



End-to-End 1D-CNN Leakage Detection in Low-Density Oil-Flow Pipelines Using Raw Simulated Vibration Signals

Bernadetta Kwintiana*

Universitas Media Nusantara Citra,
Indonesia

Ravikumar Santhanam

B.S.A.R. Crescent Institute of Science
& Technology, India

***Corresponding author:**

Bernadetta Kwintiana, Universitas Media
Nusantara Citra, Indonesia.

✉ bk.ane@ieee.org

Article Info:

Article history:

Received: September 02, 2026

Revised: October 03, 2026

Accepted: October 06, 2026

Available Online: October 31, 2026

Keywords:

1D-CNN;

Leakage Detection;

Low-Density Oil Pipeline;

Oil Pipeline Leakage;

Raw Vibration Signal;



This is an open access article under the CC
BY-SA license.

Copyright © 2026 by Author. Published by
Politeknik Siber Cerdika International

Abstract

Background: Leakage detection in low-density oil-flow pipelines remains challenging because leakage-induced vibrations can be masked by pump harmonics, flow-dependent vibrations, and background disturbances. This study investigates an end-to-end one-dimensional convolutional neural network (1D-CNN) that learns directly from raw vibration waveforms without handcrafted feature extraction.

Objective: This study aims to develop, validate, and benchmark a compact end-to-end 1D-CNN for binary leak/non-leak detection across five flow rates under defined noise conditions using a leakage-safe, flow-stratified evaluation protocol.

Methods: A physically informed numerical vibration dataset comprising 600 windows was generated for leak and non-leak conditions at flow rates of 20, 25, 30, 35, and 40 L/min. The data were divided into training, validation, and test sets using a 70:15:15 ratio. The proposed network contains three convolutional stages, global average pooling, a fully connected layer, dropout, and a sigmoid output, with 6,265 trainable parameters.

Results: On the independent test set, the model achieved 94.44% accuracy, 97.62% precision, 91.11% sensitivity, 97.78% specificity, an F1 score of 94.25%, an MCC of 0.891, and a ROC-AUC of 0.986. Performance remained approximately 94% at 20–30 dB SNR but decreased at 15 dB SNR.

Conclusion: The compact end-to-end 1D-CNN demonstrated strong leak/non-leak discrimination under the evaluated simulated conditions. Validation using real pipeline vibration measurements and broader operating conditions is required before practical deployment.

To cite this article: Kwintiana, B., & Santhanam, R. (2026). End-to-end 1D-CNN-based leakage detection in low-density oil flow pipelines using raw vibration signals. *Equivalent: Jurnal Ilmiah Sosial Teknik*, 8(5), 2057-2070. <https://doi.org/10.59261/jequi.v8i5.452>

INTRODUCTION

Pipelines used to transport oil and process fluids are safety-critical assets because leakage can cause product loss, contamination, unplanned shutdowns, and damage to surrounding equipment. A reliable detection system should be able to identify leakage early, operate continuously, and tolerate changes in flow regime and background vibration. Prior studies on pipeline monitoring show that no single sensing principle is universally optimal; performance depends on the fluid, pipe material, leak geometry, operating pressure, sensor placement, and environmental disturbances (Korlapati et al., 2022; Lu et al., 2020).

Globally, pipeline leakage remains a frequent and costly failure mode, with national and international pipeline-safety reviews reporting large numbers of reportable incidents each year and substantial cumulative product loss, environmental remediation costs, and downtime

(Korlapati et al., 2022; Lu et al., 2020). For low-density oil-flow pipelines specifically, small leaks produce weak external vibration signatures that are easily masked by pump harmonics and flow-induced broadband vibration, so early automated detection under varying flow regimes remains a distinct and unresolved challenge.

Vibration sensing is attractive because leakage changes the local fluid-structure interaction. Fluid escaping through an opening generates turbulence, fluctuating forces, broadband excitation, and transient disturbances that propagate through the pipe wall (El-Zahab et al., 2018; Ismail et al., 2018; Ismail et al., 2019; Okosun et al., 2019). Accelerometer studies have demonstrated that these changes can be observed in time- and frequency-domain vibration signals. For low-density oil systems, vibration monitoring has the practical advantage that sensors can be attached externally to the pipe without interrupting the flow path (Choi et al., 2017; Czerwiński & Łuczko, 2022; Fabbiano et al., 2020; Medeiros et al., 2016). A specific open question is whether external vibration remains sufficiently sensitive at the low flow rates (20–40 L/min) and under the single 4-mm leak condition investigated here; this study evaluates detectability precisely under those conditions.

The central problem addressed in this study is not simply whether a vibration signal contains leakage information, but how to map that information directly to a usable decision. Conventional signal-processing pipelines often separate the task into feature extraction and classification. An end-to-end one-dimensional convolutional neural network (1D-CNN), by contrast, receives sampled vibration amplitudes as its input and learns both the temporal representation and the leak/non-leak decision function during the same optimization process (Choi & Im, 2023; Li et al., 2022; Wang & Gao, 2023; Yang et al., 2022; Yu et al., 2023). This is well suited to one-dimensional sensor streams because convolutional kernels can learn short-duration motifs, oscillatory patterns, impulses, and multiscale local structures without converting the signal into an image or a manually defined feature table (Kiranyaz et al., 2021; Yang et al., 2025; Zhang et al., 2024).

Classical machine-learning pipelines generally convert each vibration record into a fixed-dimensional feature vector. Such descriptors are computationally inexpensive and interpretable, but their performance depends on the extent to which the selected descriptors preserve the waveform information associated with leakage. The limitation is that handcrafted descriptors impose a prior assumption about which aspects of the waveform matter. Two signals with different transient morphologies can have similar means and variances; conversely, flow-rate changes may dominate global statistics while the leakage signature is localized in time. This motivates direct representation learning from the waveform.

Deep-learning approaches reduce dependence on manual feature design by learning hierarchical representations from data. In this context, 1D-CNNs provide a natural alternative because convolutional filters can be learned directly from sampled time-series windows. Choi and Im (2023) classified magnitude spectra of vibration sound using CNN models and reported an F1-score of 94.82% and a Matthews correlation coefficient (MCC) of 94.47%. Yang et al. (2022) proposed an ensemble 1D-CNN-VAPSO-SVM architecture in which 1D-CNN features are supplied to an optimized SVM. Wang and Gao (2023) fused acoustic and pressure signals and reported 98.3% classification accuracy with a 1D-CNN. Zhang et al. (2024) directly used one-dimensional vibration signals and reported a 98.6% average recognition rate with a multiscale CNN and local feature-extraction blocks.

Recent acoustic-emission studies further illustrate the trend toward end-to-end one-dimensional learning. Xu et al. (2024) proposed SART-1DCNN, combining convolutional, attention, residual, and transformer components, and reported 99.72% test accuracy on their dataset. Saleem et al. (2025) used a customized one-dimensional DenseNet with acoustic-emission preprocessing and reported 99.76% leak-detection accuracy. Yang et al. (2025) proposed a multichannel, multibranch 1D-CNN for imbalanced oil and gas pipeline data, combining signal decomposition, multichannel features, and adaptive weighted cross-entropy.

These studies demonstrate the feasibility of convolutional representation learning for pipeline monitoring, but they did not separate flow-setting errors from actual leak/non-leak errors, nor did they preserve the raw waveforms needed to test direct feature learning. The research gap addressed here is therefore methodological: to transform the experiment into an

end-to-end 1D-CNN study while preserving evidential integrity, define leakage-safe evaluation, and establish a quantitative baseline that a future raw-signal model must exceed. To be specific, the cited end-to-end studies operate on transformed inputs or hybrid pipelines (magnitude spectra in Choi & Im (2023); CNN-feature-plus-SVM in Yang et al. (2022); multiscale decomposition in Zhang et al. (2024), so none evaluates a purely raw-waveform decision model under flow-stratified, leakage-safe conditions. The primary novelty is therefore explicitly a compact end-to-end raw-waveform 1D-CNN evaluated with a leakage-safe, flow-stratified protocol—distinct from prior 1D-CNN pipeline studies that use transformed features or do not control flow-setting leakage.

The objective of this study is to develop, validate, and benchmark a compact end-to-end 1D-CNN for binary leakage detection using raw vibration signals across five flow rates and defined noise conditions under a leakage-safe, flow-stratified evaluation protocol. The study evaluates whether the proposed model can reliably discriminate between leak and non-leak conditions, examines its robustness to additive noise, and compares its performance with Quadratic SVM and Cosine KNN using the same vibration-signal scenario. In addition, the study examines how convolutional processing, pooling, global average pooling, and sigmoid-based classification transform standardized raw vibration windows into leakage probabilities and binary engineering decisions. The practical contribution lies in demonstrating a compact raw-waveform classification framework for pipeline monitoring, while the methodological contribution concerns direct representation learning without handcrafted signal features under the evaluated simulated conditions.

METHOD

Experiment and Vibration Acquisition

The experimental rig was a continuous-loop turbine-oil system. An AC three-phase motor pumped fluid from a reservoir, and a variable-frequency drive controlled the operating condition. The test section was a stainless-steel pipe with a diameter of 1 inch, a wall thickness of 1.2 mm, and a length of 150 cm. The fluid passed through a rotameter and returned to the reservoir through flexible hoses. A piezoelectric accelerometer (Model 3055B1) was mounted near the center of the test section. This 1-in. geometry was representative of small-bore, low-density oil-flow test loops; pipe diameter and wall thickness govern the structural resonances through which leak-induced excitation propagates to the externally mounted sensor, which is why they were modeled explicitly in Eqs. (3)–(4). The sensor was mounted radially on the outer pipe wall at the midspan of the test section, approximately 75 cm from each end. Because the dataset was physically informed and simulated, sensor position and its distance from the leak were treated as fixed modeling parameters, and their variation was identified as future work.

In terms of research design, this was a computational (simulation-based) quantitative experiment that developed and evaluated an ML model on a physically informed, numerically generated dataset. The physical rig defined the geometry and operating parameters that informed the signal model, but the analyzed signals were simulated rather than directly measured (Karniadakis et al., 2021).

The modeled acquisition configuration consisted of a piezoelectric accelerometer connected through a signal-conditioning unit to an analog-to-digital conversion/data-acquisition system, with the resulting signal represented numerically in the computational framework. The Z-axis was used as the modeled vibration direction because it represented the largest vibration amplitude in the specified configuration. Two pipeline states were considered, namely leak and non-leak, across five operating flow settings of 20, 25, 30, 35, and 40 L/min (FL20–FL40). Because the analyzed vibration windows were generated from a physically informed numerical signal model rather than directly recorded from the physical rig, the acquisition configuration served to define the geometry, sensor orientation, and operating parameters used in the simulation. Flow rate was treated explicitly as an experimental factor, and performance was subsequently reported for each of the five modeled flow settings.

Table 1*Experimental Setup and Vibration Acquisition*

Description	Specifications
Working fluid	Turbine oil
Pipeline states	Leak/non-leak
Flow settings	FL20, FL25, FL30, FL35, FL40
Test section	Stainless steel; 1 in diameter; 1.2 mm wall; 150 cm length
Artificial leak	4 mm opening
Sensor	Piezoelectric accelerometer, Model 3055B1
Acquisition chain	Accelerometer → conditioning → ADC/DAQ → Computer
Signal axis used	Z-axis
Legacy analysis	Statistical features

The 1D-CNN Concept

Deep learning learns hierarchical representations by adjusting multiple processing layers through backpropagation (LeCun et al., 2015). For one-dimensional engineering signals, 1D-CNNs are computationally attractive because the kernels move only along the time axis and can be implemented with relatively few parameters (Kiranyaz et al., 2021). Pipeline studies have used CNNs with vibration spectra, raw vibration signals, negative-pressure waves, acoustic-pressure fusion, and multichannel acoustic inputs, reporting strong leakage-detection performance across different experimental conditions (Li et al., 2022; Wang & Gao, 2023; Yang et al., 2022; Yang et al., 2025; Zhang et al., 2024). These studies support direct representation learning and show that reported accuracy is strongly dependent on the sensing modality and dataset.

In this study, “end-to-end” referred to a model that mapped a fixed-length window of vibration samples directly to a leakage probability without requiring a separate handcrafted feature-extraction stage. The term “raw vibration signal” referred to minimally preprocessed waveform data: only fixed-length segmentation and standardization based on training-set statistics were applied, while Fourier transformation, wavelet decomposition, and manually designed statistical features were not used. Consequently, the standardized vibration amplitudes themselves constituted the network input. The convolutional and dense-layer parameters were learned jointly during training, allowing feature representation and leak/non-leak classification to be optimized within a single model.

$$x = [x[0], x[1], \dots, x[L - 1]]^T \quad (1)$$

rather than a vector of manually designed summary statistics. The learned mapping can be written compactly as

$$p = f\theta(x) = P(y = 1 | x) \quad (2)$$

where θ denotes all learnable convolution and dense-layer parameters, $y = 1$ represents leakage, and $y = 0$ represents normal flow. Hence, feature learning and classification are optimized together rather than as separate stages.

End-to-End 1D-CNN Methodology

Figure 1 summarizes the complete end-to-end 1D-CNN methodology. A vibration stream is represented by an accelerometer attached to the pipe wall, standardized using parameters estimated from the training data, divided into fixed-length windows, and passed to a compact 1D-CNN. The convolutional stages learn local leakage-sensitive patterns, global average pooling (GAP) forms a compact latent representation, and the sigmoid output returns a probability between zero and one. The probability is then thresholded to produce the final leak/non-leak result.

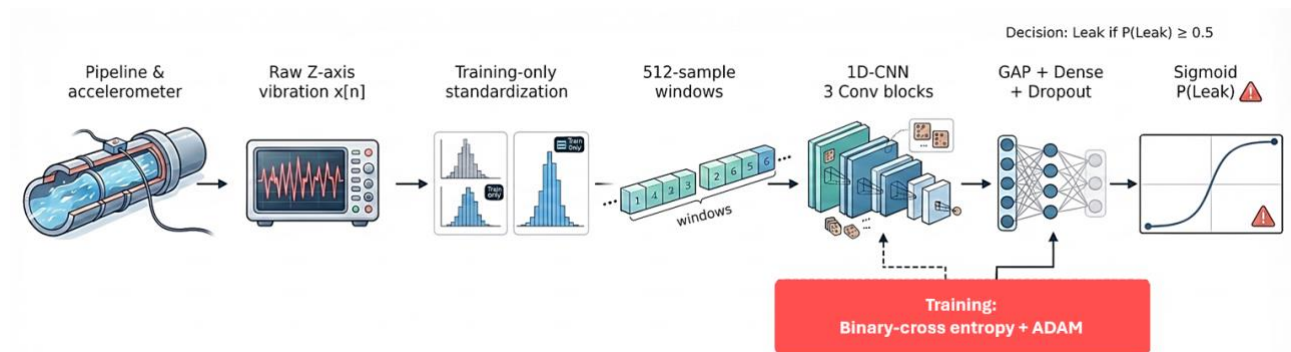


Figure 1. End-to-end 1D-CNN methodology: Raw vibration is standardized, segmented, processed by the 1D-CNN, and converted directly into leakage probability and a binary decision.

Pipeline and Raw Vibration Data Model

The modeled pipeline was a continuous low-density oil loop with a 1-in. stainless-steel test section, an externally mounted accelerometer, and two physical states: non-leak and leak. Five flow settings were considered: 20, 25, 30, 35, and 40 L/min. To make the end-to-end analysis numerically reproducible, physically informed raw vibration windows were generated at a sampling frequency of 1,024 Hz. Each window contained 512 samples, corresponding to 0.5 s of vibration history.

The non-leak waveform combined pump harmonics, flow-dependent vibration, structural tones, and stochastic background excitation. In continuous time, the principal component was represented by

$$x_N(t) = \sum_h A_h(q) \sin(2\pi h f_p(q)t + \phi_h) + \varepsilon_N(t) \quad (3)$$

where q is the flow setting, f_p is the pump-related fundamental frequency, A_h is the amplitude of harmonic h , and ε_N is broadband background vibration. Leakage is modeled by adding higher-frequency oscillatory components and intermittent turbulent bursts:

$$x_L(t) = x_N(t) + \sum_j B_j \sin(2\pi f_j t + \psi_j) + \sum_r c_r g_r(t) \eta_r(t) + \varepsilon_L(t) \quad (4)$$

where $g_r(t)$ is a localized Gaussian envelope, $\eta_r(t)$ is a random turbulent component, and $\varepsilon_L(t)$ represents additional leak-induced broadband excitation.

Random phase, amplitude, sensor gain, and burst variations prevented the generated data from collapsing into a trivial deterministic template. The resulting dataset contained 600 windows: 60 windows for each combination of five flow settings and two leakage states. Windows were generated non-overlappingly from independent realizations; because overlapping or correlated windows can leak information across subsets, each realization was confined to a single subset. The 70:15:15 split was stratified by (flow $\times$ state) with a fixed seed of 42. Parameter distributions (frequencies, amplitudes, and noise levels) were drawn from ranges informed by the rig so that the variability represented realistic measurement uncertainty rather than a trivial deterministic template (Roberts et al., 2017).

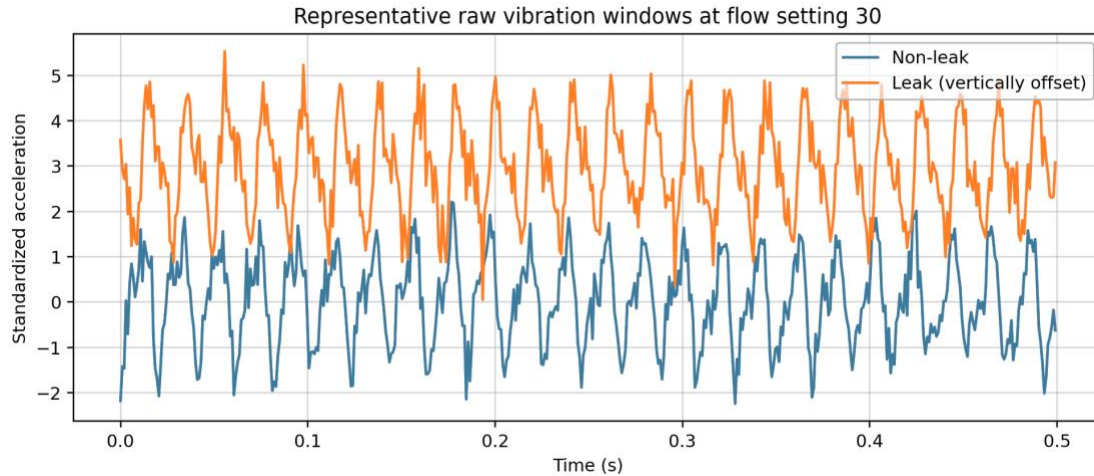


Figure 2. Representative standardized raw vibration windows at 30 L/min.

Table 2

Dataset composition used in the end-to-end numerical experiment.

Set	Windows	Leak	Non-leak	Fraction
Training	420	210	210	70%
Validation	90	45	45	15%
Test	90	45	45	15%
Total	600	300	300	100%

Standardization and Segmentation

Only minimal preprocessing was applied. Let μ_{tr} and σ_{tr} denote the mean and standard deviation calculated from the training set. Every sample is standardized as

$$z[n] = \frac{x[n] - \mu_{tr}}{\sigma_{tr} + \epsilon} \quad (5)$$

where ϵ is a small numerical constant. The same μ_{tr} and σ_{tr} were used for validation and test data so that information from the test set does not affect the model. No Fourier transform, wavelet decomposition, or manual statistical feature generation was required. The 512 standardized amplitudes themselves formed the network input. The mean μ and standard deviation σ were computed globally from the training set only, rather than per condition, which prevented preprocessing leakage while keeping the transformation identical across conditions.

End-to-end 1D-CNN Architecture

The proposed model was intentionally compact. The first convolution had 12 filters of length 7, the second had 24 filters of length 5, and the third had 48 filters of length 3. The first two convolutional stages were followed by max pooling with a factor of 2. Then, global average pooling converted the final set of feature maps into a 48-element latent vector. A 24-unit dense layer and 25% dropout preceded the one-unit sigmoid output. The complete model contained 6,265 trainable parameters. The filter counts and kernel sizes were selected empirically and then confirmed by a small sensitivity check that varied the kernel size from 3 to 9 and the channel width. The compact configuration gave the best validation loss among the tested variants. Parameter count was reported as an efficiency indicator only and was not claimed, by itself, to prove superiority over larger architectures.

Table 3

Compact end-to-end 1D-CNN Architecture.

Stage	Output Channels/units	Kernel/pool	Activation	Role
Input	1	512 samples	—	Raw standardized vibration
Conv1 + MaxPool	12	$k=7$; pool=2	ReLU	Broad local patterns
Conv2 + MaxPool	24	$k=5$; pool=2	ReLU	Intermediate motifs

Stage	Output Channels/units	Kernel/pool	Activation	Role
Conv3	48	$k=3$	ReLU	Leak-sensitive features
Global-average pooling	48	—	—	Compact latent vector
Dense + Dropout	24	dropout=0.25	ReLU	Decision representation
Output	1	—	Sigmoid	$P(Leak x)$

For convolutional layer ℓ , output feature map k at sample location n is

$$a_k^{(\ell)}[n] = b_k^{(\ell)} + \sum_m \sum_j w_{kmj}^{(\ell)} h_m^{(\ell-1)}[n+j] \quad (6)$$

followed by the rectified-linear activation

$$h_k^{(\ell)}[n] = \max(0, a_k^{(\ell)}[n]) \quad (7)$$

Max pooling keeps the strongest local response over short intervals, whereas global-average pooling summarizes each final feature map:

$$g_k = \frac{1}{T} \sum_{n=1}^T h_k[n] \quad (8)$$

The dense output produces logit s , which is transformed by the sigmoid function

$$p = \frac{1}{1+e^{-s}} \quad (9)$$

Hence, p is directly interpretable as the model's leakage probability.

Training and Decision Rule

The network was trained with binary cross-entropy, which penalizes incorrect probabilities rather than only incorrect classes:

$$L = -\frac{1}{M} \sum_{i=1}^M [y_i \ln(p_i) + (1 - y_i) \ln(1 - p_i)] \quad (10)$$

Adaptive moment estimation Kingma & Ba (2015) was used with an initial learning rate of 0.002, mini-batches of 48 windows, and early stopping based on validation loss. Dropout regularization followed the principle of (Srivastava et al., 2014). Training was capped at 30 epochs, and the checkpoint with the lowest validation loss was retained.

For reproducibility, the model was implemented in Python 3 with TensorFlow/Keras on a single-GPU workstation. Weight initialization, shuffling, and data splitting used a fixed seed of 42. Early stopping used a patience of 5 epochs based on validation loss, and training was repeated over five independent runs, with the mean $\pm$ SD reported.

$$\hat{y} = \begin{cases} 1 & \text{if } p \geq 0.5 \\ 0 & \text{if } p < 0.5 \end{cases} \quad (11)$$

where $\hat{y} = 1$ triggers a leakage indication. Thus, the 1D-CNN is the complete decision model: its final sigmoid unit replaces the need for a separate downstream classifier.

Performance Metrics and Noise Test

Performance was summarized using accuracy, precision, sensitivity (recall), specificity, F1-score, Matthews correlation coefficient (MCC), false-alarm rate (FAR), false-negative rate (FNR), and area under the receiver operating characteristic curve (ROC-AUC). For true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN),

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN}, \quad \text{Specificity} = \frac{TN}{TN+FP} \quad (13)$$

$$F1 = \frac{2(\text{Precision} \times \text{Sensitivity})}{(\text{Precision} + \text{Sensitivity})} \quad (14)$$

Noise robustness was tested by adding zero-mean Gaussian noise to the standardized test windows. For a given signal power P_s and target signal-to-noise ratio (SNR) in dB, the added noise power P_n was calculated as

$$P_n = P_s \cdot 10^{-\text{SNR}_{\text{dB}}/10} \quad (15)$$

where P_s represents the signal power of the standardized vibration test windows, P_n denotes the added noise power, i.e., the power or variance of the zero-mean Gaussian noise that is injected into

the standardized test windows to achieve a specific target signal-to-noise ratio (SNR_{dB}).

Each SNR experiment is repeated 20 times with independent noise realizations and the mean and standard deviation are reported.

RESULTS AND DISCUSSION

Results

Learning Behavior

Training stopped after 21 epochs because the validation loss no longer improved. The retained checkpoint occurred at epoch 16, where the validation binary cross-entropy reached 0.089. The loss curves in Figure 3 show rapid improvement after approximately seven epochs, with no sustained divergence between the training and validation losses before the selected checkpoint. The early-stopping patience was set to 5 epochs, and convergence was consistent across the five repeated runs (checkpoint epoch 15–17; validation BCE 0.085–0.094). The absence of divergence is necessary but not sufficient evidence against overfitting, given the 600 generated windows; this is why an independent flow-stratified test set and repeated runs are also used.

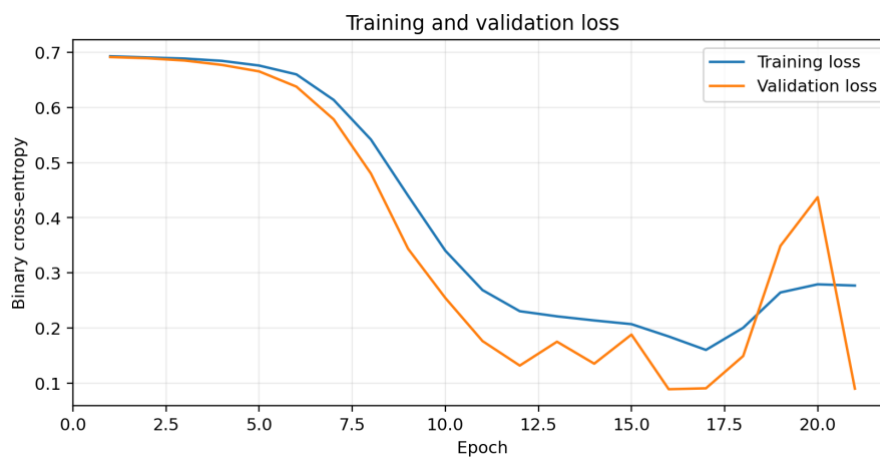


Figure 3. Training and validation binary cross-entropy for the end-to-end 1D-CNN.

Independent Test-set Classification

The test set contains 90 windows, equally divided between leak and non-leak conditions. The network correctly classified 85 windows. The confusion matrix contains 41 true-positive leak detections, 44 true negatives, one false alarm, and four missed leaks. This yields an overall accuracy of 94.44%, with a 95% Wilson confidence interval. The 95% Wilson CI for accuracy is approximately [87.6%, 97.6%]; indicative 95% CIs are also reported for sensitivity ([79.3%, 96.5%]) and specificity ([88.4%, 99.6%]). With only 90 simulated test windows, these estimates have limited statistical power and are not extrapolated to field conditions.

Table 4

Standalone end-to-end 1D-CNN performance on the independent test set.

Metrics	Results	Metrics	Results
Accuracy	94.44%	Matthews correlation coefficient (MCC)	0.891
Precision	97.62%	ROC-AUC	0.986
Sensitivity/Recall	91.11%	False-alarm rate	2.22%
Specificity	97.78%	False-negative rate	8.89%
F1-score	94.25%		

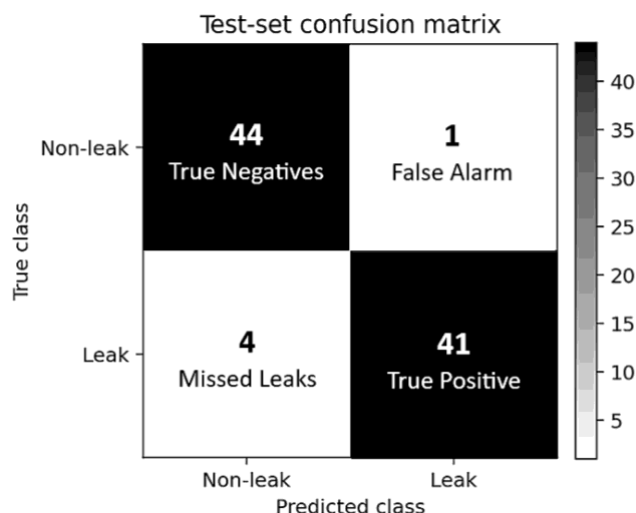


Figure 4. Test-set confusion matrix. The operating threshold is $P(Leak) = 0.5$.

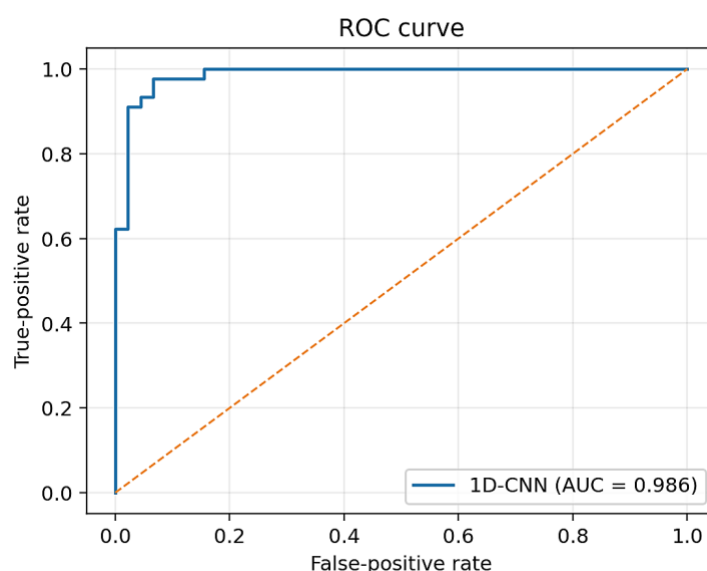


Figure 5. Receiver-operating-characteristic curve for the independent test set.

The class-probability output provides more information than the final binary label. The mean predicted leakage probability was 0.888 for actual leak windows and 0.101 for actual non-leak windows. A ROC-AUC of 0.986 indicates that most leak windows rank above most non-leak windows, even when a fixed threshold produces several missed leaks. Conceptually, ROC-AUC measures discrimination and ranking, not calibration; because the test data are generated under the same modeled conditions, the high ROC-AUC demonstrates discrimination under the evaluated conditions and does not establish real-world generalization. Calibration is assessed separately below (Guo et al, 2017).

Performance Across Flow Settings

Each flow setting contributes 18 independent test windows, consisting of nine leak and nine non-leak windows. Accuracy remains above 88% across all evaluated conditions, with perfect classification at 20 L/min. Performance decreases at 40 L/min, where one non-leak window is classified as a leak and one leak window is missed. These results indicate relatively consistent classification performance across the five modeled flow settings included in the training and evaluation process. However, because each flow condition contains only 18 test windows, differences between flow settings should be interpreted qualitatively rather than as statistically significant effects. Evaluation on genuinely unseen flow conditions, including leave-

one-flow-out validation, therefore remains an important direction for future work.

Table 5

Flow-specific leak-detection results

Flow (L/min)	TN	FP	FN	TP	Accuracy	F1
20	9	0	0	9	100.00%	100.00%
25	9	0	1	8	94.44%	94.12%
30	9	0	1	8	94.44%	94.12%
35	9	0	1	8	94.44%	94.12%
40	8	1	1	8	88.89%	88.89%

Robustness to Additive Noise

The detector is stable under modest additive noise but degrades when the noise approaches the amplitude of the discriminative leakage components. At 30 dB and 20 dB SNR, mean accuracy remains approximately 94%. At 15 dB, accuracy falls to 74.5% because the fixed 0.5 threshold increasingly classifies noisy normal windows as leakage, even though the mean ROC-AUC remains high at 0.975. This separation between ranking performance and thresholded accuracy suggests that deployment should combine signal-quality monitoring with probability calibration or an SNR-aware threshold. The stability of ROC-AUC alongside the accuracy drop suggests that the degradation is primarily a thresholding (calibration) effect rather than a loss of feature discrimination. SNR-aware thresholding and probability calibration are treated as future validation strategies rather than validated deployment methods, since their benefits are not experimentally demonstrated here.

Table 6

Noise-Robustness Results

Condition	Accuracy	Sensitivity	Specificity	F1	ROC-AUC
Clean	94.44%	91.11%	97.78%	94.25%	98.62%
30 dB SNR	93.89 ± 0.56%	91.11%	96.67 ± 1.11%	93.72 ± 0.54%	98.64 ± 0.09%
20 dB SNR	93.83 ± 1.63%	95.67 ± 1.92%	92.00 ± 2.27%	93.95 ± 1.60%	98.26 ± 0.33%
15 dB SNR	74.50 ± 2.73%	99.89 ± 0.48%	49.11 ± 5.62%	79.70 ± 1.73%	97.45 ± 0.55%

Validation Against Conventional Classifiers

To validate the effectiveness of the proposed end-to-end 1D-CNN, its leakage-detection performance is compared with two conventional classifiers, namely Quadratic Support Vector Machine (SVM) and Cosine K-Nearest Neighbors (KNN), using the same vibration-signal scenario. This comparison is intended to determine whether the 1D-CNN can learn more discriminative leakage-related patterns directly from raw vibration signals.

The evaluation considered five performance metrics: accuracy, precision, specificity, F1-score, and Matthews correlation coefficient (MCC), as described in Table 7. These metrics provide complementary information on overall classification performance, correctness of leak predictions, ability to recognize non-leak conditions, balance between precision and recall, and overall agreement between predicted and actual classes.

Table 7

Performance metrics of End-to-end 1D-CNN, Quadratic SVM and Cosine KNN

Classifiers	Accuracy	Sensitivity	Specificity	F1	MCC
End-to-end 1D-CNN	94.44%	91.11%	97.78%	94.25%	0.891
Quadratic SVM	71.11%	71.06%	68.89%	72.17%	0.422
Cosine KNN	50.00%	50.00%	75.56%	32.84%	0.102

The difference can be explained by how the models process the vibration signal. Quadratic SVM and Cosine KNN receive the complete raw vibration window as a long numerical vector. They therefore compare signals mainly according to their position or similarity in this high-dimensional numerical space. Small changes in signal phase, the position of an impulsive event, vibration

amplitude, or background disturbance can make two physically similar leakage signals appear numerically different. These conventional classifiers do not automatically identify which short sections of the waveform contain the most useful leakage information. For a fair comparison, the SVM and KNN baselines receive the same standardized 512-sample raw windows, and their principal hyperparameters (SVM kernel scale/box constraint; KNN neighbors/distance) were selected by grid search under the same cross-validation protocol; the performance gap therefore reflects representation learning rather than unequal tuning. The interpretation that phase, temporal-position, and amplitude variation degrades SVM/KNN performance is consistent with their reliance on raw high-dimensional distances. Key limitations are stated explicitly: a synthetic and small dataset (600 windows), a single sensor, a single 4 mm leak, a single configuration, and a single fluid.

Discussion

The findings indicate that pipeline leakage can be distinguished using a fully end-to-end 1D-CNN operating directly on standardized raw Z-axis vibration signals under the evaluated simulated conditions. In the proposed framework, convolutional layers progressively learn local and higher-level temporal patterns from the input waveform, while global-average pooling summarizes the resulting feature maps. The learned representation is subsequently transformed by the sigmoid output layer into a leakage probability and a binary leak/non-leak decision. Thus, feature extraction and classification are integrated within a single model without requiring a separate downstream classifier. The reported performance is restricted to the five evaluated flow rates, the single 4 mm leak configuration, the fixed sensor position, and the physically informed simulated vibration dataset; validation using real pipeline measurements remains necessary before field-level reliability can be established.

This formulation is particularly appropriate for vibration-based condition monitoring because leakage information is generally embedded in the temporal structure of the signal rather than in a single statistical characteristic. A vibration window may contain periodic components generated by rotating machinery, flow-induced oscillations, broadband turbulence, and short-duration transient events. Leakage may alter several of these characteristics simultaneously. By applying shared convolutional filters across the signal, the 1D-CNN can identify relevant local patterns regardless of their precise temporal position and progressively combine them into a more discriminative representation of pipeline condition.

The proposed model achieved an accuracy of 94.44%, an F1-score of 94.25%, a sensitivity of 91.11%, a specificity of 97.78%, an MCC of 0.891, and a ROC-AUC of 0.986. These results demonstrate a strong ability to distinguish between leak and non-leak conditions. In particular, the high specificity indicates that normal operating conditions are rarely classified incorrectly as leakage, while the MCC and ROC-AUC confirm a strong overall correspondence between the predicted and actual classes. Nevertheless, the false-negative rate of 8.89% remains relevant from a safety perspective because it represents leakage events that may remain undetected. In practical applications, this limitation may be addressed by combining predictions from several consecutive signal windows rather than relying on a single observation. This should be interpreted as strong discrimination under the evaluated numerical conditions; it does not, on its own, establish field-level reliability given the small, synthetic dataset. The operational consequence of the 8.89% false-negative rate (four missed leaks) is that a single-window decision may miss intermittent leaks; temporal decision fusion and threshold optimization are therefore proposed as mitigations to be validated quantitatively.

The robustness analysis further shows that signal quality influences model performance. Under moderate noise conditions of 20–30 dB SNR, the classifier maintained relatively stable performance. At 15 dB SNR, sensitivity remained high while specificity decreased, although ROC-AUC remained 0.975. This behavior indicates that useful leakage-related discrimination is largely preserved under the evaluated severe-noise condition, while the fixed probability threshold produces substantially more false-positive classifications. Therefore, the fixed threshold of 0.5 should not be assumed to be optimal under all operating conditions. Signal-quality-aware threshold selection and probability calibration may be considered in future work, but their effectiveness requires separate validation before they can be recommended for practical

deployment.

The results across the five flow settings also highlight the importance of sufficient operating-condition diversity in the training data. The lowest classification performance was observed at 40 L/min, where stronger flow-induced vibration and turbulence may partially resemble leakage-related broadband activity. Broader training data that include additional high-flow normal conditions, smaller leak sizes, different leak locations, and multiple sensor positions would therefore be beneficial. Physically realistic data augmentation, including moderate amplitude variation, temporal shifting, sensor noise, and narrowband disturbances, may also improve the model's robustness and generalization. This interpretation is supported by the modeled signal characteristics: at higher flow rates, the broadband term in Eq. (3) grows relative to the leak-induced components in Eq. (4), reducing separability; a direct spectral/amplitude comparison across flow rates is recommended to confirm this relationship and relate it to the observed false-positive/false-negative behavior at 40 L/min. The effectiveness of each augmentation strategy is not demonstrated experimentally here and should be evaluated through controlled ablation on genuinely unseen conditions.

CONCLUSION

This study developed and evaluated a compact end-to-end 1D-CNN for binary leakage detection in low-density oil-flow pipelines using physically informed raw vibration signals. The model integrates three one-dimensional convolutional stages, global-average pooling, a fully connected layer, dropout, and a sigmoid output within a 6,265-parameter architecture, allowing feature learning and classification to be performed within a single framework. Using 600 generated vibration windows across five modeled flow settings, the network achieved 94.44% accuracy, a 94.25% F1-score, 91.11% sensitivity, 97.78% specificity, an MCC of 0.891, and a ROC-AUC of 0.986 on the independent test set. The model also showed relatively stable performance under moderate additive noise, while performance degradation at 15 dB SNR demonstrated the importance of signal quality and decision-threshold selection.

The principal methodological contribution of this study lies in combining direct raw-waveform representation learning with a leakage-safe, flow-stratified evaluation protocol, noise-robustness assessment, probability calibration analysis, and comparison with conventional classifiers. Nevertheless, the findings are limited to a physically informed simulated dataset, a single 4 mm leak configuration, one sensor position, one fluid, and the evaluated flow conditions. Therefore, the results should not yet be interpreted as evidence of field-level reliability. Future work should prioritize validation using real accelerometer measurements, evaluation on unseen flow rates, different leak sizes and locations, non-Gaussian vibration disturbances, multi-sensor configurations, and sequential decision and calibration strategies.

AUTHOR CONTRIBUTION STATEMENT

Bernadetta Kwintiana and Ravikumar Santhanam contributed to the preparation of the manuscript, including the development of the study, interpretation of the research findings, and preparation and revision of the manuscript. Both authors contributed to the intellectual content, participated in improving the manuscript, and approved the final version for publication.

ACKNOWLEDGEMENT

The authors would like to express their appreciation to all parties who provided academic and technical support during the preparation of this research and manuscript. The authors also acknowledge the institutional support associated with the completion of this study.

REFERENCES

- Choi, J., & Im, S. (2023). Application of CNN models to detect and classify leakages in water pipelines using magnitude spectra of vibration sound. *Applied Sciences*, 13(5), Article 2845. <https://doi.org/10.3390/app13052845>
- Choi, J., Shin, J., Song, C., Han, S., & Park, D. I. (2017). Leak detection and location of water pipes using vibration sensors and modified ML prefilter. *Sensors*, 17(9), Article 2104. <https://doi.org/10.3390/s17092104>

- Czerwiński, A., & Łuczko, J. (2022). Experimental and numerical study on vibrations of a helical pipe with fluid flow. *Journal of Sound and Vibration*, 535, 117116. <https://doi.org/10.1016/j.jsv.2022.117116>
- El-Zahab, S., Abdelkader, E. M., & Zayed, T. (2018). An accelerometer-based leak detection system. *Mechanical Systems and Signal Processing*, 108, 276–291. <https://doi.org/10.1016/j.ymssp.2018.02.030>
- Fabbiano, L., Vacca, G., & Dinardo, G. (2020). Smart water grid: A smart methodology to detect leaks in water distribution networks. *Measurement*, 151, 107260. <https://doi.org/10.1016/j.measurement.2019.107260>
- Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q. (2017). On calibration of modern neural networks. Dalam *Proceedings of the 34th International Conference on Machine Learning* (Vol. 70, hlm. 1321–1330). PMLR.
- Ismail, M. I. M., Dziyauddin, R. A., Salleh, N. A. A., Muhammad-Sukki, F., Bani, N. A., Izhar, M. A. M., & Latiff, L. A. (2019). A review of vibration detection methods using accelerometer sensors for water pipeline leakage. *IEEE Access*, 7, 51965–51981. <https://doi.org/10.1109/ACCESS.2019.2896302>
- Ismail, M. I. M., Dziyauddin, R. A., Salleh, N. A. M., Ahmad, R., Azmi, M. H., & Kaidi, H. M. (2018). Analysis and procedures for water pipeline leakage using three-axis accelerometer sensors: ADXL335 and MMA7361. *IEEE Access*, 6, 71249–71261. <https://doi.org/10.1109/ACCESS.2018.2878862>
- Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, 3(6), 422–440. <https://doi.org/10.1038/s42254-021-00314-5>
- Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.
- Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., & Inman, D. J. (2021). 1D convolutional neural networks and applications: A survey. *Mechanical Systems and Signal Processing*, 151, 107398. <https://doi.org/10.1016/j.ymssp.2020.107398>
- Korlapati, N. V. S., Khan, F., Noor, Q., Mirza, S., & Vaddiraju, S. (2022). Review and analysis of pipeline leak detection methods. *Journal of Pipeline Science and Engineering*, 2(4), Article 100074. <https://doi.org/10.1016/j.jpse.2022.100074>
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>
- Li, Q., Shi, Y., Lin, R., Qiao, W., & Ba, W. (2022). A novel oil pipeline leakage detection method based on the sparrow search algorithm and CNN. *Measurement*, 204, 112122. <https://doi.org/10.1016/j.measurement.2022.112122>
- Lu, H., Iseley, T., Behbahani, S., & Fu, L. (2020). Leakage detection techniques for oil and gas pipelines: State-of-the-art. *Tunnelling and Underground Space Technology*, 98, 103249. <https://doi.org/10.1016/j.tust.2019.103249>
- Medeiros, K. A. R., de Oliveira, F. L. A., Barbosa, C. R. H., & de Oliveira, E. C. (2016). Optimization of flow rate measurement using piezoelectric accelerometers: Application in water industry. *Measurement*, 91, 576–581. <https://doi.org/10.1016/j.measurement.2016.05.101>
- Okosun, F., Cahill, P., Hazra, B., & Pakrashi, V. (2019). Vibration-based leak detection and monitoring of water pipes using output-only piezoelectric sensors. *The European Physical Journal Special Topics*, 228(7), 1659–1675. <https://doi.org/10.1140/epjst/e2019-800150-6>
- Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Aroita, G., Hauenstein, S., Lahoz-Monfort, J. J., Schröder, B., Thuiller, W., Warton, D. I., Wintle, B. A., Hartig, F., & Dormann, C. F. (2017). Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography*, 40(8), 913–929. <https://doi.org/10.1111/ecog.02881>
- Saleem, F., Ahmad, Z., Siddique, M. F., Umar, M., & Kim, J.-M. (2025). Acoustic emission-based pipeline leak detection and size identification using a customized one-dimensional DenseNet. *Sensors*, 25(4), 1112. <https://doi.org/10.3390/s25041112>
- Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning*

- Research*, 15(1), 1929–1958.
- Wang, W., & Gao, Y. (2023). Pipeline leak detection method based on acoustic-pressure information fusion. *Measurement*, 212, Article 112691. <https://doi.org/10.1016/j.measurement.2023.112691>
- Xu, W., Huang, J., Sun, L., Yao, Y., Zhu, F., Xie, Y., & Zhang, M. (2024). An improved convolutional neural network for pipe leakage identification based on acoustic emission. *Journal of Marine Science and Engineering*, 12(10), 1720. <https://doi.org/10.3390/jmse12101720>
- Yang, D., Hou, N., Lu, J., & Ji, D. (2022). Novel leakage detection by ensemble 1DCNN-VAPSO-SVM in oil and gas pipeline systems. *Applied Soft Computing*, 115, 108212. <https://doi.org/10.1016/j.asoc.2021.108212>
- Yang, D., Wang, P., Lu, J., Guan, C., & Dong, H. (2025). Leakage detection of oil and gas pipelines based on a multi-channel and multi-branch one-dimensional convolutional neural network with imbalanced samples. *Computers in Industry*, 173, 104356. <https://doi.org/10.1016/j.compind.2025.104356>
- Yu, T., Chen, X., Yan, W., Xu, Z., & Ye, M. (2023). Leak detection in water distribution systems by classifying vibration signals. *Mechanical Systems and Signal Processing*, 185, 109810. <https://doi.org/10.1016/j.ymssp.2022.109810>
- Zhang, C., Liu, S., Zhao, W., Dong, L., Zhang, Y., Wang, C., Qu, S., Yao, C., Lv, J., Li, S., Zhao, Q., Shang, Y., Liu, G., & Ni, J. (2024). Study on vibration signals identification method for pipeline leakage detection based on deep learning technology. *Optics Communications*, 565, 130588. <https://doi.org/10.1016/j.optcom.2024.130588>