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Infrastructure automated defect detection with machine learning: a systematic review

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ABSTRACT
Infrastructure defects pose significant public safety risks and, if undetected, can lead to costly repairs. While machine learning (ML) technologies have significantly enhanced the capabilities for inspecting infrastructure, a comprehensive synthesis of these advancements and their practical application across various infrastructures is lacking. This study addresses this gap by providing a literature review, offering a consolidated view of current ML methodologies in Infrastructure Automated Defect Detection (IADD). This research employs a systematic literature review (SLR) approach to analyse 123 papers on ML methodologies applied to IADD. The analysis reveals the wide use of deep learning architectures like Convolutional Neural Network and its variants, which perform well in defect detection across various infrastructures, including roads, bridges, and sewers. However, standardised, comprehensive datasets are critical to train and test these models more effectively. The study also highlights the importance of developing ML approaches that can accurately assess the severity of defects, an area currently underexplored but with significant implications for risk management in infrastructure. This SLR provides a consolidated perspective on ML technologies' advancements and practical applications in IADD, and it offers substantial value to researchers, engineers, and policymakers engaged in infrastructure asset management.

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KEYWORDS
Machine learning; automated defect detection; infrastructure; image processing; classification algorithms; infrastructure defects

Introduction

Critical infrastructures globally are frequently exposed to severe physical stress from acute and chronic catastrophes such as earthquakes, floods, and ageing deterioration (Munawar et al. 2021). Managing these infrastructures often falls under the purview of municipal bodies and governments, which deploy asset management plans to ensure stability and longevity. Condition monitoring is integral to asset management plans, significantly contributing to extending the service life of an asset (Le Gat et al. 2025). It offers insight into the current state of assets and facilitates predicting their future performance (Assaad and El-Adaway 2020). A crucial outcome of condition monitoring is defect detection. Substantial financial investments are directed annually towards procuring techniques and resources for defect detection in critical infrastructures such as roads, bridges, buildings, and water assets (Ni et al. 2019; Mukherjee et al. 2023).

Traditionally, experts conduct visual inspections, using specialised tools to detect defects manually. Despite its widespread use, this approach is labour-intensive, hazardous, time-consuming, and prone to human error (Ahmadi et al. 2022). Hence, there has been a discernible shift towards Infrastructure Automated Defect Detection (IADD) in recent years, fuelled by emerging technologies' ability to expedite and improve defect detection and assessment reliability (Cheng and Wang 2018; Hsieh and Tsai 2020; Zhu et al. 2020; Munawar et al. 2021).

Various approaches have been developed in automated defect detection to analyse and interpret the vast and complex image data collected. Methods range from thresholding and edge detection to machine learning (ML) algorithms (Munawar et al. 2021). Notably, ML techniques have been identified as robust solutions to the challenges in infrastructure defect detection, offering advantages such as accuracy, automation, speed, customisability, and scalability over conventional methods (Assaad and El-Adaway 2020). Consequently, research leveraging ML algorithms for automated defect detection, including image classification-based techniques, object detection, and semantic segmentation, has proliferated in recent years (Pan et al. 2020). For instance, Protopapadakis et al. (2019) demonstrated the application of Convolutional Neural Networks (CNNs) with heuristic post-processing techniques for crack detection in tunnels, achieving high accuracy. While their study focuses on tunnel-specific infrastructure, it highlights the broader potential of ML approaches across various infrastructure types.

Despite rapid advancements in ML techniques for IADD, comprehensive reviews synthesising these developments and assessing their practical applications across various infrastructures are lacking. Particularly, the integration of diverse ML algorithms, their efficacy in different settings, and the evaluation of performance metrics in the context of varying data characteristics have not been thoroughly explored. This paper seeks to fill this gap by presenting a comprehensive review of state-of-the-art research employing diverse ML techniques in IADD. This study would benefit researchers in this

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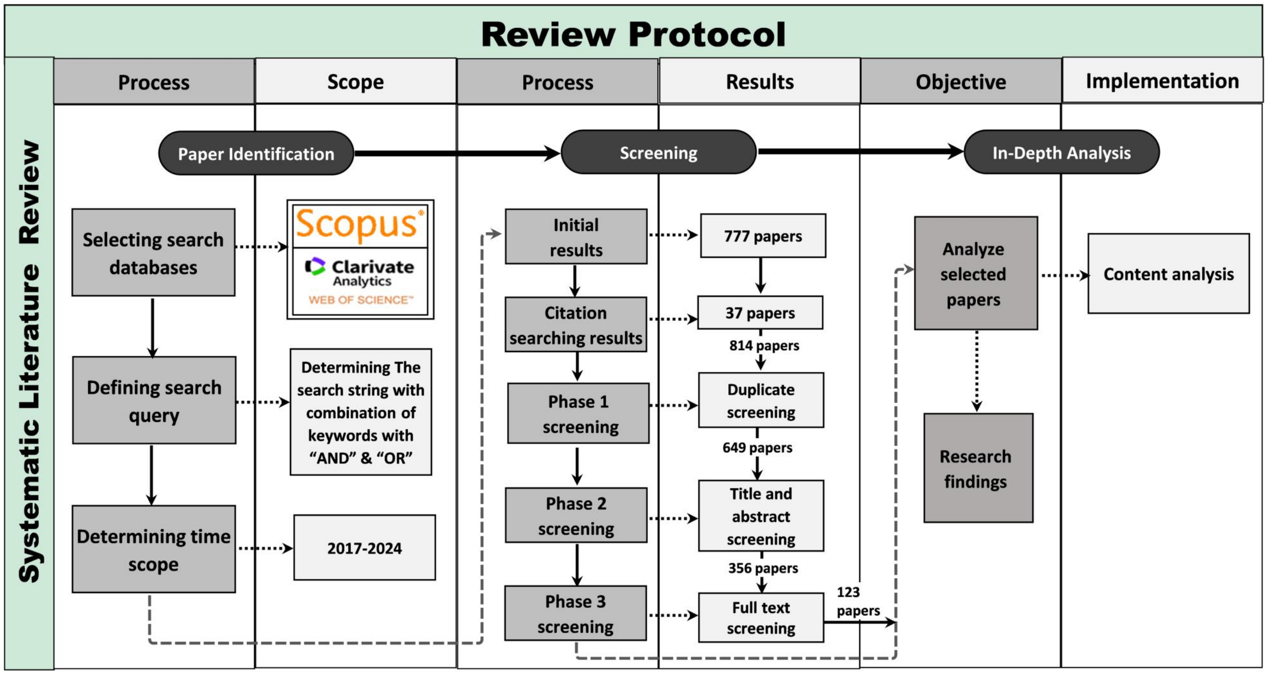

Figure 1. Review protocol.

field and enhance existing knowledge by gaining insights into the algorithms, datasets, characteristics, performance metrics, and significant defects detected by ML algorithms. The subsequent sections elaborate on our research methodology, analyses, and findings, followed by a discussion, conclusions, and recommendations for future research and development.

Research methodology

Review protocol

The study utilises a Systematic Literature Review (SLR) approach to explore the application of ML techniques in IADD. The protocol for this literature review encompassed three phases: data acquisition, screening, and in-depth analysis. Figure 1 illustrates this process, which is elaborated upon in the subsequent sections. The utilised protocol incorporates key elements of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, such as transparent reporting of search strategies, screening processes, and inclusion criteria, tailored to the engineering and infrastructure domains.

Paper identification

The primary objective of this phase was to identify the most pertinent academic articles for our analysis. Initially, we chose Scopus, Web of Science (WoS), and Google Scholar as our research engines. However, we excluded Google Scholar due to an overabundance of partially relevant articles. We formulated keywords using 'AND' and 'OR' to retrieve relevant articles, limiting our study to papers published post-2017. To delineate the scope related to infrastructure types, we conducted a preliminary search using a specific query, revealing that roads, bridges, and sewers account for 83% of research in ML-based automated defect detection (Figure 2). Consequently, we focused on these three types of infrastructure. The keywords for the main search were based on our research questions and scope, as shown in Table 1, to retrieve data on IADD research papers.

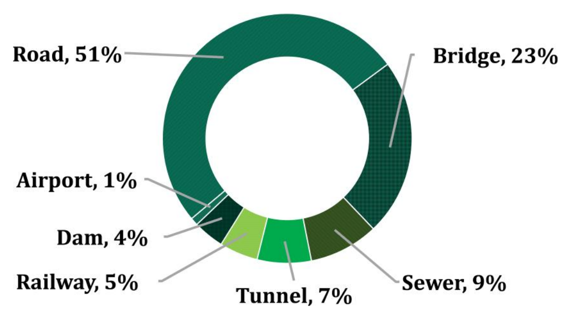

Figure 2. Infrastructure types with IADD research.

Table 1. Search query.

Search	String
Initial	('Road' OR 'Bridge' OR 'Sewer' OR 'Tunnel' OR 'Railway' OR 'Airport' OR 'Dam') AND ('Image processing' OR 'Machine learning' OR 'Deep learning') AND ('Defect detection' OR 'Crack detection' OR 'Damage detection') AND ('image' OR 'video')
Final	('Bridge' AND 'Road' AND 'Pavement' AND ('Sewer' OR 'Sewer pipe')) AND ('Image processing' OR 'Machine learning' OR 'Deep learning') AND ('Defect detection' OR 'Crack detection' OR 'Damage detection') AND ('image' OR 'video')

Screening

In the screening phase, we utilised formulated keywords in Scopus and Web of Science databases, aligning with our research questions on ML-based image processing techniques for IADD. Searches focused on titles, abstracts, and keywords from 2017 to 2024, yielding 777 papers. This period was chosen due to significant technological advancements in ML and IADD. To ensure comprehensive coverage, backwards and forward searching methods added 37 papers. A duplicate check reduced the total to 649 papers.

A three-stage filtering process further narrowed down the papers. The first stage, title filtration, excluded review papers, articles with vague titles, and those out of scope (e.g. thermal images, 3D images, radar images), reducing the papers to 383. The second stage, abstract filtration, used similar criteria. Papers focusing on very specific issues (e.g. camera angles) and those with non-standard abstracts (unclear

Table 2. Inclusion and exclusion criteria.

Phases	Criteria	Justification
Title and abstract screening	- Review papers are excluded. - Irrelevant titles are excluded. - Only articles on bridges, roads and sewer infrastructures are included. - Articles not aligning with research questions and scope are excluded.	- Focus on primary research. - Ensure clarity and relevance. - Broad coverage of key infrastructures - Relevance to the study's aim and scope - Broad thematic relevance - Ensure clear and comprehensive abstracts
Full-text screening	- Only articles on bridge, road and sewer infrastructure are included. - Articles considering very specific defects (e.g. bolt failing) are excluded. - Articles with insufficient information (e.g. algorithm, model, dataset) in methodologies are excluded.	- Relevance to core infrastructure - Alignment with the study's aim and scope - Focus on broadly applicable issues. - Exclude narrowly focused studies. - Ensure methodological clarity and rigour.

purpose, vague methodology, undisclosed findings) were excluded. This left 356 papers, which were downloaded for full-text analysis. In the final stage, full-text analysis, papers focusing on specific defects (e.g. bolt failure) or with unclear methodologies (sparse information on algorithm, model, datasets) were excluded. After this filtration, 123 papers remained for in-depth analysis. All protocol steps were independently verified by two researchers to ensure validity. The multi-phase screening approach (title, abstract, and full-text) follows systematic review principles akin to those outlined in PRISMA to ensure transparency and replicability Table 2.

In-depth analysis

In-depth analysis employed content analysis to address the research questions and evaluate the articles extracted from the screening phase. These methods align with a common objective of SLR, which involves examining the development of a specific research area (Saedi et al. 2022). Content analysis was used to synthesise the progression and intricacies of the IADD research domain, focusing on ML-based image processing techniques for IADD.

Analysis and results

Infrastructure defects classification

The type and severity of defects are essential criteria in risk assessment for deciding on infrastructure maintenance and repair activities (Ellingwood 2005). Consequently, many standards, such as the manual of sewer condition classification in the United Kingdom (Water Research Centre 2004), offer criteria and methods for infrastructure maintenance. Identifying defect types is the first step in risk assessment. Using ML-based image processing, several researchers have attempted to discover infrastructure defects (Li et al. 2020a; Yang et al. 2020a; Yin et al. 2021; Ahmadi et al. 2022). Figure 3 depicts the classification of detected defects in three types of infrastructure: roads, bridges, and sewers. Cracks are identified as the most prevalent defect in roads and bridges, while roots and obstacles are the most typical defects in sewer pipes. It also reveals a higher variety of defects detected in sewer pipes. This diversity could be attributed to the pronounced similarity among defects in this type of infrastructure. For instance, differentiating between various defects such as breakages, roots, cracks, fractures, and joint offsets through ML algorithms presents a significant challenge due to their visual similarity (Pan et al. 2020). A comparable issue arises when attempting to identify different types of cracks in road and bridge infrastructures (Mraz et al. 2020).

Machine learning techniques analysis on infrastructure automated defect detection

In the past decade, ML techniques have achieved exceptional success across various computer vision domains. They have been utilised in many image processing challenges, such as defect detection, and other civil engineering realms like construction progress monitoring (Dimitrov and Golparvar-Fard 2014; Elghaish et al. 2022; Talebi et al. 2022). A typical pipeline for employing ML-based image processing methods consists of several stages, including image capture, pre-processing, model training, and model testing (Munawar et al. 2021).

The subsequent sections will delve into critical specifics associated with deploying ML techniques for automated defect detection across three infrastructural settings: roads, bridges, and sewers. These specifics encompass training datasets, programming languages, tools and libraries, task analysis (such as segmentation, object detection, and classification), prevalent algorithms and specific models, as well as performance evaluation metrics.

Training datasets

In the realm of IADD using ML models, most published studies train and test their models on self-collected datasets (Li et al. 2020a; Yin et al. 2021; Ahmadi et al. 2022). These self-constructed datasets present a hurdle when comparing models (Sholevar et al. 2022). A standard dataset could address this issue (Eisenbach et al. 2017), allowing researchers to bypass the data collection stage. Numerous public image defect collections have been compiled for roads and bridges. However, due to the relatively recent adoption of ML for defect detection in sewer pipes, no public dataset is currently available. Figure 4 shows the proportion of public and self-collected datasets used in related literature for each infrastructure.

The resolution and distance of the captured images are critical factors in determining the quality of data used for ML-based defect detection. High-resolution images enable the detection of fine-grained details, such as micro-cracks or surface wear, while lower-resolution images may limit accuracy, particularly for subtle or distant defects (Abdellatif et al. 2021). Similarly, the distance from which images are captured influences the level of detail and the field of view. Close-range images provide higher detail but are limited in coverage, whereas distant captures are suitable for large-scale assessments but may compromise the resolution of finer defects (Murao et al. 2019). For instance, studies like Zhu et al. (2020) have demonstrated that optimising resolution and distance can significantly enhance the accuracy and reliability of defect detection models.

Prominent public datasets for roads include IEEE Big Data Cup Challenge 2020 (Jeong 2020; Kortmann et al. 2020), Deep Crack (Chen and Jahanshahi 2020; Qu et al. 2020; Al-Huda et al. 2023a), Crack Forest Dataset (CFD) (Chen and Jahanshahi 2020; Qu et al. 2020; Al-Huda et al. 2023a), Crack500 (Chen and Jahanshahi 2020; Qu et al. 2020; Al-Huda et al. 2023a), GAPs384 (Chen and Jahanshahi 2020; Yang et al. 2020b; Matarneh et al. 2024), AigleRN (Li et al. 2019a; Fang et al. 2021), CrackTree200 (Yang et al. 2020b; Fang et al. 2021;

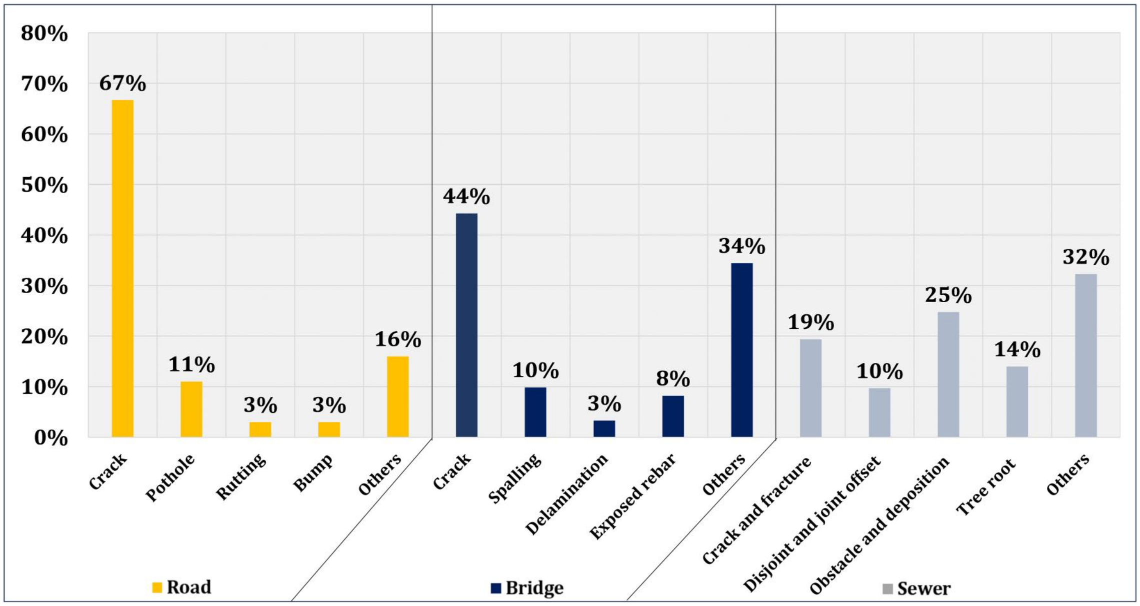

Figure 3. Infrastructure defects classification.

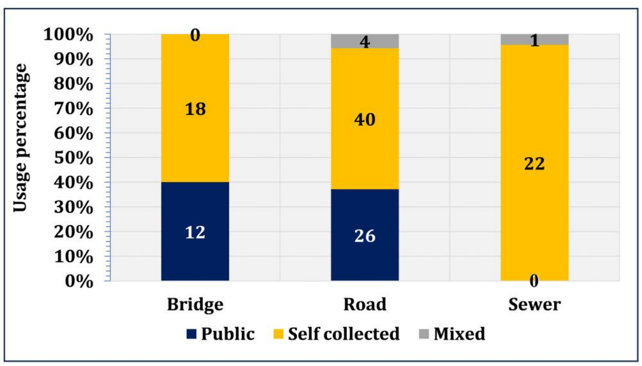

Figure 4. Dataset types for each infrastructure used in ML-based defect detection models.

Nooralishahi et al. 2022; Matarneh et al. 2024), and Crack IT (Abdellatif et al. 2021). For bridges, commonly used public datasets are Bridge88 (Jiang et al. 2021), BridgeTL58 (Jiang et al. 2021), BridgeXQ48 (Jiang et al. 2021), LiuYang128 (Jiang et al. 2021), BridgeDB288 (Jiang et al. 2021), Crack500 (Zhu et al. 2021a), SYD Crack (Zhu et al. 2021a), COCO-Bridge (Bianchi et al. 2021), SDNET (Yang et al. 2020a; Xiong et al. 2024), CCIC (Yang et al. 2020a), and BCD (Yang et al. 2020a). A significant limitation of public datasets for defect detection is the limited variety of defect types. Most of these datasets document only cracks. This constraint has been highlighted as a research limitation in studies by Angulo et al. (2019), Gong and Wang (2021), and Kruachottikul et al. (2021).

Analysis of programming languages, tools, and libraries

Python, a freely available programming language, and TensorFlow, an open-source ML library developed by Google, are the most frequently used tools for implementing ML-based image processing algorithms in infrastructure defect detection. Figure 5(a) and (b) highlight the distribution of programming languages and frameworks used to develop ML-based algorithms in three infrastructures: roads, bridges, and sewers. Factors contributing to the widespread use of Python and TensorFlow for implementing ML-based algorithms for IADD include simplicity and consistency, availability of high-level libraries and frameworks for Artificial Intelligence and ML, flexibility, platform independence, and expansive community support (Sholevar et al. 2022).

In addition to Python and TensorFlow, other platforms like MATLAB and the Caffe deep learning framework have facilitated the implementation of ML-based algorithms in fields beyond computer science, such as civil engineering. While these ready-to-use tools enhance accessibility and ease of use, it is important to note that they may also limit the flexibility and customisability that researchers have in developing their unique ML solutions.

Tasks analysis (segmentation/object detection/classification)

The strategies utilised for IADD leveraging ML-based image processing can be categorised into four main types: segmentation, classification, object detection, and hybrid methods. The choice of the most suitable approach for defect detection depends on factors such as the type of infrastructure, the nature of the defect, the dataset, and the standard guidelines and manuals for infrastructure asset management.

For instance, in the context of sewer pipe condition assessment, guidelines like the WRC manual in the UK (Water Research Centre 2004) stipulate various tasks necessary for a comprehensive evaluation. These tasks include defect type identification (such as root intrusion, joint offset, and infiltration), determination of defect location and orientation in the image, distance from the starting manhole, severity rating of the defect, and the tally of defects in each category. Consequently, a multitude of deep learning tasks ensue for sewer inspection, including (1) defect detection/classification of an image (Hu et al. 2023), (2) defect detection accompanied by bounding boxes to signify defect type and location (Zhang et al. 2023), and (3) pixel-level defect segmentation for quantitative assessment (Dang et al. 2023).

As depicted in Figure 6, in the context of road infrastructures, segmentation is the dominant detection approach, occupying 69% (25 out of 36) of the proportion. In bridges, classification is the most dominant task type. Due to the homogeneous nature of defect types, predominantly cracks, detection at the pixel level is

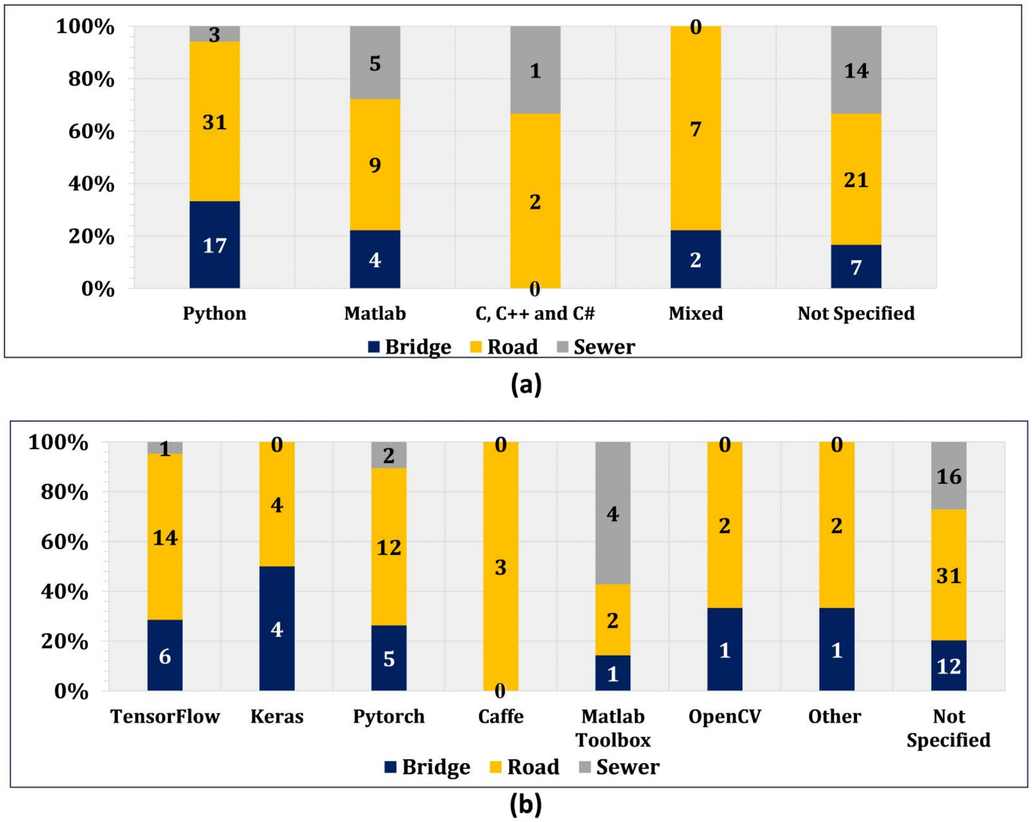

Figure 5. (a) Distribution of programming languages for implementing ML-algorithm in IADD, (b) distribution of libraries/frameworks/tools for developing ML-algorithm in IADD.

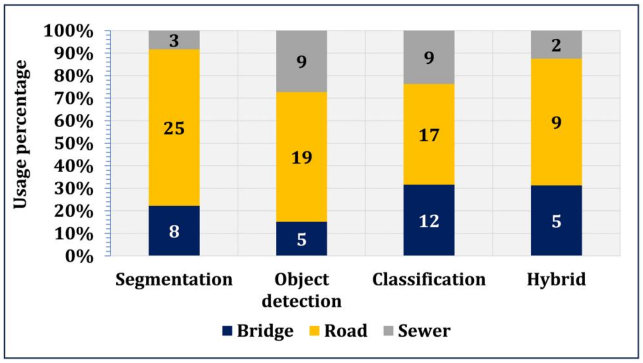

Figure 6. Categorisation of task types for each infrastructure.

paramount (Zhang et al. 2017). Additionally, given the enhanced importance of defect location in sewer pipes and the more advanced stage of robotics employment for inspections compared to other infrastructures, object detection and classification constitute the majority of tasks in sewer infrastructure analysis.

Performance metrics

The most frequently utilised evaluation metrics in the literature across infrastructures are accuracy, precision, recall, and F1 score for assessing ML models' performance. Most studies report high values for these metrics, suggesting strong performance in these applications. Precision, with a mean of 76.26% and a median of 83%, indicates models' high ability to identify positive instances correctly. Recall averages 75.59%, indicating robust performance in capturing positive instances, while the F1 Score, balancing precision and recall, averages 73.99%. The Area Under the Curve (AUC), though reported in fewer studies, has a mean of 79.76%, showing good class distinction capabilities. Mean Intersection over Union (MIoU), crucial for segmentation tasks, averages 68.98%, and accuracy, the most common metric, averages 89.57%, reflecting overall model correctness. Although AUC and MIoU are less frequently reported, they also show robust performance metrics when available. Some lower outliers indicate variability due to different datasets, models, or experimental conditions. This comprehensive performance overview demonstrates the effectiveness of ML techniques in this domain while also highlighting areas where further improvements and standardisations could be beneficial.

Figure 7 shows the relationship between dataset size and these metrics, revealing weak negative correlations for most metrics. Precision (−0.03), recall (−0.17), F1 score (−0.13), MIoU (−0.07), and accuracy (−0.07) indicate minimal impact of dataset size on performance, suggesting that larger datasets slightly challenge models but do not significantly degrade performance. Notably, AUC shows a moderate negative correlation (−0.67), implying that larger datasets complicate the model's ability to distinguish between classes effectively, likely due to increased data complexity and variability.

These insights highlight the robustness of ML models in infrastructure defect analysis, despite the increasing complexity of larger datasets. The minor negative trends suggest that as datasets grow, maintaining top performance becomes slightly more challenging, particularly for AUC. This underscores the importance of developing models that can adapt to and handle larger, more complex datasets. Future research should focus on enhancing model robustness and adaptability to ensure sustained high performance across varying dataset sizes. This comprehensive analysis of performance metrics provides valuable guidance

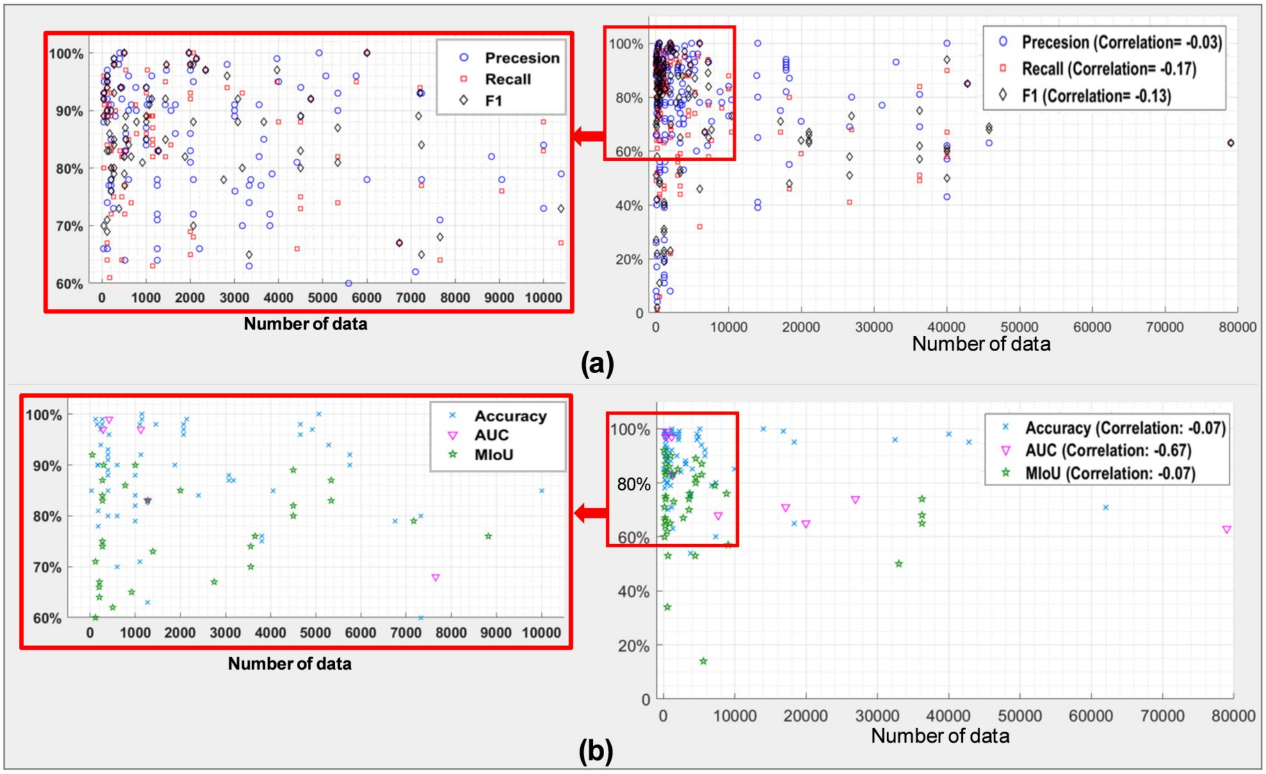

Figure 7. (a): Relationship between the number of data points and performance metrics (precision, recall and F1 score), (b): relationship between the number of data points and performance metrics (accuracy, AUC and MIoU).

for the continued application and improvement of ML techniques in infrastructure asset defect analysis.

In addition to performance metrics like accuracy and precision, computational cost is an important consideration when assessing the practicality of ML models for infrastructure defect detection. Classic CNNs, such as AlexNet and ResNet, provide high accuracy but often require significant computational resources, including high-end GPUs and extended training times, making them less feasible for real-time or edge-based applications (Protopapadakis et al. 2019). Lightweight models, such as MobileNet and SqueezeNet, address this challenge by optimising network architectures to reduce complexity and resource demands while maintaining reasonable accuracy. Ranjbar et al. (2022) demonstrate the practical feasibility of such lightweight models by applying MobileNet for asphalt defect detection, achieving a balance between efficiency and accuracy suitable for resource-constrained settings. Furthermore, tasks like pixel-level segmentation (e.g. U-Net) and multi-class object detection (e.g. YOLO) are computationally intensive due to their fine-grained processing requirements, which impact deployment feasibility in resource-constrained environments (Augustauskas and Lipnickas 2020). The trade-off between accuracy and computational efficiency remains a key challenge (Zhou et al. 2022c).

Algorithm analysis according to infrastructure type

The analysis of algorithms utilised for IADD reveals a diverse array of ML techniques employed across different infrastructure types. This section categorises these algorithms into non-deep learning and various forms of CNNs, providing a comprehensive overview based on the reviewed literature (Table 3).

Non-deep learning algorithms. Traditional ML algorithms, such as Support Vector Machines (SVMs), Decision Trees, K-Nearest Neighbours (KNN), Logistic Regression, and the Hough Transform, have been adapted for classification tasks in IADD. These models are generally less complex and require less computational power compared to deep learning models. However, they often rely on manually engineered features, which can limit their performance in more complex scenarios. For bridges, Li et al. (2020b) utilised these algorithms, demonstrating their applicability in this domain. While the simplicity and low computational requirements of traditional ML algorithms make them suitable for basic classification tasks, their reliance on manual feature engineering limits scalability to complex or large datasets (Hsieh and Tsai 2020). In the context of roads, studies by Majidifard et al. (2020), Ahmadi et al. (2022), and Cubero-Fernandez et al. (2017) showed effective use of traditional algorithms for defect detection. For sewer pipes, Moradi et al. (2020) and Myrans et al. (2018) applied SVM and Decision Trees, illustrating their utility in this infrastructure type. Despite these applications, these methods often fall short in handling intricate patterns or achieving high accuracy compared to deep learning models (Cheng and Wang 2018).

Classification – classic CNNs. Classic CNN architectures such as AlexNet, VGG, ResNet, Inception, and DenseNet have been extensively used for image classification tasks. These models leverage deep layers to automatically extract features from images, making them highly effective for defect detection. In bridge defect detection, Zhu et al. (2020) and Kruachottikul et al. (2021) employed ResNet, highlighting the superior performance of deep learning models. For road defect identification, Zhang et al. (2024) and Dung et al. (2019) used VGG and ResNet, showing significant accuracy improvements. For sewer pipe defect detection, Qu et al. (2020) and Gao et al. (2022) applied AlexNet and Inception, demonstrating the versatility of CNNs. While these models achieve high accuracy, they are computationally

Table 3. Analysing ML algorithms for automated defect detection in different structures.

Algorithm/Model	Bridge	Road	Sewer pipe
Non-deep learning algorithms*: • SVM • Decision Trees • KNN • Logistic Regression, • Hough transform	Li et al. (2020b)	Majidifard et al. (2020) Ahmadi et al. (2022) Cubero-Fernandez et al. (2017) Hoang (2019) Matarneh et al. (2025)	Moradi et al. (2020) Myrans et al. (2018)
Classification –Classic CNNs*: • AlexNet • VGG • ResNet • Inception • DenseNet	Zhu et al. (2020) Kruachottikul et al. (2021) Zhang et al. (2024) Deng et al. (2021) Dung et al. (2019) Zhang and Alavi (2021), Yang et al. (2020a)	Qu et al. (2020) Zhou et al. (2022a) Maniat et al. (2021) Gao et al. (2022) Zhang et al. (2020a) Ranjbar et al. (2022) Matarneh et al. (2024) Elghaish et al. (2025)	Chen et al. (2018) Situ et al. (2021) Li et al. (2019b)
Classification –Customised CNNs	Xu et al. (2019) Kun et al. (2022) Vignesh et al. (2021) Zhang et al. (2021)	Nhat-Duc et al. (2018) Park et al. (2019)	Ma et al. (2023)
Classification –Lightweight CNNs*: • SqueezeNet • MobileNet		Ranjbar et al. (2022) Hou et al. (2021) Yang et al. (2020b)	Zhou et al. (2021a) Chen et al. (2018) Situ et al. (2021)
Object Detection – CNNs*: • R-CNN • YOLO • SSD • RetinaNet	Xiong et al. (2024) Jiang et al. (2023) Deng et al. (2021) Zhang et al. (2018) Yu et al. (2021) Teng et al. (2022) Bianchi et al. (2021) Murao et al. (2019) Reghukumar and Anbarasi (2021) Zhu et al. (2020)	Zhou et al. (2022b) Angulo et al. (2019) Gou et al. (2019) Kortmann et al. (2020) Ranjbar et al. (2022) Jeong (2020) Ukhwah et al. (2019) Hu et al. (2021) Zhang et al. (2020a) Hegde et al. (2020) Silva et al. (2020) Li et al. (2021a) Lin et al. (2021) Wang et al. (2023a) Cano-Ortiz et al. (2024) Xing et al. (2023)	Cheng and Wang (2018) Wang and Cheng (2018) Wang et al. (2021) Kumar et al. (2020) Wang et al. (2023b) Zhou et al. (2022a) Yin et al. (2020) Kumar et al. (2020) Yu et al. (2024) Kumar et al. (2020) Yin et al. (2021) Kumar and Abraham (2019) Li et al. (2021c)
Segmentation – CNNs*: • U-Net • FCN • SegNet • DeepLab • PAN	Li et al. (2020a) Mohammed et al. (2022) Rubio et al. (2019) Jang et al. (2021) Lopez Droguett et al. (2022) Jiang et al. (2021) Sun et al. (2024) Zhu et al. (2021) Bae et al. (2021)	Li et al. (2019a) Fang et al. (2021) Augustauskas and Lipnickas (2020) Hsieh and Tsai (2020) Fan et al. (2020a) Chen et al. (2019) Chun and Ryu (2019) Liu et al. (2020) Al-Huda et al. (2023b) Wang and Su (2020) Peng et al. (2024) Li et al. (2022a) Li et al. (2022b) Joshi et al. (2022) Fan et al. (2020b) Alfarraj (2020) Jiang et al. (2021) Kaddah et al. (2020) Chen and Jahanshahi (2020) Yang et al. (2020b) Abdellatif et al. (2021) Qiao et al. (2021) Zhang et al. (2020b) Li et al. (2021b) Tong et al. (2020) Al-Huda et al. (2023a) Liu et al. (2020); Tsuchiya et al. (2019) Majidifard et al. (2020) Jung et al. (2019) Wang et al. (2023c)	Wang et al. (2023b) Guo et al. (2022) Zhou et al. (2022c) Khalid et al. (2021) Guo et al. (2022) Pan et al. (2020)

*Fine-tuned or variant versions of the ML model or algorithm.

expensive, as noted by Eisenbach et al. (2017) and Chen et al. (2018), requiring high-end GPUs and extended training times. This makes them less suitable for real-time applications or deployments in resource-constrained environments.

Classification – customised CNNs. Customised CNNs tailored for unique applications or datasets have also been utilised. These models are often modified versions of classic CNN architectures, adjusted to better handle specific tasks or data characteristics. Xu et al. (2019) and Kun et al. (2022) developed customised CNNs for bridge inspection, showing improved performance through architectural modifications. In the context of roads, Nhat-Duc et al. (2018) created specific CNN models, achieving higher precision. For sewer pipes, Ma et al. (2023) implemented customised CNNs, enhancing detection accuracy through tailored network designs. Although customised CNNs offer significant advantages in addressing task-specific challenges, their performance heavily depends on the availability of high-quality, task-specific training datasets, which can limit their broader applicability Elghaish et al. (2022).

Classification – lightweight CNNs. Lightweight CNN architectures designed for resource-constrained environments, such as SqueezeNet and MobileNet, have been employed. These models are optimised for speed and efficiency, making them suitable for deployment on devices with limited computational resources. For bridge defect detection, Ranjbar et al. (2022) used MobileNet, demonstrating the feasibility of lightweight models. In road inspections, Zhou et al. (2021a) and Chen et al. (2018) utilised SqueezeNet, balancing performance with efficiency. For sewer pipes, Situ et al. (2021) applied MobileNet, proving its adaptability to different infrastructure types. However, lightweight CNNs may trade off some degree of accuracy compared to classic CNNs, making them more suitable for scenarios prioritising efficiency over precision, as discussed by Dang et al. (2023).

Object detection – CNNs. CNN-based models for object detection, such as R-CNN, YOLO, SSD, and RetinaNet, are widely used for detecting and localising defects within images. These models can identify multiple defect types and provide bounding boxes for their locations. In bridge defect detection, Xiong et al. (2024) and Jiang et al. (2023) used YOLO, showcasing its ability to handle complex detection tasks. For road inspections, Deng et al. (2021) and Bianchi et al. (2021) employed SSD and YOLO, achieving high accuracy in defect localisation. In sewer pipe defect detection, Kumar et al. (2020) and Yin et al. (2021) utilised YOLO, highlighting its robustness in diverse environments. Although these models excel in defect localisation and multi-class detection, their performance can degrade when dealing with small or less distinct defects, as noted by Gao et al. (2022).

Segmentation – CNNs. CNN models for segmentation tasks, such as U-Net, FCN, SegNet, DeepLab, and PAN, have been adopted. These models partition images into meaningful segments, which is crucial for detailed defect analysis. For bridge defect segmentation, Li et al. (2020a) and Mohammed et al. (2022) used U-Net, enabling precise identification of defect areas. In road defect segmentation, Rubio et al. (2019) and Jang et al. (2021) employed DeepLab and SegNet, demonstrating their capability in handling complex segmentation tasks. For sewer pipes, Hsieh and Tsai (2020) and Peng et al. (2024) applied U-Net, providing detailed analysis of defect extents. However, segmentation models are computationally intensive, making their deployment challenging in real-time or resource-constrained environments, as highlighted by Deng et al. (2021).

Common tasks and most used algorithms by infrastructure type. In the context of bridges, classification tasks using classic CNNs, particularly ResNet, and traditional algorithms such as SVM and Decision Trees, are most common. The primary focus in this area is on identifying and classifying defects such as cracks and structural damages. For roads, object detection tasks are predominant, with YOLO and SSD being the most frequently employed algorithms. These models are used extensively to detect and localise various types of road defects, including potholes, cracks, and surface deformations. In sewer pipes, segmentation tasks are the most common, with U-Net and customised CNNs being the primary algorithms. These models focus on segmenting and identifying specific defects within the pipes, such as blockages and fractures, to provide detailed insights into their condition.

The integration of ML-based algorithms into existing inspection systems poses several challenges (Ahmadi et al. 2022; Elghaish et al. 2022). Computationally intensive models like ResNet and U-Net may require significant hardware upgrades (Augustauskas and Lipnickas 2020), while lightweight models such as MobileNet, despite their efficiency, may compromise accuracy in critical applications (Gao et al. 2022). Interoperability with legacy systems and data formats often necessitates middleware solutions to interpret ML outputs within existing workflows (Elghaish et al. 2025). Additionally, the transition to ML-based inspections requires investment in operator training, workflow redesign, and infrastructure upgrades (Assaad and El-Adaway 2020). These integrability challenges highlight the need for tailored solutions that balance computational requirements, performance, and cost to facilitate seamless adoption of ML algorithms in real-world inspection systems (Deng et al. 2021).

The integration of ML-based algorithms into inspection workflows increasingly involves robotic systems and drones. These technologies enhance defect detection by enabling remote, automated, and precise inspections, particularly in hazardous or hard-to-reach areas (Murao et al. 2019; Du et al. 2021). For example, drones equipped with high-resolution cameras and multi-modal sensors facilitate the collection of detailed data for defect analysis (Bianchi et al. 2021; Deng et al. 2021). Robotic platforms, such as autonomous ground vehicles, can be integrated with ML models to conduct inspections and even perform maintenance tasks, reducing the need for manual interventions (Jang et al. 2021). The EU-funded HERON initiative is a notable example, combining drones and robotic technologies with advanced ML-based tools to execute tasks like crack sealing, pothole repairs, and road marking in an automated workflow (Katsamenis et al. 2022). These innovations demonstrate the potential for ML-driven defect detection systems to evolve into comprehensive inspection and maintenance solutions (Bakalos et al. 2024). In summary, the most commonly used algorithms for each infrastructure type are:

- Bridges: Traditional algorithms (e.g. SVM, Decision Trees) and Classic CNNs (e.g. ResNet), primarily for classification tasks.
- Roads: Classic CNNs (e.g. VGG, ResNet) and Object Detection CNNs (e.g. YOLO, SSD), primarily for object detection tasks.
- Sewer Pipes: Customised CNNs, Lightweight CNNs (e.g. MobileNet), and Segmentation CNNs (e.g. U-Net), primarily for segmentation tasks.

This comprehensive analysis underscores the effectiveness and versatility of various ML models in IADD, providing a clear direction for future research and application development in this field. The algorithms and models listed in Table 3 are in their base forms, and most of the referenced studies include fine-tuned or variant versions, which are highlighted using an asterisk

(*) symbol. Ma et al. (2023) used the Transformer in addition to the CNN model listed in Table 3.

Conclusion, recommendations and limitations

This systematic review has critically analysed recent studies on IADD, covering 123 papers that address defect classification, datasets, programming languages, and performance metrics. The research domain was structured to analyse studies involving roads, bridges, and sewer systems. One major challenge identified is the difficulty in detecting similar defects, such as cracks, across different infrastructures due to the use of self-compiled datasets, which hinders the cross-comparison of model performances. Nevertheless, the review highlights a clear trend towards deep learning models, surpassing traditional ML approaches by eliminating the need for manual feature engineering, resulting in speed, accuracy, and applicability gains.

This review has highlighted several areas needing further investigation and underscored the dynamic nature of ML applications in infrastructure defect detection. Future efforts should focus on creating shared, well-annotated datasets representing various infrastructure defects to enhance model performance comparisons and support the development of models with broader applicability. Additionally, there is a significant need to investigate the severity of defects using ML to establish a hierarchy of defect criticality, aiding in the prioritisation of maintenance tasks and efficient resource allocation. Developing and validating models capable of functioning across different infrastructure types will improve the breadth and effectiveness of defect detection. Conducting longitudinal studies to monitor the real-world performance of ML models will provide insights into their long-term effectiveness and maintenance needs. Furthermore, research into integrating ML models with automated repair and maintenance systems could lead to a more proactive and streamlined approach to infrastructure management.

Future research should also focus on developing hybrid models that combine the strengths of traditional ML and deep learning techniques to enhance detection accuracy and efficiency. Applying transfer learning to use models trained with data from one type of infrastructure for others can help address the dataset creation problem. Enhancing the robustness of ML models to varying environmental conditions, such as light and weather, which affect image quality and defect detection accuracy, is also crucial. Moreover, improving the interpretability and explainability of ML models will help build trust among infrastructure managers, thereby facilitating better decision-making.

Recent developments in the field include large language models, which could be leveraged to automatically analyse vast numbers of inspection and maintenance reports, identifying patterns and predicting potential defects through natural language processing. Their ability to generate insightful reports and easily extract knowledge from text data can lead to user-friendly ML tools for non-experts, fostering the adoption of advanced defect detection technologies in infrastructure.

It is important to note that this review includes literature up to April 2024. Potential biases may exist in both the selection of databases and search terms, as relevant studies not indexed in the selected databases or not meeting the search criteria may have been overlooked. Similarly, papers not written in English may have been missed, omitting significant contributions. Despite these limitations, the review provides a thorough overview of the state of research up to the point of writing. The authors intend to pursue further work in developing a framework to identify the most suitable ML methods for effectively detecting specific defects and infrastructures, enabling more targeted and effective ML applications in infrastructure defect detection.

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analysed in this study.

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