# Implementation of Artificial Intelligence (AI) in Smart Manufacturing: A Status Review

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**Abstract.** In today's world, artificial intelligence (AI) is widely considered one of the highly innovative technologies. Usage of AI has been implemented nearly in all sectors such as manufacturing, R&D, education, smart cities, agriculture, etc. The new era of the Internet plus AI has resulted in the high-speed evolution of the central technologies, analyzed based on research regarding recent artificial intelligence (AI) applications in smart manufacturing. It is necessary to set up an industry that must be flexible with turbulent changes and adequately manage highly skilled employees and workers to design a more suitable working atmosphere for both men and technology. Google Scholar is widely used to explore several keywords and their combinations and search and examine the relevant articles, papers, journals, and study data for conducting this manuscript. The recent progress in intelligent manufacturing is discussed by observing the outlook of intelligent manufacturing technology and its applications. Lastly, the study talks about the scope of AI and how it is implemented in today's smart manufacturing sector of India, focusing on its present status, limitations, and suggestions for overcoming problems.

**Keywords:** Artificial intelligence · Smart manufacturing · Industry 4.0 · IIOT · CPS · Machine learning · Deep learning · RUL · ICT

## 1 Introduction

AI refers to technology having perceptive and psychological abilities. It has also authorized first-class coherent processes such as thinking, learning, perceiving, decision-making, problem-solving, data collection, segregation, and analysis to supplement human brainpower. In 1956, computer scientists Allen Newell, Marvin Minsky, John McCarthy, Arthur Samuel, and Herbert Simon developed artificial intelligence theory. Late in the 1990s and early in the twenty-first century, AI usage is rapidly transforming the globe, increasing the significance of analytics and enormous growth of computing ability [1]. Figure 1 tells us about the applications of AI/ML algorithms in different processes such as fault prediction, security, etc. In Fig. 2, various machine learning classifications and their characteristics are discussed. According to the training system and the input data type, there are three types of machine learning algorithm classifications:


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supervised learning, unsupervised learning, and reinforcement learning [2, 5].

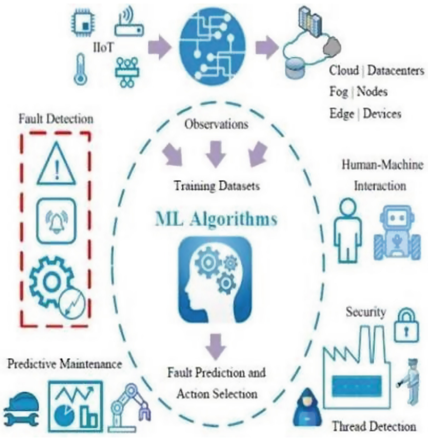


**Fig. 1.** Applications of AI/ML algorithms [5].

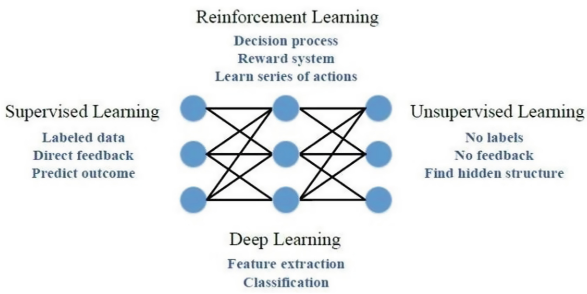


**Fig. 2.** Machine learning classifications and their significant characteristics [5].

Semi-supervised learning: this method has a small set of labeled information, and the remaining data is unlabelled hence the name semi-supervised.

Now smart manufacturing refers to the manufacturing technology aiming to provide the industrial setting for intelligent, real-time, autonomous, and interoperable production environments.

It integrates recent and innovative information and communication technologies (including 5G networks and Wifi), such as the Internet of Things (IoT), cloud computing (CC), and cyber-physical systems (CPS) powered by AI/ML decision-making technologies, and results in accurate fault detection and also real-time defective product recognition [3]. This paper describes the cycle of Industry 4.0, such as data acquisition, monitoring, connectivity, big data, smart assembling, control, and scheduling [47]. AI in intelligent manufacturing is utilized in various applications such as quality inspection, energy conservation, supply chain, and predictive maintenance [48]. The lifecycle of industry 4.0 in smart manufacturing is mentioned below in Fig. 3. While Fig. 4 describes the model of an intelligent manufacturing system and its applications [4].

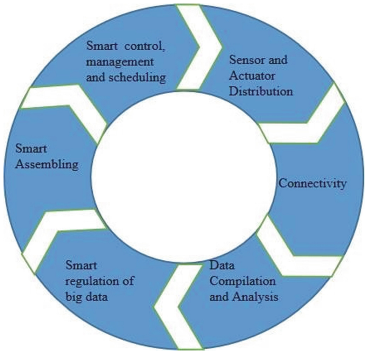


**Fig. 3.** Lifecycle of Industry 4.0 in smart manufacturing [47].

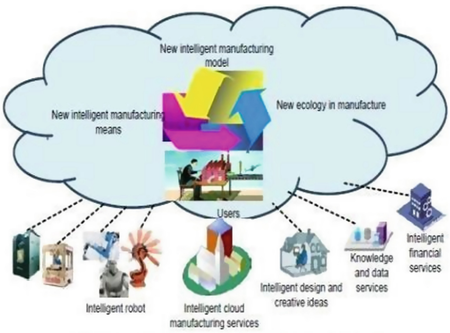


**Fig. 4.** Intelligent manufacturing model design [4].

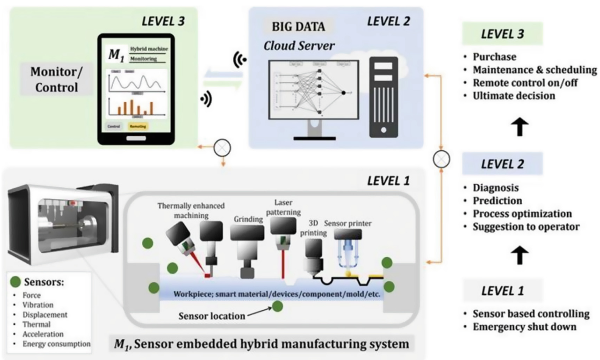


**Fig. 5.** Smart hybrid manufacturing system [2].

Autonomous sensing, learning, analysis, interconnection, cognition, decision-making, control, and information execution are included in the above figure, which integrates and optimizes the copious features of a manufacturing enterprise. AI-based

Smart manufacturing leads to enhanced worker safety, product quality, energy use, production efficiency, and fault predictions leading to a more high-yielding and secure workspace, thus engaging smart machines to carry out big tasks and assisting the human labor force getting rid of routine procedures [5]. Recently, the rise in usage of data-driven approaches has led to the achievement of monitoring and diagnosis by CPS observation and analysis that collect and communicate immense data through standardized interfaces, which gives rise to the Internet of Things [6]. Figure 5 shows an image of an intelligent hybrid manufacturing system consisting of sensors and new technology such as big data.

Machinery industries around the world have utilized the technology of smart machines and the automation of assembly lines to send the production data of these machines to a monitoring platform in real-time, such as inspection of ball-bearing malfunction, industrial data-driven monitoring, ball-bearing vibration data, remote wind turbine condition monitoring, vibration monitoring for smart maintenance and analysis of vibration time [7]. Significant cost reduction is made using predictive maintenance. This method can be proposed by prolonging the functional life of manufacturing machines and increasing overall equipment effectiveness [8]. In Industry 4.0 manufacturing, condition monitoring has been a valuable tool for improving safety, health, and equipment performance. In smart and sophisticated industrial equipment [9]. The knowledge-based intelligent supervisory system proposes a pattern recognition strategy and learning process to inspect rare quality events [10]. In this article, different types of ML and their applications in Industry 4.0 have been discussed. Also, how AI has taken place in Indian manufacturing, its scope, possibilities, and suggestions are discussed. This paper has been written to help future scientists to undergo further research regarding artificial intelligence and its algorithms in smart manufacturing. The article has also been reported to depict the Indian scenario in Industry 4.0. The Indian Government, Indian scientists, and engineers will be aware of the actual condition of Indian manufacturing and get encouraged to work with this new-age technology. Simultaneously, this article will also encourage Indian industrialists to invest capital in India's AI-based manufacturing. Last but not least, this manuscript tells us about the consequences of AI technology implementation in less developed countries, such as unemployment (due to lack of skill), to aware factory workers as well as skilled professionals of the reality regarding its actual implementation so that they will become ready to get accustomed with this new AI-based manufacturing technology.

## 2 Literature Review

AI and its powerful technologies, such as machine learning (ML), deep learning (DL), etc., are generally widespread in manufacturing. It has been evident that applying these technologies in real life requires enormous capital and efficient human resources capable of cooperative effort in surroundings [1]. The rapid advancement of machine learning has led to the massive revolution in the artificial intelligence field through which machines are allowed to learn, improve and optimize specific tasks without being programmed directly. Machine learning can be used widely in smart machining (consisting of CPSs) [2]. The Industrial Internet of Things (IIoT) provides real-time production data collecting with enhanced wireless connectivity, leading to Industry 4.0 powered by AI [5]. Remarkable progress has been made in recent years regarding database technologies, computer power, machine learning (ML), big data, and optimization methods to attain fault-free (defect-free) processes with the help of ISCS(Intelligent Supervisory Control Systems) [10]. Predictive model-based quality inspection is an innovative solution developed for industrial manufacturing applications using edge cloud computing technology, machine learning techniques, and IOT architecture. The quality inspection processes based on the predictive model are shown in Fig. 6 [11].

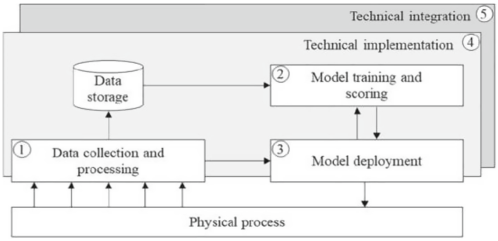


**Fig. 6.** Predictive model-based quality inspection framework arrangement [11].

Automation results in affordable cost, high reliability, and highly endurant quality inspection process in smart manufacturing industries. This helps to optimize high productivity, reliability, and repeatability. The automation process in manufacturing is run and regulated by a Programmable Logic Controller (PLC) [12]. Numerous applications of data science technologies or big data analytics in industries include process adjustment, monitoring, and optimization [13]. DL-based fault diagnosis of rotating machinery eradicates the drawbacks of traditional fault diagnosis methods [14]. Artificial neural networks (ANNs) have a long history of detecting equipment health conditions and RUL prediction in smart machines because of their effectiveness, adaptability, and many other factors [15]. If the engineers accurately implement inactive state detection in smart appliances in manufacturing, it will be beneficial in performing maintenance works, error reduction, and catastrophic failure detection [16]. The advancement of the IIoT has led to the rapid development and installation of sensors to monitor the machine condition and check whether the machine is operating and working correctly or not [17]. Incorrect readings and values of malfunctioning sensors can be estimated by accurately performing predictive analysis of big data, which can also be used in decision-making, including operation and maintenance planning [18]. Artificial intelligence, data mining, and other applications all use neural networks. A Deep Neural Network (DNN) is mainly proposed for non-linear high-dimensional regression problems, leading to the ambiguous process due to complexity [19]. Extreme learning methods are generally applied to eradicate the difficulties of a single hidden layer feedforward network and enhance generalization performance and learning capability [20]. One of the essential bearing types is the rolling element bearing. It is commonly used in the mechatronics field. The various bearing failures of rolling elements affect industrial equipment, such as productivity reduction, the rise of safety risks, and accuracy loss within this severe and harsh working environment. RUL (Remaining Useful Life) prediction is helpful in industrial manufacturing and production optimization [21]. The time-domain vibration signal features are extracted through fault diagnosis from the rotating machinery consisting of standard and flawed bearings. This can be possible with the help of ANN having input, hidden, and output layers [24]. Figure 7 shows various time-domain vibration signals.

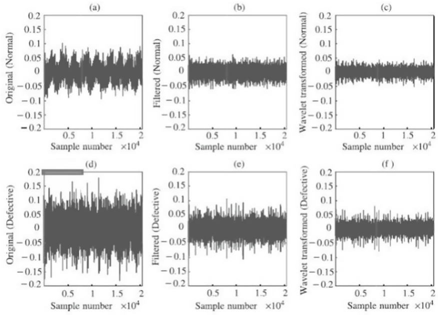


**Fig. 7.** Time-domain vibration signal: (a) acquired (normal), (b) band-pass filtered (normal), (c) wavelet transformed D2 (normal), (d) acquired (defective), (e) band-pass filtered (defective), (f) wavelet transformed D2 (normal) [24].

Machine learning techniques like neural networks help maintain and manage the considerable data complexities [23]. Cyber-Physical Production Systems (CPPS) and reducing this amount also helps to enhance machine efficiency, leading to more cost-effective output in industrial plants [22]. Data mining and ML (Machine Learning) algorithms can be executed to the data present in the SAP application to build classification models for predicting the reliability of industrial machines. [25]. Bearings are a crucial part of rotating machinery operation in most manufacturing systems. RUL and health analysis of bearings are performed to predict reliability and safety in manufacturing by increasingly providing powerful methods and processes that enable smart prognosis and bearing health management [26]. Defects present in rolling bearing may result in machine failure. But to avoid malfunctioning, early detection of faults is essential [27]. In comparison to other rotating machinery defects, rotor faults (mainly bearing and gear faults) have attracted more attention from the AI research community regarding the use of fault-specific traits in feature engineering [28]. Therefore, the vibration analysis technique predicts better reports in rolling bearing condition monitoring and fault diagnosis [46]. Oil and gas industry projects require colossal capital, including equipment acquisition and installation. The current drop in petroleum prices has limited spending, highlighting the necessity of proper maintenance management in the oil and gas business. Rotating mechanical equipment such as compressors, pumps, and induction motors are essential elements widely used in manufacturing procedures [28]. Image analysis powered by artificial intelligence enables accurate material characterization and measurement, displaying the quality of composite materials [30]. For the high-resolution images in the dataset, such as (the LCD panel cutting wheel degradation dataset), to enhance the computational efficiency, one will first extract the regions of interest from the raw image data, with 1400 × 80 pixels. After that, those regions are transformed into grey-scale images for further processing and then pretraining unsupervised data based on the dataset information [45]. Machine Learning and artificial intelligence will better identify failures, ensure quality, and improve preventative maintenance in real-world applications [31].

## 3 Methodology

We gathered, inspected, and clustered the data relevant to countless websites and different research papers as per the research requirements. The data has been collected from multiple websites together with the help of a brief introduction to AI technology and Industry 4.0. After that, the information was put compactly. Different AI and ML algorithms are used in smart manufacturing [1].

**Table 1.** Different models of prediction [11].

| Model | Accuracy (%) | Stand ard deviation (%) | Recall (%) | Pre cision (%) | Training time (1000 rows) in ms | Scoring time (1000 rows) in ms |
|---|---|---|---|---|---|---|
| Naïve Bayes | 83.5 | ±2.7 | 94.7 | 75.5 | 3 | 9 |
| Decision Tree | 88.2 | ±1.5 | 91.9 | 84.0 | 39 | 6 |
| LR | 71.9 | ±1.3 | 77.0 | 66.8 | 49 | 27 |
| SVM | 92.9 | ±1.3 | 96.4 | 89.3 | 300 | 360 |
| GBT | 92.6 | ±1.0 | 89.9 | 93.1 | 2 | 40 |

Methods such as CNN and ELM are applied in gearbox and motor-bearing datasets. The Continuous Wavelet Transform (CWT) is initially implemented to get pre-processed presentations of raw vibration signals. After that, the CNN algorithm is developed to extract high-level features, and ELM is further used to enhance the classification performance [32]. While ANN is used to classify the machine status into standard or faulty bearings, R-ELM is used to extract stator current vibration signals, detect bearing faults, and accurately achieve reliable classification, satisfying the need to see online bearing fault [33, 24]. The performance of different prediction models is shown in Table 1. Various signal processing techniques, such as STFT, WPT, FFT, etc., are proposed to overcome the challenges, such as removing background noise from vibration signals to extract the fault features with high resolution [34]. Mainly deep learning algorithms are used for regression of rotorcraft vibrational spectra [35]. Below at Table 2, it has been discussed about the input signal effect.

Generative Adversarial Networks (GAN) solve the current problems effectively encountered in defect examination of industrial datasets and identify unrevealed defects in future processing events, which led to its increased usage in Industrial Anomaly Detection [36]. In AI diagnostic techniques, spectral envelope analysis of the current remnant eliminates noise, manifesting the characteristic bearing faults [37]. Integration

**Table 2.** Effects of input signals on identifying machine conditions with five features (RMS, s2, g3,g4, g6) [24].

| Case no | Input signals | Training success | Test success | Epochs |
|---|---|---|---|---|
| 1 | 1 | 24/24 (100%) | 13/16 (81.25%) | 28 |
| 2 | 2 | 24/24 (100%) | 14/16 (87.50%) | 17 |
| 3 | 3 | 24/24 (100%) | 12/16 (75.00%) | 33 |
| 4 | 4 | 24/24 (100%) | 15/16 (93.75%) | 24 |
| 5 | 5 | 24/24 (100%) | 15/16 (93.75%) | 19 |
| 6 | 2,3 | 48/48 (100%) | 32/32 (100%) | 12 |
| 7 | 2, 3, 4 | 72/72 (100%) | 48/48(100%) | 22 |
| 8 | 1, 2, 3, 4 | 96/96 (100%) | 63/64 (98.44%) | 23 |
| 9 | 1, 2, 3, 4, 5 | 120/120 (100%) | 79/80 (98.75%) | 32 |

of RNN with LSTM can mitigate risk in rotating equipment predictive maintenance, leading to cost reduction in oil and gas operations [38]. GDAU Neural Network describes the tendency of rolling bearing degradation to have more vital short-term and long-term prediction ability, so it is more worthy for RUL prediction of bearings [21]. After undergoing extraction from the raw image data, the grey-scale images and pretraining unsupervised ML-based RUL prediction algorithms such as DCNN, DCNN-M, LSTM, NoAtt, and Nosupatt are used in the LCD panel cutting wheel degradation dataset containing images of multiple wheels having high-resolution. These RUL prediction methods provide a practical approach to prognosticative problems and partial observations [45]. Thus, recently there has been a rise in AI-based predictive maintenance and fault diagnosis in smart manufacturing, mechanical processes, and machinery.

## 4 Findings and Discussion

AI is a technology with perceptive and psychological abilities, having some high-yielding research relevant fields such as image processing, natural language processing, machine learning, etc., which is currently used in industry 4.0 manufacturing systems. Different manufacturing abilities such as Computer Numerical Control (CNC), automated guided vehicles (AGV), Direct Numerical Control (DNC), robotics, etc., are being used in smart manufacturing. Recently, the Internet of Things has taken manufacturing to another new level. The disadvantage is that, in many developing and underdeveloped countries such as India, there is a lack of resources to set up a basic structure; as most businesses operate in villages, there is a high cost of the smart infrastructure, skills, and training deficit among people in these technologies and a profitable proper investment put a barrier to implement this AI-based smart manufacturing technology. In less developed countries, unemployment is the central issue that led to numerous constraints in the absolute implementation of artificial intelligence. Other than that, according to experts AI and new age technologies only become a crisis for people who cannot adapt themselves, readjust according to the market's needs, or fail to become accustomed to new technology and skills, leading to joblessness. The probability of jobs in various fields due to artificial intelligence is shown in Fig. 8.

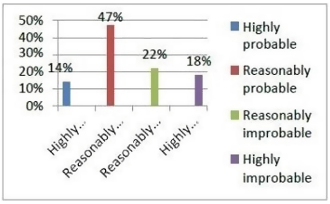


**Fig. 8.** The perceived probability of jobs due to Artificial Intelligence [45].

## 5 Research Limitation and Future Scope

Artificial intelligence and machine learning are extensively applied in today's world in different fields and purposes. Among them, smart manufacturing is one of the fields where the implementation of AI technology is at its peak. But, there are many ways to reap the benefits of artificial intelligence, such as smart maintenance, better product development, quality improvement, market adaptation, etc. Innovative care means maintaining manufacturing machines and systems more brilliantly, i.e., reducing the maintenance cost of appliances and types of equipment. As maintenance of equipment is one of the most significant expenses in manufacturing, it is necessary to implement smart maintenance such as predictive maintenance (powered by AI algorithms such as neural networks and machine learning), which will help save enormous amounts of money and enhance RUL of machinery. Through better product development, one can assess and examine the different parameters in production, such as available production resources, budget, and time, which can be implemented with the help of deep learning models and algorithms. To meet the highest standard and quality of products, machine learning, and machine vision can be used to identify, detect and eliminate faults in products and alert about the problems at the production line which may affect the overall production, leading toward production quality improvement. AI and ML techniques will help the smart manufacturing industries improve supply chains and strategic vision and make them interact with changes in the market by generating estimates relating to several factors like political situation, weather, consumer behavior, the status of the economy, etc. The utilization of AI, robots, and CPS will probably revolutionize mass production robots. CPS can perform any laborious tasks at high speed in smart factory units, eradicating human error and delivering superior levels of quality assurance. Unlike humans, AI and industrial automation can easily carry out tasks in hazardous places. Overall, AI-run smart machines can provide skilled workers, engineers, and scientists opportunities to focus on their complex and innovative functions in science, engineering, and technology rather than tedious and ordinary human tasks. But, the lack of necessary skills of workers regarding AI technology, especially in developing countries like India, may hinder the progress of AI in the Industry 4.0 manufacturing, which can only be solved by educating and equipping them with these AI-based technologies.

## 6 Indian Scenario

In India, Industry 4.0 smart manufacturing induces the industrial stalwarts to lay the groundwork for smart factories and adopt modern and innovative technologies. The Indian Government has recently initiated the Smart Advanced Manufacturing and Rapid Transformation Hub (SAMARTH). To improve the application of AI-based smart manufacturing in the current context, the Indian Government is developing a National Policy on Advanced Manufacturing [1]. Our country has achieved technological excellence by integrating Cyber-Physical Systems (CPS) and Information and Communication Technologies (ICT) into Advanced Manufacturing Technologies (AMTs). Increased automation in additive manufacturing, Advanced Manufacturing Systems, manufacturing robotics, advanced analytics, and Big Data are all worth mentioning in the design of smart manufacturing for Industry 4.0. They will help Indian MSMEs become more internationally competitive and contribute to global value creation [39]. Though adoption of artificial intelligence is less in India, there has been a remarkable transformation in all the Indian industrial sectors where companies are adopting, developing, and integrating AI technologies in their products and industrial processes, such as electronics, heavy electricals, automobiles, fintech, software/IT, agriculture, agrobased industries, etc. [40]. In terms of government funding, the Union Cabinet approved the launch of the National Mission regarding Interdisciplinary Cyber-Physical Systems (NM-ICPS) in 2019, which the Department of Science and Technology (DST) will execute with an unlimited budget of INR 3660 Cr (USD 494 Mn) for five years to make India a leader in Cyber-Physical Systems (which includes AI, ML, and IoT) (FY 2019–20 to 2023–24). The mission's goal is to build a strong and stable ecosystem for CPS technologies in India, which would help the country's Industry 4.0 manufacturing sector thrive [41]. SMEs have significant advantages in terms of innovation in general, but they face a variety of obstacles in India [42]. Though several countries have decided on their strategy for AI, India has not yet formulated its strategy in Industry 4.0 [43]. Another disadvantage is the lack of skilled workers in AI technology in our country; unemployment will rise in India. On one side cities will be equipped with all modern facilities and will be becoming smart and other side jobs will be killed due to transformation. Low and Middle skills level jobs will be shrunk, but high-skilled jobs where the critical decision will have to take will exist as machines cannot resemble human intelligence in case of making critical decisions. This transformation will add new development aspects to India's infrastructure and enhance the economic status in the coming years. However, few jobs in a few sectors will disappear because of transformation through AI in the next 5 to 10 years [44].

## 7 Conclusion

Although AI is still considered a nascent stage in Industry 4.0 manufacturing, one can still hopefully say that technological transformations are occurring. 5G technologies in communication can improve the overall efficiency and productivity, which has high network reliability and support IoT and CPS devices according to the industry requirements. Other advancements include lights-out manufacturing, which can create and regulate production with minimal human interaction, and smart and dynamic technology, which can be effective in areas with high production rates and low human error rates. Setting up an AI infrastructure platform may be costly due to advanced machines and equipment, but this reduces the labor required to finish the final product. But the advanced technology of AI-based applications in the Indian scenario will be extracted fully in the SME sector, which can be achieved 100% by providing incentives and encouragement to SMEs (because most of the people in India are employed in this sector). Similarly, the Indian educational system needs to be enhanced to enormously extract the potential benefits of these technologies.

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