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Classification and analysis of deep learning applications in construction: A systematic literature review

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ABSTRACT

In recent years, the construction industry has experienced an expansion in the multitude of projects and emergent information. With the advent of deep learning, new opportunities have emerged for utilizing this vast amount of data to solve construction-related issues. While the use of deep learning has been increasing in construction, there has been no review on these applications to date. Therefore, this paper presents a Systematic Literature Review on the use of deep learning applications in construction. A total of 80 journal papers were identified and analyzed. Among these papers, six application-based topics were identified: equipment tracking, crack detection, construction work management, sewer assessment, 3D point cloud enhancement, and miscellaneous topics. Analysis shows that deep learning has been beneficial in leveraging data in areas such as crack detection and segmentation of infrastructure and sewers; equipment and worker detection and; and analysis and reporting on construction-related operations. Additionally, a discussion of the various deep learning techniques is provided as well as a contrast between deep learning, machine learning, and artificial intelligence.

1. Introduction

In the past few years, the applications of deep learning have developed into a topic of interest in the construction industry. This has spurred from deep learning's benefits in many fields for data recognition, processing, and decision-making [1,2]. Recent advances in information technology have provided large amounts of information that still require manual parsing and processing, which is time-consuming, inefficient, and prone to errors. The ability to automate such tasks would lead to quicker detection of variances and enable fast intervention to reduce any possible adverse impacts. Deep learning has demonstrated its ability to be an effective tool in solving many problems related to object recognition and process monitoring, which would vastly improve the daily construction cycle. The attractiveness of deep learning comes from its ability to create predictive models without the need to pre-define relationships [3].

Even though the construction industry is one of the largest industries in any economy, it is still plagued by many problems. Traditionally, the success of a project is dependent on constraints such as time, cost, and quality. These metrics are tracked throughout a project to determine its status. However, it is not uncommon for a construction project to face time delays or exceed the allocated budget. Project success is tied to several variables and quantifiable metrics; however, uncertainties can impact projects and incur delays and damages. Automatic detection of anomalies onsite would be of immense help. Post-construction, techniques are needed for the effective monitoring of structures/infrastructure for swift damage detection. Hence, this paper focuses on how deep learning can fill the gaps in many of the problems that modern construction projects face. It can be the solution that unlocks the key to effective project control and infrastructure management.

The number of researches on deep learning in construction has exponentially increased over the past few years and the applications have spread over many areas of construction since their inception. Examples of that include using deep learning to track and monitor construction operations, equipment usage, worker efficiency and uncovering methods for enhancing the productivity and performance of project resources [5]. Furthermore, there are several methods through which deep learning can assist in unsafe work detection and worker monitoring. Additionally, deep learning can be used to automatically identify construction workers through video and pair each worker with their respective qualifications to ensure that they are working within the scope of their knowledge [6].

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Therefore, with the increasing interest in deep learning, there is a need for systematically reviewing and summarizing state-of-the-art applications of deep learning in construction to inform the academic community on past work and possible future recommendations. The objectives of this study are to: 1) systematically identify and analyze research on deep learning applications in construction; and 2) identify research gaps and suggest areas of future research. The next section presents the background with a focus on: contrasting between artificial intelligence, machine learning, and deep learning; and discussing the various common deep learning architectures.

2. Background

2.1. Artificial intelligence vs. machine learning vs. deep learning

This section is dedicated to differentiating between three terms, which are sometimes wrongly misconstrued as interchangeable: artificial intelligence (AI), machine learning (ML), and deep learning (DL).

2.2. Artificial intelligence

Artificial Intelligence (AI) can be defined as the study of intelligent agents. It involves machines acting in an intelligent way similar to humans in their learning and problem solving [4]. AI uses computer-processing techniques to learn, perceive, process natural language, or make human-like decisions [5]. It can process large amounts of complex data and conduct real-time decision-making. AI encompasses both machine learning and deep learning, which are discussed next.

2.3. Machine learning

Machine Learning (ML) is a subset of AI and is a field of work that addresses how computers can learn without being programmed [4]. It has evolved from artificial intelligence, specifically pattern recognition and computational learning theory [4]. A ML algorithm is used to choose the best function among a set of possible ones and to explain the relationship between features of a dataset. It is used in applications for computer vision, optical character recognition (OCR), and prediction. ML can be supervised, unsupervised, semi-supervised, or reinforcement learning. It involves training machines based on available datasets and algorithms and relies on being fed a particular set of features about the dataset.

2.4. Deep learning

Deep learning is a subset of machine learning that allows computers to learn from past experience [6]. It uses artificial neural networks and other machine learning algorithms containing more than one layer and imitates biological neural networks. These many layers are used for feature extraction, transformation, and pattern analysis using supervised or unsupervised learning [4]. Similar to the brain, to understand data, DL processes, labels, and categorizes the input received. This technique has the ability to be fed numerous data sets and distinguish and learn multiple complexity levels that some machine learning algorithms might not be able to [7]. It can also perform without supervision and with unstructured and unlabeled data [8]. It is 'deep' due to the number of layers available in it. Generally, DL models contain three types of layers: input later (received data), hidden layer (extracts patterns), and output layer (produces the results). The output of one layer is used as an input into the next one.

As a result of its contribution to the automation of tasks that were previously manual and time-consuming, deep learning has significantly enhanced many industries, which is the reason for its increasing popularity in this digital world. DL models are able to understand deep structures in different domains such as natural language, speech recognition, image recognition and processing, and video and voice recognition [2,9,10].

2.5. Deep learning architectures

There are multiple architectures that can be implemented when it comes to deep learning. Each of these architectures has its uses and compatibilities with certain applications. For the purpose of this paper, a definition of the most commonly used types of networks in construction is presented next.

2.5.1. Convolutional neural networks

Convolutional Neural Networks (CNNs) are one of the most widely used deep learning methods. They were inspired by the "natural visual perception mechanism of living creatures" [11]. They are a feed-forward network composed of multiple convolutional, pooling, and fully-connected layers and generally require large datasets for training [3]. The convolutional layer's purpose is to identify and study the input's characteristics. This enables them to identify low-level features such as edges and lines as well as high-level features such as objects and shapes [11]. The pooling layer is placed between two convolutional layers and acts like a funnel that minimizes the amount of features fed to it [11]. There can be multiple layers depending on how complex the system needs to be since their role is to deliver an output regarding the message classification (using the output data from the pooling/convolutional layer) [12]. The fully connected layers are usually the last few layers and are used to summarize information [11]. CNN is used in image recognition by inserting the values from the image pixels to identify features [13]. Its strength is in feature extraction and representation learning and weakness is its need for parameter tuning [14]. There are variations to the CNN technique such as region-based CNN (or R-CNN), fast R-CNN, and faster R-CNN.

2.5.2. Recurrent neural networks

Recurrent Neural Networks (RNNs) are an extension to feed-forward networks and additionally allow the use of the previous output as a current input [3]. They are mainly used for time-series and sequential data [15]. RNNs have also been used for tracking objects and humans in videos. A variation or modified version of RNN are LSTMs, which have an additional memory set that enables the processing of information with memory gaps. They are able to learn temporal and sequential patterns from sequences of data [7]. RNNs have been mainly used in literature to study human poses and fall detection [18].

2.5.3. Convolutional encoder-decoder networks

Convolutional encoder-decoder networks use convolutional layers to deconstruct an image for feature extraction and then reconstruct an image [16]. The encoder network is responsible for creating the representation of the architectures while the decoder network is responsible for classification by producing the features [17]. One example of this network is SegNet, which is used for pixel-wise semantic segmentation [17].

2.5.4. Fully convolutional networks (FCN)

FCN uses fully convolutional layers instead of the last fully connected layers to extract image features and does not use dense layers to reduce computation time [19]. It has been used for semantic segmentation, object tracking, and image restoration.

2.5.5. Restricted Boltzmann Machines (RBM)

Restricted Boltzmann Machines are graphical models used to study a dataset's probability distribution [9,15]. They consist of visible layers, which contain the components of an observation, while the hidden layers model the dependencies between these layers [20]. RBMs are used for feature learning and classification.

Previous researches in construction have focused on specific applications in deep learning and proposed models to solve problems in construction. However, no research has conducted a literature review on deep learning in construction. Therefore, this paper systematically identifies research on deep learning in construction to report on the patterns observed, applications conducted, and challenges. Additionally, recommendations for the future are also presented.

3. Research methodology

Systematic Literature Review (SLR) was used in this study to identify and report on previous research in a methodic and efficient manner. In this paper, we follow the steps of SLR as proposed by Kitchenham [21]. Five steps are done to conduct SLR, synthesize the data collected, and report on the findings. These steps are: identify the research questions, identify the search process and inclusion and exclusion criteria, conduct quality assessment, perform data collection, and perform descriptive analysis [22].

3.1. Identify the research questions

In this first step, the research questions are outlined. The search questions addressed by this research are:

RQ1. How can we classify deep learning applications in construction?
RQ2. What are the challenges for deep learning applications in construction?

To address these research questions, previous research was collected where deep learning was used in the construction sector. To address RQ1, all previous research was collected, analyzed, and reported on in a tabular format to visualize the different deep learning techniques used. Additionally, a taxonomy was proposed to understand the applications of deep learning in construction. To address RQ2, a deep dive was conducted on the reported challenges of deep learning techniques as well as the challenges reported by the previous researches and applications in construction.

3.2. Identify the search process and inclusion/exclusion criteria

The search process involved a manual search of the articles to be included for study. The authors conducted this review, which was then verified by an independent reviewer. The Scopus database was used as the main scientific database for its comprehensiveness with "*deep learning*" as the main keyword that was searched. Alternative searches for deep learning were its specific techniques such as "*convolutional neural networks*" and "*long short-term memory networks.*" Additional key words were used to limit the search to construction-related areas only, including "*construction*", "*building*", or "*AEC*". Fig. 1 shows the SLR process conducted.

After retrieving the initial batch of articles, multiple refinements of the search were also conducted based on the contexts/topics collected to address specific applications of deep learning in construction. Backward and forward snowballing were used where the reference list of the identified articles was searched as well the articles citing them. Only peer-reviewed articles were included to ensure a high quality standard. The collected articles were then evaluated by reading the abstract of each article for inclusion/exclusion. Exclusion was mainly for researches that: were not in English; were not peer-reviewed; focused on the technical aspects of deep learning; those that did not discuss deep learning applications (e.g. applied machine learning and only included deep learning as a recommendation for future work); or conference papers (2 were identified and eliminated).

3.3. Conduct data collection

The data collected from each study includes:

- Authors(s)
- Source (journal title)
- Year
- Objective of research
- Deep learning technique used
- Data type
- Dataset used and source
- Research results
- Challenges observed

This data was used to create tables to visually present and summarize the work to fulfill RQ1 and RQ2.

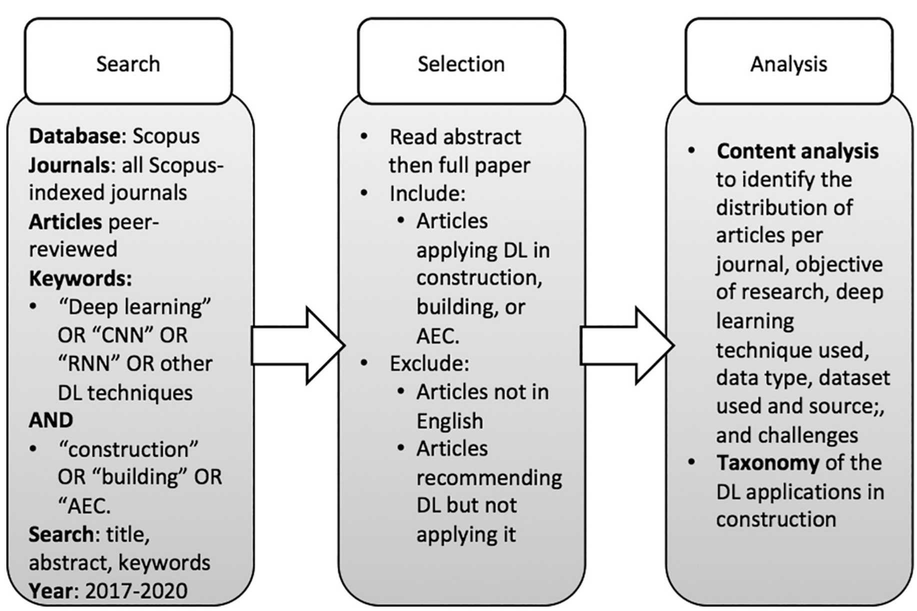

Fig. 1. Systematic literature review process.

3.4. Conduct quality assessment

Following Kitchenham et al. [21], quality assessment was conducted using a questionnaire where the authors identified five questions.

1. Do the authors state the research aims clearly?
2. Do the authors describe the methodology?
3. Do the authors define the data collection method?
4. Do the authors discuss their findings clearly?
5. Do the authors discuss the limitations in their study?

The authors applied a coding scheme similar to that proposed by Rauch et al. [23] to evaluate the suitability of the articles in answering the proposed research questions. A rating of 3 was given to papers with high suitability, 2 for medium, and 1 for low suitability. The two authors conducted this step independently and coded the work separately to verify the work, which was also verified by an independent researcher afterwards. This was conducted to ensure the reliability and validity of the research by testing interrater reliability through this independent coding [23]. The results were compared and the independent reviewer was consulted in case of dissent until agreement was reached. This resulted in a list of articles with similar coding among the researchers.

3.5. Perform descriptive analysis

This SLR process resulted in 80 journal articles published between 2017 and 2020 as shown in Table A1. The identified papers were then objectively reviewed and data was extracted and examined for the following items: research methodology, algorithm used, descriptive attributes of the models, journal, findings, and challenges and limitations. The results of this extraction were then documented in tabular format and evaluated independently by the authors and by an independent researcher to verify their eligibility. The resulting papers underwent thematic content analysis to reach a classification structure as discussed in the next section. Table 1 shows the distribution of the 80 articles in their respective journals.

These articles were then analyzed to produce a taxonomy of deep learning applications in construction. Several iterations were conducted to reach the best taxonomy after reading the abstracts and the full papers. This resulted in six topics, which are: 1) equipment tracking, 2) crack detection, 3) construction work management, 4) sewer assessment, 5) 3D point cloud enhancement, and 6) miscellaneous topics. The detailed analysis of these topics is discussed in the next section.

Table 1
Count of articles in each journal.

Journal	Count
Advanced Engineering Informatics	5
Advances in Structural Engineering	2
Alexandria Engineering Journal	1
Applied Energy	3
Automation in Construction	24
Building Services Engineering Research and Technology	1
Cement and Concrete Research	1
Computer-Aided Civil and Infrastructure Engineering	8
Construction and Building Materials	4
Construction Innovation	1
Energies	3
Energy	1
Engineering, Construction and Architectural Management	1
IEEE Transactions on Automation Science and Engineering	1
Journal of Bridge Engineering	1
Journal of Computing in Civil Engineering	12
Journal of Construction Engineering and Management	3
Journal of Infrastructure Systems	2
Journal of Management in Engineering	1
KSCE Journal of Civil Engineering	1
Smart Materials and Structures	1
Structural Control and Health Monitoring	2
Structural Health Monitoring	1

4. Taxonomy of deep learning applications

This section addresses RQ1. "How can we classify deep learning applications in construction?". No previous literature has addressed the classification of deep learning techniques in construction. Therefore, this paper proposes a taxonomy for these applications based on the identified studies. An application-based classification was proposed since it was shown to fit technology-related areas [24,25]. The thematic content analysis yielded six topics, which are: 1) equipment tracking, 2) crack detection, 3) construction work management, 4) sewer assessment, 5) 3D point cloud enhancement, and 6) miscellaneous topics. These topics are discussed in detail in the following section with respect to the identified papers.

4.1. Equipment tracking

Equipment tracking in construction sites has garnered interest from many researchers as it directly contributes to site safety analysis and the productivity of operations, among others. This subsection discusses deep learning applications related to equipment tracking and management. Eleven research papers were identified and analyzed as shown in Table 2. Majority of these researches proposed models to detect, track, and locate physical objects. Arabi et al. [26] proposed a model to detect construction vehicles while Guo et al. [27] used images from Unmanned Aerial Vehicles to detect dense vehicles onsite. Luo et al. [28] proposed three models to detect poses of construction equipment and Roberts and Golparvar-Fard [29] focused on detecting and tracking earthmoving equipment. Jeong et al. [30]proposed a DL algorithm to assess the pavement roughness using data from vehicles. Deep learning applications have have not only been limited to construction site equipment. Wei et al. [31] proposed a model to track office equipment such as printers and computers to enable the real-time control of HVAC systems and adapt them to actual energy demands. Furthermore, energy management/saving can be improved with electric vehicle charging [32] and path planning [22]. Management of vehicles is also possible by regulating the oxygen available in the fuel cells as proposed by Wang et al. [34]. Additionally, it can enable the classification of safe and unsafe operations and potential hazards. In the identified studies, convolutional neural networks (CNN) were found to be the most common deep learning technique used due to its competence in obtaining quality features from the raw input features in an automated manner [35].

However, several limitations were found in these studies, which can be grouped into: input/output, software, and hardware limitations. Input/output limitations include prediction discrepancies [30] and complexity of the model [27]. The prediction discrepancies were present when vehicle dynamics data was used to assess pavement roughness in the higher range of the International Roughness Index (IRI) [30]. Collecting more data samples (with high IRI in this case) and using them to train the model can resolve this issue. Another limitation is the model complexity, especially when deployed with other equipment such as Unmanned Aerial Vehicles to detect dense vehicles [27]. This issue can be simplified by using model reduction methods.

The accuracy of these prediction models is also influenced by the insufficient training data, low quality of the data, as well as location-specific issues such as angle and position of capture, which will affect the localization of equipment [31]. Therefore, the creation of a larger dataset with high-quality images/videos captured from different angles/positions is a solution that can increase the accuracy of prediction and stability of the model. Additionally, in cases where the detection of equipment requires knowledge of other equipment they are dependent on, the ambiguity in the system will increase [29] and will need to be addressed in the model. Finally, dataset size is an important factor affecting the model's performance. If a study is conducted on a limited dataset, a model trained on a large dataset cannot be expected to

Table 2
Literature on deep learning for equipment tracking.

Authors	Objective	Results
Arabi et al. (2020) [26]	Proposes a method to detect construction vehicles and deals with solution deployment.	Detected six equipment types with high mean average precision (dump truck, excavator, grader, loader, mixer truck, and roller).
Guo et al. (2020) [27]	Proposes a network to detect dense vehicles in construction sites using images from Unmanned Aerial Vehicles.	Adding a feature fusion model yielded an average precision of 0.988 for the detection accuracy.
Jeong et al. (2020) [30]	Develops an algorithm and uses multimetric vehicle dynamics data to assess pavement roughness.	Using multimetric vehicle dynamics provided better results over single metrics.
Luo et al. (2020) [28]	Uses computer vision to automatically estimate the poses of construction equipment in videos.	The poses of various construction equipment were determined with high accuracy using three deep learning models
Nath et al. (2019) [37]	Proposes a model to detect and label construction scenes.	The proposed model was able to predict and categorize construction work, equipment, and labor from images.
Rashid and Louis (2019) [38]	Proposes a model to recognize equipment activities.	The proposed data augmentation techniques were able to simulate real datasets.
Roberts and Golparvar-Fard (2019) [29]	Proposes a model to detect and track objects and a dataset to validate vision-based methods.	The Average Precision was higher when detecting excavators than dump trucks, especially when they were in the process of filling.
Wang et al. (2020) [34]	Proposed a model to predict vehicle speed and solve oxygen stoichiometry control problems.	The proposed model helps avoid air starvation, which avoids power waste and improves the system's output power.
Tan and Chen (2020) [32]	Proposes a model to improve the energy management of multiple microgrid systems with electrical vehicle charging.	Forecasting error was reduced by 36.86% using deep learning.
Wei et al. (2020) [31]	Proposes a model that detects and recognizes equipment (computer, printer, and kettle) usage and heat emissions in office spaces.	An annual cooling energy demand reduction was achieved while using this model.
Zhu et al. (2019) [33]	Proposes a model for energy saving for electric vehicles through path planning.	The energy-based path yielded less energy than other methods and yielded less travel time than the distance-based path but more travel time than the time-based path.

perform better than a model trained on a small dataset [26,36].

Software limitations include increased detection and training time in some models and the associated high computational costs [28]. Examples of hardware limitations include limited memory and system freezing (using the Jetson Nano and R. Pi with NCS) to detect vehicles onsite [26]. Other conditions that need to be controlled, especially when using vision-detecting equipment include its position, location, angle, as well as the ambient lighting. The presence of obstacles or congested space can affect the detection [31]; the resizing of images during processing can affect the accuracy [26]; and the presence of multiple equipment that are dependent on other equipment can increase the complexity of detection [29].

Additionally, some of these models need to be tested before their expansion to other building types or locations [31], and the camera locations and angles need to be varied [29] to improve the tolerance in forecasting errors [34]. To improve the convergence stability of deep learning models, the learning efficiency needs to be enhanced. In order to do this, Tan and Chen [32] proposed a data-driven adaptive method.

4.2. Crack detection

Cracks are a main form of deterioration in structures. Crack detection has attracted a significant amount of interest considering the importance of the detection, classification, and repairing of cracks. With the advent of deep learning, many applications related to crack detection for buildings, bridges, pavements, and other structural elements have been proposed. A total of 30 papers that discussed deep learning applications related to crack detection were found. Table 3 shows the list of identified papers in this theme. Majority of the papers were found to propose models for crack detection whereas one paper proposed a deep learning model to address motion blur from excessive movement of the UAV platform during visual crack inspection and detection [40]. Deep learning was mainly used in this theme for feature extraction, preprocessing, learning, and feedback. It was shown to have many benefits in the detection, classification, and localization of cracks.

Throughout these studies, several limitations were present. False-positives and false-negatives were often detected by the proposed models. False-negative classifications were encountered in thin cracks [41]. They were also found in cracks that were close to large holes or near the border of the image. A proposed model falsely categorized a long crack as multiple cracks with shorter length. It also underestimated the crack length of larger or more complex cracks [42]. Meanwhile, other models extracted false-positive pixels in the crack images, leading to a noisy mask image [43]. In some cases, linear features were mistakenly classified as cracks. This occurred when the image contained the borders of a road marking or shadows of trees and vehicles [44]. Sealed cracks were also falsely identified as cracks, which might have occurred due to the similarity of the aspect ratio and color intensities between real cracks and sealed cracks.

Another limitation of the proposed models lies in their inability to detect cracks in various materials. In a study that was conducted by Zhu et al. [39], four different crack-detecting networks performed well on a cement concrete bridge deck, but performed worse when the concrete bridge deck was made of asphalt. The background of the images was another factor that influenced the performance of the models [46]. The noise that was present in more complex backgrounds had negative effects on the detection of several crack characteristics, including spots or patterns that were present on the cracks [40]. The crack-detectors performed worse when the color or the pixel intensity of the cracks and the background were similar [47].

4.3. Construction site management

Unsafe worker movement and incorrect equipment location and motion have led to many fatalities in construction sites [67]. Nineteen papers were identified under this theme as shown in Table 4. They focused on tracking workers, detecting objects, and monitoring sites. Applications include locating workers onsite [68–70]; detecting worker unsafe behavior [71], analyzing construction safety [72]; classifying accident reports [73]; detecting worker compliance with PPE [74], hardhat usage [75–77], and worker physical loading [78]; and detecting structures and information onsite [13,35,79–83].

This area shows high potential for safety monitoring and enforcement, worker behavior analysis, and detection of structural and MEP elements. However, several limitations arise including limited training dataset and the need for the manual labeling of data. For example, Zhong et al. [73] proposed a model for classifying and visualizing accident narratives based only on accident text from OSHA's website. In order to expand this research, accident data will need to be collected from multiple sources and big data can be utilized in this case. Since the manual labeling of data is time-consuming and prone to errors, it should be automated in future research [38]. Computationally, some networks

Table 3
Literature on deep learning for crack detection.

Reference	Objective	Results
Alipour et al. (2019) [48]	Proposes a network for pixel-level defect detection in concrete infrastructure systems.	The proposed model was able to quantify crack characteristics and detect cracks with high accuracy using images of various sizes.
Cha et al. (2017) [49]	Proposes an architecture to detect concrete cracks without calculating the defect features.	The CNN model was accurate in detecting thin cracks under adverse lighting conditions and also had lower levels of noise in the images.
Cha et al. (2018) 101]	Proposes a model for visual inspection of damages.	Five defect types were introduced for the quasi realtime damage detection.
Dung et al. (2019) [50]	Develops a model for crack detection in gusset plate welded joints of steel bridges.	The fine-tuned method of the pre-trained CNN was found to be superior to the other two (CNN trained from scratch and the pre-trained non fine-tuned CNN) in terms of precision, robustness, and recall scores.
Gulgec et al. (2019) [51]	Proposes a model to diagnose damage in structures using a noise-sensitive approach.	The proposed model used a CNN that was able to detect cracks with high accuracy and computer efficiency and holds potential for future use in real-time crack detection.
Huyan et al. (2020) [46]	Proposes a pixelwise crack detection method.	The proposed method achieved higher performance for pixelwise crack detections than traditional approaches and FCN.
Jang et al. (2020) [52]	Proposes an automated evaluation technique for high-rise bridge pier cracks using a robot.	The technique was tested on a bridge in South Korea and showed a high precision and recall. It was also able to lower the time taken to inspect the bridge as well as reach areas that would normally be more difficult to access.
Kalfarisi et al. (2020) [43]	Proposes two deep learning-based approaches for crack detection and segmentation: 1) using FRCNN with (SRFED); 2) using Mask RCNN.	The study observed that approach speed is inversely proportional to the performance.
Kang et al. (2020) [53]	Proposes an automatic crack detection, localization, and quantification method.	Integrating three methods (Faster R-CNN, modified TuFF method, and modified DTM) for the crack detection and localization led to higher accuracy.
Lee et al. (2020) [54]	Uses semantic segmentation for the detection and the measurement of the maximum crack width in railway infrastructure.	The proposed function was able to predict crack width more precisely by one or two pixels over conventional models.
Li and Sun (2020) [55]	Proposes a model that detects structural damage in bridge structures by continuously monitoring the bridge deflection.	The model proposed in this pilot study was able to accurately detect bridge deformations. The CNN-based model performed better than the other models.
Liu et al. (2020) [40]	Proposes a deblurring model to address motion blur from UAV platform vibrations.	The proposed model showed improvements in deblurring performance in crack images.
McLaughlin et al. (2020) [56]	Presents a model that detects spalls and delamination by gathering 3D spatial data.	The proposed model was able to automatically detect spalls and delaminations using robotics, SLAM, lidar data, and image data.
Mei and Gül (2020a) [113]	Proposes a deep learning technique for crack segmentation at pixel-level.	The feature fusion method performed the best in terms of precision and recall, which suggests that the use of fusion methods can be more effective than individual layers.
Mei and Gül (2020b) [45]	Proposes the use of a GoPro and ConnCrack for road crack detection.	In terms of precision, recall, and F1 score, the proposed method achieved higher performance compared to other methods.
Mei et al. (2020) [57]	Proposes a new method for automatic pavement crack detection that considers the connectivity of pixels.	The proposed model was tested on two datasets and performed better than other available models.
Nhat-Duc et al. (2018) [58]	Two approaches are used for asphalt pavement crack detection: using two edge detectors and using a CNN.	The CNN model produces a higher Classification Accuracy Rate than the edge detection model.
Park et al. (2019) [44]	Develops a network for automated crack detection using a car black box camera.	Road surface elements were categorized into crack, road marking, and intact area with a ~ 90% accuracy.
Park et al. (2020) [59]	Develops a model to detect cracks on concrete surfaces.	The model performed crack-detection and laser-detection in real-time with high precision and accuracy
Ren et al. (2020) [60]	Proposes a deep fully convolutional neural network for crack segmentation of tunnels.	The proposed network yielded a higher accuracy than conventional image processing methods, which deems it suitable for tunnel inspection.
Song et al. (2020) [61]	Proposes a method for structural crack detection.	The proposed method was able to detect microcracks with small crack opening displacements (~23 μm).
Wang et al. (2019) [62]	Integrates crowd mobile sensing (CMS) with deep learning to detect damage to the Great Wall of China.	The model was able to classify the bricks correctly according to the degree of damage and even quantified it.
Wang et al. (2020) [63]	Proposes a framework for surface crack detection of concrete and uses an active learning sampling and training method.	This framework was found to ensure data integrity and can reduce annotation work.
Yang et al. (2018) [42]	Proposes a technique for automatic pixel-level crack detection for buildings and infrastructure.	The model was able to detect cracks of varying lengths, widths, and complexities. It was also able to detect more than one crack simultaneously.
Ye et al. (2019) [41]	Proposes a network for structural crack identification.	The technique was tested and found to perform better than edge detection methods in structural damage detection.
Zhang et al. (2018a) [64]	Proposes an improved version of CrackNet.	CrackNet II was 5 times faster than CrackNet, and performed better in detecting fine cracks
Zhang et al. (2018b) [65]	Proposes a model that trains a CNN to identify cracks, sealed cracks, and backgrounds.	The model was able to distinguish between cracks and sealed cracks.
Zhang et al. (2019) [47]	Proposes a semantic segmentation network for crack detection in structural infrastructure.	The proposed semantic segmentation network achieved higher results when tested on the three datasets.
Zhang, et al. (2020) [66]	Proposes a self-supervised structure learning network for crack detection.	The proposed self-supervised approach achieved performance comparable to that of supervised crack detection methods.
Zhu and Song (2020) [39]	Proposes a network for asphalt concrete deck crack segmentation and detection.	The proposed network achieved better segmentation effects on the six defect types as compared to other methods.

Table 4
Literature on deep learning for construction site management.

Authors	Objective	Results
Angah and Chen (2020) [68]	Proposes a three-stage framework for improving the current performance of multiple worker tracking.	Two improvements for worker detection were proposed: a method to predict location and tracking.
Chen et al. (2020) [79]	Proposes a deep learning method that identifies and labels the regions with relevant information in images of construction sites.	The model was able to detect semantic regions in construction site images with an average precision of ~0.68.
Ding et al. (2018) [71]	Proposes a hybrid model to detect worker unsafe behavior.	The proposed hybrid CNN + LSTM model was able to detect and classify workers' unsafe behaviors onsite using videos.
Fang et al. (2018a) [75]	Proposes a model to detect the non-hardhat use (NHU) of construction workers.	The proposed model was able to detect the workers' NHU under different conditions.
Fang et al. (2018b)	Proposes a framework for worker trade recognition.	The proposed framework was able to detect workers performing work they are not certified to do.
Fang et al. (2020) [35]	Develops a model that classifies near-miss information on construction sites.	The proposed model can reduce the occurrence of future accidents by determining where or how accidents are likely to occur.
Hou et al. (2020) [80]	Proposes a model to detect objects inside structures.	The model detected structural components with high precision, recall rate, and speed.
Jiang and Bai (2020) [13]	Proposes a model that uses drone images to estimate elevations in construction sites.	The elevations were predicted using only one frame from an image taken by a drone, as well as a 3D reconstruction method.
Kim et al. (2018) [84]	Proposes a model that identifies construction workers, objects, and materials in construction sites.	The proposed model performed well in detecting equipment. Additionally, a dataset was created for dump trucks, excavators, loaders, concrete mixer trucks, and road rollers.
Kim and Cho (2020) [69]	Proposes a motion recognition model for construction workers.	Using sensors to collect data proved useful in recognizing 13 motion types by construction workers.
Kim et al. (2020) [83]	Proposes a vision-based monitoring tool for construction sites.	Two experiments were conducted: one with active learning and the other without. The first experiment required less images to achieve a high mean average precision.
Marzouk and Zaher (2020) [82]	Proposes a model to detect and locate mechanical, electrical and plumbing (MEP) elements.	The proposed model is able to detect MEP elements and was integrated with an expert system on an Android application.
Nath et al. (2020) [74]	Proposes three models to detect worker compliance with PPE.	One model showed superior performance and was able to simultaneously detect workers and PPE.
Shen et al. (2020) [76]	Proposes a model that detects safety helmets in construction sites.	The proposed method is less sensitive to occlusion issues and background pixels.
Son et al. (2019) [70]	Proposes a model to detect different poses of construction workers.	The proposed method is able to detect workers under different poses and changing backgrounds.
Won et al. (2020) [81]	Uses an integrated unmanned aerial vehicle-RFID platform with deep learning algorithms to locate construction resources.	The proposed model can be used for both horizontal and vertical monitoring in construction sites.
Wu et al. (2019) [77]	Proposes a model that monitors the use of hardhats during construction work on sites to improve the site safety.	This study provides a dataset for hardhat detection and proposes a model for real-time on-site monitoring.
Yang et al. (2020) [78]	Proposes a model to analyze worker physical loading.	Using wearable sensors enabled the detection of workers' physical loading.
Yu et al. (2019) [72]	Presents a model that performs an ergonomic assessment on construction safety and productivity.	Proposes a novel "two-dimensional (2D) video–based three-dimensional (3D) pose estimation" algorithm.
Zhong et al. (2020) [73]	Proposes a model to analyze and classify accident reports.	The proposed NLP and CNN model is able to process and analyze large volumes of accident reports.

such as the Long Short Term Memory (LSTM) network require high computational power and time as opposed to shallow networks [38].

4.4. Sewer assessment

The deterioration of sewer pipes is a critical issue that is difficult to accurately predict. Sewer inspection can be expensive due to the high cost of assessment technologies [85]. Results of the SLR identified six researches in this area as shown in Table 5. Deep learning was used for the detection ([86,87], classification [88], localization [89], and assessment of defects [90]. The final research used Augmented Reality with deep learning for facility management with a case study on sanitary pipe visualization [91].

These researches aimed to solve the sewer damage detection and localization problem with a less expensive and automated technique that would not rely on the use of many workers and regular physical inspection. Majority of the researches obtained learning data from CCTV images or videos since they can easily enter sewers and capture detailed information [86,87,89,90]. Baek et al. [91] captured images as well but used wearable Microsoft HoloLens to gather the input. Xie et al. [88] captured videos using a quickview device. The collected images/videos were then classified into defect and non-defect frames and used to train the deep networks [88]. These networks contain superficial layers that detect basic patterns like edges and deep layers that collect complex

Table 5
Literature on deep learning for sewer assessment.

Authors	Objective	Results
Baek et al. (2019) [91]	Proposes a two-module system for facility management. Firstly, an AR device is used to capture an image and deep learning is used to estimate the location and orientation indoors.	A case study was conducted on a building where the proposed tool was able to visualize the holographic sanitary pipes.
Hassan et al. (2019) [90]	Proposes a model to classify sewer defects based on CCTV inspection videos.	The proposed model was able to detect, classify, and locate sewer defects.
Kumar et al. (2020) [87]	Proposes a deep learning framework to classify and localize sewer defects.	Evaluated three methods of detecting sewer defects for their speed and precision (SSD, YOLO, Faster R-CNN)
Li et al. (2019) [86]	Proposes a deep learning method to detect and classify defects in sewers from CCTV inspections.	The proposed method was able to distinguish defect images from normal images and then categorize the different defects.
Moradi et al. (2020) [89]	Proposes a CNN model that detects and localizes damage in sewers	The model was able to accurately detect and localize anomalies in sewer CCTV videos.
Xie et al. (2019) [88]	Proposes a framework for automatic feature representation followed by sewer defect classification.	Six types of sewer defects are used here: "deposition, stagger, fracture, high water level, disjunction, barrier, and others"

patterns. The identified models were able to distinguish defect from non-defect images and classify sewer defects.

However, these researches reported several challenges such as occlusion and the misclassification of defects from the collected 2D images [87,89]. Some deep learning models were usually able to detect only one type of defect per image, hence multilabel classification is encouraged as a recommendation for future work [88]. Additionally, some models were unable to detect correlation between multiple defect types [88]. Identifying this correlation can aid in root cause analysis and early detection of sewer damage problems, which can prevent failure.

4.5. 3D point cloud enhancement

Over the past few years, laser scanning and photogrammetry have become main sources of data collection in construction projects. These techniques create point cloud data that can then be transformed for 3D object recognition and semantic segmentation [92]. Deep learning was applied in this area for generating 3D point cloud [93], automating progress monitoring [94], as-built modeling [92], detecting elements from laser-scanned point cloud scenes [95], and predicting design commands from log data obtained from Building Information Modeling [96]. The results of the SLR for this area are shown in Table 6.

Ma et al. [92] proposed a methodology to create synthetic point clouds from 3D BIM data using three different software programs. The neural networks were then trained under three conditions: real, synthetic, and a combination of both point clouds, for semantic segmentation. Pan and Zhang [96] proposed a framework to learn and predict design commands from BIM event log data. Zi et al. [93] enhanced the resolution of 3D point clouds using a deep learning super resolution model. Chen et al. [95] proposed a framework for the detection and classification of components from laser-scanned point cloud scenes. Braun et al. [94] proposed a model to detect objects in construction and compare them to a digital model to determine project progress.

However, several limitations exist in these researches. The proposed models can be case-specific and not generalizable to other construction projects or countries since they are built based on specific construction elements [94]. Also, since BIM must be aligned with the structure onsite, a manual step might be required to add markers that help in the aligning [94].

Table 6
Literature on deep learning for point cloud enhancement.

Authors	Objective	Results
Braun et al. 2020 [94]	Proposes a model to detect objects in construction and compare them to a digital model to determine project progress.	The proposed model applied a 'Scan-vs-BIM' technique and fused information from images, point clouds, and BIM.
Chen et al. (2019) [95]	Proposes a framework to detect and classify elements from laser-scanned point cloud scenes.	The proposed model measured the deviations between the as-planned BIM model and the as-built structure.
Li et al. (2018) [93]	Proposes a deep learning-based super resolution method for 3D point cloud.	Two methods were proposed. The method with multiple CNNs showed superiority in the speed and performance of high-resolution phase image acquisition.
Ma et al. (2020) [92]	Proposes a method to convert digital 3D BIMs into synthetic point clouds, which are used to train a deep neural network, followed by the segmentation process.	Three software systems were used to convert 3D BIMs to synthetic point clouds, which were used to augment datasets.
Pan and Zhang (2020) [96]	Proposes a deep learning framework to learn and predict design commands from BIM event log data.	The accuracy of this process outperformed other methods such as k nearest neighbor, random forest, and support vector machine.

Table 7
Literature for deep learning in miscellaneous applications.

Authors	Objective	Results
Rafsanjani et al. (2020) [97]	Proposed an IoT-based smartphone energy assistant that uses deep learning to identify the user's energy usage and send them feedback.	The proposed framework was developed in order to increase energy efficiency in commercial buildings. Results show an improvement in behaviors relating to energy use in a commercial building application.
Zeiler and Labeodan (2019) [99]	Uses Big and Small Data with deep learning to capture user demand from the individual up to the neighborhood to optimize the energy management.	The proposed approach collected and analyzed data to create strategies for optimizing energy/carbon control.
Marinakis (2020) [98]	Proposed a decision-making and data analytics solution combining blockchain, deep learning, and big data for energy management of buildings.	The proposed method enables monitoring or energy performance, visualization of data and improving the energy performance.
Lorenzoni et al. (2020) [100]	Analyzes investigations of mechanical and 3D-micro-structural highstrength strain-hardening cement-based composites (SHCC) using deep learning.	Investigated three factors that affect the strain distribution and fracture localization: loading conditions, specimen geometry and material heterogeneity.
Khumprom and Yodo (2019) [110]	Presents a preliminary deep neural network method for predicting the State of Health (SoH) and the Remaining Useful Life (RuL) of lithium-ion batteries.	Presented a benchmark for the SoH and RuL of lithium-ion batteries.
Tong et al. (2019) [101]	Proposes a deep learning technique to characterize the carbon fiber morphology in carbon fiber reinforced cement-based composites.	The proposed method can be used as a nondestructive test to evaluate CFRC properties.
Jang et al. (2020) [102]	Proposed a model to predict failure of construction contractors within 1–3 years using accounting variables, construction market and macroeceonomic variables.	The proposed model showed higher prediction performance over accounting variables only.
Wu et al. (2020) [103]	Uses deep learning and NLP to develop a binary classifier to identify if a patent is relevant to information and communication technology in construction automatically.	The proposed method showed better performance over traditional deep learning techniques.
Zhong et al. (2020b) [104]	Proposes a model to analyze and classify accident reports.	The proposed NLP and CNN model was able to process and analyze large volumes of accident reports.

4.6. Miscellaneous topics

This subsection refers to deep learning applications in construction that do not fall under any of the previous topics. Nine research papers were found in this area as shown in Table 7. In these researches, deep learning was mainly used for energy applications and material investigations, among other areas. It was used to model energy usage and provide feedback to users [97], manage energy and develop energy-efficient buildings [98], and capture user demand [99]. It was also used for the investigation and evaluation of the properties of materials [100,101], business failure prediction [102], patent screening [103], and extraction of constraints from construction regulations [104].

However, several limitations arise from these researches including a small dataset size, pixel size limitations, as well as the requirement of manual work and post processing. Some of the proposed models were also found to be effective only for specific uses and were ineffective for generalization. For example, the model proposed by Baek et al. [91] was intended for facility management but experts in the study deemed it fit for visualization and converting plans to 3D only. Another limitation includes inability to track color in PPE, especially vests [74]. However, Zhao et al. [105] solved this issue of color by proposing a neural network model that included converting the vest area into HSV color space to detect pedestrians.

5. Challenges of deep learning applications

Despite the promising results seen from the collected studies on deep learning applications for the construction sector, several challenges and limitations were identified. This section answers RQ2 and delineates the observed challenges, which can be classified into three areas: functional, informational, and technical.

5.1. Functional issues

Deep learning models are known to be domain specific [106]. Each model is created for a specific purpose and is not necessarily transferable to other applications. Additionally, dataset size affects model performance. A deep learning model trained on large datasets cannot produce the same results as a model trained on a smaller dataset. Hence, large datasets are needed to train the models to produce accurate results.

5.2. Informational issues

These issues mainly relate to the data needed for the learning aspect of the neural networks and can be classified into volume, quality, interpretability, and temporality [3]. Large volumes of data are needed to train the models, which are not always available. Crack detection and other areas have online repositories collected by previous research such as the CrackForest Dataset (CFD), Tomorrow's Road Infrastructure and Monitoring Management (TRIMM) dataset and a Customized Field Test Dataset (CFTD) [45,47,66]. Other available datasets are the Stanford large-scale indoor spaces (S3DIS) for 3D indoor spaces [92,107], and ImageNet, which is a large-scale ontology [26,29,84]. However, not all topics have datasets available online. This causes inconsistencies in the data and models since the authors have to rely on their own data collection techniques. Additionally, these repositories are sometimes limited in use, case or project-specific, and cannot be generalized to all project types.

There are also a multitude of variables that can affect images collected for vision-based detection researches such as: camera angle and position, presence of obstructions, dense construction, and inconsistency in worker posture/movement [29,31]. These issues pose a concern to modelers and can reduce the accuracy and precision of detection.

Data quality is another issue that depends on the mode of collection itself. Two modes of data acquisition were identified in this SLR, which are: 1) proprietary (or ground truth data collected); and 2) public data (e.g. from online datasets and repositories). Both methods have problems that include noise and quality. Examples of public datasets used are: CFD, TRIMMD, CFTD, CrackTree, Python Library, ImageNet, COCO, Open Image, AIM, Pictor v.1.0, ICCV'17 PoseTrack Challenge, AlexNet, Datafountain, NASA, and S3DIS.

Data interpretability can also be an impediment since the deep learning models use data for their self-learning, which in certain cases needs to be manually validated. In some deterministic cases such as in damage detection, this may not pose an issue since the user can easily validate the tags.

Temporality refers to whether there are changes in inputs over time [3]. In cases where deep learning is used for real-time analysis, the dynamic inputs may pose a complexity in modeling. Additionally, vision-based researches relying on image and video data for detection of physical objects face occlusion [68,80,94], which can be solved by installing additional cameras or using drones to capture data from multiple angles and positions.

5.3. Technical issues

Manual extraction and segmentation of information is costly, time-consuming, and prone to errors. This has pushed for the use of deep learning to improve construction processes. It must be noted, however, that deep learning algorithms are complex and require high technology and hardware. Some models require fine-tuning for analysis improvement. For example, models based on motion capture algorithm require improvements for more accurate detection [71]. In certain cases, more cameras may be needed onsite for facial detection to detect safety helmet-wearing workers in situations where the model was unable to detect a worker's face if the camera captured an image of his back [76].

6. Threats to validity and implications

6.1. Threats to validity

Finally, a discussion on threats to validity is presented. According to previous literature, several threats to validity exist for systematic literature reviews, including threats to conclusion, internal, external, and construction validity [111]. Conclusion validity threats refer to drawing inaccurate conclusions from the observations. To reduce bias in article selection, a preset roadmap was created and applied. To reduce bias in drawing conclusions, the coding was conducting by the authors independently and reviewed afterwards. Additionally, several methods of taxonomy were explored until the authors and the independent researcher agreed on one. Hence, conclusion bias was reduced in this research and replicating this research would yield similar results.

Internal validity refers to threats that were not taken into consideration and affected the results such as assuming causal relationships [111]. To capture as many articles as possible, Scopus was used for the first search, followed by Google Scholar as a secondary search. Additionally, snowballing was used as a complementary search method.

External validity refers to threats that affect the generalizability of the results. Since the articles were identified in a systematic manner and they represent all available research on deep learning (withstanding the inclusion/exclusion criteria), therefore the conclusions drawn are valid. However, if all previous researches on deep learning applications in construction were included, regardless of any inclusion/exclusion criteria, this would lead to a much larger dataset and the conclusions made in this paper might not be generalizable to this larger dataset.

Lastly is construction validity, which refers to threats that affect the relationship between the observation and theory. It would not pose a threat to this research since the authors did not have any expectations or preconceived ideas prior to conducting this SLR.

6.2. Implications for academia and practitioners

While there are previous literature reviews for artificial intelligence and machine learning applications in construction, no previous research has addressed deep learning applications in this field to the authors' knowledge. Thus, this paper provides a comprehensive state-of-the-art on deep learning applications in construction. This is intended to aid researchers in the field in identifying the current status, hot topics, and possible future research. For example, it can be observed from this study that majority of the work has focused on crack detection followed by construction site management. Since DL is fairly recent in construction, this SLR can aid practitioners and managers in identifying the current status and paving the path for real-life applications. The methodology conducted can be replicated to expand the application to other areas beyond construction as well.

Table 8
Analysis of the identified literature based on deep learning method and data source.

	Authors	Deep Learning Method	Data source
Crack Detection	Alipour et al. (2019) [48]	FCN	Camera images
	Cha et al. (2017) [49]	CNN	Camera images
	Cha et al. (2018) [112]	Faster R-CNN	Camera images
	Dung et al. (2019) [50]	CNN	Camera images (public and proprietary datasets)
	Gulgec et al. (2019) [51]	CNN	Online dataset (Python library)
	Huyan et al. (2020) [46]	CNN	Smart phones + High-speed camera pictures
	Jang et al. (2020a) [52]	Deep convolutional encoder-decoder (SegNet)	Camera on a robot
	Kalfarisi et al. (2020) [43]	1) Faster-RCNN 2) Mask-RCNN	Camera (mounted or handheld) images
	Kang et al. (2020) [53]	Faster R-CNN	Camera images
	Lee et al. (2020) [54]	CNN	Images from a Track Measurement Vehicle with camera
	Li and Sun (2020) [55]	CNN	Fiber optic gyroscope
	Liu et al. (2020) [40]	GAN	UAV + camera
	McLaughlin et al. (2020) [56]	CNN	UGV + Digital camera + Infrared imaging + Lidar + GPS sensor
	Mei and Gül (2020a) [113]	DenseCrack	Online dataset (CFD)
	Mei and Gül (2020b) [45]	WGAN + FCN	GoPro camera videos
	Mei et al. (2020) [57]	DenseNet201	Camera images (mounted on a car) + smart phone
	Nhat-Duc et al. (2018) [58]	CNN	Camera images
	Park et al. (2019) [44]	CNN	Black box images
	Park et al. (2020) [59]	YOLO	Laser + sensors (distance and vision)
	Ren et al. (2020) [60]	F-CNN	Camera images
	Song et al. (2020) [61]	CNN	Optical fiber sensor data
	Wang et al. (2019) [62]	Faster R-CNN	Smart phone camera images
	Wang et al. (2020) [63]	CNN	Mobile phone camera images
	Yang et al. (2018) [42]	FCN	Internet and camera images
	Ye et al. (2019) [41]	FCN (Ci Net)	Camera images
	Zhang et al. (2018a) [64]	CNN (Crack Net II)	3D laser sensors
	Zhang et al. (2018b) [65]	T-DCNN	Camera images
	Zhang et al. (2019) [47]	Deep convolutional encoder-decoder (SegNet)	Online datasets (CFD, CrackTree, FCN, and industry data gathered by authors)
	Zhang, et al. (2020) [66]	GAN	Online datasets (CFD, TRIMMD, CFTD)
	Zhu and Song (2020) [39]	CNN + FCN	Camera images
Equipment Tracking	Arabi et al. (2020) [26]	SSD MobileNet	Datasets online (ImageNet, COCO, Open Image) and webcrawling techniques
	Guo et al. (2020) [27]	OAFF-SSD	UAV + camera images
	Jeong et al. (2020) [30]	CNN	Smartphones as sensors (road roughness)
	Luo et al. (2020) [28]	HG, CPN, and and HG-CPN	Surveillance camera videos and images
	Nath et al. (2019) [37]	CNN	Online dataset (Pictor v.1.0, ImageNet)
	Roberts and Golparvar-Fard (2019) [29]	CNN	Online dataset (AIM, originally from ImageNet)
	Rashid and Louis (2019) [38]	LSTM-based RNN	Sensor data
	Tan and Chen (2020) [32]	BPNN + LSTM	Collected real data
	Wang et al. (2020) [34]	BPNN	Collected real data
	Wei et al. (2020) [31]	CNN	Internet images (Office)
	Zhu et al. (2019) [39]	LSTM	Data from battery-powered EV model + Traffic simulations
Construction Work Management	Angah and Chen (2020) [68]	Mask R-CNN	Online dataset (ICCV'17 PoseTrack Challenge)
	Chen et al. (2020) [79]	CNN	Digital camera images + Online search images
	Ding et al. (2018) [71]	CNN + LSTM	Video cameras
	Fang et al. (2018) [75]	R-CNN	Surveillance videos (construction sites)
	Fang et al. (2020) [35]	Encoder-decoder (using BERT)	Safety reports (Wuhan metro-rail network)
	Hou et al. (2020) [80]	DSOD	Collected real data
	Jiang and Bai (2020) [13]	CNN	UAV + Camera
	Kim and Cho (2020) [69]	LSTM	Body motion sensors
	Kim et al. (2018) [84]	R-FCN	R-FCN
	Kim et al. (2020) [83]	Faster R-CNN	Camera images (from construction sites)
	Marzouk and Zaher (2020) [82]	CNN	Online dataset (AlexNet)
	Nath et al. (2020) [74]	Yolo + CNN	Dataset created using crowd-sourcing and web-mining
	Shen et al. (2020) [76]	DenseNet	Online dataset (Datafountain, private)
	Son et al. (2019) [70]	Faster R-CNN	Camera images
	Won et al. (2019) [81]	LSTM	UAV + RFID
	Wu et al. (2019) [77]	CNN	Camera images (construction sites)
	Yang et al. (2020) [78]	Bi-LSTM	Wearable sensor
	Yu et al. (2019) [72]	HSN	Images from construction videos
	Zhong et al. (2020) [73]	CNN	Accident reports from the Occupational Safety and Health Administration
Sewer Assessment	Baek et al. (2019) [91]	CNN	Images from the wearable Microsoft HoloLens
	Hassan et al. (2019) [90]	CNN	CCTV videos
	Kumar et al. (2020a) [87]	SSD, YOLO, Faster R-CNN	CCTV videos
	Li et al. (2019) [86]	CNN	CCTV images
	Moradi et al. (2020) [89]	CNN	CCTV videos
	Xie et al. (2019) [88]	CNN	Videos using a quickview device
3D Point Cloud Enhancement	Braun et al. 2020 [94]	CNN	Camera images (construction sites)
	Chen et al. (2019) [95]	PointNet	Online data set (S3DIS) + proprietary point cloud data
	Li et al. (2018) [93]	CNN	Camera images
	Ma et al. (2020) [92]	PointNet and DGCNN	Online data set (S3DIS)

(continued on next page)

Table 8 (*continued*)

	Authors	Deep Learning Method	Data source
	Pan and Zhang (2020) [96]	LSTM	Log data (Autodesk Revit)
Miscellaneous Topics	Jang et al. (2020) [102]	LSTM (RNN)	Online data on financial and statistical information of construction companies (from multiple sources)
	Khumprom and Yodo (2019) [110]	DNN	NASA dataset
	Lorenzoni et al. (2020) [100]	CNN	X-ray scans
	Marinakis, V. (2020) [98]	CNN	Multiple energy-related data (e.g.smart meters, sensors, etc.)
	Rafsanjani et al. (2020) [97]	iSEA	Load data (internet meters)
	Tong et al. (2020) [101]	FCN	X-ray images
	Wu et al. (2020) [103]	MLP	Crawled data from the United States Patent and Trademark Office
	Zeiler and Labeodan (2019) [99]	FFW-CRBM	Sensors (chair and motion)
	Zhong et al. (2020b) [104]	Bi-LSTM	Chinese construction regulations

7. Discussion

Digitization has catalyzed the process of acquiring data in the construction sector. Internet of Things (IoT) and sensor technologies are now able to connect multiple devices together, extract information from them, and share it across networks [108]. Reality capture technologies such as 3D laser scanning and photogrammetry are used to acquire spatial information and create point cloud data [108]. Building Information Modeling (BIM) can be used to visualize design and share information throughout the lifecycle of a building. Previously, data collection and analysis had been mainly conducted through traditional means such as visual inspection, site visits, and other manual methods [109]. These methods are time and labor intensive, sometimes inaccurate, and inconsistent across projects. This can lead to incorrect analysis and inaccurate prognostics. Hence, an automatic and systematic way would be beneficial to collect data for further processing and creating analytic platforms.

Recently, with the advent of deep learning, automated processes have been created to analyze data using different models. These models need large amounts of data to be captured for the learning part to occur. Table 8 shows the deep learning method used and data source for each paper. The data acquisition techniques in construction can be classified into two subsets: proprietary data and public data. Proprietary data is collected by the authors themselves and includes camera images [27,28,31,39–41,43–50,52–54,58,60,62–64,70,72,83,93,94,103], X-ray images [100,101] CCTV images/videos [86,87,89,90], wearable Holo Lens [91], sensor data [30,38,44,61,64,69,78,98,99], or a combination of these sources [50,56]. Public data is classified into data obtained from online datasets [29,37,45,51,52,66,68,76,82,84,92,102, 110],crawled data [103], or using a combination of both [26]. Several researches have used both proprietary and public data to: 1) train their model using one set and conduct the analysis using the other [42,95]; or 2) evaluate the model's performance on multiple datasets [47,79].

It can be observed that CNN (with its variations) is the most widely exploited DL method, which was used in 36 out of the 80 papers (or 45%). Additionally, the most commonly used data source has been capturing images using handheld smartphones or digital cameras while some researchers mounted the cameras on Unmanned Aerial Vehicles (UAVs) [27,40], Unmanned Ground Vehicles (UGVs) [56], or robots [52]. Although smart phones can be used for image detection, their use as embedded devices is not recommended due to their low speed performance and inability to work in harsh conditions [26].

Majority of the sewer defect detection researches used CCTV images/videos to capture defect data for processing. Table 8 also contains information on the online datasets used and the studies that have created new datasets for benchmarking [29,77,110]. This information aims to help researchers in identifying the state-of-the-art on deep learning techniques used in construction as well as the most recent datasets for conducting research.

8. Recommendations for future work

Based on the SLR conducted, six topics of research for deep learning applications in construction were identified: 1) equipment tracking, 2) crack detection, 3) construction work management, 4) sewer assessment, 5) 3D point cloud enhancement, and 6) miscellaneous. Several areas have been identified for future research such as construction site management, site safety monitoring, and productivity assessment of construction resources. These applications can be monitored real-time to assess conditions, identify variances from the planned conditions, and take immediate actions accordingly. Additionally, this can be automated to reduce the time and effort needed from detection to decision-making. Preinstalled sensors and Radio Frequency Identification (RFID) tags can be used for construction resource management onsite. For site safety monitoring, real-time monitoring of construction work and workers' behaviors can lead to the detection of unsafe actions and immediate corrective actions. It can also aid in identifying worker safety level/ practice before and after training to evaluate the effectiveness of the training. Productivity assessment of construction resources can be conducted to determine the working states and daily output.

In addition to the use of deep learning for the detection of construction equipment and workers, it can be advanced for the detection of construction operations. This data can then be analyzed to determine the best sequence of work, shortest possible activity duration, optimum crew formation, and safety plans to reduce hazards. Deep learning architecture combined with drone images/videos can be used to extract project progress, compare it to planned progress from time schedules, and can even be integrated with Building Information Modeling (BIM) data to create one central repository of project data. This can also enable the evaluation of site work in a systematic and automated manner. Therefore, deep learning can reduce data processing time and cost as it can automate and reduce the need for manual labor work.

Deep learning can also enable real-time proximity analysis (for workers and equipment) and congestion/density analysis of sites [67]. It can be used for automatic triggering of video-capturing based on prespecified criteria to address security issues onsite [26]. Future researches can also focus on obstacle identification in sites to suggest an optimum site layout or to control autonomous vehicles/equipment onsite (while training the model for obstacle avoidance) [67]. Semantic data extraction can be performed on contracts and other project documents for quick extraction and processing.

Finally, integrating deep learning with other recent technologies can also be useful. Utilizing big data for the creation of large datasets in different areas would facilitate the training of models. Different models can also be compared for accuracy of output using the same learning and testing datasets to obtain optimum algorithms.

9. Conclusions

Collecting accurate information and analyzing it is the key to adopting digitalization and information technology in construction projects. Deep learning is now advocated as the next wave in transforming data analysis and reporting in construction. Through the identified studies, it was found to be efficient at detecting and locating objects and defects, learning patterns from image or video dataset, and for project monitoring. This paper contributes to literature by providing a state-of-the-art systematic review on deep learning applications in construction. Systematic literature review was conducted to identify researches and report on the common topics addressed, methodologies conducted, limitations, and recommendations for future work. Based on SLR, 80 journal papers were identified and classified into six topics: equipment tracking, crack detection, construction work management, sewer assessment, 3D point cloud enhancement, and miscellaneous topics. This paper aims to aid researchers in identifying areas of improvement and points of future work to enhance construction site work and assessment of structures. It can also assist practitioners in the creation of applications for improving construction project monitoring and damage detection in structures. Additionally, it can enable the integration of full lifecycle assessment from design, construction, as-built model creation, and finally facility management.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1
Systematic literature review studies.

Authors	Year	Title	Journal
Alipour et al.	2019	Robust Pixel-Level Crack Detection Using Deep Fully Convolutional Neural Networks	Journal of Computing in Civil Engineering
Angah and Chen	2020	Tracking multiple construction workers through deep learning and the gradient based method with re-matching based on multi-object tracking accuracy	Automation in Construction
Arabi et al.	2020	A deep-learning-based computer vision solution for construction vehicle detection	Computer-Aided Civil and Infrastructure Engineering
Baek et al.	2019	Augmented reality system for facility management using image-based indoor localization	Automation in Construction
Braun et al.	2020	Improving progress monitoring by fusing point clouds, semantic data and computer vision	Automation in Construction
Cha et al.	2017	Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks	Computer-Aided Civil and Infrastructure Engineering
Cha et al.	2018	Autonomous Structural Visual Inspection Using Region-Based Deep Learning for Detecting Multiple Damage Types	Computer-Aided Civil and Infrastructure Engineering
Chen et al.	2020	Detecting semantic regions of construction site images by transfer learning and saliency computation	Automation in Construction
Chen et al.	2019	Deep Learning Approach to Point Cloud Scene Understanding for Automated Scan to 3D Reconstruction	Journal of Computing in Civil Engineering
Ding et al.	2018	A deep hybrid learning model to detect unsafe behavior: Integrating convolution neural networks and long short-term memory	Automation in Construction
Dung et al.	2019	A vision-based method for crack detection in gusset plate welded joints of steel bridges using deep convolutional neural networks	Automation in Construction
Fang et al.	2020	Automated text classification of near-misses from safety reports: An improved deep learning approach	Advanced Engineering Informatics
Fang et al.	2018a	Detecting non-hardhat-use by a deep learning method from far-field surveillance videos	Automation in Construction
Fang et al.	2018b	A deep learning-based method for detecting non-certified work on construction sites	Advanced Engineering Informatics
Gulgec et al.	2019	Convolutional Neural Network Approach for Robust Structural Damage Detection and Localization	Journal of Computing in Civil Engineering
Guo et al.	2020	Dense construction vehicle detection based on orientation-aware feature fusion convolutional neural network	Automation in Construction
Hassan et al.	2019	Underground sewer pipe condition assessment based on convolutional neural networks	Automation in Construction
Hou et al.	2020	Detecting Structural Components of Building Engineering Based on Deep-Learning Method	Journal of Construction Engineering and Management
Huyan et al.	2020	CrackU-net: A novel deep convolutional neural network for pixelwise pavement crack detection	Structural Control and Health Monitoring
Jang et al.	2020a	Automated crack evaluation of a high-rise bridge pier using a ring-type climbing robot	Computer-Aided Civil and Infrastructure Engineering
Jang et al.	2020b	Business Failure Prediction of Construction Contractors Using a LSTM RNN with Accounting	Journal of Management in Engineering
Jeong et al.	2020	Convolutional neural networks for pavement roughness assessment using calibration-free vehicle dynamics	Computer-Aided Civil and Infrastructure Engineering
Jiang and Bai	2020	Estimation of Construction Site Elevations Using Drone-Based Orthoimagery and Deep Learning	Journal of Construction Engineering and Management
Kalfarisi et al.	2020	Crack Detection and Segmentation Using Deep Learning with 3D Reality Mesh Model for Quantitative Assessment and Integrated Visualization	Journal of Computing in Civil Engineering
Kang et al.	2020	Hybrid pixel-level concrete crack segmentation and quantification across complex backgrounds using deep learning	Automation in Construction
Khumprom and Yodo	2019	A data-driven predictive prognostic model for lithium-ion batteries based on a deep learning algorithm	Energies
Kim and Cho	2020	Effective inertial sensor quantity and locations on a body for deep learning-based worker's motion recognition	Automation in Construction
Kim et al.	2018	Detecting Construction Equipment Using a Region-Based Fully Convolutional Network and Transfer Learning	Journal of Computing in Civil Engineering
Kim et al.	2020	Automation in Construction Towards database-free vision-based monitoring on construction sites: A deep active learning approach	Automation in Construction
Kumar et al.	2020	Deep Learning-Based Automated Detection of Sewer Defects in CCTV Videos	Journal of Computing in Civil Engineering
Lee et al.	2020	Estimation of crack width based on shape-sensitive kernels and semantic segmentation	Structural Control and Health Monitoring

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Table A1 (*continued*)

Authors	Year	Title	Journal
Li and Sun	2020	Detectability of Bridge-Structural Damage Based on Fiber-Optic Sensing through Deep-Convolutional Neural Networks	Journal of Bridge Engineering
Li et al.	2019	Sewer damage detection from imbalanced CCTV inspection data using deep convolutional neural networks with hierarchical classification	Automation in Construction
Liu et al.	2020	Deep Learning-Based Enhancement of Motion Blurred UAV Concrete Crack Images	Journal of Computing in Civil Engineering
Lorenzoni et al.	2020	Combined mechanical and 3D-microstructural analysis of strain-hardening cement-based composites (SHCC) by in-situ X-ray microtomography	Cement and Concrete Research
Luo et al.	2020	Full body pose estimation of construction equipment using computer vision and deep learning techniques	Automation in Construction
Ma et al.	2020	Semantic segmentation of point clouds of building interiors with deep learning: Augmenting training datasets with synthetic BIM-based point clouds	Automation in Construction
Marinakis	2020	Big data for energy management and energy-efficient buildings	Energies
Marzouk and Zaher	2020	Artificial intelligence exploitation in facility management using deep learning	Construction Innovation
McLaughlin et al.	2020	Automated Defect Quantification in Concrete Bridges Using Robotics and Deep Learning	Journal of Computing in Civil Engineering
Mei and Gül	2020	Multi-level feature fusion in densely connected deep-learning architecture and depth-first search for crack segmentation on images collected with smartphones	Structural Health Monitoring
Mei and Gül	2020	A cost effective solution for pavement crack inspection using cameras and deep neural networks	Construction and Building Materials
Mei et al.	2020	Densely connected deep neural network considering connectivity of pixels for automatic crack detection	Automation in Construction
Moradi et al.	2020	Automated Anomaly Detection and Localization in Sewer Inspection Videos Using Proportional Data Modeling and Deep Learning-Based Text Recognition	Journal of Infrastructure Systems
Nath et al.	2020	Deep learning for site safety: Real-time detection of personal protective equipment	Automation in Construction
Nath et al.	2019	Single- And multi-label classification of construction objects using deep transfer learning methods	Automation in Construction
Nhat-Duc et al.	2018	Automatic recognition of asphalt pavement cracks using metaheuristic optimized edge detection algorithms and convolution neural network	Automation in Construction
Pan and Zhang	2020	BIM log mining: Learning and predicting design commands	Automation in Construction
Park et al.	2019	Patch-Based Crack Detection in Black Box Images Using Convolutional Neural Networks	Journal of Computing in Civil Engineering
Park et al.	2020	Concrete crack detection and quantification using deep learning and structured light	Construction and Building Materials
Rafsanjani et al.	2020	iSEA: IoT-based smartphone energy assistant for prompting energy-aware behaviors in commercial buildings	Applied Energy
Rashid and Louis	2019	Times-series data augmentation and deep learning for construction equipment activity recognition	Advanced Engineering Informatics
Ren et al.	2020	Image-based concrete crack detection in tunnels using deep fully convolutional networks	Construction and Building Materials
Roberts and Golparvar-Fard	2019	End-to-end vision-based detection tracking and activity analysis of earthmoving equipment filmed at ground level	Automation in Construction
Shen et al.	2020	Detecting safety helmet wearing on construction sites with bounding-box regression and deep transfer learning	Computer-Aided Civil and Infrastructure Engineering
Son et al.	2019	Detection of construction workers under varying poses and changing background in image sequences via very deep residual networks	Automation in Construction
Song et al.	2020	Deep learning method for detection of structural microcracks by brillouin scattering based distributed optical fiber sensors	Smart Materials and Structures
Tan and Chen	2020	Multi-objective energy management of multiple microgrids under random electric vehicle charging	Energy
Tong et al.	2019	A new method for CF morphology distribution evaluation and CFRC property prediction using cascade deep learning	Construction and Building Materials
Wang et al.	2020	Hierarchical model predictive control via deep learning vehicle speed predictions for oxygen stoichiometry regulation of fuel cells	Applied Energy
Wang et al.	2020	A vision-based active learning convolutional neural network model for concrete surface crack detection	Advances in Structural Engineering
Wang et al.	2019	Novel System for Rapid Investigation and Damage Detection in Cultural Heritage Conservation Based on Deep Learning	Journal of Infrastructure Systems
Wei et al.	2020	Vision-based detection and prediction of equipment heat gains in commercial office buildings using a deep learning method	Applied Energy
Won et al.	2020	UAV-RFID Integration for Construction Resource Localization	KSCE Journal of Civil Engineering
Wu et al.	2019	Automatic detection of hardhats worn by construction personnel: A deep learning approach and benchmark dataset	Automation in Construction
Wu et al.	2020	Screening patents of ICT in construction using deep learning and NLP techniques	Engineering, Construction and Architectural Management
Xie et al.	2019	Automatic Detection and Classification of Sewer Defects via Hierarchical Deep Learning	IEEE Transactions on Automation Science and Engineering
Yang et al.	2020	Deep learning-based classification of work-related physical load levels in construction	Advanced Engineering Informatics
Yang et al.	2018	Automatic Pixel-Level Crack Detection and Measurement Using Fully Convolutional Network	Computer-Aided Civil and Infrastructure Engineering
Ye et al.	2019	Structural crack detection using deep learning–based fully convolutional networks	Advances in Structural Engineering
Yu et al.	2019	Joint-level vision-based ergonomic assessment tool for construction workers	Journal of Construction Engineering and Management
Zeiler and Labeodan	2019	Human-in-the-loop energy flexibility integration on a neighborhood level: Small and Big Data management	Building Services Engineering Research and Technology
Zhang et al.	2018a	Deep Learning-Based Fully Automated Pavement Crack Detection on 3D Asphalt Surfaces with an Improved CrackNet	Journal of Computing in Civil Engineering
Zhang et al.	2018b	Unified Approach to Pavement Crack and Sealed Crack Detection Using Preclassification Based on Transfer Learning	Journal of Computing in Civil Engineering
Zhang et al.	2019	Concrete crack detection using context-aware deep semantic segmentation network	Computer-Aided Civil and Infrastructure Engineering

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Table A1 (*continued*)

Authors	Year	Title	Journal
Zhang et al.	2020	Self-Supervised Structure Learning for Crack Detection Based on Cycle-Consistent Generative Adversarial Networks	Journal of Computing in Civil Engineering
Zhong et al.	2020	Deep learning and network analysis: Classifying and visualizing accident narratives in construction	Automation in Construction
Zhong et al.	2020	Deep learning-based extraction of construction procedural constraints from construction regulations	Advanced Engineering Informatics
Zhu and Song	2020	Weakly supervised network based intelligent identification of cracks in asphalt concrete bridge deck	Alexandria Engineering Journal
Zhu et al.	2019	Research on the energy-saving strategy of path planning for electric vehicles considering traffic information	Energies

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