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Research Article

Smart Manufacturing through Machine Learning: A Review, Perspective, and Future Directions to the Machining Industry

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Nowadays, to reach progressive growth although being competitive in the market, the manufacturing industries are using advanced technologies such as cloud computing, the Internet of things (IoT), artificial intelligence, 3D printer, nanotechnology, cryogenics, robotics, and automation in smart manufacturing sectors. One such subclass of artificial intelligence is machine learning, which uses a computer system for making predictions and performing definite tasks without any use of specific instructions to enhance the quality of the product, and rate of production, and to optimize the processes and parameters in machining operations. A broad category of manufacturing that is technology-driven utilizes internet-connected machines to monitor the performances of manufacturing processes referring as smart manufacturing. The current paper presents a comprehensive survey and summary of different machine learning algorithms which are being employed in various traditional and nontraditional machining processes, and also, an outlook of the manufacturing paradigm is presented. Subsequently, future directions in the machining industry were proposed based on trends and challenges that are accompanying machine learning.

1. Introduction

The manufacturing industry takes on many paradigm changes over the past due to industrial revolution that took place in the eighteenth century with the invention of steam engine to the development of information and communication technology. Moving on, automation and robotization in the late twentieth century followed by industry 4.0, the worldwide manufacturing sectors are currently dealing with smart manufacturing areas to get ready for improving their profitability through the elimination of nonvalued operations to attain a higher profit. Significant innovations such as deep learning, data analytics, cloud computing, IoT, 3D printing, robotics, and artificial intelligence have been applied to different fields of manufacturing to achieve higher productivity [1]. The technological development that takes place in the field of advanced smart systems has reached a high level which leads to the way to use of modern tools like machine learning algorithms to a greater extent in the field of manufacturing. Figure 1 represents the different phases present in artificial intelligence for solving problems.

Collecting necessary data and information to preprocess for the subsequent analysis is necessary for choosing an appropriate machine learning algorithm to solve properly defined problems. According to the gathered data, the right kind of model must be established, and it should be trained properly with the required amount of data to achieve the best results. Furthermore, obtained results should be analyzed and validated for fetching the best-improved results.

Smart manufacturing takes conventional manufacturing to a leading edge. To attain the objectives, machining parameters respond smartly to the changes according to the process. By the effective collaboration of all the resources together to make strategic innovation in the existing manufacturing industry to achieve a predefined set of objectives in real time [2]. It has an effective data-driven system coupled with 5 Ms' (man, machine, material, method, and

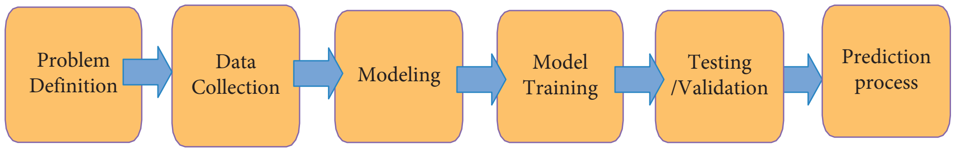

Figure 1: Steps involved in problem-solving using artificial intelligence.

money) and all other resources to achieve desired benefits which are displayed in Figure 2.

Here, this paper focused on different machine learning algorithms used in various smart machining processes were reviewed and summarized, and a perspective on the machining industry was suggested. Furthermore, future trends and challenges with smart machining using machine learning were indicated as future research directions.

The manufacturing industry has made huge advancements over the years, from the early machining process to today's automated manufacturing process [3]. Manufacturing and industrialization systems have reached their fourth generation of industrial revolution after undergoing various inventions and repeated trials over the years. Several improvements and changes have taken place during this time period [4].

In the current industrial age, smart manufacturing systems play an important role in implementing better manufacturing technology. Global economic growth is strengthened by smart manufacturing technologies that increase operational efficiency and productivity. IoT and IIoT have played a significant role in enhancing the manufacturing system equipped with smart manufacturing systems with the emergence of IoT and IIoT. Many industries are developing their manufacturing systems using smart technologies, according to various researches in manufacturing systems. Compatible existing machines and systems with the new technology are one of the challenges for a smart manufacturing system [5].

2. Machine Learning Algorithms Used for Smart Machining

2.1. Processes. An ample amount of work has been done by several researchers to describe the significance of machining learning algorithms in different categories of smart machining operations. Machining processes are categorized as traditional and nontraditional machining, and a summary of algorithms is used for its dealt with herein [6].

2.2. Traditional Machining. Traditional machining is based on the removal of materials by the use of harder tools by using mostly mechanical energy. This section emphasizes different cases of traditional machining processes which use machine learning algorithms to optimize the process thereby increasing productivity. Turning, milling, grinding, and drilling operations are discussed and summarized in Table 1.

2.3. Turning Operation. Here, 5 recent papers based on turning operations that employed different types of machine learning algorithms are reviewed for many reasons viz, parameter optimization, tool monitoring, and Ra predictions. It reviewed in detail the use of the multiobjective genetic algorithm (MOGA) for analysis of tool selection and tool path length by optimizing the cutting forces that are induced in the turning process [7]. It reviewed and studied the way to determine the optimum cutting parameters in terms of tool life and operation time by the modified harmony search algorithm. This has predicted the surface roughness using vibration signals acquired in the turning process. Most used algorithms are artificial neural network (ANN), MOGA, genetic algorithm (GA), etc. [8].

2.4. Milling Operation. A total of 5 cases are studied here to know the importance of artificial intelligence (AI) algorithms in milling machining operations [9]. For the high-speed milling process, he developed a model to predict surface roughness based on the backpropagation (BP) algorithm and GA [10]. Shankar et al. [11] studied the effects of machining force and sound pressure to design an efficient tool monitoring system using ANFIS. Garcia-Ordas et al. [12] studied the characterization of tool wear and monitoring using shape and texture descriptors by support vector machine (SVM) and K-NN. Cho et al. [13]explained the effects of cutting force and power consumption on milling machines for the detection of tool breakage using SVM. Wu et al. [14] proposed comparative studies on machine learning (ML) algorithms for the prediction of tool wear using random forests are reviewed. Most used algorithms include GA, K-NN, and SVM.

2.5. Grinding Operation. Despite the fact that very few cases for grinding operations were found for study, efforts to anticipate the prediction of surface finishing quality were reviewed. Gao et al. [15] have attempted to optimize material removal rate (MRR) using the XGBoost algorithm by identifying the undesirable noise and idle time during operations. Zhang et al. [16] utilized many input parameters to monitor the surface roughness of the work material by IFSVR.

2.6. Drilling Operation. Similar to the grinding process, here also a very few cases were found for the study to analyze the finishing quality of the work material. This part contains a summary of 2 papers. Shaban et al. [17] diagnosed the machining outcome by a logical analysis of data for evaluation of product finishing quality and geometric profile by considering process parameters. Shi et al. [18] have studied the characteristics of drilling in real time to detect influx and loss during machining operations using random forests and

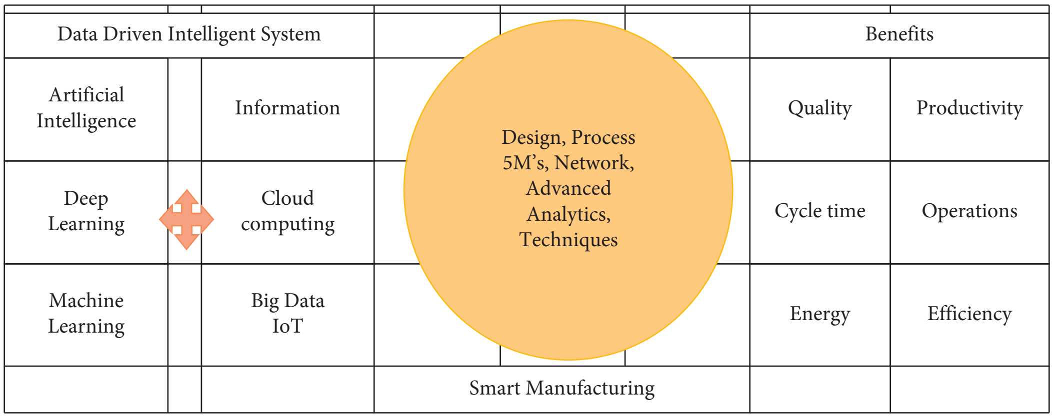

FIGURE 2: Smart manufacturing: elements and its benefits.

TABLE 1: Cases of Traditional machining processes using machine learning algorithms.

Sl no	Purpose	Algorithms	Input parameters	Ref. (Year)
1	Optimization of machining parameters	MOGA, AI	Tool path cutting force	[1] (2019)
2	Multi-objective optimization	Modified harmony search Algorithm, GA	Cutting velocity, DOC, feed	[2] (2017)
3	Carbon emission quantification and prediction, cutting parameter optimization	Regression, MOTLBO	Speed, feed, depth of cut	[3] (2015)
4	Surface roughness prediction	Multiple linear Regression (MLR)	Speed, feed, depth of cut, flank wear, vibration	[4] (2015)
5	Microhardness and grain size prediction	RF, GA	Cutting speed, feed rate, tool edge radius, tool coating status	[5] (2015)
Cases of Milling processes using Machining Learning Algorithms				
1	Prediction model of milling surface roughness	Genetic algorithm range analysis	Milling depth, milling row spacing, speed	[6] (2019)
2	Tool condition monitoring	Adaptive neuro-fuzzy Inference, ANFIS model	Sound pressure, Cutting force	[7] (2018)
3	Tool wear monitoring	K-NN, SVM	Tool images	[8] (2017)
4	Tool breakage detection	SVM, SVR	Cutting force and power consumption data	[9] (2005)
5	Tool wear prediction	RF	Cutting force, vibration, Acoustic emission	[10] (2017)
Cases of grinding processes using machining learning algorithms				
1	Monitoring of surface roughness (Ra) and surface shape peak valley	IFSVR	Acoustic emission, grinding force, vibration	[11] (2015)
2	Material removal prediction method	XGBoost learning algorithm	Contact time, belt velocity Mesh size	[12] (2019)
Cases of drilling processes using machining learning algorithms				
1	Evaluation of quality and geometric profile circularity, dimensional error, delamination	Logical analysis of data	Thrust force, cutting force, torque	[13] (2015)
2	Detection of influx and loss	Random forests, support vector machine	Time-indexed drilling measurement parameters	[14] (2019)

support vector machine. The most likely used algorithm in these studies is RF and SVR.

3. Nontraditional Machining

Nontraditional machining is based on the removal of materials mostly by electrical energy. Very less cases are found in the study. The main objective is to improve the finishing quality of a product while optimizing the MRR and Ra predictions. Here, machining processes such as EDM, ECM, LBM, and AJM operations are discussed and summarized in Table 2.

3.1. Electric Discharge Machining Process—EDM. The fundamental reason for implementing ML algorithms is to enhance the surface quality of the product. It was used to investigate the surface integrity, bio-activity, and performance characteristics of WEDM on biomedical alloy for medical applications [19]. Experiments were done on

Table 2: Cases of nontraditional machining processes using machine learning algorithms.

Sl. No.	Purpose	Algorithms	Input parameters	Ref. (Year)
1	Predict optimum process parameter for minimum wear ratio and maximum MRR	BpNN, particle swarm optimization, simulated annealing, GA	Pulse current, pulse-on time, pulse-off time	[15] (2015)
2	Investigations of surface integrity and bio-activity performance	TRMGP	Servo voltage pulse off-time pulse on-time	[16] (2019)
3	Prediction of surface roughness and MRR	Taguchi, GRA ANNs	Pulse on & off time wire feed rate	[17] (2018)
Cases of Electrochemical Machining processes using Machining Learning Algorithms				
1	Process parameter optimization for MRR and Ra	LS-SVM, MFNN, Taguchi technique, ANOVA	Flow rate, feed voltage	[18] (2012)
2	Process parameter optimization for maximizing MRR and minimizing radial overcut	TLBO	Electrolyte concentration, electrolyte flow rate, applied voltage, inter-electrode gap,	[19] (2011)
Cases of laser machining processes using machining learning algorithms				
1	Process monitoring and control	Convolutional neural networks (CNNs)	Beam translation beam rotation	[20] (2019)
2	Prediction of surface quality, dimensional features, and productivity	NN, decision trees, K-NN, linear regression	Scanning speed, pulse intensity, pulse frequency	[21] (2015)
Cases of abrasive water jet machining processes using machining learning algorithms				
1	Surface roughness prediction	Extreme machine learning, ANN, GPR	Cutting speed, material thickness, abrasive flow, measurement position	[22] (2016)
2	Prediction of process parameters	Adaptive neuro-fuzzy inference system	Jet pressure standoff distance number of shots	[23] (2019)
3	Surface roughness prediction	Feed-forward BpNN, regression model	Traverse speed, water jet pressure, stand-off distance, abrasive grit	[24] (2008)

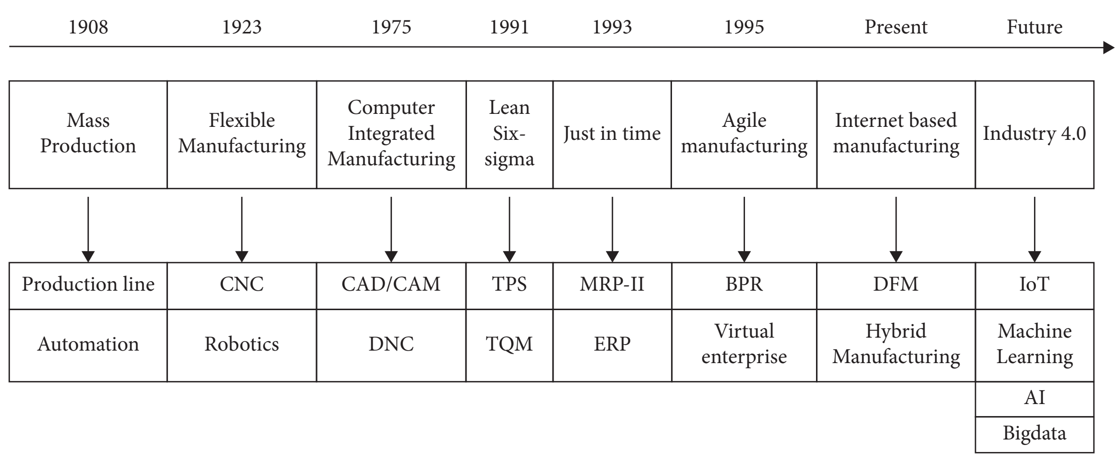

Figure 3: Manufacturing paradigm.

advanced material like composites using RA and ANN. Most of the studies were focused on process voltage, pulse ON/OFF time, wire feed rate, etc.

3.2. Electrochemical Machining Process—ECM. In this process, major focus is on the chemical aspects of the electrolyte used, flow rate, and gap to access and improve the quality of the workpiece. Nayak et al. [20] successfully compared LSSVM and FFNN algorithm to predict MRR and Ra and suggested that LS-SVM is the most powerful machine learning tool. The most likely used algorithm in these studies includes SVR, NN, Taguchi, ANOVA, and TLBO tech.

3.3. Laser Beam Machining Process—LBM. In today's global requirements for the finest quality of products in terms of precision and accuracy, LBM plays a vital role. However, the process parameter is optimized using many algorithms that are dealt with herein. Kang et al. [21] monitored the process and its parameters viz beam translation and beam rotation to control the process using CNNs. Many kinds of NN algorithms were used to monitor and control the process and its parameter to achieve the predetermined objectives. The study concludes that the productivity rate of this process was found to be high.

3.4. Abrasive Water Jet Machining Process—AWJM. This process mainly emphasizes on prediction of surface roughness and process parameters. Cojbasic et al. [22] predicted the surface roughness of the process using flow, speed, and material thickness as input parameters using ANNs and GPR. Many other researchers have tried a lot to predict using different kinds of ML algorithms to predict the Ra.

A novel revolution for today's industrial settings is to effectively examine the field of machine learning and its impact on smart machining in order to attract worldwide attention. The contextual analyses reviewed in this paper have for the most part been published in the ongoing years.

Evolution of Manufacturing paradigm.

Figure 3 shows the development in the field of manufacturing during the last century. It also explains the importance of advanced manufacturing methods, techniques, and technologies in the industry. By looking at it, one can say that there is significant scope for artificial intelligence and its algorithms in manufacturing to attain a benchmark.

4. Conclusions

Machining strategies play a major role in the substantial growth of the machining industry. The use of ML algorithms is becoming increasingly prevalent in many industries in order to meet market demands in the current global environment. A review of past and present smart machining processes with machine learning algorithms was conducted in this paper, as well as future directions for the machining industry were outlined. Based on the present study, ML algorithms have a huge potential in manufacturing industries.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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