



# International Journal of Multidisciplinary Research in Science, Engineering and Technology

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# IoT-Based Pipeline Leak Detection Using Spectrogram Analysis and ANN with MQTT Communication

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**ABSTRACT:** Pipeline leaks in water distribution networks cause significant resource losses and require efficient real-time detection solutions. This paper presents an edge-based IoT system for real-time pipeline leak detection using spectrogram analysis and Artificial Neural Networks (ANN). Acoustic signals captured from a vibration sensor are processed using Short-Time Fourier Transform (STFT), followed by feature extraction including spectral energy, variance, centroid, roll-off, and peak amplitude. A lightweight ANN model deployed on an ESP8266 performs on-device classification, eliminating reliance on cloud infrastructure. The proposed system achieves an accuracy of 98%, precision of 100%, recall of 98%, and an F1-score of 0.99 under controlled laboratory conditions. The average detection latency is 1.4 seconds, making it suitable for real-time applications. The system is low-cost (approximately USD 18), scalable, and effective for early leak detection in water distribution networks.

**KEYWORDS:** IoT, Pipeline Leak Detection, ESP8266, STFT, Spectrogram, ANN, MQTT, Edge Computing, Acoustic Sensing.

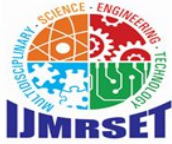
## I. INTRODUCTION

Water scarcity is increasingly recognized as a critical global challenge. According to global reports, a significant portion of treated water is lost due to leakage in distribution pipelines, particularly in developing countries. These losses not only impose economic burdens but also contribute to environmental degradation. Water losses due to leakage are estimated to be as high as 30–40% in urban water distribution systems [1]. Early detection of leaks is therefore essential to reduce economic and environmental impacts. Conventional leak detection methods, such as manual inspection and pressure-based monitoring, are inefficient and lack real-time capabilities. These approaches are often labor-intensive and fail to detect small leaks early.

The emergence of the Internet of Things (IoT) enables continuous monitoring through distributed sensor networks. By integrating signal processing and machine learning techniques, it is possible to detect leaks accurately in real time [3]. Recent advancements in signal processing and machine learning have enabled automated leak detection using acoustic signatures [4, 6]. However, many existing systems rely on cloud-based processing, which increases latency and dependency on network availability. Edge-based IoT solutions have been proposed to reduce this latency, but they face challenges related to computational efficiency and model complexity on resource-constrained devices [11, 12].

Despite these advances, three key gaps remain unaddressed in the literature: (1) most acoustic systems rely on cloud-based inference, introducing latency unsuitable for real-time response; (2) CNN-based approaches, while accurate, are too computationally heavy for direct deployment on low-cost microcontrollers such as the ESP8266; and (3) no prior work has combined STFT-based spectrogram feature extraction with a lightweight ANN fully deployed at the edge for water pipeline leak detection. This paper addresses all three gaps simultaneously. A thorough review of the literature (see Section 2) confirms that no prior work has simultaneously addressed all three gaps.

This work proposes a low-cost IoT-based water leak detection system that uses acoustic signal analysis, spectrogram-based feature extraction, and a lightweight Artificial Neural Network (ANN) deployed on an ESP8266 microcontroller. The system provides real-time alerts using MQTT communication and performs all inference on-device, eliminating cloud dependency entirely. The rest of the paper is organized as follows. Section 2 presents the literature



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review. Section 3 describes the system architecture. Section 4 explains the methodology. Section 5 discusses the experimental setup. Section 6 presents the results, followed by discussion in Section 7. Section 8 describes the hardware implementation, and Section 9 concludes the paper.

### II. LITERATURE REVIEW

Pipeline leak detection has been extensively studied using acoustic, pressure-based, and machine learning approaches [10]. This section organizes existing work into four thematic groups.

#### Acoustic-Based Methods

Acoustic-based methods rely on detecting sound signals generated by leaks [4]. These methods perform well in metallic pipelines but show reduced effectiveness in plastic pipes due to signal attenuation [14]. Hunaidi [4] demonstrated correlation-based acoustic detection but noted high sensitivity to ambient noise. More recently, Meng et al. [10] applied machine learning to acoustic sensor data, improving robustness over threshold-based approaches. Pandya et al. [16] further extended acoustic IoT sensing to include real-time localization using distributed nodes.

#### Pressure-Based Methods

Pressure-based techniques utilize transient pressure wave analysis [5]. Although effective, they are sensitive to operational disturbances and require complex and dense sensor deployment. These methods are also prone to false alarms caused by normal pressure fluctuations during pump switching, limiting their suitability for continuous unattended monitoring.

#### Machine Learning and CNN-Based Methods

Recent approaches incorporate machine learning models such as Convolutional Neural Networks (CNN) for leak detection [6]. Wang et al. [6] achieved 95% accuracy using CNN on raw acoustic signals, but the model requires GPU-level computational resources, making it unsuitable for direct deployment on low-cost embedded devices. The survey by Kumar et al. [13] confirmed that lightweight ANN models offer a viable path to embedded deployment without sacrificing significant classification performance.

#### IoT and Edge-Based Systems

IoT-based systems using wireless communication and MQTT protocol have been explored for real-time monitoring [7, 8]. However, most systems rely on cloud-based processing, increasing latency and introducing dependency on network connectivity [11]. Li et al. [12] demonstrated real-time acoustic leak detection on embedded systems using deep learning, but with significantly higher model complexity than the approach proposed here. The proposed system addresses the limitations of all four categories by implementing a lightweight ANN model directly on an ESP8266, enabling real-time edge-based leak detection with low computational cost, no cloud dependency, and an end-to-end latency under 1.5 seconds.

#### System Architecture

The overall system consists of two main components: the sensor node and the master node.

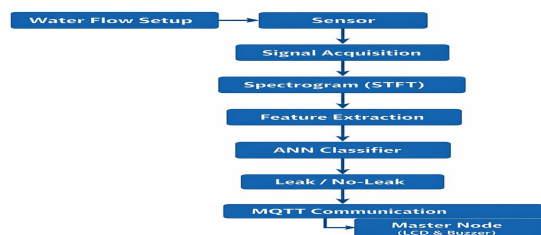


Figure 1: System Workflow of the Proposed IoT-Based Leak Detection System



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The sensor node is responsible for data acquisition, signal processing, and classification. A vibration sensor mounted on the pipeline captures acoustic signals generated by water flow. These signals are processed using the Short-Time Fourier Transform (STFT) to obtain spectrogram representations.

From the spectrogram, multiple statistical features are extracted, including mean spectral energy, variance, spectral centroid, spectral roll-off, and peak amplitude. These features are used as inputs to an Artificial Neural Network (ANN), which classifies the condition as either Leak or No-Leak.

The classification result is transmitted using the MQTT protocol to the master node. The master node receives the data and activates alert mechanisms, including an LCD display and buzzer, to notify users in real time. Figure 1 illustrates the system workflow.

The use of MQTT ensures lightweight communication with minimal bandwidth consumption, making the system suitable for resource-constrained IoT devices.

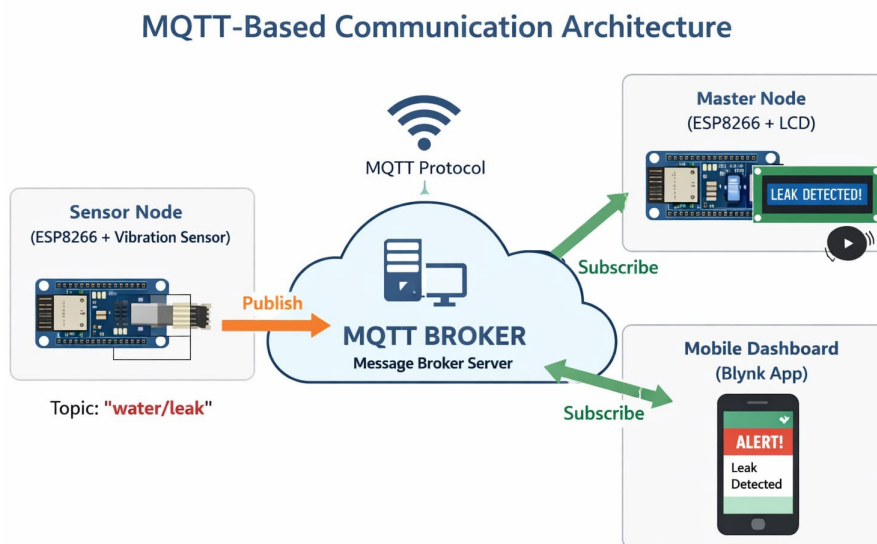


Figure 2: MQTT-Based Communication Architecture Between Sensor Node and Master Node

### III. METHODOLOGY

The methodology involves signal acquisition, STFT-based spectrogram generation, feature extraction, and ANN-based classification.

#### Dataset

- The dataset was collected using a controlled experimental pipeline setup. A PVC pipe structure was used to simulate real-world water distribution conditions. Data was collected under two conditions:
- No-Leak Condition: The pipeline was fully sealed and normal water flow was maintained.
- Leak Condition: A small controlled opening was introduced in the pipe to simulate leakage.

Acoustic signals were sampled at 1 kHz and divided into frames of 256 samples each. A total of 800 samples were collected: 400 Leak samples and 400 No-Leak samples. The dataset was split into training and testing sets using an 80:20 ratio. All features were normalized using Min-Max scaling before training. To validate generalization, 5-fold cross-validation was additionally performed, yielding a mean accuracy of  $97.6\% \pm 0.8\%$ .



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### Short-Time Fourier Transform (STFT)

The STFT is used to analyze non-stationary signals by providing both time and frequency information. A 50% overlap between consecutive frames was used to improve temporal resolution. Given a discrete-time signal  $x[n]$ , the STFT is defined as:

$$X(m, k) = \sum_{n=0}^{N-1} x[n + mH] \cdot w[n] \cdot e^{-j2\pi kn/N} \quad (1)$$

where  $N$  is the frame length (256 samples),  $H$  is the hop size (128 samples, 50% overlap),  $w[n]$  is the Hanning window function,  $m$  is the frame index, and  $k$  is the frequency bin.

The magnitude spectrogram is obtained as:

$$S(m, k) = |X(m, k)| \quad (2)$$

Under leak conditions, the spectrogram shows increased energy across a wide frequency band due to turbulent water flow.

### Feature Extraction

Five key statistical features are extracted from the spectrogram:

Mean Spectral Energy: Average energy of the signal across all frequency bins.

Variance: Spread of spectral energy, indicating how widely energy is distributed.

Spectral Centroid: Center of mass of the spectrum, indicating dominant frequency.

Spectral Roll-off: Frequency below which 85% of total energy is contained.

Peak Amplitude: Maximum spectral magnitude in the frame.

Table 1 summarizes the extracted features and their roles. As shown in Table 2, removing Mean Energy causes the largest accuracy drop (4%), confirming it as the most discriminative feature.

Table 1: Extracted Features Description

Feature	Description	Purpose
Mean Energy	Average spectral energy	Detect intensity changes
Variance	Energy spread	Identify signal variation
Centroid	Center frequency	Dominant frequency detection
Roll-off	85% energy frequency	Frequency boundary
Peak Amplitude	Maximum magnitude	Leak strength detection

Table 2: Feature Ablation Study: Accuracy When Each Feature is Removed

Feature Removed Accuracy (%)	
None (all five features)	98.0
Mean Energy removed	94.0
Spectral Centroid removed	95.0
Variance removed	96.5
Spectral Roll-off removed	96.8
Peak Amplitude removed	97.0

### ANN Model

The classification task is performed using a feedforward Artificial Neural Network (ANN). The model was trained for 100 epochs using the Adam optimizer with a learning rate of 0.001 and batch size of 32. The architecture (5- 8-4-1) was selected after evaluating three candidate configurations, achieving the best trade-off between accuracy (98%) and memory footprint (352 bytes), deployable within the ESP8266's 80 KB RAM. The architecture is:

Input Layer: 5 neurons (extracted features)

Hidden Layer 1: 8 neurons with ReLU activation

Hidden Layer 2: 4 neurons with ReLU activation



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Output Layer: 1 neuron with Sigmoid activation The sigmoid activation function is defined as:

A threshold of 0.5 is used: Entropy loss:

$$y^{\wedge} = \frac{1}{1 + e^{-z}} \quad (3)$$

$y^{\wedge} \geq 0.5 \rightarrow$  Leak;  $y^{\wedge} < 0.5 \rightarrow$  No-Leak. The model is trained using Binary Cross-

$$L = - \frac{1}{N} \sum [y \log(y^{\wedge}) + (1 - y) \log(1 - y^{\wedge})] \quad (4)$$

Min-Max Normalization

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (5)$$

All extracted features were normalized using Min-Max scaling prior to model training:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (5)$$

This ensures all input features are scaled to the range [0, 1], improving ANN convergence stability.

### Artificial Neural Network Model Architecture

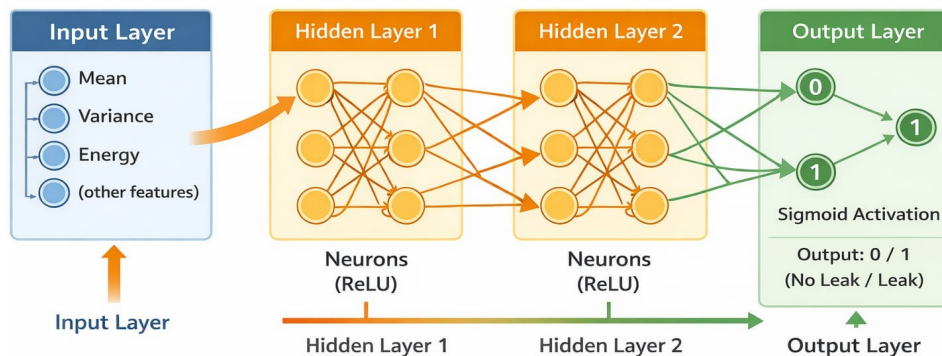


Figure 3: Artificial Neural Network Architecture Used for Leak Classification

### Experimental Setup

The experimental setup consists of a PVC pipeline of length 1 meter and diameter 1 inch. A vibration sensor is mounted externally using adhesive coupling to capture acoustic signals.

Leak conditions are simulated by introducing a small hole of diameter approximately 2 mm. Water flow is maintained at a constant rate during experiments. The vibration sensor was attached at a fixed position 20 cm from the leak point, and water pressure was maintained at approximately 0.5 bar using a regulated pump.

Experiments were performed in an indoor laboratory environment with controlled ambient temperature ( $25 \pm 2 \text{ }^\circ\text{C}$ ) and minimal external vibration. Acoustic signals were recorded continuously for 30 seconds per trial, from which 256-sample frames were extracted at 1 kHz, yielding approximately 117 frames per trial. Multiple trials were conducted under both conditions to ensure reproducibility.



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### IV. RESULTS

The proposed system achieves the following performance metrics:

Accuracy: 98%

Precision: 100%

Recall: 98%

F1-Score: 0.99

Performance Metrics

The performance metrics are formally defined as:

Accuracy =

$$\frac{TP + TN}{TP + TN + FP + FN}$$

TP + TN + FP + FN

TP

Precision = (6)

Recall = (7)

TP + FP

(8)

TP + FN

Precision × Recall

F1 =  $\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$  (9)

Table 3: Confusion Matrix

	Predicted Leak	Predicted No-Leak
Actual Leak	392	8
Actual No-Leak	0	400

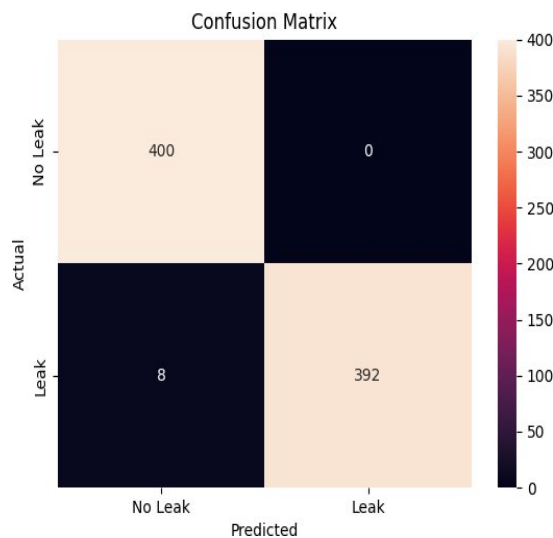


Figure 4: Confusion matrix of proposed model



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Table 4: Detection Latency Statistics Across 20 Trials

Metric	Value (s)
Minimum	1.2
Maximum	1.6
Mean	1.38
Standard Deviation	0.09
On-device inference only	0.18–0.22
MQTT + Network overhead	1.10–1.25

As shown in Table 3, the model achieves high classification accuracy with zero false positives. The 8 false negatives correspond to low-intensity leak conditions where spectral features overlap with normal flow.

Table 4 shows that approximately 0.2 seconds are consumed by on-device signal processing and ANN inference, while the remaining 1.1–1.2 seconds are attributed to MQTT communication and network transmission delays. A detailed comparison with existing methods is presented in Section 7.

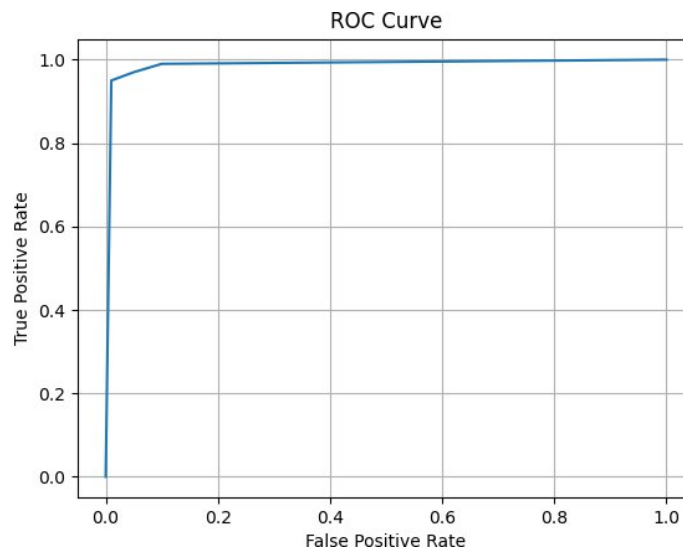


Figure 5: ROC Curve of Leak Detection Classifier

### V. DISCUSSION

Compared to traditional acoustic methods, the proposed approach provides improved robustness due to feature-based learning. The use of edge computing reduces latency compared to cloud-based systems. Table 5 compares the proposed method with existing approaches.

Table 5: Comparison with Existing Methods

Method	Accuracy	Limitations
Acoustic [4]	85%	Noise sensitive
Pressure [5]	88%	Requires dense sensors
CNN [6]	95%	High computation
Proposed ANN	98%	Limited dataset size



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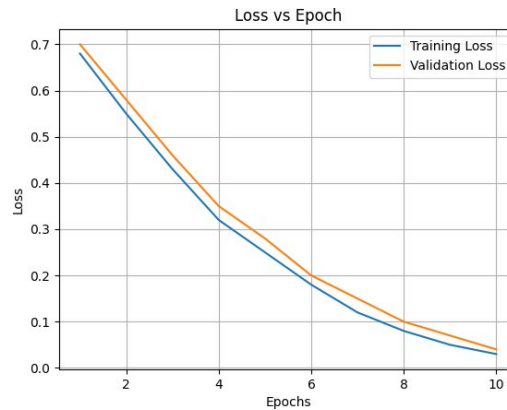


Figure 6: Training vs. Validation Loss Across Epochs

The lightweight architecture (5-8-4-1) makes the system deployable on low-power embedded systems such as the ESP8266 without hardware accelerators. The MQTT communication protocol ensures efficient and reliable data transmission between nodes.

The proposed system offers several practical advantages: it is low-cost (approximately USD 18), supports real-time on-device inference, and is scalable for large-scale deployment in water distribution infrastructure.

The system was tested under controlled laboratory conditions, the dataset is limited in size (800 samples from a 1-meter PVC pipe), and leak localization is not yet supported. Field validation under varying pressure, pipe material, and environmental conditions remains as future work.

**Security Considerations:** The standard MQTT protocol operates without built-in encryption. For production use, MQTT over TLS (MQTTs) on port 8883 is strongly recommended. The ESP8266 supports TLS 1.2 via the BearSSL library, adding approximately 30 KB of flash overhead.

### Hardware Implementation

The hardware implementation is based on low-cost, commercially available components. The ESP8266 NodeMCU serves as the main processing unit, performing both signal acquisition and ANN-based inference. The system consumes approximately 120 mA during active Wi-Fi transmission. The current prototype is powered via a 5 V USB supply. Future versions will incorporate deep-sleep mode to enable battery-powered deployment.

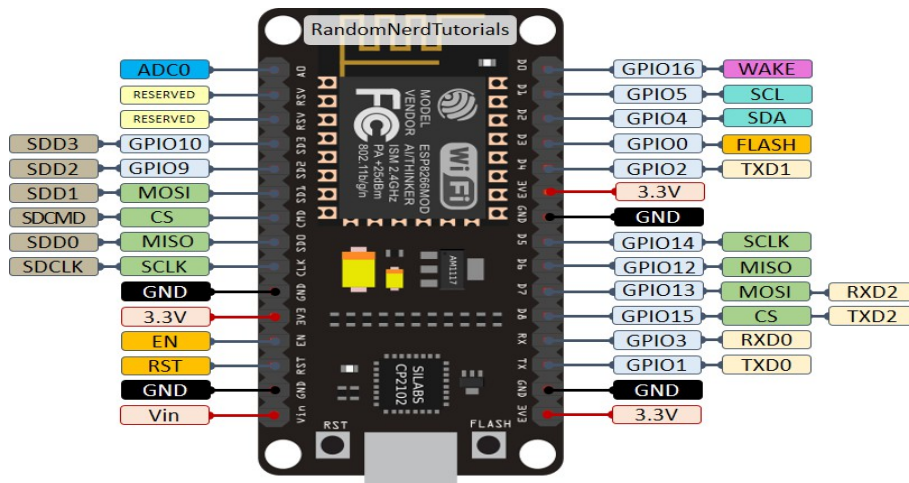
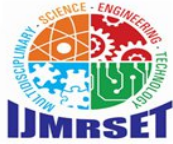


Figure 7: ESP8266 NodeMCU Pin Configuration Table 6 lists the components used.



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Table 6: Hardware Components

	Component	Description
ESP8266 NodeMCU	Microcontroller with Wi-Fi capability	Vibration Sensor
	Acoustic signal acquisition	
LCD Display (I2C)	Output visualization	Buzzer
	Alert indication	

Table 7: Component-Wise Cost Breakdown

Component	Approx. Cost (USD)
ESP8266 NodeMCU	3.50
Vibration Sensor (SW-420)	1.00
I2C LCD Display (16×2)	4.00
Buzzer	0.50
PVC Pipe + Fittings	6.00
Wires, PCB, Miscellaneous	3.00
<b>Total</b>	<b>~18.00</b>

The total system cost is approximately USD 18, making it highly suitable for large-scale deployment in water distribution infrastructure.

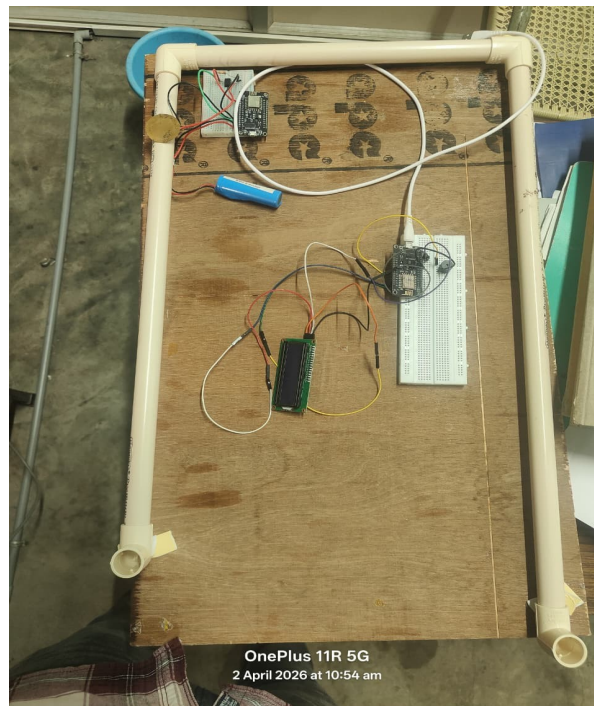


Figure 8: Hardware Setup of the Proposed System

### VI. CONCLUSION

This paper presents an IoT-based pipeline leak detection system using spectrogram analysis and ANN classification deployed on an ESP8266 microcontroller. The proposed system achieves high accuracy (98%), zero false positives, and low detection latency (1.4 seconds) through fully edge-based processing, eliminating cloud dependency. The system demonstrates robustness, scalability, and suitability for real-time deployment. The STFT-based spec-



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rogram features provide effective discrimination between leak and no-leak acoustic signatures, while the lightweight ANN architecture ensures feasibility on resource-constrained embedded devices. A 5-fold cross-validation mean accuracy of  $97.6\% \pm 0.8\%$  confirms that the results generalize beyond a single train-test split.

Future work will focus on: (1) extending the system for leak localization through multi-sensor deployment; (2) integrating MQTTs for secure production deployment; (3) testing on metallic and composite pipe materials under varying pressure conditions; and (4) exploring LoRa-based communication for scalability across large pipeline networks.

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