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# Deep learning for smart manufacturing: Methods and applications

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ABSTRACT

Smart manufacturing refers to using advanced data analytics to complement physical science for improving system performance and decision making. With the widespread deployment of sensors and Internet of Things, there is an increasing need of handling big manufacturing data characterized by high volume, high velocity, and high variety. Deep learning provides advanced analytics tools for processing and analysing big manufacturing data. This paper presents a comprehensive survey of commonly used deep learning algorithms and discusses their applications toward making manufacturing "smart". The evolvement of deep learning technologies and their advantages over traditional machine learning are firstly discussed. Subsequently, computational methods based on deep learning are presented specially aim to improve system performance in manufacturing. Several representative deep learning models are comparably discussed. Finally, emerging topics of research on deep learning are highlighted, and future trends and challenges associated with deep learning for smart manufacturing are summarized.


## 1. Introduction

Over the past century, the manufacturing industry has undergone a number of paradigm shifts, from the Ford assembly line (1900s) to Toyota production system (1960s), flexible manufacturing (1980s), reconfigurable manufacturing (1990s), agent-based manufacturing (2000s), cloud manufacturing (2010s) [1,2]. Various countries have developed strategic roadmaps to transform manufacturing to take advantage of the emerging infrastructure, as presented by Internet of Things (IoTs) and data science. As an example, Germany introduced the framework of Industry 4.0 in 2010, which has been evolved into a collaborative effort among member countries in the European Union. Similarly, in 2011 the Smart Manufacturing Leadership Coalition (SMLC) in the U.S. created a systematic framework for implementing smart manufacturing. The plan "China Manufacturing 2025", introduced in China in 2015, aims to promote advanced manufacturing. As manufacturing machines are increasingly equipped with sensors and communication capabilities, there is significant potential to further improve the condition-awareness of manufacturing machines and processes, reduce operational downtime, improve the level of automation and product quality and response more timely to dynamically changing customer demands [3–8]. Statistics shows that 82% of the companies using smart manufacturing technologies have experienced increased efficiency and 45% of the companies of the companies experienced increased customer satisfaction [9].

Smart manufacturing refers to a new manufacturing paradigm where manufacturing machines are fully connected through wireless networks, monitored by sensors, and controlled by advanced computational intelligence to improve product quality, system productivity, and sustainability while reducing costs. Recent advancement of Internet of Things (IoTs), Cloud Computing, Cyber Physical System (CPS) provides key supporting technologies to advance modern manufacturing [10–13]. By leveraging these new technologies in manufacturing, data at different stages of a product's life, ranging from raw materials, machines' operations, facility logistics, and even human operators, is collected and processed [12]. With the proliferation of manufacturing data, data driven intelligence with advanced analytics transforms unprecedented volumes of data into actionable and insightful information for smart manufacturing as illustrated in Fig. 1. Data driven intelligence models the complex multivariate nonlinear relationships among data, with no in-depth understanding of system physical behaviours required.

Data driven intelligence has attracted extensive research effort for manufacturing data distilling and decision making. In [14],

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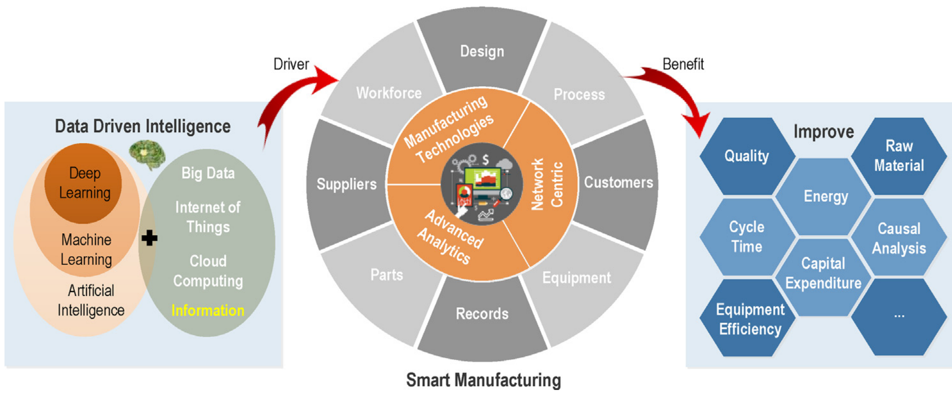


**Fig. 1.** The role of data driven intelligence in smart manufacturing.

data mining techniques are classified into five categories, including characterization and description, association, classification, prediction, clustering and evolution analysis. The barriers to data-driven decision making in manufacturing are also identified. Typical machine learning techniques are reviewed in [15,16] for intelligent manufacturing, and their strengths and weaknesses are also discussed in a wide range of manufacturing applications. A comparative study of machine learning algorithms including Artificial Neural Network, Support Vector Machine, and Random Forest is performed for machining tool wear prediction. The schemes, techniques and paradigm of developing decision making support systems are reviewed for the monitoring of machining operations, and these techniques include neural networks, fuzzy logic, genetic algorithms, and hybrid systems [17,18]. The potential benefit and successful application examples of typical machining learning techniques including Bayesian Networks, instance-based learning, Artificial Neural Network, and ensemble methods are discussed in [19]. Cloud enabled prognosis techniques including data driven approach, physics based as well as model-based techniques are reviewed in [20], with the benefits from both advanced computing capability and information sharing for intelligent decision making. Traditional machine learning is usually designed with shallow structures, such as Artificial Neural Network, Support Vector Machine, and logistic regression, etc. By coping with limited handcrafted features, it achieves decent performance in a variety of applications. However, the massive data in smart manufacturing imposes a variety of challenges [18,19], such as the proliferation of multimodal data, high dimensionality of feature space, and multicollinearity among data measurements. These challenges render traditional algorithms struggling and thus greatly impede their performance.

As a breakthrough in artificial intelligence, deep learning demonstrates outstanding performance in various applications of speech recognition, image recondition, natural language processing (e.g. translation, understanding, test questions & answers), multimodal image-text, and games (e.g. Alphago). Deep learning allows automatically processing of data towards highly nonlinear and complex feature abstraction via a cascade of multiple layers, instead of handcrafting the optimum feature representation of data with domain knowledge. With automatic feature learning and high-volume modelling capabilities, deep learning provides an advanced analytics tool for smart manufacturing in the big data era. It uses a cascade of layers of nonlinear processing to learn the representations of data corresponding to different levels of abstraction. The hidden patterns underneath each other are then identified and predicted through end-to-end optimization. Deep learning offers great potential to boost data-driven manufacturing applications, especially in the big data era [17,21].

In light of the above challenges, this paper aims to provide a state-of-the-art review of deep learning techniques and their applications in smart manufacturing. Specifically, the deep learning enabled advanced analytics framework is proposed to meet the opportunistic need of smart manufacturing. The typical deep learning models are briefly introduced, and their applications to manufacturing are outlined to highlight the latest advancement in relevant areas. The challenges and future trends of deep learning are discussed in the end.

The rest of paper is constructed as follows. Firstly, data-driven artificial intelligence techniques are reviewed in Section 2, with the superiority of deep learning techniques outlined. Next, the challenge and opportunistic need of deep learning in smart manufacturing are presented, and typical deep learning models are briefly discussed in Section 3. Then, the latest applications of deep learning techniques in the context of smart manufacturing are summarized in Section 4. Finally, the challenges as well as future trends of deep learning in smart manufacturing are discussed.

## 2. Overview of data driven intelligence

### 2.1. The evolution of data-driven artificial intelligence

Artificial intelligence is considered as a fundamental way to possess intelligence, and listed as the first place in Gartner's Top 10 strategic technology trends in 2017 [22]. Artificial intelligence has experienced several lifecycles, from the infancy period (1940s), through the first upsurge period (1960s) and the second upsurge period (1980s), and the present third boom period (after 2000s). The development trend and typical artificial intelligence models are summarized in Table 1.

The origin of Artificial Neural Network started back in 1940s, when MP model [23] and Hebb rule [24] were proposed to discuss how neurons worked in human brain. At the workshops in Dartmouth College, significant artificial intelligence capabilities like playing chess games and solving simple logic problems were developed [24]. The pioneering work brought artificial intelligence to the first upsurge period (1960s). In 1956, a mathematical model named Perceptron [25] was proposed to simulate the nervous system of human learning with linear optimization. Next, a network model called Adaptive Linear Unit [26] was developed in 1959 and had been successfully used in practical applications such as communication and weather forecasting. The limitation of early artificial intelligence was also criticized due to the difficulty in handling non-linear problems, such as XOR (or XNOR) classification [27].

With the development of Hopfield network circuit [28], artificial intelligence stepped forward to the second upsurge (1980s). Back Propagation (BP) algorithm was proposed to solve non-linear problems in complex neural network in 1974 [29]. A random mech-