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Review

Computer vision in drone imagery for infrastructure management

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ABSTRACT

Tertiary studies are conducted to offer a comprehensive perspective on a subject by compiling secondary literature at a meta-level. This study appraises secondary studies in computer vision applications for infrastructure management using drone-captured imagery to investigate different dimensions, trends and quality of secondary studies. This tertiary study uses three databases to select studies published from 2018 to 2023. A total of 57 secondary studies are analyzed. Various demographic and temporal patterns are examined by assessing the prevalence of secondary studies concerning the year of publication, publishing platforms, and the nature of the synthesis carried out. The quality of the secondary studies is evaluated using the Database of Abstracts of Reviews of Effects (DARE) criteria. The thematic analysis identifies six major application areas in infrastructure management, with miscellaneous applications categorized separately. The findings of the study offer a comprehensive overview of technological advancements, challenges, and potential applications in infrastructure management using drone imagery.

1. Introduction

Infrastructure refers to the fundamental physical and organizational frameworks required for the operation of a society or business, as well as the essential services and facilities necessary for the smooth functioning of an economy [1]. These encompass tangible fixed assets such as highways, bridges, airports, harbors, telecommunication networks, energy sources, water distribution systems, public utilities for sanitation, and information communication technology systems [2]. Infrastructure management involves the strategic oversight and optimization of these assets to ensure efficient operation, maintenance, and longevity of critical infrastructure elements. The significance of infrastructure management cannot be overstated, as it directly impacts the safety, efficiency, and sustainability of societies [3].

Traditional infrastructure inspections, reliant on visual assessment, have drawbacks such as subjectivity, human errors, and logistical inefficiencies [4–8]. These methods require physical access, leading to time and cost inefficiencies, often resulting in limited coverage and potential oversights. Additionally, they demand manual assessment, specialized personnel, and equipment, with safety concerns in hazardous environments. Furthermore, visual inspections lack real-time monitoring and continuous data collection, hindering prompt issue identification or change detection [8].

In recent years, Unmanned Aerial Vehicles (UAVs), commonly known as drones, equipped with sophisticated imaging sensors and intelligent algorithms, have found extensive applications in various civil sectors, including infrastructure management [9]. The introduction of small unmanned airborne systems (S-UAS) has enabled cost-effective data collection, precision at lower altitudes, and the capture of high spatial resolution imagery [10]. Advances in sensor technologies and seamless data integration further amplify their impact, contributing to the evolution of infrastructure management practices. This revolutionizes inspecting, monitoring, and maintaining critical infrastructure such as roads, bridges, buildings, and utility networks [11–13].

This research paper presents a systematic tertiary review of secondary studies focused on using image processing and computer vision techniques for drone spatial resolution imagery in infrastructure management. A tertiary review refers to a type of literature review that involves synthesizing and analyzing existing secondary reviews [14, 15]. The conducted study was designed systematically, and the quality of the secondary studies was assessed before inclusion. This study provides comprehensive insights into the evolving landscape of drone infrastructure management as synthesized in published secondary studies. We investigated three key research questions to unravel trends and patterns within this domain. Firstly, the demographics, data sources, and temporal patterns prevalent in the secondary studies are addressed. Secondly, the quality of published secondary studies is analyzed using the Database of Abstracts of Reviews (DARE) criteria [16]. Finally, the thematic analysis identified the six primary application areas in infrastructure management that are mostly managed by the analysis of drone imagery. These application areas include roads and pavements,

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bridges, buildings, traffic, construction management, and railways. All other applications were addressed under the heading of miscellaneous applications. The common computer vision methodologies used for infrastructure management are discussed. The limitations, challenges, and future directions are identified based on the synthesis of secondary studies. Therefore, the study is a comprehensive reference for researchers and practitioners in infrastructure management.

The major contributions of this paper include:

- The research methodologically synthesizes 57 secondary studies, offering a detailed overview and analysis of the existing literature in the field,
- Through the synthesis of secondary studies, the research identifies emerging trends, common approaches, and patterns in image processing and computer vision techniques for infrastructure management with drones,
- By analyzing the synthesized literature, the research identifies gaps and research opportunities within the domain.

The paper is structured as follows: Section 2 provides background information, including the motivation for conducting a tertiary review and an overview of existing related work. Section 3 outlines the research methodology employed in the tertiary study, while Section 4 delves into the results concerning demographics, data sources, and temporal trends. Section 5 presents findings related to the quality of selected secondary studies. Section 6 focuses on identifying and discussing the most prevalent infrastructure elements and the computer vision methods that are used. Moving forward, Section 7 explores the findings, emphasizing challenges faced and identifying prospects in the field. Lastly, Section 8 serves as the conclusion of the paper.

2. Background

Tertiary studies seek to address a broader scope of a phenomenon by providing meta-level contributions, employing the same methodology as a systematic literature review [15]. A tertiary study addresses broader research questions and compiles individual secondary studies [17]. This form of synthesis aids in pinpointing gaps, challenges, and potential future directions that can be explored. The decision to undertake a tertiary review is motivated by the extensive literature on various applications of infrastructure management using drone-captured imagery, accompanied by a proliferation of secondary studies synthesizing evidence in different application areas. The increasing number of these secondary studies, dispersed across various publication venues, presents a challenge for researchers in terms of locating and synthesizing pertinent information efficiently.

Motivated by this landscape, the presented tertiary review systematically consolidates and summarizes the secondary studies, offering a comprehensive overview of the research in infrastructure management utilizing drone-captured imagery. The presented tertiary review facilitates a more efficient understanding of the field by streamlining access to key findings, trends, and gaps. Additionally, the study identifies gaps in the existing literature, guiding future research efforts and contributing to advancing knowledge in the specific domain of infrastructure management by applying computer vision algorithms to drone imagery.

While the literature on infrastructure management using drone imagery is extensive, our decision to conduct a tertiary review stems from the limited existing contributions in this specific domain. Only a single tertiary review [18] exists in this area of research. The authors conducted a tertiary review with the aim of extracting in-depth information on the applications of unmanned aircraft systems (UAS) in civil engineering domains, encompassing construction, infrastructure operation, and environmental areas. The authors utilized the preferred reporting items for systematic reviews and meta-analysis (PRISMA) method to conduct a systematic tertiary review of 33 secondary articles published between 2011 and 2019. However, the broad scope of this tertiary review, encompassing all aspects of civil engineering, including construction, infrastructure operation, and environment, and incorporating methods beyond camera-based sensors, poses challenges in presenting a targeted and focused synthesis of the current state of literature. Moreover, this tertiary review covers literature till 2019. Unmanned aircraft systems (UAS) applications have witnessed significant advancements in recent years, with emerging technologies and methodologies continually shaping the landscape. As a result, the literature till 2019 may not fully capture the latest developments, cutting-edge methods, or transformative trends that have emerged in the field. Consequently, the review may not provide insights into the most current state-of-the-art practices and innovations in UAS applications within civil engineering contexts.

These deficiencies in the existing tertiary review underscore the necessity for more current and specific examinations within the realm of drone technology and infrastructure management. Our tertiary review ensures a more current and relevant field examination. The specific emphasis on image processing and computer vision schemes for infrastructure management using drone imagery adds precision and depth to the review, allowing for a nuanced exploration of the advancements, challenges, and applications within this rapidly evolving domain. In essence, our tertiary review addresses the limitations of existing literature reviews, providing a timely, specialized, and in-depth analysis that caters directly to the needs of researchers, practitioners, and decision-makers involved in the intersection of drone technology and infrastructure management.

3. Research method

The systematic review methodology outlined by Kitchenham and Charters [15] was used for this tertiary study. The review process encompassed various steps, such as formulating research questions, defining inclusion and exclusion criteria, constructing a search string, validating the search string, and identifying pertinent databases for the study. The subsequent sub-sections (Sections 3.1–3.8) provide detailed explanations of the research methodology utilized in this study.

3.1. Research questions

Research questions (RQs) and sub-research questions were designed to collect evidence from the research on the usage of image processing/computer vision in drone image infrastructure management. The research questions drew inspiration from the framework proposed by Kitchenham and Charters [15].

RQ1: What insights can be gained from published secondary studies regarding the trends in demographics, data sources, and temporal patterns?

- RQ 1.1 What online databases have been included as sources?
- RQ 1.2 How are the secondary studies distributed among different publishers?
- RQ 1.3 What is the count of primary studies incorporated in the secondary studies?
- RQ 1.4 How many citations does each secondary study receive?
- RQ 1.5 What is the yearly distribution of the secondary studies?
- RQ 1.6 Which countries are leading in conducting secondary research on drone infrastructure management?
- RQ 1.7 What is the temporal and country-specific pattern of publications concerning publishers?

RQ2: What patterns can be observed in the quality of published secondary studies over time?

- RQ 2.1 What kind of synthesis has been performed in the secondary studies?
- RQ 2.2 How has the standard of secondary studies published evolved through the years?

Table 1
Mapping of research questions to sections.

Research question	Section
RQ1.1, RQ1.2	4.1
RQ1.3	4.2
RQ1.4	4.3
RQ1.5	4.4
RQ1.6	4.5
RQ1.7	4.6
RQ2.1	5.1
RQ2.2, RQ 2.3	5.2
RQ3.1, RQ3.2	6.1-6.7
RQ3.3	7.1
RQ3.4	7.2

RQ 2.3 What are secondary studies' quality weaknesses and strengths?

RQ3: What are the prevalent applications of computer vision methods in infrastructure management using drone imagery discussed in the secondary studies?

RQ 3.1: What are the most common infrastructure management applications using computer vision for drone imagery?

RQ 3.2: What are the most common computer vision methods used in infrastructure management with drone imagery?

RQ 3.3 What are the limitations and challenges faced when implementing computer vision methods in infrastructure management with drone imagery?

RQ 3.4 What are some promising research areas as indicated in the secondary studies?

3.2. Mapping research questions to sections

Table 1 presents the relationship between specific research questions and the corresponding sections in a research paper. Each research question is identified by its unique label (such as RQ1.1) and is associated with the specific section it addresses. This table serves as a reference to quickly locate the sections that discuss the corresponding research questions, providing a clear overview of how the research paper is organized.

3.3. Approach used to generate search terms

Following the guidelines suggested by Kitchenham and Charters [15], the known papers were initially explored to extract keywords from them. The key terms for this work are drones, image processing, computer vision, infrastructure management, and different infrastructure management applications. These keywords' synonyms were identified using domain knowledge, titles, keywords, abstracts, and text of known papers. Different aspects of infrastructure, such as road damage, traffic, etc., were found, and search terms were identified for each.

The terms Unmanned Aircraft System (UAS) and Unmanned Aerial Vehicle (UAV) are often used interchangeably in the literature, but they represent distinct concepts within the realm of unmanned aerial technology. A UAS includes the UAV, ground control station, and communication link, emphasizing holistic integration. In contrast, UAV specifically refers to unmanned aircraft, excluding ground-based elements. While the UAV emphasizes the flying vehicle, UAS considers the entire system's functionality and interaction, encompassing the airborne platform and its associated ground control and communication components. Therefore, the term UAS imagery has been explicitly mentioned in the search string.

The search terms were combined using boolean operations, resulting in the following search term:

((computer vision) OR (image processing) OR (image analysis) OR (object detection) OR (image segmentation) AND (drone imagery) OR (remote sensing) OR (unmanned aerial vehicle imagery) OR (UAV imagery) OR (Unmanned Aircraft Systems Imagery) OR (UAS imagery) OR (low altitude aerial imagery) AND (infrastructure management) OR (infrastructure inspection) OR (infrastructure planning) OR (civil infrastructure) OR (civil applications) OR (asset management) OR (urban application) OR (smart cities) OR (Building) OR (Road) OR (Traffic) OR (Bridge) OR (Railway) OR (Crack Detection) OR (Power Infrastructure) OR (Applications) AND (systematic literature review) OR (SLR) OR (meta-analysis) OR (survey of the literature) OR (review of the literature) OR (secondary study) OR (review))

Due to its excessive length, the final search query could not be executed on the databases because of restrictions on the number of terms. The search term was simplified by consolidating similar terms and removing specific keywords such as "urban application", "building", "road", "traffic", "bridge", "railway", and "crack detection" were excluded as they are encompassed within the broader category of infrastructure management. Further, the terms used to find literature reviews are also excluded, as all databases provide an option to select only the review papers. The reduced search term is:

((computer vision) OR (image processing) AND (drone imagery) OR (remote sensing) OR (unmanned aerial vehicle imagery) OR (UAV imagery) OR (Unmanned Aircraft Systems Imagery) OR (UAS imagery) OR (low altitude aerial imagery) AND (infrastructure management) OR (infrastructure inspection) OR (infrastructure planning) OR (civil infrastructure) OR (civil applications) OR (asset management))

3.4. Validation of search strings

A validation process was undertaken to gauge the effectiveness of the finalized search string in retrieving pertinent results. This validation procedure entailed comparing the retrieved records using the search string against a quasi-gold standard, which served as a reference collection of relevant studies that an ideal search strategy should identify [19]. The objective was to ascertain if the known studies included in the quasi-gold standard were present among the records obtained by executing the finalized search string. Consequently, all three known studies were successfully identified, affirming the validation of the search string. Initially, the selection of known studies commenced with a search on Google Scholar employing identified keywords(drones, image processing, computer vision, and infrastructure management). Subsequently, the keywords and abstract of the retrieved papers were matched with the identified keywords. The three known studies were as follows:

1. Unmanned aerial vehicles (UAVs): A survey on civil applications and key research challenges, IEEE Access, vol. 7, pp. 48572–48634, 2019.
2. Synthesis of unmanned aerial vehicle applications for infrastructures, Journal of Performance of Constructed Facilities, vol. 32, no. 4, pp. 04018046, 2018
3. A review on deep learning in UAV remote sensing", International Journal of Applied Earth Observation and Geoinformation, vol. 102, p. 102456, 2021.

3.5. Databases used for search

Scopus [20], Web of Science [21], and ScienceDirect [22] were the databases selected for the tertiary review. These are widely recognized as comprehensive and multidisciplinary databases encompassing various scholarly literature. The search across these databases was conducted to achieve comprehensive coverage of relevant literature about the research topic. The time restriction for selecting papers published after 2018 was imposed to ensure that the study primarily includes the most recent research and findings. The initial search was conducted in March 2023 during the first iteration and subsequently updated in July 2023 for the second iteration, followed by another update in December 2023. After performing the search query in these databases, the obtained records were methodically organized for additional documentation and processing purposes.

The first author searched the databases. Subsequently, the second author independently verified the results obtained by the first author. This verification process involved cross-referencing the identified papers to ascertain their relevance based on the predefined criteria. Any discrepancies or uncertainties were resolved through discussion between the two individuals. Both individuals adhered strictly to the established search protocol to ensure consistency throughout the search process.

3.6. Inclusion/exclusion criteria

The papers meeting the following criteria are included:

1. The study focuses on computer vision techniques applied to drone imagery for infrastructure management.
2. The study is a secondary review article published in English.
3. The study must have been conducted with a publication date of 2018 to 2023.

The papers were excluded based on the following criteria:

1. Studies that do not focus on computer vision techniques applied to drone imagery for infrastructure management.
2. Studies that are not written in English.
3. Studies that are not available in scholarly journals or conference proceedings.
4. Studies older than 2018.
5. Studies that discuss energy infrastructure, urban planning and development, agricultural applications, and environment monitoring.

3.7. Quality assurance protocols and guidelines

To evaluate the quality of every secondary study, an assessment was conducted for each study using the Centre for Reviews and Dissemination Database of Abstracts of Reviews of Effects (DARE) criteria [16]. The DARE questions and ranking are as follows:

1. Are the criteria for including and excluding studies in the review clearly stated and appropriate? (Ranking Criteria: Defined Explicitly (1 point), Defined Implicitly: 0.5 points, Not defined: 0 points)
2. Has the literature search been comprehensive enough to encompass all pertinent studies? (Ranking Criteria: Databases used to search are mentioned (1 point), Database searched is implicitly mentioned (0.5 points), No database searched (0 points))
3. Have the reviewers assessed the quality and validity of the studies incorporated in the review? (Ranking Criteria: Explicit quality criteria were established (1 point), Quality criteria were evaluated without being explicitly specified or defined (0.5 points), No evaluation or assessment of the quality criteria has been conducted (0 points))
4. Have the fundamental data and details of the studies been adequately presented? (Ranking Criteria: The information provided is presented clearly and can be attributed to specific studies. (1 point), The information is organized into categories or groups but is not directly linked to individual studies (0.5 points), The information provided does not include references to sources or citations (0 points))

The quality assessment of selected secondary studies was conducted using the DARE criteria. A triad of Yes, Partial, and No (assigned values of 1, 0.5, and 0) was established for each question to determine the rigor of each study. Based on the responses, 1, 0.5, or 0 scores were assigned to each study's four DARE criteria questions. The quality of each paper was determined by calculating the sum of scores for each question. The quality score for each study ranged from 0 to 4, with higher scores indicating better quality based on the conducted review. To ensure the inclusion of only studies of the highest quality, those with scores below 2 were excluded. While this exclusion decision was subjective, its purpose was to guarantee the inclusion of only the highest-quality studies in the analysis.

3.8. Selection process

The selection process entailed matching the studies with the inclusion criteria to ascertain their suitability for incorporation into the synthesis. Any study that did not meet the inclusion criteria was excluded from the analysis. Initially, all abstracts were reviewed, and only those meeting the predefined inclusion and exclusion criteria were included. Subsequently, a thorough screening of full-text articles was conducted to assess their relevancy to the study. Finally, a comprehensive quality check was performed to ensure that only articles meeting the predefined quality criteria were included in the final synthesis. This three-phase selection process enabled the acquisition of high-quality and reliable data for the study.

Identifying studies involved conducting searches in specified databases using the finalized search terms and performing initial scrutiny in March 2023, resulting in 110 studies. The flow of study inclusion throughout the systematic review was visually presented using the PRISMA diagram (see Fig. 1). The initial searches in the databases yielded 110 studies. To update the systematic literature review (SLR), a second search iteration was conducted in July 2023, followed by a third iteration in December 2023, resulting in an additional 20 and 13 studies, respectively (Fig. 1). After eliminating duplicate studies, 88 unique studies remained—62 from the first iteration, 16 from the second iteration, and 10 from the third iteration. Upon screening the abstracts according to the inclusion and exclusion criteria, 14 studies were excluded. Consequently, 76 studies met the criteria for full-text screening (N = 76). Of these, 15 studies did not meet the inclusion criteria, making 61 studies eligible for screening in phase 3. Applying the DARE quality criteria, it was found that 4 studies scored below 50%, resulting in a final selection of 57 primary studies (N = 57).

4. Demographics, data sources and temporal trends

4.1. Databases used and selected studies

As mentioned in Section 3.5, Scopus [20], Web of Science [21], and ScienceDirect [22] were the databases used for searching the secondary studies. Table 2 categorizes the selected studies by their respective publishers, includes references for each study, and assigns a unique code to facilitate referencing throughout the paper. The codes are based on the publisher names for easy identification and citation in the text and figures. Table 2 also answers RQ 1.2 by showing the distribution of the studies among different publishers.

4.2. No. of primary studies in each secondary study

Of 57 secondary studies, 31 explicitly listed the number of primary research papers. The corresponding number of primary studies for each of these 31 studies is displayed in Fig. 2.

However, for the remaining 26 studies, the number of primary studies was not mentioned. To determine the number of included primary studies for these papers, the title of each paper was carefully examined from the list of references in each secondary study. The review papers and those that laid down foundational arguments, such as introductions to deep learning, computer vision, or the history of UAVs, were excluded. In cases where the title did not distinguish between the studies, the abstracts of the primary studies were consulted. Fig. 3 displays the calculated primary studies included in each secondary study for which the number was not directly provided.

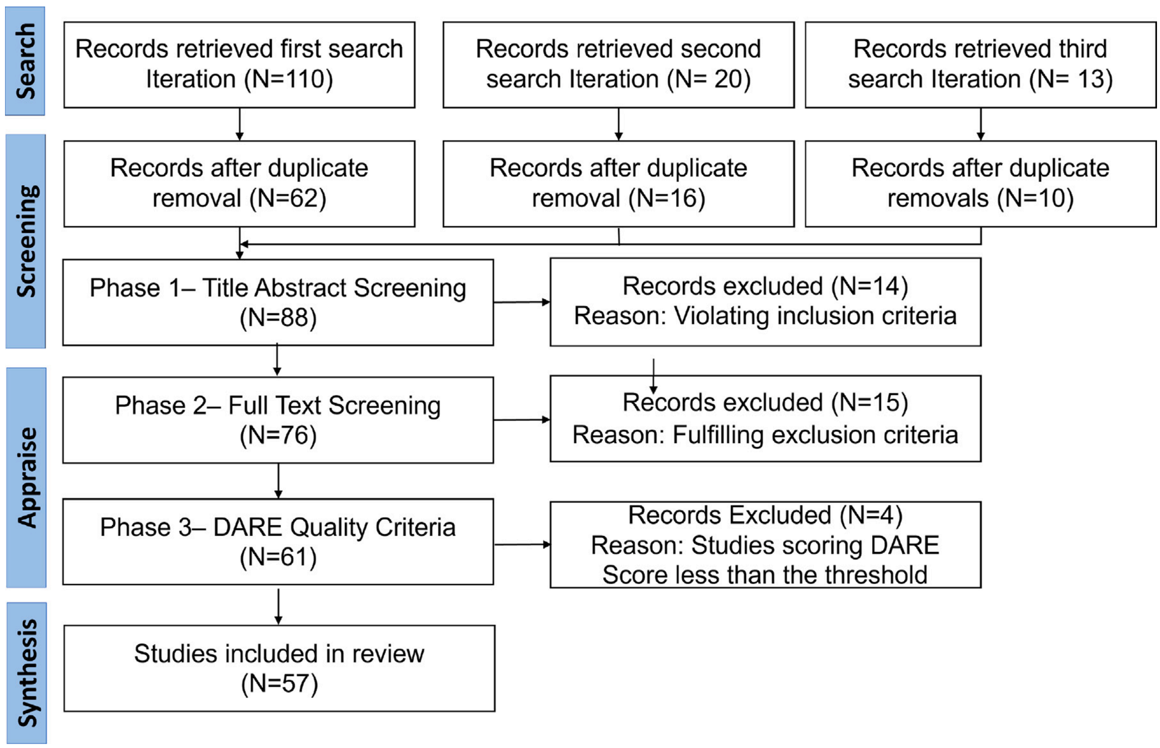

Fig. 1. Prisma Diagram.

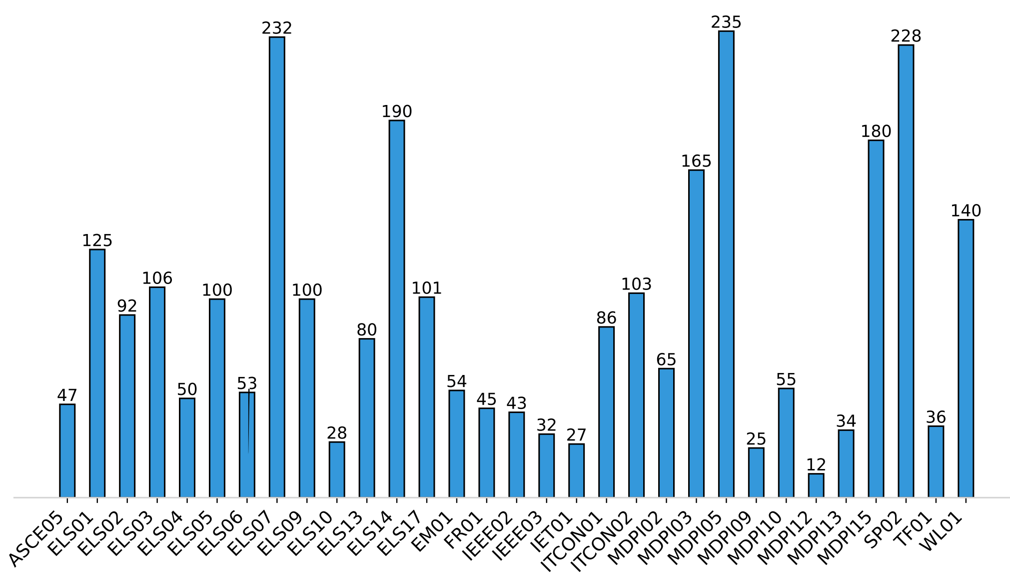

Fig. 2. No. of Primary Studies included (Directly given).

4.3. Citation count

A frequency analysis was employed to ascertain the count of citations received by each secondary study. The citation data was extracted from Google Scholar on June 06, 2023, and then updated on January 2, 2024. Assessing the number of citations for a specific secondary study provides an approximate measure of its research impact.

To ensure a fair assessment, the citation count was normalized by considering the publication year of the secondary study. Calculating the normalized citation count involved dividing the actual citation count by the time gap between the publication year of the study and the present year (2023). One has been added to the denominator to avoid dividing by zero error. Fig. 4 depicts the normalized citation score for each secondary study.

4.4. Year wise distribution

The selected studies were published across multiple years, and publications' distribution varies yearly, as shown in Fig. 5. In 2023, 12 publications were identified as relevant to our review. The preceding year, 2022, witnessed the highest number of publications, totaling 17. In 2021 there were 8 publications, followed by 7 in 2020 and 5 in 2019. Additionally, the year 2018 also yielded 8 publications. This year-wise distribution provides insights into the temporal trends of relevant studies, showing fluctuations in research output over the years.

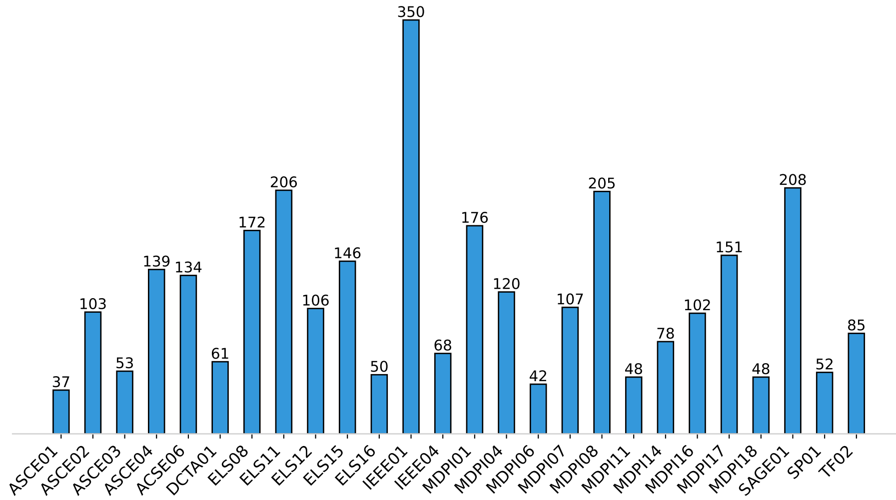

Fig. 3. No. of Primary Studies included (Not Directly given).

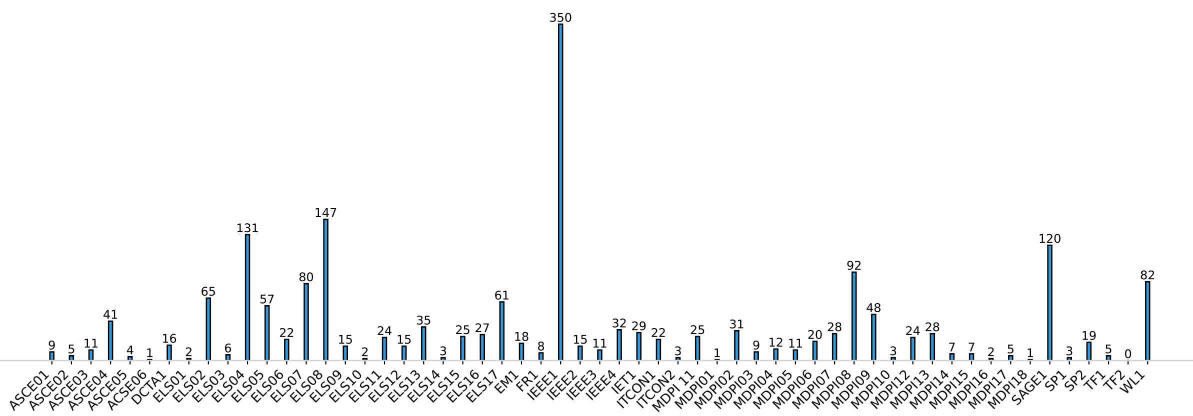

Fig. 4. Number of Normalized Citations for each Secondary Study.

Table 2
Publisher and secondary studies codes.

Publisher	Codes assigned to secondary studies
Elsevier	ELS1 [23], ELS2 [24], ELS3 [25], ELS4 [26], ELS5 [27], ELS6 [5], ELS7 [28], ELS8 [29], ELS9 [30], ELS10 [31], ELS11 [32], ELS12 [33], ELS13 [34], ELS14 [35], ELS15 [36], ELS16 [37], ELS17 [11]
MDPI	MDPI1 [38], MDPI2 [39], MDPI3 [40], MDPI4 [41], MDPI5 [42], MDPI6 [43], MDPI7 [44], MDPI8 [45], MDPI9 [46], MDPI10 [47], MDPI11 [48], MDPI12 [49], MDPI13 [13], MDPI14 [50], MDPI15 [51], MDPI16 [52], MDPI17 [53], MDPI18 [54]
ASCE	ASCE1 [55], ASCE2 [56], ASCE3 [57], ASCE4 [58], ASCE5 [59], ASCE6 [60]
IEEE	IEEE1 [9], IEEE2 [61], IEEE3 [62], IEEE4 [63]
Springer	SP1 [64], SP2 [65]
Taylor & Francis	TF1 [66], TF2 [67]
ITCON	ITCON1 [68], ITCON2 [69]
Miscellaneous	Wiley: WL1 [70], Frontiers: FR1 [71], Emerald: EM1 [72], IET: IET1 [73], SAGE: SAGE1 [74], DCTA: DCTA1 [75]

4.5. Country-wise distribution of studies

Based on the collected literature, analyzing the country-wise distribution of publications reveals a diverse landscape of research contributions. Fig. 6 shows the country-wise distribution of secondary studies. In cases where the authors of the studies hailed from different countries, the country of the corresponding author was selected as the designated country of publication. The United States of America (USA) had the highest count, with 18 publications. China had 6 publications, while India had 6 publications. Canada had 4 publications. United Arab Emirates (UAE) had 3 publications, followed by Australia, Italy and Korea with 2 publications each. Algeria, Brazil, Egypt, Greece, Iran, Iceland, Malaysia, New Zealand, Portugal, Qatar, Romania, Russia, Saudi Arabia and Spain each had 1 publication. The wide distribution of publications across various countries underscores the collaborative nature of scientific research and the collective pursuit of knowledge on a global scale.

4.6. Temporal and country-specific publication patterns involving publishers

Fig. 7 visually represents the distribution of the selected secondary studies across different years and publishers. It can be seen that for most of the publishers, most of the secondary studies were published in 2022 and 2023. Fig. 8 illustrates the publisher-wise distribution of secondary publications from different countries. Elsevier and ASCE seem to be the popular publishing venues for authors from the USA and China.

5. Quality of selected secondary studies

5.1. Types of secondary reviews

The selected secondary studies encompassed various types of reviews. Table 3 categorizes the 57 secondary studies (or literature reviews) into systematic, comprehensive, and narrative reviews. A

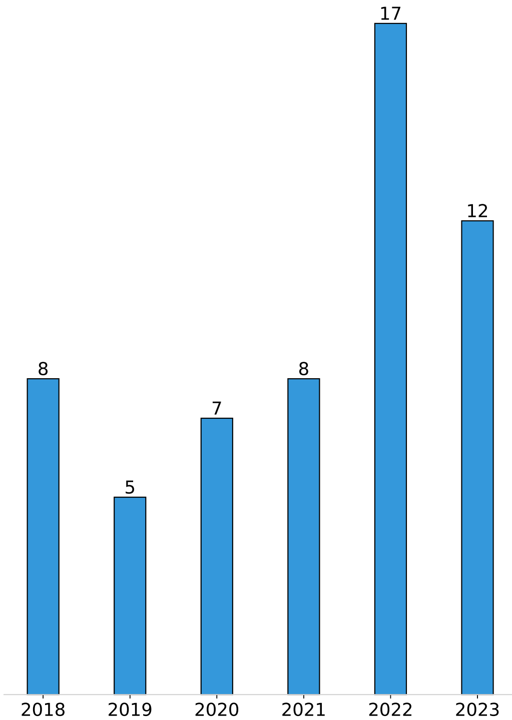

Fig. 5. Yearly Distribution of Selected Studies.

Table 3
Literature review types.

Literature review type	Corresponding publications
Systematic Literature Review	ASCE5, ELS1, ELS3, ELS6, ELS7, ELS9, ELS10, ELS14, ELS17, IEEE3, EM1, IEEE2, MDPI2, MDPI3, MDPI5, MDPI9, MDPI10, MDPI13, MDPI15, ITCON1, ITCON2, FR1
Comprehensive Review	ASCE2, ASCE3, ASCE6, DCTA1, ESL5, ELS11, ELS12, ELS13, ELS15, IEEE1, SP2, IEEE4, MDPI4, MDPI6, MDPI7, MDPI8, MDPI11, MDPI14, MDPI16, MDPI17, MDPI18, SAGE1, WL1, TF2
Narrative Review	ASCE1, ASCE4, ELS2, ELS4, ELS8, ELS16, IET1, MDP1, MDPI12, SP1, TF1

systematic literature review (SLR) follows a rigorous and structured approach, employing predetermined criteria and protocols to analyze existing literature. It involves a systematic search and selection process, critical appraisal of studies, and synthesis of findings. On the other hand, comprehensive reviews aim to provide a comprehensive overview of the literature on a specific topic, surpassing the scope of systematic reviews. They include a broader range of studies, such as empirical research, theoretical perspectives, and conceptual frameworks. The narrative reviews offer a subjective summary and interpretation of the literature on a particular topic. They do not adhere to a systematic or rigorous methodology and instead provide a narrative description and discussion of selected studies. Of the selected 57 studies, 22 were SLRs, 24 were comprehensive reviews, and the rest were narrative reviews.

5.2. Quality assessment score

The quality assessment scores of all 57 studies are provided in Appendix (Table A.1), where the evaluation is based on the criteria outlined in Section 3.7. The quality scores for each secondary study varied between 2 and 4. The overall quality of the selected secondary studies was deemed relatively high, as evidenced by a mean score of 3.06 out of 4.0. The quality scores were categorized as low (ranging from 1 to 2), medium (score of 2.5), and high (ranging from 3 to 4). Studies with a DARE score below 2 had already been excluded from consideration.

Out of the 57 analyzed studies, only one received a DARE score of 2, accounting for only 1.75% of the total studies. The majority of studies, 26 out of 57 (45.61%), received a DARE score of 2.5, which suggests that they were of slightly better quality or met the DARE criteria more closely. Meanwhile, 9 studies (15.79%) earned a DARE score of 3, indicating that they performed well in meeting the criteria. 6 studies (10.53%) received a DARE score of 3.5, suggesting they adhered even more closely to the DARE criteria. Finally, the highest DARE score of 4 went to 15 studies (26.32%), which demonstrated exceptional adherence to the criteria and were of the highest quality.

Fig. 9 shows the quality of the selected secondary studies in terms of year of publication from 2018 to 2023. No significant correlation was observed between the year of publication and the DARE score.

The DARE scores exhibit significant variation based on the type of review. Systematic Literature Reviews (SLRs) attained an average DARE score of 3.80, suggesting a relatively strong adherence to the DARE criteria. SLRs are known for their rigorous and comprehensive methodology, encompassing all the information outlined in the DARE criteria. This accounts for their higher average score compared to other review types. On the other hand, comprehensive reviews garnered an average DARE score of 2.60, indicating a slightly lower score than SLRs. Although comprehensive reviews offer a comprehensive overview of the literature, they may have specific limitations regarding methodology or adherence to the DARE criteria. Similarly, narrative reviews received an average DARE score of 2.59, suggesting that narrative reviews also encountered similar challenges concerning methodology and adherence to the DARE criteria. Overall, the results show that SLRs had the highest average DARE score, indicating higher quality and adherence to the DARE criteria. Comprehensive and narrative reviews had lower average scores, suggesting they had some limitations regarding methodology or the extent to which they met the DARE criteria. It is essential to consider these differences in the interpretation and reliability of the findings when assessing the quality and evidence provided by each type of review.

6. Thematic analysis

To address RQ3, the themes were coded using NVIVO software. A comprehensive examination of each secondary study was conducted to thoroughly understand the discussed infrastructural elements. These studies' objectives and research questions were carefully analyzed and categorized into appropriate themes through systematic coding. This thematic analysis helped us comprehend the various dimensions synthesized in the studies (Fig. 10), enabling us to answer RQ3.1. The analysis revealed six significant applications, while all others were grouped under the miscellaneous applications category. Therefore, seven types of applications were identified, including Bridge Inspection, Building Inspection, Construction Management, Railways Management, Roads and Pavements Management, Traffic Management, and miscellaneous applications.

Some studies reviewed one narrow infrastructure management domain, while others have a broader scope. Table 4 displays the distribution of the selected studies according to the infrastructure types discussed in them. Most studies collated evidence on the management of roads, pavements, and highway management with 33 studies, followed by Bridges Inspection and Building Inspection with 31 and 28 studies, respectively. 16 studies contributed to traffic management. 8 studies discussed construction management, while 5 reviews discussed railway management. Finally, 13 papers discuss miscellaneous applications.

In the following subsections (Section 6.1 to Section 6.7), we will discuss each of these applications.

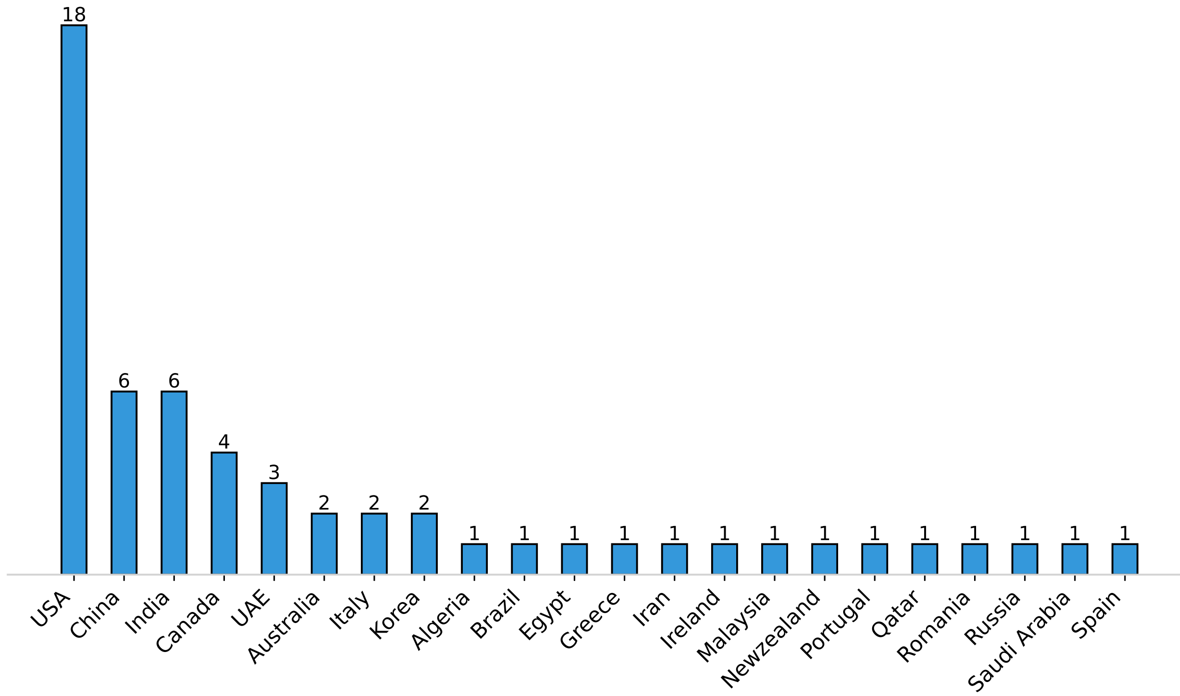

Fig. 6. Country wise Distribution of studies.

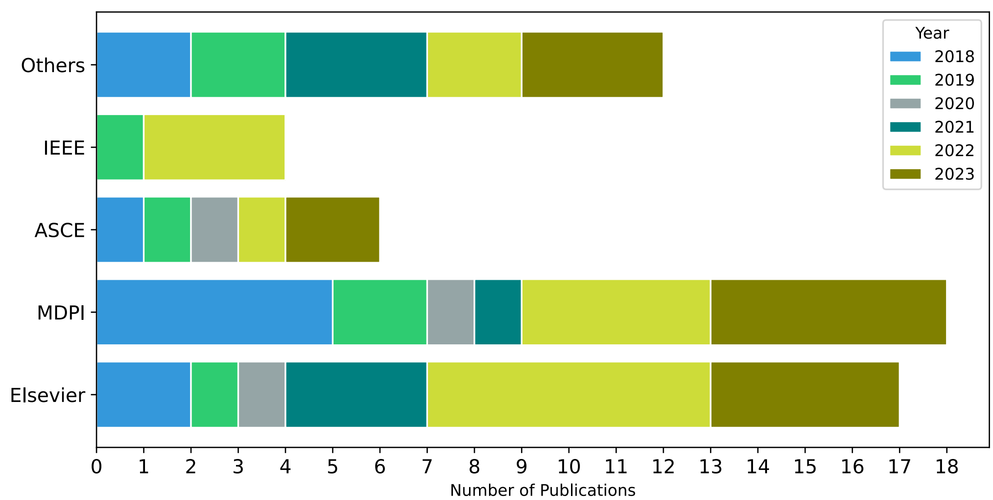

Fig. 7. Yearly Distribution of publications by Publisher.

6.1. Management of roads and pavements

Of 33 studies, 9 are specific to roads and pavements, whereas the rest cover other infrastructure components. The initial step in road management involves extracting roads from UAV imagery. The second task is to identify the specific locations of distress on the road. Lastly, the third step entails quantifying the severity or level of distress observed on the road.

The authors in Abdollahi et al. [46] provided a dedicated review of the task of road extraction using deep learning models. Models such as GANs (Generative Adversarial Networks), deconvolutional networks, FCNs (Fully Convolutional Networks), and patch-based CNNs (Convolutional Neural Networks) were utilized. Ayman and Fakhr [35] also included a pavement/road detection review.

Various image processing methods, including edge detection, segmentation, curvature estimation, color scale transformations, and dense point cloud generation [60] have been for road distress detection used. Structure-from-Motion (SfM) and multi-view stereo (MVS) methods have been developed to process large datasets of images and generate detailed 3D surface and elevation profiles. SfM is a photogrammetric technique that involves the creation of a three-dimensional representation of an object or scene using a series of two-dimensional images. This process includes identifying overlapping frames and determining corresponding points within the images. By considering intrinsic and extrinsic camera properties, the geometry of the image network is established. Subsequently, the MVS method utilizes the mapped two-dimensional image coordinates of the identified corresponding points to calculate their three-dimensional coordinates, generating a dense 3D point cloud.

As with other fields, deep learning algorithms have been widely used for image analysis in recent years. Gopalakrishnan [49], Ali et al. [40] reviews deep learning methods used for distress detection, but

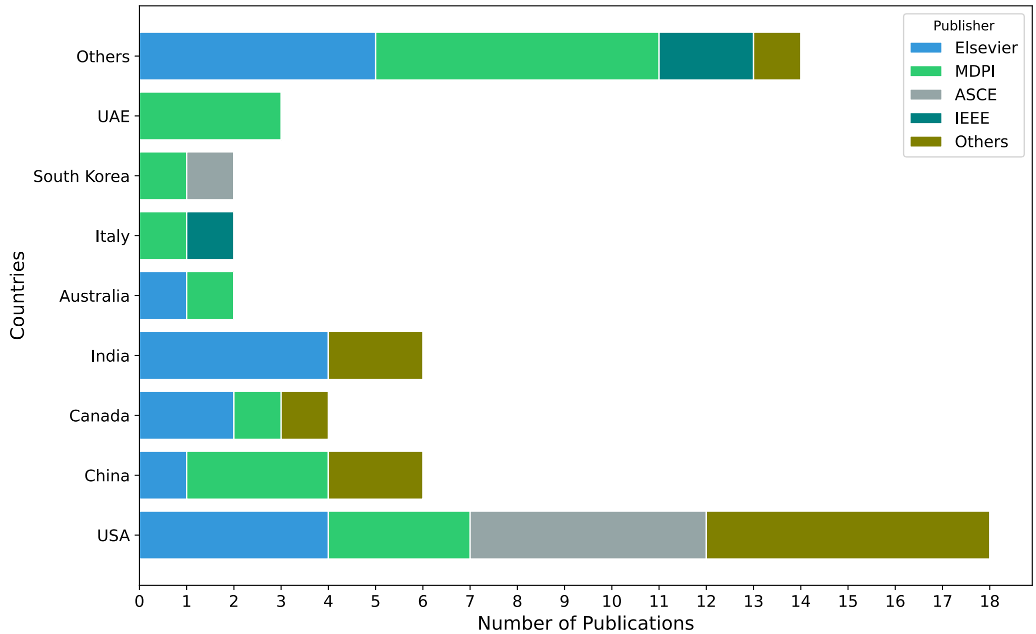

Fig. 8. Publisher Country-wise Distribution.

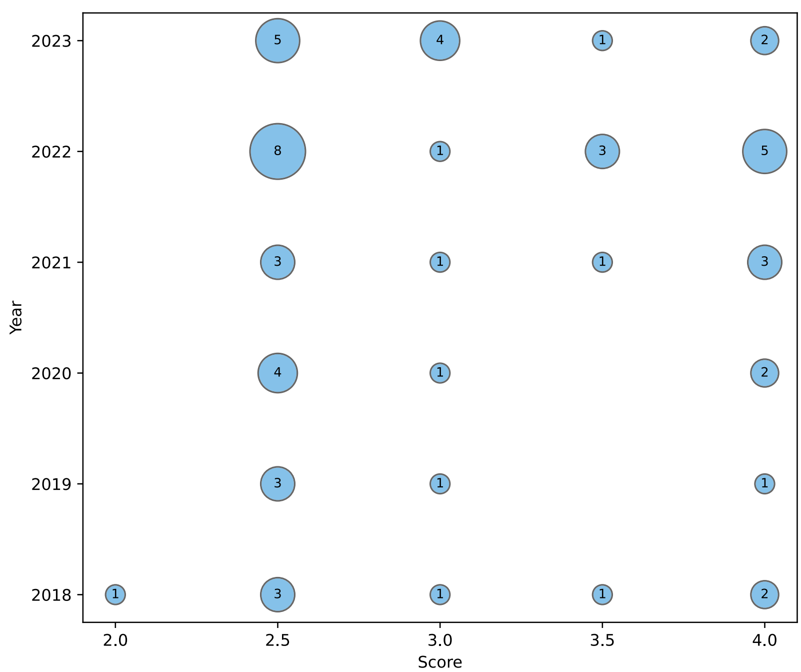

Fig. 9. Yearly Quality wise trend.

all other recent reviews also discuss deep learning methods and their success in achieving good results. Some datasets are also there as reported by some reviews [34–36,46,60]. Other studies that discussed pavement and road distress are listed in Table 4.

6.2. Bridge inspection

Bridges are vital to transport infrastructure that requires regular inspections to prevent potential disasters. Over time, bridges are inevitably subjected to wear and tear, and any bridge failures can lead to significant loss of human safety and infrastructure. Hence, monitoring and detecting damages is crucial to ensure bridges' safety and proper functioning.

Out of the studies that were selected, 28 of them dealt with the automation or semi-automation of bridge inspections. Six of these studies [25,38,39,53,55,64] focused solely on bridge inspections, while the rest covered other applications besides bridge inspections.

According to Zhang et al. Zhou et al. [23], the general studies conducted did not entirely depict the current status of UAV-assisted bridge inspection. Moreover, Zhou et al. [23] conducted the review from the perspective of gauging the level of automation achieved by primary studies for bridge inspection. The paper covers a range of bridge inspection tasks, including visual examination of the surface for issues like cracks, spalling, rust, corrosion, and delamination. Physical inspections such as tap testing and condition monitoring techniques like modal analysis and cable tension force estimation are also conducted.

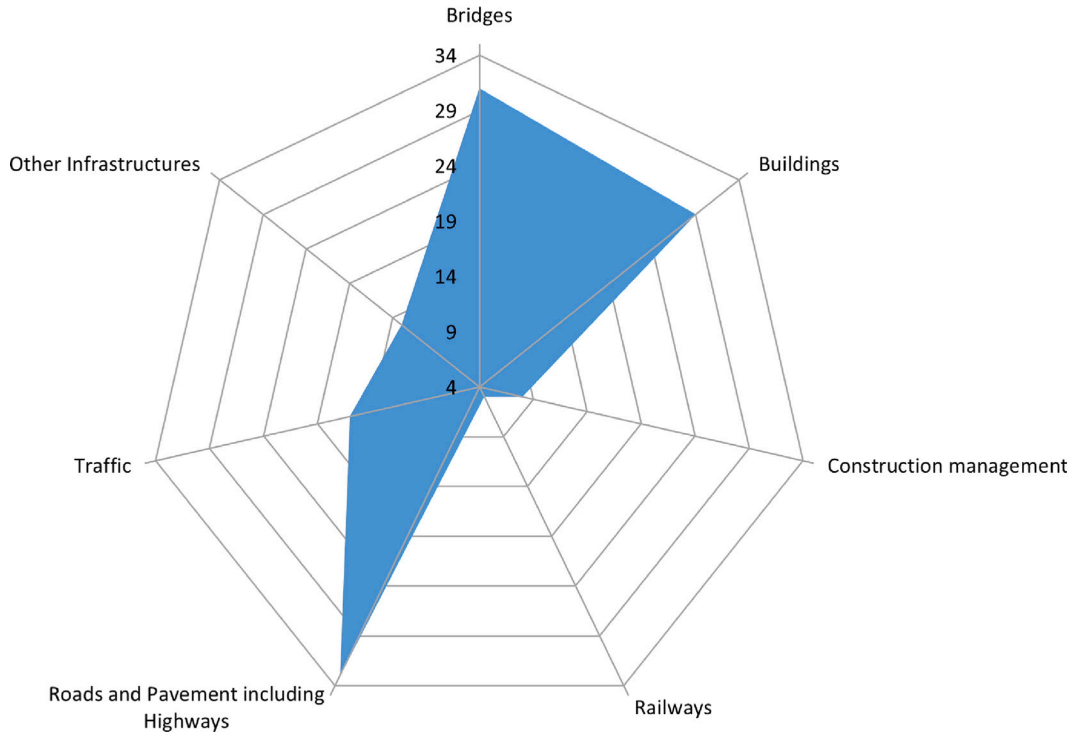

Fig. 10. Commonly Studied Infrastructure Elements.

Table 4
Infrastructure types and corresponding studies.

Infrastructure type	References
Roads & Pavements including Highways	[5], [11], [23], [27], [28], [30], [32], [33], [34], [35], [36], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [52], [60], [9], [61], [65], [66], [67], [68], [70], [71], [72], [75]
Bridges	[5], [11], [23], [25], [27], [29], [30], [32], [33], [38], [39], [40], [41], [42], [43], [45], [52], [53], [54], [55], [57], [58], [9], [61], [64], [68], [70], [71], [73], [74], [75]
Building Inspection	[5], [23], [24], [26], [27], [28], [29], [30], [32], [33], [40], [41], [42], [43], [45], [52], [56], [57], [9], [61], [65], [66], [70], [68], [71], [72], [73], [74], [75]
Traffic	[11], [13], [23], [28], [37], [42], [50], [58], [9], [61], [62], [63], [65], [68], [70], [75]
Construction Management	[30], [31], [51], [56], [58], [69], [72], [75]
Railway	[27], [32], [52], [59], [73]
Other Infrastructures	[5], [23], [27], [33], [35], [40], [51], [58], [9], [65], [72], [66], [75]

The paper also delves into predicting the remaining lifespan of bridges through multi-hazard performance assessment methods. The interesting contribution of this paper is the development of an assessment matrix for the level of automation in bridge inspection, which is used to gauge the level of automation achieved in each primary study. The level of automation has been more generally addressed by Agnisarman et al. [5]. According to the study, deep learning algorithms on imaging and structure from motion (reconstructing the 3D structure of a scene from a collection of 2D images) were able to achieve complete automation in bridge inspection.

Jeong at al. Jeong et al. [55] synthesized primary studies based on the presentation of algorithms for high-quality image selection, image processing methods used for damage detection, damage quantification, visual inspection, and the usage of digital image correlation for damage quantification.

In bridge inspection, Li et al. [38],Feroz and Abu Dabous [39] explicitly review UAV platforms, peripherals, and sensing equipment commonly employed. Spencer et al. [29] discussed bridge inspection and other civil infrastructure using aspects of inspection and monitoring. Ai et al. [32], Deng et al. [33] presented evaluation metrics of crack detection algorithms, although they are generic and not specific to bridges. The focus of Luleci et al. [71] is specifically on applying Generative Adversarial Networks (GANs) for civil infrastructure monitoring, particularly on bridges. The paper explores how GANs can be utilized in this context, drawing insights from the work of Goodfellow et al. [76] on generative adversarial networks.

Most papers mention conventional image processing(edge detection, segmentation, pixel clustering, etc.) and deep learning-based damage identification and quantification methods. However, with advances in deep learning in the last decade, a lot of newly published literature is using classification and regression methods employing deep learning. Hence, the reviews [64] and Azimi et al. [45] focus solely on deep learning methods for bridge health monitoring.

Many authors have highlighted the importance of the quality of available imaging data. Moreover, the imaging data captured through UAVs are highly vulnerable to distortions like poor illumination and fog [64]. However, only [55] discussed the methods used in literature for selecting high-quality images based on metrics like kurtosis and frequency, the relationship of entropy and sharpness, no-reference sharpness metric, Fourier and discrete cosine transform, cumulative probability, perceptual metric, discrete cosine transform, saliency-weighted foveal pooling and algebraic multi-grid [9,11,30,61].

For damage detection using images, the literature reports various methods, including various edge detection algorithms (including Gradient and Laplacian-based methods), image segmentation methods (rule-based, learning-based, semantic), Digital Image Correlation (DIC), and clustering of pixels. However, these methods are prone to error because they are sensitive to environmental noise. The width and length of cracks need to be determined for damage quantification. The literature reported various methods, including semantic segmentation, the Zernike moment operator, and deep learning methods.

Almost all studies reported the promising results of advancements in deep learning and its applications to bridge image analysis. However, the availability of quality datasets hinders the potential of deep learning.

Another emerging trend in bridge inspection involves using 3D models for visual assessments [55]. In generating these 3D models, two primary methods of 3D scene reconstruction are commonly employed: image mosaicking and structure from motion. Image mosaicking involves stitching together images into a pre-existing 3D geometric model of the bridge. On the other hand, structure from motion enables the creation of a 3D bridge model directly from overlapping images without prior knowledge of the scene's geometry. Comparatively, methods using structure from motion have demonstrated superior outcomes than image mosaicking methods, as image mosaicking techniques often suffer from modeling accuracy issues, mainly when dealing with curved surfaces.

6.3. Building inspection

Building inspections aim to identify various types of faults and issues. Some typical faults inspected during building inspections include structural deficiencies, including identifying cracks, deformations, or structural weaknesses in the foundation, walls, columns, or beams [32,40]. Next is Roofing problems, in which UAVs can capture detailed images of roofs, enabling inspectors to identify missing shingles, damaged areas, leaks, or improper installation. This information is crucial for assessing the overall integrity and condition of the roof. Then, it is Facade and Exterior Evaluation, where the UAV imagery assists in examining the building's facade for signs of deterioration, such as cracks, peeling paint, water stains, or corrosion. It helps identify areas requiring maintenance or repairs.

Most literature reviews discuss structural deficiencies [9,30,32,33,40]. The damage detection and quantification methods are similar to those used for roads and bridges, with image segmentation and edge detection being the most popular methods and deep learning gaining popularity in previous years. For roofing problems, image stitching and object detection methods have been used [41]. For Facade and Exterior Evaluation, texture analysis methods have been utilized to assess the condition of the building's exterior along with color analysis using Color-based segmentation techniques can be employed to differentiate different regions of the facade, highlighting areas with discoloration or stains [42,43,65].

[28,66] focus only on deep learning CNN model-based methods. Among the deep learning models, CNNs have been the most popular. Besides CNN, transfer learning-based methods also gained popularity as drone imagery is collected in different geographical regions and environments. Thus, models must be adapted to counter the challenge of slightly different image data.

6.4. Traffic management

Using drones in traffic management includes innovative ways to gather real-time data, monitor traffic conditions, and improve transportation systems. The tasks discussed for traffic management include vehicle detection, counting, tracking, and traffic flow analysis.

The first task in traffic management is vehicle detection. A detailed review of this task using deep learning methods is provided by Srivastava et al. [37], Bouguettaya et al. [63], highlighting that handcrafted features suffer from poor accuracy and lack of generalization. Additionally, Bisio et al. [62] offers a comprehensive review on vehicle detection, counting, and tracking. The datasets utilized for these tasks are also listed in Bisio et al. [62], Bouguettaya et al. [63]. The prevalent approach for vehicle detection involves employing object detection frameworks in images and videos, where deep learning methods have demonstrated significant performance improvements.

An essential task in traffic monitoring is tracking the traffic. Traffic tracking becomes exceptionally valuable when traditional object detection methods encounter difficulties caused by motion blur, occlusion, and variations in scale and angle [13,50,68]. The tracking algorithms can be classified into various categories, including online and offline methods, single object tracking (SOT), multiple object tracking (MOT), and detection-based and detection-free approaches. Objects are tracked throughout their motion in SOT methods, independent of their initial detection. On the other hand, MOT techniques track objects only if they are initially detected and localized, making it a detection-based tracking approach. Moreover, MOT solutions employ both offline and online methods, with offline approaches offering better performance but online solutions being more robust. Survey papers provide an overview of diverse methodologies employed in object tracking, which encompass Intersection over Union (IoU)-based tracking, particle filtering, Discriminative Correlation Filter (DCF), Kalman Filtering (KF), trackers based on object texture features, Minimum Output Sum of Squared Error (MOSSE), and Long Short-Term Memory (LSTM) approaches.

Data from drones and UAVs for traffic monitoring is typically sent to servers and clouds for later analysis. However, real-time traffic surveillance is necessary for critical situations like search and rescue, accident identification, and busy road monitoring. To meet this need, onboard deep learning frameworks are used for instant data collection and traffic monitoring. Nevertheless, local processing methods suffer from the disadvantage of increased computational costs, resulting in higher power consumption, reduced flight duration, and shorter battery life [62].

For traffic flow analysis, optical flow methods [11,13] have been widely used for the flow patterns using the direction and speeds of vehicles. Density estimation methods are also used to count the number of vehicles within specific regions of interest or lanes; the traffic density can be estimated [9,65,70].

6.5. Construction management

Drone imagery has been increasingly employed in construction management to enhance various aspects of the construction process. The first application in construction management is real-time monitoring of construction project sites [9,42,54]. For this purpose, image segmentation, object detection, and 3D Mapping and Modeling have been utilized [42]. These techniques help identify and analyze elements of interest within the aerial images, such as construction equipment, structures, safety hazards, or anomalies.

Another application in construction management is the progress monitoring of civil projects whereby UAVs can be deployed periodically to capture images or videos of construction sites from different angles and heights [68,75]. Image processing algorithms can compare these images with previous captures or reference models to track progress, detect deviations, and generate reports on construction milestones. This aids in monitoring project timelines, identifying delays, and facilitating effective project management.

Aerial images or videos can be used to make highly accurate 3D maps and models of construction sites. Image processing techniques such as photogrammetry and point cloud analysis extract geometric data, measurements, and detailed site representations [9,68,75]. These 3D models facilitate better visualization, spatial planning, clash detection, and coordination among various stakeholders.

UAV imagery combined with image processing can be used for quality control, as reported in Videras Rodríguez et al. [42]. High-resolution images can be analyzed to detect defects, deviations from design specifications, and structural anomalies.

UAVs with cameras can monitor construction sites in real time, providing surveillance and enhancing safety. Image processing algorithms can analyze the captured footage to detect potential safety risks, unauthorized access, and security breaches [68]. This enables proactive measures to mitigate risks, maintain site security, and ensure compliance with safety protocols.

6.6. Railway management

Only four secondary studies mention the management of railway assets [24,41,59,66]. Out of these, only one [59] is dedicated to railway management.

UAVs equipped with cameras have been used for track and railway defect identification [41,59]. Lately, deep learning methods on drone imagery have been employed for the localization of defects. Image processing methods have been used for irregular track geometry identification.

Drone imagery assesses the risks associated with natural hazards, such as heavy snowfall, avalanches, and mudflows on railway infrastructure [59]. It provides crucial information on natural disasters and can be used to create 3D models that simulate potential accidents. These models help develop safety plans and evacuation strategies to prepare for future emergencies.

The utilization of drone imagery has been successful in deterring trespassing and theft of railway assets. In the realm of railway asset management, numerous research studies have delved into techniques for assessing the upkeep of railway infrastructure assets, including monitoring railway tunnels, bridges, crossings, signal devices, and traffic control devices. Another exciting application is the detection of obstructions on the tracks. Mainly, the vegetation growth near railway tracks has been reported to be identified using deep learning methods. Other studied obstructions include rockfall and storage materials. Deep learning-based object detection and tracking techniques are frequently utilized in these particular applications [59,66].

6.7. Miscellaneous applications

Apart from the above-mentioned infrastructure applications, some other applications are discussed in the literature review. For instance, Image processing techniques applied to drone imagery have been used effectively to detect wind turbine surface damage in hard-to-reach areas as discussed in Shakhatreh et al. [9], Zhou et al. [23].

One of the applications is site surveying and mapping for urban planning, which involves the provision of immediate mapping and readily available data to facilitate urban planning [72,75]. By capturing multiple aerial images of a site using a drone, image processing algorithms can stitch these images together to create high-resolution orthomosaics. Orthomosaics provide a detailed and accurate site representation, allowing for precise measurements, analysis, and mapping. Image processing can be utilized to generate Digital Elevation Models (DEMs) from drone imagery. DEMs provide valuable information about the surveyed area's topography, elevation, and contours. This data can be used for terrain analysis, volume calculations, and other geospatial applications.

Oil, gas, and water pipelines are infrastructure components with significant consequences of failure. Drones have been used to capture data of long-range pipelines [5,9,27,58,75]. Pipeline inspection, thus, is an important area. Drone imagery can provide high-resolution visuals of pipeline infrastructure, enabling inspectors to remotely assess the condition of pipelines, identify potential defects, and detect anomalies such as corrosion, leaks, or physical damage. Image processing algorithms can enhance and analyze these visuals, making detecting and highlighting areas of concern easier. Image processing techniques can automatically identify and classify various defects or anomalies in pipeline imagery. Using pattern recognition, edge detection, and machine/deep learning algorithms, potential issues such as cracks, corrosion spots, weld failures, or abnormal bulges can be detected and flagged for further inspection. Image processing algorithms can identify changes or differences along the pipeline route by comparing images captured during inspection cycles. This allows for monitoring potential shifts, structural deformations, or the appearance of new defects over time. Change detection algorithms can highlight areas that require closer inspection or preventive maintenance. Finally, unwanted vegetation growth around pipelines can risk their integrity. Image processing techniques can help identify and classify vegetation encroachment by distinguishing between pipeline and surrounding vegetation. This analysis can assist in identifying areas where vegetation needs to be cleared to ensure pipeline safety and prevent damage.

Using image processing on drone imagery in power infrastructure management offers numerous benefits, including improved asset inspection, proactive vegetation management, early fault detection, and enhanced maintenance planning [27,58]. Among the used methods are object detection for the detection and recognition of specific objects within power infrastructure imagery, change detection for anomaly detection, image segmentation for segmenting power lines, towers, or other relevant structures, thresholding, edge detection, and clustering algorithms for analyzing and interpreting thermal imagery.

Image processing applied to drone imagery can play a valuable role in waste management by identifying garbage sites [75]. Moreover, drone imagery has been used to assess dams' structural integrity [35,40,58]. By analyzing drone imagery, the algorithms can detect irregularities, identify areas of concern, and provide quantitative measurements related to structural stability, such as displacement or deformation of dam components.

7. Discussions

In this research, we have undertaken a tertiary study, focusing on secondary literature exploring computer vision techniques in drone imagery for infrastructure management. By incorporating 57 secondary studies, our research has successfully elucidated demographic, temporal, thematic, and quality trends. These trends were examined and analyzed by addressing three distinct research questions. The examination of demographic and temporal trends aids in comprehending the robustness of the literature compiled for understanding the phenomenon of drone imagery usage in infrastructure management. Specifically, factors such as the number of primary studies included in each systematic literature review, the duration covered by these studies, and the utilization of online databases contribute to identifying secondary studies that encompass the most significant number of primary studies over an extensive period. This information enables the selection of secondary studies that offer a comprehensive overview of the topic.

The presentation of citation counts for each secondary study and the distribution of publishers reveals the influence of research conducted in this field. The geographical distribution of the research is valuable in identifying regions actively involved in research and highlighting areas where research is limited. For instance, the predominant origin of secondary studies from the USA indicates the active engagement of researchers in that country. There is a strong correlation between the high number of secondary studies conducted in the USA and China and the report published by Statista on the leading countries in the global drone market by revenue in 2022 [77]. As expected, there is little or no work in developing and under-developing countries, showing a lack of resources, regulatory and legal challenges, expertise and capacity, and access to technology and equipment.

Section 6 delves into six prominent application areas leveraging drone imagery for infrastructure management alongside miscellaneous applications. The section provides an in-depth examination of these applications and the corresponding computer vision methods utilized.

The quality trends analyzed in this tertiary study assess the adequacy and rigor of search and evidence collection in the secondary studies. These trends shed light on the strengths and weaknesses of the included studies in terms of their quality. Consequently, this provides insights into the factors that impact the reproducibility of secondary studies. The SLRs, among other secondary studies, achieve relatively high DARE scores because of clarity in identifying research questions, inclusion/exclusion criteria and objective assessment of the evidence. Thus, the SLRs were found to be more reproducible and transparent.

For comprehensive and narrative reviews with low DARE scores, the readers have to implicitly extract the trivial questions such as the number of primary studies, inclusion/exclusion criteria, number of years covered in the research, and research objectives.

7.1. Limitations and challenges

This section synthesizes the limitations and challenges identified in various secondary studies on using image processing methods for UAV imagery in infrastructure management.

7.1.1. Limitations

i. Drone-captured images may vary in quality due to factors such as weather conditions, lighting, and camera specifications. Poor image quality can affect the accuracy of computer vision algorithms [24,27,33].
ii. Drones have a limited field of view, so capturing a comprehensive view of large infrastructure projects may require multiple flights or passes. This limitation can impact the efficiency of data collection [9,43].
iii. Training, computer vision models, often requires annotated data, and manually labeling images for infrastructure analysis can be time-consuming and labor-intensive. Obtaining a diverse and well-labeled dataset is crucial for the performance of the models [29].
iv. Drones may encounter obstacles in their flight path, leading to incomplete data capture. Ensuring obstacle avoidance mechanisms in the drone's navigation system is crucial to obtaining comprehensive and accurate data [9].
v. Complex building structures can hinder UAV access to specific components due to size or location [41].
vi. Infrastructure analysis often involves capturing images of buildings, facilities, or other sensitive areas. Addressing privacy concerns and ensuring regulation compliance is essential in deploying drone-based computer vision systems.
vii. Drones have limited payload capacity, and adding advanced sensors or cameras for high-quality imagery may impact flight performance [32].

7.1.2. Challenges related to drone operations

i. Ensuring precise GPS positioning and reliable communication for drones is vital. Inaccurate positioning or communication disruptions can impede inspection effectiveness and safety [9,61,75].
ii. Drones typically have limited battery life, resulting in restricted flight times for inspection [9].
iii. UAV operations create vibrations that disrupt data acquisition, degrading image and sensor accuracy. Stabilization mechanisms and advanced sensors mitigate these vibrations for dependable data collection [56].
iv. Maintaining a reliable communication link between the drone and the ground control station is essential. Communication issues can arise due to interference, signal loss, or other technical challenges, affecting real-time control and data transmission [9,57]
v. The absence of publicly accessible datasets with appropriate annotations poses a significant challenge that impedes the progress of this field. Ai et al. [32].

7.1.3. Challenges of data processing

i. Post-acquisition, the dataset may need extensive annotation and labeling for training machine learning models [29,32].
ii. Developing and training effective computer vision models is a continual challenge. Optimizing these models for accuracy, speed, and adaptability to various infrastructure types is an ongoing process that demands further work in machine learning [75].
iii. Analyzing large-scale infrastructure projects may demand highly efficient algorithms and parallel processing capabilities [9,75].
iv. Achieving real-time or near-real-time analysis of drone-captured imagery for infrastructure management can be demanding [23,25,29]. The need for quick decision-making may require optimized algorithms and high-performance computing resources.
v. Infrastructure types vary significantly, from buildings and roads to bridges and power lines. A persistent challenge is ensuring that computer vision models are adaptable and generalize well across diverse infrastructure elements [9,29,32].
vi. Detecting changes in infrastructure over time and monitoring structural dynamics present challenges. Adapting computer vision models to identify and track changes in real-world conditions is essential for effective infrastructure management [23].
vii. Validation at a laboratory scale or field testing under tightly controlled conditions is frequently conducted. In these scenarios, the uncertainties that can negatively impact the reliability of damage detection are minimal. It is crucial not to disregard these uncertainties in real-world applications, e.g. extreme weather conditions [23].
viii. It is important to acknowledge that the damage scenarios observed in real-world structures might exceed those covered in the training dataset. Consequently, deep learning is expected to expand its inference capabilities to tackle these evolving challenges [23,32,36].
ix. The diverse range of damage states in infrastructure imagery data leads to imbalances, posing challenges that impede the effectiveness of deep learning methods [32].

7.2. Future directions

Based on the literature, the future directions of research in the domain can be directed toward three areas: (i) Drone Operations, (ii) Data Management, and (iii) Data Analysis. Fig. 11 summarizes the potential research topics in these areas.

7.2.1. Future direction in drone operations

i. Future research may involve developing UAV control algorithms for autonomous hovering without collisions, ensuring mission success [9,11]. Leveraging emerging technologies such as the Internet of Things (IoT), cloud computing, and UAVs equipped with computer vision capabilities, there is a heightened emphasis on developing a condition assessment system for UAVs that is autonomous, operates in real-time, and is resilient.
ii. Another potential area of research and development is to extend drone flight times and operating ranges. This could involve advancements in battery technology, energy-efficient propulsion systems, and optimized aerodynamics. Further work involves implementing technologies such as in-flight recharging or automated drone stations to enable longer and more extensive missions [32].
iii. Another direction of work is on the improvement of using drone swarms for large-scale infrastructure monitoring. Swarm technology allows multiple drones to work collaboratively, covering extensive areas more efficiently. More efficient algorithms are needed for coordinated swarm operations, ensuring safe and effective collaboration between drones during data collection [37].
iv. Further investigation is needed to explore future research opportunities in advancing standardized algorithms for determining flight paths. These optimized paths should prioritize the proximity to the target surface, ensure heightened flight speed to enhance image clarity and establish a geometry that efficiently covers the entire target area [9,29,37].

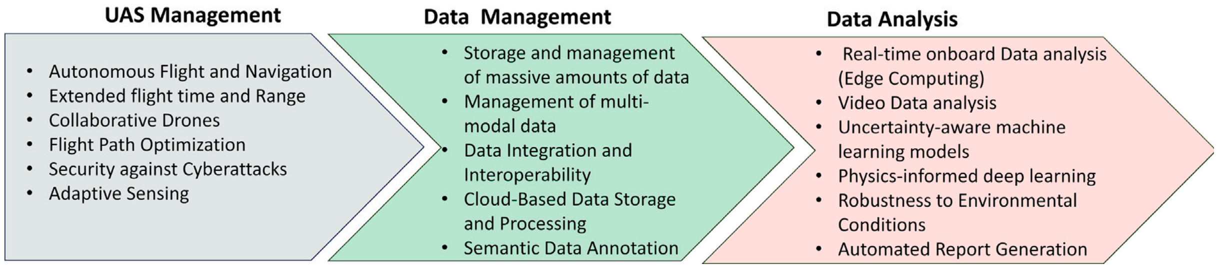

Fig. 11. Future Directions in Computer Vision for Drone-Generated Imagery in Infrastructure Management.

v. The diverse components within UAV systems create a substantial attack surface susceptible to malicious intruders, posing significant cybersecurity challenges. Future research is essential to address and mitigate these emerging cybersecurity threats to UAV systems. Exploring the integration of blockchain technology for the secure and tamper-proof recording of drone communication and control data is also an interesting area of research [9].

vi. Advance research is needed to establish adaptive sensing capabilities for drones, enabling dynamic adjustments in sensor configurations tailored to specific infrastructure monitoring tasks. A research direction involves exploring modular payload systems that facilitate rapid changes in sensors and instruments to cater to diverse data collection needs [9].

7.2.2. Future directions in data management

i Work is needed on implementing scalable big data analytics solutions capable of handling the massive amount of data drones generate during infrastructure inspections [35].

ii Subsequent research endeavors can concentrate on creating a consolidated framework for managing various data types, including RGB images, infrared images, and point clouds. Ayman and Fakhr [35].

iii A future research direction involves working on standardizing data formats and protocols to enhance interoperability between different drone platforms, sensors, and data sources. Additionally, there is a potential work area in developing middleware solutions that facilitate the seamless integration of drone imagery data with existing infrastructure management systems [9, 32,35]

iv A promising avenue is to investigate the utilization of cloud computing for storing and processing drone imagery data, enabling scalable and on-demand resources. Additionally, there is a need to develop secure and compliant cloud-based solutions to ensure the confidentiality and integrity of sensitive infrastructure data [9].

v An area for future research involves semantic annotation techniques to enhance the contextual understanding of infrastructure elements in drone imagery. Another aspect is the development of tools that enable the automated annotation of features in drone data, facilitating more meaningful analysis and decision support [35].

7.2.3. Future direction in data analysis using computer vision

i The data analysis phase in infrastructure management can be conducted in real-time, implying the simultaneous detection of defects during inspections using onboard edge devices. This is in contrast to storing collected data first and identifying defects after the completion of the inspection. This real-time analysis will help decide to obtain more data, if necessary, for a more rigorous inspection. For this purpose, power-efficient and lightweight deep learning models processing on edge devices are needed [9,25]

ii The majority of existing methods are confined to static images and do not extend to video data analysis. Subsequent research efforts should be directed toward obtaining high-definition videos and developing corresponding processing techniques [27].

iii A future direction of work involves exploring uncertainty-aware machine learning and optimization techniques to analyze and comprehend the impact of uncertainties, also known as uncertainty quantification, on decision-making processes. This exploration aims to mitigate false predictions and enhance the system's overall accuracy.

iv To achieve comprehensive damage detection, it is necessary to integrate physical knowledge and constraints into deep learning models, leading to the concept of physics-informed deep learning. The inference of unknown damages based on known damages can be improved by leveraging the inherent physical correlations among different damage types. However, identifying the most suitable approach to incorporate physical knowledge remains an open challenge. Given the proposed improvements in deep learning and integrating new features, developing a unified deep learning framework is crucial [32].

v Consistent progress and refinement in image pre-processing algorithms are required to reduce the adverse influence of uncertainties to a considerable extent [61].

vi The large language models (LLMs) can be used for automated report generation in standardized formats.

8. Conclusions

A systematic tertiary study was conducted on drone imagery for infrastructure management, encompassing 57 secondary studies spanning the period from 2018 to 2023. This tertiary study aimed to discern and synthesize the research trends and implications in infrastructure management utilizing drone imagery. The examination involved identifying the number of primary and most referenced secondary studies, the publication countries, prevalent publication venues, and the types of secondary studies. A significant contribution lies in identifying widely used applications and mapping literature along those dimensions. Beyond the thematic analysis of literature applications, an additional contribution involves evaluating the quality of published secondary studies and analyzing their strengths and weaknesses in terms of quality. Additionally, challenges and future research directions in infrastructure management using drone imagery were compiled through this study. This tertiary study is a valuable resource for researchers and practitioners because it systematically consolidates the extensive literature in infrastructure and offers a central reference point for abstract-level literature review.

Table A.1
DARE score of all selected secondary studies.

No.	Paper code	Q1	Q2	Q3	Q4	Total
1	ASCE1	0.5	0.5	0.5	1	2.5
2	ASCE2	0.5	0.5	0.5	1	2.5
3	ASCE3	0.5	0.5	0.5	1	2.5
4	ASCE4	0.5	0.5	0.5	1	2.5
5	ASCE5	1	1	1	1	4
6	ACSE6	0.5	0.5	0.5	1	2.5
7	DCTA1	0.5	0.5	0.5	1	2.5
8	ELS02	0.5	0.5	1	1	3
9	ELS03	1	1	1	1	4
10	ELS04	0.5	0.5	0.5	1	2.5
11	ELS05	0.5	0.5	0.5	1	2.5
12	ELS06	1	1	1	1	4
13	ELS07	0.5	0.5	1	1	3
14	ELS01	0.5	0.5	1	1	3
15	ELS08	0.5	0.5	0.5	1	2.5
16	ELS09	1	1	1	1	4
17	ELS11	0.5	0.5	0.5	1	2.5
18	ELS10	1	1	1	1	4
19	ELS12	0.5	1	0.5	1	3
20	ELS13	0.5	0.5	0.5	1	2.5
21	ELS14	0.5	1	1	1	3.5
22	ELS15	0.5	0.5	0.5	1	2.5
23	ELS16	0.5	0.5	0.5	1	2.5
24	ELS17	0.5	1	0.5	1	3
25	EM1	1	1	1	1	4
26	FR1	1	1	1	1	4
27	IEEE1	0.5	1	0.5	1	3
28	SP2	0.5	1	1	1	3.5
29	IEEE2	1	1	1	1	4
30	IEEE3	0.5	1	1	1	3.5
31	IEEE4	0.5	0.5	0.5	1	2.5
32	IET1	1	1	0.5	1	3.5
33	MDPI01	0.5	0.5	0.5	1	2.5
34	MDPI02	1	1	1	1	4
35	MDPI03	1	1	1	1	4
36	MDPI04	0.5	0.5	0.5	1	2.5
37	MDPI05	1	1	1	1	4
38	MDPI06	0.5	0.5	0.5	1	2.5
39	MDPI07	0.5	0.5	0.5	1	2.5
40	MDPI08	0.5	0.5	0.5	1	2.5
41	MDPI09	1	1	1	1	4
42	MDPI10	1	1	1	1	4
43	MDPI11	0.5	0.5	0.5	0.5	2
44	MDPI12	0.5	0.5	0.5	1	2.5
45	MDPI13	1	1	1	1	4
46	MDPI14	0.5	0.5	0.5	1	2.5
47	MDPI15	1	1	0.5	1	3.5
48	MDPI16	0.5	1	0.5	1	3
49	MDPI17	0.5	1	0.5	1	3
50	MDPI18	0.5	1	0.5	1	3
51	SAGE1	0.5	0.5	0.5	1	2.5
52	SP1	0.5	0.5	0.5	1	2.5
53	TF1	0.5	0.5	0.5	1	2.5
54	TF2	.5	0.5	0.5	1	2.5
55	WL1	0.5	0.5	0.5	1	2.5
56	ITCON1	1	1	1	1	4
57	ITCON2	1	1	1	0.5	3.5

CRediT authorship contribution statement

Naveed Ejaz: Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft. **Salimur Choudhury:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Validation, 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.

Data availability

All of the used data has been described in the study.

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Appendix. DARE score of all secondary studies

See Table A.1.

References

[1] S. Thacker, D. Adshead, M. Fay, S. Hallegatte, M. Harvey, H. Meller, N. O'Regan, J. Rozenberg, G. Watkins, J.W. Hall, Infrastructure for sustainable development, Nat. Sustain. 2 (4) (2019) 324–331, http://dx.doi.org/10.1038/s41893-019-0256-8.

[2] T. Macaulay, Critical Infrastructure: Understanding Its Component Parts, Vulnerabilities, Operating Risks, and Interdependencies, CRC press, 2008.

[3] H. Osman, Agent-based simulation of urban infrastructure asset management activities, Autom. Constr. 28 (2012) 45–57, http://dx.doi.org/10.1016/j.autcon.2012.06.004.

[4] S.A. Dabous, S. Feroz, Condition monitoring of bridges with non-contact testing technologies, Autom. Constr. 116 (2020) 103224, http://dx.doi.org/10.1016/j.autcon.2020.103224.

[5] S. Agnisarman, S. Lopes, K.C. Madathil, K. Piratla, A. Gramopadhye, A survey of automation-enabled human-in-the-loop systems for infrastructure visual inspection, Autom. Constr. 97 (2019) 52–76, http://dx.doi.org/10.1016/j.autcon.2018.10.019.

[6] V. Hoskere, Y. Narazaki, B. Spencer, Learning to detect important visual changes for structural inspections using physics based graphics models, in: 9th International Conference on Structural Health Monitoring of Intelligent Infrastructure: Transferring Research Into Practice, 2019, pp. 1484–1490.

[7] B. Alsadik, F. Nex, The Rise in UAV Inspections for Civil Infrastructure, GIM International, 2021, URL https://www.gim-international.com/content/article/the-rise-in-uav-inspections-for-civil-infrastructure. (Accessed 6 June 2023).

[8] S. Halder, K. Afsari, J. Serdakowski, S. DeVito, M. Ensafi, W. Thabet, Real-time and remote construction progress monitoring with a quadruped robot using augmented reality, Buildings 12 (11) (2022) pp. 2027, http://dx.doi.org/10.3390/buildings12112027.

[9] H. Shakhatreh, A.H. Sawalmeh, A. Al-Fuqaha, Z. Dou, E. Almaita, I. Khalil, N.S. Othman, A. Khreishah, M. Guizani, Unmanned aerial vehicles (UAVs): A survey on civil applications and key research challenges, IEEE Access 7 (2019) 48572–48634, http://dx.doi.org/10.1109/ACCESS.2019.2909530.

[10] C.D. Lippitt, S. Zhang, The impact of small unmanned airborne platforms on passive optical remote sensing: A conceptual perspective, Int. J. Remote Sens. 39 (15–16) (2018) 4852–4868, http://dx.doi.org/10.1080/01431161.2018.1490504.

[11] F. Outay, H.A. Mengash, M. Adnan, Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges, Transp. Res. A 141 (2020) 116–129, http://dx.doi.org/10.1016/j.tra.2020.09.018.

[12] Y. Ham, K.K. Han, J.J. Lin, M. Golparvar-Fard, Visual monitoring of civil infrastructure systems via camera-equipped unmanned aerial vehicles (UAVs): a review of related works, Visual. Eng. 4 (1) (2016) 1–8, http://dx.doi.org/10.1186/s40327-015-0029-z.

[13] E.V. Butilă, R.G. Boboc, Urban traffic monitoring and analysis using unmanned aerial vehicles (UAVs): A systematic literature review, Remote Sens. 14 (3) (2022) pp. 620, http://dx.doi.org/10.3390/rs14030620.

[14] B. Kitchenham, S. Charters, D. Budgen, P. Brereton, M. Turner, S. Linkman, G. Visaggio, Guidelines for performing Systematic Literature Reviews in Software Engineering, Technical Report, Nottingham University, 2007, URL https://userpages.uni-koblenz.de/~laemmel/esecourse/slides/slr.pdf. (Accessed 15 April 2023).

[15] B. Kitchenham, R. Pretorius, D. Budgen, O.P. Brereton, M. Turner, M. Niazi, S. Linkman, Systematic literature reviews in software engineering–a tertiary study, Inf. Softw. Technol. 52 (8) (2010) 792–805, http://dx.doi.org/10.1016/j.infsof.2010.03.006.

[16] Centre for Reviews and Dissemination, University of York, The database of abstracts of reviews of effects (DARE), Effect. Matters 6 (2) (2002) 1–4, URL https://pure.york.ac.uk/portal/en/publications/the-database-of-abstracts-of-reviews-of-effects-dare.

[17] C. Martins, M. Pato, Supply chain sustainability: A tertiary literature review, J. Clean. Prod. 225 (2019) 995–1016, http://dx.doi.org/10.1016/j.jclepro.2019.03.250.

[18] S. Kim, K. Kim, Systematic tertiary study for consolidating further implications of unmanned aircraft system applications, J. Manage. Eng. 37 (2) (2021) 03120001, http://dx.doi.org/10.1061/(ASCE)ME.1943-5479.0000880.

[19] H. Zhang, M.A. Babar, P. Tell, Identifying relevant studies in software engineering, Inf. Softw. Technol. 53 (6) (2011) 625–637, http://dx.doi.org/10.1016/j.infsof.2010.12.010.

[20] Scopus, 2023, https://www.scopus.com/. (Accessed 20 June 2023).

[21] Web of science, 2023, https://www.webofscience.com/. (Accessed 20 June 2023).

[22] ScienceDirect, 2023, https://www.sciencedirect.com/. (Accessed 20 June 2023).

[23] K. Zhou, Z. Wang, Y.-Q. Ni, Y. Zhang, J. Tang, Unmanned aerial vehicle-based computer vision for structural vibration measurement and condition assessment: A concise survey, J. Infrastruct. Intell. Resilience 2 (2) (2023) pp. 100031, http://dx.doi.org/10.1016/j.iintel.2023.100031.

[24] T. Rakha, A. Gorodetsky, Review of unmanned aerial system (UAS) applications in the built environment: Towards automated building inspection procedures using drones, Autom. Constr. 93 (2018) 252–264, http://dx.doi.org/10.1016/j.autcon.2018.05.002.

[25] C. Zhang, Y. Zou, F. Wang, E. del Rey Castillo, J. Dimyadi, L. Chen, Towards fully automated unmanned aerial vehicle-enabled bridge inspection: Where are we at? Constr. Build. Mater. 347 (2022) pp. 128543, http://dx.doi.org/10.1016/j.conbuildmat.2022.128543.

[26] A. Mohan, S. Poobal, Crack detection using image processing: A critical review and analysis, Alex. Eng. J. 57 (2) (2018) 787–798, http://dx.doi.org/10.1016/j.aej.2017.01.020.

[27] S. Sony, K. Dunphy, A. Sadhu, M. Capretz, A systematic review of convolutional neural network-based structural condition assessment techniques, Eng. Struct. 226 (2021) 111347, http://dx.doi.org/10.1016/j.engstruct.2020.111347.

[28] L.P. Osco, J.M. Junior, A.P.M. Ramos, L.A. de Castro Jorge, S.N. Fatholahi, J. de Andrade Silva, E.T. Matsubara, H. Pistori, W.N. Gonçalves, J. Li, A review on deep learning in UAV remote sensing, Int. J. Appl. Earth Obs. Geoinf. 102 (2021) pp. 102456, http://dx.doi.org/10.1016/j.jag.2021.102456.

[29] B.F. Spencer Jr., V. Hoskere, Y. Narazaki, Advances in computer vision-based civil infrastructure inspection and monitoring, Engineering 5 (2) (2019) 199–222, http://dx.doi.org/10.1016/j.eng.2018.11.030.

[30] K. Mostafa, T. Hegazy, Review of image-based analysis and applications in construction, Autom. Constr. 122 (2021) pp. 103516, http://dx.doi.org/10.1016/j.autcon.2020.103516.

[31] S. Gupta, S. Nair, A review of the emerging role of UAVs in construction site safety monitoring, Mater. Today: Proc. (2023) http://dx.doi.org/10.1016/j.matpr.2023.03.135.

[32] D. Ai, G. Jiang, S.-K. Lam, P. He, C. Li, Computer vision framework for crack detection of civil infrastructure—A review, Eng. Appl. Artif. Intell. 117 (2023) 105478, http://dx.doi.org/10.1016/j.engappai.2022.105478.

[33] J. Deng, A. Singh, Y. Zhou, Y. Lu, V.C.-S. Lee, Review on computer vision-based crack detection and quantification methodologies for civil structures, Constr. Build. Mater. 356 (2022) pp. 129238, http://dx.doi.org/10.1016/j.conbuildmat.2022.129238.

[34] N. Sholevar, A. Golroo, S.R. Esfahani, Machine learning techniques for pavement condition evaluation, Autom. Constr. 136 (2022) pp. 104190, http://dx.doi.org/10.1016/j.autcon.2022.104190.

[35] H. Ayman, M.W. Fakhr, Recent computer vision applications for pavement distress and condition assessment, Autom. Constr. 146 (2023) pp. 104664, http://dx.doi.org/10.1016/j.autcon.2022.104664.

[36] N.S.P. Peraka, K.P. Biligiri, Pavement asset management systems and technologies: A review, Autom. Constr. 119 (2020) 103336, http://dx.doi.org/10.1016/j.autcon.2020.103336.

[37] S. Srivastava, S. Narayan, S. Mittal, A survey of deep learning techniques for vehicle detection from uav images, J. Syst. Archit. 117 (2021) 102152, http://dx.doi.org/10.1016/j.sysarc.2021.102152.

[38] H. Li, Y. Chen, J. Liu, Z. Zhang, H. Zhu, Unmanned aircraft system applications in damage detection and service life prediction for bridges: A review, Remote Sens. 14 (17) (2022) pp. 4210, http://dx.doi.org/10.3390/rs14174210.

[39] S. Feroz, S. Abu Dabous, UAV-based remote sensing applications for bridge condition assessment, Remote Sens. 13 (9) (2021) pp. 1809, http://dx.doi.org/10.3390/rs13091809.

[40] L. Ali, F. Alnajjar, W. Khan, M.A. Serhani, H. Al Jassmi, Bibliometric analysis and review of deep learning-based crack detection literature published between 2010 and 2022, Buildings 12 (4) (2022) 432, http://dx.doi.org/10.3390/buildings12040432.

[41] H. Liang, S.-C. Lee, W. Bae, J. Kim, S. Seo, Towards UAVs in construction: Advancements, challenges, and future directions for monitoring and inspection, Drones 7 (3) (2023) pp. 202, http://dx.doi.org/10.3390/drones7030202.

[42] M. Videras Rodríguez, S.G. Melgar, A.S. Cordero, J.M.A. Márquez, A critical review of unmanned aerial vehicles (UAVs) use in architecture and urbanism: Scientometric and bibliometric analysis, Appl. Sci. 11 (21) (2021) pp. 9966, http://dx.doi.org/10.3390/app11219966.

[43] S. Guan, Z. Zhu, G. Wang, A review on UAV-based remote sensing technologies for construction and civil applications, Drones 6 (5) (2022) pp. 117, http://dx.doi.org/10.3390/drones6050117.

[44] E. Ranyal, A. Sadhu, K. Jain, Road condition monitoring using smart sensing and artificial intelligence: A review, Sensors 22 (8) (2022) pp. 3044, http://dx.doi.org/10.3390/s22083044.

[45] M. Azimi, A.D. Eslamlou, G. Pekcan, Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review, Sensors 20 (10) (2020) pp.2778, http://dx.doi.org/10.3390/s20102778.

[46] A. Abdollahi, B. Pradhan, N. Shukla, S. Chakraborty, A. Alamri, Deep learning approaches applied to remote sensing datasets for road extraction: A state-of-the-art review, Remote Sens. 12 (9) (2020) pp. 1444, http://dx.doi.org/10.3390/rs12091444.

[47] M. Amândio, M. Parente, J. Neves, P. Fonseca, Integration of smart pavement data with decision support systems: A systematic review, Buildings 11 (12) (2021) pp. 579, http://dx.doi.org/10.3390/buildings11120579.

[48] A. Ragnoli, M.R. De Blasiis, A. Di Benedetto, Pavement distress detection methods: A review, Infrastructures 3 (4) (2018) pp. 58, http://dx.doi.org/10.3390/infrastructures3040058.

[49] K. Gopalakrishnan, Deep learning in data-driven pavement image analysis and automated distress detection: A review, Data 3 (3) (2018) pp. 28, http://dx.doi.org/10.3390/data3030028.

[50] S. Iftikhar, M. Asim, Z. Zhang, A. Muthanna, J. Chen, M. El-Affendi, A. Sedik, A.A. Abd El-Latif, Target detection and recognition for traffic congestion in smart cities using deep learning-enabled UAVs: A review and analysis, Appl. Sci. 13 (6) (2023) pp. 3995, http://dx.doi.org/10.3390/app13063995.

[51] M. Sami Ur Rehman, M.T. Shafiq, F. Ullah, Automated computer vision-based construction progress monitoring: A systematic review, Buildings 12 (7) (2022) pp. 1037, http://dx.doi.org/10.3390/buildings12071037.

[52] A. Kyriou, V. Mpelogianni, K. Nikolakopoulos, P.P. Groumpos, Review of remote sensing approaches and soft computing for infrastructure monitoring, Geomatics 3 (3) (2023) 367–392, http://dx.doi.org/10.3390/geomatics3030021.

[53] K. Luo, X. Kong, J. Zhang, J. Hu, J. Li, H. Tang, Computer vision-based bridge inspection and monitoring: A review, Sensors 23 (18) (2023) 7863, http://dx.doi.org/10.3390/s23187863.

[54] S. Ivanova, A. Kuznetsov, R. Zverev, A. Rada, Artificial intelligence methods for the construction and management of buildings, Sensors 23 (21) (2023) 8740, http://dx.doi.org/10.3390/s23218740.

[55] E. Jeong, J. Seo, J. Wacker, Literature review and technical survey on bridge inspection using unmanned aerial vehicles, J. Perform. Constr. Facilities 34 (6) (2020) 04020113, http://dx.doi.org/10.1061/(ASCE)CF.1943-5509.0001519.

[56] S. Zhang, S.M. Bogus, C.D. Lippitt, V. Kamat, S. Lee, Implementing remote-sensing methodologies for construction research: An unoccupied airborne system perspective, J. Constr. Eng. Manag. 148 (9) (2022) 03122005, http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.000234.

[57] L. Duque, J. Seo, J. Wacker, Synthesis of unmanned aerial vehicle applications for infrastructures, J. Perform. Constr. Facilities 32 (4) (2018) 04018046, http://dx.doi.org/10.1061/(ASCE)CF.1943-5509.0001185.

[58] W.W. Greenwood, J.P. Lynch, D. Zekkos, Applications of UAVs in civil infrastructure, J. Infrastruct. Syst. 25 (2) (2019) 04019002, http://dx.doi.org/10.1061/(ASCE)IS.1943-555X.0000464.

[59] T. Askarzadeh, R. Bridgelall, D.D. Tolliver, Systematic literature review of drone utility in railway condition monitoring, J. Transp. Eng. A 149 (6) (2023) 04023041, http://dx.doi.org/10.1061/JTEPBS.TEENG-772.

[60] P.R. Peddinti, H. Puppala, B. Kim, Pavement monitoring using unmanned aerial vehicles: An overview, J. Transp. Eng. B 149 (3) (2023) 03123002, http://dx.doi.org/10.1061/JPEODX.PVENG-1291.

[61] A. Gohari, A.B. Ahmad, R.B.A. Rahim, A. Supa'at, S. Abd Razak, M.S.M. Gismalla, Involvement of surveillance drones in smart cities: A systematic review, IEEE Access 10 (2022) 56611–56628, http://dx.doi.org/10.1109/ACCESS.2022.3177904.

[62] I. Bisio, C. Garibotto, H. Haleem, F. Lavagetto, A. Sciarrone, A systematic review of drone based road traffic monitoring system, IEEE Access 10 (2022) 101537–101555, http://dx.doi.org/10.1109/ACCESS.2022.3207282.

[63] A. Bouguettaya, H. Zarzour, A. Kechida, A.M. Taberkit, Vehicle detection from UAV imagery with deep learning: A review, IEEE Trans. Neural Netw. Learn. Syst. (2021) 6047–6067, http://dx.doi.org/10.1109/TNNLS.2021.3080276.

[64] G.-Q. Zhang, B. Wang, J. Li, Y.-L. Xu, The application of deep learning in bridge health monitoring: a literature review, Adv. Bridge Eng. 3 (1) (2022) 22, http://dx.doi.org/10.1186/s43251-022-00078-7.

[65] Y. Akbari, N. Almaadeed, S. Al-Maadeed, O. Elharrouss, Applications, databases and open computer vision research from drone videos and images: a survey, Artif. Intell. Rev. 54 (2021) 3887–3938, http://dx.doi.org/10.1007/s10462-020-09943-1.

[66] X. Liu, K.H. Ghazali, F. Han, I.I. Mohamed, Review of CNN in aerial image processing, J. Imaging Sci. 71 (1) (2023) 1–13, http://dx.doi.org/10.1080/13682199.2023.2174651.

[67] M. Manjusha, V. Sunitha, A review of advanced pavement distress evaluation techniques using unmanned aerial vehicles, Int. J. Pavement Eng. 24 (2) (2023) 2268796, http://dx.doi.org/10.1080/10298436.2023.2268796.

[68] G. Albeaino, M. Gheisari, B.W. Franz, A systematic review of unmanned aerial vehicle application areas and technologies in the AEC domain, J. Inf. Technol. Constr. 24 (2019) 381–405, URL https://www.itcon.org/2019/20.
[69] Z. Jiang, J.I. Messner, E. Matts, Computer vision applications in construction and asset management phases: A literature review, J. Inf. Technol. Constr. 28 (2023) 176–199, http://dx.doi.org/10.36680/j.itcon.2023.009.
[70] S. Sony, S. Laventure, A. Sadhu, A literature review of next-generation smart sensing technology in structural health monitoring, Struct. Control Health Monit. 26 (3) (2019) pp. e2321, http://dx.doi.org/10.1002/stc.2321.
[71] F. Luleci, F.N. Catbas, O. Avci, A literature review: Generative adversarial networks for civil structural health monitoring, Front. Built Environ. Struct. Sens. Control Asset Manag. 8 (2022) 1027379, http://dx.doi.org/10.3389/fbuil.2022.1027379.
[72] S. Zhou, M. Gheisari, Unmanned aerial system applications in construction: a systematic review, Constr. Innov. 18 (4) (2018) 453–468, http://dx.doi.org/10.1108/CI-02-2018-0010.
[73] S. Jordan, J. Moore, S. Hovet, J. Box, J. Perry, K. Kirsche, D. Lewis, Z.T.H. Tse, State-of-the-art technologies for UAV inspections, IET Radar Sonar Navig. 12 (2) (2018) 151–164, http://dx.doi.org/10.1049/iet-rsn.2017.0251.
[74] C.-Z. Dong, F.N. Catbas, A review of computer vision–based structural health monitoring at local and global levels, Struct. Health Monit. 20 (2) (2021) 692–743, http://dx.doi.org/10.1177/14759217209355.
[75] M. Sivakumar, N.M. TYJ, A literature survey of unmanned aerial vehicle usage for civil applications, J. Aerosp. Technol. Manag. 13 (2021) http://dx.doi.org/10.1590/jatm.v13.1233.
[76] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial networks, Commun. ACM 63 (11) (2020) 139–144, http://dx.doi.org/10.1145/3422622.
[77] Statista, Revenue of the drone market by country 2022, 2023, URL https://www.statista.com/forecasts/1302524/revenue-of-the-drone-market-worldwide.