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AI-Enabled Cognitive Predictive Maintenance of Urban Assets Using City Information Modeling—Systematic Review

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Abstract: Predictive maintenance of built assets often relies on scheduled routine practices that are disconnected from real-time stress assessment, degradation and defects. However, while Digital Twin (DT) technology within building and urban studies is maturing rapidly, its use in predictive maintenance is limited. Traditional preventive and reactive maintenance strategies that are more prevalent in facility management are not intuitive, not resource efficient, cannot prevent failure and either underserve the asset or are surplus to requirements. City Information Modeling (CIM) refers to a federation of BIM models in accordance with real-world geospatial references, and it can be deployed as an Urban Digital Twin (UDT) at city level, like BIM's deployment at building level. This study presents a systematic review of 105 Scopus-indexed papers to establish current trends, gaps and opportunities for a cognitive predictive maintenance framework in the architecture, engineering, construction and operations (AECO) industry. A UDT framework consisting of the CIM of a section of the University of Florida campus is proposed to bridge the knowledge gap highlighted in the systematic review. The framework illustrates the potential for CNN-IoT integration to improve predictive maintenance through advance notifications. It also eliminates the use of centralized information archiving.

Keywords: City Information Model; Urban Digital Twin; asset management; predictive maintenance; Artificial Intelligence

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1. Introduction

Predictive maintenance (PM) is rapidly transforming into a domain where physicality and virtuality are combined [1], with information technology being the most critical enablers of a Digital Twin framework [2]. Artificial Intelligence (AI), Digital Twins (DTs), cloud computing, edge computing and machine learning (ML) are techniques of digital transformation that bring gains for efficiency, productivity and operational safety [3]. Condition monitoring is critical for uninterrupted industrial operations and optimal performance of installations [4]. The industry 4.0 framework will be characterized mainly by the integration of AI with DT systems for optimized economic value [5], as AI has proven to be a reliable method for automating PM. The underlying question in this study is how a decentralized DT system can enhance trust in AI decisions and analytics. AI and ML techniques offer a proactive maintenance strategy towards achieving a more sophisticated PM by predicting potential failure to enable timely corrective actions [6]. AI's revolutionary advancement to sustainable building practices has been documented, with DTs and Internet of Things (IoT) being reported as promising technologies offering significant benefits across the building lifecycle [7]. AI has also been used for decentralized learning in federated settings [8].

A DT is a virtual replica of a physical asset, system or process, encompassing physical and digital realms and allowing for real-time information exchange, interaction and feedback [9], enabling rapid analysis and real-time decision making through accurate information analytics [10]. DT can proactively identify potential issues with its real physical replica, allowing for prediction of the state of its physical twin by combining physics-based modeling with data-driven analytics [11]. It also integrates with AI to improve efficiency in fault detection while saving time and cost [12], therefore making it suitable for predictive maintenance. The three main characteristics that comprise a DT are synchronization with a real asset, active data acquisition from the real environment and the ability for simulation [13]. However, this study will focus on the first two as a proof of concept.

PM through automated monitoring can be achieved by integrating building information modeling (BIM), geographic information systems (GIS) and AI to improve integrity and long-term asset performance [14,15]. The need for ML to process the quantity and complexity of data generated by sensors and to optimize production and process monitoring cannot be overemphasized as the interpretation and ingestion of large data is beyond human capability [16].

While the existing literature highlights extensive deployment of intuitive condition-based real-time system monitoring in manufacturing and other highly industrialized sectors, there has been very little mention of this approach in managing built assets. Therefore, this paper leverages advancements in DT to enhance the accurate and efficient automation of PM. Following a state-of-the-art review in Section 2, Section 3 explains the systematic literature review (SLR) using the PRISMA workflow to identify and evaluate relevant studies [17]. Section 4 highlights the Urban DT (UDT) use case scenario using part of the University of Florida campus as federated BIM models integrated with GIS and connected to a real-time data stream through IoT devices or remote sensing. Then, a convoluted neural network (CNN) was trained using 604 images of defective road surfaces to develop a defect detection model that integrated with the DT to augment its accuracy. In Section 5, observations, limitations and opportunities are discussed, while Section 6 concludes and enumerates future research potentials.

2. State of the Art

PM can be categorized under scheduled, automated and autonomous maintenance. Automated, remote or condition-based PM has revolutionized many industries, with DTs being integral to many of these successful examples. DT has become a paradigm for cyber-physical systems monitoring with respect to resilience, self-healing and trustworthy autonomy while serving as a decision support system [18].

DT has become integral in the roadmap for automated PM [19], especially when integrated with AI. Siddiqui et al. (2023) developed a novel PM algorithm framework to detect faults in automation systems well in advance [4]. Artificial neural networks (ANNs) have been deployed for monitoring port structures by training ANNs using a finite element model connected to sensors, thereby yielding higher accuracy and augmenting expert opinions [1,20]. Kamat et al. (2021) argued that deep learning modeling provided a higher accuracy than other AI techniques like ANN and random forest [21]. While conventional PM practices rely on condition monitoring and fault identification, a failure prediction framework using DT concepts in the building industry can utilize a semi-supervised generative adversarial network (GAN) to effectively use labelled and unlabeled data [22]. There are scalable architectures for intelligent DTs that improve forecasting for fault diagnosis and optimization to improve efficiency [23,24].

In manufacturing, AI-powered predictive modeling has been deployed to optimize power consumption for optimum economic and performance outputs through energy-efficient scheduling, downtime reduction, optimized tool selections and cutting parameters [25]. Palchevskyi and Krestyanpol (2020) developed a DT of technological equipment that self-tests manufacturing systems for proactive maintenance through a data analysis and feedback mechanism to adjust diagnostics and forecasting [26]. However, Abdoune et al. (2021) questioned the efficiency and reliability of AI-based monitoring by developing an AI-based observation framework, which elaborates predictions and reactions to assist supervisors in adjusting maintenance decisions [27]. Ren, Wan and Deng (2022) proposed a technical system that embeds ML into DT by combining DT in maintenance with ML in PM [28]. Furthermore, AI can create a self-improvement system that learns from its own outcomes. Prior knowledge can be embedded into AI techniques, thereby creating a hybrid learning modeling concept that combines additional parameters observed from the environment as inputs to increase the reliability of modeling outcomes [29]. However, it is pertinent to note that the greatest challenge to a perfectly functioning cyber-physical production system is the integration of numerous data sources, thereby requiring an end-to-end architecture [30].

In maritime applications, DT's PM system has grown exponentially since 2016 [31]. There are frameworks for monitoring vessel conditions and providing decision support based on quantitative risk assessment using a vessel state observer that self-times important parameters from prior knowledge [32]. Predictive DT also improves efficiency in autonomous surface vessels [33] and in the digital health engineering (DHE) of aging ships and marine vessels through data analytics, visualization and computational fluid dynamics simulations of ocean environmental conditions [34].

In power generation, AI and DTs are innovative operation and maintenance (O&M) technologies through their smart sensing and condition monitoring of nuclear power plants; AI models can be trained to react effectively to operational conditions, while DTs can provide a valuable tool for PM and real-time monitoring [35]. Meanwhile, in agriculture, IoT-enabled smart farming practices use Industry 5.0 technologies like AI and DT to revolutionize operations and improve crop yields [36].

In aerospace, DTs have been introduced for high-accuracy simulations, real-time status monitoring and advanced decision support to enhance mission safety and diagnose and resolve issues during mission execution [37]. Through a distributed network based on big data-augmented AI, DT has been a successful device performance tracker by detecting and fixing defects before they reach failure [38]. AI-based DTs have improved maintenance, repair and overhaul (MRO) operations by combining physics-based modeling with an ML model specifically to optimize the performance of a power electronics cooling system (PECS) [39]. The ability of aircraft manufacturers and operators to manage on-board software can also be significantly enhanced through network security, AI and DT technologies [40]. The condition monitoring of aircraft fleet through AI-enabled DT can also yield tremendous economic and safety benefits [41]. AI can provide some level of autonomy through AI+DT integration, as seen in space missions.

In oil and gas applications, AI and ML have also enhanced operational efficiency and increased productivity through remote condition monitoring using DT/IoT technology [42] and unmanned interventions such as drones and robots [43] for numerous assets across single and multiple sites [44]. Digitalization and AI for PM using DTs of reservoirs can be used for quantitative decision making under uncertainty, thereby shortening the time for on-field planning and improving decision making [45].

In infrastructure management, DTs for railway bridges are used for inspection, monitoring, maintenance and management to compliment prior knowledge [3,46] by using risk-based PM to determine maintenance schedules and save cost [47] and deploying software to optimize maintenance and support decision making using advanced analytics as strategic indicators on performance [48]. However, the application of PM in building and infrastructure facilities is scarce [49]. Sadri et al. (2023) proposed the integration of blockchains into AI-enabled DTs for trust and transparency of recorded data for smart management of buildings [50], while GIS has been introduced into AI, DT and ML studies for geospatial PM in building and facilities management [51].

3. Methodology

A qualitative literature review (in Section 2) preceded an SLR in accordance with the PRISMA workflow, where 105 Scopus-indexed papers were reviewed and analyzed and another 13 papers from a domain-specific keyword search were also reviewed and analyzed. A DT framework was proposed by integrating federated BIM models with GIS and linked with data streams through real-world sensing. Figure 1 below shows the research methodology workflow.

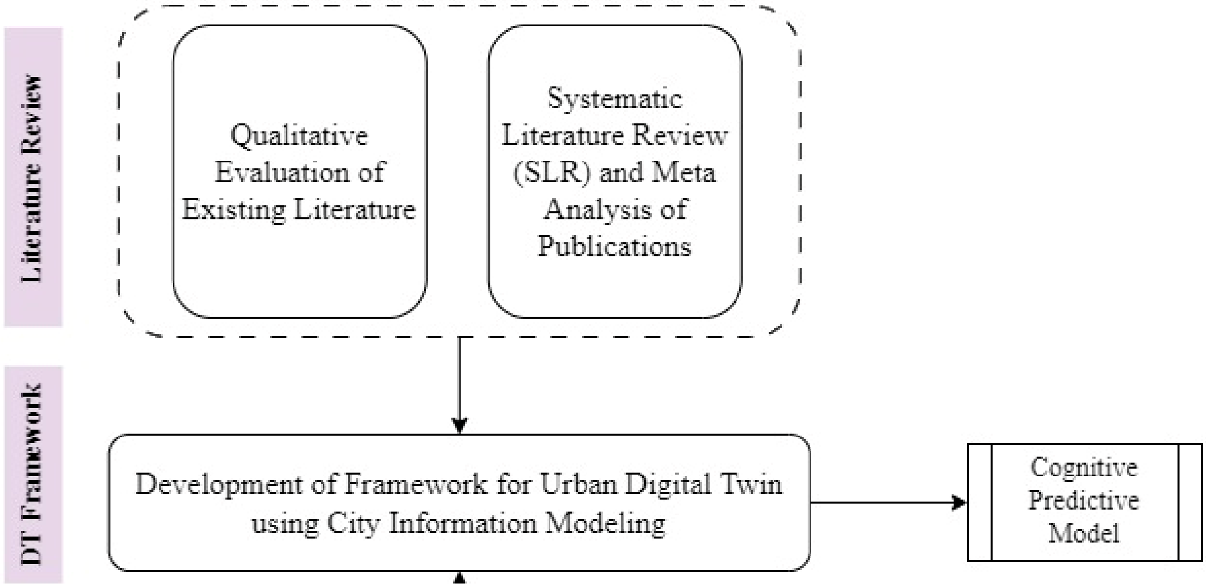

Figure 1. Research methodology workflow.

3.1. Systematic Literature Review

The SLR workflow and data collection and screening results are shown in Figure 2 below. There are four steps grouped under three stages. First, relevant publications were identified through keyword searches to ensure a broad coverage of related studies. These keywords were “Predictive Maintenance” AND “Artificial Intelligence” AND “City Information Modeling” OR “Digital Twin. CIM and UDT were used interchangeably in certain contexts as CIM may be seen as precursors to Urban or City DTs [52,53].

Figure 2. Keyword search.

A total of 130 articles were identified. Documents in the search results included journal articles, conference proceedings, reviews, book series and books published between 2019 and 2024, suggesting the timeliness of this research. Ten conference reviews were excluded, leaving 120 valid results. Then after a subject-based evaluation, twelve articles not related to engineering, or the built environment were excluded. After excluding 3 articles that were not in English, 105 valid articles selected for review. Figure 3 shows the graphical illustration of this workflow.

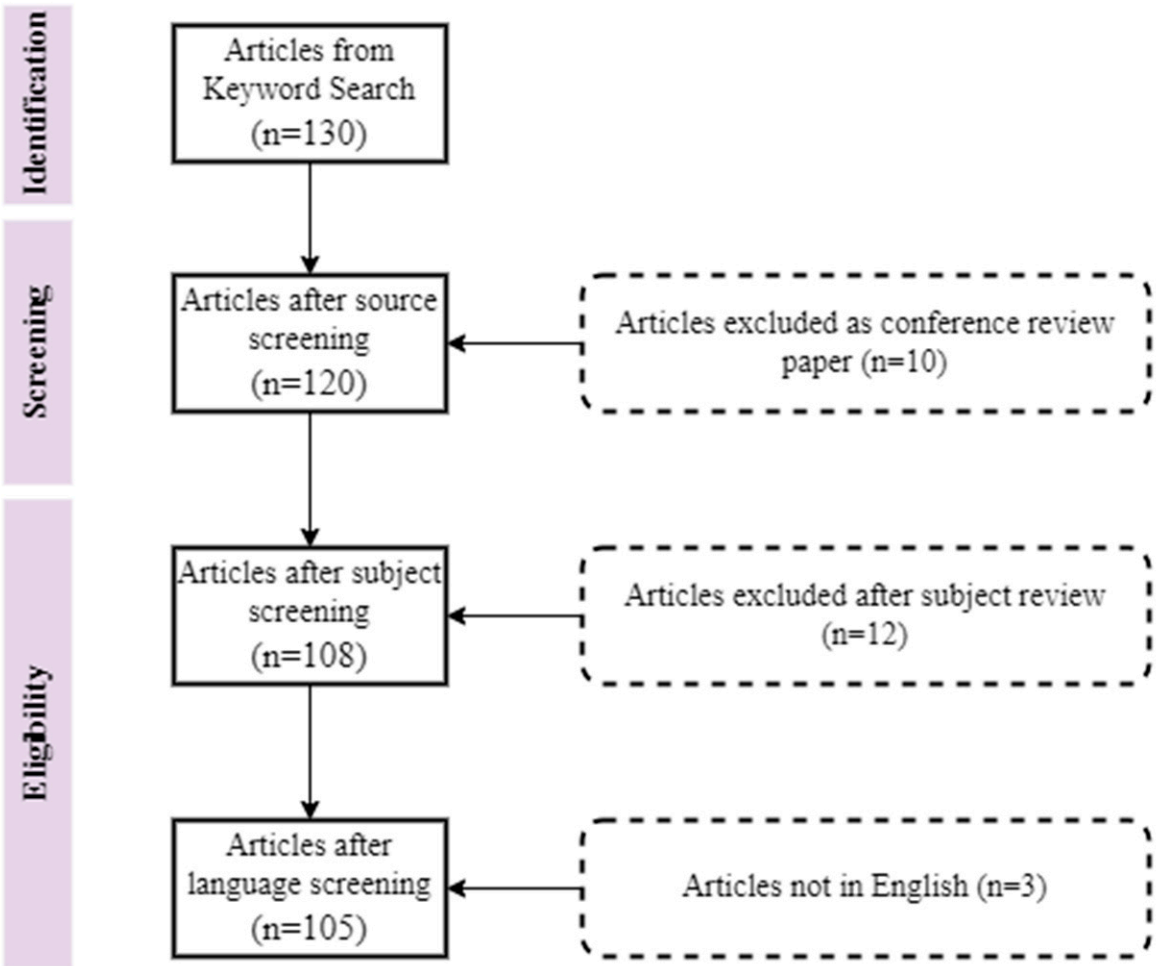

Figure 3. Systematic literature review workflow.

3.1.1. Keyword Co-Occurrence

Keyword co-occurrences were visualized using VOSviewer version 1.6.20 to evaluate links between keywords and illustrate the knowledge structure of results, intellectual provenance and indebtedness [49]. The two types of co-occurrence analyses used are cluster-based visualization and density visualization. In the cluster-based visualization, the nodes represent the keywords, and the connecting edges represent the intellectual links. Edge thickness indicates the strength of the relationships between keywords. Node sizes depend on the number of keyword co-occurrences. Keyword font sizes also indicate the level of keyword co-occurrences in the literature sample. Figure 4 shows a dense network of keyword co-occurrences, with PM being the most prominent keyword, followed by DT and then Industry 4.0. The three clusters closest to themselves are PM, DT and deep learning. This proximity is also evident in the density visualization in Figure 5.

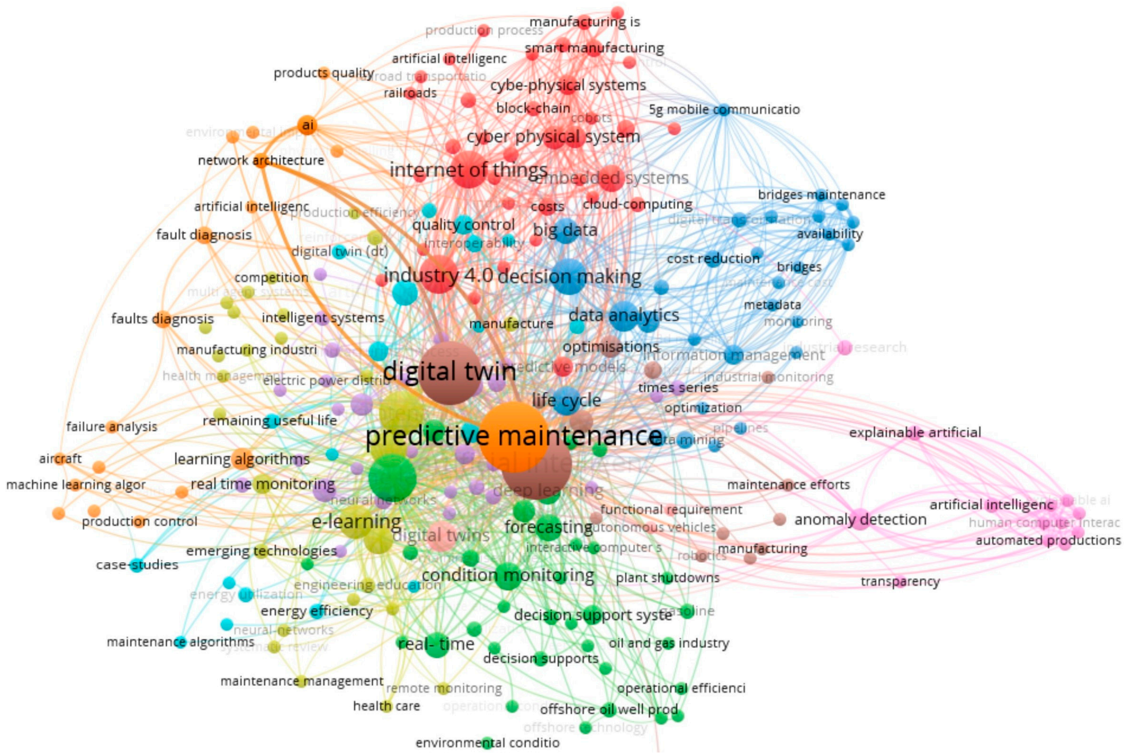

Figure 4. Keyword co-occurrence analysis.

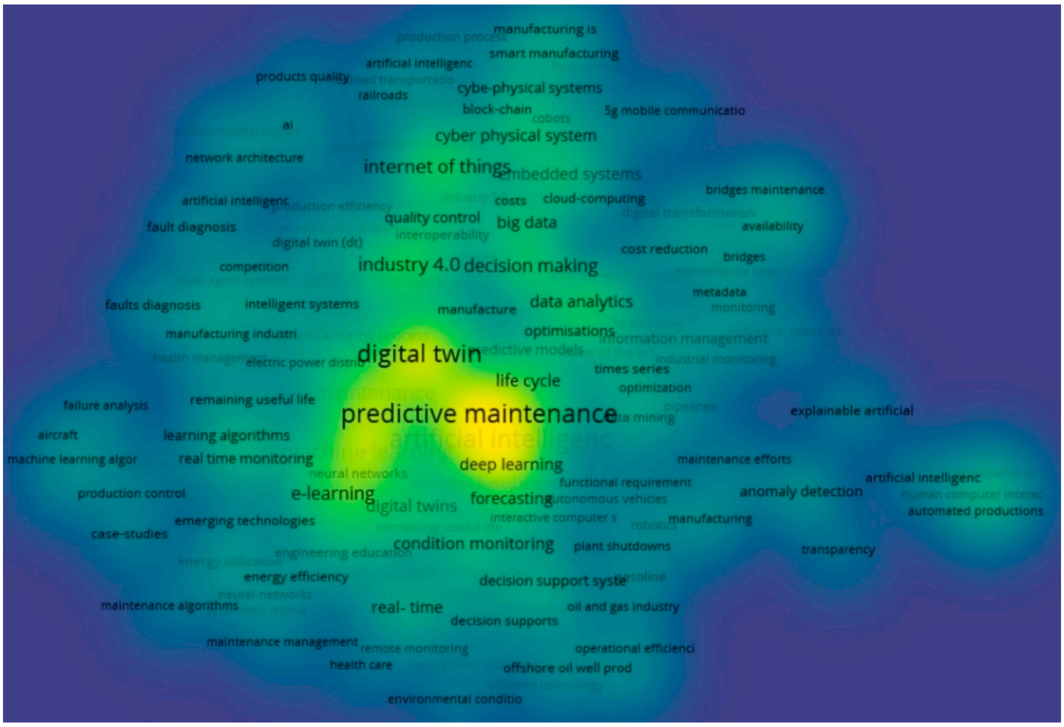

Figure 5. Density visualization.

3.1.2. Bibliometric Distribution by Subject Overlap

The density visualization above illustrates the knowledge overlaps. The distance between nodes, diameter and weight of nodes indicate the keyword relationships. At the nucleus of the density visualization is “predictive maintenance”, “digital twin”, “lifecycle” and “deep learning”. This indicates that these four keywords are prevalent in most of the literature in review. Figure 6 below shows a bibliometric distribution by subject overlap, with 53% of reviewed articles focused on AI, DT and PM; 18% focused on AI and DT; 16% focused on DT and PM; and 6% focused on general DT studies. This chart and the density visualization suggests that most of the reviewed literature focused on the interconnected relationship between AI, DT and PM.

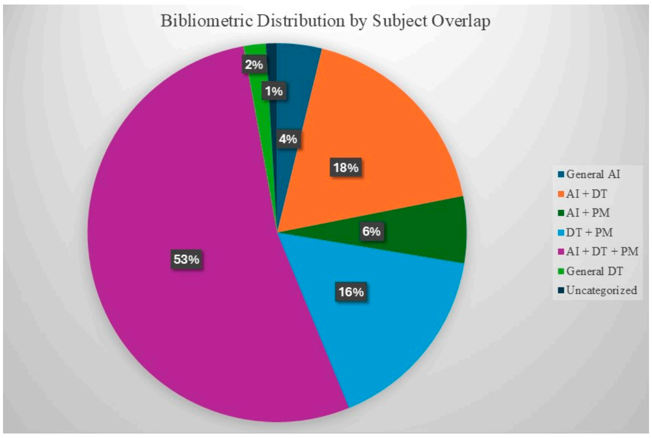

Figure 6. Bibliometric distribution by subject overlap.

3.1.3. State of the Art per Industry

Nearly a quarter of the articles reviewed were in the manufacturing industry. Twelve articles were on transportation/infrastructure, nine were general DT studies and eight were on power generation. Only six papers were in the architecture, engineering, construction and operation (AECO) industry. This suggests a significant knowledge gap in the field. Figure 7 below shows a publication distribution chart with an emphasis on the number of publications in the AECO industry (at six publications) in comparison with other industries

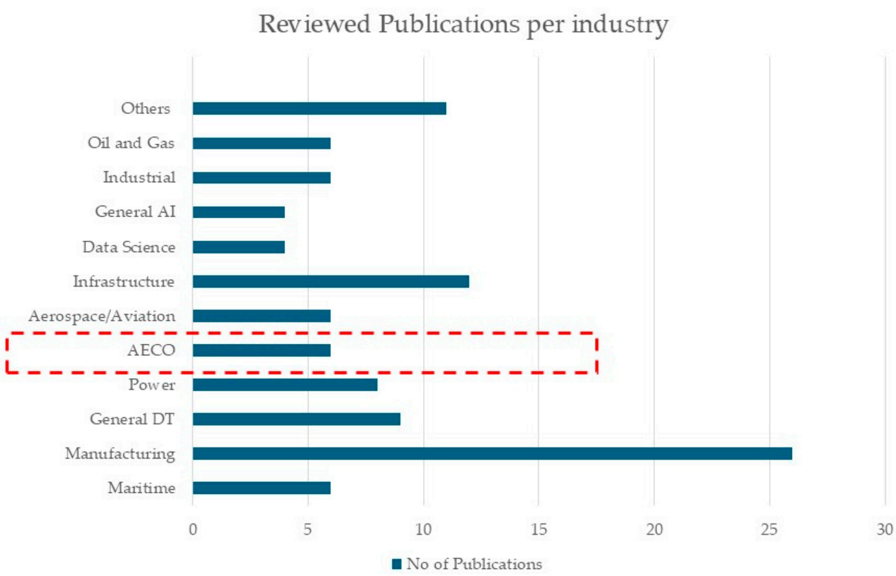

Figure 7. Publication count per industry.

The research contents of reviewed articles were summarized under six (6) headings shown in Table 1 below, namely: (1) review of prior arts, case studies, bibliometric analyses; (2) integration with other Industry 4.0 technologies towards newer paradigms; (3) application of ML, deep learning and advanced AI algorithms; (4) condition monitoring, fault detection and diagnostics; (5) integration with blockchain, edge computing, cloud computing, IoT for enhanced security, trust and transparency; and (6) reduction in human interference during maintenance towards improved automation and autonomy.

Table 1. Industry meta-analysis of the literature with respect to thematic areas in DT studies.

Theme	Maritime	Manufacturing	General DT	Power	AECO	Infrastructure	Aviation/Aerospace	Industrial/Oil and Gas
Review of prior art, literature and case studies to examine existing research endeavors, level of applications and future opportunities.	[31,34,54]		[55–57]	[58]	[7,59,60]	[61,62]	[37,41]	
Integration with Industry 4.0 and other emerging technologies towards developing a new paradigm contributes to smart infrastructure	[20]	[30,63–67]	[68]	[69]	[51]	[48]		[70,71]
Application of machine learning, deep learning and neural network techniques		[5,21,27,28,72–75]	[22,76]	[25,77]	[78]	[46,79,80]	[39]	[42,44,81,82]
Condition monitoring and smart manufacturing, predictive maintenance, fault detection and diagnostics	[32]	[2,4,16,23,24,26,83–86]		[38,87,88]		[3,15,47,49,89]	[90]	[45,91,92]
Integration with blockchain, edge computing, cloud computing and IoT			[93]		[50]			[8]
Quest for reduced "human in the loop" intervention, towards smart predictive maintenance through automation and ultimately autonomy	[33]	[13,29]				[94]	[95]	[43]

Knowledge gaps in the AECO industry were reinforced with a meta-analysis. Of the six studies within the AECO industry, three focused on bibliometric reviews and one focused on integration with Industry 4.0 technologies, the deployment of ML and deep learning algorithms and blockchain integration. These endeavors are miniscule compared with studies in the manufacturing and infrastructure industries. Automation and autonomy, which are slightly more advanced aspects of condition monitoring [94,96], have already been implemented in manufacturing [13,29].

A narrowed keyword search on Scopus-indexed articles was conducted, which focused specifically on applications of predictive maintenance in the construction (AECO) industry and further revealed the need for more research efforts. Three keyword search groups were used. The first was "Cognitive Predictive Maintenance" AND "Building Industry" which yielded 6 results, of which only 3 were valid results after applying the same screening criteria as enumerated in Section 3.1 and Figure 3. The second search was with keywords "Predictive Maintenance" AND "Building Industry", which also yielded 6 results. After screening and exclusion of duplications, only two results were valid for the study. The third keywords search was "Cognitive Predictive Maintenance" AND "AEC Industry", which yielded 1 result that was not relevant to the study. Figures 8 and 9 below illustrate the domain-specific keyword search process and SLR workflow.

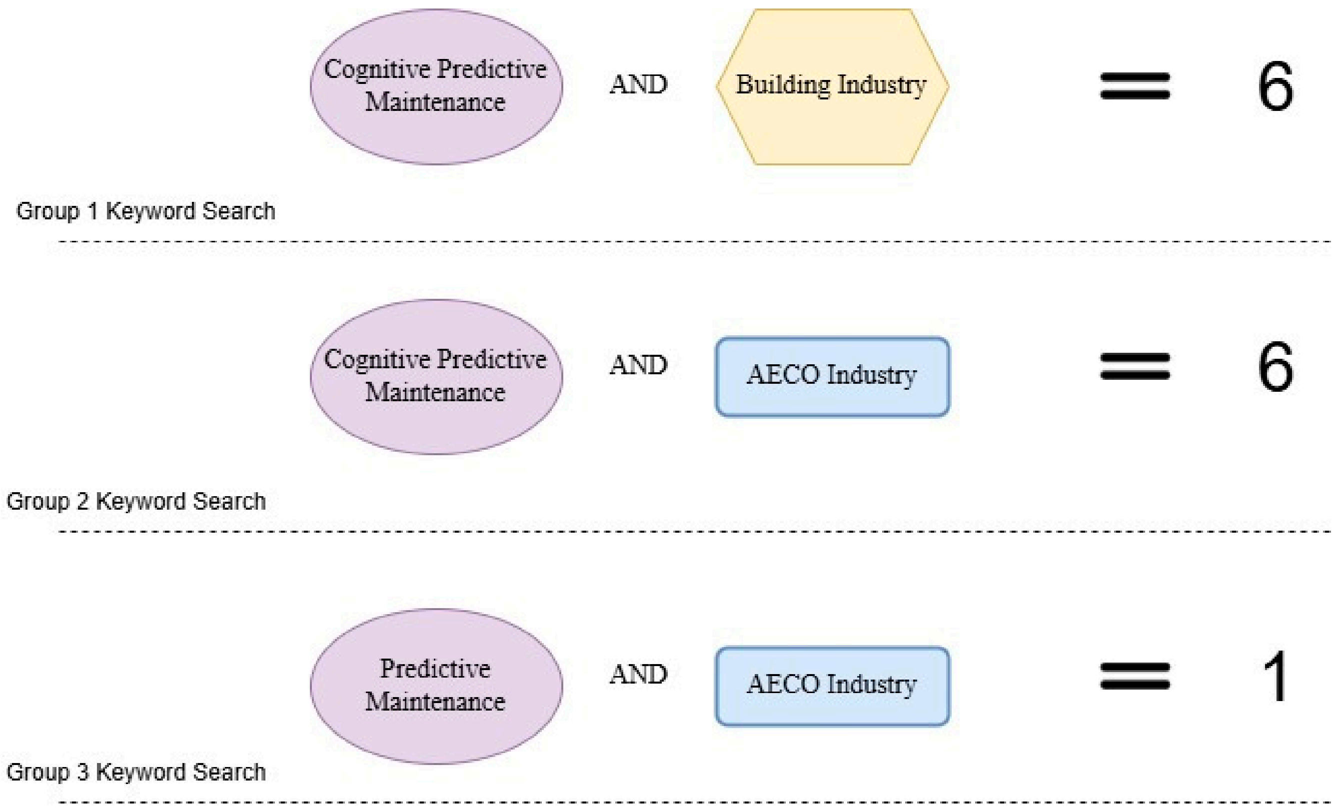

Figure 8. Domain-specific keyword search.

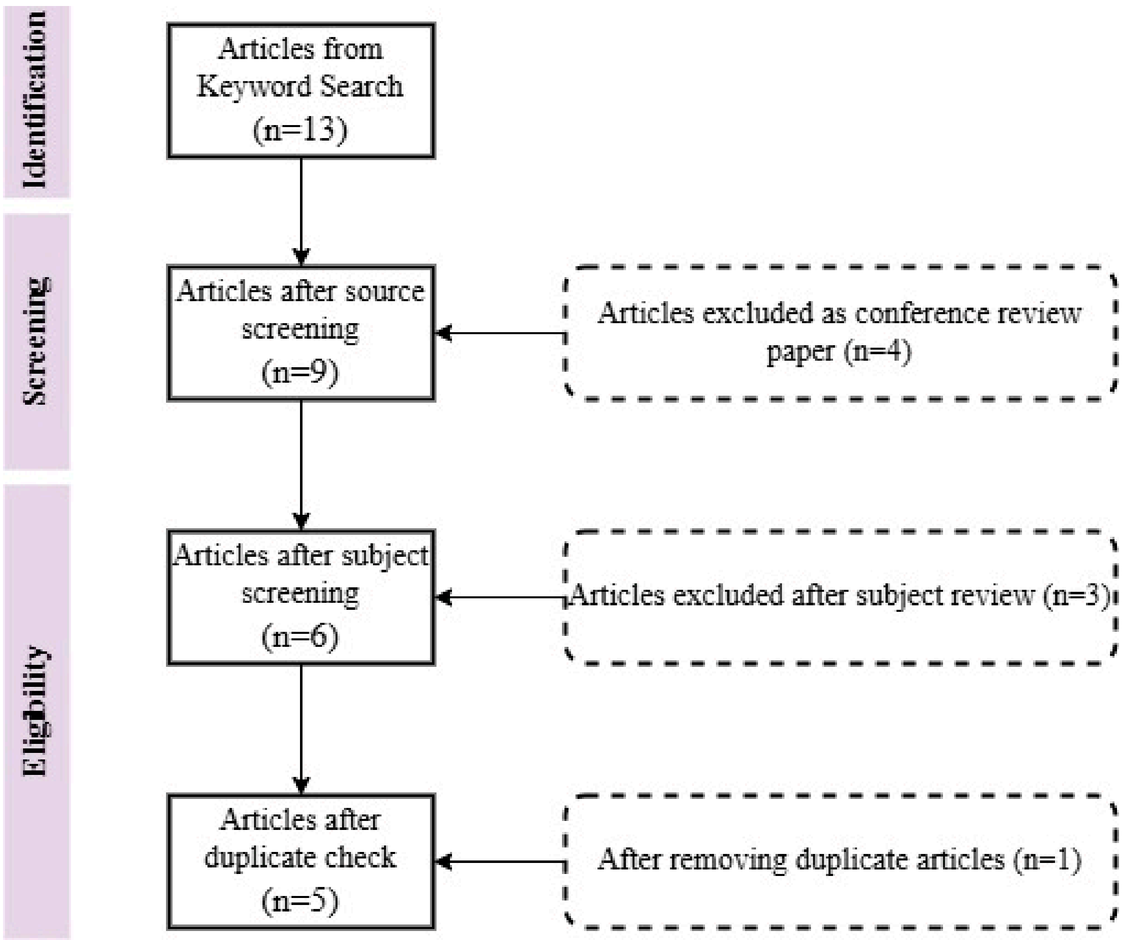

Figure 9. Domain-specific SLR workflow.

Table 2 below shows the meta-analysis of the 5 selected publications in the additional domain-specific keyword search above. Using the same headings shown in Table 1 above, the selected articles were categorized under three of the six headings namely; (1) review of prior arts, case studies, bibliometric analyses; (2) integration with other Industry 4.0 technologies towards newer paradigms; (3) application of ML, deep learning and advanced AI algorithms; and (4) integration with blockchain, edge computing, cloud computing, IoT for enhanced security, trust and transparency.

Table 2. Industry-specific meta-analysis of literature with DT in the AECO industry.

Theme	General DT	AECO	Aviation/Aerospace
Review of prior art, literature and case studies to examine existing research endeavors, level of applications and future opportunities.		[97]	[98]
Integration with Industry 4.0 and other emerging technologies towards developing a new paradigm contributes to smart infrastructure	[99]		
Application of machine learning, deep learning and neural network techniques		[100]	
Integration with blockchain, edge computing, cloud computing and IoT		[100,101]	

Following the above images and AECO-focuses meta-analysis, all 5 eligible articles deployed DT as a technique for predictive maintenance, despite not being featured in the keyword search. The low number of results from research and the limited application of BIM-DT-AI integration suggests an existing knowledge gap, which this study has sought to highlight. The reviews have established the need for more efforts on DT and PM in the AECO industry. The value of PM, condition monitoring and fault detection is well documented; therefore, subsequent sections of this study will seek to theorize a PM framework for urban assets as a use case scenario to validate the findings of the systematic literature review.

4. Use Case Scenario

The origin of DTs is attributed to Micheal Grieves and his work with John Vickers of NASA [102]. He described a DT as an environment where data and information are populated and consumed on a product-centric basis from the functional areas over the entire product lifecycle [103]. The UDT feeds into a condition monitoring dashboard that also receives prompts from an R-CNN model trained to recognize defects. While the UDT communicates with the dashboard through sensors, the R-CNN receives remote-sensing images of assets and communicates with the dashboard. Figure 10 shows the overview of the UDT framework.

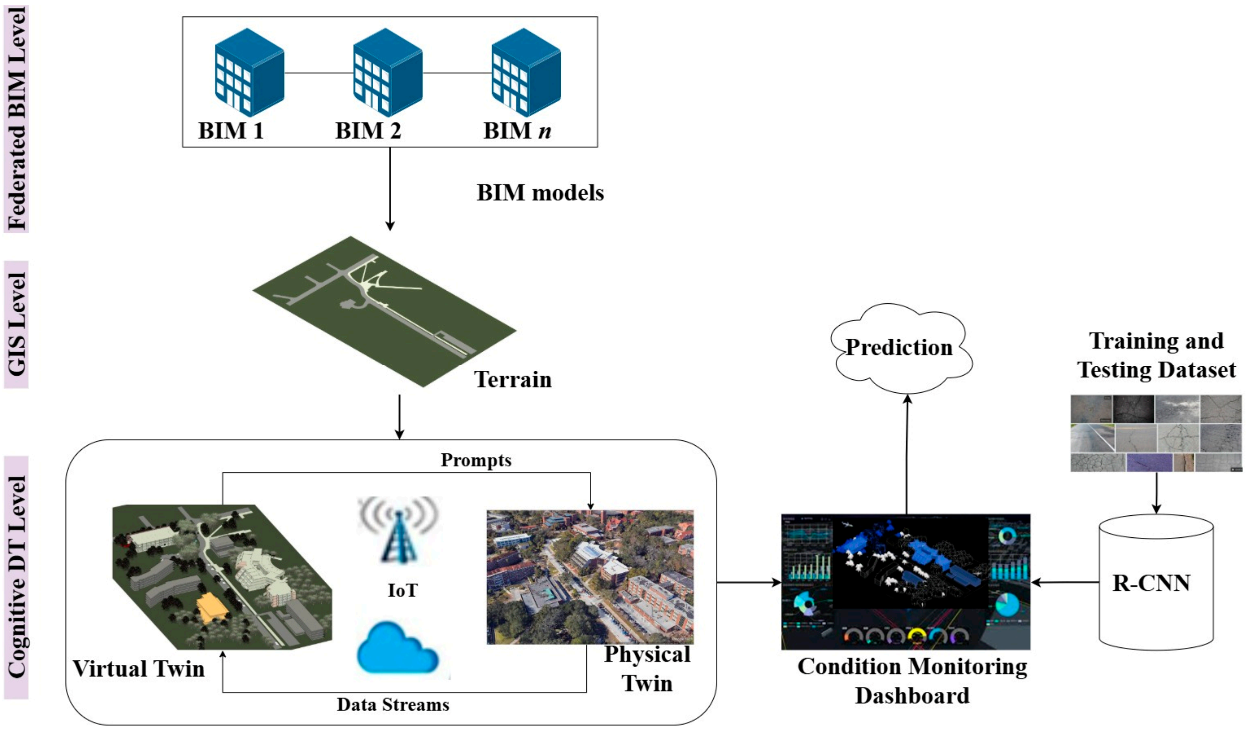

Figure 10. Cognitive DT implementation framework.

The road infrastructure connecting the BIM models is condition-monitored with simulated hypothetical data. The BIM models for the M.E. Rinker School of Construction Management, the Architecture School and the adjoining Inner Road are federated as a single entity. There are four prominent layers to the DT implementation, namely the federated BIM layer, the terrain layer, the infrastructure model layer and the site component layers, as shown in Figure 11 below.

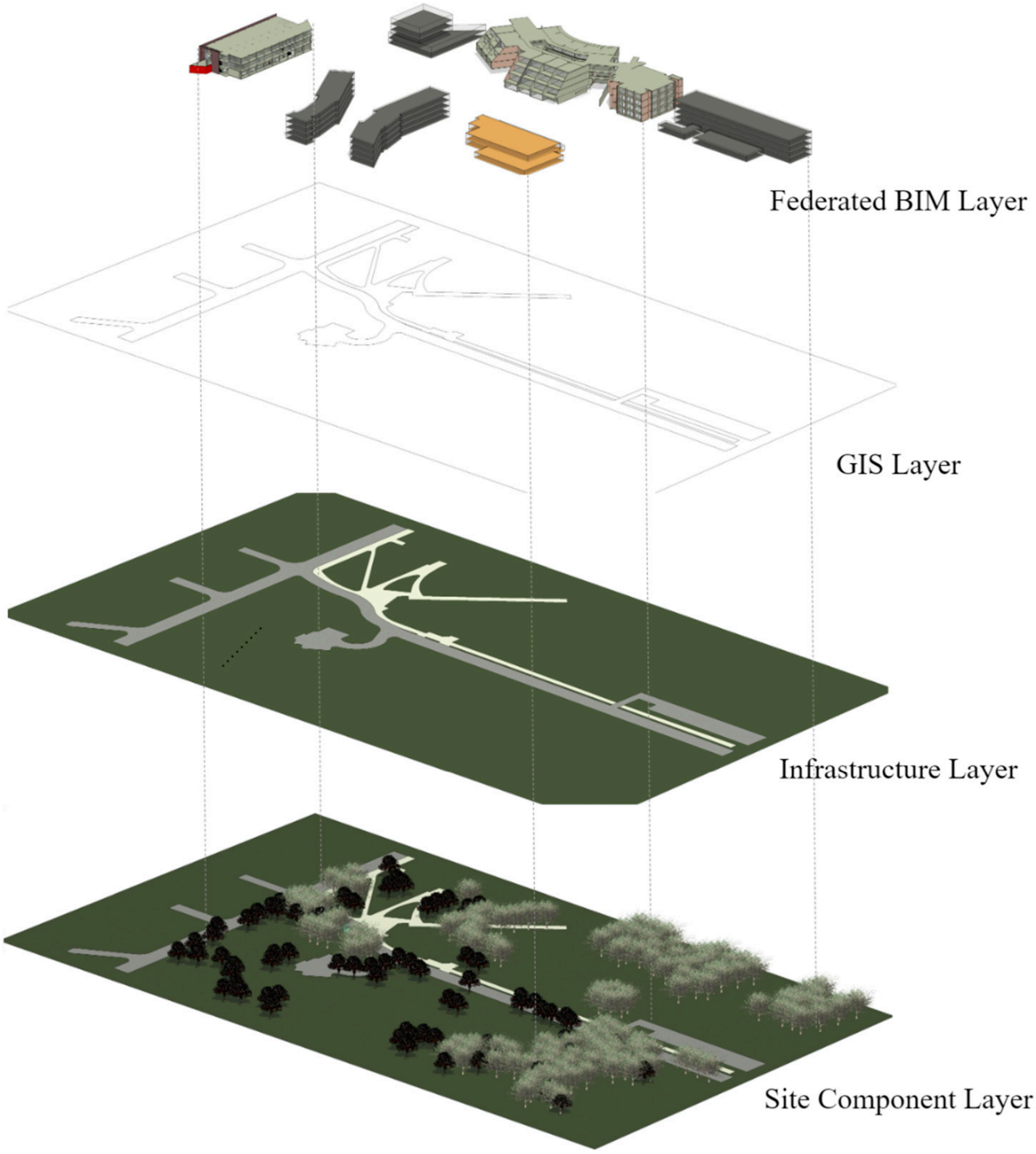

Figure 11. Components of an Urban Digital Twin.

The BIM models are integrated into the Autodesk Tandem web-based DT platform. Figure 12 below is an Autodesk Tandem interface that shows the various features that enable data transfer from the physical twin to the digital twin, while Figure 13 illustrates the condition monitoring dashboard, which interprets the Tandem DT input to advise on the level of asset degradation and forecast maintenance requirements. Item 1 is the asset of focus, which is Inner Road, University of Florida campus. Item 2 is the input data class which displays the type of data introduced into the interface. In this case traffic volume data is fed through the connection tab in item 7. Item 3 is the BIM model of the School of Architecture which is uploaded into the CIM. Item for is BIM mode for M.E Rinker School of Construction Management. Item 5 is the road design and installation guide—an analogue document which describes the asset of focus. Item 6 is the document attachment tab while Item 7 is the connection tab for data streams from physical sensors.

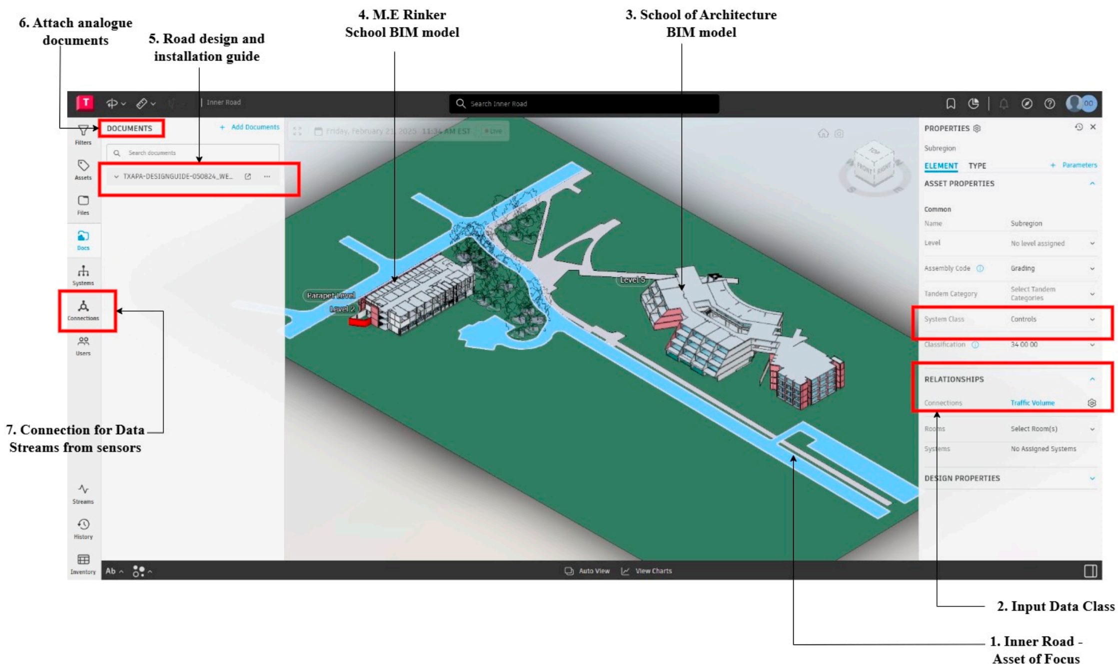

Figure 12. Autodesk Tandem Urban Digital Twin interface.

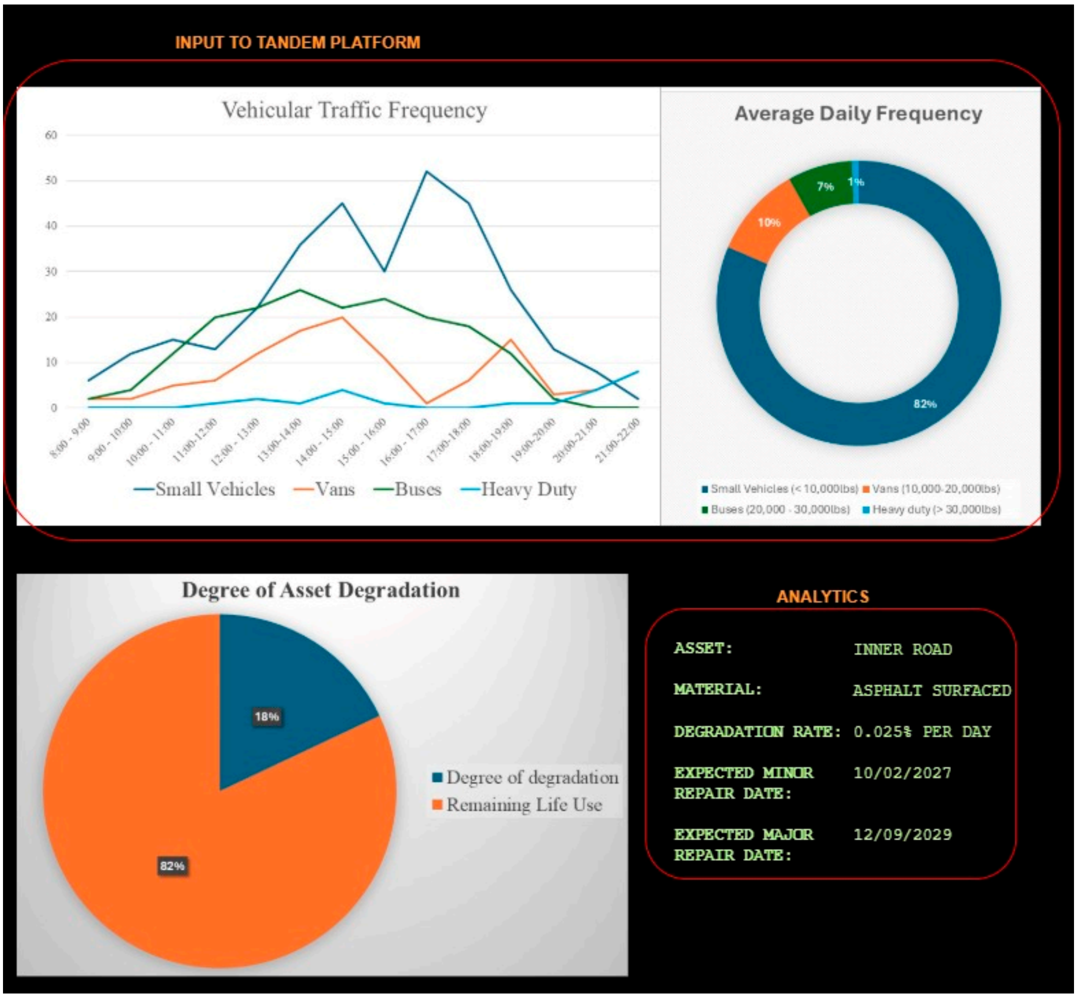

Figure 13. Hypothetical UDT dashboard.

4.1. Internet of Things Integration with the City Information Model

For virtual representation of physical entities to become intuitive, there is a need for data streams and data entry points from the physical twin to the DT [104]. This DT then sends information to the physical twin to impact conditions in response to the data received. This technology spans the lifecycle of an asset, using real-time simulation, AI and intuition to assist with decision making in the process [105]. The cognitive DT level in Figure 10 above illustrates the direction of information flow between physical and digital components by installing IoT sensors at critical points in the city. In this case, IoT sensors send traffic information ranging from types of vehicles to traffic volumes to the Tandem interface in Figure 12. This information goes into the condition monitoring dashboard. Based on codified logic, asset degradation information can be computed.

4.2. R-CNN Integration with the City Information Model

Meta-analysis results in Table 1 indicate that sectors such as manufacturing, oil and gas and infrastructure have deployed ML and DT to achieve a more efficient PM. This case scenario has a condition monitoring mechanism using deep learning algorithms to detect degradation and its severity in systems [81] in addition to its reliance on IoT-based data. An R-CNN approach to object detection is used, where data-driven PM is unable to identify sudden failure. Figure 14 below shows the AI training workflow in which an AI model is trained to identify road cracks whose wear may not have been in accordance with IoT predictions.

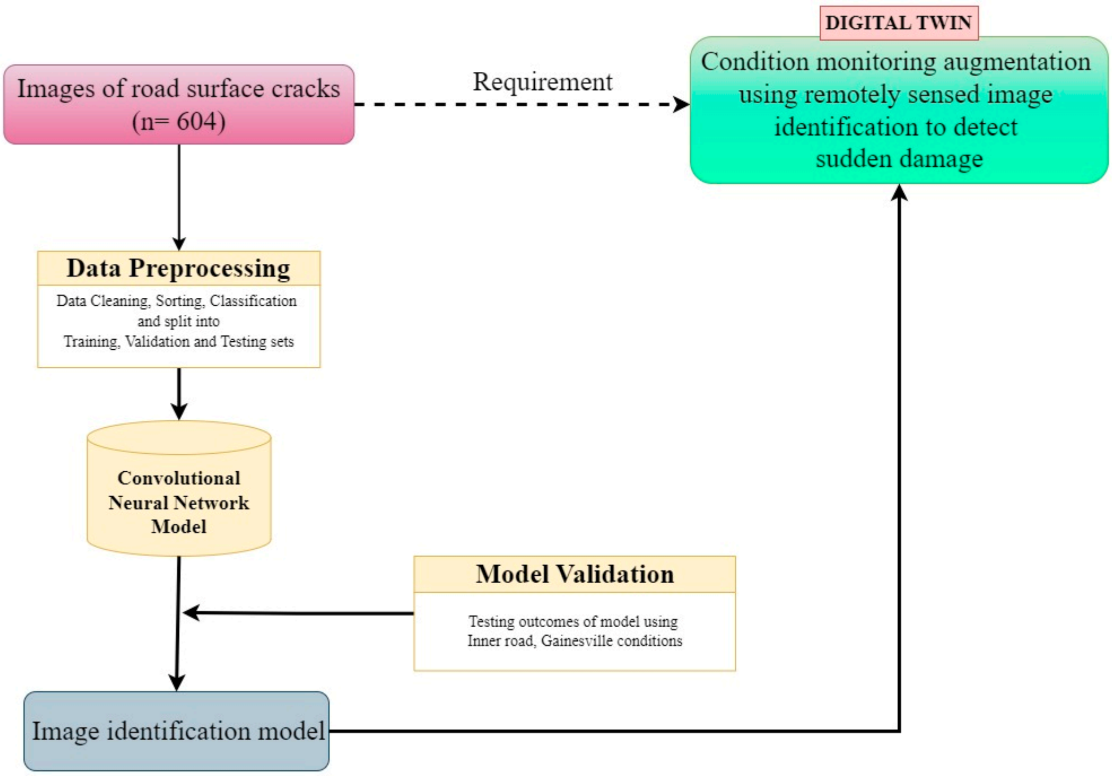

Figure 14. R-CNN workflow.

The pretrained faster R-CNN [106] model was chosen as the object detection model. The architecture consists of a backbone network that extracts feature maps from input images and a region proposal network (RPN) that generates potential bounding box proposals. The RPN uses a series of convolution layers with ReLU [107]. A softmax activation function was implemented for classification to ensure the model can assign a probability for each category of interest plus background and thus classify the categories present in the image. In this implementation, only the weights of the box predictor were updated during training, while the rest of the model was left as is.

4.2.1. Training and Testing Approach

Labeled images of defective roads and sidewalks were the model input, while the output was the predicted bounding box of the identified defects in the images. The image dataset used was curated by the authors from images available online. The data were manually annotated, and 604 images were created for training and validation. The dataset was randomly split into 80% training data and 20% test data. Some examples of annotations are shown in Figure 15 with the defect within the box representing the defect which the model is trained to identify.

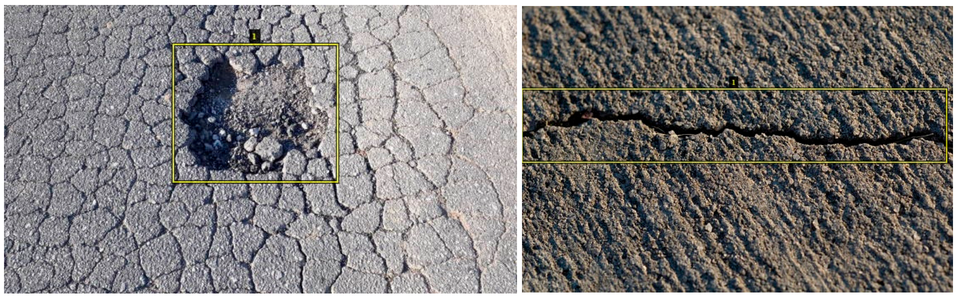

Figure 15. Examples of manually annotated images.

For training, the objective is to minimize a multi-task loss that encompasses two components: classification loss and bounding box regression loss. The classification loss computes the cross-entropy over two classes, i.e., defect vs. non-defect. The intersection of union (IOU) was also monitored during training.

4.2.2. Testing Results

Figure 16 shows examples of defect detection as predicted by the trained model. The model is largely able to accurately identify the defect areas in the images. The IOU computed for the predictions shown below are 0.6525, 0.7827 and 0.7690, respectively. IOU scores are between 0 and 1, with 1 meaning perfect overlap between predicted box and ground truth. In practical terms, an IOU score above 0.5 is often considered satisfactory in object detection. Hence, the model's predictions indicate a decent level of accuracy and localization for defect detection. The red box illustrates the models prediction of defects on road based on the training in Section 4.2.1.

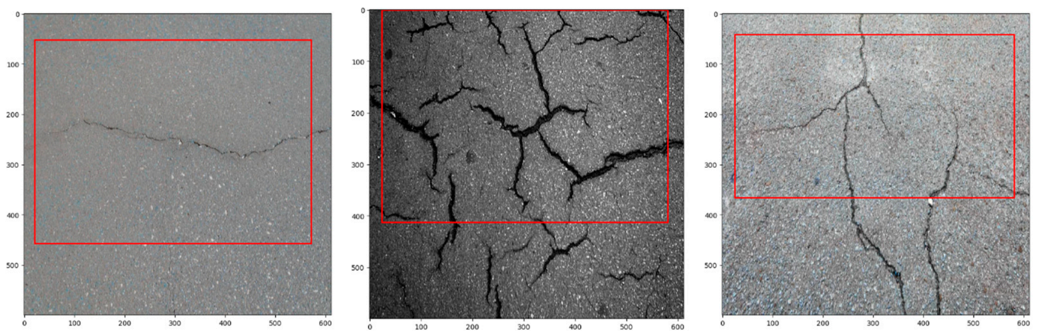

Figure 16. Example results of defect detection.

5. Results and Discussion

5.1. Literature Evaluation

The economic importance of condition monitoring and PM has been sufficiently established in the literature, and its applicability in the built environment has been highlighted. The reviews indicated the need for further efforts in DT applications enabled by emergent technologies within the AECO industry. ML techniques and integration with other emergent technologies in DT for the AECO industry is also limited, as shown in the non-existent application of automation and autonomy in urban asset management.

The close relationship between PM, DT, lifecycle and deep learning supports the bibliometric analysis that more than 50% of reviewed articles deployed DT, PM and AI to solve challenges. However, four out of six AECO-related articles focused on the deployment of DT and AI for PM practices. This amounts to a 66% adoption level, second only to manufacturing, where 73% of reviewed articles focused on DT-AI collaboration for PM practices. This suggests that with intensified research, the industry will benefit from smart PM.

5.2. DT Performance Evaluation

Federated BIM models within the CIM ensure a decentralized system, facilitating the participation of multiple asset owners while retaining full control of their asset model. Autodesk Tandem allows for the integration of digital/numeric and analog data. Digital data such as vehicular traffic data impact the DT in real time and can be obtained from the Department of Transportation (DOT), county or municipal authorities or be surveyed in real time using IoT sensors. The outcome of these data is populated on the UDT dashboard as shown in Figure 11. Analog data include operation manuals, data sheets, schedules and quantity documents and do not impact the DT dashboard in real time. They are information repositories for human interpretation.

5.3. AI Performance Evaluation

The model was trained with 604 images of defective asphalt surfaces to develop a defect detection capacity. Using R-CNN, the model yielded a performance accuracy of between 65 and 80%, which is considered adequate; however, for optimum performance, the accuracy can increase by using different training models or by increasing the number of sample images and the epoch. There are also opportunities to re-integrate identified defects into the AI training dataset. The size of the training and testing dataset can be doubled or tripled for improved performance.

The highlight of this approach is its ability to manage measurable and non-measurable infrastructure defects. Challenges to the approach include non-standardization of automation in the AECO industry, the human-centric and analog tendencies within the industry and the high computational demands of a cognitive PM system, thereby raising the entry requirements for personnel and hardware.

6. Conclusions

This paper reports a literature review of three broad concepts, namely UDT, PM and AI, and their interdisciplinary overlaps through qualitative and quantitative methods to evaluate the potential of these concepts in enhancing smart condition monitoring in the built environment. This resulted in the AI-enabled CIM for condition monitoring.

Following the review of relevant articles and the use of keyword co-occurrences visualization and meta-analysis, a UDT framework was developed using Autodesk Tandem as the web-based platform connected to a condition monitoring dashboard accessible via intandem.autodesk.com, which was augmented with an R-CNN-based model for the detection of unforeseen failure. The outcome, vastly supported by the literature, suggests that the AI-CIM framework is feasible for a more intuitive PM.

Material stress analytics and image-based defect detection are integrated into a cognitive predictive framework to demonstrate the feasibility of AI-enabled UDT for enhanced prediction accuracy, bridging the knowledge and application gap between AECO and many other technologically advanced industries. The following points are opportunities for future research:

- **Time-series data integration and image re-integration:** By using remote sensing to capture the state of assets periodically, the AI model is capable of continuous self-retraining. The state of assets can be captured through terrestrial laser scanning (TLS), LIDAR, etc. This loop ensures continuity and improvement of the AI-CIM using ML and deep learning algorithms.
- **Autonomous predictive and corrective maintenance:** UDT automation can improve through a more seamless integration of AI and not as an augmenting layer. A self-improving image recognition system enhances PM capabilities towards a less human-centric asset management.

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