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Deep learning in the construction industry: A review of present status and future innovations

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ABSTRACT

The construction industry is known to be overwhelmed with resource planning, risk management and logistic challenges which often result in design defects, project delivery delays, cost overruns and contractual disputes. These challenges have instigated research in the application of advanced machine learning algorithms such as deep learning to help with diagnostic and prescriptive analysis of causes and preventive measures. However, the publicity created by tech firms like Google, Facebook and Amazon about Artificial Intelligence and applications to unstructured data is not the end of the field. There abound many applications of deep learning, particularly within the construction sector in areas such as site planning and management, health and safety and construction cost prediction, which are yet to be explored. The overall aim of this article was to review existing studies that have applied deep learning to prevalent construction challenges like structural health monitoring, construction site safety, building occupancy modelling and energy demand prediction. To the best of our knowledge, there is currently no extensive survey of the applications of deep learning techniques within the construction industry. This review would inspire future research into how best to apply image processing, computer vision, natural language processing techniques of deep learning to numerous challenges in the industry. Limitations of deep learning such as the black box challenge, ethics and GDPR, cybersecurity and cost, that can be expected by construction researchers and practitioners when adopting some of these techniques were also discussed.

1. Introduction

Technology adoption in the construction industry is accelerating at a slower pace when compared to industries like finance, entertainment, healthcare and education [1]. Several businesses within these industries keep searching for innovative ways of staying ahead and remaining productive using technology. However, productivity in the construction industry is unstable or sometimes on the decline with under-investment in technology being a partial culprit [2]. Construction digitisation goes beyond acquiring the latest computers, software, servers or network even though these are also necessary components in technological advancement. The introduction of digital technologies such as Artificial Intelligence (AI), Big Data, machine learning and Internet of Things (IoT) into well-known construction practices can help place the industry among the top productive sectors [3]. However, if construction companies are ready to make this switch to digitisation, what about construction employees? The general reluctance of construction employees to embrace innovation if it involves a steep learning curve is a cause for concern. These professionals prefer the hands-on and practical way of working and are less interested in fancy tools that could take a while to learn [4]. Nevertheless, companies are still able to enforce compliance with these adoptions through disciplinary measures and training when necessary [5]. According to UKGOV [6]; digitisation will allow the construction sector to deliver cheaper, faster and smarter services with even low-cost labour. Studies have attempted to leverage the massive amount of data generated continuously in the industry to address challenges such as supply chain management, sustainability problems, project performance management, as well as reduced productivity and profitability. AI and its subsets remain one of the prominent technologies adopted for tackling these drawbacks.

The advent of AI has brought about an attempt to replicate the acute reasoning and problem-solving capabilities of the human brain [7].

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Application areas of AI were limited in the beginning since the field had little recognition [8]. However, AI is starting to gain its deserved significance with the recent emergence of new algorithms that keep evolving and maturing. Neural networks, particularly deep learning, is one of these algorithms. Neural networks have been around for a while and were introduced as algorithms that use layers of connected nodes to mimic the neurological system in solving problems. Famous neural networks such as the multi-layer perceptrons (MLPs) were mainly used for recognition, classification and regression problems [9]. However, the major breakthrough came at the 2012 ImageNet large scale visual recognition challenge where Convolutional Neural Networks – a deep learning variant was used for image recognition [10]. The adoption of deep learning for similar tasks have been on the rise ever since. The strength of the algorithm lies in the extra layers it uses for better extraction of characteristics (features) within the problem it is trying to solve [9]. This efficiency, however, comes with additional computational requirements.

Researchers in the construction industry have made several remarkable attempts to keep up with the pace of applying deep learning. The rapid advancement of GPU-accelerated computation techniques and availability of structured and labelled data has contributed to this adoption within the industry. Still, the level of efficiency achievable with the available unlabelled data remains unclear even though deep learning is good at supporting this kind of data [11]. It is therefore paramount to review existing applications and identify gaps in research which are yet to be addressed. To achieve this aim, this study first provides foundation knowledge on deep learning and then discusses existing implementations in construction. The study goes on to highlight prevalent challenges attributable to these and similar implementations. The paper is structured as follows: Section 2 discusses the research methodology and article selection process adopted in this study. Section 3 briefly introduces deep learning and its architectures, while section 4 discusses applications to constructionspecific challenges. Section 5 presents future innovations and prospective challenges that could arise from the use of deep learning. Finally, section 6 summarises the research findings and suggests future research directions.

2. Research methodology

An extensive literature search was conducted to identify publications on existing applications of deep learning in the construction industry. Queries were run on two accessible journal databases: Scopus and ScienceDirect for dates ranging from 2012 to 2020 (exceptions were made for some conceptual theories dating earlier than 2012). The chosen dates were largely influenced by the deep learning revolution that happened in the period and also the recent adoption of deep learning in the construction industry. Deep learning became popular with the achievements of convolutional neural networks in the 2012 Imagenet Large Scale Visual Recognition Challenge (ILSVRC2012), and applications in the construction industry gained significance only as recent as 2014. It was observed from the query results that most of these researches focused on using specific architectures for state-of-the-art implementation, hence the reason for our choice of deep learning architectures. A search was carried out using keywords such as "deep learning", "deep learning in the construction industry", "recurrent neural networks", "deep neural networks", "convolution neural networks", "Auto-Encoders". More focus was placed on construction journals to further streamline our query towards the aim of our research. Also, query results were limited to just English publications.

Articles were selected based on the title of the publication and the abstract. The final selection process involved the use of the 2017 Journal Citation Report (JCR) science edition for recognisable impact factors. As such, papers published in a journal that did not have a JCR recognisable impact factor were discarded. A total of 45 articles were reviewed and were mainly published in journals such as Advanced Engineering Informatics, Automation in construction, ICTACT journal of soft computing, Construction and Building Materials, Journal of Constructional Steel Research, Case studies in construction materials, Journal of Construction Engineering and Management, International Journal of Online Engineering, International Journal of Control and Automation, Sustainable Energy, Grids and Network.

3. Deep learning overview and architectures

The ability of intelligent systems to learn and improve through experience gained from historical data is known as *machine learning* [12]. Machine learning requires an appropriate *representation* of input data in order to predict accurately. For example, a machine learning algorithm that is designed to predict the likelihood of a building contractor bidding for a project does not need to question the contractor physically. Instead, the algorithm makes a decision based on historical data of the contractor's bid opportunities. Every representation of the project characteristics that enable the system to reach a decision is known as a *feature*. *Representation learning* (RL) helps machine learning algorithms not just to learn feature mappings but also the representation itself [13]. RL is usually not sufficient to solve the challenge of feature extraction, which often involves abstract features (patterns or groupings of more low-level features) critical to a prediction system's decision in real-world applications. *Deep learning* (DL) addresses this challenge by building complex representations from simpler ones and having multiple layers of abstraction. The algorithm allows models consisting of several processing layers to operate on and learn data representations using multiple levels of abstraction [14]. The relationship between deep learning, representation learning, machine learning and artificial intelligence ($DL \subset RL \subset ML \subset AI$) is depicted in Fig. 1.

A widely adopted approach used in training a DL model involves minimising the loss function – *the difference (error) between the network output based on the model parameters θ and the actual expected output y* through backpropagation [15]. This process can be challenging since it involves searching through the parameter space of multiple layers of non-linear operations. Due to the depth of the network, this usually takes longer time than a shallow neural network, thereby resulting in a time-consuming training process. Also, a statistical trade-off exists in the bias – *closeness of the learning algorithm's guess to its target* and variance – *error in the responsiveness of a learning algorithm to changes in the training set* of predictive models since a higher bias (underfitting) would result in a lower variance in parameter estimation and vice versa [16]. *Overfitting* occurs when a model learns too closely to input data, and it affects its ability to predict unseen data (generalisation error) [17]. *Regularisation* is a technique used to tackle DL model overfitting [18]. The relationship between the loss function and the regularisation term $\Omega(\theta)$ is represented as:

$$\tilde{L}(X, y, \theta) = L(f(x|\theta), y) + \alpha\Omega(\theta) \quad (1)$$

In recent times, several deep learning architectures have been explored for solving image classification, object detection, object tracking and activity recognition challenges [19]. Fig. 2 illustrates some of the common application areas of some of these architectures.

3.1. Deep learning architectures

Like most neural network architectures, DL architectures are composed of layers (input, hidden and output), neurons, activation functions 'a' and weights $\{W,b\}$. The neurons act as feature detectors and are organised in lower and higher layers. Lower layers detect basic features and feed them into higher layers which then identify the more complex features. Although most deep learning architectures are applicable to a range of prediction or classification tasks, they are sometimes combined through ensemble modelling for better performance. This section describes some of the conventional deep learning architectures while highlighting their learning model and general

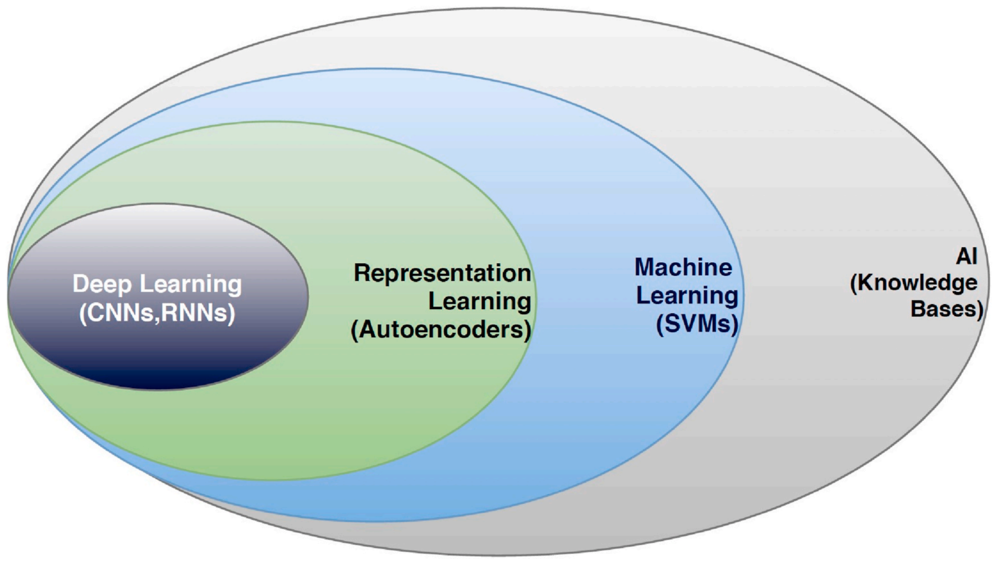
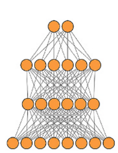
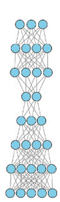
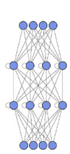
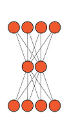
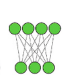
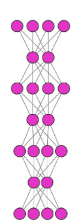
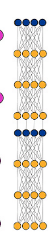


Fig. 1. Deep learning illustrated as a subset of Representation learning which is a subset of Machine learning, which is also a subset of Artificial Intelligence.

Fig. 2. Key Deep Learning Tasks: Deep learning addresses the limitations of hand-crafted feature extraction by automatically extracting features within an image. The algorithm excels in computer vision problems such as image classification, image captioning object detection and tracking. Deep learning is sometimes used to enhance and augment training data of low quality in order to improve a model's accuracy.

Table 1
General Application Areas for selected deep learning Architectures (DLA).

DLA	Key Function	Structure	General Application Areas									
			Image Classification	Image Captioning	Object Detection	Object tracking	Semantic segmentation	Activity Recognition	Data Augmentation	Sequence Recognition	Pattern Recognition	Feature Extraction
Deep Neural Network (DNN)	Representation learning		×	✓	✓	✓	✓	✓	×	✓	✓	✓
Convolutional Neural Network (CNN)	Image modelling		✓	✓	✓	✓	✓	✓	×	×	✓	✓
Recurrent Neural Network (RNN)	Sequence modelling		×	✓	✓	✓	✓	✓	×	✓	×	×
Auto-encoders	Dimensionality reduction		×	✓	✓	✓	✓	✓	✓	×	×	✓
Restricted Boltzmann Machines (RBM)	Higher level feature extraction		✓	×	✓	✓	✓	✓	×	×	×	✓
Deep Belief Networks (DBN)	Non-linear dimensionality reduction		✓	×	✓	✓	✓	✓	✓	✓	✓	✓
Generative Adversarial Network (GAN)	Generative modelling		✓	✓	✓	✓	✓	✓	✓	×	×	×

application areas. Table 1 summarises the essential functions, structure and general application areas of the discussed DL architectures.

3.1.1. *Deep neural network (DNN)*

A Deep Neural Network is typically a standard neural network with “depth”. The depth of a neural network is determined by the number of hidden layers (second and third layers in Fig. 3) between the input and output layers. Even though no threshold determines when a neural network can be identified as “Deep”, most researchers have agreed that a CAP (Credit Assignment Path) depth > 2 can be considered “Deep” while Schmidhuber [20] considers CAP > 10 to be very deep learning. DNNs are trained to model complex non-linear relationships by extracting uniquely abstract features that help improve its performance. Each layer of its multi-layered composition is dedicated to a particular feature identification [21].

3.1.2. *Convolutional neural network (CNN)*

CNNs are widely used for image processing applications [10]. The architecture came into limelight after the results of AlexNet (A deep learning network used for image classification) at the ImageNet competition [10]. Unlike conventional MLPs, CNN neurons are arranged in a way that matches the width, height and depth of images. In addition to input layers, output layers and activation functions, CNNs particularly have two additional layers, the convolution and pooling layers (depicted as the second to seventh layers in Fig. 4). The convolution layer convolves the image by using different convolutional filters and shifting the receptive fields gradually. It is common practice to insert a pooling layer between successive convolutional layers. The pooling layer, on the other hand, reduces the size of the output from the convolution layer by calculating the mean, max, median or other statistical features of the image at different pixels.

3.1.3. *Recurrent neural network (RNN)*

RNNs are best suited for handling sequential data. They outshine other forms of deep learning when processing time-dependent information [22]. Parameters across different time steps are shared based on sequential data properties. RNNs are mostly applied in video and speech processing since they can keep information on a previously processed audio chunk or video frame in order to make predictions of successive data. A RNN's output y_t at any time t is dependent not only on input x_t but also on x_{t-i} at times t i. Like other deep learning architectures, RNNs can also be trained using the backpropagation algorithm. More specifically, a backpropagation variant – Back Propagation Through Time (BPTT), is the standard training algorithm for RNNs [20,23]. A sample of RNN architecture is shown in Fig. 5.

3.1.4. *Auto-encoder (AE)*

Auto-Encoders (AEs) are mainly used for data denoising and dimensionality reduction [24,25]. Unlike other MLPs, AEs extract features from the input layer with the aim of replicating the same input data in the output layer. AEs involve an encoding and decoding process which forces the network to ignore the noisy part of the input and instead focus on encoding/representation of the more informative segments. The output layer in AEs has the same dimension (number of nodes) as the input layer (illustrated in Fig. 6) aimed at replicating the input data rather than having to predict Y given X like in most MLPs. The hidden layer plays a vital role by ensuring that the network actually learns the features of the input data and not just output the same version of the input data.

3.1.5. *Restricted Boltzmann machine (RBM)*

RBMs are a variant of Markov Random Field (MRF) used to learn probability distributions of its inputs even when the target outputs are not specified. Its architecture is a bipartite graph of hidden and visible units that may have symmetric connections between them but without connecting neurons within each unit (exemplified in Fig. 7). This form of

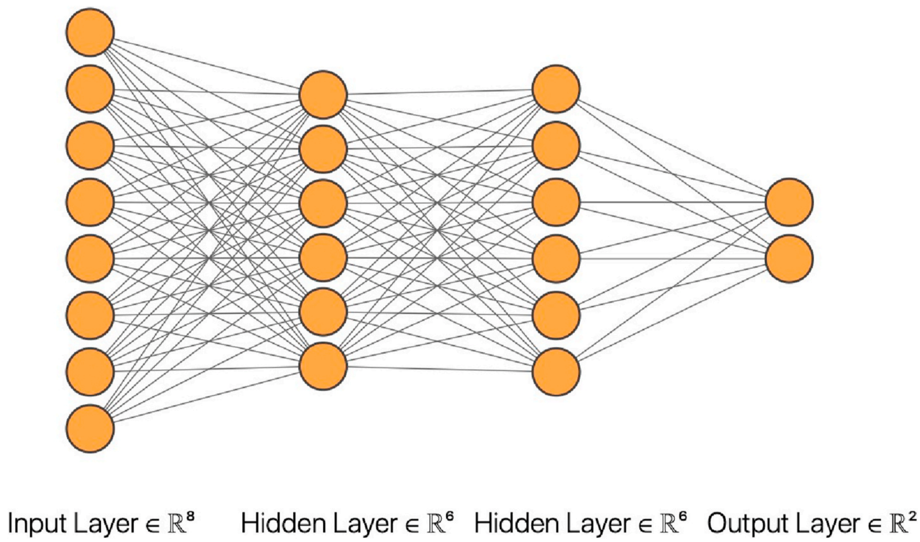


Fig. 3. Deep neural networks (DNNs) architecture.

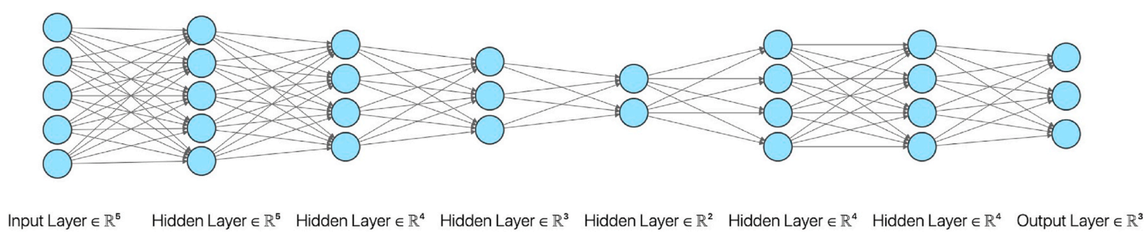


Fig. 4. Convolutional neural Networks (CNNs) architecture.

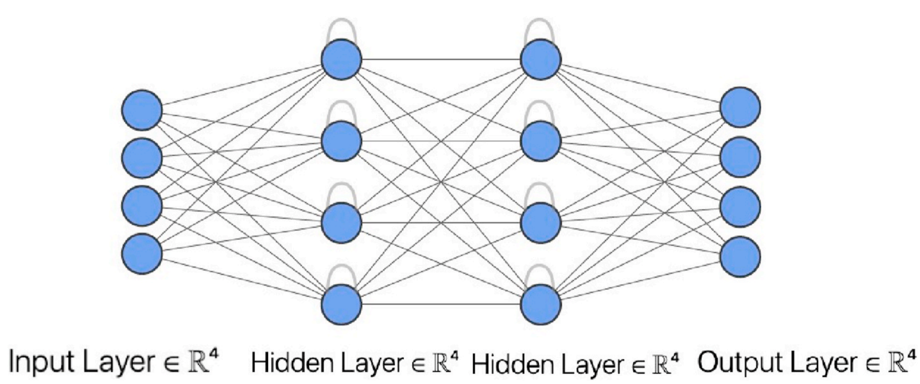


Fig. 5. Recurrent neural networks (RNNs) architecture.

connection ensures conditional independence of the hidden and visible units [26]. RBMs have been applied to feature learning, collaborative filtering and dimensionality reduction.

3.1.6. *Deep Belief Network (DBN)*

Connections in DBNs exist between adjacent layers but not necessarily between all units of every layer. The network is a generative model composed of a stack of SAEs (stacked autoencoders) or RBMs (shown in Fig. 8) which singularly are in some way limited by what they can represent. Training a DBN involves initial steps of unsupervised learning as the network learns input reconstruction through probability. A variant of DBNs, Convolutional DBN(CDBN) is well known for image processing and object recognition tasks. One key feature of the model is its ability to scale quite well with images with high dimensionality [27].

3.1.7. *Generative Adversarial Networks (GAN)*

The name "GAN" was proposed and popularised by Goodfellow et al. [28]. The network is composed of two sub-networks: (1) The Generative network – a conventional multilayer perceptron whose goal is to map the input vector X using its parameters θ_G to a feature space G (X, θ_G), with or without prior knowledge of the input vector data distribution. (2) The discriminative network – a binary classifier that finds the differences between the original data and data generated by the generative network. GANs are mostly used for data distribution learning (that is, generating same data distribution in output as is in input) from unlabelled datasets and image generation [29]. A sample of GAN architecture is shown in Fig. 9.

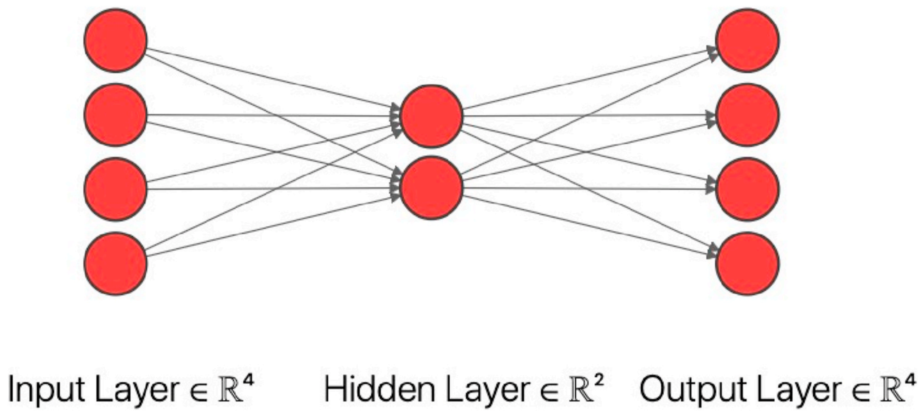


Fig. 6. Autoencoders (AEs) architecture.

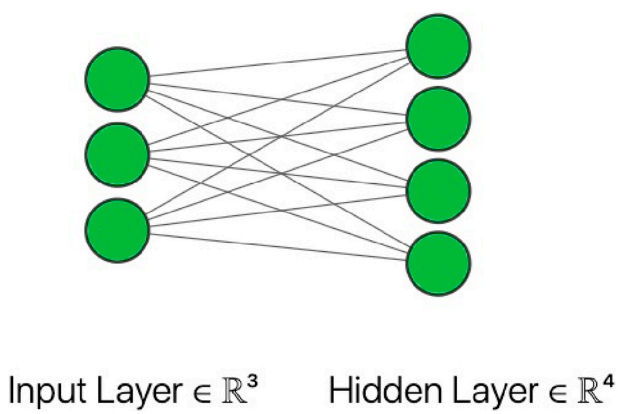


Fig. 7. Restricted Boltzmann machines (RBMs) architecture.

4. Existing DLA applications to construction-specific challenges

In this section, existing applications of the deep learning architectures highlighted in the previous section are discussed. The construction problems addressed using these techniques are mentioned while drawing attention to the accuracies of some of these applications. Some of the construction challenges presented in this section include Structural health monitoring and prediction, Construction operations and site safety, Building occupancy modelling and energy prediction, among others. Fig. 10 shows the number of reviewed publications where each deep learning architecture was applied. It is evident from the chart that CNN is the most implemented architecture in addressing construction problems and GANs are the least applied. Other architectures are also sparsely employed and need to be also explored. To this end, the next section highlights innovative ideas with more diverse applications. Table 2 below summarises reviewed papers, the architecture utilised, and challenges addressed.

4.1. *Structural health monitoring and prediction*

Early detection of damage in high-rise building structures has been the centre of structural engineering research in recent times. This has resulted in the proposition of visionbased [61] and vibration-based monitoring techniques [62,63]. Deep learning approaches like CNN, DNN and DBNs are being used to investigate the durability of building construction materials before and after construction. For instance, Deng et al. [40] proposed a **CNN** model developed with softmax regression to predict the compressive strength of recycled concrete before construction. The model was based on learning the apposite fine and coarse aggregate replacement ratio, cement-water ratio, as well as suitable combinations of recycled concrete. Similarly, a prediction tool based on a trained **DNN** model was proposed by Nguyen et al. [64] to predict the strength of foamed concrete and help engineers in mixture design optimisation of this type of concrete.

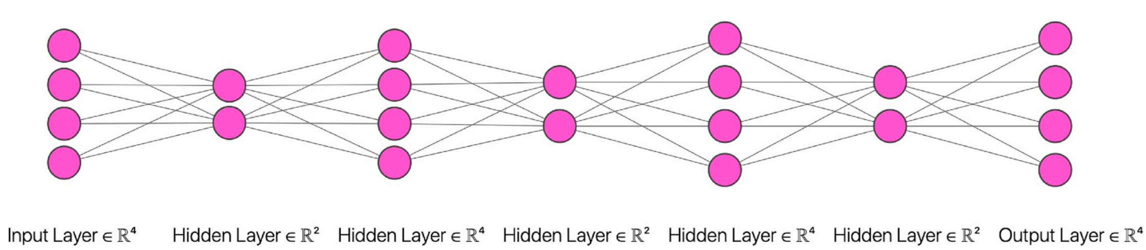


Fig. 8. Deep belief network (DBN) architecture.

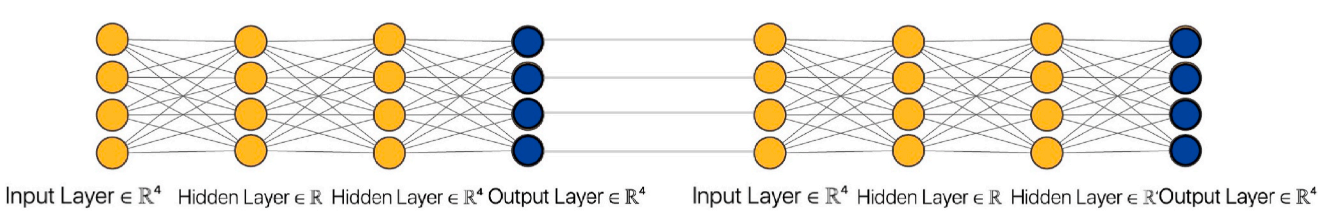


Fig. 9. Generative adversarial networks (GAN) architecture.

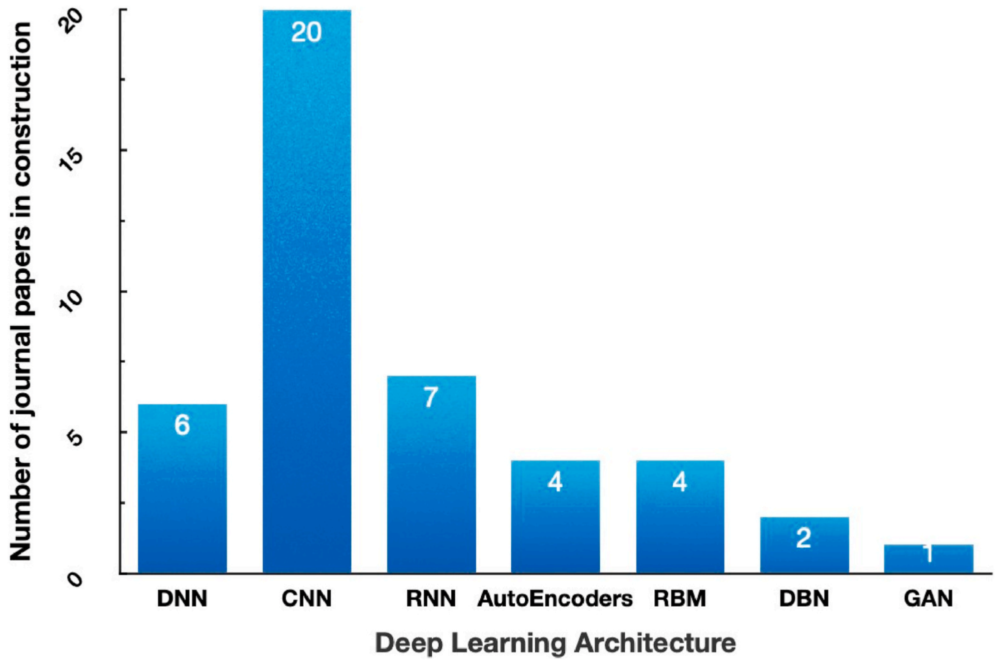


Fig. 10. Application chart of deep learning architectures in construction journals.

Table 2
Summary of existing deep learning applications in the construction industry.

Application	DNN	CNN	RNN	Autoencoders	RBM	DBN	GAN	Reference
Classification of Building Information Modelling 3D models				✓		✓		[30,31]
Housing/Construction cost prediction					✓			[32,33]
Building energy system behaviour prediction					✓			[34]
Short-term building cooling load prediction	✓							[35]
Pavement stress detection and classification		✓						[36]
Asphalt pavement rut prediction	✓							[37]
Building-design energy prediction	✓							[38]
Compressive strength and crack prediction of recycled concrete		✓						[39–42]
Safety guardrail detection		✓						[43]
Workforce Activity Assessment		✓						[44,45]
Long term electricity and heating load prediction			✓					[46,47]
Construction equipment activity recognition			✓					[48–51]
Heavy equipment parameters prediction			✓					[52]
Occupancy Modelling							✓	[53]
Worker's protective equipment detection		✓						[54–56]
Worker's postural evaluation		✓	✓					[57–60]

Structural damages resulting from concrete crack can also be detected after construction using deep learning. A review by Koch et al. [39] revealed that **DBNs** are now gaining interests in concrete damage assessment as they are suitable for concrete texture/shape analysis and classification. In the study of Dorafshan et al. [41]; a refined version of the conventional **AlexNet-DCNN** (Deep Convolutional Neural Network) was used for image-based concrete crack detection. Similar **CNN**-based approaches were implemented in the studies of Cha et al. [65] and Pathirage et al. [66] to detect concrete crack and autonomous crack, respectively. Also, Beckman et al. [42] used a depth camera and faster region-based **CNN** (RCNN) for concrete spalling damage detection. Rafiei & Adeli [67] highlighted the importance of ambient vibrations in the structural health assessment of completed structures. These vibrations indicate the local and global health indices of a building and a high vibration resistance suggests a healthy structure. The authors proposed an unsupervised **RBM** model for predicting the structural health index (SHI) of a building. In closely related research, Pathirage et al. [66] also proposed an **autoencoder** based framework for identifying structural damages. The proposed framework employs dimensionality reduction techniques combined with **DNNs** to learn the relationship between structural damage and vibration attributes.

In addition, road construction projects have seen applications of deep learning to asphalt and pavement rut prediction upon the realisation that conventional Mechanistic-Empirical Pavement Design Guide (MEPDG) functions are incapable of accurate predictions [68,69]. Gong et al. [37] combined both approaches and integrated **DNNs** with MEPDG for better rut prediction. The proposed DNN architecture took predicted rut data (asphalt concrete type, subgrade type and granular base type) as well as other features such as climate, traffic, structure and material parameters as inputs from the MEPDG. In closely related research, Khaitan et al. [36] proposed a **DCNN** model trained on Imagenet dataset to detect pavement stress and classification. This automated detection has remained a significant research focus for transportation agen-cies who are primarily focused on identifying cracks in Portland Cement Concrete (PCC) and Hot-Mix Asphalt (HMA) surfaces. Zhang et al. [70] also made a similar proposition of more fine-grained, pixel-level **CNN** technique for pavement crack detection.

In a completely different approach to structural condition evaluation, Zhong et al. [71] proposed a **CNN**-based method of classifying building quality problems. The suggested technique automatically classifies texts contained within a building quality complaint (BQC) document using word embedding techniques. The idea was to enhance the efficiency of complaint management.

4.2. Construction site safety

Construction tasks that involve manual operations can be physically demanding and often require abnormal postures that lead to temporary or permanent injuries and pain. Conventional methods of workers observation involve posture data collection through questionnaires and site observations. These methods are prone to subjective bias and are mostly inefficient [72]. Modern approaches of addressing postural-based hazards include computer vision-based [73,74] and wearable sensor-based [75,76] solutions. For example, the study of Yang et al. [60] combined both solutions by using wearable sensors and a variant of RNN (long short-term memory (LSTMs)) to examine a worker's lower body movements during physical loading. Likewise, the study of Zhang et al. [57] combined 3D-view invariant features from an onsite camera with **CNN** architecture for a better and more accurate postural ergonomic evaluation and classification. The 3D-view invariant features were needed for almost real-time non-ergonomic posture recognition of the arms, legs and back postures [58]. combined CNN and anthropometric planes to detect workers and their body joints. In another study, Yu et al. [59] used **CNN** combined with a physical fatigue model and biomechanical analysis to detect fatigue in construction workers automatically. Similarly, Weili et al. [77] used **CNN** for safety harness detection while Qi et al. [78] used the same approach for steeplejack detection. Both studies sought to address construction accidents caused by falls from heights.

The study of Zdenek et al. [43] investigated how to improve safety on construction sites by using **CNN** models for safety guardrail detection. The research was inspired by the fact that most construction accidents are caused by unguarded edges that result in falls from heights. In closely related research, Fang et al. [54] proposed a method of automatically detecting the use of personal protective equipment (PPE) by construction workers. The suggested approach used another variant of **CNN**, faster **RCNN** due to its high speed and precision in detecting workers without their hats from site images. Nath et al. [56] also used CNNs for multiple PPE detection (hard hats and safety vests) from images. Similarly, a single shot multibox detector (SSD) and **CNN** was suggested by Wu et al. [55] for detecting construction personnel wearing hardhats.

4.3. Workforce assessment and activity recognition

The study of Luo & Xiong [44] proposed a **CNN** model that monitors and assesses activities carried out by construction workers during reinforcement installation. Training and testing were carried out on a dataset which contained videos of workers during reinforcement installation in Wuhan, China. The model was intended to assist construction managers in ensuring that project deliverables were met. In a similar study by Fang et al. [79]; a method of automatically detecting if a construction worker is working within his/her certification restriction was proposed. The proposed system was composed of subsystems for video clips extraction, worker's face and competency identification and worker's trade recognition. Luo et al. [45] trained a model for recognising construction activities from still site images rather than videos. The model involved a two-step method of learning and was first trained to recognise 22 classes of construction objects using **CNN**. The second learning step clustered the identified objects into construction activities using a semantic correlation between two different objects. The model was able to detect a total of 17 construction activities in an entirely automated manner. Similarly, Rashid & Louis [48] used an LSTM-based **RNN** for real-time, automated construction equipment activity recognition. The suggested approach used data-augmentation techniques to generate time-series data for better and more reliable equipment recognition. The study of Seo et al. [74] further emphasised the capability of **CNNs** to train efficient classifiers for construction object detection.

A deep learning framework was proposed by Hernandez et al. [49] for heavy construction equipment activity analysis. Heavy construction equipment like tunnel boring machines (TBMs) are prominent for underground drilling. Recent studies have focused on the harmonisation and analysis of TBM operating status and parameters [80]. Being able to predict essential operating parameters for TBMs contributes majorly to this cause since the prediction of geographical conditions before initiating excavation can be quite challenging. A TBM parameter prediction approach proposed by Gao et al. [52] involved a combination of three different kinds of Recurrent Neural Networks – long-short term memory (**LSTM**) networks, gated recurrent unit (**GRU**) networks and traditional **RNNs**. Results of experiments proved that the three types of RNN-based predictors recorded reliable prediction accuracy of parameters including the thrust, velocity, pressure and torque. Similarly, Slaton et al. [50] in their work combined **CNN** and **LSTM** to predict the activities of heavy construction equipment (roller compactor and excavator) monitored using accelerometers. Sherafat et al. [51] used **DNNs** and Time-Frequency masks (TFMs) to achieve the same purpose. A comprehensive review and comparison of automated worker and equipment activity recognition methods was reported in the study of Ahn et al. [81].

4.4. Building occupancy modelling and performance simulation

Occupancy modelling helps predict the energy requirement of a building based on its potential number of occupants. This information is important for construction companies to be able to simulate the building requirements even before construction. Building facilities can then be properly allocated to ensure optimal energy efficiency based on simulation results. Chen & Jiang [53] proposed a **GAN** model for occupancy modelling. The model's reliability was tested and compared against two other conventional occupancy modelling approaches (Inhomogeneous Markov Chain (IMC) and agent-based model (ABM)), and results showed that the GAN model outperformed other approaches.

Likewise, Singaravel et al. [38] developed a **DNN** model capable of mimicking and outperforming the performance of a Building Performance Simulation (BPS) at an even faster response rate. The research aimed to match the ever-increasing requirements of identifying energy-efficient design options right from the building design stage. The results of the research showed that: (1) DNNs have higher accuracies when compared to a simple Artificial Neural Network, (2) BPS has a slower computation speed when compared to DNNs (BPS took 1145s to simulate 201 cases while DNNs required just 0.9s) (3) DNN models are reusable for learning new situations using transfer learning (a technique that involves reusing existing architectures or models known for good classification or prediction performances). (4) DNNs can be used for multi-task representations in component-based ML models. The authors concluded that deep models are highly suitable for exploring design space due to its high computation speed. Similarly, Fan et al. [35] developed a model using **DNNs** for short-term building cooling load prediction in their research. The authors concluded that deep learning enhances the performance of cooling load prediction systems, even without specifying the target output.

4.5. Building energy demand prediction

Innovations in smart technologies have empowered the prediction of long to mediumterm electricity consumption of residential and commercial buildings right from the design stage. Native information modelling systems have limited access to building schedule and equipment information required for forecasting. Rahman et al. [46] addressed this issue by developing a **RNN** model targeted at medium to long term electricity load prediction at an hourly rate. A performance analysis was carried out to test the reliability of the predictions using different electricity consumption patterns. The test cases included: (1) The public safety building in Salt Lake City, Utah (2) Residential buildings in Austin, Texas. Results showed that in the Salt Lake City public safety building test case, the proposed **RNN** models performed better than native MLPs in predicting HVAC critical and normal load profiles over an 83-day time horizon. Prediction of energy demand on the second test case (Austin, TX) for one year revealed more forecast errors in conventional MLPs compared to the RNN models.

Mocanu et al. [34] proposed the use of two RBM variants – Conditional Restricted Boltzmann Machine **(CRBM)** and Factored Conditional Restricted Boltzmann Machine **(FCRBM)** in the prediction of energy systems behaviours. Research motivation was drawn from the complexity of energy consumption prediction as it is influenced by factors such as occupancy patterns, climate change and thermal system performance. The complexity of other prediction methods resulting from the influence of these variables instigated the need for a novel prediction method. Experimental results showed the efficacy of **FCRBM** as it outperformed SVMs, RNNs and other ANNs. In similar research, **RNN** models were used by Rahman & Smith [47] to predict heating demand in commercial buildings for long periods. A framework was developed in the study to describe how these long-term predictions could help in the design of thermal tanks. The models were tested on University of Utah's campus building heat demands over several weeks and performed better than a 3-layer MLP. The authors also reported that the prediction accuracy of the models could also work for future sizing designs of a thermal storage tank.

4.6. *Construction cost prediction*

Construction cost prediction is usually influenced by factors such as the duration of construction, construction type, labour and equipment. These factors, as well as changes in economic variables and indexes (EV&Is), are often overlooked by conventional construction cost estimators. However, these features are essential in predicting an already hard-to-predict construction cost. Rafiei & Adeli [33] presented a construction cost estimation model based on an **RBM** variant **DBMs** (Deep Boltzmann Machines) and took EV&Is into account. Test data from the construction cost for 372 multi-storey and mid-rise buildings (three to nine stories) were used to verify the model's accuracy. Estimated costs and target costs were not far off with the DBM model, which recorded better accuracies than backpropagation neural networks and SVM models. In similar research by the same authors, housing cost was predicted right from the design stage using an **RBM** model and an eccentric genetic algorithm Rafiei & Adeli [32]. The proposed model took seasonal changes, time-dependent variables as well as other economic indices as input. The goal of the research was to help construction companies make decisions on whether to embark on a construction project based on the magnitude of the sale market.

4.7. *BIM model classification*

The adoption of BIM models has brought about a change in the construction industry over the years [82]. The introduction of 3D geometric models made BIM models even more robust, and have become the centre for recent academic research [83]. These studies focus on managing the complexities of 3D modelling and maintaining 3D model libraries for BIM. Conventional CAD 3D modelling has been able to generate enough 3D models sufficient for reuse in future BIM projects. Wang, Zhao & Wu [31] trained a deep learning model for 3D model classification in a BIM environment using Stacked **Auto-Encoders** (SAE). The authors went ahead to test the model on a publicly available 3D model library and achieved good results. Likewise, Wang et al. [30] also proposed another approach to 3D BIM model classification using **DBNs**. In their approach, the authors made use of a feature extraction algorithm to extract features of 3D models and generate a feature matrix. The feature matrix was then trained on a **DBN** architecture built from a stack of **RBMs** using an efficient training procedure. The proposed method also recorded good classification performance on a 3D model library taken from a PSB model database just like with the first approach.

5. Future innovations and prospective DL challenges

This section discusses potential DL application areas in construction and also highlights challenges that can be encountered in these applications.

5.1. *Future innovations*

The vast amount of data continuously generated by small and large construction firms provides opportunities yet to be explored by the construction industry, which is still at the nascent stage of applying AI solutions. This section discusses potential deep learning approaches to construction problems like Generative design, cash flow prediction and project risk analysis.

5.1.1. *Better building designs using generative design (GD)*

Designers and architects often need to explore several alternatives when designing complex artefacts like buildings and highways. Generative design helps designers with a wide range of design choices than what is manually achievable. GD allows automatic generation of design ideas based on initial design objectives specified [84]. The challenge then lies in the selection of the best design idea. The final design choice is dependent on the subjective discretion of the architect, indicating his taste and intentions. Deep learning can be exploited in the selection of the best design choice. First, the building requirements and constraints are identified using either CNN or RNNs. A system can then be developed for contextual design suggestions using GANs. Building images available on the internet can be downloaded using tools such as Google's custom search API and used to train GAN models. Generative adversarial networks (GANs) are known to be best suited for photorealistic image designs [85]. Also, autoencoders have been explored for the rapid design, synthesis and evaluation of engineered systems. An example of this application to offshore structures was demonstrated in the study of McComb [86].

5.1.2. *Cash flow prediction*

Cash remains a critical element in construction that affects the profitability and robustness of a project. Inadequate cash flow can negatively influence contractors' delivery since it would imply a shortage of resources to support their daily activities [87]. Hence, the need to predict cash flow over a time series spanning the period of project delivery. Contractors would appreciate a forecast of the cash flow for an opportunity right from the beginning of the tendering process as this information can be used to identify likely problems on time. Thereby leading to the overall success of the project. Also, contractors can assess the effects of determining factors/levers like sales, labour costs, material costs, margin, retention and risks on the overall outcome of the project. Several models and different approaches have been put forward for construction cash flow prediction. Common techniques include the use of fuzzy logic [88,89] and neural networks [90,91]. However, these models focused on just variable cost weights. Recurrent neural networks can be trained on time-dependent real-world data for cashflow prediction. Some level of uncertainty and explainability using interpretable models should also be included in these predictions as it would help improve the credibility of these predictions to project managers.

5.1.3. *Integration of chatbots and BIM*

BIM has been employed mostly by large subcontractors while its adoption by smaller subcontractors is yet to be fully explored [92]. A significant hindrance to the full implementation of BIM is the fact that existing BIM tools only provide mobile and web interfaces that might require some time and efforts to master. Input interfaces such as keyboards and touchscreen are unrealistic for construction workers whose hands are often busy with other construction works. The achievements of deep learning can be leveraged as it provides promising opportunities for the modernisation of BIM interfaces. More specifically, the integration of voice recognition techniques like natural-language-understanding (NLU) and automatic-speech-recognition (ASR) would provide construction operatives with a more natural form of interacting with BIM tools and an even faster way of exploring and reviewing 3D designs. Existing research has used voice recognition techniques for construction tasks such as recording and updating of site material logs [93] as well as project progress tracking and documentation [94,95]. Given the susceptibility of construction sites to noise, there is a need for voice technologies that can distinguish a site worker's voice from noise generated by construction equipment. A site worker should be able to query the BIM tool using commands like "*How do I install the window type A?* "or "*Show me materials in stock that meet this design specification*". Up-to-date information in BIM models can be queried and searched just by using few words to interact with the voice assistants. The introduction of this feature would improve the productivity of construction firms even at the level of downstream subcontractors.

5.1.4. *Retrofitting adviser for energy savings*

Building engineers have been able to integrate a Building Performance Simulation (BPS) system into the building design process to achieve a significant decrease in the contributions of residential and commercial buildings to overall energy consumption in cities. However, the industry still needs a retrofitting adviser to suggest what components of a building should be taken out or replaced in order to cut energy expenses. Building component recognition and classification can be achieved using CNNs after which the likely contribution of each component can then be estimated. These contributions should be compared with other substitute components to determine whether a replacement would result in improved energy savings.

5.1.5. *On-site safety and health monitoring*

Early detection of tiredness or fatigue in construction workers can go a long way in improving their productivity on a construction project and also facilitate early project completion. A deep learning model to detect fatigue in construction workers will enable project managers to quickly identify which of their workers need to be taken off for a short rest rather than keep them working and reducing their efficiency on the job. A model was proposed by Ding et al. [96] that currently outperforms other descriptor-based methods targeted at detecting unsafe behaviours on construction sites. The model was trained using a combination of CNN and LSTM. The same approach could be used to identify workers' fatigue from video feeds collected on construction sites.

Besides, researchers can leverage the achievements of CNN and other deep learning techniques in object recognition to encourage the use of robotic technologies in the construction industry. This would improve safety on sites as robots will be able to identify and avoid objects within their navigation area accurately. Evidence from previous studies shows that BIM is currently explored for providing navigation details to robots deployed for internal usage in buildings [97–99]. Future research could look at integrating object recognition models in similar systems to improve the robot's navigation accuracy.

5.1.6. *Project risk mitigation and analysis*

Construction projects encounter time, safety, quality and cost risks. A large project is prone to more risks since several sub-contractors work in parallel on job sites. Deep learning can help contractors prioritise risks on site and enable the team to direct their limited resources and time towards the bigger risk factors. To be able to perform a project risk analysis, milestones need to be identified and probable problem occurrences highlighted. A robust deep learning model can be trained to recognise milestones and tasks straight from Gantt charts using historical data on the project manager's landmarks. This approach would look to train a model directly on the chart, unlike traditional project management prediction models that use UML representations [100] for predicting. The charts used for training would contain milestones that are split into tasks and uniquely identified with an ID, name, expected duration, type and start date.

5.2. *Prospective challenges of DL applications*

Some challenges are persistent in the application of deep learning despite its success in several sectors. It is envisaged that some of these challenges are expected to be encountered with applications in the construction industry. The availability of data, data privacy and ethics, lack of in-house capability for DL, adversarial ML are some of the discussed challenges in this section. The presented list of challenges in the section is not exhaustive, and there are other challenges that could emerge with the application of DL in the industry.

5.2.1. *The black box challenge*

Earlier machine learning applications developed and applied models without having to worry about explaining how the models have arrived at those decisions. However, the need for prediction explanations has surfaced recently to have a better understanding of underlying learning techniques and also make better-informed decisions. Deep learning algorithms have to ascertain that the predictions made are right and can be trusted. For example, a DL system that estimates a reduction in the amount of concrete used should be able to explain this reduction. Project managers would benefit from these explanations as they would be able to better work with involved engineers in making decisions.

Researchers have recently come up with different explanation tools, some of which include: LIME (Local Interpretable Model-agnostic Explanations), DALEX (Descriptive mAchine Learning EXplanations), IML (Interpretable Machine Language). Unlike earlier proposed explanatory tools like Modeltracker [101] and Gestalt [102], these tools are now able to provide specific explanations of predictions. However, these earlier tools can still be used to complement LIME and other more recent interpretation tools since some of them require additional feature engineering and sometimes do not explain why a decision cannot be trusted. All of these models follow the model-agnostic rather than the model-specific interpretability method because the latter has the disadvantage of accuracy loss and single algorithm use. The model-agnostic approach does not inspect internal model parameters but extracts explanations by treating the model as a black-box while ruffling the model inputs and studying how it reacts [103–105]. Table 3 gives a summary of state-of-the-art machine learning explanation

Table 3
Summary of Interpretable model Algorithms.

Algorithm	Acronym	Completeness	Technique	Reference
Local Interpretable Model-Agnostic Explanations	LIME	Individual Explanation	Model Agnostic	[106]
Descriptive mAchine Learning EXplanations	DALEX	Individual Explanation	Model Agnostic	[107]
Partial Dependency (PD) Plots	PDP	Average Explanation	Model Agnostic	[108]
Interpretable Machine Learning	IML	Individual Explanation	Model Agnostic	[109]
Individual Conditional Expectation PD	ICEPD	Individual Explanation	Model Agnostic	[110]
Plot a Model's Residuals, Response and PD	PLOTMO	Average Explanation	Model Specific	[111]

models.

5.2.2. Data availability

Deep learning best works with the availability of large data; otherwise, models would struggle if trained on small data. Being able to access data for a particular problem freely is often difficult, most especially with the recent introduction of the data ethics and GDPR (General Data Protection Regulation) regulations. Data augmentation techniques involving minor alterations such as image rotation and flipping may be required to supplement limited training data. However, data augmentation can also lead to potential loss of relevant data or outliers needed for training. A wider range of data in the construction industry is structured, and data augmentation of this kind of data can be tricky. Fortunately, researchers have recently looked into solutions to help with automatic structured data extraction and to enable centralised focus on other aspects of training and model optimisation [112,113]. Nonetheless, most companies are still at the nascent stage of experimenting with these solutions as they are working towards understanding the challenges that come with the use of some machine learning tools for data extraction.

5.2.3. Ethics, data privacy and protection

The number one challenge most deep learning researches face is the issue of data privacy. Care must be taken with data sources though as the recent introduction of GDPR applies to all companies holding data from EU citizens [114]. More specifically, GDPR gives human rights protections against the use of a person's data without meaningful information about the logic behind the usage and also possible impacts. Ethical issues can be hard and complex. A deep learning model may introduce an unintended bias based on sex or race, for example. Although these models are targeted at increasing productivity and profit levels, they may result in unintended consequences. Researchers have therefore introduced guides as to what level of explanations is needed for an algorithm in order to prevent ethical complications [115–117]. Deep learning researchers still need to be conscious of this challenge and consider it in every research that involves data collection.

5.2.4. Lack of a one-size-fits-all model

All of the existing and suggested application areas discussed in preceding sections cannot be addressed using one generic deep learning model. Every problem needs to be addressed separately with a model trained specifically for that purpose. Techniques such as *transfer learning* (reusing existing architectures or models known for good classification or prediction performances) may be used to kick-start model training but adequate weight optimisation and hyper-parameter tuning is still needed. This is not a one-size-fits-all solution in its entirety, and this remains one of the main challenges of deep learning to be investigated.

5.2.5. CyberSecurity/adversarial ML

Deep learning models are prone to threat from hackers/adversaries as they constantly keep working relentlessly to ensure they remain innovative enough to beat security defences. In some cases, machine learning has even been thought of as a tool for possible malware threat creation [118]. A breach in a security defence believed to be resistant to human intervention but easily compromised using machine/deep learning techniques can bring about a drop in the level of trust that has been accorded with AI. Examples of security attacks using AI include password generation using Generative Adversarial Networks [119], CAPTCHA bypassing systems [120,121] and machine learning-based voice cloning systems [122,123]. In addition, deep learning is susceptible to a completely different result if an alteration occurs in its dataset [124]. Adversaries may take advantage of this feature of the algorithm and distort results that may have adverse implications. Recently, researchers have begun to look into this and have started exploring possible attack resilient and defensive models for deep learning [125].

5.2.6. Lack of in-house capability for AI/DL/ML

Finding engineering experts with enough information technology knowledge to apply deep learning techniques can be difficult. A reasonable approach could be to train these engineering experts on the job. However, this might not be feasible since these engineers best understand construction problems and optimal solutions and machine learning is out of their expertise. The same challenge occurs in outsourcing construction challenges to deep learning experts without construction background. These experts do not have an understanding of how the construction sector works. Also, deep learning experts with the technical expertise and experience to bring in innovative solutions to construction problems are generally scarce.

5.2.7. Cost implications

The implementation of state-of-the-art technology always comes at a price. Training a model on a deep neural network requires powerful machines with GPU processors in order to avoid months of training. However, these machines are not cheap even though they are capable of speeding up the entire training process to just a few hours. Companies that are willing to adopt deep learning technique should also understand that there is a financial sacrifice involved. It is worth noting that employing the services of deep learning experts can be quite costly. The exact cost implication of implementing deep learning is difficult to quantify as it depends on expertise requirements and hardware used for training. More studies should focus on finding cost-efficient approaches to the full adoption of deep learning in the industry.

6. Conclusions

This review was conducted with an underlying objective of advocating for the investigation of areas where deep learning could be applied in the construction industry. However, it is worth noting that deep learning is not an automatic algorithm with a plug 'n' play functionality. Just like any other machine learning technique, numerous procedures still need to be followed in order to achieve the best results. Steps such as data cleansing and preprocessing, data augmentation, hyper-parameter tuning, and model validation are critical to attaining optimal model performance. The omission of any of these steps or improper execution could result in models that do not meet expectations. For example, the selection technique when choosing a validation dataset is important because it influences a model's generalisability. The study of Rafiei & Adeli [33] is a perfect example of an application that failed to explore the model's validity in different scenarios. The proposed model fails in unbalanced economic scenarios as well as in unpredictable government policies. Similarly, hyper-parameter tuning is equally essential since it determines how quickly a model converges to its global optimum. The research conducted by Chen & Jiang [53] exemplifies how the chosen number of hidden nodes or weight initialisation of an architecture can influence a model's performance. In other studies, model predictions or estimations do not occur in real-time even though it could highly influence the quick implementation of mitigation measures. In structural health monitoring, for example, wireless sensors can be exploited for real-time estimates which could prove useful in the event of earthquakes or heavy winds. Despite these and similar limitations, the authors conclude that remarkable progress is being made in the adoption within the industry, and even more accomplishments could be recorded.

In conclusion, the authors have through this review revealed how the success of deep learning could be leveraged and successfully applied in the construction domain as it has been in other sectors. This acceptance will bring about a great leap in the productivity levels of construction engineers. Construction companies would also be able to save more on project cost and time management. This study has carefully reviewed the current state of deep learning applications in the construction industry and highlighted future opportunities. An overview of the deep learning algorithm and its architectures was presented. To achieve the aim of this study, the authors also carefully analysed previous researches that have implemented each of these deep learning algorithms. The authors believe that there is currently insufficient applications of deep learning in this domain as compared to the applications of other digital technologies like BIM and other machine learning algorithms. As a result, possible applications of deep learning have been proposed. However, these opportunities are not exhaustive, and future research can further explore additional areas of the industry where deep learning can be applied. Previous applications of deep learning have encountered challenges like ethics and data privacy, lack of in-house expertise, and it is foreseen that similar challenges might be experienced in the construction industry. The authors have, therefore mentioned the implications of some of these challenges to serve as advanced notice for future research. Highlighted challenges are not exhaustive either and should be further investigated in future research.

Finally, this research also highlighted some state-of-the-art interpretable models that could be exploited for deep learning explanations. Recent research has found that these models are a probable approach to finally solving the machine learning/deep learning "black box challenge". To the best of our knowledge, this is the first comprehensive review of the applications of deep learning in the construction industry and would serve as a utility tool for construction engineers and researchers who would like to explore the possibilities of exploiting the use of deep learning in tackling construction problems.

CRediT authorship contribution statement

Taofeek D. Akinosho: Investigation, Methodology, Writing - original draft. **Lukumon O. Oyedele:** Conceptualization, Resources, Supervision, Funding acquisition. **Muhammad Bilal:** Formal analysis, Writing - review & editing. **Anuoluwapo O. Ajayi:** Validation, Writing - review & editing. **Manuel Davila Delgado:** Visualization, Writing - review & editing. **Olugbenga O. Akinade:** Writing - review & editing. **Ashraf A. Ahmed:** Writing - review & editing.

Declaration of competing interest

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

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