

Development of Smart Underground Drainage Leak Detection and Localization Using Acoustic and Flow Sensing with TINYML and IOT

Elezabeth Skaria¹, Kavitha Issac², Aby Krishnan U³, Aginesh K L⁴, Abhinand S R⁵, Mohamed Islah K I⁶

Assistant Professor Department of EEE, Mar Athanasius College of Engineering, Kothamangalam, Kerala

Associate Professor Department of EEE, Mar Athanasius College of Engineering, Kothamangalam, Kerala

UG Student Department of EEE, Mar Athanasius College of Engineering, Kothamangalam, Kerala

UG Student Department of EEE, Mar Athanasius College of Engineering, Kothamangalam, Kerala

UG Student Department of EEE, Mar Athanasius College of Engineering, Kothamangalam, Kerala

UG Student Department of EEE, Mar Athanasius College of Engineering, Kothamangalam, Kerala

Abstract -Underground pipeline leakage leads to significant water loss, infrastructure damage, and economic impact, necessitating efficient detection and localization methods. This paper presents a smart leak detection system that integrates acoustic sensing, flow monitoring, Tiny Machine Learning (TinyML), and Internet of Things (IoT) technologies for real-time analysis. A hybrid sensing approach is employed, where flow sensors detect anomalies and trigger acoustic analysis using digital microphones. A lightweight TinyML model is deployed on an ESP32 microcontroller to classify leak signatures from background noise, reducing false alarms. Leak localization is achieved using the Time Difference of Arrival (TDOA) algorithm based on synchronized acoustic signals. Simulation studies using MATLAB Simulink and ANSYS validate the localization accuracy and fluid dynamics behavior. Experimental results demonstrate reliable leak detection with real-time cloud monitoring via Firebase. The proposed system offers a low-cost, energy-efficient, and scalable solution for smart water infrastructure monitoring.

Key Words: Leak Detection, TinyML, IoT, Acoustic Sensing, Flow Sensor, TDOA, ESP32

I. INTRODUCTION

Underground pipeline networks form the backbone of modern urban infrastructure, enabling efficient water distribution across residential, industrial, and agricultural sectors. However, pipeline leakage remains a persistent and critical issue, leading to substantial water loss, infrastructure damage, and economic burden. This loss, commonly referred to as Non-Revenue Water (NRW), accounts for a significant percentage of total water supply in many regions, particularly in developing countries. In

addition to economic impact, prolonged leakage can cause soil erosion, structural instability, and contamination of surrounding environments.

Traditional leak detection techniques, including manual inspection, pressure monitoring, and periodic acoustic surveys, are predominantly reactive in nature. These approaches are labor-intensive, time-consuming, and often fail to detect leaks at an early stage. Moreover, the underground nature of pipelines makes direct inspection difficult, resulting in delayed identification and increased repair costs. As urban infrastructure continues to expand, there is an urgent need for automated, real-time, and scalable leak detection solutions.

Recent advancements in sensing technologies and embedded systems have enabled the development of intelligent monitoring systems. Acoustic sensing methods detect leak-induced vibrations generated by pressurized fluid escaping through pipe defects, while flow sensors identify anomalies in hydraulic behavior. Although both approaches provide valuable information, standalone implementations suffer from limitations. Acoustic methods are highly sensitive to environmental noise and signal attenuation, whereas flow-based methods lack the capability to accurately localize leaks.

To address these challenges, hybrid sensing approaches combining multiple modalities have gained attention. By integrating flow and acoustic data, it is possible to improve detection reliability and reduce false alarms. Furthermore, the emergence of Tiny Machine Learning (TinyML) has enabled the deployment of machine learning models directly on resource-constrained embedded devices. This allows real-time data processing at the edge, eliminating the need for continuous cloud communication, reducing latency, and enhancing data privacy.

In this work, a smart underground pipeline leak detection and localization system is proposed, integrating flow sensing, acoustic sensing, TinyML, and IoT technologies. The system employs a two-stage detection mechanism, where flow sensors first identify potential anomalies, triggering acoustic analysis for confirmation using a lightweight neural network model. Leak localization is achieved using the Time Difference of Arrival (TDOA) algorithm, which calculates the leak position based on the time delay between signals received by spatially separated sensors.

The remainder of this paper is organized as follows. Section II presents the related work on acoustic leak detection, flow-based monitoring, TinyML, and IoT-enabled pipeline systems. Section III describes the proposed system architecture, including the hybrid sensing framework and overall workflow. Section IV details the methodology, covering data acquisition, preprocessing, feature extraction, TinyML model deployment, and TDOA-based localization. Section V explains the simulation and validation studies carried out using MATLAB Simulink and ANSYS to verify the localization algorithm and pipeline behavior. Section VI presents the hardware implementation of the ESP32-based prototype, acoustic sensors, flow sensor, and IoT communication module. Section VII discusses the experimental results and system performance. Finally, Section VIII concludes the paper and outlines future scope.

II. RELATED WORK

Recent research on underground pipeline leak detection has increasingly focused on integrating acoustic sensing, machine learning, and embedded systems to improve detection reliability in complex environments. Studies have shown that acoustic feature extraction can effectively capture the unique sound signatures generated by leaks and distinguish them from background noise [1]. These approaches demonstrate high accuracy and feasibility for real-world deployment using TinyML on resource-constrained devices. However, acoustic-based systems remain sensitive to environmental noise, sensor placement, and soil conditions, which can significantly affect performance.

To improve signal quality, several works have incorporated advanced preprocessing techniques. Signal decomposition methods combined with convolutional neural networks (CNNs) have been used to denoise acoustic signals before classification, resulting in high

detection accuracy under controlled conditions [2]. Despite these improvements, many such approaches treat leak detection and localization as separate processes, increasing system complexity and processing latency.

Alternative approaches have explored simplified deep learning architectures capable of performing both detection and localization using a single sensor [3]. While these systems reduce hardware complexity and eliminate the need for separate preprocessing stages, they introduce reliability concerns due to the lack of redundancy. Dependence on a single sensing unit makes the system vulnerable to failure, which is undesirable in critical infrastructure monitoring.

The influence of pipeline material properties on acoustic signal propagation has also been extensively studied. Investigations into PVC pipeline monitoring highlight challenges such as signal attenuation and reduced wave propagation clarity compared to metallic pipelines [4]. These factors must be considered when designing detection systems, particularly for underground drainage networks where accurate modeling of sound velocity and signal loss is essential.

In addition to acoustic analysis, flow-based anomaly detection techniques have been proposed to enhance system reliability. Methods that model normal operating conditions under time-varying flow environments enable the identification of subtle deviations indicative of leaks [5]. Such approaches help distinguish actual leak events from normal fluctuations in pipeline usage, thereby reducing false positives.

Recent advancements also emphasize the benefits of combining multiple sensing modalities. Hybrid approaches that integrate transient flow simulation with multi-feature data fusion and artificial intelligence have demonstrated improved accuracy and robustness compared to single-method systems [6]. These findings support the use of integrated frameworks that combine acoustic sensing, flow analysis, and machine learning for comprehensive leak detection and localization.

From the reviewed literature, it is evident that many existing systems focus on either detection, signal processing, or localization independently. There remains a significant need for a unified, low-cost solution that integrates acoustic classification, flow-based verification, and TDOA-based localization within an embedded edge computing framework. The present work addresses this gap by combining simulation-driven validation, TinyML-based acoustic confirmation, spatial localization techniques, and IoT-enabled monitoring into a single cohesive system.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed system is designed as a hybrid, edge-based leak detection and localization platform that integrates flow sensing, acoustic analysis, embedded machine learning, and IoT communication. The architecture follows a hierarchical two-stage detection strategy to ensure high reliability, low power consumption, and real-time operation.

3.1 Overall System Architecture

The overall system architecture is composed of four tightly coupled modules:

- Hydraulic Monitoring Module (Flow Sensing)
- Acoustic Sensing Module
- Edge Intelligence Module (ESP32 + TinyML)
- IoT Communication and Visualization Module

These modules interact in a sequential and conditional workflow to ensure accurate leak detection and localization.

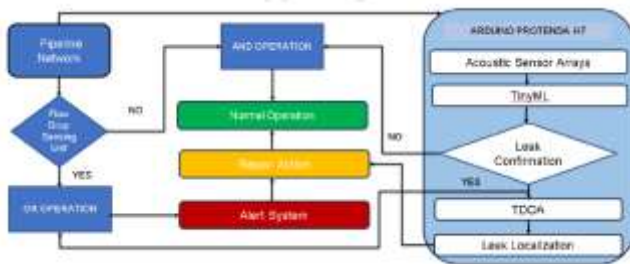


Figure 1: Block Diagram

3.2 Hydraulic Monitoring Module

The hydraulic monitoring module acts as the primary detection layer. A Hall-effect based flow sensor continuously measures the volumetric flow rate within the pipeline. Under normal operating conditions, the flow rate remains within a stable range determined through calibration.

A deviation in flow rate beyond a predefined threshold indicates a potential leak or abnormal condition. This deviation serves as a trigger signal for activating the acoustic sensing module. By limiting acoustic processing to only anomalous conditions, the system achieves significant power savings and reduces unnecessary data processing.

3.3 Acoustic Sensing Module

The acoustic sensing module consists of two high-sensitivity digital microphones placed along the pipeline at a known distance. These sensors capture the acoustic emissions generated due to turbulence and pressure release when a leak occurs.

The microphones operate using the I2S protocol, ensuring synchronized sampling with high temporal resolution (typically 16 kHz). This synchronization is critical for accurately capturing the time delay between signals required for localization.

The placement of sensors at a fixed baseline allows the system to capture spatially distributed acoustic data, forming the basis for Time Difference of Arrival (TDOA) analysis.

3.4 Edge Intelligence Module

The ESP32 microcontroller serves as the central processing unit, responsible for executing signal processing, machine learning inference, and localization algorithms.

The processing pipeline includes:

- Acquisition of synchronized acoustic signals
- Preprocessing and noise filtering
- Feature extraction using Mel-Frequency Energy (MFE)
- Classification using a lightweight TinyML model
- Cross-correlation analysis for time delay estimation
- Leak position calculation using TDOA

The TinyML model is optimized for embedded deployment, enabling real-time classification with minimal memory and computational requirements. This edge-based approach eliminates the need for continuous cloud communication, reducing latency and improving data privacy.

3.5 Two-Stage Leak Detection Strategy

The system implements a logical two-stage detection mechanism:

- Stage 1: Detection of flow anomaly
- Stage 2: Confirmation using acoustic classification

A leak is confirmed only when both conditions are satisfied. This dual-validation approach significantly improves system robustness by minimizing false positives caused by transient flow variations or environmental acoustic noise.

3.6 Leak Localization Using TDOA

Upon confirmation of a leak, the system initiates localization using the Time Difference of Arrival (TDOA) algorithm. The method estimates the time delay between acoustic signals received at the two microphones.

Using the known sensor spacing and acoustic wave velocity, the leak position is computed. The accuracy of localization depends on precise synchronization, signal quality, and correct estimation of wave propagation speed.

This method enables real-time localization without requiring additional sensors, making it cost-effective and scalable.

3.7 IoT Communication and Visualization

The final stage involves transmitting processed data to a cloud platform using the ESP32's integrated Wi-Fi module. The transmitted data includes:

- Leak detection status
- Flow rate values
- Estimated leak location

A real-time dashboard (web or mobile application) provides visualization of system parameters, enabling remote monitoring and rapid response. This integration supports scalability and facilitates deployment in smart water management systems.

Overall, the proposed architecture combines hybrid sensing, edge intelligence, and IoT connectivity to deliver an efficient and reliable solution for pipeline leak detection and localization.

IV. METHODOLOGY

The methodology adopted in this work presents a structured framework for real-time leak detection and localization using a hybrid sensing approach combined with embedded machine learning and IoT integration. The system is designed to operate in an event-driven manner,

ensuring efficient utilization of computational and energy resources while maintaining high detection accuracy.

4.1 System Operation Strategy

The system follows a hierarchical two-stage detection mechanism. Initially, the hydraulic monitoring unit continuously observes the pipeline flow conditions. A deviation in flow rate beyond a predefined threshold indicates a potential anomaly and triggers the activation of the acoustic sensing and processing pipeline.

Once activated, synchronized acoustic data is captured and processed in real time using a TinyML classifier deployed on the ESP32 microcontroller. If the classifier confirms the presence of a leak, the system proceeds to estimate the leak location using the Time Difference of Arrival (TDOA) algorithm. The final results are transmitted to a cloud-based IoT platform for visualization and monitoring.

4.2 Data Acquisition and Synchronization

Accurate data acquisition is critical for both detection and localization. The system employs dual sensing modalities:

• Flow Data Acquisition:

The YF-S201 flow sensor generates pulse signals proportional to the volumetric flow rate. These pulses are captured using hardware interrupts to ensure precise timing and minimal CPU intervention. The flow rate is computed based on pulse frequency, enabling continuous monitoring.

• Acoustic Data Acquisition:

Two INMP441 digital microphones are interfaced with the ESP32 using the I2S protocol. The use of I2S ensures synchronized sampling of both channels, which is essential for accurate time delay estimation. The sampling frequency is set to 16 kHz, providing sufficient resolution to capture leak-induced acoustic signatures.

• Synchronization Considerations:

Synchronous acquisition of acoustic signals is crucial for TDOA accuracy. The ESP32 utilizes its dual-core architecture and DMA buffers to ensure consistent and simultaneous data capture from both microphones without timing jitter.

4.3 Signal Conditioning and Preprocessing

Raw acoustic signals are often contaminated with environmental noise, mechanical vibrations, and electrical interference. To improve signal quality, preprocessing is performed as follows:

- Segmentation of continuous signals into fixed-length frames
- Amplitude normalization to maintain consistency across samples
- Basic filtering to suppress low-frequency noise and high-frequency artifacts
- Removal of DC offset to stabilize signal baseline

These preprocessing steps ensure that the input to the feature extraction stage is clean, stable, and suitable for classification.

4.4 Feature Extraction Using Time-Frequency Analysis

To enable efficient machine learning inference, the preprocessed acoustic signals are transformed into compact feature representations using time-frequency analysis.

Mel-Frequency Energy (MFE) features are extracted using Short-Time Fourier Transform (STFT). This transformation converts the one-dimensional time-domain signal into a two-dimensional representation capturing both temporal and spectral characteristics. The parameters used for feature extraction are:

- Frame length: 20 ms
- Frame stride: 10 ms
- FFT size: 256 points
- Number of Mel filter banks: 40

The Mel scale is used to emphasize perceptually relevant frequency bands, which helps the model distinguish leak signatures from background noise. This feature representation significantly reduces data dimensionality while preserving essential information.

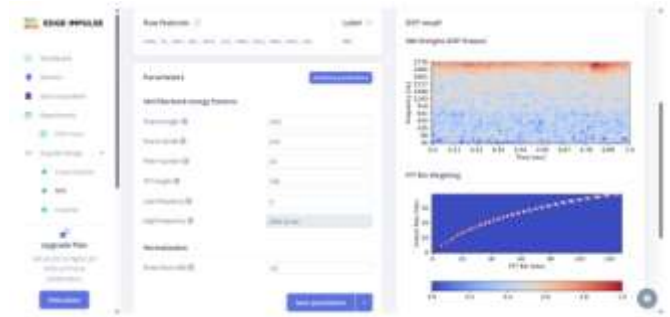


Figure 2: Acoustic Feature Extraction and TinyML Classification Pipeline

4.5 TinyML Model Design and Deployment

A lightweight 1D Convolutional Neural Network (CNN) is employed for acoustic classification. The model is trained using the Edge Impulse platform, which provides an optimized pipeline for embedded machine learning.

- Model Architecture:

The CNN consists of convolutional layers for feature extraction followed by fully connected layers for classification. The architecture is designed to balance accuracy and computational efficiency.

- Training Process:

The dataset includes labeled samples of leak sounds and background noise. The model is trained to minimize classification error while maintaining generalization capability.

- Model Optimization:

Post-training quantization is applied to reduce model size and enable efficient execution on the ESP32. The final model is deployed as an embedded inference engine using C/C++ libraries.

- Real-Time Inference:

During operation, extracted features are fed into the TinyML model, which outputs a probability score. A threshold-based decision rule is used to classify the signal as either "Leak" or "No Leak."

4.6 Time Delay Estimation and TDOA Localization

Upon confirmation of a leak, the system estimates its location using the Time Difference of Arrival (TDOA) algorithm. The method calculates the time delay between acoustic signals received at the two microphones

The delay is estimated using cross-correlation of the two signals. The peak of the cross-correlation function corresponds to the time lag between signals. The leak position is then computed using:

$$p=(x1+x2)/2+(v\Delta t)/2$$

where x_1 and x_2 represent sensor positions, v is the acoustic wave velocity, and Δt is the measured time difference.

- Cross-Correlation Method:

The time delay between signals received at the two microphones is calculated using cross-correlation. The peak of the cross-correlation function indicates the time lag between signals.

- Localization Equation:

The leak position is computed based on the relationship between sensor positions, acoustic velocity, and time delay.

- Acoustic Velocity Consideration:

The speed of sound in the pipeline depends on factors such as pipe material, fluid properties, and temperature. This parameter is estimated based on simulation and experimental calibration.

4.7 IoT Communication and Data Handling

The ESP32 transmits processed data to a Firebase cloud database using its built-in Wi-Fi module. The data includes leak detection status, flow rate, and estimated location.

The cloud platform enables real-time storage and visualization of system parameters. A mobile application developed using MIT App Inventor provides a user-friendly interface for monitoring system status and receiving alerts.

4.8 System Integration and Implementation Considerations

The complete system integrates sensing, processing, machine learning, and communication into a unified embedded platform. Key design considerations include:

- Minimization of power consumption through event-driven processing

- Efficient memory utilization for TinyML deployment
- Robust communication for real-time IoT updates
- Scalability for deployment in larger pipeline networks

The proposed methodology ensures reliable and efficient leak detection and localization while maintaining compatibility with resource-constrained embedded systems.

V. SIMULATION AND VALIDATION

This section presents a comprehensive simulation-based validation of the proposed hybrid leak detection and localization system. The objective of this phase is to verify the mathematical correctness of the localization algorithm, analyze the physical behavior of leaks in pipelines, and establish the feasibility of acoustic and hydraulic sensing prior to hardware implementation.

The validation is carried out using MATLAB Simulink for algorithm verification and ANSYS Fluent for fluid dynamics and acoustic analysis.

5.1 Validation of TDOA-Based Localization

The Time Difference of Arrival (TDOA) algorithm forms the core of the leak localization process. To verify its correctness, a simulation model was developed in MATLAB Simulink. The model replicates the behavior of two spatially separated acoustic sensors receiving signals generated by a leak source.

The inputs to the simulation include:

- Positions of the two sensors
- Speed of sound in the medium
- Time delay between the received signals

Based on these inputs, the model computes the leak position using the derived localization equation.

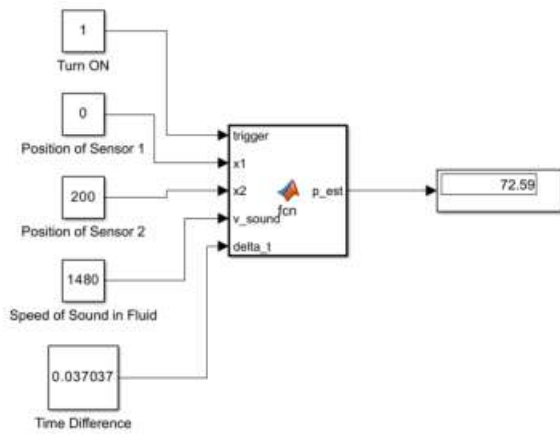


Figure 3: Simulink Model Of TDOA

The simulation results demonstrate that the estimated leak position closely matches the theoretical value. For a given time delay input, the deviation between the simulated and expected positions is minimal, confirming the mathematical validity of the TDOA formulation. This establishes that the localization algorithm is suitable for real-time implementation.

5.2 Analysis of Acoustic Signal Delay

To further validate the localization principle, the time-domain acoustic signals received at the two sensors were analyzed. Due to the finite propagation speed of sound, the signal originating from the leak reaches each sensor at slightly different times.

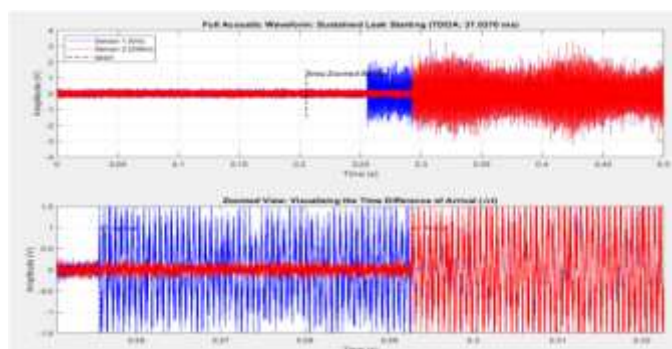


Figure 4: Acoustic Sensor Inputs For TDOA Calculation

The plotted signals clearly show a temporal shift between the two waveforms. This time shift corresponds to the propagation delay of the acoustic wave along the pipeline. The ability to detect this delay is critical for accurate localization.

The analysis confirms that even small time differences can be captured and used effectively for position estimation, provided that the sampling rate and synchronization are sufficiently precise.

5.3 Fluid Dynamics Analysis Using ANSYS

To understand the physical impact of leakage on pipeline behavior, a Computational Fluid Dynamics (CFD) simulation was conducted using ANSYS Fluent. A pipeline model of length 2 m and diameter 35 mm was constructed, with a leak introduced at a distance of 1.5 m from the inlet.



Figure 5: Ansys Simulation of Whole Pipe

The simulation reveals a localized pressure drop at the leak point. This occurs due to the escape of fluid through the leak, resulting in a reduction in internal pressure. The pressure gradient observed in the simulation validates the effectiveness of flow-based anomaly detection.

Additionally, the simulation demonstrates that the magnitude of pressure variation is sufficient to be detected by standard flow sensing mechanisms, supporting the use of flow sensors as the primary detection stage.

5.4 Velocity Distribution and Flow Behaviour

The velocity profile along the pipeline was analyzed to evaluate the effect of leakage on fluid flow characteristics.

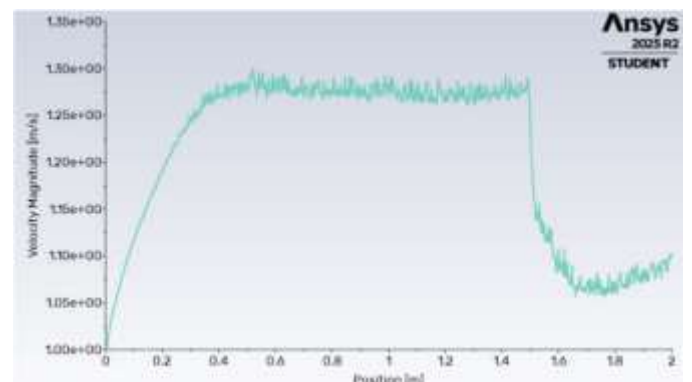


Figure 6: Fluid Flow Velocity Along Pipe Length

The results indicate that the fluid velocity remains relatively stable upstream of the leak. However, a noticeable reduction in velocity is observed downstream of the leak location. This behavior occurs because a portion of the fluid exits through the leak, reducing the flow rate in the remaining pipeline.

This observation confirms that flow sensors can effectively detect anomalies caused by leakage, providing a reliable trigger for activating the acoustic analysis stage.

5.5 Acoustic Energy Distribution Analysis

The acoustic characteristics of the leak were analyzed through simulation to validate the feasibility of acoustic-based detection.

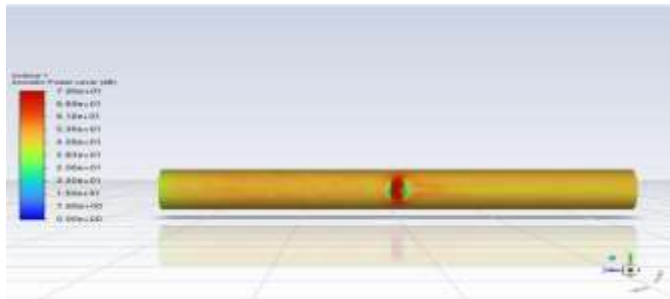


Figure 7: Acoustic Power Level in Db Throughout the Pipe

The results show a strong concentration of acoustic energy at the leak location, which propagates along the pipeline. The leak acts as a localized acoustic source, generating high-frequency signals due to turbulence and pressure release.

This behavior validates the use of acoustic sensors for leak detection and confirms that the generated signals are sufficiently distinguishable from background noise.

5.6 Integrated Validation of Hybrid Sensing Approach

The combined simulation results demonstrate that leakage produces both hydraulic and acoustic signatures that can be effectively detected using the proposed hybrid sensing approach.

- Flow simulation confirms the presence of measurable anomalies in velocity and pressure
- Acoustic simulation validates the existence of detectable sound signatures

- MATLAB simulation confirms the accuracy of the localization algorithm

These findings collectively establish that the integration of flow sensing, acoustic analysis, and TDOA-based localization provides a robust framework for leak detection.

5.7 Discussion on Simulation Limitations

While the simulation results validate the theoretical framework, certain limitations must be acknowledged:

- Real underground conditions such as soil interaction and environmental noise are not fully modeled
- Acoustic attenuation in practical scenarios may vary depending on pipe material and surroundings
- CFD simulations assume ideal boundary conditions, which may differ from real-world operation

Despite these limitations, the simulation phase provides strong evidence supporting the feasibility and effectiveness of the proposed system.

Overall, the simulation and validation results confirm that the proposed methodology is both mathematically sound and physically feasible, providing a solid foundation for hardware implementation and experimental testing.

VI. HARDWARE IMPLEMENTATION

This section presents the hardware implementation of the proposed smart underground pipeline leak detection and localization system. The objective of the hardware design is to realize the hybrid sensing architecture in a compact, energy-efficient, and real-time embedded platform.

The system integrates flow sensing, acoustic sensing, embedded processing, and wireless communication to achieve end-to-end functionality.

6.1 System Overview

The hardware setup is designed as a closed-loop pipeline testbed to simulate real-world underground conditions. The system consists of a water circulation unit, sensor array, processing unit, and communication interface.

The ESP32 microcontroller acts as the central processing unit, interfacing with sensors, executing algorithms, and transmitting data to the cloud.



Figure 8: Hardware Setup

6.2 Embedded Processing Unit (ESP32)

The ESP32 microcontroller is selected due to its dual-core architecture, integrated Wi-Fi capability, and support for high-speed data acquisition interfaces such as I2S.

Its key functions include:

- Acquisition of acoustic data via I2S interface
- Flow sensor pulse counting using hardware interrupts
- Execution of TinyML inference
- Implementation of TDOA-based localization
- Wireless transmission of processed data

The use of Direct Memory Access (DMA) ensures efficient handling of continuous audio streams without interrupting real-time processing.



Figure 9: ESP 32

6.3 Acoustic Sensing Module

The acoustic sensing module consists of two INMP441 digital microphones placed along the pipeline at a fixed distance (approximately 60 cm). These microphones capture high-frequency acoustic signals generated due to leakage.

Unlike analog sensors, the INMP441 provides digital output through the I2S protocol, reducing susceptibility to electrical noise and eliminating the need for external ADCs.

The synchronized stereo configuration ensures that both microphones capture time-aligned signals, which is essential for accurate Time Difference of Arrival (TDOA) computation.



Figure 10: INMP441 Acoustic Mic

6.4 Flow Monitoring Module

The flow monitoring module employs a YF-S201 Hall-effect water flow sensor to continuously measure the flow rate within the pipeline.

The sensor generates digital pulses corresponding to the rotation of an internal turbine. These pulses are counted using hardware interrupts in the ESP32, enabling precise measurement of flow rate in real time.

A sudden decrease in pulse frequency indicates a reduction in flow rate, which is used as a trigger for activating the acoustic analysis stage.



Figure 11: Flow Sensor YF S-201

6.5 Hydraulic Testbed and Pump System

To simulate pipeline conditions, a closed-loop water circulation system is constructed using PVC pipes. A submersible pump is used to maintain a continuous flow of water through the pipeline.

The pump provides a stable flow rate, ensuring consistent operating conditions for testing. Leak conditions are artificially introduced at predefined locations to evaluate system performance.

The physical setup is designed to minimize external noise and vibrations, ensuring accurate acoustic measurements.



Figure 12: Submersible Pump

6.6 TinyML Deployment on Embedded System

The trained machine learning model is deployed on the ESP32 using an optimized inference engine generated from the Edge Impulse platform.

The deployment process involves:

- Converting the trained model into a C/C++ library
- Integrating the model into embedded firmware
- Allocating memory for feature buffers and inference

The model processes real-time acoustic data and outputs a classification result indicating the presence or absence of a leak. The lightweight nature of the model ensures minimal latency and efficient execution on the microcontroller.

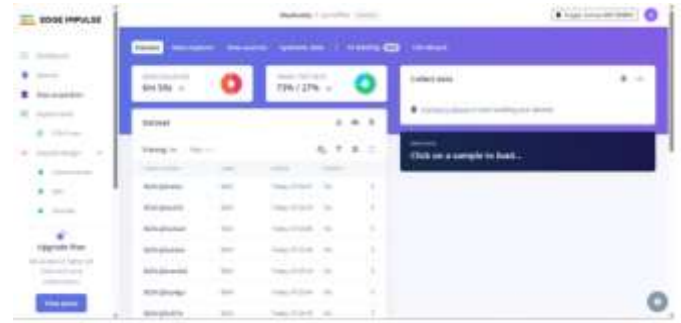


Figure 13: Training AI Model For Classification

6.7 IoT Integration and Data Visualization

The ESP32 transmits processed data to a Firebase cloud database using its built-in Wi-Fi module. The transmitted parameters include:

- Leak detection status
- Flow rate
- Estimated leak location

A mobile application interface is developed to visualize the data in real time. The dashboard displays system status, enabling users to monitor pipeline conditions and respond to leak events promptly.



Figure 14: Firebase Database Dashboard

6.8 System Integration and Performance Considerations

The hardware implementation integrates sensing, processing, and communication into a unified system. Key considerations include:

- Real-time processing capability for continuous monitoring
- Efficient power usage through event-driven operation
- Robust sensor synchronization for accurate localization
- Reliable wireless communication for IoT integration

The successful integration of all components demonstrates the feasibility of deploying the proposed system in real-world scenarios.

Overall, the hardware implementation validates the practical applicability of the proposed hybrid leak detection and localization system.

VII. RESULT

This section presents the experimental results obtained from the hardware implementation of the proposed leak detection and localization system. The objective is to evaluate the system's performance in terms of detection accuracy, localization capability, real-time operation, and overall reliability.

7.1 Experimental Setup

The experimental validation was carried out using the developed pipeline testbed. The system consists of a closed-loop PVC pipeline with controlled leak points, a submersible pump for maintaining flow, and a sensor array comprising flow and acoustic sensors.

Leak conditions were artificially introduced at predefined locations along the pipeline. Acoustic and flow data were collected under both normal and leak conditions to evaluate system performance.

7.2 Leak Detection Performance

The TinyML model was evaluated for its ability to distinguish between leak and non-leak conditions. The classification performance is assessed based on observed predictions during real-time operation.

The system successfully identified leak events with high reliability, demonstrating clear separation between leak signatures and background noise. The hybrid sensing approach significantly reduced false positives compared to standalone methods.

7.3 Localization Performance

The TDOA-based localization algorithm was tested by introducing leaks at different known positions along the pipeline. The estimated leak positions were compared with actual positions.

The system demonstrated consistent localization capability, with small deviations attributed to environmental noise and sensor placement limitations. The results confirm that the proposed method can effectively estimate leak location in real time.

7.4 Real-Time System Performance

The system operates in an event-driven manner, ensuring efficient utilization of computational resources. Key observations include:

- Immediate detection of flow anomalies
- Low-latency TinyML inference on ESP32
- Real-time computation of leak location
- Continuous data transmission to cloud

The use of edge processing minimizes latency and reduces dependency on cloud computation.

7.5 IoT Monitoring and Visualization

The Firebase-based cloud system successfully received and displayed real-time data from the ESP32. The mobile dashboard provided continuous updates of:

- Leak detection status
- Flow rate values
- Estimated leak location

The system demonstrated stable communication without significant delay or data loss.

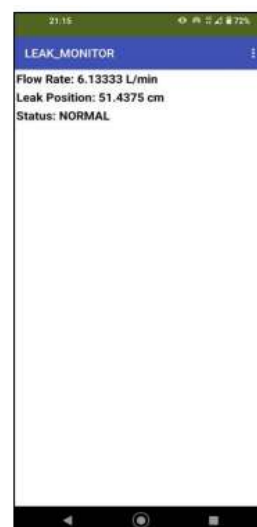


Figure 15: Mobile App Interface

7.6 Discussion

The experimental results validate the effectiveness of the proposed hybrid leak detection system. The combination of flow sensing and acoustic analysis improves detection reliability and reduces false alarms.

The TinyML model enables real-time classification on resource-constrained hardware, while the TDOA algorithm provides accurate localization without additional sensors.

However, certain limitations were observed:

- Acoustic noise may affect classification in uncontrolled environments
- Localization accuracy depends on precise sensor placement
- Limited dataset may affect generalization

Despite these limitations, the system demonstrates strong potential for practical deployment in smart water monitoring applications.

VIII. CONCLUSIONS

This paper presented the design and implementation of a smart underground pipeline leak detection and localization system based on a hybrid sensing approach. The proposed system integrates flow monitoring, acoustic sensing, Tiny Machine Learning (TinyML), and Internet of Things (IoT) technologies to achieve real-time and reliable leak detection.

The system employs a two-stage detection strategy in which flow anomalies trigger acoustic analysis, followed by classification using a lightweight neural network model deployed on an ESP32 microcontroller. Leak localization is performed using the Time Difference of Arrival (TDOA) algorithm, enabling accurate estimation of leak position without additional hardware complexity.

Simulation results using MATLAB Simulink and ANSYS validated the mathematical correctness of the localization algorithm and the physical behavior of leaks in pipelines. Hardware implementation further demonstrated the feasibility of the proposed system, with successful real-time detection, localization, and cloud-based monitoring. The integration of edge computing ensures low latency and reduced dependence on cloud infrastructure, making the system suitable for practical deployment.

The experimental results confirm that the proposed hybrid approach improves detection reliability and minimizes false alarms compared to single-sensor methods. The system provides a cost-effective, scalable, and energy-efficient solution for smart water infrastructure and contributes to reducing water loss and improving maintenance efficiency.

Future work will focus on enhancing system robustness under real underground conditions, expanding the dataset for improved model generalization, and integrating advanced signal processing techniques for noise reduction. Additionally, large-scale deployment and integration with smart city infrastructure and geographic information systems (GIS) can further extend the applicability of the proposed solution.

In conclusion, the presented work demonstrates that the combination of hybrid sensing, embedded intelligence, and IoT connectivity offers a practical and effective approach for real-time pipeline monitoring and leak management.

REFERENCES

1. S. Zhao, Q. Lu, T. Zhang, S. He, P. Shi, and J. Li, "Leak detection of underground water pipelines using acoustic feature extraction," *IEEE Internet of Things Journal*, 2025.
2. M. Zhou, Z. Pan, Y. Liu, Q. Zhang, Y. Cai, and H. Pan, "Leak detection and location based on islmd and cnn in a pipeline," *IEEE Access*, vol. 7, pp. 30457-30464, 2019.
3. U. Rajasekaran and M. Kothandaraman, "A novel custom one-dimensional time series densenet for water pipeline leak detection and localization using acousto-optic sensor," *IEEE Access*, vol. 12, pp. 7966-7973, 2024.
4. V. Q. Tran, D. V. Le, D. R. Yntema, and P. J. Havinga, "A review of inspection methods for continuously monitoring pvc drinking water mains," *IEEE Internet of Things Journal*, vol. 9, no. 16, pp. 14336-14354, 2021.
5. C. Hu, J. Wu, C. Sun, X. Chen, A. K. Nandi, and R. Yan, "Unified flowing normality learning for rotating machinery anomaly detection in continuous time-varying conditions," *IEEE Transactions on Cybernetics*, 2025.
6. N. S. Aminaho, E. N. Aminaho, and F. Aminaho, "Artificial intelligence based solutions for co2 pipeline monitoring: A review," Available at SSRN 5265609, 2025.