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Artificial intelligence techniques for implementation of intelligent machining

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A B S T R A C T

For the past few years, the rapid progress and development of artificial intelligence (AI) based technologies have been analyzed for the applications of the intelligent manufacturing industry, i.e., industry 4.0. this has triggered a valuable transformation in means, models, and ecosystems within the manufacturing industry and AI development. With the advancement in manufacturing technology, there is a need to execute these technologies and AI more efficiently and cost-effectively. It can be possible by combining traditional manufacturing and machining technologies with recently developed intelligent manufacturing technologies comprising hardware and software techniques. This review paper discusses various AI implementation-based intelligent manufacturing industries with their architecture and technology systems based on the integration of AI with manufacturing and information communication. Furthermore, AI-based manufacturing application, their implementation, and current development in intelligent manufacturing have also been discussed.

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1. Introduction

The manufacturer systems set specific quality standards to assure the high quality of generated products to keep pace with the upgraded requirements. There comes the need to utilize the persistently emerging novel engineering principles [1]. The growth and progression of these upgraded engineering tools are interrelated with the development of the industrial phases of several systems [2]. In the currently existing industrial grade, there is a high possibility of converting the conventional manufacturing systems and techniques into highly advanced and optimum manufacturing techniques, which is only possible by integrating them with the trending optimization algorithms. Up till now, the industrial world has seen four momentous revolutionary phases. The first industrial revolution started at the end of the 18th century, where the industrial settings could utilize the mechanical systems based on steam power [3]. The second industrial revolution that the world experienced came at the end of the 19th century. In this industrial revolution, electricity was exploited as an energy source to provide power to the new familiarized "mass production systems." After that, the third revolution came in the middle of the 1960 s, when the production systems were shifted towards automation. Artificial Intelligence (AI), Cyber-physical systems (CPS), and Machine Learning (ML) are now known as the 4th industrial revolution represented as Industrial 4.0 [4]. Fig. 1 illustrates the progress of the industrial revolution in intelligent machining starting from 1860 till this time.

Development in AI and ML techniques has boosted up the abilities of intelligent machining tools. In CPS systems, information is taken and shifted to cloud-based systems, enabling machines to connect and gain innovative solutions in real-time [5]. These intelligent techniques bring about massive enhancements compared to the conventional manufacturing and machining operations, where some parameters have to be selected before the job or task execution. The parameter selection is swayed by procedure and process constraints. It has opted based on the machine running experience of the operator, trial and error-based attempts, availability of machining handbooks with set standards. Conventional techniques

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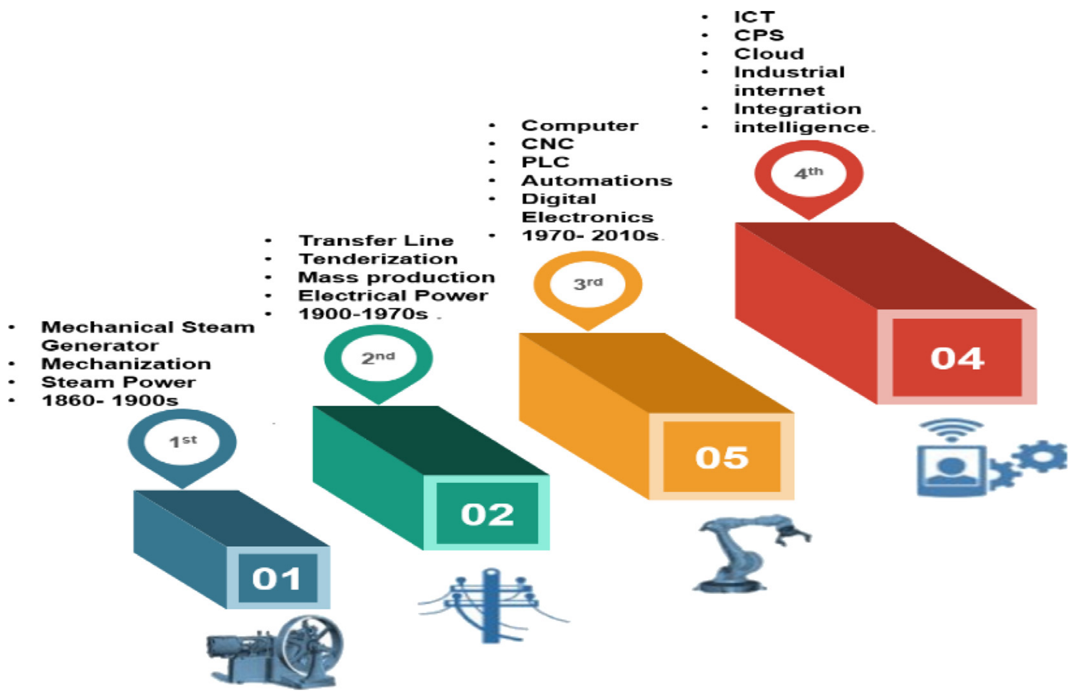

Fig. 1. Progress of Industrial revolution in Intelligent Machining.

are intended to be designed conservatively, which eventually minimize the efficiency of the manufacturing process and confines its acquirable "material removal rate (MRR)" [6,7]. In addition to this, machining is considered to be a complex, advanced and dynamic process. Therefore, even an experienced and professional operator can take a long time to figure out the possible solution to these machining process challenges [8].

Fig. 2 below shows the application of AI and ML in intelligent manufacturing and machining systems and their functions.

Several researchers have shown interest in studying intelligent machining systems as these systems are constantly developing and have great potentials [10]. This development and enhancement in manufacturing and machining systems are acquired by integrating the analytical algorithms with optimization algorithms and enhancing the machinery equipped with sensors. Analytical techniques and models are intended to elaborate and simulate the machining processes based on mathematical algorithms. These mathematical algorithms have been represented in detail in

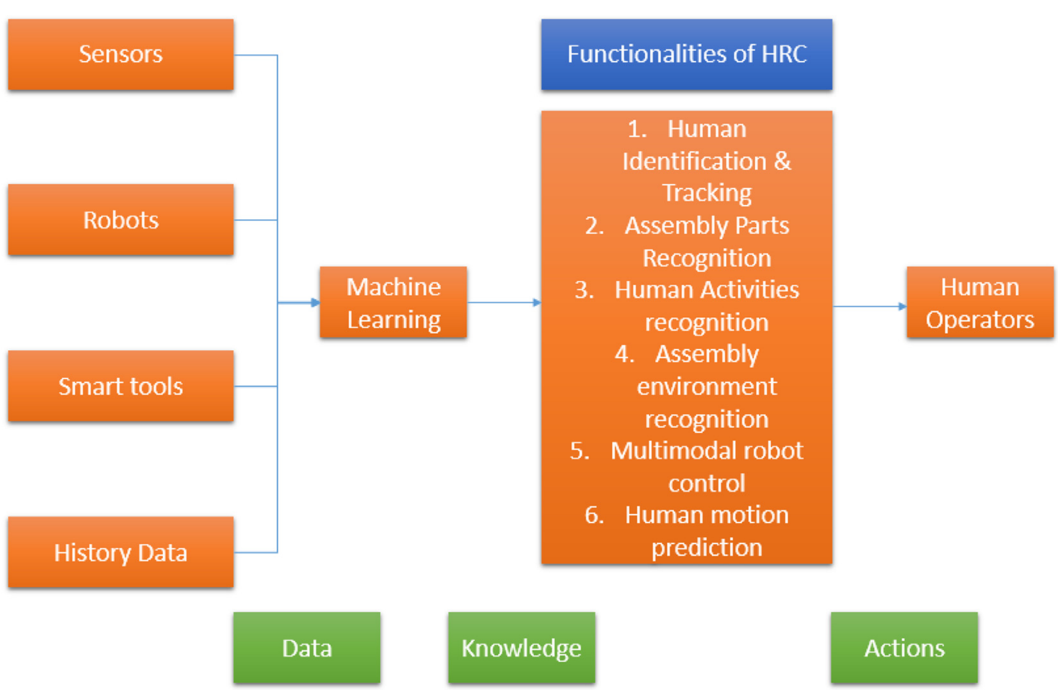

Fig. 2. Applications of AI and ML in intelligent machining and manufacturing [9].

[11,12 13,14]. Furthermore, these mathematical tools and models are improved to reduce faults and errors during the machining processes. By giving sensors to the machining tools makes it possible to collect the information in real-time. Thus, real-time information sharing makes the system create or produce optimum solutions to the unique challenges without requiring long downtime periods [5].

Considering this scenario, the author Ahmed et al. [15] has presented a work where he has reviewed the use of intelligent cutting tools as well as technologies that particularly comes under milling processes, and it has also been elaborated that implementation of these technologies and tools plays the crucial role in the development of innovative industries. In [2], similar work has been presented where ML algorithms have been emphasized to enhance the tool's surface quality, path efficiency, and process scheduling.

Fig. 3 below represents a classification flow chart of some essential components of intelligent manufacturing.

This review article discusses the range of technologies of the intelligent machining domain divided into two sections; one describes the software-based intelligent machining systems in perspective of techniques, and the other represents the hardware-based intelligent machining systems in view hardware tools and technologies.

The software section reviews the latest developments in intelligent planning, intelligent scheduling, intelligent process control, and machining parameters.

From a software perspective, intelligent planning is considered to optimize essential parameters required to implement the task correctly and efficiently. Intelligent scheduling intends to optimization of the flow shop as well as the scheduling issue of the job shop; furthermore, intelligent process regulation signifies the techniques of process control ensuring steady and balanced machining operations [17–20]. This review paper will discuss some of the critical optimization techniques that are used in intelligent machining. The execution of these optimization techniques is done to determine the adequate amalgamation of tool parameters and machining parameters.

From a hardware perspective, the review paper will discuss the integration of sensors with some of the cutting tools used for monitoring tool condition and chatter reduction, etc. Furthermore, the manuscript discusses enhancements that have been made in the intelligent cutting tool domain, which is defined as the tool that is used in combination with the sensory controllers and systems to enhance its performance [21]. Intelligent tools are exploited for several applications, like improving productivity, monitoring processes, and other supplementary methods [22].

The article describes the latest developments in machining parameters from a software and hardware perspective with the development of AI and how it facilitates the development of intelligent manufacturing in terms of new means, models, and forms of intelligent manufacturing and its architecture. The article provides future recommendations in the field of intelligent machining.

2. Optimization and modelling algorithms in intelligent systems

Completing the task requires proper control and selection of the essential vital parameters, including cutting conditions and tool parameters. With optimized parameter selection, processing time and energy consumption can be minimized [8,23]. As per [24], problems of metal cutting procedures are categorized into optimization and modelling techniques.

The category of modelling technique is devoted to the modification and modelling of mechanical systems. The category includes Artificial Neural network (ANN) [25,26], Linear Regression Modelling (LRM) [27] and Fuzzy Theory (FT) [28]. These modelling techniques are designed and applied to craft a relationship among the input and output parameters of the system. Table 1 presents some of the pros and cons of the AI/ML modelling techniques mentioned above.

The category of optimization techniques augments the input processes into the desirable output processes. The optimization technique is classified into non-conventional and conventional techniques. The conventional technique involves the "Design of

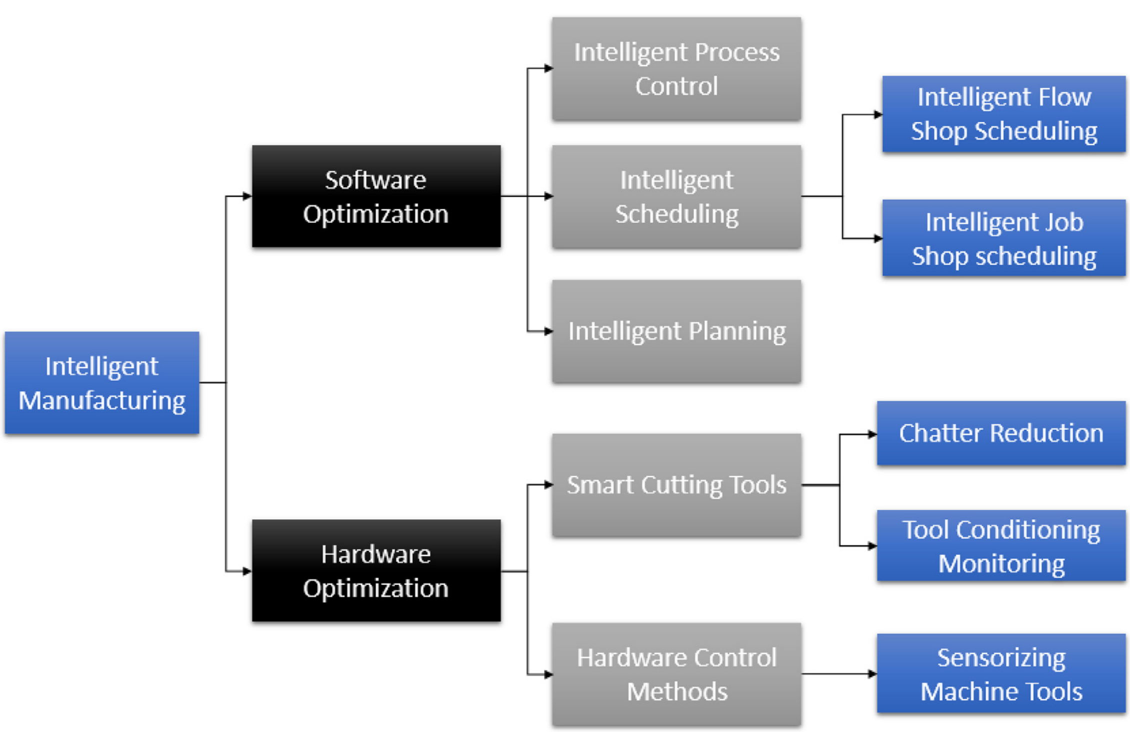

Fig. 3. Flowchart of essential components of Intelligent manufacturing [16].

Table 1
Pros & cons of modelling techniques.

Authors (year)	References	Modelling Techniques	Pros	Cons
Dagli et al. (2021), Praszkiewicz et al. (2008)	[29,30]	ANN	– Vigorous in predicting outputs. – Provide effective solutions for non-mathematical techniques and non-linear challenges.	– Training is required for predicting the precise and optimized results making the process computationally costly. – Always requires large data for accurate prediction.
Kovac et al. (2013)	[31]	FL	– Adaptable to varying conditions. – Resembles human reasoning and linguistic modelling. – Complex problems can be solved with this technique.	– Computation takes time. – Lack of real-time responsiveness.
Cheng et al. (2020)	[32]	LRM	– An unpretentious model when appropriately developed.	– Requires extra effort for model development.

Table 2
Summarization of Literature of AI and deep learning-based optimization models.

Authors (Year)	References	AI/ Deep Learning (DL) Technique	Purpose
Li et al. (2015)	[40]	BPANN	Reduces the machine time and energy consumption
Composeco et al. (2015)	[41]	DL Regression Technique	Maximize MRR and reduce the surface roughness
Gupta et al. (2016)	[42]	PSO, BDO	Effectiveness of input parameters on output parameters
Li et al. (2017)	[43]	GA	Reduction in processing time
D'Mello et al. (2017)	[44]	FA, BA, PSO	Reduction in surface roughness and carbon emission
Hegab et al. (2018)	[45]	NSGA-II	To minimize the tool wear and power consumption
Jiang et al. (2019)	[46]	NSGA-II	To determine the balance among carbon emissions, cutting time as well as the cost of cutting

Table 3
Literature Summary of smart cutting tools for intelligent machining.

Article (Year)	References	Proposed Approach	Goals and Objectives
Sugita et al. (2015)	[58]	Measuring normalized cutting force	Verification of tool conditioning through integrated sensors
Luthje et al. (2004)	[59]	Electric sensors of Lathe inserts	To sense wear in the cutting process
Alemohammad et al. (2017)	[60]	Implementation of fiber optical sensors	To develop the approaches for transmitting data from tool face
Wright et al. (2008)	[61]	Wireless sensors implemented on the spindle	Transmission of data wirelessly.
Neslusan et al. (2015)	[62]	Multiple AE sensors	To identify the cracks in the tool
Plogmeyer et al. (2021)	[63]	Automated PNN	To detect the failure of the tool

Experiment (DOE)" method and the mathematical iterative search approach. The non-conventional algorithm includes metaheuristic technique and problem-specific search technique. All of these techniques are exploited for compound non-linear challenges [33,34]. Particle Swarm Optimization (PSO) [35,36], Genetic Algorithm, and Differential Evolution (DE) [37,38] come under optimization techniques [39]. Table 2 represents some of the latest literature regarding AI and deep learning optimization techniques used for intelligent machining.

2.1. Intelligent system processes - from software perspective

In [47], CNC machines' geometrical and mechanistic model has been investigated to reduce material removal time using cutting forces and plan feed rates. A reduction of 35% could be achieved in variable feed rates compared to the constant feed rates.

In [48], a "multi-objective Elitist Non-dominated Sorting planning model (NSGA)" has been proposed, which was designed to solve and integrate the planning issues in machining processes. For this purpose, three machining goals were taken into consideration: reduction of machine idle time, reduction of machining cost, reduction in total make the span of process. The proposed model could achieve its goals regarding computational time and bring assortment in solutions.

A cluster PSO model has been proposed by the [49–51] to optimize the adeptness of scheduling processes and improve environmental friendliness. This algorithm has been adopted to enable various machines to operate in parallel in each of the workstations. With this process, a decrease in production cost and increase in volume production could be achieved.

2.2. Intelligent system processes – From hardware perspective

In recent times, various innovative methods have been proposed to control and monitor the machining processes. Similarly, incorporating sensors with cutting tools has been directed to create a creative domain of intelligent and intelligent cutting tools. In this section, these intelligent systems have been reviewed and presented from a hardware perspective i.e., chatter reduction and cutting tools and techniques [52].

[53] has presented a smart chatter detection module integrated with the sensors. The system model makes use of accelerometers that are mounted over the spindle head and makes a sensor to calculate the force in the direction of plunging off the tool. A signal processing approach could be created through this proposed system independent of the tool path and machine variable dynamics.

An intelligent control fixture has been presented in [54] to mitigate the chatter in the milling. The proposed fixture has used enhanced piezoelectric actuators having higher bandwidths. In the proposed system, accelerometers have been used to determine the intensity of vibration throughout the million operations and also determine if the chatter is occurring or not. With the proposed algorithm, milling vibration was reduced by 77% at the axial depth of cut, proving that the fixture can enhance the MRR (material-removing rate) without activating chatter [55,56].

In [57], a technique was presented. An array of micro-sensors was placed over the turning pool rake face to calculate the temperature distribution while the cutting process provided more data at the tool-workpiece interface.

Table 3 summarises the literature regarding smart cutting tools and condition monitoring approaches in the intelligent machining domain.

3. Artificial intelligence (AI) integrated with intelligent manufacturing (IM)

In intelligence science, there are 2 types of areas that are greatly discussed and talked about. These are Artificial Intelligence (AI) and Natural Intelligence (NI). AI is one of the significant branches of intelligent and smart science.

NI describes the intelligent behavior of all living beings on this planet, while AI discusses the engineering and science of developing intelligent system software.

It is believed that IM has proven to be an innovative technical means through which intelligent science, information and communication technology (ICT), production, design management testing, system engineering-based technology all have been integrated within a system of product development [64,65]. The manufacturing life cycle uses autonomous sensing, collaboration, interconnection, learning, cognition, analysis, decision making, and environmental information to facilitate the optimization and integration of several aspects of the manufacturing group. This simplifies the production and delivers high quality, more efficient, cost-effective [66] and environment-friendly service to the users, eventually improving the market competitiveness of the manufacturing group.

From the literature, it has been studied that the first and foremost AI tool was a computer program for chess play named Deep Blue [67, p. 100], which IBM built. Another example of an AI tool in manufacturing is the Honda ASIMO robot that was built in 2005. This was the very first robot that had the potential to move and roam around in an unstructured environment. It could climb the stairs. Also, it was commanded by humans. For designing this robot, computer vision, Natural language processing (NLP), object recognition, ML, and motion control were required in run time.

In the past decade, an algorithm was designed named AlphaGo [68], which can play Go games by using reinforcement learning, cloud computing, and a Monte Carlo-based algorithm integrated with DL-NN for decision making. Proceeding with the previous version, AlphaGo zero [69] was designed with more abilities than AlphaGo.

In this era of technological invention, AI algorithms and techniques have prevailed in every walk of life, robotic systems or digital games, designing aeroplane autopilots or diagnosing diseases, smart designs, or intelligent manufacturing.

3.1. The architecture of intelligent manufacturing (IM) mechanism

AI and ML are integrated with IM via IM systems. Autonomous sensing, decision making, human–machine integration, cognition, environmental aspects, information of the whole system, and life cycle characterize the IM systems.

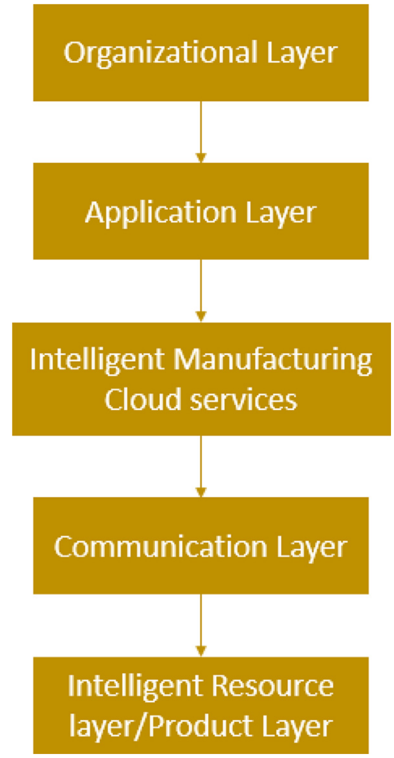

Fig. 4. The architecture of the IM system [9].

The system includes resources, service platform, ubiquitous network, cloud service, and security management system. Fig. 4 depicts the flow chart of all of the system layers.

3.2. New means, model, and form of AI for IM

- New Means: Intelligent human–machine incorporated intelligent manufacturing mechanisms that feature the Internet of Things (IoT), digitalization, virtualization, flexibility, and customization [70].
- New Models: Web-based collaborative, service-oriented smart manufacturing processes facilitate production processes and deliver services to the clients.
- New Forms: Smart manufacturing ecosystem having features of ubiquitous links, autonomous intelligence, data-driven-ness, and cross-border incorporation.

The in-depth application integration of such means, models, and forms will eventually create an environment of IM, as depicted in Fig. 5 below.

Artificial Intelligence (AI) enhances the progression of new means, models, and forms of technology systems and architecture in the intelligent manufacturing domain.

3.3. Example of Artificial intelligence (AI) in manufacturing

AI contributes significantly to designing and constructing intelligent manufacturing (IM) systems using ML models and approaches in manufacturing systems. One example is Human-machine or Human-robot collaboration (HRC). In this scenario, the information is shared or transferred from field devices and sensors to the knowledge after applying suitable ML algorithms and models [71]. In the next step, knowledge is converted into action through domain-specific decision models of HRC. Therefore, humans can perform their tasks alongside robots in immersive conditions. On the other hand, robots will have the tendency to

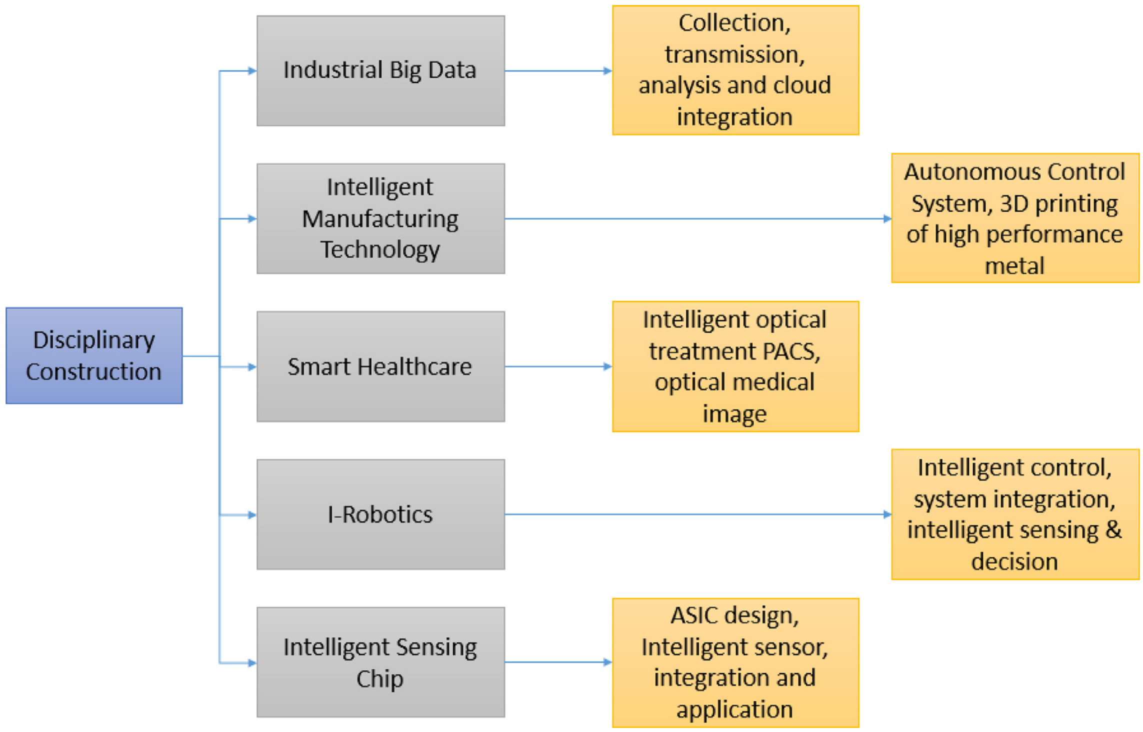

Fig. 5. New means, models, and forms of Intelligent manufacturing.

predict the idea of human action in the future, thus would help in providing situ assistance when required [72,73].

Brain Robotics [74] also comes under AI-enabled intelligent manufacturing. This robot is controlled and regulated through the brain waves of highly skilled and professional human operators. In this scenario, instead of following the chain of data ≫ Knowledge ≫ action, the active development of brainwave is realized through mapping the brain wave patterns of humans providing commands to the robots via proper training. For this mechanism, 14-channel based EMOTIV device is exploited to receive the signals from the human brainwave. Alike commands are transferred after signal processing towards the robot controller for adaptive process execution.

4. Evaluation of AI application in IM

The evaluation of the assessment of AI application in the domain of IM can be taken place by taking into account three basic aspects: Application Technology, Application Effect, and last Industry development.

In application technology evaluation, capability and level of infrastructure, synergy, and single applications along with business development are assessed.

In industry evaluation, intelligent products that finalize their task autonomously without human intervention along with other linked products and industrial software (for commissioning, security, management, and design & production) are assessed.

In application effects evaluation, more focus is given to variation in competitiveness and economic and social benefits to signify the effects of IMS.

4.1. Challenges and opportunities

AI and recent IT-enabled technologies like big data analytics [75], cloud computing [76], IoT along with 5G [77], and mobile internet, there lies a huge platform of opportunities ahead for Intelligent manufacturing. These tools and technologies simplify the processes of sharing information in real-time, KDD (knowledge discovery) [78] as well as decision making in IM [79–81]; as follows:

- IoT allows it to collect data in real-time by providing better and enhanced connectivity of field devices and machines [17,82].
- Practicality has been achieved through Mobile internet and 5G to pass on vast data in ultra-low latency for sharing information in real-time.
- Cloud computing delivers data analysis in seconds, provides a huge data storage space, and enables users to share this with authorized users.
- Big data can identify the meaning information and hidden patterns in the data and then transform it into a piece of important information and then change this to knowledge.

For instance, the massive platform of opportunities in IM can include:

- Remote-based control and monitoring in real-time with bearable delay.
- Machining (detect free) using process scheduling and planning.
- Secure and cost-efficient predictive management of resources.
- Control and complete planning on intricate processes of supply chains.

In addition to these, soon, IM would greatly benefit from all of the technologies mentioned above in various temporal scales in the following ways:

- In 5 years, better vertical and horizontal integrations would probably minimize the gaps among automation fields by 80%, mobile internet and IoT enabled.

- In the next ten years, knowledge-driven operations of intelligent manufacturing may evolve to be data-driven with existing knowledge support, which would be big data and cloud computing enabled.
- In the next twenty years, various "small and medium-sized enterprises (SMEs)" would probably gain a high edge around the world powered by cloud manufacturing, and it would be available to everyone.

However, the uncertainty and complexity of the processes will remain a significant concern in intelligent manufacturing in the coming years. AI algorithms and their techniques like ML and DL can resolve such issues to a great extent. For instance, the DL-based approaches [2] can be exploited to understand the manufacturing context better. It would also accurately predict the future challenges or failures in manufacturing mechanisms before their occurrences, which eventually would lead the whole system towards defect-free intelligent machining/ mechanism [83,84].

Another problem in developing flexible and intelligent automation is building a secure HRC system that involves human intervention with robots. This type of human–machine collaboration is essential and beneficial, particularly in manufacturing assembly, where DL can assist in designing intelligent robots that would eventually help human operators. This would increase "context awareness" about the safety of human beings entire.

5. Conclusion

This review has provided a comprehensive analysis regarding the progression and developments in the field of intelligent machining along with applications of AI in intelligent manufacturing. The paper has discussed IM both from a software and hardware perspective. From a software perspective, optimization and modelling techniques of intelligent manufacturing have been elaborated, including intelligent scheduling, planning, processing, and parametric optimization. While from a hardware perspective, cutting tools, as well as control methods, have been described. These tools and strategies included chatter reduction tools, along with tool condition monitoring and also process improvement.

Various innovative trends can be seen by categorizing, collecting, and summarizing all of the work presented from these two perspectives of intelligent machining and manufacturing. The review has discussed the research gaps, promising technologies, and several AI-based applications in intelligent manufacturing industries, along with AI use cases and instances.

5.1. Future work

One of the main issues that haven't been discussed in the literature is the security issue in future work. There are high chances of breaching in the intelligent and intelligent manufacturing process because of being linked with AI and ML. All of these machining tools will be linked with cyber communication networks. Therefore, external malware attacks like breaching and hacking can interrupt and mess up the manufacturing mechanism, possibly by diffusing malicious fake sensor data.

In addition to that, several machine learning and Artificial intelligence-based algorithms like deep learning models are susceptible to the insignificant variation in input data, which the intruder or hacker himself can conduct. There is a need to resolve the security issues of smart manufacturing systems integrated with AI and ML algorithms. More importantly, it has become the need of time to generate secure ML algorithms and models that would potentially alleviate the adverse effect of manipulated data over the intelligent machining and manufacturing processes.

CRediT authorship contribution statement

Abdul Wahab Hashmi: Conceptualization, Methodology, Data curation, Writing – original draft. **Harlal Singh Mali:** Visualization, Investigation, Supervision, Writing – review & editing. **Anoj Meena:** Supervision, Writing – review & editing. **Irshad Ahamad Khilji:** Writing – review & editing. **Mohammad Farukh Hashmi:** Supervision, Writing – review & editing. **Siti Nadiah binti Mohd Saffe:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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