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Multiclass gas pipeline leak detection using multi-domain signals and genetic algorithm-optimized classification models

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Abstract: Pipeline networks are critical infrastructure for oil and gas transport because the occurrence of leaks can rapidly escalate into safety, economic, and environmental crises. Operators are practically required to identify the presence and type of leaks; however, applying multiclass recognition is challenging when labeled data and computing power are limited. Therefore, this study proposes a three-stage pipeline which consists of: (1) adopting the GPLA-12 dataset of acoustic or vibration signals spanning 12 leak types; (2) extracting multi-domain features by combining time-domain descriptors with Power Spectral Density (PSD)-based spectral features; and (3) applying a genetic algorithm (GA) as a wrapper for feature selection to enhance discriminability and reduce dimensionality, which was followed by benchmarking seven conventional classifiers and GA-based refinement of the top model with a focus on the feature subset and hyperparameters. A maximum accuracy of 96.35% was achieved on the GPLA-12 dataset with low computation time and a simple model architecture. The proposed pipeline also attained similar or better accuracy at substantially lower complexity and data requirements compared with prior deep CNN approaches. These results support timely multiclass decision-making in resource-constrained industrial settings. A key observation was that the focus was on supervised leak-type classification from acoustic or vibration signals, while localization, severity estimation, and multi-sensor fusion were beyond the scope of this study.

Keywords: gas pipeline leak detection; multiclass classification; acoustic signal; genetic algorithm

1. Introduction

The use of gaseous media plays a crucial role in the production of chemicals, apparatus, and construction materials. The transportation of liquid and gaseous energy sources, such as oil and natural gas, is often through a pipeline which is considered to have substantial transport capacity, rapid delivery speed, and minimal economic cost [1]. However, pipeline leaks are frequently unavoidable due to a multitude of unpredictable circumstances, including third-party damage, welding imperfections, natural corrosion, or the use of inadequate pipeline materials. Explosions occurring near pipeline infrastructure due to a leak can have dire consequences which lead to substantial losses, including fatalities, property destruction, and environmental contamination [2], [3]. The trend consequently shows the need for the application of a proficient leak detection algorithm with elevated recognition accuracy to ascertain the nature of the issue, particularly when leaks are not readily apparent. The prompt identification facilitates immediate emergency interventions to avert the intensification of gas pipeline malfunctions and guarantee the protection of personnel and essential assets.

Conventional gas pipeline leak detection approaches typically identify only the presence of a leak by monitoring changes in pressure, flow, vibration, or acoustic signals. However, the accurate identification of the type of leak under diverse operating conditions remains technically challenging and is insufficiently addressed in current practice. This limitation has been observed in studies showing that sensor arrays can broaden coverage and sensitivity [4], [5] but conventional workflows often depend on manual feature engineering, incur high costs, and do not generalize effectively across media and operating regimes. Acoustic approaches are also attractive for fast response, high localization precision, and non-destructive nature [6], [7] but most published systems implement binary classification. In real-world deployments, signals originate from diverse media and materials, thereby revealing a clear research gap in developing efficient, data-efficient multiclass leak identification approaches considered reliable under realistic, heterogeneous conditions.

Conventional machine-learning models have shown several advantages over deep learning in recent years, specifically in settings with limited data and compute resources. Classifiers, such as Naive Bayes (NB), K-Nearest Neighbors (KNN), and Support Vector Machines (SVM), are simple, fast to train, and robust on small to moderate datasets [8], [9], [10]. Meanwhile, deep configurations, particularly convolutional neural networks (CNNs), have been shown to require large labeled datasets and substantial training to generalize effectively [11], [12]. Classical models with carefully designed features can reach high accuracy under data scarcity, are easier to deploy on constrained hardware, and offer improved interpretability and stability [13]. These properties lead to the designation as strong candidates for multiclass gas-pipeline leak identification, where labeled data are expensive and rapid iteration is needed.

The gap identified motivates this study to design and validate an end-to-end pipeline for multiclass gas-pipeline leak identification customized to limited-data regimes. The process required integrating time- and frequency-domain acoustic features to capture complementary information, applying a genetic algorithm (GA) to select a compact and informative subset that reduced complexity while preserving class separability, and benchmarking seven widely used classifiers on the GPLA-12 dataset with a focus on 12 leak types. The best classifier was subsequently refined through GA-based feature and hyperparameter optimization. The contributions of this study are fourfold. The first is the explicit crafting of a multidomain acoustic feature set for multiclass discrimination under small-sample conditions. The second is a GA-driven wrapper that jointly performs feature selection and model refinement to balance accuracy and efficiency. The third is a systematic and reproducible comparison of seven classifiers on GPLA-12. Moreover, the fourth is an empirical presentation of high accuracy (96.35%) with low computational cost and a simple architecture to show the competitiveness of the proposed approach with deep CNN baselines when data and compute are constrained. This study focuses exclusively on acoustic sensing and supervised leak-type classification, while localization, severity estimation, and sensor fusion with pressure or flow data are beyond the scope. All evaluations are conducted on the GPLA-12 benchmark with broader validation across different assets, media, geometries, and sensor layouts expected to be explored in future studies. Moreover, open-set recognitions or domain shifts, such as unseen leak mechanisms or pipeline materials, are not addressed and considered important directions for subsequent studies.

2. Material and methods

The methodology applied in this study was structured into three main stages as presented in Figure 1. The first stage was the adoption of the GPLA-12 dataset which consisted of acoustic signals captured from gas pipeline leakage scenarios using different sensors. Sound and vibration data corresponding to 12 different types of gas leak events were collected through the sensors. In the second stage, signal processing was performed in the temporal and spectral domains to extract relevant features. Time-domain features captured transient signal behaviors, while spectral-domain features obtained via Power Spectral Density (PSD) analysis showed underlying frequency patterns associated with different leak types. The extracted features from both domains were then combined to form a comprehensive feature set. In the final stage, a GA was applied for feature selection to enhance the discriminative power and reduce dimensionality.

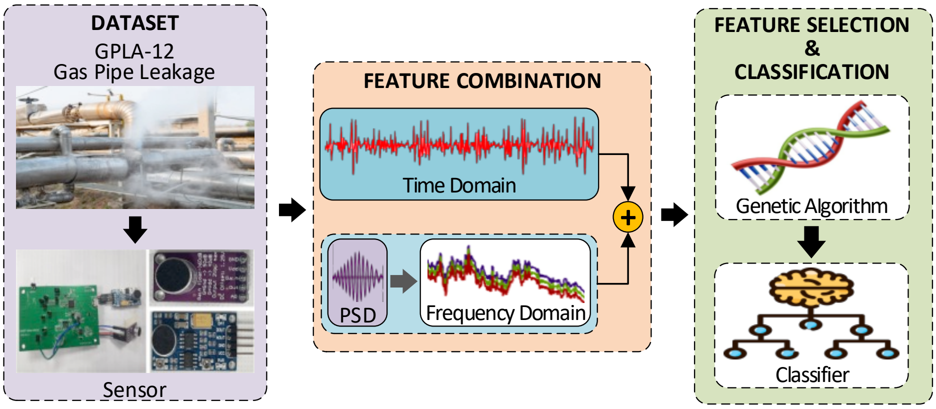

Figure 1. Overview of the proposed multiclass gas pipeline leak detection framework

The selected features were subsequently classified using a set of conventional machine learning models, and the model with the best performance is optimized and further analyzed. This multi-domain and evolution-based approach aims to improve the accuracy, efficiency, and robustness of multiclass gas leak detection systems.

2.1 Tools

All experiments were conducted using MATLAB 2024b and the models were trained from scratch using a fully supervised learning approach. The computational procedures were also executed on a desktop computer running on Windows 11 64-bit equipped with a 14th-generation Intel Core i9 processor and an RTX 4080 Super graphics card. However, the graphics processing unit was not utilized during any stage of the computation. This showed that all training and evaluation tasks were conducted using only CPU resources.

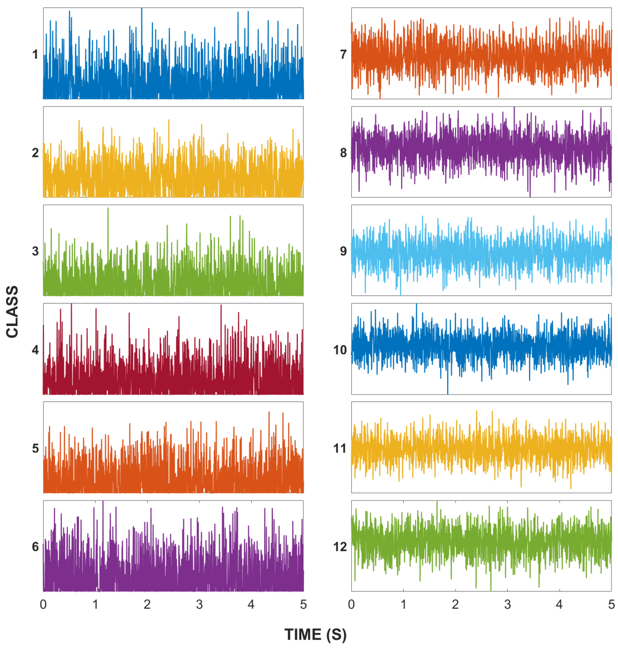

Figure 2. Raw data for each class

2.2 Dataset

A publicly available dataset previously used in related studies was adopted [14]. The dataset included two files in the GPLA-12 dataset, namely data.csv for acoustic signal data and label.csv to ensure appropriate labels. Each sample is represented by a row in data.csv. The data.csv file contains 684 rows (samples) and 1,460 columns (features/variables). The corresponding label.csv file contains 684 rows and one column, providing the class label for each sample. In total, there are 12 categories of acoustic gas leak signals recorded under diverse settings, with 57 samples per category (684/12 = 57). The classes were selected randomly to maintain balance among the types of data, while the number and diversity of the dataset were intentionally constrained. The GPLA-12 dataset had 12 classes with the details of each presented in Table 1. The collection included several audio signals captured in diverse circumstances. For simplification, the classes were further grouped into three main categorical dimensions: (1) 0.2 PM versus 0.4 PM versus 0.5 PM; (2) noisy versus non-noisy surroundings, and (3) comparison of Microphone 1 with Microphone 2. Each sample in the dataset was treated as a time series, and 12 samples were randomly selected from each distinct class, as presented in Figure 2. The acoustic signal characteristics of gas pipeline leaks were not easily observed in the time domain, and this led to the need for algorithms with strong feature extraction capabilities. The algorithms should be able to identify correlations between acoustic signals and specific types of leakage.

2.3 Feature extraction

Feature extraction was conducted using PSD to characterize the distribution of signal power over frequency [15]. The PSD was estimated using the Welch approach, which is widely adopted due to its ability to reduce variance in the spectral estimate by partitioning the signal into overlapping segments, calculating a modified periodogram for each segment, and subsequently averaging the outcomes. Let $x[n]$ be discrete-time data of length *N* and the Welch approach partitions the signal into K segments with the length of (where $M < N$) overlapping. A window function was also applied to each segment through $w[m]$. For the *k*-th segment, the modified periodogram is provided in equation (1).

$$P_k(f) = \frac{1}{MU}\left|\sum_{m=0}^{M-1} x_k[m]\omega[m]e^{-j2\pi fm}\right|^2 \quad (1)$$

Where:

- $x_k[m]$ is the *k*-th segment of the signal
- $\omega[m]$ is the Hann window function
- $U = \frac{1}{M}\sum_{M=0}^{M-1}\omega^2[m]$ is the window normalization factor to compensate for power loss due to windowing.

The Welch estimate of the PSD, $\hat{P}_{Welch}(f)$, can be obtained by averaging the periodograms of all K segments as shown in equation (2).

$$\hat{P}_{Welch}(f) = \frac{1}{K}\sum_{k=1}^{K} P_k(f) \quad (2)$$

This approach smoothed the spectral estimate and mitigates the effects of noise to ensure better stability for use in downstream classification tasks. The computation of PSD was followed by the concatenation of the frequency-domain features produced with the raw time-domain signal to form a multi-domain feature set. The time-domain features preserved waveform shape and transient characteristics, while the PSD features captured frequency-related anomalies possibly connected to different types of gas leaks. The integration of these two types of information ensured that the feature representation became more informative and discriminative. The enriched input was subsequently used in machine learning classifiers to allow the system to distinguish between the 12 types of acoustic gas leak signals in the GPLA-12 dataset more accurately. This multi-domain feature fusion approach enhanced by the statistical robustness of the Welch approach was critical in achieving strong performance in multiclass leak classification.

2.4 Classification

Classification is defined as a machine learning process used to predict class labels based on input features. This study adopted seven distinct classification models including NB, KNN, Random Forest (RF), Linear Discriminant Analysis (LDA), Decision Tree (DT), SVM, and Artificial Neural Networks. The models were selected due to their capacity to manage tiny datasets and mitigate overfitting, which is a prevalent challenge when working with minimal data.

2.4.1 Naive Bayes (NB)

NB is a probabilistic algorithm commonly used in text classification and other applications specifically when only small datasets are available [16]. It assumes independence among features but is effective for small-scale datasets due to the simplicity and robustness. NB handles limited variables effectively and offers computational efficiency which makes the model ideal for imbalanced data scenarios.

2.4.2 KNN

The operation of KNN is carried out by comparing an unknown data point with the existing dataset to identify the most similar neighbors [17]. KNN is effective on small datasets but sensitive to noise which can negatively affect the results when data is limited. Moreover, the selection of the appropriate value of K is critical to balance model simplicity and accuracy.

2.4.3 RF

RF is an ensemble model that constructs multiple DTs and combines their outputs to produce more stable predictions [18]. However, when applied to small datasets, RF can lead to overfitting due to the complexity introduced by multiple trees. The effort to mitigate the problem requires certain adjustments such as reducing the number of trees or simplifying model parameters.

2.4.4 LDA

LDA is a classification approach that aims to maximize class separation using linear combinations of input features [19]. The model is effective when data follows a normal distribution and the number of classes is limited. LDA is particularly suitable for small datasets because it does not require a large amount of data to achieve effective class separation and has a lower risk of overfitting compared to more complex models.

2.4.5 DT

The DT model splits the dataset into smaller subsets based on feature values to construct a DT [20]. The model is easy to interpret but is highly prone to overfitting, specifically with limited data.

Therefore, strategies such as pruning or limiting tree depth are essential to maintain generalizability.

2.4.6 SVM

SVM is designed to locate the optimal decision boundary that maximizes the separation between classes [16]. The model remains highly accurate in high-dimensional feature spaces but can also overfit small datasets, particularly when using complex kernels or poorly tuned parameters. Therefore, careful parameter selection is very important in small data scenarios.

2.4.7 ANN

ANNs are developed based on the biological neural systems and are capable of modeling complex relationships within data [21]. However, the networks are highly prone to overfitting when trained on small datasets. To address this issue, regularization strategies such as dropout and architectural simplification are implemented in addition to fewer layers and neurons to maintain model performance and generalization.

2.5 Feature selection

GA was applied to select the optimal subset of features that enhanced classification accuracy while concurrently minimizing model complexity [22]. This optimization approach is derived from the principles of natural selection. Each "individual" within the population represented a prospective solution to the feature selection challenge. The objective was to identify the feature subset that maximized a designated fitness criterion. Therefore, the population was subjected to iterative evolution through selection, crossover, and mutation processes to produce progressively superior solutions. The initial population for N features was defined, and each individual was formulated as in equation (3).

$$X = [x_1, x_2, \cdots, x_N] \tag{3}$$

$x_i \in \{0,1\}$ where $x_i = 1$ when the i=th feature is selected and $x_i = 0$ when not selected. Moreover, a fitness function was defined to evaluate the performance of each individual. $f(X)$ represents the fitness score of individual X and is presented in equation (4).

$$f(X) = \text{model\_performance}(X) \tag{4}$$

where, model_performance(X) evaluates the trained model using the feature subset X. Individuals were selected based on the ranking of the fitness scores. Therefore, the probability of selecting an individual X_i is defined in equation (5).

$$P(X_i) = \frac{f(X_i)}{\sum_{j=i}^{M} f(X_j)} \tag{5}$$

where, M is the population size and $P(X_i)$ is the probability of selecting an individual. The generation of new individuals was achieved through the combination of the characteristics of two parents. Furthermore, random crossover points c were used in the single-point crossover and defined in equation (6).

$$X_{\text{child}} = [x_1, x_2, \cdots, x_c]_{\text{parent1}} + [x_{c+1}, x_{c+2}, \cdots, x_N]_{\text{parent2}} \tag{6}$$

A binary vector mutation was subsequently applied with a low probability by flipping bits from 0 to 1 or 1 to 0. The mutation for the feature position i is defined in equation (7).

$$x_i' = \begin{cases} 1 & \text{if } x_i = 0 \text{ and mutation occurs} \\ 0 & \text{if } x_i = 1 \text{ and mutation occurs} \\ x_i & \text{otherwise} \end{cases} \tag{7}$$

The selection, crossover, and mutation processes were repeated for 300 generations or until no further improvement was observed in the fitness score.

2.6 Model performance evaluation

A 5-fold cross-validation approach was used to evaluate the performance of the classification model as presented in Figure 3. K-fold cross-validation was typically preferred over simple hold-out validation due to its ability to offer a more dependable assessment of model performance by utilizing all data points repeatedly for both training and testing.

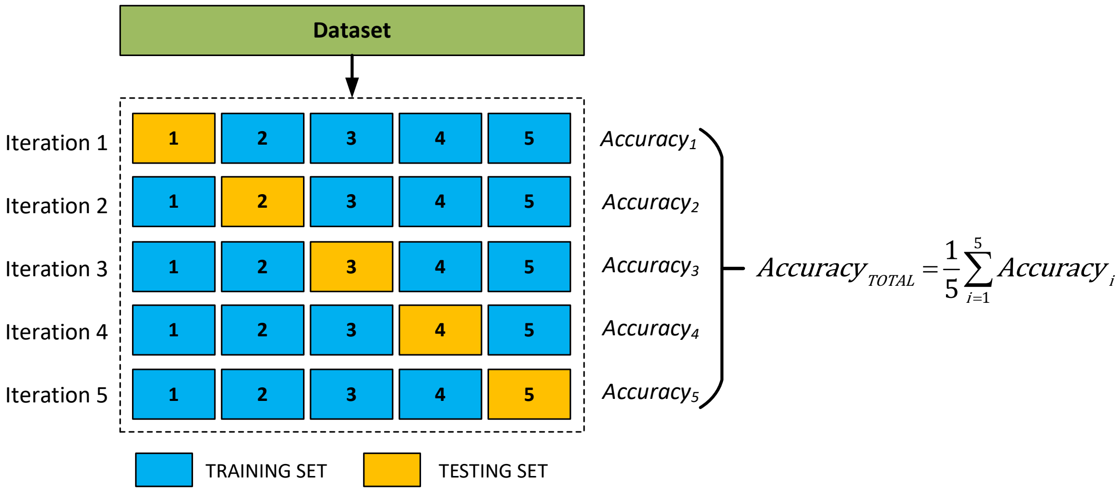

Figure 3. Concept of 5-fold cross-validation

Moreover, iterative division reduced the variance in evaluation metrics particularly with smaller datasets. The 5-fold cross-validation required dividing the dataset into five equal segments. In each iteration, four segments were allocated for training and one for testing. The procedure was executed five times, with each fold serving once as the test set. The mean accuracy for all the folds was subsequently computed as in equation (8-12).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$Sensitivity\ (Re\,c\,all) = \frac{TP}{TP + FN} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Specificity = \frac{TN}{TN + FP} \tag{11}$$

$$\text{F-}score = \frac{2TP}{2TP + FP + FN} \tag{12}$$

Classification model evaluation had four types of prediction outcomes which include true positive (TP), true negative (TN), false positive (FP), and false negative (FN). A true positive occurs when the actual value is positive and the predicted outcome is also positive. Meanwhile, a true negative is when both the actual and predicted values are negative. A false positive refers to a situation where the actual value is negative but the model predicts a positive outcome and is commonly known as a Type I error. A false negative occurs when the actual value is positive but the model predicts it as negative and is referred to as a Type II error.

3. Results and discussion

This section presents the experimental results and analysis aimed at examining the performance of seven classification models in detecting multiclass gas pipeline leaks using a GA based on multi-domain signals. A novel approach that combined signal analysis from two domains, including time and frequency, with an optimization strategy based on GA was adopted to improve the accuracy of leak detection in gas pipelines. The results were in the form of a performance comparison of the classification models applied to the gas pipeline leak dataset based on several metrics, including accuracy, precision, recall, and F1-score. Evaluation was conducted using a 5-fold cross-validation scheme where the dataset was evenly divided into five subsets. Each model was tested five times, with a different subset designated for the test in each iteration, while the other four were used as the training set. Each fold served once as the test set, ensuring unbiased performance estimation. This approach ensured more reliable generalization of results and reduced bias caused by random data splits. Furthermore, comparisons were made between traditional classification models and those optimized using GA to identify the most effective approach for classifying 12 types of gas leak signals.

3.1 Analysis of model performance based on signal domain

The predictive capability of classification models optimized using GA was evaluated on signals with a focus on the time, frequency, and a combination of both in the form of the time-frequency domain. Each analysis domain provided different types of information with the time-domain signals tending to be less effective in directly showing changes in gas characteristics, while frequency-domain signals were better at capturing more complex patterns related to pipeline leakage. This analysis aimed to identify the most effective domain to improve the model performance for leak detection and to compare the ability of the information in each to influence the achievement of higher accuracy, reduction of false positives, and enhancement of detection precision in multiclass gas pipeline leak scenarios. The results related to the comparison of the accuracy are presented in Figure 4 with each model represented by bars across the three domains.

The adoption of the signals from the combined domains generally produced the best performance across most classification models, followed by the frequency, and time-domain features yielded the lowest accuracy. High accuracy for the NB model was achieved when using signals from combined domains with a slight improvement observed in the adoption of only those related to the frequency. Meanwhile, the KNN model showed a significant improvement in accuracy when using frequency and combined domains compared to the application of only time-domain signals. The RF model produced a similar accuracy pattern to NB, SVM, DT, and ANN.

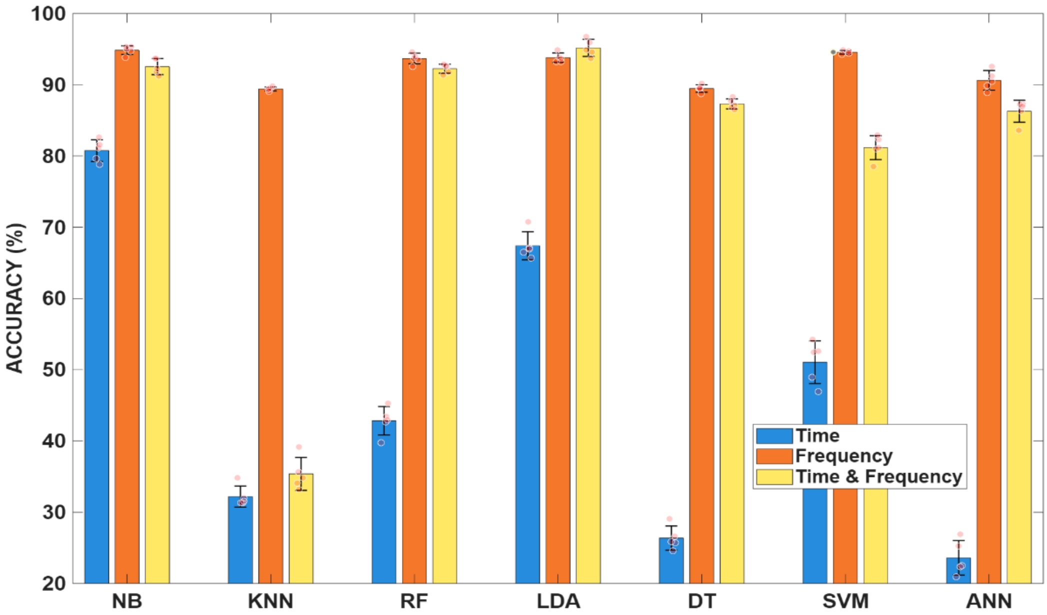

Figure 4. Accuracy comparison of classification models based on the signal domain

The LDA model had the best performance when using combined signal domains by recording the highest accuracy compared to all the models evaluated. The results presented in the figure generally showed that the signal-based approach using the frequency domain significantly improved the accuracy of gas pipeline leak detection across all tested classification models. In the case of LDA, combining both domains enabled the model to recognize more complex patterns in the leak signals which could not be fully represented by a single domain. This enhanced the capacity of the model to identify leaks more accurately. Figure 5 shows the testing time required by each classification model based on input signals from the three domains.

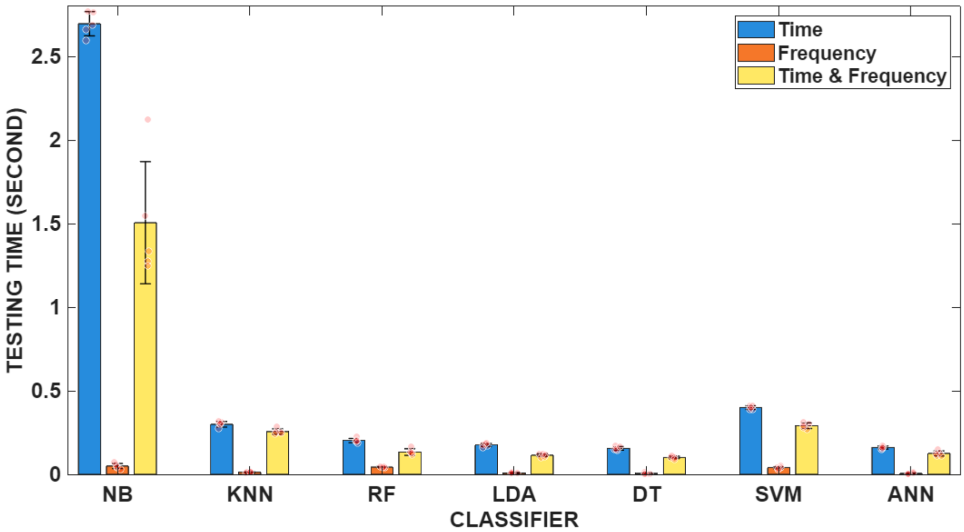

Figure 5. Testing time required for models in the signal domain

Each bar represents the time to test the model using signals from the corresponding domain. NB was observed to require the longest testing time with the time-domain signals but the duration reduced significantly for the combined domain. The LDA and DT models exhibited the shortest testing times across all domains compared to the others. Combined domains generally tended to speed up the testing process for most models despite variations based on the specific approach.

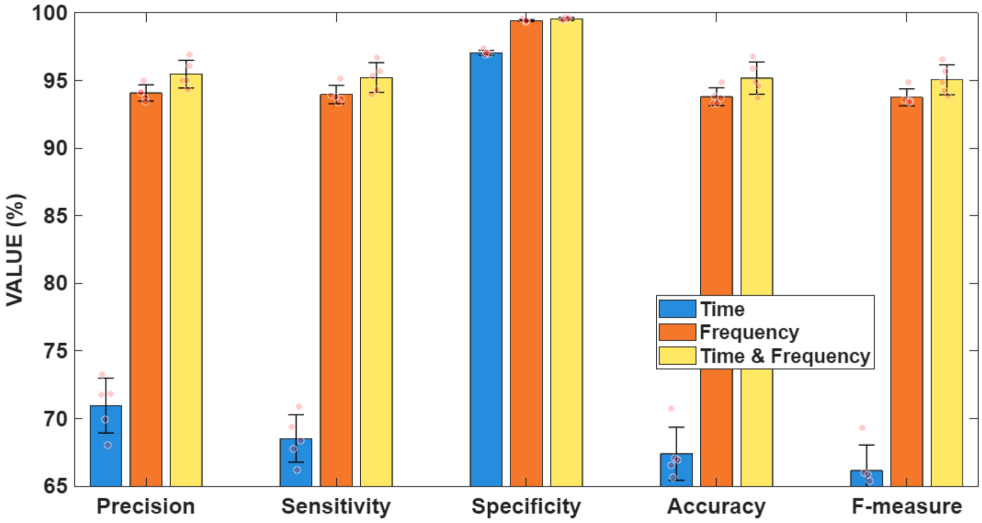

Figure 6. LDA metric performance based on the signal domain

The LDA showed very low testing time which was a reflection of high efficiency in comparison to the others in terms of computational cost. The model also achieved the highest general performance as observed in the capability to detect gas pipeline leaks with high precision in Figure 6. The combination of accuracy and computational efficiency led to the selection of the LDA as the primary candidate for further optimization using GA. The optimization was further used to improve the performance of the LDA model in terms of detection accuracy and training speed towards ensuring more suitability for real-time gas pipeline breach detection systems that required a rapid and precise response.

3.2 LDA optimization using GA

The optimization process of the LDA model applied to the gas pipeline leak detection dataset was conducted using a GA as presented in Figure 7. A dynamic decrease was observed in the error over generations during the evolutionary process. Moreover, two curves identified include the best fitness which represents the lowest error in each generation and the mean fitness for the average error across the population.

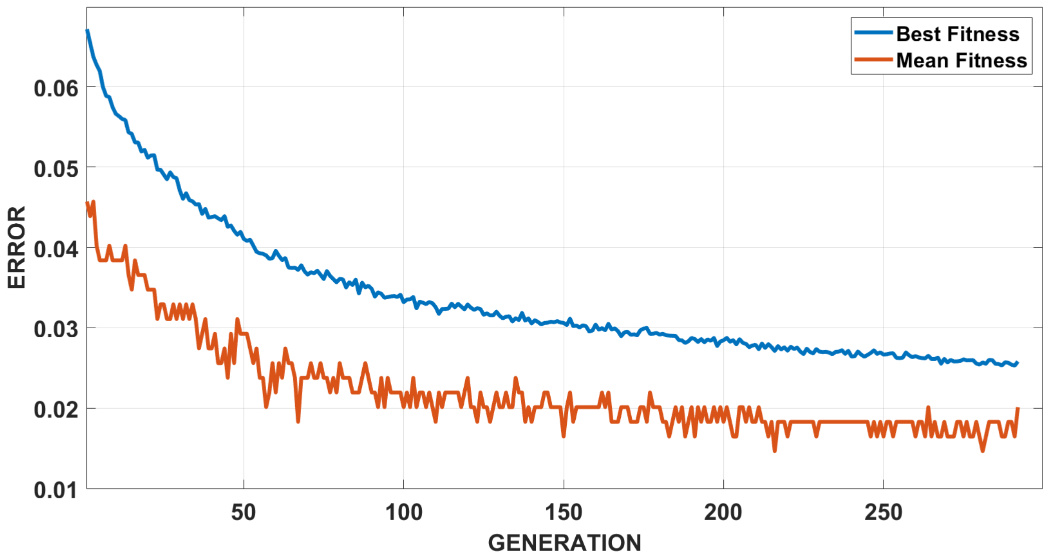

Figure 7. Convergence curve of LDA optimization using a GA

A significant reduction in error was observed in the early phase of generation at approximately 0 to 70. This showed the ability of the algorithm to effectively explore the parameter space and enhance model performance. After generation 100, the error reduction became more gradual and the mean fitness curve showed minor fluctuations while continuing to decrease consistently. The trend suggested that the population was starting to converge toward an optimal solution. In the final phase, both curves stabilized at approximately between generations 250 and 300 to show the occurrence of convergence. The final average error at the end of the evolution process was recorded at 0.0258 which confirmed the optimization process significantly improved the accuracy of the LDA model. The results generally showed that the GA-based approach was effective in optimizing the parameters of the LDA model for the task of gas pipeline leak detection by achieving superior classification performance through a stepwise evolutionary process. Furthermore, the confusion matrix in Figure 8 reflects the performance of the optimized LDA model in classifying 12 different classes with each representing a specific gas pipeline leak condition. The vertical axis is the true class while the horizontal axis shows the predicted class.

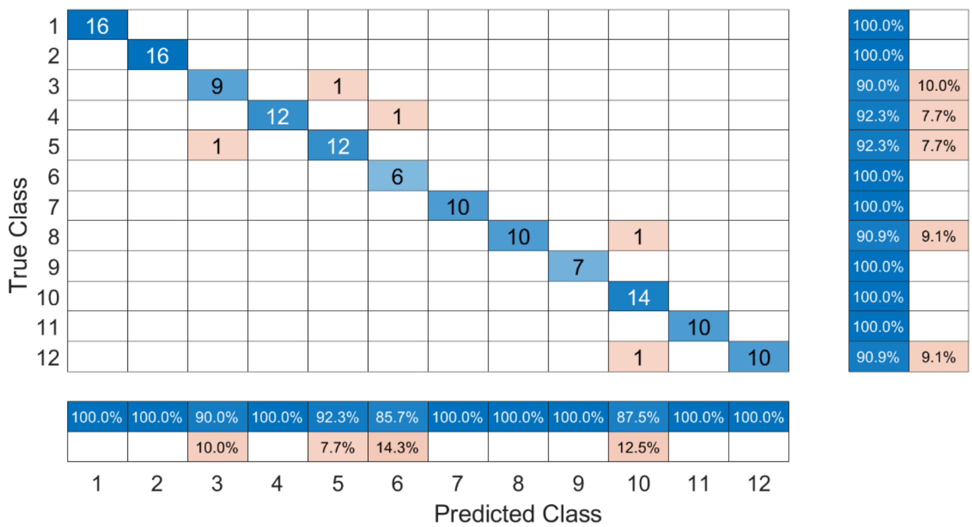

Figure 8. Performance visualization of the LDA model across 12 gas pipeline leak classes

Each cell in the confusion matrix contains the number of predictions with the blue in the main diagonal aspect representing correct classifications while the orange in off-diagonal boxes represents misclassifications. The model generally showed excellent classification performance because most classes were classified accurately as reflected through the dominant values along the diagonal. Classes 1, 2, 6, 7, 9, 10, and 11 even achieved perfect accuracy by reaching 100%. Other classes such as 3, 4, 5, and 12 experienced minor misclassifications but also maintained high accuracy levels above 90%. For example, class 3 had one sample misclassified as class 4 which led to an accuracy of 90.0%. A similar observation was in class 6 where one sample was misclassified as class 5 with an accuracy of 85.7% and class 12 had one sample misclassified as class 11 with an accuracy of 90.9%.

The matrix provides information in the form of accuracy percentages per row and column in addition to raw prediction counts and this ensures easier comprehensive assessment of the efficacy associated with the model. The ability of the model to maintain high accuracy across all classes showed that the GA-based optimization approach effectively enhanced the generalization capability. Therefore, this approach has proven to be effective in improving classification accuracy for complex and multiclass gas pipeline leak detection tasks.

The boxplot visualization of the LDA model performance based on optimized features is shown in Figure 12. The model was tested five times using different training and testing data splits to examine consistency and generalization across varying data partitions. The boxplot presents five evaluation metrics which are precision, sensitivity, specificity, accuracy, and F-measure. Each boxplot shows the distribution of values from the five trials which covers the minimum, median, third quartile, and maximum. The black dots represent individual data points from each test while the red 'x' marks denote outliers.

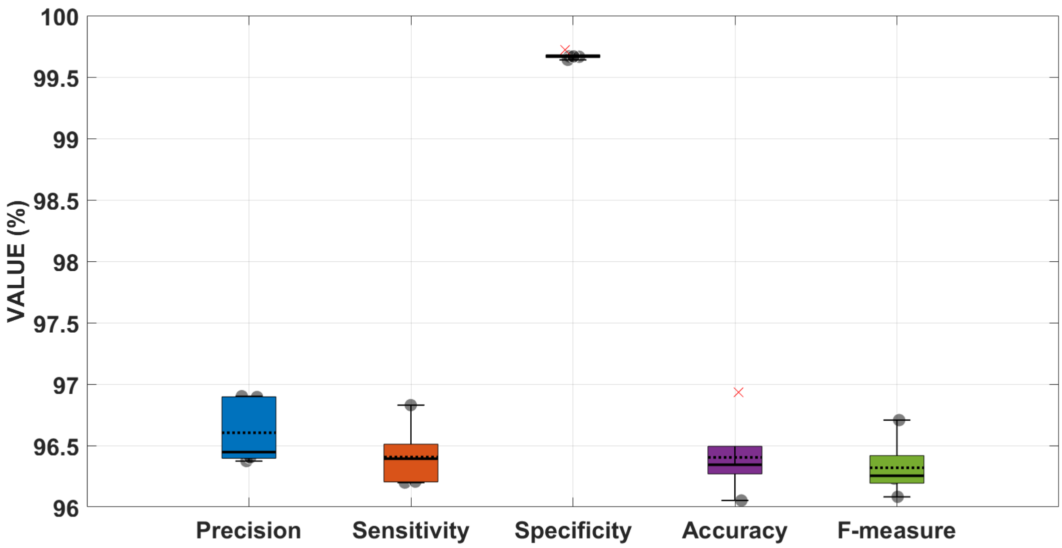

Figure 9. LDA model performance evaluation based on repeated tests using optimized features

All the metrics showed high and stable performance with the values ranging from approximately 96% to 100%. Specificity had the highest and most stable value by approaching 100% with very low variation. This showed the strong ability of the model to consistently identify negative classes. The other metrics such as precision, sensitivity, accuracy, and F-measure had slightly greater variation but reflected excellent performance with median values above 96%. These results showed that GA-based feature selection significantly enhanced the effectiveness of the LDA model both in prediction accuracy and test-to-test consistency. The model was both highly accurate generally and also balanced in proportionally identifying all 12 gas leak classes.

3.3 Discussion

3.3.1 Effect of signal domain on classification model performance

Experimental results showed that the choice of signal domain had a significant impact on enhancing the effectiveness of classification models for gas pipeline leak detection. The combination of time and frequency domain signals generally produced better accuracy than using only a single domain. This can be explained by the fact that the time domain captures the temporal dynamics of signals while the frequency domain is capable of exploring deeper spectral characteristics. The combination of both allowed the model to utilize more relevant hidden information within the signal to enable more accurate recognition of leak patterns.

The best performance was generally achieved using the LDA model with signals from both domains. The trend shows that LDA was highly responsive to combined domain features. The others such as KNN, NB, and RF also had significant accuracy improvements in the frequency and the combined domain. These findings indicate that domain transformation plays a critical role in enhancing multiclass classification performance. The analysis of testing time showed that using the combined domain did not consistently lead to longer computation time. Meanwhile, using the combined domain reduced testing time for some models such as NB compared to the adoption of only the time domain. The LDA and DT models consistently showed low testing times to emphasize their algorithmic efficiency. The consideration of both computational efficiency and accuracy led to the consideration of LDA as a promising option for real-time applications in gas leak detection systems requiring rapid response.

3.3.2 LDA optimization using GA

The LDA optimization process using a GA successfully reduced the error rate of the model significantly during the evolutionary process. The convergence curve shown in Figure 7 indicates a sharp decrease in the early generations and stability in later generations to reflect the success of the algorithm in reaching an optimal solution. The final average error value of 0.0258 shows the effectiveness of this strategy in determining the ideal parameter combinations to improve classification accuracy. Moreover, the confusion matrix of the optimized LDA model shows excellent classification performance across 12 leak classes. The dominance of diagonal values reflects the capacity of the model to accurately distinguish most of the leak categories. Perfect accuracy for classes 1, 2, 6, 7, 9, 10, and 11 proves the precision of the model in identifying specific leak patterns. There were some misclassifications in classes 3, 5, and 12 but the accuracy remained above 85% to show strong generalization and robustness to data variation.

The evaluation of the LDA model using randomly split datasets over five iterations produced consistent results. The boxplots of five key metrics showed a narrow and high distribution with most medians exceeding 96%. Specificity even achieved the highest and most stable value to reflect a low false positive rate. These results confirmed that GA-based feature selection improved the general effectiveness of the model and also enhanced the robustness across different data conditions. Furthermore, the model performed with high overall accuracy as well as ensured a balanced and consistent detection of all 12 types of gas leaks across various environments.

3.3.3 Comparison with state-of-the-art models

The success of the proposed approach was measured through a performance comparison against several others from previous studies that used similar datasets and classification tasks with the results presented in Table 4. The focus was on the accuracy values of four different approaches including the one proposed in this study, an acoustic signal model which used the FAE-1D-CNN+EAB architecture achieved an accuracy of 95.17% [23] . Meanwhile, Liao H et al. [24] applied a deep residual model that utilized thresholds on a per-channel basis and achieved a lower accuracy of 76.47%. The trend showed that the residual network-based approach was less effective in detecting complex gas leak patterns in the dataset used.

Table 1. Performance of the proposed approach compared with previous studies

Author	Approach	Accuracy (%)
Yao L et al [23]	FAE-1D-CNN+ EAB	95.17
Liao H et al [24]	Deep residual network with channel-wise thresholds	76.47
Pan X et al [25]	1D-CNN and Mamba modules	93.24
Current study	Multi-Domain Signal and LDA-Genetic Algorithm	96.35

A strategy using 1D-CNN with Mamba modules achieved an accuracy of 93.24% which was considered a competitive performance [25]. However, the approach proposed in this study by integrating multi-domain signal analysis and LDA optimization using a GA produced the highest accuracy of 96.35% compared to strategies adopted in the selected previous studies. The exceptional performance can be attributed **to** the robustness of the multi-domain feature representation as well as the effectiveness of the GA in fine-tuning the LDA model parameters. This combination improves the performance of the model to distinguish between 12 gas leak types and also maintains computational efficiency. The results confirmed that the proposed model was theoretically sound and empirically superior to other state-of-the-art approaches. Therefore, this model is an exceptionally strong candidate for implementation in accurate and real-time multiclass gas pipeline leak detection systems.

4. Conclusion

In conclusion, this study presented a novel approach for multiclass gas pipeline leak detection by integrating multi-domain signal analysis with a specific focus on time and frequency domains with LDA optimized using a GA. The rigorous testing and evaluation conducted showed that the proposed approach consistently outperformed conventional classification models in accuracy, computational efficiency, and prediction stability. Among the seven classification models tested, the LDA-GA model proved to be the most effective by achieving an impressive 96.35% accuracy in identifying 12 leak classes. The GA optimization significantly improved model convergence and minimized errors, as evident from the fitness curve and confusion matrix evaluations. Moreover, high performance was maintained across multiple classes and evaluation metrics, including precision, recall, specificity, and F1-score. The comparisons with state-of-the-art approaches also further emphasized the superior performance of the proposed model. The results suggested that the Multi-Domain Signal and LDA-GA-based approach was a robust and reliable solution for real-world gas pipeline leak detection by offering high accuracy, rapid response, and excellent generalization capability. However, several key limitations were identified, which included the utilization of only acoustic sensing, evaluation of a single benchmark (GPLA-12), focus on only supervised leak-type classification, and lack of assessment for the robustness to domain shift or unseen leak mechanisms. Future studies should extend this work by incorporating multi-dataset validation, multimodal fusion with on-device deployment, domain adaptation with open-set handling and uncertainty calibration, as well as extensions to joint classification, localization, and semi- or self-supervised and continual learning to reduce labeling costs and maintain models in changing conditions.

Author’s declaration

Author contribution

Wiwit Suprihatiningsih: Conceptualization, Data curation, Formal analysis, Investigation, Writing, Original draft. **Dedik Romahadi**: Supervision, Methodology, Resources, Writing, review and editing. **Hadi Pranoto**: Validation, Data curation, Writing, Review and editing. **Rikko Putra Youlia**: Visualization, Investigation, Writing, Original draft. **Fajar Anggara**: Validation and Visualization. **Rizky Rahmatullah**: Data curation, Formal analysis, Investigation.

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Data Availability

The data used in this study were sourced from publicly available datasets and fully cited and listed in the references section.

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Competing interest

The authors declare no competing interests.

Ethical clearance

Ethical approval was not applicable, as this study did not involve human or animal subjects.

AI statement

This manuscript represents the work of the authors based on an original study, and no content or figure was created using AI.

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