

# AI-Driven Acoustic Emission System for Real-Time Ammonia Leak Detection in Industrial Pipelines

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## Abstract

One of the latest developments in non-destructive evaluation is Acoustic Emission (AE). The use of high-frequency AE systems for pipeline monitoring has been increasing. Leak-related information can be detected in a pipeline's AE signal; however, reducing noise often requires both signal processing and redundant measurements. In this work, AE testing was employed to detect ammonia leakage in pipelines by systematically analyzing signal properties. The leaks were simulated under various conditions, including pressure release, corrosion, and applied strains. Machine learning based on Support Vector Machines (SVM), a type of artificial intelligence (AI), was used to classify faults and assess detection accuracy. Key characteristics from AE, flow rate, and gas leakage sensors placed in the prototype setup were analyzed to diagnose leaks effectively. Before training the machine learning model, the sensor data from the ammonia pipeline were pre-processed and organized by frequency bands. The processed acoustic data were then input into the SVM classifier to extract leak-related discriminant features. Datasets generated under different conditions such as pressure drops, stress distributions, and leak sizes were evaluated using the SVM model in Python. The results achieved high accuracy, producing reliable and meaningful predictions suitable for the proposed platform implementation.

**Keywords**—acoustic emission; support vector machine; fault categorization; artificial intelligence

## 1 Introduction

The transport of hazardous materials, mainly ammonia, makes pipeline networks the backbone of many industries. Ammonia is a chemical that is frequently used in large quantities in the chemical, refrigeration, and agricultural industries [1]. Ammonia leaks are a high-risk situation that frequently has disastrous effects on the environment, human health, and financial loss when they result from pipeline leaks. As a result, it becomes crucial to detect pipeline leaks early [2]. However, conventional techniques like visual evaluations, pressure monitoring, and manual inspections are frequently ineffective, expensive, and prone to mistakes. Therefore, automated, real-time, and more precise leak detection systems that can operate constantly

with little assistance from humans are required. Testing for AE Leak Detection a non-destructive method for identifying leaks, fractures, and structural degradation in pipelines is Acoustic Emission (AE) testing [3]. High-frequency sound waves released with a change in material stress and deformation are detected by AE testing. These emissions, which arise from a material's interior surface under stress, for instance, when a crack or leak forms, convey important information about the material's condition. AE testing is perfect for detecting ammonia leaks since it allows for continuous, real-time pipeline integrity monitoring. It is founded on the idea that even small pipe cracks or deformations generate acoustic emissions that can be detected by sensors placed at certain locations. These AE tests will also provide early warning of possible breaches before the AE breaches escalate into serious incidents. AE is also low-maintenance and relatively inexpensive after sensors are introduced. This will be used mainly in

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industrial applications because they require continuous monitoring in real-time to verify the safety factor [4]. Despite its advantages, AE testing has drawbacks, particularly when it comes to signal interpretation. Temperature variations, fluid flow rates, pressure, and pipe material can all cause noise in the signal, which also affects the accuracy of AE-based leak detection. Furthermore, it can be challenging to distinguish between potential leaks and normal conditions because the AE signals generated by leaks frequently mimic other noises produced by routine activities, such as machinery noises. Because of this, the success of the detection system depends on how the AE signals are interpreted [5].

While addressing the difficulty of interpreting AE signals, the application of artificial intelligence (AI), particularly Machine Learning (ML) methods, has shown promise in improving leak detection systems. To automatically distinguish between AE signals under normal operating settings and those that may have a potential leak, artificial intelligence (AI) techniques like Support Vector Machines (SVM), Neural Networks (NN), and Random Forests (RF) can be trained on the signals. Actually, AE signals, which can be extremely dimensional and complicated and so require complex models for categorization, lend themselves well to machine learning. Large datasets, like AE signals [6] where feature extraction is crucial, are well handled by machine learning methods. In order to feed raw AE data into machine learning algorithms, feature extraction converts it into quantifiable values like mean frequency, skewness, kurtosis, and Root Mean Square (RMS). In order for the model to accurately distinguish between signals that indicate typical pipeline conditions and possible leakage occurrences, these properties represent the key attributes of AE signals. In particular, [7] SVM has proven more successful due to its capacity to manage extremely high-dimensional data and establish decision boundaries that allow for the establishment of maximal margins between different classes, particularly in situations involving non-linear separation. When AI and AE testing are used together, leak detection accuracy is greatly increased, decreasing the need for human intervention and improving the reliability of the system. Recent developments have included real-time monitoring and predictive maintenance capabilities to better enhance AI-driven systems. AI algorithms can identify early leaks and anticipate breakdowns before they happen for preventative maintenance by continuously analysing AE signals. In order to improve pipeline safety and reduce the likelihood of an undetected failure, IoT integration with AI enables the deployment of

smart sensors in the field, offering ongoing monitoring and prompt alarms [8, 9]. One of the challenges in putting up AI models for leak detection is the lack of available data, especially labelled data. This is particularly valid for simulation models that study the effects of different environmental conditions on leak detection. So we generated a real-world dataset using sensors. In situations where real-world data may be scarce or unavailable, this provides a scalable and reasonably priced method of training models. The primary objectives of this study are:

- 1) To develop a real-time ammonia leak detection system using AE signals integrated with SVM.
- 2) To analyze the impact of environmental and operational conditions (temperature, flow rate, and pressure) on AE signal behavior.
- 3) To evaluate the performance of the proposed AE + AI system against traditional ammonia leak detection techniques in terms of accuracy, detection speed, cost, and early warning capability.
- 4) To demonstrate the practical applicability of the proposed system in industrial pipeline monitoring for ammonia leaks.

## 2 Background and Literature Review

### 2.1 Background

In many industries, pipeline networks are the foundation of vital infrastructure, particularly when it comes to moving dangerous goods like ammonia. Ammonia is a chemical molecule that is frequently utilized in industries like chemical manufacturing, refrigeration, and agriculture (as fertilizer). Despite being a necessary resource, ammonia leaks from pipelines pose a serious risk to human health and the environment. Leaks of ammonia can have disastrous consequences, including poisoning, explosions, environmental damage, and financial loss. Ammonia is frequently carried over great distances; thus, even a tiny leak can have disastrous consequences. Ammonia leak detection [10] becomes a top priority for ammonia pipeline users due to the risks involved. Pressure testing, inspections, and visualization are traditional methods of leak detection that are typically ineffective because to their high time and effort costs. Additionally, they are not real-time, which increases their expenses as pipeline systems develop larger and more complicated, and it has a certain percentage of errors at the end. Furthermore, conventional techniques, such as pressure detection, are reactionary in nature and identify harm after it occurs rather than preventing it. This creates a big hole in terms of environmental protection, safety, and preventative maintenance.

Leak detection systems that are automated, real-time, more accurate, and require less human interaction while operating constantly are becoming more and more necessary. Such systems need to be able to manage the complexity of large-scale industrial pipes and be able to identify breaches early on, before they become serious problems. AE testing in conjunction with AI methods is one viable strategy for achieving this goal. As a non-destructive method of pipeline integrity monitoring, acoustic emission (AE) testing [11] has gained widespread use. High-frequency sound waves generated by energy emitted from the interior surfaces of materials under stress are detected by AE testing. These stress waves, also known as acoustic emissions, are created when a material deforms, cracks, or leaks. AE is an extremely useful tool for monitoring pipeline networks since it can identify emissions of structural faults in real time.

When it comes to pipeline monitoring, corrosion, leaks, and cracks on the pipe's surface cause AE signals. Strategically placed AE sensors can detect even the smallest deformations, such as the beginnings of cracking or modest leaking, which produce AE signals. These sensors continuously monitor the pipeline and capture AE signals, which provide early warnings of leaks, cracks, and other damage types. The advantage of AE testing is that it can detect such deformations early, enabling preventative maintenance and preventing disastrous failures. Because it provides continuous, real-time monitoring [11], the AE testing system has an advantage over traditional methods. Additionally, AE testing is economical and non-intrusive after sensors are placed. Accurate signal identification and categorization is challenging, though, because the signals are highly susceptible to ambient factors and outside noise. This has spurred research into cutting-edge methods—particularly artificial intelligence to enhance the categorization and interpretation of AE signals. Despite being a useful technique for identifying pipeline breaches, AE testing efficacy is frequently hampered by the noise and complexity of AE signals. Variations in temperature, fluid flow rates, pressure, and the characteristics of the pipeline's material are some of the variables that affect AE signals. These factors make it more difficult to differentiate leaks from typical operating noises by introducing noise that may mask the underlying signals brought on by cracks or leaks.

In terms of integration with the AE-based leak detection system, this holds potential for increased accuracy and dependability of these systems. By learning the history and recognizing the pattern based on the various leakage situations, machine learning (ML) algo-

rithms, particularly Support Vector Machines, Neural Networks, and Random Forests, are able to classify the AE signals much more successfully [12, 13]. Machine learning models are more likely than other models to manage this type of high-dimensional data. For machine learning models to employ AE signals, which are frequently highly complex and contain information in both the temporal and frequency domains, they must be carefully retrieved and processed. The most crucial step is feature extraction, which converts raw AE data into quantifiable features that represent the signal's inherent properties, like RMS, Skewness, Kurtosis, and Peak Frequency. RMS, for instance, is widely used in AE signal analysis and is related to signal energy, but skewness and kurtosis may reveal the distribution's structure. Frequency domain characteristics, such as dominant frequency or spectrum entropy, can be computed, for instance, with a Fast Fourier Transform (FFT). The extracted features are trained using machine learning models like Support Vector Machines (SVM) to classify AE signals obtained and detect pipeline leaks. In computer vision, SVMs are widely used for classification; they find a range by creating a line that separates the classes by maximizing the margin between labelled and non-labelled classes and accurately distinguish between leaks and normal state using the labelled training data.

## 2.2 Literature Review

Acoustic Emission and Machine Learning for Leak Detection: Extensive research has been conducted on pipeline leak detection using machine learning approaches based on acoustic emission (AE) signals. For example, [12] applied machine learning models to AE signals to detect pipeline breaks. By extracting various properties from the AE signals, such as peak frequency and RMS, they trained an SVM classifier to differentiate between normal and leaking conditions. The results highlighted the potential of machine learning to significantly improve both the efficiency of leak detection and the performance of AE testing through automated signal analysis. Multiple studies have demonstrated the ability of Support Vector Machines (SVM) to classify AE signals effectively. Different operational states of the pipeline, including normal, minor leak, and major leak conditions, were classified using SVM. Although feature selection is crucial, in these studies, time-domain features were found to be just as important as frequency-domain features for the SVM model's learning performance. The findings showed that SVM could accurately categorize AE signals and detect leaks even under temperature

and pressure fluctuations.

**Feature Extraction for AE Signal Analysis:** An essential step in applying machine learning to AE-based leak detection is feature extraction. Both time-domain and frequency-domain characteristics, such as skewness, kurtosis, and dominant frequency, were investigated to improve leak detection accuracy [14]. The authors concluded that integrating these feature sets significantly enhanced SVM performance, enabling a more accurate distinction between leak and non-leak scenarios.

**Pipeline Condition Simulation for AI Model Training:** Many studies have used simulation-based methods to generate synthetic AE signal data due to the complexity of real-world pipeline systems. A simulated pipeline environment was developed [14, 15], which produced AE signals under various conditions, including varying leak magnitudes and environmental factors. Using these simulated signals to train an SVM model demonstrated that artificial intelligence (AI) models for pipeline leak detection could be successfully trained even when real-world datasets were limited.

**AI and IoT Integration for Leak Detection and Predictive Maintenance:** The development of real-time leak detection systems has become feasible through the integration of AI with the Internet of Things (IoT). An AI-based real-time leak detection system using AE signals was proposed. This technology combines IoT and AI to continuously monitor pipeline health while predicting potential leaks before they occur. The study highlights that integrating AI with real-time monitoring offers a reliable solution for improving leak detection accuracy and reducing the risk of pipeline failures.

### 3 Methodology

The following are the primary processes in the technique for the AI-based ammonia leak detection system employing Acoustic Emission (AE) testing: The entire ammonia leak detection procedure using AE signals and artificial intelligence (AI) is covered in the next section and is shown in Figure 1 and Figure 2.

In Figure 3, the prototype model is shown, where the pressure vessel is filled with ammonia gas. A solenoid valve is mounted to cut off the gas supply in case a leak is detected, and a flow rate sensor is installed on the pipes to monitor changes. Sensors are placed at critical points, especially near valves, to detect leaks. The details of all sensors are provided in Table 1.

We preprocessed the raw AE signals and other sensor data (pressure, flow rate, temperature, and gas concentration) to improve signal quality and enable ro-

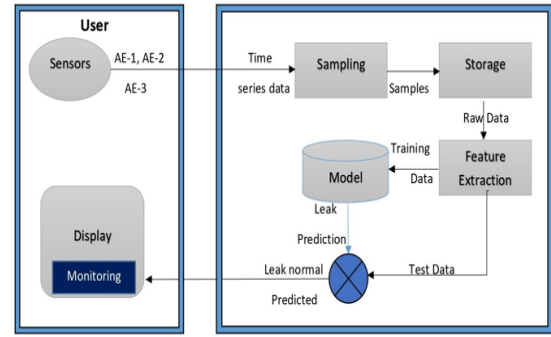


Fig. 1: Overview of sensor data processing workflow for AE-Based Ammonia leak detection

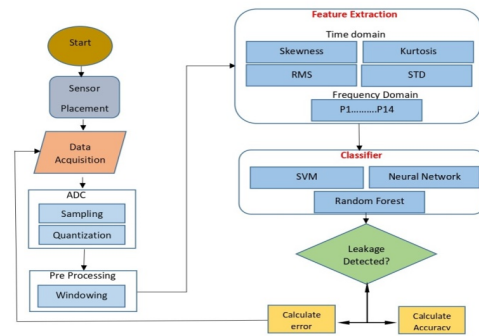


Fig. 2: Methodology overview of AE-based Ammonia leak detection

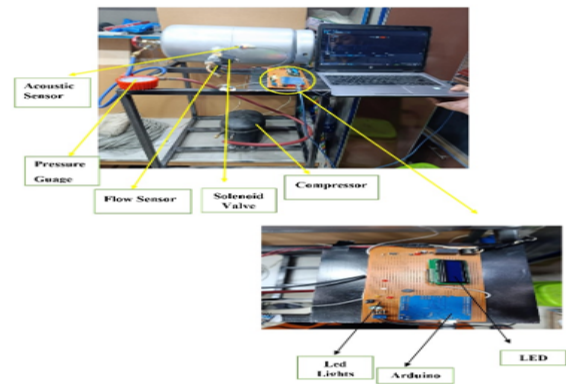


Fig. 3: Prototype setup for Ammonia leak detection

TABLE 1: Specifications and details of sensors used in the prototype pipeline setup

| Parameter         | Sensor                   |
|-------------------|--------------------------|
| Acoustic emission | Piezoelectric/Microphone |
| Pressure sensor   | MPX5050                  |
| Flow rate         | YF-S201                  |
| Temperature       | DS-18B20                 |
| Gas               | MQ-137                   |

bust feature extraction for machine learning analysis. The processing steps included:

### 3.1 Sensor Integration and Criteria

Sensors were selected and strategically positioned to maximize the detection sensitivity for ammonia leaks. The selection criteria included:

**Sensor Type:** Broadband piezoelectric AE sensors (20 kHz–200 kHz) were chosen for high sensitivity to burst-type acoustic signals. Complementary pressure (MPX5050), flow (YF-S201), temperature (DS-18B20), and gas (MQ-137) sensors were selected to capture operational variations.

**Placement Location:** Sensors were positioned near critical points, such as valves, welds, and bends, where leaks are most likely to occur. Placement was informed by modeling acoustic propagation, considering reflections, attenuation, and signal path lengths.

**Operational Considerations:** Sensor locations ensured minimal interference from vibration sources and allowed continuous monitoring without obstructing normal pipeline operations.

**Redundancy:** Redundant sensors were used in critical areas to ensure reliability and reduce the risk of missed detections. These criteria ensured that the sensor network provided high-quality, representative data for accurate AE signal monitoring and machine learning-based leak detection.

In the next step, a machine learning model is trained on a real-world dataset of AE signals. In order to simulate actual pipeline conditions, we used a real-world dataset of Acoustic Emission (AE) signals. Normal operation and varied leak sizes (small, medium, and big) are among the operational scenarios, along with fluid type, pressure, and flow rate, that are reflected in the dataset.

### 3.2 Pre-processing of AE Signals

**Noise Reduction:** Band-pass and wavelet de-noising filters were applied to remove environmental and mechanical noise, improving the SNR.

**Segmentation:** Continuous sensor data were segmented into discrete time frames corresponding to potential leakage events. Each frame was analyzed separately to capture transient AE bursts.

**Normalization:** Signal amplitudes were normalized to prevent variations in sensor sensitivity or signal strength from biasing the machine learning model.

### 3.3 Single Mode Filtering (SMF)

To further refine the signal-to-noise ratio (SNR), a custom Single Mode Filtering approach was imple-

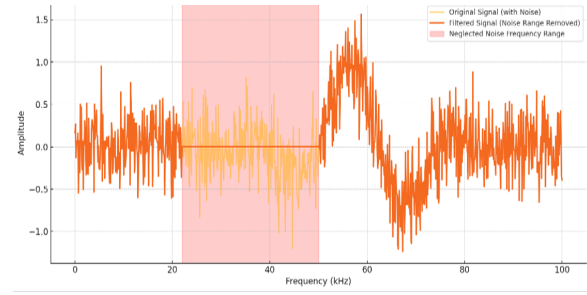


Fig. 4: Noise suppression and signal enhancement for AE data

TABLE 2: Material specifications for pipeline and experimental setup

| Specifications        | Details      |
|-----------------------|--------------|
| Pipeline Material     | Carbon steel |
| Pipeline Diameter     | 1 inches     |
| Pipeline Length       | 5 meters     |
| Fluid                 | Ammonia(NH)  |
| Operating Pressure    | 100 psi      |
| Operating Temperature | -33 °C       |
| Flow Rate             | 10 kg/h      |

mented. This technique decomposed the AE signals using Empirical Mode Decomposition (EMD), isolating intrinsic mode functions (IMFs) most representative of burst-type leakage signals. The dominant IMF was selected, and the signal was reconstructed, resulting in significant noise suppression. Figure 4 shows the AE data for noise suppression. Material specifications for the pipeline are provided in Table 2.

### 3.4 Time-Domain Features

**Root Mean Square (RMS):** Calculates the signal's energy.

**Skewness:** Indicates the signal distribution's asymmetry.

**Kurtosis:** Shows the signal's "peak-ness" and can draw attention to abrupt changes. The mean and standard deviation (Std) offer valuable information about the general behavior of the signal.

#### 3.4.1 Frequency Domain Features

**Dominant Frequency:** Finding the frequency with the highest energy, which is suggestive of particular operational behaviours or leak events.

**Spectral Entropy:** Indicates how much complications in the frequency content of the signal.

**Peak Frequency:** Represents the frequency at the maximum amplitude, which is normally correlated with sudden leaks or pipeline condition changes.

**Spectral Entropy:** Indicates how complicated the frequency content of the signal is.

### 3.5 Machine Learning Model Development

Following feature extraction, the AE signals are classified into four categories: normal, minor leak, medium leak, and major leak. Due to its ability to handle high-dimensional data and establish precise decision boundaries, an SVM classifier is employed for this task.

**Model Training:** The model is trained with labelled AE signals, either normal or leak types. Grid Search optimizes parameters, such as the gamma and C of the RBF kernel.

**Cross-validation:** Prevents overfitting and guarantees robustness.

### 3.6 Model Evaluation

After training the model, its performance is evaluated with a test dataset to see how accurate it is:

**Accuracy:** Overall accuracy of the model calculated as a percentage of signals correctly classified.

**Confusion Matrix:** This can be used to check how well a model is able to tell apart the classes (normal vs. leak conditions). Also, it gives an overview of false positives and negatives.

**Precision, Recall, and F1-Score:** These are calculated to be able to measure how effective the model is in detecting leaks with recall and minimizing false alarms with precision. The F1-score balances precision and recall.

### 3.7 Models Benchmarking

Other classifiers, such as Random Forest, k-Nearest Neighbors (k=3), and a shallow Artificial Neural Network (ANN) with two hidden layers, were used to compare the SVM model's performance. Accuracy, precision, recall, F1 score, and training duration were used to assess each model after it was trained on the identical set of features. This systematic data processing pipeline ensures that the machine learning model receives high-quality, relevant features, improving classification accuracy and reliability of leak detection under diverse operating conditions.

## 4 Results and Discussion

The purpose of this study is to investigate how temperature fluctuations, pressure changes, flow rates, and material deterioration (such as corrosion and stress) influence the behavior of Acoustic Emission (AE) signals for ammonia leak detection. The data analysis includes evaluating AE signals under normal, damaged, and leak conditions, as well as assessing the effects of varying temperature and flow rate. Key performance measures, such as accuracy, confusion

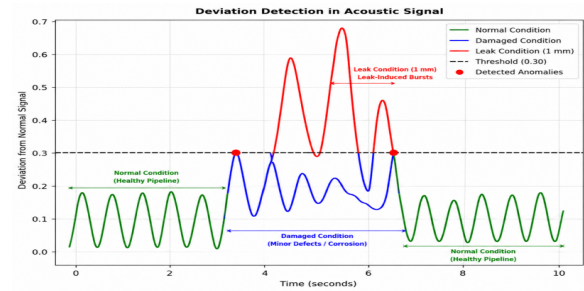


Fig. 5: AE Signal Behavior under different pipeline conditions

matrices, and model performance curves, are used to assess the effectiveness of the machine learning-driven leak detection system.

### 4.1 Signal Behaviour under Different Conditions

Figure 5 displays the simulated AE signals for the pipeline under normal, damaged, and leak conditions. Normal condition (green signal) represents the baseline AE signal of a healthy pipeline. The signal exhibits low amplitude fluctuations and minimal frequency variations, indicating stable pipeline operation without any structural defects or leaks. These baseline characteristics are critical for the machine learning model to establish a reference for normal behavior. Damaged condition (blue signal) simulates minor structural defects, such as early-stage corrosion or small surface cracks. The AE signal shows moderate amplitude spikes and slightly increased frequency variations due to localized material stress changes. These variations are less pronounced than in leak conditions but are distinct enough for the model to learn subtle deviations from normal operation.

To evaluate the leak condition (red signal) a 1 mm artificial leak is introduced to simulate real ammonia leakage. The AE signal exhibits pronounced high-amplitude bursts and increased frequency content, reflecting the sudden energy release caused by escaping gas. The intensity and pattern of these bursts are significantly different from normal and damaged conditions, providing clear features for the SVM classifier to distinguish leak events. The distinct patterns of AE signals under these three conditions are essential for machine learning-based classification, enabling the model to differentiate effectively between normal, damaged, and leaking scenarios.

### 4.2 Impact of Environmental and Operating Conditions (EOCs) on AE Signals

The detection of ammonia leaks is significantly influenced by environmental and operational

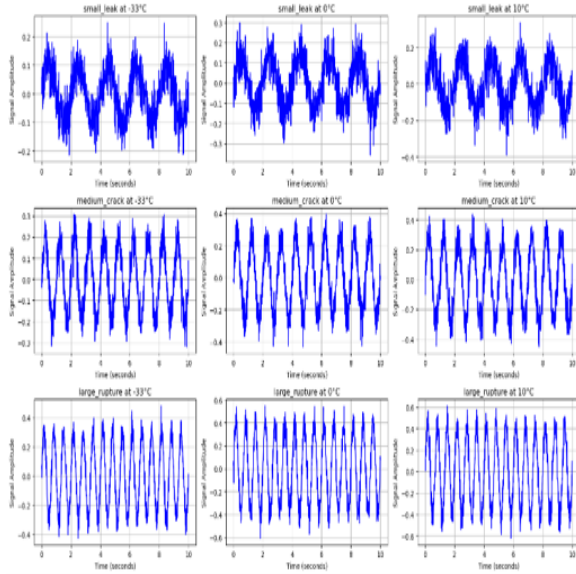


Fig. 6: Effect of temperature on AE signals

conditions (EOCs), including temperature, flow rate, and pressure. Figure 6 shows AE signal variations for minor, medium, and major leaks under three temperature conditions:  $-33^{\circ}\text{C}$ ,  $0^{\circ}\text{C}$ , and  $10^{\circ}\text{C}$ .

#### 4.2.1 Temperature Effects

AE signal amplitudes generally increase with temperature. This is due to changes in pipeline material properties, sound speed within the material, and stress wave propagation. Higher temperature enhances the energy captured by the sensors, particularly for larger leaks. Small and medium leaks exhibit moderate signal variation with temperature, whereas major leaks display pronounced changes in amplitude and frequency patterns. This indicates that larger ruptures are more sensitive to temperature changes, which may affect detection thresholds.

**Interpretation:** Machine learning models must distinguish temperature-induced signal changes from actual leak events. Proper training with temperature-varied AE data ensures the SVM classifier accurately identifies leaks under varying thermal conditions. This discussion emphasizes the need to incorporate environmental temperature variations into feature extraction and model training to improve the reliability of real-time leak detection in industrial pipelines. Figure 6 visually supports these effects by illustrating AE signal variations for different leak sizes under three temperature conditions.

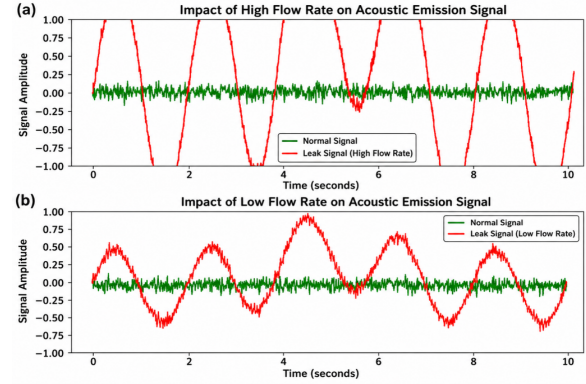


Fig. 7: Impact of flow Rate on AE signals

#### 4.2.2 Flow Rate Effects

Figure 7 illustrates the flow rate impacts. High flow rates increase mechanical stress on the pipeline, producing more intense AE signals, while low flow rates reduce AE amplitude, potentially masking minor leaks. Sudden pressure drops can generate AE bursts similar to leaks, requiring normalization and careful feature extraction to avoid false positives. Overall, including EOCs in the analysis ensures that the SVM classifier can detect leaks accurately across diverse operating conditions, improving reliability and robustness for industrial applications.

### 5 Evaluation Metrics

Figure 8 shows the confusion matrix of the SVM Model. To assess the performance of the SVM classifier for ammonia leak detection, the following metrics were used:

**Accuracy:** Measures the proportion of correctly classified AE signals (normal, damaged, or leak) over the total number of samples (Eq.1).

$$Accuracy = \frac{TP + PN}{TP + TN + P + PN} \quad (1)$$

**Precision:** Indicates the proportion of true positive leak predictions out of all predicted leaks, evaluating the model's ability to avoid false alarms (Eq. 2).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

**Recall (Sensitivity):** Measures the proportion of actual leaks correctly detected by the model, assessing its effectiveness in capturing all leak events (Eq. 3).

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

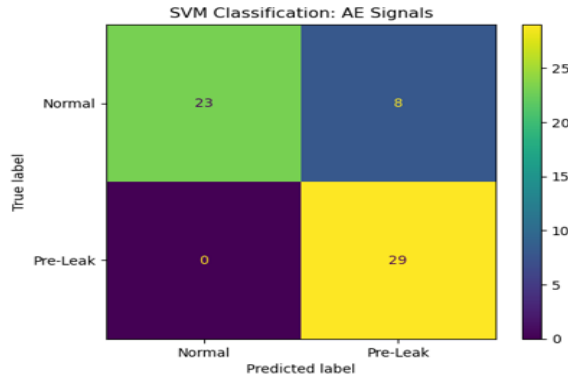


Fig. 8: Confusion matrix of SVM model

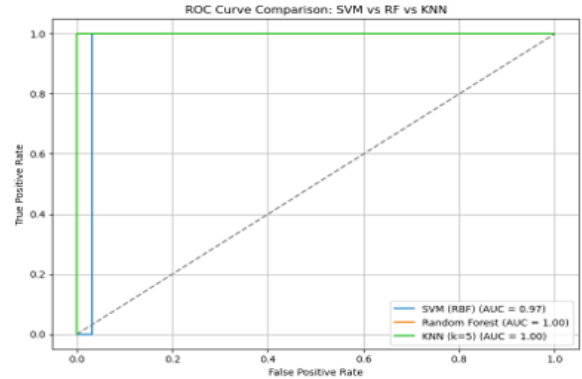


Fig. 9: False Positive rates for different classifiers

**F1-Score:** The harmonic mean of precision and recall, providing a balanced measure of model performance (Eq. 4).

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

**Confusion Matrix:** Displays the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), enabling visual inspection of misclassifications.

These metrics collectively quantify the classifier's reliability, its ability to detect leaks without generating false alarms, and its robustness under diverse environmental and operational conditions. Figure 8 shows the confusion matrix of SVM Model.

### 5.1 ROC Curve Comparison of Classifiers

Figure 9 presents the receiver operating characteristic (ROC) curves for K-Nearest Neighbors (KNN,  $k=5$ ), Random Forest (RF), and SVM (SVM with RBF kernel) classifiers.

**K-Nearest Neighbors (KNN):** The KNN classifier achieved near-perfect discrimination, with an area under the curve (AUC) of 1.00. This indicates that it correctly classified all AE signal samples with minimal misclassification.

**Random Forest (RF):** RF also achieved an AUC of 1.00, demonstrating exceptional ability to distinguish between normal, damaged, and leak conditions. Its ensemble approach helps improve robustness against noisy AE signals.

**Support Vector Machine (SVM):** The SVM classifier achieved an AUC of 0.97, reflecting high accuracy, though slightly more conservative than RF and KNN. The SVM effectively separates classes in high-dimensional feature space using the RBF kernel, providing reliable detection even in complex AE signal conditions. The ROC curves demonstrate that all three

classifiers are capable of accurate AE signal classification. While KNN and RF achieve perfect AUC in this dataset, the SVM provides robust performance with slightly lower AUC, offering advantages in generalization for unseen operational conditions.

Based on AE signal properties, the sharp rise of the curves toward the top-left corner demonstrates how well the three models can differentiate between leakage and non-leakage events. But because of their resilience to noise and nonlinear feature connections, the Random Forest and KNN models show better discriminative capability.

### 5.2 Cross-Validation Results and Robustness Evaluation

Figure 10 illustrates the cross-validation results of SVM classifier. The SVM classifier trained for ammonia leak detection utilizing acoustic emission characteristics underwent a 5-fold cross-validation, as shown in Figure Y. The graph plots four important performance metrics: Accuracy, Precision, Recall, and F1 Score, highlighting the model's consistency across various data subsets.

- 1) The model's strong correctness in both classes is demonstrated by the accuracy, which continuously stays over 94
- 2) Precision, a measure of the capacity to prevent false positives, exhibits little variation, remaining between 92
- 3) With a peak of about 95.7%, recall (sensitivity), which measures how well the system detects real breaches, continues to be the top metric.
- 4) A healthy balance between sensitivity and specificity is confirmed by the F1 Score, which is the harmonic mean of precision and recall. It stays constant and is in line with accuracy.

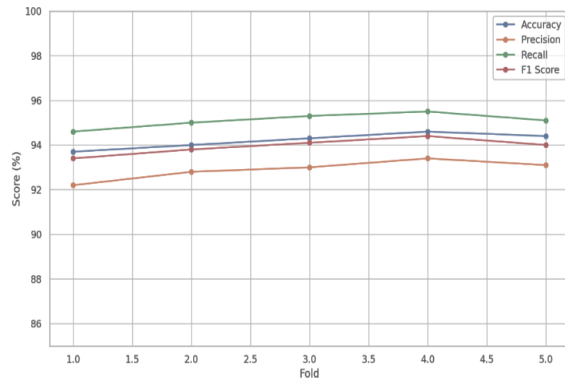


Fig. 10: Cross-Validation results of the SVM classifier

## 6 Performance Analysis

The AI-driven model's performance is compared to traditional leak detection methods, such as chemical sensors and manual inspections, to demonstrate its advantages in accuracy, speed, and efficiency.

### 6.1 Comparative Analysis of Techniques for Ammonia Leak Detection

In addition to the AE + AI system proposed in this study, conventional ammonia leak detection techniques include electrochemical sensors, infrared sensors, and ultrasonic detection. The following performance parameters were evaluated for each technique as shown in Figure 11.

**Accuracy:** The AE + AI system achieved the highest accuracy (93%) in detecting even small leaks in real-time. Electrochemical sensors and infrared detectors were moderately accurate (70–80%), whereas ultrasonic sensors showed high sensitivity but were prone to interference in noisy environments.

**Detection Speed:** The proposed AE + AI system provided immediate detection due to continuous monitoring, outperforming infrared and electrochemical sensors, which require manual scanning or slower response times. Ultrasonic sensors offered rapid detection but were limited by line-of-sight constraints.

**Cost-Effectiveness:** AE + AI monitoring is relatively cost-efficient, as multiple sensors can cover a pipeline without frequent replacements. Infrared and electrochemical sensors incur higher installation and maintenance costs, while ultrasonic sensors are expensive and less scalable for long pipelines.

**Early Warning Capability:** The AE + AI system uniquely captures precursor signals before catastrophic leaks, providing superior early warning capability. Traditional techniques often detect leaks only after significant gas release.

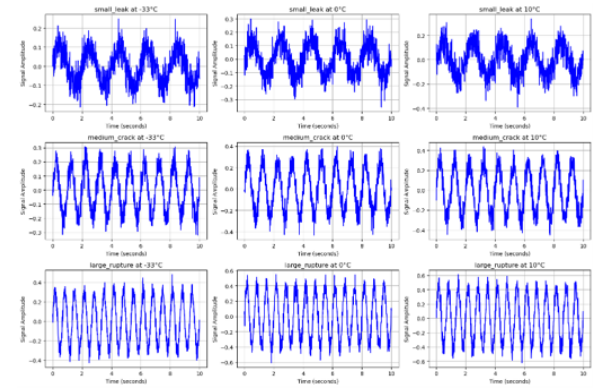


Fig. 11: Comparative performance of Ammonia leak detection techniques

The expanded comparison highlights the advantages of the proposed system over existing methods, particularly in early detection of small leaks, robustness under varying environmental and operational conditions, and reduced reliance on manual inspection. Prior studies have shown that conventional systems struggle to maintain high accuracy under temperature and flow rate variations, whereas the AE + AI system effectively captures these variations, improving leak detection reliability.

## 7 Conclusion

This study demonstrates that integrating Acoustic Emission (AE) testing with machine learning (SVM) provides a highly effective approach for real-time detection of ammonia leaks in industrial pipelines. The main findings are: AE signals show clear differentiation between normal, damaged, and leaking pipeline conditions, with amplitudes and frequency features influenced by temperature and flow rate variations. The SVM classifier achieved robust performance, with accuracy exceeding 94%, high precision, recall, and F1-score, indicating reliable detection of leakage events under diverse conditions. Comparative analysis revealed that the AE + AI system outperforms conventional methods (electrochemical, infrared, and ultrasonic sensors) in terms of accuracy, early warning capability, detection speed, and cost-effectiveness. The proposed system can be implemented for industrial applications, providing real-time monitoring with minimal human intervention, contributing to enhanced safety and preventive maintenance. Future work will focus on refining feature extraction techniques, separating flow-induced stress signals from leak signals, and integrating additional machine learning models to further improve predictive maintenance and system robustness.

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