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Automation in Construction 141 (2022) 104440

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Review

Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications

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ARTICLE INFO

Keywords:
Artificial intelligence
Machine learning
Deep learning
Automation
Internet of things
Building information modelling
Smart vision
Convolution neural network
Generative adversarial network
Artificial neural network

ABSTRACT

This article presents a state-of-the-art review of the applications of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in building and construction industry 4.0 in the facets of architectural design and visualization; material design and optimization; structural design and analysis; offsite manufacturing and automation; construction management, progress monitoring, and safety; smart operation, building management and health monitoring; and durability, life cycle analysis, and circular economy. This paper presents a unique perspective on applications of AI/DL/ML in these domains for the complete building lifecycle, from conceptual stage, design stage, construction stage, operational and maintenance stage until the end of life. Furthermore, data collection strategies using smart vision and sensors, data cleaning methods (post-processing), data storage for developing these models are discussed, and the challenges in model development and strategies to overcome these challenges are elaborated. Future trends in these domains and possible research avenues are also presented.

1. Introduction

Building and construction industry is slowly but constantly evolving embracing new technologies such as Digital Twin (DT), Building Information Modelling (BIM), Artificial Intelligence (AI), Internet of Things (IoTs) and Smart Vision (SV) to further enhance the efficiency, productivity, accuracy, and safety of the built environments. Industry 4.0, or the fourth industrial revolution, refers to the transformation of the traditional industry practices and manufacturing methods into autonomous smart systems using state-of-the-art digital technologies. Along a similar line of thought, building and construction industry 4.0 can be identified as the confluence of state-of-the-art industrial production systems, cyber-physical systems, and digital and computing technologies to redefine the building and infrastructure design, construction, operation, and maintenance while considering the circularity. Industrial production systems would include 3D printing and assembly, prefabrication and offsite manufacturing, cyber-physical systems would include IoT, robots, cobots, actuators, and digital and computing technologies would include BIM, AI, deep learning (DL), machine learning (ML), cloud computing, big data and data analytics, Blockchain, augmented reality (AR), digital twins. Due to this digital transformation, massive amounts of data are generated, and systematic analysis of these data and predictive modeling can be used to generate innovative architectural and structural designs, improve construction and operational safety, reduce the embodied and operational energy requirements, reduced construction and operational costs, increased construction speeds, improved payback periods and enhance sustainability.

However, analyzing massive amounts of data and recognizing patterns by human or conventional computer programs using rule-based approaches is not realistic. Therefore, the capability of AI to process massive amounts of data, recognize the pattern, and ability to build large-scale statistical models is a key facilitator of the building and construction industry 4.0 to process its digitized data. However, AI is a concept introduced in the 1940s, and in general, AI can be identified as the science of developing intelligent machines or computer programs to mimic human intelligence. In the last few years, the field of AI has seen a substantial improvement in various domains such as computer vision, robotics, autonomous vehicles, language translation, gaming, medical

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https://doi.org/10.1016/j.autcon.2022.104440
Received 24 November 2021; Received in revised form 7 June 2022; Accepted 14 June 2022
Available online 24 June 2022

diagnosis, speech recognition, and generative designs. The core technologies behind these advancements are machine learning and deep learning. Machine learning is a subfield of AI where predictions are made based on past experiences. Machine learning can meaningfully transform the data and learn useful patterns and representations using the input data. Deep learning is a subfield of machine learning, and it can be identified as a machine learning technique with multiple layers of simple and adjustable computing elements. Deep learning is generally performed using a stack of layers called neural networks. Deep learning with a stack of Convolution Neural Networks (CNN) is a widely used technique at present due to the enhancement of computer power and this is used extensively in the domains of visual object recognition, speech recognition, image synthesis, speech synthesis, and machine translation. Domains of AI, ML, DL and widely used algorithms are illustrated in Fig. 1: where MLP is Multi-Layer Perceptron, GAN is Generative Adversarial Network, CNN is Convolutional Neural Networks, RNN is Recurrent Neural Network, LSTM is Long Short-Term Memory Network and RBFN is Radial Basis Function Network.

There is a multitude of applications of AI, ML, and DL in the building and construction industry, and most of these applications came to reality in the past few years due to the increased computational power with high performing graphics processing units (GPU), availability of advanced ML and DL algorithms and relative convenience of implementation of these algorithms using widely used computer languages, ML and DL libraries, and software.

This paper aims to summarise and review the state-of-the-art ML/DL algorithms, data acquisition methods, applications of AI, ML, and DL in construction and building 4.0 and challenges. Applications of AI in the building construction industry have been divided into seven segments in this paper. These segments are architectural design and visualization; material design and optimization; structural design and analysis; offsite manufacturing and automation; construction management, progress monitoring and safety; smart operation, building management and health monitoring; and durability, life cycle analysis and circular economy as shown in Fig. 2. This review paper presents a holistic perspective of applications of artificial intelligence and computer vision in the building and construction industry 4.0 and this paper is unique compared to other papers because this covers the applications of AI and computer vision in the whole building lifecycle from the planning stage, construction stage to operational and maintenance stages.

It is essential to have a good understanding about cutting-edge ML and DL algorithms and the next section discusses the basics of these algorithms and how to obtain input data that are necessary to train these ML and DL models. Then the applications of AI, ML and DL are discussed aligning with the previously specified sections.

2. ML/DL algorithms and data acquisition

This section will give a brief introduction to the ML/DL process, widely used ML/DL algorithms and state-of-the-art sensors and vision technologies that can be used to collect data to be input into these algorithms.

2.1. Machine learning

Machine learning is a subfield of artificial intelligence where a computer observes a given set of data and generates a model based on the input data which can be used to solve problems. ML is different from traditional programming. In traditional programming, rules are coded in a computer language without explicit learning from the data. In contrast to traditional programming, ML uses data to generate predictive models which are then used for predictions with the unseen data. For some problems, it is extremely difficult to develop a rule-based program due to the complexity of the code and ML can be used in these instances provided sufficient data is available relevant to the considered problem.

Machine learning methods can be categorized in a variety of ways. One of the prominent methods of categorization of ML models is by the amount of supervision they get during the model training process. Here, the ML models can be categorized mainly as supervised learning, unsupervised learning, or reinforcement learning as presented in Fig. 3. Supervised learning is where the dataset has both the predictors as well as the results which are termed 'labels'. Initially, the supervised machine learning model is trained using the labeled dataset as shown in Step 1 of Fig. 3 and then inferences can be made for unseen data using the trained ML model. Two of the most widely used supervised tasks are classification and regression. In classification tasks, a discrete class label is predicted, whereas in regression tasks, a continuous value is predicted. Some of the widely used supervised learning algorithms are k-Nearest Neighbors, Support Vector Machines (SVMs), Logistic Regression, Linear Regression, and Neural Networks.

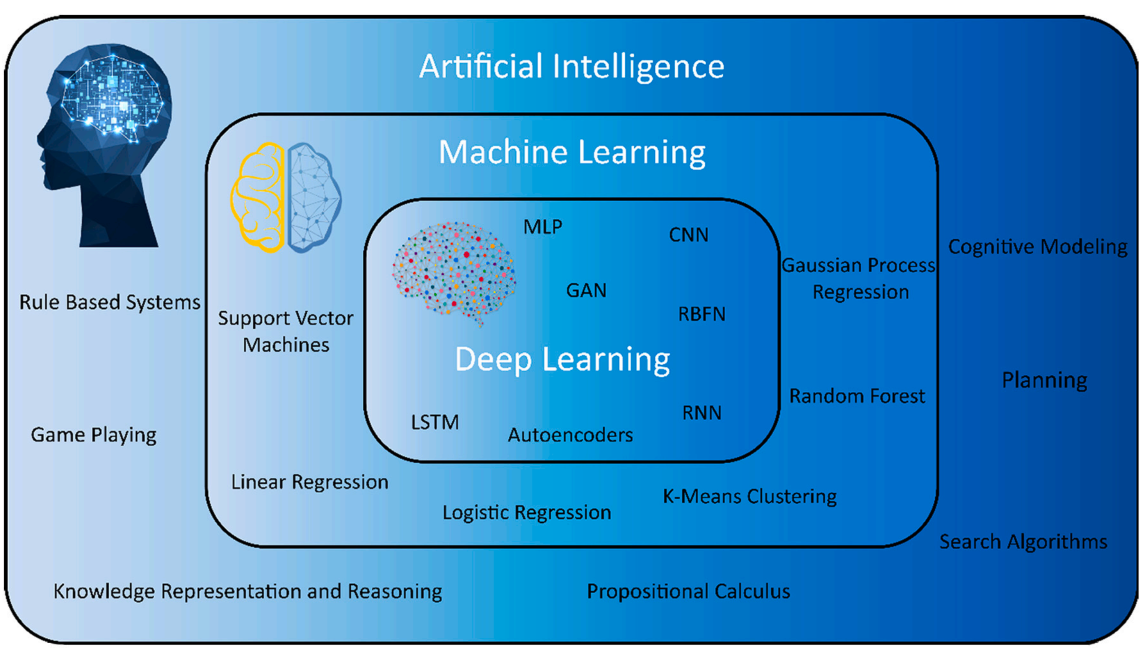

Fig. 1. Domains of AI, ML, DL and widely used algorithms.

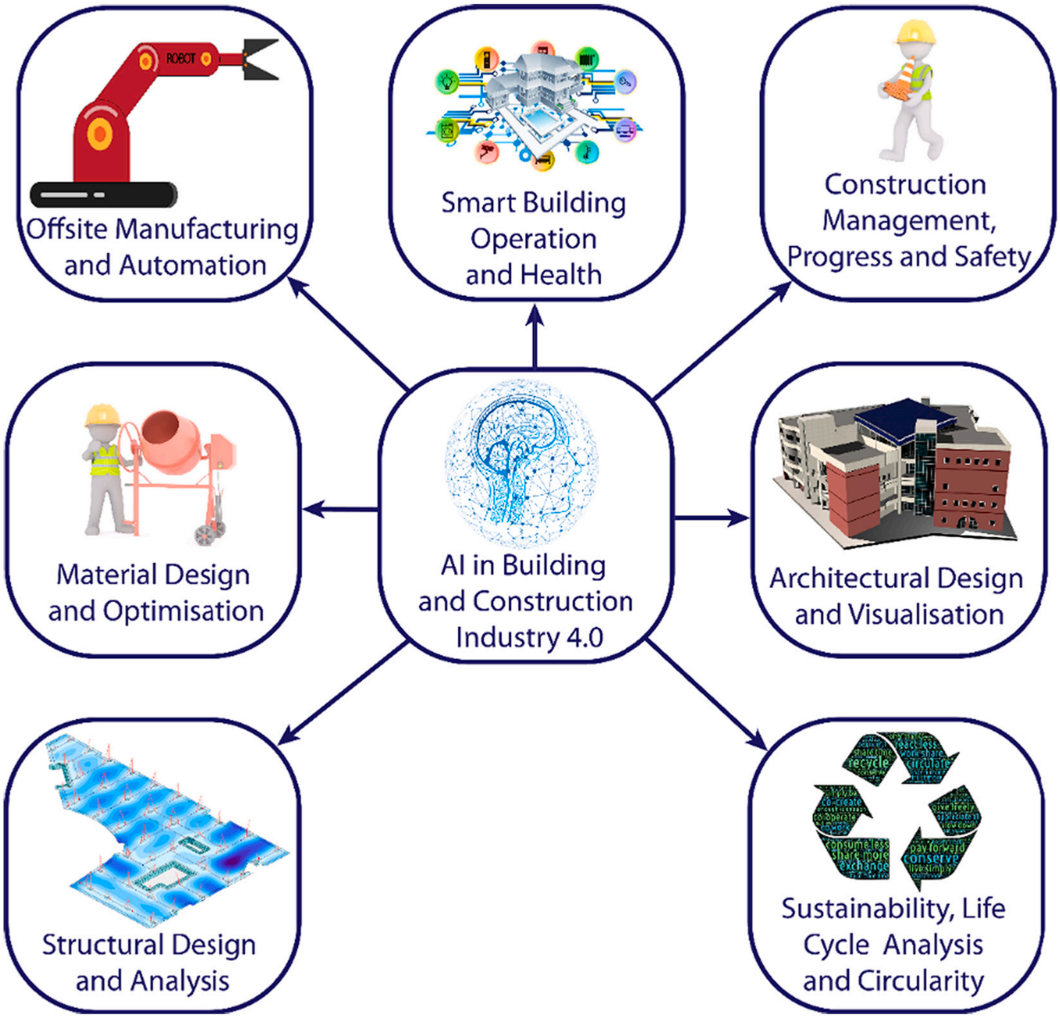

Fig. 2. Application AREAS of AI in building and construction industry 4.0.

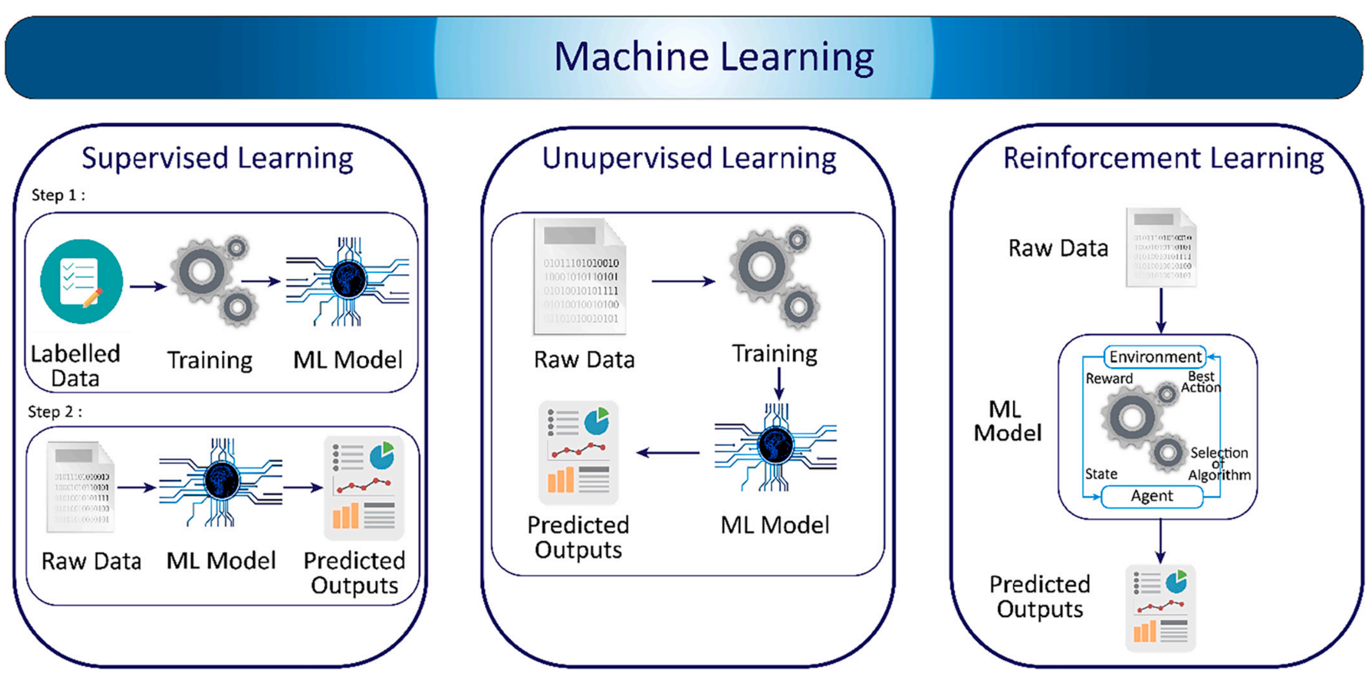

Fig. 3. Categorization of machine learning.

In unsupervised learning, an unlabelled dataset is used to determine hidden patterns or intrinsic structures in data. Unsupervised learning is widely used for tasks such as clustering, anomaly detection, and novelty detection, visualization and dimensionality reduction. Reinforcement learning is an ML method that trains the ML model by rewarding the desired behaviors and penalizing the undesired behaviors. The learning system known as reinforcement learning agent observes the environment and take actions that will incur rewards or penalties. The aim is to find the best strategy called 'policy' by achieving the maximum rewards over time. The action to be implemented in a given instance is determined by the policy.

In addition to supervised, unsupervised and reinforcement learning, another category called semi-supervised learning is sometimes used. Semi-supervised learning is used in instances where the dataset is only partially labeled.

2.2. Deep Learning

DL is a subfield of machine learning as shown in Fig. 1 and DL can be understood as the study of artificial neural networks and other related machine learning algorithms which consists of more than one hidden layer. Hence, the computation path in a deep learning algorithm has several steps from the inputs to the outputs.

Compared with the previously discussed ML algorithms, DL algorithms are generally useful with the higher dimensional data such as images, video and audio due to the presence of long computational paths. Some of the widely used DL algorithms in the construction and building industry are briefly introduced in the following subsections.

2.2.1. Feedforward neural networks

Feedforward neural networks (FNN), which are also known as the "Multi-Layer Perceptrons" (MLPs), are a widely used deep learning algorithm that only has information flowing in the forward direction without any feedback. The architecture of the FNNs is shown in Fig. 4, where circles represent the neurons. FNNs have multiple layers of neurons which are interconnected, and the input data is fed into the input layer and data is streamed through the hidden layers and the output layer yields the result.

A neuron in the hidden layer takes the input from the previous layer, calculates the weighted input ($w_i x_i$) with the addition of a bias term (b), and transfers the result through a nonlinear activation function, $f(x)$ as shown in Fig. 4. Various nonlinear activation functions such as ReLu, sigmoid, softmax, tanh can be used depending on the application.

The neural network can be trained using the dataset, and in this training process, the output from the output layers of the network is compared with the expected real values and the loss is calculated. There are numerous methods to calculate the losses such as mean squared error, mean absolute error, and binary cross-entropy. By summing up the losses for the entire training dataset and adding any regularization to reduce the overfitting, the cost function will be calculated. The aim is to minimize the cost function by adjusting the weights of the neural network by a method called backpropagation. The backpropagation calculates the gradient between error and the weights. Based on the gradient between error versus weights, optimization algorithms such as Adam, NAdam, Adadelta, Gradient descent can calculate the weights which minimise the loss. The same dataset is processed numerous times to adjust these weights and then the trained model with minimized error can be obtained. The trained models have the adjusted weights for each input data at each neuron and these weights are proportional to the relevance of input data for the output results. Finally, the model is used to predict output using new data.

2.2.2. Convolutional neural networks

Convolutional Neural Network (CNN) is a unique type of Artificial Neural Network (ANN) that can be used to process data with grid-like topology. CNNs are mostly used in classification using images and computer vision applications. CNNs mainly have three types of layers in their architecture. These are convolution layer, pooling layer and fully connected (FC) layer. In a typical CNN, convolutional layers are followed by a pooling layer, or another convolutional layer and the FC layer is at the end as shown in Fig. 5.

Input layer of the CNN holds the input image data. The convolution layer is the core building block of the CNN, and it uses a few components such as filter/kernel/feature detector and a feature map. The feature detector/filter/kernel is a 2D array of weights that is smaller than the size of the image. A dot product is calculated between the pixel value of the image and the weights of the filters, and the result is fed into an output array. This process is known as convolution and the feature detector is moved across the whole image to do this computation and determine the features. In this method, all the neurons of a layer are not inter-connected to neurons of the next layer like in NN (Fig. 4). Only neurons belonging to the filter are connected to the convolved neuron of the next layer (Fig. 5). The output from this process is known as a feature map or an activation map, or a convolved feature and this method revolutionized the deep learning by reducing the links between neurons leading to lower memory and processing demand for large input such as images, video, and audio. The depth of the output from the convolution layer will depend on the number of filters. After the convolution layer, an activation function is applied. The pooling layer is used to reduce the dimension of the image by taking the sum and average of the domain. This process is also known as downsampling. The fully connected layer is at the end of the network as shown in Fig. 5 and neurons in this layer

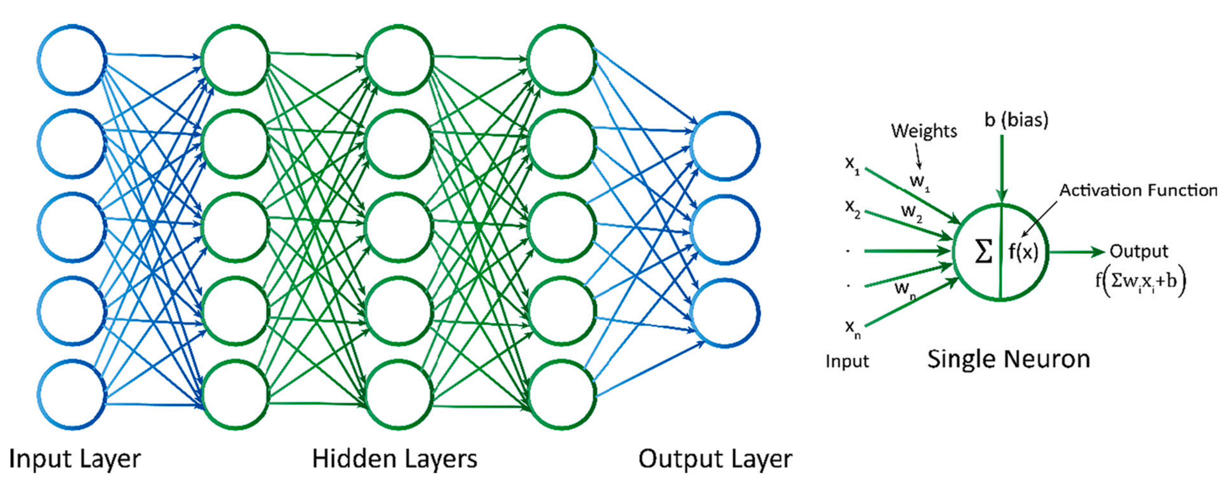

Fig. 4. Schematic of a feedforward neural network and a single neuron.

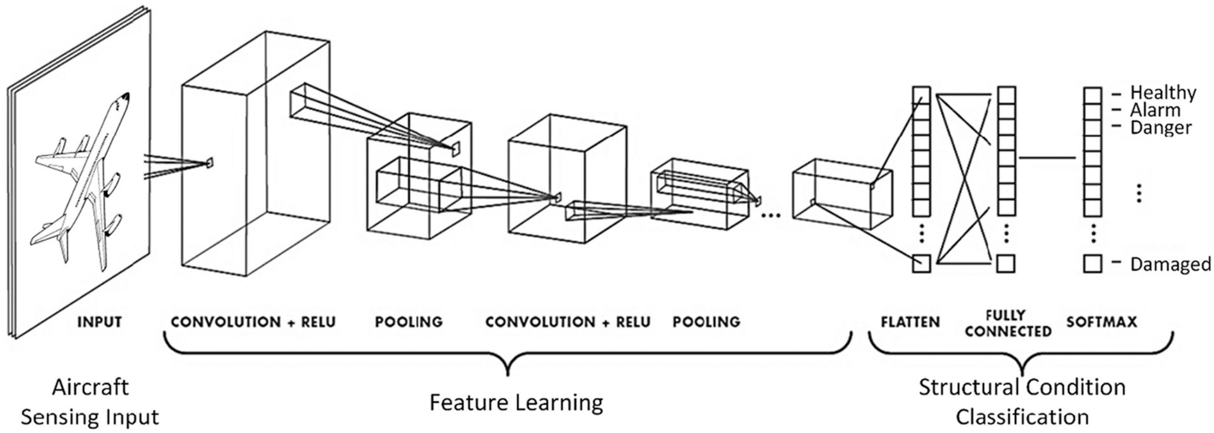

Fig. 5. Typical architecture of a CNN [1].

are fully connected to the activations in the previous layer. The filter size, number of filters, padding and strides are the hyperparameters that decide the architecture of the DL algorithms. The cost function will then be calculated based on the results compared with actual values, and the weights of the kernels are updated by backpropagating this error.

There are different CNN types that have been developed by various researchers. Some of the well-known CNNs are AlexNet, VGGNet, and ResNet.

2.2.3. Generative adversarial networks

Generative Adversarial Network (GAN) is a deep learning algorithm that focuses on generative modeling to create images, videos, and audios. Using GANs, new data instances can be created resembling the data in the training dataset. GANs use two types of deep neural networks called 'generator' and 'discriminator' in their architecture. The generator is responsible for creating new features resembling the trained data in the dataset incorporating the feedback from the discriminator. The discriminator is responsible for identifying the real data from the data created by the generator and providing feedback to the generator about the quality of the output images compared with the real images in the dataset. At the initial stages of the training, the generator creates obvious fake results and the discriminator can clearly identify these fake results. However, as the training progresses, the generator can create results that can deceive the discriminator and if the training process is successful, the discriminator starts to classify the fake data as real, and the accuracy of the discriminator reduces. Architectures of the GAN and conditional GANs are represented in Fig. 6.

There are several variations in GANs such as Progressive GANs,

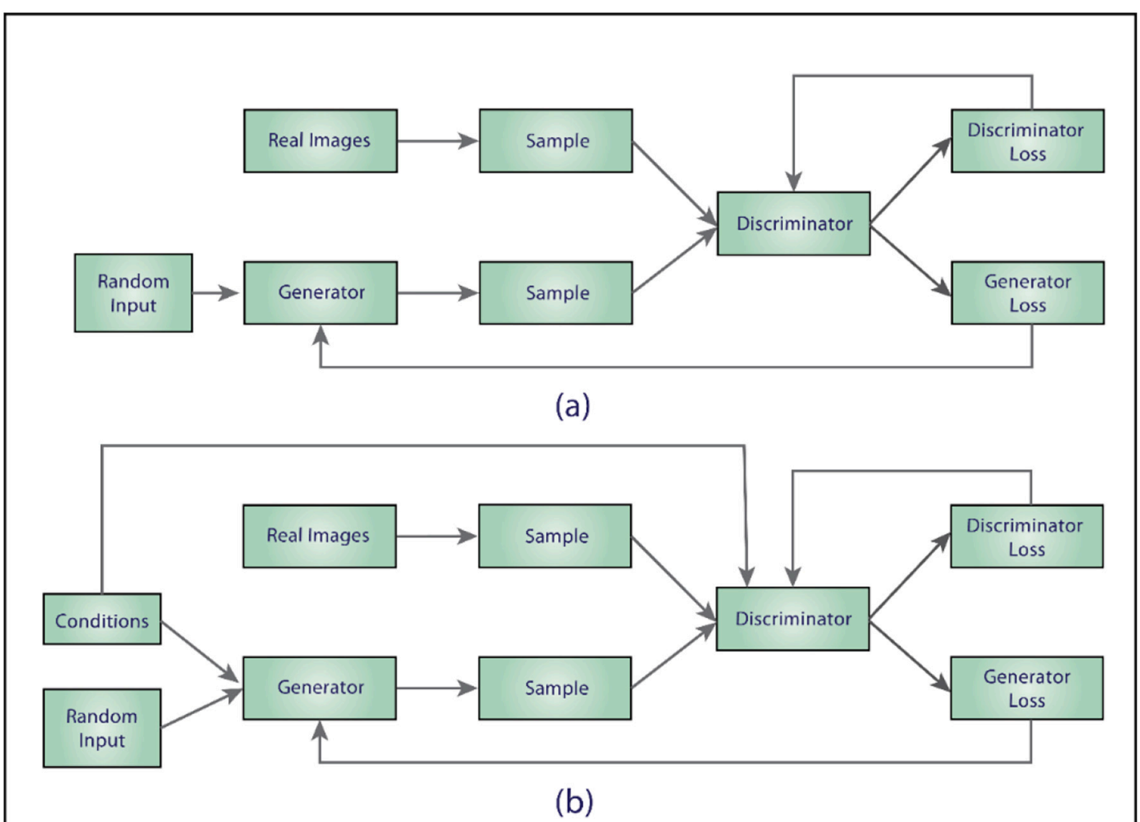

Fig. 6. Architecture of (a) GAN and (b) cGAN.

Conditional GANs, Cycle GANs, Text-to-image GANs, Super Resolution GANs, InfoGANs, DCGANs and Wasserstein GANs. Most of these algorithms have been used in generative designs in building and construction industry.

2.2.4. Variational autoencoders

Variational Autoencoder (VAE) is another deep generative algorithm that has been widely used. A VAE is an autoencoder whose encodings distribution is regularised throughout the training. An autoencoder consists of an encoder and a decoder neural network and a latent space (encoded space) as shown in Fig. 7. The encoder transforms old features into a new feature representation in the latent space and the decoder reverses this process to try to reconstruct the original features. An Autoencoder is trained using the data and the best encoding-decoding scheme is sought through an iterative optimization process. When the latent space is well organized, new data can be generated through the decoder by decoding the points sampled from the latent space. Hence, variational autoencoders regularize the training to ensure that the latent space is well organized to facilitate the generative process.

2.2.5. Recurrent neural networks

Recurrent Neural Network (RNN) is useful for generating predictions for sequential or time-series data. Similar to the ANNs and CNNs, RNNs use a dataset to train the algorithm. However, in contrast to the ANNs and CNNs, RNNs use prior inputs to influence the current input and output from the network as shown in Fig. 8.

RNN also has different variants such as Long Short-Term Memory (LSTM), Bidirectional recurrent neural networks, Gated recurrent units (GRUs) which have been used in construction applications.

2.2.6. Other machine learning and deep learning algorithms

In addition to the previously discussed algorithms, a multitude of ML and DL algorithms have been used by researchers in the domain of construction and building industry. Some of these widely used ML and DL algorithms are presented in Table 1 with very brief descriptions. Even though ML and statistics have inherent similarities, there are some obvious differences between the two. Statistics mainly focuses on drawing population inferences from a sample and the main aim of machine learning is to find generalizable predictive patterns using data.

2.3. Sensors and vision systems for data acquisition

ML and DL need data for training the models. The accuracy and versatility of the developed models will vastly depend on having a good dataset. The majority of the time for an end-to-end ML/DL model deployment is spent on the dataset which involves collecting, cleaning, analyzing, visualizing and feature engineering [2]. This section briefly discusses the approaches for data collection in ML/DL in construction and building industry applications.

Strain gauges, load cells, accelerometers, displacement measuring devices (Laser, Linear Variable Differential Transformer (LVDT), Draw-wire), thermal, Infrared (IR), Ultraviolet (UV), air quality, sound, and other basic sensors are widely used for data collection and these devices must be connected to a dedicated data acquisition system for data collection. Sensors are available with or without specific data collecting systems. These data collection systems could be a large-scale Input/Output (I/O) device, a portable data acquisition system, or a microcontroller-based device capable of immediately connecting to the internet. Most new sensors with embedded microcontroller-based data gathering systems include cloud compatibility via Internet of Things (IoT). IoT entails embedding sensors in everything with the help of smaller size, lower cost, and less energy consumption in new sensors and connecting them to the internet via specific protocols for information exchange and communications to achieve intelligent analysis, monitoring, and management over a cloud-based system. Widely used sensor types and connectivity protocols can be found in the literature.

RGB and Infrared Images and video-based vision systems are becoming increasingly used in deep learning algorithms and variety of cameras can be used for collecting image and video data. Cameras are distinguished by the presence of an image sensor connected to a specialized visual data acquisition system. Depending on the type of the sensors, there are various types of cameras available. The cost of the camera is primarily determined by the type of sensor utilized. The most prevalent are RGB and monochrome cameras, which cover the visible wavelength range of 380–700 nm and are inexpensive. In newer RGB and Monochrome cameras, CMOS sensors are utilized, whereas in older cameras, CCD sensors are used. CCD and CMOS sensors can detect signals in the 200 nm to 1100 nm wavelength range, which also includes the UV, VNIR. InGas sensors are utilized in the Short-Wave Infrared (SWIR) wavelength range of 900 nm to 2400 nm. To detect MWIR (2400 nm to 5000 nm), InSb sensors are employed. Based on these camera designs, there are primarily two forms of data gathering. One method is to capture the entire image and process the data based on pixels, which is then used in a vision system. A vision system consists of cameras attached to a dedicated computer or PLC that run vision software and can interface with other devices (robots) via output ports (serial, parallel, PCI). Reflected energy from objects, on the other hand, can be recorded in individual wavelengths utilizing spectroscopic imaging technologies alongside camera sensors. Once the reflected wave energy is recorded, chemometrics methods can be used to identify the substance based on its chemical properties.

3. Methodology

A three-step procedure was followed to identify the literature to be included in this review article. In the first step, journal papers, conference papers and books were extracted from sources such as Scopus, Web of Science, Google Scholar, SpringerLink and ProQuest. For the preliminary search of the literature, previously mentioned seven major sections (architectural design and visualization; material design and optimization; structural design and analysis; offsite manufacturing and automation; construction management, progress monitoring and safety; smart operation, building management and health monitoring; and durability, life cycle analysis and circular economy) were used as

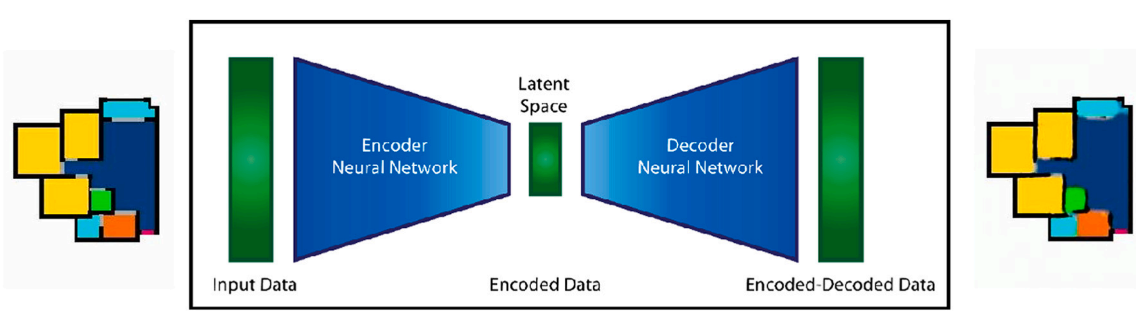

Fig. 7. Schematic of an autoencoder.

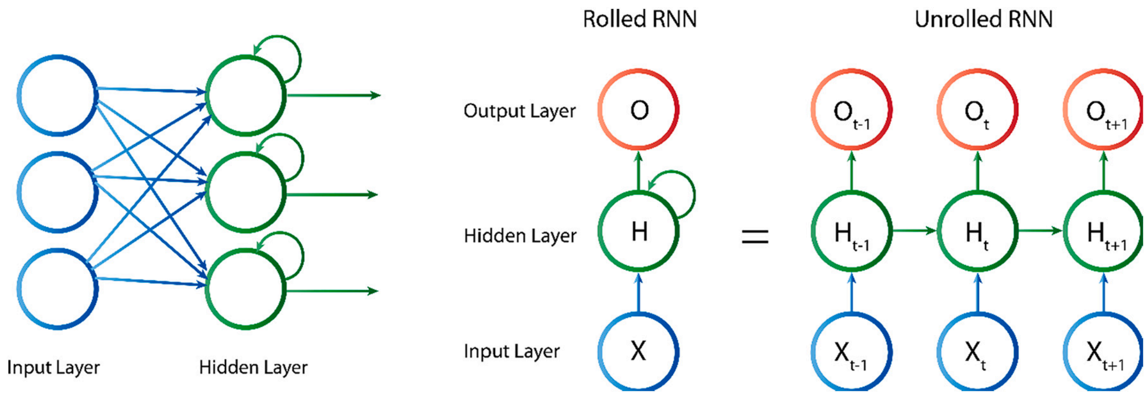

Fig. 8. Schematic of an RNN.

Table 1
Widely Used ML and DL algorithms in building and construction applications.

ML/DL Algorithm	Description
Linear Regression	This is a supervised ML method that finds the linear line of best fit for the given data.
Logistic Regression	Logistic regression is a supervised ML algorithm that is mostly used in binary classification which outputs the probabilities for classification classes.
Support Vector Machines	This algorithm can be used for linear, non-linear regression, classification, and outlier detection. However, this is mostly used for classification. SVM algorithm tries to find an optimal hyperplane in an N-dimensional space to classify data points.
Decision Trees	Decision trees are also a supervised ML method that can be used for both regression and classification. This algorithm creates a tree-like model to predict the class or the value by using simple decision rules.
K- Nearest Neighbours	This can be used for both regression and classification. This algorithm estimates the likelihood of a data point belonging to one class depending on the neighboring points in the dataset.
Random Forests	This algorithm is an ensemble of decision trees and attempts to achieve a more accurate and stable result by merging the decision trees

keywords with the terms machine learning, deep learning and artificial intelligence. Two thousand five-hundreds and sixty-four articles were identified through the preliminary search of the databases.

In the second step, 1245 of these papers were excluded after reading the abstract and not meeting the relevant criteria for this paper. In the third step, manual screening of 1247 full articles was carried out and based on the suitability of these articles for this review article, 200 literature papers were selected and included.

The critical focus of a paper and topics covered by the article can be understood by reading keywords. Accordingly, the occurrence of keywords to understand the correlation amongst papers was analyzed. VOSviewer software [3] was used to create a network map of these keywords which is presented in Fig. 9. The network map generated by the software clearly represents several clusters of keywords where the central theme of "Artificial Intelligence" is connected to key research outlined before. The size of a node in Fig. 9 directly represents the frequency of a keyword's occurrence in the literature, while the density of link between any two nodes shows how frequently they are cited as a pair within the literature.

In the upcoming sections, applications of AI, ML and DL methods for the previously mentioned seven segments in the building and construction industry are reviewed.

4. Architectural design and visualisation

Architectural design in the construction industry involves planning and development of the structures considering the aesthetics and the function of the structure. The main components in the architectural design include planning the shape of the structure, considering the aesthetics of the structure including the colours, texture, materials, generation of the layouts of the structures with the architectural elements. Architectural design and visualization is a complex process that requires the expertise, past experience and creativity of the architects. AI can assist in architectural design and visualization by considering the patterns in previous design data to generate new designs. Deep learning algorithms have been used extensively in the architectural design and visualization domain with applications such as 2D and 3D generative architectural design, classification of architectural styles and building types, architectural drawings and space recognition and indoor scene synthesis.

Generative deep learning models such as GANs and VAEs have demonstrated remarkable capabilities for generating innovative architectural designs in both 2D and 3D. GANs have revolutionized the automated generative design of architectural features such as building masses, floor plans, interior design plans and facades.

The generation of architectural floor plans using deep learning algorithms is a widely researched area. Chaillou [4] used GANs to generate architectural drawings using a trained model with an image dataset and this model was named 'ArchiGAN'. In his work, several steps were followed to finally generate fully furnished architectural plans of a building when the shape of the land is given as the input. Nauata et al. [5] proposed House-GAN algorithm to generated layouts of houses using an innovative graph constrained GAN. Workflow of this algorithm is illustrated in Fig. 10. Initial input to this algorithm is a bubble diagram specifying the constraints such as connectivity of rooms, number of rooms and type of the room. In this bubble diagram, nodes represent the rooms with their type and the edges represent the adjacency of the rooms. Then the room masks are generated depending on the room type. Wasserstein GAN Gradient Penalty (WGAN-GP) algorithm was used to train the models.

Radford et al. [6] improved the conventional GAN and proposed Deep Convolutional GAN (DCGAN) by including a set of constraints on the architecture of GAN and generated new bedroom designs. Use of DCGANs improved the stability of the generator training across a wide range of datasets and facilitated training with deeper networks and images with higher resolutions.

Isola et al. [7] developed 'pix2pix' software using a conditional generative adversarial network (cGAN) and it was used to generate building façades using a given layout of the façade. cGANs were proposed by Mirza and Osindero in 2014 [8]. cGAN is also a generative algorithm that considers conditions on an input image when generating the output images. This pix2pix software has a wide range of applications including generating photos provided a sketch, generating color images from the input black and white pictures and synthesizing photos from architectural labels. Wang et al. [9] proposed 'pix2pixHD' software

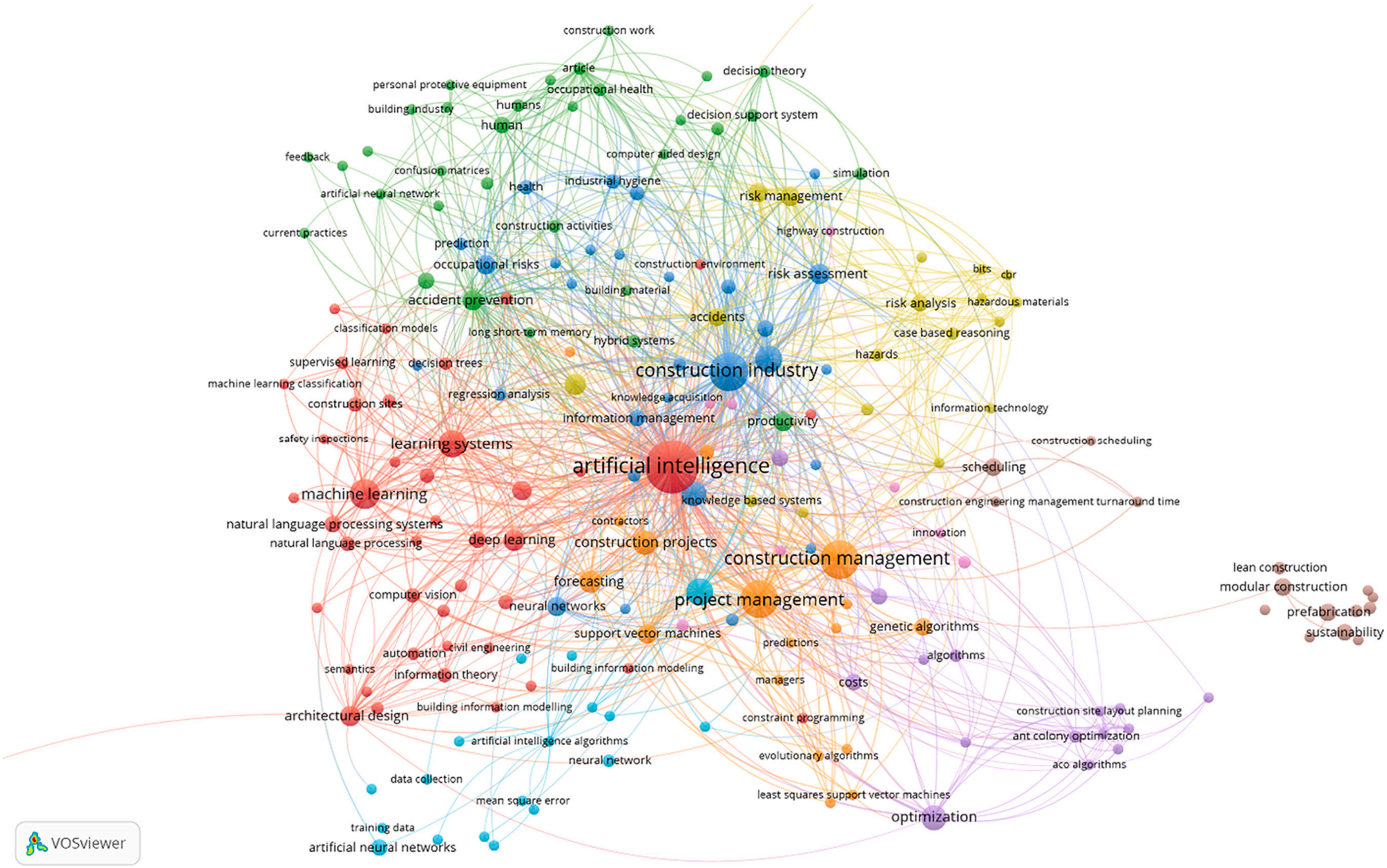

Fig. 9. Main research interest clusters using co-occurrence network of keywords.

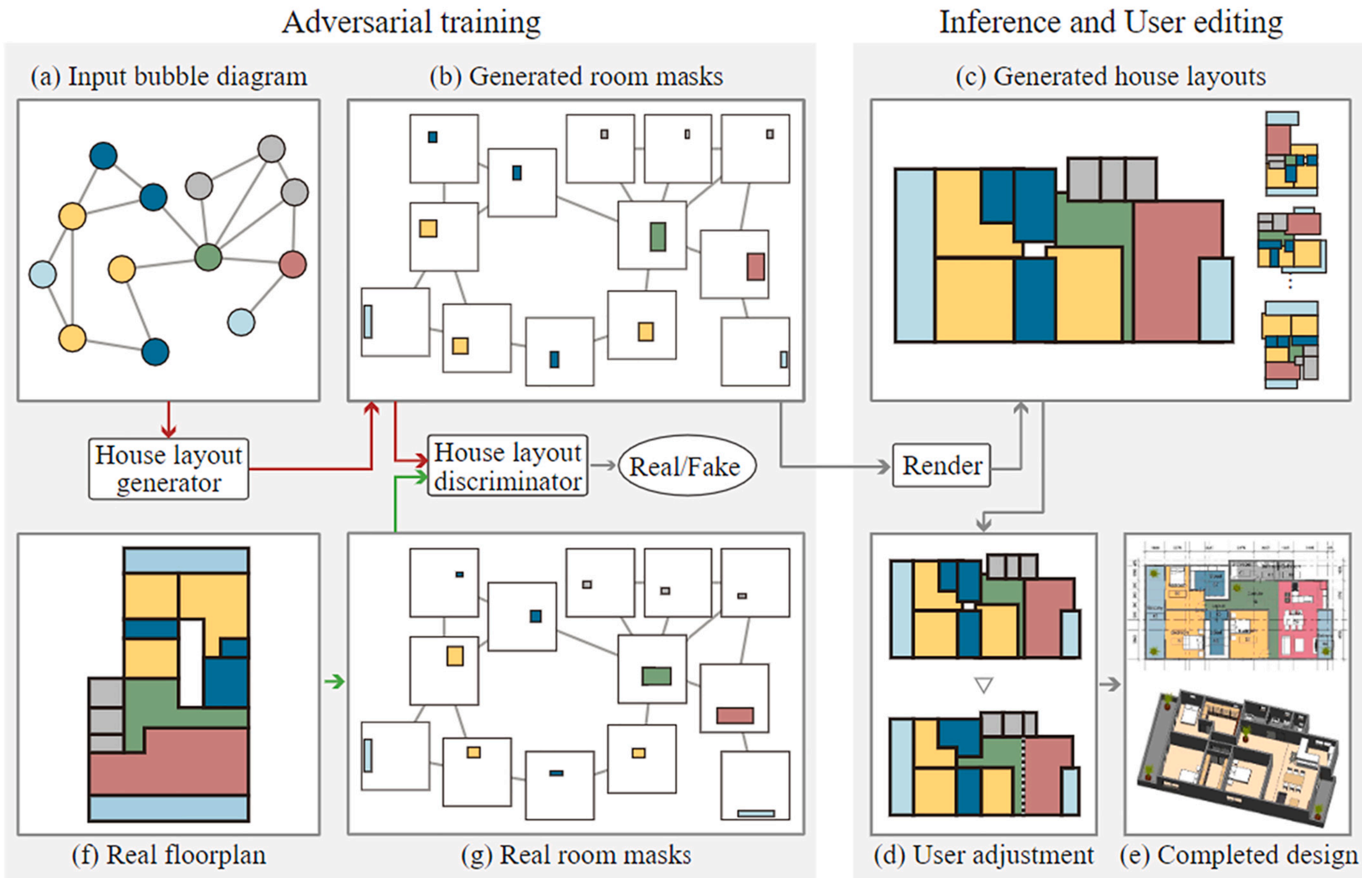

Fig. 10. Workflow of House-GAN [5].

to extend the conditional image generation to high-resolution images. A new objective function, a novel generator and a new discriminator were proposed in pix2pixHD, and the resolution of the generated images was enhanced to 2048 × 1024 compared with the 256 × 256 resolution in the original pix2pix software. Huang and Zheng [10] utilized pix2pixHD algorithm to recognize and generate architectural drawings and generate apartment layouts as shown in Fig. 11.

Apart from 2D architectural generative design, 3D generative designs have also been performed by researchers using GANs. In this scenario, the 3D representation of the architectural features can be achieved using point clouds, voxel-based methods and using 2D views. However, 3D generative models require significant computational resources compared with the 2D generative models.

Even though GANs are very promising in the architectural design discipline, it has some challenges and drawbacks as well. GANs are not able to generate architectural designs that are truly novel or innovative since the algorithm is trained using the previously available data. Also, the lack of architectural data sets for some architectural subjects is

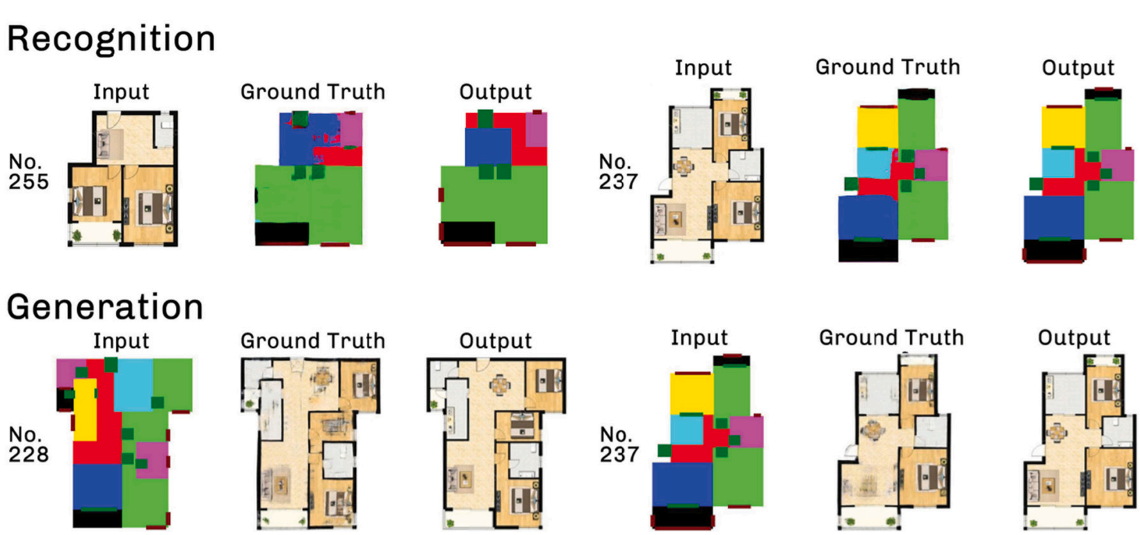

Fig. 11. Apartment Floor Layout Recognition and Generation using cGANs [10].

another challenge. This issue can be mitigated to some extent using data augmentation techniques such as rotation, tilting and oversizing to generate more data for the smaller datasets. Rapid convergence of the generator network can occur when working with GANs yielding only few outputs with little diversity and this issue is known as "mode collapse". Also, training instability is another major issue in the GANs. However, many remedial methods such as using modified objective functions, adding regularization to the objective and normalization of parameters have been proposed to alleviate these issues [11].

In the realm of deep generative models, variational autoencoders is another type of algorithm which is widely used. VAEs are used both in the 2D and 3D generative architectural designs. Wu et al. [12] proposed an algorithm based on an encoder-decoder network to generate residential floor plans by taking the perimeter of the house as an input. In the proposed method, a living room is placed initially in the floor plans using a CNN and then the other rooms are generated iteratively using two deep neural networks as shown in Fig. 12. Then the walls are generated using an encoder-decoder network and locations of doors and windows are determined. Some of the generated floor plans using this algorithm are shown in Fig. 13. This algorithm could enforce the room location constraints. However, more meaningful constraints such as the area of different rooms and the orientation of the house could not be introduced.

'Graph2Plan' is another algorithm proposed for floor plan layout generation based on GCNs and CNNs considering the user input layout [13]. In this algorithm, a more detailed introduction of layout constraints including room adjacencies was possible.

Generating vectorized architectural floor plans from rasterized images using deep learning is another widely investigated area. Many researchers [14,15] have used deep learning algorithms such as GANs, ResNET, CNN, Fully Convolutional Network (FCN) to generate vectorized floor plans with high accuracy using rasterized images with varying complexities.

Table 2 presents a non-exhaustive list of the attempts to apply AI in architectural design in addition to the previously discussed applications.

Even though the application of AI in architectural design is very promising, there are some important factors and challenges that need to be considered to attain the full potential of these algorithms. One major consideration is the sourcing of a high-quality dataset suitable for the investigated issue. Another major consideration is the time and resources taken to pre-process the data to be used in these algorithms. Data pre-processing is an integral aspect of obtaining an ML model with high accuracy. However, some algorithms require intensive data pre-processing before inputting into the model. Hence, this needs to be considered when the data collection experiments are planned and attempts should be made to generate more robust algorithms to automate this time-consuming data pre-processing component. Training deep learning models with a large dataset is computationally intensive and the time consumed for training can be reduced by using high-performance cloud computing with GPUs.

In addition to the machine learning and deep learning algorithms discussed previously, rule-based generative algorithms such as genetic algorithms (GA) [26], simulated annealing [27], cellular automata [28] have been widely used to generate architectural features. Many applications of these optimization algorithms in building form generation [29], façade design [30], energy efficient architectural design [31], floor plan generation [32] can be found in previous literature.

There are numerous commercial applications of AI in architecture. Higharc company [33] uses AI to generate various architectural layouts for houses. Software tools such as Finch [34] uses ML and DL in various aspects in Architecture such as conceptual designs, plan generation and building form generation.

5. Material design and optimisation

Selecting an appropriate construction material is an important aspect once the architectural design phase is completed. Construction material affects the speed of construction, durability, strength, energy efficiency, emission, aesthetics and thermal comfort of the structure; and high-performing materials and composites can be designed and developed considering these criteria using AI techniques.

To minimize material consumption, cost, and time due to exhaustive testing, current investigations to develop models incorporating ML that predict mechanical properties were performed by researchers [35]. Present technologies with AI applications commonly focus on concrete, steel and timber, targeting material properties and their microstructure. Concrete is the most used construction material in the world, and it has been thoroughly researched [36]. Several studies have been conducted to predict concrete behavior using ANN, DL, SVM, GA and fuzzy logic. Most of the applications use ANN or SVM to predict concrete compressive strength [37], tensile strength [38] and other mechanical properties such as elastic modulus [39]. Other applications consider concrete exposed in an extreme environment, for instance, high temperature [40]. Few studies used ANN to predict the strength of concrete with nanomaterials [41], granulated blast furnace slag [42], fly ash [43], and other mineral admixtures [44]. In the previous years, a growing interest in ANN and DL applications has been observed in property prediction of Fibre Reinforcement Polymer (FRP) [45], Recycled Concrete Aggregate (RCA) [46], and permeable pavements [47]. Durability aspects of concrete have also been widely investigated using AI algorithms. Concrete property prediction under sulphate attack [48], chloride penetration [49], and other durability aspects such as predicting carbonation depth [50] have been investigated in this domain.

The main challenge to optimizing the use of concrete, timber and steel is to optimize the use and design based on an objective function and various constraints. ML and DL algorithms can assist in this process of predicting various objective functions based on previous data. There can be a single objective function or multiple objective functions for the optimization. These objective functions generally include cost, performance criteria such as compressive strength, shear strength and environmental criteria such as embodied carbon and embodied emissions [51]. Various constraints are based on different decision variables in the optimization problem and these can be imposed by the designer, client requirements and building standards. Construction material optimization is mostly carried out for concrete due to its composite nature with multiple ingredients.

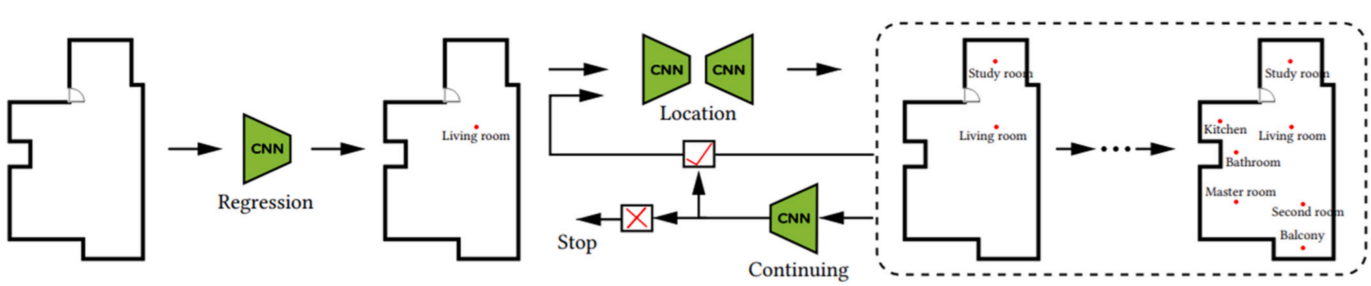

Fig. 12. Schematic of the Workflow to Determine Room Locations [12].

Fig. 13. Generated Floor Plans by Wu et al. [12].

Table 2
Applications of artificial intelligence in architectural design.

Application	Algorithm Used/Proposed	Reference
Generate floor plans using a video	FloorNet (A combination of three neural networks)	[16]
Generate 3D room layouts using a single RGB panaroma	DuLa-Net	[17]
Generate conceptual architectural designs	GCN and GAN	[18]
Indoor scene synthesis	CNN	[19]
Automated recognition of spaces in an architectural floor plan	DeepLabV3+ [20]	[21]
Generation of urban building forms	ANN	[22]
Generation of early-stage architectural design sketches	self-sparse GAN	[23]
Generation of 3D decorative architectural parts	CurveInfoGAN, VAE and Evolutionaly Algorithm	[24]
House style recognition	CNN	[25]

Most optimizations are mainly performed using optimization algorithms such as linear programming, second-order conic optimization, metaheuristic optimization algorithms and ML/DL is applied mainly for the property prediction as a part of the optimization process [51]. Applications of ML/DL in material optimization in previous research are mostly on optimization of environmental performance [52], cost [53], strength [54].

A non-exhaustive list of ML, DL algorithms used in material property prediction is presented in Table 3 with the algorithms used.

DL/ML can assist in microstructural analysis, surface and bond characteristics investigation of construction materials. Most of these investigations have also used ANN. They are summarized in Table 4.

6. Structural analysis and design

AI algorithms can assist in structural analysis and design process once the construction material has been selected. Structural design is commonly carried out using analytical models created from fundamentals or simply through codes of practice or/and using computer simulations based on numerical simulations such as Finite Element Analysis (FEA). When it comes to AI algorithms, their blackbox nature is the main challenge to integrating in real-world structural engineering design. However, there are some ambiguous and unpredictable design challenges where designs are based on statistical analysis and probabilistic theories where the benefits of AI in resolving those uncertainties outweigh the disadvantage of blackbox nature. This section discusses the use of artificial intelligence (AI) to improve certain aspects of structural engineering. Seismological design, buckling and fatigue analysis, loading capacity prediction, and damage level prediction of existing structures for retrofitting are among the topics discussed. Finally, in comparison to traditional design approaches, how new features such as generative design can aid structural design by providing a greater number of design possibilities are discussed.

Table 3
Applications of ML, DL algorithms in construction materials.

Construction Material	Predicted Property	ML/DL Algorithm Used with References
Concrete	Compressive Strength	ANN [35] SVM [35] Decision Trees [55] Linear Regression [56] Random Forest [57] Naïve Bayes [58] Logistic Regression [58] k-Nearest Neighbors [58] Ensemble [59]
	Damage Index	Decision Trees [60]
	Shear Capacity	ANN [61] SVM [62] Gaussian Process Regression [63] Random Forest [64] XGBoost [65]
	Tensile Strength	ANN [66] SVM [67]
	Slump	ANN [68]
	Drying Shrinkage	ANN [69]
	Coefficient of Thermal Expansion	Random Forest [70]
	Chloride Permeability	ANN [71] Ensemble [72]
	Elastic Modulus	ANN [73] SVM [74] Non Linear Regression [75]
Steel	Yield Strength	SVM [76] Random Forests [76]
	Tensile Strength	SVM [76] Random Forests [76]
	Fatigue Strength	ANN [77] k-Nearest Neighbors [77] Random Forest [77] XGBoost [78]
	Fracture Strength	ANN [77] k-Nearest Neighbors [77] Random Forest [77]
Timber	Compressive Strength	ANN [79]
	Bending Strength	ANN [80]
	Moisture Content	ANN [81]
	Thermal Conductivity	ANN [82]

The complexity of seismic events makes it difficult to efficiently identify the earthquake response and extract indicative features from continuously detected seismic data, affecting the performance of traditional seismic load and response models for structures and impeding seismology growth in general. AI techniques can aid in this and can be used as effective statistical tools to address these difficulties, leveraging their advantages in data analysis. AI helps in finding unknown features by extracting useful sensing data from noisy data and revealing seismic occurrences that are below the detection level. Another significant aspect is the use of AI to assist in the architectural design process with

Table 4
DL/ML assisted microstructural analysis of construction materials.

Application	Description	ML/DL Algorithm Used with References
Material microstructure analysis	Concrete compressive strength prediction using microstructural images	CNN [83]
	Self-healing of concrete	ANN [84]
	Prediction of steel reinforcement microstructure based on manufacturing processes such as rolling and cooling	ANN [85]
	Carbonation of reinforced concrete causing steel corrosion	ANN [86]
	Microcosmic variation in timber affecting compressive strength	ANN [87]
Surface and bond investigation	Model and predict surface roughness indices of concrete	ANN [88]
	Tile-wall bonding integrity considering surface roughness	SVM [89]
	Estimate concrete surface roughness through image processing	CNN [90]
	Investigation of surface roughness coefficients of metals and reinforcements	ANN [91]
	Failure assessment of steel-steel connections due to earthquake	ANN [92]
	Estimate the ultimate capacity of arc spot welding	ANN [93]
	Estimate stress concentration factors of steel joints	ANN [94]
	Evaluate bending stresses in bolt connection to steel plates	ANN [95]

the knowledge of seismology. The failure of the structural system which did not considered well in the architectural design phase leads to unexpected revisions in the implementation project phase and cost time and money. To circumvent this, deep learning and ImageAI python library can be used to construct an Irregularity Control Assistant (IC Assitant) that can offer architects with general information regarding the suitability of structural system decisions [96].

Buckling and fatigue analysis of structural components can also be improved using AI algorithms and models. Jimenez-Martinez and Alfaro-Ponce [97] studied the fatigue of steel components using a neural network approach. In terms of structural member instability, the buckling behaviour of structural elements under axial stress was predicted using an artificial neural network technique for a variety of geometries including shells [98], panels [99], and I-section beams [100].

Loading capacity and damage level prediction in existing structures for retrofitting can also be improved using AI. Tan et al. [101] and Padil et al. [102] used a non-probabilistic artificial neural network models using vibration data to detect, localise, and quantify damage in steel beams. More detailed review of application of vibration based damage detection from traditional methods to machine learning and deep learning has been discussed by Avci et al. [103]. Determining the flexural loading capacity of existing RC structures is problematic since cracks and damage at the time of assembly are difficult to quantify. As a result, retrofitting is frequently done on the safe side with a lot of cost associated. In one study by Zhang et al. [104] used ML techniques to estimate the steel weight loss distribution from the observational corrosion-induced crack distribution of RC beams, which can then be used to predict flexural load.

Deep learning-based automated generative design and analysis can be conducted using AI algorithms. By using a deep learning approach, automated structural analysis and design of prestressed members can be achieved. For example, deep learning and grid search accessible hyperparameters can be used to anticipate optimum prestressing of members without requiring structural engineers to perform endless analysis and design iterations [105]. Yoo et al. [106] has actively conducted a conceptual computer-aided engineering (CAE) to demonstrate the future possibilities of structural engineering. In their study, they proposed a deep learning-based CAD/CAE system in the conceptual design phase that generates 3D CAD drawings automatically and analyses their engineering performance. Fig. 14 depicts the usage of DNN, CNN, and transfer learning in CAD and CAE.

7. Offsite manufacturing and automation

Offsite manufacturing and automation can accelerate the construction of the building than conventional on-site construction once the structural analysis and design process is complete. This domain is an integral part of the building and construction industry 4.0. Currently, offsite manufacturing is widely used in prefabricated buildings where modules or panels are fabricated in a factory and then transported and assembled on site. However, from the design of the layouts of the modules to the fabrication of the modules are done using either manual methods or using programmed software. The future of offsite manufacturing, which is closely associated with expanding automation through robotics and AI, inevitably makes prefabricated and modular buildings a more obvious choice in substituting for many conventional construction practices [107]. Transitioning from conventional construction practices to an industrialized construction system required many drivers such as AI, BIM, Lean construction as shown in Fig. 15. Integrated analysis for manufacturing's big data, which is the source of intelligence, is beneficial to all aspects of automation in offsite manufacturing. The uptake of smart offsite manufacturing through prefabrication and standardized modular systems closely depends on the successful employment of main emerging enablers such as automation and AI, so the raw materials are efficiently converted to components and sub-assemblies that fit into the manufacturing and assembly process [108]. Besides, the digital twin paves the way for the cyber-physical integration of offsite manufacturing, which is an important bottleneck towards the industrialized production of smart buildings.

For the automation of construction manufacturing, a tremendous transformation has taken place in the past years with the emerging applications of AI. Automated construction includes different techniques, such as prefabrication of building parts, ready-made modules, and robotic technology. Smart robotics have been progressing rapidly to drive a wide range of semi- or fully autonomous construction applications. For offsite manufacturing, robots can typically be divided into ground robots and aerial robots. Ground robots have been developed to automate some manual processes and take over repeatable tasks, such as brick-laying, masonry, prefabrication, assembly, model creation, rebar tying, demolition, and some other activities to enhance efficiency, quality and safety. Aerial robots, on the other hand, equipped with image acquisition systems are widely being employed for and efficiently automated land survey, scanning, site monitoring, and structure health monitoring. Both types of robots are being trained by various machine and deep learning algorithms, and thus they can be equipped with the talent to learn from data and conditions.

To evaluate measurements and precisely verify the quality of precast concrete panels, trained inspectors are currently used, and the process is time-consuming. One such method of dimensional quality testing of precast concrete panels is terrestrial laser scanning [111]. In the manufacturing stage, with camera sensors, and in the assembly stage, with 3D laser sensors, AI can be employed as a more cost-effective option for these quality assessment criteria.

Machine learning algorithms are being incorporated into the additive manufacturing processes, also known as 3D printing, and change the future of digital and intelligent manufacturing. Increasing the level of automation, involvement of more sophisticated robots, and flexibility of shapes and consequently more optimised solutions are some advantages of additive manufacturing techniques being improved by AI [110]. In practice though, the applications of AI methods in additive manufacturing are still limited to checking printability [112], and

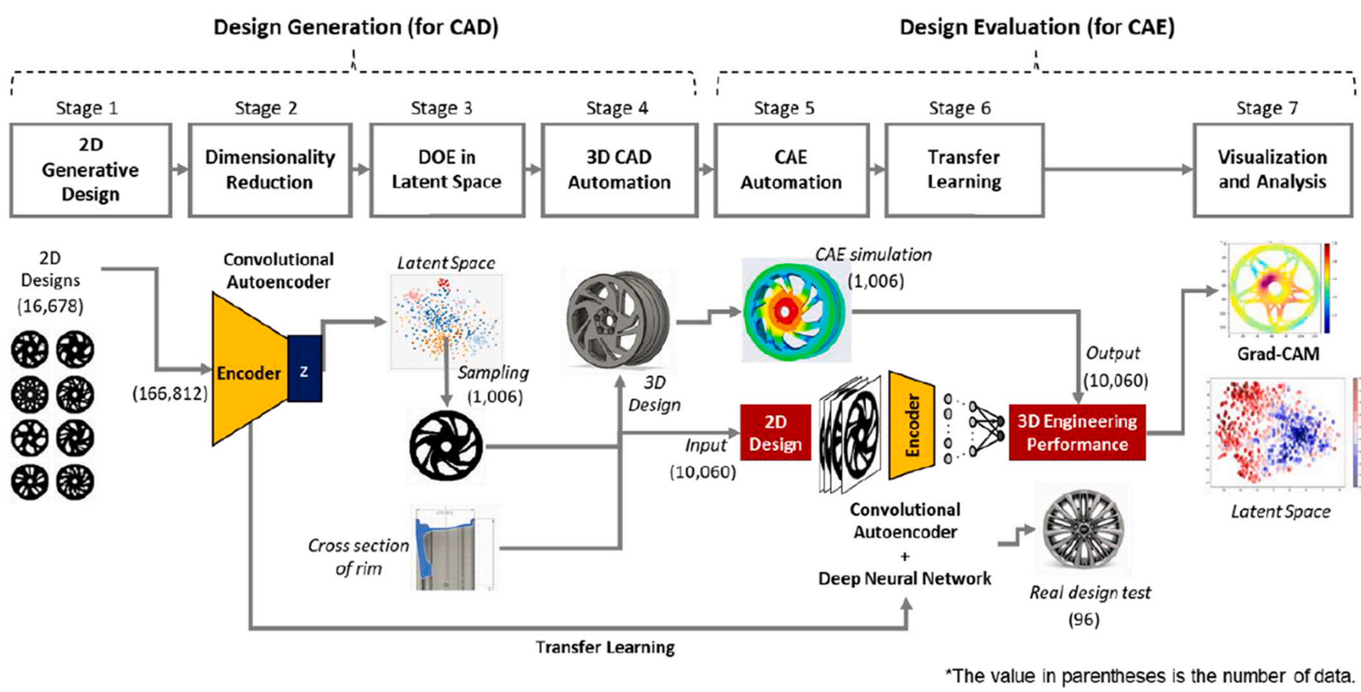

Fig. 14. Deep CAD/CAE framework [106].

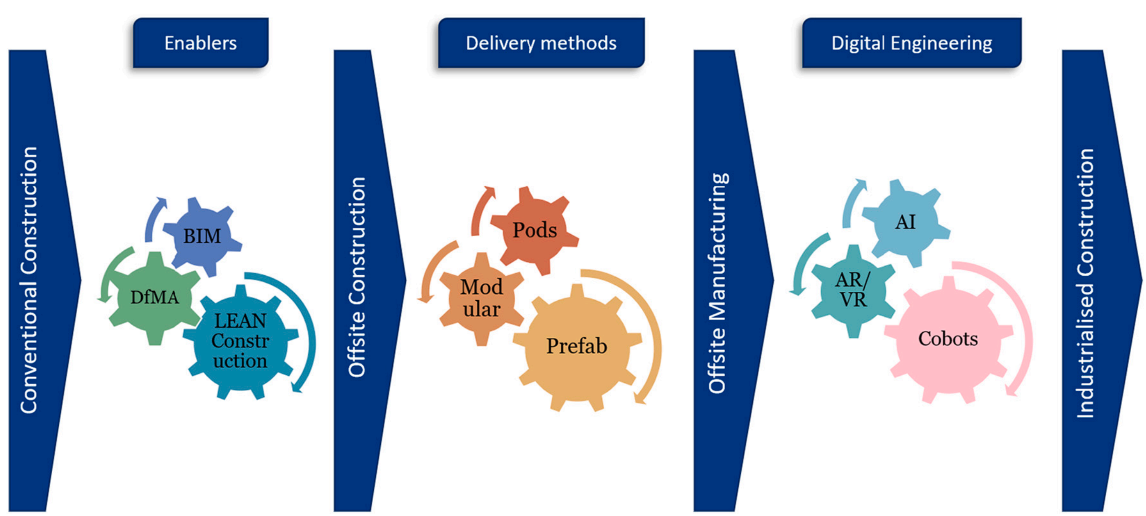

Fig. 15. Transitioning from a conventional construction to industrialised construction.

modularisation for prefabrication techniques [113]. AI techniques can also play even a more effective role in the emerging technology of 4D printing, which adds the fourth dimension of time into 3D printing, enabling the 3D printed objects to change their shape and behavior over time in response to external stimuli, like heat, light, temperature, and others [114]. Also, in the past decade, a great improvement has been achieved in the applications of 3D or 4D printing in manufacturing through cloud-based 3D printing empowered with AI techniques that can optimize and enhance the printing processes and management with regard to productivity, knowledge transfer, collaboration, and universal software development [115].

Regarding the advancement in the development of AI algorithms in offsite manufacturing, a wide range of heuristic algorithms have been developed for automation and modularisation of construction, whose data can be used for combining the knowledge domains in construction manufacturing with machine learning techniques. Over the past few decades, a number of prediction models including ANN and Ant Colony Optimisation (ACO) have been developed in this regard [116]. ANNs are utilized by Navarro-Rubio, Pineda [117] as a predictive analysis technique to anticipate the efficient structural design of a prefab concrete connection. Several other algorithms have also been developed to identify the collision-free tool path for optimum performance additive manufacturing techniques in offsite construction. On application of these algorithms are on the performance of multiple nozzle systems based on the single-nozzle approach in 3D printers that can help develop an intelligent additive manufacturing system [110]. He et al. [118] developed a program interfaced within BIM for generating the geometry details of 3D-printed modules, while providing a robotic simulation of 3D printing to explore a flexible plan in producing the 3D-printed modules or components. Steuben et al. [119] proposed an automated AI algorithm for optimum geometry partitioning for 3D printing of different objects used in prefabrication. Also, generative algorithms are being employed to optimize the material distribution, which is a key benefit associated with additive Manufacturing [120]. Vacharapoom and Dawood [121] developed an innovative planning system and its prototype called artificial intelligence planner for data integration to encourages the automation in the offsite manufacturing planning process and improve the efficiency of the production plans for bespoke precast concrete products.

Chen et al. [122] proposed an algorithm to facilitate automated scheduling problems of the production of prefabricated bathroom units manufacturing with space constraints. A similar approach was employed to address the problem with precast concrete systems by Li et al. [123]. An integrated, comprehensive planning system dubbed the 'Artificial Intelligence Planner' (AIP) has been developed to improve the efficiency of production planning processes in order to eliminate uncertainties in design and offsite manufacturing by Benjaoran and Dawood [124]. Kaveh and Sharafi [125] developed some algorithms using design structure matrices with applications in the modularisation of complex building systems that facilitate automated design for manufacture and assembly (DfMA) of modular systems. AI algorithms also have a great potential in the management of manufacturing platforms with regard to processes and supply chain, as well as error compensation.

8. Construction management, progress and safety

Improvements in construction technology have led to better construction quality with improved construction durations. Construction management involves managing the construction project through project planning, coordination, budgeting, supervision. At present, these processes are performed using the experience of the engineers and using commercially available software. Progress monitoring is also carried out using manual extraction of information from sites such as taking photos and documenting the progress. Construction safety is also administered onsite using manual supervision methods. However, these processes can be automated using AI to enhance the efficiency and the accuracy. This section reviews the applications of AI in construction management, progress monitoring and construction safety.

8.1. *Application of AI for improvements in construction management*

Focus of the majority of publications in construction management was on the optimization of project costs by application of AI. Another main focus was on cost or cash flow optimization for construction projects using intelligent algorithms such as GA, SVM and ANN, Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). SVM was used across multiple publications to optimize cash flow [126], and for project duration prediction by Cheng et al. [127] and for solving complex problems related to resourcing, cost optimization and waste minimization [128].

Another area of focus for construction management was prediction of project success based on multiple factors. Decision support systems (DSS) employing various algorithms such as ANNs and GAs were used to categorize, predict and optimize factors leading to project success [129]. ACO was used for determining the critical path for complex projects by Duan et al. [130] while constraint programming was used to solve multimode resource-constrained project scheduling problems by Menesi et al. [131]. Estimation of worker productivity has also been investigated by various researchers using AI algorithms [132]. Computer vision and DL algorithms have been used to identify workers onsite and monitor their productivity as shown in Fig. 16 [133].

Risk management is another aspect of construction management that has benefitted from application of artificial intelligence. Long short-term memory (LSTM) was used for cost index forecasting (price trend indicator) for highway construction industry by Cao et al. [134] to minimize cost risks. Similarly, an AI based system to rank and select contractors best suited for the job while minimizing project management efforts and project costs without delays was developed by Kashiwagi et al. [135]. Addressing traditional method for risk management, use of SVM in combination with Random Forest (RF), K-nearest neighbor (KNN), Logistics Regression (LR) and Decision Tree (DT) algorithms to develop safety indicator for the risk level of a site was demonstrated by Poh et al. [136]. The only use of Natural Language Processing (NLP) was seen in

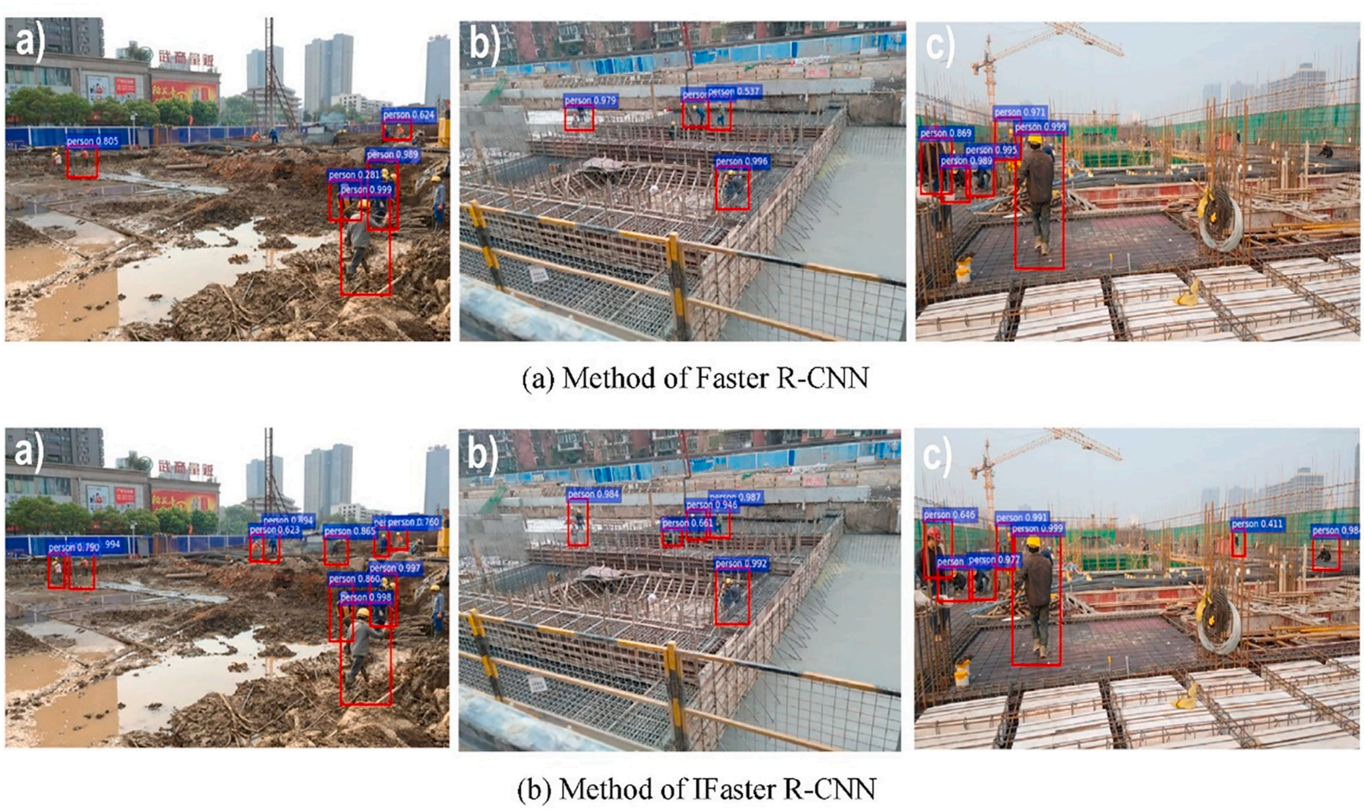

Fig. 16. Construction worker identification using computer vision and DL algorithms [133].

the method developed by Soibelman et al. [137] for generating a database for construction knowledge documentation.

8.2. Application of AI for improvements in construction safety

There have been a lot of applications of AI, ML and DL in monitoring and improving construction safety and most of the research in this domain employ neural networks. Region-based convolutional neural network (RCCN) and single-shot multi-box detector (SSD) were used for object detection and increased safety in construction environments by Liu et al. [138]. ANN-based approach was used to predict the adoption potential or acceptability of a new formwork system by Elazouni et al. [139]. Similarly, ANN was used to estimate the factor of safety for slope stabilization during construction by Foong et al. [140] and to analyze data from wearable sensors used by workers while manually lifting loads by Pistolesi et al. [141]. Automated training was developed by Bangaru et al. [142] to train workers for earplug wearing. ANNs were used by Aythan et al. [143] to predict future safety problems by utilizing collected big data and to predict outcomes of construction incidents.

Furthermore, SVM was used to analyze complicated scaffolding structures in real-time and assess scaffold safety conditions by Sakhakarmi et al. [144] while it was used in combination with linear discriminant analysis (LDA), ANN, and k-nearest neighbor for analysis of cloud data by Chen et al. [145] in multiple project areas such as safety management and construction management. SVM was also used by Goh et al. [146] along with other ML algorithms to develop models for predicting unsafe behavior by analyzing the relationship between the cognitive factors and behavioral data.

NLP was used for the analysis of databases and to predict outcomes of safety incidents, provided an incident has taken place or there are sufficient indicators present in a construction project to predict an incident. NLP was used in conjunction with CNNs to review accident precursors from injury reports and to provide a prediction of the outcome of an incident given that an incident has occurred by Baker et al. [147]. Case-Based Reasoning (CBR) was combined with Rule-based reasoning (RBR) algorithm by Niu et al. [148] to interpret data from smart construction objects (sensors), ultimately leading to an OHS management system. Similarly, CBR was used by Campbell et al. [149] to improve hazard identification and management during a worker's daily tasks of identifying hazards and determining appropriate mitigations. Construction equipment tracking has also been investigated widely using AI algorithms [150] and most of these studies used CNN. This can ensure worker safety as well as the productivity of operations.

Innovative platforms such as Newmetrix [151] are commercially available to provide onsite safety monitoring and predictive analytics and suggest best practices for enhanced construction safety.

8.3. Application of AI for improvements in progress monitoring

Construction progress monitoring is an essential aspect of delivering the project on time. SVM has been used for progress monitoring using point clouds and 4D BIM by Golparvar-Fard et al. [152] while it has been used to identify and document concrete regions in construction photographs for as-built component identification by Zhu et al. [153]. Answer Set Programming (ASP) has been used to analyze a knowledge base generated using Ultra-wideband (UWB) sensors for progress monitoring by Johansen et al. [154]. Markov process was used to update real-time forecast of tunneling project based on lithology when using Tunnel boring machine (TBM) while fuzzy logic and fusion-regression were used to predict the productivity of workers and machinery in order to provide progress forecasts [155].

Commercial applications such as BuildAI [156] is currently used by the construction industry to monitor the progress using AI combined with a plethora of sensors fixed in the construction sites.

A non-exhaustive list of the applications of ML/DL algorithms in construction management, progress monitoring and construction safety is presented in Table 5.

9. Smart building operation and health monitoring

9.1. Introduction

Traditional buildings lack sensors, resulting in a lack of important data that is crucial in the decision-making phase of building management and maintenance. Collecting data and designing a building management system that combines all elements is a difficult challenge due to significant variations in building components, large amounts of data, variability of building dynamics, weather, and unavoidable uncertainties. In modern buildings, IoT is the backbone for efficiently collecting this data and later analyzing it using technologies such as AI. The use of AI in operational and building management cannot be discussed without mentioning the term “smart building,” which refers to an efficient environment achieved through optimized structures, services, systems, as well as the interrelationships between them. In a smart building, various technologies are combined to provide the occupants with high-grade and safe, secure and cost-efficient services, including data analytics, data collecting, data storage and data viewing [164]. A schematic of a smart building and integration of AI is shown in Fig. 17.

The key component of AI is “data”. If the training data is varied and copious, AI/ML solutions will deliver superior results. IoT devices provide a large volume of data that contains critical information about the physical environment. The pattern and irregularities will not be recognized if they are processed using traditional programming. AI could be used to analyze patterns and trends and make judgments based on that information. Cloud computing systems make big data processing easier and allow for intelligent decision-making based on machine learning and big data analysis.

Historically, the primary focus of AI research in the context of smart buildings has been on energy conservation. Building owners and operators also have a preference for technology and tactics that may immediately lead to cost reductions. In addition, an integrated building management system (BMS), which offers protocol access to various manufacturers and the use of IoT technology to make substantive energy savings is utilized for energy management, monitoring and comfort purposes. This novel integration method's approach is backed by new trials with developing AI technologies and interaction with robotic ML, among other things.

9.2. Energy and emission management

Buildings utilise around 40% of all energy produced globally. Because of global warming, energy conservation in buildings is an

Table 5
Applications of ML/ DL algorithms in construction management, progress monitoring and construction safety.

Application	ML/DL algorithm used with references
Construction Management	ANN [138] [155] Long Short-Term Memory (LSTM) [157] SVM [158] Decision Trees [159] K-Nearest Neighbours (KNN) [160] Logistics Regression [160]
Progress Monitoring	ANN [161] CNN [134] SVM [153] [161] KNN [162]
Construction Safety	ANN [141] [144] CNN [163] KNN [145] SVM [145] [148] LSTM [140] Random Forest [136] Decision Trees [136]

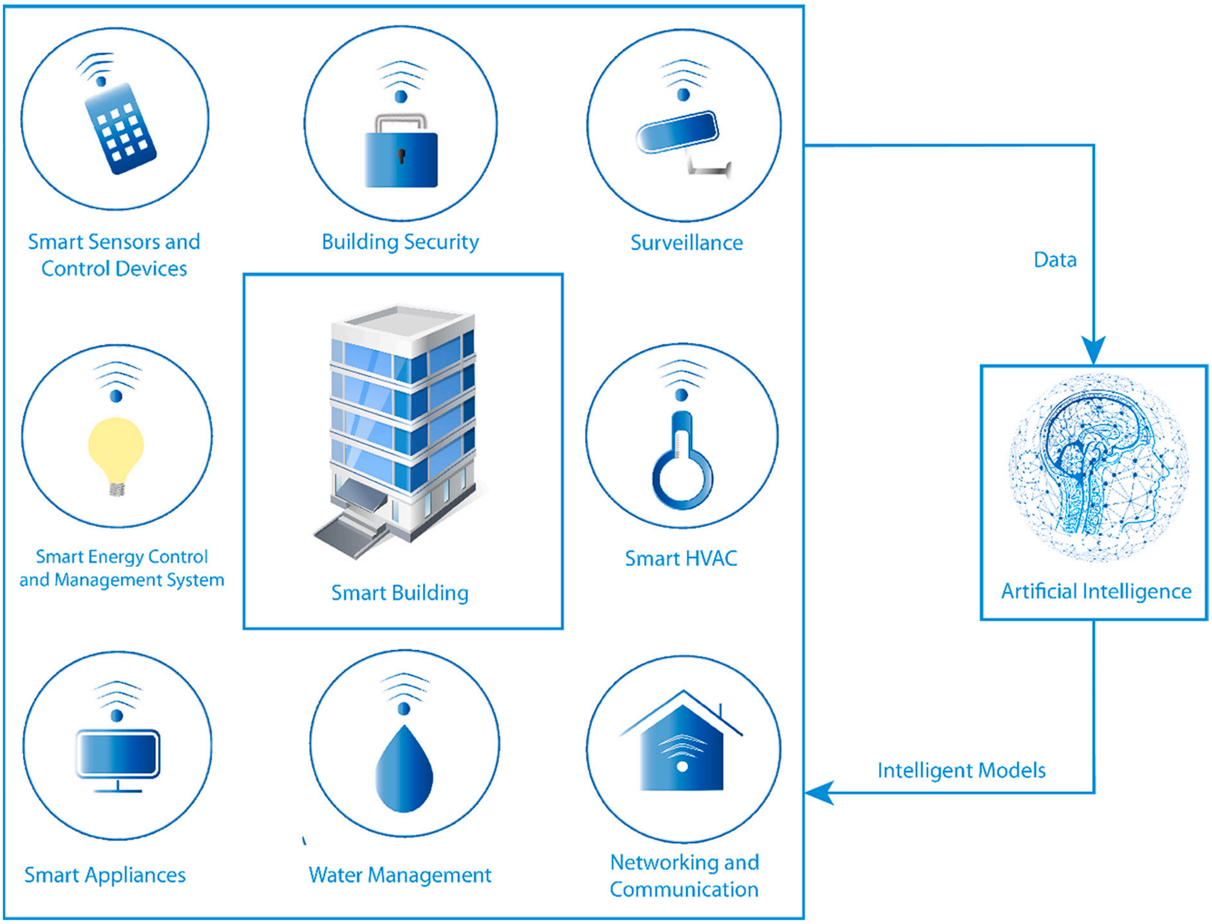

Fig. 17. Components of a smart building and integration of AI.

essential subject. A significant portion of this energy is utilised to keep the building's inhabitants comfortable. Current systems are inefficient because they rely on sensors that run pre-programmed software that do not adapt to changing conditions. There are many AI-based methodologies being used to enhance thermal comfort in indoor spaces. A review of the current state-of-the-art can be found in Ngarambe et al. [165] focused on thermal comfort predictive models using diverse ML algorithms and their deployment in building control systems for energy saving purposes. Seyedzadeh et al. [166] have also provided a review on the use of four main ML approaches including ANN, support vector machine, Gaussian-based regressions and clustering, in forecasting and improving building energy performance. Mehmood et al. [167] reemphasized in their review paper that AI, when combined with big data, can tremendously increase the energy efficiency and cost-effectiveness of buildings that are designed to provide occupants with comfortable indoor living environment. Some interesting energy optimization methods developed using AI are discussed in the following sections.

Data-driven predictive modeling has gained huge interest due to its flexibility in model development and the rich data available in modern buildings. Fan et al. [168] used deep learning to enhance the performance of building cooling load prediction. Balancing between energy conservation and comfort management is an issue in modern building automation which can often be diametrically opposed to each other. Verma et al. [169] proposed a design for a multi-agent topology-based building management system using AI to optimize energy consumption and comfort by managing temperature, illuminance and CO_2 concentration within a building. Mocanu et al. [170] sought to use deep learning methods to predict a building's energy consumption through the application of Conditional Restricted Boltzmann Machines (CRBM) and Factored Conditional Restricted Boltzmann Machines (FCRBM) which they compared to traditional ANNs, SVMs and RNNs. Ma et al. [171] introduced the concept of Smart Building Cluster (SBC) as the joint operation of multiple Smart Buildings (SBs) could be more advantageous than the independent operation of each individual SB In a smart grid environment. Zhang et al. [172] have performed data analysis using the IoT generated building data to derive an accurate thermal comfort model for smart building control. A deep neural network (DNN) is used by them to model the relationship between the controllable building operations and thermal comfort. Pham et al. [173] suggested a Random Forests (RF)-based prediction model to estimate short-term energy usage in numerous buildings at the hourly level. The efficacy of the RF model was tested using five one-year datasets of hourly building energy usage. One Taikoo Place is Hong Kong's first AI-enabled building, completed in 2018, and equipped with Arup Neuron, an AI smart building console that saves energy through advanced data analytic capabilities, machine learning, and predictive maintenance algorithms [174].

9.3. *Climate controlling systems*

Sustainable use of total energy consumption with heating, ventilation, and air-conditioning (HVAC) accounts for a substantial percentage of a building's energy end-use. Compared to current technology, automated Fault Detection and Diagnosis (AFDD) has the potential to significantly enhance the energy efficiency of various HVAC systems and components. Lee et al. [175] proposed a real-time fault diagnostic model for air-handling units (AHUs); the model used deep learning to improve the operational efficiency of AHUs and thereby reduce the energy consumption of HVAC heating, ventilating, and air conditioning systems in buildings. On the other hand, the effects of operating restrictions on the chiller, duct, damper, and ventilation are critical for determining energy savings. They have proposed a large multizone commercial building energy management system that blends distributed optimization with adaptive learning. One Taikoo Place's Neuron system uses a central repository or a common data model to improve operation workflows and replace manual processes through digitalization and automation [174].

9.4. Security

Another critical operational function of a structure is occupant security. There is considerable potential for AI technology to be used to improve the safety of building inhabitants and security based on the vision systems and sensors. The literature reveals that some research efforts have been conducted into the use of AI to improve safety within Smart Buildings and that these systems have clear use cases and potential benefits as discussed in following paragraphs.

There are technologies ranging from fire and danger detection systems to systems capable of detecting hazardous chemical pollutants. The present state-of-the-art fire detection and alarm systems in smart buildings have been examined by Liu et al. [176]. They identified new technologies and concepts created to increase the capacity of the fire protection systems for smart buildings. The study outlined the advantages of a fire sensor system using video cameras, computers and AIs for sensing and tracking flames. Chooch.ai, an AI-based company, sells readily available AI algorithms that can detect fire and smoke and can be deployed at edge computers in a matter of days [177].

Detecting and tracking pedestrians is an important part of smart building surveillance. Architects are focused on the design of smart buildings as sensor technology advances. Traditional image classification approaches, such as histograms of orientated gradients filters and ML algorithms, struggle to perform effectively with large volumes of pedestrian input photos [178]. The advancements in deep learning algorithms perform exponentially good in handling the huge volume of image data and Kim et al. [178] proposed a pedestrian detection model based on deep CNN for the classification of pedestrians from the input images.

9.5. Smart building cities

Smart buildings are the primary starting point for transforming cities into smart cities. Smart cities must have three characteristics: they must be instrumented, linked, and intelligent. Smart buildings are microcosms of smart cities, with overlapping demands ranging from controlling lighting and energy to providing people with security and safety. The concept of a smart city is the most prominent modern trend, combining the concepts of smart mobility, smart economics, smart people, smart governance, smart environment, and smart lifestyle. Smart city characteristics need the construction and operation of buildings and infrastructure. A conceptual illustration of an operational smart city [179] is shown in Fig. 18.

When the smart buildings are interconnected into a smart city network, the smart building itself can impact the behavior of the other smart buildings or infrastructure because it becomes a consistent outside environment element influencing the other elements of the network. When confronted with complicated environmental challenges and vast amounts of data, AI systems have the ability to make knowledge-based judgments that balance the city's environmental results against its people's social and economic well-being. AI systems may be used to detect environmental changes like temperature, moisture, emissions, water pollutants, noise, and other environmental indicators. AI systems can detect such abnormalities to react to the changes and swiftly implement solutions to any problems [180]. Most importantly, disaster management in cities improved with these AI-driven variation detection systems [181]. Toyota is currently constructing a 175-acre smart city in Japan

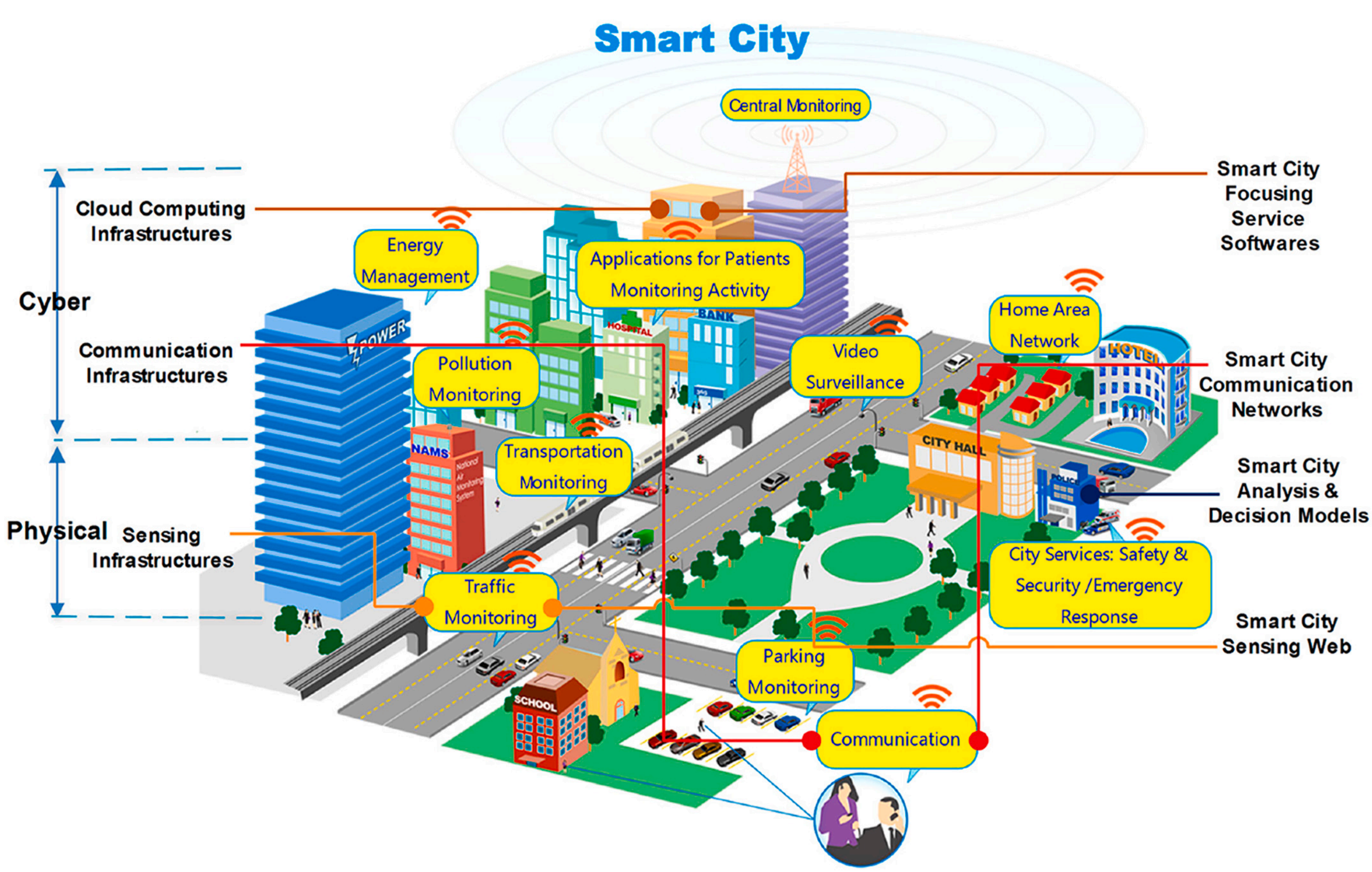

Fig. 18. Conceptual Illustration of an operational smart city [179].

[182], and Terminus Group, a Chinese technology firm, is planning to build an AI city in the Chongqing Hi-Tech Industrial Development Zone [183].

9.6. Structural health monitoring (SHM) and durability

Material deterioration through time, as well as dynamic loading such as wind, earthquake, and ambient vibration, can cause infrastructure to lose its design capacity and require maintenance or demolition due to loss of intended performance. Historically, these conditions were assessed through manual inspection or testing. SHM, on the other hand, has arisen, utilizing various sensors to expedite periodic inspections and decrease the direct and indirect expenses associated with undesired failure of aging infrastructure [184].

Recently, the constraints on sensor measuring capabilities have been addressed as the cost of micro-controllers has decreased dramatically. However, as datasets grow larger and larger, the process of data analysis must increase as well. Unlike classic statistic and physics-based structural health monitoring (SHM) models, data-driven models provide solutions for identification and forecasting durability and life cycle, including damage detection and remaining life prediction [185].

The application of ML to SHM and damage detection involves three main steps. First, field data are collected using applicable sensors. Relevant features are then extracted from the collected data. Finally, extracted features are processed and results are assessed for insights on the condition of a structural system. Research studies in the application of ML to SHM have commonly used classification techniques and anomaly detections to identify potential problems early on. The implementation of SHM algorithms can be further classified into the visual approach and non-visual approach.

The visual SHM approach has been widely used in damage identification. Visual techniques mainly use edge detection in identifying damage and cracks. Techniques implemented for damage identification are primarily pattern recognition, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Deep Learning (DL) [186]. Visual SHM was used in various structural applications such as bridges, buildings, tunnels and pavements, and structural concrete elements [187]. In the past, the most advanced vision-based method utilized in civil engineering was digital image correlation to quantify stress. The common goal of computer vision is to replace traditional inspection with a rapid, affordable, safe, and totally autonomous method. Deep learning-based method of classifying concrete cracks from photography can be used to expedite the crack detection process [188]. AI based SHM techniques have been used for: general SHM [189], multi-level damage detection [190], non-contact assessment of deflection [191], corrosion detection [192], concrete surface bug hole recognition [193], concrete crack detection [194], concrete spalling [195], steel crack detection [196], fatigue detection [197], and surface and subsurface damages [198], pavement crack detection [199], brick building condition assessment [200].

The non-visual SHM approach usually involves measuring features using accelerometers, acoustic sensors, and electromagnetic devices. Accelerometers measure vibration or natural frequency as a diagnostic feature in structural assessment. Techniques implemented to vibration monitoring are ANN, DL, Support Vector Machine (SVM), Principal Component Analysis (PCA), k-Nearest Neighbour (KNN), and low-rank matrix decomposition [201]. SHM through vibration analysis was applied to various structures such as bridges [202], wind turbines [203], power plants [204], and high-rise buildings [205]. On the other hand, acoustic sensors detect mechanical waves that can be used to detect cracking, specifically in concrete members [206]. Lastly, electromagnetic anomaly detection can be performed to investigate corrosion in concrete as presented by Butcher et al. [207]. This measures the magnetic flux transmitted by the device within a structural concrete element through non-destructive testing.

In general, major ML-based problems include three techniques: classification, localization, and segmentation. Fig. 19 illustrates the frequent crack detection approaches: classification, object localization, and pixel-level segmentation.

The majority of deep computation vision-based algorithms rely heavily on pre-processing methods such as edge detection and segmentation. Current crack detection algorithms in use, such as CrackNET [208], CrackNETR [209], UNET [210], etc. have various reported drawbacks when used in real-world applications due to demanding situations such as weather, temperature, camera position, and quality, shadow, and light, and so on. Compared to manufacturing, where computer vision is more advanced, and conditions are controlled, these issues are more severe in civil engineering.

Effective maintenance techniques can save building maintenance expenses, which account for more than 65% of annual facility management costs [211], as well as lengthen the service life of building components. Predictive maintenance, also known as condition-based maintenance, differs from reactive or preventive maintenance in that it aims to detect incipient failures and eventual degradation based on the detection of trends in component conditions using historical data so that early actions can be taken [212]. This method is heavily reliant on operational data gathered and communicated by sensors. Several machine-learning algorithms, such as ANN, SVM, and Markov chains, can be used to anticipate the status of building components. However, deep learning is not well suited to every problem/building as not every building produces large data sets for training. Other limitations of implementing such system often associated with technical limitations related to solution complexity as well as to legal and financial restrictions. Also, the performance of predictive maintenance applications depends on the appropriate choice of the machine learning method.

Through artificial neural network (ANN) layers, deep learning based SHM techniques seek to build completely automated feature extraction and hierarchical representation mechanisms from raw input data [213]. However, the lack of sensor data corresponding to different damage scenarios continues to remain a challenge. Most of the supervised machine-learning/deep-learning techniques, when trained using this inherently limited data, lack robustness and generalizability. Physics-informed learning, which involves the integration of domain knowledge into the learning process can be considered as a potential remedy to this challenge [214].

10. Sustainability, life cycle analysis and circularity

Employing AI in areas of civil engineering can increase our ability to create regenerative systems based on the principles of circularity. Also, AI can be a hugely powerful tool that can be used to accelerate the transition to a circular economy specifically in the process of Reuse, Repair and Recycle. The applicability of clustering algorithms can be used by any organization to improve resource sharing through digital sharing platforms which encourages Reuse. Time Series analysis can be used to identify repeated patterns or to forecast future occurrences that urge repair [215]. Applications include preventative maintenance of structures through health monitoring and monitoring of urban resources such as water.

Traditional design methods are time-consuming and costly when producing multiple variations of the same design. Due to the speed with which an AI algorithm can analyze huge amounts of data and offer initial designs or design revisions, engineers and researchers working with AI can build products, components, and materials that are suited for the circular economy by applying AI for better designs faster. AI also aids in reducing complexity by shifting countless ideas and recommending the ones that best suit the circular design requirements [216]. In a circular economy, AI provides autonomous and remote monitoring of efficiency during the manufacturing process as well as the product's final lifecycle. Companies such as Autodesk, IBM, and Microsoft have already developed facilitating software as well as cloud operations to enable this. At the end of their useful life, items must typically be manually inspected

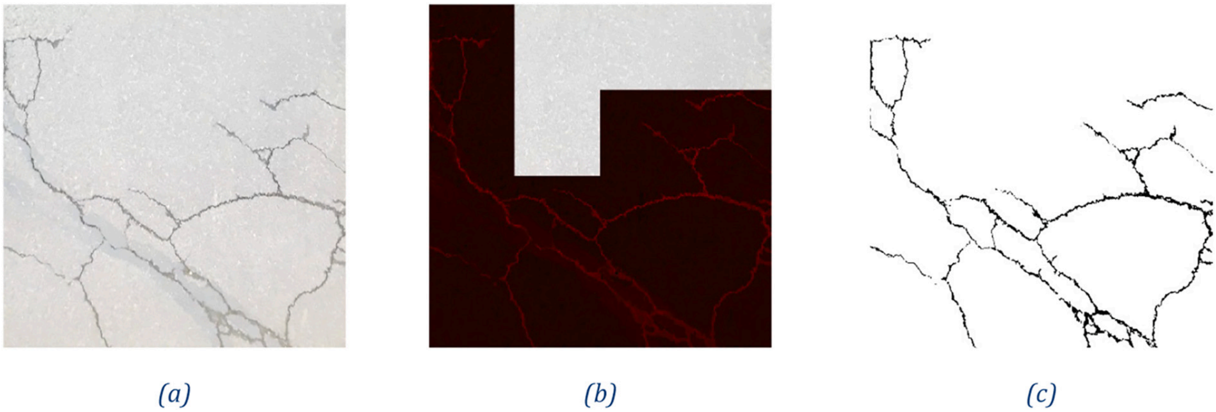

Fig. 19. AI enabled asphalt crack detection (a) cracked image (b) crack identification (c) Segmentation.

for damage and wear before being disassembled, sorted, and separated in order to circulate resources in the economy. There are numerous chances for AI to assist in streamlining the infrastructure required in the process. To maximise value preservation, condition evaluation can be automated using machine vision, and recommendations for reuse, resale, repair, or recycling can be made. Deep neural networks could help demolition engineers estimate demolition materials more rapidly.

Although the circular economy clearly goes beyond a waste perspective, waste management (recycling) will also have to be radically improved in order to recover high-quality secondary raw materials. AI enables automation of waste recycling process, which is economical and provide higher material recovery than conventional methods with lower costs. These systems employ several sensors and cameras (Visible range, Near infrared spectroscopy, metal, 3D laser sensors, RGB cameras) to detect objects and their materials and deliver data to the control software. There, a combination of Artificial Intelligence and Machine Learning algorithms can detect individual objects in data and determine robot movement.

The procedures for material or item recognition, as well as the related algorithms and software in the background, are critical for waste sorting. If this software is paired with appropriate hardware and an extra Artificial Intelligence implementation is carried out, robotic systems may conduct multitasking jobs and therefore execute many sorting tasks at the same time. Once the system is in place, it is simple to train the system for new material, making the technology highly future-proof in terms of shifting waste streams. The robots employed in certain cases replace human sorters and/or find use in previously unsortable regions (e.g., construction site waste, marine waste, hazardous waste) and/or allow for automatic quality verification and improvements (e.g., plastics). Human sorting is hampered, particularly in the case of building and demolition waste, by the limiting item size (in terms of occupational health and safety requirements) and the dust or other hazards involved such as asbestos.

Deep CNN can be applied in numerous different levels in the field of item detection, sorting and waste recycling, while using pretrained networks (PCNN) at the lower layers. These PCNN offer the advantage of saving training time while also requiring fewer photos to achieve successful trained network convergence. To date, works on digital image analysis approaches have been published by [217]. A market analysis that identifies different commercial solutions available to fully automate the waste treatment process is shown in Fig. 20. All robots use AI-based machine vision system works in the visible range for determining waste. The Zen robot [218] has so far only been used for construction and demolition waste.

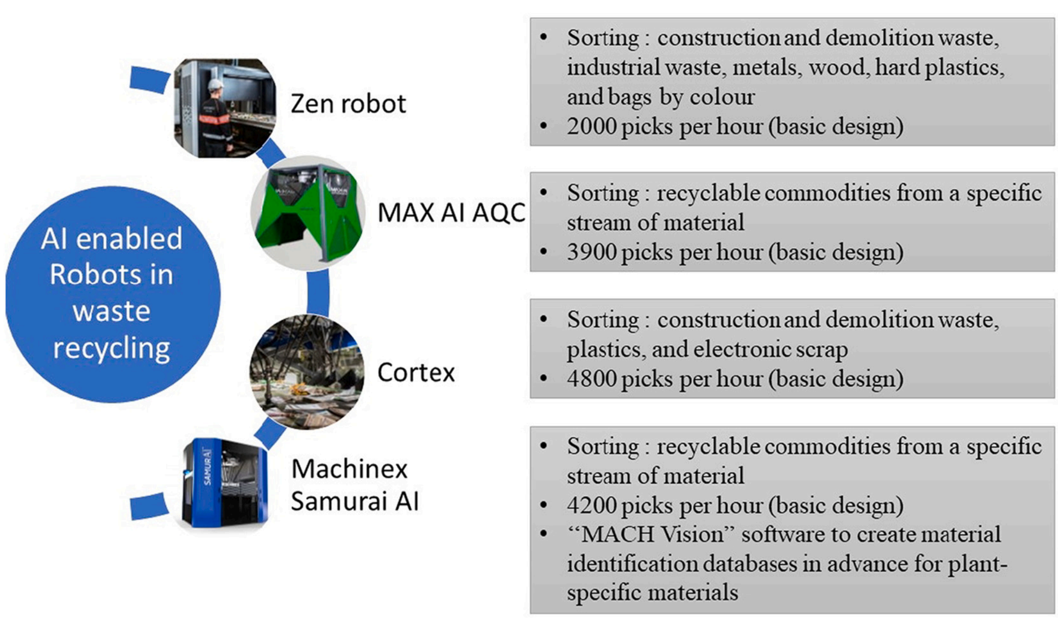

Fig. 20. Commercial solutions for automated waste sorting.

11. Future trends

Even though the current adoption of AI-based applications in the building and construction industry is relatively low, in future more progressive implementation of these AI-based techniques is expected. Currently, the adoption of AI is mostly used in design and monitoring domain. However, novel techniques such as 3D and 4D printing and robotics are starting to get popular.

Pan and Zhang [114] reviews the future trends in AI in construction industry as illustrated in Fig. 21. Smart robotics, Cloud Virtual Reality (VR)/Augmented Reality (AR), Artificial Intelligence of Things (AIoT), Digital Twins, 4D printing and blockchain were listed as most promising AI-assisted technologies which will prevail in the future construction industry. These technologies are currently being widely researched and in future, direct applications in the construction field are anticipated. Robotics are already prevalent in manufacturing settings and recycling process. However, AI-enabled robotics can become prominent in the construction industry for applications such as module fabrication for prefabricated buildings, additive manufacturing, brick and block laying, welding, and rebar tying [219].

Cloud VR/AR is the deployment of AR/VR technologies in the cloud so that continuous sharing of VR/AR technologies can be performed across multiple devices. AR adds a layer of digital objects to the actual environment which augments the reality, and this can be viewed using a mobile device or another viewing device. VR generates an immersive experience in a virtual environment containing computer-generated imagery. This cloud VR/AR technologies will become predominant in applications such as BIM incorporated clash detection, worker education and training and architectural model refinements. AIoT incorporated AI algorithms to IoT for an efficient operation. IoT can generate vast amounts of data which can be processed using AI algorithms to make accurate predictions. AIoT can assist in automating and remote-control construction operations, yield accurate predictions for construction project planning and maintenance.

Digital twins generate a digital replica of a building, and this replica can continuously evolve with time as more data become available during the lifecycle of the building. AI technology can be combined with digital twins to improve the accuracy of the digital twin models and continuously advance these models based on the massive amounts of data collected during the construction phase and remaining lifecycle of

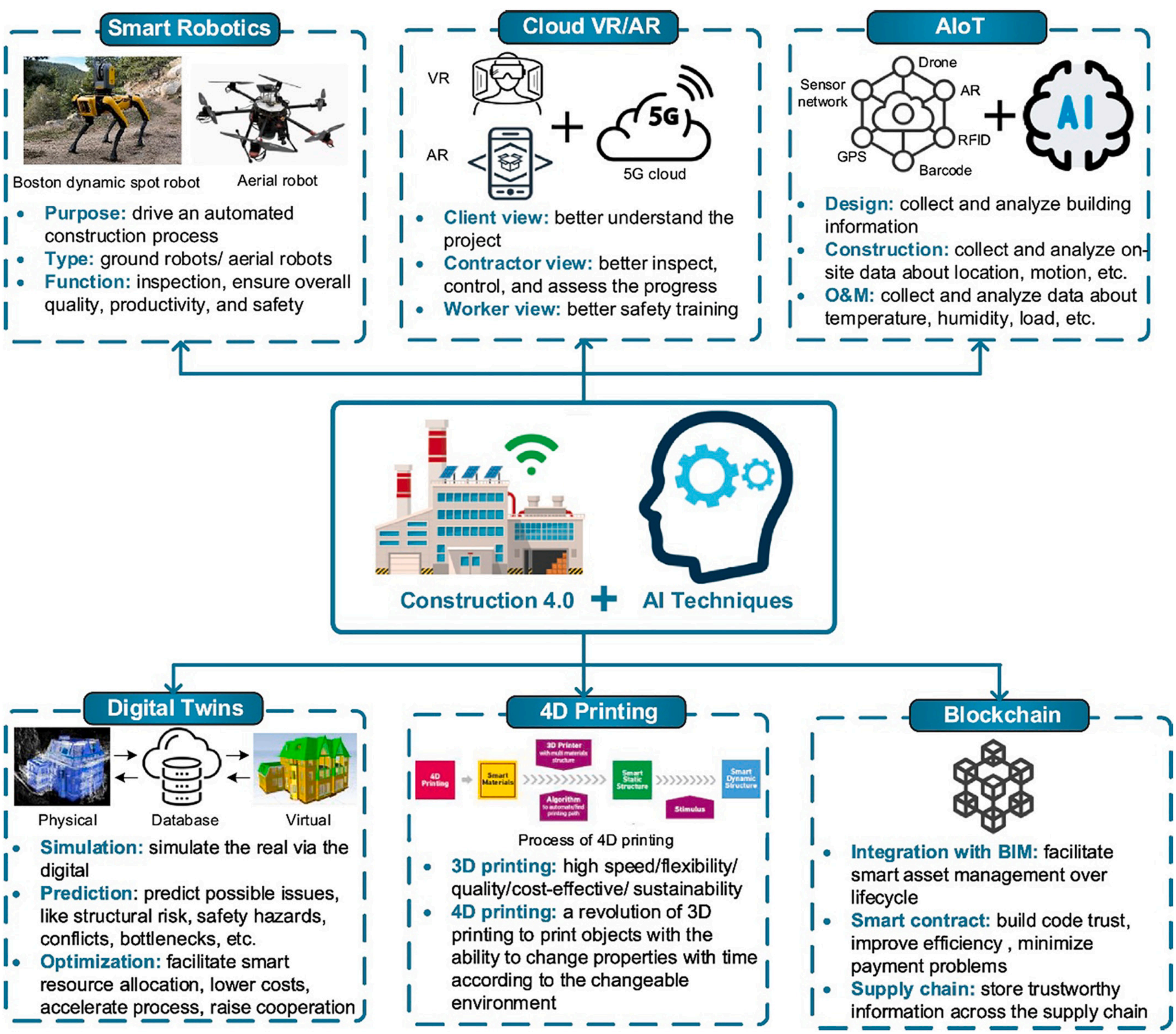

Fig. 21. Future trends of applications of AI in construction 4.0 [114].

the building. 4D printing extends the additive manufacturing technology to another dimension to incorporate time-dependent variation of the printed model influenced by various factors such as heat, pressure, electricity and magnetism. This technology is still at its inception and in future, 4D printed structures with materials such as concrete, geopolymer and mortar can be expected which can change its true form influenced by external stimuli. AI can be linked with 4D printing similar to the 3D printing process to develop generative designs, modeling and prediction of robotic arm motion and quality control of printed elements. Blockchain refers to a linked series of block of data which forms a distributed ledger. This facilitates a distributed, encrypted, and secure recording of digital transactions. In the construction field, blockchain concepts can be applied into predictive asset maintenance, accelerated payment processing and streamlined supply chains. Furthermore, applications of blockchain in the construction industry have been reported in integration with BIM as a procurement solution [220], implementing smart contracts including automated delivery of agreed contracts and enhanced copyright for project documentation [221], construction supply chain management with improved product compliance and authenticity [222]. Even though the current applications of blockchain in the construction industry are limited, this can be widely used in the future with AI as chains of blocks (ledgers) will generate a huge amount of data.

12. Conclusions

This paper reviews the state-of-the-art applications of AI/ML/DL algorithms in building and construction industry 4.0 with a special focus on the domains of architectural design and visualization; material design and optimization; structural design and analysis; offsite manufacturing and automation; construction management, progress monitoring and safety; smart operation, building management and health; and sustainability, life cycle analysis and circular economy. This paper presents a novel investigation into the applications of AI/DL/ML in building and construction industry encompassing the complete building lifecycle. Researchers have successfully used AI/ML/DL algorithms in these domains to improve and automate the processes in building and construction industry and following conclusions can be drawn from this review article:

- ML and DL are the core of AI-based applications and these are being extensively used in the construction industry due to the enhanced computational capacity and the massive amounts of data generated.
- Generative deep learning models such as GANs and VAEs are widely used for automated architectural generative design in applications such as floor plan generation, innovative conceptual designs and indoor scene synthesis.
- ML algorithms are widely used in property prediction of construction materials such as concrete, steel, timber and these algorithms can assist in optimization of materials to develop cost-effective, sustainable, and robust materials and composites.
- AI assisted structural design is still at its inception. However, other application of ML/DL models in structural domain such as strength and performance prediction of structural elements, buckling and fatigue analysis are prevalent.
- AI techniques can be incorporated into offsite manufacturing and 3D printing of buildings to enhance the efficiency in manufacturing, facilitate automated design for manufacture and assembly of modular systems and robotic arm path improvements. Also, smart vision can be used to automate the manufacturing process and quality control.
- Smart buildings and cities can generate massive amounts of data which can be processed using AI algorithms to develop intelligent systems which can improve the operational efficiency including energy and emission and user comfort.
- Sustainable disposal of end-of-life buildings can be carried out though recycling construction demolition waste through AI enabled robot systems and these robotic sorting systems can be used to sort and recycle any waste material type promoting circular economy.

From this review paper, it could be seen that the widespread applications of AI in industry 4.0 domain is prevalent. However, use of smart vision technologies with AI is becoming more popular due to the advances in colour cameras and hyperspectral cameras, improvements in the computational capacity to process streaming data with high pixel densities, seamless integration of computer vision with deep learning algorithms and advances in the deep learning algorithms for classification and object detection. Robotics is becoming popular as the end of the pipeline operators when combined with computer vision and AI algorithms. Construction 4.0 can accelerate the digital transformation of the construction industry, and this will generate massive amounts of data that can be used effectively to improve operational efficiency, make informed decisions, drive innovation and growth and enhance sustainability. As this research paper suggested, most of the applications of AI in the construction domain are still in the research phase with only a few companies offering promising commercial solutions. However, it can be forecasted that this will soon be changed considering the exponential growth of AI applications research and the highly successful outcomes.

The future evolution of Building and Construction 4.0 into Building and Construction 5.0 will close the gap and add the missing ingredient intelligence. This enables us to combine the power of intelligent, precise, and accurate machinery with human creativity and ingenuity. Also, adopting AI in a human-centric manner will result in environmentally friendly manufacturing and personalized solutions. Intelligent, human-centered design, manufacturing, and maintenance will emerge as AI advances to Construction 5.0. Cost optimization and reduction of human factor failure are other advantages. In future, customers will benefit from more personalized designs with 3D printing. Smart cities communicate and collaborate with AI and humans, 3D printed and optimized prefab modules, AI-based notifications for regular maintenance, and more energy-efficient generative designs will be important in meeting the global goal of reducing carbon equivalent emissions in the future.

Furthermore, collaborative robots will gain market share in the 3D printing robot industry. Advanced systems will control different materials that behave differently during the printing process, as well as printing process parameters such as layer thickness and material mass. AI-enabled cobot systems will recognize the materials used in the printers and configure the jobs accordingly. During the printing process, additional cobots will embed supplementary elements such as sensors and other personalized items. Future 3D printing techniques, with more personalized AI integration, will enable a much faster iterative loop of initial production, component testing, and creation of a redesigned object in both prefabricated and onsite construction. As a result, processes that take weeks now will be able to be completed in hours in the future.

Declaration of Competing Interest

None.

Acknowledgements

None.

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