

Multi-class gas pipeline leak detection using Hilbert transform and a lightweight convolutional neural network

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ABSTRACT

Ensuring the safety and sustainability of gas distribution networks depends heavily on the timely detection of pipeline leaks, since leaks that go unnoticed can cause substantial losses and create serious safety risks. When applied to multi-class leak types, however, conventional detection approaches often prove insufficiently accurate. To address this limitation, the present study proposes a novel multi-class gas pipeline leak detection approach based on acoustic signal analysis, aiming to enhance both detection accuracy and processing efficiency. In this approach, features are first extracted from leak-generated acoustic signals through application of the Hilbert transform, after which classification is performed using a lightweight convolutional neural network (CNN) architecture referred to as LightCNN. The method was tested using the gas pipeline leakage assessment-12 (GPLA-12) dataset, comprising 12 distinct leak categories. According to the evaluation outcomes, the proposed approach peaked at 96.18% accuracy while employing a more streamlined model architecture than earlier techniques. Overall, this work contributes meaningfully to advancing leak detection systems that are more reliable, faster, and more efficient, with potential for broad application across the gas pipeline industry and in signal processing technologies more generally.

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1. INTRODUCTION

Detecting leaks in gas pipelines remains a major challenge for energy distribution networks worldwide, given that leaks left undetected are capable of inflicting heavy economic losses, endangering human safety, and damaging the surrounding environment [1], [2]. As a fuel consumed across industrial, residential, and transportation sectors, natural gas ranks among the principal energy sources sustaining contemporary life [3], [4]. Even minor leaks carry the potential to trigger explosions, ignite fires, or release harmful pollutants into the air. Consequently, detecting leaks swiftly and precisely is essential for safeguarding the public and keeping gas distribution networks operating efficiently. Despite the development of numerous leak-detection technologies, current systems continue to grapple with limited sensitivity to minute leaks, sluggish response times, and notably steep operating expenses. Such difficulties intensify further when leaks arise within noisy settings, for instance industrial facilities or crowded urban areas. Background noise generated by machinery,

traffic, or human activity frequently drowns out the acoustic signature of a gas leak, complicating efforts to separate genuine leak signals from other sources of interference.

For leak detection to remain reliable amid noisy conditions, the underlying technology must be able to filter out competing background sounds while still recognizing genuine gas leak signals, even where acoustic interference is considerable. Systems that detect leaks accurately shorten the time needed to respond, curb the risks that leaks create, and buy responders extra time to manage emergencies [5], [6]. Furthermore, because leaks of different sizes, locations, and intensities call for their own response strategies, being able to accurately detect every category of gas leak is critical. Small leaks may not pose an immediate danger, yet they can turn into serious hazards if left unattended. Large, sudden leaks, on the other hand, require an emergency response that is both quick and accurate [7], [8]. As a result, precisely identifying and sorting gas leaks by type gives decision-makers the information needed to shape their response according to risk level and the distinguishing features of each leak detected. A method capable of identifying diverse leak types with high accuracy would considerably speed up and improve mitigation efforts, reduce the scale of potential losses, and make the gas distribution network both safer and more sustainable overall.

Over the past several decades, numerous methods for identifying gas pipeline leaks have emerged. Industry practice has long relied on conventional approaches such as gas sensors, visual inspection, and thermal and infrared monitoring [9], [10]. Although gas sensors are capable of delivering precise readings of leaked-gas concentration, they typically demand extensive upkeep and come at a considerable cost. In addition, achieving broad coverage requires installing these sensors at numerous locations, which drives up operational expenses. Thermal cameras and infrared imaging, for their part, can pick up on the temperature shifts that accompany a gas leak, yet their effectiveness is often curtailed by particular circumstances, such as limited visibility or severe weather. Acoustic-based monitoring presents a more adaptable alternative, since the low-frequency sounds produced by gas leaks can be captured with microphones or sound recorders irrespective of adverse local conditions [11], [12]. Nevertheless, a major difficulty with this approach lies in isolating relevant information from acoustic signals whose properties fluctuate significantly.

To enhance both accuracy and efficiency of acoustic-based gas leak detection, more sophisticated techniques are needed for extracting features from the sound signals that leaks generate [13], [14]. The Hilbert transform stands out as one such promising solution, offering a means of processing non-stationary signals [15]–[17]. Applying this transform yields an analytic representation of the original signal, which offers a more detailed view of its frequency and amplitude characteristics. When applied to gas leak scenarios, it is capable of picking up on subtle shifts in frequency or amplitude that arise from minor leaks, and it isolates the relevant signal components in a way that improves detection accuracy. Despite its extensive use in signal analysis more broadly, the extent to which the Hilbert transform has been applied specifically to detecting leaks in gas pipelines using acoustic signals remains limited. Introducing this technique into the gas leak detection context therefore represents a vital innovation for advancing the development of more sophisticated leak detection technologies.

Beyond signal extraction, categorizing the types of gas leaks from the resulting acoustic signals calls for a machine learning model that is both dependable and efficient. Among available options, convolutional neural networks (CNNs) have demonstrated strong capability in recognizing intricate patterns across diverse data types, including image, audio, and signal data [18]–[20]. Because CNNs are able to capture patterns that unfold across space or time within input data, they are especially well suited to acoustic signal analysis. A notable drawback, however, is that training and operating sophisticated CNN architectures typically demands substantial computational resources [21], [22]. For gas pipeline leak detection specifically, a model must combine accuracy with computational efficiency so that it can support fast, real-time responses. Accordingly, this study adopts lightweight CNN models capable of producing precise detection outcomes while consuming fewer computational resources. Such lightweight CNNs are anticipated to address the shortcomings of conventional CNN architectures, offering a more practical solution for detecting gas pipeline leaks.

Despite ongoing efforts, several key obstacles remain in achieving accurate and resource-efficient gas leak detection under noisy conditions: i) conventional signal processing techniques often fail to isolate the relevant frequency and amplitude components of gas leak sounds, particularly when noise levels are high; ii) existing deep learning models used to classify gas leak types generally require substantial computational resources, which limits their suitability for real-time or resource-constrained applications; and iii) integrated approaches capable of both sharpening signal clarity and sustaining lightweight classification performance in complex industrial or urban settings remain scarce. Motivated by these obstacles, the present study puts forward a new hybrid framework that combines a sophisticated signal-transformation stage with a deep learning component optimized for computational efficiency, aimed at improving the detection of gas leaks. The main contributions can be summarized as follows: i) apply the Hilbert transform to extract frequency and amplitude components embedded within gas leak sound signals, thereby uncovering hidden features that conventional signal processing methods tend to miss, especially under noisy conditions, and offering a new avenue for improving detection accuracy; ii) develop and test LightCNN, a compact and efficient CNN for

classifying different gas leak types, which attains strong accuracy while keeping computational demands low and is therefore well suited to real-time use in settings with limited computing resources; and iii) by merging the Hilbert transform with LightCNN, a practical solution capable of accurately detecting gas leaks within acoustically challenging settings such as industrial and urban areas is delivered, a contribution anticipated to speed up emergency response, lower the risk of accidents, and provide additional time for effective mitigation measures.

2. METHOD

The overall framework adopted for developing the LightCNN-based gas pipeline leak detection model is depicted in Figure 1. To tackle the difficulties inherent in gas leak detection, the Hilbert transform is employed in this study as a means of deriving salient features from the acoustic signals captured at the leakage point. The procedure begins with the acquisition of sensor-based leakage signal data, which subsequently undergoes Hilbert transform processing. Through this transformation, the raw signal is broken down into distinct components, namely the amplitude envelope, the instantaneous phase, and the instantaneous frequency, each of which preserves meaningful information about the acoustic behavior produced by the leak. These components then serve as the input fed into the LightCNN model, a compact and computationally efficient variant of the CNN. Through LightCNN, patterns within the extracted features are analyzed so that the type of gas leak can be classified from the acoustic signal data obtained. This approach is chiefly aimed at improving detection accuracy while keeping computational resource demands to a minimum, thereby enabling swift, real-time detection of leaks.

When acoustic signals associated with gas leaks are processed by means of the Hilbert transform, the resulting detection accuracy is anticipated to improve, even under conditions where background noise is present. This hypothesis is examined by comparing the leak detection accuracy obtained before and after the Hilbert transform is applied to signals contaminated with noise, with the classification accuracy achieved by the LightCNN model (used to determine gas leak types from the processed signal data) serving as the measure of performance. The model itself is built to classify gas leak types efficiently while demanding fewer computational resources than conventional CNN architectures. Validation of this hypothesis involves benchmarking LightCNN against a standard CNN model with respect to both processing time and accuracy, drawing on data from the publicly available gas pipeline leakage assessment-12 (GPLA-12) dataset. The resulting evaluation indicates whether such a lightweight model is capable of meeting the requirements of detecting leaks in real time without sacrificing detection accuracy.

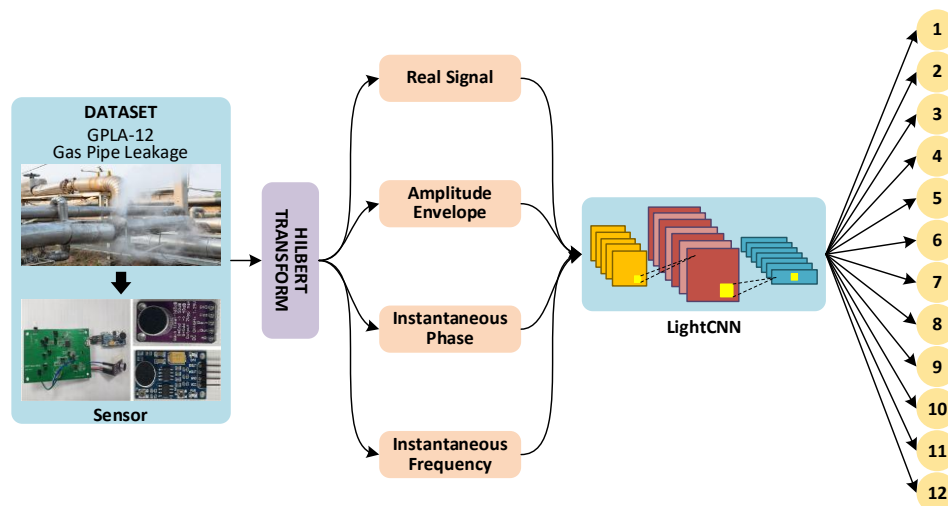


Figure 1. The overall framework of the proposed model

2.1. Dataset

In this research, the GPLA-12 dataset made available by earlier researchers is adopted [23]. It consists of acoustic signals produced by leaking gas pipelines, recorded through acoustic sensors mounted on the pipes so that leaks could be identified from the sound or vibration patterns they generate. As this dataset has already been employed in earlier studies, it offers a credible and trustworthy basis for the present research.

The GPLA-12 dataset is made up of two files: data.csv, which stores the acoustic signal readings, and label.csv, which holds the corresponding class labels. Data.csv is structured with 684 rows and 1,460 columns, each row representing a distinct sample. Label.csv similarly contains 684 rows, each row holding a single column that records the label assigned to that sample. Altogether, the compiled data spans 12 categories of acoustic gas-leak signals captured across diverse conditions. To achieve a balanced representation across leak types, the classes within the dataset were selected at random, even though the overall volume and diversity of the data remain somewhat limited. GPLA-12 is made up of 12 categories, the detailed specifications of which are set out in Table 1. Audio signals spanning a broad range of gas-leak scenarios are included in the dataset. To streamline the classification analysis, these categories may further be consolidated into several predefined major classes.

Table 1. Overview of each category in the GPLA-12 dataset

Label	Filename	Explanation	Total
1	Data1_0:2MP_none	At a gas pressure of 0.2 MPa, the pipeline signal was captured by microphone 1 in a noiseless environment.	57
2	Data1_0:2MP_noisy	Microphone 1 recorded the pipeline signal at a gas pressure of 0.2 MPa under a strongly noisy environment.	57
3	Data1_0:4MP_none	Under a noiseless environment, the pipeline's gas pressure was 0.4 MPa while microphone 1 captured the signal.	57
4	Data1_0:4MP_noisy	This entry captures microphone 1's signal from the pipeline at a gas pressure of 0.4 MPa under a strongly noisy environment.	57
5	Data1_0:5MP_none	At a gas pressure of 0.5 MPa, the pipeline signal was captured by microphone 1 in a noiseless environment.	57
6	Data1_0:5MP_noisy	Microphone 1 recorded the pipeline signal at a gas pressure of 0.5 MPa under a strongly noisy environment.	57
7	Data2_0:2MP_none	Under a noiseless environment, the pipeline's gas pressure was 0.2 MPa while microphone 2 captured the signal.	57
8	Data2_0:2MP_noisy	This entry captures microphone 2's signal from the pipeline at a gas pressure of 0.2 MPa under a strongly noisy environment.	57
9	Data2_0:4MP_none	At a gas pressure of 0.4 MPa, the pipeline signal was captured by microphone 2 in a noiseless environment.	57
10	Data2_0:4MP_noisy	Microphone 2 recorded the pipeline signal at a gas pressure of 0.4 MPa under a strongly noisy environment.	57
11	Data2_0:5MP_none	Under a noiseless environment, the pipeline's gas pressure was 0.5 MPa while microphone 2 captured the signal.	57
12	Data2_0:5MP_noisy	This entry captures microphone 2's signal from the pipeline at a gas pressure of 0.5 MPa under a strongly noisy environment.	57

2.2. Feature extraction using the Hilbert transform

Following the collection of the acoustic signal dataset, feature extraction is performed using the Hilbert transform. For a real-valued signal $x(t)$, the Hilbert transform is defined by convolving the signal with the function $\frac{1}{\pi t}$, as expressed in (1). Here, $\hat{x}(t)$ denotes the outcome of applying the Hilbert transform to the original signal $x(t)$, while P.V. denotes the Cauchy principal value of the integral.

$$\hat{x}(t) = \frac{1}{\pi} P \cdot V \cdot \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} dt \quad (1)$$

Once the Hilbert transform result $\hat{x}(t)$ has been obtained, it can be used to construct the analytic signal $x_a(t)$, as presented in (2), with j representing the imaginary unit. This analytic signal then serves as the basis for deriving the following key parameters.

$$x_a(t) = x(t) + j\hat{x}(t) \quad (2)$$

Where j is the imaginary unit ($j = \sqrt{-1}$). From analytic signal, the following key parameters can be derived:

- i) Amplitude envelope: computing the modulus of the analytic signal produces the amplitude envelope as in (3).

$$A(t) = |x_a(t)| = \sqrt{x^2(t) + \hat{x}^2(t)} \quad (3)$$

- ii) Instantaneous phase: the instantaneous phase corresponds to the phase component of the analytic signal as in (4).

$$\phi(t) = \arctan\left(\frac{\hat{x}(t)}{x(t)}\right) \quad (4)$$

- iii) Instantaneous frequency: the instantaneous frequency is given by the time derivative of the instantaneous phase as in (5).

$$f(t) = \frac{1}{2\pi} \cdot \frac{d\phi}{dt} \quad (5)$$

These three parameters, namely amplitude envelope, instantaneous phase, and instantaneous frequency, serve as the input features supplied to the LightCNN model for gas leak classification. Because they effectively capture the distinctive characteristics of the leak signals, the model is better able to accurately distinguish among different leak types.

2.3. Classification using LightCNN

Once the features derived from the Hilbert transform have been obtained, these are combined with the original signal and fed into the LightCNN model for processing, as depicted in Figure 2. LightCNN denotes a CNN architecture built to operate on one-dimensional input, which in this case comprises the raw acoustic signal together with the amplitude envelope, instantaneous phase, and instantaneous frequency produced through signal transformation. The resulting model classifies acoustic signals into distinct gas-leak categories on the basis of patterns identified within these features.

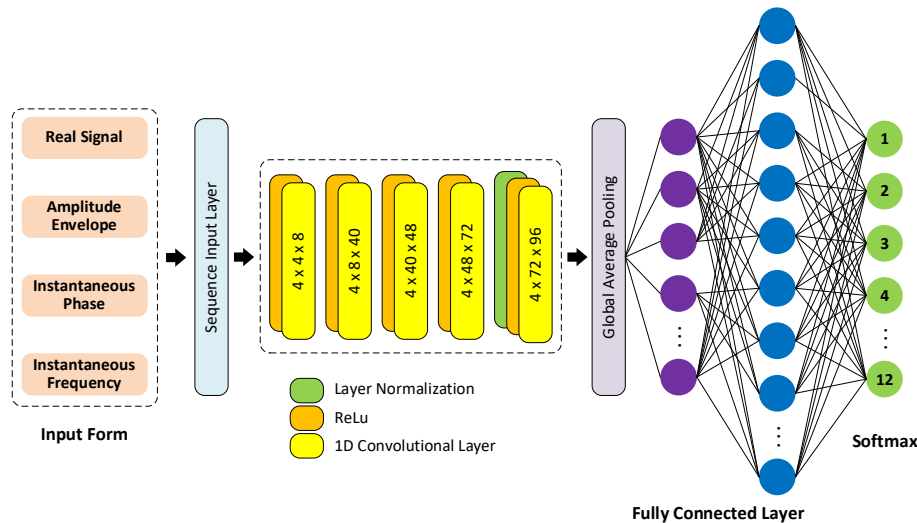


Figure 2. LightCNN network architecture for gas leak detection based on acoustic signals

For gas-leak detection, the LightCNN architecture combines multiple layers that jointly extract features from the acoustic signals to yield accurate leak classifications. Processing starts at the input layer, into which the raw acoustic signal and the three Hilbert-derived features (amplitude envelope, instantaneous phase, and instantaneous frequency) are supplied. From there, the inputs move to a sequence input layer, which treats the data as sequential information for subsequent analysis. The data then progresses through a succession of 1D convolutional layers responsible for extracting the principal signal features, with each layer applying kernels of different sizes to capture a range of signal patterns and characteristics.

Each layer's output feeds forward into the next, with the number of feature maps growing progressively along the way. Layer normalization is incorporated at these stages to keep training stable, while rectified linear unit (ReLU) activation functions supply non-linearity and strengthen the network's learning capacity. Once the signal has traversed the convolutional layers, it is further condensed by a global average pooling layer, which consolidates the extracted feature information, lowers data dimensionality, and helps guard against overfitting. The pooled output is subsequently passed to a fully connected layer, where neurons from the preceding layers are linked together to render classification decisions from the processed information. A softmax layer then converts the network's output into class probabilities, enabling the model to assign each acoustic signal to one of 12 classes corresponding to different gas-leak conditions. In this way, the LightCNN network is built to detect gas leaks by drawing features out of the processed acoustic signals, yielding a classification model that is both accurate and computationally efficient for identifying gas pipeline leaks. Implementation and training of the LightCNN model were carried out in MATLAB via the deep learning toolbox, following the dlnetwork and trainnet workflow. The Adam optimizer was used for

training, with a mini-batch size of 128 over a maximum of 1,000 epochs; since no override was specified, the initial learning rate, gradient decay factor, squared gradient decay factor, and epsilon remained at MATLAB's default Adam-solver values of 0.001, 0.9, 0.999, and 1×10^{-8} , respectively.

2.4. LightCNN performance metrics

To assess how effectively the proposed LightCNN network performs gas leak detection in this study, the model's performance was examined on a test dataset by applying the hold-out validation technique, whereby the dataset was split into 90% for training and 10% for testing. Such a split enables the network to learn from the majority of the available data while reserving a separate portion for testing, thereby confirming its capacity to generalize beyond the training data. Model performance was assessed through five key indicators (accuracy, precision, sensitivity, specificity, and F1-score), which together offer a comprehensive picture of how effectively the model identifies gas leaks in pipelines.

- i) Accuracy, as a metric, quantifies the share of correctly made predictions (encompassing both positive and negative outcomes) relative to the entire set of tested data, and is obtained through the formula shown in (6).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Within this framework, four core components underpin the calculation of the accuracy metric: true positives (TP), denoting the count of gas leaks that the model correctly identifies; true negatives (TN), denoting the count of non-leak conditions correctly classified as such; false positives (FP), denoting non-leak conditions that are mistakenly classified as gas leaks; and false negatives (FN), denoting actual gas leaks that are mistakenly classified as non-leak conditions. Together, these four components feed into the accuracy formula, which expresses the proportion of correct predictions the model produces across the entire test dataset.

- ii) Precision indicates the extent to which the model's positive predictions are accurate (in other words, how many of the predicted gas leaks correspond to genuine leaks) and is computed as in (7).

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

When precision is high, it signifies that a leak prediction made by the model is very likely to be accurate.

- iii) Sensitivity gauges the model's capability to detect genuine gas leaks, reflecting how accurately it identifies positive cases, and is derived from (8).

$$Sensitivity = \frac{TP}{TP+FN} \quad (8)$$

As sensitivity increases, the model becomes more capable of detecting gas leaks that actually occur, although a number of leaks may nonetheless remain undetected.

- iv) Specificity captures how effectively the model recognizes non-leak conditions and how precisely it classifies negative cases, and it is obtained using (9).

$$Specificity = \frac{TN}{TN+FP} \quad (9)$$

A high specificity value shows that the model is proficient at recognizing non-leak conditions while avoiding mistaken classification of such conditions as gas leaks.

- v) Combining precision and sensitivity into a single balanced measure, the F1-score offers particular value when class distribution is uneven; it is obtained through (10), defined as the harmonic mean of precision and sensitivity.

$$F1 - score = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity} \quad (10)$$

An elevated F1-score reflects the model's accuracy in detecting gas leaks together with its robustness in keeping both false positives and false negatives under control.

This assessment was performed on a distinct test dataset that had not been involved in the training process. Employing these five-performance metrics makes it possible to objectively gauge the effectiveness and efficiency of the LightCNN network in detecting gas leaks and to gain insight into how it would perform under real-world conditions. Through this evaluation, the study seeks to show that the proposed method carries considerable potential for detecting gas leaks with high accuracy and precision, while simultaneously keeping classification errors to a minimum, an aspect that can be critical within industrial safety contexts.

3. RESULTS AND DISCUSSION

The objective of this research is to build a leak detection system for gas pipelines that relies on acoustic signals, with the Hilbert transform employed for signal analysis and LightCNN employed for classification. Following the stages set out in the research proposal, the dataset was partitioned using the hold-out validation method, allocating 90% of the data for training and the remaining 10% for testing. This chapter reports the data that were gathered, the analytical results obtained, and the outcomes produced during the first year of the research implementation.

3.1. Results of the Hilbert transform

During the first stage, the Hilbert transform was applied to the acoustic signals drawn from the GPLA-12 dataset to derive three key parameters, and these parameters subsequently served as the input features supplied to the LightCNN model. This procedure yielded three important features that characterize the gas leak signals, as shown in Figure 3. The real signal panel depicts the raw acoustic signals recorded by the sensors for each gas leak class, revealing intricate patterns and pronounced amplitude differences among the various classes. The amplitude envelope panel presents the envelope extracted via the Hilbert transform, with each class showing a characteristic pattern of amplitude variation.

Notably, certain classes (class 5 in particular) exhibit markedly higher envelope amplitudes than the rest, pointing to stronger signal intensity that arises from differing gas leak conditions. The instantaneous phase panel captures the real-time phase shifts of the acoustic signals, spanning a range from $-\pi$ to π radians, and this representation exposes clear differences among the gas leak classes, indicating that phase information is likewise an important parameter for telling leak types apart. The instantaneous frequency panel displays the frequency fluctuations derived from the acoustic signals; because these fluctuations vary from one leak class to another, frequency content stands out as a further key indicator for leak classification. Taken together, the visualization of these four parameters shows that the Hilbert transform is highly effective at producing distinctive and informative features, which are then fed into the classification stage of the LightCNN model. These findings confirm the essential role played by the Hilbert transform within the signal processing pipeline in achieving highly accurate gas leak detection.

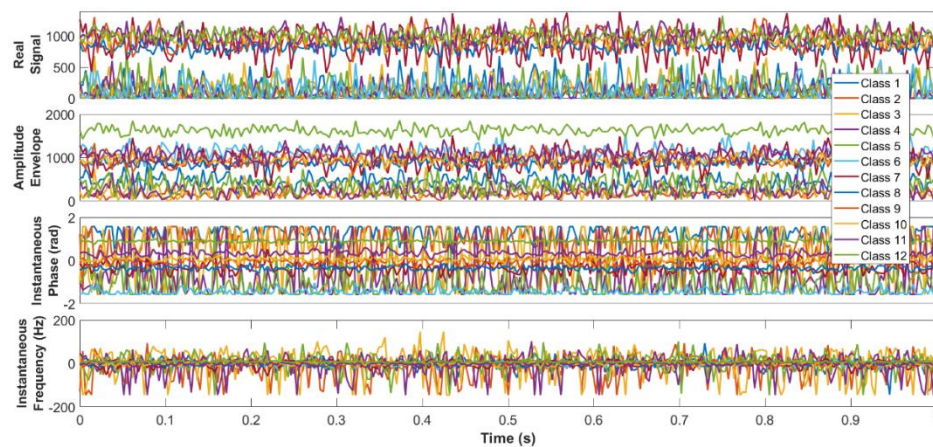


Figure 3. Hilbert transform results

3.2. LightCNN training progress

The training progress of the LightCNN model, illustrating two key performance metrics (loss and accuracy) throughout the training iterations, is shown in Figure 4. This graph provides an overview of the model's learning trajectory from start to finish. The model shows a significant reduction in loss as the number of iterations increases, indicating improved learning and classification performance. At the beginning of training, the loss is relatively high, around 3.5, suggesting that the model initially struggles to map the acoustic signals accurately. However, as training progresses, loss decreases sharply, reaching approximately 0.5 by iteration 1500 and stabilizing between 0.4 and 0.5 thereafter. This steep decline in loss demonstrates that the model is learning effectively and that optimization is functioning well. The consistent drop in loss indicates a successful reduction in prediction errors and enhanced generalization capability to unseen data.

Meanwhile, the accuracy graph (shown in blue) reveals a rapid and steady improvement. Initially, the accuracy is very low, around 10%. However, there is a significant increase between the first and roughly

the 1000th iteration, with accuracy surpassing 50%. After iteration 1500, the accuracy continues to rise steadily, reaching over 90% around iteration 3000 and stabilizing at approximately 92% toward the end of the training process. This sharp increase in accuracy suggests that the model becomes increasingly adept at recognizing complex patterns in the data and classifying gas leaks with high precision. These results also reflect the effectiveness of the features extracted via the Hilbert transform, which provide highly informative inputs that enable the model to differentiate between various gas leak classes more accurately.

Although both loss and accuracy exhibit positive trends, both metrics observe some fluctuations, particularly between iterations 1000 and 2000. These fluctuations may be attributed to larger weight update steps during the exploration phase of training, which often occurs in the early stages when training more complex models. Such variability typically diminishes once the model converges in subsequent iterations, where the loss stabilizes and continues to decrease, while accuracy increases consistently. Overall, the graph demonstrates that the LightCNN training process has progressed successfully.

The marked decline in loss values together with the consistent improvement in accuracy demonstrates that the model successfully learns patterns from the training data, enabling it to classify gas leaks with a high degree of accuracy. Fluctuations observed at the early stages of training are typical of the learning process and diminish naturally as training progresses. These outcomes suggest that the LightCNN model is adequately prepared for evaluation on unseen data and for wider application in gas leak detection systems.

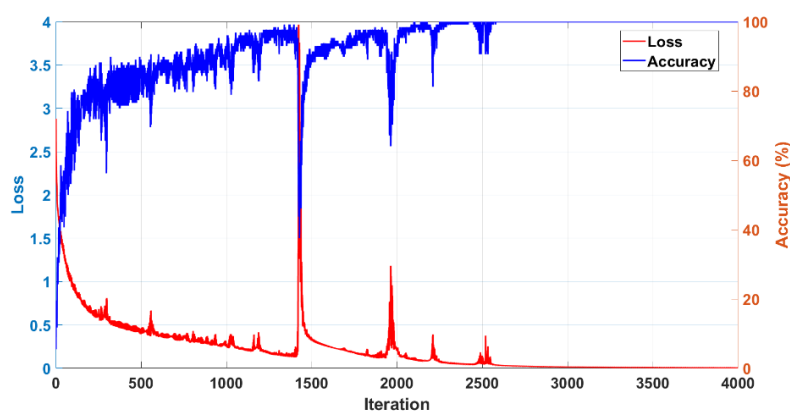


Figure 4. Accuracy and loss values during LightCNN training

3.3. LightCNN performance metrics

On the test dataset, the LightCNN model's classification outcomes point to strong performance in pipeline gas leak detection. As illustrated in Figure 5, the model's precision was measured at approximately 95.60%, signifying that the majority of its gas leak predictions proved to be correct. This outcome illustrates the model's capacity to recognize genuine gas leaks while keeping false positives to a minimum, that is, correctly distinguishing instances in which non-leak conditions were mistakenly flagged as leaks. Moreover, sensitivity reached 96.01%, reflecting how effectively the model captured actual gas leak events. Such accuracy is especially valuable for field deployment, since reliable leak detection helps avert potential hazards and safeguard operational safety.

In addition, the model's specificity reached almost 99.66%, underscoring its robustness in correctly recognizing non-leak conditions rather than misclassifying them as leaks. Such a high level of specificity points to a well-balanced model capable of detecting leaks effectively while keeping false alarms to a minimum. Overall accuracy stood at 96.18%, confirming that the model could reliably distinguish between leak and non-leak conditions. Lastly, an F1-score of approximately 95.33% underscores the balance the model achieves between precision and sensitivity, a quality that is essential for practical gas leak detection systems.

Notably, the classification procedure was carried out 10 times to verify that the results were both reliable and consistent. Since each run produced comparable outcomes, this confirms that the LightCNN model delivers stable and dependable gas leak detection performance. The distribution of metric values is further depicted in the accompanying boxplot, where the majority of results cluster around high mean values, underscoring the model's consistency and reliability. A degree of variability appeared in the specificity measure, although its values remained consistently high throughout. Taken together, these findings confirm that the LightCNN model performs exceptionally well in classifying gas leaks, achieving very low error rates alongside an exceptionally high degree of reliability. These findings suggest that the LightCNN model is well

suited for real-world implementation in gas leak detection systems, functioning as an effective and efficient safeguard that helps prevent hazardous incidents and enhance overall safety.

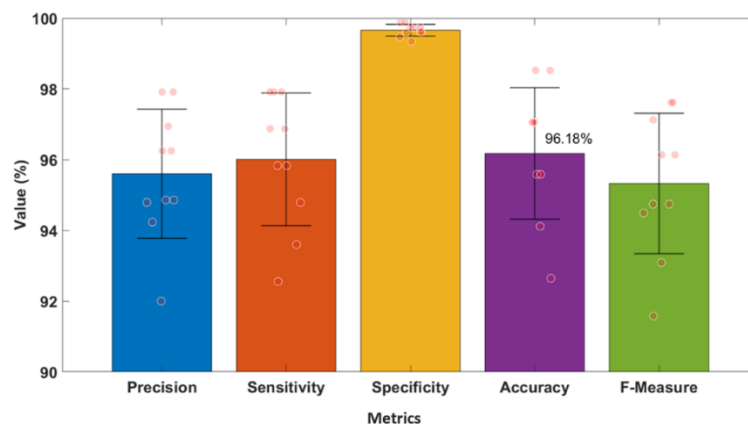


Figure 5. LightCNN performance metrics

3.4. Comparison with previous models

A comparison of the accuracy achieved by the proposed model against several existing gas leak detection models is presented in Table 2. By combining the Hilbert transform with LightCNN, the proposed model reached an accuracy of 96.18%, a result that confirms its strong capability in classifying gas leaks and shows that it surpasses a number of previously published detection models. As an example, Yao *et al.* [24] proposed a model based on an expanded-structural feature encoder-based one-dimensional convolutional neural network (FAE-1D-CNN) combined with energy modal clustering, association-function feature enhancement, and Butterworth low-pass filtering (EAB), which achieved an accuracy of 95.17%. Although this result is commendable, it remains below the accuracy obtained by our proposed method. This comparison shows that despite the effectiveness of the FAE-ID-CNN + EAB technique, the approach presented here, which combines the Hilbert transform with LightCNN, achieves better performance in detecting gas leaks. A further benchmark is provided by Liao *et al.* [25], who applied a deep residual network with channel-wise thresholds and obtained an accuracy of 76.47%, considerably lower than the accuracy of our proposed model. Even though deep residual networks generally perform robustly across many classification tasks, the model proposed in this study shows a substantially stronger capacity for recognizing patterns related to leak events within the gas leak detection domain.

Furthermore, Xu and Chen [19] combined a 1D-CNN with Mamba modules and obtained an accuracy of 93.24%. Although this outcome is fairly promising, it nevertheless remains lower than the result achieved by our proposed model, suggesting that the integration of Hilbert transform-based feature extraction with LightCNN classification provides a clear advantage in terms of detection accuracy. As shown by the comparison summarized in the table, the proposed model, built on the combination of the Hilbert transform and LightCNN, attains the highest accuracy among the current state-of-the-art approaches considered. The accuracy of 96.18% confirms that the proposed model detects gas leaks more effectively than the previous methods examined, supporting the conclusion that pairing Hilbert-based feature extraction with the classification strength of LightCNN yields a highly reliable and superior solution for pipeline leak detection.

Table 2. Accuracy of the proposed model compared to state-of-the-art models

Reference	Approach	Accuracy (%)
Yao <i>et al.</i> [24]	FAE-1D-CNN+ EAB	95.17
Liao <i>et al.</i> [25]	Deep residual network with channel-wise thresholds	76.47
Xu and Chen [19]	1D-CNN and Mamba modules	93.24
This work	Hilbert transform and LightCNN	96.18

4. CONCLUSION

In this study, an efficient and accurate system for detecting gas leaks was successfully constructed through the integration of a LightCNN model with Hilbert transform-based feature extraction of acoustic

signals. On the test dataset, the proposed model attained an accuracy of 96.18%, a result that points to considerable promise for practical deployment, especially in strengthening industrial gas pipeline monitoring systems. Because the Hilbert transform enabled extraction of key descriptors, namely the amplitude envelope, instantaneous phase, and instantaneous frequency, the LightCNN model was able to recognize gas-leak patterns more effectively than models used in earlier studies. Despite these encouraging outcomes, difficulties persist owing to the variability of leak conditions present in the GPLA-12 dataset. Subsequent work will therefore involve evaluating the model on larger and more varied datasets, along with fine-tuning to raise its performance further. Taken as a whole, the research met its intended objective of producing a gas leak detection model that is both more efficient and more accurate, and the approach carries meaningful potential for industrial adoption aimed at improving safety and averting hazardous gas leak incidents. Directions for future research should include broadening dataset diversity, employing fine-tuning or transfer-learning strategies, and building real-time detection systems equipped with advanced sensors. Additionally, testing the model under varied field conditions would help confirm its reliability and suitability for industrial use.

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- Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors confirm that no financial interests or personal relationships could have been perceived as influencing the research presented in this paper.

DATA AVAILABILITY

The data used in this study are sourced from publicly available datasets, which are fully cited and listed in the references section of this manuscript.

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