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Review

Role and Applications of Artificial Intelligence and Machine Learning in Manufacturing Engineering: A Review

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ABSTRACT

The advent of cutting-edge technology and more efficient production processes in Industry 4.0 is being shaped by the use of AI, ML, embedded systems, cloud computing, Big Data, and the IoT. As smart and learning machines continue to make great strides, the need for AI is only going to grow. The integration of AI into smart manufacturing has the potential to address critical sustainability concerns while simultaneously improving supply chain efficiency, resource use, and waste management. The goal of customer-driven manufacturing capabilities, which are the foundation of Industry 4.0, is to increase productivity, sustainability, and agility. The primary use of AI and ML in contemporary manufacturing is process improvement and monitoring. Numerous disciplines, including machine learning, robotics, and the internet of things, contribute to the study of industrial AI systems. Sustainable manufacturing solutions are created, validated, deployed, and maintained using industrial AI. The proliferation of cloud computing and the subsequent precipitous decline in the price of data storage have made it possible to store and transfer vast amounts of data to ML and AI algorithms, which in turn automate and expedite many business processes. Smart process design, monitoring, control, scheduling, and industrial applications form the basis of smart manufacturing and Industry 4.0. Originally known as Internet of Things (IoT)-based technology, smart manufacturing now covers a wide variety of fields.

Keywords
Artificial intelligence (AI); Manufacturing engineering; Machine learning; Industry 4.0; Sustainability; Embedded systems; Internet of Things (IoT); Robotics; Mechanical engineering.

INTRODUCTION

Innovative and intelligent production units are necessary for the quality and sustainability of industrial operations. The Internet of Things (IoT), embedded systems, cloud computing, big data, artificial intelligence (AI), and machine learning (ML) are all playing a role in the paradigm shift toward more efficient industrial processes and cutting-edge technology. "Artificial intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs," said John McCarthy, widely recognized as AI's progenitor.[1] Machines with artificial intelligence can learn and solve problems just like humans. Several types of artificial intelligence exist, subject areas such as machine learning, computer science, data mining, genetic algorithms, neural networks, artificial intelligence, and computational theory. A number of disciplines are making extensive use of AI, including engineering, teaching, research, healthcare, finance, and marketing.

The demand for AI is always growing as a result of the fast advancement made possible by intelligent and learning technologies. The integration of AI into smart manufacturing has the potential to address critical sustainability concerns while simultaneously improving supply chain efficiency, resource use, and waste management. Optimization of industrial processes with artificial intelligence may lead to environmentally friendly production. "If we properly incorporate artificial intelligence, we can achieve a revolution with regard to sustainability," said Hendrik Fink in 2019, while serving as head of sustainability services at PricewaterhouseCoopers. AI is going to be the engine that propels the fourth industrial revolution.[2] in Industry 4.0 aims to improve production capabilities based on consumer needs, leading to more agility, sustainability, and productivity. The primary use of AI and ML in contemporary manufacturing is process improvement and monitoring. Machine learning (ML) is a branch of artificial intelligence (AI) concerned with the collection of data for the purpose of automating learning processes and building a knowledge base. In industrial processes, AI and ML may form a complete data monitoring system that is backed by cyber-physical systems (CPS), IoT architectures, and the ability to analyze Big Data. Industries may equip themselves with substantial increases in efficiency, quality, and productivity via the exploitation of critical data, which is primarily driven by the technological paradigm shift for Industry 4.0. In today's industrialized world, ML is important for optimizing processes. By developing new services with the intelligence to operate independently and using analytically adept tools, AI may boost production performance. In smart manufacturing, optimization of the whole value chain is done in real-time, in addition to enhancing the core production process. Self-awareness, self-monitoring, and self-optimization are techniques that CPS's use to improve industrial processes. Artificial intelligence is a game-changer in Industry 4.0, which is shaking up production methods and the way companies do business as usual. Artificial intelligence systems have the ability to see their surroundings, analyze pertinent facts, resolve complex issues, and adapt their answers over time.

Numerous disciplines, including machine learning, robotics, and the internet of things, contribute to the study of industrial AI systems. Sustainable manufacturing solutions are created, validated, deployed, and maintained using industrial AI. By including these domains, industrial systems are able to adapt and solve problems autonomously within certain limits. Using AI, which is easily accessible, managers, scientists, and executives may increase company efficiency. Massive data sets may be stored and sent to ML and AI algorithms to automate and expedite various organizational operations, thanks to the proliferation of cloud computing and the dramatic drop in data storage prices. In addition, machinery and tools are becoming more intelligent. To adapt to the ever-shifting needs of a global market, intelligent manufacturing makes use of cutting-edge AI technology to achieve smart, adaptable, and reconfigurable machine processes. The whole product lifecycle and value chain are enhanced using smart sensors, improved materials, data analytics, smart devices, and flexible decision-making tools and models. Incorporating cutting-edge models and efficient techniques, the Intelligent production System (IMS) has transformed traditional production processes into smart systems, realizing this vision for the future of manufacturing.[4]

According to the German Ministry of Education and Research, "Industry is on the threshold of the fourth industrial revolution" [5]. The convergence of the physical and digital realms is giving rise to the "Internet of Things," which is being propelled by the expansion of the internet. Connectivity and communication between smart devices are made possible by the Internet of Things (IoT), a network system. When setting up an IoT system, two separate but equally important factors are needed: first, a full suite of tags and sensors to collect data from different processes and stages; and second, software protocols for transmitting and storing this data to a central server.[6] Data sent across this network of systems connecting physical and computational elements is managed and analyzed by the CPS. The Internet of Things (IoT) is an integral part of modern networks and systems, allowing for post-data feedback and real-time information collecting.[7] Data collecting, smart sensing, autonomy, and feedback mechanisms are the different systems that make up CPS. Furthermore, cloud computing is a crucial part of Industry 4.0 since it allows for the management and storage of real-time data as well as the provision of data storage and Big Data analytics. Potentially game-changing uses of Industry 4.0 include data storage and analysis of massive data flows.

Both businesses and universities are interested in Industry 4.0. Various studies have focused on the business sector 4.0 together with its uses, developments, structure, and obstacles. While smart manufacturing has advanced thanks to the integration of AI and ML, very few studies have attempted to link Industry 4.0 with this development. The function of artificial intelligence and machine learning in Industry 4.0 must be clarified, and the results of academic and business studies on smart manufacturing must be compared. The main reason for this review is this. The writers will use Table 1, which gives an overview of industry-wide technology integration, to set the stage for their discussion of artificial intelligence and machine learning, smart manufacturing, process optimization and control, defect detection, computing, and data storage.

2. AI in Smart Manufacturing and Industrial Evolution

Smart process design, monitoring, control, scheduling, and industrial applications form the basis of smart manufacturing and Industry 4.0. Figure 1 shows the main parts of this structure. Originally known as Internet of Things (IoT)-based technology, smart manufacturing now covers a wide variety of fields. Methods connected to CPS, the IoS, Big Data, analytics, and sophisticated robots are all part of smart manufacturing. Products have become accessible and networked thanks to the spread of CPS/IoT and smart items, which has allowed data-gathering to facilitate precise targeting for fast and effective decision-making. Also, when you include in the impact of real-time data,

Fig. 1 Advantages of integrating smart manufacturing and AI in industrial processes.

2.1 Process design

Modern technology, such as AR and VR, has transformed smart and efficient production from the old ways of doing things.The use of hybrid prototypes has made virtual reality (VR) a reality in manufacturing, and CAD/CAM software can now have direct, real-time conversations with physical systems via AR, VR, and CPS. In order to accomplish the pinnacle of automation, current engineering techniques are adapting to integrate smart production technologies.[8]

2.2 The use of VR and AR

Virtual reality (VR) is a technology that uses computer-generated images to create an illusion of a real-world environment for its users. Tech workers in smart manufacturing are getting their training in virtual reality. Virtual reality allows engineers and technicians to experience production processes and the difficulties they face in the workplace. Virtual reality (VR) creates a digital replica of a process or product, eliminating the need to invest in costly prototyping and testing.[9] Manufacturing and testing digital processes may be seen in virtual simulations, which allows for more efficient product cycles and quicker innovation. Then then, augmented reality is a virtual setting made to study actual industrial issues and their solutions. Training, data validation, and product testing form the basis of the process, which provides substantial time and money savings.[10]

2.3 Intelligent devices

A new era in production has begun with the introduction of intelligent tools, robotics, and manufacturing agents. Autonomous behavior and decision-making supported by real-time data are hallmarks of agent-based systems. In a similar vein, CPS systems enhance smart machine tools by recording and processing data via cloud computing. Due to the inherent quality control processes in smart systems, quality checks performed after processing are superfluous. the eleventh

24. Smart surveillance

When it comes to smart manufacturing, monitoring systems are vital for scheduling, routine equipment maintenance, and day-to-day operations. Temperature, vibration, speed, and energy usage are only some of the metrics recorded by a sensor network that spans the whole production line. All production processes are monitored by data visualizations and CPS systems, which may send out warnings when anything out of the ordinary happens. The tools needed for these huge data analytics are provided by multi-task agents, CPS, cloud computing, and the Internet of Things (IoT).[12]

2.5 Smart command

Industry 4.0 equipment can be better controlled with the help of CPSs and multi-agent systems. Smart control controls and monitors processes remotely with cloud computing. Manufacturing may be optimized and process efficiency can be increased via the use of decisions. Thanks to the proliferation of mobile internet devices, cloud computing, and mobile communication technologies (such 5G), industrial AI has become an essential component of smart industry, which relies on the contemporary internet. The integration of industrial AI with generic use AI to achieve new uses, such as creating cutting-edge models, smart manufacturing, better decision-making, and resource allocation. With the help of industrial AI, smart industries and machines can now observe, execute, learn, adapt, and decide on their own. This means that the system can handle a wide range of industrial duties and adapt to different circumstances as they arise. Consequently, it becomes possible to maximize the utilization of resources and equipment, enhance product quality, and streamline processes. Businesses and smart industries may improve their operations with the help of industrial Big Data collected over the internet and cloud computing. This data supports their efforts to study and create new AI technologies, such as:

Revolution in industry (2.5.1)

In 1760, as a result of the textile industry's development, the first industrial revolution began. In terms of investment, opportunity, and outputs, industries saw substantial expansion. This expansion potential mainly benefited the railway, mining, coal, and iron sectors. For financial and material benefit, economies that relied on agriculture moved to industry.in [13]

The discovery of fossil fuels like coal, gas, and oil sparked the second industrial revolution, which in turn led to the creation of cutting-edge machinery and consumer goods. Steel, fertilizers, dyes, motors, ships, chemicals, apparel, and transportation were all greatly improved by new industrial techniques. Contemporary means of communication, such the telephone and telegraph, played an essential role in this transformation. A framework for energy development and distribution was established to include electricity into society's modernization.[14]

Programmable logic controllers (PLCs) and robotics for process automation ushered in the third industrial revolution immediately after WWII. Massive R&D in telecommunications, processors, computing, transistors, and computers has created new possibilities for long-term industrial growth. When it came to automation, information technology and electronics saw revolutionary developments throughout this third revolution.[15]

The phrase "Industry 4.0" was first used by German researchers in 2011 to characterize the fourth industrial revolution.[16] The convergence of cloud computing, the internet of things (IoT), artificial intelligence (AI), machine learning (ML), and the real-time gathering of data for financial analytics is the foundation of this fourth revolution. In addition to integrating various production systems and processes, Industry 4.0 also uses artificial intelligence algorithms to make intelligent judgments. It encompasses manufacturing process automation, augmented reality, and virtual reality. However, traditional production methods may not be completely upgraded and adopted to an Industry 4.0 infrastructure.[13]

3. Applications of ML and AI in manufacturing industries

When it comes to smart manufacturing and other contemporary industrial processes, AI plays a crucial role in solving problems. The modern industrial sector has seen substantial advancements in a crucial subset of artificial intelligence and machine learning. Datasets that may be used by ML models are in high demand due to the fact that industrial processes are constantly evolving. Tools like data analytics, automation, and deep learning rely on these datasets. A key component of contemporary industry, neural networks help improve production efficiency by constantly monitoring processes and identifying outliers.[17] Figure 2 shows the industrial AI framework and system architecture, which includes these important parts.

3.1 Optimisation of processes

Manufacturing processes may be optimized and improved with the use of data analytics and ML, which can give the best possible parameters. Faster, more tailored mass production with little waste will be possible in the next decade thanks to manufacturing and industrial analytics made possible by the growing convergence of machine learning and process optimization. The effective use of real-time data sets to enhance injection molding operations was investigated by Rønsch et al.[18], who gathered information from over a hundred molding machines. Achieving high process accuracy via the integration of ML was the focus of their investigation. According to the study's findings, current The data from manufacturing processes does not capture or reveal the variations in raw materials that impact product quality. However, by including extra monitoring sensors into the molding process, more accurate raw data may be obtained. In order to have accurate and up-to-the-minute data, the study worked with many industries.

To increase output in make-to-stock product production, Lorenz et al. [19] introduced a novel data-driven strategy. The method that was put into place made use of process mining to dynamically map and analyze complicated manufacturing processes that needed automation variations in a methodical manner to boost efficiency. Experimental validation of the data was carried out by the research, which used this model as a case study for a prominent manufacturer of sanitary products. The findings provided producers with suggestions for improving manufacturing procedures. Using regression trees and classification techniques, Zangaro et al.[20] outlined and evaluated a learning-driven supervised solution for the line feeding problem (LEP). A decision tree was constructed using data from various components, tools, and real-time production processes. The tree then proposed a line feeding mechanism for optimization. In addition, they established a repair approach that provided workable answers and suggestions with acceptable average cost addition for cases when no apparent solution could be found. In terms of optimising the line feeding mode, the proposed solution was spot on. 'Progress in hardware, data analytics, and software in integrating AI for industrial applications.' Table 2 presents topics that these research support. Use of artificial intelligence and data analytics in business settings is appropriate for the approaches outlined in the table.

3.1 Human and robot collaboration

Industrial AI offers significant potential to strengthen human– robot collaboration and give support to existing human-centric jobs on the production line, whether by increasing operator safety and welfare or by optimizing tasks in a more efficient manner. Current potential for Industrial AI in the manufacturing sector includes workforce training, planning, monitoring, assistance, and collaborations with robots. Given this potential, human–robot collaboration must be studied further to enable stakeholders within manufacturing to fully utilize the advantages of Industrial AI. By using AR or VR, human–robot interaction may facilitate and improve such manufacturing processes as maintenance, assembly, and remote diagnostics.

3.1.1 Operations and planning

Various industries have complex work sequences, and any slight issue can have a significant impact on process efficiency, cost, quality, time, and waste management. The operation of any machine consists of various tasks and requires different tools. AI and ML can be used to operate and plan these complex work sequences through neural networks and algorithms. Research studies have used various AI and ML models to plan, optimize, and increase the efficiency of manufacturing processes.

Rentsh et al.[21] employed fitness function algorithms and genetic models to optimize resource and energy efficiency in production line designs and process operations. Brik et al.[22] classified employees and workers in a model based on the disruption model, utilizing supervised techniques such as regression, random forest (RF), and decision-making tree techniques. In choosing an algorithm, the study evaluated the classification accuracy of a process and considered modeling and prediction times. Using completely random trees, gradient-boosting trees (GBT), and RF, Walther et al.[23] forecasted and predicted the factory load in advance. Before selecting an algorithm, researchers carried out selection or detection by modeling it and eliminating repetitive features. The study implemented the model with a feature of engineering that makes use of moving averages to improve the performance and efficiency of the selected algorithms.

3.1.2 Monitoring

Monitoring is one of the most important processes to optimize manufacturing and gather real-time data for analytics. Industries need constant monitoring of the manufacturing process to identify faults and rectify or even predict the fault to avoid undesirable results. ML can train the models by feeding the data of these complex processes; based on the input data, these models can then predict future faults. Smart sensors can gather data that is, otherwise, impossible to gather. Smart monitoring integrates with IoT, data analytics, and cloud computing in Industry 4.0. In this context, Table 3 presents an overview of the diverse processes and algorithms employed in manufacturing. The table serves as a valuable reference for the discussion on the utilization of ML and AI in manufacturing, as demonstrated in the following examples.

Computer-based monitoring is an important aspect of Industry 4.0 that includes both ML and AL. The latest sensors, such as RGB detection camaras equipped with ML, have proven efficient and effective in monitoring with higher output for inspection. Computer vision gathers data in the form of videos and images fed to ML for analysis and optimization, enabling a process to continuously monitor the smart manufacturing. Chen et al.[24] analyzed and implemented a data-driven system to detect wire bonding defects in the manufacturing of integrated circuits (ICs). The method used data processing to separate and locate defects in images of ICs. Data were gathered through X-ray imaging from the assembly line. ML algorithms such as SVM (Support Vector Machine), VDS (Velocity Distance Support), and CNN (Convolutional Neural Network) were employed to develop the modern monitoring and inspection system for ICs fabrication. SVM was found to be the most useful of the algorithms in terms of fault detection. Zhang and Gao[25] employed an ML-based detection system for optimization of reagent for floatation during extraction of iron ore. During the extraction of minerals, especially iron, workers must constantly adjust the dose of reagent; the quality of the final extracted mineral is dependent on the dosage. ML algorithms were developed using neural networks. A database was built using images of flotation tailings to differentiate the grade of iron ore. After using more than 13 artificial neural networks, an optimized ML-based system was developed that had 97% accuracy in detection variations.

3.2 Process control and fault detection

The efficiency of smart manufacturing improves with advanced fault detection systems that aid in process sustainability. Modern tools combined with ML algorithms help in achieving a strategic edge over competitors. The use of high-end manufacturing fault detection systems not only improves the production time but also ensures high-quality products for end users. Wang et al.[52] explained and analyzed a method based on CNN-DLSTM learning to detect faults in the manufacturing of rolling bearings. The fault diagnostic system was based on deep long short-term memory (DLSTM) and convolutional neural networks (CNN). The study primarily focused on the faults in bearings for different working conditions in which gathering large-scale data proved difficult. Deformable CNN enhanced the ability

of standard CNNs for local feature extraction using fixed geometric structures. DLSTM further encoded the sequential information contained in the output of deformable CNN. Dense layers were applied to capture high-level features and then classify them into data samples for different fault types. Approaches such as transfer learning were used to feed data for pre-training a fault detection mechanism using sample data from various working conditions. The model could then be used to optimize other conditions and processes. The developed framework, combined with real-time data, exhibited better output efficiency and results. Additionally, Glaser et al.[53] studied the vibrations of various production machine to assess the conditions of machines. Deep learning techniques, such as deep tree (DT) and CNN, were used to study the relationship between machine condition and faults in products. Data on vibrations of machines in cold forging industries were collected. CNN was able to detect faults with 99.6% accuracy, while DT detected faults with 92.5% accuracy without classification.

3.3 Quality assurance

Using ML and AI, quality control can be automated completely. Smart manufacturing and AI can inspect all the final output for quality checks. This can dramatically reduce the number of products reaching end users. Smart monitoring systems can detect color, texture, physical shape, tolerance, and packaging. The intrinsic complexity of modern manufacturing units (comprising machining, production line, and assembly), together with unanticipated interruptions and various uncertainties, make it extremely difficult to ensure product quality in sectors like aerospace and automotives and in modern manufacturing in general. As a result, effective solutions for automating and detecting problems are valuable to manufacturers. These solutions are based on real-time data and AI and ML models. Automated detection and visual inspections—enhanced with deep learning approaches to predict possible defects—are used to prevent issues in manufacturing processes, opening the possibility of zero-fault production models.[54]

3.4 Enhanced security of industries

Industry 4.0 uses many data sets and sources, as well as newer technologies such as cloud computing, IoT, blockchain, and AI, to improve and optimize manufacturing process efficiency. However, this comes at the expense of potential cybersecurity vulnerabilities and threats.

Federated learning techniques, which distribute the training and learning process among industrial manufacturing nodes, have recently emerged as a solution to address stated scalability and privacy difficulties. These nodes have the ability to collaborate by using only local characteristics in development of a model using central learning tools without sharing any sensitive and important private data sets.[55] Although this is a significant improvement in terms of addressing important security and data privacy issues, new studies have pointed out a number of risks associated with federated learning tools, particularly with regard to attacks, such as reverse engineering, that can directly extract important information based on real-time datasets.[56] Future research must focus on privacy aspects of AI and ML models by employing differential privacy and safe multi-party computational techniques.

Smart and modern manufacturing industries are using integrated communication frameworks to share real-time data for processing units. The communication is based on network connectivity through the internet. This massive movement of data requires state-of-the-art security protocols and end-to-end data encryption to avoid data misuse and attack. Every networking node must be protected by designing the smart manufacturing unit with integrated security systems in place.[57]

3.5 Data analytics

The goal of smart manufacturing is to translate and transform real-time data analytics into efficient output for intelligent manufacturing processes. Modern industries have more than 100 EB data gathered annually from manufacturing processes. Big Data analytics can be used in optimizing and maximizing process efficiency through timely decisions.[58] In short, Big Data is a necessary part of smart manufacturing and Industry
4.0. Manufacturers have started to realize that this enormous amount of data holds great strategic value, dependent not merely on the collection of the data but the underlying knowledge base that can be proven very effective. Dubay et al.[59] explained the worldwide manufacturing practices and use of AI and Big Data analytics for sustainable growth. The integration of IoT, Big Data and smart manufacturing units has enabled the exploitation of the data to the fullest. The study briefly explained the relationship between Big Data and smart manufacturing, arguing that the lack of implementation of research studies to industrial manufacturing has resulted in a huge gap in defining the effective role of data analytics. Research on Big Data concentrates on value addition, but there are other factors of considerable relevance to smart manufacturing, including velocity, volume, and variety. Studies by Brown et al.[60] stressed the importance of Big Data analytics for manufacturing planning, business decision-making, sustainability, environmental implications, supply chain, human resources, and lean manufacturing. Smart manufacturing and Industry 4.0 are dependent on customer satisfaction using Big Data analytics for enhanced efficiency, speed, cost, and quality. Ultimately, Big Data analytics boost the user experience through constant process innovation and timely business decision-making.

Big Data involves multi-source product data gathered from the life cycle analysis in manufacturing. The data are considered based on quantity (volume), variety (diverse heterogeneous data sources), velocity (high-speed data gathering), veracity (diverse uncomplete data with errors, approximations, and inconsistency), and value addition (the outcome of data analytics). Big Data from manufacturing can be divided into management data, user data, product data, and public data.[61] Management data can be collected through smart manufacturing systems, and data analytics aids in planning, management, maintenance, job assigning, sales, marketing, and inventory management. The management data analytics can further be extended to customer service as well as financial management of the manufacturing units. The equipment data is used to optimize the processes and monitor process parameters to assess real-time performance. Different internet sources and public data can strengthen the supply chain for different demographics and meet the supply and needs of end users. Large industries use efficient and cost- effective data collection and processing systems, such as IoT and data computing, to digitize manufacturing capabilities.

3.5.1 Data collection

The data collection process in the manufacturing industry takes a variety of forms, such as IoT, smart sensors, and intelligent systems. In industrial manufacturing units and products, for example, built-in integrated sensors enable continuous measurement, monitoring, and reporting of real- time operational parameters like pressure, temperature, and vibrations. RFID is used in identification, management of numerous workpieces, tracking, and raw material inventory management for production. Additionally, the development of internet connectivity opens the door to collecting user data via smart terminals such as PCs, mobile phones, tablets, and laptops. Data can also be gathered using software development kits and other programming interfaces. Additionally, web crawling is a popular data acquisition method to gather public data based on specific criteria and boundaries established by engineers and AI. Web crawling is the process of using "crawler" programs to search publicly accessible web pages and information to gather useful data.

3.5.2 Data storage

The massive amount of data gathered within manufacturing operations needs successful integrating and secure storage. Manufacturing data comprises three categories: structured data, e.g., numbers and tables; semi-structured data, e.g., graphs, trees, and XML documents; and unstructured data, e.g., log books, audio files, videos, and imaging. The management of unstructured data in corporate databases is challenging, which is why industrial manufacturers have always placed a strong emphasis on storing structured data. Cloud computing provides cost-effective and efficient data storage solutions.

3.5.3 Data processing

Data processing is a term for operations used to extract information from a massive chunk of data. Data visualization aids manufacturers in making calculated, informed, and logical decisions. Data must be pre-processed systematically to eliminate redundant, identical, false, and inconsistent information. Data sorting and cleaning includes the following tasks: missing values, improper format, duplication, and junk data cleaning. The latest data reduction processing can organize and simplify the enormous volume of data. ML and AI can be applied to process filtered data. Data analytics employs computing resources, various forecasting models, data crunching techniques, and predictions to present insights and forecasting of manufacturing unit performance.

3.5.4 Data-driven smart manufacturing

Optimization of manufacturing is dependent on the exploitation of Big Data. Data analytics through AI and ML have shifted the paradigm toward smart manufacturing. Big Data analytics is employed to process, store, and gather real- time data. As Tao et al.[61] explained, the data-based smart manufacturing framework is divided into four unit types: manufacturing, data, monitoring, and processing. Manufacturing units may be autonomous and perform various manufacturing activities, including input and output of products, collection of data, and monitoring of human interactions. Data units are related to collecting manufacturing data that is fed through cloud computing. The data are thoroughly analyzed for actionable decisions and outcomes. Data analytics is employed in planning, designing, and manufacturing to enhance process efficiency. Monitoring units get the manufacturing data in real time for the development of optimal and sustainable process strategies. Processing units are designed for the swift processing of massive amounts of data to predict issues, diagnose problems, and recommend effective solutions.

3.5.5 Tuning AI and ML models for manufacturing

Once an AI or ML model has been trained, it is important to tune the model to improve its performance on manufacturing data. Tuning can be done by adjusting the hyperparameters of the model. Hyperparameters are parameters that are not learned from the data but are instead set by the user.

There are a variety of hyperparameters that can be tuned in AI and ML models. Some common hyperparameters include the following:

- Learning rate: The learning rate controls how quickly the model updates its parameters during training.
- Number of epochs: The number of epochs is the number of times the model will iterate over the training data.
- Batch size: The batch size is the number of training examples that are used to update the model's parameters at each iteration.
- Regularization parameters: Regularization parameters are used to prevent the model from overfitting the training data.

The optimal hyperparameters for a given model will vary depending on the specific manufacturing data that is being used. It is important to experiment with different hyperparameters to find the set of hyperparameters that results in the best model performance.

Here are some specific examples of how tuning can be used to improve the performance of AI and ML models in manufacturing:

- Tuning a predictive maintenance model: A predictive maintenance model can be tuned to improve its accuracy at predicting when machines are likely to fail. This can be done by adjusting the hyperparameters of the model, such as the learning rate and the number of epochs.
- Tuning a quality control model: A quality control model can be tuned to improve its accuracy at detecting defects in products. This can be done by adjusting the hyperparameters of the model, such as the batch size and the regularization parameters.
- Tuning a production optimization model: A production optimization model can be tuned to improve its accuracy at predicting the optimal production schedule. This can be done by adjusting the hyperparameters of the model, such as the learning rate and the number of epochs.

Tuning is an important part of the process of developing and deploying AI and ML models in manufacturing. By carefully tuning the hyperparameters of a model, manufacturers can improve the performance of the model and achieve better results.

4. Limitations and prospects of AI and ML

Most manufacturing systems carry out multiple operations following predetermined production logic and plans utilizing conventional process machines. To support these machines, manual and paper-based working methods are frequently employed. Under this method, there are several difficulties. First, low working efficiency is caused by the lengthy procedures, executions, and interactions that take place on shop floors when many people are involved. For instance, whenever there are re-engineered designs, the technicians, machine operators, chief engineers, and floor supervisors typically gather to propose a solution. It is extremely normal for these meetings to take four hours or longer, as all parties must first share information or related data to assess the present situation to find a workable solution. Second, paper data sheets or record books are typically used for data collection. The WIP level, working components, and other crucial information must be recorded by various personnel. Workers are often preoccupied with running equipment and dislike spending time entering data for non-value-added operations. Third, shop floor supervisors must utilize data to make decisions about scheduling and planning production. Unfortunately, most decisions are based on information and data from paper sheets or record books, and these decisions are often irrational and impractical. This is because managing a large number of paper sheets and cards, where the information collected is constantly delayed, takes a great deal of time and work.[62] For most industrial organizations, real- time data collection is necessary to progress with Industry 4.0. IoT and CPS may present a solution.

4.1 Trust in AI and ML

Trust features extensively in a wide range of social scientific topics. There are different definitions and analytical frameworks used to examine the trust factor. Although trust is frequently and naturally used in speech and everyday work, it remains difficult to explain and define the concept. Andras et al. explained how trust is treated across several disciplines and professions:

"In the social world trust is about the expectation of cooperative, supportive, and non-hostile behavior. In psychological terms, trust is the result of cognitive learning from experiences of trusting behavior with others. Philosophically, trust is the taking of risk based on a moral relationship between individuals. In the context of economics and international relations, trust is based on calculated incentives for alternative behaviors, conceptualized through game theory.[63]

Mayer et al.[64] identified three main aspects of trust: Benevolence, Ability, and Integrity. Similarly, Dietz and Hortog[65] discussed different forms and types of trust, i.e., belief, decision, and respective actions. This study emphasized the importance of these three crucial forms of trust to get useful results out of the system. As concerns the latest technologies and systems, the main issues requiring trust are the handling of vast amounts of data, safeguarding privacy, and preventing data misuse. A trusted and secure cybersecurity setup, as illustrated in Fig. 3, goes a long way in establishing user trust.

Fig. 3 Lifecycle of trust for AI and ML.

5. Discussion

The discussion portion delves further into the issue at hand, offering a thorough analysis that emphasizes the significance of artificial intelligence and machine learning in the industrial sector. In addition to outlining the potential benefits and drawbacks of these technologies, this part shows how you may get engaged in creating and using AI and ML in production in the future.

5.1 AI and ML in smart manufacturing

The industrial sector is seeing fast change as a result of AI and ML. Automation, increased efficiency, and process optimization are all goals of these technological advancements. Systems driven by AI and ML may gather and evaluate data from many different places, such as sensors, machines, and humans. Better judgments about industrial processes may be made using this data. Artificial intelligence and machine learning have the potential to automate many human-intensive processes in the industrial industry. Workers may then be free to concentrate on tasks that provide more value. Quality assurance, predictive maintenance, and other similar processes may be mechanized with the help of AI and ML.to the administration of the supply chain.

Manufacturing efficiency may also be enhanced with the aid of AI and ML. Production schedule optimization, waste reduction, and product quality improvement are all possible with AI-powered systems. Improved and more environmentally friendly production methods are another area where AI and ML may be put to use.

5.2 Problems and possibilities

Although artificial intelligence and machine learning have great promise for the industrial sector, there are still certain obstacles that must be overcome. New data storage and processing solutions are needed to manage the enormous volumes of data produced by industrial processes, which is a difficulty. A further obstacle is the need to create trustworthy and safe ML and AI systems. Producers must have faith that these systems are foolproof and impervious to hacking attempts.

Despite these obstacles, AI and ML provide enormous prospects for the industrial sector. By increasing manufacturing's efficiency, productivity, and sustainability, AI and ML may completely transform the sector.

5.3.3 Artificial intelligence and machine learning's place in the industrial sector's future

It seems like AI and ML will have a bright future in manufacturing. These technologies are already quite strong and adaptable, and they will only grow in strength and versatility from here. As a result, artificial intelligence and machine learning will find novel uses in the industrial sector. One potential use of AI and ML is the creation of adaptive, self-optimizing industrial systems. Personalization of goods to suit specific tastes and requirements is a potential use of these technologies. More eco-friendly and long-lasting production methods might be created with the help of AI and ML. One potential use of AI and ML is to improve energy usage while simultaneously reducing waste. The use of AI and ML in production has promising future prospects. These innovations may revolutionize manufacturing by making it greener, faster, and more efficient.

5.4 The Function of Both Government and Business

When it comes to manufacturing, AI and ML may be game-changers if the government and industry work together. Governments have the power to support technological advancement by allocating funds for research and development and by enacting laws that promote the use of these technologies. The private sector may contribute by funding AI and ML studies and by collaborating with public agencies to create rules that encourage the use of these technologies.

6. Conclusion

This overview follows the evolution and widespread use of algorithms based on artificial intelligence and machine learning in the business world. Findings from the study shed light on the most important current tendencies in industrial AI as they pertain to the study and deployment of cutting-edge technologies and domains for AI that leverage real-time data analytics. When it comes to incorporating AI into different applications, it finds, names, and describes the basic design ideas that are involved. The development, application, and deployment of next-generation Industrial AI systems, especially for the manufacturing industry, are influenced by these ideas. Smart process design, monitoring, control, scheduling, and industrial applications form the basis of smart manufacturing units' operations, according to this comprehensive assessment that analyzed the capabilities of these contemporary systems in detail. Smart manufacturing integrates techniques from CPS, the Internet of Things (IoT), sophisticated robots, big data, and analytics. Through intelligent manufacturing, these technologies are revolutionizing the globe. Data analytics, sophisticated artificial intelligence algorithms, human factors, and real-time data all work together to improve production capacities. The integrated capabilities of modern AI and ML-based production systems, including smart monitoring, defect detection, and smart controls, have caused a revolution inside industries.

REFERENCES

1. 1. In their article titled "Emerging Technologies to Combat the COVID-19 Pandemic" published in May 2020, Raju Vaishya, Abid Haleem, Abhishek Vaish, and Mohd Javaid discuss
A novel COVID-19 detection and diagnostic system using an Internet of Things (IoT) based smart helmet was developed by M. N. Mohammed, Halim Syamsudin, S. Al-Zubaidi, Sairah A.K., Rusyaizila Ramli, and Eddy Yusuf in 2020.
3. In 2020, the authors Maghdid, Ghafoor, Sadiq, Curran, and Rabie published a study. A design study for an innovative AI-enabled framework for coronavirus COVID-19 diagnosis utilizing sensors integrated in smartphones. publication date: 2003.07434.

Section 4, Karvekar, S. B. (2019). utilizing gait analysis, humans may be detected in industrial settings utilizing smartphones. That may be found at: https://scholarworks.rit.edu/theses/10275/. Last updated on February 1, 2020

5. The authors of the article are Rodríguez Jimenez, Bennett, Ortiz Garcia, and Cuesta Vargas (2019). A case study on the use of surface electromyography and acceleration for fatigue detection during the sit-to-stand test. No. 19, Sensors, 2019, 4202

6. The authors of the article are Story, A., Smith, C. M., Garber, E., Hall, J., Ferenando, G., and Abubakar, I. The publication year is 2019. Conducting a multi-center, analyst-blinded, randomized, controlled experiment to determine the superiority of smartphone-enabled video-observed vs directly observed therapy for TB. Volume 393, Issue 10177, Pages 1216–1224 of The Lancet.

In 2018, Lawanont, Inoue, Mongkolnam, and Nukoolkit published a study. Using the idea of extended use categorization, a system may be built to monitor neck position using image recognition and sensors included in smartphones. 13(10), 1501–1510, International Journal of Electrical and Electronics Engineering (IEEE Journal).

8. In a study published in September 2019, Nemati, Rahman, Nathan, Vatanparvar, and Kuang were involved. A thorough technique for cough type identification. Proceedings of the 2019 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE) (pp. 15-16). The IEEE

AI and Big Data for Coronavirus (COVID-19) by Quot-Viet Pham, Dinh C. Nguyen, Thein Huynh-The, Won-Joo Hwang, and Pubudu N. Pathirana Volume 8, 2020: Pandemic: A Survey on the Current State of the Art

10. Brunschwiler, T., Wang, S., Ko, B., Wood, D., and Vhaduri, S. (2019, June). Detecting snoring and coughing throughout the night using smartphone microphones in loud situations. Paper presented at the 2019 IEEE International Conference on Healthcare Informatics (ICHI), volume 1, pages 1–7.

11. In 2020, Rao and Vazquez published a study. During a quarantine, an artificial intelligence framework surveying the populace via mobile phones may help identify cases of COVID-19 more quickly. Hospital Epidemiology and Infection Control, 1–18.This article has a DOI of 10.1017/ice.2020.61.

12. An article published in March 2020 by Allam and Jones. Regarding the COVID-19 pandemic and the smart city network: using AI and universal data sharing standards to improve municipal health management and monitoring. Healthcare (issue 8, number 1, page 46). MDPI.

13. In a publication by Maddah and Beigzadeh (2020). The pilot research examined the use of a smartphone thermometer to track changes in heat conductivity in diabetic foot ulcers. Article published in the Journal of Wound Care, volume 29, issue 1, pages 61–66.

14. Ai Ting, Yang Zing, Hou Hing, Zhan Cing, Chen Chen, Lv W, Tao Q, Sun Z, Xia L. "An analysis of 1014 cases involving coronavirus disease 2019 (COVID-19) in China: correlation of chest CT and RT-PCR testing" (2020), according to Radiology, doi:10.1148/radiol.2020200642.

15. J.P. Liu, M. Yang, N. Robinson, S.B. Liang, Y.X. Shang, Q.L. Tang, H. Luo, and M. "Can the 2019 coronavirus disease (COVID-19) be prevented through the use of Chinese medicine?" A survey of seminal works from the past,

scientific data and existing initiatives for disease prevention "Chinese Journal of Integrative Medicine" (2020), 10.1007/s11655-020-3192-6

Matthew Javaid, A. Haleem, R. Vaishya, and I.H. Khan "A cutting-edge technology to embrace: artificial intelligence (AI) applications in orthopaedics" The article "J Clin Orthop Trauma" was published in 2019 and may be accessed at 10.1016/j.jcot.2019.06.012.

The COVID-19 coronavirus epidemic is space-time dependent, according to Biswas and Sen (17). March 6, 2020, arXiv:2003.03149.

P. Richardson, O. Oechsle, C. Tucker, J. Stebbing, A. Phelan, I. Griffin, D. Smith, and A. PhelanCOVID-19: avoiding inflammation while combating the virus Public Health Diagnosis (2020 February 27)

R. Agha, C. Sohrabi, Z. Alsafi, N. O'Neill, M. Khan, A. Kerwan, A. Al-Jabir, C. Iosifidis, 19. The 2019 new coronavirus (COVID-19) has been reviewed in the International Journal of Surgery (2020 Feb 26), and the World Health Organization has declared a worldwide emergency.

R. Bärnighausen, S. Chen, J. Yang, W. Yang, C. Wang, and 20. New Year's Lancet (2020), 10.1016/S0140-6736(20)30421-9, discusses COVID-19 control in China amid large-scale population migrations.

S. Bobdey and S. Ray, 21Beyond clinical practice: a new vantage point for viral-COVID-19 effect evaluation J Mar Med Soc, vol. 22, no. 1, January 1, 2020, p. 9.

The authors of the article are Gozes O, Frid-Adar M, Greenspan H, Browning PD, Zhang H, Ji W, Bernheim A, and Siegel E. A short artificial intelligence development cycle for the COVID-19 pandemic: first findings for automated detection and patient monitoring using deep learning ct. March 10, 2020, arXiv preprint arXiv:2003.05037.

Twenty-three. B. Pirouz, S. Shaffiee Haghshenas, and P. PiroAn investigation into a major obstacle to sustainable development: the use of artificial intelligence and regression analysis for binary categorization of confirmed cases of COVID-19, a novel coronavirus. Sustainability, volume 12, issue 6, January 2020, page 2427.

24-Digital technology and COVID-19, in: Nat Med (2020 Mar 27), pp. 1-3, by D.S. Ting, L. Carin, V. Dzau, and T.Y. Wong

25. Wan, K.H., Huang, S.S., Young, A., and Lam, D.S. Ophthalmologists must take precautions in the event of a 2019 coronavirus pandemic (COVID-19). March 29, 2020, in Acta Ophthalmol.

26. Li, Li, Xu, Wang, Kun, Kong, Bai, Lu, Fang, Song, and Cao, K. Using AI, chest CT scans for COVID-19 may be differentiated from those for community-acquired pneumonia (2020 Mar 19), p. 200905.

The role of the internet of things in preventing the spread of the COVID-19 pandemic, Krishna Kumar, Narendra Kumar, and Rachna Shah, 2020, Vol. 1.

28. A.W. Smeulders, A.M. Van Ginneken, A study of pathology knowledge and decision making for the creation of consultation systems based on artificial intelligence Volume 11, Issue 3, June 1, 1989, Pages 154–165, Anal Quant Cytol Histol

29. R. Gupta, A. Misra, Controversial topics and developing ideas in the clinical presentation and treatment of individuals infected with COVID-19, particularly as it pertains to the utilization of treatments and other medications for co-morbid conditions (such as diabetes and hypertension). Clinical Research Review, Volume 14, Issue 3, May 2020, Pages 251-254, on the subject of diabetes and metabolic syndrome.

A.K. Singh, A. Misra, R. Gupta, A. Ghosh, Clinical concerns for diabetic patients during the COVID-19 pandemic, 30. Clinical Research on Diabetes and Metabolic Syndrome, Volume 14, Issue 3, Pages 211-212, 2020.

31. The Second Million People Needed to Combat the COVID-19 Outbreak Took Thirteen Days. The Hindustan Times, April 16, 2020. It took the globe thirteen days to obtain its second million instances of the COVID-19 pandemic, according to an article that can be found at https://www.hindustantimes.com/india-news/covid-19-outbreak/story-EUpP3YyAvbrnEF5Zq3qO0H.html.

World Economic Forum, Xiaoxia Q., April 8, 2020. A Look at How China's Next-Generation IT Battled the COVID-19 Pandemic. You can find this article at: https://www.weforum.org/agenda/2020/04/how-next-generation-information-technologies-tackedled-covid-19-in-china/.

The authors of the article are Reeves, Hollandsworth, and Torriani. An academic health system's quick reaction to the COVID-19 pandemic: health informatics assistance with outbreak management. Journal of the American Medical Informatics Association, 2020, doi: 10.1093/jamia/ocaa037.

34. The Coronavirus at Worldometers.info