Stockwell Transform and CNN-Based Pipeline Leak Detection Using Sobel-Filtered Acoustic Emission Signals

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Abstract. Pipeline leak detection is vital for preventing failures, reducing environmental risks, and minimizing downtime in the energy and utility sectors. This study proposes a deep learning-based method for detecting pipeline leaks using acoustic emission (AE) signals. AE data from leak and non-leak conditions were pre-processed with a low-pass filter to extract fault-specific frequencies, followed by transformation into time-frequency scalograms using the Stockwell transform. Sobel edge filtering was applied to enhance key signal features, essential for distinguishing between leak and non-leak conditions. A Convolutional Neural Network (CNN) was used to automatically extract features from the Sobel-filtered scalograms, achieving highly accurate classification. The proposed method demonstrated better performance across key performance metrics, outperforming existing techniques. Comparative analysis with other methods confirmed the effectiveness of this approach in handling complex signal patterns and noise. This method offers a reliable framework that enhances operational safety and can be adapted to various pipeline systems, providing a scalable solution for real-time leak detection.

Keywords: Pipeline Leak Detection, Acoustic Emission, Stockwell Transform, Sobel Edge Filtering, Convolutional Neural Networks.

1 Introduction

Pipelines are essential for the distribution of liquid and gas resources across various industries; however, they are highly susceptible to environmental and operational impacts that can lead to leaks. These leaks, particularly in their early stages, are difficult to detect when the leak flow is less than 1.2% of the normal flow. At this stage, physical indicators such as pressure and flow rate often fail to exhibit noticeable changes, making traditional detection methods ineffective [1]. However, acoustic signals, which are highly sensitive even in cases of small leaks, have become a reliable method for detecting early-stage leaks across various pipeline systems, including gas, oil, high-pressure, and buried pipelines [2]. In recent years, a variety of methods have been proposed for pipeline condition monitoring, ranging from reflectometry in the time domain to vibration-based and pressure wave techniques, along with AE technology [3], [4]. Among these, AE technology has gained significant attention due to its real-time response and sensitivity to small leaks. AE technology is particularly advantageous because acoustic signals remain highly sensitive even when traditional parameters like pressure and flow rate show no significant changes [5]. As a result, AE has become a reliable method for early-stage leak detection in pipelines, making it applicable across various industries [6].

AE technology has been widely used in condition monitoring for pipelines. For example, researchers used AE to detect crack initiation in pipelines while combining AE waveform features with machine learning techniques such as support vector machines (SVMs) and relevance vector machines for leak detection [7]. Feature exploration techniques, which include methods such as fast Fourier transform (FFT), short-time Fourier transform (STFT), and wavelet transform (WT), are often utilized to analyze the acoustic signals generated by leaks [8]. WT is effective for analyzing non-stationary signals like those produced by pipelines, enabling noise reduction and feature extraction in both time and frequency domains. However, these traditional methods come with inherent challenges. They require careful balancing between the accuracy of feature extraction and the precision of classification, often making them time-consuming and complex for real-time applications [9]. For instance, researchers developed a pipeline leak indicator using AE waveform features and a two-sample Kolmogorov–Smirnov test, highlighting the labor-intensive nature of such feature extraction processes. Despite their utility, these methods may not always provide the necessary speed and accuracy required for modern pipeline monitoring systems [10].

To address the limitations of traditional techniques, researchers have turned towards artificial intelligence and deep learning as more effective tools for leak detection. AI enhances the process of automation, providing fast, precise, and efficient solutions for monitoring complex systems such as pipelines. Deep learning methods, particularly convolutional neural networks, have shown a powerful alternative to traditional feature extraction techniques [11]. Unlike conventional approaches that require manual feature selection, CNNs can learn directly from raw data, making them highly effective for handling large and complex datasets like those generated by acoustic signals [12]. CNNs offer significant advantages in terms of processing speed and accuracy. By eliminating the need for extensive preprocessing and manual feature extraction, they reduce the time and complexity involved in leak detection while improving the precision of the results. This ability makes CNNs highly suitable for real-time leak detection applications, where traditional methods may fall short due to the intricacies of acoustic signal analysis and the noisy environments in which pipelines operate [13].

This paper introduces a new framework for pipeline leak detection that combines the S-transform and CNNs. AE signals are first filtered to remove noise and then transformed into time-frequency scalograms using the S-transform, which provides frequency-dependent resolution. A Sobel edge filter is applied to these scalograms to enhance important features, highlighting changes in signal intensity that indicate leaks. The enhanced scalograms are then fed into a CNN, which automatically extracts features and classifies leak and non-leak conditions. This method improves accuracy by eliminating manual feature selection and reducing the complexity of traditional techniques. Overall, the framework offers a more effective and reliable solution for detecting pipeline leaks, with strong performance across key metrics.

1. The study proposes a hybrid method combining Stockwell Transform scalograms and Sobel edge detection for enhanced feature extraction from acoustic emission signals.
2. Application of a CNN-based classification model for detecting pipeline leaks, achieving superior performance in distinguishing between leak and non-leak conditions.
3. The proposed methods were evaluated using real-world AE data from pipeline leak and non-leak conditions.

The study is further divided into proposed methodology in section 2, followed by section 3 which covers the technical background. Section 4 explains the experimental setup, section 5 is about performance evaluation and comparison, and finally, section 6 is about the conclusions and future work.

2 Proposed Methodology

AE signals are collected from the pipeline system under different conditions. The conditions can include both leak and non-leak scenarios. A data acquisition system is used to record the vibration signals at high sampling rates. To isolate important fault-specific information, the AE signals are passed through a low-pass filter. This filtering process helps to eliminate high-frequency noise and retain key frequency components that are relevant to leak detection. The filtered signals represent useful characteristics related to pipeline faults, such as those arising from leakages or normal operational conditions. After filtering, the signals are transformed into a time-frequency domain representation. In this step, the S-transform is used to generate scalograms which are particularly useful for analyzing non-stationary signals. The resulting scalograms represent the localized frequency content over time, providing a rich visual representation of the pipeline conditions. To further enhance the extracted features, Sobel edge detection is applied to the scalograms. This step generates Sobel Edge Scalograms, where the edges corresponding to sharp transitions in frequency content are highlighted. These edges are helpful as they may correspond to faults or leaks in the pipeline. The edges detected by Sobel filtering highlight discontinuities, potentially indicating faults or leaks in the pipeline. This preprocessing step enhances the ability of a CNN classifier to detect leakage patterns by focusing on filtered Sobel Edge Scalograms. CNN consists of multiple convolutional layers followed by fully connected layers, enabling it to distinguish between Leak and Non-Leak classes by learning hierarchical features from the scalograms. The network is trained with the Adam optimizer and Cross-Entropy loss to minimize classification errors, using a split dataset for training and validation to assess performance and prevent overfitting. Once trained, this CNN classifier enables real-time leak detection in pipeline operations. The trained model achieves high accuracy in distinguishing between normal pipeline conditions and those associated with leaks. The overall flowchart of the proposed method is depicted in Fig. 1.

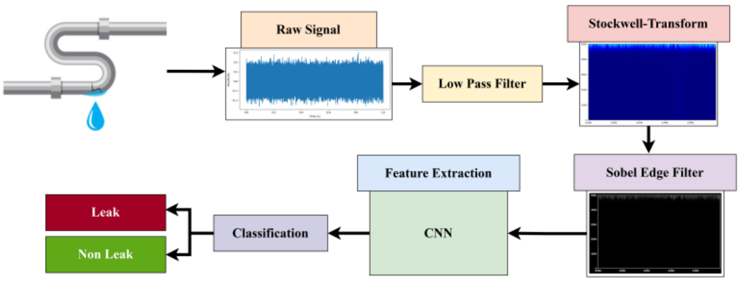


Fig. 1. Flow diagram of the proposed method.

A detailed description of the proposed method is given below:

Step 1: Acquire vibration signals from pipelines using a data acquisition system.

Step 2: Apply a low-pass filter to extract fault-specific frequencies.

Step 3: Generate scalograms using Stockwell-transform.

Step 4: Use the Sobel filter to enhance scalograms, producing Sobel Edge Scalograms.

Step 5: Train a CNN classifier to classify filtered scalograms into Leak and Non-Leak.

Step 6: Classify real-time pipeline vibration signals using the trained CNN model.

3 Technical Background

3.1 Acoustic Emission

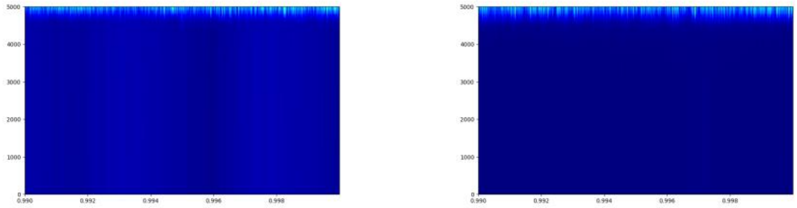
AE signals are widely used in fault detection for mechanical systems, including pipeline leak detection. AE signals, generated from the rapid release of localized stress waves during pipeline operations, contain valuable information about the structural integrity of the pipeline. These signals are often non-stationary, meaning their frequency content changes over time due to varying operational conditions or the development of faults, such as leaks. Accurately analyzing AE signals requires advanced signal processing techniques capable of capturing these temporal and frequency variations.

3.2 Stockwell Transform for Time-Frequency Representation

S-transform is a powerful time-frequency analysis tool that provides a localized view of a signal's frequency content over time. It extends the Short-Time Fourier Transform by using a scalable Gaussian window that varies with frequency, improving time-frequency resolution. The S-transform is defined according to equation 1.

$$S\{x(t)\} = X(t,f) = \int_{\infty}^{\infty} x(\tau)\frac{1}{\sqrt{2\pi}} e^{\frac{t-\tau^2}{2f^2}} e^{-2\pi f \mathrm{T}} d\tau \quad (1)$$

where, $X(t, f)$ represents the time-frequency representation of the signal $x(t)$. The Gaussian window $\frac{1}{\sqrt{2\pi}} e^{\frac{t-\tau^2}{2f^2}}$ adjusts its width with frequency, providing better resolution for low and high frequencies. In the context of pipeline leak detection, the S-transform converts AE signals into 2D time-frequency scalograms as shown in Fig. 2, where leak conditions are reflected as distinct patterns in the frequency domain, allowing for more effective analysis.



(a) **(b)**

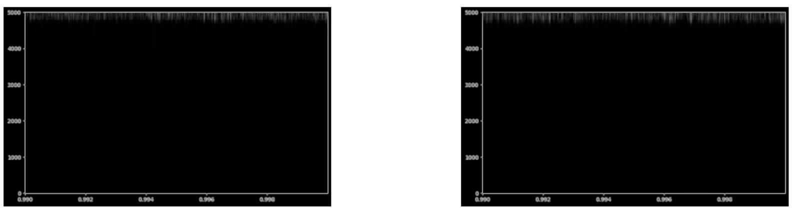
Fig. 2. AE S-transform scalograms: **(a)** non-leak condition; **(b)** leak condition.

3.3 Sobel Edge Detection for Feature Enhancement

The Sobel operator is a first-order edge detection technique used to highlight changes in intensity within an image, which corresponds to identifying edges in a 2D time-frequency scalogram. By applying the Sobel filter to the scalograms generated from AE signals, we can emphasize the significant transitions in frequency and amplitude, which are indicative of leaks. The Sobel operator computes two gradients: one in the horizontal direction and one in the vertical direction using the following 3×3 convolution kernels as given in matrix equation 2.

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \; G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{2}$$

The result of applying these kernels to the scalograms is an enhanced feature map where important leak-related patterns are more distinct as illustrated in Fig. 3, facilitating more accurate classification by the subsequent machine learning model.



(a) **(b)**

Fig. 3. Sobel-filtered scalograms for feature enhancement: **(a)** non-leak; **(b)** leak.

3.4 Convolutional Neural Network for Feature Extraction

CNNs are a deep learning model particularly well-suited for extracting local features from images. In the case of pipeline leak detection, CNNs are used to extract important patterns from the Sobel-enhanced scalograms. They consist of multiple layers, including convolutional layers, activation functions, pooling layers, and fully connected layers. Each layer captures progressively more complex features from the input image. The convolutional layer performs as from equation 3.

$$h_{i,j,k} = \sigma\left(\sum_{m,n} x_{i+m,j+n} . w_{m,n,k} + b_k\right) \tag{3}$$

Where: $x_{i,j}$ is the input at the pixel (i, j). $w_{m,n,k}$ is the weight of the kernel, b_k is the bias term, and σ is the activation function ReLU. This structure enables CNN to detect localized changes in the scalograms, such as sharp transitions in frequency due to a pipeline leak and use them for classification. The combined local and global features from the Sobel-filtered scalograms are fed into the fully connected layers of the CNN for final classification. CNN outputs a probability distribution over the two classes (leak and non-leak) using the softmax function as in equation 4.

$$y = softmax(W^{(L)} h^{(L-1)} + b^{(L)} \tag{4}$$

Where y is the output vector of probabilities, $h^{(L-1)}$ is the feature representation from the final hidden layer, and $W^{(L)}$ and $b^{(L)}$ are the weights and bias of the last layer. This classification process allows CNN to predict the pipeline's condition based on the learned features, providing an accurate and reliable leak detection mechanism.

4 Experimental Setup

The experimental setup as depicted in Fig. 4 was designed to simulate and analyze pipeline leaks using AE signals. A stainless-steel pipeline with a 6 mm thickness and an outer diameter of 114 mm was equipped with AER15I-AST sensors from Mistras Group, Inc. (New Jersey, USA), to detect AE signals. A National Instruments data acquisition system (model NI-9223) was used to capture signals at a sampling rate of 1 MHz Leaks were simulated by drilling holes of various sizes into the pipeline and controlling fluid flow through a welded valve at each leak site. Water was used as the test fluid for its safety and environmental benefits. To create varying leak conditions, holes of 0.5 mm, 0.7 mm, and 1 mm were drilled into the pipeline. The AE signals were recorded under different pressures i.e. 13 bars, 18 bars, and 7 bars. Data was collected for each scenario with an intact and leaking pipeline. 240 samples were recorded for each leak size and pressure condition: 120 from normal operation and 120 from leakage. The results, presented through AE signal plots, demonstrated distinct patterns for both normal operation and leak events. All leaking fluid was safely collected in a container for proper disposal. This setup allowed for a comprehensive analysis of AE signal variations associated with pipeline leaks.

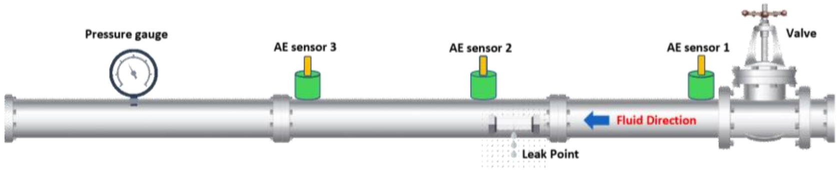


Fig. 4. Pipeline architecture for the experiment.

5 Performance Evaluation and Comparison

This study introduces a novel approach for pipeline leak detection using vibration signals combined with advanced deep learning techniques. AE data is collected from a pipeline under different conditions, including both leak and non-leak conditions, with 120 samples for normal conditions and 240 for leak conditions. The collected data is processed through a series of signal processing, including low-pass filtering, scalogram generation, and Sobel edge filtering. The Sobel filtering emphasizes key frequency patterns, enhancing the clarity of the features and reducing noise. A CNN is then employed to extract relevant features from these Sobel Edge Scalograms for binary classification, detecting whether the pipeline is in a leak or non-leak state. To evaluate the effectiveness of the proposed method, several performance metrics are used, including accuracy, precision, recall, and F1-score as in Equations 5, 6, 7, and 8. These metrics help assess the model's ability to correctly classify pipeline conditions. The mathematical definitions of these metrics are given below.

$$Accuracy = \frac{(TN+TP)}{(TP+TN+FP+FN)} \times 100\% \tag{5}$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \tag{6}$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \tag{7}$$

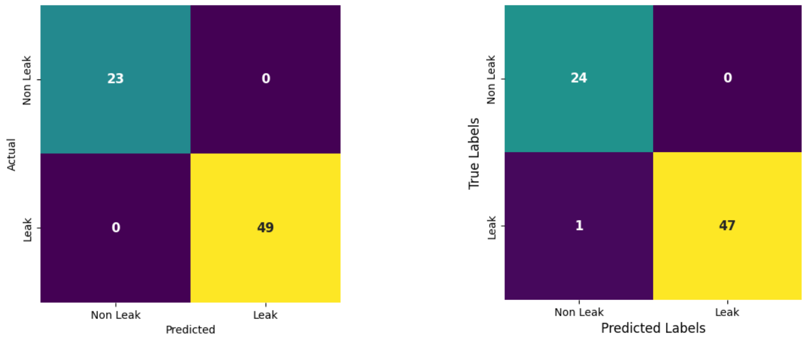
$$F1-Score = \frac{2TP}{2TP+FP+FN} = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \tag{8}$$

The proposed pipeline leak detection method achieves exceptional results across all evaluation metrics, with an accuracy of 99.5% precision of 99.5%, recall of 99.5%, and F1-score of 99.5%. Table 1 presents a comparison between the proposed method and a reference model, demonstrating that our method outperforms the alternative approaches in terms of classification performance.

Table 1. Performance comparison.

Models	Accuracy	Precision	Recall	F-1 Score
Proposed Model	99.5	99.5	99.5	99.5
Lijiang et al. [14]	96	96	96	96

The high performance of the proposed method can be attributed to the combination of S-transform scalograms and Sobel edge filtering for feature extraction, along with the use of a CNN classifier for accurate classification. CNN is particularly effective in capturing these patterns, as it learns both local and hierarchical features directly from the Sobel Edge Scalograms. By doing so, the model can distinguish between leak and non-leak conditions with high precision. Moreover, the use of low-pass filtering at the preprocessing stage helps to remove high-frequency noise and retain critical information related to faults, which further enhances the classifier's performance. In addition to standard performance metrics, confusion matrices from Fig. 5 were used to analyze the classification results and feature distinguishability. Fig. 5 (a) shows the confusion matrix for the proposed model, where the classifier correctly predicts almost all instances of both leak and non-leak conditions. Fig. 5 (b) represents the confusion matrix for reference to Lijiang et al. [14] model shows that the reference model has lower classification accuracy and misclassifies instances. The study used a CWT-based acoustic image transformation technique. It focused on non-metallic pipelines, specifically PVC pipelines. The experimental setup was conducted in a controlled laboratory environment. Leak conditions were simulated in PVC pipelines with different leak sizes. The pipeline material significantly impacts acoustic signal propagation, and while their method achieved 96% accuracy, precision, recall, and F1 score, it is specialized for non-metallic PVC pipelines.



(a) **(b)**

Fig. 5. Confusion matrices: **(a)** proposed model; **(b)** CWT-CNN.

The results indicate that the proposed method's ability to accurately detect leaks can be largely credited to its effective use of time-frequency signal processing techniques and deep learning-based feature extraction. The CWT provides rich time-frequency information, while Sobel edge filtering enhances these features by reducing noise and emphasizing key signal transitions. CNN extracts both localized and global features within the scalograms, making it a highly effective tool for leak detection in complex pipeline systems. The proposed approach also demonstrates resilience to noisy data, as it achieves a high degree of accuracy and robustness across different operational conditions. Overall, the combination of these techniques results in a robust, efficient, and accurate solution for pipeline leak detection, with significant potential for real-time deployment in industrial settings.

6 Conclusion

In conclusion, this study proposes a novel approach for pipeline leak detection by combining signal analysis with advanced deep learning techniques. AE data collected under leak and non-leak conditions were preprocessed through low-pass filtering and transformed into time-frequency scalograms using the S-transform. The application of Sobel edge filtering further enhanced useful signal features, facilitating clearer and more accurate analysis. A Convolutional Neural Network was utilized for feature extraction and classification, demonstrating high performance in accurately distinguishing between leak and non-leak conditions. The proposed method achieved robust results across key metrics, including accuracy, precision, recall, and F1-score, underscoring its effectiveness for pipeline condition monitoring. Future research could explore extending the method to multi-class classification tasks, identifying localization and size identification.

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