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Deep learning for manufacturing sustainability: Models, applications in Industry 4.0 and implications

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ABSTRACT

Recent advancements and developments in artificial intelligence (AI) based approaches have shifted the manufacturing practices towards the fourth industrial revolution, considered as Industry 4.0 practices. A positive impact of AI-based techniques on sustainability can be seen in manufacturing organisations' at the system, product and process levels. Adopting AI-based strategies in manufacturing improves decision making, productivity and system performance. Despite sustainability and other benefits, the adoption of AI-based approaches in manufacturing organisations is still limited due to employees' knowledge and digital skills. In the present time, due to the digitalisation of manufacturing activities, intelligent sensors, and supply chain activities, industries are facing challenges with the generation of high volume, different variety and velocity of data. This data can be helpful for manufacturing organisations to enhance their performance and sustainability. However, managing this big data is still a significant challenge due to a lack of knowledge and limited literature. Deep learning (DL) based models can be a suitable choice to provide advanced analytics tools for manufacturing data processing and analysis. However, literature on the DL is still limited in the manufacturing context with its relationship to sustainability. The present study discusses the evolution of DL approaches in manufacturing and different DL-based models. This study also highlights how DL-based approaches can enhance the sustainability performance of industries. In the study, primary research areas, i.e., fault diagnosis, quality management, and predictive maintenance, have been discussed. Finally, a conceptual DL-based framework is proposed for the manufacturing industries to enhance their sustainability performance in manufacturing activities.

1. Introduction

Artificial intelligence (AI) based algorithms are transforming the service and manufacturing organisations into high-efficiency industries by improving productivity and reducing maintenance costs and production defects (Chien et al., 2020; Li et al., 2017). The adoption of machine learning (ML) and deep learning (DL) has significantly increased in the last few years in the manufacturing sector due to the generation of a large amount of data (Lee et al., 2018; Rawat et al., 2021). Shop floor, supply chain activities and manufacturing processes generate a variety of data in large volumes, which is not effectively used by industries (Yao et al., 2017). Extracting relevant information is crucial and significant, which DL algorithms can do effectively. DL approaches are based on AI and ML, which imitates how humans gain a specific type of knowledge (Wang et al., 2018). DL approaches can be considered critical in data science, including predictive modelling and statistics (Wuest et al., 2016). Information management with AI and ML is an emerging research area in present time in various domains such as: manufacturing, management and social sciences. The role of DL in manufacturing organisations is vital to collect, analyse and interpret a large amount of data (Akter et al., 2021; Ashok et al., 2022; Lee et al., 2020; Zhang et al., 2021). Unlike traditional ML approaches, DL is based on predictive analytics rather than linear.

The past studies conducted on Industry 4.0 shows that 82% of manufacturing and service organisations have increased their efficiency by using Industry 4.0 technologies, i.e., AI-based approaches and the Internet of things (IoT) (Akter et al., 2021). In the last few years, both developed and developing countries started the development of roadmaps for the Industry 4.0 transition (Mittal et al., 2018; Yadav et al., 2020). Industries are now more focused on infrastructure development for adopting data science and IoT-enabled manufacturing practices (de Sousa Jabbour et al., 2018; Kamble et al., 2020; Khan & Javaid, 2021). For example, the German Federal Government introduced "Industry 4.0" as the high technology plan for their industries in 2010 as a collaborative effort of countries from the European Union. In 2011, the United States introduced the concept of "smart manufacturing" under the "Smart Manufacturing Leadership Coalition".

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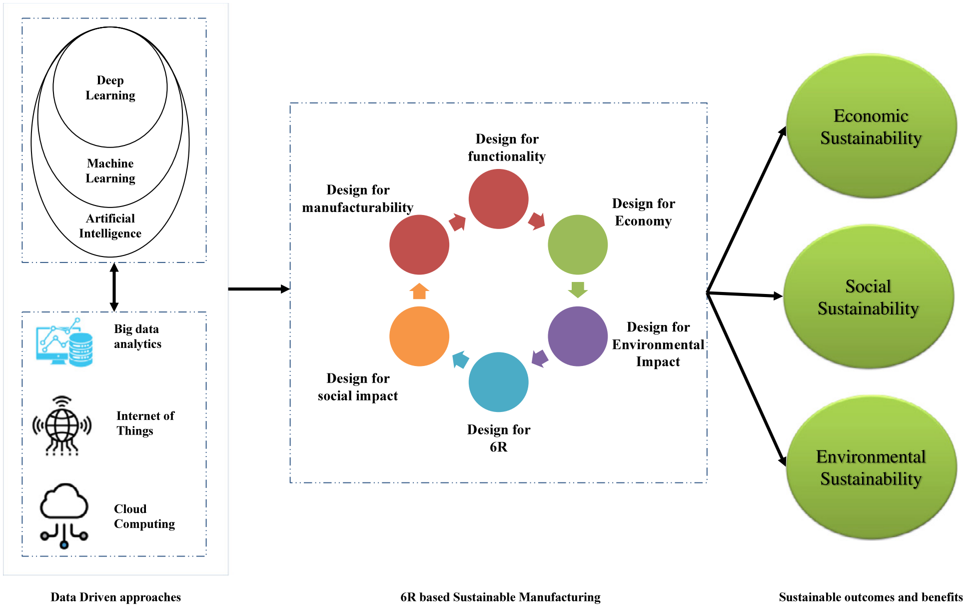

Fig. 1. Role of data-driven approaches for sustainable manufacturing (Wang et al., 2018).

Similarly, China has introduced their manufacturing strategy, “China 2025”, which is focused on promoting advanced manufacturing (Machado et al., 2020). The dynamic changes in the market drive these plans and industrial revolutions. Currently, manufacturing industries are equipped with the Internet and sensors to collect and transmit data from machines to servers (Chauhan et al., 2021). This helps reduce the industry’s downtime and improve the automation level of manufacturing organisations (Sharma et al., 2020).

Sensors are used to collect the data, and advanced computational algorithms based on AI, ML and DL are used for real-time process monitoring (Syafrudin et al., 2018). Industry 4.0 technologies positively impact product, process and system-level sustainability (Enyoghasi & Badurdeen, 2021). Few researchers have highlighted “smart manufacturing” as the new trend in manufacturing systems in which machines within a system are connected through a wireless network (Wang et al., 2018; Yao et al., 2017). These machines are continuously monitored by intelligent sensors, which capture data and share it to the cloud, where analysed by intelligent computational algorithms. The data collected from the different activities within the shop floor is used to increase sustainability, system productivity, maintenance operations and product quality (Akdil et al., 2017; Dikhanbayeva et al., 2020). In past years, many new technologies have been developed, which has boosted the fourth industrial revolution wave (Carvalho et al., 2018). As discussed by (Sung, 2018), many technologies related to Industry 4.0 came into existence before the evolution of the term “Industry 4.0”. So, in Korea, the term “Fourth industrial revolution” is more popular than the “Industry 4.0”. The developments in AI, DL, blockchain technology (BT), cyber-physical systems (CPS), decentralised manufacturing systems (DMS), cloud computing (CC) and the Internet of Things (IoT) are supporting the innovations in manufacturing organisations (Bag et al., 2021; Javaid et al., 2021; Lee et al., 2018). Now manufacturers can collect, analyse and process the product life cycle data, ranging from raw material extraction to the disposal phase of the product (Ferrari et al., 2021).

ML and AI-based computational algorithms can help process and analyze the large volume of data sets and provide critical insights to the manufacturers from these data sets (Verma et al., 2021; Yang et al., 2020). The valuable information collected from these datasets can be used for predictive maintenance, demand forecasting and condition monitoring (Arinez et al., 2020). However, few AI-based algorithms can be used for generative design purposes (Wan et al., 2020). The role of AI-based approaches in sustainable production is illustrated in Fig. 1, which represents how data-driven strategies can be used in the manufacturing practices in organisations (Wang et al., 2018). In this, it can be seen that computational approaches based on AI and DL algorithms act as drivers for intelligent manufacturing or smart production in the Industry 4.0 context, which have benefits in terms of quality, cycle time reduction, and waste management (Chui et al., 2018). Generally, all the data-driven approaches model the complex relationship between the input data provided by the system. A depth understanding of a physical system is not required for the analysis.

In recent years, many efforts have been made on AI-based tools for manufacturing applications (Sahu et al., 2021). However, now research is more focused on the sustainability aspects of manufacturing through the use of advanced computational algorithms (Bag et al., 2021; Liu et al., 2020). (Cioffi et al., 2020) highlighted the role of cutting-edge computational approaches, i.e., ML and AI-based algorithms, for sustainable production. (Jamwal et al., 2021b) discussed the limitations and advantages of various ML approaches for sustainable manufacturing. Recent studies on AI and ML show that manufacturers are now more focused on adopting advanced computational algorithms for manufacturing operations (Alexopoulos et al., 2020; Chien et al., 2020). However, few studies have highlighted the importance of identifying challenges related to data-driven approaches for decision-making in manufacturing organisations (Cohen & Macek, 2021; Niri et al., 2022). In the manufacturing sector, few studies have studied the limitation and advantages of ML and AI-based approaches to manufacturing practices (Carvalho et al., 2019). Compared to AI techniques, DL-based algorithms perform better in manufacturing-based applications such as condition monitoring, predictive maintenance and real-time process monitoring (Yang et al., 2020). Generally, DL-based approaches allow automatic data processing, which is collected through the sensors connected to machines and transmitted to the cloud by the Internet (LeCun et al., 2015). In Industry 4.0, DL offers a wide range of economic, social and environmental benefits for manufacturing organisations, which helps achieve sustainability (Bai et al., 2020). AI and DL based approaches are providing solutions for many applications in the industries. Despite of AI and DL benefits to industries the adoption level is limited in many industry sector due to lack of knowledge about and understanding about the benefits of AI and DL in manufacturing. Apart from this, there is limited literature available on DL approaches and its benefits to achieve sustainability in manufacturing practices. To fill these research gaps, the main research questions of this study are as follows:

RQ1: What are the different deep learning models and their applications in manufacturing to achieve sustainability?
RQ2: What are the main research themes in deep learning for manufacturing?
RQ3: What are the main challenges for manufacturing organisations to adopt deep learning models?

In the light of literature gaps related to DL methods, this study aims to discuss DL methods and applications in Industry 4.0 for manufacturing and its relationship with sustainability. Based on the literature analysis, we have provided an integrated DL-based sustainable production framework for manufacturing organisations to achieve sustainability. In this study, we have discussed the evolution of data-driven approaches and their applications to manufacturing organisations. Various DL models have also been discussed with their advantages and limitations in manufacturing.

The rest of the paper has eight sections. Section 2 discusses about the overview and history of deep learning; Section 3 discusses about the basic structures in deep learning; Section 4 discusses about the applications of deep learning to sustainability; Section 5 discusses the challenges of deep learning adoption; Section 6 discusses the deep learning-based framework for sustainable production; Section 7 discuss the implications and Section 8 discuss the conclusion and limitation of the study.

2. Literature Review

Due to evolution of Industry 4.0 practices, generation of data from manufacturing and production activities has been increased which is challenging for organizations when finding an optimal solution of problem (Kotsiantis et al., 2006; Votto et al., 2021). These issues can be addressed by application of bio-inspired algorithms which can provide solution based on incomplete information and limited computation facility (Chakraborty & Kar, 2017; Kar, 2016; Kushwaha et al., 2021). Machine learning which is now presented as the sub-set of artificial intelligence can be referred as the intelligence. In the history of manufacturing activities various intelligence approaches have been used which is time consuming and requires higher costs (Carvalho et al., 2019). In last few years, machine learning tools have been used which have numerous applications in manufacturing sector such as: quality control, optimization and forecasting. As a part of artificial intelligence machine learning approaches can learn and adapt any new changes in the production environment (Loyer et al., 2016). Therefore, machine learning approaches are the area of interest why these are important in manufacturing sector in many applications. Generally, machine learning algorithms are designed in such a way that they can derive the required knowledge from the large data sets (Herath & Mittal, 2022; Priore et al., 2001).

However, after evolution of Industry 4.0 practices manufacturing data has moved into the era of "Big Data" in which machine learning approaches have been evolved into deep learning techniques (Cioffi et al., 2020). These techniques can handle large amount of data and more powerful than traditional machine learning approaches with wide range of application areas such as: condition monitoring, predictive maintenance and accurate forecasting (Wang et al., 2018).

2.1. Evolution of deep learning

Deep learning approaches are the subset of ML-based on neural network layers. These layers are used to learn the representation of a large volume of data with multiple levels of abstraction (Guo et al., 2016). In the past few years, DL methods have improved state of art in object detection, speech recognition and manufacturing decision-making (Li et al., 2020). DL-based network drives many applications and services, including information, analytics without human intervention and predictive maintenance (Nikolakis et al., 2020).

Frank Rosenblatt first introduced neural networks in 1957, consisting of two processing layers for recognising simple patterns (LeCun et al., 2015). In 1969, neural networks entered the dark phase of research and development when MIT professors argued that they could not learn simple XOR functions (Zhao et al., 2019). The other MIT professors' findings dampened the research motivation for deep neural networks (DNN). During the analysis, it is found that the universal approximation theorem can solve any continuous problem using a single hidden layer (Shrestha & Mahmood, 2019). The mathematical validation of the universal approximation theorem has put a question on the validation of the DNN algorithm. DNN has a feature extraction benefit which differentiates DNN from other ML techniques (Miotto et al., 2018). Generally, DNN is also a type of NN having a multilayer perceptron. DNN algorithms are trained to learn and analyse the representations from more extensive data sets (Voulodimos et al., 2018). DL-based approaches found many applications in the manufacturing sector, as it doesn't require manual design for information extraction from data sets (Wang et al., 2018). The advancement in DL can solve non-linear functions and more complex manufacturing problems efficiently. These advancements in DL can be implemented by cheaper processing units and big data for model training and representation (Shrestha & Mahmood, 2019). (Vinuesa et al., 2020) argued that AI-based approaches will continue to impact sustainability in healthcare, finance and manufacturing. Further, Fig. 2 shows the evolution of different AI-based models with their timeline, which can be categorised into four main periods (1) Infacy period,(2) First upsurge period,(3) Second upsurge period and (4) Third boom period.

2.2. Comparison between traditional approaches of machine learning and deep learning approaches

Traditional approaches of machine learning and deep learning algorithms are trendy in Industry 4.0 for manufacturing organisations as it helps to increase efficiency and productivity through predictive maintenance and condition monitoring (Mao et al., 2019). These approaches are part of data-driven tools used to model the complex relationship between any process's input and output variables (Yao et al., 2017). Both ML and DL are critical enabling technologies for Industry 4.0, often overlapping in the literature (Davis et al., 2015). Few studies have investigated and highlighted the differences between both the terms ML and DL with their similarities (Shinde & Shah, 2018). DL approaches are the advanced form of ML algorithms used when data is colossal and unstructured. Thus, DL approaches can solve more complex problems than ML (Salloum et al., 2020). DL approaches have a higher hierarchical structure than ML and distinctive attributes in model development, training and feature learning (Chauhan & Singh, 2018). DL techniques integrate both the model development and feature learning in one phase by selecting different kernels or tuning the input variables or parameters with the help of end-to-end optimisation (Nosratabadi et al., 2020).

3. Basic structures in deep learning

3.1. Auto encoders (AE)

AE are the types of ANN used to learn the data encoding in an unsupervised manner. The main aim of the AE is to understand the encoding (lower-dimensional representation) for the higher-dimensional data (Khan & Yairi, 2018). Generally, AE is a neural network with unsupervised algorithms representing and learning the input data. Based on the input data set, it reduces the data dimensionality helps and recreate the original data set (Shrestha & Mahmood, 2019). Figure 3 (A) represents the autoencoder nodes.

3.2. Restricted Boltzmann machine (RBM)

RBM is a type of NN in which an unsupervised learning algorithm can be applied (See Figure: 3[B]). This DL approach can build non-linear

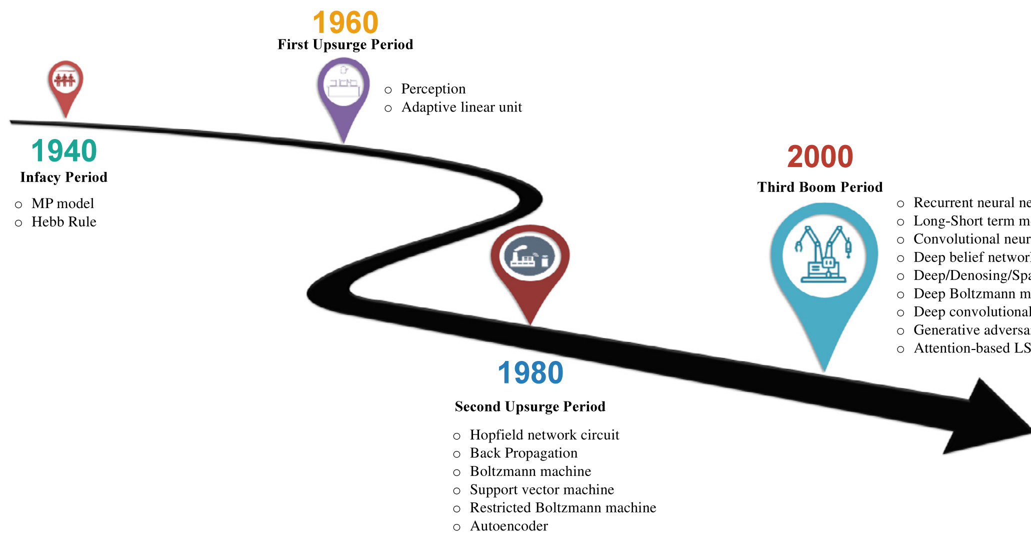

Fig. 2. Different AI models with their timeline.

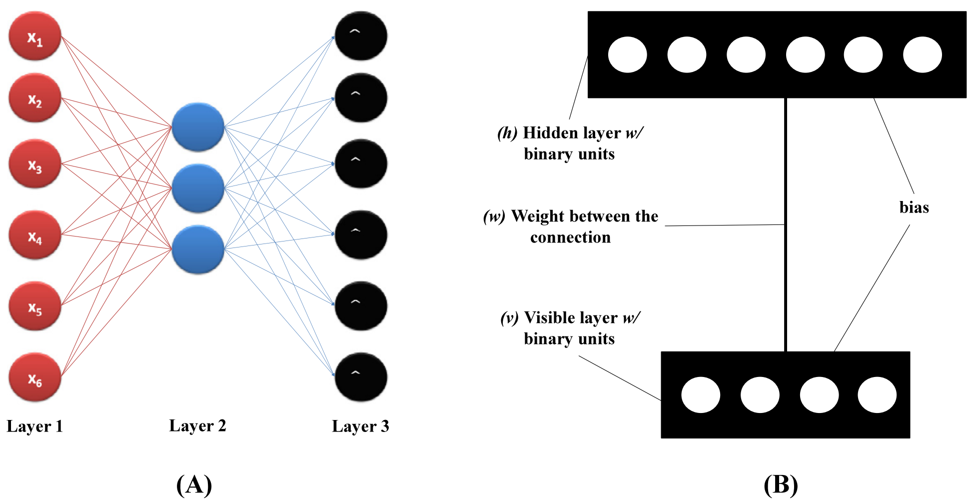

Fig. 3. (A) Autoencoder Nodes (Khan & Yairi, 2018) (B) Restricted Boltzmann machine (Zhao et al., 2019).

generative models from a more extensive data set consisting of unlabeled data (Zhao et al., 2019). The main principle of RBM is to train the network to increase log or product functions. RBM algorithms can learn the probability distribution of a function over the different inputs (Ardabili et al., 2019). RBM consists of a two-layer network in which each visible layer of the network is connected to the hidden layer. There is no connection between the different units in the same layers.

3.3. Long Short term memory (LSTM)

LSTM was introduced by (Hochreiter & Schmidhuber, 1997) as the implementation of RNN 1997. Unlike other feed-forward architectures, LSTM can capture the knowledge from previous stages of data and train the model for the manufacturing applications in which state awareness or memory is required. LSTM was introduced to address the limitation of DNN (LeCun et al., 2015). The architecture of LSTM is presented in Fig. 4.

AI and DL are no more mere buzzwords in manufacturing organisations (Li et al., 2017). In the last few years, developing and developed nations have realised the need to adopt AI-based approaches in manufacturing activities (Yadav et al., 2020). Using these approaches in business activities has brought a significant shift in how manufacturing and service-based organisations invest in AI-based methods (Sahu et al., 2021). Implementation of DL approaches is quite challenging in the case of manufacturing activities. Today, many DL-based frameworks can provide a better level of abstraction with the programming solution and simplify complex problems (Hansen & Bøgh, 2021). In this study, we have discussed the eight most popular frameworks for manufacturing activities. Each framework has its limitation and purpose in manufacturing. Further, Table 1 shows the different frameworks and their description.

4. Applications of deep learning to achieve sustainability in manufacturing

AI-based tools, i.e., DL and ML algorithms, are the ally that sustainable development needs to advise, execute and design the future of upcoming generations (Vinuesa et al., 2020). These days, advanced data analytic tools based on AI help to use the resource in the industry more efficiently, waste reduction and reduce carbon emissions (Carvalho et al., 2019). AI is contributing to sustainability in the supply chain also. Applying AI tools to supply chain practices helps to reduce carbon emissions and supply chain optimisation (Belhadi et al., 2021). The optimal supply chain design with AI-based tools minimises mobility and the negative impact of the supply chain on the environment (Abdirad & Krishnan, 2020). UN 2030 sustainability agenda has motivated the manufacturing organisation to adopt renewable energy sources as the primary energy source. Renewable energy sources have

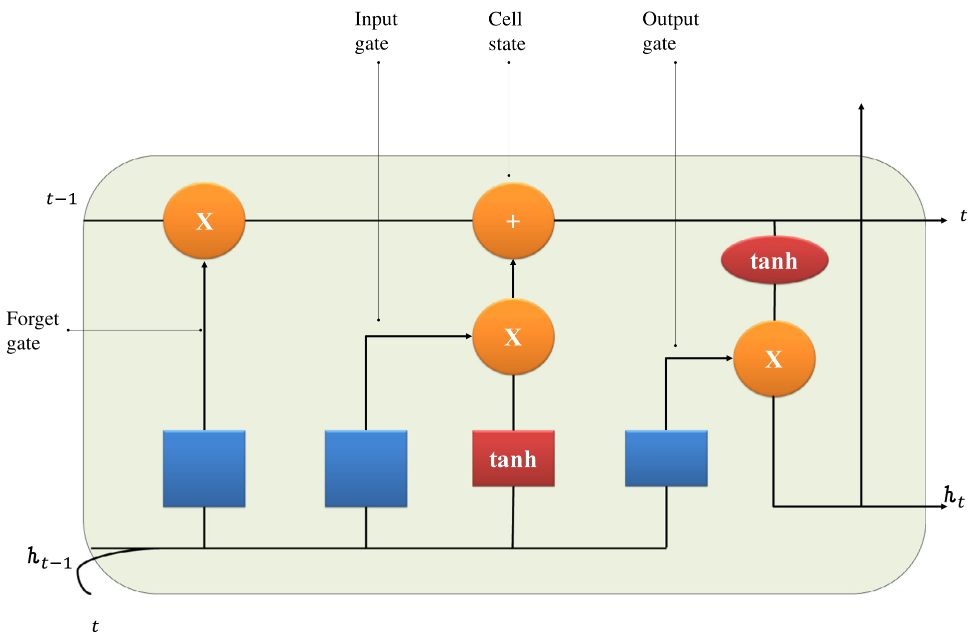

Fig. 4. LSTM architecture (LeCun et al., 2015).

Table 1
Popular Deep learning frameworks and their benefits for manufacturing organisations.

Deep learning tool	Tool type	Description	Benefits in manufacturing
TensorFlow (Chung et al., 2017)	Open Source	TensorFlow is ap popular DL framework which supports languages, e.g., R, C++ and Python, to create DL models. TensorFlow has natural language processing, forecasting, text classification and summarization capabilities.	1. Manufacturing graphs visualisation and queues using TensorBoard 2. Robust GUI support for various manufacturing applications
Torch/Pytorch (Shams et al., 2017)	Open-Source	Torch/Pytorch provides Lua-based DL frameworks. Generally, Torch/Pytorch employs CUDA along with C or C++ libraries for data processing.	1. It helps to facilitate the exchange the manufacturing data with the external libraries 2. Better performance in rapid prototyping 3. It provides a cleaner interface and is easier to use in case of manufacturing data
Deeplearning4J (Parvat et al., 2017)	Commercial	Deeplearning4J is a DL library for Java virtual machines (JVM). However, it supports other JVM languages such as Kotlin, Clojure and Scala. It supports deep networks through RNN, CNN, RBM, and DBM.	1. It can process a large amount of data quickly 2. It includes both single-thread and multi-thread deep learning frameworks 3. It can bring the entire Java ecosystem to execute DL models
Microsoft cognitive toolkit (Chung et al., 2017)	Open-Source	Microsoft cognitive toolkit is an open-source platform which efficiently uses the CNN and training for the text-based data	1. Results are more accurate 2. Easy to use as compared to other interfaces 3. Detailed documentation with command interfaces
Accors.Net (Parvat et al., 2017)	Open-source	Accors.Net uses C# as a writing language for the deep learning algorithms. It provides a combined machine learning framework for image and audio processing.	1. Data clustering, classification, data hypothesis and data distribution, Real-time defect detection
Keras (Han et al., 2020)	Open source	Keras is a python based framework which supports recurrent networks and convolutional networks. Unlike other frameworks, Keras provide a simplistic framework for users for quick prototyping.	1. Data classification, text generation and Speech recognition 2. It supports multiple deep learning backends.
ONYX (Han et al., 2020)	Open-source	ONNX is an open-source deep-learning ecosystem that Microsoft develops and can switch between different platforms. ONNX provides in-built operator definition and standard data types. Unlike other platforms, ONNX is more flexible for DL-based models.	1. Provides flexibility, interoperability, compatible libraries and runtimes 2. Performance maximisation across the hardware

some limitations related to efficiency compared to non-renewable energy sources (Hidayatno et al., 2019). AI-based approaches are also helping manufacturing industries enhance the efficiency of renewable energy sources (Jena et al., 2020). The main application areas are energy production, prediction and fault diagnosis of energy plants (Carvalho et al., 2019). Beyond the energy sector, AI-based tools have other applications in industries like food manufacturing, healthcare and agriculture supply chain, which have reported the benefits of using AI-based models to enhance sustainability (Collins et al., 2021).

At present, manufacturing activities rely on data-driven technologies. The advanced data-driven technologies of Industry 4.0 support manufacturing innovations and sustainability in manufacturing organisations (Raj et al., 2020). Computational intelligence can be considered an essential factor in achieving manufacturing sustainability

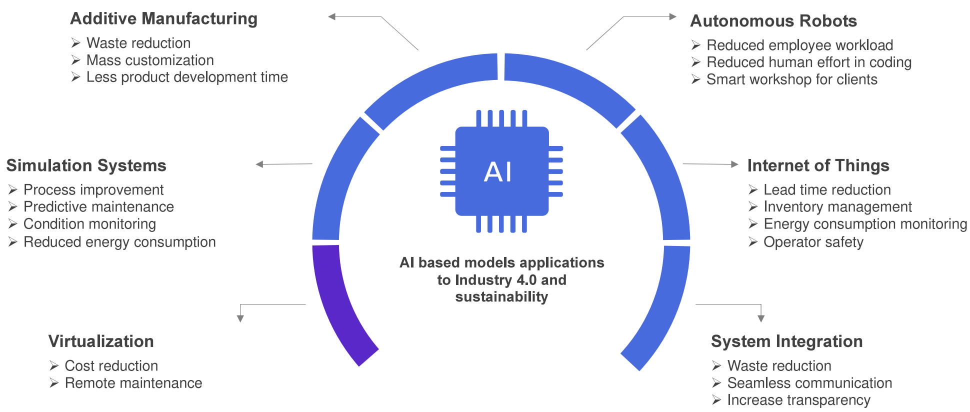

Fig. 5. AI-based models applications to Industry 4.0 and sustainability (Jamwal et al., 2021).

(Ram & Tyagi, 2020). The manufacturers are now focusing on adopting AI-based tools such as DL and ML with sustainable manufacturing practices for better decision-making and optimisation (Hansen & Bøgh, 2021). Optimising manufacturing systems can be critical in manufacturing organisations due to many industry constraints related to resources, energy and carbon emission policies (Enyoghasi & Badurdeen, 2021). Manufacturing organisations have already accepted ML approaches and are widely used in the design, product life cycle management, production activities, manufacturing operations and sustainability-related aspects (Jung et al., 2021). The typical scenario of ML approaches in manufacturing organisations is presented in Fig. 6.

However, few studies have highlighted the importance of data mining and analytics in manufacturing in the literature (Collins, 2020). It has been found that data analysis is a critical issue for manufacturing organisations. Various data in different formats are generated from machines that can be used for multiple industry maintenance applications (Kim, 2017). The main application area of AI tools is fault detection, decision support system, quality control and maintenance (Shivajee et al., 2019). The importance of AI-based tools, i.e., ML and DL applications, has been briefly discussed by (Wang et al., 2018). It is found that ML approaches can help reduce energy consumption, cost reduction, waste reduction and remote maintenance, which positively impact the sustainability of manufacturing (Vinuesa et al., 2020). From the social sustainability perspective, DL helps reduce employee workload by reducing human efforts in various process monitoring operations. Also, few studies have reported on the DL applications in real-time warnings, improving workplace operator safety (Yang et al., 2020). The effect of various technologies and DL approaches on sustainability is presented in Fig. 5.

However, in past literature, many deep learning-based models have been proposed, which have a wide range of applications in manufacturing and positively impact sustainability performance. Table 2 shows the various deep learning models' applications to the manufacturing sector.

4.1. Research themes in deep learning for manufacturing applications

4.1.1. Predictive maintenance with deep learning

Predictive maintenance uses deep learning tools and predictive analytics to estimate the corrective maintenance schedule, which should be done before product failure (Nguyen & Medjaher, 2019). Predictive maintenance in manufacturing organisations is essential as it helps reduce maintenance costs and machine downtime (Sajid et al., 2021 Wang & Wang, 2017). Predictive maintenance in Industry 4.0 era aims to schedule the maintenance of a product or machine at the most efficient and convenient time, which allows the optimise the lifespan of a machine or equipment (Çınar et al., 2020). The architecture of predictive maintenance includes the data storage and acquisition, condition monitoring approaches, data transformation, decision support system, prognostics, asset health evaluation and human interface layer (Carvalho et al., 2019). Generally, predictive maintenance technologies include non-destructive testing approaches such as corona detection, oil analysis, acoustic, sound level measurement, thermal imaging, predictive maintenance and operations data in real-time using smart sensors (Butte et al., 2018). Currently, manufacturing organisations are using IoT-based and AI-based predictive maintenance services for machines and equipment maintenance operations (Zonta et al., 2020). (Chen et al., 2021) proposed an RUL-based model with the geographical information system data for automobile maintenance. The M-LSTM network-based deep learning system is designed for predictive maintenance in the study. (Berghout et al., 2021) proposed a deep learning approach for condition monitoring in the navel industry. The study focuses on extracting and learning essential factors and patterns generated from a small amount of data to predict health estimation. It is found that the proposed algorithms are more effective and have a high level of accuracy in terms of generalisation and approximation as compared to other variants of machine learning approaches.

(Nguyen & Medjaher, 2019) proposed a dynamic maintenance framework for failure prognostics in manufacturing organisations. The study presents an extended short-term memory-based network, which provides the probabilities that a system can fail in different time frames. A real-time industry case scenario validates the proposed algorithm and framework. The proposed algorithm shows better performance than the other algorithms. (Namuduri et al., 2020) stated that predicting failures in manufacturing organisations using the smart sensors and data collected from these sensors helps to reduce machine downtime and maintenance operations. The use of machine learning and deep learning tools is vital to predicting failures based on the available historical data. (Butte et al., 2018) stated that predictive maintenance operations are essential in the microelectronics industries to reduce the cycle time and cost due to unplanned machine downtime and maintenance. Big data analytics can develop a predictive maintenance strategy for manufacturing organisations (Kushwaha et al., 2021). In the study, a deep neural network is proposed, and the results reveal that the proposed approach is more effective in predictive maintenance than the other machine learning algorithms.

4.1.2. Reliability analysis with deep learning

In manufacturing organisations, reliability can be defined as the probability of a system performing its functionalities under uncertainties. Due to the availability of a large volume of manufacturing data is important to do an accurate reliability analysis of system performance (Chen et al., 2020). However, traditionally analytical approaches such as first-order and second-order reliability methods have been extensively used for the reliability analysis in manufacturing organisations in which limit state function can be approximated by the reliability estimation or Taylor expansion (Rajawat et al., 2022). Generally, the manufacturing-related issues are non-linear and based on non-linear functions. These approaches suffer the problem of non-convergence during the sampling methods, i.e., line sampling, importance sampling and Monte Carlo sim-

Table 2
Deep learning models for manufacturing applications

S.No.	Model Name	Training model/Equation	Application in manufacturing	Sustainability Impact	Reference
1.	D-CNN	$v^t = \beta_t v_{t-1} + (1-\beta_1) g_t^2$ $m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$ $\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\hat{v}_t}+\varepsilon}\hat{m}_t$	Cost estimation in manufacturing	Economic (√) Environment (√) Social (√)	(Imoto et al., 2018; Ning et al., 2020)
2.	R-CNN	$L_{box}(t^u, v) = \sum_{i \in \{x,y,w,h\}} smoot\ h_{L_1}(t_i^u - V_j)$ $L_{mask} = \frac{1}{m^2} \sum_{1 \le i,j \le m} \left[y_{ij}.log\hat{y}_{ij}^k + (1-y_{ij}) \log(1-\hat{y}_{ij}^k) \right]$	Spectroscopic analysis in manufacturing	Economic (√) Environment (√) Social (√)	(Bhuvaneswari et al., 2021)
3.	CNN	$S_j(X) = \frac{e^{x_j}}{\sum_{i=1}^{n\_class} e^{xl}}$ $L(y_i, \hat{y}_i) = -\frac{1}{N} \sum_i^N y_i \log(\hat{y}_i)$	Crack detection in manufacturing	Economic (√) Environment (√) Social (√)	(Alipour et al., 2019)
4.	CNN	$L_{indi} = \sum_{k=1}^{n_{un} n_{bk}} \frac{1}{N_c} V_{ar}\left(\{g(\mathrm{P}_k), S^n, S^b\}\right)_1$ $P_k \in \left\{ \left\{ x_{i,j}^{un} \right\}_{j=1}^{n_{bk}} \right\}_{i=1}^{n_{un}}$ $S^n = \left\{ g(P_{k,m}^n) \right\}_{m=1}^{N_{indi}},\ S^b = \left\{ g(P_{k,m}^b) \right\}_{m=1}^{N_{indi}}$	Additive manufacturing quality assessment	Economic (√) Environment (√) Social (√)	(Li et al., 2020)
5.	RBM, DBM and AE	Bayesian belief network, tanh functions, Deionizing, contractive and sparse autoencoder stochastic gradient descent	Fault diagnosis	Economic (√) Environment (√) Social (√)	(J. Wang et al., 2018)
6.	RNN and CNN	Point-wise thermal concatenation and thermal imaging	Distortion prediction	Economic (√) Environment (√) Social (√)	(Alipour et al., 2019)
7.	D-CNN and Virtual-AE	$OS = 2 \times 2 \left[1 - \frac{\sum_{i=1}^{Q} q_i - \frac{1}{2}(Q^2+Q)}{\frac{1}{2}(2N-Q+1)Q - \frac{1}{2}(Q^2+Q)} \right] = \frac{NQ+Q-2\sum_{i=1}^{Q} q_i}{NQ-Q^2}$	Crystal structure	Economic (√) Environment (√) Social (√)	(Ryan et al., 2018)
8.	Virtual-AE	$S_i^P = \frac{1}{N} \sum_{j=1}^{N} \cos(\phi_i^{aug},\ \phi_j^{non-aug}), N = 5$	Virtual material synthesis	Economic (√) Environment (√) Social (√)	(Bhuvaneswari et al., 2021)
9.	MFNN	$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{A_i - F_i}{Ai} \right|$	Mechanical properties	Economic (√) Environment (√) Social (√)	(Sun et al., 2019)
10.	CNN, RNN and LSTM	Stochastic gradient descent, transfer learning and large-scale visual representation	Material degradation	Economic (√) Environment (√) Social (√)	(Alipour et al., 2019)

ulation approaches (Bichon et al., 2008). Due to a large amount of data employing sampling methods requires high computational resources, which is a significant constraint in the case of SMEs (small and medium enterprises) in developing nations (Mittal et al., 2018). To overcome such issues, many studies have addressed the reliability issues with the help of deep learning approaches in literature (Wang et al., 2018). (Chen et al., 2020) proposed a deep learning-based framework for reliability analysis using the distance-based adaptive sampling method. The Monte Carlo simulation approach in the study is also used with the Gaussian process for the probability analysis in manufacturing organisations. The proposed approach is validated with the three case studies to investigate the effectiveness and efficiency of the proposed approach. (Chen et al., 2020) stated that deep integration of cyber physical-based manufacturing systems has increased the data generated from the shop floor activities. The role of data is important for predictive maintenance operations in Industry 4.0. The study proposes a reliability analysis model based on the time series. The study uses, TensorFlow enabled deep learning model for the reliability analysis. The proposed model is validated and tested in the automobile industry. (Tripathi et al., 2021) stated that data mining approaches are now widely accepted in manufacturing industries. In the study, a detailed review of CRISP-data mining approaches is done. A framework is proposed to ensure the reliability and robustness of data-driven knowledge in manufacturing industries. (Zhang et al., 2021) stated that reliability can be considered the central aspect in manufacturing organisations, which helps reduce maintenance costs and increase efficiency. Due to the wave of Industry 4.0, industries are now adopting reconfigurability in their manufacturing systems. The study proposes conceptual maps for the reliability analysis of the reconfigurable manufacturing systems. (Zhang et al., 2020) stated that work in progress and reliability degradation in manufacturing organisations leads to loss of reliability. In the study, a quality variation-centred novel modelling approach is proposed to analyse the reliability of manufacturing processes. The proposed method is adequate to evaluate and predict product reliability for smart manufacturing. (Chen et al., 2021) proposed a deep learning-based system reliability method in stochastic flow manufacturing. Capability assessment of a manufacturing system is significant in the manufacturing industries. Industries use automated machines for mass production, resulting in complex network formulation for reliability analysis. Due to the present manufacturing scenario, it is challenging to calculate system reliability in shorter times. The study proposes a neural network-based deep learning approach, which can predict the system reliability with a 0.002 Root mean square error. (Zhang et al., 2020) stated that product reliability can be improved by identifying weak links in the manufacturing and production activities. The study proposes a Rough set Bayesian network model to improve the system reliability. The study results show that the proposed approach is more effective than the three other approaches for system reliability.

4.1.3. Quality assurance with deep learning

Industry 4.0 practices have opened many opportunities for manufacturing organisations to reduce production losses or errors (Ammar et al., 2021; Haleem & Javaid, 2019; Müller, 2019). In manufacturing, industries' quality can be considered a primary concern which has a significant impact on the performance and sustainability of an organisation (Horváthová et al., 2019). Industry 4.0 tools such as deep learning have played an important role in quality assurance in the past few years. Deep learning approaches based on computer vision can detect the defect in the product in real-time with minimum error (Li et al., 2020). Deep learning approaches enable manufacturers to fix the quality issue at the early stages of production, which helps to save rework costs. Deep learning models represent the data models that use manufacturing-related data from a large volume of data sets and make predictions

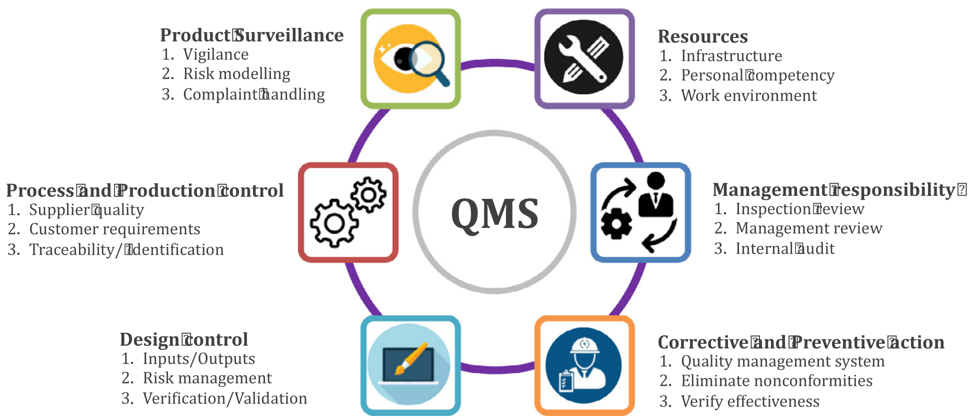

Fig. 6. Quality management system in Industry 4.0.

(Ozdemir & Koc, 2019). Generally, deep learning methods use neural network-based approaches for quality assurance (Wang et al., 2018). Currently, quality management systems (QMS) in Industry 4.0 are different from the conventional management system, which is presented in Fig. 6.

(Wang et al., 2018) proposed a cost-efficient and reliable quality control method for additive manufacturing processes. The proposed AI-based approach shows an accuracy of 98.9% on the destructive testing results. It is stated that deep convolutional neural networks in quality assurance can minimise the quality issues and throughput times. (Gaikwad et al., 2020) additive manufacturing technologies are beneficial to achieving manufacturing sustainability and complex geometry shapes. Machine learning-based assessments in additive manufacturing help improve the quality control in the additive manufacturing processes. (Zhang & Gao, 2021) stated that Industry 4.0 practices aim to improve the reliability and throughput of manufacturing processes. Deep learning approaches have opened many opportunities to achieve this goal. In the study, data curation techniques such as imputation, denoising, balancing, and outlier detection have been briefly discussed to improve the effectiveness of smart manufacturing processes. (Bhandari & Park, 2021) Many manufacturing organisations have introduced the concept of smart factories, which aims to promote high-efficiency, low-cost operations by applying AI and IoT technologies in manufacturing-related facilities. For surface roughness evaluation, deep learning methods play an important role. The study adopted a CNN+LSTM neural network-based approach, which reports an accuracy of 85.185%. It is said that the proposed system is fast, efficient and economical compared to conventional techniques. (Kim et al., 2022) proposed a CNN-based stitch detection method for sewing operations. The proposed approach shows an accuracy of 92.3% in defect detection. (Abou Tabl et al., 2021) stated that manufacturing systems are generating a large amount of data due to technological advancements.

Data extraction and data processing are significant concerns for manufacturing organisations. In the study, a CNN-based is proposed to predict the defective items in the production line. The proposed algorithm shows up to 96.75% accuracy in decision-making. (Jamwal et al., 2021) stated that manufacturing organisations are applying ML and AI-based in industries to improve product quality, employee safety and efficiency. Due to digital transformation, m manufacturing organisations have experienced the Industry 4.0 benefits such as agility, better customer experience, profitability, sustainability and efficiency in production systems. Digitalisation in industries runs on the Agile development framework having shorter release cycles, or delivery needs to be done in a shorter time (Mittal et al., 2018). There is a need to adopt new quality assurance strategies presented in Fig. 7.

There are two driving forces for the QMS in the Industries a) Continuous quality assurance and b) Quick response to market fluctuations. The quality assurance team needs proper training in the agile development model (Bai et al., 2017). Traditional test automation for quality assurance is inadequate for quality management in the Industry 4.0 era. Industries are adopting Deep learning-based approaches to make better predictions and quality control on larger data sets generated from different manufacturing activities.

4.1.4. Fault assessment with deep learning

Manufacturing organisations can face unpredictive failures in their manufacturing operations and activities (Azamfar et al., 2020). Abnormal operating conditions of machines can cause these failures, degradation of manufacturing systems, excessive loads, overheating issues, corrosive environment and fracture or wear of machine tools (Tang et al., 2019). Unpredictive failures in manufacturing organisations can lead to loss of operating hours, manufacturing costs, waste generation, higher carbon emissions, downtimes and lower productivity (Arellano-Espitia et al., 2020). However, digital solutions of Industry 4.0 for smart factories can monitor the machine's condition and shop floor activities in real-time, which can identify the defect or failures in real-time (Kim, 2017). This helps diagnose the root cause of fault or negligence in the early stages so that downtimes can be reduced. In the last few years, the use of smart sensors has increased in manufacturing-related operations (Javaid et al., 2021; Wang & Gao, 2020). These intelligent sensors can catch the real-time data from the manufacturing activities and help investigate the fault assessment or diagnosis (Shao et al., 2017). In past studies, CNN has been used for defect diagnosis applications such as rotor, gearbox, and bearing (Wang et al., 2018). (He & He, 2017) stated that bearing is one of the critical components in manufacturing. Effective fault diagnosis of bearing is important to operate manufacturing activities normally and efficiently. The study proposes a DL-based approach for fault diagnosis of bearing applications. The results show better performances at the lower rotating bearing speeds compared to higher bearing speeds than the previous methods reported in the literature. (Jia et al., 2018) stated that traditional methods are less automatic for fault diagnosis than intelligent approaches. DL tools can be considered the potential tool for extracting mechanical signals in manufacturing activities. Conventional encoders have problems with feature extraction, which a local connection network can overcome.

The proposed approach is validated with the dataset of a gearbox, and the results show better performance than traditional approaches. (Hoang & Kang, 2019) stated that DL tools have many applications in the manufacturing sector for fault diagnosis. The paper uses a systematic literature review approach to find the research progress in fault diagnosis of bearing. It is found that RBM, AE, and CNN are primarily used tools in fault diagnosis. (Zhao et al., 2016) developed a prognostic and fault diagnosis-based system and compared it with traditional models. It is found that conventional models have limitations related to expression capacity, which can be overcome with DL approaches.

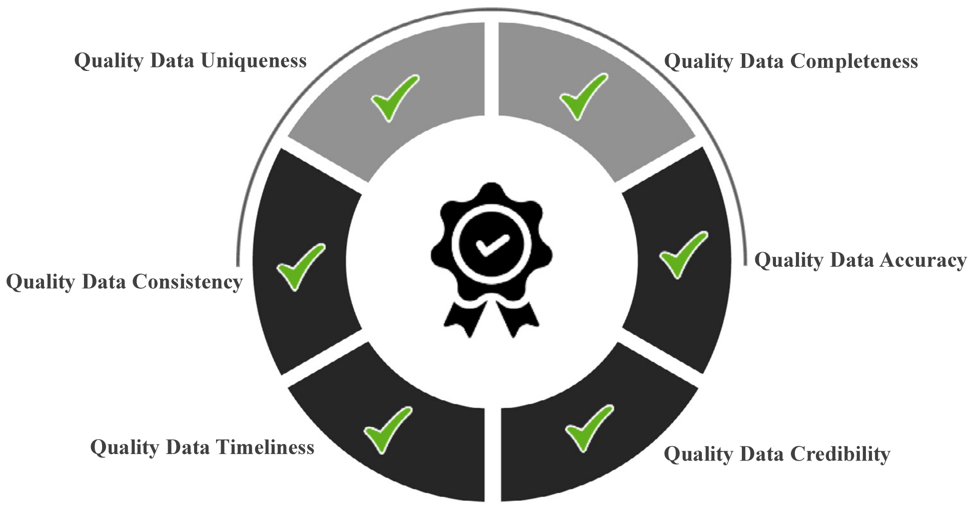

Fig. 7. Requirement for quality assurance with deep learning.

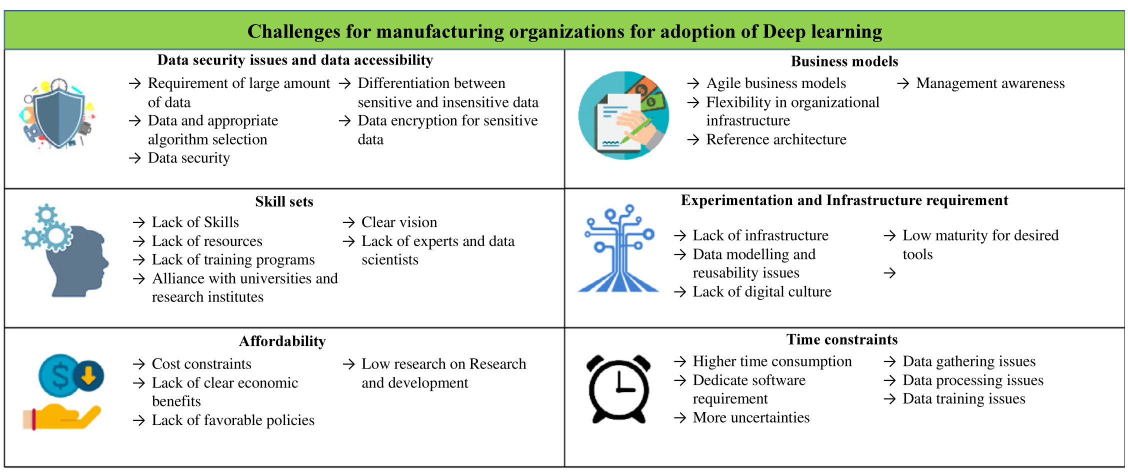

Fig. 8. Challenges for deep learning adoption.

5. Challenges for manufacturing organisations for adoption of deep learning

Deep learning approaches are helping manufacturing organisations to automate manufacturing processes and increase their efficiency and productivity (Wang et al., 2018). Manufacturing organisations are keen on adopting deep learning algorithms and face many challenges. The significant issues are management mindset, business goal alignment and lack of knowledge regarding the algorithms (Wuest et al., 2016). Further, Fig. 8 shows the main challenges manufacturing organisations face in adopting deep learning-based approaches in their manufacturing practices.

6. Deep learning-based framework for manufacturing sustainability

Recent advancements in AI-based approaches, i.e., ML and DL, have shifted manufacturing to a new paradigm considered Industry 4.0. Due to data-driven processes in Industry 4.0, data generated from the manufacturing and supply chain activities have been increased. However, DL approaches are suitable for solving these complex issues in a large volume of datasets. But, in the literature sustainability aspect of DL approaches for manufacturing sustainability is still missing. This study presents the general structure of DL approaches, applications to manufacturing industries and their relationship with sustainability. Based on the literature review, a DL-based conceptual framework is proposed for manufacturing organisations to enhance their sustainability performance (See Fig. 9). In the proposed framework, there are five main layers, i.e., (1) Sustainable, connected processes, (2) IIOT layer, (3) Big data layer, (4) Deep learning layer (5) Application layer.

In the sustainable, connected processes layer, five principal components have been considered, i.e., (1) Products, (2) Equipment, (3) Process, (4) People (5) Environment. Few studies have reported that most of the emissions dare one in the production stage. In this layer, industries need to consider sustainable manufacturing processes. Smart IoT-based sensors can be used for sustainability metrics. Employee involvement plays a vital role in sustainability practices. Sustainability awareness and training programs will help industries to execute DL-based practices efficiently. This layer is connected with the IIoT (Industrial Internet of things). Previous studies (Mittal et al., 2018) reported that shop floor digitalisation is better in a large enterprise compared to SMEs (Small and Medium enterprises). (Jamwal et al., 2021d; Yadav et al., 2020) reported that MNCs (Multinational Companies) now invest in emerging economies due to cheap labour costs. The SMEs sector is the major contributor to the economy of developing nations. SMEs are still struggling with shop floor digitalisation. To experience the benefits of DL approaches in manufacturing industries need to make sure about the shop floor digitalisation. In the third layer, data is stored in a larger volume of datasets called the Big data analytics layer. This layer has three main components, i.e., (1) Process level, (2) Enterprise level and (3) Supply

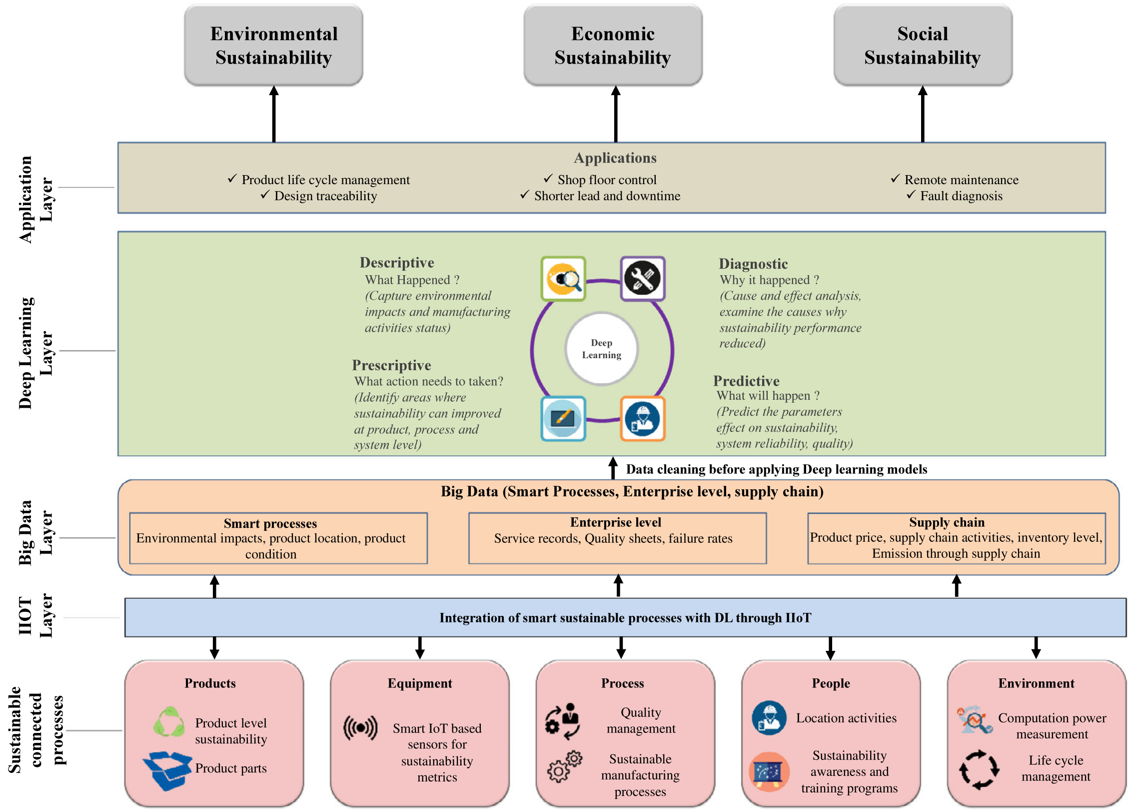

Fig. 9. Proposed Deep learning-based framework to enhance manufacturing sustainability.

chain activities. In this layer, data of different activities is stored, which is further processed and analysed with DL approaches. DL layer consists of four main components:

(1) Descriptive analytics: It helps to analyse what has happened? What are the main areas which caused the environmental impacts? Which processes need to be optimised?
(2) Diagnostic analytics: This helps to find the root cause of the problem. This layer will help to find out what the main reasons for the emissions were? Why has the sustainability performance of the organisation been reduced?
(3) Predictive Analytics: This helps predict the effect of parameters that need to be optimised to improve the sustainability performance of the manufacturing activity.
(4) Prescriptive analytics: This helps determine what action to take to improve the sustainability performance of manufacturing activity. What steps can reduce the environmental impacts and enhance the organisation's economic performance?

In the application layer, different applications of DL approaches have been presented, i.e., product life cycle management, shop floor management, quality management, fault diagnosis and predictive maintenance.

7. Research implications

The research and reports available in the field of deep learning approaches for sustainable production support the view that there are a lot of opportunities for deep learning-based tools in Industry 4.0 to support sustainable production. This has motivated many researchers to work in the area of deep learning approaches. In the present study, we have conducted a state of the art-based review to address the various research opportunities in this area. Based on the literature review following are some implications for policymakers, practitioners and researchers to drive future research.

7.1. Theoretical contributions of the study

The present study discusses the opportunities and research progress on the deep learning approaches for sustainable production. Moreover, this article discusses the various models and their applications in sustainable production. The uniqueness of this study is the identification of different research themes in deep learning for sustainable production, i.e., predictive maintenance, quality management and condition monitoring. Based on the literature review, we have also presented a deep learning-based framework for sustainable products, which industries can adopt in future to address the various sustainability issues in Industry 4.0 context.

7.2. Implications for researchers

Based on the literature review and proposed framework following research implications can be drawn for researchers for future research studies:

1. The present study discusses the role of deep learning approaches in manufacturing. However, this study also discusses the different deep learning models to achieve sustainable production. The literature on deep learning in manufacturing shows that researchers have paid less attention in the past in the manufacturing area.
2. The present study's findings also indicate that there are many opportunities for sustainable production through the deep learning approaches. The adoption of Industry 4.0 practices is helping industries to achieve sustainable production. However, it will be more interesting to investigate the impact of deep learning approaches on sustainable production for small and medium enterprises. This study provides the guidelines for the manufacturing industries on how deep learning approaches can contribute to sustainable production.
3. In future studies, energy consumption-related issues, predictive maintenance and quality management-related matters can be ad-

dressed for small-scale industries as small-scale industries are the major contributors to developing nations' economies.
4. There is a lack of empirical investigations in eh area of deep learning approaches. In future studies, empirical analyses can be done to find the challenges, enabling factors and impact of deep learning techniques for sustainable production.
5. In future studies, the impact of deep learning approaches on the existing production systems can be addressed. How deep learning approaches can transform the current predictive maintenance and quality management practices can be addressed in future studies.

7.3. Managerial contributions to study

This review article delivers many important insights related to deep learning, which will be helpful for policymakers and practitioners to understand the importance of deep learning approaches in Industry 4.0 for sustainable production. The main concern of developing Industry 4.0 practices is the loss of manual jobs. In this study, it is also discussed how deep learning can create job opportunities in the industries in future. The managers of manufacturing organisations can address the various research issues and challenges in the practical industrial scenario, which will help them experience more sustainability topics. The main question which arises from the present stud is whether the adoption of deep learning approaches can be helpful for industries to achieve sustainable production. Also, how the proposed framework can be beneficial for the enterprises to overcome the challenges in adopting the deep learning-based approaches. However, there is a need to conduct an extensive survey to investigate whether the deep learning approaches are contributing to sustainable production. The practitioners and policymakers can address these issues in future studies.

8. Conclusion

The present study is focused on presenting a state-of-the-art review of the deep learning approaches for sustainable production. In this study, the role of different deep learning models for sustainable production, various research themes and a framework for sustainable production is discussed with implications for the practitioners, policymakers and researchers. In this study, three major digital scientific databases, i.e., IEEE, Scopus and Web of Science, are considered for the state-of-the-art review. The analysis shows that research in deep learning in the manufacturing area is still limited. Industries are still struggling with the lack of knowledge and benefits of the deep learning approaches for sustainable production. Our study shows how deep learning approaches can contribute to quality management, predictive maintenance, reliability analysis and fault diagnosis. The relationship between deep learning techniques and sustainability is also discussed. The study's main contribution is developing a deep learning-based framework for sustainable production, which will benefit the manufacturing organisations to achieve sustainable production in the Industry 4.0-based business models. However, the proposed framework is not empirically tested, which can be done in future studies by conducting the age survey across the various industry sectors. The study also reveals that many deep learning approaches have been developed in the past few years, making new research scopes in manufacturing. The advantages of various deep learning models in manufacturing are also discussed in the present study. Adopting deep learning approaches has sustainability benefits in predictive maintenance, reducing machine downtime, quality management and fault diagnosis.

8.1. Limitations

This study has a limitation related to considering the digital scientific databases for the article collection. In this study, we have considered only three significant databases. Other scientific databases, i.e., Google Scholar, ScienceDirect and InderscienceOnline, can be followed in future studies. In future studies, bibliometric analysis can be done for the statistical analysis of the documents related to this area. Moreover, in future studies, applications of deep learning approaches in the various industry sectors in the different regions of the world can be explored, which will help provide a holistic overview and understanding of the potential of deep learning approaches for sustainable production.

References

Abdirad, M., & Krishnan, K. (2020). Industry 4.0 in logistics and supply chain management: A systematic literature review. *EMJ - Engineering Management Journal, 00*(00), 1–15. 10.1080/10429247.2020.1783935.

Abou Tabl, A., Alkhateeb, A., & ElMaraghy, W. (2021). Deep learning method based on big data for defects detection in manufacturing systems Industry 4.0. *International Journal of Industry and Sustainable Development, 2*(1), 1–14.

Akdil, K. Y., Ustundag, A., & Cevikcan, E. (2017). Maturity and readiness model for Industry 4.0 strategy. *Springer Series in Advanced Manufacturing*, 61–94. 10.1007/978-3-319-57870-5_4.

Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y. K., D'Ambra, J., & Shen, K. N. (2021). Algorithmic bias in data-driven innovation in the age of AI. *International Journal of Information Management, 60*, Article 102387.

Alexopoulos, K., Nikolakis, N., & Chryssolouris, G. (2020). Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. *International Journal of Computer Integrated Manufacturing, 33*(5), 429–439.

Alipour, M., Harris, D. K., & Miller, G. R. (2019). Robust pixel-level crack detection using deep fully convolutional neural networks. *Journal of Computing in Civil Engineering, 33*(6), Article 04019040.

Ammar, M., Haleem, A., Javaid, M., Walia, R., & Bahl, S. (2021). Improving material quality management and manufacturing organizations system through Industry 4.0 technologies. *Materials Today: Proceedings, 45*, 5089–5096.

Ardabili, S., Mosavi, A., Dehghani, M., & Várkonyi-Kóczy, A. R. (2019). Deep learning and machine learning in hydrological processes climate change and earth systems a systematic review. In *International Conference on Global Research and Education* (pp. 52–62).

Arellano-Espitia, F., Delgado-Prieto, M., Martinez-Viol, V., Saucedo-Dorantes, J. J., & Osornio-Rios, R. A. (2020). Deep-learning-based methodology for fault diagnosis in electromechanical systems. *Sensors, 20*(14), 3949.

Arinez, J. F., Chang, Q., Gao, R. X., Xu, C., & Zhang, J. (2020). Artificial intelligence in advanced manufacturing: Current status and future outlook. *Journal of Manufacturing Science and Engineering, 142*(11), Article 110804.

Ashok, M., Madan, R., Joha, A., & Sivarajah, U. (2022). Ethical framework for artificial intelligence and digital technologies. *International Journal of Information Management, 62*, Article 102433.

Azamfar, M., Li, X., & Lee, J. (2020). Deep learning-based domain adaptation method for fault diagnosis in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing, 33*(3), 445–453.

Bag, S., Gupta, S., & Kumar, S. (2021). Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. *International Journal of Production Economics, 231*. 10.1016/j.ijpe.2020.107844.

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change, 163*. 10.1016/j.techfore.2020.120420.

Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics, 229*. 10.1016/j.ijpe.2020.107776.

Bai, Y., Li, C., Sun, Z., & Chen, H. (2017). Deep neural network for manufacturing quality prediction. In *2017 Prognostics and System Health Management Conference (PHM-Harbin)* (pp. 1–5).

Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2021). Building supply-chain resilience: An artificial intelligence-based technique and decision-making framework. *International Journal of Production Research*, 1–21.

Berghout, T., Mouss, L.-H., Bentrcia, T., Elbouchikhi, E., & Benbouzid, M. (2021). A deep supervised learning approach for condition-based maintenance of naval propulsion systems. *Ocean Engineering, 221*, Article 108525.

Bhandari, B., & Park, G. (2021). Development of a surface roughness evaluation method from light and shade composition using deep learning. *IEIE Transactions on Smart Processing & Computing, 10*(3), 189–198.

Bhuvaneswari, V., Priyadharshini, M., Deepa, C., Balaji, D., Rajeshkumar, L., & Ramesh, M. (2021). Deep learning for material synthesis and manufacturing systems: A review. *Materials Today: Proceedings, 46*, 3263–3269. 10.1016/j.matpr.2020.11.351.

Bichon, B. J., Eldred, M. S., Swiler, L. P., Mahadevan, S., & McFarland, J. M. (2008). Efficient global reliability analysis for nonlinear implicit performance functions. *AIAA Journal, 46*(10), 2459–2468.

Butte, S., Prashanth, A., & Patil, S. (2018). Machine learning based predictive maintenance strategy: A super learning approach with deep neural networks. 1–5.

Carvalho, N., Chaim, O., Cazarini, E., & Gerolamo, M. (2018). Manufacturing in the fourth industrial revolution: A positive prospect in sustainable manufacturing. In K. H. Shpitalni M. Seliger G.,. Wertheim R.,. Fischer A. (Ed.), *Procedia Manufacturing* (Vol. 21, pp. 671–678). Elsevier B.V. https://doi.org/10.1016/j.promfg.2018.02.170

Carvalho, T. P., Soares, F. A., Vita, R., Francisco, R., da, P., Basto, J. P., & Alcalá, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering, 137*, Article 106024.
Chakraborty, A., & Kar, A. K. (2017). Swarm intelligence: A review of algorithms. *Nature-Inspired Computing and Optimization*, 475–494.
Chauhan, C., Singh, A., & Luthra, S. (2021). Barriers to industry 4.0 adoption and its performance implications: An empirical investigation of emerging economy. *Journal of Cleaner Production, 285*. 10.1016/j.jclepro.2020.124809.
Chauhan, N. K., & Singh, K. (2018). A review on conventional machine learning vs deep learning. In *2018 International Conference on Computing, Power and Communication Technologies (GUCON)* (pp. 347–352).
Chen, B., Liu, Y., Zhang, C., & Wang, Z. (2020). Time series data for equipment reliability analysis with deep learning. *IEEE Access, 8*, 105484–105493.
Chen, C., Liu, Y., Sun, X., Di Cairano-Gilfedder, C., & Titmus, S. (2021). An integrated deep learning-based approach for automobile maintenance prediction with GIS data. *Reliability Engineering & System Safety, 216*, Article 107919.
Chen, Y.-F., Lin, Y.-K., & Huang, C.-F. (2021). Using deep neural networks to evaluate the system reliability of manufacturing networks. *International Journal of Performability Engineering, 17*(7).
Chien, C.-F., Dauzère-Pérès, S., Huh, W. T., Jang, Y. J., & Morrison, J. R. (2020). Artificial intelligence in manufacturing and logistics systems: Algorithms, applications, and case studies. *International Journal of Production Research, 58*(9), 2730–2731.
Chui, K. T., Lytras, M. D., & Visvizi, A. (2018). Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption. *Energies, 11*(11), 2869.
Chung, Y., Ahn, S., Yang, J., & Lee, J. (2017). Comparison of deep learning frameworks: About theano, tensorflow, and cognitive toolkit. *Journal of Intelligence and Information Systems, 23*(2), 1–17.
Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. *Sustainability (Switzerland), 12*(2). 10.3390/su12020492.
Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability, 12*(19), 8211.
Cohen, S., & Macek, J. (2021). Cyber-physical process monitoring systems, real-time big data analytics, and industrial artificial intelligence in sustainable smart manufacturing. *Economics, Management & Financial Markets, 16*(3).
Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management, 60*, Article 102383.
Collins, K. (2020). Cyber-physical production networks, real-time big data analytics, and cognitive automation in sustainable smart manufacturing. *Journal of Self-Governance and Management Economics, 8*(2), 21–27. 10.22381/JSME8220203.
Davis, R., Sessions, B.-O., & Check, A. R. (2015). *Industry 4.0.* Digitalisation for Productivity and Growth. European Parliament, Members' Research Service.
de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Foropon, C., & Filho, M. G. (2018). When titans meet – Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change, 132*, 18–25. 10.1016/j.techfore.2018.01.017.
Dikhanbayeva, D., Shaikholla, S., Suleiman, Z., & Turkyilmaz, A. (2020). Assessment of industry 4.0 maturity models by design principles. *Sustainability (Switzerland), 12*(23), 1–22. 10.3390/su12239927.
Enyoghasi, C., & Badurdeen, F. (2021). Industry 4.0 for sustainable manufacturing: Opportunities at the product, process, and system levels. *Resources, Conservation and Recycling, 166*. 10.1016/j.resconrec.2020.105362.
Ferrari, A. M., Volpi, L., Settembre-Blundo, D., & García-Muiña, F. E. (2021). Dynamic life cycle assessment (LCA) integrating life cycle inventory (LCI) and Enterprise resource planning (ERP) in an industry 4.0 environment. *Journal of Cleaner Production, 286*. 10.1016/j.jclepro.2020.125314.
Gaikwad, A., Giera, B., Guss, G. M., Forien, J.-B., Matthews, M. J., & Rao, P. (2020). Heterogeneous sensing and scientific machine learning for quality assurance in laser powder bed fusion–A single-track study. *Additive Manufacturing, 36*, Article 101659.
Guo, Y., Liu, Y., Oerlemans, A., Lao, S., Wu, S., & Lew, M. S. (2016). Deep learning for visual understanding: A review. *Neurocomputing, 187*, 27–48.
Haleem, A., & Javaid, M. (2019). Additive manufacturing applications in industry 4.0: A review. *Journal of Industrial Integration and Management, 4*(04), Article 1930001.
Han, J., Shihab, E., Wan, Z., Deng, S., & Xia, X. (2020). What do programmers discuss about deep learning frameworks. *Empirical Software Engineering, 25*(4), 2694–2747.
Hansen, E. B., & Bøgh, S. (2021). Artificial intelligence and internet of things in small and medium-sized enterprises: A survey. *Journal of Manufacturing Systems, 58*, 362–372.
He, M., & He, D. (2017). Deep learning based approach for bearing fault diagnosis. *IEEE Transactions on Industry Applications, 53*(3), 3057–3065.
Herath, H., & Mittal, M. (2022). Adoption of artificial intelligence in smart cities: A comprehensive review. *International Journal of Information Management Data Insights, 2*(1), Article 100076.
Hidayatno, A., Destyanto, A. R., & Hulu, C. A. (2019). Industry 4.0 technology implementation impact to industrial sustainable energy in Indonesia: A model conceptualization. In H. B (Ed.), *5th International Conference on Power and Energy Systems Engineering, CPESE 2018: 156* (pp. 227–233). Elsevier Ltd. 10.1016/j.egypro.2018.11.133.
Hoang, D.-T., & Kang, H.-J. (2019). A survey on deep learning based bearing fault diagnosis. *Neurocomputing, 335*, 327–335.
Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780.
Horváthová, M., Lacko, R., & Hajduová, Z. (2019). Using industry 4.0 concept – digital twin – to improve the efficiency of leather cutting in automotive industry. *Quality Innovation Prosperity, 23*(2), 1–12. 10.12776/QIP.V23I2.1211.
Jamwal, A., Agrawal, R., Sharma, M., & Giallanza, A. (2021). Industry 4.0 technologies for manufacturing sustainability: A systematic review and future research directions. *Applied Sciences, 11*(12), 5725.
Jamwal, A., Agrawal, R., Sharma, M., Kumar, A., Kumar, V., & Garza-Reyes, J. A. (2021). Machine learning applications for sustainable manufacturing: A bibliometric-based review for future research. *Journal of Enterprise Information Management*.
Jamwal, A., Agrawal, R., Sharma, M., Kumar, V., & Kumar, S. (2021). Developing A sustainability framework for Industry 4.0. *Procedia CIRP, 98*, 430–435.
Javaid, M., Haleem, A., Singh, R. P., Khan, S., & Suman, R. (2021). Blockchain technology applications for Industry 4.0: A literature-based review. *Blockchain: Research and Applications*, Article 100027.
Javaid, M., Haleem, A., Singh, R. P., Rab, S., & Suman, R. (2021). Significance of sensors for industry 4.0: Roles, capabilities, and applications. *Sensors International, 2*, Article 100110.
Jena, M. C., Mishra, S. K., & Moharana, H. S. (2020). Application of Industry 4.0 to enhance sustainable manufacturing. *Environmental Progress and Sustainable Energy, 39*(1). 10.1002/ep.13360.
Jia, F., Lei, Y., Guo, L., Lin, J., & Xing, S. (2018). A neural network constructed by deep learning technique and its application to intelligent fault diagnosis of machines. *Neurocomputing, 272*, 619–628.
Jung, H., Jeon, J., Choi, D., & Park, J.-Y. (2021). Application of machine learning techniques in injection molding quality prediction: Implications on sustainable manufacturing industry. *Sustainability, 13*(8), 4120.
Kamble, S. S., Gunasekaran, A., Ghadge, A., & Raut, R. (2020). A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs- A review and empirical investigation. *International Journal of Production Economics, 229*. 10.1016/j.ijpe.2020.107853.
Kar, A. K. (2016). Bio inspired computing–a review of algorithms and scope of applications. *Expert Systems with Applications, 59*, 20–32.
Khan, I. H., & Javaid, M. (2021). Role of Internet of Things (IoT) in adoption of Industry 4.0. *Journal of Industrial Integration and Management*, Article 2150006.
Khan, S., & Yairi, T. (2018). A review on the application of deep learning in system health management. *Mechanical Systems and Signal Processing, 107*, 241–265.
Kim, H., Jung, W.-K., Park, Y.-C., Lee, J.-W., & Ahn, S.-H. (2022). Broken stitch detection method for sewing operation using CNN feature map and image-processing techniques. *Expert Systems with Applications, 188*, Article 116014.
Kim, J. H. (2017). A review of cyber-physical system research relevant to the emerging IT trends: Industry 4.0, IoT, big data, and cloud computing. *Journal of Industrial Integration and Management, 2*(03), Article 1750011.
Kotsiantis, S. B., Zaharakis, I. D., & Pintelas, P. E. (2006). Machine learning: A review of classification and combining techniques. *Artificial Intelligence Review, 26*(3), 159–190.
Kushwaha, A. K., Kar, A. K., & Dwivedi, Y. K. (2021). Applications of big data in emerging management disciplines: A literature review using text mining. *International Journal of Information Management Data Insights, 1*(2), Article 100017.
LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. 10.1038/nature14539.
Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. *Manufacturing Letters, 18*, 20–23.
Lee, J., Lee, Y. C., & Kim, J. T. (2020). Fault detection based on one-class deep learning for manufacturing applications limited to an imbalanced database. *Journal of Manufacturing Systems, 57*, 357–366.
Li, B., Hou, B., Yu, W., Lu, X., & Yang, C. (2017). Applications of artificial intelligence in intelligent manufacturing: A review. *Frontiers of Information Technology & Electronic Engineering, 18*(1), 86–96.
Li, S., Ma, Y., Lu, X., Qiao, F., & Liu, J. (2020). Adaptive scheduling for smart shop floor based on deep Q-network. In *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)* (pp. 618–623).
Liu, J., Chang, H., Forrest, J. Y.-L., & Yang, B. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. *Technological Forecasting and Social Change, 158*, Article 120142.
Loyer, J.-L., Henriques, E., Fontul, M., & Wiseall, S. (2016). Comparison of Machine Learning methods applied to the estimation of manufacturing cost of jet engine components. *International Journal of Production Economics, 178*, 109–119. 10.1016/j.ijpe.2016.05.006.
Machado, C. G., Winroth, M. P., & Ribeiro da Silva, E. H. D. (2020). Sustainable manufacturing in Industry 4.0: An emerging research agenda. *International Journal of Production Research, 58*(5), 1462–1484. 10.1080/00207543.2019.1652777.
Mao, S., Wang, B., Tang, Y., & Qian, F. (2019). Opportunities and challenges of artificial intelligence for green manufacturing in the process industry. *Engineering, 5*(6), 995–1002.
Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). Deep learning for healthcare: Review, opportunities and challenges. *Briefings in Bioinformatics, 19*(6), 1236–1246.
Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2018). A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs). *Journal of Manufacturing Systems, 49*, 194–214.
Müller, J.M. (2019). Contributions of Industry 4.0 to quality management—A SCOR perspective. In Y. F. Ivanov D. Dolgui A. (Ed.), *IFAC-PapersOnLine* (Vol. 52, Issue 13, pp. 1236–1241). Elsevier B.V. https://doi.org/10.1016/j.ifacol.2019.11.367
Namuduri, S., Narayanan, B. N., Davuluru, V. S. P., Burton, L., & Bhansali, S. (2020). Deep learning methods for sensor based predictive maintenance and future perspectives for electrochemical sensors. *Journal of The Electrochemical Society, 167*(3), Article 037552.
Nguyen, K. T., & Medjaher, K. (2019). A new dynamic predictive maintenance framework using deep learning for failure prognostics. *Reliability Engineering & System Safety, 188*, 251–262.
Nikolakis, N., Siaterlis, G., & Alexopoulos, K. (2020). A machine learning approach for

improved shop-floor operator support using a two-level collaborative filtering and gamification features. *Procedia CIRP, 93*, 455–460.

Ning, F., Shi, Y., Cai, M., Xu, W., & Zhang, X. (2020). Manufacturing cost estimation based on a deep-learning method. *Journal of Manufacturing Systems, 54*, 186–195.

Niri, M. F., Liu, K., Apachitei, G., Román-Ramírez, L. A., Lain, M., Widanage, D., & Marco, J. (2022). Quantifying key factors for optimised manufacturing of Li-ion battery anode and cathode via artificial intelligence. *Energy and AI, 7*, Article 100129.

Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S. S., Reuter, U., Gama, J., & Gandomi, A. H. (2020). Data science in economics: Comprehensive review of advanced machine learning and deep learning methods. *Mathematics, 8*(10), 1799.

Ozdemir, R., & Koc, M. (2019). A quality control application on a smart factory prototype using deep learning methods. In *2019 IEEE 14th International Conference on Computer Sciences and Information Technologies (CSIT): 1* (pp. 46–49).

Parvat, A., Chavan, J., Kadam, S., Dev, S., & Pathak, V. (2017). A survey of deep-learning frameworks. In *2017 International Conference on Inventive Systems and Control (ICISC)* (pp. 1–7).

Priore, P., De la Fuente, D., Gomez, A., & Puente, J. (2001). A review of machine learning in dynamic scheduling of flexible manufacturing systems. In *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: 15* (pp. 251–263). 10.1017/s0890060401153059.

Raj, A., Dwivedi, G., Sharma, A., Lopes de Sousa Jabbour, A. B., & Rajak, S. (2020). Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. *International Journal of Production Economics, 224*(August 2019), Article 107546 –107546. 10.1016/j.ijpe.2019.107546.

Rajawat, A. S., Bedi, P., Goyal, S. B., Shaw, R. N., & Ghosh, A. (2022). Reliability analysis in cyber-physical system using deep learning for smart cities industrial IoT network node. In *AI and IoT for Smart City Applications* (pp. 157–169). Springer.

Ram, S. K., & Tyagi, R. D. (2020). Artificial intelligence and computational sustainability. *Sustainability*, 627–649. 10.1002/9781119434016.ch29.

Rawat, S., Rawat, A., Kumar, D., & Sabitha, A. S. (2021). Application of machine learning and data visualization techniques for decision support in the insurance sector. *International Journal of Information Management Data Insights, 1*(2), Article 100012.

Ryan, K., Lengyel, J., & Shatruk, M. (2018). Crystal structure prediction via deep learning. *Journal of the American Chemical Society, 140*(32), 10158–10168.

Sahu, C. K., Young, C., & Rai, R. (2021). Artificial intelligence (AI) in augmented reality (AR)-assisted manufacturing applications: A review. *International Journal of Production Research, 59*(16), 4903–4959.

Sajid, S., Haleem, A., Bahl, S., Javaid, M., Goyal, T., & Mittal, M. (2021). Data science applications for predictive maintenance and materials science in context to Industry 4.0. *Materials Today: Proceedings, 45*, 4898–4905.

Salloum, S. A., Alshurideh, M., Elnagar, A., & Shaalan, K. (2020). Machine learning and deep learning techniques for cybersecurity: A review. In *AICV* (pp. 50–57).

Shams, S., Platania, R., Lee, K., & Park, S.-J. (2017). Evaluation of deep learning frameworks over different HPC architectures. In *2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS)* (pp. 1389–1396).

Shao, S.-Y., Sun, W.-J., Yan, R.-Q., Wang, P., & Gao, R. X. (2017). A deep learning approach for fault diagnosis of induction motors in manufacturing. *Chinese Journal of Mechanical Engineering, 30*(6), 1347–1356. 10.1007/s10033-017-0189-y.

Sharma, R., Jabbour, C. J. C., & Lopes de Sousa Jabbour, A. B. (2020). Sustainable manufacturing and industry 4.0: What we know and what we don't. *Journal of Enterprise Information Management*. 10.1108/JEIM-01-2020-0024.

Shinde, P. P., & Shah, S. (2018). A review of machine learning and deep learning applications. In *2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)* (pp. 1–6).

Shivajee, V., Singh, R. K., & Rastogi, S. (2019). Manufacturing conversion cost reduction using quality control tools and digitization of real-time data. *Journal of Cleaner Production, 237*. 10.1016/j.jclepro.2019.117678.

Shrestha, A., & Mahmood, A. (2019). Review of deep learning algorithms and architectures. *IEEE Access, 7*, 53040–53065.

Sun, W., Li, M., Li, Y., Wu, Z., Sun, Y., Lu, S., Xiao, Z., Zhao, B., & Sun, K. (2019). The use of deep learning to fast evaluate organic photovoltaic materials. *Advanced Theory and Simulations, 2*(1), Article 1800116.

Sung, T. K. (2018). Industry 4.0: A Korea perspective. *Technological Forecasting and Social Change, 132*, 40–45.

Syafrudin, M., Alfian, G., Fitriyani, N. L., & Rhee, J. (2018). Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing. *Sensors (Basel, Switzerland), 18*(9), 2946 PubMed. 10.3390/s18092946.

Tang, S., Yuan, S., & Zhu, Y. (2019). Deep learning-based intelligent fault diagnosis methods toward rotating machinery. *IEEE Access, 8*, 9335–9346.

Tripathi, S., Muhr, D., Brunner, M., Jodlbauer, H., Dehmer, M., & Emmert-Streib, F. (2021). Ensuring the robustness and reliability of data-driven knowledge discovery models in production and manufacturing. *Frontiers in Artificial Intelligence, 4*, 22.

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights, 1*(1), Article 100002.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Nerini, F. F. (2020). The role of artificial intelligence in achieving the sustainable development goals. *Nature Communications, 11*(1), 1–10.

Votto, A. M., Valecha, R., Najafirad, P., & Rao, H. R. (2021). Artificial intelligence in tactical human resource management: A systematic literature review. *International Journal of Information Management Data Insights, 1*(2), Article 100047.

Voulodimos, A., Doulamis, N., Doulamis, A., & Protopapadakis, E. (2018). Deep learning for computer vision: A brief review. *Computational Intelligence and Neuroscience, 2018*.

Wan, J., Li, X., Dai, H.-N., Kusiak, A., Martínez-García, M., & Li, D. (2020). Artificial-intelligence-driven customized manufacturing factory: Key technologies, applications, and challenges. In *Proceedings of the IEEE: 109* (pp. 377–398).

Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. *Journal of Manufacturing Systems, 48*, 144–156.

Wang, K., & Wang, Y. (2017). How AI affects the future predictive maintenance: A primer of deep learning. In *International Workshop of Advanced Manufacturing and Automation* (pp. 1–9).

Wang, P., & Gao, R. X. (2020). Transfer learning for enhanced machine fault diagnosis in manufacturing. *CIRP Annals, 69*(1), 413–416.

Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research, 4*(1), 23–45. 10.1080/21693277.2016.1192517.

Yadav, G., Kumar, A., Luthra, S., Garza-Reyes, J. A., Kumar, V., & Batista, L. (2020). A framework to achieve sustainability in manufacturing organisations of developing economies using industry 4.0 technologies' enablers. *Computers in Industry, 122*. 10.1016/j.compind.2020.103280.

Yang, J., Li, S., Wang, Z., Dong, H., Wang, J., & Tang, S. (2020). Using deep learning to detect defects in manufacturing: A comprehensive survey and current challenges. *Materials, 13*(24), 5755.

Yao, X., Zhou, J., Zhang, J., & Boër, C.R. (2017). From intelligent manufacturing to smart manufacturing for industry 4.0 driven by next generation artificial intelligence and further on. 311–318.

Zhang, A., He, Y., Han, X., Li, Y., Yang, X., & Zhang, Z. (2020). Modeling Product Manufacturing Reliability with Quality Variations Centered on the Multilayered Coupling Operational Characteristics of Intelligent Manufacturing Systems. *Sensors, 20*(19), 5677.

Zhang, D., Pee, L. G., & Cui, L. (2021). Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's smart warehouse. *International Journal of Information Management, 57*, Article 102304.

Zhang, J., & Gao, R. X. (2021). Deep learning-driven data curation and model interpretation for smart manufacturing. *Chinese Journal of Mechanical Engineering, 34*(1), 1–21.

Zhang, T., Homri, L., Dantan, J., & Siadat, A. (2021). Conceptual maps of reliability analysis applied in reconfigurable manufacturing system. 136–145.

Zhang, W., Wang, X., Cabrera, D., & Bai, Y. (2020). Product quality reliability analysis based on rough Bayesian network. *International Journal of Performability Engineering, 16*(1).

Zhao, G., Zhang, G., Ge, Q., & Liu, X. (2016). Research advances in fault diagnosis and prognostic based on deep learning. In *2016 Prognostics and System Health Management Conference (PHM-Chengdu)* (pp. 1–6).

Zhao, Z.-Q., Zheng, P., Xu, S., & Wu, X. (2019). Object detection with deep learning: A review. *IEEE Transactions on Neural Networks and Learning Systems, 30*(11), 3212–3232.

Zonta, T., da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, Article 106889.