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Convolutional and generative adversarial neural networks in manufacturing

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Manufacturing is undergoing transformation driven by the developments in process technology, information technology, and data science. A future manufacturing enterprise will be highly digital. This will create opportunities for machine learning algorithms to generate predictive models across the enterprise in the spirit of the digital twin concept. Convolutional and generative adversarial neural networks have received some attention of the manufacturing research community. Representative research and applications of the two machine learning concepts in manufacturing are presented. Advantages and limitations of each neural network are discussed. The paper might be helpful in identifying research gaps, inspire machine learning research in new manufacturing domains, contribute to the development of successful neural network architectures, and getting deeper insights into the manufacturing data.

Keywords: manufacturing; smart manufacturing; intelligent manufacturing; deep learning; machine learning; convolutional neural networks; generative adversarial networks

1. Introduction

The industry relies on information technology designed around specific functions, for example, enterprise resource planning (ERP) system, customer relationship management (CRM), and process planning. The emergence of the software-as-a-service (SaaS) paradigm has moved many applications to a cloud. There is no limit on the number of SaaS solutions to reside in the cloud.

The presence of data and services in the cloud has accelerated interest in enterprise digitisation and predictive analytics. Digitisation of industry aims at creating models of products and processes from data. Some of the models may be high fidelity, in essence, become digital replicas (called digital twins) of processes, products, and logistics. Digital models open doors to new opportunities, including decision-making at different time horizons. The latter will be enabled by predictive analytics allowing to simulate future states of the phenomena of interest.

Progress in sensor and software technology has led to a new generation of industrial and service robots. Traditionally, the most effective deployment of industrial robots has been in hazardous and repetitive environments. In the past, the cost and functionality of robotic technology have been the main barriers of their wide deployment. Latest robots have become more agile, functional, and affordable due to the developments in sensor, programming, and control technology. Automation of previously difficult to accomplish manufacturing and service functions are emerging, e.g. robots inspecting products, drones counting inventory in a warehouse, robots performing equipment and facility maintenance tasks, and surveyance and security robots.

Digital manufacturing has enabled developmant of applications and solutions versed in data (Kusiak 2017). Machine learning solutions are ideally suited to offer value-derived from the manufacturing data. In fact, machine learning is not new to manufacturing as algorithms have been deployed in the past, e.g. cluster algorithms (Song and Kusiak 2009; Emre Celebi 2015), decision tree algorithms (Wang et al. 2008; Choudhary, Harding, and Tiwari 2009), neural networks (Dreyfus 2005; Zhu et al. 2010), and a broader framework of computational intelligence (Andina and Pham 2007; Kordon 2010; Marwala 2012). The fact that manufacturing data is not always complete, e.g. labels might be missing (Kang et al. 2018) and not well balanced (Rahim et al. 2019) across different outcomes (e.g. low number of process abnormality data vs normal status data), offers opportunities to apply the recently developed machine learning algorithms, convolutional and generative adversarial neural networks discussed in this paper.

Before details of the convolutional and generative adversarial networks and their applications are discussed, a brief background of machine learning is provided.

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2. Learning from data

There is a growing interest in artificial intelligence which aims at creating software (e.g. voice recognition) and hardware solutions (e.g. robots) that exhibit intelligent behaviour. While discussions of the impact of artificial intelligence on manufacturing are plentiful (e.g. Li et al. 2017), this paper focuses on machine learning that involves building models from data with algorithms, generally grouped in three classes: supervised, unsupervised, and semi-supervised. Machine learning appears under different names, e.g. in engineering and business applications, it is frequently referred to as data analytics or predictive modelling.

Deep learning, though proposed decades ago, has received a well-deserved research attention rather recently. It usually involves neural networks with many hidden layers (e.g. 100) assembled in different architectures (Aggrawal 2018). A traditional neural network may have one to three hidden layers. For example, the network in Figure 1 involves one hidden layer.

Such a neural network (Figure 1) would need to be trained with the data set illustrated in Table 1. The training data set includes two independent variables (inputs), vibration and temperature, and quality as an dependent variable (output).

In the training process, each connection of the neural network in Figure 1 acquires a weight. Once fully trained, given any combination of previously unseen inputs (vibration and temperature) the neural network would generate an output (quality).

Neural networks have found many applications in manufacturing and service industry. An illustrative application of a neural network in additive manufacturing is presented in Qi et al. (2019). Performance and quality of additive manufacturing products depends on the process parameters that are difficult to tune. Since they impact the printed microstructure and performance of the subsequent products, Qi et al. (2019) focused on modeling the process–structure–property–performance of 3D printed products using machine learning algorithms. Current challenges in applying neural networks to additive manufacturing and potential solutions for these problems were outlined.

The growing width, depth, and volume of data calls for algorithms able to build complex models. This has prompted the research community to propose new algorithms and models. Deep learning in the context of neural networks, has emerged as a preferred solution.

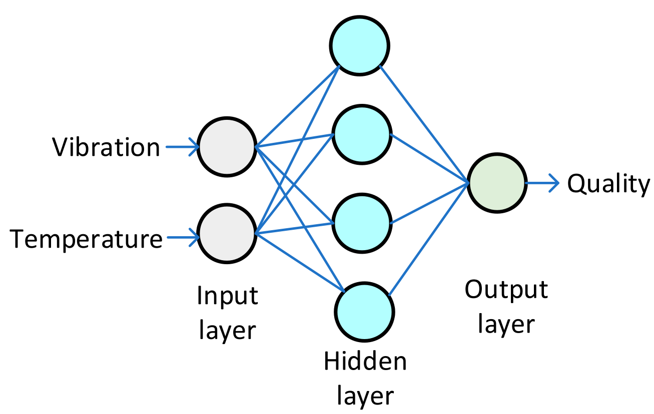

Figure 1. A neural network for prediction of product quality.

Table 1. Training (historical) data set.

Vibration	Temperature	Quality
1776	180	High
4888	298	Low
2400	245	Acceptable
1400	167	High
2344	261	Acceptable
5400	320	Low

3. Deep learning

Deep learning is part of a broader family of machine learning methods. Deep neural networks have become the most widely applied tool of deep learning. The term 'deep'; in a 'deep neural network' refers to the number of layers in the network (Skansi 2018). Deep learning has naturally emerged as researchers began modelling complex problems in domains such as vision and voice recognition. Manufacturing is one of the latest additions to the application areas of deep neural networks.

The relationship between artificial intelligence, machine learning, and deep learning is illustrated in Figure 2.

3.1. *Industrial applications of deep neural networks*

Deep neural networks have been successfully deployed in industry. Three industrial applications of deep neural networks are listed next. As the technology around deep learning is new, it is natural that details of the new solutions could be sketchy.

Based on the advances in gaming industry, Nvidia Corporation, Santa Clara, California has developed a software platform incorporating the latest artificial intelligence technology, including deep neural networks, for industrial and service applications.

Jabil, St. Petersburg, Florida has deployed deep neural network technology for detection of defects in printed circuit boards (Salvaris, Dean, and Tok 2018). The image analysis of printed circuit boards has replaced the manual inspection.

eSmarts Systems, Halden, Norway provides artificial intelligence software solutions for energy industry and service applications (Salvaris, Dean, and Tok 2018). The solution is cloud-based and it offers real-time data analytics.

3.2. *Differences between traditional and deep learning*

A traditional machine learning process begins with the identification of features. For example, in image recognition, the relevant features are extracted from the images by a model developer. The features are then used to create a model that categorises the objects in the images. In deep learning, the relevant features are autonomously extracted from the images. Deep learning performs 'end-to-end learning' – where a network is provided with raw data and the intended task, e.g. classification, is performed by the model.

Another key difference is that deep learning algorithms scale with data, i.e. their performance often continues to improve as more data is provided. Traditional machine learning algorithms usually plateau at a certain level of performance as additional training data is provided.

In the survey paper, Wang et al. (2018) reviewed commonly used deep-learning algorithms and discussed their applications in manufacturing. Emerging research and future trends in deep learning were presented.

Deep learning is well suited to model complex high-dimensional data and it has applications beyond the ones discussed above. Dargan et al. (2019) characterised broad applications of deep learning in business, science, government, image classification, computer vision, cancer detection, natural language processing, object detection, face recognition, speech recognition, stock market, and smart cities. Basic and advanced architectures of neural networks were discussed. Major differences between deep learning and classical machine learning were outlined.

Training a neural network with a few layers can be time consuming and may produce a model that is not acceptable in the application of interest. The computational complexity of training a fully connected deep-neural network with many layers raises to another level. To reduce the computational complexity, researches have been looking into deep neural network architectures with reduced connectivity.

One of the most widely used deep networks with reduced connectivity is a convolutional neural network (CNN).

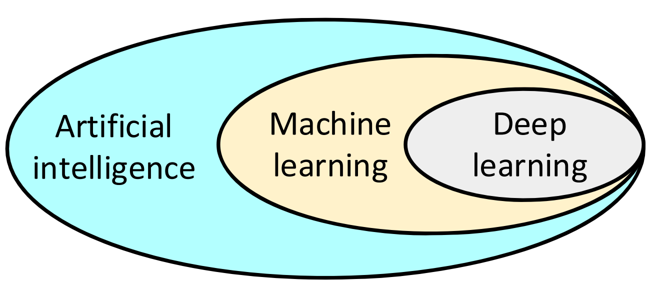

Figure 2. Relationship between artificial intelligence, machine learning, and deep learning.

4. Convolutional neural networks

Convolutional neural networks (CNNs) are regularised versions of traditional neural networks that are usually fully connected. The latter makes the classical neural networks prone to overfitting. The CNN departs from the fully connected network architecture by utilising hierarchical patterns in data and constructing complex patterns with simpler and smaller patterns. A CNN requires relatively limited data pre-processing compared to other algorithms, i.e. the network learns the filters that in the traditional algorithms are manually prepared.

CNNs are widely used in learning from two-dimensional (2D) data, e.g. images. The complexity of CNN learning increases with each hidden layer, with the recognition of simple features (e.g. edges) at the initial layers and the specific shapes being recognised at the final layers. CNN's performance usually improves as more data becomes available.

Manufacturing is at early stages of benefiting from convolutional neural networks. Representative applications of CNNs in manufacturing are discussed next.

4.1. Applications of convolutional neural networks in manufacturing

4.1.1. Surface inspection

Lin et al. (2020) proposed a convolutional neural network to detect defects at the steel surface. The proposed network architecture involved two components. The first one, was a single-shot multi-box detector model that learned all possible defects. The second one, was a deep residual network for classifying three types of defects: rust, scar, and sponge. Testing the network on an industrial data set has produced promising results.

A convolutional neural network (CNN) for inspecting welding defects such as craters, pores, foreign substances, and fissures on the surface of engine transmission was developed by Park, An, and Kang (2018) using data from a single RGB (red-blue-green) camera. The computational process involved two stages. First, a CNN detected the centre of the engine transmission in the image. Then, the extracted area was analysed by a different CNN to classify the image as a defective or non-defective. The second stage CNN was trained with a class-specific batch sampling method to minimise the data imbalance (the number of collected defective images was small relatively to the non-defective images).

4.1.2. Condition monitoring

Convolutional neural networks are promising solutions for condition monitoring of mechanical systems. Zhu et al. (2019) applied a CNN to learn features from the pressure data collected during supersonic combustion experiments. The proposed network revealed intrinsic features from the raw data and successfully classified four main combustion modes of a combustor.

4.1.3. Fault diagnosis

Huang et al. (2019) proposed a CNN named multi-scale cascade convolutional neural network (MC-CNN) to accurately classifiy faults based on the bearing vibration signal. The MC-CNN included an additional layer before the convolutional layers to construct a more distinguishable signal. The effectiveness of MC-CNN was studied in bearing fault diagnosis under nonstationary working conditions. The proposed MC-CNN was more accurate than the CNN.

Grezmak et al. (2019) developed an explainable convolutional network for analysis of gearbox faults. The authors have applied a wavelet to transform the time-series data to the time-frequency spectral images. The effectiveness of the proposed approach was tested on classification of faults and their severity using a gearbox testbed data set.

Wen, Li, and Gao (2019) addressed the fault diagnosis problem with a 51-layer convolutional neural network. The network capability has been enhanced with transfer learning. The tests performed with three benchmark data sets have demonstrated that the developed network performed better than other deep neural networks.

Liang et al. (2019) proposed a convolutional neural network to detect faults in a customised machining process. The signal data was partitioned and de-noised to enhance performance of the diagnostic system. The network was embedded in a fog architecture.

4.1.4. Quality control

Recognition of control chart patterns is of interest to quality control in manufacturing. Zan et al. (2019) proposed a one-dimensional (1D) convolutional neural network for recognition of patters in control charts. The proposed network has been tested on Monte-Carlo generated data sets. It has performed better that the traditional multi-layer perceptron.

4.1.5. Prediction of the remaining useful life

A convolutional neural network (CNN) based on regression for estimating the remaining useful life of components and systems was discussed by Babu, Zhao, and Li (2016). In the proposed CNN, the convolution and pooling filters were applied along the temporal dimension over the multi-channel sensor data. Automated feature learning from the raw sensor data was enabled. The CNN learned features were a higher-level representation of the low-level raw sensory data. Furthermore, feature learning and remaining useful life estimation were mutually enhanced by the supervised feedback. The test results have demonstrated that the proposed approach met the expected efficiency and prediction accuracy of the remaining useful life.

4.1.6. Vibration analysis

In the paper by Fu et al. (2017) the image signal was used to construct a model, rather than the measured signal. A convolutional neural network was introduced to connect pictured signals to different vibration states. The performance of the proposed approach has been validated in computational experiments.

One of the latest additions to deep learning is a generative adversarial network (GAN). The concept of GAN, inspired by the minimax two-player game (i.e. the two players learn from each other by pursuing conflicting goals), was proposed by Goodfellow et al. (2014).

5. Generative adversarial networks

A basic generative adversarial network (GAN) consists of two networks, a generator and a discriminator network, maintaining an adversarial relationship (see Figure 3). For a vector of independent variables **x**, and a dependent variable y, GAN is focusing on how to capture **x** rather than determining the relationship between y and **x** expressed by a generative model, i.e. p(**x**|y). A generative model captures the distribution of individual classes, rather than the boundary between classes expressed by the discriminative model.

GANs are emerging as powerful tools for unsupervised and semi-supervised learning. A basic GAN consists of the following:

- A generative model (i.e. generator) generates objects. The generator does not know anything about the actual objects and learns by interacting with the discriminator. For example, a generator can produce an image.
- A discriminative model (i.e. discriminator) determines whether an object is actual (real, usually represented by a probability value close to 1) or fake (represented by a value close to 0).
- An adversarial loss (or error signal) is provided by the discriminator to the generator, thus enabling the generator to produce objects that are similar to the actual objects.

The generator network (Figure 3) randomly generates synthetic objects that are fed to the discriminator network with the actual training objects. Based on the actual and synthetic data, the discriminator predicts an outcome (it outputs probability).

Two feedback loops are involved in training: (1) the discriminator that has access to the actual labels, and (2) the generator in a feedback loop of the discriminator. The two networks are trained simultaneously with, for example, a back-propagation algorithm. Thus, training the generator network, optimises the probability of the discriminator network arriving at an erroneous decision.

The discriminator network distinguishes between the training data and the generated data, which is learned in a traditional supervised mode.

Generative adversarial networks (GANs) can be implemented in different forms. Thus far, a convolutional neural network appears to be the architecture of choice for GANs.

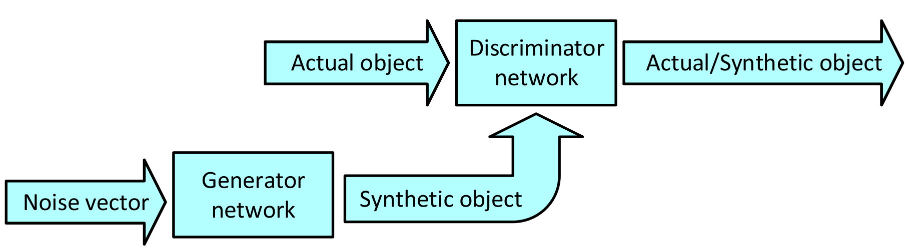

Figure 3. A generative adversarial network.

5.1. *Research in generative adversarial networks*

5.1.1. *GAN architectures*

The introduction of generative adversarial networks has prompted the research community to explore new architectures. For example, Shao, Wang, and Yan (2019) introduced a variant architecture of the GAN by leveraging additional class labels for both the discriminator and the generator. The class conditional generation process improved quality of the generated data. The discriminator was combined with an auxiliary part to output specific class labels so that the improved discriminator would recognise the data source and differentiate among classes. The network combining the class conditional architecture and auxiliary network for classification was named an auxiliary classifier generative adversarial network (ACGAN). Compared with regular GANs, the ACGAN generates high-quality data and provides label information simultaneously. Furthermore, a unique training and testing strategy has been introduced to evaluate whether the generated samples are suitable as independent training data sets in fault classification. First, the actual (true) data set was divided into two parts, training and testing data sets. Then, the training data set was used to train the generative model and a set of fake data was produced. Afterwards, the data set generated by the GAN was applied to build a model, which was validated by the test data. The test results have demonstrated potential of the generated samples to be applied in practice.

5.1.2. *Unbalanced data sets*

Many applications involve data sets that are not balanced across different classes. At the same time classification algorithms maximise the percentage of class labels that are predicted correctly, which leads to misclassification of examples from the minority category. Liu, Luo, and Li (2018) classified vehicles from traffic surveillance images that were unbalanced. Their approach involved three stages. Stage 1, where several GANs were trained with the original data set to generate adversarial samples for the minority classes. At Stage 2, an ensemble of CNN models with different architectures were trained on the original imbalanced data set, followed by filtering out the low-quality adversarial samples. At Stage 3, the ensemble model was refined using the original data set augmented with the selected adversarial samples. Experiments with the classification challenge data set, MIOvision Traffic Camera Data set (MIO-TCD, see the *Data Repositories and Computer Codes* section at the end of this paper), that was highly imbalanced demonstrated improved classification accuracy.

Fanny and Cenggoroa (2018) proposed a class expert generative adversarial network (CE-GAN) for imbalanced data classification. The class expert concept arranged neural network layers in parallel, with each layer pretrained to recognise the characteristics of a single class in the training data. The weights of the pretrained layers were transferred to the main neural network model for further training in a supervised mode.

5.2. *Applications of generative adversarial networks in manufacturing*

5.2.1. *Image synthesis*

Radford, Metz, and Chintala (2015) developed a deep convolutional model using GAN architecture, called DCGAN, for synthesis of images. They demonstrated that DCGAN could generate realistic images that were not presented in the training data set. Since the network was difficult to train, the authors introduced a list of restrictions on the discriminator and generator architectures. They proposed building more powerful GANs that could process images by adopting the best practices from generative and discriminative models. Zamyatin and Filchenkov (2018) developed a model for accurate synthesise of images. Their research followed the model presented in Dosovitskiy, Springenberg, and Brox (2014). Zamyatin and Filchenkov (2018) provided the architecture and implementation details of the proposed GAN. The effectiveness of their model was demonstrated with three different data repositories: Chairs, CelebFaces, and Cifar10 (see the *Data Repositories and Computer Codes* section at the end of this paper). The Chairs data set contains 3D images of chairs in different projections was used in Dosovitskiy, Springenberg, and Brox (2014). The image of each chair was labelled, and its view-point v was described by four numbers corresponding to the sine and cosine of azimuth and altitude angles. The CelebFaces data set includes labelled images and attributes of faces, while Cifar10 contains images with each image being one of ten classes, e.g. airplane, car, horse, dog.

5.2.2. *Engineering design*

Radhakrishnan et al. (2018) presented a system based on a generative adversarial network to create novel car designs from sketches. To train and test the systems, the authors have developed a paired data set of about 100,000 car images (with transparent backgrounds) and their sketches. The system has reduced the cycle time of the sketch-to image process and enhanced design visualisation.

5.2.3. Surface inspection

Liu et al. (2019) applied the concept of a generative adversarial network to deal with the limited number of defective samples encountered in manufacturing. An encoder-decoder architecture was proposed as the simulation network. The simulation and discriminative networks were trained in an adversarial mode offering a priority to the translation of the defective area. The defect-free area was refined in a wavelet fusion. The experimental results have demonstrated that the proposed approach generated defective samples of better quality than the general image translation methods.

In a manufacturing relevant domain, Wang et al. (2019) applied a modified least-square generative adversarial network (LSGAN) with regularisation to denoise acoustic emission signal used in detection of rail cracks. The proposed approach was effective in the removal of statistical and mechanical noise in detection of rail defects.

5.2.4. Condition monitoring

Wang, Wang, and Wang (2018a) combined a generative adversarial network (GAN) with a stacked denoising autoencoder (SDAE) for fault diagnosis. The GAN generator produced new samples with a distribution similar to the original vibration samples from a planetary gearbox. The generated and the original samples were fed to the discriminator. SDAE acted as the discriminator of GAN to automatically extract fault features from the input samples and discriminate their authenticity and fault categories. The generator and discriminator were optimised to enhance the quality of the generated samples and the accuracy of fault classification. The effectiveness of the proposed approach against traditional neural networks has been demonstrated with the planetary gearbox data that was imbalanced (low number of faults).

In many applications labelling data is a challenge. For example, determining the quality of a component based on the imaging data or determining process efficiency based on the recorded parameters is far from obvious. Sometimes inaccurate models or schemes are devised to assign data labels. In a medical domain, that is relevant to technology, Schlegl et al. (2019) developed a generative adversarial network (GAN) based unsupervised learning approach (named f-AnoGAN) for identifying anomalous images and image segments. Real (healthy) training data was used to build a generative model. A fast mapping technique was applied to propose and evaluate new data to GAN. The mapping was based on a trained encoder with anomalies being detected based on the score derived from a discriminator feature residual error and an image reconstruction error. Computational results with f-AnoGAN have shown increased accuracy of anomaly detection.

5.2.5. Fault diagnosis

The development of models in fault diagnosis usually faces a limited number of fault-related data samples or samples could be mislabelled. Han et al. (2019) proposed a novel deep adversarial convolutional neural network to tackle the two challenges. By incorporating a discriminative classifier, an adversarial learning framework trained the convolutional blocks with the split data sets.

Computational experience with two fault data sets have demonstrated the superiority of the proposed method over the with conventional deep models.

Cao et al. (2018) designed a generative adversarial network using 2D images of the transformed fault diagnosis signal in the time domain. Computational results have revealed the application potential of generative adversarial networks in diagnosis of manufacturing faults.

5.2.6. Service and social robotics

Social robots are intended for functioning in complex human contexts (Breazeal 2004). Robot behaviour requires modelling human-like capabilities of sensing, processing, and interacting. Depending on the envisioned application, different degree of emotion, intention, motivation, and other cognitive functions are desirable. Social robots are of interest to service applications, e.g. marketing, handling emails and phone call, equipment maintenance, and security. Rodriguez et al. (2019) applied a generative adversarial network to a develop a talking gesture generation system. The system produced a sequence of joint positions of the robot's upper body in response to an uttered sentence. The proposed approach has been demonstrated with an actual robot.

5.2.7. Energy

Energy is the key commodity in manufacturing. Due to environmental, balance across the grid, and cost concerns, it is important that its consumption is minimised. Optimisation of energy consumption is best accomplished over long-time horizons. Accurate prediction of the building-energy use is becoming increasingly vital for energy management, equipment

Table 2. Summary of representative CNN and GAN applications in manufacturing.

CNN	References	GAN	References
		Image synthesis	Radford, Metz, and Chintala (2015)
			Zamyatin and Filchenkov (2018)
			Dosovitskiy, Springenberg, and Brox (2014)
		Engineering design	Radhakrishnan et al. (2018)
			Wang et al. (2019)
Surface inspection	Lin et al. (2020)	Surface inspection	Liu et al. (2019)
	Park, An, and Kang (2018)		Wang et al. (2019)
Condition monitoring	Zhu et al. (2019)	Condition monitoring	Wang, Wang, and Wang (2018a)
			Schlegl et al. (2019)
Fault diagnisis	Grezmak et al. (2019)	Fault diagnosis	Han et al. (2019)
	Wen, Li, and Gao (2019)		Cao et al. (2018)
	Liang et al. (2019)		
Quality control	Zan et al. (2019)		
Prediction of RUL	Babu, Zhao, and Li (2016)		
Vibration analysis	Fu et al. (2017)		
		Service robotics	Breazeal (2004)
			Rodriguez et al. (2019)
		Energy	Tian et al. (2019)
		Business and finance	Takahashi, Chen, and Tanaka-Ishii (2019)
		Security	Fiore et al. (2019)
			Zheng et al. (2018)
			Chhetri et al. (2019)

efficiency improvement, and the interaction between the building consumed energy and the power grid. Tian et al. (2019) offered an approach for prediction of building energy consumption with a generative adversarial network. A small set of application collected data was used to generate a parallel data set with GAN. A prediction model was developed with a mixed set of application and artificial data. Experimental results have shown that the parallel data set had a distribution similar to the application collected data. A gain in prediction accuracy of the model trained with the mixed data over the one trained with the application data only has been demonstrated.

5.2.8. Business and financial applications

Modelling natural and social phenomena is of interest to enterprises. Many phenomena are complex and difficult to explain. Takahashi, Chen, and Tanaka-Ishii (2019) developed a generative adversarial network (GAN) for financial time-series. The GAN model produced a time-series with the desired statistical properties, e.g. linear unpredictability, heavy-tailed price return distribution, and coarse-fine volatility correlation.

Fiore et al. (2019) applied a generative adversarial network to credit card fraud detection, a domain that is known for imbalanced training data. This application was motivated by the fact that the traditional machine learning algorithms have difficulties in copying with imbalanced data sets, where the prediction accuracy undesirably reflects the prevailing class of the training data. The authors trained the GAN to predict outcomes using examples mimicking the minority class. These examples were merged with the commercial data to create an augmented training set. Computational experience has shown that the augmented set trained classifier performed better than the classifier built with the commercial data only. Zheng et al. (2018) discussed other business applications of GANs.

5.2.9. Security of cyber-physical systems

To address the challenge of security in cyber-physical production systems, Chhetri et al. (2019) proposed a novel conditional generative adversarial network for abstracting and estimating the relationship between the cyber and physical domains. The authors were able to determine whether the security requirements such as confidentiality, availability, and integrity are met.

Convolutional and generative adversarial networks have attracted a large community of researchers and practitioners. New research results are frequently published in diverse areas.

A snapshot of papers published to date that represent applications of convolutional and generative adversarial networks in manufacturing is summarised in Table 2.

The list of papers in Table 2 does not include applications of deep neural networks as more specialised architectures are likely to dominate the future coverage in the literature. Some of the application domains (surface inspection, condition monitoring, and fault diagnosis in Table 2) are common to the CNNs and GANs and they may validate the benefits to those areas as well as inspire research in other domains.

6. Advantages and limitations of CNNs and GANs

Based on the applications discussed in this paper, the advantages and limitations of convolutional neural networks (CNNs) and generative adversarial networks (GANs) are summarised.

Advantages of convolutional neural networks:

(1) Ability to capture features that classical neural networks cannot accomplish.
(2) Less complex (reduced number of weights as some parameters are shared) and memory and more computationally efficient.
(3) Improved performance of models for performing tasks such as image recognition.
(4) Ability to extract features from a trained network. This CNN property is related to pre-training.
(5) Useful in developing of 1D models (e.g. from time series) and 3D image classification (due to the property that the location of extracted features is preserved).

Limitations of convolutional neural networks:

(1) Large training data sets are needed.
(2) Lack of ability to be spatially invariant to the input data (i.e. positions and orientations of objects are not captured by a model).
(3) Tuning of hyperparameters can be challenging.
(4) Input normalisation is needed for data sets with heterogeneous parameters.

Advantages of generative adversarial networks:

(1) Ability to model partially labelled data.
(2) Training beyond the available data.
(3) Limited analyst's involvement in training.
(4) Efficient generation of samples.
(5) High fidelity models.

Limitations of generative adversarial networks:

(1) Challenges in training (determining an equilibrium).
(2) Modelling discrete data (e.g. text) is difficult.
(3) Can be selective in modelling (e.g. given the value of one pixel it is difficult to determine the value of another one).

7. Conclusion

This paper was inspired by the trend of industry becoming digital. Perhaps the best way to accelerate the digitisation progress of enterprises is to demonstrate how the existing data has benefited manufacturing. This in turn could accelerate generation of more data and lead to the development of new applications. One of the shortcomings of past models in manufacturing has been the time variable, i.e. many models were static. Predictive models bring the time dimension to manufacturing modelling, which unravels new opportunities for optimisation of manufacturing systems. This paper offers a token contribution to the recently published research results in convolutional and generative adversarial neural networks. The latter networks are often characterised as the most promising development in computational intelligence of in the past two decades. The research synthesis conducted in this paper may inspire novel research in the machine learning domain to benefit manufacturing. Irrespectively what label is attached to the manufacturing of the future, there is no doubt that its progress will be aligned with that of artificial intelligence. This paper has signalled that besides benefiting from artificial intelligence, the manufacturing research could benefit smart solutions in other domains (Kusiak 2019). Advantages and limitations of convolutional and generative adversarial networks were listed. Data repositories and computer codes used in some of applications discussed in the paper are included.

Data repositories and computer codes

Chairs: https://github.com/EvgenyZamyatin/chair-gan-code
CelebFaces: http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html
Cifar10: https://www.cs.toronto.edu/~kriz/cifar.html
MIO-TCD: http://tcd.miovision.com/challenge/dataset/
f-AnoGAN code: https://github.com/tSchlegl/f-AnoGAN
Keras Applications: https://keras.io/applications/
Deep Learning Studio: https://deepcognition.ai/products/

Disclosure statement

No potential conflict of interest was reported by the author.

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