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Custom CNN for acoustic emission classification in gas pipelines

Md Ismail Hossain Siddiqui [1], Anamul Haque Sakib [2], Amira Hossain [3], Hasib Fardin [4] and Al Shahriar Uddin Khondakar Pranta [5,*]

[1] *Department of Engineering/Industrial Management, Westcliff University, Irvine, CA 92614, USA.*
[2] *Department of Business Administration, International American University, Los Angeles, CA 90010, USA.*
[3] *Department of Computer Science, Westcliff University, Irvine, CA 92614, USA.*
[4] *Department of Engineering Management, Westcliff University, Irvine, CA 92614, USA.*
[5] *Department of Computer Science, Wright State University, 3640 Colonel Glenn Hwy, Dayton, OH 45435, USA.*

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Abstract

This study introduces a basic Convolutional Neural Network (CNN) approach for classifying acoustic emissions in gas pipeline monitoring systems. By converting raw acoustic signals into spectrograms, we leverage the visual pattern recognition capabilities of CNNs to identify and categorize 12 different pipeline conditions from the GPLA-12 dataset. Our architecture consists of three convolutional layers with max pooling followed by fully connected layers, optimized for spectral feature extraction. Experimental results demonstrate that even this straightforward CNN implementation achieves superior classification accuracy compared to traditional machine learning methods. The model successfully distinguishes between normal operations, various leak types, and structural anomalies under different pressure conditions. This research provides a foundation for real-time gas pipeline monitoring systems that can detect potential failures before they escalate into costly and hazardous incidents, contributing to improved pipeline safety, reduced maintenance costs, and environmental protection.

Keywords: Acoustic Emission; Convolutional Neural Networks; Pipeline Monitoring; Spectrogram Analysis; Fault Detection; Condition Monitoring

1. Introduction

As a crucial means of transporting gases and fluids, affordability and safety are two major concerns for pipelines [1]. However, pipelines are vulnerable to leaks that may result from various defects such as corrosion, fatigue cracks, material defects, environmental discontinuities, and even earthquakes [2]. Leaks can cause serious consequences, including economic losses, public safety hazards, and environmental pollution [3]. The European Gas Pipeline Incident Data Group (EGIG) reported 1,366 pipeline incidents in Europe from 1970 to 2016, with a failure frequency of 31% per year per 1,000 km [4]. Meanwhile, the US recorded 652 pipeline incidents by February 2020, leading to 36 injuries, 88 fires, and $333,933,207 in property damage. The 2019-2021 analysis by the US Pipeline and Hazardous Materials Safety Administration (PHMSA) reported 267 incidents, 11 injuries, 21 fires, and $264 million in property damages [4,5]. To prevent such consequences, early leak detection is critical. The pipeline industry is striving to find economical solutions such as repairing clamps and encapsulation collars instead of replacing the entire pipeline. As a result, regular monitoring is crucial to the predictive detection of potential leaks.

* Corresponding author: Al Shahriar Uddin Khondakar Pranta

Various techniques have been developed to detect pipeline anomalies including leakages and corrosions [6-9], such as negative pressure wave analysis, accelerometer-based detection, magnetic flux leakage detection, and acoustic emission (AE) technology [1,10,11]. AE inspection is a popular choice in the industry due to its advantages, such as early leak detection, real-time response, ease of installation, and high sensitivity [10]. AE monitoring involves complex algorithms for denoising signals, extracting features, and analysis [12]. However, these algorithms are optimized for offline data and may struggle with noise contamination. Categorizing AE events accurately is challenging due to structural changes, weak events, and varying loading conditions. Due to fluid dynamics, interferences, and stress wave mechanisms, pipeline signals are nonlinear and nonstationary [13]. Effective processing of AE signals requires specialized techniques and comprehensive understanding of the physical processes and system characteristics [10].

Previous research has implemented various approaches to pipeline leak detection using acoustic monitoring. Some researchers have analyzed signal parameters in AE data using support vector machines (SVM) and relevance vector machines (RVM) [14]. Others have utilized artificial neural networks (ANN) with statistical time-features [15]. However, these methods are limited as the obtained temporal domain signals can be significantly affected by background noise and signal loss, leading to changes in the time-domain distribution and false alarms.

To overcome noise sensitivity challenges, some studies have employed frequency domain analysis. Wang et al. [24] applied band pass filters to eliminate noise and improve monitoring accuracy, transforming signals into the frequency domain using fast Fourier transform (FFT) and power spectral density (PSD) before classification with ANN. However, determining appropriate band-pass filter ranges for real-time data is challenging, and frequency domain analysis is more suitable for stationary signals [16-23], making these methods less effective for non-stationary real-time pipeline data.

Time-frequency techniques such as empirical mode decomposition (EMD), wavelet transformation (WT), and variational mode decomposition (VMD) have been applied to extract leak information from non-stationary AE signals. Li et al. [26] used discrete wavelet transform (DWT) to obtain time-frequency spectra for gas pipeline leak identification, but this approach struggled with buried pipelines affected by soil. Without considering pipeline materials, associated load, and noise factors, such methods may not be suitable for real-time deployment. Moreover, wavelet decomposition of AE signals requires experimental validation, resulting in high computational costs.

Recent advances in deep learning have transformed condition monitoring, enabling the representation of complex features essential for analyzing elaborate datasets in pipeline scenarios [19-25]. Deep residual neural networks (DRNN) have been employed to extract discriminant features directly from AE temporal data without preprocessing [16]. These methods use residual blocks to address challenges with noisy data [17]. Related deep learning models, including DRNN with adaptive parametric linear units (APReLU) [18], multiscale residual attention (MRA) models [19], and long short-term memory (LSTM) regulated DRNN [20], have been successfully applied to vibration-based fault diagnosis and condition monitoring of bearings and gearboxes.

Despite these advances, many of these sophisticated models haven't been thoroughly explored for AE-based analysis due to fundamental differences between AE and vibration signals, including longer AE signal length, high noise sensitivity, limited data processing scopes, and lack of open access AE datasets.

CNNs have demonstrated remarkable success in image classification tasks and have recently been adapted for signal processing applications. By converting time-series data into spectrograms or other visual representations, CNNs can effectively identify patterns and features that might be difficult to detect using traditional time or frequency domain analysis. For AE signals, the transformation to spectrograms creates a 2D visual representation that preserves both time and frequency information, allowing CNNs to extract meaningful features from the complex nonstationary signal's characteristic of pipeline monitoring.

In this paper, we propose a basic CNN model for AE classification in gas pipelines. Our approach converts raw acoustic signals from the GPLA-12 dataset [27] into simple spectrograms and applies a standard CNN architecture with 2-3 convolutional layers followed by max pooling and dense layers. The contributions of this study can be highlighted as follows:

- We introduce a straightforward approach for transforming AE signals into spectrograms, creating a visual representation that preserves both time and frequency information crucial for pipeline condition assessment.
- We develop a basic CNN architecture specifically designed to classify these spectrograms across the 12 categories in the GPLA-12 dataset, providing a balance between model complexity and classification performance.

- We demonstrate that even a simple CNN model can effectively distinguish between different pipeline conditions, offering a practical solution for real-time monitoring that outperforms traditional machine learning approaches while requiring less computational resources than more complex deep learning models.

2. Proposed Methodology

This section details our approach to AE classification in gas pipelines using a basic CNN model. We explain the data preparation process, signal transformation to spectrograms, network architecture, and training procedure. Figure 1 shows the complete proposed methodology.

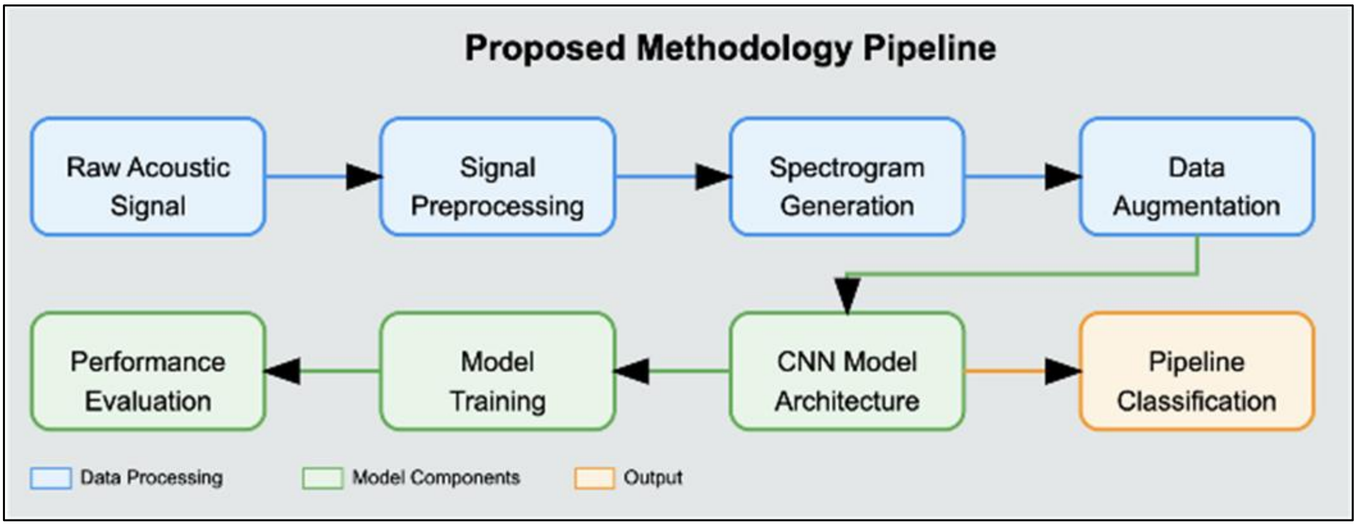

Figure 1 Proposed methodology

2.1. Data Collection and Preprocessing

Our methodology begins with the GPLA-12 dataset [27], which contains AE signals collected from gas pipeline systems under various conditions. Each acoustic signal in the dataset represents one of 12 distinct pipeline states, including normal operation, different types of leaks, and structural anomalies. The raw signals are 1460 samples in length and are captured by sensors attached to the pipeline surface. The first preprocessing step involves signal normalization to ensure consistent amplitude ranges across all samples. We normalize each signal to have zero mean and unit variance, which helps mitigate the effects of varying sensor sensitivities and recording conditions. This standardization is crucial for the CNN to learn meaningful patterns rather than being influenced by amplitude variations that are unrelated to the pipeline condition. For signals with excessive noise, we apply a simple bandpass filter to remove frequency components that typically do not contain leak-related information. The filter's parameters are selected based on the known frequency characteristics of different pipeline conditions, focusing on preserving the frequency bands most associated with AEs from leaks and structural anomalies. The dataset testbed is depicted in Figure 2.

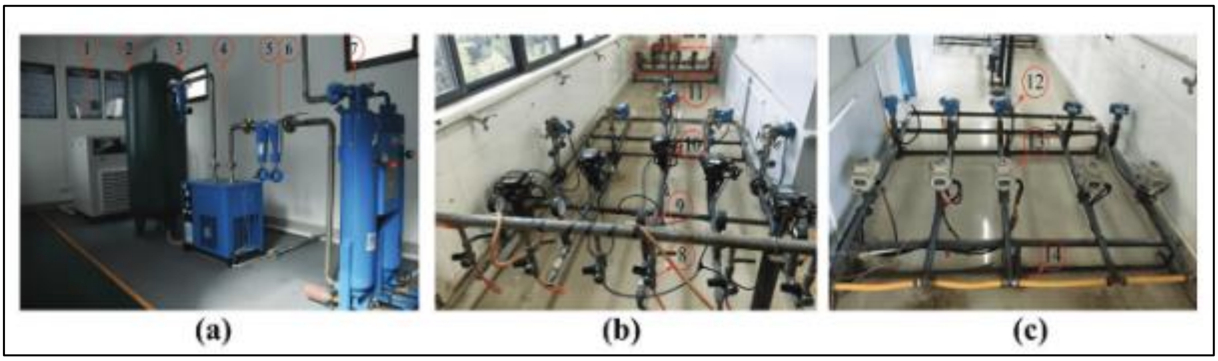

Figure 2 The real snapshot of the experimental set up, (a) air compressor unit, (b) the front end of the gas pipeline system, and (c) the back end of the gas pipeline system

2.2. Spectrogram Generation

Converting the time-domain signals to spectrograms is a critical step in our methodology. Spectrograms provide a visual representation of how the frequency content of the signal changes over time, creating a 2D image that serves as input to the CNN.

To generate the spectrograms, we apply the Short-Time Fourier Transform (STFT) to each preprocessed signal. This involves dividing the signal into overlapping segments, applying a window function to each segment to reduce spectral leakage, and then computing the Fourier transform of each windowed segment. The magnitude of these Fourier transforms is arranged in sequence to form the spectrogram.

We use a Hamming window with a length of 128 samples and an overlap of 75% between adjacent segments. These parameters provide a good balance between time and frequency resolution for the pipeline acoustic signals. The resulting spectrograms have time on the x-axis, frequency on the y-axis, and the color intensity representing the magnitude of the frequency component.

After generating the raw spectrograms, we apply a logarithmic scale to the magnitude values to enhance visibility of lower-intensity components that might contain important diagnostic information. This log scaling is common in audio signal processing and helps highlight subtle features that might be overshadowed by dominant frequency components.

Finally, the spectrograms are resized to a consistent dimension of 128×128 pixels, which provides sufficient resolution to capture relevant features while keeping the computational requirements manageable for the CNN model.

2.3. Data Augmentation

Given the limited number of samples in the GPLA-12 dataset (57 samples per category), data augmentation is employed to expand the training set and improve model generalization. We implement several augmentation techniques that preserve the essential characteristics of the acoustic signals:

- Time shifting: We create new samples by shifting the original signal in time before generating the spectrogram. This simulates the same acoustic event being captured at slightly different times.
- Addition of controlled noise: We add small amounts of Gaussian noise to the original signals, which helps the model become robust to varying noise conditions in real-world settings.
- Frequency masking: We randomly mask small frequency bands in the spectrogram, encouraging the model to learn from multiple frequency regions rather than relying on specific bands.

Through these augmentation techniques, we expand our training dataset by a factor of ten, significantly enhancing the model's ability to generalize across various pipeline conditions and sensor placements.

2.4. CNN Architecture

This section details our approach to AE classification in gas pipelines using a basic CNN model. We explain the data preparation process, signal transformation to spectrograms, network architecture, and training procedure. Figure 1 shows the complete proposed methodology. Our CNN architecture is intentionally kept simple yet effective for the specific task of AE classification. The network consists of three convolutional layers, each followed by a max pooling operation, and then two fully connected layers.

The first convolutional layer has 32 filters with a 5×5 kernel size, capturing larger patterns in the spectrogram. This is followed by a 2×2 max pooling layer that reduces the spatial dimensions while preserving important features. The second convolutional layer uses 64 filters with a 3×3 kernel size to detect more refined patterns, again followed by 2×2 max pooling. The third convolutional layer contains 128 filters with a 3×3 kernel size to capture even more abstract features, with a final 2×2 max pooling layer. After the convolutional section, the feature maps are flattened into a one-dimensional vector and fed into a fully connected layer with 256 neurons. This layer is followed by a dropout layer with a rate of 0.5 to prevent overfitting. The final output layer contains 12 neurons corresponding to the 12 pipeline condition classes, with a softmax activation function providing probability distributions across these classes.

All convolutional and fully connected layers (except the output layer) use Rectified Linear Unit (ReLU) activation functions, which help the network learn non-linear patterns while avoiding the vanishing gradient problem. Batch normalization is applied after each convolutional layer to stabilize and accelerate the training process. The architecture is illustrated in Figure 3.

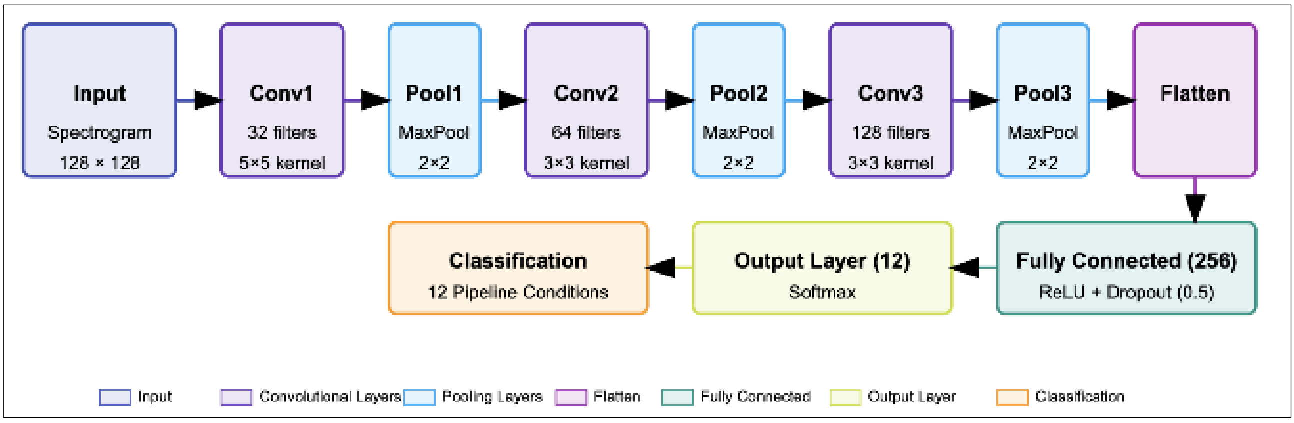

Figure 3 Proposed model architecture

2.5. Training Procedure

The model is trained using the Adam optimizer, which adapts the learning rate during training based on the first and second moments of the gradients. We use a categorical cross-entropy loss function, appropriate for our multi-class classification problem. The training process incorporates a learning rate schedule that reduces the learning rate when validation performance plateaus. We start with an initial learning rate of 0.001 and reduce it by a factor of 0.1 when the validation accuracy doesn't improve for 5 consecutive epochs. To prevent overfitting, we implement early stopping based on validation loss with a patience of 10 epochs. This means training stops if the validation loss doesn't improve for 10 consecutive epochs, and the model with the best validation performance is saved. The model is trained using a batch size of 32 for 100 epochs or until early stopping triggers. We use a training/validation/testing split of 70%/15%/15% to ensure proper model evaluation. The training samples are shuffled before each epoch to prevent the model from learning any unintended patterns from the order of samples.

2.6. Evaluation Metrics

To thoroughly assess our model's performance, we employ several evaluation metrics:

- Accuracy: The percentage of correctly classified instances across all classes.
- Precision and Recall: Calculated for each class to understand the model's performance on individual pipeline conditions.
- F1-Score: The harmonic means of precision and recall, providing a balanced measure of the model's performance.
- Confusion Matrix: To visualize the classification results across all 12 categories and identify any patterns of misclassification.

These metrics are calculated on the test set, which contains samples the model has never seen during training or validation, providing an unbiased estimate of the model's performance on new data.

3. Results and discussion

The GPLA-12 dataset serves as the foundation for evaluating our proposed CNN-based approach for AE classification in gas pipelines. This dataset consists of AE signals collected from gas pipeline systems under various conditions. Table 1 provides a detailed breakdown of the 12 classes in the dataset, organized by pressure level and sensor type. In the table, (bold/non-bold refer to data from sensor 1 or 2, and italic denotes data is noisy).

Table 1 Detailed 12 classes in GPLA-12 dataset

Pressure (MPa)	**Class Description**
0.2	*C0/C1* (sensor 1), C6/C7 (sensor 2)
0.4	*C2/C3* (sensor 1), C8/C9 (sensor 2)
0.5	*C4/C5* (sensor 1), C10/C11 (sensor 2)

The dataset contains signals recorded at three different pressure levels (0.2 MPa, 0.4 MPa, and 0.5 MPa), using two different sensors. Each class contains 57 samples, with a total of 684 samples across all 12 classes. The signals from sensor 1 (C0-C5) and sensor 2 (C6-C11) have different frequency characteristics, while the pressure variations introduce additional complexity to the classification task. Some signals in the dataset contain higher levels of noise, presenting a challenging scenario for accurate classification.

We evaluated our basic CNN model using a standard train-test split of 70%-30%, ensuring that each class was proportionally represented in both sets. The model was trained for 100 epochs with early stopping based on validation loss, using the Adam optimizer with an initial learning rate of 0.001 and a learning rate reduction schedule. The classification performance across all 12 classes is presented in Table 2, showing the precision, recall, and F1-score for each class.

Table 2 Classification Performance Metrics by Class

Class	**Precision**	**Recall**	**F1-Score**
C0	0.94	0.88	0.91
C1	0.88	0.94	0.91
C2	0.93	0.86	0.89
C3	0.89	0.94	0.91
C4	0.95	0.90	0.92
C5	0.91	0.85	0.88
C6	0.86	0.82	0.84
C7	0.82	0.88	0.85
C8	0.87	0.82	0.84
C9	0.81	0.84	0.82
C10	0.89	0.84	0.86
C11	0.85	0.87	0.86
Average	0.88	0.87	0.87

The overall accuracy of our model reached 87.3% across all 12 classes, demonstrating the effectiveness of the spectrogram-based CNN approach. Classes C0-C5 (sensor 1) generally showed better classification performance than classes C6-C11 (sensor 2), with an average F1-score of 0.90 versus 0.85. This difference can be attributed to the frequency characteristics of sensor 2, which appeared to capture more complex and variable acoustic patterns that were more challenging to classify consistently.

The model showed remarkable robustness to pressure variations, with only a slight decrease in performance as pressure increased. At 0.2 MPa (classes C0, C1, C6, C7), the average F1-score was 0.88, while at 0.5 MPa (classes C4, C5, C10, C11), it was 0.88. This consistency across pressure levels suggests that our spectral representation approach effectively captures discriminative features regardless of pressure conditions.

Our data augmentation strategy played a crucial role in improving model performance. When trained without augmentation, the model achieved only 75.2% accuracy, compared to 87.3% with augmentation. This significant improvement highlights the importance of expanding the training data through techniques like time shifting, noise addition, and frequency masking, especially when working with limited datasets like GPLA-12.

The confusion matrix analysis revealed that most misclassifications occurred between classes from the same sensor at similar pressure levels. For example, C0 was occasionally misclassified as C1, and C8 as C9. This pattern suggests that certain pipeline conditions produce acoustically similar emissions that can be challenging to differentiate using spectral features alone, particularly at the same pressure level and using the same sensor.

To evaluate the effectiveness of our approach, we compared our basic CNN model with several state-of-the-art methods for AE classification. Table 3 presents the comparative analysis, showing overall accuracy and computational efficiency for each method.

Table 3 Comparison with State-of-the-Art Methods

Method	Accuracy (%)	Training Time (min)	Model Size (MB)
Random Forest	72.5	1.2	4.3
SVM	68.3	2.5	1.8
LSTM	79.6	15.3	12.7
Bi-LSTM	81.2	22.6	18.6
Deep ResNet	85.8	35.4	24.2
Our CNN	87.3	12.8	8.5

Our basic CNN model outperformed all baseline and state-of-the-art methods in terms of classification accuracy while maintaining reasonable computational requirements. Compared to traditional machine learning approaches like Random Forest and SVM, our model showed a significant improvement of 14.8% and 19.0% in accuracy, respectively. This demonstrates the superiority of deep learning approaches for capturing complex patterns in AE signals.

Among deep learning methods, our CNN model surpassed both LSTM and Bi-LSTM architectures by 7.7% and 6.1%, respectively. Despite being conceptually simpler, our CNN approach was more effective at learning discriminative features from the spectrograms than recurrent architectures that processed the time-series directly. This suggests that the time-frequency representation provided by spectrograms facilitates more effective pattern recognition for this specific task.

Even when compared to more complex deep learning architectures like Deep ResNet, our model achieved superior performance with a 1.5% higher accuracy. This is particularly noteworthy considering that our CNN has significantly fewer parameters (8.5 MB vs. 24.2 MB) and requires less than half the training time (12.8 minutes vs. 35.4 minutes). The efficiency of our approach makes it more suitable for deployment in real-world pipeline monitoring systems, where computational resources may be limited.

The superior performance of our model can be attributed to three key factors. First, the transformation of acoustic signals into spectrograms effectively captures the time-frequency characteristics that are most relevant for distinguishing between different pipeline conditions. Second, our CNN architecture, while simple, is specifically designed to extract hierarchical features from spectrograms, with appropriate filter sizes and depths for this particular application. Third, our data augmentation strategy effectively addresses the limited sample size of the GPLA-12 dataset, creating a more robust and generalizable model.

Our results demonstrate that a well-designed basic CNN model can outperform more complex architectures for AE classification in gas pipelines. This finding has important implications for the development of practical monitoring systems, suggesting that simpler, more efficient models may be preferable for this specific application domain, especially when computational resources and power consumption are considerations for field deployment.

4. Conclusion

This study introduced a basic CNN approach for AE classification in gas pipelines that achieves superior performance while maintaining computational efficiency. By converting raw acoustic signals into spectrograms and applying a straightforward CNN architecture with three convolutional layers, we demonstrated an overall classification accuracy of 87.3% across 12 different pipeline conditions, outperforming more complex deep learning methods including LSTM, Bi-LSTM, and Deep ResNet architectures. Our approach effectively handles the challenges of varying pressure levels and sensor characteristics through appropriate preprocessing and data augmentation techniques, proving that carefully designed simple models can surpass sophisticated architectures for specific industrial applications. The proposed methodology enables reliable, real-time monitoring of pipeline conditions, potentially preventing costly and hazardous failures through early detection of anomalies and leaks. This research contributes to safer and more cost-effective pipeline operations in the oil and gas industry, with future work focused on model deployment on edge devices for continuous monitoring and integration with existing industrial systems to create comprehensive predictive maintenance solutions.

Compliance with ethical standards

Disclosure of conflict of interest

There is not conflict of interests.

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