# Applications of ‘deep learning’ in construction site management: Scientometric, thematic and critical analysis

## Abstract

**Purpose:** The digital construction transformation requires utilizing emerging digital technology such as deep learning to automate implementing tasks. Therefore, this article evaluates the current state of utilizing deep learning in the construction management tasks to enable researchers to determine the capabilities of current solutions, as well as, finding research gaps to carry out more research to bridge revealed knowledge and practice gaps.

**Design and Methodology:** The scientometric analysis is conducted for 181 articles in order to assess the density of publications in different topics of deep learning-based construction management applications. After that, a thematic and gap analysis are conducted to analyze contributions and limitations of key published articles in each area of application.

**Findings:** The scientometric analysis indicates that there is main four applications of deep learning in construction management, namely, automating progress monitoring, automating safety warning for workers, managing construction equipment, Integrating IoT with deep learning to automatically collect data from the site. The thematic and gap analysis refer to many successful cases of utilizing deep learning in automating site management tasks, however, more validations are recommended to test developed solutions, as well as additional research is required to consider practitioners and workers perspectives to implement mentioned applications in their daily tasks.

**Practical Implications:** This article enables researchers to directly find the research gaps in the developed solutions and develop more workable applications to bridge revealed gaps.

Accordingly, this will be reflected on speeding the digital construction transformation, which is a strategy over the world.

**Originality/value:** This article is the first of its kind to adopt a structured technique to assess deep learning-based construction site management applications to enable researcher/practitioners to either adopting these applications in their projects or conducting further research to extend developed solutions and bridging revealed knowledge gaps.

**Keywords:**

Deep learning, Internet of Things (IoT), automated health and safety warning, Progress monitoring, object detection

## 1. Introduction

The transformation to digital construction requires employing different emerging technologies in order to automate most of construction tasks, one of these technologies is the Artificial Intelligence (AI). The adoption of AI can bring several benefits to the construction industry (Blanco *et al.*, 2018; Cao *et al.*, 2021). During the last few years, AI has been improved and different subsets were developed to provide wider solutions, one of these subsets is deep learning, which is defined as a set of computational models that includes multiple processing layers to learn representations of different types of data with different levels of abstraction (LeCun *et al.*, 2015). During the last a few years, research in adopting deep learning in the construction industry has commenced, the density of these research was focused on using deep learning to detect distresses in buildings and pavements (Hou *et al.*, 2020; Qin *et al.*, 2021). However, deep learning was also considered to develop solutions to automate construction site management tasks including equipment detection, sites health and safety, labor management and progress evaluation.

The integration of different emerging technologies is highly recommended in order to develop workable solutions for complex projects as a part of digital construction transformation (Elghaish *et al.*, 2021). The coupling of deep learning and other emerging digital technologies started from 2015 in order to automate objects recognitions such as workers and equipment through using Internet of Things (IoT) sensors.

There are a few attempts to review deep learning applications for construction industry, however, most of studies either focused on distresses detection or general review. For example, Elghaish et al. (2021) studied the recent published articles regarding employing deep learning to detedct distresses in pavements and buildings, Akinosho et al. (2020) presented a study to summarize different applications of deep learning for construction industry, however, the construction site management applications were not critically highlighted. As such, there is a need for sch study to critically analyze the existing and future applications of deep learning to enhance the construction site management practices.

The scientometric analysis of 181 articles was conducted and major revealed construction management applications-based deep learning are site workers health and safety; managing machines in risky projects such as excavators; risk predictions; progress monitoring. Meanwhile, there are some applications that have low density levels in the analysis such as decision making, designing protective clothes, smart cities. All published articles for each theme were analysed to highlight the research knowledge gap.

In this paper, three types of analysis were considered, namely, scientometric analysis in order to analyze relationships between published articles (topics) in order to highlight the most attained areas of applications, then thematic analysis to categories applications (published articles) into specific themes, finally, gap analysis through analyse key published articles in each area according to their focus of study, methodology, findings and limitation(s).

With all above in the mind, this article provides a clear view of the utilization of deep learning in integration with emerging digital technologies to manage construction management tasks, particularly, site management operations. This will enable future researchers to find knowledge gap in the key published articles, as well as, the maturity level of existing solutions, subsequently, working to either bridge mentioned gaps or enhancing the maturity level of existing applications.

The paper is structured as section 2 to present the research methodology and logic, followed by section 3 that includes the scientometric analysis of collected data (181 articles). The first theme, which is object and information detection is presented in section 4. The second theme, which is health and safety using deep learning is presented in section 5. The third theme is the deep learning and IoT is presented in section 6 including smart cities and operations assessment. Section 7 includes discussion on findings and finally the conclusion is presented in section 8.

## 2. Methodology and logic

Wrigh (2020) identified the gap analysis of the literature review is to find missing pieces in any study, literature review or program analysis. In this study, Scopus data base was used to search for relevant articles. Given this study discusses the deep learning applications in construction management in integration with emerging digital technologies such as IoT. Therefore, specific keywords were used to retrieve relevant articles such as *( deep AND learning AND in AND construction ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) ) AND ( LIMIT-TO ( SUBJAREA , "ENGI" ) ) AND ( LIMIT-TO ( EXACTKEYWORD , "Construction Equipment" ) OR LIMIT-TO ( EXACTKEYWORD , "Object Recognition" ) OR LIMIT-TO ( EXACTKEYWORD , "Construction Sites" ) OR LIMIT-TO ( EXACTKEYWORD , "Monitoring" ) OR LIMIT-TO ( EXACTKEYWORD , "Project Management" ) OR LIMIT-TO ( EXACTKEYWORD , "Construction Workers" ) OR LIMIT-TO ( EXACTKEYWORD ,* *"Quality Control" ) OR LIMIT-TO ( EXACTKEYWORD , "Data Acquisition" ) OR LIMIT-TO ( EXACTKEYWORD , "Automation" ) OR LIMIT-TO ( EXACTKEYWORD , "Excavation" ) OR LIMIT-TO ( EXACTKEYWORD , "Big Data" ) OR LIMIT-TO ( EXACTKEYWORD , "Construction Projects" ) OR LIMIT-TO ( EXACTKEYWORD , "Construction Safety" ) OR LIMIT-TO ( EXACTKEYWORD , "Architectural Design" ) OR LIMIT-TO ( EXACTKEYWORD , "Visualization" ) OR LIMIT-TO ( EXACTKEYWORD , "Decision Making" ) OR LIMIT-TO ( EXACTKEYWORD , "Risk Assessment" ).* After that, results were refined to only include articles that published between 2015 and 2021 and 'Q1 and Q2' journals.

Mooghali *et al.* (2012) state that the scientometric analysis is an efficient way to measure the progress of scientific production, as well as, defining the overlapping interests with bibliometrics and informatics. Therefore, the outcome of the mentioned search was 181 journal articles, a scientometric analysis was conducted to check the relationships between these wide ranges of application as well as the density of each application. Subsequently, thematic analysis was used to categories deep learning and emerging digital technologies applications for construction management and defining the capabilities and weaknesses that needs to be bridged by conducting more research, Figure 1 shows the process of conducting this scientometric, thematic and gap analysis research. Given, Scan and skim techniques are recommended to get presented themes in a research article, as well as, sorting relevant articles (Machi & McEvoy, 2016).therefore, the results were analysed and classified into main themes and sub-themes to be critically analysed to highlight the aim of study, methods and limitation.

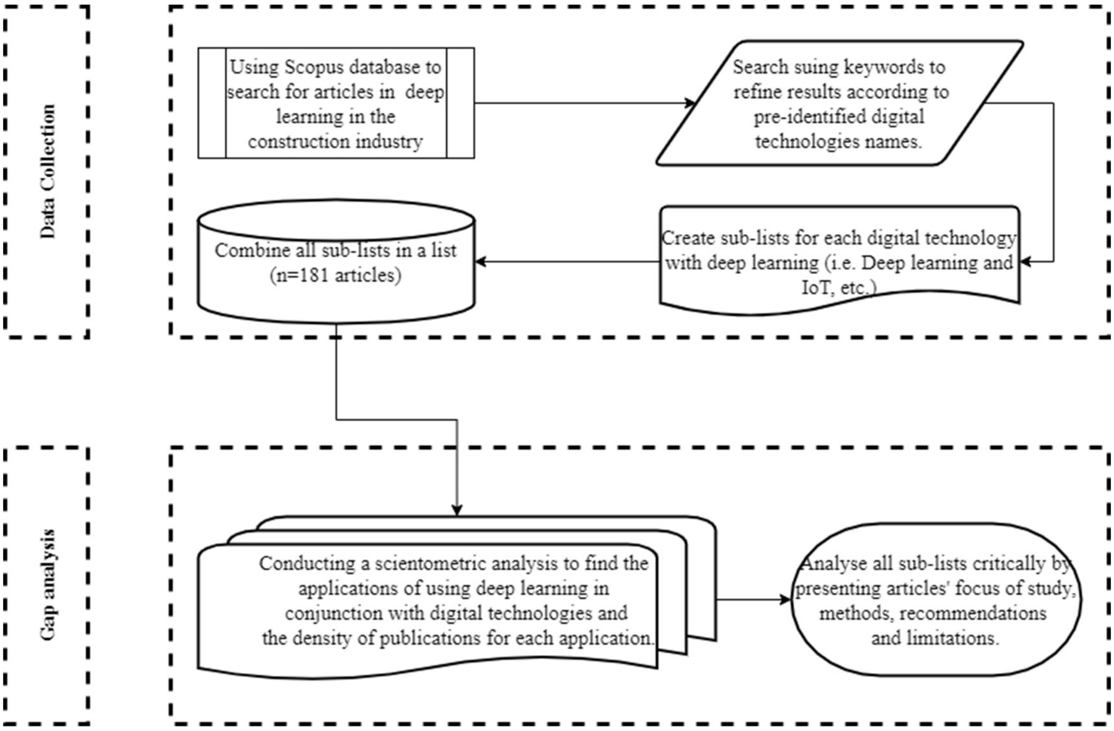


**Figure 1. Research design and logic**

## 3. Scientometric analysis:

Figure 2 shows the progress of deep learning applications in conjunction with emerging digital technologies in the construction industry. It can be seen that the utilization of deep learning-based emerging technologies (i.e. IoT, BIM, RFID, etc.) actually started from 2015 and stared to be steadily increasing from 2018. This is an indication of the significant attention that deep learning with emerging technologies received over the last five years.

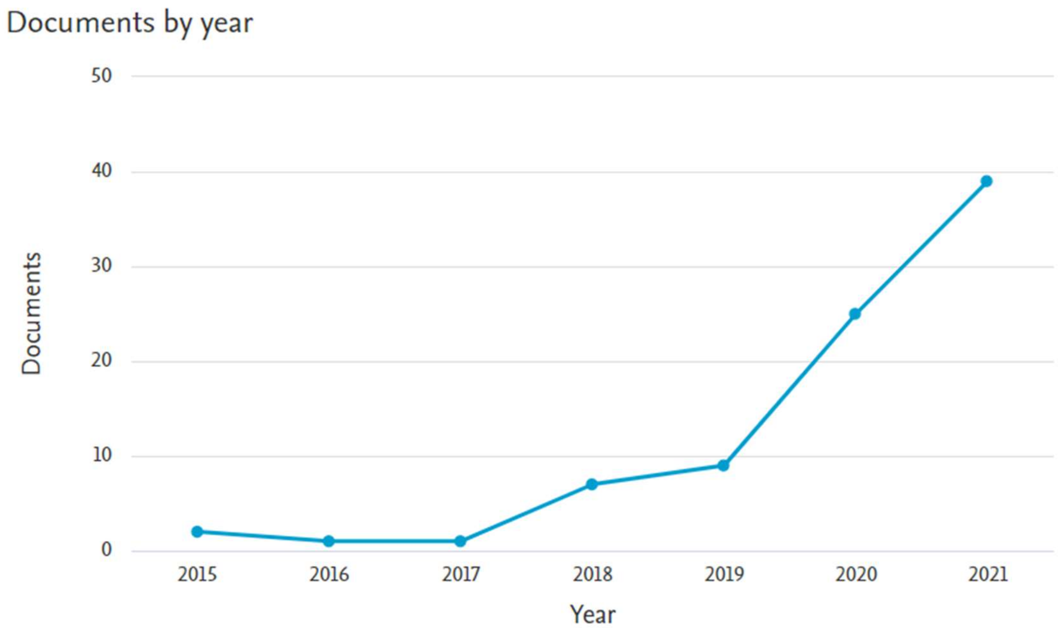

Figure 2. The progress of deep learning with emerging technologies publications per year

The majority of selected publications were published in top-ranked journals as shown in figure 3, for example, (n=36) articles were published in automation in construction journal, (n=8) articles were published in journal of computing in civil engineering and another eight articles in Journal of construction engineering and management.

| Source ↓ | Documents |
|---|---|
| Automation In Construction | 36 |
| Journal Of Computing In Civil Engineering | 8 |
| Journal Of Construction Engineering And Management | 8 |
| Computer Aided Civil And Infrastructure Engineering | 3 |
| Engineering Construction And Architectural Management | 3 |
| Sensors Switzerland | 3 |

Figure 3. An example of reliable sources that used to collect data

Figure 4 shows the network analysis of (m=181) papers, it can be seen that from figures 4 that there are specific usages of integrating deep learning and emerging digital technologies, namely, equipment management, smart warning of health and safety issues, managing labor productivity in site, monitoring the project progress and detecting excavators under risky excavation zones.  Figure 5 presents the density of mentioned applications of analyzing (n=181) papers, it is obvious that IoT technology is highly employed in integration with deep learning to provide a wide range of workable solutions.

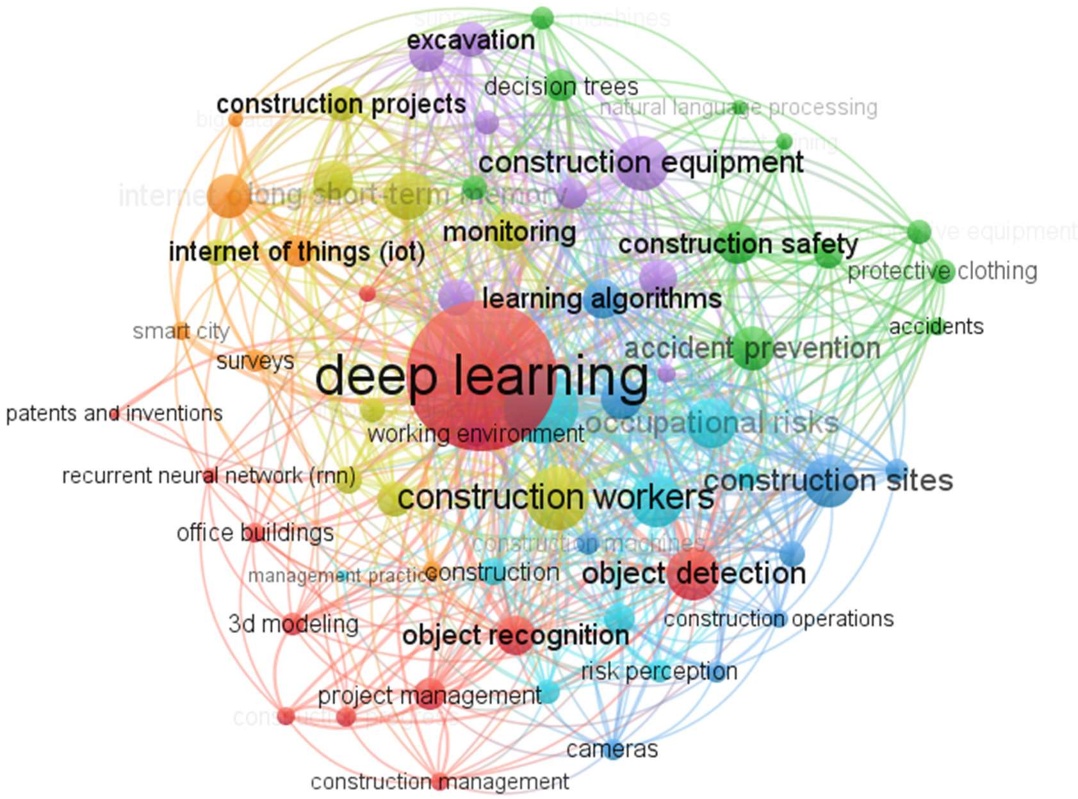


Figure 4. Network analysis of deep learning-based emerging technologies applications

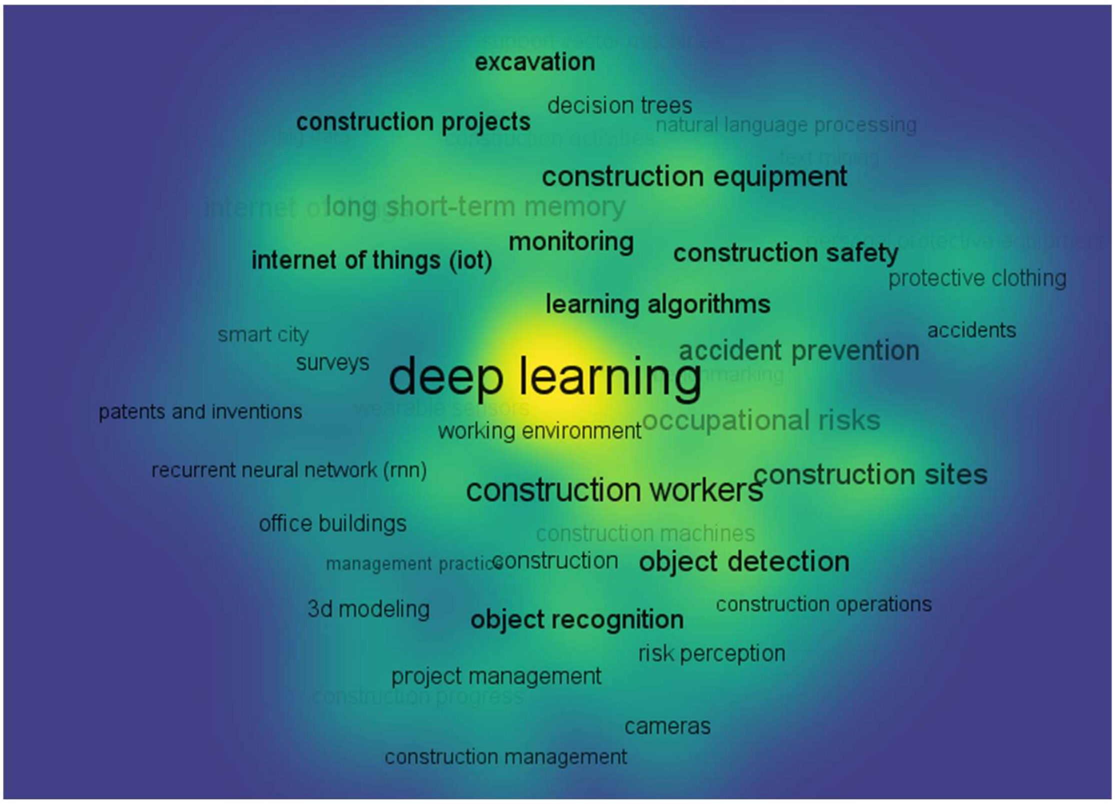


Figure 5. Density analysis of deep learning-based emerging technologies applications

## 4. Objects and Information detection on site

### 4.1. Field detection

Table 1 includes the major research of object and information detection-based deep learning. Articles were classified into two main applications, namely field inspection and progress monitoring of construction works. It can be seen from table 1 that most of articles that related to objects detection focus on employing deep learning to detect the places of structural rebars, inspecting accuracies of placing precast elements, particularly, large elements for bridges and detecting large rock fragments for tunnels. Regarding information detection, majority of publications are related to collect workers and equipment information during executing daily tasks.

Table 1. articles for object and information detections using deep learning

| Author/ Year | Focus of study | Methods | Limitation |
|---|---|---|---|
| **Field Inspection** | | | |
| (Qin *et al.*, 2021) | To develop an automatic recognition method to identify steel ribs, voids, and initial linings for tunnel lining inspection. | Based on the Mask R-CNN | The training and testing GPR images were labelled manually based on personal experience instead of ground truth. Thus, the performance of the network might be subject to manual judgment |
| (Kruachottikul *et al.*, 2021) | To develop a visual defect-inspection system for reinforced concrete bridge substructure to support field inspectors for developing faster defect detection and inspection processes with high accuracy on a large scale. | By using a modified ResNet-50 CNN model and ANN. | In this study, the number of bridge image datasets is limited. In addition, severity prediction in this research is still limited to a binary output. |

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| (Zhou *et al.*, 2021) | To solve the problem of the automatic segmentation of rock chips in complex muck images using deep learning techniques to determine the size and shape of rock chips. | Based on a deep learning-approach composed of a dual UNet with multi-scale inputs and side-output (MSD-UNet) and a post-processing algorithm | The over-segmentation problem appeared during the process. |
| (Yang *et al.*, 2021) | To detect large rock fragments produced by tunnel boring machine using convolutional neural networks | Based on a convolutional neural network (CNN), AlexNet. | The lack of open-source datasets of rock fragments |
| **On-site objects and information detection** | | | |
| (Wang *et al.*, 2021) | To achieve a synthetic visual understanding of objects on construction sites | Based on a DeepLabV3 + network, data augmentation and transfer learning | There are concerns of how much mIoU is sufficient for a sound system. |
| (Lu *et al.*, 2021) | To estimate fill factor and localize the bucket for both manually controlled and autonomous construction vehicles during on-site operation. | By incorporating ResNet into Faster R-CNN for fill factor estimation and bucket detection | The study focused on one construction vehicle |
| (Hou *et al.*, 2020) | To detect objects inside structures | Based on the Deeply Supervised Object Detector (DSOD) | Limited number of datasets |
| (Sharma and Sen, 2020) | To detect joint damage to locate weakened joints in semi-rigid frames. | Based on a CNN architecture | The proposed method observed to raise significantly low false-positive/negative alarms. |
| (Fang *et al.*, 2020a) | To enhance the monocular vision technique for the localization of construction-related entities to help facilitate safety early warning, activity recognition, and productivity analysis. | Based on a Mask-RCNN model. | The biggest limitation is if occlusions block key parts of an entity and the proposed method cannot know the location of the entity in an image. |
| (Guo *et al.*, 2020) | To detect precisely the dense of multiple construction vehicles | Based on a deep learning and CNN based end-to-end approach using images from UAVs. | The complexity of the deep learning model, which is hardly deployed to UAVs to |

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| | | | realize real-time online detection. |
| (Won *et al.*, 2020) | To localize construction resources for understanding the context of a construction site | UAV-based platform that integrates an RFID receiver and processes collected signals based on a deep learning, LSTM model. | There could still be high-rise impediments, such as tower cranes, electric poles, and wires, that could have adverse effects on the operation of the platform. |
| (Wang *et al.*, 2019) | To automatically detect damage for historic brick masonry structures | Based on a deep CNN, which was used to identify and locate two categories of damage to brick masonry: efflorescence and spalling. | the detection precision needs to be improved by expanding the database with more damage types, a wider range of distances and angles between the damage and the camera, and more types of structural samples. |
| (Zheng *et al.*, 2020) | To automatically detect progress monitoring and control in real-life modular construction | By combining transfer-learning (A Mask R-CNN-based model) and virtual-prototyping techniques. | The study only focused on module detection from images or videos, whereas the tracking of a module from one camera to another was not considered |

### 4.2.Automated progress monitoring

Table 2 presents key published articles of automating progress monitoring based on analyzing data-based deep learning. The applications focus on (1) comparing the actual performed works on the site with the expected (planned) design models, (2) analyzing detected motions of equipment and estimate productivity.

Table 2. Automated progress monitoring major articles

| Author/ Year | Focus of study | Methods | Limitation |
|---|---|---|---|
| (Braun *et al.*, 2020) | To supports progress monitoring by verifying element categories compared | By using additional information provided through the Structure-from- | A manual step is required to find the exact orientation and scaling |

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|---|---|---|---|
| | to the expected data from the digital model. | Motion process (images and camera positions), as well as the as-de-signed building information model (semantic data, geometric re-presentation of elements, and position and dependencies of elements). | |
| (Kim *et al.*, 2020) | To develop a vision-based monitoring tool for construction sites. | Based on a deep active learning approach | |
| (Rashid and Louis, 2019) | To develop an automated, real-time, and reliable activity recognition framework for construction equipment to monitor and assess productivity, safety, and environmental impact on construction site | Based on an LSTM activity recognition framework using multiple IMUs attached to different articulated elements of the equipment | Manual labelling of the data |
| (Luo *et al.*, 2020) | To develop a framework to facilitate the real-time safety monitoring on construction sites. | Using computer vision and deep learning techniques. | The location of construction equipment may vary during construction activities, which suggests that the location information of the equipment should also be considered when estimating the full body poses. |

### 4.3. Analyzing projects historical records

Table 3 includes research articles for employing deep learning to analyze historical records from previous site reports to classify and predict issues/accidents, accordingly, avoiding causes of these issues for new projects.

Table 3. analyzing historical site reports-based deep learning

| Author/ Year | Focus of study | Methods | Limitation |
|---|---|---|---|
| (Zhong *et al.*, 2020) | To enable accident narratives to be automatically classified and visualized and therefore help improve the effectiveness of decision-making. | By integrating NLP with a CNN deep learning and then using visual network analysis. | NA |
| (Nath *et al.*, 2020) | To develop and evaluate three DL-based approaches to verify PPE compliance of workers, i.e., if a worker is wearing hard hat, vest, or both, | Built on You-Only-Look-Once (YOLO) architecture | One of the main limitations of vision-based detection methods is that they are susceptible to occlusion, poor illumination, and blurriness. |
| (Fang *et al.*, 2020b) | To classify near-miss data contained within safety reports automatically to enable site engineers and managers to understand better the nuances of hazards that can prevail on construction sites | Based on deep learning approach using Bidirectional Transformers for Language Understanding (BERT) | The developed model was unable to 100% accurately classify near-miss reports due to sheer number of categories(L=170), which contained too few events. |

Limitations in these applications including limited training dataset and the need for the manual labeling of data. Qin et al. (2021) developed an automatic recognition of tunnel lining elements from GPR images using deep convolutional networks with data augmentation to facilitate tunnel lining inspection. However, in this study the training and testing GPR images were labeled manually based on personal experience instead of ground truth. Thus, the performance of the network might be subject to manual judgment. To facilitate a real-time muck analysis for assisting tunnel boring machines (TBMs), Zhou et al. (2021) developed a deep learning-based approach to obtain size distribution and shape estimation of rock chips. However, the annotation accuracy of muck images needs to be further improved. Since rock chips were labeled by drawing polygons on the image, their complex contours cannot be accurately annotated, resulting in a degradation of the quality of ground truths. In other incidents, the classification may be a multi-label text classification task. To avoid having an accident with multiple categories, Zhong, et al (2020) suggested to assign a label according to the principle of identifying the primary and first occurrence of the uncontrolled or unintended action, if more than one event can occur during an accident identification. However, an interesting study conducted by Kim et al. (2020) developed a method for construction monitoring which saves time and costs needed for human labeling, thereby enhancing the practical acceptability of vision systems on construction sites.

One of the key limitations is if occlusions block key parts of an entity and the proposed method cannot know the location of the entity in an image. In Fang et al. (2020) study, one of the key drawbacks in their method is the occlusions on key parts of an entity which influenced results. Similar drawback of other proposed method was reported by Luo et al. (2020) when occluded key points of equipment led to erroneous estimation results. The complexity of the background affects the object detection. Guo et al. (2020) noticed in their study that the more the complexity of the background increases, the difficulty of the object detection increases sequentially. Nath et al. (2020) stated that one of the main limitations of vision-based detection methods is that they are susceptible to occlusion, poor illumination, and blurriness.

Two common limitations are related to: the CNN model being a black-box, the lack of transparency with multi-layer nonlinear structure is still a common problem. Yang et al. (2021) reported this problem in their study when they used CNN model to detect large rock fragments, and the low false-positive/negative alarms is another common limitation which has been identified in several studies. Sharma and Sen (2020) highlighted that their proposed method observed to raise significantly low false-positive/negative alarms.

The limited data significantly hinders the application of deep learning in training the intelligent models for automated construction. Several studies highlighted the issue of the limited number of image datasets. For example, Kruachottikul et al. (2021) reported the challenge of the limited number of image datasets in developing their deep learning-based visual defect-inspection system for reinforced concrete bridge substructures. Hou et al. (2020) study failed to make a comparison of multiple sets of test experiments to determine the proposed system effectiveness and generalizability due to limited number of datasets. Wang et al. (2019) recommend to expanding the database to overcome this limitation and enhance the accuracy of their proposed system. To overcome the challenge of limited real-life image datasets, Zheng et al (2020) used a Mask R-CNN-based model to automatically detect modules during module installation. Their study method proved to be effective for the implementation of deep learning methods in the construction industry when real-life data were insufficient.

## 5. Health and Safety using Deep Learning

Although safety has been a concern for the construction industry for decades, the industry around the globe has unsatisfactory occupational health and safety records. This is because the construction sites are one of the most perilous environments where many potential hazards may occur. To improve the safety performance of the industry, many studies have proposed the use of deep learning to enhance the construction site safety. Reviewing the literature has revealed two main related themes namely; health and safety text analysis and health and safety monitoring using picture, videos and sensors.

### 5.1.Safety text analysis

Nowadays, there is an increase availability of digitally recorded safety reports in the construction industry. This has impacted the need to develop methods to exploit these data to improve our understanding and actions towards construction safety and risks. Jallan & Ashuri (2020) has created a state-of-the-art learning algorithm named FastText to identify risk and safety patterns and classify the text into appropriate risk types. Another study has focused on text analysis to improve safety through effectively managing the construction constraints by developing a bidirectional long short-term memory and conditional random field (Bi-LSTM-CRF) model and knowledge representation learning (KRL) model (C. Wu et al., 2021). Other studies have used state-of-the-art deep learning architectures for Natural Language Processing (NLP), Convolutional Neural Networks (CNN) and Hierarchical Attention Networks (HAN) to automatically classify accidents narratives and learn injury precursors from construction accident reports (Baker, Hallowell, & Tixier, 2020; Zhong, Pan, Love, Ding, & Fang, 2020).

### 5.2.Safety Monitoring

As stated earlier, construction sites are one of the most perilous environments where many potential hazards may occur. This has raised the bar to the significant need of monitoring and detecting construction activities, construction workers and construction machines. Many studies have focused on using deep learning applications to detect and monitor the construction site, workers and equipment.

#### 5.2.1. Construction site safety

In the field of Architecture, Engineering, Construction, and Facility Management (AEC/FM), the site surveying is critical for activities such as construction progress monitoring. Table 4 shows many studies on using deep learning methods to improve safety in the construction site. Angah & Chen (2020) applies an orginal deep learning architecture (Context Encoders model) to remove moving obstacles that often occlude the sight of view through removing redundant objects in images and inpaint the background context. More clear construction images will positively impact the construction activities scenes. In order to automate the manifesting construction activity scenes by image captioning, general model architecture of image captioning is instituted by combining an encoder-decoder framework with deep neural networks (Liu et al., 2020). Another study used a vision-based method to automatically generate video highlights from construction videos to support safety control (Xiao, Yin, & Kang, 2021). Analysing the captioned consecutive image and data from construction sites using deep learning approaches was studied by Lin, Chen, & Hsieh (2021). The data analytics includes four steps: object detection, object tracking, action recognition, and operational analysis, in which Faster R-CNN, SORT approach, a hybrid model integrating CNN and Long Short Term Memory (LSTM) and line chart were utilized (Lin et al., 2021). Construction site data analytic will enhance the recognition of unsafe conditions, Kyungki Kim, Kim, & Shchur (2021), have used deep learning, game engine-based ITCP and unmanned aircraft systems (UAS) as safety monitoring systems to effectively identify unsafe conditions.

The inspection of safety behaviours and conditions in the construction site is heavily relying on human efforts which are limited onsite. This has raised the need to have efficient automated approaches to identify and detect the unsafe conditions. Kolar, Chen, & Luo (2018) focused on developing a safety guardrail detection model using convolutional neural network (CNN). Shen, Yan, Li, & Xiong (2021) have developed automated object identification for two-dimensional (2D) objects in the construction site to better the site safety. He used an enhanced feature pyramid network, R-CNN, automatic camera parameter estimation, vision-based method, and space filter.

Table 4: Construction Site Safety

| Author/ Year | Focus of the study | Methods | Limitation |
|---|---|---|---|
| (Angah & Chen, 2020) | This research applies Context Encoders to remove redundant objects in images and inpaints the background context. | Based on deep learning architecture, U-Net | Images have been taken in specific time of the day to avoid other objects such as pieces of equipment or materials. Therefore, the model needs to be trained with a more complete set of data |

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|---|---|---|---|
| (Liu et al., 2020) | This study proposed an automated method for manifesting construction activity scenes by image captioning – an approach rooted in computer vision and natural language generation. | A general model architecture of image captioning is instituted by combining an encoder-decoder framework with deep neural networks | It was not been implemented on a real case studies |
| (Xiao, Yin, et al., 2021) | Obtaining and storing useful video footage systematically and concisely to optimise the project management tasks such as productivity analysis and safety control. | Proposing a vision-based method to automatically generate video highlights from construction videos to support project management tasks such as productivity analysis and safety control. | The proposed approach only offers potential benefits to construction management in terms of significantly reducing video storage space and efficiently indexing construction video footage. |
| (Lin et al., 2021) | To propose the analysis of consecutive image sequences for automatic identification of irregular operations and their visualization. | Faster R-CNN, the Simple Online and Realtime Tracking (SORT) approach, a hybrid model integrating CNN and Long Short-Term Memory (LSTM)and line chart are utilized. | The proposed image analytics framework was validated only in earthmoving operations. Moreover, scenarios of multiple excavators and other activities have not been tested. |
| (Kyungki Kim, Kim, & Shchur, 2021) | To effectively identify unsafe conditions due to a lack of integration between internal traffic control plans (ITCP) that can guide safe activities in construction worksites and safety monitoring systems. | Proposing the novel concept of a safety monitoring system by leveraging unmanned aircraft systems (UAS), game engine-based ITCP, and deep learning. | The low number of aerial images to train deep learning model. |
| (Kolar et al., 2018) | This research developed a safety guardrail detection model. | Based on convolutional neural network (CNN) | This research used a dataset with only one type of safety guardrail only. Also, occlusion was not addressed in this research, assuming the guardrail will always be visible. |
| (Shen, Yan, et al., 2021) | To use 2D object detection, instance segmentation and camera vision to compute pseudo-light detection and ranging (LiDAR) point cloud for 3D object identification. | An enhanced feature pyramid network, R-CNN , automatic camera parameter estimation, vision-based method, and space filter. | The AIM dataset and our new dataset rarely contain some challenges like fog, dust, and rainy weather. Moreover, dataset only includes one type of heavy equipment with the Mask. Finally, the depth estimation range is limited. |

### 5.2.2. Construction Workers detections

Detecting the behaviour and location of construction workers have been recognized by many studies as a means of providing beneficial information for safety management. Different deep learning methods were employed to improve the construction workers detections (see Table 5). Yu, Umer, Yang, & Antwi-Afari (2021) have reviewed and assess different deep learning method on collect posture-related data for construction workers. Son, Choi, Seong, & Kim (2019) have used (ResNet-152) and bounding box regression and labelling from the original image via (R-CNN) to detect construction workers in a more accurate and rapid way. Roberts, Torres Calderon, Tang, & Golparvar-Fard (2020) has also used novel deep leaning method to tracks two-dimensional (2D) worker pose using red-green-blue (RGB) video footage of a construction worker operation. Son & Kim (2021) has moved a step forward by developing integrating construction real-time worker detection and tracking scheme using (CMOS) image sensors and YOLO and the Siamese network, which are based on CNN. Motion sensors were investigated on their effectiveness in terms of numbers and locations and a construction worker's motion recognition model was developed using Long Short-Term Memory (LSTM) network (Kinam Kim & Cho, 2020; Kinam Kim & Cho, 2021).

Other studies have focused on using deep learning methods to detect and assess the health of construction workers.  Yu, Yang, et al. (2019) used advanced deep learning methods and construction workers' skeleton data from videos to develop an automatic and detailed ergonomic assessments of construction workers. Anothor research by Yu, Li, et al., (2019) was on developing a non-intrusive method to monitor the whole-body physical fatigue with computer vision for construction workers.

Table 5: Construction Workers detections

| Author/ Year | Focus of the study | Methods | Limitation |
|---|---|---|---|
| (Yu et al., 2021) | Reviewing previous methods to collect posture-related data for construction workers | 1) summarizing working principles and applications of posture-related data collection in construction management<br>2) comparing the above methods based on data quality and feasibility on construction sites | The application of posture-related data in robotics is not considered in the research. Moreover, it is used in a simulation case instead of on-site application |
| (Son et al., 2019) | To accurately and rapidly detect construction workers under varying poses and against changing backgrounds in image sequences. | Based on very deep residual networks (ResNet-152) and bounding box regression and labelling from the original image (R-CNN). | This study has only detect construction workers with no inclusion of other project entities, such as construction equipment. |
| (Roberts et al., 2020) | This research estimates and tracks two-dimensional (2D) worker pose and outputs per-frame worker activity labels given input red-green-blue (RGB) video footage of a construction worker operation. | Using a novel deep learning method. 317 annotated videos of bricklaying and plastering operations were used to train and validate the proposed method. | The data set contains videos of single workers. Moreover, this paper only focused on videos of bricklaying and plastering activities. Finally, the potential interactions between construction workers were not taken into consideration. |
| (Son & Kim, 2021) | This study proposes integrated construction worker detection and tracking scheme using complementary metal-oxide semiconductor (CMOS) image sensors for real-time monitoring. | Based on the fourth version of you only look once (YOLO) and the Siamese network, which are based on convolutional neural networks. | This research used only existing publicly available datasets. Collecting additional datasets is needed to train the process to advance the network to further improve the reliability. |
| (Kinam Kim & Cho, 2021) | This study proposes Long Short-Term Memory (LSTM) networks for recognizing construction workers' motions. | The LSTM networks were validated through case studies in one bridge construction site and two road pavement sites. | The developed networks can't recognize hand motions, such as swinging and holding a tool or material. |
| (Kinam Kim & Cho, 2020) | This study proposes a construction worker's motion recognition model using the Long Short-Term Memory (LSTM) | 1. Generating different datasets containing motion sensor data collected from the sensors located on different body parts.<br>2. Comparing the performance of five machine learning models trained using the datasets, the desired numbers and locations of motion sensors. | The datasets were not collected from real construction workers. |

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|---|---|---|---|
| (Yu, Yang, et al., 2019) | This paper proposed a joint-level vision-based ergonomic assessment tool for construction workers (JVEC) to provide automatic and detailed ergonomic assessments of construction workers based on construction videos. | This research extracts construction workers' skeleton data from videos with advanced deep learning methods. | The current version of JVEC can only be applied to frames containing only one worker. Moreover, the on-site experiment only recorded a 10-min video for each worker. Longer videos are needed. |
| (Yu, Li, et al., 2019) | This research proposes a novel non-intrusive method to monitor the whole-body physical fatigue with computer vision for construction workers. | A computer vision-based 3D motion capture algorithm to model the motion of various body parts using an RGB camera. | The 3D motion estimation method in this research cannot provide accurate 3D motion estimation when there are severe vision obstructions or under top-down perspectives. Moreover, this study identifies the worker's work/rest status manually. |

#### 5.2.3. Construction machines detections

Tracking construction machines is an essential and significant step in the automated surveillance of construction safety. However, a high tacking precision is not achieved in the current used vision-based tracking methods. Many studies have tackled this issue though implementing various deep learning methods (see Table 6). To ease the construction machine tracking, Xiao & Kang (2021a) have developed an image data set named the Alberta Construction Image Data Set (ACID) through manually collecting 10,000 images and it was validated through using four existing deep learning object detection algorithms Inception-SSD, Faster-RCNN-ResNet101, Inception-SSD and YOLO-v3. Moreover, Xiao & Kang (2021b) have proposed a vision-based method, called construction machine tracker (CMT), to track multiple construction machines in videos. Xiao, Lin, & Chen (2021) have also proposed a vision-based method specifically for automatic tracking of construction machines at night-time by integrating the deep learning illumination enhancement. Slaton, Hernandez, & Akhavian (2020) have moved a step forward by proposing a framework to recognise the construction equipment's activities, in which deep learning architectures were used to predict the activities of heavy construction equipment monitored via accelerometers.

Other applications of deep learning methods were undertaken to enhance construction machines tracking and operation. Shi et al. (2020) has proposed deep long short-term memory network to predict the brake pedal aperture for different braking types. H. Lee, Yang, Kim, & Ahn (2020) have proposed an automatic detecting technique for excessive carrying-load (DeTECLoad) uses a hybrid Convolutional Neural Network-Long Short-Term Memory to predict load-carrying weights and postures simultaneously.

Table 6: Construction machines detections

| Author/ Year | Focus of the study | Methods | Limitation |
|---|---|---|---|
| (Xiao & Kang, 2021a) | This research presents a case study on developing an image data set specifically for construction machines named the Alberta Construction Image Data Set (ACID). | In the case of ACID, 10,000 images are manually collected. To validate the feasibility of ACID, four existing deep learning object detection algorithms, including YOLO-v3, Inception-SSD, R-FCN-ResNet101, and Faster-RCNN-ResNet101 were used. | The ACID data set is only for the object detection task. |
| (Xiao & Kang, 2021b) | This research proposes a vision-based method, called construction machine tracker (CMT), to track multiple construction machines in videos. | The proposed CMT was integrated into a framework of analysing excavator productivity in earthmoving cycles and achieved 96.9% accuracy. | This research is only suitable for tracking construction machines. |
| (Xiao, Lin, et al., 2021) | To reduce the risk of accidents from the low lighting conditions and fatiguing environments in the night-time construction. | This study proposes a vision-based method specifically for automatic tracking of construction machines at night-time by integrating the deep learning illumination enhancement. | This research is only suitable for tracking construction machines from night-time videos. |
| (Slaton, Hernandez, & Akhavian, 2020) | This paper proposes a construction equipment activity recognition | The performance of a simple baseline convolutional neural | Obtaining more training data to push accuracy |

| | | | |
|---|---|---|---|
| | framework that uses deep learning architectures to predict the activities of heavy construction equipment monitored via accelerometers. | network (CNN) is compared to a hybrid network that contains both convolutional and recurrent long short-term memory (LSTM) layers. | and reliability of the models higher. |
| (Shi et al., 2020) | This research proposed a deep long short-term memory network to predict the brake pedal aperture for different braking types. | By combining the driving data of experienced drivers in different driving environments with deep learning. | This research only used the method of combining the driving data of an experienced driver and machine learning in a limited driving environment to achieve the prediction of the brake pedal. |
| (Lee et al., 2020) | This research proposes an automatic detecting technique for excessive carrying-load (DeTECLoad) to predict load-carrying weights and postures simultaneously. | Based on using DeTECLoad to converts the IMU data into image data using a Gramian Angular Field, and then uses a hybrid Convolutional Neural Network-Long Short-Term Memory to classify load-carrying modes from the image data. | DeTECLoad classifies the load-carrying modes based on the training data of predefined load-carrying modes which limits the practicality of the technique. |

#### 5.2.4. Personal Protective Equipment's

Collisions and traumatic brain injuries are the main causes for construction fatalities. Many international health and safety organisations have require the contractors to enforce and monitor appropriate usage of personal protective equipment (PPE) of workers at all times. Nath, Behzadan, & Paal (2020) have used a single convolutional neural network (CNN) framework and three deep learning models built on (YOLO) architecture to verify PPE compliance of workers. Other studies have used deep learning method to detect the compliance of construction workers on wearing a safety helmets. Shen, Xiong, et al. (2021), proposed a methodology using CNN-based face detection and bounding-box regression and a deep transfer learning based on DenseNet for safety helmet recognition. J. Wu, Cai, Chen, Wang, & Wang (2019) have used CNN method to automatically detect whether construction workers are wearing hardhats and identify the corresponding colours. On the other hand, Fang et al. (2018) have used R-CNN method to detect construction workers' non-hardhat-use. Table 7 includes key published articles to develop smart Personal Protective Equipment.

Table 7. Personal Protective Equipment

| Author/ Year | Focus of the study | Methods | Limitation |
|---|---|---|---|
| (Nath et al., 2020) | This paper presents three deep learning models built on You-Only-Look-Once (YOLO) architecture to verify PPE compliance of workers. | This research used a single convolutional neural network (CNN) framework and classified by CNN-based classifiers. | The proposed methods were only tested on hat and vest classes. Moreover, the colour of the PPE components were not identified in the proposed methods |
| (Shen, Xiong, et al., 2021) | This article proposes a new methodology for detecting safety helmet wearing. | This research used of CNN-based face detection and bounding-box regression and a deep transfer learning based on DenseNet. | The proposed model cannot detect the workers with their back to the surveillance camera. Moreover, a face recognition algorithm to identify the carrier of a safety helmet. |
| (J. Wu et al., 2019) | To automatically monitor whether construction personnel are wearing hardhats and identify the corresponding colours. | Based on CNN method. | Difficulty in detecting small-scale hardhats. |
| (Fang et al., 2018) | This paper proposes the use of a high precision, high speed and widely applicable Faster R-CNN method to detect construction workers' non-hardhat-use. | Based on Faster R-CNN. | The algorithm is able to detect NHU workers but not identity the workers involved. |

### 6. Internet of Things (IoT) and Deep Learning (DL)

Recently, Internet of Things (IoT) technologies have been increasingly used. Such technologies result in massive amount of generated data. This data requires reliable data analysis techniques to enable efficient exploitation. A new area of Artificial Intelligent (AI) called Deep Learning has demonstrated the potential for more efficient performance of IoT big data analytics.

Reviewing the literature has revealed three main themes namely; deep leaning and IoT to deliver smart cities and structures, deep leaning and IoT applications and deep leaning and IoT for assessment.

Few studies have focused on the practical applications using deep learning and IoT. Zhang, Qi, Myint, & Wen (2021) have propose a fine transmission image deep convolutional regression network (FT-DCRN) to obtain the coarse transmission image, then the dehazed images generated by the FT-DCRN dehazing algorithm were used for 3D reconstruction. Another research was conducted to develop an adaptive approach for path planning against the rapid environmental changes in fires, in which the author integrate MAT, VG and buffer zone to form a graph based network and then used this network to detect and tally the number of people in a target area using real-time videos from closed-circuit television (CCTV) cameras facilitated by deep learning algorithms (Cheng, Chen, Wong, Chen, & Li, 2021).

The usage of deep learning and Iot application on energy saving is a challenging issue. The question has been raised is on how IoT and existing developed systems could be improved and be further developed to address issues of energy saving (Sepasgozar et al., 2020). Rafsanjani, Ghahramani, & Nabizadeh (2020) have conducted a novel IoT-based smartphone energy assistant (iSEA) framework which prompts energy-aware behaviors in commercial buildings, in which deep learning approach and IoT were used.

### 6.1.Deep leaning and IoT to deliver smart cities and structures

The purpose of delivering smart cities and structures is to improve the resident's quality of live and to optimize the usage of scarce resources. Few research have focused on exploring the applications of deep learning utilizing IoT to deliver smart cities and structures. Muhammad et al. (2021) conducted a dedicated survey on the applications of deep learning in smart cities, in which many applications of deep leaning utilization with IoT have been revealed. Another survey has been undertaken by Atitallah, Driss, Boulila, & Ghezala (2020) to review the literature regarding the use of IoT and deep learning to develop smart cities, in which IoT definitions and the characteristics of IoT-generated big data were listed.

Achieving different types of smart project through the implementation of deep learning and IoT were also the focus of researchers. A study has focused on smart homes in which the applications, systems, or methods of using IoT, artificial intelligence (AI), and geographic information system (GIS) at homes were reported (Sepasgozar et al., 2020). Delivering smart public services using IoT and deep learning were also investigated (Ma et al., 2020). Lin, Chen, & Ho (2021) has tackle an important issues in which he focused on delivering smart hospital in the COVID19 pandemic through establishing a smart hospital evaluation system with evaluation criteria and sub-criteria, which were then further prioritized and mapped to BIM-related alternatives to inform asset information management (AIM) practices. More research are needed on exploring the current implementation of deep learning and IoT in different case studies to achieve smart cities

### 6.2.Deep learning and IoT for construction assessment

Condition assessment is a key application of Internet of Things (IoT). Deep learning has been used by researchers to utilize the application of IoT. Wu, Singla, Jahanshahi, & Bertino (2019) have incorporated deep learning algorithms into edge devices for assessment and damage detection to achieve quick inference and low memory demands through transfer learning and network pruning. Another research has studied the technological feasibility of autonomous corrosion assessment of reinforced concrete structures, in which the use of internet of things (IoT) and machine learning for autonomous corrosion condition assessment of RC structures were recommended (Taffese & Nigussie, 2020). (Maraveas & Bartzanas (2021) have studied another type of structure through employing various sensors for accurate and real-time monitoring of agricultural building structures, including electrochemical, ultrasonic, fiberoptic, piezoelectric, wireless, fiber Bragg grating sensors, and self-sensing concrete. They confirmed the improvement of the functionality and accuracy of these sensors to assess the concrete structure through deployment of machine learning, deep learning, and artificial intelligence in smart IoT-based agriculture. Another paper has focused on the operating condition of road infrastructure through exploring a digital and smart bridge crack system for improving the efficiency and risk factor for bridge security diagnosis, in which deep learning and artificial intelligence have proved their enhancement of the inspection of concrete bridge structures (Chehri & Saeidi, 2021).

## 7. Discussion on findings

This article discusses the utilization of deep learning for construction management tasks and processes including the early warning of health and safety issues in construction sites through integrating IoT sensors, automating the equipment tracking while working in risky construction environments, particularly, excavators. This research find that deep learning is successfully implemented in a few case studies to detect different objects including workers detection while executing a wide range of tasks.

Deep learning is implemented to enable detect the quality of implemented works such as concrete surfaces, as well as, checking the tolerances values of placing infrastructure objects, particularly, for bridges and tunnels. Moreover, inspecting the quality of raw materials such as rocks before using them in construction works. However, all these applications were used in small case studies, therefore, the proposed CNN deep learning models by researchers should be tested

In addition to employing deep learning for field inspection, it is recognized that deep learning is also employed to determine places and quantities of resources in the site, as well as, managing using multiple equipment in crowded construction sites to avoid accidents and maximise the productivity of equipment by finding the optimal locations.

The progress monitoring of different construction works was significantly appeared in the analysis of data (181 articles), for example, deep learning is used to evaluate the progress of prefabricated projects, to detect the existing performed construction works and compare these data with images from the 4D BIM model. However, these monitoring tools were not fully automated as the link between cameras and sensors to collect data from sites and entre these data to the deep learning models in order to process these data to be compared with entered training data. Moreover, the deep learning models will be also able to detect specific types of works that their images (information) were entered as training sets.

The construction health and safety were significantly considered by researcher to exploit deep learning technology. The analysis of data indicates that deep learning was used to monitor the real-time safety of construction workers trough wearing specific designated clothes (i.e., hard hat, vest, etc.) that include sensors that send data to deep learning system synchronously. Studies propose to use using the Long Short-Term Memory (LSTM) to collect workers motion in the site and then analyse workers' motions to understand the attitude of workers while executing different tasks. Moreover, analyzing the historical health and safety reports in order to understand the nuance of hazards, then proposing a plan to mitigate them. Furthermore, enabling construction workers and practitioners to detect weather through wearing hardhats.

IoT is integrated with deep learning in order to automate the process of collecting data from construction sites and subsequently deep learning CNN models start to process these data to provide results with high accuracy as designed. However, all presented case studies were small and the proposed solutions should be validated using large scale case studies. Moreover, a wider industry perspective should be considered by conducting interviews and focus groups to measure the attitude of workers and practitioners to adopt such solutions in their daily tasks.

This study provides a critical and wider evaluation of major studies of using deep learning in construction management tasks. Based on the outcome of this study, the future researchers can define the gap and the contribution of each study, then further developments can be conduction either using the same successful methods to revalidate solutions or developing new solutions to bridge the highlighted gap. Researchers adopted a structured analysis of articles by evaluating the focus of study, methods, findings and limitations, therefore, the outcome based on this analysis is comprehensive. Figure 6 shows the summary of applications of deep learning for the construction site management.

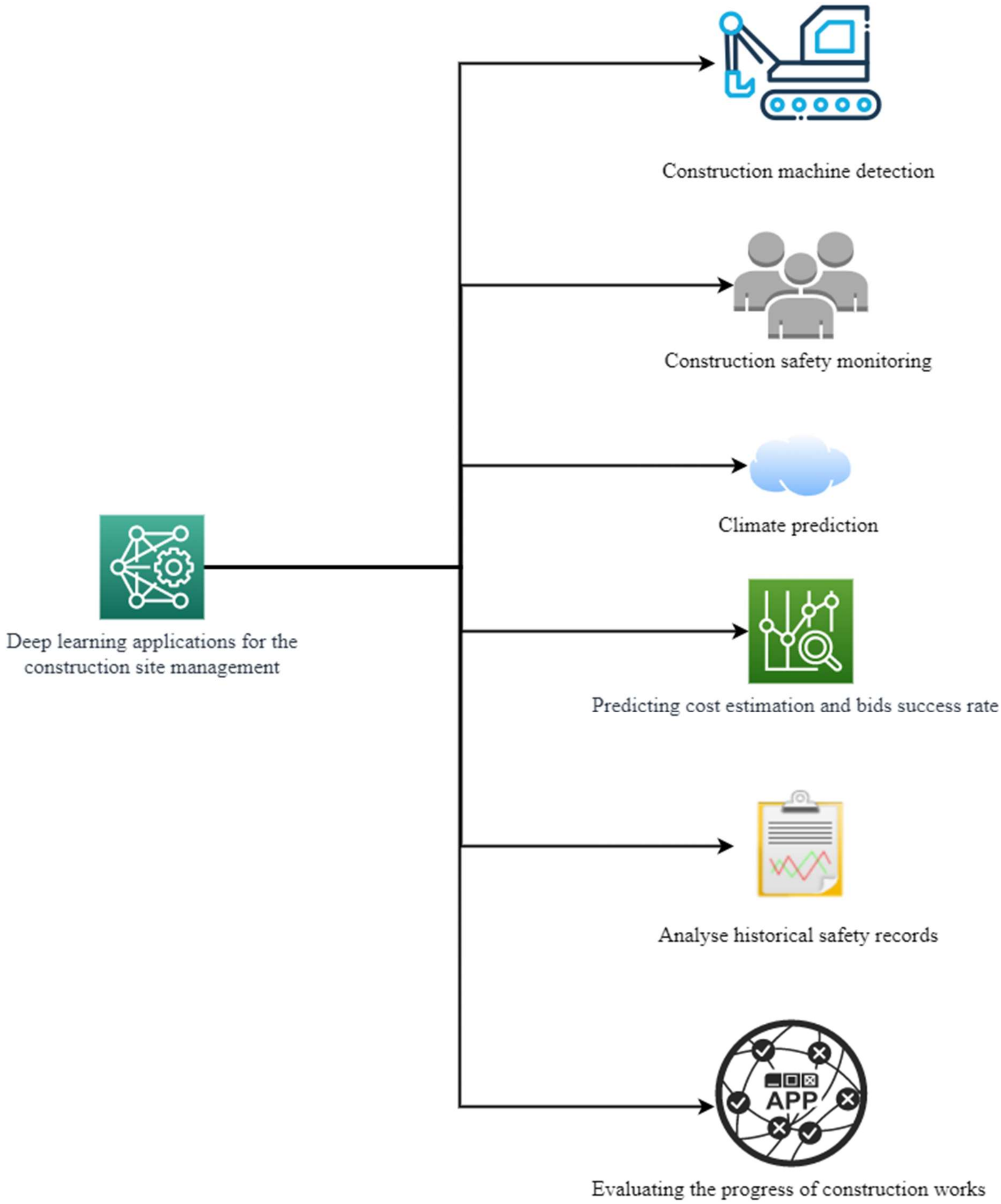

Figure 6. A summary of deep learning applications for construction site management

Given, this research focuses on the utilization of deep learning for construction management tasks, therefore, this paper does not cover all aspects of deep learning application for the construction industry and other research is required to cover other applications such as crack detection, structural health assessment, etc.

## 8. Conclusion

This paper provides a comprehensive scientometric and critical review of key published articles (n=181) in deep learning applications for construction management tasks. The scientometric analysis is conducted to assess the general applications of deep learning-based construction site management tasks before categorizing applications and giving a clear view of the density of these applications. The outcome of scientometric analysis indicates that deep learning is significantly used to detect objects such as equipment and workers to (1) automate controlling equipment motions in the site, (2) detect workers motions while executing tasks, (3) early safety warnings through using smart hats to collect data and process it. Moreover, the scientometric analysis refers that IoT is highly used to collect data from sites automatically.

The outcome of scientometric analysis supported categorizing articles according to applications of deep learning. This paper categorized and analysed applications as field inspection, construction machines detection health and safety, IoT and deep learning. The results showed that there are successful implementations cases of deep learning for all mentioned categorieses, however, additional validations is needed either using large scale case studies and/or assessing applications from industry perspectives in order to evaluate workers attitudes towards adopting such technologies in their daily tasks.

This article enables researchers to define research gaps for key published articles of deep learning-based construction management applications. Therefore, it can be considered as a knowledge base to evaluate current status of research in this area. Given, this article only considered applications of deep learning for construction site management, therefore, other research to investigate different applications is required, as well as a scientometric analysis to present all applications of deep learning in construction is recommended to be conducted in order to assess the current state of art and practice of deep learning utilization in construction.

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