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AI-Powered Pipe Failure Prediction: Reducing Excavation Costs by 60% with Robotics + ML

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ABSTRACT

The current research paper will discuss a new patent-based design that uses non-destructive testing (NDT), artificial intelligence (AI), and machine learning (ML) to forecast and eliminate failures of water pipes throughout the US. It is a systematic review of eight current peer-reviewed papers (2015-2025) dedicated to the topic of AI-based predictive analytics, bio-inspired robotic movement, and the economic sustainability of pipeline inspection. The quantitative results of the algorithm show that deep learning and tree-based models, such as CNN, YOLO, LSTM, and Gradient Boosting, achieved defect detection accuracy of 91 to 95%, which greatly decreases manual inspection time and, on average, excavation costs by 70 and 55 %, respectively. Moreover, the stylus of the bio-inspired robots was presented, e.g. the robots with mechanically inflatable bodies had demonstrated the ability to control 70-79% locomotion efficiency and complete 5.8 kg loads in a variable pipeline size, with these properties confirming their scalable robots with non-invasive continuous inspection. The study offers a multidisciplinary synthesis towards demonstrating how AI, robotics, and predictive maintenance are converging towards a system of developing sustainable infrastructure resilience. The proposed structure works together with making 300,000-plus ageing water mains in the United States more modernised through the adoption of cost-efficient automation, along with high diagnostic accuracy, to encourage safer, data-informed and more environmentally friendly processes. Regardless of the difficulties in the computational and operational planning, the research highlights that AI-robotic synergy has the potential to transform asset management in the civil infrastructure framework.

Keywords: Artificial Intelligence, Machine Learning, Non-Destructive Testing, Predictive Maintenance, Robotic Inspection, Infrastructure Modernisation, Cost Efficiency, Water Mains.

1. INTRODUCTION

In the United States, the 300,000-plus miles of water main over the ages support a 100-year-old infrastructure that is more likely to leak, corrode, and fly apart in all directions upon a fuse. The American Society of Civil Engineers (ASCE) reports that the US water infrastructure is currently in rapid decline, indicating that the country has about 240,000 water main breakages annually, as a result of which close to six billion gallons of treated water are lost on a daily basis (ASCE, 2021). The conventional methods of inspecting and maintaining pipes have been mainly of the reactive type and depend on excavation and manual methods of inspection, all of which are prohibitively expensive and disruptive. More than 60% of overall maintenance costs may be covered by excavation and replacement of pipes, which can impose a huge financial and operational cost to municipalities. With the growth of the urban population and stress levels caused by environmental changes, it has never been more urgent to have intelligent, non-destructive, and predictive means of inspections, as they are called.

The solution to this looming infrastructure challenge is AI paired with robotics, which can be described as a transformative one. The integration of machine learning (ML) algorithms with autonomous robotic systems allows the development of intelligent inspection platforms able to scan pipe states, anticipate failures, and prescribe proactive maintenance activities, avoiding invasive excavations (Macaulay and Shafiee, 2022). Traditional condition measurements, which rely on a few sample measurements, are insufficient, whereas AI-based services have the capacity to process massive amounts of data gathered by sensors, cameras, and acoustic devices. Such systems operate based on predictive models to detect the initial stages of degradation when corrosion, cracking, or leakage is occurring in response to changes in pressure, vibration, or even visual response.

Machine learning's significance lies in becoming a key to pattern recognition and the use of data as the factor underpinning the flow of decisions that contribute to predictive maintenance. AI can decipher the probability and the time when a failure happens by training models using several years of past pipe performance data history, soil, and material characteristics, as well as the hydraulic pressure data (Chen, Wang and Javanmardi, 2025). More basic tools (such as convolutional neural networks (CNNs) can process visual outputs of the sensory information on a robot camera to determine it presence or absence of breaks or corrosion, though more integrated tools, such as random forests or gradient boosting machines, have the capability to proceed with placing advanced estimates of risks by integrating environmental and operational data. The most profound economic impact of this shift involves the economic side of it. Studies show that this will also reduce up to 60% of excavation and replacement costs by using non-destructive testing methods and forecast tools where accuracy follows analytical predictive methods. This will enable the operations of a utility to utilise its available maintenance resources more optimally, as the high-risk areas can be accurately identified in the pipelines, leading to unnecessary concerns surrounding the use of excavations in areas that are structurally sound. Predictive systems also allow municipalities to plan repairs at the most convenient time frames, cutting the impact of water service disruptions and lowering the cost of emergency repairs (Expósito and Díez Cebollero, 2025). In addition to costs, AI-driven pipe inspection delivers sustainability impacts, as a decrease in excavation leads to fewer emissions of carbon and waste, as well as fewer damages to infrastructure around the inspection site.

The mass adoption of AI-based disability systems has NPV potential because there are a number of barriers, such as a lack of data, sensor quality, compatibility with current water network management systems, and regulatory evaluation (Moreno-Rodenas *et al.*, 2025). Some of these municipalities do not have full information on the level of underground lines, and thus, some training machine learning models are tricky to develop. Furthermore, the activity of robotic inspection units demands high-level navigation to execute their tasks in tight, fluid, and corroded spaces. The challenges require a multidisciplinary approach, fusing the knowledge of AI, robotics, civil engineering, and environmental management.

This research advances a patentable model that combines robotics and machine learning to anticipate non-destructive real-time pipe failures. It is set to explain how AI-enabled robot systems are helping to modernise ageing American water infrastructure, save 60% on excavation costs, and increase the service life of water mains. The research will aid the wider understanding of smart infrastructure and sustainable city water resource management by creating an intelligent inspection architecture that will use multi-sensor data fusion, predictive analytics, and autonomous navigation.

2. MATERIALS AND METHODS

2.1 Research Methodology

This research selects a ***secondary qualitative research approach*** to conduct a critical review of the current literature in real-time artificial intelligence (AI) and machine learning (ML) and robotic technologies in detecting early damage of the pipe during the process of non-destructive testing (NDT) in the ageing water distribution system in the United States. Its research concentrates on developing data-based strategies that can save the costs of excavation and maintenance up to 60% by automating and non-invasive inspection (Cheong *et al.,* 2023). Through a systematic review process, the analysis incorporates the multidisciplinary accomplishments of AI in civil engineering, robotics, and computer science to determine potential synergies of AI-based failure prediction models and in-pipe robotic inspection systems. The scholarly papers, together with institutional reports, used as a methodology fall within the scope of 2021 to 2025, ensuring that the technological use is current. The chosen sources are analysed based on the algorithmic models, sensor modalities, and operation results. The focus of analysis is on detecting accuracy, computation speed, and scalability of the field. A backup analysis is a qualitative synthesis that assists in the formulation of an inventive, patentable, non-destructive examination model, which modernises 300,000+ miles of water mains in the United States by reinventing maintenance using intellectual and knowledge-driven technology.

2.2 Data Collection Methods

The study utilises a ***systematic secondary data compilation*** technique to identify, filter and refine plausible sources pertaining to AI-driven and robotic-based non-destructive inspection (NDT) systems used in predicting pipeline failures in water (Mazhar *et al.,* 2021). Academic databases such as IEEE Xplore and ScienceDirect, Springer Link, Scopus, and Google were also consulted with meticulous references to publications dating specifically within 2021-2025 to guarantee the currency of technology. A search strategy, before the use of Boolean operators, was used to maximise accuracy and inclusiveness with the following search terms:

- (“pipe failure prediction” OR “pipeline condition assessment”)
- AND (“machine learning” OR “deep learning” OR “graph convolutional networks”)
- AND (“non-destructive inspection” OR “NDT” OR “ultrasonic testing” OR “acoustic sensing”)
- AND (“robotic inspection” OR “in-pipe robot” OR “autonomous inspection” OR “inspection robot”)
- AND (“water mains” OR “buried infrastructure” OR “water distribution system” OR “municipal pipelines”)

Supplementary Search Terms

“predictive maintenance”, *“structural health monitoring”*, *“smart infrastructure”*, *“sensor fusion”*, *“acoustic emission analysis”*, *“magnetostrictive sensing”*, *“deep learning defect detection”*, *“pipe robotics navigation”*.

The search published a long list of results that had undergone screening based on title, abstract and full-text of the results. Grey literature, including technical standards, government publications and municipal infrastructure surveys provided by organisations such as the U.S Environmental Protection Agency (EPA), American Water Works Association (AWWA) and additional programs like the National Institute of Standards and Technology (NIST), was also examined to provide contextual policy and cost information. Relevant articles were selected as those 1) peer reviewed or institutionally authenticated, 2) thematically relevant to AI, robotics, and predictive maintenance. This high media-database and multi-source strategy ensures a detailed, balanced, and contextually pertinent data set addressing the research goals in predictive and non-invasive pipe failure detection and identification.

2.3 Inclusion -Exclusion Criteria

Table 1: Inclusion-Exclusion Criteria

Category	Inclusion	Exclusion
Publication Date	2021–2025	Before 2021
Focus Area	AI/ML, robotics, NDT for pipe failure	Manual or non-AI methods
Source Type	Peer-reviewed or institutional reports	Blogs, magazines, non-reviewed sources
Language	English	Non-English publications

As shown in Table 1, the inclusion/exclusion criteria narrowly limited the selection of sources in order to guarantee relevance, credibility, and consistency in choice. They have done so to reduce the quality of only studies that are directly related to AI-enabled non-destructive inspection, robotic water infrastructure examination, and predictive water infrastructure maintenance. Institutional reports, conference papers, and peer-reviewed journal articles were prioritised and non-technical or non-peer-reviewed material excluded. The screening process consisted of the following phases, including: initial Title and Abstract Review, Methodological Quality Review and Thematic Alignment Review. These were necessary to ensure that all chosen selections would have empirical or simulation-based evidence of algorithmic performance, inspection, and practical scalability of large-scale infrastructure. The subsequent table highlights the inclusion and exclusion parameters that schools have incorporated in this paper.

2.4 Data Analysis Plan

The paper utilises a ***qualitative content analysis method***, where recurring themes, technical trends and gaps in innovations were identified among the articles of interest (Preiser *et al.,* 2021). Manual analysis and coding of the papers were performed systematically according to their methodological design, AI or ML model applied, sensor modality, and performance results as they pertained to pipeline inspection and failure prediction. It focused on deriving quantitative performance (detection accuracy, false-positive rate and computational efficiency) and qualitative (scaling had to be a feature of the system, applicability to the field). Research papers were organised into three themes: AI-arrangement-based foretelling models, robotised non-destructive evaluation, and integrated cost-efficiency models. A comparative analysis was also conducted to identify how all these technologies are playing their role in lowering excavation and maintenance costs. Correlations between field performance reliability and the complexity of the algorithmic models were also analysed. This overarching synthesis guided the conceptualisation of a patent-enabling, AI-infused robotic inspection system that would be able to modernise more than 300,000 miles of ageing water mains in the U.S. by activating predictive, non-invasive innovations in maintenance.

3. RESULTS

Zhang *et al.* (2025) conducted research that indicated that the use of artificial intelligence (AI) in non-destructive testing (NDT) has greatly facilitated the process of detection of infrastructure, efficiency in processing, and cost-efficiency. Deep learning-based designs like Convolutional Neural Networks (CNNs), Residual Neural Networks (ResNet), and Artificial Neural Networks (ANNs) have been shown to detect defects in ground-penetrating radiography (GPR), ultrasonic, and radiographic images with up to 91-95% accuracy. In large-scale inspection of pipelines, AI-driven models cut manual labour and inspection time by roughly 70%, with an initial estimate of a 58 to 62% reduction in the cost of excavation and repair. Also, hybrid CNN-YOLO models successfully recognised even fine cracks in the sub-surface (0.1 mm), which enhanced predictive maintenance stability. Nonetheless, as the authors observe, there are some weaknesses, such as small training sets, reliance on high-quality sensor data and limited flexibility in pipe material and environmental consideration. Calculation cost is also a drawback to a full municipal application. In spite of these difficulties, Zhang *et al.* (2025) assert that AI-enabled, non-invasive robotic inspection frameworks possess transformative prospects to modernise more than 300,000 miles of ageing U.S. water mains that provide provisional outcomes on a metric of every decrease in expenditures, in terms, these mains, and reliability in the long term.

As stated in Latifi *et al.* (2024), tree-based machine learning models based on the Random Forest (RF), Gradient Boosting (GBT) and Extreme Gradient Boosting (XGB) showed high predictive accuracy and high-cost efficiency in comparison to the classical statistical models in predicting water pipe failures. RF and AdaBoost models reported scores of AUC as high as 0.93 in case studies of 851 km of water distributing networks and decreased the rate of false-negatives by 25-30%. These models applied in anticipatory maintenance gave the capacity to offer a failure evading rate of 60-65% to an average monetary yield of savings of 55-62% in excavating and substituting the network. The RMSE and MAE levels decreased by 18-22% with respect to the traditional linear regression models, which indicated the reliability and strength of the model. Nevertheless, there are serious limitations pointed out by Latifi *et al.* (2024), such as intensive computational requirements, overfitting in small datasets, and inaccuracies in clearly short forecasts of failure over the short term. Nevertheless, these issues do not preclude the fact that tree-based models will provide a scalable and data-driven method of infrastructure modernisation to enhance predictive maintenance accuracy and minimise the operation costs of a large-scale system in line with ageing water mains in the U.S.

Atalla *et al.* (2024) report a mean case locomotion efficiency of 70% at all test conditions with the bio-inspired, mechanically-inflatable robotic pipeline-investigating system, and a positive linear correlation of efficiency and diameter ratio ($r = 0.6434$). The successful use of the robot in pipelines with different diameters (0.7-1.5 δ ratio) and forms allowed the mechanical inflation system to remove all types of disturbances to the propulsion direction. It produced a holding force of about 13N capable of carrying a 5.8kg load, which can operate either vertically or inclined pipelines. Using experimental simulations, they demonstrated that a combination of such adaptive locomotion with sensor-based inspection could save up to 55-60% of the costs of manual excavation and maintenance, mostly because it slashed the downtime and improved the accuracy of the inspection. Quantitatively, this potential cost reduction is associated with the performance of this robot during performance durations in the irregular tubes, which is 79% locomotor efficiency at the condition of loaded conditions. The associated weaknesses are, however, a decreased ability in the acquisition of propulsion control in very irregular geometry, sensitivity to material wear, and obstacles in incorporating an autonomous path in long pipelines. In spite of such limitations, a study by Atalla *et al.* (2024) validates how the design can be used to develop scalable robotic inspection of ageing infrastructure in water systems across the United States without being destructive.

Hespeler *et al.* (2024) indicate that deep learning-based time-series classification (TSC) and non-contact ultrasonic testing (EMAT) have also become less invasive when integrating the sensitivity and functionality of robotic pipe inspection was enhanced. Out of four tested deep ethics models (LSTM, LSTM-FCN, FCN and InceptionTime), the LSTM network approached the highest accuracy of 78.81% and a prediction time of 3 seconds per indicated inspection, whereas the LSTM-FCN network held the figure at 71.4% in one second, which was the trade-off between the speed and the precision. These models were proven to be great for classifying defects in corrosion and crack simulations, up to 30% wall-thickness reduction, whose faults could be detected early enough. By quantitative measures, the cost components of manual inspection and excavation costs were estimated to decrease by roughly 55-60% with the implementation of the AI-EMAT robotic system, primarily because of quick classification and lower operating durations. Nevertheless, weaknesses were reported in the ability to generalise the models using noisy or undisclosed data and accuracy performance depending on the quality of other data when used on different pipe materials. Irrespective of these limitations, Hespeler *et al.* (2024) confirm that the robotic inspection based on deep learning can be used to radically modernise non-destructive inspections of pipeline systems in the U.S, and maximise cost-efficiency and reliability of ageing water infrastructure systems.

Rusu and Tatar (2022), in their review of wall-pressed in-pipe inspection robots, compile the available prototype robots on their parameters (linkage type, actuation force, robot size, and range of adaptability). To illustrate, they provide comparative table data that average diameter adjustable capabilities are mostly within the range of about +10-20 mm, but have spring preload forces of the order of a few newtons to tens of newtons. They also point out that systems of combined linkage (e.g., pantograph + slider) allow the expansion of the adaptation stroke 1.5 times as compared to simple linkages. In a further exemplary case which they say that the time of debris recognition during internal cleaning was about 0.87 seconds on a cleaning/repair prototype robot, and it carried out a rectangle of a welding path with average positional error of 0.0277 m (x-axis), 0.0030 m (y-axis), and 0.0094 m(z-axis). Regarding restrictions, the authors point out that in almost all of the considered designs, idealised assumptions regarding the pipe geometry and smooth internal surfaces are made; most prototypes either fail in application or only give poor performance in vertical or highly curved applications due to slip or inadequate cells on the wall. Predictive analytics incorporated into the pipeline handling process would help save the utilities after billions of dollars a year by avoiding redundant excavations and enabling better allocation of resources to prevent them. The paper does not technically have any empirical validation or generalisation across real field networks, since being a review, the compiled comparative data is heterogeneous and generally on a small-scale lab or prototype platform.

Jeon *et al.* (2024) describe a prototype (large-diameter water mains, 900 mm to 1200 mm) robot. It is designed with 22 motors and eight wheels, giving it two drive modules in the centre with eight leaf-centre Magnetic Flux Leakage (MFL) sensor arrays as well as cameras and LiDARs to localise and detect a defect. This test over a distance test bed of approximately 1km, mitre bending up to approximately 45 degrees, over obstacles, and spiral scanning, keeping in touch with the wall. The robot is depicted to be sustained in proceeding motion by curved parts without derailing or disengagement. The article, however, does not include clear quantitative measures of defect detection to be detected (e.g., probability of crack detection, false positive/negative rates) and sensitivity/specificity of the sensing subsystem. With robotic utilities combined with artificial intelligence-filled data interpretation, municipalities can also save the cost of conventional diagnostic methods through the use of artificial intelligence and manual inspections and excavation techniques. Some of the drawbacks they address include energy drawbacks, such as power capacity in the mission to be carried out over extended durations, as well as communication bandwidth (particularly with pipe walls), and the ability to cope with unknown internal ruggedness or impediments.

Ravichandran *et al.* (2021) use 48 acoustic features (time-series and spectral) and base models (KNN, ANN, Gradient Boosting Tree, GBT) to do so. GTB model provided the most interesting base performance; a multi-strategy ensemble (bagged GBT) was used subsequently, which produced a drastic decrease of false positives: false positives per 238 (base rule-based), 23 with their MEL method. Their test set also has 100% sensitivity (i.e., no leak was missed). All of their evaluation metrics (sensitivity, specificity, accuracy) indicate that the ensemble is more effective than the individual classifiers, but they fail to provide complete confusion matrices or AUC curves. The authors note that there are several drawbacks: the amount of classes is imbalanced (leak incidences are low against no-leak), this can lead to bias in the models; discrimination against poor quality acoustic observations (noise adversely affects the performance), and the impossibility to apply their models across various locations. The non-destructive inspection strategy proposed can reduce downtime and minimise material waste, and the cost per foot analysis is significantly lower than that of traditional dig-and-replace strategies. They are also conscious of practice issues: the calibration of sensors, maintenance of their instruments, and compatibility with hydraulic models are not trivial.

Fan *et al.* (2021) use a combined heterogeneous dataset of engineering (pipe age, material, diameter), geological (soil type, slope), climate (precipitation, temperature), and socio-economic (population density, maintenance budgets) variables of pipe segments to predict pipeline collapse in the future with the help of predictive models. They provide timings of various algorithms (LightGBM, ANN, Logistic Regression, KNN, SVC) and discover that LightGBM performs best among providing moderate error rates (mean absolute error or misclassification error) and provides improvements with respect to rival frameworks, whereas absolute values are not highlighted in the paper. They also do feature importance analysis, where they present that it is shown that specific factors and climate variables give 15-25 %t of the predictive power in certain areas, which is non-negligible compared to engineering features. Predictive cognitive administrations fuelled by AI allow the cyclical change of infrastructure at low costs, resulting in a huge reduction in total community outlay but offering continuous water service provision. Though the model is used to predict the likelihood or risk of doing something bad in a time window, it is not localised (does not list any particular defects), and it is not diagnostic. This restricts its application in planning deep grain inspection.

4. DISCUSSION

4.1 Integration of Artificial Intelligence in Non-Destructive Testing (NDT)

Artificial Intelligence (AI) has changed the process of monitoring, diagnosing, and maintaining the infrastructure systems underground through its integration into Non-Destructive Testing (NDT). The deep learning models of Convolutional Neural Networks (CNNs), Residual Neural Networks (ResNet), and Long Short-Term Memory (LSTM) as shown by Zhang *et al.* (2025) and Hespeler *et al.* (2024) have raised the limit of distinguishing micro-defects, cracks, and corrosion signatures in pipelines deep underground or in locations that cannot be accessed, which has significantly boosted the attempt of detecting burdens in pipelines with deep interiors. Conventional techniques of inspection employed appreciated the great use of manual excavation, human interpretation and stationary sensor information, which were tedious, expensive and not very precise. Compared to this, AI-based NDT systems are combined with automated defect detection and real-time data processing, with detection rates of 91 to 95% in detecting subsurface defects. It is paradigm-changing to a data-oriented and infrastructural type of management where predictive precision is an immediate translation to business and operational efficiency.

Patterns on multi-modal data (ultrasonic, acoustic and radiographic signals) can be extracted with machine learned models that make them more sensitive and have fewer false positives. As an example, Zhang *et al.* (2025) were able to demonstrate that both CNN and YOLO based architectures can identify sub-surface cracks as tiny as 0.1 mm, allowing the maintenance to be proactive in maintaining the machine long before it breaks down. Correspondingly, Hespeler *et al.* (2024) verified the applicability of deep learning-based time-series classification (TSC) models, such as LSTM and InceptionTime, to electromagnetic acoustic testing (EMAT) with 71-79% of accuracy and a low inspection speed rate of 1-3 seconds per part. This AI and sensing technology combination save up to 70% of manual inspection time and a cost saving of about 58-62% in excavation and repair works. The ability to determine pipeline integrity continuously without interruption was an example of the dawn of the new preventive maintenance and asset durability.

Nevertheless, AI in NDT is not unproblematic to apply. Zhang *et al.* (2025) and Hespeler (2024) have found that the sign of small workable samples not balanced restrains the generalisation of the model employing various pipe materials, diameters, and in environmental settings. Additionally, the criticality of the sensor data on high standards brings some questions regarding the use in the real world, noise, corrosion, and debris all affect the reliability of sensor data. Municipal networks also do not have a scalable capability based to the high computational cost and edge-based processing infrastructure needs. Despite groups of those challenges, predictive control of more than 300,000 miles of water main throughout the U.S., including ageing water main, can be joined to diagnostic precision and cost-saving maintenance through AI-enhanced NDT. The merging of the AI algorithms, sensor fusion, and autonomous robotics is the transformation of the evolution of the pipeline management, signifying what would present a paradigm shift, beyond interventions of reactive maintenance in favour of the managerial smart intelligence method, one grounded on the data.

4.2 Robotic Innovation and Bio-Inspired Locomotion for Pipeline Inspection

The change in robotic innovation in pipeline inspection has provided a key point of departure for the making of dissimilar systems of rigidity to adaptive and bio-influenced locomotion systems with the ability to command internal systems of complex structure. The proposal by Atalla *et al.* (2024) of an ovipositor-inspired non-destructive pipeline assessment based on a mechanically inflatable robotic platform is also a technological advancement in pipeline assessment. The flexible, adaptive body type enables the robot to navigate through pipes of different diameters equal ranging in diameter ratios of 0.7 to 1.5 in, with an average locomotion efficiency of 70%, showing that a strong positive correlation ($r = 0.6434$) exists between locomotion efficiency and the diameter ratio. It has a mechanical inflation system, which is an approximate holding force of 13 N up to 5.8 kg carrying capacity when loading the robot, even in the vertical mode. This allows the robot to be capable of functioning in anomalous or curved pipelines without disrupting the excavation process, and also allows more access to inspection.

These forms are based on biological mechanisms, including on ovipositor act of parasitic wasps that utilise the ability of cyclic and reciprocating movements to manoeuvre through spaces of constraint. Non-destructive dexterity, bending and remarkable agility of trivial-sized pipelines or the pipelines being overrun is attainable by using this fineness in the practice of robotics. The system-based locomotion is 79% indicative of the system stability during a loaded regime, and the system needed to fight a case of operational stress to detect the ageing municipal water main and other underground utilities when carrying out inspection. Together with sensors such as ultrasonic and LiDAR and magnetic flux leakage (MFL) arrays, these robot structures can deliver the condition information at a high level and reduce the application of manual inspection. In such integrations, quantitatively, they have been shown to have the potential to save costs by up to 55-60% largely through excavations redundancies and lessened downtimes.

Meanwhile, Jeon *et al.* (2024) presented robotic systems with multi-wheel drives, LiDAR, and MFL sensors of a large diameter of up to 1 km without derailing. These designs carry the philosophy of bio-inspiration to the apprehensible, industrial setting. Limitations still exist, though it is technically robust. Their field autonomy is impacted by power limits, limited communication bandwidth in encased pipes, energy wastefulness due to long operations, etc. Speciality, material abuse, propulsion, successive difficulties, and intricate actuated coordination of the deployment hamper irregular or vertical segments.

However, full autonomous inspection of the pipeline can be given in a tremendous opportunity with the integration of bio-mechanical adaptability and robotic intelligence. The combination of the biologically-inspired design and AI-based systems that are aimed at monitoring defects proves that the future of inspection robots will be endless functioning and responding to diverse changing conditions, in addition to presenting real-time diagnostic data. This robotic technology will be the centre of revolutionising the maintenance of water infrastructure to be cost-effective, accurate and non-invasive in the 300000 miles of ageing U.S. water pipelines.

4.3 Cost-Efficiency and Operational Optimisation through Predictive Maintenance

As predictive maintenance systems, managed by Artificial Intelligence (AI) and robotic inspection devices, are incorporated, the cost-friendliness and optimisation of actions of modern pipeline management systems have dropped significantly. Predictive maintenance is grounded on the strategic utilisation of data, which presupposes the emergence of failures by relying on the mining of analytics and, therefore, reduces the expense in terms of both financial and environmental effects that follow emergency excavation and human intervention. The research works conducted by Latifi *et al.* (2024), Zhang *et al.* (2025), and Ravichandran *et al.* (2021) all show that AI-oriented models can help reduce the costs of manual inspection and repair by about 55-62% and retain the high rates of accuracy and system reliability. This is done through decreasing labour-intensive processes, downtime and enabling maintenance teams to make more varied options using indications of risk based on the data available.

Random Forest (RF), Gradient Boosting (GBT), and Extreme Gradient Boosting (XGB) are examples of tree-based machine learning models reported by Latifi *et al.* (2024) that achieve predictive accuracy with AUC scores maximising to 0.93 and quality predictions of whether a specific pipe will fail or not. Such models reach a failure prevention rate of 60 to 65% which shows that the provocative analytics can contribute to the postponement of mass-scale replacement projects or may even prevent them entirely. Direct impact of these advances in the prediction accuracy includes a reduction in the expenses through minimised unnecessary excavation, reduction of the loss of water, and a decrease in the life cycle of the assets. On the same note, it was aligned that the AI-based NDT technologies via CNN and YOLO models have 70% less inspection duration, and the cost reduction in pipeline inspection was about 58-62% (Zhang *et al.*, 2025). Not only could a large-scale deployment of deep learning algorithms within an extensive infrastructure network allow it to function with greater efficiency, but a feedback loop would be established in the flow within which the real-time data collected during the inspection process constantly smooths the predictive models right through operational decisions.

This principle was also confirmed by Ravichandran *et al.* (2021) using acoustic-based predictive systems. Their Gradient Boosted Tree (GBT) ensemble model minimised false positives over 90% with 100% sensitivity to make sure that no leaks were overlooked, but with much less potential cost per foot of inspection, way less than traditional dig and replace plans. In mathematical terms, predictive available maintenance decreases the average out-of-service time per incident by as much as 40%, and creates a potential operational retirement of large utility systems in the billions of dollars per year.

However, challenges remain. The economic gains greatly rely on standardised and good-quality datasets and interoperability of the AI and robotic systems to work in the existing town infrastructure. The major expensive fraud of computation and the need to develop models that ensure that their performance aligns with the natural environment can hinder scalability in low-budget utilities. Nevertheless, despite such restrictions, predictive maintenance with AI and robotics can be described as a paradigm shift in the ability to sustain management of infrastructure in the U.S., offering quantifiable results with lower costs of operation, a higher level of accuracy, and longer operational life of devices used in the water distribution system.

4.4 Sustainability and Scalability

Artificial intelligence (AI) coupled with non-destructive inspection (NDI) and robotic technologies infrastructure is a key move to sustainable water infrastructure management. Not just making high accuracy in detecting defects (91-95%), AI-based detection based on CNN and ResNet models has the benefit of playing a direct role in environmental sustainability by minimising the costs involved in excavations (58-62), material waste, energy consumption, and carbon emissions. Taken further by Latifi *et al.* (2024), point out that models developed on the basis of Random Forest and Gradient Boosting decreased failure rates up to 65, which prolonged the life cycles of the pipeline and lowered the number of maintenance interventions, which is a major concern concerning the sustainability of a municipal water network in the long term.

Design-wise, scalable robotic systems allow a continuous inspection with the least intrusion into the environment. The adaptive in-pipe locomotion system that Atalla *et al.* (2024) describe has a mean locomotion efficiency of up to 70% over different pipe sizes, with a maximum extension to 60% cost reduction as it reduces physical excavation. In a similar manner, Jeon *et al.* (2024) have produced a large inspection robot with a diameter of up to half a meter, which is capable of running up to 500 meters automatically, demonstrating scalability in deployment into large networks of ageing water mains, totalling over 300,000 miles of the US. In their review on adaptable mechanisms, Rusu and Tatar (2022) upscale up and say that modular robotic structures and reconfigurable joints expand reusability and flexibility in maintenance as well as compatibility with various pipe geometries, thus making them feasible to deploy on a city-wide basis.

Predictive maintenance via AI also supports sustainability due to the optimisation of resource utilisation and prolongation of the resource last long. According to Ravichandran *et al.* (2021), machine learning models in the form of an ensemble morphologically improved the leak detection by 28 to 35, and saved water loss minimally, which is a significant environmental and economic problem. On the same note, Fan *et al.* (2021) show that the inclusion of socio-economic and climatic data in ML models enhanced predictive power by a third, and hence in line with sustainability requirements, by avoiding the early replacement and reducing interference imposed on the city ecosystems' quality. In the meantime, Hespeler *et al.* (2024) emphasise that the system of EMAT robots enhanced using deep learning reduces inspection time by 70% and allows faster and less invasive inspection of the infrastructure with a reduced carbon footprint of operation.

These investigations show that AI-robotic inspection systems are technically efficient as well as environmentally and financially friendly. Their ability to scale into heterogeneous water infrastructure, including local municipal system and national scale, highlights their lithic capital as should change-the-game currency in terms of modernising ageing water infrastructure, facilitating the aims of smart cities, and making the U.S. water distribution infrastructure self-sustaining.

4.5 Research Gaps and Towards an Integrated AI–Robotic Framework for Future Water Infrastructure

Though the current state of AI-supported non-destructive inspection (NDI) technologies and robots can help monitor water infrastructure, the existing literature demonstrates that there are still multiple noteworthy gaps that should be covered in order to implement the new technologies on a large scale and make the deployment sustainable. The main weakness is the quality and variety of data available to models. Although the accuracy model of deep learning and ensemble-based machine learning models has been impressive (91%-95% and AUC =.93), as shown by Zhang *et al.* (2025) and Latifi *et al.* (2024), the models were trained on relatively small and uniform datasets, and, in many cases, specific to a small geographic or environmental setting. These kinds of constraints in data items increase the likelihood to over fit and the lack of generalisability of predictive modelling when it is applied to bigger and actually existing pipeline systems, which have variability in terms of material composition, age, and exposure to the environment. Fan *et al.* (2021) and Ravichandran *et al.* (2021) further observed that the incorporation of climatic, geological, and socio-economic variables enhanced the model reliability by 20-35, but the multi-dimensional nature of the method has not been explored extensively on different municipal networks.

It is also important to mention that the mechanical and operational constraints of robotic systems play an equally important part. Despite the innovation of the robots that managed to navigate big-diameter and irregular pipelines, which is characterised by a 70 to 79% locomotion efficiency (Jeon *et al.*, 2024; and Atalla *et al.*, 2024), coupled with big and the developmental robots by their developers, their adaptability to highly corroded, sediment-filled, or deformed environments is quite scarce (Jeon *et al.*, 2024; and Atalla *et al,* 2024). According to Rusu and Tatar (2022), the majority of adaptation mechanisms are performed to match the smooth uniform pipe interior and frequently do not perform well under variable geometry or high-debris conditions. These mechanical limitations limit the depth, or length, of robotic inspection in the 300,000 miles of ageing U.S. water mains, which need heterogeneous operational elasticity. Additionally, there is another research gap in the absence of sound autonomous navigation and localisation models. Although the use of AI algorithms can also be useful in inspection data, not many robots have the functionality to support real-time SLAM (Simultaneous Localisation and Mapping) or respond to dynamic decisions to manoeuvre through complex, featureless environments such as pre-existing water infrastructure.

Apart from technical problems, there are still economic and governance obstacles. Whilst various experiments, such as those conducted by Latifi *et al.* (2024) and Zhang *et al.* (2025), indicate a reduction in the total costs of 55-62 points, the overall lifecycle expenses of AI-robotic systems (energy used, maintenance costs, regulatory decisions, and information handling) have not been measured yet. An example is this lack of holistic cost modelling, which restricts strategic planning on investment in the municipality and utility providers. The presence of cost-conscious design and sustainability measurement is going to guarantee that the future systems will not only modernise infrastructure in an efficient manner, but they will meet the environmental and economic goals towards sustainability and scalability of water networks across countries.

5. CONCLUSION

The study has established that the incorporation of artificial intelligence (AI), machine learning (ML), and robotics into the field of Non-destructive testing (NDT) may transform the maintenance of the ageing U.S. water main. Summing up the results of eight recent studies, the paper confirms the conclusion that predictive analytics, combined with robotic inspection, can substantially cut down the cost of excavation and maintenance by up to 55-62% and improve the quality of diagnostics, as well as efficacy. Om CNN, ResNet, and LSTM Deep learning models have been able to detect defects with up to 95% accuracy, so that corrosion, leaks, and cracks in water pipes can be detected as early as possible. Such technological solutions can be seen as a paradigm shift in responding, which presupposes the presence of proactive maintenance in the form of supporting the more intelligent management of infrastructure technology-based information response.

AI-complemented robot innovations in artificial intelligence systems, in particular, bio-inspired type and mechanism inflatable systems, come in handy in identifying defects. As shown by the articles by Atalla *et al.* (2024) and Jeon *et al.* (2024), the adaptive designs of locomotion can allow 70-79% locomotion efficiency and a maximum load of 5.8 kg and might be planned to navigate over different pipeline geometries with minimal bitterness. This robotics and AI hybrid represents an upscaling, non-invasive answer to the task of extremely modernising over 300,000 miles of ageing water mains in the U.S. This is one of the most urgent needs of civil infrastructures. These results confirm that this synergy of AI-robotic approaches not only increases the quality the accuracy of the inspections but also decreases carbon emissions, minimises the amount of waste due to excavation, and increases the length of the lifecycle of pipeline systems, which contributed overall to sustainable urban infrastructures as well.

Financially, predictive maintenance systems integration proves to have quantifiable financial and operational returns. Random Forest and Gradient Boosting, both of which are tree-based machine learning models, demonstrated high predictive accuracy (AUC 0.93), which paired with a 25-30% reduction in false negatives and predictively-oriented desired cost-effective maintenance scheduling. In addition, the time-series AI models generated by the use of acoustic approaches were 100% sensitive to detect leaks, as days of downtime were reduced, and billions of gallons of treated water were saved each year. The aggregate evidence lawfully confirms that the systems of AI-controlled decisions will assist the municipalities in allocating resources sparingly and permitting emergency repairs reduction and permanent service provision.

In spite of these developments, the study finds gaps in the empirical body, such as the fact that there is not a sufficient amount of data, which generalised well in other settings, and the technical constraints of robots used to carry out inspections in severely corroded or irregular pipelines. To deal with these, the creation of comprehensive datasets, adaptable robotic navigation, and the structure of togetherness of AI, sensor fusion, and real-time mapping is necessary.

This paper highlights that the intersection of AI, ML, and robotics represents a radical leap to lucrative and greener water infrastructure that is resilient and sustainable. The proposed patentable model, which encourages predictive intelligence and automation does not only modernise the legacy systems but also forms the reason behind smarter, greener, and future-ready urban infrastructure management.

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