquisition (SCADA) data and fine-tuning with limited labelled samples.

However, most existing methods focus on learning from available operational data without fully addressing the heterogeneity and imbalance across different pipeline operating conditions. This limitation restricts their ability to accurately capture complex nonlinear dependencies and latent patterns, particularly under conditions with non-uniform sample dimensions or scarce anomalous states. As a result, existing models often exhibit suboptimal recognition performance and limited applicability in real-world pipeline operations.

3. Methodology

To tackle the challenges of heterogeneous operational conditions, non-uniform data lengths, and scarce anomalous samples in refined oil pipelines, this paper proposes a novel data-driven framework for pipeline condition recognition. The framework is designed to standardize and augment operational data while enabling robust feature extraction and accurate classification. Unlike conventional methods that may struggle with variable-length sequences or imbalanced datasets, the proposed approach integrates three key modules into an end-to-end architecture. The first module transforms raw operational sequences of varying lengths into standardized grayscale images, preserving essential information and ensuring consistent dimensionality for subsequent processing. The second module employs a Conditional Wasserstein Generative Adversarial Network (CWGAN) (Zheng et al. 2020) to generate synthetic images of rare operating conditions, mitigating the impact of imbalanced data and enhancing the representation of anomalous states. The third module utilizes an enhanced convolutional neural network (CNN) (Ajit, Acharya, and Samanta 2020) to extract multi-scale features from the standardized and augmented images, capturing complex operational patterns and nonlinear dependencies, and ultimately producing accurate condition predictions. These three modules are cohesively integrated, providing a robust, scalable, and effective solution for intelligent recognition of pipeline operating conditions under diverse and challenging real-world scenarios.

3.1. Adaptive Grayscale Data Encoding Module

The first module, termed the Adaptive Grayscale Data Encoding Module, transforms operational sequences of varying lengths into standardized grayscale images while preserving key temporal and amplitude information. By addressing heterogeneous operating conditions and non-uniform sequence lengths in refined oil pipelines, this adaptive encoding enables effective feature extraction and classification in subsequent CNN-based learning stages.

Step 1: Adaptive Data Preprocessing

Raw operational sequences, including flow rates and pressures, are first cleaned and normalized to ensure data quality and stability. Normalization is applied in a manner adaptive to each sequence statistical properties, mitigating biases due to magnitude differences among variables:

$$x_i' = \frac{x_i - \min(X)}{\max(X) - \min(X)}, i = 1,2, \dots, N \quad (1)$$

where x_i is the $i-th$ measurement in sequence X, x_i' is the normalized value, and N is the sequence length.

Step 2: Grayscale Encoding

The normalized sequence is mapped to a grayscale image by transforming each value x_i' into a pixel intensity p_i ranging from 0 to 255:

$$p_i = [255 \cdot x_i'] \quad (2)$$

where p_i is the corresponding pixel intensity, and $[\cdot]$ denotes the floor operation.

Step 3: Dimensional Normalization

Since durations differ, multivariate sequences (specifically pressure and flow rate) are first aligned as distinct rows to construct the initial 2D matrix. This matrix is then normalized to fixed dimensions $H \times W$ using bilinear interpolation, which ensures the preservation of critical transient signatures and inflection points during resizing:

$$I_{\text{resized}} = \text{Resize}\left(I_{\text{original}}, H, W\right) \tag{3}$$

Here, I_{original} is the original grayscale image, I_{resized} is the resized image, and H, W are the predefined height and width of the CNN input.

3.2. CWGAN–Based Data Augmentation Module

The second module of the proposed framework, referred to as the Conditional Wasserstein GAN–Based Data Augmentation Module, is designed to alleviate the severe class imbalance commonly encountered in refined oil pipeline operating condition datasets, particularly the scarcity of anomalous samples. In real pipeline systems, abnormal operating conditions occur infrequently compared to normal states, resulting in highly imbalanced datasets that hinder the learning capability and generalization performance of data-driven models.

To address this challenge, a CWGAN is employed to generate condition-specific synthetic samples by learning the conditional data distribution $P_r(x \mid y)$, thereby enriching minority classes and improving dataset balance. Let $(x, y) \sim P_z(z, y)$ denote the joint distribution of real grayscale images and their corresponding operating condition labels, where $x \in R^{H\times W}$ represents a grayscale image and $y \in$ Y denotes the operating condition category.

In the CWGAN framework, both the generator G and the discriminator D are conditioned on operating condition labels. The generator aims to learn a conditional mapping from a noise distribution to the image space, which can be expressed as

$$\tilde{x} = G(z, y) \tag{4}$$

where $z \sim P_z(z)$ is a random noise vector sampled from a predefined prior distribution and $\tilde{x}$ denotes the generated grayscale image associated with condition label y. The discriminator is formulated as a condition-aware scoring function

$$D: (x, y) \to R \tag{5}$$

which assigns a scalar score to an input image under a given operating condition, with higher scores indicating a higher likelihood that the sample is drawn from the real data distribution corresponding to that condition.

By adopting the Wasserstein distance as the optimization objective, the CWGAN improves training stability and alleviates common issues such as mode collapse that are often observed in conventional GAN-based approaches. The overall adversarial objective of the CWGAN is defined as

$$\begin{aligned} \mathcal{L}_{\text{CWGAN}} &= E_{(x,y)\sim P_r}[D(x, y)] \\ &- E_{(z,y)\sim P_z}[D(G(z, y), y)] \end{aligned} \tag{6}$$

where the discriminator is trained to maximize this objective, while the generator is optimized to minimize it, leading to the following minimax formulation:

$$\min_G \max_D \mathcal{L}_{\text{CWGAN}} \tag{7}$$

During training, to rigorously enforce the 1-Lipschitz constraint essential for the Wasserstein distance, a gradient penalty term is incorporated into the discriminator objective. This term constrains the gradient norm to unity along the interpolation lines between real and generated data, effectively replacing weight clipping to eliminate gradient vanishing and ensure convergence stability. Through iterative optimization, the discriminator progressively enhances its ability to distinguish real and synthetic samples within the same operating condition, while the generator gradually learns to produce condition-consistent samples whose conditional distributions approach those of the real data for each class. After training convergence, the generator can be employed to perform targeted data augmentation by fixing a specific operating condition label and sampling multiple noise vectors, yielding a set of synthetic samples

$$\left\{\widetilde{x_i^y}\right\}_{i=1}^{N_y} = \{G(z_i, y)\}_{i=1}^{N_y} \tag{8}$$

where N_y denotes the number of generated samples for operating condition y. These synthetic samples are combined with real samples to construct a more balanced training dataset for subsequent condition recognition models, as shown in Fig. 1.

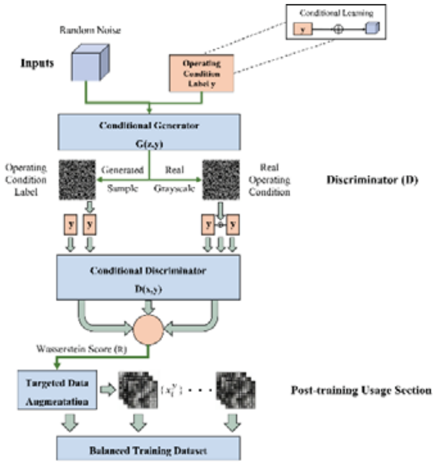

Fig. 1 CWGAN-based data augmentation process

3.3. Enhanced Convolutional Neural Network Condition Recognition Module

The third module, termed the Enhanced CNN–Based Condition Recognition Module, identifies refined oil pipeline operating conditions from grayscale images generated by data encoding and CWGAN augmentation. To address the nonlinearity and heterogeneity of pipeline data, which hinder conventional CNNs with fixed receptive fields, an enhanced CNN with parallel convolutional kernels and an attention mechanism is introduced to improve feature representation and recognition robustness.

Given an input grayscale image $I \in R^{H\times W}$, the feature extraction process begins with a set of parallel convolutional operations using kernels of different sizes, enabling the network to capture multi-scale spatial patterns associated with different operating conditions. The output of the $k-$th convolutional branch is expressed as:

$$F_k = \sigma(W_k * I + b_k) \tag{9}$$

where $*$ denotes the convolution operation, W_k and b_k are learnable parameters, and $\sigma(\cdot)$ represents a nonlinear activation function. The resulting feature maps are then fused through channel-wise concatenation to form a unified multi-scale representation

$$F = \mathrm{Concat}(F_1, F_2, \dots, F_K) \tag{10}$$

which integrates complementary information extracted at different receptive field sizes. To further enhance the discriminative capability of the fused feature representation, an attention mechanism is introduced to explicitly model interdependencies among spatial locations and feature channels. Instead of treating all features equally, the attention mechanism enables the network to adaptively assign higher weights to regions and channels that are more informative for operating condition discrimination, while suppressing irrelevant or redundant responses. The attention-enhanced feature representation can be expressed as

$$F_{att} = \mathcal{A}(F) \tag{11}$$

where $\mathcal{A}(\cdot)$ denotes the attention operation. Through this mechanism, the network is able to capture long-range correlations and global contextual information that may not be fully represented by convolutional operations alone, particularly under complex and rapidly changing operating conditions.

From an optimization perspective, the attention mechanism adaptively emphasizes condition-sensitive features during training, enabling the model to focus on patterns most relevant to accurate classification. This dynamic reweighting enhances robustness to operational fluctuations and data heterogeneity, while improving feature selectivity, stabilizing gradient propagation, and accelerating convergence in end-to-end training.

The attention-enhanced features are subsequently transformed into a compact representation and mapped to the output space via a SoftMax classifier. The predicted probability of operating condition c is given by

$$p_c = \frac{e^{\left(w_c^T f_{att}\right)}}{\sum_{j=1}^{C} e^{\left(w_j^T f_{att}\right)}} \tag{12}$$

where f_{att} denotes the flattened attention-enhanced feature vector, w_c represents the classification weight associated with condition c, and C is the total number of operating condition categories. The network parameters are optimized by minimizing the cross-entropy loss

$$\mathcal{L}_{cls} = -\sum_{c=1}^{C} y_c \log p_c \tag{13}$$

where y_c denotes the ground-truth label indicator. By jointly leveraging multi-scale convolutional feature extraction and attention-based feature refinement, the enhanced CNN effectively captures complex nonlinear dependencies and latent patterns in pipeline operating data, as shown in Fig. 2.

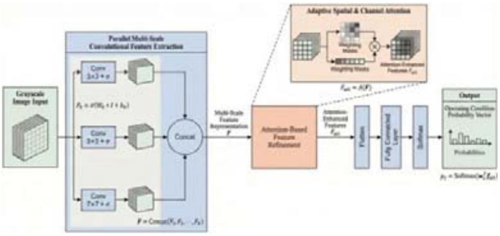

Fig. 2 Enhanced CNN architecture

4. Results and discussion

4.1. Data Description

The data used in this study are generated through numerical simulation based on a refined oil pipeline system constructed in the Stoner Pipeline Simulator (SPS). SPS is a widely used commercial software for pipeline hydraulic simulation, capable of modelling complex pipeline networks and reproducing transient operating behaviours under various operational scenarios.

To comprehensively capture the diversity of pipeline operating conditions, multiple operational scenarios are simulated, including start-up, shutdown, flow rate increase and decrease, product delivery and diversion, pump trip events, valve internal leakage, pipeline blockage, and leakage conditions. These scenarios are designed to reflect both normal operations and abnormal or fault-related states that may occur in real pipeline systems. Due to differences in system dynamics and stabilization times across operating scenarios, the lengths of the recorded time series are not uniform. In order to simulate the situation where abnormal conditions are absent in real scenarios, we simulated 200 samples for normal conditions, while only 30 samples were obtained for abnormal conditions.

4.2. Evaluation Metrics

To comprehensively evaluate the performance of operating condition recognition and the quality of generated samples, two groups of evaluation metrics are adopted. For operating condition recognition, Accuracy, Recall, Precision, F1-score, and Specificity are used (Zheng et al. 2022).

To assess the quality of synthetic data generated by the CWGAN-based augmentation module, Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Kullback–Leibler (KL) divergence are adopted. Together, these metrics enable a comprehensive evaluation of both recognition accuracy under imbalanced conditions and the fidelity of generated samples.

4.3. Results Analysis

4.3.1. Performance Evaluation of CWGAN-Based Data Augmentation

To evaluate the effectiveness of the proposed CWGAN-based data augmentation strategy, the quality of the generated grayscale images is quantitatively assessed against a conventional GAN under four representative abnormal operating conditions: pipeline blockage (PB), pipeline leakage (PL), pump trip events (PTE), and valve internal leakage (VIL). The results are summarized in Table 1 (CWGAN) and Table 2 (GAN).

At the pixel level, CWGAN consistently achieves lower MSE and higher PSNR values across all conditions. Notably, under PL and VIL, the MSE values decrease to 5.96 and 8.04, respectively, with corresponding PSNR values exceeding 39 dB, indicating high reconstruction fidelity and limited distortion. In contrast, the GAN exhibits lower PSNR values, particularly under PB and PTE conditions, reflecting increased reconstruction noise and degraded image quality.

In terms of structural similarity, CWGAN attains SSIM values above 0.91 for all scenarios, reaching 0.992 under PL, demonstrating its ability to preserve intrinsic structural patterns and spatial correlations. The GAN, however, yields SSIM values ranging from 0.78 to 0.94, with a pronounced decline under PTE, suggesting weaker structural consistency when modelling complex transient behaviours.

More importantly, distribution-level consistency evaluated using KL divergence demonstrates the key advantage of CWGAN in capturing the underlying data distribution of each operating condition. As summarized in Table 1, the KL divergence values of CWGAN remain relatively low across all abnormal conditions, ranging from 0.67 to 2.23. In particular, the PL condition exhibits the lowest KL divergence, indicating a close alignment between the generated and real data distributions. In contrast, the GAN-based results presented in Table 2 show significantly larger KL divergence values across all conditions. Under PB and PTE conditions, the KL divergence exceeds 3.9 and 5.8, respectively, revealing substantial distributional discrepancies and unstable conditional generation performance.

Table 1 Quantitative Evaluation Results of CWGAN-Generated Images

Metric	PB	PL	PTE	VIL
MSE	50.152	5.961	94.231	8.042
SSIM	0.956	0.992	0.916	0.983
PSNR(db)	33.146	40.377	30.923	39.077
KL divergence	1.427	0.667	2.234	1.096

Table 2 Quantitative Evaluation Results of GAN-Generated Images

Metric	PB	PL	PTE	VIL
MSE	98.713	14.365	225.621	19.842
SSIM	0.875	0.942	0.785	0.913
PSNR(db)	25.131	32.447	21.267	30.684
KL divergence	3.950	1.784	5.826	2.973

4.3.2. Performance Evaluation of Operating Condition Recognition

To further evaluate the recognition capability of different network architectures, a comparative experiment is conducted under a balanced data setting, where eight operating conditions are considered and the number of samples for each condition is fixed at 200. This experimental design eliminates the influence of class imbalance and allows a fair assessment of the intrinsic discriminative ability of each model.

As shown in Table 3, the simple CNN exhibits relatively limited recognition performance, achieving an overall accuracy of 84.81 percent and an F1 score of 0.84. Although its precision remains high, the comparatively lower recall of 0.85 indicates insufficient sensitivity to certain operating conditions, suggesting that a single-scale convolutional structure struggles to capture the complex and heterogeneous patterns embedded in pipeline operational data. The cascaded CNN introduces deeper feature extraction through serial convolutional layers, leading to moderate performance improvements, with accuracy and F1 score increasing to 88.19 percent and 0.86, respectively. However, the serial architecture still relies on a fixed receptive field expansion strategy, which restricts its ability to simultaneously model both local variations and broader operational trends.

The parallel CNN further enhances recognition performance by incorporating multiple convolutional branches with different kernel sizes. This design enables multi-scale feature extraction and significantly improves the model’s ability to distinguish between diverse operating conditions. As a result, the parallel CNN achieves an accuracy of 92.00 percent and an F1 score of 0.91, demonstrating clear advantages over the simple and cascaded CNN structures. Nevertheless, its performance remains constrained by the absence of explicit mechanisms for modelling long-range dependencies and feature importance.

In contrast, the proposed model delivers a substantial performance improvement across all evaluation metrics, achieving an overall accuracy of 98.00 percent, with recall, precision, F1 score, and specificity all approaching 0.98. This superior performance can be attributed to the combined effect of multi-scale feature extraction and attention-based feature refinement, which enables the model to focus on condition-sensitive patterns while suppressing irrelevant information. The consistently high recall and specificity indicate that the proposed model not only accurately identifies abnormal operating conditions but also effectively avoids misclassification of normal states. These results demonstrate that, under balanced data conditions, the proposed architecture exhibits significantly stronger discriminative capability and robustness than the basic compared models.

To further substantiate the robustness of the framework, we prioritize Accuracy, Recall, and F1 Score as the most representative metrics for evaluation, with all reported results representing the average of 10 independent runs. The model without the data augmentation module yields an average Accuracy, Recall, and F1 Score of 92.13%, 0.92, and 0.91, respectively, showing a distinct performance decline compared to the proposed model. This quantitative gap confirms the significant contribution of the label-conditioned CWGAN generation in classifying imbalanced operating conditions. Furthermore, Table 3 effectively completes the ablation analysis regarding the attention mechanism, demonstrating that its inclusion further enhances the model performance.

Table 3 Comparison of Operating Condition Recognition Performance of Different Models

Model	Accuracy/%	Recall	Precision	F1 Score	Specificity
Simple CNN	84.81	0.85	0.92	0.84	0.94
Cascaded CNN	88.19	0.88	0.93	0.86	0.95
Parallel CNN	92.00	0.92	0.95	0.91	0.97
Proposed Model	98.00	0.98	0.98	0.98	0.98

5. Conclusion

This study proposes a data-driven framework for refined oil pipeline operating condition identification that explicitly addresses data heterogeneity, non-uniform sample dimensions, and class imbalance. Multivariate operational data are transformed into standardized grayscale image representations, enabling a unified input space for deep learning–based analysis. To mitigate abnormal-sample scarcity, a Conditional Wasserstein GAN is introduced for condition-aware data augmentation, yielding generated samples with high fidelity and distributional consistency, as evidenced by SSIM values above 0.91, PSNR exceeding 30 dB, and KL divergence ranging from 0.67 to 2.23.

Building on the augmented dataset, an enhanced convolutional neural network with parallel convolutional kernels and an attention mechanism is developed for operating condition recognition. Under balanced data settings involving eight operating conditions, the proposed framework achieves an overall accuracy of 98.00%, with recall, precision, F1 score, and specificity all approaching 0.98, substantially outperforming baseline CNN models. Overall, the proposed framework integrates standardized data representation, CWGAN-based augmentation, and multi-scale feature learning, offering a robust and effective solution for refined oil pipeline operating condition identification. Future work will focus on validation using real field data and extension to other industrial pipeline systems.

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