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Systematic Review

A Systematic Review of Automated Construction Inspection and Progress Monitoring (ACIPM): Applications, Challenges, and Future Directions

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Abstract: Despite the subjective and error-prone nature of manual visual inspection procedures, this type of inspection is still a common process in most construction projects. However, Automated Construction Inspection and Progress Monitoring (ACIPM) has the potential to improve inspection processes. The objective of this paper is to examine the applications, challenges, and future directions of ACIPM in a systematic review. It explores various application areas of ACIPM in two domains of (a) transportation construction inspection, and (b) building construction inspection. The review identifies key ACIPM tools and techniques including Laser Scanning (LS), Uncrewed Aerial Systems (UAS), Robots, Radio Frequency Identification (RFID), Augmented Reality (AR), Virtual Reality (VR), Computer Vision (CV), Deep Learning, and Building Information Modeling (BIM). It also explores the challenges in implementing ACIPM, including limited generalization, data quality and validity, data integration, and real-time considerations. Studying legal implications and ethical and social impacts are among the future directions in ACIPM that are pinpointed in this paper. As the main contribution, this paper provides a comprehensive understanding of ACIPM for academic researchers and industry professionals.

Keywords: automated construction inspection; automated progress monitoring; automated inspection technologies; automation in construction; systematic literature review

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1. Introduction

Construction inspection is currently a task performed mostly by human inspectors through manual visual inspection procedures. In these traditional procedures, inspectors refer to a set of plans, specifications, manuals, and standards to check different elements' compliance with the criteria defined by these references. Depending on the type and size of the project, inspectors from different specialties of civil, electrical, and mechanical are involved in these manual inspections [1].

Despite the subjective and error-prone nature of these manual inspection procedures [2–6], this type of inspection is still the common process in most construction projects. However, in the last few decades, there have been attempts to utilize advancing tools and technologies for automating the inspection processes in construction projects. Automated techniques are also used for progress monitoring purposes to evaluate progress deviations.

Recent advancements in technology have significantly impacted the construction industry, particularly in the areas of inspection and progress monitoring. The integration of Automated Construction Inspection and Progress Monitoring (ACIPM) systems has emerged as a pivotal factor in enhancing efficiency, accuracy, and safety in construction projects. With the deployment of various tools such as Laser Scanning (LS), Uncrewed Aerial Systems (UAS), and Building Information Modeling (BIM), the industry is witnessing a paradigm shift from traditional manual inspection methods to more sophisticated, automated solutions. These technologies offer the potential to not only streamline the inspection process but also provide real-time data, facilitating active decision making.

However, the adoption of ACIPM in the construction industry is not without its challenges. Issues related to data integration, interoperability, and the need for specialized skills to operate and manage these technologies pose significant barriers to widespread adoption [7]. Additionally, the construction industry must navigate the legal and regulatory implications of adopting such technologies, ensuring compliance with standards and addressing concerns related to privacy and data security. Despite these challenges, the potential benefits of ACIPM in transforming the construction industry are immense. By fostering collaboration between academia and industry, and investing in research and development, the construction industry can overcome these challenges and fully harness the capabilities of ACIPM technologies.

The objective of this paper is to systematically review the state of the art in ACIPM. The reviewed literature consists of 138 journal papers, conference papers, theses, and reports from 2002 to 2022. Five Research Questions (RQ) are defined to structure this review. These questions investigate (a) application areas of ACIPM, (b) frequency of each domain, (c) tools and techniques to enable ACIPM, (d) challenges and limitations of implementing ACIPM, and (e) future directions to implement and benefit from ACIPM to its fullest extent.

2. Review Methodology

In comprehensively reviewing the existing literature, a systematic methodology was employed in five steps. These steps are taken to (a) ensure the originality of the work, (b) define RQs to better frame the review, (c) identify the main keyworks to conduct a search, and (d) collect, filter, and store the articles. The last step is to (e) analyze the articles, before answering the RQs. Each of these steps are explained in the following. Figure 1 summarizes the review paper selection process, from identification to screening and final inclusion.

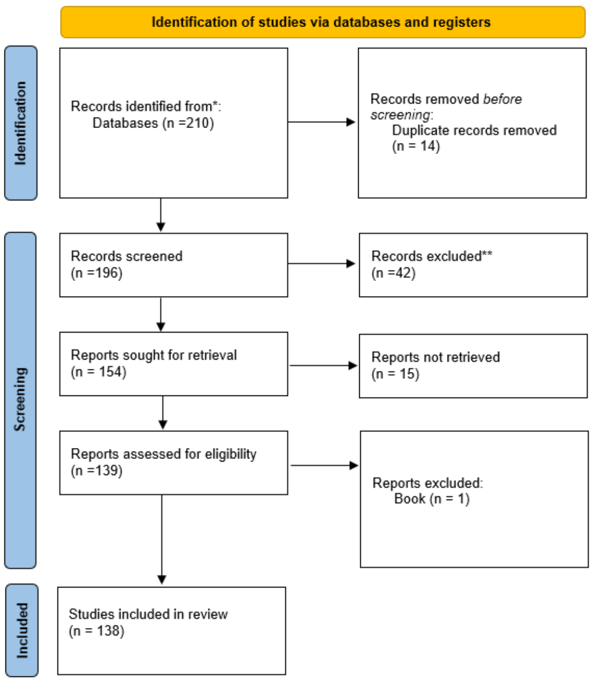

Figure 1. The PRISMA diagram detailing this systematic review.

2.1. *Significance of Work (Originality)*

Considering the novelty of ACIPM research in academia, there are no systematic approaches to comprehensively review the existing literature, with the purpose of identifying the gaps and recommending a direction for future research in this area. By creating a comprehensive review on different publication categories, including journal and conference papers, reports, and theses, this research paves the way to draw progress on this area and enable further advancements.

In this paper, ACIPM is defined as the use of advanced tools and technologies to automate the inspection processes and progress monitoring in construction projects. ACIPM leverages different (a) data collection tools such as Radio Frequency Identifiers (RFID), Laser Scanning (LS), and Uncrewed Aerial Systems (UAS), (b) data processing tools such as Photogrammetry and Computer Vision (CV), and (c) data analysis tools such as Augmented Reality (AR), Virtual Reality (VR), and Building Information Modeling (BIM).

The scope of this research covers any related research associated with ACIPM, applied in both transportation construction and building construction domains. It also covers research on progress monitoring, considering it within the scope of building construction. This research excludes any research that does not involve at least one automated tool or technique in at least one of three steps of data collection, data processing, and data analysis.

2.2. Frame Research Questions (RQs)

The next step after defining the scope of this systematic review, is to establish a set of RQs as the foundation of this research. These questions facilitate the process of gathering related scholarly work and analyzing it. Five RQs are designed as follows to structure this research:

1. What are the different application areas of ACIPM?
2. What is the frequency based on construction domain and structure?
3. What are the tools and techniques that enable ACIPM?
4. What are the challenges of implementing ACIPM in construction projects?
5. What are the future directions to improve the application of ACIPM in construction projects?

These RQs are answered in the following.

2.3. Identify Related Keywords

The next step after defining the RQs is to identify related keywords. All possible combinations related to ACIPM are created. Some of these keywords include "Automated Construction Inspection", "Automated Bridge Inspection", "Automated Highway Inspection", "Automated Progress Monitoring", "Automated Crack Detection" and "Automated Building Inspection". After defining these keywords, a keyword search is performed in internet search engines. IEEE Xplore, Scopus, and Google Scholar were mainly used for this purpose.

2.4. Collect, Store, and Filter Articles

In the next step, a broad top-down approach was taken to find as many articles as possible that were relevant to the topic. Duplicated articles were filtered out. Also, any article that was non-relevant to the ACIPM was filtered out, after reviewing its abstract and keywords. A total of 196 articles were identified at this point to be collected. Inter Library Loan (ILL) service was used to access these articles. After collecting the articles available through ILL, magazines, manuals, and books were excluded, and a total of 138 resources were collected and stored, after the final filtration.

2.5. Analyze the Data

The last step after collecting the articles was to categorize them into two categories of (a) academic publications including journal and conference publications, and (b) other publications including reports, and theses. Figure 2 illustrates the article breakdown, based on type and year. After two rounds of screening, a total of 138 articles were analyzed in this paper. As shown in this Figure, the research on ACIPM has increased in the last few years.

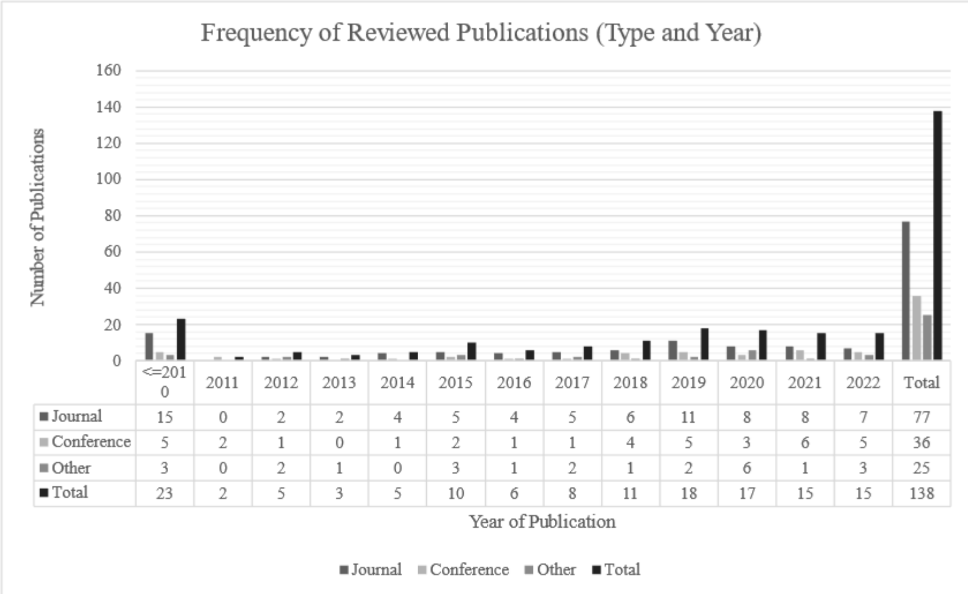

Figure 2. Frequency of reviewed publications (type and year).

Table 1 illustrates the major areas of the reviewed academic publications, and the journal/conference title and publisher within each area. There were further areas and publishers, with only one publication, which are not displayed in this Table. As shown in this Table, Elsevier's Automation in Construction journal has attracted the most publications, followed by the Proceedings of the International Symposium on Automation and Robotics in Construction (ISARC).

Table 1. Major research areas of reviewed publications.

Research Area	Total Number	Journal/Conference Title	Publisher	Frequency
Applications of Automation, Robotics, and Digital Technologies	31	Automation in Construction	Elsevier	21
		Proceedings of the ISARC	ISARC	10
Construction Engineering and Management	6	CRC International Conference	CRC	6
Advancement of Technology and Engineering Fields	5	IEEE International Conference	IEEE	5
Application of Advanced Information and Communication Technologies	5	Advanced Engineering Informatics	Elsevier	5
Application of Computing, Information Technology, and Digital Innovations	5	Computing in Civil Engineering	ASCE	3
		Journal of Computing in Civil Engineering	ASCE	2
Engineering and Computer Science	4	Procedia Engineering	Elsevier	2
		IEEE Access	IEEE	2
Science and Technology of Sensors and Sensing Systems	4	Sensors	MDPI	4
Applied Sciences	2	Applied Sciences	MDPI	2
Built Environment	2	Buildings	MDPI	2
Energy Science	2	Energies	MDPI	2
Transportation Engineering	2	Transportation Research Record	SAGE	2

3. RQ1: What Are the Different Application Areas of ACIPM?

ACIPM has been applied to several areas withing the construction industry, including (a) transportation construction inspection, and (b) building construction inspection (Figure 3). Each of these areas of applications are studied in this section to answer RQ1 and investigate different applications of ACIPM.

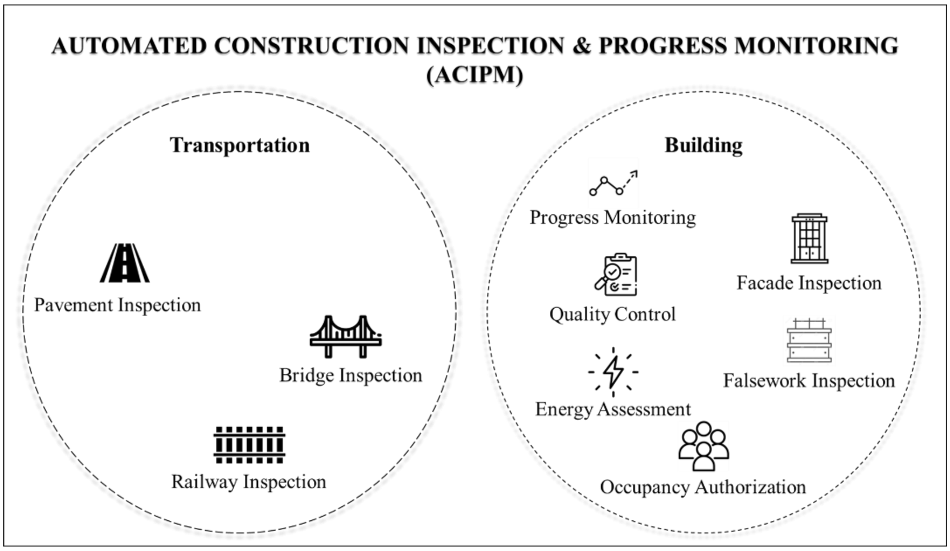

Figure 3. Different application areas within ACIPM, divided into two domains of transportation and building inspection.

3.1. Automated Inspection in Transportation Domain

Transportation infrastructure plays a critical role in supporting the economic and social progress of any country, as it ensures the reliable, safe, and efficient movement of people and goods. However, as the population continues to grow and transportation structures age, there is a pressing need for more efficient technologies and solutions for construction inspection [7,8]. ACIPM is one of the proven solutions that has been adopted in the last few decades.

This section reviews the state of the art in automated transportation inspection, in three subsections of (a) pavement inspection, (b) bridge inspection, and (c) railway inspection.

3.1.1. Pavement Inspection

Vehicle traffic, weather conditions, and material aging are some of the reasons for pavement surface deterioration [9]. A pavement inspection system is required to maintain the optimal service of a road and guarantee its safety [10]. Several studies have studied the application of ACIPM in pavement condition assessment and crack detection.

Automated Road Inspection Vehicles were one of the early tools that enabled ACIPM. In this framework, cameras and sensors are mounted on a vehicle to acquire images and videos of the road surface. One method to analyze the visual data is to use the Shadow Moire method. Through this method, the image distortions are analyzed to identify the road surface characteristics such as texture and roughness [11].

One recent approach for pavement distress inspection was creating an image- or video-based automated inspection system, by collecting 2D and 3D information [9,10,12–14]. In this approach, 2D pavement images are adjusted using the depth information retrieved from 3D models. Then Convolutional Neural Networks (CNNs) are used to detect distress patterns and classify the types of distress. For this purpose, the collected data must be processed (resized, normalized, filtered, etc.) and labeled as an input for the training phase. After training the model, it is evaluated using a separate set of images, and the model's performance is assessed based on its accuracy. Figure 4 illustrates this approach.

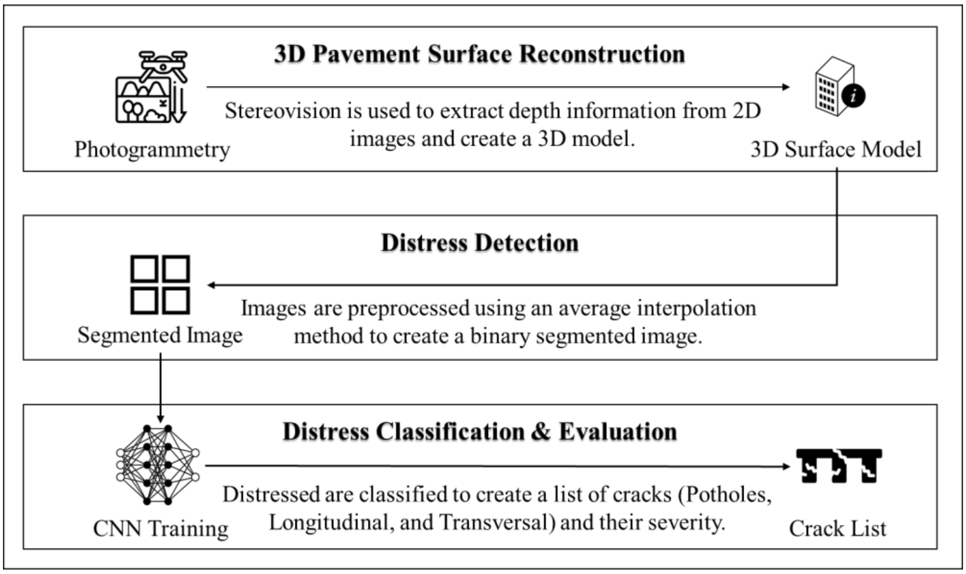

Figure 4. Automated 3D and CNN-based pavement inspection framework proposed by [10].

Another approach is to use a Laser Crack Measurement System (LCMS) where 3D laser profilers are mounted on an inspection vehicle [15]. The acquired 2D and 3D data are processed to detect the types and severity of cracks. This approach is generally more expensive than the image-based CNN system [9].

Automated Hot Mix Asphalt (HMA) thermal profiling is a further approach. In this approach, different tools such as paver-mounted Infra-Red (IR) sensors [15], roller-mounted GPS [16], and Uncrewed Aerial Systems (UAS) [17,18] are used to collect mat temperature and create a thermal profile of the mat. As a result, thermal and density segregated areas are detected on the mat, and the segregation impacts on the pavement's performance is reduced. Figure 5 illustrates this approach.

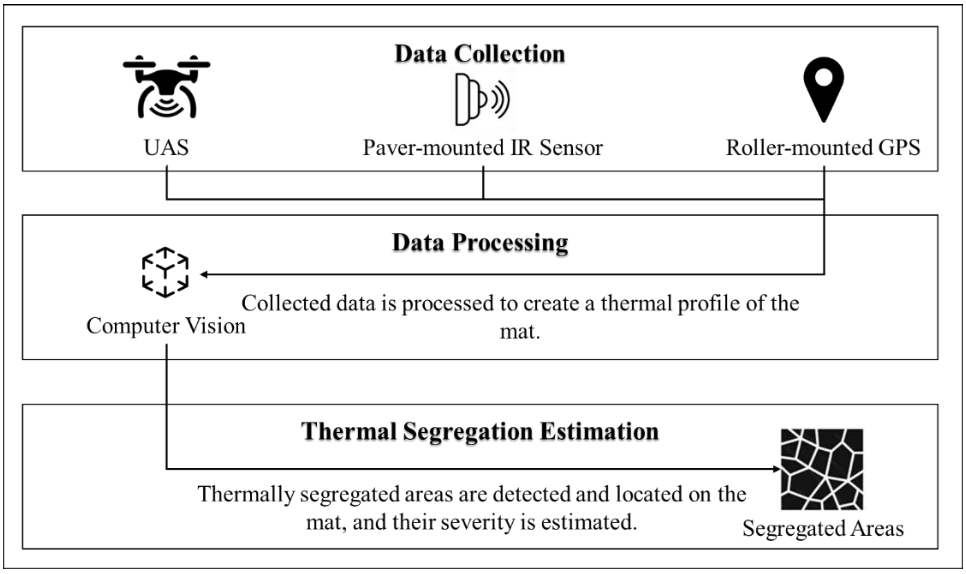

Figure 5. Automated HMA inspection framework.

E-ticketing is also another tool to support ACIPM. By installing GPS on construction equipment, and integrating a GIS interface, it is possible to collect load and haul information. Other technologies such as bar codes, magnetic stripes, RFDI, smart card, and voice recognition devices are also used for E-ticketing [19]. E-tickets enable tracking the equipment on the road, and acquire delivery and dump times, as well as documenting the load tonnage. This information assists the project managers in remote inspection and efficiently managing the equipment on site [15]. Figure 6 illustrates the E-ticketing framework for construction projects.

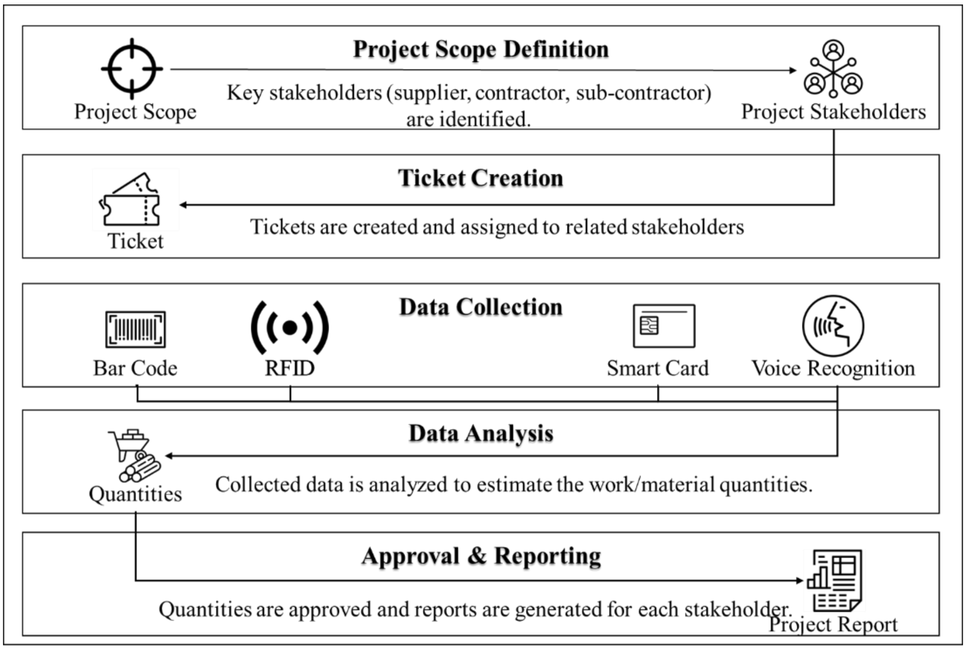

Figure 6. E-ticketing framework for construction projects.

3.1.2. Bridge Inspection

According to America's 2021 Infrastructure Report Card, 42% of the nation's bridges are at least 50 years old, and 7.5% of these bridges are considered structurally deficient [20]. In a traditional inspection process, every bridge is inspected manually and visually at regular intervals, to determine their physical and functional conditions [21]. The National Bridge Inspection Standard by FHWA [22] is used as the main reference by certified bridge inspectors, and bridge elements are assessed based on the inspectors' observations [21].

Understanding the need for automated tools and procedures, several studies have proposed automated methods to inspect bridges. Both steel and concrete bridges are studied for (a) crack detection, (b) structural element detection, and (c) delamination detection. Some other areas of research include (d) random inspection spot selection, (e) coating inspection, and (f) route planning. In addition, there are few studies looking at defect detection for masonry arch bridges.

The main approach in these studies is based on vision-based data collection. In this approach, site images and videos are collected using UAS. Route planning is required before flying the UAS to generate collision-free paths [23]. The collected data are then analyzed to detect different defects, such as cracks and delamination. Several methods are used for data analysis purposes, such as Image Processing (threshold segmentation and edge detection) and Deep Learning (CNN). In addition, defects are located on the bridge, and a damage map is created to visualize the results in a 3D BIM. The final results are utilized for decision making (condition evaluation and maintenance strategy generation) by related stakeholders. Figure 7 illustrates this framework.

UAS route planning can be automated using different methods. Zou et al. have studied this using BIM-GIS data [24]. Their study integrates GIS data with a BIM. In the next step, surrounding environment information and geometry data for the bridge are collected to be used as the input for the path planning algorithm. The final result is the shortest closed polygon as the desired path. This path is used to collect data from a case study bridge and create a 3D model of it using photogrammetry. Figure 8 illustrates this framework.

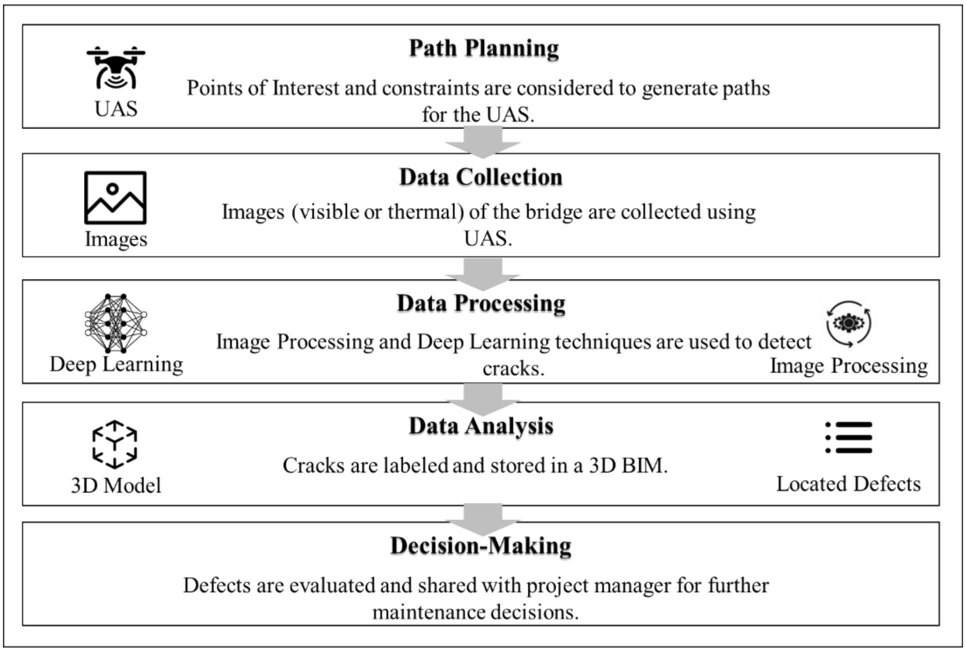

Figure 7. UAV-based bridge inspection framework, proposed by [23,24].

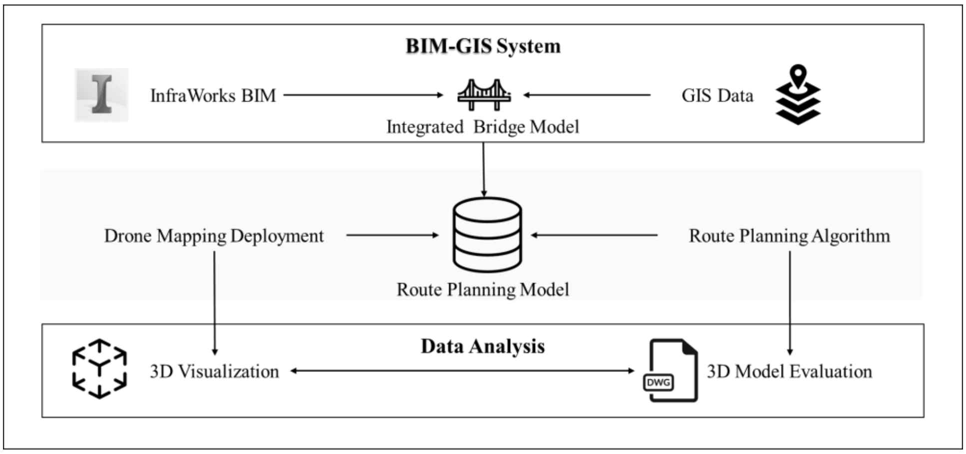

Figure 8. BIM-GIS route planning framework, proposed by [25].

In another approach, robots are used for automated bridge inspection. In this approach, a ground [3] or climbing [25] robotic platform is equipped with on-board computers to create 3D point cloud maps. These point clouds can be later used to detect bridge defects and their characteristics (area or volume). In a study by Charron et al. the overall scale error of their designed ground robotic platform was only 1.3%, which was a considerably low error [3].

McCrea et al. have also reviewed the steel bridge inspection methods in a systematic review [26]. They have studied different areas of steel bridges, as well as different methods and equipment for automating the bridge inspection. The authors of [27] have also conducted a review on fully automated bridge inspection. While their focus was on using UAS, they have approached the research topic in three steps of (a) data collection, (b) data analysis, and (c) decision making. In addition, they have studied the Level of Automation (LoA) for each step, and identified the challenges associated with each step. Their study also proposed visions on answering each challenge. Similar steps are taken by Zhang et al. to systematically review the literature using UAS for bridge inspection [27].

3.1.3. Railway Inspection

Railways are also another vital component of a transportation system. Due to the increased demand for long-distance tunnels and subways, the railway sector has expanded in recent years [28]. Despite the advancements in rail vehicle operations, railway inspection still relies heavily on traditional manual inspection. In addition to common challenges of manual inspection, railway tunnels are often located in dusty and humid environments, with limited lighting, which increases the safety and health risks for inspectors [28]. As a solution, there has been an interest in automating the inspection operations for railways.

One approach is to develop a robotic system for defect inspection on rail tunnels [28]. In this approach, visual images and videos are collected from rail surfaces, using cameras mounted on a robot. A simulation is carried out to understand how the robot operates before testing it on an actual project. The collected data are analyzed using Image Processing algorithms to detect cracks on the images. MATLAB's Image Processing Toolbox function (Tubularity Flow Field (TuFF)) is one of the existing tools for processing collected images. It detects different types of cracks on the rail surface. Figure 9 illustrates this framework.

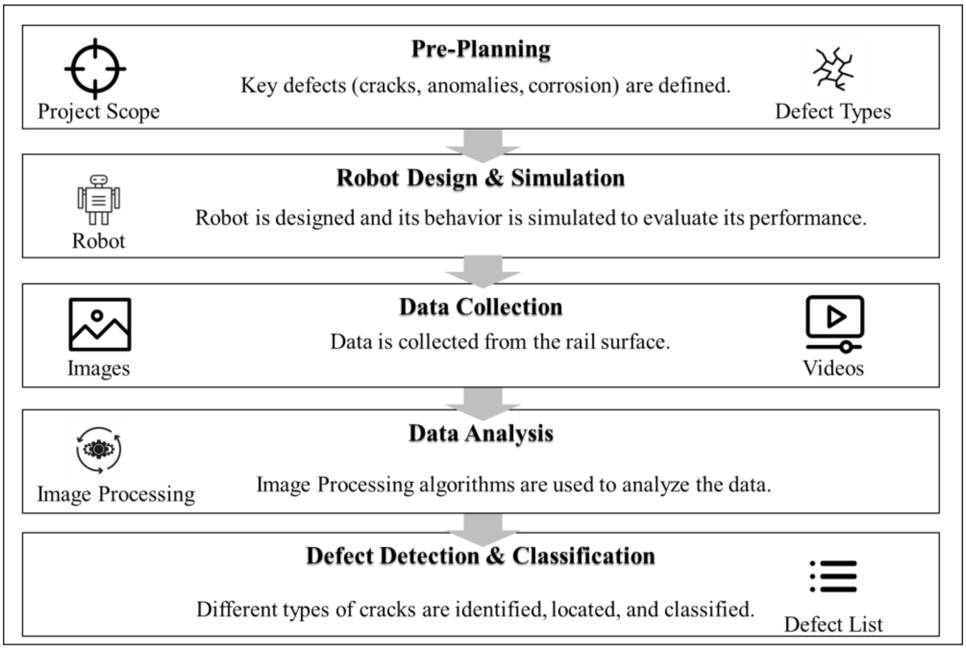

Figure 9. Robotic railway inspection framework.

Track images and videos can also be collected through manual data collection using different cameras [29,30]. The next step after collecting the images is to create a point cloud of the railway and generate a 3D mesh model. PhotosScan and RealityCapture are some of the photogrammetry applications that can be used for 3D object reconstruction. Finally, cracks are detected and classified on reconstructed images.

Another approach is to use Laser Scanning (LS) for detecting concrete spalling [28]. In this approach, 3D point clouds are generated to model the spatial position and surface features of the spalling regions. Image Processing and Deep Learning methods including CNN are used to interpret the collected data and report a 3D mesh model of the spalling defects. Figure 10 illustrates this framework.

Last but not least, Panella et al. have conducted a cost–benefit analysis to compare two approaches of using Photogrammetry and Laser Scanning for rail tunnel inspection [31]. Their study discovered that photogrammetry is a better option, in terms of cost and global accuracy. It is also more versatile and easier in comparison to Laser Scanning.

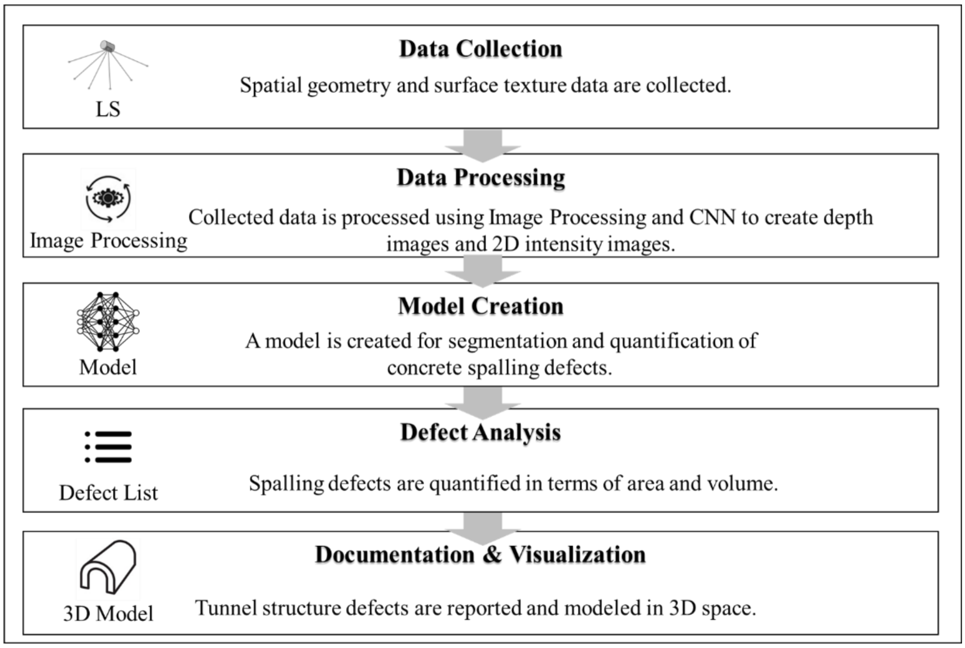

Figure 10. Concrete tunnel spalling inspection framework using LS, proposed by [31].

3.2. Automated Inspection in Building Domain

Building inspection using traditional methods has proven to be inefficient [32]. However, similar to the transportation domain, there are advanced technologies to support automated building inspection, to overcome the inefficiencies.

This section studies the application of ACIPM in the building domain. Main categories of (a) façade inspection, and (b) quality management, as well as (c) falsework inspection, (d) energy assessment, and (e) occupancy authorization are among the main areas of application within the building domain. Since the majority of progress monitoring applications are related to the building domain, progress monitoring is studied under this section.

3.2.1. Progress Monitoring

In traditional progress monitoring, progress information is collected manually, to act as an as-built record of the project. These as-builts are compared to the as-planned quantities of the project, to detect progress discrepancies. On the other hand, ACIPM enables automated progress monitoring, in three steps of (a) data collection, (b) data processing, and (c) progress estimation and visualization. There are different tools and techniques that support each of these steps. ACIPM benefits from at least one of the data collection tools, to replace manual data collection with an advanced tool. A data processing technique is also required to process the collected data, and ultimately estimate the project progress and visualize it. Figure 11 is a schematic diagram for progress monitoring.

There are several approaches to automate progress monitoring. The first approach is to collect digital images and videos of project sites using handheld cameras. Another solution is to use UAS. While handheld fixed cameras have limited views, using multiple cameras or cameras mounted on a UAS provides a more comprehensive depiction of the project progress. Collected data are analyzed (a) manually or (b) automatically using photogrammetry and Computer Vision, to estimate the project progress. In automated data analysis procedures, different features such as color, shape, and texture are extracted for different activities. Project progress is estimated using these features. BIM is also used in some projects to better visualize the progress of the project. Image-based systems are inexpensive in comparison to most data collection tools, such as Laser Scanners [33].

Another prevalent approach is to use LS to collect 3D point clouds and generate an as-built BIM for the project. While the accuracy of this method is high, it has several disadvantages in comparison to image-based approaches. Some of these disadvantages are

(a) high initial and maintenance costs, (b) requiring trained operators, (c) slow warm-up, and (d) noisy data [33]. Furthermore, processing the point clouds for object detection purposes is cost- and time-consuming [33]. To improve these disadvantages, there has been some research [34] on combining photogrammetry and LS to enhance the data quality.

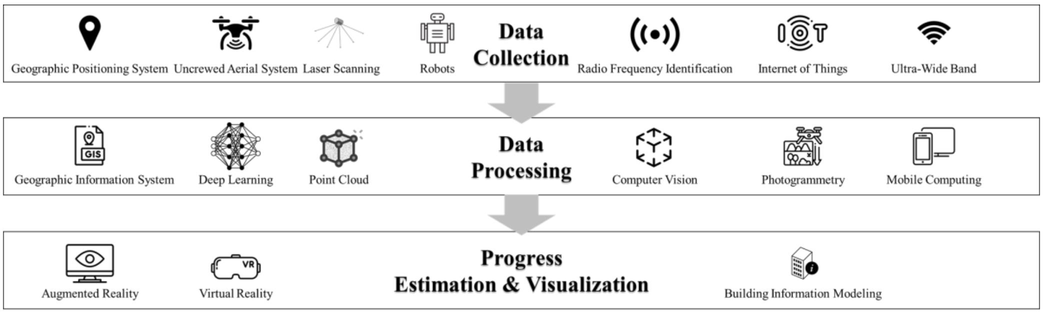

Figure 11. Progress monitoring framework.

A different method is to use RFID to detect equipment and material and collect related information. In this method, tags are placed on construction equipment and material. By scanning these tags, it is possible to track equipment and material and estimate the project progress. One major disadvantage of this method is the need for installing tags on the target equipment and material in the dynamic environment of any construction project [33].

3.2.2. Façade Inspection

Building facades are one of the critical components of a building and can cause serviceability and safety concerns if deteriorated [35]. Façade deterioration is caused by loading and environmental factors. In manual practices, façade inspection is carried out in two steps of (a) initial visual inspection and (b) closer inspection of potentially damaged areas. To improve the safety and efficiency of these inspections, several automated approaches are designed by [32,35–38].

The most common approach is to use UAS for collecting high-quality images of the building façade [35,38]. Proper flight planning is necessary to ensure compliance with safety and legal requirements. A Structure from Motion (SfM) technique is later used to reconstruct the images into a 3D model. This approach is supported by Machine Learning algorithms which detect defects on collected images, as well as their extent and other features. Finally, a list of existing defects is created, and defects are ranked based on predefined severity criteria to prioritize the maintenance process for more severe defects. Building on this approach, [39] have developed an open-source software for exterior crack inspection on buildings.

3.2.3. Quality Control

Quality control in construction projects relies heavily on construction specifications. These specifications are complex, due to the existing cross-referencing and the large number of criteria. One approach is to automate processing of these specifications to extract requirements associated with each product or process. In this approach, formal framework is developed to utilize the project information extracted from highly semantic project models. By integrating this framework with reality-capturing technologies, it is possible to compare the building's as-built information with the deducted requirements. This results in a list of deviations for each building component. This list is ultimately used for correcting the defects [40].

Similar to bridges, crack detection is also carried out for buildings in quality control procedures. These procedures can be automated using CNN. As explained before, this involves image learning through a labeling process for one dataset and testing the trained model on another dataset to evaluate its accuracy [41]. Figure 12 schematically illustrates this crack detection framework in four steps of (a) data collection, (b) 3D model reconstruction, (c) data analysis, and (d) post-processing.

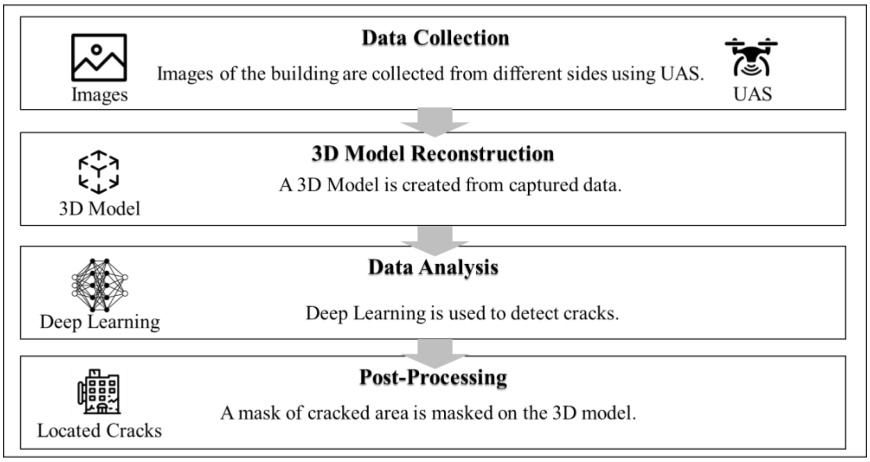

Figure 12. Building crack detection framework using UAS, proposed by [33].

BIM can also be used for quality control applications [42]. In these applications, BIM is utilized to present 4D data (3D design data + schedule). This 4D model visualizes the construction sequences to identify any issue or clash. It results in timely identification of defects and resolves them, without future rework and claims. However, the increased cost and complexity of implementation have been the main drawbacks on using BIM for quality control purposes.

3.2.4. Falsework Inspection

Falsework inspection is another area that can benefit from automation. Atherinis et al. have designed a smart system to use RFID for falsework inspection [43]. Their system identifies different members using RFID and compares them with a 3D model represented by AutoCAD 360 drawing viewer. This system locates members significantly faster than manual inspectors and resulted in higher accuracy. Figure 13 illustrates their proposed methodology. It consists of two systems of quantification and positioning, which communicate with the database, and identify falsework members that are equipped with RFID tags. The results are shared with the inspection team, on their portable devices such as tablets and smartphones.

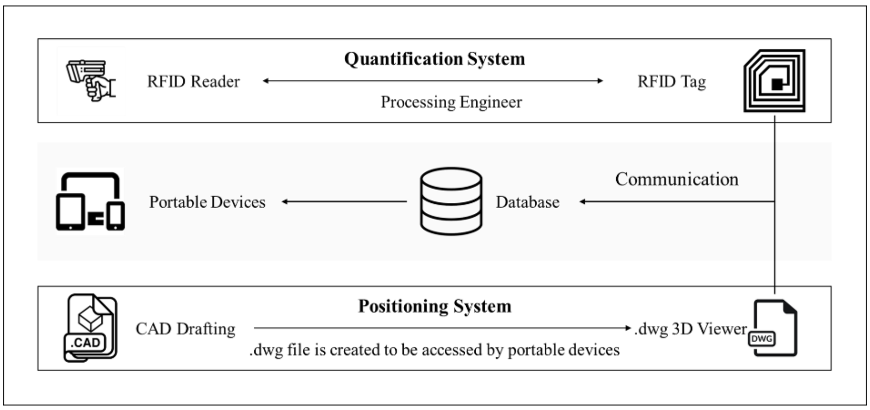

Figure 13. Automated falsework inspection framework [44].

3.2.5. Energy Assessment

The building sector requires immediate action to prioritize energy efficiency [44]. A detailed building inspection can help improve energy efficiency. A vision-based energy inspection approach is proposed by Mirzabeigi et al. (2022) [45]. In that approach, UAS is used to collect thermal images from building sites, and the collected data are analyzed using Image Processing. Finally, thermal anomalies of the building envelope are detected for a case study. The proposed methodology can be integrated with building simulation processes to generate a comprehensive building energy assessment. Figure 14 illustrates this framework in five steps of (a) flight planning, (b) data collection, (c) pre-processing, (d) thermal anomaly detection, and (e) post processing.

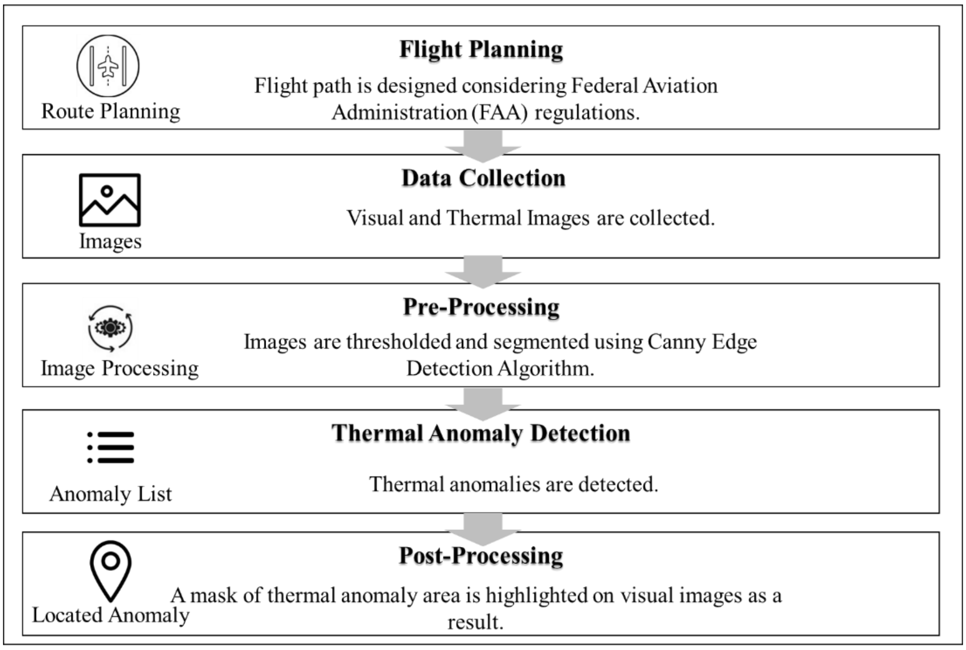

Figure 14. Energy assessment framework using UAS, proposed by [46].

3.2.6. Occupancy Authorization

Building occupancy inspection is the final step in the permitting process. This process can be automated using advanced technologies. Lee et al. have proposed an ACIPM framework to use UAS for occupancy authorization inspection. Their framework uses photogrammetry to process the UAS collected images and create a BIM for the building. The created BIM can be used for occupancy authorization purposes and complements the traditional inspection processes. Their study has been successful in inspecting several elements of a case study building [46].

4. RQ2: What Is the Frequency Based on Construction Domain and Structure?

While the first RQ investigated different applications of ACIPM, it did not study the frequency of each domain structure type (bridge, road, railway, building, etc.). For this purpose, the second RQ investigated different structures and reviewed the frequency of scholarly work on each sub-domain. This information offers two potential benefits. Firstly, it provides valuable insights into the structures that are well suited for ACIPM implementation. Secondly, it serves as a guide for future researchers, pointing out areas in the existing literature where gaps exist and further exploration is needed.

As Table 2 shows, bridges have been the most frequent structure in the transportation domain, while roads and railroads are placed at the second rank. The high interest in applying ACIPM in bridge inspection is because of several reasons, such as (a) complexity of bridges, (b) safety and accessibility challenges, (c) larger inspection scale, (d) cost effectiveness of ACIPM, and (e) continuous health monitoring needs of bridges.

Table 2. Domain and sub-domain (structure based) comparison for reviewed papers.

Domain	Sub-Domain (Structure)	Frequency	Publications
Transportation (Total Reviewed: 58)	Bridge Inspection	31	[2–6,21,23–27,47–64]
	Highway Inspection	13	[7,10–17,65–69]
	Railway Inspection	14	[28–31,70–79]
Building (Total Reviewed: 70)	Progress Monitoring	52	[18,80–130]
	Quality Inspection	9	[1,40–42,45,127,128,131,132],
	Façade Inspection	5	[25–28,38]
	Crack Inspection	3	[32,37,39]
	Energy Assessment	1	[44]
	Falsework Inspection	1	[43]
	Occupancy Authorization	1	[46]
Others (Related to both Domains)		8	[133–140]
Total Reviewed		138	

Under the building construction inspection domain, progress monitoring is a prevalent area of research. Some reasons for widespread adoption of ACIPM for progress monitoring are (a) time efficiency, (b) labor saving, (c) improved accuracy, (d) enhanced consistency, (e) real-time availability, (f) comprehensive documentation, and (g) safety benefits of using ACIPM in this sub-domain.

5. RQ3: What Are Data Collection and Processing Tools and Techniques?

In this section, all tools and techniques enabling ACIPM are reviewed. Table 3 summarizes each tool, its brief description, and the frequency of using it in the reviewed literature. As shown in this table, handheld cameras are the most utilized data collection tools for collecting visual site data. LS, AR, CV, Deep Learning, and UAV are some other tools that enable data collection and processing. The advancement of these tools, from simple handheld devices to complicated analytical algorithms, showcases the construction industry's dedication to enhancing operational efficiency and fostering innovation in the field of ACIPM.

Table 3. Tools and techniques utilized for ACIPM.

Tools and Techniques	Description	Frequency
Handheld Cameras	A traditional camera to capture optical images and videos from jobsite.	39
Laser Scanning (LS)	A technology that uses laser light to digitally capture the exact size and shape of a target object.	31
Augmented Reality (AR)	A computer technology to add visual, auditory, haptic, and somatosensory data on top of the current real world.	28
Computer Vision (CV)	An interdisciplinary tool for processing and analyzing visual data (digital images/video). This tool seeks to simulate, an interpreting process performed by a human visual system.	24
Deep Learning	Subset of machine learning that uses artificial neural networks with multiple layers to process and analyze complex patterns in data.	24

Table 3. *Cont.*

Tools and Techniques	Description	Frequency
Uncrewed Aerial System (UAS)	An aircraft without a human pilot on board. A system consisting of a UAV, a ground-based controller, and a communication system between these is called an Unmanned Aerial System (UAS). Cameras and sensors are mountable on a UAS to capture different types of data.	23
Building Information Modeling (BIM)	A process that integrates different tools and technologies to generate visual/functional models of a built asset/facility.	21
Robots	Mechanical or virtual devices that perform tasks autonomously or semi-autonomously and are often able to mimic human actions.	14
Radio Frequency Identification (RFID)	RFID is a system consisting of a radio transponder, a radio receiver, and a transmitter. This system utilizes electromagnetic fields to detect and track the tags/smart labels attached to the target objects.	8
Geographic Information System (GIS)	Technology to captures, analyzes, and visualizes spatial data to understand patterns, relationships, and make informed decisions about the real world.	5
Geographic Positioning System (GPS)	Satellite-based navigation system to provide positioning data. GPS is one of global navigation satellite systems (GNSS) to provide geo-location and time information to a GPS receiver.	4
Point Cloud	Collection of 3D data points in space, typically obtained through laser scanning or 3D imaging techniques.	3
Photogrammetry	Technique for processing and interpreting the visual data collected using different data collection technologies, such as aerial images collected with UAS. It allows 2D/3D digital model generation of a target object.	3
Paver Mounted Thermal Profiler	Device mounted on a paver to capture temperature profiles of the asphalt pavement during construction to ensure proper quality and compaction.	1
Smartphone	Mobile device that combines the functionalities of a cellular phone with advanced features such as internet connectivity, touchscreen interface, multimedia capabilities, and a wide range of applications for various tasks	1
Internet of Things (IoT)	Network of interconnected physical devices, vehicles, appliances, and other objects embedded with sensors, software, and connectivity capabilities, to remotely collect and exchange data.	1
Mobile Computing	Using portable computing devices, such as smartphones, tablets, and laptops, to access and process information, perform tasks, and communicate while moving.	1
Virtual Reality (VR)	A computer technology that uses software to produce images /sound and create the sensation of presence at a target place.	1
Ultra-Wide Band (UWB)	Radio communication technology for target sensor data collection and tracking and precision locating. UWB consumes low level of energy, and creates short-range, high-bandwidth communication data.	1

6. RQ4: What Are the Challenges?

This RQ addresses the limitations and challenges of using ACIPM. Each publication is reviewed to collect a pool of challenges. These challenges are then categorized in categories of (a) limited generalization and adaptability, (b) data quality and variability, (c) integration and compatibility, (d) real-time data analysis, (e) complex construction contexts, (f) human–technology interface, (g) cost and efficiency, and (h) computation optimization. The frequency of each category is also investigated, and the results are summarized in Table 4.

Table 4. Challenges of implementing ACIPM.

Category	Frequency	Challenge	Publications
Limited Generalization and Adaptability	9	Models might lack generalization.	[17,35,37–39,41,59,63,76]
Data Quality and Variability	8	Data formats and quality are inconsistent across construction projects.	[7,12,24,39]
		Data accuracy is affected by different factors, including lighting and weather conditions.	[5,43]
		There are no standardized data collection methods.	[27,39]
Integration and Compatibility	7	It is difficult to integrate ACI systems with existing construction processes and technologies.	[27,40]
		Different ACI platforms might not be compatible or interoperable with each other.	[7]
Real-time Data Analysis	4	It is challenging to capture and analyze the data in real time.	[5,35,39,42]
Complex Construction Contexts	2	Complexity due to dynamic and diverse construction, as well as irregularity in geometry and design environment needs to be studied.	[39,43]
Cost and Efficiency	2	Cost–benefit and efficiency analysis need to be studied, especially for smaller project.	[24,43]
Human-Technology Interface	1	It is challenging for construction personnel to operate the ACIPM tools.	[7]
Computation Optimization	1	Computation burden is high for the developed ACI models.	[6]

Enhancements in data processing algorithms, interoperability standards, and user interface design are crucial for overcoming the limitations of generalization, integration, and human-technology interaction. Furthermore, addressing the variability in data quality demands the development of robust, adaptive models capable of accurate performance under diverse conditions. By focusing research efforts on these strategic areas, it is possible to improve the efficacy, reliability, and user-friendliness of ACIPM systems, thereby enabling their broader adoption and more effective application in the construction industry.

7. RQ5: What Are the Future Directions?

The last RQ to address is to define the future direction for implementing ACIPM in the construction industry. A main area of further study is to enable continuous training for models to generate reliable results for different projects. This includes exploring different data processing techniques and algorithms to improve the adaptability of the ACIPM models to various construction contexts, and the development of robust frameworks that facilitate the integration of diverse data sources to enhance model accuracy and versatility.

Another prevalent area is the integration of BIM and ACIPM. While there have been several studies on integrating BIM for as-built generation and project status visualization purposes, there is still a gap in utilizing BIM for real-time monitoring and visualization of the project. Enhancing the interoperability between BIM and ACIPM could lead to more efficient project management and execution, by providing a more dynamic and comprehensive understanding of project progress and potential issues.

One of the novel directions is to study legal and regulatory considerations. Within the context of ACIPM, legal implications of automated inspections need to be examined. In addition, liability in case of differences between ACIPM and manual inspection needs to be determined by project stakeholders, and prior to the implementation of ACIPM. It is also critical to establish clear standards for ACIPM implementation to ensure compliance and protect all parties involved.

Last but not least, is the ethical and social implications of using ACIPM. The effect of automation on the workforce needs to be studied. Furthermore, ethical considerations and data privacy, as well as transparency needs in decision making, must be defined to fully enable ACIPM. It is crucial to consider the human aspect of ACIPM adoption, including the potential for job displacement and the need for retraining programs to equip the workforce with the skills necessary for new roles created by ACIPM technologies.

8. Conclusions

The objective of this paper was to systematically review the state of the art in ACIPM. This paper presented the first comprehensive literature review on ACIPM, distinguishing itself by exploring applications, challenges, and future directions of ACIPM, not previously addressed in the existing reviews. Through a comprehensive analysis of existing research, it filled a significant gap in the academic discourse, offering new insights and frameworks that promise to advance the field of construction inspection and progress monitoring.

A total of 138 journal papers, conference articles, theses, and reports were collected, filtered, and stored for the review purpose. Five RQs were defined and answered based on this collection of the literature. The first RQ investigated application areas of ACIPM in two different domains of transportation and building. Pavement inspection, bridge inspection, and railway inspection were studied as the main application areas in the transportation domain. Progress monitoring, quality control, façade inspection, falsework inspection, energy assessment, and occupancy authorization were studied in the building domain.

The second RQ tested frequency of each domain. It was concluded that ACIPM has been mostly applied in the building domain, in comparison to the transportation domain. Progress monitoring, followed by bridge inspection, are the two sub-domains where ACIPM is mostly implemented.

Tools and techniques to enable ACIPM were studied in the third RQ. Handheld cameras that collect site images and videos are the most frequently used data collection tools. LS, AR, CV, Deep Learning, and UAV are some other frequently used tools and techniques for data collection, processing, and visualization purposes.

The fourth question investigated challenges and limitations of implementing ACIPM. Limited generalizations and adaptability was identified as the main challenge of using ACIPM. Data quality and variability, and integration and compatibility, were also other frequent challenges.

The last RQ prompted future directions to implement and benefit from ACIPM to its fullest extent. Improving the data processing algorithms that expand the adaptability of ACIPM to different construction contexts was the first major area for future work. Integration of BIM was also identified as another future direction.

It must be noted that, while this research is pioneering in its systematic review of ACIPM across transportation and building construction domains, it operates under certain limitations. Primarily, the scope of the literature included is limited to academic publications including journal and conference publications, and other publications including reports and theses that are accessible through academic institutional channels, excluding potentially relevant magazines, books, and manuals, and references not available via these means. Additionally, while the review comprehensively analyzes existing methodologies, tools, and applications, it acknowledges the rapid evolution of technologies and methodologies in ACIPM, which may outpace this review's findings. Such limitations underscore the importance of ongoing research to continuously update and expand the understanding of ACIPM's applications, challenges, and future directions.

Last, but not least, while this paper contributes to the state-of-knowledge by systematically investigating the existing literature, future work will focus on reviewing the state-of-practice and implementations of ACIPM by Departments of Transportation (DOTs) and government agencies. It will concentrate on studying real-world projects where ACIPM has been implemented, aiming to identify and analyze the tangible impacts and outcomes of these technologies in improving project efficiency, reducing costs, and enhancing safety standards across various construction projects.

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