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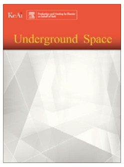

Review Article

A hybrid review of sewer inspection tools and automated CCTV image analysis techniques

Mohamed Nashat[a,b,*], Tarek Zayed[a]

[a] Department of Building and Real Estate, Faculty of Construction and Environment, The Hong Kong Polytechnic University, Hong Kong 999077, China
[b] Department of Public Works Engineering, Faculty of Engineering, Mansoura University, Mansoura 35516, Egypt

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Abstract

Maintaining the integrity of sewage networks is crucial for sustainable urban development. Despite extensive research on inspection tools, machine learning applications, and condition assessment for sewer defects, a holistic review of these elements remains absent. This paper addresses this gap by presenting a comprehensive review within a unified framework, employing a mixed-method approach that includes bibliometric, scientometric, and systematic analyses. Our findings reveal that integrating in-pipe and out-pipe inspection methods enhances outcomes. The current literature identifies modified RegNet, dilation segmentation with conditional random field (DilaSeg-CRF), you only look once (YOLO) models, and faster region-based convolutional neural network (Faster R-CNN) as effective algorithms for classification, segmentation, and object detection, both on-site and off-site, respectively. However, machine learning is an evolving field, and future algorithms may surpass these models. Identifying key challenges, we propose recommendations aimed at advancing research and enhancing replicability: notably, the expansion of international research collaborations, particularly in under-represented regions such as the Middle East, Africa, Asia, and South America; applying the latest version of YOLOv11 in object detection; and investigating defect patterns in polyvinyl chloride (PVC) sewer and rehabilitated pipes using advanced diagnostic methods. This review anticipates aiding policymakers in adopting informed strategies, thereby contributing to the development of smarter, more sustainable cities.

Keywords: Sewer pipelines; Scientometric analysis; Automated defects detection; Digital technologies; Sustainable drainage systems

1 Introduction

The burgeoning growth of urban centres worldwide has underscored the critical importance of sustainable infrastructure in supporting the essential services that underpin urban life (Wang & Yin, 2022). Among the various components of urban infrastructure, sewer networks are particularly vital, necessitating continuous monitoring and inspection to ensure their operational efficacy and to preempt any failure indicators that could precipitate environmental and societal issues (Alshami et al., 2023b). Asset management, recognizing the significance of sewer pipeline networks, has become a focal point of attention in numerous countries. This is particularly true for networks that are antiquated and have surpassed their intended design life. For instance, the Canadian Infrastructure Report Card has highlighted the suboptimal condition of sewer pipelines in Canada, categorizing many as being in poor or very poor condition. Similarly, the American Society of Civil Engineers (ASCE) has assigned a disconcerting grade of D to the sanitation infrastructure in the United States (Moradi et al., 2019). The financial implications of replacing these critical assets are staggering, potentially amounting to millions of dollars, thereby accentuating the need for diligent maintenance. The aging of sewer systems has catalysed a heightened focus on their inspection,

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* Corresponding author at: Department of Building and Real Estate, Faculty of Construction and Environment, The Hong Kong Polytechnic University, Hong Kong 999077, China.
E-mail address: 23123796R@connect.polyu.hk (M. Nashat).
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defect detection, automation, condition assessment, and life expectancy prediction, all of which contribute to cost reduction in maintenance and enhance the quality of rehabilitation decision-making by municipal authorities and utility providers (Salihu et al., 2022). Historically, sewer inspections posed considerable challenges, relying heavily on manual labour, which was not only labour-intensive but also fraught with risks to human health. The advent of closed-circuit television (CCTV) cameras in the 1960s marked the beginning of technological integration into sewer inspections (Wang et al., 2024). In the current decade, inspection techniques have evolved to include ultrasound (Pan et al., 2021) and ground-penetrating radars (GPR) (Xu et al., 2023). However, the suitability of these innovative technologies for inspection varies and must be carefully considered against factors such as pipe type and budget constraints. Despite advancements in inspection technologies, the subsequent analysis of CCTV footage or data from other technologies often still relies on human intervention. This stage can be time-consuming and labour-intensive, given the expansive nature of sewer networks. However, the remarkable surge in artificial intelligence (AI) has spurred research interest in employing computer vision techniques for the automated detection and evaluation of sewer defects. This encompasses defect classification, segmentation, object detection, image quality enhancement, and text discovery for defect localization and tracking, thereby streamlining the process of sewer pipe inspection (Fu et al., 2022).

The application of machine learning and deep learning models has revolutionized sewer pipe network management in recent times (Dang et al., 2021; Kumar et al., 2020; Moradi et al., 2020; Yin et al., 2020a). Researchers have developed comprehensive frameworks for inspection and condition evaluation (Alqahtani et al., 2023; Karabij et al., 2022), while others have focused on the automated detection of sewer defects (Q. Zhou et al., 2021, 2022a, 2023). Some studies have also scrutinized the uncertainty inherent in model results when compared to manual inspections (Caradot et al., 2020). Given the interdisciplinary nature of automated sewer pipe inspection, the body of research in this domain is extensive, resulting in a plethora of scholarly articles. To synthesize this wealth of information and track the progress in this field, this review has been undertaken. While previous reviews, as summarized in Table 1, have made significant contributions, they primarily focus on singular aspects, such as specific technologies or timeframes, leaving gaps in providing a comprehensive perspective on the field. In contrast, this review paper sets itself apart by delivering an integrated examination of sewer defect inspection tools, defect detection methodologies, pipe condition management, and the role of robotics in addressing challenges in automated detection. This holistic perspective is achieved through a tripartite approach that combines bibliometric analysis, scientometric evaluation, and a systematic review. This methodology bridges gaps left by prior studies and offers a more robust understanding of the research landscape.

The objectives of this review paper are as follows:

(1) To review existing studies on sewer defect detection using bibliometric methods to ascertain the volume of research conducted.
(2) To present a comprehensive scientometric analysis that illustrates publication trends, keyword co-occurrence, and the contributions of countries to the field.
(3) To identify the techniques and tools utilized for defect inspection and to categorize the types of defects detectable by each tool.
(4) To highlight the techniques employed in classifying, segmenting, and detecting objects, enhancing CCTV images, detecting text, pinpointing defect locations, and determining the most effective models for each procedure.
(5) To illuminate the management of sewer pipe network inspections, the assessment of their condition, and the evaluation of risks and uncertainties in automated defect detection models.
(6) To discuss research gaps and suggest areas of focus for future studies.

The remainder of this review paper is structured as follows: Section 2 outlines the research methodology and bibliometric analysis. Section 3 presents the results of the bibliometric analysis. Section 4 delves into data acquisition in sewer pipe defect inspection. Section 5 discusses the development and enhancement of analytical models for sewer inspection. Section 6 examines management and evaluation strategies for sewer defects. Section 7 identifies research gaps and future directions, and Section 8 offers conclusions.

2 Research methodology

The study employed a mixed-method approach, combining bibliometric analysis, scientometric analysis, and a systematic review of previous studies. As depicted in Fig. 1, the comprehensive review process began with defining the research objectives, followed by a bibliometric search in the Scopus and Web of Science (WoS) databases. Relevant publications were identified through keyword selection, and filters were applied to remove irrelevant studies. Additionally, forward and backward snowballing techniques were utilized to retrieve more related research. The scientometric analyses were conducted using VOSviewer software, which included examinations of publication trends, keyword correlations, contributing countries, and influential journals. This quantitative analysis provided insights into the bibliometric landscape of the research field. Subsequently, a systematic review was undertaken to discuss sewer defect inspection tools and the models

Table 1
A summary of existing reviews relating to sewer defects.

Study	Review period	Focus	Limitations/Shortage	Contribution of current study
(Fu et al., 2022)	2003–2022	Examined the role of deep learning in urban water and wastewater management.	Lack of specific focus on sewer systems.	(1) This research conducts a comprehensive review of deep learning models, sewer inspection techniques, and recent advancements in machine learning (post-2018), addressing key gaps in previous studies. (2) Explores the latest innovations in automated inspection tools, highlighting the significant progress in robotic technologies for sewer inspection. (3) Provides an in-depth analysis of classification, segmentation, and object detection methods applied to sewer defect detection, with a focus on CCTV images.
(Haurum & Moeslund, 2020)	1994–2019		Absence of comparative evaluation across models and techniques.	
(Moradi et al., 2019)	1998–2018	Focused on sewer inspection technologies using computer vision and machine learning	Rapid advancements in ML models and automated inspection tools after 2018 remain unaddressed.	
(Wang & Yin, 2022)	1998–2022	Discussed automated data interpretation, condition assessment, and mapping	Lacked focus on classification, segmentation, or object detection techniques for sewer defects	
(Salihu et al., 2022)	1983–2021	Studied sewer deterioration models and pipeline deterioration factors.	Lacked focus on automation or defect detection tools	

used in processing CCTV images of sewer defects, focusing on classification, segmentation, object detection, defect location, and the integration of multiple models. Additionally, the review explored strategies for the management and evaluation of sewer defects, encompassing condition assessment, frameworks, and uncertainties in the models used to study sewer defects. Finally, the study identified research gaps and proposed future research directions in the field of sewer defect detection.

The bibliometric analysis consisted of three main stages, as depicted in Fig. 2. In the first stage, relevant research was retrieved by specifying the keywords (“waste water pipe*” OR “wastewater pipe*” OR “sewer” OR “sewerage” OR “stormwater pipe*” OR “storm water pipe*”) AND (“defect*” OR “fault*” OR “flaw*” OR “glitch*”) AND (“forecast*” OR “Predict” OR “Possibility” OR “Estimation” OR “Prediction” OR “probability”), which resulted in 272 search results from the Scopus and WoS databases. Applying filters to include only original articles in English, published between 2019 and May 2024, reduced the number of articles to 80. After removing duplicates, the final set of articles for the initial review was 51. In the second stage, the downloaded articles were examined by reading the titles and abstracts, followed by a full evaluation. To further ensure the comprehensiveness of the search, forward and backward snowballing techniques were employed (Alshami et al., 2023a), which involved examining the citations of the papers being reviewed, as well as their reference lists (Ma et al., 2024b). The final stage of the bibliometric analysis resulted in a total of 78 research papers that met the established criteria and were included in the comprehensive review study.

3 Scientometric analysis

The scientometric analysis is an approach to drawing objective maps of the research field by importing bibliometric data for relevant articles into a program. The open-source text mining program “VOSviewer” was used. This program produces scientometric networks in the form of nodes and links, so that the size of the node expresses the extent of importance and frequency, the distance expresses the level of closeness between the nodes, and the thickness of the line expresses the strength of the connection between them. The procedures used in this study are discussed in the next section.

3.1 Publication trends

The graphical representation of annual publications related to sewer defect detection, as shown in Fig. 3, provides a clear and insightful overview of the temporal trends in this research field. The polynomial regression line indicates an overall upward trend in the number of publications over the period from 2000 to 2024. This suggests that research interest and activity in the area of sewer defect detection have been growing steadily over the past two and a half decades. The analysis reveals three distinct phases in the deployment of publications: (1) Low growth period (2000–2013). During this initial phase, the number of annual publications did not exceed 3 papers, indicating a relatively slow pace of research activity in the field. (2) Moderate growth period (2014–2020). The publication rate increased during this phase, with the number of annual papers ranging between 4 and 11, signaling a gradual acceleration in research output. (3) Significant growth period (2021 onwards). The most recent phase has seen a very substantial increase in the publication rate, with a record 21 research papers published in 2022 alone. It is worth mentioning that the last 3 years (2022, 2023, 2024) collectively account for 35% of the total number of publications in the field of sewer defect detection. Given this observed trend, it is reasonable to expect that the research output in the field of sewer defect detection will continue to increase in the

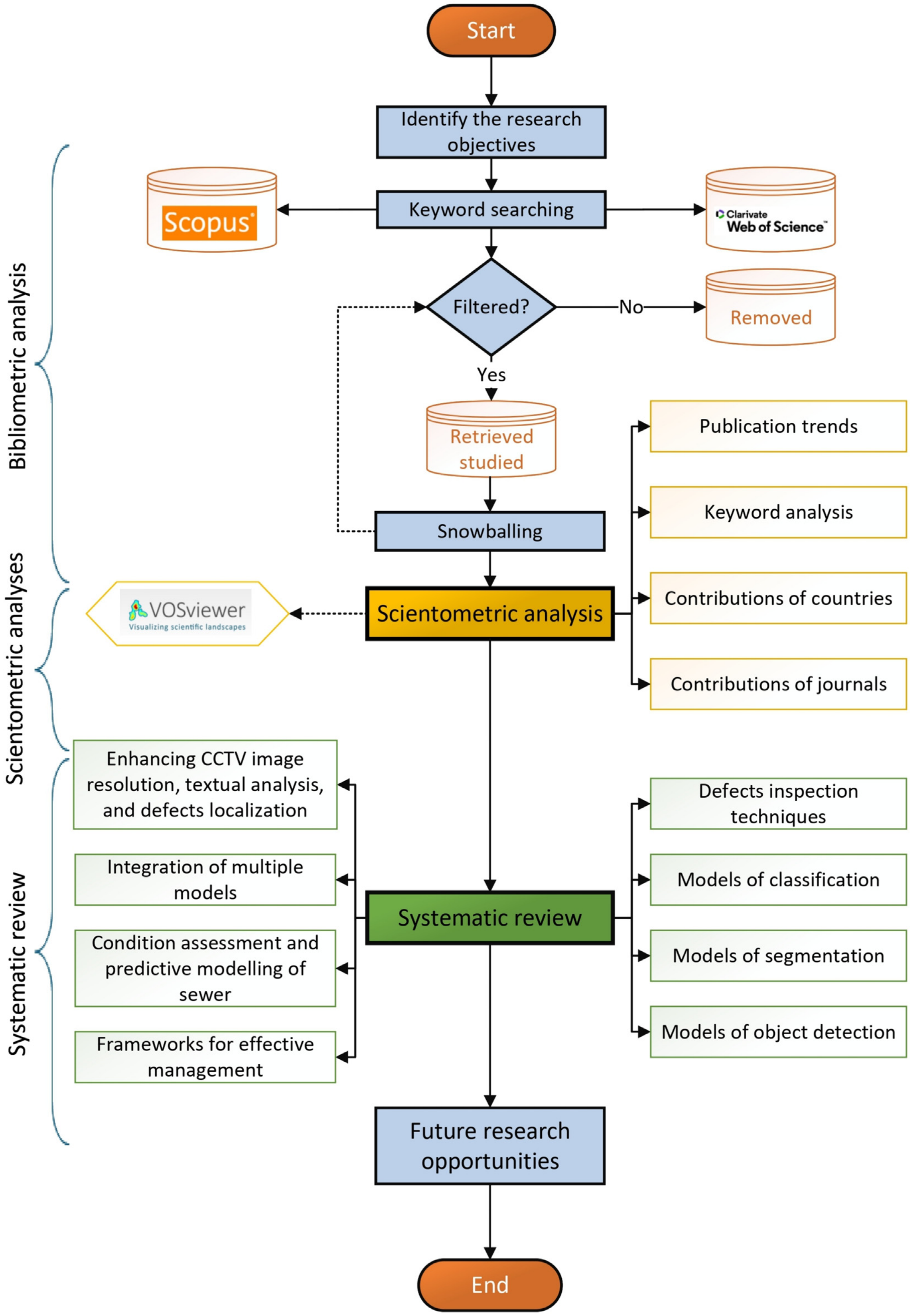


Fig. 1. Framework of the study illustrates the key components and methodology used throughout the research.

coming years. Since this was discussed in our previous review research from 1998 to 2018 (Moradi et al., 2019), our current research will address publications from 2019 until May 2024.

3.2 Keyword co-occurrence analysis

Co-occurrence analysis of keywords is a widely used technique in bibliometric studies to identify research trends

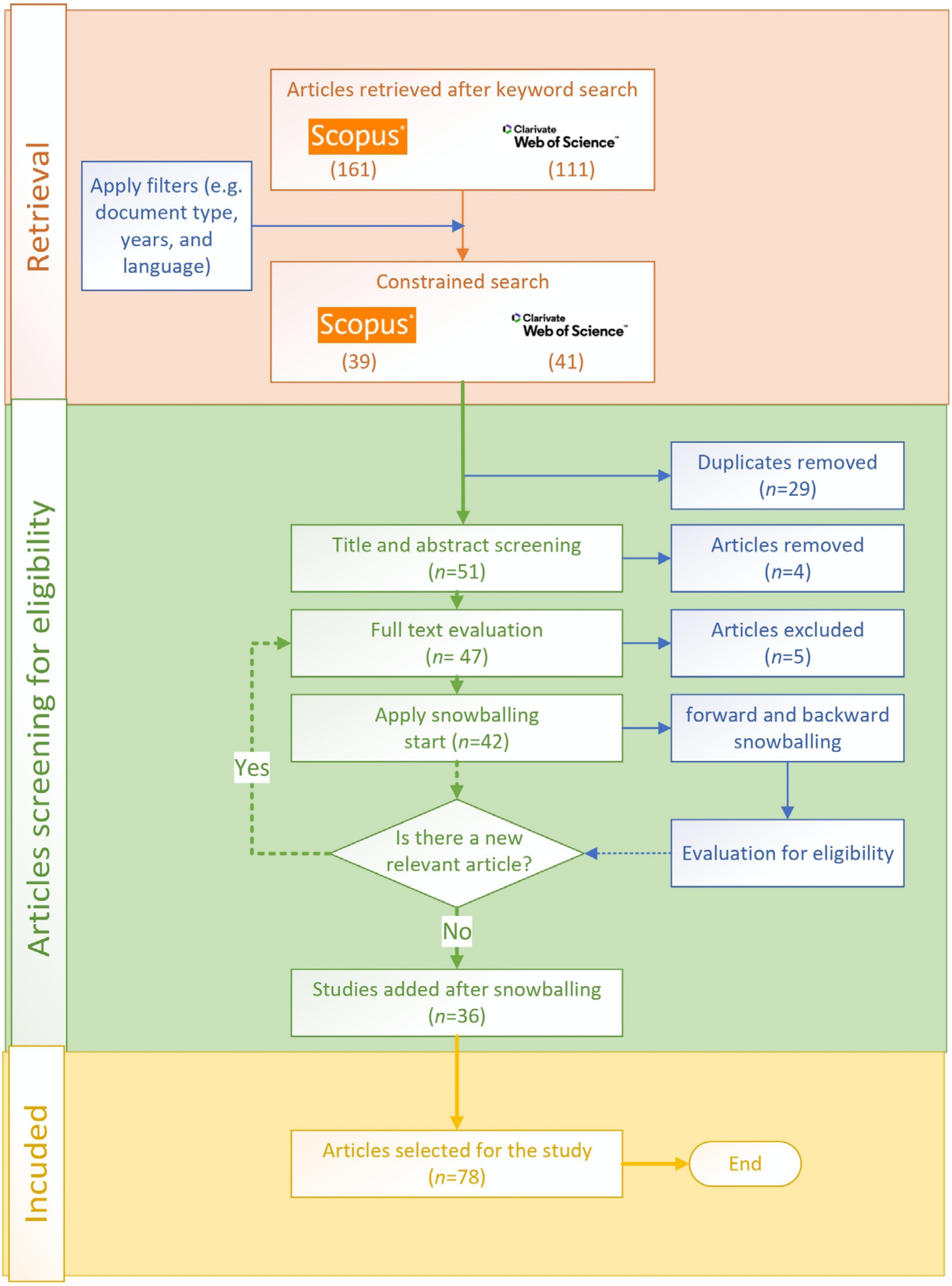


Fig. 2. Flowchart of the bibliometric analysis process, showing article retrieval, screening, and inclusion steps.

and hotspots within a particular research domain. This approach examines the co-occurrence of keywords in the published literature, revealing the relationships and connections between different concepts, methodologies, and areas of focus (Salihu et al., 2022). Figure 4 illustrates the interconnections between various keywords and the frequency of their co-occurrence. After merging similar terms, the minimum number of repetitions for a keyword was set at five, resulting in the identification of 21 keywords organized into 3 distinct colored groups. The red cluster focuses on defect detection, classification, object detection, and image processing techniques. The green cluster includes CCTV image processing methods, as the widespread use of deep learning approaches, such as convolutional neural networks and machine learning, in the automated detection of defects is evident. The larger size of the keyword “deep learning” indicates its prominence in this research area. Regarding the blue cluster, it centres on the sewer, the

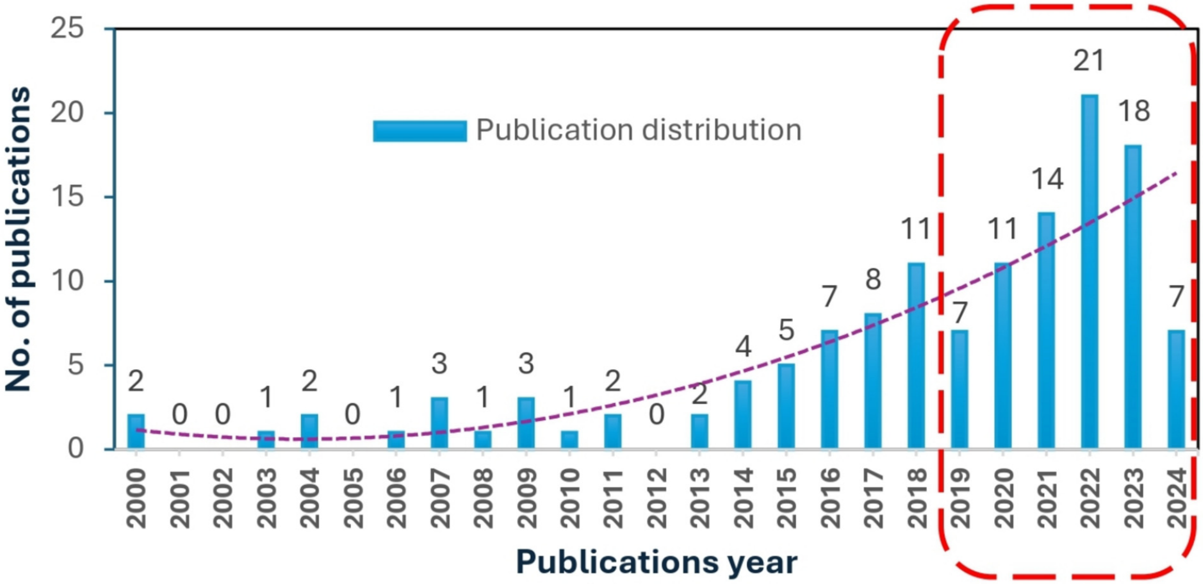


Fig. 3. Annual production growth research from 2000 to 2024.

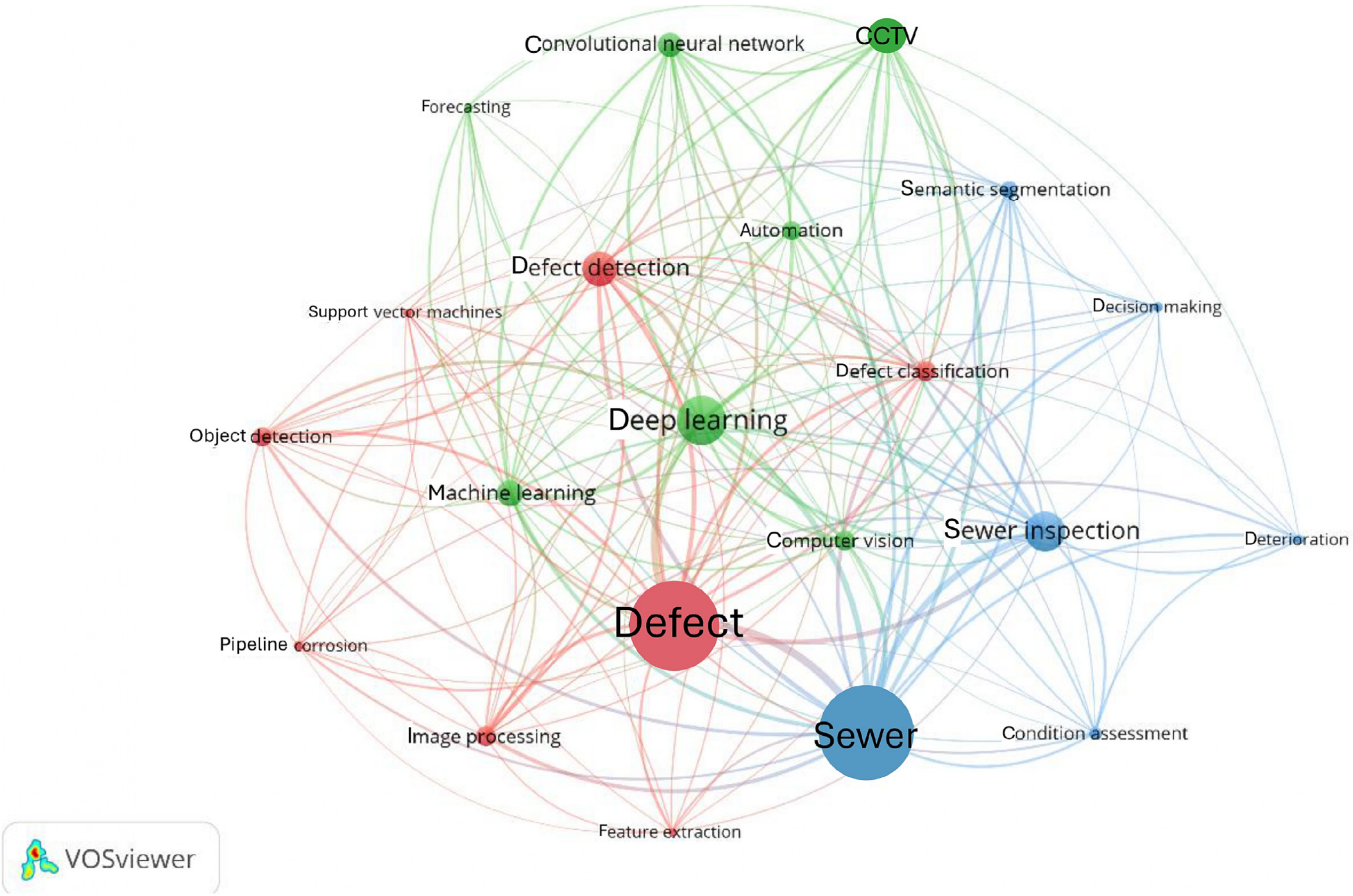


Fig. 4. Co-occurrence network of all keywords in the research.

inspection of sewer systems, and the evaluation of the condition. This cluster contains keywords such as “sewer”, “sewer inspection”, and “condition assessment”, among others.

3.3 Countries co-authorship analysis

The co-authorship network of countries analysis provides a valuable visualization of the global research landscape and collaborative relationships in the domain of research. By adhering to a minimum of 3 documents and zero citations per country, the bibliometric analysis identified 9 countries organized into 3 distinct color-coded clusters. The size of the nodes represents the degree to which a country has produced joint research documents, while the thickness of the lines indicates the significance of the co-authorship occurrences between the respective countries. Figure 5 reveals that China is the country with the most publications in this research area. Furthermore, the network analysis highlights that China has the largest co-authorship ties with the United States, while Vietnam has the strongest collaborative links with Republic of Korea. These international partnerships share the same research trends, as evidenced by the link strength of 5, as well as the placement of these country dyads within the same color cluster.

The quantitative analysis presented in Table 2 provides a comprehensive overview of the leading countries in the study of sewer defects, based on the number of publications. The analysis reveals that China, Canada, and the United States are the most prolific countries, accounting for 50%, 8%, and 8% of the total journal articles, respectively. Furthermore, the data highlight the strength of research collaboration among authors from these leading countries, as evidenced by the high degree of total link strength.

4 Sewer pipe defects and inspection tools

4.1 Common types of sewer defects

Sewer pipeline systems are susceptible to a range of structural and operational defects that can significantly impact their reliability and functionality, as shown in Fig. 6. Structural defects refer to issues that compromise the physical integrity of sewer pipes, affecting their ability to maintain shape and withstand external and internal pressures (Moradi et al., 2019). These defects include various types of cracks and fractures, such as longitudinal cracks that extend along the pipe’s length due to stress from soil pressure or shifting, and circumferential cracks that encircle the pipe’s circumference, usually resulting from vertical load pressures. Multiple cracks represent a combination of these patterns within a localized area, indicating significant structural distress (Zuo et al., 2020). Fractures are severe breaks or separations in the pipe material where segments are visibly disjointed, marking a critical loss of structural continuity (Xie et al., 2019). Deformation refers to alterations in the pipe’s original shape, often caused by external pressure and resulting in a compromised cross-section (Ye et al., 2019). Additional issues with joints include displacement, offset, and breakage, which disrupt alignment between pipe sections and increase the potential for leakage and misalignment (Li et al., 2019). Broken sections of pipe are characterized by visible cracks, missing parts, or segments that are out of alignment, often due to aging materials or physical impacts (Ma et al., 2024a).

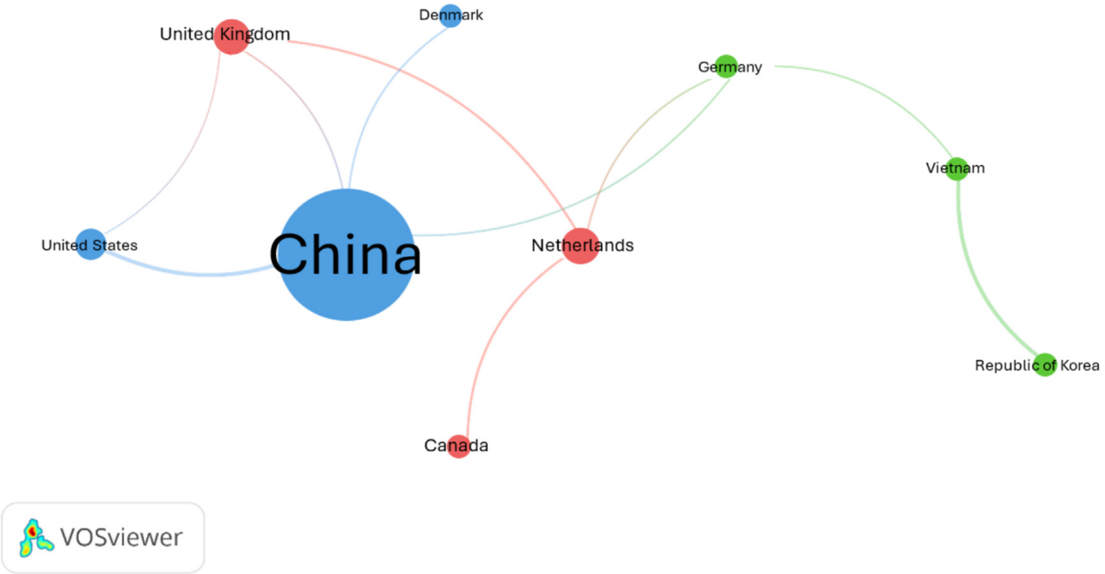


Fig. 5. Co-authorship network of countries in the research.

Table 2
Quantitative summary of active countries with regard to publication count.

Rank	Country	Number of documents	Total link strength
1	China	50	17
2	Canada	8	7
3	The United States	8	6
4	The United Kingdom	7	5
5	Republic of Korea	7	5
6	Netherlands	7	5
7	Vietnam	6	6
8	Denmark	4	1
9	Germany	4	3

On the other hand, operational defects affect the functionality of sewer systems without necessarily compromising their structural form. These defects include infiltration, which occurs when groundwater seeps into sewer pipes through cracks or openings, increasing flow volume and often leading to higher treatment cost (Ye et al., 2019). Corrosion, particularly in concrete pipes, results from chemical reactions with hydrogen sulfide gas; when hydrogen sulfide is converted to sulfuric acid by certain bacteria, it degrades concrete surfaces and significantly reduces pipe durability (Zounemat-Kermani et al., 2021). Other operational issues include accumulating deposits within the pipe, such as settled sediment or encrustations formed by evaporated water, which restricts flow and increases the risk of blockage (Li et al., 2019). Obstacles, including foreign materials or protruding objects, can further obstruct the sewer system, reducing efficiency and causing flow disturbances (Zhou et al., 2021). Root intrusion is another common issue, as roots from surrounding vegetation penetrate pipes through existing cracks or joints, blocking flow and potentially causing additional structural damage by expanding within the pipe (Pan et al., 2020). Figure 7 provides images that illustrate examples of these defects.

4.2 Inspection tools for sewer defects

In recent decades, the traditional approach of conducting manual inspections of sewer systems has been progressively replaced by a suite of sophisticated methodologies. Our preceding research provided a comprehensive analysis of the utilization of these technologies (Moradi et al., 2019). However, the landscape of sewer inspection tools and methods has evolved significantly since 2018, particularly in the realm of robotics. This section aims to explore these novel advancements, categorizing them according to various tools, technologies, and equipment based on different types of cameras and robotic systems. Additionally, it will compare these technologies in terms of the types of defects each can inspect, as well as the advantages and challenges/limitations associated with each tool, as illustrated in Table 3. This comparison will provide a comprehensive understanding of the latest sewer inspection technologies. CCTV is the oldest widespread technology for inspecting sewer pipes from the inside, as it appeared

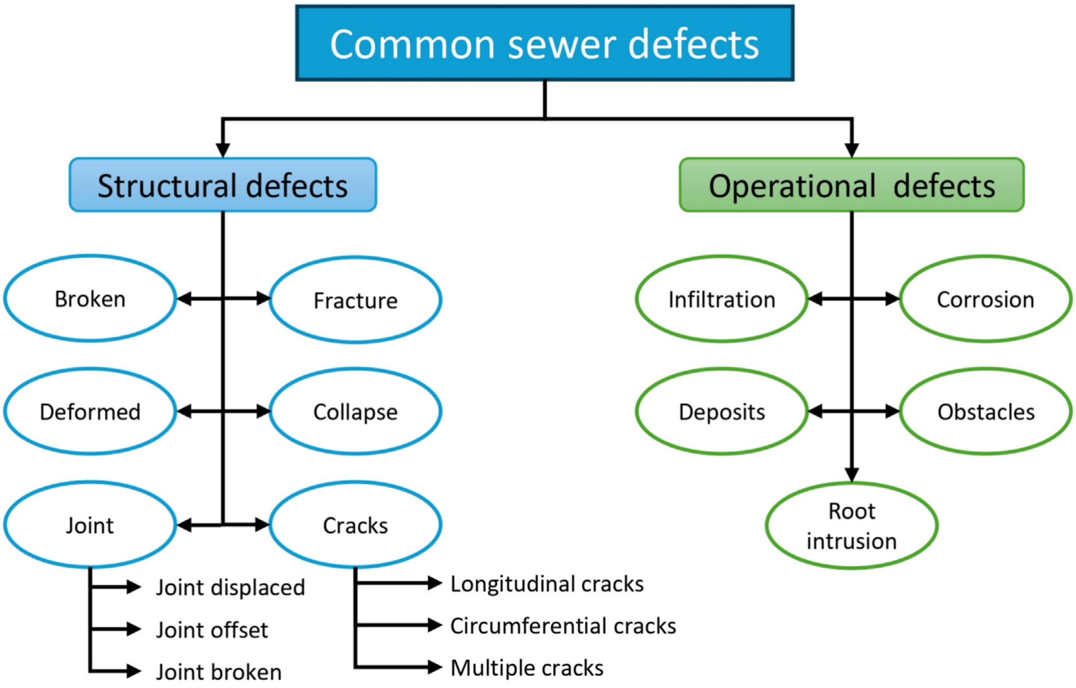


Fig. 6. Classification of common sewer pipeline defects.

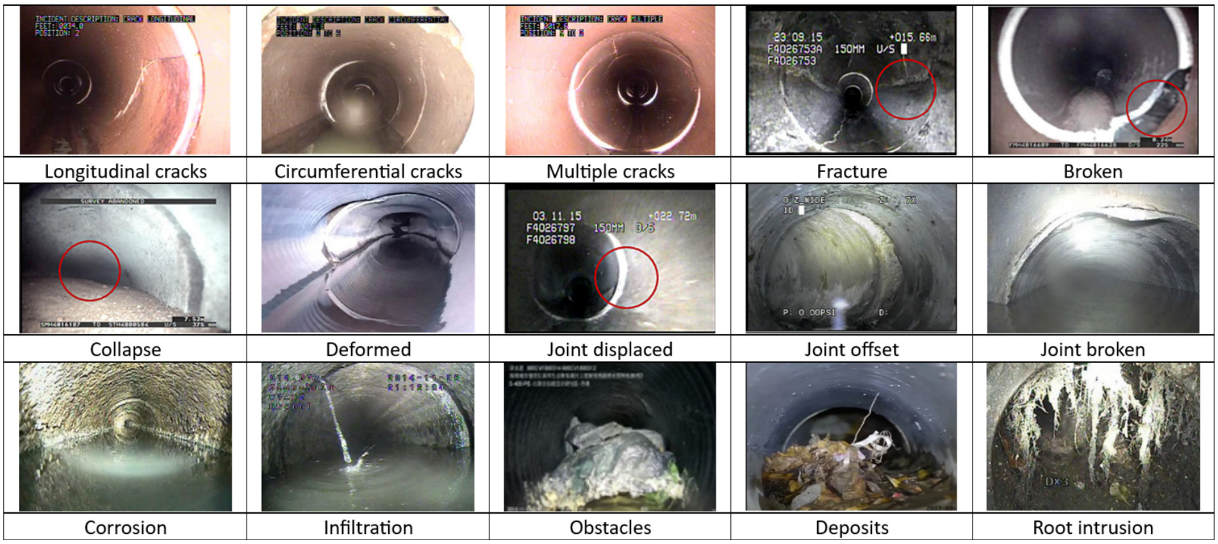


Fig. 7. Examples of common sewer defect images (Li et al., 2019; Zuo et al., 2020; Ma et al., 2024a; reproduced with permission, courtesy of Elsevier; Ye et al., 2019, reproduced with permission, courtesy of Springer Nature).

in 1960, and it is still the most widespread tool to date (Wang et al., 2022). The CCTV system consists of a camera mounted on a crawler, a control platform, and cables, as depicted in Fig. 8. However, CCTV has limitations; it cannot detect defects in areas submerged in wastewater or obscured by sludge, necessitating that the pipe be emptied and cleaned prior to inspection (Wang et al., 2022).

CCTV extracts two-dimensional images, which makes determining the depth, diameter, and length of defects in sewer pipes impossible. The solution was to convert these images into three-dimensional images to detect the defects, their size, diameter, and length more accurately. Wang et al. (2024) simulated defective pipes (drilling holes in the shapes of squares, triangles, and circles of different sizes) to train a 3D camera to detect them using an Azure Kinect DK camera. However, this model is limited to detecting 3 types of defects that rely on drilling only. It must be trained on other types of defects (Wang et al., 2024). One further application of a 3D camera is to accurately determine the internal diameter of sewage pipes, a crucial step in the process of renovating them with custom linings. The cylinder's diameter is used as a substitute for the pipe's diameter and is estimated using a random sample Consensus (RANSAC)-based approach using the point clouds generated by the sensors. The inner diameter of the pipes is measured to extend their longevity by an additional 50 years (Bahnsen et al., 2023). Chuang and Sung (2020) utilized inexpensive infrared-based 3D cameras and g-sensor depth cameras. In addition, they explored the incorporation of learning and simultaneous localization and mapping (SLAM) techniques to create a thorough and automated platform for pipeline inspection. The integration of point cloud SLAM with image-based pose estimation aims to mitigate drift and enhance the precision of positioning. The PMD Pico Flexx time-of-flight (TOF) sensor, a core component of light detection and ranging (LiDAR) technology, represents a significant advancement in sewer inspection systems. LiDAR operates by emitting laser pulses and measuring the time delay (time-of-flight) between emission and reflection to calculate distances. This principle enables the sensor to generate high-resolution 3D point cloud data, capturing detailed spatial information about the sewer environment (Y. Zhou et al., 2022). A fish-eye lens is used to capture the entire area surrounding the tractor; it features wide-angle images. The most used system for fisheye lenses is IBAK PANORAMO (Haurum & Moeslund, 2020). The QuickView (QV) device is a portable tool designed for the rapid assessment of sewer pipe conditions. It utilizes a rotatable camera to capture detailed images of the interior pipe wall. The QV device is particularly advantageous for its efficiency, allowing for the collection of extensive condition information in a shorter timeframe compared to traditional inspection methods.

Recently, robotics has witnessed remarkable advancements, particularly in the field of pipeline and sewer inspection. These developments have introduced innovative tools that enhance the detection, maintenance, and management of underground infrastructure. One such tool is the floating capsule robot, designed specifically for defect detection in sewer pipes. This robot utilizes a high-resolution fish-eye camera that records video as it floats along with the water flow, eliminating the cable constraints of conventional CCTV systems. Figure 9 illustrates its data collection method, which significantly simplifies inspection by utilizing the natural flow of water to guide its movement (Fang et al., 2022). Another example of a floating capsule technology is the pipeline capsule machine (PCM). This non-powered inspection tool leverages the flow of the pipeline to move through its interior, capturing high-resolution images via a wide-angle digital camera and a large-view angle photo module. The PCM's boat-shaped, waterproof

Table 3
Defect types identified by various sewer inspection technologies, along with their advantages and challenges/limitations.

Category	Techniques	Defects												Advantages	Challenges/Limitations	Ref.
		Blockage	Broken	Corrosion	Cracks	Deformed	Holes	Infiltration	Root	Joint displacement	Leakage	Obstacles	Deposits			
Camera-based	CCTV	√	√	√	√				√	√	√	√	√	– Widely used – Provides real-time video – Cost-effective	– Cannot detect defects submerged in wastewater – Requires pipes to be emptied and cleaned – Limited to 2D imaging	(Ma et al., 2021); (Dang et al., 2022)
	3D point cloud				√	√	√			√	√	√		– High-resolution 3D point cloud data collection – Fast acquisition speed – Cost-effective for large-scale inspections	– Limited to specific types of defects – Requires training on various defect types – Non-uniform data distribution – Environmental interference challenges	(Bahnsen et al., 2023; Chuang & Sung, 2020; Wang et al., 2024; Y. Zhou et al., 2022)
	CCTV (Fisheye lens systems)				√		√	√	√	√			√	– Captures wide-angle images – Provides comprehensive views	– May not provide detailed measurements – Limited by the quality of the lens	(Meijer et al., 2019)
	QV	√			√					√		√	√	– Rapid assessment of sewer pipe conditions – Portable and efficient – Captures detailed images of pipe walls	– Limited to recording frames on the pipe orifice – Manual inspection of captured video required	(Xie et al., 2019)
Robotic based	Floating capsule robots		√		√	√								– Overcomes cable limitations – Can operate autonomously – Can access difficult areas – Equipped with various sensors	– High cost – Limited to specific environments – May struggle in heavily obstructed pipes – Limited battery life	(Fang et al., 2022)
	PCM			√	√	√								– Rapid and wide-scale image data collection – High-resolution imaging – Stable design – Waterproof (IP67)	– Manual identification of defects required – Complexity of operating environment	(Guo et al., 2022)
	Inspection robot		√	√	√		√	√	√	√		√		– 360° rotation and up/down motion – Powerful LED for dark environments	– Environmental conditions may affect performance – Requires substantial computational resources	(Dang et al., 2023)
	SIAR	√		√	√		√						√	– Autonomous operation – Versatile sensor suite – Battery autonomy of up to 4 h	– Space limitations – Communication difficulties – Sensor constraints	(Alejo et al., 2021)
	CIPbot-1	√							√				√	– Compact and adjustable for various pipe sizes – Real-time inspection capabilities	– Space limitations (150–300 mm diameter) – Motor load challenges	(Tugeumwolachot et al., 2021)
	PIR			√	√									– Self-adjusts to varying pipe diameters – High-resolution camera and sensors – Operates in dry and wet environments	– Space limitations (400–500 mm diameter) – Motor load challenges	(Jain et al., 2021)
Others	GPR			√			√				√			– Fast operation – Good accuracy – Non-invasive	– Limited penetration depth in certain soil types – May require calibration for different environments	(Liu et al., 2023; Xu et al., 2023)
	LiDAR	√		√	√	√								– High accuracy in blockage detection – Quantitative assessment	– High cost – Requires specialized training for operation	(Zhao et al., 2023)
	Ultrasonic inspection	√												– Can detect defects without direct access – Measures sound intensity changes	– Performance can be affected by ambient noise – May require extensive data analysis	(Pan et al., 2021)
	Urban flooding										√	√		– Links defects to flood modeling	– Inability to detect all types of defects – Complexity of flood modeling	(Q. Zhou et al., 2024)

Notes: The defects listed are derived from the documented types of defects associated with each tool in the referenced papers. It’s important to note that some tools may have the capability to detect additional defects beyond those specified.

Fig. 8. CCTV-detecting device consists of a tractor (mark 1), a control system (mark 2), and a cable tray (mark 3) (Ma et al., 2021; reproduced with permission, courtesy of Elsevier).

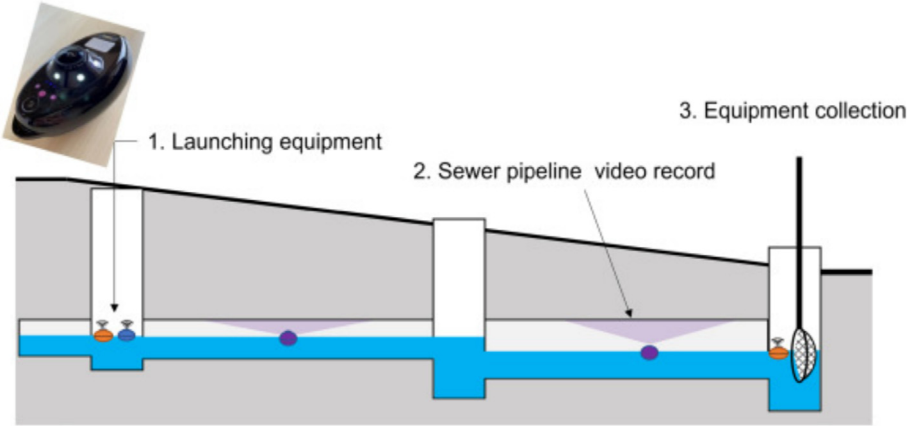


Fig. 9. Illustration of the data collection process by sewer floating capsule robot (Fang et al., 2022; reproduced with permission, courtesy of Elsevier).

design ensures stable performance across different pipeline conditions, while its integrated control module, including an ARM circuit board, memory card, and Wi-Fi communication system, streamlines data collection and transfer. These floating robots, while simple and effective, rely on the natural flow of liquid within the pipeline to conduct their operations (Guo et al., 2022). In contrast, cable-connected robots have also been developed to perform sewer inspections with greater precision and control. For example, one such robot is equipped with a high-resolution SONY Exmor CMOS camera capable of 360° rotation and up/down motion. Combined with a powerful light-emitting diode (LED) bulb, this system captures detailed videos in pitch-dark, high-humidity environments, significantly improving inspection efficiency and accuracy. Its tethered connection ensures stable operation, even in challenging sewer conditions (Dang et al., 2023). Integrated robotic solutions such as the sewer inspection autonomous robot (SIAR) provide enhanced versatility for sewer network inspection. This advanced robot combines autonomous navigation capabilities with a suite of sensors, including red green blue-depth (RGB-D) cameras, inertial measurement units (IMUs), and gas sensors, to conduct thorough inspections. SIAR's adjustable width allows it to navigate various sewer sections via standard manholes, making it highly adaptable to different environments. With a battery autonomy of up to four hours, SIAR can deliver real-time data on structural integrity and environmental conditions, minimizing the need for human intervention in hazardous sewer environments (Alejo et al., 2021).

Robotic systems have also evolved to go beyond inspection, taking on maintenance and repair tasks. For instance, the CIPbot-1 is a compact robot designed for inspecting, maintaining, and repairing sewer pipes with diameters ranging from 150 to 300 mm. Its adjustable locomotion mechanism ensures stability, while a manipulator with 3 degrees of freedom (3-DOF) equipped with a cutting tool enables tasks such as cutting, drilling, and grinding to remove blockages like fatbergs, roots, and debris. Real-time inspection is facilitated through an integrated camera system, allowing operators to monitor and control the robot's actions remotely (Tugeumwolachot et al., 2021). Similarly, the pipeline inspection robot (PIR) is a versatile tool for inspecting and maintaining pipelines with diameters of 400–500 mm. Featuring a scissor mechanism for self-adjustment, the PIR provides stability during operation and is equipped with high-resolution cameras, ultrasonic thickness probes, and gas sensors. It operates in both dry and wet environments, making it adaptable to various industrial applications and providing an effective solution for pipeline integrity management (Jain et al., 2021). These advanced robots, such as the CIPbot-1 and PIR, demonstrate how robotic technologies are no longer confined to inspection tasks but are now integral to the maintenance and repair of sewer and pipeline systems. Together, these innovations reflect the rapid progression of robotics in infrastructure management, offering safer, more efficient, and more versatile solutions for underground utilities.

Many researchers have resorted to using easier, faster, and more flexible methods than CCTV cameras to inspect sewer pipe defects remotely or using indicators of the surrounding environment. GPR is widely used to inspect roads and bridges, as well as to locate pipes and detect defects in them. It is a physical technique that relies on electromagnetic induction through sending and receiving electromagnetic pulses. It features easy operation, high detection speed, and good accuracy (Liu et al., 2023; Xu et al., 2023). LiDAR technology (as previously defined in this section) complements GPR and other methods by offering quantitative accuracy in assessing blockage levels and structural defects in internal pipes. When combined with 3D laser scanning, it enhances the reliability of defect identification and analysis, particularly in complex sewer environments (Zhao et al., 2023). Through the manhole, the acoustic equipment system can be used to inspect defects in sewage pipes. This system depends on measuring the sound intensity by emitting sound waves from an audio sensor that contains a speaker, a microphone, and an electronic block, so that every defect in the pipe leads to a change in the sound of the wave's reflection, and then signals are analysed using the multi-feature fusion and multi-criteria feature evaluation (MFF-MCFE) model, this technology can also determine the water level in the pipes (Pan et al., 2021). Q. Zhou et al. (2024) studied the effect of drainage pipe defects on floods in the Guangzhou region of China using deep learning and engineering characterization. They used deep learning to model the defects and then also used artificial intelligence to determine the geometric specifications of the pipes (diameter, center, and water height). After that, they modeled the floods, linked them all together, and finally extracted geographic information system (GIS) maps to determine the locations of the expected floods based on the faults. One of the disadvantages of this study is the low quality of the images and their differences from one place to another. It is not possible to detect all types of defects. Flood modeling is complex and completely incorrect (Q. Zhou et al., 2024). Table 3 categorizes sewer defect detection technologies by approach: camera-based, robotic, and others. CCTV and fisheye lenses detect cracks and joint displacement but not deformations. Robotic systems offer wider capabilities. LiDAR and 3D point cloud are precise for detecting deformations, while ultrasonic inspection excels in identifying blockages. Figure 10 provides visual depictions of these tools, allowing readers to better understand their physical designs and operational contexts. By combining the analytical insights from Table 3 with the visual representations in Fig. 10, a clearer picture emerges of the innovative technologies driving advancements in sewer inspection and defect detection.

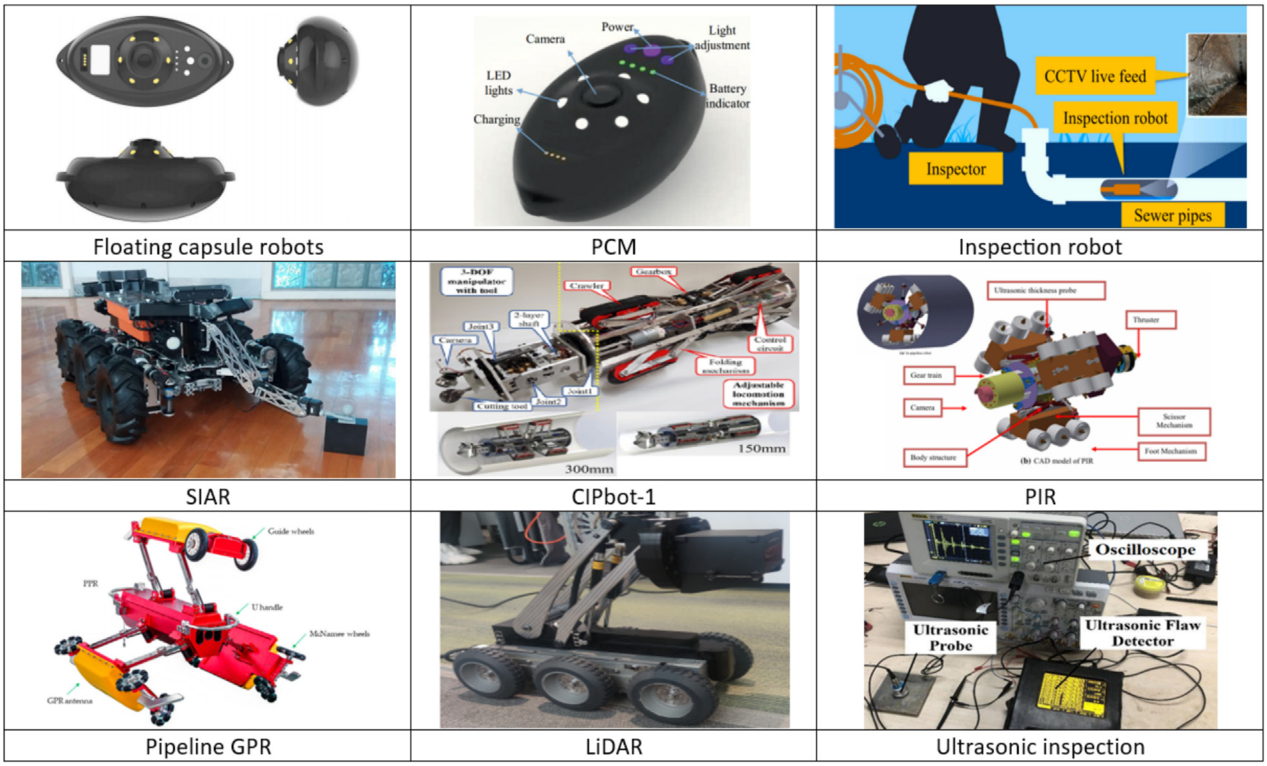
5 Development and enhancement of analytical models for automated sewer defect detection

In the past, the analysis of CCTV camera images was a manual process conducted by trained inspectors, a method that was both time-intensive and dependent on the inspector's proficiency. To surmount these challenges, and in light of advancements in machine learning and deep learning, researchers have pivoted towards automated defect detection from CCTV footage (Kumar et al., 2020). This automation involves processing the images using various techniques such as classification, segmentation, object detection, image enhancement, and textual analysis to accurately pinpoint defects. This section will delve into these automated approaches, highlighting their contributions to the field of defect detection.

5.1 Models for classification of CCTV images in sewers

To enhance the efficiency and precision of sewer defect reporting, automated classification methodologies have been increasingly adopted, with convolutional neural networks (CNNs) emerging as a particularly effective strategy. CNNs, which are composed of several layers of artificial neurons, possess the capability to autonomously learn image characteristics and execute classification tasks, thereby significantly diminishing human labor by 60.50% (Meijer et al., 2019). The apex of classification accuracy recorded stands at an impressive 96.33% (Hassan et al., 2019). In pursuit of further elevating classification precision, a nuanced two-level hierarchical strategy was employed. This approach initially segregates images into defective and non-defective categories, subsequently classifying them into specific types of defects (Xie et al., 2019). The challenge of imbalanced data presents a notable impediment to the efficacy of CNN models. To counteract this issue, a sophisticated deep CNN model leveraging ResNet18 as its foundational architecture was adapted for hierarchical classification, specifically to tackle the challenges posed by imbalanced datasets. This adjustment facilitated an enhancement in the accuracy of identifying high-level defects (first level) from 78.4% to 83.2%. Nevertheless, the classification accuracy for low-level defects (second level) necessitates further refinement (Li et al., 2019). Additionally, a multi-defect classification model (MDCM) that integrates a fusion CNN, amalgamating the Inception network with the Residual network, was implemented (Ma et al., 2021). This model has proven effective in addressing the complications associated with imbalanced data. To alleviate the issues of ambiguity, a self-purification module (SPM) was incorporated into the CNN framework, yielding a superior performance by approximately 8% in terms of the $F2_{\mathrm{CIW}}$ metric, which was recorded at 63.38%, and the $F_{1,\mathrm{Normal}}$ metric, which achieved 91.57% (Hu et al., 2023). Furthermore, the application of cost-sensitive learning and ensemble learning techniques, notably the extreme gradient boosting (XGBoost) and light gradient boosting machine (LightGBM) algorithms, was explored (Dang et al., 2021). In a parallel vein, the employment of transfer learning (TL) from the SqueezeNet model was investigated, culminating in a higher average prediction accuracy of 95%. It is crucial to acknowledge, however, that the SqueezeNet model necessitated a significantly extended processing duration, approximately 13 times longer than that of a bespoke CNN model (Zhou et al., 2021). On the other hand, Haurum et al. (2022) innovated an extension to the conventional CNN by integrating a multi-scale hybrid vision transformer (MSHViT) and a Sinkhorn tokenizer for the classification of sewer defects. The MSHViT architecture facilitates the non-local aggregation of features across multiple scales, while the Sinkhorn tokenizer employs Sinkhorn distances for clustering purposes. This synergistic approach markedly enhances the model's classification performance, bolstering its accuracy and overall effectiveness. Collectively, these investigations highlight the pivotal role of CNNs in the domain of sewer defect classification, showcasing a variety of methodologies to augment accuracy, address data imbalance, and diminish ambiguity.

The support vector machine (SVM) model has been extensively employed for the classification of CCTV images depicting sewer defects. The efficacy of SVM in terms of classification accuracy is contingent upon the volume of training samples, as reported by Ye et al. (2019). In a specific application, SVM was adeptly combined with a pipeline viewpoint detector and a structure edge detector to detect and classify various types of cracks. This integrated approach yielded commendable recall rates, achieving 91% for longitudinal cracks, 88% for circumferential cracks, and 90% for multiple cracks, while maintaining a rapid processing capability of 10 frames per second (FPS). Despite these successes, the SVM-based method encountered difficulties in accurately identifying short and thin cracks, and it was observed that enhancing performance in this regard necessitated the use of high-resolution video streams (Zuo et al., 2020). In addition to



Floating capsule robots | PCM | Inspection robot

SIAR | CIPbot-1 | PIR

Pipeline GPR | LiDAR | Ultrasonic inspection

Fig. 10. Images of various sewer inspection tools. (Alejo et al., 2021; reproduced with permission, courtesy of John Wiley & Sons) (Tugeumwolachot et al., 2021; reproduced with permission, courtesy of Springer Japan KK) (Jain et al., 2021; reproduced with permission, courtesy of Springer India) (Pan et al., 2021; reproduced with permission, courtesy of WSPC) (Fang et al., 2022; Guo et al., 2022; Dang et al., 2023; reproduced with permission, courtesy of Elsevier).

SVM, alternative classification models have been explored. For instance, Li et al. (2023) developed an intelligent identification model for defect classification and visualization, based on an enhanced RegNetY network along with gradient-weighted class activation mapping (Grad-CAM). They improved the RegNetY network by incorporating the LeakyReLU activation function. Similarly, Chen et al. (2023) made modifications to the RegNet model by incorporating the LeakyReLU activation function and modifying the squeeze excitation (SE) block. This modified model stands out for its capability to classify 20 different types of defects, achieving the highest classification accuracy of 99.5%, precision of 98.83%, recall of 98.85%, and F_1-score of 98.83%. However, it is important to note that the performance of this model declines when faced with images containing multiple defects. Despite its high efficiency, its effectiveness is reduced in such scenarios. Zhou et al. (2022c) developed an efficient and accurate method for classifying sewer defects using 3D point clouds, addressing the challenges posed by non-uniform distribution and irregularity in the data. Their model, called the Transformer-based point cloud classification network (TransPCNet), achieved superior classification results. To train the model, they utilized real and artificial point cloud data, leveraging a comprehensive dataset for training and evaluation purposes.

Table 4 offers a concise overview of the various models that have been applied to the task of sewer defect classification, encapsulating the classification accuracy of each model and the number of training images utilized in their development, and the type of defects. The sample size is indicative of the reliability of the classification accuracy outcomes; a larger corpus of training samples generally correlates with a higher degree of confidence in the reported classification accuracy rates. It is noteworthy that the modified RegNet model stands out with an exceptional classification accuracy, achieving a classification accuracy of 99.50%, which suggests a robust model performance likely attributable to the architecture of the model.

5.2 Models for the segmentation of defects in CCTV imagery of sewers

In the field of segmenting sewage defects, Q. Zhou et al. (2022b) pioneered the use of DeepLabv3 + for pixel-level segmentation of sewage defects. Specifically, they employed the DeepLabv3 + model with the ResNet-50 network architecture. Their work resulted in achieving a correct severity prediction rate of 70%. Building upon this, Dang et al. (2023) further developed and improved the DeepLabv3 + model by utilizing ResNet-152. Their enhanced model aimed to determine the type, location, information, and severity of sewer defects while reducing the number of frames required for prediction. It is important to note that this model has limitations in accurately predicting segmentation results when faced with challenges such as contrast, brightness variations, and overlapping defects, which can lead to incorrect and inaccurate predictions. However, they achieved superiority in performance metrics such as pixel accuracy (PA) and mean intersection over union (mIoU), as indicated in the provided Table 5. The mIoU is a crucial metric for evaluating the performance of image segmentation algorithms. It calculates the average overlap between the predicted segmentation (A_p) and the ground truth (A_g) across all classes (N). The formula for mIoU is given by Eq. (1) (Q. Zhou et al., 2022b). On the other hand, the PA measures the ratio of correctly segmented pixels to the total number of pixels in the image. It is calculated as Eq. (2), where the true positive (TP) denotes the actual object pixel that has been accurately predicted. The false positive (FP) occurs when a non-object pixel is incorrectly classified as an object pixel. False negative (FN): An actual object pixel is incorrectly classified as a non-object pixel. True negative (TN): A genuine non-object pixel is accurately identified (M. He et al., 2022).

$$\mathrm{mIoU} = \frac{\frac{\mathrm{Area}(A_\mathrm{p} \cap A_\mathrm{g})}{\mathrm{Area}(A_\mathrm{p} \cup A_\mathrm{g})}}{N} \tag{1}$$

$$\mathrm{PA} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN} + \mathrm{TN}} \tag{2}$$

Wang and Cheng (2020) developed a deep learning model, called DilaSeg, to improve the accuracy and refinement of segmentation results, particularly for small and thin sewer defects. Their approach integrated a deep convolutional neural network with dense conditional random field (CRF) as recurrent neural network (RNN) layers. Their results demonstrated superiority over the fully convolutional network with 8-step skip connections (FCN-8 s) in terms of mIoU, achieving a 32% improvement. Additionally, they outperformed the DilaSeg model by 20%. However, it is important to note that this model did not consider the severity level of the defects or evaluate the condition of sewer pipes, unlike the DeepLab-v3 + model. Furthermore, the DilaSeg model was limited to detecting and segmenting only three types of defects. Subsequently, Pan et al. (2020) introduced the PipeUNet model, which is a novel semantic segmentation network based on U-Net. PipeUNet incorporates a feature reuse and attention mechanism (FRAM) block between the encoder and decoder to enhance feature extraction capabilities and address semantic differences. It also employs focal loss to mitigate the class imbalance issue. The model achieved high-speed image processing, capable of handling up to 32 images per second. However, one limitation of this model is the limited amount of training data used. The researchers only utilized 1106 images, covering only four types of defects. This limited training data may impact the model's generalization ability and robustness. M. He et al. (2022) implemented the SegNet network model, which is a deep convolutional neural network, for the purpose of automatic image segmentation and labeling of sewer defects. Their model achieved a pixel accuracy of 80% in image segmentation. However, one limitation of

Table 4
Review of models for classifying CCTV images/video in sewers.

Data processing technique		Year	Accuracy	Datasets				Defects	Ref.
Category	Sub-category			Source	Equipment	Size	Quality		
CNN models	CNN	2019	N/A	Dutch sewer inspection company Vandervalk + degroot	CCTV	2 202 582 images	24-bit RGB, 1040 × 1040 pixels	Fissure, surface damage, intruding connection, defective connection, intruding sealing material, displaced joint, porous pipe, and roots	(Meijer et al., 2019)
	CNN	2019	96.33%	KICT*	CCTV	6605 videos 47 072 images	256 × 256 pixels	Crack longitudinal, debris, joint fault, joint open, lateral damage, and surface damage.	(Hassan et al., 2019)
	A two-level hierarchical deep (CNN)	2019	94.96%	N/A	CCTV + Quickview (QV)	> 40 000	256 × 256 pixels before processing	Fractures, depositions, disjunctions, and others	(Xie et al., 2019)
	CNN + Resnet18 modified for hierarchical classification	2019	83.20%	Two cities in China	CCTV	18 333 images 24.7 km sewer lines	from 296 × 166 to 1435 × 1054 pixels	Deposits settlement, joint offset, broken pipes, obstacles, water level stag, and deformation.	(Li et al., 2019)
	MDCM based on fusion CNN	2021	95.64%	N/A	CCTV	1612	256 × 256 pixels	Misalignment, corrosion, leakage, and obstacles	(Ma et al., 2021)
	CNN + XGBoost, LightGBM	2021	95.70%	KICT*	CCTV	7733 videos, 38 386 images	1280 × 720 pixels	Cracks, debris, and faulty joints	(Dang et al., 2021)
	Self-developed CNN model	2021	90.00%	Raw images were captured by sewer experts	CCTV	7200 images	128 × 128 pixels before processing	Cracks, disjoints, obstacles, residential walls, and tree roots	(Zhou et al., 2021)
	MSHViT	2022	N/A	Public dataset Sewer-ML	CCTV	1 300 000 images	224 × 224 pixels	N/A	(Haurum et al., 2022)
	CNN + SPM	2023	N/A	Public dataset Sewer-ML	CCTV	1 300 000 images	224 × 224 pixels	N/A	(Hu et al., 2023)
SVM models	SVM	2019	84.10%	sewer in a Chinese city	CCTV	1043	Greyscale	Deformation, crack, infiltration, attached deposits, settled deposits, displaced joint, and joint damage	(Ye et al., 2019)
	SVM	2020	89.67%	Southern United States	CCTV	Video	320 × 240 pixels	Longitudinal, circumferential, and multiple cracks	(Zuo et al., 2020)
Other models	TransPCNet	2022	N/A	Publicly available dataset	PMD Pico Flexx time-of-flight (TOF) sensor	17 027 point clouds	1024 points	Blockages, collapses, or overflows	(Y. Zhou et al., 2022)
	Improved RegNetY + Grad-CAM	2023	95.44%	City in China	CCTV	5000	224 × 224 pixels	Root intrusion, disjointedness, deformation, deposit accumulation, rupture, misalignment, scaling, and interface material failure	(Li et al., 2023)
	Modified RegNet	2023	99.50%	KICT*	CCTV	7733 videos with duration from 30 s to 15 min	1280 × 720 pixels	20 defects	(Chen et al., 2023)

Note: KICT is Korea Institute of Civil Engineering and Building Technology.

Table 5
Review of models for the segmentation of defects in CCTV imagery of sewers.

Data processing technique	Year	PA	mIoU	Datasets				Defects	Ref.
				Source	Equipment	Size	Quality		
DilaSeg-CRF	2020	98.69%	84.85%	Sewer pipe inspection company in the United States	CCTV	1880 images	512 × 256 pixels	Cracks, deposits, and roots	(Wang & Cheng, 2020)
PipeUNet	2020	N/A	76.37%	Tianjin Municipal Engineering Design and Research Institute	CCTV	3654 images	256 × 256 pixels	Crack, infiltration, joint offset, and intruding lateral	(Pan et al., 2020)
DeepLabv3+ + ResNet-50	2022	90.00%	53.00%	City in southern China	CCTV	600 images	512 × 512 pixels	Crack, disjoint, obstacle, residential wall, and tree root	(Q. Zhou et al., 2022b)
SegNet network model	2022	80.09%	67.00%	Old city in northwest China	CCTV	700 images	360 × 480 pixels	Sediment, scum, corrosion, roots, mismatch, obstacles, and branch pipes	(M. He et al., 2022)
Pipe-SOLO mode	2022	N/A	mAP of 59.30%	The Seoul Digital Foundation	Inspection robots equipped with high-resolution RGB cameras	3888 images	From 640 × 480 to 1280 × 720 pixels	Crack, faulty joint, open joint, protruding lateral, broken pipe, and surface damage	(Li et al., 2022)
DeepLabV3+ + ResNet-152	2023	97.00%	68.00%	Republic of Korea	Inspection robot equipped with a high-resolution 1/3-inch SONY Exmor CMOS camera that supports 360° rotation	11 124 images	512 × 512 pixels	Broken pipes, longitudinal cracks, circumferential cracks, displaced joints, lateral protruding, lateral sealing, surface damage, root intrusion, holes, and permanent obstruction	(Dang et al., 2023)

the SegNet model is its lack of generalization to scenarios that differ from the ones it was trained on. Another segmentation model was introduced by Y. Li et al. (2022) called Pipe-SOLO by proposing an efficient backbone structure (Res2Net-Mish-BN-101) and designing an enhanced BiFPN (EBiFPN), which performs pixel-wise semantic and instance labeling simultaneously. Pipe-SOLO achieved a notable improvement of 7.3% in mean average precision (mAP) compared to the existing state-of-the-art method. However, the model encounters challenges when dealing with complex scenes that involve multiple defects. Additionally, it lacks generalization to other types of pipes or defects. Table 5 presents the types of defects that each model can detect and segment, along with the corresponding performance metrics for each model or network.

5.3 Models for object detection of CCTV images in sewers

There are one-stage and two-stage models that differ in their approach and suitability for different applications. One-stage models, such as the you only look once (YOLO) series, are known for their rapid detection capabilities, making them suitable for on-site detection scenarios where real-time performance is crucial. On the other hand, two-stage models, like the faster region-based convolutional neural network (Faster R-CNN) models, operate in two stages and are typically employed in applications where accuracy is prioritized over speed. The two-stage approach allows for more precise localization and handling of complex scenes, making them better suited for tasks outside the site where detection accuracy is crucial (Fu et al., 2022). Yin et al. (2020a) were among the first in applying YOLOv3 for enhancing object detection speed in sewer pipe defect identification, focusing on improving detection efficiency. Tan et al. (2021) introduced an enhanced version of YOLOv3, characterized by its high speed and low computational cost, making it well-suited for real-time detection applications at a large scale, such as sewer pipe inspection. J. Zhang et al. (2023) achieved the highest mAP of 92.3% by incorporating spatial pyramid pooling (SPP) into an improved YOLOv4 model. Their work significantly enhanced the accuracy of object detection in sewer pipe defects. Wang et al. (2023) made notable progress by achieving a 2.4% increase over the baseline using an enhanced YOLOv5s model, while increasing the detection speed to 75 frames per second. Their contributions offer improved accuracy and speed for sewer pipe defect detection. X. Zhang et al. (2023) addressed the challenges posed by complex structures, large computational requirements, and low accuracy by proposing the YOLOv5-GBC model, a lightweight discovery model designed for resource-constrained computing platforms. In the same context, Situ et al. (2024) integrated transfer learning and channel pruning techniques with YOLO_v5s model, resulting in a significant reduction of parameters by 81% and operations by 48.8%. Their optimized model is well-suited for deployment on portable devices and inspection robots, enhancing practicality in sewer pipe defect detection applications. Yu et al. (2024) introduced YOLOv6, which improved the efficiency of object detection by optimizing the network architecture and incorporating advanced techniques such as anchor-free detection and decoupled head design. These enhancements significantly reduced computational costs while maintaining high detection accuracy. Yussuf et al. (2024) developed a YOLOv8 model that integrates instance segmentation to identify various defect types in stormwater pipes. This model leverages advanced features like cross stage partial (CSP) connections, path aggregation network (PANet), and spatial pyramid pooling fast (SPPF) to enhance detection accuracy and efficiency, making it highly effective for real-time condition assessment of stormwater infrastructure. Table 6 and Fig. 11 compare YOLO models for sewer defect detection, emphasizing metrics like accuracy (mAP), precision, recall, inference speed (FPS), and dataset size, with dataset characteristics playing a key role in performance trends as larger or specialized datasets often enhance model capabilities; YOLOv8 achieves top-tier performance with 92% accuracy and 96% precision, trained on 2503 images from 900 videos, making it ideal for complex environments, while earlier models like YOLOv3, trained on 3664 images with 4056 defects, remain robust for general applications, and enhanced variants such as improved YOLOv4 + SPP (2700 images) and enhanced YOLOv5s (2122 images) excel in specialized tasks like small-object detection and real-time monitoring, though discrepancies in FPS—e.g., YOLOv5-GBC (2700 images) having lower FPS than YOLOv3—stem from hardware configurations, optimizations, or dataset differences, with missing precision or recall values for some models reflecting dataset limitations, and overall, while YOLOv8 demonstrates superior accuracy and precision, other models cater to specific use cases like real-time detection (e.g., YOLOv6 with 6756 images) or mobile platforms (improved YOLOv3), highlighting the importance of selecting models based on both dataset characteristics and task requirements.

The Faster R-CNN stands out as one of the most precise object detection models. Wang et al. (2021b) utilized the Faster R-CNN model within their framework to evaluate the condition of pipes based on CCTV images. By applying the Faster R-CNN model, they were able to detect and assess the condition of pipes, providing valuable insights for maintenance and inspection purposes. It enhances defect detection by incorporating image edges to improve image resolution. This model is commonly implemented with ResNet-101 as the backbone architecture, further enhancing its performance (Guo et al., 2022). Siu et al. (2022) proposed a framework to improve the accuracy of defect detection models by combining synthetic data generation, style transfer, and contrastive learning. They applied this framework using the Faster R-CNN, visual geometry group (VGG) network, and a hierarchical CNN framework. By employing both methods, they observed a signif-

Table 6
Comparison of YOLO models for sewer defect detection.

Criterion	YOLOv3 (Yin et al., 2020a)	Improved YOLOv3 (Tan et al., 2021)	Improved YOLOv4 + SPP (J. Zhang et al., 2023)	Enhanced YOLOv5s (Wang et al., 2023)	YOLOv5-GBC model (X. Zhang et al., 2023)	YOLOv5s (Situ et al., 2024)	YOLOv6 (Yu et al., 2024)	YOLOv8 (Yussuf et al., 2024)
Detection accuracy (mAP)	85.37%	92.00%	92.30%	@0.5: 80.5%	@0.5: 87.21%	91.80%	71.90%	92.00%
Precision	87.80%	91.30%	N/A	N/A	85.38%	87.60%	92.00%	96.00%
Recall	85.50%	N/A	89.00%	75.90%	82.43%	88.60%	97.90%	91.00%
Inference speed (FPS)	33.0	175.0	12.0	75.0	9.0	192.0	13.4	N/A
Datasets	3664 images with 4056 defects	3000 images extracted from 33 videos	2700 images	2122 images	2700 images	2000 images	6756 images	2503 images from 900 videos
Best use case	General object detection	Advanced tasks requiring speed and accuracy	Detecting and classifying sewer defects	On-site sewer pipeline defect detection	Mobile platform sewer defect detection	Real-time sewer defect detection on portable devices	High-performance tasks requiring precision	Complex detection in challenging environments

icant increase in the mAP percentage, achieving an improvement of 7.7%. However, it is important to note that this method has limitations when applied to different types of sewer pipes or real-world conditions, which should be taken into consideration. Wang et al. (2021a) addressed the challenge of tracking pipe defects by proposing a comprehensive framework that combines Faster R-CNN for defect detection, OSNet for metric learning, and a Kalman filter and distance metrics for defect tracking. Their framework enabled the tracking of sewer defects in CCTV videos and achieved a respectable identification F_1-score (IDF1) of 57.4%. However, it is important to note that this framework specifically focuses on three types of sewer defects, namely fractures, tree roots, and laterals, and may not cover all possible defects that can occur in sewer pipes. To improve the generalization and robustness of the framework for detecting sanitation defects, Fang et al. (2022) employed an enhanced version of the Mask R-CNN model. They integrated a split attention module and a balanced L1 loss module to enhance the representation of robust features. Their research yielded impressive results, achieving an mPA rate of 92.7%, which stands as the highest percentage achieved in this context.

Li et al. (2021) developed a deep learning approach for defect detection by incorporating a strengthened region proposal network (SRPN) and a fine-grained classification network. This method has been successfully applied in inspecting sewer pipes across several Chinese cities. The integration of SRPN into their deep learning method has proven effective in identifying and classifying defects within sewer pipes, contributing to the overall success of the approach. B. Zhou et al. (2024) proposed the SPPF feature fusion and dual detection heads based on fully convolutional one-stage object detector (FCOS) (SDH-FCOS) model, which serves as an enhanced version of FCOS. Their model incorporated SPPF feature fusion and dual detection heads to strike a favorable balance between accuracy and speed in object detection. By leveraging these advancements, the SDH-FCOS model outperformed, offering improved accuracy without compromising detection speed. This highlights the effectiveness of their approach in achieving a desirable trade-off between accuracy and efficiency in object detection tasks. Dang et al. (2022) employed ResNet-50 in conjunction with the detection transformer (DETR) to extract feature vectors from input images. This model demonstrated its effectiveness in detecting objects of varying sizes, including small and large objects, as well as objects with diverse aspect ratios and orientations.

Table 7 provides a comprehensive summary of the various models employed for object detection in the analysis of sewer defects. It includes key performance metrics for each model to comparatively evaluate the efficacy of models, such as recall and mAP, which are defined in Eqs. (3)–(6):

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{3}$$

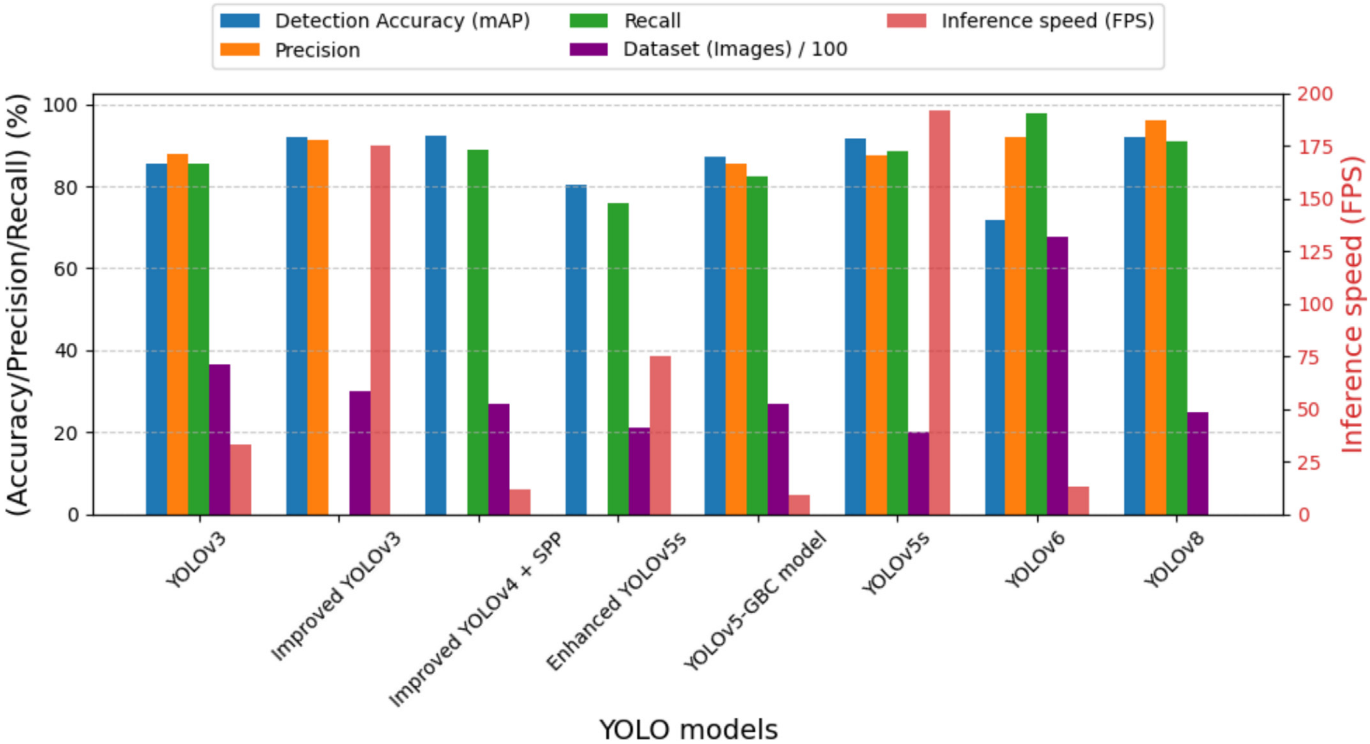


Fig. 11. Comparison of YOLO models for object detection.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{4}$$

$$\text{AP} = \int_0^1 P(R)\mathrm{d}R, \tag{5}$$

$$\text{mAP} = \frac{\sum_{i=1}^{X}\text{AP}}{X}, \tag{6}$$

where TP denotes the number of sewer defects correctly classified as defective, FN represents the sewer defects that are incorrectly predicted as non-defective, and FP indicates the sewer defects that are erroneously identified as defective. In Eq. (5), AP is the average value of Precision. In Eq. (6), X indicates the number of categories (B. Zhou et al., 2024).

5.4 Other models for enhancing CCTV image resolution, textual analysis, and defects localization

The blurring of CCTV images within sewage pipes, caused by the presence of gases leading to high humidity, as well as the presence of obstructions at the bottom of the pipes, resulting in shaky camera movement, are recognized as significant challenges in sewage defect inspection. Consequently, numerous researchers have endeavoured to enhance image quality through various approaches. Xia et al. (2023) focused on enhancing CCTV images by employing a map-based approach to delineate water boundaries within the pipes and mitigating the haze induced by the humid environment. They accomplished this through the utilization of the structure-aware nonlocal network (SANL-Net), which demonstrated remarkable efficacy and superiority in addressing these challenges. However, it is important to note that a limitation of this research is the absence of a comprehensive dataset, as well as the challenges associated with accurately determining depth due to the similarity of colors and textures in sewage environments. In a related study, Li et al. (2022) employed a gated context aggregation network (GCA-Net)-based dehazing model to effectively remove fog from images. This approach aimed to improve the visibility of CCTV images captured in foggy conditions. Karabij et al. (2022) focused on enhancing the accuracy and robustness of image registration by incorporating the histogram of triangle area representation (TAR). Additionally, they employed image processing techniques to estimate the relative changes in sewer pipe defects over time based on CCTV videos. However, it is important to note that their proposed method is specifically designed for crack detection and may not effectively handle other types of defects such as deposits, roots, or holes. Moreover, the method relies on the availability of a sufficient number of matching points between images depicting the same defect, which may not always be feasible in certain scenarios. Another research approach involved the processing of images, where prominent defects were automatically identified utilizing a style-based generative adversarial network with a sharpness discrimination model (StyleGAN-SDM). The system exhibited remarkable accuracy rates in defect detection, with a mean accuracy of 95.64% and a macro F_1-score of 0.955, following the application of StyleGAN-SDM for enhancement purposes (Ma

Table 7
Review of models for object detection of CCTV images in sewers.

Data processing technique		Year	Recall	mAP	IoU	FPS	Datasets				Defects	Ref.
Category	Sub-category						Source	Equipment	Size	Quality		
YOLO models	YOLOv3	2020	85.50%	85.37%	N/A	33.0	EPCOR drainage services based in Edmonton, Canada	CCTV	3664 images with 4056 defects	N/A	Broken, hole, deposit, crack, fracture, root, and tap	(Yin et al., 2020a)
	Improved YOLOv3	2021	N/A	92.00%	N/A	175.0	Sewer inspection company in Georgia, US	CCTV	3000 images extracted from 33 videos	Resolution between 1440 × 720 and 320 × 256	Root, deposit, infiltration, and crack	(Tan et al., 2021)
	Improved YOLOv4 + SPP	2023	89.00%	92.30%	N/A	12.0	Public dataset Sewer-ML	CCTV	2700 images	416 × 416 pixels	Crack, deposition, root, and stagger	(J. Zhang et al., 2023)
	Enhanced YOLOv5s	2023	75.90%	@0.5 = 80.50%	N/A	75.0	Public dataset Sewer-ML	CCTV	2122 images	N/A	Break, displaced joint, roots, intruding sealing material, branch pipe, and obstacle	(Wang et al., 2023)
	YOLOv5-GBC model	2023	82.43%	@0.5 = 87.21%	N/A	9.0	Public dataset Sewer-ML	CCTV	2700 images	416 × 416 pixels	Crack, deposition, stagger, and root	(X. Zhang et al., 2023)
	YOLO_v5s	2024	88.60%	91.80%	N/A	192.0	Project in southern China	CCTV	2000 images	640 × 640 pixels	Disjoint, obstacle, residential wall, and tree root	(Situ et al., 2024)
	YOLOv6	2024	97.90%	71.90%	N/A	13.4	Chinese cities: Zhongshan, Zhuhai, and Suqian	CCTV	6756 images	640 × 640 pixels	Mismatch, deposition, deformation, root, disjointed, concealed Joint, cracking, barrier, and foreign body penetration	(Yu et al., 2024)
	YOLOv8	2024	91.00%	92.00%	N/A	N/A	Banyule City Council, Australia	CCTV	2503 images from 900 videos	720 × 579 pixels	Joint opening, breaking, cracking, spalling, hole, and exposed rebar	(Yussuf et al., 2024)
Faster R-CNN models	Faster R-CNN	2021	87.96%	88.99%	84.85%	9.0	Inspection company in the United States	CCTV	3000 images	N/A	Cracks, holes, collapse, deposit, tree root, and infiltration	(Wang et al., 2021b)
	Faster R-CNN + OSNet + distance metrics	2021	N/A	77.00%	N/A	9.0	Florida and Georgia, the United States	CCTV	3600 images	N/A	Fractures, tree roots, and laterals	(Wang et al., 2021a)
	Faster R-CNN + SRPN	2021	86.20%	71.30%	N/A	7.8	N/A	CCTV + QV	10,000 images	600 × 480 pixels	Barrier, fraction, deposition, distortion, and inserted foreign body	(Li et al., 2021)
	Faster R-CNN-P-EFPN + Resnet-101	2022	85.00%	75.39%	N/A	12.0	Pipeline inspections in Hefei, Shenzhen, and other cities in China	PCM	7000 images	30 frames of 1080 × 1080 pixels per second	Deformation, corrosion, and cracks	(Guo et al., 2022)
	Faster R-CNN + VGG	2022	N/A	+7.70%	N/A	N/A	N/A	CCTV	4500 images	N/A	Cracks, deposits, and tree roots	(Siu et al., 2022)
	Improved Mask R-CNN	2022	N/A	92.70%	N/A	N/A	Sewer inspection videos in Shenzhen and Hefei City, China	Floating capsule	1744 images	1250 × 1080 pixels	Cracks, breaks, and deformations	(Fang et al., 2022)
Other models	ResNet-50 + DETR model	2022	69.70%	60.20%	N/A	12.0	Republic of Korea	CCTV	47 100 images	N/A	Broken pipe, longitudinal crack, circumferential crack, debris, silty, displaced joint, faulty joint, separated joint, protruding lateral, surface damage, and root intrusion	(Dang et al., 2022)
	SDH-FCOS model	2024	79.67%	85.96%	N/A	30.3	Public dataset Sewer-ML	Robots	1013 images	N/A	Concealed connection, deposition, misalignment, scaling, root, and obstacle	(B. Zhou et al., 2024)

et al., 2021). On the other hand, Myrans et al. (2019) addressed errors in CCTV camera imaging, including camera distortion and image instability, by employing random forest classifiers and GIST descriptors for the processing and categorization of detected faults within CCTV footage. This approach attained a maximum accuracy of 73% for faults that were well-represented, indicating its viability for practical applications within the water industry. However, the study's limitation lies in its constrained dataset, which could impact the accuracy of fault identification due to the potential underrepresentation of certain fault types.

Models are utilized to detect and analyze text information present in CCTV images. This enables the determination of defect locations and provides insight into the timing of defect capture, facilitating the tracking of defect development over time. Oh et al. (2022) utilized the TPS-ResNet-BiLSTM-Attn (TRBA) model to recognize textual information extracted from CCTV videos. They employed an improved version of the YOLOv5 architecture, incorporating a convolutional block attention module (CBAM) to enable micro-scale detection. The integration of CBAM enhanced the model's ability to capture channel and spatial features effectively. The proposed real-time sewer defect detection model achieved a mAP of 75.9% on the dataset, surpassing the performance of other standard models such as YOLO and single- shot multibox detector (SSD). However, it is important to acknowledge that the model faces challenges associated with poor image quality and variations in brightness conditions, which can limit its performance in certain scenarios. Moradi et al. (2020) utilized the maximally stable extremal regions (MSER) algorithm to identify text regions in the foreground of images. They also employed a modified version of the scale-invariant feature transform (SIFT) algorithm, called 3D SIFT, to extract spatio-temporal features from consecutive video frames. In addition, a CNN was utilized to recognize characters within the detected text regions. This model achieved a character recognition accuracy of 94.7% and a word recognition accuracy of 88.9% on the sewer image dataset. However, it is important to note that this model has limitations, including the reliance on a limited dataset and its sensitivity to noise present in images. These factors can impact the performance and accuracy of the model.

Determining the location of defects plays a crucial role in evaluating their severity. Kumar et al. (2022) conducted research in this area by evaluating the condition of pipes through the integration of spatial information related to defects. They employed defect cluster analysis (DCA) to identify clusters of defects and quantify their severity. Additionally, defect co-occurrence mining was utilized to identify groups of defects that frequently occur together. This approach is highly valuable as it helps in understanding the spatial relationships between defects and their impact on the likelihood of pipe failure. It allows for a comprehensive assessment of the seriousness of defects, even if individual defects may appear minor when considered in isolation. Figure 12 provides a visual representation of this concept. J. He et al. (2022) pinpointed defect locations by calculating the longitudinal distance from the inspection robot to the defect, utilizing Zhang's calibration method for camera calibration. This approach was enhanced through the development of image processing and monocular ranging algorithms, crafted using Python with the NumPy and OpenCV libraries. The findings revealed that the ranging model's relative error was confined to 17.41%, with an absolute error not exceeding 0.27 m, showcasing stable accuracy and robust performance suitable for practical engineering contexts. This study stands out for its automated method of determining the longitudinal distance between the inspection robot and pipe defects, thereby enhancing the spatial accuracy of defect localization. However, it acknowledges certain limitations, including uncorrected system errors of the robot's meter and a constant CCTV robot distance compensation value across varying pipe diameters.

5.5 Integration of multiple models for enhanced performance

In pursuit of enhancing the reliability and effectiveness of models used in sewer pipes, researchers have explored the combination of multiple models. The comparative analysis of different models allows researchers to identify the most suitable model for a given application or enhance the accuracy of the system as a whole. Table 8 shows a summary of the research that used more than one model and its purpose. In comparing object detection models to improve sewer defect detection, Kumar et al. (2020) conducted a comparative study between the Faster R-CNN, YOLO, and SSD models to evaluate their speed and precision in detecting sewer defects. Their findings revealed that the Faster R-CNN model achieved the highest average precision (0.718) among the three models, followed by YOLOv3 (0.695) and SSD (0.530), at an intersection over union (IoU) threshold of 0.2. However, it is important to note that the Faster R-CNN model exhibited the slowest detection time, with an average of 110 ms per image. YOLOv3 followed with an average detection time of 57 ms, while SSD had the shortest detection time of 33 ms. One limitation of this study is that the models were trained and tested only on two specific types of defects, namely root intrusions and deposits. The performance of the models on other types of defects, such as cracks, infiltration, or deformation, remains unknown. Q. Zhou et al. (2022a) also conducted a comparative study between the Faster R-CNN model and YOLO_v2 for object detection. Their findings align with Kumar et al. (2020), indicating that the Faster R-CNN model exhibited higher accuracy in object detection, while YOLO_v2 demonstrated faster processing speed. Notably, Q. Zhou et al. (2022a) also observed that the processing speed of the Faster R-CNN model improved with increasing training data, suggesting a positive impact on processing speed as the model was exposed to more training data. Conversely,

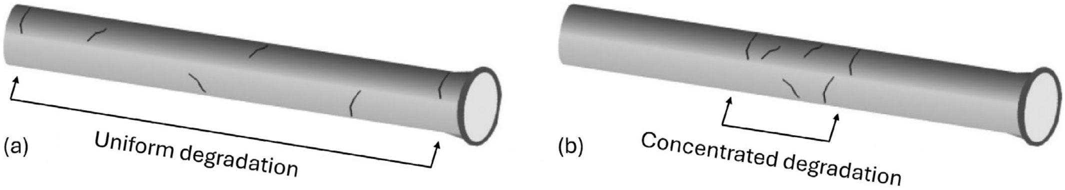


Fig. 12. Illustration of the importance of locating defects. (a) Evenly distributed cracks, and (b) localized cracks (Kumar et al., 2022; reproduced with permission, courtesy of Taylor & Francis).

YOLO_v2 did not show any notable influence on processing speed with increased training data. To enhance the accuracy of the YOLO network, Situ et al. (2023) employed transfer learning techniques. In their study, they utilized 11 pre-trained CNNs models and compared them with four object detection methods: R-CNN, Fast R-CNN, Faster R-CNN, and SSD. The research findings demonstrated the effectiveness of utilizing transfer learning to improve the efficiency of YOLO, establishing its superiority over the other examined methods. On the other hand, it is widely acknowledged that increasing the amount of data can contribute to improving the accuracy of models. In the context of object detection, Zhou et al. (2023) conducted a study comparing the impact of traditional data augmentation techniques with StyleGAN on the performance of the YOLO_v2 network. Their research revealed a significant enhancement in defect detection accuracy, with improvement rates ranging from 16% to 32% when utilizing StyleGAN.

In a study conducted by Zounemat-Kermani et al. (2021), six different models were compared for predicting concrete corrosion in sewer pipes. The models investigated in the study were: extreme learning machine (ELM), kernel extreme learning machine (KELM), online sequential extreme learning machine (OS-ELM), artificial neural network (ANN), classification and regression tree (CART), and statistical multiple linear regression (MLR). The study found that the OS-ELM model outperformed the other models in predicting the concrete mass loss across different types of concrete, as assessed by several statistical measures. However, it is important to note that the study had certain limitations. One limitation mentioned is the reliance on a small dataset consisting of only 96 samples across six different types of concrete. This limited dataset may not be fully representative of the diversity and complexity of concrete corrosion in wastewater systems. Therefore, the generalizability of the findings may be influenced by the dataset's size and composition. Mezhoud et al. (2022) proposed a new model for prioritizing sewer network defects by integrating three decision support methods: analytic hierarchy process (AHP), weighted product model (WPM), and technique for order preference by similarity to ideal solution method (TOPSIS). The study concluded that certain defects, namely collapse, chemical attack, pipe surface degradation, and abrasion, were identified as critical defects requiring immediate intervention. However, the study had certain limitations. Firstly, the findings were based on subjective judgments provided by experts, which may introduce a level of bias and not fully reflect the actual conditions of the sanitation network. Secondly, the model did not account for the uncertainty and variability of data and criteria weights. Ma et al. (2024a) compared eight models to assess the exfiltration severity index (ESI) based on sewer pipe defects. The models included the following: light gradient boosting machine (LGBM), gradient boosting (GB), *K*-nearest neighbors

Table 8
Review of comparisons among multiple models for the same purpose.

Year	Purpose	Compare	Merge	Data processing techniques	Best technique	Ref.
2020	Object detection	√		SSD + YOLOv3 + Faster R-CNN	Faster R-CNN	(Kumar et al., 2020)
2022		√		Faster R-CNN + YOLOv2	Faster R-CNN	(Q. Zhou et al., 2022a)
2023		√		YOLO (with TL by 11 models) + R-CNN + Fast R-CNN + Faster R-CNN + SSD	YOLO Network	(Situ et al., 2023)
2023		√		YOLOv2 with (Traditional data augmentation) OR (StyleGAN)	YOLOv2 with StyleGAN	(Zhou et al., 2023)
2021	Predicting the corrosion rate of concrete sewer pipes	√		ELM + K-ELM + OS-ELM + ANN + CART + MLR	OS-ELM	(Zounemat-Kermani et al., 2021)
2022	Prioritize the defects of sewer networks		√	AHP + WPM + TOPSIS	–	(Mezhoud et al., 2022)
2024	Exfiltration severity index (ESI)	√		LGBM + GB + SVM + ANN + KNN + DT + LSTM + CNN	LGBM	(Ma et al., 2024a)

(KNN), decision tree (DT), long short-term memory (LSTM), SVM, ANN, and CNN. To enhance the accuracy of the predictions, the researchers utilized GridSearchCV. The findings revealed that the LGBM model outperformed the other models in terms of accuracy. Additionally, the diameter of the pipe and the number of residents were identified as the most significant factors influencing the intensity of filtration.

In addition, several researchers have employed multiple models for various purposes, as depicted in Table 9. These studies demonstrate the versatility and applicability of utilizing multiple models in different contexts. Ye et al. (2019) aimed to enhance the accuracy and efficiency of defect classification through the utilization of an SVM model. To achieve this, they developed an algorithm that combined various techniques for feature extraction, including Hu invariant moments, texture features, lateral Fourier transform, and Daubechies (DBn) wavelet transform. The results of the study demonstrated the effectiveness of their approach. The developed system achieved an overall accuracy of 84.1% in defect classification. Notably, the highest accuracy was achieved in identifying settled deposits, with an accuracy rate of 99.3%. Furthermore, the study highlighted the significance of the quantity of training samples in influencing the accuracy of the diagnosis system. Wang et al. (2021b) presented a framework for evaluating the condition of sewer pipes. The proposed framework employed the Faster R-CNN model for object detection. This model was utilized to detect objects of interest within the sewer pipe images. Additionally, the researchers incorporated a semantic segmentation model that integrated a CNN with CRF for segmenting defects. This approach allowed for the accurate identification and delineation of defects within the sewer pipe images. Ma et al. (2021) performed image pre-processing and automated identification of clear images using the StyleGAN-SDM model in their study. For image classification, the researchers employed the MDCM (as previously explained).

Fang et al. (2022) employed a combination of models to enhance the accuracy and robustness of sewer defect detection. They utilized Mask R-CNN integrated with a split attention module and a balanced L1 loss module to achieve robust feature representation. This integration allowed for more effective detection and characterization of sewer defects. Additionally, the researchers employed the practical data augmentation method. Data augmentation techniques play a crucial role in increasing the diversity and quantity of training data, which in turn improves the generalization and performance of the models. By combining Mask R-CNN with the split attention module, balanced L1 loss module, and the practical data augmentation method, Fang et al. (2022) aimed to achieve enhanced accuracy and robustness in sewer defect detection. Q. Zhou et al. (2024) conducted a study to investigate the influence of sewer pipe defects on floods in Guangzhou, China. They employed DeepLabv3 + segmentation, geometric characterization, and storm water management model (SWMM)-based hydrodynamic modeling techniques to evaluate the impact of sewer defects on urban flooding. Through their analysis, the researchers were able to identify the location and time of floods on maps and assess the extent of their impact. However, it is important to acknowledge certain limitations of this study. One limitation is the low quality of the images used, which may have affected the accuracy of defect detection. Additionally, it should be noted that not all types of defects may have been detectable within the scope of this research. Furthermore, it is worth mentioning that flood modeling is a complex task, and achieving complete accuracy in such models is challenging. While efforts were made to develop a reliable modeling approach in this study, it is important to recognize that no model can provide a completely precise representation of real-world flood events.

Figure 13 illustrates the temporal distribution of model utilization in sewer defect detection from 2019 to May 2024. A notable surge in model deployment is observed

Table 9
Review of some of the research studies on multiple models to automate the detection and evaluation of sewer defects.

Year	First purpose		Second purpose		Ref.
	Purpose	Data processing technique	Purpose	Data processing technique	
2019	Feature extraction	Hu invariant moments, texture features, lateral Fourier transform, and Daubechies (DBn) wavelet transform	Defects classification	SVM	(Ye et al., 2019)
2021	Object detection	Faster R-CNN	Defects segmentation	CNN + CRF	(Wang et al., 2021b)
2021	Image generation	StyleGAN-SDM	Defects classification	MDCM based on fusion CNN	(Ma et al., 2021)
2022	Object detection	Improved Mask R-CNN	Data augmentation	Practical data augmentation method	(Fang et al., 2022)
2024	Defects segmentation	DeepLabv3+	Defect evaluation	Geometric characterization and severity quantification module	(Q. Zhou et al., 2024)

in 2022, indicating a pivotal year for advancements in this domain. The analysis reveals that object detection models have been the subject of 18 publications, closely followed by classification models with 14 articles. Conversely, emerging areas like textual analysis and CCTV image enhancement have gained scholarly attention predominantly within the past five years. Collectively, the data presented in this figure underscore the significant evolution and increasing sophistication in the application of various models to facilitate the automation of sewer defect detection.

6 Management and evaluation strategies for sewer defects

Asset management plays a crucial role in refining maintenance priorities, with infrastructure assets, particularly sewer pipe networks, ranking among the most critical and hazardous (Yin et al., 2020b). This section delves into research that has assessed sewer systems based on identified defects, forecasting pipe condition, and predicting failure timelines. Additionally, it examines the frameworks proposed by scholars aimed at managing sewer defects, evaluating risks, and thereby determining maintenance priorities. A significant focus will also be on the challenges faced, including the uncertainty surrounding model reliability and the implications this has for confidence in predictive maintenance strategies.

6.1 Condition assessment and predictive modelling of sewer

In this section, the condition assessment of sewer pipes, prediction of sewer condition, prediction of deteriorating sewers, and uncertainty in deteriorating modeling are discussed. When assessing the condition of sewer infrastructure, researchers have developed various analytical approaches. Yin et al. (2021) developed a novel video interpretation algorithm for sewer pipes (VIASP) and employed an optimization algorithm using simulated annealing (SA) for the development of VIASP. The proposed VIASP algorithm aims to automate the process of evaluating sewer pipes by processing labelled videos, extracting useful information, and generating a textual assessment report for sewer pipes. The algorithm utilizes SA to optimize the interpretation of the videos and improve the accuracy of the assessment. The VIASP algorithm has the potential to streamline and expedite the evaluation process, providing efficient and reliable results for sewer pipe assessment. The severity of each defect was classified on a scale of 1–5 using the Water Research Centre (WRC) classification system. Jia et al. (2023) developed a defect severity assessment model known as the defect severity assessment based on automated pipe calibration (DSA-APC) to automatically evaluate the severity of sewer pipe defects. The DSA-APC model incorporates automated pipe calibration and utilizes a pipe cross-section feature extraction algorithm based on restricted Hough gradient transform (RHGT). Additionally, it employs a fine-defect feature extraction method based on edge detection. Through experiments conducted on the Songbai dataset and Level-sewer10 dataset, the DSA-APC model demonstrated promising results. It achieved an average absolute deviation of 2.008% and an average accuracy of 86.73%. These findings highlight the effectiveness and accuracy of the DSA-APC model in automatically assessing the severity of sewer pipe defects. Makris et al. (2020) conducted a comparative analysis between scientific literature and empirical inspection data concerning polyvinyl chloride (PVC) pipes, uncovering a notable discrepancy. While the literature suggests that PVC pipes possess an extended lifespan of up to 100 years and exhibit a slow degradation

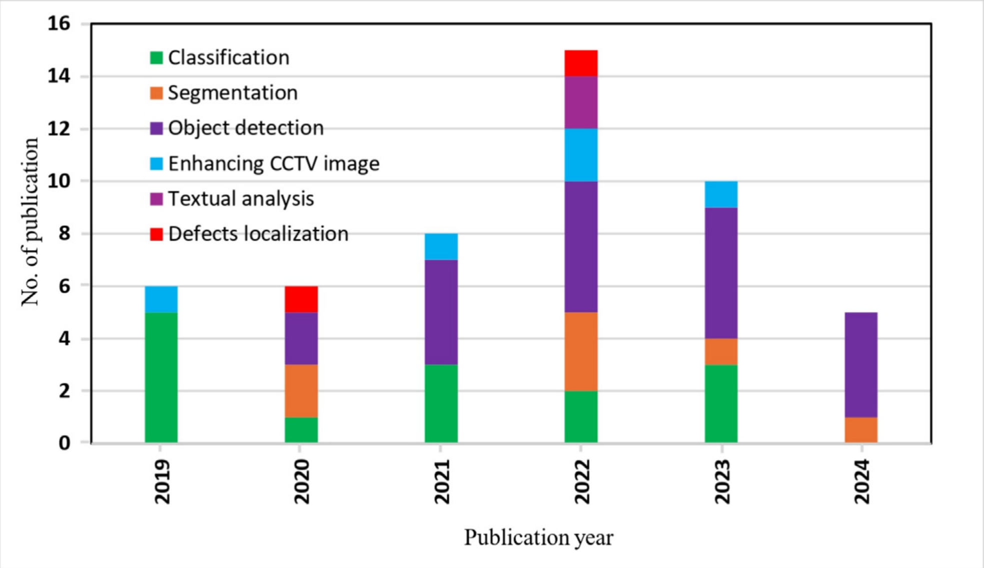


Fig. 13. Yearly distribution of analytical models in sewer defect detection by job role.

rate, practical observations have documented the emergence of cracks and deformations after just 30 years. This disparity prompts a re-evaluation of the models and mechanisms applied to PVC pipes, which have traditionally been informed by data from other pipe materials.

The prediction of sewer conditions over time is a critical component of effective asset management. Several studies have explored modelling techniques to forecast the future state of sewer networks. These models take into consideration several factors, including pipe material, age, environmental conditions, and operational factors. By incorporating these variables, the predictive models provide valuable insights that facilitate proactive maintenance planning and enhance asset management strategies. Yang et al. (2023) conducted a study aimed at predicting the mechanical properties of concrete sewer pipes with defects. They proposed a combined approach utilizing self-organizing maps (SOM), genetic algorithms (GA), and SVM termed SOM-GA-SVM. This approach was employed to predict the bearing capacity and circumferential strain of the pipes. A notable aspect of their study was the consideration of defect volume as a variable instead of defect depth and width. This simplified the prediction model and resulted in improved prediction performance. The evaluation metrics used, including mean absolute percentage error (MAPE), root mean square error (RMSE), and coefficient of determination (R^2), indicated that the SOM-GA-SVM model produced prediction results within acceptable ranges. This suggests that the model was reasonable and reliable in predicting the mechanical properties of the concrete sewer pipes with defects. However, it is important to acknowledge a limitation of their study. Yang et al. (2023) conducted their experiments solely in laboratory settings, without investigating the practical application of the model on actual pipes in real-world engineering scenarios. Therefore, the effectiveness and performance of the SOM-GA-SVM model in practical engineering situations remain unknown.

Similarly, researchers have directed efforts towards predicting deteriorating sewer systems. Makana et al. (2022) explored methods for predicting pipe deterioration, specifically focusing on the consideration of the intricate and dynamic interactions between pipes and their surrounding environment, such as soil and adjacent infrastructure. However, it is important to note that the study does not provide a quantitative or qualitative assessment of the proposed techniques. The research heavily relies on literature review and expert opinions as sources of information. While these sources can provide valuable insights, it is worth considering that they may not fully reflect the actual practices and challenges encountered in the field. The absence of empirical data or experimental validation limits the ability to evaluate the effectiveness and reliability of the discussed methods. Uncertainty is an inherent aspect of managing sanitation models in the academic realm, arising from various factors. These factors encompass uncertainties in data quality, models, and their limitations, influencing factors, spatial and temporal variations of defects, and uncertainties in decision-making processes. Addressing uncertainty in sanitation models calls for acknowledging and quantifying uncertainties where feasible. Additionally, enhancing data quality, incorporating uncertainty considerations in model development, and embracing adaptive management approaches can improve decision-making under uncertainty in the field of sanitation management. Caradot et al. (2020) conducted a study on the uncertainty in models for predicting the deterioration of sewer pipes. They employed a statistical deterioration model based on the Cox proportional hazards model, which correlates the survival probability of a sewer segment with a set of explanatory factors. The researchers concluded that failure to account for uncertainties in decision-making regarding the replacement of deteriorated pipes could result in a 20% overestimation of the replacement rate. This discrepancy is particularly notable in older pipes, as they exhibit a higher number of false negative defects compared to false positive defects, with a confidence interval of ±12% per 100 years. However, one limitation of this model is its reliance on a small sample size, which may not be fully representative of the entire sewer network. Assessing the current condition, predicting the future condition, and estimating the remaining service life of the pipes collectively contribute to effective decision-making, resource allocation, and maintenance strategies in sewer asset management. Table 10 shows the research that dealt with this part and the techniques used.

6.2 Frameworks for effective management of sewer systems

A multitude of scholarly investigations have yielded a variety of frameworks dedicated to the effective management of sewer pipe assets. The primary objective of these frameworks is the early detection and prediction of defects within the sewer infrastructure, thereby preventing their occurrence. By employing these systematic approaches, inspectors are equipped with a holistic perspective that enhances decision-making processes, ensuring that interventions are timely and judicious. Alqahtani et al. (2023) developed a comprehensive framework that encompasses all stages of the life cycle of sewer pipelines, ranging from planning and design to operation and maintenance. In their study, they employed the relative importance index (RII), a statistical method, to assess the relative significance of each defect in terms of its probability and impact. Additionally, they utilized the risk index (RI) to prioritize the defects by multiplying their probability and impact. To evaluate the probability and impact of 15 types of defects, the researchers conducted a survey involving 18 experts. The findings highlighted that the framework did not consider the cost-effectiveness and feasibility of the proposed solutions. It is worth noting that the cost-effectiveness and feasibility of solutions can vary significantly depending on the specific context and the availability of resources. Kumar et al. (2022) introduced a two-component framework, as depicted in Table 11. The first component of the framework focuses on identifying areas where multiple defects occur in close proximity and evaluating their severity. The second component of the framework is designed to identify defects that manifest simultaneously in the pipes. This temporal aspect is crucial for understanding the dynamics of deterioration and detecting patterns of simultaneous failures. Experts noted that this framework greatly assists in making rehabilitation decisions because it makes a fine-grained analysis of the condition of the pipes. Proposed by Li et al. (2022), a framework is presented for the examination of defects in sewer pipes. The framework incorporates two key components: segmentation and the removal of fog and blurring from images. Each individual model utilized within the framework has been extensively discussed previously in this paper. By integrating segmentation and image enhancement techniques, the proposed framework by Li et al. (2022) provides a systematic approach for examining defects in sewer pipes. It offers enhanced visualization and accurate identification of defects, ultimately contributing to improved decision-making and maintenance strategies in sewer pipe management. Introduced by Wang et al. (2021b), an encompassing framework is proposed for the evaluation of sewer pipe conditions (Fig. 14). The framework comprises stages, including defect discovery and segmentation, pipe connection detection, defect severity assessment, and sewer pipe condition classification. The framework yields results that closely align with evaluations conducted by professional inspectors. However, it is notable that this framework does not account for temporal information in inspection videos or the spatial correlation of defects along the pipe.

Dang et al. (2021) implemented a highly accurate framework for sewer defect detection. They employed a defect classification model that was previously discussed in this research. Furthermore, they effectively reduced the number of frames that needed to be processed by utilizing an algorithm capable of recognizing the distance covered by the robot's movement. The framework exhibited exceptional efficiency when tested against various obstructions, including noise and rotation. Additionally, it demonstrated low false alarm rates, further enhancing its reliability and practicality. Yin et al. (2020b) developed a framework for modelling the CCTV video recording process using multiple linear regression, the random sample consensus (RANSAC) algorithm, and a discrete event simulation model (Fig. 15). They successfully simulated the recording duration and validated it using historical data, demonstrating the framework's ability to accurately predict the duration of CCTV registration. Nevertheless, one limitation of this framework is the exclusion of geographic variables, such as road condition and sewage community, which could potentially impact the recording process. These variables are known to influence the efficiency and duration of CCTV registration but were not considered in the proposed framework. Table 11 presents a comprehensive overview of the frameworks, the technologies utilized, and their respective purpose.

7 Research gaps and future directions

Following a thorough review of the existing literature on sewer defect inspection, several research gaps have been identified that merit further exploration in future investigations within this domain. Figure 16 outlines these key research gaps and emerging trends, which will be discussed in greater detail in the subsequent paragraphs.

From the scientometric analysis of countries' contributions, it is clear that studies have been concentrated in a very small number of countries (for example, China, Canada, the United States, the United Kingdom, and others). There is a significant backwardness in South American and African countries in the field of examining defects in sewage pipes. It is known that the consequences of sewage failure are very harmful environmentally and socially. To address this gap, future research efforts must focus on increasing international research cooperation across all countries. For every country in the world, researchers should work to foster greater collaboration and knowledge sharing. Expanding the geographic scope

Table 10
Review of some of the research studies on condition assessment and predictive modelling of sewer infrastructure.

Category	Data processing technique	Description	Year	Ref.
Assessing the condition of sewer pipes	VIASP + SA	Condition assessment by CCTV video	2021	(Yin et al., 2021)
	DSA-APC	Evaluate the severity of defects	2023	(Jia et al., 2023)
	N/A	Comparing research results in the case of PVC sewer pipes with experimental inspection	2019	(Makris et al., 2020)
Predicting the condition pipes	SOM-GA-SVM	Predicting the mechanical properties of concrete sewer pipes with defects	2023	(Yang et al., 2023)
Predicting pipe deterioration	N/A	Explore methods for predicting pipe deterioration	2022	(Makana et al., 2022)
	The Cox proportional hazards model	Uncertainty in models for predicting the deterioration of sewer pipes	2020	(Caradot et al., 2020)

Table 11
Review of some studies that proposed a framework for effective management of sewer systems.

Data processing technique	Purpose of framework	Ref.
Relative importance index (RII), Risk index (RI)	Comprehensive maintainability framework for sewer pipeline systems	(Alqahtani et al., 2023)
Defect cluster analysis (DCA), Defect co-occurrence mining	Integrating spatial and temporal information to perform pipe condition-grained analysis	(Kumar et al., 2022)
Pipe-SOLO mode + GCANet	Instance segmentation-based sewer defect inspection model	(Li et al., 2022)
Faster R-CNN	Evaluating sewer pipe condition from CCTV images using computer vision and deep learning methods	(Wang et al., 2021b)
CNN + XGBoost, LightGBM	To automatically detect and evaluate sewer defects	(Dang et al., 2021)
RANSAC algorithm	The CCTV recording process is thoroughly investigated and well-understood	(Yin et al., 2020b)

of studies on sewage pipe defects is crucial to gaining a more comprehensive understanding of the problems and potential solutions applicable worldwide. By facilitating international collaboration, researchers can share knowledge, data, and best practices to tackle this important issue on a global scale. There is a paucity of studies that have utilized an integrated approach to inspection tools for sewer pipes. Current methods relying solely on CCTV cameras inside the pipes are limited in their ability to detect defects beneath the water surface or on the external pipe surface. To address this limitation, future research should focus on developing innovative inspection technologies that can

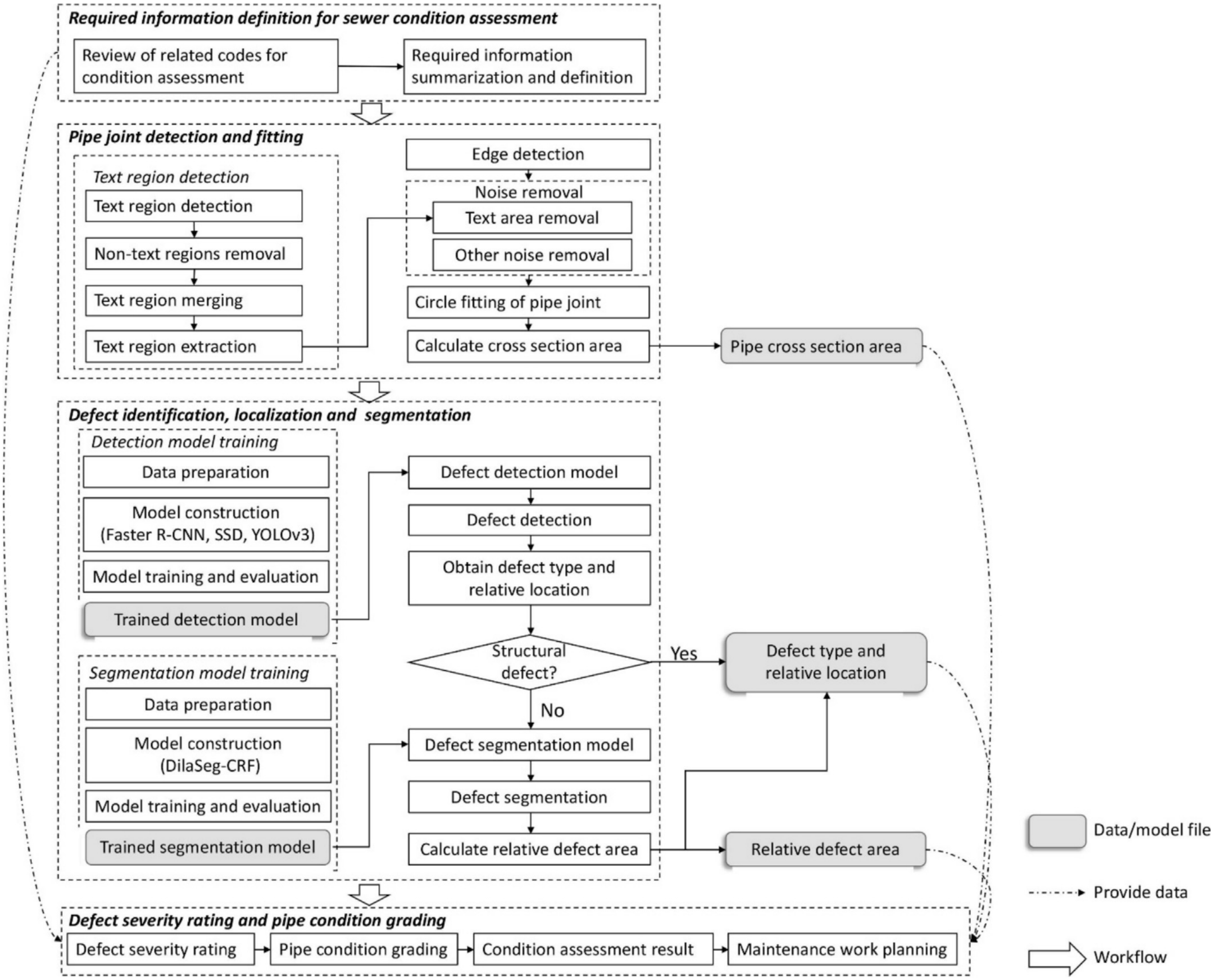


Fig. 14. Framework for automated condition assessment of sewer pipe systems (Wang et al., 2021b; reproduced with permission, courtesy of Elsevier).

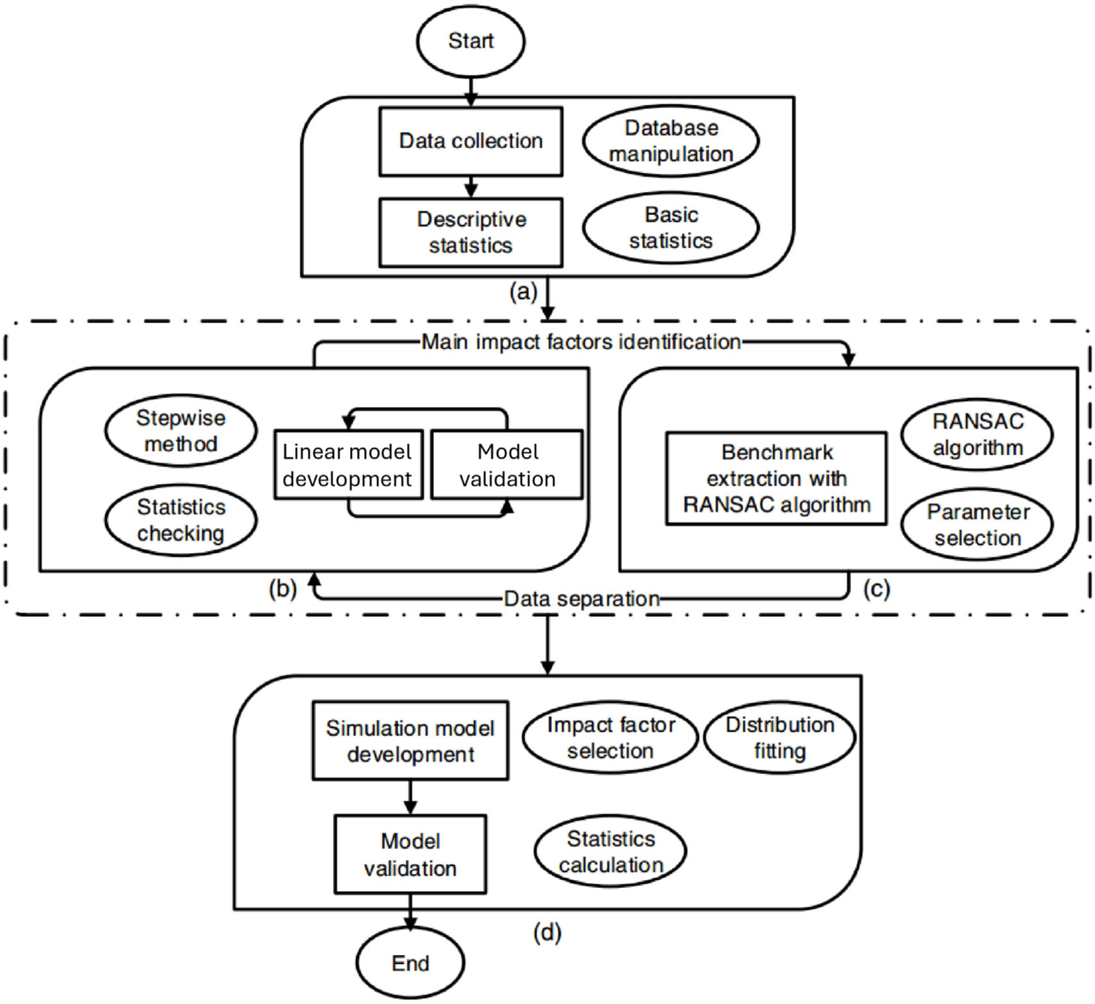


Fig. 15. Framework to model the productivity of the CCTV video recording process (Yin et al., 2020b; reproduced with permission, courtesy of ASCE).

integrate multiple modalities, such as CCTV, sonar, and ground-penetrating radar. This integrated approach would enable a comprehensive assessment of both the internal and external conditions of sewer pipes.

Despite significant advancements in robotics, research on robotic systems for sewer pipe inspection is still limited. Robotic platforms provide advantages over traditional CCTV cameras, including intelligent systems that can automatically detect defects and adjust imaging parameters. Future studies should focus on developing these intelligent systems, emphasizing advanced sensor integration, machine learning-driven defect recognition, and adaptive navigation capabilities. Additionally, integrating laser-based imaging technologies could enhance the detection of subsurface defects that typical CCTV cameras may miss. Current research has insufficient emphasis on verifying the quality of CCTV images used in sewer inspections, and there is a lack of studies aimed at improving image quality prior to processing for classification or defect detection. This oversight may compromise the accuracy of automated analysis techniques. Future research should prioritize developing frameworks for assessing and enhancing CCTV image quality, including image enhancement algorithms, calibration techniques, and quality control protocols. Improving image quality is essential for achieving more accurate and reliable defect identification and classification.

Current research in this field has utilized a limited number of data generation models, such as Style-GAN, and has rarely employed transfer learning techniques to train these models. This is particularly problematic, as the availability of sufficient training data remains a significant challenge for many machine learning applications. The use of automated data generation and transfer learning approaches has the potential to overcome these limitations. To build upon these initial efforts, future research should further explore the application of advanced data generation techniques and transfer learning strategies to enhance the development of robust machine learning models. This could involve investigating the efficacy of integrating multiple data generation approaches and optimizing transfer learning frameworks to maximize model performance

Fig. 16. Research gaps and future directions, outlining areas for further exploration and potential advancements in the field.

despite limited training data. In object detection, one of the most advanced models is YOLO. However, the latest version used for sewer anomaly detection is YOLOv8. Therefore, future research should use the latest versions to ensure greater efficiency, detection accuracy, and better speed. YOLOv11 was released when this paper was written. Current research on sewer defects predominantly focuses on traditional materials like concrete and clay, neglecting modern materials such as PVC and neglecting rehabilitated pipes. These types, increasingly used in contemporary sewer systems, have unique properties and potential defect patterns that are not well-documented. Understanding these defects is crucial for maintenance and longevity. Future studies should employ advanced diagnostic tools to analyze these types, providing insights into their specific failure mechanisms and informing better rehabilitation strategies. This will ensure more efficient and effective sewer system management. Current research in this field has primarily utilized a limited range of data generation models, such as Style-GAN, and has rarely incorporated transfer learning techniques. This is problematic, as insufficient training data poses a significant challenge for many machine learning applications. Automated data generation and transfer learning could help address these limitations. Future research should explore advanced data generation techniques and transfer learning strategies to enhance the development of robust machine learning models. This may involve integrating multiple data generation approaches and optimizing transfer learning frameworks to improve model performance with limited training data. In object detection, YOLO is one of the most advanced models, with YOLOv8 and earlier versions having been used for detecting sewer defects. With the release of newer versions, including YOLOv11, future research should utilize these updates to achieve improved performance, accuracy, and faster detection of sewer defects.

Moreover, current research on sewer defects predominantly focuses on traditional materials like concrete and clay, often neglecting modern materials such as PVC and rehabilitated pipes. These materials, increasingly used in contemporary sewer systems, have unique properties and defect patterns that are not well-documented. Understanding these defects is crucial for effective maintenance and longevity. Future studies should employ advanced diagnostic tools to analyze these materials, providing insights into their specific failure mechanisms and informing better rehabilitation strategies for improved sewer system management. Comprehensive frameworks are essential for improving the accuracy and reliability of sewer pipe inspections. These frameworks should begin with the integration of diverse inspection tools, including robotic systems and CCTV cameras, to provide a complete assessment of pipe conditions. The next step involves evaluating and enhancing the quality of CCTV images to optimize input data for analysis. Subsequently, advanced machine learning techniques, such as data generation and transfer learning, should be employed to develop robust models for classification, segmentation, and object detection of defects. Additionally, integrating text detection capabilities will allow for precise localization and description of defects. While automated detection models have shown promise, there is a lack of research on the uncertainties inherent in these models. Future studies should focus on creating uncertainty-aware models that can effectively address the diverse nature of sewer defects. By quantifying and managing these uncertainties, the models will provide more reliable insights for infrastructure management.

8 Conclusions

This study presents an integrated review of sewer defect detection research using bibliometric, scientometric, and systematic analyses. The main findings are summarized below:

(1) Research on sewer defect detection has grown significantly, with deep learning models increasingly adopted. China has emerged as a leading contributor in this field over the past five years.
(2) While CCTV remains the primary inspection method due to its cost-effectiveness, combining it with complementary techniques such as laser-based tools and out-pipe inspections enhances defect detection accuracy.
(3) Several deep learning models have demonstrated outstanding performance. Modified RegNet achieved a classification accuracy of 99.5%, DilaSeg-CRF attained a pixel accuracy of 98.69% and a mIoU of 84.85%, while YOLO and Faster R-CNN stand out for their speed and accuracy in object detection, respectively.
(4) Integrating multiple models, employing transfer learning, and enhancing image quality have significantly improved detection reliability. However, managing false negatives, which have been reported at rates of up to 20%, remains critical for ensuring accurate maintenance decisions.

Limitations

This review focused exclusively on original research papers published in peer-reviewed journals, excluding conference proceedings and other formats to maintain analytical depth. By restricting the analysis to the two most widely recognized databases (Elsevier and Web of Science) from 2019 onward, the study ensured a concentrated examination of recent, high-impact contributions, resulting in a curated dataset of 78 papers. While this approach strengthens the relevance and rigor of the findings, future research could explore broader sources to capture emerging innovations across diverse publication formats. Despite these limitations, these findings support the development of smarter, AI-driven inspection frameworks, offering valuable direction for practitioners and researchers working to improve infrastructure maintenance and urban resilience.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Mohamed Nashat: Writing – original draft. **Tarek Zayed:** Supervision, Writing – review & editing.

Declaration of competing interest

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

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References

Alejo, D., Chataigner, F., Serrano, D., Merino, L., & Caballero, F. (2021). Into the dirt: Datasets of sewer networks with aerial and ground platforms. *Journal of Field Robotics, 38*(1), 105–120.

Alqahtani, F. K., Alsharef, A., Hommadi, G. M., & Alammari, M. A. (2023). Assessment framework for the maintainability of sewer pipeline systems. *Applied Sciences, 13*(21), 11828.

Alshami, A., Elsayed, M., Ali, E., Eltoukhy, A. E. E., & Zayed, T. (2023a). Harnessing the power of ChatGPT for automating systematic review process: Methodology, case study, limitations, and future directions. *Systems, 11*(7), 351.

Alshami, A., Elsayed, M., Ali, E., Eltoukhy, A. E. E., & Zayed, T. (2023b). Monitoring blockage and overflow events in small-sized sewer network using contactless flow sensors in Hong Kong: Problems, causes, and proposed solution. *IEEE Access, 11*, 87131–87149.

Bahnsen, C. H., Clement, A., Larsen, H. C. Ø., & Moeslund, T. B. (2023). Measuring the interior of in-use sewage pipes using 3D vision. *Automation in Construction, 151*.

Caradot, N., Riechel, M., Rouault, P., Caradot, A., Lengemann, N., Eckert, E., Ringe, A., Clemens, F., & Cherqui, F. (2020). The influence of condition assessment uncertainties on sewer deterioration modelling. *Structure and Infrastructure Engineering, 16*(2), 287–296.

Chen, Y., Sharifuzzaman, S. A. S. M., Wang, H., Li, Y., Minh Dang, L., Song, H.-K., & Moon, H. (2023). Deep learning based underground sewer defect classification using a modified RegNet. *Computers, Materials and Continua, 75*(3), 5451–5469.

Chuang, T.-Y., & Sung, C.-C. (2020). Learning and SLAM based decision support platform for sewer inspection. *Remote Sensing, 12*(6).

Dang, L. M., Kyeong, S., Li, Y., Wang, H., Nguyen, T. N., & Moon, H. (2021). Deep learning-based sewer defect classification for highly imbalanced dataset. *Computers and Industrial Engineering, 161*.

Dang, L. M., Wang, H., Li, Y., Nguyen, L. Q., Nguyen, T. N., Song, H.-K., & Moon, H. (2023). Lightweight pixel-level semantic segmentation and analysis for sewer defects using deep learning. *Construction and Building Materials, 371*.

Dang, L. M., Wang, H., Li, Y., Nguyen, T. N., & Moon, H. (2022). DefectTR: End-to-end defect detection for sewage networks using a transformer. *Construction and Building Materials*, 325.

Fang, X., Li, Q., Zhu, J., Chen, Z., Zhang, D., Wu, K., Ding, K., & Li, Q. (2022). Sewer defect instance segmentation, localization, and 3D reconstruction for sewer floating capsule robots. *Automation in Construction, 142*.

Fu, G., Jin, Y., Sun, S., Yuan, Z., & Butler, D. (2022). The role of deep learning in urban water management: A critical review. *Water Research*, 223.

Guo, W., Zhang, X., Zhang, D., Chen, Z., Zhou, B., Huang, D., & Li, Q. (2022). Detection and classification of pipe defects based on pipe-extended feature pyramid network. *Automation in Construction, 141*.

Hassan, S. I., Dang, L. M., Mehmood, I., Im, S., Choi, C., Kang, J., Park, Y.-S., & Moon, H. (2019). Underground sewer pipe condition assessment based on convolutional neural networks. *Automation in Construction, 106*.

Haurum, J. B., Madadi, M., Escalera, S., & Moeslund, T. B. (2022). Multi-scale hybrid vision transformer and Sinkhorn tokenizer for sewer defect classification. *Automation in Construction, 144*.

Haurum, J. B., & Moeslund, T. B. (2020). A survey on image-based automation of CCTV and SSET sewer inspections. *Automation in Construction, 111*.

He, J., Hou, Z., Zhu, D., Li, Z., & Li, Z. (2022a). Automatic accurate longitudinal location of structural defects in sewer pipes via monocular ranging. *Applied Optics, 61*(27), 7899–7911.

He, M., Zhao, Q., Gao, H., Zhang, X., & Zhao, Q. (2022b). Image segmentation of a sewer based on deep learning. *Sustainability (Switzerland), 14*(11).

Hu, C., Dong, B., Shao, H., Zhang, J., & Wang, Y. (2023). Toward purifying defect feature for multilabel sewer defect classification. *IEEE Transactions on Instrumentation and Measurement, 72*.

Jain, R. K., Das, A., Mukherjee, A., Ray, D. N., & Karmakar, P. (2021). Experimental performance of robotic inspection system for underground pipelines. *Journal of The Institution of Engineers (India): Series C, 102*(3), 683–703.

Jia, P., Liao, Y., Zhao, Q., He, M., & Guo, M. (2023). Defect severity assessment model for sewer pipeline based on automated pipe calibration. *Journal of Pipeline Systems Engineering and Practice, 14*(3).

Karabij, M., Yin, X., Bouferguene, A., & Al-Hussein, M. (2022). Image processing-based framework for determining deterioration in sewer pipe defects. *Journal of Infrastructure Systems, 28*(4).

Kumar, S. S., Abraham, D., & Choi, J. (2022). A hybrid framework for mining spatial characteristics of sewer defects from inspection databases. *Urban Water Journal, 19*(1), 51–61.

Kumar, S. S., Wang, M., Abraham, D. M., Jahanshahi, M. R., Iseley, T., & Cheng, J. C. P. (2020). Deep learning-based automated detection of sewer defects in CCTV videos. *Journal of Computing in Civil Engineering, 34*(1).

Li, D., Cong, A., & Guo, S. (2019). Sewer damage detection from imbalanced CCTV inspection data using deep convolutional neural networks with hierarchical classification. *Automation in Construction, 101*, 199–208.

Li, D., Xie, Q., Yu, Z., Wu, Q., Zhou, J., & Wang, J. (2021). Sewer pipe defect detection via deep learning with local and global feature fusion. *Automation in Construction, 129*.

Li, M., Li, M., Ren, Q., Liu, H., & Liu, C. (2023). Intelligent identification and classification of sewer pipeline network defects based on improved RegNetY network. *Journal of Civil Structural Health Monitoring, 13*(2–3), 547–560.

Li, Y., Wang, H., Dang, L. M., Jalil Piran, M., & Moon, H. (2022). A robust instance segmentation framework for underground sewer defect detection. *Measurement: Journal of the International Measurement Confederation, 190*.

Liu, H., Yue, Y., Liu, C., Spencer, B. F., & Cui, J. (2023). Automatic recognition and localization of underground pipelines in GPR B-scans using a deep learning model. *Tunnelling and Underground Space Technology, 134*.

Ma, D., Liu, J., Fang, H., Wang, N., Zhang, C., Li, Z., & Dong, J. (2021). A Multi-defect detection system for sewer pipelines based on StyleGAN-SDM and fusion CNN. *Construction and Building Materials, 312*.

Ma, S., Elshaboury, N., Ali, E., & Zayed, T. (2024a). Proactive exfiltration severity management in sewer networks: A hyperparameter optimization for two-tiered machine learning prediction. *Tunnelling and Underground Space Technology, 144*.

Ma, S., Zayed, T., Xing, J., & Shao, Y. (2024b). A state-of-the-art review for the prediction of overflow in urban sewer systems. *Journal of Cleaner Production, 434*, 139923.

Makana, L. O., Shepherd, W. J., Tait, S., Rogers, C. D. F., Metje, N., Boxall, J. B., & Schellart, A. N. A. (2022). Future inspection and deterioration prediction capabilities for buried distributed water infrastructure. *Journal of Pipeline Systems Engineering and Practice, 13*(3).

Makris, K. F., Langeveld, J., & Clemens, F. H. L. R. (2020). A review on the durability of PVC sewer pipes: Research vs. practice. *Structure and Infrastructure Engineering, 16*(6), 880–897.

Meijer, D., Scholten, L., Clemens, F., & Knobbe, A. (2019). A defect classification methodology for sewer image sets with convolutional neural networks. *Automation in Construction, 104*, 281–298.

Mezhoud, C., Berreksi, A., Bedjou, A., & Bosseler, B. (2022). Prioritization of maintenance work in wastewater networks using decision support methods. *Journal of Water Sanitation and Hygiene for Development, 12*(2), 186–199.

Moradi, S., Zayed, T., & Golkhoo, F. (2019). Review on computer aided sewer pipeline defect detection and condition assessment. *Infrastructures, 4*(1).

Moradi, S., Zayed, T., Nasiri, F., & Golkhoo, F. (2020). Automated anomaly detection and localization in sewer inspection videos using proportional data modeling and deep learning-based text recognition. *Journal of Infrastructure Systems, 26*(3).

Myrans, J., Everson, R., & Kapelan, Z. (2019). Automated detection of fault types in CCTV sewer surveys. *Journal of Hydroinformatics, 21*, 153–163.

Oh, C., Dang, L. M., Han, D., & Moon, H. (2022). Robust sewer defect detection with text analysis based on deep learning. *IEEE Access, 10*, 46224–46237.

Pan, F., Tang, D., Guo, X., & Pan, S. (2021). Defect identification of pipeline ultrasonic inspection based on multi-feature fusion and multi-criteria feature evaluation. *International Journal of Pattern Recognition and Artificial Intelligence, 35*(11).

Pan, G., Zheng, Y., Guo, S., & Lv, Y. (2020). Automatic sewer pipe defect semantic segmentation based on improved U-Net. *Automation in Construction, 119*.

Salihu, C., Hussein, M., Mohandes, S. R., & Zayed, T. (2022). Towards a comprehensive review of the deterioration factors and modeling for sewer pipelines: A hybrid of bibliometric, scientometric, and meta-analysis approach. *Journal of Cleaner Production, 351*, 131460.

Situ, Z., Teng, S., Feng, W., Zhong, Q., Chen, G., Su, J., & Zhou, Q. (2023). A transfer learning-based YOLO network for sewer defect detection in comparison to classic object detection methods. *Developments in the Built Environment, 15*.

Situ, Z., Teng, S., Liao, X., Chen, G., & Zhou, Q. (2024). Real-time sewer defect detection based on YOLO network, transfer learning, and channel pruning algorithm. *Journal of Civil Structural Health Monitoring, 14*(1), 41–57.

Siu, C., Wang, M., & Cheng, J. C. P. (2022). A framework for synthetic image generation and augmentation for improving automatic sewer pipe defect detection. *Automation in Construction, 137*.

Tan, Y., Cai, R., Li, J., Chen, P., & Wang, M. (2021). Automatic detection of sewer defects based on improved you only look once algorithm. *Automation in Construction, 131*.

Tugeumwolachot, T., Seki, H., Tsuji, T., & Hiramitsu, T. (2021). Development of a compact sewerage robot with multi-DOF cutting tool. *Artificial Life and Robotics, 26*(4), 404–411.

Wang, M., & Cheng, J. C. P. (2020). A unified convolutional neural network integrated with conditional random field for pipe defect segmentation. *Computer-Aided Civil and Infrastructure Engineering, 35*(2), 162–177.

Wang, M., Kumar, S. S., & Cheng, J. C. P. (2021a). Automated sewer pipe defect tracking in CCTV videos based on defect detection and metric learning. *Automation in Construction, 121*.

Wang, M., Luo, H., & Cheng, J. C. P. (2021b). Towards an automated condition assessment framework of underground sewer pipes based on closed-circuit television (CCTV) images. *Tunnelling and Underground Space Technology*, 110.

Wang, M., & Yin, X. (2022). Construction and maintenance of urban underground infrastructure with digital technologies. *Automation in Construction, 141*.

Wang, N., Ma, D., Du, X., Li, B., Di, D., Pang, G., & Duan, Y. (2024). An automatic defect classification and segmentation method on three-dimensional point clouds for sewer pipes. *Tunnelling and Underground Space Technology, 143*.

Wang, T., Li, Y., Zhai, Y., Wang, W., & Huang, R. (2023). A sewer pipeline defect detection method based on improved YOLOv5. *Processes, 11*(8).

Wang, Y., Li, P., & Li, J. (2022). The monitoring approaches and non-destructive testing technologies for sewer pipelines. *Water Science and Technology, 85*(10), 3107–3121.

Xia, Z., Guo, S., Sun, D., Lv, Y., Li, H., & Pan, G. (2023). Structure-aware dehazing of sewer inspection images based on monocular depth cues. *Computer-Aided Civil and Infrastructure Engineering, 38*(6), 762–778.

Xie, Q., Li, D., Xu, J., Yu, Z., & Wang, J. (2019). Automatic detection and classification of sewer defects via hierarchical deep learning. *IEEE Transactions on Automation Science and Engineering, 16*(4), 1836–1847.

Xu, M., Yang, F., & Yan, R. (2023). Design and implementation of three-channel drainage pipeline ground penetrating radar device. *Sensors, 23*(9).

Yang, K., Fang, H., Liu, H., Li, B., Zhang, X., Xia, Y., & Zhai, K. (2023). An intelligent model to predict the mechanical properties of defected concrete drainage pipes. *International Journal of Mechanical Sciences, 260*.

Ye, X., Zuo, J., Li, R., Wang, Y., Gan, L., Yu, Z., & Hu, X. (2019). Diagnosis of sewer pipe defects on image recognition of multi-features and support vector machine in a southern Chinese city. *Frontiers of Environmental Science and Engineering, 13*(2).

Yin, X., Chen, Y., Bouferguene, A., Zaman, H., Al-Hussein, M., & Kurach, L. (2020a). A deep learning-based framework for an automated defect detection system for sewer pipes. *Automation in Construction*, 109.

Yin, X., Chen, Y., Bouferguene, A., Zaman, H., Al-Hussein, M., & Russell, R. (2020b). Data-driven framework for modeling productivity of closed-circuit television recording process for sewer pipes. *Journal of Construction Engineering and Management, 146*(8).

Yin, X., Ma, T., Bouferguene, A., & Al-Hussein, M. (2021). Automation for sewer pipe assessment: CCTV video interpretation algorithm and sewer pipe video assessment (SPVA) system development. *Automation in Construction, 125*.

Yu, Z., Li, X., Sun, L., Zhu, J., & Lin, J. (2024). A composite transformer-based multi-stage defect detection architecture for sewer pipes. *Computers, Materials and Continua, 78*(1), 435–451.

Yussuf, A. N., Weerasinghe, N. P., Chen, H., Hou, L., Herath, D., Rashid, M., Zhang, G., & Setunge, S. (2024). Leveraging deep learning techniques for condition assessment of stormwater pipe network. *Journal of Civil Structural Health Monitoring, 15*, 619–633.

Zhang, J., Liu, X., Zhang, X., Xi, Z., & Wang, S. (2023a). Automatic detection method of sewer pipe defects using deep learning techniques. *Applied Sciences (Switzerland), 13*(7).

Zhang, X., Zhang, J., Tian, L., Liu, X., & Wang, S. (2023b). A lightweight method for detecting sewer defects based on improved YOLOv5. *Applied Sciences (Switzerland), 13*(15).

Zhao, M., Fang, Z., Ding, N., Li, N., Su, T., & Qian, H. (2023). Quantitative detection technology for geometric deformation of pipelines based on LiDAR. *Sensors, 23*(24).

Zhou, B., Li, B., Lan, W., Tian, C., & Yao, W. (2024a). SDH-FCOS: An efficient neural network for defect detection in urban underground pipelines. *Computers, Materials and Continua, 78*(1), 633–652.

Zhou, Q., Situ, Z., Feng, W., Liu, H., Liao, X., Zhang, J., Ge, X., & Chen, G. (2024b). Deep learning, geometric characterization and hydrodynamic modeling for assessing sewer defect impacts on urban flooding: A case study in Guangzhou, China. *Journal of Environmental Management, 351*.

Zhou, Q., Situ, Z., Teng, S., & Chen, G. (2021a). Convolutional neural networks-based model for automated sewer defects detection and classification. *Journal of Water Resources Planning and Management, 147*(7).

Zhou, Q., Situ, Z., Teng, S., & Chen, G. (2023). Comparative effectiveness of data augmentation using traditional approaches versus StyleGANs in automated sewer defect detection. *Journal of Water Resources Planning and Management, 149*(9).

Zhou, Q., Situ, Z., Teng, S., Chen, W., Chen, G., & Su, J. (2022a). Comparison of classic object-detection techniques for automated sewer defect detection. *Journal of Hydroinformatics, 24*(2), 406–419.

Zhou, Q., Situ, Z., Teng, S., Liu, H., Chen, W., & Chen, G. (2022b). Automatic sewer defect detection and severity quantification based on pixel-level semantic segmentation. *Tunnelling and Underground Space Technology, 123*.

Zhou, Y., Ji, A., & Zhang, L. (2022c). Sewer defect detection from 3D point clouds using a transformer-based deep learning model. *Automation in Construction, 136*.

Zounemat-Kermani, M., Alizamir, M., Yaseen, Z. M., & Hinkelmann, R. (2021). Concrete corrosion in wastewater systems: Prediction and sensitivity analysis using advanced extreme learning machine. *Frontiers of Structural and Civil Engineering, 15*(2), 444–460.

Zuo, X., Dai, B., Shan, Y., Shen, J., Hu, C., & Huang, S. (2020). Classifying cracks at sub-class level in closed circuit television sewer inspection videos. *Automation in Construction, 118*.