Efficient data management for intelligent manufacturing

10

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10.1 Introduction

The history of manufacturing is accompanied by the evolution of the role that manufacturing data plays, from a passive information carrier in the early days to an indispensable value enabler in the 21st century.

10.1.1 Data-enhanced decision-making

Since the inception of the first industrial revolution in the 18th century, marked by mechanization of human labors, the face of manufacturing has undergone several transformative shifts, as shown in Fig. 10.1 (Deane, 1979). The subsequent Industry 2.0 in the early 20th century introduced the use of electricity and assembly lines, which is widely considered the birth of "mass production" (Hu, 2013). Industry 3.0 in the late 20th century saw the invention of computers and industrial robots, representing the start of automation in manufacturing (Yao & Lin, 2016).

The manufacturing industry entered Industry 4.0 at the beginning of the 21st century, an era that promises the synergistic fusion of the digital and physical worlds (Zhong, Xu, Klotz, & Newman, 2017). Industry 4.0 is typified by the deployment of cyber-physical production systems (CPPS) (Monostori et al., 2016) and digital twins (DT) (Schleich, Anwer, Mathieu, & Wartzack, 2017) that lean heavily on real-time sensor data, Internet-enabled edge/cloud computing, and data analytics algorithms. In Industry 4.0, sensing data, which has long been an underutilized coproduct of manufacturing, has taken the center spot (Gao, Wang, Helu, & Teti, 2020). With the advances in data analytics algorithms, especially deep learning (DL) (Lecun, Bengio, & Hinton, 2015), manufacturers have the effective tools to extract, analyze, and utilize the rich information embedded in data collected from the shop floor such as high-speed time series, images, and videos to establish data-driven association to the manufacturing tasks of interest, without being constrained by the limitations of manufacturing domain knowledge.

Data-driven CPPS and DT have already shown proficient in real-time machine condition monitoring, root cause analysis of functional failures (Zhao et al., 2019), and predicting future evolution of machine performance (Wang, Zhao, & Addepalli, 2020).

Manufacturing from Industry 4.0 to Industry 5.0. DOI: https://doi.org/10.1016/B978-0-443-13924-6.00010-7

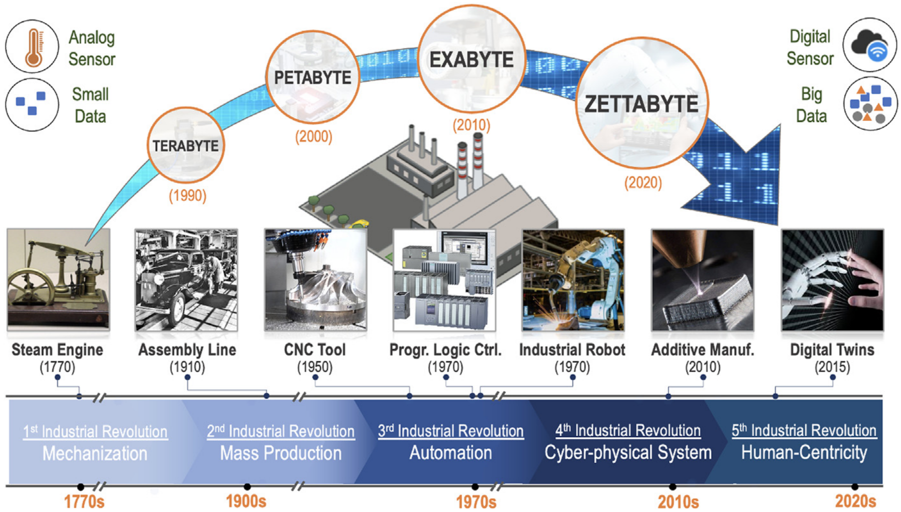

Figure 10.1 Industrial revolutions and manufacturing paradigm shifts.
Source: Modified from Gao, R. X., Wang, L., Helu, M., & Teti, R. (2020). Big data analytics for smart factories of the future. *CIRP Annals, 69* (2), 668−692. https://doi.org/10.1016/j.cirp.2020.05.002.

For example, one-dimensional (1D) and 2D convolutional neural networks (CNNs) have demonstrated excellent capability to extract fault-related features from either waveform or time-frequency images of machine vibration data and thereby, enabling detection of various machine faulty types and their respective severity levels (Wang, Ananya, Yan, & Gao, 2017). As another example, recurrent neural network (RNN) and its variants, such as long short-term memory (LSTM) and gated recurrent units (GRU), have shown to be useful in parsing sequential patterns underlying machine performance degradation (Zhang, Wang, Yan, & Gao, 2018). The sequential analysis capability has seen its wide usage for degradation prognosis for engine, bearing, gearbox, and machining tools. Additionally, researchers have developed methods to integrate data-driven methods with physical domain knowledge, which not only allows data to enhance the physical understanding of the machine health status, but also uses physical knowledge to ensure the generalizability and robustness of data-enhanced decision-making (Wang, Li, Gao, & Zhang, 2022). Furthermore, various techniques for data-driven model interpretation have also been developed such that the prediction logic of DL can be verified against domain knowledge to ensure the reliability of data-enhanced decision-making in critical manufacturing applications (Grezmak, Zhang, Wang, Loparo, & Gao, 2020). Data-enhanced decision-making for diagnosis and prognosis facilitates the early discovery and prediction of machine functional failure, which provides the basis for manufacturers to optimize maintenance strategy and reduce failure-induced machine downtime and production interruption.

Beyond machine diagnosis and prognosis, advances of sensing technologies, computational infrastructure, and DL algorithms have also ushered in new manufacturing paradigms in Industry 4.0, such as human−robot collaboration (HRC) (Wang et al., 2019) and additive manufacturing (AM) enabled by data-enhanced decision-making (Wang, Tan, Tor, & Lim, 2020). For example, RNN has shown the capability of parsing the complex sequential patterns underlying human action and motion trajectory data. Coupled with probabilistic analysis and uncertainty quantification, they provide the basis for prediction of future human action and motion and for mitigation of uncertainty-induced robot mis-triggering that are critical to ensuring robot to achieve robust and safe collaborative action, such as part/tool handover (Zhang, Liu, Chang, Wang, & Gao, 2020). In AM, data-driven methods such as CNN and RNN have demonstrated exceptional performance in identifying abnormal printing conditions and extracting melt pool geometry based on image or time series data from vision sensors (Mehta & Shao, 2022; Zhang, Hong, Ye, Zhu, & Fuh, 2018). By combining these methods with process physics such as the law of heat transfer, temperature distribution, and thermal history can be accurately predicted (Liao et al., 2023). These advances pave the way for subsequent development of data-enhanced optimization and control algorithms and broader deployment of this manufacturing process.

Collectively, data-enhanced decision-making has demonstrated a high level of accuracy, automation, and adaptability in connected and optimized manufacturing systems in Industry 4.0 as compared to the precedent industrial revolutions. As manufacturing enters the dawn of Industry 5.0, the industry builds upon the advances in Industry 4.0 and is experiencing another paradigm shift, with a renewed emphasis on human-centric processes (Xu, Lu, Vogel-Heuser, & Wang, 2021). This transition is driving the need for decision-making systems that can integrate human domain knowledge with data-enhanced decision-making, thereby blurring the lines between human and machine capabilities (Virkkunen, Koskinen, Jessen-Juhler, & Rinta-aho, 2021; Wang et al., 2022; Zhang, Liu, & Gao, 2022).

10.1.2 Challenges in data management

The advent of Industry 5.0, distinguished by its focus on human-centricity as one of the core values (Fig. 10.2), is predicted to result in a continual surge in data volume, variety, and complexity within the manufacturing sector (Xu et al., 2021). This multifaceted data environment poses significant difficulties for data management (Siddiqa et al., 2016), notably in the domain of data curation. Industry 5.0 posits that manufacturing processes and machines are likely to grow more complex, encompassing various data types such as time series, images, videos, and text. This increased intricacy and data heterogeneity produce challenges in maintaining data quality and meaningful interpretation.

For instance, time series data collected from machines and processes are often contaminated by a range of noise sources, while images and videos deployed for quality control or fault diagnosis are directly influenced by aspects such as illumination conditions or camera perspectives, exacerbating the difficulties of handling

Figure 10.2 Core values of Industry 5.0.
Source: From Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. *Journal of Manufacturing Systems, 61*, 530–535. https://doi.org/10.1016/j.jmsy.2021.10.006.

diminished signal-to-noise ratio (SNR). Thus to ensure the effectiveness and robustness of data-driven decision-making, data denoising techniques are of importance to augment the accuracy and robustness of the decisions based on these data (Yan & Gao, 2012).

Moreover, the human-centric paradigm of Industry 5.0 requires the capacity to understand and interpret the relevance of data, in relation to the corresponding manufacturing context, where data annotation assumes a pivotal role. By appending semantic labels and contextual details to the data, data annotation assists in bridging the gap between raw data and human comprehension, rendering data more interpretable and accessible to human operators and decision-makers. However, automated data annotation remains a challenge due to the inherent complexity within data types such as images and text. The datasets investigated in the published studies often do not require specific labeling effort due to the fact that typically examined scenarios, such as faults in the inner or outer race of a rolling bearing, are prelabeled and integrated into the testing equipment prior to data collection. In contrast, in realistic manufacturing scenarios, structural faults or anomalies are not prelabeled as they are not known in advance, and hence, must be inferred from the gathered data a posteriori (Zhao et al., 2019).

Further, Industry 5.0 underscores a more personalized approach to manufacturing, with the intention to cater to individual customer's demands (Xu et al., 2021). This "mass personalization" can result in imbalanced datasets, where certain classes of data are overrepresented, while others are underrepresented. The imbalance can distort decision-making algorithms, resulting in biased outcomes that do not accurately represent the true variability across different data categories that are of interest. While such data imbalance has already started to pose challenges in applications like machine fault diagnosis in Industry 4.0, where gathering extensive data from faulty machines for algorithm training is often infeasible due to safety and economic considerations, Industry 5.0 is envisioned to intensify this data curation challenge. Consequently, data balancing techniques, which aims to produce a uniform representation of all classes in the dataset, are becoming crucial in Industry 5.0 (Zhang, Chen, et al., 2022).

In addressing these issues, the manufacturing research community is placing increasing emphasis on establishing data curation methods to improve data quality and provide meaningful semantic annotations. This involves developing data denoising techniques to alleviate data noise contamination, establishing generative models to discern the underlying data patterns and synthesize samples for small or imbalanced datasets, and automating the data labeling and contextualization process through semantic data annotation to facilitate human comprehension.

Over the years, researchers have investigated machine learning (ML)-based data curation methods, which commonly consists of a feature extraction step (e.g., principal component analysis) and a classification or regression step (e.g., support vector machine [SVM]) (Stavropoulos, Bikas, Sabatakakis, Theoharatos, & Grossi, 2022). The increase in complexity of manufacturing-related data has posed challenges for traditional ML techniques that rely on empirical knowledge for manual feature extraction (Zhao et al., 2019). Advancement in DL over the past decade has inspired researchers to explore its potential for data curation. The DL techniques are characterized by automated feature learning and have shown especially suited for handling images (Wiederkehr, Finkeldey, & Merhofe, 2021) and texts (Thomas & Sangeetha, 2020) that are expected to permeate the manufacturing industry. This chapter provides an overview of several key techniques in DL-based data curation, highlighting breakthroughs in data denoising, annotation, and balancing, which have shown effective in extracting information from noisy, unannotated, and imbalanced datasets to improve human comprehension and support the next generation of intelligent manufacturing. The remainder of this chapter is arranged as follows: Section 10.2 will delve deeper into the latest advances in data denoising, data annotation, and data balancing facilitated by DL techniques. Section 10.3 will present the manufacturing applications of these methodologies, followed by a discussion on the remaining challenges and opportunities in Section 10.4, and conclusions in Section 10.5.

10.2 Data curation techniques

Data, the coproduct of manufacturing, encapsulates pivotal information reflecting the dynamics of manufacturing processes and machines, forming the basis for data analytics and decision-making. Advancements in sensing have resulted in an increasing volume of data acquisition in manufacturing environments. This surge in data volume, variety, and complexity brings to light obstacles in addressing data quality issues such as noise contamination and imbalanced and unannotated data. Ensuring the effectiveness of data analysis necessitates that these challenges are addressed. The subsequent sections delve into these techniques, with a particular emphasis on those that are DL-based.

10.2.1 Data denoising

The process of data denoising is crucial to augment the SNR in data, which provides the basis for uncovering critical information (such as machine fault characteristics) from background noise. Data denoising has long been an active research field with commonly utilized techniques such as local geometric projection (LGP) (Yan & Gao, 2012), empirical mode decomposition (EMD) (Liu, Gao, John, Staudenmayer, & Freedson, 2013), wavelet transform (Wink & Roerdink, 2004), and stochastic resonance (SR) (Zhao, Yan, & Gao, 2013).

The method of LGP maps data into a high-dimensional phase space, for which an orthogonal projection decomposes useful information and noise into different subspaces. During the reconstruction stage, only information for the subspaces containing relevant information is used and thereby, eliminating the noise components (Yan & Gao, 2012). Specifically, the projection is computed using the most significant eigenvectors from singular value decomposition. The intuition is that these eigenvectors captures the majority of data variance, which commonly reflects useful data information rather than the pattern-less data noise. LGP does not assume knowledge a priori about the characteristics of noise contamination, making it more adaptive to data as compared to traditional filter-based methods. Researchers have reported an improvement of 10 dB in SNR for the application of fault diagnosis.

With EMD, time series data is decomposed into a set of intrinsic mode functions (IMFs), with each representing a dominant frequency in the data at different scales (Liu et al., 2013). Using metrics such as the mutual information ratio (MIR), the suited range of IMFs can be determined, and the cutoff point is commonly chosen as the one that leads to the highest increase in MIR. Intuitively, this represents the threshold where valuable data information is captured by the IMF, as noise cannot induce large information gain.

Different from LGP and EMD that are generally performs on raw waveforms, wavelet transform is a time-frequency technique. The main idea of wavelet-based method is to threshold small coefficients in wavelet time-frequency spectra before data reconstruction using the inverse wavelet transform. The underlying assumption of wavelet-based data denoising is that the useful data information is associated with large wavelet coefficients (Wink & Roerdink, 2004). The cutoff threshold in this approach is typically determined based on metrics such as data variance (Gao, Sultan, Hu, & Tung, 2010). An 8x improvement in SNR of bearing's vibration data has been demonstrated in Holm-Hansen, Gao, and Zhang (2004) using the wavelet-based method.

The objective of SR is to amplify a critical frequency (such as a fault characteristic frequency) via the interaction between the data and a bistable system (Zhao et al., 2013). It is found that the addition of time series to the bistable system's input results in amplified critical frequency at the system's output if the system's "switch" frequency is tuned to match the critical frequency (Collins, Chow, & Imhoff, 1995). The SR-based method has demonstrated accurate extraction of fault-related frequency that was previously undetectable, and it can be utilized in a broad range of critical frequency extraction applications. More recently, DL-based data denoising methods have emerged that leverage the pattern recognition capability of neural networks.

Denoising autoencoder (AE). One of the most widely used methods is denoising AE (Vincent, Larochelle, Lajoie, Bengio, & Manzagol, 2010). An AE network structure commonly involves an encoder and a decoder for data feature extraction. The encoder usually features network layers with reducing layer size, with the structure inverted to serve as the decoder. By minimizing the discrepancy between the input to the encoder (raw data) and the output of the decoder (reconstructed data), the information in the middle layer, which can have a much smaller dimension than the raw data, is considered a feature of the data. The denoising AE builds upon the AE structure and introduces one change: it uses noise-contaminated data as the input and tries to reconstruct the clean data. This allows the denoising AE to learn, given contaminated data, what it means by "data noise" using simulated examples where the ground truth clean data is available. Denoising AE also provides very flexible configurations to adapt to different data types by using different network layers, such as convolutional layers for images and recurrent layers for time series. However, one major limitation with denoising AE is that its training requires ground truth samples, which can be difficult to obtain in realistic manufacturing settings.

Noise2Void (N2V). To tackle the limitation of denoising AE, the technique of N2V has been developed with the primary objective of using a modified convolutional layer for image denoising (Krull, Buchholz, & Jug, 2019). Different from standard convolutional layers that analyze the images region falling with its neuron's receptive field for feature extraction, N2V leverages the convolution operation to predict the pixel intensity value in the middle of the receptive field, while excluding it from the input to the convolution operation. The intuition is that only when the network learns to predict the data part of the pixel rather than the noise part would the prediction error be minimized. Compared with denoising AE-based approach, N2V can be directly trained using the noise-contaminated image of interest as long as the independent noise assumption is satisfied, without requiring any additional training data.

10.2.2 Data annotation

Data annotation is the practice of associating data with relevant contextual details in an appropriate semantic format, based on how the data was acquired. One particularly critical type of data is image data, which provides rich spatial information not contained in time series and is increasingly essential in data analytics in manufacturing (Gao et al., 2020). However, labeling and annotating regions of interest (ROIs) in these images, which often indicate vital machine, process, and product conditions, pose challenges due to the absence of effective techniques for deciphering abstract image patterns. Conventional approaches, such as thresholding, have been broadly employed with the aim to segregate ROIs from other regions by setting a pixel intensity threshold (Clijsters, Craeghs, Buls, Kempen, & Kruth, 2014). Yet, these techniques operate under assumptions that often do not hold true in real-world scenarios. For example, change of lightning conditions can significantly alter the pixel intensity in a captured image and requires frequency calibration of the threshold. Additionally, thresholding requires that the pixels from different ROIs of interest in the image have no overlapping intensity range, which often does not hold.

One of the early DL-based solutions is fully convolutional network (FCN), which exploits the image analysis capabilities of CNN (Long, Shelhamer, & Darrell, 2015). The FCN structure consists of an encoder (composed of convolutional layers and pooling layers), which extracts essential information from the input image pertinent to semantic annotation, and a decoder, which generates an annotated image corresponding to the input image through sequential upsampling operations and a classification layer (similar to AE structure). Different from standard CNN whose output is the image-level classification, FCN carries out pixel-level classification, namely, each pixel will be classified into semantic ROIs of the image through a softmax function in the classification layer. Over the past years, several semantic annotation techniques that leverage FCNs have been developed, among which U-Net (Ronneberger, Fischer, & Brox, 2015) and mask region-based convolutional neural networks (RCNN) (He, Gkioxari, Dollar, & Girshick, 2017) are the most widely adopted.

Fig. 10.3 shows the underlying network structure of U-Net, designed symmetrically to match the encoder layers with the progressive upsampling layers in the decoder. The corresponding layers in the encoder and the decoder are also connected through skip connection to more effectively pass gradient of the error during

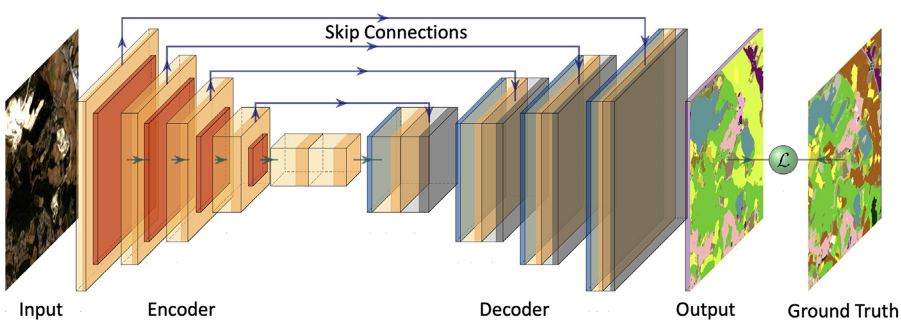

Figure 10.3 Structure of U-Net.

training stage (Lei et al., 2019). In contrast, the mask RCNN operates by first focusing on small regions potentially containing ROIs using a region proposal network, before proceeding with FCN-based semantic annotation (He et al., 2017). The annotated image can then serve, not only diagnostic purposes (e.g., surface defect diagnosis, tool wear evaluation), but also provide input to DL models for predictive tasks by extracting information from the ROIs, like area and geometric features.

Beyond semantic segmentation which aims to extract the complete boundaries among different ROIs, image annotation can also be carried out through ROI detection, which assigns ROI-specific bounding boxes to surround each instances of ROIs, rather than determining the exact boundary of each. One of the most widely used concepts for ROI detection is single-shot detector (Liu et al., 2016). This method allows to adapt the existing, standard CNN structure as the backbone for ROI detection, as shown in Fig. 10.4. The main idea is to: (1) utilize feature maps in each layer of the CNN as a grid of the same size to cover the input image, and (2) use each grid cell to predict a fixed number of bounding boxes and the types of the surrounded ROIs. Specifically, each prediction from a grid cell consists of a vector describing the relative distances between the center of the predicted bounding box and the center of the grid cell, the changes in the width and height of the bounding box relative to the grid cell dimension, and a set of scores each of which indicating how likely there would be an ROI surrounded by the bounding box that belongs to one of the candidate ROI types. The scores then pass through a softmax function to obtain the predicted ROI type. As the CNN structure goes deeper, the size of the feature maps becomes smaller and the grid changes from “fine” to “coarse” effectively allowing multiscale ROI analysis and annotation.

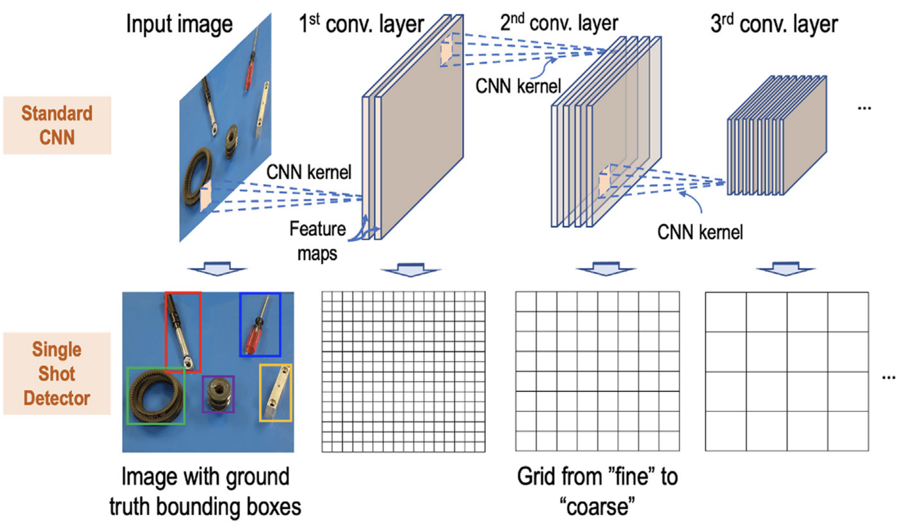

Figure 10.4 Image annotation based on single-shot detector.

With more recent development of natural language processing and large language models, semantic annotation and labeling of text data are gaining increased interest (Otter, Medina, & Kalita, 2021). The critical challenge that text annotation faces in manufacturing contexts, such as maintenance logs or inspection reports, lies in transforming text (e.g., English words) into computable representations without sacrificing their relationship at semantic level. For example, semantically similar words in the representation space should be closer, while semantically opposite words in the representation space should be separated by a larger distance. One frequently explored technique to achieve such text representation is embedding, such as word2vec, which uses similarity computed based on dot-product to ensure the semantically meaningful distribution of the words in the representation space (Mikolov, Chen, Corrado, & Dean, 2013).

With text represented by embedding, a variety of DL-based language models can then be trained to convert relevant texts into interpretable labels useful for diagnostic and prognostic purposes (Thomas & Sangeetha, 2020). Several advanced, pretrained language models, such as transformers and its variants, have also surfaced. The fundamental idea of transformer is to replace the recurrent part of the RNN with attention module. The intuition is to lift the limitation in RNN that information can only flow in one direction and uses attention module to learn the relationship among different words in a free and adaptive manner to the tasks of interest.

10.2.3 Data balancing

Data balancing ensures the availability of data representing each semantic data categories of interest (e.g., different machine fault types) and the reduction of learning bias induced by potential data imbalance (Zhang, Li, Gao, Wang, & Wen, 2018). Balanced dataset is traditionally crucial for tasks such as fault diagnosis (Santos, Maudes, & Bustillo, 2018). However, manufacturing constraints make collecting data in a balanced manner impractical as it would require manufacturers to deliberately operate machines under faulty conditions. The problem can be exacerbated in Industry 5.0 where "mass personalization" can lead to significant data imbalance. One commonly deployed strategy is to synthesize data that captures the characteristics of the real ones, with the objective of increasing the sample size and reduce data imbalance.

Early developed approach for data synthesis commonly relied on data interpolation. For example, the method of synthetic minority oversampling technique or SMOTE (Chawla, Bowyer, Hall, & Kegelmeyer, 2002) operates by first selecting a minority class sample and one of its neighbors at random. Then, SMOTE generates a synthetic sample as a convex interpolation between the two chosen samples. SMOTE performs well in the scenario when the data is of low dimension, such as process parameters and machine settings. However, it is shown to be limited in capturing complex characteristics exhibited by high-dimensional data, such as high-speed time series or images (Kozjek, Vrabič, Kralj, & Butala, 2017). With the advances of DL, more systematic data synthesis techniques have emerged that have drastically improved the quality of the synthetic data to support data analytics.

The first development is the variational autoencoder (VAE) (Kingma & Welling, 2014). Different from the denoising AE, the objective of VAE is not to find a numerical mapping that maps any noise-contaminated input to its clean version. Instead, VAE learns a distribution underlying certain category of data (e.g., a specific machine fault type), such that new data can be synthesized from this underlying distribution. In practice, the distribution is often assumed to be Gaussian, and the objective of VAE training is to determine the distribution mean and variance through the technique of variational inference. However, one of the main limitations of VAE is that the training is supervised by the mean reconstruction error of the input data. As a result, the synthetic data often show to be smoothened, without high-frequency details (such as clear lines). This challenge was addressed with the invention of generative adversarial network (GAN) (Goodfellow et al., 2020).

The fundamental structure of a GAN includes two primary components: a generator and a discriminator. Its primary objective is to enable the generator to transform random samples from a known distribution into synthetic samples that closely mirrors real ones. The discriminator, on the other hand, evaluates the performance of the generator by distinguishing between "real" and "generated" data. More specifically, the discriminator operates by randomly choosing real or generated synthetic data and outputs a scalar value indicating the likelihood of the input data being "real." Meanwhile, the generator strives to create synthetic data that closely resembles real ones, effectively tricking the discriminator. The culmination of this training process is a state of equilibrium where the discriminator is no longer capable of differentiating between real and generated data, and the generator ceases to improve its data output as it no longer gets feedback from the discriminator. When the GAN reaches this stage, the generator can produce high-quality synthetic data that can be used to increase the number of samples in underrepresented classes, thus resolving issues related to dataset imbalance.

10.3 Toward Industry 5.0: application highlights

The goal of data curation is to continuously improve data quality to ensure effectiveness of data analytics to support data-enhanced decision-making. In this section, several applications in manufacturing that have benefited from data curation techniques are presented.

10.3.1 Machine diagnosis and prognosis

Data-enhanced machine diagnosis involves mapping fault-related data features to the corresponding machine fault types or severity levels. To create a data-driven fault diagnosis model, a large number of training samples are generally required to represent all candidate machine conditions. However, in real-world manufacturing shop floor, production schedule and safety procedure prevent the collection of faulty data, resulting a training dataset that is often biased toward normal machine conditions.

Recently, GAN-based faulty data synthesis methods have been developed, which has shown great potential to alleviate the data imbalance issue for machine diagnosis. For example, the effectiveness of GAN has been demonstrated for synthesizing faulty motor data, such as those associated with broken rotor bar or motor bearing fault at the inner race and outer race (Lee, Jo, & Hwang, 2017). To demonstrate the effectiveness of GAN as the imbalance level varies, the authors evaluated the GAN-based method by investigating different ratios of data imbalance between the normal and faulty samples. The network structure of the GAN (i.e., generator and discriminator) consists of fully connected layers. Once trained, the data synthesized from the generator serves as input for motor fault diagnosis using a multilayer perceptron (MLP). The authors have shown that the GAN-based data synthesis method achieved higher fault recognition accuracy as compared to SMOTE-based approach in a consistent manner across different imbalance ratios.

While the discriminator in the standard GAN only serves the purpose of distinguishing real data from synthetic ones, researchers have extended its capability by incorporating machine fault diagnosis directly into its function (Shao, Wang, & Yan, 2019). In this work, an auxiliary classifier GAN has been developed, as show in Fig. 10.5, which not only aims to synthesize vibration signal from faulty motors, but also allows to carry out the fault diagnosis directly. Both the generator and the discriminator are in the form of 1D CNNs, which allows to evaluate the sequential pattern in vibration waveform data. The authors evaluated the developed method using six different motor conditions, including normal, inner race bearing fault, unbalanced rotor, stator winding defect, bowed rotor, and broken rotor bar.

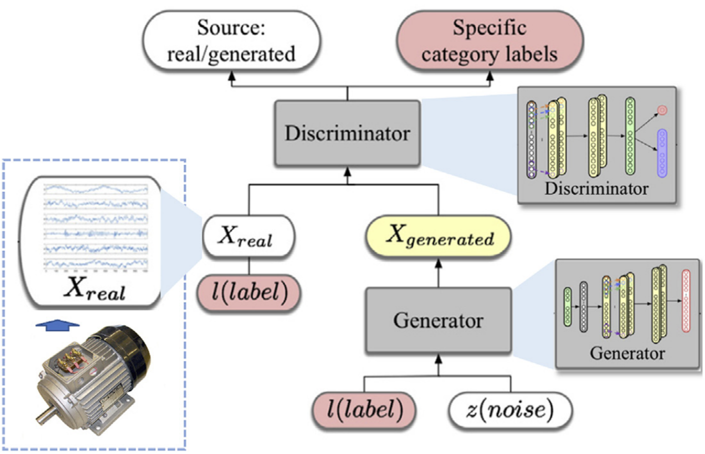

Figure 10.5 Auxiliary classifier GAN. *GAN*, Generative adversarial network.
Source: From Shao, S., Wang, P., & Yan, R. (2019). Generative adversarial networks for data augmentation in machine fault diagnosis. *Computers in Industry, 106*, 85−93, https://doi.org/10.1016/j.compind.2019.01.001.

The GAN-based method has led to significantly higher diagnosis accuracy as compared to 1D CNN trained using imbalanced dataset. A similar method has been developed by Wang et al., in which the GAN-based method has been shown effective for gearbox fault diagnosis (Wang, Wang, & Wang, 2018).

The field of fault diagnosis has also benefited from recent advancements in text annotation techniques. One study (Chen, Zhu, Zeng, & Jia, 2021) introduced a novel approach that utilizes bidirectional encoder representations from transformers (BERT), a pretrained language model based on transformer, to extract fault-related details directly from text documents. This method attached a LSTM and conditional random field (CRF) (Huang, Xu, & Yu, 2015) to BERT, which serve as the task model that takes as input the BERT-extracted text features and carries out text annotation. Through extensive experimentation, this approach demonstrated superior performance compared to the method using LSTM + CRF alone with annotation accuracy as evaluation metric for various annotation categories, such as "equipment," "fault," "cause," and "solution."

Besides machine diagnosis, prognosis involves forecasting the evolution of machine performance from the current step until the functional failure, which is critical for optimizing predictive maintenance and reducing unexpected machine downtime (Gao et al., 2015). In general, data-driven models for prognosis consists of learning the mapping that associates historical trajectory of machine performance to its performance in a future time step. One limitation in creating these data-driven models is the requirement of run-to-failure training sequences, which requires deliberate running a machine until its failure and can raise safety issues. Similar to data synthesis in machine diagnosis, this limitation has shown to be well addressed using GAN-based method for run-to-failure data synthesis.

For example, GAN-based method has been investigated for bearing degradation prognosis (Khan, Prosvirin, & Kim, 2018). In this work, the evolution of bearing condition is represented as the temporal progression of the root mean square of its vibration signal. The authors demonstrated high resemblance between the degradation trajectories synthesized by GAN and the run-to-failure data collected from the real experiment, indicating GAN as a viable approach to tackle the challenge of run-to-failure data for data-driven prognosis modeling.

In Hou, Xu, Zhou, Yang, and Fu (2020), a hybrid approach based on GAN and LSTM for remaining useful life (RUL) prediction has been developed. Distinct from standard GAN-based approach, the data synthesis function of GAN is utilized in this work to improve the quality of the feature extracted from the sequential data for RUL prediction, rather than synthesizing additional training sequences. Specifically, the generator is formed as an AE, and its training is guided by a discriminator that is based on 1D CNN. The latent feature learned using the GAN is then mapped to RUL using a LSTM. The training of the GAN and LSTM is guided by two objectives: improving data synthesis based on the latent features and the prediction accuracy of RUL. After training, the encoder of the generator and the LSTM are directly used to take an ongoing sequence as input and predict its RUL. The authors demonstrated that the developed method has led to a reduction in RUL prediction error of up to 15% as compared to the previous state-of-the-art.

10.3.2 Quality inspection

Traditionally carried out with time-consuming manual procedure, process and product quality inspection, especially estimation of tool condition and detection of surface defect using image-based sensing, has benefited significantly from DL-enabled image annotation over the past years. This is due to the capability in techniques like CNN that is far superior at extracting and assembling low-level local image features into task-related high-level patterns as compared to the non-DL methods.

In Miao, Zhao, Sun, Li, and Yan (2021), a U-Net based approach has been developed with the objective of segmenting wore regions in cutting tool. One challenge that semantic segmentation of tool wear faces is that the tool worn region often accounts for a very small portion of the whole image of the cutting tool. As a result, there can be significant data imbalance between the regions with normal tool condition and the wore tool region. To resolve this issue, the authors investigated a Matthews Correlation Coefficient−based loss function that dynamically accounts for the data imbalance during network training. The developed U-Net has shown to achieve over 95% accuracy in tool wear annotation. A similar work has been reported in Xia et al. (2022), where U-Net has been successfully utilized for drilling bit wear annotation. One of the contributions of this work is the design of a squeeze-excitation (SE) block for the U-Net, leading to a SE-U-Net structure. The SE block, consisting of a convolutional layer, a global maximum pooling layer, scale blocks, jump paths, allows to explicitly find the corresponding relationship between low-level and high-level features during learning process and improves performance of tool wear annotation. The effectiveness of the developed method is validated using experimental investigation.

In Wiederkehr et al. (2021), FCN has been investigated for grinding tools surface condition characterization. The objective is the accurate segmentation of individual grains on the grinding tool surface from the background (i.e., bond). The accurate characterization of grain patterns, as shown in Fig. 10.6 provides the basis for process optimization, reduction of tool wear, and avoidance of chatter to achieve desired surface topology. In this work, the decoder part of the standard FCN is enhanced through a modified deconvolutional network by connecting to the corresponding layers in the encoder through skip connections (similar to U-Net). The authors also augmented dataset through data preprocessing using transformations such as rotation, cropping, and flipping. Experimental evaluation has shown that the developed FCN can achieve close to 100% grain segmentation accuracy.

In addition to tool wear annotation, the other successful application of image annotation is for surface defect detection in AM. As the AM process is dictated by a large number of influential factors, from material properties, powder sizes, to laser power and printing speed, surface defect has been one of the major issues that hampers broader application of AM. In Scime, Siddel, Baird, and Paquit (2020), the authors investigated surface anomaly detection and evaluation for laser fusion, binder jetting, and electron beam fusion, using DL-based image annotation techniques. The surface anomalies investigated in this work include spatter and recoater streaking, etc. Similar to (Xia et al., 2022), a U-Net structure has been used as the

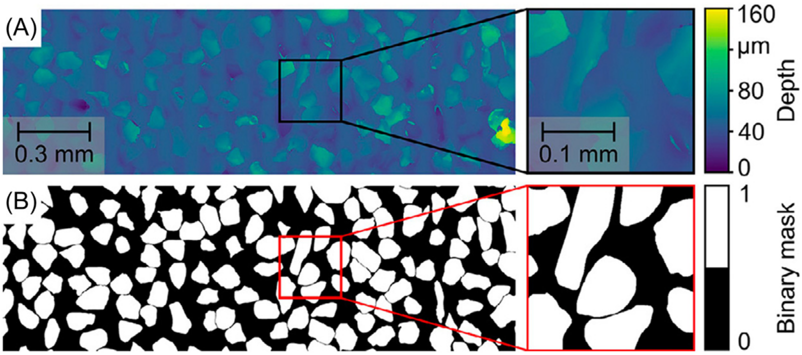

Figure 10.6 Images of: (A) measured depth information; and (B) the corresponding segmentation mask.
Source: From Wiederkehr, P., Finkeldey, F., & Merhofe, T. (2021). Augmented semantic segmentation for the digitization of grinding tools based on deep learning. *CIRP Annals, 70* (1), 297−300. https://doi.org/10.1016/j.cirp.2021.04.051.

backbone DL model, and it is further enhanced in this work using multistream analysis that operates at different image scales. Experimental evaluation has shown that the developed method can enable real-time defect detection in AM at an image resolution of up to 3672 × 5496 pixels. The authors also demonstrated improved defect ROI segmentation accuracy as compared to that of previous state-of-the-art. A similar work has been investigated in Jin, Zhang, Ott, and Gu (2021) for overextrusion detection in the fused filament fabrication AM process.

In addition to the AM processes, an image annotation method based on mask RCNN has been developed for solder joint inspection (Wu, Gao, & Xu, 2020). The objective of this work is to locate, segment, and classify solder joint regions simultaneous as it is critical to ensure quality of the manufactured printed circuit board (PCB). One challenge the authors face is the lack of training solder joint images in general, and the solution they come up with is the method of transfer learning. Specifically, a pretrained network established using large-scale "common objects in context" dataset has been adapted for annotation of solder joint on PCB. In total, four different joint defect conditions are evaluated. The mask RCNN has shown to achieve 100% condition recognition accuracy and 97.4% joint defect segmentation accuracy. Mask RCNN has also been investigated for weld pool annotation in welding, which provides the basis for welding process control to ensure performance of the welded product (Xia et al., 2020).

Other than image ROI annotation, image denoising techniques have also been investigated to support defect inspection. In Dey et al. (2021), the authors utilized the N2V method for denoising of images captured by scanning electron microscope. In this work, the authors builds N2V on top of the U-Net structure and evaluated the method to support defect detection on circuit pattern in the lithography process. They compared the power spectral density of both the original noisy and denoised images and noted that the low-frequency component, which is directly related to the actual morphology of the circuit feature, is unaltered before and after denoising. This indicates that the information content of the denoised images was not degraded by the N2V approach, unlike the other existing approaches such as the Gaussian filtering.

Beyond CNN-based methods, RNN and its variant such as LSTM have also played an important role in quality inspection. For example, in Stavropoulos, Sabatakakis, Papacharalampopoulos, and Mourtzis (2022), a quality assessment system for robotized resistance spot welding has been developed. The system relies on effective analysis of video image sequence from infrared camera and used LSTM for welding quality identification. The authors also made a comprehensive performance comparison between the LSTM and other ML methods such as SVM and artificial neural network, with LSTM achieving both the highest true positive and true negative rates among all ML methods.

10.3.3 Human−robot collaboration

In the realm of human-centric Industry 5.0, a fundamental element is the integration of industrial robots into assembly processes, where humans and robots share a workspace and work together to perform tasks that involve direct contact (Wang et al., 2019). This collaborative approach deviates from the traditional assembly setup, where humans and robots are strictly separated for safety reasons and perform their tasks sequentially. By embracing HRC, assembly operations can become more flexible and efficient.

For successful implementation of HRC, it is crucial to enable robots to monitor the workspace, interpret the context of collaboration based on sensing data, and respond accordingly. To achieve this, extensive research has been conducted on recognizing and predicting human actions. These efforts serve as the foundation for robots to comprehend the required parts or tools for subsequent operations. However, the current research landscape still has limitations when it comes to recognizing, localizing, and grasping specific parts or tools in an appropriate manner. Previous studies on HRC have rigidly predefined the placement of parts and tools, and research focused on robotic object grasping has primarily emphasized the outcome (success or failure) rather than distinguishing between different object types. Given that the positions and orientations of parts and tools are not static over time and collaborative operations like object handover may necessitate specific grasping orientations, semantic image data annotation becomes a critical factor in enabling the robot to understand and assist HRC at a human-like level.

One of the early works involves the development of an object detection method (Zhang, Liu, Huang, & Gao, 2022). This method leverages the concept of single-shot detection, allowing the utilization of pretrained CNN as the computational backbone. The object detection algorithm extracts the desired position and orientation of the robotic arm end-effector for object grasping, which are then fed into a MLP to predict the corresponding robotic arm joint angles. Through evaluation in a collaborative testbed assembly case study, the object detection method has

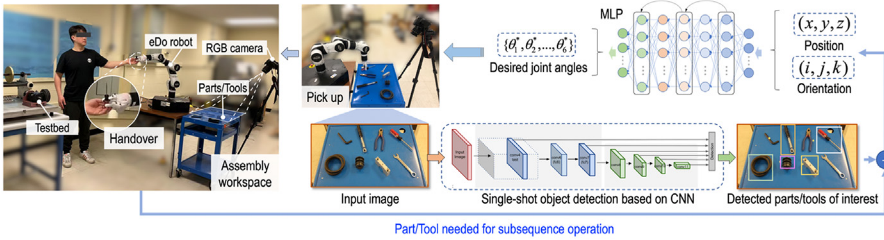

Figure 10.7 Object annotation for robotic grasping and HRC. *HRC*, Human−robot collaboration.

demonstrated reliable annotation of parts and tools of interest, without inducing false identifications for previously unseen objects, as shown in Fig. 10.7.

10.4 Discussion and outlook

The advancement of manufacturing drives companies to enhance the quality of data captured from diverse manufacturing processes and transforming it into valuable insights for optimization. Nevertheless, there remain several gaps in data curation that must be resolved to effectively harness the potential of data analytics in realizing the future's intelligent manufacturing. This section outlines four recommendations for future research.

Uncertainty quantification. Ensuring the reliability of data analytics relies heavily on the quantification of uncertainty in data (Fujishima et al., 2016). DL algorithms inherently lack the incorporation of data uncertainty in their analysis, and research on uncertainty quantification has not been reported in the context of DL-enabled data curation. This scarcity of research poses a challenge when attempting to implement algorithms developed in academic settings into critical applications on the factory floor. In such industrial settings, analysis and prediction outcomes that lack uncertainty quantification of data itself cannot be deemed realistic or trustworthy. Although some uncertainty quantification techniques for DL models have emerged recently, such as Bayesian DL, they still require further refinement and development to establish more rigorous and universally applicable approaches.

Physics-informed curation. While researchers have made strides in integrating neural networks with physics by directly incorporating pertinent physical knowledge into data analytics models to ensure their alignment with physical laws (Zhang et al., 2022), the application of physics-informed learning in data curation remains largely unexplored. For certain data curation tasks, such as data denoising, leveraging the understanding of the underlying physics governing noise formation can significantly enhance denoising performance. Recently, hybrid denoising methods have been conceptualized (Tian et al., 2020), capitalizing on both the pattern recognition capabilities of DL and the physical insights into noise contamination. These methods begin by constructing a contamination model based on knowledge about the contaminants. This model acts as a guide for data denoising, ensuring that only the clean data consistent with the model is recovered, thereby improving SNR in a physically meaningful manner. Since retrieving clean data from a contaminated version generally poses an ill-posed problem, the solution must be regularized to align with prior knowledge about the data itself. This regularization process leads to an iterative Bayesian approach that alternates between optimization steps to satisfy both the contamination model and the prior knowledge about the data.

Handling unlabeled data. While pretraining DL models using large-scale public dataset have demonstrated the potential in generalizing manufacturing settings via model refinement through the use of only a small amount of labeled manufacturing data to alleviate the challenge of scarcity of labeled data (Fredriksson, Mattos, Bosch, & Olsson, 2020), the method can be challenging as pretrained DL models are not available for many manufacturing applications. Recent advances of unsupervised and semisupervised learning (Okaro et al., 2019; Zeiser, Özcan, van Stein, & Bäck, 2023) have shown solutions to tackle the challenge. For example, GAN, which is an unsupervised method and has been utilized to learn the data-underlying pattern and synthesize new data samples, has been investigated to address the lack of labeled quality data for anomaly detection (Zeiser et al., 2023) in AM. Also, semisupervised learning, which learns simultaneously from labeled and unlabeled dataset, has been successfully implemented for AM fault detection (Okaro et al., 2019). Future investigation of unsupervised and semisupervised methods using a variety of manufacturing applications will further contribute to resolving the data labeling limitation.

Small data problem. In Industry 5.0, while data volume and variety is expected to continue to grow, the small data problem will also continue to occur for applications such as machine fault diagnosis and process quality inspection, due to the cost and safety concerns associated with data collection on a faulty machine. The lack of sufficient training data will lead to performance degradation of DL-based curation such as annotation of defect from process images. The generative method described in Section 10.2.3 can help alleviate this problem by synthesizing high fidelity data samples. Beyond generative method, other methods such as federated learning (FL) has also been increasingly investigated (Mehta & Shao, 2022). The concept is to allow different data owners (e.g., small- and medium-sized manufacturers) contribute to the creation of a global DL model by computing a local update of relevant model parameters based on its own data. The local updates are then aggregated by a central server to train a global model. Since only model parameters instead of customer data are shared across the data owners, data privacy in FL is preserved. Despite its potential, several research questions on FL remain open, such as understanding the convergence behavior of the FL algorithm, as well as its capability in handling heterogeneity in data and task. Future research to answer these open questions in FL can further advance the state-of-the-art in handling small datasets to achieve more robust data curation for Industry 5.0.

10.5 Conclusions

While the convergence of sensing, computation, and data analytics has provided unprecedented opportunities to advance human-centric manufacturing for Industry 5.0, the complexity associated with data and the resulting low data quality have posed significant challenges to the effectiveness of data analytics algorithms for optimization of manufacturing processes with human-in-the-loop. To improve data quality, the topic of data curation has been comprehensively reviewed in this chapter, with focus on the aspects of data denoising, annotation, and balancing that directly affect the performance and reliability of data analytics. Typical manufacturing applications that were enabled by these techniques are highlighted to explain how these techniques are utilized in practical scenarios. As the manufacturing industry enters the era of Industry 5.0, data curation techniques and industrial case studies can facilitate adoption and optimization of human-centric systems in intelligent manufacturing.

Acknowledgments

Robert Gao and Jianjing Zhang acknowledge the support from the U.S. National Science Foundation under award CMMI-1830295 and from the U.S. National Science Foundation Engineering Research Center for Hybrid Autonomous Manufacturing: Moving from Evolution to Revolution (ERC-HAMMER) under award EEC-2133630.

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