Significance of Machine Learning in Industry 4.0 Scenario—A Review

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1 Introduction

Industry 4.0 includes machine learning, big data analytics, sensors, RFID, Internet, cyber-physical systems (CPS), mobile devices, camera, wireless network, cloud, robotics, machine learning, and artificial intelligence (Fig. 1). With the introduction of Industry 4.0, it has become possible to connect different machines connected with sensors (CPS) used in manufacturing, over a wireless network, for interaction, data sharing and independent decision making, without human intervention. The use of Industry 4.0 in manufacturing would help in achieving operational excellence. Figure 2 shows the different functions of a manufacturing company that can be benefitted from Industry 4.0. Machine learning is a set of algorithms that are used to automatically detect the hidden patterns in the given data set either for making predictions or for making decisions under uncertainties [1]. Machine learning may also be defined as exploring knowledge from a given data set for making future decisions/predictions.

Machine learning is applicable in different domains, viz. manufacturing, agriculture, food processing, pharma companies, space applications, etc. In this research work, machine learning is studied as applied to manufacturing.

While modeling by machine learning technique, the given data set is sliced into the training set and a test set. The training set is a portion of data used for training the model. Whereas, the test set is a portion of data used for testing a model.

Supervised learning (*S*) is a type of training model where both input and output are given to the model. Whereas, in unsupervised learning, the model is required to identify the classes (output) by looking at the data (input) features.

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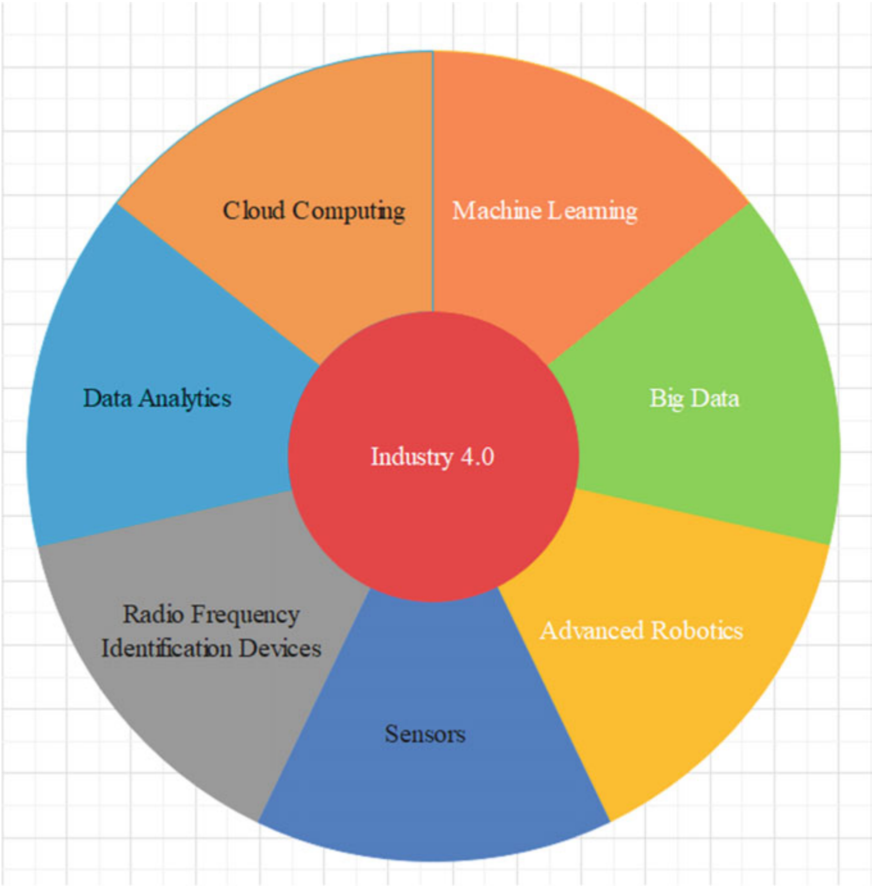

Fig. 1 Industry 4.0 technologies

Section 2 highlights how these technologies can be implemented in a manufacturing company for making it smart.

The objective of any manufacturing company is to transform raw materials into a finished product in the most economical way possible. So that the company can sell its products easily to its customers against the competition. Thus, a company sells its product only if it can attract a customer amid competition. Attracting customers is possible only if the product has better quality than the competitor and the price of the product is reasonable. Manufacturing companies were using mass production-based techniques to sell the product to the customer at a cheaper price than the competitor. This sounds good if there is a huge demand for the product. However, the scenario is changing nowadays. Today expectations are different for different customers. In this scenario, manufacturing companies cannot manufacture products in bulk, using large batch sizes, by mass production techniques. This scenario has compelled companies to devise new methods for solving the problem.

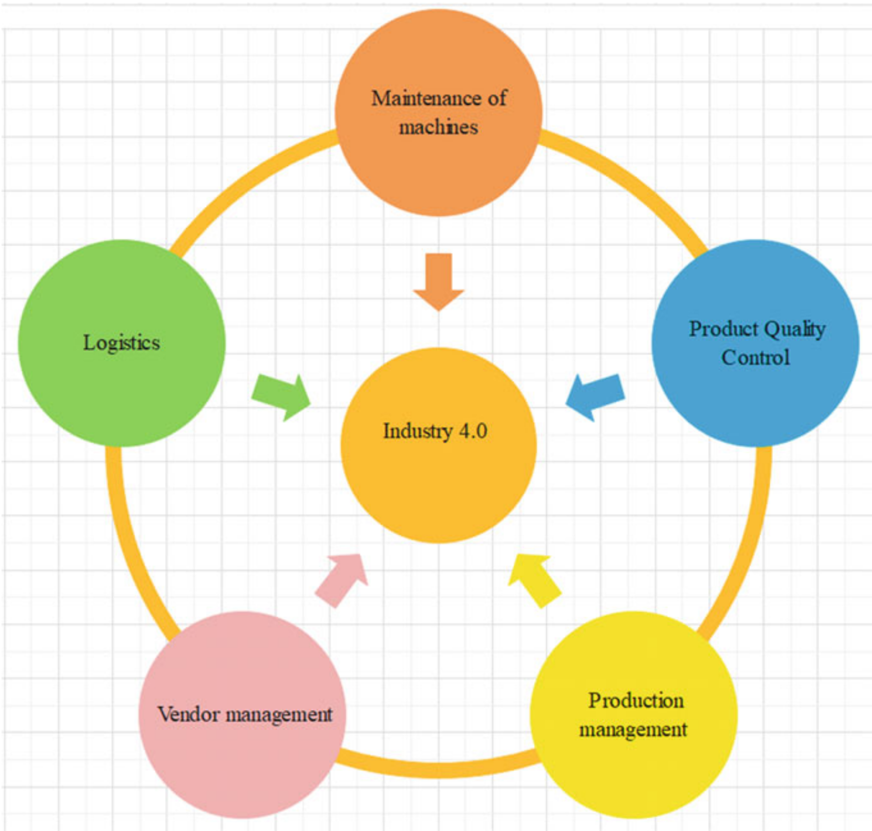

Fig. 2 Significance of Industry 4.0 in a manufacturing company

Additionally, manufacturing companies were storing large amounts of raw materials in the storeroom, for protecting themselves against the supply side variation. That is, companies want to play safely in case of failure of suppliers from supplying raw materials on time. As this will affect the manufacturing and subsequently the customer. Companies used to maintain large amounts of inventory of raw materials. Maintaining large amounts of inventory is costly and is very risky. Thus, companies are expecting new ways of solving the problem.

Companies are also facing difficulty in producing consistent quality products over some time. This may be due to multiple reasons. One of the significant reasons is the lack of standardization.

The study also showed that there is a significant amount of waiting time for the work-in-process. That is, the material had to wait for subsequent processing. This involves a significant amount of space for storing work-in-process and would clutter the workplace. However, companies have been regularly maintaining their machine tools. The total cost of maintenance is becoming very high. Companies are looking for new ways of reducing the overall maintenance cost.

Many of the existing product inspection techniques in industries are post-process in nature. That is, the product inspection is being done only after product manufacturing. This means that statistical quality-based sampling inspection is being done for product quality testing. Sampling-based inspections are not foolproof, and there are chances of accepting a defective product or rejecting a quality product. Thus, there is a chance of defective products reaching the customer. When this happens, this would result in customer dissatisfaction and will affect the company's reputation. Therefore, manufacturers are again looking for new ways of inspecting products to achieve 100% inspection at the same time bring down the cost of the inspection.

An attempt has been made, in the above paragraphs, to highlight only a few problems being faced by manufacturing companies. Likewise, manufacturing companies are being faced with a multitude of challenges. The manufacturers are looking for new technologies, new techniques, and tools for addressing their problems. In this context, the present study assumes special significance.

2 Literature Review

Many manufacturing companies are looking for solving their problems using Industry 4.0. Many researchers have been working on using Industry 4.0 for solving industry problems. The following paragraphs try to explain how the different Industry 4.0 technologies, including machine learning, are being used in addressing the different problems in manufacturing companies.

2.1 Maintenance of Machines

Cho et al. [2] have studied the milling process. They collected data about cutting forces and the power consumed during the machine, by using sensors. They used support vector (SVM) regression for identifying the tool breakage identification. The method uses a supervised classification technique, for classifying the defects. Saxena and Saad [3] had studied the health of a roller bearing. Data is collected by using sensors. They proposed a technique that combines both genetic algorithms and neural networks (NN) for feature selection and subsequent classification. Kankar et al. [4] devised a scheme of using both NN and SVM for analyzing defects in ball bearings. They have concluded that the method is feasible. The method again is a supervisory classification technique. Azadeh et al. [5] have studied on performance data of a centrifugal pump. They proposed a method that makes use of NN, GA, and SVM techniques for defect classification. The method is based on the supervisor learning technique. The authors claim that the method works even with corrupted data of centrifugal pumps.

Zhang et al. [6] designed a method which makes use of SVM and ant colony-based supervisory methods for defect identification in roller bearings of a locomotive. Li et al. [7] have proposed an ensemble learning technique based on machine learning for tool wear classification. The authors have claimed very good accuracy in classification. Bukkapatnam et al. [8] designed a supervisory-based technique for the prediction of machine failures based on random forest technique. Authors have claimed good accuracy in prediction. Alegeh et al. [9] have proposed a method for maintenance prediction using the machine learning technique. The method is a supervisory learning technique. The method is based on the K-nearest neighbor and SVM method. Susto et al. [10] have applied machine learning in solving maintenance problems. The method gave a maintenance schedule for minimizing maintenance costs. The method is based on a supervised learning technique. They had used KNN and SVM for classification.

Wan et al. [11] proposed a technique based on NN for assessment of the remaining life of different parts of machine tools. They proposed a preventive maintenance method in a big data environment. Kuhnle et al. [12] proposed a method for reducing maintenance cost and downtime. The method is based on the reinforcement learning approach. The main advantage of this technique is that simulation has produced complementary data in addition to the historical data obtained through sensors. Liu et al. [13] have proposed a scheme for fault diagnostics for the FDM process, using the machine learning method. They have used acoustic signals for data collection.

2.2 *Product Quality Control*

Kusiak and Kurasek [14] have studied the printed circuit board manufacturing process. They proposed a technique for identifying and classification of defects. They have successfully identified different types of solder defects by using the machine learning (ML) technique. Specifically, they employed rough set technique for classifying defects. They have also used data mining techniques for identifying the cause of defects. Kim et al. [15] have worked in a semiconductor (wafer) manufacturing company. They observed different types of defects and proposed a scheme for identifying different types of defects. They have used ML algorithms for the identification and classification of defects related to wafers. They have achieved a very high classification accuracy in classification. Figure 3 shows the types of inspection systems.

Çaydas et al. [16] have studied the CNC machining process. They tried to estimate surface roughness in CNC machining using the SV technique. They had used austenitic stainless steel as raw material for turning operation. They have successfully estimated surface roughness during the turning operation. The authors have also used NN-based technique for comparison. They concluded that SV-based techniques gave higher prediction accuracies. This technique is based on supervisor classification. Ye et al. [17] have studied printed circuit board manufacturing. They have used a combination of NN decision trees and SVM for identifying defects in the printed

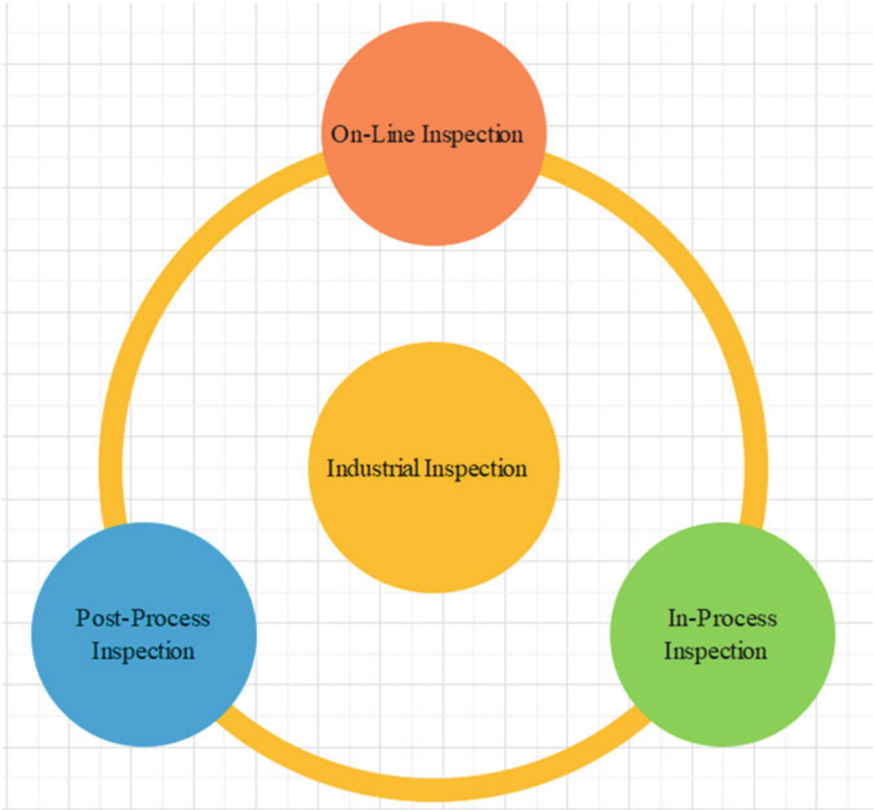

Fig. 3 Types of industrial inspection system

circuit board. This is a supervisor learning method. The method was successfully used for estimating the dielectric thickness in the manufacturing of semiconductors.

Lenz et al. [18] have worked in the semiconductor industry and studied defects and proposed a technique for defect identification. This is a supervised classification technique. They have used a combination of NN decision trees and SVM for identifying defects in wafer manufacturing. The authors have claimed high classification rates. Tan et al. [19] have also proposed a technique based on supervised classification technique for defect classification. The method makes use of an evolutionary neural network for classification. Gao et al. [20] have studied metal manufacturing companies. They proposed an unsupervised learning technique for the classification of defects. The method uses a non-negative matrix factorization method. When the different classes are not represented equally in a classification problem, it would result in an imbalanced data set. Lee et al. [21] have studied different supervised-based learning techniques for process fault detection and classification. Authors have claimed that Random forests offer very good results, especially with the imbalanced data set. Wang et al. [22] have used SVM for predicting quality in an abrasion-resistant manufacturing process. They have achieved good results. Ko et al. [23] have worked on anomaly detection problems using machine learning and have claimed to have got very good results. The authors have rightly identified the anomalies in different machinery systems.

Tusar et al. [24] have proposed a supervisory technique that is based on machine learning and decision tree for predicting the quality of machined components. Liu et al. [25] proposed an unsupervised learning method for fault detection as well as an isolation method. Kim et al. [26] have proposed a new scheme for identifying defects. The method is based on the supervised learning method. They used die-cast data set. They have shown that the decision tree-based technique works superior to other types of classifiers. Khanzadeh et al. [27] designed algorithm based on in supervised learning method. The method uses a self-organizing map for defect detection. They studied additive manufacturing molten pool, and Manohar et al. [28] have studied aircraft assembly. They proposed an unsupervised learning method based on machine learning for defect identification by looking at the molten pool. Zhu et al. [29] designed a supervised learning algorithm for identifying defects in additive manufacturing.

2.3 Production Management

Shin et al. [30] have studied manufacturing systems for process control using a fuzzy reinforcement learning algorithm. The method is a reinforcement learning algorithm. The main characteristic of the method is that it can dynamically set goals. Garcia Nieto et al. [31] designed a supervisory learning algorithm which uses SVM and NN to control the manufacturing process of a paper mill. Wang et al. [22] designed a prediction model for tool wear prediction in a manufacturing company. They claim that they got high accuracy in tool wear prediction.

Maggipinto et al. [32] have designed a supervised learning algorithm using CNN for manufacturing process control. Mezzogori et al. [33] have proposed a supervisory learning-based technique for controlling the manufacturing process. The method uses a deep learning-based neural network and regression model to predict the throughput time after knowing current state of system. Authors have claimed higher prediction accuracies.

2.4 Vendor Management

The following paragraphs highlight the significance of machine learning in vendor management. Zan et al. [34] have proposed a supervisor-based learning method using both CNN and NN for process control.

2.5 Logistics

Logistics operation consists of different activities—delivering goods as per customer requirement, receiving customer order, etc. Manufacturing companies are currently facing many problems and in-efficiencies, concerning logistics and the companies are exploring means for addressing them through Industry 4.0. Digitization through Industry 4.0 has helped in reducing the carbon emission [35]. Industry 4.0 is also helping in making the logistics more reliable [36].

3 Conclusion

With the advent of Industry 4.0, many industries including manufacturing have attempted implementing machine learning for operational excellence and to meet customer expectations. Current research work attempts to study the different machine learning algorithms being proposed by many researchers for solving many production-related problems/ or challenges. From the above paragraphs, it is clear that there is an increase in the use of machine learning in the manufacturing sector. It is also evident from the above paragraphs that a significant number of researchers have implemented machine learning in addressing problems related to maintenance and quality. Researchers have proposed algorithms for designing effective maintenance strategies using machine learning. Researchers have also proposed techniques for assessing the remaining useful life of a machine tool. However, the accuracy of prediction requires improvement. Also, none of the papers reported the repeatability of measurement machine learning-based systems to help a manufacturing organization in selecting the right maintenance policy for a given machine tool. Machine learning algorithms are also widely used in automated product inspection. By using machine learning, researchers have demonstrated that 100% product inspection are possible in product inspection by making use of machine learning. Only 100% inspection techniques are capable of ensuring quality product reaching the customer. This will also make the customer happy and will improve company's reputation. This is a significant contribution of machine learning in improving the productivity of manufacturing organization. Table 1 shows the problem areas that are to be addressed by researchers.

However, many researchers have been contributing to defect identification and classification. The accuracy and robustness of classification algorithms require improvement. There is a huge need for designing and developing new and novel techniques for defect detection and classification. It is also evident that the machine learning algorithms are being applied in designing effective production schedules, to determine the best route for manufacturing a given product, scheduling, dispatching, and expediting activities. Many of the machine learning techniques proposed by researchers are based on supervisory and un-supervisory learning techniques. The least number of techniques was reported based on reinforcement learning techniques.

Table 1 Directions for further research

Area	Problems to be addressed	Remarks
Product quality assessment	Online quality assessment of manufactured products in the context of Industry 4.0	Inspection time reduction, Improved and effective quality metrics
	In-process quality assessment of manufactured products in the context of Industry 4.0	
	Product quality assessment of moving parts with fixed orientation/random orientation	Design and development of effective deblurring algorithms
	Defect identification and classification	Robustness, accuracy improvement
Machine maintenance	To assess the remaining life of components	To minimize the overall maintenance cost
	To select appropriate maintenance policy for a given machine/or material handling equipment	Accuracy and robustness in prediction
	To make use of the merits of different supervised/unsupervised/and reinforcement learning methods	
	To reduce the requirement of data sets for training the neural network	
	Assessment of maintenance policy effectiveness	
	Condition-based maintenance	To improve effectiveness
	Data mining and artificial intelligence-based techniques for prediction	
	Maintenance budget performance estimation	
	Effectiveness of preventive maintenance schedules	
	Reliability assessment and productivity enhancement	
	Customer satisfaction prediction using maintenance policies	
Vendor management	Vendor effectiveness assessment	

(continued)

Table 1 (continued)

Area	Problems to be addressed	Remarks
	Integration of manufacturing with vendor management for achieving supply chain excellence	
	Items tracking and inventory management	
	Vendor selection/switching effectiveness	
	Assessment of waste and developing standards for continuous improvement	
	Direct/or indirect integration with customers	
Production planning and production control	Effectiveness of routing prediction	
	Process capability assessment	
	Tool wear assessment and predicting tool life in the context of Industry 4.0	
	In-process material inspection and integrating with vendor assessment	
	Effectiveness of dispatching methods	
	Machine selection for performing machining of components	
	Cutting tool selection and estimation of tool life	Robustness of prediction model
	Reducing the number of trips required by automated guided vehicles	
Supply chain	Post-delivery customer support or reverse logistics	
	To measure supply chain leanness/or effectiveness	
	Assessment of supply chain flexibility	
	Supplier–company relationship assessment	
	Assessment of supply chain	Through metrics

(continued)

Table 1 (continued)

Area	Problems to be addressed	Remarks
	Predicting customer satisfaction of the company's supply chain	
	Enhance the effectiveness of company's supply chain	
	Measuring supply chain volatility in terms of misaligned corporate goals	
	Assessment of government policy effect on supply chain volatility	
	Supply lead time prediction	Accuracy improvement
	Assessment of reliability of business processes	

Thus, there is a need to explore the benefits of reinforcement learning techniques in solving production-related problems. The least number of research works have been reported, in literature, on vendor selection, vendor management, vendor assessment area, integrating operations and procurement, designing the best supply chain for a given organization, and designing effective logistics. Not much research work is reported in the use of both simulation and machine learning-based systems for improving operational productivity. With the advent of Industry 4.0, CPS is made available. There is a huge potential for designing robust security infrastructure for cyber-physical systems by making use of machine learning techniques. Also, protecting CPS is a dynamic problem and it is very challenging. There is also a need for identifying and classifying different types of intruders in the case of protecting cyber-physical systems. One more requirement for protecting cyber-physical systems is that the security application should be robust and foolproof.

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References

1. Murphy K (2012) Machine learning: a probabilistic perspective. The MIT Press, Cambridge
2. Cho S, Asfour S, Onar A, Kaundinya N (2005) Tool breakage detection using support vector machine learning in a milling process. Int J Mach Tools Manuf 45(3):241–249
3. Saxena A, Saad A (2007) Evolving an artificial neural network classifier for condition monitoring of rotating mechanical systems. Appl Soft Comput 7(1):441–454
4. Kankar PK, Sharma SC, Harsha SP (2011) Fault diagnosis of ball bearings using machine learning methods. Expert Syst Appl 38(3):1876–1886

5. Azadeh A, Saberi M, Kazem A, Ebrahimipour V, Nourmohammadzadeh A, Saberi Z (2013) A flexible algorithm for fault diagnosis in a centrifugal pump with corrupted data and noise based on ANN and support vector machine with hyperparameters optimization. Appl Soft Comput 13(3):1478–1485
6. Zhang Y, Harik R, Fadel G, Bernard A (2019) A statistical method for build orientation determination in additive manufacturing. Rapid Prototyp J 25(1):187–207
7. Li S, Liu G, Tang X, Lu J, Hu J (2017) An ensemble deep convolutional neural network model with improved D-S evidence fusion for bearing fault diagnosis. Sensors 17(8):1729
8. Bukkapatnam STS, Afrin K, Dave D, Kumara SRT (2019) Machine learning and AI for long-term fault prognosis in complex manufacturing systems. CIRP Ann 68(1):459–462
9. Alegeh N, Shagluf A, Longstaff AP, Fletcher S (2019) Accuracy in detecting a failure in Ballscrew assessment towards machine tool servitization. Int J Mech Eng Robot Res 8(5):667–673
10. Susto GA, Schirru A, Pampuri S, McLoone S, Beghi A (2015) Machine learning for predictive maintenance: a multiple classifier approach. IEEE Trans Industr Inf 11(3):812–820
11. Wan J, Tang S, Li D, Wang S, Liu C, Abbas H, Vasilakos AV (2017) A manufacturing big data solution for active preventive maintenance. IEEE Trans Industr Inf 13(4):2039–2047
12. Kuhnle A, Jakubik J, Lanza G (2018) Reinforcement learning for opportunistic maintenance optimization. Prod Eng Res Devel 13(1):33–41
13. Liu J, Hu Y, Wu B, Wang Y (2018) An improved fault diagnosis approach for FDM process with acoustic emission. J Manuf Process 35:570–579
14. Kusiak A, Kurasek C (2001) Data mining of printed-circuit board defects. IEEE Trans Robot Autom 17(2):191–196
15. Kim D, Kang P, Cho S, Lee H, Doh S (2012) Machine learning-based novelty detection for faulty wafer detection in semiconductor manufacturing. Expert Syst Appl 39(4):4075–4083
16. Çaydas U, Ekici S (2010) Support vector machine models for surface roughness prediction in CNC turning of AISI 304 austenitic stainless steel. J Intell Manuf 23(3):639–650
17. Ye F, Zhang Z, Chakrabarty K, Xinli GU (2013) Board-level functional fault diagnosis using artificial neural networks, support vector machines, and weighted majority voting. IEEE Trans Comput Aided Des Integr Circuits Syst 32(5):723–736
18. Lenz B, Barak B, Muhrwald J, Leicht C, Lenz B (2013) Virtual metrology in semiconductor manufacturing through predictive machine learning models. In: 2013 12th international conference on machine learning and applications
19. Tan SC, Watada J, Ibrahim Z, Khalid M (2015) Evolutionary fuzzy ARTMAP neural networks for classification of semiconductor defects. IEEE Trans Neural Netw Learn Syst 26(5):933–950
20. Gao B, Woo WL, Tian GY, Zhang H (2016) Unsupervised diagnostic and monitoring of defects using waveguide imaging with adaptive sparse representation. IEEE Trans Industr Inf 12(1):405–416
21. Lee T, Lee KB, Kim CO (2016) Performance of machine learning algorithms for class-imbalanced process fault detection problems. IEEE Trans Semicond Manuf 29(4):436–445
22. Wang J, Yan J, Li C, Gao RX, Zhao R (2019) Deep heterogeneous GRU model for predictive analytics in smart manufacturing: application to tool wear prediction. Comput Ind 111:1–14
23. Ko T, Lee JH, Cho H, Cho S, Lee W, Lee M (2017) Machine learning-based anomaly detection via integration of manufacturing, inspection, and after-sales service data. Ind Manag Data Syst 117(5):927–945
24. Tusar T, Gantar K, Koblar V, Zenko B, Filipiˇc B (2017) A study of overfitting in optimization of a manufacturing quality control procedure. Appl Soft Comput 59:77–87
25. Liu Z, Jia Z, Vong C-M, Bu S, Han J, Tang X (2017) Capturing high discriminative fault features for electronics-rich analog systems via deep learning. IEEE Trans Ind Inf 13(3):1213–1226
26. Kim A, Oh K, Jung J-Y, Kim B (2018) Imbalanced classification of manufacturing quality conditions using cost-sensitive decision tree ensembles. Int J Comput Integr Manuf 31(8):701–717
27. Khanzadeh M, Rao P, Jafari-Marandi R, Smith BK, Tschopp MA, Bian L (2017) Quantifying geometric accuracy with unsupervised machine learning: using the self-organizing map on

fused filament fabrication additive manufacturing parts. J Manuf Sci Eng 140(3). https://doi.org/10.1115/1.4038598
28. Manohar K, Hogan T, Buttrick J, Banerjee AG, Kutz JN, Brunton SL (2018) Predicting shim gaps in aircraft assembly with machine learning and sparse sensing. J Manuf Syst 48:87–95
29. Zhu Z, Anwer N, Huang Q, Mathieu L (2018) Machine learning in tolerancing for additive manufacturing. CIRP Ann 67(1):157–160
30. Shin M, Ryu K, Jung M (2012) Reinforcement learning approach to goal regulation in a self-evolutionary manufacturing system. Exp Syst Appl 39(10):8736–8743
31. García Nieto PJ, Martínez Torres J, Araújo Fernandez M, Ordonez Galan C (2012) Support vector machines and neural networks used to evaluate paper manufactured using Eucalyptus globulus. Appl Math Model 36(12):6137–6145
32. Maggipinto M, Terzi M, Masiero C, Beghi A, Susto GA (2018) A computer vision-inspired deep learning architecture for virtual metrology modeling with 2- dimensional data. IEEE Trans Semicond Manuf 31(3):376–384
33. Mezzogori D, Zammori F (2019) An entity embeddings deep learning approach for demand forecast of highly differentiated products. Proc Manuf 39:1793–1800
34. Zan T, Liu Z, Wang H, Wang M, Gao X (2019) Control chart pattern recognition using the convolutional neural network. J Intell Manuf 31(3):703–716
35. Engelhardt-Nowitzki C (2012) Improving value chain flexibility and adaptability in build-to-order environments. Int J Phys Distrib Log Manag 42:318–337
36. Christopher M, Holweg M (2017) Supply chain 2.0 revisited: a framework for managing volatility-induced risk in the supply chain. Int J Phys Distrib Log Manag 47:2–17