TOPICAL REVIEW

A Review on Current Technologies and Future Direction of Water Leakage Detection in Water Distribution Network

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ABSTRACT Water leakage in the supply system is a silent problem that costs billions of dollars yearly. As these supply pipes are mostly underground, this leakage remains undetected for a long time. In 2019, Liemberger and Wyatt estimated an annual loss of thirty-nine billion dollars due to water leakage in the supply pipe. In this systematic review, we have analyzed forty-seven articles about water leakage detection and location research. The aim is to find the new technology, trends, and possible direction in this research field. We have derived four research questions. The first question was about how the research evolved over time, and we have observed that researchers focus more on experimental data collection, ML algorithms, and IoT technology. The second question was about the sensor the researcher was using. The most popular sensors researchers have used are: vibration, acoustic, and flow sensors, as they are cheap and easy to install. We can also see some novel applications of image and optical fiber sensors. The third question was about the trend in the algorithm. ML and threshold-based algorithms are dominating the field. The fourth question was about the communication technology trend, and WIFI, cellular IoT, and LoRa technology are leading the space capturing 80% of the research.

INDEX TERMS Leakage detection, leakage localization, Internet of Things (IoT), machine learning (ML), review.

ABBREVATION

AI	Artificial Intelligence
ASIC	Application Specific Integrated Circuit
BPNN	Backpropagation Neural Network
CFD	Computational Fluid Dynamics
DBSCAN	Density Based Spatial Clustering of Application with Noise
EMD	Empirical Mode Decomposition
EEMD	Ensemble Empirical Mode Decomposition
FPGA	Field Programmable Gate Array
GPR	Ground Penetrating Radar
HHT	Hilbert-Huang Transform
IMF	Intrinsic mode functions
IoT	Internet of Things
KNN	k-Nearest Neighbor
ML	Machine Learning
MLP	Multilayer perceptron
MFCN	Multiscale Fully Convolutional Network
MIF	Monitor Index Efficiency
NBC	Naïve Bayes Classifier
PVDF	Polyvinylidene Difluoride
SVM	Support Vector Machine
SoC	System on Chip
TENG	Triboelectric Nanogenerator
TIF	Time domain Impendence Function
VMD	Variational Mode Decomposition
V-DMA	Virtual District Metering Area
V-AHP	Visual Analytic Hierarchical Process
WDS	Water Distribution System.

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Wang.

I. INTRODUCTION

Water leakage in the supply system is a silent problem that costs the world billions of dollars each year. A good portion of the water supply pipes are underground, so leakages remain unnoticed and undetected for a long time. Water is a precious natural resource, and according to Liemberger and Wyatt, the estimated cost of annual water loss is 126 billion cubic meters per year and is conservatively valued at thirty-nine billion dollars in 2019 [1]. Clean potable water is a fundamental human right, but even today, around half of the world's population, or 3.6 billion people, suffer from water scarcity at least once a month every year, and by the year 2050, this number is expected to be around 4.8 to 5.7 billion people [2].

In 2016, the World Energy Outlook estimated that 4% of global electricity consumption was by water in 2014. Of this consumption, 60% of it was for the extraction and distribution of water. If all the countries reduce water supply leakage to less than 6%, then the energy savings equates to 130TWh, the entire energy needs of Poland. The EU has an average of 24% water leakage, the USA has 12% water leakage, and Australia has 10% water leakage [3]. This water loss has a chain reaction effect on the economy and public health. Long-term water leakage can cause structural damage, cause sinkholes, and even cause disease-causing pathogens to contaminate the water supply system. Due to water loss, the revenue decreases, and eventually, the water cost goes up, and the service goes down. This leakage also causes the water quality to deteriorate.

The authorities regularly perform water audits, interventions, and performance evaluations to minimize water loss in the system [4]. Water consumption and use can be categorized into authorized consumption, real losses, apparent losses, and non-revenue water [4]. Authorities try to find the reason for "real losses" that are mainly leakage loss in the transmission line, service connection, and overflow from storage tanks. A water audit provides information about the portion of the system that is losing water. Further information is gathered after the water audit to detect and locate leakage. Then the leakage is repaired or the pipe is replaced. Finally, the network's performance is monitored to make sure the major loss points are fixed. The problem with this approach is that it is time-consuming, and labor intensive.

In [5], [6], and [7] researchers have summarized the fundamental way the WDS is set up, the cause of leakage, and the current technologies that are used to detect and locate the water leakage. Water leakage detection and location work can be divided into three parts. The first one is data capture; the second part is the data processing and finally alerting the authority if there is any issue detected. There are a range of sensors to capture acoustic, vibration, flow, pressure, and temperature data. There are lot of ways to use these sensors for leakage detection work. The simplified method is the listening stick. It probes the ground to detect the leakage sound and locate the leakage sound based on the "loudness" of the sound [8]. Usually, the detection work was entirely based on human experience and with the development and improvement of signal processing algorithms and cheap computers, now researches are developing automatic leakage detection techniques [9]. There are two major way the signals are being processed in this field. The first one is threshold based and the other one is machine learning based. Machine learning (ML) based techniques are getting traction because of their flexibility and accuracy. One of issues of ML based techniques is that, it requires a lot of computational resources to run ML models. In 2016, Obeid et al. reviewed water leakage technology based on micro-controller, digital signal processor, FPGA, and ASIC. The author suggested that a custom SoC (System on Chip) design is ideal for high-performance and low-power leakage detection nodes [10]. Previously, "leakage detection survey" was the only way authority can detect, locate and fix leakage but it is expensive and wasteful. Researchers have developed noise loggers with custom radio, hardware and protocols but with the advent of standardized IoT, it is becoming easy for the researches to integrate IoT systems into their research [11].

This research focuses on sensor-based leakage detection solutions that use IoT, AI, and ML. The remainder of the article is arranged in the following fashion. Section II provides a background and history of leakage detection methods, their merits and disadvantages. Section III describes articles selection process, their sources and data assembly process. In section IV, articles are organized and a systematic review performed to assess the article quality. Finally, the data is analyzed based on sensors, signal type, experiment type, experiment outcome and methodology. Section V addresses the research questions, and lastly, we have made a conclusion in section VI.

II. BACKGROUND

An underground leak can be discovered in various ways. Researchers have classified these techniques considering a wide range of criteria. Chan et al. have classified these systems as active or passive systems [7], Adedeji et al. [6] have classified them as internally and externally systems, and Ismail et al. have [12] classified them as their historical appearance. We have categorized these approaches as invasive and non-invasive in this research. The way the sensor is mounted to the pipe determines this categorization. If the sensors must be placed within the pipe, this is an invasive method. These are invasive procedures, such as using a hydrophone within a pipe to collect audio data or using a flow meter between pipes. Vibration sensors, on the other hand, can be mounted to a pipe, making it a non-invasive procedure. Techniques that use non-invasive methods are less expensive to implement. The purpose of providing background information on leakage detection methods is to provide the reader with the context in which this literature is written. A review of classical approaches will aid the reader in comprehending their algorithms, the challenges that researchers are encountering with each method, and the advantages and disadvantages of each technique.

The acoustic method is the most primitive method. Listening sticks, vibration sensors, and hydrophones belong to the acoustic method. Most of the early leakage detection methods are based on acoustic methods. Then there is the vibration sensor. When there is a leakage, generally, it produces noise, and vibration sensors can pick up the noise. Accelerometers, piezo transducers are examples of vibration sensors. The most modern non-intrusive technique is the ground-penetrating radar (GPR). GPR was developed mainly for understanding geologic materials [13]. With an experienced operator, it is possible to locate leakage using GPR. It is a very accurate leakage detection tool but is very slow. Recently as the thermal camera or infrared camera (IR) attachments for mobiles are getting cheaper, academics are trying to explore this field. Some research has been done to detect leakage using the thermal camera, but there is a lot of room for improvement. Flow sensors work based on the conservation of mass principal. The input volume of water and the used water have to be equal. Due to the loss in the system, the input and measured output are different. Pressure sensor sensors are generally installed on every water supply network to make sure the WDS (Water Distribution System) does not cross a certain pressure; otherwise, pipe will burst. These pressure sensor data are used in different models to predict leakage location. The optical method is the newest technology, but the optical fiber is very expensive. If optical fiber becomes cheaper, we might see water supply pipes embedded with optical fiber in the future. Finally, there is the noise logger. It can accept a variety of sensors. The noise logger listens to the acoustic or vibration noise. If the noise logger detects any anomaly, then it alerts the authority. To avoid the influence of environmental noise, these loggers generally operate at a predetermined time at night. The rest of the section explains all the established technologies in detail, as shown in Figure 1, to give the reader the context of the literature review.

A. LISTENING STICK
The oldest and the simplest way of detecting leakage is to use the listening stick. It is like a stethoscope but for the ground. First, the location of the underground pipe must be marked then the operator tries to get the loudest leakage sound by probing the surface. It is best suited for metallic pipes between 75mm to 250mm and with pressure above 15psi. One major benefit of this method is that irrespective of the pipe material or size, the user can pinpoint the leak from the surface [8]. The drawback of this method is that the accuracy of leakage detection depends on the expertise of the operator. In the case of weak sound, the operator may fail to detect a leak. Background noise can also interfere with leak noise, causing a false alarm. This method can be improved via signal processing, noise filtering, and using advanced computational algorithms [9].

B. VIBRATION SENSOR
When water flows down the pipe, the water molecules alongside with the flow and very few particles collide with the wall of the pipe causing minor vibration. When there is a leakage in the pipeline, the water pressure tends to equalize with the outer pressure. This creates a water jet and turbulent flow, causing perpendicular vibration to the flow. This vibration can be used to detect and locate leakage in water pipeline. Micro electro-mechanical systems or MEMS sensors are miniature 3D structures fabricated from silicon using deposition and etching techniques. The movement of the nanostructures enables them to detect movement. They are used as accelerometers, strain gauges, microphones, air mass flow sensors, pressure sensors, gyroscopes, yaw-rate sensors, compasses, hydrophones [14], [15], [16]. MEMS accelerometers are being extensively used in leakage detection. Ismail et al. have only focused on accelerometer sensor-based technologies, their costs, and their accuracy [12]. Ismail in his research has investigated the impact of considering vibration on all three axes of an accelerometer in water leak detection. A few widely available cheap accelerometer IC with several leak diameter has been compared. Considering the time-domain graph and Fast Fourier Transform (FFT), a relationship between leak size and z-axis vibration has been established [17]. According to the researcher, ADXL345 is suitable for several leak scenarios. Similarly, Yazdekhasti, Sepideh, et al. have used an accelerometer is also used to detect and locate leakage [18].

C. GROUND PENETRATING RADAR (GPR)
Ground Penetrating Radar (GPR) works by transmission and reflection of radio waves. These waves vary between 10 MHz to 2.6 GHz. GPR uses a directional antenna to introduce radio waves into the ground. When the radio wave passes through different material with different dielectric[1] properties, they generate different types of hyperbolae or arc-like reflections. It is one of the non-destructive techniques available for leakage detection work. GPR shows the amplitude change and frequency shift of the radio wave. With this information, an experienced operator can identify the shape and depth of a buried object. As the GPR passes through rock, boulder, buried pipe, electric cables or anything different than that of the surrounding material, it shows up the difference on the screen [19]. There are a few benefits to this method. First, it is a non-invasive method, so nothing needs to be attached or inserted into the pipe. There are a few types of devices, for instance, low- frequency devices have a higher depth penetration but have a low vertical resolution. High-frequency devices have a low ground penetration range but have higher vertical resolution and accuracy [20]. One of the limitations of GPR is that the units are very expensive. It is slow in operation and the operator needs to know the pipe location otherwise it becomes difficult to cover a large area. The accuracy of leak detection depends on the operator's experience. The radio wave interacts with different materials differently. For example, the dielectric signature of dry soil

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[1]Dielectric constant is the ratio of electric field storage capacity of a material to that of a material to that of a free space.
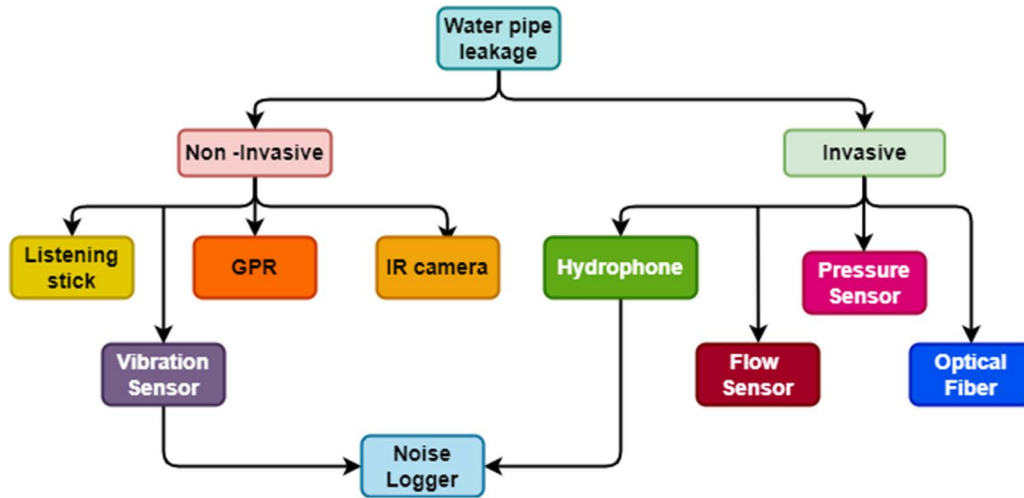
FIGURE 1. An overview of the selected methods and the connections between them.

is different from wet saturated soil. Similarly, the subsurface condition also impacts the reading of the device like the bare ground, pavement, or concrete slab all of them have quite different characteristics [20]. Lai, Chang, and Sham have conducted a blind test to test the effectiveness of a GPR in detecting a void of pavement or ground surface. The test result was not consistent as there were many false-positive cases. It may be because the effectiveness of GPR is heavily dependent on the operator [21]. Researchers are also developing different algorithms and mathematical models to identify the reasons for the false-positive results and eliminate this phenomenon. Demirci has used the near-field back-projection imaging algorithm and concluded that the homogeneity of the medium plays a vital role in the output. According to Demirci, the soil's void can sometimes also raise a false alarm [22]. The limitations of GPR are recognized by researchers, mainly the interpretation of the GPR images to locate leakage. Ocaña et al. have tried to identify and extract feature GPR images and produce a 3D model to visualize them quickly. They have used a variance filter to characterize the anomalies. In a controlled lab experiment, the researchers were able to identify the leak as well as the wet zone surrounding it [23].

D. INFRARED (IR) CAMERA

Infrared (IR) thermography is a promising field, but the application of IR thermography in water leakage detection has not gained high traction. The earliest use of the thermal camera in leak detection can be traced back to 1980. Eidenshink [24], Weil and Graf [25], and Weil [26], who have discussed leak detection trials in the 1980s. Their study could detect buried pipes, erosion, and void surrounding them. Alaa Al Hawari in his paper titled ''Non-Destructive Visual-Statistical Approach to Detect Leaks in Water Mains'', used IR images and statical analysis to identify leaks in the pipe on the ground surface. This method used the normal distribution

curve to predict the leakage location [27]. For buried pipes, Peter and Jayantha conducted a study, where they wanted to understand the reliability of detecting leaks in buried pipes using infrared thermography [28]. They have focused on small diameter buried pipes (i.e., around 100 – 400 mm) with depths ranging from 0.8 to 1.2 m. Carreño has tried to detect buried pipes using thermal images and data mining [29]. A simple experiment to showcase the effect of different resolution thermal cameras in leakage detection has been presented in [30]. Penteado in 2018 has experimented with the digital image processing method with thermal images. Particularly, the authors have used the q-sigmoid function to process the images. Their experiment was lab-based, and in their investigation, they could separate the leakage location from the other areas. The researchers have included both sandy and clay soil for the experiment, and at 10cm pipe depth, this result can be used for garden or backyard leak detection [31].

Fahmy and Moselhi [32] have conducted extensive research in Montreal (Canada) about the factors that affect the applicability and limitation of IR cameras in leak detection. The researchers have developed a model that was able to detect a leak in the fall and spring but failed in summer and winter. The model was not generalized. It was specifically designed for pavement. They have compared their findings with the acoustic method, and the minimum error was 1.01 m to a maximum of 2.30 m [32].

Atef et al. in their researcher have conducted more thorough research on leakage detection using IR images and ground-penetrating radar (GPR) [33]. Their research included simulated leaks as well as verifying actual leak data. They have verified their result with ground-penetrating radar (GPR). They have used a seeded region-growing algorithm on each IR image to differentiate the leakage and non-leakage area. The centroid of the leakage area is then calculated using Green's theorem to pinpoint the leakage. They have claimed

their method can achieve accuracy up to 97% by verifying their claim with GPR reading.

From the research discussed above, it can be seen that the researchers have used the manual method to differentiate the leakage. Some researchers have used simple algorithms, but they are not fully automated. The number of scenarios the researchers have considered is also very limited. All the researchers have used a one-dimensional approach, which means using only IR images. Most of the researchers have taken a single shot of the location apart from Bach and Kodikara [28], they have taken multiple shots of the same area and considered the temperature gradient. There is a potential to use RGB images and AI to differentiate the scenario and conditions.

E. HYDROPHONE
Hydrophones are listening devices that are designed to be used underwater. These devices are placed into the water at convenient fitting such as a fire hydrant or another outlet along the pipeline. This device is particularly useful for the environment where there is high background noise. In the plastic pipe, the sound energy absorbs into the elastic pipe material, but the water-borne waves travel a large distance. In this scenario, the hydrophone is a good choice [8]. One of the benefits of using a hydrophone is that it can be connected to a fire hydrant. As there are fire hydrants at regular intervals in a city, it is easy to connect and disconnect a hydrophone for regular leak detection check-ups [34]. Khulief et al. have investigated the feasibility, potential, and limitation of in pipe hydrophone [35]. They have observed that the frequency band of the leak acoustic signature depends on the leak size. They have also observed that on the downstream side of the port, the acoustic energy of the leak signal drops to a lower value. They have also observed that the leak signal becomes noticeable for line pressure above one bar.

Sadeghioon et al. have explored the possibility of deploying smart wireless devices to detect leakage. As smart wireless devices are meant to be connected to the pipe for a long time, and water can corrode the hydrophone sensor. To counter this problem, they have used the relative pressure sensing method based on a force-sensitive resistor (FSR) [36]. One of the major hurdles of the sensor network is the cost of the sensor, particularly in this case, the cost of the hydrophone. Due to the emergence of microelectromechanical sensors (MEMS), researchers are investigating the possibility of using cheap sensors in the systems. Xu, J., et al. have investigated the potential for low-cost MEMEs hydrophones. They have used a custom fabricated Mo-AlN-Mo[2] piezoelectric stack. The results look promising on equivalent noise density vs frequency curve. The device has an acoustic sensitivity of -180 dB and a bandwidth of 10Hz to 8Khz [14].

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[2]It is a sandwich of Molybdenum on top and bottom and Aluminium Nitride in the middle.

F. NOISE LOGGER
Noise loggers or acoustic loggers are programable data loggers. Different types of sensors can be attached to it. Generally, they are deployed in large numbers at underground valves, generally 200 to 500 meters apart. To have the minimum background noise, they are programmed to operate between 2 a.m. to 4 a.m. Every night, they start at their specified time and listen to the sound. If there is any sound, it transmits an alert to a receiver [34]. Noise loggers can store data in the memory for further development of the algorithms. Noise loggers have their drawbacks too. Zahab et al. have pointed out that the city of Montreal was recording false alarms from the installed noise loggers [37]. To improve the detection accuracy, the researchers have incorporated Decision Tree, Naïve Bayes, Deep Learning, and genetic algorithm to develop an augmented approach. The researchers were able to reach a hundred percent accuracy in distinguishing leaked noise from non-leaked noise [37].

G. FLOW SENSOR
Flow sensor is the simplest way to detect leakage in a WDS. It is based on the conservation of mass theory. The summation of input volume of water will be equal to the output volume of water. Rahmat et al. has used the simplest algorithm to implement a leakage detection system based on flow sensor [38]. As there are measuring tolerances in a flow meter, implementing the system in real life is difficult. In [39], researchers have used city of Harare's water utility data to train a ANN model to predict water consumption. The deviation from predicted consumption and actual consumption have been used to predict leakage in a section. Similarly, in [40] researchers have used fizzy logic to detect leakage in the a WDS. Leakage location using flow sensor is a bit challenging and Narayanan et al. have used network structure and static properties to detect leakage in WSN [41].

H. PRESSURE SENSOR
Pressure sensors detect water pressure in a network and usually installed at an interval to monitor the optimum pressure of the network. If the pressure is high then there is a chance that pipe network could burst and low pressure could cause problem to the household users. Usually these are used injunction with the pump to maintain a steady flow to the end user. To detect leakage events in water distribution networks, [41] provides an optimization methodology based on a hybrid information-entropy approach (WDN). Optimization-based approaches are commonly used in the literature; nevertheless, they are limited by time-consuming processes. As a result, to reduce the computing cost, researchers exclude sections of the choice space. To explore the whole choice space, this paper represents an information theory-based strategy that uses Value of Information (VOI) and Trans information Entropy (TE) approaches in combination with an optimization model. In [42], researchers have used genetic algorithm and simulated data to develop a model NSGA-II that requires

minimum number of sensor nodes and minimum time to detect a leakage. An issue with pressure sensor is that it cannot detect minor leakages as small leakage does not cause considerable pressure change in the system.

I. OPTICAL FIBER

A fiber-optic sensor can be used in several ways to detect a leak in a pipeline. When a leak occurs, the temperature, the pressure of the fluid changes, and the hoop strain of the pipe wall also change. Liang and his team have used distributed optical fiber technology to monitor pipeline corrosion and leak monitoring [43], [44]. In their research, they have used optical frequency domain reflectometry to measure hoop strain. When a leak occurs, the hoop strain slumps rapidly. Yang and his team have focused on multiple leak detection along the pipeline using optical fiber [45]. Similarly, when a leak occurs, there is a temperature change along the pipeline. By scanning the temperature profile of the entire length of the pipeline, the researchers pinpoint the anomaly location. With this technology, a 55km long pipeline can be monitored in under ten minutes [46]. These distributed temperature sensors are also used in dikes for leaks detection as well [47]. Benefits of using fiber-optic sensors include immune to electromagnetic interference. As these fibers do not conduct electricity, so they can be deployed in volatile gas pipelines. Can survive a harsh environment [48]. One major weakness of this technology is that currently, it cannot be used in branched networks, and the price of fiber optic is very high

J. COMPARISON OF TRADITIONAL TECHNOLOGIES

So far, we have talked about nine common technologies used the leakage detection. After considering all of the factors of the traditional methods, we can see that each method has pros and cons. We have made a comparative analysis of the described methods, and a relative comparison of leak detection methods is presented in Table 1.

In this section, we have discussed how researchers use sensors to detect leakage. We can observe that leakage detection research is evolving. IR, acoustic and vibration-based methods are getting more traction, and a move toward non-invasive-based techniques is observed. Initially, the leakage detection methods were completely based on experience. Then we have seen algorithm and threshold-based methods, and currently, a push toward ML-based algorithms can be observed. In ML-based techniques, researchers can use different kinds of water supply data and fuse them together to get higher accuracy leakage detection methods. In particular, researchers consider different feature extraction and diurnal patterns in the leakage detection algorithm. Researchers are exploring different communication technologies to make leakage respond quicker to minimize water loss. After discussing all the previous work, we believe there is still room for improvement. Further research is required to understand the research gaps and develop an efficient leakage detection method. In the next section, we have used a systematic review of the papers to explore leakage detection in detail.

III. RESEARCH METHODOLOGY

In this chapter, water leakage and leakage location-related studies have been identified. A systematic review was conducted to have a clear understanding of the research trend and interest in water leakage detection and where the academic community is moving. It also reveals the research opportunity in this sector. We have limited our systematic review to water leakage detection research and its technologies, and for this, we have developed four research questions. According to the research questions, we have searched the literature.

A. RESEARCH QUESTION

The purpose of this investigation is to provide answers to the following questions:

1. RQ1: How the leakage detection techniques are evolving over time?
2. RQ2: What kinds of sensors are being used?
3. RQ3: What kind of algorithms are used in the data processing?
4. RQ4: Which communication technologies are currently being used?

B. DATA SOURCES

In order to locate relevant literature, the following academic repositories were consulted:

1. Google Scholar
2. Elsevier
3. IEEE Xplore
4. Science Direct
5. CDU library
6. MDPI
7. ACM

Two reviewers worked on the project, and a search of all databases yielded 3892 results. They returned many non-related results due to a lack of advanced search capabilities in academic repositories. As a result, just the first 200 most relevant results from these databases were included.

C. EARCH QUERIES

We have used the following strings to search the articles. All the repositories returned a lot of unrelated articles. We went through the title, abstract and conclusion before downloading the articles. When searching the academic databases, we have used some search quarries and the list of the queries are given below:

D. INCLUSION AND EXCLUSION CRITERIA

After the electronics search results, the carefully specified inclusion and exclusion criteria were used to refine the results. The list of inclusion and exclusion criteria are listed in Table 3. All the studies that meet the inclusion criteria and exclusion criteria were downloaded.

We have recently explored the online repositories. The "leakage detection" covers a board range of literature like,

TABLE 1. A comparison of leak detection methods.

Method	Advantages	Disadvantages
Listening stick	• Low-cost device. • Simple and cheap to operate.	• Accuracy depends on the experience of the operator. • Background noise affects performance.
Vibration sensor	• Low-cost sensors. • Can be attached to existing pipes without any pipe rework. • Good accuracy.	• Does not work well with plastic pipes. • External environmental vibration can interfere with the sensor. • Detection range is short.
GPR	• Accuracy depends on the operators' experience. • Non-invasive method.	• The device is expensive. • Accuracy depends on the experience of the operator. • Susceptible to electromagnetic interference. • The exact pipe location must be known.
Thermal imaging	• Moderately accurate. • Non-invasive. • Cheap to operate. • Can cover a large area in a short time.	• Cannot be used at all times of the day. • Performance depends on the ambient temperature. • Not fully automatic, need an operator to handle the data.
Hydrophone	• Easy to attach the sensor with a fire hydrant. • Good accuracy.	• Will not work in an environment where there is no convenient fitting. • Background noise affects performance. • Requires two listening points.
Noise logger	• Can work with multiple types of sensors. • Automatic leak detection. • Can store data in the memory for further analysis.	• Require regular maintenance. • Can raise a false alarm. • Needed to be deployed in large numbers.
Flow Sensor	• Can sense leakage in branched pipelines. • Requires simple algorithm to detect leakage.	• Sensor requires installation in the pipeline. • Installation is expensive.
Pressure sensor	• With transient method it can cover a large area. • Can detect leakage in branched network.	• Sensor requires installation in the pipeline. • Installation is expensive. • Cannot detect small leakage.
Optical Fiber	• Highly accurate. • Can monitor pressure and temperature at once. • Can detect multiple leaks at once. • Can monitor kilometre long pipeline in hours. • Immune to electromagnetic interferences. • Does not require electricity along the pipeline. • Can survive a harsh environment.	• Very expensive to install. • Cannot work on junctions.

industrial leakage detection of fluids, data leakage detection in information technology, and even blood leakage detection in the human body. So, the query was intentionally made to get results related to water leakage technology,
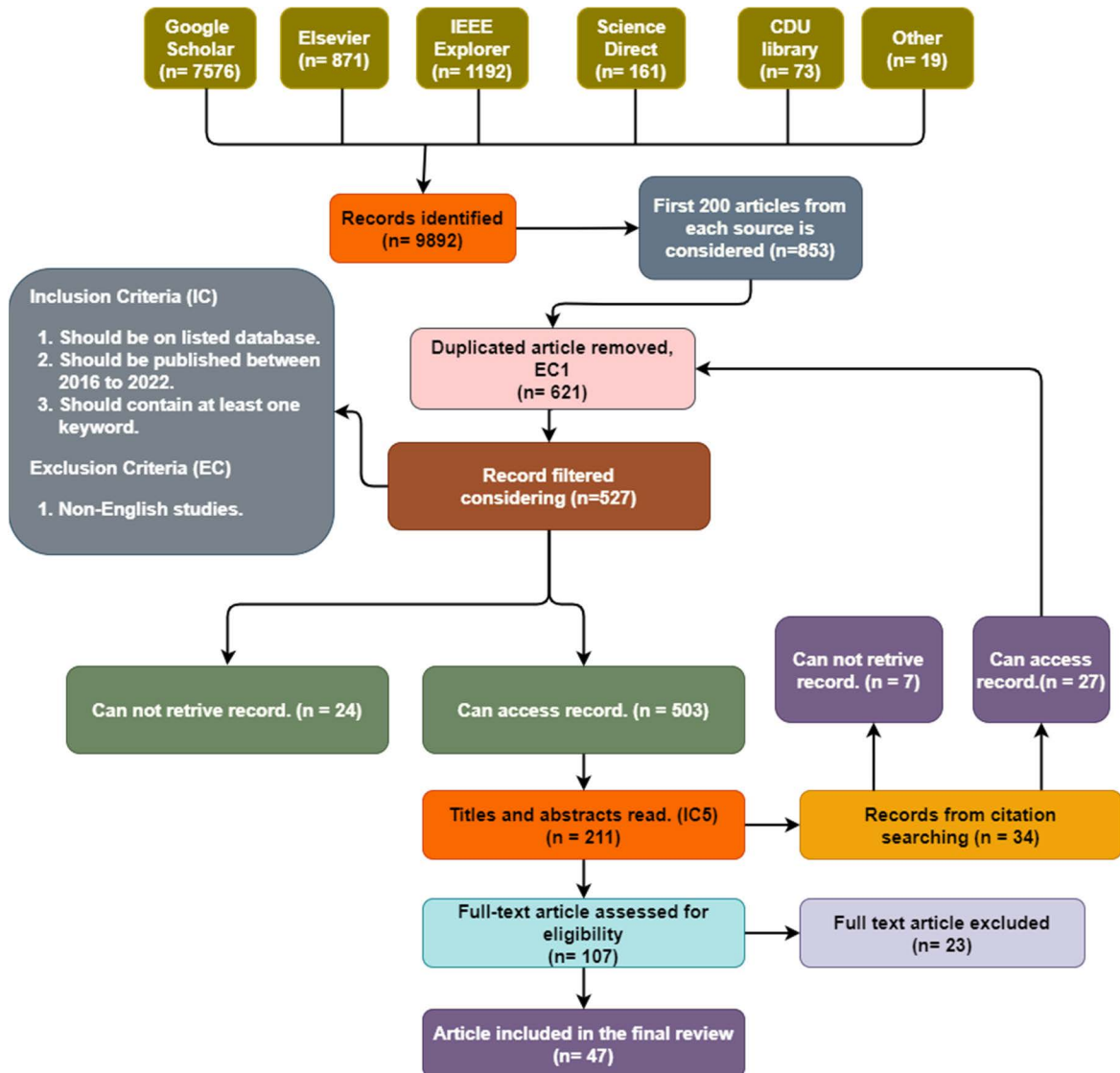
FIGURE 2. Chart for systematic review.

TABLE 2. Search queries used for systematic literature review.

Search queries	
SQ1	"Water leakage" AND detection AND OR location
SQ2	"Water leakage" AND detection AND sensors
SQ3	"Water leakage" AND management
SQ4	"Water leakage" AND communication AND OR systems

algorithms, and the use of IoT in water leakage detection. Table 2 summarizes the selection process of literature. A total of 9892 papers, including journal and conference papers, are selected. Due to the lack of an advance search option, many non-related articles also showed up. As a result, we only included the first 200 most relevant results from these datasets.

A total of 853 articles were included in the dataset. All the duplicated articles are removed from the list. Due to access issues, we cannot access 29 papers, and these items are removed. Then the titles and the abstracts are read, and the ones that are irrelevant to this research are removed. An emphasis was given to journal articles than conference articles. If the literature aligns with this research, it was added to the literature database; otherwise, the paper was discarded. This bought down the number of articles to 211. The articles with no new ideas, no implementations, or have very basic and generic information been removed. Finally, the full text was analyzed, and it reduced the articles to 47. The remaining articles were thoroughly studied and used to answer our research questions.

E. SELECTION OF DATA
The data were assembled to answer the research questions. The steps are shown below:

TABLE 3. List of inclusion and exclusion of cite.

Inclusion Criteria (IC)	
IC 1	Should be on listed database.
IC 2	Should be published between 2016 to 2022.
IC 3	Should contain at least one keyword.
IC 4	Should be published in a journal or in a conference.
IC 5	The study should match title, abstract and conclusion.
Exclusion Criteria (EC)	
EC 1	Duplicated items.
EC 2	Non-English studies.
EC3	Article cannot be accessed.

Step 1: In the first step, the selected literature was classified according to its content. Selected papers are listed in Table 5. along with publication year, type of publication, Google Scholar citation number, source, if the research paper is based on simulated data or experimental data, and the journal name.

Step 2: In the second step, the research papers were summarized. The sensor it uses, the type of data it collects, the methodology it follows, the outcomes it produces, and the wireless technology it uses.

Step 3: Finally, the IoT components like the sensors and the communication technology and protocol are compared in detail.

F. QUALITY ASSESSMENT FOR SYSTEMATIC REVIEW

The quality of the papers is appraised using two ways to guarantee that they are trustworthy and appropriate for this systematic review. The first method is evaluation questions (QE). This questions are adopted from previous SLRs [49, 50] and systematic reviews [51]. Each of the question is answered by no (0), partially (1) and yes (2). Each reviewer can provide a score of 0 to 2 to each of the five questions.

The papers are assessed with quality evaluation questions to find suitability for systematic review. Two reviewers scored the papers with five questions. Each question's score is a two-mark cumulative score, with a maximum score of four. Highest grade a publication can get is 20. Both reviewers agreed that a cumulative score of 0 to 10 would be regarded as a failure, requiring the article to be removed from consideration. A pass is a score of 11 to 20, indicating that the work is extremely suitable for inclusion in the review. Table 4 summarizes the quality rating of the publications included in the systematic review.

A total 47 papers have passed the threshold mark. Table 4 shows a snap shot of the papers that passes the quality assessment tests. From figure 3, we can see that there is almost an equal distribution of assessment score. Further details of the selected papers are discussed in the section IV.
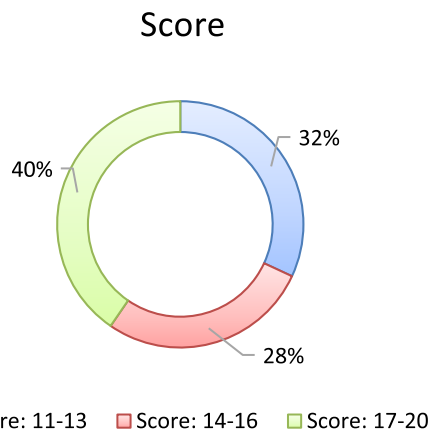

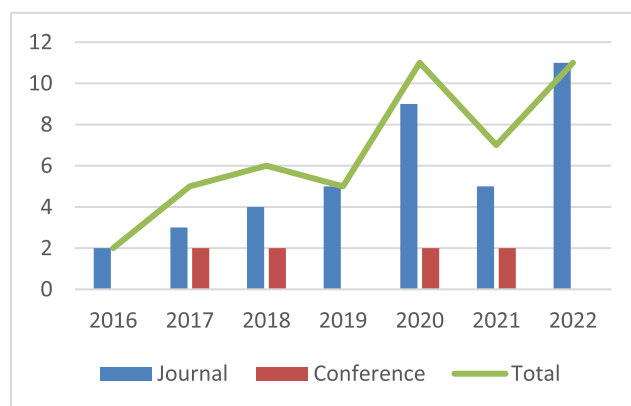**FIGURE 3.** Distribution of quality assessment score.

FIGURE 4. Number of articles vs year.

IV. LITERATURE ANALYSIS

A. OVERVIEW

Table 5 contains the basic information about the publications. This information includes reference ID, author's name, year of publication, type of article, number of citations, publisher name and journal name. All of the articles are published in peer reviewed journals or conference.

Figure 4 shows the number of articles published per year. It is clear that the overall interest in the research community is increasing year over year. Research dipped in 2021, probably because of the worldwide pandemic. In this review, we have primarily tried only to include journal and peer-reviewed articles followed by conference publications. Figure 4 shows detail of the bibliographic overview. Out of 47 publications, 8 were conference preceding and the rest of them were journals. A more detail discussion of the selected articles is presented in the next section.

B. ANALYSIS OF GATHERED DATA

Table 6 shows the information of the analyzed publications. This table contains the sensors used, type of data used, experiment type, if the experiment detects and locates a leak on not, the methodology used, and the IoT technology used.

TABLE 4. Summary of quality assessment.

No	Ref	Is the publication related to IoT and/or water leakage?	Is the solution well defined?	Are the challenges addressed?	Limitation of the solution defined?	Is the solution implemented?	Total
1.	[52]	4	4	4	4	4	20
2.	[53]	4	4	3	2	4	15
3.	[11]	4	4	2	2	4	16
4.	[54]	4	4	4	2	4	18
5.	[55]	4	4	4	2	2	16
6.	[56]	4	4	3	3	2	16
7.	[57]	4	2	3	2	0	11
8.	[58]	4	4	4	2	4	18
9.	[59]	4	4	4	2	4	18
10.	[60]	4	3	3	2	4	16
11.	[61]	4	4	2	1	3	14
12.	[62]	4	2	2	0	3	11
13.	[63]	4	3	2	0	4	13
14.	[64]	4	2	2	2	3	13
15.	[65]	4	4	4	2	4	18
16.	[66]	4	4	4	4	4	20
17.	[67]	4	4	3	3	4	18
18.	[68]	4	3	2	1	3	13
19.	[69]	4	2	2	1	3	12
20.	[70]	4	4	4	4	4	20
21.	[71]	4	2	2	2	2	12
22.	[15]	4	4	3	2	4	17
23.	[72]	4	4	4	4	4	20
24.	[73]	4	4	2	2	4	16
25.	[74]	4	2	0	2	3	11
26.	[75]	4	4	4	4	4	20
27.	[76]	4	3	3	3	4	17
28.	[77]	4	4	4	4	4	20
29.	[78]	4	4	2	2	3	15
30.	[79]	4	4	4	2	4	18
31.	[80]	4	2	1	1	4	12
32.	[81]	4	2	0	1	4	11
33.	[82]	4	4	2	2	4	16
34.	[83]	4	4	3	4	4	19
35.	[28]	4	2	2	4	0	12
36.	[84]	4	2	2	2	2	12
37.	[85]	4	3	2	2	4	15
38.	[86]	4	4	4	4	4	20
39.	[87]	4	3	2	2	0	11
40.	[88]	4	4	3	2	2	15
41.	[89]	4	4	3	3	3	17
42.	[90]	4	4	2	1	4	15
43.	[91]	4	3	2	0	4	13
44.	[92]	4	4	4	4	4	20
45.	[93]	4	4	2	1	2	13
46.	[94]	4	4	2	1	4	15
47.	[95]	4	4	4	4	2	18

TABLE 5. Selected articles.

No	Ref	Authors	Year	Type	Cit.	Publisher	Journal Name
1	[52]	Bao, N., et al.	2022	Journal	9	MDPI	Sensors
2	[89]	Nascime, Willian, and Luiz	2022	Journal	2	Taylor and Francis	Urban Water Journal
3	[53]	Wang, Zhoufeng, et al	2022	Journal	3	SD	Information Processing & Management
4	[11]	Ali, A.S., et al.	2022	Journal	-	SD	Control Engineering Practice
5	[54]	Xu, Weinan, et al.	2022	Journal	-	SD	Measurement
6	[55]	Zhang, Y., et al.	2022	Journal	-	SD	Mechanical Systems and Signal Processing
7	[56]	Kim S.	2022	Journal	-	SD	Mechanical Systems and Signal Processing
8	[57]	Zhou, Renlian, Huaizhi Su, and Zhiping Wen.	2022	Journal	-	SD	NDT & E International
9	[58]	Guo, C., K. Shi, and X. Chu	2022	Journal	7	MDPI	Sensors
10	[59]	Yang, Xuehua, et al.	2022	Journal	3	SD	Optical Fiber Technology
11	[93]	Zhang, Chi, et al.	2022	Journal	-	SAGE	Structural Health Monitoring
12	[60]	Hu, X., et al.	2021	Journal	33	SD	Journal of Cleaner Production
13	[61]	Vrachimis, Stelios G., et al.	2021	Journal	5	SD	
14	[92]	Li, Weijie, Tiejun Liu, and Huangbin Xiang.	2021	Journal	9	SAGE	Journal of Intelligent Material Systems and Structures
15	[62]	Wang, Yuanhao.	2021	Conference	2	IOP	Journal of Physics: Conference Series
16	[63]	Che, N. N., et al.	2021	Conference	1	IOP	Journal of Physics: Conference Series
17	[64]	Feng, Yu-Xi, et al.	2021	Journal	-	SD	Sustainable Cities and Society
18	[94]	Fan, X., & Yu, X.	2021	Journal	-	SAGE	Structural Health Monitoring
19	[65]	Xie,Y., et al.	2020	Journal	6	MDPI	Sensors
20	[66]	Shukla, Harshit, and Kalyan Piratla.	2020	Journal	28	SD	Automation in Construction
21	[91]	Fuentes, Henry, and David Mauricio.	2020	Journal	21	Springer	Environmental Monitoring and Assessment
22	[67]	Juan Li et al	2020	Journal	14	SD	Measurement
23	[68]	Gautam, Jyoti, et al.	2020	Journal	14	IWA	Water supply
24	[90]	Pérez-Padillo, José, et al.	2020	Journal	13	MDPI	Sensors
25	[69]	Lin, Huiwen, et al.	2020	Conference	6	IEEE	IEEEXplore
26	[70]	Alves Coelho, J., A. Glória, and P. Sebastião	2020	Journal	3	MDPI	IoT
27	[71]	Gericke, G. A., and R. B. Kuriakose	2020	Conference	3	IOP	Journal of Physics: Conference Series.

TABLE 5. *(Continued.)* **Selected articles.**

28	[15]	Phua, W.K., et al.	2020	Journal	3	MDPI	Water
29	[88]	Li, Xin, et al.	2020	Journal	3	IWA	Water Supply
30	[72]	Zhou, M., et al.	2019	Journal	39	IEEE	IEEEAccess
31	[73]	Liu, Y., et al.	2019	Journal	33	MDPI	Sensors
32	[74]	Okosun, F., et al	2019	Journal	27	Springer	Eur. Phys. J. Spec
33	[75]	Sohaib el at	2019	Journal	22	MDPI	Applied Sciences
34	[95]	Pal, A., & Kant, K.	2019	Journal	7	ACM	Transactions on Sensor Networks
35	[76]	Li, S., Y. Song, and G. Zhou	2018	Journal	75	SD	Measurement
36	[77]	El-Zahab, S., E.M. Abdelkader, and T. Zayed	2018	Journal	78	SD	Mechanical Systems and Signal Processing
37	[78]	Zhang el at.	2018	Journal	40	SD	Nano Energy
38	[79]	Marmarokopos, Konstantinos, et al.	2018	Journal	19	Sage	Measurement and Control
39	[80]	Srihari, M. M.	2018	Conference	17	IEEE	IEEE Xplore
40	[81]	Wang, Jian-xiong, et al.	2018	Conference	11	ACM	ICCET
41	[82]	Kang, J., et al.	2017	Journal	151	IEEE	IEEE Transactions on Industrial Electronics
42	[83]	Choi, J., et al.	2017	Journal	53	MDPI	Sensors
43	[28]	Bach, P.M. and J.K. Kodikara,	2017	Journal	32	IEEE	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing
44	[84]	Sophocleous, Sophocles, et al.	2017	Conference	20	SD	Procedia Engineering
45	[85]	Predescu, et al.	2017	Conference	16	IEEE	ICSTCC
46	[86]	Kim, Y., et al.	2016	Journal	41	ELSEVIER	Computers & Chemical Engineering
47	[87]	Lai, W.W., et al.	2016	Journal	63	SD	Tunnelling and underground space technology

The researchers have used a variety of sensors for capturing data. The most common ones are flow, pressure, acoustic, and accelerometer and comprise 60% of the research. Some researchers have used unconventional sensors like optical fiber, vision systems, TENG, and very few have used simulated sensor data. Out of 47 articles, 30 of them were only experimental, 7 of them were only simulated, 2 of them were historical data, and 8 of them were both simulated and verified by experiment. We can see a greater emphasis on experimental implementation in leakage detection tasks.

Based on the sensor attached to the pipe, leakage detection can be divided into two types, namely invasive and non-invasive. Examples of invasive processes are in line pressure and flow meter and hydrophone. The invasive sensor installation process is expensive, requires rework of the pipe network, and is costly. We can see from Table 6 that there is a shift toward non-invasive techniques, and 67% of the research focuses on non-invasive sensor data. Vibration-induced data like accelerometer data, contact audio, and image-based leakage detection techniques are getting more attention. The most

common way of processing audio and vibration data is to transform it into Short-time Fourier transform (STFT) or decompose it to Intrinsic Mode Function (IMF) to get the feature space and then use thresholding or some form of ML classifier to classify leak and non-leak sound. Details of the methodology are discussed in section 5. A steady increase in leak location research along with leak detection can be observed. 90% of the research focuses on leak detection, and 55% of the total research study location. Compared to leak detection, leak location is difficult as it requires signal measurement and comparison in the microsecond range. This precision measurement was not possible on low-end hardwires. As the DSP-based MCU is getting cheaper, a surge in leakage location research is observed.

Internet of things or IoT is the umbrella term that focuses on data collection devices. Information is the key element in the computer and internet, and the focus of IoT is to automate that process [88]. Table 6 shows a broad range of IoT devices used in this field of research. IoT devices are designed to serve a broad market. Many low-power communication methods

TABLE 6. Article comparison.

No	Ref	Sensor	Data	Exp[3]. type	Location/ Detection[4]	Methodology	Communication
1	[52]	IR and visible light cameras	Images	E	LD	Machine vision. Otsu thresholding, black and white top hat transform	Wifi
2	[53]	Piezoelectric acceleration sensor	Acoustic vibration signal	E	D	Use VDM to decompose acoustic signal to obtain IMF. Kurtosis, sample entropy, and centre frequency value are extracted from the first four IMF components. Feature vectors are constructed from these values and classified using SVM.	-
3	[11]	pH level, turbidity and flow	Time series flow data	E	D	Based on the conservation of mass and pre-set threshold values. A prototype and system development process are shown here.	Wifi
4	[54]	Accelerometer	Vibration data	E	D	The vibration signal is used to make 22 feature spaces. Bourta algorithm is used to remove nine features. Then RandomForest (RF), GBDT, Xgboost, and LightGBM, are for comparative analysis.	-
5	[55]	Transducers	Impulse	SE	D	Leak-induced reflection is derived considering the damping effect. Experiments were done to see the influence on the leak factor.	-
6	[56]	Pressure transducer	Pressure wave	SE	D	TIF is based on hydraulic impedance to detect a transient event.	-
7	[57]	Infrared thermography	Images	E	LD	Spatial distribution and temporal characteristics of thermal images of a leaked location are analyzed.	-
8	[58]	Hydrophone	Acoustic signal	SE	D	The acoustic signal was decomposed. EEDM, and IMF that reacts to leakage were selected. The signal is then reconstructed and converted to an image by Hilbert transform and classified with a CNN.	-
9	[59]	Optical fiber	Light intensity	E	LD	Addressable LEDs are scanned through the length of the pipes. If there is a leakage, the coupling structure changes due to reflective index. Leakage is identified through the intensity change on the sensor at the end.	Optical fiber
10	[60]	DMA	Flow and pressure	S	LD	WSN is divided into a number of zones by DBSCAN. Multiscale decomposed of the data is done based on Fourier transform. Finally, MFCN is used to train on the data.	-
11	[61]	Pressure and Flow	Flow and pressure	H	LD	Historic data is used to formulate non-linear hydraulic model. Considering the initial bounding state, bounding linearization is performed and the linear constrains are formulized. If model is invalid then leak is detected and located.	-
12	[62]	Water meters	Water consumption	E	D	Water consumption data over time was feed into an MLP. If it crossed a certain threshold, it will flag it as leakage.	-
13	[63]	Turbidity sensor, flow sensor and water sensor	Periodic sampling of sensors	E	LD	Household water quality setup with moisture sensor to detect water leakage. Can notify the user via SMS or telegram message.	GSM
14	[64]	Leakage point density, pipe age and material, road load and average pressure	-	S	LD	Object density matrix of leakage density, leakage point, road loads, pipe age, pressure and network density are used to create a number of V-DMA. V-DMAs are used subjectively and objectively to produce V-AHP. Heat map clustering is generated by V-AHP.	-
15	[65]	Hydrophone	Acoustic signal	E	D	EEMD decomposition, HHT, CNN 95.5%	-
16	[66]	Acceleration	Scalogram	E	D	Raw acceleration data was used to create scalogram images. The data was then classified with ANN, CNN and pre trained AlexNet.	-
17	[67]	Acceleration	Time domain acceleration signal	SE	L	Adaptive denoising using VMD is used. The leakage component is identified by calculating signal clarity of mode decomposition by VMD. Signal related to leakage was extracted and reconstructed by maximum difference.	-
18	[68]	Ultrasonics sensor	Consumption over time	E	D	Daily water consumption is recorded on overhead tank. SVM is used to predict the consumption. If there is any difference then it is classified as leakage.	Wifi
19	[69]	Ultrasonic flow meter	Flow data	E	L	Flow data is captured with ultrasonic flow meter and sent to server via Nb-IoT modem. One-Class-SVM automatically determines threshold point and can report when it detects one.	Nb-IoT
20	[70]	Flow sensor	Volumetric flow data	E	D	The researchers have simulated the water leak location and used field data along with the mentioned prefilters. Using STFT and wavelet transform with Roth, Smooth coherent transform (SCOT), Phase transform (PHAT), Eckart, Wiener, Maximum likelihood (ML). SVM, RF, DT, NN	LoRa, Nb-IoT.
21	[71]	Pressure sensor	Pressure drops	E	LD	A conceptual IoT node-based water leakage detection method is proposed here.	Sigfox
22	[15]	MEMS hydrophone	Audio	E	L	A MEMS hydrophone was developed, and the sensor data was converted to spectrogram, spectral centroids, and FFT to get the lag time to locate the leakage.	Wifi
23	[72]	Simulated Pressure Sensor	Negative pressure wave	S	LD	Spline local mean decomposition is done to eliminate noise. The signal is converted to a 2D image and classified with Alexnet and LSSVM.	-
24	[73]	Acceleration	Vibration	SE	LD	The signal in analysed with EMD, ApEn, PCA and classified with SVM.	4G + Zigbee
25	[74]	PVDF Piezoelectric	Vibration	E	D	Possibility of being used as a of self-powered sensor to detect leakage.	-
26	[75]	Audio	Acoustic signal	E	LD	Audio data was a time-domain signal. A total of 13 statical features were used along with the SVM classifier.	-
27	[76]	Acoustic transducer	Acoustic signal	E	D	Leakage socket joint identification is the purpose of this exp. Peak, Mean, Peak Frequency, and Kurtosis features of the acoustic signal is determined and classified through an ANN-based model.	-
28	[78]	Trioelectric nanogenerator	Analog current	E	D	The current response due to small liquid leakage was studied and classified with SVM.	-
29	[77]	Accelerometer	Vibration	E	D	MI and MIE were determined from the signal and classified with SVM, DT, and NB.	-
30	[79]	Accelerometer	Vibration	E	D	FFT, PSD, CPSD, and WT are used with threshold values to detect leakage.	-

TABLE 6. *(Continued.)* Article comparison.

31	[80]	Water flow and pH sensor	Fluid volume over time	SE	D	Data from the water flow sensor and pH sensor is stored on a cloud server and can be managed through a mobile application.	IoT module
32	[81]	Ultrasonic flow meter	Fluid volume over time	E	D	Researchers have a proposed intelligent water meter with a data centralizer and intelligent valve. It can detect leakage and turn off the water supply if necessary.	3G/ 4G
33	[82]	Accelerometer	Vibration	E	LD	The authors used 1D CNN to extract features and SVM for classification for leakage detection. The graph-based optimal localization algorithm is used for localizing leakage location.	-
34	[83]	Accelerometer	Vibration	SE	LD	Time-domain analysis of the signal is performed to transform STFT and wavelet transform. SVM is used for detection, and the maximum likelihood model is used for localizing.	900 Mhz + Internet
35	[28]	Infrared Thermography	IR image	E	LD	Used thermal images of predetermined leakage location to characterize thermal signature in an IR image	-
36	[84]	Pressure	Time series pressure	H	L	A genetic algorithm is used along with two-stage calibration to detect leakage hotspots.	-
37	[85]	Flow and water sensor	Flow rate	E	LD	A prototype named AGRI2L is designed. It can detect anomalies in water supply and alert the user via e-mail.	Wifi
38	[86]	Pressure	Time series pressure	E	LD	The cumulative integral of changed pressure data, floor function, and curvature to detect small leakage. Interval estimation is used for localization.	-
39	[87]	GPR	GPR image	E	LD	1.6GHz and 2GHz radio waves reflections. B-scan and C-scan images were used. Signatures of wet and dry soils were studied to identify the fingerprint of underground leakage.	-
40	[88]	Simulated pressure sensor	Time series	S	LD	The "dominate sensor sequence" is determined using spatial correlations between sensor and leakage. Leak localization is accomplished using sensors that are closely connected to leaking. A leaking situation is simulated, and the leakage location is determined by comparing real measurements and simulated data.	-
41	[89]	DMA district metering area	Water consumption over time	S	D	AutoML is used to automate data curation, ML model training and deployment of to detect outlier. It is a semi-supervised approach. It aims to reduce implementation and deployment cost.	-
42	[90]	Pressure transducer, float switch and limit switch.	Time series pressure	E	D	The researchers have developed a prototype that loges pressure data in online database. Based on the data they can differentiate regular operation, leak occurrence and pump operation. The detection operation is not automated and requires human interpretation.	SigFox
43	[91]	Flow sensor	Flow data over time.	E	D	The researchers have developed an architecture consisting of a flow sensor node prototype along with edge gateway. The leakage is detected based on historical consumption pattern of the household, and user location. The algorithm is hosted on the cloud.	Wifi
44	[92]	Optical fiber temperature sensor	Temperature over time	SE	LD	A leakage detection method was proposed based on fiber Bragg grating based quasi distributed fiber optic temperature sensor. Heating element was put in place along the fiber optic temperature sensor. Temperature response was measured to detect and locate water leakage in the system.	-
45	[93]	Accelerometer	Acoustic	E	L	Accelerometer data was transformed to spectogram. The spectogram was then classified with a CNN and if there is any anomaly then the data is then fed to Siamese CNN to check for scheduled events. If it is an anomaly then a field investigation is initiated.	-
46	[94]	Pressure	Time series pressure	S	LD	A framework is proposed that includes WDN leak zone partition, leak detection, and leak zone location. The architecture uses autoencoder algorithm and k-mean model.	-
47	[95]	Simulated flow and pressure	Time series flow and pressure data	S	D	A sensor network system is proposed that uses water flow to power itself. A simulated WDS and real flow and pressure data are compared. If there are a wide variation of reading for a long time then water leakage is suspected.	Wifi/ Zigbee

[3] E = **E**xperimental, S = **S**imulation, **H** = **H**istorical, SE = **S**imulation and **E**xperimental
[4] D = **D**etection L= **L**ocation LD = **L**ocation and **D**etection

have been suggested to fulfill IoT devices' requirements. Depending on the transmission and receiving range, there are several IoT devices in the market. For example, Bluetooth devices are used for short-range communication, Wi-Fi and Zigbee devices are for medium-range communication, and Nb-IoT, GSM, and LoRa devices are suitable for long-range communication. We can see that researchers are combining two different technologies in their research. They are using low-power sensor nodes with a central node that does all long-distance communication. Some articles use optical fiber for sensing and communication, but research in this area is very small.

1) SENSOR TYPE

Figure 5 shows the types of sensors used and their frequency in the research. A total of 12 types of sensors are used in this research. Some researchers have used multiple sensors to increase reliability and accuracy [11], [61], [63], [85], [90], [95]. It should be noted that, in our study, we are focusing on leakage detection, location, related sensors, algorithms, and communication technologies. That's why we have excluded water quality-related sensors like turbidity and pH sensors, as they are irrelevant to our research [11], [63], [80], [90]. Five types of sensors dominate the research field: flow, pressure, accelerometer, acoustic, and camera sensor. Vibration sensors and their derivatives like acoustic and accelerometers account for 36% of the sensors in the research. The reason for the high intake of the vibration-based sensor in the research is that they are non-invasive and does not require rework of the pipe network. These sensors can be attached to the outside of the pipe. The generated data is generally time series vibration data and are easy to process with generic signal processing algorithms. Apart from regular sensors, researchers are also leaning
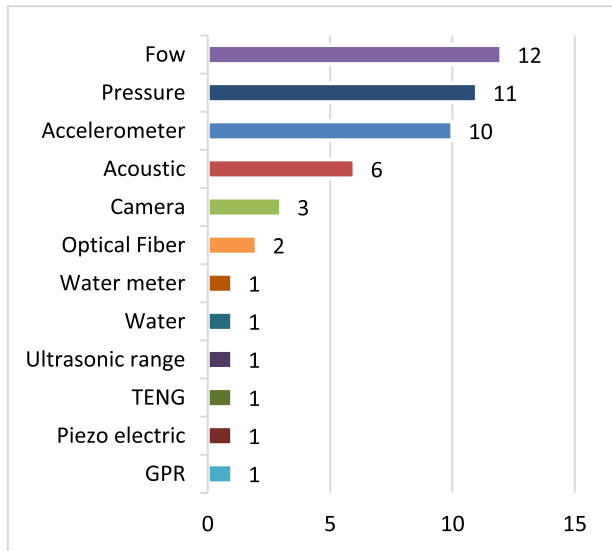
FIGURE 5. Sensor used.

towards the characteristics of new sensors. TENG, visible light and thermal camera, custom piezoelectric sensors, and optical fiber are some of the new routes the researchers are exploring.

2) DATA TYPE

We can observe two data collection procedures: single shot and time-bound sampling. Single-shot data in our review means that the information is captured all at once. IR [28], [57], visible light [52], and GPR [87] images are example of single-shot data. In the case of optical fiber, single-shot data are used on each section through the length to check the whole pipe to evaluate leakage [59]. The last one is the water sensor data [63], [85]. The water sensor is dependent on the conductivity of the water. If water is present, then the sensor triggers the controller. The second type of data is time-domain sampling. It means that data is captured for a duration of time. Then signal processing and algorithm are applied to that captured signal. We have observed two types of time-domain signals discrete and continuous signals. The relationship between the signal types we have observed is presented in Figure 6. In our review, discrete means sampling for a short amount of time and continuous meaning sampling all the time. In general, in this review, we have observed that researchers have taken a short time sample of vibration and acoustic signals, but in the case of pressure, flow, and ultrasonic range-based sensors, they have taken a continuous reading. Mainly when the researchers are using the diurnal pattern as a reference point [68], [69], or considering conservation of mass [11], [62] for leakage detection. The rest of the acoustic and vibration-based detection relies on discrete-time data. Also, in [67], the researcher has converted raw acceleration data to an image. They are essentially converting time-series data to an image. This one actually blurs the line of the classification.

3) EXPERIMENT TYPE

Figure 7 shows the experiment type and its classifications. 64% of the literature had an experimental element, 15% of the research had only simulated data, 17% had simulated data and algorithms verified by the experimental result, and only 4% of the research work used historical data to develop their algorithm. Overall, we can see an emphasis on experimental data.

The dominance of experimental data in leakage detection is because of the variety of sensor types and the pipe condition. Researchers have organized their experiments in three ways. The first one is the location of the pipe. Researchers have used a straight or looped pipe above ground to conduct their experiment [53], [54], [69], [74], [77], [79], [85]. Shukla et al. have experimented on underground water supply pipes to comprehensively understand the environmental dynamics [66].

The second type of experiment is a portion of the pipe network considered. The most common way is to set up a long straight line or a loop, flow water through a pipe and capture the data. Li et al. and El-Zahab have used a portion of the pipe to collect data [76], [77]. Shukla et al. and Okosun et al. have used an isolated pipe network to conduct the experiment [66], [74]. On the other hand, [59], [62], [68], [77], [79] have used a small section of the whole system to gather information. Similarly, Zhou et al., Alves et al., and Lai et al. used a real case's scaled-down model to conduct their experiment [57], [70], [87]. Sohaib et al. used a full-sized vessel to conduct their experiment [75]. The third type is the actual data from industrial or real-life setups. Some researchers can get their hands on industrial access, and Bao et al. have used the power plant flow as an experimental ground [52]. Depending on the access to the network, the experiments varied significantly. Kang et al. were able to collect data from a running WDS [82]. Shukla et al. have used underground pipe setup to study leakage noise characteristics [66]. Xie et al. have done a flow field model and underwater experiment to verify the results [65].

There are two main type of simulation namely numerical simulation and software simulation. Li et al. have used historical demand data and numerical simulation to develop dormant sensor sequence [67]. On the other hand, there are a number of software packages available for water system network design and water flow. Researchers in Zhou et al. have used FlowMaster [72], and Xu et al. have used the EPANET package to generate their data [60].

In case of simulation and experiment, the researches have used mathematical calculation to establish their model and finally experimented to verify their accuracy and suitability. In [55], [56], [58], [67], [73], [80], and [83], researchers have shown mathematical calculation and simulation and finally verified the results with experiment. Vrachimis et al., Feng et al., and Sophocleous et al. have used historical data or case studies to develop and validate their model.
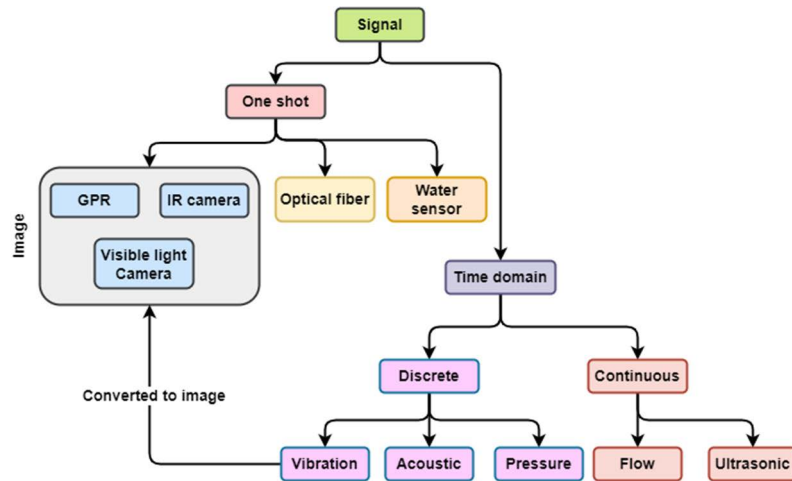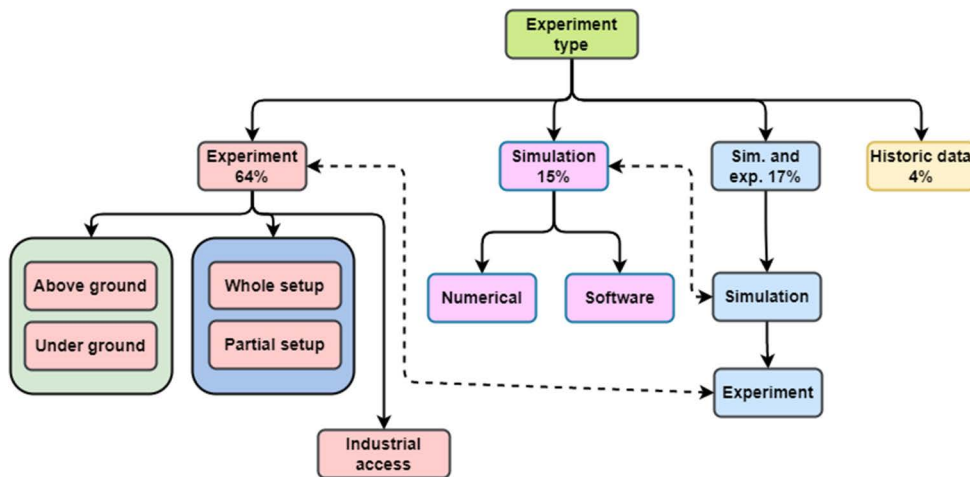
FIGURE 6. Data type.

FIGURE 7. Experiment distribution.

4) OUTCOME

Figure 8 shows the experimental objective of the research. 47% of the research has focused on leak detection, 42% of considered has considered leakage detection and location, and only 11% of research focuses on leak location alone. For leakage detection, there are many techniques available. For acoustic and vibration-based sensors, decomposition of signal to obtain feature space and classify the features with an ML classifier or a preset threshold is the most common technique to detect leakage [53], [54], [58], [65], [66], [75], [82], [83]. The second approach is the conservation of mass theory can be applied to a system for a period of time to get leakage scrutiny. Systems with flow sensors can capture water consumption patterns and cumulative volume of water to detect leakage [11], [61], [69], [81]. Leakage detection is comparatively easy than leakage location. For locating leakage, Predescu et al. systematically manipulated the water valves to generate a sensitivity matrix that can be used to locate the leakage [85]. Similarly, Sophocleous et al. has proposed two-stage calibration for detecting leakage [84]. Vision[52], infrared [28], [52], [57], and GPR [87] bases-systems have an inherent benefit for leakage location as these devices need to be pointed at the leakage. The three most prominent techniques described in the literature are, based on the arrival time of acoustic or vibration sensor [72], [75], [83], [86], based on the difference of sound intensity, and the last one is based on the hydraulic [61], graph-based [82] or ML model [73], [84] calibration.

5) METHODOLOGY

Figure 9 shows the major methodologies, their components, and their relationships. From Figure 9, we can see four major ways the researchers have processed the data. 8% of the researchers have used image-based methods, 30% have used either acoustic or vibration-based methods, 26% have used
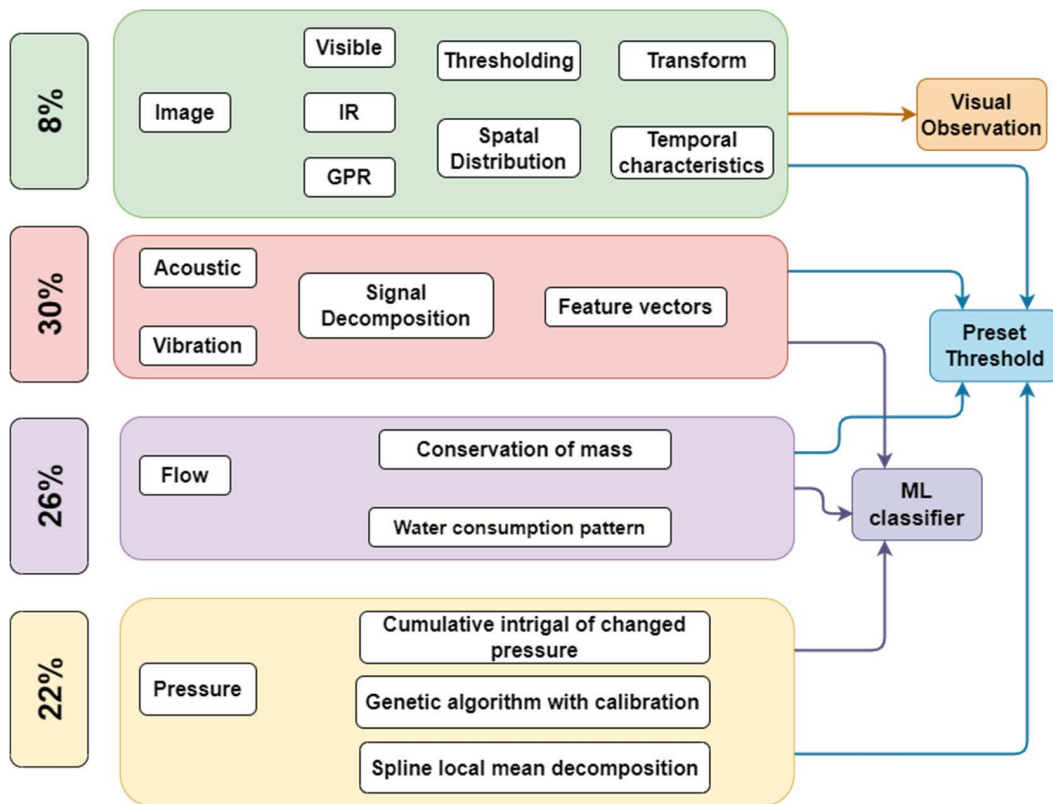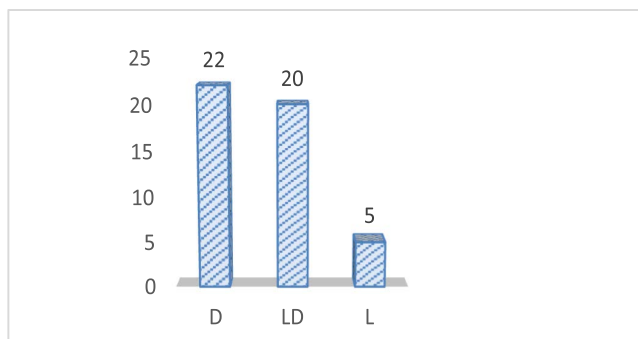
FIGURE 9. Major methodologies.

FIGURE 8. Experiment objective.

flow and 22% have used pressure-based methods. Some of the researchers have used multiple sensors to increase accuracy.

The first one is image-based. Only Bao et al. have used image processing, but the rest of the researchers have tried to quantify the observed change [52]. Bao et al. have used a combination of IR and visible light cameras [52], and the rest of the research focuses on spatial [57] and temporal [28] characteristics of the thermal images. Only preliminary thresholding and transformation are observed here. GPR signal-based images are a new addition in this area and have not observed any automated process in this area to detect leakage [87].

The second one is the methodology for vibration and acoustic sensor data. These sensor data are processed in three steps. At first, the signals are decomposed, then feature

vectors are made and finally compared with preset thresholds or fed to an ML algorithm to classify the data.

Pressure sensors are generally installed at an interval at the WSN to ensure the pipelines are within the expected pressure range. High pressure can rupture pipelines, so the whole system is monitored to balance the water pressure. One issue with using a pressure sensor to detect leakage is that it cannot detect small leakages. Kim et al. have used cumulative integral to detect small leakage to address this issue [86]. As leakage changes the pressure distribution of a significant part of the WDN, researchers have used genetic algorithms along with other algorithms to detect and locate leakage [84].

The last way is the application of flow sensor-based data. The primary theory is the conservation of mass. Researchers are considering water consumption patterns in their model to detect leakage [68].

6) COMMUNICATION
Of 47 publications, 17 or 36% used IoT technology for communication. This research comprises both homogeneous networks and hybrid networks. WiFi was the first choice comprising 35%, followed by cellular IoT modems, 25%, LoRa modems, 15%, other technologies, 20%, and 5% are not defined.

WiFi is the most common and widely available. Bao et al. have used Wifi for video transmission and robot control [52]. In the rest of the research, the WiFi modem is only used as a low-power sensor node [11], [15], [68], [85], [91],

[95]. The second most popular option is the cellular network 3G/4G GSM, and Nb-IoT [63], [69], [70], [73], [81]. These modem uses cellular network and have extended coverage. One issue with GSM and Nb-IoT networks is that users need to pay for the services. LoRa is a network that can cover a large area and does not need any service charge to use. SigFox is a type of LoRa technology, and Gericke et al. and Pérez-Padillo et al. used it in their research [71], [90]. Some researchers have used less popular technologies like Yang et al. have used optical fiber [59], Choi et al. have used custom solution for wireless communication [83] and Pal et al. have used Zigbee [95]. Shihari et al. have not clearly defined the wireless modem they are using [80]. The solution choice is entirely based on the power consumption, nodal distance, and sampling frequency.

In the next section, we have discussed the research questions in detail.

V. DISCUSSION
The research questions are answered here based on the analyzed data.

A. HOW THE LEAKAGE DETECTION RESEARCH TECHNIQUES ARE EVOLVING OVER TIME?
In the past decade, most leakage detection procedures depended on the human experience. With the advent of the powerful microprocessor and efficient signal processing techniques, a massive shift in automation can be observed in leakage detection techniques. For this systematic review, we looked for papers published between 2016 and 2022 that studied communication technologies, new algorithms, and sensor implementations utilized in water leak detection and location research. The observations are listed below:

- We can see an emphasis on experimental research. Thirty articles were based on experimental data, eight were based on simulation and then verified by experiment, seven were based only on simulation, and only two were based on historic data.
- The incorporation of IoT in leakage detection has increased from 2018 and onward. Before 2018, five articles incorporated IoT in leakage detection research, and after 2018, it jumped to thirteen articles. IoT in water leakage detection is a very niche field. Out of all research, only four articles gave a complete solution that incorporated algorithm development and IoT integration.
- The rest of the publications gave the bare minimum execution of the IoT.
- A leakage produces visual, thermal, acoustic, and vibration signature outside the pipe and pressure and flow differences inside the pipe. Vibration and acoustic-based methods comprise 30% of all research, and flow and pressure-based methods account for 48% of the study. Image, optical fiber, TENG, and other novel methods make up the rest of the research. We believe the reason

for vibration and acoustic methods make most of the research is that these sensors are easy to install on pipe compared to pressure and flow sensors that require inline installation with the pipe.
- Visual and thermal signature is the latest edition on leakage detection. We saw them first in 2017, and in 2022 two publications are using the image and IR-based technology. Optical fiber is a promising technology, but it is the most expensive one but it cannot be used on a branched network.
- TENG is in the early stage of development and will require substantial research work before it can be implemented in mass numbers.
- We can see a shift from rigid algorithm-based techniques to more ML-based approaches. From 2020 onward, we can see that 40% of all research used some form of ML algorithms. ML algorithms have much higher accuracy than traditional methods.
- In the case of IoT, there is no one to dominate in the leakage detection field. IoT is relatively new in this domain, and the application scenario is extensive.

B. WHAT KIND OF SENSOR ARE BEING USED?
summarizes the characteristics of different sensors used for leakage detection purposes. For each sensor, there are multiple models available and we have chosen one of them to make the comparison table. Accelerometer, and hydrophone sensors capture the vibration-induced data like noise and oscillation in the pipe and water. Deformation of piezo-electric crystal due to vibration is the main working principle of these acoustic and vibration sensors. On the other hand, MEMS sensors work by the change in capacitance of microstructure and a fixed plate and are widely used on mobile phones, tablets, and other electronic devices.

There are two types of acceleration meters used in the research field. The first one is a digital accelerometer, and the second one is a piezoelectric element-based analog sensor. The digital sensor Wilow AX-3D has many advanced features, including wireless data transfer and control and a built-in battery for mobile applications [77]. The analog sensor data is captured using a capture card, and then further processing is done. Wang et el., Xu et al., Shukla et al., lie et al., and Marmarokopos et al. used a piezoelectric accelerometer in their experiment [53], [54], [66], [73], [79].

A hydrophone is a microphone system that can detect sound waves under water. As it remains inside the water, it is less prone to environmental noise. It is like a stethoscope but underwater. Piezo [65] and MEMS [15] based hydrophones are available.

A water sensor, commonly known as a moisture sensor, detects the presence of water. The main problem with this sensor is that it needs to get wet to detect the presence of water, limiting the cases where these can be reliably used. Che et al. have used their IoT-based leakage detection system [63].

TABLE 7. Sensor comparison.

Parameters	Accelerometer		Hydrophone		Water sensor	Pressure	Flow	Range sensor
	MEMS	Piezo	MEMS	Piezo				
Accuracy	4 mg	-	± 0.3 dB	±1.5 dB	-	~0.5%	±5%	3mm
Range	±2 ~ ±16g	±50 m/s2	10 ~100 Hz	7Hz ~ 80kHz	-	0~ 600 kpsi	1 ~30 L/min	2cm ~ 400cm
Operating Mode	Capacitance change due to movement	Piezoelectric Effect of Ceramic	Piezoelectric AlN-based MEMS	-	Conductivity of water	Piezoresistive effect	Rotor, hall effect	Sound echo
Output	Digital	Analog	Analog	Digital	Digital	Analog	Pulse signal	Pulse signal
Application	Vibration Measurement		Under water data recording.		Wet/dry sensing	Water pressure	Rate of fluid flow	Distance measurement
Current Consumption	30 mA	20 mA	-	600mA	<20 mA	20 mA	15 mA	15 mA
Voltage	Built in battery, 5V	30V	-	5V	5V	5V	4.5 ~12v	5V
Cost	-	-	-	-	3$	197.49	4$	3$
Size	100mm x 60mm x 31mm	22.1 mm × 12.2 mm × 10.7 mm	15mm x 20mm x 1mm (approx.)	43mm (D)x 250mm (L)	64.7mm x 20mm x 7.7mm	56 mm x 30 mm x 18mm	60mm x 34 mm x 34mm	45mm x 20mm x 15mm
Resolution	12 bits	1 mV/ms–2	1 Vrms/μPa	-	1 bit	-	1L = 450 pulse	0.3 cm
Temp. Range	-40° ~ 65° C	-60° ~ 125° C	-	-	10° ~ 30°C	-40~85°C	Max 120°C	-
Part Number	Wilow AX-3D	B&K 4535-B-001	-	DHP8501	Grove water sensor	Honeywell transducer	YF-S201	HC-SR04
Datasheet	[96]	[97]	[15]	[98]	[99]	[100]	[101]	[102]
Reference	[77]	[54, 66]	[15]	[65]	[63]	[90]	[11, 63, 80, 85]	[68]

When leakage occurs in a water distribution system, the average pressure at that point changes. This pressure change also affects the nearby nodes. This is the principle of leakage detection via pressure sensors. Padillo et al. have used a pressure sensor in a field experiment to design their algorithms [90].

The conservation of mass theorem can detect leakage. The summation of inbound and outbound water should be equal, and this is the backbone for using flow and range sensors. Range sensors are used in the literature to measure the water volume in the overhead tank, and flow sensors are used in the links to measure water consumption. Gautam et al. have used a range sensor to measure the depth of the overhead water tank to estimate water volume [68]. The flow sensor is one of the popular choices for water leakage detection. There are two types of flow sensors. The non-contact ultrasonic and inline hall sensor-based. Lin et al. have implemented an ultrasonic flow sensor based on propagation time and transmission time difference [69]. The second one is the commercially available YF-S201 uses a hall sensor to detect water flow. Ali et al., Coelho et al., Srihari et al., and Predescu et al. have incorporated YF-S201 in work [11], [63], [80], [85]. Coelho et al. have used a similar sensor but a different model, YF-B2 [70].

On paper, the flow sensor might look easy to integrate into the system and develop the algorithm, but due to the accuracy of ±5 ~10, there is a high chance of false alarm.

We have seen the use of some novel sensors in the literature, like PVDF piezoelectric sensor [74] and triboelectric nanogenerator [78], but they are not commercially available. The researchers have fabricated these sensors themselves. In the articles, pH [11], [80] and turbidity [11], [63] sensors are also mentioned but are not included in the table because they are used for water quality information and are not related to leakage detection.

The MEMS accelerometer sensors are mass-produced and suitable for deployment in large quantities. From our observation, we can see from the table that the MEMS accelerometer is the best choice as a sensor as it consumes the least amount of power, is small in size, has a reasonable cost and is commercially available in large quantities.

C. WHAT KIND OF ALGORIOTHMS ARE USED IN DATA PROCESSING?

The algorithm used the leakage detection can be grouped into two groups. The first one is simple signal processing and thresholding-based, and the other is ML-based.

TABLE 8. ML models used for classification.

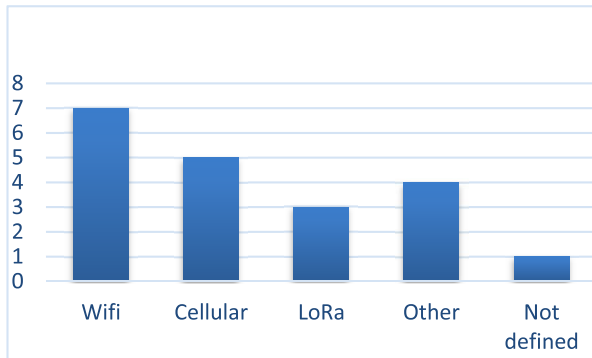|	Year	Models										
		SVM	RF	GBDT	Xgboost	LightGBM	CNN	ANN	Alexnet	DT	NB	Other
[53]	2022	✓										
[54]	2022		✓	✓	✓	✓						
[58]	2022						✓					
[89]	2022											AutoML
[93]	2022						✓					
[94]	2021											AutoML, k-mean
[65]	2020						✓					
[66]	2020						✓	✓	✓			
[68]	2020	✓										
[69]	2020	✓										
[70]	2020	✓	✓					✓		✓		
[72]	2019	✓										
[73]	2019	✓										
[75]	2019	✓										
[76]	2018							✓				
[78]	2018	✓										
[77]	2018	✓								✓	✓	
[82]	2017	✓										
[83]	2017	✓										

FIGURE 10. Wireless modem technology distribution.

We can see that in Figure 11 researchers have used image-based leakage detection and location method. Three types of input images can be seen. The first one is the infrared or thermal image [28], [52], [57], the second one is the visible light image [52], and finally GPR images [87]. In [28], [57], and [87] researchers have only characterized the spatial, and temporal variation in the image due to the temperature change over the time and tried to identify the fingerprint of the underground leakage. Bao et al. have used visible light and IR camera along with Otsu thresholding with black and white hat transform to detect and classify leak location automatically [52]. None of the image-based papers have used machine learning models for classification.

Figure 11 shows the flow of acoustic and vibration-based models. Signal decomposition is done in three major ways. Time series data is decomposed to get frequency domain data, IMF, EMD, EEDM, VDM are done to get harmonic signals and finally PCA is done to get spectral band envelop. Then the data is converted to feature space and finally passed through ML models to get classification results.

Flow meters are used on the basis of the conservation of mass. According to the conservation of mass, the mass of water entering the system and the water getting out of the system must be equal. Vhimis et al., and Wang et al. use flow data along with a preset value to detect leakage [61], [62].

Table 8 shows the uptake in the ML model is leakage detection. It is clear that SVM is the first choice and neural network (CNN, ANN and AlexNet) is the second choice, followed by DT and RF. Although it is possible to feed the raw signal to the ML classifier directly, we have not observed it here. Researchers have extracted features from the audio and vibration-based signals and then fed the feature vector into the classifier. Feature vector reduces the dimensionality of the signal and makes it easy for the ML model to classify the data. Xu et al. have used the most number of feature vectors, a total of 22 of them [54], and Sohaib et al. have used 13 features [75]. Accuracy increases with the number of feature vectors used. The FFT, STFT, and IMF was the most common mode of feature extraction. Guo et al., and Shukla et al. have used the feature vectors and converted them into an image, and then used neural network to classify them [58], [66]. Kang et al. have used CNN to extract feature and SVM
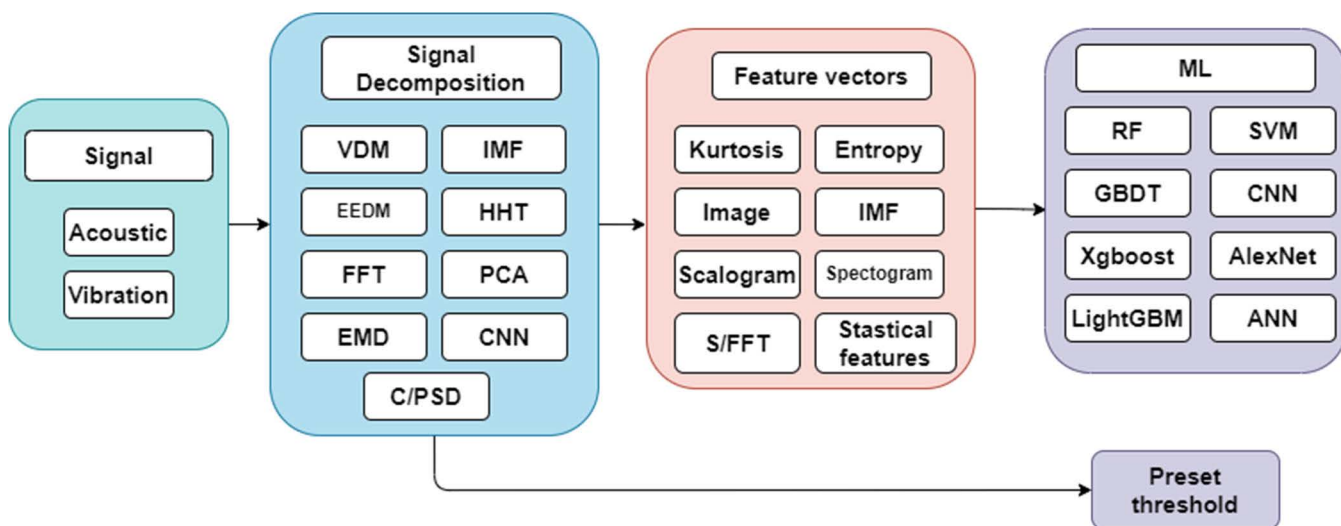
FIGURE 11. Flow of leakage detection using acoustic and vibration sensor data.

TABLE 9. Comparison of communication technologies used in research.

	Wi-Fi	Nb-IoT (4G)	GSM (2G/3G)	LoRa	Zigbee
Operating frequency	2.4GHz	700-2200 MHz	850/900/ 1800/1900MHz	433Mhz	2.4GHz
Standard	IEEE 802.11 b/g/n	IEEE 1451.0	-	IEEE 802.15.4	IEEE 802.15.4
Data rate	54Mbps	30/60 kbps	14.4 kbps	0.18-37.5 kbps	20-250 kbps
Operating voltage	2.2 − 3.3 V	3.0-5.5 V	3.4 to 4.4 V	1.8-3.7 V	(2 V–3.6 V
Max current draw	240mA	435mA	2000mA	120mA	39.6mA
Range	1000m	10,000m	6500m	10,000m	60m
Networking capability	Point to point, star, mesh	Cellular	Cellular	Point to point, Star	Mesh
Application	Sensor node	Cellular IoT application	Cellular module with GPRS transmission and receiving capability.	Low power ultralong range communication	Short range communication
IC/Module	ESP8266	SIM7000E	SIM800L	RFM95W	CC2530
Datasheet	[103]	[104]	[105]	[106]	[107]
Ref	[11]	[70]	[63]	[70]	[73]

for classification [82]. Xu et al, Shukla et al., Alves et al., and El-Zahab et al. have used multiple ML models to compare their model's performance [54], [66], [70], [77].

ML based models are easy to train and have better performance than their signal processing and thresholding-based counterpart. ML model will lead the future in this sector.

D. WHICH COMMUNICATION TECHNOLOGIES ARE CURRENTELY BEING USED?

There are many devices with the same technologies. For example, ESP8266 and ESP32 are WIFI SoC and use similar technology but different integrated peripheral supports. In this section, we have chosen one IC from each category to make the comparison.

IoT devices are designed to serve a wide market. For example, Wi-Fi was designed to replace the highspeed wired ethernet, Bluetooth was primarily designed to stream audio, Zigbee was for controlling home, and office appliances, Nb-IoT and GSM technology were for machine-to-machine communication, and LoRa for long-range, low-power communication. Table 9 shows a comparative analysis of the available IoT technologies. It is up to the researchers to think about the use cases and use the appropriate technology for their purpose.

In IoT research, Wi-Fi was chosen 35% of the time, followed by cellular IoT modems (25%), LoRa modems (15%), and other technologies (20%). We can see that Wi-Fi is the most popular choice for IoT applications. As Wi-Fi was the most common form of wireless device before the popularity of IoT, the vendors designed their devices to meet the Wi-Fi requirement. About one-third of the research papers have used Wi-Fi for their application.

The chips and modems come in two forms. SIM900L and RFM95W are modems and require an external microcontroller to operate. On the other hand, ESP8266, and CC2530 are SoC which has a built-in controller making the footprint small.

The operating frequency plays an important role as higher RF frequencies are blocked by walls, trees, and other obstructions, but lower RF frequencies are less susceptible to this kind of issue. That's why Nb-IoT and LoRa have lower operating frequencies than other technologies. Antenna size and frequency have an inverse relationship. So, lower frequency means longer antennas. On the other hand, data transmission speed is another vital factor that gives us information about how long it will take to send data to a base station. LoRa has the lowest data transfer speed, followed by Bluetooth, Zigbee, Nb-IoT, GSM, and Wi-Fi.

If the device is only a sensor node and only requires periodic transmission, then LoRa or Zigbee is a good choice. On the other hand, if the device needs to transmit a bulk amount of data, then Wi-Fi is the best choice. Another two crucial factors are power consumption and the range of the device. LoRa and Nb-IoT have a similar range of 10 km, but the Nb-IoT modem has a higher data rate.

There is no one ideal solution for wireless technology for leakage detection. We will see a mixture of wireless technologies for different use cases. For example, for an apartment building where there already is a Wi-Fi infrastructure in place, we will see Wi-Fi node-based leakage detection sensors. For small homes or farms, LoRa will be an ideal choice, and for monitoring remote locations, Nb-IoT will be used. An ideal IoT chip needs to have very low power consumption during operation, ultra-low deep sleep current, and long-distance communication capability for the research community.

VI. CONCLUSION

Leakage detection and localization is the first step to reducing the water loss in a network. The quickly it is possible to detect the leakage, the maintenance crew can fix it to save the precious resource.

In this paper, the authors have reviewed the existing technologies and the current trend in the domain. There are three main parts in this field, namely data collection via sensors, analyzing the data with an algorithm, and sending the result to the server via a communication link. An MCU is used to manage these three tasks on site.

Flow and pressure sensors have a lower sensitivity, thus an ideal choice for burst detection. This leaves room for background leakage or small leakage detection tasks. Vibration sensors and their derivatives like acceleration sensors, contact microphones, and hydrophones are getting more attention as they are highly sensitive and cheap compared to other sensors. We can see an uptake of the acceleration sensor in leakage detection studies as it is the cheapest one among all other sensors. It is mass-manufactured, requires a very low lower, and is small in size.

In this study, three ways researchers have implemented their algorithms. The first one is a simple threshold-based algorithm. The second one is a practical algorithm based on feature extraction and thresholding, and the last one is an ML-based algorithm. Out of these three types of algorithms, ML has far superior performance. One catch is that ML-based algorithm is that it requires preprocessing and feature extraction and generally requires more computation power as well as more memory. Even though this drawback, researchers are leaning toward machine learning models to achieve higher accuracy in leakage detection in a water supply network. ML will play a vital role in this field.

In this review, we can see three trends in the communication side. The first one is WIFI based network, the second one is a cellular network, and the third one is a hybrid network. WIFI is the popular choice for IoT modems because it is cheap and does not require monthly subscription costs. The WIFI and cellular-based sensor nodes can connect directly to the internet without any middle man and report if any issue is found. Depending on the user's need, a heterogeneous mixture of short-range and long-range devices will dominate in this field. – We hope to see more sensor node-based implementation of leakage detection technologies in the future. This sensor will have some form of vibration sensor and ML models built into them, thus resulting in higher accuracy. We will also see a move away from rigid algorithm-based techniques and incorporate over-the-air updates on the MCU. This over-the-air update will help the nodes update the ML model. IoT will enable close to real-time water leakage detection. These steps will make reliable leakage detection technology possible in large volumes.

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