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Autonomous robotic pipeline inspection technologies

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Abstract. Pipeline infrastructure carries oil, gas, water, and industrial fluids across vast distances, and require careful maintenance. Visual inspections, scheduled digs, inline gauging tools, etc. have been industry standards for years, but struggle with expensive operations, scheduled downtime, and the inability to provide continuous monitoring. Autonomous robots have the potential to improve pipeline inspection workflows. Some robotic inspection platforms are equipped with advanced locomotion technologies like wheels, tracks, as well as embedded sensor payloads to detect corrosion, cracks, leakage, etc. Optical inspections can be augmented with ultrasonic testing, magnetic flux leakage, thermal imaging, acoustic sensors to provide comprehensive pipeline assessments. AI and machine learning allow for increased automation of anomaly detection and failure prediction. Beyond sensing, data storage and transfer allows for processed information to be used by operational teams and management. Edge computing allows for time-critical processes to be run on-board, while cloud computing allows for data storage and big-data analysis. SCADA integration can connect robotic inspections to enterprise-level risk analysis. Current limitations of pipeline inspection robots include limited energy storage, complex data analysis, deployment in difficult terrains/depths, and a lack of skilled pipeline operators. Some areas of development include energy harvesting robots, swarm robotics for distributed inspection, and multi-modal sensing/data fusion.

Keywords: Autonomous robotics, pipeline inspection, in-pipe robots, structural integrity, sensor fusion, predictive maintenance, artificial intelligence, digital twins, energy infrastructure, industrial monitoring.

1 Introduction

Pipelines are among the most critical yet least visible infrastructure systems supporting modern society. They transport crude oil, refined products, natural gas, hydrogen, drinking water, wastewater, and industrial chemicals across vast distances, linking production, processing, storage, and consumption networks [1,2]. Their reliability underpins energy security, environmental protection, and public health. When pipelines operate as intended, they remain largely unnoticed; however, when failures occur, the consequences can be severe, ranging from environmental contamination and economic loss to threats to human safety and irreversible ecological damage. Maintaining pipeline integrity is therefore not only a technical responsibility but also a broader social and environmental obligation [3,4].

Despite their importance, the inspection methods traditionally used to maintain pipeline systems face persistent limitations. Manual inspections are labor-intensive, infrequent, and often impractical in hazardous or remote environments. Excavation-based approaches disrupt operations and incur significant costs. Inline inspection tools, commonly known as Pipeline Inspection Gauges (PIGs), have improved coverage but remain constrained by pipeline geometry, require specialized infrastructure, and lack adaptability once deployed [5]. Semi-automated systems have reduced human exposure to risk but continue to depend heavily on operator control, struggle with complex pipeline configurations, and often fail to detect early-stage defects such as micro- corrosion [6]. These limitations highlight a widening gap between the increasing complexity of pipeline systems and the capabilities of conventional inspection approaches.

In response, autonomous robotic inspection technologies have emerged as a promising solution. By integrating intelligent mobility, advanced sensor systems, and artificial intelligence-driven data analysis, these technologies enable continuous, high- resolution inspection with reduced reliance on human intervention [7, 8]. Various platforms, including in- pipe crawlers, flow-driven robots, and hybrid aerial– subsea systems, offer adaptable solutions across diverse pipeline environments [9]. While these developments signal a significant technological shift, the current body of literature reveals several important gaps that limit a comprehensive understanding of their effectiveness and real-world applicability.

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First, existing studies tend to adopt a technology-specific focus, examining individual robotic systems or sensing techniques in isolation, with limited efforts to provide a holistic, cross-sector synthesis of autonomous inspection technologies across energy, water, chemical, and industrial applications. Second, there is a lack of standardized evaluation frameworks for assessing system performance, making it difficult to compare solutions in terms of accuracy, reliability, cost-effectiveness, and scalability under operational conditions. Third, although significant attention has been given to sensing and data acquisition, there is insufficient exploration of how inspection data is translated into actionable maintenance decisions, particularly in the context of predictive and risk-based asset management. Fourth, critical deployment challenges including navigation through complex geometries, power constraints, data communication limitations, and regulatory considerations are often discussed in isolation rather than within an integrated operational perspective. Finally, there is limited attention to contextual differences between developed and developing regions, where infrastructure maturity, resource availability, and implementation constraints vary significantly.

These gaps underscore the need for a more integrated and application-oriented understanding of autonomous robotic pipeline inspection technologies. Accordingly, the objective of this study is to provide a comprehensive and systematic review that bridges these limitations by synthesizing current technological developments, evaluating their performance across multiple sectors, and examining their practical implications for pipeline integrity management. Specifically, the study seeks to address the following research questions: What are the current types and capabilities of autonomous robotic pipeline inspection systems across different sectors? How do these systems compare in terms of performance, adaptability, and operational efficiency? To what extent can autonomous inspection technologies support predictive maintenance and decision-making processes? What are the key technical, operational, and regulatory challenges affecting their deployment in real-world contexts? How do these challenges and opportunities differ across developed and emerging infrastructure environments?

By addressing these questions, this study contributes to the literature by offering a structured synthesis that connects technological innovation with operational realities, thereby providing clearer guidance for researchers, industry practitioners, and policymakers seeking to advance pipeline inspection practices.

2.0 Methodology

A systematic literature review was conducted to ensure a transparent, replicable, and comprehensive synthesis of existing research on autonomous robotic pipeline inspection technologies. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to enhance methodological rigor and reduce bias in study selection and reporting. The study period covered publications from January 2000 to March 2026, allowing the inclusion of both foundational studies and recent technological advancements in robotics, sensing, and artificial intelligence relevant to pipeline inspection.

A structured search strategy was applied across multiple academic databases, including ScienceDirect, IEEE Xplore, SpringerLink, and Google Scholar. The search strings combined key terms such as "autonomous pipeline inspection," "in-pipe robots," "robotic inspection systems," and "AI-based pipeline monitoring." To ensure sensitivity and completeness, variations and related terms were iteratively tested, including broader phrases such as "infrastructure inspection robotics" and "robotic condition monitoring." This iterative search approach helped capture studies that may not have been retrieved through narrow keyword combinations. The initial search yielded 320 records, which were exported into a reference management system for further processing. Duplicate records were identified and removed using a combination of automated software filtering and manual verification. The automated process flagged records with identical titles, authors, and publication years, while manual checks ensured that slightly varied entries referring to the same study were also removed. A total of 60 duplicate records were identified and excluded, resulting in 260 unique records retained for screening. This step ensured that the dataset used for analysis was free from redundancy and accurately reflected the breadth of available literature.

The remaining records were screened based on titles and abstracts to assess relevance to the research focus. Studies were included if they addressed autonomous or semi-autonomous robotic systems applied to pipeline inspection, incorporated sensing or AI-based analysis, or contributed to understanding system design, performance, or deployment challenges. Studies were excluded if they were non-technical, unrelated to pipeline systems, or lacked sufficient methodological detail. Following this screening stage, 180 records were excluded, leaving 80 articles for full-text assessment. Full-text screening was conducted to evaluate the methodological quality, relevance, and contribution of each study. Articles were assessed based on criteria such as clarity of research objectives, robustness of methodology, relevance to autonomous inspection systems, and evidence of practical or experimental validation. During this stage, 40 studies were excluded due to insufficient technical depth, lack of relevance, or duplication of findings already captured in higher-quality studies. The final dataset therefore consisted of 40 high-quality studies included in the review.

To strengthen the reliability of the selection process, a sensitivity analysis was conducted by revisiting the search strategy with adjusted keywords and inclusion thresholds. This step ensured that no significant studies were omitted due to overly restrictive criteria. Additionally, backward and forward citation tracking was applied to key review articles and highly cited papers to identify any influential studies that may not have been captured in the initial database search. This validation process confirmed that the selected studies provided comprehensive coverage of the domain. Data extraction from the selected studies focused on key attributes, including study location, research methods, type of robotic system, sensing technologies used, and major findings. This allowed for a structured comparison across studies and supported the identification of trends, strengths, and limitations in the existing literature. The synthesis approach combined qualitative analysis with comparative evaluation to provide a balanced and critical understanding of the field.

3.0 Results.

3.1 Field Applications and Case Studies

The technical capabilities of autonomous robotic pipeline inspection systems are most comprehensively understood through their actual deployment contexts. In oil and gas production, water distribution, and offshore energy infrastructure, real-world applications have confirmed the performance claims of laboratory and simulation-based studies while also revealing operational challenges that theory alone cannot predict [4, 9, 10]

In the oil and gas industry, autonomous inspection has been used on a large scale on both onshore and offshore pipeline networks. [9] recorded the creation and use of a crawler-based inspection robot that can move through the complicated shapes of industrial pipelines and collect high-resolution ultrasonic and visual data over long pipeline runs. The system worked all the time without having to take the pipeline offline, which showed that it was better than traditional inline PIG-based inspection. [1] also tested a differential-drive in-pipe robot in urban gas distribution networks. They found that modular, adaptable locomotion systems could keep reliable contact with gas mains of different diameters while collecting structural integrity data at speeds that were similar to those of traditional methods. These deployments showed that autonomous robots could work in pipes and be useful in tough production settings.

Some of the most dangerous places to inspect are offshore pipeline networks. There are high hydrostatic pressures, strong currents, water columns that are hard to see, and it's almost impossible for people to get to quickly when something goes wrong. [10] examined the utilization of autonomous and semi-autonomous inspection platforms in offshore oil and gas fields, detailing the application of robotic systems with multi-modal sensor suites to evaluate structural integrity in subsea pipeline segments that traditional remotely operated vehicles could not efficiently access. Their study found that combining acoustic emission and ultrasonic sensors with AI-assisted classification consistently improved the ability to find anomalies. This shows how useful sensor fusion is in underwater environments with low visibility and high noise. [6] also talked about machine learning-enhanced models that were used on offshore pipeline integrity data. They showed that AI-driven pattern recognition made predictions about how corrosion would progress more accurate than traditional threshold-based assessment methods.

The integration of robotic inspection with risk-based frameworks has also improved the management of subsea pipeline integrity. [4] thoroughly examined the integration of autonomous inspection data into quantitative risk assessment models for subsea systems, focusing on the management of corrosion, pressure cycling fatigue, and third-party damage in deepwater and nearshore settings. Their approach to integrated inspection and risk management workflows shows that robotic inspection outputs are not just replacements for manual data collection. Instead, they are inputs to a more advanced analytical process that helps make decisions about when to do maintenance, when to limit operations, and when to replace equipment.

The inspection of water and wastewater networks is another interesting area of application. Old municipal water systems, with cast iron and asbestos cement mains put in place long before modern inspection standards, make it very hard to assess the structure. [11] investigated machine learning applications in predictive maintenance within utility infrastructure, such as water distribution networks, and discovered that data-driven methodologies for defect classification and failure prediction significantly enhanced inspection efficiency compared to calendar-based scheduling. By using historical failure data, soil chemistry records, and operational pressure logs to focus inspection resources on high-risk areas, the total number of inspections needed was reduced and the chances of finding pre-failure conditions before they caused service disruptions were increased.

Digital twin applications are one of the most important new ways to use technology in the field. [12] recorded how real-time monitoring data from robotic inspection platforms was used to keep digital twin models of pipeline systems that work in harsh environments up to date and in good shape. The constant flow of inspection data into simulation models let operators try out different maintenance scenarios, guess how known defects would get worse, and check their decisions about interventions against simulated results before they spent money on real repairs. This combination of robotic field data with digital twin infrastructure shows that the technology has grown from a one-time inspection tool to a platform for ongoing asset management.

In all of these deployment situations, there are a few common operational lessons that come out. First, the value of autonomous inspection goes up a lot when the data is combined with existing asset management and SCADA systems instead of being treated as separate data collection tasks. Second, sensor fusion always works better than single-modality inspection, especially in places where there is a lot of noise, the coating changes, or the geometry is hard to understand. Third, switching from periodic to continuous monitoring, even if full autonomy isn't possible yet, makes it easier to find problems early and cuts down on unplanned maintenance events. These field observations are very similar to the technical design principles we talked about earlier. They also give us a good starting point for the technology roadmap that follows.

3.2 New Technologies and Future Directions

The current generation of autonomous robotic pipeline inspection systems signifies a substantial advancement from traditional methodologies; however, it does not constitute the culmination of the technology's evolution. The next generation of pipeline inspection capability will probably be shaped by a number of new research areas and engineering methods. These will have an effect on performance, scalability, and the range of things that can be monitored continuously and automatically [8, 13].

Swarm robotics is one of the most important new fields that is growing. Instead of using one powerful platform to check a pipeline segment, swarm-based methods use many smaller, simpler robots that work together to cover the whole area. The benefits are significant: swarms are naturally redundant, so the mission isn't affected if one unit fails; they can be used at the same time across large pipeline networks, which cuts down on the time it takes to inspect the whole thing; and they can work together to sense things, combining data from multiple points of view to create a more detailed picture of an anomaly than any one robot could do on its own [7, 8]. The engineering problems are just as real. Coordination protocols, communication overhead, and the difficulty of managing distributed autonomy across different types of robots are still being studied. Advancements in multi-agent reinforcement learning and decentralized control theory are anticipated to facilitate the development of operational swarm inspection systems within the forthcoming decade.

Another important area of research is self-healing and fault-tolerant robotic systems. Current autonomous inspection platforms are built to be strong, but they can't really fix themselves. When a part breaks, the mission usually ends and a person has to go get it and fix it. New research on modular robotic architectures, adaptive reconfiguration, and onboard diagnostic and recovery systems hopes to change this. A robot that can find its own mechanical or sensor problems and change how it behaves or its physical structure to make up for them could finish inspections that would otherwise have to be stopped. Self-healing capability would greatly improve operational reliability and mission economics in subsea or remote pipeline environments where retrieval is expensive and time-consuming [4, 10].

Energy harvesting is an important technology that makes it possible to extend the length of a mission and make it less reliant on battery power or a tethered power supply. Robotic inspection platforms that work inside active pipelines are surrounded by possible sources of energy, such as fluid flow, pressure differences, vibrations from pipeline operations, and temperature differences between the pipe wall and the fluid being moved. Getting even a small amount of this ambient energy could greatly increase the range of operations, especially for flow-driven or semi-passive inspection systems. Studies on piezoelectric transducers, thermoelectric generators, and miniaturized turbine-based flow harvesters have shown that they work in the lab. However, turning these into reliable systems that can be deployed with robotic inspection platforms is still a challenge for engineers [8].

The next generation of AI for inspection may be the most important set of improvements that are coming up. Most current AI applications for pipeline inspection, like defect classification, anomaly detection, and scheduling predictive maintenance, are supervised learning systems that learn from labeled historical datasets. There are a few things that limit their performance: it costs a lot to make labeled training data, and it doesn't always show rare or new failure modes; model performance goes down when they are used in environments that are different from the ones they were trained in; and current systems don't have the kind of causal reasoning that would let them explain why a certain feature is a risk instead of just saying that it is statistically unusual [14, 15]. Few-shot and self-supervised learning are making progress, which should make it less necessary to use large labeled datasets. This will allow inspection AI to generalize more reliably from a small number of examples. Foundation models large pre-trained models that are fine-tuned for specific inspection tasks might be able to generalize better than current task-specific architectures. It is not just an academic goal to make model reasoning clear; it is also a requirement for operations. Regulators, operators, and maintenance engineers need to understand and trust the basis of AI recommendations before acting on them [5, 1].

Swarm coordination, self-healing hardware, energy autonomy, and advanced AI are all coming together to create a long-term vision of fully autonomous pipeline monitoring networks. In this vision, robotic inspection platforms set up, run, and fix themselves in pipeline infrastructure. They constantly send high-quality structural and operational data to AI-driven analytics and digital twin systems, which can find, diagnose, and escalate problems on their own without needing human help. Pipeline operators would go from running inspection programs to overseeing them. Instead of doing inspections, they would review AI-generated risk assessments, approve maintenance responses, and handle exceptions. The technical groundwork for this future is currently being established; its realization necessitates ongoing investment in both engineering expertise and the regulatory frameworks that dictate how autonomous systems make significant decisions regarding critical infrastructure [8, 10, 15].

4.0 Discussion.

Autonomous robotic pipeline inspection technologies show stronger overall performance than conventional manual inspection and traditional PIG-based inspection when assessed against safety, accessibility, data richness, adaptability, and predictive- maintenance potential. Across the reviewed studies, conventional inspection remains useful where pipelines are simple, accessible, and periodically assessed, but autonomous robotic systems demonstrate clearer advantages in difficult-to-access, hazardous, subsea, confined, or geometrically complex pipeline environments. The evidence suggests that the greatest value of autonomous systems is not only their ability to detect defects, but their capacity to combine mobility, sensing, data processing, and decision-support into a more continuous inspection model. The main limitation of this evidence base is that many studies remain prototype-based, simulation-based, or laboratory-based, which means that field validation is still weaker than the technical promise of the systems suggests. The reviewed source list includes foundational and recent works on in-pipe robots, navigation, magnetic flux leakage, ultrasonic guided waves, machine learning, digital twins, and robotic inspection applications.

The findings can be interpreted through four major themes: inspection technologies, navigation and control strategies, sensing and leak-detection methods, and performance evaluation metrics. In terms of inspection technologies, in-pipe robots, wall-pressing crawlers, screw-drive robots, snake-like robots, underwater vehicles, and UAV-supported systems each offer different strengths. In-pipe crawlers are most suitable for internal corrosion, weld, crack, and obstruction detection because they move directly inside the pipe and can carry cameras, ultrasonic sensors, magnetic sensors, or acoustic devices. However, their performance is limited by pipe diameter, bends, deposits, fluid flow, and power capacity. Snake robots and articulated robots perform better in constrained and curved environments because their flexible bodies allow them to negotiate bends and irregular geometries. However, they are mechanically complex and may have lower speed and payload capacity. UAVs and underwater autonomous vehicles are more useful for external inspection, especially in long-distance surface pipelines, offshore pipelines, and subsea environments. Their advantage lies in rapid coverage and reduced human exposure, but they are less effective for detecting internal wall defects unless combined with advanced imaging or external sensing techniques.

When compared with established benchmarks, autonomous robotic systems perform better than manual inspection in safety and repeatability, better than excavation-based methods in cost and disruption reduction, and better than conventional PIGs in adaptability. However, PIGs still remain stronger for long-distance internal inspection in standardized pipelines because they are mature, industry-accepted, and capable of high-throughput inspection. Autonomous robots become more valuable where PIG deployment is impossible, such as small-diameter pipes, non-piggable pipelines, complex bends, water networks, gas distribution mains, subsea structures, and confined industrial pipes. Therefore, the evidence does not suggest that autonomous robotics fully replaces existing inspection technologies. Rather, it shows that autonomous systems extend inspection capability into environments where established methods are limited.
A useful comparison is presented as follows in table 1, 2 and 3:

Table 1. Comparative Assessment of Pipeline Inspection Technologies.

Technology	Typical BenchMark Strength	Main Limitation	Relative Performance of Autonomous Robotics
Manual Inspection	Simple, low equipment cost	Unsafe, slow, subjective, limited access	Better, safe, repeatability and data capture
Excavation based inspection	Direct physical access	Expensive, disruptive, localized	Better coverage and less operational disruption
Conventional PIGs	Strong for long piggable pipelines	Poor adaptability, requires launch/ retrieval systems	Better for non-piggable and complex pipelines
Semi automated robots	Improved operator safety	Still dependent on human control	Better autonomy and real time data potential
Fully autonomous robots	Adaptive inspection and intelligent sensing	Cost, power, validation regulation	Strongest for high risk and complex environments

The second major theme is navigation and control. Navigation remains one of the most important determinants of inspection success. Earlier robotic inspection systems depended heavily on teleoperation, but newer autonomous platforms increasingly use computer vision, simultaneous localization and mapping, inertial measurement units, odometry, reinforcement learning, and sensor fusion. The reviewed studies suggest that autonomy improves inspection consistency, but reliable navigation inside pipelines remains difficult because pipes are dark, repetitive, GPS-denied, narrow, and sometimes filled with fluid, debris, or deposits. SLAM-based systems provide better localization than simple odometry, especially when supported by visual or LiDAR-based mapping, but their accuracy may decline in feature-poor pipe environments. Control strategies based on adaptive locomotion are more effective in pipes with bends, vertical sections, diameter changes, or obstacles.

However, the literature still lacks a common benchmark for comparing navigation success across studies. For example, some studies report distance travelled, others report turning ability, localization error, obstacle-crossing ability, or mission completion rate. This inconsistency makes direct comparison difficult.
To improve comparability, this review adopts a standardized set of impact indicators: detection accuracy, localization accuracy, coverage efficiency, autonomy level, energy endurance, inspection speed, adaptability to pipe geometry, data-processing capability, and field-readiness level. Using these indicators, autonomous inspection systems can be more rigorously compared. Detection accuracy refers to the ability to correctly identify defects such as corrosion, cracks, leaks, weld flaws, and wall thinning. Localization accuracy refers to how precisely the system identifies the position of a defect. Coverage efficiency reflects the length or area inspected within a given time. Autonomy level measures the degree of human intervention required. Energy endurance reflects how long the system can operate before recharge or retrieval. Inspection speed measures movement or inspection rate. Adaptability refers to the robot's ability to handle bends, diameter changes, vertical sections, and complex layouts. Data-processing capability refers to whether the system only collects data or also interprets it using AI. Field-readiness refers to whether the system has been validated in laboratory, pilot, or real operating conditions.

Table 2. Performance Benchmarking of Autonomous Pipeline Inspection Robots.

Performance Indicator	**Conventional benchmark**	**Stronger autonomous robotic contribution**	**Remaining weakness**
Detection accuracy	Manual NDT, PIG inspection	Multi-sensor and AI-based defect recognition	Limited comparable datasets
Localization accuracy	PIG odometer-based tracking	SLAM, vision, IMU, sensor fusion	Poor performance in featureless pipes
Coverage efficiency	PIGs for long pipe	Robots for complex/non-piggable pipelines	Slower than PIGs in long straight pipelines
Autonomy level	Manual/semi-automated control	Reduced operator dependence	Full autonomy still limited
Energy endurance	PIGs powered by flow	Battery-powered robotic control	Battery life remains a constraint
Adaptability	Limited by pipe geometry	Better in bends, small pipes, confined spaces	Payload and stability trade-offs
Data analytics	Post-inspection interpretation	AI-assisted defect classification	Real-time decision-making still emerging
Field readiness	Mature PIG practice	Growing pilot use	Many studies remain experimental

The third thème concerns sensing and leak-detection methods. The reviewed literature shows that no single sensor is sufficient for all pipeline inspection conditions. Visual cameras are useful for surface defects, corrosion appearance, weld irregularities, and obstruction identification, but they depend heavily on lighting, image clarity, and fluid conditions. Magnetic flux leakage is highly valuable for detecting metal loss and corrosion in ferromagnetic pipelines, but it may be less suitable for non-metallic pipes or complex geometries. Ultrasonic testing provides strong wall-thickness measurement and crack detection but requires good coupling and may be affected by surface condition. Acoustic emission methods are promising for leak detection and active defect monitoring, especially where leaks generate detectable sound patterns. Infrared thermography and thermal imaging can support external defect detection, but their effectiveness depends on temperature contrast and environmental stability. AI-based image recognition and machine learning models improve classification and pattern recognition, especially for weld defects, corrosion severity, and predictive maintenance. However, AI models are only as reliable as the datasets used to train them, and many studies do not provide enough detail on dataset size, validation method, or generalizability.

Table 3. Comparison of Sensor and AI Methods for Pipeline Inspection.

Sensor/AI method	**Best suited for**	**Main strength**	**Main limitation**
Visual camera	Surface damage, corrosion appearance, blockage	Low cost, easy interpretation	Poor visibility in dark/fluid-filled pipes
Magnetic flux leakage	Metal loss, corrosion in steel pipes	Strong industrial relevance	Limited for non-ferromagnetic materials
Ultrasonic testing	Wall thinning, cracks, thickness measurement	High defect-resolution potential	Coupling and surface-condition issues

Acoustic emission	Leak detection, active fault monitoring	Useful for early leak signals	Noise sensitivity
Infrared thermography	External thermal anomalies	Non-contact inspection	Environmental dependence
LiDAR/3D mapping	Shape, deformation, mapping	Supports navigation and geometry modelling	Cost and processing load
Machine learning/CNNs	Defect classification	Improves automated recognition	Requires strong training datasets
Digital twin models	Risk prediction and maintenance planning	Links inspection to decision-making	Still limited by data integration quality

The fourth theme is performance evaluation. The reviewed studies show a clear weakness in benchmarking. Many papers describe robot design, locomotion, sensor integration, or algorithmic performance, but fewer provide standardized performance metrics that allow direct comparison. For example, some studies report qualitative success in navigating bends, while others report classification accuracy, sensor resolution, or inspection feasibility. This makes synthesis difficult because “performance” is not measured consistently across the field. To improve rigour, future studies should report a minimum set of indicators: defect detection accuracy, false-positive rate, false-negative rate, localization error, inspection speed, maximum inspection distance, battery endurance, pipe diameter range, bend-navigation success, payload capacity, communication reliability, and level of field validation. Without these indicators, claims about superiority remain difficult to verify.

The discussion of findings shows that autonomous robotic inspection is strongest when viewed as part of a wider pipeline integrity management system rather than as a standalone technology. Robots collect data, but the value of inspection depends on whether the data improves maintenance decisions. This is where AI, predictive analytics, digital twins, and risk-based maintenance become important. Some reviewed studies indicate that machine learning and digital twins can support corrosion prediction, defect classification, and risk estimation. However, the link between robotic inspection data and actual maintenance scheduling is still underdeveloped. Many studies stop at detection rather than showing how detected defects are prioritized, repaired, monitored, or integrated into asset-management systems. This is a major research gap because pipeline operators require decision-ready information, not only inspection images or sensor readings.

The findings also show that the maturity of autonomous pipeline inspection varies by application context. Oil and gas pipelines have received the most attention because failures are high-risk and inspection investment is better established. Water and sewer networks are increasingly important, especially because many are aging, difficult to access, and unsuitable for conventional inspection. Chemical and industrial pipelines remain comparatively underrepresented, even though they may carry hazardous materials and require strict monitoring. Subsea inspection has advanced through underwater robotics, but communication, localization, and energy constraints remain severe. Developing regions are also underrepresented in the literature, despite having expanding pipeline infrastructure and fewer resources for continuous manual monitoring. This creates a geographical and infrastructural bias in the evidence base.

The limitations of this review must also be acknowledged. Although the review considered 40 selected studies, the field is broad and rapidly developing, and relevant industrial systems may not be fully represented in peer-reviewed literature. Publication bias may also be present because successful prototypes and positive results are more likely to be published than failed trials or poorly performing systems. There is also possible database bias, since studies indexed in major academic databases are more visible than local technical reports, industry white papers, or non-English publications. Another limitation is that many reviewed studies did not report complete quantitative data, making formal meta-analysis difficult. As a result, the comparison presented here relies on structured thematic synthesis and standardized impact indicators rather than pooled statistical effect sizes.

Overall, the evidence indicates that autonomous robotic pipeline inspection technologies offer strong potential for improving safety, inspection coverage, defect detection, and predictive maintenance. However, their performance advantage depends heavily on context. They outperform manual methods in safety and repeatability, outperform excavation in non-disruptive inspection, and outperform conventional PIGs in complex or non-piggable pipelines. At the same time, they do not yet consistently outperform mature PIG systems for long, standardized pipelines where PIGs remain efficient and industry-proven. The strongest future direction is therefore a hybrid inspection model in which autonomous robots, PIGs, fixed sensors, AI analytics, and digital twins work together. For the field to mature, future studies must move beyond prototype demonstration and provide standardized, quantitative, field-validated performance evidence. This will improve comparability, support regulatory confidence, and help industry users determine which robotic technologies are most suitable for specific pipeline inspection challenges.

5.0 Conclusion

Autonomous robotic pipeline inspection is a transformative advancement in infrastructure management. Combining intelligent mobility, advanced sensors, and AI-driven analytics, these systems provide continuous, high-resolution monitoring that improves defect detection, anomaly localization, and predictive maintenance. This reduces catastrophic failures, lowers maintenance costs, and minimizes human exposure to hazardous environments. By enabling early identification of corrosion, cracks, and other defects, autonomous robots support a shift from reactive to proactive maintenance. Looking ahead, their integration with digital twins, AI-assisted decision systems, and smart infrastructure networks positions them as a key technology for enhancing the resilience, efficiency, and sustainability of future pipeline operations.

The detailed list of studies included in this review is available upon request.
All authors contributed to the writing and review process of this study.

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