buildings

Review

Review of Water Leak Detection Methods in Smart Building Applications

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Abstract: In recent years, the identification of water leak detection methods has entered a wide range of fields. Pipeline failures in water distribution networks lead to the loss of a considerable amount of high-quality water. Different monitoring methods are often used to identify the failing infrastructure, which is subsequently maintained. Increased pressures on a fast-expanding water supply network needs the development of better leak detection technologies, particularly for use in smart building applications. This paper offers a detailed examination of water leak detection methods, intending to determine the state-of-the-art approaches and make recommendations for future research. It is designed to demonstrate smart buildings, but it may also be utilized in another similar context. This review concludes that, despite prior achievements, there is still much room for improvement, particularly in the domain of real-time models for earlier leak detection methods in building automation. These models should enable the integration of leakage detection, evaluation, and control system that, with minimal human interaction, may be customized for efficient leakage detection in real-world circumstances.

Keywords: Leakage detection; artificial intelligence; smart buildings

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1. Introduction

On Earth, there is no life without water. A basic need for the survival of all life forms on the planet. Water is, without a doubt, the reason that the earth is the only planet where life can exist. Global water consumption is anticipated to increase by 55 percent, while around 25 percent of big cities are now facing some form of water stress [1]. Approximately 2.2 billion people in the world do not have access to clean drinking water [1]. One of the most important resources we have on this planet is this universal solvent. Without water, life would be difficult to function. Apart from lowering daily consumption through campaigns and water restrictions, as well as recycling water for non-portable reuse, the most important approach is minimizing water wastage, which is often larger than the quantity provided to the user [2]. Pipe defects can result in a significant loss of immaculate grade water as well as energy wasted on purification [3].

Access to clean water is never free. Collecting, storing, treating, and distributing water are all necessities. Everyone is responsible for water, and we are all part of the answer. However, maintaining sustainable development in a period of rapid economic expansion, urbanization, and climate change is a challenge. Sustainable Development Goals (SDG) 6 addresses the sustainability of water and sanitation access by concentrating on the quality, availability, and management of freshwater resources, building on the applicable Millennium Development Goal [4]. One of the potential causes of these targets not being met is water leakage in the distribution network. Water availability is a critical component of long-term urban development. Thus, a systems approach to develope a water leak detection method is needed. Building automation as a kind of technical intelligence in smart buildings will be discussed in this paper.

The idea of leveraging smart building technologies is not new, from buildings to smart buildings. The three main elements of smart buildings are the intelligence of managing indoor environments, the enterprise of integrating building systems on a common network, and the materials and constructions that can adapt to changes in use and climate [5]. This paper will focus on the first of the aforementioned components which is in the context of monitoring and control of water leak detection methods in smart buildings. In addition, delivering building services to ensure occupant's productivity while minimizing the cost and environmental effects throughout the building is the essential characteristic of an intelligent building [6]. Intelligent buildings are emerging as responsive controlled environments for inhabitants, companies, and society because of technological advancements in regulating the interior environment. By using computational technology, the idea of expanded intelligent buildings has been put up to address both sustainability and intelligence [7]. Buildings in the future will be referred as the thinking buildings since they will be built with the smart buildings concept [7]. Thinking buildings will enable communication and adaptation between physical and virtual forms based on the ambiguous data using new technologies, procedures, and knowledge [5]. The graphic in Figure 1 shows the development of the building's perimeter.

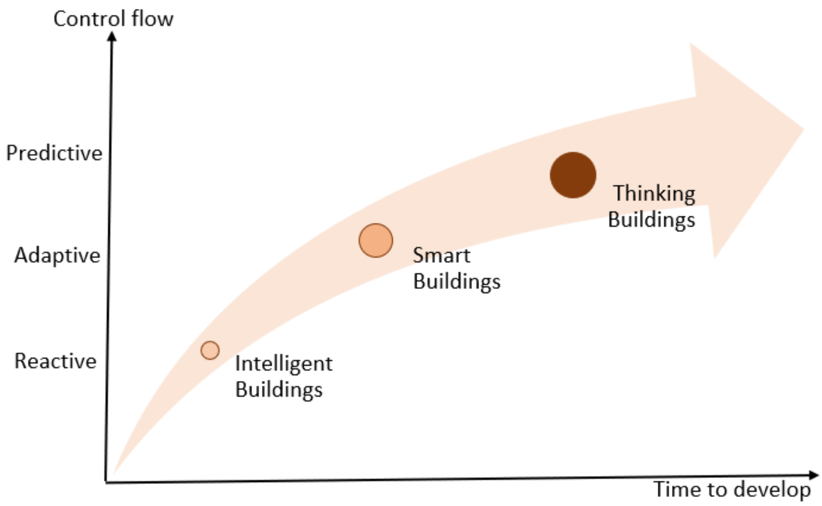

Figure 1. Building concept development throughout time based on the most cutting-edge knowledge and technology [8].

The goal of smart buildings is for them to be able to self-manage, learn, predict, and adapt without the intervention or awareness of their users. Sensors and monitors can quickly and automatically alter the room temperatures, lighting, shading, energy, and water consumption. The utilization of information and communication technology to improve the quality of the occupants in smart building applications is one of the IoT applications in the urban context [9]. In this paper, a smart water leak detection system, like smart energy systems that can capture real-time data using IoT-enabled sensors will be further discussed. This allows for the optimization of water facilities by identifying leaks and monitoring how water is distributed across the network, allowing individuals to make better water management decisions.

Current methods for detecting water leakage in distribution networks have several limitations in certain cases. In general, the efficiency of the system is only applicable for a specific case that is high-cost and time-consuming approach. For example, a Closed-Circuit Television (CCTV) is one of the famous methods for leak detection [10]. A remote-controlled platform and a camera installed on a robot traveling between two manholes inside the pipeline are part of the system [10]. As a result, identifying water leaks quickly and effectively is critical for lowering overall costs and improving the reliability of water-dependent systems [11]. In addition, several governmental and industrial parties are concerned about detecting water leaks due to the financial losses it caused as well as the safety risks it raised. Thus, this paper aims to analyze the most recent research methodologies on water leak detection systems in the context of building automation applications, which has piqued the interest of many researchers and yielded a significant number of potential solutions. The Table 1 below is a comparative summary of a few previous reviews on water leak detection methods studies. Currently, the majority of the leak detection technology is being covered in a water distribution and pipeline network. Therefore, this paper will examine a depth study of water leak detection in automation buildings as an application. The three objectives are to (1) present an organized and thorough review of hardware/software literature methods, (2) draw attention to the processing techniques used for these methods, and (3) use applications for these methods in smart buildings.

Table 1. Summary of the previous review work on water leak detection methods.

Review	Highlight	Leak Detection Techniques	Data Analysis Techniques	Application
[12]	Advantages, limitations, and solutions approach for various pipeline systems	• Steady-state methods • Transient state methods	• Mass balance • Pressure flow deviation • Inverse analysis	Pipeline systems
[9]	Fiber optics research developments in water leak utilizing bibliometric and systemic analysis	• Fiber optic-based sensor	• Reflection and transmission principle	Water distribution networks
[13]	Model-based and data-driven techniques to detect leaks in water distribution systems	• Model-based • Data-driven	• Hydraulic model • Statical and signal processing analysis	Water distribution networks
[14]	Comparison of hydrophones with other sensing technologies for detecting water leaks	• Acoustic technology	• Time Delay Estimation (TDE) • Novelty detection	Pipeline systems
[15]	A scientometric investigation and qualitative discussions based on micro-electromechanical systems (MEMS) in leak detection	• Micro-Electromechanical Systems (MEMS)	• Wireless Sensor Networks (WSNs) • Linear Regression models • Measure vibration	Water distribution networks
[16]	History of leak detection in pipelines by using visualization tools VOSviewer and CiteNetExplorer	• Listening devices • Leak noise loggers • Infrared thermography • Traces gas • Groung Penetrating radar • Leak detecting robots • Smart ball • Wireless Micro-Electromechanical Systems (MEMS) • Data analysis-based methods	• Frequency acoustic signal • Logger system • Wavelength range • Gas injection • Electromagnetic waves • Embedded pipeline • Acoustic sensor • Regression analysis • Machine learning	Water distribution networks
[11]	Two distinct concepts in water leak detection technique which is sensor data fusion and federated learning	• Sensor data fusion • Federated learning paradigms	• JDL model • Lou and Kay model • Dasarathy model • Durrant-Whyte model • Machine learning	Pipeline systems
[17]	The distinctions, pros, and cons between water distribution networks, oil/gas networks, and district heating networks	• Physical model-based methods • Data-driven methods • Unmanned Air-borne Infrared Thermography (UAIT) methods	• Pressure gradient method • ANSYS software • Classification model • OLGA software • WDNetXL system • Post-processing and automated processing	District heating networks

2. Sensing Technologies

Various sensing systems for water leak detection have been created around the world as electronic and information technologies have advanced. In the creation of IoT solutions, sensors are critical. Sensors are devices that detect and replace external data with an understandable signal for humans and machines. The most basic level of a sensor is a device that detects the feature amount of a measuring item and converts it into a readable signal that may be shown on an instrument. Simply described, sensing technology is a system that uses sensors to collect data by detecting physical, chemical, or biological property amounts and converting them into readable signals. The various sensor technologies concepts utilized in water leak detection systems will be discussed separately in this section.

Through the observation from literature, the leak detection method can be divided into two main categories which are hardware-based leak detection and software-based leak detection [11,18,19]. The two classes of the system can be defined as: (1) hardware-based leak detection, where the system focuses on sensors and data collectors that are being used to detect pipeline leakage, and (2) software-based leak detection, in which the system relies on software programs to predict leakages [20].

The state of the art at the moment shows that several approaches, including hardware and software solutions, are put forth for leak detection. Hardware techniques, which involve investing in hardware industrial instruments and devices, particularly for finding leaks can be considered a demanding method used in the industry. Scalability, installation and maintenance expenses and significant power consumption are these technologies' key drawbacks. While software-based methods rely on the analysis of hydraulic data and employ both conventional and sophisticated techniques using image processing and machine learning algorithms. Many of the dependability, efficiency, sensitivity, and location accuracy issues that researchers and developers encountered remain unanswered.

The major difference between both classes is that hardware-based leak detection also to be known as static leak detection systems can inform the leaks occur immediately, while software-based leak detection also to be known as dynamic leak detection systems need to gather some information for further investigation where's the location of the leaks occurs [16]. These two classes are commonly utilized to develop reliable leak detection systems. Although each class is capable of recognizing, locating, and pinpointing leaks on its own, it is typical to use both classes together [21]. In this section, all types of literature-proposed methods are examined, and their suitability in building automation is discussed.

2.1. Hardware Methods

The first category of leak detection methods is hardware-based methods. It makes use of hardware sensing devices such as acoustic emission detectors, fiber optic sensors, ultrasonic technology, and infrared thermography to locate leaks and directly identify their presence. Below are some of the major hardware-based methods discussed.

2.1.1. Closed-Circuit Television (CCTV)

A remote-controlled platform and a camera installed on a robot traveling between two manholes inside the pipeline are part of the system. The in-service video technology is built on a technological platform that allows for the insertion of a tethered sensor into pressurized water pipes. The CCTV images can only be used to identify an interior view of the sewage pipes' state as they are unable to detect the depth of the fractures [22]. Additionally, no information concerning void development in the exterior section of the sewage pipes is provided by the analyses of CCTV photos [23].

There was a study that combined leak detection and Closed-Circuit Television (CCTV) inspection Sensor head (Sahara AV) technology for pinpointing leak locations [24]. The illustration of the platform can be seen in Figure 2.

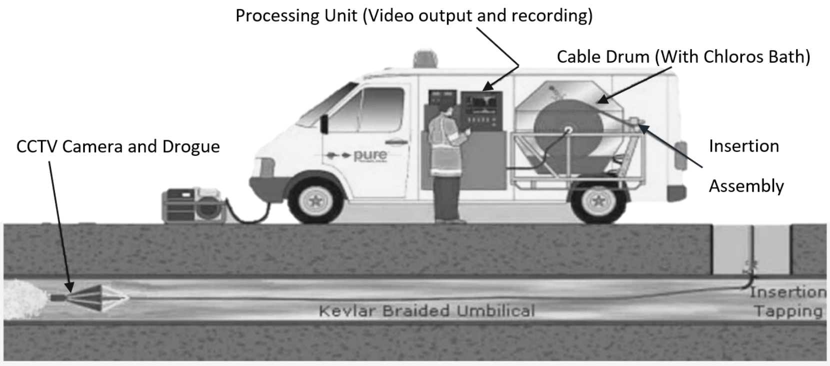

Figure 2. Illustration of Sahara System that utilizes the use of the CCTV camera in detecting pipe leaks [24].

The CCTV modules were moved through the pipe by a winch and pulley system [25]. The Sensor head (Sahara AV) with a built-in leak detection module, pinpointing location module, CCTV camera, and lighting arrangement in a small waterproof pressure-resistant housing was replaced by integrating leak detection and CCTV inspection. The author highlighted that the in-line leak detection combined with the video inspection was a cost-effective means of decreasing leaks, theft, and locating unknown connections [24]. The system reliability was increased by providing clear signals of the pipeline status [24].

2.1.2. Ground Penetration Radar (GPR)

The Ground Penetration Radar (GPR) method is one of several Near-Surface Geophysical (NSG) methods for analyzing various wave and induction properties in materials. It is a nondestructive testing (NDT) technique that makes use of microwave-frequency electromagnetic radiation [22]. This approach uses high-frequency electro-magnetic pulses to send out and receive reflected echoes [26]. It detects gaps in the soil caused by leaking water as it circulates the pipe to discover leaks in buried water pipes. Processing GPR data and signals require a significant amount of efforts. Two main pieces of equipment, which consist of antennas and transmitters, are required to make the GPR work. These systems use two or three antennas with different frequencies to identify leaks in buried water pipes [25]. They detects underground cavities formed by leaking water or irregularities in the depth of the pipes when the radar propagation velocity varies owing to the soil saturation with leaking water [25].

GPR is frequently used to discover buried facilities [27] and evaluate the state of sub-surface infrastructures [28,29]. In the variety of sectors, including earth sciences, archaeology, the military, vehicle localization, pavement research, and structures excavation, GPR has also been extensively employed [22]. Its primary application is to find flaws in subsurface objects, such as voids and fractures [30,31]. The most reliable approach for locating leaks in underground pipelines has been proven to be GPR through several studies. For example, a researcher in South Korea used poorly graded standard sand in laboratory model studies to explore the mechanisms causing cavities to form because of the sewage pipe damage in sandy soils. The impact of relative density and degree of compaction on ground sinking was investigated and it has been proven that when the groundwater level developed close to the surface, a rise in the seepage force speeds up the cavity's construction [32]. The relationship between the soundness of the sewer pipe and the surrounding environment of the pipelines has been analyzed [33]. One of the causes of ground sinking is sewer leaks since it eroded the nearby soil. As a result, pinpointing areas of ground subsidence can assist in determining where sewer pipeline leaks were occurring. Then they proposed a reliable method for assessing the risk of road subsidence that considered a variety of deteriorated sewer pipelines and the surrounding area [33]. As a preliminary symptom that led to an uneven ground settlement, the soil's density in the places where ground subsidence occured became low or its strength declines [22].

To identify ground subsidence, test methods sensitive to changes in soil density, porosity, and strength, such as GPR, were preferred [22].

2.1.3. Acoustic Emission

Another hardware-based water leak detection method is the acoustic emission method which is also known as a non-destructive testing method [34]. Acoustic emission occurs when fluid leakage, crack propagation, plastic deformation, and fracture in materials are generated by pressure waves [35]. These approaches rely on the fact that as water left the pipe, it produces a distinct sound or noise, with minor leaks produce higher-frequency noises and big breaches producing lower-frequency sounds. Leak detection via acoustic emissions relies on escaping fluids emitting a low-frequency acoustic signal. To track the noise levels inside the pipeline, acoustic sensors have been positioned all along its length [36]. The illustration of this mentioned method can be seen in Figure 3.

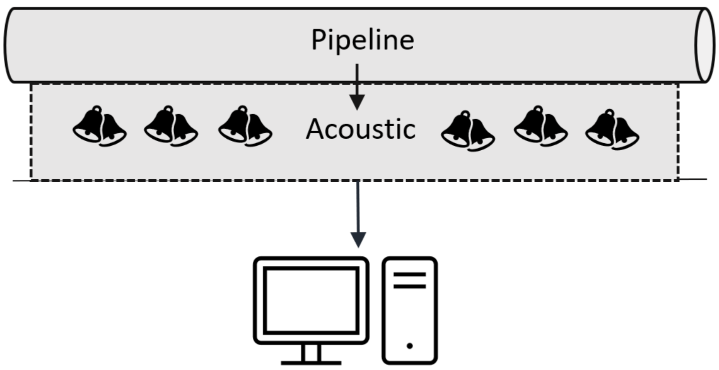

Figure 3. Illustration of Acoustic Emission Technique located all along in the monitoring pipeline [24].

The permissible noise levels for the pipeline are established as a baseline [37]. To be specific, acoustic sensors, such as pressure sensors, accelerometers, and hydrophones, are deployed on or within the pipeline in acoustic technology. As a result, the purpose of these procedures is to discover unusual sounds or noises caused by the water leaks in pipes. An alarm system is activated if there are any variations outside of a certain range. It will be feasible to find the leak since the acoustic signal will be the highest when close to the leak. The detection period, which is constrained by the speed of sound, the distance between the monitors, the time required for data connection, and the required computational time, is typically between 15 and 1 min [38]. Within 30 m, the leak's location may be roughly pinpointed [38].

2.1.4. Fiber Optics

Fiber optic leak detection systems are based on Distributed Temperature Sensing (DTS) technology to detect and identify leaks using the idea of local temperature variations. Since pipeline leaks normally generate local temperature anomalies, an optical fiber line put throughout the whole pipeline could identify the leak by taking temperature readings in fiber optics techniques [39]. Temperature variations and vibration signals can be captured by the fiber optic sensor that is used in conjunction with the pipe laying [40] and it is often taking a reading every 0.5 m [38].

The Raman or Brillouin scattering process is used as the basis for the examination of scattered light to obtain this temperature information [38]. According to the Joule Thompson effect, gas leaks would cause the immediate region to cool, but liquid leaks normally cause the immediate area to heat up. This procedure should not cause false alarms if carried out correctly, but it does require first obtaining a baseline profile of safe temperatures along the pipeline. This technique has a maximum sensitivity of 50 mL/min, and leaks may be located using data from nearby fiber optic probes [41]. The position of the leak may be determined to be within a one-meter range if the sensors are placed, as is customary, every 0.5 m [38]. The amount of the leak and the fluid being transferred are both indicated by the magnitude and the rate of the temperature change [42]. Even if the temperature change indicates the amount of the leaks, it is still challenging to estimate any leakage within a certain range. It turns out to be more of a large, medium, or tiny sign. Depending on the length of the pipeline, it may take anywhere between 30 s and 5 min to generate a comprehensive profile [41]. However, this approach comes at a high cost. The material expenses for this technology can reach upwards of 18 million for a 1200 km pipeline [38].

Due to the advantages of geometric versatility, immunity to electromagnetic interference, multi-parameter measurements (strain, temperature, rotation, etc.), and fitting for measurement in harsh environments, fiber optic sensors are becoming increasingly important in the field of pipeline monitoring [43]. This approach has been frequently employed in pipeline non-destructive examination because of its exceptional capabilities [39]. A fiber-optic humidity sensor system has been designed and evaluated to detect and measure leakage in sewerage tunnels [44]. Figure 4 depicts the sensory system used for detecting leaks inside wastewater tunnels. The system consists of Fiber Bragg Grating-based humidity sensors mounted at the junction of two sewage pipes and fiber optic swellable polymeric sensors installed along the pipes. From the experimental results, it is shown that the fiber optic swellable polymeric sensor can detect leakage along the sewerage tunnel with outstanding sensitivity, hysteresis, and long-term stability.

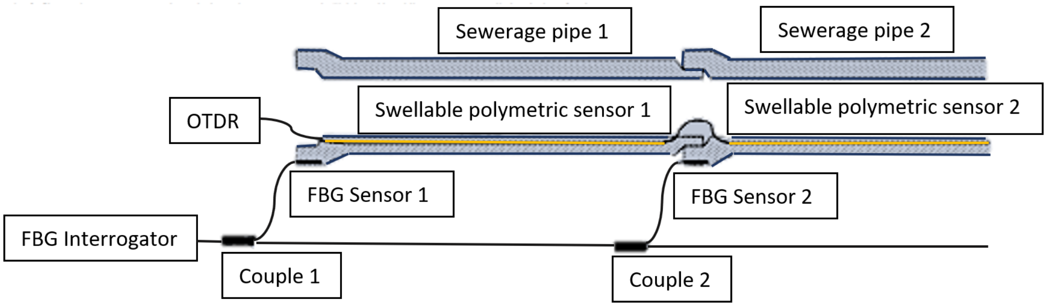

Figure 4. A Fiber optic sensor system diagram for finding water leaks in sewer tunnels. FBG humidity sensors are used at the intersection of two sewage lines and fiber optic swellable polymeric sensors are applied along the sewerage tunnel [44].

2.1.5. Infrared Thermography

Infrared thermography is a method that utilizes a thermal imager to detect radiation (heat) originating from an object, convert it to temperature readings, and show an image of the temperature distribution. Contactless infrared (IR) sensors are usually used to estimate distance in a variety of applications, including obstacle avoidance, obstacle detection, indoor location, tracking systems, industrial robot applications, mobile robot applications, healthcare, automotive, and unmanned aerial vehicle applications [45–48]. Besides its contactless feature, the IR thermography technique, which depends on fluctuations in thermal emission, is a potent tool for detecting leakage on a vast scale [21,49–52]. The analysis of underground pipeline networks using this technique has been done using the thermal properties of the soil [53]. This method has the benefit of allowing for extensive coverage without the need for excavation.

Additionally, the IR thermography technique is unaffected by pipe materials or sizes [21] but the approach is only reliable when the soil is close to being at ambient temperatures [54]. These advantages make the deployment of an infrared camera feasible for overcoming the constraints of conventional leak detection technologies [55]. The test area's surface conditions, sun radiation, cloud cover, and ambient temperature can all have an impact on this method's capabilities [56]. The fundamental drawback of this approach is that it can only be applied to pipeline systems that transfer gases or liquids at temperatures greater than the soil's ambient temperature, such as those used to transmit hot water or steam [57]. In addition, the cost of the toolset, the requirement for operators to complete extensive training and gain expertise, and the method's reliance on the weather are some of the drawbacks of this approach.

The reliability of IR thermography in water leak detection has been investigated [50]. A comprehensive IR thermographic leak detection field research was conducted on 27 pipeline breaches beneath soil or grassed surfaces on the nature strips. Water seeps beneath the soil and grass nature strips were used to test the procedure in the field at 27 locations across Melbourne. The passive leak detection approach using IR thermography was shown to be able to identify 59 percent of leaks clearly, with an additional 22 percent of locations exhibiting prominent but inconclusive thermal signatures.

2.1.6. RFID Tag Sensor

Radio Frequency IDentification (RFID) tags sensor is a type of sensor that can detect environmental changes, events and wirelessly transmit the data to an RFID reader. RFID tags can hold more data and frequently used in conjunction with barcodes. Ordinary RFID tags are used as moisture sensors that can be read remotely. One of the tags is implanted in a moisture-absorbent substance, while the other is left uncovered, and the two tags are combined into one label. These markers often take the shape of tiny plastic objects, such as 100 mm diameter plastic balls [23]. They may be programmed with little data and afterward "read" using a unique location and the tag is excited by the locator to reply at the specified frequency [23]. After determining the frequency, the locator reports the relevant asset, such as the Electronic Marking System (EMS) [23].

Different microwave methods are used in existing technologies for remote sensing of humidity levels in concealed areas, such as inside walls [58]. Moisture measurement with an RFID tag might potentially be done with just one tag, but this would need to keep the distance between the reader and the tag constant. Due to the lower frequency at which they operate, these RFID marker systems have the benefit of being detectable in moist environments where GPR would struggle to obtain adequate signal penetration [23].

An experiment has been carried out for the remote reading of the humidity and wetness levels inside walls [59]. For a passive RFID system, the relative humidity or quantity of water in the absorbent material was obtained by measuring the differences in RFID readers on the output power required to power up the open and embedded tags, respectively. The results demonstrate that those passive tags used as pure wetness sensors functioned well in terms of power level differences as a few grams of water within the absorbing material resulted in a difference of several dBs. Besides, recent's work focused on creating a multi-frequency passive tagging system that improved the identification of subterranean utility locations has been discovered [60]. Applying multi-frequency passive RFID tags that were sensitive to changes in a pipeline's condition, such as those caused by leaks and deterioration, was a similar concept that has been patented for monitoring the state of utilities [60].

2.1.7. Leakage Pinpointing Methods

Leakage Pinpointing Methods is one of the most precise strategies being used in today's leak detection methods. Three major groupings will be presented in this section which are Leak Noise Correlators (LNC), Tracer Gas Technique (TGT), and Pig-Mounted Acoustic (PMA).

Correlators are a type of sound measurement instrument that are used to determine the acoustic frequency induced by a leaky pipe. Leak Noise Correlators (LNCs) are the most frequent method for locating leaks, and they were originally commercially available in the late 1970s [61]. A comparison was made between two microphones, one on either side of the leak, in contact with the pipe, to determine the leak time distance. The correlator calculated the leak location by recording the signal delay, sensor distance, and sound velocity from two identical sensors placed along the pipe [61]. In the high-water-pressure situations, where hard pipe backfill was employed, the approach worked best with clean, small-diameter metallic pipes [62].

Next, Trace Gas Technique (TGT) operates by detecting various gas levels in the atmosphere. These devices are used for security and are often battery-operated. When they detect a higher-than-normal quantity of gas in the air, they issue a sequence of auditory beeps that are difficult to miss. Following that, a ground scan with a very sensitive gas detector is performed, which should reveals any indications of released gas from the leak spot, as shown in Figure 5 [62]. This figure illustrates that the length of the reaction is determined by the gas utilized, and the size of the response is determined by the volume of gas injected [62]. This method is widely used in machinery testing, but the high cost makes it impractical for leak detection [62].

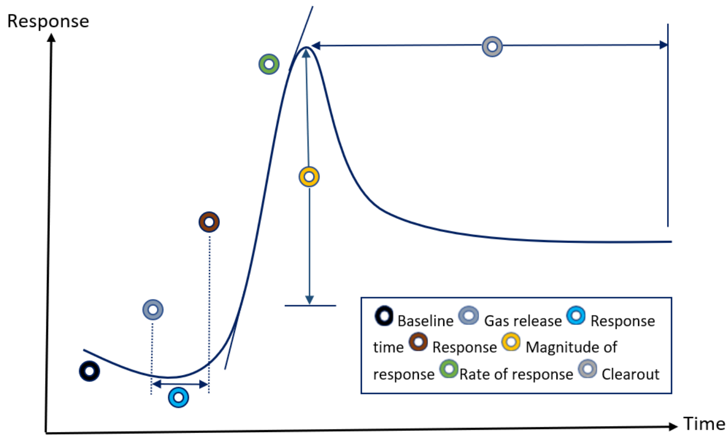

Figure 5. Scenario of estimated leak reaction recording while using the tracer gas approach [62].

The most often utilized tracer gas in leak detection is helium. It is non-flammable, non-destructive, non-toxic, and inert, with only a trace of its existence in our atmosphere. The helium gas is mostly injected or pumped into a pipe system through valves or tapping points [63]. It is then released into the air through gaps or drilled holes in the pavement surfaces at a leaky point, where it is combined with other residual gases [64]. The used gases tend to leak and subsequently seep through the ground or pavement since they are lighter than air and so more prone to do so. Later, leak locations are determined by detecting the seepage of tracer gases using a man-operated detector that tracks and detects these gases. The helium gas is detected at the leaking spot using a helium leak detector [64]. The leak detection with helium gas is highly accurate (more than 80 percent) in detecting all leaks, whether tiny or large, as well as leaks caused by high or low pressured networks [64].

Tracer gases can find leaks in the pipes with a diameter of 75 mm to 1000 mm [16], but due to its expense and time commitment, this method cannot be utilized for routine leak checks of pipeline systems. The technique depends on understanding the water flow and preventing the gas from finding simpler ways to leave the system. The tracer gas injection technique is costly and has significant maintenance needs, including the need for a skilled operator to handle the machinery. Closing branches and cutting off the suspected leak region block the alternative channels, which may disrupt the water delivery service [16].

Lastly, Pig-Mounted Acoustic (PMA) is used to record the leak noise, in which one or more microphones are put into a pipe under pressure. This strategy may also be utilized with other devices, even more, advanced ones. The microphone is carried to the leak location by the velocity of the water, while the noise and its location are continually recorded [62]. This is a challenging procedure that is not always achievable. The approach relies on water flow to take the sensors downstream, which always necessitates insertion upstream and sufficient flow to carry the sensor. A pull cable is used to draw the sensor down the pipe in a modified version of the test. This allows the test to be run even if there is no flow. However, it is a significantly more time-consuming technique.

2.2. Software Methods

The second category of leak detection methods is software-based methods. These techniques use soft computing techniques and data collecting as their main components of methodologies and usage applications. Real-time pressure or flow sensors, as well as a variety of artificial intelligence tools, statistical data analysis, and employing computer software programs to continuously track pipeline leaks. In theory, software-based techniques offer a promising foundation for delivering a nearly comprehensive leak control solution for spills of all sizes. Despite these real advantages, software-based leak monitoring and detection methods are still not widely used by the utility services since they are extremely data-intensive and need the installation of a sufficient number of data-measuring sensors in the pipeline system. These programs range widely in terms of their complexity and dependability. Below are some of the popular software-based methods discussed.

2.2.1. Negative Pressure Waves (NPW)

The negative pressure wave approach is based on the analysis of pressure signals accounts on a pipeline model. When a leak occurs, it causes a negative pressure wave propagating in both directions, upstream and downstream of a leak's location as shown in Figure 6. The system is based on the energy conservation law. When a leak first appears, liquid or gas flows into the environment, releasing a pressure inside the pipeline and causing a negative pressure wave (NPW).

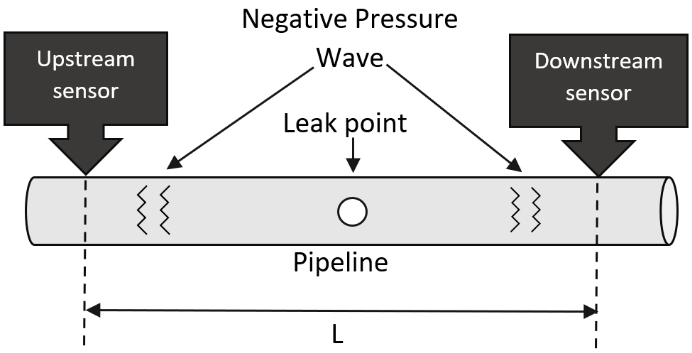

Figure 6. Negative Pressure Wave technique that applies from the leak site in the upstream and downstream directions [10].

The negative pressure wave approach has been widely used in the water distribution networks and oil/gas networks. Low equipment investment and convenient construction and maintenance expenses are some of its benefits, but its shortcomings include poor detection accuracy and inapplicability for tiny or intermittent leakage. To identify the smallest detectable leakage flow rate using the negative pressure wave approach, it is helpful to utilize the amplitude of negative pressure waves, which may be used to gain information about the severity of the damage (for example, leak flow rate and leak area). The location of the leak may be identified using the propagation time difference.

Some NPW methods, like ATMOS Wave, are commercially accessible and may be used to determine the magnitude of leaks [65]. However, putting long-distance pipelines into practice is a challenging task. The reflected wave approach makes use of the transient pressure fluctuations caused by changes in flow conditions [10]. Consequently, pressure waves spread throughout the system and are represented by the modifications in the geometric or hydraulic parameters. A reflected wave will be produced at the site of a pipeline leak when one is present. These places may be found using recorded pressure time series, and the size of the reflected wave will precisely correspond to the extent of the leak. Finding the source of a reflected wave is the key-challenge with this approach. The reflected waves are affected by junctions, nodes, and bends, making them difficult to pinpoint the source of the leak. Systems that don't take pipeline inventory into account invariably produce major leak location mistakes.

2.2.2. Computational Fluid Dynamics (CFD)

The term "computational fluid dynamics" (CFD) refers to the use of numerical analysis and data structures for the study and resolution of issues involving fluid flows [66]. The computations are necessary to model the fluid's free-stream flow and its interactions with surfaces constrained by the boundary conditions (both liquids and gases) are done on computers by calculation and simulation of the stream flow fluids and their interaction with surrounding surfaces [66]. It is recommended to use a high-speed supercomputer, which is frequently needed to address the most challenging issues. Software that enhances the precision and speed of complicated modeling situations, such as transonic or turbulent flows, is the result of the ongoing research.

The flow and turbulence fields surrounded a leak of various sizes have been studied using steady and unsteady CFD models. Using a 3D turbulent flow model of a well-proven commercial CFD system, steady-state CFD simulations of minor leaks in a pipe with a diameter of 0.1 m at realistic speeds and pressures had been conducted [67]. The simulations clearly demonstrated how the leak affected the pressure gradient along the various flow routes inside the pipe. The fluctuations in pressure and pressure gradient throughout the pipe had a definite signature, according to the steady-state simulations. This impact was not very apparent in the pressure signal for very tiny leaks (less than 1 L/min), but it was extremely obvious in the pressure gradient [67]. For several regions surrounding the leak spot, the averaged power spectral density (PSD) and FFT of the pressure fluctuations based on transient Detached Eddy Simulations (DESs) were displayed [67]. An experimental setup has been created and developed to use dynamic pressure transducers based on the findings. The research project's objective was to develop trustworthy and reliable methods for identifying leaks in underground water pipeline networks including both numerical and experimental have been discovered.

The use of ANSYS FLUENT software and a CFD-based technique has been carried out which specialized in researching sub-sea pipeline leakage [68]. The simulation is done by comprehending the internal flow within the pipeline and the effects of leaks. According to the simulation's outcomes, the flow rate of the escaping fluid increased as the operating pressure of the pipeline rose [68]. Additionally, it was shown that high-pressure fluid flows produce more noise than low-pressure fluid flows [68].

2.2.3. Fuzzy Methods

Fuzzy-based methods use fuzzy logic fundamentals and principles to characterize and detect potential leaks. Instead of the traditional "true or false" (1 or 0) Boolean logic on which the contemporary computer was built, fuzzy logic bases computation on "degrees of truth". The truth value of variables in fuzzy logic, a kind of many-valued logic, may be any real integer between 0 and 1. It can handle the concept of partial truth [69] where the true value might vary from totally true to false. In contrast, only the integer values 0 or 1 were permitted as the truth values of variables in Boolean logic [70].

Fuzzy logic is founded on the idea that individuals frequently base their judgments on incomplete and non-numerical information. Mathematical methods for describing ambiguity and imprecise information include fuzzy models or sets (hence the term fuzzy). These models can identify, represent, manipulate, understand, and exploite ambiguous and uncertain facts and information [70]. Many domains, including control theory and artificial intelligence, have used fuzzy logic.

A unique way to identify and treat leakage in the water distribution system by using a fuzzy-based approach has been proposed. Various uncertainties in several water distribution system parameters including roughness, nodal demands, and water reservoir levels have been considered. The degree of membership and severity of leakage have been estimated using monitored pressure in various nodes and flow in various pipes in terms of the index of leakage propensity (ILP) [71]. The closest leaking node or leaky pipe has been located using the degrees of leakage memberships and the ILPs [71]. A leakage detection and locating system has been created using MATLAB based on the presented technique [71]. The investigation demonstrates that the created model can identify the leakage and pinpoint its precise location.

Both hardware and software approaches for leakage detection have seen major advancements in the past. The Table 2 below is a comparison summary that lists the benefits and drawbacks of both methods. The software models are still considerably more affordable to utilize than the hardware-based approaches, which nevertheless have far higher detection accuracy. Effective equipment-based leak detection techniques are expected to undergo further improvement.

Table 2. Comparison of hardware and software-based methods advantages and limitations.

Type	Method	Advantages	Limitations
Hardware	Closed-Circuit Television (CCTV)	• Useful in sewer and storm drainpipes systems [55] • Provide a direct illustration of an image [23]	• High-cost, time-consuming, need experience in labor [10] • Low level of reliability [55]
	Acoustic Emission	• Real-time detection [72] and localization accurately [10]	• Ineffective for large leaks [73]
	Ground Penetration Radar (GPR)	• Can detect leaks in most of the pipe materials [25,55] • High-resolution images	• Type of soil and wetness impact accuracy • Ineffective inhomogeneous soil [49,55] and cold climates [74] • High operational cost [75]
	Fiber optics	• Long distance sensing capability, stability, and corrosion resistant [76]	• Costly and can only be used in linear pipelines [10,76]
	Infrared Thermography	• Low-cost and can be used in real-time application	• The wavelength of IR radiation is Invisible to naked eyes • Weather conditions will impact the accuracy [72] • Need experience and expertise in analyzing IR images [55]
	RFID tags sensor	• Low-cost and long lifespan [59]	• Difficult to detect leaks with thick multi-layer walls [77,78]
	Leak Noise Correlators (LNC)	• High precision [79]	• Cannot be used in plastic pipe [79]
	Tracer Gas Technique (TGT)	• Can detect leaks in pipes of various sizes and materials [79] • High precision [79]	• Costly and depends on the leak location in the pipe [79]
	Pig-Mounted Acoustic (PMA)	• High precision [79]	• The old pipe cannot be used [79] • Water quality issues can arise in indoor pipe access [79]
Software	Negative Pressure Wave (NPW)	• Most suitable for liquid transportation pipelines [10]	• Not suitable for long-range use [10] • The position of the sensors and the size of the leak impact accuracy [10]
	Computational Fluid Dynamics (CFD)	• Ideal for short, straight pipelines [18]	• Difficult to predict the leaks in pipelines [18]
	Fuzzy Methods	• High accuracy and easy-to-interpret outputs [69]	• High computational complexity [69]

3. Processing Methods

Various sensing techniques in water leak detection have been discussed above. All the methods have their own set of advantages and disadvantages according to their own scenarios. This section will explain an alternate way of processing images collected through image processing and machine learning method. It should be emphasized that the approach for object detection and recognition is still a hot topic in image or video processing and computer vision research. Adapting and improving existing image reasoning and computer vision algorithms for water leak detection systems will require further study in the future.

3.1. Imaging Processing

Image processing refers to a method of performing operations on an image in order to obtain an improved image or extract relevant information from it. It is a sort of signal processing, in which the input is an image, and the output is either that picture or its characteristics by using a digital computer to run an algorithm on digital photographs. The goal of early image processing was to enhance image quality. The input of image processing is a low-quality image, and the output is a higher-quality image. Image processing methods include image augmentation, restoration, encoding, and compression. The reason behind this method is an argument that a picture includes a tremendous amount of information, and image processing consists of extracting that information, which might range from object quantification to higher degrees of processing. All this progress is attributable to the continuous growth of technology in computer science, particularly with the advancement of artificial intelligence.

In the water leak detection methods, the use of the image processing technique purposely highlights the region of interest of an image, where the leak occurs. The q-sigmoid function is one example of a digital image processing alternative to the pre-processing phase [79]. A q-sigmoid function is a continuous non-linear function, where it is employed when the reflectance of the areas under investigation is known [79]. The q-sigmoids are used in the image processing algorithm core, and the results are compared to the original sigmoid functions as well as two additional well-known picture enhancing methods, i.e., slicing and histogram equalization. This non-linear function may adjust reflectance values to increase contrast smoothing performance and may serve as a differential in designated regions of interest [80]. This function is presented in Equation (1):

$$f(x) = (Max - Min)\frac{1}{1 + e^{-\lambda x}} + Min, \tag{1}$$

where $(Max - Min)$ refers to the total reflectance in the image, and λ value is based on q-exponential distribution.

A derivation of q-exponential function from the Tsallis entropy was proposed by using q-exponential distribution and such as $x \geq 0$, as shown in Equation (2):

$$I(x, y) = \frac{L}{1 + e^{-\lambda(\frac{I(x,y)-\beta}{\alpha})^2}}, \tag{2}$$

where L is the maximum luminance, β is input image, and α is the luminance to its surrounding.

The use of Equation (2) is to improve the contrast enhancement to a known luminance $\beta \in (0 : L)$ within a range $\alpha \in (0 : L)$. Figure 7 illustrates the usage of parameters β and α [81]. The top row represents the input image, while the output is shown in the bottom row, with a neighboring enhanced region $I(x, y)$ [81]. Furthermore, the q function is used to fine-tune the image processing methods.

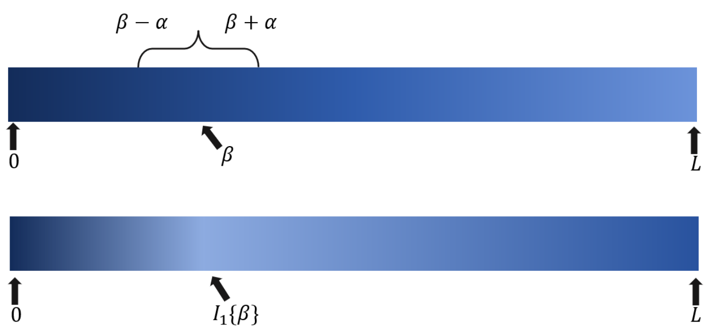

Figure 7. The improvement of the contrast image in the bottom row is demonstrated via luminance transformation using the sigmoid function [79].

3.2. Machine Learning

Machine Learning has emerged as one of the most game-changing technological advancements of the previous decade since it is one of the most effective methods for automating the process of recognizing patterns in data and then dealing with them to complete specific tasks. Machine learning is assisting businesses in accelerating their digital transformation and ushering in an era of automation. Machine learning algorithms could improve through training by forecasting new output values from past data as input. In addition, there are three types of machine learning algorithms for leak detection now available, i.e., supervised learning, unsupervised learning, and reinforcement learning, each with its own set of advantages and drawbacks. Due to their high degree of dynamicity and adaptiveness, these algorithms have been proposed in the literature to identify water leaks. They allow systems to "learn" without being taught what to do. This section will go through a few machine learning algorithms that are currently being applied in water leak detection research.

3.2.1. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a type of supervised machine learning algorithm that may be used to solve classification and regression problems. This model can handle both linear and non-linear problems and is useful for a wide range of applications. The basic concept of the SVM is that the algorithm generates a line or hyperplane that divides the data into categories from the nearest point with the greatest margin [69]. In addition, this linear model has been presented as an efficient leak detection approach employing data acquired by many types of sensors, ranging from optical signals to pressure sensors and flow sensors, due to its adaptability and classification accuracy compared to other classification techniques [82].

An unsupervised learning method called one-class SVM (OCSVM) has been utilized to find outliers in acoustic data obtained from a test bed in a lab. The system's accuracy at detecting leaks was 97 percent [83]. On the other hand, a multiclass SVM (MSVM) has been employed as a supervised method to separate six groups based on the presence and types of leaks: normal, abnormal, break or burst, major leak, moderate leak, and minor leak [84]. Two case studies have been provided and employed M-SVM for leak detection with pressure data [85]. K-means clustering was used in Case 1 to separate the water distribution networks into several leaking zones. A hydraulic model was then used to produce the training sample. A leaking zone was discovered using the M-SVM as a leakage identification model. With a short data set, the technique proved effective at recognizing nonlinear, high-dimensional patterns. To increase the efficacy and efficiency of leakage detection for big water distribution systems, Case 2 merged the prior approach with pressure-dependent leakage detection (PDLD) [85].

Besides, SVM was also evaluated in the leak detection methods random forest, decision trees, and neural networks [86]. These systems use wireless sensor networks and the internet of things (IoT) to gather flow data and evaluate it with analytical algorithms. The acquired findings demonstrated that random forest gave the greatest accuracy, at around 75 percent, whereas SVM delivered the poorest accuracy in practically all tests, at best 57 percent [86]. These findings were in contrast to another research study, which used SVM to assess gathered water flow data using a comparable technique and achieved 92 percent accuracy [87]. The disparity between the test environment circumstances and the system creation parameters may be the root of this large difference. The SVM technique generates alerts more quickly than an ANN system. The fundamental advantages of SVM are that they offer an ideal classification solution by maximizing the margin of the decision boundary and eliminating the dimensionality issue and no explicit statistical model is needed [37].

An SVM learning was combined with the Relevance Vector Machine (RVM) pattern recognition algorithms to develop the hyperplanes and classified the leakage by using binary and multi-class classification [88]. A steel pipe with a length of 2000 mm, an internal diameter of 254 mm, and a thickness of 5 mm was used in an experiment [88]. The findings of the study showed that the SVM and RVM enabled AE characteristics may be used to successfully identify and localize pipeline leaks [88].

3.2.2. Kalman Filtering

Another machine learning technique that is used in leak detection methods is Kalman Filtering which is also known as Linear Quadratic Estimation (LQE). By estimating a joint probability distribution over the variables for each timeframe, the algorithm used in statistics and control theory uses a series of measurements that are observed over time, including statistical noise and other inaccuracies, to produce estimates of unknown variables that are typically more accurate than those based on a single measurement alone. In addition, Kalman filtering is a time series analysis technique that is commonly used in fields like signal processing and econometrics. One of the crucial components of robotic motion planning and control is the utilization of Kalman filtering for trajectory optimization. Modeling the regulation of movement by the central nervous system may also be done using Kalman filtering. The use of Kalman filters offers a realistic model for estimating the present state of a motor system and delivering updated commands because of the latency between issuing motor commands and receiving sensory data.

In a linear dynamical system that has been disturbed by Gaussian white noise, a Kalman filter is a technique that estimates the state [37]. In a linear stochastic system, the filter is employed to reduce covariance error [37]. The benefit of a Kalman filter is that it can tolerate data with significant uncertainty and frequent noise. For nonlinear systems, the Kalman filter has an expanded form. An algorithm for automatically detecting bursts of flow and pressure data using the Kalman filtering technique has been figured out. To identify unusual water user patterns, the filter's residual was defined as the difference between the measurement of the filter outputs [89]. By computing the residuals of the filter, which represent the discrepancy between the projected flow and the actual flow, this approach may estimate the leakage rate. That investigation demonstrated the computational efficiency, quick detection, and lack of need for vast data sets of the Kalman filter [37]. In contrast to quick bursts, it was less effective in detecting long-term persistent leakage [37]. The detection state estimator and the Kalman filter were contrasted. They claimed that the detection state estimator provided more accurate results [90]. A fracture detection approach based on the normal residual, moving average of the residual, and normalized moving average of residual indicators of residual flow/pressure was introduced. They noted that when it came to leakage identification, flow-based indexes outperformed pressure-based indexes [91].

3.2.3. K-Nearest Neighbors (KNN)

K- Nearest Neighbors (KNN) is a supervised learning classifier that employs proximity to produce classifications or predictions about a group of a single data point. This algorithm believes that related objects are located nearby. In other words, related objects are located close to one another. It is straightforward to implement.

KNN can be called a lazy learner as it does not go through a learning period like other AI algorithms [37]. This approach has been utilized in finding leakage and calculating their sizes using data from the measured pressure waves method (NPW). Two different classification methods were used which are a binary classification with leak and non-leak classes, which had an accuracy of 78.51 percent, and a five-class-based technique for estimating sizes, which had an accuracy of 90.1 percent [92]. On the other sides, the KNN algorithm also has been integrated with the binary relevance approach and the pressure data has been analyzed in order to identify and find leaks in real-time. To provide independent predictions for each label, this modification of KNN conducted a single search of the k's nearest neighbors [93]. This approach proves a better result and speeds up response time when compared to a single KNN algorithm. Next, the leak detection performance of KNN, random forest, and Bayesian network methods have been evaluated by using the flow data gathered from a pipeline network. Numerous test situations revealed that the naïve Bayesian and random forest models produced the best outcomes [94]. It was interesting to see that the amount of leaks in the training data had a direct impact on KNN performance. As a lazy learner, the KNN method does not require any training and is simple to use. It is, nevertheless, quite sensitive to noisy data.

3.3. Deep Learning

Deep learning is a subset of machine learning that instructs computers to learn by doing what comes naturally to people. These neural networks try to mimic how the human brain functions; however, they fall far short of being able to match it, enabling it to "learn" from vast volumes of data. Learning can be either fully or partially guided. A computer model learns to carry out classification tasks directly from images, text, or voice using deep learning. High precision may be acquired by deep learning models, sometimes even outperforming human ability. A sizable collection of labeled data and multi-layered neural network architectures are used to train models. Few neural networks will be further discussed in this section.

3.3.1. Artificial Neural Network (ANN)

A neural network is a machine learning technique that uses a neuron model as its foundation. The human brain has millions of neurons. It sends and receives information via electrical and chemical impulses. Synapses are the structures that link these neurons together. Neurons interact with one another through synapses. Neural networks are formed from a huge number of simulated neurons. Artificial Neural Networks (ANNs) are a well-known supervised classification approach of machine learning method that will be examined in depth in this paper. An ANN is a type of data processing system. It works in the same way as a human brain does [95]. It is made up of many interconnected processing units that collaborate to process data. As indicated in Figure 8, it has three layers, i.e., an input layer, a hidden layer, and an output layer.

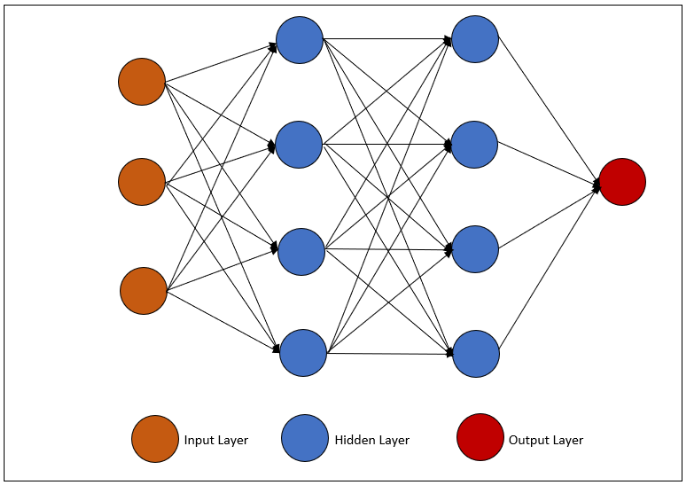

Figure 8. ANN architecture which consists of three-layer : Input Layer (orange color), Hidden Layer (blue color) and Output Layer (red color).

The use of an ANN algorithm in a data-driven machine learning model to detect a leak in a water supply network using sensor data servicing a District Meter Area (DMA) was investigated. Both models, which needed balanced or imbalanced datasets, were shown to produce acceptable results. The author emphasized that the 11 monitored nodes of the ANN model were represented by 11 neurons in the input layer. The first hidden layer has 128 neurons, followed by the second and third hidden layers, each with 258 neurons. An ANN was discovered to have a high level of accuracy for testbed WSNs in both non-leaky and leaking situations. However, a balanced dataset with an equal quantity of data in both settings was needed. Thus, the Autoencoder Neural Network (AE) model was an unsupervised ANN model that learns from imbalanced data to categorize leaking and non-leaking circumstances were introduced. The findings show that AE was able to detect leaks with reasonable accuracy. The fundamental drawback of ANNs is that their success depends on a wide range of variables, including the size of the training data sets required, the complexity of the computation, and the number of parameter tunings [37]. In reality, statistical analysis forms the basis of the ANN forecast. The effectiveness of these approaches will typically suffer when the size of the training samples is minimal [37]. It can only produce good results with huge training sample sizes [37]. The amount of the training samples does, however, affect how long an ANN takes to learn. Additionally, if a water system's physical characteristics change, ANN needs to be retrained and when sensor data is noisy, ANN accuracy suffers. Therefore, there is no way to reduce ANN faults.

3.3.2. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are another machine learning based leak detection method. A CNN is a type of deep neural network used to evaluate visual images in deep learning in the sense that it consists of artificial neurons with biases, weights, and activation functions [96]. These neurons are mathematical functions that provide weighted outputs for any dataset depending on a collection of inputs [96]. A mathematical technique called convolution takes two functions and produces a third function that describes how the structure of one is altered by the other. At many levels, CNN models perform a spatial breakdown of input pictures using alternate convolutional and pooling layers for pattern identification.

Translation invariant neural networks include convolutional neural networks (CNNs). As a result, they produce positive outcomes for grid-structured topologies, such as for two-dimensional (2D) data (images) [37]. Convolutional layers for extracting image features and fully connected layers (dense layers), which employ the output of the convolution process and classify the images using the features gathered in the earlier phases, make up the majority of the CNN architecture [37]. With the use of a water distribution network's sensory input, CNNs are used for leak detection. When the input is a single sensor reading, the data can be categorized as one-dimensional data or as two-dimensional data when the input is a temporal window of the sensor reading. The CNNs pick up on the regional similarities in sensor inputs and take into account the leak as a difference in sensor readings that result from a change in flow or pressure.

It is feasible to pinpoint the location of a leak in an underground pipe based on the temperature variation of the soil that comes into touch with the leaking water. Thus, a CNN model was derived from a pre-trained AlexNet network in utilizing vibration data gathered from an experimental pipeline test bed. The architecture of AlexNet is illustrated in Figure 9. 80 percent of the total 9000 photos are classed as training data (288 images per scenario), 18 percent as testing data (65 images per scenario), and 2 percent as prediction data to train and verify the CNN model (7 images per scenario) [96]. The experimental results showed that the CNN model was demonstrated to have 95 percent accuracy in detecting leaks in Polyvinyl Chloride (PVC) pipelines [96].

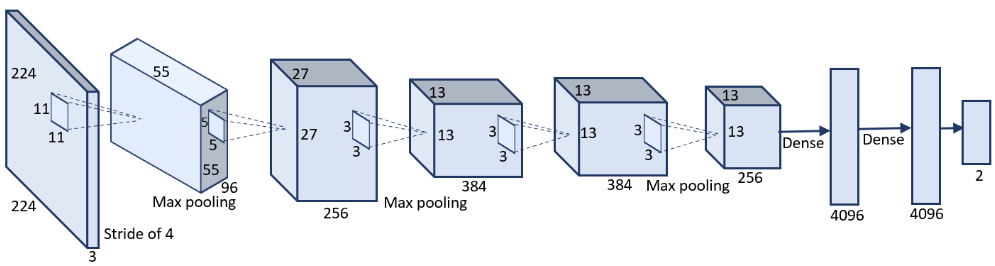

Figure 9. A pre-trained AlexNet CNN detail structural framework layers [97].

Similar to this, the used of hydroacoustic data in conjunction with 2D-CNN and a variational autoencoder (VAE) to identify abnormalities in a laboratory test bed has been discovered. Convolutional layers and max pooling layers driven by the VAE made up the encoder network [98]. The reverse design of the encoder network served as the basis for the decoder network. This method identified a 0.25 L/s leak with 97.2 percent accuracy [98]. CNN is also being applied as a physics-guided neural network (PGNN) to classify satellite photos and find leaks in canal sections. In fact, environmental factors such as soil moisture [temperature/vegetation dryness index (TVDI)], fractional vegetation cover (FVC), and land surface temperature (LST) were used to assess the status of canals [8]. In order to categorize the canal portions into leaking and nonleaking parts, these properties were calculated and used as CNN's input features.

4. Discussion

Although improvements in leak detection research have accelerated in recent years, leak detection is not a new area of study. The dangers posed by pipeline breaches piqued researchers' interest in discovering dependable and rapid remedies to address leaking problems. This review aims to acquire a perspective on the scientific work on leak detection in pipelines that have been studied. Various hardware and software water leak detection methods were covered in the previous sections. In this section, the advantages and drawbacks of such strategies will be discussed.

CCTV techniques are useful in sewer and storm drainpipes systems and mainly being used in repairing water mains [55]. It can provide a direct illuminated image from the installed camera [23]. On the other side, the traditional visual inspection method using CCTV has its own set of restrictions. This leak detection method can be considered expensive, time-consuming, labor-intensive, and has a low level of reliability [55]. The accuracy of the method is determined by the users' prior experience [10]. Commercially available CCTV systems provide a variety of options. Inspection findings are now interpreted manually, but machine vision approaches are expected to be developed in the future [25]. Defects or deficiencies can be coded, awarded scores, and monitored to offer a view of the pipe's overall condition.

GPR technologies have been extensively researched since the 1970s for several applications, including environmental and agricultural monitoring, as well as glaciological monitoring. GPR can detect leaks in deep groundwater pipelines by detecting underneath voids formed by leaking water or by identifying anomalies in the depth of the pipe when the radar propagation velocity varies due to leaking water saturation. Most pipe materials, including concrete, stone, plastic, masonry materials, wood, and various ceramics, can be utilized without restriction in terms of size and kind [25,55]. The capabilities of GPR reportedly include high-resolution images with non-contact nature. On the other hand, this technology has several drawbacks, including the fact that the type of soil and its wetness could impact the accuracy of leak detection, and it is ineffective in inhomogeneous soil applications [49,55]. It cannot be used in cold climates either [74]. Also, because a wide spectrum of frequencies is required to pinpoint precisely where the leak happened, this method is costly. The acquired results are difficult to interpret [75]. As a result, GPR systems require further assistance in the form of decision support systems and competent algorithms that enable quicker and more accurate leak identification.

A leakage detection technique using acoustic emission enables to detect leaks in real-time with great accuracy in detection [72] and localization [10]. Acoustic emission-based technologies have been employed in a wide range of pipe system applications. Background noise from the surroundings [99], as well as those types of pipe materials and pipeline sections [72], has a significant impact on acoustic signals. When it is used for short-range pipelines, this approach offers the benefits of high detection and localization accuracy. However, the system requires a high number of sensors for longer pipeline applications [10], and this technique is ineffective for large leaks [73]. On the other hands, fiber optics applications can detect and locate leaks with great accuracy [100]. It has a long-distance sensing capability with multiple measurement points provided by a hone optical fiber line, which is immune to electrical noise. Also, it has long-term measurement stability, and is corrosion resistant [76]. This technique, however, is costly and can only be used to keep track of linear pipelines [10,76].

The rapid response rate of IR sensors makes them appealing for real-time applications. Furthermore, environmental elements, such as temperature, sound, and humidity, have little effect on them. IR sensors are frequently used since they are also cost-effective. It can be used at any time of day or night, and it does not matter what kind of pipe it is or how big it is. These benefits make the employment of an infrared camera possible, overcoming the constraints of conventional leak detection technologies. IR water leak detection approaches, on the other hand, are based on the detection of thermal anomalies in a scalar IR picture taken at a certain moment. Despite the benefits of scalar IR, the detection accuracy was poor due to false positives caused by other thermal anomalies, such as shadows. The wavelengths of IR radiation are invisible to the naked eye. The soil wetness [49] and weather conditions [72] will impact the accuracy of thermal sensor functionality. Thus, analyzing the image is also necessitates at a certain level of experience where the use of image processing and machine learning techniques is included [55].

With the rise of "Smart Cities," one of whose goals is resource management, these problems have grown increasingly common. Technologies like the Smart Water Grids outlined in allow for the efficient and dynamic regulation of water utilities in order to address these problems [101]. For the water distribution system, these technologies increase leak detection, maintenance, and network sensing. However, these Smart Water Grids would require an initial investment as well as damaging methods to access the water distribution networks and perform the necessary alterations [101]. These requirements make it hard to adopt these systems since several economies throughout the world lack infrastructural investments. This idea may be essential for controlling water supplies in smart cities, especially in places with low technology investment. It is conceivable to use these IR methods with drone applications by using a tracking algorithm to carry out an automated system [79].

Next, RFID tag sensor is a well-known low-cost passive RFID chip [59] with a sensor data input port technology that has a lifespan because no internal power supply is required. This technique with basic one-layer antennae is highly dependent on the surrounding environment, particularly close metallic objects and water [77,78]. It can be difficult to detect a moisture measurement precisely in some settings, especially those with thick multi-layer walls.

Three main groups of leakage pinpointing methods that have been discussed earlier are based on Leak Noise Correlator (LNC), Tracer Gas Technique (TGT), and Pig Mounted Acoustic (PMA) methods. For LNC techniques, the technology cannot be applied to plastic pipes [79]. In order to improve this, smaller distance sensors must be used, along with slow turns [79]. The helium detection method is effective for detecting leaks in pipes of various sizes and materials. However, TGT technology is costly and may not always work depending on where the leak is in the pipe [79]. Besides, for PMA technology, old pipes cannot be used with this technique since corrosion prevents their use [79]. The pipe must be clean. Likewise, water quality issues can arise with indoor pipe access. Even though those three methods are the most precise technologies in leak detection, these approaches have very high costs in terms of equipment ownership or rental, as well as the man-hours required to conduct surveys [79].

Table 3 summarizes several key performance comparisons that may be capable of analyzing or monitoring water leakage. The advantages of the techniques are noted, as well as technical problems and potential solutions. Because the approach was designed for diverse practical circumstances, such as different types of pipe materials, different utility types, different soil conditions, and different ground surfaces, the advantages of one technique may well correlate to the downsides of another technique. The collection of various approaches allows us to make our own decisions, but in certain cases, one technique is insufficient to offer satisfactory inspection findings, and other techniques must be used.

Table 3. Key performance summary of sensing technology in water leak detection method. "/" and "X" indicate the advantages and disadvantages of the method, respectively.

Method	Performance			
	Low Cost	Easy Installation	High Accuracy	Fast Response Time
Closed-Circuit Television (CCTV)	X	X	/	X
Acoustic Emission	X	/	/	/
Ground Penetration Radar	X	/	X	X
Fiber optics	X	/	/	/
Infrared Thermography	/	/	X	/
RFID tags sensor	/	/	X	/
Leak Noise Correlators (LNC)	X	X	/	X
Tracer Gas Technique (TGT)	X	X	/	X
Pig-Mounted Acoustic (PMA)	X	X	/	X
Negative Pressure Waves (NPW)	/	/	X	/
Computational Fluid Dynamics (CFD)	/	X	/	/
Fuzzy Methods	X	X	/	/

Moving on to software methods that were previously described, some pros and cons of the suggested method will be further discussed below. In NPW methods, it is challenging to identify the leak's source since junctions, nodes, and bends have an impact on the reflected waves. Systems that don't account for pipeline inventory always result in significant leak location errors. The fact that the reflected wave approach can only be applied to pipelines in series is another drawback. Another significant drawback is the huge number of false alerts it generates [11]. Large pressure drops are typically seen when pipes are operated transiently, such as when valves are opened and closed [11]. As a result, an NPW technique classifies this as a leak event and issues a false alarm [11]. An effort in improving the NPW method was conducted. Data quality, adaptive thresholding, and false alarm reduction are the three key areas applied to enhance the reliability and accuracy of this technique [102]. Besides, the author created an NPW-based technique that uses the NPW's attenuation to find leaks [102]. As a result, the authors created a model to locate the leak that uses the pressure difference rather than the time difference. The suggested NPW-based method's accuracy was demonstrated by the authors' trials, which revealed that it detected and localized pipeline leaks with an average error of 0.355 to 1.161 percent [102].

Next, the inability to detect pipeline leaks is one drawback of the CFDs approach [18]. The approach does a good job of supplying an analytical model to describe the magnitude and location of the leak, but the key difficulty is fitting this model to the data that is gathered. Therefore, this approach is better suited for short, straight pipelines where a visual examination may be quickly carried out based on the data gathered [18]. Besides, although fuzzy approaches tend to have significant computational complexity, they tend to have high accuracy and straightforward results [11]. More specifically, depending on the number of inputs, outputs, and produced rules, different stages of fuzzy-based systems may exhibit quadratic complexity. When taking into account neuro-fuzzy systems, which have the added complexity of the classification approach employed, this is further made worse [103,104]. As a result, these approaches are challenging to process, especially when dealing with huge datasets, as is clear from the fact that the training has to be done offline [105].

Water leak detection approaches based on local sensors or systems are still effective in terms of detection accuracy, but they are more expensive to set up and operate than mobile systems, such as unmanned vehicles. Besides being low-cost, these vehicles have the flexibility to access every corner of the building and to examine the building conditions using onboard sensors. Nevertheless, computational efficient algorithms need to be investigated so that the water leak detection with mobile systems could be useful in smart building applications. Table 4 summarizes several key performance comparisons of algorithms used that may be capable of analyzing or monitoring water leakage. These techniques greatly outperformed conventional techniques for anomaly detection applications, notably in terms of accuracy and speed. By using various methods, this science was afterwards widely advocated in the literature for the problem of leak detection.

Table 4. Performance summary of algorithms discussed in water leak detection method. "/" and "X" indicate the advantages and disadvantages of the algorithm, respectively.

Algorithms	Method		Performance			
	Classification	Prediction	Large Data Sets	Easy Implementation	Fast Detection Time	Sensitive to Noise Data
Support Vector Machine (SVM)	/	X	X	/	/	/
Kalman Filtering	/	X	X	X	/	X
K-Nearest Neighbors (KNN)	X	/	X	/	/	/
Artificial Neural Networks (ANN)	X	/	/	X	X	/
Convolutional Neural Networks (CNN)	/	X	/	X	X	X

"Buildings that use building technology systems to enable services and the operation of a building for the benefit of its occupants and management" are the terms used to describe the smart buildings [106]. For example, they handle practically everything with the Internet of Things (IoT) sensors, raised floors, and building automation, including Heating, Ventilation and Air Conditioning (HVAC), lighting, shading, security, and even user-centric tasks like wayfinding and meeting room booking [107]. This research focuses a significant emphasis on sensor-actuator applications in intelligent buildings, as seen in Figure 10. The use of smart building technology tries to adapt existing buildings to be more energy and water efficient, with the aim of providing an environment for living and working that consumes fewer resources and produces less waste [108].

Water can be considered as one of the most precious and necessary goods on the planet. The fact is that it might be both unanticipated and harmful at the same time. One of the biggest fears for facility managers and property owners is water damage [109]. Each occurrence poses a hazard to the furnishings, electronics, and building structures, and is followed by high repair and cleanup expenditures [109]. The harm is more severe the longer it takes to find the leak. Early-stage water leakage can be exceedingly difficult to find in multi-story buildings and huge industrial complexes, especially if it happens in cabinets or secret places. Frequently, an incident stays unreported for days or even months before significant harm is apparent. It would be exceedingly expensive and challenging to repair the damaged structure at this time. Fortunately, automated, remote water management methods made possible by IoT and smart building technology are providing facility managers with peace of mind.

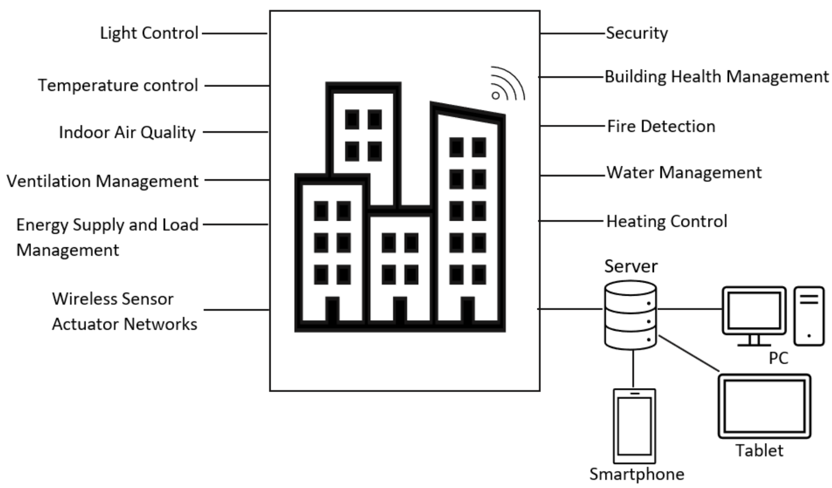

Figure 10. The elements should be included in a conceptual illustration of an intelligent building [6].

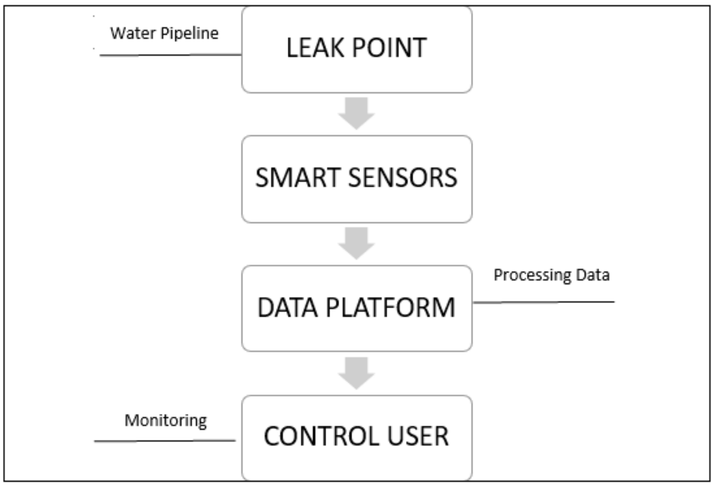

Figure 11. The development of water leak detection techniques using Internet of Things (IoT) technology and smart building sensors [6].

According to the definition of smart buildings, the structures should be controlled by users and monitored to maximize energy usage, comfort, and carbon emissions [110]. The flow chart in Figure 11 shows the relation from discussed water leak detection method that can be applied with the smart building as an application in the monitoring system. The sensor should be designed in a way that can relate to a smartphone, tablet or computer, or any device that enables the user to track the system. It will give an alert to the user either by notification or alarm to send the signal if the device detects any water leaks that occur so that the user can act. This idea puts the user in control of what's going on in their buildings/homes. A leak detection system that protects buildings from one of the most common and costly damages that tend to occur. A plumbing leak is more likely to damage our buildings than fire, lightning, or burglary as it would cost a lot of loss either in terms of money or damages. In addition to severe weather conditions like storms and floods, broken pipes and malfunctioning plumbing systems are among the most frequent causes of water damage. Corrosion or excessive water pressure are frequent causes of bursts. Water within pipes may readily freeze into ice in places with harsh winters, expanding in volume and putting too much strain on the pipe. With the invention of this kind of monitoring system in smart buildings, lots of benefits can be achieved both for the user and property owner.

5. Conclusions

This paper conducted a comprehensive review of current water leakage detection approaches, as well as research advancements in this field. This survey shows that existing leakage detection technologies have varying accuracies, implementation costs, and application contexts. However, integrating multiple leakage detection technologies to create a hybrid system is a frequent practice that is advised. The existing approaches can identify burst-type leakages to some extent, according to the review. The water leak detection method is a developing study subject driven by the importance of conserving valuable resources and avoiding the consequences of leakage. Early identification of leaks can avoid large gas spills, water seeping into the soil beneath roadways causing sinkholes, infrastructure damage, damage to the surrounding environment or people, and financial loss.

The conversion to smart buildings is crucial for the development of commercial structures like factories or shopping complexes. A significant amount of money will be saved by the organizations as a result of enhanced effectiveness and better building operation. The IoT has created an entry to assist in the management of such buildings. Sensible Buildings and sensible cities region unit ceaselessly remodeling activities meted out by folks on each day. Smart cities will soon emerge with services such as temperature management, water management, disaster management, machine failure management, and lighting facilities which in turn are connected to the internet/cloud facilities. In today's comparison, some cities have started enforcing this kind of smart management approach by conjunction everything about the community with the internet. Along with energy conservation, smart buildings aid to save money.

The difficulty of reliably transmitting the readings of these hardware-based sensors from an underground sensor node to a distant control or admin center remains unsolved. Numerous studies have highlighted the significance of continued pipeline leakage detection and diagnostic research. In general, the literature on leakage detection and diagnosis accepts that there are many unknowns and that a viable leakage detection approach has yet to be developed. Multiple new technologies are being used to study quicker and more competent features of leak detection in pipelines, which are developing in terms of technology usage. The profession is likely to expand as the need for gas and water network infrastructure grows. Access to networks and chances for field studies could improve as researchers form new relationships with municipalities and private engineering firms. Future experiments will be documented, which will be a valuable contribution to the literature. Only time and persistent work will allow a full picture of transitory approaches potential and capabilities to emerge.

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