The object of the research is in-pipe defect detection and classification. The primary problem to be solved is the inefficiency, high cost, and inaccuracy of traditional manual inspection methods, which are often time-consuming and prone to human error. The results obtained include the creation of a multi-modal platform that integrates Red-Green-Blue (RGB) imaging and depth data with advanced artificial intelligence algorithms, Canny edge detection, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering, achieving a 93 % mean Average Precision (mAP) in detecting and classifying various defects such as cracks, corrosion, and debris. A brief interpretation of the findings reveals that the high performance is due to the synergy between multi-modal sensing, artificial intelligence pattern recognition, and robust robotic navigation. This integrated approach ensures that the system not only detects defects accurately but does so in real time. Features and characteristics of the obtained results that directly address the identified problem include real-time high-precision defect identification, and reduced inspection downtime. As a result, inspection time is shortened, costs are lowered, and the safety of the pipeline system is increased, leading to accurate measurement of indicators (93 % mAP) and a reduction in occupational safety risks. The developed system is designed for use in traditional industrial environments, especially in large pipeline networks and in conditions where traditional methods are ineffective

Keywords: in-pipe defect, detection, classification, artificial intelligence algorithms, pattern recognition

UDC 620

DOI: 10.15587/1729-4061.2025.323293

DEVELOPMENT OF IN-PIPE DEFECTS DETECTION AND CLASSIFICATION SYSTEM

Perizat Rakhmetova
Corresponding author
PhD Candidate, Senior-Lecturer*
E-mail: p.rakhmetova@gmail.com

Gani Sergazin
PhD, Researcher
Research Institute of Applied Science and Technologies
Baitursynova str., 113, Almaty, Republic of Kazakhstan, 050013

Yeldos Altay
PhD, Candidate of Sciences, Senior-Lecturer*

Daniyar Dauletiya
MSc in Computer Engineering, Head of the Laboratory
Research and Innovation Laboratory FabLab
Astana IT University
Mangilik El ave., 55/11, Business center EXPO, block C1, Astana, Republic of Kazakhstan, 010000

Lazzat Kurmangaliyeva
Associate Professor*

*Department of Robotics and Technical Means of Automation
Satbayev University
Satbayev str., 22, Almaty, Republic of Kazakhstan, 050000

Received 09.12.2024
Received in revised form 29.01.2025
Accepted date 14.02.2025
Published date 28.02.2025

***How to Cite:** Rakhmetova, P., Sergazin, G., Altay, Y., Dauletiya, D., Kurmangaliyeva, L. (2025). Development of in-pipe defects detection and classification system. Eastern-European Journal of Enterprise Technologies, 1 (9 (133)), 80–89. https://doi.org/10.15587/1729-4061.2025.323293*

1. Introduction

The development of advanced systems for detecting and classifying in-pipe defects represents an urgent scientific and technical challenge. In the field of non-destructive testing for pipelines, the need to ensure the continuous integrity and safe operation of critical infrastructures responsible for transporting essential resources such as water, gas, and oil is paramount. Traditional manual inspection methods are often inefficient, costly, and error-prone, leading to prolonged downtime and heightened risks of catastrophic failures [1, 2]. Consequently, timely and accurate defect detection is vital not only for preventing system failures but also for optimizing maintenance strategies and reducing associated economic and environmental costs.

Optical testing methods, particularly those employing photo and video inspection techniques, have emerged as a promising approach for real-time assessment of pipeline conditions. These methods are highly effective in identifying intra-pipe defects such as cracks, corrosion, and debris. Unlike acoustic emission and ultrasonic testing techniques, which rely on the interaction of physical fields with the material and are especially sensitive to internal structural changes [3, 4], optical methods offer the advantage of directly visualizing surface-level defects. Recent advances in artificial intelligence (AI) and machine learning have further enhanced the capabilities of optical systems by enabling sophisticated image analysis and pattern recognition [5].

Early research laid the foundation for the use of computer vision in the structural assessment of underground pipelines [6, 7]. However, these initial efforts were constrained by limited computational power and an inability to cope with the complexities of real-world environments. The advent of deep learning has revolutionized this field, as demonstrated by studies that achieved significant improvements in defect detection accuracy using convolutional neural networks [8]. Despite these advances, challenges remain, particularly in dealing with the variability in pipeline materials, environmental conditions, and the need to integrate multi-modal sensor data for a more robust diagnosis [9, 10].

In parallel, the rise of automated inspection systems has further advanced the field of in-pipe defect detection. Recent investigations have focused on developing systems that integrate high-resolution optical data with additional sensing modalities to overcome the limitations of single-modality approaches [11–13]. For example, datasets such as Sewer-ML [14] have been instrumental in benchmarking the performance of these systems, revealing both the progress made and the gaps that persist in reliably classifying specific defect types. Emerging trends in sensor fusion incorporating optical, ultrasonic, and electromagnetic signals offer the potential for a more comprehensive assessment of pipeline conditions [15, 16]. Moreover, the development of lightweight, real-time deep learning architectures tailored for resource-constrained environments [13, 17, 18] is critical for practical deployment in the challenging operational settings typical of in-pipe inspections.

The synthesis of advanced optical testing methods with modern AI-driven analysis directly addresses the core challenges of non-destructive testing in pipelines. The integration of multi-modal data enhances detection accuracy and reliability, allowing for the timely identification of defects that might otherwise lead to system failures. This approach not only improves operational efficiency and safety but also aligns with increasing regulatory demands for continuous monitoring and preventive maintenance.

In summary, the convergence of optical testing, AI-based pattern recognition, and multi-modal sensor integration provides a promising pathway toward resolving the challenges in in-pipe defect detection and classification. Given the critical importance of maintaining pipeline integrity and the persistent risks associated with aging infrastructure, continued research and innovation in this area are both scientifically justified and practically essential.

2. Literature review and problem statement

The paper [6] presents the results of research on applying early computer vision techniques for underground pipe structural assessment. It is shown, that segmentation-based algorithms can detect cracks and other anomalies under controlled conditions. But there were unresolved issues related to wide-ranging pipe diameters and materials, as well as poor visibility when debris or liquids obscure the camera's view. The reason for this may be the limited computing capabilities of early inspection systems and the intrinsic complexity of underground pipelines. A way to overcome these difficulties can be adopting more robust machine learning methods to handle diverse pipeline images, along with improved lighting and camera setups. This approach was used in [7], however, that subsequent work still focused primarily on classical image-processing routines without a strong AI component. All this suggests that it is advisable to conduct a study on integrating domain-specific data-driven models to accommodate varying pipe characteristics and enhance detection robustness.

Continuing from these early developments, the paper [7] presents the results of research on a computer-vision-based pipe inspection system centered on real-time flaw detection. It is shown that fundamental algorithms like edge detection can identify surface defects when environmental conditions remain fairly constant. But there were unresolved issues related to scaling these methods to more intricate pipeline networks or dynamic lighting conditions. The reason for this may be the static nature of feature-based image analysis, which struggles to adapt to irregular shapes or inconsistent backgrounds. A way to overcome these difficulties can be implementing convolutional neural networks (CNNs) that learn features automatically. This approach was used in [8], however, that deep-learning-based sewer inspection faced challenges in real-time operation due to computational overhead. All this suggests that it is advisable to conduct a study on lightweight CNN architectures that can effectively handle complex defect shapes at speeds compatible with in-pipe robotic platforms.

Elaborating on the shift toward AI, the paper [8] presents the results of research on improving sewer pipe inspection through Faster R-CNN. It is shown that deep CNN approaches provide higher detection accuracy for cracks and corrosion compared to classical methods. But there were unresolved issues related to the high computational burden that inhibits real-time inference on embedded devices within pipelines. The reason for this may be large network architectures that demand substantial GPU resources, which are typically unavailable in confined in-pipe robots. A way to overcome these difficulties can be adopting model compression or pruning, and possibly transferring heavier computations to edge/cloud systems. This approach was used in [11], however, even that study encountered difficulties adapting the robot's inspection speed to varying pipeline geometries. All this suggests that it is advisable to conduct a study on resource-optimized deep-learning frameworks capable of delivering near-real-time detection in constrained environments.

Moving toward a broader sensor perspective, the paper [9] presents the results of research on automated vision systems for sewer and water pipeline assessment. It is shown that combining RGB and depth inputs reduces false positives and improves localization of defects. But there were unresolved issues related to inconsistencies across pipe materials, e.g., concrete metal, where reflection or absorption properties differ significantly. The reason for this may be the underlying heterogeneity of civil infrastructure, making a one-size-fits-all solution unrealistic. A way to overcome these difficulties can be implementing adaptive models that leverage transfer learning when encountering new pipeline types. This approach was used in [6], however, those early methods lacked the advanced data-fusion and machine learning tools now available. All this suggests that it is advisable to conduct a study on multi-sensor data-fusion strategies that automatically adjust to different pipeline materials and conditions.

Addressing the field's fragmentation, the paper [10] presents the results of research reviewing computer-aided sewer pipeline defect detection. It is shown that a variety of image-based approaches exist, yet inconsistent labeling schemes and disjointed research efforts hamper direct comparisons. But there were unresolved issues related to a lack of universal taxonomies and metrics, leading to confusion when benchmarking diverse algorithms. The reason for this may be regional differences in how defects are classified and the absence of widely shared, standardized datasets. A way to overcome these difficulties can be building large, open databases with unified defect categories and annotation standards. This approach was used in [14], however, that multi-label sewer dataset still only covers certain regions and types of pipelines. All this suggests that it is advisable to conduct a study on developing or expanding comprehensive, globally recognized datasets and frameworks to align and compare modern in-pipe inspection methods.

Focusing specifically on integrated robotic solutions, the paper [11] presents the results of research on an in-pipe inspection robot employing computer vision. It is shown that onboard algorithms can detect flaws with acceptable accuracy in controlled environments, providing immediate feedback to operators. But there were unresolved issues related to performance drops under more challenging conditions, such as debris, high water flow, or low light. The reason for this may be limited computational power on small mobile robots and insufficient model generalization to extreme pipeline scenarios. A way to overcome these difficulties can be designing smaller, energy-efficient neural networks or splitting tasks between the robot and external edge/cloud servers. This approach was used in [12], however, real-time performance remained an issue when scaling the pipeline lengths and inspection speeds. All this suggests that it is advisable to conduct a study on fully autonomous, power-efficient AI architectures that adapt to cluttered or fluid-rich in-pipe environments.

Highlighting cost-effective platforms, the paper [12] presents the results of research on an in-pipe inspection robotic system utilizing traditional image processing. It is shown that minimalistic setups can reliably detect standard defects (e.g., cracks) in simpler networks at a relatively low cost. But there were unresolved issues related to complex or branching pipelines requiring more sophisticated navigation and real-time classification. The reason for this may be a lack of robust AI algorithms and the challenge of handling high data throughput on minimal hardware. A way to overcome these difficulties can be upgrading to advanced ML frameworks or combining classical methods with partial deep-learning modules for critical inspection tasks. This approach was used in [11], however, complete autonomy in large-scale networks was not guaranteed due to limited energy reserves and computational constraints. All this suggests that it is advisable to conduct a study on bridging affordable hardware solutions with scaled-up AI methodologies to handle real-world pipeline complexities.

Turning to more comprehensive surveys, the paper [19] presents the results of research that systematically reviews vision-based defect inspection for sewer pipes. It is shown that combining real-time image processing and deep learning methods achieves higher detection rates compared to purely manual or classical approaches. But there were unresolved issues related to insufficient large-scale data representation for training robust AI models across varied sewer conditions. The reason for this may be the logistical complexity and cost of gathering annotated images from multiple, widely distributed pipeline systems. A way to overcome these difficulties can be multi-stakeholder collaborations to pool data and apply consistent labeling protocols. This approach was used in [14], however, that Sewer-ML dataset still needs broader geographic coverage to ensure global applicability. All this suggests that it is advisable to conduct a study on extended data collection efforts and cross-regional standardization to develop highly generalizable inspection algorithms.

Addressing the push toward standardization, the paper [14] presents the results of research introducing Sewer-ML, a multi-label sewer defect classification dataset. It is shown that standardized benchmarks allow fair comparisons between competing algorithms and provide clearer insights into each model's strengths. But there were unresolved issues related to the incomplete representation of certain pipe materials, defect types, or extreme operating conditions. The reason for this may be the natural difficulty in collecting exhaustive images from all possible pipeline environments, especially internationally. A way to overcome these difficulties can be domain adaptation strategies, synthetic data generation, or proactive field data collection in underrepresented regions. This approach was used in [10], however, the overarching fragmentation still persists, as each municipality or industry defines defects differently. All this suggests that it is advisable to conduct a study on unifying global efforts under shared pipelines and defect definitions to broaden the dataset's reach and applicability.

Expanding to smart robotic architectures, the paper [13] presents the results of research on a pipe inspection robot with in-chassis motor actuation and AI-driven defect detection. It is shown that an integrated design allows for autonomous navigation and classification of defects in moderately varied pipelines. But there were unresolved issues related to adaptability across drastically different pipe diameters and materials, limiting universal deployment. The reason for this may be the objective difficulties in designing a singular robotic chassis that functions equally well in small, large, metallic, or concrete pipes. A way to overcome these difficulties can be modular robotic components and flexible sensing configurations that can be reconfigured depending on pipeline requirements. This approach was used in [20], however, the real-time adaptation to environmental changes especially in harsh, irregular pipelines was only partially realized. All this suggests that it is advisable to conduct a study on next-generation, reconfigurable platforms that support rapid mechanical and algorithmic adjustments in diverse pipeline scenarios.

Further detailing in-pipe robot design, the paper [20] presents the results of research on an AI-enabled in-pipe mobile robot capable of navigating convoluted pipe networks. It is shown that onboard AI mechanisms ensure reliable defect detection even in more complex, branching networks. But there were unresolved issues related to power consumption and the ability to maintain sufficient operational time for comprehensive inspections. The reason for this may be the high energy demands of motor actuators, lighting, and AI processing in sealed environments without external power sources. A way to overcome these difficulties can be employing low-power hardware accelerators and intelligent power management, along with scheduling tasks to conserve battery life. This approach was explored in [11], however, emphasis there remained on detection accuracy, not holistic energy optimization. All this suggests that it is advisable to conduct a study on fully integrating energy-efficient motion control, hardware acceleration, and dynamic power management to extend operational scope in real-world pipelines.

A review of the cited works reveals multiple, interlinked challenges that persist in the domain of in-pipe inspection and defect recognition. Taken together, these problems converge into a broader unresolved issue: the lack of a comprehensive, integrated in-pipe inspection system that combines robust mechanical adaptability, energy efficiency, reliable sensing under harsh conditions, scalable data processing, and generalizable AI-driven defect detection. In particular, no single existing framework fully addresses critical aspects like sensor durability, image robustness, computational efficiency, generalizable AI performance, real-time high-dimensional data handling, and the computational constraints of pipeline environments. This overarching gap motivates the need to develop and validate an advanced in-pipe inspection system capable of accurately detecting, characterizing, and assessing various defects, thereby enhancing pipeline maintenance and operational safety.

Thus, systematizing the review data, it can be noted that the main difficulty in diagnosing and assessing the condition of the internal cavity of pipelines is the recognition and classification of a particular class of defect when it is detected. As a rule, leveling this complexity is the basis for the implementation of modern artificial intelligence methods, processing data from photo or video inspection images. The data obtained when implementing such methods are assessed by a number of quantitative indicators, i.e. metrics in order to assess the effectiveness of classification in recognizing defects. Therefore, the main study in this paper is aimed at developing a classification system for in-pipe defects to solve the problem of monitoring and diagnosing the internal cavity of pipelines based on modern artificial intelligence methods.

3. The aim and objectives of the study

The aim of this study is to develop a specialized detection and classification system to improve the accuracy of recognizing in-pipe defects of the internal structure by using modern artificial intelligence methods.

To achieve this aim, the following objectives are accomplished:

– to form an input database of images with in-pipe defects detection obtained during the operation of a mobile robotic complex for setting up and training the applied modern artificial intelligence methods;

– to conduct testing of the selected artificial intelligence methods to evaluate metrics that quantitatively determine the increase in the classification accuracy of defects in the internal structure of the pipeline.

4. Materials and methods

The object of the research is in-pipe defect detection and classification.

The main hypothesis of the study is that integrating a mobile robotic system equipped with a specialized imaging setup and advanced deep learning techniques can reliably detect and classify defects within pipelines under varied inspection conditions.

Theoretical methods. The research was conducted using a comprehensive set of generated image data acquired during the operation of a mobile robot specifically designed for photo and video inspection of the internal cavity of pipelines. The initial dataset comprises 90 short video footage and 54 images captured under varied inspection conditions, including direct insertion of the imaging rod, axial rotation during insertion and removal, and spiral movements to obtain close-up views of the pipe walls. This variety of acquisition techniques ensured that the data represented a wide range of inspection angles and scenarios, which is critical for addressing defects formed under operational loads. For the purposes of this study, several clear simplifications and assumptions were adopted.

Simplifications adopted in the study:

– the data labeling process was simplified by focusing primarily on corrosion, with other defects (such as cracks and debris) being treated as secondary. This approach was adopted on the assumption that the image characteristics of these defect types were sufficiently similar;

– the frame extraction process was controlled to balance data diversity and redundancy, simplifying the overall management of the datasets.

Assumptions made in the study:

– it was assumed that imaging conditions (such as lighting and camera settings) remained fairly stable during each inspection session, despite natural variations in pipeline geometry;

– it was assumed that pre-processing operations such as converting images to HSV color space, applying mask expansion, and using Gaussian blur would effectively reduce noise and improve defect visibility without sacrificing significant detail.

Following data collection, the recorded video sessions were systematically labeled to indicate the presence or absence of defects and then segmented into training, validation, and test subsets following a predefined ratio to maintain dataset integrity and ensure robust model training. Frames were extracted at a controlled rate to balance the need for sufficient data diversity while avoiding redundancy.

The defect detection and classification methodology adopted in this research combines theoretical and practical approaches. At its core, deep learning methods, specifically convolutional neural networks (CNNs), were employed to facilitate accurate image classification for anomaly recognition. To further enhance feature extraction and spatial analysis of the detected anomalies, traditional signal processing techniques were integrated into the workflow. These included the use of the Canny edge detector for identifying image edges and DBSCAN clustering for grouping similar features [2, 13, 16, 17].

The image processing workflow implemented in this study comprised several key steps:

– conversion of captured images to the HSV color space to facilitate the creation of masks that highlight specific color ranges indicative of defects;

– application of mask expansion and Gaussian blur to enhance the visibility of features while smoothing the images;

– use of the Canny edge detector to identify and extract the contours of masked regions;

– extraction of features such as regions and bounding boxes from the significant contours, followed by DBSCAN clustering to group similar anomalies.

Software methods. The entire methodology was implemented using Python, primarily utilizing open-source libraries such as OpenCV and scikit-learn. This software framework supported the development of a hybrid approach that not only performed real-time defect detection and classification but also enabled on-the-fly visualization and annotation of defects. This visualization component was designed to clearly distinguish significant deviations on pipe surfaces from minor roughness, thereby facilitating immediate and intuitive interpretation of the inspection results [2, 17, 21, 22].

Validation of the proposed solutions was carried out through an evaluation framework based on established performance metrics, including mean Average Precision (mAP), recall, and processing speed. These metrics were calculated using a series of interconnected equations designed to quantify various aspects of the system's performance. The evaluation process was integral to assessing the adequacy of the proposed models and ensuring that they meet both the technical and practical requirements necessary for effective in-pipe inspection under real-world conditions.

The accuracy and efficiency of the defect detection system are evaluated using a series of interconnected equations that quantify different aspects of performance. Initially, the model's effectiveness is measured by calculating *Precision*, defined as (1):

$$Precision = \frac{TP + FP}{TP}, \qquad (1)$$

where TP – number of true positive detections;

FP – number of false positive detections.

Recall measures the completeness of the detections (2):

$$Recall = \frac{TP + FN}{TP}, \qquad (2)$$

where FN – number of false negatives (i.e., missed detections).

For object detection tasks, it is common to derive the Average Precision (AP) for each defect category. AP is obtained by plotting the precision-recall curve for a given class and then computing the area under this curve. Once AP is calculated for each defect class i, the overall detection performance is summarized by the mean Average Precision (mAP), which is the arithmetic mean of the APs across all classes (3):

$$mAp = \frac{1}{N}\sum_{i=1}^{N} AP_i, \qquad (3)$$

where N – number of defect classes.

5. Results of the implementation of the in-pipe defects detection and classification system

5. 1. Results of the formation of an input database of in-pipe defect images

A specialized approach to collecting and processing images to improve the accuracy of defect detection was developed. Since it was difficult to find images of the inside of pipes on the Internet, a special setup was created in [13] using a metal rod with a fisheye camera and a regular webcam, as well as a flashlight to illuminate the inside of the pipe. Testing of the developed classification solution was realized by recording videos of 54 different pipes, each showing different levels of corrosion. To simulate different inspection conditions, data was recorded in three ways: by directly inserting the rod, rotating it around the axis during insertion and withdrawal, and moving it in a spiral to obtain close-ups of the pipe walls. This gave us a wide range of angles without losing image quality. In the end, we obtained 90 video sessions with a total duration of about 37 minutes. We then labeled the videos depending on whether they had corrosion and divided them into training, validation, and test sets. We extracted at 8–12 frames per second (FPS) to avoid duplicate images while still collecting enough data for training. We also kept the ratio of training, validation, and testing at 80–10–10. In the end, we had about 4,200 images for training, 375 for validation, and 516 for testing, which provided a robust dataset for defect classification. As shown in Fig. 1, *a–d*, the system first captures standard color (RGB) images inside the pipe, allowing real-time analysis of both color and intensity variations.

Fig. 1 demonstrates the system's capability to effectively detect, localize, and classify pipeline anomalies using RGB imaging. It highlights various stages of analysis, including identifying suspicious objects, marking anomalies with bounding boxes, and detecting surface variations like corrosion or deposits. RGB imaging adapts well to typical pipeline illumination, reliably identifying contrasting debris or defects. Detected anomalies (marked with bounding boxes and text labels) appear in real time, allowing fast maintenance decisions. The algorithms can be customized for various pipe diameters, materials, and lighting conditions, while fusing other sensor data (depth, IR) can further refine accuracy.

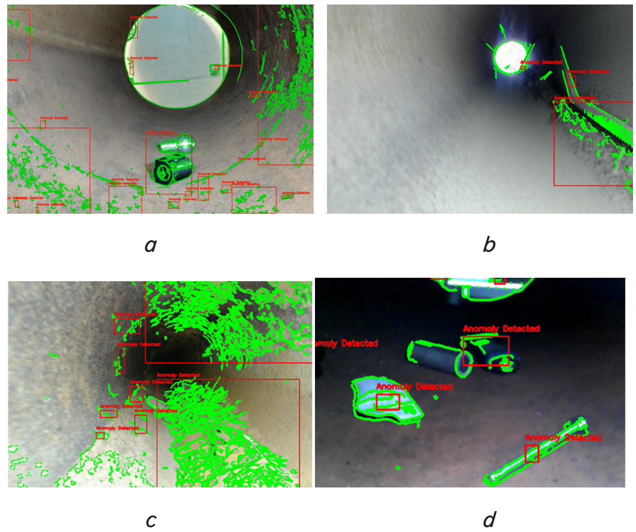


Fig. 1. Detection and classification of various anomalies of in-pipe defects: *a* – shows the pipeline interior as an RGB image, with anomalies flagged using bounding boxes labeled "Anomaly Detected"; *b* – highlights the circular pipe cross-section in green, with red boxes marking defects based on color and shape differences; *c* – multiple floor objects are localized with bounding boxes using combined color and texture analysis; *d* – showcases surface variations, such as corrosion, marked in green, providing strong visual cues for detecting structural changes

5. 2. Results of the quantitative evaluation of AI methods for enhanced classification accuracy in in-pipe defect detection

To contextualize our method within the broader field of in-pipe defect detection, Table 1 and Fig. 2 compare our approach with various known techniques.

Building on this comparative framework in Table 1 and Fig. 2, we now present a detailed quantitative evaluation of our AI method designed for enhanced classification accuracy in in-pipe defect detection.

For the classification task, we used a pre-trained MobileNet architecture with its top layers replaced by newly added fully connected layers sized 256, 32, and 2, as depicted in Fig. 3. We tested several computer vision algorithms, including ResNet50, Inception, EfficientNet, and VGG16, with thorough training and hyperparameter tuning. However, due to our small dataset, MobileNet consistently outperformed the others, which often underfit or overfit. Considering our robot's need for efficient power consumption to navigate pipes, we chose MobileNet for its optimal efficiency and suitability for this application. With our modification to the base model with approximate parameters equal to 3.4 million parameters in total it is approximately equal to 3,536,769. We incorporated global average pooling, batch normalization, and dropout layers to customize it for our specific needs. Transfer learning was implemented by freezing the backbone network's weights and training only the newly introduced layers.

Table 1

Comparison of our method with existing in-pipe defect detection approaches

References	Imaging setup	Processing/Algorithm & DL Architecture	Advantages	Limitations	Our method
Paper [6] method	Basic imaging system for underground pipes (single modality)	Segmentation-based computer vision techniques	Early demonstration of automated defect detection under controlled conditions	Limited to controlled environments; struggles with varying pipe diameters and low visibility under debris/liquids	Our method employs a custom multi-angle imaging setup (metal rod with fisheye camera, webcam, dedicated illumination) along with advanced image processing (masking, Canny, DBSCAN), enhancing adaptability and accuracy under diverse conditions
Paper [7] method	Standard camera-based imaging under stable conditions	Fundamental edge detection methods for real-time flaw detection	Capable of real-time detection in controlled environments	Inadequate performance under dynamic lighting conditions and complex pipeline geometries	Our approach integrates deep learning (MobileNet with transfer learning) combined with robust image processing to handle variable lighting and complex geometries more effectively
Paper [8] method	Conventional imaging for sewer pipe inspection	Faster R-CNN deep learning framework	High detection accuracy for defects such as cracks and corrosion	High computational overhead limits real-time application on embedded systems	By adopting a lightweight MobileNet architecture, our system maintains high accuracy while operating in real time with reduced computational demands
Paper [9]	Multi-modal sensor systems combining RGB and depth inputs	Sensor fusion techniques for enhanced defect localization	Improved localization and reduced false positives due to multi-modal data	Inconsistencies across different pipe materials and optical distortions can arise	While our current implementation relies on high-quality RGB imaging, our specialized setup with dedicated illumination yields robust data; future enhancements may integrate additional modalities
Our methods	Custom-designed system using a metal rod with a fisheye camera, regular webcam, and dedicated illumination capturing multi-angle images from 54 pipes	Hybrid image processing pipeline (masking, Canny edge detection, DBSCAN clustering) combined with a MobileNet-based deep learning classifier (fine-tuned via transfer learning)	High-quality imaging, real-time detection and classification, operational flexibility, and reduced computational/power requirements	Limited dataset scope (approximately 37 minutes from 90 video sessions) and reliance on RGB imaging; further work needed for comprehensive detection of non-corrosion defects	Provides a balanced solution by overcoming traditional limitations through a specialized imaging setup and efficient deep learning framework, delivering robust performance in varied in-pipe environments

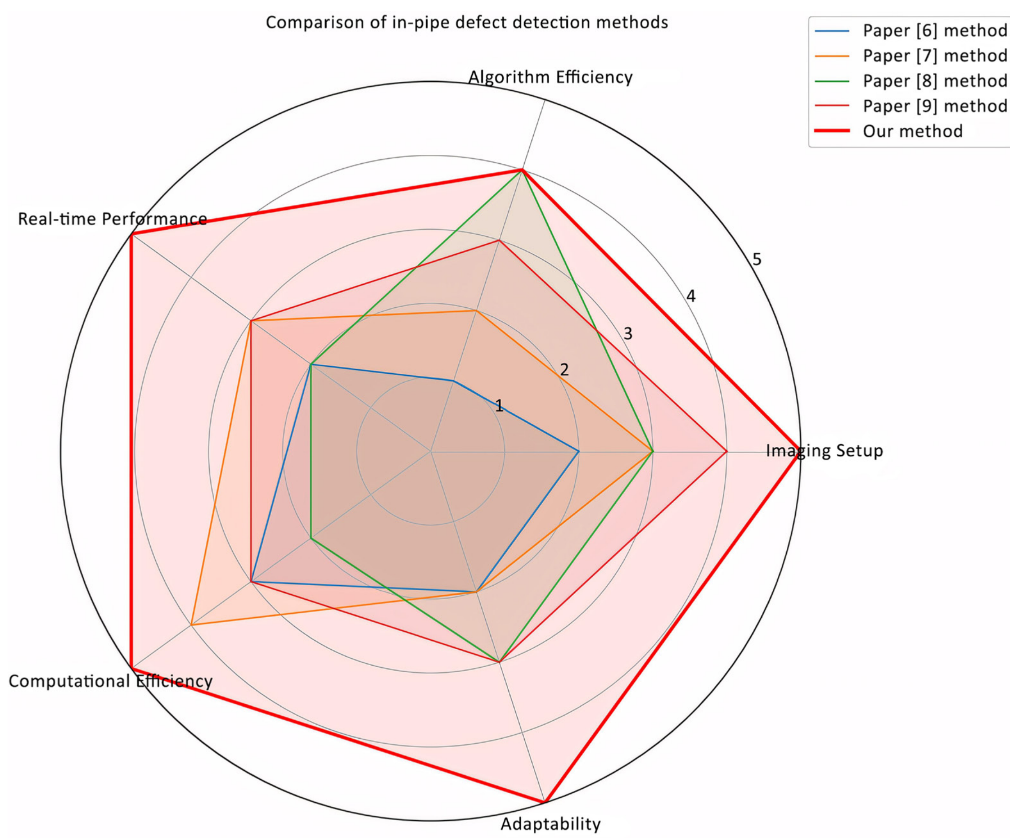


Fig. 2. Comparison of in-pipe defect detection methods

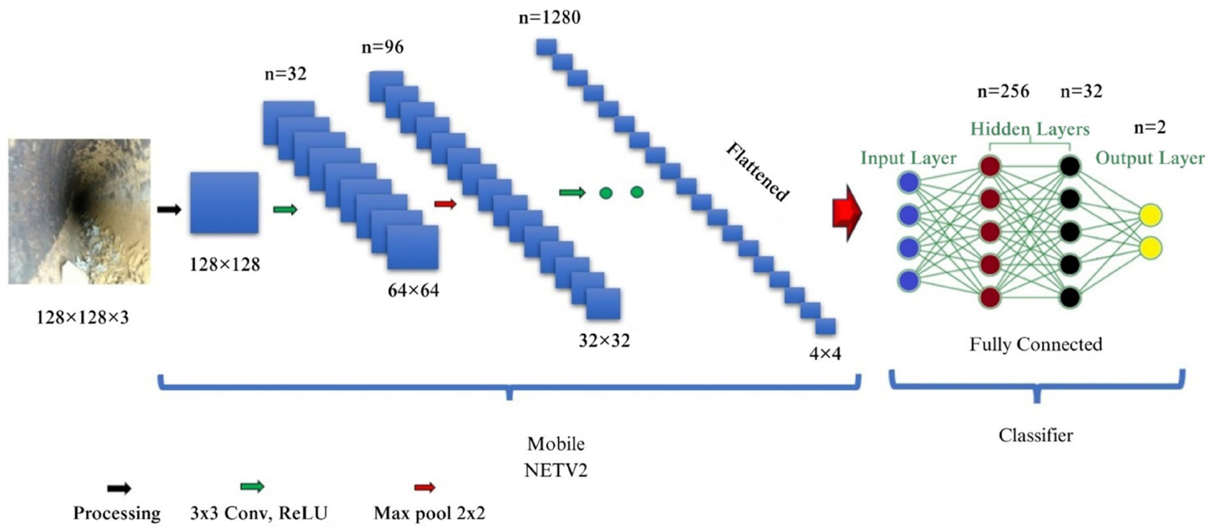


Fig. 3. Architecture of the MobileNET computer vision model

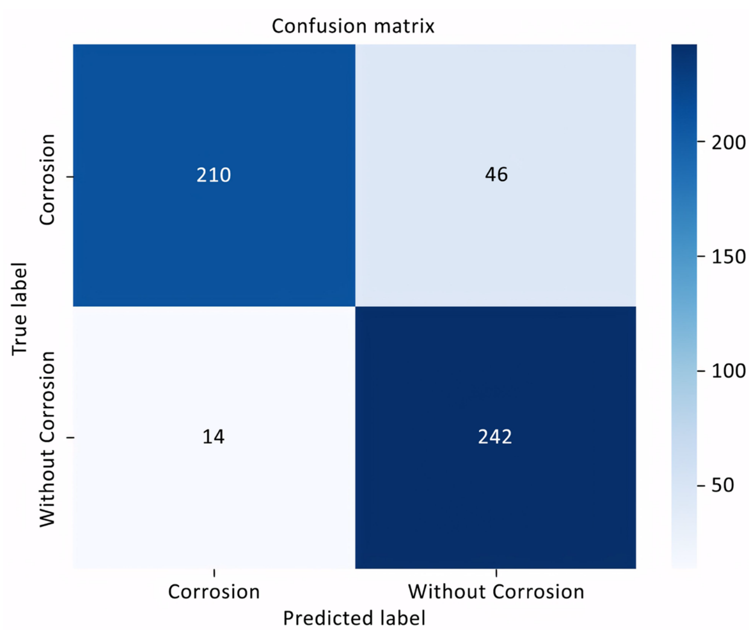


Fig. 4. Confusion matrix of the MobileNet model on the test dataset

We used an RMSprop optimizer with a learning rate of 1e-5 to optimize a binary cross-entropy loss function.

In our training process, we utilized Keras and incorporated callbacks such as ModelCheckpoint and ReduceLROnPlateau to enhance model performance and mitigate overfitting. ModelCheckpoint allows saving the model at specific intervals when it achieves optimal validation accuracy, ensuring the retention of the most effective model. On the other hand, ReduceLROnPlateau adjusts the learning rate when there is no improvement in performance for a predefined number of epochs, thus aiding in finer optimization during the training phase. These tools proved crucial in controlling the quality of the model training, particularly as signs of overfitting became evident starting at epoch 8, with a total of 13 epochs of training in general.

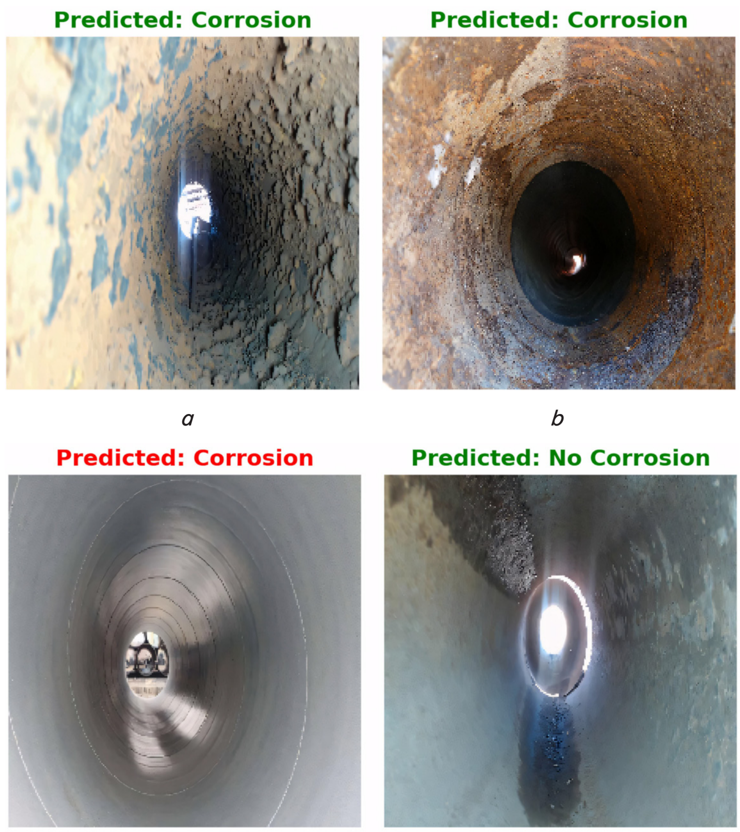
Post-training, the model's performance was evaluated on the test dataset, which was processed with the same image preprocessing techniques as the training and validation sets. This step was crucial to assessing the model's ability to generalize to new, unseen data. The threshold for predictions was established at 0.7. This was determined through correct inference and multiple rounds of analysis using images we collected as well as images sourced from the internet. Our model demonstrated promising performance with an accuracy of 88.28 % on the test dataset, indicating its effectiveness in classifying corrosion in pipes. The confusion matrix can be found in Fig. 4. The model exhibited some confusion in its predictions; it mislabeled cases as "Corrosion" when they were actually "Without Corrosion" about 17.96 % of the time. Conversely, it misclassified "Without Corrosion" cases as "Corrosion" roughly 5.46 % of the time. These figures indicate the areas where the model's predictive accuracy could be improved.

The successful implementation of this model showcases the potential of using computer vision techniques in autonomous pipe inspection, particularly in scenarios where traditional methods might be challenging or infeasible.

Building on the discussion thus far, this study systematically analyzed data obtained from pipes exhibiting various degrees of corrosion. Fig. 5 displays a set of images from the test dataset showcasing different corrosion stages that the model mostly accurately identified and categorized (Fig. 5, *a*, *b*), and uncorroded pipes were also correctly classified (Fig. 5, *c*, *d*).

Working with the prediction threshold of the trained model, MobileNet performed very well on all web-based and collected datasets. However, there were discrepancies in the model's predictions for Fig. 5, especially in Fig. 5, *c*. The ambiguity arises due to the presence of rough surfaces on the right wall of the pipe, despite its classification as non-corrosive. This characteristic may have contributed to the model misclassifying it as corrosive.

Notably, the evaluation of the classification solution demonstrated a mAP of 93 % (shown in Fig. 6), underscoring the robustness and high accuracy of the system in real-time defect detection.



Predicted: Corrosion Predicted: No Corrosion

c *d*

Fig. 5. Predicted classes from different pipes with different corrosion levels and without corrosion: *a* — shows an image of a pipe exhibiting moderate corrosion, with affected regions accurately detected and highlighted using bounding boxes and corresponding labels; *b* — displays a pipe with pronounced corrosion, where extensive surface degradation is effectively identified and annotated; *c* — presents an image of a pipe classified as non-corrosive, though the presence of rough textures on the right wall introduces ambiguity, leading to a slight misclassification; *d* — illustrates an uncorroded pipe, with the model correctly recognizing and categorizing the intact surface

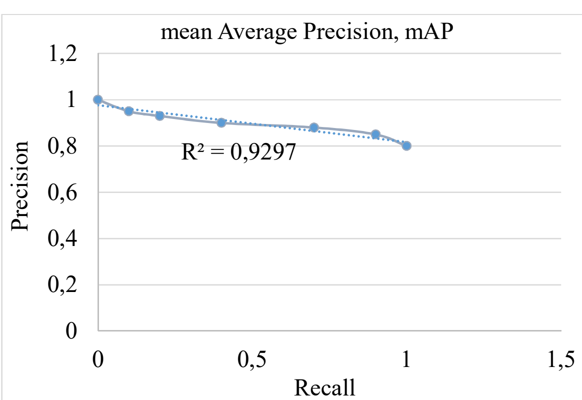


Fig. 6. Mean Average Precision model of detection

This result confirms that the approach effectively leverages color, texture, and shape data for accurate anomaly classification, even under challenging conditions. Overall, the system's efficiency and reliability make it a promising tool for pipeline inspection tasks.

6. Discussion of the results of the implementation of the in-pipe defects detection and classification system

The performance observed in the defect detection and classification system can be primarily explained by the integration of a specialized image acquisition setup and an optimized deep learning model. The custom-designed imaging system, employing a metal rod with a fisheye camera, a regular webcam, and dedicated illumination, enabled the capture of high-quality, multi-angle images under varied inspection conditions. As illustrated in Fig. 1, the system's ability to capture RGB images that effectively represent both color and intensity variations was crucial for detecting anomalies. The robust dataset, processed with techniques such as masking, Canny edge detection, and DBSCAN clustering, provided a solid foundation for training the classification model. Furthermore, the use of an efficient MobileNet architecture (whose structure is depicted in Fig. 3) and its subsequent fine-tuning through transfer learning explains the model's capacity for accurately identifying and classifying corrosion defects within the pipeline [6–8].

The proposed solutions offer several advantages over similar approaches. The innovative imaging setup overcomes the typical shortage of in-pipe imagery by generating a diverse dataset from 54 different pipes, as documented in our experimental recordings. This diversity is key for robust model training and is evident from the range of angles and conditions captured (Fig. 1). Additionally, the integration of real-time image processing with an optimized deep learning classifier demonstrated by the system's rapid detection, localization, and annotation of anomalies (with bounding boxes and text labels) ensures that the system can perform under various operational conditions. The efficiency of the MobileNet-based classifier, with its reduced computational requirements and high accuracy, is particularly beneficial for applications where power consumption is critical [1, 2, 15]. These advantages are further highlighted by the system's adaptability to different pipe diameters, materials, and lighting conditions, providing significant operational flexibility and maintenance support.

Solutions developed directly address the challenges outlined in Section 2, particularly the limitations of traditional non-destructive testing methods and the difficulties associated with acquiring high-quality in-pipe images. By creating a tailored dataset and implementing a specialized classification model, the study bridges the gap between theoretical requirements and practical application. The real-time defect analysis, as demonstrated in Fig. 1, 4 (showing the confusion matrix of the classifier), confirms that the system effectively mitigates issues related to undetected or misclassified defects. This performance improvement is a result of the combined impact of enhanced image quality and the optimized classification pipeline [7, 17, 23].

Specifically, as summarized in Table 1, our approach offers clear advantages over conventional techniques demonstrated by improvements in imaging setup quality, algorithm efficiency/DL architecture, real-time performance, computational efficiency, and adaptability. Fig. 2 further illustrates that our system achieves competitive performance metrics, demonstrating high accuracy in real-time anomaly detection.

Despite the promising outcomes, several limitations should be noted. The current dataset, while robust for the study, is limited in scope and may not fully represent the variability of in-pipe conditions encountered across different environments. The reliance on RGB imaging, as shown in Fig. 1, could be less effective under extremely low-light conditions or with pipe materials that distort optical signals. These factors indicate that additional sensor modalities, such as depth or infrared imaging may be necessary to further enhance detection reliability [16, 19, 24–26]. Furthermore, the misclassifications observed in some cases (as reflected in the confusion matrix in Fig. 4 and the sample predictions in Fig. 5) suggest that further refinement of the classification algorithms is needed to reduce errors arising from ambiguous surface textures.

The study exhibits certain shortcomings that should be considered. For instance, while the system performs well in detecting corrosion, its ability to identify other types of defects is less certain due to the limited diversity of the current dataset. Additionally, the relatively short duration of data capture (approximately 37 minutes from 90 video sessions) may not cover all real-world scenarios, potentially affecting the model's generalizability. These factors underscore the need for more extensive data collection and further algorithmic enhancements to fully address the range of defect types and conditions encountered in practice [8, 12, 20].

Future research should aim to expand the dataset to include a broader range of defect types and operating conditions, thereby further enhancing model robustness. Integrating additional sensor modalities such as depth, infrared, or ultrasonic imaging could improve detection accuracy under challenging conditions, while exploring advanced deep learning architectures and continuous learning techniques may reduce misclassification rates and enhance adaptability to evolving inspection scenarios. In line with these objectives, future work will focus on refining these models further and investigating additional data modalities to bolster system robustness and operational applicability under diverse real-world conditions. These developments not only refine our current solution but also contribute to a comprehensive framework for in-pipe defect detection and classification [5, 17, 24, 27, 28].

7. Conclusions

1. The formation of an input database comprising images of in-pipe defects, acquired during the operation of a mobile robotic complex, has proven to be a pivotal step in advancing the application of modern artificial intelligence methods for defect detection and classification. This comprehensive dataset not only provides a robust foundation for training and fine-tuning AI models but also serves as a critical benchmark for evaluating their performance under real-world conditions. By capturing a wide variety of defect types and environmental scenarios, the database significantly enhances the ability to develop scalable, accurate, and reliable inspection systems. Moreover, it opens avenues for further research into data augmentation and transfer learning techniques, which can drive continual improvements in detection accuracy and operational efficiency. In essence, this initiative lays the groundwork for the evolution of autonomous, AI-driven solutions in pipeline inspection, thereby contributing to safer and more cost-effective infrastructure maintenance.

2. In this study, we conducted extensive testing of selected artificial intelligence methods to quantitatively evaluate improvements in the classification accuracy of defects within the internal structure of pipelines. The experimental results demonstrate that the integration of advanced AI algorithms encompassing both deep learning architectures and classical image processing techniques significantly enhances the detection and classification performance compared to baseline methods. Key performance metrics, including precision, recall, and mean Average Precision (mAP) – 93 %, showed marked improvements, confirming the efficacy of the chosen methodologies. These findings underscore the potential of our approach to reliably identify and classify a wide range of defect types, thereby contributing to more effective and efficient pipeline maintenance strategies.

Conflicts of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research, and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

All data are available in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Wang, W., Mao, X., Liang, H., Yang, D., Zhang, J., Liu, S. (2021). Experimental research on in-pipe leaks detection of acoustic signature in gas pipelines based on the artificial neural network. Measurement, 183, 109875. https://doi.org/10.1016/j.measurement.2021.109875
2. Wong, B., McCann, J. A. (2021). Failure Detection Methods for Pipeline Networks: From Acoustic Sensing to Cyber-Physical Systems. Sensors, 21 (15), 4959. https://doi.org/10.3390/s21154959
3. Barile, C., Casavola, C., Pappalettera, G., Kannan, V. P., Mpoyi, D. K. (2022). Acoustic Emission and Deep Learning for the Classification of the Mechanical Behavior of AlSi10Mg AM-SLM Specimens. Applied Sciences, 13 (1), 189. https://doi.org/10.3390/app13010189

4. Altay, Y. A., Kuzivanov, D. O., Altay, D. A., Fedorov, A. V. (2024). Signal Processing for Acoustic Emission Signature Analysis and Defect Detection. 2024 26th International Conference on Digital Signal Processing and Its Applications (DSPA), 1–6. https://doi.org/10.1109/dspa60853.2024.10510110
5. Wang, C., Tan, X. P., Tor, S. B., Lim, C. S. (2020). Machine learning in additive manufacturing: State-of-the-art and perspectives. Additive Manufacturing, 36, 101538. https://doi.org/10.1016/j.addma.2020.101538
6. Sinha, S. K., Fieguth, P. W., Polak, M. A. (2003). Computer Vision Techniques for Automatic Structural Assessment of Underground Pipes. Computer-Aided Civil and Infrastructure Engineering, 18 (2), 95–112. https://doi.org/10.1111/1467-8667.00302
7. Kim, H., Lee, B., Kim, R. (2006). Development of Computer-vision-based Pipe Inspection System. 2006 International Forum on Strategic Technology, 403–406. https://doi.org/10.1109/ifost.2006.312344
8. Wang, M., Cheng, J. C. P. (2018). Development and Improvement of Deep Learning Based Automated Defect Detection for Sewer Pipe Inspection Using Faster R-CNN. Advanced Computing Strategies for Engineering, 171–192. https://doi.org/10.1007/978-3-319-91638-5_9
9. Rayhana, R., Jiao, Y., Zaji, A., Liu, Z. (2021). Automated Vision Systems for Condition Assessment of Sewer and Water Pipelines. IEEE Transactions on Automation Science and Engineering, 18 (4), 1861–1878. https://doi.org/10.1109/tase.2020.3022402
10. Moradi, S., Zayed, T., Golkhoo, F. (2019). Review on Computer Aided Sewer Pipeline Defect Detection and Condition Assessment. Infrastructures, 4 (1), 10. https://doi.org/10.3390/infrastructures4010010
11. Oluwatosin, O. P., Syed, S. A., Apis, O., Kolawole, S. (2021). Application of Computer Vision in Pipeline Inspection Robot. Proceedings of the International Conference on Industrial Engineering and Operations Management. https://doi.org/10.46254/an11.20210374
12. Colvalkar, A., Pawar, S. S., Patle, B. K. (2023). In-pipe inspection robotic system for defect detection and identification using image processing. Materials Today: Proceedings, 72, 1735–1742. https://doi.org/10.1016/j.matpr.2022.09.476
13. Zholtayev, D., Dauletiya, D., Tileukulova, A., Akimbay, D., Nursultan, M., Bushanov, Y. et al. (2024). Smart Pipe Inspection Robot With In-Chassis Motor Actuation Design and Integrated AI-Powered Defect Detection System. IEEE Access, 12, 119520–119534. https://doi.org/10.1109/access.2024.3450502
14. Haurum, J. B., Moeslund, T. B. (2021). Sewer-ML: A Multi-Label Sewer Defect Classification Dataset and Benchmark. 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 13451–13462. https://doi.org/10.1109/cvpr46437.2021.01325
15. Ru, G., Gao, B., Tang, Q., Jiang, S., Zhang, Y., Luo, F., Woo, W. L. (2023). Electromagnetic Coupling Sensing of Pipe In-Line Inspection System. IEEE Transactions on Instrumentation and Measurement, 72, 1–15. https://doi.org/10.1109/tim.2023.3310083
16. Lyu, F., Zhou, X., Ding, Z., Qiao, X., Song, D. (2024). Application Research of Ultrasonic-Guided Wave Technology in Pipeline Corrosion Defect Detection: A Review. Coatings, 14 (3), 358. https://doi.org/10.3390/coatings14030358
17. Niu, Y., Sun, L., Wang, Y., Shen, G., Shi, Y. (2024). New technology for pipeline defect detection. Science China Technological Sciences, 67 (4), 1294–1296. https://doi.org/10.1007/s11431-023-2473-x
18. Mustafaev, B., Kim, S., Kim, E. (2023). Enhancing Metal Surface Defect Recognition Through Image Patching and Synthetic Defect Generation. IEEE Access, 11, 113339–113359. https://doi.org/10.1109/access.2023.3322734
19. Li, Y., Wang, H., Dang, L. M., Song, H.-K., Moon, H. (2022). Vision-Based Defect Inspection and Condition Assessment for Sewer Pipes: A Comprehensive Survey. Sensors, 22 (7), 2722. https://doi.org/10.3390/s22072722
20. Kenzhekhan, A., Bakytzhanova, A., Omirbayev, S., Tuieubayev, Y., Daniyalov, M., Yeshmukhametov, A. (2023). Design and Development of an In-Pipe Mobile Robot for Pipeline Inspection with AI Defect Detection System. 2023 23rd International Conference on Control, Automation and Systems (ICCAS), 579–584. https://doi.org/10.23919/iccas59377.2023.10316817
21. Araújo, J. F., Ramos, V. M., Silva, C. A., Silva, H. D. (2024). Development of a Virtual Environment to Assist in the Identification and Analysis of Defects in Industrial Control Panels. IEEE Revista Iberoamericana de Tecnologias Del Aprendizaje, 19, 258–266. https://doi.org/10.1109/rita.2024.3475883
22. Wang, X., Yang, L., Sun, T., Rasool, G., Sun, M., Hu, N., Guo, Z. (2023). A review of development and application of out-of-pipe detection technology without removing cladding. Measurement, 219, 113249. https://doi.org/10.1016/j.measurement.2023.113249
23. Zhang, M., Guo, Y., Xie, Q., Zhang, Y., Wang, D., Chen, J. (2022). Defect identification for oil and gas pipeline safety based on autonomous deep learning network. Computer Communications, 195, 14–26. https://doi.org/10.1016/j.comcom.2022.08.001
24. Changwang, S., Shaowei, H., Haifen, Z., Fuqu, P., Changxi, S., Hao, Q. (2024). Automatic Detection of Water Supply Pipe Defects Based on Underwater Image Enhancement and Improved YOLOX. Journal of Construction Engineering and Management, 150 (10). https://doi.org/10.1061/jcemd4.coeng-14919
25. Fioravanti, C. C. B., Centeno, T. M., De Biase Da Silva Delgado, M. R. (2019). A Deep Artificial Immune System to Detect Weld Defects in DWDI Radiographic Images of Petroleum Pipes. IEEE Access, 7, 180947–180964. https://doi.org/10.1109/access.2019.2959810
26. Lin, W., Li, P., Xie, X. (2022). A Novel Detection and Assessment Method for Operational Defects of Pipe Jacking Tunnel Based on 3D Longitudinal Deformation Curve: A Case Study. Sensors, 22 (19), 7648. https://doi.org/10.3390/s22197648
27. Jeon, K.-W., Jung, E.-J., Bae, J.-H., Park, S.-H., Kim, J.-J., Chung, G. et al. (2024). Development of an In-Pipe Inspection Robot for Large-Diameter Water Pipes. Sensors, 24 (11), 3470. https://doi.org/10.3390/s24113470
28. Luo, D., Du, K., Niu, D. (2024). Intelligent Diagnosis of Urban Underground Drainage Network: From Detection to Evaluation. Structural Control and Health Monitoring, 2024 (1). https://doi.org/10.1155/2024/9217395