International Journal of Scientific Research in Computer Science, Engineering and Information Technology

ISSN : 2456-3307 OPEN ACCESS

Available Online at : www.ijsrcseit.com

DOI: https://doi.org//10.32628/CSEIT2425449

Deep Learning for Smart Water Grids: A Targeted Review of Leak Detection Technologies

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ARTICLEINFO

Article History:

Accepted: 10 Feb 2024

Published: 19 Feb 2024

Publication Issue

Volume 10, Issue 1

January-February-2024

Page Number

344-355

ABSTRACT

Deep learning is a revolutionary technology in improving leak detection in smart water grids which make water management more accurate, automated and data-driven. Recent advancements indicate that deep learning models, convolutional, recurrent and hybrid models are superior in detecting subtle hydraulic anomalies as compared to traditional models. Combined with sensor networks and cloud analytics using IoT, real-time monitoring and scalability has also been enhanced. Nevertheless, issues like the scarcity of labeled data, generalization of models under a variety of network conditions, and interpretability are some of the major obstacles. New developments show the development of interest in reinforcement learning, explainable AI, and edge computing to develop adaptive and transparent leak detection systems. This review preheced is a systematic synthesis of the latest five years of research in the field of deep learning, breaking down the progress of the main methods of deep learning and defining further research directions that will help to guarantee the sustainability and resilience of smart water grids.

Keywords : Deep Learning, Leak Detection, Smart Water Grids, IoT-Based Monitoring, Reinforcement Learning & Explainable AI

1. Introduction

Water distribution networks (WDNs) are the essential urban elements that guarantee sustainable supply of water, but have remained a challenge because of leakage, deterioration of assets and poor management systems. Leakages represent a significant amount of non-revenue water loss that has economic, as well as environmental effects, particularly in fast urbanizing areas (Giudicianni et al., 2020; Farah and Shahrour, 2024). Since the traditional hydraulic models are often ineffective to measure the complicated leakage behaviors under different working conditions, smart water grids have become an effective solution that combines highly sensitive sensing, data transmission as well as computational intelligence (Wu et al., 2022; Kammoun et al., 2022).

New developments in artificial intelligence (AI), specifically deep learning (DL), have increased the rate of automated leak detection and localization because systems can learn using large amounts of collected flow, pressure, and acoustic sensors (Islam et al., 2022; Wan et al., 2022). These data-based methods help in the near real-time monitoring and predictive maintenance and enhance resilience and efficiency in the operations (Joseph et al., 2023; Yussof and Ho, 2022). In addition, heterogeneous data streams can be incorporated into DL-based structures and adjusted to network-related dynamics, which is more effective than the threshold or model-based ones (Hu et al., 2021; Rajan and Li, 2025).

The overlapping of the IoT, machine learning, and digital water infrastructure then has transformed intelligent leak detection to become a central part of smart city sustainability strategies (Mandal et al., 2025; Kanyama et al., 2024). Nevertheless, the implementation of powerful and understandable models in the various water networks is a challenge that is yet to be achieved despite these developments. This overview presents a selective literature review of the deep-learning-based leak-detection technologies that have been developed in 2019-2025 with a specific emphasis on the innovations in the models, data fusing, and further research perspectives toward fully autonomous and resilient smart water systems.

A. Justification for Deep Learning–Based Approaches

The increasing complexity and scale of modern water distribution networks demand advanced analytical tools capable of processing large, heterogeneous datasets generated by smart meters, sensors, and supervisory systems. Traditional leak detection methods—based on physical modeling, statistical thresholds, or simple pattern recognition—often fail to generalize across dynamic hydraulic conditions and are sensitive to sensor noise and data sparsity (Hu et al., 2021; Nagaraj et al., 2021). In contrast, deep learning (DL) models can autonomously extract hierarchical features from multidimensional data, offering robust pattern recognition and adaptive learning under uncertain operating environments (Wu et al., 2022; Lee et al., 2024).

DL approaches have demonstrated superior accuracy and scalability in detecting leaks of varying sizes and durations by leveraging temporal and spatial correlations in pressure and flow signals (Jun & Jung, 2025; Rajan & Li, 2025). Convolutional and recurrent neural architectures, for example, have been successfully applied to classify and localize leak events in real-world networks, reducing false alarms and improving operational decision-making (Choudhary et al., 2023; Fares et al., 2023). Furthermore, hybrid frameworks integrating deep learning with IoT and GIS-based systems enhance situational awareness and automate leakage management through continuous monitoring and feedback (Elshazly et al., 2024; Giudicianni et al., 2020).

The adaptability of deep models to diverse data types—including hydraulic, acoustic, and cyber-physical signals—positions them as essential components in developing predictive, resilient, and self-learning smart water grids (Taloma et al., 2025; Javed et al., 2025). As water utilities transition toward data-centric infrastructure management, deep learning-based solutions represent a critical step toward achieving operational sustainability and intelligent decision support in digital water systems (Mandal et al., 2025; Kanyama et al., 2024).

B. Scope of the Review

This specific review combines the recent advances in the field of the application of deep learning to detect leaks in smart water grids, considering only the literature published in 2019 and onwards. The chosen articles focus on data-driven and hybrid models based on the innovation of the neural network structures, integration of IoT, and intelligent sensing to manage leaks in real-time (Farah and Shahrour, 2024; Rajan and Li, 2025). Instead of historical overview, it focuses on the current state of the art, which includes convolutional, recurrent, and reinforcement learning models, that have already been shown as improved in accuracy of detection, computational efficiency, and scalability (Javed et al., 2025; Taloma et al., 2025).

The research classifies the results into three main themes, namely: (1) data-based and hybrid systems of automated leak sensors, (2) deep learning and internet of things (IoT) systems of smart water networks, and (3) emerging trends, such as cybersecurity-conscious and adaptive learning systems (Addeen et al., 2021; Mandal et al., 2025). Through the synthesis of these studies, the paper will seek to give a summary of the innovations currently happening, identify the current challenges in research including data scarcity and interpretability, and the paper will also outline the future research directions on creating transparent, efficient, and resilient leak detection systems in future digital water infrastructures (Komba, 2025; Kanyama et al., 2024).

2. Thematic Review of Deep Learning Applications for Leak Detection

i. Data-Driven and Hybrid Frameworks for Leak Detection

Recent studies concentrate on the increased efficiency of information-based models in dealing with and detecting leaks in water distribution systems. Hybrid models, which allow leveraging machine learning and deep learning algorithms with physical simulation tools like EPANET, predict leaks better and increase the accuracy of hydraulic forecasts, incorporating real-time data analytics (Nagaraj et al., 2021; Hu et al., 2021). Research has also shown that deep neural networks that are trained on pressure and flow data are able to surpass traditional threshold-based models because they learn a complex spatial-temporal behavior of the network (Rajan & Li, 2025; Wan et al., 2022). In addition, hybrid architectures where the model-based and data-driven components are combined have enhanced generalization in networks that have little labeled data. Giudicianni et al. (2020) and Farah and Shahrour (2024) demonstrated that the combination of energy management principles and intelligent systems of anomaly detection is an effective way to increase leak localization and efficiency. The frameworks have also been reinforced by the ensemble and transfer learning mechanisms that can be used to adapt pre-trained models to new water systems with the minimum amount of retraining (Wu et al., 2022; Taloma et al., 2025).

ii. Deep Learning and IoT-Enabled Leak Detection

In the integration of deep learning models, IoT is instrumental in providing the smart water grids with continuous monitoring and dynamic response. The recent reports emphasize the role of IoT-based sensors to produce high-resolution flow, pressure, and acoustic data that is directly converted into neural network structures to detect leaks in real-time (Yussof & Ho, 2022; Elshazly et al., 2024). To process these data streams, deep convolutional and recurrent models have been applied, which detect non-linear dependencies, which the traditional algorithms commonly fail to capture (Choudhary et al., 2023; Lee et al., 2024).

Scalability The combination of IoT and deep learning also allows centralization or edge deployment in large utility networks. Mandal et al. (2025) and Joseph et al. (2023) have shown that AI- and IoT-based solutions minimize the time to respond to detection and improve resilience of the network by providing automated decision-making. Moreover, GIS-based solutions have made possible the process of spatial pattern identification and made the process of leak localization more precise in intricate pipeline layouts (Elshazly et al., 2024; Giudicianni et al., 2020). All these innovations are building up toward the purpose of entirely autonomous and adaptive smart water systems.

iii. Sensor-Based Anomaly Detection and Cyber-Physical Resilience

The use of smart sensors has transformed the granularity and reliability of data available for leak detection, but it also introduces vulnerabilities that require cyber-physical protection. Deep learning models have been instrumental in anomaly detection for both hydraulic irregularities and security threats in sensor networks (Kanyama et al., 2024; Addeen et al., 2021). Acoustic, pressure, and flow sensors are now analyzed through deep architectures capable of distinguishing leaks from transient pressure events or sensor noise (Fares et al., 2023; Wu et al., 2022).

Furthermore, recent frameworks combine signal processing and machine learning to improve resilience against false alarms and cyberattacks targeting water distribution infrastructure (Lee et al., 2024; Taloma et al., 2025). Cyber-aware deep learning models enhance trust in smart grid operations by incorporating domain knowledge and anomaly labeling, ensuring system integrity while maintaining detection precision (Addeen et al., 2021; Kammoun et al., 2022).

iv. Emerging Trends: Reinforcement Learning, Edge Computing, and Explainability

The new research trends are based on reinforcement learning and edge computing as the new frontiers of intelligent water management. Reinforcement-based models of learning have been demonstrated to be useful in adaptive leak management in which systems are capable of autonomously modifying operational parameters based on feedback and long-term performance objectives (Javed et al., 2025; Komba, 2025). Edge intelligence also helps in real-time device-level analytics, reducing network latency and enhancing privacy of data in a large-scale network (Mandal et al., 2025; Tipon Tanchangya et al., 2024).

The creation of explainable AI (XAI) within the deep learning paradigms is yet another significant trend, as this approach is aimed at the issues of transparency and responsibility. XAI-powered models can be used to explain the decision-making processes to users, improving their level of trust and supporting the process of regulatory compliance (Taloma et al., 2025; Farah and Shahrour, 2024). More progress in interpretable and hybrid AI solutions should be expected to bridge the gap between high model performance and operational transparency and this will provide a foundation of resilient, intelligent, and sustainable smart water grids.

3. Comparative Synthesis and Key Insights

A cross-comparative analysis of the present research shows that there are a number of overlapping tendencies in the evolution of employing deep learning-based leak detection system, and a number of unaddressed gaps that restrict the implementation at scale. In the literature reviewed, deep learning is clearly superior in its accuracy and strength to traditional statistical or purely model-based methods, especially in research where high-dimensional, non-linear, and noisy hydrostatic data need to be represented (Hu et al., 2021; Wan et al., 2022). Convolutional and recurrent models are considered better than hybrid machine learning approaches because they consider both spatial and temporal dependencies of sensor signals, which allows a more accurate classification of leaks and localization of leakages (Choudhary et al., 2023; Lee et al., 2024). Nevertheless, the hybrid architecture where physical models or GIS data are combined can be more generalizable in real-world systems, which implies that deeper architecture combined with domain knowledge can be a more balanced and scalable solution (Giudicianni et al., 2020; Elshazly et al., 2024).

There are also studies that indicate unequivocal variations in the data requirements and model transferability. Models based purely on data need large quantities of labeled data and do not tend to be able to generalize across networks with different hydraulic structure (Nagaraj et al., 2021; Kanyama et al., 2024). Conversely, reinforcement learning, and cyber-aware models are flexible, but require a simulated training environment, which creates concerns about its response to real operating uncertainty (Javed et al., 2025; Addeen et al., 2021). IoT-based solutions have more detailed streams of data and can be used to perform continuous monitoring, but they have issues regarding hardware faults, connection congestion, and false warnings in the absence of sophisticated filtering tools (Yussof and Ho, 2022; Joseph et al., 2023).

A. Direct Comparison of Studies: Strengths, Gaps, and Innovations

Recent research demonstrates substantial progress in deep learning–based leak detection, yet the studies differ significantly in data requirements, model robustness, and operational feasibility.

i. Strengths Across Studies

A number of articles demonstrate the good predictive ability of deep neural networks. Convolutional and recurrent architectures are superior in terms of space-time dependencies of sensor data, providing high accuracy and fewer false alarms (Choudhary et al., 2023; Lee et al., 2024). Researchers implement frameworks with IoT functionality, which show effective continuity and responsiveness of monitoring processes because of the high frequency flow and pressure data (Yussof and Ho, 2022; Elshazly et al., 2024). More advanced hybrid models that combine model-based hydraulics with deep learning also enhance generalizability especially in networks with fluctuating demand distributions (Giudicianni et al., 2020; Wan et al., 2022).

The reinforcement learning methodologies are highly flexible and learn the best leakage management behaviors in changing circumstances, which is more effective than the detection models (Javed et al., 2025; Komba, 2025). Cyber-aware models are also found to be effective in the detection of hydraulic abuse as well as malicious network activity to facilitate secure smart water operations (Addeen et al., 2021).

ii. Gaps Identified

Although there is an improvement in performance, a number of constraints arise. Unconditionally data-driven models need massive labeled data, and they do not readily hand over across network topologies, which restricts scalability (Nagaraj et al., 2021; Kanyama et al., 2024). Acoustic-based systems are very sensitive and susceptible to noise in the environment, as well as necessitating a high density of sensors, which increases the cost of operation (Fares et al., 2023). Layered models imbedded in IoT systems have the problem of sensor fault, communication latency, and device reliability, which may contribute to misleading false alarm (Joseph et al., 2023; Hu et al., 2021). Reinforcement learning is a promising learning approach that depends on simulated environments, which is problematic in regard to transferability to the real-world (Javed et al., 2025). The frameworks of cyber-physical anomaly detection are still in their initial phases and are not fully validated to meet any dynamic threat (Addeen et al., 2021; Kammoun et al., 2022). The explainability is also scarce, and most of the studies are concerned with accuracy and not with the interpretability (Farah and Shahrour, 2024; Taloma et al., 2025).

iii. Key Innovations

Current publications have significant innovations that add scalability and value to operations. Deep learning piping systems that can be GIS enabled can recognize spatial patterns and identify the location of the leak in the complex pipe networks (Elshazly et al., 2024). Physics-informed constraints added in the neural networks have shown to be more stable and capable of generalizing less on the data (Giudicianni et al., 2020; Rajan and Li, 2025). The domain knowledge based models minimize the false positives by introducing operational precedents and professional regulations within deep architectures (Lee et al., 2024).

The development of edge computing allows the use of a decentralized inference with less latency and communication overhead in large-scale networks (Mandal et al., 2025; Tipon Tanchangya et al., 2024). The reinforcement learning models bring adaptive decision-making in leak management, which is an important change in comparison with the traditional detection system but proactive control of the system (Javed et al., 2025; Komba, 2025).

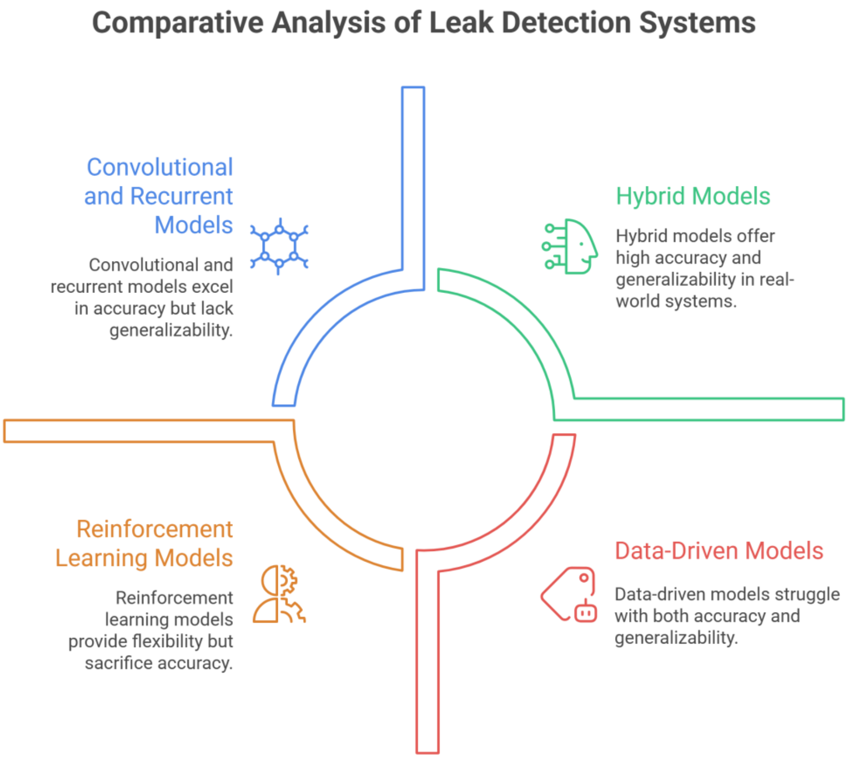

Figure: The above diagram show the Comparative Analysis of leak Detection Systems

B. Cross-Cutting Insights from Recent Studies

Across recent research, several consistent insights emerge regarding the behavior, performance, and deployment challenges of deep learning models in smart water grids.

i. Information Quality Decides on Model Reliability.

Majority of the studies point out that data limitations are more likely to limit model performance rather than model architecture. Functional high-resolution flow and pressure information is a significant enhancement to anomaly detection, but a large fraction of utilities are not dense enough in sensors or have noise problems (Choudhary et al., 2023; Fares et al., 2023). Interventions that utilize the deployment of the IoT record better detection fidelity, though are susceptible to sensor outages and unstable communication (Joseph et al., 2023; Hu et al., 2021).

One common lesson has been that synthetic data provided by simulators do not necessarily provide full hydraulic variability to generalize in reinforcement learning and supervised deep learning models (Javed et al., 2025; Nagaraj et al., 2021).

ii. Knowledge-Guided Models and Hybrid Are More Robust.

In multiple studies, it is shown that stability and false alarms are significantly increased by using a combination of physical models and deep learning. Physics-informed models perform better when working with networks that feature sharp changes in demand or a lack of training examples (Giudicianni et al., 2020; Rajan and Li, 2025). The domain-aware deep learning also minimizes overfitting by including expert thresholds or hydraulic constraints as part of the model logic (Lee et al., 2024; Taloma et al., 2025).

This is an indication of a visible shift towards hybrid kinds of intelligence designs as opposed to single neural networks.

iii. Functional Deployment Demands Sparsely-defined Models.

Even though there are high-capacity architectures like CNN-LSTM hybrids that are highly efficient, they tend to be resource-intensive to be deployed to the edge in a distributed water network (Yussof and Ho, 2022; Mandal et al., 2025). Various studies point out the necessity of computing efficient models that can be used on low power embedded hardware without affecting responsiveness.

Another cross-cutting challenge that arises is that of interpretability. Less explainable deep learning models decrease operator trust and do not allow them to be applied to the real world, which is reflected in the literature on the necessity to have traceable anomaly reasoning (Farah and Shahrour, 2024; Kammoun et al., 2022).

iv. Cyber-Physical Security Is Evolving into a Requirement.

Numerous recent facts prove that water networks are increasingly vulnerable to cyber-physical threats because of the implementation of the IoT and remote monitoring systems. The leak detection models should be able to thus differentiate between natural hydraulic anomalies and malicious discontinuities (Addeen et al., 2021; Kanyama et al., 2024). Deep neural classifiers and reinforcement learning have potential, and cybersecurity validation has not been done extensively.

This is an indication of increased demand of hybrid leak detection and intrusion detection systems.

v. Scalability, Transferability Weaknesses Cross-model.

One of the clear observations is that most of the models work well with the datasets they are trained with but fail to work with new network setups or conditions. Even highly developed hybrid models experience a difficulty in case of the change of pipe materials, network structure, or seasonal demand curves (Wan et al., 2022; Elshazly et al., 2024).

Table 1: Cross-Study Comparison of Key Insights in Deep Learning–Based Leak Detection

Study	Main Strength	Main Limitation / Gap	Key Innovation
Choudhary et al. (2023)	High leak-classification accuracy using spatiotemporal deep learning	Requires dense sensor data; limited transferability	CNN-LSTM fusion for pressure pattern learning
Fares et al. (2023)	Robust signal feature extraction under noise	Struggles with abrupt hydraulic changes	Noise-resilient deep feature encoder

Joseph et al. (2023)	Effective use of IoT pressure nodes	Vulnerable to sensor faults and communication drops	IoT-driven real-time leak monitoring
Hu et al. (2021)	Strong performance on multi-sensor data streams	Model degradation with missing data	Multi-sensor deep learning anomaly model
Javed et al. (2025)	Adaptive reinforcement learning	Over-reliance on synthetic training data	RL-based control-aware detection
Nagaraj et al. (2021)	Good classification accuracy on small datasets	Poor cross-network generalization	Lightweight leak-detection classifier
Giudicianni et al. (2020)	Stable predictions using physical priors	Higher computational overhead	Physics-informed deep learning
Rajan & Li (2025)	Better generalization under demand fluctuations	Limited scalability	Physical-knowledge-guided ML
Lee et al. (2024)	Low false alarms under dynamic loads	Requires high computation	Constraint-aware deep architecture
Taloma et al. (2025)	Improved interpretability	Preliminary explainability tools	Integrated XAI mechanisms
Yussof & Ho (2022)	Suitable for embedded/edge devices	Lower accuracy compared to large models	Lightweight deep model for WDNs
Mandal et al. (2025)	High efficiency for distributed grids	Limited validation in large cities	Edge-optimized leak detection
Farah & Shahrour (2024)	Operator-traceable decisions	Subjective interpretation of explanations	Rule-enhanced explainable DL
Kammoun et al. (2022)	Robust anomaly reasoning	Hard to scale to large networks	Explainability-focused DL
Addeen et al. (2021)	Detection of cyber-physical disruptions	Limited leak-only testing	Cyber-aware anomaly framework
Kanyama et al. (2024)	Combined hydraulic and cyber anomaly modeling	Lacks real-time validation	Dual cyber–hydraulic detection model
Wan et al. (2022)	High detection accuracy under varying flows	Weak transfer learning capability	Flow-adaptive deep model
Elshazly et al. (2024)	Strong integration of GIS/topology data	Model complexity	Topology-aware hybrid deep model

4. Emerging Trends and Future Research Directions

Recent advancements reveal a clear shift toward more adaptive, interpretable, and operationally feasible deep learning frameworks for leak detection in smart water grids. Across the reviewed studies, several emerging trends point to where the field is heading and what challenges remain for real-world adoption.

4.1. Motion toward Hybrid Intelligence and Physics-Guided Deep Learning.

Consent is increasing that a combination of data-driven models and physical knowledge will take preeminence in the next generation of leak detection structures. When hydraulic constraints or domain heuristics are included, the studies demonstrate that the stability of neural networks is high and the number of false alarms is lower than in the case of isolated neural networks (Giudicianni et al., 2020; Rajan and Li, 2025; Lee et al., 2024). This tendency implies the development of the future systems that will combine simulation, hydraulic knowledge, and neural inversion to compensate the shortage of data and enhance robustness in the non-stationary conditions.

4.2. Edge and Distributed AI to a Real-Time Monitor.

Low-power models of deep learning optimized to work on IoT devices and edges are in vogue as utilities seek to maintain constant real-time monitoring on assets spread across geographical locations. The increasing maturity of lightweight architectures can be observed (Yussof and Ho, 2022; Mandal et al., 2025), but it is important to balance the performance of the computing system and the accuracy of the detection. The current research is shifting towards pruning, quantization, and federated learning to minimize the resource requirements whilst preserving accuracy.

4.3. Explainable AI (XAI) as a Need, Not a Function.

Model transparency is becoming an essential factor in operator acceptance. Research on interpretability suggests a paradigm change in an attempt to incorporate the concept of explainability in leak detection processes (Farah and Shahrour, 2024; Kammoun et al., 2022; Taloma et al., 2025). Nevertheless, existing XAI tools are still weak in terms of their compliance to give clear and hydraulically meaningful explanations. The next generation of research should not be post-hoc visualization but more of integrating interpretability into model architectures on the whole.

4.4. Cyber-Physical Security as a part of leaks detection models.

As the utilities have more cyber risks, research on leak detection starts to combine cybersecurity and hydraulic modeling. Cyber aware systems show the possibility to differentiate between the leak, the sensor hacking, malicious disturbance (Addeen et al., 2021; Kanyama et al., 2024). The second step will probably be coherent structures that would be able to process physical abnormalities and cyber invasions in parallel with reinforcement learning and multimodal detecting.

4.5. To Scalable, Transferable Frameworks of Varied Water Networks.

Most of the more sophisticated models are system-dependent and have difficulty in extrapolating between networks with dissimilar layouts or demand patterns (Nagaraj et al., 2021; Wan et al., 2022; Elshazly et al., 2024). The trend has pointed to a serious requirement of scalable, transferable architectures, which do not need retraining to fit new environments. Models like domain adaptation, meta-learning and topology-aware deep learning are also coming out as promising directions towards developing a broader range of operation.

5. Conclusion

This review identifies the increasing importance of deep learning in improving leak detection in smart water grids, in particular, in its ability to process high resolution, complex sensor data and be superior to the conventional hydraulic and heurist based techniques. In recent literature (20192025), deep learning always proves strong in recognizing patterns, describing anomalies and detecting them in real-time especially when augmented with modern sensor networks and sophisticated data analytics pipelines present.

Nevertheless, the sphere is yet to be transferred between experimental achievement and operational maturity. Some of the common challenges associated with the current models include lack of data, systems training, interpretability, and computer cost. New areas of research promise an apparent ability to seal these gaps. The most promising directions towards robust, scalable and trustworthy leak detectors are hybrid physics-guided learning, architecture edge-optimised architectures, explainable AI, cyber-physical resilience and transferable model designs.

Throughout, deep learning has become a critical technology to develop smart water grids, and its further influence will be determined by the ability of scientists and utility companies to identify gaps between domain knowledge, security concerns, and practical limits of development and implementation of leak detection systems in the future.

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