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# A Comprehensive Review of AI and IoT-Based Water Pipeline Leakage Detection, Prediction and Monitoring Systems

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**Abstract:** *Water pipeline leakage is a major challenge in water distribution and supply systems because undetected leaks can result in water loss, infrastructure damage, economic losses, and inefficient water management [5], [13]. Conventional leakage inspection methods often depend on manual inspection, periodic maintenance, or specialized equipment, which may not provide continuous real-time monitoring [5], [13]. Recent developments in the Internet of Things (IoT), sensor technology, artificial intelligence (AI), and machine learning (ML) have created opportunities for automated and intelligent pipeline monitoring [9], [11]. This review presents a study of recent techniques used for water pipeline leakage detection, localization, prediction, and monitoring. Different sensing approaches, including flow, pressure, acoustic, and vibration measurements, are reviewed along with machine-learning and deep-learning methods [1], [3], [4], [8], [12], [13]. Existing research demonstrates that pressure and flow measurements are widely used for hydraulic anomaly detection, while vibration and acoustic measurements can provide additional information about leakage events [5], [6], [7]. AI models such as Artificial Neural Networks, Random Forest, Support Vector Machines, K-Nearest Neighbors, Convolutional Neural Networks, and ensemble techniques have been investigated for leakage classification and localization [1], [3], [4], [8], [12], [13]. IoT-based systems further enable continuous data acquisition, remote monitoring, and real-time alerts [9], [11]. However, challenges remain in obtaining representative real-world datasets, reducing false alarms, handling sensor noise, and deploying models on resource-constrained edge devices [13], [14], [15]. Based on the reviewed literature, a multi-sensor IoT and AI architecture using flow, pressure, and vibration measurements with Raspberry Pi-based processing is proposed as a suitable direction for a low-cost academic prototype [5], [9], [11], [12]..*

**Keywords:** Artificial Intelligence, Internet of Things, Machine Learning, Leakage Detection, Leakage Prediction, Pressure Sensor, Flow Sensor, Raspberry Pi.

## I. INTRODUCTION

Water is an essential resource for domestic, agricultural, industrial, and municipal applications. Water distribution systems consist of extensive networks of pipelines, pumps, valves, storage tanks, and other components. Over time, pipelines can develop leakage because of aging, corrosion, pressure variation, joint failure, mechanical damage, and environmental conditions [5], [13]. Leakage may remain undetected for significant periods, particularly when pipelines are underground or inaccessible [5], [13].

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Traditional pipeline inspection techniques include manual inspection, acoustic investigation, pressure analysis, flow measurement, and other specialized methods. Although these methods can be effective, continuous monitoring of a large pipeline network can be difficult and expensive. Therefore, researchers have increasingly investigated automated data-driven techniques for detecting abnormal pipeline conditions [5], [13].

Machine learning provides another approach by learning relationships between sensor measurements and pipeline conditions. Pressure, flow, acoustic, and vibration measurements can be processed to identify abnormal operating conditions. Recent research has also combined IoT with AI to enable continuous data acquisition, predictive analysis, anomaly detection, and remote monitoring [1], [3], [4], [13].

Therefore, an effective modern leakage monitoring system should not only identify an existing leak but should also analyze multiple sensor parameters, classify pipeline conditions, provide real-time information, and support early warning. This review investigates existing water pipeline leakage detection and prediction approaches and identifies research gaps that can be addressed through a multi-sensor AI and IoT-based system [5], [9], [11], [12].

## II. REVIEW METHODOLOGY

The review was conducted by studying research articles related to water pipeline leakage detection, water distribution network monitoring, pressure-based leakage detection, flow-based leakage detection, acoustic and vibration-based detection, machine-learning-based leakage classification, deep-learning-based leakage detection and localization, IoT-based water monitoring, real-time leakage monitoring, and AI-based prediction and anomaly detection [1], [5], [8], [9], [13].

Research papers from IEEE Xplore, ScienceDirect, Springer, MDPI, ASCE, IWA Publishing, and other scholarly sources were considered. The reviewed literature indicates a progression from traditional single-parameter monitoring toward multi-sensor, data-driven, and IoT-enabled systems [9], [11].

## III. LITERATURE REVIEW

Another important aspect discussed in previous studies is the use of multiple parameters for identifying leakage conditions. Flow and pressure sensors can help detect unusual changes in pipeline operation. Analysing these measurements using machine-learning techniques may help distinguish normal pipeline conditions from possible leakage conditions [1], [5].

The integration of IoT with AI-based systems provides an opportunity to monitor pipeline conditions continuously. Sensor data can be transmitted to a monitoring platform, where users can observe the current status of the pipeline. Such connected systems can support remote monitoring and reduce dependence on frequent manual inspection [9], [11].

Leak localization is also an important area of research. Detecting a leak indicates that an abnormal condition may exist, while localization aims to identify the position of the leakage. Research has explored AI-based and integrated techniques to improve both leakage detection and localization [9], [12]. The effectiveness of localization depends on the available sensor data, system design, and the method used for analysis.

Machine-learning models can analyse collected sensor readings and identify patterns associated with different pipeline conditions. These patterns can support the classification of pipeline status and help identify unusual behaviour. The studies reviewed in [1] and [12] provide a basis for considering AI techniques in automated pipeline monitoring.

Overall, the reviewed literature highlights the importance of combining sensor measurements, artificial intelligence, and IoT connectivity in water pipeline monitoring. These technologies provide useful approaches for detecting abnormal pipeline conditions, monitoring water flow, and supporting leakage-related decision-making [5], [9], [11], [12].

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## IV. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR LEAK DETECTION

The machine-learning process begins with sensor data collection, followed by data preprocessing and feature extraction. The processed features are provided to a machine-learning model for classification, which supports the final leakage decision.

A practical monitoring system may classify pipeline conditions as Normal, Warning, or Leakage.

### A. Artificial Neural Network

Artificial Neural Networks can learn complex relationships between multiple pressure or sensor measurements. They are useful when the relationship between sensor features and leakage conditions is nonlinear, but they require suitable training data [1], [3].

### B. Random Forest

Random Forest is an ensemble machine-learning algorithm that combines multiple decision trees. It can be useful when several sensor parameters are available because it can model nonlinear relationships between input variables and output classes [4], [12], [13].

### C. Support Vector Machine

Support Vector Machine is commonly used for classification problems. It attempts to find a decision boundary that separates different classes and can be suitable when the available dataset is relatively limited and features are well selected [3], [13].

### D. K-Nearest Neighbors

KNN classifies an unknown observation according to nearby training observations. It has been investigated for pressure/transient-based leak localization and vibration-based detection [6], [7].

### E. Deep Learning

Deep-learning methods can automatically learn complex features from raw or processed sensor signals. Lightweight 1D-CNN approaches have been investigated for water leak detection and localization in IoT environments [8], [9], [12].

## V. IOT-BASED WATER PIPELINE MONITORING

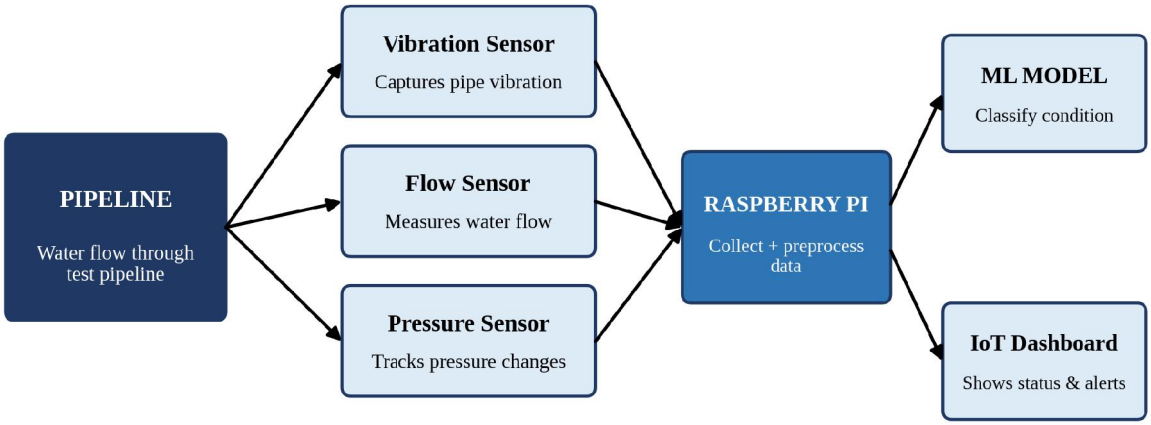



Fig. 1. Proposed AI and IoT-based water pipeline monitoring architecture.

The Internet of Things enables physical sensors to communicate measurements to a computing platform and monitoring interface. A typical architecture is: Sensors → Controller/Edge Computer → Data Processing → AI Model → Internet → Dashboard → Alert [9], [11].

IoT enables continuous sensor monitoring, remote data access, real-time visualization, automatic alerts, historical data storage, and integration with AI models [9], [11].

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## VI. COMPARATIVE REVIEW OF EXISTING METHODS

Table I compares the main leakage-detection approaches in terms of their input data, analysis technique, main advantage, and major limitation.

TABLE I: Comparison of Existing Leakage Detection Methods

| Method | Main Input | Technique | Main Advantage | Major Limitation |
|---|---|---|---|---|
| Manual Inspection | Visual/physical | Human inspection | Simple | Not continuous |
| Flow-Based | Flow rate | Threshold/analytics | Direct water-loss indication | Small leaks may be difficult to detect |
| Pressure-Based | Pressure | Statistical/ML | Useful for hydraulic changes | Sensitive to operating conditions |
| Acoustic | Acoustic signal | Signal processing/ML | Captures leak-generated sound | Environmental noise |
| Vibration | Acceleration | ML | Additional mechanical information | Pump interference |
| ANN | Sensor measurements | Neural network | Models nonlinear relationships | Needs training data |
| Random Forest | Multiple features | Ensemble ML | Robust classification | Needs a trained model |
| SVM | Extracted features | Classification | Works with limited data | Feature selection required |
| CNN | Signal/time series | Deep learning | Automatic feature learning | Higher computation |
| IoT + AI | Multiple sensors | AI + edge/cloud | Real-time intelligent monitoring | Implementation complexity |

## VII. SUMMARY OF IMPORTANT RESEARCH STUDIES

Table II summarises the important studies reviewed, together with the sensing input, AI/ML technique, and main contribution of each.

TABLE II: Summary of Important Research Studies

| Study | Approach | Input | AI/ML Technique | Main Contribution |
|---|---|---|---|---|
| Fan et al., 2021 [1] | Pressure-based | Pressure | ANN, Autoencoder | Leak detection using pressure relationships |
| Nagaraj et al., 2021 [2] | EPANET + ML | Pressure/flow | ML classifiers | Simulation-based leakage prediction |
| Ravichandran et al., 2021 [3] | Acoustic | Acoustic signal | Ensemble ML (GBT) | Ensemble-based leak detection in water mains |
| Sun et al., 2020 [7] | Pressure-based leak localization | Pressure + flow | LDA, NNET + Bayesian temporal reasoning | Data-driven leak localization using pressure measurements |
| Wan et al., 2022 [5] | Review | Pressure + flow | Data analytics | Review of pressure/flow smart-sensor analytics |
| Tariq et al., 2022 [6] | Vibration | MEMS accelerometer | KNN, DT, RF, AdaBoost | Real-network experimentation |
| Zhang et al., 2023 [8] | Signal-based | Pipeline signal | CNN | Deep-learning leak detection |
| IoT lightweight DL study, 2023 [9] | IoT | Sensor data | 1D-CNN | Real-time detection/localization |

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| Study | Approach | Input | AI/ML Technique | Main Contribution |
|---|---|---|---|---|
| Rajasekaran et al., 2023 [10] | Vibration/acoustic | EDFL sensor | ML/DL | Comparative experimental study |
| Guezouli et al., 2024 [11] | IoT + AI | Water monitoring data | AI | Real-time monitoring and leak detection |
| Rajasekaran et al., 2025 [12] | Vibration/acousto-optic | Acousto-optic sensor | 1D-CNN + modified AdaBoost | Leak detection and localization using integrated AI |
| Chen et al., 2021 [4] | Leakage-zone identification | Pressure | K-means + Random Forest | Leakage-zone identification |
| Anozie et al., 2026 [14] | Systematic review | Multiple modalities | Hybrid ML | Transparent hybrid ML framework review |
| Farah and Shahrour, 2026 [15] | Systematic review | Multiple sensing modalities | ML/DL | Dataset and evaluation standardization |

## VIII. RESEARCH GAP

Several research gaps remain in water pipeline leakage monitoring. Many machine-learning studies rely on simulated or laboratory-generated datasets, which can limit their generalization to real-world conditions. Although flow, pressure, acoustic, and vibration sensors provide complementary information, some systems depend mainly on a single sensing modality. Small leaks may be difficult to distinguish from normal fluctuations, while pumps, valves, changes in water demand, vibration, and sensor noise can cause false alarms. Traditional approaches may also rely on manual or periodic inspection rather than continuous monitoring. In addition, advanced AI models can require more computational resources than small edge devices can provide. Differences in datasets, validation procedures, leakage scenarios, and evaluation metrics also make it difficult to compare results consistently.

## IX. PROPOSED RESEARCH DIRECTION

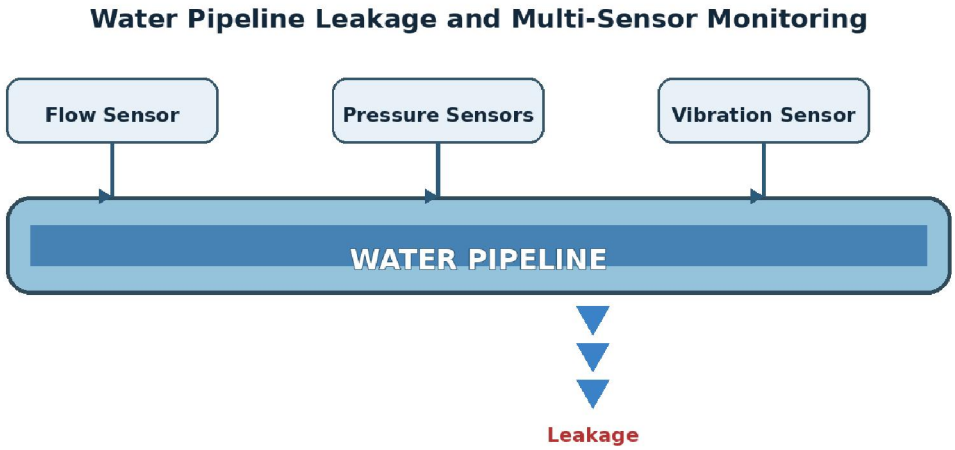



Fig. 2. Conceptual multi-sensor pipeline leakage monitoring arrangement.

The reviewed literature supports a multi-sensor AI and IoT-based water pipeline monitoring system. The proposed academic architecture is supported by multi-sensor and IoT approaches discussed in the literature [5], [9], [11], [12].

The proposed system consists of a water tank, pump, and pipeline monitored by flow, pressure, and vibration sensors. The sensor readings are collected and preprocessed by a Raspberry Pi, after which features are extracted and passed to

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a machine-learning model. The model classifies the pipeline condition as Normal, Warning, or Leakage. The result is then transmitted through Wi-Fi/IoT to a web dashboard, where the status and alerts can be viewed.

The proposed prototype can use multiple pressure measurement points along the pipeline. Flow measurement provides information about water movement, while vibration measurement provides additional information related to leakage-induced mechanical effects. Raspberry Pi can act as an edge computing platform for sensor acquisition, preprocessing, trained-model inference, and communication with a monitoring dashboard [5], [9], [11], [12].

## X. PROPOSED MACHINE LEARNING WORKFLOW

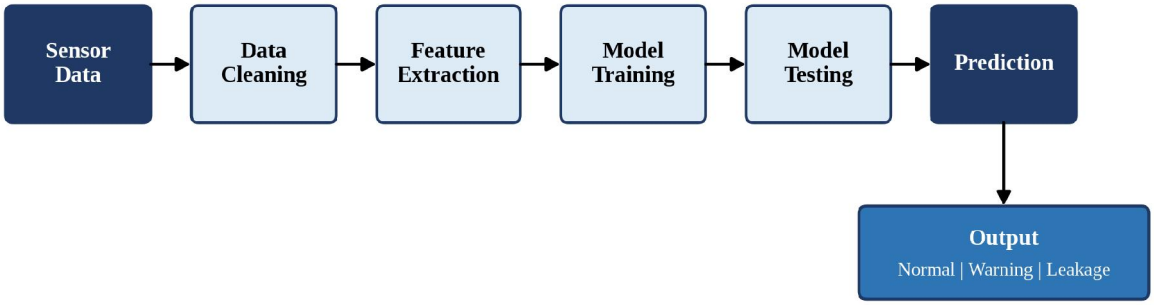



Fig. 3. Machine-learning workflow for pipeline leakage classification.

The machine-learning workflow begins with data collection, in which pressure, flow, vibration, and operating-condition measurements are gathered. A labelled dataset is then created for normal, small-leakage, medium-leakage, and large-leakage conditions. During preprocessing, invalid readings are removed and sensor values are normalized or scaled when required. Feature extraction is used to calculate pressure differences, flow variations, vibration amplitude, and other statistical or time-series features. Candidate models, including Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Network (ANN), can then be trained and compared. The selected model is evaluated using data that were not used during training. After testing, the trained model can be deployed on Raspberry Pi for local inference, and its prediction results can be sent through Wi-Fi to a web dashboard for IoT-based monitoring.

## XI. EXPECTED OUTPUT

The system is expected to classify pipeline conditions into three categories: Normal, Warning, and Leakage. The Normal category indicates that pressure and flow remain within the expected operating range. Warning indicates that sensor values show an abnormal trend that may point to a developing problem. Leakage indicates that the sensor measurements show a pattern consistent with a leakage condition.

## XII. ADVANTAGES OF THE PROPOSED APPROACH

The proposed approach supports continuous pipeline monitoring and real-time sensor data acquisition. Combining hydraulic measurements with vibration information can provide a broader view of pipeline behaviour, while AI-based classification can help identify abnormal conditions. IoT connectivity enables remote monitoring and alerts, and the system may provide early warning of possible leakage. The approach can reduce dependence on manual inspection, support future scalability, use Raspberry Pi for edge processing, and allow historical data to be stored for further analysis.

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## XIII. CHALLENGES

Several challenges may affect the proposed system. Incorrect sensor calibration can lead to inaccurate predictions, and the AI model depends strongly on the quality and diversity of its training dataset. Pumps, motors, valves, and external mechanical activity may introduce environmental noise into vibration measurements. Differences in pipe materials, diameters, lengths, and operating pressures can also change sensor responses. A model trained on a laboratory pipeline may not perform identically in a real field environment. Reliable communication is required between the monitoring device and the dashboard, while deep-learning models may require more computational resources than traditional machine-learning methods.

## XIV. FUTURE SCOPE

Future work may evaluate the system on longer pipeline networks and with different pipe materials. Further development could include automatic leakage-location estimation, cloud-based storage of historical data, and integration with a mobile application. Advanced deep-learning models and digital-twin-based pipeline simulation could also be investigated. Solar-powered remote sensor nodes may support deployments in locations with limited power access. The approach could be extended to large-scale industrial pipeline monitoring, with predictive maintenance based on long-term sensor trends.

## XV. CONCLUSION

Water pipeline leakage is an important infrastructure problem that requires reliable and timely detection. Traditional inspection approaches can be limited when continuous monitoring is required. Recent research demonstrates that pressure, flow, acoustic, and vibration sensing can provide valuable information for detecting abnormal pipeline conditions [5], [6], [7], [13].

Machine-learning methods such as ANN, Random Forest, SVM, KNN, and deep-learning approaches have demonstrated potential for automated leakage detection and localization. IoT technology further enables continuous data acquisition, remote monitoring, and real-time alert generation [1], [3], [4], [8], [12], [13].

The literature also indicates that no single sensing method or machine-learning algorithm is universally optimal. Sensor noise, changing operating conditions, limited real-world datasets, false alarms, and differences in pipeline characteristics remain important challenges. A multi-sensor architecture combining pressure, flow, and vibration measurements with Raspberry Pi-based edge processing and an AI model provides a promising direction for an academic prototype [5], [13], [14], [15].

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