# Optimizing Leak Detection in Urban Water system: A Survey of Sensor Technologies and Data Analytics

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**Abstract: Urban water systems are facing increasing pressure to reduce non-revenue water losses, making efficient leak detection a global priority. This review offers a comprehensive examination of sensor technologies and data analytics methods, with a particular focus on their integration within intelligent IoT-enabled monitoring frameworks. The evolution of sensors has been traced from early acoustic tools to modern smart meters, fiber optics, and hybrid multi-sensor solutions, highlighting trade-offs in accuracy, cost, scalability, and deployment feasibility. Parallel advances in data analytics were reviewed, spanning statistical and signal-processing approaches to machine learning, deep learning, and hybrid AI models, demonstrating significant improvements in detection accuracy and robustness. By synthesizing these two dimensions, this study introduces a practical selection framework for aligning sensor choices with the analytical requirements and operational contexts. Comparative analyses and tabular summaries provide actionable insights for utilities, while research gaps, including small leak detection, field validation, cost–scalability challenges, and cybersecurity, are explicitly outlined. The review concludes that integrated sensor–analytics solutions, supported by IoT and digital twin technologies, represent the most promising direction for optimizing leak detection in urban water systems, bridging academic advances with practical implementation.**

**Keywords: Water Distribution System, Leak Detection, Sensors, Wireless Sensor Networks, Signal Processing.**

## I. INTRODUCTION

Detecting leaks in water distribution systems (WDS) is essential for sustainable urban water management. As infrastructure ages, water demand increases, and climate change places growing pressure on utilities worldwide, early detection and localization of leaks have become vital for reducing water losses, mitigating economic and environmental impacts, and ensuring reliable service delivery. Non-revenue water, mainly due to leaks, remains a significant global concern, accounting for approximately 30% of total urban water use (Guo et al., 2021). A wide array of sensor technologies has been developed for leak detection, each with unique operating principles and varying capabilities and limitations. These include acoustic, pressure, flow, electromagnetic, and fiber-optic sensors. Selecting the appropriate sensor depends on several factors, such as the pipe material and diameter, network configuration, installation and maintenance costs, and data transmission and analysis requirements. This review aims to provide a comprehensive evaluation of the current sensor technologies used for leak detection in WDS. It compares their performance characteristics, practical applicability under field conditions, and potential integration with emerging smart water network platforms. The goal is to assist utility managers, engineers, and researchers in making informed decisions regarding suitable sensing solutions tailored to specific system needs and operational constraints.

### 1.1 Significance of Urban Water Systems and Leak Detection

Urban water distribution networks (WDNs) are essential for ensuring safe water supply and supporting urban development. However, leakage accounts for nearly 30% of the total urban water use (Guo et al., 2021), resulting in more than 120 billion $m^3$ of water lost annually and financial losses exceeding 39 billion USD worldwide (Daniel et al., 2022). Beyond economic repercussions, leaks diminish service reliability, escalate pumping and treatment costs, and permit contaminant intrusion, which poses health risks (Wan et al., 2022). Additionally, they contribute to subsidence and sinkholes, exacerbating the environmental damage (Barros et al., 2025). Therefore, timely detection is crucial to maintain sustainability and safety.

### 1.2 Challenges in Leak Detection

Leak detection is challenged by buried infrastructure, intricate branching networks, and variable demands. Traditional methods, such as acoustic surveys and night-flow analysis, are labour-intensive and lack scalability (Guo et al., 2021; Wang et al., 2025b). Even advanced techniques encounter limitations, such as noise interference, sparse pressure/flow data, and model uncertainties that compromise accuracy (Xing et al., 2022; Sitaropoulos et al., 2023). In addition, acoustic and vibration systems are susceptible to false alarms in noisy environments (Yu et al., 2023; Fereidooni et al., 2021; Boadu et al., 2024).

### 1.3 Technological Advancement

The progress has been marked by a series of innovations. Manual inspections have evolved into acoustic sensing methods such as accelerometers, hydrophones, and noise loggers (Yu et al., 2023; Sitaropoulos et al., 2023; Uchendu et al., 2025). These were followed by transient-based (Xing et al., 2022; Zecchin et al., 2022) and hydraulic-model-based methods (Steffelbauer et al., 2022; Idachaba & Tomomewo, 2023). Advances in fiber optics (Guo et al., 2021; Mishra et al., 2025), IoT-enabled wireless sensor networks (Ismail et al., 2022; Alghamdi et al., 2022; Rahman et al., 2025), and optimization-based placement (Li & Cai, 2025; Ebrahimi et al., 2023) have further expanded monitoring capabilities. Recently, MEMS hydrophones (Zong et al., 2025), bio-inspired strain sensors (Zhou et al., 2025), and electrical impedance sensors (Qi et al., 2025) have emerged, along with specialized optical systems (Menon et al., 2025). The progression of these innovations from manual inspections to AI-enabled hybrid systems is summarized in Table 1.

Table 1. Evolution of Leak Detection Sensors and Methods in WDNs

| Era | Sensor / Method | Key Features | Citations |
|---|---|---|---|
| Early (pre-1970s → 1980s) | Manual inspections, listening sticks, tracer tests | Simple, low-cost, labor-intensive, time-consuming, imprecise | (Guo et al., 2021; Wang et al., 2025b) |
| | Pressure gauges & flow meters (hydraulic balance) | Mass/volume balance; detects system-wide water loss but sensitive to demand variation and sparse measurements | (Wan et al., 2022; Idachaba & Tomomewo, 2023) |
| 1980s–1990s | Acoustic sensors (accelerometers, hydrophones, noise loggers) | Leak noise correlation; cost-effective, non-intrusive; challenged by background noise and small leaks | (Yu et al., 2023; Sitaropoulos et al., 2023; Uchendu et al., 2025) |
| 1990s–2000s | Transient-based methods (negative pressure wave, inverse transient analysis) | Rapid leak/burst detection via pressure wave propagation; effective but complex in large networks | (Xing et al., 2022; Zecchin et al., 2022) |
| | Hydraulic model-based approaches | Compare simulated vs. measured pressure/flow; precise but calibration-sensitive | (Steffelbauer et al., 2022; Idachaba & Tomomewo, 2023) |
| 2000s | Fiber optic sensors | Distributed real-time monitoring; highly sensitive but costly and intrusive | (Guo et al., 2021; Mishra et al., 2025) |
| 2010s | Wireless Sensor Networks (WSNs), IoT-enabled monitoring | Continuous monitoring; low-power comms (LoRaWAN, LPWAN); scalable for wide-area urban systems | (Ismail et al., 2022; Alghamdi et al., 2022; Rahman et al., 2025) |
| | Optimization-based sensor placement | Entropy, sensitivity, metaheuristics; maximize information with limited sensors | (Li & Cai, 2025; Yang & Wang, 2023; Ebrahimi et al., 2023; Yousefi-Khoshqalb et al., 2023; Örn Garðarsson et al., 2022) |
| Late 2010s–2020s | MEMS-based hydrophones | Miniaturized, low-power, high sensitivity acoustic detection | (Zong et al., 2025) |

| | | | |
|---|---|---|---|
| | Bio-inspired flexible strain sensors | Real-time, ultrasensitive, adaptable to difficult environments | (Zhou et al., 2025) |
| | Electrical impedance sensors (plastic pipes) | High sensitivity to small leaks; cost-effective, easy deployment | (Qi et al., 2025) |
| | Optical sensors (hydrogen, oil, multipurpose pipelines) | High-precision, specialized applications in hazardous environments | (Menon et al., 2025) |
| Recent (2020s → present) | Machine Learning (ML) methods | Classification, anomaly detection; effective under noise | (Daniel et al., 2022; Barros et al., 2023) |
| | Deep Learning (DL: CNNs, LSTMs, Transformers) | Automatic feature extraction from time-series data; robust against noise | (Ahmad et al., 2022; Liu et al., 2025; Obunga et al., 2025) |
| | Hybrid frameworks (Model + AI) | Combines hydraulic models with ML/DL; balances accuracy and robustness | (Daniel et al., 2022; Basnet et al., 2025) |
| | Multi-sensor fusion systems (acoustic + pressure + flow) | Higher accuracy, fewer false alarms, real-time operation | (Daniel et al., 2022; Wang & Gao, 2023; Satterlee et al., 2025) |

1.4 Importance of Data Analysis

The rise of smart sensors has shifted the emphasis in leak detection from merely collecting and interpreting data. Analytical methods now range from traditional signal processing to regression- and graph-based anomaly detection (Barros et al., 2023) (Barros et al., 2025). Machine learning techniques aid in classification and predictive tasks (Daniel et al., 2022; Barros et al., 2023), whereas deep learning models such as CNNs, LSTMs, and Transformers can learn directly from raw time-series data, enhancing robustness against noise (Ahmad et al., 2022; Liu et al., 2025; Obunga et al., 2025). Semi-supervised learning reduces reliance on labeled datasets (Wang et al., 2025a; Shen et al., 2025), and sensor fusion frameworks such as dual Kalman filters improve resilience against missing or corrupted data (Wang & Gao, 2023; Romero-Ben et al., 2024; Satterlee et al., 2025). Benchmarking initiatives, such as BattLeDIM, offer standardized evaluation platforms that encourage innovation and comparability across different methods (Daniel et al., 2022). A comparative overview of these analytical approaches along with their advantages and limitations is presented in Table 2. Together, Tables 1 and 2 demonstrate the parallel evolution of leak detection technologies: sensors serve as primary data sources and analytical methods function as interpreters for decision-making. To emphasize their complementary roles, a direct comparison of the sensor technologies (hardware) and analytical approaches (software) is presented in Table 3.

Table 2. Data Analysis Approaches for Leak Detection in WDNs

| Approach | Example Techniques | Advantages | Limitations | Citations |
|---|---|---|---|---|
| Traditional signal processing | Acoustic signal filtering, frequency analysis | Simple, interpretable; effective for noise reduction | Limited scalability; requires manual interpretation | (Wan et al., 2022; Sitaropoulos et al., 2023) |
| Regression-based analysis | Gaussian Process interpolation | Estimates unmonitored nodal pressures; probabilistic outputs | Sensitive to model assumptions; requires training data | (Barros et al., 2023; Barros et al., 2025) |
| Graph & topology-based models | Graph Signal Processing, Multilayer networks | Exploit network topology; effective anomaly localization | Requires accurate system topology; complex implementation | (Barros et al., 2023; Barros et al., 2025) |
| Machine Learning (ML) | Classification, anomaly detection, clustering | Robust under noise; adaptive to diverse data | Requires labeled datasets; may overfit small datasets | (Daniel et al., 2022; Barros et al., 2023) |
| Deep Learning (DL) | CNNs, LSTMs, Transformers | Automatic feature learning; high accuracy with time-series data | Data- and compute-intensive; black-box nature | (Ahmad et al., 2022; Liu et al., 2025; Obunga et al., 2025) |

| | | | | |
|---|---|---|---|---|
| Semi-supervised / Multitask learning | Self-training, joint leak classification + localization | Reduces labeled data needs; improves generalization | Still requires some labeled data; model complexity | (Wang et al., 2025a; Shen et al., 2025) |
| Sensor fusion & state estimation | Dual Unscented Kalman Filter, multi-sensor fusion | Integrates pressure, flow, acoustic, vibration data; resilient to missing/corrupted data | Higher computation cost; requires synchronized data | (Wang & Gao, 2023; Romero-Ben et al., 2024; Satterlee et al., 2025) |
| Benchmarking & datasets | BattLeDIM competitions, open datasets | Standardized evaluation; promotes innovation | Limited dataset diversity; real-world validation gaps | (Daniel et al., 2022) |

Table 3. Comparison of Sensors and Methods for Leak Detection in WDNs

| Category | Examples | Strengths | Limitations | Typical Applications |
|---|---|---|---|---|
| Sensors (Hardware) | Acoustic (hydrophones, accelerometers), Pressure/Flow meters, Fiber optics, MEMS, Strain & Impedance sensors | Provide direct measurements; real-time monitoring; high sensitivity (esp. fiber optics, MEMS) | Cost, installation complexity, sensitivity to noise, limited coverage if sparsely deployed | Continuous leak monitoring, early detection, field inspections |
| Methods (Software/Analytics) | Traditional (mass/volume balance, night flow), Model-based (hydraulic, transient), Data-driven (ML, DL), Hybrid frameworks | Transform raw sensor data into actionable leak insights; scalable anomaly detection; capable of handling noisy environments (AI-based) | Require data quality and calibration; ML/DL need labeled data; high computational demand | Leak detection, localization, prediction, optimization of sensor placement |

### 1.5 Selection Criteria for Leak Detection Sensors and Methods

The selection of an appropriate leak detection method depends on both the technical capability and operational feasibility. To align research advancements with field implementation, this review assesses sensors and analytical methods against a set of practical selection criteria, including detection accuracy and sensitivity: the ability to identify both large bursts and small intermittent leaks under various network conditions (Daniel et al., 2022; Boadu et al., 2024). Cost-effectiveness: Balancing the costs of equipment, installation, and maintenance with the benefits of recovered water and reduced non-revenue water (Yousefi-Khoshqalb et al., 2023; Basnet et al., 2025). Ease of deployment and scalability: Suitability for buried and complex urban networks, with potential for expansion across extensive utility systems (Guo et al., 2021; Alghamdi et al., 2022). Data requirements and computational demands: compatibility with available sensor coverage, data quality, and processing resources (Ahmad et al., 2022; Obunga et al., 2025). Integration with smart water networks: The capacity to interact with IoT platforms, wireless sensor networks, and real-time decision support systems (Ismail et al., 2022; Rahman et al., 2025). These criteria form the foundation for the comparative analysis presented in Tables 1–3 and guide the discussion of research gaps and future directions in this review.

### 1.6 Gap, Purpose, and Objectives of this Review

Previous review articles have predominantly focused on either the hardware aspect, summarizing sensor technologies such as acoustic, pressure, or fiber-optic devices (Guo et al., 2021; Yu et al., 2023), or the software aspect, concentrating on analytical models, machine learning, or optimization frameworks (Daniel et al., 2022; Barros et al., 2023). However, few studies have attempted to integrate these two aspects into a cohesive framework that underscores their complementary role. This review addresses this gap by jointly examining sensors (as data sources) and analytical methods (as data interpreters) and evaluating them against practical selection criteria for real-world deployment. In doing so, it provides a more comprehensive foundation for both researchers and utility managers than previous reviews do. Despite these advances, several significant limitations persist: Limited real-world validation: Many solutions are demonstrated under laboratory or simulated conditions but have yet to be scaled to full utility operations (Yu et al., 2023; Yousefi-Khoshqalb et al., 2023). Insufficient focus on small or intermittent leaks: Persistent, low-volume losses that significantly contribute to nonrevenue water remain underexplored (Boadu et al., 2024). Economic and operational constraints: Optimization and placement strategies often overlook maintenance costs, energy demands, and cost–benefit considerations critical for utilities (Yousefi-Khoshqalb et al., 2023; Basnet et al., 2025). Fragmented integration: Although progress has been made in both sensing and data analytics, their integration into comprehensive, utility-ready frameworks is still limited (Guo et al., 2021; Wan et al., 2022; Qi et al., 2025). Accordingly, the purpose of this review is to consolidate sensor technologies and analytical methods into a unified framework, with an emphasis on deployment readiness. This dual focus highlights not only technological advances but also practical pathways for utility adoption (Guo et al., 2021; Qi et al., 2025). The specific objectives were to summarize the sensor- and data-driven methods for leak detection. The role of analytics in improving accuracy, resilience, and scalability is evaluated (Daniel et al., 2022; Barros et al., 2023). Examine optimization strategies for practical deployment in real-world networks (Li & Cai, 2025; Ebrahimi et al., 2023). Identify persistent research gaps and propose directions for future development (Guo et al., 2021; Wan et al., 2022; Qi et al., 2025).

## II. EVOLUTION OF SENSOR TECHNOLOGIES FOR LEAK DETECTION

Leak detection technologies in water distribution have advanced considerably, transitioning from manual acoustic methods, such as listening sticks, correlators, and noise loggers, to sensor-driven and intelligent frameworks. While early manual and acoustic techniques were cost-effective and straightforward, their efficiency diminished in noisy environments and plastic pipe networks, underscoring their operational limitations (Guo et al., 2021). In subsea environments, methods have evolved from threshold-based internal monitoring to wireless sensor networks (WSNs). Distributed acoustic sensors within WSNs enable each node to independently determine the presence or absence of leaks and communicate with a fusion center, thereby enhancing reliability under challenging subsea conditions (Tabella et al., 2021). Similarly, in water distribution networks (WDNs), leak detection has progressed from manual techniques to smart sensor-based systems that utilize pressure and flow measurements. With the integration of the IoT and big data, sensors now produce continuous time-series data for real-time analytics (Wan et al., 2022).

In addition to acoustics, non-acoustic methods such as CCTV inspection, gas injection, ground-penetrating radar (GPR), and infrared imaging have emerged. Notably, low-cost MEMS accelerometers stand out for their ability to detect vibration signals from leaks with high robustness and minimal maintenance, making them ideal for large-scale deployment (Yu et al., 2023). More advanced approaches now incorporate information-theoretic methods that optimize sensor placement using metrics such as detection, distinction, identification, and homogeneity, ensuring a more reliable differentiation of leakage events (Xing et al., 2022). In oilfield and industrial settings, evolution has progressed to optical and multispectral imaging sensors. Initially, discrete physical/chemical sensors (pH, turbidity, flow, etc.) were employed, but modern optical sensors offer noninvasive, real-time analysis with near-laboratory accuracy, suitable for harsh conditions (Ismail et al., 2022). Concurrently, hybrid methods that combine hardware-based sensors with data-driven analytics have gained popularity, with virtual or "soft" sensors complementing physical sensors to enhance robustness against noise (Steffelbauer et al., 2022).

Another crucial milestone is the optimization of pressure sensor placement based on information theory. Unlike metaheuristic approaches, such as GA and PSO, this method enhances pressure sensing by maximizing information relevance and minimizing redundancy, thereby increasing effectiveness and efficiency (Li & Cai, 2025). The broader adoption of IoT-enabled smart sensors integrated into hydraulic systems signifies a shift from solely hardware-based detection to hybrid sensing and computational models (Daniel et al., 2022). This progression also encompasses the next-generation communication infrastructure. Systems have transitioned from short-range, energy-intensive networks such as Wi-Fi, cellular, and Bluetooth to Low-Power Wide-Area Networks (LPWANs) such as LoRaWANs, which support scalable, real-time leakage monitoring in large complexes (Alghamdi et al., 2022). Recent research has emphasized multisensor fusion frameworks, combining acoustic with pressure and vibration with NPW, to leverage complementary strengths for enhanced accuracy and robustness (Wang & Gao, 2023). Further studies highlight a shift from reactive to proactive monitoring by integrating pressure, flow, vibration, acoustic, and thermal sensors with IoT-enabled networks (Aslam et al., 2022; Zecchin et al., 2022). Additionally, risk-based leakage functions have been introduced to prioritize sensor placement in areas where leaks have the greatest socio-economic and hydraulic impacts (Hu et al., 2022).

Leak detection has evolved from manual, acoustic, and threshold-based methods to IoT-enabled, risk-aware, and hybrid sensor networks. This progression highlights a shift toward continuous, intelligent, and proactive monitoring utilizing low-cost accelerometers, fiber-optic sensing, MEMS hydrophones, vibration-based detection, and multi-sensor fusion integrated with data analytics for scalable, real-world water distribution systems (Romero-Ben et al., 2024; Liu et al., 2025; Basnet et al., 2025; Sohn et al., 2025).

## III. COMPARISON BETWEEN SENSOR TECHNOLOGIES

Leak-detection methods in water distribution systems encompass a diverse range of sensor technologies, each with distinct advantages and limitations. Traditional acoustic devices, such as listening sticks and correlators, are cost-effective and easy to use, rely heavily on operator expertise, and are susceptible to environmental noise, particularly in urban settings (Guo et al., 2021). Standalone capacitive and acoustic sensors offer low-cost localized detection but are noise-prone and provide limited coverage, whereas networked wireless sensor networks (WSNs) enhance reliability through collaborative detection and data fusion (Tabella et al., 2021).

Pressure and flow sensors, widely deployed in SCADA systems, facilitate real-time monitoring and anomaly detection (Wan et al., 2022). However, they are generally more adept at identifying bursts than small or background leaks are. Accelerometer-based MEMS sensors have emerged as low-cost vibration-sensitive alternatives suitable for both metal and plastic pipes, enhancing automated leak detection (Yu et al., 2023). Optimized placement strategies, such as information-theoretic approaches, maximize the efficiency of pressure sensors by minimizing redundancy and ensuring broader network coverage (Xing et al., 2022; Li & Cai, 2025).

Non-acoustic sensors enhance detection capabilities in environments where acoustic methods are limited. For instance, optical and multispectral sensors offer precise, non-invasive monitoring in oilfields and harsh conditions, although their cost and complexity hinder their widespread deployment (Ismail et al., 2022). Similarly, fiber optic sensors provide high sensitivity and continuous distributed monitoring, but they are expensive and challenging to integrate into existing networks (Idachaba & Tomomewo, 2023; Satterlee et al., 2025). Infrared thermography, gas injection, and ground-penetrating radar (GPR) are also employed to detect subsurface or surface anomalies; however, they are costly and operationally demanding (Obunga et al., 2025; Khalifeh et al., 2021).

The latest advancements in smart sensors and IoT-enabled technologies involve the integration of acoustic, pressure, flow, and multiparameter sensors (pH, turbidity, and conductivity) with wireless networks. These devices produce continuous data streams that facilitate predictive and proactive leak management through big data analytics (Wan et al., 2022; Romero-Ben et al., 2024). Communication protocols have also progressed, with LoRaWAN-based IoT sensors offering scalable, low-power deployments over long distances, surpassing earlier GSM/Wi-Fi systems (Alghamdi et al., 2022).

Hybrid and fusion approaches integrate multiple types of sensors to address the individual limitations. For example, combining acoustic and pressure sensors enhances both sensitivity and stability, thereby reducing false alarms (Wang & Gao, 2023). Systems that incorporate hydrophones for long-distance detection and accelerometers for nearby leaks achieve a balance between coverage and accuracy (Zong et al., 2025). Hybrid sensing, which merges physical and virtual (data-driven) sensors, minimizes the need for dense deployment while enhancing robustness (Basnet et al., 2025; Sohn et al., 2025).

In conclusion, while traditional sensors offer cost-effective but limited solutions, advanced optical, fiber-optic, and IoT sensors deliver greater precision and scalability, albeit at a higher cost. The integration of multiple modalities and analytics in hybrid and smart sensing technologies is the most promising approach for efficient, real-time, and scalable leak detection in urban water systems.

Leak detection methods in water distribution systems encompass a wide range of sensor technologies, each of which offers unique advantages and limitations. Traditional acoustic devices remain low-cost and are widely used, whereas modern IoT-enabled hybrid sensors provide real-time monitoring and scalability. A detailed comparison of major sensor technologies is presented in Table 4.

Table 4. Comparison Between Sensor Types

| Sensor Type | Strengths | Limitations | References |
|---|---|---|---|
| Acoustic sensors (listening sticks, correlators, loggers) | Low-cost, simple, widely used; effective in metal pipes. | Operator-dependent; limited in noisy environments and plastic pipes. | (Guo et al., 2021; Tabella et al., 2021) |
| Pressure/Flow sensors | Real-time monitoring via SCADA; effective for burst detection; widely deployed. | Limited in detecting small/background leaks; require optimized placement for efficiency. | (Wan et al., 2022; Xing et al., 2022; Li & Cai, 2025) |
| MEMS Accelerometers | Low-cost; sensitive to vibrations; suitable for both metal and plastic pipes; easy to deploy. | May be affected by external vibrations; less effective without integration. | (Yu et al., 2023) |
| Optical/Multispectral sensors | High accuracy; non-invasive; reliable in harsh oilfield/industrial environments. | High cost; complex installation; limited scalability in WDNs. | (Ismail et al., 2022) |
| Fiber Optic sensors | High sensitivity; continuous distributed monitoring; robust for long pipelines. | Expensive; complex to retrofit; maintenance challenges. | (Idachaba & Tomomewo, 2023; Satterlee et al., 2025) |
| Infrared Thermography / GPR / Gas Injection | Useful for subsurface and surface anomaly detection. | Costly; equipment-intensive; limited field scalability. | (Obunga et al., 2025; Khalifeh et al., 2021) |
| IoT-enabled Smart Sensors (acoustic, pressure, multiparameter) | Real-time monitoring; scalable; integrates with big data and predictive analytics. | Dependent on communication/power infrastructure; may increase operational costs. | (Wan et al., 2022; Romero-Ben et al., 2024) |
| LoRaWAN-based IoT Sensors | Long-range, low-power, cost-effective; scalable deployments. | Still developing; may face connectivity and security challenges. | (Alghamdi et al., 2022) |
| Hybrid / Fusion Systems (e.g., Acoustic + Pressure, Hydrophone + Accelerometer) | Combine strengths of multiple sensors; improve robustness; reduce false alarms. | Increased complexity and cost; require advanced analytics for integration. | (Wang & Gao, 2023; Zong et al., 2025; Basnet et al., 2025; Sohn et al., 2025) |

Beyond tabular comparison, visual representation significantly enhances the comprehension of relative strengths and weaknesses across various sensor categories. Figure 1 depicts the comparative landscape of the sensor types, emphasizing their performance trade-offs in terms of accuracy, cost, scalability, and robustness.

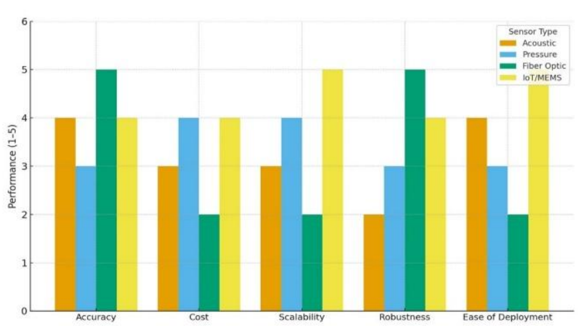


Figure1. Comparison Between Sensor Types

## IV. DATA ANALYTICS FOR LEAK DETECTION:

Data analytics has become integral to modern leak detection in urban water systems, transitioning the focus from solely sensor-based monitoring to intelligent data-driven decision-making. Initial efforts employed signal processing methods such as cross-correlation, wavelet transform, and filter diagonalization to address noise sensitivity. More sophisticated techniques now include machine learning and deep learning models such as Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and Time–Frequency Convolutional Neural Networks (TFCNNs), which have achieved detection accuracies exceeding 98% (Guo et al., 2021).

In subsea networks, data analytics consolidates sensor outputs at a fusion center, utilizing fusion rules such as the Counting Rule (CR), which is computationally straightforward but less precise; the Correlation-based Voting Rule (CVR), which is statistically optimal but necessitates complete knowledge of local detection probabilities; and the Modified CVR (MCVR), which strikes a balance between practicality and accuracy by estimating detection statistics (Tabella et al., 2021).

Leak detection methods are generally divided into two categories: data-driven approaches, which include statistical process control, clustering, and classification; and hydraulic model-based approaches, such as calibration, sensitivity analysis, and residual modeling. These methods are assessed using metrics such as the detection time, true positive rate (TPR), false positive rate (FPR), and localization accuracy (Wan et al., 2022). Signal processing enhances analytics by extracting time, frequency, and nonlinear features such as fractal dimension and entropy from vibration signals. Among the classifiers, the SqueezeNet CNN achieved approximately 95% accuracy, whereas KNN achieved approximately 91% sensitivity, illustrating the trade-offs between detection precision and sensitivity (Yu et al., 2023).

Multi-criteria decision frameworks merge data analytics with the information theory. For example, PROMETHEE assesses leak detection performance while weighing the cost of sensor installation and maintenance (Xing et al., 2022). With the advent of IoT-based systems, data analytics combines cloud and edge computing with ML/AI to facilitate anomaly detection, predictive maintenance, and risk assessment, including the forecasting of leakage, scale formation, and contamination (Ismail et al., 2022).

Advanced studies have approached sensor placement as a feature selection problem, utilizing mutual information measures to enhance leak detection accuracy while minimizing redundancy (Li & Cai, 2025). Similarly, Graph Signal Processing (GSP) models Water Distribution Networks (WDNs) as graphs and interprets pressure values as node signals to effectively identify anomalies (Daniel et al., 2022). IoT-enabled frameworks process data streams from wireless sensor networks (WSNs) for real-time anomaly detection, whereas LoRaWAN-based analytics systems assess packet delivery ratio, throughput, and energy consumption in both leak and no-leak scenarios (Ahmad et al., 2022; Alghamdi et al., 2022).

Simulation-based analytics is integral. The Detection Coverage Rate (DCR) and Total Detection Sensitivity (TDS) measure the effectiveness of sensor networks in identifying leaks under varying demand scenarios (Yang & Wang, 2023). In subsea pipelines, analytical approaches include machine learning classifiers, CFD-based leak modeling, and statistical interpretation of pressure transients, offering predictive and context-specific insights (Idachaba & Tomomewo, 2023). Hybrid methods, such as dual Pearson thresholds with EEMD filtering and 1D-CNNs, achieve 98.3% accuracy, significantly surpassing single-signal models (Wang & Gao, 2023). Similarly, CNN–LSTM hybrids capture both spatial and temporal leakage features, providing higher accuracy than standalone models (Sitaropoulos et al., 2023).

Statistical and information-theoretic methods also play crucial roles in enhancing leak detection. For example, entropy analysis can differentiate between leak-induced pressure fluctuations and normal consumption patterns (Ebrahimi et al., 2023), whereas wavelet and spectral analyses help identify frequency bands linked to leakage (Yousefi-Khoshqalb et al., 2023). Graph Signal Processing (GSP) approaches employ graph centrality and PageRank algorithms to detect anomalies with an accuracy of 86% in simulated networks (Barros et al., 2023). Additionally, innovative models such as autoencoder–Deep Learning (AE-DL) combined with U-Net further boost localization accuracy to 98% by utilizing synthetic datasets (Sehgal et al., 2023).

Recent studies have highlighted the integration of big data and AIoT platforms, where supervised methods such as SVM and decision trees are used to classify leaks, unsupervised approaches identify consumption anomalies, and hybrid models combine sensors with cloud analytics for predictive detection (Romero-Ben et al., 2024; Boadu et al., 2024; Liu et al., 2025). Advanced techniques also utilize graph Fourier transforms, impedance-based modeling, and ensemble classifiers such as Random Forests with feature importance analysis to enhance localization and interpretability (Li & Cai, 2025; Al Ghasheem, 2025; Qi et al., 2025).

In the realm of leak detection research, machine learning, deep learning, and hybrid frameworks have taken centre stage. These approaches range from

Growing Neural Gas (GNG) algorithms used for unsupervised anomaly detection (Mishra et al., 2025) to hybrid physics-informed AI models that merge hydraulic principles with neural networks (Basnet et al., 2025; Sohn et al., 2025). By integrating statistical, model-based, and AI-driven methods, modern data analytics converts raw sensor signals into actionable insights for both detection and localization (Lin et al., 2021).

## V. COMPARISON BETWEEN DATA ANALYTICS METHODS:

Data analytics methods for detecting leaks in urban water systems range from traditional statistical tools to advanced deep learning frameworks, each presenting unique trade-offs in terms of accuracy, scalability, and computational demand. Traditional signal processing methods, such as cross-correlation and wavelet analysis, are effective in controlled environments but require prior knowledge and tend to degrade in noisy conditions. Classical machine learning (ML) techniques, including SVM, Random Forests, and ANNs, enhance detection accuracy, but rely heavily on feature extraction and data quality. In contrast, deep learning models such as CNNs and TFCNNs process raw data directly, achieving accuracies above 98% and demonstrating strong noise robustness, albeit with higher computational and data demands (Guo et al., 2021).

Decision fusion rules further distinguish between analytics. The Counting Rule (CR) is computationally straightforward but less precise, whereas the Chair–Varshney Rule (CVR) achieves statistical optimality, necessitating complete knowledge of local detection probabilities, which is often impractical. The Modified CVR (MCVR) strikes a practical balance by estimating unknown parameters and enhancing accuracy without excessive complexity (Tabella et al., 2021). Various approaches balance the accuracy, interpretability, and computational efficiency. Statistical process control (SPC) remains simple and intuitive but offers limited accuracy and high false-positive rates. In contrast, prediction classification methods (ANNs, SVMs, and DNNs) achieve 98–100% accuracy for burst detection. Clustering methods such as SOM and DBSCAN facilitate unsupervised leak localization but require careful parameterization. Hydraulic model-based methods provide superior localization accuracy but are computationally intensive and sensitive to modeling assumptions (Wan et al., 2022). Comparative studies revealed variability in classifier performance. SVMs demonstrate stability with small datasets but achieve a lower accuracy of approximately 81%. Decision Trees offer interpretability, with a moderate accuracy of approximately 84%. KNN exhibits a high sensitivity of approximately 91% but struggles with noise. CNN-based models such as SqueezeNet excel with an accuracy of approximately 95%, underscoring the superiority of deep learning approaches in complex water distribution systems (Yu et al., 2023). Multi-criteria decision methods, such as PROMETHEE, extend evaluation beyond detection accuracy by incorporating criteria such as identification, distinction, homogeneity, and cost, providing more comprehensive assessments (Xing et al., 2022). Meanwhile, big data platforms with ML integration support predictive and adaptive detection, particularly for nonlinear water system behaviours, whereas edge/cloud frameworks enable real-time monitoring across distributed systems (Ismail et al., 2022).

Model-based approaches remain reliable baselines when properly calibrated, although they incur high computational costs (Steffelbauer et al., 2022). Alternatives, such as graph signal processing (GSP), offer scalability and efficiency with fewer sensors, although they are still in the early testing phases (Daniel et al., 2022). Hybrid methods that integrate physical models with ML or AI enhance robustness, interpretability, and generalization; however, they encounter challenges related to data requirements and complexity (Basnet et al., 2025; Sohn et al., 2025; Satterlee et al., 2025). Advanced techniques have increasingly focused on fusion and optimization. CNN–LSTM hybrids merge spatial and temporal learning to deliver a superior performance in noisy environments (Sitaropoulos et al., 2023). The weighted fusion of acoustic and pressure signals achieved over 98% accuracy, surpassing that of single-signal models (Wang & Gao, 2023). Optimization strategies, including metaheuristics (GA and PSO) and information-theoretic heuristics, enhance sensor placement and input efficiency, boosting classification accuracy to over 99% while reducing computational demands (Li & Cai, 2025).

In summary, the comparison highlights that, although statistical methods are straightforward, they are susceptible to false alarms. Classical machine learning provides a balance between interpretability and moderate accuracy. Deep learning, on the other hand, delivers the highest performance in detection and localization but demands extensive datasets and computational resources. Hybrid and ensemble methods, however, offer robustness and scalability, making them the most promising option for future real-world implementations of leak detection analytics (Romero-Ben et al., 2024; Liu et al., 2025; Al Ghasheem, 2025; Aslam et al., 2022; Todini et al., 2021). Approaches to data analytics for leak detection differ significantly in terms of methodology, accuracy, scalability, and computational requirements. Traditional statistical methods remain simple and interpretable, whereas machine-learning and deep-learning approaches improve accuracy and robustness. Table 5 provides a structured comparison of these methods and summarizes their strengths, limitations, and relevant references.

Table 5. Comparison Between Data Analytics Methods

| Method | Strengths | Limitations |
|---|---|---|
| Statistical / Signal Processing (Cross-correlation, Wavelets, SPC) | Simple, interpretable, cost-effective; effective in controlled settings. | Sensitive to noise; requires prior knowledge; high false positives; low accuracy for complex leaks. |
| Classical ML (SVM, ANN, Decision Trees, KNN, Random Forest) | Higher accuracy than statistical methods; interpretable (DTs); moderate computational needs. | Feature engineering required; less robust in noisy or highly nonlinear conditions. |
| Deep Learning (CNN, TFCNN, SqueezeNet) | Handles raw data directly; robust to noise; very high accuracy (>95–98%). | High computational demand; requires large labeled datasets. |
| Fusion Rules (CR, CVR, MCVR) | CR: simple; CVR: statistically optimal; MCVR: balances practicality and accuracy. | CR: less accurate; CVR: impractical (needs local probabilities). |
| Clustering (SOM, DBSCAN) | Supports unsupervised leak detection/localization; flexible. | Sensitive to parameter selection; may misclassify under noisy data. |
| Hydraulic Model-Based | High localization accuracy; interpretable. | Computationally intensive; sensitive to calibration errors. |
| Multi-Criteria Decision (PROMETHEE) | Balances technical performance with cost and decision-maker preferences. | Requires structured evaluation criteria; more complex to implement. |
| Big Data & Edge/Cloud ML | Scalable; supports predictive and adaptive detection; real-time monitoring. | High infrastructure requirements; integration complexity. |
| Graph Signal Processing (GSP) | Computationally efficient; works with fewer sensors; robust to noise. | Still in early-stage testing; limited field validation. |
| Hybrid/Ensemble (Model + ML, CNN–LSTM, Multi-signal fusion) | Combines strengths; robust to noise; >98–99% accuracy; adaptable. | High complexity; data and computation intensive. |

To further illustrate these trade-offs, Figure. 2 visually compares the major data analytics methods used for leak detection. The figure highlights their relative performance in terms of accuracy, interpretability, scalability, and robustness against noise, clearly demonstrating the advantages of the hybrid and deep learning approaches.

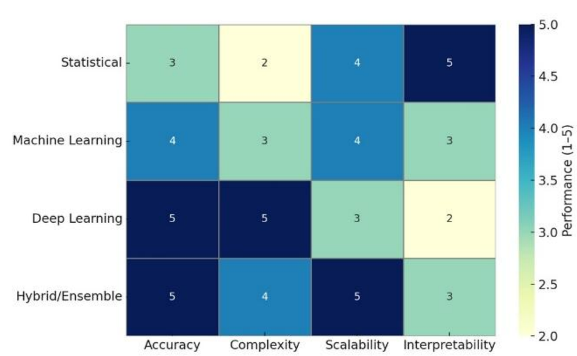


Figure 2. Comparison Between Data Analytics Methods

In summary, the comparison underscores that while statistical and signal-processing methods offer straightforward and cost-effective solutions, their limitations in noisy real-world environments render them less dependable for urban water systems. Classical machine learning approaches enhance accuracy and interpretability but are heavily reliant on data preprocessing and feature engineering. Deep learning models, such as CNNs and hybrid CNN–LSTM architectures, exhibit the highest accuracy and robustness yet demand substantial computational resources and large datasets. The most promising avenues for optimizing leak detection in urban water systems are hybrid and ensemble approaches, which integrate model-based knowledge, machine learning, and multi-sensor fusion to balance accuracy, scalability, and operational feasibility. These methods align with the growing adoption of IoT and big data platforms, enabling predictive, adaptive, and real-time monitoring frameworks for sustainable water management (Romero-Ben et al., 2024; Liu et al., 2025; Todini et al., 2021; Al Ghasheem, 2025; Aslam et al., 2022).

## VI. INTEGRATION OF SENSOR AND DATA ANALYTICS

The integration of sensor technologies with data analytics has become a fundamental element in intelligent leak detection in urban water systems. This combination harnesses the capabilities of physical sensing devices and computational intelligence, thereby facilitating automatic, real-time, and scalable leak detection.

Early integration efforts merged acoustic sensors with AI-based analytics, transforming sensor data into spectrograms that were then processed by deep learning models, such as CNNs. This approach significantly enhances robustness under low signal-to-noise conditions (Guo et al., 2021). In subsea applications, distributed sensors are paired with statistical fusion algorithms (e.g., MAP and MMSE), facilitating not only the detection but also the precise localization of leaks (Tabella et al., 2021).

In urban water systems, sensor networks integrated with SCADA or IoT platforms deliver real-time data streams that are pre-processed, analyzed, and visualized through leak maps to aid operator decision-making. By merging multi-sensor data with advanced analytics, such as multivariate models and fusion methods, these systems minimize false alarms and enhance reliability (Wan et al., 2022). Similarly, accelerometers connected to IoT platforms transmit vibration data for centralized ML-based processing, facilitating large-scale automatic monitoring (Yu et al., 2023).

Integration strategies encompass multicriteria decision-making approaches. For instance, sensor placement designs are assessed not only for their technical performance but also for cost-effectiveness using PROMETHEE, ensuring that deployments satisfy both the engineering and economic requirements (Xing et al., 2022). Additionally, IoT-enabled systems link sensors through communication technologies such as ZigBee, LoRa, and WiFi, transmitting data to cloud or edge platforms, where AI/ML algorithms provide predictive maintenance and leak risk assessments (Ismail et al., 2022; Ahmad et al., 2022; Boadu et al., 2024; Romero-Ben et al., 2024).

The integration of hardware with machine learning is increasingly being acknowledged as the most practical solution. Physical sensors, such as acoustic, pressure, or vibration sensors, produce raw signals that are then pre-processed 0and classified using ML algorithms such as k-NN, QDA, or hybrid CNN–LSTM models. These frameworks achieve a high localization accuracy and reduce reliance on dense sensor networks (Steffelbauer et al., 2022; Li & Cai, 2025; Sitaropoulos et al., 2023). Hybrid sensor–analytics systems also utilize A–P signal fusion (acoustic + pressure) processed by CNNs for automatic feature extraction, which enhances robustness against noise and reduces false alarms (Wang & Gao, 2023).

Advanced frameworks increasingly integrate graph signal processing (GSP) with pressure sensor networks, treating data as graph signals analyzed using filters and spectral methods to efficiently localize leaks (Daniel et al., 2022; Barros et al., 2023; Li & Cai, 2025). Other strategies involve simulation-based optimization of sensor deployment to maximize detection coverage (Yang & Wang, 2023) or hybrid frameworks that combine CFD models with physical sensor inputs to predict leak propagation in complex environments (Idachaba & Tomomewo, 2023).

The integration of Internet of Things (IoT) technology is pivotal for the advancement of next-generation water systems. Smart meters, hydrophones, and flow and pressure sensors continuously feed data into cloud or edge computing platforms, where ML and AI algorithms facilitate anomaly detection, predictive maintenance, and decision support (Liu et al., 2025; Basnet et al., 2025; Sohn et al., 2025; Wang et al., 2025b). For instance, MEMS-based hydrophone–accelerometer modules utilize signal fusion to enhance detection accuracy under varying conditions (Zong et al., 2025). Similarly, AIoT-driven systems combine physical sensing with deep learning models (AE-DL, U-Net, and GNG networks), enabling adaptive detection and robust classification in real-world scenarios (Zhao et al., 2025).

In summary, the integration of sensor technologies and analytics has marked a paradigm shift from reactive to proactive leak management. The fusion of IoT-enabled sensing, advanced data-driven modeling, and optimization frameworks creates comprehensive systems that not only detect leaks in real-time but also predict, localize, and support automated interventions, laying the groundwork for resilient and sustainable urban water systems (Dong et al., 2024; Medio et al., 2024; Santos-Ruiz et al., 2022; Sheeja Rani et al., 2025).

## VII.PRACTICAL SELECTION CRITERIA FOR LEAK DETECTION

The choice of leak detection methods in water distribution systems is shaped by various practical factors such as leak type, data availability, environmental conditions, cost, scalability, and computational efficiency. Burst leaks are typically easier to identify than persistent background leaks, whereas noisy environments can compromise the accuracy of acoustic sensors. Data requirements vary significantly: machine learning (ML) methods require large, labeled datasets, whereas signal-processing approaches rely on predefined leakage signal characteristics. Acoustic methods are cost-effective and widely used, whereas AI-driven models, which require more computational resources, offer scalability for smart-network applications (Guo et al., 2021). In subsea operations, the computational efficiency, robustness to uncertainty, and adaptability are crucial. Rules such as (CVR) yield optimal results but are impractical under unknown local probabilities, prompting the use of Modified CVR (MCVR) to balance accuracy and feasibility (Tabella et al., 2021). For water distribution networks (WDNs), data-driven methods require extensive long-term datasets, making them suitable for well-instrumented systems, whereas model-based approaches perform effectively with limited data. Sensor placement and density directly influence leak localization accuracy, and robust systems must manage the uncertainty from noise and fluctuating demand patterns (Wan et al., 2022).

Model selection is crucial in plastic pipelines, where balancing the accuracy and sensitivity is essential. For instance, SqueezeNet offers higher accuracy, whereas (KNN) provides greater sensitivity. Detection outcomes are significantly influenced by factors such as pipe material, diameter, and dataset size, with RMS and fractal dimensions consistently proving to be reliable features (Yu et al., 2023). The optimization of the sensor placement involves a careful balance between detection, distinction, and cost efficiency. Techniques such as PROMETHEE combine technical performance with decision-maker preferences, whereas scalability ensures adaptability to various WDN sizes (Xing et al., 2022). In harsh oilfield environments, optical sensors are favored because of their durability under extreme pressures, temperatures, and corrosive conditions, whereas multispectral sensors are more expensive, although more accurate. Communication constraints often require fiber optic or laser-based links supported by robust stainless-steel packaging for longevity (Ismail et al., 2022). In water distribution systems, soft sensors and hybrid methods strike a balance between cost and accuracy, whereas deep learning methods achieve high precision but demand large datasets and computational resources (Steffelbauer et al., 2022).

The optimization of sensor placement remains a fundamental design criterion. Beyond traditional metaheuristics, information-theoretic methods offer similar accuracy with reduced computational time, thereby making them effective for large-scale networks (Li & Cai, 2025). Similarly, Graph Signal Processing (GSP) provides computational efficiency and reduced sensor density while maintaining robustness against noisy real-world data (Daniel et al., 2022). When selecting sensors for IoT deployment, factors such as application type, environmental resilience, communication protocol compatibility, packaging durability, and scalability must be considered (Ahmad et al., 2022). Emerging communication technologies such as LoRaWAN support long-range, low-power, and cost-effective IoT deployments with high reliability, thereby eliminating the need for costly repeaters (Alghamdi et al., 2022). Optimal deployment in WDNs requires balancing coverage, sensitivity, budget, reliability, and adaptability to fluctuations in water load (Yang & Wang, 2023). For pipelines, the leak detection design depends on the environment (subsea, Arctic, or surface), fluid type, and required detection speed. Fiber-optic and distributed sensing technologies are often integrated to enhance the reliability and safety (Idachaba & Tomomewo, 2023).

Hybrid detection models significantly affect the selection processes. The fusion of acoustic pressure (A-P) with CNNs enhances their robustness in noisy environments, achieving over 95% accuracy, whereas CNN-LSTM hybrid models surpass standalone models in terms of accuracy, scalability, and noise resilience (Liy-González et al., 2024). Optimizing pressure gauge networks (PGNs) involves entropy-based placement, measurement intervals of approximately 60 h, and independence from leak parameters, thereby improving their adaptability (Ebrahimi et al., 2023). Low-cost acoustic hydrant and pressure sensors with thresholding offer practical and scalable solutions for utilities (Yousefi-Khoshqalb et al., 2023; Barros et al., 2023). Other essential criteria include noise resilience, system costs, ease of installation, energy efficiency, and adaptability to various pipe materials. For example, AE sensors can detect leaks as small as 0.3 mm and operate effectively across different pressure ranges while resisting environmental noise, with Growing Neural Gas (GNG) algorithms reducing data requirements (Mishra et al., 2025). In underwater pipelines, hydrophones are excellent for detecting large leaks over long distances, whereas accelerometers are effective for detecting small leaks at shorter ranges. Integrated modules that combine both technologies optimize adaptability (Zong et al., 2025). Ultimately, the decision hinges on a multicriteria balance: accuracy, sensitivity, scalability, robustness, integration with SCADA/IoT platforms, and economic feasibility. Risk-based frameworks, such as hazard–vulnerability–exposure (HVE) models, assist in prioritizing sensor placement in areas with higher socio-economic or infrastructural consequences, ensuring efficient resource allocation (Medio et al., 2024).

## VIII. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite significant advancements in leak detection, several gaps persist that impede the large-scale real-world implementation of advanced solutions, as depicted in Figure 3. Limited Field Validation: Most algorithms and sensor frameworks have been tested in laboratory or simulated settings. Real urban water networks with their complex demand variations and aging infrastructure remain largely unexplored. Detection of Small and Background Leaks: While major bursts are easily detected, small leaks that accumulate into significant losses often go unnoticed because of sensitivity limitations and high false-alarm rates. High Cost and Scalability Constraints – Advanced sensors (e.g., fiber optics and multispectral devices) provide high accuracy but remain costly and impractical for large-scale retrofitting. Energy and communication bottleneck-IoT-enabled solutions rely on continuous monitoring but face unresolved challenges in terms of battery life, bandwidth, and low-power wide-area network (LPWAN) integration. Cyber-Physical Security and Data Privacy – As AIoT-based monitoring expands, water networks have become increasingly vulnerable to cyber threats. Research on secure architectures and resilient communication protocols has been limited. Integration and Interoperability – Many studies have treated sensors and analytics independently, lacking standardized frameworks for unified, interoperable leak detection platforms. Data Limitations for Machine Learning – Deep learning requires large, labeled datasets, which are scarce in practice. Synthetic data, transfer learning, and physics-informed modeling are promising, but underdeveloped. Digital twins and physics-informed AI – digital twins and hybrid models that combine physical laws with AI are in their early stages but could offer robust, adaptive solutions for real-time monitoring and prediction.

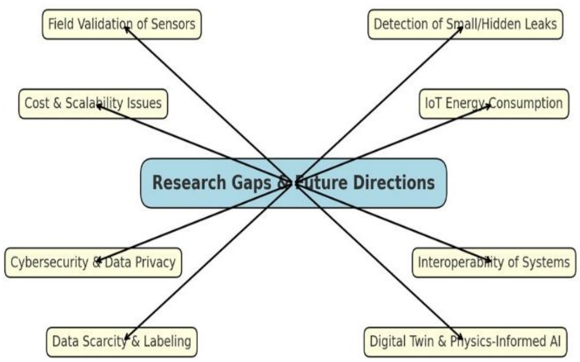


Figure 3. Research Gap and Future Directions

## IX. CONCLUSION

Leak detection has evolved from manual acoustic inspections to IoT-enabled smart sensing and advanced AI analytics, presenting unprecedented opportunities for the real-time, predictive monitoring of water systems. This review consolidates the developments in sensor technologies, data analytics methods, and their integration, highlighting how these domains collectively support proactive and scalable leak management in urban water systems. Comparative analyses revealed that while traditional sensors are cost-effective, they lack robustness in complex environments. In contrast, the modern IoT and hybrid sensors offer scalability and integration potential, although they are more expensive. On the analytics front, statistical methods remain simple but limited, classical ML strikes a balance between accuracy and interpretability, and deep learning and hybrid frameworks deliver superior performance (>95–98%), albeit with higher data and computational demands. The integration of sensors with IoT platforms, cloud/edge computing, and AI-driven analytics signifies a paradigm shift toward adaptive, real-time decision-making frameworks.

Despite these advances, significant gaps persist, particularly in field-scale validation, the detection of small leaks, cost and energy constraints, interoperability, and cybersecurity. Addressing these challenges necessitates hybrid adaptive approaches that integrate physics-informed AI, digital twins, and optimized IoT infrastructures. This study uniquely contributes by offering a holistic framework that integrates sensor evolution, analytics development, and practical selection criteria, providing both researchers and practitioners with structured guidance for optimizing leak detection. By bridging technological innovation with operational needs, this review lays the groundwork for future resilient and sustainable water-management systems.

DATA AVAILABILITY STATEMENT:

The data supporting the findings of this study are derived exclusively from previously published sources, which are cited in the reference list. No new datasets were generated or analyzed during the current study. Therefore, data sharing is not applicable to this article.

DECLARATIONS:

Author Contributions

S. Ranganathan: Conceptualization, literature survey, manuscript drafting.

Dr. N. Vinoth Kumar: Supervision, technical validation, review, editing and final approval of the manuscript.

E. Muthuramalingam: Methodology guidance, critical revisions,

Competing Interests

The authors declare that they have no competing interests.

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Data Availability

All data used in this study are derived from previously published works, as cited in the reference list. No new datasets were generated during this study.

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