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AI in Manufacturing and Processing: Shaping the Factories of the Future

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Abstract: This is a review of Artificial Intelligence (AI) and its impact in manufacturing and processing sectors. It emphasizes the fact that AI is to be integrated with Industry 4.0 technologies processes, i.e., the IoT, big data, edge computing, and cyber-physical systems that will allow monitoring in real-time, predictive maintenance, intelligent automation, and process optimization. The most important ones are the enhanced level of productivity, quality of goods, efficiency in terms of costs and better decision-making skills. Poor quality of data, high cost of implementation, employee resistance, and cybersecurity are some of the challenges of AI implementation in spite of its superiority. Future trends are also reviewed and they include explainable AI, human-AI collaboration, sustainable manufacturing, evaluation of federated learning and the presence of digital twins. With further development of AI, its ability to develop more intelligent, adaptive and environmentally friendly industrial systems is huge. Given that current main obstacles to the successful implementation of AI can be addressed by conducting research, innovating, and making important investments, it will lead to the next step of the industrial revolution.

Keywords: Artificial Intelligence, Industry 4.0, manufacturing, processing, IoT, predictive maintenance, automation, big data, edge computing, cyber-physical systems, quality control, sustainability, explainable AI, digital twins, federated learning.

INTRODUCTION

The phenomenon of Artificial Intelligence (AI) is one of the most influential processes that affect various industries, and the manufacturing and processing sphere is the first industry that faces this revolution. Historically these industries have in general been typified by mechanical systems, standardized processes and over dependence on human labor to keep them running including supervision, maintenance and control [1]. Nevertheless, the shortcomings of the traditional systems have become highly manifested due to the growing complexity and demands of production, customization and sustainability. This has increased the pace at which AI driven technologies are being adopted in order to develop more intelligent, adaptive and efficient industrial settings [2].

In the manufacturing and processing sense, AI has been used in or is defined as the application of algorithms and modeling techniques that are capable of analyzing information and using a certain pattern to make decisions, predict, and even execute some of the functions that might otherwise demand human intellect. The examples of such tasks are visual inspection, anomaly detection, predictive maintenance, process control, demand forecasting, and supply chain optimization [3]. With the data produced by industrial machines and sensors expanding exponentially, it has been necessitated to seek the help of AI systems in real-time in decoding the information dislodged and converting it into actionable information.

The AI-intake is strongly related to the whole Industry 4.0-paradigm that involves the combination of smart factories, cyber-physical systems, and networked production spheres. The role of AI in such a system is that it serves as the brain of the digital ecosystem to interpret sensor information, intelligently guide robotics systems, forecast failures, and anticipate performance [4]. As an example, the use of AI in predictive maintenance can cut unplanned outage by a significant margin by anticipating wear or malfunction of equipment prior to failure. Likewise, AI applications of computer vision-based quality control sensors would allow isolating a microscopic flaw faster and more efficiently on assembly lines than a human inspector working outside of assembly lines with microscopes [5].

AI is used to provide precision, compliance and traceability in the processing industries, i.e., food, pharmaceuticals, chemicals, and metals. Such fields are frequently characterized by non-linear interactions that are non-linear and not predictable because it is responsive to parameters that are not consistent such as the temperature, press and even composition. These processes are complex spaces that can be represented by AI algorithms and can be predicted and tune on the fly with the same type of predictable behavior and compliance with the regulatory demands [6].

Along with the numerous benefits, the introduction of AI to the manufacturing and processing industries implies serious struggles as well. These are the necessity of big-quality set of data, high initial investment, the necessity to combine with older systems, the absence of qualified staff, and data privacy and cybersecurity issues [7]. Workforce cultural opposition and job displacement situations are key issues that cannot be ignored by organizations and only exposed to training and strategic change management.

It is believed that as the AI technologies keep improving, there is an even brighter future in the manufacturing and processing industries. Industrial possibilities can be further improved by such innovations as explainable artificial intelligence, edge computing, federated learning, and artificially enhanced sustainability measures. This review seeks to document a systematic review of the promotion of AI in manufacturing and processing, AI applications, its advantages, disadvantages, and its future, and give information involving the utilization of AI in route to long-term prosperity in the industries [8].

SUMMARY OF THE AI TECHNOLOGY IN INDUSTRIAL USES

Artificial Intelligence (AI) represents an array of technologies that allow machines and systems to complete the tasks normally requiring human intelligence. AI technologies are also being implemented into the life of the manufacturing and processing industries to make processes automatized, operations optimized, improve the quality of the product manufactured, and utilize information-powered decision-making. This part dwells upon the main technologies of AI which are predetermining the scene of the modern industry [9].

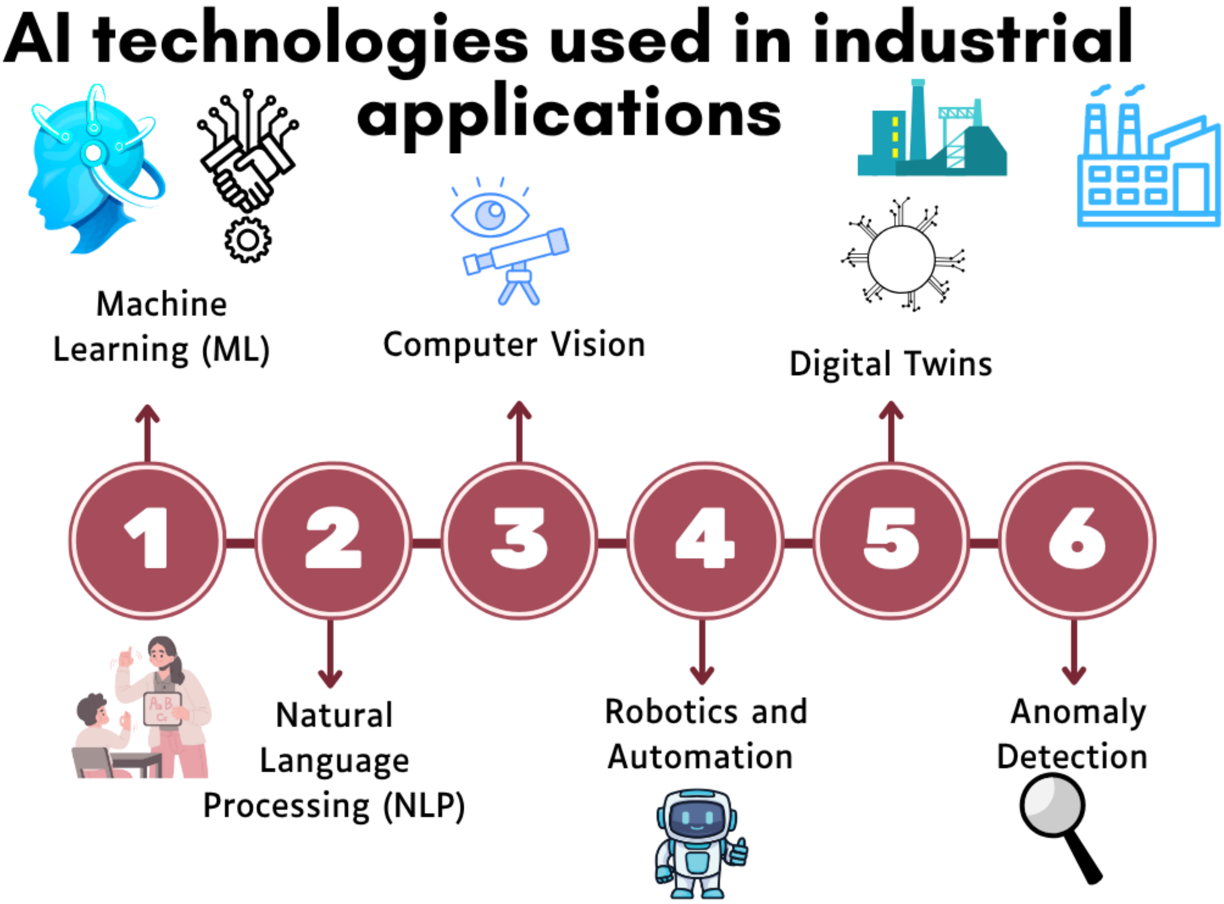

Figure: 1 showing AI technologies used in industrial applications

One of the most used AI technologies promoted in industrial practice is Machine Learning. ML comprises training algorithms using past information to be used to make predictions or decisions that have not been explicitly programmed to handle each scenario. ML finds applications in the manufacturing and processing industries, where maintenance can be predicted, based on demand forecasting, optimizing the process and detecting anomalies [10]. The decision tree and support vector machines are specific examples of supervised learning strategy, which is especially helpful in terms of classification and regression, whereas the pattern recognition and clustering are performed using the unsupervised learning [11].

Deep Learning, a subfield of ML, applies complicated models on data (using neural networks) having a lot of layers, to predict complex patterns in the data. The DL has become successful in manufacturing processing fields because of its performance in image recognition, speech recognition, resulting in significance most useful in applications such as visual inspection automatization, defects identification and fault diagnosis. Conventional Neural Networks (CNNs) have been applied in computer vision systems, but Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks could be used in processing time-series data and predictive models [12]. Computer vision gives machines the possibility to make sense of the visual data in the real world. Surface quality control, inspection of defects, assembly line monitoring and consistency of products, particularly in terms of surface inspection, are all tasks that this technology is important to manufacturing. Computer vision can be performed in real time by combining the high-resolution cameras and image processing algorithms, thus becoming faster and more error resistant to human beings [13].

Natural Language Processing is a possibility that enables machines to comprehend, interpret, and produce human language. Its uses in manufacturing are still nascent but applications exist in maintenance report analysis, customer service automation and extraction of knowledge based on documents in the technical field. NLP can also help in human-machine interaction in the form of chat boxes and verbal-generated systems within the factory floor further which will help in the course of better operations. Reinforcement Learning (RL) Reinforcement Learning (RL) train agent to make decisions through rewards and desirable actions. In industrial settings, RL can be used to optimize control policies in complicated systems like path planning of robots, energy management and adaptive process control [14]. RL-based intelligent agents are capable of learning about their environment during its interactions with it and developing over time to produce system performance, which is increasingly autonomous in manufacturing. All of these AI technologies, when combined, comprise the core of intelligent manufacturing and processing systems, and allow moving on to transformational automation, smart, adaptive, and self-optimized operations [15].

USES OF AI IN MANUFACTURING

With the help of Artificial Intelligence (AI), the manufacturing industry is fast adapting to a world where the whole process of production is very intelligent, quick and quite feasible. AI amplifies all the manufacturing life cycle practices through the employment of data-supported algorithms, via design and production processes, maintenance, and quality control. In this part, several main AI applications are emphasized and are transforming the manufacturing processes [16].

AI use in manufacturing has one of the most significant applications, which is predictive maintenance. Manufacturers can harness machine learning abilities by analyzing sensors that collect information in the form of vibration, temperature, pressure, etc. on equipment and create predictions of when a machine is about to break and place maintenance at that time [17]. The method limits the level of unexpected downtime, lowers the expenditure on repair, and prolongs the life of the equipment. The models of artificial intelligence (AI) are constantly getting better with time on the basis of historical failures and their accuracy predictions grow stronger and more precise [18].

There is the possibility of using AI algorithms in order to analyze a complex production process and discern certain patterns that human operators will not be able to pay enough attention to. This can enable process parameters to be real-time optimised; this includes temperature, speed and pressure. As an illustration, AI can make dynamic changes to input variables to enhance yield, minimise wastages and guarantee the quality of the output products. Deep learning and reinforcement learning models are exceptionally functional in adjusting to the diversifying circumstances and streamlining multi-step production systems [19].

Deep learning-based computer vision systems are transforming quality control in a dramatic way. The cameras on the production lines take pictures of the products on the line in real time which is then analyzed by the AI models that detect defects in the product which may include crack, alignment issues or surface irregularities. Such systems are more accurate and consistent besides being faster than human inspectors. By training AI, it will be possible to implement even finer flaws and attain a higher standard of quality that will lead to lesser complaints by customers [20]. Exert a larger flexibility and intelligence to automated manufacturing systems is being provided by AI-enhanced robotics. In contrast to the traditional robots, which behave according to strict routines, AI-equipped robots are able to learn their surroundings, work on different tasks and even acquire new skills [21]. Smart robots (also known as cobots) have the ability to work closely with people using AI and can increase output in their lines such as assembly, packaging, and welding. Robotic vision is able to detect and handle objects accurately allowing complicated and tailored tasks [22].

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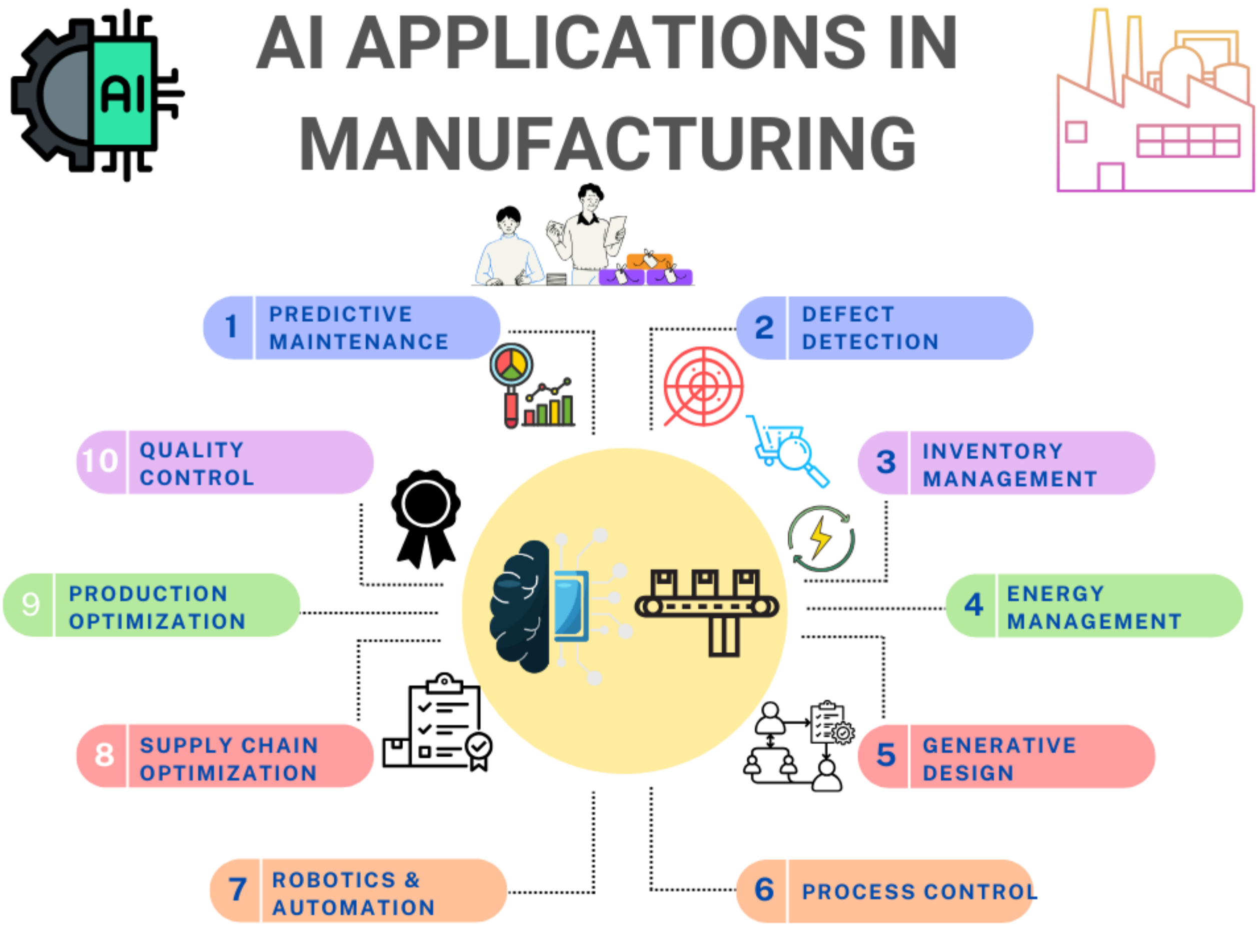

Figure: 2 showing AI applications in manufacturing

Digital twin can be defined as a representation of a physical manufacturing system in virtual format that reflects real-time operations. The AI is important in the simulation and optimization of digital twins by using data and providing predictions of future events. The sense of the central intelligence in the smart factories is AI, which interrelates different subsystems: machines, sensors, and workers, as well as creates a self-healing ecosystem. This results in higher agility, real-time progressing, and incessant enhancement of manufacturing performance [23].

PROCESSING INDUSTRIES APPLICATIONS OF AI

Artificial Intelligence (AI) is not only the discontinuous manufacturer, but AI is also contributing to transformations in the processing industries, including chemical, food processing, pharmaceutical, and metallurgical processes. These are industries whose admission to continuous or batch processes is essential because the accuracy, safety, and productivity are considered to be vital [24]. The application of AI technologies, in particular, machine learning and real-time analytics, mastered to optimize the processes, better the quality of products, minimize waste, and make the processes safer. This part presents a high-value summary of AI application in different fields of processing [25].

AI finds application in the optimization of the processes and emissions and detection of faults in the chemical and petrochemical industries. Compound procedures are known to have lots of variables which prove to be tricky to model them using traditional approaches. As compared with linear systems that have only a few variables, AI is capable of handling multivariable systems that are non-linear and can give insights that aid in the optimization of reaction conditions, catalyst and yield [26]. As an example, machine learning can be used to forecast the action of chemical reactions based on different inputs which help engineers to optimise parameters to be the most efficient. Also, AI-based systems used to monitor the equipment identify anomalies in time and mitigate the possibility of the equipment malfunction and dangerous accidents.

In food processing, AI is becoming more widespread in quality management, automation of the process, and supply chains. Deep learning technologies can be used to check the quality of food products in real-time with the help of computer vision. The mixing, heating, and cooling process with the help of AI algorithms are also optimized according to the response of sensors, so the mixing and heating and cooling processes are consistent and do not harm the safety standards [27]. The AI can assist in demand creation and management of the inventory, diminishing the number of wasted foods and increasing sensitivity to the needs of the consumers.

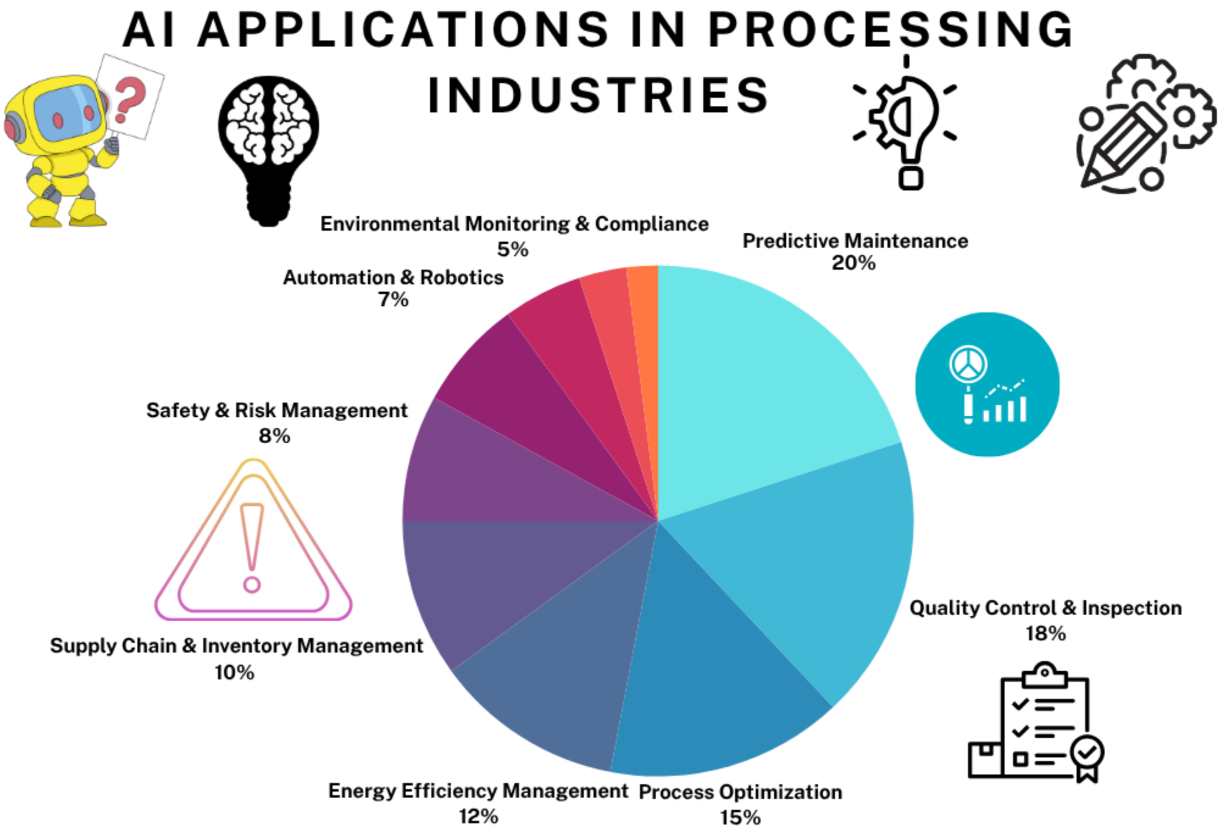

Figure: 3 showing AI applications in processing industries

The pharmaceutical processing must comply with regulatory requirements, precision, and consistency. AI is helpful to analogy to understanding of process analytical technology (PAT) that enables real-time monitoring and control of important quality characteristics of the drug manufacturing process. Cost reductions: It is possible to model machine learning to predict results, given raw material properties and process variables thus making a stronger formulation and the less likelihood of batch failures [28]. AI also aids in drug design and development using large volumes of information to recognize potential compounds and maximize clinical trials. In manufacturing, AI guarantees compliance, lower variance, and enhanced operation efficiency [29].

In metal making industries including steel making, glass manufacture and ceramics, AI finds application in energy-use optimization, furnace process management, and product consistency. Real-time AI models study sensor data to control temperatures, forecast the property of materials, and minimize defects. An example can be metallurgy where AI-driven simulations can be used to optimize the composition of alloys or casting procedures that confer preferred strength and durability properties. Such gains are reflected in the manner of reduced expenses, better quality, and sustainability [30].

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ARTIFICIAL INTELLIGENCE COMBINED AND USED WITH THE INDUSTRY 4.0 TECHNOLOGIES

Artificial Intelligence (AI) is redefining the industry of manufacturing and processing together with Industry 4.0 technologies. Industry 4.0 would be the transformation of the digitalization of industrial processes, integrating cyber-physical systems, intelligent sensors, IoT (Internet of Things), big data analysis and cloud computing [31]. AI is the brain in this ecosystem, that makes machines and systems learn by observing data and making automatic choices and adjusting to any changing situations in real time. In this section, how AI complements the essential Industry 4.0 drivers to establish smart, networked and highly productive industrial settings is discussed [32].

The Internet of Things (IoT) is regarded as the connection of industrial equipment along with sensors to the internet, which would provide them with permanent data collection and communication. AI uses the large amounts of information that are created by IoT devices to find patterns, anomalies, and inefficiencies. As an example, data of sensors that measure pressure, temperature, or vibration could be used in real-time to input into AI models to provide outcomes on predictive maintenance or quality assurance [33].

Since computation is located too far away from the place where the data is created then edge computing is vital. This minimizes latencies and bandwidth which allows real-time AI decision-making at the factory level itself. As an example, an AI-enabled smart camera placed on a packaging line can scan defects real time without requiring transmissions to the cloud. Since manufacturing and processing industries produce enormous sets of both structured and unstructured data using machines, enterprise systems and external sources [34]. With the help of big data analytics, AI makes it possible to extract meaning out of this data. Analytics using AI can optimize the processes, predict customer demand, control quality, and the supply chain. Such insights enable organizations to transform reactive decision-making to predictive and prescriptive decision-making [35].

AI models get more and more accurate as they are trained on historical data and real-time information consistently. As an example, historical and current machine running and environment measurements may be used to optimize production times and limit energy use. Cyber-physical systems are actually physical systems augmented with computer-based intelligence, and therefore promise simultaneous monitoring, control and automation [36]. AI improves CPS because it allows adaptive and autonomous decision-making. In a smart factory, AI enabled CPS are able to adapt to disturbances (such as a change in the supply chain rates or failures of equipment) and can flexibly reactivate operations without direct human action. This makes production environment quite fluid and hardy [37].

One example of CPS that has a high potential in the application of AI is digital twins or virtual representations of actual systems. With the ability to simulate the real world and predict behaviors, AI-powered digital twins are beneficial to proactive maintenance, design optimization, and planning of operational activity. AI tools cannot work without much computational power and storage, which are provided by cloud computing frequently [38]. The cloud enables the possibility of centralized large-scale analytics, model training and data storage. At the same time, fog computing is an intermediary between edge and cloud that provides local computing power to make nearly timely AI-based decisions and remain in sync with cloud-based systems. Combined, these integrations enable the AI to flourish within the complicated industrial scenarios providing intelligent, scalable, and diving solutions that decontextualize the manufacturing and processing within the era of Industry 4.0 [39].

BENEFITS AND IMPACT OF AI ADOPTION

Embarking on Artificial Intelligence (AI) in manufacturing and processing has been revolutionary towards changes in operations, quality control, supply chain, and business models. Through the power of machine learning, computer vision, predictive analytics and intelligent automation companies are now operating at new efficiencies, accuracies and agilities. This part mentions the main advantages and the overall effect of AI adoption to a working industry [40]. Among the short-term advantages of AI in the manufacturing and processing sector is the high increase in the efficiency of the operations. AI algorithms have the capabilities to track production parameters in real-time, decreasing the cycle times, minimizing the downtimes, and removing the bottlenecks. To illustrate, the resources and work processes may be distributed with AI-based scheduling systems and fulfil their purpose based on allowed throughput [41]. Moreover, robotic process automation (RPA) and AI-powered machine perform repetitive tasks more consistently and quickly than human hands and enable an increase in productivity.

Computer vision combined with deep learning allows finding even minor flaws using AI-based quality control systems in real-time. This will make sure that only items that uphold predetermined standards of quality will go through the assembly line. AI can also make processes, products, and services more consistent with each other by keeping a close hold on any variables that have an impact on their quality (i.e. temperature, pressure, material composition) [42]. This leads to increased customer satisfaction and reduction in the rate of returns or rework by a large margin. The cost savings that are made through AI are in several forms. Predictive maintenance saves money by reducing unscheduled downt 且 time and maintaining or replacing equipment and preserving equipment life cheaply. Optimization of the processes reduces the waste, energy and ineffective labor use [43]. The utilization of AI will streamline the inventory management process as it will serve in forecasting the demand, minimizing the over production and costs of holding stock. This is a cumulative saving that yields a greater level of Return on Investment (ROI) to AI-powered systems.

AI delivers practical knowledge through data mining and processing in big amounts of data found in different sources like machines, sensors, supply chains, and customer reviews. These learnings will help decision-makers make strategic plans, risk evaluations, and operational changes. As an example, AI-powered dashboards in real-time may warn managers of the system inefficiencies or deviations and make timely adjustments [44]. Another role that AI plays in dynamic environments is scenario planning and simulation, which allow more informed, swift responses to changes in market demand, or disruption in the supply chain. The reason is that the use of the AI in the manufacturing/processing industries has wider implications than simply automation does. It gives organizations the power to create more competitive, adaptive and sustainable organizations that will lead to smarter factories and data driven industrial ecosystems. These advantages are still increasing as the AI technologies are developing and are becoming more accessible in many fields [45].

ISSUES AND PROBLEMS OF IMPLEMENTATION

Artificial Intelligence (AI) has a transformative power in manufacturing and processing sectors, but the introduction of the latter does not go without issues. To introduce AI technologies, several barriers need to be overcome: they cannot be based only on one or another type but must be a synthesis of technical, organizational, financial, and ethical obstacles. Such problems are capable of slowing or preventing integration unless proper control is observed. In this section, the paper discusses some of the most notable challenges that industries encounter during the implementation of AI solutions [46].

The decision-making and training of AI systems highly depend on vast amounts of correctly labeled, quality, and precise data. Nevertheless, disintegrated or insufficient information sources are predominant in a lot of industrial settings. Old equipment might lack sensors and connectivity to receive real time data. There might also be instances when the data is not structured, not consistent, or sparse and this does not enable efficient model training [47]. In the absence of hygienic and accessible data, AI application performance and reliability is badly damaged. The deployment of AI-and particularly at scale-can be extensive. The costs might be involved in improving the current infrastructure, buying new devices, introducing software systems, and recruiting special skills [48]. These start-up expenses might be too high on small and medium sized enterprises (SMEs). Also, organizations might find it difficult to measure definite return on investment (ROI) since long-term performance and values created are not predictable. This financial risk is usually at the cost of reluctance or smaller pilot-scale installations [49].

Implementation of AI demands knowledge of data science, machine learning, industrial automation as well as cyber-security skills which are in high demand but low supply. The manufacturing and the processing companies have either the deficiency of the in-house capabilities or the availability of the desired talent pool. In addition, resistance by the workforce may also be a problem. Automation may present the employees with the fear of displacement of their jobs, and they may also refuse to embrace new technologies hence creating a cultural hindrance to the acceptance of AI [50].

Since machines are at the connected facilities, there is a growing concern that cyber threats will also rise. Weaknesses in the AI or data pipelines may leak sensitive details of an operation or cause a cyber attack. Excessive security measures will ensure safe AI implementation. Also, ethical issues, including bias of algorithms, transparency (black-box models), and responsibility of decisions, should be mentioned, especially in regulated fields such an industry, like pharmaceuticals or food processing [51]. Although manufacturing and processing industries have large potential to exploit the capabilities of AI, solving such issues is important to achieve successful implementation. The systemic reduction of data quality, making better decisions with limited investments and upskilling the employees alongside establishing trust in AI systems will bring sustainability and responsible industrial transformation driven by AI [52].

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DIRECTIONS IN AI-BASED FUTURE RESEARCH AND TRENDS IN MANUFACTURING AND PROCESSING

Artificial Intelligence (AI) is finding other uses in manufacturing and processing industries besides automation and optimization as it keeps transforming. Tender is that in the future, smarter, self-governing, and intelligent industrial framework would be perceived more adaptive and responsive to dynamic conditions, changing market needs, and environmental factors [53]. Future artificial intelligence applications are in progress with continuous research and development along with the technological progress to create more explainable, sustainable and humane applications. It gives in this section the major future trends and active research directions elsewhere in the field [54].

The very next crucial direction relates to the development of the so-called explainable AI (XAI)- systems capable of not just making the predictions or decisions but also explaining them. Black-box AI models can be troublesome in the manufacturing and processing, where safety, consistency, and traceability are at stake [55]. Scientists are already developing methods, which would inject greater transparency to AI models, so that operators and engineers can learn to trust, understand AI systems and work with them efficiently. This even promotes regulatory compliance, especially in such industries as pharmaceuticals and food processing [56].

Instead of automating the work of human employees, the industry of the future with AI would be used to complement human judgment. High-performance human-AI interfaces, including those based on AI assistants, voice-based interfaces, and mixed reality, will extend the performance of operators in monitoring, maintenance, and control. There is increasing research interest in adaptive systems, which through input by people learn and make collaboration between machine and worker easier. This also responds to the workforce issues and leads to upskilling and job reshaping instead of the destruction [57].

The volume of data is growing and the demand to make decisions faster is rising, which makes AI models closer to the data source in the form of edge computing. A new crop of systems will include Edge AI, in which models run on local devices (smart sensors, controller, or embedded systems). This minimizes latency, better-improves data privacy, and allows real-time critical process monitoring and control. Future works are dedicated to the creation of energy-efficient, lightweight AI that will be able to work in edge settings reliably [58].

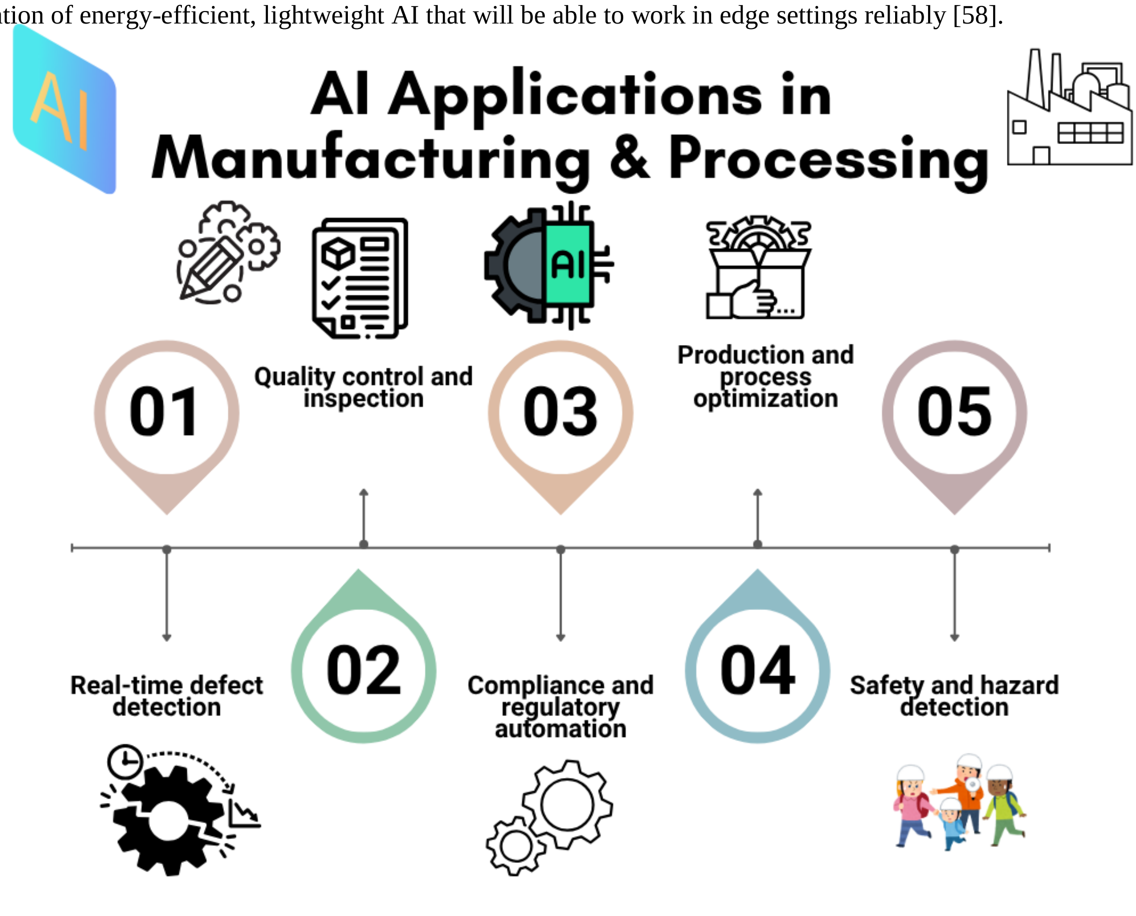

Figure: 4 showing AI applications in manufacturing and processing

The concept of sustainability is gaining prominence amongst industries. AI will become an essential contributor to green manufacturing by maximizing the use of energy, minimizing wastes, and promoting the practices of a circular economy. Example: AI may process information about the production process and determine the inefficiencies or propose options to use other materials that have a lesser environmental cost [59]. Research is also in progress to see how AI may be used to monitor carbon footprints and undergo recycling processes as well as allow sustainable planning in supply chains.

The next industrial AI will be more integrated with the rest of the innovative technologies such as 5G, blockchain, quantum computing, and digital twins. The AI systems will become responsive and scalable at ultra-fast data transmission with the 5G. The data integrity and traceability in a multi-stakeholder setting, such as food and pharmaceutical processing, can be improved by the use of blockchain [60]. Quantum computing has the potential to solve complex optimization, in manufacturing, and AI-powered digital twins will be able to simulate an entire factory or supply chains to allow predictive planning and scenario analysis [61].

With privacy rules becoming more stringent worldwide, the field of study is shifting to federated learning, where machine learning models obtain training at decentralized repositories without necessarily exchanging unprocessed data. This will enable a group of plants or companies to better AI models without necessarily sharing any proprietary or sensitive information. Federated learning also has high potential in the industries where the sharing of data is limited by competitive or legal issues [62]. The AI in the manufacturing and processing industry has an optimistic future. New directions are shifting towards more explainable, sustainable, distributed, and collaborative on AI systems. It will be important to constantly research and innovate to take full advantage of AI and overcome the existing shortcomings in AI to realize the next generation of smart and resilient and adaptive industrial processes.

CONCLUSION

Artificial Intelligence (AI) has become a fortress on the way to changing the production and processing industries. The potential of AI technologies or use cases are led to the possibility to not only improve the efficiency of operations, but also to create predictive maintenance and intelligent automation capabilities. This review has discussed the increasing relevance of AI in the industrial industry and how it has come to intertwine with technologies being used in industry 4.0, its many applications and some of its advantages as well as its shortcomings. The significance of the AI in the contemporary manufacturing and processing can hardly be overemphasized. It allows analyzing the data in real-time, find faults, control quality, and optimize processes, and a lot more. Not only do all those abilities lead to effective production due to efficiency and reduced operation costs, but safer and more sustainable practices are provided. Specifically, processing industries such as food, pharmaceuticals, chemicals and littoral industries are progressively turning to AI to guarantee regularity, conformity as well as accuracy.

The industrial manifestation of AI can be characterized by the synergy it has with the Industry 4.0 technologies. AI transforms into an effective agent of the smart, connected, and autonomous industrial environment after integration with such solutions as IoT, edge computing, big data analytics, cyber-physical systems, and cloud platforms. AI is used to process raw sensor data into insights and inform about what should be done to make the system change on the fly and provide smart decisions. Such technologies as digital twins and edge AI provide a good example of how AI may be centralized to optimize operation, and decentralized to control in real-time. The advantages of the usage of AI are obvious: an increased productivity and the quality of the products offered, less downtimes, a better usage of the resources available, and smarter decision making assets. Nevertheless, the way to total integration does not run without obstacles. Poor data quality, initial high costs, talent shortages, and issues associated with cybersecurity are the challenges that industries encounter. Another dimension is resistance to change especially when it comes to the workforce. To solve such problems, it is important that the technical methods should be supplemented by those of organization and long-range vision.

In the future, the potential in AI in the manufacturing and processing industries is considerable. Such trends as explainable AI, human-AI collaboration, edge intelligence, and sustainable AI deliver indications toward the new era of more transparent, efficient, and environmentally conscious industrial processes. Innovation will also be driven by research in federated learning, quantum-enhanced optimization and AI-based digital twins. Certainly the industry is shifting to the adaptation of not only smart but also adaptive, ethical, and human-friendly systems. AI does not exist as a simple tool but is a revolutionizing aspect that is redefining the industrial scene. A comprehensive view should be adopted by stakeholders, which includes investing in infrastructure, developing digital talent, becoming innovative, and trusting AI systems. Through this, the manufacturing and processing industries will be able to access new ideas of performance, sustainability, resilience, never seen before.

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