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Machine learning in construction: From shallow to deep learning

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ABSTRACT

The development of artificial intelligence technology is currently bringing about new opportunities in construction. Machine learning is a major area of interest within the field of artificial intelligence, playing a pivotal role in the process of making construction "smart". The application of machine learning in construction has the potential to open up an array of opportunities such as site supervision, automatic detection, and intelligent maintenance. However, the implementation of machine learning faces a range of challenges due to the difficulties in acquiring labeled data, especially when applied in a highly complex construction site environment. This paper reviews the history of machine learning development from shallow to deep learning and its applications in construction. The strengths and weaknesses of machine learning technology in construction have been analyzed in order to foresee the future direction of machine learning applications in this sphere. Furthermore, this paper presents suggestions which may benefit researchers in terms of combining specific knowledge domains in construction with machine learning algorithms so as to develop dedicated deep network models for the industry.

1. Introduction

Over the past 40 years, machine learning (ML) and in particular deep learning (a branch of machine learning) has been making significant technological progress, initiating major changes in various industries. It has also become a powerful tool, capable of automating processes in construction, which, in terms of performance and productivity, lags behind other industries (Teicholz, 2013). Machine learning technologies play an important role, especially when processing large amounts of data brings a significant added value to saving time and maximizing computing resources. For example, they can be used for text mining in project related documents (Zhang et al., 2019) or automatic monitoring (Seong et al., 2017) to help reduce the demand on human resources while simultaneously increasing safety. Since 2017, due to the excellent performance of deep learning in the field of computer vision, deep learning has been widely adopted in many areas of construction such as: safety (Fang et al., 2018, 2019; Wu and Cai, 2019), road survey (Zhang and Yang, 2016; Wu et al., 2019), bridge inspection (Deng et al., 2020; Dorafshan and Azari, 2020; Zhang and Yang, 2020), and on site operation monitoring (Fang and Li, 2018a; Fang and Ding, 2018; Guo et al., 2020).

In construction, researchers focus on combinations of algorithms and application scenarios to solve their problems. There have been several reviews on machine learning for life cycle management (Gao et al., 2019; Zhang and Shi, 2020). However, limited studies have been conducted in relation to analyzing the strategies for choosing specific algorithms for different scenarios, as well as synthesizing a road map for guiding subsequent research to advance the proper use of machine learning in construction. Furthermore, there are few works focused on the fundamental machine learning models in construction.

Therefore, in order to provide systematic and comprehensive guidance for subsequent research, an in-depth literature review on the application of machine learning in construction is presented herein. The aim of this paper is to help researchers working in this field quickly place their work within the current spectrum bearing in mind the current challenges and potential, feasible solutions available. The paper is organized as follows: Section 2 presents the research methodology used in this study while section 3 provides an overview of the development history of machine learning theory. In Sections 4 and 5 reviews of shallow and deep learning applications in construction are provided and, finally, the challenges and future directions of machine learning in construction are identified in Sections 6 and 7.

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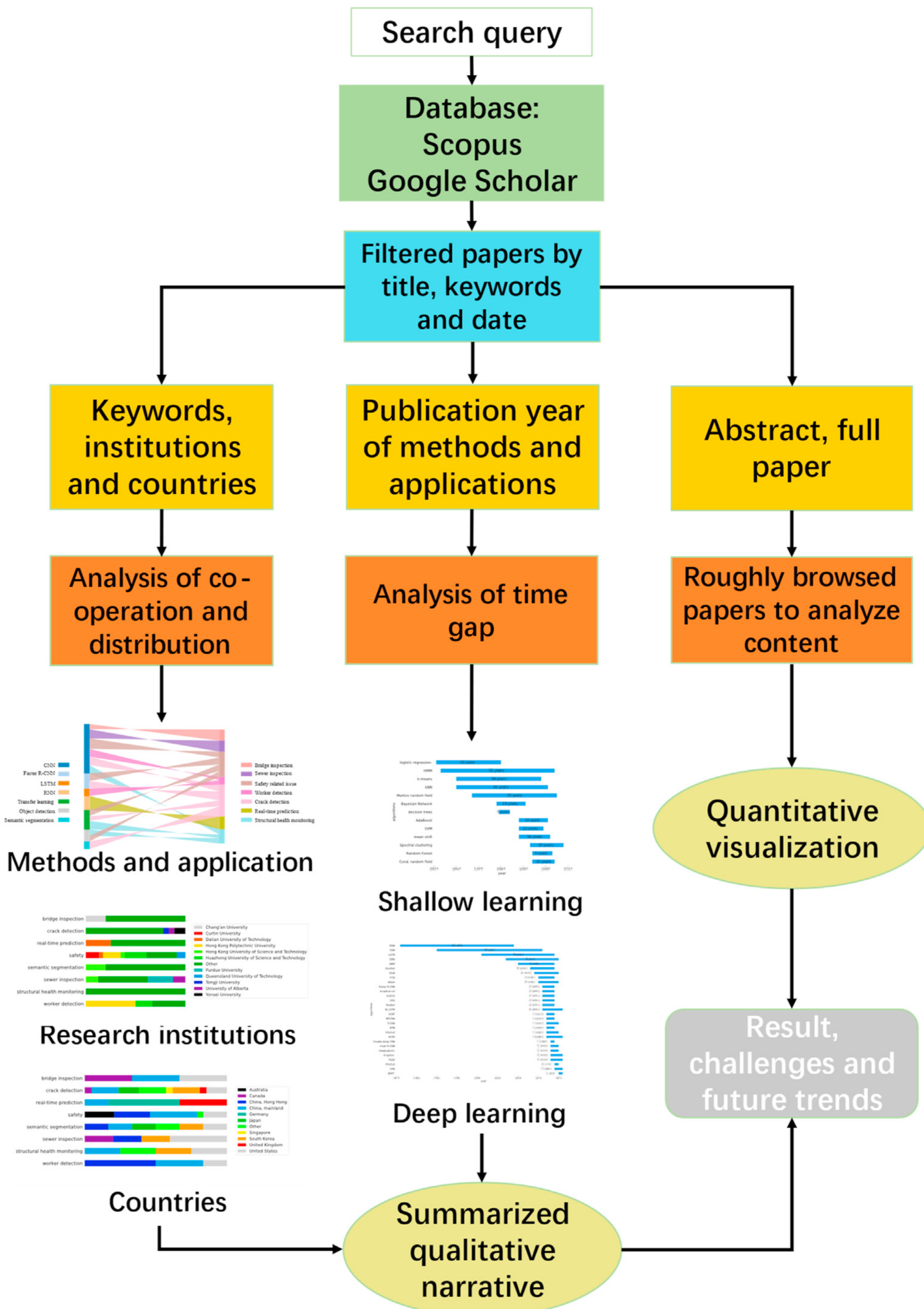

Fig. 1. The research map.

2. Research approach and scientometric analysis

In this study, machine learning is divided into two parts: 1) shallow learning, and 2) deep learning, according to its development history. Shallow learning refers to the majority of machine learning models proposed prior to 2006, including so-called shallow neural networks (neural networks with only one hidden layer of nodes). Deep learning itself is a branch of machine learning, which can be understood as neural networks with multiple hidden layers. Compared with shallow learning-based applications, deep learning models require large amounts of training data. Furthermore, the structures of the network have a great impact on the performance of the deep learning models.

The literature presented in this paper was collected from the Scopus and Google Scholar databases. Scopus and Google Scholar are abstract and index databases, and the papers relevant to this study were collected utilizing a query string. By limiting the subject, keywords, and publication names, the relevance and quality of the collected papers were guaranteed.

2.1. Research map

There are many shallow learning algorithms (e.g., Linear Regression, Logistic Regression, Support Vector Machines (SVM), Decision Trees (DT), K-nearest Neighbors (KNN), and shallow neural networks) which have been applied over a vast time span. In this study, we have analyzed the articles pertaining to the aforementioned most popular shallow

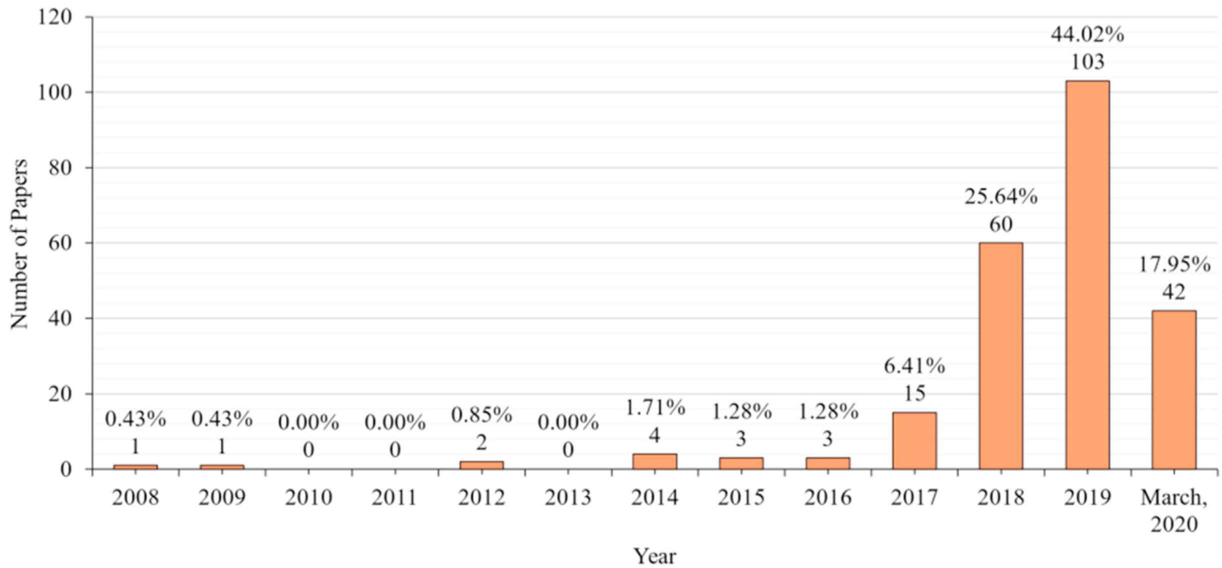

Fig. 2. The number of papers in recent years.

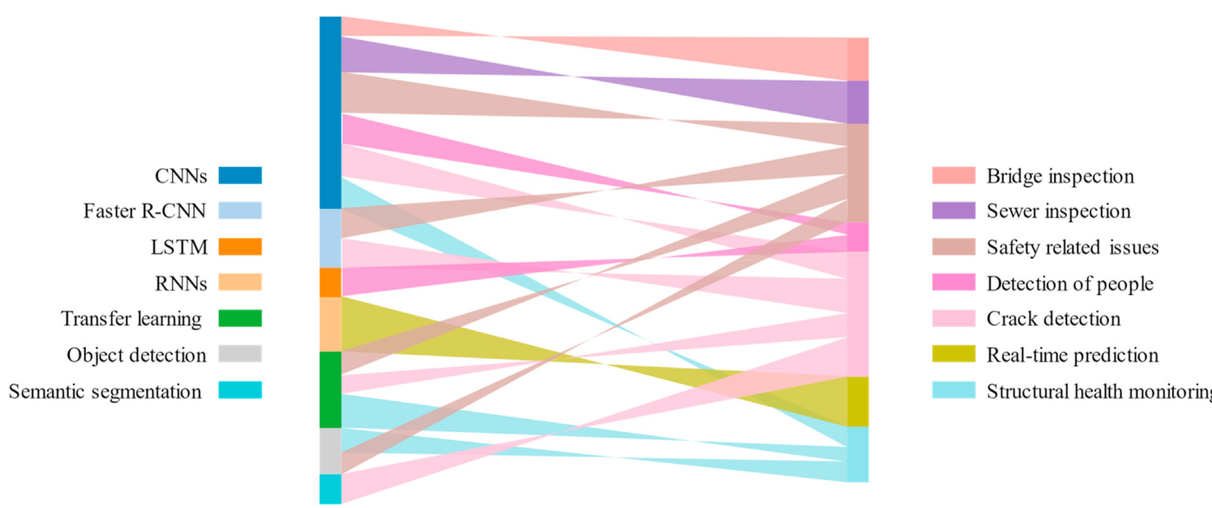

Fig. 3. Research field: algorithms (left) and applications (right).

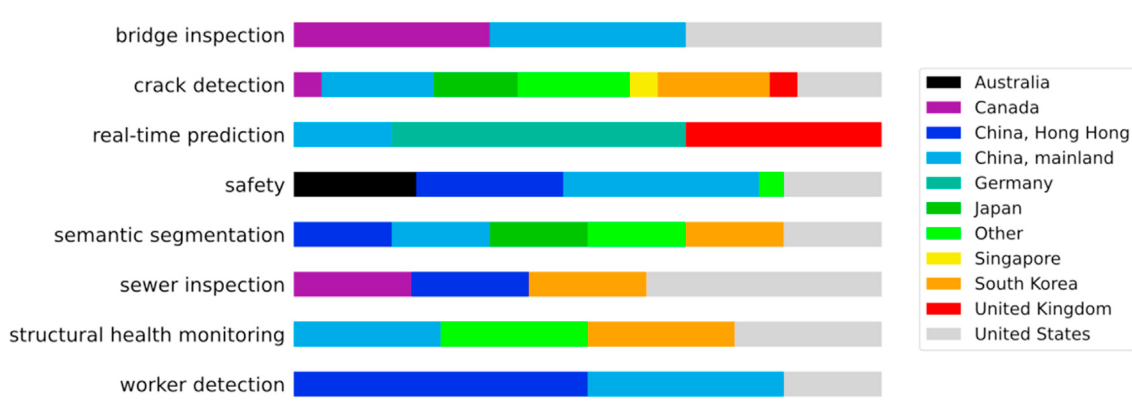

Fig. 4. The relative participation of countries in different application fields (limited to the application fields specified in at least four papers).

learning algorithms and their first applications in construction. Furthermore, we have collected and analyzed a selection of papers from the 1990s that have been frequently cited in recent years.

As the range of deep learning theory is relatively concentrated, it is decidedly easier and less time-consuming to select relevant articles. Therefore, in the deep-learning-related aspect of this analysis, qualitative

Table 1
Research content of initial applications.

Algorithm	Initial application	Creation year	Application year	Research content
Logistic Regression	Wilson et al. (1987)	1958	1987	Examines factors that influence the success of the tendering process
Decision Tree	Birnie and Yates (1991)	1986	1991	Cost prediction
Bayesian Network	McCabe et al. (1998)	1985	1998	Construction performance diagnostics
k-Means	Lee and Chang (2005)	1967	2005	Bridge painting rust defects assessing
SVM	Shu-quan et al. (2006)	1995	2006	Dynamic monitoring for safety during construction
KNN	Chen (2008)	1967	2008	A knowledge-sharing model for severe change order disputes in construction
AdaBoost	Shin et al. (2008)	1995	2008	Proposing a decision support model to select formwork systems in high-rise building construction
Mean Shift	Teizer and Vela (2009)	1995	2009	Tracking site labor
Random Forest	Liu et al. (2010)	2001	2010	Exploring the relationship between soil properties and metallic pipe deterioration.
HMM	Leu and Adi (2011)	1960	2011	Probabilistic prediction of tunnel geology
Conditional Random Field	Xiong and Huber (2010)	2001	2011	Automatic creation of semantically rich 3D building models
Markov Random Field	Wu et al. (2012)	1974	2012	Improving laser image resolution for pitting corrosion measurement
Spectral Clustering	Zhang et al. (2015)	2000	2015	Planar patches extraction from noisy point-cloud data for BIM

content inspection and scientometric analysis were conducted. Fig. 1 provides the research methodology map of this research.

2.2. Material

Contrary to deep learning algorithms, the majority of shallow learning algorithms are not that closely related. In addition, there is a large time span between the development of shallow learning algorithms and their applications in construction. Thus, several researchers did not use "machine learning" or "shallow learning" as the keywords in their research (Maloney, 1990; Russell and Jaselskis, 1992). Therefore, the names of mainstream algorithms such as Logistic Regression, DT, Bayesian network, K-means, SVM, KNN, AdaBoost, Mean Shift, Random Forest, Hidden Markov Models (HMM), Conditional Random Field, Markov Random Field, and Spectral Clustering were used as search keywords for the collection of shallow learning articles. Taking this into consideration, we did not only use the term “construction” as the search keyword, but also the terms "civil", "building" and "engineering" were used. Following this selection process, a manual review was conducted to filter out any irrelevant articles obtained by using the query string “((KEY (construction) OR SRCTITLE (construction OR civil OR building OR engineering)) AND TITLE-ABS-KEY (machine learning OR mainstream theoretical name))”. Through utilizing the abovementioned processes, we were able to gather highly-cited and relevant articles pertaining to the application of shallow learning in construction.

As for deep learning, in the early stage, some Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) focused papers were not tagged with the “deep learning” keyword, whereas papers using deep learning methods such as Faster Region-CNN (Faster R–CNN) were generally attached to the “deep learning” group. To ensure that the analyzed papers describe deep learning-based technologies or solutions, the phrases "deep learning", "CNNs", "RNNs", "convolutional neural networks", and "recurrent neural networks" were used to filter the results of the search. The applied query string was ((KEY (construction) OR SRCTITLE (construction OR civil)) AND TITLE-ABS-KEY (deep learning OR CNNs OR RNNs OR convolutional neural networks OR recurrent neural networks)). As the concept of deep learning was first proposed in 2006 - the search period was limited from 2006 to date. The language of the papers was set to English. In the consequent step, the literature derived from the search area was filtered manually i.e., by reading the titles and abstracts to guarantee the relevance of the papers in terms of construction and deep learning.

2.3. Scientometric analysis

Fig. 2 provides a bar chart that shows the number of papers published from 2008 to early 2020. What stands out in this figure is the overall growth in the number of papers, which have significantly increased since 2016. This growth seems to follow the rising interest in deep learning, which started in 2012 with the paper that introduced AlexNet – a deep neural network designed to classify images (Krizhevsky et al., 2012). Assuming that the pace of publishing papers in 2020 will be maintained (14 papers per month), we may expect 168 papers by the end of 2020, which will be more than the number of papers published jointly in 2018 and 2019. Moreover, the scale of deep learning application in construction is also likely to be further extended.

By analyzing the keywords of the collected articles, we were able to determine the focus of research and the connections between the algorithms and the applications. In Fig. 3 specific colors stand for different keywords. Each keyword was assigned to either algorithms or applications. The algorithms are on the left-hand side of the figure, whereas the applications are on the right. The lines show the connections between the algorithms and applications, and the color of the lines is consistent with the color of the applications. The lengths of the strands correspond to the number of occurrences of keywords, whereas the widths of the lines correspond to the numbers of connections.

It can be seen from Fig. 3 that the deep learning algorithms that have gained attention in construction are mainly CNNs, RNNs, and transfer learning. The specific models are Faster R-CNNs and Long Short-Term Memory (LSTM). The main application areas are - safety problems during construction, concrete, crack detection, and bridge inspection. It may be concluded that image data is mainly used when applying deep learning in construction, whereas other data sources are employed only occasionally. This is related to the strong performance of deep learning tools in the image processing field.

From the perspective of application fields, the main application areas are defect detection during construction, such as concrete crack recognition, and bridge inspection. Although they all used object detection and image segmentation related algorithms, the vision characteristics are different, thus, there is no uniform algorithms or network structures which can be applied in every scenario. Researchers are required to select and reconstruct the algorithms as well as network structures to solve different construction problems.

The majority of research from China mainly focuses on safety management during construction, which can be seen in Fig. 4. One possible

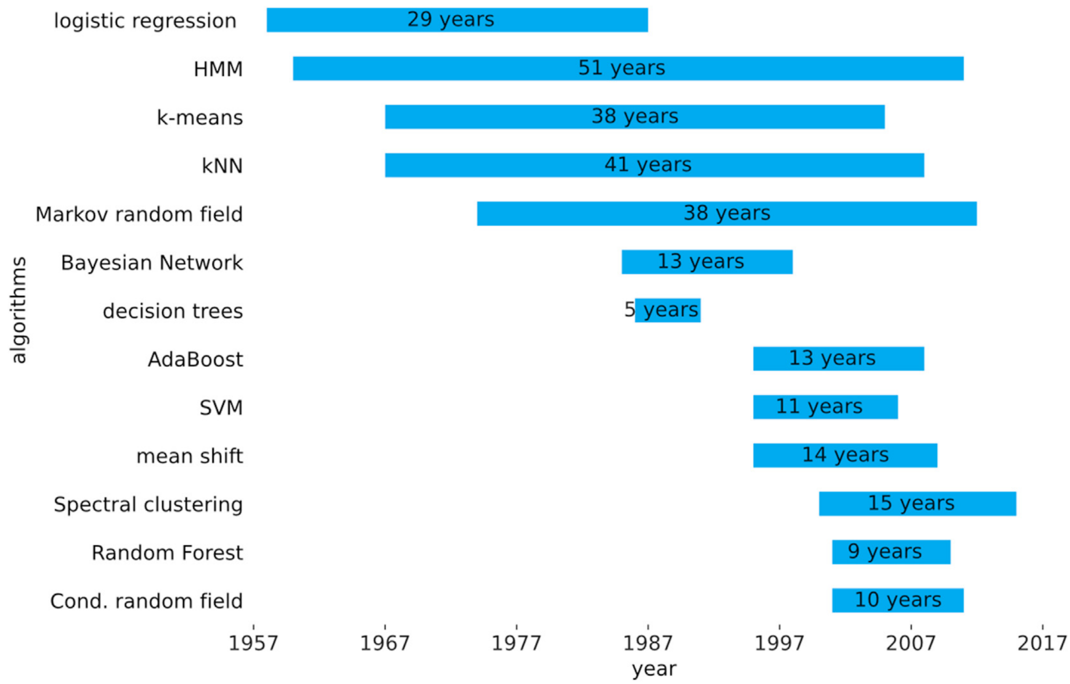

Fig. 5. The timeline of the concept of shallow learning algorithms and their actual application in construction.

reason is that China is investing a huge amount of money in infrastructure development, and the government encourages the implementation of advanced technologies in the process of urbanization. In 2018, infrastructure investment accounted 2604.04 billion USD for 19.6% of China's annual GDP (Source: China's National Bureau of Statistics, WIND). Furthermore, one can also notice that research from the United States (US) is quite diverse in comparison to other countries.

3. Development of machine learning

This section of our paper introduces the development history and the main algorithms of both shallow and deep learning.

3.1. Shallow learning

There are three main types of shallow learning: (1) supervised learning; (2) unsupervised learning; and (3) reinforcement learning (RL. Supervised learning can learn a pattern from labeled data and predict the outcome of new inputs based on this pattern. Supervised learning applies a vast selection of algorithms in which the main early algorithms are Logistic Regression (Cox, 1958), Perceptron (Rosenblatt, 1958) and kNN (Cover and Hart, 1967). While Perceptron undoubtedly laid the foundation for machine learning algorithms, they were fragmented and unstructured before the publication of the Decision Tree algorithm. The most widely used supervised learning algorithms in the construction industry are SVM (Cortes and Vapnik, 1995), AdaBoost (Freund, 1995) and Random Forest (Breiman, 2001). In the majority of cases, they are used for data classification.

Unsupervised learning discovers knowledge from unlabeled data and focuses on data reduction and clustering problems. Unsupervised learning is not widely used in construction due to the limited information that can be extracted from unlabeled data as compared with labeled ones. Therefore, researchers tend to use supervised learning algorithms when they solve real construction problems. The main algorithms of data reduction in unsupervised learning are Principal Component Analysis (PCA) (Pearson, 1901), kernel PCA (Schölkopf et al., 1998), and t-SNE (Maaten and Hinton, 2008). K-means (MacQueen, 1967), EM (Dempster et al., 1977), mean shift (Cheng, 1995) and spectral clustering (Shi and Malik, 2000) are typical clustering algorithms.

In comparison to supervised and unsupervised learning, few works have been published using RL algorithm in the construction research field. The main reason for this may be that RL is a trial and error based algorithm, which is costly in construction.

3.2. Deep learning

Deep learning can be understood as a deep neural network, which is a further development of artificial neural networks. As the basis of the complete neural network theory, back propagation was initially proposed, which sparked the first wave of machine learning (Rumelhart et al., 1986). Prior to this, artificial neural networks lacked effective algorithm support and thus were unable to train multilayer neural networks.

After back propagation was proposed, two classical neural network frameworks were developed: LeNet (LeCun et al., 1989) and Long-Short Term Memory Networks (LSTM) (Hochreiter and Schmidhuber, 1997). There were three main limitations of neural networks in that stage: (1) the algorithm itself: with the increase of the network's depth, the vanishing/exploding gradient problems make it impossible to effectively train the network; (2) data: it is difficult to obtain a sufficient amount of labeled data for training powerful neural networks; (3) hardware: the performance of the hardware cannot meet the requirements of the computing resources when training complex neural networks. To solve these problems, in 2006, Hinton (Hinton and Salakhutdinov, 2006) published a paper in Science that proposed the concept of deep learning and a new training strategy, making it possible to train deeper neural networks. Then, in 2012, the success of AlexNet (Krizhevsky et al., 2012) in ImageNet – an image classification competition – brought about a comeback in deep neural networks. The main contribution of AlexNet was to combine effectively deep learning with large datasets.

Two typical network structures in deep learning are CNNs and RNNs. There are two main advantages of CNNs. Firstly, the knowledge that is stored in a CNN kernel can be applied to any part of a dataset. For example, if there is a kernel or a set of kernels responsible for detecting humans, the humans can be detected in an entire image, regardless of their location. This is difficult to achieve with fully connected neural

Table 2
Typical object detection applications in PPE-use.

Title	Object	Year	Model	Application details
Detecting non-hardhat-use by a deep learning method from far-field surveillance videos (Fang and Li, 2018c)	hardhat	2018	Faster R-CNNs	1) data source: images from remote field surveillance videos 2) data sets were grouped according to weather, light, individual posture, visual distance, and occlusion for testing in different environments
Transfer learning and deep convolutional neural networks for safety guardrail detection in 2D images (Kolar et al., 2018)	guardrail	2018	VGG-16 (Simonyan, 2015)	1) add the background image to the guardrail 3D model to generate an enhanced data set 2) using transfer learning with the VGG-16 model for basic feature extraction 3) the CNN-based guardrail detection model proposed in this paper achieves 96.5% high accuracy
Computer vision aided inspection on falling prevention measures for steeplejacks in an aerial environment (Fang and Li, 2018b)	hardhat harness anchorage	2018	SSD	1) first detect workers and the entrance of the aerial operation area (such as windows) to determine whether the worker is entering the aerial operation area 2) then detect whether the worker is wearing PPEs (hardhat, harness, and anchorage in this research)
Deep learning for site safety: Real-time detection of personal protective equipment (Nath et al., 2020)	hardhat worker vest	2020	YOLO-v3 VGG-16 ResNet-50 Xception (Chollet, 2017)	1) the wearing of PPEs is divided into 4 categories: W, WH, WV, WHV (W: worker; H: hardhat; V: vest) 2) method 1: used a YOLO-v3 model to detect hardhats, vests and workers separately, then traditional ML algorithms were applied to implicitly learn the positional relationship between them for classification 3) method 2: used YOLO-v3 for direct classification (worst classification result) 4) method 3: first used YOLO-v3 to detect PPEs and workers, then transfer learning models were used (assembling VGG-16, ResNet-50 and Xception) for classification (best classification result)

networks, where each input feature is connected to each neuron in a fixed way. Secondly, in comparison with fully connected layers, CNNs have far fewer parameters, which significantly speeds up the learning process and allows the use of much more complex networks. Currently, CNNs are the basic structures used in many fields of Machine Learning - predominantly in computer vision (such as image recognition, object detection, and image segmentation).

RNNs are mainly used in the field of time series processing, such as speech recognition and natural language processing. There are two main variants of RNN –LSTM and Gated Recurrent Units (GRU) (Cho et al., 2014). Both LSTM and GRU work in a similar way – they allow the storing of values in "LSTM/GRU" cells and use these values when needed. At present, LSTM and GRU are the most popular Deep Recurrent Neural Network architectures.

4. Applications of shallow learning in construction

In this section, we analyze the applications of shallow learning algorithms in construction, starting from the initial applications of the mainstream theories and progressing to the recent, highly cited literature.

4.1. Analysis of research trends

Table 1 presents the research content of the initial applications of some mainstream shallow learning algorithms. Fig. 5 compares the time intervals between the emergence of new algorithms and their applications in construction.

The Decision Tree algorithm was published in the 1980s, yet it was used for the cost prediction of a housing refurbishment contract (Birnie and Yates, 1991) in 1991; Bayesian networks were published in 1985, and were first (McCabe et al., 1998) used to provide construction performance diagnostics in 1998; SVM (Cortes and Vapnik, 1995) was developed in 1995 and applied in construction to achieve dynamic monitoring on sites in 2006; HMM (Baum and Petrie, 1966) was proposed in 1960 and put forward in (Leu and Adi, 2011) for probabilistic prediction of tunnel geology in 2011. However, some algorithms, such as Q-learning (Watkins, 1989), have yet to be applied in construction. The time gap exists in Fig. 5 due to little attention being paid to data analysis

Table 3
Typical object detection applications in site monitoring.

Title	Object	Year	Model	Application details
A deep learning-based method for detecting non-certified work on construction sites (Fang and Li, 2018a)	worker materials equipment	2018	Faster R-CNNs MTCNN (Zhang et al., 2016)	1) trained a Faster R–CNN model to detect the workers, equipment, and materials in surveillance videos 2) using MTCNN to extract the worker's face to check his information 3) compared the worker's current work with the scope of his registered work to detect non-certified work
End-to-end vision-based detection, tracking and activity analysis of earthmoving equipment filmed at ground level (Roberts and Golparvar-Fard, 2019)	excavators dump trucks	2019	ResNet-101 T-CNNs	1) used ResNet-101 to detect excavators and dump trucks, and T-CNNs to track this engineering equipment
Dense construction vehicle detection based on an orientation-aware feature fusion convolutional neural network (Guo and Xu, 2020)	vehicle	2020	FSSD (Li and Zhou, 2018) VGG-16	1) used VGG-16 as a feature extraction module, FSSD to detect vehicles 2) Proposed an orientation-aware bounding box (OABB) to extract the direction of the target, effectively segmenting the target from the background, and therefore more effectively separating the target in dense vehicles
Recognizing Diverse Construction Activities in Site Images via Relevance Networks of Construction-Related Objects Detected by Convolutional Neural Networks (Luo et al., 2018)	equipment worker	2018	Faster R-CNNs ResNet-50	1) defined multiple behavior patterns through the spatial relationship between workers and materials, and established an associated network based on the target detection results, to directly use static images to identify construction activities
A deep learning-based approach for mitigating falls from height with computer vision: Convolutional neural network (Fang and Zhong, 2019)	worker support	2019	Mask R-CNNs	1) detect workers and structure supports based on Mask R-CNNs 2) proposed the Overlapping Detection Module. The bounding boxes and masks generated by Mask R-CNNs were used as inputs. If the mask of the worker and supports overlap, the behavior of this worker was unsafe

in the construction industry for a long time.

4.2. Research cases

Shallow learning algorithms were mostly used for safety management in the construction industry. Seong et al. (2017) proposed a safety vest detection method which could be the precursor to on-site people detection. This method uses the color pixels of the safety vests to detect the workers. Three algorithms (SVM, ANN and Logistic Regression) were used to classify pixels in different color spaces. The method proposed in this study can be used as a front-end method for onsite people positioning, recognition, motion analysis and other miscellaneous work which helps to determine the general position of onsite workers. Another research area identified by Ryu (Ryu et al., 2019) studied the feasibility of using a wrist-worn accelerometer activity tracker for onsite people motion recognition. The classification accuracy of four algorithms (kNN, multi-layer perceptron, DT, and multi-class SVM) was analyzed using different window sizes to study classification performance.

4.3. The advantages and disadvantages of shallow learning

Shallow learning has many advantages. Logistic regression is easily applied and does not require a lot of computational or storage resources; the Decision Tree-based approach is highly interpretable and able to process samples with missing attributes and unrelated features; SVM can deal with nonlinear problems utilizing little data.

However, shallow learning also has some shortcomings. Logistic regression is easy to underfit and the accuracy is relatively low when handling a large number of multi-type variables; decision trees are prone to overfitting and ignore the problems caused by inter-data correlation; SVM is not very efficient when handling large samples and sometimes it is difficult to find a suitable kernel function that can deal with missing data.

Therefore, shallow learning applications are used mostly in dealing with structured data in the construction industry, such as safety monitoring early warning indicators (Zhou et al., 2017). As for processing unstructured data such as image/video, deep learning is a better solution.

5. Applications of deep learning in construction

Deep learning took the lead in image processing in the second decade of the twenty-first century. According to the data types noted in the collected literature, the four main categories of deep learning methods in

Table 4
Examples of objection detection applications in automatic detection and evalution.

References	Categories of problem	Types of data resource	Deep learning technologies	Application details
Zhang and Yang, (2020)	Moisture damage of asphalt pavements	Radar image	ResNet-50 YOLO-v2	The newly-proposed incremental random sampling (IRS) approach is used to select a suitable plot scale for GPR images. ResNet-50 (pre-trained on ImageNet) and YOLO-v2 is combined to detect and locate the special waveform of moisture damage.
Li et al. (2019)	Sewer damage	Videos	ResNet-18	Making modifications on ResNet-18 to perform hierarchical classification to avoid the imbalance between defects and non-defects in CCTV images. First detecting whether there are defects, and then classifying the defects.
Kouzehgar et al. (2019)	Cracked glass of high-rise structures	Videos	Adam	Real-time glass surface crack detection is realized with a robot. The performances of different optimizers are compared, the result is that the Adam optimizer provides higher accuracy.
Lei et al. (2019)	Buried objects	Radar image	Faster R-CNNs	Faster R-CNNs are used for automatic detection and location of buried objects, which applied hyperbolic signatures from a gray GPR B-scan image.
Beckman et al. (2019)	Volumetric damage of concrete	Depth image	Faster R-CNNs	The bounding boxes generated by Faster R-CNNs are utilized as the fitting plane to execute the Random Sample Consistency (RANSAC) algorithm, which can perform surface segmentation. Depth information is used on segmentation results for damage assessment.
Kalfarisi et al. (2020)	Cracks in bridges, roads, tunnel, water tower, and building	2D image	Faster R-CNNs Mask R-CNNs	Faster R-CNNs are used to detect cracks and generated some frames of cracks, and then used SRFED to segment the cracks inside the frames. Mask R-CNNs is directly used to detect and segment cracks.

Table 5
Examples of image segmentation applications in construction.

References	Categories of problem	Types of data resource	Deep learning technologies	Application details
Alipour et al. (2019)	Crack of concrete infrastructure systems	2D image	FCN	Sensitivity analysis shows that this study can correctly detect more than 92% of cracked pixels and 99.9%of non-cracked pixels.
Wu et al. (2019)	Road pothole	2D image 3D point cloud	Deeplab-v3	Used Deeplab-v3 to segment the road image to extract two-dimensional candidate potholes
Deng et al. (2020)	Delamination and rebar exposure of bridges	2D image	Deeplab-v3 LinkNet	LinkNet (Chaurasia and Culurciello, 2017) is combined with the ASSP module in Deeplab-v3 to realize the pixel-level detection of bridge structure damage.
Balado et al. (2020)	Urban objects	2D image 3D point cloud	Inception-v3	A multi-directional 2D image (pc-image) of the target object is negated from the 3D point clouds, thereby enhancing the data.

construction can be categorized as: object detection, image segmentation, action recognition, and natural language processing.

5.1. Object detection

5.1.1. Object detection in safety during construction

Safety research in construction with deep learning focuses on the field of PPE, using object detection methods and algorithms.

From the studies listed in Tables 2 and 3, some common practices for using object detection methods in PPE inspection can be identified. These practices usually follow a three-step process: 1) using transfer learning

Table 6
Examples of action recognition applications in construction.

References	Categories of problem	Types of data resource	Deep learning technologies	Application details
Yu et al. (2019)	physical fatigue assessment	2D image	Stacked Hourglass Networks	Stacked Hourglass Networks (Newell et al., 2016) are applied to identify and locate key joints of the human body. However, it turned out to be difficult to provide accurate 3D motion estimations in the presence of severe visual impairment or a top-down perspective.
Kim and Cho (2020)	Road pothole	Sensors	LSTM	21 sensors are installed on a human body to directly obtain the key points, and then traditional machine learning algorithms were used to determine the combination scheme of the number and location of the sensors. Finally, LSTM is trained on the sequence data of the human key points generated in the previous steps in order to obtain an action recognition model for on-site people.
Slaton et al. (2020)	Activities of heavy construction equipment	Sensors 2D image	CNNs LSTM	Accelerometers are installed in key parts of heavy equipment to monitor their actions. The accelerometer readings are used as training data for the action recognition model, while video monitoring is used only for data annotation.
Zhou et al. (2019)	Attitude and position in shield tunneling	Sensors	CNNs LSTM	A hybrid model is established by combining wavelet transform (WT), CNNs and LSTM for dynamic prediction of shield machine attitude and position during shield tunneling. Wavelet transform is used to filter noise, CNNs are used to extract the basic features from the input waveform, and LSTM is used to predict the attitude and position of shield machines.
Krishna Lakshmanan et al. (2020)	Path planning for a cleaning and maintenance robot	Sensors State map	CNNs LSTM ACER	The state map (including the robot's current location and surrounding environment; which can be regarded as a kind of raster map) of the cleaning and maintenance robot was the input to the network, the CNN-LSTM model was the decision network, and ACER (Actor-Critic with Experience Replay, a RL strategy) (Wang et al., 2017) was applied for training.

techniques and pretrained models (such as VGG-16, ResNet-50) for basic feature extraction, 2) detecting workers and PPEs with object detection models (such as Faster R-CNNs (Ren et al., 2015), Single Shot Detection (SSD) (Liu et al., 2016), Mask Region-CNN (Mask R-CNNs) (He et al., 2018), You Only Look Once (YOLO)-v2 (Redmon and Farhadi, 2017), and YOLO-v3 (Redmon and Farhadi, 2018)), 3) developing classification or recognition schemes based on the detection results, such as traditional machine learning algorithms, specific mathematical skills, or direct usage of deep learning networks.

In the final step, the object detection results are further processed to provide the final outcomes. It can be seen that traditional machine learning methods or specific mathematical techniques are suitable for small data sets while the deep learning model is a better solution for large data sets (Nath et al., 2020). Deep learning-based object detection algorithms, such as Faster R–CNN, YOLO, mask R–CNN and SSD, are widely used in this field, and attain a high precision rate or other good performance measures when applied in practice. What cannot be ignored is that there are many limitations regarding the application of object detection methods. The main limitations are dataset sizes and cluttered sites. Cluttered sites will also cause occlusions, poor illumination and other adverse conditions, which may affect the performance of these deep learning methods (Fang and Ding, 2018).

5.1.2. Object detection in automatic detection and evaluation

Over time, due to multiple factors, cracks or defects are likely to appear on the surface of civil infrastructures. The development of automated testing tools will not only ensure effective maintenance management and guarantee maximum use of the facilities through prompt fault

Table 7
Examples of text mining and miscellaneous applications in construction.

References	Categories of problem	Types of data resource	Deep learning technologies	Application details
(Zhong and Pan, (2020)	Text classification	Accident narrative text	CNNs	The accident narrative text is segmented, expressed as a real-valued matrix through word embedding, and finally classified using CNNs, so as to realize automatic classification. The Latent Dirichlet Allocation (LDA) model is applied to examine the exiting interdependence between causal variables for visualization of the accident narrative.
Fang et al. (2020)	Text classification	Safety reports	BERT	BERT is applied for automated text classification of near-misses from safety reports. The main limitations are a lengthy training time and too few categories in the database, which makes the developed model unable to contain all types of near-misses. The training data is translated from Chinese to English, and the quality of the translation may affect the performance of the model.
Pan and Zhang (2020)	Text mining	BIM log data	LSTM	The BIM design logs that automatically record the modeling process in detail are the basis for data collection and data mining. The LSTM-based intelligent command prediction method proposed in this research generates specific knowledge in the form of probability, which can quantitatively provide users with suggestions for the next most likely command class through the entire design process.

detection but will additionally reduce the need for human resources. Table 4. lists some typical example studies that show the processes and several key points of using object detection methods to detect defects in buildings or materials.

In summary, there are two main methods for automatic defect detection and evaluation: 1) when the defect is on the building surface, the data source is the image of the building surface, and an object detection algorithm is used to detect the defect; 2) when the defect or detection target is not on the surface, ground penetrating radar or other detection devices are usually applied. Generally, the detection results of these devices are waveform diagrams. In this case, object detection methods are used to locate anomalies in the waveform diagrams, which represent defects.

In the field of the automatic detection and evaluation of sewer pipes, roads, bridges, buildings and other materials, there is an underlying issue in that the data sets are generally unbalanced. In a sample image, the defect typically only occupies a small part of the image, and the remainder of the image contains non-defected structures. This is the source of dataset imbalance issues as the non-defected part is substantially greater than the defected part. This problem may be solved by modifying the model according to (Li et al., 2019) recommendations. Furthermore, a class weight factor can be added to the loss function, increasing the proportion of the defected parts in the dataset, and thereby alleviating the issue of imbalance.

5.2. Image segmentation

Long et al. proposed FCN (Long et al., 2015) in 2014 – the pioneering work of applying deep learning in the field of image segmentation. Both FCN and DeepLab-v3 (Chen et al., 2017) are examples of semantic segmentation, while Mask R-CNNs is an example of instance segmentation.

Image segmentation is mainly used in construction to segment infrastructure surface images for automatic defect detection. Table 5 lists several examples of image segmentation used in construction. Two of these studies (Wu and Yao, 2019) and (Balado et al., 2020) applied different approaches in comparison to the others. Wu and Yao (Wu and Yao, 2019) applied Deeplab-v3++ for road pothole extraction. In 2D images, the texture features of potholes and plaques are similar, thus potholes cannot be directly identified by segmentation results alone. In this research, depth information is used to distinguish potholes from patches in order to conduct automatic detection of road potholes. Balado (Balado et al., 2020) proposed a method to segment and recognize urban objects by combining 3D point cloud data and urban images. The ground and walls are detected without deep learning image segmentation. This is because their 3D point clouds form a plane, which is characteristic of many urban objects. By removing the 3D point clouds of the ground and walls, urban objects can be easily segmented. Then, the 3D point clouds of the segmented urban object are projected onto multiple 2D images from different angles, which leads to the enlargement of the dataset (so-called data augmentation). Finally, the authors used Inception-v3 for classification. These two studies show the potential of applying image segmentation combined with non-image data, which may be a new direction in applying deep learning in the construction industry.

5.3. Action recognition

Action recognition is a challenging subject in computer vision as it needs to analyze not only the spatial information of the object, but also temporal patterns. A suitable method for better extraction of spatial-temporal features is the crux of the issue in action recognition, and deep learning can play a vital role in this. Table 6 lists typical examples of action detection in the construction industry. Based on the examples presented in this table, one may conclude that it is difficult to detect the actions of people or equipment solely through the use of images or videos. Therefore, the use of sensors is suggested as the data generated from them are much easier to handle and analyze.

In general, the first step in action recognition is to define and detect key points. In construction, the targets of action recognition are the onsite workers or equipment. The key points can be detected through computer vision or deep learning technology. It is also possible to determine the location of the key points more directly with sensors, which can be achieved on site, especially for the equipment. The second

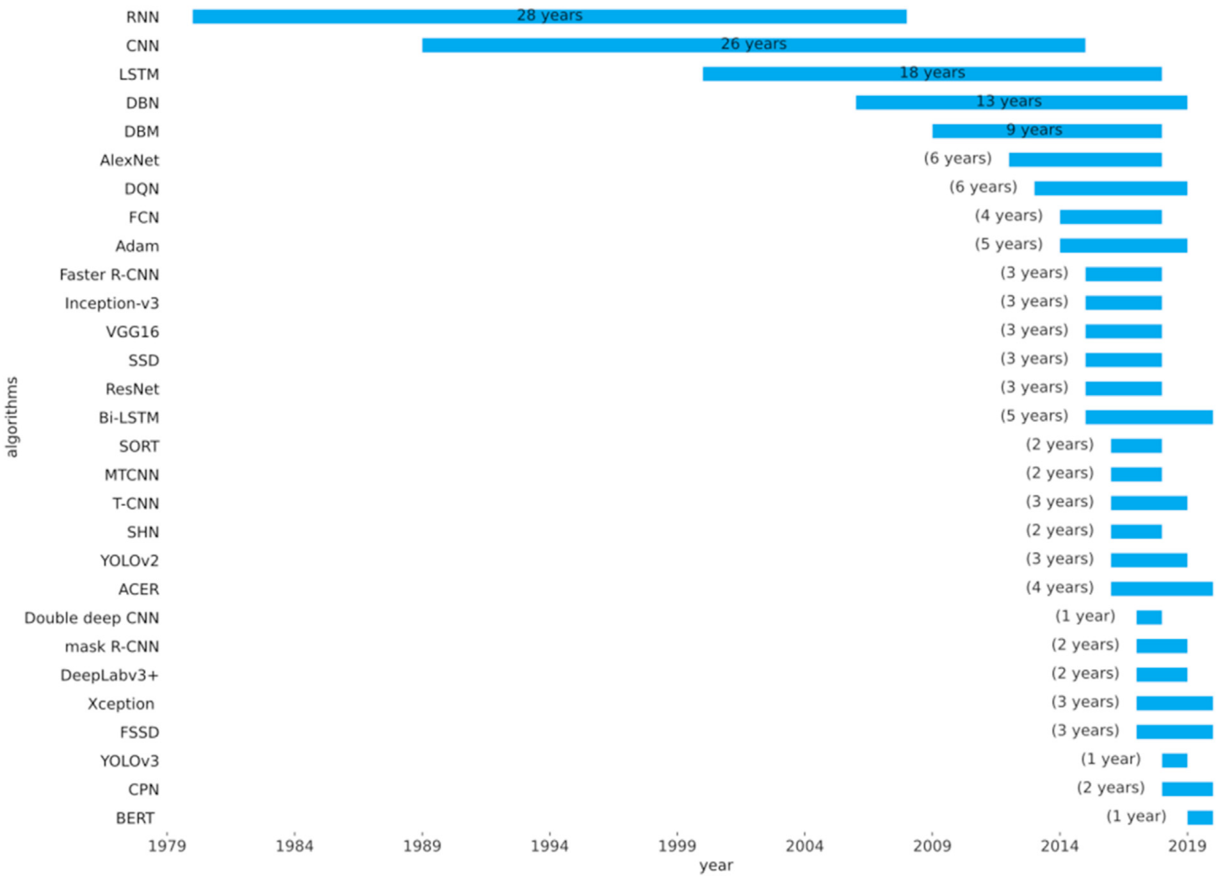

Fig. 6. The development time of deep learning algorithms and their actual application in construction.

step is to train an action recognition model according to the sequence data of the key points. As actions and data forms are serialized, LSTM turned out to be a good choice.

5.4. Text mining and miscellaneous

Text mining refers to the acquisition of valuable information and knowledge from text data, it is a method of data mining. The most important and rudimentary applications of text mining are text classification and clustering. The former is conducted by supervised mining algorithms, while the latter by unsupervised mining algorithms.

Project documents (such as accident reports and construction logs) store a lot of important information and hidden rules which can help Project Managers identify the causes and effects of accidents or specific patterns occurring in the project. This is highly beneficial for project management; however, manual analysis of these documents is very time-consuming and inefficient. Therefore, it is necessary to develop automated text mining tools. The list of selected papers addressing this issue is presented in Table 7. However, the main challenge for text mining is the non-repeatability of accidents and projects. Models trained for certain types of projects or accidents may function poorly while processing earlier unseen data.

5.5. Analysis and research trends

The time frame when deep learning algorithms were developed and the time of the actual application of these algorithms in construction has been compared in Fig. 6. Data from this figure can be compared with the data in Fig. 5, which shows a substantial difference between the applications of shallow learning and deep learning in construction. In the case of older algorithms, the time span between the development of the algorithm and its application in construction was relatively long. For example, RNNs were proposed in the 1980s and used for obstacle avoidance for robotic excavators twenty-six years later (Park et al., 2008), CNNs were developed in 1989 and became popular after 2012, when they were used to detect trip hazards on sites (McMahon et al., 2015). Nowadays, the construction industry is highly aware of the potential benefits brought by new deep learning technologies and the time span between the development and the application of algorithms has been significantly reduced. For example, the YOLOv3 algorithm was published in 2018 and applied to achieve an automated structural defect detection system for sewer pipelines in 2019 (Kumar and Abraham, 2019).

6. Challenges and future directions

Currently, in the construction industry, machine learning has mostly been applied for supervision purposes. As for the automation of construction operation such as automated bricklaying, relevant studies are still in the initial stages of research. This is caused by the inability of machine learning technology to guarantee absolute accuracy. Once an error occurs, the resulting security threats (e.g., falling objects caused by machine misoperation) and cost losses are unbearable. In this chapter, some challenges and future research directions concerning the application of machine learning in construction are introduced.

6.1. Challenges

Despite the promising results stemming from the application of deep learning technologies in construction, a lot of research questions remain unanswered. Some of these challenges come from the machine learning algorithms themselves, some from the limitations of the construction industry.

The first limitation is the lack of data. Machine learning is a data-driven field. Machine learning algorithms require a large amount of training data to achieve performances which are good enough to be used in construction processes. Transfer learning technologies can reduce the demand for data volume, but the lack of data is still the major problem hindering the large-scale application of machine learning in construction. This is primarily due to the difficulties in manual data annotation and data acquisition in construction.

The second challenge is that the accuracies of some existing machine learning algorithms are not high enough for practical applications, a prime example being action recognition. The limitations of the algorithms hinder action recognition applications in the construction industry. Therefore, more effort should be made to improve the performance of the algorithms or to find alternative ways for solving these kinds of problems.

The third challenge is the complicated site environment, which limits the performance of machine learning algorithms. Complex environments can significantly affect the quality of images and other types of data.

6.2. Future directions

The construction industry is labor-intensive, which conflicts with current trends such as an aging population. With the gradual disappearance of the demographic dividend and an increase in labor costs, labor cost losses and the lack of onsite workers are becoming the greatest constraints on construction industry profits. Under these circumstances, it is an inevitable trend to utilize artificial intelligence technologies, such as machine learning, to improve the degree of automation in construction.

There are two main points to consider when assessing the application of machine learning in construction. Firstly, the field related to computer vision will develop rapidly, as the technology in this field is already quite mature, and the vision-related aspect is the most frequently employed element in the construction industry. The models for object detection or action recognition trained in previous projects can generally achieve good performance in other projects because the tasks they target remain constant. Safety problems in construction or automatic detection will be common and deep learning will play a more important role, while shallow learning will rather be employed for preprocessing prior to applying deep learning.

Secondly, data plays a crucial role in the applications of machine learning in construction. It is important to establish a public data set for the construction industry. A similar general-purpose dataset called ImageNet has greatly promoted research in the image processing deep learning field, so a construction-related dataset could do the same for construction automation. With these kinds of public data sets, researchers can focus more on deep learning algorithms.

7. Conclusions

As of 2000, machine learning technology has gradually been receiving significantly more attention in the construction industry and is playing an increasingly important role in the development of automated technologies. Despite the breakthroughs in machine learning research in construction, many challenges have yet to be completely resolved. The main challenges are data acquisition and overcoming the impact of the site environment. After thoroughly researching the literature on this topic, this paper suggests that multiple teams could jointly establish a large and complete database with the same annotation rules to ease the dilemma of data acquisition. At present, researchers in construction have mostly implemented machine learning as a tool for feature extraction or detection. The main innovation lies in using machine learning results for further judgment, rather than improving the algorithms themselves. A promising future research direction would be to fully understand the machine learning algorithms and combine them with the specific knowledge domains in construction to develop dedicated deep network models for the construction industry.

Declaration of competing interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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