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DEEP LEARNING AND BIG DATA IN MANUFACTURING: APPLICATIONS, CHALLENGES AND THE ROLE IN THE FOURTH INDUSTRIAL REVOLUTION

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ABSTRACT

The advent of the fourth industrial revolution (industry 4.0) has sparked a transformation in manufacturing through the integration of deep learning (DL) and big data technologies. These innovations have enhanced the ability of manufacturers to process and analyze vast amount of data, providing insights that improve decision-making, efficiency, and overall productivity. Deep learning, a subset of artificial intelligence (AI), offers advanced capabilities in data pattern recognition and predictive modeling, while big data facilitates the management of large and complex datasets from various sources. However, literature on the integration of deep learning, big data and industry 4.0 is still limited in the manufacturing context. This paper provides a detailed overview of big data, deep learning and industry 4.0 in manufacturing. It explores the applications of deep learning and big data in manufacturing, highlighting their role in optimizing production processes, predictive maintenance, quality control, and supply chain management. Furthermore, the paper addresses the key challenges and solutions associated with the integration of these technologies, such as data privacy, security, computational complexity, and the need for skilled labor.

KEYWORDS: *Deep learning, Industry 4.0, Supply chain management, Big data, Predictive maintenance, Artificial intelligence, ERP systems.*

1.0 INTRODUCTION

The relationship between deep learning (DL), big data and manufacturing is increasingly significant in modern industries. Big data and deep learning are two of the most powerful technologies that are transforming the manufacturing industry. With the rise of artificial intelligence (AI) in the last decade, many organizations started adopting AI technologies, such as machine learning (ML) and DL to transform their manufacturing processes (Kinkel et al., 2022). The adoption of DL has significantly increased in the last few years in the manufacturing sector due to the generation of large amount of data. Organizations now use deep learning ranging from small scale enterprises to large-scale organizations (Bettoni et al., 2022; Kaymakci et al., 2022). DL enables organizations to uncover insights from data more quickly and accurately, leading to better decision-making. ML and deep learning algorithms are being applied in various areas, such as predictive analytics, natural language processing, and image recognition (Bharadiya, 2023, Cioffi et. al., 2020). Big data refers to datasets that are too large or complex for traditional data-processing applications, and it includes structured, semi-structured, and unstructured data (Gartner, 2020). Together, these technologies offer significant potential for optimizing manufacturing operations and reshaping the entire sector. Deep learning and big data are being applied across several manufacturing domains to achieve efficiency gains, reduce costs, and enhance product quality.

As we navigate the fourth industrial revolution, characterized by the convergence of digital, physical, and biological realms, the adoption of deep learning in manufacturing becomes not just advantageous but imperative for staying competitive in the global market. This is a comprehensive exploration of deep learning (DL) technologies and their impact on the manufacturing sector. It highlights the transformative role of deep learning in reshaping the future of industrial production.

2.0 LITERATURE REVIEW

In recent times, quite a number of studies and reviews have been published on big data and DL in manufacturing. While individual applications of big data and deep learning in manufacturing have

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been explored, there is lack of studies focusing on their combined application to achieve sustainable objectives. Also challenges and solutions related to data privacy, security, computational complexity and data integration from diverse sources remain underexplored. Addressing these issues is crucial for the effective application of big data and DL in manufacturing.

Carlos et al (2021) explores the concept of quality 4.0**,** a new paradigm in manufacturing that leverages big data**,** advanced analytics, and industry 4.0 technologies to enhance product quality management. It discusses the integration of big data with manufacturing processes, highlighting how it can transform traditional quality management practices and overcome challenges to achieve greater efficiency and quality standards. It also emphasizes the importance of developing standardized frameworks and tools to help organizations implement and scale quality 4.0 initiatives effectively.

Senthil et al., 2020 discussed a detailed overview of a wide range of AI and big data techniques and explore the Industry 4.0 applications that have benefited from AI and big data. The paper also identifies and discusses key technological, data-related, and security issues and challenges associated with a successful deployment of AI and Big Data in Industry 4.0.

Tosi et al (2024) summarizes the current state of the art of the previous 15 years of research about big data by providing answers to a set of research questions related to the main application domains for big data analytics; the significant challenges and limitations researchers have encountered in big data analysis, and emerging research trends and future directions in big data.

Anbesh et al., (2022) discussed 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 are fault diagnosis, quality management, and predictive maintenance. Finally, a conceptual DL-based framework is proposed for the manufacturing industries to enhance their sustainability performance in manufacturing activities.

Rathore et al., (2021) explores diverse applications of big data analytics across industries like healthcare, energy, and manufacturing. It underscores the evolution of these applications, highlighting a focus on optimization, diagnostics, and predictive analytics. It anticipates future trends, emphasizing the integration of AI, machine learning, and big data, particularly in digital twinning. It sets the stage for ongoing research in optimizing industrial processes, predictive analytics, healthcare, and smart city implementations.

Sarker et al., (2023) investigates the transformative impact of big data analytics in industries, and manufacturing. In manufacturing, it facilitates data-driven decision-making, comprehensive product quality assessment, and streamlined supply chain management for increased operational efficiency. Machine learning and data analytics play a pivotal role in overcoming challenges, particularly in fault detection.

Bansal et al., (2020) navigates the evolution of big data, emphasizing challenges and the rise of machine learning, particularly deep learning. It proposes a review focusing on deep learning in big data analytics. It emphasizes deep learning's strength in handling extensive datasets, its versatility, and its ability to prevent over fitting. The proposed review, specifically focusing on deep learning in big data analytics, not only captures current advancements but also suggests there's more to discover in the future where big data and machine learning intersect.

Ikegwu et al., (2022) provides presents an all-inclusive survey of current trends of big data analytics (BDA) tools, methods, their strengths, and weaknesses. It identifies and discusses data sources and real-life applications where big data analytics have potential impacts. It identifies BDA challenges and solutions, and future research prospects that require further attention by researchers. The study identifies some emerging trends: sourcing data from education and diverse IoT devices, refining pre-processing, advancing data management, enhancing privacy, and exploring deep learning methods.

A closely related review was presented by Rishi et al (2023) and discussed the applications of deep learning being employed in manufacturing, including identifying defects, optimizing processes, streamlining the supply chain, predicting maintenance needs, and recognizing human activity. The paper draws attention to the current challenges and limitations that need to be addressed to fully realize the potential of deep learning technology in manufacturing. On the other hand, our study differs with their review in many ways. First, our review provides a detailed view on big data in manufacturing. Secondly, we discussed the role of industry 4.0 in manufacturing. Thirdly, the study presents the challenges and solutions associated with the integration of big data and deep learning and the role of industry 4.0 in manufacturing.

3.0 OVERVIEW OF BIG DATA AND DEEP LEARNING

Big data refers to large and complex datasets that cannot be effectively processed using traditional data processing applications. Big data are characterized by various vectors which include volume, variety, velocity, veracity, and value. The big data volume focuses on the size of data set generated through various applications and sources. They are growing at the rate of megabytes to petabytes and beyond. Variety aims at the diverse nature of data that constitute big data. These include textual data, social media data, traffic information, health-related data, and other multimodal data. Velocity refers to the speed and dynamic nature of the data collection process and how to generate these data in real-time. Furthermore, veracity depicts the reliability of data sources and if the sources of data generation can be trusted. Finally, the value of big data shows the insight and hidden values

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that can be discovered from a large amount of dataset (Hashem et al., 2015).

Data has become one of the most valuable assets for modern organizations (Albergaria and Jabbour., 2020). Big data has garnered lots of attention recently in government, industries, sciences, engineering, healthcare and medicine, finance and prominently in businesses (Hashem et al., 2015). In today's data-driven world, big data has become integral components of business operations, enabling organizations to extract valuable insights and make informed decisions (Elgendy, Elragal and Päivärinta, 2022, Sarker, 2021, Yu, et. al., 2021). Big data in manufacturing refers to the vast amount of data generated by machines, sensors, processes and employees throughout the production cycles. This data comes from various sources, such as equipment sensors, enterprise resource planning (ERP) systems, supply chain logistics, social media, sensors, and transactional systems and even customer feedback. Extracting accurate and trustworthy data is a big challenge for enterprises in order to derive insights and support decision-making processes. The ability to collect, analyze, and leverage vast amounts of data has become a key differentiator for companies seeking to gain a competitive edge in the market (Bresciani, et. al., 2021). By analyzing data, companies can identify trends, patterns, and opportunities that can inform strategic decision-making and drive business growth.

The 2000s saw the emergence of big data, driven by the exponential growth in data volume, velocity, and variety. Organizations started using advanced analytics techniques, such as data mining, machine learning, deep learning and predictive analytics, to extract insights from big data. The adoption of cloud computing and the Internet of Things (IoT) in the 2010s further accelerated the use of big data. Around 90% of the world's digitized data was captured in the last few years, and it keeps going on (Al Nuaimi et al., 2015). Big data is also suitable for cost reduction, faster and better decision making, new products and services, product recommendations, and fraud detection. Big data are transforming businesses through the advancement of robotics and automation system.

Deep learning is a subset of machine learning that leverages artificial neural networks to extract valuable insights from vast amounts of structured and unstructured data. In the context of manufacturing, deep learning algorithms analyze complex datasets generated from various sources such as sensors, cameras, and production equipment to extract valuable insights and make data-driven decisions. By applying advanced image and signal recognition techniques to manufacturing, deep learning can detect and classify product defects early and, subsequently, improve final product quality. Using historical data, deep learning models detect objects or anomalies in images or videos captured by production line cameras. Manufacturers can identify defects quickly and accurately without any manual inspection. In addition, deep learning models can predict when equipment is likely to fail and schedule maintenance and repairs in advance, reducing downtime and extending equipment life. Sensor readings can be analyzed over time to predict when components need service. It also enables the optimization of production processes and the scheduling of resources to improve efficiency. Moreover, deep learning requires less feature engineering than traditional machine learning techniques. This method is more accurate than others at detecting complex patterns in large datasets. Additionally, deep neural networks generalize well. When a model is trained on one dataset, it can easily be applied to another similar dataset without additional training.

ML and DL 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). Extracting relevant information from these data is crucial and DL algorithms do it effectively. The role of DL in manufacturing organizations is to collect, analyze and interpret large amount of data (Ashok et al., 2022; Zhang et al., 2021).

The adoption of 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 (Rawat et al., 2021). Deep learning algorithms extract high-level, complex abstractions as data representations through a hierarchical learning process. A key benefit of deep learning is the analysis and learning of massive amounts of unsupervised data, making it a valuable tool where raw data is largely unlabeled and un-categorized. In today's highly competitive manufacturing setting, companies are constantly seeking ways to improve efficiency, quality, and productivity while reducing costs. Deep learning offers a transformative solution by enabling manufacturers to leverage their data effectively and optimize various aspects of their operations. By harnessing the power of deep learning, manufacturers can enhance quality control, predict equipment failures before they occur, optimize production processes, and personalize products to meet individual customer needs. As such, deep learning has become a cornerstone of the Fourth Industrial Revolution, driving innovation and reshaping the future of manufacturing.
Unlike traditional ML approaches such as support vector machines, K-nearest neighbors, Naive Bayes, and decision-trees that require hand-engineered features to represent data and can be time-consuming, deep learning algorithms automatically learn features from raw data, making them more flexible and adaptable to different types of data. With their capacity to analyze and learn from huge volumes of data, deep learning and big data provide a possible path toward achieving sustainability goals (Kim et al., 2022; Malik et al., 2023; Liskiewics et al., 2023). By combining big data and deep learning, manufacturers can gain valuable insights into their production processes, products, markets, and customers and use them to optimize production efficiency and reduce costs.

A. Recurrent Neural Network (RNN)

Any network in which neurons communicate back and forth is referred to as a recurrent neural network (RNN). They were created to address learning issues where generating predictions about the future requires knowledge of the past (i.e., previous instants or events). The analysis of sequential data, such the words in a sentence, has historically been done using RNNs. RNNs have been used in text analysis tasks such machine translation, speech recognition, language modeling, time-series data, event sequence, text prediction, and image caption synthesis because of their capacity to produce text (Sutskever *et al.,* 2011; Karpathy *et al.,* 2015). In a simple RNN, each layer's output is added to the following input and fed back into the layer, creating a capacity for contextual "memory. Such sequential examples are commonly utilized in many real-world applications, such as language modeling, where the words that came before the next one in the sentence are used to predict what word will come next. The most recent hourly, daily, and weekly stock prices serve as a predictor of future stock movement in the stock market. For time series or sequential jobs, RNNs are especially suited. With the help of this feedback architecture, the network can take into account input from time-dependent datasets or previous sequences while making a prediction.

B. Long Short-Term Memory (LSTM)

This is a type of RNN designed to handle long-term dependencies in sequential data, such as speech, text, and time-series data. LSTMs are particularly effective in scenarios where the information in the sequence is relevant to predicting future values, and where the gap between relevant inputs and outputs can be large. LSTMs are composed of a series of memory cells, each of which contains an input gate, an output gate, and a forget gate. These gates control the flow of information into and out of the cell, allowing the network to selectively remember or forget information over time. The input gate determines which information should be stored in the cell, based on the current input and the previous output. The forget gate decides which information should be forgotten, based on the previous output and the current input. The output gate determines which information should be outputted from the cell, based on the current input and the previous output. The ability of LSTMs to selectively store and retrieve information over long sequences makes them well suited for a variety of tasks. They have also been used in combination with other types of neural networks, such as convolutional neural networks (CNNs), to improve the performance of deep learning models on complex tasks.

C. Multilayer Perceptron (MLP)

The most basic type of deep neural network is the multilayer perceptron (MLP). Hidden layers make up the architecture of an MLP in order to grasp intricate relationships in the training dataset. It is the most widely used, successful, and simple to understand model for intricate, multilayered networks (Zhao *et al.,* 2010). An input layer made up of a number of source nodes, one or more hidden layers of computation nodes, and an output layer of nodes make up a typical multilayer perceptron network. Layer after layer, the input signal spreads throughout the network. The network is trained using a multi-layer feed-forward-back propagation algorithm, and its performance is evaluated. Typically, MLP networks are employed to solve supervised learning problems. This means that the network must learn to predict the dependency between a training set of input-output pairs. In the sense that the neural network knows the desired output and the weight coefficients are adjusted so that the calculated and desired outputs are as close to each other as possible. The multilayer perceptron network is a common learning algorithm and is frequently used for classification and speech recognition applications. Assuming we have a set of image data measuring 28 x 28, a feed-forward neural network or multilayer perceptron will require 784 input weights in addition to a bias. This is a large number of learning parameters, which uses a lot of memory and computational resources. The spatial links between the pixels in an image are lost when it is flattened in MLP.

D. Convolutional Neural Network

Convolutional Neural Networks (CNN) is a form of deep neural network that are incredibly effective at solving image classification challenges (Zhang *et al.*, 2018). In the field of deep learning, convolutional neural network is the most well-known and often used approach (Krizhevsky *et al.*, 2017; Al-Azzawi *et al.,* 2020; Wang *et al.*, 2020; Li *et al.*, 2021). The availability of large scale annotated datasets like ImageNet has enabled tremendous advancements in image recognition (Krizhevsky *et al.,* 2012). They are multi-layered networks that recognize visual patterns. They aim to imitate the neural connectivity seen in the visual cortex of the brain. The most extensively studied deep learning algorithm for analyzing medical images is CNN (Litjens *et al.,* 2017). This is because when filtering incoming images, CNNs maintain spatial information. The convolutional network's job is to simplify the images without losing any of the features that are essential for making accurate predictions. Only some inputs are connected to the following layer due to the sparse connections in CNN neurons. The effectiveness of the method is increased by having a limited, local receptive field (i.e., the region covered by the filter every stride), which enables relevant characteristics to be gradually learned and drastically reduces the number of weights that must be calculated. The most prevalent ways to increase the performance of CNN include data augmentation, transfer learning, regularization methods, and hyper parameter adjustment. An input layer, a convolution layer, a pooling layer, a fully-connected layer, and an output layer make up a convolutional neural network (Simonyan *et al.,* 2015). There are two steps to these layers: feature extraction and classification. In contrast to classification, which comprises of an output layer and a fully connected layer, feature extraction consists of an input layer, a convolutional layer, and a pooling layer.

Using convolutional and pooling layers, a CNN transforms an input image made up of raw pixels. The input is then classified into the class with the highest probability by being fed into a fully connected layer that assigns class scores or probabilities.

Neurons in each layer have biases and weights that can be learned. The weights used by CNN are kernel or filter. After feeding data to the network and decreasing the loss function at the top layer, the perfect model is attained. CNN automatically learns features based on these filters during training. When a face image is fed into a CNN, the filters will first pick up on low-level features like lines and edges. As the feature maps serve as inputs for the future layer in the CNN architecture, these gradually rise to higher features like a nose, eye, or ear.

I. The first layer extract basic features from raw pixel data such as horizontal or vertical edges, dots, lines, corners etc
II. The output is passed to the second layer which uses these edges to detect shapes in the second layer.
III. As you move deeper into the network, it uses the shapes to detect more complex features like faces, body, objects.
IV. Finally, it uses the highest-level features to make prediction in the last layer.

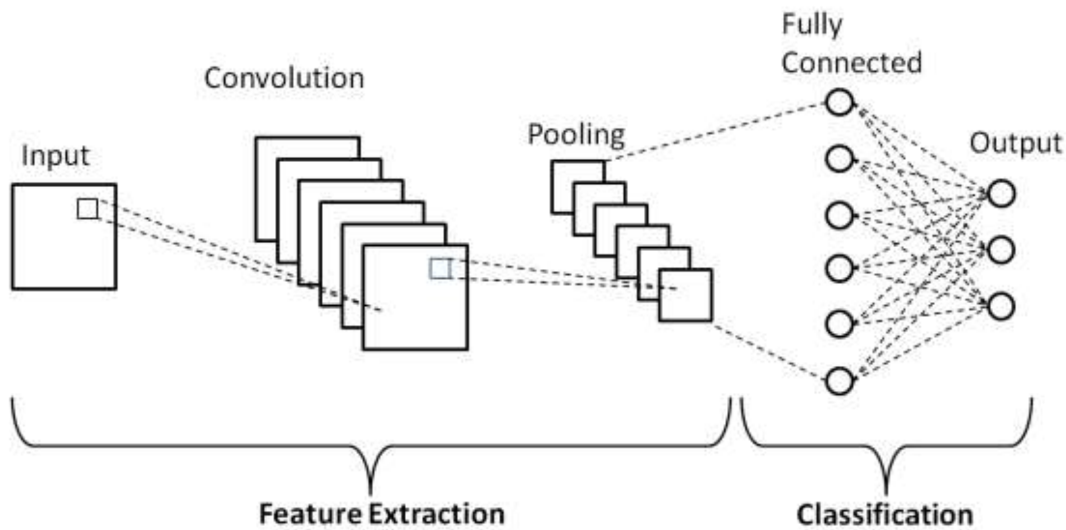

Figure 1: Convolutional Neural Network (Szegedy *et al.*, 2016)

4.0 INDUSTRY 4.0

The rise of Industry 4.0 is characterized by the widespread application of advanced technologies such as machine learning, deep learning and big data in manufacturing. Due to evolution of Industry 4.0 practices, generation of data from manufacturing and production activities has increased (Cioffi et al., 2020). This is challenging for organizations. The past studies conducted on Industry 4.0 shows that 82% of manufacturing and service organizations have increased their productivity by using industry 4.0 technologies, such as deep learning, machine learning and internet of things (Akter et al., 2021). Industry 4.0 is defined by Dogru and Keskin (2020) as the transition into the digital age, including the digitization of manufacturing, adoption of computers and automated processes towards enhanced smart and autonomous systems powered by computers, algorithms, data and automated processes. According to Schwab (2016), Industry 4.0 marks a fundamental shift in industrial processes, enabling automation, connectivity, computational self-awareness, smart manufacturing, enhanced supervision and real-time data-driven decision-making (Lepasepp and Hurst., 2022). It is the rapid change in how organizations execute manufacturing practices (Vuković & Thalmann, 2022). It represents a paradigm shift in manufacturing driven by advancements in digital technologies. It is characterized by the integration of internet of things (IoT), cloud computing, and artificial intelligence into the manufacturing processes. In the manufacturing sector, industry 4.0 embraces technological, economic, organization and societal changes and relies on technology (Bécue et al., 2021). Critical foundations of industry 4.0 include automation, interconnectivity, real time data analytics, and deep learning (DL) (Yuan et al., 2022). Such integration has proven industry 4.0 to be imperative in modern manufacturing, revolutionizing the industry by increasing productivity, reducing waste output and decreasing the overall product lifecycle (Huang et al., 2021).

Deep learning and big data are central to the transformative potential of Industry 4.0, ushering in a new era of manufacturing that is smarter, more efficient, and highly adaptive in Industry 4.0, DL offers a wide range of economic, social and environmental benefits for manufacturing organizations, which helps achieve sustainability (Bai et al., 2020). In the context of manufacturing, these technologies hold the power to revolutionize everything from production processes to product development, supply chain management, and customer relations. Deep learning plays a pivotal role by providing the intelligence needed to analyze the vast amounts of data generated by interconnected systems, ultimately driving autonomous decision-making and optimization in manufacturing operations.

5.0 APPLICATION OF DEEP LEARNING (DL) IN MANUFACTURING

a) Predictive Maintenance

One of the most significant applications of deep learning and big data in manufacturing is in predictive maintenance. In traditional maintenance systems, companies follow scheduled maintenance to react to equipment failures. However, deep learning algorithms, in combination with big data, allow for the prediction of equipment failures before they happen. Predictive maintenance in Industry 4.0 era aims to schedule the maintenance of a product or machine at the most efficient and convenient time (Cinar et al., 2020). Sensor data from machinery is used to track performance metrics such as vibration, temperature, and pressure (Lee et al., 2018). Deep learning models, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, process these datasets to identify patterns that indicate potential equipment failures. This predictive capability helps reduce downtime, minimize maintenance costs, and increase operational efficiency. Predictive maintenance in manufacturing organizations is essential as it helps reduce maintenance costs and machine downtime (Sajid et al., 2021). Predictive maintenance is the maintenance of machinery carried out by predicting when the optimal time is required for scheduled maintenance to be performed (Tristan, 2022). Deep learning algorithms can estimate the remaining useful life (RUL) of equipment based on historical usage and sensor data (Al-Dulaimi et al., 2019). Accurate RUL predictions can help operators plan maintenance schedules more accurately, save costs, improve safety, and reduce downtime. The data from sensors, maintenance logs, and other sources are then fed into a deep learning model, which is trained to recognize patterns and anomalies in the data. It supports the running and lifespan of machinery by preventing unexpected machinery downtime, improving the availability of machinery and detecting faults and defects that occur when machines are in use (Rai et al., 2021). Predictive maintenance is a prime example of the benefits derived from the digitalization of manufacturing processes (Fahle et al., 2020).

b) Quality Control and Defect Detection

Deep learning models, particularly convolutional neural networks (CNNs), are widely used in quality control and defect detection in manufacturing. These models can analyze high-resolution images or videos of products during the production process to detect defects, such as cracks, dents, and color discrepancies (Chen et al., 2020). By training deep learning models on large datasets of product images, manufacturers can achieve a level of accuracy in defect detection that surpasses human inspectors. This automation of quality control reduces human error, speeds up the inspection process, and improves product quality.

c) Process Optimization

By analyzing large datasets from sensors, machinery, and production lines, manufacturers can identify inefficiencies and bottlenecks within production systems. Deep learning algorithms can model these complex systems and recommend process adjustments to maximize throughput and reduce waste (Zhang et al., 2021). For example, deep learning algorithms can analyze historical production data to optimize process parameters and improve output quality. An industrial deep learning model can be trained on a dataset of images of products and associated quality scores and then used to predict the quality of new product images. By identifying low-quality products early in the production process, manufacturers can take corrective action to improve the quality of the final product.

d) Supply Chain and Inventory Management

The role of big data in manufacturing extends to supply chain and inventory management. Big data technologies enable manufacturers to track inventory levels, shipments, and raw material availability in real time (Suh et al., 2019). Supply Chain Management (SCM) is a crucial area that is linked to the function of manufacturing. According to Bertolini et al. (2021), SCM involves planning, controlling and executing logistical flows. It ranges from acquiring raw materials to delivering end products in the most cost-effective way possible. SCM activities include inventory management and transportation, demand planning and sourcing.

Accurate demand forecasting is a crucial part of supply chain optimization, and deep learning algorithms can help improve the accuracy of demand forecasting by analyzing large amounts of historical data and identifying patterns and trends that might not be immediately apparent to human analysts (Husna et al., 2021; Pacella et al., 2021). Better prediction of the demand can help optimize inventory levels by minimizing the risk of stock outs and overstocks. Deep learning algorithms can help optimize the logistics of the supply chain by analyzing shipping routes, transportation modes, and other variables to identify the most efficient and cost effective routes and modes of transportation (Liu et al., 2019). With DL algorithms in sales and demand estimation, the accuracy in predicting inventory level requirements and sales can be improved. Additionally, deep learning models are employed to predict disruptions in the supply chain, such as delays or shortages, allowing manufacturers to take proactive measures to mitigate risks. In general, the application of deep learning in supply chain optimization can help companies identify inefficiencies, reduce costs, and improve overall performance

e) Demand Forecasting and Customization

Big data and deep learning are also transforming demand forecasting and product customization. Time-series analysis, powered by deep learning, allows manufacturers to predict future demand with higher accuracy, taking into account various external factors such as market trends, seasonality, and economic conditions (Zhou et al., 2018). Moreover, deep learning models facilitate mass customization, where manufacturers can tailor products to individual customer needs while maintaining high levels of efficiency.

Big data and machine learning can help manufacturers improve their product design by using data from customer feedback, market trends, competitor analysis, simulations, etc. Machine learning algorithms can also generate new design ideas or optimize existing ones based on predefined criteria or objectives.

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Challenges associated with the integration of deep learning and big data in manufacturing

Despite the promising applications, there are several challenges associated with the integration of deep learning and big data in manufacturing.

One major issue is the need for vast amounts of high-quality data to train deep learning models. Big data and machine learning require large amount of high-quality, relevant, and reliable data to produce accurate and meaningful results. However, collecting, storing, processing, analyzing, and securing such data can be difficult, costly, or risky for manufacturers due to technical, organizational, or legal constraints. The effectiveness of deep learning relies heavily on the availability and quality of data. Manufacturing systems generate vast amounts of data, but much of them are noisy, incomplete, or unstructured (Chien et al., 2021). Preprocessing and cleaning the data to make it suitable for deep learning models is a significant challenge. Moreover, without high-quality labeled data, supervised deep learning models may not perform well. As highlighted by Zhang et al., (2021), the quality and quantity of data available are critical to the effectiveness of machine learning algorithms. However, many manufacturers still struggle with poor data quality, which hinder the adoption of these technologies. Data augmentation techniques (such as generating synthetic data) can help expand the available dataset. This can be particularly useful in situations where acquiring real-world data is expensive or time-consuming. For example, in image recognition tasks, techniques like rotation and flipping can augment the dataset. In some fields, advanced tools generate entirely synthetic data that can mimic real-world patterns. Also, Instead of training models from scratch, which requires large datasets, manufacturers can use pre-trained models such as convolutional neural network, visual geometry group 16 and 19, Resnet 50 etc and adapt them to their specific task using much smaller datasets. By transferring knowledge from a model trained on a large general dataset, businesses can often achieve good results with less data.

Additionally, the computational complexity of deep learning models presents challenges. Training deep learning algorithms requires significant computational power and resources, which may be inaccessible to small and medium-sized enterprises (SMEs) (Zhang et al., 2021). Access to the necessary computing resources, such as high-performance GPUs or cloud computing infrastructure, may be limited. The cost of scaling these technologies across multiple production sites can be a significant barrier. Furthermore, the integration of big data technologies demands substantial investments in infrastructure, data storage, and management systems (Kumar et al., 2019). SMEs can take advantage of cloud platforms like AWS, Google Cloud, or Microsoft Azure, which offer scalable resources for training deep learning models without the need to invest heavily in infrastructure. Also, instead of training deep learning models from scratch, SMEs can leverage pre-trained models (such as those available in TensorFlow Hub or Hugging Face) and fine-tune them for specific tasks. This reduces the computational resources needed, as the model has already been trained on large datasets and only requires minor adjustments to fit the problem at hand.

Another critical challenge is the shortage of skilled labor capable of managing, analyzing, and interpreting big data and deep learning models. Big data and deep learning require specialized skills and knowledge to develop, implement, maintain, and use effectively. However, finding, hiring, training, or retaining such talent can be challenging for manufacturers due to skill shortages, high demand, or competition (Felfernig et al., 2020). The manufacturing industry is yet to fully address this skills gap (Barton et al., 2020). Bridging the skill gap requires investments in training programs, collaboration with educational institutions, and recruitment strategies to attract talent with the requisite skills. Additionally, fostering a culture of continuous learning and innovation within the organization is essential to nurture talent and adapt to evolving technological landscapes.

Big data and deep learning raise ethical issues regarding the privacy of data used (Zheng et al., 2021). Privacy and security are also more significant concerns under big data (Sun et al., 2020). However, addressing these issues can be challenging for manufacturers due to the complexity, ambiguity, or uncertainty of the ethical implications or regulations. Collaborating with legal experts and regulatory agencies can help manufacturers navigate complex compliance requirements and uphold ethical principles while leveraging the benefits of deep learning technology.

Many manufacturers still rely on legacy systems that are not designed to work with modern AI technologies like deep learning. Integrating deep learning models into existing manufacturing infrastructure, including machinery and enterprise resource planning (ERP) systems, can be a complex and costly process. Achieving seamless integration requires careful planning, interoperability assessments, and customization to ensure compatibility and functionality across the entire manufacturing ecosystem. Collaborating with experienced technology partners and leveraging standardized interfaces and protocols can streamline the integration process and minimize disruptions to ongoing operations.

Deep learning models are often criticized for being "black-box" models that lack transparency in their decision-making processes. In manufacturing, where safety and quality are paramount, the inability to explain how a model arrived at a decision can undermine trust in its outputs. There is a need for more interpretable AI models that can provide insights into the reasoning behind predictions.

Incorporating deep learning into manufacturing processes introduces significant data security concerns. The risk of cyber-attacks increases as manufacturing systems become more connected and reliant on data-driven AI systems. Manufacturers must safeguard sensitive information, such as proprietary designs, production data, and customer details from potential breaches and cyber-attacks. The integration of IoT devices, cloud computing,

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and AI models opens up new vulnerabilities, and manufacturers must invest in robust cyber security measures to protect sensitive data and prevent disruptions in production (Yampolskiy, R. V. 2020). Implementing robust encryption protocols, access controls, and regular security audits are essential to mitigate the risks associated with data breaches and ensure the integrity and confidentiality of critical manufacturing data.

6.0 METHODOLOGY

This study utilized a system review approach. A comprehensive literature search was conducted across major databases such as ACM Digital Library, PubMed and Google Scholar. The search focused on studies published between 2015 and 2024. Our search focus was on the deep learning and big data in manufacturing and its role in fourth industrial revolution. A total of 20 studies met the criteria after a good quality assessment.

6.0 CONCLUSION

Deep learning and big data technologies are revolutionizing the manufacturing industry by improving operational efficiency, quality control, maintenance practices, and supply chain management. However, the integration of these technologies faces several challenges, including data quality issues, data privacy, computational complexity, lack of skilled labor, and cyber security concerns. Despite these obstacles, the potential benefits of deep learning and big data in manufacturing are immense, contributing to the broader transformation of the industry as part of the fourth industrial revolution. To fully realize these benefits, manufacturers must address the challenges and invest in the necessary infrastructure, skills, and data governance frameworks.

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