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Systematic Review

Smart Leak Detection in Water Distribution Networks: A Systematic Review and D-A-T Taxonomy

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Abstract

Leaks in water distribution networks present a significant challenge for water resource management, necessitating timely and reliable detection methods. However, the literature remains fragmented across sensing technologies, data-processing approaches, and diagnostic capabilities. This article presents a systematic review of technologies and methods for water leak detection, localisation, and characterisation, providing a structured classification and critical analysis of the available evidence. The review was conducted and reported in accordance with PRISMA 2020 and included 91 publications, comprising 70 primary studies and 21 review articles. Literature searches were performed in June 2026 across Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, ASCE, and Taylor & Francis. The studies were classified according to the D-A-T taxonomy, encompassing three dimensions: data acquisition, processing architecture, and diagnostic task. Among the 70 primary studies, hydraulic sensing (D1) was identified in 37 studies (52.9%), signal and statistical processing (A2) in 48 (68.6%), and leak detection (T1) in 67 (95.7%). The principal challenges identified concerned validation under real-world operating conditions, generalisation across networks, and the comparability of findings between studies. The review further identifies gaps in the availability of real-world data and highlights multimodal data acquisition, hybrid or fusion-based processing, and multitask diagnosis as potential avenues for future research.

Keywords: systematic review; water distribution networks (WDNs); leak detection; D-A-T taxonomy; multimodal sensing

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1. Introduction

Water distribution networks experience substantial water losses due to pipe leaks. Early leak detection enables a timely response, helping to reduce both water losses and operational costs. However, conventional detection methods are often time-consuming and costly to implement. Consequently, there is a growing need for faster, more cost-effective approaches to detecting leaks in water distribution networks.

Water pipeline infrastructure plays a vital role in urban water supply and irrigation systems. Advances in technology have improved the accessibility of monitoring solutions and the communication capabilities of Internet of Things (IoT) networks. Technologies used

for leak detection and monitoring include acoustic sensors, infrared cameras, IoT systems, multispectral and hyperspectral imaging, fibre-optic sensors, light detection and ranging (LiDAR), unmanned aerial vehicles (UAVs), and machine learning and wavelet-based algorithms. The rapid development of these technologies has created a need for a more systematic organisation of the literature. Furthermore, differences in sensing technologies, data processing methods, and deployment configurations make it difficult to compare existing approaches using consistent criteria.

The challenges in this field are closely linked to the varying pace at which cities adopt advanced technologies and the rapid development of new methods for water leak detection and monitoring. Although several reviews are available in the literature, they employ different classification criteria, making it difficult to compare the sources of leak-related evidence, the methods used to process the data, and the diagnostic outcomes achieved. This systematic review addresses this fragmentation by integrating these aspects within a common analytical framework.

This article aims to review, classify, and characterise the literature on established and emerging technologies for water leak detection, examining their applications and the contexts in which they have been deployed. Particular attention is given to sensing technologies, data processing methods, and diagnostic capabilities. Technologies such as the Internet of Things and unmanned aerial vehicles (UAVs) are examined to identify their limitations, existing research gaps, and potential directions for future developments in water leak detection.

This systematic review proposes the D-A-T taxonomy as a multidimensional framework for examining water leak detection, localisation, and characterisation technologies. Whereas existing review approaches are primarily organised around sensing technologies, computational methods, or monitoring applications, the proposed taxonomy distinguishes three complementary dimensions: data acquisition (D), processing architecture (A), and diagnostic task (T). Rather than simply classifying individual technologies, the taxonomy provides a consistent basis for examining how sensing modalities, processing approaches, and diagnostic capabilities are combined within individual studies. By considering these dimensions together, the framework may help identify recurrent technological configurations, gaps in diagnostic capabilities, and limitations in the available evidence. It may also facilitate more systematic comparisons across heterogeneous leak detection approaches.

Research Questions

The five research questions formulated for this systematic review are presented in Table 1.

Table 1. Research questions.

Code	Research Question	Purpose
RQ1	What are the main approaches, methods and techniques employed for the detection, localisation, and characterisation of leaks in water distribution networks?	To classify the literature.
RQ2	What sensor configurations are being integrated into Internet of Things infrastructures and unmanned aerial vehicles (UAVs), and which performance metrics are used to evaluate these configurations?	To identify evaluation practices.
RQ3	What are the advantages and limitations of existing technological approaches to water leak detection?	To conduct a critical analysis.

Table 1. *Cont.*

Code	Research Question	Purpose
RQ4	What are the main research gaps that need to be addressed to achieve autonomous, continuous, and low-cost monitoring?	To identify opportunities.
RQ5	What are the most promising future directions for developing an integrated water leak detection system?	To propose a research agenda.

2. Review Methodology

The systematic review was reported in accordance with the PRISMA 2020 statement [1]. The study selection process is documented in Table 2 and Figure 1, while compliance with the applicable PRISMA 2020 reporting items is detailed in the completed checklist provided in Table 3. Following this reporting framework was intended to enhance the transparency and reproducibility of the review by providing a clear record of the study-selection process, from the initial identification of studies across the information sources to their final inclusion.

Table 2. Summary of the PRISMA study selection process.

Stage	Quantity	Description
Records identified	160	Total found
Duplicates removed	9	Duplicate records were removed
Titles/abstracts assessed	151	Initial filter
Excluded after abstract screening	35	Discarded as they fell outside the scope of water leak detection methods, sensing technologies, or related water conveyance systems
Reports sought for retrieval	116	Records selected for full-text retrieval
Reports not retrieved	1	Full text could not be retrieved or independently verified
Reports assessed for eligibility	115	Detailed review
Studies excluded	24	Excluded due to ineligible document type (theses, conference proceedings) or non-transferable non-water fluid systems
Studies included	91	Final corpus

Table 3. PRISMA 2020 checklist for the present systematic review.

PRISMA Item	Reporting Topic	Location in Manuscript	Status
1	Title	Title	Reported
2	Abstract	Abstract	Reported
3	Rationale	Section 1, Introduction	Reported
4	Objectives	Section 1 and Section Research Questions	Reported
5	Eligibility criteria	Section 2.3	Reported
6	Information sources	Section 2.1	Reported
7	Search strategy	Section 2.2	Reported
8	Selection process	Section 2.4; Table 2; Figure 1	Reported
9	Data collection process	Section 2.5/D-A-T classification procedure	Reported
10	Data items	Sections 4.1–4.4; Tables 4 and 5	Reported
11	Study risk-of-bias assessment	Section 2.6/limitations	Not formally performed
12	Effect measures	Not applicable	N/A
13	Synthesis methods	Sections 4 and 5	Reported

Table 3. *Cont.*

PRISMA Item	Reporting Topic	Location in Manuscript	Status
14	Reporting bias assessment	Not formally performed	Not performed
15	Certainty assessment	Not applicable to this descriptive technological review	N/A
16	Study selection	Section 2.4; Table 2; Figure 1	Reported
17	Study characteristics	Tables 5 and 6	Reported
18	Risk of bias in studies	Not formally assessed	Not performed
19	Results of individual studies	Sections 4 and 5; Tables 5 and 6	Reported
20	Results of syntheses	Section 5	Reported
21	Reporting biases	Section 2.6	Not formally assessed; methodological limitations discussed in Sections 2.6 and 2.7.
22	Certainty of evidence	Not applicable	N/A
23	Discussion	Sections 5 and 6	Reported
24	Registration and protocol	No prospective public registration	Not registered
25	Support	Funding statement	Reported
26	Competing interests	Conflicts of interest statement	Reported
27	Availability of data/materials	Data availability statement	Reported

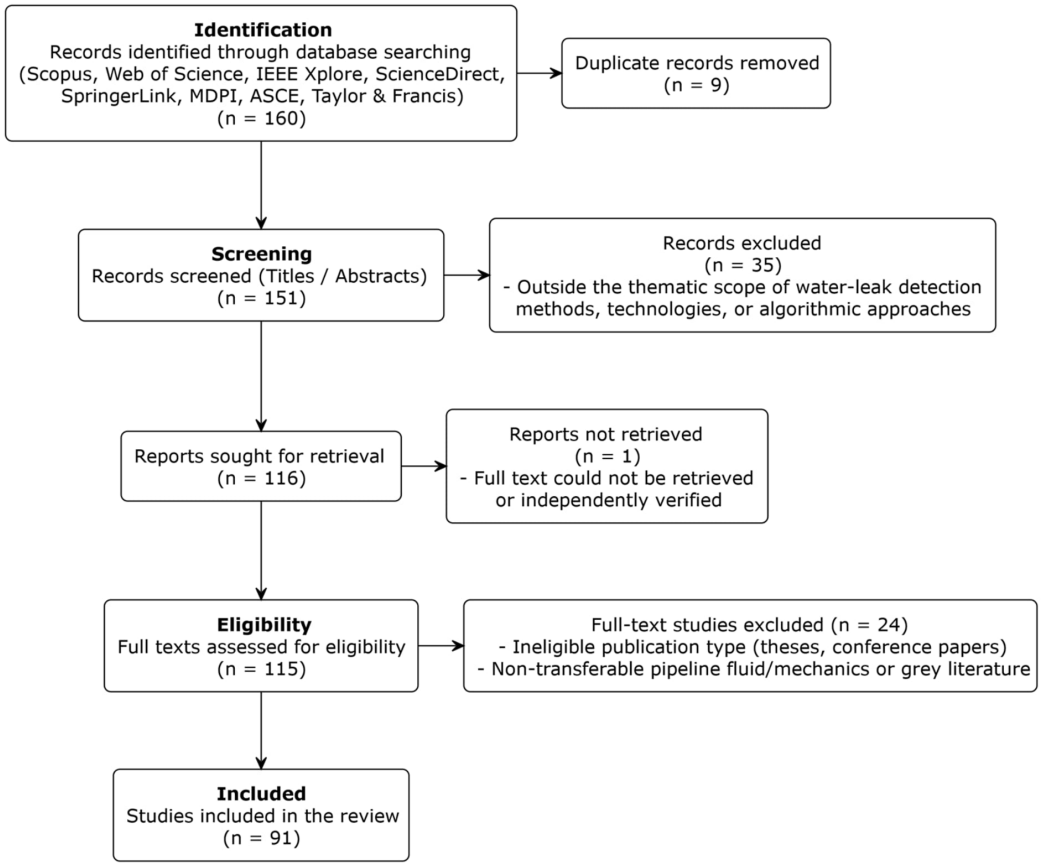


Figure 1. PRISMA 2020 flow diagram of the study selection process.

This paper presents a systematic review of water leak detection methods. This approach provides a structured and objective framework for addressing the research questions. The systematic review was not prospectively registered, and no formal written review pro-

tocol was prepared. Consequently, no registration number or publicly accessible protocol is available.

2.1. Information Sources

The literature search was conducted in June 2026 using eight information sources: Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, ASCE Library, and Taylor & Francis Online. Scopus and Web of Science were consulted to identify multidisciplinary peer-reviewed publications, while IEEE Xplore was used to retrieve studies on sensing systems, communication technologies, and computational approaches. The remaining five sources—ScienceDirect, SpringerLink, MDPI, ASCE Library, and Taylor & Francis Online—were searched to extend coverage of hydraulic modelling, water distribution infrastructure, leak detection technologies, and related engineering applications.

The search strategy covered four conceptual components: water distribution and leakage, sensing and monitoring technologies, analytical and computational methods, and diagnostic objectives. The Boolean search strategy is described in Section 2.2, with database-specific search expressions.

2.2. Search String

The search was structured by dividing the topic into four conceptual blocks: domain, core technologies, action/metrics, and types/models.

The Boolean operator OR was used to group synonymous search terms in English and Spanish, while AND was used to combine the four search blocks.

The final string used was:

(“water leak*” OR “fuga* de agua” OR “water distribution network” OR “pipeline leakage” OR “non-revenue water”) AND (“sensor*” OR “IoT” OR “drone*” OR “UAV” OR “pressure sensor*” OR “remote sensing” OR “LiDAR” OR “fiber optic”) AND (“acoustic” OR “thermal” OR “machine learning” OR “hydraulic model”) AND (“detection” OR “detección” OR “leak localisation”).

To improve the transparency of the search methodology, the general Boolean strategy was reconstructed as database-specific search expressions for the eight information sources included in this review: Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, ASCE Library, and Taylor & Francis Online. The reconstructed expressions retain the four conceptual blocks covering water leakage and distribution infrastructure, sensing technologies, analytical approaches, and diagnostic tasks. However, the original database-specific search histories were unavailable for verification. The expressions presented below should, therefore, be regarded as reconstructed adaptations, rather than exact historical records of the searches conducted.

Scopus. The reconstructed search expression for the title, abstract, and keyword fields is: TITLE-ABS-KEY((“water leak*” OR “fuga* de agua” OR “water distribution network” OR “pipeline leakage” OR “non-revenue water”) AND (sensor* OR IoT OR drone* OR UAV OR “pressure sensor*” OR “remote sensing” OR LiDAR OR “fiber optic”) AND (acoustic OR thermal OR “machine learning” OR “hydraulic model”) AND (detection OR detección OR “leak localisation”)).

Web of Science. The reconstructed search expression using the Topic field is: TS = ((“water leak*” OR “fuga* de agua” OR “water distribution network” OR “pipeline leakage” OR “non-revenue water”) AND (sensor* OR IoT OR drone* OR UAV OR “pressure sensor*” OR “remote sensing” OR LiDAR OR “fiber optic”) AND (acoustic OR thermal OR ”machine learning” OR “hydraulic model”) AND (detection OR detección OR “leak localisation”)).

IEEE Xplore. The reconstructed Boolean expression proposed for metadata searching is: (“water leak” OR “water leaks” OR “fuga de agua” OR “fugas de agua” OR “water

distribution network" OR "pipeline leakage" OR "non-revenue water") AND (sensor OR sensors OR IoT OR drone OR drones OR UAV OR "pressure sensor" OR "remote sensing" OR LiDAR OR "fiber optic") AND (acoustic OR thermal OR "machine learning" OR "hydraulic model") AND (detection OR detección OR "leak localisation").

ScienceDirect. The reconstructed expression proposed for searching titles, abstracts, and author-specified keywords is: ("water leak" OR "water leaks" OR "fuga de agua" OR "fugas de agua" OR "water distribution network" OR "pipeline leakage" OR "non-revenue water") AND (sensor OR sensors OR IoT OR drone OR drones OR UAV OR "pressure sensor" OR "remote sensing" OR LiDAR OR "fiber optic") AND (acoustic OR thermal OR "machine learning" OR "hydraulic model") AND (detection OR detección OR "leak localisation").

SpringerLink. The reconstructed general Boolean expression is: ("water leak" OR "water leaks" OR "fuga de agua" OR "fugas de agua" OR "water distribution network" OR "pipeline leakage" OR "non-revenue water") AND (sensor OR sensors OR IoT OR drone OR drones OR UAV OR "pressure sensor" OR "remote sensing" OR LiDAR OR "fiber optic") AND (acoustic OR thermal OR "machine learning" OR "hydraulic model") AND (detection OR detección OR "leak localisation").

MDPI. The reconstructed general Boolean expression is: ("water leak" OR "water leaks" OR "fuga de agua" OR "fugas de agua" OR "water distribution network" OR "pipeline leakage" OR "non-revenue water") AND (sensor OR sensors OR IoT OR drone OR drones OR UAV OR "pressure sensor" OR "remote sensing" OR LiDAR OR "fiber optic") AND (acoustic OR thermal OR "machine learning" OR "hydraulic model") AND (detection OR detección OR "leak localisation").

ASCE Library. The reconstructed general Boolean expression is: ("water leak" OR "water leaks" OR "fuga de agua" OR "fugas de agua" OR "water distribution network" OR "pipeline leakage" OR "non-revenue water") AND (sensor OR sensors OR IoT OR drone OR drones OR UAV OR "pressure sensor" OR "remote sensing" OR LiDAR OR "fiber optic") AND (acoustic OR thermal OR "machine learning" OR "hydraulic model") AND (detection OR detección OR "leak localisation").

Taylor & Francis Online. The reconstructed general Boolean expression is: ("water leak" OR "water leaks" OR "fuga de agua" OR "fugas de agua" OR "water distribution network" OR "pipeline leakage" OR "non-revenue water") AND (sensor OR sensors OR IoT OR drone OR drones OR UAV OR "pressure sensor" OR "remote sensing" OR LiDAR OR "fiber optic") AND (acoustic OR thermal OR "machine learning" OR "hydraulic model") AND (detection OR detección OR "leak localisation").

The expressions presented above are reconstructed adaptations of the general search strategy. Scopus and Web of Science use explicit search field operators, while those for the remaining sources are provided in general Boolean form. Differences in indexing coverage, field availability, truncation, phrase searching, and Boolean operator handling may affect the records retrieved. As these expressions have not been independently validated against the original search histories, they should not be taken as evidence that identical queries were executed across all eight sources.

The search strategy was organised into four conceptual blocks covering water leakage, monitoring technologies, analytical methods, and diagnostic objectives. However, the third Boolean block included a relatively narrow range of methodological terms, which may have limited the retrieval of studies employing pressure analysis, hydraulic transients, signal processing, statistical methods, wavelet analysis, anomaly detection, and deep learning. This potential restriction in coverage is acknowledged when assessing the comprehensiveness of the literature search.

2.3. Inclusion and Exclusion Criteria

This review included only peer-reviewed journal articles, comprising original research and review articles published in English or Spanish. Eligible studies examined technologies, methods, or computational approaches for detecting, localising, or characterising leaks in water distribution networks (WDNs). Studies conducted in experimental or operational water conveyance environments other than conventional WDNs were considered eligible provided that three conditions were met: (i) the study addressed leakage in a water conveyance system; (ii) the sensing measurements, physical processes, or computational methods were relevant to at least one WDN leak diagnosis task, detection, localisation, or characterisation; and (iii) the technological approach could be meaningfully interpreted in relation to WDN applications without assuming that experimental and operational conditions were equivalent. Studies involving non-water fluids or without a demonstrable link to water leak diagnosis were excluded. Studies conducted outside conventional WDNs were included to examine methodological applicability rather than to establish operational performance or direct generalisability to municipal networks. Accordingly, differences in system configuration, operating conditions, and validation environment were taken into account as limitations when interpreting the reported findings.

The included literature also encompasses water conveyance applications outside conventional municipal WDNs. As indicated by the application environments specified in the study titles, these include vineyard irrigation systems, irrigation canals, drip irrigation systems, and underground water conveyance tunnels. These studies were included because their sensing, monitoring, or diagnostic approaches may be methodologically relevant to water leak detection in conveyance infrastructure. However, their inclusion does not imply that the reported performance can necessarily be transferred directly to municipal WDNs. Their findings must, therefore, be interpreted in light of differences in hydraulic conditions, infrastructure characteristics, and operational environments.

The approaches considered included physical sensing technologies, signal processing methods, Internet of Things systems, remote sensing, unmanned aerial vehicles (UAVs), machine learning, deep learning, and hydraulic or mathematical models.

The grey literature, including theses and conference papers, was excluded from the review. Studies were also excluded if they did not directly address water leak detection or provide a clearly transferable technological contribution to leak detection in water distribution networks.

2.4. Study Selection Process

The study selection process is summarised in Table 2 and Figure 1. Two reviewers screened the titles of the identified records.

The identification and selection process yielded 160 records. After removing nine duplicates, 151 records remained for title and abstract screening, of which 35 were excluded. Full-text retrieval was sought for 116 reports, but one could not be retrieved, leaving 115 reports for eligibility assessment. Following full-text assessment, 24 reports were excluded, resulting in 91 included publications. These comprised 70 primary research articles and 21 review articles. During evidence synthesis, primary studies were distinguished from review articles to avoid treating secondary summaries as independent experimental evidence. Figure 1 illustrates the study selection procedure following the PRISMA 2020 framework. The central flowchart represents the sequential stages of identification, screening, eligibility assessment, and inclusion. The boxes positioned alongside the main flow provide supplementary information associated with the corresponding stages and do not represent additional or independent selection procedures. The arrows indicate the progression of

records through the review process, and the reported counts are consistent with those summarised in Table 2.

2.5. Data Extraction and Coding

For each included study, bibliographic information, sensing modality, processing architecture, diagnostic task, and relevant technological characteristics were extracted. The extracted data were organised into the three dimensions of the D-A-T taxonomy: data acquisition (D), processing architecture (A), and diagnostic task (T). To assess the consistency of the D-A-T classification, a second author independently examined the coding assignments against the operational definitions and decision rules established for each of the three taxonomy dimensions. The verification included data acquisition (D), processing architecture (A), and diagnostic task (T) labels, as well as studies assigned to multiple categories. Discrepancies between the initial classification and the independent review were examined and resolved through discussion, drawing on the methodological information reported in the respective publications. This procedure introduced an additional verification step intended to strengthen the consistency and transparency of the study-level classifications presented in Table 5.

The evidence synthesis was structured around the five research questions presented in Table 1. For RQ1, the main structured variables comprised sensing modality (D), processing architecture (A), and diagnostic task (T), forming the basis for the study-level classifications in Table 5 and the descriptive analyses of category frequencies and co-occurrences in Section 5.1. For RQ2, the synthesis examined reported sensor configurations, IoT, WSN or UAV deployments, communication arrangements, processing methods, diagnostic objectives, and performance metrics. These characteristics were assessed narratively to identify documented configurations and evaluation practices, rather than coded into a comprehensive, standardised quantitative dataset covering all 70 primary studies. For RQ3, the synthesis examined reported technological advantages and limitations in relation to measurement requirements, operating constraints, sensitivity to uncertainty, and deployment considerations. For RQ4, the analysis focused on recurring challenges associated with data availability, validation conditions, transferability, sensor placement, false alarms, energy consumption, and the availability of economic evidence. For RQ5, these findings were considered alongside the D-A-T classification to identify potential research directions encompassing multimodal acquisition, hybrid processing, multitask diagnosis, and connected monitoring architectures.

The synthesis methods varied according to the nature and availability of the reported information. D-A-T assignments were examined quantitatively using descriptive frequencies and category co-occurrences, while performance metrics, deployment characteristics, advantages, limitations, and research gaps were synthesised qualitatively on the basis of the available evidence. As these latter attributes were neither consistently reported nor standardised across the reviewed publications, the review does not provide a comprehensive quantitative comparison of performance, validation maturity, cost, or energy consumption for the corpus as a whole. Information that was missing or not reported was not taken to indicate the absence of the corresponding characteristic. This distinction differentiates the systematically coded D-A-T variables from the contextual evidence drawn upon to address RQ2–RQ5.

Multiple labels may be assigned within each dimension when the corresponding characteristics are explicitly reported. For example, a study combining pressure and acoustic measurements may receive both D1 (hydraulic sensing) and D2 (vibroacoustic sensing). Similarly, both A2 and A3 may be assigned to studies combining signal processing and machine learning, provided that both approaches contribute to the diagnostic method.

Diagnostic task labels are assigned on the basis of the capabilities explicitly demonstrated in each study. Localisation (T2) does not necessarily imply that leak detection (T1) was independently evaluated. Accordingly, studies estimating the location of an already known leak may receive T2 without T1. Characterisation (T3) is assigned only when leak properties are explicitly estimated or classified.

Where the available information does not provide sufficient evidence to support a particular category, the corresponding label should not be assigned solely on the basis of the authors' terminology. Primary studies and review articles were coded separately to distinguish evidence derived from implemented approaches from that summarised in the secondary literature.

2.6. PRISMA 2020 Reporting Checklist

The reporting of this systematic review was assessed against the PRISMA 2020 statement [1]. The completed PRISMA 2020 checklist, presented in Table 3, indicates where each applicable reporting item is addressed in the manuscript. Items deemed inapplicable to this review, as well as procedures that were not undertaken, are explicitly identified.

No formal study-level risk-of-bias or methodological quality assessment was undertaken. The primary objective of this review was to characterise the technological features of the eligible literature using the D-A-T taxonomy, rather than to estimate pooled diagnostic performance or determine the comparative effectiveness of individual methods. The reviewed studies vary considerably in their sensing technologies, computational approaches, diagnostic objectives, and evaluation settings. This heterogeneity could complicate the application of a single conventional risk-of-bias instrument without substantial adaptation. Nevertheless, the absence of a structured quality assessment constrains the conclusions that can be drawn regarding the reliability, maturity, and operational applicability of the reported technologies. Relevant considerations include whether studies used simulated, laboratory, or field data; whether independent validation was performed; whether baseline methods were used for comparison; and how closely the evaluation conditions reflected operational environments. These aspects were not systematically appraised across the complete corpus. Accordingly, D-A-T category frequencies are treated as measures of research coverage, rather than as evidence of methodological quality, diagnostic superiority, or readiness for field deployment. Table 3 summarises the PRISMA 2020 reporting items and their corresponding locations in the manuscript. A comprehensive item-by-item PRISMA 2020 checklist is provided as Supplementary Table S1.

2.7. Methodological Threats to the Research

Potential sources of bias include the restriction of the search to a selected set of information sources, which may have resulted in the omission of the relevant literature available through other restricted-access or unindexed repositories. Furthermore, limiting the search to publications in English and Spanish may have excluded relevant studies published in other languages. The search strategy may also have failed to identify studies that used alternative terminology or synonyms not covered by the selected search terms.

3. Conceptual Framework and Background

3.1. Key Concepts

Early fault detection in water distribution networks is a priority for urban water management [2]. One of the main challenges facing these networks is non-revenue water (NRW), which includes water losses resulting from leaks, theft, and measurement inaccuracies. Water losses are estimated to account for 20–30% of the water supplied through distri-

bution systems [2]. Addressing this challenge requires an understanding of the physical characteristics of different types of faults.

Background leaks are generally small and difficult to detect but may lead to substantial cumulative water losses over time [2]. By contrast, sudden pipe ruptures involve structural failures that release large volumes of water [3]. Such events are commonly identified through pressure drops within the distribution network [2].

Leak localisation is generally formulated as an inverse problem, in which the discrepancy between measured pressures and model-predicted values is minimised. In this approach, equivalent orifice areas are treated as unknown parameters to be estimated [4].

To address these challenges, recent research has incorporated technologies associated with the Fourth Industrial Revolution. Acoustic emission (AE) involves the generation of transient elastic waves caused by the rapid release of energy from leaks in pressurised pipes [5]. The Internet of Things (IoT) comprises distributed networks of interconnected sensors, devices, and actuators [6]. Unmanned aerial vehicles (UAVs) provide remote sensing platforms that can carry thermal and multispectral cameras, enabling non-invasive aerial inspections across extensive sections of water distribution networks. These capabilities extend monitoring beyond conventional underground inspection methods by incorporating aerial observations [7].

3.2. Historical Evolution of the Field

Selected publications highlight technological developments that provide context for the present review. Earlier studies investigated the physical properties of leak-related signals, including acoustic propagation in plastic pipes and the use of cross-correlation techniques for leak localisation [8]. Hydraulic transient analysis was likewise examined as an approach to leak identification based on changes in pipeline pressure [9].

Further developments encompass remote communication and distributed monitoring technologies. GSM-based interfaces have been employed to communicate leak alerts via SMS [10], while the deployment of sensors within district metered areas (DMAs) has been explored for network monitoring purposes [11]. Additional examples include the incorporation of sensors into Internet of Things (IoT) infrastructures [12] and the use of artificial intelligence for leak detection and monitoring [13].

These examples demonstrate the diversity of technological approaches rather than a chronological progression established by quantitative analysis of the 91-publication corpus. The present review neither quantifies the annual prevalence of technological categories nor establishes that conventional methods have been systematically superseded by remote monitoring, IoT, or artificial intelligence. Accordingly, this subsection serves to provide contextual background, while the systematic classification and quantitative synthesis are presented in Sections 4 and 5.

3.3. Physical and Theoretical Foundations of Leak Detection Modalities

The development of leak detection technologies draws on principles of hydraulic mechanics, acoustic wave propagation, inverse problem theory, and the physical interaction between escaping water and its surrounding environment. These principles influence both the variables that can be measured and the diagnostic information that can be inferred from those measurements. Accordingly, the D-A-T taxonomy can be interpreted in terms of the relationships among physical observables (D), methods for extracting information from them (A), and diagnostic objectives supported by the available evidence (T). Technological performance is, therefore, subject to constraints associated with sensor sensitivity, signal propagation, network configuration, measurement uncertainty, and the identifiability of the underlying leak parameters.

- Hydraulic sensing and inverse problem theory (D1). Hydraulic approaches rely primarily on pressure and flow measurements. Leakage disturbs the mass balance and hydraulic energy distribution in a pressurised network, potentially producing measurable changes in flow, pressure residuals, or the estimated network state. Under steady or quasi-steady conditions, leak discharge is commonly represented by a pressure-dependent relationship:

$$Q_L = C_d\, A_L \sqrt{\frac{2\Delta p}{\rho}}$$

where Q_L denotes leak discharge, C_d is a discharge coefficient, A_L is the effective leak area, Δp is the pressure difference across the opening, and ρ is fluid density. This relationship links leakage magnitude to hydraulic measurements, although both the effective discharge coefficient and opening area may vary with pipe material, defect geometry, and operating conditions.

Identifying leaks from hydraulic measurements involves solving an inverse problem. Rather than calculating pressures and flows from a known network state, inverse methods estimate unknown leak locations or parameters from observed hydraulic responses. Hydraulic leak localisation can be formulated as an inverse problem in which unknown leak locations or parameters are estimated from observed pressure and flow responses. The reliability of these estimates depends on network observability, sensor placement, hydraulic model calibration, and uncertainty in water demand. However, different leak configurations may produce similar measurement patterns, particularly when sensor coverage is sparse, or demands are uncertain. The resulting problem may be poorly conditioned or non-unique. Consequently, hydraulic methods are sensitive to model calibration, boundary conditions, sensor placement, and the ability to distinguish leak-induced changes from normal variations in consumption. These limitations may partly explain why hydraulic measurements are widely used to detect anomalous conditions but may require additional information or modelling assumptions for reliable localisation and characterisation.

Hydraulic transient methods build on these principles by analysing pressure waves generated by rapid changes in flow or pressure. Leaks can alter the amplitude, phase, and reflection patterns of these waves, potentially allowing their locations to be inferred from measured transient responses. Nevertheless, wave damping, pipe wall viscoelasticity, junction reflections, uncertain boundary conditions, and operational disturbances may complicate the interpretation of transient signals. Methods performing well in controlled pipelines may, therefore, require further modelling and validation before application to complex operational distribution networks:

- Vibroacoustic sensing and wave propagation (D2). Vibroacoustic approaches measure pressure fluctuations, fluid-borne sound, or structural vibrations associated with water escaping through a defect. Turbulent flow through the leak opening, together with interactions between the jet, pipe wall, and surrounding medium, can generate broadband acoustic and mechanical disturbances. These signals propagate through the water column, pipe wall, and surrounding soil. Their propagation characteristics depend on pipe material, diameter, wall thickness, pressure, burial conditions, and sensor coupling. Acoustic leak signals are affected by pipe material, wave attenuation, dispersion, and sensor coupling. These effects can be particularly important in plastic pipes, where the propagation characteristics may limit the distance over which leak-related disturbances can be reliably detected and localised. Compared with rigid metallic pipes, plastic pipes can exhibit greater attenuation and dispersion of leak-related signals because of their mechanical and viscoelastic properties and interactions with the surrounding medium. As a result, leak signals may remain distinguishable

from background noise over shorter distances, potentially affecting the reliability of correlation-based localisation. In simplified two-sensor arrangements, the estimated position depends on the measured arrival time difference and effective propagation velocity. Errors in either quantity can introduce substantial localisation uncertainty. Acoustic detection and localisation, therefore, depend not only on the signal processing algorithm but also on the physical transmission path and sensor coupling quality.

- Distributed strain, temperature, and vibration sensing (D3). Distributed sensing systems can provide spatially resolved measurements along a sensing cable, potentially capturing temperature, strain, or vibration variations over extended pipeline sections. Their diagnostic potential depends on the measured physical quantity and the coupling between the fibre, pipeline, and surrounding environment. For example, distributed acoustic sensing responds to dynamic strain variations, whereas distributed temperature sensing measures temperature changes that may be associated with escaping water under suitable environmental conditions. Extensive spatial coverage does not, however, necessarily ensure leak detectability. Sensitivity depends on installation geometry, interrogation parameters, spatial resolution, environmental noise, and the magnitude of the leak-induced disturbance. Although no primary study in the analysed corpus was assigned to D3, this category remains relevant as a distinct distributed measurement approach requiring separate empirical evaluation of its applicability.
- Optical and remote sensing (D4). Optical and remote sensing methods typically detect secondary manifestations of leakage rather than measuring hydraulic discharge directly. Depending on the sensing configuration, these may include changes in surface temperature, soil moisture, vegetation condition, or spectral reflectance. Thermal infrared observations depend on detectable temperature contrasts between affected and unaffected surfaces, whereas multispectral approaches use variations in the optical properties of vegetation or soil. The relationship between an underground leak and its remotely observable signature is indirect. It depends on burial depth, soil permeability, weather conditions, surface materials, and the time elapsed since leakage began. Consequently, thermal or spectral anomalies cannot be regarded as unambiguous evidence of pipe leakage without considering alternative explanations and appropriate validation.
- Geophysical sensing (D5). Geophysical methods investigate subsurface changes associated with escaping water, including variations in electrical properties or other measurable characteristics of soil and surrounding materials. Their effectiveness depends on the contrast between affected and unaffected regions, target geometry and depth, and the resolution of the measurement configuration. Geophysical interpretation also constitutes an inverse problem, as different subsurface conditions may produce similar measured responses. Reliable localisation may, therefore, require background measurements, site-specific calibration, or corroboration using hydraulic and other sensing data.

Implications for the D-A-T taxonomy. These theoretical considerations offer a physical basis for interpreting the observed category frequencies. The predominance of hydraulic acquisition (D1) in the primary study corpus is consistent with the central role of pressure and flow in describing network operation and their direct integration into hydraulic models. However, the frequency of hydraulic approaches in the reviewed literature does not establish their universal superiority in accuracy or suitability over other sensing modalities. Similarly, the greater representation of detection (T1) compared with localisation (T2) and characterisation (T3) may be consistent with increasing demands for information and parameter identifiability. Detecting deviations from normal operation may require fewer assumptions than determining leak location, estimating magnitude, or distinguishing

physical characteristics. These relationships represent theoretical interpretations of the observed distribution rather than causal findings derived from the frequency analysis. They suggest the importance of evaluating sensing modalities, processing architectures, and diagnostic tasks jointly, with consideration of their physical constraints and the conditions under which they were validated.

3.4. Key Techniques

The processing methods employed in water leak detection can be categorised by their analytical functions rather than considered as a homogeneous group of algorithms. Signal processing techniques are frequently applied to acoustic, vibration, and hydraulic measurements to suppress noise, extract diagnostic features, and detect changes indicative of leakage. These techniques encompass filtering, correlation analysis, Fourier-based spectral analysis, the short-time Fourier transform (STFT), continuous wavelet transform (CWT), discrete wavelet transform (DWT), and Wavelet Scattering Transform (WST). Their suitability is influenced by acquired signal characteristics, particularly non-stationarity, background noise, and propagation effects [14,15].

Classical machine learning methods analyse measured or extracted features to recognise patterns indicative of leakage. Support vector machines (SVMs) have been used to classify leak-induced vibrations, achieving reported accuracies above 93% [16]. XGBoost has similarly been applied to sensor-based leak detection, with a reported accuracy of 99.79% [17]. Additional approaches encompass k-nearest neighbours (K-NNs) for identifying groups of pipes affected by leakage using transient pressure data [18], artificial neural networks (ANNs) for modelling fluid behaviour [19,20], and genetic algorithms for optimising sensor placement according to flow patterns and network topology [21]. As these approaches address distinct analytical objectives, they should not be regarded as directly interchangeable.

Deep learning approaches can derive diagnostic representations directly from measurements, reducing dependence on manually engineered features. One-dimensional convolutional neural networks (CNNs), including DenseNet variants, have been employed to analyse acoustic emission signals, with reported accuracies reaching 99.76% for leak detection and classification [22]. Nevertheless, the performance reported for both classical machine learning and deep learning methods is influenced by dataset characteristics, sensor configurations, leak properties, and validation procedures. Consequently, accuracy figures obtained under different experimental conditions do not provide a valid basis for concluding that any processing family is universally superior.

Image-based and remote sensing approaches require processing techniques suited to spatially distributed observations. UAV-acquired LiDAR measurements have been investigated by analysing variations in return intensity associated with wet surfaces [23], while multispectral image classification and multi-temporal infrared thermography have been explored to identify surface anomalies potentially indicative of underground leakage [24,25]. These approaches differ from acoustic and hydraulic signal analysis in both the characteristics of their input data and the physical indicators underpinning diagnosis. Within the D-A-T taxonomy, sensing modalities and observation platforms are considered within the acquisition context, while algorithms that interpret the resulting measurements are categorised according to their processing architecture. Maintaining this distinction enables consistent comparison of the reviewed approaches without conflating sensors, communication platforms, and analytical methods.

3.5. Selected Patent Applications

This subsection presents a non-systematic contextual overview of selected patents illustrating applications of sensing, monitoring, and computational technologies to water leak detection. The examples were selected as illustrative technological references rather than identified through a predefined patent search protocol. Neither a comprehensive patent search nor a patent-specific eligibility assessment or patent landscape analysis was undertaken. Accordingly, the patents were excluded from the 91-publication systematic-review corpus and the PRISMA study selection counts, and they did not contribute to the D-A-T classifications or frequency analyses. They serve exclusively to illustrate applications of the technologies examined in the review, without supporting inferences regarding the prevalence or chronological development of patented approaches.

Recent patents describe several approaches to automating leak detection. Yu [26] patented a system that divides water distribution networks into physical zones and applies real-time clustering algorithms to identify and isolate areas affected by leaks. Another development involves integrating computational algorithms directly into monitoring hardware. Shi [27] patented a smart water meter incorporating an autoencoder-based neural network within its circuitry, enabling dynamic estimation of consumption baselines and autonomous generation of data-driven alerts. Kulkarni [28] proposed a distributed network of sensor nodes combining pressure, flow, and acoustic measurements along pipelines. The system incorporates power management circuitry that switches between low-power and high-performance operating modes when artificial intelligence algorithms detect anomalies.

Developments in acoustic and contact vibration sensing hardware have also sought to address signal attenuation and background noise. Liu [29] patented an auscultation system employing fibre-optic channels coupled to the pipeline. The system combines fibre-optic vibration measurements with phase delay information to identify leaks. Ren [30] proposed a leak localisation system for water supply networks that integrates a hydrophone array, deep learning-based feature extraction, and short-time Fourier transform (STFT) spectral analysis.

Other patented approaches focus on signal processing and feature fusion for improved pattern recognition. J. Li [31] described a leak detection method integrated into acoustic data acquisition equipment that employs a dual-channel, multi-head self-attention mechanism to filter low-frequency noise commonly associated with buried pipelines. Srivastava and Singhvi [32] patented a real-time leak detection approach combining ultrasonic acoustic sensing with pressure measurements. The method uses correlations between acoustic signals and water meter measurements to support leak localisation and automated alert generation.

3.6. Differences from Previous Reviews

Previous reviews have examined water leak detection from different perspectives, using a range of classification criteria. Most focus on particular aspects, such as sensing technologies, computational methods, system architectures, or diagnostic objectives. However, direct comparisons remain challenging when differences in sensing modalities, processing approaches, and diagnostic capabilities are considered simultaneously.

A first group of reviews focuses on sensing and data acquisition technologies. Ismail et al. [33] examine vibration-based methods using accelerometer sensors. Ibrahim et al. [34] focus on fibre-optic technologies for leak detection and localisation. Tariq et al. [35] analyse microelectromechanical systems (MEMS)-based technologies for water distribution networks. Fan et al. [36] focus on acoustic approaches to leak detection. Qi et al. [37] examine the detection of small underground leaks using sensors placed inside the pipeline. Hu, Tariq, and Zayed [38] analyse the acoustic localisation of leaks in pressurised pipelines.

Together, these reviews provide detailed analyses of specific sensing technologies, with their classification structures primarily determined by the physical modality used to obtain evidence of leakage.

A second group classifies the literature according to the computational or inferential methods used to process the acquired data. Hu et al. [39] distinguish between model-based and data-driven approaches to leak detection and localisation. Romero-Ben et al. [40] analyse the evolution, advantages, and limitations of data-driven approaches. Wu et al. [41] focus on data limitations and classify approaches according to how information is used in model development. Anozie et al. [42] examine hybrid machine learning frameworks. Zuñiga-Uribe et al. [13] analyse machine learning, deep learning, and hybrid approaches, considering input variables, datasets, and output strategies.

A third group examines leak detection from a functional or system-level perspective. Islam et al. [12] analyse sensing technologies, algorithms, and communication mechanisms for water leak detection. Joseph et al. [43] distinguish between software- and hardware-based technologies for detecting leaks and pipe breaks. Moubayed et al. [44] emphasise data fusion and federated learning. Rajan and Li [45] identify data acquisition and management, management models, and monitoring platforms as key components of automated leak management systems.

Across these reviews, three recurring analytical elements can be identified: the physical source of evidence of leakage, the computational mechanisms used to process that evidence, and the diagnostic information generated by the system. The contribution of the present review is not based on the assumption that sensing technologies, algorithms, and diagnostic objectives have never previously been examined together. Rather, among the publications examined in this systematic review, no previous review was identified that explicitly organised these three elements as separate but interrelated dimensions within a common classification framework.

The reviewed frameworks differ in their primary analytical emphasis. Reviews focusing on vibration, fibre-optic, acoustic, and other sensing technologies [33–38] primarily classify studies by data acquisition modality (D). Those examining model-based methods, data-driven approaches, and machine learning [13,39–42] place greater emphasis on processing architectures (A). Other reviews consider system-level components, such as sensing, communication, and monitoring platforms [12,43–45], encompassing aspects of both acquisition and processing within broader technological frameworks. Although some previous reviews address several of these elements, they do not appear to consistently distinguish data acquisition, processing architecture, and diagnostic task as three separate but interrelated classification dimensions. The additional analytical value of D-A-T lies in its capacity to classify individual studies across all three dimensions simultaneously: the evidence acquired (D), the methods used to process it (A), and the diagnostic capability demonstrated (T). This may facilitate comparisons of technological combinations rather than isolated technology categories.

To address this gap in the organisation of the literature, the present review introduces the D-A-T taxonomy, comprising three dimensions: acquisition (D), processing architecture (A), and task resolution (T). The framework characterises each leak detection approach according to the source of the evidence, the methods used to process it, and the diagnostic information produced. This distinction is important because a single sensing modality may support different computational architectures and diagnostic objectives, while the same modelling or machine learning technique may be applied to different physical measurements.

The principal contribution of the proposed taxonomy is, therefore, to provide a common basis for comparing heterogeneous leak detection technologies without imposing a single

classification hierarchy based solely on sensors, algorithms or applications. The D-A-T framework provides the conceptual basis for the classification presented in Section 4 and the subsequent synthesis of the 91 studies included in this systematic review. It also supports the identification and analysis of technological trends, limitations, research gaps and opportunities for future development in water leak detection.

4. Taxonomy of the Literature

The studies included in this systematic review reveal considerable variation in the technologies and methods employed for water leak detection. Some approaches rely on hydraulic variables, such as pressure and flow rate, while others use acoustic, vibration, optical, thermal, or geophysical data. The acquired data may be analysed using physical or hydraulic models, signal processing techniques, machine learning, deep learning, or combinations of these methods. The diagnostic objectives also differ, ranging from identifying the presence of a leak to determining its location or characterising its properties. To classify these approaches consistently, this review introduces the D-A-T taxonomy, which comprises three dimensions: data acquisition (D), processing architecture (A), and task resolution (T). For descriptive purposes, the classification of an individual study, s_i, can be expressed as follows:

$$\tau(s_i) = [D_i, A_i, T_i] \quad (1)$$

where

1. Data Acquisition (D_i): Classifies the studies according to the nature of the physical or observable evidence used to detect the leak, including hydraulic, vibroacoustic, distributed, optical/remote, and geophysical/electromagnetic data.

2. Processing Architecture (A_i): Classifies the mechanisms used to transform acquired data into diagnostic evidence, including methods based on physical models, statistical and signal processing, machine learning, deep learning, and hybrid or fusion approaches.

3. Task Resolution (T_i): Classifies the diagnostic objective achieved by the study, distinguishing between the detection, localisation, and characterisation of the leak.

Where s_i represents each included study, whilst D_i, A_i, and T_i represent, respectively, its data acquisition characteristics, processing architecture, and task resolution. Each dimension may contain one or more labels when the study incorporates multiple modalities, methods, or diagnostic tasks.

This notation is intended solely to illustrate the multidimensional structure of the taxonomy and does not constitute a mathematical model of the leakage phenomenon. As some technological solutions integrate multiple sensors, computational methods, and diagnostic objectives, a single study may be assigned to more than one subcategory where justified by its methodology. The D-A-T classification permits multiple labels and does not treat categories as mutually exclusive. Accordingly, category frequencies indicate how many studies were assigned each label, rather than representing mutually exclusive groups. In particular, diagnostic task frequencies cannot be used to determine the prevalence of studies addressing detection, localisation, or characterisation exclusively without examining the corresponding combinations of labels.

4.1. Data Acquisition Dimension (D)

This dimension classifies the physical quantities or observable phenomena that provide evidence of leakage, rather than the hardware, communication infrastructure or deployment platforms used to collect measurements. The five categories encompass hydraulic responses (D1), acoustic and mechanical disturbances (D2), spatially distributed measurements of strain, temperature or vibration (D3), optical and remotely observed surface responses (D4), and subsurface geophysical or electromagnetic responses (D5). Although some categories

involve related physical quantities, the distinction between them is based on the nature and spatial representation of the diagnostic evidence. Multiple D labels may be assigned when a study employs distinct sensing modalities.

D1. Hydraulic sensing: This includes measurements relating to the hydraulic behaviour of the system, such as pressure, flow rate, consumption, and related network variables. Pressure measurements have been used for localisation and as inputs for computational methods [18]. They can be collected using fixed sensors, smart meters, or distributed systems.

D2. Vibroacoustic sensing: Uses mechanical and acoustic disturbances caused by water outflow. This includes vibration sensors, accelerometers, hydrophones, and acoustic emission sensors. Some approaches combine these techniques with machine learning and deep learning [5,14,46,47].

D3. Distributed strain, temperature, and vibration sensing: This category encompasses spatially resolved measurements of physical variations along an extended sensing path, including changes in strain, temperature, and dynamic vibration that may be associated with leakage. Unlike point-based sensors, distributed sensing provides spatially continuous or densely sampled measurements along the monitored length. Fibre-optic technologies, such as distributed acoustic sensing and distributed temperature sensing, represent specific measurement implementations rather than defining characteristics of the category [34]. Assignment to D3 requires the use of spatially distributed measurements as diagnostic evidence; the presence of fibre-optic cables or distributed communication infrastructure alone is insufficient.

D4. Optical and remote sensing: Infrared/thermal imagery, RGB, multispectral/hyperspectral detection, and LiDAR. These techniques infer leaks based on surface variables, such as humidity and temperature. Examples include drone-based LiDAR and thermal imaging [23–25,48].

D5. Geophysical and electromagnetic sensing: This includes ground-penetrating radar (GPR) for detecting changes in the subsoil [49,50].

A distinction should be made between sensing modalities and the platforms or communication infrastructures used to deploy sensors and transmit data. Technologies such as unmanned aerial vehicles (UAVs), the Internet of Things (IoT), and Long Range Wide Area Networks (LoRaWANs) support sensor deployment, data acquisition, or communication but do not constitute sensing modalities in their own right. A LoRaWAN is a low-power, long-range wireless networking protocol that enables communication between distributed monitoring devices and network gateways.

4.2. Processing Architecture Dimension (A)

The processing architecture dimension characterises how acquired information is processed to derive diagnostic evidence. It comprises four methodological families (A1–A4) and a complementary integration modifier (A5). Categories A1–A4 represent the main processing paradigms, while A5 denotes the explicit integration of multiple data sources, models or inference mechanisms within a study. Accordingly, A5 is treated as an integration modifier rather than as a separate methodological family equivalent to A1–A4. It is assigned alongside the relevant processing labels when the reported implementation provides evidence of an integration or fusion strategy. The five coding labels are defined below.

A1. Physics-based/model-based methods: Explicit representations of hydraulic or physical behaviour, such as hydraulic modelling, inverse analysis, transient analysis, or model validation [4,51,52].

A2. Signal processing and statistics: Transforms measurements to identify patterns, such as filtering, correlation, STFT, wavelets, and statistical indicators [14,53–55].

A3. Classical machine learning: Learns decision patterns without deep architectures, such as SVMs, decision trees, clustering, and anomaly detection [17,56,57].

A4. Deep learning: Neural architectures that automatically learn complex representations, such as 1D/3D CNNs and sequential models [22,47,58].

A5. Hybrid/fusion integration modifier: This label denotes the explicit integration of multiple data sources, processing methods, models, or inference mechanisms within a diagnostic architecture. A5 is assigned alongside the relevant A1–A4 categories when the reported implementation demonstrates such integration. It does not constitute an independent processing paradigm, nor does the use of multiple sequential processing steps alone justify its assignment [15].

No processing paradigm can be regarded as inherently superior under all operating conditions, as its suitability depends on data availability, diagnostic objectives, and the validation context. The frequency of A5 should, therefore, be interpreted as the prevalence of explicitly reported integration strategies, rather than compared directly with A1–A4 frequencies, since the five labels do not represent equivalent methodological families.

4.3. Task Resolution Dimension (T)

This dimension describes the type and level of diagnostic information generated by the system.

T1. Detection: Determines whether there is a leak or an anomaly (binary decision or indicator).

T2. Localisation: Determines the location of the leak at the spatial level or resolution supported by the method, such as an area, pipe, pipe section, or geographical location [18,58].

T3. Characterisation: Provides additional properties such as magnitude, leakage rate, orifice size, or severity.

These tasks are not mutually exclusive. Support activities (sensor optimisation, data transmission) are not classified as diagnostic tasks.

The overall structure of the proposed D-A-T taxonomy is illustrated in Figure 2.

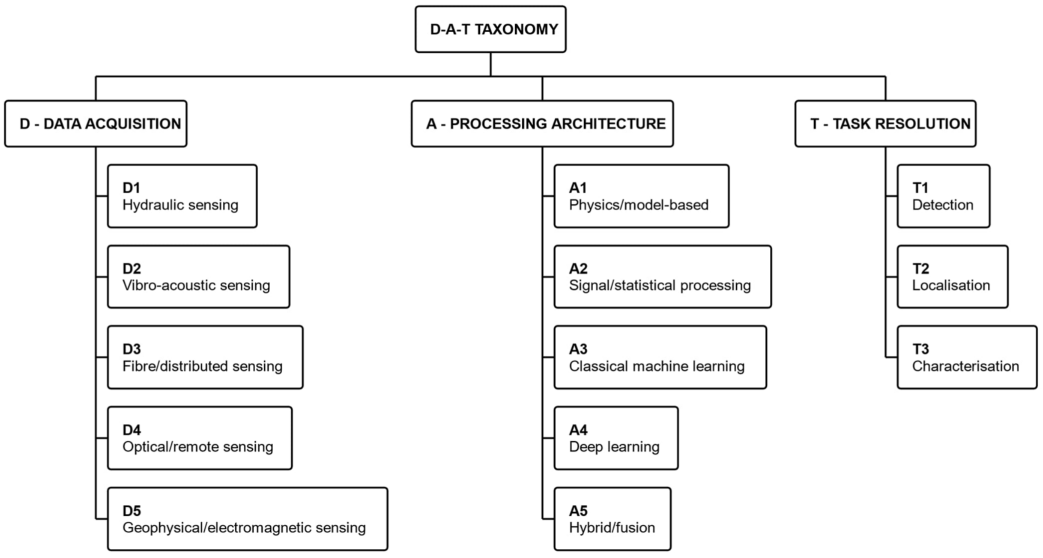


Figure 2. Proposed D-A-T taxonomy for classifying the reviewed studies according to three complementary dimensions: data acquisition (D), processing architecture (A), and task resolution (T).

Table 4 presents representative studies for each subcategory of the D-A-T taxonomy. As the classification allows multiple labels, individual studies may be assigned to more than one subcategory when their methodologies combine different data acquisition modalities,

processing architectures, or diagnostic tasks. Table 5 provides the complete classification of the 70 primary studies included in the review, while Table 6 summarises the D-A-T coverage of the 21 review articles.

Table 4. Proposed D-A-T taxonomy for classifying approaches to water leak detection.

Category	Subcategory	Description	Representative Studies	Comments
D—Data Acquisition	D1. Hydraulic sensing	It uses pressure, flow rate, consumption, or other variables that represent the hydraulic behaviour of the network.	Levinas et al. (2021) [18]; Steffelbauer et al. (2022) [59]; Bartkowska et al. (2024) [60]	It provides evidence directly related to changes in the system's hydraulic behaviour.
D—Data Acquisition	D2. Vibroacoustic sensing	It uses acoustic signals, sound emissions, vibrations, accelerometers, or hydrophones triggered by water escaping.	Hunaidi & Chu (1999) [8]; Bentoumi et al. (2017) [14]; Liu et al. (2025) [46]; Ullah et al. (2023) [5]	It enables the identification of mechanical disturbances associated with the leak and can be combined with signal processing or AI.
D—Data Acquisition	D3. Fibre-optic sensing and distributed	It uses optical fibre or other distributed sensing systems to obtain measurements along sections of the infrastructure.	Ibrahim et al. (2021) [34]	It facilitates distributed or continuous monitoring over long stretches.
D—Data Acquisition	D4. Optical and remote sensing	It includes thermal/IR, RGB, multispectral, hyperspectral, and LiDAR imagery.	Fahmy & Moselhi (2010) [48]; Krapez et al. (2022) [24]; Yahia et al. (2021) [25]; Bretreger et al. (2026) [23]	It generally detects indirect signs of a leak, such as changes in humidity or surface temperature.
D—Data Acquisition	D5. Geophysical and electromagnetic surveying	It uses GPR and other electromagnetic responses to identify subsurface anomalies associated with leaks.	Gamal et al. (2023) [49]; Zhu et al. (2024) [50]	It enables the study of buried pipes by analysing changes in the properties of the subsoil.
A—Processing Architecture	A1. Physics-based methods/models	It uses hydraulic or physical models, inverse analysis, sensitivity analysis, transient analysis, and model validation.	Pudar & Liggett (1992) [4]; Vrachimis et al. (2021) [51]; Marzola et al. (2022) [52]; Ranginkaman et al. (2025) [61]	The inference is based on an explicit representation of the system's behaviour.
A—Processing Architecture	A2. Signal processing and statistics	It applies filtering, correlation, FFT/STFT, wavelets, autocorrelation, or other statistical indicators.	Lay-Ekuakille et al. (2013, 2017) [53,54]; Bentoumi et al. (2017) [14]; Martini et al. (2018) [55]	It enables the extraction of leak-related characteristics from the acquired signals.
A—Processing Architecture	A3. Classical machine learning	It includes supervised and unsupervised methods such as SVMs, decision trees, clustering, anomaly detection, and other traditional classifiers.	Quiñones-Grueiro et al. (2018) [56]; Fan et al. (2021) [62]; Lee & Kim (2023) [17]; Elshazly et al. (2024) [57]	It learns discriminative patterns based on features derived from measured or simulated data.
A—Processing Architecture	A4. Deep learning	It includes CNN, 1D-CNN, 3D-CNN, DenseNet, and sequential neural architectures.	Boujelben et al. (2023) [63]; Jun et al. (2024) [58]; Ullah et al. (2024) [47]; Saleem et al. (2025) [22]	It enables machine learning of complex representations directly from the data.
A—Processing Architecture	A5. Hybrid/fusion approaches	It explicitly integrates multiple data sources, models, or inference mechanisms into the decision-making process.	Fereidooni et al. (2021) [64]; Martinez-Ríos et al. (2024) [15]; Chen et al. (2026) [65]; Zhu et al. (2024) [50]	It combines complementary evidence from different computational approaches or strategies.
T—Task Resolution	T1. Detection	It determines whether or not there is a leak or an associated fault.	Bentoumi et al. (2017) [14]; Vanijjirattikhan et al. (2022) [66]; Ullah et al. (2023) [5]	This constitutes the basic diagnostic capability: determining whether there is a leak.
T—Task Resolution	T2. Localisation	It identifies the area, pipe, section, or location where the leak is situated.	Levinas et al. (2021) [18]; Tyagi et al. (2023) [67]; Barros et al. (2025) [68]; Jun et al. (2024) [58]	It adds spatial information to leak detection.
T—Task Resolution	T3. Characterisation	It estimates additional characteristics of the leak, such as magnitude, flow rate, hole size, or severity.	Adedeji et al. (2017) [69]; Saleem et al. (2025) [22]	It provides additional quantitative information to assess the leak.

Table 5. D-A-T coverage of primary studies.

ID	Study	Year	D—Data Acquisition	A—Processing Architecture	T—Diagnostic Task
1	Adedeji et al. (2017) [69]	2017	D1	A1	T1, T3
3	Al Hassani et al. (2023) [70]	2023	D1, D4	A2, A5	T1, T2
4	Ali et al. (2022) [6]	2022	D1	A2	T1
6	Awwad et al. (2020) [71]	2020	D2	A2	T1
7	Ayamga & Nakpih (2024) [72]	2024	D1	A2	T1, T2
8	Balamurugan et al. (2025) [73]	2025	D1	A2	T1
9	Barros et al. (2025) [68]	2025	D1	A1, A2, A5	T1, T2
10	Bartkowska et al. (2024) [60]	2024	D1	A1, A2, A3	T2
11	Bentoumi et al. (2017) [14]	2017	D2	A2	T1
12	Boujelben et al. (2023) [63]	2023	D2	A4	T1, T2
13	Bretreger et al. (2026) [23]	2026	D4	A2	T1
14	Bykerk & Valls Miro (2022) [74]	2022	D2	A2, A3	T1
15	Bykerk & Valls Miro (2022) [75]	2022	D2	A2, A4	T1
16	Carratù et al. (2021) [76]	2021	D1	A2	T1
18	Chen et al. (2026) [65]	2026	D1, D2	A2, A5	T1, T2
19	Cheng et al. (2024) [77]	2024	D1	A1, A2	T2
23	Eliades & Polycarpou (2012) [11]	2012	D1	A2	T1
24	Elshazly et al. (2024) [57]	2024	D1	A3	T1, T2
25	Fahmy & Moselhi (2010) [48]	2010	D4	A2	T1,T2
27	Fan et al. (2021) [62]	2021	D1	A3, A4	T1
29	Fereidooni et al. (2021) [64]	2021	D1	A1, A3, A5	T1, T2, T3
30	Fuentes-Mariles et al. (2011) [78]	2011	D1	A1	T1, T2, T3
31	Gamal et al. (2023) [49]	2023	D5	A1	T1
32	Guezouli et al. (2024) [79]	2024	D1	A2, A3	T1
33	Hamamed et al. (2023) [80]	2023	D2	A2	T1
36	Hunaidi & Chu (1999) [8]	1999	D2	A2	T1, T2
41	Joseph et al. (2024) [81]	2024	D1	A2, A3	T1
42	Jun et al. (2024) [58]	2024	D1	A4	T1, T2
44	Krapez et al. (2022) [24]	2022	D4	A2	T1
45	Ladino-Moreno et al. (2024) [82]	2024	D1	A1, A2, A5	T1
46	Lay-Ekuakille et al. (2013) [53]	2013	D5	A2	T1
47	Lay-Ekuakille et al. (2017) [54]	2017	D5	A2	T1, T2
48	Lee & Kim (2023) [17]	2023	D2	A2, A3	T1
49	Levinas et al. (2021) [18]	2021	D1	A1, A3	T1, T2
50	Liu et al. (2025) [46]	2025	D2	A2, A3	T1
51	Liu et al. (2019) [83]	2019	D2	A2, A3	T1
52	Makaya & Hensel (2015) [19]	2015	D1	A3	T1
53	Martinez-Ríos et al. (2024) [15]	2024	D1, D2	A2, A3, A5	T1
54	Martini et al. (2018) [55]	2018	D2	A2	T1
55	Marzola et al. (2022) [52]	2022	D1	A1	T2
56	Mohammed et al. (2021) [84]	2021	D1	A1, A5	T1, T2
57	Essouabni et al. (2024) [85]	2024	D1	A2	T1
58	Moreno et al. (2010) [10]	2010	D1	A2	T1
60	Nkemeni et al. (2020) [86]	2020	D2	A2, A5	T1

Table 5. *Cont.*

ID	Study	Year	D—Data Acquisition	A—Processing Architecture	T—Diagnostic Task
61	Pádua et al. (2024) [87]	2024	D4	A2	T1, T2
62	Phua et al. (2020) [88]	2020	D2	A2	T1, T2
63	Pudar & Liggett (1992) [4]	1992	D1	A1	T1, T2, T3
65	Quiñones-Grueiro et al. (2018) [56]	2018	D1	A2, A3	T1,T2
66	Rahman et al. (2025) [89]	2025	NR	A2	T1
68	Rajasekaran et al. (2025) [90]	2025	D2	A3, A4, A5	T1, T2
69	Ranginkaman et al. (2025) [61]	2025	D1	A1, A2	T1, T2, T3
71	Roy et al. (2017) [20]	2017	D1	A1, A2, A3, A5	T1, T2
72	Saleem et al. (2025) [22]	2025	D2	A2, A4	T1, T3
73	Salman & Hasar (2025) [91]	2025	D2	A2	T1
74	Samsumar et al. (2024) [92]	2024	D1	A3	T1
75	Shiddiqi et al. (2024) [21]	2024	D1	A2	T1, T2
76	Steffelbauer et al. (2022) [59]	2022	D1	A1, A2, A5	T1, T2
78	Tatara & Kowalczuk (2024) [93]	2024	D1	A1	T1, T2, T3
79	Torres et al. (2014) [94]	2014	D1	A1	T1, T2, T3
80	Traoré et al. (2022) [95]	2022	D4	A2	T1
81	Türkler et al. (2023) [96]	2023	D4	A2	T1
82	Tyagi et al. (2023) [67]	2023	D1	A2, A3	T1, T2
83	Ullah et al. (2023) [5]	2023	D2	A2, A3	T1, T3
84	Ullah et al. (2024) [47]	2024	D2	A4	T1, T3
85	Vanijjirattikhan et al. (2022) [66]	2022	D2	A3, A4	T1, T2
86	Virk et al. (2020) [16]	2020	D2	A3	T1
87	Vrachimis et al. (2021) [51]	2021	D1	A1	T1, T2
88	Wang et al. (2026) [97]	2026	D4	A1, A2	T1
90	Yahia et al. (2021) [25]	2021	D4	A2	T1, T2
91	Zhu et al. (2024) [50]	2024	D5	A1, A5	T1

Note: NR = not reported or insufficient information was available to assign a category in that dimension.

Table 6. D-A-T coverage of review articles.

ID	Review	Year	D—Coverage	A—Coverage	T—Coverage
2	Adedeji et al. (2017) [98]	2017	D1, D2, D3, D5	A1, A2	T1, T2, T3
5	Anozie et al. (2026) [42]	2026	D1, D2	A2, A3, A4, A5	T1, T2, T3
17	Chan et al. (2018) [99]	2018	D1	A1, A2, A3, A4	T1, T2
20	Chiang Cruz et al. (2024) [3]	2024	D1	A2, A3, A4	T1, T2, T3
21	Colombo et al. (2009) [9]	2009	D1	A1, A2	T1
22	El-Zahab & Zayed (2019) [100]	2019	D1, D2, D3, D4, D5	A1, A2, A3	T1, T2, T3
26	Fan et al. (2022) [36]	2022	D2, D3	A2, A3	T1
28	Farah & Shahrour (2024) [2]	2024	D1, D2, D3, D4, D5	A1, A2, A3, A4	T1, T2
34	Hu et al. (2021) [39]	2021	D1	A1, A3	T1, T2
35	Hu et al. (2021) [38]	2021	D2	A2	T2
37	Ibrahim et al. (2021) [34]	2021	D3	A2, A5	T1, T2
38	Islam et al. (2022) [12]	2022	D1, D2, D3, D4	A2, A3	T1, T2

Table 6. *Cont.*

ID	Review	Year	D—Coverage	A—Coverage	T—Coverage
39	Ismail et al. (2019) [33]	2019	D1, D2, D4, D5	A1, A2, A3	T1, T2
40	Joseph et al. (2023) [43]	2023	D1, D2	A1, A3	T1, T2
59	Moubayed et al. (2021) [44]	2021	D1, D2, D3, D5	A1, A2, A3, A5	T1, T2, T3
64	Qi et al. (2024) [37]	2024	D1, D2, D3	A1, A2, A3, A4, A5	T1
67	Rajan & Li (2025) [45]	2025	D1	A1, A2, A3, A4, A5	T1, T2, T3
70	Romero-Ben et al. (2023) [40]	2023	D1	A1, A3, A5	T1, T2
77	Tariq et al. (2021) [35]	2021	D1, D2	A2, A3	T1, T2
89	Wu et al. (2024) [41]	2024	D1, D2	A2, A3, A4	T1
92	Zuñiga-Uribe et al. (2026) [13]	2026	D1, D2, D3	A3, A4, A5	T1, T2, T3

The three diagnostic task categories denote distinct capabilities rather than a sequence of stages that must necessarily be demonstrated together. T1 refers to the detection of leakage, T2 to the estimation of leak location, and T3 to the estimation or classification of leak-related characteristics. Although these capabilities may coexist within a single study, the assignment of T2 or T3 does not necessarily indicate that T1 was demonstrated independently. Accordingly, diagnostic task frequencies should be interpreted as marginal counts of reported capabilities, whereas mutually exclusive task combinations offer a more precise account of the diagnostic scope addressed by individual studies.

4.4. Application of the D-A-T Taxonomy to the Reviewed Corpus

The D-A-T taxonomy was applied to all 91 studies included in the systematic review using a multi-label classification approach. For the 70 primary studies, the assigned labels indicate components that were implemented or evaluated, whereas for the 21 review articles, they reflect the scope of the literature covered. Individual studies may, therefore, be assigned multiple labels when they address several technologies or diagnostic tasks. Rather than establishing a linear hierarchy, the taxonomy provides complementary dimensions for comparing heterogeneous approaches.

The study-level classifications are presented in the main manuscript to allow direct examination of how the D-A-T taxonomy was applied. Table 5 reports the classifications of the 70 primary studies, while Table 6 provides those of the 21 review articles. Retaining both tables in the main text allows readers to trace the assignment of acquisition modalities, processing architectures, and diagnostic tasks to individual publications, rather than relying solely on aggregated frequencies. The distinction between primary studies and review articles is maintained to prevent secondary evidence from being interpreted as independent experimental findings.

In addition to the assignment of individual D, A, and T labels, the study-level classification allows relationships between the three taxonomy dimensions to be examined. Accordingly, pairwise co-occurrences were analysed between data acquisition and processing architecture (D × A), data acquisition and diagnostic task (D × T), and processing architecture and diagnostic task (A × T). These relationships were derived from the 70 primary studies, with the 21 review articles excluded to avoid counting the secondary literature as independent evidence of implemented approaches. The resulting frequencies are reported and interpreted in the Cross-Dimensional Relationships Among D-A-T Categories section.

The assignment of multiple D-A-T labels is illustrated by representative studies. Within the processing architecture dimension, combinations involving A5 should be interpreted as processing method labels accompanied by an integration modifier. For example, the A2 + A5

assignments reported for Al Hassani et al. [70] and Chen et al. [65] reflect the combination of signal or statistical processing with an explicitly identified integration strategy. These examples distinguish the processing methods employed from the way in which they were integrated. Accordingly, A5 should be interpreted alongside the corresponding A1–A4 labels, rather than treated as an independent processing family. Al Hassani et al. [70] were classified under D1 and D4 based on their reported data acquisition modalities, A2 and A5 for their processing and integration approaches, and T1 and T2 for their diagnostic tasks. Chen et al. [65] were assigned D1 and D2 for hydraulic and vibroacoustic data acquisition, A2 and A5 for signal/statistical processing and hybrid integration, and T1 and T2 for detection and localisation. In contrast, Bartkowska et al. [60] were assigned D1 and three processing labels (A1, A2, and A3), but only T2 in the diagnostic dimension. This distinction reflects the coding principle that a localisation label does not automatically entail a detection label unless detection was separately identified as an evaluated task. Together, these examples illustrate the multi-label coding approach used in Table 5, whereby labels identify distinct methodological components reported in each study rather than mutually exclusive study categories.

Study IDs retain the original screening and coding sequence; consequently, the numbering may be non-consecutive following the exclusion of studies.

Deployment and communication platforms, including IoT, WSNs, LoRaWANs, and UAVs, were not treated as a separate dimension within the taxonomy because their functions extend across the three dimensions. These technologies can be integrated with different data acquisition methods, processing architectures, and diagnostic tasks.

5. Results and Synthesis of the Research Questions

This review identified a diverse range of technological approaches for the detection and localisation of water leaks. The evidence was synthesised using the previously defined research questions. The D-A-T taxonomy was used as an analytical framework to organise sensing modalities, processing architectures, and diagnostic tasks.

5.1. RQ1. Key Approaches, Methods, and Techniques for the Detection and Localisation of Leaks

Among the 70 primary studies, 67 were classified as addressing leak detection (T1), 32 as addressing localisation (T2), and 10 as addressing characterisation (T3). These frequencies are not mutually exclusive, as individual studies may address multiple diagnostic tasks. Accordingly, the reported counts reflect the representation of each diagnostic task within the reviewed corpus, rather than the number of studies exclusively concerned with detection, localisation, or characterisation.

Figure 3 Distribution of data acquisition (D), processing architecture (A), and diagnostic task (T) categories across the 70 primary studies. Categories are non-mutually exclusive; therefore, individual studies may contribute to multiple categories.

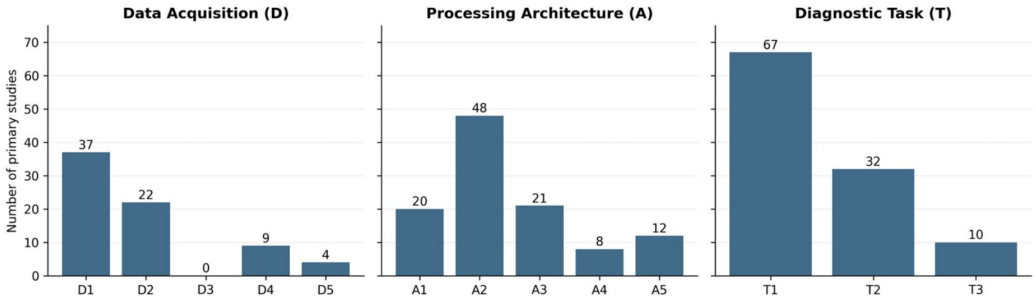


Figure 3. Distribution of D-A-T.

The literature indicates that water leak detection cannot be addressed through a single technological approach, as studies employ different sources of evidence, computational methods, and diagnostic objectives. Regarding data acquisition, the main approaches include hydraulic sensing based on pressure, flow rate, and consumption measurements; vibroacoustic sensing using acoustic emissions, vibration signals, accelerometers, or hydrophones; distributed fibre-optic sensing; optical and remote sensing techniques based on thermal, RGB, multispectral, or LiDAR data; and geophysical or electromagnetic methods, such as ground-penetrating radar (GPR).

In terms of processing architecture, the literature encompasses physics-based approaches, signal processing and statistical models, classical machine learning methods, deep learning architectures, and hybrid or data fusion strategies. These approaches are not mutually exclusive, as several studies integrate physical models, signal processing techniques, and learning-based methods within a single diagnostic workflow.

The diagnostic capabilities of these systems can also be classified according to the type of information they provide. Some approaches are limited to identifying the presence of a leak, whereas others determine its location at the level of a zone, pipe segment, or specific spatial position. A smaller group extends the diagnostic process to leak characterisation by estimating properties such as leak magnitude, leakage flow rate, opening size, or severity. These diagnostic tasks may be performed within the same system.

Cross-Dimensional Relationships Among D-A-T Categories

To examine the multidimensional structure of the D-A-T taxonomy, cross-tabulations were derived from the study-level classifications of the 70 primary studies reported in Table 5. Each cross-tabulation records the number of studies assigned to categories in two different dimensions simultaneously. As multi-label coding was permitted, individual studies could contribute to multiple category combinations. The resulting frequencies, therefore, represent patterns of co-occurrence rather than mutually exclusive technological configurations.

In the relationship between data acquisition and processing architecture, hydraulic acquisition (D1) most frequently co-occurred with signal and statistical processing (A2), with 22 studies assigned to both categories. This was followed by physics-based or model-based approaches (A1; 17 studies) and classical machine learning (A3; 13 studies). Vibroacoustic acquisition (D2) showed a similar predominance of A2 (17 studies), followed by A3 (nine studies) and deep learning (A4; six studies). By contrast, only two studies combined D1 with A4. Optical and remote acquisition (D4) was primarily associated with A2 (nine studies), while no primary studies were classified under distributed or fibre-based acquisition (D3).

Cross-tabulations of processing architecture and diagnostic task revealed further differences in the distribution of research activities. Signal and statistical processing (A2) co-occurred with detection (T1) in 46 studies and localisation (T2) in 18 studies. For classical machine learning (A3), the corresponding frequencies were twenty and nine studies, compared with eight and four studies for deep learning (A4). Physics-based or model-based approaches (A1) co-occurred with detection in 17 studies, localisation in 15, and characterisation (T3) in seven. Across acquisition modalities, hydraulic approaches (D1) were associated with localisation in 23 studies, compared with six studies using vibroacoustic acquisition (D2). These patterns suggest that the D-A-T taxonomy can support analysis of relationships among technological components and diagnostic objectives beyond individual category frequencies. However, the observed co-occurrences should not be interpreted as evidence of superior diagnostic performance or causal relationships.

The co-occurrence analysis was derived directly from the study-level D-A-T assignments in Table 5. For each primary study, every assigned acquisition label was paired with each processing label to calculate D × A frequencies, with the same procedure used to determine D × T and A × T frequencies. Each study contributed once to each applicable category pair, regardless of the number of additional labels assigned. Thus, a study classified as D1, D2/A2, A5/T1, and T2 contributes to four D × A pairs, four D × T pairs, and four A × T pairs. The resulting counts represent the occurrence of category combinations within the corpus, and their totals are, therefore, not expected to equal 70. In particular, A5 indicates explicitly reported hybrid or fusion-based integration and should not be regarded as a processing family distinct from A1–A4.

The D × T co-occurrence analysis shows that hydraulic acquisition (D1) was associated with detection (T1) in 34 studies, localisation (T2) in 23, and characterisation (T3) in seven. For vibroacoustic acquisition (D2), the corresponding frequencies were 22, six, and three studies. Optical and remote sensing (D4) co-occurred with T1 in nine studies and T2 in four, while geophysical or electromagnetic sensing (D5) co-occurred with T1 in four studies and T2 in one. Neither D4 nor D5 co-occurred with T3 among the classified primary studies. For the A × T combinations, characterisation was associated with physics-based processing (A1) in seven studies, compared with three for signal and statistical processing (A2), two for machine learning (A3), two for deep learning (A4), and one for the A5 integration modifier. These frequencies characterise the technological combinations documented in the review but do not demonstrate that any acquisition or processing category is inherently better suited to a particular diagnostic task.

The classification of the 70 primary studies presented in Table 5 provides a quantitative overview of the technological approaches identified within the reviewed corpus. Within the data acquisition dimension, hydraulic sensing (D1) was assigned to 37 studies, vibroacoustic sensing (D2) to 22, optical and remote sensing (D4) to nine, and geophysical or electromagnetic sensing (D5) to four. No primary study was assigned to spatially distributed strain, temperature, or vibration sensing (D3). Within the processing architecture dimension, physics-based approaches (A1) were identified in 20 studies, signal and statistical processing (A2) in 48, machine learning (A3) in 21, and deep learning (A4) in eight. Hybrid or fusion-based integration (A5) was reported in 12 studies and is treated separately as an integration modifier rather than as an independent processing family directly comparable with A1–A4. For the diagnostic task dimension, detection (T1) was assigned to 67 studies, localisation (T2) to 32, and characterisation (T3) to 10. As individual studies could receive multiple labels, these frequencies indicate category occurrences rather than counts of mutually exclusive study groups.

Diagnostic task combinations. To account for the multi-label structure and partial nesting of categories within the diagnostic task dimension, the 70 primary studies were grouped by their exact combinations of T1, T2, and T3 labels, as presented in Table 5. Unlike the marginal category frequencies, these combinations are mutually exclusive, with each primary study assigned to a single group. Detection alone (T1) was reported in 34 studies (48.6%), while 23 studies (32.9%) addressed both detection and localisation (T1 + T2). Six studies (8.6%) covered all three tasks, detection, localisation, and characterisation (T1 + T2 + T3), whereas four studies (5.7%) addressed detection and characterisation without being assigned T2 (T1 + T3). The remaining three studies (4.3%) were classified as localisation only (T2), as detection had not been independently coded as a demonstrated capability. No studies were assigned exclusively to T3 or to the T2 + T3 combination.

These results provide further context for interpreting the marginal frequencies. Although T1 was assigned to 67 studies, only 34 addressed detection exclusively. The remaining 33 studies assigned to T1 also covered at least one other diagnostic task. Thus,

the predominance of the T1 label does not imply that all 67 studies were restricted to leak detection. Rather, the analysis of task combinations indicates that approximately half of the primary studies addressed detection alone, whereas the remainder also addressed localisation, characterisation, or both. This distinction offers a clearer account of the range of diagnostic capabilities documented in the reviewed literature.

5.2. RQ2. Sensor Configurations, IoT/UAV Integration, and Evaluation Metrics

This section presents a qualitative synthesis of sensor configurations, deployment platforms, and evaluation metrics documented in the studies examined below. The analysis differentiates physical sensing modalities from IoT, WSN, and UAV infrastructures, whose primary roles concern data acquisition, communication, or spatial deployment. Performance measures are interpreted in the context of the diagnostic objectives and evaluation conditions described in each study. As these attributes were not systematically cross-tabulated across the entire corpus, the selected examples illustrate reported configurations and evaluation practices without implying differences in their relative prevalence or comparative effectiveness.

The configurations reported in the reviewed literature can be analysed in terms of the relationships between physical measurements, deployment or communication infrastructure, processing methods, diagnostic objectives, and evaluation criteria. IoT and wireless sensor networks (WSNs) primarily represent deployment and communication infrastructures rather than distinct sensing modalities. Among these configurations, Liu et al. [83] combined wireless pipeline monitoring with machine learning-based leak detection and 4G data transmission. Their system also employed leak-triggered communication designed to reduce energy consumption and prolong network lifetime. Nkemeni et al. [86] investigated distributed pipeline monitoring using a WSN architecture incorporating a distributed Kalman filter. These examples demonstrate distinct processing approaches within connected monitoring systems, namely, learning-based inference and distributed state estimation. However, the information presented does not provide a common quantitative benchmark against which their detection performance, communication efficiency, or validation conditions can be compared.

Other connected monitoring configurations incorporate acoustic, vibration, or force-sensitive sensing technologies. Phua et al. [88] employed aluminium nitride MEMS infrasonic hydrophones within an IoT architecture to collect acoustic measurements for leak detection and approximate localisation. Reported advantages of these devices include their compact dimensions and low power consumption; however, these properties do not constitute a quantified comparison of energy consumption with alternative monitoring systems. Essouabni et al. [85] investigated LoRaWAN-based connectivity, while a wireless monitoring approach employing force-sensitive resistive sensors was reported for multiple leak detection [91]. Collectively, these studies illustrate the range of physical measurements and communication technologies that can be incorporated into connected monitoring architectures. Nevertheless, the reported information lacks a consistent set of sensor specifications, processing requirements, diagnostic metrics, and validation conditions necessary for direct comparison between configurations.

UAV-based configurations are distinguished from fixed or distributed wireless monitoring systems primarily by their deployment arrangements and spatial observation capabilities. Krapez et al. [24] examined airborne hyperspectral and thermal infrared measurements for identifying moisture-related signatures potentially associated with leakage, while drone-based LiDAR measurements were investigated for detecting wet surface signatures [23]. In these configurations, the acquisition dimension refers to the optical or remote sensing measurements, whereas the UAV serves as the observation platform. Diagnostic interpretation

relies on the relationship between observed surface characteristics and subsurface leakage. Accordingly, the ability to inspect extensive areas should not be equated with demonstrated leak detection accuracy, localisation precision, or operational validation.

The evaluation criteria reported in the literature reflect different dimensions of diagnostic and operational performance. Ladino-Moreno et al. [82] reported 95% accuracy for an IoT-supported early leak detection approach. Lee and Kim [17] reported 99.79% accuracy using vibration measurements and XGBoost; although this provides an example of processing-related performance, the use of sensor data alone does not establish that the study employed an IoT or UAV deployment. Barros et al. [68] reported anomaly detection within 15 min and leak localisation within approximately 50 m, highlighting the distinction between detection response time and spatial localisation performance. Additional evaluation criteria include sensitivity, false alarm behaviour, communication efficiency, energy consumption, and network lifetime, where explicitly documented. As these measures relate to different diagnostic or operational objectives, they cannot be meaningfully consolidated into a single comparative ranking of system performance.

Across these configurations, the relationships among sensing modality, deployment platform, processing method, diagnostic task, performance metric, and validation environment are reported with varying degrees of detail. The studies discussed above illustrate identifiable connected and airborne monitoring configurations but do not represent an exhaustive cross-tabulation of IoT-, WSN-, and UAV-related studies across the 70-study corpus. In particular, the study-level D-A-T classifications do not include communication infrastructure, evaluation metrics, or validation conditions as comprehensively coded structured variables. The present synthesis, therefore, describes documented technological configurations and variations in evaluation practices without imputing values for unreported attributes or inferring the prevalence of specific deployment strategies from the selected examples. A corpus-wide comparison would require systematic and consistent extraction of these additional characteristics from the original primary studies.

5.3. RQ3. Advantages and Limitations of Existing Technological Approaches

The advantages and limitations examined in this section are drawn from a qualitative synthesis of the reviewed publications. The comparison takes into account the physical evidence acquired, processing-method requirements, diagnostic objectives, and operational constraints documented for each approach. Given the differences in experimental conditions and reporting practices across studies, these findings are not interpreted as a standardised quantitative ranking of technological approaches. The distinction between acquisition modalities and processing architectures is maintained in accordance with the D-A-T framework introduced in Section 4.

The suitability of a particular technology depends on network characteristics, available instrumentation, leak size, operating conditions, and diagnostic objectives.

To maintain consistency with the D-A-T taxonomy, the comparison of technological approaches differentiates among data acquisition modalities (D), processing architectures (A), and diagnostic capabilities (T). Data acquisition modalities are evaluated in terms of the physical quantities measured, spatial coverage, installation requirements, sensitivity to environmental conditions, and available evidence concerning deployment costs and operational maturity. Processing architectures are considered in relation to their input-data requirements, reliance on physical assumptions or training data, interpretability, computational demands, and sensitivity to uncertainty. Diagnostic tasks are differentiated according to whether the system under evaluation detects the presence of a leak (T1), estimates its location (T2), or characterises its properties (T3). These criteria establish a common framework for qualitative comparisons within each dimension. However, the evidence

reported across the reviewed studies is insufficiently standardised to support a numerical ranking of all categories.

Hydraulic sensing (D1) provides pressure and flow measurements that directly reflect the hydraulic state of a distribution network. Its principal advantages include compatibility with existing pressure and flow instrumentation and the potential to monitor hydraulic responses across the network. However, the diagnostic information derived from these measurements is influenced by sensor coverage, measurement precision, operating conditions, and the ability to distinguish leak-induced changes from normal demand fluctuations. These acquisition-related constraints should be distinguished from those associated with physics-based processing (A1). Hydraulic models and inverse methods can use pressure and flow data to estimate leak location or magnitude, but their reliability depends on model calibration, parameter uncertainty, and network observability. Pudar and Liggett [4] highlighted the importance of pressure measurement locations and hydraulic parameters in estimating leak location and magnitude. Thus, the limitations of hydraulic sensing and model-based inference, although related, remain analytically distinct.

Vibroacoustic sensing (D2) captures acoustic emissions and mechanical vibrations produced by escaping water. Unlike hydraulic measurements, these signals provide an alternative physical indication of leakage, although their diagnostic utility is influenced by pipe material, signal attenuation, background noise, sensor coupling, and installation geometry. Acoustic measurements may support detection (T1) or localisation (T2), depending on the processing method employed and the evaluation conducted. Noise filtering, correlation analysis, and feature extraction are classified within the processing dimension (A2) and should not be regarded as distinct acquisition modalities. Consequently, vibroacoustic system performance must be considered in terms of both acquired signal quality and the assumptions and constraints associated with the methods used to derive diagnostic information.

Optical and remote sensing (D4) enable non-contact measurements and offer the potential to inspect large spatial areas. Depending on the configuration, thermal, multispectral, and LiDAR-based measurements may reveal temperature variations, surface moisture, or other indirect indicators associated with underground leakage. Their principal limitations arise from the indirect relationship between observable surface signatures and the underlying leak, together with sensitivity to weather, soil conditions, vegetation, burial depth, and observation geometry. UAVs serve as deployment platforms for appropriate sensors rather than constituting an independent acquisition category within the D-A-T taxonomy. Similarly, image classification and anomaly identification belong to the processing dimension rather than representing sensing modalities. Accordingly, the demonstrated diagnostic capability of an optical or remote sensing system should be evaluated independently of its spatial coverage and deployment platform.

Distributed strain, temperature, and vibration sensing (D3) enables spatially resolved measurements along extended sections of infrastructure. Potential advantages include continuous spatial coverage and the ability to monitor changes at multiple locations along a sensing path. However, its performance is influenced by the physical quantity measured, installation and coupling conditions, interrogation settings, spatial resolution, and the magnitude of leak-related disturbances. Ibrahim et al. [34] discuss fibre-optic sensing approaches and the challenges associated with their application. The use of fibre-optic hardware does not, in itself, warrant classification as D3, which is defined by the acquisition of spatially distributed physical measurements. Because no primary study in the analysed corpus was assigned to D3, comparative conclusions regarding its diagnostic performance or operational maturity cannot be drawn from the primary-study frequencies.

Within the processing architecture dimension, physics-based methods (A1), signal and statistical processing (A2), machine learning (A3), and deep learning (A4) are evaluated according to their data requirements and underlying inferential assumptions, rather than the sensing modalities employed. Physics-based methods rely on appropriate representations of hydraulic behaviour and are susceptible to uncertainty in models and parameters. Signal and statistical methods enable the extraction of diagnostic features from measured data, although their effectiveness is influenced by signal quality, feature selection, and underlying statistical assumptions. Machine learning methods can recognise patterns without requiring a fully specified hydraulic model, but their reliability depends on the representativeness of training and validation datasets. Deep learning methods may reduce reliance on manually engineered features in certain applications, although they can entail substantial data and computational demands. Differences in reported classification accuracy do not provide a sufficient basis for ranking these processing families, given the variation in datasets, validation conditions, and diagnostic objectives across studies.

Multimodal acquisition and hybrid processing represent distinct aspects of diagnostic system design. A system may collect multiple types of physical measurements without integrating them within a shared inferential procedure. Conversely, hybrid or fusion-based integration (A5) denotes the combination of complementary information sources or processing mechanisms and is classified as an integration modifier rather than a methodological family directly comparable with A1–A4. Chen et al. [65] illustrate a configuration incorporating pressure and acoustic emission information. Such configurations may provide complementary diagnostic evidence, although any resulting benefits depend on the integration strategy and evaluation conditions. Finally, diagnostic capabilities must be evaluated independently: detection (T1) establishes leak presence, localisation (T2) estimates leak position, and characterisation (T3) estimates or classifies leak properties. Demonstrated capability in one task does not imply equivalent performance in another, and the available evidence is insufficient to establish a universally applicable ranking of D-A-T configurations.

5.4. RQ4. Research Gaps in Achieving Autonomous, Continuous, and Low-Cost Monitoring

The research gaps examined in this section were identified through a qualitative synthesis of recurrent limitations and unresolved requirements documented in the reviewed literature. The analysis addresses data availability and representativeness, validation under operational conditions, transferability across networks, sensor placement, false alarms, energy requirements, and the economic evidence needed to evaluate low-cost monitoring approaches. As these aspects were neither consistently reported nor systematically coded quantitatively across all primary studies, they are discussed as recurring research challenges rather than ranked by their frequency of occurrence within the corpus.

The reviewed literature indicates that fully autonomous, continuous, and economically scalable water leak monitoring remains an unresolved challenge. The main research gaps concern not the availability of individual detection technologies, but their integration into robust systems capable of moving beyond controlled experimental settings or network-specific applications. Such systems must be able to operate reliably over extended periods under diverse real-world conditions.

A first gap relates to the availability and representativeness of data. Data-driven methods are increasingly employing machine learning, deep learning, and hybrid approaches. Experimental and field datasets remain less common than simulated ones, as obtaining real-world leakage data is costly and operationally complex. Zuñiga-Uribe et al. [13] reported that many studies rely on simulations generated by EPANET, which highlights the difference between algorithmic validation and deployment under real-world network conditions. This

limits the extent to which it can be assumed that the reported performance of the models transfers directly between different networks.

Another significant challenge is achieving generalisation across different water distribution networks and operating conditions. These networks vary in topology, water demand patterns, pipe materials, sensor availability, and hydraulic behaviour. Some data-driven approaches suffer a decline in performance as network complexity increases; Tyagi et al. [67], for example, reported a decrease in performance as the network size increased. These observations indicate that scalability cannot be inferred solely from successful validation on a single network or experimental setup.

A third research gap concerns the long-term autonomous operation of distributed sensing infrastructures. IoT and WSN architectures enable continuous monitoring, but energy consumption, communication overhead, and network lifetime become critical when sensors must remain deployed for extended periods. Nkemeni et al. [86] specifically addressed energy consumption and the lifespan of WSNs through distributed processing. MEMS-based sensing has been investigated partly due to its low energy consumption and small physical size.

Sensor placement and sensing coverage represent further unresolved challenges. In model-based leak detection, localisation accuracy may depend directly on the number, placement, and quality of the measurements. Pudar and Liggett [4] demonstrated the importance of the location of measurements for both localising the leak and estimating its magnitude. More recent studies investigate sensor placement strategies specifically designed to improve detection efficiency. Deploying additional sensors does not automatically result in a scalable solution: the spatial configuration of the sensing infrastructure must balance diagnostic resolution against installation and operational requirements.

Balancing detection sensitivity against false alarm rates under uncertain real-world operating conditions remains another significant challenge. Although high sensitivity is essential for identifying small or incipient leaks, normal hydraulic fluctuations, measurement uncertainty, and environmental noise can generate ambiguous signals. Comparative reviews of model-based and data-driven methods highlight different aspects of this challenge. Model-based approaches are particularly sensitive to modelling and measurement uncertainties, whereas data-driven methods may be more prone to false positives. Further progress, therefore, requires not only improved detection sensitivity but also more reliable discrimination between genuine leaks and normal variations in network operating conditions.

The literature remains fragmented across sensing, computing, and deployment technologies. Reviews describe leak monitoring systems in terms of data acquisition, analytical models, and monitoring platforms. Other works propose data fusion and federated learning paradigms to improve existing detection methods. However, relatively few solutions demonstrate all these elements simultaneously as a persistent system deployed in the field. The research challenge is shifting from developing high-performance, isolated components to integrating sensing, communication, processing, and diagnostic decision-making—all within a single operational architecture.

An additional research gap concerns the economic evidence required to assess low-cost monitoring. Reduced energy consumption, efficient communication, and extended sensor lifetime may improve operational efficiency, but these characteristics are not equivalent to low overall system cost. Economic affordability also depends on sensor procurement, installation, communication infrastructure, calibration, maintenance, component replacement, and long-term operation. The reviewed publications do not report these cost components consistently enough to support a systematic economic comparison across D-A-T configurations. Therefore, this review does not identify any particular technology as the least expensive or infer economic affordability from energy efficiency alone. Future evalua-

tions should report installation, operating, and maintenance costs alongside diagnostic performance and energy requirements.

5.5. RQ5. Future Directions for Comprehensive Water Leak Detection Systems

The research directions outlined in this section were formulated by combining the descriptive D-A-T classification with the technological limitations and research gaps identified in Sections 5.2–5.4. Together, they constitute a qualitative research agenda grounded in the reviewed literature. These directions should not, however, be regarded as experimentally validated development pathways or as demonstrating that any particular combination of acquisition modalities, processing architectures, and diagnostic capabilities necessarily yields superior performance.

The reviewed literature documents examples of multimodal sensing, hybrid processing, and systems addressing multiple diagnostic tasks; however, these approaches should not be regarded as successive stages in an empirically established technological progression. Drawing on the D-A-T taxonomy, we propose a conceptual framework for future research that integrates these elements: complementary data acquisition modalities (D) may yield distinct sources of leak-related evidence; hybrid or fusion-based processing (A) may integrate information from these sources; and the resulting diagnostic systems may be designed to address detection, localisation, and characterisation (T). This framework constitutes a research hypothesis rather than a conclusion supported by the frequency or co-occurrence analyses. Specifically, the available evidence does not demonstrate that multimodal acquisition consistently results in hybrid processing, that hybrid approaches enable a wider range of diagnostic capabilities, or that integrating these elements necessarily enhances system robustness.

A first promising direction involves multimodal sensing and data fusion. Individual sensing technologies provide different, and sometimes incomplete, indications of leakage. Hydraulic measurements capture changes in network behaviour, vibroacoustic sensors detect mechanical disturbances, and optical or remote sensing systems identify surface-level manifestations of underground leaks. Integrating these complementary information sources may improve diagnostic robustness when individual sensing modalities are affected by operational or environmental conditions. Existing studies have explored multimodal acquisition and fusion by combining complementary measurements, including pressure and acoustic sensing and the integration of acceleration, pressure, and acoustic data [15,32]. Sensor data fusion has also been identified as a promising research direction for improving water leak detection.

Hybrid and ensemble approaches discussed in the reviewed literature illustrate that physics-based and data-driven processing need not be treated as mutually exclusive methodological options; however, their comparative advantages depend on the implementation and validation conditions. Future monitoring systems could incorporate hydraulic or physical constraints into machine learning models to improve robustness while preserving a meaningful connection between diagnostic predictions and the underlying hydraulic behaviour of the network.

A third research direction involves the development of multi-task diagnostic systems. Although much of the existing literature focuses on determining whether a leak is present, effective operational water management also requires information about its location and characteristics. Comprehensive monitoring architectures should, therefore, extend beyond isolated leak detection to integrate leak detection, localisation, and estimation of leak magnitude or severity. Within the D-A-T framework, the proposed research direction involves investigating systems that integrate T1, T2, and T3 capabilities where such integration is justified by operational requirements. The study-level task combinations presented in

Section 5.1 indicate that certain approaches already address multiple diagnostic objectives; however, they do not demonstrate that incorporating additional tasks necessarily enhances diagnostic performance.

Another key area is distributed, energy-efficient, and connected monitoring. IoT and WSN technologies already enable remote and continuous data acquisition. Other devices, such as low-power MEMS, LoRaWAN communication, and distributed processing, have been explored to reduce communication or energy requirements. Nkemeni et al. [86], for example, demonstrated that distributed processing can improve energy efficiency and extend the service life of WSNs, whilst Phua et al. [88] highlighted the low-power and compact nature of MEMS sensing for IoT applications. These developments suggest that future monitoring architectures must evaluate energy consumption, communication requirements, and maintainability alongside diagnostic accuracy, rather than treating connectivity as a secondary consideration. The literature also supports greater use of distributed intelligence and collaborative learning. Moubayed et al. [44] identified sensor data fusion and federated learning as paradigms with the potential to improve leak detection methods. These approaches are relevant when information is distributed across multiple sensing locations or water networks. Centralising all the data is impractical. Their value for the operational management of WDNs will require validation beyond conceptual or simulation-based studies.

One of the most important priorities for future research is field validation and transferability across different water distribution networks. High predictive accuracy achieved under specific experimental or simulated conditions does not necessarily translate into comparable performance in other networks. The reviewed literature indicates that simulated datasets remain widely used, whereas experimental and field data are more difficult and costly to obtain. Future research should, therefore, prioritise long-term validation under real-world operating conditions, encompassing diverse pipe materials, network topologies, demand patterns, leak sizes, and environmental conditions. Furthermore, standardised reporting of detection performance, localisation error, false alarm rates, response times, and operational requirements would facilitate more consistent comparisons between emerging leak detection systems.

Taken together, these guidelines suggest a transition from isolated solutions towards comprehensive monitoring architectures, which, from the D-A-T perspective, can be summarised as multimodal acquisition (D) → hybrid and fusion processing (A) → multitask diagnosis (T), supported by efficient communication and sustained validation under real-world conditions.

6. Discussion

The findings indicate that water leak detection is a multidimensional technological challenge encompassing diverse sensing methods, processing techniques, deployment platforms, and diagnostic objectives. This diversity reveals distinct patterns in the approaches adopted to address the problem. A collective analysis of the reviewed studies allows established technologies and emerging approaches to be distinguished, while highlighting challenges related to methodological comparability and the transition from experimental validation to continuous monitoring systems capable of operating reliably under real-world conditions.

6.1. Patterns Observed

The quantitative distributions and diagnostic task combinations presented in Section 5.1 form the empirical basis for the discussion that follows. Interpreting these findings requires consideration of the physical observables, processing requirements, and diagnostic objectives associated with each D-A-T dimension. Importantly, category frequencies indicate the extent to which different approaches are represented in the reviewed corpus,

but do not, in themselves, demonstrate technological superiority, diagnostic accuracy, or operational maturity.

The first pattern concerns the distribution of physical sensing modalities across the primary studies. Of the 70 studies analysed, 37 incorporated hydraulic measurements, such as pressure, flow rate, or consumption (D1), while 22 used vibroacoustic or mechanical disturbances (D2). Optical or remote sensing observations (D4) were reported in nine studies, and geophysical or electromagnetic measurements (D5) in four. No primary study was assigned to D3, which encompasses spatially distributed measurements of strain, temperature, or vibration, although distributed sensing approaches are discussed in the review literature. The absence of D3 assignments indicates that this particular measurement category was not represented among the classified primary studies, rather than an absence of fibre-optic or distributed sensing technologies from the wider field. D3 is retained to account for spatially distributed physical measurements within the taxonomy, rather than to define a category solely by sensor hardware. As the D-A-T taxonomy permits multiple labels, the reported frequencies represent occurrences of sensing modalities rather than mutually exclusive groups of studies.

Within the processing architecture dimension, signal and statistical processing (A2) was identified in 48 of the 70 primary studies, followed by classical machine learning (A3; 21 studies), physics-based or model-based methods (A1; 20 studies), and deep learning (A4; 8 studies). These four labels denote methodological families and may be assigned concurrently when a study employs distinct processing approaches. Separately, 12 studies were assigned the A5 modifier, reflecting explicitly reported hybrid or fusion-based integration strategies. The A5 frequency, therefore, represents the occurrence of integration strategies rather than a fifth processing paradigm directly comparable with A1–A4. The concurrent use of conventional signal processing, physical models, and machine learning approaches should be examined through their individual and combined label assignments, rather than interpreted as evidence that one methodological family directly replaces another. Moreover, an A5 assignment alone does not establish improvements in diagnostic accuracy, robustness, or operational applicability.

The distribution of D-A-T categories should also be interpreted in light of the physical and mathematical constraints associated with leak diagnosis. Among the 70 primary studies, hydraulic sensing (D1) was the most frequently reported acquisition category, with 37 assignments, followed by vibroacoustic sensing (D2), with 22. These frequencies indicate the technological emphasis of the included literature rather than the relative diagnostic effectiveness of the approaches. Hydraulic measurements can be integrated into network-wide monitoring and model-based inference, although their diagnostic resolution depends on sensor placement, demand uncertainty, and the identifiability of leak parameters. Vibroacoustic approaches may provide more direct evidence of disturbances generated locally by leaks, but signal attenuation, dispersion, and background noise can limit their effective range, particularly in plastic pipes.

The task combination analysis presented in Section 5.1 offers a more precise account of diagnostic capabilities than marginal frequencies alone. Of the 70 primary studies, 34 were classified as addressing detection exclusively (T1), whereas 36 also addressed localisation, characterisation, or both. Thus, although detection was the most frequently assigned individual diagnostic task, the prevalence of T1 does not imply that all 67 studies assigned this label were restricted to detection. Characterisation remained comparatively uncommon, being reported in only 10 studies. From a theoretical perspective, localisation and characterisation may depend on additional information and more restrictive assumptions than anomaly detection, particularly in relation to sensor placement, hydraulic uncertainty, and parameter identifiability. However, these considerations represent physically informed

interpretations rather than causal relationships demonstrated by the review findings. The observed frequencies are also shaped by the literature search, study selection, and multi-label classification procedures.

A further pattern emerging from the reviewed literature is the increasing integration of complementary technologies. The IoT, wireless sensor networks, and unmanned aerial vehicles do not constitute data acquisition methods or processing architectures in themselves; rather, they serve as deployment and communication platforms that integrate sensing, data transmission, and processing capabilities. The reviewed studies include, for example, IoT-based systems incorporating hydraulic sensors or microelectromechanical systems (MEMS) hydrophones, WSNs equipped with vibroacoustic sensors, and UAV-based applications employing optical or LiDAR sensors. This diversity highlights the importance of distinguishing between the sensing technologies used to acquire diagnostic evidence and the platforms through which these technologies are deployed or their data are transmitted.

The cross-dimensional analysis presented in the Cross-Dimensional Relationships Among D-A-T Categories section provides further insight into how the reviewed approaches integrate acquisition modalities, processing methods, and diagnostic capabilities. The frequent co-occurrence of hydraulic acquisition (D1) with signal and statistical processing (A2), together with that of vibroacoustic acquisition (D2) and A2, demonstrates that this processing family is employed across distinct physical measurement modalities. Furthermore, the co-occurrence of hydraulic acquisition with physics-based processing and localisation or characterisation tasks is consistent with the role of hydraulic relationships in inverse diagnostic problems. Nevertheless, these associations do not establish the superiority of any particular combination in terms of accuracy, robustness, or transferability. Similarly, they do not demonstrate that multimodal acquisition necessarily entails hybrid processing or enables a broader range of diagnostic capabilities. Addressing these questions would require comparisons at the study level based on consistent performance metrics and validation conditions.

Regarding evaluation, no fully standardised practice was identified. Some studies use classification metrics such as accuracy, whilst others assess localisation error, spatial resolution, detection time, sensitivity to small leaks, false alarms, energy consumption, or communications performance.

6.2. Critical Comparison

The limitations identified in the reviewed literature should be interpreted in relation to the corresponding D-A-T dimension. For data acquisition (D), the main considerations relate to measurement sensitivity, spatial coverage, sensor placement, installation requirements, and environmental interference. For processing architectures (A), key constraints encompass model uncertainty, training data availability, computational requirements, interpretability, and transferability across networks. For diagnostic tasks (T), the relevant limitations vary according to the required diagnostic output: detection entails identifying the presence of a leak while managing false alarms, localisation involves estimating leak position and quantifying the associated spatial error, and characterisation entails estimating or classifying leak-related properties. Although these limitations may interact within integrated systems, they should not be regarded as equivalent indicators of technological performance.

The comparison of data acquisition modalities (D) highlights trade-offs associated with the physical evidence available for diagnosis. Hydraulic sensing (D1) provides pressure and flow measurements that closely reflect network operating conditions, but leak-induced variations may be difficult to distinguish from demand fluctuations or other hydraulic disturbances. Vibroacoustic sensing (D2) detects mechanical vibrations or acoustic emis-

sions associated with leakage, although signal attenuation, background noise, and sensor coupling may limit its effective spatial coverage. Distributed sensing (D3) provides a conceptually distinct approach based on spatially resolved measurements; however, its practical advantages cannot be established from the primary study corpus, as no included study was assigned to this category. Optical and remote sensing (D4) enable non-contact inspection across extensive areas, although the resulting observations frequently rely on indirect surface manifestations that are sensitive to environmental conditions. Geophysical sensing (D5) allows subsurface changes to be investigated, but their interpretation is influenced by site conditions, measurement resolution, and the ability to distinguish leak-related effects from other subsurface variations. These distinctions reflect differences in measurement characteristics and deployment constraints rather than the inherent superiority of particular diagnostic algorithms.

Processing architectures (A) involve a different set of methodological trade-offs. Physics-based approaches (A1) can account for hydraulic relationships and network constraints, although their reliability depends on model fidelity, calibration, and parameter identifiability. Signal and statistical processing (A2) enables the identification of relevant features or variations in measured signals, with performance dependent on measurement quality and the validity of the underlying analytical assumptions. Machine learning (A3) and deep learning (A4) can capture complex relationships within available datasets, but their reliability is affected by data representativeness, class balance, validation procedures, and transferability across networks. Deep learning may also require larger training datasets and greater computational resources. Hybrid or fusion-based integration (A5) may bring together complementary methods or information sources; however, the use of multiple sensors does not, in itself, establish that information fusion has been implemented. Accordingly, processing approaches should be evaluated in terms of their input requirements, underlying assumptions, computational demands, and validation conditions, rather than on the basis of isolated accuracy figures.

Diagnostic capabilities (T) constitute a third, analytically distinct basis for comparison. Detection (T1) involves establishing the presence of a leak and should be assessed using appropriate detection metrics, including sensitivity and false alarm behaviour where these are reported. Localisation (T2) involves estimating leak position, requiring consideration of spatial error, resolution, and the conditions under which the estimate was obtained. Characterisation (T3) involves estimating or classifying leak-related properties, such as magnitude or severity, and, therefore, requires evaluation criteria specific to these outputs. As individual studies may address multiple diagnostic tasks, marginal task frequencies cannot be used to rank diagnostic performance. The mutually exclusive task combinations presented in Section 5.1 characterise the scope of reported diagnostic capabilities but do not demonstrate that systems addressing a greater number of tasks necessarily achieve higher accuracy or greater operational maturity.

Across all three dimensions, a major challenge for comparative evaluation is the heterogeneity of the available evidence. The reviewed studies vary in terms of network configuration, pipe materials, leak sizes, operating pressures, sensor placement, background conditions, datasets, and validation procedures. Performance values obtained under different experimental conditions or for different diagnostic outputs cannot be assumed to be directly comparable. Similarly, findings derived from simulations, controlled experiments, and operational networks should not be regarded as equivalent forms of validation evidence. The review, therefore, examines technological trade-offs and limitations within each D-A-T dimension without attempting an unsupported numerical ranking of sensing modalities, processing architectures, or complete diagnostic configurations. Future comparative assess-

ments would benefit from greater consistency in the reporting of validation environments, diagnostic performance metrics, and operational constraints.

6.3. Theoretical and Practical Implications

The D-A-T framework is designed to facilitate comparisons between concepts at the same analytical level while characterising their integration within complete diagnostic systems. Comparisons within the D dimension address the physical evidence acquired and the associated deployment constraints; those within A examine how this evidence is processed; and those within T focus on the diagnostic information generated. Cross-dimensional combinations should, therefore, be considered as configurations that link specific measurements, processing methods and diagnostic objectives, rather than as technologies competing at a common analytical level. Although these configurations can be distinguished using the study-level classifications in Table 5, the available evidence is insufficient to determine whether any particular D × A combination is universally more effective for a given diagnostic task. Establishing such conclusions would require comparable performance metrics and validation conditions across studies.

The results show that leak detection technologies can be analysed more clearly when three fundamental questions are distinguished: where the evidence of the leak comes from, how it is processed, and what diagnostic information is obtained. This distinction constitutes the main benefit of the D-A-T taxonomy. The framework avoids classifying concepts of different natures at the same level; for example, sensors, algorithms, IoT platforms, and localisation tasks. Furthermore, it allows multi-technology systems to be represented using various labels without assuming a hierarchy amongst them. The coding rules used explicitly distinguish between experimental implementation and the coverage provided by review articles and treat the IoT, WSNs, LoRaWANs, and UAVs as platform or deployment descriptors, rather than as D or A categories in their own right.

From a future research perspective, the D-A-T taxonomy offers a conceptual foundation for investigating integrated monitoring systems that bring together complementary measurements, processing methods, and diagnostic capabilities. The relatively limited representation of characterisation (T3) highlights an opportunity to investigate systems capable of providing diagnostic information beyond leak presence, including leak location and properties. Multimodal acquisition may provide complementary physical observations, whereas hybrid or fusion-based processing may facilitate the integration of information from different sources or analytical methods. Accordingly, we propose the sequence multimodal acquisition (D) → hybrid or fusion-based processing (A) → multitask diagnosis (T) as a conceptual framework for future research rather than a technological progression empirically demonstrated by the present review. Although the co-occurrence analysis in the Cross-Dimensional Relationships Among D-A-T Categories section identifies existing combinations of acquisition modalities, processing methods, and diagnostic tasks, it does not establish that multimodal systems consistently employ hybrid processing, that such processing enables a broader range of diagnostic capabilities, or that these configurations exhibit greater robustness. Evaluating these potential relationships would require explicit study-level comparisons and assessments of diagnostic performance under comparable validation conditions.

From a practical perspective, these findings indicate that technology selection should not be based solely on algorithmic accuracy. Water utilities and system designers must also consider instrumentation availability, spatial coverage, energy consumption, communication infrastructure, maintenance requirements, environmental conditions, localisation capabilities, and deployment costs. Internet of Things systems and wireless sensor networks can support continuous monitoring, whereas unmanned aerial vehicles and remote

sensing technologies can extend spatial coverage without requiring physical instrumentation throughout the network. Although these platforms serve different purposes, they may perform complementary functions within an integrated monitoring architecture. The reviewed literature encompasses IoT- and WSN-based systems, UAV applications, and multimodal configurations, illustrating how these platforms can be combined with different data acquisition modalities (D) and processing architectures (A).

These findings have important implications for operational decision-making and the assessment of emerging leak detection systems. Validation efforts should progressively move beyond isolated demonstrations of methodological feasibility towards comprehensive assessments of system-level performance. Such assessments should address performance in operational networks, transferability across different infrastructures, false alarm behaviour, energy consumption, maintenance requirements, and long-term operational reliability. Greater standardisation of evaluation criteria would also improve comparability across studies, as the current heterogeneity of performance metrics and validation scenarios makes it difficult to establish whether improvements in algorithmic performance translate into meaningful operational benefits. Ultimately, future progress will depend not only on improving leak detection performance but also on developing monitoring systems capable of operating reliably and continuously while providing actionable information for the effective management of water distribution networks.

6.4. Limitations of the Review

This review has some limitations that should be taken into account when interpreting the results. Firstly, the search strategy focused on Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, ASCE, and Taylor & Francis, and it included only peer-reviewed publications in English and Spanish. Although this combination enabled us to cover various technological areas related to water distribution networks, it is possible that studies published in other languages, in non-indexed repositories or in sources not included in the search strategy may have been excluded from the corpus. No formal risk-of-bias or methodological quality appraisal was performed because the review focused on the technological classification and structured synthesis of approaches rather than on pooled effect estimation.

A second limitation stems from the methodological heterogeneity of the included studies. The studies utilise different networks, pipe materials, sensor configurations, leak sizes, experimental conditions, datasets, and evaluation metrics. This variability prevents a direct quantitative comparison between all methods and means that the reported accuracy values cannot be interpreted as if they were derived from equivalent experimental conditions. For this reason, the present review primarily carried out a structured and critical synthesis, rather than a meta-analysis of performance.

The D-A-T classification also involves an interpretative component. To reduce ambiguity, operational definitions and explicit coding rules were used, including multi-label classification, distinguishing between implementation and coverage in review articles, and separating deployment platforms.

Finally, the corpus includes both primary studies and review articles. To avoid equating experimental evidence with secondary synthesis, the two groups were analysed separately: the final corpus comprised 91 studies, of which 70 were primary studies and 21 were review articles. The D-A-T frequencies used to identify technological patterns were calculated from the primary studies, whilst the review articles were used to analyse coverage and contextualise the findings.

An additional limitation is the lack of a formal assessment of methodological quality across the included primary studies. Although the D-A-T taxonomy provides a consistent

basis for describing technological approaches and diagnostic objectives, it does not assess the strength of the underlying evidence. In particular, methods evaluated exclusively through simulation or controlled laboratory experiments cannot be assumed to perform equivalently under operational field conditions. Reported performance may also depend on the availability of independent test data, appropriate baseline comparisons, and representative hydraulic and environmental conditions. As these factors were not systematically assessed across all primary studies, the available evidence does not support study-level quality rankings or general conclusions regarding technological readiness. Future evidence syntheses should include a structured appraisal framework that accounts for differences in validation environments, independent evaluation, baseline comparisons, and operational realism.

7. Conclusions

This systematic review examined the principal technologies, computational methods, and monitoring strategies employed for water leak detection, localisation, and characterisation. The findings reveal considerable technological diversity, with no single sensing modality or processing architecture demonstrating universal superiority. The suitability and performance of individual approaches depend on network hydraulic characteristics, available instrumentation, environmental conditions, leak size, and diagnostic objectives.

The D-A-T taxonomy was used to examine relationships among data acquisition, processing architectures, and diagnostic capabilities across the 70 primary studies. Its application revealed diverse technological configurations and highlighted the need to distinguish the presence of leak detection functions from the broader diagnostic capabilities demonstrated by individual approaches. This distinction may facilitate a more precise interpretation of the available evidence and help identify areas requiring further investigation.

The findings further indicate that technological progress in this field cannot be characterised simply as the replacement of conventional approaches by machine learning or deep learning. Physical models, signal processing techniques, machine learning methods, and hybrid architectures continue to coexist, each offering distinct advantages and presenting specific limitations. Meanwhile, the IoT, wireless sensor networks, Long Range Wide Area Networks (LoRaWANs), and unmanned aerial vehicles extend deployment and communication capabilities but should be distinguished conceptually from the sensing modalities and computational methods used to acquire and process diagnostic information. Maintaining this distinction enables a more consistent assessment of integrated systems that combine sensing, communication, and processing within a single monitoring architecture.

The principal research gaps concern the availability of representative real-world datasets, generalisability across different networks, sensor placement and density, energy consumption, false alarm management, continuous operation, and long-term validation under operational conditions. These limitations highlight why high diagnostic accuracy under controlled conditions is insufficient, on its own, to establish the operational maturity of a monitoring system. Successful deployment requires a comprehensive assessment encompassing diagnostic accuracy, robustness, transferability, spatial coverage, communication requirements, maintenance demands, and implementation costs.

Based on these findings, a promising research direction involves the development of integrated monitoring systems combining multimodal data acquisition (D), hybrid or fusion-based processing architectures (A), and multi-task diagnostic capabilities (T). Such systems would integrate complementary information sources, combine physical knowledge with data-driven methods, and extend diagnostic functionality beyond isolated leak detection to include localisation and characterisation. These developments should be supported by efficient communication architectures and more extensive validation in operational water distribution networks.

Overall, this review provides a structured synthesis of current water leak detection technologies and introduces a framework for comparing diverse approaches while maintaining clear distinctions between sensing modalities, processing methods, deployment platforms, and diagnostic tasks. Rather than supporting the selection of a universally dominant technology, the findings suggest that progress towards autonomous, continuous, and operationally viable leak monitoring will depend on the effective integration of data acquisition, processing, and diagnostic capabilities, supported by rigorous validation criteria that demonstrate their practical utility under real-world conditions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w18212797/s1. Table S1: Completed PRISMA 2020 checklist for the systematic review.

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