

Review Article

Artificial Intelligence-Driven Construction Defect Identification System in Construction: Adoption Opportunities and Implementation Barriers

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Article Info	Abstract
Article History	The integration of Artificial Intelligence (AI) within the Architecture, Engineering, and Construction (AEC) sector has transformed traditional project delivery by improving efficiency, safety, and decision-making. However, the use of AI in defect detection and management a critical yet underexplored domain remains limited in methodological depth. This study conducts a systematic and bibliometric review using the Scopus database, analyzed through Microsoft Excel to evaluate AI's efficacy in identifying, classifying, and managing construction defects. Publications between 2020 and 2024 were screened based on inclusion and exclusion criteria, focusing on AI applications in Construction Defect Identification Systems (CDIS). Quantitative synthesis indicates that AI-driven methods such as pre-trained Convolutional Neural Networks (~99%), laser vision (97.10%), and Operational Modal Analysis (97%) consistently outperform conventional methods like grey correlation analysis (86.81%) and visual inspection (80%) by 10–20% in accuracy. Despite these advances, research in predictive and real-time defect assessment remains fragmented. The study emphasizes the need for integrated, data-driven frameworks that leverage AI's predictive capabilities to establish proactive defect management systems, thereby enhancing quality standards and sustainable practices in the AEC industry.
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1. Introduction

The construction sector faces persistent challenges that directly affect project success. Each project involves unique personnel, equipment, logistics, and site conditions, while factors such as cost variations and economic fluctuations further complicate planning and execution. These uncertainties often lead to overspending, schedule delays, and disputes among stakeholders [1]. Moreover, project data are frequently collected manually and stored in decentralized, non-digital formats. Conventional management practices still depend heavily on the project manager's experience, resulting in decisions that are often based on incomplete or delayed information [2].

To overcome these inefficiencies, AI has emerged as a promising tool for enhancing data-driven decision-making in construction. AI-based Decision Support Systems (DSS) have improved productivity and safety in several industries, but their integration into the AEC sector remains limited and slower than in other domains [3]. Within the AEC context, the application of AI to construction defect management a critical determinant of quality and cost performance represents an emerging area of research.

This study investigates the current state of AI applications in the AEC industry with a specific focus on construction defect management. It critically examines how AI contributes to defect identification, classification, and management, while exploring its broader advantages, limitations, and implementation challenges. The objectives of this study are to examine the existing literature on the causes and conventional detection methods of construction defects, to assess the potential of AI-based approaches for improving defect management, and to develop a conceptual framework for integrating AI into proactive defect management strategies. To address these objectives, the study focuses three key research questions: What are the predominant AI techniques applied for defect detection and management in construction? How do AI-based methods compare with conventional approaches in terms of accuracy, efficiency, and practicality? what are the main challenges, barriers, and opportunities for implementing AI-driven Construction Defect Identification Systems (CDIS) in practice?

The AEC industry is currently undergoing digital transformation, with AI increasingly supporting functions such as cost estimation, scheduling, and safety monitoring. However, its potential in defect management remains underutilized. Construction defects contribute significantly to project delays, cost overruns, and reduced quality. Conventional inspection methods—such as visual assessments and manual documentation—are time-consuming, reactive, and prone to human error. In contrast, AI techniques, particularly those based on machine learning, computer vision, and natural language processing, enable early detection and classification of defects, offering greater precision and efficiency [4].

Automation of field inspections and real-time monitoring through AI can significantly enhance quality control and streamline communication among stakeholders. Yet, current project management systems often lack the integration necessary to effectively track and manage defects. In practice, defects may occur both before and after handover [5]. While pre-handover defects lead to hidden rework costs, post-handover defects can damage contractor reputation and client relationships [6]. Despite these consequences, defect identification in most projects continues to rely on traditional, experience-based methods rather than intelligent, predictive systems.

Existing literature on AI in construction remains fragmented, with limited studies focusing exclusively on defect management. Few works offer comprehensive comparisons between traditional and AI-based defect detection techniques, and even fewer combine bibliometric analysis with qualitative synthesis. Furthermore, the integration of stakeholder perspectives, real-time data, and AI tools for

proactive defect prevention remains largely unexplored.

By addressing these gaps, this study provides both academic and practical contributions to the understanding of AI's role in improving quality management in construction. It synthesizes research trends, highlights key barriers and enablers, and proposes a roadmap for future research and industrial implementation. Ultimately, this work emphasizes the potential of AI to transform conventional, reactive approaches to defect management into intelligent, data-driven systems—enhancing productivity, safety, and the overall quality of construction projects.

2. Literature Review

The construction industry is undergoing a slow yet steady digital transformation. Among the technological advancements, Artificial Intelligence (AI) has emerged as a transformative force capable of redefining how construction projects are planned, executed, and maintained. This literature review examines the increasing role of AI in the construction sector, highlighting both its benefits and limitations. It begins with an overview of AI's applications in construction and proceeds to discuss the recognized advantages, prevailing barriers, and implementation challenges. The section concludes with a discussion of construction defects—a critical area where AI applications can have tangible impacts.

2.1. Use of Artificial Intelligence in the Construction Sector

Construction companies have access to more structured data thanks to AI technology, enabling them to make decisions more quickly, intelligently, and thoroughly. However, its adoption remains limited. Construction management is still in its early stages of development and is utilizing AI at a significantly slower rate than other industries [7]. AI applications have accelerated in recent years, driven by "Industry 4.0," and possess all the necessary components to serve as the foundation for effective digital initiatives in the AEC sector[8]. In the construction phase, every project is distinct, requiring unique, project-specific work often described as bespoke. To produce high-quality outputs that enable a quicker, more flexible, and less expensive construction project, process optimization is crucial. Similar to Industry 4.0, which refines automation and process optimization, Construction 4.0 is centered on the idea of creating smart construction sites, utilizing simulations and virtual data storage for optimal delivery and process simplification, as well as large-scale production [9]. These ideas help construction companies organize and compare data from various project stages, as well as data from end users after the project is completed. According to MGI [10], by 2030, AI is expected to be worth \$13 trillion to the global economy, representing a 16% increase over the total global GDP in 2018. While there are many definitions of AI, the EU Commission appointed the High-Level Expert Group (HLEG) to define AI as "software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning

on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal" [11, 12].

Researchers have contributed to applying AI and its related domains to address challenges unique to the construction industry over the past few decades. For example, machine learning has been applied to risk prediction, supply chain and logistics process optimization, cost estimation, and health and safety monitoring, among other applications [13]. Early risk detection refers to the proactive identification of potential issues or threats before they escalate into significant problems during a construction project [14]. Traditional methods often rely on periodic site inspections, checklists, or expert judgments, which may fail to capture emerging risks in real time. In contrast, Machine Learning (ML) enables dynamic, data-driven detection by continuously analyzing construction data and identifying patterns associated with past risk occurrences. Robotics has been utilized in off-site assembly, construction material handling, plant operations, equipment management, site monitoring, and performance evaluation [15]. Moreover, knowledge-based systems have been utilized for evaluating sustainability, risk, and waste management, as well as dispute resolution and tender evaluation [16]. Despite this, the construction sector remains among the least digitally advanced globally, and it continues to face challenges in embracing artificial intelligence and other digital technologies. The following sections discuss the benefits, barriers, and challenges associated with the adoption of AI in the AEC sector.

2.2. Benefits of Artificial Intelligence Adoption in the Architectural Engineering and Construction Sector

Numerous benefits have been previously highlighted in the literature; however, most of these benefits originated from the academic and research perspectives (Figure 1) [17-19].

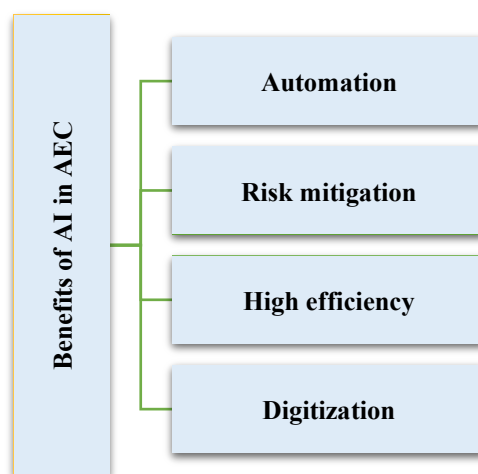


Figure 1. Benefits of AI adoption in the AEC sector

Project management becomes more objective and technically automated through the use of AI. AI-based solutions help address some drawbacks of traditional construction management, which is more

biased, subjective, and inconsistent because it relies on manual observation and operation. AI can monitor, detect, assess, and forecast potential hazards in terms of cost, quality, safety, and efficiency across teams and work areas—even in situations where there is considerable uncertainty. To improve the smoothness and efficiency of the construction process, AI techniques are heavily utilized in optimization challenges [20].

The digitization of the construction industry has been driven by Building Information Modeling (BIM), which provides a wealth of information about the entire project lifecycle, extending far beyond 3D modeling. AI and BIM can work together to streamline information digitization in intelligent AEC processes. Although these benefits have increased interest in the AEC industry, the majority of research is derived from Research and Development (R&D) initiatives. As the potential of technologies like BIM and AI in the AEC sector is being explored through such initiatives, these advancements have not yet been fully adopted and integrated into the industry's daily practices. The current spread of AI applications in the sector remains underexplored. Thus, to illustrate deployment margins and future strategic objectives for increased penetration of digital technologies, this study presents an exploratory examination of existing AI usage in the construction industry [21].

Lastly, research on AI applications, potentials, benefits, and trends is the primary focus of recent literature. However, assessing the benefits or barriers acknowledged by construction specialists is lacking. The long-term application of AI in the construction sector depends on these elements.

2.3. Challenges in Deploying Artificial Intelligence in the Architectural Engineering and Construction Sector

The study identified several barriers that prevent AI from being widely adopted in AEC. This part examined four issues that resulted from the barriers: the lack of case studies or standards, the cost-benefit analysis, the data quality challenge, and the shortage of experienced personnel with AI skills [22, 23]. Figure 2 illustrates the challenges associated with AI adoption in the AEC sector.

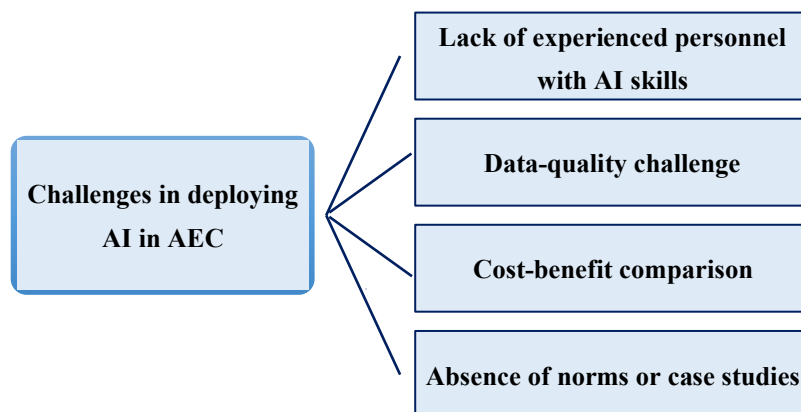


Figure 2. Challenges of AI adoption in the AEC sector.

2.3.1. Lack of Experienced Personnel with Artificial Intelligence Skills

According to predictions, AI will gradually transform economies, reshape global economic structures, and become a vital tool for helping companies meet their goals and improve key performance indicators. Therefore, in the coming years, it is expected that there will be a sharp increase in demand for workers with AI training, according to Forbes [24]. There are policies in place in many developed economies worldwide, most notably in the United States and the European Union, to encourage the adoption of AI technology [25].

Although more academic institutions are offering courses in AI and machine learning, it will take some time for the industry to meet the demand for workers with this knowledge. Talented machine-learning engineers are in high demand, making it harder to recruit suitable candidates and necessitating more staff retraining. Governments may provide their workforce a competitive advantage by promoting the development of individuals with advanced computing and analytical skills and ensuring their availability. Industry and academia should collaborate to create apprenticeship programs that enable students to transition between multiple organizations and gain experience with AI applications across various sectors and job functions, as AI education requires practical experience [26]. Employers need to be able to use academic experts to impart their knowledge to students.

2.3.2. Data Quality Challenge

Data quality is the degree to which a dataset is suitable for the particular purpose of machine learning applications. For the successful application of machine learning to real-world scenarios, high-quality data is significantly more important than the quantity of data [27]. Although data quality is crucial for training machine learning systems, it is much more crucial for guaranteeing the reliability of the applications' decisions. When data is collected from more sources and becomes more unstructured, the quality of the data declines. Machine learning requires structured data; however, more data is being generated in unstructured formats (such as text, video, and image data), which conventional data-management technologies cannot handle. Real-time machine learning systems will need to be able to identify and process unstructured data. Companies should establish a data-quality assessment process to provide quality measurements, collect fresh data, review data quality, remove inaccurate data from the training dataset, and examine the trade-off between gains and costs associated with quality assurance. The majority of approaches in the twelve key data-quality assessment models involve objective measurements or a mix of analytics and subjective measurements. Total Data Quality Management (TDQM) is one of the most prominent frameworks [28].

In the past, images or time series data were digitally copied. It is not easy to use current data arbitrarily for (R&D) with commercialization goals or intended for specialized professional fields due to copyrights and privacy regulations, and intellectual property protections. It is necessary to have a method for

individually validating each dataset after it is acquired. While a program is available to automate this process, it is not yet complete; therefore, human participation is required at every stage [28]. Studies have indicated that enhancing the precision of AI models necessitates the participation of a refinement manager and workers with training who possess a scholarly understanding of the development domain. Furthermore, an adequate data-quality approach must include data improved by individuals with professional development education rather than the general public.

2.3.3. Cost-Benefit Comparison

AI technologies in the construction sector offer clear advantages, such as improved productivity, enhanced safety, and reduced errors. However, these benefits often require a substantial initial investment, particularly in technologies such as robotics and automation systems [29]. As a result, construction firms must assess where AI can deliver the most immediate and measurable value. Investments should be guided by a well-defined business case, focusing on areas that align with the company's current level of digital maturity and operational priorities. Without a clear understanding of Return on Investment (ROI) or tangible cost savings, organizations risk inefficient allocation of time and resources, which can lead to dissatisfaction and a loss of momentum [29]. Smaller firms and subcontractors, which form a significant part of the construction industry, may find these technologies cost-prohibitive in the short term [29]. Therefore, it becomes essential to evaluate AI solutions not only in terms of their potential but also in terms of their scalability and ongoing operational costs. Encouragingly, as AI technologies continue to mature and gain broader adoption, their costs are expected to decrease, making them more accessible to smaller players in the industry [30]. In conclusion, a strategic, ROI-focused approach is essential when investing in AI. By targeting high-impact, easily implementable applications, construction firms can ensure sustainable adoption and long-term cost benefits.

2.3.4. Absence of Norms or Case Studies

Every disruptive technology reshapes society, often necessitating some form of regulation. The first obstacle in selecting the optimal legal structure for artificial intelligence is assessing its social implications. The other is to keep pace with the rapid development of artificial intelligence. The intricacy, independence, capacity for self-learning, and widespread use of AI in various industries are additional barriers. These features require a qualified interdisciplinary ability for policymaking that is both flexible (capable of envisioning frameworks that, while enforceable, can be modified over time) and informed (able to comprehend technology and anticipate consequences). Structured data and industry standards are also essential elements for improved interoperability. This suggests that people and technology may be able to integrate information, enabling the extraction of more valuable knowledge. Across sectors, comparable information formats are used to achieve consistency, repeatability, and predictability. This will result in

real efficiency gains for businesses, and the data architecture for the linked future will be ready [31].

2.4. Construction defect

A defect is a malfunction or weakness that affects how a building performs, meets user needs, or both. It can appear in the building's structure, fabric, services, or other amenities [30]. Construction defects are widespread and frequently arise during construction projects, especially in those with poor workmanship and inadequate project management on the construction site. A construction defect is one of the most significant issues in the construction sector that could lower a building's worth. The earlier a defect is identified during the construction process, the easier it is to complete the project within the planned timeline and enhance structural stability. This helps to prevent or reduce errors in subsequent work. Whether a building issue is the result of poor design, use of the wrong materials, or poor craftsmanship can only be determined by an expert, such as an engineer or architect.

Existing studies have primarily focused on developing standalone defect detection algorithms or reviewing general AI applications in construction. There is no comprehensive synthesis that systematically compares traditional and AI-based methods for construction defect identification. Furthermore, there is limited integration of bibliometric analysis with qualitative assessment to reveal publication trends, methodological evolution, and performance benchmarking. The absence of research frameworks that incorporate real-time data, stakeholder perspectives, and predictive AI models highlights a critical gap in achieving proactive defect management.

3. Methodology

This study adopts a mixed systematic–bibliometric review approach to comprehensively analyze Artificial Intelligence (AI) applications in construction defect management. The Scopus database was selected for its broad coverage of peer-reviewed publications, using two keyword sets—“Construction Defect Identification System” and “Construction Defect Identification System AND Artificial Intelligence” to retrieve relevant studies published between 2020 and 2024 in the engineering and construction domains. Only English-language journal and conference papers directly addressing AI or digital technologies in defect detection, classification, or management were included, while duplicates, editorials, and unrelated studies were excluded. Bibliometric data were organized and analyzed in Microsoft Excel to assess publication trends, country distribution, and subject areas. Qualitative synthesis was performed to interpret the findings and identify dominant methods, benefits, and gaps. To ensure accuracy, data extraction and analysis were independently verified by two reviewers, with discrepancies resolved through consensus and replication of the search process to confirm reliability. The adopted methodological framework, illustrated in Figure 3, integrates bibliometric mapping with systematic review principles to evaluate, synthesize, and contextualize AI-driven construction defect identification research.

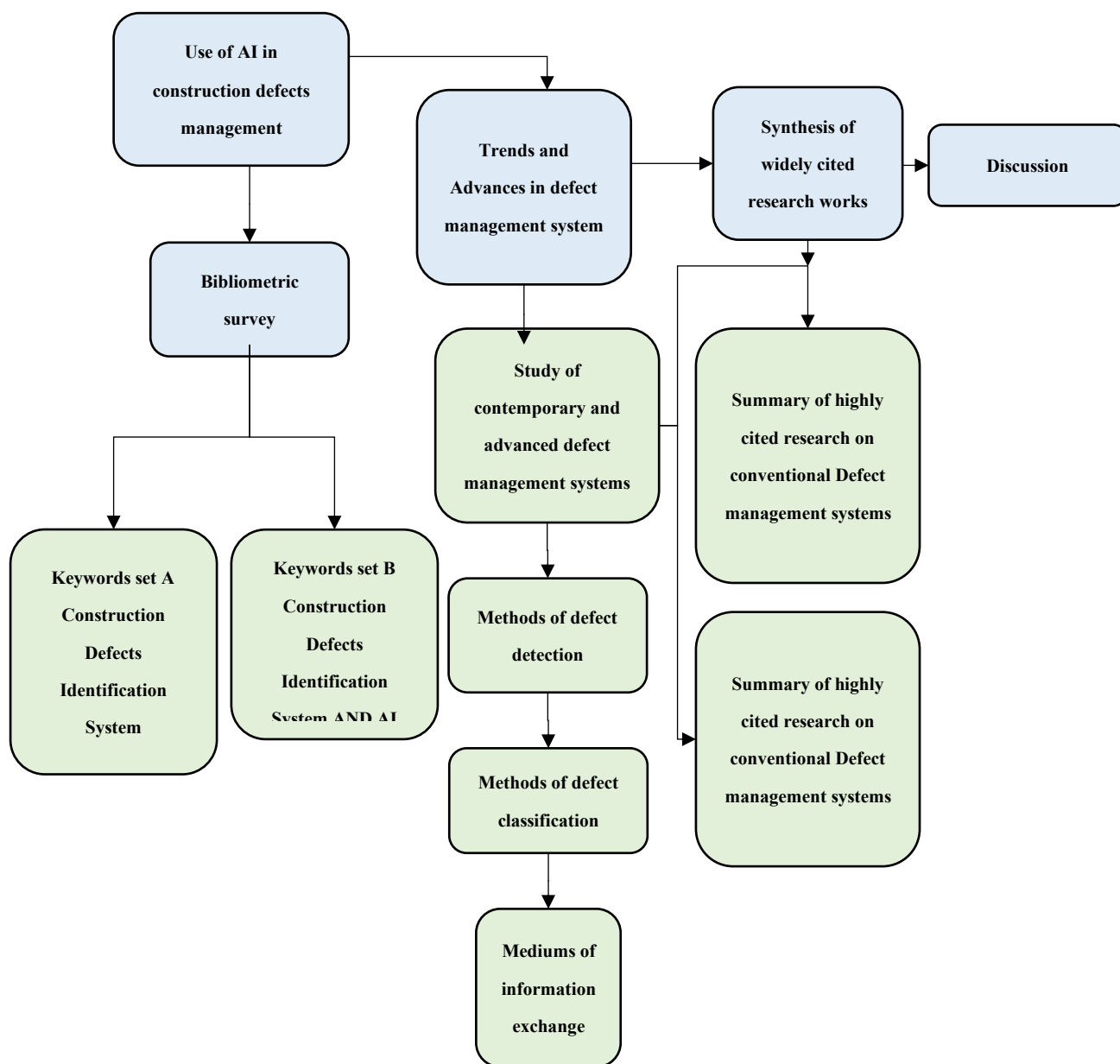


Figure 3. Sequential process flow of the study

4. Result and Discussion

The search for Set A keywords has identified 90 publications in the domain, whereas it limits to only 3 when AI and CDIS are searched (Figure 4). The analysis of documents retrieved from the Scopus database on the study of defect identification systems reveals that the majority of research has been concentrated in the field of Engineering, which accounts for 60% of the total publications. This dominance underscores the critical importance of defect detection in engineering applications, where safety, performance, and regulatory compliance are paramount (Figure 5). Meanwhile, both Decision Sciences and Social Sciences contribute 3% each, indicating a smaller but notable interest in the managerial, organizational, and societal aspects associated with defect identification systems. Overall, this distribution suggests that while technical disciplines dominate research in this area, interdisciplinary perspectives are gradually gaining attention.

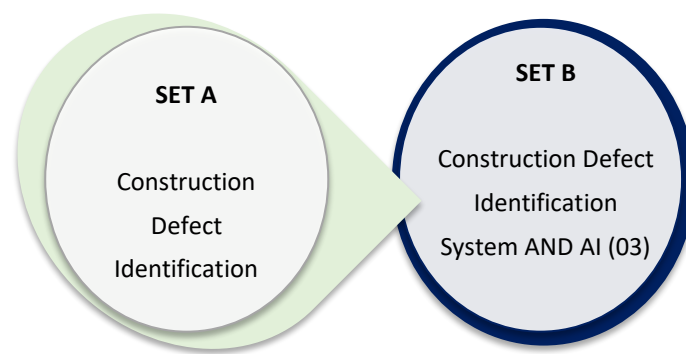


Figure 4. Search results of selected keywords

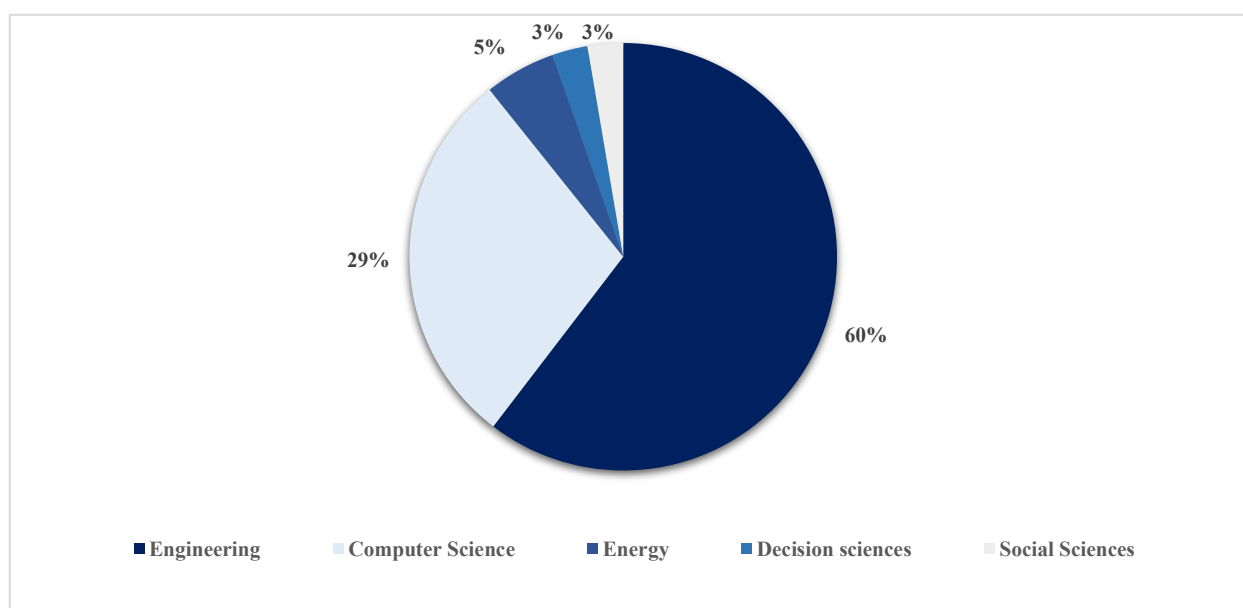


Figure 5. Statistical analysis of data based on the subject area for Set A

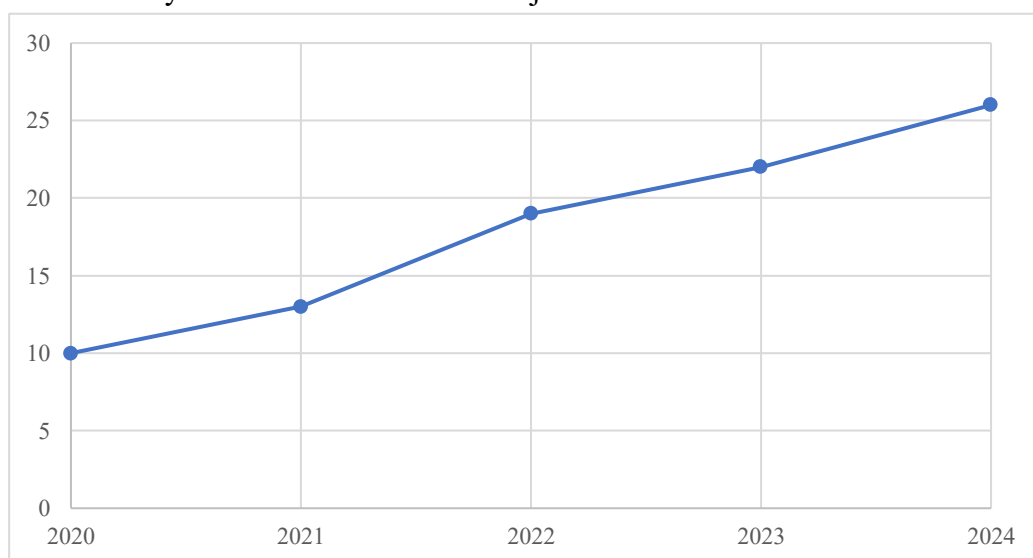


Figure 6. Statistical analysis of data based on year-wise publication for Set A

Figure 6 displays a chart of documents published by year. The survey was conducted over a period of five years, from 2020 to the present. The incremental rise in the number of documents indicates a positive approach towards this research area, as 10 documents were published in 2020, and by 2024, this number had increased to 26.

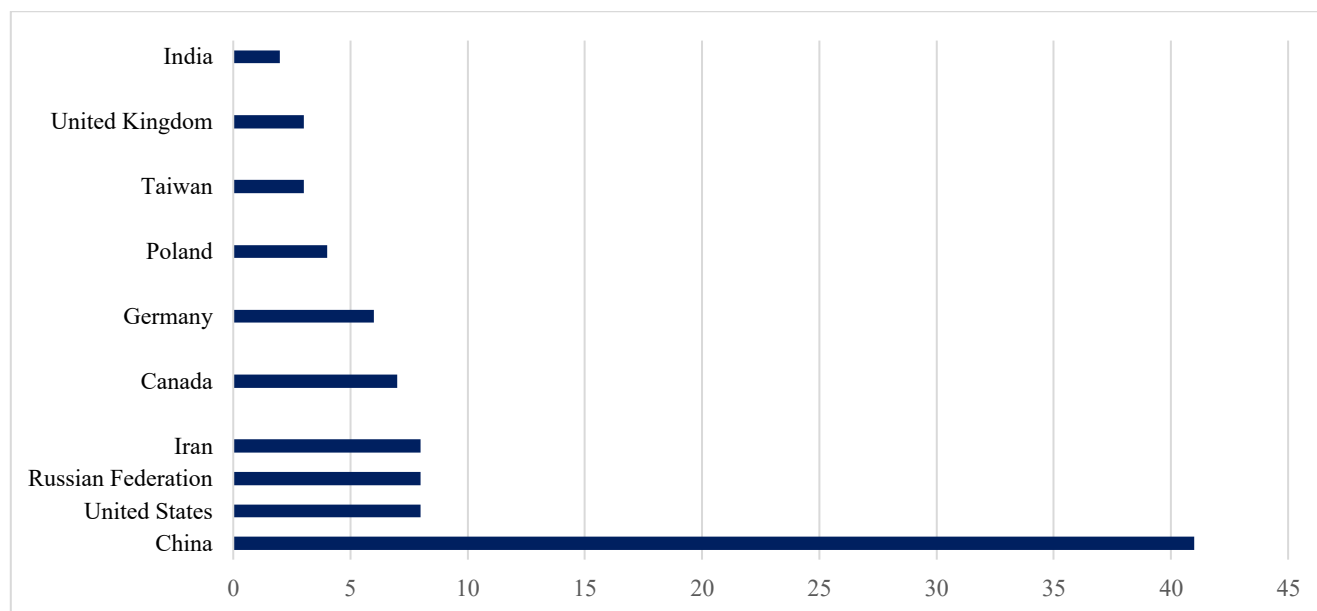


Figure 7. Statistical analysis of data based on country-wise publications for Set A

Figure 7 displays a chart of documents published by country. It is observed that most research originates from China, with 41 published documents, followed by the United Kingdom with eight documents. In India, the construction defect identification system requires greater attention, as only two documents have been published to date.

The survey is then initiated with a selection of keywords, broadly defined as "Construction Defect Identification system AND AI." The group of these keywords is referred to as Set B. It is observed that the highest number of documents was subsequently conducted using broader keywords, i.e., "Construction Defect Identification System AND AI", which are from the engineering sector, accounting for 34%. Next to engineering is the 'computer science' stream with 22%. Further study is confined to documents from the engineering sector alone. The survey was conducted over a period of five years, from 2020 to the present. The only document was published in 2022, 2023, and 2024. It is observed that the research is initiated by China, Hong Kong, and Vietnam, with one publication. In India, the topic of construction defect identification systems remains a research priority, as no documents have been published to date.

4.1. Detection of Construction Defects: Observed Methods and Effectiveness

The study demonstrated the most efficient methods of minimizing the defect, such as increasing workmanship quality, accepting responsibility, holding frequent progress meetings, choosing high-quality materials, employing modern construction techniques, improving the ability to read and understand

drawings, adhering to specifications, proper inspection, improving quality control, and improving oversight in the inspection. These flaws are caused by several factors, including human errors [32]. Figure 8 illustrates various methods for defect detection.

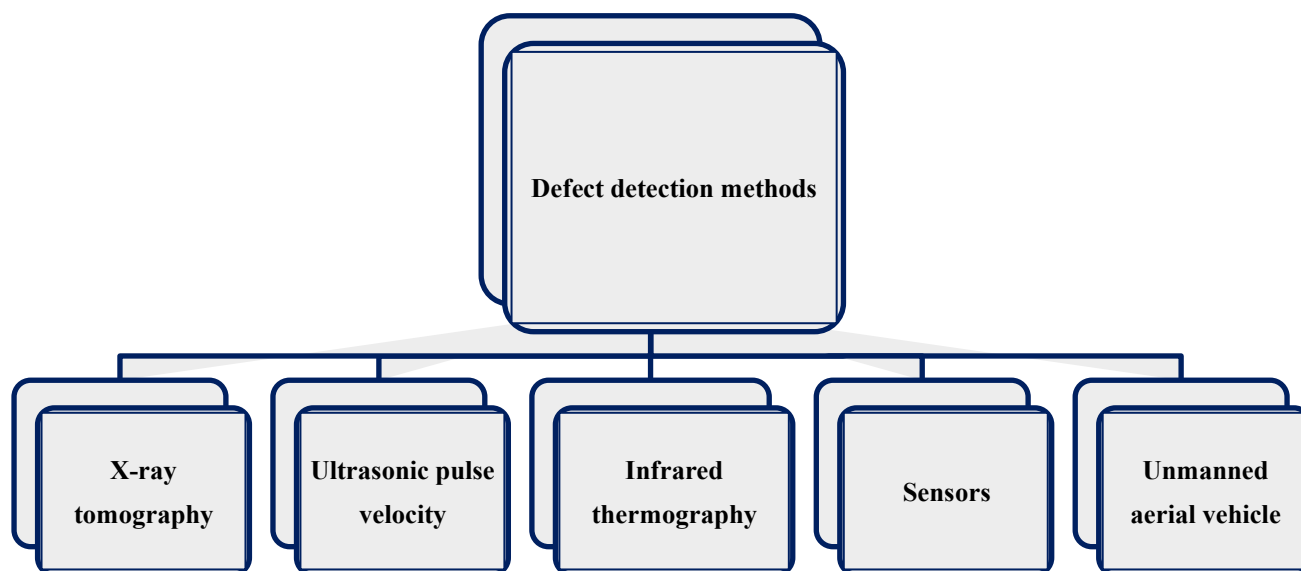


Figure 8. Diagrammatic representation of available methods for defect detection

The used methods have emerged as a common yet advanced technique for defect detection. Every method has its advantages and disadvantages. To gain a clear understanding, details of each method are summarized in Table 1 below.

Table 1. Summary of advantages and disadvantages of defect classification methods

Sr. No.	Method	Advantages	Disadvantages	Reference
1	X-ray tomography	Very rapid, easy to handle, and cost-effective	It can be applied for experimental purposes only	[33]
2	Ultrasonic pulse velocity	Fast and more accurate results	The test is performed manually and requires the careful attention of experienced technicians.	[34]
3	Infrared thermography	Determines and quantifies near-surface flaws	It must be done in a radiation- and weather-safe environment. Training and knowledge are a must.	[35]
4	Sensors	Provide real-time data, their precision, and accuracy	Cost, susceptibility to interference and damage, and limited lifespan.	[36]
5	Unmanned Aerial Vehicle	Small enough to fly over the areas where humans cannot possibly reach.	It cannot be used for curved edges. For irregular shapes not applicable	[37]

4.2. Observed Techniques for Classifying Construction Defects

To raise the level of automation of asset condition inspection, researchers have recently experimented with a range of soft computing and machine learning-based detection approaches. Figure 9 illustrates various methods for defect classification.

A larger family of Machine Learning (ML) techniques based on Artificial Neural Networks (ANN) and representation learning includes Deep Learning (DL). DL algorithms use multiple layers to

progressively extract higher-level features from raw data input, such as in image processing. DL algorithms break down complex hierarchies into simpler ones. Convolutional Neural Networks (CNNs), a subset of deep learning techniques, are typically employed to address fundamental issues, including segmentation, object identification, classification, and localization. Feature extraction/detection using filters is performed in the first part of the CNN, and image classification is carried out in the second part of the CNN [38].

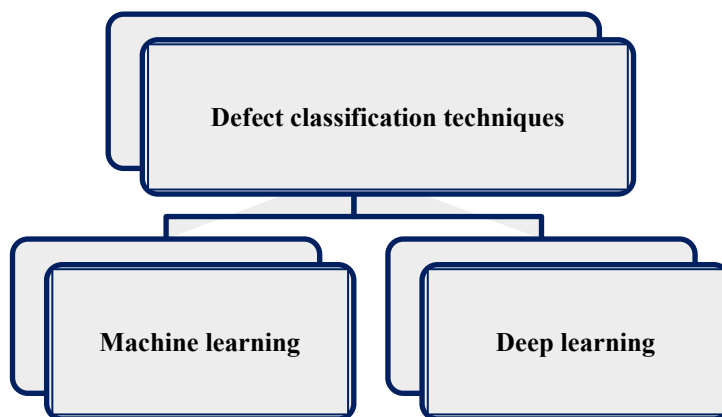


Figure 9. Methods for defect classification.

The most straightforward kind of neural network is the Perceptron. This single-layer neural network has just one input layer and one output layer. By joining many perceptrons together, one can construct a multi-layer neural network with one input and one output, and numerous intermediate layers, also known as hidden layers [9]. The deeper the neural network (hence the name "deep neural network"), the more hidden layers it has [38]. A neural network's input layer typically has the same number of nodes as features contained in the input data. For instance, the number of nodes in our input layer is $3 \times 224 \times 224$, as our inputs are pictures with three channels (Red, Green, and Blue) and 224×224 pixels [9]. On the other hand, the neural network setup determines the number of nodes in the output layer [38].

4.3. Observed Mediums for Sharing Inspected Data

Building-defect data are handled during the inspection by noting inspections into a paper-based or digital checklist. The traditional method for on-site inspections relies heavily on physical labor, which raises the possibility of errors, inaccuracies, or data loss before, during, or after the inspection. Additionally, setting up the inspection and compiling post-inspection data requires a substantial amount of time when using traditional defect management approaches. A more effective information exchange medium is needed to increase productivity and reduce unnecessary delays and rework caused by inaccurate information transfer between three-dimensional and two-dimensional contexts, as well as misreading of plans and drawings [39]. Figure 10 illustrates the various mediums used for exchanging information on construction sites.

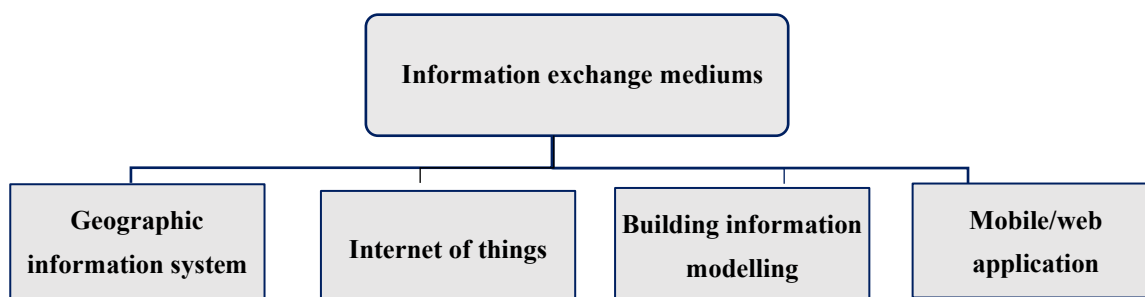


Figure 10. Mediums used for the exchange of information on construction sites.

None of the suggested methods performs as effectively as they do in ideal conditions, and the optimal approach depends on the circumstances (such as whether the situation is indoors or outdoors, the type of structure, the available budget, and the required accuracy, among others). Therefore, an overarching strategy cannot be universally applied to the objectives mentioned above. A few research projects on indoor progress tracking offer only limited automation. Either manually assigning data or manually comparing the as-planned and as-built models is needed by the user [39]. According to recent global research studies, the use of intelligent technologies and related new technologies is crucial for enhancing quality control in residential building construction. However, the industry's inability to adopt these technologies is primarily due to financial constraints. Long-term research focuses on utilizing affordable, innovative technology-enabled platforms for effective quality control in the construction of residential building structures [40].

4.4. Summary of the Most Cited Research on Non-AI-Based and AI-Based Defect Identification Systems

This section provides a summary of papers related to defect identification in various structures, both with and without the use of AI. It primarily demonstrates the identification and rectification of defects using manual methods, as well as with the aid of AI. It summarizes the techniques investigated by various authors under both non-AI and AI-based approaches. This section covers the major types of civil structures, their defects, defect identification methods, and how these methods work.

4.4.1. Defect Identification Without AI

For defect identification, methods like manual inspection, operational modal analysis, grey correlation analysis, rebound hammer tests, and moisture content measurements, Unmanned Aerial Vehicles (UAV), Non-Destructive Testing (NDT), laser vision, BIM with Radio Frequency Identification (RFID) are used. In all these methods, a major requirement is human involvement. In the traditional construction method, defects are identified primarily through manual inspection. It takes around 120 minutes to supervise any average residential building. There are also some limitations to manual inspection in high-rise buildings. The following table 2 provides a summary of various conventional methods of defect identification implemented in highly cited research papers[36, 40].

Table 2. Summary of papers related to non-AI-based defect identification methods for a variety of structures.

Sr. No	Structure	Defects focused	Method used	Summary	Accuracy
1	Dam	Material handling, batch metering, pneumatic, and stirring system faults	Grey correlation analysis (2015)	The study investigates the identification and assessment of factors impacting defects in dam concrete production systems (CPS) using grey correlation analysis. In dam projects, these systems are essential for guaranteeing the effectiveness and quality of concrete production. Material handling, batch measuring, pneumatic, and stirring system defects are the four primary classes into which the study divides defects. These are then further divided into 22 subcategories according to the location and form of the defect. The complex nature of CPS operations—which include feeding, batching, mixing, and discharging—is highlighted by the study. Better troubleshooting and maintenance techniques are made possible by the use of the grey correlation analysis approach, which establishes links between different components that contribute to system problems. The results are intended to enhance CPS's dependability and effectiveness in major concrete dam projects [41].	86.81%
2	Bridge	Strand failure, cracking, and loss of prestress	Operational Modal Analysis (2019)	This study examines the application of Operational Modal Analysis (OMA) to assess the structural integrity and dynamic behavior of scaled prestressed concrete (PC) beams, which are commonly used as typical decks for girder bridges. Through variations in modal parameters, such as natural frequencies and mode shapes, under various test conditions, the study aims to identify damage, including strand failure, cracking, and loss of prestress. The findings indicate that whereas localized damage, such as strand rupture, causes notable changes in modal frequencies, mild cracking at service load levels does not significantly affect them. This study highlights OMA's potential as a tool for structural health monitoring and predictive maintenance in bridge engineering, facilitating efficient damage diagnosis and risk reduction in civil infrastructure [42].	97%
3	Low Rise Buildings	Structural defects, such as cracks due to settlement, uneven loading, and thermal expansion, and non-structural defects, like water seepage, plaster delamination, and paint failures.	Manual inspection (2020)	The research explains the typical defects found in load-bearing wall systems and their impact on the structural and functional performance of low-rise buildings. It divides problems into two categories: non-structural defects, such as water seepage, plaster delamination, and paint failures, and structural defects, including settlement cracks, unequal loading, and thermal expansion. These issues are often linked to poor construction methods, inadequate design, and exposure to the elements. To prevent these problems, the study emphasizes the importance of thorough inspections, selecting suitable materials, and adhering to construction standards. It also emphasizes the importance of routine maintenance on low-rise buildings to ensure their longevity, safety, and aesthetic appeal [43].	—
4	Commercial Buildings	Water pooling, structural deterioration, and leakage	Rebound hammer tests and moisture content measurements (2022)	The study examines the common issues with flat roofs, including leaks resulting from inadequate drainage and waterproofing, water pooling, and structural damage. These defects can lower customer comfort and property value, increase maintenance expenses, and compromise a building's structural integrity. To resolve these flaws and mitigate their functional and economic impacts, the study emphasizes the importance of prompt inspections and preventive measures. Five Malaysian commercial buildings with flat roofs are the subject of case studies as part of the research methodology. The condition of the roofs was assessed using non-destructive testing techniques, including moisture content readings and rebound hammer tests. To effectively address the issues, the report also recommends remediation strategies, such as improved waterproofing and routine maintenance [44].	96.67%

5	Road	Surface irregularities, wear, and damage	Unmanned Aerial Vehicles (2022)	The study outlines a process for employing Unmanned Aerial Vehicles (UAVs) to monitor road conditions in mining areas. The study's main objective is to assess and track the state of mining truck haul routes using photogrammetric data collected by unmanned aerial vehicles. The technique guarantees a more precise evaluation of road characteristics, such as surface imperfections, wear, and corrosion by matching the recorded data with the truck's path's major curve. By providing timely and accurate information about the road's condition, this method minimizes vehicle wear and tear, reduces operating costs, and enhances the efficiency of road maintenance. Road monitoring in challenging mining areas can be accomplished in a non-invasive, economical, and scalable manner by integrating UAV photogrammetry [36].	90%
6	Heritage masonry structures	Cracks, deformations, and material degradation	Visual inspections, non-destructive testing (NDT), structural health monitoring (SHM), and advanced methods learning (2022)	The study focuses on a thorough examination of the tools and techniques used to detect and track degradation in historic brick buildings. Visual inspections, non-destructive testing (NDT), structural health monitoring (SHM), and cutting-edge approaches like digital imaging and machine learning are among the conventional and contemporary techniques highlighted in the review. It addresses the challenges of balancing structural safety with historical integrity. The study emphasizes the importance of integrating cutting-edge technologies with historical conservation principles to detect cracks, deformations, and material degradation. The study aims to enhance long-term management plans, refine monitoring systems, and inform conservation efforts for culturally significant masonry structures by synthesizing existing data [45].	80%
7	Weld surface	Cracks, porosity, and undercuts	Laser vision (2022)	The research presents a laser vision-based technique for accurately identifying and locating weld surface defects. High-resolution pictures of weld surfaces are taken using laser scanning equipment, and these are subsequently examined using sophisticated image processing and flaw identification algorithms. The technique is highly accurate in detecting a variety of weld flaws, including undercuts, porosity, and cracks. The method ensures accurate flaw localization by integrating automated systems with laser vision, enabling more efficient quality control in welding operations. In industrial manufacturing, this technique promotes increased safety and dependability while enhancing efficiency and reducing inspection time [46].	97.1%
8	Construction process All(Material)	Comprehensive overview of the construction process, helping to ensure that materials and methods comply with design specifications	Building Information Modeling (BIM) with Radio Frequency Identification (RFID) (2022)	The study introduces a method that enhances construction quality inspection by integrating Radio Frequency Identification (RFID) technology with Building Information Modeling (BIM). The system aims to enhance the effectiveness, precision, and transparency of the construction project quality control process. The method enables the detection and real-time monitoring of construction progress by integrating RFID tags into building materials and components. To provide a comprehensive view of the building's construction process and ensure that the materials and techniques used meet design requirements, BIM serves as a digital representation of the structure, linked to RFID data. The article covers the design concepts of the integrated system, its application in building projects, and its capacity to automate inspections, reduce human error, and enhance decision-making. RFID and BIM, when combined, hold significant promise for enhancing construction quality control by increasing the precision, data-driven nature, and efficiency of inspections [47].	89.6%

9	High-rise building	Waterproofing	Manual inspection (2023)	This research emphasizes the significance of effective waterproofing systems in preserving the structural integrity of tall buildings and preventing water-related damage. Construction flaws, poor workmanship, and inadequate joint and window sealing are common sources of leaks. It highlights the adverse effects of water seepage, including weakened structures and increased maintenance costs. The paper describes several waterproofing techniques, including sheet membranes, cementitious coatings, and epoxy-based systems, highlighting their applicability in specific circumstances. Common obstacles to successful waterproofing include issues such as a shortage of qualified labor, poor material selection, and cost-cutting measures in building. To mitigate these problems, the authors recommend utilizing expert waterproofing specialists, high-quality materials, and meticulous planning and execution. Long-term durability can be assured, and waterproofing solutions can be improved with an approach that incorporates modern decision-making frameworks [15].
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Figure 11 compares the accuracies of various defect detection methods across different applications. Laser vision and Operational Modal Analysis achieved the highest accuracies, at 97.10% and 97% respectively, followed closely by rebound hammer tests and moisture content measurements at 96.67%. BIM with RFID demonstrated strong performance at 89.60%, while grey correlation analysis and UAV-based inspections yielded slightly lower accuracies of 86.81% and 90%, respectively. Visual inspections combined with NDT, SHM, and advanced methods had the lowest accuracy in the set, at 80%, indicating that AI- and sensor-based techniques generally outperform traditional methods.

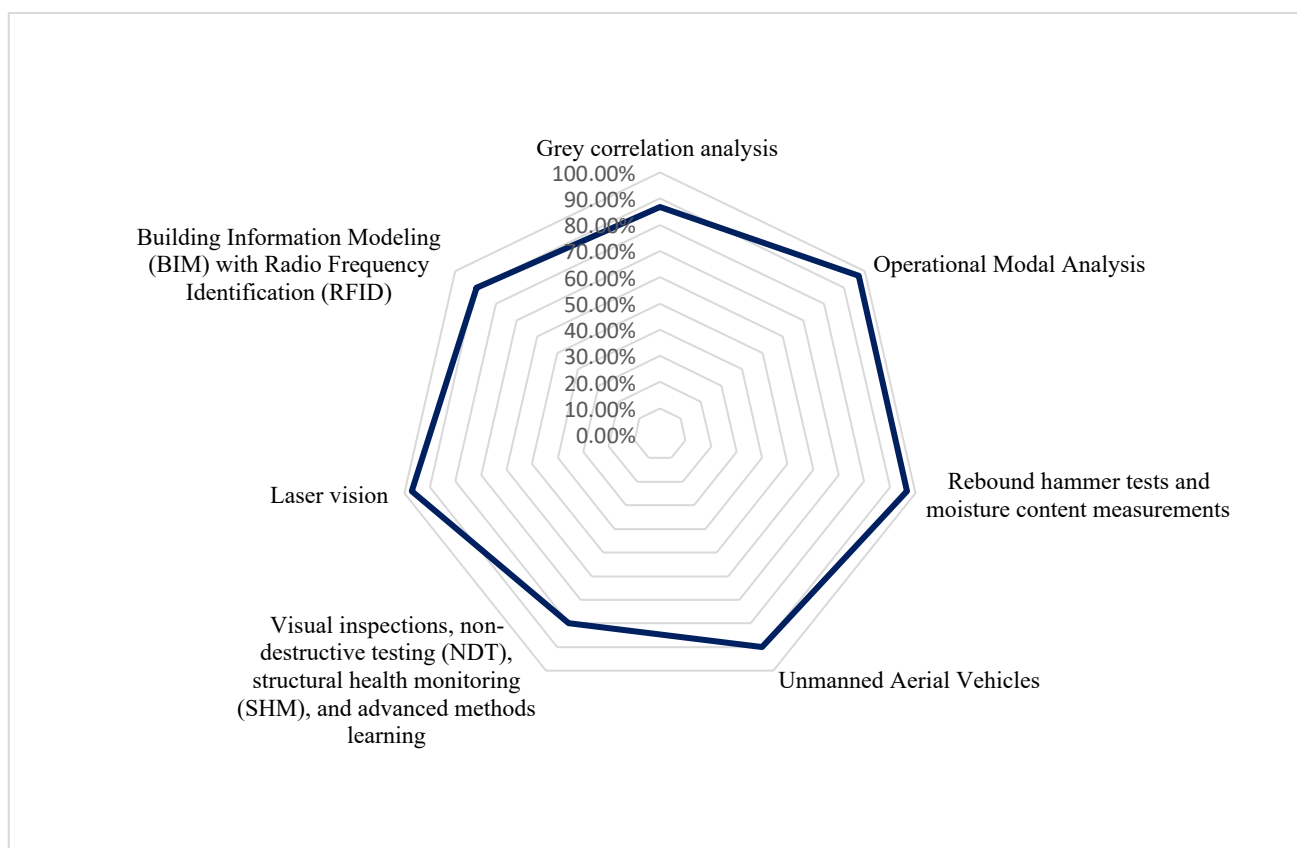


Figure 11. Accuracies of Non-AI-based methods.

4.4.2. AI in CDIS

To raise the level of automation of asset condition inspection, researchers have recently experimented with a range of soft computing and machine learning-based detection approaches. A larger family of ML techniques based on Artificial Neural Networks (ANN) and representation learning includes Deep Learning (DL). DL algorithms utilize multiple layers to progressively extract higher-level features from raw data, such as in image processing. DL algorithms break down complex hierarchies into simpler ones. CNNs, a subset of deep learning techniques, are typically employed to address fundamental issues, including segmentation, object identification, classification, and localization. Feature extraction/detection using filters is performed in the first part of the CNN, and image classification is carried out in the second part of the CNN [48]. Table 3 provides a summary of various AI-based approaches to defect identification implemented in highly cited research papers.

Table 3. Summary of papers related to AI-based defect identification methods for a variety of structures.

Sr.No	Structure	Defects focused	Method used	Summary	Accuracy
1	Concrete structures	Crack detection	pre-trained convolutional neural network (CNN) architectures—VGG16, AlexNet, ResNet18, and DenseNet161(2022)	The research emphasizes that transfer learning may automate crack detection, lower expenses, and increase infrastructure longevity. Additionally, it lays the foundation for the development of sophisticated monitoring systems that utilize automation technologies and high-resolution sensors to enhance structural safety and reliability. For the specific position, four pre-trained convolutional neural network (CNN) architectures were utilized: DenseNet-161, ResNet-18, AlexNet, and VGG-16. Because of their proven performance in image recognition tasks, these models were selected. The study achieved excellent accuracy in crack detection while reducing the requirement for large, domain-specific datasets by utilizing transfer learning, a process that adapts previously trained models for new tasks. This method reduced reliance on human inspections and saved time by streamlining the process of identifying structural flaws. The VGG16 model proved to be the most successful of the examined models, providing a reliable method for categorizing and analyzing cracks and other surface irregularities [38]	CNN-99% RNN-50%
2	Underground Parking Lots	Cracks, potholes, and other surface issues in the parking lot environment.	Computer vision (2022)	The study focuses on using computer vision techniques to identify and assess defects in underground parking lots. In particular, it automatically detects surface problems in the parking lot environment, such as cracks and potholes, using an image object-detection algorithm. The model analyses photos taken by cameras positioned across the parking lot using deep learning methods, specifically convolutional neural networks (CNNs). By enabling more effective, automated problem identification, reducing the need for human labor, and providing prompt, precise assessments to enhance safety and maintenance planning in underground parking facilities, the proposed system aims to expedite the maintenance process. The article also addresses the challenges of using image-based detection in such settings, including lighting and visual clutter, and provides solutions to enhance accuracy and reliability [49].	61.29%

3	Tunnel	Cracks, spalling, and deformations	Drones equipped with Edge-AI technology (2018)	This study proposes a state-of-the-art method for utilizing drones equipped with edge AI technology to inspect tunnel surfaces in real-time. Without transferring large amounts of data to distant servers, the device utilizes onboard AI processing to analyze high-resolution photos and identify surface defects, including cracks, spalling, and deformations. In challenging environments, such as tunnels, this method ensures accuracy while enhancing inspection speed and efficiency. Drone utilization reduces physical labour and inspection time while enabling safe and economic data collection. The study demonstrates how real-time, autonomous surface evaluations, made possible by combining Edge-AI with drones, can completely transform infrastructure maintenance [50].	98.58%
4	Railway track	Cracks	Deep learning and image processing techniques (2019)	This study explains how to utilize deep learning and image processing techniques to detect and diagnose cracks on rail surfaces. To precisely identify cracks of various sizes and orientations, the method involves capturing images of rail surfaces and processing them using sophisticated algorithms, such as convolutional neural networks (CNNs). The study demonstrates the effectiveness of deep learning in overcoming obstacles, including surface imperfections, noise, and varying illumination conditions. By automating the inspection process, this approach enhances rail safety by enabling prompt maintenance and preventing potential breakdowns, while also improving detection accuracy and reducing manual labor [51].	99%
5	Newly Constructed Apartments	Construction defects, poor design, inadequate materials, or maintenance issues.	Natural language processing (2022)	The study utilizes sophisticated text mining and semantic network analysis tools to investigate the reasons for occupant dissatisfaction in new apartment buildings. To pinpoint major sources of discontent, such as poor design, subpar materials, construction errors, or maintenance issues, the study analyzes resident comments and grievances. Through the use of natural language processing, the study uncovers significant linkages and patterns in textual data, offering insights into the residents' top concerns. The results aim to support developers, architects, and legislators in enhancing the overall quality of life in newly constructed apartments by addressing occupant demands more effectively and improving building quality and design [52].	87.88%
6	Bridge Pier	Cracks, corrosion, or structural damage on the surfaces of bridge piers	crawling robot, equipped with advanced sensors and imaging capabilities (2024)	The research explains an innovative method that utilizes a robotic crawling device to detect and segment defects on underwater bridge piers. It suggests a deep learning-based approach designed for underwater settings, where lighting and visibility are major obstacles. The system utilizes instance segmentation techniques to identify and diagnose defects on the surface of bridge piers, including corrosion, cracks, or structural issues. With its sophisticated sensors and imaging capabilities, the crawling robot guarantees accurate navigation and inspection. In addition to providing thorough evaluations for maintenance and repair planning, this technique enhances the precision and effectiveness of underwater structural examinations, potentially reducing the need for physical intervention and associated risks [53].	79.8%

The results (Figure 12) indicate that modern AI-driven methods, including pre-trained CNN architectures, drones equipped with edge AI technology, and deep learning image processing techniques, achieved a defect detection accuracy of around 100%. Natural language processing and crawling robots equipped with advanced sensors also demonstrated high performance, with accuracies ranging from 90% to 95%. In contrast, RNN architectures and conventional computer vision methods achieved comparatively lower accuracies, ranging from approximately 50% to 65%, highlighting the superior precision of advanced

AI-based approaches.

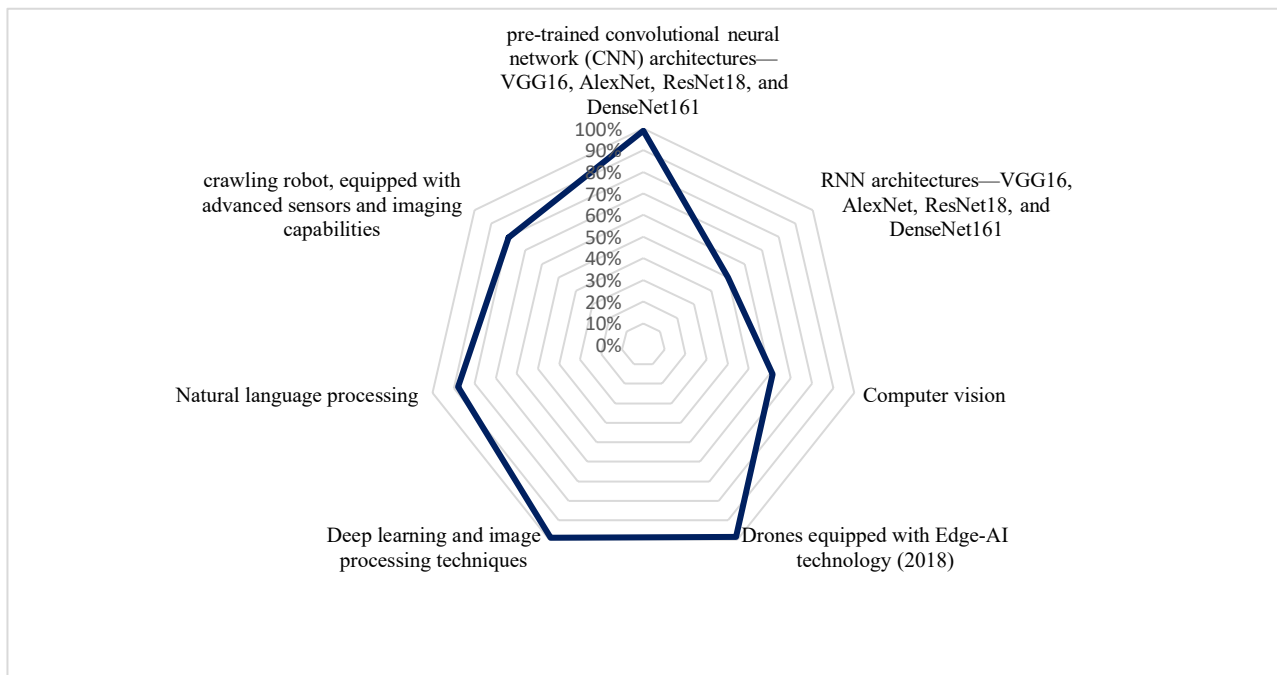


Figure 12. Accuracies of AI-based methods of defect identification.

From the comparison of defect detection methods across various structures, it is evident that advanced sensing and automated inspection technologies generally yield higher and more consistent accuracy than manual or purely visual inspections.

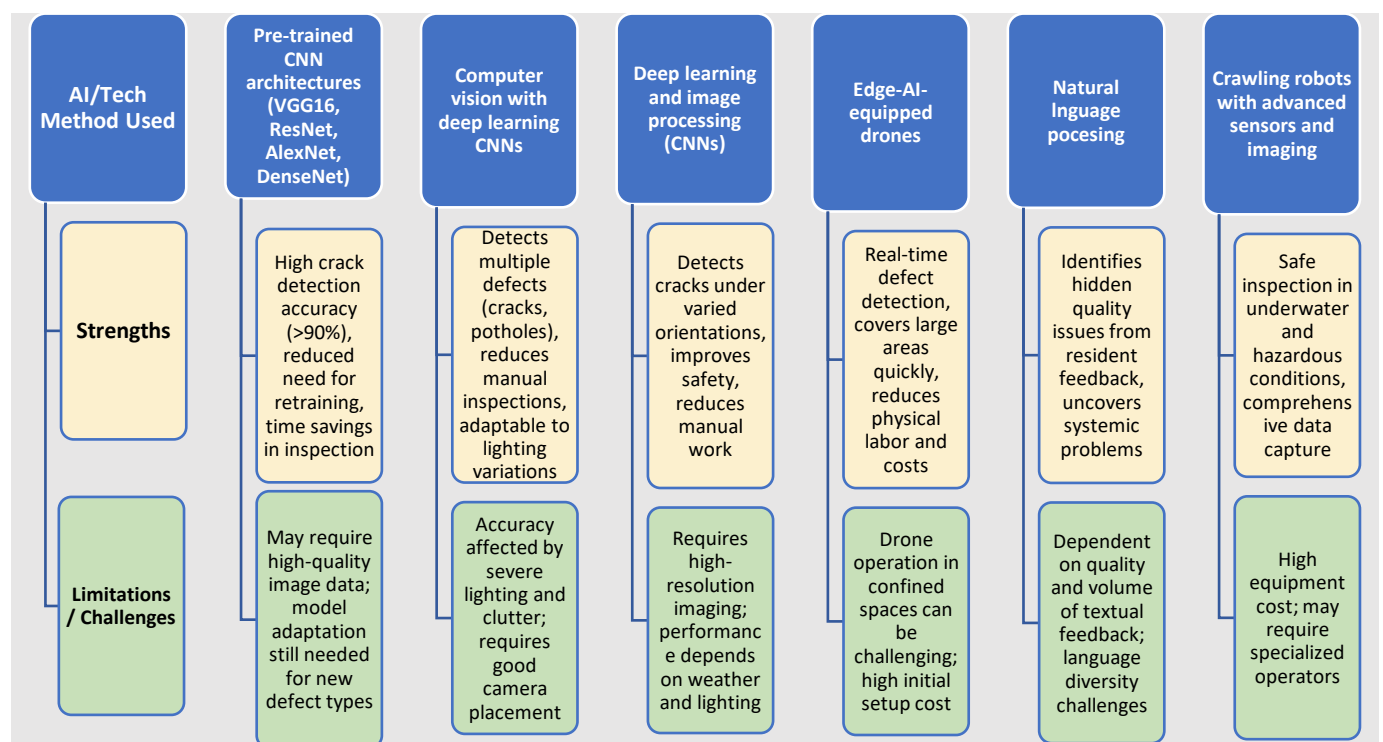


Figure 13. Strengths and limitations of AI-based defect identification methods.

As discussed in the earlier sections, construction defects can arise at any stage of the project. Design defects are mostly solved with BIM. Post-handover defects are identified using techniques such as image processing. Defects in the under-construction stage still need to be addressed. It is accomplished using UAV technology, but it is not feasible for every project. Although AI technology is time-saving, it requires a significantly higher initial investment compared to traditional methods. Additionally, training people takes time and money, necessitating the need for integration of technology with traditional methods.

In order to increase the feasibility, effectiveness, and general quality of building projects, this study evaluates the current status of research on AI-based Construction Defect Identification Systems (CDIS). The work starts with an analysis of the advantages and difficulties of AI in the AEC industry, guided by the structured research approach described in the study framework. This is followed by a bibliometric survey that maps the extent of research using specific keyword sets. In the era of Industry 4.0, digital technologies that facilitate automation, boost productivity, increase safety, and lessen environmental effect are being adopted by construction enterprises more and more. However, stakeholders such as contractors, operators, owners, and suppliers can no longer afford to approach AI as an optional tool due to the enormous volumes of data generated throughout a building's lifecycle [54]. The literature review stage looks into recent and advanced defect management systems, defect detection techniques, classification strategies, and information sharing platforms. While an enormous amount of work has been done on defect identification, classification and early-stage prediction have received very less attention, indicating a large research gap, according to a review of frequently cited literature. The conversation focuses on the potential advantages of AI as well as its adoption hurdles, such as practicality, affordability, and the absence of a universal model that can recognize, categorize, and convey any flaw in building. The comparison demonstrates that while CNN-based techniques provide excellent detection accuracy, these techniques rely on high-quality picture data and ideal imaging conditions. Edge-AI drones save money and labor by enabling quick, wide-area flaw identification. Despite their high setup costs and difficulties flying in tight locations, drones continue to show excellent accuracy in identifying defects. Deep learning-based image processing shows excellent accuracy in fault detection when the weather and illumination are right. Tools for natural language processing (NLP) can reveal latent quality problems in textual feedback, but how well they work depends on the quantity, caliber, and variety of the data. Although they are expensive, crawling robotic systems are excellent at examining dangerous or submerged locations and provide thorough data collection. AI-driven and sensor-based approaches continuously beat conventional inspection methods in terms of flaw identification accuracy across both analyses. Accuracy levels at or over 97% were attained using pre-trained CNN architectures, Edge-AI drones, deep learning/image processing, and laser vision, proving the resilience of automated, data-driven methods. On the other hand, conventional and semi-manual methods like grey correlation analysis (86.81%) and visual inspections using NDT/SHM (80%) shown reduced

reliability, especially under challenging real-world circumstances. Particularly for large-scale, real-time monitoring, domain-specific solutions like BIM combined with RFID (89.60%) and UAV photogrammetry (90%) also demonstrated strong performance. These findings demonstrate how combining AI with specific sensing technologies can close the gap between field applicability and laboratory accuracy, establishing a new standard for accuracy and efficiency in the detection of building defects.

Creating integrated, multimodal systems that incorporate computer vision, natural language processing, and robotics to offer thorough and real-time monitoring is the key to the future of AI-based detection of defects in the construction industry. In order to handle a variety of defect types, different building situations, and many structural categories without requiring a great deal of retraining, efforts should be directed toward developing universal, flexible models. While lowering latency and operating expenses, developments in Edge-AI and IoT integration may allow for continuous, on-site inspection with little assistance from humans. In order to promote acceptance in small- and medium-sized projects, inspection hardware must also be made smaller and more affordable. Technologies that integrate digital modeling (BIM), automated data processing (machine learning, correlation analysis), and high-resolution sensing (e.g., laser vision, UAVs) perform better than manual and solely visual methods. To guarantee high accuracy and operational efficiency in a variety of construction contexts, future defect detection systems should place a high priority on automation, multi-sensor data integration, and real-time analytics. By using predictive analytics in conjunction with BIM for early-stage defect detection, stakeholders may be able to resolve problems before they become more serious, improving safety and cost effectiveness. The viability, scalability, and ROI of AI-driven Construction Defect Identification Systems will ultimately depend on extensive pilot research and practical validations.

5. Conclusion

AI has demonstrated a great deal of promise to transform AEC defect management. According to this study, AI-based approaches outperform conventional inspection methods in terms of accuracy and efficiency, particularly CNNs, deep learning, and Edge-AI drones. However, obstacles including exorbitant expenses, a lack of experience, and problems with data quality prevent widespread implementation. Proactive, real-time defect management can be made possible by combining AI with digital tools like BIM and IoT. Future research should concentrate on creating affordable, flexible AI models that are verified by practical uses. AI-driven solutions have the potential to greatly improve construction quality, lower rework, and support sustainable project delivery by bridging the gap between technology and practice.

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References

- [1] L. Rampini, A. Khodabakhshian, and F. R. Cecconi, "Artificial Intelligence Feasibility in Construction Industry," *Proceedings of the European Conference on Computing in Construction*, pp. 99-106, 2022, doi: <https://doi.org/10.35490/EC3.2022.189>.
- [2] M. Johnson et al., "Impact of Big Data and Artificial Intelligence on Industry: Developing a Workforce Roadmap for a Data Driven Economy," *Global Journal of Flexible Systems Management* vol. 22, no 3, pp. 197-217, 2021, doi: <https://doi.org/10.1007/s40171-021-00272-y>.
- [3] X. Yao, J. Zhou, J. Zhang, and C. R. Boer, "From Intelligent Manufacturing to Smart Manufacturing for Industry 4.0 Driven by Next Generation Artificial Intelligence and Further On," in *2017 5th International Conference on Enterprise Systems (ES)*, 22-24 Sept. 2017 2017, pp. 311-318, doi: <https://doi.org/10.1109/ES.2017.58>.
- [4] M. Sandanayake, W. Yang, N. Chhibba, and Z. Vrcelj, "Residential building defects investigation and mitigation – a comparative review in Victoria, Australia, for understanding the way forward," *Engineering, Construction and Architectural Management*, vol. 29, no. 9, pp. 3689-3711, 2022, doi: <https://doi.org/10.1108/ECAM-03-2021-0232>.
- [5] N. Forcada, M. Macarulla, M. Gangolells, and M. Casals, "Assessment of construction defects in residential buildings in Spain," *Building Research & Information*, vol. 42, no. 5, pp. 629-640, 2014, doi: <https://doi.org/10.1080/09613218.2014.922266>.
- [6] R. Asadi, S. Wilkinson, and J. O. B. Rotimi, "The common causes of rework in construction contracts: a diagnostic approach," *Journal of Engineering, Design and Technology*, vol. 21, no. 4, pp. 1107-1133, 2023, doi: <https://doi.org/10.1108/JEDT-04-2021-0215>.
- [7] C. Stentoumis, E. Protopapadakis, A. Doulamis, and N. Doulamis, "A holistic approach for inspection of civil infrastructures based on computer vision techniques," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 41, pp. 131-138, 2016, doi: <https://doi.org/10.5194/isprs-archives-XLI-B5-131-2016>.
- [8] G. Psuj and B. Szymanik, "Structural Health Monitoring: Latest Applications and Data Analysis," *Applied Sciences*, vol. 13, no. 13, 2023, doi: <https://doi.org/10.3390/app13137617>.
- [9] H. Shalaka, S. Sayali, and R. Kirti, "Technology Landscape for BIM in Construction Site Safety Management," Cham, 2024: Springer Nature Switzerland, in *Proceedings of SECON'23*, pp. 931-943, doi: https://doi.org/10.1007/978-3-031-39663-2_78.
- [10] A. Hauashdh, J. Jailani, I. Abdul Rahman, and N. Al-Fadhali, "Factors affecting the number of building defects and the approaches to reduce their negative impacts in Malaysian public universities' buildings," *Journal of Facilities Management*, vol. 20, no. 2, pp. 145-171, 2022, doi: <https://doi.org/10.1108/JFM-11-2020-0079>.
- [11] P. Kot, M. Muradov, M. Gkantou, G. S. Kamaris, K. Hashim, and D. Yeboah, "Recent Advancements in Non-Destructive Testing Techniques for Structural Health Monitoring," *Applied Sciences*, vol. 11, no. 6, 2021, doi: <https://doi.org/10.3390/app11062750>.
- [12] C. J. Smith and A. T. C. Wong, "Advancements in Artificial Intelligence-Based Decision Support Systems for Improving Construction Project Sustainability: A Systematic Literature Review," *Informatics*, vol. 9, no. 2, 2022, doi: <https://doi.org/10.3390/informatics9020043>.

- [13] D.-G. J. Opoku, S. Perera, R. Osei-Kyei, M. Rashidi, T. Famakinwa, and K. Bamdad, "Drivers for digital twin adoption in the construction industry: A systematic literature review," *Buildings*, vol. 12, no. 2, p. 113, 2022, doi: <https://doi.org/10.3390/buildings12020113>.
- [14] T. McCabe, E. Erdogmus, A. Kody, and G. Morcous, "Early detection of honeycombs in concrete pavement using GPR," *Journal of Performance of Constructed Facilities*, vol. 35, no. 1, p. 04020138, 2021, doi: [https://doi.org/10.1061/\(ASCE\)CF.1943-5509.0001547](https://doi.org/10.1061/(ASCE)CF.1943-5509.0001547).
- [15] S. Nanukuttan, K. Yang, and P. A. M. Basheer, "Non-destructive testing and structural health monitoring," *ICE Handbook of Concrete Durability: A practical guide to the design of resilient concrete structures*, no. M1, pp. 449-491, 2023, doi: <https://doi.org/10.1680/icehcd.63754.449>.
- [16] R. N. Milion, T. d. C. L. Alves, J. C. Paliari, and L. H. B. Liboni, "CBA-Based Evaluation Method of the Impact of Defects in Residential Buildings: Assessing Risks towards Making Sustainable Decisions on Continuous Improvement Activities," *Sustainability*, vol. 13, no. 12, p. 6597, 2021, doi: <https://doi.org/10.3390/su13126597>.
- [17] P. Desai, S. Sandbhor, A. K. Kaushik, A. Patil, and V. Dabir, "Patentometric Analysis of AI Based Structural Health Monitoring," *Civil and Environmental Engineering*, vol. 20, no. 2, pp. 812-823, 2024, doi: <https://doi.org/10.2478/cee-2024-0060>.
- [18] M. Bérubé, T. Giannelia, and G. Vial, "Barriers to the implementation of AI in organizations: Findings from a Delphi study," *Proceedings of the Annual Hawaii International Conference on System Sciences*, vol. 2020-January, pp. 6702-6711, 2021, doi: <https://doi.org/10.24251/hicss.2021.805>.
- [19] M. Craglia *et al.*, *Artificial Intelligence - A European perspective*. 2018.
- [20] H. Perez, J. H. M. Tah, and A. Mosavi, "Deep Learning for Detecting Building Defects Using Convolutional Neural Networks," *Sensors (Basel)*, vol. 19, no. 16, Aug 15 2019, doi: <https://doi.org/10.3390/s19163556>.
- [21] Y. Pan and L. Zhang, "Roles of artificial intelligence in construction engineering and management: A critical review and future trends," *Automation in Construction*, vol. 122, 2021, doi: <https://doi.org/10.1016/j.autcon.2020.103517>.
- [22] W. A. Altabey and M. Noori, "Artificial-Intelligence-Based Methods for Structural Health Monitoring," *Applied Sciences*, vol. 12, no. 24, 2022, doi: <https://doi.org/10.3390/app122412726>.
- [23] P. K. Wan and T. L. Leirno, "Human-centric zero-defect manufacturing: State-of-the-art review, perspectives, and challenges," *Computers in Industry*, vol. 144, 2023, doi: <https://doi.org/10.1016/j.compind.2022.103792>.
- [24] Z. You and C. Wu, "A framework for data-driven informatization of the construction company," *Advanced Engineering Informatics*, vol. 39, pp. 269-277, 2019, doi: <https://doi.org/10.1016/j.aei.2019.02.002>.
- [25] Z. Irani, A. Beskese, and P. E. D. Love, "Total quality management and corporate culture: constructs of organisational excellence," *Technovation*, vol. 24, no. 8, pp. 643-650, 2004, doi: [https://doi.org/10.1016/s0166-4972\(02\)00128-1](https://doi.org/10.1016/s0166-4972(02)00128-1).
- [26] P. E. D. Love, "Influence of Project Type and Procurement Method on Rework Costs in Building Construction Projects," *Journal of Construction Engineering and Management*, vol. 128, no. 1, pp. 18-29, 2002, doi: [https://doi.org/10.1061/\(asce\)0733-9364\(2002\)128:1\(18\)](https://doi.org/10.1061/(asce)0733-9364(2002)128:1(18)).
- [27] M. H. Rafiei and H. Adeli, "Novel Machine-Learning Model for Estimating Construction Costs Considering Economic Variables and Indexes," *Journal of Construction Engineering and Management*, vol. 144, no. 12, 2018, doi: [https://doi.org/10.1061/\(asce\)co.1943-7862.0001570](https://doi.org/10.1061/(asce)co.1943-7862.0001570).
- [28] S. O. Abioye *et al.*, "Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges," *Journal of Building Engineering*, vol. 44, 2021, doi: <https://doi.org/10.1016/j.jobbe.2021.103299>.
- [29] A. Akanmu, C. Anumba, and J. Messner, "Scenarios for cyber-physical systems integration in construction," *Journal of Information Technology in Construction*, vol. 18, no. April, pp. 240-260, 2013.
- [30] T. T. Awasho and S. K. Alemu, "Assessment of public building defects and maintenance practices: Cases in Mettu town, Ethiopia," *Heliyon*, vol. 9, no. 4, p. e15052, Apr 2023, doi: <https://doi.org/10.1016/j.heliyon.2023.e15052>.

- [31] V. M. Di Mucci, A. Cardellicchio, S. Ruggieri, A. Nettis, V. Renò, and G. Uva, "Artificial intelligence in structural health management of existing bridges," *Automation in Construction*, vol. 167, 2024, doi: <https://doi.org/10.1016/j.autcon.2024.105719>.
- [32] S. Erdem, "X-ray computed tomography and fractal analysis for the evaluation of segregation resistance, strength response and accelerated corrosion behaviour of self-compacting lightweight concrete," *Construction and Building Materials*, vol. 61, pp. 10-17, 2014, doi: <https://doi.org/10.1016/j.conbuildmat.2014.02.070>.
- [33] A. J. Brunner, "Structural Health and Condition Monitoring with Acoustic Emission and Guided Ultrasonic Waves: What about Long-Term Durability of Sensors, Sensor Coupling and Measurement Chain?," *Applied Sciences*, vol. 11, no. 24, 2021, doi: <https://doi.org/10.3390/app112411648>.
- [34] S. Pamera and A. Gurmu, "Framework for building defects and their identification technologies: Case studies of domestic buildings in Melbourne, Australia," *Proceedings of the International Conference of Architectural Science Association*, vol. 2020-November, no. 2009, pp. 501-510, 2020.
- [35] E. Pruteanu and P. Gabriel, "Intelligent Measuring System Using Network Wireless Sensors for Structural Diagnostics," *2019 22nd International Conference on Control Systems and Computer Science (CSCS)*, Bucharest, Romania, 2019, pp. 492-495, doi: <https://doi.org/10.1109/CSCS.2019.00090>.
- [36] Y. Tan, G. Li, R. Cai, J. Ma, and M. Wang, "Mapping and modelling defect data from UAV captured images to BIM for building external wall inspection," *Automation in Construction*, vol. 139, p. 104284, 2022, doi: <https://doi.org/10.1016/j.autcon.2022.104284>.
- [37] P. Kruachottikul, N. Coocharojanane, G. Phanomchoeng, T. Chavarnakul, K. Kovitanggoon, and D. Trakulwaranont, "Deep learning-based visual defect-inspection system for reinforced concrete bridge substructure: a case of Thailand's department of highways," *Journal of Civil Structural Health Monitoring*, vol. 11, no. 4, pp. 949-965, 2021, doi: <https://doi.org/10.1007/s13349-021-00490-z>.
- [38] P. Jayaraju, K. Somasundaram, A. S. Suprakash, and S. Muthusamy, "A Deep Learning- Image Based Approach for Detecting Cracks in Buildings," *Traitement du Signal*, vol. 39, no. 4, pp. 1429-1434, 2022, doi: <https://doi.org/10.18280/ts.390437>.
- [39] K. London, Z. Pablo, and N. Gu, "Explanatory defect causation model linking digital innovation, human error and quality improvement in residential construction," *Automation in Construction*, vol. 123, 2021, doi: <https://doi.org/10.1016/j.autcon.2020.103505>.
- [40] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861-874, 2006, doi: <https://doi.org/10.1016/j.patrec.2005.10.010>.
- [41] H. Zhou et al., "Identification Model of Fault-Influencing Factors for Dam Concrete Production System Based on Grey Correlation Analysis," *Applied Sciences*, vol. 14, no. 11, p. 4745, 2024, doi: <https://doi.org/10.3390/app14114745>.
- [42] L. R. Ticona Melo, R. S. Y. R. C. Silva, T. N. Bittencourt, and L. M. Bezerra, "Identification of Modal Parameters in a Scale Model for a Railway Bridge," *International Journal of Structural Stability and Dynamics*, vol. 16, no. 09, p. 15500595, 2016, doi: <https://doi.org/10.1142/s0219455415500595>.
- [43] N. L. Othman, M. Jaafar, W. M. W. Harun, and F. Ibrahim, "A Case Study on Moisture Problems and Building Defects," *Procedia - Social and Behavioral Sciences*, vol. 170, pp. 27-36, 2015, doi: <https://doi.org/10.1016/j.sbspro.2015.01.011>.
- [44] N. Hashim, M. A. O. Mydin, and R. Omar, "Appraisal of Flat Roof Defects in Commercial Buildings and the Remediation Techniques," *Journal of Advanced Research in Applied Mechanics*, vol. 119, no. 1, pp. 204-219, 2024, doi: <https://doi.org/10.37934/aram.119.1.204219>.
- [45] A. Douglas, M. Langenderfer, and C. Johnson, "Road Condition Monitoring Utilizing UAV Photogrammetry Aligned to Principal Curve of Mine Haul Truck Path," *Mining, Metallurgy & Exploration*, vol. 41, no. 1, pp. 61-72, 2024, doi: <https://doi.org/10.1007/s42461-023-00877-0>.

- [46] W. Huang and R. Kovacevic, "A laser-based vision system for weld quality inspection," *Sensors*, vol. 11, no. 1, pp. 506-21, 2011, doi: <https://doi.org/10.3390/s110100506>.
- [47] H. E. Huo, Y. Ji, K. Xie, and Y. Lu, "Design and Application of Intelligent Construction Quality Inspection System Based on BIM-RFID," *Advances in Civil Engineering*, vol. 2023, p. 5638265, 2023, doi: <https://doi.org/10.1155/2023/5638265>.
- [48] G. Azuara, M. Ruiz, and E. Barrera, "Damage Localization in Composite Plates Using Wavelet Transform and 2-D Convolutional Neural Networks," *Sensors*, vol. 21, no. 17, p.5825 2021, doi: <https://doi.org/10.3390/s21175825>.
- [49] H. Kyu Shin, S. Woon Lee, G. Pyo Hong, S. Lee, S. Hyo Lee, and H. Young Kim, "Defect-Detection Model for Underground Parking Lots Using Image Object-Detection Method," *Computers, Materials & Continua*, vol. 66, no. 3, pp. 2493-2507, 2021, doi: <https://doi.org/10.32604/cmc.2021.014170>.
- [50] C. H. Tan *et al.*, "A smart unmanned aerial vehicle (UAV) based imaging system for inspection of deep hazardous tunnels," *Water Practice & Technology*, vol. 13, no. 4, pp. 991-1000, 2018, doi: <https://doi.org/10.2166/wpt.2018.105>.
- [51] F. Di Nuzzo, D. Brunelli, T. Polonelli and L. Benini, "Structural Health Monitoring System With Narrowband IoT and MEMS Sensors," in *IEEE Sensors Journal*, vol. 21, no. 14, pp. 16371-16380, 15 July15, 2021, doi: <https://doi.org/10.1109/JSEN.2021.3075093>.
- [52] S. Li, H. Cai, and V. R. Kamat, "Integrating Natural Language Processing and Spatial Reasoning for Utility Compliance Checking," *Journal of Construction Engineering and Management* vol. 142, no 12, pp. 1-13, 2016, doi: [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001199](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001199).
- [53] F. Xie, G. Song, J. Mao, F. Wang, J. Zhou, and A. Song, "An Underwater Defect Instance Segmentation Method for a Bridge Pier Inspection Crawling Robot," *Proceedings - 2024 9th International Conference on Automation, Control and Robotics Engineering, CACRE 2024*, pp. 340-344, 2024, doi: <https://doi.org/10.1109/CACRE62362.2024.10635024>.
- [54] P. Desai, S. Sandbhor, and A. Kaushik, "AI and BIM-based Construction defects, rework, and waste optimization," In *International Conference on Emerging Smart Computing and Informatics, ESCI 2023*, Pune, India, pp. 1-6, 2023, doi: <https://doi.org/10.1109/ESCI56872.2023.10099726>.