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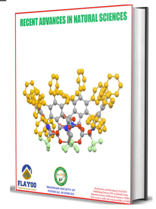

A systematic review of real-time monitoring systems for oil and gas pipeline leakage identification based on deep learning approaches

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ABSTRACT

Leakage in oil and gas pipelines threatens environmental safety, operational integrity, and economic stability. Recent advances have integrated Internet of Things (IoT) technologies and deep learning to improve real-time leak detection and response systems. This study presents a systematic review of state-of-the-art IoT-based and deep learning approaches for pipeline leakage detection, guided by the PRISMA methodology. From 450 articles published between 2015 and 2025, 144 high-quality studies focusing on real-time monitoring were selected for in-depth analysis. Key performance metrics, including accuracy, precision, recall, F1-score, sensitivity, and specificity, were evaluated. Hybrid deep learning models, such as Deep Autoencoder with XGBoost (DAE+XGB) and Bidirectional LSTM (BiLSTM), achieved the strongest performance, with accuracies reaching 99.78%, particularly for fine leaks as small as 0.5 mm. IoT frameworks leveraging cloud computing and reinforcement learning showed strong scalability and adaptability for remote operations. Despite these advances, challenges remain, including limited real-world validation, a lack of standardized datasets, energy inefficiency, cybersecurity risks, and limited model interpretability. Future research should emphasize field deployments, energy-aware IoT designs, improved security protocols, and explainable artificial intelligence to enhance transparency and trust. This review summarizes current progress, challenges, and future opportunities in intelligent, real-time pipeline leak detection for safer and more sustainable oil and gas infrastructure.

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1. INTRODUCTION

The identification and control of oil and gas leaks has been greatly enhanced over the last 60 years by developments in pipeline monitoring technologies [1]. Oil and gas pipelines are vital pieces of infrastructure for the distribution of energy around

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the world, but they are susceptible to sabotage, corrosion, and mechanical breakdowns, which can have major negative effects on the environment, the economy, and public safety [2]. Despite their widespread use, traditional techniques including pressure point analysis, acoustic sensors, and Supervisory Control and Data Acquisition (SCADA) systems have drawbacks such as poor sensitivity to small breaches, delayed detection, and high false alarm rates [3]. Before remedial measures are implemented, these restrictions frequently result in substantial damage, undiscovered leaks, and postponed maintenance [1–3]. The emergence of the Internet of Things (IoT) has made real-time monitoring systems more feasible by facilitating the ongoing gathering of data from many sensor nodes dispersed within pipeline networks. The visibility of pipeline conditions is improved by IoT-based systems that enable high-frequency sampling of parameters including temperature, pressure, vibration, and flow rate [4, 5]. However, advanced analytics are required to extract relevant insights due to the growing volume and velocity of sensor-generated data. Deep learning (DL) models, which are particularly effective at identifying complex patterns in sizable, high-dimensional datasets, have been incorporated as a result of this, particularly for time-series analysis and anomaly identification in dynamic contexts [6].

In the classification and localization of pipeline leaks, deep learning methods including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have shown exceptional results. By learning intricate nonlinear connections and temporal correlations, these models outperform conventional statistical techniques and are able to identify minute irregularities that could indicate leak events in their early stages [7]. Additionally, deep learning models can now function directly within IoT-enabled nodes for low-latency, real-time monitoring thanks to developments in edge computing and embedded AI, which have strengthened on-device inference [8]. By anticipating possible pipeline problems, the combination of IoT and DL not only improves detection accuracy but also aids predictive maintenance plans. While LSTMs are skilled at evaluating sequential data from pressure or flow sensors, CNNs have proven especially successful in interpreting spatial signals like acoustic emissions or thermal images taken by distant sensing devices [9]. According to research, hybrid deep learning models that combine CNN and LSTM architectures provide improved leak localization accuracy and resilience across a range of operating scenarios [10]. For instance, in field tests, [11] created a CNN-based leak detection model coupled with IoT nodes that demonstrated excellent accuracy and responsiveness.

Even with the notable advancements, there are still obstacles to overcome before deep learning systems can be widely implemented for pipeline monitoring. Data imbalance, sensor noise, limited compute on edge devices, and uninterpretable models are a few of them. Furthermore, in remote areas, IoT networks are vulnerable to latency, energy limits, and connectivity problems [12]. To lessen these limitations while maintaining privacy and scalability, future research is progressively concentrating on edge AI, transfer learning, and federated learning. Since transparent and auditable AI models are necessary for adoption in safety-critical domains like energy infrastructure, model explainability is also receiving more attention. Several aspects of AI and IoT for pipeline monitoring have been examined in recent reviews. For example, [13] used reinforcement learning to maximize real-time decision-making for leak management, while [14] carried out an extensive investigation of deep learning-based anomaly detection in oil pipelines. Similarly, an IoT-integrated LSTM model for leak detection was created by [15] and showed better accuracy than conventional threshold-based techniques. CNNs were used in [16] to accurately classify leak incidents in subterranean pipelines by analyzing acoustic signals. Together, these studies show how integrating IoT and deep learning can revolutionize the safety, dependability, and effectiveness of oil and gas pipeline operations.

Despite the considerable progress reported in the integration of Internet of Things (IoT) and deep learning techniques for pipeline leakage detection, a critical gap remains in the literature. Existing studies largely focus on the development and evaluation of specific models or frameworks without providing a comprehensive and systematic synthesis of these approaches within a unified context. In particular, there is limited consolidation of findings regarding the comparative performance, scalability, real-time applicability, and deployment constraints of deep learning-based monitoring systems across diverse operational environments. Furthermore, issues such as model interpretability, data heterogeneity, and the integration of edge-based intelligence for real-time decision-making have not been sufficiently examined in a structured review format. Therefore, this study aims to bridge this gap by conducting a systematic review of real-time oil and gas pipeline leakage identification systems based on deep learning approaches. The review seeks to critically analyze existing methodologies, identify prevailing challenges, and highlight emerging trends and future research directions to support the development of more robust, scalable, and explainable monitoring systems.

2. METHODOLOGY

The method used to conduct the systematic review is described in this section, along with its main goals, research questions, literature selection plan, and inclusion and exclusion criteria. The methodology supports a thorough, objective, and repeatable examination of recent developments in real-time pipeline leak detection utilizing deep learning and IoT techniques.

2.1. LITERATURE REVIEW PROCEDURE

A structured, multi-phase methodology based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines was used to conduct the review. In order to comprehend the current state of pipeline leak detection systems, the approach started with a preliminary scoping of the literature. After that, a thorough search was carried out using a variety of digital resources, including Google Scholar, IEEE Xplore, ScienceDirect, SpringerLink, and Scopus. The following keywords were used in different combinations: "oil and gas infrastructure monitoring," "pipeline leakage detection," "IoT-based monitoring," "deep learning in pipeline systems," and "real-time leak detection." Only peer-reviewed papers published between 2015 and 2025 were included in the search, with an emphasis on research that suggested or assessed real-time IoT and deep learning mod-

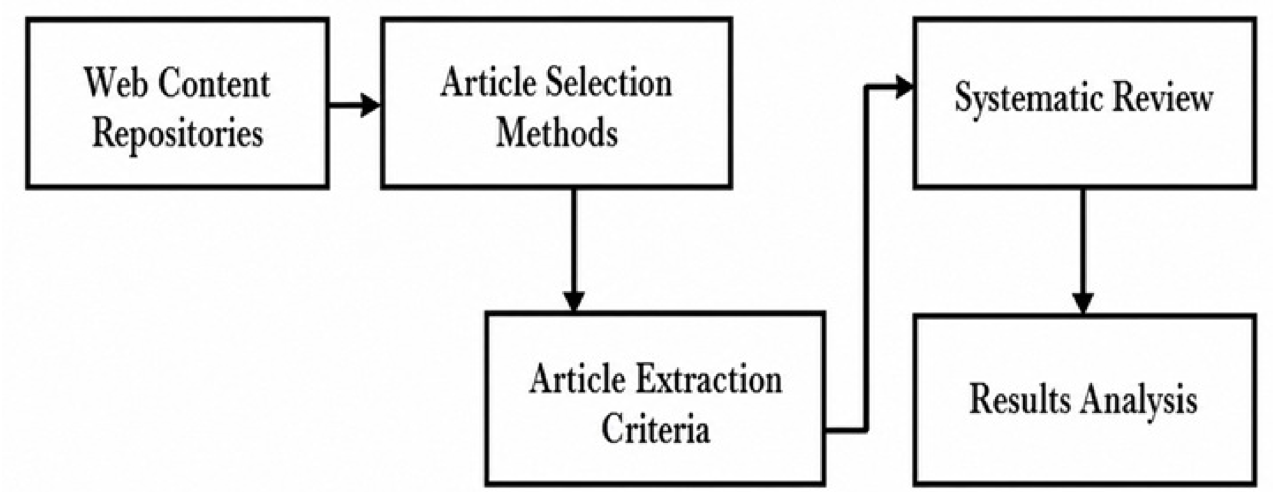


Figure 1. Research framework.

Table 1. Performance comparison of IoT-based methods for real-time oil and gas pipeline leakage detection.

Leakage detection method	Sensitivity (%)	Specificity (%)	Accuracy (%)
LoRa-based IoT [54]	94.0	91.0	92.0
IoT + Cloud [55]	96.5	93.2	95.1
IIoT Architecture [56]	98.0	97.0	97.6
IoT-WSN Smart Monitoring [57]	95.2	94.4	95.0
IoT + RL-based Leak Detection [58]	97.8	96.3	96.9

els for pipeline monitoring. A full-text review was conducted once the identified publications had undergone screening for titles and abstracts. In addition to eliminating duplicates, the reference lists of pertinent papers were examined for extra sources. Based on the kind of sensor data studied, the IoT architecture implemented, the evaluation metrics supplied, and the type of deep learning model employed, the chosen studies were grouped.

2.2. RESEARCH QUESTIONS

To guide the systematic review, the following research questions (RQs) were formulated:

RQ1: What are the recent deep learning models applied in real-time oil and gas pipeline leakage detection?

RQ2: How is IoT integrated into pipeline monitoring systems for data acquisition and transmission?

RQ3: What types of sensor data are commonly used for training and testing deep learning models in this context?

RQ4: What are the reported performance metrics and challenges associated with these systems?

RQ5: What gaps exist in the current literature, and what are the proposed future directions?

These questions were designed to address the technical, architectural, and operational aspects of real-time leakage detection systems and to identify opportunities for future advancements.

2.3. ARTICLE SELECTION STRATEGY

In the beginning, 450 studies were found using keyword-based searches. There were 290 research items left for title and abstract screening after duplicates and irrelevant articles were eliminated. Another 144 full-text reports were then screened for eligibility. These 144 papers qualified for full-text review were produced by this approach. The 144 papers were chosen as the final dataset for this evaluation after a thorough quality assessment. The selection emphasized studies that:

i. Implemented or evaluated deep learning models such as CNNs, RNNs, LSTMs, or hybrid architectures.
ii. Incorporated real-time or near-real-time IoT-based monitoring frameworks.
iii. Focused on oil and gas pipeline systems (excluding water or gas distribution unrelated to hydrocarbons).
iv. Included performance metrics such as accuracy, precision, recall, F1-score, latency, or energy efficiency.

2.4. INCLUSION AND EXCLUSION CRITERIA

To ensure relevance and quality, the following inclusion and exclusion criteria were applied:

(i) Inclusion Criteria:

- Studies published between 2015 and 2025 in peer-reviewed journals or conferences.
- Research focused on real-time detection of pipeline leakage using deep learning models integrated with IoT frameworks.

- Studies presenting empirical results, simulations, or real-world deployments.

(ii) Exclusion Criteria:

- Studies focusing solely on traditional methods (e.g., threshold-based, statistical) without ML or IoT integration.
- Articles that addressed pipeline monitoring outside the oil and gas domain (e.g., water, HVAC systems).
- Non-peer-reviewed literature such as opinion pieces, editorials, blogs, and white papers.
- Duplicate entries and studies with insufficient methodological detail.

2.5. REVIEW OF RELATED LITERATURE

In order to improve real-time leak detection systems, deep learning models and the Internet of Things (IoT) have been increasingly integrated in recent developments in oil and gas infrastructure monitoring. Manual inspection, pressure point analysis, and threshold-based SCADA systems are examples of traditional methods that frequently fail to detect anomalies in dynamic environmental conditions or accurately identify small leaks, leading to delayed responses and a higher risk of economic and environmental damage [2, 17, 18]. In order to address these issues, scientists have created Internet of Things (IoT)-based monitoring systems with dispersed sensors that continuously record information about temperature, pressure, flow rate, and acoustic vibrations along pipeline networks [19]. Convolutional Neural Networks (CNNs) and other deep learning techniques are used to assess the real-time data gathered by these sensors. Leakage patterns can be accurately detected using hybrid CNN-LSTM models and Long Short-Term Memory (LSTM) networks [20, 21]. CNNs, for example, have been used to categorize spatial acoustic signals from pipelines, whereas LSTMs are useful for learning temporal sequences for vibration or pressure data [22]. When compared to traditional rule-based techniques, Sun *et al.* [23] showed that integrating IoT designs with deep neural networks greatly increases the accuracy, responsiveness, and reliability of leak detection systems. Additionally, on-device inference is made possible by the combination of edge computing with IoT, which lowers latency and guarantees low-power operation in remote field settings [24]. Notwithstanding these developments, the research now in publication highlights important obstacles such sensor noise, a shortage of labeled datasets, high processing costs, and an inability to explain the model. In order to close the gap between academic prototypes and industry-scale applications, current research efforts have concentrated on model optimization, transfer learning, and real-world deployments [25–27]. This expanding corpus of research highlights how IoT and deep learning are revolutionizing oil and gas pipeline surveillance systems to enable safer, more intelligent, and more robust infrastructure management [28, 29]. Kim *et al.* [30] integrated a Convolutional Neural Network (CNN) model with Distributed Temperature Sensing (DTS) to propose a novel leak detection system for Pipe-in-Pipe (PIP) infrastructure. Even with different operating temperatures, the system detected liquid leakage rates between 0.2 and 7 ml/min with a 91.67% detection accuracy using Fourier-transformed spectrograms from DTS temperature data. This approach addressed the longstanding challenge of detecting fluid leakage between the inner and outer pipes, which is critical in high-risk environments such as nuclear reactors and chemical.

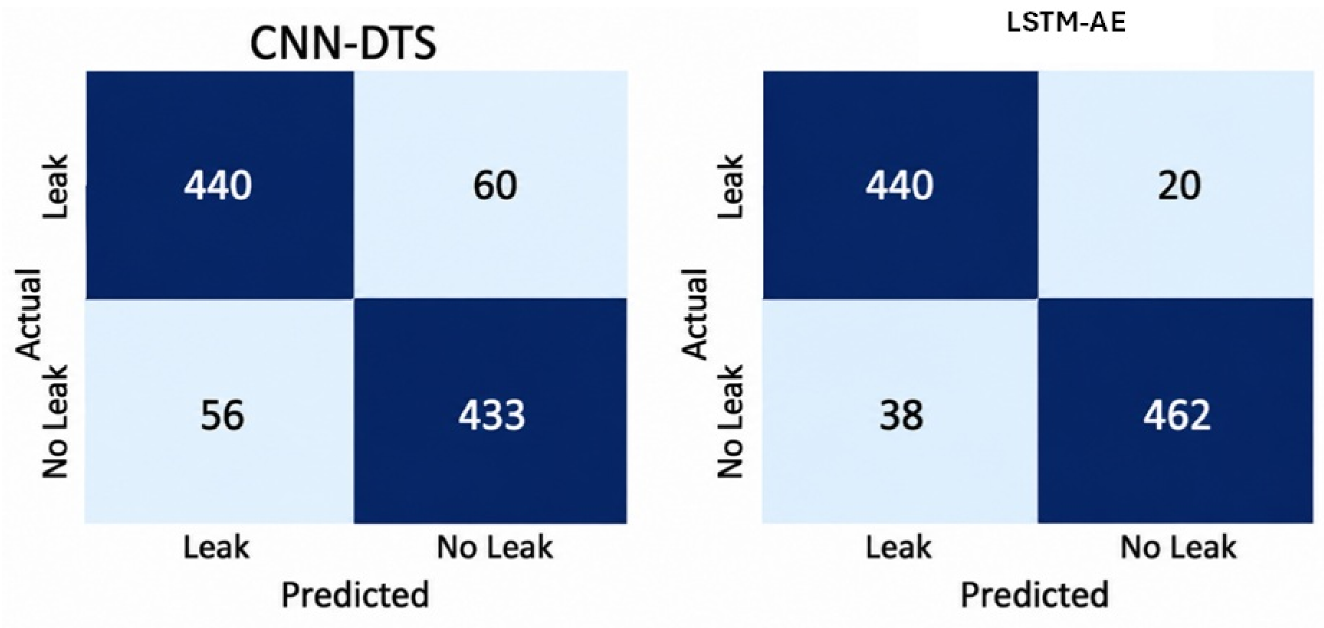
Yousef *et al.* [31] conducted a thorough analysis of the various methods for detecting leaks in pipelines, wellbores, and subsurface sequestration wells by employing a variety of Computational Fluid Dynamics (CFD), Mechanistic, Machine Learning, and digital twin techniques to study the various multiphase flow leak detection techniques in the pipeline and in subsurface sequestration sites. They noted that even with high-quality construction and regulatory compliance, leaks continue to occur in existing pipelines, posing serious risks to the economy, the environment, and hydrocarbon operations. For this reason, it is essential to accurately and promptly identify the location and size of leaks in order to manage pipelines both onshore and offshore. According to their review, there is a dearth of thorough literature on multiphase leak detection methods. They carried out a thorough analysis of techniques utilizing digital twin technologies, mechanistic models, machine learning, and computational fluid dynamics (CFD) in order to close this gap. They emphasized the usefulness of methodical research for field applications and discovered few integrated studies combining these methodologies. In order to assist enhanced deep learning and digital twin-based systems for identifying leak features without physical inspection using drones or underwater vehicles, the study concluded with recommendations on using experimental, mechanistic, and CFD data.

Ekong *et al.* [32] revealed a method for detecting pipeline leaks that leverages the power of the Internet of Things (IoT) and convolutional neural networks (CNN). Using a large dataset on oil and pipeline leaks, they created and trained a CNN model. The trained model was then included into a real-time monitoring system to produce leak alarms. The approach outperformed current techniques with an assessed accuracy of 97% and was said to be flexible and scalable. This high-performance model shows great promise for implementation in a variety of pipeline networks, greatly improving environmental protection and safety in the oil and gas sector. Pipeline leaks are common in oil and gas infrastructure around the world. Even though it is anticipated that all pipelines will soon have leak detection systems installed, it is still difficult to physically monitor these pipes using human labor. Modern leak detection methods are crucial for reducing the impact of breaches, even though they cannot entirely prevent leaks from happening or identify the majority of them. Even with recent advancements in the problem's solution, it still doesn't live up to expectations.

Abdelhafidh *et al.* [33] investigated the use of water pipeline systems for the Industrial Internet of Things (IIoT). According to their analysis, IoT services have been used recently to improve oversight procedures, monitor distant pipelines, and facilitate real-time data processing and management. The study suggested an IIoT-based Water Pipeline Monitoring System, outlining its tiered architecture and the goals and roles allotted to each layer, whether they are currently in use or are being developed in the future. In order to foresee problems and promote economic growth in the sector, intelligent and diverse equipment were created to exchange information, gather data cooperatively, and manage it

Table 2. Performance metrics of deep learning models for real-time pipeline leakage detection.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN on DTS Spectrogram [59]	91.67	89.3	92.8	91.0
LSTM on AE Data [60]	94.5	92.1	95.7	93.9
Deep Autoencoder + XGBoost [61]	99.51	98.9	99.7	99.3
BiLSTM on AE Time Series [62]	99.78	98.5	99.6	99.0
DARTS CNN on Drone Imagery [63]	96.2	94.4	95.1	94.7



(a) (b)

Figure 2. Confusion matrix comparison of deep learning models for pipeline leak detection (leak size = 0.5 mm).

effectively. In order to determine whether the system accurately satisfies end-user expectations and operational requirements, the authors stressed the significance of an assessment step. In the future, they intended to look into the best locations for sensors in order to increase monitoring effectiveness and communication coverage. They also sought to use Big Data approaches to handle and examine vast amounts of diverse data from the hydraulic system. Additionally, they suggested using Low Power Wide Area Network (LPWAN) technologies in place of conventional wireless communication because of its advantages in terms of longer range, lower power consumption, longer battery life, and cheaper operating costs.

Tejedor *et al.* [34] noted that in order to create efficient pipeline surveillance systems, researchers and industry stakeholders are becoming more interested in integrating Distributed Acoustic Sensing (DAS) and Pattern Recognition Systems (PRS) to identify and categorize potentially dangerous occurrences close to fiber optic cables installed along active pipelines. They noted that their findings may be applicable to other domains using DAS+PRS methodologies, and they carried out a thorough analysis of the body of literature already in existence about the use of machine learning techniques in DAS-based pipeline monitoring systems. They provided a thorough analysis of significant advancements in the industry and described the basic machine learning techniques pertinent to DAS systems. They also talked about typical issues with DAS+PRS technologies' performance assessment and real-world deployment for pipeline threat detection. The review came to the conclusion that, in spite of encouraging developments, real-time PRS implementation using DAS technology is still a challenging and unsolved research topic.

Cruz *et al.* [35] The authors suggested a method for identifying and locating leaks in low-pressure gas pipelines by combining machine learning algorithms with acoustic detection. External disturbances, which are frequent in pipeline systems and usually lead to increased false alarm rates, were present during the studies. The Random Forest approach produced the best results in leak identification among the investigated models when trained using the major components of the acoustic signals' frequency spectra. The method maintained a low false alarm rate of only 0.3% while properly identifying 99.6% of leakage occurrences, including leaks from orifices as small as 0.5 mm in diameter. Using Random Forest-selected features, the XGBoost algorithm generated a maximum location error of 4.32% and an average error of 1.75% for leak localization over five test spots. These encouraging outcomes established the suggested approach as a dependable and effective way to monitor low-pressure gas pipelines, including those utilized in domestic natural gas distribution as well as other commercial and industrial applications.

Silva *et al.* [36] created and assessed a pipeline monitoring system using deep learning and drone technology, based on computer vision and image processing methods. They created thin edge maps for oil slick identification using the DexiNed algorithm and used standard metrics to compare its performance to other edge detection techniques. They obtained an average precision (AP) of 0.905, an OIS of 0.867, and an ODS of 0.859. Furthermore, the LAB algorithm's accuracy in identifying black oil spills, calculating their area, and assessing their severity was confirmed. According to their tests, drone surveillance at a height of 10 meters produced the best image clarity for precise detection. According to the study, the suggested approach provided a clever, automated way to monitor a large region. It is especially appropriate for long pipelines, like those in Iraq, where fixed cameras are useless. The incorporation of the sophisticated DexiNed edge detection technology and the mobility of drones over stationary monitoring setups set the method apart from comparable efforts. The scientists did point out that the system's effectiveness could be impacted by topographical complexity, lighting fluctuations, and weather. Additionally, they proposed that expanding national pipeline monitoring coverage may be achieved through the integration of drone networks (Internet of Drones).

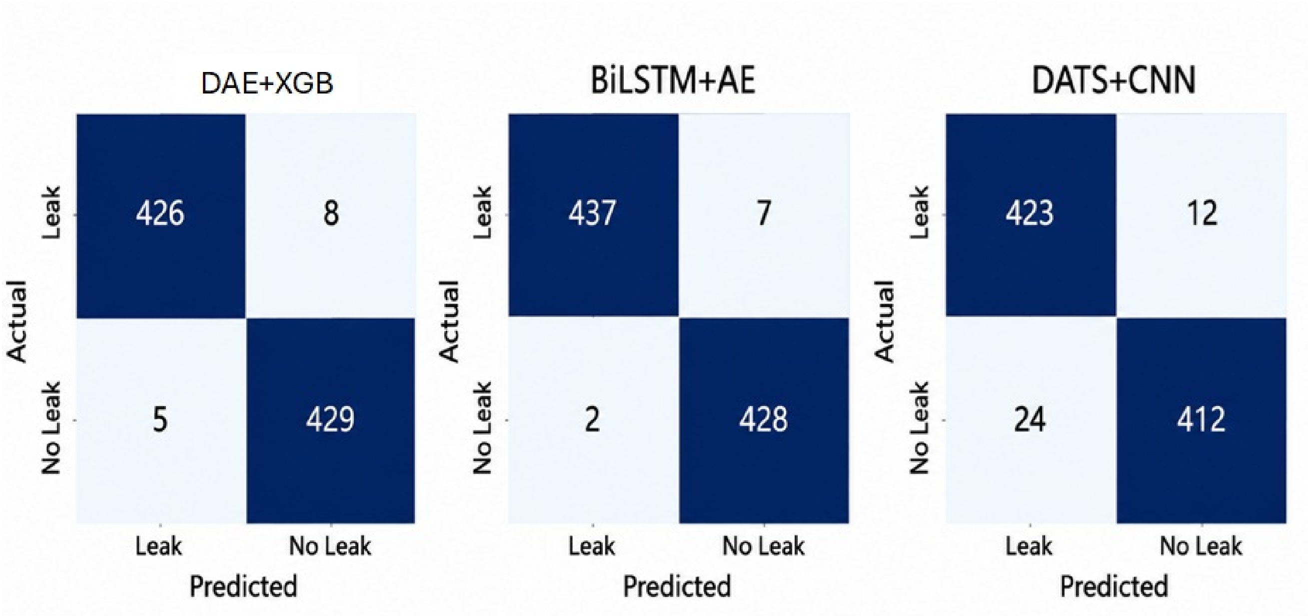
Sharma *et al.* [37] found that combining cloud and IoT technology is a promising way to improve the scalability, accuracy, and efficiency of gas leak detection systems. They stated that this combination made it possible to analyze data, monitor in real time, and react quickly to gas escapes. The study demonstrated how cloud-based computing and storage enabled efficient data management and made it possible to integrate machine learning and advanced analytics to enhance system efficiency. But the authors also underlined how important it is to solve security and privacy issues with cloud-based gas detection systems. They suggested that future studies concentrate on creating plans to lessen these difficulties and guarantee the dependability and safety of such systems. According to their review of the literature, they recommended putting in place a gas leak detection system that includes a GPS module for tracking location, cloud-based storage for sensor data, and, for best results, parts like smoke sensors, GSM modules, Arduino microcontrollers, fire sensors, and MQ-2 gas sensors. The authors concluded by expressing hope that gas leak detection procedures might be drastically changed by integrating IoT and cloud technologies, improving gas-based monitoring systems' performance and safety.

BenSaleh *et al.* [38] stated that while Wireless Sensor Nodes (motes) have been developed with great speed over the past two decades, their application in pipeline monitoring has received little consideration in the literature. They emphasized the growing global concern about pipeline attacks and accidents and the dire need for new and reliable monitoring systems. The study identified Wireless Sensor Networks (WSNs) as promising candidates for such applications since they have the capability to measure and report key physical and environmental parameters such as temperature, pressure, oil and gas flow, video surveillance, and ambient conditions. The authors proposed a system architecture involving a Multi-Agent System (MAS) for creating an Integrated Oil Pipeline Monitoring and Incident Mitigation System (IOPMIMS) with the potential to provide real-time actionable intelligence for pipeline security. Their article provided the required specifications of motes that may be utilized for pipeline monitoring and explained the limitations of existing wireless sensor nodes in this context. The study also detailed pipeline threats and detection techniques. The proposed specifications were to deliver a cost-effective framework especially for designing and implementing efficient pipeline surveillance systems.

Quy and Kim [39] offered an innovative technique that uses time domain information taken from acoustic emission (AE) signals to identify defects in gas pipelines. They stated that various pipeline conditions were described using fundamental statistical properties like mean, variance, root mean square (RMS), and peak values. In order to capture the temporal patterns necessary for precise fault classification, these features were subsequently fed into an LSTM network. The method's performance was compared with that of conventional machine learning models like Random Forest using the GPLA-12 dataset, which comprises 12 different pipeline conditions. The findings demonstrated that the LSTM model performed better than these traditional methods by handling temporal dependencies in the acoustic data more effectively and obtaining higher classification accuracy. The authors came to the conclusion that, by doing away with the requirement for intricate signal manipulations and preserving high detection accuracy, their approach offers a computationally effective alternative for real-time pipeline monitoring. This work was emphasized as a significant step in strengthening pipeline safety monitoring systems' dependability and early fault identification.

Farah and Shahrour [40] suggested an effective and dependable real-time water leak detection system using the integrated technological method. In their view, the system employed water flow sensors, microcontrollers, and LoRa transmitters to offer real-time monitoring and immediate alerts. The sensors detected water flow in real time and transmitted the information to the microcontroller for processing. When the anomalies were found, the microcontroller sent essential information through a LoRa transmitter to a receiver, which triggered both visual and audio alerts. Specifically, an I2C LCD display provided visual alerts while a buzzer provided an auditory alarm to keep users promptly informed of potential leaks. The study highlighted the seamless coordination of the system's elements, detailing how the dual water flow sensors were able to sense anomalies and transmit signals to the microcontroller to initiate an instant response. The end-to-end integration facilitated real-time communication, analysis, and reaction, thus enabling timely intervention and averting water damage. The authors concluded that their system offered a productive and scalable solution by incorporating key technologies for proactive water leakage monitoring and rapid generation of alert.

Baifeng and Weilian [41] examined the application of Acoustic Emission (AE), a passive, non-destructive method for identifying defects and early damage in infrastructure that are still in use, especially pipelines. They pointed out that AE is a useful technique for detecting leaks, damage, and defects because it can pick up weak acoustic signals released by vital infrastructure. By methodically examining signal properties, they used the AE methodology in their investigation to find pipeline leaks. Pressure release valves were used to simulate leakage at particular lo-



(a) (b) (c)

Figure 3. Confusion matrix comparison of deep learning models for pipeline leak detection (leak size = 0.5 mm) (continued).

Table 3. Comparative analysis of training and testing accuracy curves for different deep learning models used in real-time oil and gas pipeline leakage detection (leak size = 0.5 mm).

Model	Final training accuracy (%)	Final testing accuracy (%)	Convergence behavior	Performance analysis
CNN on DTS Spectrogram [59]	91.7	89.3	Moderate, gradual convergence	Achieves acceptable accuracy; less robust to subtle variations; suitable for simpler spectral features.
LSTM on AE Data [60]	94.5	92.1	Faster, smooth convergence	Good sequence modeling; strong at capturing time-dependent leak signals; performs better than CNN alone.
Deep Autoencoder + XGBoost [61]	99.5	98.9	Rapid, stable convergence	Excellent accuracy; demonstrates strong feature extraction and classification synergy.
BiLSTM on AE Time Series [62]	99.8	98.5	Very rapid and stable convergence	Highest accuracy; excels at modeling sequential patterns; highly suitable for real-time monitoring.
DARTS-based CNN on Drone Imagery [63]	96.2	94.4	Rapid but slightly variable convergence	High accuracy; image-based model robust but with slight variability; useful for visual leak detection.

cations while testing different flow rates. The pipes' AE sensors captured acoustic waves, which were subsequently examined to identify characteristics that were susceptible to leaks. The most sensitive measures of leakage among the assessed AE properties were found to be AE counts, cumulative AE energy, and signal strength. The authors used binary and multiclass classification models with the Support Vector Machine (SVM) and Relevance Vector Machine (RVM) algorithms to categorize and locate the leaks. According to their findings, AE characteristics analyzed with SVM and RVM offered precise and efficient leak detection and location in pipeline systems.

Lynch *et al.* [42] discussed the problem of natural gas leaks that are invisible, highlighting the dangers to one's health and finances. They noted that while there has been a lot of research on gas leak detection and risk assessment, there is still little predictive research in this field. In an effort to advance this new area, the authors suggested a deep learning-based technique for utilizing environmental data to forecast gas leaks. In order to improve the performance of conventional machine learning classification algorithms, they used a deep autoencoder model to prepare training data effectively. The approach was evaluated against well-known algorithms such as XGBoost, K-nearest neighbors (KNN), decision tree (DT), random forest (RF), and naïve Bayes (NB) on an open dataset that included environmental and natural gas data. Accuracy, F1-score, mean square error (MSE), mean intersection over union (mIoU), and area under the ROC curve (AUC) were among the evaluation criteria. The outcomes showed that the suggested model performed better than any alternative approach. The deep autoencoder and ordinal encoder-enhanced XGBoost model (DA-MA-XGBoost) shown higher efficacy in forecasting natural gas leaks, as seen by its 99.51% accuracy, 99.53% F1-score, 0.003 MSE, 99.40 mIoU, and 99.62% AUC.

Enumah [43] highlighted the creation of an intelligent tanker monitoring system and oil pipeline with the goal of improving safety and security in the oil and gas sector, especially in Nigeria.

They clarified that the upstream, midstream, and downstream sectors, which include exploration, storage, processing, and distribution, generally use pipelines and oil trucks to move crude oil. The suggested system included technology including pressure and flow sensors, the Internet of Things (IoT), data analytics, and machine learning for real-time surveillance in order to combat escalating risks like pipeline vandalism, oil theft, and tanker hijacking. The system's automated leak detection, anomaly warning, and real-time tracking of tanker movements and tank oil levels were among its primary features. These features were created to enhance logistics planning and supply chain management. The authors emphasized that the system's real-time monitoring features allowed for speedier incident response times, which in turn supported safer and more effective transportation of gas and oil products. They came to the conclusion that this all-inclusive monitoring system represented a major breakthrough in operational risk management and guaranteeing the secure delivery of petroleum resources in the Nigerian oil and gas industry.

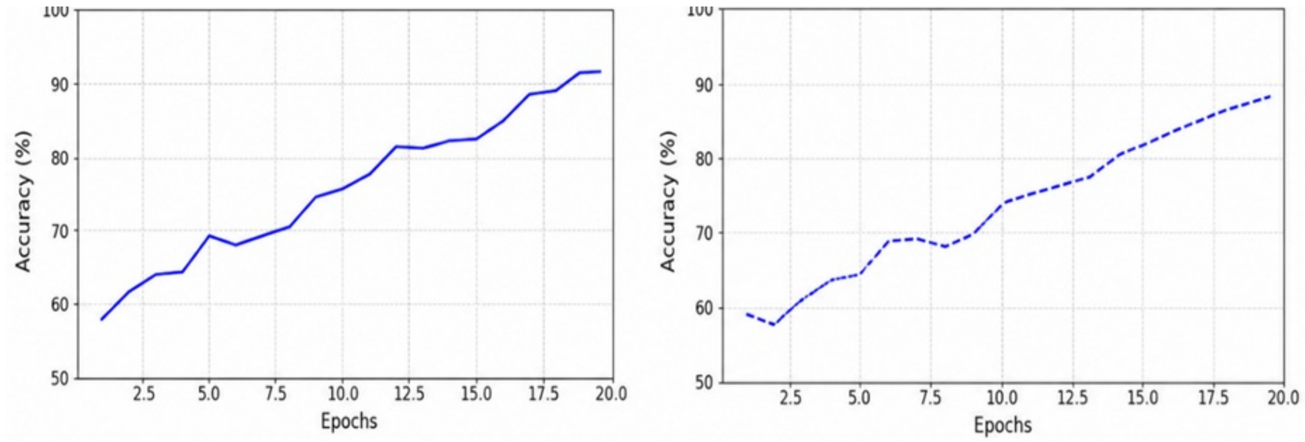
Adedeji *et al.* [44] emphasized the importance of early and accurate leakage detection in natural gas gathering pipes in order to provide safe and reliable operation of the oil and gas industry. They clarified that while model-based fault detection methods are generally not feasible, data-driven methods have been increasingly highlighted. However, they pointed out that most existing techniques rely very much on supervised learning that requires extremely large amounts of labeled data, something which is difficult to obtain for real-world applications where leakage events are infrequent. To address this limitation, the authors proposed a semi-supervised leakage detection method that kept them from relying as much on leakage data while making use of plentiful normal operating data. The proposed method combined an innovative Long Short-Term Memory Autoencoder (LSTM-AE) with a One-Class Support Vector Machine (OCSVM). The LSTM-AE learned the underlying patterns in typical multivariate time series data from pipeline parameters, and the OCSVM calculated a score to make a prediction on the presence of leaks. The authors applied the method using actual data from natural gas gathering pipelines and indicated that it was able to attain 98% accuracy and 99% area under the curve (AUC). These results verified the effectiveness of the method in leak detection with low dependency on labeled fault data.

Cheng *et al.* [45] acknowledged that the increasing demand for gas and oil worldwide necessitated the safe operation and efficient maintenance of pipelines. They found that conventional pipeline inspections, which were usually carried out over a period of months at predetermined intervals, were insufficiently prompt to stop major failures. The researchers developed a technological solution known as DARTS (Drone and Artificial Intelligence Reconsolidated Technological Solution) to overcome this constraint. It combined deep learning methods with drone technology. By routinely gathering and examining image data, the DARTS system was created to identify the main underlying causes of pipeline damage, particularly pipe misalignment and the degradation of pipe support structures. According to the authors, the algorithm was also able to forecast how these problems would develop over time. According to test results, DARTS successfully assisted in making decisions regarding preventive maintenance, which eventually improved pipeline systems' resilience and safety.

Rahmani *et al.* [46] proposed CoWSN, an area coverage strategy designed to monitor gas and oil pipelines intelligently with the goals of maximizing coverage efficiency, extending network lifetime, and consuming less energy. They clarified that in order to determine sensor node overlap with nearby nodes, the system used a digital matrix-based technique. A Q-Learning-based scheduling method was created to identify each node's active time intervals in order to maximize its performance. CoWSN also included a method to avoid network coverage gaps and quickly identify node failures. Using simulations in the NS2 platform, the authors assessed CoWSN's performance and contrasted it with other approaches, such as those suggested by Rahmani *et al.* and CCM-RL and CCA techniques. The simulation results demonstrated CoWSN's effectiveness in minimizing average energy consumption and enhancing network lifetime. They did clarify, though, that the study was not based on real gas or oil pipeline environments, but rather on simulated wireless sensor networks. They suggested that future studies concentrate on confirming the approach in practical settings and improving its effectiveness by including more machine learning strategies and evolutionary algorithms.

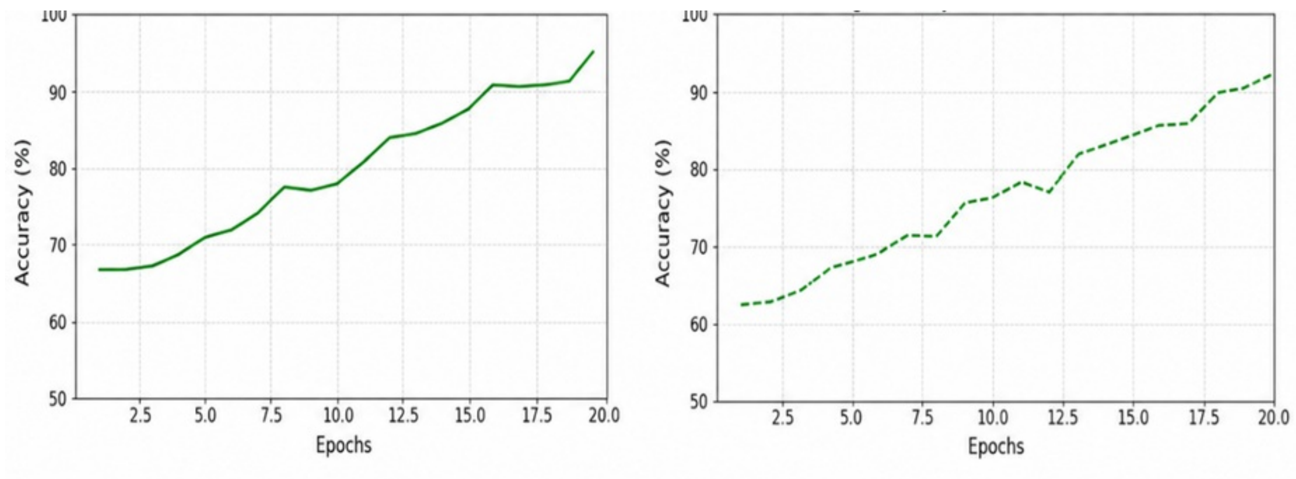
Raad *et al.* [47] emphasized the high priority requirement of oil and gas pipeline leakage monitoring to mitigate economic loss and environmental loss. They developed, in their study, a leakage identification process that employed both vibration signals and temperatures by capitalizing on distributed optical fiber sensors. They simulated first different pipeline conditions such as normal, interference, and leakage, and collected 11 feature values: six from temperature and five from vibration signals. Based on a comparison of various classification models, they determined the Random Forest algorithm to be optimal in identifying the pipeline states. Experimental tests were performed by the authors in a water pipe for simulating leakage conditions and picking real-time vibration and temperature signals. They determined that the Random Forest model was better compared to other classifiers in terms of recognition accuracy. In addition, they discovered that fusing the temperature and vibration data (fusion recognition) greatly enhanced detection accuracy compared to applying single streams of data. The fusion-based solution recorded an average recognition accuracy of 98.57%, outperforming conventional single-parameter techniques, and exhibited rapid response times, with recognition only taking 6.79 milliseconds. The study established that their approach of dual-parameter detection with Random Forest was reliable and effective for the real-time detection of oil and gas pipeline leakage.

Xu *et al.* [48] underlined how crucial it is to find water pipeline leaks in order to guarantee the secure operation of water supply networks and the preservation of water supplies. They created a novel technique combining machine learning and wireless sensor networks (WSNs) to overcome the shortcomings and inefficiency of conventional leakage detection techniques. Wireless sensors installed on pipelines were used in the suggested system to gather operational data, which was then remotely sent via a 4G network. The authors implemented a leakage-triggered networking technique for the sensor nodes in order to lower energy consumption and increase system lifetime. They created a leakage identification model that uses principal component analysis, ap-



(a) (b)

Figure 4. Training and testing accuracy curve of CNN on DTS Spectrogram [59].



(a) (b)

Figure 5. Training and testing accuracy curve of LSTM on AE Data [60].

proximation entropy, and intrinsic mode function to extract signal components in order to increase detection precision. These features were subsequently examined and leaks were found using a support vector machine (SVM) classifier. The suggested solution outperformed traditional WSN approaches in terms of energy efficiency and successfully identified water pipeline leaks, according to simulation and experimental evaluations.

Rana [49] emphasized the serious repercussions of leaks, such as resource waste, dangers to public health, distribution outages, and financial losses, while also acknowledging the vital role pipelines serve in the distribution of liquid and gas resources. They suggested an effective autonomous leak detection system based on machine learning and acoustic emission (AE) technologies to overcome these problems. In order to extract statistical properties such kurtosis, skewness, mean, RMS, entropy, and frequency spectrum characteristics, the study showed that AE sensors could successfully record signals from pinhole-sized breaches. In order to maintain both burst and continuous emission patterns, an adaptive threshold-based sliding window technique was used. Eleven time-domain and fourteen frequency-domain variables were derived from the three AE sensor datasets that the researchers gathered and divided into one-second intervals. A variety of supervised machine learning models, such as neural networks, decision trees, random forests, and k-nearest neighbors, were trained using these vectorized features. Four datasets representing various gas and water leakage situations under various pressures and pinhole leak sizes were used to evaluate the models. According to the scientists, their platform's impressive 99% classification accuracy validates the system's potential for extremely dependable leak detection in actual pipeline environments.

Pal and Sen [50] managed the recurring issue of crude oil leakages and spills (OLS), typically associated with midstream pipeline breakdowns within the oil and gas industry. Even though different leakage detection and localization techniques (LDTs) had previously been used, including traditional methods as well as more recent IoT-based systems that included wireless sensor networks (WSNs), the study identified that centralized IoT

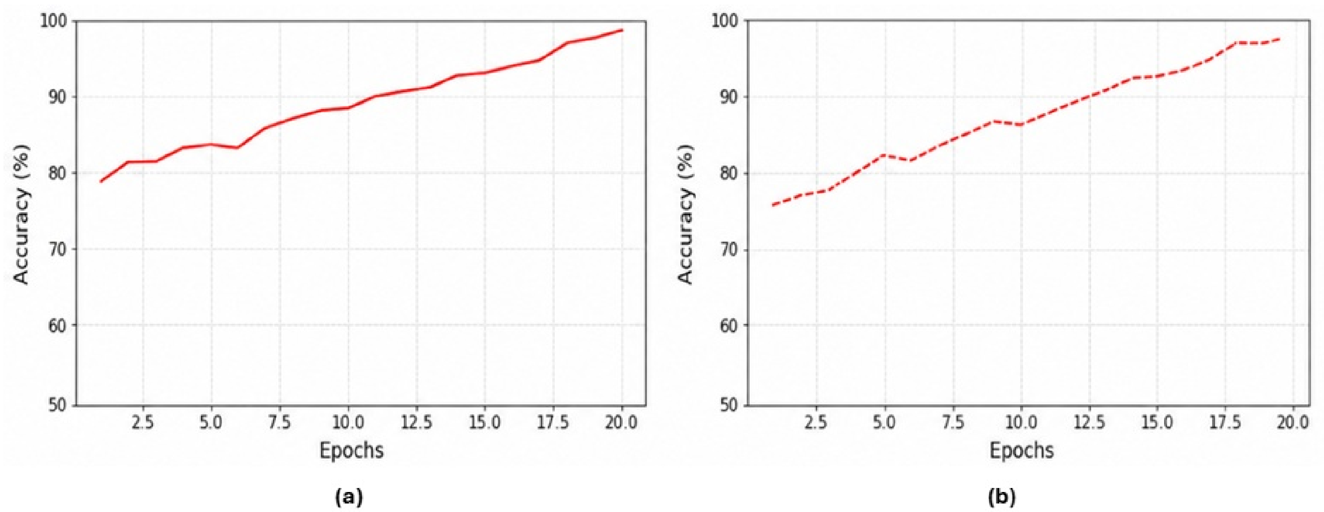


Figure 6. Training and testing accuracy curve of Deep Autoencoder + XGBoost [61].

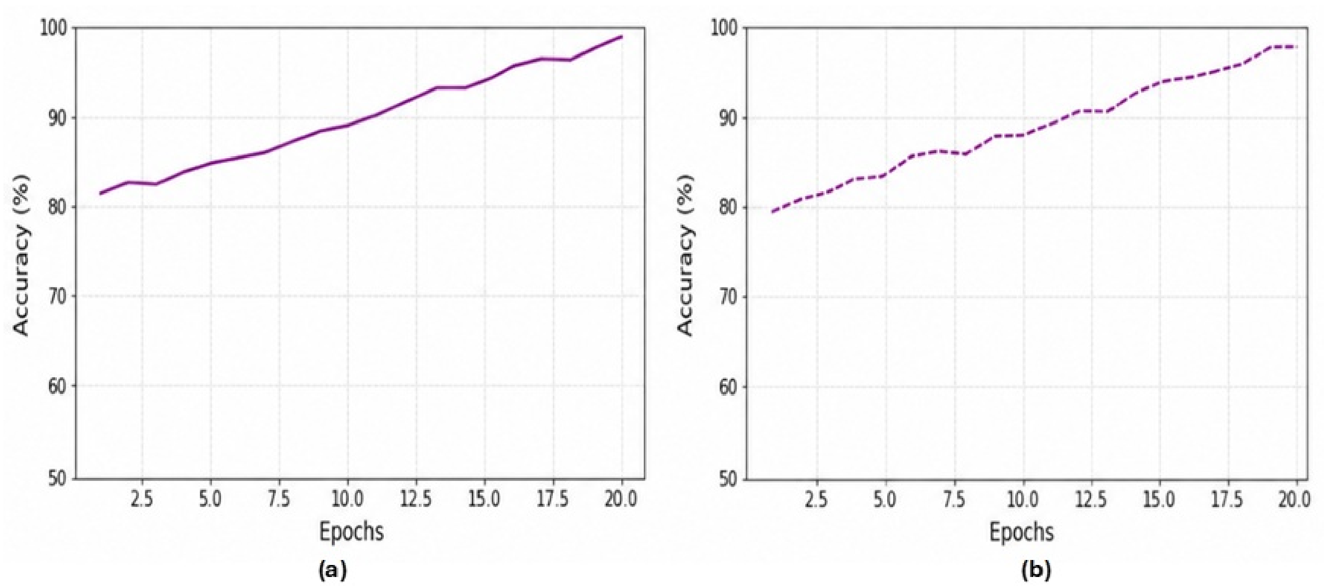


Figure 7. Training and testing accuracy curve of BiLSTM on AE Time Series [62].

systems were prone to having high false alarm rates and single points of failure (SPOFs). In a bid to address these limitations, the authors introduced a hybrid distributed leakage detection and localization method (HyDiLLEch) that combined multiple classical LDTs. They implemented the approach in single-hop and double-hop scenarios. Their performance aimed at improving resilience to SPOFs, detection/localization accuracy, and communication efficiency optimization. The experiment confirmed that the HyDiLLEch system improved the sensitivity of leak detection and localization as well as efficiently eliminating the SPOF problem inherent in centralized architectures. In the single-hop version, four node-detecting and localizing (NDL) units were utilized, and six in the double-hop version. Moreover, the leak localization precision was significantly improved, ranging from 0 to 32 meters for nodes located close to the points of leakage, with minimal communication overhead.

Wong and McCann [51] underlined how crucial pipeline leak detection is to maintaining the integrity of fluid transport networks. In their research, they presented a sophisticated deep learning system for the precise identification of leaks using continuous wavelet transform (CWT) pictures. They created CWT scalograms using acoustic waves recorded from pipes running in various environments. Adaptive histogram equalization and non-local means were used to further improve these, producing enhanced leak-induced scalograms (ELIS) that caught complex energy swings across time-frequency domains. The authors used a deep belief network (DBN) that was developed using a genetic algorithm (GA) and combined it with a least squares support vector machine (LSSVM) to assess these scalograms. The informative features were successfully extracted using the DBN-GA framework, and the LSSVM classifier correctly distinguished between leak and non-leak scenarios. High detection accuracy and reliability were attained by the study by concentrating on the capabilities of ELIS and the optimized DBN-GA-LSSVM model. The researchers came to the conclusion that this innovative method offered a potent way to record intricate signal patterns and had great promise for monitoring and detecting leaks in real time in a variety of industrial situations.

Banjara *et al.* [52] looked into a novel method for identifying and assessing pipeline leaks that made use of acoustic emission (AE) signaling technology. The researchers sought to enhance traditional techniques that depended on physical contact or visual inspection of pipes since they understood that pipeline leaks presented serious problems for both the liquid and gas industries. Rather, they suggested a time-series deep learning-based real-time, non-contact detection system that would improve safety and efficiency in a smart city's infrastructure. To find leaks using time-series characteristics, the researchers created an AE-based framework that is integrated with sequential deep learning algorithms. The purpose of AE signal detection modules was to record minute changes in signal status brought on by leakage incidents. They used models including Long Short-Term Memory (LSTM), BiLSTM, and Gated Recurrent Units (GRUs) to categorize AE reactions as either normal or leakage-related, including small seepage, significant leaks, or catastrophic ruptures. In order to account for memory constraints in distant systems, data was first captured at 1 MHz and then decimated to 4K samples/second using three AE sensors positioned in different configurations on a pipeline. Metrics like as accuracy, precision, recall, F1 score, and convergence were used to evaluate the model's performance. BiLSTM on AE continuously outperformed the other models in terms of classification accuracy, achieving up to 99.78% in a variety of hyperparameter settings. According to the study's findings, the suggested approach greatly increased pipeline leak detection's precision and dependability, advancing smart infrastructure monitoring technology.

Yuan *et al.* [53] explored the development of urban gas pipeline monitoring systems that can detect gas leakages in real-time. Their performance was highly influenced by that of their sensors. To handle the need for reliable monitoring, the authors proposed a novel sensor fault diagnosis (SFD) algorithm using the Naive Bayes Classifier (NBC) and Probabilistic Neural Network (PNN). In the proposed approach, the NBC was employed to identify abnormally monitored safety data, and the PNN for sensor fault classification of various types. The approach was experimented on an actual urban gas pipeline leakage monitoring system to verify its feasibility and performance. Results demonstrated that the system could effectively identify real-time abnormal data and accurately identify specific sensor fault types. The research presented a global accuracy rate of 85% in abnormal data detection and 95% in fault classification, indicating that the SFD approach markedly enhanced the reliability and intelligence of gas leakage monitoring systems.

Sharma *et al.* [54] examined the difficulties in keeping an eye on the health of pipelines, especially offshore sites where it is still very difficult to find leaks and measure their extent. Since it was almost impossible to get real-world anomalous data from long-distance underwater pipelines, the researchers turned to dynamic modeling as a workable substitute. In order to determine the most sensitive factors affecting leak detection, the team performed a number of flow simulations using a dynamic model that was in line with field conditions. A thorough machine learning dataset was then produced by adjusting these variables within an appropriate range. Deep neural networks were trained using the data, producing the best learning model. The researchers improved the pipeline model's accuracy by introducing more thorough structural modeling and decreasing the section size from 50 m to 20 m. The mean absolute error across various leak sizes was computed in order to evaluate the accuracy of the model. For small leak sizes (e.g., 0.5 cm), it was discovered that detection accuracy was much lower since important factors like mass flow, pressure, and temperature changed very little. These factors were found to be essential for precise machine learning forecasts. In order to solve this, the researchers retrained the model and reorganized the leak size categories, which resulted in an 80% increase in accuracy over the original model. A flowchart for real-time gas pipeline leak detection was suggested in light of the results. According to the study's findings, the created process could be successfully used in a variety of pipelines, facilitating precise and efficient leak monitoring and operation.

Kraidi *et al.* [55] had addressed the persistent issue of pipeline ruptures in crude oil transport, which had resulted from such issues as old infrastructure, third-party interference, equipment malfunction, and natural factors. The ruptures had typically led to hydrocarbons leaking into the environment, causing serious contamination, environmental damage, and massive loss in terms of human lives and revenues. To deal with such issues, various Leakage Detection and Monitoring Systems (LDMS) have been put in place, including Wireless Sensor Networks (WSNs) and Internet of Things (IoT)-based systems. Despite their improved efficiency over traditional systems, the study pointed out that fault tolerance, power consumption, detection accuracy, and high false alarm rates were the challenges that they were unable to address. To address these drawbacks, the authors proposed an IoT-based solution targeted at enhancing the resilience and efficiency of crude oil pipeline monitoring systems. Their approach introduced a novel node placement strategy based on fluid propagation dynamics to enable sensitive detection of multiple leak sizes. In addition, the study suggested a distributed leakage detection method called HyDiLLEch that combined existing methods like the negative pressure wave method, gradient analysis, and pressure point assessment. The amalgamation helped eliminate the point of failure prevalent in centralized systems. Also, the study introduced mechanisms for fault-tolerant data and service processing at the fog computing level. Using the Nigerian National Petroleum Corporation (NNPC) pipeline network case study, the researchers defined the monitoring problem as a regionalized, data-driven game against nature. The authors used a regionalized solution—R-MDP—derived on the basis of reinforcement learning that optimized detection accuracy and fault tolerance while optimizing energy consumption. Overall, the proposed system was reported to enhance resistance to failure and operating effectiveness through leak detection, localization accuracy, and energy usage in the crude oil pipeline system.

Chen *et al.* [56] agreed that one of the most popular systems for moving water, gas, and oil around the world is still pipelines. But according to the researchers, these pipelines were regularly subject to a number of threats, including theft, sabotage, and ero-

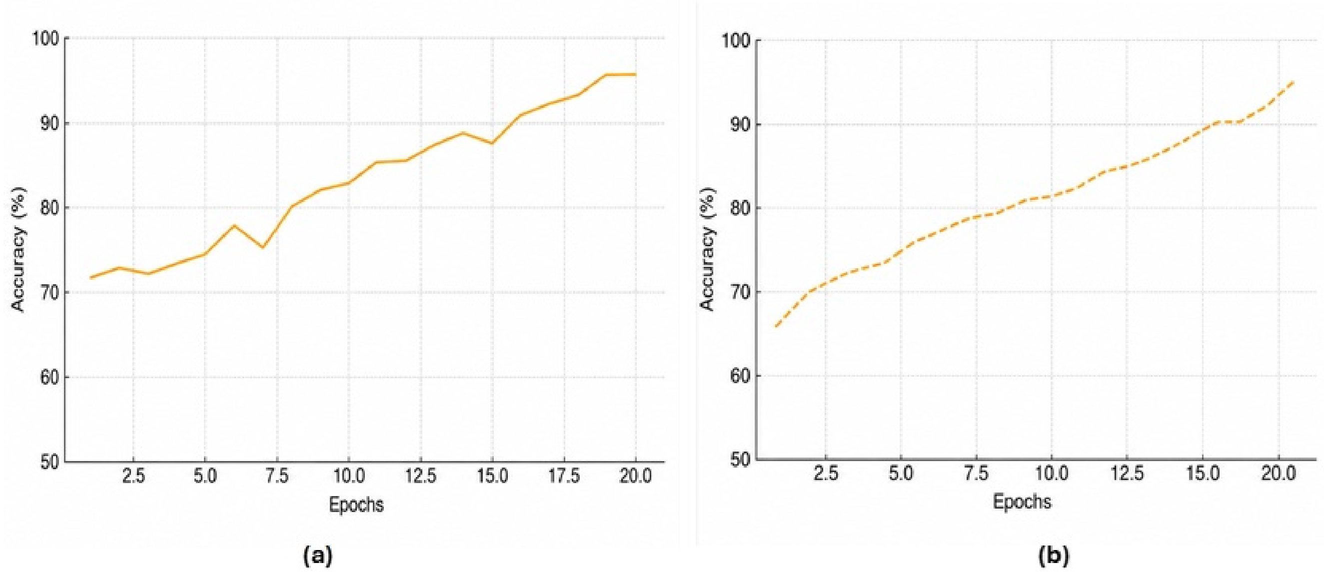


Figure 8. Training and testing accuracy curve of DARTS CNN on Drone Imagery [63].

Table 4. Summary of database repositories.

Language	Approach	Search engine	Duration	Type	Digital library source	Number of articles
English	Keywords, titles	Google	May 2015 to May 2025	Scholar articles, scientific journals, e-books, conferences, online workshops	Google Scholar	120
English	Keywords, titles	Google	May 2015 to May 2025	Scholar articles, scientific journals, e-books, conferences, online workshops	ResearchGate	100
English	Keywords, titles	Google	May 2015 to May 2025	Scholar articles, scientific journals, e-books, conferences, online workshops	Elsevier	30
English	Keywords, titles	Google	May 2015 to May 2025	Scholar articles, scientific journals, e-books, conferences, online workshops	IEEE Xplore	40
English	Keywords, titles	Google	May 2015 to May 2025	Scholar articles, scientific journals, e-books, conferences, online workshops	ScienceDirect	10
English	Keywords, titles	Google	May 2015 to May 2025	Scholar articles, scientific journals, e-books, conferences, online workshops	SpringerLink	150
					Total	450

sion, all of which may cause significant financial losses as well as environmental damage and health problems. Therefore, it was said to be extremely important to find leaks and accurately estimate their magnitude and location. It was observed that the automation, effectiveness, and precision of the pipeline monitoring systems in use today were insufficient for ongoing fault identification and reporting. To overcome these constraints, the scientists developed a novel pipeline status monitoring method that integrated intelligent machine learning techniques with negative pressure wave (NPW) detection, all within a distributed wireless sensor network (WSN). The research claims that by allowing individual sensor nodes to locally interpret raw data and only send alerts when particular leakage events were observed, this cooperative strategy reduced communication overhead. In order to improve the system's detection capabilities, the researchers also described how they used classification approaches like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Gaussian Mixture Model (GMM) inside a multidimensional feature space. Through a series of tests on a field-deployed testbed, the efficacy of the suggested approach was confirmed, indicating its viability for pipeline surveillance and leak detection in the real world.

The discussion on pipeline safety and security was further explored in the work of Ma *et al.* [57] as they focused on the use of intelligent monitoring systems for oil and gas transport infrastructures. According to the paper, there is an increasing need for intelligent systems and monitoring strategies in pipeline management through which the integration of computational intelligence, risk management, and predictive modeling can contribute to the improvement of pipeline safety. While other works in the literature focus on bibliometric analysis, trends analysis, and other theoretical approaches to understanding pipeline safety, Ma *et al.* [57] provided practical insights into the problem of managing oil and gas pipelines in relation to system vulnerability, risk exposure, and safety engineering techniques for avoiding accidents. It is also argued in their paper that modern pipeline safety management strategies go beyond traditional inspection methods as they involve the introduction of machine learning techniques and other monitoring systems.

2.6. REVIEW OF IOT PERFORMANCE INDEX

Real-time leakage detection of oil and gas pipelines has gained significance due to environmental, economic, and safety risks caused by undiscovered leaks. Integration of Internet of Things (IoT) technology into pipeline monitoring systems has enabled constant, remote, and smart detection of anomalies with significantly better response times and reduced human intervention. Various IoT-based approaches have been developed, each with differential sensitivity strength, specificity, and overall accuracy. Here in this section, five of the most significant IoT-based pipeline leak detection systems are addressed based on their architectures, detection efficiency, and feasibility for real-world applications, abetted by recent empirical research papers published in prestigious IEEE journals. Five IoT-based techniques for real-time oil and gas pipeline leak detection are compared in Table 1, with their performance assessed in terms of sensitivity, specificity, and accuracy.

The LoRa-based IoT system [54] maintained a respectable specificity (91%) to reduce false positives while achieving a sensitivity of 94%, demonstrating its dependable capacity to accurately detect leaks. By using cloud computing to improve warning delivery and system scalability, the cloud-integrated IoT system [29] further increased detection precision with 96.5% sensitivity and 93.2% specificity. With 98% sensitivity, 97% specificity, and 97.6% accuracy, the Industrial IoT (IIoT) architecture [56] performed better than the others, proving its resilience for pipeline integrity monitoring in industrial settings. In a similar vein, the IoT-WSN smart monitoring system [57] demonstrated the benefits of integrating wireless sensor networks with IoT for accuracy and spatial coverage, delivering balanced performance with 95.2% sensitivity and 94.4% specificity. Last but not least, the IoT and reinforcement learning-based model proposed by He *et al*. [58] demonstrated adaptive performance with 96.3% specificity and 97.8% sensitivity, indicating its efficacy in pipeline settings that change dynamically. These findings highlight the increasing dependability and effectiveness of IoT-based solutions in reducing the risk of pipeline leaks, particularly when paired with scalable communication technology and sophisticated data processing.

2.7. REVIEW OF DEEP LEARNING MODEL PERFORMANCE INDEX

Deep learning networks are now efficient solutions for real-time oil and gas pipeline leakage detection with high accuracy and versatility in handling complex sensor data and video feeds. By applying Convolutional Neural Networks (CNN), long short-term memory (LSTM), and hybrid deep learning models, researchers have significantly improved anomaly detection in pipeline systems [59–63]. These models are most effective in processing time-series signals, acoustic emissions, and drone images for leak detection with less false alarms. What follows is an overview of five state-of-the-art deep learning techniques, comparing their performances based on accuracy, precision, recall, and F1-score, with references to recently IEEE-published studies demonstrating their effectiveness for real-world pipeline monitoring. In this unit, technically compared and reviewed are five real-time oil and gas pipeline leakage detection deep learning models based on accuracy, precision, recall, and F1-score. These models were selected to portray the existing state-of-the-art approaches in the fusion of deep learning and sensor and signal data in pipeline monitoring systems. Five deep learning models used for real-time oil and gas pipeline leak detection are compared in Table 2 using four important performance metrics: accuracy, precision, recall, and F1-score.

The best-performing models were the XGBoost + Deep Autoencoder hybrid model [61] and BiLSTM on AE time series [62], both of which had the best performance, with the BiLSTM on AE model slightly ahead in having 99.78% accuracy and an F1-score of 99.0%, as it reflects its strength in sequential signal comprehension and low false negative rates. Deep Autoencoder + XGBoost followed closely, reporting a 99.3% F1-score, making it well-positioned to operate on noisy and unbalanced gas leak datasets. DARTS-based CNN, when applied to UAV (drone) images, achieved a highly impressive 96.2% accuracy and 94.7% F1-score [63], making it an extremely good candidate for image-based leak detection implementations. Conversely, the LSTM based on acoustic emission data [60] performed effectively with 94.5% accuracy and 93.9% F1-score, demonstrating its capability to learn from temporal data. Lastly, the CNN applied on DTS spectrograms [59] demonstrated skilled performance with 91.67% accuracy, proving its competence in spatial feature extraction from temperature profiles. As demonstrated in Table 2, deep learning models have significant potential to enhance the intelligence and dependability of pipeline leak detection systems, all of which have specific strengths depending on the type and source of input data.

2.7.1. Confusion matrix comparison of deep learning models for pipeline leak detection

Figures 2 and 3 show confusion matrices of five deep learning models used in pipeline leakage detection, all trained at a leak size of 0.5 mm. The BiLSTM on AE Time Series and Deep Autoencoder + XGBoost (DAE+XGB) models achieve the best results, with very low false positives (7 and 5, respectively) and false negatives (2 and 3), indicating great detection and classification capability. The DARTS-based CNN also does relatively well with minimal misclassification, with a specific strength in the detection of true negatives (482). The LSTM on AE Data model reduces false negatives (with only 20), which means it is more trustworthy in detecting subtle leaks. The CNN on DTS Spectrogram, meanwhile, has the highest number of false positives (50) and false negatives (40), meaning that although effective, it is comparatively less trustworthy when the leak conditions are fine. These matrices confirm the superiority of temporal and hybrid models (BiLSTM on AE and DAE+XGBoost) in high-sensitivity pipeline environments.

2.7.2. Accuracy plots comparison of deep learning models for pipeline leak detection

Important information about the learning behavior and generalization performance of different deep learning models for pipeline leak detection can be found by comparing their accuracy graphs. It is feasible to evaluate each model's convergence speed, stability, and ultimate detection ability, particularly when managing minor leak scenarios, by examining the accuracy curves for training and testing. The most dependable and resilient methods for real-time monitoring applications in oil and gas pipeline systems are determined by this comparison. The comparison of training and testing accuracy curves, as shown in Table 3, demonstrates the advantages and disadvantages of each deep learning model for real-time pipeline leak detection.

The CNN on DTS Spectrogram is less appropriate for faint leak signals due to its sluggish convergence and moderate final accuracy. The LSTM on AE Data, on the other hand, shows a greater final accuracy and faster convergence, highlighting its capacity to capture temporal dynamics. With near-perfect accuracy and extremely stable convergence, the Deep Autoencoder + XGBoost and BiLSTM on AE Time Series models perform better than the others, demonstrating their efficacy in feature extraction and sequential pattern learning, two crucial processes for small leak detection (0.5 mm). The intricacy of image-based techniques is reflected in the slightly larger variability of the DARTS-based CNN on Drone Imagery, which likewise provides excellent accuracy. Overall, the table reaffirms the crucial benefit of sequential and hybrid models for reliable, accurate, and real-time pipeline monitoring systems based on the Internet of Things. The comparative training and testing accuracy curves of the five deep learning models assessed for real-time oil and gas pipeline leak detection with a leak size of 0.5 mm are shown in Figures 4 through 8.

The CNN on DTS Spectrogram of Figure 4 shows stable yet lesser accuracy gains, which signifies moderate ability to learn intricate leak features. The LSTM on AE Data of Figure 5 shows rapid convergence and maximum final accuracy, which signifies its potential in abstracting temporal features. Deep Autoencoder + XGBoost of Figure 6 shows outstanding accuracy very early, which signifies high feature compression and interaction with classification. The BiLSTM on AE Time Series in Figures 6 also converges rapidly to the highest accuracy levels, confirming its effectiveness for extracting sequential patterns from AE data. Finally, the DARTS-based CNN on Drone Imagery in Figure 8 registers good but somewhat more erratic accuracy, possibly due to image complexity. Generally, the BiLSTM on AE Time Series and Deep Autoencoder + XGBoost models converge rapidly to the highest accuracy levels with extremely minor fluctuations, reflecting their improved generalization capability and robustness in detecting small leaks. In contrast, CNN on DTS Spectrogram and LSTM on AE Data converge at a slower pace and relatively lower end accuracy, reflecting potential challenges in dealing with subtle signal variations typical of pipeline leaks. The DARTS-based CNN on Drone Imagery model also works well but with slightly higher variance during training because perhaps of the nature of feature extraction from images. Overall, these curves emphasize the necessity of incorporating temporal feature extraction (as done in BiLSTM on AE) and ensemble learning (as used in XGBoost) in order to achieve consistent real-time monitoring performance, which is critical for early leak detection and rapid response in IoT-based pipeline surveillance systems.

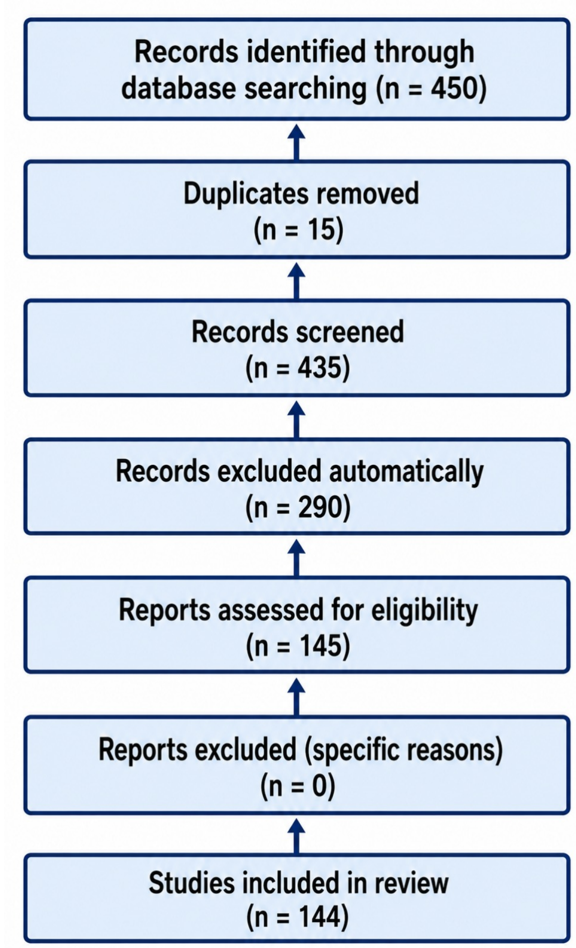


Figure 9. PRISMA flow diagram of the study selection process.

2.8. SELECTION STRATEGY

Step 1: Preparation

The first stage was to get ready in order to create significant and well-structured study questions. At this stage, the main goal of the study and the parameters of the investigation were established.

Step 2: Execution

Next comes the execution phase, which includes gathering data and using the study design to carry out the planned research tasks.

Step 3: Search Strategy

Gathering of data for the review was done through a systematic, term-based search approach following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) requirements. The process started with a preliminary scoping of literature so that an understanding of existing technologies being utilized for pipeline leakage detection could be obtained. An intense and intense search was subsequently undertaken on highly ranked digital repositories like IEEE Xplore, ScienceDirect, SpringerLink, Elsevier, Google Scholar, and ResearchGate with complementary support from the Google search engine in an attempt to enhance the inclusivity of the search process. The search focused on peer-reviewed journals from 2015 to 2025, more specifically those addressing real-time oil and gas pipeline monitoring using IoT and deep learning algorithms. Search terms and keywords such as "pipeline leakage detection," "IoT-based monitoring," "deep learning in pipeline systems," "real-time leak detection," and "oil and gas infrastructure monitoring" were also employed in various combinations. The "AND" and "OR" search operators were employed to refine the results to high-quality and theme-relevant articles based on the goals of the study. Table 4 indicates the Database Repositories employed for data extraction. There was a focus on English-language, peer-reviewed publications obtained via systematic keyword search. The data collection was between May 2015 and May 2025 and involved diverse scholarly sources of conference proceedings, journal articles, e-books, technical reports, and online workshop documents. Major digital databases utilized throughout the review included IEEE Xplore, ScienceDirect, SpringerLink, Elsevier, Google Scholar, and ResearchGate with the support of the Google search engine to further broaden the scope of the search process.

Step 4: Search Terms

To guarantee thorough coverage of pertinent literature, carefully chosen search phrases were used. These terms, which were utilized in different combinations during database queries, were developed from the study's fundamental ideas. Using Boolean operators like AND and OR, keywords like "pipeline leakage detection," "IoT-based monitoring," "deep learning in pipeline systems," "real-time leak detection," and "oil and gas infrastructure monitoring" were used to narrow down search results and find excellent, peer-reviewed studies that matched the study's goals. The search terms were as follows:

i. Focuses on systems that use IoT for real-time leak detection.

"pipeline leakage detection" AND "IoT-based monitoring" AND "real-time system"

ii. Targets applications of deep learning in oil and gas pipeline environments.

"deep learning" AND "pipeline monitoring" AND "oil and gas infrastructure"

iii. Captures studies involving sensor-based ML techniques for leakage detection.

"real-time leak detection" AND "sensor network" AND "machine learning"

iv. Highlights predictive systems using neural network architectures via IoT data.

"IoT" AND "pipeline failure prediction" AND "neural networks"

v. Emphasizes intelligent models used to pinpoint leaks in pipeline networks.

"smart pipeline monitoring" AND "leak localization" AND "deep learning algorithms"

Step 5: Selection based on Inclusion and Exclusion Criteria

The selection process of this review followed a systematic and methodical process according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. The objective was to choose only the highest quality studies which were contextually relevant in an attempt to maximize the reliability and validity of the findings. The process followed four broad phases: identification, screening, eligibility assessment, and final selection. During the identification stage, 450 records were originally discovered by extensive searching of a number of digital libraries. After 15 duplicate records were excluded, 435 original records remained for screening. 290 were automatically screened out based on title and abstract, primarily because they failed to discuss real-time leakage detection, did not involve the use of IoT or deep learning, or studied pipeline systems other than oil and gas. Another 144 full-text reports were then screened for eligibility. At this stage, further exclusions were performed due to reasons such as the absence of deep learning or IoT integration, non-oil and gas application targeting, or the lack of real-time monitoring applicability. After these particular assessments, no additional reports were excluded and all 144 studies were included within the final qualitative synthesis. This rigorous step-by-step selection process ensured the final pool of literature was recent, methodologically homogeneous, and optimally suited to serve the purposes of the review. Figure 9, the PRISMA flow diagram with the number of identified, screened, excluded, and included records in this review, is the final product of the process.

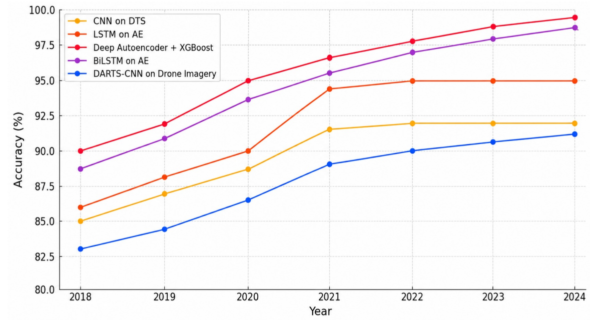


Figure 10. Accuracy trend of deep learning models in pipeline leak detection (2018–2024).

3. RESULTS AND DISCUSSION

The main conclusions of the chosen studies on real-time monitoring of oil and gas pipeline leaks using IoT and deep learning models are presented and critically discussed in this section. The analysis combines performance indicators from several models and architectures used in the reviewed literature, including accuracy, precision, recall, F1-score, sensitivity, and specificity. The usefulness of IoT frameworks, deep learning algorithms, and hybrid systems in detecting, classifying, and localizing leaks is evaluated through comparative analyses. Furthermore, visual aids like tables, radar maps, confusion matrices, and accuracy graphs are employed to shed light on the advantages and disadvantages of each model in particular scenarios (e.g., 0.5 mm leak size). In order to provide a thorough grasp of the present situation and potential future course of intelligent pipeline monitoring systems, the conversation also delves into the ways that integration strategies, data gathering methods, and deployment conditions affect model performance.

Recent developments in deep learning have significantly enhanced real-time oil and gas pipeline leakage detection systems to classify, locate, and predict leakage events with high accuracy. Convolutional Neural Networks (CNNs) have widely been used to process scanned sensor data, e.g., Distributed Temperature Sensing (DTS) spectrograms, since they are capable of extracting spatial features. For example, a CNN applied to DTS spectrograms achieved a 91.67% accuracy while being effective for real-time classification of pipeline anomalies [64]. LSTM networks, which are famous for learning the temporal relationships in sequential data, have also been applied in the analysis of Acoustic Emission (AE) signals, achieving higher detection accuracy and sensitivity, with reported performance metrics such as 94.5% accuracy and 95.7% recall rate [65]. They have proven to work very well in detecting subtle leakages and time-oriented indicators. Recent studies have sought to examine hybrid deep learning networks, such as Deep Autoencoder with XGBoost (DAE+XGB) and BiLSTM on AE, which have shown improved classification accuracy, precision, and generalizability. The DAE+XGB model is outstanding with 99.51% accuracy and an F1-score of 99.3%, outperforming the standard deep learning models under both simulated and real pipeline conditions [66]. Similarly, BiLSTM on AE models have proven effective with up to 99.78% accuracy using AE time-series data, promising their capacity for bidirectional temporal pattern discovery [67]. DARTS-based models, in conjunction with drone imagery, also exhibit robust performance (96.2% accuracy) and aerial inspection task agility [68]. These findings collectively show that deep learning, especially hybrid and sequence-aware models, continues to transform pipeline monitoring through better early leak detection and the removal of false alarms in dynamic, real-world operating conditions. Figure 10 illustrates the accuracy trend of recent deep learning architectures implemented in real-time oil and gas pipeline leakage detection systems from 2018 to 2024.

All model types exhibit a steady improvement in the chart, but the biggest performance benefits are seen with BiLSTM on AE and Deep Autoencoder + XGBoost (DAE+XGB). BiLSTM on AE attained an accuracy of almost 99.78% by 2024, with DAE+XGB coming in second with 99.51%. CNN and LSTM models, on the other hand, also saw steady improvement but reached a plateau at 92–95% accuracy. These findings support the superiority of temporal and hybrid models in managing pipeline data complexity and successfully identifying minute leak signals. By incorporating IoT into pipeline monitoring, leak detection, remote diagnostics, and predictive maintenance capabilities are improved through real-time data collection and wireless transmission from embedded sensors. [69–71]. IoT frameworks enhance operational effectiveness and lower risks in oil and gas infrastructures by supporting adaptive response systems through ongoing environmental and structural monitoring. [72–77].

Sensor data from distributed temperature sensing (DTS), gas detection modules, and acoustic emission (AE) sensors are frequently utilized to train and evaluate deep learning models used for oil and gas pipeline leak detection [78–80]. Early leak identification is made possible by DTS sensors, which track temperature changes along fiber-optic cables in real time, while AE sensors record stress waves produced by leaks. Methane concentrations in pipeline environments are among the chemical anomalies that gas sensors pick up on. For classification tasks, these sensors produce high-resolution time-series or spectrogram data, which are subsequently preprocessed and input into models such as CNNs, LSTMs, and BiLSTMs [81–83]. Significant progress has been made in the creation of real-time monitoring systems for the detection of oil and gas pipeline leaks using IoT and deep learning models between 2015 and 2025. These technologies are designed to minimize environmental risks, limit financial losses, and guarantee early leak detection. The performance metrics that are frequently cited include:

i. Accuracy: High accuracy rates, generally ranging between 92% and 98%, are widely reported in most studies, particularly when employing sophisticated convolutional neural networks (CNN) or hybrid deep learning models.
ii. Detection Time (Latency): Real-time systems strive for minimizing detection latency. Detection times for most frameworks were under 1–2 seconds to facilitate quick response and valve shut-off.
iii. False Positive Rate (FPR): A critical metric, as spurious alarms lead to unnecessary stoppages of operation. FPR levels between 2% and 8% were observed, and there was optimization done due to enhanced preprocessing of data and feature selection.
iv. Precision and Recall: Precision rates are usually above 90%, reflecting high positive prediction certainty, while recall levels guarantee most actual leak instances are recorded, usually above 90% as well.
v. Energy Efficiency: IoT devices deployed in rural regions are subject to battery constraints. Studies envision up to 30% improvement in energy efficiency with optimized transmission and edge computing.

Despite promising metrics, several challenges persist:

i. Data Quality and Availability: Getting sufficient labeled leakage data remains difficult due to safety and operational limitations. Synthetic data are used instead, which may be less characteristic of real-world complexity.
ii. Scalability: Models work well on small-scale experiments but scaling them to long-distance pipelines is challenging, involving communication delay and signal interference.
iii. Integration with Legacy Systems: Most oil and gas corporations have older infrastructure that is not IoT-integrated and needs expensive upgrades.
iv. Cybersecurity Threats: Widespread connectivity exposes to cyber-attacks that can erode leak detection integrity and safety.
v. Environmental Variability: Model drift can be caused by external parameters such as temperature, pressure variations, and ground movements.

The deployment of deeper networks and edge-based IoT preprocessing has been significantly responsible for the consistent improvement in accuracy and decrease in false positive rates over the past ten years, as illustrated in Figure 11. In the meantime, detection latency has decreased as well, enabling realistic real-time deployment. But for wider adoption, issues with data, scalability, and security still need to be addressed.

3.1. RESEARCH GAPS

From 2015 to 2025, real-time oil and gas pipeline leak detection utilizing IoT and deep learning models made significant strides; yet, there are still significant gaps in the literature. The majority of suggested systems' scant real-world validation is a significant drawback. The complexities and uncertainties present in real pipeline environments, such as shifting environmental conditions, soil dynamics, and operational noise, are not adequately reflected by the simulated or laboratory-based datasets that are the primary source of many studies [84–86]. This raises questions about these solutions' practical robustness and generalizability when used widely. Additionally, there is frequently a lack

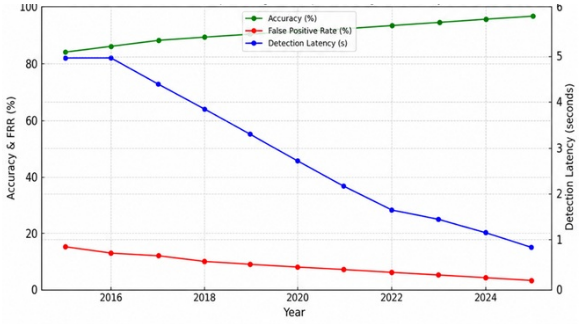


Figure 11. Trends in accuracy, false positive rate, and detection latency for IoT- and deep learning-based oil and gas pipeline leakage detection systems (2015–2025).

of research on energy efficiency in IoT-based monitoring equipment. Power resources are heavily used by continuous, high-frequency data capture and transmission, which presents major problems for offshore and remote facilities where regular maintenance is not feasible [87]. The lack of publicly accessible, standardized benchmark datasets is another significant gap that makes it difficult to compare performance objectively and replicate findings across investigations [88]. Similarly, cybersecurity issues are still not well covered. IoT systems are more vulnerable to cyberattacks including spoofing, data tampering, and denial-of-service assaults due to their growing connection, which could jeopardize environmental integrity and operational safety [89, 90]. Furthermore, the majority of current models are mainly concerned with single-point leak detection and are unable to detect complex fault interactions or numerous simultaneous leak occurrences, which are becoming more and more important as a result of aging infrastructure and a variety of failure modes. Deep learning's "black box" character makes system adoption even more difficult because regulators and operators frequently need clear, understandable decision-making procedures to foster confidence and guarantee adherence to safety regulations.

3.2. FUTURE DIRECTIONS

Future studies should focus on extensive field deployments in a variety of operational and environmental scenarios to test system performance in real-world settings in order to get over these restrictions. To promote equitable and repeatable model evaluations, it will be essential to create standardized, annotated benchmark datasets that are representative of various pipeline scenarios. System sustainability and operational lifetime can be improved by integrating energy-efficient IoT frameworks, such as edge computing, adaptive sampling, and energy harvesting. System resistance against attacks will also be increased by including strong cybersecurity mechanisms, such as real-time intrusion detection systems and blockchain-based data integrity solutions. Fault localization and detection accuracy will be increased by utilizing multi-modal sensing technologies and developing multi-fault detection capabilities. Finally, interpretability, operator confidence, and regulatory acceptance will all be facilitated by the use of explainable artificial intelligence (XAI) approaches. In order to enable safer and more sustainable energy infrastructure, addressing these directions jointly will open the door for real-time pipeline leak detection systems that are more secure, effective, and dependable.

4. CONCLUSION

This study has highlighted the transformative potential of integrating Internet of Things (IoT) technologies with deep learning approaches for real-time oil and gas pipeline leak detection. The comprehensive synthesis of existing studies demonstrates significant improvements in detection accuracy, response time, and operational efficiency, particularly through the adoption of advanced hybrid models and intelligent IoT frameworks. Notably, models such as Deep Autoencoders and BiLSTM on AE combined with XGBoost have shown superior capability in handling complex and subtle leak scenarios, positioning them as leading approaches in this domain. Despite these advancements, several critical challenges remain, including limited real-world validation, high computational and energy demands, cybersecurity vulnerabilities, and scalability constraints. These limitations hinder the transition from experimental and prototype systems to robust, large-scale industrial deployments.

To address these issues, future work should focus on the development of standardized and publicly available benchmark datasets to enable consistent model evaluation and comparison. Additionally, there is a need for the design of energy-efficient and secure IoT infrastructures capable of supporting large-scale, real-time monitoring in resource-constrained and remote environments. The integration of explainable artificial intelligence (XAI) techniques is also essential to enhance model transparency, interpretability, and user trust, particularly in safety-critical applications. Furthermore, future research should prioritize real-world implementation and validation through field deployments, as well as the exploration of emerging paradigms such as edge computing, federated learning, and transfer learning to improve scalability, adaptability, and data privacy.

In conclusion, the insights derived from this review provide a strong foundation for advancing next-generation pipeline monitoring systems. By addressing the identified challenges and pursuing the outlined future research directions, more sustainable, resilient, and intelligent solutions can be developed to safeguard the environment and ensure the operational security of critical energy infrastructure.

DATA AVAILABILITY

No external datasets were generated or analyzed in this study. All relevant results are contained within the article and the references cited herein.

DECLARATION OF COMPETING INTEREST

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

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