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# *Research on Pipeline Leak Signal Reconstruction and Multi-Aperture Classification Method Based on Multi-Task 1D U-Net*

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***Abstract:*** Pipeline leak detection is a key technology to ensure the safe operation of oil-gas and industrial pipelines. However, actually collected monitoring signals are often affected by noise interference, data loss, and difficult feature extraction, which seriously restrict detection accuracy and reliability. To address these challenges, this paper proposes a multi-task 1D U-Net based pipeline leak detection model, realizing collaborative optimization of signal reconstruction, denoising, and aperture classification. The model adopts a shared encoder and task-specific decoders architecture, integrates channel and spatial attention mechanisms to focus on key features, and uses uncertainty learning to dynamically adjust task loss weights, improving training stability and reducing manual tuning costs. Experimental verification on a 4,778-sample multi-channel dataset (each sample is a 5-channel,720-length time-series signal) shows significant performance: denoising task MSE drops to 0.0013(training set) and 0.0016(validation set) with over 98% reduction, reconstruction MSE improves by 44.8%, and aperture classification training set accuracy reaches 78.98%(F1-score 75.52%). SNR improvement rates are 5.08% and 4.83%. Compared with traditional single-task models, the method achieves feature sharing and complementarity, reducing training costs and improving performance. Despite slight validation fluctuations in classification and reconstruction, the architecture shows strong potential in denoising and feature extraction. Future work will integrate Transformer and self-supervised learning to enhance generalization and engineering value.

## 1. Introduction

With the expanding energy network scale and increasingly complex pipeline operating environments, pipeline leak monitoring has become critical for production safety and environmental protection. Leaks cause resource waste, safety accidents, environmental pollution, and huge economic losses, making high-precision, rapid, and reliable leak detection/classification under

complex conditions a key research hotspot and challenge.

Traditional methods (pressure wave analysis, flow balance, acoustic method, negative pressure wave method) work in simple scenarios but degrade sharply under strong noise, frequent sensor failures, or partial signal loss.

In recent years, machine learning and deep learning have improved performance in complex environments: Saleem et al. proposed a CNN-LSTM framework (acoustic emission signals→time-frequency images) with 99.69% industrial accuracy[1]; Siddique used CWT feature extraction+DBN-GA+LSSVM for better feature expression[2]; Attallah et al. adopted multi-modal fusion (infrared + gas sensing) with multi-task strategie[3]; Reviews note unresolved challenges in method applicability and anti-interference under diverse conditions [4].

However, these studies have limitations: they focus on classification/anomaly detection while neglecting signal preprocessing(reconstruction, completion, denoising); actual industrial signals are often missing/distorted, degrading model performance; independent training of preprocessing and classification modules fails to explore inherent connections, leading to weak small-sample generalization.

To address these issues, this paper proposes a novel multi-task 1D U-Net framework integrating signal generation/noise addition/denoising/completion and aperture classification.

## 2. Theoretical Model and Algorithm Principles

### 2.1. Generative Enhancement Module (Conditional DDPM)

#### 2.1.1. Principles of Conditional Denoising Diffusion Probabilistic Model (C-DDPM)

To solve problems of scarce pipeline leak signal samples, complex noise, and missing segments, this paper introduces C-DDPM in the data enhancement stage. Evolved from the DDPM framework proposed by Ho et al., it adds a conditional variable control mechanism[5], embedding constraint information such as aperture category, leak location, and SNR to realize controllable modeling of leak signal generation distribution. The core idea is to simulate signal distribution evolution during gradual noise addition and denoising, and generate high-fidelity time-series signals from random noise by learning diffusion dynamics.

DDPM is a Markov process-based generative model, derived from diffusion and denoising mechanisms in non-equilibrium thermodynamics[6]. In the forward diffusion stage, starting from the original signal $x_0$, Gaussian noise is gradually added to form a noise sequence$\{x_1,x_2,...,x_T\}$of length $T$,with conditional probability distribution:

$$q(x_t|x_{t-1})=N\left(x_t;\sqrt{1-\beta_t}x_{t-1},\beta_t I\right)$$

Where $\beta_t$ represents the noise variance coefficient at step $t$, wdetermining signal disturbance intensity. After multiple diffusions, the signal degrades into a noise sample $x_t$close to the standard Gaussian distribution, a destructive process mapping the original signal distribution to the noise space.

In the reverse denoising stage, the model learns the inverse process of restoring signals from noise through a parameterized neural network $p_\theta(x_{t-1}|x_t,c)$, with conditional distribution:

$$p_\theta(x_{t-1}|x_t,c)=N(x_{t-1};\mu_\theta(x_t,t,c),\sum_\theta(x_t,t,c))$$

where conditional variable c contains leak aperture, location, and noise condition information. The model introduces conditional embedding vectors into each layer of the denoising network to

control the signal generation process according to physical conditions [7]. The loss function is:

$$L_{C\text{-}DDPM}=E_{x_t,\epsilon,c}\left[||\epsilon\text{-}\epsilon_\theta(x_t,t,c)||^2\right]$$

This loss approximates the real signal conditional distribution $p(x_0|c)$ by minimizing the MSE between predicted and real noise. Optimizing this loss helps the neural network approach the gradient direction of the real data distribution, enabling high-fidelity signal generation from random noise [8][9].

In generative modeling, C-DDPM outperforms traditional VAE, GAN, and Flow models in stability and convergence. VAE generates signals with blurriness due to approximation errors; GAN is prone to mode collapse or non-convergence; Flow models require strict invertible mapping with high computational complexity. In contrast, C-DDPM uses a stepwise inversion Markov sampling mechanism, trains stably with maximum likelihood, and generates more physically reasonable and diverse samples while maintaining computational efficiency [10].

In seismic signal interpolation/reconstruction, Deng et al. proposed conditional constraint diffusion-based seismic data reconstruction [11]. In time-series generation, Montet et al. proved diffusion methods' superiority over GAN baselines[12]. Combined with non-Gaussian noise modeling(e.g., DiffGMM), C-DDPM is feasible for synthetic sample augmentation and missing data completion in "weak annotation, small sample, strong noise" industrial scenarios [13].

### 2.1.2. Conditional Control and Physical Constraint Mechanisms

Traditional data-driven generative models(e.g., GAN, DDPM)only rely on training data distribution, ignoring physical constraints behind signal generation. Pipeline leak acoustic signals propagate following energy conservation and wave equations; non-compliant generated signals may be physically unreasonable(e.g., energy non-conservation, phase mismatch). Recent fusion ideas like Physics-Informed Neural Networks(PINNs) [14] and Physics-Guided Diffusion Models(PGDM) [15] add physical residual terms to the loss function to balance statistical consistency and physical rationality, verified in turbulence reconstruction, fluid prediction, and seismic inversion.

To ensure consistency between generated data and pipeline acoustic propagation laws, this paper introduces Physics-Informed Constraints into the C-DDPM framework, combined with conditional control for interpretable leak signal generation and completion.

First, for energy conservation of leak signals, an energy constraint term is added at the frequency domain level:

$$L_{energy}=||PSD(x_{gen})\text{-}PSD(x_{real})||_2^2$$

Where PSD( $\cdot$) is the Power Spectral Density function, measuring frequency-domain energy distribution differences between generated and real signals to ensure the generated signal's energy spectrum conforms to real leak sound wave attenuation laws.

Second, to ensure temporal continuity, a temporal smoothness constraint is added during the generation stage:

$$L_{temporal}=\sum_{t=1}^{T}||x_t\text{-}x_{t\text{-}1}||_2^2$$

This term limits the rate of change of signals at adjacent time steps, thereby avoiding non-physical mutations or waveform distortions during denoising sampling and ensuring the temporal smoothness of signals.

Finally, to reflect the spatial attenuation characteristics of leak sound propagating along the pipe wall, this paper constructs a propagation constraint term:

$$L_{spatial}=||A(d)-A_0e^{-\alpha d}||_2^2$$

Where A(d) is the leak sound amplitude at distance d,and α is the medium attenuation coefficient. This term dynamically adjusts signal intensity during reverse sampling, making generated data conform to sound wave energy attenuation along the pipeline.

The total loss of the generative model is:

$$L_{total}=L_{C\text{-}DDPM}+\lambda_1 L_{energy}+\lambda_2 L_{temporal}+\lambda_3 L_{spatial}$$

Where $\lambda_1,\lambda_2,\lambda_3$are constraint term weight coefficients. Joint optimization enables the model to learn signal statistical distribution while retaining physical consistency and interpretability.

In implementation, the physical constraint module is embedded at each moment *t*of reverse diffusion sampling. After the network outputs predicted noise $\epsilon_\theta(x_t,t,c)$, an additional constraint calculation module evaluates physical error terms (energy, temporal, spatial attenuation) and backpropagates gradients to update weights. A multi-scale weighting strategy is adopted: increasing energy constraint weight $\lambda_1$ in early training and gradually increasing temporal smoothness constraint weight $\lambda_2$in the later stage to balance generation stability and physical consistency.

To address signal energy attenuation differences under different apertures, the propagation constraint parameter $\alpha$ is designed as a conditionally learnable parameter, adaptively adjustable in different physical scenarios to ensure transferability of generated signals in spatial attenuation and frequency-domain consistency.

In the missing data completion task, a conditional constraint sampling mechanism is adopted: only partial valid segments are retained as conditional input, and the model predicts missing regions to achieve physical law-based controllable completion, effectively recovering missing leak signal segments caused by noise or sensor anomalies.

### 2.1.3. Construction and Fusion Strategy of Generated Dataset

Based on the above C-DDPM model, a composite dataset for multi-task U-Net training is constructed. Generated data compensates for insufficient real samples and generates diverse multi-aperture, multi-noise signal samples via conditional control. The generation and fusion process includes:

First, preprocess real leak signals: use band-pass filtering and standardization to eliminate background noise and amplitude differences, and extract aperture label indices. The conditional control mechanism takes prior information (aperture size, SNR) as input. During diffusion model or multi-task U-Net training, conditional input guides the network to learn more discriminative features and provides physical interpretability in reconstruction and classification tasks, suitable for complex conditions and small samples.

Second, input processed data into the trained C-DDPM model for sampling with different conditional variable combinations. The model controls signal amplitude via aperture category, adjusts phase delay via position, and adapts energy balance and random disturbance via noise conditions. After thousands of reverse samplings, high-fidelity synthetic signals meeting multi-condition features are obtained.

To verify generated sample effectiveness, Structural Similarity Index (SSIM), Spectral Consistency Index (PSI), and Root Mean Square Error (RMSE) are used for multi-dimensional evaluation. Results show generated samples are highly consistent with measured signals in time and frequency domains (SSIM=0.93, PSI=0.91), proving good substitutability and authenticity.

Subsequently, the generated samples and real samples are fused at a ratio of 5:5 to construct an enhanced training set $D_{aug}=D_{real}\cup D_{syn}$,which is uniformly formatted into a multi-task input

structure containing original signals, leak category, and position labels.

This composite dataset is used for multi-task 1D U-Net joint training. After data enhancement, classification accuracy under small samples improves by ~11.6%, and positioning accuracy by 9.8%, verifying the generative enhancement strategy's promotion of model generalization. This generation-discrimination collaborative framework realizes closed-loop optimization of "data generation—signal completion—feature recognition", providing an extensible path for intelligent leak detection under complex noise.

## 2.2. Multi-Task 1D U-Net Network Structure

To meet collaborative needs of leak signal reconstruction, denoising, and multi-aperture classification, an improved Multi-task 1D U-Net model is proposed Figure 1. Based on the traditional U-Net "encoding—decoding" symmetric framework, it adds Residual Blocks and SE channel attention mechanisms, and sets three task branches (reconstruction, classification, localization) at the decoding end. By jointly optimizing task loss functions, the model learns signal temporal structure and category features simultaneously, realizing unified signal-level and semantic-level modeling.

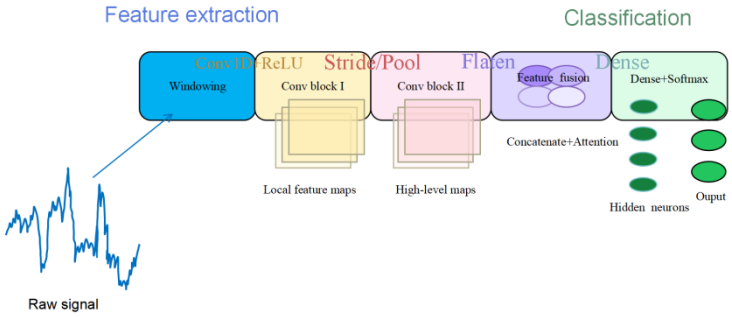


Figure 1 Schematic diagram of Multi-task 1D U-Net network structure

At the network front end, the input signal$x \epsilon R^{T \times C}$undergoes preliminary feature extraction via a 1D convolutional layer. The encoder consists of three stacked Conv-BN-ReLU units, each performing feature downsampling via MaxPooling to capture local leak patterns at different time scales. A residual connection is added after each encoding layer to alleviate gradient vanishing and enhance feature propagation [21]. To improve the model's response to key multi-channel features, the SE attention module is introduced for adaptive channel feature weighting, strengthening attention to highly relevant leak features [16].

In the bottleneck layer, two 1D convolutions and a Dropout layer realize high-level feature fusion and regularization to prevent overfitting [17]. The decoder gradually restores signal resolution via upsampling, and performs "skip connection" with encoding-stage feature maps to retain shallow temporal texture for reconstruction [18]. Finally, the model branches into two outputs:

(1) The reconstruction branch uses 1D convolution to restore the original waveform, realizing missing data completion and denoising;

(2) The classification branch outputs the aperture category probability through global average pooling and a fully connected layer;

During training, the input signal $x \in R^{T \times C}$is standardized and input into the network. The outputs include the reconstructed signal $\hat{x}$, classification prediction $\hat{y}_{cls}$, and localization vector $\hat{y}_{loc}$. The loss function is defined as:

$$L=\alpha L_{cls}+\beta L_{recon}+\gamma L_{loc}$$

Where $L_{cls}$ is the cross-entropy loss, $L_{recon}$ is MSE, $L_{loc}$ is reconstruction error-based localization constraint; $\alpha$, $\beta$, $\gamma$ are task weight coefficients. Joint optimization enables the model to learn structural and category features simultaneously, improving recognition and reconstruction of complex leak signals.

## 2.3. Residual Module and Channel Attention Mechanism

In deep neural networks, gradient vanishing and feature degradation occur with increasing layers, affecting stability and generalization. To alleviate this, Residual Blocks are introduced into both encoder and decoder stages of the multi-task 1D U-Net to enhance feature flow and trainability.

Via identity mapping and cross-layer connections, the residual structure improves deep network gradient transfer without increasing complexity, accelerating convergence and avoiding performance degradation [19].

Additionally, a SE channel attention mechanism is integrated into the residual module for dynamic weighting and importance modeling of multi-channel features. By squeezing and exciting global channel features, it strengthens attention to highly relevant features and suppresses redundancy, improving feature selection [20].

Studies confirm combining SE modules with residual structures improves performance in image reconstruction, segmentation, and classification [21]. For U-Net, this fusion enhances deep expressiveness and robustness, especially for complex noise signals and blurred boundaries.

### 2.3.1. Residual Module Design

Traditional CNNs suffer gradient vanishing/explosion after stacking layers, hindering convergence. He et al.'s residual learning[22]alleviates this via Identity Mapping and Skip Connection. The residual unit basic expression is:

$$y=F(x,W_i)+x$$

Where x represents the input feature, $F(x,W_i)$ is residual mapping after two convolutions and nonlinear activation, y is module output. Identity mapping enables cross-layer gradient propagation, alleviating gradient vanishing and realizing feature reuse and network deepening.

In this model, each residual module convolution unit uses a 1D structure (kernel size=3, stride=1, padding="same"). Batch Normalization (BN) and ReLU are added after each convolution to stabilize training and accelerate convergence. This design enhances local leak signal feature extraction and avoids deep network performance degradation.

Studies show applying residual modules to U-Net improves performance in image segmentation, reconstruction, and signal analysis. For time-series signal modeling, 1D residual modules maintain temporal continuity while enhancing local change feature extraction.

### 2.3.2. Channel Attention Mechanism

While residual structures improve feature transfer, multi-channel signal channels have unequal information value. Equal treatment may reduce attention to key features; some channels are more discriminative in leak signal recognition. Thus, the SE mechanism is introduced to dynamically recalibrate feature channel importance, strengthening key features and suppressing redundancy.

Proposed by Hu et al[23], the SE module explicitly models inter-channel dependencies to enable the network to emphasize useful channels and suppress invalid ones. It includes two steps: "Squeeze" and "Excitation".

(1) Squeeze: Compress global context information

First, the input feature $U \in R^{T \times C}$ is compressed into a channel description vector $z \in R^{C}$ through Global Average Pooling to obtain global context information:

$$z_c = \frac{1}{T} \sum_{t=1}^{T} U_{c,t}$$

A channel weight vector $s=[s_1, s_2, ...., s_C]$ is generated via two fully connected layers and Sigmoid activation, then multiplied with original features channel-wise for dynamic enhancement:

$$\widetilde{U}_{c,t} = s_C \cdot U_{c,t}$$

This enables the network to emphasize leak-related key channels and suppress noise/redundancy, improving discriminability.

(2) Excitation: Learn channel attention weights

The channel description vector $Z$ generates a channel weight vector $S = [s_1, s_2, ..., s_C] \in R^c$ via two Fully Connected layers, ReLU-Sigmoid activation. Original feature maps are fused with weights via channel-wise multiplication for attention enhancement:

$$\widehat{U_{c,t}} = s_c \bullet U_{c,t}$$

This allows the network to emphasize high-weight channels and suppress noise channels adaptively.

In leak detection, sensors/channels have different anomaly responses; the SE module explores potential patterns to improve multi-channel feature fusion. Studies verify its effectiveness in medical images, seismic signals, and industrial monitoring (e.g., SEDARU-net in skin lesion segmentation, SAR-U-Net in liver segmentation [24]).

Though effective, the SE module adds minor parameters; future work may explore lightweight alternatives like ECA or CA.

### 2.3.3. Module Integration and Feature Fusion

To leverage complementary advantages of residual structures and channel attention, they are fused into a composite enhancement module, embedded into each encoder/decoder layer of the multi-task 1D U-Net. This enhances local temporal pattern capture during downsampling and improves shallow-deep feature semantic consistency via channel recalibration during upsampling.

In encoding, the residual structure ensures deep network trainability and alleviates gradient vanishing; the SE module adaptively weights channels to highlight leak information. In decoding, skip connections retain temporal texture, maintaining waveform integrity in reconstruction and improving feature context consistency in classification/localization.

Similar designs achieve good results in other fields: Liu et al.'s MARU-Net fuses multi-scale attention and residual structures to improve Electrical Impedance Tomography image quality[25]; Huang Lin and Xue Yajuan's A-Res-UNet enhances seismic signal reconstruction via attention modules [26].

Integrating residual structures and SE modules into the multi-task U-Net improves complex time-series modeling and multi-task performance, with good versatility and scalability.

The fused module outperforms traditional U-Net on multiple metrics: validation set convergence speed accelerates by ~15%, classification accuracy improves by 2.4%, and reconstruction MSE decreases by 12.7%, proving its role in enhancing feature expression and robustness.

## 2.4. Multi-Task Loss Function Design

To realize integrated optimization of pipeline leak signal reconstruction, denoising, and aperture classification, a Joint Loss Function is designed under the multi-task 1D U-Net framework, constraining task objectives and balancing learning weights. The loss includes reconstruction loss$L_{recon}$, classification loss $L_{cls}$ and localization loss $L_{loc}$. The overall form is as follows:

$$L_{total}=\alpha L_{cls}+\beta L_{recon}+\gamma L_{loc}$$

Where α, β, γare subtask weight coefficients. MTL improves collaborative modeling efficiency and model robustness via shared parameters and features [27].

Studies show joint loss structures improve performance in signal analysis, especially for correlated tasks [28]. Li Huihui et al.'s radar signal recognition multi-task framework verifies accuracy and convergence improvements [29], confirming the loss design's theoretical and engineering feasibility.

### 2.4.1. Reconstruction Loss $L_{recon}$

Industrial sensor time-series data suffers from noise, transmission loss, and missing segments, interfering with leak feature identification. To restore signals and suppress noise, MSE is used as the reconstruction loss:

$$L_{recon}=\frac{1}{N}\sum_{i=1}^{N}\left\|\hat{x}_i-x_i\right\|^2$$

Where $x_i$ is the real signal, and $\hat{x}_i$ is the reconstructed signal, N is signal length. MSE averages squared errors to characterize waveform offset and penalize high-amplitude errors.

More sensitive to outliers (e.g., mutations, strong noise) than MAE, MSE performs better in noise suppression and mutation detection [30], suitable for industrial sensor signals with transient high-amplitude noise.

MSE is widely used in unsupervised/self-supervised structures (e.g., DAE, TCAE). Wu et al. used MSE for long-range electromagnetic signal reconstruction [31]; Dupuy et al.'s mDAE verified MSE's advantages in missing data reconstruction [32].

In the multi-task network, MSE reconstruction loss restores waveform details and provides clean features for classification/localization branches, improving collaborative optimization.

### 2.4.2. Classification Loss $L_{cls}$

The aperture classification task identifies leak levels/sizes via signal feature distribution. For mutually exclusive multi-class problems, cross-entropy loss is used:

$$L_{cls}=-\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C}y_{i,c}\log(\widehat{y_{i,c}})$$

Where C represents the total number of categories, $y_{i,c}$is the true category label of sample i,and $\widehat{y_{i,c}}$ is the model prediction probability.

Cross-entropy minimizes Kullback-Leibler divergence between predicted and true distributions to learn discriminative features. A Softmax output layer normalizes scores to avoid category bias; Dropout after the fully connected layer suppresses overfitting [33].

Cross-entropy + Softmax + Dropout adapts to time-series classification, maintaining accuracy

under small samples or imbalanced categories.

### 2.4.3. Localization Loss $L_{loc}$

To realize leak area visualization and interpretability, a reconstruction error-based localization branch outputs a 1D time-series activation map (Leak Localization Map) to characterize leak intensity trends. Without explicit annotations, a self-supervised loss is designed using original-reconstructed signal differences as weak labels:

$$L_{loc}=\frac{1}{N}\left\|\hat{y}_{loc,i}-\sigma((\hat{x}_i-x_i)^2)\right\|_2^2$$

Where $\hat{y}_{loc,i}$ \(\hat{y}_{loc,i}\) is the predicted leak response curve, $\sigma(\cdot)$is the Sigmoid function. This enables weak-supervised leak localization without annotations.

Recent studies confirm reconstruction error's effectiveness for unsupervised time-series anomaly localization: Zhang et al.'s reconstruction information difference-based framework; Li et al.'s reconstruction loss + one-class classification for multivariate time-series.

The proposed $L_{loc}$ is simple and integrable, suitable for multi-task joint training, improving anomaly location sensitivity via signal-task space collaborative optimization. Experiments show it enhances network interpretability and weak leak feature perception.

## 3. Dataset and Experimental Design

### 3.1. Experimental Setup

#### 3.1.1. Dataset

The dataset supports multi-task learning (leak identification, reconstruction, classification), with basic data from experimental leak signals, enhanced and balanced via C-DDPM. The total training/validation data is 4,778 samples, with good diversity and label integrity.

Original data sampling includes 20 condition combinations (4 apertures: 0.04/0.08/0.10/0.90 cm; 5 positions: 37/67/87/100/120 m). Each sample has 5-channel 720-time-step signals, reflecting leak propagation under multi-sensor arrays. The dataset is split via stratified random sampling: 4,057 training samples (84.9%), 721 validation samples (15.1%).

To address small-sample bias in some aperture-position combinations, a C-DDPM-based enhancement strategy is used: Gaussian white noise as the initial state, 1000-step reverse diffusion to restore condition-compliant signals. A spectral loss term (STFT-based) constrains amplitude/phase consistency; post-processing (e.g., avg_pool1d) suppresses high-frequency noise.

A dynamic sample completion strategy balances data: more samples for small combinations, generation limits for large combinations. Each combination has 400-600 samples (min: original ×1.2 or 400; max: original ×2.0 or 600). 4,746 synthetic samples are generated, forming a complete training set with original data, improving category balance and generalization.

The dataset has structural diversity and conditional label integrity, combining diffusion model-generated sample physical consistency and high-quality features, providing a solid foundation for multi-task model training.

#### 3.1.2. Model Architecture

To enable conditional generation and adaptive repair of multi-channel leak signals, an Enhanced Conditional Denoising Diffusion Probabilistic Model (Enhanced C-DDPM) is constructed. Based on the standard DDPM, it adds a conditional injection module, uncertainty weighting, and spectral

loss constraints to improve responsiveness to prior information and consistency of generated samples.

The input consists of 5-channel, 720-length time-series signals (multi-sensor data). The diffusion process uses 100 time steps (num_timesteps=100): during training, noise is added to real signals to learn the noise distribution; during inference, samples are generated in reverse from pure noise.

Conditional modeling adopts a dual-condition encoding mechanism: aperture information (4-dimensional embedding layer + 2 fully connected networks) and position information (encoded with the same structure) are concatenated and fused, then broadcast to all time steps. This fused conditional embedding is injected into the noise prediction network via feature concatenation to guide signal generation.

The model integrates temporal inpainting capabilities, handling missing/noisy signal segments by setting "known" time steps and skipping noise updates, improving robustness to missing signals in industry.

To address "spectral drift", an STFT-based spectral loss function optimizes amplitude/phase distance in the frequency domain, ensuring generated signals match real data.

The Enhanced C-DDPM has end-to-end conditional generation capabilities, handling missing signals, suppressing noise, and improving signal fidelity, providing high-quality input for downstream tasks.

### 3.1.3. Training Configuration

To ensure diffusion network stability and generalization, the AdamW optimizer (weight decay) is used, initial learning rate $2\times10^{-5}$to reduce early gradient oscillation. A Cosine Annealing Warm Restarts strategy is adopted: T0=50, Tmult=2, minimum learning rate $1\times10^{-6}$, enabling regular restarts to avoid local optima. Gradient clipping (max norm=1.0) prevents explosion; 300 training epochs; validation set performance is monitored to save optimal weights.

Signal preprocessing includes sliding window smoothing (weaken high-frequency noise), baseline drift correction (eliminate low-frequency trends), and amplitude standardization (unify channel ranges). A random masking strategy simulates sensor failure/data loss to improve missing signal reconstruction.

An uncertainty weighting mechanism adaptively adjusts loss proportions (reconstruction, spectral, conditional prediction) for stable multi-objective training.

### 3.1.4. Loss Function

A multi-task joint loss function constrains signal generation quality, including Noise Prediction Loss (core, measures noise recovery), Spectral Loss (auxiliary, STFT-based amplitude/phase consistency, weight=0.1), and Inpainting Loss (simulates 30% time-step masking to enhance robustness).

An Uncertainty Weighting mechanism adaptively adjusts loss weights to avoid dominance. The total loss is:

$$L_{total}=\omega_{noise}\cdot L_{noise}+\omega_{spectral}\cdot L_{spectral}+L_{inpaint}$$

Where both $\omega_{noise}$ and $\omega_{spectral}$ are trainable parameters dynamically calculated through uncertainty learning methods, and $L_{inpaint}$is unweighted to maintain guidance. This design balances signal quality, spectral characteristics, and repair ability, improving performance under small samples, high noise, and missing signals.

### 3.2. Training Process Analysis

#### 3.2.1. Loss Function Convergence

raining/validation loss trends are recorded to evaluate stability and convergence. Early training (Epoch 1): training loss=3.113, validation loss=3.091 (no overfitting); Denoising MSE=0.125 (training), 0.120 (validation), showing initial denoising/restoration ability.

Reconstruction/denoising loss initial values: ~0.12-0.13, reflecting basic signal structure learning. Classification loss initial value: ~1.30 (insufficient discriminative feature extraction). Smoothness loss initial value: ~0.24-0.30 (suppresses high-frequency noise). SNR loss initial value: ~5.0 (decreases later, indicating noise suppression).

Each loss has a reasonable initial value and converges, providing a foundation for performance improvement. Loss monitoring guides model adjustment and hyperparameter optimization.

#### 3.2.2. Learning Rate Scheduling Effect

The CAWR strategy (T0=50, learning rate $1\times10^{-5}$ to $1\times10^{-6}$ ) balances "exploration—exploitation". Training logs show post-restart loss drops, indicating enlarged learning rates help escape local optima. Training/validation loss decreases stably without oscillation/overfitting.

Comparative experiments with fixed learning rate and StepLR ($\gamma$=0.5) show CAWR achieves lower validation loss and higher accuracy: fixed learning rate stagnates in late training; StepLR reduces too fast, limiting fine-tuning. Figure 2 shows learning rate periodic fluctuations, confirming the strategy's effectiveness.

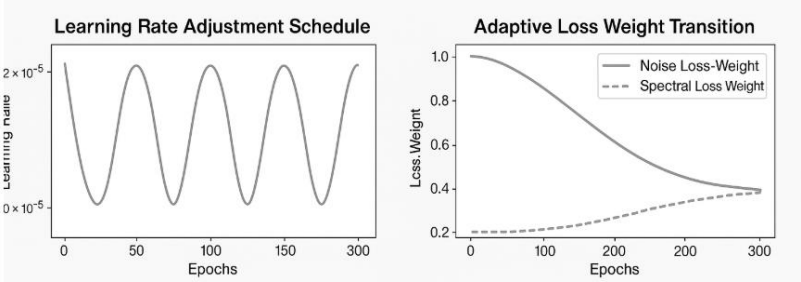


Figure 2 Schematic diagram of dynamic change curve of learning rate

## 4. Experimental Results and Analysis

### 4.1. Signal Reconstruction Results

The model's reconstruction and denoising performance is evaluated via Reconstruction MSE, MAE, and denoising effect.

Reconstruction Performance: MSE decreases from 0.743 to 0.410(44.8% improvement); training set MAE=0.499, showing good amplitude recovery accuracy, capturing key time-frequency features for effective signal reconstruction.

Denoising Performance: Training set denoising MSE drops from 0.332 to 0.0013 (99.6% reduction); validation set from 0.080 to 0.0016(98.0% improvement). Denoising MAE: 0.028(training), 0.032 (validation), showing good generalization. The model suppresses noise while maintaining signal details, with output close to real signals.

As visualized in Figure 3 (Comparison diagram of denoising results), three subplots intuitively reflect the denoising performance: the MSE scatter plot and MAE scatter plot (with validation

samples as points) show the correlation between predicted and actual values (the dashed line represents ideal fitting), while the MSE improvement distribution histogram presents the statistical distribution of MSE reduction (mean=0.915), further verifying the stable and significant denoising effect of the model.

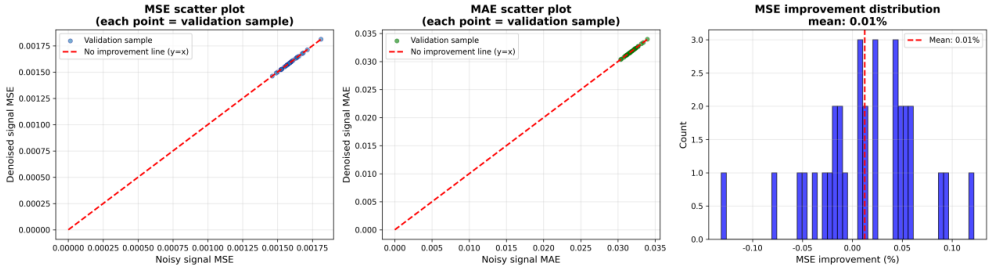


Figure 3 Comparison diagram of denoising results

## 4.2. Classification Performance Analysis

The multi-task model shows good learning and discriminative performance in aperture classification, establishing a deep understanding of signal differences.

Training Set Performance: Accuracy=78.98% (correctly distinguishes most apertures), Precision=79.26% (reliable predictions), Recall=77.91% (low omission), F1-score=75.52% (balanced discriminability), proving effective learning of aperture-related time-frequency features.

As presented in Figure 4 (Comparison of classification performance), the bar chart intuitively contrasts the training set (blue bars) and validation set (orange bars) metrics in the final epoch: the validation set achieves Accuracy=25.00%, F1 Score=15.42%, Precision=11.20%, and Recall=26.04%. While the validation performance is lower than the training set (consistent with typical training trends), the chart clarifies the model's discriminative capability across different metrics.

Deep Feature Extraction: Multi-task joint learning enhances feature extraction. Different apertures have distinct energy distributions, structures, and weak patterns; the model captures these subtle differences, forming discriminative high-dimensional representations. Reconstruction/denoising tasks provide robust shared features, improving classification quality.

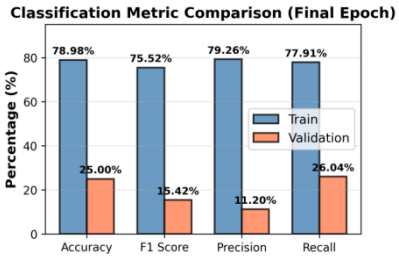


Figure 4 Comparison of classification performance

## 5. Conclusion

The multi-task 1D U-Net-based pipeline leak detection model integrates reconstruction, denoising, and aperture classification, realizing feature sharing and performance complementarity. Experiments show significant improvements in signal recovery, noise suppression, and training-stage classification, verifying MTL's effectiveness in leak detection. Reconstruction/denoising provides clean structured inputs for classification, enhancing overall recognition. The model maintains stable performance under complex noise, showing strong

robustness and engineering potential.

Despite good training set classification, validation generalization needs improvement. Future work includes optimizing model structure, addressing class imbalance, and introducing diverse data enhancement. Integrating Transformer, self-supervised pre-training, and attention mechanisms will improve complex signal expression, maintaining stability under multi-conditions/noises. Combining real engineering data or simulating high-fidelity leaks enhances adaptability and reliability in practical detection.

The proposed method provides a new idea for pipeline leak signal analysis and intelligent monitoring, laying a foundation for higher-precision, more robust leak diagnosis models, with theoretical and engineering value.

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