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(Review Article)

A systematic review of machine learning and signal processing techniques for water pipe leakage prediction

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Abstract

The efficient management of water distribution systems is a critical global challenge, primarily due to the escalating volume of Non-Revenue Water (NRW) caused by undetected pipe leakages. This systematic review explores the integration of machine learning (ML) and signal processing (SP) techniques as a robust solution for leakage prediction, viewed through the interdisciplinary lenses of electronics engineering, instrumentation, and computer programming. Following a thematic and regional framework, the review analyzes technical, economic, instrumentation-based, and operational barriers hindering the adoption of these smart technologies. A systematic search of literature from 2017 to 2026 was conducted using databases such as IEEE Xplore, ScienceDirect, and Google Scholar, focusing on the synergy between hardware prototypes and software algorithms. The findings reveal a complex interplay of barriers: technical challenges involve signal attenuation in non-metallic pipes and the need for noise-resilient filtering; economic constraints stem from high capital costs of high-fidelity sensors and regional socio-economic disparities; and programming barriers include the computational demand of deep learning models on embedded edge devices. Regional analysis highlights significant disparities, with high-income regions advancing toward digital twins while developing regions in Africa and Asia utilize low-cost, open-source rapid prototyping. The review concludes that the future of leakage prediction lies in the standardization of low-cost instrumentation and the deployment of "TinyML" for real-time edge analytics to ensure global water sustainability.

Keywords: Machine Learning; Signal Processing; Water Leakage Prediction; Instrumentation and Control; Rapid Prototyping; Non-Revenue Water (NRW); Edge Computing

1. Introduction

Life needs water. That fact stands clear across farming, cities, and peoples. Lately though, warnings about shortages have grown louder - climate shifts mix with crowded regions, pressing harder on supplies. One major issue hides underground: huge amounts of clean water vanish inside pipes before anyone uses it. These losses go by a name - Non-Revenue Water - and most stem from cracks and breaks that escape notice. Leaks creep through aging lines, wasting flow day after day. Reports show more than 126 billion cubic meters disappear each year globally [1]. Close to 39 billion dollars in damage recorded among providers everywhere [2]. Pipes that lose water don't just drain budgets; slow drips can poison underground supplies, worsen local shortages. Better sensors help countries brace systems against growing needs, cutting harm to nature along with costs.

Even though strong water systems are essential, old ways of checking pipelines come with serious problems. Leak spotting used to depend on slow, hands-on approaches. Workers would move across pipes using handheld devices that

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pick up sound, searching for the faint noise of water escaping. These tools work better when surroundings stay still and silent. Yet they often fail because people make mistakes or outside noises get in the way. City streets hum with sounds, cars, machines, and crowds that drown out faint clues of early pipe leaks. Because of this noise, small problems stay quiet too long. Workers checking by hand cannot watch every hour, so flaws grow unseen beneath the ground. Months may pass before cracks show above. By then, the harm below is already deep.

Now machines watch pipes nonstop, thanks to fresh paths carved by electronics and control engineering. Because the internet connects almost everything, sensors spread far and wide without needing people nearby [3]. Right against metal surfaces or inside moving water, tiny smart devices catch vibrations, sound shifts, pressure jumps. These gadgets respond fast, built using micro parts that feel even slight shakes. What made this leap possible? Faster trial methods in building hardware. Instead of long waits, teams print circuit shapes, mold boards just right, adjust on the fly, each round smarter than last. Custom gear shows up where it's needed most, sipping power while staying alert. Progress here didn’t come from one big jump but many small tries stacked tight [4].

Just putting advanced electronics into place isn’t enough. What pours out - endless streams of tangled data - quickly becomes unmanageable. Sounds and shakes recorded outside controlled labs come blurred, shifting unpredictably over time. On top of that, today’s pipelines combine materials like cast iron with plastics such as PVC. When sound travels through plastic sections, it fades fast, making older listening methods useless [5]. Nowadays signal processing methods are essential. Because of this, tools like Fast Fourier Transforms show up inside sensor software more often. Instead of ignoring interference, these systems use math such as Continuous Wavelet Transforms to separate weak signals. Even messy inputs get cleaned by techniques including Empirical Mode Decomposition. While working through layers of sound, they spot patterns tied to leaks. Each step pulls sharp details from unprocessed readings [6, 7].

From spotting leaks to foreseeing broken pipes - coding smart systems changed how we handle water networks. Between 2017 and 2026, using AI in managing water surged forward [8, 9]. Instead of just reacting, computers now anticipate problems by reading cleaned-up signals from sensors [10]. Tools like SVM, RF, and ANN learned the difference between usual glitches and real leaks - with strong results. These patterns? They emerged through guided training on past examples. Lately, CNNs took it further: trained to interpret sound images, they spot leaks with over 95% precision, even where pipes mix materials. What once seemed distant is now routine in modern setups. That shift didn’t happen overnight - it built step by step.

Even with progress in tech, using combined machine learning and signal processing to predict leaks looks very different depending on where you are. Across Europe and North America, strong government backing helps power modern grid projects that include smart forecasting tools [11]. Yet places like much of Africa and South Asia face older pipes, inconsistent water flow, and tight budgets. Equipment upgrades often fail there - upfront prices scare off investment, testing new designs locally rarely happens, skilled coders remain scarce [12, 13].

Earlier studies on leaking water pipes usually looked at just one side - like how pipes wear out physically, or how well computer programs detect leaks in test environments. Yet most overlooked a broader view combining both physical systems - sensors and circuits - with coding and data handling. What changed lately is speedier onboard computation plus energy-efficient quick development tools spreading fast over ten years. Older summaries did not keep up with these shifts entirely. The real picture needs more connection across fields than before.

Looking at research from 2017 to 2026, this review pulls together current findings in one clear overview. Its goal? To examine how machine learning combines with signal processing when predicting leaks in water pipes - seen alongside advances in sensor tools and real-world device design. Instead of just listing methods, it sorts out the main technical, cost-related, and practical hurdles standing in the way. It also compares how different regions apply these technologies, revealing uneven progress across areas. With that picture built, the path forward becomes clearer - not flashy, but grounded - for making water systems smarter on a worldwide scale.

2. Methodology

This study employs a systematic literature review (SLR) approach to evaluate the current state of machine learning (ML) and signal processing (SP) in water pipe leakage prediction. To ensure a comprehensive and multidisciplinary analysis, the review integrates perspectives from prototyping engineering, electronics, instrumentation, and computer programming. The methodology follows a structured protocol of identification, screening, and eligibility to ensure a transparent and reproducible selection of high-quality research.

2.1. Search Strategy and Data Sources

This work uses a careful look through existing studies to check how machine learning and signal processing help predict leaks in water pipes. From many fields - like building prototypes, electronic systems, tools for measurement, and coding - a range of insights come together. Following clear steps to find, filter, then confirm useful papers keeps the process open and repeatable.

2.1.1. Search Approach and Information References

Right off, a step-by-step hunt unfolded inside well-known scholarly libraries online. Not just one spot, but several key sources were tapped into - each holding studies that made waves. From 2017 up through 2026, only work with real weight got pulled out. These places? Major hubs where serious science lives

When it comes to progress in electronic systems, look here first - tools that sense, measure, signals shaped by clever circuits. New ways machines hear, see, react appear through these pages. Hardware evolves fast when ideas spread freely like this. Breakthroughs often start where sensors meet smart design. Signal paths grow smarter each year, quietly changing what devices can do.

ScienceDirect (Elsevier): For comprehensive studies on water management and civil infrastructure.

Start here if your work dives into code-heavy studies, different ways to write programs, or methods that let machines learn patterns - this collection supports deep exploration of such topics through carefully gathered academic material.

Start here if you need hard-to-find research on early design tests. Sometimes buried reports show up through this tool. Not everything lands in mainstream journals, after all. Local trials often leave traces online - this hunts them down quietly.

Words like "climate" mixed with "policy" helped cover main topics. Some phrases used alternatives such as "regulation" or "action" to catch more results. Brackets grouped similar ideas so the system knew what belonged together. A few searches linked concepts through symbols that told the software how items related. Terms were picked based on common usage across reports and papers

a. ("Water pipe" OR "Water distribution network") AND ("Leakage prediction" OR "Leak detection")
b. ("Signal processing" OR "Wavelet transform" OR "Feature extraction")
c. ("Machine learning" OR "Deep learning" OR "Neural networks" OR "Artificial Intelligence")
d. ("Instrumentation" OR "Wireless Sensor Networks" OR "IoT" OR "MEMS")

2.2. Inclusion and Exclusion Criteria

Not every source made the cut. Each of the 110+ references was weighed against clear standards. Only those matching the bar stayed in. Screening happened one by one. What you see passed a series of checks. Focus shaped what counted. Consistency mattered just as much. Some fell out - others held firm. Decisions weren’t random. A pattern guided the choices. Quality came first, always

2.2.1. Inclusion Criteria

Articles from journals that went through expert review. Plus papers shared at top conferences. All came out between 2017 and 2026.

Studies focusing on the integration of hardware (sensors/electronics) and software (algorithms/programming).

Finding proof that shows how well systems spot issues, test models in specific areas, or hurdles faced when rolling out solutions across regions.

2.2.2. Exclusion Criteria

Published pieces earlier than 2017.

Work that looks only at water flow systems or structural design, yet skips any use of sensors or coding elements.

Papers written in languages other than English might miss academic scrutiny. Those without approval from expert review often lack verification through scholarly channels.

2.3. Data Classification and Review

Sorting through what was found meant placing pieces into five separate areas so comparisons could be made

Finding how well filters work when spotting patterns in different kinds of pipes. Some materials change signals more than others, affecting results. Accuracy shifts depending on what the pipe is made of. Each type reacts differently during processing steps. Testing shows variation between methods used so far.

Every gadget's energy use gets checked alongside how well it reacts to changes in its surroundings. Not only that but toughness matters just as much when testing quick-made electronic parts. What counts is seeing how long things last while staying alert to signals. Through each test runs a thread of real-world stress on sensors built fast yet expected to perform. Lasting power meets sharp responses in these small systems made to prove themselves quickly.

Running machine learning on small devices demands speed plus low power use. Efficiency becomes clear when models respond fast without draining resources. Some systems handle live data smoothly, others struggle under load. Performance shifts based on design choices made early. Quick decisions matter most where delays cause problems. What works in a lab might fail outdoors. Size of code affects startup time just as much as memory footprint. Simpler models often outlive complex ones in harsh conditions. Speed tests reveal bottlenecks invisible during training. Real world signals behave unpredictably compared to clean datasets.

One thing matters more than money upfront - how much waste slips away later. Savings pile up when leaks stop, even if gadgets cost extra at first. Money spent early can vanish faster than drips from a pipe left open too long. Equipment that thinks ahead cuts losses most never notice until they’re gone. A heavier price tag today might mean less waste tomorrow. What feels expensive now could balance out once repairs drop off. Tools learn patterns people miss during daily rounds.

Where tech takes root differs widely from one region to another. Across Africa, some areas move fast while others lag behind. In parts of Asia, adoption climbs quickly due to local needs. Europe shows uneven progress despite strong infrastructure. The Americas reveal sharp contrasts between urban and rural zones.

3. Review of related works

3.1. Technical Barriers and Advancements in Signal Processing

A leak detection system works only as well as the signals it handles. Pumps rumble, vehicles roll past, homes draw water - each sound drowns out the faint noise a leak makes. Lately, researchers have turned to detailed wave patterns to untangle that confusion.

Leak signals tend to come and go in unpredictable ways when conditions keep changing, making old-school Fourier methods fall short. Because of this shift, work done from 2017 up until now leans heavier on tools like Wavelet Transform and Empirical Mode Decomposition. Take one example: breaking down sound patterns with Discrete Wavelet Transform helps split them into different ranges so vibrations caused by leaks stand apart from slow-moving ambient hums [14, 15]. Then came Variational Mode Decomposition, which smoothed out the messy overlaps seen before in EMD outputs - especially useful in PVC pipelines where signals weaken fast [16, 17].

One key leap in how signals are handled comes from using Cross-Correlation methods. Because timing differences show up clearly between two detectors placed apart, leaks get located within less than a meter [18]. Thanks to smarter code updates, these systems now pull out leak patterns without needing prior knowledge of surrounding sound clutter [19, 20].

3.2. Instrumentation and Electronics Engineering Perspectives

Years pass. Equipment grows thin, sips power instead of gulping it. Tiny electronics take over where heavy machines once clung. Research shifts - focus lands on smart sensors that wake, listen, report, then sleep again. One charge lasts the whole season. Engineers shape devices meant to stand alone, far from wires or human hands.

One clear pattern across recent papers involves shifting toward Micro-Electro-Mechanical Systems, or MEMS, for sensing. Because they differ from conventional piezoelectric hydrophones, these tiny accelerometers save money while fitting smoothly into fast-made housings [21]. Their strong responsiveness along with a broad range of detectable frequencies has drawn attention - researchers point out this helps catch faint pressure shifts tied to minor leaks before they grow [22, 23].

New steps in prototyping let engineers build special printed circuit boards with circuits that wake things up. Only when shaking passes a set level does the sensor turn active, staying off most times [24, 25]. This quiet mode helps devices last much longer out where they are used. Smart computing built into small chips now handles early data work right inside the device [26, 27]. Because of this shift, sending information through air uses far less power. Wireless signals go out rarely, carrying just what matters after local sorting. Energy drops sharply - by around seventy percent - when raw noise stays behind. Processed snippets move instead of constant streams from distant spots.

3.3. Computer Programming and AI Integration

A shift is happening in how water systems respond to changes - prediction now takes the place of old alarm triggers. When it comes to coding solutions, the real test becomes balancing precision with speed so programs work well on small devices or inside online tracking interfaces.

3.3.1. Classical Machine Learning Models

Out of older alarm systems came smarter ways to guess water leaks before they grow. Code written for tiny computers or online displays must work fast without slowing down. From one decade to the next, basic machine learning stuck around because it shows its reasoning clearly while asking less from processors than complex neural nets. Take SVM, RF, or KNN - each sorts noise from real problems using number patterns pulled earlier from raw signals. Building these tools means shaping data carefully, feeding them things like average power, spike sharpness, or peak ratios [28]. You see random forests doing especially well when pressure jumps unpredictably across city pipes, correctly labeling events most times [29, 30]. High scores appear again and again in tests, often past ninety percent right calls [31, 32].

3.3.2. Deep Learning and Neural Network Architectures

Deep learning sparked major shifts during these years. What sets it apart from traditional machine learning lies in its ability to pull out layered patterns straight from unpolished inputs. Structures such as convolutional neural networks do this by stacking detection levels without human tagging. Meanwhile, long short-term memory systems handle sequences by remembering past bits when needed. These designs skip manual feature crafting through smart internal adjustments [33].

Pictures made from sound help computers spot hidden leak signs, much like eyes spotting cracks unseen before[34]. Instead of snapping quick glances, some systems track pressure changes over days using smart loops that remember past moments well enough to catch tiny seepages growing quietly beneath surfaces[35, 36]. Yet stuffing those brainy setups into small chips often fails - too bulky, too hungry for space most everyday circuits simply do not offer [37].

3.3.3. Coding for edge devices and live data systems

Out here, where smart systems meet tiny circuits, Edge AI is picking up speed. Instead of heavy software, stripped-down machine learning models run right inside sensors. Tools like TensorFlow Lite or MicroPython make it happen [38]. The code lives in the device itself - firmware gets smarter without calling home.

Trying out new designs lately has meant using Quantization along with Pruning to shrink models while keeping detection sharp [39]. Running analysis directly on local devices means less raw sound must travel across slow wireless links such as LoRaWAN or NB-IoT - that saves power, cuts delays when fast responses matter most [40, 41].

3.4. Regional Insights and Social Economic Challenges

3.4.1. Africa

Water losses hit hard across Africa, with many cities losing well over half their supply. Old metal pipes crumble while unapproved taps add pressure. Cost keeps most from using advanced tools to track leaks. Devices that listen for pipe breaks need pricey gear brought in from abroad. Spare parts rarely exist nearby, so broken units wait months for repairs. Engineers on the ground lack spaces to build fixes locally. Though less accurate than top-tier European models, leak-detection units built with Raspberry Pi or ESP32 chips have been tested in Nigeria and South Africa [42]. Running on free software like Python, these devices rely on simple data analysis to spot large water breaks. Basic signal methods do the job well enough, despite missing fine detail. Cost stays low thanks to open designs and widely available parts. Research shows promise without needing complex gear [43, 44].

3.4.2. Asia

From bustling cities to quieter towns across Asia, things look different everywhere. Where places such as Japan and Singapore sit at the top end, machines watch pipelines closely through digital copies updated by smart learning systems [45]. Over in countries growing fast - India and Vietnam for instance - the pipes twist and turn too much, making fixes tough. Water comes and goes unpredictably there, which shakes up pressure levels suddenly, tripping regular prediction tools [46]. Lately, scientists have been shaping smarter software, built to tell apart normal flow restarts from actual leaks underground [47, 48].

3.4.3. Europe

Old rules push Europe to act, because its underground systems often stretch past one hundred years. Not shifting fast enough from metal lines to newer plastic ones - like PVC or MDPE - slows progress down [49]. High-pitched noise from leaks fades fast through these modern tubes, making detection harder without clever fixes. That’s why syncing several sensors matters more now, pulling clues together where sound vanishes early [50, 51]. Work here blends underwater microphones with brain-like software patterns that spot faint rumbles others miss. Listening closely gets help from engineering tricks tuned by machine thinking models trained on real pipe behavior. Privacy stays central when coding tools meant to guard flowing networks treated like vital state assets. Hack-proof logic runs deep since breaches could ripple across cities relying on steady supply lines.

3.4.4. The Americas

North America pushes hard into Big Data, its AI setups built to grow fast. Cloud programs need serious muscle just to handle the flood coming from thousands of sound sensors spread across U.S. and Canadian water networks [52]. Workers face a shift - swapping old field checks for reading machine learning screens, which means new training becomes key [53]. Down in Latin America, money and society shape limits more than tech does. Yet workshops now craft custom sensor housings at speed, tailored for steamy tropics where gear usually fails too soon [54, 55].

4. Findings and discussion

Looking back at studies from 2017 to 2026 shows progress in tools and math models for predicting leaks has leveled off. Yet how well they work outside labs depends on how smoothly sensors link with code. These results unfold next through three key angles.

4.1. Technical Performance Meets Algorithmic Accuracy

One key result here shows how much detection precision varies depending on what a pipe is made of. Metal lets high-frequency signals move through easily, whereas PVC and HDPE slow them down, filtering out the higher tones needed for standard sound-based tracking methods [56]. Studies point out movement from older signal analysis techniques toward deep learning approaches has helped reduce this gap somewhat. Instead of relying only on classic models like SVMs, systems using CNNs or LSTMs perform better by around 15 to 20 percent when working with plastic pipelines [57, 58].

Still, one big tech problem stands out - models often learn too much from training data. When tested outside clean lab setups, they stumble in messy city settings [59]. Real-world water flow varies wildly. That means tests must happen in varied real-life conditions. Only then can systems adapt wherever they’re used.

4.2. Instrumentation Cost vs. Predictive Value

Turns out there's a twist in the numbers. While gear like hydrophones and fiber-optic sensors delivers top-tier info for machine learning systems, its steep price tag puts it out of reach - especially for service providers across poorer areas [60].

Talk in past studies leans on Electronics Engineering paired with quick model building to tackle this hurdle. Thanks to cheaper MEMS sensors hooked up to open hardware such as ESP32, getting into smart tracking now costs far less - down about tenfold [61, 62]. Even if these budget models pick up more background noise, results show sharp coding tricks - take Variational Mode Decomposition, for example - can scrub the signals well enough to spot leaks reliably [63, 64].

4.3. Programming In Edge And Cloud Analytics

One big change between 2017 and 2026? More systems mix edge and cloud computing. Sending all data to a central cloud uses too much energy, takes time, plus it's expensive - research confirms this [65]. So what happens now? Smart setups split tasks: basic number crunching runs on-site, right inside the device at the Edge. Heavy lifting like forecasting patterns or tracking slow shifts gets handed off to remote servers later [66, 67]. Because of this teamwork, gadgets last longer on one charge, even as their brainy software keeps improving without slowing down

Recommendations

Looking at studies from 2017 to 2026, experts suggest changes that could help leak detection in water pipes work better. Though technology has improved, real-world performance often falls short without proper setup. Where sensors go matters just as much as how many you install. Instead of adding more hardware, fine-tuning data flow might deliver stronger results. Some models fail because they ignore local conditions like soil type or pipe age. While machine learning draws attention, simpler methods sometimes match their output. Testing predictions against actual leaks reveals gaps few expect. Even accurate alerts lose value if maintenance teams can’t respond fast enough. Because city budgets differ, one-size-fits-all fixes rarely stick. Still, sharing system designs across regions brings slow but steady gains

One big hurdle in prototyping engineering? The steep price tag blocking progress in poorer areas. A clear fix might be shared blueprints for cheap, repeatable designs. Picture small sensor units snapping together like puzzle pieces - no special tools needed. These bits could fit different kinds of pipes, any size, almost anywhere. When parts follow common rules, swapping and fixing gets simpler. Open plans mean more people tweak, test, improve. Cost drops when nobody reinvents the wheel each time. Custom fixes become normal instead of rare [68]. Progress speeds up if everyone builds on what works. That kind of system already helps elsewhere - why not here?

One way forward? Tackle the flood of sensor data by fitting smart algorithms straight onto tiny chips. These small models chew less power, so gadgets run longer without charging. Instead of sending everything somewhere else for processing, decisions happen right inside the device itself. That shift cuts down on bulky cloud systems while speeding up responses where it matters most - right at the tool doing the job [69].

Teamwork across fields changes how schools and factories prepare people. When fixing leaks well matters, workers must handle circuit boards just as easily as they decode smart software alerts [70].

Money talks when it comes to fixing water systems. Across parts of Asia and Africa, local rules could tilt the playing field toward smarter networks by covering part of the cost. Instead of waiting for markets to act, officials might hand out funds specifically for building sensor gear nearby. That kind of support hits right at the wallet concerns raised earlier in this analysis [71].

5. Conclusion

A fresh look at how machines learn to spot leaks in water pipes emerged between 2017 and 2026, using signals pulled from sensors. Although methods evolved, cost issues slowed their spread across regions, especially where tech access was limited. Instead of focusing only on code, researchers mixed ideas from circuit design, tool development, and software logic. Because real-world conditions differ, progress faced roadblocks beyond just engineering concerns.

Though methods such as Wavelet Transforms plus CNNs boost accuracy in intricate pipe systems, expensive precision tools still block wide use - especially where signals fade in plastic pipelines. Yet because fast model building grows more accessible, compact computing opens doors to cheaper setups that can spread easily.

Facing ahead, staying one step before leaks matter most. Instead of fixing breaks after they happen, smart systems now see them coming. Machines learn patterns through sensors built into pipes and pumps. These tools work better when software thinks clearly, not just fast. Less wasted water means every community keeps what it needs. Fair access grows where tech meets real daily demand. Looking forward, that balance shapes how cities survive droughts, growth, stress.

Compliance with ethical standards

The researchers have adhered to the ethical standards for academic publishing and technical review. This study was conducted in accordance with the ethical principles of the Committee on Publication Ethics (COPE).

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Disclosure of conflict of interest

The researchers declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Statement of ethical approval

As this study is a systematic review of existing literature and publicly available technical standards regarding water pipe compliance, it did not involve direct interaction with human participants or animals. Consequently, formal ethical approval from an Institutional Review Board (IRB) or Ethics Committee was not required.

Statement of informed consent

All sources in the research were properly cited.

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