Automation in Construction 141 (2022) 104445

Contents lists available at ScienceDirect

Automation in Construction

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

Review

Application of deep learning in facility management and maintenance for heating, ventilation, and air conditioning

Mirza Rayana Sanzana [a,*], Tomas Maul [b], Jing Ying Wong [a], Mostafa Osama Mostafa Abdulrazic [b], Chun-Chieh Yip [c]

[a] Department of Civil Engineering, Faculty of Science and Engineering, University of Nottingham Malaysia, Hulu Langat District, 43500 Semenyih, Selangor, Malaysia
[b] Department of Computer Science, Faculty of Science and Engineering, University of Nottingham Malaysia, Hulu Langat District, 43500 Semenyih, Selangor, Malaysia
[c] Department of Civil Engineering, University Tunku Abdul Rahman, Bandar Sungai Long, 43000 Cheras, Kajang, Selangor, Malaysia

ARTICLE INFO

Keywords:
Deep learning (DL)
Facility management (FM)
Facility management and maintenance (FMM)
Heating, ventilation, and air conditioning (HVAC)
Deep neural networks

ABSTRACT

Despite the promising results of deep learning research, construction industry applications are still limited. Facility Management (FM) in construction has yet to take full advantage of the efficiency of deep learning techniques in daily operations and maintenance. Heating, Ventilation, and Air Conditioning (HVAC) is a major part of Facility Management and Maintenance (FMM) operations, and an occasional HVAC malfunction can lead to a huge monetary loss. The application of deep learning techniques in FMM can optimize building performance, especially in predictive maintenance, by lowering energy consumption, scheduling maintenance, as well as monitoring equipment. This review covers 100 papers that show how neural networks have evolved in this area and summarizes deep learning applications in facility management. Furthermore, it discusses the current challenges and foresees how deep learning applications can be useful in this field for researchers developing specific deep learning models for FMM. The paper also highlights how establishing public datasets relevant to FM for predictive maintenance is crucial for the effectiveness of deep learning techniques. The utilization of deep learning methods for predictive maintenance on Thermal-Storage Air-Conditioning (TS-AC) in HVAC is necessary for environmental sustainability, as well as to improve the cost-efficiency of buildings.

1. Introduction

Deep learning, a branch of machine learning has evolved significantly in the last ten years initiating drastic changes in technological approaches in various industries from medical research to electronics. In processing large amounts of data, deep learning can achieve accuracies in such an advanced way that it can exceed human-level performance and productivity, as well as save time and resources. Deep learning completely shifted the automotive industry with its applications from automated driving to automatically detecting traffic lights, stop signs, obstacles, and such. In automation in the construction industry, deep learning is also being used to detect people around heavy machinery to improve safety. The high-performance levels of deep learning in the field of computer vision have made several areas of construction adopt deep learning. For example, Zhang et al. [108] discussed the utilization of text mining and natural language processing techniques for accident report analysis at construction sites. Computer vision-based construction safety vest detection, an earlier method of construction worker detection improves safety by detecting the motion of workers and the colour pixels of safety vests [94].

In terms of Facilities Management (FM) in the construction industry, a large number of stakeholders handle the operation. During this process, they appear and leave at various times during the building operation life cycle which causes information to be lost or distorted if not managed properly. Operation and maintenance in FM sector rely on effective and prompt decision-making from facility managers. It is an extremely hard challenge for facility managers to cater for quality services at a minimum cost as they are required to be cost-efficient and responsible [28].

Nevertheless, maintenance is required to be monitored as accurately as possible because it plays an important role in the sustainability of buildings or the built environment. Improper and delayed maintenance has led facility managers into challenging situations regarding repairs, high maintenance costs and arduous repairs [90]. Hence, it is essential for sustainability in Industry 4.0 context in the FM industry to employ advanced intelligent digital technologies as they can help facilitate the

* Corresponding author.
E-mail address: sanzanarayana@gmail.com (M.R. Sanzana).

https://doi.org/10.1016/j.autcon.2022.104445
Received 1 February 2022; Received in revised form 8 June 2022; Accepted 17 June 2022
Available online 23 June 2022

flow of information, along with drawing conclusions from predictions based on sensor data [5,107]. There are quite a few reviews on Machine Learning for life cycle management implementing combinations of different algorithms and discussing solutions for various scenarios [37,109]. The focus however has been more on predictive maintenance as this sort of maintenance can warn of a problem before it actually happens thanks to machine learning (ML), or more specifically deep learning as it is capable of making predictions [20]. Facility managers want advanced predictive maintenance assistance mainly in Heating, Ventilation, and Air Conditioning (HVAC). Focusing on HVAC is important as it encompasses a significant part of building life-cycle management.

Deep Learning has gained interest in Construction and Maintenance according to the Google Keywords trends. It is more popular within Machine Learning compared to Reinforcement Learning and Transfer Learning in Facility Management and Construction. Fig. 1 shows how the interest of Deep Learning over time increased in Construction and Maintenance. The comparison clearly validates the interest in researching and reviewing Deep Learning applications in FM in order to digitize and make it more efficient. Deep Learning has superiority in terms of prediction accuracy and better performance when trained with a large amount of data compared to other Machine Learning algorithms. Another factor is that deep learning solves problems end to end e.g., You-Only-Look-Once (YOLO) net. Other Machine Learning techniques require to break down the problem into different parts first before combining to the final stage e.g., Support Vector Machine (SVM). When there is a lack of domain understanding for feature analysis which maybe the case in FM for researchers, Deep Learning techniques prove to be a better alternative since feature engineering is less of a concern. In terms of large data size, which is the case for Facility Management, deep learning outperforms other Machine Learning techniques. When it comes to solving complex problems or prediction, deep learning outshines other methods which is why it can greatly benefit FM by optimizing energy efficiency and maintenance.

However, not much research has been conducted those analyze deep learning applications for HVAC using specific algorithms in the Facility Maintenance and Management (FMM) of the construction industry. Furthermore, not many studies have been focused on deep learning models to improve automation in construction for better maintenance of assets. Therefore, this paper provides a thorough literature review of deep learning applications in the FMM sector focusing on HVAC which can act as a useful comprehensive guide for subsequent research studies. The aim of this paper is to help researchers understand the current progress, and challenges of the various algorithms in deep learning to overcome challenges in FM for HVAC. The paper is organized as follows: Section 1 introduces the topic of this paper briefly; Section 2 demonstrates the research methodology for this study. Section 3 gives an overview of neural networks, and . Section 4 gives an overview of predictive maintenance. Section 5 reviews deep learning applications in the facility management and maintenance sector in the construction industry. Section 6discusses the challenges and possible approach for deep learning in FMM. Lastly, Section 7 summarizes and discusses the main findings.

2. Research methodology

2.1. Research design

Deep learning is a branch of machine learning that overlaps significantly with the area traditionally known as artificial neural networks. In most cases deep learning models are neural networks that adopt a large number of processing layers. In general, deep learning models require large amounts of training data. The network structures have a significant impact on performance, as measured by different metrics, including accuracy, training time, robustness to noise, and so on. An extensive literature discussed in this paper was collected from Scopus and Google Scholar databases. Scopus and Google Scholar provide the abstracts of all indexed publications, apart from additional information, including citation counts. The papers relevant to this study were filtered using a query string. The relevance and quality of the collected papers were ensured by defining the subject, and keywords. Deep learning theory in FMM is quite concentrated, therefore qualitative content analysis and quantitative analysis were conducted. The research framework is shown in Fig. 2.

2.2. Materials

The phrases “deep learning”, “convolutional neural networks (CNN)”, “recurrent neural networks (RNN)”, “Facility Management (FM)”, “Facility Management and Maintenance (FMM)”, were used to filter the results of the search to guarantee that the analyzed papers contained relevant deep learning-based solutions or applications. The query string used was ((KEY (Facility Management) OR SRCTITLE (construction OR civil)) AND TITLE-ABS-KEY (“deep learning” OR “CNN” OR “RNN” OR “convolutional neural networks” OR “recurrent neural networks”)). The search was specified from 2006 to date since deep learning in its modern form is generally perceived to have started around 2006. During the research, the language of the papers was set to be in English. The literature collected from the search was filtered manually by reading the titles, and abstracts. Then the filtration involved roughly browsing the papers to ensure that they were relevant to the subject of deep learning-based solutions for facility management and maintenance. A Microsoft Excel workbook was used to keep and organize the information of the collected papers. The deep learning approach taken for the type of FM task, the year of each paper, and the number of papers in each year, were recorded for further analysis. In the end, 100 papers on deep learning applications in the FM sector were obtained and reviewed.

3. Overview of neural networks

3.1. Brief historical remarks

A neural network generally consists of three parts, i.e., input layer,

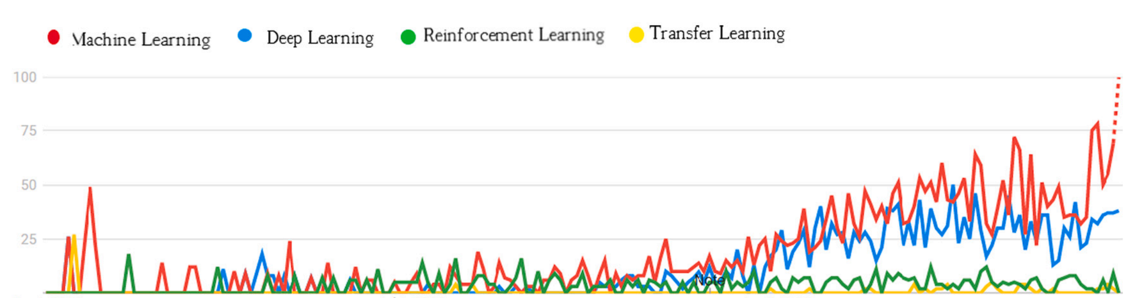

Fig. 1. Deep Learning interest over time in Construction and Maintenance.

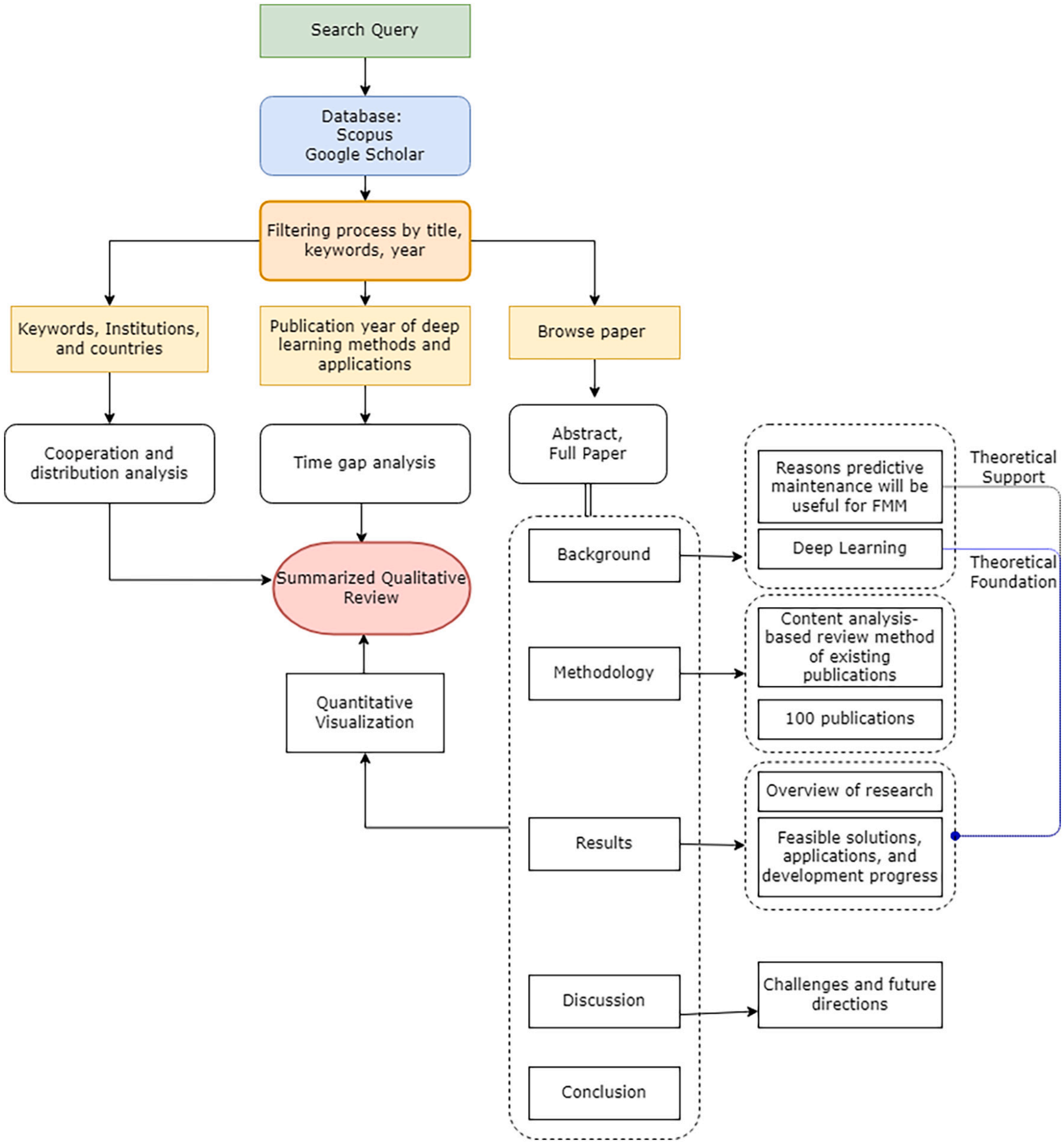

Fig. 2. Research framework.

hidden layer(s), and output layer. A deep neural network typically has *many* hidden layers, thus making the network *deep*. This in turn allows it to form rich hierarchical representations, which facilitates the capture of complex causal factors underlying the data. In other words, the rationale for depth is that it allows for the learning of abstract multi-level features of an input [101]. In traditional feature engineering human designers need to manually and painstakingly construct relevant features which are then fed into machine learning algorithms [13]. The deep neural network approach has typically replaced the more time-consuming and traditional approach of feature engineering [83].

Apart from the structural or architectural aspects of neural networks, the other key ingredient to the success of this field lies in learning algorithms. Rumelhart et al. [89] demonstrated the effective application of the backpropagation algorithm for training neural networks, in the context of a richer and deeper history of optimization. This was a key step in the development of the area. Deep learning techniques implement the back-propagation algorithm to find complex structures in large data sets and determine how the internal parameters of a model should change to compute the representation in each layer from the representation in the previous layer and perform predictions at a high-level accuracy [65]. As such, deep learning methods are also known as “representation learning”. Other algorithms commonly known for training ANNs include, simulated annealing, and genetic algorithms. Chen et al. [23] adapted ANNs for fault detection in engineering structures resulting from vibration or fatigue. ANNs have also been used for structural damage detection implementing backpropagation algorithms, empowered by a heuristics-based tunable steepest descent method for training, and Frequency response functions (FRF) used for structural damage detection [36].

Since their early days, ANNs have primarily been used for classification problems or function estimation due to which they are widely used for solving complex industrial problems [14]. Supervised learning is a type of learning where the machine is trained using labeled data (i.e., for every input the dataset has a corresponding target label). Whereas in unsupervised learning, the dataset consists only of input instances without target labels [11]. ANNs are applicable to both supervised and unsupervised learning. Moselhi et al. [77] mentioned how ANNs can be implemented with conventional expert-based FM systems and guarantees ideal performance over the systems. ANNs are particularly suited for Big Data which involves a very large number of data instances typically with high dimensionality, which makes it important in all the construction industry applications.

Following the early demonstrations of backpropagation, several other landmarks in the history of neural networks ensued, including the development of LeNet [48,64,65], whose general architectures will be briefly discussed in the following sections. Other than finding it hard to get adequate amount of labeled data for training, the neural network algorithms in the initial stage faced difficulty training the network properly. The training difficulty was also due to the vanishing gradient problem when the depth of the network expanded and also the hardware could not handle the complexity of training. Hinton and Salakhutdinov [47] first proposed deep learning as a solution to the vanishing gradient problems in deeper neural networks. Although the early days of neural networks exhibited many of the key ingredients required for the success of the field, they still exhibited some key limitations. Some of these limitations included limited processing power, limited availability of labeled data for training, and the vanishing gradient problem. Over time, these limitations were gradually eroded due to the advancement of deep learning. Deep learning field experienced a renaissance around 2006, marked by papers such as the one authored by Hinton and Salakhutdinov [47].

3.2. Multilayer perceptron (MLP)

The Multilayer Perceptron (MLP) is one of the most commonly used ANNs and, as with most architectures, can be used for both classification and regression [14,24]. Data samples are first normalized and then inserted into the input layer which then pass through the hidden layers resulting in the output according to the network's structure. Generally, for an MLP with a single hidden layer, the ANN topology is described as x:y:z. In x:y:z topology, x denotes the number of nodes in input layer, y denotes the number of nodes in hidden layer, and z denotes number of nodes in the output layer. In terms of the connectivity, nodes are typically referred to as fully connected, since all nodes from a layer are connected to all nodes in the subsequent (adjacent) layer. By using MLPs and Mixed Integer Linear Programming (MILP), Rajith et al. [86] developed a real-time optimized HVAC control system that was setup on top of an existing IoT framework. The optimized control system showcased just how powerful the combination of both could be in prediction, resulting in a turnaround in terms of predictive maintenance [86].

3.3. Convolutional neural network (CNN)

Convolutional Neural Networks (CNNs) exploit several design principles found in biological visual systems, namely the fact that representations are hierarchically composed from localized and repetitive receptive fields. In CNN terminology this translates into localized kernels that share weights across an image, both of which ultimately provide the network with prior knowledge that exploits the statistical regularities known to exist in images. In most CNNs this architectural feature is usually also combined with a more traditional fully connected structure, typically at the output side of the network. Apart from exploiting prior knowledge, which improves accuracy, CNNs also require fewer parameters compared to fully connected networks. This tends to make the learning process easier and faster and reduces some memory requirements. Today CNNs are often the method of choice in different computer vision applications, for example in object detection and image recognition. A classic early example of a successful CNN would be AlexNet, which demonstrated the power of combining deep learning, specifically a deep CNN, with very large datasets [58].

3.4. Recurrent neural network (RNN)

Another classic neural network structure is the Recurrent Neural Network (RNN) which is used in time series data processing, for example in speech recognition. Two main types of RNN, and the most popular Deep RNN architectures, are Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM), which differentiate themselves from more classic recurrent architectures by the use of gates that control the temporal flow of information [25]. LSTMs and GRUs in general are able to capture long-term dependencies in a sequence which is why they are widely used in multiple applications including natural language applications [15], time-series prediction [38], and anomaly detection [97] [22].

LSTMs have also been integrated with autoencoders [16]; a special form of neural network designed for unsupervised learning tasks [35]. An autoencoder consists of an encoder that transforms the input data into a hidden representation, while the decoder attempts to reconstruct the input data from the same hidden representation [35,69] with a minimum amount of distortion and noise [10]. Due to this characteristic, autoencoders have been used for dimensionality reduction applications [104], signal reconstruction applications, and anomaly detection applications [6,35].

4. Overview of predictive maintenance

Digitization and mainly the advent of big data brought about the possibility of developing efficient smart monitoring and predictive maintenance applications. Modern data-driven applications with distributed computing architectures caused major improvements in maintenance service efficiency. Predictive maintenance, an important part of the revolution of Industry 4.0 is based on the Computerized Maintenance Management System (CMMS) concept that takes advantage of state-of-the-art technological innovations [61]. CMMS coordinates all activities related to the availability, productivity, and maintainability of cyber-physical systems (CPSs). Procedures in a computerized maintenance process take place with minimal human involvement which minimizes human error. In such procedures, a high degree of automation with complex CMMS is required. However, predictive maintenance faces the challenge of bringing together technologies from different application domains including big data, Internet of things (IoT), augmented reality (AR), virtual reality (VR), machine learning and deep learning [31].

These complex CMMS solutions work completely autonomously, and with the learning capability can collect, store, and analyze data continuously. Although, to predict future failures, or downtimes, it is required to analyze historical data, as well as constantly monitor data in real-time. With the application of mathematical and statistical methods, smart maintenance can detect where, when, and why a component may fail, hence in predictive maintenance, the component gets repaired or replaced before the failure occurs saving costs and increasing the reliability of equipment [82].

Predictive Maintenance optimizes asset management and improves overall facilities management and maintenance. Time to failure (TTF) prediction and remaining useful life (RUL) prediction are well-known features of predictive maintenance. The TTF prediction denotes the amount of time a component is expected to last in operation. Whereas, RUL is the estimated lifespan of a component after which it is no longer capable of serving its intended purpose. Estimating TTF and RUL, albeit challenging, has proven to be useful for applications especially in characterizing rotating machines, such as pumps, and fans. Facility Managers can prepare to either maintain or change such machineries beforehand.

5. Applications of deep learning in FMM

Deep learning has greatly advanced the construction industry's FM by assisting facility managers in decision making and effective maintenance. Industrial maintenance processes are important as the productivity of the companies depend significantly on that. There are five types of maintenance that are frequently implemented in industry which are corrective, preventive, predetermined, condition-based and predictive [90]. Different companies adopt different types of maintenance depending on their specific needs. Fig. 3 shows where FMM is located in the Building Information Modeling (BIM) domain of construction industry. Facility managers generally conduct preventive or reactive maintenance for building maintenance management. However, these strategies have their limitations as preventive maintenance would not be able to predict when certain mechanical, electrical and plumbing (MEP) components would need repair in advance and reactive maintenance would not be able to prevent failures. Hence, predictive maintenance strategies, incorporated with advanced technologies such as IoT have become the preferred choice to improve the efficiency of facility management and maintenance (FMM) [24].

Since deep learning is particularly well-suited for perception-oriented tasks (as applied to IoT and other data), its applications are useful in predictive maintenance [63]. According to the literature, deep learning methods were found mostly in predictive maintenance rather than other types of proactive maintenance. Applications for building operation and maintenance were found specifically in fault detection and diagnostics, occupancy evaluation, and energy efficiency improvement [49]. Common accessible tools for developing deep learning models are Python with the help of TensorFlow [1], Keras [26,27], and PyTorch [81]; MATLAB with the help of Deep Learning Toolbox (Mathworks) [75], and R [98].

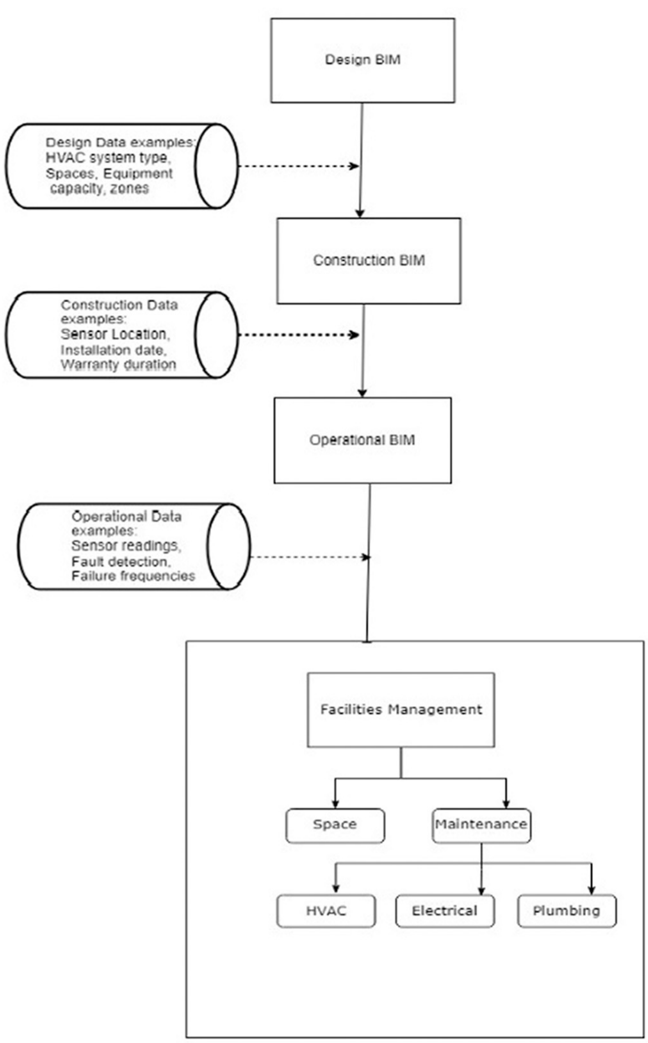

Fig. 3. Building Information Modeling (BIM) domain.

The following sub-sections are titled according to the deep learning approaches adopted in FM; 5.1 discusses image classification, 5.2 summarizes failure detection, and 5.3 is concerned with occupancy and energy detection or prediction. Section 5.4 reviews anomaly detection tasks, and is followed by a section on fault detection, and a section on monitoring or scheduling maintenance. The topic of data classification is discussed in Section 5.7, Natural Language Processing in 5.8, and object movement and detection in 5.9. Section 5.10 concludes with a brief analysis regarding the deep learning methods and research trends in the FM industry.

5.1. *Image classification*

Predictive maintenance aims to predict equipment failures to enable advance corrective maintenance scheduling to prevent unanticipated downtime, in turn improving service quality. Marzouk and Zaher [73] proposed a proactive maintenance application to maintain, upgrade, and operate assets of three fire protection systems in a cost-effective way with a deep-learning pre-trained model to assist facility management and maintenance. The deep learning model proposed was able to classify MEP components in the fire protection systems by image classification with a deep CNN using a support vector machine (SVM) technique with supervised learning [73]. The following research suggests an automated decision support system by integrating CNNs for image recognition to identify cracks or degradation phenomena directly in three-dimensional (3D) models [29]. By using 3D geometry, an automated decision support system could lead to suitable interventions by facility managers by evaluating multiple criteria in various scenarios.

In smart museums, computer vision algorithms are used to recognize images and to attribute an exhibit to an artist or epoch. Computer vision algorithms also analyze sentiments to identify the emotional states of images. With deep learning and computer vision techniques, it is possible to classify images into millions of predefined categories [99]. It is also possible to detect image details, read printed and handwritten text, and create valuable metadata for smart museum image catalogues for better asset management [99]. This research uses deep learning models for smart surveillance systems and offers mechanisms for compressing DNNs thereby improving the processing latency for a group of networked cameras [52]. A vision and learning-based indoor localization framework that uses a shared CNN for feature extraction from images was proposed [106]. This framework performed localization and object recognition simultaneously for facility management and did not require the deployment of radio-frequency identification (RFID) tags [106]. With the implementation of deep learning, RGB-D images can be automatically segmented into building components [30].

5.2. *Failure detection*

Nguyen and Medjaher [79] presented a dynamic predictive maintenance framework on a LSTM network in their research that depends on sensor measurements and prognostics according to the requirements of management planners. An LSTM can be used to compute the probabilities that a system may fail at specific times, and it thus contributes to better decisions regarding maintenance [79,103]. As there is an increasing demand for the reliability, availability, safety and maintainability of systems, there is also a great interest in the development of predictive maintenance (PdM). PdM helps facility managers schedule activities in a way that reduces machine or system downtime. Intelligent sensors can help in this real-time system monitoring process, providing managers with relevant information [42,92,103].

Limiting carbon dioxide emissions can be achieved through a general reduction of energy consumption, and by moving towards renewable energy sources. Establishing optimal energy consumption of buildings is necessary as they contribute significantly to the world's energy demand. Markoska [71] developed a framework for optimal forecasting of expected building performance by estimating expected energy consumption and indoor climate. The framework implemented an LSTM network using the Keras library for deep learning [26,27], which further uses the library TensorFlow, an open-source ML library [2]. The system identified numerous faults during operation and helped facility managers find issues regarding faulty wiring in meters and defective sensors. [16] proposed a predictive maintenance approach; an LSTM based deep learning model with an autoencoder architecture to predict failures for HVAC and validated it in a sports facility. Autoencoders were part the proposed framework since they adopt an unsupervised learning approach, which doesn't require labeled data and can thus be easily adapted to several applications. LSTM layers allow sequential data processing such as time-series which is the case for temperature or energy consumption data.

5.3. Occupancy detection/prediction & energy management

Incorrect estimation of occupancy leads to poor management of building resources like HVAC and lighting systems. Occupancy prediction models are developed with the data collected by occupancy sensors during the occupancy monitoring period. In general, ANN models do not make assumptions about data distributions before learning, which is consistent with their applicability for occupancy prediction. These models play an important role in occupancy prediction as occupancy levels can be highly dynamic and contextual. Advanced occupancy prediction methods use assumption-independent ANN techniques to obtain the hidden patterns in the collected sensor data making their predictive power more reliable [67,96].

Mutis et al. [78] utilize a multi-stream deep neural network to identify human activities and uses the You Only Look Once (YOLO) V3 deep CNN for multiple object detection to estimate occupancy counts in a room. The research results had a promising outcome as the application of the platform for accurate occupancy detection resulted in energy savings of approximately 10%–15%, thereby improving FM [3]. Martani et al. [72] described analyzing occupancy and measuring activity of occupants for energy consumption patterns (electricity, steam, and chilled water) by employing Wi-Fi connections as a proxy for occupancy level. The results of the research also showed that the operation of the HVAC systems depended on factors such as external temperature other than human occupancy, although a minimal part of electricity consumption was correlated to occupancy [72]. An effective CNN architecture for visual parking occupancy detection was introduced in [4], where the solution was compressed to run on smart cameras. Sonetti et al. [95] suggests implementing deep learning to analyze human behaviors for smart and sustainable environments to lessen energy consumption.

Predicting occupancy in real buildings rather than buildings under construction is very important because actual building occupancy has a significant effect on energy consumption. Kim et al. [57] proposed a machine learning framework with IoT data for HVAC where three machine learning based occupancy estimation algorithms, i.e., decision trees, support vector machines, and ANNs, were evaluated according to their performance in estimating occupancy status. The study showed that ANNs had an overall better accuracy in occupancy estimation compared to the other approaches.

Research is being carried out to employ new DL techniques to develop the next generation of occupancy models, that will be able to predict the behavior of occupants with a high level of accuracy [91]. Hammad [45] proposed a method by integrating BIM with an ANN model for limiting the deviation between predicted and actual energy consumption rates. Accurate BIM representations are produced by training a deep neural network for predicting occupant behavior that indicates the actual performance of the building under examination, which is further validated via energy simulations [45]. Lee et al. [66] reported that by using thermal cameras on-site and deep learning, an adaptive comfort model could be developed. The adaptive comfort model would be capable of achieving intelligent control of an air-conditioning system considering the dynamic interaction between occupants and their environment [66]. Deep learning techniques have enabled the detection of standing/sitting postures of individuals even from a distance [74]. Commercial buildings, and retail shops require the constant monitoring and control of HVAC and refrigeration systems. From the IoT data collected from various sources, it has been possible to show that unnecessary energy consumption occurs due to manual activity. Recently, supermarkets have become smart and handle the HVAC and refrigeration systems automatically for improving customer satisfaction as well as optimizing energy consumption. Optimizing resources in turn optimizes the energy consumption of a building. Hence, this research proposed a firefly based optimized LSTM (FOLSTM) model with real-time HVAC and refrigeration sensor data for a supermarket [55]. The focus was to enable resource optimization by forecasting relevant variables such as temperature [55].

For efficient energy consumption, a renewable solar and wind energy-enabled hybrid HVAC-DHW (heating, ventilation, and air conditioning-Domestic Hot Water) system utilizes an optimized nonlinear autoregressive network with exogenous inputs artificial neural network (NARX-ANN) and fuzzy controller based on user needs, dynamic behavior of the atmospheric environment, and the spatial distribution of the energy supply [111]. Initially, the heating and cooling effect of the environment and building is sensed via sensors and these sensed inputs are fed into a deep learning-based NARX-ANN model that predicts internal building temperatures, which are then fed into a fuzzy controller for optimizing energy distributions based on user demands [111]. Deng and Chen [32] developed an ANN model for a smart HVAC control system for multi-occupant offices to improve overall thermal comfort and energy consumption. This was done using the data collected from a thermostat that enabled a building automation system (BAS) to control the room air temperature based on physiological wristband parameters [32]. The wristband parameters represented the thermal sensation of occupants. Revati et al. [87] suggested a hybrid model implementing RNN and BiLSTM for load profile prediction in smart buildings. The results showed that the proposed hybrid model outperformed other deep learning models [87].

Human occupancy prediction is more meaningful if occupant crowdedness can be predicted a day prior to improve facility management. However, most research so far involves estimating the current number of people in a specific location, though the data can be used to further predict the occupant crowdedness in the future to improve decision-making processes [60,112]. Deep learning-based time-series crowd prediction is formulated to help facility managers schedule maintenance during periods of lowest pedestrian movement, i.e., an off-peak hour, thus minimizing disturbance [85]. Poon et al. [85] overcome the two primary limitations where prediction accuracy decreases as prediction time increases [46], and only the consecutive time steps in the most recent input data get exploited [70], by adopting a Long-Time Gap Two-Dimensional method (LT2D) to increase the crowd prediction length with high accuracy. The LT2D approach consists of long-time gap prediction, which extends the prediction length to 1 day with high accuracy, and 2D inputs, which exploit temporal patterns from previous days. By integrating the proposed LT2D-method into different baseline models like LSTM, BiLSTM, and GRU, the accuracy is generally improved by around 22% [85].

5.4. Anomaly detection and analysis

An anomaly in this context is essentially an odd occurrence, which typically requires the facility management to take corrective measures. Anomaly detection can become problematic for HVAC systems because sometimes odd patterns in the data can happen due to the normal operation of the system. Data variability usually occurs because of common changes in various operating conditions. The following paper suggested an anomaly detection system based on a kernelized One-Class Support Vector Machine (OCSVM) classifier reinforced by Principal

Component Analysis (PCA) to understand the difference between variabilities due to anomalies or standard system operation [12].

Katona and Panfilov [56] recommended a predictive maintenance framework for a smart HVAC application system with IoT that would handle big data streams from various data sources. It would also utilize deep learning for anomaly detection or outlier detection on the data based on a Gaussian model to alert the connected system in case of unexpected behaviors [56]. The classification problem depended on recorded (historical) data which analyzed the incoming temperature and humidity measurements and flagged them by assigning them to an "anomalous" class in case of suspicious behavior [56]. Guss and Linus [43] discussed the improvement of energy efficiency by detecting anomalies through developing a model using the K-means method. The model was used for clustering substations with similar consumption patterns to create electricity profiles, and using Gaussian process regression for electricity consumption prediction with a 24-h time frame [43]. Although both models performed anomaly detection in electricity consumption data, the K-means based model was faster and more reliable [43].

Jung et al. [54] focused on anomaly analysis using a long-short term memory (LSTM) model. High prediction accuracy was reported based on time-series data collected from Internet-of-Things (IoT) devices at indoor office space conditions, for facility management.

5.5. Fault detection

ANNs and deep learning models have been used in both supervised and unsupervised fault detection and diagnostics (FDD) [41]. Kumar and Abraham [59] used a two-step defect detection framework by automatically interpreting images with a 5-layered CNN for classification followed by a YOLO model for detecting pipe fractures from closed-circuit television (CCTV) videos. Most of the studies reviewed that implement automated fault detection and diagnostics (AFDD) are supervised methods and treat the FDD as essentially a classification problem [41]. Unsupervised methods are mainly adopted in a pre-processing phase or are used for fault detection through clustering.

Pump faults can be diagnosed if data and analytics are closely monitored; conversely, false negatives are a common occurrence when limited monitoring is employed. By closely monitoring MEP components, an effective asset management can be carried out. There sometimes may be the occurrence of false alarm but it can be quickly checked which is better than an underlying defect. Some researchers have explored using Digital Twin (DT), which is a relatively new framework for real-time intelligent asset maintenance, energy servicing, and condition monitoring [34,105]. Hallaji et al. [44] suggested a BIM-enabled DT (Digital Twin) framework to enhance the performance of deep learning methods for handling multivariate and low-quality, high-volume data after a thorough analysis.

5.6. Maintenance scheduling/monitoring

Cheng et al. [24] proposed a data-driven predictive maintenance planning framework based on BIM and IoT technologies for FMM of MEP components consisting of an information and an application layer. Data was collected and integrated among a BIM/IoT framework with an of FM system in the information layer. The application layer contained modules needed for attaining predictive maintenance utilizing ANN and SVM models. Braun [17] addressed the automation of construction progress monitoring using computer vision to detect construction elements in progress, and a CNN based framework to identify deviations between the as-planned and the as-performed schedule automatically. González-Domínguez et al. [40] proposed a preventive maintenance scheduling tool for healthcare centers using Markov chains. The tool proved to be useful in choosing the most suitable maintenance policies for each healthcare building without exceeding a specific degradation boundary, in turn allowing an ideal maintenance frequency to be achieved. Markov chains have also been shown to be effective in optimizing routine maintenance tasks, guaranteeing a suitable level of maintenance according to the frequency of failures and reducing costs and the associated carbon footprint [40].

Unsolicited building occupant complaint logs can result in unstructured data sets, so the following study focused on a data driven MLP model to predict the number of thermal complaints as a predictive maintenance strategy [8]. Thermal complaints are one of the most common complaints [39], and the developed MLP model showed that it can assist facility managers in planning for the staffing resources needed to handle these complaints thus enhancing the satisfaction of occupants as well as the building performance [8]. Assaf and Srour [8] reported that the MLP model showed a 21% lower Root-Mean-Square-Error (RMSE) when compared to a traditional Autoregressive Integrated Moving Average (ARIMA) model related to cooler complaints.

The urban building energy model (UBEM) is the foundation to support the design of energy efficient communities, but it is limited in its abilities to capture the inter-building interdependency due to its dynamic and non-linear characteristic. The data-driven UBEM synthesizing the solar-based building interdependency and spatial-temporal graph convolutional network (ST-GCN) was developed for predicting hourly energy consumption and showed significant improvements in building energy simulation based on a case study [50]. Tsai et al. [100] proposed a system to assist in the management of site equipment for construction management called SEMA that collects data from raw videos, extracts equipment-related information, and delivers that information based on a deep learning model that was first trained to automatically identify and track construction equipment passing by the site monitor [100]. SEMA also integrated a user-friendly chatbot interface to obtain data from the database containing the extracted information from videos such as date, time for equipment entering, exiting construction site, as well as the quantity, and it was proven to effectively save valuable time in getting related information for facility managers [100].

5.7. Data classification

Large buildings have been using IoT platforms for managing indoor climate ever since the growth of wireless smart HVAC systems. However, the controllers and sensors are from different manufactures and communication between these devices requires a human translator to make them compatible for integration purposes. Cashion et al. [21] suggested a smart translator for the inter-communication of IoT devices using Deep Neural Networks (DNNs) for assigning registers exhibiting identifiable data patterns to standardized labels automatically. Jeong [53] mentions how deep learning can be useful in dividing BIM data into structured and unstructured types in the developed Evaluation, Analytics, and Prediction (EAP) Framework. The accuracy of supervised deep learning methods in 3D scene selection has improved drastically since 2017. The drastic change has been possible due to the availability of large, labeled datasets of indoor spaces, but the semantic object categories generally do not cover HVAC and plumbing systems. An annotated dataset of 3D reconstructions of building facilities such as HVAC called 3DFacilities, was presented where supervised deep learning for Scan-to-BIM, i.e., a process of converting 3D reconstructions into BIM, was implemented [29].

5.8. Natural language processing

Automated energy compliance checking focuses on automatically checking the compliance of a BIM with appropriate energy requirements. Existing automated compliance checking (ACC) mostly focuses on code-checking and still requires manual extraction from text into computer-processable representations and then matching these to BIM standards. Zhou [110] proposed an automated ACC to check compliance of BIM-represented building designs with energy codes and contract specifications by developing a semantic, natural language processing (NLP)-enabled, rule-based information extraction method. A variant of a three-layer feedforward neural network, the hierarchical softmax skip-gram, was used to learn the distributed representation. The network exhibited promising performance due to its computational efficiency and accuracy on large datasets [110]. Deep learning further enriches the applications of NLP. A residual convolutional neural network (Res-CNN) model was selected for its training speed and high accuracy, to perform the task of distantly supervised noisy relation extraction [51]. Generally, knowledge regarding Mechanical, Electrical, and Plumbing (MEP) is represented in unstructured text form and heterogeneously dispersed in design documents and the Internet. To address this issue, MEP text documents were collected from multiple websites and then text segmentation was carried out by implementing NLP models to extract entities and find out the relationship from the documented information to speed up the process [68].

Different personnel in the property management business, including owners, property managers, investors, vendors, as well as other users like tenants and renters, use property management software (PMS) technology. These personnel use PMS to collect, share and distribute data related to property management. PMS refers to online platforms that facilitate the management, maintenance, and operation process of properties and increase efficiency simply by updating and visualizing all data via a centralized computer system. The following research reported how deep neural networks advance the automation of property management, focusing on integrating a smart chatbot into a PMS for real-time automated customer support, engaging website/platform visitors, and understanding their intent [93]. Bouabdallaoui et al. [15] proposed an NLP based solution to classify maintenance requests in healthcare facilities thus assisting FM to handle day-to-day maintenance activities.

5.9. Object/movement detection

Region-based convolutional neural networks (R-CNN) have made major advances in object detection. Such advances involve scanning an input image for desirable objects using selective search, which in turn generates region proposals from which features are extracted and then classified.

Arslan et al. [7] used a Hidden Markov Model (HMM) to improve worker safety in dynamic environments by categorizing the trajectory movements and extracting movement patterns because human mobility is described as a series of Markovian stochastic processes. In HMMs, minimal training data is required. The probability distribution of a future state in a series (i.e., safe, or unsafe behavior, or a subsequent location) of a of a Markov stochastic process is only dependent on its current state or a present location. Hence, it eliminates the need of incorporating the whole history of preceding states. Baek et al. [9] proposed a two-module system where an Augmented Reality (AR) device captured a holographic image of a sanitary pipe and then indoor location and orientation were estimated with a CNN.

5.10. Analysis and research trends

Smart grid and smart city trends are emerging making energy management a crucial factor for their sustainability and management. Energy management requires forecasting that is as precise as possible regarding a building's electrical energy usage. With deep learning, energy efficiency was improved approximately 10%–15% by occupancy prediction [3]. Deep learning has clearly proven to be useful in predictive maintenance according to the literature, where it tries to predict the number of occupants to understand thermal energy requirement in advance, so facility managers can be prepared [12]. Predictive building control increases the efficiency of building operations assisting facility managers [82].

FM has become aware of the benefits of deep learning-based solutions for asset management, and fault/failure detection, hence the time span between development and deployment has been greatly reduced. RNNs were initially proposed in the 1980s but were applied only in 2008 to avoid obstacles for robotic excavators [80]. CNNs were also introduced in the 1980s but became popular in FM-related applications after being used to detect trip hazards on construction sites [76]. Conversely, the YOLO v3 algorithm was first introduced in 2018 and was quickly applied in facility management in construction [59,78]. Crowd prediction significantly increases efficiency for building management, but deep learning time-series is rarely used for crowd prediction. The literature in the field of facility management in construction mostly focus on the energy and cost saving aspects of buildings rather than user satisfaction [62].

The focus is mainly on managing energy and preserving it. Of all the papers reviewed, energy management was the subject of application in 18% of the papers, the highest percentage, followed by 14% for maintenance scheduling, 12% for occupancy detection, 10% each for anomaly detection, fault detection and image classification, 8% failure detection, 6% each for natural language processing and movement detection and finally 2% for data classification.

Fig. 4 shows that only recently researchers have started to pay attention to using DL techniques for FM, whereas research has been more concentrated in the construction industry as a whole. Fig. 5 shows a stacked bar graph displaying the different deep learning methods used in different research papers and in which years those papers were published. It can be noticed that CNNs and MLPs, sometimes referred to as a Feed-Forward Neural Networks were the most commonly used methods, and they were also used in recent years. Fig. 6 shows a stacked bar graph displaying each of the main deep learning methods and which applications there were used in. Given increasing demands for reducing energy consumption, it is perhaps unsurprising that energy management is one of the main focus areas of recent research. It can also be noticed that some deep learning methods are more suitable than others depending on the application type.

6. Challenges and possible approach for deep learning in FM

6.1. Challenges

Despite the promising outcome in automating and assisting FMM, it is still a big challenge to make the majority of the industry employ deep learning techniques [88]. An important limitation and contributing factor consists of the lack of good quality labeled data, specifically related to FM of HVAC [49]. This hampers the creation of large training sets, which in turn dampens the performance of deep learning algorithms. Useful industry applications of deep learning for energy optimization and building life-cycle management are still limited [49]. Transfer learning utilizes and reuses the relevant parts of a pre-trained model and applies it to a similar problem speeding up and overcoming the issue of data availability [84]. The main applications of transfer

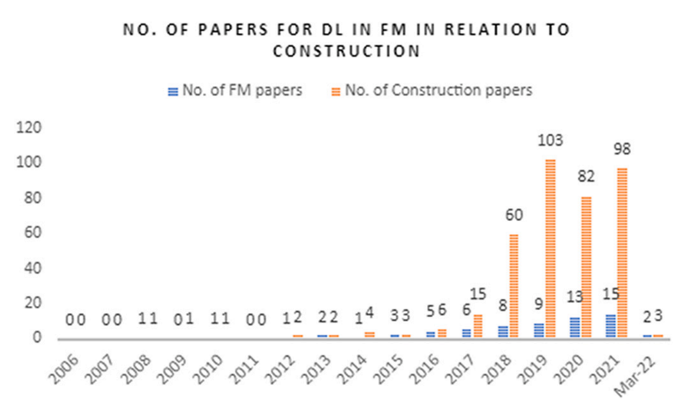

Fig. 4. Comparison of DL research productivity as applied to FM or construction.

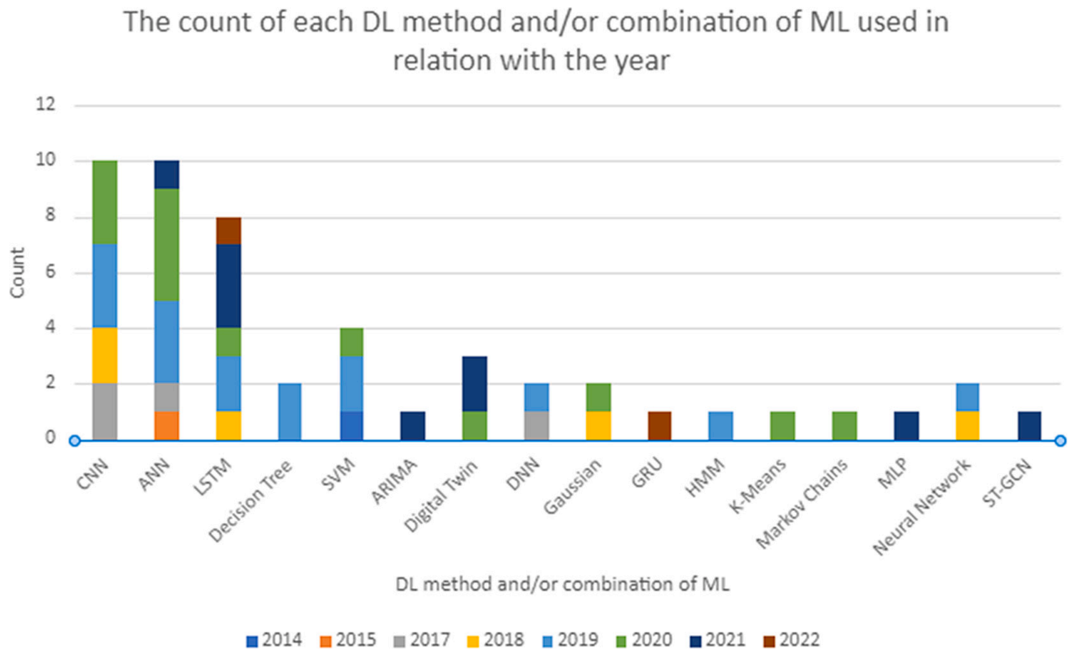

Fig. 5. Application of Deep Learning(DL) techniques in FM.

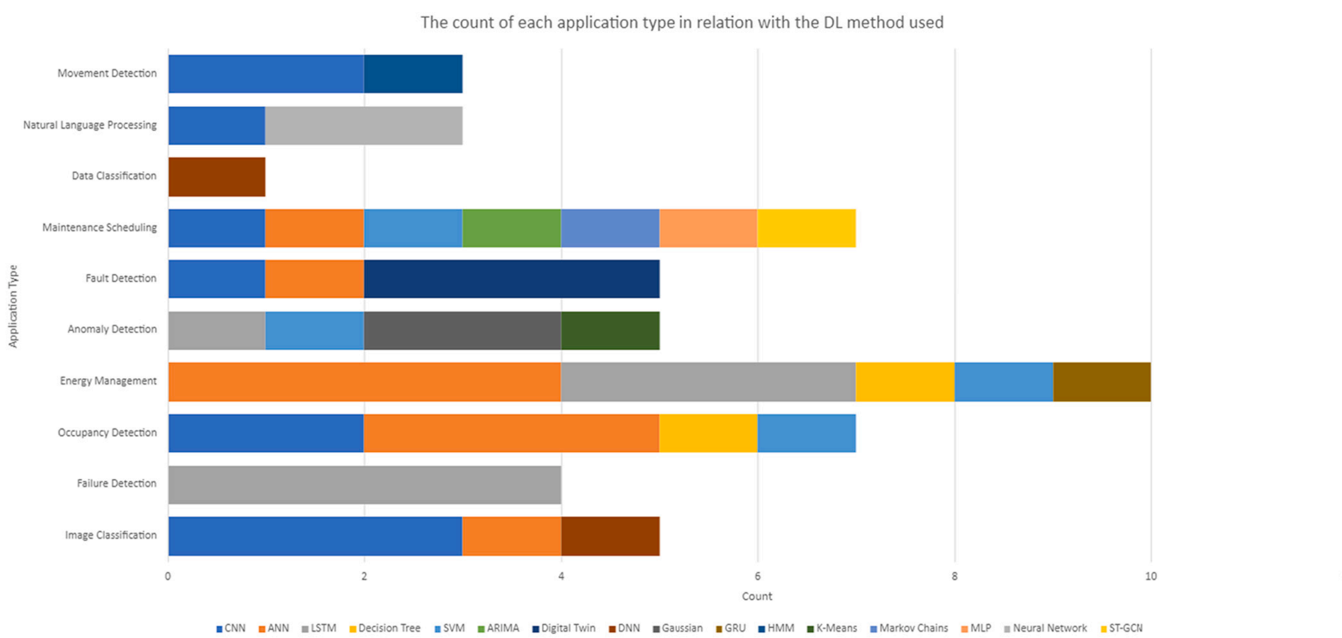

Fig. 6. Types of FM tasks that adopt DL techniques.

learning albeit mostly limited to smart buildings involve load prediction, occupancy detection, activity recognition, building dynamics prediction, and energy systems control [84]. In the future, transfer learning techniques may reduce the demand for large volumes of data as currently only a few studies have been deployed in real world [84]. However big data is still required to build the first models from which transfer learning can then be applied. Lack of data happens mostly because of the manual nature of data handling and collection.

Reinforcement learning may pose to be a better alternative as well compared to conventional HVAC FM. Nonetheless, actual applications in real buildings are scarce Wang and Hong [102]; Hong et al. [49] report only three reinforcement learning applications for HVAC. Although deep learning methods are popular for sentiment analysis, they can be generally semantically weak, requiring large amounts of text input [18]. Hybrid approaches, combine both knowledge-based and statistical methods like deep learning to achieve objectives such as emotion recognition for commercial building occupant satisfaction and polarity detection from text or multimodal data [19,33]. Another problem of implementing deep learning methods for fault detection and diagnosis is the lack of data containing information about the system's operational conditions. It poses as a hindrance when it comes to developing effective Fault Detection (FD) methods for HVAC installations. More research needs to be done on improving automated fault detection and diagnosis methods for HVAC.

6.2. Possible approach

Regulating an appropriate indoor temperature has clearly been a primary objective for facility managers. Crowd prediction, occupancy detection, and prediction with deep learning has successfully proven to make a building more energy efficient. For a more sustainable environment, decreasing carbon dioxide emission is necessary, which means optimizing the energy consumption of a building due to the fact that people stay mostly indoors. Many research studies have focused on optimizing energy consumption, but not much research has been done on the application of deep learning techniques to green and sustainable methods. Such sustainable methods involve thermal-storage air-conditioning (TS-AC) systems rather than conventional ACs, which could improve the energy efficiency of a building and lower carbon dioxide emission for a better environment. It would be a promising future direction to use deep learning methods to predict how much water the chiller of a TS-AC system requires for water circulation the next day.

Utilizing deep learning technique to estimate energy requirements for commercial buildings by predicting peak and off-peak hours depending on the number of building occupants during a certain time period could greatly reduce energy loads. This would also be useful for scheduling HVAC maintenance by predicting peak hours a day before, increasing occupant satisfaction. More research studies need to utilize deep learning for increasing prediction timespans.

The field of deep learning has grown substantially in the last five years. With the growth of deep learning, automatic detection of faults and failures with deep learning is becoming common due to its adaptability in a dynamic environment. However, it requires added focus on automatic fault detection in HVAC equipment and automatic maintenance scheduling for optimizing building performance. Many previous techniques for fault detection include IoT implementations, but many commercial buildings show unwillingness to change their current HVAC equipment and update it with IoT. Because of this, it is necessary to further explore how deep learning can be help when such IoT features are absent from existing equipment.

Since deep learning requires data for training, it is crucial to establish one or more public datasets relevant to facility management and predictive maintenance. The quantity and quality of this data significantly affects the performance of deep learning solutions. Public datasets are limited in terms of buildings and energy systems. This makes it more challenging for researchers to focus on building energy management and maintenance. Building energy related public datasets for maintaining or managing HVAC equipment will allow researchers to focus more on deep learning techniques for improving facility management and maintenance.

7. Conclusions

An occasional HVAC malfunction can lead to a huge financial loss for the FM sector in the construction industry. This is why it is important to utilize deep learning techniques for handling FMM effectively with predictive maintenance. A scheduled maintenance system to predict maintenance time during reduced pedestrian flow and automated fault detection and diagnosis for HVAC equipment can greatly benefit FM. Hence the goals of lowering carbon dioxide emission as well as optimizing the energy consumption of a building, should be primary research focus areas. The literature surveyed in this paper, indicates the importance of implementing an automated maintenance scheduling for TS-AC since it is a major part of HVAC and the focus of FM teams. It is also crucial to utilize deep learning techniques by developing models for targeted domains, since this effort can generate environmental benefits by facilitating HVAC to be green and sustainable. Fig. 7 shows a summary of research objectives and answers this review paper focuses on. However, most research so far involves estimating the current number of people in a specific location, though the data can be used to further predict the occupant crowdedness in the future to improve decision-making processes. Additionally, more focus needs to be on automatic fault detection on HVAC equipment and automatic maintenance scheduling to ensure building efficiency and occupant comfort. According to the literature review, DL shows promising results in improving the FMM of building efficiency, and hence requires more research in developing DL applications for FMM of HVAC.

Declaration of Competing Interest

We hereby declare that we do not have any conflict of interest in

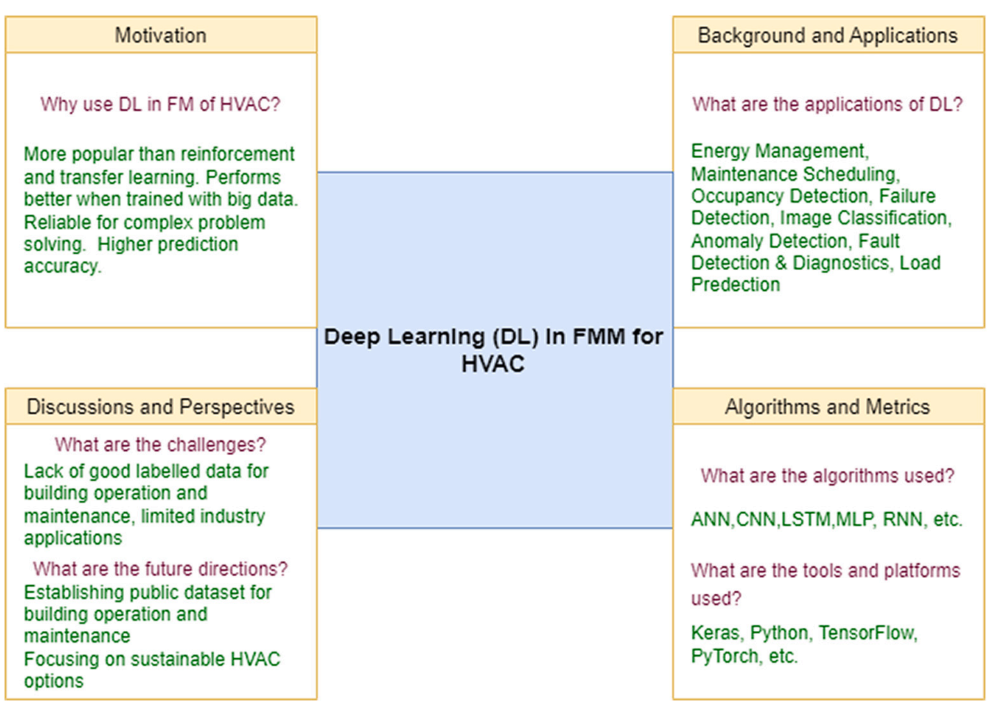

Fig. 7. Summary of Research Objectives and Answers.

connection with the work submitted.

References

[1] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G.S. Corrado, A. Davis, X. Zheng, TensorFlow: An end-to-end Open Source Machine Learning Platform, Retrieved 01 28, 2022, from, https://www.tensorflow.org/, 2015.

[2] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, et al., Tensorflow: A system for large-scale machine learning, in: Proceedings of the 12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI}) vol. 16, USENIX - The Advanced Computing Systems Association, Savannah, GA, USA, 2016, pp. 265–283, https://doi.org/10.48550/arXiv:1605.08695.

[3] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, T. Weng, Occupancy-driven energy management for smart building automation, in: BuildSys '10: Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building, Association for Computing Machinery, Zurich, Switzerland, 2010, pp. 1–6, https://doi.org/10.1145/1878431.1878433.

[4] G. Amato, F. Carrara, F. Falchi, C. Gennaro, C. Meghini, C. Vairo, Deep learning for decentralized parking lot occupancy detection, Expert Syst. Appl. 72 (2017) 327–334, https://doi.org/10.1016/j.eswa.2016.10.055.

[5] K. Araszkiewicz, Digital technologies in facility management – the state of practice and research challenges, Proc. Eng. 196 (2017) 1034–1042, https://doi.org/10.1016/j.proeng.2017.08.059.

[6] D. Araya, K. Grolinger, H. El Yamany, M. Capretz, G. Bitsuamlak, An ensemble learning framework for anomaly detection in building energy consumption, Energy Build. 144 (2017) 191–206, https://doi.org/10.1016/j.enbuild.2017.02.058.

[7] M. Arslan, C. Cruz, D. Ginhac, Semantic trajectory insights for worker safety in dynamic environments, Autom. Constr. 106 (2019), https://doi.org/10.1016/j.autcon.2019.102854.

[8] S. Assaf, I. Srour, Using a data driven neural network approach to forecast building occupant complaints, Build. Environ. 200 (2021), https://doi.org/10.1016/j.buildenv.2021.107972.

[9] F. Baek, I. Ha, H. Kim, Augmented reality system for facility management using image-based indoor localization, Autom. Constr. 99 (2019) 18–26, https://doi.org/10.1016/j.autcon.2018.11.034.

[10] P. Baldi, Autoencoders, unsupervised learning, and deep architectures, in: Proceedings of ICML workshop on unsupervised and transfer learning 27, PMLR, Washington, 2012, pp. 27–49. https://dl.acm.org/doi/10.5555/3045796.3045801.

[11] S. Bansal, Supervised and Unsupervised Learning, Retrieved 01 24, 2022, from GeeksForGeeks: https://www.geeksforgeeks.org/supervised-unsupervised-learning/, 2021.

[12] A. Beghi, L. Cecchinato, C. Corazzol, M. Rampazzo, F. Simmini, G. Susto, A one-class SVM based tool for machine learning novelty detection in HVAC chiller systems, IFAC Proc. 47 (3) (2014) 1953–1958, https://doi.org/10.3182/20140824-6-ZA-1003.02382.

[13] Y. Bengio, Learning deep architectures for AI, in: Y. Bengio (Ed.), Foundations and Trends® in Machine Learning vol. 2, now Publishers Inc., Hanover, MA, USA, 2009, pp. 1–127 (doi:ISBN 978-1-60198-294-0).

[14] M. Bilal, L.O. Oyedele, J. Qadir, K. Munir, S.O. Ajayi, O.O. Akinade, et al., Big data in the construction industry: A review of present status, opportunities, and future trends, Adv. Eng. Inform. 30 (3) (2016) 500–521, https://doi.org/10.1016/j.aei.2016.07.001.

[15] Y. Bouabdallaoui, Z. Lafhaj, P. Yim, L. Ducoulombier, B. Bennadji, Natural language processing model for managing maintenance requests in buildings, Buildings 10 (9) (2020) 1–12, https://doi.org/10.3390/buildings10090160.

[16] Y. Bouabdallaoui, Z. Lafhaj, P. Yim, L. Ducoulombier, B. Bennadji, Predictive maintenance in building facilities: A machine learning-based approach, Sensors 21 (4) (2021) 1044, https://doi.org/10.3390/s21041044.

[17] A. Braun, Automated BIM-Based Construction Progress Monitoring by Processing and Matching Semantic and Geometric Data, mediaTUM- Media and Publication, 2020. Retrieved from, https://www.researchgate.net/publication/345808918_Automated_BIM-based_construction_progress_monitoring_by_processing_and_matching_semantic_and_geometric_data.

[18] E. Cambria, Affective computing and sentiment analysis, Int. Underw. Syst. Des. 31 (2) (2016) 102–107, https://doi.org/10.1109/MIS.2016.31.

[19] E. Cambria, Y. Li, F.Z. Xing, S. Poria, K. Kwok, SenticNet 6: Ensemble Application of Symbolic and Subsymbolic AI for Sentiment Analysis. *CIKM '20:* Proceedings of the 29th ACM International Conference on Information & Knowledge Management, Association for Computing Machinery, Virtual Event, Ireland, 2020, pp. 105–114, https://doi.org/10.1145/3340531.3412003.

[20] T.P. Carvalho, F. Soares, R. Vita, R.D. Francisco, J.P. Basto, S.G. Alcalá, A systematic literature review of machine learning methods applied to predictive maintenance, Comput. Ind. Eng. 137 (2019), https://doi.org/10.1016/j.cie.2019.106024.

[21] K. Cashion, S. Ravindran, N. Powar, J. Gold, IOT Device Code Translators Using LSTM Networks. 2017 IEEE National Aerospace and Electronics Conference (NAECON), IEEE, Dayton, OH, USA, 2017, pp. 88–90, https://doi.org/10.1109/NAECON.2017.8268750.

[22] R. Chalapathy, S. Chawla, Deep learning for anomaly detection: A survey, arXiv (2019), https://doi.org/10.48550/arXiv.1901.03407.

[23] Q. Chen, Y.W. Chan, K. Worden, Structural fault diagnosis and isolation using neural networks based on response-only data, Struct. Comput. 81 (22−23) (2003) 2165–2172, https://doi.org/10.1016/S0045-7949(03)00295-5.

[24] J.C. Cheng, W. Chen, K.C. Wang, Q. Wang, Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms, Autom. Constr. 112 (2020) 1–21, https://doi.org/10.1016/j.autcon.2020.103087.

[25] K. Cho, B.V. Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, Y. Bengio, Learning Phrase Representations Using RNN Encoder–Decoder for Statistical Machine Translation. Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), Association for Computational Linguistics, Doha, Qatar, 2014, pp. 1724–1734, https://doi.org/10.3115/v1/D14-1179.

[26] F. Chollet, Keras, Retrieved 01 28, 2022, from, https://keras.io/, 2015.

[27] F. Chollet, Keras, Retrieved 01 08, 2022, from Github: https://github.com/fchollet/keras, 2015.

[28] I. Connelly, Aligning training with priority outcomes at NPS, Public Manag. 39 (2) (2010, April 6) 22–27. Retrieved January 23, 2022, from, https://www.td.org/magazines/the-public-manager/aligning-training-with-priority-outcomes-at-nps.

[29] T. Czerniawski, F. Leite, 3DFacilities: Annotated 3D Reconstructions of Building Facilities, in: Advanced Computing Strategies for Engineering vol. 10863, Springer, 2018, pp. 186–200, https://doi.org/10.1007/978-3-319-91635-4_10.

[30] T. Czerniawski, F. Leite, Automated segmentation of RGB-D images into a comprehensive set of building components using deep learning, Adv. Eng. Inform. 45 (2020), https://doi.org/10.1016/j.enbuild.2020.109872.

[31] C.N. Deac, G.C. Deac, C.L. Popa, M. Ghinea, C.E. Cotet, Using Augmented Reality in Smart Manufacturing. Proceedings of the 28th DAAAM International Symposium, DAAAM International, Vienna, 2017, pp. 727–732, https://doi.org/10.2507/28th.daaam.proceedings.102.

[32] Z. Deng, Q. Chen, Development and validation of a smart HVAC control system for multi-occupant offices by using occupants' physiological signals from wristband, Energy Build. 214 (2020), https://doi.org/10.1016/j.enbuild.2020.109872.

[33] M. D'Orazio, E.D. Giuseppe, G. Bernardini, Automatic detection of maintenance requests: comparison of human manual annotation and sentiment analysis techniques, Autom. Constr. (2021), https://doi.org/10.1016/j.autcon.2021.104068.

[34] I. Errandonea, S. Beltrán, S. Arrizabalaga, Digital twin for maintenance: a literature review, Comput. Ind. 123 (2020), https://doi.org/10.1016/j.compind.2020.103316.

[35] C. Fan, F. Xiao, Y. Zhao, J. Wang, Analytical investigation of autoencoder-based methods for unsupervised anomaly detection in building energy data, Appl. Energy 211 (2018) 1123–1135, https://doi.org/10.1016/j.apenergy.2017.12.005.

[36] X. Fang, H. Luo, J. Tang, Structural damage detection using neural network with learning rate improvement, Comput. Struct. 83 (25–26) (2005) 2150–2161, https://doi.org/10.1016/j.compstruc.2005.02.029.

[37] X. Gao, P. Pishdad-Bozorgi, D.R. Shelden, Y. Hu, Machine learning applications in facility life-cycle cost analysis: A review, in: ASCE International Conference on Computing in Civil Engineering 2019, ASCE, Georgia, 2019, https://doi.org/10.1061/9780784482445.034.

[38] A. Gasparin, S. Lukovic, C. Alippi, Deep learning for time series forecasting: the electric load case, CAAI Trans. Intel. Technol. 7 (2021) 1–25, https://doi.org/10.1049/cit2.12060.

[39] J. Goins, M. Moezzi, Linking occupant complaints to building performance, Build. Res. Inf. 41 (3) (2013) 361–372, https://doi.org/10.1080/09613218.2013.763714.

[40] J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, Scheduling of preventive maintenance in healthcare buildings using Markov chain, Appl. Sci. 10 (5) (2020), https://doi.org/10.3390/app10155263.

[41] A.H. Gourabpasi, M. Nik-Bakht, Knowledge discovery by analyzing the state of the art of data-driven fault detection and diagnostics of building HVAC, CivilEng 2 (4) (2021) 986–1008, https://doi.org/10.3390/civileng2040053.

[42] R. Gouriveau, K. Medjaher, N. Zerhouni, From Prognostics and Health Systems Management to Predictive Maintenance 1: Monitoring and Prognostics vol. 4, Wiley Online Library, 2016, https://doi.org/10.1002/9781119371052.

[43] H. Guss, R. Linus, Applying Machine Learning Algorithms for Anomaly Detection in Electricity Data: Improving the Energy Efficiency of Residential Buildings, Digitala Vetenskapliga Arkivet, 2020. Retrieved from, https://www.utn.uu.se/sts/student/wp-content/uploads/2020/07/2007_Linus_Rustas_Herman_Guss.pdf.

[44] S.M. Hallaji, Y. Fang, B.K. Winfrey, Predictive maintenance of pumps in civil infrastructure: state-of-the-art, challenges and future directions, Autom. Constr. 134 (2021), https://doi.org/10.1016/j.autcon.2021.104049.

[45] A.W. Hammad, Minimising the deviation between predicted and actual building performance via use of neural networks and BIM, Buildings 9 (5) (2019), https://doi.org/10.3390/buildings9050131.

[46] P. Hewage, M. Trovati, E. Pereira, A. Behera, Deep learning-based effective fine-grained weather forecasting model, Pattern. Anal. Applic. 24 (2021) 343–366, https://doi.org/10.1007/s10044-020-00898-1.

[47] G. Hinton, R. Salakhutdinov, Reducing the dimensionality of data with neural networks, Science 313 (5786) (2006) 504–507, https://doi.org/10.1126/science.1127647.

[48] S. Hochreiter, J. Schmidhuber, Long-short term memory, Neural Comput. 9 (8) (1997) 1735–1780, https://doi.org/10.1162/neco.1997.9.8.1735.

[49] T. Hong, Z. Wang, X. Luo, W. Zhang, State-of-the-art on research and applications of machine learning in the building life cycle, Energy Build. 212 (2020), https://doi.org/10.1016/j.enbuild.2020.109831.

[50] Y. Hu, X. Cheng, S. Wang, J. Chen, T. Zhao, E. Dai, Times series forecasting for urban building energy consumption based on graph convolutional network, Appl. Energy 307 (2022), https://doi.org/10.1016/j.apenergy.2021.118231.
[51] Y.Y. Huang, W.Y. Wang, Deep Residual Learning for Weakly-Supervised Relation Extraction. Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, Association for Computational Linguistics, Copenhagen, Denmark, 2017, https://doi.org/10.18653/v1/D17-1191.
[52] K. Jayarajah, Exploiting Mobility for Predictive Urban Analytics & Operations, Singapore Management University, Singapore, 2019. Retrieved from, https://ink.library.smu.edu.sg/etd_coll/227/.
[53] Y. Jeong, A study on the BIM evaluation, analytics, and prediction (EAP) framework and platform in linked building ontologies and reasoners with clouds, Adv. BIM Appl. Construct. Industry 2018 (2018), https://doi.org/10.1155/2018/5478381.
[54] Y. Jung, T. Kang, C. Chun, Anomaly analysis on indoor office spaces for facility management using deep learning methods, J. Build. Eng. 43 (2021) 1–8, https://doi.org/10.1016/j.jobe.2021.103139.
[55] R. Karthikeyan, B. Raghu, A Firefly Optimized LSTM Risk Detection & Prediction Model for IoT enabled super markets, Ind. J. Comput. Sci. Eng. 11 (6) (2020) 851–858, https://doi.org/10.21817/indjcse/2020/v11i6/201106216.
[56] A. Katona, P. Panfilov, Building Predictive Maintenance Framework for Smart Environment Application Systems. *29th DAAAM International Symposium on Intelligent Manufacturing and Automation*, DAAAM International, Vienna, Austria, 2018, https://doi.org/10.2507/29th.daaam.proceedings.xxx.
[57] S. Kim, Y. Song, Y. Sung, D. Seo, Development of a consecutive occupancy estimation framework for improving the energy demand prediction performance of building energy modeling tools, Energies 12 (3) (2019), https://doi.org/10.3390/en12030433.
[58] A. Krizhevsky, I. Sutskever, G.E. Hinton, ImageNet classification with deep convolutional neural networks, Commun. ACM 60 (6) (2017) 84–90, https://doi.org/10.1145/3065386.
[59] S.S. Kumar, D.M. Abraham, A Deep Learning Based Automated Structural Defect Detection System for Sewer Pipelines. ASCE International Conference on Computing in Civil Engineering 2019, ASCE Library, Atlanta, Georgia, 2019, https://doi.org/10.1061/9780784482445.029.
[60] K. Kumar, M. Parida, V. Katiyar, Short term traffic flow prediction for a non urban highway using artificial neural network, Soc. Behav. Sci. 104 (2013) 755–764, https://doi.org/10.1016/j.sbspro.2013.11.170.
[61] A. Labib, K.A. Kobbacy, D.N. Murthy, Computerised maintenance management systems, in: Complex System Maintenance Handbook, Springer, London, 2008, pp. 417–435, https://doi.org/10.1007/978-1-84800-011-7_17.
[62] S. Laing, N. Kühl, Comfort-as-a-service: designing a user-oriented thermal comfort artifact for office buildings, in: 39th International Conference on Information Systems (ICIS 2018). San Francisco: ArXiv, 2018, https://doi.org/10.48550/arXiv.2004.03323.
[63] F. Lamnabhi-Lagarrigue, A. Annaswamy, S. Engell, A. Isaksson, P. Khargonekar, R.M. Murray, H. Nijmeijer, T. Samad, D. Tilbury, P.V. Hof, Systems & control for the future of humanity, research agenda: current and future roles, impact and grand challenges, Annu. Rev. Control. 43 (2017) 1–64, https://doi.org/10.1016/j.arcontrol.2017.04.001.
[64] Y. LeCun, B. Boser, J.S. Denker, D. Henderson, R.E. Howard, W. Hubbard, L. D. Jackel, Backpropagation applied to handwritten zip code recognition, Neural Comput. 1 (4) (1989) 541–551, https://doi.org/10.1162/neco.1989.1.4.541.
[65] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–442, https://doi.org/10.1038/nature14539.
[66] C.K. Lee, H.Y. Chan, C.Y. Poon, K.M. Yip, P.H. Yuen, Smart BIM-AM Journey to Green Buildings. *IOP Conference Series: Earth and Environmental Science. 290*, IOP Publishing Ltd., Prague, 2019, https://doi.org/10.1088/1755-1315/290/1/012050.
[67] E. Lejlic, The Advantages of Machine Learning, Retrieved January 21, 2022, from Innofactor: https://blog.innofactor.com/en/the-advantages-of-machine-learning, 2017.
[68] S. Leng, Z. Hu, Z. Luo, J. Zhang, J. Lin, Automatic MEP Knowledge Acquisition Based on Documents and Natural Language Processing. Proceedings of the 36th CIB W78 2019 Conference, 2019, pp. 800–809. Newcastle, United Kingdom. Retrieved from, https://linjiarui.net/files/2019-09-18-automatic-mep-knowledge-acquisition-based-on-nlp.pdf.
[69] C. Li, Z. Ding, D. Zhao, J. Yi, G. Zhang, Building energy consumption prediction: an extreme deep learning approach, Energies 10 (10) (2017) 1525, https://doi.org/10.3390/en10101525.
[70] J. Ma, J.C. Cheng, C. Lin, Y. Tan, J. Zhang, Improving air quality prediction accuracy at larger temporal resolutions using deep learning and transfer learning techniques, Atmos. Environ. 214 (2019), https://doi.org/10.1016/j.atmosenv.2019.116885.
[71] E. Markoska, A Framework for Automated Real-Time Performance Evaluation of Smart Buildings, 2019, https://doi.org/10.21996/5hay-tm27.
[72] C. Martani, D. Lee, P. Robinson, R. Britter, C. Ratti, ENERNET: studying the dynamic relationship between building occupancy and energy consumption, Energy Build. 47 (2012) 584–591, https://doi.org/10.1016/j.enbuild.2011.12.037.
[73] M. Marzouk, M. Zaher, Artificial intelligence exploitation in facility management using deep learning, Constr. Innov. 20 (4) (2020) 609–624, https://doi.org/10.1108/CI-12-2019-0138.
[74] J.G. Mathai, A Comfort-Based Control Strategy in Buildings Using an Infrared Camera, ProQuest Dissertations Publishing, Idaho, 2020. Retrieved from, https://www.proquest.com/openview/6fde7d9c7e37c51d0b87a6d7a6ab7b7c/1?pq-origsite=gscholar&cbl=18750&diss=y.
[75] Mathworks, The Mathworks: Deep Learning Toolbox, Retrieved 01 29, 2022, from, https://www.mathworks.com/products/deep-learning.html.
[76] S. McMahon, N. Sunderhauf, M. Milford, B. Upcroft, TripNet: Detecting Trip Hazards on Construction Sites. Australasian Conference on Robotics and Automation, ACRA, Brisbane, 2015, pp. 388–397. Retrieved from, https://www.araa.asn.au/acra/acra2015/papers/pap158.pdf.
[77] O. Moselhi, T. Hegazy, P. Fazio, Neural networks as tools in construction, J. Constr. Eng. Manag. 117 (4) (1991), https://doi.org/10.1061/(ASCE)0733-9364(1991)117:4(606).
[78] I. Mutis, A. Ambekar, V. Joshi, Real-time space occupancy sensing and human motion analysis using deep learning for indoor air quality control, Autom. Constr. (2020) 116, https://doi.org/10.1016/j.autcon.2020.103237.
[79] K.T. Nguyen, K. Medjaher, A new dynamic predictive maintenance framework using deep learning for failure prognostics, Reliab. Eng. Syst. Saf. 188 (2019) 251–262, https://doi.org/10.1016/j.ress.2019.03.018.
[80] H. Park, S. Lee, B. Chu, D. Hong, Obstacle avoidance for robotic excavators using a recurrent neural network, in: 2008 International Conference on Smart Manufacturing Application, IEEE, 2008, https://doi.org/10.1109/ICSMA.2008.4505593.
[81] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, et al., PyTorch: An Imperative Style, High-Performance Deep Learning Library. NIPS'19: 33rd Conference on Neural Information Processing Systems, Curran Associates Inc., Vancouver, 2019, pp. 8026–8037, https://doi.org/10.5555/3454287.3455008.
[82] A. Patwardhan, A.K. Verna, U. Kumar, A survey on predictive maintenance through big data, in: Current Trends in Reliability, Availability, Maintainability and Safety, Springer International Publishing, 2016, pp. 437–445, https://doi.org/10.1007/978-3-319-23597-4_31.
[83] J. Pingel, Introduction to Deep Learning: Machine Learning Vs. Deep Learning, Retrieved 01 25, 2022, from, https://www.mathworks.com/videos/introduction-to-deep-learning-machine-learning-vs-deep-learning-1489503513018_b.html, 2017.
[84] G. Pinto, Z. Wang, A. Roy, T. Hong, A. Capozzoli, Transfer learning for smart buildings: A critical review of algorithms, applications, and future perspectives, Adv. Appl. Ener. 5 (2022), https://doi.org/10.1016/j.adapen.2022.100084.
[85] K.H. Poon, P.K.-Y. Wong, J.C. Cheng, Long-time gap crowd prediction using time series deep learning models with two-dimensional single attribute inputs, Adv. Eng. Inform. 51 (2022), https://doi.org/10.1016/j.aei.2021.101482.
[86] A. Rajith, S. Soki, M. Hiroshi, Real-Time Optimized HVAC Control System on Top of an IoT Framework. 2018 Third International Conference on Fog and Mobile Edge Computing (FMEC), IEEE, Barcelona, Spain, 2018, https://doi.org/10.1109/FMEC.2018.8364062.
[87] G. Revati, U. Suryawanshi, A. Sheikh, S. Bhil, Load Profile Prediction in Smart Building using Data Driven Approaches, in: *2021* 31st Australasian Universities Power Engineering Conference (AUPEC), IEEE, Perth, Australia, 2021, https://doi.org/10.1109/AUPEC52110.2021.9597702.
[88] E.P. Rondeau, R.K. Brown, P.D. Lapides, Facility Management, 2nd ed., John Wiley & Sons, Inc., New Jersey, 2017.
[89] D. Rumelhart, G. Hinton, R. Williams, Learning representations by back-propagating errors, Nature 323 (1986) 533–536, https://doi.org/10.1038/323533a0.
[90] C. Sagnier, Types of maintenance: 5 definitions you should know (Mobility Work) Retrieved 01 2020, from, https://www.mobility-work.com/blog/5-types-maintenance-you-should-know, 2018.
[91] S. Salimi, A. Hammad, Critical review and research roadmap of office building energy management based on occupancy monitoring, Energy Build. 182 (2019) 214–241, https://doi.org/10.1016/j.enbuild.2018.10.007.
[92] M. Sanchez-Silva, D. Frangopol, J.E. Padgett, M.R. Soliman, Maintenance and operation of infrastructure systems: Review, J. Struct. Eng. 142 (9) (2016), https://doi.org/10.1061/(ASCE)ST.1943-541X.0001543.
[93] K. Sapkota, Artificial Intelligence in Property Management Automation : Technologies, Current Applications, and Challenges, Turku University of Applied Sciences, 2019. Theseus. Retrieved from, https://www.theseus.fi/bitstream/handle/10024/273564/Krishna%20sapkota%20thesis_TUAMK.pdf?sequence=2&isAllowed=y.
[94] H. Seong, H. Choi, H. Cho, S. Lee, H. Son, C. Kim, Vision-Based Safety Vest Detection in a Construction Scene. ISARC. 2017 Proceedings of the International Symposium on Automation and Robotics in Construction vol. 34, ProQuest, Taipei, Taiwan, 2017, pp. 288–293, https://doi.org/10.22260/ISARC2017/0039.
[95] G. Sonetti, E. Naboni, M. Brown, Exploring the potentials of ICT tools for human-centric regenerative design, Sustainability 10 (4) (2018), https://doi.org/10.3390/su10041217.
[96] Srivastava, T. (2015). Difference Between Machine Learning & Statistical Modeling. Retrieved 11 07, 2021, from Analytics Vidya: https://www.analyticsvidhya.com/blog/2015/07/difference-machine-learning-statistical-modeling/#:~:text=Machine%20learning%20does%20really%20well,they%20end%20up%20over%20fitting.
[97] Y. Su, Y. Zhao, C. Niu, R. Liu, Robust Anomaly Detection for Multivariate Time Series through Stochastic Recurrent Neural Network. *KDD '19:* Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, Association for Computing Machinery, Anchorage, USA, 2019, https://doi.org/10.1145/3292500.3330672.
[98] Team, R. C, R: A Language and Environment for Statistical Computing, Retrieved 01 28, 2022, from, https://www.r-project.org/, 2017.

[99] I. Tregubova, Developing Data Maturity Prescriptive Indicators as Starting Points of Museums' Big Data Adoption within "Smart Museum" Index Elaboration, National Research University Higher School of Economics, Graduate School of Business, Moscow, 2019. Retrieved from, https://www.hse.ru/en/edu/vkr/296293300.
[100] M.-H. Tsai, C.-H. Yang, C.-H. Wang, I.-T. Yang, S.-C. Kang, SEMA: A site equipment management assistant for construction management, KSCE J. Civ. Eng. 26 (2021) 1144–1162, https://doi.org/10.1007/s12205-021-0972-2.
[101] Z. Wang, Multimedia Delivery in Smart Home Environments, Insitute for Digital Technologies, London, 2016. Loughborough University London. Retrieved from, https://ctoresearch.irdeto.com/materials/zelin_1st_year_report.pdf.
[102] Z. Wang, T. Hong, Reinforcement learning for building controls: The opportunities and challenges, Appl. Energy (2020) 269, https://doi.org/10.1016/j.apenergy.2020.115036.
[103] K. Wang, Y. Wang, How AI Affects the Future Predictive Maintenance: A Primer of Deep Learning. International Workshop of Advanced Manufacturing and Automation IWAMA 2017: Advanced Manufacturing and Automation VII, Springer, Singapore, 2018, pp. 1–9, https://doi.org/10.1007/978-981-10-5768-7_1.
[104] Y. Wang, H. Yao, S. Zhao, Auto-encoder based dimensionality reduction, Neurocomputing 184 (2016) 232–242, https://doi.org/10.1016/j.neucom.2015.08.104.
[105] Z. Wang, L. Itard, A. Meijer, Trends in Digital Twinning for Design, Operation And Maintenance In Non-Residential Buildings: A Short Review from Literature, Delft University of Technology, 2021. Retrieved from, https://btic.nu/wp-content/uploads/2021/11/Report-IEBB-Thema-2-activity-1.4-final.pdf.
[106] Y. Wei, B. Akinci, A vision and learning-based indoor localization and semantic mapping framework for facility operations and management, Autom. Constr. (2019, November), https://doi.org/10.1016/j.autcon.2019.102915.
[107] J. Xu, W. Lu, C.J. Anumba, Y. Niu, From smart construction objects to cognitive facility management, Cyber-Physical Syst. Built Environ. 273-296 (2020), https://doi.org/10.1007/978-3-030-41560-0_15.
[108] F. Zhang, H. Fleyeh, X. Wang, M. Lu, Construction site accident analysis using text mining and natural language processing techniques, Autom. Constr. 99 (2019) 238–248, https://doi.org/10.1016/j.autcon.2018.12.016.
[109] M. Zhang, R. Shi, Z. Yang, A critical review of vision-based occupational health and safety monitoring of construction site workers, Saf. Sci. 126 (2020), https://doi.org/10.1016/j.ssci.2020.104658.
[110] P. Zhou, Automated energy compliance checking in construction, in: Graduate Dissertations and Theses at Illinois, 2018. Retrieved from, https://www.ideals.illinois.edu/bitstream/handle/2142/102907/ZHOU-DISSERTATION-2018.pdf?sequence=1&isAllowed=y.
[111] H. Zhuang, J. Zhang, B.A. Muthu, Sustainable smart city building construction methods, Sustainability 12 (12) (2020), https://doi.org/10.3390/su12124947.
[112] H. Zou, Y. Wu, H. Zhang, Y. Zhan, Short-Term Traffic Flow Prediction Based on PCC-BiLSTM. 2020 International Conference on Computer Engineering and Application (ICCEA), IEEE, Guangzhou, China, 2020, pp. 489–493, https://doi.org/10.1109/ICCEA50009.2020.00110.