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# *LISTEN – A Robotic Leak Identification System Using TDNN and ENhanced Acoustic Features for Pipeline Detection*

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***Abstract.*** Gas pipeline leakage leads to serious environmental, economic and mortal risks, yet current detection methods often rely on manual inspection, stationary sensors, or drones with methane sensors, which suffer from low efficiency, limited coverage, and inconsistent accuracy under varying conditions. Aiming to solve the problem, the project proposes "LISTEN," a robotic Leak Identification System using TDNN and ENhanced acoustic features for pipeline detection. The robot's structural components are 3D printed and then assembled with electrical components such as the microphone or the Raspberry Pi, where a novel AI algorithm, ECAPA-TDNN, is deployed. The experimental setup was implemented in the school laboratory, where different pipeline leakage conditions were systematically simulated. Audio samples were collected under varying pressure conditions (0.2 bar and 0.5 bar) and different leakage configurations (1.5 mm hole, 5 mm hole, and 35 mm × 2 mm gap). The algorithm can reach 91% accuracy in the test dataset even with background noises and the robot "LISTEN" can achieve continuous and accurate gas leakage detection during pipeline patrol operations. The system, "LISTEN," offers a promising acoustic-based robot for real-time, high-accuracy gas pipeline leakage detection in the industrial and municipal fields.

***Keywords:*** Pipeline Leakage Detection, Out-pipe Robots, Acoustic Emission, ECAPA-TDNN

## 1. Introduction

Pipelines are crucial for the long-distance transportation of chemicals, petroleum and other resources. However, pipeline leaks can pollute the environment, waste resources and pose a threat to human safety. For instance, if a gas pipeline with a diameter of 0.5 meters leaks, the hazardous area can extend up to 200 meters from the leak point [1, 2] .

The current detection methods include acoustic sensors, pressure monitoring, and unmanned aircraft equipped with methane sensors. Manual detection is also an option, though time-consuming and inefficient [3]. The acoustic emission (AE) method has shown high leakage detection accuracy. Deep learning models such as ECAPA-TDNN, PANNS, and ERes2Net have further improved the performance of AE by extracting time-domain and multi-scale features from acoustic signals,

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enhancing its robustness in noisy industrial environments [4-6]. This study adopts ECAPA-TDNN because it can handle time-domain acoustic data using the attention mechanism and channel feature enhancement.

The implementation methods of leak detection robots are diverse. Some robots combine visual detection with gas, temperature or humidity sensors [7, 8]. However, most robots require manual intervention or threshold-based alerts, which limits their efficiency. The system LISTEN (a robot leak identification system based on TDNN and enhanced acoustic features) can operate completely autonomously, combining acoustic emission with ECAPA-TDNN to achieve high-precision pipeline monitoring. To the author's knowledge, this is the first time that acoustic technology has been implemented on a mobile robot platform, enabling real-time leak detection during patrol operations.

The objective of this study is to design a new type of external structure optimized for pipeline inspection, and fully integrate the acoustic-based AI into the LISTEN system. This system aims to achieve high detection accuracy, operational stability during movement, and adaptability to various environmental conditions, pipeline dimensions, and coverage lengths, while not affecting efficiency or cost-effectiveness.

## 2. Robot design and system integration

### 2.1. Design objectives

This robot is designed to achieve stable and efficient pipeline inspection, while also supporting real-time acoustic leak detection. Based on previous research, an external wheel-driven structure was selected, being highly adaptable, stable, and able to conduct pipeline inspections without interrupting the pipeline operation. Compared to the internal system, the external robot has a lower cost and is more suitable for pipelines with different diameters and environmental conditions.

To improve the accuracy of leak identification, this robot combines the AE sensing system with the ECAPA-TDNN deep learning model. The overall system design aims to maintain stable movement, support autonomous detection, and reduce the limitations of manual pipeline monitoring.

### 2.2. Mechanical structure

This robot adopts a double-ring wheel drive structure to enhance stability during horizontal and vertical movements. Each ring contains multiple motors and wheels to ensure sufficient contact and traction on the pipe surface. The semi-ring configuration also enables the robot to adapt to pipes of different diameters.

All structural components were designed in SolidWorks and manufactured using 3D printing technology. Electrical components including Raspberry Pi, drive motors, batteries, and microphone systems were integrated onto the connection plate between the two rings. This layout can reduce vibration interference to the acoustic sensing system and simplify maintenance and assembly. Figures 1 and 2 show the structural design and prototype development process of the robot, and Figure 3 demonstrates the operation of the robot in horizontal and vertical pipe configurations.

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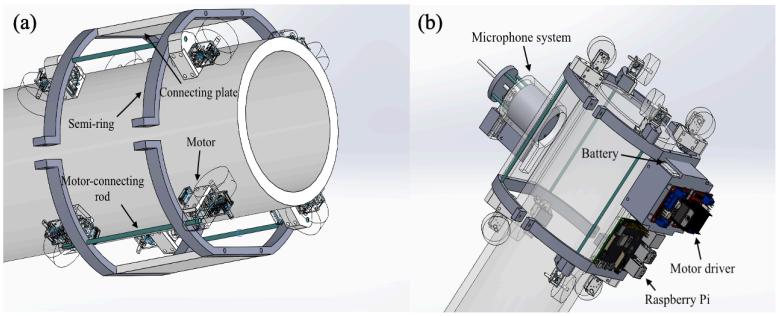


Figure 1. The 3D model of the pipeline detection robot "LISTEN" designed in SolidWorks(a) The external structural assembly (b) The electrical components layout

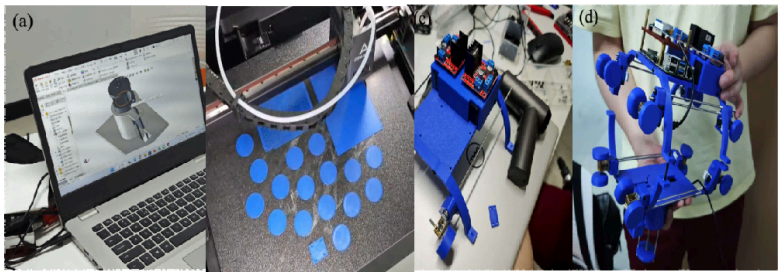


Figure 2. Key stages in the development of the pipeline detection robot "LISTEN" (a) 3D modeling the robot in SolidWorks (b) 3D printing out the structural components (c) Partially assembled robot during construction (d) Integration of electrical and mechanical subsystems

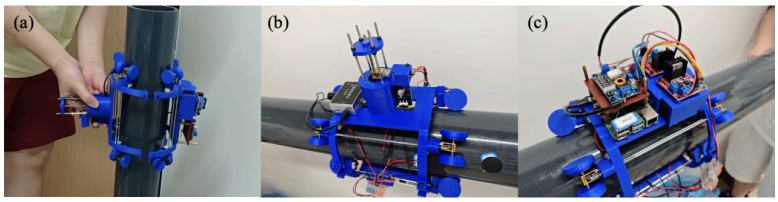


Figure 3. Testing the robot vertically and horizontally on a pipeThe robot vertically on the pipe (b), (c) The robot horizontally on the pipe

## 2.3. Prototype development

The robot uses a contact microphone leak detector to capture the acoustic signals generated by pipeline leaks. The microphone system employs PCM encoding and WAV audio storage to maintain high-fidelity acoustic information for AI analysis.

To ensure the stability of signal acquisition, the microphone is installed on a telescopic mechanism driven by an electric motor. The system integrates a collision sensor to prevent excessive contact force and protect the sensor during operation. During the inspection process, the microphone will record near the pipe surface and retract when the robot moves.

This design minimizes environmental interference and enhances the reliability of leak data collection. Figures 4 and 5 show the microphone system and sensor deployment mechanism.

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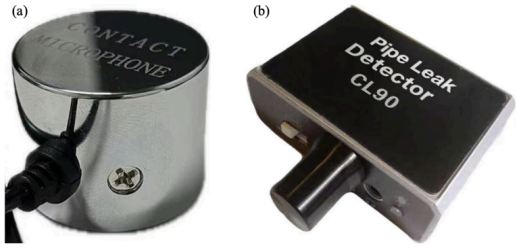


Figure 4. Major components of the microphone system (a) The contact microphone (b) The pipe leak detector that will be connected to the microphone

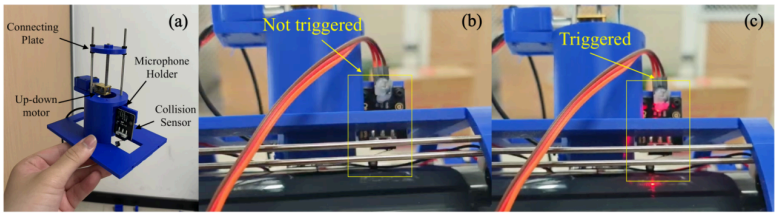


Figure 5. Microphone system layout (a) The overall view of the system (b) The system when the collision sensor is not triggered (c) The system when the collision sensor is triggered

## 2.4 Motion control and system communication

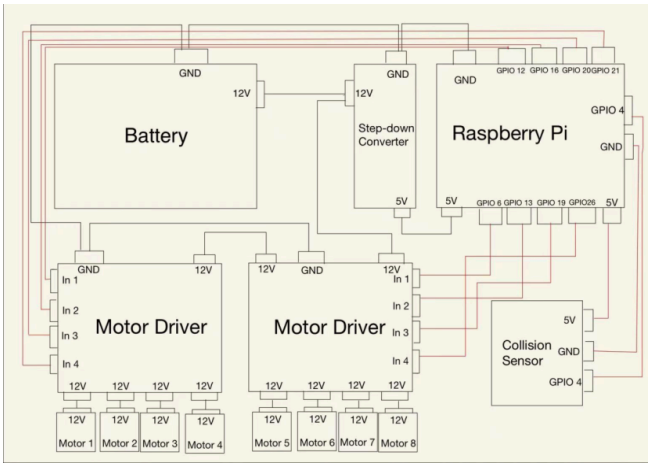


Figure 6. The wiring diagram

The robot is controlled by the Raspberry Pi and the motor drive system. A wireless communication link is established between the robot and the control computer via the TCP protocol, enabling remote operation during pipeline inspection.

The control program manages the movement of the wheels, the extension of the microphone, and the emergency stop function. The collision monitoring algorithm continuously checks the sensor status. If an abnormal contact is detected, the robot will automatically stop, thereby enhancing operational safety and the accuracy of acoustic perception. Figures 6 and 7 show the wiring configuration used by the robot and the collision monitoring system.

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```python
def collision_monitor():
    """
    Background thread that continuously checks collision sensor
    Runs every 10ms for real-time response
    """
    global collision_detected
    while True:
        # Active-low sensor: LOW = collision detected
        if GPIO.input(COLLISION_SENSOR_PIN) == GPIO.LOW:
            if not collision_detected:  # Only act on new collisions
                print("COLLISION DETECTED! Stopping all motors")
                collision_detected = True
                stop_all_motors()  # Emergency stop
        else:
            collision_detected = False
        time.sleep(0.01)  # 10ms polling interval

def stop_all_motors():
    """Immediately stops ALL motor movement"""
    global sensor_moving

    # Stop main motors
    for pin in MAIN_MOTORS['forward'] + MAIN_MOTORS['backward']:
        GPIO.output(pin, GPIO.LOW)

    # Stop sensor motor
    GPIO.output(SENSOR_MOTOR['extend'], GPIO.LOW)
    GPIO.output(SENSOR_MOTOR['retract'], GPIO.LOW)
    sensor_moving = False  # Update state flag
```

Figure 7. The collision detection algorithm

## 3. AI model development

### 3.1. Time Delay Neural Network (TDNN)

The framework adopted in this study, ECAPA-TDNN, is based on the Time Delay Neural Network (TDNN), which is a neural network architecture originally developed for speech recognition tasks [9]. TDNN aims to process temporal acoustic information by analyzing multiple time-delayed features, thereby extracting short-term and long-term patterns from audio signals. This capability makes TDNN suitable for pipeline leak detection, where the acoustic emissions from leaks change over time.

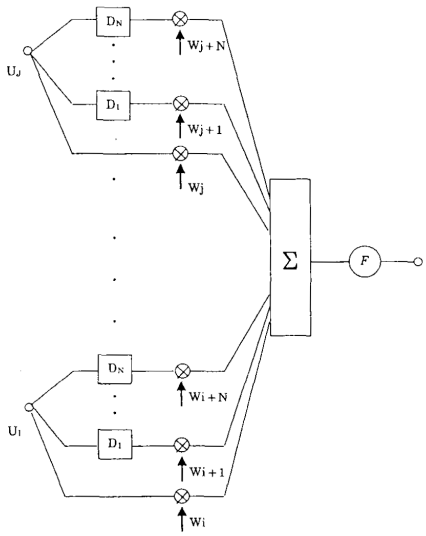


Figure 8. A time-delay neural network (TDNN) unit [9]

Each TDNN unit calculates the weighted combination of acoustic features across multiple time steps and applies a nonlinear activation function to generate higher-level temporal representations. Compared to traditional feedforward neural networks, TDNN offers stronger robustness in sequence

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acoustic analysis and in noisy environments. Figure 8 illustrates the structure of the TDNN unit and its time processing mechanism.

### 3.2. ECAPA-TDNN architecture

To improve the leakage detection performance, this study adopted ECAPA-TDNN (Enhanced Channel Attention, Propagation and Aggregation Time-Delay Neural Network), which is an enhanced version of TDNN and is widely used in acoustic classification and speaker recognition tasks [10].

ECAPA-TDNN introduced several improvements on the traditional TDNN architecture:

• Channel attention statistical pooling, which emphasizes important acoustic regions through the attention mechanism;

• SE-Res2 block, which improves feature extraction by modeling the interdependence of channels and multi-scale acoustic patterns;

• Multi-layer feature aggregation, enabling the model to combine representations from different network depths to achieve more robust classification.

These mechanisms enable the model to better distinguish leakage sounds from background noise and mechanical interference generated during the robot's movement. Figures 9 shows the SE-Res2 block used in this study and the overall ECAPA-TDNN architecture.

Compared with traditional acoustic analysis methods, ECAPA-TDNN demonstrates stronger feature representation capabilities and higher robustness in noisy industrial environments, making it suitable for real-time pipeline leakage monitoring.

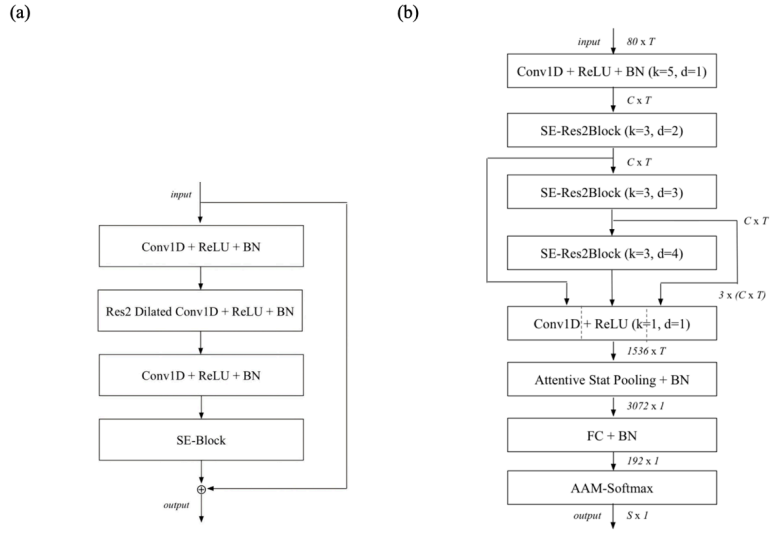


Figure 9. ECAPA-TDNN's architecture (a) The SE-Res2Block of the ECAPA-TDNN architecture (b) Network topology of the ECAPA-TDNN [10]

### 3.3. AI model implementation and open-source framework

The artificial intelligence model used in this study was implemented based on the open-source PyTorch framework. The ECAPA-TDNN architecture was adapted from an available public implementation and modified for acoustic-based pipeline leakage detection.

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This model processes audio recordings collected by a contact microphone system and extracts time-based acoustic features for classification. WAV audio files encoded in PCM format were used as the input format to preserve high-fidelity leakage information.

Fivefold cross-validation was employed for training and evaluation. Data augmentation techniques, including background noise addition, audio cropping, and pitch variation, were applied to enhance the model's robustness in actual industrial environments.

The lightweight structure implemented in PyTorch also enables its deployment on Raspberry Pi hardware, allowing the robot to perform real-time acoustic analysis during pipeline inspection.

## 4. Experiment and performance evaluation

### 4.1. Experimental setup

To evaluate the performance of the proposed system, a leakage condition was simulated using DN80 and DN100 pipes with a length of 1 meter. Both ends of the pipes were sealed, and compressed air was injected through an external air pump to create internal pressure conditions. Based on the preliminary safety tests, the experiments were conducted at pressures of 0.2 bar and 0.5 bar.

Three different types of leakage were designed to simulate actual pipeline failures:

- A circular hole with a diameter of 1.5 millimeters,
- A circular hole with a diameter of 5 millimeters, and
- A rectangular crack with dimensions of 35 millimeters by 2 millimeters.

These leakage configurations represent minor perforations, severe structural damage, and cracks caused by corrosion. Figures 10 and 11 show the experimental pipeline setup and leakage configurations.

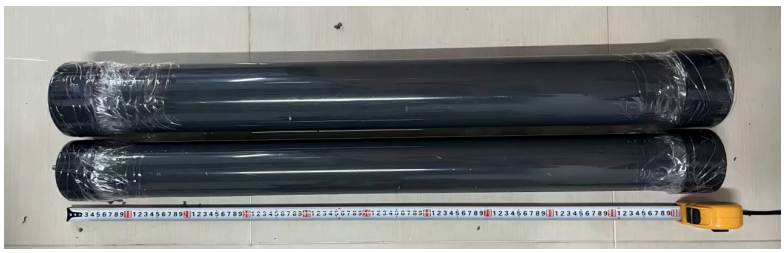

Figure 10. The two pipes used for simulation: the upper pipe has size DN100 and the lower pipe has size DN80; both pipes have length one meter

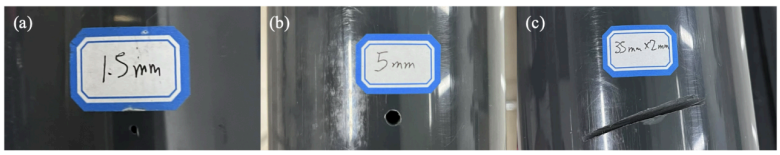


Figure 11. Three types of leakages (a) Hole of 1.5 mm diameter (b) Hole of 5 mm diameter (c) A 35 mm × 2 mm gap

To enhance the diversity of the dataset, acoustic recordings were collected at multiple locations around the leakage area. Additional background noise simulations, including pipe knocking sounds and wheel rolling sounds, were introduced to evaluate the model's robustness under actual operating conditions.

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## 4.2. Data collection and processing

The audio recordings were collected using a contact microphone system integrated in the robot. In each experiment, compressed air was injected into the pipeline until the target pressure was reached, then the leak hole was released and the acoustic signals were recorded. Each recording lasted approximately 8 seconds.

All audio samples were stored in WAV format with PCM encoding to preserve detailed acoustic information for AI analysis. The collected dataset includes:

- The situation without leakage under normal pipeline conditions,
- Leakage conditions under different pressures,
- Different leak geometries,
- Background noise simulation.

After data collection was completed, the audio files were classified and processed for model training and evaluation. Figures 12 and 13 show the recording locations and the experimental process.

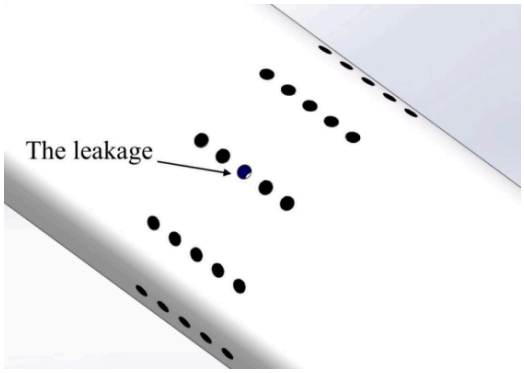


Figure 12. The locations where the microphone collects data marked on the pipe, with 1 cm between circles and the blue one being the leakage

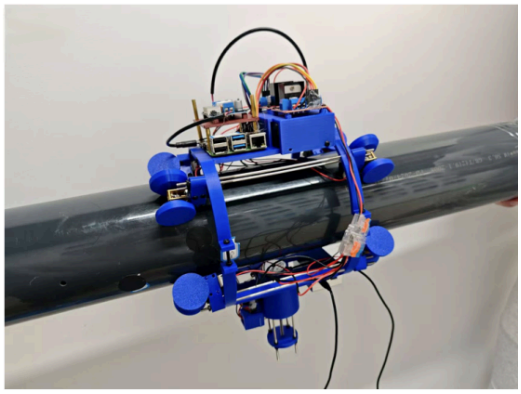

Figure 13. The completed robot in operation

## 4.3. Model training and evaluation

The ECAPA-TDNN model was trained and evaluated using five-fold cross-validation to enhance generalization performance and reduce overfitting. Data augmentation methods were applied, including background noise addition, audio cropping, and pitch variation, to increase the diversity

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and robustness of the dataset. Multiple experiments were conducted with different dataset sizes and training iteration numbers to evaluate the model performance.

The initial model achieved approximately 73% accuracy with limited data and training iterations. After increasing the dataset size and applying robust training, the final model achieved approximately 91% accuracy in distinguishing between leakage and non-leakage conditions. The training results showed that as the training progressed, the loss gradually decreased and the accuracy gradually stabilized, indicating good feature learning and optimization effects.

As shown in Figure 14, the learning rate changed during the training process, which helped the model gradually converge during optimization. Figure 15 presents the confusion matrix of the final classification results, showing that the model achieved high classification performance for both leakage and normal conditions. The confusion matrix indicates that most leakage samples and normal samples were correctly classified, with only a small proportion of misclassifications.

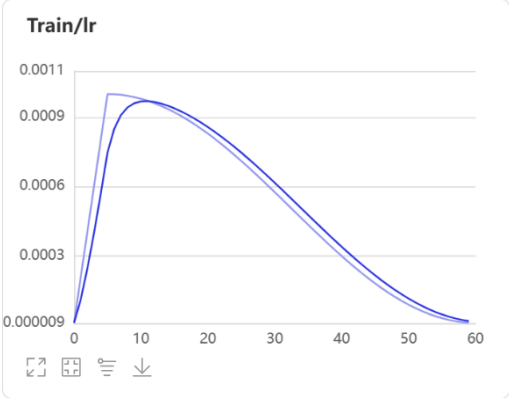


Figure 14. Learning rate of the initial model

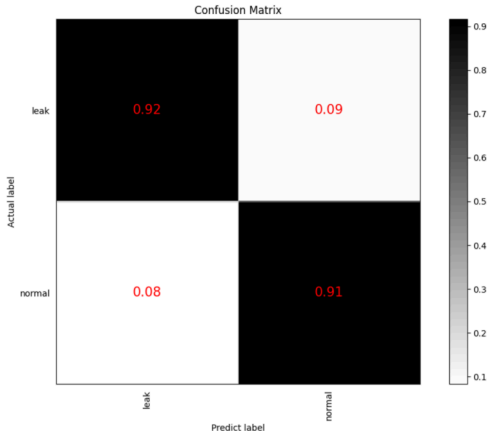


Figure 15. The confusion matrix

In addition, Figures 16 and 17 show the accuracy and loss curves of the model on the testing and training datasets, respectively. The testing curves in Figure 16 demonstrate that the model performance became more stable as training progressed, while the training curves in Figure 17 show that the training accuracy increased and the training loss decreased over time. These results indicate that the ECAPA-TDNN model successfully learned discriminative acoustic features for pipeline leakage detection.

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Figure 16. Accuracy and loss graphs of the initial model detecting testing sets' leakages

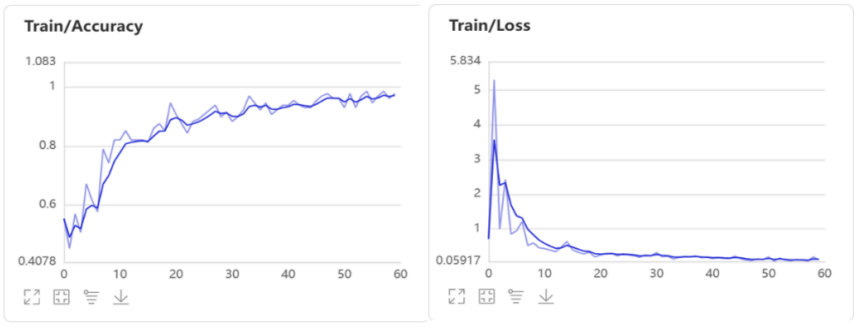


Figure 17. The accuracy and loss graphs of the initial model detecting training sets' leakage

Overall, Figures 14–17 demonstrate the complete training and evaluation process, including the learning rate schedule, confusion matrix, testing performance, and training convergence behavior. The results confirm that the proposed acoustic deep learning model can achieve reliable leakage detection under different leakage conditions and background noise environments.

### 4.4. System performance and discussion

The experimental results show that the proposed LISTEN system can perform stable and accurate acoustic-based pipeline leakage detection under various pressure conditions and noise environments. By integrating the wheeled-driven robot platform with the ECAPA-TDNN model, the pipeline can achieve continuous inspection and autonomous acoustic monitoring.

Compared with traditional manual inspection and threshold-based sensing systems, the proposed method not only maintains a lower system cost but also enhances the degree of automation, adaptability and detection accuracy. The results also indicate that acoustic-based artificial intelligence detection has great potential in industrial and municipal pipeline inspection applications.

## 5. Data analysis and results

### 5.1. Model performance metrics

The ECAPA-TDNN model was evaluated for pipeline leakage detection using the collected dataset. The key performance indicators included accuracy, precision, recall rate and F1 score, which were calculated using the confusion matrix.

The results of the final model are shown in Table 1:

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Table 1. ECAPA-TDNN model performance

| Metric | Leak Class | Normal Class |
|---|---|---|
| Accuracy | 0.91 | 0.92 |
| Precision | 0.91 | 0.91 |
| Recall | 0.92 | 0.91 |
| F1 Score | 0.91 | 0.91 |

The overall accuracy rate is 91%, indicating that the classification is reliable under various leakage types and background noise conditions. The confusion matrix (Figure 15) visually shows the clear distinction between the leakage signal and the normal signal.

### 5.2. Robustness evaluation

To assess the robustness of the model, data augmentation techniques were applied during the training process, including:

- Adding simulated background noises (such as pipe knocking sounds and wheel rolling sounds),
- Trimming audio samples,
- Modifying pitch and tone.

These enhancement methods improved the generalization ability of the model, enabling accurate detection even in noisy and variable operating conditions. The model consistently maintained an accuracy rate of over 90% in multiple test scenarios, demonstrating its reliability for practical deployment.

## 6. Conclusion

The results confirmed that the LISTEN system can effectively integrate acoustic perception with deep learning for pipeline leakage detection. The main advantages include:

1. Automation and efficiency: The robot can inspect the pipeline without human intervention, thereby reducing labor costs.

2. High accuracy: ECAPA-TDNN can achieve precise detection even in small leaks and noisy environments.

3. Operational adaptability: The wheel-driven external pipe design enables it to move stably on pipes of different diameters.

4. Cost-effectiveness: Compared to traditional sensing systems, 3D-printed components and open-source AI frameworks can achieve low-cost implementation.

Overall, the combination of robot mobility and acoustic deep learning shows significant potential in industrial and municipal pipeline monitoring.

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